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(71) Applicant: NVIDIA CORPORATION [US/US]; 2788

San Tomas Expressway, Santa Clara, California 95051 (US).

(72) Inventors: CHOI, Jiwoong; 2788 San Tomas Expressway,

Santa Clara, California 95051 (US). ALVAREZ LOPEZ,

Jose Manuel; 2788 San Tomas Expressway, Santa Clara, California 95051 (US).

(74) Agent: ROSENTHAL, Gregory B. et al.; c/o IP Docketing Dept., Davis Wright Tremaine LLP, 920 Fifth Avenue, Suite 3300, Seattle, Washington 98104-1610 (US).

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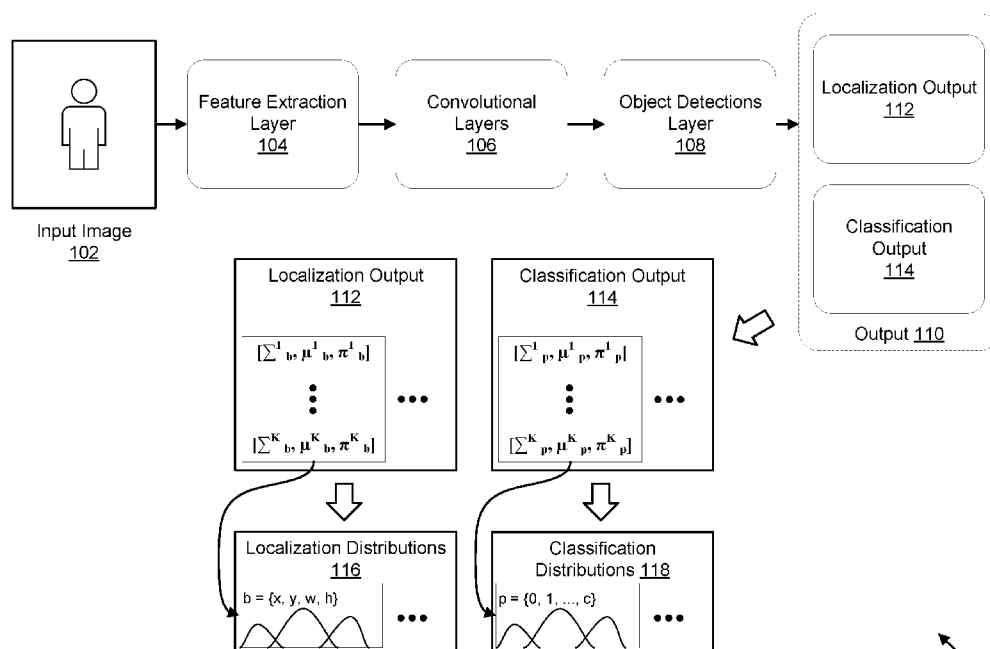


FIG. 1

100

(57) Abstract: Apparatuses, systems, and techniques to identify one or more objects in one or more images. In at least one embodiment, one or more objects are identified in one or more images based, at least in part, on a likelihood that one or more objects is different from other objects in one or more images.

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5 ENHANCED OBJECT IDENTIFICATION USING ONE OR MORE
 NEURAL NETWORKS

CROSS REFERENCE TO RELATED APPLICATION

[0001] This application claims priority to U.S. Patent Application No. 16/990,881, filed August 11, 2020, entitled “ENHANCED OBJECT IDENTIFICATION USING ONE OR
10 MORE NEURAL NETWORKS,” the entire contents of which is incorporated herein by reference in its entirety and for all purposes.

TECHNICAL FIELD

[0002] At least one embodiment pertains to identifying one or more objects in one or more images. For example, at least one embodiment pertains to identifying one or more objects in
15 one or more images based, at least in part, on a likelihood that one or more objects is different from other objects in one or more images.

BACKGROUND

[0003] Identifying objects in images can use significant memory, time, or computing resources. Amounts of memory, time, or computing resources used to identify objects in
20 images can be improved.

BRIEF DESCRIPTION OF DRAWINGS

[0004] FIG. 1 illustrates a diagram of a network architecture, according to at least one embodiment;

[0005] FIG. 2 illustrates a diagram of determining probability distribution parameters,
25 according to at least one embodiment;

[0006] FIG. 3 illustrates a diagram of determining image scores, according to at least one embodiment;

[0007] FIG. 4 shows an illustrative example of a process to determine an informativeness score for an image, according to at least one embodiment;

30 [0008] FIG. 5 shows an illustrative example of a process to train a network, according to at least one embodiment;

- 5 [0009] FIG. 6A illustrates inference and/or training logic, according to at least one embodiment;
- [0010] FIG. 6B illustrates inference and/or training logic, according to at least one embodiment;
- [0011] FIG. 7 illustrates training and deployment of a neural network, according to at least
10 one embodiment;
- [0012] FIG. 8 illustrates an example data center system, according to at least one embodiment;
- [0013] FIG. 9A illustrates an example of an autonomous vehicle, according to at least one embodiment;
- 15 [0014] FIG. 9B illustrates an example of camera locations and fields of view for the autonomous vehicle of FIG. 9A, according to at least one embodiment;
- [0015] FIG. 9C is a block diagram illustrating an example system architecture for the autonomous vehicle of FIG. 9A, according to at least one embodiment;
- [0016] FIG. 9D is a diagram illustrating a system for communication between cloud-based
20 server(s) and the autonomous vehicle of FIG. 9A, according to at least one embodiment;
- [0017] FIG. 10 is a block diagram illustrating a computer system, according to at least one embodiment;
- [0018] FIG. 11 is a block diagram illustrating a computer system, according to at least one embodiment;
- 25 [0019] FIG. 12 illustrates a computer system, according to at least one embodiment;
- [0020] FIG. 13 illustrates a computer system, according to at least one embodiment;
- [0021] FIG. 14A illustrates a computer system, according to at least one embodiment;
- [0022] FIG. 14B illustrates a computer system, according to at least one embodiment;
- [0023] FIG. 14C illustrates a computer system, according to at least one embodiment;
- 30 [0024] FIG. 14D illustrates a computer system, according to at least one embodiment;

- 5 [0025] FIGS. 14E and 14F illustrate a shared programming model, according to at least one embodiment;
- [0026] FIG. 15 illustrates exemplary integrated circuits and associated graphics processors, according to at least one embodiment;
- [0027] FIGS. 16A and 16B illustrate exemplary integrated circuits and associated graphics
10 processors, according to at least one embodiment;
- [0028] FIGS. 17A and 17B illustrate additional exemplary graphics processor logic according to at least one embodiment;
- [0029] FIG. 18 illustrates a computer system, according to at least one embodiment;
- [0030] FIG. 19A illustrates a parallel processor, according to at least one embodiment;
- 15 [0031] FIG. 19B illustrates a partition unit, according to at least one embodiment;
- [0032] FIG. 19C illustrates a processing cluster, according to at least one embodiment;
- [0033] FIG. 19D illustrates a graphics multiprocessor, according to at least one embodiment;
- [0034] FIG. 20 illustrates a multi-graphics processing unit (GPU) system, according to at
20 least one embodiment;
- [0035] FIG. 21 illustrates a graphics processor, according to at least one embodiment;
- [0036] FIG. 22 is a block diagram illustrating a processor micro-architecture for a processor, according to at least one embodiment;
- [0037] FIG. 23 illustrates a deep learning application processor, according to at least one
25 embodiment;
- [0038] FIG. 24 is a block diagram illustrating an example neuromorphic processor, according to at least one embodiment;
- [0039] FIG. 25 illustrates at least portions of a graphics processor, according to one or more embodiments;
- 30 [0040] FIG. 26 illustrates at least portions of a graphics processor, according to one or more embodiments;

- 5 [0041] FIG. 27 illustrates at least portions of a graphics processor, according to one or more embodiments;
- [0042] FIG. 28 is a block diagram of a graphics processing engine of a graphics processor in accordance with at least one embodiment;
- [0043] FIG. 29 is a block diagram of at least portions of a graphics processor core,
10 according to at least one embodiment;
- [0044] FIGS. 30A and 30B illustrate thread execution logic including an array of processing elements of a graphics processor core according to at least one embodiment;
- [0045] FIG. 31 illustrates a parallel processing unit (“PPU”), according to at least one embodiment;
- 15 [0046] FIG. 32 illustrates a general processing cluster (“GPC”), according to at least one embodiment;
- [0047] FIG. 33 illustrates a memory partition unit of a parallel processing unit (“PPU”), according to at least one embodiment;
- [0048] FIG. 34 illustrates a streaming multi-processor, according to at least one
20 embodiment.
- [0049] FIG. 35 is an example data flow diagram for an advanced computing pipeline, in accordance with at least one embodiment;
- [0050] FIG. 36 is a system diagram for an example system for training, adapting, instantiating and deploying machine learning models in an advanced computing pipeline, in
25 accordance with at least one embodiment;
- [0051] FIG. 37 includes an example illustration of an advanced computing pipeline 3610A for processing imaging data, in accordance with at least one embodiment;
- [0052] FIG. 38A includes an example data flow diagram of a virtual instrument supporting an ultrasound device, in accordance with at least one embodiment;
- 30 [0053] FIG. 38B includes an example data flow diagram of a virtual instrument supporting an CT scanner, in accordance with at least one embodiment;
- [0054] FIG. 39A illustrates a data flow diagram for a process to train a machine learning model, in accordance with at least one embodiment; and

- 5 [0055] FIG. 39B is an example illustration of a client-server architecture to enhance annotation tools with pre-trained annotation models, in accordance with at least one embodiment.

DETAILED DESCRIPTION

- 10 [0056] In at least one embodiment, a deep detection neural network is a neural network that detects and classifies objects in one or more images. In at least one embodiment, accuracy of deep detection neural networks often rely on large datasets for training and can require large labeling budgets. In at least one embodiment, active learning is a neural network training method that reduces labeling costs by selecting only those samples that are informative to improve an accuracy of a network.

- 15 [0057] In at least one embodiment, deep active learning is utilized for object detection. In at least one embodiment, a deep object detection network outputs a complete mixture distribution for localization and classification outputs and utilizes them to estimate uncertainty of each sample. In at least one embodiment, a mixture density network is utilized to predict parameters of a Gaussian mixture model. In at least one embodiment, a deep object
20 detection network, through determining localization and classification probability distributions, estimates epistemic and aleatoric uncertainties separately, without requiring Monte Carlo sampling or ensembles.

- [0058] Deep learning in object detection neural networks can require large scale data sets that comprise training images. Training images can comprise one or more objects, and each
25 object can require a category and a bounding box; labeling training images can require large amounts of time and resources. In at least one embodiment, active learning aims at selecting a smallest possible training set to solve a specific task. In at least one embodiment, active learning methods involve a model in a selection of what images to learn from. In at least one embodiment, a selection process is generally based on a predictive uncertainty of an image,
30 which indicates how informative an image is for a model.

- [0059] In at least one embodiment, predictive uncertainty can be decomposed into two types of uncertainties, aleatoric and epistemic. In at least one embodiment, aleatoric uncertainty (also referred to as statistical) refers to a notion of randomness, or noise inherent in observations, such as sensor noise. In at least one embodiment, aleatoric uncertainty can be
35 attributed to occlusions, lack of visual features, or object distance. In at least one embodiment, epistemic uncertainty (also referred to as systematic) refers to an uncertainty

5 caused by a lack of knowledge. In at least one embodiment, epistemic uncertainty can be reduced given enough additional data. In at least one embodiment, epistemic uncertainty refers to a reducible part of an uncertainty while aleatoric uncertainty refers to a non-reducible part.

[0060] In at least one embodiment, an active learning method for object detection predicts
10 uncertainty for deep object detection. In at least one embodiment, an active learning method for object detection utilizes mixture density networks to learn parameters of a Gaussian mixture model. In at least one embodiment, an active learning method for object detection estimates uncertainty for both classification and localization outputs in a single forward pass. In at least one embodiment, a loss function is utilized to train a deep object detection network
15 and serves as a regularizer for inconsistent data.

[0061] In at least one embodiment, a deep object detection network is based on mixture density networks and predicts uncertainty using a single forward pass. In at least one embodiment, a loss function is utilized to train mixture model-based object detection networks. In at least one embodiment, a scoring function is utilized that combines aleatoric
20 and epistemic uncertainty scores, also referred to as uncertainties, uncertainty values, and/or variations thereof, in classification and localization outputs. In at least one embodiment, an active learning method for object detection utilizes a scoring function that uses both localization and classification-based uncertainties to quantify an informativeness of an image. In at least one embodiment, higher values of uncertainty result in higher values of
25 informativeness (e.g., uncertainty and informativeness are positively or directly correlated). In at least one embodiment, informativeness refers to a measure of how much potential information an image may have that, if labeled, can be used to increase an accuracy of a neural network. In at least one embodiment, an active learning method for object detection determines informativeness scores of one or more training images to determine which images
30 of said one or more training images are most informative, in which said determined images are labeled and utilized to train a neural network.

[0062] FIG. 1 illustrates a diagram 100 of a network architecture, according to at least one embodiment. In at least one embodiment, FIG. 1 illustrates an architecture of a deep object detection network. In at least one embodiment, a deep object detection network is utilized to
35 model uncertainty in a single forward pass. In at least one embodiment, a forward pass refers to one or more calculation processes of a neural network in which an output is determined

- 5 from an input through layers of said neural network. In at least one embodiment, a deep object detection network comprises one or more mixture density networks where outputs comprise parameters of Gaussian Mixture Models (GMMs). In at least one embodiment, a deep object detection network combines predictions from multiple feature maps with different resolutions to handle objects of various sizes.
- 10 [0063] In at least one embodiment, a deep object detection network predicts, on each location of a feature map of an image, probability distributions for coordinates of bounding boxes that potentially correspond to objects of said image, and probability distributions for potential classifications of said bounding boxes. In at least one embodiment, a deep object detection network predicts one or more probability distributions for classification and
- 15 localization. In at least one embodiment, a deep object detection network obtains an input image 102 and generates an output 110 comprising a localization output 112 and a classification output 114, and comprises a feature extraction layer 104, convolutional layers 106, and an object detections layer 108.
- [0064] In at least one embodiment, a deep object detection network receives input image
- 20 102. In at least one embodiment, input image 102 is a two-dimensional image. In at least one embodiment, input image 102 is one or more frames of one or more videos. In at least one embodiment, input image 102 is an image that depicts one or more objects of one or more classifications. In at least one embodiment, referring to FIG. 1, input image 102 is an image that comprises a depiction of a human. In at least one embodiment, feature extraction layer
- 25 104 determines feature maps from one or more input images, such as input image 102.
- [0065] In at least one embodiment, a feature map, which can be referred to as an activation map, is a data object that indicates output activations for one or more convolutional filters. In at least one embodiment, a feature map indicates an output of one or more operations applied to an input. In at least one embodiment, channels of a feature map correspond to various
- 30 features and/or aspects of said feature map. In at least one embodiment, each channel of a feature map represents an aspect of information, such as particular features (e.g., edges, corners), particular colors (e.g., red, blue, green), and/or variations thereof. In at least one embodiment, a feature map generated from an image depicts one or more features of said image.
- 35 [0066] In at least one embodiment, feature extraction layer 104 comprises various pooling, rectified linear unit (ReLU), and convolution operations that generate feature maps from an

5 input image. In at least one embodiment, pooling is a form of non-linear down-sampling in which an input is transformed into a reduced representation of said input. In at least one embodiment, a produced reduced representation of an input can comprise various details of said input, such as prominent details of said input, which can include edges, certain patterns and/or features, and/or variations thereof. In at least one embodiment, rectified linear unit
10 (ReLU) is a form of an activation function that defines an output given an input or set of inputs. In at least one embodiment, convolution is a mathematical operation on two inputs that produces an output that expresses how one input is affected by another input. In at least one embodiment, convolution can be applied to an input along with a filter, which can be denoted as a convolution filter. In at least one embodiment, convolution on an input with a
15 filter can transform said input to enhance and/or reduce various features of said input.

[0067] In at least one embodiment, feature extraction layer 104 determines one or more feature maps from an input image and outputs said one or more feature maps to convolutional layers 106. In at least one embodiment, convolutional layers 106 comprise one or more convolutional layers. In at least one embodiment, convolutional layers 106 receives one or
20 more feature maps and performs one or more convolutional operations. In at least one embodiment, convolutional layers 106 reduce sizes of feature maps output from feature extraction layer 104. In at least one embodiment, convolutional layers 106 generate one or more feature maps of various resolutions to detect objects of various sizes.

[0068] In at least one embodiment, object detections layer 108 detects one or more objects
25 in one or more feature maps. In at least one embodiment, object detections layer 108 comprises one or more neural networks that generate probability distributions indicating potential locations and classifications of objects in an image. In at least one embodiment, object detections layer 108 receives feature maps of various sizes and resolutions. In at least one embodiment, object detection layers 108 utilizes feature maps of various sizes and
30 resolutions to detect objects of various sizes. In at least one embodiment, object detections layer 108 generates output 110 comprising localization output 112, which comprises various probability distributions indicating potential locations of objects, and classification output 114, which comprises various probability distributions indicating potential classifications of objects.

35 [0069] In at least one embodiment, object detections layer 108 processes each location of each feature map output by convolutional layers 106. In at least one embodiment, a location

5 of a feature map indicates an area or region of said feature map. In at least one embodiment, for each location, object detections layer 108 determines one or more bounding boxes indicating potential bounds or locations of objects. In at least one embodiment, for each object in a location, multiple bounding boxes can be determined. In at least one embodiment, for each bounding box, object detections layer 108 models each coordinate of said bounding
 10 box as a Gaussian Mixture Model. In at least one embodiment, a Gaussian Mixture Model (GMM) is a probabilistic model that comprises one or more distributions, such as a Gaussian distribution. In at least one embodiment, a Gaussian distribution is a continuous probability distribution for a real-value random variable.

[0070] In at least one embodiment, for a given Gaussian distribution, a mean (e.g., μ)
 15 defines a center of said distribution, a variance (e.g., Σ) defines a width of said distribution, and a weight (e.g., π) defines a scale or size of said distribution. In at least one embodiment, a bounding box is defined by four coordinates, including center coordinates denoted by variables x and y , width, denoted by variable w , and height, denoted by variable h . In at least one embodiment, for each bounding box, object detections layer 108 outputs 3 groups of
 20 parameters: mean (e.g., $\hat{\mu}_x$, $\hat{\mu}_y$, $\hat{\mu}_w$, and $\hat{\mu}_h$), variance (e.g., $\hat{\Sigma}_x$, $\hat{\Sigma}_y$, $\hat{\Sigma}_w$, and $\hat{\Sigma}_h$), and weights (e.g., $\hat{\pi}_x$, $\hat{\pi}_y$, $\hat{\pi}_w$, and $\hat{\pi}_h$). In at least one embodiment, distributions for a coordinate are determined by determining potential values of said coordinate, calculating probability values for said potential values (e.g., a probability value for each potential value), and forming a distribution based on said probability values. In at least one embodiment, potential
 25 values of a particular coordinate are determined by perturbing or otherwise applying minor variations to a determined value of said particular coordinate to determine a set of potential values of said particular coordinate. In at least one embodiment, a probability value for a set of coordinates of a bounding box indicates a probability of how reliable a particular bounding box coordinate is in indicating bounds of an object.

30 [0071] In at least one embodiment, for each bounding box, object detections layer 108 outputs 3 groups of parameters, which can be referred to as localization parameters: mean (e.g., $\hat{\mu}_x$, $\hat{\mu}_y$, $\hat{\mu}_w$, and $\hat{\mu}_h$), variance (e.g., $\hat{\Sigma}_x$, $\hat{\Sigma}_y$, $\hat{\Sigma}_w$, and $\hat{\Sigma}_h$), and weights (e.g., $\hat{\pi}_x$, $\hat{\pi}_y$, $\hat{\pi}_w$, and $\hat{\pi}_h$). In at least one embodiment, for a particular bounding box, each coordinate of said bounding box is modeled as a GMM.

- 5 [0072] In at least one embodiment, parameters of a GMM with K models for each coordinate of a bounding box are determined utilizing a following equation, although any variation can be utilized:

$$\pi_b^k = \frac{\exp(\hat{\pi}_b^k)}{\sum_{j=1}^K \exp(\hat{\pi}_b^j)}, \mu_b^k = \hat{\mu}_b^k, \Sigma_b^k = \sigma(\hat{\Sigma}_b^k), b \in \{x, y, w, h\}$$

- 10 where π is a mixture weight for each component, μ is a predicted value for each output of a bounding box, and Σ is a variance for each coordinate representing aleatoric uncertainty. In at least one embodiment, a softmax function is utilized to keep π in a probability space and a sigmoid function is utilized to satisfy a positiveness constraint of variance (e.g., $\Sigma_b^k \geq 0$).

- [0073] In at least one embodiment, a negative log-likelihood (NLL) loss function is utilized to calculate localization loss for a localization output of a deep object detection network
 15 rather than a smooth L1 Norm. In at least one embodiment, loss refers to a measure of prediction error of a neural network. In at least one embodiment, a lower loss value (e.g., lower prediction error) indicates a more accurate neural network. In at least one embodiment, calculated loss is utilized to update parameters, weights, configurations, and/or variations thereof of a deep object detection network such that loss is minimized. In at least one
 20 embodiment, to calculate localization loss, a negative log-likelihood loss (NLL) is utilized to regress parameters of a GMM to offsets of a center (x, y), width (w), and height (h) of a default or anchor bounding box, and an equation such as a following is utilized, although any variation thereof can be utilized:

$$Loss_{localization}(x, l, g) = - \sum_{i \in Pos} \sum_{b \in B} \lambda_{ij} \log \left(\sum_{k=1}^K \pi_b^{ik} \mathbf{N}(\hat{g}_b^j | \mu_b^{ik}, \Sigma_b^{ik}) + \varepsilon \right),$$

$$25 \quad \lambda_{ij} = \begin{cases} 1, & \text{if } IoU > .5 \\ 0, & \text{otherwise} \end{cases}, \hat{g}_x^j = \frac{(g_x^j - d_x^i)}{d_w^i}, \hat{g}_y^j = \frac{(g_y^j - d_y^i)}{d_h^i}, \hat{g}_w^j = \log \left(\frac{g_w^j}{d_w^i} \right), \hat{g}_h^j = \log \left(\frac{g_h^j}{d_h^i} \right),$$

- where Pos denotes positive matches, IoU denotes intersection over union, N denotes a number of positive matches, B denotes an offset of a bounding box coordinate, $\hat{g}_b^j$ denotes a ground-truth (GT) of a j -th box, and λ_{ij} denotes an indicator function for matching an i -th default box (d) to a j -th GT box. In at least one embodiment, ε is set to a suitable value for
 30 numerical stability of a logarithm function. In at least one embodiment, a value of ε is e^{-9} .

- 5 [0074] In at least one embodiment, each bounding box can be classified using any number of classes. In at least one embodiment, a class refers to a classification of a potential object within a bounding box. In at least one embodiment, for example, a class can correspond to an identification of an object, such as human, cat, dog, car, and/or variations thereof. In at least one embodiment, each bounding box can be classified as belonging to a particular class. In at least one embodiment, for example, a bounding box can comprise an image of a human head, in which a class determined for said bounding box can indicate that an object within said bounding box is a human head. In at least one embodiment, there may be any number of classes corresponding to any number of classifications. In at least one embodiment, object detections layer 108 determines a probability distribution for each class for a particular bounding box. In at least one embodiment, a probability distribution for a particular class for a given bounding box indicates a probability that an object within said bounding box belongs to said class. In at least one embodiment, for a given bounding box, there may be any number of class probability distributions or outputs indicating probabilities that an object of said bounding box belongs to various classes.
- 20 [0075] In at least one embodiment, for each bounding box, every class output is modeled as a GMM. In at least one embodiment, for each component of a particular GMM, object detections layer 108 outputs following parameters, which can be referred to as classification parameters: a mean $\hat{\mu}_p^k$ and variance $\hat{\Sigma}_p^k$ for each class and weights of mixture $\hat{\pi}^k$. In at least one embodiment, parameters of a GMM are processed and a class probability distribution is determined for j -th bounding boxes by applying Gaussian noise and variance $\hat{\Sigma}_p^i$ to μ_p^i using a following equation, although any variation can be utilized:

$$\hat{c}_p^j = \mu_p^j + \sqrt{\hat{\Sigma}_p^j} \gamma, \quad \gamma \sim \mathbf{N}(0,1).$$

- [0076] In at least one embodiment, classification loss utilizes *IoU* with a bounding box as a ground truth. In at least one embodiment, classification loss comprises a loss for each positive sample $Loss_{classification}^{Positive}$ and a loss for each negative sample $Loss_{classification}^{Negative}$ and an equation such as a following equation is utilized, although any variation can be utilized:

$$Loss_{classification}^{Positive}(x, c) = - \sum_i^N \lambda_{ij} \sum_{k=1}^K \pi^{ik} (\hat{c}_g^{ik} - \log (\sum_{p=0}^C \exp (\hat{c}_p^{ik})))$$

$$Loss_{classification}^{Negative}(x, c) = - \sum_i^T \sum_{k=1}^K \pi^{ik} (\hat{c}_0^{ik} - \log (\sum_{p=0}^C \exp (\hat{c}_p^{ik})))$$

5 where N and T denote a number of positive and negative matches respectively, $\hat{c}_g^{ik}$ denotes a ground truth class for an i -th match, and C denotes a number of classes, with 0 representing a background class.

[0077] In at least one embodiment, a deep object detection network is trained utilizing a loss function such as a following equation, although any variation thereof can be utilized:

$$10 \quad L(x, c, l, g) = \begin{cases} \frac{1}{N} (Loss_{localization}(x, l, g) + Loss_{classification}^{Positive}(x, c) + Loss_{classification}^{Negative}(x, c)), & \text{if } N > 0 \\ 0, & \text{otherwise} \end{cases}$$

where x denotes input samples, c denotes classification outputs, l denotes localization outputs, and g denotes ground truth values.

[0078] In at least one embodiment, for inference, coordinates of a bounding box R_b and a confidence score for each class P_i are computed by summing components of a mixture model utilizing a following equation, although any variations thereof can be utilized:

$$Localization: R_b = \sum_{k=1}^K \pi_b^k \mu_b^k, \quad Classification: P_i = \sum_{k=1}^K \pi^k \frac{\exp(\mu_i^k)}{\sum_{j=0}^C \exp(\mu_j^k)}$$

[0079] In at least one embodiment, there may be multiple bounding boxes indicating potential locations for each object in each location of one or more feature maps. In at least one embodiment, referring to FIG. 1, a number of bounding boxes for each object is denoted by a variable K . In at least one embodiment, variable K can have any positive integer value and can be defined as part of initialization of a deep object detection network. In at least one embodiment, localization output 112 – which may also be referred to herein as a set of localization parameters – comprises all determined sets of parameters of probability distributions for coordinates of bounding boxes of each location of one or more feature maps generated from input image 102. In at least one embodiment, sets of parameters of localization output 112 are utilized to determine localization distributions 116. In at least one embodiment, localization distributions are also referred to as localization probability distributions, bounding box probability distributions, localization GMMs, and/or variations thereof. In at least one embodiment, referring to FIG. 1, for an object in a location of a feature map, localization output 112 comprises K sets of parameters for each bounding box coordinate (e.g., x, y, w, h), which are utilized to determine localization distributions 116,

5 which comprise a GMM for each bounding box coordinate, in which each GMM comprises K distributions and K corresponds to a number of bounding boxes for said object.

[0080] In at least one embodiment, classification output 114 – which may also be referred to herein as a set of classification parameters – comprises all determined sets of parameters of probability distributions for classifications for each bounding box of each location of one or
 10 more feature maps generated from input image 102. In at least one embodiment, sets of parameters of classification output 114 are utilized to determine classification distributions 118. In at least one embodiment, classification distributions 118 are also referred to as classification probability distributions, classification GMMs, confidence probability distributions, and/or variations thereof. In at least one embodiment, referring to FIG. 1, for
 15 bounding boxes for an object in a location of a feature map, classification output 114 comprises K sets of parameters for each potential classification of said object, which are utilized to determine classification distributions 118, which comprise a GMM for each class, in which each GMM comprises K distributions and K corresponds to a number of said bounding boxes for said object.

20 [0081] In at least one embodiment, a deep object detection network learns parameters of a GMM of an output y given an input x through a following equation, although any variation thereof can be utilized:

$$p(y|x) = \sum_{j=1}^K \pi_j(x) \mathbf{N}(y; \mu_j(x), \Sigma_j(x))$$

where π_j , μ_j , and Σ_j denote mixture weights, mean, and variance, respectively, of a j -th
 25 component of a GMM.

[0082] In at least one embodiment, a GMM is utilized to approximate a density function and can be utilized to estimate aleatoric and epistemic uncertainties. In at least one embodiment, uncertainties are also referred to as uncertainty values, uncertainty scores, and/or variations thereof. In at least one embodiment, given parameters of a GMM (e.g., π^i ,
 30 μ^i , and Σ^i), aleatoric u_{al} and epistemic u_{ep} uncertainties are determined through a following equation, although any variation thereof can be utilized:

$$u_{al} = \sum_{i=1}^K \pi^i \Sigma^i, \quad u_{ep} = \sum_{i=1}^K \pi^i ||\mu^i - \sum_{k=1}^K \pi^k \mu^k ||^2.$$

5 [0083] In at least one embodiment, each object of input image 102 is associated with four localization GMMs (e.g., one for each bounding box coordinate) and one or more classification GMMs (e.g., one for each potential class). In at least one embodiment, aleatoric and epistemic uncertainty values are calculated for each GMM of localization distributions 116 and classification distributions 118. In at least one embodiment, each object of input
10 image 102 is associated with eight bounding box uncertainty values (e.g., epistemic and aleatoric uncertainty for bounding box coordinate x , epistemic and aleatoric uncertainty for bounding box coordinate y , epistemic and aleatoric uncertainty for bounding box coordinate w , and epistemic and aleatoric uncertainty for bounding box coordinate h) and two classification uncertainty values for each class (e.g., epistemic and aleatoric uncertainty for
15 each class).

[0084] In at least one embodiment, for each object of input image 102, maximum epistemic and aleatoric uncertainty values are determined from eight bounding box uncertainty values, and a maximum epistemic and aleatoric uncertainty value is determined from classification uncertainty values, resulting in four uncertainty values: maximum epistemic bounding box
20 uncertainty, maximum aleatoric bounding box uncertainty, maximum epistemic classification uncertainty, and maximum aleatoric classification uncertainty. In at least one embodiment, maximum epistemic bounding box uncertainty, maximum aleatoric bounding box uncertainty, maximum epistemic classification uncertainty, and maximum aleatoric classification uncertainty values are determined for each object of input image 102. In at least
25 one embodiment, uncertainty values are normalized using z-score normalization. In at least one embodiment, maximum values are determined over all uncertainty values of objects of input image 102 to determine 4 maximum uncertainty values: overall maximum epistemic bounding box uncertainty, overall maximum aleatoric bounding box uncertainty, overall maximum epistemic classification uncertainty, and overall maximum aleatoric classification
30 uncertainty values.

[0085] In at least one embodiment, overall maximum epistemic bounding box uncertainty, overall maximum aleatoric bounding box uncertainty, overall maximum epistemic classification uncertainty, and overall maximum aleatoric classification uncertainty values for input image 102 are then aggregated to determine an informativeness score for input image
35 102. In at least one embodiment, overall maximum uncertainty values are aggregated to determine an informativeness score through determining an average of said values, in which said average indicates said informativeness score. In at least one embodiment, overall

5 maximum uncertainty values are aggregated to determine an informativeness score through determining a maximum of said values, in which said maximum indicates said informativeness score. In at least one embodiment, an informativeness score for input image 102 indicates how uncertain a deep object detection network is at identifying and classifying objects of input image 102, in which a higher informativeness score indicates a higher
10 uncertainty.

[0086] In at least one embodiment, informativeness scores are determined for one or more training images. In at least one embodiment, an informativeness score is also referred to as an informativeness value, informativeness measure, and/or variations thereof. In at least one embodiment, informativeness scores are compared for one or more training images. In at
15 least one embodiment, a threshold is defined in which images of one or more training images with informativeness scores higher than said threshold are selected to be labeled and utilized to train a neural network. In at least one embodiment, training images of one or more training images with highest informativeness scores are determined and labeled, and used to train an object detection neural network. In at least one embodiment, images with higher
20 informativeness scores are negatively (e.g., inversely) correlated with how many images it takes or is estimated to take to train one or more neural networks to a particular level of accuracy. In at least one embodiment, a set of N training images with higher informativeness scores can be used to train a first one or more neural networks to a specific accuracy level that is equal to or better to a second one or more neural networks trained on a set of M
25 training images with lower informativeness scores where $M > N$. Further information regarding training a neural network can be found in description of FIG. 5.

[0087] FIG. 2 illustrates a diagram 200 of determining probability distribution parameters, according to at least one embodiment. In at least one embodiment, diagram 200 illustrates one or more processes of one or more neural networks such as those described in connection
30 with FIG. 1. In at least one embodiment, input image 202 undergoes feature extraction 204 to generate feature map 206, in which localization output 208 and classification output 210 are determined from feature map 206.

[0088] In at least one embodiment, input image 202 is a two-dimensional image. In at least one embodiment, input image 202 is a frame of a video. In at least one embodiment, input
35 image 202 is an image that depicts one or more objects of one or more classifications. In at least one embodiment, referring to FIG. 2, input image 202 is an image that comprises a

5 depiction of a human. In at least one embodiment, input image 202 undergoes feature extraction 204. In at least one embodiment, feature extraction 204 determines feature map 206 from input image 202. In at least one embodiment, feature extraction 204 is performed by one or more feature extraction layers such as those described in connection with FIG. 1.

[0089] In at least one embodiment, a feature map, which can be referred to as an activation map, is a data object that indicates output activations for one or more convolutional filters. In
10 at least one embodiment, a feature map indicates an output of one or more operations applied to an input. In at least one embodiment, channels of a feature map correspond to various features and/or aspects of said feature map. In at least one embodiment, each channel of a feature map represents an aspect of information, such as particular features (e.g., edges,
15 corners), particular colors (e.g., red, blue, green), and/or variations thereof. In at least one embodiment, a feature map generated from an image depicts one or more features of said image.

[0090] In at least one embodiment, feature map 206 is divided into locations, in which each location indicates an area or region of feature map 206 and/or input image 202. In at least one
20 embodiment, feature map 206 is divided into a grid in which each grid cell is referred to as a location. In at least one embodiment, for each location of feature map 206, parameters for probability distributions corresponding to locations of bounding boxes and classifications of said bounding boxes are determined. In at least one embodiment, for each location of feature map 206, localization output comprising parameters corresponding to distributions of
25 coordinates of a bounding box that comprises a potential object and classification output comprising parameters corresponding to distributions of potential classifications of said bounding box are determined. In at least one embodiment, there may be one or more bounding boxes for each object and each location of a feature map, and bounding boxes may include regions from one or more locations and may not be necessarily confined to a single
30 location.

[0091] In at least one embodiment, referring to FIG. 2, for a location of feature map 206 depicting a head, localization output 208 comprising parameters corresponding to distributions of coordinates (e.g., $b = \{x, y, w, h\}$) of a bounding box comprising said head are determined, and classification output 210 comprising parameters corresponding to
35 distributions of potential classifications of said bounding box are determined. In at least one embodiment, localization output 208 comprises one or more sets of parameters for one or

5 more GMMs. In at least one embodiment, localization output 208 comprises parameters for one or more GMMs indicating different potential bounding boxes for an object in a location. In at least one embodiment, there may be multiple feature maps generated from input image 202, in which localization outputs and classification outputs are determined for each location of said multiple feature maps. In at least one embodiment, localization outputs and
10 classification outputs are determined for each object of each location of feature map 206, in which uncertainty values are determined from said localization outputs and said classification outputs to calculate an informativeness score for input image 202. Further information regarding calculating informativeness can be found in description of FIG. 1.

[0092] FIG. 3 illustrates a diagram 300 of determining image scores, according to at least
15 one embodiment. In at least one embodiment, training images 302 are processed by a deep object detector model 304 comprising a deep object detection network 306 and an uncertainty value determination 308 to determine uncertainty values, which are processed by scoring determination 310 to determine training image scores 312. In at least one embodiment, for a single training image of training images 302, a single forward pass through deep object
20 detector model 304 is required to determine uncertainty values for said training image. In at least one embodiment, deep object detector model 302 is one or more neural networks that directly learns and models uncertainties of images.

[0093] In at least one embodiment, training images 302 are two-dimensional images. In at least one embodiment, training images 302 are one or more frames of one or more videos. In
25 at least one embodiment, training images 302 are images that depict one or more objects of one or more classifications. In at least one embodiment, deep object detection network 306 is a neural network such as those described in connection with FIG. 1. In at least one embodiment, deep object detection network 306 receives an image, and determines parameters for probability distributions of potential locations of objects in said image and
30 potential classifications of said objects, in which said parameters are processed by uncertainty value determination 308 to determine uncertainty values for said image. In at least one embodiment, uncertainty value determination 308 is a set of computing resources that determines uncertainty values from parameters of probability distributions; further information regarding determining uncertainty values can be found in description of FIG. 1.

35 [0094] In at least one embodiment, uncertainty values output from uncertainty value determination 308 are processed by scoring determination 310 to determine informativeness

5 scores. In at least one embodiment, scoring determination 310 is a set of computing resources that determines an informativeness score from uncertainty values; further information regarding determining an informativeness score can be found in description of FIG. 1. In at least one embodiment, each image of training images 302 is processed by deep object detector model 304 and scoring determination 310 to determine training image scores 312. In
10 at least one embodiment, training image scores 312 is one or more databases that comprise informativeness scores for each image of training images 302. In at least one embodiment, training image scores 312 are utilized to compare informativeness scores of training images 302.

[0095] In at least one embodiment, informativeness scores are compared for one or more
15 training images. In at least one embodiment, a threshold is defined in which images of one or more training images with informativeness scores higher than said threshold are selected to be labeled and utilized to train a neural network. In at least one embodiment, training images of one or more training images with highest informativeness scores are determined and labeled, and used to train an object detection neural network. In at least one embodiment,
20 labels for training images are obtained through one or more third party labeling systems and/or services. Further information regarding training a neural network can be found in description of FIG. 5.

[0096] FIG. 4 shows an illustrative example of a process 400 to determine an informativeness score for an image, in accordance with at least one embodiment. In at least
25 one embodiment, some or all of process 400 (or any other processes described herein, or variations and/or combinations thereof) is performed under control of one or more computer systems configured with computer-executable instructions and may be implemented as code (e.g., computer-executable instructions, one or more computer programs, or one or more applications) executing collectively on one or more processors, by hardware, software, or
30 combinations thereof. Code, in at least one embodiment, is stored on a computer-readable storage medium in form of a computer program comprising a plurality of computer-readable instructions executable by one or more processors. A computer-readable storage medium, in at least one embodiment, is a non-transitory computer-readable medium. In at least one embodiment, at least some computer-readable instructions usable to perform process 400 are
35 not stored solely using transitory signals (e.g., a propagating transient electric or electromagnetic transmission). A non-transitory computer-readable medium does not necessarily include non-transitory data storage circuitry (e.g., buffers, caches, and queues)

- 5 within transceivers of transitory signals. In at least one embodiment, process 400 is performed at least in part on a computer system such as those described elsewhere in this disclosure. In at least one embodiment, process 400 is performed by one or more networks such as those described in connection with FIG. 1. In at least one embodiment, a system obtains an input image and determines an informativeness score.
- 10 [0097] In at least one embodiment, a system performing at least a part of process 400 includes executable code to obtain 402 input image. In at least one embodiment, input image is a two-dimensional image. In at least one embodiment, input image is one or more frames of one or more videos. In at least one embodiment, input image is an image that depicts one or more objects of one or more classifications. In at least one embodiment, input image is an
- 15 image of a training set of images that is utilized to train a neural network, such as an object detection neural network for detecting and classifying objects.
- [0098] In at least one embodiment, a system performing at least a part of process 400 includes executable code to extract 404 feature maps. In at least one embodiment, a system performing at least a part of process 400 extracts feature maps from an input image. In at
- 20 least one embodiment, feature maps are determined by one or more neural network layers, such as those described in connection with FIG. 1. In at least one embodiment, a feature map, which can be referred to as an activation map, is a data object that indicates output activations for one or more convolutional filters. In at least one embodiment, a feature map generated from an image depicts one or more features of said image. In at least one embodiment,
- 25 feature maps of various sizes and resolutions are generated from input image through one or more convolutional operations and/or layers.
- [0099] In at least one embodiment, a system performing at least a part of process 400 applies a process for 406 each location of feature maps. In at least one embodiment, a system performing at least a part of process 400 divides a feature map into locations, in which each
- 30 location indicates an area or region of said feature map and/or an input image that said feature map originated from. In at least one embodiment, a feature map is divided into a grid in which each grid cell is referred to as a location. In at least one embodiment, one or more processes in 408-412 are performed for each location of feature maps.
- [0100] In at least one embodiment, a system performing at least a part of process 400
- 35 includes executable code to determine 408 parameters for Gaussian Mixture Models (GMMs) indicating bounding box coordinate distributions. In at least one embodiment, a system

5 performing at least a part of process 400 determines bounding boxes for potential objects in a location. In at least one embodiment, there may be one or more bounding boxes determined for each potential object in a location, in which each bounding box indicates a potential location or bounds of a potential object. In at least one embodiment, a system performing at least a part of process 400 determines parameters for GMMs for coordinates of each
10 bounding box in a location. In at least one embodiment, for a single bounding box, parameters for four GMMs are determined corresponding to each coordinate of said bounding box (e.g., center coordinates, width, and height). In at least one embodiment, for a potential object in a location, there are four GMMs determined corresponding to each bounding box coordinate, in which each GMM comprises one or more models that correspond to a number
15 of potential bounding boxes determined for said potential object.

[0101] In at least one embodiment, a system performing at least a part of process 400 includes executable code to determine 410 parameters for Gaussian Mixture Models (GMMs) indicating class probability distributions for each bounding box. In at least one embodiment, each bounding box can be classified using any number of classes. In at least one embodiment,
20 a class refers to a classification of a potential object within a bounding box. In at least one embodiment, for a particular bounding box, a system performing at least a part of process 400 determines parameters for GMMs for each class. In at least one embodiment, a probability distribution for a particular class for a given bounding box indicates a probability that an object within said bounding box belongs to said class. In at least one embodiment, for a given
25 bounding box, there may be any number of GMMs indicating probabilities that an object of said bounding box belongs to various classes.

[0102] In at least one embodiment, a system performing at least a part of process 400 includes executable code to calculate 412 uncertainty values for objects in location. In at least one embodiment, a system performing at least a part of process 400 determines aleatoric and
30 epistemic uncertainty values for each object in a location. In at least one embodiment, each object of a location is associated with four GMMs (e.g., one for each bounding box coordinate) and one or more GMMs (e.g., one for each class). In at least one embodiment, aleatoric and epistemic uncertainty values are determined for each GMM. In at least one embodiment, each object is associated with eight bounding box uncertainty values (e.g.,
35 epistemic and aleatoric uncertainty for bounding box coordinate x , epistemic and aleatoric uncertainty for bounding box coordinate y , epistemic and aleatoric uncertainty for bounding box coordinate w , and epistemic and aleatoric uncertainty for bounding box coordinate h) and

5 two classification uncertainty values for each class (e.g., epistemic and aleatoric uncertainty for each class). In at least one embodiment, for each object, maximum epistemic and aleatoric uncertainty values are determined from eight bounding box uncertainty values, and a maximum epistemic and aleatoric uncertainty value is determined from classification uncertainty values, resulting in four uncertainty values: maximum epistemic bounding box
10 uncertainty, maximum aleatoric bounding box uncertainty, maximum epistemic classification uncertainty, and maximum aleatoric classification uncertainty. In at least one embodiment, maximum epistemic bounding box uncertainty, maximum aleatoric bounding box uncertainty, maximum epistemic classification uncertainty, and maximum aleatoric classification uncertainty values are determined for each object of location.

15 [0103] In at least one embodiment, a system performing at least a part of process 400 includes executable code to determine 414 if more locations remain. In at least one embodiment, a system performing at least a part of process 400 determines if any more locations of feature maps remain to be processed. In at least one embodiment, a system performing at least a part of process 400 includes executable code to, if locations remain,
20 perform one or more processes in 408-412 for each location.

[0104] In at least one embodiment, a system performing at least a part of process 400 includes executable code to, if no more locations remain, normalize 416 uncertainty values. In at least one embodiment, uncertainty values are normalized using z-score normalization. In at least one embodiment, z-score normalization refers to a process in which scales of values
25 are adjusted such that values can be compared with each other. In at least one embodiment, z-score normalization is performed by a system on uncertainty values to compensate for various different ranges of values that said uncertainty values can have. In at least one embodiment, each object is associated with four maximum uncertainty values, in which z-score normalization is performed on each value. In at least one embodiment, normalized
30 epistemic bounding box uncertainty, normalized aleatoric bounding box uncertainty, normalized epistemic classification uncertainty, and normalized aleatoric classification uncertainty values are determined for each object of input image.

[0105] In at least one embodiment, a system performing at least a part of process 400 includes executable code to aggregate 418 normalized uncertainty values to determine
35 informativeness score. In at least one embodiment, a system performing at least a part of process 400 determines maximum uncertainty values from all uncertainty values for all

5 objects in input image. In at least one embodiment, for an input image, maximum normalized epistemic bounding box uncertainty, maximum normalized aleatoric bounding box uncertainty, maximum normalized epistemic classification uncertainty, and maximum normalized aleatoric classification uncertainty values are determined and aggregated. In at least one embodiment, input image is associated with four uncertainty values. In at least one
10 embodiment, an informativeness score is calculated for an input image based on a maximum of associated four uncertainty values. In at least one embodiment, an informativeness score is calculated for an input image based on an average of associated four uncertainty values.

[0106] In at least one embodiment, an informativeness score an image indicates how uncertain a neural network is at identifying and classifying objects of said image, in which a
15 higher informativeness score indicates a higher uncertainty. In at least one embodiment, informativeness scores are determined for one or more training images. In at least one embodiment, informativeness scores are compared for one or more training images. In at least one embodiment, a threshold is defined in which images of one or more training images with informativeness scores higher than said threshold are selected to be labeled and utilized
20 to train a neural network. In at least one embodiment, training images of one or more training images with highest informativeness scores are determined and labeled, and used to train one or more neural networks.

[0107] FIG. 5 shows an illustrative example of a process 500 to train a network, in accordance with at least one embodiment. In at least one embodiment, some or all of process
25 500 (or any other processes described herein, or variations and/or combinations thereof) is performed under control of one or more computer systems configured with computer-executable instructions and may be implemented as code (e.g., computer-executable instructions, one or more computer programs, or one or more applications) executing collectively on one or more processors, by hardware, software, or combinations thereof.

30 Code, in at least one embodiment, is stored on a computer-readable storage medium in form of a computer program comprising a plurality of computer-readable instructions executable by one or more processors. A computer-readable storage medium, in at least one embodiment, is a non-transitory computer-readable medium. In at least one embodiment, at least some computer-readable instructions usable to perform process 500 are not stored solely
35 using transitory signals (e.g., a propagating transient electric or electromagnetic transmission). A non-transitory computer-readable medium does not necessarily include non-transitory data storage circuitry (e.g., buffers, caches, and queues) within transceivers of

5 transitory signals. In at least one embodiment, process 500 is performed at least in part on a computer system such as those described elsewhere in this disclosure. In at least one embodiment, process 500 is performed by one or more networks such as those described in connection with FIG. 1. In at least one embodiment, process 500 comprises one or more processes of an active learning method for object detection. In at least one embodiment, a
10 system obtains training images and trains a neural network.

[0108] In at least one embodiment, a system performing at least a part of process 500 includes executable code to obtain 502 training images. In at least one embodiment, training images comprise one or more two-dimensional images. In at least one embodiment, training images are one or more training images of an object detection image training dataset. In at
15 least one embodiment, training images are images that comprise one or more objects of one or more classifications. In at least one embodiment, a system performing at least a part of process 500 obtains training images from one or more datasets, databases, services, and/or variations thereof.

[0109] In at least one embodiment, a system performing at least a part of process 500
20 includes executable code to score 504 images for informativeness. In at least one embodiment, a system performing at least a part of process 500 inputs training images into one or more networks and models such as those described in connection with FIG. 1 and FIG. 3. In at least one embodiment, a system determines informativeness scores for each image of training images.

[0110] In at least one embodiment, a system performing at least a part of process 500
25 includes executable code to select 506 images with highest informativeness. In at least one embodiment, a threshold is defined in which images of one or more training images with informativeness scores higher than said threshold are selected. In at least one embodiment, one or more logical rules are defined that determine which images of a training set are to be
30 selected. In at least one embodiment, a system performing at least a part of process 500 includes executable code to obtain 508 labels for selected images. In at least one embodiment, labels for an image, which are also referred to as annotations, ground truth data, and/or variations thereof, indicate one or more classifications of one or more objects of said image. In at least one embodiment, labels for an image comprise data that indicate one or
35 more locations of objects in said image and one or more classifications of said objects. In at least one embodiment, a system performing at least a part of process 500 obtains labels from

5 one or more third parties, such as a labeling/annotation system/service, training data set, and/or variations thereof.

[0111] In at least one embodiment, a system performing at least a part of process 500 includes executable code to train 510 network on labeled images. In at least one embodiment, a network is an object detection neural network. In at least one embodiment, a network
10 comprises one or more neural networks that detect and classify objects in images, video, audio, and/or variations thereof. In at least one embodiment, a network is a neural network for identifying and classifying one or more entities in medical images. In at least one embodiment, a network is a neural network that is part of an autonomous car, and identifies and classifies objects in one or more images of one or more videos and/or video streams. In at
15 least one embodiment, a system performing at least a part of process 500 trains a neural network using labeled images by inputting images into said neural network, computing loss utilizing one or more loss functions based at least in part on labels corresponding to said images, and adjusting parameters, weights, and/or configurations of said neural network based at least in part on computed loss.

20 [0112] In at least one embodiment, a motor vehicle such as an autonomous car (e.g., self-driving car), car, drone, and/or variations thereof performs at least a part of process 500, in which training images are images captured from one or more viewpoints of said motor vehicle through one or more image capturing devices (e.g., cameras), in which said training images are analyzed and scored for informativeness, a subset of said training images are
25 selected based on an informativeness score threshold or other logic, labels are obtained for said subset, and said subset is used, in connection with said labels, to train one or more neural networks.

INFERENCE AND TRAINING LOGIC

[0113] FIG. 6A illustrates inference and/or training logic 615 used to perform inferencing
30 and/or training operations associated with one or more embodiments. Details regarding inference and/or training logic 615 are provided below in conjunction with FIGS. 6A and/or 6B.

[0114] In at least one embodiment, inference and/or training logic 615 may include, without limitation, code and/or data storage 601 to store forward and/or output weight and/or
35 input/output data, and/or other parameters to configure neurons or layers of a neural network trained and/or used for inferencing in aspects of one or more embodiments. In at least one

5 embodiment, training logic 615 may include, or be coupled to code and/or data storage 601 to store graph code or other software to control timing and/or order, in which weight and/or other parameter information is to be loaded to configure, logic, including integer and/or floating point units (collectively, arithmetic logic units (ALUs). In at least one embodiment, code, such as graph code, loads weight or other parameter information into processor ALUs
10 based on an architecture of a neural network to which such code corresponds. In at least one embodiment, code and/or data storage 601 stores weight parameters and/or input/output data of each layer of a neural network trained or used in conjunction with one or more embodiments during forward propagation of input/output data and/or weight parameters during training and/or inferencing using aspects of one or more embodiments. In at least one
15 embodiment, any portion of code and/or data storage 601 may be included with other on-chip or off-chip data storage, including a processor's L1, L2, or L3 cache or system memory.

[0115] In at least one embodiment, any portion of code and/or data storage 601 may be internal or external to one or more processors or other hardware logic devices or circuits. In at least one embodiment, code and/or code and/or data storage 601 may be cache memory,
20 dynamic randomly addressable memory ("DRAM"), static randomly addressable memory ("SRAM"), non-volatile memory (e.g., flash memory), or other storage. In at least one embodiment, a choice of whether code and/or code and/or data storage 601 is internal or external to a processor, for example, or comprising DRAM, SRAM, flash or some other storage type may depend on available storage on-chip versus off-chip, latency requirements
25 of training and/or inferencing functions being performed, batch size of data used in inferencing and/or training of a neural network, or some combination of these factors.

[0116] In at least one embodiment, inference and/or training logic 615 may include, without limitation, a code and/or data storage 605 to store backward and/or output weight and/or input/output data corresponding to neurons or layers of a neural network trained
30 and/or used for inferencing in aspects of one or more embodiments. In at least one embodiment, code and/or data storage 605 stores weight parameters and/or input/output data of each layer of a neural network trained or used in conjunction with one or more embodiments during backward propagation of input/output data and/or weight parameters during training and/or inferencing using aspects of one or more embodiments. In at least one
35 embodiment, training logic 615 may include, or be coupled to code and/or data storage 605 to store graph code or other software to control timing and/or order, in which weight and/or

5 other parameter information is to be loaded to configure, logic, including integer and/or floating point units (collectively, arithmetic logic units (ALUs).

[0117] In at least one embodiment, code, such as graph code, causes the loading of weight or other parameter information into processor ALUs based on an architecture of a neural network to which such code corresponds. In at least one embodiment, any portion of code
10 and/or data storage 605 may be included with other on-chip or off-chip data storage, including a processor's L1, L2, or L3 cache or system memory. In at least one embodiment, any portion of code and/or data storage 605 may be internal or external to one or more processors or other hardware logic devices or circuits. In at least one embodiment, code and/or data storage 605 may be cache memory, DRAM, SRAM, non-volatile memory (e.g.,
15 flash memory), or other storage. In at least one embodiment, a choice of whether code and/or data storage 605 is internal or external to a processor, for example, or comprising DRAM, SRAM, flash memory or some other storage type may depend on available storage on-chip versus off-chip, latency requirements of training and/or inferencing functions being performed, batch size of data used in inferencing and/or training of a neural network, or some
20 combination of these factors.

[0118] In at least one embodiment, code and/or data storage 601 and code and/or data storage 605 may be separate storage structures. In at least one embodiment, code and/or data storage 601 and code and/or data storage 605 may be a combined storage structure. In at least one embodiment, code and/or data storage 601 and code and/or data storage 605 may be
25 partially combined and partially separate. In at least one embodiment, any portion of code and/or data storage 601 and code and/or data storage 605 may be included with other on-chip or off-chip data storage, including a processor's L1, L2, or L3 cache or system memory.

[0119] In at least one embodiment, inference and/or training logic 615 may include, without limitation, one or more arithmetic logic unit(s) ("ALU(s)") 610, including integer
30 and/or floating point units, to perform logical and/or mathematical operations based, at least in part on, or indicated by, training and/or inference code (e.g., graph code), a result of which may produce activations (e.g., output values from layers or neurons within a neural network) stored in an activation storage 620 that are functions of input/output and/or weight parameter data stored in code and/or data storage 601 and/or code and/or data storage 605. In at least
35 one embodiment, activations stored in activation storage 620 are generated according to linear algebraic and or matrix-based mathematics performed by ALU(s) 610 in response to

- 5 performing instructions or other code, wherein weight values stored in code and/or data storage 605 and/or data storage 601 are used as operands along with other values, such as bias values, gradient information, momentum values, or other parameters or hyperparameters, any or all of which may be stored in code and/or data storage 605 or code and/or data storage 601 or another storage on or off-chip.
- 10 [0120] In at least one embodiment, ALU(s) 610 are included within one or more processors or other hardware logic devices or circuits, whereas in another embodiment, ALU(s) 610 may be external to a processor or other hardware logic device or circuit that uses them (e.g., a co-processor). In at least one embodiment, ALUs 610 may be included within a processor's execution units or otherwise within a bank of ALUs accessible by a processor's execution
- 15 units either within same processor or distributed between different processors of different types (e.g., central processing units, graphics processing units, fixed function units, etc.). In at least one embodiment, code and/or data storage 601, code and/or data storage 605, and activation storage 620 may share a processor or other hardware logic device or circuit, whereas in another embodiment, they may be in different processors or other hardware logic
- 20 devices or circuits, or some combination of same and different processors or other hardware logic devices or circuits. In at least one embodiment, any portion of activation storage 620 may be included with other on-chip or off-chip data storage, including a processor's L1, L2, or L3 cache or system memory. Furthermore, inferencing and/or training code may be stored with other code accessible to a processor or other hardware logic or circuit and fetched and/or
- 25 processed using a processor's fetch, decode, scheduling, execution, retirement and/or other logical circuits.
- [0121] In at least one embodiment, activation storage 620 may be cache memory, DRAM, SRAM, non-volatile memory (e.g., flash memory), or other storage. In at least one
- 30 embodiment, activation storage 620 may be completely or partially within or external to one or more processors or other logical circuits. In at least one embodiment, a choice of whether activation storage 620 is internal or external to a processor, for example, or comprising DRAM, SRAM, flash memory or some other storage type may depend on available storage on-chip versus off-chip, latency requirements of training and/or inferencing functions being performed, batch size of data used in inferencing and/or training of a neural network, or some
- 35 combination of these factors.

5 [0122] In at least one embodiment, inference and/or training logic 615 illustrated in FIG. 6A may be used in conjunction with an application-specific integrated circuit (“ASIC”), such as a TensorFlow® Processing Unit from Google, an inference processing unit (IPU) from Graphcore™, or a Nervana® (e.g., “Lake Crest”) processor from Intel Corp. In at least one embodiment, inference and/or training logic 615 illustrated in FIG. 6A may be used in
10 conjunction with central processing unit (“CPU”) hardware, graphics processing unit (“GPU”) hardware or other hardware, such as field programmable gate arrays (“FPGAs”).

[0123] FIG. 6B illustrates inference and/or training logic 615, according to at least one embodiment. In at least one embodiment, inference and/or training logic 615 may include, without limitation, hardware logic in which computational resources are dedicated or
15 otherwise exclusively used in conjunction with weight values or other information corresponding to one or more layers of neurons within a neural network. In at least one embodiment, inference and/or training logic 615 illustrated in FIG. 6B may be used in conjunction with an application-specific integrated circuit (ASIC), such as TensorFlow® Processing Unit from Google, an inference processing unit (IPU) from Graphcore™, or a
20 Nervana® (e.g., “Lake Crest”) processor from Intel Corp. In at least one embodiment, inference and/or training logic 615 illustrated in FIG. 6B may be used in conjunction with central processing unit (CPU) hardware, graphics processing unit (GPU) hardware or other hardware, such as field programmable gate arrays (FPGAs). In at least one embodiment, inference and/or training logic 615 includes, without limitation, code and/or data storage 601
25 and code and/or data storage 605, which may be used to store code (e.g., graph code), weight values and/or other information, including bias values, gradient information, momentum values, and/or other parameter or hyperparameter information. In at least one embodiment illustrated in FIG. 6B, each of code and/or data storage 601 and code and/or data storage 605 is associated with a dedicated computational resource, such as computational hardware 602
30 and computational hardware 606, respectively. In at least one embodiment, each of computational hardware 602 and computational hardware 606 comprises one or more ALUs that perform mathematical functions, such as linear algebraic functions, only on information stored in code and/or data storage 601 and code and/or data storage 605, respectively, result of which is stored in activation storage 620.

35 [0124] In at least one embodiment, each of code and/or data storage 601 and 605 and corresponding computational hardware 602 and 606, respectively, correspond to different layers of a neural network, such that resulting activation from one storage/computational pair

5 601/602 of code and/or data storage 601 and computational hardware 602 is provided as an input to a next storage/computational pair 605/606 of code and/or data storage 605 and computational hardware 606, in order to mirror a conceptual organization of a neural network. In at least one embodiment, each of storage/computational pairs 601/602 and 605/606 may correspond to more than one neural network layer. In at least one embodiment,
10 additional storage/computation pairs (not shown) subsequent to or in parallel with storage/computation pairs 601/602 and 605/606 may be included in inference and/or training logic 615.

[0125] In at least one embodiment, one or more systems depicted in FIGS. 6A-6B are utilized to implement a deep object detection network. In at least one embodiment, one or
15 more systems depicted in FIGS. 6A-6B are utilized to implement one or more networks and models such as those described in connection with FIG. 1 and FIG. 3. In at least one embodiment, one or more systems depicted in FIGS. 6A-6B are utilized to implement a network that is based on mixture density networks and predicts uncertainty values of images. In at least one embodiment, one or more systems depicted in FIGS. 6A-6B are utilized to
20 implement an active learning method for object detection that utilizes mixture density networks to produce one or more Gaussian mixture models for each output of a network.

NEURAL NETWORK TRAINING AND DEPLOYMENT

[0126] FIG. 7 illustrates training and deployment of a deep neural network, according to at least one embodiment. In at least one embodiment, untrained neural network 706 is trained
25 using a training dataset 702. In at least one embodiment, training framework 704 is a PyTorch framework, whereas in other embodiments, training framework 704 is a TensorFlow, Boost, Caffè, Microsoft Cognitive Toolkit/CNTK, MXNet, Chainer, Keras, Deeplearning4j, or other training framework. In at least one embodiment, training framework 704 trains an untrained neural network 706 and enables it to be trained using
30 processing resources described herein to generate a trained neural network 708. In at least one embodiment, weights may be chosen randomly or by pre-training using a deep belief network. In at least one embodiment, training may be performed in either a supervised, partially supervised, or unsupervised manner.

[0127] In at least one embodiment, untrained neural network 706 is trained using
35 supervised learning, wherein training dataset 702 includes an input paired with a desired output for an input, or where training dataset 702 includes input having a known output and

5 an output of neural network 706 is manually graded. In at least one embodiment, untrained neural network 706 is trained in a supervised manner and processes inputs from training dataset 702 and compares resulting outputs against a set of expected or desired outputs. In at least one embodiment, errors are then propagated back through untrained neural network 706. In at least one embodiment, training framework 704 adjusts weights that control untrained

10 neural network 706. In at least one embodiment, training framework 704 includes tools to monitor how well untrained neural network 706 is converging towards a model, such as trained neural network 708, suitable to generating correct answers, such as in result 714, based on input data such as a new dataset 712. In at least one embodiment, training framework 704 trains untrained neural network 706 repeatedly while adjust weights to refine

15 an output of untrained neural network 706 using a loss function and adjustment algorithm, such as stochastic gradient descent. In at least one embodiment, training framework 704 trains untrained neural network 706 until untrained neural network 706 achieves a desired accuracy. In at least one embodiment, trained neural network 708 can then be deployed to implement any number of machine learning operations.

20 [0128] In at least one embodiment, untrained neural network 706 is trained using unsupervised learning, wherein untrained neural network 706 attempts to train itself using unlabeled data. In at least one embodiment, unsupervised learning training dataset 702 will include input data without any associated output data or “ground truth” data. In at least one embodiment, untrained neural network 706 can learn groupings within training dataset 702

25 and can determine how individual inputs are related to untrained dataset 702. In at least one embodiment, unsupervised training can be used to generate a self-organizing map in trained neural network 708 capable of performing operations useful in reducing dimensionality of new dataset 712. In at least one embodiment, unsupervised training can also be used to perform anomaly detection, which allows identification of data points in new dataset 712 that

30 deviate from normal patterns of new dataset 712.

[0129] In at least one embodiment, semi-supervised learning may be used, which is a technique in which in training dataset 702 includes a mix of labeled and unlabeled data. In at least one embodiment, training framework 704 may be used to perform incremental learning, such as through transferred learning techniques. In at least one embodiment, incremental

35 learning enables trained neural network 708 to adapt to new dataset 712 without forgetting knowledge instilled within trained neural network 708 during initial training.

5 [0130] In at least one embodiment, one or more systems depicted in FIG. 7 are utilized to implement a deep object detection network. In at least one embodiment, one or more systems depicted in FIG. 7 are utilized to implement one or more networks and models such as those described in connection with FIG. 1 and FIG. 3. In at least one embodiment, one or more systems depicted in FIG. 7 are utilized to implement a network that is based on mixture
10 density networks and predicts uncertainty values of images. In at least one embodiment, one or more systems depicted in FIG. 7 are utilized to implement an active learning method for object detection that utilizes mixture density networks to produce one or more Gaussian mixture models for each output of a network.

DATA CENTER

15 [0131] FIG. 8 illustrates an example data center 800, in which at least one embodiment may be used. In at least one embodiment, data center 800 includes a data center infrastructure layer 810, a framework layer 820, a software layer 830 and an application layer 840.

[0132] In at least one embodiment, as shown in FIG. 8, data center infrastructure layer 810
20 may include a resource orchestrator 812, grouped computing resources 814, and node computing resources ("node C.R.s") 816(1)-816(N), where "N" represents a positive integer (which may be a different integer "N" than used in other figures). In at least one embodiment, node C.R.s 816(1)-816(N) may include, but are not limited to, any number of central processing units ("CPUs") or other processors (including accelerators, field
25 programmable gate arrays (FPGAs), graphics processors, etc.), memory storage devices 818(1)-818(N) (e.g., dynamic read-only memory, solid state storage or disk drives), network input/output ("NW I/O") devices, network switches, virtual machines ("VMs"), power modules, and cooling modules, etc. In at least one embodiment, one or more node C.R.s from among node C.R.s 816(1)-816(N) may be a server having one or more of above-
30 mentioned computing resources.

[0133] In at least one embodiment, grouped computing resources 814 may include separate groupings of node C.R.s housed within one or more racks (not shown), or many racks housed in data centers at various geographical locations (also not shown). In at least one
embodiment, separate groupings of node C.R.s within grouped computing resources 814 may
35 include grouped compute, network, memory or storage resources that may be configured or allocated to support one or more workloads. In at least one embodiment, several node C.R.s

5 including CPUs or processors may grouped within one or more racks to provide compute resources to support one or more workloads. In at least one embodiment, one or more racks may also include any number of power modules, cooling modules, and network switches, in any combination.

[0134] In at least one embodiment, resource orchestrator 812 may configure or otherwise
10 control one or more node C.R.s 816(1)-816(N) and/or grouped computing resources 814. In at least one embodiment, resource orchestrator 812 may include a software design infrastructure (“SDI”) management entity for data center 800. In at least one embodiment, resource orchestrator 612 may include hardware, software or some combination thereof.

[0135] In at least one embodiment, as shown in FIG. 8, framework layer 820 includes a job
15 scheduler 822, a configuration manager 824, a resource manager 826 and a distributed file system 828. In at least one embodiment, framework layer 820 may include a framework to support software 832 of software layer 830 and/or one or more application(s) 842 of application layer 840. In at least one embodiment, software 832 or application(s) 842 may respectively include web-based service software or applications, such as those provided by
20 Amazon Web Services, Google Cloud and Microsoft Azure. In at least one embodiment, framework layer 820 may be, but is not limited to, a type of free and open-source software web application framework such as Apache Spark™ (hereinafter “Spark”) that may utilize distributed file system 828 for large-scale data processing (e.g., “big data”). In at least one embodiment, job scheduler 832 may include a Spark driver to facilitate scheduling of
25 workloads supported by various layers of data center 800. In at least one embodiment, configuration manager 824 may be capable of configuring different layers such as software layer 830 and framework layer 820 including Spark and distributed file system 828 for supporting large-scale data processing. In at least one embodiment, resource manager 826 may be capable of managing clustered or grouped computing resources mapped to or
30 allocated for support of distributed file system 828 and job scheduler 822. In at least one embodiment, clustered or grouped computing resources may include grouped computing resources 814 at data center infrastructure layer 810. In at least one embodiment, resource manager 826 may coordinate with resource orchestrator 812 to manage these mapped or allocated computing resources.

35 [0136] In at least one embodiment, software 832 included in software layer 830 may include software used by at least portions of node C.R.s 816(1)-816(N), grouped computing

5 resources 814, and/or distributed file system 828 of framework layer 820. In at least one embodiment, one or more types of software may include, but are not limited to, Internet web page search software, e-mail virus scan software, database software, and streaming video content software.

[0137] In at least one embodiment, application(s) 842 included in application layer 840
10 may include one or more types of applications used by at least portions of node C.R.s 816(1)-816(N), grouped computing resources 814, and/or distributed file system 828 of framework layer 820. In at least one embodiment, one or more types of applications may include, but are not limited to, any number of a genomics application, a cognitive compute, application and a machine learning application, including training or inferencing software, machine learning
15 framework software (e.g., PyTorch, TensorFlow, Caffe, etc.) or other machine learning applications used in conjunction with one or more embodiments.

[0138] In at least one embodiment, any of configuration manager 824, resource manager 826, and resource orchestrator 812 may implement any number and type of self-modifying actions based on any amount and type of data acquired in any technically feasible fashion. In
20 at least one embodiment, self-modifying actions may relieve a data center operator of data center 800 from making possibly bad configuration decisions and possibly avoiding underutilized and/or poor performing portions of a data center.

[0139] In at least one embodiment, data center 800 may include tools, services, software or other resources to train one or more machine learning models or predict or infer information
25 using one or more machine learning models according to one or more embodiments described herein. For example, in at least one embodiment, a machine learning model may be trained by calculating weight parameters according to a neural network architecture using software and computing resources described above with respect to data center 800. In at least one embodiment, trained machine learning models corresponding to one or more neural networks
30 may be used to infer or predict information using resources described above with respect to data center 800 by using weight parameters calculated through one or more training techniques described herein.

[0140] In at least one embodiment, data center may use CPUs, application-specific integrated circuits (ASICs), GPUs, FPGAs, or other hardware to perform training and/or
35 inferencing using above-described resources. Moreover, one or more software and/or hardware resources described above may be configured as a service to allow users to train or

5 performing inferencing of information, such as image recognition, speech recognition, or other artificial intelligence services.

[0141] Inference and/or training logic 615 are used to perform inferencing and/or training operations associated with one or more embodiments. Details regarding inference and/or training logic 615 are provided herein in conjunction with FIGS. 6A and/or 6B. In at least
10 one embodiment, inference and/or training logic 615 may be used in system FIG. 8 for inferencing or predicting operations based, at least in part, on weight parameters calculated using neural network training operations, neural network functions and/or architectures, or neural network use cases described herein.

[0142] In at least one embodiment, one or more systems depicted in FIG. 8 are utilized to
15 implement a deep object detection network. In at least one embodiment, one or more systems depicted in FIG. 8 are utilized to implement one or more networks and models such as those described in connection with FIG. 1 and FIG. 3. In at least one embodiment, one or more systems depicted in FIG. 8 are utilized to implement a network that is based on mixture density networks and predicts uncertainty values of images. In at least one embodiment, one
20 or more systems depicted in FIG. 8 are utilized to implement an active learning method for object detection that utilizes mixture density networks to produce one or more Gaussian mixture models for each output of a network.

AUTONOMOUS VEHICLE

[0143] FIG. 9A illustrates an example of an autonomous vehicle 900, according to at least
25 one embodiment. In at least one embodiment, autonomous vehicle 900 (alternatively referred to herein as “vehicle 900”) may be, without limitation, a passenger vehicle, such as a car, a truck, a bus, and/or another type of vehicle that accommodates one or more passengers. In at least one embodiment, vehicle 900 may be a semi-tractor-trailer truck used for hauling cargo. In at least one embodiment, vehicle 900 may be an airplane, robotic vehicle, or other kind of
30 vehicle.

[0144] Autonomous vehicles may be described in terms of automation levels, defined by National Highway Traffic Safety Administration (“NHTSA”), a division of US Department of Transportation, and Society of Automotive Engineers (“SAE”) “Taxonomy and Definitions for Terms Related to Driving Automation Systems for On-Road Motor Vehicles”
35 (e.g., Standard No. J3016-201806, published on June 15, 2018, Standard No. J3016-201609, published on September 30, 2016, and previous and future versions of this standard). In at

5 least one embodiment, vehicle 900 may be capable of functionality in accordance with one or more of Level 1 through Level 5 of autonomous driving levels. For example, in at least one embodiment, vehicle 900 may be capable of conditional automation (Level 3), high automation (Level 4), and/or full automation (Level 5), depending on embodiment.

[0145] In at least one embodiment, vehicle 900 may include, without limitation,
10 components such as a chassis, a vehicle body, wheels (e.g., 2, 4, 6, 8, 18, etc.), tires, axles, and other components of a vehicle. In at least one embodiment, vehicle 900 may include, without limitation, a propulsion system 950, such as an internal combustion engine, hybrid electric power plant, an all-electric engine, and/or another propulsion system type. In at least one embodiment, propulsion system 950 may be connected to a drive train of vehicle 900,
15 which may include, without limitation, a transmission, to enable propulsion of vehicle 900. In at least one embodiment, propulsion system 950 may be controlled in response to receiving signals from a throttle/accelerator(s) 952.

[0146] In at least one embodiment, a steering system 954, which may include, without limitation, a steering wheel, is used to steer vehicle 900 (e.g., along a desired path or route)
20 when propulsion system 950 is operating (e.g., when vehicle 900 is in motion). In at least one embodiment, steering system 954 may receive signals from steering actuator(s) 956. In at least one embodiment, a steering wheel may be optional for full automation (Level 5) functionality. In at least one embodiment, a brake sensor system 946 may be used to operate vehicle brakes in response to receiving signals from brake actuator(s) 948 and/or brake
25 sensors.

[0147] In at least one embodiment, controller(s) 936, which may include, without limitation, one or more system on chips (“SoCs”) (not shown in FIG. 9A) and/or graphics processing unit(s) (“GPU(s)”), provide signals (e.g., representative of commands) to one or more components and/or systems of vehicle 900. For instance, in at least one embodiment,
30 controller(s) 936 may send signals to operate vehicle brakes via brake actuator(s) 948, to operate steering system 954 via steering actuator(s) 956, to operate propulsion system 950 via throttle/accelerator(s) 952. In at least one embodiment, controller(s) 936 may include one or more onboard (e.g., integrated) computing devices that process sensor signals, and output operation commands (e.g., signals representing commands) to enable autonomous driving
35 and/or to assist a human driver in driving vehicle 900. In at least one embodiment, controller(s) 936 may include a first controller for autonomous driving functions, a second

- 5 controller for functional safety functions, a third controller for artificial intelligence functionality (e.g., computer vision), a fourth controller for infotainment functionality, a fifth controller for redundancy in emergency conditions, and/or other controllers. In at least one embodiment, a single controller may handle two or more of above functionalities, two or more controllers may handle a single functionality, and/or any combination thereof.
- 10 [0148] In at least one embodiment, controller(s) 936 provide signals for controlling one or more components and/or systems of vehicle 900 in response to sensor data received from one or more sensors (e.g., sensor inputs). In at least one embodiment, sensor data may be received from, for example and without limitation, global navigation satellite systems (“GNSS”) sensor(s) 958 (e.g., Global Positioning System sensor(s)), RADAR sensor(s) 960,
- 15 ultrasonic sensor(s) 962, LIDAR sensor(s) 964, inertial measurement unit (“IMU”) sensor(s) 966 (e.g., accelerometer(s), gyroscope(s), a magnetic compass or magnetic compasses, magnetometer(s), etc.), microphone(s) 996, stereo camera(s) 968, wide-view camera(s) 970 (e.g., fisheye cameras), infrared camera(s) 972, surround camera(s) 974 (e.g., 360 degree cameras), long-range cameras (not shown in Figure 9A), mid-range camera(s) (not shown in
- 20 Figure 9A), speed sensor(s) 944 (e.g., for measuring speed of vehicle 900), vibration sensor(s) 942, steering sensor(s) 940, brake sensor(s) (e.g., as part of brake sensor system 946), and/or other sensor types.
- [0149] In at least one embodiment, one or more of controller(s) 936 may receive inputs (e.g., represented by input data) from an instrument cluster 932 of vehicle 900 and provide
- 25 outputs (e.g., represented by output data, display data, etc.) via a human-machine interface (“HMI”) display 934, an audible annunciator, a loudspeaker, and/or via other components of vehicle 900. In at least one embodiment, outputs may include information such as vehicle velocity, speed, time, map data (e.g., a High Definition map (not shown in FIG. 9A), location data (e.g., vehicle’s 900 location, such as on a map), direction, location of other vehicles
- 30 (e.g., an occupancy grid), information about objects and status of objects as perceived by controller(s) 936, etc. For example, in at least one embodiment, HMI display 934 may display information about presence of one or more objects (e.g., a street sign, caution sign, traffic light changing, etc.), and/or information about driving maneuvers vehicle has made, is making, or will make (e.g., changing lanes now, taking exit 34B in two miles, etc.).
- 35 [0150] In at least one embodiment, vehicle 900 further includes a network interface 924 which may use wireless antenna(s) 926 and/or modem(s) to communicate over one or more

5 networks. For example, in at least one embodiment, network interface 924 may be capable of communication over Long-Term Evolution (“LTE”), Wideband Code Division Multiple Access (“WCDMA”), Universal Mobile Telecommunications System (“UMTS”), Global System for Mobile communication (“GSM”), IMT-CDMA Multi-Carrier (“CDMA2000”) networks, etc. In at least one embodiment, wireless antenna(s) 926 may also enable
10 communication between objects in environment (e.g., vehicles, mobile devices, etc.), using local area network(s), such as Bluetooth, Bluetooth Low Energy (“LE”), Z-Wave, ZigBee, etc., and/or low power wide-area network(s) (“LPWANs”), such as LoRaWAN, SigFox, etc. protocols.

[0151] Inference and/or training logic 615 are used to perform inferencing and/or training
15 operations associated with one or more embodiments. Details regarding inference and/or training logic 615 are provided herein in conjunction with FIGS. 6A and/or 6B. In at least one embodiment, inference and/or training logic 615 may be used in system FIG. 9A for inferencing or predicting operations based, at least in part, on weight parameters calculated using neural network training operations, neural network functions and/or architectures, or
20 neural network use cases described herein.

[0152] FIG. 9B illustrates an example of camera locations and fields of view for autonomous vehicle 900 of FIG. 9A, according to at least one embodiment. In at least one embodiment, cameras and respective fields of view are one example embodiment and are not intended to be limiting. For instance, in at least one embodiment, additional and/or
25 alternative cameras may be included and/or cameras may be located at different locations on vehicle 900.

[0153] In at least one embodiment, camera types for cameras may include, but are not limited to, digital cameras that may be adapted for use with components and/or systems of vehicle 900. In at least one embodiment, camera(s) may operate at automotive safety
30 integrity level (“ASIL”) B and/or at another ASIL. In at least one embodiment, camera types may be capable of any image capture rate, such as 60 frames per second (fps), 1220 fps, 240 fps, etc., depending on embodiment. In at least one embodiment, cameras may be capable of using rolling shutters, global shutters, another type of shutter, or a combination thereof. In at least one embodiment, color filter array may include a red clear clear clear (“RCCC”) color
35 filter array, a red clear clear blue (“RCCB”) color filter array, a red blue green clear (“RBGC”) color filter array, a Foveon X3 color filter array, a Bayer sensors (“RGGB”) color

5 filter array, a monochrome sensor color filter array, and/or another type of color filter array. In at least one embodiment, clear pixel cameras, such as cameras with an RCCC, an RCCB, and/or an RBGC color filter array, may be used in an effort to increase light sensitivity.

[0154] In at least one embodiment, one or more of camera(s) may be used to perform advanced driver assistance systems (“ADAS”) functions (e.g., as part of a redundant or fail-
10 safe design). For example, in at least one embodiment, a Multi-Function Mono Camera may be installed to provide functions including lane departure warning, traffic sign assist and intelligent headlamp control. In at least one embodiment, one or more of camera(s) (e.g., all cameras) may record and provide image data (e.g., video) simultaneously.

[0155] In at least one embodiment, one or more camera may be mounted in a mounting
15 assembly, such as a custom designed (three-dimensional (“3D”) printed) assembly, in order to cut out stray light and reflections from within vehicle 900 (e.g., reflections from dashboard reflected in windshield mirrors) which may interfere with camera image data capture abilities. With reference to wing-mirror mounting assemblies, in at least one embodiment, wing-mirror assemblies may be custom 3D printed so that a camera mounting plate matches a
20 shape of a wing-mirror. In at least one embodiment, camera(s) may be integrated into wing-mirrors. In at least one embodiment, for side-view cameras, camera(s) may also be integrated within four pillars at each corner of a cabin.

[0156] In at least one embodiment, cameras with a field of view that include portions of an environment in front of vehicle 900 (e.g., front-facing cameras) may be used for surround
25 view, to help identify forward facing paths and obstacles, as well as aid in, with help of one or more of controller(s) 936 and/or control SoCs, providing information critical to generating an occupancy grid and/or determining preferred vehicle paths. In at least one embodiment, front-facing cameras may be used to perform many similar ADAS functions as LIDAR, including, without limitation, emergency braking, pedestrian detection, and collision
30 avoidance. In at least one embodiment, front-facing cameras may also be used for ADAS functions and systems including, without limitation, Lane Departure Warnings (“LDW”), Autonomous Cruise Control (“ACC”), and/or other functions such as traffic sign recognition.

[0157] In at least one embodiment, a variety of cameras may be used in a front-facing configuration, including, for example, a monocular camera platform that includes a CMOS
35 (“complementary metal oxide semiconductor”) color imager. In at least one embodiment, a wide-view camera 970 may be used to perceive objects coming into view from a periphery

5 (e.g., pedestrians, crossing traffic or bicycles). Although only one wide-view camera 970 is illustrated in FIG. 9B, in other embodiments, there may be any number (including zero) wide-view cameras on vehicle 900. In at least one embodiment, any number of long-range camera(s) 998 (e.g., a long-view stereo camera pair) may be used for depth-based object detection, especially for objects for which a neural network has not yet been trained. In at least one embodiment, long-range camera(s) 998 may also be used for object detection and classification, as well as basic object tracking.

[0158] In at least one embodiment, any number of stereo camera(s) 968 may also be included in a front-facing configuration. In at least one embodiment, one or more of stereo camera(s) 968 may include an integrated control unit comprising a scalable processing unit, which may provide a programmable logic (“FPGA”) and a multi-core micro-processor with an integrated Controller Area Network (“CAN”) or Ethernet interface on a single chip. In at least one embodiment, such a unit may be used to generate a 3D map of an environment of vehicle 900, including a distance estimate for all points in an image. In at least one embodiment, one or more of stereo camera(s) 968 may include, without limitation, compact stereo vision sensor(s) that may include, without limitation, two camera lenses (one each on left and right) and an image processing chip that may measure distance from vehicle 900 to target object and use generated information (e.g., metadata) to activate autonomous emergency braking and lane departure warning functions. In at least one embodiment, other types of stereo camera(s) 968 may be used in addition to, or alternatively from, those described herein.

[0159] In at least one embodiment, cameras with a field of view that include portions of environment to sides of vehicle 900 (e.g., side-view cameras) may be used for surround view, providing information used to create and update an occupancy grid, as well as to generate side impact collision warnings. For example, in at least one embodiment, surround camera(s) 974 (e.g., four surround cameras as illustrated in FIG. 9B) could be positioned on vehicle 900. In at least one embodiment, surround camera(s) 974 may include, without limitation, any number and combination of wide-view cameras, fisheye camera(s), 360 degree camera(s), and/or similar cameras. For instance, in at least one embodiment, four fisheye cameras may be positioned on a front, a rear, and sides of vehicle 900. In at least one embodiment, vehicle 900 may use three surround camera(s) 974 (e.g., left, right, and rear), and may leverage one or more other camera(s) (e.g., a forward-facing camera) as a fourth surround-view camera.

5 [0160] In at least one embodiment, cameras with a field of view that include portions of an environment behind vehicle 900 (e.g., rear-view cameras) may be used for parking assistance, surround view, rear collision warnings, and creating and updating an occupancy grid. In at least one embodiment, a wide variety of cameras may be used including, but not limited to, cameras that are also suitable as a front-facing camera(s) (e.g., long-range cameras 998
10 and/or mid-range camera(s) 976, stereo camera(s) 968), infrared camera(s) 972, etc.), as described herein.

[0161] Inference and/or training logic 615 are used to perform inferencing and/or training operations associated with one or more embodiments. Details regarding inference and/or training logic 615 are provided herein in conjunction with FIGS. 6A and/or 6B. In at least
15 one embodiment, inference and/or training logic 615 may be used in system FIG. 9B for inferencing or predicting operations based, at least in part, on weight parameters calculated using neural network training operations, neural network functions and/or architectures, or neural network use cases described herein.

[0162] FIG. 9C is a block diagram illustrating an example system architecture for
20 autonomous vehicle 900 of FIG. 9A, according to at least one embodiment. In at least one embodiment, each of components, features, and systems of vehicle 900 in FIG. 9C is illustrated as being connected via a bus 902. In at least one embodiment, bus 902 may include, without limitation, a CAN data interface (alternatively referred to herein as a “CAN bus”). In at least one embodiment, a CAN may be a network inside vehicle 900 used to aid in
25 control of various features and functionality of vehicle 900, such as actuation of brakes, acceleration, braking, steering, windshield wipers, etc. In at least one embodiment, bus 902 may be configured to have dozens or even hundreds of nodes, each with its own unique identifier (e.g., a CAN ID). In at least one embodiment, bus 902 may be read to find steering wheel angle, ground speed, engine revolutions per minute (“RPMs”), button positions, and/or
30 other vehicle status indicators. In at least one embodiment, bus 902 may be a CAN bus that is ASIL B compliant.

[0163] In at least one embodiment, in addition to, or alternatively from CAN, FlexRay and/or Ethernet protocols may be used. In at least one embodiment, there may be any number of busses forming bus 902, which may include, without limitation, zero or more
35 CAN busses, zero or more FlexRay busses, zero or more Ethernet busses, and/or zero or more other types of busses using different protocols. In at least one embodiment, two or more

5 busses may be used to perform different functions, and/or may be used for redundancy. For example, a first bus may be used for collision avoidance functionality and a second bus may be used for actuation control. In at least one embodiment, each bus of bus 902 may communicate with any of components of vehicle 900, and two or more busses of bus 902 may communicate with corresponding components. In at least one embodiment, each of any
10 number of system(s) on chip(s) (“SoC(s)”) 904 (such as SoC 904(A) and SoC 904(B), each of controller(s) 936, and/or each computer within vehicle may have access to same input data (e.g., inputs from sensors of vehicle 900), and may be connected to a common bus, such CAN bus.

[0164] In at least one embodiment, vehicle 900 may include one or more controller(s) 936,
15 such as those described herein with respect to FIG. 9A. In at least one embodiment, controller(s) 936 may be used for a variety of functions. In at least one embodiment, controller(s) 936 may be coupled to any of various other components and systems of vehicle 900, and may be used for control of vehicle 900, artificial intelligence of vehicle 900, infotainment for vehicle 900, and/or other functions.

20 [0165] In at least one embodiment, vehicle 900 may include any number of SoCs 904. In at least one embodiment, each of SoCs 904 may include, without limitation, central processing units (“CPU(s)”) 906, graphics processing units (“GPU(s)”) 908, processor(s) 910, cache(s) 912, accelerator(s) 914, data store(s) 916, and/or other components and features not illustrated. In at least one embodiment, SoC(s) 904 may be used to control vehicle 900 in
25 a variety of platforms and systems. For example, in at least one embodiment, SoC(s) 904 may be combined in a system (e.g., system of vehicle 900) with a High Definition (“HD”) map 922 which may obtain map refreshes and/or updates via network interface 924 from one or more servers (not shown in Figure 9C).

[0166] In at least one embodiment, CPU(s) 906 may include a CPU cluster or CPU
30 complex (alternatively referred to herein as a “CCPLEX”). In at least one embodiment, CPU(s) 906 may include multiple cores and/or level two (“L2”) caches. For instance, in at least one embodiment, CPU(s) 906 may include eight cores in a coherent multi-processor configuration. In at least one embodiment, CPU(s) 906 may include four dual-core clusters where each cluster has a dedicated L2 cache (e.g., a 2 megabyte (MB) L2 cache). In at least
35 one embodiment, CPU(s) 906 (e.g., CCPLEX) may be configured to support simultaneous

5 cluster operations enabling any combination of clusters of CPU(s) 906 to be active at any given time.

[0167] In at least one embodiment, one or more of CPU(s) 906 may implement power management capabilities that include, without limitation, one or more of following features: individual hardware blocks may be clock-gated automatically when idle to save dynamic
10 power; each core clock may be gated when such core is not actively executing instructions due to execution of Wait for Interrupt (“WFI”)/Wait for Event (“WFE”) instructions; each core may be independently power-gated; each core cluster may be independently clock-gated when all cores are clock-gated or power-gated; and/or each core cluster may be independently power-gated when all cores are power-gated. In at least one embodiment,
15 CPU(s) 906 may further implement an enhanced algorithm for managing power states, where allowed power states and expected wakeup times are specified, and hardware/microcode determines which best power state to enter for core, cluster, and CCPLEX. In at least one embodiment, processing cores may support simplified power state entry sequences in software with work offloaded to microcode.

20 [0168] In at least one embodiment, GPU(s) 908 may include an integrated GPU (alternatively referred to herein as an “iGPU”). In at least one embodiment, GPU(s) 908 may be programmable and may be efficient for parallel workloads. In at least one embodiment, GPU(s) 908 may use an enhanced tensor instruction set. In at least one embodiment, GPU(s) 908 may include one or more streaming microprocessors, where each streaming
25 microprocessor may include a level one (“L1”) cache (e.g., an L1 cache with at least 96 KB storage capacity), and two or more streaming microprocessors may share an L2 cache (e.g., an L2 cache with a 512 KB storage capacity). In at least one embodiment, GPU(s) 908 may include at least eight streaming microprocessors. In at least one embodiment, GPU(s) 908 may use compute application programming interface(s) (API(s)). In at least one embodiment,
30 GPU(s) 908 may use one or more parallel computing platforms and/or programming models (e.g., NVIDIA’s CUDA model).

[0169] In at least one embodiment, one or more of GPU(s) 908 may be power-optimized for best performance in automotive and embedded use cases. For example, in at least one embodiment, GPU(s) 908 could be fabricated on Fin field-effect transistor (“FinFET”)
35 circuitry. In at least one embodiment, each streaming microprocessor may incorporate a number of mixed-precision processing cores partitioned into multiple blocks. For example,

5 and without limitation, 64 PF32 cores and 32 PF64 cores could be partitioned into four processing blocks. In at least one embodiment, each processing block could be allocated 16 FP32 cores, 8 FP64 cores, 16 INT32 cores, two mixed-precision NVIDIA Tensor cores for deep learning matrix arithmetic, a level zero (“L0”) instruction cache, a warp scheduler, a dispatch unit, and/or a 64 KB register file. In at least one embodiment, streaming
10 microprocessors may include independent parallel integer and floating-point data paths to provide for efficient execution of workloads with a mix of computation and addressing calculations. In at least one embodiment, streaming microprocessors may include independent thread scheduling capability to enable finer-grain synchronization and cooperation between parallel threads. In at least one embodiment, streaming microprocessors
15 may include a combined L1 data cache and shared memory unit in order to improve performance while simplifying programming.

[0170] In at least one embodiment, one or more of GPU(s) 908 may include a high bandwidth memory (“HBM”) and/or a 16 GB HBM2 memory subsystem to provide, in some examples, about 900 GB/second peak memory bandwidth. In at least one embodiment, in
20 addition to, or alternatively from, HBM memory, a synchronous graphics random-access memory (“SGRAM”) may be used, such as a graphics double data rate type five synchronous random-access memory (“GDDR5”).

[0171] In at least one embodiment, GPU(s) 908 may include unified memory technology. In at least one embodiment, address translation services (“ATS”) support may be used to
25 allow GPU(s) 908 to access CPU(s) 906 page tables directly. In at least one embodiment, embodiment, when a GPU of GPU(s) 908 memory management unit (“MMU”) experiences a miss, an address translation request may be transmitted to CPU(s) 906. In response, 2 CPU of CPU(s) 906 may look in its page tables for a virtual-to-physical mapping for an address and transmit translation back to GPU(s) 908, in at least one embodiment. In at least one
30 embodiment, unified memory technology may allow a single unified virtual address space for memory of both CPU(s) 906 and GPU(s) 908, thereby simplifying GPU(s) 908 programming and porting of applications to GPU(s) 908.

[0172] In at least one embodiment, GPU(s) 908 may include any number of access counters that may keep track of frequency of access of GPU(s) 908 to memory of other processors. In
35 at least one embodiment, access counter(s) may help ensure that memory pages are moved to

5 physical memory of a processor that is accessing pages most frequently, thereby improving efficiency for memory ranges shared between processors.

[0173] In at least one embodiment, one or more of SoC(s) 904 may include any number of cache(s) 912, including those described herein. For example, in at least one embodiment, cache(s) 912 could include a level three (“L3”) cache that is available to both CPU(s) 906 and
10 GPU(s) 908 (e.g., that is connected to CPU(s) 906 and GPU(s) 908). In at least one embodiment, cache(s) 912 may include a write-back cache that may keep track of states of lines, such as by using a cache coherence protocol (e.g., MEI, MESI, MSI, etc.). In at least one embodiment, a L3 cache may include 4 MB of memory or more, depending on embodiment, although smaller cache sizes may be used.

15 [0174] In at least one embodiment, one or more of SoC(s) 904 may include one or more accelerator(s) 914 (e.g., hardware accelerators, software accelerators, or a combination thereof). In at least one embodiment, SoC(s) 904 may include a hardware acceleration cluster that may include optimized hardware accelerators and/or large on-chip memory. In at least one embodiment, large on-chip memory (e.g., 4 MB of SRAM), may enable a hardware
20 acceleration cluster to accelerate neural networks and other calculations. In at least one embodiment, a hardware acceleration cluster may be used to complement GPU(s) 908 and to off-load some of tasks of GPU(s) 908 (e.g., to free up more cycles of GPU(s) 908 for performing other tasks). In at least one embodiment, accelerator(s) 914 could be used for targeted workloads (e.g., perception, convolutional neural networks (“CNNs”), recurrent
25 neural networks (“RNNs”), etc.) that are stable enough to be amenable to acceleration. In at least one embodiment, a CNN may include a region-based or regional convolutional neural networks (“RCNNs”) and Fast RCNNs (e.g., as used for object detection) or other type of CNN.

[0175] In at least one embodiment, accelerator(s) 914 (e.g., hardware acceleration cluster)
30 may include one or more deep learning accelerator (“DLA”). In at least one embodiment, DLA(s) may include, without limitation, one or more Tensor processing units (“TPUs”) that may be configured to provide an additional ten trillion operations per second for deep learning applications and inferencing. In at least one embodiment, TPUs may be accelerators configured to, and optimized for, performing image processing functions (e.g., for CNNs,
35 RCNNs, etc.). In at least one embodiment, DLA(s) may further be optimized for a specific set of neural network types and floating point operations, as well as inferencing. In at least

5 one embodiment, design of DLA(s) may provide more performance per millimeter than a typical general-purpose GPU, and typically vastly exceeds performance of a CPU. In at least one embodiment, TPU(s) may perform several functions, including a single-instance convolution function, supporting, for example, INT8, INT16, and FP16 data types for both features and weights, as well as post-processor functions. In at least one embodiment,
10 DLA(s) may quickly and efficiently execute neural networks, especially CNNs, on processed or unprocessed data for any of a variety of functions, including, for example and without limitation: a CNN for object identification and detection using data from camera sensors; a CNN for distance estimation using data from camera sensors; a CNN for emergency vehicle detection and identification and detection using data from microphones; a CNN for facial
15 recognition and vehicle owner identification using data from camera sensors; and/or a CNN for security and/or safety related events.

[0176] In at least one embodiment, DLA(s) may perform any function of GPU(s) 908, and by using an inference accelerator, for example, a designer may target either DLA(s) or GPU(s) 908 for any function. For example, in at least one embodiment, a designer may focus
20 processing of CNNs and floating point operations on DLA(s) and leave other functions to GPU(s) 908 and/or accelerator(s) 914.

[0177] In at least one embodiment, accelerator(s) 914 may include programmable vision accelerator (“PVA”), which may alternatively be referred to herein as a computer vision accelerator. In at least one embodiment, PVA may be designed and configured to accelerate
25 computer vision algorithms for advanced driver assistance system (“ADAS”) 938, autonomous driving, augmented reality (“AR”) applications, and/or virtual reality (“VR”) applications. In at least one embodiment, PVA may provide a balance between performance and flexibility. For example, in at least one embodiment, each PVA may include, for example and without limitation, any number of reduced instruction set computer (“RISC”) cores, direct memory access (“DMA”), and/or any number of vector processors.
30

[0178] In at least one embodiment, RISC cores may interact with image sensors (e.g., image sensors of any cameras described herein), image signal processor(s), etc. In at least one embodiment, each RISC core may include any amount of memory. In at least one embodiment, RISC cores may use any of a number of protocols, depending on embodiment.
35 In at least one embodiment, RISC cores may execute a real-time operating system (“RTOS”). In at least one embodiment, RISC cores may be implemented using one or more integrated

5 circuit devices, application specific integrated circuits (“ASICs”), and/or memory devices. For example, in at least one embodiment, RISC cores could include an instruction cache and/or a tightly coupled RAM.

[0179] In at least one embodiment, DMA may enable components of PVA to access system memory independently of CPU(s) 906. In at least one embodiment, DMA may support any
10 number of features used to provide optimization to a PVA including, but not limited to, supporting multi-dimensional addressing and/or circular addressing. In at least one embodiment, DMA may support up to six or more dimensions of addressing, which may include, without limitation, block width, block height, block depth, horizontal block stepping, vertical block stepping, and/or depth stepping.

15 [0180] In at least one embodiment, vector processors may be programmable processors that may be designed to efficiently and flexibly execute programming for computer vision algorithms and provide signal processing capabilities. In at least one embodiment, a PVA may include a PVA core and two vector processing subsystem partitions. In at least one embodiment, a PVA core may include a processor subsystem, DMA engine(s) (e.g., two
20 DMA engines), and/or other peripherals. In at least one embodiment, a vector processing subsystem may operate as a primary processing engine of a PVA, and may include a vector processing unit (“VPU”), an instruction cache, and/or vector memory (e.g., “VMEM”). In at least one embodiment, VPU core may include a digital signal processor such as, for example, a single instruction, multiple data (“SIMD”), very long instruction word (“VLIW”) digital
25 signal processor. In at least one embodiment, a combination of SIMD and VLIW may enhance throughput and speed.

[0181] In at least one embodiment, each of vector processors may include an instruction cache and may be coupled to dedicated memory. As a result, in at least one embodiment, each of vector processors may be configured to execute independently of other vector
30 processors. In at least one embodiment, vector processors that are included in a particular PVA may be configured to employ data parallelism. For instance, in at least one embodiment, plurality of vector processors included in a single PVA may execute a common computer vision algorithm, but on different regions of an image. In at least one embodiment, vector processors included in a particular PVA may simultaneously execute different
35 computer vision algorithms, on one image, or even execute different algorithms on sequential images or portions of an image. In at least one embodiment, among other things, any number

5 of PVAs may be included in hardware acceleration cluster and any number of vector processors may be included in each PVA. In at least one embodiment, PVA may include additional error correcting code (“ECC”) memory, to enhance overall system safety.

[0182] In at least one embodiment, accelerator(s) 914 may include a computer vision network on-chip and static random-access memory (“SRAM”), for providing a high-
10 bandwidth, low latency SRAM for accelerator(s) 914. In at least one embodiment, on-chip memory may include at least 4 MB SRAM, comprising, for example and without limitation, eight field-configurable memory blocks, that may be accessible by both a PVA and a DLA. In at least one embodiment, each pair of memory blocks may include an advanced peripheral bus (“APB”) interface, configuration circuitry, a controller, and a multiplexer. In at least one
15 embodiment, any type of memory may be used. In at least one embodiment, a PVA and a DLA may access memory via a backbone that provides a PVA and a DLA with high-speed access to memory. In at least one embodiment, a backbone may include a computer vision network on-chip that interconnects a PVA and a DLA to memory (e.g., using APB).

[0183] In at least one embodiment, a computer vision network on-chip may include an
20 interface that determines, before transmission of any control signal/address/data, that both a PVA and a DLA provide ready and valid signals. In at least one embodiment, an interface may provide for separate phases and separate channels for transmitting control signals/addresses/data, as well as burst-type communications for continuous data transfer. In at least one embodiment, an interface may comply with International Organization for
25 Standardization (“ISO”) 26262 or International Electrotechnical Commission (“IEC”) 61508 standards, although other standards and protocols may be used.

[0184] In at least one embodiment, one or more of SoC(s) 904 may include a real-time ray-tracing hardware accelerator. In at least one embodiment, real-time ray-tracing hardware
30 accelerator may be used to quickly and efficiently determine positions and extents of objects (e.g., within a world model), to generate real-time visualization simulations, for RADAR signal interpretation, for sound propagation synthesis and/or analysis, for simulation of SONAR systems, for general wave propagation simulation, for comparison to LIDAR data for purposes of localization and/or other functions, and/or for other uses.

[0185] In at least one embodiment, accelerator(s) 914 can have a wide array of uses for
35 autonomous driving. In at least one embodiment, a PVA may be used for key processing stages in ADAS and autonomous vehicles. In at least one embodiment, a PVA’s capabilities

5 are a good match for algorithmic domains needing predictable processing, at low power and low latency. In other words, a PVA performs well on semi-dense or dense regular computation, even on small data sets, which might require predictable run-times with low latency and low power. In at least one embodiment, such as in vehicle 900, PVAs might be designed to run classic computer vision algorithms, as they can be efficient at object
10 detection and operating on integer math.

[0186] For example, according to at least one embodiment of technology, a PVA is used to perform computer stereo vision. In at least one embodiment, a semi-global matching-based algorithm may be used in some examples, although this is not intended to be limiting. In at least one embodiment, applications for Level 3-5 autonomous driving use motion
15 estimation/stereo matching on-the-fly (e.g., structure from motion, pedestrian recognition, lane detection, etc.). In at least one embodiment, a PVA may perform computer stereo vision functions on inputs from two monocular cameras.

[0187] In at least one embodiment, a PVA may be used to perform dense optical flow. For example, in at least one embodiment, a PVA could process raw RADAR data (e.g., using a
20 4D Fast Fourier Transform) to provide processed RADAR data. In at least one embodiment, a PVA is used for time of flight depth processing, by processing raw time of flight data to provide processed time of flight data, for example.

[0188] In at least one embodiment, a DLA may be used to run any type of network to enhance control and driving safety, including for example and without limitation, a neural
25 network that outputs a measure of confidence for each object detection. In at least one embodiment, confidence may be represented or interpreted as a probability, or as providing a relative “weight” of each detection compared to other detections. In at least one embodiment, a confidence measure enables a system to make further decisions regarding which detections should be considered as true positive detections rather than false positive detections. In at
30 least one embodiment, a system may set a threshold value for confidence and consider only detections exceeding threshold value as true positive detections. In an embodiment in which an automatic emergency braking (“AEB”) system is used, false positive detections would cause vehicle to automatically perform emergency braking, which is obviously undesirable. In at least one embodiment, highly confident detections may be considered as triggers for
35 AEB. In at least one embodiment, a DLA may run a neural network for regressing confidence value. In at least one embodiment, neural network may take as its input at least

5 some subset of parameters, such as bounding box dimensions, ground plane estimate obtained (e.g., from another subsystem), output from IMU sensor(s) 966 that correlates with vehicle 900 orientation, distance, 3D location estimates of object obtained from neural network and/or other sensors (e.g., LIDAR sensor(s) 964 or RADAR sensor(s) 960), among others.

[0189] In at least one embodiment, one or more of SoC(s) 904 may include data store(s) 916 (e.g., memory). In at least one embodiment, data store(s) 916 may be on-chip memory of SoC(s) 904, which may store neural networks to be executed on GPU(s) 908 and/or a DLA. In at least one embodiment, data store(s) 916 may be large enough in capacity to store multiple instances of neural networks for redundancy and safety. In at least one embodiment, data store(s) 916 may comprise L2 or L3 cache(s).

15 [0190] In at least one embodiment, one or more of SoC(s) 904 may include any number of processor(s) 910 (e.g., embedded processors). In at least one embodiment, processor(s) 910 may include a boot and power management processor that may be a dedicated processor and subsystem to handle boot power and management functions and related security enforcement. In at least one embodiment, a boot and power management processor may be a part of a boot sequence of SoC(s) 904 and may provide runtime power management services. In at least one embodiment, a boot power and management processor may provide clock and voltage programming, assistance in system low power state transitions, management of SoC(s) 904 thermals and temperature sensors, and/or management of SoC(s) 904 power states. In at least one embodiment, each temperature sensor may be implemented as a ring-oscillator whose output frequency is proportional to temperature, and SoC(s) 904 may use ring-oscillators to detect temperatures of CPU(s) 906, GPU(s) 908, and/or accelerator(s) 914. In at least one embodiment, if temperatures are determined to exceed a threshold, then a boot and power management processor may enter a temperature fault routine and put SoC(s) 904 into a lower power state and/or put vehicle 900 into a chauffeur to safe stop mode (e.g., bring vehicle 900 to a safe stop).

[0191] In at least one embodiment, processor(s) 910 may further include a set of embedded processors that may serve as an audio processing engine which may be an audio subsystem that enables full hardware support for multi-channel audio over multiple interfaces, and a broad and flexible range of audio I/O interfaces. In at least one embodiment, an audio processing engine is a dedicated processor core with a digital signal processor with dedicated RAM.

5 [0192] In at least one embodiment, processor(s) 910 may further include an always-on processor engine that may provide necessary hardware features to support low power sensor management and wake use cases. In at least one embodiment, an always-on processor engine may include, without limitation, a processor core, a tightly coupled RAM, supporting peripherals (e.g., timers and interrupt controllers), various I/O controller peripherals, and
10 routing logic.

[0193] In at least one embodiment, processor(s) 910 may further include a safety cluster engine that includes, without limitation, a dedicated processor subsystem to handle safety management for automotive applications. In at least one embodiment, a safety cluster engine may include, without limitation, two or more processor cores, a tightly coupled RAM,
15 support peripherals (e.g., timers, an interrupt controller, etc.), and/or routing logic. In a safety mode, two or more cores may operate, in at least one embodiment, in a lockstep mode and function as a single core with comparison logic to detect any differences between their operations. In at least one embodiment, processor(s) 910 may further include a real-time camera engine that may include, without limitation, a dedicated processor subsystem for
20 handling real-time camera management. In at least one embodiment, processor(s) 910 may further include a high-dynamic range signal processor that may include, without limitation, an image signal processor that is a hardware engine that is part of a camera processing pipeline.

[0194] In at least one embodiment, processor(s) 910 may include a video image compositor
25 that may be a processing block (e.g., implemented on a microprocessor) that implements video post-processing functions needed by a video playback application to produce a final image for a player window. In at least one embodiment, a video image compositor may perform lens distortion correction on wide-view camera(s) 970, surround camera(s) 974, and/or on in-cabin monitoring camera sensor(s). In at least one embodiment, in-cabin
30 monitoring camera sensor(s) are preferably monitored by a neural network running on another instance of SoC 904, configured to identify in cabin events and respond accordingly. In at least one embodiment, an in-cabin system may perform, without limitation, lip reading to activate cellular service and place a phone call, dictate emails, change a vehicle's destination, activate or change a vehicle's infotainment system and settings, or provide voice-
35 activated web surfing. In at least one embodiment, certain functions are available to a driver when a vehicle is operating in an autonomous mode and are disabled otherwise.

5 [0195] In at least one embodiment, a video image compositor may include enhanced temporal noise reduction for both spatial and temporal noise reduction. For example, in at least one embodiment, where motion occurs in a video, noise reduction weights spatial information appropriately, decreasing weights of information provided by adjacent frames. In at least one embodiment, where an image or portion of an image does not include motion, temporal noise reduction performed by video image compositor may use information from a previous image to reduce noise in a current image.

[0196] In at least one embodiment, a video image compositor may also be configured to perform stereo rectification on input stereo lens frames. In at least one embodiment, a video image compositor may further be used for user interface composition when an operating system desktop is in use, and GPU(s) 908 are not required to continuously render new surfaces. In at least one embodiment, when GPU(s) 908 are powered on and active doing 3D rendering, a video image compositor may be used to offload GPU(s) 908 to improve performance and responsiveness.

20 [0197] In at least one embodiment, one or more SoC of SoC(s) 904 may further include a mobile industry processor interface (“MIPI”) camera serial interface for receiving video and input from cameras, a high-speed interface, and/or a video input block that may be used for a camera and related pixel input functions. In at least one embodiment, one or more of SoC(s) 904 may further include an input/output controller(s) that may be controlled by software and may be used for receiving I/O signals that are uncommitted to a specific role.

25 [0198] In at least one embodiment, one or more Soc of SoC(s) 904 may further include a broad range of peripheral interfaces to enable communication with peripherals, audio encoders/decoders (“codecs”), power management, and/or other devices. In at least one embodiment, SoC(s) 904 may be used to process data from cameras (e.g., connected over Gigabit Multimedia Serial Link and Ethernet channels), sensors (e.g., LIDAR sensor(s) 964, RADAR sensor(s) 960, etc. that may be connected over Ethernet channels), data from bus 30 902 (e.g., speed of vehicle 900, steering wheel position, etc.), data from GNSS sensor(s) 958 (e.g., connected over a Ethernet bus or a CAN bus), etc. In at least one embodiment, one or more SoC of SoC(s) 904 may further include dedicated high-performance mass storage controllers that may include their own DMA engines, and that may be used to free CPU(s) 35 906 from routine data management tasks.

5 [0199] In at least one embodiment, SoC(s) 904 may be an end-to-end platform with a flexible architecture that spans automation Levels 3-5, thereby providing a comprehensive functional safety architecture that leverages and makes efficient use of computer vision and ADAS techniques for diversity and redundancy, and provides a platform for a flexible, reliable driving software stack, along with deep learning tools. In at least one embodiment,
10 SoC(s) 904 may be faster, more reliable, and even more energy-efficient and space-efficient than conventional systems. For example, in at least one embodiment, accelerator(s) 914, when combined with CPU(s) 906, GPU(s) 908, and data store(s) 916, may provide for a fast, efficient platform for Level 3-5 autonomous vehicles.

[0200] In at least one embodiment, computer vision algorithms may be executed on CPUs,
15 which may be configured using a high-level programming language, such as C, to execute a wide variety of processing algorithms across a wide variety of visual data. However, in at least one embodiment, CPUs are oftentimes unable to meet performance requirements of many computer vision applications, such as those related to execution time and power consumption, for example. In at least one embodiment, many CPUs are unable to execute
20 complex object detection algorithms in real-time, which is used in in-vehicle ADAS applications and in practical Level 3-5 autonomous vehicles.

[0201] Embodiments described herein allow for multiple neural networks to be performed simultaneously and/or sequentially, and for results to be combined together to enable Level 3-
5 autonomous driving functionality. For example, in at least one embodiment, a CNN
25 executing on a DLA or a discrete GPU (e.g., GPU(s) 920) may include text and word recognition, allowing reading and understanding of traffic signs, including signs for which a neural network has not been specifically trained. In at least one embodiment, a DLA may further include a neural network that is able to identify, interpret, and provide semantic understanding of a sign, and to pass that semantic understanding to path planning modules
30 running on a CPU Complex.

[0202] In at least one embodiment, multiple neural networks may be run simultaneously, as for Level 3, 4, or 5 driving. For example, in at least one embodiment, a warning sign stating “Caution: flashing lights indicate icy conditions,” along with an electric light, may be
independently or collectively interpreted by several neural networks. In at least one
35 embodiment, such warning sign itself may be identified as a traffic sign by a first deployed neural network (e.g., a neural network that has been trained), text “flashing lights indicate icy

5 conditions” may be interpreted by a second deployed neural network, which informs a vehicle’s path planning software (preferably executing on a CPU Complex) that when flashing lights are detected, icy conditions exist. In at least one embodiment, a flashing light may be identified by operating a third deployed neural network over multiple frames, informing a vehicle’s path-planning software of a presence (or an absence) of flashing lights.
10 In at least one embodiment, all three neural networks may run simultaneously, such as within a DLA and/or on GPU(s) 908.

[0203] In at least one embodiment, a CNN for facial recognition and vehicle owner identification may use data from camera sensors to identify presence of an authorized driver and/or owner of vehicle 900. In at least one embodiment, an always-on sensor processing
15 engine may be used to unlock a vehicle when an owner approaches a driver door and turns on lights, and, in a security mode, to disable such vehicle when an owner leaves such vehicle. In this way, SoC(s) 904 provide for security against theft and/or carjacking.

[0204] In at least one embodiment, a CNN for emergency vehicle detection and identification may use data from microphones 996 to detect and identify emergency vehicle
20 sirens. In at least one embodiment, SoC(s) 904 use a CNN for classifying environmental and urban sounds, as well as classifying visual data. In at least one embodiment, a CNN running on a DLA is trained to identify a relative closing speed of an emergency vehicle (e.g., by using a Doppler effect). In at least one embodiment, a CNN may also be trained to identify emergency vehicles specific to a local area in which a vehicle is operating, as identified by
25 GNSS sensor(s) 958. In at least one embodiment, when operating in Europe, a CNN will seek to detect European sirens, and when in North America, a CNN will seek to identify only North American sirens. In at least one embodiment, once an emergency vehicle is detected, a control program may be used to execute an emergency vehicle safety routine, slowing a vehicle, pulling over to a side of a road, parking a vehicle, and/or idling a vehicle, with
30 assistance of ultrasonic sensor(s) 962, until emergency vehicles pass.

[0205] In at least one embodiment, vehicle 900 may include CPU(s) 918 (e.g., discrete CPU(s), or dCPU(s)), that may be coupled to SoC(s) 904 via a high-speed interconnect (e.g., PCIe). In at least one embodiment, CPU(s) 918 may include an X86 processor, for example. CPU(s) 918 may be used to perform any of a variety of functions, including arbitrating
35 potentially inconsistent results between ADAS sensors and SoC(s) 904, and/or monitoring

5 status and health of controller(s) 936 and/or an infotainment system on a chip (“infotainment SoC”) 930, for example.

[0206] In at least one embodiment, vehicle 900 may include GPU(s) 920 (e.g., discrete GPU(s), or dGPU(s)), that may be coupled to SoC(s) 904 via a high-speed interconnect (e.g., NVIDIA’s NVLINK channel). In at least one embodiment, GPU(s) 920 may provide
10 additional artificial intelligence functionality, such as by executing redundant and/or different neural networks, and may be used to train and/or update neural networks based at least in part on input (e.g., sensor data) from sensors of a vehicle 900.

[0207] In at least one embodiment, vehicle 900 may further include network interface 924 which may include, without limitation, wireless antenna(s) 926 (e.g., one or more wireless
15 antennas for different communication protocols, such as a cellular antenna, a Bluetooth antenna, etc.). In at least one embodiment, network interface 924 may be used to enable wireless connectivity to Internet cloud services (e.g., with server(s) and/or other network devices), with other vehicles, and/or with computing devices (e.g., client devices of passengers). In at least one embodiment, to communicate with other vehicles, a direct link
20 may be established between vehicle 90 and another vehicle and/or an indirect link may be established (e.g., across networks and over the Internet). In at least one embodiment, direct links may be provided using a vehicle-to-vehicle communication link. In at least one embodiment, a vehicle-to-vehicle communication link may provide vehicle 900 information about vehicles in proximity to vehicle 900 (e.g., vehicles in front of, on a side of, and/or
25 behind vehicle 900). In at least one embodiment, such aforementioned functionality may be part of a cooperative adaptive cruise control functionality of vehicle 900.

[0208] In at least one embodiment, network interface 924 may include an SoC that provides modulation and demodulation functionality and enables controller(s) 936 to communicate over wireless networks. In at least one embodiment, network interface 924
30 may include a radio frequency front-end for up-conversion from baseband to radio frequency, and down conversion from radio frequency to baseband. In at least one embodiment, frequency conversions may be performed in any technically feasible fashion. For example, frequency conversions could be performed through well-known processes, and/or using super-heterodyne processes. In at least one embodiment, radio frequency front end
35 functionality may be provided by a separate chip. In at least one embodiment, network interfaces may include wireless functionality for communicating over LTE, WCDMA,

5 UMTS, GSM, CDMA2000, Bluetooth, Bluetooth LE, Wi-Fi, Z-Wave, ZigBee, LoRaWAN, and/or other wireless protocols.

[0209] In at least one embodiment, vehicle 900 may further include data store(s) 928 which may include, without limitation, off-chip (e.g., off SoC(s) 904) storage. In at least one embodiment, data store(s) 928 may include, without limitation, one or more storage elements
10 including RAM, SRAM, dynamic random-access memory (“DRAM”), video random-access memory (“VRAM”), flash memory, hard disks, and/or other components and/or devices that may store at least one bit of data.

[0210] In at least one embodiment, vehicle 900 may further include GNSS sensor(s) 958 (e.g., GPS and/or assisted GPS sensors), to assist in mapping, perception, occupancy grid
15 generation, and/or path planning functions. In at least one embodiment, any number of GNSS sensor(s) 958 may be used, including, for example and without limitation, a GPS using a USB connector with an Ethernet-to-Serial (e.g., RS-232) bridge.

[0211] In at least one embodiment, vehicle 900 may further include RADAR sensor(s) 960. In at least one embodiment, RADAR sensor(s) 960 may be used by vehicle 900 for long-
20 range vehicle detection, even in darkness and/or severe weather conditions. In at least one embodiment, RADAR functional safety levels may be ASIL B. In at least one embodiment, RADAR sensor(s) 960 may use a CAN bus and/or bus 902 (e.g., to transmit data generated by RADAR sensor(s) 960) for control and to access object tracking data, with access to Ethernet channels to access raw data in some examples. In at least one embodiment, a wide
25 variety of RADAR sensor types may be used. For example, and without limitation, RADAR sensor(s) 960 may be suitable for front, rear, and side RADAR use. In at least one embodiment, one or more sensor of RADAR sensors(s) 960 is a Pulse Doppler RADAR sensor.

[0212] In at least one embodiment, RADAR sensor(s) 960 may include different
30 configurations, such as long-range with narrow field of view, short-range with wide field of view, short-range side coverage, etc. In at least one embodiment, long-range RADAR may be used for adaptive cruise control functionality. In at least one embodiment, long-range RADAR systems may provide a broad field of view realized by two or more independent scans, such as within a 250 m (meter) range. In at least one embodiment, RADAR sensor(s)
35 960 may help in distinguishing between static and moving objects, and may be used by ADAS system 938 for emergency brake assist and forward collision warning. In at least one

5 embodiment, sensors 960(s) included in a long-range RADAR system may include, without limitation, monostatic multimodal RADAR with multiple (e.g., six or more) fixed RADAR antennae and a high-speed CAN and FlexRay interface. In at least one embodiment, with six antennae, a central four antennae may create a focused beam pattern, designed to record vehicle's 900 surroundings at higher speeds with minimal interference from traffic in
10 adjacent lanes. In at least one embodiment, another two antennae may expand field of view, making it possible to quickly detect vehicles entering or leaving a lane of vehicle 900.

[0213] In at least one embodiment, mid-range RADAR systems may include, as an example, a range of up to 160 m (front) or 80 m (rear), and a field of view of up to 42 degrees (front) or 150 degrees (rear). In at least one embodiment, short-range RADAR systems may
15 include, without limitation, any number of RADAR sensor(s) 960 designed to be installed at both ends of a rear bumper. When installed at both ends of a rear bumper, in at least one embodiment, a RADAR sensor system may create two beams that constantly monitor blind spots in a rear direction and next to a vehicle. In at least one embodiment, short-range RADAR systems may be used in ADAS system 938 for blind spot detection and/or lane
20 change assist.

[0214] In at least one embodiment, vehicle 900 may further include ultrasonic sensor(s) 962. In at least one embodiment, ultrasonic sensor(s) 962, which may be positioned at a front, a back, and/or side location of vehicle 900, may be used for parking assist and/or to create and update an occupancy grid. In at least one embodiment, a wide variety of ultrasonic
25 sensor(s) 962 may be used, and different ultrasonic sensor(s) 962 may be used for different ranges of detection (e.g., 2.5 m, 4 m). In at least one embodiment, ultrasonic sensor(s) 962 may operate at functional safety levels of ASIL B.

[0215] In at least one embodiment, vehicle 900 may include LIDAR sensor(s) 964. In at least one embodiment, LIDAR sensor(s) 964 may be used for object and pedestrian detection,
30 emergency braking, collision avoidance, and/or other functions. In at least one embodiment, LIDAR sensor(s) 964 may operate at functional safety level ASIL B. In at least one embodiment, vehicle 900 may include multiple LIDAR sensors 964 (e.g., two, four, six, etc.) that may use an Ethernet channel (e.g., to provide data to a Gigabit Ethernet switch).

[0216] In at least one embodiment, LIDAR sensor(s) 964 may be capable of providing a list
35 of objects and their distances for a 360-degree field of view. In at least one embodiment, commercially available LIDAR sensor(s) 964 may have an advertised range of approximately

5 100 m, with an accuracy of 2 cm to 3 cm, and with support for a 100 Mbps Ethernet connection, for example. In at least one embodiment, one or more non-protruding LIDAR sensors may be used. In such an embodiment, LIDAR sensor(s) 964 may include a small device that may be embedded into a front, a rear, a side, and/or a corner location of vehicle 900. In at least one embodiment, LIDAR sensor(s) 964, in such an embodiment, may provide
10 up to a 120-degree horizontal and 35-degree vertical field-of-view, with a 200 m range even for low-reflectivity objects. In at least one embodiment, front-mounted LIDAR sensor(s) 964 may be configured for a horizontal field of view between 45 degrees and 135 degrees.

[0217] In at least one embodiment, LIDAR technologies, such as 3D flash LIDAR, may also be used. In at least one embodiment, 3D flash LIDAR uses a flash of a laser as a
15 transmission source, to illuminate surroundings of vehicle 900 up to approximately 200 m. In at least one embodiment, a flash LIDAR unit includes, without limitation, a receptor, which records laser pulse transit time and reflected light on each pixel, which in turn corresponds to a range from vehicle 900 to objects. In at least one embodiment, flash LIDAR may allow for highly accurate and distortion-free images of surroundings to be generated with every laser
20 flash. In at least one embodiment, four flash LIDAR sensors may be deployed, one at each side of vehicle 900. In at least one embodiment, 3D flash LIDAR systems include, without limitation, a solid-state 3D staring array LIDAR camera with no moving parts other than a fan (e.g., a non-scanning LIDAR device). In at least one embodiment, flash LIDAR device may use a 5 nanosecond class I (eye-safe) laser pulse per frame and may capture reflected
25 laser light as a 3D range point cloud and co-registered intensity data.

[0218] In at least one embodiment, vehicle 900 may further include IMU sensor(s) 966. In at least one embodiment, IMU sensor(s) 966 may be located at a center of a rear axle of vehicle 900. In at least one embodiment, IMU sensor(s) 966 may include, for example and without limitation, accelerometer(s), magnetometer(s), gyroscope(s), a magnetic compass,
30 magnetic compasses, and/or other sensor types. In at least one embodiment, such as in six-axis applications, IMU sensor(s) 966 may include, without limitation, accelerometers and gyroscopes. In at least one embodiment, such as in nine-axis applications, IMU sensor(s) 966 may include, without limitation, accelerometers, gyroscopes, and magnetometers.

[0219] In at least one embodiment, IMU sensor(s) 966 may be implemented as a miniature,
35 high performance GPS-Aided Inertial Navigation System (“GPS/INS”) that combines micro-electro-mechanical systems (“MEMS”) inertial sensors, a high-sensitivity GPS receiver, and

- 5 advanced Kalman filtering algorithms to provide estimates of position, velocity, and attitude. In at least one embodiment, IMU sensor(s) 966 may enable vehicle 900 to estimate its heading without requiring input from a magnetic sensor by directly observing and correlating changes in velocity from a GPS to IMU sensor(s) 966. In at least one embodiment, IMU sensor(s) 966 and GNSS sensor(s) 958 may be combined in a single integrated unit.
- 10 [0220] In at least one embodiment, vehicle 900 may include microphone(s) 996 placed in and/or around vehicle 900. In at least one embodiment, microphone(s) 996 may be used for emergency vehicle detection and identification, among other things.
- [0221] In at least one embodiment, vehicle 900 may further include any number of camera types, including stereo camera(s) 968, wide-view camera(s) 970, infrared camera(s) 972, surround camera(s) 974, long-range camera(s) 998, mid-range camera(s) 976, and/or other camera types. In at least one embodiment, cameras may be used to capture image data around an entire periphery of vehicle 900. In at least one embodiment, which types of cameras used depends on vehicle 900. In at least one embodiment, any combination of camera types may be used to provide necessary coverage around vehicle 900. In at least one embodiment, a number of cameras deployed may differ depending on embodiment. For example, in at least one embodiment, vehicle 900 could include six cameras, seven cameras, ten cameras, twelve cameras, or another number of cameras. In at least one embodiment, cameras may support, as an example and without limitation, Gigabit Multimedia Serial Link (“GMSL”) and/or Gigabit Ethernet communications. In at least one embodiment, each camera might be as described with more detail previously herein with respect to FIG. 9A and FIG. 9B.
- 25 [0222] In at least one embodiment, vehicle 900 may further include vibration sensor(s) 942. In at least one embodiment, vibration sensor(s) 942 may measure vibrations of components of vehicle 900, such as axle(s). For example, in at least one embodiment, changes in vibrations may indicate a change in road surfaces. In at least one embodiment, when two or more vibration sensors 942 are used, differences between vibrations may be used to determine friction or slippage of road surface (e.g., when a difference in vibration is between a power-driven axle and a freely rotating axle).
- 30 [0223] In at least one embodiment, vehicle 900 may include ADAS system 938. In at least one embodiment, ADAS system 938 may include, without limitation, an SoC, in some examples. In at least one embodiment, ADAS system 938 may include, without limitation,
- 35

5 any number and combination of an autonomous/adaptive/automatic cruise control (“ACC”) system, a cooperative adaptive cruise control (“CACC”) system, a forward crash warning (“FCW”) system, an automatic emergency braking (“AEB”) system, a lane departure warning (“LDW”) system, a lane keep assist (“LKA”) system, a blind spot warning (“BSW”) system, a rear cross-traffic warning (“RCTW”) system, a collision warning (“CW”) system, a lane
10 centering (“LC”) system, and/or other systems, features, and/or functionality.

[0224] In at least one embodiment, ACC system may use RADAR sensor(s) 960, LIDAR sensor(s) 964, and/or any number of camera(s). In at least one embodiment, ACC system may include a longitudinal ACC system and/or a lateral ACC system. In at least one embodiment, a longitudinal ACC system monitors and controls distance to another vehicle
15 immediately ahead of vehicle 900 and automatically adjusts speed of vehicle 900 to maintain a safe distance from vehicles ahead. In at least one embodiment, a lateral ACC system performs distance keeping, and advises vehicle 900 to change lanes when necessary. In at least one embodiment, a lateral ACC is related to other ADAS applications, such as LC and CW.

20 [0225] In at least one embodiment, a CACC system uses information from other vehicles that may be received via network interface 924 and/or wireless antenna(s) 926 from other vehicles via a wireless link, or indirectly, over a network connection (e.g., over the Internet). In at least one embodiment, direct links may be provided by a vehicle-to-vehicle (“V2V”) communication link, while indirect links may be provided by an infrastructure-to-vehicle
25 (“I2V”) communication link. In general, V2V communication provides information about immediately preceding vehicles (e.g., vehicles immediately ahead of and in same lane as vehicle 900), while I2V communication provides information about traffic further ahead. In at least one embodiment, a CACC system may include either or both I2V and V2V information sources. In at least one embodiment, given information of vehicles ahead of
30 vehicle 900, a CACC system may be more reliable and it has potential to improve traffic flow smoothness and reduce congestion on road.

[0226] In at least one embodiment, an FCW system is designed to alert a driver to a hazard, so that such driver may take corrective action. In at least one embodiment, an FCW system uses a front-facing camera and/or RADAR sensor(s) 960, coupled to a dedicated processor,
35 DSP, FPGA, and/or ASIC, that is electrically coupled to provide driver feedback, such as a display, speaker, and/or vibrating component. In at least one embodiment, an FCW system

5 may provide a warning, such as in form of a sound, visual warning, vibration and/or a quick brake pulse.

[0227] In at least one embodiment, an AEB system detects an impending forward collision with another vehicle or other object, and may automatically apply brakes if a driver does not take corrective action within a specified time or distance parameter. In at least one
10 embodiment, AEB system may use front-facing camera(s) and/or RADAR sensor(s) 960, coupled to a dedicated processor, DSP, FPGA, and/or ASIC. In at least one embodiment, when an AEB system detects a hazard, it will typically first alert a driver to take corrective action to avoid collision and, if that driver does not take corrective action, that AEB system may automatically apply brakes in an effort to prevent, or at least mitigate, an impact of a
15 predicted collision. In at least one embodiment, an AEB system may include techniques such as dynamic brake support and/or crash imminent braking.

[0228] In at least one embodiment, an LDW system provides visual, audible, and/or tactile warnings, such as steering wheel or seat vibrations, to alert driver when vehicle 900 crosses lane markings. In at least one embodiment, an LDW system does not activate when a driver
20 indicates an intentional lane departure, such as by activating a turn signal. In at least one embodiment, an LDW system may use front-side facing cameras, coupled to a dedicated processor, DSP, FPGA, and/or ASIC, that is electrically coupled to provide driver feedback, such as a display, speaker, and/or vibrating component. In at least one embodiment, an LKA system is a variation of an LDW system. In at least one embodiment, an LKA system
25 provides steering input or braking to correct vehicle 900 if vehicle 900 starts to exit its lane.

[0229] In at least one embodiment, a BSW system detects and warns a driver of vehicles in an automobile's blind spot. In at least one embodiment, a BSW system may provide a visual, audible, and/or tactile alert to indicate that merging or changing lanes is unsafe. In at least one embodiment, a BSW system may provide an additional warning when a driver uses a turn
30 signal. In at least one embodiment, a BSW system may use rear-side facing camera(s) and/or RADAR sensor(s) 960, coupled to a dedicated processor, DSP, FPGA, and/or ASIC, that is electrically coupled to driver feedback, such as a display, speaker, and/or vibrating component.

[0230] In at least one embodiment, an RCTW system may provide visual, audible, and/or
35 tactile notification when an object is detected outside a rear-camera range when vehicle 900 is backing up. In at least one embodiment, an RCTW system includes an AEB system to

5 ensure that vehicle brakes are applied to avoid a crash. In at least one embodiment, an RCTW system may use one or more rear-facing RADAR sensor(s) 960, coupled to a dedicated processor, DSP, FPGA, and/or ASIC, that is electrically coupled to provide driver feedback, such as a display, speaker, and/or vibrating component.

[0231] In at least one embodiment, conventional ADAS systems may be prone to false
10 positive results which may be annoying and distracting to a driver, but typically are not catastrophic, because conventional ADAS systems alert a driver and allow that driver to decide whether a safety condition truly exists and act accordingly. In at least one embodiment, vehicle 900 itself decides, in case of conflicting results, whether to heed result from a primary computer or a secondary computer (e.g., a first controller or a second
15 controller of controllers 936). For example, in at least one embodiment, ADAS system 938 may be a backup and/or secondary computer for providing perception information to a backup computer rationality module. In at least one embodiment, a backup computer rationality monitor may run redundant diverse software on hardware components to detect faults in perception and dynamic driving tasks. In at least one embodiment, outputs from
20 ADAS system 938 may be provided to a supervisory MCU. In at least one embodiment, if outputs from a primary computer and outputs from a secondary computer conflict, a supervisory MCU determines how to reconcile conflict to ensure safe operation.

[0232] In at least one embodiment, a primary computer may be configured to provide a supervisory MCU with a confidence score, indicating that primary computer's confidence in
25 a chosen result. In at least one embodiment, if that confidence score exceeds a threshold, that supervisory MCU may follow that primary computer's direction, regardless of whether that secondary computer provides a conflicting or inconsistent result. In at least one embodiment, where a confidence score does not meet a threshold, and where primary and secondary computers indicate different results (e.g., a conflict), a supervisory MCU may arbitrate
30 between computers to determine an appropriate outcome.

[0233] In at least one embodiment, a supervisory MCU may be configured to run a neural network(s) that is trained and configured to determine, based at least in part on outputs from a primary computer and outputs from a secondary computer, conditions under which that
secondary computer provides false alarms. In at least one embodiment, neural network(s) in
35 a supervisory MCU may learn when a secondary computer's output may be trusted, and when it cannot. For example, in at least one embodiment, when that secondary computer is a

5 RADAR-based FCW system, a neural network(s) in that supervisory MCU may learn when
an FCW system is identifying metallic objects that are not, in fact, hazards, such as a
drainage grate or manhole cover that triggers an alarm. In at least one embodiment, when a
secondary computer is a camera-based LDW system, a neural network in a supervisory MCU
may learn to override LDW when bicyclists or pedestrians are present and a lane departure is,
10 in fact, a safest maneuver. In at least one embodiment, a supervisory MCU may include at
least one of a DLA or a GPU suitable for running neural network(s) with associated memory.
In at least one embodiment, a supervisory MCU may comprise and/or be included as a
component of SoC(s) 904.

[0234] In at least one embodiment, ADAS system 938 may include a secondary computer
15 that performs ADAS functionality using traditional rules of computer vision. In at least one
embodiment, that secondary computer may use classic computer vision rules (if-then), and
presence of a neural network(s) in a supervisory MCU may improve reliability, safety and
performance. For example, in at least one embodiment, diverse implementation and
intentional non-identity makes an overall system more fault-tolerant, especially to faults
20 caused by software (or software-hardware interface) functionality. For example, in at least
one embodiment, if there is a software bug or error in software running on a primary
computer, and non-identical software code running on a secondary computer provides a
consistent overall result, then a supervisory MCU may have greater confidence that an overall
result is correct, and a bug in software or hardware on that primary computer is not causing a
25 material error.

[0235] In at least one embodiment, an output of ADAS system 938 may be fed into a
primary computer's perception block and/or a primary computer's dynamic driving task
block. For example, in at least one embodiment, if ADAS system 938 indicates a forward
crash warning due to an object immediately ahead, a perception block may use this
30 information when identifying objects. In at least one embodiment, a secondary computer
may have its own neural network that is trained and thus reduces a risk of false positives, as
described herein.

[0236] In at least one embodiment, vehicle 900 may further include infotainment SoC 930
(e.g., an in-vehicle infotainment system (IVI)). Although illustrated and described as an SoC,
35 infotainment system SoC 930, in at least one embodiment, may not be an SoC, and may
include, without limitation, two or more discrete components. In at least one embodiment,

5 infotainment SoC 930 may include, without limitation, a combination of hardware and software that may be used to provide audio (e.g., music, a personal digital assistant, navigational instructions, news, radio, etc.), video (e.g., TV, movies, streaming, etc.), phone (e.g., hands-free calling), network connectivity (e.g., LTE, WiFi, etc.), and/or information services (e.g., navigation systems, rear-parking assistance, a radio data system, vehicle
10 related information such as fuel level, total distance covered, brake fuel level, oil level, door open/close, air filter information, etc.) to vehicle 900. For example, infotainment SoC 930 could include radios, disk players, navigation systems, video players, USB and Bluetooth connectivity, carputers, in-car entertainment, WiFi, steering wheel audio controls, hands free voice control, a heads-up display (“HUD”), HMI display 934, a telematics device, a control
15 panel (e.g., for controlling and/or interacting with various components, features, and/or systems), and/or other components. In at least one embodiment, infotainment SoC 930 may further be used to provide information (e.g., visual and/or audible) to user(s) of vehicle 900, such as information from ADAS system 938, autonomous driving information such as planned vehicle maneuvers, trajectories, surrounding environment information (e.g.,
20 intersection information, vehicle information, road information, etc.), and/or other information.

[0237] In at least one embodiment, infotainment SoC 930 may include any amount and type of GPU functionality. In at least one embodiment, infotainment SoC 930 may communicate over bus 902 with other devices, systems, and/or components of vehicle 900.
25 In at least one embodiment, infotainment SoC 930 may be coupled to a supervisory MCU such that a GPU of an infotainment system may perform some self-driving functions in event that primary controller(s) 936 (e.g., primary and/or backup computers of vehicle 900) fail. In at least one embodiment, infotainment SoC 930 may put vehicle 900 into a chauffeur to safe stop mode, as described herein.

30 [0238] In at least one embodiment, vehicle 900 may further include instrument cluster 932 (e.g., a digital dash, an electronic instrument cluster, a digital instrument panel, etc.). In at least one embodiment, instrument cluster 932 may include, without limitation, a controller and/or supercomputer (e.g., a discrete controller or supercomputer). In at least one embodiment, instrument cluster 932 may include, without limitation, any number and
35 combination of a set of instrumentation such as a speedometer, fuel level, oil pressure, tachometer, odometer, turn indicators, gearshift position indicator, seat belt warning light(s), parking-brake warning light(s), engine-malfunction light(s), supplemental restraint system

5 (e.g., airbag) information, lighting controls, safety system controls, navigation information, etc. In some examples, information may be displayed and/or shared among infotainment SoC 930 and instrument cluster 932. In at least one embodiment, instrument cluster 932 may be included as part of infotainment SoC 930, or vice versa.

[0239] Inference and/or training logic 615 are used to perform inferencing and/or training
10 operations associated with one or more embodiments. Details regarding inference and/or training logic 615 are provided herein in conjunction with FIGS. 6A and/or 6B. In at least one embodiment, inference and/or training logic 615 may be used in system FIG. 9C for inferencing or predicting operations based, at least in part, on weight parameters calculated using neural network training operations, neural network functions and/or architectures, or
15 neural network use cases described herein.

[0240] FIG. 9D is a diagram of a system 976 for communication between cloud-based server(s) and autonomous vehicle 900 of FIG. 9A, according to at least one embodiment. In at least one embodiment, system 976 may include, without limitation, server(s) 978, network(s) 990, and any number and type of vehicles, including vehicle 900. In at least one
20 embodiment, server(s) 978 may include, without limitation, a plurality of GPUs 984(A)-984(H) (collectively referred to herein as GPUs 984), PCIe switches 982(A)-982(D) (collectively referred to herein as PCIe switches 982), and/or CPUs 980(A)-980(B) (collectively referred to herein as CPUs 980). In at least one embodiment, GPUs 984, CPUs 980, and PCIe switches 982 may be interconnected with high-speed interconnects such as, for
25 example and without limitation, NVLink interfaces 988 developed by NVIDIA and/or PCIe connections 986. In at least one embodiment, GPUs 984 are connected via an NVLink and/or NVSwitch SoC and GPUs 984 and PCIe switches 982 are connected via PCIe interconnects. Although eight GPUs 984, two CPUs 980, and four PCIe switches 982 are illustrated, this is not intended to be limiting. In at least one embodiment, each of server(s) 978 may include,
30 without limitation, any number of GPUs 984, CPUs 980, and/or PCIe switches 982, in any combination. For example, in at least one embodiment, server(s) 978 could each include eight, sixteen, thirty-two, and/or more GPUs 984.

[0241] In at least one embodiment, server(s) 978 may receive, over network(s) 990 and from vehicles, image data representative of images showing unexpected or changed road
35 conditions, such as recently commenced road-work. In at least one embodiment, server(s) 978 may transmit, over network(s) 990 and to vehicles, neural networks 992, updated or

5 otherwise, and/or map information 994, including, without limitation, information regarding traffic and road conditions. In at least one embodiment, updates to map information 994 may include, without limitation, updates for HD map 922, such as information regarding construction sites, potholes, detours, flooding, and/or other obstructions. In at least one embodiment, neural networks 992, and/or map information 994 may have resulted from new
10 training and/or experiences represented in data received from any number of vehicles in an environment, and/or based at least in part on training performed at a data center (e.g., using server(s) 978 and/or other servers).

[0242] In at least one embodiment, server(s) 978 may be used to train machine learning models (e.g., neural networks) based at least in part on training data. In at least one
15 embodiment, training data may be generated by vehicles, and/or may be generated in a simulation (e.g., using a game engine). In at least one embodiment, any amount of training data is tagged (e.g., where associated neural network benefits from supervised learning) and/or undergoes other pre-processing. In at least one embodiment, any amount of training data is not tagged and/or pre-processed (e.g., where associated neural network does not
20 require supervised learning). In at least one embodiment, once machine learning models are trained, machine learning models may be used by vehicles (e.g., transmitted to vehicles over network(s) 990), and/or machine learning models may be used by server(s) 978 to remotely monitor vehicles.

[0243] In at least one embodiment, server(s) 978 may receive data from vehicles and apply
25 data to up-to-date real-time neural networks for real-time intelligent inferencing. In at least one embodiment, server(s) 978 may include deep-learning supercomputers and/or dedicated AI computers powered by GPU(s) 984, such as a DGX and DGX Station machines developed by NVIDIA. However, in at least one embodiment, server(s) 978 may include deep learning infrastructure that uses CPU-powered data centers.

[0244] In at least one embodiment, deep-learning infrastructure of server(s) 978 may be
30 capable of fast, real-time inferencing, and may use that capability to evaluate and verify health of processors, software, and/or associated hardware in vehicle 900. For example, in at least one embodiment, deep-learning infrastructure may receive periodic updates from vehicle 900, such as a sequence of images and/or objects that vehicle 900 has located in that
35 sequence of images (e.g., via computer vision and/or other machine learning object classification techniques). In at least one embodiment, deep-learning infrastructure may run

- 5 its own neural network to identify objects and compare them with objects identified by vehicle 900 and, if results do not match and deep-learning infrastructure concludes that AI in vehicle 900 is malfunctioning, then server(s) 978 may transmit a signal to vehicle 900 instructing a fail-safe computer of vehicle 900 to assume control, notify passengers, and complete a safe parking maneuver.
- 10 [0245] In at least one embodiment, server(s) 978 may include GPU(s) 984 and one or more programmable inference accelerators (e.g., NVIDIA's TensorRT 3 devices). In at least one embodiment, a combination of GPU-powered servers and inference acceleration may make real-time responsiveness possible. In at least one embodiment, such as where performance is less critical, servers powered by CPUs, FPGAs, and other processors may be used for
- 15 inferencing. In at least one embodiment, hardware structure(s) 615 are used to perform one or more embodiments. Details regarding hardware structure(x) 615 are provided herein in conjunction with FIGS. 6A and/or 6B.

- [0246] In at least one embodiment, one or more systems depicted in FIGS. 9A-9D are utilized to implement a deep object detection network. In at least one embodiment, one or
- 20 more systems depicted in FIGS. 9A-9D are utilized to implement one or more networks and models such as those described in connection with FIG. 1 and FIG. 3. In at least one embodiment, one or more systems depicted in FIGS. 9A-9D are utilized to implement a network that is based on mixture density networks and predicts uncertainty values of images. In at least one embodiment, one or more systems depicted in FIGS. 9A-9D are utilized to
- 25 implement an active learning method for object detection that utilizes mixture density networks to produce one or more Gaussian mixture models for each output of a network.

COMPUTER SYSTEMS

- [0247] FIG. 10 is a block diagram illustrating an exemplary computer system, which may be a system with interconnected devices and components, a system-on-a-chip (SOC) or some
- 30 combination thereof formed with a processor that may include execution units to execute an instruction, according to at least one embodiment. In at least one embodiment, a computer system 1000 may include, without limitation, a component, such as a processor 1002 to employ execution units including logic to perform algorithms for process data, in accordance with present disclosure, such as in embodiment described herein. In at least one embodiment,
- 35 computer system 1000 may include processors, such as PENTIUM® Processor family, Xeon™, Itanium®, XScale™ and/or StrongARM™, Intel® Core™, or Intel® Nervana™

5 microprocessors available from Intel Corporation of Santa Clara, California, although other systems (including PCs having other microprocessors, engineering workstations, set-top boxes and like) may also be used. In at least one embodiment, computer system 1000 may execute a version of WINDOWS operating system available from Microsoft Corporation of Redmond, Wash., although other operating systems (UNIX and Linux, for example),
10 embedded software, and/or graphical user interfaces, may also be used.

[0248] Embodiments may be used in other devices such as handheld devices and embedded applications. Some examples of handheld devices include cellular phones, Internet Protocol devices, digital cameras, personal digital assistants (“PDAs”), and handheld PCs. In at least one embodiment, embedded applications may include a microcontroller, a digital signal
15 processor (“DSP”), system on a chip, network computers (“NetPCs”), set-top boxes, network hubs, wide area network (“WAN”) switches, or any other system that may perform one or more instructions in accordance with at least one embodiment.

[0249] In at least one embodiment, computer system 1000 may include, without limitation, processor 1002 that may include, without limitation, one or more execution units 1008 to
20 perform machine learning model training and/or inferencing according to techniques described herein. In at least one embodiment, computer system 1000 is a single processor desktop or server system, but in another embodiment, computer system 1000 may be a multiprocessor system. In at least one embodiment, processor 1002 may include, without limitation, a complex instruction set computer (“CISC”) microprocessor, a reduced
25 instruction set computing (“RISC”) microprocessor, a very long instruction word (“VLIW”) microprocessor, a processor implementing a combination of instruction sets, or any other processor device, such as a digital signal processor, for example. In at least one embodiment, processor 1002 may be coupled to a processor bus 1010 that may transmit data signals between processor 1002 and other components in computer system 1000.

[0250] In at least one embodiment, processor 1002 may include, without limitation, a Level 1 (“L1”) internal cache memory (“cache”) 1004. In at least one embodiment, processor 1002 may have a single internal cache or multiple levels of internal cache. In at least one embodiment, cache memory may reside external to processor 1002. Other embodiments may also include a combination of both internal and external caches depending on particular
35 implementation and needs. In at least one embodiment, a register file 1006 may store

5 different types of data in various registers including, without limitation, integer registers, floating point registers, status registers, and an instruction pointer register.

[0251] In at least one embodiment, execution unit 1008, including, without limitation, logic to perform integer and floating point operations, also resides in processor 1002. In at least one embodiment, processor 1002 may also include a microcode (“ucode”) read only memory
10 (“ROM”) that stores microcode for certain macro instructions. In at least one embodiment, execution unit 1008 may include logic to handle a packed instruction set 1009. In at least one embodiment, by including packed instruction set 1009 in an instruction set of a general-purpose processor, along with associated circuitry to execute instructions, operations used by many multimedia applications may be performed using packed data in processor 1002. In at
15 least one embodiment, many multimedia applications may be accelerated and executed more efficiently by using a full width of a processor’s data bus for performing operations on packed data, which may eliminate a need to transfer smaller units of data across that processor’s data bus to perform one or more operations one data element at a time.

[0252] In at least one embodiment, execution unit 1008 may also be used in
20 microcontrollers, embedded processors, graphics devices, DSPs, and other types of logic circuits. In at least one embodiment, computer system 1000 may include, without limitation, a memory 1020. In at least one embodiment, memory 1020 may be a Dynamic Random Access Memory (“DRAM”) device, a Static Random Access Memory (“SRAM”) device, a flash memory device, or another memory device. In at least one embodiment, memory 1020
25 may store instruction(s) 1019 and/or data 1021 represented by data signals that may be executed by processor 1002.

[0253] In at least one embodiment, a system logic chip may be coupled to processor bus 1010 and memory 1020. In at least one embodiment, a system logic chip may include, without limitation, a memory controller hub (“MCH”) 1016, and processor 1002 may
30 communicate with MCH 1016 via processor bus 1010. In at least one embodiment, MCH 1016 may provide a high bandwidth memory path 1018 to memory 1020 for instruction and data storage and for storage of graphics commands, data and textures. In at least one embodiment, MCH 1016 may direct data signals between processor 1002, memory 1020, and other components in computer system 1000 and to bridge data signals between processor bus
35 1010, memory 1020, and a system I/O interface 1022. In at least one embodiment, a system logic chip may provide a graphics port for coupling to a graphics controller. In at least one

5 embodiment, MCH 1016 may be coupled to memory 1020 through high bandwidth memory path 1018 and a graphics/video card 1012 may be coupled to MCH 1016 through an Accelerated Graphics Port (“AGP”) interconnect 1014.

[0254] In at least one embodiment, computer system 1000 may use system I/O interface 1022 as a proprietary hub interface bus to couple MCH 1016 to an I/O controller hub (“ICH”) 1030. In at least one embodiment, ICH 1030 may provide direct connections to some I/O devices via a local I/O bus. In at least one embodiment, a local I/O bus may include, without limitation, a high-speed I/O bus for connecting peripherals to memory 1020, a chipset, and processor 1002. Examples may include, without limitation, an audio controller 1029, a firmware hub (“flash BIOS”) 1028, a wireless transceiver 1026, a data storage 1024, a legacy I/O controller 1023 containing user input and keyboard interfaces 1025, a serial expansion port 1027, such as a Universal Serial Bus (“USB”) port, and a network controller 1034. In at least one embodiment, data storage 1024 may comprise a hard disk drive, a floppy disk drive, a CD-ROM device, a flash memory device, or other mass storage device.

[0255] In at least one embodiment, FIG. 10 illustrates a system, which includes interconnected hardware devices or “chips”, whereas in other embodiments, FIG. 10 may illustrate an exemplary SoC. In at least one embodiment, devices illustrated in FIG. 10 may be interconnected with proprietary interconnects, standardized interconnects (e.g., PCIe) or some combination thereof. In at least one embodiment, one or more components of computer system 1000 are interconnected using compute express link (CXL) interconnects.

25 [0256] Inference and/or training logic 615 are used to perform inferencing and/or training operations associated with one or more embodiments. Details regarding inference and/or training logic 615 are provided herein in conjunction with FIGS. 6A and/or 6B. In at least one embodiment, inference and/or training logic 615 may be used in system FIG. 10 for inferencing or predicting operations based, at least in part, on weight parameters calculated using neural network training operations, neural network functions and/or architectures, or neural network use cases described herein.

[0257] In at least one embodiment, one or more systems depicted in FIG. 10 are utilized to implement a deep object detection network. In at least one embodiment, one or more systems depicted in FIG. 10 are utilized to implement one or more networks and models such as those described in connection with FIG. 1 and FIG. 3. In at least one embodiment, one or more systems depicted in FIG. 10 are utilized to implement a network that is based on mixture

5 density networks and predicts uncertainty values of images. In at least one embodiment, one or more systems depicted in FIG. 10 are utilized to implement an active learning method for object detection that utilizes mixture density networks to produce one or more Gaussian mixture models for each output of a network.

[0258] FIG. 11 is a block diagram illustrating an electronic device 1100 for utilizing a
10 processor 1110, according to at least one embodiment. In at least one embodiment, electronic device 1100 may be, for example and without limitation, a notebook, a tower server, a rack server, a blade server, a laptop, a desktop, a tablet, a mobile device, a phone, an embedded computer, or any other suitable electronic device.

[0259] In at least one embodiment, electronic device 1100 may include, without limitation,
15 processor 1110 communicatively coupled to any suitable number or kind of components, peripherals, modules, or devices. In at least one embodiment, processor 1110 is coupled using a bus or interface, such as a I²C bus, a System Management Bus (“SMBus”), a Low Pin Count (LPC) bus, a Serial Peripheral Interface (“SPI”), a High Definition Audio (“HDA”) bus, a Serial Advance Technology Attachment (“SATA”) bus, a Universal Serial Bus
20 (“USB”) (versions 1, 2, 3, etc.), or a Universal Asynchronous Receiver/Transmitter (“UART”) bus. In at least one embodiment, FIG. 11 illustrates a system, which includes interconnected hardware devices or “chips”, whereas in other embodiments, FIG. 11 may illustrate an exemplary SoC. In at least one embodiment, devices illustrated in FIG. 11 may be interconnected with proprietary interconnects, standardized interconnects (e.g., PCIe) or
25 some combination thereof. In at least one embodiment, one or more components of FIG. 11 are interconnected using compute express link (CXL) interconnects.

[0260] In at least one embodiment, FIG 11 may include a display 1124, a touch screen
1125, a touch pad 1130, a Near Field Communications unit (“NFC”) 1145, a sensor hub
1140, a thermal sensor 1146, an Express Chipset (“EC”) 1135, a Trusted Platform Module
30 (“TPM”) 1138, BIOS/firmware/flash memory (“BIOS, FW Flash”) 1122, a DSP 1160, a drive 1120 such as a Solid State Disk (“SSD”) or a Hard Disk Drive (“HDD”), a wireless local area network unit (“WLAN”) 1150, a Bluetooth unit 1152, a Wireless Wide Area
Network unit (“WWAN”) 1156, a Global Positioning System (GPS) unit 1155, a camera
35 (“USB 3.0 camera”) 1154 such as a USB 3.0 camera, and/or a Low Power Double Data Rate (“LPDDR”) memory unit (“LPDDR3”) 1115 implemented in, for example, an LPDDR3 standard. These components may each be implemented in any suitable manner.

5 [0261] In at least one embodiment, other components may be communicatively coupled to processor 1110 through components described herein. In at least one embodiment, an accelerometer 1141, an ambient light sensor (“ALS”) 1142, a compass 1143, and a gyroscope 1144 may be communicatively coupled to sensor hub 1140. In at least one embodiment, a thermal sensor 1139, a fan 1137, a keyboard 1136, and touch pad 1130 may be
10 communicatively coupled to EC 1135. In at least one embodiment, speakers 1163, headphones 1164, and a microphone (“mic”) 1165 may be communicatively coupled to an audio unit (“audio codec and class D amp”) 1162, which may in turn be communicatively coupled to DSP 1160. In at least one embodiment, audio unit 1162 may include, for example and without limitation, an audio coder/decoder (“codec”) and a class D amplifier. In at least
15 one embodiment, a SIM card (“SIM”) 1157 may be communicatively coupled to WWAN unit 1156. In at least one embodiment, components such as WLAN unit 1150 and Bluetooth unit 1152, as well as WWAN unit 1156 may be implemented in a Next Generation Form Factor (“NGFF”).

[0262] Inference and/or training logic 615 are used to perform inferencing and/or training
20 operations associated with one or more embodiments. Details regarding inference and/or training logic 615 are provided herein in conjunction with FIGS. 6A and/or 6B. In at least one embodiment, inference and/or training logic 615 may be used in system FIG. 11 for inferencing or predicting operations based, at least in part, on weight parameters calculated using neural network training operations, neural network functions and/or architectures, or
25 neural network use cases described herein.

[0263] In at least one embodiment, one or more systems depicted in FIG. 11 are utilized to implement a deep object detection network. In at least one embodiment, one or more systems depicted in FIG. 11 are utilized to implement one or more networks and models such as those described in connection with FIG. 1 and FIG. 3. In at least one embodiment, one or more
30 systems depicted in FIG. 11 are utilized to implement a network that is based on mixture density networks and predicts uncertainty values of images. In at least one embodiment, one or more systems depicted in FIG. 11 are utilized to implement an active learning method for object detection that utilizes mixture density networks to produce one or more Gaussian mixture models for each output of a network.

5 [0264] FIG. 12 illustrates a computer system 1200, according to at least one embodiment. In at least one embodiment, computer system 1200 is configured to implement various processes and methods described throughout this disclosure.

[0265] In at least one embodiment, computer system 1200 comprises, without limitation, at least one central processing unit (“CPU”) 1202 that is connected to a communication bus
10 1210 implemented using any suitable protocol, such as PCI (“Peripheral Component Interconnect”), peripheral component interconnect express (“PCI-Express”), AGP (“Accelerated Graphics Port”), HyperTransport, or any other bus or point-to-point communication protocol(s). In at least one embodiment, computer system 1200 includes, without limitation, a main memory 1204 and control logic (e.g., implemented as hardware,
15 software, or a combination thereof) and data are stored in main memory 1204, which may take form of random access memory (“RAM”). In at least one embodiment, a network interface subsystem (“network interface”) 1222 provides an interface to other computing devices and networks for receiving data from and transmitting data to other systems with computer system 1200.

20 [0266] In at least one embodiment, computer system 1200, in at least one embodiment, includes, without limitation, input devices 1208, a parallel processing system 1212, and display devices 1206 that can be implemented using a conventional cathode ray tube (“CRT”), a liquid crystal display (“LCD”), a light emitting diode (“LED”) display, a plasma display, or other suitable display technologies. In at least one embodiment, user input is
25 received from input devices 1208 such as keyboard, mouse, touchpad, microphone, etc. In at least one embodiment, each module described herein can be situated on a single semiconductor platform to form a processing system.

[0267] Inference and/or training logic 615 are used to perform inferencing and/or training operations associated with one or more embodiments. Details regarding inference and/or
30 training logic 615 are provided herein in conjunction with FIGS. 6A and/or 6B. In at least one embodiment, inference and/or training logic 615 may be used in system FIG. 12 for inferencing or predicting operations based, at least in part, on weight parameters calculated using neural network training operations, neural network functions and/or architectures, or neural network use cases described herein.

35 [0268] In at least one embodiment, one or more systems depicted in FIG. 12 are utilized to implement a deep object detection network. In at least one embodiment, one or more systems

5 depicted in FIG. 12 are utilized to implement one or more networks and models such as those described in connection with FIG. 1 and FIG. 3. In at least one embodiment, one or more systems depicted in FIG. 12 are utilized to implement a network that is based on mixture density networks and predicts uncertainty values of images. In at least one embodiment, one or more systems depicted in FIG. 12 are utilized to implement an active learning method for
10 object detection that utilizes mixture density networks to produce one or more Gaussian mixture models for each output of a network.

[0269] FIG. 13 illustrates a computer system 1300, according to at least one embodiment. In at least one embodiment, computer system 1300 includes, without limitation, a computer 1310 and a USB stick 1320. In at least one embodiment, computer 1310 may include,
15 without limitation, any number and type of processor(s) (not shown) and a memory (not shown). In at least one embodiment, computer 1310 includes, without limitation, a server, a cloud instance, a laptop, and a desktop computer.

[0270] In at least one embodiment, USB stick 1320 includes, without limitation, a processing unit 1330, a USB interface 1340, and USB interface logic 1350. In at least one
20 embodiment, processing unit 1330 may be any instruction execution system, apparatus, or device capable of executing instructions. In at least one embodiment, processing unit 1330 may include, without limitation, any number and type of processing cores (not shown). In at least one embodiment, processing unit 1330 comprises an application specific integrated circuit (“ASIC”) that is optimized to perform any amount and type of operations associated
25 with machine learning. For instance, in at least one embodiment, processing unit 1330 is a tensor processing unit (“TPC”) that is optimized to perform machine learning inference operations. In at least one embodiment, processing unit 1330 is a vision processing unit (“VPU”) that is optimized to perform machine vision and machine learning inference operations.

[0271] In at least one embodiment, USB interface 1340 may be any type of USB connector or USB socket. For instance, in at least one embodiment, USB interface 1340 is a USB 3.0 Type-C socket for data and power. In at least one embodiment, USB interface 1340 is a USB 3.0 Type-A connector. In at least one embodiment, USB interface logic 1350 may include
30 any amount and type of logic that enables processing unit 1330 to interface with devices (e.g., computer 1310) via USB connector 1340.
35

5 [0272] Inference and/or training logic 615 are used to perform inferencing and/or training operations associated with one or more embodiments. Details regarding inference and/or training logic 615 are provided herein in conjunction with FIGS. 6A and/or 6B. In at least one embodiment, inference and/or training logic 615 may be used in system FIG. 13 for inferencing or predicting operations based, at least in part, on weight parameters calculated
10 using neural network training operations, neural network functions and/or architectures, or neural network use cases described herein.

[0273] In at least one embodiment, one or more systems depicted in FIG. 13 are utilized to implement a deep object detection network. In at least one embodiment, one or more systems depicted in FIG. 13 are utilized to implement one or more networks and models such as those
15 described in connection with FIG. 1 and FIG. 3. In at least one embodiment, one or more systems depicted in FIG. 13 are utilized to implement a network that is based on mixture density networks and predicts uncertainty values of images. In at least one embodiment, one or more systems depicted in FIG. 13 are utilized to implement an active learning method for object detection that utilizes mixture density networks to produce one or more Gaussian
20 mixture models for each output of a network.

[0274] FIG. 14A illustrates an exemplary architecture in which a plurality of GPUs 1410(1)-1410(N) is communicatively coupled to a plurality of multi-core processors 1405(1)-1405(M) over high-speed links 1440(1)-1440(N) (e.g., buses, point-to-point interconnects, etc.). In at least one embodiment, high-speed links 1440(1)-1440(N) support a
25 communication throughput of 4 GB/s, 30 GB/s, 80 GB/s or higher. In at least one embodiment, various interconnect protocols may be used including, but not limited to, PCIe 4.0 or 5.0 and NVLink 2.0. In various figures, “N” and “M” represent positive integers, values of which may be different from figure to figure.

[0275] In addition, and in at least one embodiment, two or more of GPUs 1410 are
30 interconnected over high-speed links 1429(1)-1429(2), which may be implemented using similar or different protocols/links than those used for high-speed links 1440(1)-1440(N). Similarly, two or more of multi-core processors 1405 may be connected over a high-speed link 1428 which may be symmetric multi-processor (SMP) buses operating at 20 GB/s, 30 GB/s, 120 GB/s or higher. Alternatively, all communication between various system
35 components shown in FIG. 14A may be accomplished using similar protocols/links (e.g., over a common interconnection fabric).

5 [0276] In at least one embodiment, each multi-core processor 1405 is communicatively coupled to a processor memory 1401(1)-1401(M), via memory interconnects 1426(1)-1426(M), respectively, and each GPU 1410(1)-1410(N) is communicatively coupled to GPU memory 1420(1)-1420(N) over GPU memory interconnects 1450(1)-1450(N), respectively. In at least one embodiment, memory interconnects 1426 and 1450 may utilize similar or
10 different memory access technologies. By way of example, and not limitation, processor memories 1401(1)-1401(M) and GPU memories 1420 may be volatile memories such as dynamic random access memories (DRAMs) (including stacked DRAMs), Graphics DDR SDRAM (GDDR) (e.g., GDDR5, GDDR6), or High Bandwidth Memory (HBM) and/or may be non-volatile memories such as 3D XPoint or Nano-Ram. In at least one embodiment,
15 some portion of processor memories 1401 may be volatile memory and another portion may be non-volatile memory (e.g., using a two-level memory (2LM) hierarchy).

[0277] As described herein, although various multi-core processors 1405 and GPUs 1410 may be physically coupled to a particular memory 1401, 1420, respectively, and/or a unified memory architecture may be implemented in which a virtual system address space (also
20 referred to as “effective address” space) is distributed among various physical memories. For example, processor memories 1401(1)-1401(M) may each comprise 64 GB of system memory address space and GPU memories 1420(1)-1420(N) may each comprise 32 GB of system memory address space resulting in a total of 256 GB addressable memory when M=2 and N=4. Other values for N and M are possible.

25 [0278] FIG. 14B illustrates additional details for an interconnection between a multi-core processor 1407 and a graphics acceleration module 1446 in accordance with one exemplary embodiment. In at least one embodiment, graphics acceleration module 1446 may include one or more GPU chips integrated on a line card which is coupled to processor 1407 via high-speed link 1440 (e.g., a PCIe bus, NVLink, etc.). In at least one embodiment, graphics
30 acceleration module 1446 may alternatively be integrated on a package or chip with processor 1407.

[0279] In at least one embodiment, processor 1407 includes a plurality of cores 1460A-1460D, each with a translation lookaside buffer (“TLB”) 1461A-1461D and one or more caches 1462A-1462D. In at least one embodiment, cores 1460A-1460D may include various
35 other components for executing instructions and processing data that are not illustrated. In at least one embodiment, caches 1462A-1462D may comprise Level 1 (L1) and Level 2 (L2)

5 caches. In addition, one or more shared caches 1456 may be included in caches 1462A-1462D and shared by sets of cores 1460A-1460D. For example, one embodiment of processor 1407 includes 24 cores, each with its own L1 cache, twelve shared L2 caches, and twelve shared L3 caches. In this embodiment, one or more L2 and L3 caches are shared by two adjacent cores. In at least one embodiment, processor 1407 and graphics acceleration
10 module 1446 connect with system memory 1414, which may include processor memories 1401(1)-1401(M) of FIG. 14A.

[0280] In at least one embodiment, coherency is maintained for data and instructions stored in various caches 1462A-1462D, 1456 and system memory 1414 via inter-core communication over a coherence bus 1464. In at least one embodiment, for example, each
15 cache may have cache coherency logic/circuitry associated therewith to communicate to over coherence bus 1464 in response to detected reads or writes to particular cache lines. In at least one embodiment, a cache snooping protocol is implemented over coherence bus 1464 to snoop cache accesses.

[0281] In at least one embodiment, a proxy circuit 1425 communicatively couples graphics acceleration module 1446 to coherence bus 1464, allowing graphics acceleration module 1446 to participate in a cache coherence protocol as a peer of cores 1460A-1460D. In particular, in at least one embodiment, an interface 1435 provides connectivity to proxy circuit 1425 over high-speed link 1440 and an interface 1437 connects graphics acceleration module 1446 to high-speed link 1440.

25 [0282] In at least one embodiment, an accelerator integration circuit 1436 provides cache management, memory access, context management, and interrupt management services on behalf of a plurality of graphics processing engines 1431(1)-1431(N) of graphics acceleration module 1446. In at least one embodiment, graphics processing engines 1431(1)-1431(N) may each comprise a separate graphics processing unit (GPU). In at least one embodiment,
30 graphics processing engines 1431(1)-1431(N) alternatively may comprise different types of graphics processing engines within a GPU, such as graphics execution units, media processing engines (e.g., video encoders/decoders), samplers, and blit engines. In at least one embodiment, graphics acceleration module 1446 may be a GPU with a plurality of graphics processing engines 1431(1)-1431(N) or graphics processing engines 1431(1)-1431(N) may be
35 individual GPUs integrated on a common package, line card, or chip.

5 [0283] In at least one embodiment, accelerator integration circuit 1436 includes a memory management unit (MMU) 1439 for performing various memory management functions such as virtual-to-physical memory translations (also referred to as effective-to-real memory translations) and memory access protocols for accessing system memory 1414. In at least one embodiment, MMU 1439 may also include a translation lookaside buffer (TLB) (not shown) for caching virtual/effective to physical/real address translations. In at least one embodiment, a cache 1438 can store commands and data for efficient access by graphics processing engines 1431(1)-1431(N). In at least one embodiment, data stored in cache 1438 and graphics memories 1433(1)-1433(M) is kept coherent with core caches 1462A-1462D, 1456 and system memory 1414, possibly using a fetch unit 1444. As mentioned, this may be accomplished via proxy circuit 1425 on behalf of cache 1438 and memories 1433(1)-1433(M) (e.g., sending updates to cache 1438 related to modifications/accesses of cache lines on processor caches 1462A-1462D, 1456 and receiving updates from cache 1438).

[0284] In at least one embodiment, a set of registers 1445 store context data for threads executed by graphics processing engines 1431(1)-1431(N) and a context management circuit 1448 manages thread contexts. For example, context management circuit 1448 may perform save and restore operations to save and restore contexts of various threads during contexts switches (e.g., where a first thread is saved and a second thread is stored so that a second thread can be execute by a graphics processing engine). For example, on a context switch, context management circuit 1448 may store current register values to a designated region in memory (e.g., identified by a context pointer). It may then restore register values when returning to a context. In at least one embodiment, an interrupt management circuit 1447 receives and processes interrupts received from system devices.

[0285] In at least one embodiment, virtual/effective addresses from a graphics processing engine 1431 are translated to real/physical addresses in system memory 1414 by MMU 1439. In at least one embodiment, accelerator integration circuit 1436 supports multiple (e.g., 4, 8, 16) graphics accelerator modules 1446 and/or other accelerator devices. In at least one embodiment, graphics accelerator module 1446 may be dedicated to a single application executed on processor 1407 or may be shared between multiple applications. In at least one embodiment, a virtualized graphics execution environment is presented in which resources of graphics processing engines 1431(1)-1431(N) are shared with multiple applications or virtual machines (VMs). In at least one embodiment, resources may be subdivided into “slices”

5 which are allocated to different VMs and/or applications based on processing requirements and priorities associated with VMs and/or applications.

[0286] In at least one embodiment, accelerator integration circuit 1436 performs as a bridge to a system for graphics acceleration module 1446 and provides address translation and system memory cache services. In addition, in at least one embodiment, accelerator
10 integration circuit 1436 may provide virtualization facilities for a host processor to manage virtualization of graphics processing engines 1431(1)-1431(N), interrupts, and memory management.

[0287] In at least one embodiment, because hardware resources of graphics processing engines 1431(1)-1431(N) are mapped explicitly to a real address space seen by host processor
15 1407, any host processor can address these resources directly using an effective address value. In at least one embodiment, one function of accelerator integration circuit 1436 is physical separation of graphics processing engines 1431(1)-1431(N) so that they appear to a system as independent units.

[0288] In at least one embodiment, one or more graphics memories 1433(1)-1433(M) are
20 coupled to each of graphics processing engines 1431(1)-1431(N), respectively and $N=M$. In at least one embodiment, graphics memories 1433(1)-1433(M) store instructions and data being processed by each of graphics processing engines 1431(1)-1431(N). In at least one embodiment, graphics memories 1433(1)-1433(M) may be volatile memories such as DRAMs (including stacked DRAMs), GDDR memory (e.g., GDDR5, GDDR6), or HBM,
25 and/or may be non-volatile memories such as 3D XPoint or Nano-Ram.

[0289] In at least one embodiment, to reduce data traffic over high-speed link 1440, biasing techniques can be used to ensure that data stored in graphics memories 1433(1)-1433(M) is data that will be used most frequently by graphics processing engines 1431(1)-1431(N) and preferably not used by cores 1460A-1460D (at least not frequently). Similarly, in at least one
30 embodiment, a biasing mechanism attempts to keep data needed by cores (and preferably not graphics processing engines 1431(1)-1431(N)) within caches 1462A-1462D, 1456 and system memory 1414.

[0290] FIG. 14C illustrates another exemplary embodiment in which accelerator integration circuit 1436 is integrated within processor 1407. In this embodiment, graphics processing
35 engines 1431(1)-1431(N) communicate directly over high-speed link 1440 to accelerator integration circuit 1436 via interface 1437 and interface 1435 (which, again, may be any form

5 of bus or interface protocol). In at least one embodiment, accelerator integration circuit 1436 may perform similar operations as those described with respect to FIG. 14B, but potentially at a higher throughput given its close proximity to coherence bus 1464 and caches 1462A-1462D, 1456. In at least one embodiment, an accelerator integration circuit supports different programming models including a dedicated-process programming model (no graphics
10 acceleration module virtualization) and shared programming models (with virtualization), which may include programming models which are controlled by accelerator integration circuit 1436 and programming models which are controlled by graphics acceleration module 1446.

[0291] In at least one embodiment, graphics processing engines 1431(1)-1431(N) are
15 dedicated to a single application or process under a single operating system. In at least one embodiment, a single application can funnel other application requests to graphics processing engines 1431(1)-1431(N), providing virtualization within a VM/partition.

[0292] In at least one embodiment, graphics processing engines 1431(1)-1431(N), may be shared by multiple VM/application partitions. In at least one embodiment, shared models
20 may use a system hypervisor to virtualize graphics processing engines 1431(1)-1431(N) to allow access by each operating system. In at least one embodiment, for single-partition systems without a hypervisor, graphics processing engines 1431(1)-1431(N) are owned by an operating system. In at least one embodiment, an operating system can virtualize graphics processing engines 1431(1)-1431(N) to provide access to each process or application.

25 [0293] In at least one embodiment, graphics acceleration module 1446 or an individual graphics processing engine 1431(1)-1431(N) selects a process element using a process handle. In at least one embodiment, process elements are stored in system memory 1414 and are addressable using an effective address to real address translation technique described herein. In at least one embodiment, a process handle may be an implementation-specific
30 value provided to a host process when registering its context with graphics processing engine 1431(1)-1431(N) (that is, calling system software to add a process element to a process element linked list). In at least one embodiment, a lower 16-bits of a process handle may be an offset of a process element within a process element linked list.

[0294] FIG. 14D illustrates an exemplary accelerator integration slice 1490. In at least one
35 embodiment, a “slice” comprises a specified portion of processing resources of accelerator integration circuit 1436. In at least one embodiment, an application is effective address space

5 1482 within system memory 1414 stores process elements 1483. In at least one embodiment, process elements 1483 are stored in response to GPU invocations 1481 from applications 1480 executed on processor 1407. In at least one embodiment, a process element 1483 contains process state for corresponding application 1480. In at least one embodiment, a work descriptor (WD) 1484 contained in process element 1483 can be a single job requested
10 by an application or may contain a pointer to a queue of jobs. In at least one embodiment, WD 1484 is a pointer to a job request queue in an application's effective address space 1482.

[0295] In at least one embodiment, graphics acceleration module 1446 and/or individual graphics processing engines 1431(1)-1431(N) can be shared by all or a subset of processes in a system. In at least one embodiment, an infrastructure for setting up process states and
15 sending a WD 1484 to a graphics acceleration module 1446 to start a job in a virtualized environment may be included.

[0296] In at least one embodiment, a dedicated-process programming model is implementation-specific. In at least one embodiment, in this model, a single process owns graphics acceleration module 1446 or an individual graphics processing engine 1431. In at
20 least one embodiment, when graphics acceleration module 1446 is owned by a single process, a hypervisor initializes accelerator integration circuit 1436 for an owning partition and an operating system initializes accelerator integration circuit 1436 for an owning process when graphics acceleration module 1446 is assigned.

[0297] In at least one embodiment, in operation, a WD fetch unit 1491 in accelerator
25 integration slice 1490 fetches next WD 1484, which includes an indication of work to be done by one or more graphics processing engines of graphics acceleration module 1446. In at least one embodiment, data from WD 1484 may be stored in registers 1445 and used by MMU 1439, interrupt management circuit 1447 and/or context management circuit 1448 as illustrated. For example, one embodiment of MMU 1439 includes segment/page walk
30 circuitry for accessing segment/page tables 1486 within an OS virtual address space 1485. In at least one embodiment, interrupt management circuit 1447 may process interrupt events 1492 received from graphics acceleration module 1446. In at least one embodiment, when performing graphics operations, an effective address 1493 generated by a graphics processing engine 1431(1)-1431(N) is translated to a real address by MMU 1439.

35 [0298] In at least one embodiment, registers 1445 are duplicated for each graphics processing engine 1431(1)-1431(N) and/or graphics acceleration module 1446 and may be

- 5 initialized by a hypervisor or an operating system. In at least one embodiment, each of these duplicated registers may be included in an accelerator integration slice 1490. Exemplary registers that may be initialized by a hypervisor are shown in Table 1.

Table 1 – Hypervisor Initialized Registers

<u>Register #</u>	<u>Description</u>
1	Slice Control Register
2	Real Address (RA) Scheduled Processes Area Pointer
3	Authority Mask Override Register
4	Interrupt Vector Table Entry Offset
5	Interrupt Vector Table Entry Limit
6	State Register
7	Logical Partition ID
8	Real address (RA) Hypervisor Accelerator Utilization Record Pointer
9	Storage Description Register

[0299] Exemplary registers that may be initialized by an operating system are shown in Table 2.

Table 2 – Operating System Initialized Registers

<u>Register #</u>	<u>Description</u>
1	Process and Thread Identification
2	Effective Address (EA) Context Save/Restore Pointer
3	Virtual Address (VA) Accelerator Utilization Record Pointer
4	Virtual Address (VA) Storage Segment Table Pointer
5	Authority Mask
6	Work descriptor

- 10 [0300] In at least one embodiment, each WD 1484 is specific to a particular graphics acceleration module 1446 and/or graphics processing engines 1431(1)-1431(N). In at least one embodiment, it contains all information required by a graphics processing engine 1431(1)-1431(N) to do work, or it can be a pointer to a memory location where an application has set up a command queue of work to be completed.

- 5 [0301] FIG. 14E illustrates additional details for one exemplary embodiment of a shared model. This embodiment includes a hypervisor real address space 1498 in which a process element list 1499 is stored. In at least one embodiment, hypervisor real address space 1498 is accessible via a hypervisor 1496 which virtualizes graphics acceleration module engines for operating system 1495.
- 10 [0302] In at least one embodiment, shared programming models allow for all or a subset of processes from all or a subset of partitions in a system to use a graphics acceleration module 1446. In at least one embodiment, there are two programming models where graphics acceleration module 1446 is shared by multiple processes and partitions, namely time-sliced shared and graphics directed shared.
- 15 [0303] In at least one embodiment, in this model, system hypervisor 1496 owns graphics acceleration module 1446 and makes its function available to all operating systems 1495. In at least one embodiment, for a graphics acceleration module 1446 to support virtualization by system hypervisor 1496, graphics acceleration module 1446 may adhere to certain requirements, such as (1) an application's job request must be autonomous (that is, state does not need to be maintained between jobs), or graphics acceleration module 1446 must provide a context save and restore mechanism, (2) an application's job request is guaranteed by graphics acceleration module 1446 to complete in a specified amount of time, including any translation faults, or graphics acceleration module 1446 provides an ability to preempt processing of a job, and (3) graphics acceleration module 1446 must be guaranteed fairness between processes when operating in a directed shared programming model.
- 20 [0304] In at least one embodiment, application 1480 is required to make an operating system 1495 system call with a graphics acceleration module type, a work descriptor (WD), an authority mask register (AMR) value, and a context save/restore area pointer (CSRP). In at least one embodiment, graphics acceleration module type describes a targeted acceleration function for a system call. In at least one embodiment, graphics acceleration module type may be a system-specific value. In at least one embodiment, WD is formatted specifically for graphics acceleration module 1446 and can be in a form of a graphics acceleration module 1446 command, an effective address pointer to a user-defined structure, an effective address pointer to a queue of commands, or any other data structure to describe work to be done by graphics acceleration module 1446.
- 25 30 35

5 [0305] In at least one embodiment, an AMR value is an AMR state to use for a current process. In at least one embodiment, a value passed to an operating system is similar to an application setting an AMR. In at least one embodiment, if accelerator integration circuit 1436 (not shown) and graphics acceleration module 1446 implementations do not support a User Authority Mask Override Register (UAMOR), an operating system may apply a current
 10 UAMOR value to an AMR value before passing an AMR in a hypervisor call. In at least one embodiment, hypervisor 1496 may optionally apply a current Authority Mask Override Register (AMOR) value before placing an AMR into process element 1483. In at least one embodiment, CSRP is one of registers 1445 containing an effective address of an area in an application's effective address space 1482 for graphics acceleration module 1446 to save and
 15 restore context state. In at least one embodiment, this pointer is optional if no state is required to be saved between jobs or when a job is preempted. In at least one embodiment, context save/restore area may be pinned system memory.

[0306] Upon receiving a system call, operating system 1495 may verify that application 1480 has registered and been given authority to use graphics acceleration module 1446. In at
 20 least one embodiment, operating system 1495 then calls hypervisor 1496 with information shown in Table 3.

Table 3 – OS to Hypervisor Call Parameters

<u>Parameter #</u>	<u>Description</u>
1	A work descriptor (WD)
2	An Authority Mask Register (AMR) value (potentially masked)
3	An effective address (EA) Context Save/Restore Area Pointer (CSRP)
4	A process ID (PID) and optional thread ID (TID)
5	A virtual address (VA) accelerator utilization record pointer (AURP)
6	Virtual address of storage segment table pointer (SSTP)
7	A logical interrupt service number (LISN)

[0307] In at least one embodiment, upon receiving a hypervisor call, hypervisor 1496 verifies that operating system 1495 has registered and been given authority to use graphics acceleration module 1446. In at least one embodiment, hypervisor 1496 then puts process
 25 element 1483 into a process element linked list for a corresponding graphics acceleration module 1446 type. In at least one embodiment, a process element may include information shown in Table 4.

Table 4 –Process Element Information

<u>Element #</u>	<u>Description</u>
1	A work descriptor (WD)
2	An Authority Mask Register (AMR) value (potentially masked).
3	An effective address (EA) Context Save/Restore Area Pointer (CSRP)
4	A process ID (PID) and optional thread ID (TID)
5	A virtual address (VA) accelerator utilization record pointer (AURP)
6	Virtual address of storage segment table pointer (SSTP)
7	A logical interrupt service number (LISN)
8	Interrupt vector table, derived from hypervisor call parameters
9	A state register (SR) value
10	A logical partition ID (LPID)
11	A real address (RA) hypervisor accelerator utilization record pointer
12	Storage Descriptor Register (SDR)

5 [0308] In at least one embodiment, hypervisor initializes a plurality of accelerator integration slice 1490 registers 1445.

[0309] As illustrated in FIG. 14F, in at least one embodiment, a unified memory is used, addressable via a common virtual memory address space used to access physical processor memories 1401(1)-1401(N) and GPU memories 1420(1)-1420(N). In this implementation, operations executed on GPUs 1410(1)-1410(N) utilize a same virtual/effective memory address space to access processor memories 1401(1)-1401(M) and vice versa, thereby simplifying programmability. In at least one embodiment, a first portion of a virtual/effective address space is allocated to processor memory 1401(1), a second portion to second processor memory 1401(N), a third portion to GPU memory 1420(1), and so on. In at least one embodiment, an entire virtual/effective memory space (sometimes referred to as an effective address space) is thereby distributed across each of processor memories 1401 and GPU memories 1420, allowing any processor or GPU to access any physical memory with a virtual address mapped to that memory.

[0310] In at least one embodiment, bias/coherence management circuitry 1494A-1494E within one or more of MMUs 1439A-1439E ensures cache coherence between caches of one or more host processors (e.g., 1405) and GPUs 1410 and implements biasing techniques indicating physical memories in which certain types of data should be stored. In at least one

5 embodiment, while multiple instances of bias/coherence management circuitry 1494A-1494E are illustrated in FIG. 14F, bias/coherence circuitry may be implemented within an MMU of one or more host processors 1405 and/or within accelerator integration circuit 1436.

[0311] One embodiment allows GPU memories 1420 to be mapped as part of system memory, and accessed using shared virtual memory (SVM) technology, but without suffering
10 performance drawbacks associated with full system cache coherence. In at least one embodiment, an ability for GPU memories 1420 to be accessed as system memory without onerous cache coherence overhead provides a beneficial operating environment for GPU offload. In at least one embodiment, this arrangement allows software of host processor 1405 to setup operands and access computation results, without overhead of traditional I/O DMA
15 data copies. In at least one embodiment, such traditional copies involve driver calls, interrupts and memory mapped I/O (MMIO) accesses that are all inefficient relative to simple memory accesses. In at least one embodiment, an ability to access GPU memories 1420 without cache coherence overheads can be critical to execution time of an offloaded computation. In at least one embodiment, in cases with substantial streaming write memory
20 traffic, for example, cache coherence overhead can significantly reduce an effective write bandwidth seen by a GPU 1410. In at least one embodiment, efficiency of operand setup, efficiency of results access, and efficiency of GPU computation may play a role in determining effectiveness of a GPU offload.

[0312] In at least one embodiment, selection of GPU bias and host processor bias is driven
25 by a bias tracker data structure. In at least one embodiment, a bias table may be used, for example, which may be a page-granular structure (e.g., controlled at a granularity of a memory page) that includes 1 or 2 bits per GPU-attached memory page. In at least one embodiment, a bias table may be implemented in a stolen memory range of one or more GPU memories 1420, with or without a bias cache in a GPU 1410 (e.g., to cache
30 frequently/recently used entries of a bias table). Alternatively, in at least one embodiment, an entire bias table may be maintained within a GPU.

[0313] In at least one embodiment, a bias table entry associated with each access to a GPU attached memory 1420 is accessed prior to actual access to a GPU memory, causing
following operations. In at least one embodiment, local requests from a GPU 1410 that find
35 their page in GPU bias are forwarded directly to a corresponding GPU memory 1420. In at least one embodiment, local requests from a GPU that find their page in host bias are

5 forwarded to processor 1405 (e.g., over a high-speed link as described herein). In at least one embodiment, requests from processor 1405 that find a requested page in host processor bias complete a request like a normal memory read. Alternatively, requests directed to a GPU-biased page may be forwarded to a GPU 1410. In at least one embodiment, a GPU may then transition a page to a host processor bias if it is not currently using a page. In at least one
10 embodiment, a bias state of a page can be changed either by a software-based mechanism, a hardware-assisted software-based mechanism, or, for a limited set of cases, a purely hardware-based mechanism.

[0314] In at least one embodiment, one mechanism for changing bias state employs an API call (e.g., OpenCL), which, in turn, calls a GPU's device driver which, in turn, sends a
15 message (or enqueues a command descriptor) to a GPU directing it to change a bias state and, for some transitions, perform a cache flushing operation in a host. In at least one embodiment, a cache flushing operation is used for a transition from host processor 1405 bias to GPU bias, but is not for an opposite transition.

[0315] In at least one embodiment, cache coherency is maintained by temporarily rendering
20 GPU-biased pages uncacheable by host processor 1405. In at least one embodiment, to access these pages, processor 1405 may request access from GPU 1410, which may or may not grant access right away. In at least one embodiment, thus, to reduce communication between processor 1405 and GPU 1410 it is beneficial to ensure that GPU-biased pages are those which are required by a GPU but not host processor 1405 and vice versa.

25 [0316] Hardware structure(s) 615 are used to perform one or more embodiments. Details regarding a hardware structure(s) 615 may be provided herein in conjunction with FIGS. 6A and/or 6B.

[0317] In at least one embodiment, one or more systems depicted in FIGS. 14A-14F are utilized to implement a deep object detection network. In at least one embodiment, one or
30 more systems depicted in FIGS. 14A-14F are utilized to implement one or more networks and models such as those described in connection with FIG. 1 and FIG. 3. In at least one embodiment, one or more systems depicted in FIGS. 14A-14F are utilized to implement a network that is based on mixture density networks and predicts uncertainty values of images. In at least one embodiment, one or more systems depicted in FIGS. 14A-14F are utilized to
35 implement an active learning method for object detection that utilizes mixture density networks to produce one or more Gaussian mixture models for each output of a network.

- 5 [0318] FIG. 15 illustrates exemplary integrated circuits and associated graphics processors that may be fabricated using one or more IP cores, according to various embodiments described herein. In addition to what is illustrated, other logic and circuits may be included in at least one embodiment, including additional graphics processors/cores, peripheral interface controllers, or general-purpose processor cores.
- 10 [0319] FIG. 15 is a block diagram illustrating an exemplary system on a chip integrated circuit 1500 that may be fabricated using one or more IP cores, according to at least one embodiment. In at least one embodiment, integrated circuit 1500 includes one or more application processor(s) 1505 (e.g., CPUs), at least one graphics processor 1510, and may additionally include an image processor 1515 and/or a video processor 1520, any of which
- 15 may be a modular IP core. In at least one embodiment, integrated circuit 1500 includes peripheral or bus logic including a USB controller 1525, a UART controller 1530, an SPI/SDIO controller 1535, and an I²S/I²C controller 1540. In at least one embodiment, integrated circuit 1500 can include a display device 1545 coupled to one or more of a high-definition multimedia interface (HDMI) controller 1550 and a mobile industry processor
- 20 interface (MIPI) display interface 1555. In at least one embodiment, storage may be provided by a flash memory subsystem 1560 including flash memory and a flash memory controller. In at least one embodiment, a memory interface may be provided via a memory controller 1565 for access to SDRAM or SRAM memory devices. In at least one embodiment, some integrated circuits additionally include an embedded security engine 1570.
- 25 [0320] Inference and/or training logic 615 are used to perform inferencing and/or training operations associated with one or more embodiments. Details regarding inference and/or training logic 615 are provided herein in conjunction with FIGS. 6A and/or 6B. In at least one embodiment, inference and/or training logic 615 may be used in integrated circuit 1500 for inferencing or predicting operations based, at least in part, on weight parameters
- 30 calculated using neural network training operations, neural network functions and/or architectures, or neural network use cases described herein.
- [0321] In at least one embodiment, one or more systems depicted in FIG. 15 are utilized to implement a deep object detection network. In at least one embodiment, one or more systems depicted in FIG. 15 are utilized to implement one or more networks and models such as those
- 35 described in connection with FIG. 1 and FIG. 3. In at least one embodiment, one or more systems depicted in FIG. 15 are utilized to implement a network that is based on mixture

5 density networks and predicts uncertainty values of images. In at least one embodiment, one or more systems depicted in FIG. 15 are utilized to implement an active learning method for object detection that utilizes mixture density networks to produce one or more Gaussian mixture models for each output of a network.

[0322] FIGS. 16A and 16B illustrate exemplary integrated circuits and associated graphics
10 processors that may be fabricated using one or more IP cores, according to various embodiments described herein. In addition to what is illustrated, other logic and circuits may be included in at least one embodiment, including additional graphics processors/cores, peripheral interface controllers, or general-purpose processor cores.

[0323] FIGS. 16A and 16B are block diagrams illustrating exemplary graphics processors
15 for use within an SoC, according to embodiments described herein. FIG. 16A illustrates an exemplary graphics processor 1610 of a system on a chip integrated circuit that may be fabricated using one or more IP cores, according to at least one embodiment. FIG. 16B illustrates an additional exemplary graphics processor 1640 of a system on a chip integrated circuit that may be fabricated using one or more IP cores, according to at least one
20 embodiment. In at least one embodiment, graphics processor 1610 of FIG. 16A is a low power graphics processor core. In at least one embodiment, graphics processor 1640 of FIG. 16B is a higher performance graphics processor core. In at least one embodiment, each of graphics processors 1610, 1640 can be variants of graphics processor 1510 of FIG. 15.

[0324] In at least one embodiment, graphics processor 1610 includes a vertex processor
25 1605 and one or more fragment processor(s) 1615A-1615N (e.g., 1615A, 1615B, 1615C, 1615D, through 1615N-1, and 1615N). In at least one embodiment, graphics processor 1610 can execute different shader programs via separate logic, such that vertex processor 1605 is optimized to execute operations for vertex shader programs, while one or more fragment processor(s) 1615A-1615N execute fragment (e.g., pixel) shading operations for fragment or
30 pixel shader programs. In at least one embodiment, vertex processor 1605 performs a vertex processing stage of a 3D graphics pipeline and generates primitives and vertex data. In at least one embodiment, fragment processor(s) 1615A-1615N use primitive and vertex data generated by vertex processor 1605 to produce a framebuffer that is displayed on a display device. In at least one embodiment, fragment processor(s) 1615A-1615N are optimized to
35 execute fragment shader programs as provided for in an OpenGL API, which may be used to perform similar operations as a pixel shader program as provided for in a Direct 3D API.

5 [0325] In at least one embodiment, graphics processor 1610 additionally includes one or more memory management units (MMUs) 1620A-1620B, cache(s) 1625A-1625B, and circuit interconnect(s) 1630A-1630B. In at least one embodiment, one or more MMU(s) 1620A-1620B provide for virtual to physical address mapping for graphics processor 1610, including for vertex processor 1605 and/or fragment processor(s) 1615A-1615N, which may reference
10 vertex or image/texture data stored in memory, in addition to vertex or image/texture data stored in one or more cache(s) 1625A-1625B. In at least one embodiment, one or more MMU(s) 1620A-1620B may be synchronized with other MMUs within a system, including one or more MMUs associated with one or more application processor(s) 1505, image processors 1515, and/or video processors 1520 of FIG. 15, such that each processor 1505-
15 1520 can participate in a shared or unified virtual memory system. In at least one embodiment, one or more circuit interconnect(s) 1630A-1630B enable graphics processor 1610 to interface with other IP cores within SoC, either via an internal bus of SoC or via a direct connection.

[0326] In at least one embodiment, graphics processor 1640 includes one or more shader core(s) 1655A-1655N (e.g., 1655A, 1655B, 1655C, 1655D, 1655E, 1655F, through 1655N-1, and 1655N) as shown in FIG. 16B, which provides for a unified shader core architecture in which a single core or type or core can execute all types of programmable shader code, including shader program code to implement vertex shaders, fragment shaders, and/or compute shaders. In at least one embodiment, a number of shader cores can vary. In at least
20 one embodiment, graphics processor 1640 includes an inter-core task manager 1645, which acts as a thread dispatcher to dispatch execution threads to one or more shader cores 1655A-1655N and a tiling unit 1658 to accelerate tiling operations for tile-based rendering, in which rendering operations for a scene are subdivided in image space, for example to exploit local spatial coherence within a scene or to optimize use of internal caches.

30 [0327] Inference and/or training logic 615 are used to perform inferencing and/or training operations associated with one or more embodiments. Details regarding inference and/or training logic 615 are provided herein in conjunction with FIGS. 6A and/or 6B. In at least one embodiment, inference and/or training logic 615 may be used in integrated circuit 16A and/or 16B for inferencing or predicting operations based, at least in part, on weight
35 parameters calculated using neural network training operations, neural network functions and/or architectures, or neural network use cases described herein.

5 [0328] In at least one embodiment, one or more systems depicted in FIGS. 16A-16B are utilized to implement a deep object detection network. In at least one embodiment, one or more systems depicted in FIGS. 16A-16B are utilized to implement one or more networks and models such as those described in connection with FIG. 1 and FIG. 3. In at least one embodiment, one or more systems depicted in FIGS. 16A-16B are utilized to implement a
 10 network that is based on mixture density networks and predicts uncertainty values of images. In at least one embodiment, one or more systems depicted in FIGS. 16A-16B are utilized to implement an active learning method for object detection that utilizes mixture density networks to produce one or more Gaussian mixture models for each output of a network.

[0329] FIGS. 17A and 17B illustrate additional exemplary graphics processor logic
 15 according to embodiments described herein. FIG. 17A illustrates a graphics core 1700 that may be included within graphics processor 1510 of FIG. 15, in at least one embodiment, and may be a unified shader core 1655A-1655N as in FIG. 16B in at least one embodiment. FIG. 17B illustrates a highly-parallel general-purpose graphics processing unit (“GPGPU”) 1730 suitable for deployment on a multi-chip module in at least one embodiment.

20 [0330] In at least one embodiment, graphics core 1700 includes a shared instruction cache 1702, a texture unit 1718, and a cache/shared memory 1720 that are common to execution resources within graphics core 1700. In at least one embodiment, graphics core 1700 can include multiple slices 1701A-1701N or a partition for each core, and a graphics processor can include multiple instances of graphics core 1700. In at least one embodiment, slices
 25 1701A-1701N can include support logic including a local instruction cache 1704A-1704N, a thread scheduler 1706A-1706N, a thread dispatcher 1708A-1708N, and a set of registers 1710A-1710N. In at least one embodiment, slices 1701A-1701N can include a set of additional function units (AFUs 1712A-1712N), floating-point units (FPUs 1714A-1714N), integer arithmetic logic units (ALUs 1716A-1716N), address computational units (ACUs
 30 1713A-1713N), double-precision floating-point units (DPFPUs 1715A-1715N), and matrix processing units (MPUs 1717A-1717N).

[0331] In at least one embodiment, FPUs 1714A-1714N can perform single-precision (32-bit) and half-precision (16-bit) floating point operations, while DPFPUs 1715A-1715N perform double precision (64-bit) floating point operations. In at least one embodiment,
 35 ALUs 1716A-1716N can perform variable precision integer operations at 8-bit, 16-bit, and 32-bit precision, and can be configured for mixed precision operations. In at least one

5 embodiment, MPUs 1717A-1717N can also be configured for mixed precision matrix operations, including half-precision floating point and 8-bit integer operations. In at least one embodiment, MPUs 1717-1717N can perform a variety of matrix operations to accelerate machine learning application frameworks, including enabling support for accelerated general matrix to matrix multiplication (GEMM). In at least one embodiment, AFUs 1712A-1712N
10 can perform additional logic operations not supported by floating-point or integer units, including trigonometric operations (e.g., sine, cosine, etc.).

[0332] Inference and/or training logic 615 are used to perform inferencing and/or training operations associated with one or more embodiments. Details regarding inference and/or training logic 615 are provided herein in conjunction with FIGS. 6A and/or 6B. In at least
15 one embodiment, inference and/or training logic 615 may be used in graphics core 1700 for inferencing or predicting operations based, at least in part, on weight parameters calculated using neural network training operations, neural network functions and/or architectures, or neural network use cases described herein.

[0333] FIG. 17B illustrates a general-purpose processing unit (GPGPU) 1730 that can be
20 configured to enable highly-parallel compute operations to be performed by an array of graphics processing units, in at least one embodiment. In at least one embodiment, GPGPU 1730 can be linked directly to other instances of GPGPU 1730 to create a multi-GPU cluster to improve training speed for deep neural networks. In at least one embodiment, GPGPU 1730 includes a host interface 1732 to enable a connection with a host processor. In at least
25 one embodiment, host interface 1732 is a PCI Express interface. In at least one embodiment, host interface 1732 can be a vendor-specific communications interface or communications fabric. In at least one embodiment, GPGPU 1730 receives commands from a host processor and uses a global scheduler 1734 to distribute execution threads associated with those commands to a set of compute clusters 1736A-1736H. In at least one embodiment, compute
30 clusters 1736A-1736H share a cache memory 1738. In at least one embodiment, cache memory 1738 can serve as a higher-level cache for cache memories within compute clusters 1736A-1736H.

[0334] In at least one embodiment, GPGPU 1730 includes memory 1744A-1744B coupled with compute clusters 1736A-1736H via a set of memory controllers 1742A-1742B. In at
35 least one embodiment, memory 1744A-1744B can include various types of memory devices including dynamic random access memory (DRAM) or graphics random access memory,

5 such as synchronous graphics random access memory (SGRAM), including graphics double data rate (GDDR) memory.

[0335] In at least one embodiment, compute clusters 1736A-1736H each include a set of graphics cores, such as graphics core 1700 of FIG. 17A, which can include multiple types of integer and floating point logic units that can perform computational operations at a range of
10 precisions including suited for machine learning computations. For example, in at least one embodiment, at least a subset of floating point units in each of compute clusters 1736A-1736H can be configured to perform 16-bit or 32-bit floating point operations, while a different subset of floating point units can be configured to perform 64-bit floating point operations.

15 [0336] In at least one embodiment, multiple instances of GPGPU 1730 can be configured to operate as a compute cluster. In at least one embodiment, communication used by compute clusters 1736A-1736H for synchronization and data exchange varies across embodiments. In at least one embodiment, multiple instances of GPGPU 1730 communicate over host interface 1732. In at least one embodiment, GPGPU 1730 includes an I/O hub
20 1739 that couples GPGPU 1730 with a GPU link 1740 that enables a direct connection to other instances of GPGPU 1730. In at least one embodiment, GPU link 1740 is coupled to a dedicated GPU-to-GPU bridge that enables communication and synchronization between multiple instances of GPGPU 1730. In at least one embodiment, GPU link 1740 couples with a high-speed interconnect to transmit and receive data to other GPGPUs or parallel
25 processors. In at least one embodiment, multiple instances of GPGPU 1730 are located in separate data processing systems and communicate via a network device that is accessible via host interface 1732. In at least one embodiment GPU link 1740 can be configured to enable a connection to a host processor in addition to or as an alternative to host interface 1732.

[0337] In at least one embodiment, GPGPU 1730 can be configured to train neural
30 networks. In at least one embodiment, GPGPU 1730 can be used within an inferencing platform. In at least one embodiment, in which GPGPU 1730 is used for inferencing, GPGPU 1730 may include fewer compute clusters 1736A-1736H relative to when GPGPU 1730 is used for training a neural network. In at least one embodiment, memory technology associated with memory 1744A-1744B may differ between inferencing and training
35 configurations, with higher bandwidth memory technologies devoted to training configurations. In at least one embodiment, an inferencing configuration of GPGPU 1730

5 can support inferencing specific instructions. For example, in at least one embodiment, an inferencing configuration can provide support for one or more 8-bit integer dot product instructions, which may be used during inferencing operations for deployed neural networks.

[0338] Inference and/or training logic 615 are used to perform inferencing and/or training operations associated with one or more embodiments. Details regarding inference and/or
10 training logic 615 are provided herein in conjunction with FIGS. 6A and/or 6B. In at least one embodiment, inference and/or training logic 615 may be used in GPGPU 1730 for inferencing or predicting operations based, at least in part, on weight parameters calculated using neural network training operations, neural network functions and/or architectures, or neural network use cases described herein.

15 [0339] In at least one embodiment, one or more systems depicted in FIGS. 17A-17B are utilized to implement a deep object detection network. In at least one embodiment, one or more systems depicted in FIGS. 17A-17B are utilized to implement one or more networks and models such as those described in connection with FIG. 1 and FIG. 3. In at least one embodiment, one or more systems depicted in FIGS. 17A-17B are utilized to implement a
20 network that is based on mixture density networks and predicts uncertainty values of images. In at least one embodiment, one or more systems depicted in FIGS. 17A-17B are utilized to implement an active learning method for object detection that utilizes mixture density networks to produce one or more Gaussian mixture models for each output of a network.

[0340] FIG. 18 is a block diagram illustrating a computing system 1800 according to at
25 least one embodiment. In at least one embodiment, computing system 1800 includes a processing subsystem 1801 having one or more processor(s) 1802 and a system memory 1804 communicating via an interconnection path that may include a memory hub 1805. In at least one embodiment, memory hub 1805 may be a separate component within a chipset component or may be integrated within one or more processor(s) 1802. In at least one
30 embodiment, memory hub 1805 couples with an I/O subsystem 1811 via a communication link 1806. In at least one embodiment, I/O subsystem 1811 includes an I/O hub 1807 that can enable computing system 1800 to receive input from one or more input device(s) 1808. In at least one embodiment, I/O hub 1807 can enable a display controller, which may be included in one or more processor(s) 1802, to provide outputs to one or more display
35 device(s) 1810A. In at least one embodiment, one or more display device(s) 1810A coupled with I/O hub 1807 can include a local, internal, or embedded display device.

5 [0341] In at least one embodiment, processing subsystem 1801 includes one or more parallel processor(s) 1812 coupled to memory hub 1805 via a bus or other communication link 1813. In at least one embodiment, communication link 1813 may use one of any number of standards based communication link technologies or protocols, such as, but not limited to PCI Express, or may be a vendor-specific communications interface or communications
10 fabric. In at least one embodiment, one or more parallel processor(s) 1812 form a computationally focused parallel or vector processing system that can include a large number of processing cores and/or processing clusters, such as a many-integrated core (MIC) processor. In at least one embodiment, some or all of parallel processor(s) 1812 form a graphics processing subsystem that can output pixels to one of one or more display device(s)
15 1810A coupled via I/O Hub 1807. In at least one embodiment, parallel processor(s) 1812 can also include a display controller and display interface (not shown) to enable a direct connection to one or more display device(s) 1810B.

[0342] In at least one embodiment, a system storage unit 1814 can connect to I/O hub 1807 to provide a storage mechanism for computing system 1800. In at least one embodiment, an
20 I/O switch 1816 can be used to provide an interface mechanism to enable connections between I/O hub 1807 and other components, such as a network adapter 1818 and/or a wireless network adapter 1819 that may be integrated into platform, and various other devices that can be added via one or more add-in device(s) 1820. In at least one embodiment, network adapter 1818 can be an Ethernet adapter or another wired network adapter. In at
25 least one embodiment, wireless network adapter 1819 can include one or more of a Wi-Fi, Bluetooth, near field communication (NFC), or other network device that includes one or more wireless radios.

[0343] In at least one embodiment, computing system 1800 can include other components not explicitly shown, including USB or other port connections, optical storage drives, video
30 capture devices, and like, may also be connected to I/O hub 1807. In at least one embodiment, communication paths interconnecting various components in FIG. 18 may be implemented using any suitable protocols, such as PCI (Peripheral Component Interconnect) based protocols (e.g., PCI-Express), or other bus or point-to-point communication interfaces and/or protocol(s), such as NV-Link high-speed interconnect, or interconnect protocols.

35 [0344] In at least one embodiment, parallel processor(s) 1812 incorporate circuitry optimized for graphics and video processing, including, for example, video output circuitry,

5 and constitutes a graphics processing unit (GPU). In at least one embodiment, parallel processor(s) 1812 incorporate circuitry optimized for general purpose processing. In at least embodiment, components of computing system 1800 may be integrated with one or more other system elements on a single integrated circuit. For example, in at least one embodiment, parallel processor(s) 1812, memory hub 1805, processor(s) 1802, and I/O hub
10 1807 can be integrated into a system on chip (SoC) integrated circuit. In at least one embodiment, components of computing system 1800 can be integrated into a single package to form a system in package (SIP) configuration. In at least one embodiment, at least a portion of components of computing system 1800 can be integrated into a multi-chip module (MCM), which can be interconnected with other multi-chip modules into a modular
15 computing system.

[0345] Inference and/or training logic 615 are used to perform inferencing and/or training operations associated with one or more embodiments. Details regarding inference and/or training logic 615 are provided herein in conjunction with FIGS. 6A and/or 6B. In at least one embodiment, inference and/or training logic 615 may be used in system FIG. 1800 for
20 inferencing or predicting operations based, at least in part, on weight parameters calculated using neural network training operations, neural network functions and/or architectures, or neural network use cases described herein.

[0346] In at least one embodiment, one or more systems depicted in FIG. 18 are utilized to implement a deep object detection network. In at least one embodiment, one or more systems
25 depicted in FIG. 18 are utilized to implement one or more networks and models such as those described in connection with FIG. 1 and FIG. 3. In at least one embodiment, one or more systems depicted in FIG. 18 are utilized to implement a network that is based on mixture density networks and predicts uncertainty values of images. In at least one embodiment, one or more systems depicted in FIG. 18 are utilized to implement an active learning method for
30 object detection that utilizes mixture density networks to produce one or more Gaussian mixture models for each output of a network.

PROCESSORS

[0347] FIG. 19A illustrates a parallel processor 1900 according to at least one embodiment. In at least one embodiment, various components of parallel processor 1900 may be
35 implemented using one or more integrated circuit devices, such as programmable processors, application specific integrated circuits (ASICs), or field programmable gate arrays (FPGA).

5 In at least one embodiment, illustrated parallel processor 1900 is a variant of one or more parallel processor(s) 1812 shown in FIG. 18 according to an exemplary embodiment.

[0348] In at least one embodiment, parallel processor 1900 includes a parallel processing unit 1902. In at least one embodiment, parallel processing unit 1902 includes an I/O unit 1904 that enables communication with other devices, including other instances of parallel
10 processing unit 1902. In at least one embodiment, I/O unit 1904 may be directly connected to other devices. In at least one embodiment, I/O unit 1904 connects with other devices via use of a hub or switch interface, such as a memory hub 1905. In at least one embodiment, connections between memory hub 1905 and I/O unit 1904 form a communication link 1913. In at least one embodiment, I/O unit 1904 connects with a host interface 1906 and a memory
15 crossbar 1916, where host interface 1906 receives commands directed to performing processing operations and memory crossbar 1916 receives commands directed to performing memory operations.

[0349] In at least one embodiment, when host interface 1906 receives a command buffer via I/O unit 1904, host interface 1906 can direct work operations to perform those commands
20 to a front end 1908. In at least one embodiment, front end 1908 couples with a scheduler 1910, which is configured to distribute commands or other work items to a processing cluster array 1912. In at least one embodiment, scheduler 1910 ensures that processing cluster array 1912 is properly configured and in a valid state before tasks are distributed to a cluster of processing cluster array 1912. In at least one embodiment, scheduler 1910 is implemented
25 via firmware logic executing on a microcontroller. In at least one embodiment, microcontroller implemented scheduler 1910 is configurable to perform complex scheduling and work distribution operations at coarse and fine granularity, enabling rapid preemption and context switching of threads executing on processing array 1912. In at least one embodiment, host software can prove workloads for scheduling on processing cluster array
30 1912 via one of multiple graphics processing paths. In at least one embodiment, workloads can then be automatically distributed across processing array cluster 1912 by scheduler 1910 logic within a microcontroller including scheduler 1910.

[0350] In at least one embodiment, processing cluster array 1912 can include up to “N” processing clusters (e.g., cluster 1914A, cluster 1914B, through cluster 1914N), where “N”
35 represents a positive integer (which may be a different integer “N” than used in other figures). In at least one embodiment, each cluster 1914A-1914N of processing cluster array

5 1912 can execute a large number of concurrent threads. In at least one embodiment, scheduler 1910 can allocate work to clusters 1914A-1914N of processing cluster array 1912 using various scheduling and/or work distribution algorithms, which may vary depending on workload arising for each type of program or computation. In at least one embodiment, scheduling can be handled dynamically by scheduler 1910, or can be assisted in part by
10 compiler logic during compilation of program logic configured for execution by processing cluster array 1912. In at least one embodiment, different clusters 1914A-1914N of processing cluster array 1912 can be allocated for processing different types of programs or for performing different types of computations.

[0351] In at least one embodiment, processing cluster array 1912 can be configured to
15 perform various types of parallel processing operations. In at least one embodiment, processing cluster array 1912 is configured to perform general-purpose parallel compute operations. For example, in at least one embodiment, processing cluster array 1912 can include logic to execute processing tasks including filtering of video and/or audio data, performing modeling operations, including physics operations, and performing data
20 transformations.

[0352] In at least one embodiment, processing cluster array 1912 is configured to perform parallel graphics processing operations. In at least one embodiment, processing cluster array 1912 can include additional logic to support execution of such graphics processing operations, including but not limited to, texture sampling logic to perform texture operations,
25 as well as tessellation logic and other vertex processing logic. In at least one embodiment, processing cluster array 1912 can be configured to execute graphics processing related shader programs such as, but not limited to, vertex shaders, tessellation shaders, geometry shaders, and pixel shaders. In at least one embodiment, parallel processing unit 1902 can transfer data from system memory via I/O unit 1904 for processing. In at least one embodiment, during
30 processing, transferred data can be stored to on-chip memory (e.g., parallel processor memory 1922) during processing, then written back to system memory.

[0353] In at least one embodiment, when parallel processing unit 1902 is used to perform graphics processing, scheduler 1910 can be configured to divide a processing workload into approximately equal sized tasks, to better enable distribution of graphics processing
35 operations to multiple clusters 1914A-1914N of processing cluster array 1912. In at least one embodiment, portions of processing cluster array 1912 can be configured to perform different

5 types of processing. For example, in at least one embodiment, a first portion may be configured to perform vertex shading and topology generation, a second portion may be configured to perform tessellation and geometry shading, and a third portion may be configured to perform pixel shading or other screen space operations, to produce a rendered image for display. In at least one embodiment, intermediate data produced by one or more of
10 clusters 1914A-1914N may be stored in buffers to allow intermediate data to be transmitted between clusters 1914A-1914N for further processing.

[0354] In at least one embodiment, processing cluster array 1912 can receive processing tasks to be executed via scheduler 1910, which receives commands defining processing tasks from front end 1908. In at least one embodiment, processing tasks can include indices of data
15 to be processed, e.g., surface (patch) data, primitive data, vertex data, and/or pixel data, as well as state parameters and commands defining how data is to be processed (e.g., what program is to be executed). In at least one embodiment, scheduler 1910 may be configured to fetch indices corresponding to tasks or may receive indices from front end 1908. In at least one embodiment, front end 1908 can be configured to ensure processing cluster array 1912 is
20 configured to a valid state before a workload specified by incoming command buffers (e.g., batch-buffers, push buffers, etc.) is initiated.

[0355] In at least one embodiment, each of one or more instances of parallel processing unit 1902 can couple with a parallel processor memory 1922. In at least one embodiment, parallel processor memory 1922 can be accessed via memory crossbar 1916, which can
25 receive memory requests from processing cluster array 1912 as well as I/O unit 1904. In at least one embodiment, memory crossbar 1916 can access parallel processor memory 1922 via a memory interface 1918. In at least one embodiment, memory interface 1918 can include multiple partition units (e.g., partition unit 1920A, partition unit 1920B, through partition unit 1920N) that can each couple to a portion (e.g., memory unit) of parallel processor memory
30 1922. In at least one embodiment, a number of partition units 1920A-1920N is configured to be equal to a number of memory units, such that a first partition unit 1920A has a corresponding first memory unit 1924A, a second partition unit 1920B has a corresponding memory unit 1924B, and an N-th partition unit 1920N has a corresponding N-th memory unit 1924N. In at least one embodiment, a number of partition units 1920A-1920N may not be
35 equal to a number of memory units.

5 [0356] In at least one embodiment, memory units 1924A-1924N can include various types of memory devices, including dynamic random access memory (DRAM) or graphics random access memory, such as synchronous graphics random access memory (SGRAM), including graphics double data rate (GDDR) memory. In at least one embodiment, memory units 1924A-1924N may also include 3D stacked memory, including but not limited to high
10 bandwidth memory (HBM). In at least one embodiment, render targets, such as frame buffers or texture maps may be stored across memory units 1924A-1924N, allowing partition units 1920A-1920N to write portions of each render target in parallel to efficiently use available bandwidth of parallel processor memory 1922. In at least one embodiment, a local instance of parallel processor memory 1922 may be excluded in favor of a unified memory
15 design that utilizes system memory in conjunction with local cache memory.

[0357] In at least one embodiment, any one of clusters 1914A-1914N of processing cluster array 1912 can process data that will be written to any of memory units 1924A-1924N within parallel processor memory 1922. In at least one embodiment, memory crossbar 1916 can be configured to transfer an output of each cluster 1914A-1914N to any partition unit 1920A-
20 1920N or to another cluster 1914A-1914N, which can perform additional processing operations on an output. In at least one embodiment, each cluster 1914A-1914N can communicate with memory interface 1918 through memory crossbar 1916 to read from or write to various external memory devices. In at least one embodiment, memory crossbar 1916 has a connection to memory interface 1918 to communicate with I/O unit 1904, as well
25 as a connection to a local instance of parallel processor memory 1922, enabling processing units within different processing clusters 1914A-1914N to communicate with system memory or other memory that is not local to parallel processing unit 1902. In at least one embodiment, memory crossbar 1916 can use virtual channels to separate traffic streams between clusters 1914A-1914N and partition units 1920A-1920N.

30 [0358] In at least one embodiment, multiple instances of parallel processing unit 1902 can be provided on a single add-in card, or multiple add-in cards can be interconnected. In at least one embodiment, different instances of parallel processing unit 1902 can be configured to interoperate even if different instances have different numbers of processing cores, different amounts of local parallel processor memory, and/or other configuration differences.
35 For example, in at least one embodiment, some instances of parallel processing unit 1902 can include higher precision floating point units relative to other instances. In at least one embodiment, systems incorporating one or more instances of parallel processing unit 1902 or

5 parallel processor 1900 can be implemented in a variety of configurations and form factors, including but not limited to desktop, laptop, or handheld personal computers, servers, workstations, game consoles, and/or embedded systems.

[0359] FIG. 19B is a block diagram of a partition unit 1920 according to at least one embodiment. In at least one embodiment, partition unit 1920 is an instance of one of
10 partition units 1920A-1920N of FIG. 19A. In at least one embodiment, partition unit 1920 includes an L2 cache 1921, a frame buffer interface 1925, and a ROP 1926 (raster operations unit). In at least one embodiment, L2 cache 1921 is a read/write cache that is configured to perform load and store operations received from memory crossbar 1916 and ROP 1926. In at least one embodiment, read misses and urgent write-back requests are output by L2 cache
15 1921 to frame buffer interface 1925 for processing. In at least one embodiment, updates can also be sent to a frame buffer via frame buffer interface 1925 for processing. In at least one embodiment, frame buffer interface 1925 interfaces with one of memory units in parallel processor memory, such as memory units 1924A-1924N of FIG. 19 (e.g., within parallel processor memory 1922).

20 [0360] In at least one embodiment, ROP 1926 is a processing unit that performs raster operations such as stencil, z test, blending, etc. In at least one embodiment, ROP 1926 then outputs processed graphics data that is stored in graphics memory. In at least one embodiment, ROP 1926 includes compression logic to compress depth or color data that is written to memory and decompress depth or color data that is read from memory. In at least
25 one embodiment, compression logic can be lossless compression logic that makes use of one or more of multiple compression algorithms. In at least one embodiment, a type of compression that is performed by ROP 1926 can vary based on statistical characteristics of data to be compressed. For example, in at least one embodiment, delta color compression is performed on depth and color data on a per-tile basis.

30 [0361] In at least one embodiment, ROP 1926 is included within each processing cluster (e.g., cluster 1914A-1914N of FIG. 19A) instead of within partition unit 1920. In at least one embodiment, read and write requests for pixel data are transmitted over memory crossbar 1916 instead of pixel fragment data. In at least one embodiment, processed graphics data may be displayed on a display device, such as one of one or more display device(s) 1810 of
35 FIG. 18, routed for further processing by processor(s) 1802, or routed for further processing by one of processing entities within parallel processor 1900 of FIG. 19A.

5 [0362] FIG. 19C is a block diagram of a processing cluster 1914 within a parallel processing unit according to at least one embodiment. In at least one embodiment, a processing cluster is an instance of one of processing clusters 1914A-1914N of FIG. 19A. In at least one embodiment, processing cluster 1914 can be configured to execute many threads in parallel, where “thread” refers to an instance of a particular program executing on a
10 particular set of input data. In at least one embodiment, single-instruction, multiple-data (SIMD) instruction issue techniques are used to support parallel execution of a large number of threads without providing multiple independent instruction units. In at least one embodiment, single-instruction, multiple-thread (SIMT) techniques are used to support parallel execution of a large number of generally synchronized threads, using a common
15 instruction unit configured to issue instructions to a set of processing engines within each one of processing clusters.

[0363] In at least one embodiment, operation of processing cluster 1914 can be controlled via a pipeline manager 1932 that distributes processing tasks to SIMT parallel processors. In at least one embodiment, pipeline manager 1932 receives instructions from scheduler 1910 of
20 FIG. 19A and manages execution of those instructions via a graphics multiprocessor 1934 and/or a texture unit 1936. In at least one embodiment, graphics multiprocessor 1934 is an exemplary instance of a SIMT parallel processor. However, in at least one embodiment, various types of SIMT parallel processors of differing architectures may be included within processing cluster 1914. In at least one embodiment, one or more instances of graphics
25 multiprocessor 1934 can be included within a processing cluster 1914. In at least one embodiment, graphics multiprocessor 1934 can process data and a data crossbar 1940 can be used to distribute processed data to one of multiple possible destinations, including other shader units. In at least one embodiment, pipeline manager 1932 can facilitate distribution of processed data by specifying destinations for processed data to be distributed via data
30 crossbar 1940.

[0364] In at least one embodiment, each graphics multiprocessor 1934 within processing cluster 1914 can include an identical set of functional execution logic (e.g., arithmetic logic units, load-store units, etc.). In at least one embodiment, functional execution logic can be configured in a pipelined manner in which new instructions can be issued before previous
35 instructions are complete. In at least one embodiment, functional execution logic supports a variety of operations including integer and floating point arithmetic, comparison operations, Boolean operations, bit-shifting, and computation of various algebraic functions. In at least

5 one embodiment, same functional-unit hardware can be leveraged to perform different operations and any combination of functional units may be present.

[0365] In at least one embodiment, instructions transmitted to processing cluster 1914 constitute a thread. In at least one embodiment, a set of threads executing across a set of parallel processing engines is a thread group. In at least one embodiment, a thread group
10 executes a common program on different input data. In at least one embodiment, each thread within a thread group can be assigned to a different processing engine within a graphics multiprocessor 1934. In at least one embodiment, a thread group may include fewer threads than a number of processing engines within graphics multiprocessor 1934. In at least one embodiment, when a thread group includes fewer threads than a number of processing
15 engines, one or more of processing engines may be idle during cycles in which that thread group is being processed. In at least one embodiment, a thread group may also include more threads than a number of processing engines within graphics multiprocessor 1934. In at least one embodiment, when a thread group includes more threads than number of processing engines within graphics multiprocessor 1934, processing can be performed over consecutive
20 clock cycles. In at least one embodiment, multiple thread groups can be executed concurrently on a graphics multiprocessor 1934.

[0366] In at least one embodiment, graphics multiprocessor 1934 includes an internal cache memory to perform load and store operations. In at least one embodiment, graphics multiprocessor 1934 can forego an internal cache and use a cache memory (e.g., L1 cache
25 1948) within processing cluster 1914. In at least one embodiment, each graphics multiprocessor 1934 also has access to L2 caches within partition units (e.g., partition units 1920A-1920N of FIG. 19A) that are shared among all processing clusters 1914 and may be used to transfer data between threads. In at least one embodiment, graphics multiprocessor 1934 may also access off-chip global memory, which can include one or more of local
30 parallel processor memory and/or system memory. In at least one embodiment, any memory external to parallel processing unit 1902 may be used as global memory. In at least one embodiment, processing cluster 1914 includes multiple instances of graphics multiprocessor 1934 and can share common instructions and data, which may be stored in L1 cache 1948.

[0367] In at least one embodiment, each processing cluster 1914 may include an MMU
35 1945 (memory management unit) that is configured to map virtual addresses into physical addresses. In at least one embodiment, one or more instances of MMU 1945 may reside

5 within memory interface 1918 of FIG. 19A. In at least one embodiment, MMU 1945 includes a set of page table entries (PTEs) used to map a virtual address to a physical address of a tile and optionally a cache line index. In at least one embodiment, MMU 1945 may include address translation lookaside buffers (TLB) or caches that may reside within graphics multiprocessor 1934 or L1 1948 cache or processing cluster 1914. In at least one
10 embodiment, a physical address is processed to distribute surface data access locally to allow for efficient request interleaving among partition units. In at least one embodiment, a cache line index may be used to determine whether a request for a cache line is a hit or miss.

[0368] In at least one embodiment, a processing cluster 1914 may be configured such that each graphics multiprocessor 1934 is coupled to a texture unit 1936 for performing texture
15 mapping operations, e.g., determining texture sample positions, reading texture data, and filtering texture data. In at least one embodiment, texture data is read from an internal texture L1 cache (not shown) or from an L1 cache within graphics multiprocessor 1934 and is fetched from an L2 cache, local parallel processor memory, or system memory, as needed. In at least one embodiment, each graphics multiprocessor 1934 outputs processed tasks to data
20 crossbar 1940 to provide processed task to another processing cluster 1914 for further processing or to store processed task in an L2 cache, local parallel processor memory, or system memory via memory crossbar 1916. In at least one embodiment, a preROP 1942 (pre-raster operations unit) is configured to receive data from graphics multiprocessor 1934, and direct data to ROP units, which may be located with partition units as described herein
25 (e.g., partition units 1920A-1920N of FIG. 19A). In at least one embodiment, preROP 1942 unit can perform optimizations for color blending, organizing pixel color data, and performing address translations.

[0369] Inference and/or training logic 615 are used to perform inferencing and/or training operations associated with one or more embodiments. Details regarding inference and/or
30 training logic 615 are provided herein in conjunction with FIGS. 6A and/or 6B. In at least one embodiment, inference and/or training logic 615 may be used in graphics processing cluster 1914 for inferencing or predicting operations based, at least in part, on weight parameters calculated using neural network training operations, neural network functions and/or architectures, or neural network use cases described herein.

35 [0370] FIG. 19D shows a graphics multiprocessor 1934 according to at least one embodiment. In at least one embodiment, graphics multiprocessor 1934 couples with

5 pipeline manager 1932 of processing cluster 1914. In at least one embodiment, graphics multiprocessor 1934 has an execution pipeline including but not limited to an instruction cache 1952, an instruction unit 1954, an address mapping unit 1956, a register file 1958, one or more general purpose graphics processing unit (GPGPU) cores 1962, and one or more load/store units 1966. In at least one embodiment, GPGPU cores 1962 and load/store units
 10 1966 are coupled with cache memory 1972 and shared memory 1970 via a memory and cache interconnect 1968.

[0371] In at least one embodiment, instruction cache 1952 receives a stream of instructions to execute from pipeline manager 1932. In at least one embodiment, instructions are cached in instruction cache 1952 and dispatched for execution by an instruction unit 1954. In at least
 15 one embodiment, instruction unit 1954 can dispatch instructions as thread groups (e.g., warps), with each thread of thread group assigned to a different execution unit within GPGPU cores 1962. In at least one embodiment, an instruction can access any of a local, shared, or global address space by specifying an address within a unified address space. In at least one embodiment, address mapping unit 1956 can be used to translate addresses in a
 20 unified address space into a distinct memory address that can be accessed by load/store units 1966.

[0372] In at least one embodiment, register file 1958 provides a set of registers for functional units of graphics multiprocessor 1934. In at least one embodiment, register file 1958 provides temporary storage for operands connected to data paths of functional units
 25 (e.g., GPGPU cores 1962, load/store units 1966) of graphics multiprocessor 1934. In at least one embodiment, register file 1958 is divided between each of functional units such that each functional unit is allocated a dedicated portion of register file 1958. In at least one embodiment, register file 1958 is divided between different warps being executed by graphics multiprocessor 1934.

[0373] In at least one embodiment, GPGPU cores 1962 can each include floating point units (FPUs) and/or integer arithmetic logic units (ALUs) that are used to execute instructions of graphics multiprocessor 1934. In at least one embodiment, GPGPU cores 1962 can be similar in architecture or can differ in architecture. In at least one embodiment, a first portion of GPGPU cores 1962 include a single precision FPU and an integer ALU while a second
 30 portion of GPGPU cores include a double precision FPU. In at least one embodiment, FPUs can implement IEEE 754-2008 standard floating point arithmetic or enable variable precision
 35

5 floating point arithmetic. In at least one embodiment, graphics multiprocessor 1934 can additionally include one or more fixed function or special function units to perform specific functions such as copy rectangle or pixel blending operations. In at least one embodiment, one or more of GPGPU cores 1962 can also include fixed or special function logic.

[0374] In at least one embodiment, GPGPU cores 1962 include SIMD logic capable of
10 performing a single instruction on multiple sets of data. In at least one embodiment, GPGPU cores 1962 can physically execute SIMD4, SIMD8, and SIMD16 instructions and logically execute SIMD1, SIMD2, and SIMD32 instructions. In at least one embodiment, SIMD instructions for GPGPU cores can be generated at compile time by a shader compiler or automatically generated when executing programs written and compiled for single program
15 multiple data (SPMD) or SIMT architectures. In at least one embodiment, multiple threads of a program configured for an SIMT execution model can be executed via a single SIMD instruction. For example, in at least one embodiment, eight SIMT threads that perform same or similar operations can be executed in parallel via a single SIMD8 logic unit.

[0375] In at least one embodiment, memory and cache interconnect 1968 is an interconnect
20 network that connects each functional unit of graphics multiprocessor 1934 to register file 1958 and to shared memory 1970. In at least one embodiment, memory and cache interconnect 1968 is a crossbar interconnect that allows load/store unit 1966 to implement load and store operations between shared memory 1970 and register file 1958. In at least one embodiment, register file 1958 can operate at a same frequency as GPGPU cores 1962, thus
25 data transfer between GPGPU cores 1962 and register file 1958 can have very low latency. In at least one embodiment, shared memory 1970 can be used to enable communication between threads that execute on functional units within graphics multiprocessor 1934. In at least one embodiment, cache memory 1972 can be used as a data cache for example, to cache texture data communicated between functional units and texture unit 1936. In at least one
30 embodiment, shared memory 1970 can also be used as a program managed cache. In at least one embodiment, threads executing on GPGPU cores 1962 can programmatically store data within shared memory in addition to automatically cached data that is stored within cache memory 1972.

[0376] In at least one embodiment, a parallel processor or GPGPU as described herein is
35 communicatively coupled to host/processor cores to accelerate graphics operations, machine-learning operations, pattern analysis operations, and various general purpose GPU (GPGPU)

5 functions. In at least one embodiment, a GPU may be communicatively coupled to host processor/cores over a bus or other interconnect (e.g., a high-speed interconnect such as PCIe or NVLink). In at least one embodiment, a GPU may be integrated on a package or chip as cores and communicatively coupled to cores over an internal processor bus/interconnect internal to a package or chip. In at least one embodiment, regardless a manner in which a
10 GPU is connected, processor cores may allocate work to such GPU in a form of sequences of commands/instructions contained in a work descriptor. In at least one embodiment, that GPU then uses dedicated circuitry/logic for efficiently processing these commands/instructions.

[0377] Inference and/or training logic 615 are used to perform inferencing and/or training operations associated with one or more embodiments. Details regarding inference and/or
15 training logic 615 are provided herein in conjunction with FIGS. 6A and/or 6B. In at least one embodiment, inference and/or training logic 615 may be used in graphics multiprocessor 1934 for inferencing or predicting operations based, at least in part, on weight parameters calculated using neural network training operations, neural network functions and/or architectures, or neural network use cases described herein.

20 [0378] In at least one embodiment, one or more systems depicted in FIGS. 19A-19D are utilized to implement a deep object detection network. In at least one embodiment, one or more systems depicted in FIGS. 19A-19D are utilized to implement one or more networks and models such as those described in connection with FIG. 1 and FIG. 3. In at least one embodiment, one or more systems depicted in FIGS. 19A-19D are utilized to implement a
25 network that is based on mixture density networks and predicts uncertainty values of images. In at least one embodiment, one or more systems depicted in FIGS. 19A-19D are utilized to implement an active learning method for object detection that utilizes mixture density networks to produce one or more Gaussian mixture models for each output of a network.

[0379] FIG. 20 illustrates a multi-GPU computing system 2000, according to at least one
30 embodiment. In at least one embodiment, multi-GPU computing system 2000 can include a processor 2002 coupled to multiple general purpose graphics processing units (GPGPUs) 2006A-D via a host interface switch 2004. In at least one embodiment, host interface switch 2004 is a PCI express switch device that couples processor 2002 to a PCI express bus over which processor 2002 can communicate with GPGPUs 2006A-D. In at least one
35 embodiment, GPGPUs 2006A-D can interconnect via a set of high-speed point-to-point GPU-to-GPU links 2016. In at least one embodiment, GPU-to-GPU links 2016 connect to

5 each of GPGPUs 2006A-D via a dedicated GPU link. In at least one embodiment, P2P GPU links 2016 enable direct communication between each of GPGPUs 2006A-D without requiring communication over host interface bus 2004 to which processor 2002 is connected. In at least one embodiment, with GPU-to-GPU traffic directed to P2P GPU links 2016, host interface bus 2004 remains available for system memory access or to communicate with other
10 instances of multi-GPU computing system 2000, for example, via one or more network devices. While in at least one embodiment GPGPUs 2006A-D connect to processor 2002 via host interface switch 2004, in at least one embodiment processor 2002 includes direct support for P2P GPU links 2016 and can connect directly to GPGPUs 2006A-D.

[0380] Inference and/or training logic 615 are used to perform inferencing and/or training
15 operations associated with one or more embodiments. Details regarding inference and/or training logic 615 are provided herein in conjunction with FIGS. 6A and/or 6B. In at least one embodiment, inference and/or training logic 615 may be used in multi-GPU computing system 2000 for inferencing or predicting operations based, at least in part, on weight parameters calculated using neural network training operations, neural network functions
20 and/or architectures, or neural network use cases described herein.

[0381] In at least one embodiment, one or more systems depicted in FIG. 20 are utilized to implement a deep object detection network. In at least one embodiment, one or more systems depicted in FIG. 20 are utilized to implement one or more networks and models such as those described in connection with FIG. 1 and FIG. 3. In at least one embodiment, one or more
25 systems depicted in FIG. 20 are utilized to implement a network that is based on mixture density networks and predicts uncertainty values of images. In at least one embodiment, one or more systems depicted in FIG. 20 are utilized to implement an active learning method for object detection that utilizes mixture density networks to produce one or more Gaussian mixture models for each output of a network.

[0382] FIG. 21 is a block diagram of a graphics processor 2100, according to at least one
30 embodiment. In at least one embodiment, graphics processor 2100 includes a ring interconnect 2102, a pipeline front-end 2104, a media engine 2137, and graphics cores 2180A-2180N. In at least one embodiment, ring interconnect 2102 couples graphics processor 2100 to other processing units, including other graphics processors or one or more
35 general-purpose processor cores. In at least one embodiment, graphics processor 2100 is one of many processors integrated within a multi-core processing system.

5 [0383] In at least one embodiment, graphics processor 2100 receives batches of commands via ring interconnect 2102. In at least one embodiment, incoming commands are interpreted by a command streamer 2103 in pipeline front-end 2104. In at least one embodiment, graphics processor 2100 includes scalable execution logic to perform 3D geometry processing and media processing via graphics core(s) 2180A-2180N. In at least one
10 embodiment, for 3D geometry processing commands, command streamer 2103 supplies commands to geometry pipeline 2136. In at least one embodiment, for at least some media processing commands, command streamer 2103 supplies commands to a video front end 2134, which couples with media engine 2137. In at least one embodiment, media engine 2137 includes a Video Quality Engine (VQE) 2130 for video and image post-processing and
15 a multi-format encode/decode (MFX) 2133 engine to provide hardware-accelerated media data encoding and decoding. In at least one embodiment, geometry pipeline 2136 and media engine 2137 each generate execution threads for thread execution resources provided by at least one graphics core 2180.

[0384] In at least one embodiment, graphics processor 2100 includes scalable thread
20 execution resources featuring graphics cores 2180A-2180N (which can be modular and are sometimes referred to as core slices), each having multiple sub-cores 2150A-2150N, 2160A-2160N (sometimes referred to as core sub-slices). In at least one embodiment, graphics processor 2100 can have any number of graphics cores 2180A. In at least one embodiment, graphics processor 2100 includes a graphics core 2180A having at least a first sub-core
25 2150A and a second sub-core 2160A. In at least one embodiment, graphics processor 2100 is a low power processor with a single sub-core (e.g., 2150A). In at least one embodiment, graphics processor 2100 includes multiple graphics cores 2180A-2180N, each including a set of first sub-cores 2150A-2150N and a set of second sub-cores 2160A-2160N. In at least one embodiment, each sub-core in first sub-cores 2150A-2150N includes at least a first set of
30 execution units 2152A-2152N and media/texture samplers 2154A-2154N. In at least one embodiment, each sub-core in second sub-cores 2160A-2160N includes at least a second set of execution units 2162A-2162N and samplers 2164A-2164N. In at least one embodiment, each sub-core 2150A-2150N, 2160A-2160N shares a set of shared resources 2170A-2170N. In at least one embodiment, shared resources include shared cache memory and pixel
35 operation logic.

[0385] Inference and/or training logic 615 are used to perform inferencing and/or training operations associated with one or more embodiments. Details regarding inference and/or

5 training logic 615 are provided herein in conjunction with FIGS. 6A and/or 6B. In at least one embodiment, inference and/or training logic 615 may be used in graphics processor 2100 for inferencing or predicting operations based, at least in part, on weight parameters calculated using neural network training operations, neural network functions and/or architectures, or neural network use cases described herein.

10 [0386] In at least one embodiment, one or more systems depicted in FIG. 21 are utilized to implement a deep object detection network. In at least one embodiment, one or more systems depicted in FIG. 21 are utilized to implement one or more networks and models such as those described in connection with FIG. 1 and FIG. 3. In at least one embodiment, one or more systems depicted in FIG. 21 are utilized to implement a network that is based on mixture
15 density networks and predicts uncertainty values of images. In at least one embodiment, one or more systems depicted in FIG. 21 are utilized to implement an active learning method for object detection that utilizes mixture density networks to produce one or more Gaussian mixture models for each output of a network.

[0387] FIG. 22 is a block diagram illustrating micro-architecture for a processor 2200 that
20 may include logic circuits to perform instructions, according to at least one embodiment. In at least one embodiment, processor 2200 may perform instructions, including x86 instructions, ARM instructions, specialized instructions for application-specific integrated circuits (ASICs), etc. In at least one embodiment, processor 2200 may include registers to store packed data, such as 64-bit wide MMX™ registers in microprocessors enabled with
25 MMX technology from Intel Corporation of Santa Clara, Calif. In at least one embodiment, MMX registers, available in both integer and floating point forms, may operate with packed data elements that accompany single instruction, multiple data (“SIMD”) and streaming SIMD extensions (“SSE”) instructions. In at least one embodiment, 128-bit wide XMM registers relating to SSE2, SSE3, SSE4, AVX, or beyond (referred to generically as “SSEx”) technology may hold such packed data operands. In at least one embodiment, processor 2200
30 may perform instructions to accelerate machine learning or deep learning algorithms, training, or inferencing.

[0388] In at least one embodiment, processor 2200 includes an in-order front end (“front end”) 2201 to fetch instructions to be executed and prepare instructions to be used later in a
35 processor pipeline. In at least one embodiment, front end 2201 may include several units. In at least one embodiment, an instruction prefetcher 2226 fetches instructions from memory

5 and feeds instructions to an instruction decoder 2228 which in turn decodes or interprets instructions. For example, in at least one embodiment, instruction decoder 2228 decodes a received instruction into one or more operations called “micro-instructions” or “micro-operations” (also called “micro ops” or “uops”) that a machine may execute. In at least one embodiment, instruction decoder 2228 parses an instruction into an opcode and

10 corresponding data and control fields that may be used by micro-architecture to perform operations in accordance with at least one embodiment. In at least one embodiment, a trace cache 2230 may assemble decoded uops into program ordered sequences or traces in a uop queue 2234 for execution. In at least one embodiment, when trace cache 2230 encounters a complex instruction, a microcode ROM 2232 provides uops needed to complete an operation.

15 [0389] In at least one embodiment, some instructions may be converted into a single micro-op, whereas others need several micro-ops to complete full operation. In at least one embodiment, if more than four micro-ops are needed to complete an instruction, instruction decoder 2228 may access microcode ROM 2232 to perform that instruction. In at least one embodiment, an instruction may be decoded into a small number of micro-ops for processing

20 at instruction decoder 2228. In at least one embodiment, an instruction may be stored within microcode ROM 2232 should a number of micro-ops be needed to accomplish such operation. In at least one embodiment, trace cache 2230 refers to an entry point programmable logic array (“PLA”) to determine a correct micro-instruction pointer for reading microcode sequences to complete one or more instructions from microcode ROM

25 2232 in accordance with at least one embodiment. In at least one embodiment, after microcode ROM 2232 finishes sequencing micro-ops for an instruction, front end 2201 of a machine may resume fetching micro-ops from trace cache 2230.

[0390] In at least one embodiment, out-of-order execution engine (“out of order engine”) 2203 may prepare instructions for execution. In at least one embodiment, out-of-order

30 execution logic has a number of buffers to smooth out and re-order flow of instructions to optimize performance as they go down a pipeline and get scheduled for execution. In at least one embodiment, out-of-order execution engine 2203 includes, without limitation, an allocator/register renamer 2240, a memory uop queue 2242, an integer/floating point uop queue 2244, a memory scheduler 2246, a fast scheduler 2202, a slow/general floating point

35 scheduler (“slow/general FP scheduler”) 2204, and a simple floating point scheduler (“simple FP scheduler”) 2206. In at least one embodiment, fast schedule 2202, slow/general floating point scheduler 2204, and simple floating point scheduler 2206 are also collectively referred

5 to herein as “uop schedulers 2202, 2204, 2206.” In at least one embodiment, allocator/register renamer 2240 allocates machine buffers and resources that each uop needs in order to execute. In at least one embodiment, allocator/register renamer 2240 renames logic registers onto entries in a register file. In at least one embodiment, allocator/register renamer 2240 also allocates an entry for each uop in one of two uop queues, memory uop
 10 queue 2242 for memory operations and integer/floating point uop queue 2244 for non-memory operations, in front of memory scheduler 2246 and uop schedulers 2202, 2204, 2206. In at least one embodiment, uop schedulers 2202, 2204, 2206, determine when a uop is ready to execute based on readiness of their dependent input register operand sources and availability of execution resources uops need to complete their operation. In at least one
 15 embodiment, fast scheduler 2202 may schedule on each half of a main clock cycle while slow/general floating point scheduler 2204 and simple floating point scheduler 2206 may schedule once per main processor clock cycle. In at least one embodiment, uop schedulers 2202, 2204, 2206 arbitrate for dispatch ports to schedule uops for execution.

[0391] In at least one embodiment, execution block 2211 includes, without limitation, an integer register file/bypass network 2208, a floating point register file/bypass network (“FP register file/bypass network”) 2210, address generation units (“AGUs”) 2212 and 2214, fast Arithmetic Logic Units (ALUs) (“fast ALUs”) 2216 and 2218, a slow Arithmetic Logic Unit (“slow ALU”) 2220, a floating point ALU (“FP”) 2222, and a floating point move unit (“FP move”) 2224. In at least one embodiment, integer register file/bypass network 2208 and
 20 floating point register file/bypass network 2210 are also referred to herein as “register files 2208, 2210.” In at least one embodiment, AGUs 2212 and 2214, fast ALUs 2216 and 2218, slow ALU 2220, floating point ALU 2222, and floating point move unit 2224 are also referred to herein as “execution units 2212, 2214, 2216, 2218, 2220, 2222, and 2224.” In at least one embodiment, execution block 2211 may include, without limitation, any number
 25 (including zero) and type of register files, bypass networks, address generation units, and execution units, in any combination.

[0392] In at least one embodiment, register networks 2208, 2210 may be arranged between uop schedulers 2202, 2204, 2206, and execution units 2212, 2214, 2216, 2218, 2220, 2222, and 2224. In at least one embodiment, integer register file/bypass network 2208 performs
 30 integer operations. In at least one embodiment, floating point register file/bypass network 2210 performs floating point operations. In at least one embodiment, each of register networks 2208, 2210 may include, without limitation, a bypass network that may bypass or

5 forward just completed results that have not yet been written into a register file to new dependent uops. In at least one embodiment, register networks 2208, 2210 may communicate data with each other. In at least one embodiment, integer register file/bypass network 2208 may include, without limitation, two separate register files, one register file for a low-order thirty-two bits of data and a second register file for a high order thirty-two bits of data. In at
10 least one embodiment, floating point register file/bypass network 2210 may include, without limitation, 128-bit wide entries because floating point instructions typically have operands from 64 to 128 bits in width.

[0393] In at least one embodiment, execution units 2212, 2214, 2216, 2218, 2220, 2222, 2224 may execute instructions. In at least one embodiment, register networks 2208, 2210
15 store integer and floating point data operand values that micro-instructions need to execute. In at least one embodiment, processor 2200 may include, without limitation, any number and combination of execution units 2212, 2214, 2216, 2218, 2220, 2222, 2224. In at least one embodiment, floating point ALU 2222 and floating point move unit 2224, may execute floating point, MMX, SIMD, AVX and SSE, or other operations, including specialized
20 machine learning instructions. In at least one embodiment, floating point ALU 2222 may include, without limitation, a 64-bit by 64-bit floating point divider to execute divide, square root, and remainder micro ops. In at least one embodiment, instructions involving a floating point value may be handled with floating point hardware. In at least one embodiment, ALU operations may be passed to fast ALUs 2216, 2218. In at least one embodiment, fast ALUS
25 2216, 2218 may execute fast operations with an effective latency of half a clock cycle. In at least one embodiment, most complex integer operations go to slow ALU 2220 as slow ALU 2220 may include, without limitation, integer execution hardware for long-latency type of operations, such as a multiplier, shifts, flag logic, and branch processing. In at least one embodiment, memory load/store operations may be executed by AGUs 2212, 2214. In at
30 least one embodiment, fast ALU 2216, fast ALU 2218, and slow ALU 2220 may perform integer operations on 64-bit data operands. In at least one embodiment, fast ALU 2216, fast ALU 2218, and slow ALU 2220 may be implemented to support a variety of data bit sizes including sixteen, thirty-two, 128, 256, etc. In at least one embodiment, floating point ALU 2222 and floating point move unit 2224 may be implemented to support a range of operands
35 having bits of various widths, such as 128-bit wide packed data operands in conjunction with SIMD and multimedia instructions.

5 [0394] In at least one embodiment, uop schedulers 2202, 2204, 2206 dispatch dependent operations before a parent load has finished executing. In at least one embodiment, as uops may be speculatively scheduled and executed in processor 2200, processor 2200 may also include logic to handle memory misses. In at least one embodiment, if a data load misses in a data cache, there may be dependent operations in flight in a pipeline that have left a scheduler
 10 with temporarily incorrect data. In at least one embodiment, a replay mechanism tracks and re-executes instructions that use incorrect data. In at least one embodiment, dependent operations might need to be replayed and independent ones may be allowed to complete. In at least one embodiment, schedulers and a replay mechanism of at least one embodiment of a processor may also be designed to catch instruction sequences for text string comparison
 15 operations.

[0395] In at least one embodiment, “registers” may refer to on-board processor storage locations that may be used as part of instructions to identify operands. In at least one embodiment, registers may be those that may be usable from outside of a processor (from a programmer’s perspective). In at least one embodiment, registers might not be limited to a
 20 particular type of circuit. Rather, in at least one embodiment, a register may store data, provide data, and perform functions described herein. In at least one embodiment, registers described herein may be implemented by circuitry within a processor using any number of different techniques, such as dedicated physical registers, dynamically allocated physical registers using register renaming, combinations of dedicated and dynamically allocated
 25 physical registers, etc. In at least one embodiment, integer registers store 32-bit integer data. A register file of at least one embodiment also contains eight multimedia SIMD registers for packed data.

[0396] Inference and/or training logic 615 are used to perform inferencing and/or training operations associated with one or more embodiments. Details regarding inference and/or
 30 training logic 615 are provided herein in conjunction with FIGS. 6A and/or 6B. In at least one embodiment portions or all of inference and/or training logic 615 may be incorporated into execution block 2211 and other memory or registers shown or not shown. For example, in at least one embodiment, training and/or inferencing techniques described herein may use one or more of ALUs illustrated in execution block 2211. Moreover, weight parameters may
 35 be stored in on-chip or off-chip memory and/or registers (shown or not shown) that configure ALUs of execution block 2211 to perform one or more machine learning algorithms, neural network architectures, use cases, or training techniques described herein.

5 [0397] In at least one embodiment, one or more systems depicted in FIG. 22 are utilized to implement a deep object detection network. In at least one embodiment, one or more systems depicted in FIG. 22 are utilized to implement one or more networks and models such as those described in connection with FIG. 1 and FIG. 3. In at least one embodiment, one or more systems depicted in FIG. 22 are utilized to implement a network that is based on mixture
10 density networks and predicts uncertainty values of images. In at least one embodiment, one or more systems depicted in FIG. 22 are utilized to implement an active learning method for object detection that utilizes mixture density networks to produce one or more Gaussian mixture models for each output of a network.

[0398] FIG. 23 illustrates a deep learning application processor 2300, according to at least
15 one embodiment. In at least one embodiment, deep learning application processor 2300 uses instructions that, if executed by deep learning application processor 2300, cause deep learning application processor 2300 to perform some or all of processes and techniques described throughout this disclosure. In at least one embodiment, deep learning application processor 2300 is an application-specific integrated circuit (ASIC). In at least one
20 embodiment, application processor 2300 performs matrix multiply operations either “hard-wired” into hardware as a result of performing one or more instructions or both. In at least one embodiment, deep learning application processor 2300 includes, without limitation, processing clusters 2310(1)-2310(12), Inter-Chip Links (“ICLs”) 2320(1)-2320(12), Inter-Chip Controllers (“ICCs”) 2330(1)-2330(2), high-bandwidth memory second generation (“HBM2”) 2340(1)-2340(4), memory controllers (“Mem Ctrlrs”) 2342(1)-2342(4), high
25 bandwidth memory physical layer (“HBM PHY”) 2344(1)-2344(4), a management-controller central processing unit (“management-controller CPU”) 2350, a Serial Peripheral Interface, Inter-Integrated Circuit, and General Purpose Input/Output block (“SPI, I²C, GPIO”) 2360, a peripheral component interconnect express controller and direct memory access block (“PCIe
30 Controller and DMA”) 2370, and a sixteen-lane peripheral component interconnect express port (“PCI Express x 16”) 2380.

[0399] In at least one embodiment, processing clusters 2310 may perform deep learning operations, including inference or prediction operations based on weight parameters calculated one or more training techniques, including those described herein. In at least one
35 embodiment, each processing cluster 2310 may include, without limitation, any number and type of processors. In at least one embodiment, deep learning application processor 2300 may include any number and type of processing clusters 2300. In at least one embodiment,

5 Inter-Chip Links 2320 are bi-directional. In at least one embodiment, Inter-Chip Links 2320 and Inter-Chip Controllers 2330 enable multiple deep learning application processors 2300 to exchange information, including activation information resulting from performing one or more machine learning algorithms embodied in one or more neural networks. In at least one embodiment, deep learning application processor 2300 may include any number (including
10 zero) and type of ICLs 2320 and ICCs 2330.

[0400] In at least one embodiment, HBM2s 2340 provide a total of 32 Gigabytes (GB) of memory. In at least one embodiment, HBM2 2340(i) is associated with both memory controller 2342(i) and HBM PHY 2344(i) where “i” is an arbitrary integer. In at least one embodiment, any number of HBM2s 2340 may provide any type and total amount of high
15 bandwidth memory and may be associated with any number (including zero) and type of memory controllers 2342 and HBM PHYs 2344. In at least one embodiment, SPI, I²C, GPIO 2360, PCIe Controller and DMA 2370, and/or PCIe 2380 may be replaced with any number and type of blocks that enable any number and type of communication standards in any technically feasible fashion.

20 [0401] Inference and/or training logic 615 are used to perform inferencing and/or training operations associated with one or more embodiments. Details regarding inference and/or training logic 615 are provided herein in conjunction with FIGS. 6A and/or 6B. In at least one embodiment, deep learning application processor is used to train a machine learning model, such as a neural network, to predict or infer information provided to deep learning
25 application processor 2300. In at least one embodiment, deep learning application processor 2300 is used to infer or predict information based on a trained machine learning model (e.g., neural network) that has been trained by another processor or system or by deep learning application processor 2300. In at least one embodiment, processor 2300 may be used to perform one or more neural network use cases described herein.

30 [0402] In at least one embodiment, one or more systems depicted in FIG. 23 are utilized to implement a deep object detection network. In at least one embodiment, one or more systems depicted in FIG. 23 are utilized to implement one or more networks and models such as those described in connection with FIG. 1 and FIG. 3. In at least one embodiment, one or more systems depicted in FIG. 23 are utilized to implement a network that is based on mixture
35 density networks and predicts uncertainty values of images. In at least one embodiment, one or more systems depicted in FIG. 23 are utilized to implement an active learning method for

5 object detection that utilizes mixture density networks to produce one or more Gaussian mixture models for each output of a network.

[0403] FIG. 24 is a block diagram of a neuromorphic processor 2400, according to at least one embodiment. In at least one embodiment, neuromorphic processor 2400 may receive one or more inputs from sources external to neuromorphic processor 2400. In at least one
10 embodiment, these inputs may be transmitted to one or more neurons 2402 within neuromorphic processor 2400. In at least one embodiment, neurons 2402 and components thereof may be implemented using circuitry or logic, including one or more arithmetic logic units (ALUs). In at least one embodiment, neuromorphic processor 2400 may include, without limitation, thousands or millions of instances of neurons 2402, but any suitable
15 number of neurons 2402 may be used. In at least one embodiment, each instance of neuron 2402 may include a neuron input 2404 and a neuron output 2406. In at least one embodiment, neurons 2402 may generate outputs that may be transmitted to inputs of other instances of neurons 2402. For example, in at least one embodiment, neuron inputs 2404 and neuron outputs 2406 may be interconnected via synapses 2408.

20 [0404] In at least one embodiment, neurons 2402 and synapses 2408 may be interconnected such that neuromorphic processor 2400 operates to process or analyze information received by neuromorphic processor 2400. In at least one embodiment, neurons 2402 may transmit an output pulse (or “fire” or “spike”) when inputs received through neuron input 2404 exceed a threshold. In at least one embodiment, neurons 2402 may sum or integrate signals received at
25 neuron inputs 2404. For example, in at least one embodiment, neurons 2402 may be implemented as leaky integrate-and-fire neurons, wherein if a sum (referred to as a “membrane potential”) exceeds a threshold value, neuron 2402 may generate an output (or “fire”) using a transfer function such as a sigmoid or threshold function. In at least one embodiment, a leaky integrate-and-fire neuron may sum signals received at neuron inputs
30 2404 into a membrane potential and may also apply a decay factor (or leak) to reduce a membrane potential. In at least one embodiment, a leaky integrate-and-fire neuron may fire if multiple input signals are received at neuron inputs 2404 rapidly enough to exceed a threshold value (i.e., before a membrane potential decays too low to fire). In at least one embodiment, neurons 2402 may be implemented using circuits or logic that receive inputs,
35 integrate inputs into a membrane potential, and decay a membrane potential. In at least one embodiment, inputs may be averaged, or any other suitable transfer function may be used. Furthermore, in at least one embodiment, neurons 2402 may include, without limitation,

5 comparator circuits or logic that generate an output spike at neuron output 2406 when result of applying a transfer function to neuron input 2404 exceeds a threshold. In at least one embodiment, once neuron 2402 fires, it may disregard previously received input information by, for example, resetting a membrane potential to 0 or another suitable default value. In at least one embodiment, once membrane potential is reset to 0, neuron 2402 may resume
10 normal operation after a suitable period of time (or refractory period).

[0405] In at least one embodiment, neurons 2402 may be interconnected through synapses 2408. In at least one embodiment, synapses 2408 may operate to transmit signals from an output of a first neuron 2402 to an input of a second neuron 2402. In at least one embodiment, neurons 2402 may transmit information over more than one instance of synapse
15 2408. In at least one embodiment, one or more instances of neuron output 2406 may be connected, via an instance of synapse 2408, to an instance of neuron input 2404 in same neuron 2402. In at least one embodiment, an instance of neuron 2402 generating an output to be transmitted over an instance of synapse 2408 may be referred to as a “pre-synaptic neuron” with respect to that instance of synapse 2408. In at least one embodiment, an
20 instance of neuron 2402 receiving an input transmitted over an instance of synapse 2408 may be referred to as a “post-synaptic neuron” with respect to that instance of synapse 2408. Because an instance of neuron 2402 may receive inputs from one or more instances of synapse 2408, and may also transmit outputs over one or more instances of synapse 2408, a single instance of neuron 2402 may therefore be both a “pre-synaptic neuron” and “post-
25 synaptic neuron,” with respect to various instances of synapses 2408, in at least one embodiment.

[0406] In at least one embodiment, neurons 2402 may be organized into one or more layers. In at least one embodiment, each instance of neuron 2402 may have one neuron output 2406 that may fan out through one or more synapses 2408 to one or more neuron
30 inputs 2404. In at least one embodiment, neuron outputs 2406 of neurons 2402 in a first layer 2410 may be connected to neuron inputs 2404 of neurons 2402 in a second layer 2412. In at least one embodiment, layer 2410 may be referred to as a “feed-forward layer.” In at least one embodiment, each instance of neuron 2402 in an instance of first layer 2410 may fan out to each instance of neuron 2402 in second layer 2412. In at least one embodiment, first layer
35 2410 may be referred to as a “fully connected feed-forward layer.” In at least one embodiment, each instance of neuron 2402 in an instance of second layer 2412 may fan out to fewer than all instances of neuron 2402 in a third layer 2414. In at least one embodiment,

5 second layer 2412 may be referred to as a “sparsely connected feed-forward layer.” In at least one embodiment, neurons 2402 in second layer 2412 may fan out to neurons 2402 in multiple other layers, including to neurons 2402 also in second layer 2412. In at least one embodiment, second layer 2412 may be referred to as a “recurrent layer.” In at least one embodiment, neuromorphic processor 2400 may include, without limitation, any suitable
10 combination of recurrent layers and feed-forward layers, including, without limitation, both sparsely connected feed-forward layers and fully connected feed-forward layers.

[0407] In at least one embodiment, neuromorphic processor 2400 may include, without limitation, a reconfigurable interconnect architecture or dedicated hard-wired interconnects to connect synapse 2408 to neurons 2402. In at least one embodiment, neuromorphic processor
15 2400 may include, without limitation, circuitry or logic that allows synapses to be allocated to different neurons 2402 as needed based on neural network topology and neuron fan-in/out. For example, in at least one embodiment, synapses 2408 may be connected to neurons 2402 using an interconnect fabric, such as network-on-chip, or with dedicated connections. In at least one embodiment, synapse interconnections and components thereof may be
20 implemented using circuitry or logic.

[0408] In at least one embodiment, one or more systems depicted in FIG. 24 are utilized to implement a deep object detection network. In at least one embodiment, one or more systems depicted in FIG. 24 are utilized to implement one or more networks and models such as those described in connection with FIG. 1 and FIG. 3. In at least one embodiment, one or more
25 systems depicted in FIG. 24 are utilized to implement a network that is based on mixture density networks and predicts uncertainty values of images. In at least one embodiment, one or more systems depicted in FIG. 24 are utilized to implement an active learning method for object detection that utilizes mixture density networks to produce one or more Gaussian mixture models for each output of a network.

[0409] FIG. 25 is a block diagram of a processing system, according to at least one embodiment. In at least one embodiment, system 2500 includes one or more processors 2502 and one or more graphics processors 2508, and may be a single processor desktop system, a multiprocessor workstation system, or a server system having a large number of processors 2502 or processor cores 2507. In at least one embodiment, system 2500 is a processing
30 platform incorporated within a system-on-a-chip (SoC) integrated circuit for use in mobile, handheld, or embedded devices.

- 5 [0410] In at least one embodiment, system 2500 can include, or be incorporated within a server-based gaming platform, a game console, including a game and media console, a mobile gaming console, a handheld game console, or an online game console. In at least one embodiment, system 2500 is a mobile phone, a smart phone, a tablet computing device or a mobile Internet device. In at least one embodiment, processing system 2500 can also include,
10 couple with, or be integrated within a wearable device, such as a smart watch wearable device, a smart eyewear device, an augmented reality device, or a virtual reality device. In at least one embodiment, processing system 2500 is a television or set top box device having one or more processors 2502 and a graphical interface generated by one or more graphics processors 2508.
- 15 [0411] In at least one embodiment, one or more processors 2502 each include one or more processor cores 2507 to process instructions which, when executed, perform operations for system and user software. In at least one embodiment, each of one or more processor cores 2507 is configured to process a specific instruction sequence 2509. In at least one embodiment, instruction sequence 2509 may facilitate Complex Instruction Set Computing
20 (CISC), Reduced Instruction Set Computing (RISC), or computing via a Very Long Instruction Word (VLIW). In at least one embodiment, processor cores 2507 may each process a different instruction sequence 2509, which may include instructions to facilitate emulation of other instruction sequences. In at least one embodiment, processor core 2507 may also include other processing devices, such as a Digital Signal Processor (DSP).
- 25 [0412] In at least one embodiment, processor 2502 includes a cache memory 2504. In at least one embodiment, processor 2502 can have a single internal cache or multiple levels of internal cache. In at least one embodiment, cache memory is shared among various components of processor 2502. In at least one embodiment, processor 2502 also uses an external cache (e.g., a Level-3 (L3) cache or Last Level Cache (LLC)) (not shown), which
30 may be shared among processor cores 2507 using known cache coherency techniques. In at least one embodiment, a register file 2506 is additionally included in processor 2502, which may include different types of registers for storing different types of data (e.g., integer registers, floating point registers, status registers, and an instruction pointer register). In at least one embodiment, register file 2506 may include general-purpose registers or other
35 registers.

5 [0413] In at least one embodiment, one or more processor(s) 2502 are coupled with one or more interface bus(es) 2510 to transmit communication signals such as address, data, or control signals between processor 2502 and other components in system 2500. In at least one embodiment, interface bus 2510 can be a processor bus, such as a version of a Direct Media Interface (DMI) bus. In at least one embodiment, interface bus 2510 is not limited to a DMI
10 bus, and may include one or more Peripheral Component Interconnect buses (e.g., PCI, PCI Express), memory busses, or other types of interface busses. In at least one embodiment processor(s) 2502 include an integrated memory controller 2516 and a platform controller hub 2530. In at least one embodiment, memory controller 2516 facilitates communication between a memory device and other components of system 2500, while platform controller
15 hub (PCH) 2530 provides connections to I/O devices via a local I/O bus.

[0414] In at least one embodiment, a memory device 2520 can be a dynamic random access memory (DRAM) device, a static random access memory (SRAM) device, flash memory device, phase-change memory device, or some other memory device having suitable performance to serve as process memory. In at least one embodiment, memory device 2520
20 can operate as system memory for system 2500, to store data 2522 and instructions 2521 for use when one or more processors 2502 executes an application or process. In at least one embodiment, memory controller 2516 also couples with an optional external graphics processor 2512, which may communicate with one or more graphics processors 2508 in processors 2502 to perform graphics and media operations. In at least one embodiment, a
25 display device 2511 can connect to processor(s) 2502. In at least one embodiment, display device 2511 can include one or more of an internal display device, as in a mobile electronic device or a laptop device, or an external display device attached via a display interface (e.g., DisplayPort, etc.). In at least one embodiment, display device 2511 can include a head mounted display (HMD) such as a stereoscopic display device for use in virtual reality (VR)
30 applications or augmented reality (AR) applications.

[0415] In at least one embodiment, platform controller hub 2530 enables peripherals to connect to memory device 2520 and processor 2502 via a high-speed I/O bus. In at least one embodiment, I/O peripherals include, but are not limited to, an audio controller 2546, a network controller 2534, a firmware interface 2528, a wireless transceiver 2526, touch
35 sensors 2525, a data storage device 2524 (e.g., hard disk drive, flash memory, etc.). In at least one embodiment, data storage device 2524 can connect via a storage interface (e.g., SATA) or via a peripheral bus, such as a Peripheral Component Interconnect bus (e.g., PCI,

5 PCI Express). In at least one embodiment, touch sensors 2525 can include touch screen sensors, pressure sensors, or fingerprint sensors. In at least one embodiment, wireless transceiver 2526 can be a Wi-Fi transceiver, a Bluetooth transceiver, or a mobile network transceiver such as a 3G, 4G, or Long Term Evolution (LTE) transceiver. In at least one embodiment, firmware interface 2528 enables communication with system firmware, and can
10 be, for example, a unified extensible firmware interface (UEFI). In at least one embodiment, network controller 2534 can enable a network connection to a wired network. In at least one embodiment, a high-performance network controller (not shown) couples with interface bus 2510. In at least one embodiment, audio controller 2546 is a multi-channel high definition audio controller. In at least one embodiment, system 2500 includes an optional legacy I/O
15 controller 2540 for coupling legacy (e.g., Personal System 2 (PS/2)) devices to system 2500. In at least one embodiment, platform controller hub 2530 can also connect to one or more Universal Serial Bus (USB) controllers 2542 connect input devices, such as keyboard and mouse 2543 combinations, a camera 2544, or other USB input devices.

[0416] In at least one embodiment, an instance of memory controller 2516 and platform
20 controller hub 2530 may be integrated into a discreet external graphics processor, such as external graphics processor 2512. In at least one embodiment, platform controller hub 2530 and/or memory controller 2516 may be external to one or more processor(s) 2502. For example, in at least one embodiment, system 2500 can include an external memory controller 2516 and platform controller hub 2530, which may be configured as a memory controller hub
25 and peripheral controller hub within a system chipset that is in communication with processor(s) 2502.

[0417] Inference and/or training logic 615 are used to perform inferencing and/or training operations associated with one or more embodiments. Details regarding inference and/or training logic 615 are provided herein in conjunction with FIGS. 6A and/or 6B. In at least
30 one embodiment portions or all of inference and/or training logic 615 may be incorporated into graphics processor 2500. For example, in at least one embodiment, training and/or inferencing techniques described herein may use one or more of ALUs embodied in a 3D pipeline. Moreover, in at least one embodiment, inferencing and/or training operations described herein may be done using logic other than logic illustrated in FIGS. 6A or 6B. In at
35 least one embodiment, weight parameters may be stored in on-chip or off-chip memory and/or registers (shown or not shown) that configure ALUs of graphics processor 2500 to

5 perform one or more machine learning algorithms, neural network architectures, use cases, or training techniques described herein.

[0418] In at least one embodiment, one or more systems depicted in FIG. 25 are utilized to implement a deep object detection network. In at least one embodiment, one or more systems depicted in FIG. 25 are utilized to implement one or more networks and models such as those
10 described in connection with FIG. 1 and FIG. 3. In at least one embodiment, one or more systems depicted in FIG. 25 are utilized to implement a network that is based on mixture density networks and predicts uncertainty values of images. In at least one embodiment, one or more systems depicted in FIG. 25 are utilized to implement an active learning method for object detection that utilizes mixture density networks to produce one or more Gaussian
15 mixture models for each output of a network.

[0419] FIG. 26 is a block diagram of a processor 2600 having one or more processor cores 2602A-2602N, an integrated memory controller 2614, and an integrated graphics processor 2608, according to at least one embodiment. In at least one embodiment, processor 2600 can include additional cores up to and including additional core 2602N represented by dashed
20 lined boxes. In at least one embodiment, each of processor cores 2602A-2602N includes one or more internal cache units 2604A-2604N. In at least one embodiment, each processor core also has access to one or more shared cached units 2606.

[0420] In at least one embodiment, internal cache units 2604A-2604N and shared cache units 2606 represent a cache memory hierarchy within processor 2600. In at least one
25 embodiment, cache memory units 2604A-2604N may include at least one level of instruction and data cache within each processor core and one or more levels of shared mid-level cache, such as a Level 2 (L2), Level 3 (L3), Level 4 (L4), or other levels of cache, where a highest level of cache before external memory is classified as an LLC. In at least one embodiment, cache coherency logic maintains coherency between various cache units 2606 and 2604A-
30 2604N.

[0421] In at least one embodiment, processor 2600 may also include a set of one or more bus controller units 2616 and a system agent core 2610. In at least one embodiment, bus controller units 2616 manage a set of peripheral buses, such as one or more PCI or PCI express busses. In at least one embodiment, system agent core 2610 provides management
35 functionality for various processor components. In at least one embodiment, system agent

5 core 2610 includes one or more integrated memory controllers 2614 to manage access to various external memory devices (not shown).

[0422] In at least one embodiment, one or more of processor cores 2602A-2602N include support for simultaneous multi-threading. In at least one embodiment, system agent core 2610 includes components for coordinating and operating cores 2602A-2602N during multi-
10 threaded processing. In at least one embodiment, system agent core 2610 may additionally include a power control unit (PCU), which includes logic and components to regulate one or more power states of processor cores 2602A-2602N and graphics processor 2608.

[0423] In at least one embodiment, processor 2600 additionally includes graphics processor 2608 to execute graphics processing operations. In at least one embodiment, graphics
15 processor 2608 couples with shared cache units 2606, and system agent core 2610, including one or more integrated memory controllers 2614. In at least one embodiment, system agent core 2610 also includes a display controller 2611 to drive graphics processor output to one or more coupled displays. In at least one embodiment, display controller 2611 may also be a separate module coupled with graphics processor 2608 via at least one interconnect, or may
20 be integrated within graphics processor 2608.

[0424] In at least one embodiment, a ring-based interconnect unit 2612 is used to couple internal components of processor 2600. In at least one embodiment, an alternative interconnect unit may be used, such as a point-to-point interconnect, a switched interconnect, or other techniques. In at least one embodiment, graphics processor 2608 couples with ring
25 interconnect 2612 via an I/O link 2613.

[0425] In at least one embodiment, I/O link 2613 represents at least one of multiple varieties of I/O interconnects, including an on package I/O interconnect which facilitates communication between various processor components and a high-performance embedded memory module 2618, such as an eDRAM module. In at least one embodiment, each of
30 processor cores 2602A-2602N and graphics processor 2608 use embedded memory module 2618 as a shared Last Level Cache.

[0426] In at least one embodiment, processor cores 2602A-2602N are homogeneous cores executing a common instruction set architecture. In at least one embodiment, processor cores 2602A-2602N are heterogeneous in terms of instruction set architecture (ISA), where one or
35 more of processor cores 2602A-2602N execute a common instruction set, while one or more other cores of processor cores 2602A-2602N executes a subset of a common instruction set or

- 5 a different instruction set. In at least one embodiment, processor cores 2602A-2602N are heterogeneous in terms of microarchitecture, where one or more cores having a relatively higher power consumption couple with one or more power cores having a lower power consumption. In at least one embodiment, processor 2600 can be implemented on one or more chips or as an SoC integrated circuit.
- 10 [0427] Inference and/or training logic 615 are used to perform inferencing and/or training operations associated with one or more embodiments. Details regarding inference and/or training logic 615 are provided herein in conjunction with FIGS. 6A and/or 6B. In at least one embodiment portions or all of inference and/or training logic 615 may be incorporated into graphics processor 2610. For example, in at least one embodiment, training and/or
- 15 inferencing techniques described herein may use one or more of ALUs embodied in a 3D pipeline, graphics core(s) 2602, shared function logic, or other logic in FIG. 26. Moreover, in at least one embodiment, inferencing and/or training operations described herein may be done using logic other than logic illustrated in FIGS. 6A or 6B. In at least one embodiment, weight parameters may be stored in on-chip or off-chip memory and/or registers (shown or
- 20 not shown) that configure ALUs of processor 2600 to perform one or more machine learning algorithms, neural network architectures, use cases, or training techniques described herein.
- [0428] In at least one embodiment, one or more systems depicted in FIG. 26 are utilized to implement a deep object detection network. In at least one embodiment, one or more systems depicted in FIG. 26 are utilized to implement one or more networks and models such as those
- 25 described in connection with FIG. 1 and FIG. 3. In at least one embodiment, one or more systems depicted in FIG. 26 are utilized to implement a network that is based on mixture density networks and predicts uncertainty values of images. In at least one embodiment, one or more systems depicted in FIG. 26 are utilized to implement an active learning method for object detection that utilizes mixture density networks to produce one or more Gaussian
- 30 mixture models for each output of a network.
- [0429] FIG. 27 is a block diagram of a graphics processor 2700, which may be a discrete graphics processing unit, or may be a graphics processor integrated with a plurality of processing cores. In at least one embodiment, graphics processor 2700 communicates via a memory mapped I/O interface to registers on graphics processor 2700 and with commands
- 35 placed into memory. In at least one embodiment, graphics processor 2700 includes a memory interface 2714 to access memory. In at least one embodiment, memory interface

5 2714 is an interface to local memory, one or more internal caches, one or more shared external caches, and/or to system memory.

[0430] In at least one embodiment, graphics processor 2700 also includes a display controller 2702 to drive display output data to a display device 2720. In at least one embodiment, display controller 2702 includes hardware for one or more overlay planes for
10 display device 2720 and composition of multiple layers of video or user interface elements. In at least one embodiment, display device 2720 can be an internal or external display device. In at least one embodiment, display device 2720 is a head mounted display device, such as a virtual reality (VR) display device or an augmented reality (AR) display device. In at least one embodiment, graphics processor 2700 includes a video codec engine 2706 to encode,
15 decode, or transcode media to, from, or between one or more media encoding formats, including, but not limited to Moving Picture Experts Group (MPEG) formats such as MPEG-2, Advanced Video Coding (AVC) formats such as H.264/MPEG-4 AVC, as well as the Society of Motion Picture & Television Engineers (SMPTE) 421M/VC-1, and Joint Photographic Experts Group (JPEG) formats such as JPEG, and Motion JPEG (MJPEG)
20 formats.

[0431] In at least one embodiment, graphics processor 2700 includes a block image transfer (BLIT) engine 2704 to perform two-dimensional (2D) rasterizer operations including, for example, bit-boundary block transfers. However, in at least one embodiment, 2D graphics operations are performed using one or more components of a graphics processing engine
25 (GPE) 2710. In at least one embodiment, GPE 2710 is a compute engine for performing graphics operations, including three-dimensional (3D) graphics operations and media operations.

[0432] In at least one embodiment, GPE 2710 includes a 3D pipeline 2712 for performing 3D operations, such as rendering three-dimensional images and scenes using processing
30 functions that act upon 3D primitive shapes (e.g., rectangle, triangle, etc.). In at least one embodiment, 3D pipeline 2712 includes programmable and fixed function elements that perform various tasks and/or spawn execution threads to a 3D/Media sub-system 2715. While 3D pipeline 2712 can be used to perform media operations, in at least one embodiment, GPE 2710 also includes a media pipeline 2716 that is used to perform media
35 operations, such as video post-processing and image enhancement.

5 [0433] In at least one embodiment, media pipeline 2716 includes fixed function or programmable logic units to perform one or more specialized media operations, such as video decode acceleration, video de-interlacing, and video encode acceleration in place of, or on behalf of, video codec engine 2706. In at least one embodiment, media pipeline 2716 additionally includes a thread spawning unit to spawn threads for execution on 3D/Media sub-system 2715. In at least one embodiment, spawned threads perform computations for media operations on one or more graphics execution units included in 3D/Media sub-system 2715.

[0434] In at least one embodiment, 3D/Media subsystem 2715 includes logic for executing threads spawned by 3D pipeline 2712 and media pipeline 2716. In at least one embodiment, 15 3D pipeline 2712 and media pipeline 2716 send thread execution requests to 3D/Media subsystem 2715, which includes thread dispatch logic for arbitrating and dispatching various requests to available thread execution resources. In at least one embodiment, execution resources include an array of graphics execution units to process 3D and media threads. In at least one embodiment, 3D/Media subsystem 2715 includes one or more internal caches for thread instructions and data. In at least one embodiment, subsystem 2715 also includes 20 shared memory, including registers and addressable memory, to share data between threads and to store output data.

[0435] Inference and/or training logic 615 are used to perform inferencing and/or training operations associated with one or more embodiments. Details regarding inference and/or training logic 615 are provided herein in conjunction with FIGS. 6A and/or 6B. In at least one embodiment portions or all of inference and/or training logic 615 may be incorporated into graphics processor 2700. For example, in at least one embodiment, training and/or inferencing techniques described herein may use one or more of ALUs embodied in 3D pipeline 2712. Moreover, in at least one embodiment, inferencing and/or training operations 30 described herein may be done using logic other than logic illustrated in FIGS. 6A or 6B. In at least one embodiment, weight parameters may be stored in on-chip or off-chip memory and/or registers (shown or not shown) that configure ALUs of graphics processor 2700 to perform one or more machine learning algorithms, neural network architectures, use cases, or training techniques described herein.

35 [0436] In at least one embodiment, one or more systems depicted in FIG. 27 are utilized to implement a deep object detection network. In at least one embodiment, one or more systems

5 depicted in FIG. 27 are utilized to implement one or more networks and models such as those described in connection with FIG. 1 and FIG. 3. In at least one embodiment, one or more systems depicted in FIG. 27 are utilized to implement a network that is based on mixture density networks and predicts uncertainty values of images. In at least one embodiment, one or more systems depicted in FIG. 27 are utilized to implement an active learning method for
10 object detection that utilizes mixture density networks to produce one or more Gaussian mixture models for each output of a network.

[0437] FIG. 28 is a block diagram of a graphics processing engine 2810 of a graphics processor in accordance with at least one embodiment. In at least one embodiment, graphics processing engine (GPE) 2810 is a version of GPE 2710 shown in FIG. 27. In at least one
15 embodiment, a media pipeline 2816 is optional and may not be explicitly included within GPE 2810. In at least one embodiment, a separate media and/or image processor is coupled to GPE 2810.

[0438] In at least one embodiment, GPE 2810 is coupled to or includes a command streamer 2803, which provides a command stream to a 3D pipeline 2812 and/or media
20 pipeline 2816. In at least one embodiment, command streamer 2803 is coupled to memory, which can be system memory, or one or more of internal cache memory and shared cache memory. In at least one embodiment, command streamer 2803 receives commands from memory and sends commands to 3D pipeline 2812 and/or media pipeline 2816. In at least one embodiment, commands are instructions, primitives, or micro-operations fetched from a
25 ring buffer, which stores commands for 3D pipeline 2812 and media pipeline 2816. In at least one embodiment, a ring buffer can additionally include batch command buffers storing batches of multiple commands. In at least one embodiment, commands for 3D pipeline 2812 can also include references to data stored in memory, such as, but not limited to, vertex and geometry data for 3D pipeline 2812 and/or image data and memory objects for media
30 pipeline 2816. In at least one embodiment, 3D pipeline 2812 and media pipeline 2816 process commands and data by performing operations or by dispatching one or more execution threads to a graphics core array 2814. In at least one embodiment, graphics core array 2814 includes one or more blocks of graphics cores (e.g., graphics core(s) 2815A, graphics core(s) 2815B), each block including one or more graphics cores. In at least one
35 embodiment, each graphics core includes a set of graphics execution resources that includes general-purpose and graphics specific execution logic to perform graphics and compute operations, as well as fixed function texture processing and/or machine learning and artificial

5 intelligence acceleration logic, including inference and/or training logic 615 in FIG. 6A and FIG. 6B.

[0439] In at least one embodiment, 3D pipeline 2812 includes fixed function and programmable logic to process one or more shader programs, such as vertex shaders, geometry shaders, pixel shaders, fragment shaders, compute shaders, or other shader
10 programs, by processing instructions and dispatching execution threads to graphics core array 2814. In at least one embodiment, graphics core array 2814 provides a unified block of execution resources for use in processing shader programs. In at least one embodiment, a multi-purpose execution logic (e.g., execution units) within graphics core(s) 2815A-2815B of graphic core array 2814 includes support for various 3D API shader languages and can
15 execute multiple simultaneous execution threads associated with multiple shaders.

[0440] In at least one embodiment, graphics core array 2814 also includes execution logic to perform media functions, such as video and/or image processing. In at least one embodiment, execution units additionally include general-purpose logic that is programmable to perform parallel general-purpose computational operations, in addition to graphics
20 processing operations.

[0441] In at least one embodiment, output data generated by threads executing on graphics core array 2814 can output data to memory in a unified return buffer (URB) 2818. In at least one embodiment, URB 2818 can store data for multiple threads. In at least one embodiment, URB 2818 may be used to send data between different threads executing on graphics core
25 array 2814. In at least one embodiment, URB 2818 may additionally be used for synchronization between threads on graphics core array 2814 and fixed function logic within shared function logic 2820.

[0442] In at least one embodiment, graphics core array 2814 is scalable, such that graphics core array 2814 includes a variable number of graphics cores, each having a variable number
30 of execution units based on a target power and performance level of GPE 2810. In at least one embodiment, execution resources are dynamically scalable, such that execution resources may be enabled or disabled as needed.

[0443] In at least one embodiment, graphics core array 2814 is coupled to shared function logic 2820 that includes multiple resources that are shared between graphics cores in graphics
35 core array 2814. In at least one embodiment, shared functions performed by shared function logic 2820 are embodied in hardware logic units that provide specialized supplemental

5 functionality to graphics core array 2814. In at least one embodiment, shared function logic 2820 includes but is not limited to a sampler unit 2821, a math unit 2822, and inter-thread communication (ITC) logic 2823. In at least one embodiment, one or more cache(s) 2825 are included in, or coupled to, shared function logic 2820.

[0444] In at least one embodiment, a shared function is used if demand for a specialized
10 function is insufficient for inclusion within graphics core array 2814. In at least one embodiment, a single instantiation of a specialized function is used in shared function logic 2820 and shared among other execution resources within graphics core array 2814. In at least one embodiment, specific shared functions within shared function logic 2820 that are used extensively by graphics core array 2814 may be included within shared function logic 3116
15 within graphics core array 2814. In at least one embodiment, shared function logic 3116 within graphics core array 2814 can include some or all logic within shared function logic 2820. In at least one embodiment, all logic elements within shared function logic 2820 may be duplicated within shared function logic 2826 of graphics core array 2814. In at least one embodiment, shared function logic 2820 is excluded in favor of shared function logic 2826
20 within graphics core array 2814.

[0445] Inference and/or training logic 615 are used to perform inferencing and/or training operations associated with one or more embodiments. Details regarding inference and/or training logic 615 are provided herein in conjunction with FIGS. 6A and/or 6B. In at least one embodiment portions or all of inference and/or training logic 615 may be incorporated
25 into graphics processor 2810. For example, in at least one embodiment, training and/or inferencing techniques described herein may use one or more of ALUs embodied in 3D pipeline 2812, graphics core(s) 2815, shared function logic 2826, shared function logic 2820, or other logic in FIG. 28. Moreover, in at least one embodiment, inferencing and/or training operations described herein may be done using logic other than logic illustrated in FIGS. 6A
30 or 6B. In at least one embodiment, weight parameters may be stored in on-chip or off-chip memory and/or registers (shown or not shown) that configure ALUs of graphics processor 2810 to perform one or more machine learning algorithms, neural network architectures, use cases, or training techniques described herein.

[0446] In at least one embodiment, one or more systems depicted in FIG. 28 are utilized to
35 implement a deep object detection network. In at least one embodiment, one or more systems depicted in FIG. 28 are utilized to implement one or more networks and models such as those

5 described in connection with FIG. 1 and FIG. 3. In at least one embodiment, one or more systems depicted in FIG. 28 are utilized to implement a network that is based on mixture density networks and predicts uncertainty values of images. In at least one embodiment, one or more systems depicted in FIG. 28 are utilized to implement an active learning method for object detection that utilizes mixture density networks to produce one or more Gaussian
10 mixture models for each output of a network.

[0447] FIG. 29 is a block diagram of hardware logic of a graphics processor core 2900, according to at least one embodiment described herein. In at least one embodiment, graphics processor core 2900 is included within a graphics core array. In at least one embodiment, graphics processor core 2900, sometimes referred to as a core slice, can be one or multiple
15 graphics cores within a modular graphics processor. In at least one embodiment, graphics processor core 2900 is exemplary of one graphics core slice, and a graphics processor as described herein may include multiple graphics core slices based on target power and performance envelopes. In at least one embodiment, each graphics core 2900 can include a fixed function block 2930 coupled with multiple sub-cores 2901A-2901F, also referred to as
20 sub-slices, that include modular blocks of general-purpose and fixed function logic.

[0448] In at least one embodiment, fixed function block 2930 includes a geometry and fixed function pipeline 2936 that can be shared by all sub-cores in graphics processor 2900, for example, in lower performance and/or lower power graphics processor implementations. In at least one embodiment, geometry and fixed function pipeline 2936 includes a 3D fixed
25 function pipeline, a video front-end unit, a thread spawner and thread dispatcher, and a unified return buffer manager, which manages unified return buffers.

[0449] In at least one embodiment, fixed function block 2930 also includes a graphics SoC interface 2937, a graphics microcontroller 2938, and a media pipeline 2939. In at least one embodiment, graphics SoC interface 2937 provides an interface between graphics core 2900
30 and other processor cores within a system on a chip integrated circuit. In at least one embodiment, graphics microcontroller 2938 is a programmable sub-processor that is configurable to manage various functions of graphics processor 2900, including thread dispatch, scheduling, and pre-emption. In at least one embodiment, media pipeline 2939 includes logic to facilitate decoding, encoding, pre-processing, and/or post-processing of
35 multimedia data, including image and video data. In at least one embodiment, media pipeline

5 2939 implements media operations via requests to compute or sampling logic within sub-cores 2901A-2901F.

[0450] In at least one embodiment, SoC interface 2937 enables graphics core 2900 to communicate with general-purpose application processor cores (e.g., CPUs) and/or other components within an SoC, including memory hierarchy elements such as a shared last level
10 cache memory, system RAM, and/or embedded on-chip or on-package DRAM. In at least one embodiment, SoC interface 2937 can also enable communication with fixed function devices within an SoC, such as camera imaging pipelines, and enables use of and/or implements global memory atomics that may be shared between graphics core 2900 and CPUs within an SoC. In at least one embodiment, graphics SoC interface 2937 can also
15 implement power management controls for graphics processor core 2900 and enable an interface between a clock domain of graphics processor core 2900 and other clock domains within an SoC. In at least one embodiment, SoC interface 2937 enables receipt of command buffers from a command streamer and global thread dispatcher that are configured to provide commands and instructions to each of one or more graphics cores within a graphics
20 processor. In at least one embodiment, commands and instructions can be dispatched to media pipeline 2939, when media operations are to be performed, or a geometry and fixed function pipeline (e.g., geometry and fixed function pipeline 2936, and/or a geometry and fixed function pipeline 2914) when graphics processing operations are to be performed.

[0451] In at least one embodiment, graphics microcontroller 2938 can be configured to
25 perform various scheduling and management tasks for graphics core 2900. In at least one embodiment, graphics microcontroller 2938 can perform graphics and/or compute workload scheduling on various graphics parallel engines within execution unit (EU) arrays 2902A-2902F, 2904A-2904F within sub-cores 2901A-2901F. In at least one embodiment, host software executing on a CPU core of an SoC including graphics core 2900 can submit
30 workloads to one of multiple graphic processor paths, which invokes a scheduling operation on an appropriate graphics engine. In at least one embodiment, scheduling operations include determining which workload to run next, submitting a workload to a command streamer, pre-empting existing workloads running on an engine, monitoring progress of a workload, and notifying host software when a workload is complete. In at least one embodiment, graphics
35 microcontroller 2938 can also facilitate low-power or idle states for graphics core 2900, providing graphics core 2900 with an ability to save and restore registers within graphics core

5 2900 across low-power state transitions independently from an operating system and/or graphics driver software on a system.

[0452] In at least one embodiment, graphics core 2900 may have greater than or fewer than illustrated sub-cores 2901A-2901F, up to N modular sub-cores. For each set of N sub-cores, in at least one embodiment, graphics core 2900 can also include shared function logic 2910,
10 shared and/or cache memory 2912, geometry/fixed function pipeline 2914, as well as additional fixed function logic 2916 to accelerate various graphics and compute processing operations. In at least one embodiment, shared function logic 2910 can include logic units (e.g., sampler, math, and/or inter-thread communication logic) that can be shared by each N sub-cores within graphics core 2900. In at least one embodiment, shared and/or cache
15 memory 2912 can be a last-level cache for N sub-cores 2901A-2901F within graphics core 2900 and can also serve as shared memory that is accessible by multiple sub-cores. In at least one embodiment, geometry/fixed function pipeline 2914 can be included instead of geometry/fixed function pipeline 2936 within fixed function block 2930 and can include similar logic units.

[0453] In at least one embodiment, graphics core 2900 includes additional fixed function logic 2916 that can include various fixed function acceleration logic for use by graphics core 2900. In at least one embodiment, additional fixed function logic 2916 includes an additional geometry pipeline for use in position-only shading. In position-only shading, at least two geometry pipelines exist, whereas in a full geometry pipeline within geometry and fixed
25 function pipelines 2914, 2936, and a cull pipeline, which is an additional geometry pipeline that may be included within additional fixed function logic 2916. In at least one embodiment, a cull pipeline is a trimmed down version of a full geometry pipeline. In at least one embodiment, a full pipeline and a cull pipeline can execute different instances of an application, each instance having a separate context. In at least one embodiment, position
30 only shading can hide long cull runs of discarded triangles, enabling shading to be completed earlier in some instances. For example, in at least one embodiment, cull pipeline logic within additional fixed function logic 2916 can execute position shaders in parallel with a main application and generally generates critical results faster than a full pipeline, as a cull pipeline fetches and shades position attributes of vertices, without performing rasterization and
35 rendering of pixels to a frame buffer. In at least one embodiment, a cull pipeline can use generated critical results to compute visibility information for all triangles without regard to whether those triangles are culled. In at least one embodiment, a full pipeline (which in this

5 instance may be referred to as a replay pipeline) can consume visibility information to skip culled triangles to shade only visible triangles that are finally passed to a rasterization phase.

[0454] In at least one embodiment, additional fixed function logic 2916 can also include machine-learning acceleration logic, such as fixed function matrix multiplication logic, for implementations including optimizations for machine learning training or inferencing.

10 [0455] In at least one embodiment, within each graphics sub-core 2901A-2901F includes a set of execution resources that may be used to perform graphics, media, and compute operations in response to requests by graphics pipeline, media pipeline, or shader programs. In at least one embodiment, graphics sub-cores 2901A-2901F include multiple EU arrays 2902A-2902F, 2904A-2904F, thread dispatch and inter-thread communication (TD/IC) logic
 15 2903A-2903F, a 3D (e.g., texture) sampler 2905A-2905F, a media sampler 2906A-2906F, a shader processor 2907A-2907F, and shared local memory (SLM) 2908A-2908F. In at least one embodiment, EU arrays 2902A-2902F, 2904A-2904F each include multiple execution units, which are general-purpose graphics processing units capable of performing floating-point and integer/fixed-point logic operations in service of a graphics, media, or compute
 20 operation, including graphics, media, or compute shader programs. In at least one embodiment, TD/IC logic 2903A-2903F performs local thread dispatch and thread control operations for execution units within a sub-core and facilitates communication between threads executing on execution units of a sub-core. In at least one embodiment, 3D samplers 2905A-2905F can read texture or other 3D graphics related data into memory. In at least one
 25 embodiment, 3D samplers can read texture data differently based on a configured sample state and texture format associated with a given texture. In at least one embodiment, media samplers 2906A-2906F can perform similar read operations based on a type and format associated with media data. In at least one embodiment, each graphics sub-core 2901A-2901F can alternately include a unified 3D and media sampler. In at least one embodiment,
 30 threads executing on execution units within each of sub-cores 2901A-2901F can make use of shared local memory 2908A-2908F within each sub-core, to enable threads executing within a thread group to execute using a common pool of on-chip memory.

[0456] Inference and/or training logic 615 are used to perform inferencing and/or training operations associated with one or more embodiments. Details regarding inference and/or
 35 training logic 615 are provided herein in conjunction with FIGS. 6A and/or 6B. In at least one embodiment, portions or all of inference and/or training logic 615 may be incorporated

5 into graphics processor 2910. For example, in at least one embodiment, training and/or
inferencing techniques described herein may use one or more of ALUs embodied in a 3D
pipeline, graphics microcontroller 2938, geometry and fixed function pipeline 2914 and 2936,
or other logic in FIG. 29. Moreover, in at least one embodiment, inferencing and/or training
operations described herein may be done using logic other than logic illustrated in FIGS. 6A
10 or 6B. In at least one embodiment, weight parameters may be stored in on-chip or off-chip
memory and/or registers (shown or not shown) that configure ALUs of graphics processor
2900 to perform one or more machine learning algorithms, neural network architectures, use
cases, or training techniques described herein.

[0457] In at least one embodiment, one or more systems depicted in FIG. 29 are utilized to
15 implement a deep object detection network. In at least one embodiment, one or more systems
depicted in FIG. 29 are utilized to implement one or more networks and models such as those
described in connection with FIG. 1 and FIG. 3. In at least one embodiment, one or more
systems depicted in FIG. 29 are utilized to implement a network that is based on mixture
density networks and predicts uncertainty values of images. In at least one embodiment, one
20 or more systems depicted in FIG. 29 are utilized to implement an active learning method for
object detection that utilizes mixture density networks to produce one or more Gaussian
mixture models for each output of a network.

[0458] FIGS. 30A and 30B illustrate thread execution logic 3000 including an array of
processing elements of a graphics processor core according to at least one embodiment. FIG.
25 30A illustrates at least one embodiment, in which thread execution logic 3000 is used. FIG.
30B illustrates exemplary internal details of a graphics execution unit 3008, according to at
least one embodiment.

[0459] As illustrated in FIG. 30A, in at least one embodiment, thread execution logic 3000
includes a shader processor 3002, a thread dispatcher 3004, an instruction cache 3006, a
30 scalable execution unit array including a plurality of execution units 3007A-3007N and
3008A-3008N, a sampler 3010, a data cache 3012, and a data port 3014. In at least one
embodiment, a scalable execution unit array can dynamically scale by enabling or disabling
one or more execution units (e.g., any of execution unit 3008A-N or 3007A-N) based on
computational requirements of a workload, for example. In at least one embodiment, scalable
35 execution units are interconnected via an interconnect fabric that links to each execution unit.
In at least one embodiment, thread execution logic 3000 includes one or more connections to

5 memory, such as system memory or cache memory, through one or more of instruction cache 3006, data port 3014, sampler 3010, and execution units 3007 or 3008. In at least one embodiment, each execution unit (e.g., 3007A) is a stand-alone programmable general-purpose computational unit that is capable of executing multiple simultaneous hardware threads while processing multiple data elements in parallel for each thread. In at least one
10 embodiment, array of execution units 3007 and/or 3008 is scalable to include any number individual execution units.

[0460] In at least one embodiment, execution units 3007 and/or 3008 are primarily used to execute shader programs. In at least one embodiment, shader processor 3002 can process various shader programs and dispatch execution threads associated with shader programs via
15 a thread dispatcher 3004. In at least one embodiment, thread dispatcher 3004 includes logic to arbitrate thread initiation requests from graphics and media pipelines and instantiate requested threads on one or more execution units in execution units 3007 and/or 3008. For example, in at least one embodiment, a geometry pipeline can dispatch vertex, tessellation, or geometry shaders to thread execution logic for processing. In at least one embodiment,
20 thread dispatcher 3004 can also process runtime thread spawning requests from executing shader programs.

[0461] In at least one embodiment, execution units 3007 and/or 3008 support an instruction set that includes native support for many standard 3D graphics shader instructions, such that shader programs from graphics libraries (e.g., Direct 3D and OpenGL) are executed with a
25 minimal translation. In at least one embodiment, execution units support vertex and geometry processing (e.g., vertex programs, geometry programs, and/or vertex shaders), pixel processing (e.g., pixel shaders, fragment shaders) and general-purpose processing (e.g., compute and media shaders). In at least one embodiment, each of execution units 3007 and/or 3008, which include one or more arithmetic logic units (ALUs), is capable of multi-
30 issue single instruction multiple data (SIMD) execution and multi-threaded operation enables an efficient execution environment despite higher latency memory accesses. In at least one embodiment, each hardware thread within each execution unit has a dedicated high-bandwidth register file and associated independent thread-state. In at least one embodiment, execution is multi-issue per clock to pipelines capable of integer, single and double precision
35 floating point operations, SIMD branch capability, logical operations, transcendental operations, and other miscellaneous operations. In at least one embodiment, while waiting for data from memory or one of shared functions, dependency logic within execution units

5 3007 and/or 3008 causes a waiting thread to sleep until requested data has been returned. In at least one embodiment, while an awaiting thread is sleeping, hardware resources may be devoted to processing other threads. For example, in at least one embodiment, during a delay associated with a vertex shader operation, an execution unit can perform operations for a pixel shader, fragment shader, or another type of shader program, including a different vertex
10 shader.

[0462] In at least one embodiment, each execution unit in execution units 3007 and/or 3008 operates on arrays of data elements. In at least one embodiment, a number of data elements is an “execution size,” or number of channels for an instruction. In at least one embodiment, an execution channel is a logical unit of execution for data element access, masking, and flow
15 control within instructions. In at least one embodiment, a number of channels may be independent of a number of physical arithmetic logic units (ALUs) or floating point units (FPUs) for a particular graphics processor. In at least one embodiment, execution units 3007 and/or 3008 support integer and floating-point data types.

[0463] In at least one embodiment, an execution unit instruction set includes SIMD
20 instructions. In at least one embodiment, various data elements can be stored as a packed data type in a register and execution unit will process various elements based on data size of elements. For example, in at least one embodiment, when operating on a 256-bit wide vector, 256 bits of a vector are stored in a register and an execution unit operates on a vector as four separate 64-bit packed data elements (Quad-Word (QW) size data elements), eight separate
25 32-bit packed data elements (Double Word (DW) size data elements), sixteen separate 16-bit packed data elements (Word (W) size data elements), or thirty-two separate 8-bit data elements (byte (B) size data elements). However, in at least one embodiment, different vector widths and register sizes are possible.

[0464] In at least one embodiment, one or more execution units can be combined into a
30 fused execution unit 3009A-3009N having thread control logic (3011A-3011N) that is common to fused EUs such as execution unit 3007A fused with execution unit 3008A into fused execution unit 3009A. In at least one embodiment, multiple EUs can be fused into an EU group. In at least one embodiment, each EU in a fused EU group can be configured to execute a separate SIMD hardware thread, with a number of EUs in a fused EU group
35 possibly varying according to various embodiments. In at least one embodiment, various SIMD widths can be performed per-EU, including but not limited to SIMD8, SIMD16, and

5 SIMD32. In at least one embodiment, each fused graphics execution unit 3009A-3009N includes at least two execution units. For example, in at least one embodiment, fused execution unit 3009A includes a first EU 3007A, second EU 3008A, and thread control logic 3011A that is common to first EU 3007A and second EU 3008A. In at least one embodiment, thread control logic 3011A controls threads executed on fused graphics
10 execution unit 3009A, allowing each EU within fused execution units 3009A-3009N to execute using a common instruction pointer register.

[0465] In at least one embodiment, one or more internal instruction caches (e.g., 3006) are included in thread execution logic 3000 to cache thread instructions for execution units. In at least one embodiment, one or more data caches (e.g., 3012) are included to cache thread data
15 during thread execution. In at least one embodiment, sampler 3010 is included to provide texture sampling for 3D operations and media sampling for media operations. In at least one embodiment, sampler 3010 includes specialized texture or media sampling functionality to process texture or media data during sampling process before providing sampled data to an execution unit.

20 [0466] During execution, in at least one embodiment, graphics and media pipelines send thread initiation requests to thread execution logic 3000 via thread spawning and dispatch logic. In at least one embodiment, once a group of geometric objects has been processed and rasterized into pixel data, pixel processor logic (e.g., pixel shader logic, fragment shader logic, etc.) within shader processor 3002 is invoked to further compute output information
25 and cause results to be written to output surfaces (e.g., color buffers, depth buffers, stencil buffers, etc.). In at least one embodiment, a pixel shader or a fragment shader calculates values of various vertex attributes that are to be interpolated across a rasterized object. In at least one embodiment, pixel processor logic within shader processor 3002 then executes an application programming interface (API)-supplied pixel or fragment shader program. In at
30 least one embodiment, to execute a shader program, shader processor 3002 dispatches threads to an execution unit (e.g., 3008A) via thread dispatcher 3004. In at least one embodiment, shader processor 3002 uses texture sampling logic in sampler 3010 to access texture data in texture maps stored in memory. In at least one embodiment, arithmetic operations on texture data and input geometry data compute pixel color data for each geometric fragment, or
35 discards one or more pixels from further processing.

5 [0467] In at least one embodiment, data port 3014 provides a memory access mechanism for thread execution logic 3000 to output processed data to memory for further processing on a graphics processor output pipeline. In at least one embodiment, data port 3014 includes or couples to one or more cache memories (e.g., data cache 3012) to cache data for memory access via a data port.

10 [0468] As illustrated in FIG. 30B, in at least one embodiment, a graphics execution unit 3008 can include an instruction fetch unit 3037, a general register file array (GRF) 3024, an architectural register file array (ARF) 3026, a thread arbiter 3022, a send unit 3030, a branch unit 3032, a set of SIMD floating point units (FPUs) 3034, and a set of dedicated integer SIMD ALUs 3035. In at least one embodiment, GRF 3024 and ARF 3026 includes a set of
15 general register files and architecture register files associated with each simultaneous hardware thread that may be active in graphics execution unit 3008. In at least one embodiment, per thread architectural state is maintained in ARF 3026, while data used during thread execution is stored in GRF 3024. In at least one embodiment, execution state of each thread, including instruction pointers for each thread, can be held in thread-specific registers
20 in ARF 3026.

[0469] In at least one embodiment, graphics execution unit 3008 has an architecture that is a combination of Simultaneous Multi-Threading (SMT) and fine-grained Interleaved Multi-Threading (IMT). In at least one embodiment, architecture has a modular configuration that can be fine-tuned at design time based on a target number of simultaneous threads and
25 number of registers per execution unit, where execution unit resources are divided across logic used to execute multiple simultaneous threads.

[0470] In at least one embodiment, graphics execution unit 3008 can co-issue multiple instructions, which may each be different instructions. In at least one embodiment, thread arbiter 3022 of graphics execution unit thread 3008 can dispatch instructions to one of send
30 unit 3030, branch unit 3032, or SIMD FPU(s) 3034 for execution. In at least one embodiment, each execution thread can access 128 general-purpose registers within GRF 3024, where each register can store 32 bytes, accessible as a SIMD 8-element vector of 32-bit data elements. In at least one embodiment, each execution unit thread has access to 4 kilobytes within GRF 3024, although embodiments are not so limited, and greater or fewer
35 register resources may be provided in other embodiments. In at least one embodiment, up to seven threads can execute simultaneously, although a number of threads per execution unit

5 can also vary according to embodiments. In at least one embodiment, in which seven threads may access 4 kilobytes, GRF 3024 can store a total of 28 kilobytes. In at least one embodiment, flexible addressing modes can permit registers to be addressed together to build effectively wider registers or to represent strided rectangular block data structures.

[0471] In at least one embodiment, memory operations, sampler operations, and other
10 longer-latency system communications are dispatched via “send” instructions that are executed by message passing to send unit 3030. In at least one embodiment, branch instructions are dispatched to branch unit 3032 to facilitate SIMD divergence and eventual convergence.

[0472] In at least one embodiment, graphics execution unit 3008 includes one or more
15 SIMD floating point units (FPU(s)) 3034 to perform floating-point operations. In at least one embodiment, FPU(s) 3034 also support integer computation. In at least one embodiment, FPU(s) 3034 can SIMD execute up to M number of 32-bit floating-point (or integer) operations, or SIMD execute up to 2M 16-bit integer or 16-bit floating-point operations. In at least one embodiment, at least one FPU provides extended math capability to support high-
20 throughput transcendental math functions and double precision 64-bit floating-point. In at least one embodiment, a set of 8-bit integer SIMD ALUs 3035 are also present, and may be specifically optimized to perform operations associated with machine learning computations.

[0473] In at least one embodiment, arrays of multiple instances of graphics execution unit 3008 can be instantiated in a graphics sub-core grouping (e.g., a sub-slice). In at least one
25 embodiment, execution unit 3008 can execute instructions across a plurality of execution channels. In at least one embodiment, each thread executed on graphics execution unit 3008 is executed on a different channel.

[0474] Inference and/or training logic 615 are used to perform inferencing and/or training operations associated with one or more embodiments. Details regarding inference and/or
30 training logic 615 are provided herein in conjunction with FIGS. 6A and/or 6B. In at least one embodiment, portions or all of inference and/or training logic 615 may be incorporated into thread execution logic 3000. Moreover, in at least one embodiment, inferencing and/or training operations described herein may be done using logic other than logic illustrated in FIGS. 6A or 6B. In at least one embodiment, weight parameters may be stored in on-chip or
35 off-chip memory and/or registers (shown or not shown) that configure ALUs thread of

5 execution logic 3000 to perform one or more machine learning algorithms, neural network architectures, use cases, or training techniques described herein.

[0475] In at least one embodiment, one or more systems depicted in FIGS. 30A-30B are utilized to implement a deep object detection network. In at least one embodiment, one or more systems depicted in FIGS. 30A-30B are utilized to implement one or more networks
10 and models such as those described in connection with FIG. 1 and FIG. 3. In at least one embodiment, one or more systems depicted in FIGS. 30A-30B are utilized to implement a network that is based on mixture density networks and predicts uncertainty values of images. In at least one embodiment, one or more systems depicted in FIGS. 30A-30B are utilized to implement an active learning method for object detection that utilizes mixture density
15 networks to produce one or more Gaussian mixture models for each output of a network.

[0476] FIG. 31 illustrates a parallel processing unit (“PPU”) 3100, according to at least one embodiment. In at least one embodiment, PPU 3100 is configured with machine-readable code that, if executed by PPU 3100, causes PPU 3100 to perform some or all of processes and techniques described throughout this disclosure. In at least one embodiment, PPU 3100
20 is a multi-threaded processor that is implemented on one or more integrated circuit devices and that utilizes multithreading as a latency-hiding technique designed to process computer-readable instructions (also referred to as machine-readable instructions or simply instructions) on multiple threads in parallel. In at least one embodiment, a thread refers to a thread of execution and is an instantiation of a set of instructions configured to be executed by PPU
25 3100. In at least one embodiment, PPU 3100 is a graphics processing unit (“GPU”) configured to implement a graphics rendering pipeline for processing three-dimensional (“3D”) graphics data in order to generate two-dimensional (“2D”) image data for display on a display device such as a liquid crystal display (“LCD”) device. In at least one embodiment, PPU 3100 is utilized to perform computations such as linear algebra operations and machine-
30 learning operations. FIG. 31 illustrates an example parallel processor for illustrative purposes only and should be construed as a non-limiting example of processor architectures contemplated within scope of this disclosure and that any suitable processor may be employed to supplement and/or substitute for same.

[0477] In at least one embodiment, one or more PPUs 3100 are configured to accelerate
35 High Performance Computing (“HPC”), data center, and machine learning applications. In at least one embodiment, PPU 3100 is configured to accelerate deep learning systems and

5 applications including following non-limiting examples: autonomous vehicle platforms, deep learning, high-accuracy speech, image, text recognition systems, intelligent video analytics, molecular simulations, drug discovery, disease diagnosis, weather forecasting, big data analytics, astronomy, molecular dynamics simulation, financial modeling, robotics, factory automation, real-time language translation, online search optimizations, and personalized user
10 recommendations, and more.

[0478] In at least one embodiment, PPU 3100 includes, without limitation, an Input/Output (“I/O”) unit 3106, a front-end unit 3110, a scheduler unit 3112, a work distribution unit 3114, a hub 3116, a crossbar (“XBar”) 3120, one or more general processing clusters (“GPCs”) 3118, and one or more partition units (“memory partition units”) 3122. In at least one
15 embodiment, PPU 3100 is connected to a host processor or other PPUs 3100 via one or more high-speed GPU interconnects (“GPU interconnects”) 3108. In at least one embodiment, PPU 3100 is connected to a host processor or other peripheral devices via a system bus 3102. In at least one embodiment, PPU 3100 is connected to a local memory comprising one or more memory devices (“memory”) 3104. In at least one embodiment, memory devices 3104
20 include, without limitation, one or more dynamic random access memory (“DRAM”) devices. In at least one embodiment, one or more DRAM devices are configured and/or configurable as high-bandwidth memory (“HBM”) subsystems, with multiple DRAM dies stacked within each device.

[0479] In at least one embodiment, high-speed GPU interconnect 3108 may refer to a wire-
25 based multi-lane communications link that is used by systems to scale and include one or more PPUs 3100 combined with one or more central processing units (“CPUs”), supports cache coherence between PPUs 3100 and CPUs, and CPU mastering. In at least one embodiment, data and/or commands are transmitted by high-speed GPU interconnect 3108 through hub 3116 to/from other units of PPU 3100 such as one or more copy engines, video
30 encoders, video decoders, power management units, and other components which may not be explicitly illustrated in FIG. 31.

[0480] In at least one embodiment, I/O unit 3106 is configured to transmit and receive communications (e.g., commands, data) from a host processor (not illustrated in FIG. 31) over system bus 3102. In at least one embodiment, I/O unit 3106 communicates with host
35 processor directly via system bus 3102 or through one or more intermediate devices such as a memory bridge. In at least one embodiment, I/O unit 3106 may communicate with one or

5 more other processors, such as one or more of PPUs 3100 via system bus 3102. In at least one embodiment, I/O unit 3106 implements a Peripheral Component Interconnect Express (“PCIe”) interface for communications over a PCIe bus. In at least one embodiment, I/O unit 3106 implements interfaces for communicating with external devices.

[0481] In at least one embodiment, I/O unit 3106 decodes packets received via system bus
10 3102. In at least one embodiment, at least some packets represent commands configured to cause PPU 3100 to perform various operations. In at least one embodiment, I/O unit 3106 transmits decoded commands to various other units of PPU 3100 as specified by commands. In at least one embodiment, commands are transmitted to front-end unit 3110 and/or transmitted to hub 3116 or other units of PPU 3100 such as one or more copy engines, a
15 video encoder, a video decoder, a power management unit, etc. (not explicitly illustrated in FIG. 31). In at least one embodiment, I/O unit 3106 is configured to route communications between and among various logical units of PPU 3100.

[0482] In at least one embodiment, a program executed by host processor encodes a command stream in a buffer that provides workloads to PPU 3100 for processing. In at least
20 one embodiment, a workload comprises instructions and data to be processed by those instructions. In at least one embodiment, a buffer is a region in a memory that is accessible (e.g., read/write) by both a host processor and PPU 3100 — a host interface unit may be configured to access that buffer in a system memory connected to system bus 3102 via memory requests transmitted over system bus 3102 by I/O unit 3106. In at least one
25 embodiment, a host processor writes a command stream to a buffer and then transmits a pointer to a start of a command stream to PPU 3100 such that front-end unit 3110 receives pointers to one or more command streams and manages one or more command streams, reading commands from command streams and forwarding commands to various units of PPU 3100.

30 [0483] In at least one embodiment, front-end unit 3110 is coupled to scheduler unit 3112 that configures various GPCs 3118 to process tasks defined by one or more command streams. In at least one embodiment, scheduler unit 3112 is configured to track state information related to various tasks managed by scheduler unit 3112 where state information may indicate which of GPCs 3118 a task is assigned to, whether task is active or inactive, a
35 priority level associated with task, and so forth. In at least one embodiment, scheduler unit 3112 manages execution of a plurality of tasks on one or more of GPCs 3118.

5 [0484] In at least one embodiment, scheduler unit 3112 is coupled to work distribution unit 3114 that is configured to dispatch tasks for execution on GPCs 3118. In at least one embodiment, work distribution unit 3114 tracks a number of scheduled tasks received from scheduler unit 3112 and work distribution unit 3114 manages a pending task pool and an active task pool for each of GPCs 3118. In at least one embodiment, pending task pool
10 comprises a number of slots (e.g., 32 slots) that contain tasks assigned to be processed by a particular GPC 3118; an active task pool may comprise a number of slots (e.g., 4 slots) for tasks that are actively being processed by GPCs 3118 such that as one of GPCs 3118 completes execution of a task, that task is evicted from that active task pool for GPC 3118 and another task from a pending task pool is selected and scheduled for execution on GPC
15 3118. In at least one embodiment, if an active task is idle on GPC 3118, such as while waiting for a data dependency to be resolved, then that active task is evicted from GPC 3118 and returned to that pending task pool while another task in that pending task pool is selected and scheduled for execution on GPC 3118.

[0485] In at least one embodiment, work distribution unit 3114 communicates with one or
20 more GPCs 3118 via XBar 3120. In at least one embodiment, XBar 3120 is an interconnect network that couples many of units of PPU 3100 to other units of PPU 3100 and can be configured to couple work distribution unit 3114 to a particular GPC 3118. In at least one embodiment, one or more other units of PPU 3100 may also be connected to XBar 3120 via hub 3116.

25 [0486] In at least one embodiment, tasks are managed by scheduler unit 3112 and dispatched to one of GPCs 3118 by work distribution unit 3114. In at least one embodiment, GPC 3118 is configured to process task and generate results. In at least one embodiment, results may be consumed by other tasks within GPC 3118, routed to a different GPC 3118 via XBar 3120, or stored in memory 3104. In at least one embodiment, results can be written to
30 memory 3104 via partition units 3122, which implement a memory interface for reading and writing data to/from memory 3104. In at least one embodiment, results can be transmitted to another PPU 3104 or CPU via high-speed GPU interconnect 3108. In at least one embodiment, PPU 3100 includes, without limitation, a number U of partition units 3122 that is equal to a number of separate and distinct memory devices 3104 coupled to PPU 3100, as
35 described in more detail herein in conjunction with FIG. 33.

5 [0487] In at least one embodiment, a host processor executes a driver kernel that implements an application programming interface (“API”) that enables one or more applications executing on a host processor to schedule operations for execution on PPU 3100. In at least one embodiment, multiple compute applications are simultaneously executed by PPU 3100 and PPU 3100 provides isolation, quality of service (“QoS”), and independent
10 address spaces for multiple compute applications. In at least one embodiment, an application generates instructions (e.g., in form of API calls) that cause a driver kernel to generate one or more tasks for execution by PPU 3100 and that driver kernel outputs tasks to one or more streams being processed by PPU 3100. In at least one embodiment, each task comprises one or more groups of related threads, which may be referred to as a warp. In at least one
15 embodiment, a warp comprises a plurality of related threads (e.g., 32 threads) that can be executed in parallel. In at least one embodiment, cooperating threads can refer to a plurality of threads including instructions to perform task and that exchange data through shared memory. In at least one embodiment, threads and cooperating threads are described in more detail in conjunction with FIG. 33.

20 [0488] Inference and/or training logic 615 are used to perform inferencing and/or training operations associated with one or more embodiments. Details regarding inference and/or training logic 615 are provided herein in conjunction with FIGS. 6A and/or 6B. In at least one embodiment, deep learning application processor is used to train a machine learning model, such as a neural network, to predict or infer information provided to PPU 3100. In at
25 least one embodiment, deep learning application processor 3100 is used to infer or predict information based on a trained machine learning model (e.g., neural network) that has been trained by another processor or system or by PPU 3100. In at least one embodiment, PPU 3100 may be used to perform one or more neural network use cases described herein.

[0489] In at least one embodiment, one or more systems depicted in FIG. 31 are utilized to
30 implement a deep object detection network. In at least one embodiment, one or more systems depicted in FIG. 31 are utilized to implement one or more networks and models such as those described in connection with FIG. 1 and FIG. 3. In at least one embodiment, one or more systems depicted in FIG. 31 are utilized to implement a network that is based on mixture density networks and predicts uncertainty values of images. In at least one embodiment, one
35 or more systems depicted in FIG. 31 are utilized to implement an active learning method for object detection that utilizes mixture density networks to produce one or more Gaussian mixture models for each output of a network.

5 [0490] FIG. 32 illustrates a general processing cluster (“GPC”) 3200, according to at least one embodiment. In at least one embodiment, GPC 3200 is GPC 3118 of FIG. 31. In at least one embodiment, each GPC 3200 includes, without limitation, a number of hardware units for processing tasks and each GPC 3200 includes, without limitation, a pipeline manager 3202, a pre-raster operations unit (“preROP”) 3204, a raster engine 3208, a work distribution crossbar (“WDX”) 3216, a memory management unit (“MMU”) 3218, one or more Data
10 Processing Clusters (“DPCs”) 3206, and any suitable combination of parts.

[0491] In at least one embodiment, operation of GPC 3200 is controlled by pipeline manager 3202. In at least one embodiment, pipeline manager 3202 manages configuration of one or more DPCs 3206 for processing tasks allocated to GPC 3200. In at least one
15 embodiment, pipeline manager 3202 configures at least one of one or more DPCs 3206 to implement at least a portion of a graphics rendering pipeline. In at least one embodiment, DPC 3206 is configured to execute a vertex shader program on a programmable streaming multi-processor (“SM”) 3214. In at least one embodiment, pipeline manager 3202 is configured to route packets received from a work distribution unit to appropriate logical units
20 within GPC 3200, in at least one embodiment, and some packets may be routed to fixed function hardware units in preROP 3204 and/or raster engine 3208 while other packets may be routed to DPCs 3206 for processing by a primitive engine 3212 or SM 3214. In at least one embodiment, pipeline manager 3202 configures at least one of DPCs 3206 to implement a neural network model and/or a computing pipeline.

25 [0492] In at least one embodiment, preROP unit 3204 is configured, in at least one embodiment, to route data generated by raster engine 3208 and DPCs 3206 to a Raster Operations (“ROP”) unit in partition unit 3122, described in more detail above in conjunction with FIG. 31. In at least one embodiment, preROP unit 3204 is configured to perform optimizations for color blending, organize pixel data, perform address translations, and more.
30 In at least one embodiment, raster engine 3208 includes, without limitation, a number of fixed function hardware units configured to perform various raster operations, in at least one embodiment, and raster engine 3208 includes, without limitation, a setup engine, a coarse raster engine, a culling engine, a clipping engine, a fine raster engine, a tile coalescing engine, and any suitable combination thereof. In at least one embodiment, setup engine
35 receives transformed vertices and generates plane equations associated with geometric primitive defined by vertices; plane equations are transmitted to a coarse raster engine to generate coverage information (e.g., an x, y coverage mask for a tile) for primitive; output of

5 a coarse raster engine is transmitted to a culling engine where fragments associated with a primitive that fail a z-test are culled, and transmitted to a clipping engine where fragments lying outside a viewing frustum are clipped. In at least one embodiment, fragments that survive clipping and culling are passed to a fine raster engine to generate attributes for pixel fragments based on plane equations generated by a setup engine. In at least one embodiment,
10 an output of raster engine 3208 comprises fragments to be processed by any suitable entity, such as by a fragment shader implemented within DPC 3206.

[0493] In at least one embodiment, each DPC 3206 included in GPC 3200 comprises, without limitation, an M-Pipe Controller (“MPC”) 3210; primitive engine 3212; one or more SMs 3214; and any suitable combination thereof. In at least one embodiment, MPC 3210
15 controls operation of DPC 3206, routing packets received from pipeline manager 3202 to appropriate units in DPC 3206. In at least one embodiment, packets associated with a vertex are routed to primitive engine 3212, which is configured to fetch vertex attributes associated with a vertex from memory; in contrast, packets associated with a shader program may be transmitted to SM 3214.

20 [0494] In at least one embodiment, SM 3214 comprises, without limitation, a programmable streaming processor that is configured to process tasks represented by a number of threads. In at least one embodiment, SM 3214 is multi-threaded and configured to execute a plurality of threads (e.g., 32 threads) from a particular group of threads concurrently and implements a Single-Instruction, Multiple-Data (“SIMD”) architecture
25 where each thread in a group of threads (e.g., a warp) is configured to process a different set of data based on same set of instructions. In at least one embodiment, all threads in group of threads execute a common set of instructions. In at least one embodiment, SM 3214 implements a Single-Instruction, Multiple Thread (“SIMT”) architecture wherein each thread in a group of threads is configured to process a different set of data based on that common set
30 of instructions, but where individual threads in a group of threads are allowed to diverge during execution. In at least one embodiment, a program counter, call stack, and execution state is maintained for each warp, enabling concurrency between warps and serial execution within warps when threads within a warp diverge. In another embodiment, a program counter, call stack, and execution state is maintained for each individual thread, enabling
35 equal concurrency between all threads, within and between warps. In at least one embodiment, execution state is maintained for each individual thread and threads executing

5 common instructions may be converged and executed in parallel for better efficiency. At least one embodiment of SM 3214 is described in more detail herein.

[0495] In at least one embodiment, MMU 3218 provides an interface between GPC 3200 and a memory partition unit (e.g., partition unit 3122 of FIG. 31) and MMU 3218 provides translation of virtual addresses into physical addresses, memory protection, and arbitration of
10 memory requests. In at least one embodiment, MMU 3218 provides one or more translation lookaside buffers (“TLBs”) for performing translation of virtual addresses into physical addresses in memory.

[0496] Inference and/or training logic 615 are used to perform inferencing and/or training operations associated with one or more embodiments. Details regarding inference and/or
15 training logic 615 are provided herein in conjunction with FIGS. 6A and/or 6B. In at least one embodiment, deep learning application processor is used to train a machine learning model, such as a neural network, to predict or infer information provided to GPC 3200. In at least one embodiment, GPC 3200 is used to infer or predict information based on a trained machine learning model (e.g., neural network) that has been trained by another processor or
20 system or by GPC 3200. In at least one embodiment, GPC 3200 may be used to perform one or more neural network use cases described herein.

[0497] In at least one embodiment, one or more systems depicted in FIG. 32 are utilized to implement a deep object detection network. In at least one embodiment, one or more systems depicted in FIG. 32 are utilized to implement one or more networks and models such as those
25 described in connection with FIG. 1 and FIG. 3. In at least one embodiment, one or more systems depicted in FIG. 32 are utilized to implement a network that is based on mixture density networks and predicts uncertainty values of images. In at least one embodiment, one or more systems depicted in FIG. 32 are utilized to implement an active learning method for object detection that utilizes mixture density networks to produce one or more Gaussian
30 mixture models for each output of a network.

[0498] FIG. 33 illustrates a memory partition unit 3300 of a parallel processing unit (“PPU”), in accordance with at least one embodiment. In at least one embodiment, memory partition unit 3300 includes, without limitation, a Raster Operations (“ROP”) unit 3302, a level two (“L2”) cache 3304, a memory interface 3306, and any suitable combination thereof.
35 In at least one embodiment, memory interface 3306 is coupled to memory. In at least one embodiment, memory interface 3306 may implement 32, 64, 128, 1024-bit data buses, or

5 like, for high-speed data transfer. In at least one embodiment, PPU incorporates U memory
interfaces 3306 where U is a positive integer, with one memory interface 3306 per pair of
partition units 3300, where each pair of partition units 3300 is connected to a corresponding
memory device. For example, in at least one embodiment, PPU may be connected to up to Y
memory devices, such as high bandwidth memory stacks or graphics double-data-rate,
10 version 5, synchronous dynamic random access memory (“GDDR5 SDRAM”).

[0499] In at least one embodiment, memory interface 3306 implements a high bandwidth
memory second generation (“HBM2”) memory interface and Y equals half of U. In at least
one embodiment, HBM2 memory stacks are located on a physical package with a PPU,
providing substantial power and area savings compared with conventional GDDR5 SDRAM
15 systems. In at least one embodiment, each HBM2 stack includes, without limitation, four
memory dies with Y=4, with each HBM2 stack including two 128-bit channels per die for a
total of 8 channels and a data bus width of 1024 bits. In at least one embodiment, that
memory supports Single-Error Correcting Double-Error Detecting (“SECCDED”) Error
Correction Code (“ECC”) to protect data. In at least one embodiment, ECC can provide
20 higher reliability for compute applications that are sensitive to data corruption.

[0500] In at least one embodiment, PPU implements a multi-level memory hierarchy. In at
least one embodiment, memory partition unit 3300 supports a unified memory to provide a
single unified virtual address space for central processing unit (“CPU”) and PPU memory,
enabling data sharing between virtual memory systems. In at least one embodiment
25 frequency of accesses by a PPU to a memory located on other processors is traced to ensure
that memory pages are moved to physical memory of PPU that is accessing pages more
frequently. In at least one embodiment, high-speed GPU interconnect 3108 supports address
translation services allowing PPU to directly access a CPU’s page tables and providing full
access to CPU memory by a PPU.

30 [0501] In at least one embodiment, copy engines transfer data between multiple PPUs or
between PPUs and CPUs. In at least one embodiment, copy engines can generate page faults
for addresses that are not mapped into page tables and memory partition unit 3300 then
services page faults, mapping addresses into page table, after which copy engine performs a
transfer. In at least one embodiment, memory is pinned (i.e., non-pageable) for multiple copy
35 engine operations between multiple processors, substantially reducing available memory. In
at least one embodiment, with hardware page faulting, addresses can be passed to copy

5 engines without regard as to whether memory pages are resident, and a copy process is transparent.

[0502] Data from memory 3104 of FIG. 31 or other system memory is fetched by memory partition unit 3300 and stored in L2 cache 3304, which is located on-chip and is shared between various GPCs, in accordance with at least one embodiment. Each memory partition
10 unit 3300, in at least one embodiment, includes, without limitation, at least a portion of L2 cache associated with a corresponding memory device. In at least one embodiment, lower level caches are implemented in various units within GPCs. In at least one embodiment, each of SMs 3214 in FIG. 32 may implement a Level 1 (“L1”) cache wherein that L1 cache is private memory that is dedicated to a particular SM 3214 and data from L2 cache 3304 is
15 fetched and stored in each L1 cache for processing in functional units of SMs 3214. In at least one embodiment, L2 cache 3304 is coupled to memory interface 3306 and XBar 3120 shown in FIG. 31.

[0503] ROP unit 3302 performs graphics raster operations related to pixel color, such as color compression, pixel blending, and more, in at least one embodiment. ROP unit 3302, in
20 at least one embodiment, implements depth testing in conjunction with raster engine 3208, receiving a depth for a sample location associated with a pixel fragment from a culling engine of raster engine 3208. In at least one embodiment, depth is tested against a corresponding depth in a depth buffer for a sample location associated with a fragment. In at least one embodiment, if that fragment passes that depth test for that sample location, then ROP unit
25 3302 updates depth buffer and transmits a result of that depth test to raster engine 3208. It will be appreciated that a number of partition units 3300 may be different than a number of GPCs and, therefore, each ROP unit 3302 can, in at least one embodiment, be coupled to each GPC. In at least one embodiment, ROP unit 3302 tracks packets received from different GPCs and determines whether a result generated by ROP unit 3302 is to be routed to through
30 XBar 3120.

[0504] In at least one embodiment, one or more systems depicted in FIG. 33 are utilized to implement a deep object detection network. In at least one embodiment, one or more systems depicted in FIG. 33 are utilized to implement one or more networks and models such as those described in connection with FIG. 1 and FIG. 3. In at least one embodiment, one or more
35 systems depicted in FIG. 33 are utilized to implement a network that is based on mixture density networks and predicts uncertainty values of images. In at least one embodiment, one

5 or more systems depicted in FIG. 33 are utilized to implement an active learning method for object detection that utilizes mixture density networks to produce one or more Gaussian mixture models for each output of a network.

[0505] FIG. 34 illustrates a streaming multi-processor (“SM”) 3400, according to at least one embodiment. In at least one embodiment, SM 3400 is SM of FIG. 32. In at least one
10 embodiment, SM 3400 includes, without limitation, an instruction cache 3402, one or more scheduler units 3404, a register file 3408, one or more processing cores (“cores”) 3410, one or more special function units (“SFUs”) 3412, one or more load/store units (“LSUs”) 3414, an interconnect network 3416, a shared memory/level one (“L1”) cache 3418, and/or any suitable combination thereof.

15 [0506] In at least one embodiment, a work distribution unit dispatches tasks for execution on general processing clusters (“GPCs”) of parallel processing units (“PPUs”) and each task is allocated to a particular Data Processing Cluster (“DPC”) within a GPC and, if a task is associated with a shader program, that task is allocated to one of SMs 3400. In at least one embodiment, scheduler unit 3404 receives tasks from a work distribution unit and manages
20 instruction scheduling for one or more thread blocks assigned to SM 3400. In at least one embodiment, scheduler unit 3404 schedules thread blocks for execution as warps of parallel threads, wherein each thread block is allocated at least one warp. In at least one embodiment, each warp executes threads. In at least one embodiment, scheduler unit 3404 manages a plurality of different thread blocks, allocating warps to different thread blocks and then
25 dispatching instructions from plurality of different cooperative groups to various functional units (e.g., processing cores 3410, SFUs 3412, and LSUs 3414) during each clock cycle.

[0507] In at least one embodiment, Cooperative Groups may refer to a programming model for organizing groups of communicating threads that allows developers to express granularity at which threads are communicating, enabling expression of richer, more efficient parallel
30 decompositions. In at least one embodiment, cooperative launch APIs support synchronization amongst thread blocks for execution of parallel algorithms. In at least one embodiment, applications of conventional programming models provide a single, simple construct for synchronizing cooperating threads: a barrier across all threads of a thread block (e.g., syncthreads() function). However, in at least one embodiment, programmers may
35 define groups of threads at smaller than thread block granularities and synchronize within defined groups to enable greater performance, design flexibility, and software reuse in form

- 5 of collective group-wide function interfaces. In at least one embodiment, Cooperative Groups enables programmers to define groups of threads explicitly at sub-block (i.e., as small as a single thread) and multi-block granularities, and to perform collective operations such as synchronization on threads in a cooperative group. In at least one embodiment, that programming model supports clean composition across software boundaries, so that libraries and utility functions can synchronize safely within their local context without having to make assumptions about convergence. In at least one embodiment, Cooperative Groups primitives enable new patterns of cooperative parallelism, including, without limitation, producer-consumer parallelism, opportunistic parallelism, and global synchronization across an entire grid of thread blocks.
- 10 [0508] In at least one embodiment, a dispatch unit 3406 is configured to transmit instructions to one or more functional units and scheduler unit 3404 and includes, without limitation, two dispatch units 3406 that enable two different instructions from a common warp to be dispatched during each clock cycle. In at least one embodiment, each scheduler unit 3404 includes a single dispatch unit 3406 or additional dispatch units 3406.
- 20 [0509] In at least one embodiment, each SM 3400, in at least one embodiment, includes, without limitation, register file 3408 that provides a set of registers for functional units of SM 3400. In at least one embodiment, register file 3408 is divided between each functional unit such that each functional unit is allocated a dedicated portion of register file 3408. In at least one embodiment, register file 3408 is divided between different warps being executed by SM
- 25 3400 and register file 3408 provides temporary storage for operands connected to data paths of functional units. In at least one embodiment, each SM 3400 comprises, without limitation, a plurality of L processing cores 3410, where L is a positive integer. In at least one embodiment, SM 3400 includes, without limitation, a large number (e.g., 128 or more) of distinct processing cores 3410. In at least one embodiment, each processing core
- 30 3410 includes, without limitation, a fully-pipelined, single-precision, double-precision, and/or mixed precision processing unit that includes, without limitation, a floating point arithmetic logic unit and an integer arithmetic logic unit. In at least one embodiment, floating point arithmetic logic units implement IEEE 754-2008 standard for floating point arithmetic. In at least one embodiment, processing cores 3410 include, without limitation, 64 single-precision
- 35 (32-bit) floating point cores, 64 integer cores, 32 double-precision (64-bit) floating point cores, and 8 tensor cores.

5 [0510] Tensor cores are configured to perform matrix operations in accordance with at least one embodiment. In at least one embodiment, one or more tensor cores are included in processing cores 3410. In at least one embodiment, tensor cores are configured to perform deep learning matrix arithmetic, such as convolution operations for neural network training and inferencing. In at least one embodiment, each tensor core operates on a 4x4 matrix and
10 performs a matrix multiply and accumulate operation, $D = A \times B + C$, where A, B, C, and D are 4x4 matrices.

[0511] In at least one embodiment, matrix multiply inputs A and B are 16-bit floating point matrices and accumulation matrices C and D are 16-bit floating point or 32-bit floating point matrices. In at least one embodiment, tensor cores operate on 16-bit floating point input data
15 with 32-bit floating point accumulation. In at least one embodiment, 16-bit floating point multiply uses 64 operations and results in a full precision product that is then accumulated using 32-bit floating point addition with other intermediate products for a 4x4x4 matrix multiply. Tensor cores are used to perform much larger two-dimensional or higher dimensional matrix operations, built up from these smaller elements, in at least one
20 embodiment. In at least one embodiment, an API, such as a CUDA 9 C++ API, exposes specialized matrix load, matrix multiply and accumulate, and matrix store operations to efficiently use tensor cores from a CUDA-C++ program. In at least one embodiment, at a CUDA level, a warp-level interface assumes 16x16 size matrices spanning all 32 threads of warp.

25 [0512] In at least one embodiment, each SM 3400 comprises, without limitation, M SFUs 3412 that perform special functions (e.g., attribute evaluation, reciprocal square root, and like). In at least one embodiment, SFUs 3412 include, without limitation, a tree traversal unit configured to traverse a hierarchical tree data structure. In at least one embodiment, SFUs 3412 include, without limitation, a texture unit configured to perform texture map filtering
30 operations. In at least one embodiment, texture units are configured to load texture maps (e.g., a 2D array of texels) from memory and sample texture maps to produce sampled texture values for use in shader programs executed by SM 3400. In at least one embodiment, texture maps are stored in shared memory/L1 cache 3418. In at least one embodiment, texture units implement texture operations such as filtering operations using mip-maps (e.g., texture maps
35 of varying levels of detail), in accordance with at least one embodiment. In at least one embodiment, each SM 3400 includes, without limitation, two texture units.

5 [0513] Each SM 3400 comprises, without limitation, N LSUs 3414 that implement load and store operations between shared memory/L1 cache 3418 and register file 3408, in at least one embodiment. Interconnect network 3416 connects each functional unit to register file 3408 and LSU 3414 to register file 3408 and shared memory/L1 cache 3418 in at least one embodiment. In at least one embodiment, interconnect network 3416 is a crossbar that can be
10 configured to connect any functional units to any registers in register file 3408 and connect LSUs 3414 to register file 3408 and memory locations in shared memory/L1 cache 3418.

[0514] In at least one embodiment, shared memory/L1 cache 3418 is an array of on-chip memory that allows for data storage and communication between SM 3400 and primitive engine and between threads in SM 3400, in at least one embodiment. In at least one
15 embodiment, shared memory/L1 cache 3418 comprises, without limitation, 128 KB of storage capacity and is in a path from SM 3400 to a partition unit. In at least one embodiment, shared memory/L1 cache 3418, in at least one embodiment, is used to cache reads and writes. In at least one embodiment, one or more of shared memory/L1 cache 3418, L2 cache, and memory are backing stores.

20 [0515] Combining data cache and shared memory functionality into a single memory block provides improved performance for both types of memory accesses, in at least one embodiment. In at least one embodiment, capacity is used or is usable as a cache by programs that do not use shared memory, such as if shared memory is configured to use half of a capacity, and texture and load/store operations can use remaining capacity. Integration
25 within shared memory/L1 cache 3418 enables shared memory/L1 cache 3418 to function as a high-throughput conduit for streaming data while simultaneously providing high-bandwidth and low-latency access to frequently reused data, in accordance with at least one embodiment. In at least one embodiment, when configured for general purpose parallel computation, a simpler configuration can be used compared with graphics processing. In at
30 least one embodiment, fixed function graphics processing units are bypassed, creating a much simpler programming model. In a general purpose parallel computation configuration, a work distribution unit assigns and distributes blocks of threads directly to DPCs, in at least one embodiment. In at least one embodiment, threads in a block execute a common program, using a unique thread ID in calculation to ensure each thread generates unique results, using
35 SM 3400 to execute program and perform calculations, shared memory/L1 cache 3418 to communicate between threads, and LSU 3414 to read and write global memory through shared memory/L1 cache 3418 and memory partition unit. In at least one embodiment, when

5 configured for general purpose parallel computation, SM 3400 writes commands that scheduler unit 3404 can use to launch new work on DPCs.

[0516] In at least one embodiment, a PPU is included in or coupled to a desktop computer, a laptop computer, a tablet computer, servers, supercomputers, a smart-phone (e.g., a wireless, hand-held device), personal digital assistant (“PDA”), a digital camera, a vehicle, a
10 head mounted display, a hand-held electronic device, and more. In at least one embodiment, a PPU is embodied on a single semiconductor substrate. In at least one embodiment, a PPU is included in a system-on-a-chip (“SoC”) along with one or more other devices such as additional PPUs, memory, a reduced instruction set computer (“RISC”) CPU, a memory management unit (“MMU”), a digital-to-analog converter (“DAC”), and like.

15 [0517] In at least one embodiment, a PPU may be included on a graphics card that includes one or more memory devices. In at least one embodiment, that graphics card may be configured to interface with a PCIe slot on a motherboard of a desktop computer. In at least one embodiment, that PPU may be an integrated graphics processing unit (“iGPU”) included in chipset of a motherboard.

20 [0518] Inference and/or training logic 615 are used to perform inferencing and/or training operations associated with one or more embodiments. Details regarding inference and/or training logic 615 are provided herein in conjunction with FIGS. 6A and/or 6B. In at least one embodiment, deep learning application processor is used to train a machine learning model, such as a neural network, to predict or infer information provided to SM 3400. In at
25 least one embodiment, SM 3400 is used to infer or predict information based on a trained machine learning model (e.g., neural network) that has been trained by another processor or system or by SM 3400. In at least one embodiment, SM 3400 may be used to perform one or more neural network use cases described herein.

[0519] In at least one embodiment, one or more systems depicted in FIG. 34 are utilized to
30 implement a deep object detection network. In at least one embodiment, one or more systems depicted in FIG. 34 are utilized to implement one or more networks and models such as those described in connection with FIG. 1 and FIG. 3. In at least one embodiment, one or more systems depicted in FIG. 34 are utilized to implement a network that is based on mixture density networks and predicts uncertainty values of images. In at least one embodiment, one
35 or more systems depicted in FIG. 34 are utilized to implement an active learning method for

5 object detection that utilizes mixture density networks to produce one or more Gaussian mixture models for each output of a network.

[0520] Embodiments are disclosed related a virtualized computing platform for advanced computing, such as image inferencing and image processing in medical applications. Without limitation, embodiments may include radiography, magnetic resonance imaging
10 (MRI), nuclear medicine, ultrasound, sonography, elastography, photoacoustic imaging, tomography, echocardiography, functional near-infrared spectroscopy, and magnetic particle imaging, or a combination thereof. In at least one embodiment, a virtualized computing platform and associated processes described herein may additionally or alternatively be used, without limitation, in forensic science analysis, sub-surface detection and imaging (e.g., oil
15 exploration, archaeology, paleontology, etc.), topography, oceanography, geology, osteology, meteorology, intelligent area or object tracking and monitoring, sensor data processing (e.g., RADAR, SONAR, LIDAR, etc.), and/or genomics and gene sequencing.

[0521] With reference to FIG. 35, FIG. 35 is an example data flow diagram for a process
3500 of generating and deploying an image processing and inferencing pipeline, in
20 accordance with at least one embodiment. In at least one embodiment, process 3500 may be deployed for use with imaging devices, processing devices, genomics devices, gene sequencing devices, radiology devices, and/or other device types at one or more facilities
3502, such as medical facilities, hospitals, healthcare institutes, clinics, research or diagnostic labs, etc. In at least one embodiment, process 3500 may be deployed to perform genomics
25 analysis and inferencing on sequencing data. Examples of genomic analyses that may be performed using systems and processes described herein include, without limitation, variant calling, mutation detection, and gene expression quantification.

[0522] In at least one embodiment, process 3500 may be executed within a training system
3504 and/or a deployment system 3506. In at least one embodiment, training system 3504
30 may be used to perform training, deployment, and implementation of machine learning models (e.g., neural networks, object detection algorithms, computer vision algorithms, etc.) for use in deployment system 3506. In at least one embodiment, deployment system 3506 may be configured to offload processing and compute resources among a distributed computing environment to reduce infrastructure requirements at facility 3502. In at least one
35 embodiment, deployment system 3506 may provide a streamlined platform for selecting, customizing, and implementing virtual instruments for use with imaging devices (e.g., MRI,

5 CT Scan, X-Ray, Ultrasound, etc.) or sequencing devices at facility 3502. In at least one embodiment, virtual instruments may include software-defined applications for performing one or more processing operations with respect to imaging data generated by imaging devices, sequencing devices, radiology devices, and/or other device types. In at least one embodiment, one or more applications in a pipeline may use or call upon services (e.g.,
10 inference, visualization, compute, AI, etc.) of deployment system 3506 during execution of applications.

[0523] In at least one embodiment, some of applications used in advanced processing and inferencing pipelines may use machine learning models or other AI to perform one or more processing steps. In at least one embodiment, machine learning models may be trained at
15 facility 3502 using data 3508 (such as imaging data) generated at facility 3502 (and stored on one or more picture archiving and communication system (PACS) servers at facility 3502), may be trained using imaging or sequencing data 3508 from another facility or facilities (e.g., a different hospital, lab, clinic, etc.), or a combination thereof. In at least one embodiment, training system 3504 may be used to provide applications, services, and/or other resources for
20 generating working, deployable machine learning models for deployment system 3506.

[0524] In at least one embodiment, a model registry 3524 may be backed by object storage that may support versioning and object metadata. In at least one embodiment, object storage may be accessible through, for example, a cloud storage (e.g., a cloud 3626 of FIG. 36) compatible application programming interface (API) from within a cloud platform. In at least
25 one embodiment, machine learning models within model registry 3524 may be uploaded, listed, modified, or deleted by developers or partners of a system interacting with an API. In at least one embodiment, an API may provide access to methods that allow users with appropriate credentials to associate models with applications, such that models may be executed as part of execution of containerized instantiations of applications.

[0525] In at least one embodiment, a training pipeline 3604 (FIG. 36) may include a scenario where facility 3502 is training their own machine learning model, or has an existing machine learning model that needs to be optimized or updated. In at least one embodiment, imaging data 3508 generated by imaging device(s), sequencing devices, and/or other device types may be received. In at least one embodiment, once imaging data 3508 is received, AI-
30 assisted annotation 3510 may be used to aid in generating annotations corresponding to imaging data 3508 to be used as ground truth data for a machine learning model. In at least
35

5 one embodiment, AI-assisted annotation 3510 may include one or more machine learning models (e.g., convolutional neural networks (CNNs)) that may be trained to generate annotations corresponding to certain types of imaging data 3508 (e.g., from certain devices) and/or certain types of anomalies in imaging data 3508. In at least one embodiment, AI-assisted annotations 3510 may then be used directly, or may be adjusted or fine-tuned using
10 an annotation tool (e.g., by a researcher, a clinician, a doctor, a scientist, etc.), to generate ground truth data. In at least one embodiment, in some examples, labeled clinic data 3512 (e.g., annotations provided by a clinician, doctor, scientist, technician, etc.) may be used as ground truth data for training a machine learning model. In at least one embodiment, AI-assisted annotations 3510, labeled clinic data 3512, or a combination thereof may be used as
15 ground truth data for training a machine learning model. In at least one embodiment, a trained machine learning model may be referred to as an output model 3516, and may be used by deployment system 3506, as described herein.

[0526] In at least one embodiment, training pipeline 3604 (FIG. 36) may include a scenario where facility 3502 needs a machine learning model for use in performing one or more
20 processing tasks for one or more applications in deployment system 3506, but facility 3502 may not currently have such a machine learning model (or may not have a model that is optimized, efficient, or effective for such purposes). In at least one embodiment, an existing machine learning model may be selected from model registry 3524. In at least one embodiment, model registry 3524 may include machine learning models trained to perform a
25 variety of different inference tasks on imaging data. In at least one embodiment, machine learning models in model registry 3524 may have been trained on imaging data from different facilities than facility 3502 (e.g., facilities remotely located). In at least one embodiment, machine learning models may have been trained on imaging data from one location, two locations, or any number of locations. In at least one embodiment, when being trained on
30 imaging data from a specific location, training may take place at that location, or at least in a manner that protects confidentiality of imaging data or restricts imaging data from being transferred off-premises (e.g., to comply with HIPAA regulations, privacy regulations, etc.). In at least one embodiment, once a model is trained – or partially trained – at one location, a machine learning model may be added to model registry 3524. In at least one embodiment, a
35 machine learning model may then be retrained, or updated, at any number of other facilities, and a retrained or updated model may be made available in model registry 3524. In at least one embodiment, a machine learning model may then be selected from model registry 3524 –

5 and referred to as output model 3516 – and may be used in deployment system 3506 to perform one or more processing tasks for one or more applications of a deployment system.

[0527] In at least one embodiment, training pipeline 3604 (FIG. 36) may be used in a scenario that includes facility 3502 requiring a machine learning model for use in performing one or more processing tasks for one or more applications in deployment system 3506, but
10 facility 3502 may not currently have such a machine learning model (or may not have a model that is optimized, efficient, or effective for such purposes). In at least one embodiment, a machine learning model selected from model registry 3524 might not be fine-tuned or optimized for imaging data 3508 generated at facility 3502 because of differences in populations, genetic variations, robustness of training data used to train a machine learning
15 model, diversity in anomalies of training data, and/or other issues with training data. In at least one embodiment, AI-assisted annotation 3510 may be used to aid in generating annotations corresponding to imaging data 3508 to be used as ground truth data for retraining or updating a machine learning model. In at least one embodiment, labeled clinic data 3512 (e.g., annotations provided by a clinician, doctor, scientist, etc.) may be used as ground truth
20 data for training a machine learning model. In at least one embodiment, retraining or updating a machine learning model may be referred to as model training 3514. In at least one embodiment, model training 3514 – e.g., AI-assisted annotations 3510, labeled clinic data 3512, or a combination thereof – may be used as ground truth data for retraining or updating a machine learning model.

25 [0528] In at least one embodiment, deployment system 3506 may include software 3518, services 3520, hardware 3522, and/or other components, features, and functionality. In at least one embodiment, deployment system 3506 may include a software “stack,” such that software 3518 may be built on top of services 3520 and may use services 3520 to perform some or all of processing tasks, and services 3520 and software 3518 may be built on top of
30 hardware 3522 and use hardware 3522 to execute processing, storage, and/or other compute tasks of deployment system 3506.

[0529] In at least one embodiment, software 3518 may include any number of different containers, where each container may execute an instantiation of an application. In at least one embodiment, each application may perform one or more processing tasks in an advanced
35 processing and inferencing pipeline (e.g., inferencing, object detection, feature detection, segmentation, image enhancement, calibration, etc.). In at least one embodiment, for each

5 type of imaging device (e.g., CT, MRI, X-Ray, ultrasound, sonography, echocardiography, etc.), sequencing device, radiology device, genomics device, etc., there may be any number of containers that may perform a data processing task with respect to imaging data 3508 (or other data types, such as those described herein) generated by a device. In at least one embodiment, an advanced processing and inferencing pipeline may be defined based on
10 selections of different containers that are desired or required for processing imaging data 3508, in addition to containers that receive and configure imaging data for use by each container and/or for use by facility 3502 after processing through a pipeline (e.g., to convert outputs back to a usable data type, such as digital imaging and communications in medicine (DICOM) data, radiology information system (RIS) data, clinical information system (CIS)
15 data, remote procedure call (RPC) data, data substantially compliant with a representation state transfer (REST) interface, data substantially compliant with a file-based interface, and/or raw data, for storage and display at facility 3502). In at least one embodiment, a combination of containers within software 3518 (e.g., that make up a pipeline) may be referred to as a virtual instrument (as described in more detail herein), and a virtual
20 instrument may leverage services 3520 and hardware 3522 to execute some or all processing tasks of applications instantiated in containers.

[0530] In at least one embodiment, a data processing pipeline may receive input data (e.g., imaging data 3508) in a DICOM, RIS, CIS, REST compliant, RPC, raw, and/or other format in response to an inference request (e.g., a request from a user of deployment system 3506,
25 such as a clinician, a doctor, a radiologist, etc.). In at least one embodiment, input data may be representative of one or more images, video, and/or other data representations generated by one or more imaging devices, sequencing devices, radiology devices, genomics devices, and/or other device types. In at least one embodiment, data may undergo pre-processing as part of data processing pipeline to prepare data for processing by one or more applications.
30 In at least one embodiment, post-processing may be performed on an output of one or more inferencing tasks or other processing tasks of a pipeline to prepare an output data for a next application and/or to prepare output data for transmission and/or use by a user (e.g., as a response to an inference request). In at least one embodiment, inferencing tasks may be performed by one or more machine learning models, such as trained or deployed neural
35 networks, which may include output models 3516 of training system 3504.

[0531] In at least one embodiment, tasks of data processing pipeline may be encapsulated in a container(s) that each represent a discrete, fully functional instantiation of an application

5 and virtualized computing environment that is able to reference machine learning models. In at least one embodiment, containers or applications may be published into a private (e.g., limited access) area of a container registry (described in more detail herein), and trained or deployed models may be stored in model registry 3524 and associated with one or more applications. In at least one embodiment, images of applications (e.g., container images) may
10 be available in a container registry, and once selected by a user from a container registry for deployment in a pipeline, an image may be used to generate a container for an instantiation of an application for use by a user's system.

[0532] In at least one embodiment, developers (e.g., software developers, clinicians, doctors, etc.) may develop, publish, and store applications (e.g., as containers) for performing
15 image processing and/or inferencing on supplied data. In at least one embodiment, development, publishing, and/or storing may be performed using a software development kit (SDK) associated with a system (e.g., to ensure that an application and/or container developed is compliant with or compatible with a system). In at least one embodiment, an application that is developed may be tested locally (e.g., at a first facility, on data from a first
20 facility) with an SDK which may support at least some of services 3520 as a system (e.g., system 3600 of FIG. 36). In at least one embodiment, because DICOM objects may contain anywhere from one to hundreds of images or other data types, and due to a variation in data, a developer may be responsible for managing (e.g., setting constructs for, building pre-processing into an application, etc.) extraction and preparation of incoming DICOM data. In
25 at least one embodiment, once validated by system 3600 (e.g., for accuracy, safety, patient privacy, etc.), an application may be available in a container registry for selection and/or implementation by a user (e.g., a hospital, clinic, lab, healthcare provider, etc.) to perform one or more processing tasks with respect to data at a facility (e.g., a second facility) of a user.

30 [0533] In at least one embodiment, developers may then share applications or containers through a network for access and use by users of a system (e.g., system 3600 of FIG. 36). In at least one embodiment, completed and validated applications or containers may be stored in a container registry and associated machine learning models may be stored in model registry 3524. In at least one embodiment, a requesting entity (e.g., a user at a medical facility) – who
35 provides an inference or image processing request – may browse a container registry and/or model registry 3524 for an application, container, dataset, machine learning model, etc., select a desired combination of elements for inclusion in data processing pipeline, and submit

5 an imaging processing request. In at least one embodiment, a request may include input data (and associated patient data, in some examples) that is necessary to perform a request, and/or may include a selection of application(s) and/or machine learning models to be executed in processing a request. In at least one embodiment, a request may then be passed to one or more components of deployment system 3506 (e.g., a cloud) to perform processing of data
10 processing pipeline. In at least one embodiment, processing by deployment system 3506 may include referencing selected elements (e.g., applications, containers, models, etc.) from a container registry and/or model registry 3524. In at least one embodiment, once results are generated by a pipeline, results may be returned to a user for reference (e.g., for viewing in a viewing application suite executing on a local, on-premises workstation or terminal). In at
15 least one embodiment, a radiologist may receive results from an data processing pipeline including any number of application and/or containers, where results may include anomaly detection in X-rays, CT scans, MRIs, etc.

[0534] In at least one embodiment, to aid in processing or execution of applications or containers in pipelines, services 3520 may be leveraged. In at least one embodiment, services
20 3520 may include compute services, artificial intelligence (AI) services, visualization services, and/or other service types. In at least one embodiment, services 3520 may provide functionality that is common to one or more applications in software 3518, so functionality may be abstracted to a service that may be called upon or leveraged by applications. In at least one embodiment, functionality provided by services 3520 may run dynamically and
25 more efficiently, while also scaling well by allowing applications to process data in parallel (e.g., using a parallel computing platform 3630 (FIG. 36)). In at least one embodiment, rather than each application that shares a same functionality offered by a service 3520 being required to have a respective instance of service 3520, service 3520 may be shared between and among various applications. In at least one embodiment, services may include an
30 inference server or engine that may be used for executing detection or segmentation tasks, as non-limiting examples. In at least one embodiment, a model training service may be included that may provide machine learning model training and/or retraining capabilities. In at least one embodiment, a data augmentation service may further be included that may provide GPU accelerated data (e.g., DICOM, RIS, CIS, REST compliant, RPC, raw, etc.) extraction,
35 resizing, scaling, and/or other augmentation. In at least one embodiment, a visualization service may be used that may add image rendering effects – such as ray-tracing, rasterization, denoising, sharpening, etc. – to add realism to two-dimensional (2D) and/or three-

5 dimensional (3D) models. In at least one embodiment, virtual instrument services may be included that provide for beam-forming, segmentation, inferencing, imaging, and/or support for other applications within pipelines of virtual instruments.

[0535] In at least one embodiment, where a service 3520 includes an AI service (e.g., an inference service), one or more machine learning models associated with an application for
10 anomaly detection (e.g., tumors, growth abnormalities, scarring, etc.) may be executed by calling upon (e.g., as an API call) an inference service (e.g., an inference server) to execute machine learning model(s), or processing thereof, as part of application execution. In at least one embodiment, where another application includes one or more machine learning models for segmentation tasks, an application may call upon an inference service to execute machine
15 learning models for performing one or more of processing operations associated with segmentation tasks. In at least one embodiment, software 3518 implementing advanced processing and inferencing pipeline that includes segmentation application and anomaly detection application may be streamlined because each application may call upon a same inference service to perform one or more inferencing tasks.

[0536] In at least one embodiment, hardware 3522 may include GPUs, CPUs, graphics cards, an AI/deep learning system (e.g., an AI supercomputer, such as NVIDIA's DGX supercomputer system), a cloud platform, or a combination thereof. In at least one
20 embodiment, different types of hardware 3522 may be used to provide efficient, purpose-built support for software 3518 and services 3520 in deployment system 3506. In at least one embodiment, use of GPU processing may be implemented for processing locally (e.g., at facility 3502), within an AI/deep learning system, in a cloud system, and/or in other processing components of deployment system 3506 to improve efficiency, accuracy, and efficacy of image processing, image reconstruction, segmentation, MRI exams, stroke or heart attack detection (e.g., in real-time), image quality in rendering, etc. In at least one
25 embodiment, a facility may include imaging devices, genomics devices, sequencing devices, and/or other device types on-premises that may leverage GPUs to generate imaging data representative of a subject's anatomy.

[0537] In at least one embodiment, software 3518 and/or services 3520 may be optimized for GPU processing with respect to deep learning, machine learning, and/or high-
35 performance computing, as non-limiting examples. In at least one embodiment, at least some of computing environment of deployment system 3506 and/or training system 3504 may be

5 executed in a datacenter one or more supercomputers or high performance computing
systems, with GPU optimized software (e.g., hardware and software combination of
NVIDIA's DGX system). In at least one embodiment, datacenters may be compliant with
provisions of HIPAA, such that receipt, processing, and transmission of imaging data and/or
other patient data is securely handled with respect to privacy of patient data. In at least one
10 embodiment, hardware 3522 may include any number of GPUs that may be called upon to
perform processing of data in parallel, as described herein. In at least one embodiment, cloud
platform may further include GPU processing for GPU-optimized execution of deep learning
tasks, machine learning tasks, or other computing tasks. In at least one embodiment, cloud
platform (e.g., NVIDIA's NGC) may be executed using an AI/deep learning
15 supercomputer(s) and/or GPU-optimized software (e.g., as provided on NVIDIA's DGX
systems) as a hardware abstraction and scaling platform. In at least one embodiment, cloud
platform may integrate an application container clustering system or orchestration system
(e.g., KUBERNETES) on multiple GPUs to enable seamless scaling and load balancing.

[0538] In at least one embodiment, one or more systems depicted in FIG. 35 are utilized to
20 implement a deep object detection network. In at least one embodiment, one or more systems
depicted in FIG. 35 are utilized to implement one or more networks and models such as those
described in connection with FIG. 1 and FIG. 3. In at least one embodiment, one or more
systems depicted in FIG. 35 are utilized to implement a network that is based on mixture
density networks and predicts uncertainty values of images. In at least one embodiment, one
25 or more systems depicted in FIG. 35 are utilized to implement an active learning method for
object detection that utilizes mixture density networks to produce one or more Gaussian
mixture models for each output of a network.

[0539] FIG. 36 is a system diagram for an example system 3600 for generating and
deploying an imaging deployment pipeline, in accordance with at least one embodiment. In
30 at least one embodiment, system 3600 may be used to implement process 3500 of FIG. 35
and/or other processes including advanced processing and inferencing pipelines. In at least
one embodiment, system 3600 may include training system 3504 and deployment system
3506. In at least one embodiment, training system 3504 and deployment system 3506 may be
implemented using software 3518, services 3520, and/or hardware 3522, as described herein.

35 [0540] In at least one embodiment, system 3600 (e.g., training system 3504 and/or
deployment system 3506) may implemented in a cloud computing environment (e.g., using

5 cloud 3626). In at least one embodiment, system 3600 may be implemented locally with respect to a healthcare services facility, or as a combination of both cloud and local computing resources. In at least one embodiment, in embodiments where cloud computing is implemented, patient data may be separated from, or unprocessed by, by one or more components of system 3600 that would render processing non-compliant with HIPAA and/or
10 other data handling and privacy regulations or laws. In at least one embodiment, access to APIs in cloud 3626 may be restricted to authorized users through enacted security measures or protocols. In at least one embodiment, a security protocol may include web tokens that may be signed by an authentication (e.g., AuthN, AuthZ, Gluecon, etc.) service and may carry appropriate authorization. In at least one embodiment, APIs of virtual instruments
15 (described herein), or other instantiations of system 3600, may be restricted to a set of public IPs that have been vetted or authorized for interaction.

[0541] In at least one embodiment, various components of system 3600 may communicate between and among one another using any of a variety of different network types, including but not limited to local area networks (LANs) and/or wide area networks (WANs) via wired
20 and/or wireless communication protocols. In at least one embodiment, communication between facilities and components of system 3600 (e.g., for transmitting inference requests, for receiving results of inference requests, etc.) may be communicated over a data bus or data busses, wireless data protocols (Wi-Fi), wired data protocols (e.g., Ethernet), etc.

[0542] In at least one embodiment, training system 3504 may execute training pipelines
25 3604, similar to those described herein with respect to FIG. 35. In at least one embodiment, where one or more machine learning models are to be used in deployment pipelines 3610 by deployment system 3506, training pipelines 3604 may be used to train or retrain one or more (e.g., pre-trained) models, and/or implement one or more of pre-trained models 3606 (e.g., without a need for retraining or updating). In at least one embodiment, as a result of training
30 pipelines 3604, output model(s) 3516 may be generated. In at least one embodiment, training pipelines 3604 may include any number of processing steps, such as but not limited to imaging data (or other input data) conversion or adaption (e.g., using DICOM adapter 3602A to convert DICOM images to another format suitable for processing by respective machine learning models, such as Neuroimaging Informatics Technology Initiative (NIfTI) format),
35 AI-assisted annotation 3510, labeling or annotating of imaging data 3508 to generate labeled clinic data 3512, model selection from a model registry, model training 3514, training, retraining, or updating models, and/or other processing steps. In at least one embodiment, for

5 different machine learning models used by deployment system 3506, different training pipelines 3604 may be used. In at least one embodiment, training pipeline 3604 similar to a first example described with respect to FIG. 35 may be used for a first machine learning model, training pipeline 3604 similar to a second example described with respect to FIG. 35 may be used for a second machine learning model, and training pipeline 3604 similar to a
10 third example described with respect to FIG. 35 may be used for a third machine learning model. In at least one embodiment, any combination of tasks within training system 3504 may be used depending on what is required for each respective machine learning model. In at least one embodiment, one or more of machine learning models may already be trained and ready for deployment so machine learning models may not undergo any processing by
15 training system 3504, and may be implemented by deployment system 3506.

[0543] In at least one embodiment, output model(s) 3516 and/or pre-trained model(s) 3606 may include any types of machine learning models depending on implementation or embodiment. In at least one embodiment, and without limitation, machine learning models used by system 3600 may include machine learning model(s) using linear regression, logistic
20 regression, decision trees, support vector machines (SVM), Naïve Bayes, k-nearest neighbor (Knn), K means clustering, random forest, dimensionality reduction algorithms, gradient boosting algorithms, neural networks (e.g., auto-encoders, convolutional, recurrent, perceptrons, Long/Short Term Memory (LSTM), Hopfield, Boltzmann, deep belief, deconvolutional, generative adversarial, liquid state machine, etc.), and/or other types of
25 machine learning models.

[0544] In at least one embodiment, training pipelines 3604 may include AI-assisted annotation, as described in more detail herein with respect to at least FIG. 39B. In at least one embodiment, labeled clinic data 3512 (e.g., traditional annotation) may be generated by any number of techniques. In at least one embodiment, labels or other annotations may be
30 generated within a drawing program (e.g., an annotation program), a computer aided design (CAD) program, a labeling program, another type of program suitable for generating annotations or labels for ground truth, and/or may be hand drawn, in some examples. In at least one embodiment, ground truth data may be synthetically produced (e.g., generated from computer models or renderings), real produced (e.g., designed and produced from real-world
35 data), machine-automated (e.g., using feature analysis and learning to extract features from data and then generate labels), human annotated (e.g., labeler, or annotation expert, defines location of labels), and/or a combination thereof. In at least one embodiment, for each

5 instance of imaging data 3508 (or other data type used by machine learning models), there may be corresponding ground truth data generated by training system 3504. In at least one embodiment, AI-assisted annotation may be performed as part of deployment pipelines 3610; either in addition to, or in lieu of AI-assisted annotation included in training pipelines 3604. In at least one embodiment, system 3600 may include a multi-layer platform that may include
10 a software layer (e.g., software 3518) of diagnostic applications (or other application types) that may perform one or more medical imaging and diagnostic functions. In at least one embodiment, system 3600 may be communicatively coupled to (e.g., via encrypted links) PACS server networks of one or more facilities. In at least one embodiment, system 3600 may be configured to access and referenced data (e.g., DICOM data, RIS data, raw data, CIS
15 data, REST compliant data, RPC data, raw data, etc.) from PACS servers (e.g., via a DICOM adapter 3602, or another data type adapter such as RIS, CIS, REST compliant, RPC, raw, etc.) to perform operations, such as training machine learning models, deploying machine learning models, image processing, inferencing, and/or other operations.

[0545] In at least one embodiment, a software layer may be implemented as a secure,
20 encrypted, and/or authenticated API through which applications or containers may be invoked (e.g., called) from an external environment(s) (e.g., facility 3502). In at least one embodiment, applications may then call or execute one or more services 3520 for performing compute, AI, or visualization tasks associated with respective applications, and software 3518 and/or services 3520 may leverage hardware 3522 to perform processing tasks in an effective
25 and efficient manner.

[0546] In at least one embodiment, deployment system 3506 may execute deployment pipelines 3610. In at least one embodiment, deployment pipelines 3610 may include any number of applications that may be sequentially, non-sequentially, or otherwise applied to imaging data (and/or other data types) generated by imaging devices, sequencing devices,
30 genomics devices, etc. – including AI-assisted annotation, as described above. In at least one embodiment, as described herein, a deployment pipeline 3610 for an individual device may be referred to as a virtual instrument for a device (e.g., a virtual ultrasound instrument, a virtual CT scan instrument, a virtual sequencing instrument, etc.). In at least one embodiment, for a single device, there may be more than one deployment pipeline 3610
35 depending on information desired from data generated by a device. In at least one embodiment, where detections of anomalies are desired from an MRI machine, there may be

5 a first deployment pipeline 3610, and where image enhancement is desired from output of an MRI machine, there may be a second deployment pipeline 3610.

[0547] In at least one embodiment, applications available for deployment pipelines 3610 may include any application that may be used for performing processing tasks on imaging data or other data from devices. In at least one embodiment, different applications may be
10 responsible for image enhancement, segmentation, reconstruction, anomaly detection, object detection, feature detection, treatment planning, dosimetry, beam planning (or other radiation treatment procedures), and/or other analysis, image processing, or inferencing tasks. In at least one embodiment, deployment system 3506 may define constructs for each of applications, such that users of deployment system 3506 (e.g., medical facilities, labs, clinics,
15 etc.) may understand constructs and adapt applications for implementation within their respective facility. In at least one embodiment, an application for image reconstruction may be selected for inclusion in deployment pipeline 3610, but data type generated by an imaging device may be different from a data type used within an application. In at least one embodiment, DICOM adapter 3602B (and/or a DICOM reader) or another data type adapter
20 or reader (e.g., RIS, CIS, REST compliant, RPC, raw, etc.) may be used within deployment pipeline 3610 to convert data to a form useable by an application within deployment system 3506. In at least one embodiment, access to DICOM, RIS, CIS, REST compliant, RPC, raw, and/or other data type libraries may be accumulated and pre-processed, including decoding, extracting, and/or performing any convolutions, color corrections, sharpness, gamma, and/or
25 other augmentations to data. In at least one embodiment, DICOM, RIS, CIS, REST compliant, RPC, and/or raw data may be unordered and a pre-pass may be executed to organize or sort collected data. In at least one embodiment, because various applications may share common image operations, in some embodiments, a data augmentation library (e.g., as one of services 3520) may be used to accelerate these operations. In at least one
30 embodiment, to avoid bottlenecks of conventional processing approaches that rely on CPU processing, parallel computing platform 3630 may be used for GPU acceleration of these processing tasks.

[0548] In at least one embodiment, an image reconstruction application may include a processing task that includes use of a machine learning model. In at least one embodiment, a
35 user may desire to use their own machine learning model, or to select a machine learning model from model registry 3524. In at least one embodiment, a user may implement their own machine learning model or select a machine learning model for inclusion in an

5 application for performing a processing task. In at least one embodiment, applications may be selectable and customizable, and by defining constructs of applications, deployment and implementation of applications for a particular user are presented as a more seamless user experience. In at least one embodiment, by leveraging other features of system 3600 – such as services 3520 and hardware 3522 – deployment pipelines 3610 may be even more user
10 friendly, provide for easier integration, and produce more accurate, efficient, and timely results.

[0549] In at least one embodiment, deployment system 3506 may include a user interface 3614 (e.g., a graphical user interface, a web interface, etc.) that may be used to select applications for inclusion in deployment pipeline(s) 3610, arrange applications, modify or
15 change applications or parameters or constructs thereof, use and interact with deployment pipeline(s) 3610 during set-up and/or deployment, and/or to otherwise interact with deployment system 3506. In at least one embodiment, although not illustrated with respect to training system 3504, user interface 3614 (or a different user interface) may be used for selecting models for use in deployment system 3506, for selecting models for training, or
20 retraining, in training system 3504, and/or for otherwise interacting with training system 3504.

[0550] In at least one embodiment, pipeline manager 3612 may be used, in addition to an application orchestration system 3628, to manage interaction between applications or containers of deployment pipeline(s) 3610 and services 3520 and/or hardware 3522. In at
25 least one embodiment, pipeline manager 3612 may be configured to facilitate interactions from application to application, from application to service 3520, and/or from application or service to hardware 3522. In at least one embodiment, although illustrated as included in software 3518, this is not intended to be limiting, and in some examples (e.g., as illustrated in FIG. 37) pipeline manager 3612 may be included in services 3520. In at least one
30 embodiment, application orchestration system 3628 (e.g., Kubernetes, DOCKER, etc.) may include a container orchestration system that may group applications into containers as logical units for coordination, management, scaling, and deployment. In at least one embodiment, by associating applications from deployment pipeline(s) 3610 (e.g., a reconstruction application, a segmentation application, etc.) with individual containers, each
35 application may execute in a self-contained environment (e.g., at a kernel level) to increase speed and efficiency.

5 [0551] In at least one embodiment, each application and/or container (or image thereof) may be individually developed, modified, and deployed (e.g., a first user or developer may develop, modify, and deploy a first application and a second user or developer may develop, modify, and deploy a second application separate from a first user or developer), which may allow for focus on, and attention to, a task of a single application and/or container(s) without
10 being hindered by tasks of another application(s) or container(s). In at least one embodiment, communication, and cooperation between different containers or applications may be aided by pipeline manager 3612 and application orchestration system 3628. In at least one embodiment, so long as an expected input and/or output of each container or application is known by a system (e.g., based on constructs of applications or containers), application
15 orchestration system 3628 and/or pipeline manager 3612 may facilitate communication among and between, and sharing of resources among and between, each of applications or containers. In at least one embodiment, because one or more of applications or containers in deployment pipeline(s) 3610 may share same services and resources, application orchestration system 3628 may orchestrate, load balance, and determine sharing of services
20 or resources between and among various applications or containers. In at least one embodiment, a scheduler may be used to track resource requirements of applications or containers, current usage or planned usage of these resources, and resource availability. In at least one embodiment, a scheduler may thus allocate resources to different applications and distribute resources between and among applications in view of requirements and availability
25 of a system. In some examples, a scheduler (and/or other component of application orchestration system 3628) may determine resource availability and distribution based on constraints imposed on a system (e.g., user constraints), such as quality of service (QoS), urgency of need for data outputs (e.g., to determine whether to execute real-time processing or delayed processing), etc.

30 [0552] In at least one embodiment, services 3520 leveraged by and shared by applications or containers in deployment system 3506 may include compute services 3616, AI services 3618, visualization services 3620, and/or other service types. In at least one embodiment, applications may call (e.g., execute) one or more of services 3520 to perform processing operations for an application. In at least one embodiment, compute services 3616 may be
35 leveraged by applications to perform super-computing or other high-performance computing (HPC) tasks. In at least one embodiment, compute service(s) 3616 may be leveraged to perform parallel processing (e.g., using a parallel computing platform 3630) for processing

5 data through one or more of applications and/or one or more tasks of a single application, substantially simultaneously. In at least one embodiment, parallel computing platform 3630 (e.g., NVIDIA's CUDA) may enable general purpose computing on GPUs (GPGPU) (e.g., GPUs 3622). In at least one embodiment, a software layer of parallel computing platform 3630 may provide access to virtual instruction sets and parallel computational elements of
10 GPUs, for execution of compute kernels. In at least one embodiment, parallel computing platform 3630 may include memory and, in some embodiments, a memory may be shared between and among multiple containers, and/or between and among different processing tasks within a single container. In at least one embodiment, inter-process communication (IPC) calls may be generated for multiple containers and/or for multiple processes within a
15 container to use same data from a shared segment of memory of parallel computing platform 3630 (e.g., where multiple different stages of an application or multiple applications are processing same information). In at least one embodiment, rather than making a copy of data and moving data to different locations in memory (e.g., a read/write operation), same data in same location of a memory may be used for any number of processing tasks (e.g., at a same
20 time, at different times, etc.). In at least one embodiment, as data is used to generate new data as a result of processing, this information of a new location of data may be stored and shared between various applications. In at least one embodiment, location of data and a location of updated or modified data may be part of a definition of how a payload is understood within containers.

25 [0553] In at least one embodiment, AI services 3618 may be leveraged to perform inferencing services for executing machine learning model(s) associated with applications (e.g., tasked with performing one or more processing tasks of an application). In at least one embodiment, AI services 3618 may leverage AI system 3624 to execute machine learning model(s) (e.g., neural networks, such as CNNs) for segmentation, reconstruction, object
30 detection, feature detection, classification, and/or other inferencing tasks. In at least one embodiment, applications of deployment pipeline(s) 3610 may use one or more of output models 3516 from training system 3504 and/or other models of applications to perform inference on imaging data (e.g., DICOM data, RIS data, CIS data, REST compliant data, RPC data, raw data, etc.). In at least one embodiment, two or more examples of inferencing
35 using application orchestration system 3628 (e.g., a scheduler) may be available. In at least one embodiment, a first category may include a high priority/low latency path that may achieve higher service level agreements, such as for performing inference on urgent requests

5 during an emergency, or for a radiologist during diagnosis. In at least one embodiment, a second category may include a standard priority path that may be used for requests that may be non-urgent or where analysis may be performed at a later time. In at least one embodiment, application orchestration system 3628 may distribute resources (e.g., services 3520 and/or hardware 3522) based on priority paths for different inferencing tasks of AI services 3618.

[0554] In at least one embodiment, shared storage may be mounted to AI services 3618 within system 3600. In at least one embodiment, shared storage may operate as a cache (or other storage device type) and may be used to process inference requests from applications. In at least one embodiment, when an inference request is submitted, a request may be received by a set of API instances of deployment system 3506, and one or more instances may be selected (e.g., for best fit, for load balancing, etc.) to process a request. In at least one embodiment, to process a request, a request may be entered into a database, a machine learning model may be located from model registry 3524 if not already in a cache, a validation step may ensure appropriate machine learning model is loaded into a cache (e.g., shared storage), and/or a copy of a model may be saved to a cache. In at least one embodiment, a scheduler (e.g., of pipeline manager 3612) may be used to launch an application that is referenced in a request if an application is not already running or if there are not enough instances of an application. In at least one embodiment, if an inference server is not already launched to execute a model, an inference server may be launched. In at least one embodiment, any number of inference servers may be launched per model. In at least one embodiment, in a pull model, in which inference servers are clustered, models may be cached whenever load balancing is advantageous. In at least one embodiment, inference servers may be statically loaded in corresponding, distributed servers.

[0555] In at least one embodiment, inferencing may be performed using an inference server that runs in a container. In at least one embodiment, an instance of an inference server may be associated with a model (and optionally a plurality of versions of a model). In at least one embodiment, if an instance of an inference server does not exist when a request to perform inference on a model is received, a new instance may be loaded. In at least one embodiment, when starting an inference server, a model may be passed to an inference server such that a same container may be used to serve different models so long as inference server is running as a different instance.

5 [0556] In at least one embodiment, during application execution, an inference request for a given application may be received, and a container (e.g., hosting an instance of an inference server) may be loaded (if not already), and a start procedure may be called. In at least one embodiment, pre-processing logic in a container may load, decode, and/or perform any additional pre-processing on incoming data (e.g., using a CPU(s) and/or GPU(s)). In at least one embodiment, once data is prepared for inference, a container may perform inference as necessary on data. In at least one embodiment, this may include a single inference call on one image (e.g., a hand X-ray), or may require inference on hundreds of images (e.g., a chest CT). In at least one embodiment, an application may summarize results before completing, which may include, without limitation, a single confidence score, pixel level-segmentation, voxel-level segmentation, generating a visualization, or generating text to summarize findings. In at least one embodiment, different models or applications may be assigned different priorities. For example, some models may have a real-time (TAT less than one minute) priority while others may have lower priority (e.g., TAT less than 10 minutes). In at least one embodiment, model execution times may be measured from requesting institution or entity and may include partner network traversal time, as well as execution on an inference service.

[0557] In at least one embodiment, transfer of requests between services 3520 and inference applications may be hidden behind a software development kit (SDK), and robust transport may be provide through a queue. In at least one embodiment, a request will be placed in a queue via an API for an individual application/tenant ID combination and an SDK will pull a request from a queue and give a request to an application. In at least one embodiment, a name of a queue may be provided in an environment from where an SDK will pick it up. In at least one embodiment, asynchronous communication through a queue may be useful as it may allow any instance of an application to pick up work as it becomes available. In at least one embodiment, results may be transferred back through a queue, to ensure no data is lost. In at least one embodiment, queues may also provide an ability to segment work, as highest priority work may go to a queue with most instances of an application connected to it, while lowest priority work may go to a queue with a single instance connected to it that processes tasks in an order received. In at least one embodiment, an application may run on a GPU-accelerated instance generated in cloud 3626, and an inference service may perform inferencing on a GPU.

5 [0558] In at least one embodiment, visualization services 3620 may be leveraged to generate visualizations for viewing outputs of applications and/or deployment pipeline(s) 3610. In at least one embodiment, GPUs 3622 may be leveraged by visualization services 3620 to generate visualizations. In at least one embodiment, rendering effects, such as ray-tracing, may be implemented by visualization services 3620 to generate higher quality
10 visualizations. In at least one embodiment, visualizations may include, without limitation, 2D image renderings, 3D volume renderings, 3D volume reconstruction, 2D tomographic slices, virtual reality displays, augmented reality displays, etc. In at least one embodiment, virtualized environments may be used to generate a virtual interactive display or environment (e.g., a virtual environment) for interaction by users of a system (e.g., doctors, nurses,
15 radiologists, etc.). In at least one embodiment, visualization services 3620 may include an internal visualizer, cinematics, and/or other rendering or image processing capabilities or functionality (e.g., ray tracing, rasterization, internal optics, etc.).

[0559] In at least one embodiment, hardware 3522 may include GPUs 3622, AI system 3624, cloud 3626, and/or any other hardware used for executing training system 3504 and/or
20 deployment system 3506. In at least one embodiment, GPUs 3622 (e.g., NVIDIA's TESLA and/or QUADRO GPUs) may include any number of GPUs that may be used for executing processing tasks of compute services 3616, AI services 3618, visualization services 3620, other services, and/or any of features or functionality of software 3518. For example, with respect to AI services 3618, GPUs 3622 may be used to perform pre-processing on imaging
25 data (or other data types used by machine learning models), post-processing on outputs of machine learning models, and/or to perform inferencing (e.g., to execute machine learning models). In at least one embodiment, cloud 3626, AI system 3624, and/or other components of system 3600 may use GPUs 3622. In at least one embodiment, cloud 3626 may include a GPU-optimized platform for deep learning tasks. In at least one embodiment, AI system
30 3624 may use GPUs, and cloud 3626 – or at least a portion tasked with deep learning or inferencing – may be executed using one or more AI systems 3624. As such, although hardware 3522 is illustrated as discrete components, this is not intended to be limiting, and any components of hardware 3522 may be combined with, or leveraged by, any other components of hardware 3522.

35 [0560] In at least one embodiment, AI system 3624 may include a purpose-built computing system (e.g., a super-computer or an HPC) configured for inferencing, deep learning, machine learning, and/or other artificial intelligence tasks. In at least one embodiment, AI

5 system 3624 (e.g., NVIDIA's DGX) may include GPU-optimized software (e.g., a software stack) that may be executed using a plurality of GPUs 3622, in addition to CPUs, RAM, storage, and/or other components, features, or functionality. In at least one embodiment, one or more AI systems 3624 may be implemented in cloud 3626 (e.g., in a data center) for performing some or all of AI-based processing tasks of system 3600.

10 [0561] In at least one embodiment, cloud 3626 may include a GPU-accelerated infrastructure (e.g., NVIDIA's NGC) that may provide a GPU-optimized platform for executing processing tasks of system 3600. In at least one embodiment, cloud 3626 may include an AI system(s) 3624 for performing one or more of AI-based tasks of system 3600 (e.g., as a hardware abstraction and scaling platform). In at least one embodiment, cloud
15 3626 may integrate with application orchestration system 3628 leveraging multiple GPUs to enable seamless scaling and load balancing between and among applications and services 3520. In at least one embodiment, cloud 3626 may tasked with executing at least some of services 3520 of system 3600, including compute services 3616, AI services 3618, and/or visualization services 3620, as described herein. In at least one embodiment, cloud 3626 may
20 perform small and large batch inference (e.g., executing NVIDIA's TENSOR RT), provide an accelerated parallel computing API and platform 3630 (e.g., NVIDIA's CUDA), execute application orchestration system 3628 (e.g., KUBERNETES), provide a graphics rendering API and platform (e.g., for ray-tracing, 2D graphics, 3D graphics, and/or other rendering techniques to produce higher quality cinematics), and/or may provide other functionality for
25 system 3600.

[0562] In at least one embodiment, in an effort to preserve patient confidentiality (e.g., where patient data or records are to be used off-premises), cloud 3626 may include a registry – such as a deep learning container registry. In at least one embodiment, a registry may store containers for instantiations of applications that may perform pre-processing, post-
30 processing, or other processing tasks on patient data. In at least one embodiment, cloud 3626 may receive data that includes patient data as well as sensor data in containers, perform requested processing for just sensor data in those containers, and then forward a resultant output and/or visualizations to appropriate parties and/or devices (e.g., on-premises medical devices used for visualization or diagnoses), all without having to extract, store, or otherwise
35 access patient data. In at least one embodiment, confidentiality of patient data is preserved in compliance with HIPAA and/or other data regulations.

5 [0563] In at least one embodiment, one or more systems depicted in FIG. 36 are utilized to implement a deep object detection network. In at least one embodiment, one or more systems depicted in FIG. 36 are utilized to implement one or more networks and models such as those described in connection with FIG. 1 and FIG. 3. In at least one embodiment, one or more systems depicted in FIG. 36 are utilized to implement a network that is based on mixture
10 density networks and predicts uncertainty values of images. In at least one embodiment, one or more systems depicted in FIG. 36 are utilized to implement an active learning method for object detection that utilizes mixture density networks to produce one or more Gaussian mixture models for each output of a network.

[0564] FIG. 37 includes an example illustration of a deployment pipeline 3610A for
15 processing imaging data, in accordance with at least one embodiment. In at least one embodiment, system 3600 – and specifically deployment system 3506 – may be used to customize, update, and/or integrate deployment pipeline(s) 3610A into one or more production environments. In at least one embodiment, deployment pipeline 3610A of FIG. 37 includes a non-limiting example of a deployment pipeline 3610A that may be custom
20 defined by a particular user (or team of users) at a facility (e.g., at a hospital, clinic, lab, research environment, etc.). In at least one embodiment, to define deployment pipelines 3610A for a CT scanner 3702, a user may select – from a container registry, for example – one or more applications that perform specific functions or tasks with respect to imaging data generated by CT scanner 3702. In at least one embodiment, applications may be applied to
25 deployment pipeline 3610A as containers that may leverage services 3520 and/or hardware 3522 of system 3600. In addition, deployment pipeline 3610A may include additional processing tasks or applications that may be implemented to prepare data for use by applications (e.g., DICOM adapter 3602B and DICOM reader 3706 may be used in deployment pipeline 3610A to prepare data for use by CT reconstruction 3708, organ
30 segmentation 3710, etc.). In at least one embodiment, deployment pipeline 3610A may be customized or selected for consistent deployment, one time use, or for another frequency or interval. In at least one embodiment, a user may desire to have CT reconstruction 3708 and organ segmentation 3710 for several subjects over a specific interval, and thus may deploy pipeline 3610A for that period of time. In at least one embodiment, a user may select, for
35 each request from system 3600, applications that a user wants to perform processing on that data for that request. In at least one embodiment, deployment pipeline 3610A may be

5 adjusted at any interval and, because of adaptability and scalability of a container structure within system 3600, this may be a seamless process.

[0565] In at least one embodiment, deployment pipeline 3610A of FIG. 37 may include CT scanner 3702 generating imaging data of a patient or subject. In at least one embodiment, imaging data from CT scanner 3702 may be stored on a PACS server(s) 3704 associated with
10 a facility housing CT scanner 3702. In at least one embodiment, PACS server(s) 3704 may include software and/or hardware components that may directly interface with imaging modalities (e.g., CT scanner 3702) at a facility. In at least one embodiment, DICOM adapter 3602B may enable sending and receipt of DICOM objects using DICOM protocols. In at least one embodiment, DICOM adapter 3602B may aid in preparation or configuration of
15 DICOM data from PACS server(s) 3704 for use by deployment pipeline 3610A. In at least one embodiment, once DICOM data is processed through DICOM adapter 3602B, pipeline manager 3612 may route data through to deployment pipeline 3610A. In at least one embodiment, DICOM reader 3706 may extract image files and any associated metadata from DICOM data (e.g., raw sinogram data, as illustrated in visualization 3716A). In at least one
20 embodiment, working files that are extracted may be stored in a cache for faster processing by other applications in deployment pipeline 3610A. In at least one embodiment, once DICOM reader 3706 has finished extracting and/or storing data, a signal of completion may be communicated to pipeline manager 3612. In at least one embodiment, pipeline manager 3612 may then initiate or call upon one or more other applications or containers in
25 deployment pipeline 3610A.

[0566] In at least one embodiment, CT reconstruction 3708 application and/or container may be executed once data (e.g., raw sinogram data) is available for processing by CT reconstruction 3708 application. In at least one embodiment, CT reconstruction 3708 may read raw sinogram data from a cache, reconstruct an image file out of raw sinogram data
30 (e.g., as illustrated in visualization 3716B), and store resulting image file in a cache. In at least one embodiment, at completion of reconstruction, pipeline manager 3612 may be signaled that reconstruction task is complete. In at least one embodiment, once reconstruction is complete, and a reconstructed image file may be stored in a cache (or other storage device), organ segmentation 3710 application and/or container may be triggered by
35 pipeline manager 3612. In at least one embodiment, organ segmentation 3710 application and/or container may read an image file from a cache, normalize or convert an image file to format suitable for inference (e.g., convert an image file to an input resolution of a machine

5 learning model), and run inference against a normalized image. In at least one embodiment, to run inference on a normalized image, organ segmentation 3710 application and/or container may rely on services 3520, and pipeline manager 3612 and/or application orchestration system 3628 may facilitate use of services 3520 by organ segmentation 3710 application and/or container. In at least one embodiment, for example, organ segmentation
10 3710 application and/or container may leverage AI services 3618 to perform inference on a normalized image, and AI services 3618 may leverage hardware 3522 (e.g., AI system 3624) to execute AI services 3618. In at least one embodiment, a result of an inference may be a mask file (e.g., as illustrated in visualization 3716C) that may be stored in a cache (or other storage device).

15 [0567] In at least one embodiment, once applications that process DICOM data and/or data extracted from DICOM data have completed processing, a signal may be generated for pipeline manager 3612. In at least one embodiment, pipeline manager 3612 may then execute DICOM writer 3712 to read results from a cache (or other storage device), package results into a DICOM format (e.g., as DICOM output 3714) for use by users at a facility who
20 generated a request. In at least one embodiment, DICOM output 3714 may then be transmitted to DICOM adapter 3602B to prepare DICOM output 3714 for storage on PACS server(s) 3704 (e.g., for viewing by a DICOM viewer at a facility). In at least one embodiment, in response to a request for reconstruction and segmentation, visualizations 3716B and 3716C may be generated and available to a user for diagnoses, research, and/or
25 for other purposes.

[0568] Although illustrated as consecutive application in deployment pipeline 3610A, CT reconstruction 3708 and organ segmentation 3710 applications may be processed in parallel in at least one embodiment. In at least one embodiment, where applications do not have dependencies on one another, and data is available for each application (e.g., after DICOM
30 reader 3706 extracts data), applications may be executed at a same time, substantially at a same time, or with some overlap. In at least one embodiment, where two or more applications require similar services 3520, a scheduler of system 3600 may be used to load balance and distribute compute or processing resources between and among various applications. In at least one embodiment, in some embodiments, parallel computing platform
35 3630 may be used to perform parallel processing for applications to decrease run-time of deployment pipeline 3610A to provide real-time results.

5 [0569] In at least one embodiment, and with reference to FIGS. 38A-38B, deployment system 3506 may be implemented as one or more virtual instruments to perform different functionalities – such as image processing, segmentation, enhancement, AI, visualization, and inferencing – with imaging devices (e.g., CT scanners, X-ray machines, MRI machines, etc.), sequencing devices, genomics devices, and/or other device types. In at least one
10 embodiment, system 3600 may allow for creation and provision of virtual instruments that may include a software-defined deployment pipeline 3610 that may receive raw/unprocessed input data generated by a device(s) and output processed/reconstructed data. In at least one embodiment, deployment pipelines 3610 (e.g., 3610A and 3610B) that represent virtual instruments may implement intelligence into a pipeline, such as by leveraging machine
15 learning models, to provide containerized inference support to a system. In at least one embodiment, virtual instruments may execute any number of containers each including instantiations of applications. In at least one embodiment, such as where real-time processing is desired, deployment pipelines 3610 representing virtual instruments may be static (e.g., containers and/or applications may be set), while in other examples, container and/or
20 applications for virtual instruments may be selected (e.g., on a per-request basis) from a pool of applications or resources (e.g., within a container registry).

[0570] In at least one embodiment, system 3600 may be instantiated or executed as one or more virtual instruments on-premise at a facility in, for example, a computing system deployed next to or otherwise in communication with a radiology machine, an imaging
25 device, and/or another device type at a facility. In at least one embodiment, however, an on-premise installation may be instantiated or executed within a computing system of a device itself (e.g., a computing system integral to an imaging device), in a local datacenter (e.g., a datacenter on-premise), and/or in a cloud-environment (e.g., in cloud 3626). In at least one embodiment, deployment system 3506, operating as a virtual instrument, may be instantiated
30 by a supercomputer or other HPC system in some examples. In at least one embodiment, on-premise installation may allow for high-bandwidth uses (via, for example, higher throughput local communication interfaces, such as RF over Ethernet) for real-time processing. In at least one embodiment, real-time or near real-time processing may be particularly useful where a virtual instrument supports an ultrasound device or other imaging modality where
35 immediate visualizations are expected or required for accurate diagnoses and analyses. In at least one embodiment, a cloud-computing architecture may be capable of dynamic bursting to a cloud computing service provider, or other compute cluster, when local demand exceeds

5 on-premise capacity or capability. In at least one embodiment, a cloud architecture, when implemented, may be tuned for training neural networks or other machine learning models, as described herein with respect to training system 3504. In at least one embodiment, with training pipelines in place, machine learning models may be continuously learn and improve as they process additional data from devices they support. In at least one embodiment, virtual
10 instruments may be continually improved using additional data, new data, existing machine learning models, and/or new or updated machine learning models.

[0571] In at least one embodiment, a computing system may include some or all of hardware 3522 described herein, and hardware 3522 may be distributed in any of a number of ways including within a device, as part of a computing device coupled to and located
15 proximate a device, in a local datacenter at a facility, and/or in cloud 3626. In at least one embodiment, because deployment system 3506 and associated applications or containers are created in software (e.g., as discrete containerized instantiations of applications), behavior, operation, and configuration of virtual instruments, as well as outputs generated by virtual instruments, may be modified or customized as desired, without having to change or alter raw
20 output of a device that a virtual instrument supports.

[0572] In at least one embodiment, one or more systems depicted in FIG. 37 are utilized to implement a deep object detection network. In at least one embodiment, one or more systems depicted in FIG. 37 are utilized to implement one or more networks and models such as those described in connection with FIG. 1 and FIG. 3. In at least one embodiment, one or more
25 systems depicted in FIG. 37 are utilized to implement a network that is based on mixture density networks and predicts uncertainty values of images. In at least one embodiment, one or more systems depicted in FIG. 37 are utilized to implement an active learning method for object detection that utilizes mixture density networks to produce one or more Gaussian mixture models for each output of a network.

[0573] FIG. 38A includes an example data flow diagram of a virtual instrument supporting an ultrasound device, in accordance with at least one embodiment. In at least one embodiment, deployment pipeline 3610B may leverage one or more of services 3520 of system 3600. In at least one embodiment, deployment pipeline 3610B and services 3520 may leverage hardware 3522 of a system either locally or in cloud 3626. In at least one
30 embodiment, although not illustrated, process 3800 may be facilitated by pipeline manager 3612, application orchestration system 3628, and/or parallel computing platform 3630.
35

- 5 [0574] In at least one embodiment, process 3800 may include receipt of imaging data from an ultrasound device 3802. In at least one embodiment, imaging data may be stored on PACS server(s) in a DICOM format (or other format, such as RIS, CIS, REST compliant, RPC, raw, etc.), and may be received by system 3600 for processing through deployment pipeline 3610 selected or customized as a virtual instrument (e.g., a virtual ultrasound) for
- 10 ultrasound device 3802. In at least one embodiment, imaging data may be received directly from an imaging device (e.g., ultrasound device 3802) and processed by a virtual instrument. In at least one embodiment, a transducer or other signal converter communicatively coupled between an imaging device and a virtual instrument may convert signal data generated by an imaging device to image data that may be processed by a virtual instrument. In at least one
- 15 embodiment, raw data and/or image data may be applied to DICOM reader 3706 to extract data for use by applications or containers of deployment pipeline 3610B. In at least one embodiment, DICOM reader 3706 may leverage data augmentation library 3814 (e.g., NVIDIA's DALI) as a service 3520 (e.g., as one of compute service(s) 3616) for extracting, resizing, rescaling, and/or otherwise preparing data for use by applications or containers.
- 20 [0575] In at least one embodiment, once data is prepared, a reconstruction 3806 application and/or container may be executed to reconstruct data from ultrasound device 3802 into an image file. In at least one embodiment, after reconstruction 3806, or at a same time as reconstruction 3806, a detection 3808 application and/or container may be executed for anomaly detection, object detection, feature detection, and/or other detection tasks related to
- 25 data. In at least one embodiment, an image file generated during reconstruction 3806 may be used during detection 3808 to identify anomalies, objects, features, etc. In at least one embodiment, detection 3808 application may leverage an inference engine 3816 (e.g., as one of AI service(s) 3618) to perform inference on data to generate detections. In at least one embodiment, one or more machine learning models (e.g., from training system 3504) may be
- 30 executed or called by detection 3808 application.
- [0576] In at least one embodiment, once reconstruction 3806 and/or detection 3808 is/are complete, data output from these application and/or containers may be used to generate visualizations 3810, such as visualization 3812 (e.g., a grayscale output) displayed on a workstation or display terminal. In at least one embodiment, visualization may allow a
- 35 technician or other user to visualize results of deployment pipeline 3610B with respect to ultrasound device 3802. In at least one embodiment, visualization 3810 may be executed by leveraging a render component 3818 of system 3600 (e.g., one of visualization service(s)

5 3620). In at least one embodiment, render component 3818 may execute a 2D, OpenGL, or ray-tracing service to generate visualization 3812.

[0577] FIG. 38B includes an example data flow diagram of a virtual instrument supporting a CT scanner, in accordance with at least one embodiment. In at least one embodiment, deployment pipeline 3610C may leverage one or more of services 3520 of system 3600. In at
10 least one embodiment, deployment pipeline 3610C and services 3520 may leverage hardware 3522 of a system either locally or in cloud 3626. In at least one embodiment, although not illustrated, process 3820 may be facilitated by pipeline manager 3612, application orchestration system 3628, and/or parallel computing platform 3630.

[0578] In at least one embodiment, process 3820 may include CT scanner 3822 generating
15 raw data that may be received by DICOM reader 3706 (e.g., directly, via a PACS server 3704, after processing, etc.). In at least one embodiment, a Virtual CT (instantiated by deployment pipeline 3610C) may include a first, real-time pipeline for monitoring a patient (e.g., patient movement detection AI 3826) and/or for adjusting or optimizing exposure of CT scanner 3822 (e.g., using exposure control AI 3824). In at least one embodiment, one or
20 more of applications (e.g., 3824 and 3826) may leverage a service 3520, such as AI service(s) 3618. In at least one embodiment, outputs of exposure control AI 3824 application (or container) and/or patient movement detection AI 3826 application (or container) may be used as feedback to CT scanner 3822 and/or a technician for adjusting exposure (or other settings of CT scanner 3822) and/or informing a patient to move less.

[0579] In at least one embodiment, deployment pipeline 3610C may include a non-real-time pipeline for analyzing data generated by CT scanner 3822. In at least one embodiment, a second pipeline may include CT reconstruction 3708 application and/or container, a coarse detection AI 3828 application and/or container, a fine detection AI 3832 application and/or container (e.g., where certain results are detected by coarse detection AI 3828), a
30 visualization 3830 application and/or container, and a DICOM writer 3712 (and/or other data type writer, such as RIS, CIS, REST compliant, RPC, raw, etc.) application and/or container. In at least one embodiment, raw data generated by CT scanner 3822 may be passed through pipelines of deployment pipeline 3610C (instantiated as a virtual CT instrument) to generate results. In at least one embodiment, results from DICOM writer 3712 may be transmitted for
35 display and/or may be stored on PACS server(s) 3704 for later retrieval, analysis, or display by a technician, practitioner, or other user.

5 [0580] In at least one embodiment, one or more systems depicted in FIGS. 38A-38B are utilized to implement a deep object detection network. In at least one embodiment, one or more systems depicted in FIGS. 38A-38B are utilized to implement one or more networks and models such as those described in connection with FIG. 1 and FIG. 3. In at least one embodiment, one or more systems depicted in FIGS. 38A-38B are utilized to implement a
10 network that is based on mixture density networks and predicts uncertainty values of images. In at least one embodiment, one or more systems depicted in FIGS. 38A-38B are utilized to implement an active learning method for object detection that utilizes mixture density networks to produce one or more Gaussian mixture models for each output of a network.

[0581] FIG. 39A illustrates a data flow diagram for a process 3900 to train, retrain, or
15 update a machine learning model, in accordance with at least one embodiment. In at least one embodiment, process 3900 may be executed using, as a non-limiting example, system 3600 of FIG. 36. In at least one embodiment, process 3900 may leverage services 3520 and/or hardware 3522 of system 3600, as described herein. In at least one embodiment, refined models 3912 generated by process 3900 may be executed by deployment system 3506
20 for one or more containerized applications in deployment pipelines 3610.

[0582] In at least one embodiment, model training 3514 may include retraining or updating an initial model 3904 (e.g., a pre-trained model) using new training data (e.g., new input data, such as customer dataset 3906, and/or new ground truth data associated with input data). In at least one embodiment, to retrain, or update, initial model 3904, output or loss layer(s) of
25 initial model 3904 may be reset, or deleted, and/or replaced with an updated or new output or loss layer(s). In at least one embodiment, initial model 3904 may have previously fine-tuned parameters (e.g., weights and/or biases) that remain from prior training, so training or retraining 3514 may not take as long or require as much processing as training a model from scratch. In at least one embodiment, during model training 3514, by having reset or replaced
30 output or loss layer(s) of initial model 3904, parameters may be updated and re-tuned for a new data set based on loss calculations associated with accuracy of output or loss layer(s) at generating predictions on new, customer dataset 3906 (e.g., image data 3508 of FIG. 35).

[0583] In at least one embodiment, pre-trained models 3606 may be stored in a data store, or registry (e.g., model registry 3524 of FIG. 35). In at least one embodiment, pre-trained
35 models 3606 may have been trained, at least in part, at one or more facilities other than a facility executing process 3900. In at least one embodiment, to protect privacy and rights of

5 patients, subjects, or clients of different facilities, pre-trained models 3606 may have been trained, on-premise, using customer or patient data generated on-premise. In at least one embodiment, pre-trained models 3606 may be trained using cloud 3626 and/or other hardware 3522, but confidential, privacy protected patient data may not be transferred to, used by, or accessible to any components of cloud 3626 (or other off premise hardware). In
10 at least one embodiment, where a pre-trained model 3606 is trained at using patient data from more than one facility, pre-trained model 3606 may have been individually trained for each facility prior to being trained on patient or customer data from another facility. In at least one embodiment, such as where a customer or patient data has been released of privacy concerns (e.g., by waiver, for experimental use, etc.), or where a customer or patient data is included in
15 a public data set, a customer or patient data from any number of facilities may be used to train pre-trained model 3606 on-premise and/or off premise, such as in a datacenter or other cloud computing infrastructure.

[0584] In at least one embodiment, when selecting applications for use in deployment pipelines 3610, a user may also select machine learning models to be used for specific
20 applications. In at least one embodiment, a user may not have a model for use, so a user may select a pre-trained model 3606 to use with an application. In at least one embodiment, pre-trained model 3606 may not be optimized for generating accurate results on customer dataset 3906 of a facility of a user (e.g., based on patient diversity, demographics, types of medical imaging devices used, etc.). In at least one embodiment, prior to deploying pre-trained model
25 3606 into deployment pipeline 3610 for use with an application(s), pre-trained model 3606 may be updated, retrained, and/or fine-tuned for use at a respective facility.

[0585] In at least one embodiment, a user may select pre-trained model 3606 that is to be updated, retrained, and/or fine-tuned, and pre-trained model 3606 may be referred to as initial model 3904 for training system 3504 within process 3900. In at least one embodiment,
30 customer dataset 3906 (e.g., imaging data, genomics data, sequencing data, or other data types generated by devices at a facility) may be used to perform model training 3514 (which may include, without limitation, transfer learning) on initial model 3904 to generate refined model 3912. In at least one embodiment, ground truth data corresponding to customer dataset 3906 may be generated by training system 3504. In at least one embodiment, ground
35 truth data may be generated, at least in part, by clinicians, scientists, doctors, practitioners, at a facility (e.g., as labeled clinic data 3512 of FIG. 35).

5 [0586] In at least one embodiment, AI-assisted annotation 3510 may be used in some examples to generate ground truth data. In at least one embodiment, AI-assisted annotation 3510 (e.g., implemented using an AI-assisted annotation SDK) may leverage machine learning models (e.g., neural networks) to generate suggested or predicted ground truth data for a customer dataset. In at least one embodiment, user 3910 may use annotation tools
10 within a user interface (a graphical user interface (GUI)) on computing device 3908.

[0587] In at least one embodiment, user 3910 may interact with a GUI via computing device 3908 to edit or fine-tune annotations or auto-annotations. In at least one embodiment, a polygon editing feature may be used to move vertices of a polygon to more accurate or fine-tuned locations.

15 [0588] In at least one embodiment, once customer dataset 3906 has associated ground truth data, ground truth data (e.g., from AI-assisted annotation, manual labeling, etc.) may be used by during model training 3514 to generate refined model 3912. In at least one embodiment, customer dataset 3906 may be applied to initial model 3904 any number of times, and ground truth data may be used to update parameters of initial model 3904 until an acceptable level of
20 accuracy is attained for refined model 3912. In at least one embodiment, once refined model 3912 is generated, refined model 3912 may be deployed within one or more deployment pipelines 3610 at a facility for performing one or more processing tasks with respect to medical imaging data.

[0589] In at least one embodiment, refined model 3912 may be uploaded to pre-trained
25 models 3606 in model registry 3524 to be selected by another facility. In at least one embodiment, his process may be completed at any number of facilities such that refined model 3912 may be further refined on new datasets any number of times to generate a more universal model.

[0590] FIG. 39B is an example illustration of a client-server architecture 3932 to enhance
30 annotation tools with pre-trained annotation models, in accordance with at least one embodiment. In at least one embodiment, AI-assisted annotation tools 3936 may be instantiated based on a client-server architecture 3932. In at least one embodiment, annotation tools 3936 in imaging applications may aid radiologists, for example, identify organs and abnormalities. In at least one embodiment, imaging applications may include
35 software tools that help user 3910 to identify, as a non-limiting example, a few extreme points on a particular organ of interest in raw images 3934 (e.g., in a 3D MRI or CT scan)

5 and receive auto-annotated results for all 2D slices of a particular organ. In at least one embodiment, results may be stored in a data store as training data 3938 and used as (for example and without limitation) ground truth data for training. In at least one embodiment, when computing device 3908 sends extreme points for AI-assisted annotation 3510, a deep learning model, for example, may receive this data as input and return inference results of a segmented organ or abnormality. In at least one embodiment, pre-instantiated annotation tools, such as AI-Assisted Annotation Tool 3936B in FIG. 39B, may be enhanced by making API calls (e.g., API Call 3944) to a server, such as an Annotation Assistant Server 3940 that may include a set of pre-trained models 3942 stored in an annotation model registry, for example. In at least one embodiment, an annotation model registry may store pre-trained models 3942 (e.g., machine learning models, such as deep learning models) that are pre-trained to perform AI-assisted annotation on a particular organ or abnormality. In at least one embodiment, these models may be further updated by using training pipelines 3604. In at least one embodiment, pre-installed annotation tools may be improved over time as new labeled clinic data 3512 is added.

20 [0591] Inference and/or training logic 615 are used to perform inferencing and/or training operations associated with one or more embodiments. Details regarding inference and/or training logic 615 are provided herein in conjunction with FIGS. 6A and/or 6B.

[0592] In at least one embodiment, one or more systems depicted in FIGS. 39A-39B are utilized to implement a deep object detection network. In at least one embodiment, one or more systems depicted in FIGS. 39A-39B are utilized to implement one or more networks and models such as those described in connection with FIG. 1 and FIG. 3. In at least one embodiment, one or more systems depicted in FIGS. 39A-39B are utilized to implement a network that is based on mixture density networks and predicts uncertainty values of images. In at least one embodiment, one or more systems depicted in FIGS. 39A-39B are utilized to implement an active learning method for object detection that utilizes mixture density networks to produce one or more Gaussian mixture models for each output of a network.

30 [0593] At least one embodiment of the disclosure can be described in view of the following clauses:

Clause 1. A processor comprising one or more circuits to use one or more neural networks to identify one or more objects in one or more images based, at least in part,

35

5 on a likelihood that the one or more objects is different from other objects in the one or more images.

Clause 2. The processor of clause 1, wherein the one or more circuits are to:

determine probability distributions for a set of properties of a plurality of
10 bounding boxes detected in the one or more images;
calculate one or more uncertainty values from the probability distributions;
and
aggregate the one or more uncertainty values to determine one or more
informativeness values for the one or more images.

15 Clause 3. The processor of clause 1 or 2, wherein the one or more neural networks are to further:

compare the one or more informativeness values with each other;
select a subset of the one or more images based at least in part on the
comparison of the one or more informativeness values with each other; and
20 train a neural network using the subset of the one or more images.

Clause 4. The processor of any of clauses 1-3, wherein one or more circuits are to:

determine a Gaussian mixture model (GMM) from the probability
distributions and weights corresponding to the probability distributions; and
25 use the GMM to calculate an aleatoric uncertainty value and epistemic
uncertainty value.

Clause 5. The processor of any of clauses 1-4, wherein the one or more circuits are to train the GMM using a mixture density network to regress one or more
localization parameters of the GMM using a negative log-likelihood loss function.

30 Clause 6. The processor of any of clauses 1-5, wherein the one or more circuits are to train the GMM using a mixture density network to regress one or more
classification parameters of the GMM using a loss function based at least in part on the
probability distributions and the weights.

5 Clause 7. The processor of any of clauses 1-6, wherein the probability distributions correspond to localization parameters of the plurality of bounding boxes and classification parameters of objects in the plurality of bounding boxes.

 Clause 8. A machine-readable medium having stored thereon a set of instructions, which if performed by one or more processors, cause the one or more processors
10 to use one or more neural networks to at least identify one or more objects in one or more images based, at least in part, on a likelihood that the one or more objects is different from other objects in the one or more images.

 Clause 9. The machine-readable medium of clause 8, wherein the one or more processors are to use the one or more neural networks to:
15 determine a first set of probability distributions and a second set of probability distributions based at least in part on one or more feature maps generated from the one or more images;
 determine a first set of uncertainty values based on the first set of probability distributions;
20 determine a second set of uncertainty values based on the second set of probability distributions; and
 aggregate the first set of uncertainty values and the second set of uncertainty values to determine an informativeness score.

 Clause 10. The machine-readable medium of clause 8 or 9, wherein the
25 one or more processors are to use the one or more neural networks to:
 determine one or more informativeness scores for the one or more images;
 obtain annotations for a subset of the one or more images; and
 train a neural network using at least the subset of the one or more images and the annotations.

30 Clause 11. The machine-readable medium of any of clauses 8-10, wherein the informativeness score is based at least in part on one or more maximum values of the first set of uncertainty values and the second set of uncertainty values.

 Clause 12. The machine-readable medium of any of clauses 8-11, wherein the first set of uncertainty values comprise aleatoric uncertainty values and epistemic
35 uncertainty values.

5 Clause 13. The machine-readable medium of any of clauses 8-12, wherein:
the first set of probability distributions corresponds to a location of one or
more bounding boxes; and
the second set of probability distributions corresponds to one or more different
object classifications.

10 Clause 14. The machine-readable medium of any of clauses 8-13, wherein:
the one or more neural networks are trained using a set of loss functions based
at least in part on the first set of probability distributions and the second set of probability
distributions; and
the set of loss functions comprise one or more classification loss functions and
15 one or more localization loss functions.

 Clause 15. A system comprising:
one or more processors to use one or more neural networks to identify one or
more objects in one or more images based, at least in part, on a likelihood that the one or
more objects is different from other objects in the one or more images; and
20 one or more memories to store the one or more neural networks.

 Clause 16. The system of clause 15, wherein the one or more processors
are to use the one or more neural networks to:
determine one or more probability distributions based at least in part on the
one or more images;
25 calculate one or more informativeness scores for the one or more images based
at least in part on the one or more probability distributions;
determine a subset of the one or more images based at least in part on the one
or more informativeness scores;
obtain annotations for the subset of the one or more images; and
30 train a neural network using at least the annotations and the subset of the one
or more images.

 Clause 17. The system of clause 15 or 16, wherein:
the one or more neural networks are trained using one or more loss functions
based at least in part on the one or more probability distributions; and

5 the one or more loss functions comprise localization loss functions and classification loss functions.

 Clause 18. The system of any of clauses 15-17, wherein the one or more probability distributions comprise one or more localization probability distributions and one or more classification probability distributions.

10 Clause 19. The system of any of clauses 15-18, wherein the one or more probability distributions are defined by a plurality of parameter values that comprise:
 a set of mean parameter values;
 a set of variance parameter values; and
 a set of weight parameter values.

15 Clause 20. The system of any of clauses 15-19, wherein the one or more processors are to use the one or more neural networks to:
 calculate one or more aleatoric uncertainty values at least from the set of variance parameter values and the set of weight parameter values; and
 calculate one or more epistemic uncertainty values at least from the set of
20 mean parameter values and the set of weight parameter values.

 Clause 21. The system of any of clauses 15-20, wherein the one or more informativeness scores are calculated based at least in part on the one or more aleatoric uncertainty values and the one or more epistemic uncertainty values.

 Clause 22. A processor comprising: one or more circuits to train one or
25 more neural networks to identify one or more objects in one or more images based, at least in part, on a likelihood that the one or more objects is different from other objects in the one or more images.

 Clause 23. The processor of clause 22, wherein the one or more circuits are to use the one or more neural networks to:
30 determine a plurality of probability distributions based at least in part on the one or more images, wherein the plurality of probability distributions indicate the likelihood that the one or more objects is different from the other objects in the one or more images;
 calculate a plurality of uncertainty values based at least in part on the plurality of probability distributions;

5 determine a plurality of informativeness scores based at least in part on the
plurality of uncertainty values;
 compare informativeness scores of the plurality of informativeness scores with
each other;
 select a subset of the one or more images based at least in part on the
10 comparison of the informativeness scores of the plurality of informativeness scores with each
other;
 obtain annotations for the subset of the one or more images, wherein the
annotations indicate locations and classifications of objects in the subset of the one or more
images; and
15 train a neural network using the subset of the one or more images and the
annotations.

Clause 24. The processor of clause 22 or 23, wherein the one or more
images are obtained from one or more viewpoints of a motor vehicle.

20 Clause 25. The processor of any of clauses 22-24, wherein the plurality of
probability distributions comprise a plurality of localization probability distributions and a
plurality of classification probability distributions.

Clause 26. The processor of any of clauses 22-25, wherein the plurality of
informativeness scores are based at least in part on one or more maximum values of the
plurality of uncertainty values.

25 Clause 27. The processor of any of clauses 22-26, wherein:
 the plurality of localization probability distributions correspond to coordinates
of one or more locations of the one or more objects; and
 the plurality of classification probability distributions correspond to one or
more classifications of the one or more objects.

30 Clause 28. The processor of any of clauses 22-27, wherein the one or more
circuits are to use the one or more neural networks to:
 calculate a classification loss based at least in part on the plurality of
classification probability distributions;
 calculate a localization loss based at least in part on the plurality of
35 localization probability distributions; and

5 update the one or more neural networks based at least in part on the
classification loss and the localization loss.

 Clause 29. A machine-readable medium having stored thereon a set of
instructions, which if performed by one or more processors, cause the one or more processors
to at least: cause one or more neural networks to be trained to identify one or more objects in
10 one or more images based, at least in part, on a likelihood that the one or more objects is
different from other objects in the one or more images.

 Clause 30. The machine-readable medium of clause 29, wherein the one or
more processors are to use the one or more neural networks to:
 determine a first set of probability distributions and a second set of probability
15 distributions based at least in part on one or more feature maps generated from the one or
more images;
 determine a first set of uncertainty values based on the first set of probability
distributions;
 determine a second set of uncertainty values based on the second set of
20 probability distributions;
 aggregate the first set of uncertainty values and the second set of uncertainty
values to determine one or more informativeness scores for the one or more images;
 obtain a set of annotations for a subset of the one or more images; and
 train a neural network using at least the set of annotations and the subset of the
25 one or more images.

 Clause 31. The machine-readable medium of clause 29 or 30, wherein the
subset of the one or more images is determined based at least in part on the one or more
informativeness scores.

 Clause 32. The machine-readable medium of any of clauses 29-31,
30 wherein the first set of uncertainty values and the second set of uncertainty values comprise
aleatoric uncertainty values and epistemic uncertainty values.

 Clause 33. The machine-readable medium of any of clauses 29-32,
wherein each probability distribution of the first set of probability distributions and the
second set of probability distributions is represented as a Gaussian Mixture Model (GMM).

5 Clause 34. The machine-readable medium of any of clauses 29-33,
wherein the one or more neural networks are to further:
 determine one or more mean parameter values of the first set of probability
distributions and the second set of probability distributions;
 determine one or more variance parameter values of the first set of probability
10 distributions and the second set of probability distributions; and
 determine one or more weight parameter values of the first set of probability
distributions and the second set of probability distributions.

 Clause 35. The machine-readable medium of any of clauses 29-34,
wherein the first set of uncertainty values are determined through a first set of summations
15 based at least in part on one or more products of the one or more variance parameter values
and the one or more weight parameter values, and the second set of uncertainty values are
determined through a second set of summations based at least in part on the one or more
mean parameter values and the one or more weight parameter values.

 Clause 36. The machine-readable medium of any of clauses 29-35,
20 wherein the first set of uncertainty values correspond to aleatoric uncertainty and the second
set of uncertainty values are correspond to epistemic uncertainty.

[0594] In at least one embodiment, a single semiconductor platform may refer to a sole
unitary semiconductor-based integrated circuit or chip. In at least one embodiment, multi-
25 chip modules may be used with increased connectivity which simulate on-chip operation, and
make substantial improvements over utilizing a conventional central processing unit (“CPU”)
and bus implementation. In at least one embodiment, various modules may also be situated
separately or in various combinations of semiconductor platforms per desires of user.

[0595] In at least one embodiment, referring back to FIG. 12, computer programs in form
30 of machine-readable executable code or computer control logic algorithms are stored in main
memory 1204 and/or secondary storage. Computer programs, if executed by one or more
processors, enable system 1200 to perform various functions in accordance with at least one
embodiment. In at least one embodiment, memory 1204, storage, and/or any other storage
are possible examples of computer-readable media. In at least one embodiment, secondary
35 storage may refer to any suitable storage device or system such as a hard disk drive and/or a
removable storage drive, representing a floppy disk drive, a magnetic tape drive, a compact

5 disk drive, digital versatile disk (“DVD”) drive, recording device, universal serial bus (“USB”) flash memory, etc. In at least one embodiment, architecture and/or functionality of various previous figures are implemented in context of CPU 1202, parallel processing system 1212, an integrated circuit capable of at least a portion of capabilities of both CPU 1202, parallel processing system 1212, a chipset (e.g., a group of integrated circuits designed to
10 work and sold as a unit for performing related functions, etc.), and/or any suitable combination of integrated circuit(s).

[0596] In at least one embodiment, architecture and/or functionality of various previous figures are implemented in context of a general computer system, a circuit board system, a game console system dedicated for entertainment purposes, an application-specific system,
15 and more. In at least one embodiment, computer system 1200 may take form of a desktop computer, a laptop computer, a tablet computer, servers, supercomputers, a smart-phone (e.g., a wireless, hand-held device), personal digital assistant (“PDA”), a digital camera, a vehicle, a head mounted display, a hand-held electronic device, a mobile phone device, a television, workstation, game consoles, embedded system, and/or any other type of logic.

20 [0597] In at least one embodiment, parallel processing system 1212 includes, without limitation, a plurality of parallel processing units (“PPUs”) 1214 and associated memories 1216. In at least one embodiment, PPUs 1214 are connected to a host processor or other peripheral devices via an interconnect 1218 and a switch 1220 or multiplexer. In at least one embodiment, parallel processing system 1212 distributes computational tasks across PPUs
25 1214 which can be parallelizable — for example, as part of distribution of computational tasks across multiple graphics processing unit (“GPU”) thread blocks. In at least one embodiment, memory is shared and accessible (e.g., for read and/or write access) across some or all of PPUs 1214, although such shared memory may incur performance penalties relative to use of local memory and registers resident to a PPU 1214. In at least one
30 embodiment, operation of PPUs 1214 is synchronized through use of a command such as __syncthreads(), wherein all threads in a block (e.g., executed across multiple PPUs 1214) to reach a certain point of execution of code before proceeding.

[0598] Other variations are within spirit of present disclosure. Thus, while disclosed techniques are susceptible to various modifications and alternative constructions, certain
35 illustrated embodiments thereof are shown in drawings and have been described above in detail. It should be understood, however, that there is no intention to limit disclosure to

5 specific form or forms disclosed, but on contrary, intention is to cover all modifications, alternative constructions, and equivalents falling within spirit and scope of disclosure, as defined in appended claims.

[0599] Use of terms “a” and “an” and “the” and similar referents in context of describing disclosed embodiments (especially in context of following claims) are to be construed to
10 cover both singular and plural, unless otherwise indicated herein or clearly contradicted by context, and not as a definition of a term. Terms “comprising,” “having,” “including,” and “containing” are to be construed as open-ended terms (meaning “including, but not limited to,”) unless otherwise noted. “Connected,” when unmodified and referring to physical connections, is to be construed as partly or wholly contained within, attached to, or joined
15 together, even if there is something intervening. Recitation of ranges of values herein are merely intended to serve as a shorthand method of referring individually to each separate value falling within range, unless otherwise indicated herein and each separate value is incorporated into specification as if it were individually recited herein. In at least one embodiment, use of term “set” (e.g., “a set of items”) or “subset” unless otherwise noted or
20 contradicted by context, is to be construed as a nonempty collection comprising one or more members. Further, unless otherwise noted or contradicted by context, term “subset” of a corresponding set does not necessarily denote a proper subset of corresponding set, but subset and corresponding set may be equal.

[0600] Conjunctive language, such as phrases of form “at least one of A, B, and C,” or “at
25 least one of A, B and C,” unless specifically stated otherwise or otherwise clearly contradicted by context, is otherwise understood with context as used in general to present that an item, term, etc., may be either A or B or C, or any nonempty subset of set of A and B and C. For instance, in illustrative example of a set having three members, conjunctive phrases “at least one of A, B, and C” and “at least one of A, B and C” refer to any of
30 following sets: {A}, {B}, {C}, {A, B}, {A, C}, {B, C}, {A, B, C}. Thus, such conjunctive language is not generally intended to imply that certain embodiments require at least one of A, at least one of B and at least one of C each to be present. In addition, unless otherwise noted or contradicted by context, term “plurality” indicates a state of being plural (e.g., “a plurality of items” indicates multiple items). In at least one embodiment, number of items in
35 a plurality is at least two, but can be more when so indicated either explicitly or by context. Further, unless stated otherwise or otherwise clear from context, phrase “based on” means “based at least in part on” and not “based solely on.”

5 [0601] Operations of processes described herein can be performed in any suitable order unless otherwise indicated herein or otherwise clearly contradicted by context. In at least one embodiment, a process such as those processes described herein (or variations and/or combinations thereof) is performed under control of one or more computer systems configured with executable instructions and is implemented as code (e.g., executable
10 instructions, one or more computer programs or one or more applications) executing collectively on one or more processors, by hardware or combinations thereof. In at least one embodiment, code is stored on a computer-readable storage medium, for example, in form of a computer program comprising a plurality of instructions executable by one or more processors. In at least one embodiment, a computer-readable storage medium is a non-
15 transitory computer-readable storage medium that excludes transitory signals (e.g., a propagating transient electric or electromagnetic transmission) but includes non-transitory data storage circuitry (e.g., buffers, cache, and queues) within transceivers of transitory signals. In at least one embodiment, code (e.g., executable code or source code) is stored on a set of one or more non-transitory computer-readable storage media having stored thereon
20 executable instructions (or other memory to store executable instructions) that, when executed (i.e., as a result of being executed) by one or more processors of a computer system, cause computer system to perform operations described herein. In at least one embodiment, set of non-transitory computer-readable storage media comprises multiple non-transitory computer-readable storage media and one or more of individual non-transitory storage media
25 of multiple non-transitory computer-readable storage media lack all of code while multiple non-transitory computer-readable storage media collectively store all of code. In at least one embodiment, executable instructions are executed such that different instructions are executed by different processors — for example, a non-transitory computer-readable storage medium store instructions and a main central processing unit (“CPU”) executes some of
30 instructions while a graphics processing unit (“GPU”) executes other instructions. In at least one embodiment, different components of a computer system have separate processors and different processors execute different subsets of instructions.

[0602] Accordingly, in at least one embodiment, computer systems are configured to implement one or more services that singly or collectively perform operations of processes
35 described herein and such computer systems are configured with applicable hardware and/or software that enable performance of operations. Further, a computer system that implements at least one embodiment of present disclosure is a single device and, in another embodiment,

5 is a distributed computer system comprising multiple devices that operate differently such that distributed computer system performs operations described herein and such that a single device does not perform all operations.

[0603] Use of any and all examples, or exemplary language (e.g., “such as”) provided herein, is intended merely to better illuminate embodiments of disclosure and does not pose a
10 limitation on scope of disclosure unless otherwise claimed. No language in specification should be construed as indicating any non-claimed element as essential to practice of disclosure.

[0604] All references, including publications, patent applications, and patents, cited herein are hereby incorporated by reference to same extent as if each reference were individually
15 and specifically indicated to be incorporated by reference and were set forth in its entirety herein.

[0605] In description and claims, terms “coupled” and “connected,” along with their derivatives, may be used. It should be understood that these terms may be not intended as synonyms for each other. Rather, in particular examples, “connected” or “coupled” may be
20 used to indicate that two or more elements are in direct or indirect physical or electrical contact with each other. “Coupled” may also mean that two or more elements are not in direct contact with each other, but yet still co-operate or interact with each other.

[0606] Unless specifically stated otherwise, it may be appreciated that throughout specification terms such as “processing,” “computing,” “calculating,” “determining,” or like,
25 refer to action and/or processes of a computer or computing system, or similar electronic computing device, that manipulate and/or transform data represented as physical, such as electronic, quantities within computing system’s registers and/or memories into other data similarly represented as physical quantities within computing system’s memories, registers or other such information storage, transmission or display devices.

[0607] In a similar manner, term “processor” may refer to any device or portion of a device
30 that processes electronic data from registers and/or memory and transform that electronic data into other electronic data that may be stored in registers and/or memory. As non-limiting examples, “processor” may be a CPU or a GPU. A “computing platform” may comprise one or more processors. As used herein, “software” processes may include, for example,
35 software and/or hardware entities that perform work over time, such as tasks, threads, and intelligent agents. Also, each process may refer to multiple processes, for carrying out

5 instructions in sequence or in parallel, continuously or intermittently. In at least one embodiment, terms “system” and “method” are used herein interchangeably insofar as system may embody one or more methods and methods may be considered a system.

[0608] In present document, references may be made to obtaining, acquiring, receiving, or inputting analog or digital data into a subsystem, computer system, or computer-implemented
10 machine. In at least one embodiment, process of obtaining, acquiring, receiving, or inputting analog and digital data can be accomplished in a variety of ways such as by receiving data as a parameter of a function call or a call to an application programming interface. In at least one embodiment, processes of obtaining, acquiring, receiving, or inputting analog or digital data can be accomplished by transferring data via a serial or parallel interface. In at least one
15 embodiment, processes of obtaining, acquiring, receiving, or inputting analog or digital data can be accomplished by transferring data via a computer network from providing entity to acquiring entity. In at least one embodiment, references may also be made to providing, outputting, transmitting, sending, or presenting analog or digital data. In various examples, processes of providing, outputting, transmitting, sending, or presenting analog or digital data
20 can be accomplished by transferring data as an input or output parameter of a function call, a parameter of an application programming interface or interprocess communication mechanism.

[0609] Although descriptions herein set forth example implementations of described techniques, other architectures may be used to implement described functionality, and are
25 intended to be within scope of this disclosure. Furthermore, although specific distributions of responsibilities may be defined above for purposes of description, various functions and responsibilities might be distributed and divided in different ways, depending on circumstances.

[0610] Furthermore, although subject matter has been described in language specific to
30 structural features and/or methodological acts, it is to be understood that subject matter claimed in appended claims is not necessarily limited to specific features or acts described. Rather, specific features and acts are disclosed as exemplary forms of implementing the claims.

CLAIMS

WHAT IS CLAIMED IS:

1. A processor, comprising: one or more circuits to use one or more neural networks to identify one or more objects in one or more images based, at least in part, on a likelihood that the one or more objects is different from other objects in the one or more images.
2. The processor of claim 1, wherein the one or more circuits are to:
determine probability distributions for a set of properties of a plurality of bounding boxes detected in the one or more images;
calculate one or more uncertainty values from the probability distributions;
and
aggregate the one or more uncertainty values to determine one or more informativeness values for the one or more images.
3. The processor of claim 2, wherein the one or more neural networks are to further:
compare the one or more informativeness values with each other;
select a subset of the one or more images based at least in part on the comparison of the one or more informativeness values with each other; and
train a neural network using the subset of the one or more images.
4. The processor of claim 2, wherein one or more circuits are to:
determine a Gaussian mixture model (GMM) from the probability distributions and weights corresponding to the probability distributions; and
use the GMM to calculate an aleatoric uncertainty value and epistemic uncertainty value.
5. The processor of claim 4, wherein the one or more circuits are to train the GMM using a mixture density network to regress one or more localization parameters of the GMM using a negative log-likelihood loss function.

6. The processor of claim 4, wherein the one or more circuits are to train the GMM using a mixture density network to regress one or more classification parameters of the GMM using a loss function based at least in part on the probability distributions and the weights.

7. The processor of claim 2, wherein the probability distributions correspond to localization parameters of the plurality of bounding boxes and classification parameters of objects in the plurality of bounding boxes.

8. A machine-readable medium having stored thereon a set of instructions, which if performed by one or more processors, cause the one or more processors to use one or more neural networks to at least identify one or more objects in one or more images based, at least in part, on a likelihood that the one or more objects is different from other objects in the one or more images.

9. The machine-readable medium of claim 8, wherein the one or more processors are to use the one or more neural networks to:

determine a first set of probability distributions and a second set of probability distributions based at least in part on one or more feature maps generated from the one or more images;

determine a first set of uncertainty values based on the first set of probability distributions;

determine a second set of uncertainty values based on the second set of probability distributions; and

aggregate the first set of uncertainty values and the second set of uncertainty values to determine an informativeness score.

10. The machine-readable medium of claim 8, wherein the one or more processors are to use the one or more neural networks to:

determine one or more informativeness scores for the one or more images;

obtain annotations for a subset of the one or more images; and

train a neural network using at least the subset of the one or more images and the annotations.

11. The machine-readable medium of claim 9, wherein the informativeness score is based at least in part on one or more maximum values of the first set of uncertainty values and the second set of uncertainty values.

12. The machine-readable medium of claim 9, wherein the first set of uncertainty values comprise aleatoric uncertainty values and epistemic uncertainty values.

13. The machine-readable medium of claim 9, wherein:
the first set of probability distributions corresponds to a location of one or more bounding boxes; and
the second set of probability distributions corresponds to one or more different object classifications.

14. The machine-readable medium of claim 9, wherein:
the one or more neural networks are trained using a set of loss functions based at least in part on the first set of probability distributions and the second set of probability distributions; and
the set of loss functions comprise one or more classification loss functions and one or more localization loss functions.

15. A system comprising:
one or more processors to use one or more neural networks to identify one or more objects in one or more images based, at least in part, on a likelihood that the one or more objects is different from other objects in the one or more images; and
one or more memories to store the one or more neural networks.

16. The system of claim 15, wherein the one or more processors are to use the one or more neural networks to:
determine one or more probability distributions based at least in part on the one or more images;
calculate one or more informativeness scores for the one or more images based at least in part on the one or more probability distributions;
determine a subset of the one or more images based at least in part on the one or more informativeness scores;
obtain annotations for the subset of the one or more images; and

train a neural network using at least the annotations and the subset of the one or more images.

17. The system of claim 16, wherein:

the one or more neural networks are trained using one or more loss functions based at least in part on the one or more probability distributions; and
the one or more loss functions comprise localization loss functions and classification loss functions.

18. The system of claim 16, wherein the one or more probability distributions comprise one or more localization probability distributions and one or more classification probability distributions.

19. The system of claim 16, wherein the one or more probability distributions are defined by a plurality of parameter values that comprise:

a set of mean parameter values;
a set of variance parameter values; and
a set of weight parameter values.

20. The system of claim 19, wherein the one or more processors are to use the one or more neural networks to:

calculate one or more aleatoric uncertainty values at least from the set of variance parameter values and the set of weight parameter values; and
calculate one or more epistemic uncertainty values at least from the set of mean parameter values and the set of weight parameter values.

21. The system of claim 20, wherein the one or more informativeness scores are calculated based at least in part on the one or more aleatoric uncertainty values and the one or more epistemic uncertainty values.

22. A processor comprising: one or more circuits to train one or more neural networks to identify one or more objects in one or more images based, at least in part, on a likelihood that the one or more objects is different from other objects in the one or more images.

23. The processor of claim 22, wherein the one or more circuits are to use the one or more neural networks to:

determine a plurality of probability distributions based at least in part on the one or more images, wherein the plurality of probability distributions indicate the likelihood that the one or more objects is different from the other objects in the one or more images;

calculate a plurality of uncertainty values based at least in part on the plurality of probability distributions;

determine a plurality of informativeness scores based at least in part on the plurality of uncertainty values;

compare informativeness scores of the plurality of informativeness scores with each other;

select a subset of the one or more images based at least in part on the comparison of the informativeness scores of the plurality of informativeness scores with each other;

obtain annotations for the subset of the one or more images, wherein the annotations indicate locations and classifications of objects in the subset of the one or more images; and

train a neural network using the subset of the one or more images and the annotations.

24. The processor of claim 23, wherein the one or more images are obtained from one or more viewpoints of a motor vehicle.

25. The processor of claim 23, wherein the plurality of probability distributions comprise a plurality of localization probability distributions and a plurality of classification probability distributions.

26. The processor of claim 23, wherein the plurality of informativeness scores are based at least in part on one or more maximum values of the plurality of uncertainty values.

27. The processor of claim 25, wherein:
the plurality of localization probability distributions correspond to coordinates of one or more locations of the one or more objects; and

the plurality of classification probability distributions correspond to one or more classifications of the one or more objects.

28. The processor of claim 25, wherein the one or more circuits are to use the one or more neural networks to:

calculate a classification loss based at least in part on the plurality of classification probability distributions;

calculate a localization loss based at least in part on the plurality of localization probability distributions; and

update the one or more neural networks based at least in part on the classification loss and the localization loss.

29. A machine-readable medium having stored thereon a set of instructions, which if performed by one or more processors, cause the one or more processors to at least: cause one or more neural networks to be trained to identify one or more objects in one or more images based, at least in part, on a likelihood that the one or more objects is different from other objects in the one or more images.

30. The machine-readable medium of claim 29, wherein the one or more processors are to use the one or more neural networks to:

determine a first set of probability distributions and a second set of probability distributions based at least in part on one or more feature maps generated from the one or more images;

determine a first set of uncertainty values based on the first set of probability distributions;

determine a second set of uncertainty values based on the second set of probability distributions;

aggregate the first set of uncertainty values and the second set of uncertainty values to determine one or more informativeness scores for the one or more images;

obtain a set of annotations for a subset of the one or more images; and

train a neural network using at least the set of annotations and the subset of the one or more images.

31. The machine-readable medium of claim 30, wherein the subset of the one or more images is determined based at least in part on the one or more informativeness scores.

32. The machine-readable medium of claim 30, wherein the first set of uncertainty values and the second set of uncertainty values comprise aleatoric uncertainty values and epistemic uncertainty values.

33. The machine-readable medium of claim 30, wherein each probability distribution of the first set of probability distributions and the second set of probability distributions is represented as a Gaussian Mixture Model (GMM).

34. The machine-readable medium of claim 30, wherein the one or more neural networks are to further:

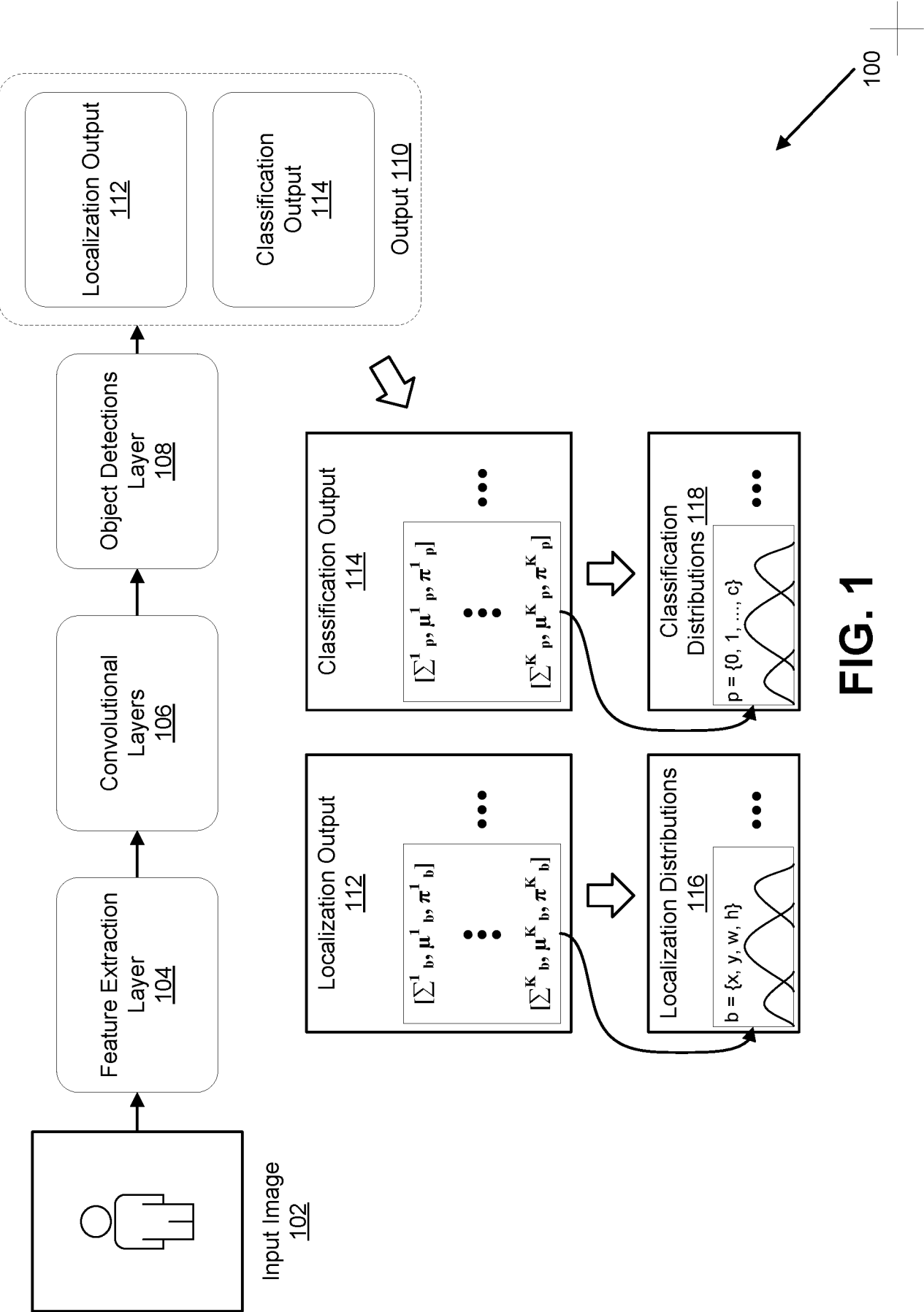
determine one or more mean parameter values of the first set of probability distributions and the second set of probability distributions;

determine one or more variance parameter values of the first set of probability distributions and the second set of probability distributions; and

determine one or more weight parameter values of the first set of probability distributions and the second set of probability distributions.

35. The machine-readable medium of claim 34, wherein the first set of uncertainty values are determined through a first set of summations based at least in part on one or more products of the one or more variance parameter values and the one or more weight parameter values, and the second set of uncertainty values are determined through a second set of summations based at least in part on the one or more mean parameter values and the one or more weight parameter values.

36. The machine-readable medium of claim 35, wherein the first set of uncertainty values correspond to aleatoric uncertainty and the second set of uncertainty values are correspond to epistemic uncertainty.



200

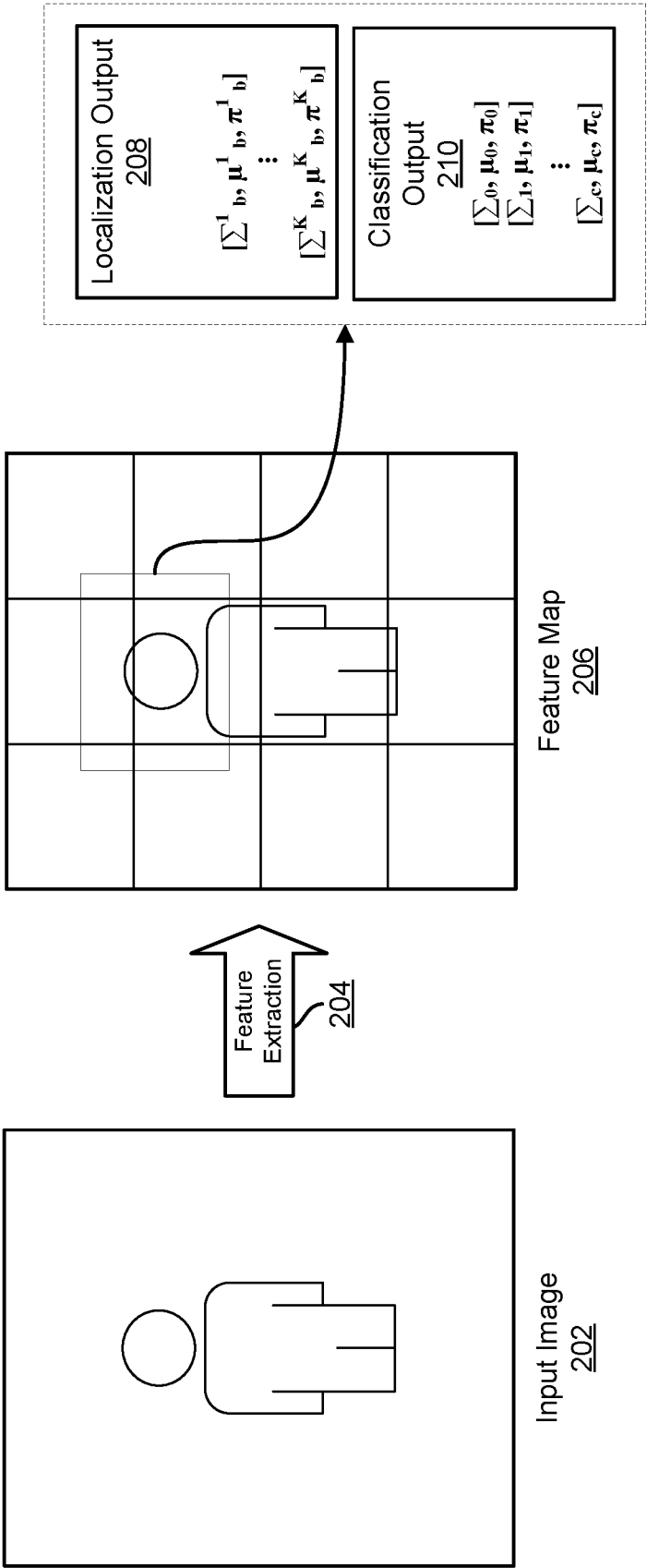


FIG. 2

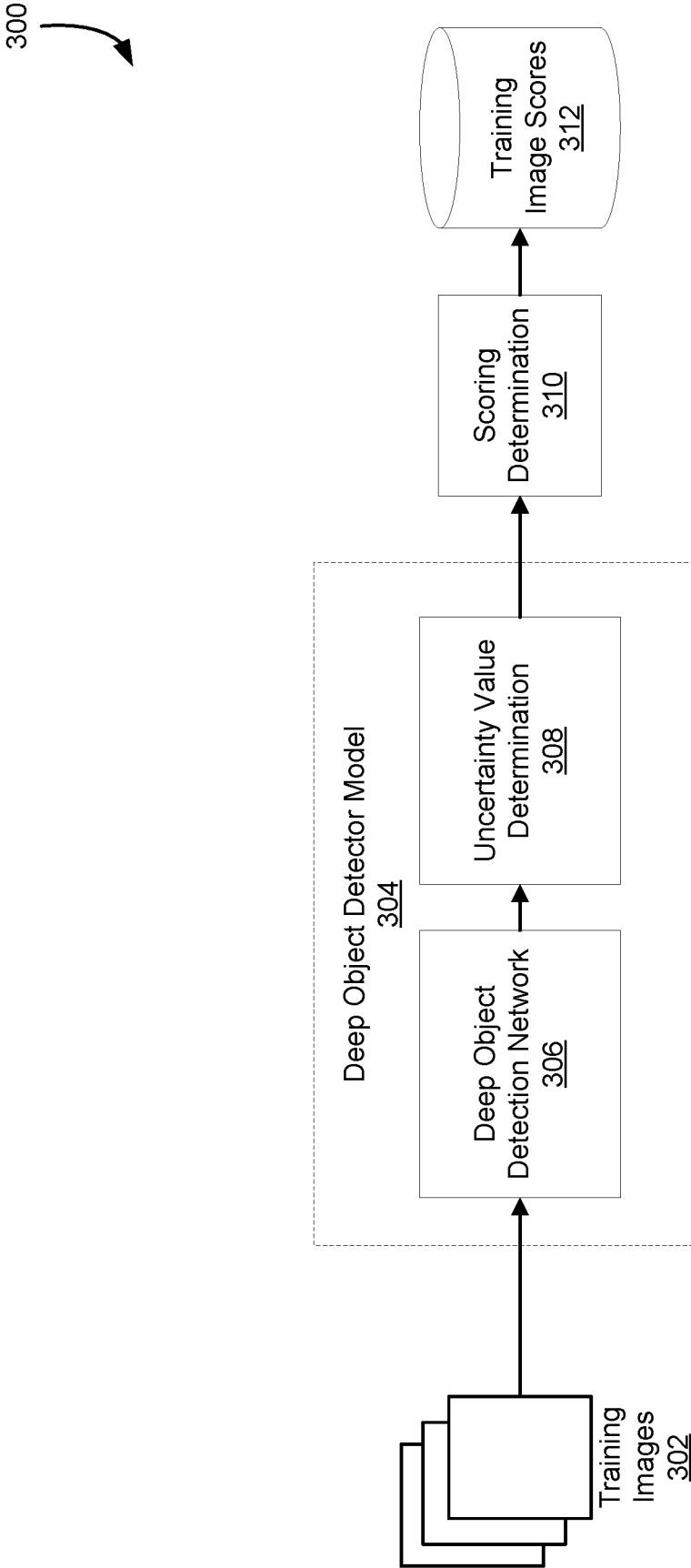


FIG. 3

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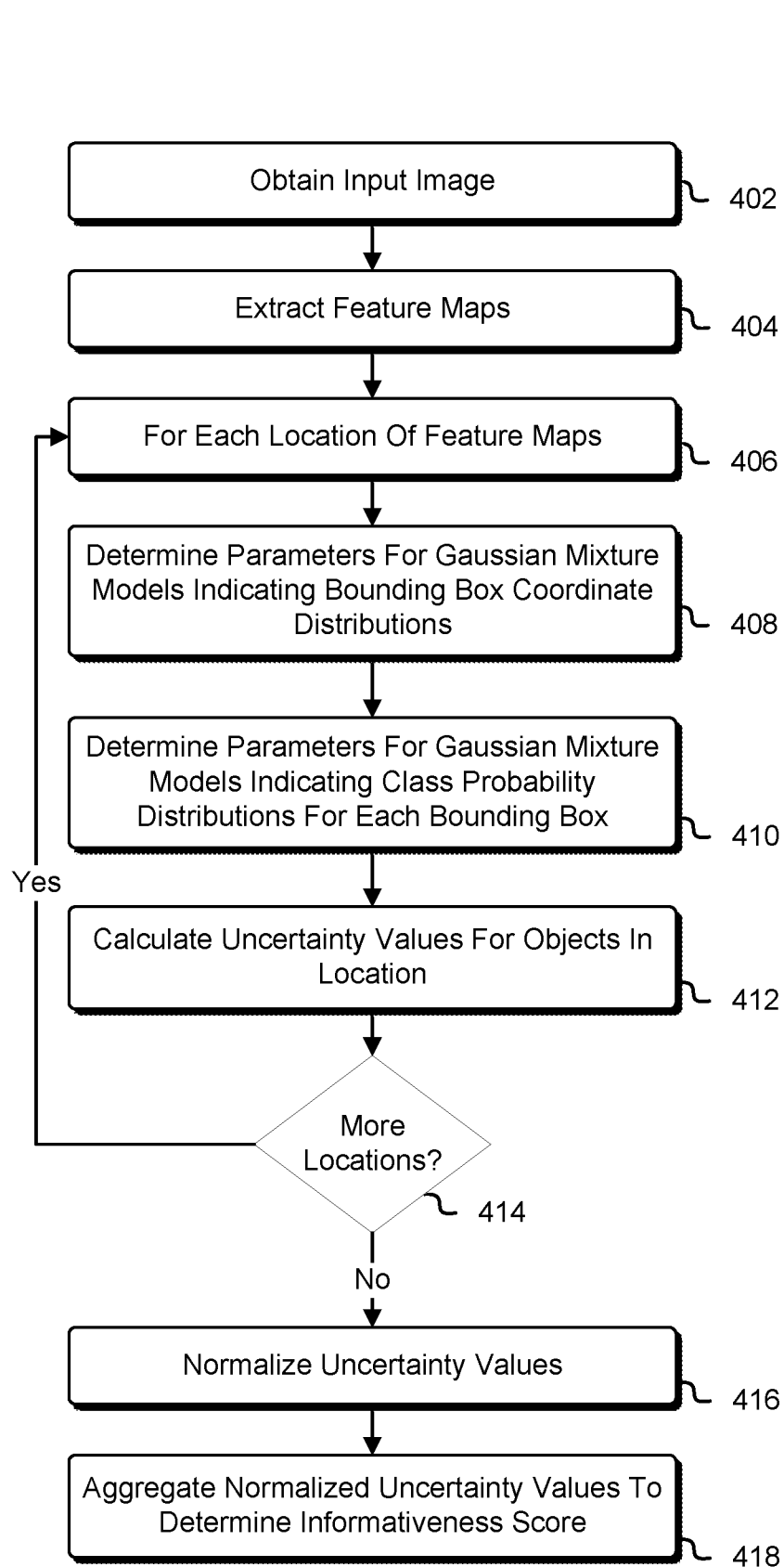
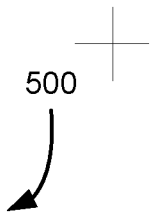
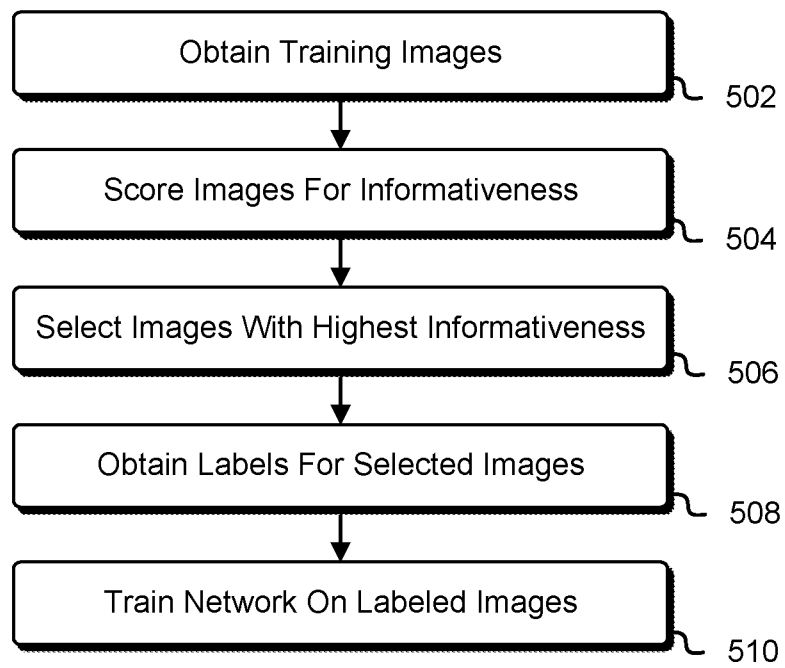


FIG. 4

5/55**FIG. 5**

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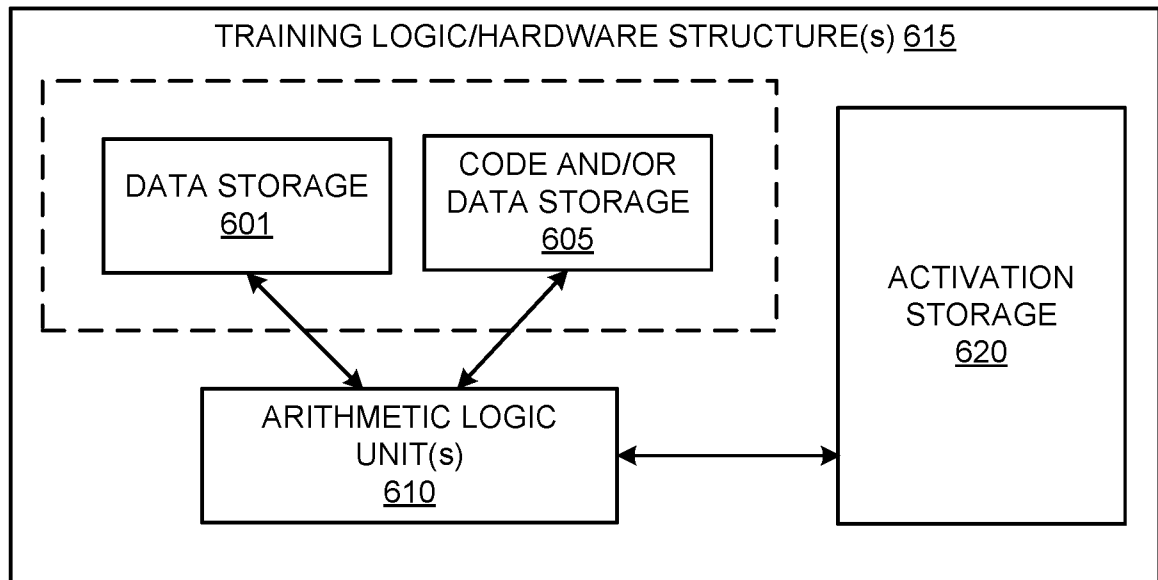


FIG. 6A

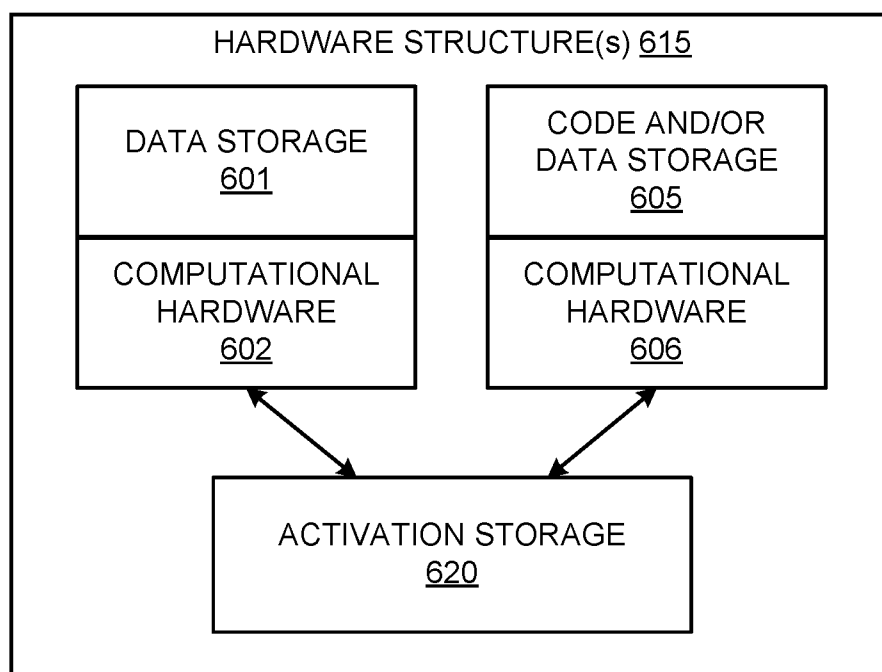


FIG. 6B

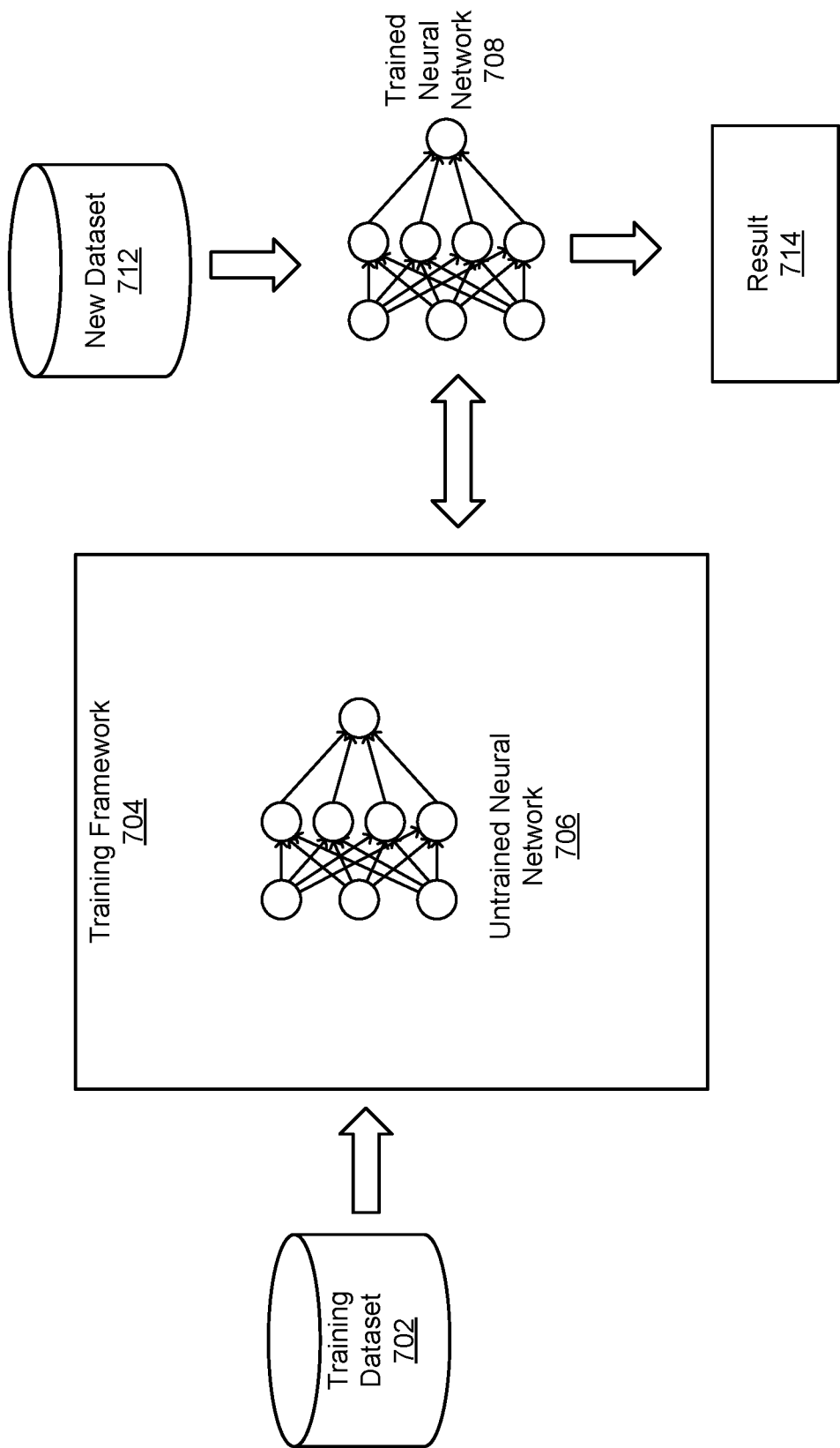


FIG. 7

DATA CENTER
800

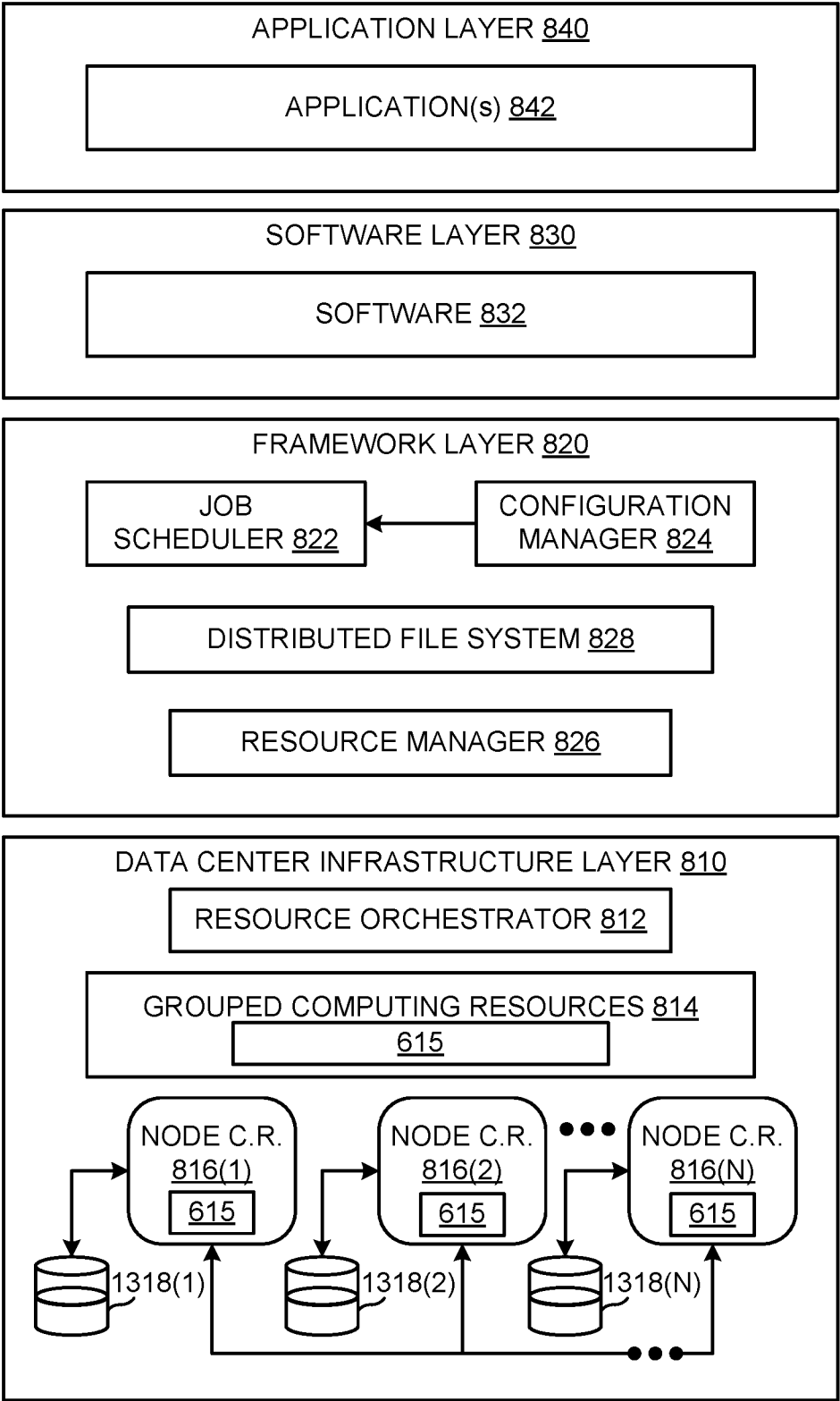


FIG. 8

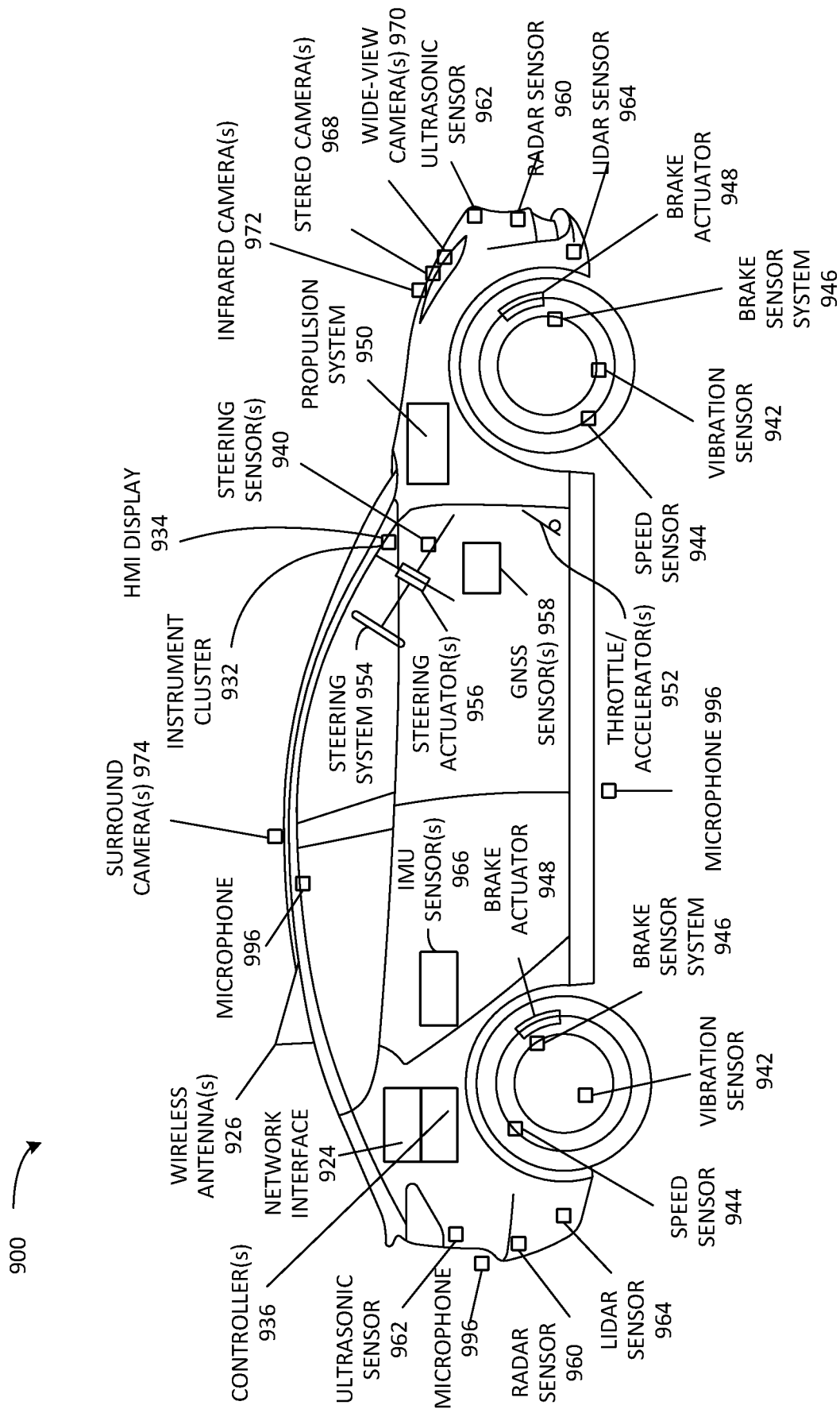


FIG. 9A

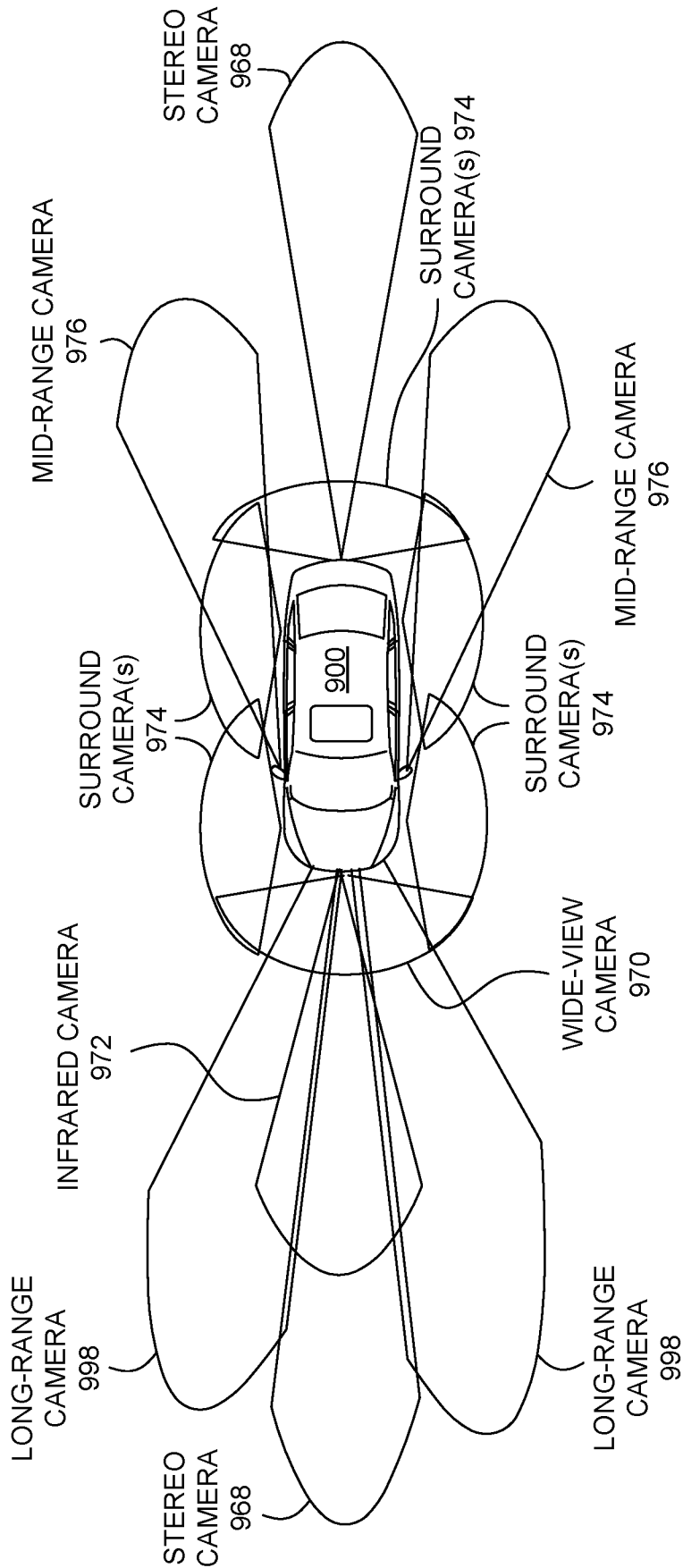


FIG. 9B

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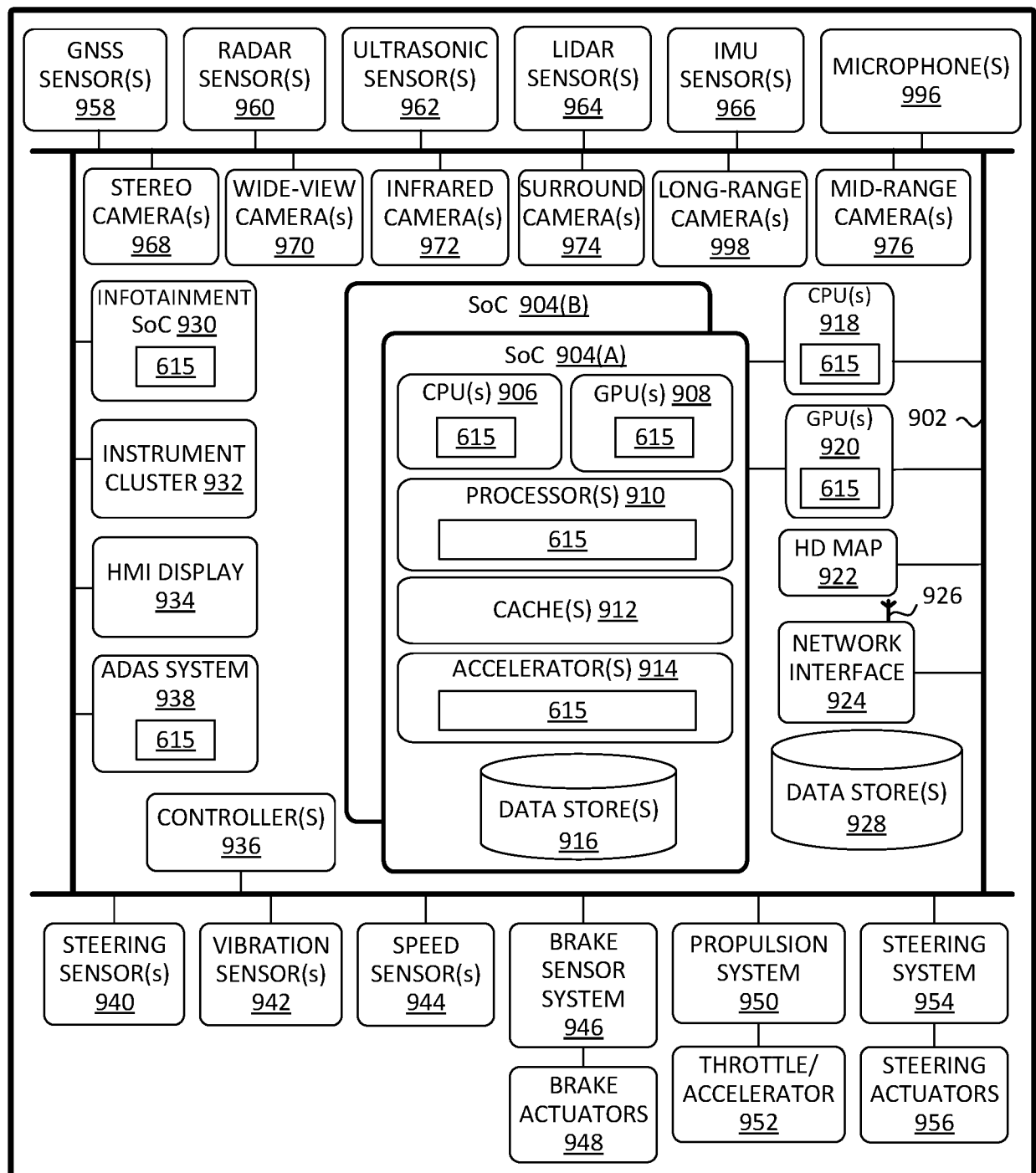
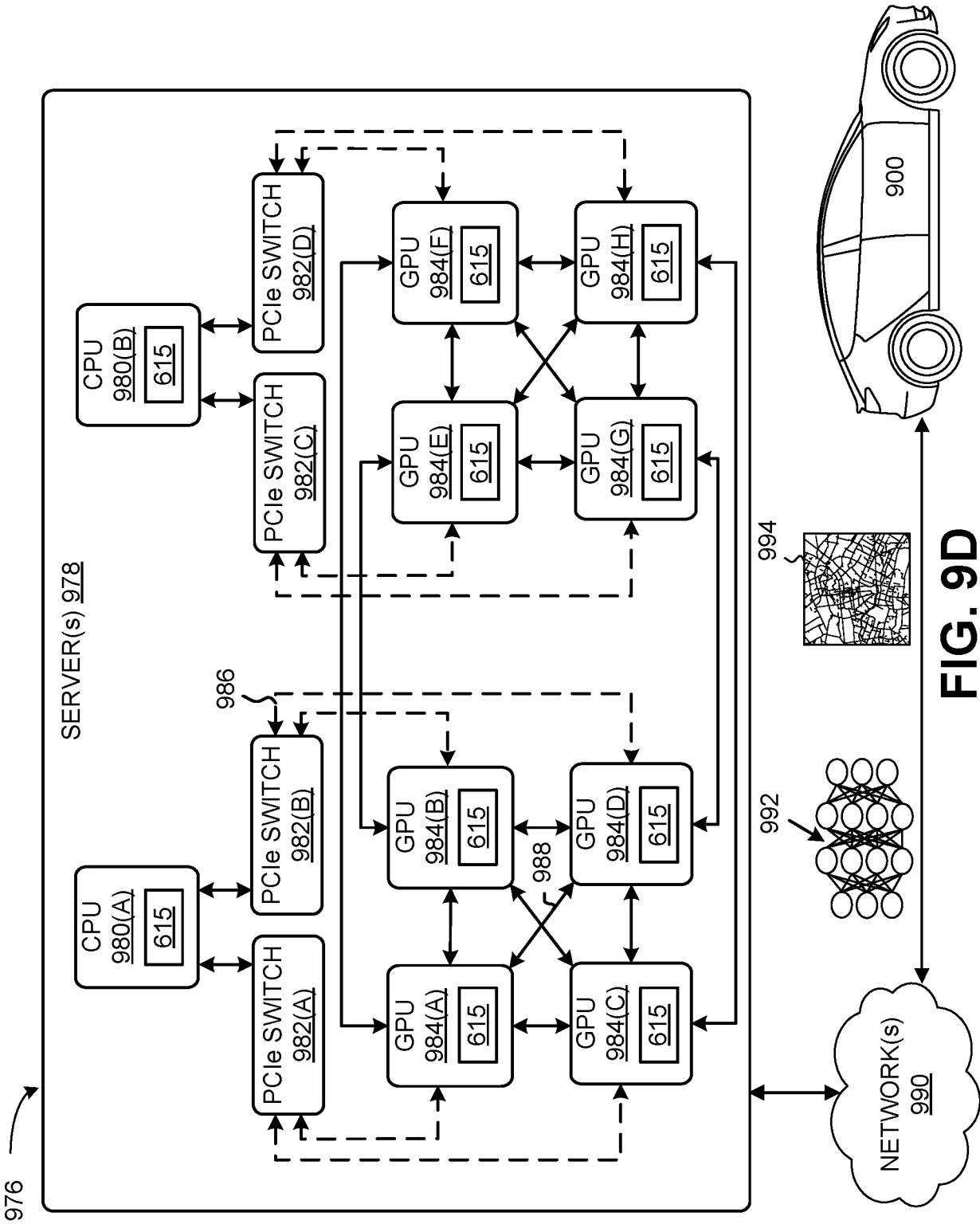


FIG. 9C



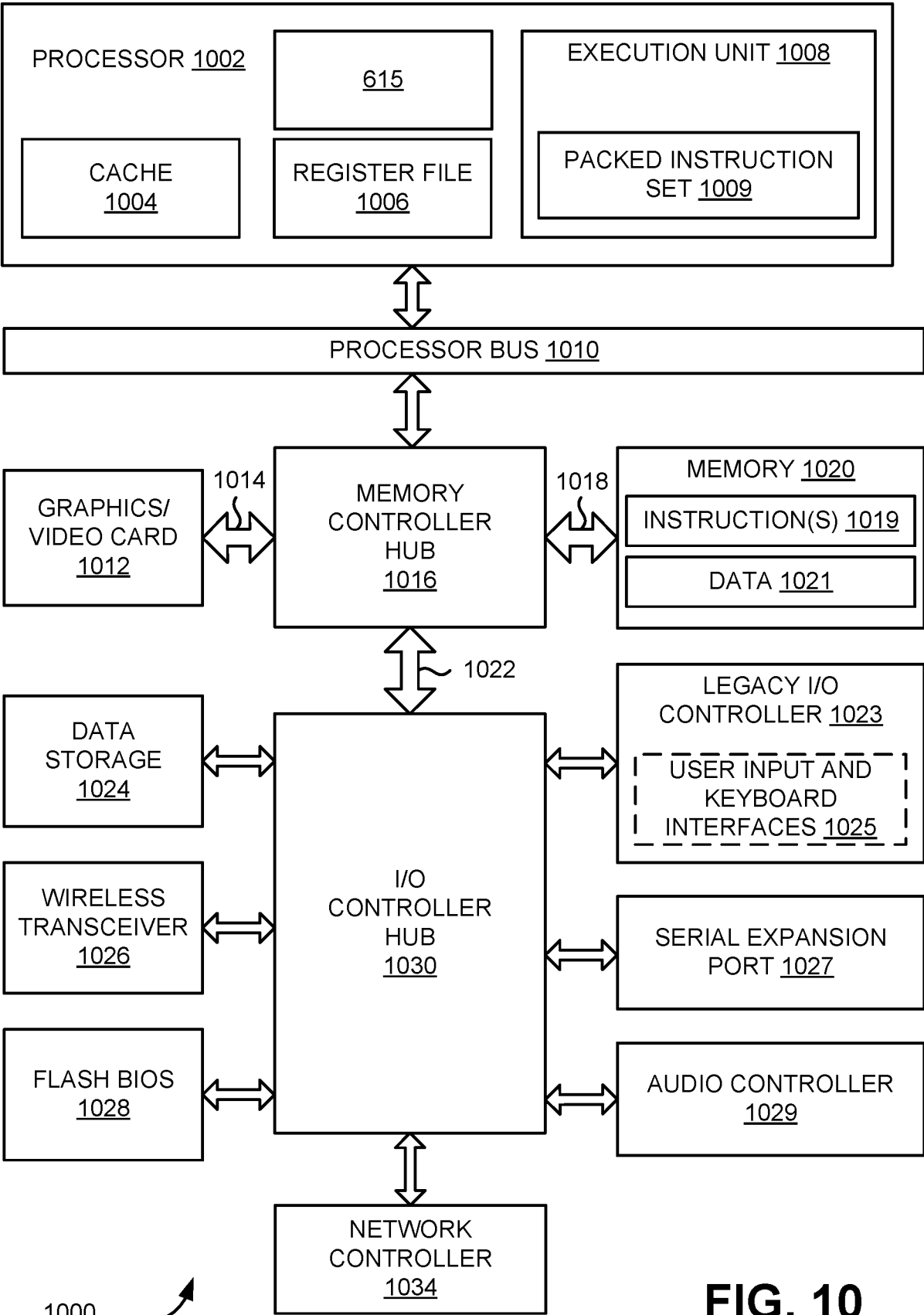


FIG. 10

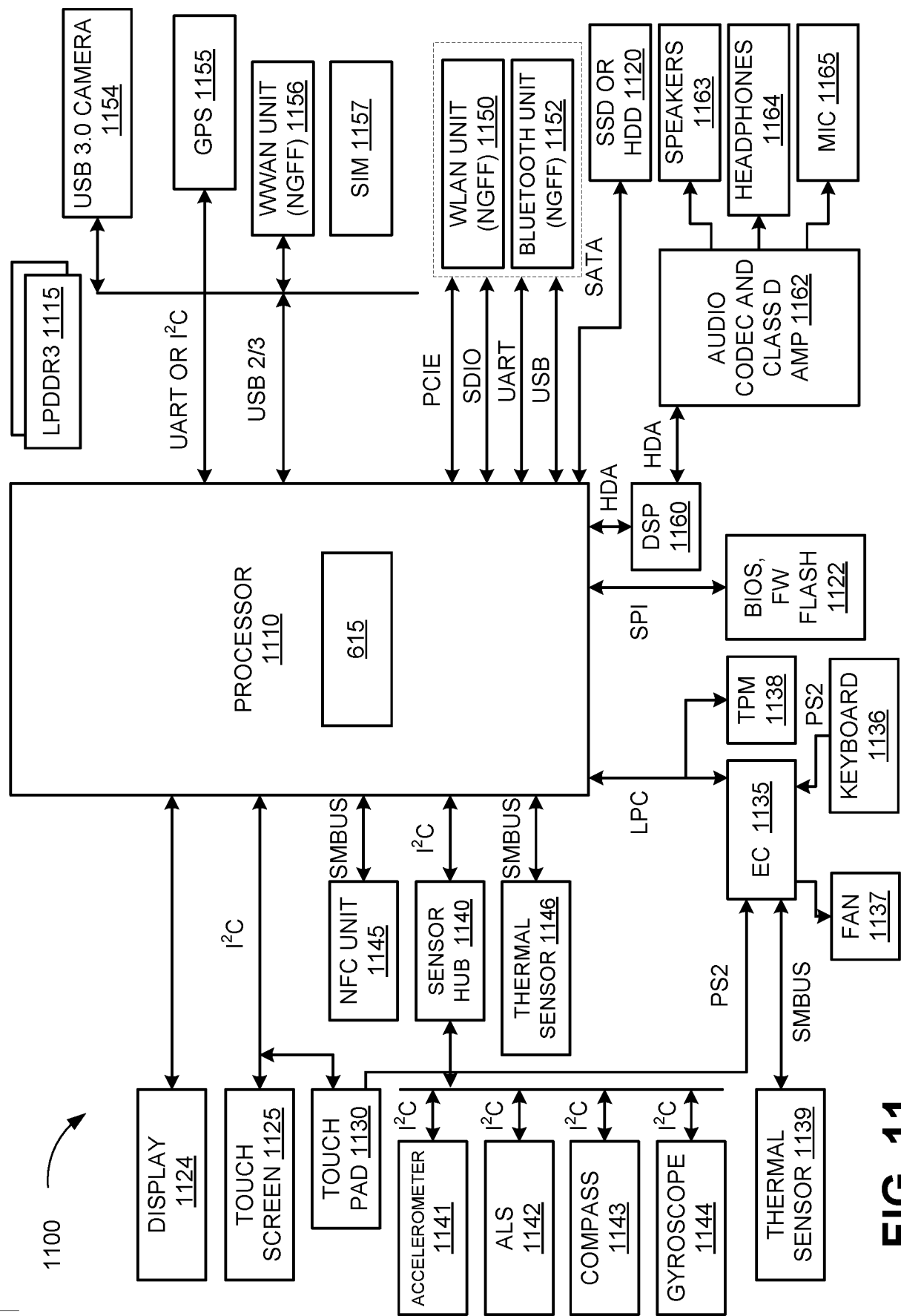


FIG. 11

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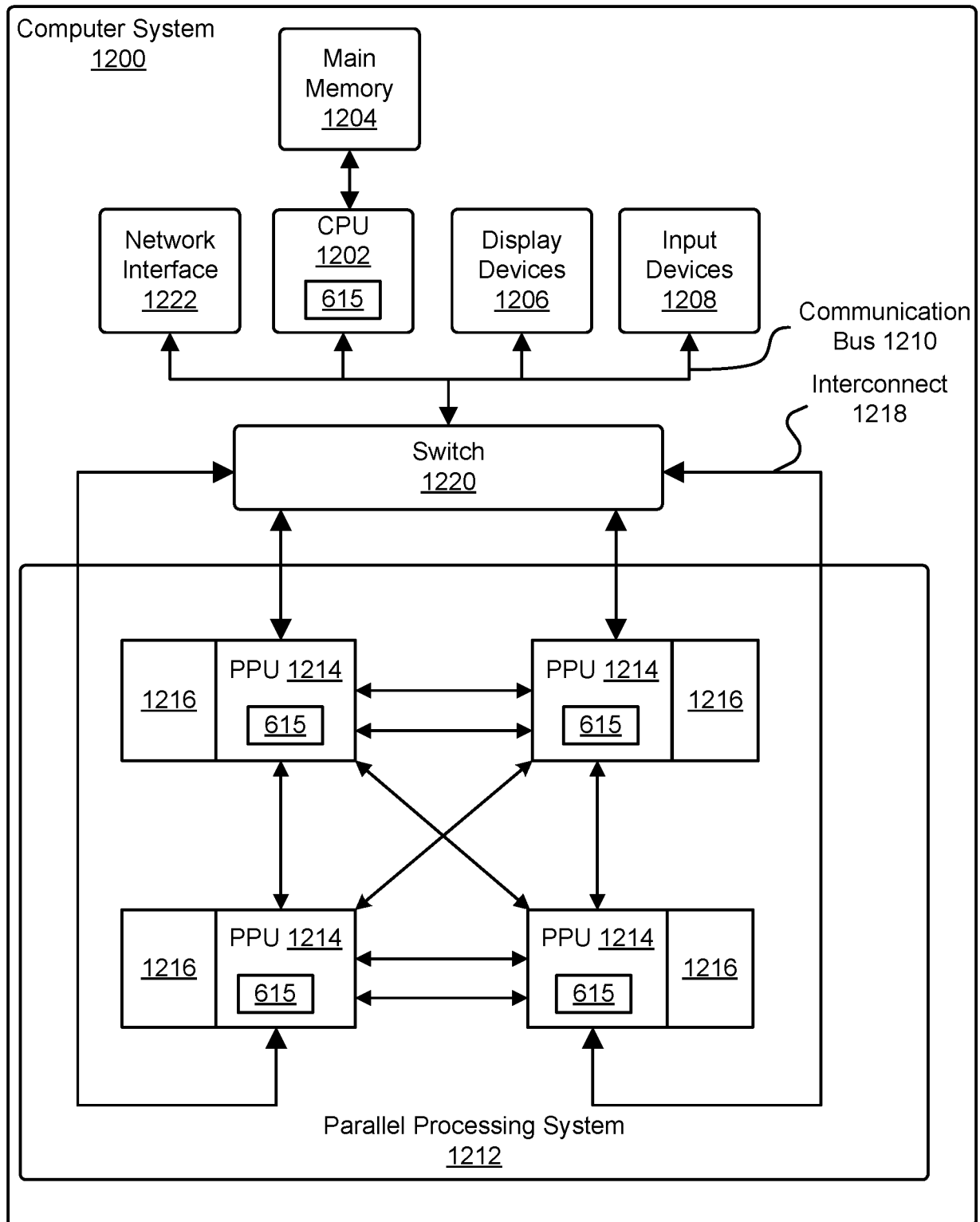


FIG. 12

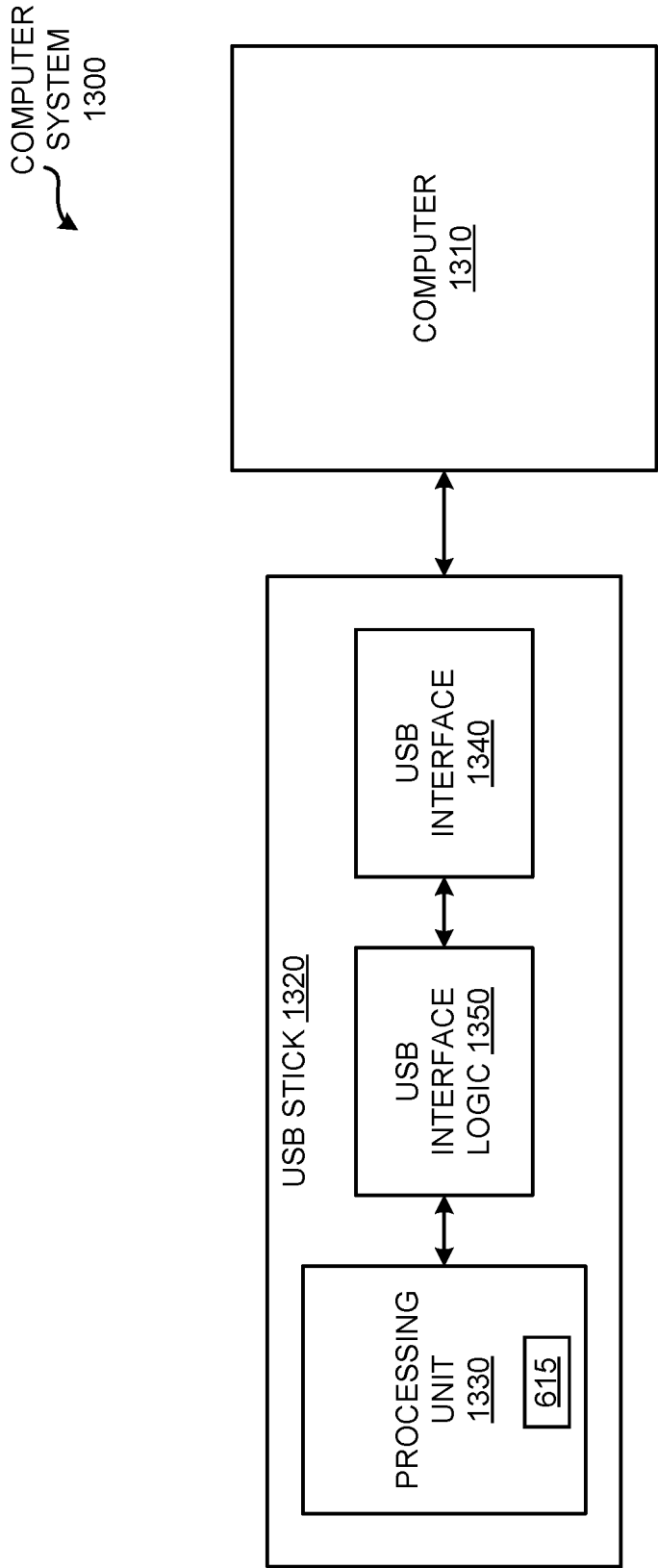


FIG. 13

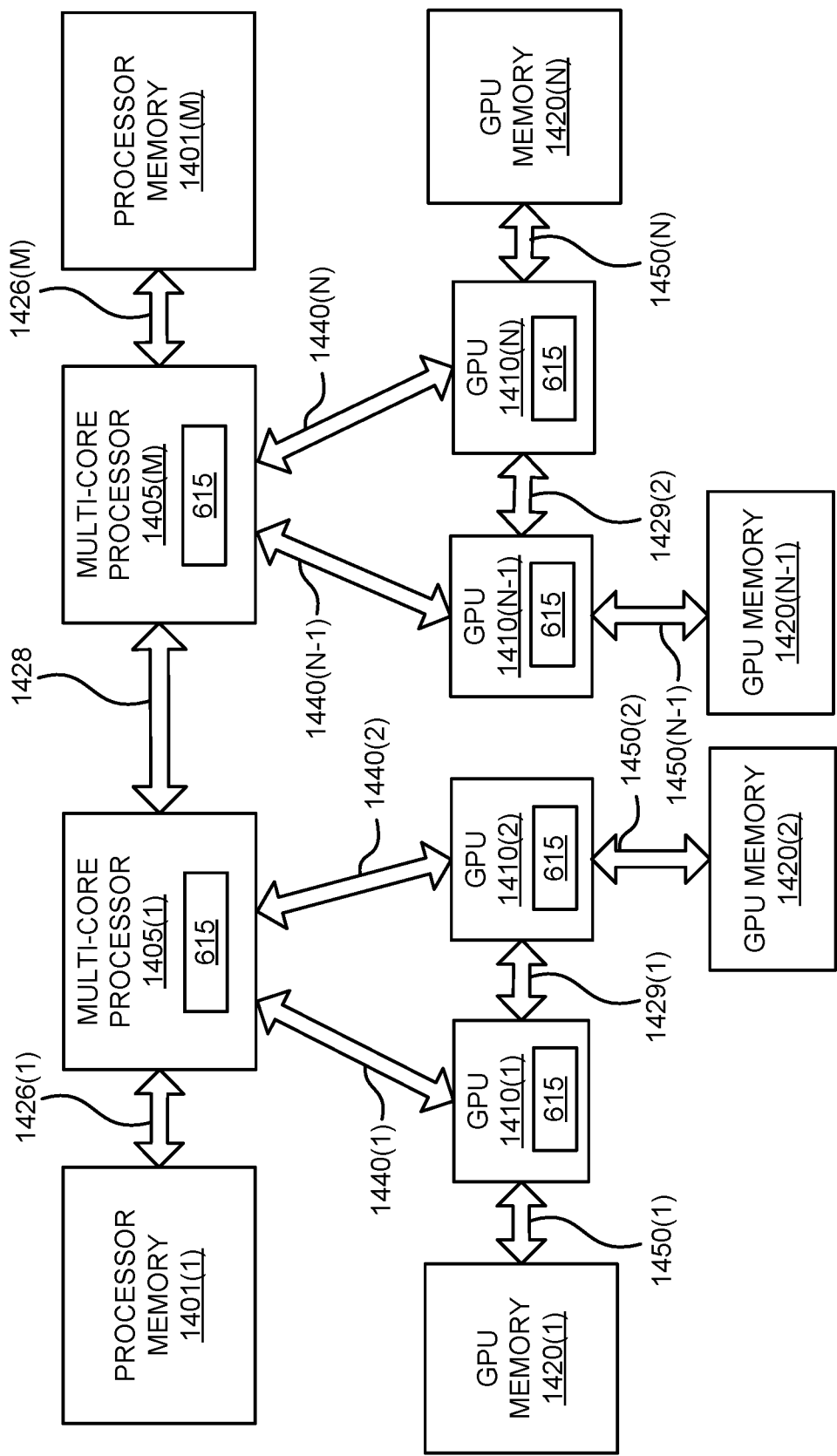


FIG. 14A

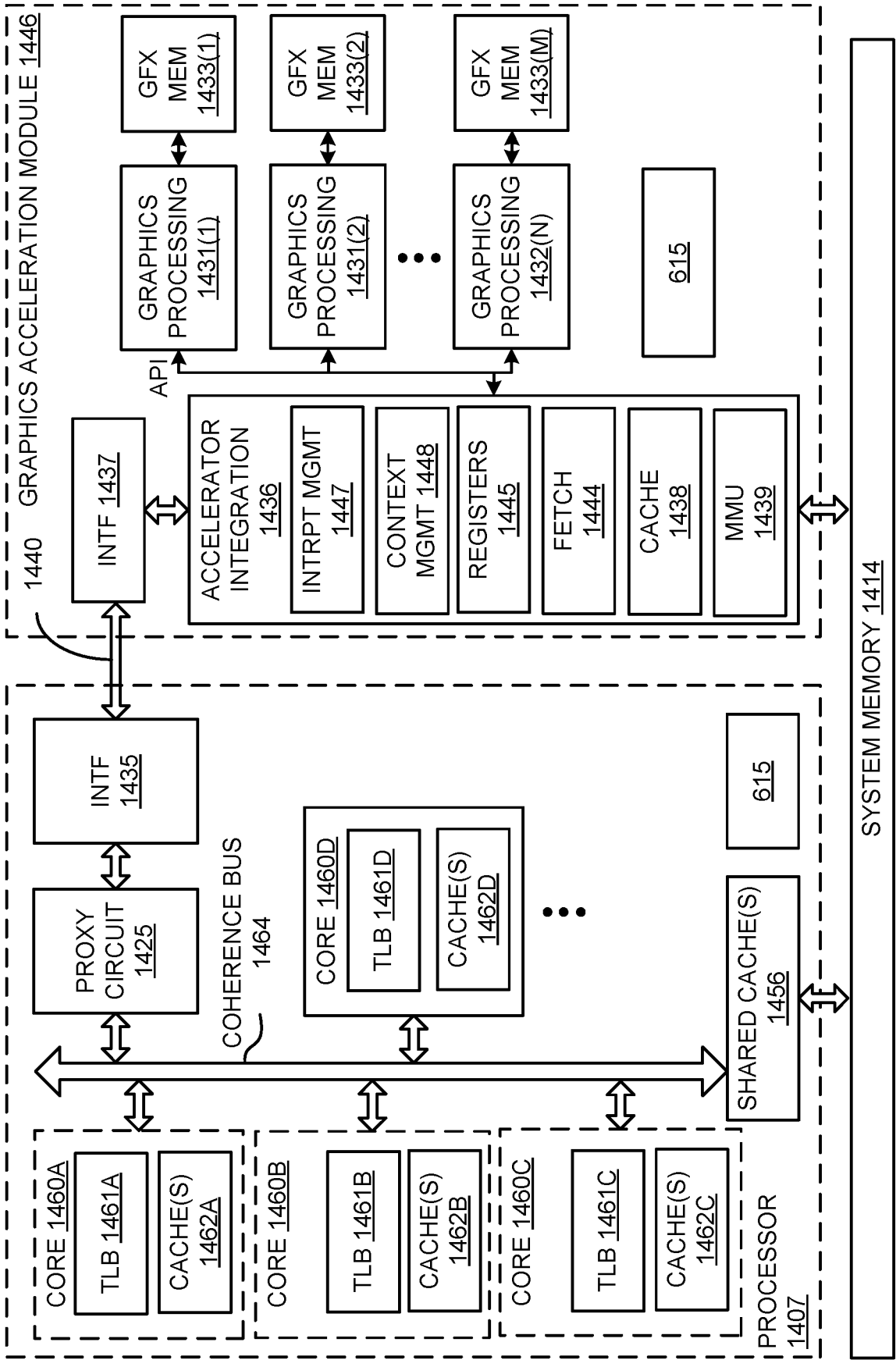


FIG. 14B

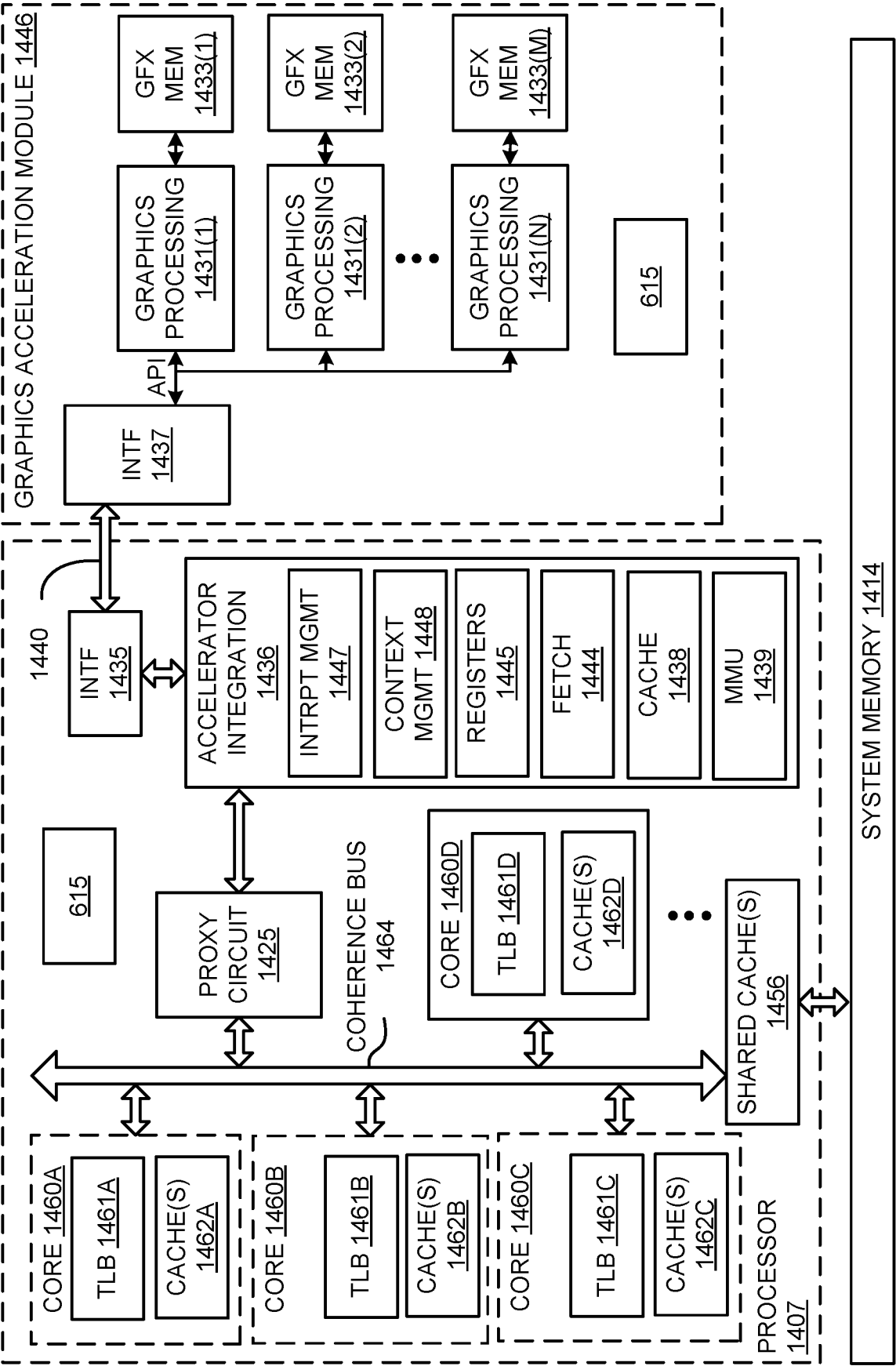


FIG. 14C

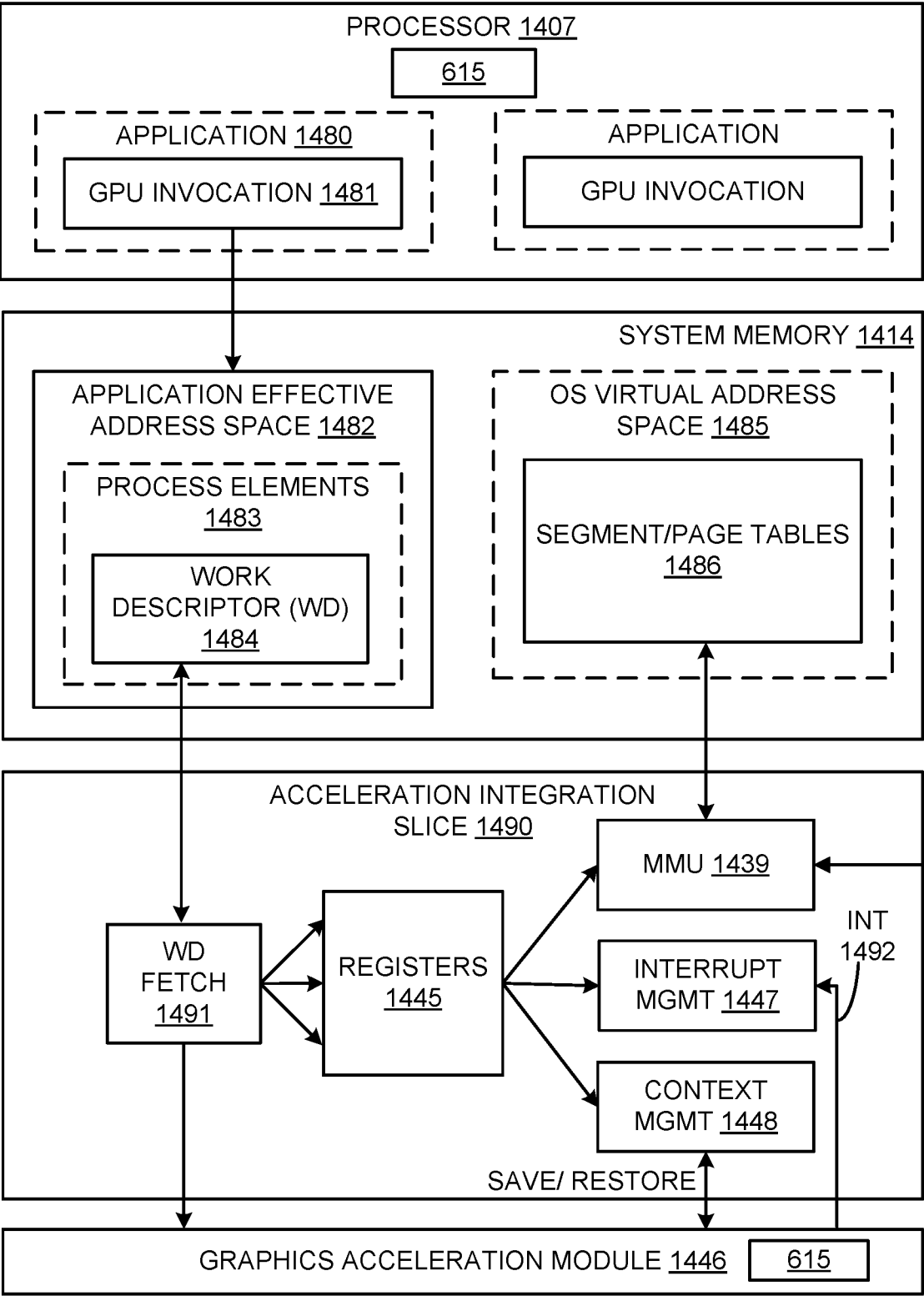


FIG. 14D

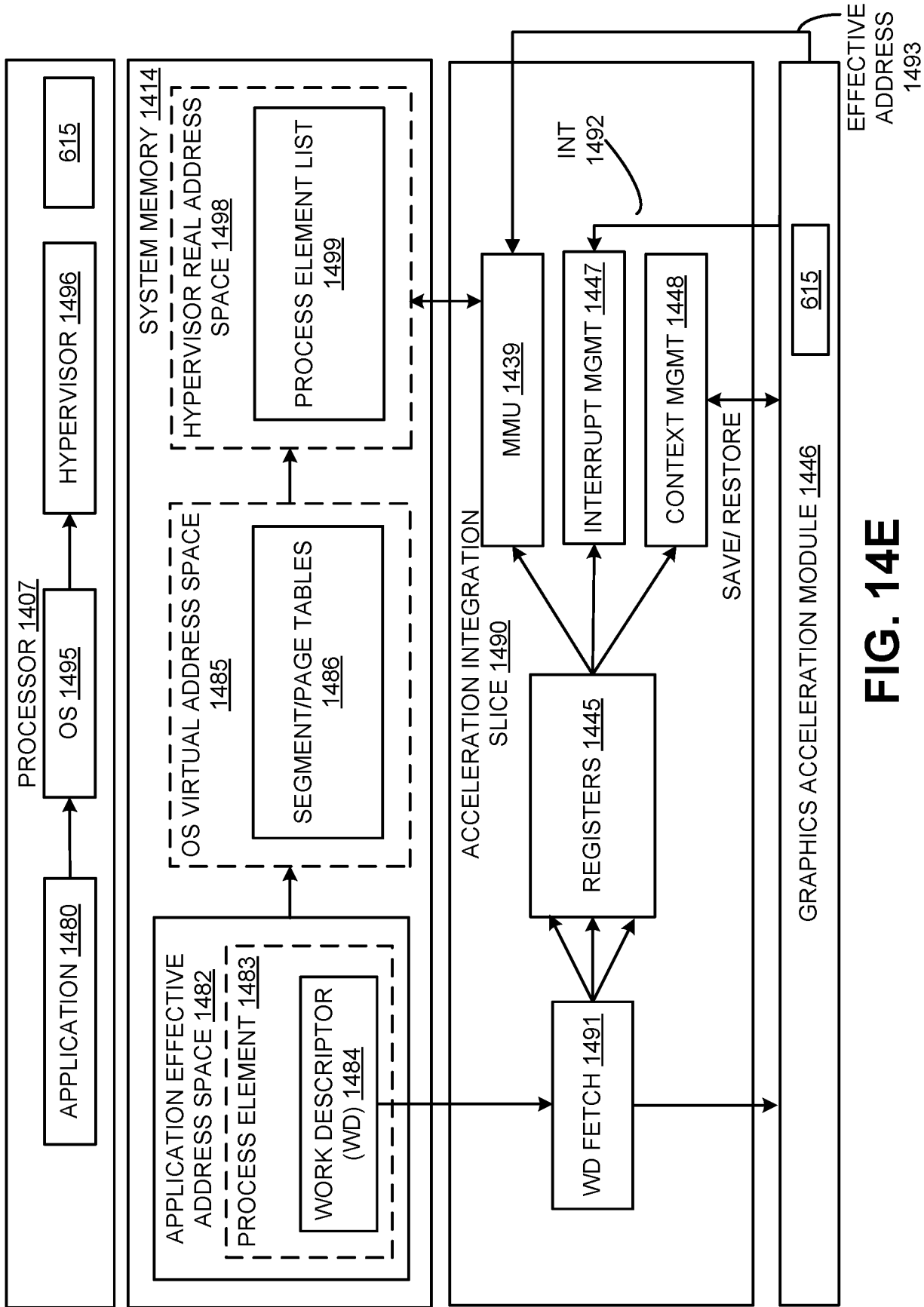


FIG. 14E

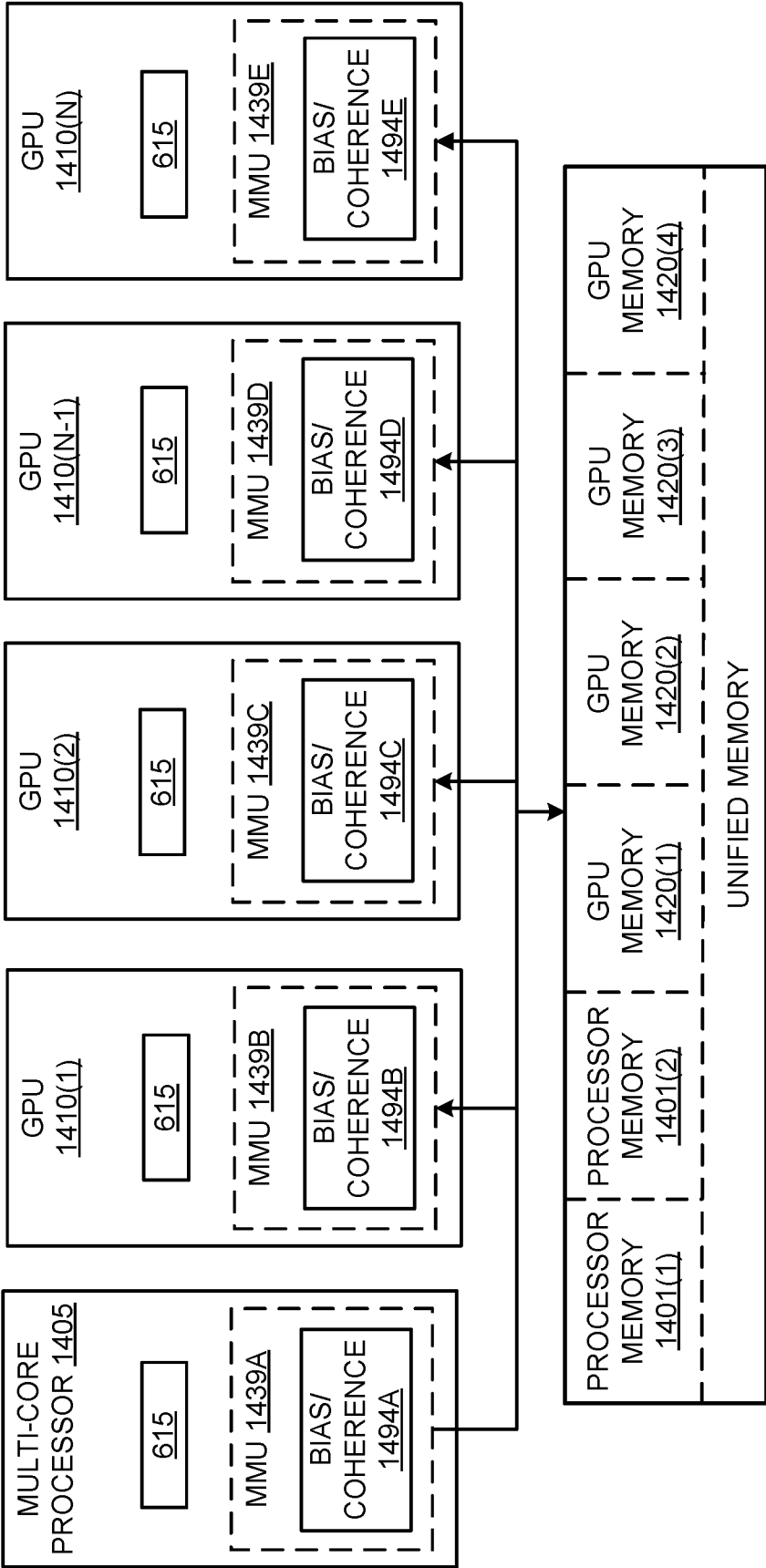


FIG. 14F

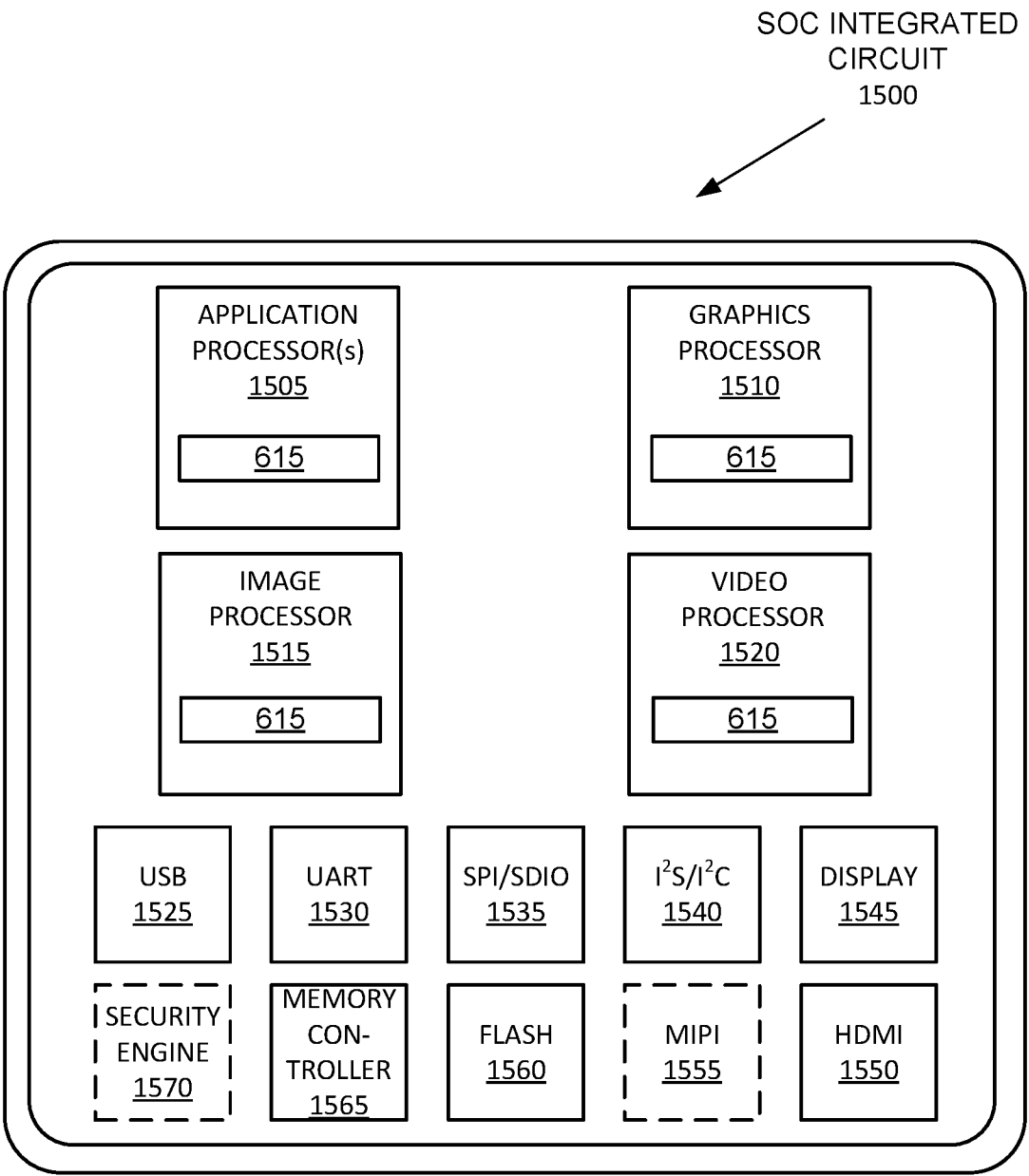


FIG. 15

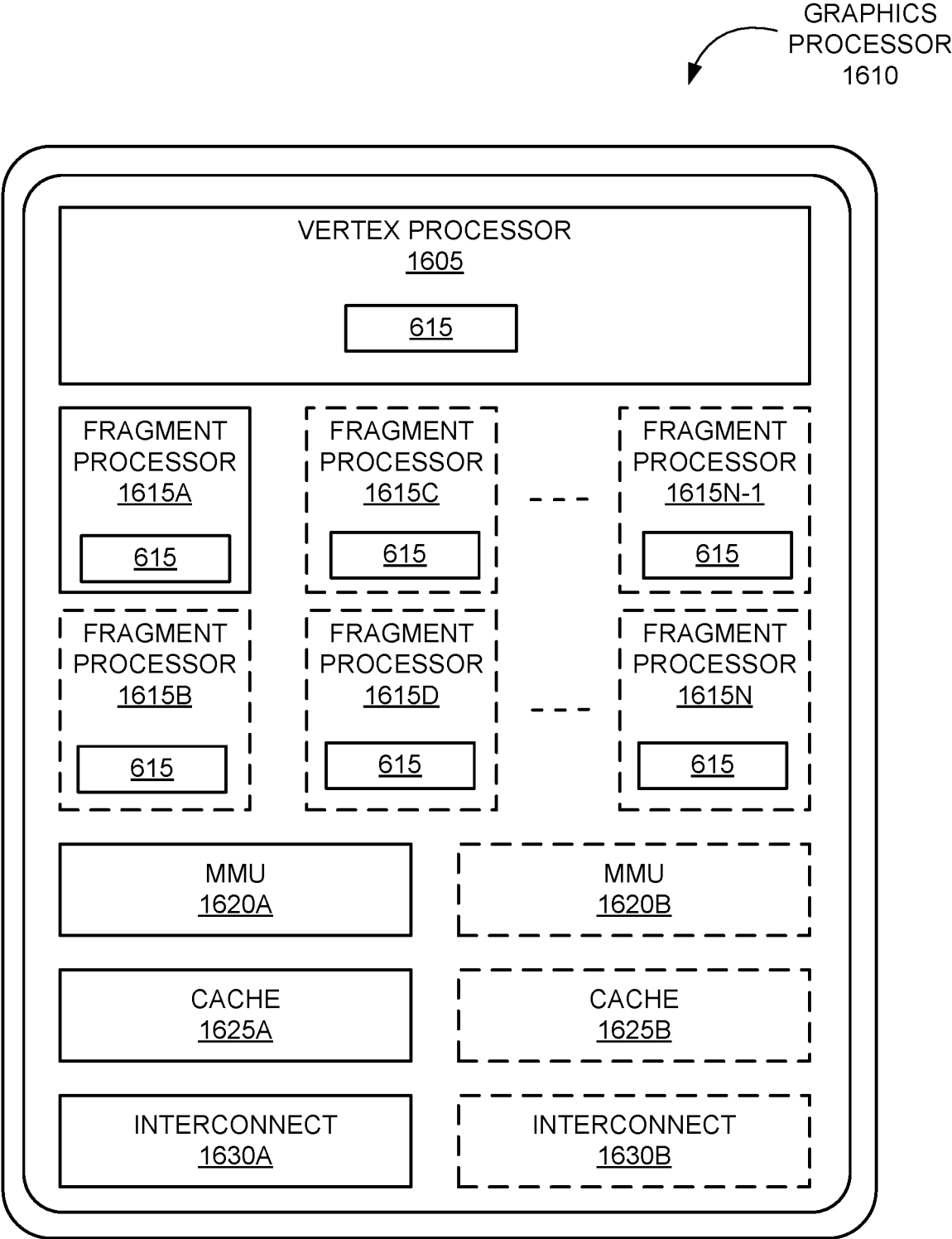


FIG. 16A



GRAPHICS
PROCESSOR
1640

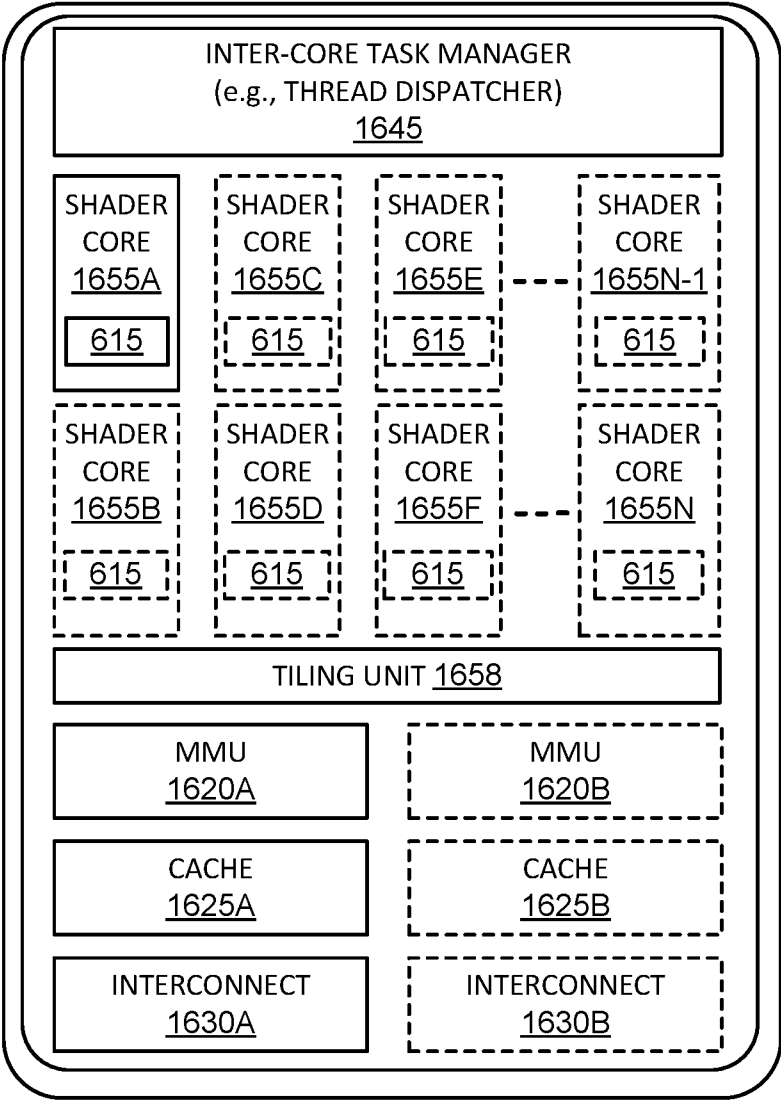


FIG. 16B



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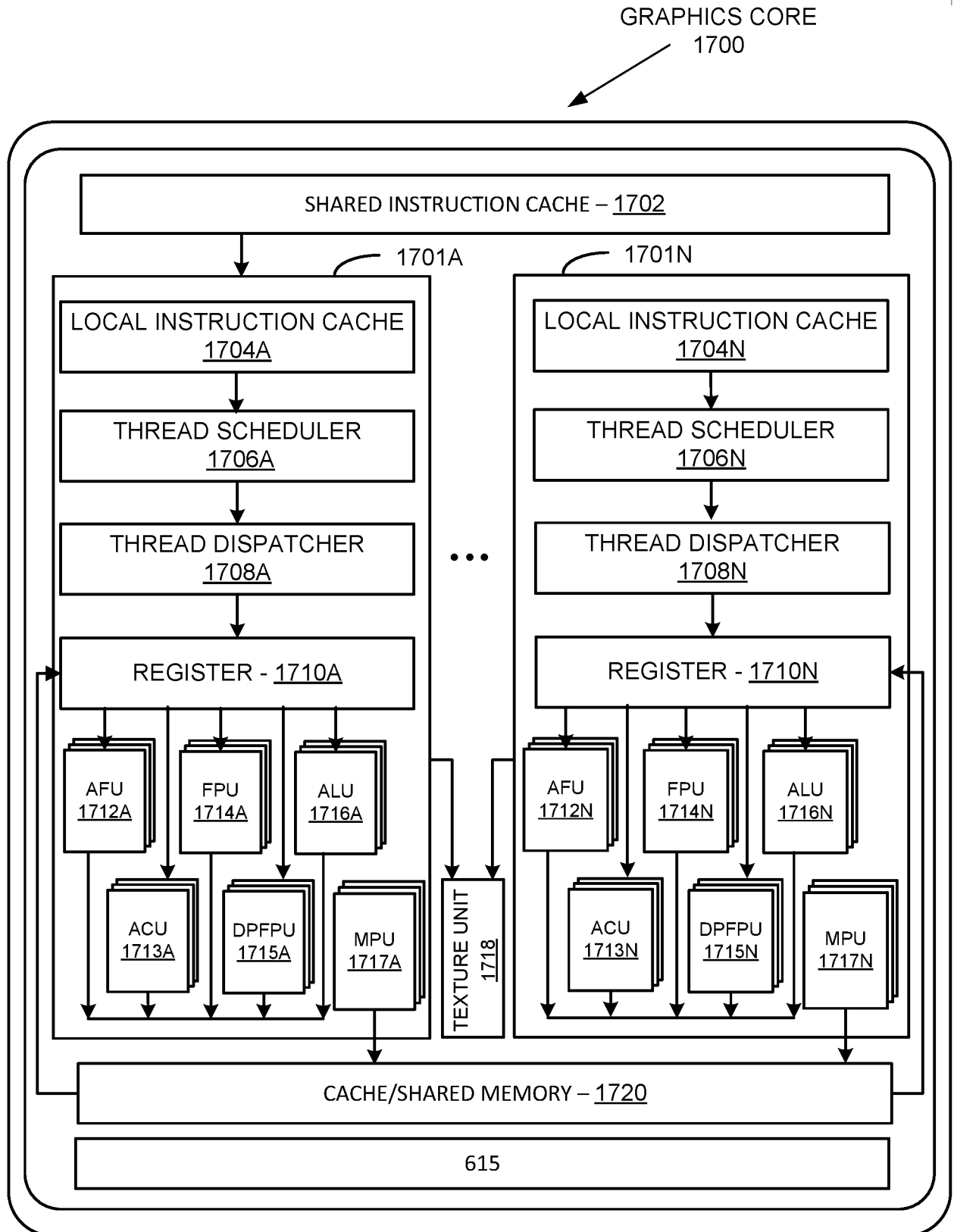


FIG. 17A

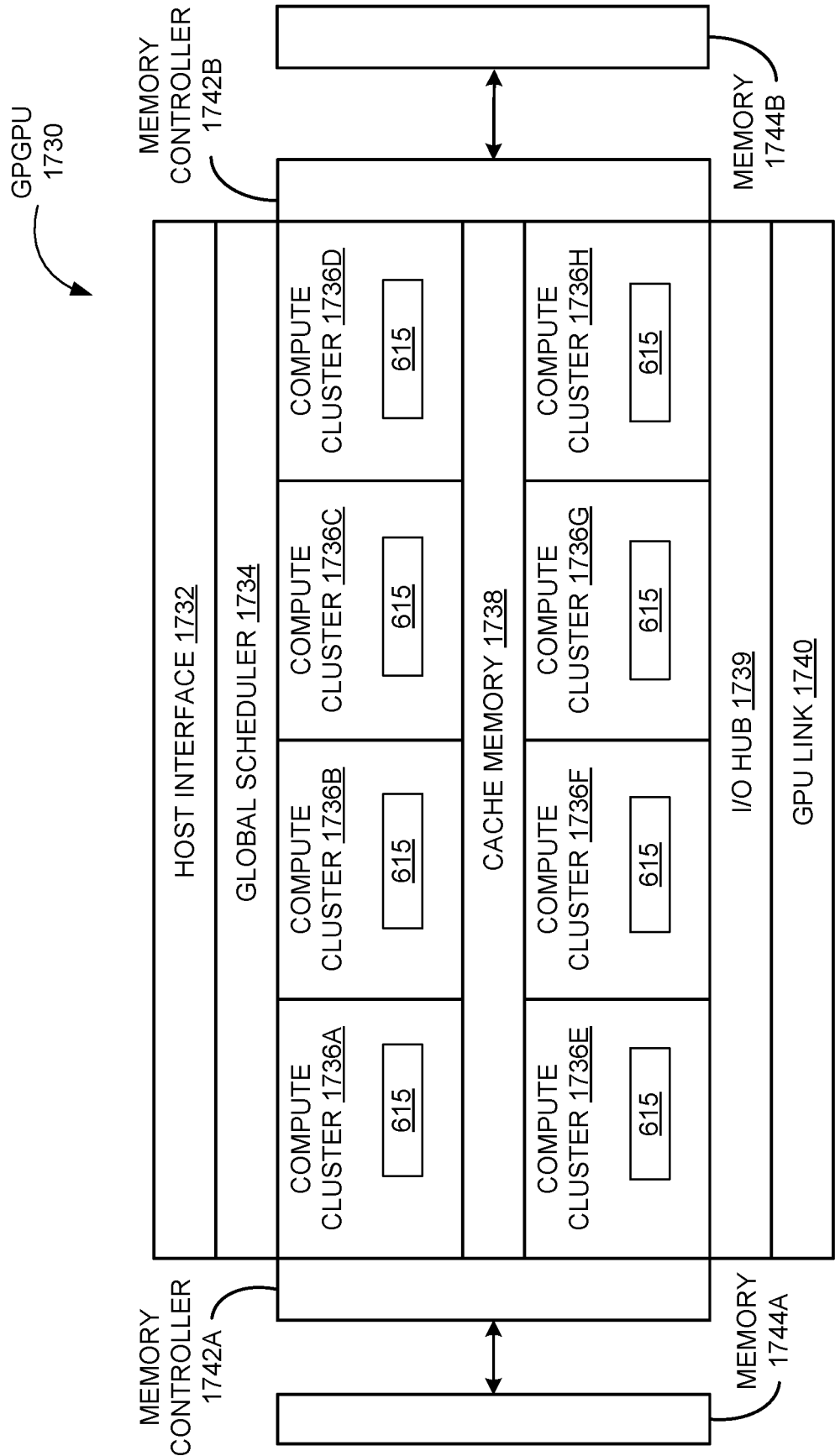


FIG. 17B

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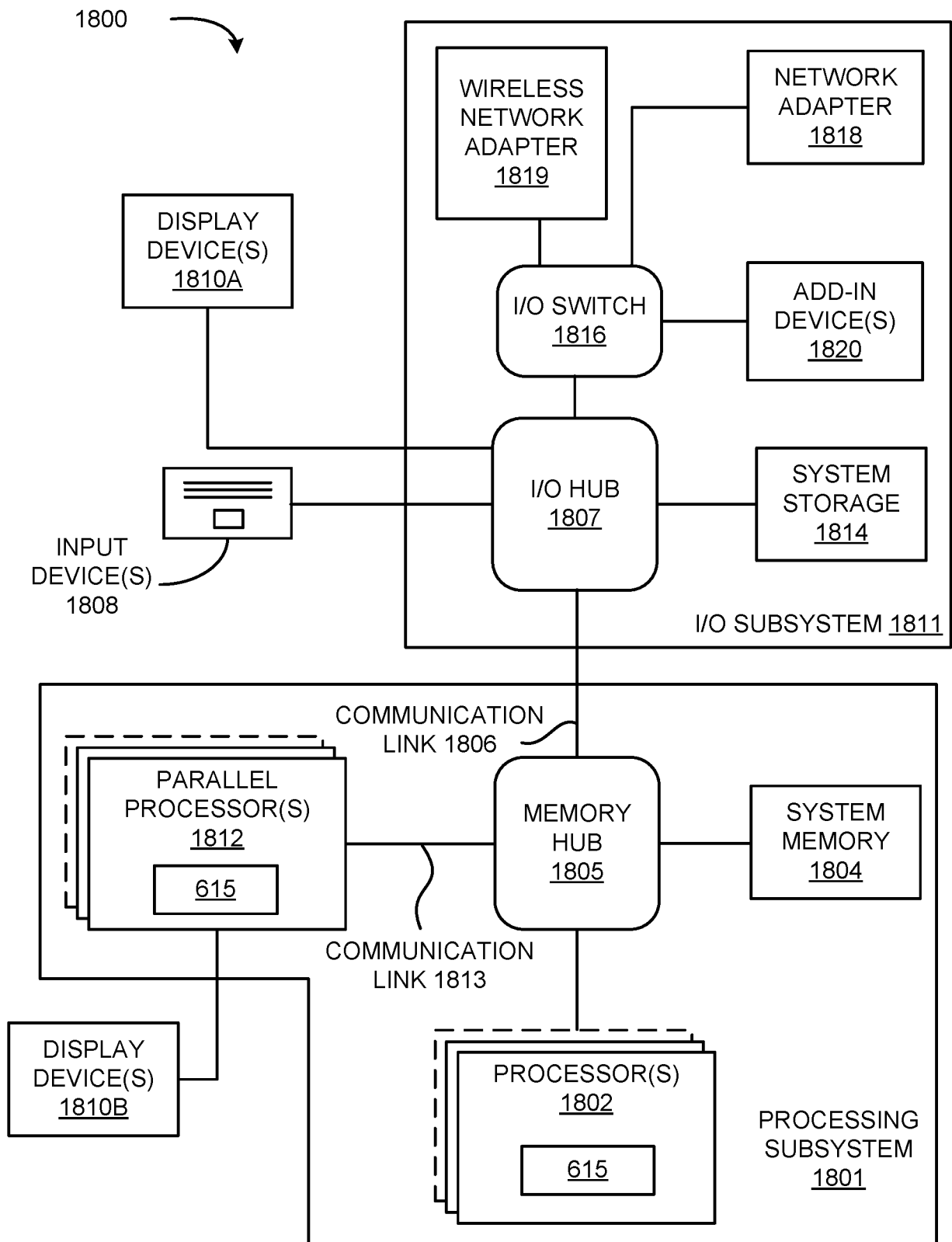


FIG. 18

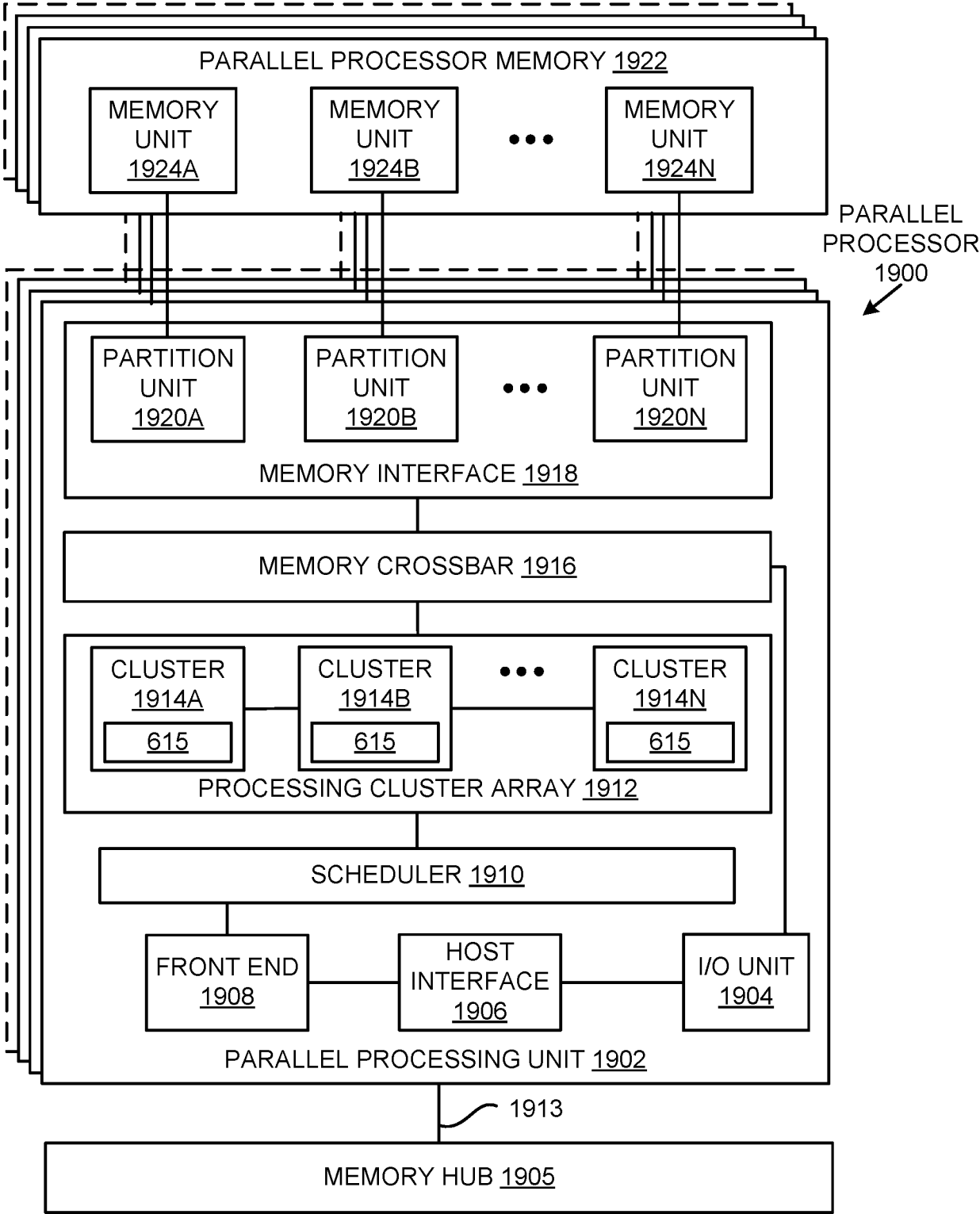


FIG. 19A

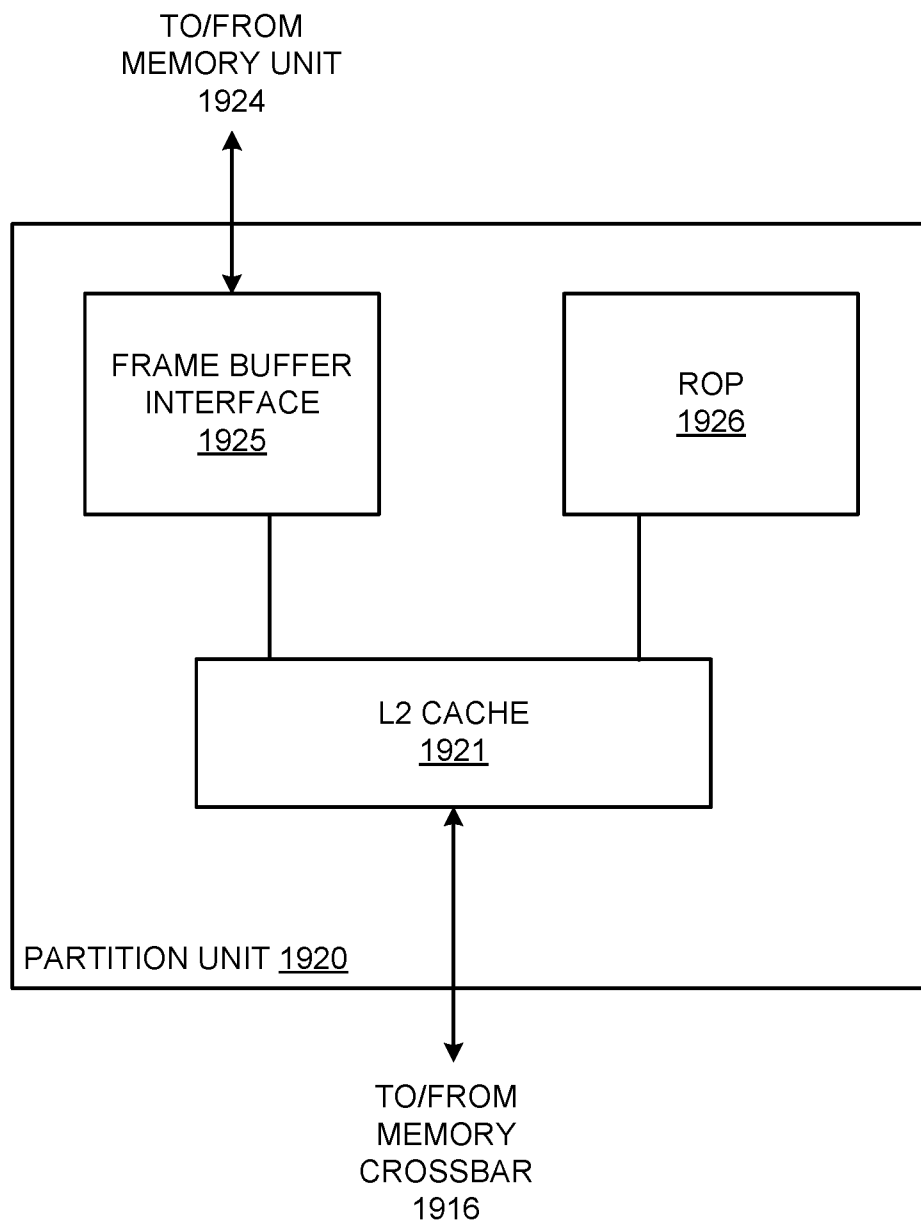


FIG. 19B

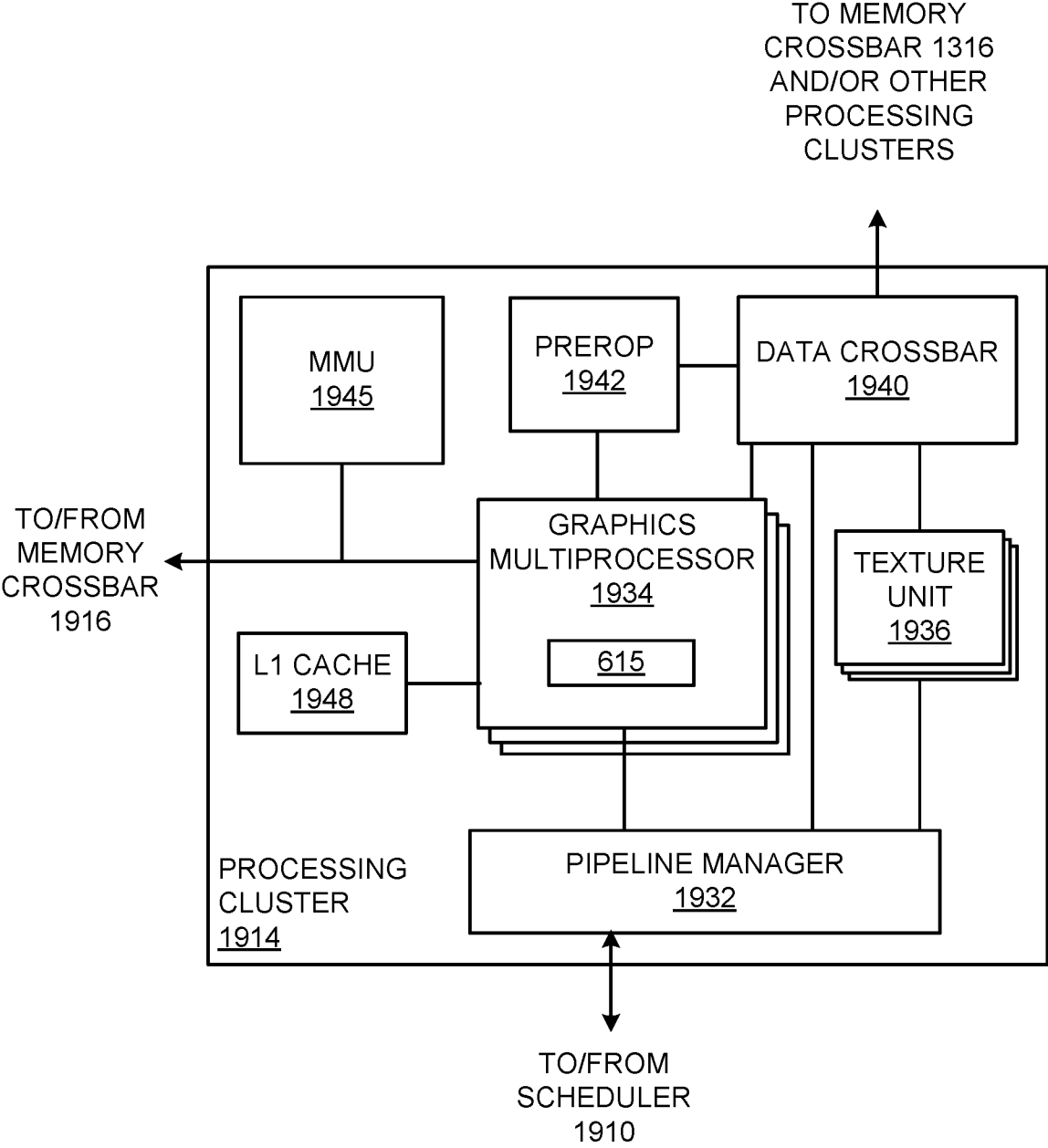


FIG. 19C

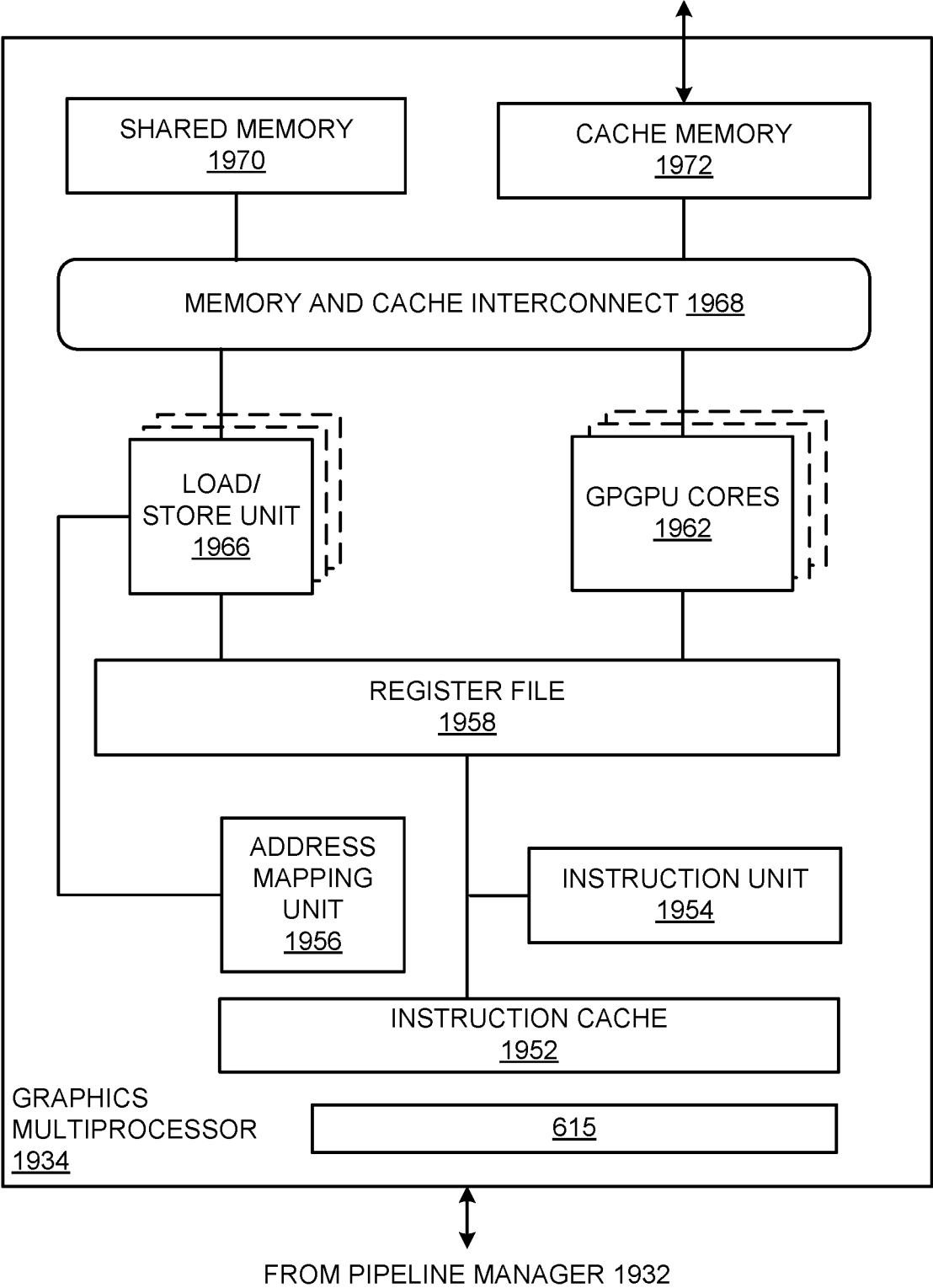
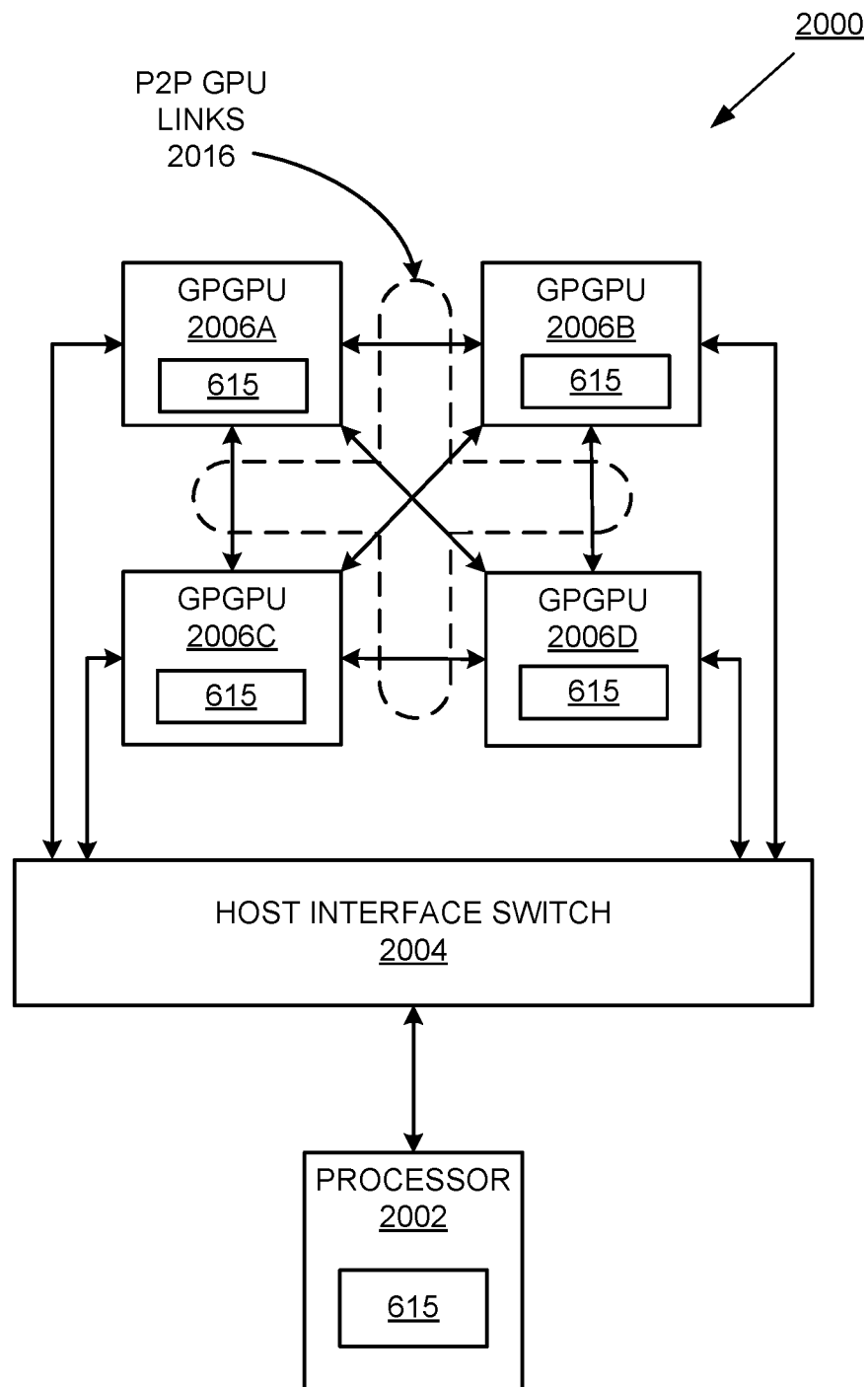


FIG. 19D

33/55**FIG. 20**

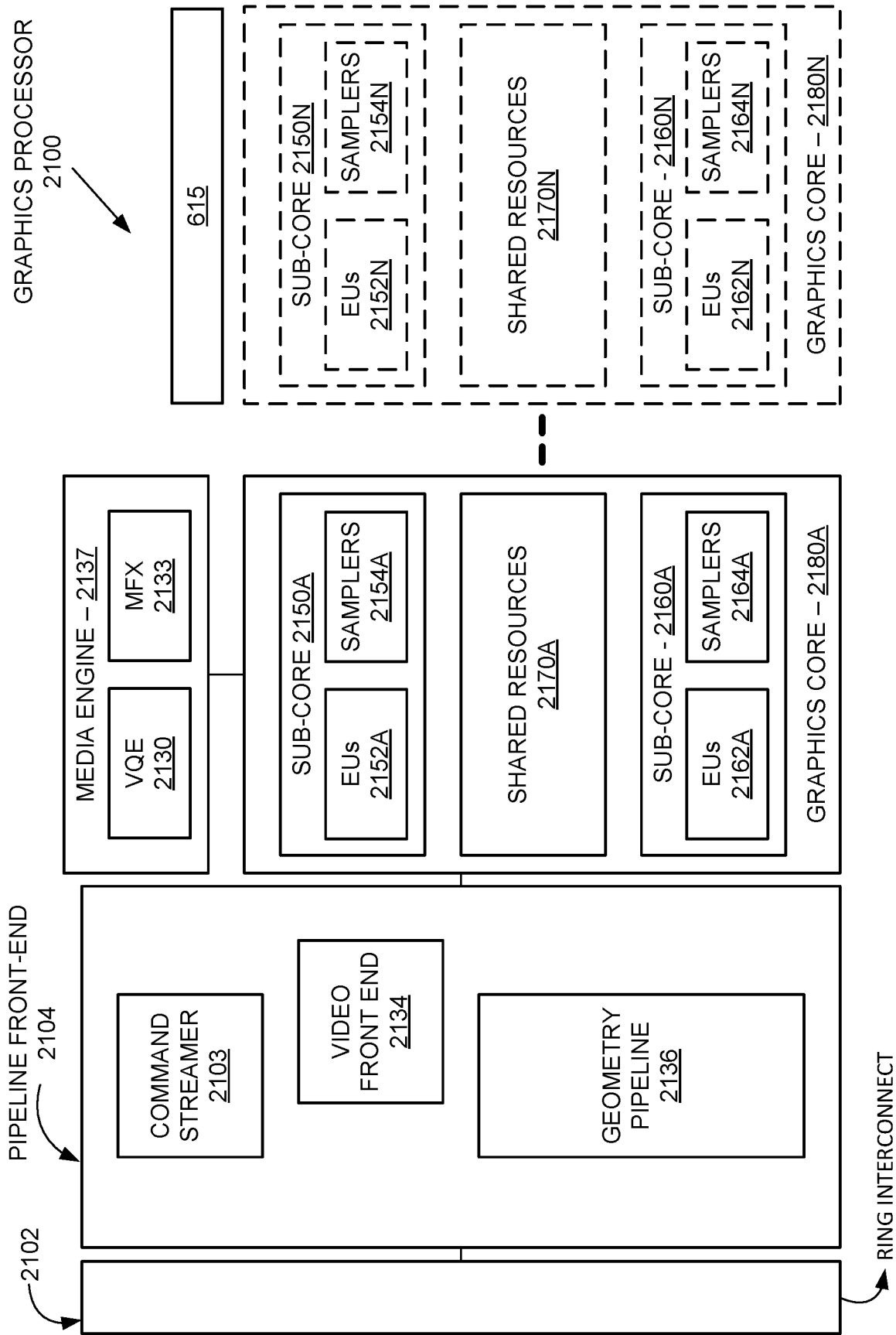


FIG. 21

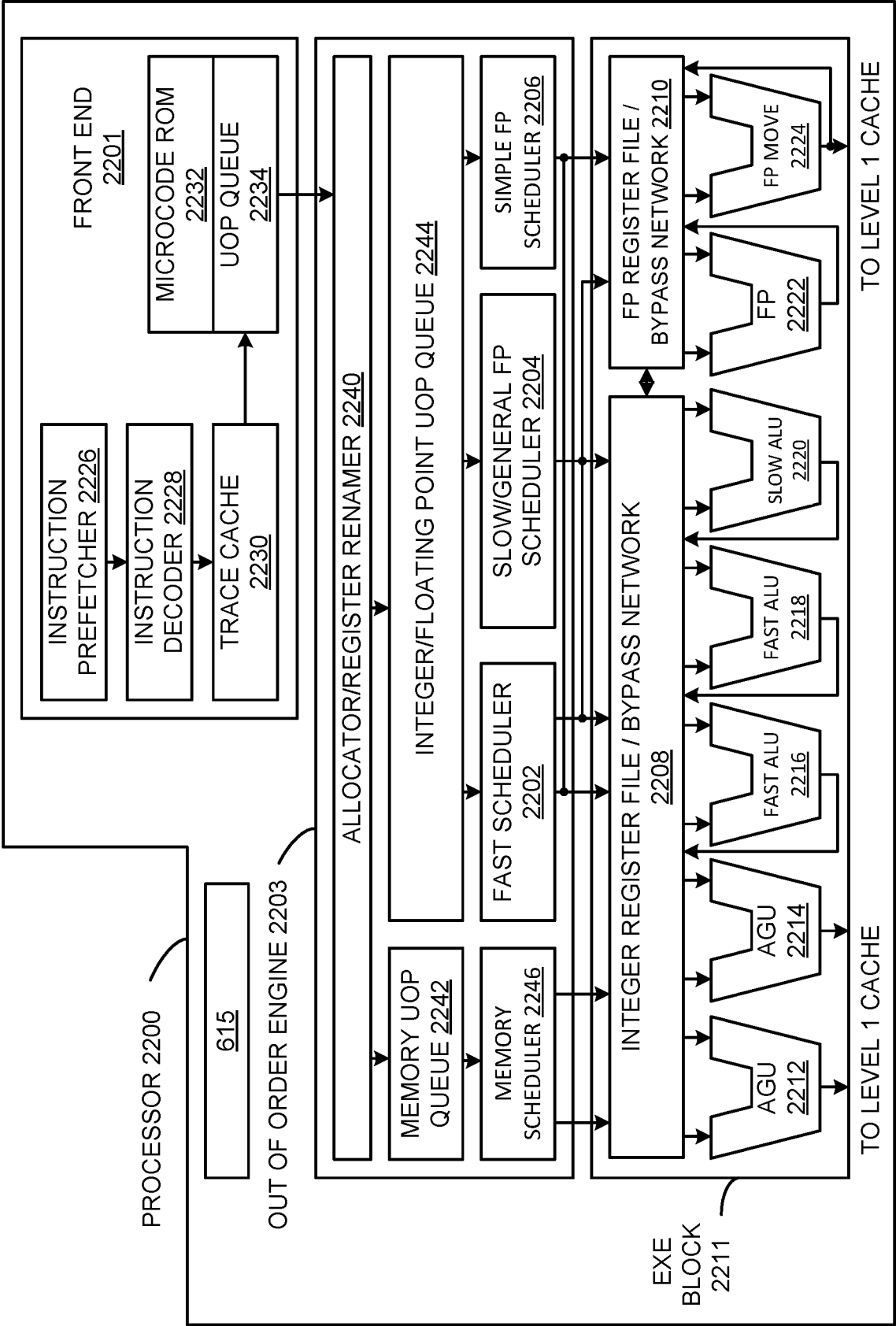


FIG. 22

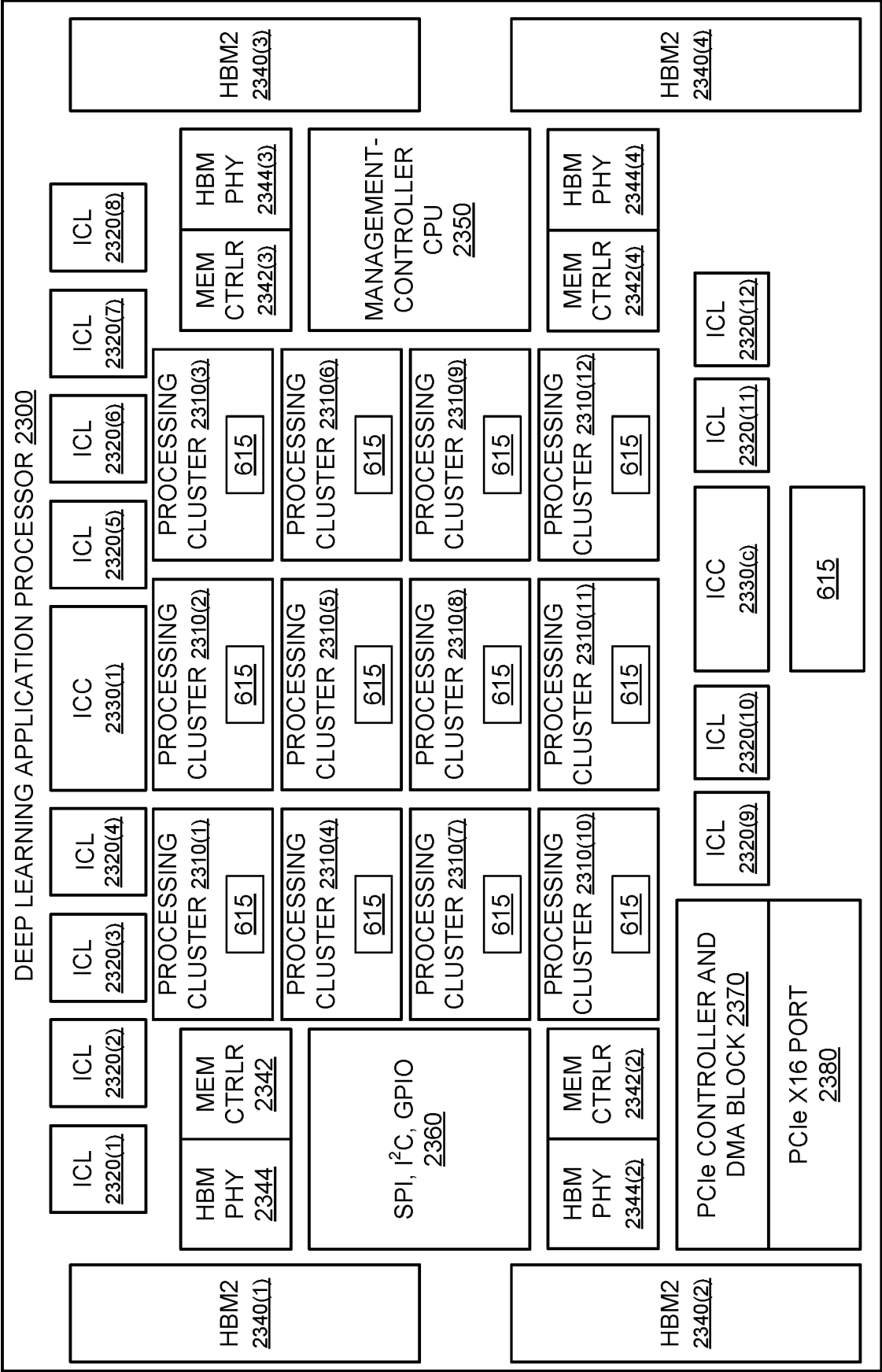


FIG. 23

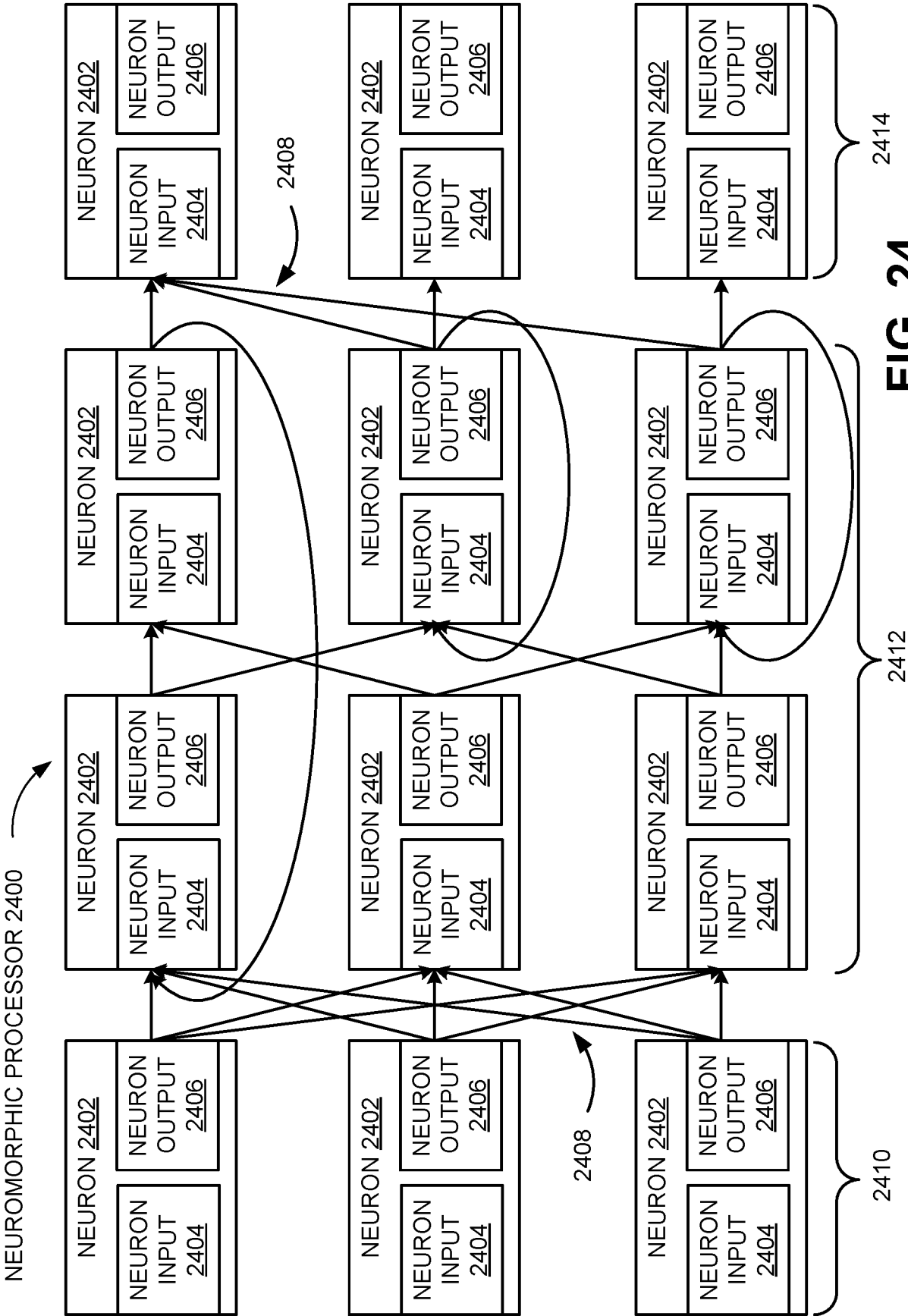


FIG. 24

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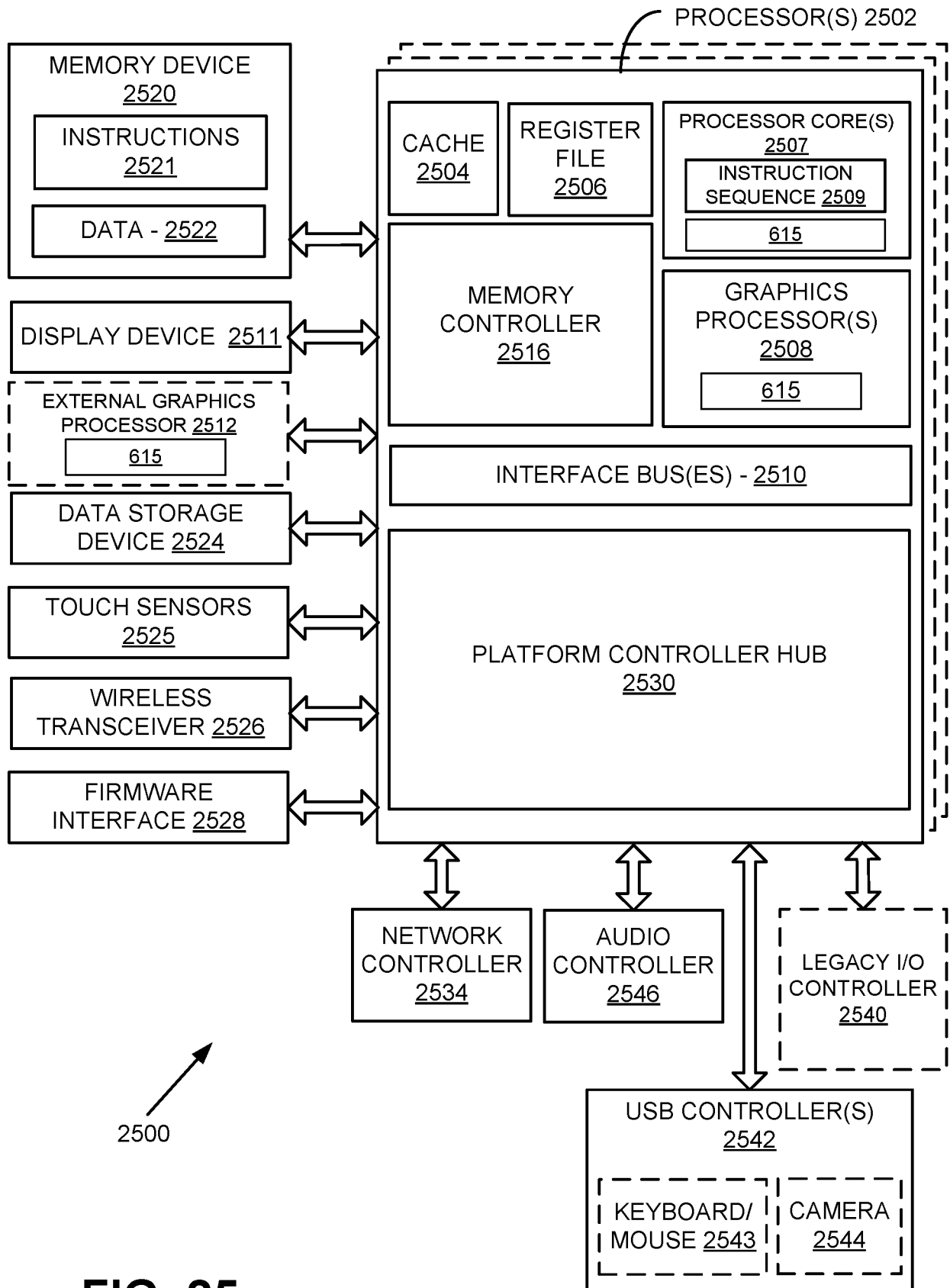


FIG. 25

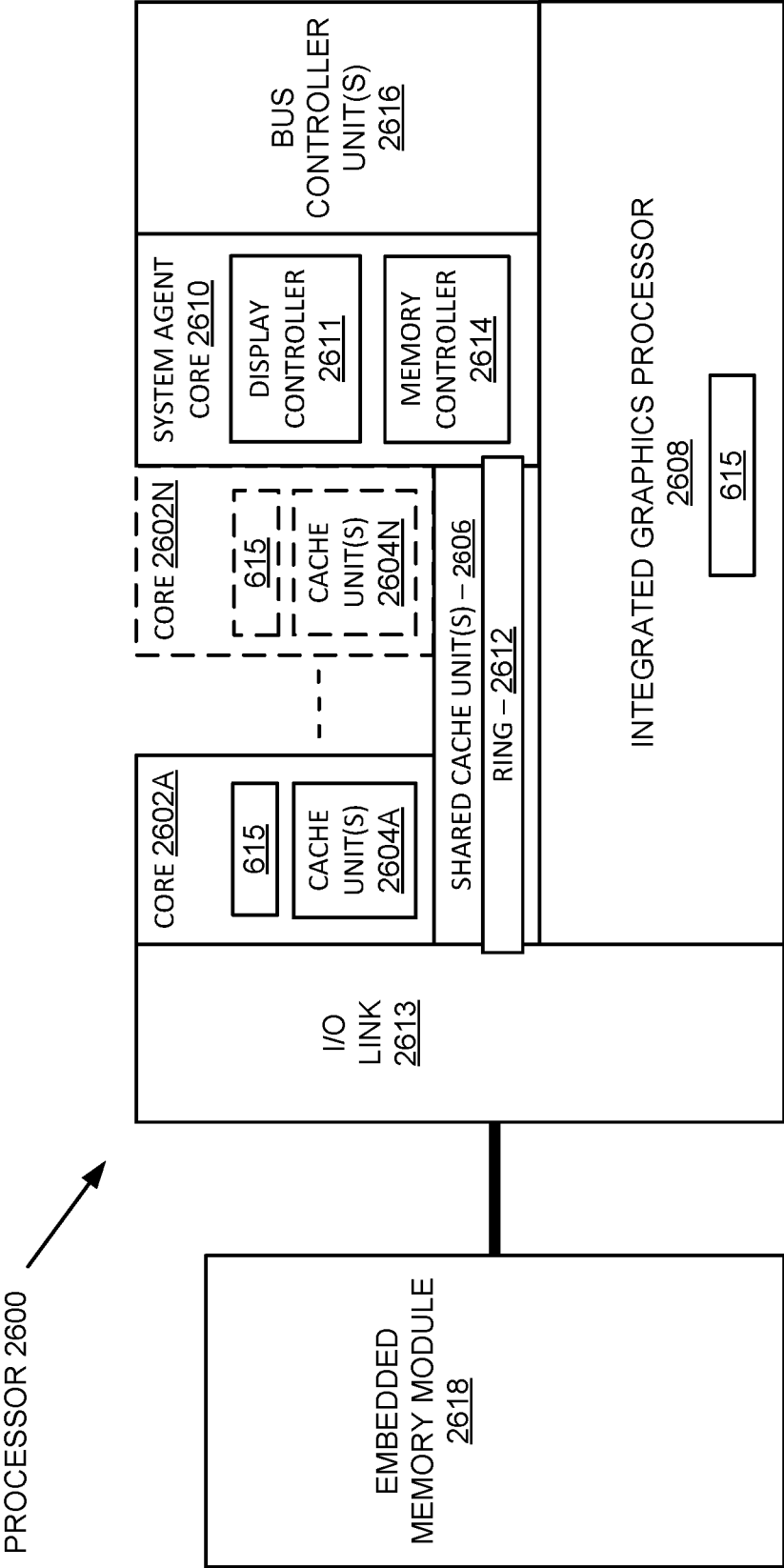


FIG. 26

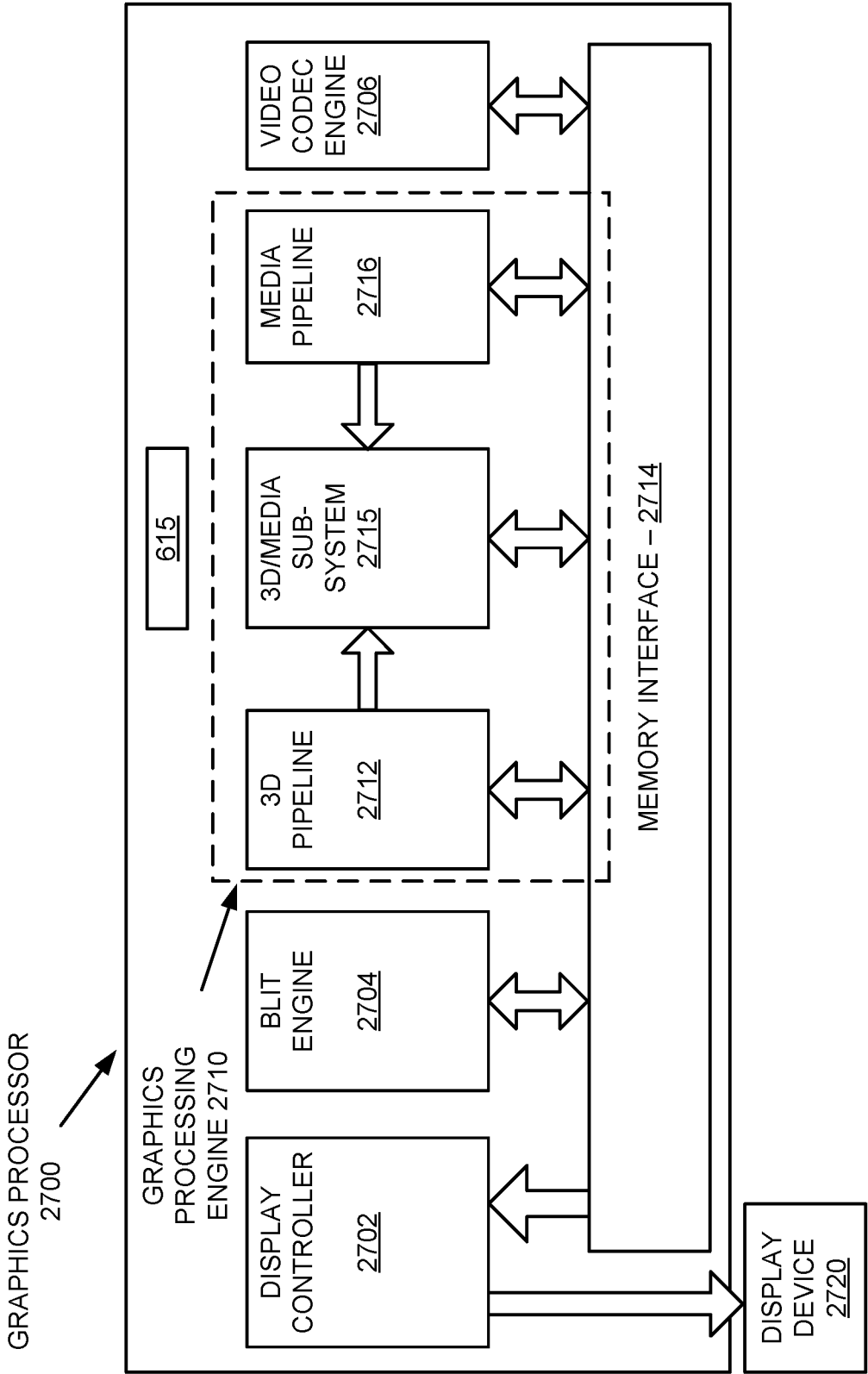


FIG. 27

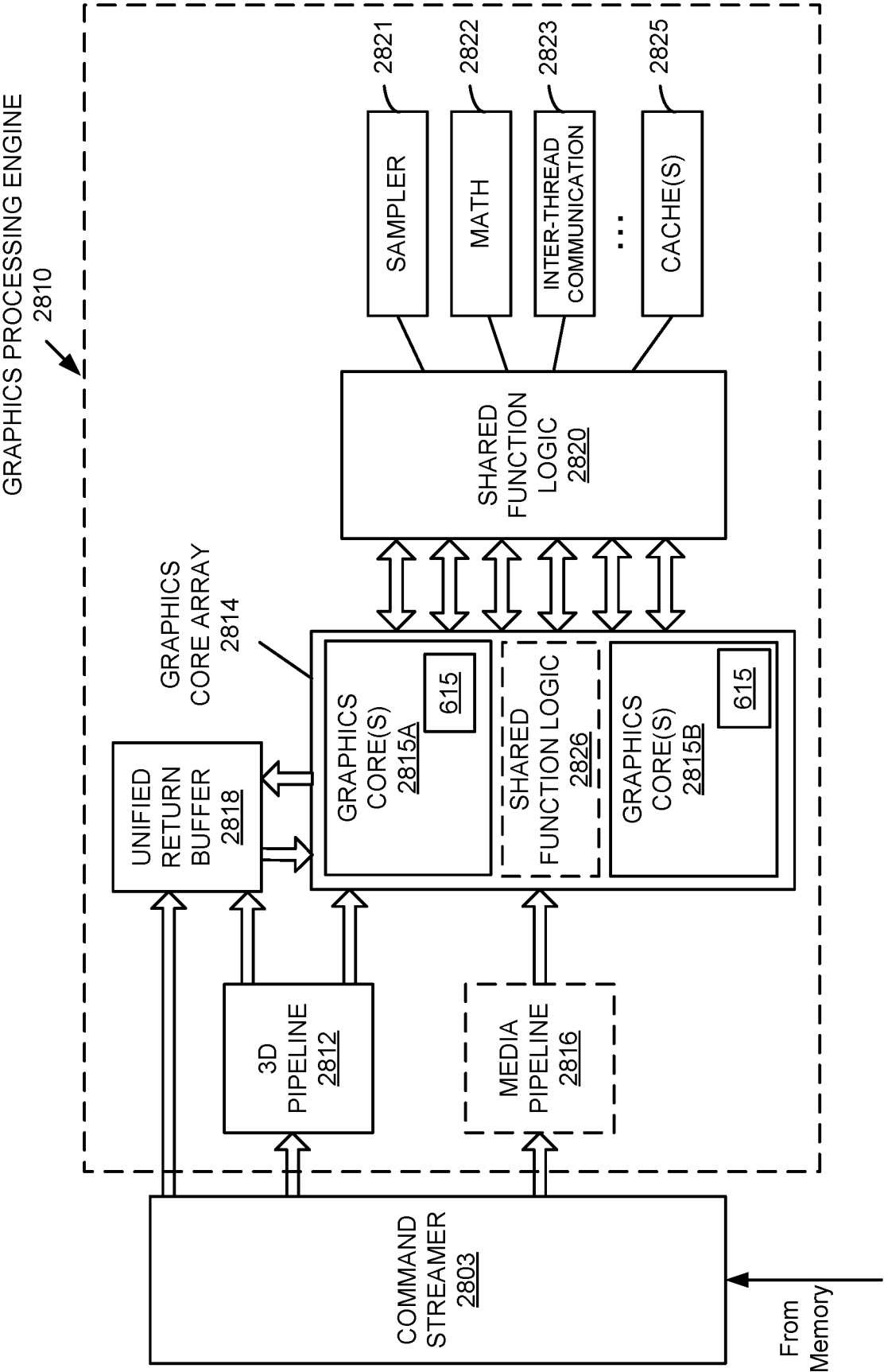
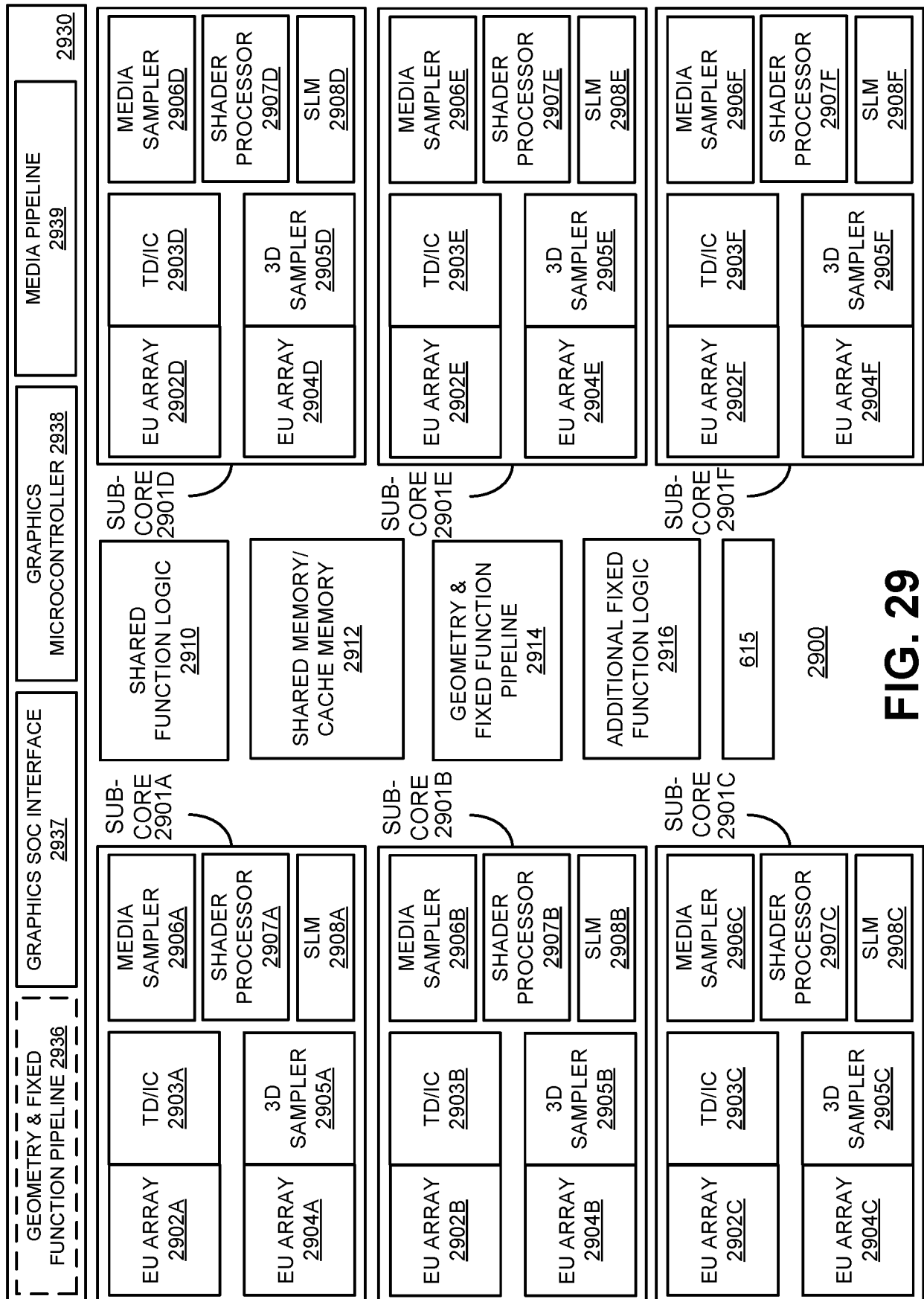


FIG. 28



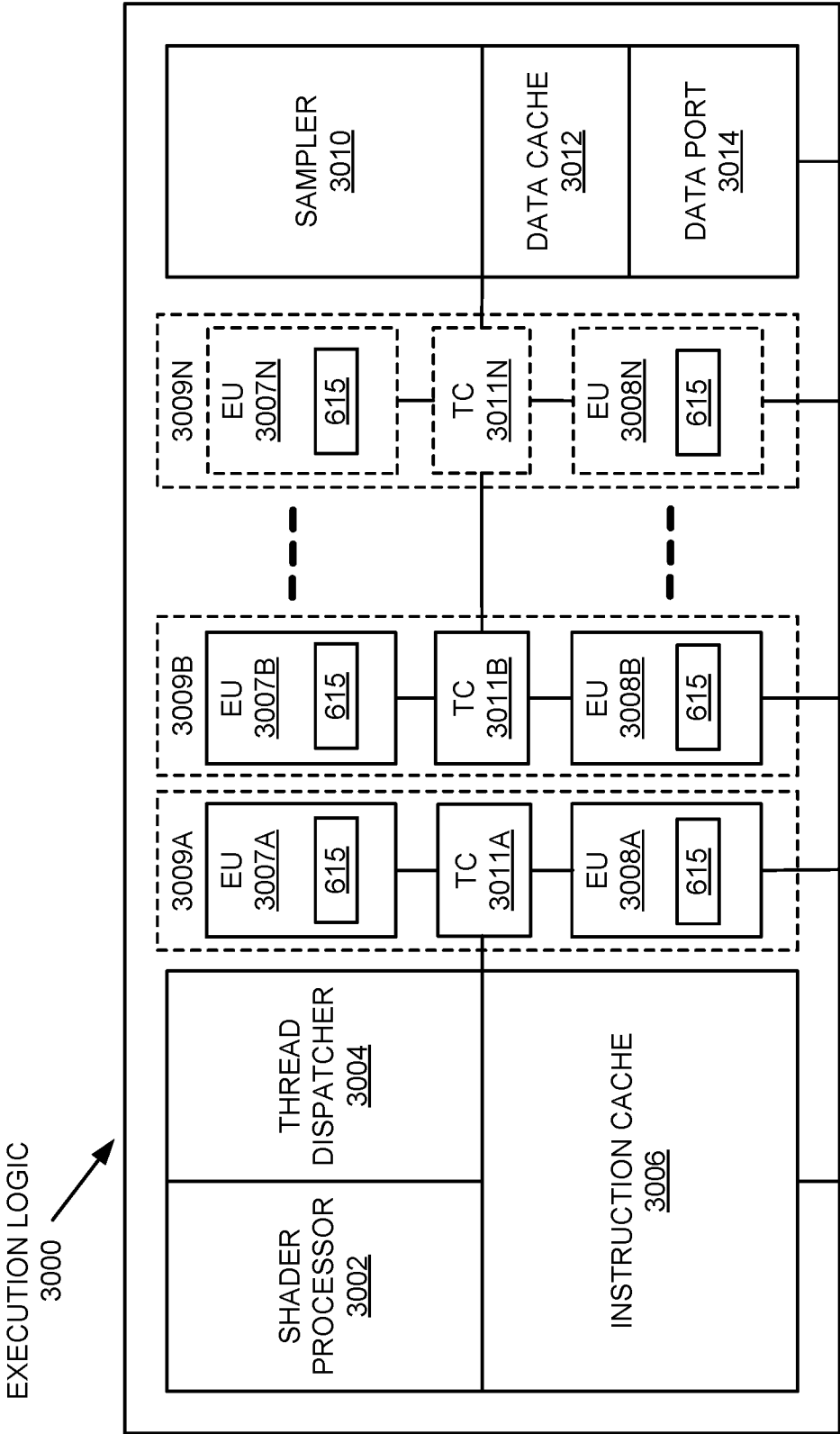


FIG. 30A

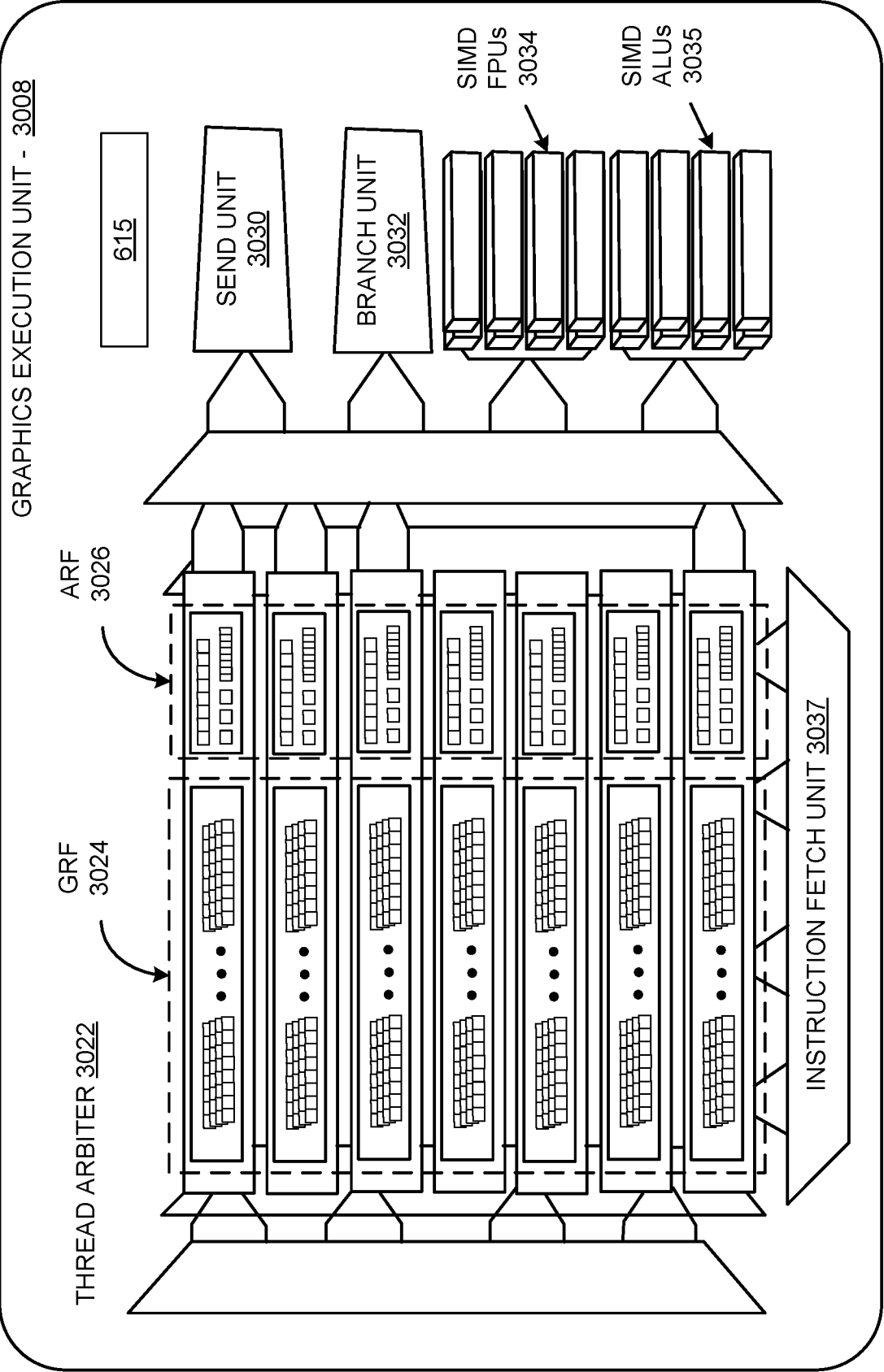


FIG. 30B

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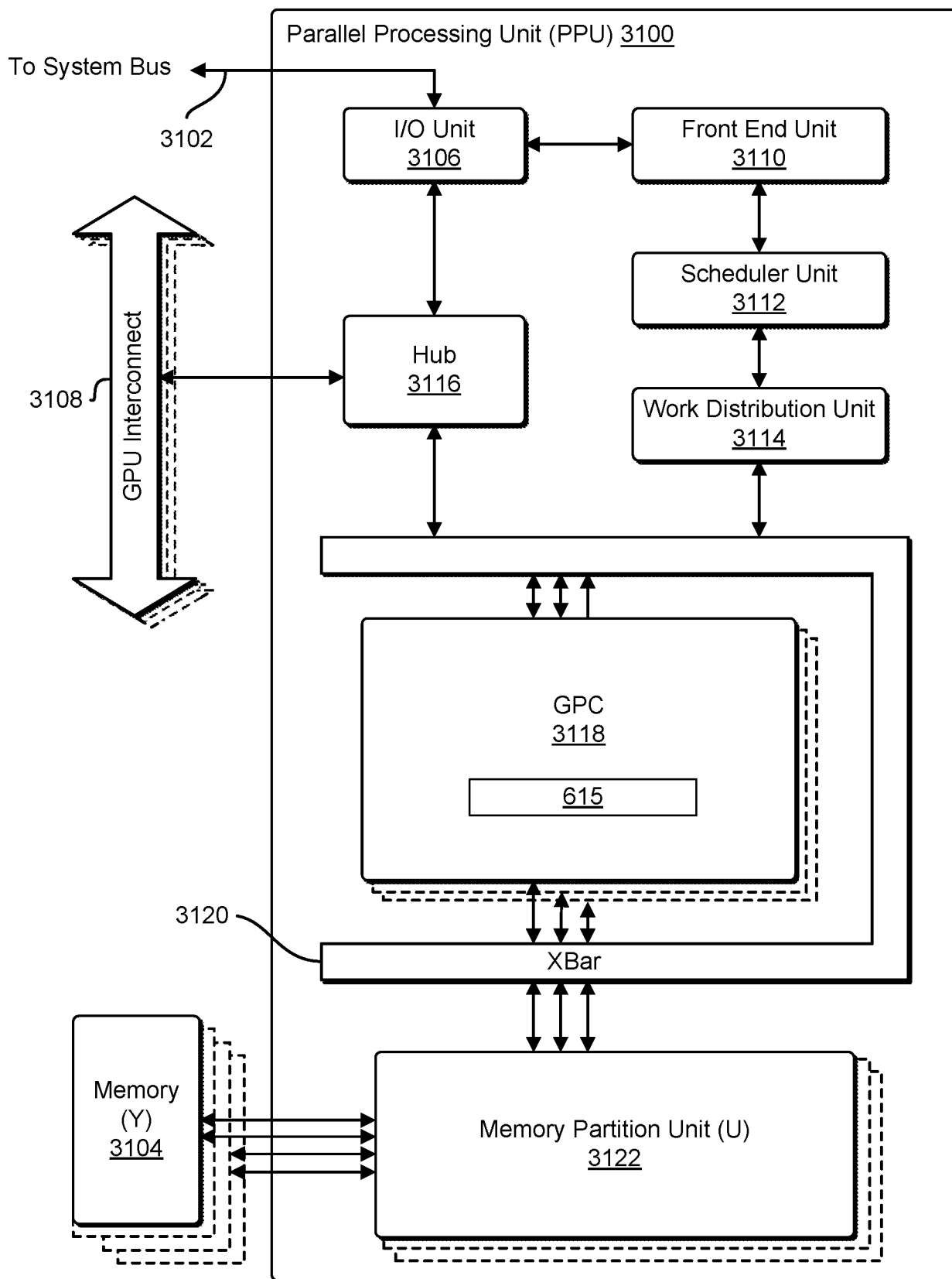


FIG. 31

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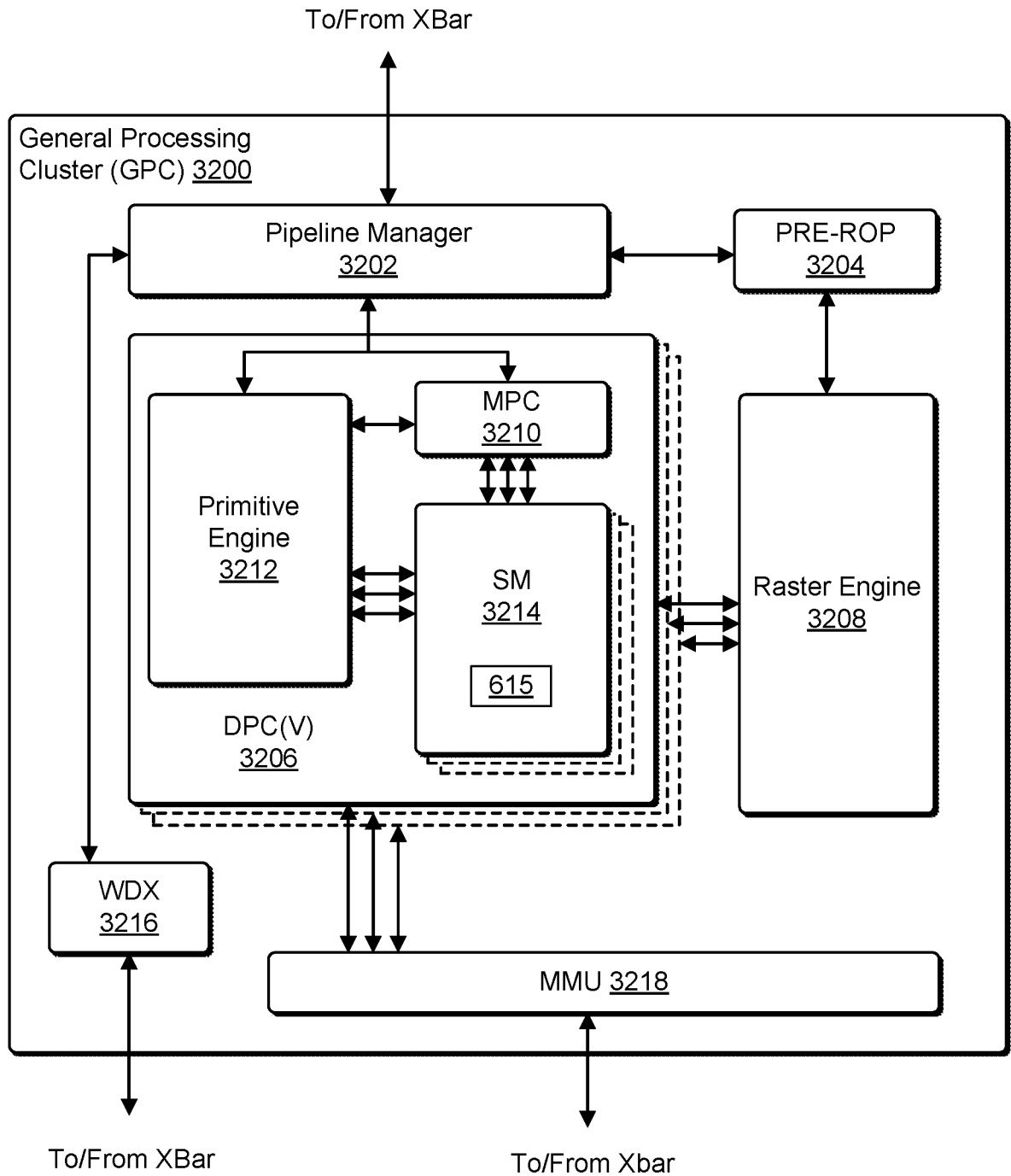


FIG. 32

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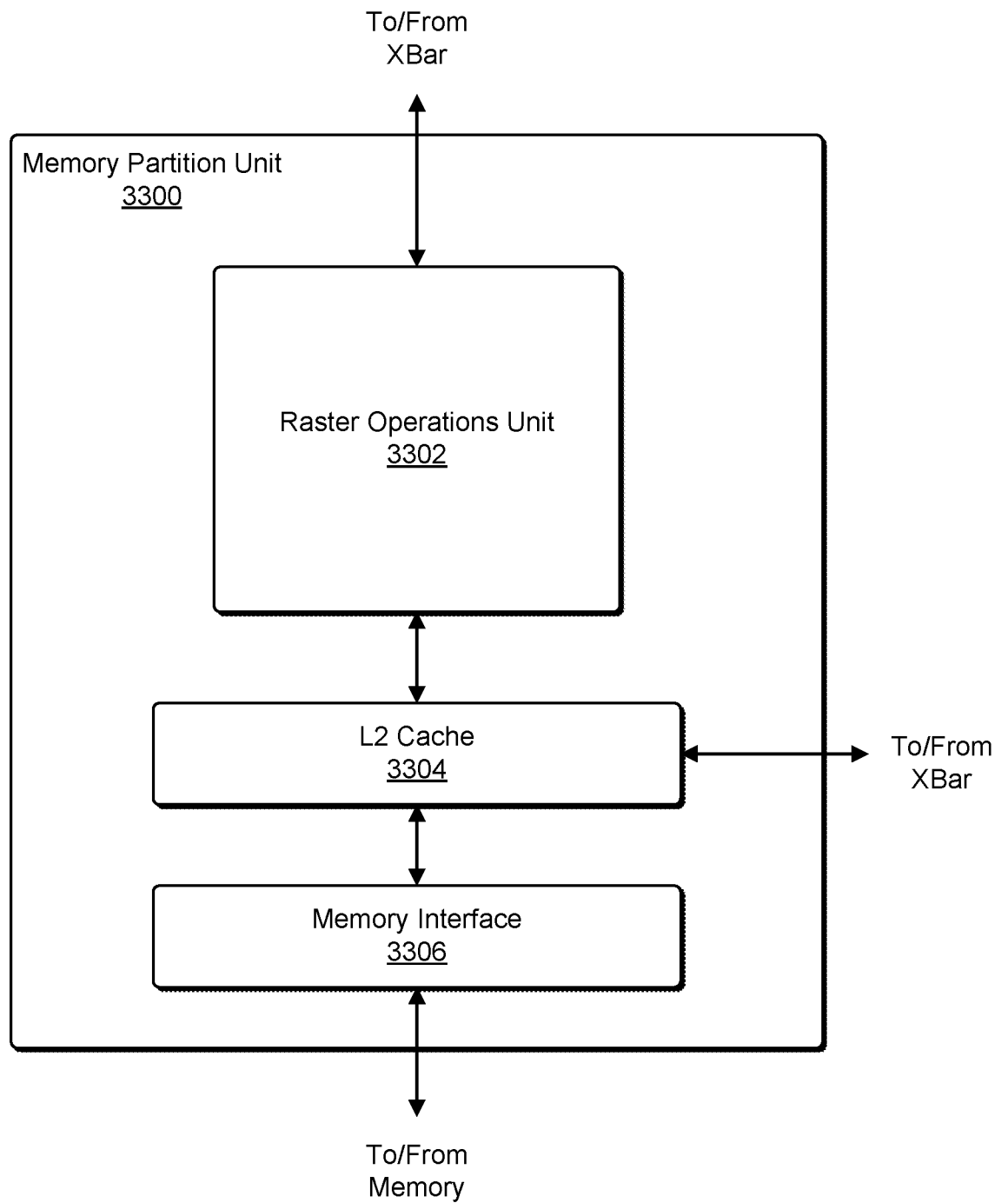


FIG. 33

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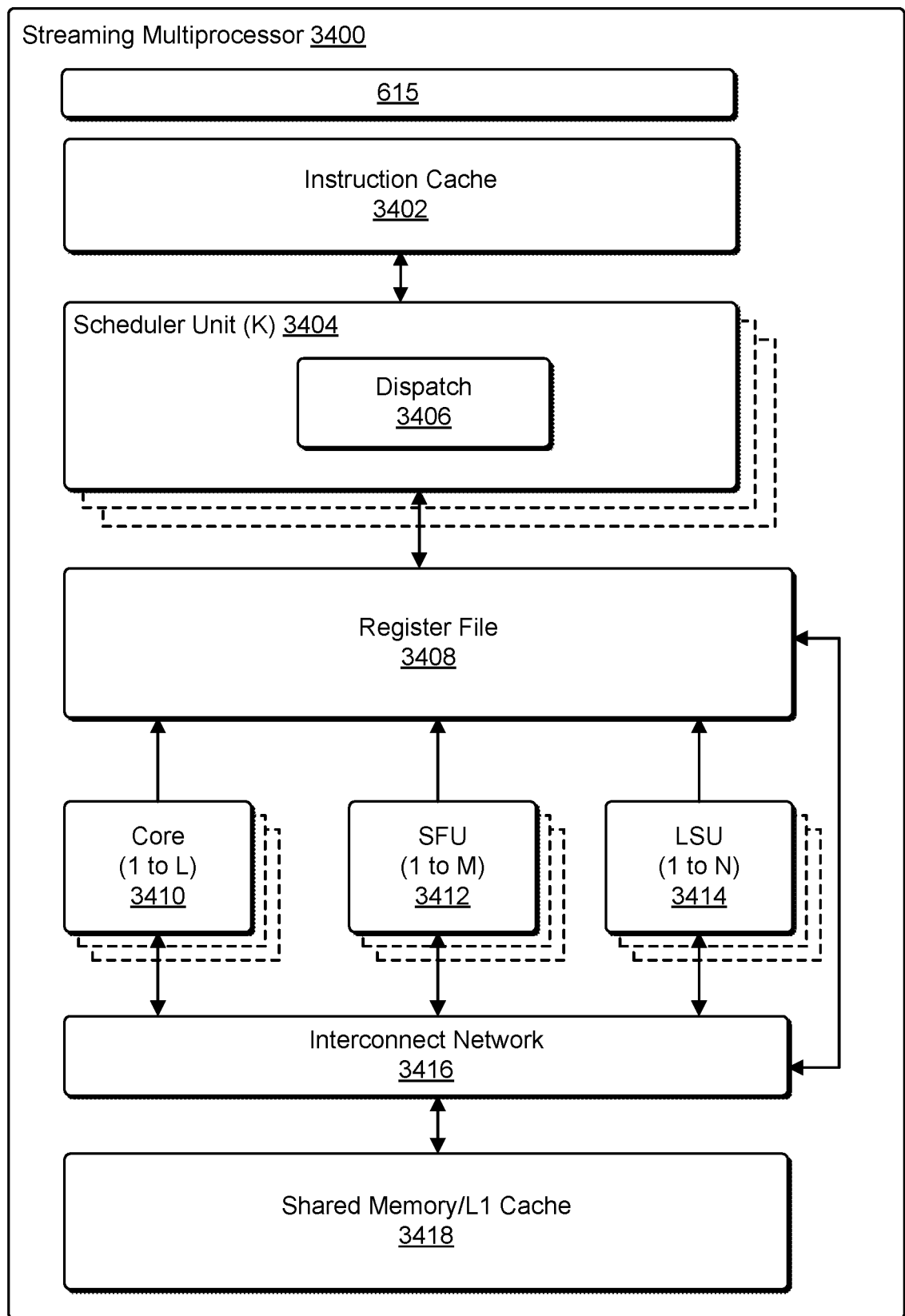


FIG. 34

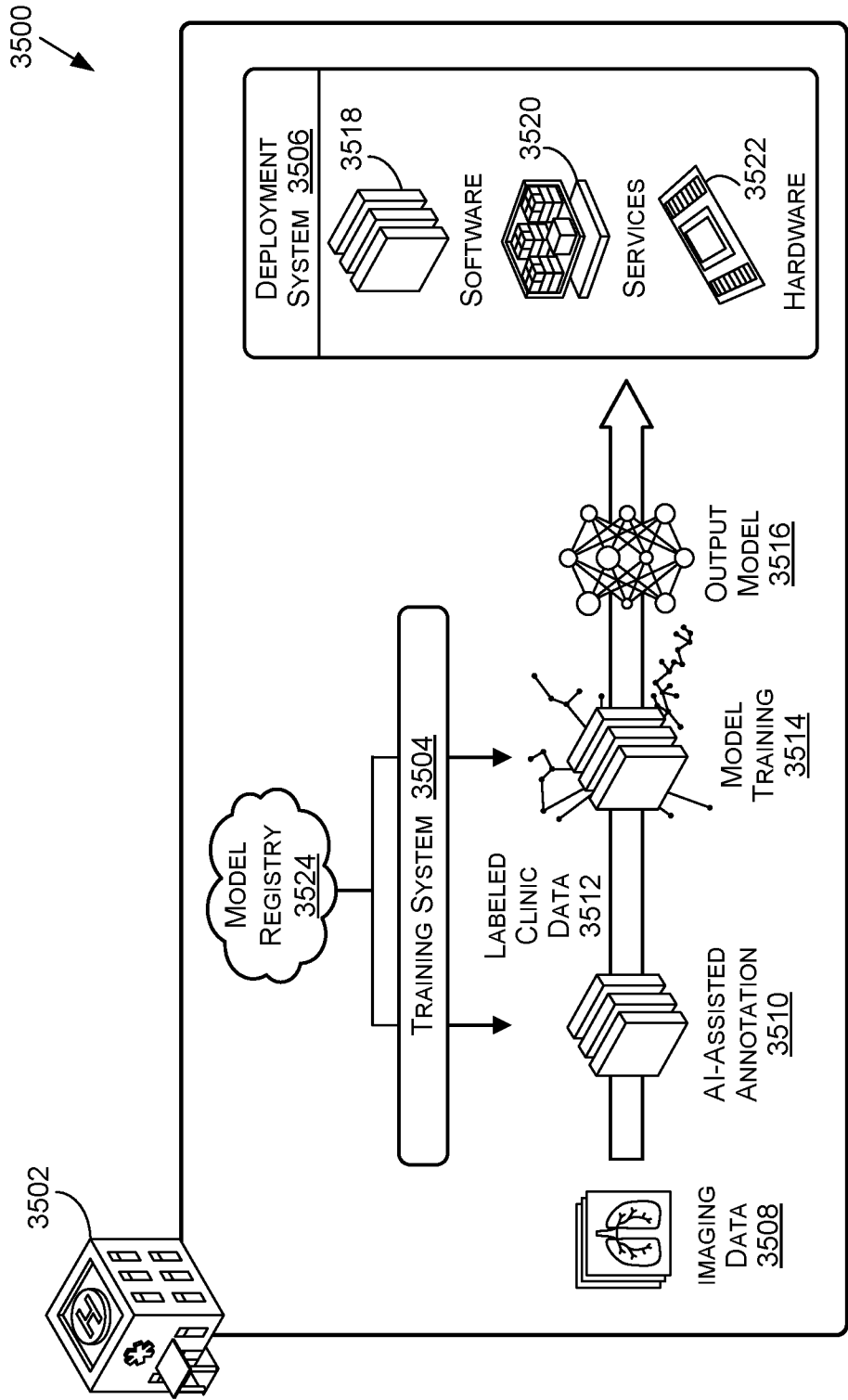


FIG. 35

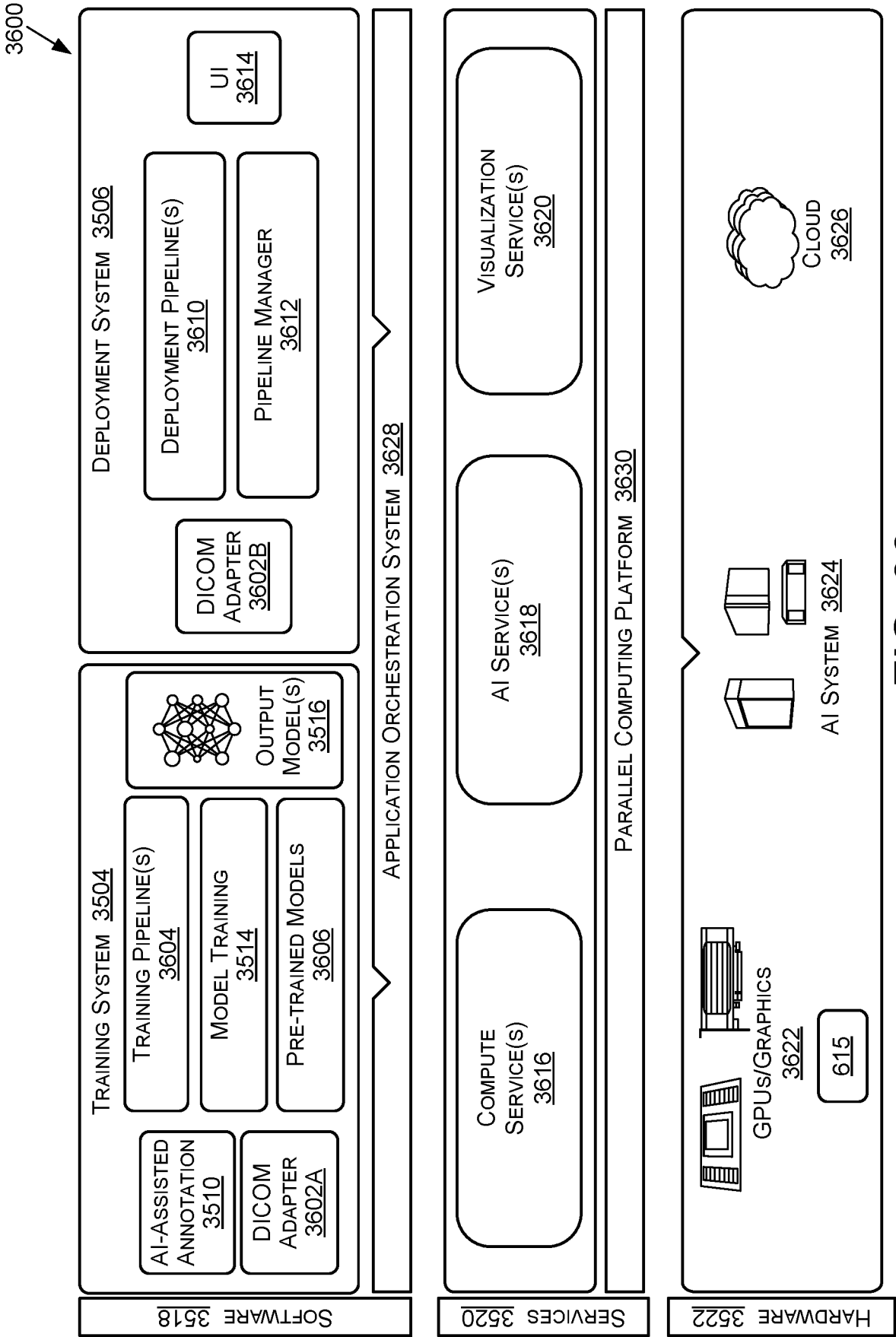


FIG. 36

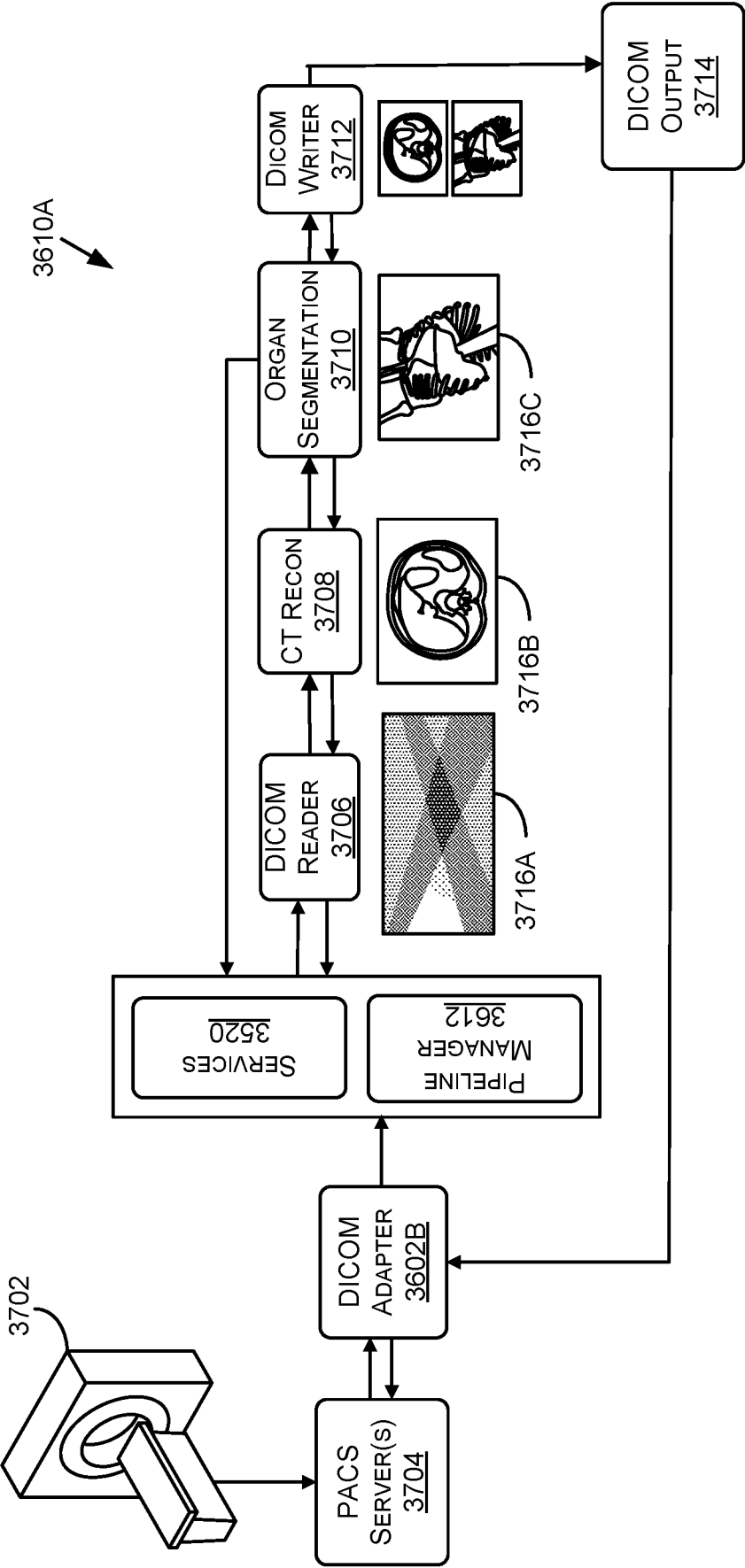


FIG. 37

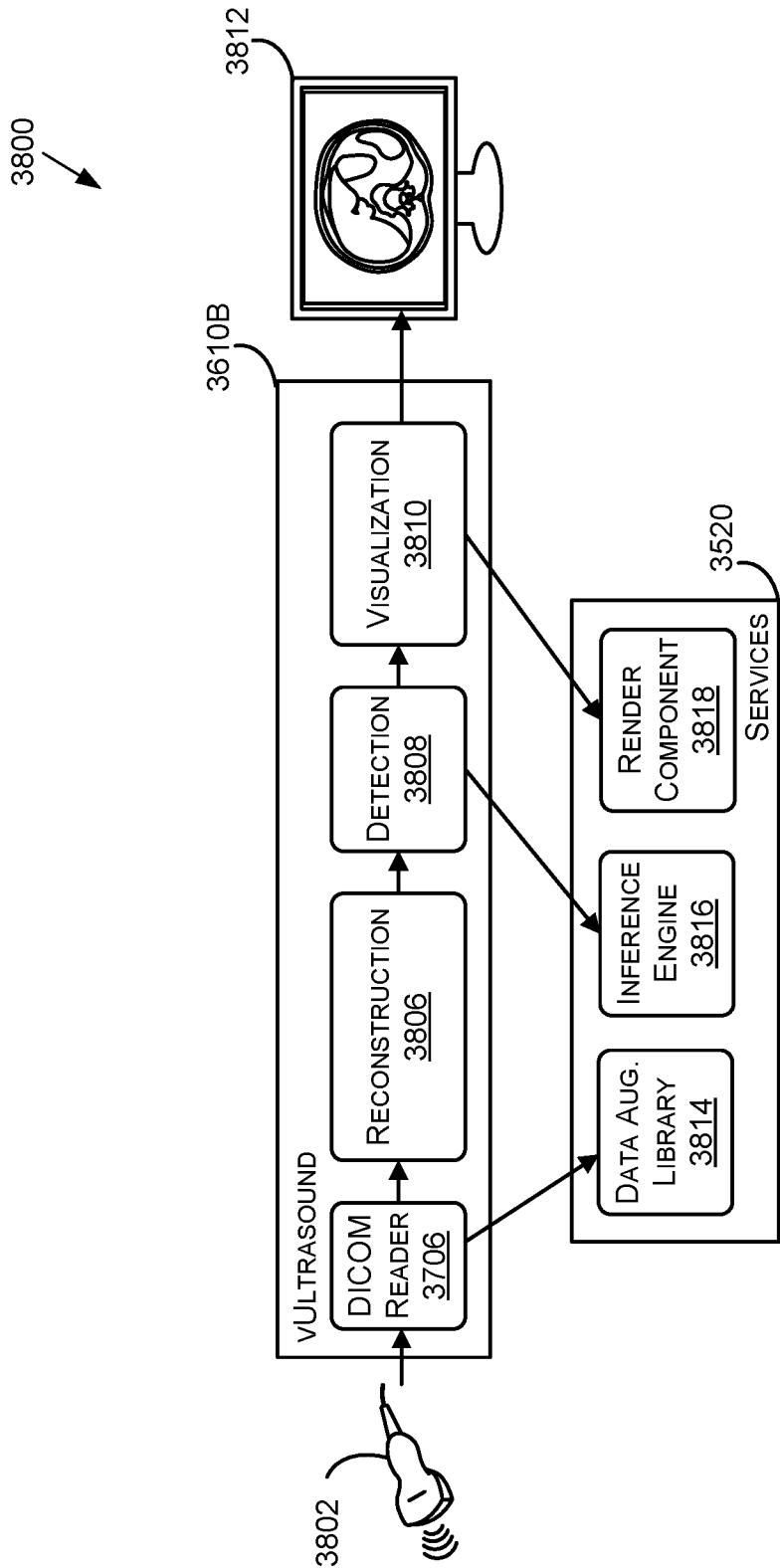


FIG. 38A

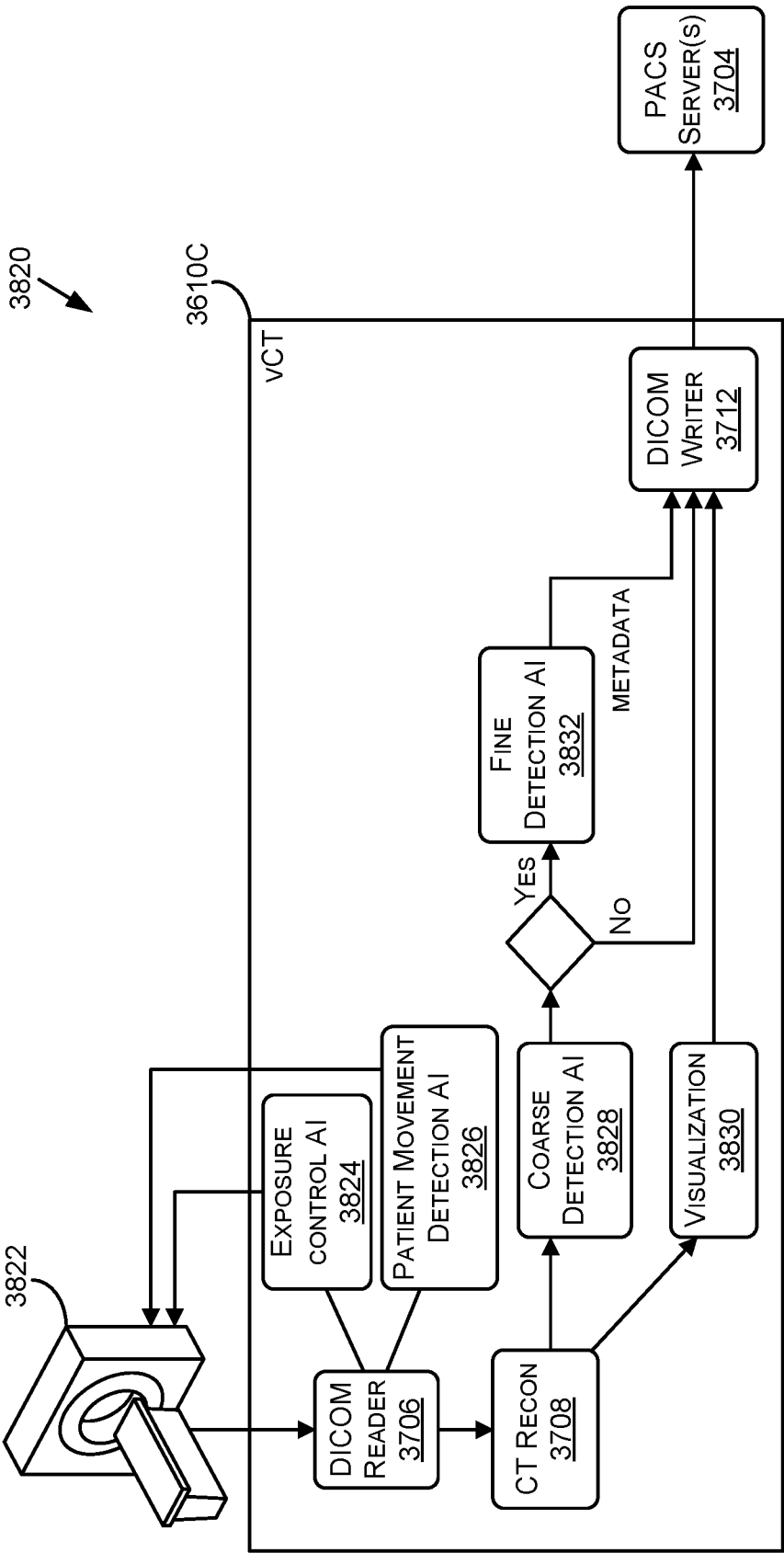


FIG. 38B

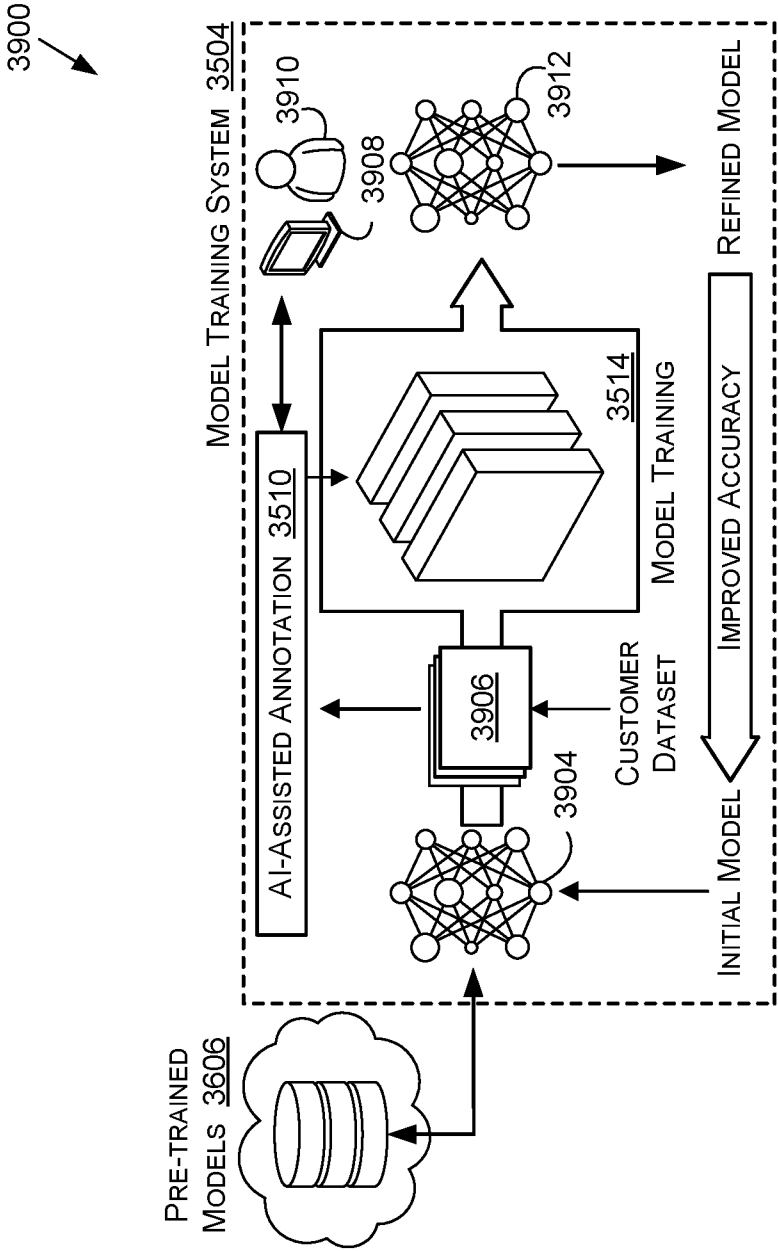


FIG. 39A

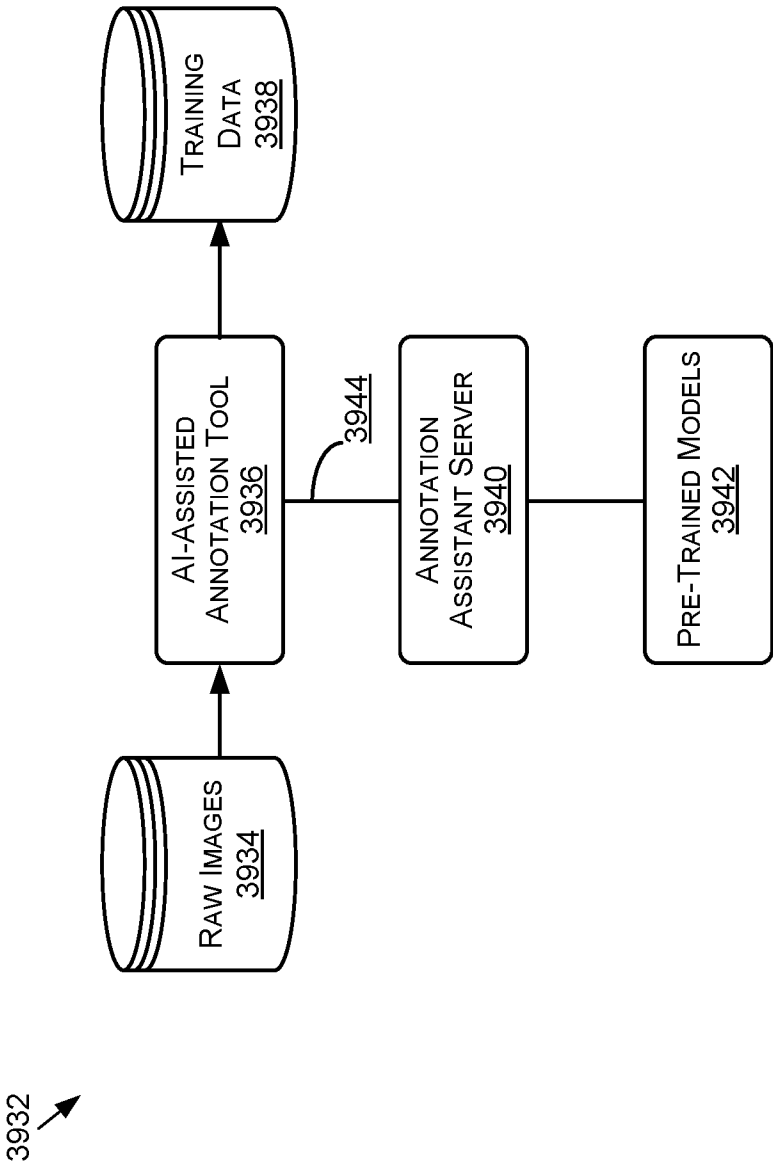


FIG. 39B

INTERNATIONAL SEARCH REPORT

International application No
PCT/US2021/045279

A. CLASSIFICATION OF SUBJECT MATTER
INV. G06K9/32 G06K9/62
ADD.

According to International Patent Classification (IPC) or to both national classification and IPC

B. FIELDS SEARCHED

Minimum documentation searched (classification system followed by classification symbols)
G06K

Documentation searched other than minimum documentation to the extent that such documents are included in the fields searched

Electronic data base consulted during the international search (name of data base and, where practicable, search terms used)

EPO-Internal

C. DOCUMENTS CONSIDERED TO BE RELEVANT

Category*	Citation of document, with indication, where appropriate, of the relevant passages	Relevant to claim No.
X	YIHUI HE ET AL: "Deep Mixture Density Network for Probabilistic Object Detection", ARXIV.ORG, CORNELL UNIVERSITY LIBRARY, 201 OLIN LIBRARY CORNELL UNIVERSITY ITHACA, NY 14853, 2 July 2020 (2020-07-02), XP081704568,	1-3,7,8, 10, 15-19, 22,29
Y	abstract section III section IV ----- -/--	4-6, 9-14,20, 21, 23-28, 30-36



Further documents are listed in the continuation of Box C.



See patent family annex.

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"E" earlier application or patent but published on or after the international filing date

"L" document which may throw doubts on priority claim(s) or which is cited to establish the publication date of another citation or other special reason (as specified)

"O" document referring to an oral disclosure, use, exhibition or other means

"P" document published prior to the international filing date but later than the priority date claimed

"T" later document published after the international filing date or priority date and not in conflict with the application but cited to understand the principle or theory underlying the invention

"X" document of particular relevance; the claimed invention cannot be considered novel or cannot be considered to involve an inventive step when the document is taken alone

"Y" document of particular relevance; the claimed invention cannot be considered to involve an inventive step when the document is combined with one or more other such documents, such combination being obvious to a person skilled in the art

"&" document member of the same patent family

Date of the actual completion of the international search

19 November 2021

Date of mailing of the international search report

29/11/2021

Name and mailing address of the ISA/

European Patent Office, P.B. 5818 Patentlaan 2
NL - 2280 HV Rijswijk
Tel. (+31-70) 340-2040,
Fax: (+31-70) 340-3016

Authorized officer

Angelopoulou, Maria

INTERNATIONAL SEARCH REPORT

International application No

PCT/US2021/045279

C(Continuation). DOCUMENTS CONSIDERED TO BE RELEVANT		
Category*	Citation of document, with indication, where appropriate, of the relevant passages	Relevant to claim No.
Y	<p>CHOI SUNGJOON ET AL: "Uncertainty-Aware Learning from Demonstration Using Mixture Density Networks with Sampling-Free Variance Modeling", 2018 IEEE INTERNATIONAL CONFERENCE ON ROBOTICS AND AUTOMATION (ICRA), IEEE, 21 May 2018 (2018-05-21), pages 6915-6922, XP033403726, DOI: 10.1109/ICRA.2018.8462978 [retrieved on 2018-09-11] section IV -----</p>	<p>4-6, 9-14,20, 21, 23-28, 30-36</p>