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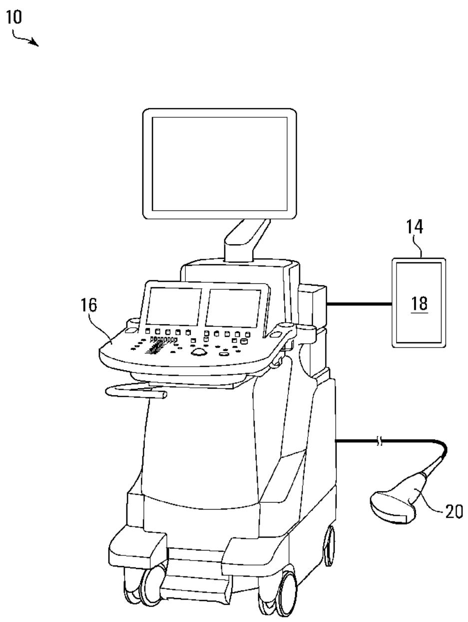

FIG. 1

(57) **Abstract:** A computer-implemented method of facilitating ultrasonic image analysis of a subject is disclosed. The method involves receiving signals representing a set of ultrasound images of the subject, deriving one or more extracted feature representations from the set of ultrasound images, determining, based on the derived one or more extracted feature representations, a quality assessment value representing a quality assessment of the set of ultrasound images, determining, based on the derived one or more extracted feature representations, an image property associated with the set of ultrasound images, and producing signals representing the quality assessment value and the image property for causing the quality assessment value and the image property to be associated with the set of ultrasound images. A computer-implemented method of training one or more neural networks to facilitate ultrasonic image analysis is also disclosed. Other apparatuses, methods, systems, and computer-readable media are also disclosed.

WO 2020/041881 A1

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ULTRASONIC IMAGE ANALYSIS

RELATED APPLICATION

This application claims the benefit of U.S. Provisional Application No. 62/725,913 entitled “ULTRASONIC IMAGE ANALYSIS”, filed on August 31, 2018, which is hereby incorporated by reference herein in its entirety.

BACKGROUND

1. Field

Embodiments of this invention relate to ultrasonic image analysis and more particularly to ultrasonic image analysis for determining image quality and image properties.

2. Description of Related Art

Accurate diagnosis in ultrasound requires high quality ultrasound images, which may need to show or contain different specific features and structures depending on various properties of the images. Some ultrasound systems may not provide feedback to operators regarding quality of the image and/or other image properties. Inexperienced ultrasound operators may have a great deal of difficulty using such known systems to recognize features in the ultrasound images and thus can fail to capture diagnostically relevant ultrasound images.

SUMMARY

In accordance with various embodiments, there is provided a computer-implemented method of facilitating ultrasonic image analysis of a subject. The method involves receiving signals representing a set of ultrasound images of the subject, deriving one or more extracted feature representations from the set of ultrasound images, determining, based on the derived one or more extracted feature representations, a quality assessment value representing a quality assessment of the set of ultrasound images, determining, based on the derived one or more extracted feature representations, an image property associated with the set of ultrasound images, and producing signals representing the quality assessment value and the image property for causing the quality assessment value and the image property to be associated with the set of ultrasound images.

The image property may be a view category.

Deriving the one or more extracted feature representations from the ultrasound images may involve, for each of the ultrasound images, deriving a first feature representation associated with the ultrasound image.

Deriving the one or more extracted feature representations may involve, for each of the ultrasound images, inputting the ultrasound image into a commonly defined first feature extracting neural network to generate the first feature representation associated with the ultrasound image.

Deriving the one or more extracted feature representations may involve concurrently inputting each of a plurality of the ultrasound images into a respective implementation of the commonly defined first feature extracting neural network.

The commonly defined first feature extracting neural network may include a convolutional neural network.

Deriving the one or more extracted feature representations may involve inputting the first feature representations into a second feature extracting neural network to generate respective second feature representations, each associated with one of the ultrasound images. The one or more extracted feature representations may include the second feature representations.

The second feature extracting neural network may be a recurrent neural network.

Determining the quality assessment value may involve inputting the one or more extracted feature representations into a quality assessment value specific neural network and determining the image property may involve inputting the one or more extracted feature representations into an image property specific neural network.

Inputting the one or more extracted feature representations into the quality assessment value specific neural network may involve inputting each of the one or more extracted feature representations into an implementation of a commonly defined quality assessment value specific neural subnetwork and inputting the one or more extracted feature representations into the image property determining neural network may involve inputting each of the one or more extracted feature representations into an implementation of a commonly defined image property specific neural network.

Producing signals representing the quality assessment value and the image property for causing the quality assessment value and the image property to be associated with the set of ultrasound images may involve producing signals for causing a representation of the quality assessment value and a representation of the image property to be displayed by at least one display in association with the set of ultrasound images.

In accordance with various embodiments, there is provided a computer-implemented method of training one or more neural networks to facilitate ultrasonic image analysis. The method involves receiving signals representing a plurality of sets of ultrasound training images, receiving signals representing quality assessment values, each of the quality assessment values associated with one of the sets of ultrasound training images and representing a quality assessment of the associated set of ultrasound training images, receiving signals representing image properties, each of the image properties associated with one of the sets of ultrasound training images, and training a neural network, the training comprising, for each set of the plurality of sets of ultrasound training images, using the set of ultrasound training images as an input to the neural network and using the quality assessment values and the image properties associated with the set of ultrasound training images as desired outputs of the neural network.

Each of the image properties may be a view category.

The neural network may include a feature extracting neural network, an image property specific neural network, and a quality assessment value specific neural network. The feature extracting neural network may be configured to take an input set of the plurality of sets of ultrasound training images as an input and to output one or more extracted feature representations. The image property specific neural network may be configured to take the one or more extracted feature representations as an input and to output a representation of an image property associated with the input set of ultrasound training images. The quality assessment specific neural network may be configured to take the one or more extracted feature representations as an input and to output a quality assessment value associated with the input set of ultrasound training images.

The feature extracting neural network may be configured to, for each of the ultrasound training images included in the input set of ultrasound training images, derive a first feature representation associated with the ultrasound image.

The feature extracting neural network may include, for each of the ultrasound images included in the input set of ultrasound training images, a commonly defined first feature extracting neural network configured to take as an input the ultrasound training image and to output a respective one of the first feature representations.

More than one implementation of the commonly defined first feature extracting neural networks may be configured to concurrently generate the first feature representations.

The commonly defined first feature extracting neural network may be a convolutional neural network.

The feature extracting neural network may include a second feature extracting neural network configured to take as an input the first feature representations and to output respective second feature representations, each associated with one of the ultrasound images included in the input set of ultrasound training images and the one or more extracted feature representations may include the second feature representations.

The second feature extracting neural network may be a recurrent neural network.

In accordance with various embodiments, there is provided a system for facilitating ultrasonic image analysis including at least one processor configured to perform any of the above methods.

In accordance with various embodiments, there is provided a non-transitory computer readable medium having stored thereon codes which when executed by at least one processor cause the at least one processor to perform any of the above methods.

In accordance with various embodiments, there is provided a system for facilitating ultrasonic image analysis, the system including means for receiving signals representing a set of ultrasound images of the subject, means for deriving one or more extracted feature representations from the set of ultrasound images, means for determining, based on the derived one or more extracted feature representations, a quality assessment value representing a quality assessment of the set of ultrasound images, means for determining, based on the derived one or more extracted feature representations, an image property associated with the set of ultrasound images, and means for producing signals representing the quality assessment value and the image property for causing the quality assessment value and the image property to be associated with the set of ultrasound images.

In accordance with various embodiments, there is provided a system for training one or more neural networks to facilitate ultrasonic image analysis, the system including means for receiving signals representing a plurality of sets of ultrasound training images, means for receiving signals representing quality assessment values, each of the quality assessment values associated with one of the sets of ultrasound training images and representing a quality assessment of the associated set of ultrasound training images, means for receiving signals representing image properties, each of the image properties associated with one of the sets of ultrasound training images, and means for training a neural network, the training comprising, for each set of the plurality of sets of ultrasound training images, using the set of ultrasound training images as an input to the neural network and using the quality assessment values and the image properties associated with the set of ultrasound training images as desired outputs of the neural network.

Other aspects and features of embodiments of the invention will become apparent to those ordinarily skilled in the art upon review of the following description of specific embodiments of the invention in conjunction with the accompanying figures.

BRIEF DESCRIPTION OF THE DRAWINGS

In drawings which illustrate embodiments of the invention,

Figure **1** is a schematic view of a system for facilitating ultrasonic image analysis of a subject according to various embodiments of the invention;

Figure **2** is a schematic view of an image analyzer of the system shown in Figure **1** including a processor circuit in accordance with various embodiments of the invention;

Figure **3** is a flowchart depicting blocks of code for directing the analyzer of the system shown in Figure **1** to perform image analysis functions in accordance with various embodiments of the invention;

Figure **4** is a representation of an exemplary neural network that may be used in the system shown in Figure **1** in accordance with various embodiments of the invention;

Figure **5** is a representation of part of the neural network shown in Figure **4** in accordance with various embodiments of the invention;

Figure **6** is a representation of part of the neural network shown in Figure **4** in accordance with various embodiments of the invention;

Figure **7** is a representation of part of the neural network shown in Figure **4** in accordance with various embodiments of the invention;

Figure **8** is a representation of part of the neural network shown in Figure **4** in accordance with various embodiments of the invention;

Figure **9** is a representation of part of the neural network shown in Figure **4** in accordance with various embodiments of the invention;

Figure **10** is a representation of a display that may be provided by the system shown in Figure **1** in accordance with various embodiments of the invention;

Figure **11** is a schematic view of a neural network trainer that may be included in the system shown in Figure **1** in accordance with various embodiments of the invention;

Figure **12** is a flowchart depicting blocks of code for directing the trainer shown in Figure **11** to perform neural network training functions in accordance with various embodiments of the invention; and

Figure **13** is a timing diagram representing thread timing that may be used in the system shown in Figure **1** in accordance with various embodiments of the invention.

DETAILED DESCRIPTION

Referring to Figure **1**, there is provided a system **10** for facilitating ultrasonic image analysis of a subject according to various embodiments. The system **10** includes a computer-implemented image analyzer **14** in communication with an ultrasound machine **16** having a transducer **20**. In various embodiments, the analyzer **14** may include a display **18**. In some embodiments, the analyzer **14** may be implemented as a mobile device, for example.

In various embodiments, the system **10** may provide feedback to an operator of the ultrasound machine **16** regarding quality of the ultrasound images being captured and other image properties. For example, in some embodiments, the system **10** may provide real-time or near real-time feedback to the operator in the form of a view category or classification and image quality estimation. In various embodiments, this may allow the operator to capture ultrasound images that facilitate more accurate analysis, which may in some embodiments allow more accurate diagnosis of a patient acting as the subject of the analysis.

In some embodiments, for example, by providing real-time or near real-time feedback to the operator, the system **10** may be used to facilitate capturing high quality images for cardiac ultrasound imaging wherein specific features and structures may need to be imaged. The required features and structures in cardiac ultrasound imaging may depend on which of the **14** standard cardiac views the operator is attempting to acquire and so real-time or near real-time feedback that provides both a quality assessment value and a view category for the images the operator is capturing may be particularly helpful. In some embodiments, by providing real-time or near real-time feedback to the operator, the system **10** may allow inexperienced operators to more easily recognize the specific features and structures required of various views and thus the system **10** may be able to capture diagnostically relevant sets of ultrasound images or heart cines.

In various embodiments, the system **10** may be particularly useful because some of the view categories for ultrasound imaging may be quite similar to an inexperienced eye and switching between them may require precise adjustments of the probe's position and orientation. In various embodiments, the system **10** may reduce the adverse effect of inter-operator variability on the quality of the acquired ultrasound images. In some embodiments, the system **10** may do this by providing the operator with real-time or near real-time feedback of both view classification and image quality.

In various embodiments, this may be done through the use of a deep learning neural network, which may, for example, be capable of simultaneously determining which view category of fourteen (**14)** possible view categories the captured images fall into and determining a quality assessment value acting as a quality estimation score. In various embodiments, the architecture of the neural network implemented by the analyzer **14** may allow the analyzer to be implemented by a device that does not require an extremely high computing power, such as, for example an application on a mobile device or running on an off-the-shelf mobile device with the result being that the analyzer **14** may be portable and/or cost effective. In some embodiments, by combining quality assessment and another image property assessment, such as view categorization, a highly shared neural network may yield faster processing time compared to using a separate quality assessment and image property assessment, such as view categorization. In some embodiments, by combining quality assessment and another image property assessment, such as view categorization, the joint training of the two modalities may prevent the neural network from overfitting the label from either modality. In some embodiments, by combining quality assessment and another image property assessment, such as view categorization, there may be cost savings since a single model needs to be maintained rather than multiple separate models.

Referring now to Figure **1**, use of the system **10** will be discussed in accordance with various embodiments. In use, the ultrasound machine **16** and transducer **20** may be controlled by an operator to send and receive ultrasound signals to and from the subject via the transducer **20**, to produce ultrasound image representations of the subject. For example, in some embodiments, the subject may be a person or patient. In some embodiments, the transducer **20** may be manipulated such that the ultrasound machine **16** produces ultrasound images of a heart of the person, for example.

In some embodiments, a representation of the ultrasound images may be transmitted to the analyzer **14**. In some embodiments, the system **10** may include a frame grabber configured to capture raw video output from the ultrasound machine **16** and to transmit a serial data stream representing a set of ultrasound images to the analyzer **14**. For example, in some embodiments, the frame grabber may be configured to receive its input directly from a DVI port of the ultrasound machine **16**, using an Epiphan AV.IO frame grabber, for example, to capture and convert the raw video output to a serial data stream. In some embodiments, the frame grabber output may be adapted from USB-A to USB-C with an On-The-Go (OTG) adapter, allowing the frame grabber to pipe video output from the ultrasound machine **16** directly into the analyzer **14**. As described below, the analyzer **14** may run or implement a neural network which is configured to process the video output received from the frame grabber. In some embodiments, the analyzer **14** may use TensorFlow Java inference interface, for example.

In some embodiments, referring to Figure **1**, the analyzer **14** may receive signals representing a set of ultrasound images of the subject. For example, in various embodiments, the analyzer **14** may receive ultrasound images from a frame grabber in communication with the ultrasound machine **16** and the analyzer **14**. In various embodiments, the set of ultrasound images received may represent a video or cine and may be a temporally ordered set of ultrasound images. In some embodiments, the set of ultrasound images received may represent an echocardiographic cine, for example, showing a patient's heart over time.

The analyzer **14** may then derive one or more extracted feature representations from the received set of ultrasound images. In some embodiments, the analyzer **14** may implement a neural network including a feature extracting neural network and the analyzer **14** may input the set of ultrasound images into the feature extracting neural network in order to derive the one or more extracted feature representations.

The analyzer **14** may then determine, based on the derived one or more extracted feature representations, a quality assessment value representing a quality assessment of the set of ultrasound images. In some embodiments, the analyzer **14** may input the one or more extracted feature representations into a quality assessment value specific neural network in order to determine the quality assessment value. In some embodiments, a neural network including the feature extracting neural network and the quality assessment specific neural network may have been previously trained such that the quality assessment value determined by the analyzer **14** may represent an assessment of suitability of the received set of ultrasound images for quantified clinical measurement of anatomical features.

The analyzer **14** may also determine, based on the derived one or more extracted feature representations, an image property associated with the set of ultrasound images. In some embodiments, the image property may be a view category, for example. Accordingly, in some embodiments, the analyzer **14** may input the one or more extracted feature representations into a view category specific neural network in order to determine a view category within which the set of ultrasound images are determined to fall. In some embodiments, the neural network including the feature extracting neural network and the view category specific neural network may have been previously trained such that the view category determined by the analyzer **14** may represent the category of view represented by the set of ultrasound images.

The analyzer **14** may then produce signals representing the quality assessment value and the image property for causing the quality assessment value and the image property to be associated with the set of ultrasound images. In some embodiments, the analyzer **14** may produce signals for causing a representation of the quality assessment value and a representation of the view category to be displayed by the display **18** in association with the set of ultrasound images. For example, the classified view and its associated quality score may be displayed in a graphical user interface (GUI) on the display **18** as feedback to the operator.

In various embodiments, this near real-time or real-time feedback to the operator may help the operator improve their skills and/or improve image quality for subsequently captured images. For example, in some embodiments, the operator may, in response to viewing a low-quality assessment value or undesired view category on the display **18**, adjust positioning of the transducer and/or adjust image capture parameters, such as, for example, depth, focus, gain, frequency, and/or another parameter which may affect image quality, and/or the view category of the images being captured. In some embodiments, the operator may make such adjustments until a high-quality assessment value and/or a desired view category is displayed by the display **18**, for example, at which point the operator may be confident that the images captured are suitable for subsequent quantified clinical measurement of anatomical features and/or to assist in diagnosing a medical condition of the subject, for example.

In some embodiments, the analyzer **14** may produce signals representing the quality assessment value and the image property in association with the set of ultrasound images for facilitating automatic adjustment, using another neural network or machine learning, of image capture parameters to maximize quality assessment values. For example, in some embodiments, another neural network may use the quality assessment value and image property as inputs for generating control signals for adjusting image capture parameters to maximize quality assessment values.

<u>Analyzer - Processor Circuit</u>

Referring now to Figure **2**, a schematic view of the analyzer **14** of the system **10** shown in Figure **1** according to various embodiments is shown. In various embodiments, the analyzer **14** may be implemented as a mobile device, such as a Samsung™ Galaxy S**8**+™ running an operating system, such as Android™, for example.

Referring to Figure **2**, the analyzer **14** includes a processor circuit including an analyzer processor **100** and a program memory **102**, a storage memory **104**, and an input/output (I/O) interface **112**, all of which are in communication with the analyzer processor **100**. In various embodiments, the analyzer processor **100** may include one or more processing units, such as for example, a central processing unit (CPU), a graphical processing unit (GPU), and/or a field programmable gate array (FPGA). In some embodiments, any or all of the functionality of the analyzer **14** described herein may be implemented using one or more FPGAs.

The I/O interface **112** includes an interface **120** for communicating with the ultrasound machine **16** or a frame grabber in communication with the ultrasound machine **16** and an interface **130** for communicating with the display **18**. In some embodiments, the I/O interface **112** may also include an interface **124** for facilitating networked communication through a network **126**. In some embodiments, any or all of the interfaces **120**, **130**, or **124** may facilitate a wireless or wired communication.

In some embodiments, the I/O interface **112** may include a network interface device or card with an input/output for connecting to the network **126**, through which communications may be conducted with devices connected to the network **126**, such as the neural network trainer (as shown at **502** in Figure **11**), for example. In some embodiments, the network **126** may be a private network to which both the analyzer **14** and the trainer **502** are connected. In some embodiments the network **126** may be a public network, such as the Internet, for example.

In some embodiments, each of the interfaces shown in Figure **2** may include one or more interfaces and/or some or all of the interfaces included in the I/O interface **112** may be implemented as combined interfaces or a single interface.

In some embodiments, where a device is described herein as receiving or sending information, it may be understood that the device receives signals representing the information via an interface of the device or produces signals representing the information and transmits the signals to the other device via an interface of the device.

Processor-executable program codes for directing the analyzer processor **100** to carry out various functions are stored in the program memory **102**. Referring to Figure **2**, the program memory **102** includes a block of codes **170** for directing the analyzer **14** to perform ultrasound image analysis functions. In this specification, it may be stated that certain encoded entities such as applications or modules perform certain functions. Herein, when an application, module or encoded entity is described as taking an action, as part of, for example, a function or a method, it will be understood that at least one processor (e.g., the analyzer processor **100**) is directed to take the action by way of programmable codes or processor-executable codes or instructions defining or forming part of the application.

The storage memory **104** includes a plurality of storage locations including location **140** for storing ultrasound image data, location **142** for storing first extracted feature data, location **144** for storing second extracted feature data, location **150** for storing determined quality assessment value data, location **152** for storing determined view category data, location **154** for storing first feature extracting neural network parameter data, location **156** for storing second feature extracting neural network parameter data, location **158** for storing quality assessment value specific neural network parameter data, location **160** for storing view category specific neural network parameter data, and location **162** for storing highest quality image data. In various embodiments, the plurality of storage locations may be stored in a database in the storage memory **104**.

In various embodiments, the block of codes **170** may be integrated into a single block of codes or portions of the block of codes **170** may include one or more blocks of code stored in one or more separate locations in the program memory **102**. In various embodiments, any or all of the locations **140**, **142**, **144**, **150**, **152**, **154**, **156**, **158**, **160**, and **162** may be integrated and/or each may include one or more separate locations in the storage memory **104**.

Each of the program memory **102** and storage memory **104** may be implemented as one or more storage devices including random access memory (RAM), a hard disk drive (HDD), a solid-state drive (SSD), a network drive, flash memory, a memory stick or card, any other form of non-transitory computer-readable memory or storage medium, and/or a combination thereof. In some embodiments, the program memory **102**, the storage memory **104**, and/or any portion thereof may be included in a device separate from the analyzer **14** and in communication with the analyzer **14** via the I/O interface **112**, for example.

In various embodiments, other device components described herein, such as memory, program memory, blocks of code, storage memory, locations in memory, and/or I/O interfaces, may be implemented generally similarly to as described above for the analyzer **14**.

Image analysis

Referring now to Figure **3**, a flowchart depicting blocks of code for directing the analyzer processor **100** shown in Figure **2** to perform ultrasonic image analysis functions in accordance with various embodiments is shown generally at **200**. The blocks of code included in the flowchart **200** may be encoded in the block of codes **170** of the program memory **102** shown in Figure **2** for example.

Referring to Figure **3**, the flowchart **200** begins with block **202** which directs the analyzer processor **100** shown in Figure **2** to receive signals representing a set of ultrasound images of a subject. In various embodiments, block **202** may direct the analyzer processor **100** to receive the set of ultrasound images from the ultrasound machine **16** and to store the received set of ultrasound images in the location **140** of the storage memory **104**. In some embodiments, block **202** may direct the analyzer processor **100** to receive the set of ultrasound images from a frame grabber in communication with the ultrasound machine **16** and the analyzer **14**. In some embodiments, the set of ultrasound images may be a temporally ordered set of ultrasound images representing a video or cine of the subject. In some embodiments, the subject may be a heart of a patient and the set of ultrasound images may be referred as an echocine. Each image of the set of ultrasound images may be referred to herein as a frame.

In some embodiments, block **202** may direct the analyzer processor **100** to pre-process raw ultrasound images received from the ultrasound machine **16** and/or to select a subset of the ultrasound images received from the ultrasound machine **16** as the set of ultrasound images to be analyzed. For example, in some embodiments, block **202** may direct the analyzer processor **100** to receive raw ultrasound images at a resolution of **640**x**480** at **30** Hz. Block **202** may direct the analyzer processor **100** to crop the raw frames down to include only the ultrasound beam, the boundaries of which may be adjustable by the user. The cropped data may be resized down to **120**x**120** to match input dimensions of the neural network implemented by the analyzer **14**. In some embodiments, block **202** may direct the analyzer processor **100** to perform a simple contrast enhancement step to mitigate quality degradation introduced by the frame grabber.

In some embodiments, block **202** may direct the analyzer processor **100** to store a subset of the received ultrasound images in the location **140** of the storage memory **104**. For example, in some embodiments, block **202** may direct the analyzer processor **100** to store ten **120**x**120** ultrasound images in the location **140** of the storage memory **104** and those ten ultrasound images may act as the received set of ultrasound images. In some embodiments, block **202** may direct the analyzer processor **100** to store the most recent ultrasound images in the location **140** of the storage memory **104**. In some embodiments, a copy of the full-resolution data may also be stored in the storage memory **104** for later expert evaluation.

Referring to Figure **3**, after block **202** has been executed, the flowchart continues to block **204**. In various embodiments, execution of blocks **204**, **206** and **208** of the flowchart **200** may result in the analyzer processor **100** being directed to input the received set of ultrasound images into a neural network **300** shown in Figure **4**, to generate an output of a quality assessment value and an image property, which in some embodiments may be a view category. The parameters defining the neural network **300** may be stored in the storage memory **104** and may have been previously determined during neural network training, which is described in further detail in accordance with various embodiments below.

Referring to Figure **3**, block **204** directs the analyzer processor **100** to derive one or more extracted feature representations from the set of ultrasound images received at block **202**. In some embodiments, deriving the one or more extracted feature representations may involve deriving a first feature representation and then deriving a second feature representation based on the first feature representation for each ultrasound image.

In various embodiments, block **204** may direct the analyzer processor to, for each of the set of ultrasound images stored in the location **140** of the storage memory **104**, derive a first feature representation associated with the ultrasound image. In some embodiments, block **204** may direct the analyzer processor **100** to derive the first feature representations by inputting each image of the set of ultrasound images (shown at **302** in Figure **4**) into a commonly defined first feature extracting neural network, instances of which are shown at **304**, **306**, and **308** of the neural network **300** shown in Figure **4**, for example. In some embodiments, block **204** may direct the analyzer processor **100** to input each of the ten ultrasound images stored in the location **140** of the storage memory **104** into one of the commonly defined first feature extracting neural networks **304**, **306**, and **308**.

In some embodiments parameters defining the commonly defined first feature extracting neural network may be stored in the location **154** of the storage memory **104** and block **204** may direct the analyzer processor **100** to retrieve the parameters from the location **154** of the storage memory **104**. In various embodiments, because the first feature extracting neural networks (e.g., **304**, **306**, and **308**) are commonly defined, this may save memory in the storage memory **104**.

In some embodiments, the commonly defined first feature extracting neural networks (e.g., **304**, **306**, and **308**) may include convolutional neural networks. For example, in some embodiments, each of the neural networks **304**, **306**, and **308** may be implemented as a seven-layer DenseNet model as described in Huang, G., Liu, Z., Weinberger, K.Q., van der Maaten, L.: Densely connected convolutional networks. In: IEEE CVPR. vol. **1-2**, p. **3** (**2017**). In some embodiments, the DenseNet model implementing the commonly defined first feature extracting neural networks **304**, **306**, and **308** may use the following hyper-parameters. First, the DenseNet may have one convolution layer with sixteen **3**x**3** filters, which turns gray-scale (**1**-channel) input images to sixteen channels. Then, the DenseNet may stack three dense blocks, each followed by a dropout layer and an average-pooling layer with filter size of **2**x**2**. In various embodiments, after the third dense block, the average-pooling layer may be applied before the dropout layer. Each dense block may have exactly one dense-layer, which may include a sequence of batch-normalization layer (as per Ioffe, S., Szegedy, C.: Batch normalization: Accelerating deep network training by reducing internal covariate shift. In: Proceedings of the **32**nd International Conference on Machine Learning. pp. **448**-**456**. ICML'**15**, JMLR (**2015**), for example), a Rectified Linear layer (ReLU) (as per Nair, V., Hinton, G.E.: Rectified linear units improve restricted boltzmann machines. In: Proceedings of the **27**th international conference on machine learning (ICML-**10**). pp. **807**-**814** (**2010**), for example), a 2D convolution layer with **3**x**3** filters, a dropout layer, a concatenation layer, another 2D convolution layer, another dropout layer, and an average pooling layer.

A batch normalization layer may first normalize the input features by the mean and standard deviation of the features themselves. For each channel (the second dimension) of input, the features from all training samples within a mini-batch may be jointly used to compute the mean and standard deviation values, hence the name *batch* normalization. After the normalization, the features may be rescaled and shifted by a linear transformation operation. A ReLU activation layer may be used to provide a non-linear transformation to the features. The ReLU activation function is noted as:

$$\mathrm{ReLU(x)} = \max(0, x),$$

Where x denotes any single element of the input feature vector. A concatenation layer may concatenate features at a given dimension, where in this case, the features may be concatenated at the channel (the second) dimension. A dropout layer may omit a percentage of feature values according to a given value between 0 and 1, which is a regularization technique to reduce overfitting towards the training data.

An exemplary implementation of portions of the commonly defined first feature extracting neural networks including dense blocks **1**, **2**, and **3** in accordance with various embodiments is shown at **310**, **312**, and **314** in Figures **5**, **6**, and **7,** respectively.

In some embodiments, the commonly defined first feature extracting neural networks (e.g., **304**, **306**, and **308** shown in Figure **4**) may be each configured to extract features that are encodings of image patterns of a single echo frame which are correlated with the image quality and view category of the single input echo frame. In some embodiments, these features (encodings or mappings) may be in the form of a vector of real-valued numbers (after the *flatten* operation), and each number may be considered as the level of presence of a specific spatial pattern in the input echo frame. In various embodiments, alternative or additional feature extracting functions and/or neural networks may be used to extract features of the input set of ultrasound images.

In some embodiments, more than one of the commonly defined first feature extracting neural networks may be run concurrently. For example, in some embodiments, block **204** may direct the analyzer processor **100** to run three of the commonly defined first feature extracting neural networks as three identical Convolutional Neural Networks (CNN-**1**, CNN-**2**, or CNN-**3**) in separate threads at the same time in order to prevent lag during particularly long inference times.

In various embodiments, the first feature representations (e.g., as shown at **320**, **322**, and **324** shown in Figure **4**) output by the commonly defined first feature extracting neural networks **304**, **306**, and **308** may act as first feature representations of the ultrasound images included in the set of ultrasound images received at block **202**. In some embodiments, for example, the first feature representations may each represent a tensor having dimensions **14**x**14**x**34** which is flattened to a tensor having length **6664** such that it can be input into a second feature extracting neural network **340**.

Block **204** may direct the analyzer processor to store the extracted first feature representations in the location **142** of the storage memory **104**, for example, in a feature buffer which may be shared between all three threads. Once all of the ultrasound images included in the set of ultrasound images have been input to an instance of the commonly defined first feature extracting neural network, block **204** may direct the analyzer processor **100** to input the stored first feature representations into a second feature extracting neural network **340** shown in Figure **4** to generate respective second feature representations, each associated with one of the ultrasound images. In some embodiments, the second feature representations generated by the second feature extracting neural network **340** may act as the one or more extracted feature representations derived by block **204** of the flowchart **200** shown in Figure **3**.

Referring to Figure **4**, in some embodiments, the second feature extracting neural network **340** may include a plurality of recurrent neural networks (RNNs) (e.g., **342**, **344**, and **346** shown in Figure **4**). In some embodiments, the RNNs may each be implemented using a long short term memory module (LSTM). In some embodiments parameters defining the second feature extracting neural network **340** may be stored in the location **156** of the storage memory **104** and block **204** may direct the analyzer processor **100** to retrieve the parameters from the location **156** of the storage memory **104**. Referring to Figure **4**, each RNN (e.g., **342**, **344**, and **346** shown in Figure **4**) may output a respective second feature representation, which may be used as an input for further processing. In various embodiments, each of the second feature representations may be a tensor having a length of **128**.

In some embodiments, the LSTM layer (which is a type of RNN layer) may operate on the outputs of the Densenet networks of multiple frames. As a result, in some embodiments, the features extracted by the LSTM networks may be encodings of both spatial and temporal patterns of a multitude of echo frames. The sequence of frames whose spatial and temporal patterns contribute to the extracted features may depend on the type of RNN layer included in the second feature extracting neural network **340**. In some embodiments, conventional RNN architectures may look backward in time and extract features from the previous N (e.g. N=**10**) frames. However, in various embodiments, other types of RNNs may be considered/used (i.e. bidirectional RNN) where features may be extracted from the collective of previous and future frames. In various embodiments, the number of frames included in the feature extraction of the RNNs (such as LSTM) could be N=**10** or more. In some embodiments, the features may be in the form of real-valued numbers (for example, the features may usually be between -**1** and **1** as the activation function of RNN is usually hyperbolic tangent). In some embodiments, each number may be considered as representing a level of presence of a specific spatial and temporal pattern.

In various embodiments, block **204** may direct the analyzer processor **100** to store the second feature representations in the location **144** of the storage memory **104**.

Referring to Figure **3**, in various embodiments, blocks **206** and **208** may be executed sequentially or in parallel. Block **206** directs the analyzer processor **100** to determine based on the derived one or more extracted feature representations from block **202**, a quality assessment value representing a quality assessment of the set of ultrasound images.

Block **206** may direct the analyzer processor **100** to retrieve the second feature representations from the location **144** of the storage memory **104**, the second feature representations acting as the one or more extracted feature representations. Block **206** may direct the analyzer processor **100** to use the second feature representations as inputs to a quality assessment value specific neural network configured to produce as an output a representation of a quality assessment value. In some embodiments, block **206** may direct the analyzer processor **100** to input each of the second feature representations into an implementation of a commonly defined quality assessment value specific neural subnetwork (e.g., **362**, **364**, and **366**) to generate a quality assessment value for each of the input second feature representations. Referring to Figure **4**, in various embodiments the commonly defined quality assessment value specific neural subnetworks may each be defined by the same neural network parameters. In some embodiments, parameters defining the quality assessment value specific neural subnetworks may be stored in the location **158** of the storage memory **104** and block **206** may direct the analyzer processor **100** to retrieve the parameters from the location **158** of the storage memory **104**.

In various embodiments, each of the commonly defined quality assessment value specific neural subnetworks may apply logistic regression to the input second feature representations to generate a scalar value representing quality of an ultrasound image. Referring to Figure **8**, there is shown a detailed representation of the quality assessment value specific neural subnetwork **362** in accordance with various embodiments. The quality assessment value specific neural subnetwork **362** shown in Figure **8** is represented in a simplified manner as it may apply to a single cine (i.e., for providing an output having dimension **1**). In various embodiments, each of the commonly defined quality assessment value specific neural subnetworks may be defined by the same neural network parameters.

Referring to Figure **8**, in some embodiments, the quality assessment value specific neural subnetwork **362** may include input nodes **380** for holding the output of the second feature extracting neural network **342**. In some embodiments, the input nodes **380** may hold a **1**x**128** feature tensor, for example. In some embodiments, input nodes **364** may be connected to a feature node **382**, which may, for example, hold a **1**x**1** feature tensor acting as an input for a logistic regression function **384**. The logistic regression function **384** may be connected to an output node **386**, which may include a **1**x**1** probability tensor holding an output of the quality assessment value specific neural subnetwork **362**. In some embodiments, output node **386** may hold a value in the range of [**0**,**1**], where a value of **0** corresponds to a bad quality and a value of **1** corresponds to perfect quality.

Block **206** may direct the analyzer processor **100** to determine an average or mean of the quality assessment values output by the quality assessment value specific determining neural subnetworks and to store the average quality assessment value in the location **150** of the storage memory **104**.

Referring back to Figure **3**, block **208** directs the analyzer processor **100** to determine, based on the derived one or more extracted feature representations, an image property associated with the set of ultrasound images. In some embodiments, the image property may be a view category. In some embodiments, block **208** may direct the analyzer processor **100** to retrieve the second feature representations from the location **144** of the storage memory **104**, the second feature representations acting as the one or more extracted feature representations. Block **208** may direct the analyzer processor **100** to use the second feature representations as inputs to a view category specific neural network configured to produce as an output a representation of a view category. In some embodiments, block **208** may direct the analyzer processor **100** to input each of the second feature representations into an implementation of a commonly defined view category specific neural subnetwork (e.g., **372**, **374**, and **376**) to determine a view category for each of the input second feature representations.

Referring to Figure **4**, in various embodiments the commonly defined view category specific neural subnetworks may each be defined by the same neural network parameters. In some embodiments parameters defining the view category specific neural network may be stored in the location **160** of the storage memory **104** and block **208** may direct the analyzer processor **100** to retrieve the parameters from the location **160** of the storage memory **104**.

In various embodiments, each of the commonly defined view category specific neural subnetworks may apply a softmax to the input second feature representations to generate a probability vector wherein each position in the vector corresponds to a view category and the value stored therein represents a probability that the ultrasound image is in the view category corresponding to the vector position. For example, where there are fourteen (**14**) possible view categories, the output of the view category specific neural subnetwork **372** may be a **14**-element length probability vector. In various embodiments, each position in the output probability vector may represent a determined probability that the input set of ultrasound images depicts a particular view category, such as, for example, one chosen from AP**2**, AP**3**, AP**4**, AP**5**, PLAX, RVIF, PSAXA, PSAXM, PSAXPM, PSAXAP, SC**4**, SC**5**, IVC, and SUPRA Referring to Figure **9**, there is shown a detailed representation of the view category specific neural subnetwork **372** in accordance with various embodiments. The view category specific neural subnetwork **372** shown in Figure **9** is represented in a simplified manner as it may apply to a single cine case (i.e., for providing an output having dimension **1**x**14**). In various embodiments, each of the commonly defined view category specific neural subnetworks may be defined by the same neural network parameters.

Referring to Figure **9**, in some embodiments, view category specific neural subnetwork **372** may include input nodes **388** for holding the output of the second feature extracting neural network **342**. In some embodiments, the input nodes **388** may hold a **1**x**128** feature tensor, for example. In some embodiments, input nodes **388** may be connected to feature nodes **390**, which may, for example, hold a **1**x**14** feature tensor acting as an input for a softmax function **392**. The softmax function **392** may be connected to an output node **394**, which may include a **1**x**14** probability tensor holding an output of the view category specific neural subnetwork **372**. In some embodiments, output node **394** may hold values that are each in the range of [**0**,**1**] and the sum of the values may be equal to **1**.

Block **208** may direct the analyzer processor **100** to determine an average of the probability vectors output by the view category specific determining neural subnetworks and to store a representation of the view category associated with the vector position having the highest average probability in the location **152** of the storage memory **104**.

Referring back to Figure **3**, block **210** directs the analyzer processor **100** to produce signals representing the quality assessment value and the image property for causing the quality assessment value and the image property to be associated with the set of ultrasound images. In some embodiments, block **210** may direct the analyzer processor **100** to produce signals for causing a representation of the quality assessment value and a representation of the image property to be displayed by the display **18** in association with the set of ultrasound images. For example, in some embodiments, block **210** may direct the analyzer processor **100** to retrieve the quality assessment value from the location **150** of the storage memory **104** and to retrieve the view category from the location **152** of the storage memory **104** and to transmit signals to the display **18** via the interface **130** of the I/O interface **112** shown in Figure **2**, representing the quality assessment value and the view category for causing the graphical user interface **400** shown in Figure **10** to be displayed by the display **18**.

Referring to Figure **10**, the graphical user interface **400** includes a bar indicator **402** showing a graphical representation of the quality assessment value and an indicator **404** representing the view category in association with a representation of an ultrasound image **406** included in the set of ultrasound images. In various embodiments, the bar indicator **402** may include a fill portion **408** which grows in length as the quality assessment value increases. In some embodiments, the fill portion **408** may change color depending on the quality assessment value. In various embodiments, an operator viewing the displayed representations of both the quality assessment value and the view category, may be able to use this information to recognize the specific features and structures required of various views and/or to capture diagnostically relevant heart cines.

In various embodiments, the flowchart **200** shown in Figure **3** may be executed repeatedly and/or continuously to update the quality assessment value bar indicator **402** and view category indicator **404** of the graphical user interface **400** shown in Figure **10**.

<u>Neural network training</u>

As discussed above, in various embodiments, the analyzer **14** may use a neural network **300** shown in Figure **4** which includes various subnetworks. In various embodiments, the parameters defining the neural network **300** may be stored in the storage memory **104** and may have been previously determined during neural network training. For example, in some embodiments, the system **10** shown in Figure **1** may include a neural network trainer configured to train the neural network **300**.

Referring to Figure **11**, a schematic view of a neural network trainer **502** which may be included in the system **10** shown in Figure **1** in various embodiments is shown. In various embodiments, the neural network trainer **502** may be incorporated in one or more computers, for example.

Referring to Figure **11**, in various embodiments, the neural network trainer **502** includes a processor circuit including a trainer processor **600** and a program memory **602**, a storage memory **604**, and an I/O interface **612**, all of which are in communication with the trainer processor **600**.

The I/O interface **612** includes an interface **620** for communicating with a training data source **504**. In some embodiments, the interface **620** may provide a connection to a network to which the training data source **504** is connected such that communication between the training data source **504** and the trainer **502** is facilitated. For example, in some embodiments, the training data source **504** may include a server computer for storing and archiving medical electronic images and associated image properties, such as, for example, an archive device. In some embodiments, the I/O interface **612** also includes an interface **624** for facilitating networked communication with the analyzer **14** through the network **126**. In some embodiments, the interface **620** may provide a connection to the network **126** and the training data source **504** may also be connected to the network **126**.

Processor-executable program codes for directing the trainer processor **600** to carry out various functions are stored in the program memory **602**. The program memory **602** includes a block of codes **660** for directing the neural network trainer **502** to perform neural network training functions.

The storage memory **604** includes a plurality of storage locations including location **640** for storing training data, location **642** for storing first feature extracting neural network data, location **644** for storing second feature extracting neural network parameter data, location **646** for storing quality assessment value specific neural network parameter data, and location **648** for storing view category specific neural network parameter data.

In various embodiments, the neural network trainer **502** may be configured to train the neural network **300** shown in Figure **4** based on a plurality of sets of ultrasound images, each set associated with a quality assessment value and an image property, such as a view category.

Referring now to Figure **12**, a flowchart depicting blocks of code for directing the trainer processor **600** shown in Figure **11** to perform neural network training to facilitate ultrasonic image analysis functions in accordance with various embodiments is shown generally at **700**. The blocks of code included in the flowchart **700** may be encoded in the block of codes **660** of the program memory **602** shown in Figure **11** for example.

Referring to Figure **12**, the flowchart **700** begins with block **702** which directs the trainer processor **600** shown in Figure **11** to receive signals representing a plurality of sets of ultrasound training images. In various embodiments, block **702** may direct the trainer processor **600** to receive the signals representing the plurality of sets of ultrasound training images from the training data source **504** via the interface **620** of the I/O interface **612** shown in Figure **11**. In various embodiments, block **702** may direct the trainer processor **600** to store the sets of ultrasound training images in the location **640** of the storage memory **604** of the trainer **502** shown in Figure **11**.

In some embodiments, each set of ultrasound images may be a temporally ordered set of ultrasound images representing a video or cine of a respective subject. In some embodiments, each subject may be a heart of a patient and each set of ultrasound images may be referred as an echocine.

Block **704** then directs the trainer processor **600** to receive signals representing quality assessment values, each of the quality assessment values associated with one of the sets of ultrasound training images and representing a quality assessment of the associated set of ultrasound training images. In some embodiments, block **704** may direct the trainer processor **600** to receive the signals representing the quality assessment values from the training data source **504** via the interface **620** of the I/O interface **612** shown in Figure **11**. In various embodiments, the quality assessment values may have been previously provided to the training data source **504**. For example, in some embodiments, the quality assessment values may have been previously provided by an expert who has been trained to determine quality of the sets of ultrasound images. For example, in some embodiments, the quality assessment values may be values between **0**% and **100**% representing whether the set of ultrasound images are suitable for subsequent quantified clinical measurement of anatomical features and/or to assist in diagnosing a medical condition.

Block **704** may direct the trainer processor **600** to store the received quality assessment values in the location **640** of the storage memory **604**. For example, in some embodiments, block **704** may direct the trainer processor **600** to store each of the quality assessment values in association with the set of ultrasound images to which they apply.

Block **706** then directs the trainer processor **600** to receive signals representing image properties, each of the image properties associated with one of the sets of ultrasound training images. In some embodiments, the image properties may each be a view category. In some embodiments, block **706** may direct the trainer processor **600** to receive signals representing view categories from the training data source **504** via the interface **620** of the I/O interface **612** shown in Figure **11**. In various embodiments, the view categories may have been previously provided to the training data source **504**. For example, in some embodiments, the view categories may have been previously provided by an expert who has been trained to determine view categories for the sets of ultrasound images. For example, in some embodiments, the subject imaged in the sets of ultrasound images may be a heart and the view categories may be chosen from the following views: AP**2**, AP**3**, AP**4**, AP**5**, PLAX, RVIF, PSAXA, PSAXM, PSAXPM, PSAXAP, SC**4**, SC**5**, IVC, and SUPRA.

Block **706** may direct the trainer processor **600** to store the received view categories in the location **640** of the storage memory **604**. For example, in some embodiments, block **706** may direct the trainer processor **600** to store each of the view categories in association with the set of ultrasound images to which they apply.

In various embodiments, the training data source **504** may send the sets of ultrasound images in association with the quality assessment values and the image properties and so blocks **702**, **704**, and **706** may be executed concurrently.

Block **708** then directs the trainer processor **600** to train a neural network, the training involving, for each set of the plurality of sets of ultrasound training images, using the set of ultrasound training images as an input to the neural network and using the quality assessment values and the image properties associated with the set of ultrasound training images as desired outputs of the neural network. For example, in some embodiments, the neural network trained at block **708** may be the neural network **300** shown in Figure **4**.

Accordingly, block **708** may direct the trainer processor **600** to train the neural network **300** shown in Figure **4** using each of the sets of ultrasound images stored in the location **640** of the storage memory **604** as inputs and using each of the associated quality assessment values and view categories stored in the location **640** of the storage memory **604** as desired outputs when the associated set of ultrasound images are used as inputs.

In some embodiments, block **708** may direct the trainer processor **600** to train the neural network **300** shown in Figure **4** using batches. For example, in some embodiments, block **708** may direct the trainer processor **600** to randomly select **32** sets of ultrasound images or cine clips from the location **640** of the storage memory **604**, and block **708** may direct the trainer processor **600** to choose **10** consecutive ultrasound images or frames from each set to make a batch such that the batch is filed with **320** frames of images with a dimension or size of **120**x**120**x**1** (in various embodiments, the ultrasound image data may be grayscale and therefore the last channel may have **1** dimension). This batch may be considered an input tensor, with the tensor size is **32**x**10**x**120**x**120**x**1**. In various embodiments, the first dimension **32** may be called the batch size. In some embodiments, a large batch size may help with parallelizing the computation. In some embodiments, batch size may be any number as long as the memory permits and, in some embodiments, **32** may be chosen as the batch size for training.

Block **708** may direct the analyzer processor **100** to feed the input tensor to the neural network **300**, where each ultrasound image first goes through an instance of the commonly defined first feature extracting neural network or DenseNet feature extraction module. The output tensor of the commonly defined first feature extracting neural networks or DenseNet modules may be **32**x**10**xAxBxC, where "AxBxC" denotes the dimensionality of the output feature for each frame. In some embodiments, the output tensor may be of dimension **32**x**10**x**14**x**14**x**34**, for example.

Block **708** then directs the trainer processor **600** to flatten the output tensor into **32**x**10**x(A*B*C), or **32**x**10**x**6664** in some embodiments, for example, so that the second feature extracting neural network **340** (e.g., the LSTM module, in some embodiments) can process it. After the second feature extracting neural network **340** processes the **32**x**10**x(A*B*C) feature tensor, it may produce a **32**x**10**x**128** feature tensor, and block **708** may direct the trainer processor **600** to use the **32**x**10**x**128** feature tensor as inputs for both the quality assessment value specific neural network and view category specific neural network.

Block **708** may direct the trainer processor **600** to compare the predictions made within the quality assessment value specific neural network and view category specific neural network with the respective ground truths, or desired outputs. In various embodiments, the predictions may be compared to the quality assessment values and view categories stored in the location **640** of the storage memory **604**. An initial output of the view category specific neural network may be of dimension **32**x**10**x**14** (classes) and block **708** may direct the trainer processor **600** to determine a mean over the **10** frames for the initial output to generate a tensor of dimension **32**x**14**. An initial output of the quality assessment value specific neural network may be of dimension **32**x**10**x**1** and block **708** may direct the trainer processor **600** to determine a mean over the **10** frames for the initial output to generate a tensor of dimension **32**x**1**.

Block **708** may direct the trainer processor **600** to determine a difference between the view classification predictions (**32**x**14**) and the ground truth (as previously provided by an expert, for example), as measured by the cross-entropy loss function, which produces scalar values, i.e. **32**x**14**->**32**x**1**. In various embodiments, block **708** may direct the trainer processor **600** to average the **32**x**1** values into **1** scalar value representing how well the predictions match the ground truth labels. Similarly, for the quality estimation, the difference may be measured by the binary cross-entropy loss function, which is the cross-entropy loss function working on two classes (i.e., bad quality:**0**, excellent quality:**1**). This also produces a scalar value, i.e., **32**x**1**->**1** representing how well the predictions match the ground truth labels. In various embodiments, a low scalar value representing how well the predictions match the ground truth labels may mean better matching. In various embodiments, the differences may also or alternatively be measured by other types of loss functions such as, for example, an absolute difference loss function or a squared difference loss function.

Block **708** may direct the trainer processor **600** to add these two loss values together and to train the network based on these summed losses. Block **708** may direct the trainer processor **600** to use a back-propagation method, wherein block **708** directs the trainer processor **600** to compute the gradient with respect to the neural network or model parameters (i.e., the weights and bias in every layer) and the gradient is used to update the neural network or model parameters. In various embodiments, the updated parameters may be stored in the locations **642**, **644**, **646**, and **648** of the storage memory **604**.

In various embodiments the flowchart **700** may be executed many times in order to train the neural network **300** shown in Figure **4** adequately. For example, in some embodiments, the plurality of sets of ultrasound training images may include **13400** sets or echo cine clips, and the trainer **502** may be configured to run **100** epochs where each epoch runs through the entire training with batch size **32**.

Accordingly, in some embodiments, the flowchart **700** may be executed **13400/32**=**419** times per epoch and **41900** times in total over all of the epochs.

In various embodiments, by adding the loss values together to train the network based on these summed losses, the neural network **300** may be trained more quickly and may provide more accurate results than a neural network which is trained based on loss values provided only by looking at desired quality assessment values or based on loss values provided only by looking at desired view categories. In some embodiments, this may also or alternatively result in a compact neural network that may consume less memory and/or use less battery power for computation.

In some embodiments, the flowchart **700** may include a block for directing the trainer processor **600** to produce signals representing the trained neural network for causing the neural network to be used to predict a quality assessment value and a view category based on an input set of ultrasound images. For example, in some embodiments, a block of codes may direct the trainer processor **600** to transmit the neural network parameter information stored in the locations **642**, **644**, **646**, and **648** of the storage memory **604**, which defines the neural network **300** to the analyzer **14** via the interface **624** and the network **126**.

A block of codes included in the block **170** of the program memory **102** of the analyzer **14** shown in Figure **2** may direct the analyzer processor **100** to receive the neural network parameter information via the interface **124** of the I/O interface **112** and to store the neural network parameter information in the locations **154**, **156**, **158**, and **160** of the storage memory **104**.

<u>Highest quality assessment value</u>

Referring to Figure **3**, in some embodiments, flowchart **200** may include a block of codes for directing the analyzer processor **100** to store an ultrasound image associated with the highest quality assessment value for each view category.

In various embodiments the block may direct the analyzer processor **100** to, for each view category, update/replace an ultrasound image stored in the location **162** of the storage memory **104** such that the ultrasound image stored is an ultrasound image that is associated with the highest quality assessment value, for that view category.

In some embodiments, the block may be executed after blocks **206** and **208** of the flowchart **200** have been executed. Upon analysis of a first set of ultrasound images for a given view category, the block may direct the analyzer processor **100** to, after determining a quality assessment value for each of the ultrasound images included in the first set of ultrasound images and determining a view category for the set of ultrasound images, identify the ultrasound image associated with the highest determined quality assessment value and store the ultrasound image in association with the determined quality assessment value and the determined view category in the location **162** of the storage memory **104**.

Upon analysis of subsequent sets of ultrasound images for the view category, The block may direct the analyzer processor **100** to, for each determined quality assessment value, determine whether the quality assessment value is higher than the quality assessment value stored in association with the ultrasound image and the same view category in the location **162** of the storage memory **104**. The block may direct the analyzer processor **100** to, if the determined quality assessment value is higher than the stored quality assessment value, store the ultrasound image associated with the determined quality assessment in the location **162** of the storage memory **104** in association with the determined quality assessment value and the determined view category. In some embodiments, the block may direct the analyzer processor **100** to replace any previously stored quality assessment value and ultrasound image stored in the location **162** of the storage memory **104** in association with the determined view category with the determined quality assessment value and the associated ultrasound image. In various embodiments, this may facilitate storage of ultrasound images associated with the highest determined quality assessment values, for each view category, in the location **162** of the storage memory **104**.

In various embodiments, an operator may not even know this is happening, but when it comes to review the high-quality cines afterwards, it may be a very useful tool to find the best quality images for each cine. In various embodiments, an operator may initiate a block of codes included in the program memory **102** for directing the analyzer processor **100** to later retrieve the ultrasound images stored in the location **162** of the storage memory and to produce signals representing the ultrasound images for causing the ultrasound images to be displayed by the display **18**. In various embodiments, in this way, the operator may easily view the best quality images for each view category.

<u>Various embodiments</u>

In some embodiments, a system generally similar to the system **10** shown in Figure **1** and discussed herein may use a neural network having additional and/or alternative architecture to the architecture of the neural network **300** shown in Figure **4** and discussed herein.

In some embodiments, the functionality provided by the quality assessment value specific neural network and the image property specific neural network may be implemented using a combined neural network configured to output both a quality assessment value and a representation of the image property.

While various embodiments have been described herein wherein the image property used in the system **10** is a view category, in some embodiments, the system **10** may use another image property. In such embodiments, the analyzer **14** may be configured to apply a neural network that outputs a quality assessment value and the other image property. Further, in such embodiments, the trainer **502** may be configured to train a neural network that outputs a quality assessment value and the other image property. For example, in some embodiments, the image property may include a representation of any or all of the elements included in the following list, for example:

- Cardiac
    - Left ventricular ejection fraction (LVEF)
    - Left atrial ejection fraction (LAEF)
    - Strain, both local and global
    - Pericardial Effusion
    - Heart rate
    - Cardiac phase
- FAST (Emergency Medicine)
    - Free Fluid
- Inferior vena cava (IVC)
- Volume Assessment
- Obstetrics
    - Ovarian torsion
    - Endometritis
    - Detection of fetal pole
    - Calculation of gestational age
- Gallbladder
    - Gallstones
- Pulmonary
    - Pneumothorax
    - Pleural Effusion
    - Pneumonia/Consolidation
- Ocular
    - Retinal Detachment
    - Vitreous Hemorrhage
- Musculoskeletal
    - Joint Effusion
    - Tendon Rupture

    - Fracture Identification
- Renal
    - Hydronephrosis
    - Nephrolithiasis
- Deep vein thrombosis (DVT)
- Aorta
- Intrauterine pregnancy
    - Intrauterine Pregnancy
    - Fetal Heart Rate
- Soft Tissue
    - Cellulitis
    - Abscess
    - Foreign body
- Scrotal
    - Testicular Torsion
    - Hydrocele
    - Epididymitis

In various embodiments, the system **10** shown in Figure **1** may be used to facilitate analysis of ultrasound images in various subjects. For example, in some embodiments, various tissues/organs may be analyzed using an embodiment of the system **10**. For example, in some embodiments, the system **10** may be used for liver analysis, spine analysis, fat tissue analysis and other tissue/organ analysis etc. For example, in some embodiments, the system **10** may be used for analysis of any or all of the elements in the above list. In various embodiments, procedures for which the system **10** may be used may include, for example:

- Heart valve repair using transesophageal echocardiography
- Nerve blocks
- Vascular access
- Arthrocentesis
- Lumbar puncture

- Paracentesis
- Thoracentesis
- Airway

In various embodiments, a system generally similar to the system **10** shown in Figure **1** may include an analyzer that performs the functionality of the analyzer **14** described herein but that takes a different form. For example, in various embodiments, the analyzer may not be implemented using a mobile device. In some embodiments the analyzer may be implemented within an ultrasound machine, for example. In such embodiments, the ultrasound monitor may provide some of the functionality described herein as provided by the display **18** and/or ultrasound image data may not need to be transferred off of the ultrasound machine.

In various embodiments, the ultrasound machine **16** may take additional or alternative forms to the schematic representation shown in Figure **1**. For example, in some embodiments, the ultrasound machine **16** may be implemented wherein the ultrasound machine and the transducer are one unit and the ultrasound machine produces wireless signals for causing a display to display the ultrasound images. For example, in some embodiments, the ultrasound machine may wirelessly transmit ultrasound data to a mobile device or phone for display. In some embodiments, the mobile device or phone displaying the ultrasound images may act as the analyzer **14** or transmit the ultrasound data to a secondary mobile device acting as the analyzer **14**, for analysis.

In various embodiments the set of ultrasound images analyzed in the system **10** described herein may be a single ultrasound image.

In some embodiments, the trainer may include a user interface and block **704** may direct the trainer processor **600** to receive the quality assessment values and/or the view category information via the user interface from an expert interacting with the user interface.

In various embodiments, the analyzer **14** may be implemented using an Android mobile device running a customized mobile implementation of the TensorFlow inference engine. In some embodiments, by multi-threading four TensorFlow instances together, the analyzer **14** may be able to execute the flowchart **200** shown in Figure **3** for analyzing images being received at **30** Hz with a latency of under **0**.**4** seconds.

In various embodiments, while three threads are running the first feature extracting neural networks for a set of ultrasound images, a fourth thread may run the rest of the neural network **300** shown in Figure **4** for a previous set of ultrasound images for which the feature representations were already determined. For example, Figure **13** shows a timing diagram **750** of how the threads **752**, **754**, **756**, and **758** may be run concurrently according to various embodiments.

Referring to Figure **13**, three first feature extracting neural network or CNN threads can be seen extracting features from ten consecutive input frames before waking a waiting RNN thread configured to run the rest of the neural network **300** shown in Figure **4**, which then runs the LSTMs, quality assessment value and view category prediction on the buffered features extracted by the CNN threads. The target frame rate for the system may be set at **30** Hz, which can be inferred by the lines **760**, **762**, **764**, **766**, and **768** representing the arrival of input frames. In some embodiments, the mean run-time for the first feature extracting neural networks (including feeding the input, running the network, and fetching the output) may be **28**.**76** ms with a standard deviation of **16**.**42** ms and the mean run time of the rest of the neural network **300** may be **157**.**48** ms with a standard deviation of **21**.**85** ms. Therefore, the mean latency of the feedback may be **352**.**58** plus or minus **38**.**27** ms, when measured from the middle of the ten-frame sequence.

In various embodiments, in order to prevent lag resulting from the build-up of unprocessed frames, the first feature extracting neural network threads and RNN need to finish running before they are requested to process the next batch of data. In some embodiments, to accomplish this reliably, all the per-frame processing must complete within $T_{max,\ first\ feature}$, calculated as follows:

$$T_{max,first\ feature} = (\#\ of\ first\ feature\ threads) * \mathbf{1}/FPS = \mathbf{3/30} = \mathbf{100}\ ms$$

while the rest of the neural network **300** may need to complete its processing before the features from the next ten frames are extracted:

$$T_{max,RNN} = (buffer\ length) * \mathbf{1}/FPS = \mathbf{10/30} = \mathbf{333}{:}\mathbf{33}\ ms$$

With the chosen three first feature extracting neural network threads and one thread for the rest of the neural network **300** configuration, in various embodiments, the application may require few threads while still providing enough tolerance to avoid frame build-up.

In various embodiments, neural networks described herein, including the first feature extracting neural networks shown in Figure **4**, for example, may be implemented by using Keras (https://keras.io/), a high-level neural networks API on top of the Tensorflow (https://www.tensorflow.org/) deep learning library backend in Python. The Keras library may be imported as tf.keras from Tensorflow (i.e., tf).

For the components included in the first feature extracting neural networks, in various embodiments, the convolution operation may be implemented by using the function tf.keras.layers.Conv2D, the batch normalization operation may be implemented by using the function tf.keras.layers.BatchNormalization, the ReLU activation operation may be implemented by using the function tf.keras.layers.ReLU, the dropout operation may be implemented by using the function tf.keras.layers.Dropout, the concatenation operation may be implemented by using the function tf.keras.layers.concatenate, and the average pooling operation may be implemented by using the function tf.keras.layers.AveragePooling2D. In various embodiments, for the second feature extracting neural network **340** shown in Figure **4**, the LSTM operation may be implemented by using the function tf.keras.layers.LSTM.

While specific embodiments of the invention have been described and illustrated, such embodiments should be considered illustrative of the invention only and not as limiting the invention as construed in accordance with the accompanying claims.

CLAIMS:

1. A computer-implemented method of facilitating ultrasonic image analysis of a subject, the method comprising:

receiving signals representing a set of ultrasound images of the subject;

deriving one or more extracted feature representations from the set of ultrasound images;

determining, based on the derived one or more extracted feature representations, a quality assessment value representing a quality assessment of the set of ultrasound images;

determining, based on the derived one or more extracted feature representations, an image property associated with the set of ultrasound images; and

producing signals representing the quality assessment value and the image property for causing the quality assessment value and the image property to be associated with the set of ultrasound images.

2. The method of claim **1** wherein the image property is a view category.

3. The method of claim **1** or **2** wherein deriving the one or more extracted feature representations from the ultrasound images comprises, for each of the ultrasound images, deriving a first feature representation associated with the ultrasound image.

4. The method of claim **3** wherein deriving the one or more extracted feature representations comprises, for each of the ultrasound images, inputting the ultrasound image into a commonly defined first feature extracting neural subnetwork to generate the first feature representation associated with the ultrasound image.

5. The method of claim **4** wherein deriving the one or more extracted feature representations comprises concurrently inputting each of a plurality of the ultrasound images into a respective implementation of the commonly defined first feature extracting neural network.

6. The method of claim **4** or **5** wherein the commonly defined first feature extracting neural network includes a convolutional neural network.

7. The method of any one of claims **4** to **6** wherein deriving the one or more extracted feature representations comprises inputting the first feature representations into a second feature extracting neural network to generate respective second feature representations, each associated with one of the ultrasound images and wherein the one or more extracted feature representations include the second feature representations.

8. The method of claim **7** wherein the second feature extracting neural network is a recurrent neural network.

9. The method of any one of claims **1** to **8** wherein determining the quality assessment value comprises inputting the one or more extracted feature representations into a quality assessment value specific neural network and wherein determining the image property comprises inputting the one or more extracted feature representations into an image property specific neural network.

10. The method of claim **9** wherein inputting the one or more extracted feature representations into the quality assessment value specific neural network comprises inputting each of the one or more extracted feature representations into an implementation of a commonly defined quality assessment value specific neural subnetwork and wherein inputting the one or more extracted feature representations into the image property determining neural network comprises inputting each of the one or more extracted feature representations into an implementation of a commonly defined image property specific neural network.

11. The method of any one of claims **1** to **10** wherein producing signals representing the quality assessment value and the image property for causing the quality assessment value and the image property to be associated with the set of ultrasound images comprises producing signals for causing a representation of the quality assessment value and a representation of the image property to be displayed by at least one display in association with the set of ultrasound images.

12. A computer-implemented method of training one or more neural networks to facilitate ultrasonic image analysis, the method comprising:

receiving signals representing a plurality of sets of ultrasound training images;

receiving signals representing quality assessment values, each of the quality assessment values associated with one of the sets of ultrasound training images and representing a quality assessment of the associated set of ultrasound training images;

receiving signals representing image properties, each of the image properties associated with one of the sets of ultrasound training images; and

training a neural network, the training comprising, for each set of the plurality of sets of ultrasound training images, using the set of ultrasound training images as an input to the neural network and using the quality assessment values and the image properties associated with the set of ultrasound training images as desired outputs of the neural network.

13. The method of claim **12** wherein each of the image properties is a view category.

14. The method of claim **12** or **13** wherein the neural network includes a feature extracting neural network, an image property specific neural network, and a quality assessment value specific neural network and wherein:

the feature extracting neural network is configured to take an input set of the plurality of sets of ultrasound training images as an input and to output one or more extracted feature representations;

the image property specific neural network is configured to take the one or more extracted feature representations as an input and to output a representation of an image property associated with the input set of ultrasound training images; and

the quality assessment specific neural network is configured to take the one or more extracted feature representations as an input and to output a quality assessment value associated with the input set of ultrasound training images.

15. The method of claim **14** wherein the feature extracting neural network is configured to, for each of the ultrasound training images included in the input set of ultrasound training images, derive a first feature representation associated with the ultrasound image.

16. The method of claim **15** wherein the feature extracting neural network includes, for each of the ultrasound images included in the input set of ultrasound training images, a commonly defined first feature extracting neural network configured to take as an input the ultrasound training image and to output a respective one of the first feature representations.

17. The method of claim **16** wherein more than one implementation of the commonly defined first feature extracting neural networks are configured to concurrently generate the first feature representations.

18. The method of claim **16** or **17** wherein the commonly defined first feature extracting neural network is a convolutional neural network.

19. The method of any one of claims **16** to **18** wherein the feature extracting neural network includes a second feature extracting neural network configured to take as an input the first feature representations and to output respective second feature representations, each associated with one of the ultrasound images included in the input set of ultrasound training images and wherein the one or more extracted feature representations include the second feature representations.

20. The method of claim **19** wherein the second feature extracting neural network is a recurrent neural network.

21. A system for facilitating ultrasonic image analysis comprising at least one processor configured to perform the method of any one of claims **1** to **20**.

22. A non-transitory computer readable medium having stored thereon codes which when executed by at least one processor cause the at least one processor to perform the method of any one of claims **1** to **20**.

23. A system for facilitating ultrasonic image analysis, the system comprising:

means for receiving signals representing a set of ultrasound images of the subject;

means for deriving one or more extracted feature representations from the set of ultrasound images;

means for determining, based on the derived one or more extracted feature representations, a quality assessment value representing a quality assessment of the set of ultrasound images;

means for determining, based on the derived one or more extracted feature representations, an image property associated with the set of ultrasound images; and

means for producing signals representing the quality assessment value and the image property for causing the quality assessment value and the image property to be associated with the set of ultrasound images.

24. A system for training one or more neural networks to facilitate ultrasonic image analysis, the system comprising:

means for receiving signals representing a plurality of sets of ultrasound training images;

means for receiving signals representing quality assessment values, each of the quality assessment values associated with one of the sets of ultrasound training images and representing a quality assessment of the associated set of ultrasound training images;

means for receiving signals representing image properties, each of the image properties associated with one of the sets of ultrasound training images; and

means for training a neural network, the training comprising, for each set of the plurality of sets of ultrasound training images, using the set of ultrasound training images as an input to the neural network and using the quality assessment values and the image properties associated with the set of ultrasound training images as desired outputs of the neural network.

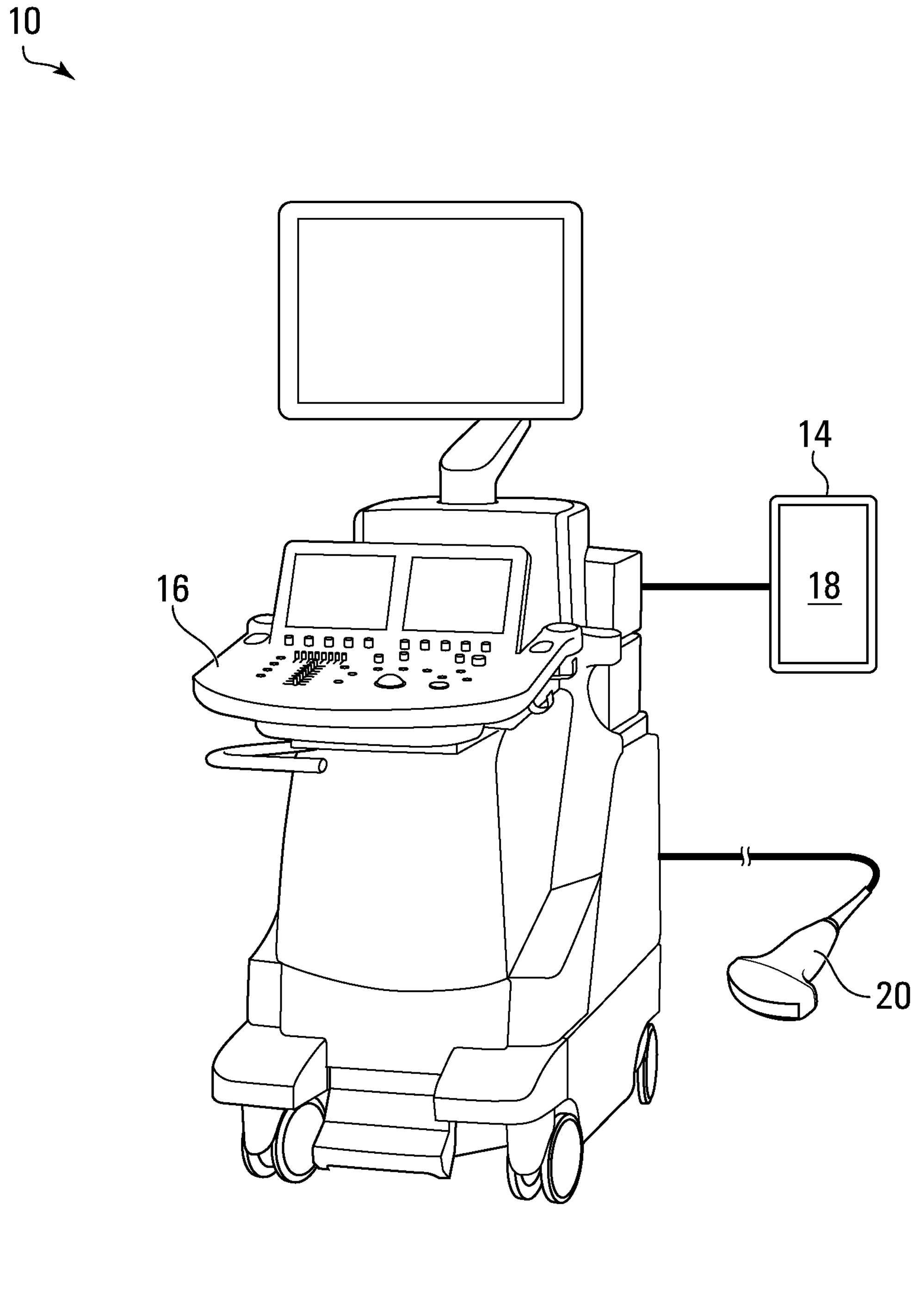

FIG. 1

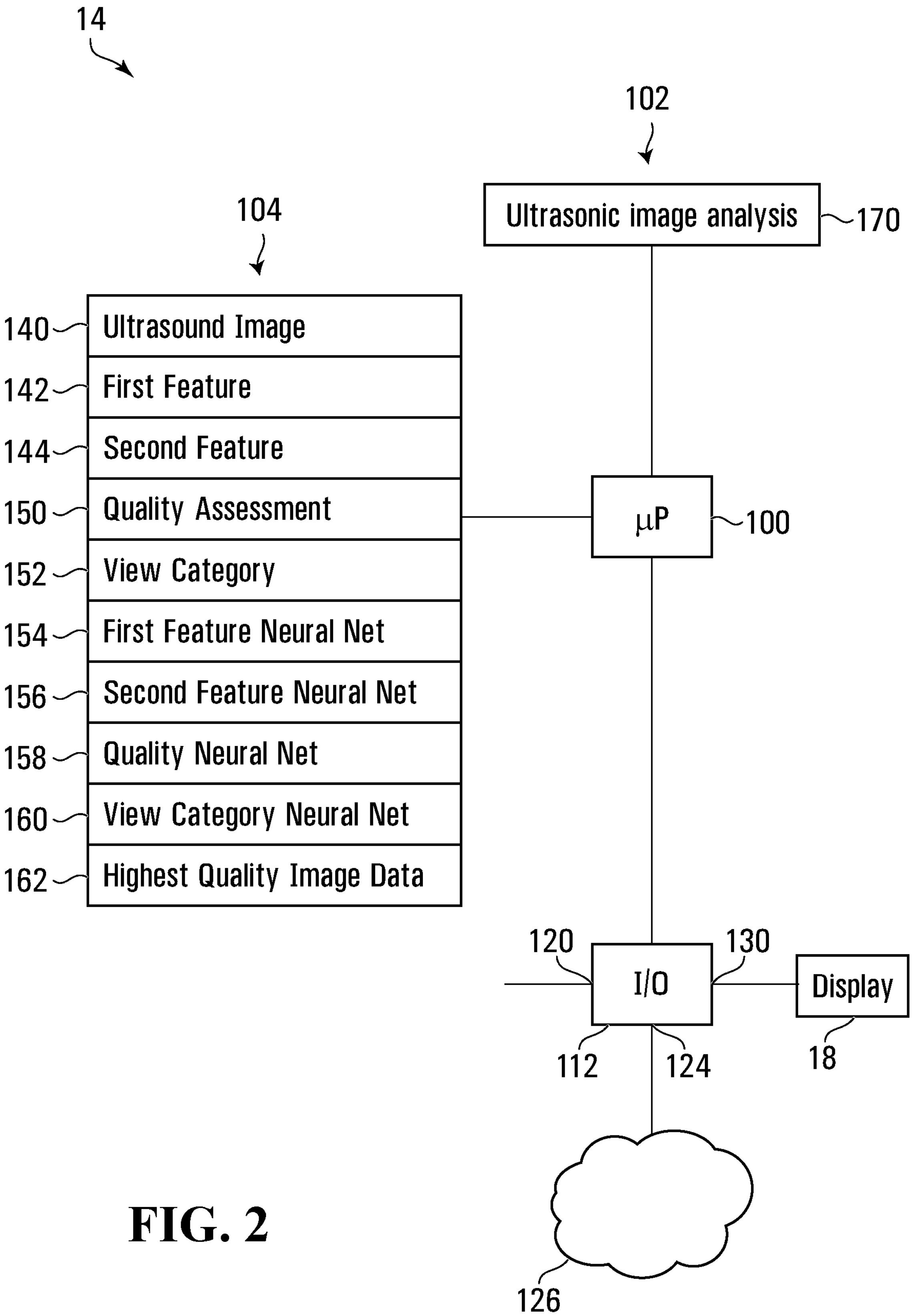
14
102
104
Ultrasonic image analysis
170
140
Ultrasound Image
142
First Feature
144
Second Feature
150
Quality Assessment
152
View Category
154
First Feature Neural Net
156
Second Feature Neural Net
158
Quality Neural Net
160
View Category Neural Net
162
Highest Quality Image Data
μP
100
120
130
I/O
Display
112
124
18
126

FIG. 2

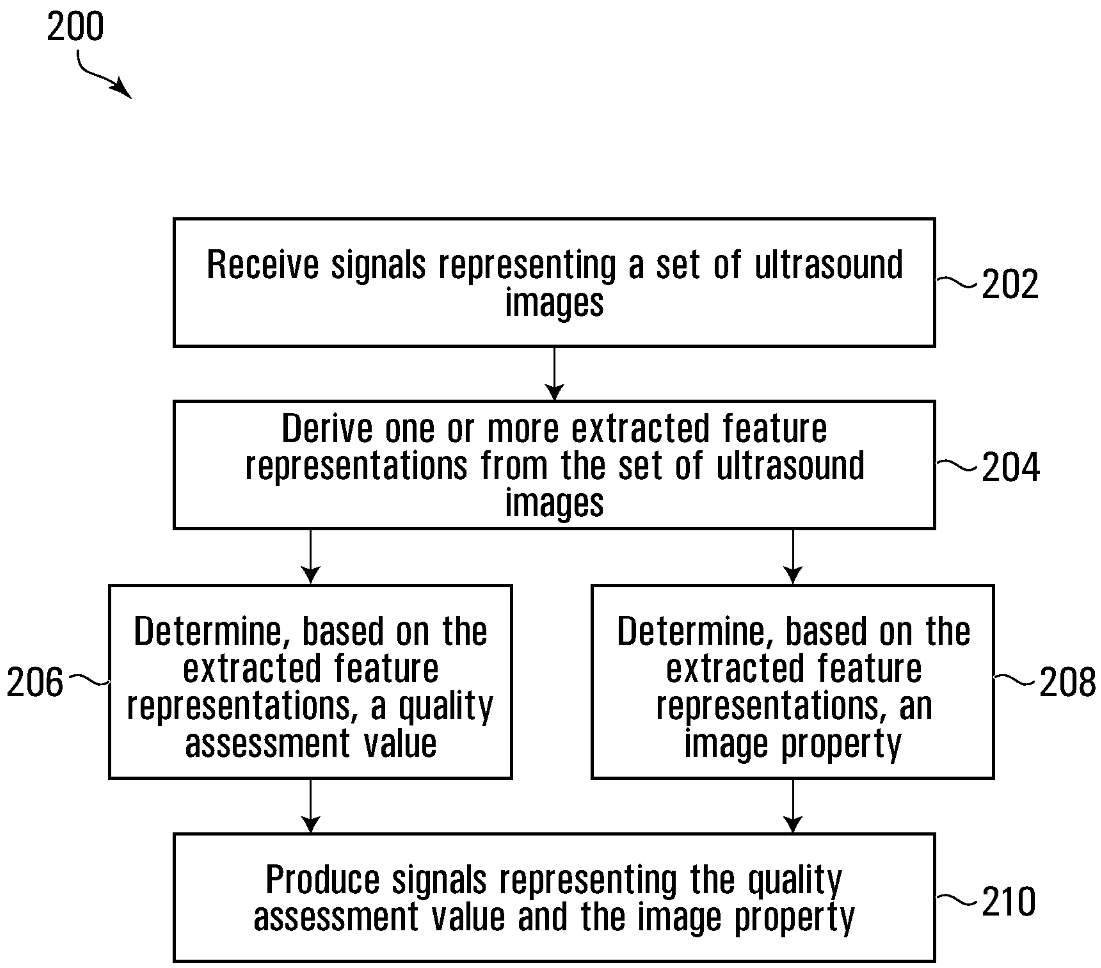
200
Receive signals representing a set of ultrasound images
202
Derive one or more extracted feature representations from the set of ultrasound images
204
Determine, based on the extracted feature representations, a quality assessment value
206
Determine, based on the extracted feature representations, an image property
208
Produce signals representing the quality assessment value and the image property
210

FIG. 3

4/13

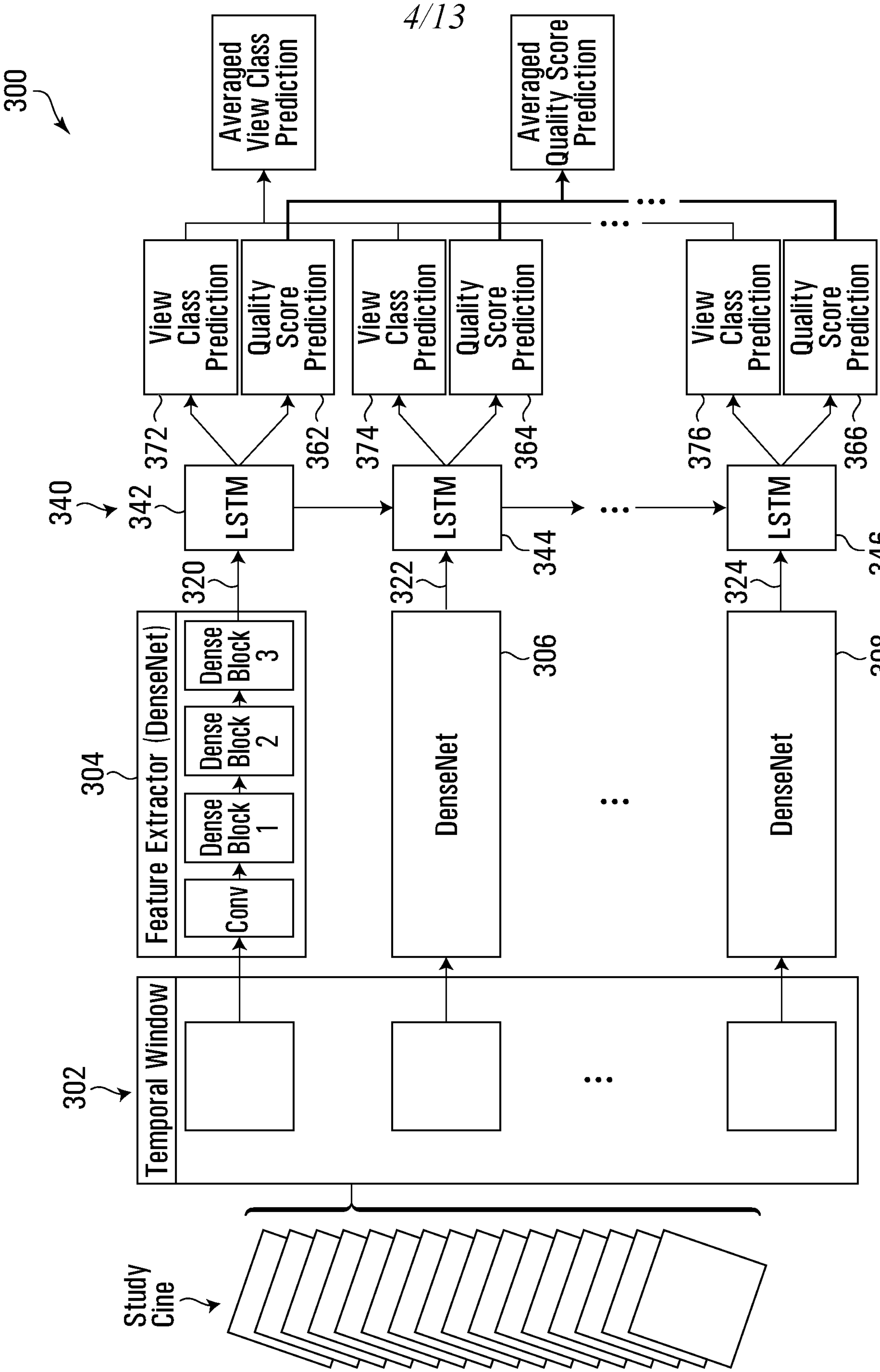
300
Averaged View Class Prediction
Averaged Quality Score Prediction
View Class Prediction
Quality Score Prediction
372
362
374
364
376
366
340
342
344
346
LSTM
320
322
324
Feature Extractor (DenseNet)
Conv
Dense Block 1
Dense Block 2
Dense Block 3
304
DenseNet
306
308
Temporal Window
302
Study Cine

FIG. 4

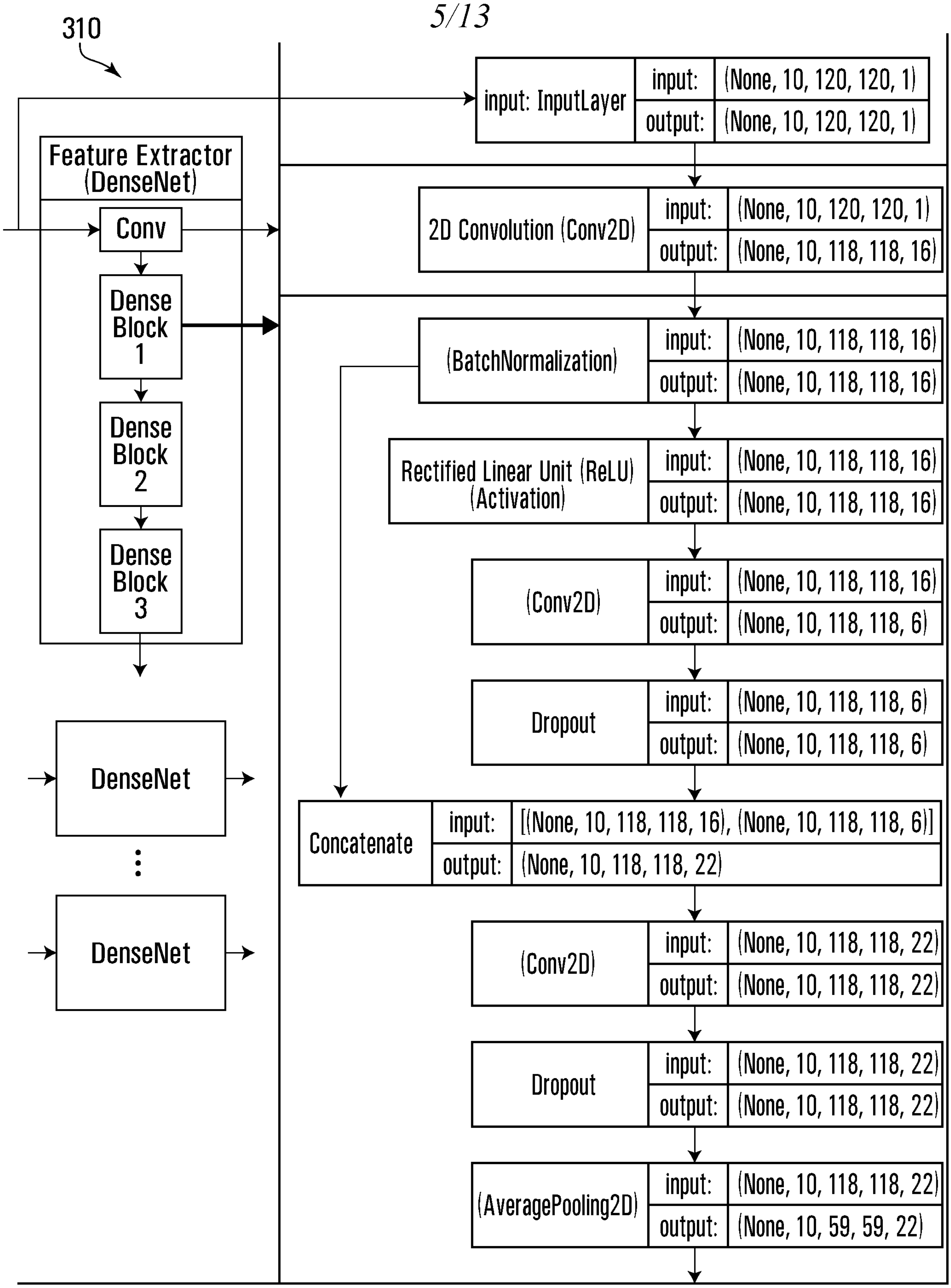
310
Feature Extractor (DenseNet)
Conv
Dense Block 1
Dense Block 2
Dense Block 3
DenseNet
DenseNet
input: InputLayer
input:
(None, 10, 120, 120, 1)
output:
(None, 10, 120, 120, 1)
2D Convolution (Conv2D)
input:
(None, 10, 120, 120, 1)
output:
(None, 10, 118, 118, 16)
(BatchNormalization)
input:
(None, 10, 118, 118, 16)
output:
(None, 10, 118, 118, 16)
Rectified Linear Unit (ReLU) (Activation)
input:
(None, 10, 118, 118, 16)
output:
(None, 10, 118, 118, 16)
(Conv2D)
input:
(None, 10, 118, 118, 16)
output:
(None, 10, 118, 118, 6)
Dropout
input:
(None, 10, 118, 118, 6)
output:
(None, 10, 118, 118, 6)
Concatenate
input:
[(None, 10, 118, 118, 16), (None, 10, 118, 118, 6)]
output:
(None, 10, 118, 118, 22)
(Conv2D)
input:
(None, 10, 118, 118, 22)
output:
(None, 10, 118, 118, 22)
Dropout
input:
(None, 10, 118, 118, 22)
output:
(None, 10, 118, 118, 22)
(AveragePooling2D)
input:
(None, 10, 118, 118, 22)
output:
(None, 10, 59, 59, 22)

FIG. 5

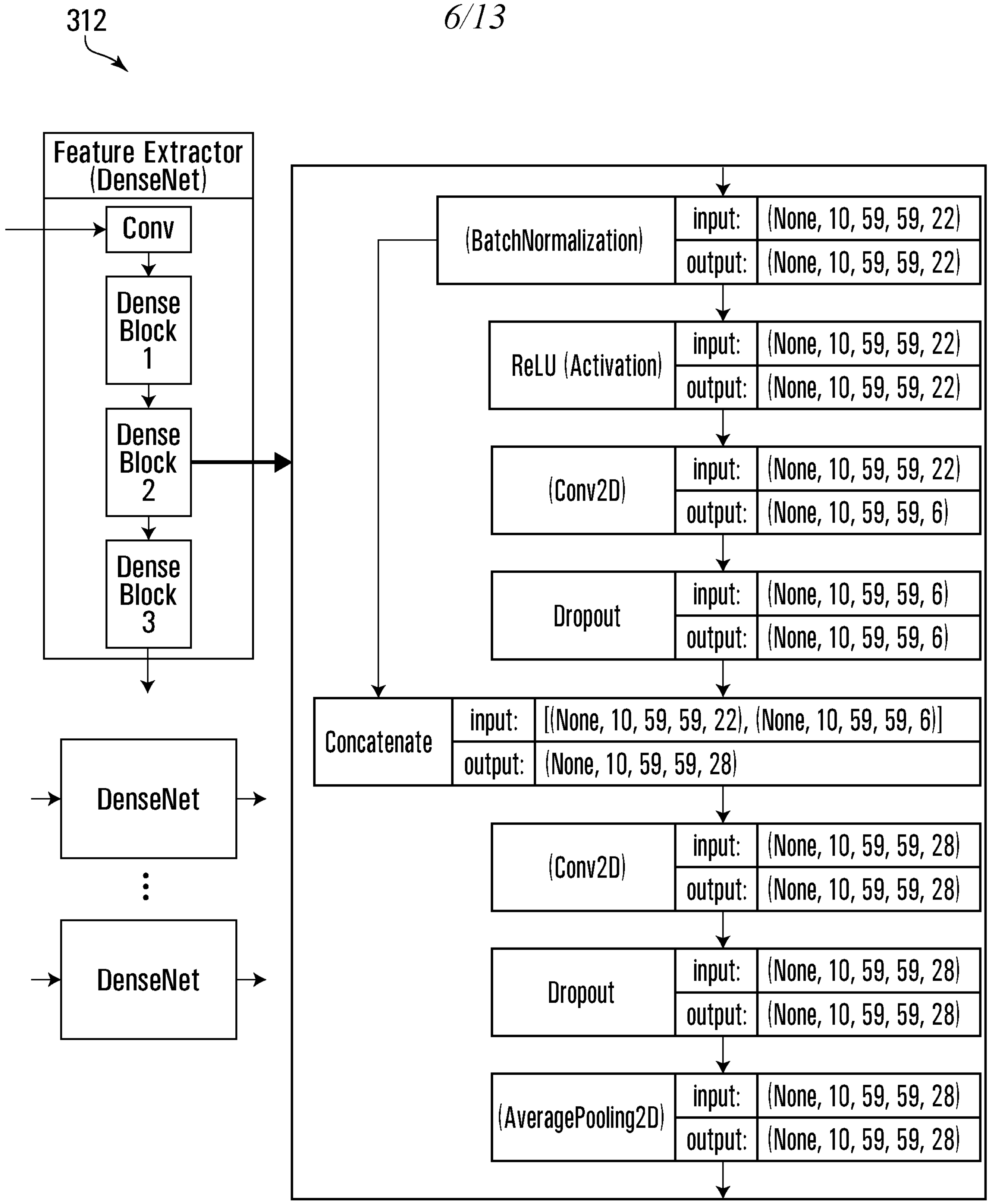
312
Feature Extractor (DenseNet)
Conv
Dense Block 1
Dense Block 2
Dense Block 3
DenseNet
DenseNet
(BatchNormalization)
input: (None, 10, 59, 59, 22)
output: (None, 10, 59, 59, 22)
ReLU (Activation)
input: (None, 10, 59, 59, 22)
output: (None, 10, 59, 59, 22)
(Conv2D)
input: (None, 10, 59, 59, 22)
output: (None, 10, 59, 59, 6)
Dropout
input: (None, 10, 59, 59, 6)
output: (None, 10, 59, 59, 6)
Concatenate
input: [(None, 10, 59, 59, 22), (None, 10, 59, 59, 6)]
output: (None, 10, 59, 59, 28)
(Conv2D)
input: (None, 10, 59, 59, 28)
output: (None, 10, 59, 59, 28)
Dropout
input: (None, 10, 59, 59, 28)
output: (None, 10, 59, 59, 28)
(AveragePooling2D)
input: (None, 10, 59, 59, 28)
output: (None, 10, 59, 59, 28)

FIG. 6

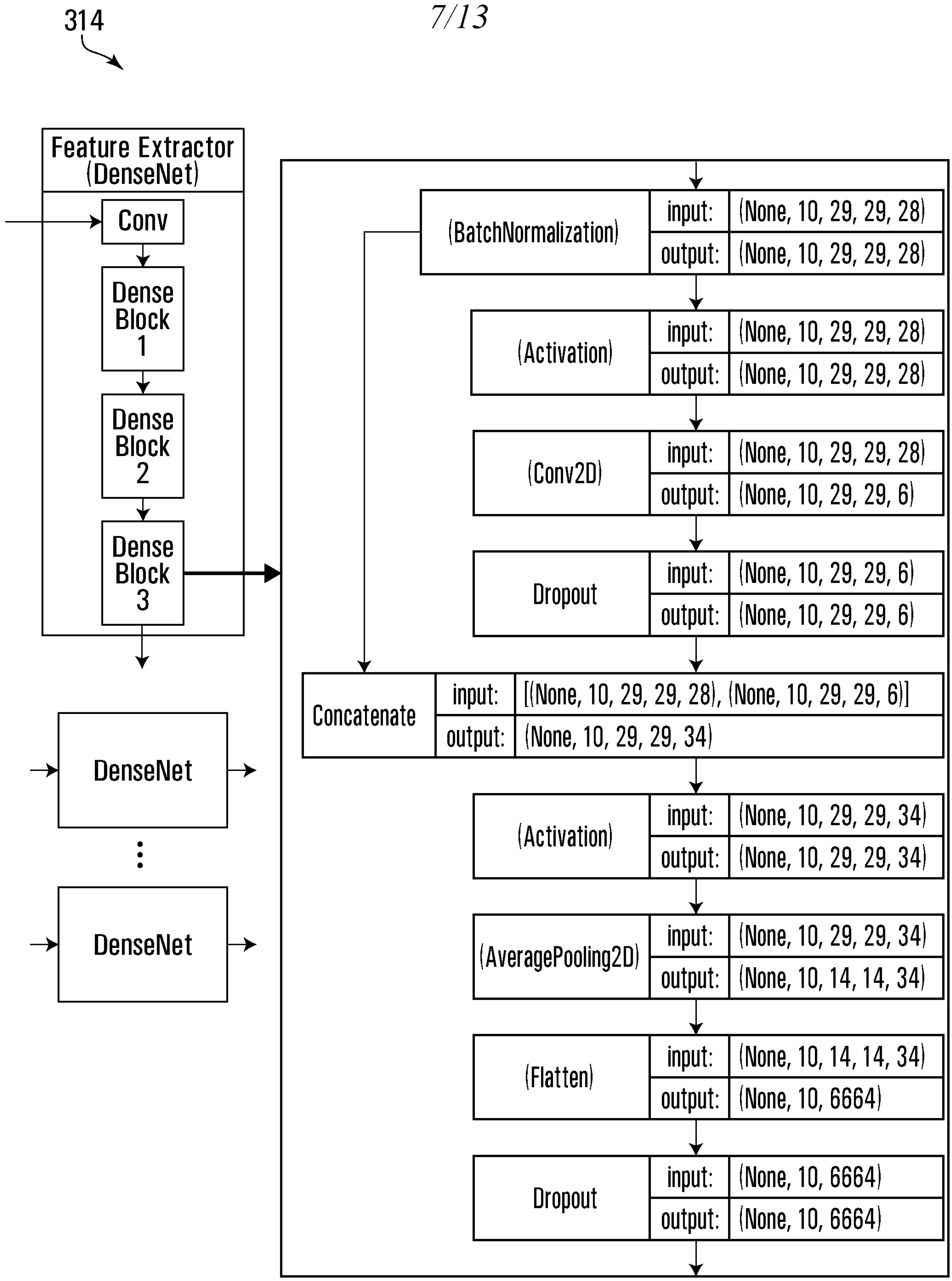
314
Feature Extractor (DenseNet)
Conv
Dense Block 1
Dense Block 2
Dense Block 3
DenseNet
DenseNet
(BatchNormalization)
input: (None, 10, 29, 29, 28)
output: (None, 10, 29, 29, 28)
(Activation)
input: (None, 10, 29, 29, 28)
output: (None, 10, 29, 29, 28)
(Conv2D)
input: (None, 10, 29, 29, 28)
output: (None, 10, 29, 29, 6)
Dropout
input: (None, 10, 29, 29, 6)
output: (None, 10, 29, 29, 6)
Concatenate
input: [(None, 10, 29, 29, 28), (None, 10, 29, 29, 6)]
output: (None, 10, 29, 29, 34)
(Activation)
input: (None, 10, 29, 29, 34)
output: (None, 10, 29, 29, 34)
(AveragePooling2D)
input: (None, 10, 29, 29, 34)
output: (None, 10, 14, 14, 34)
(Flatten)
input: (None, 10, 14, 14, 34)
output: (None, 10, 6664)
Dropout
input: (None, 10, 6664)
output: (None, 10, 6664)

FIG. 7

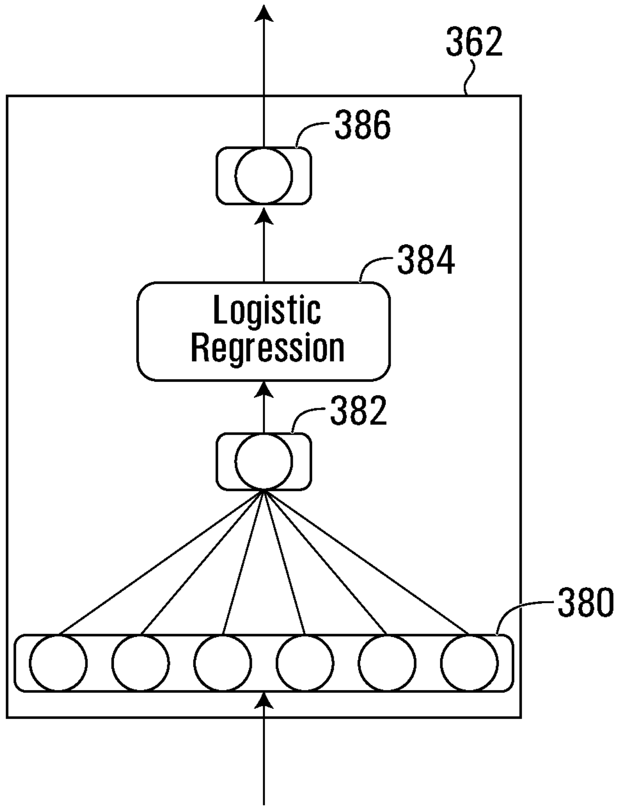

FIG. 8

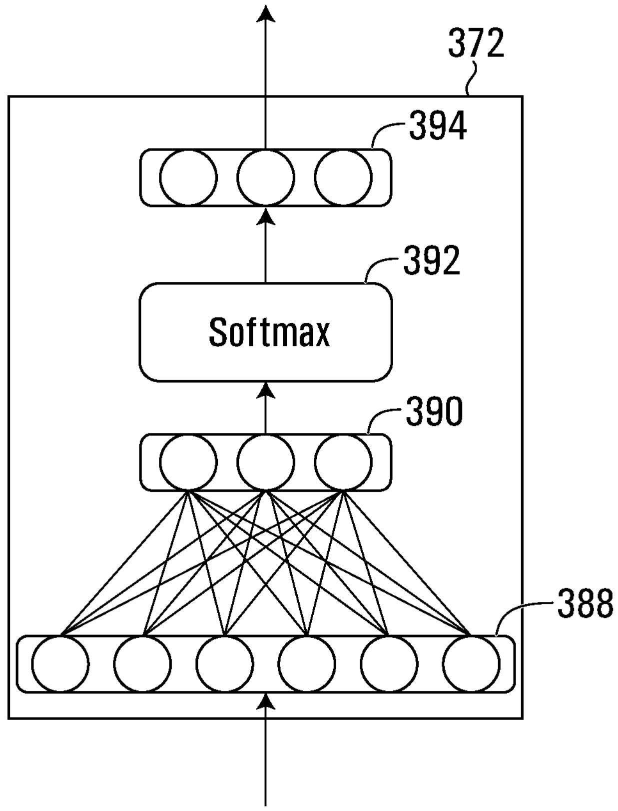

FIG. 9

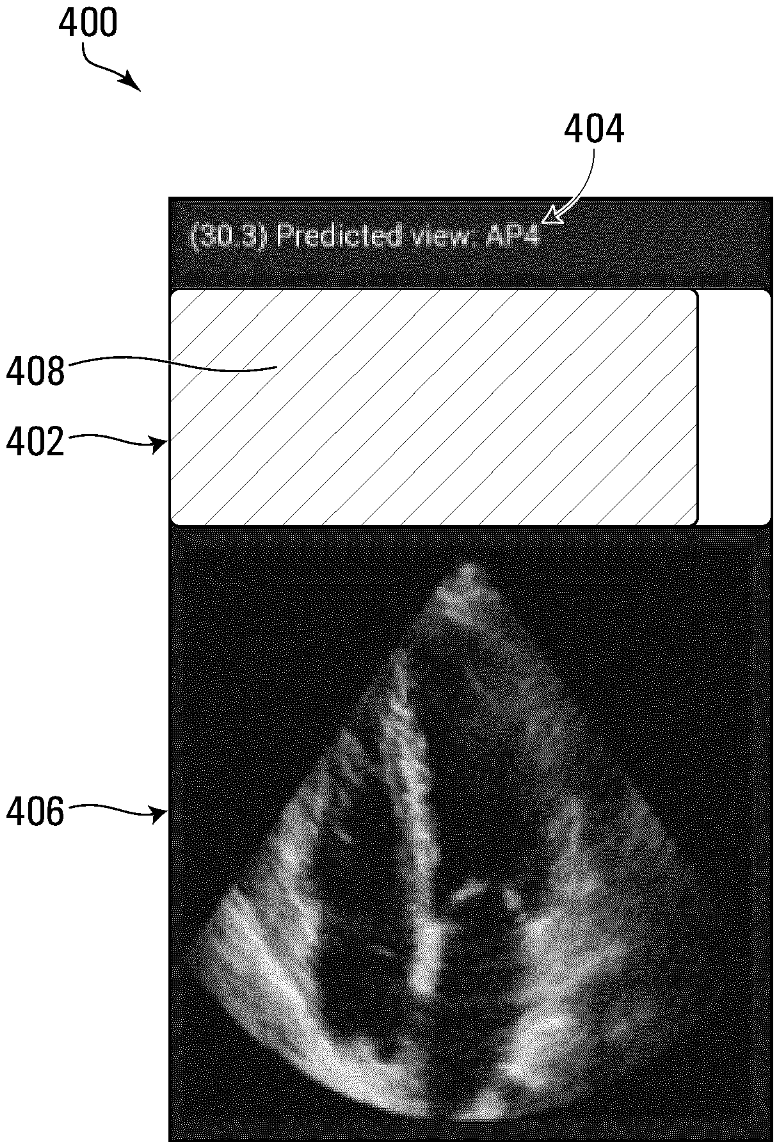

FIG. 10

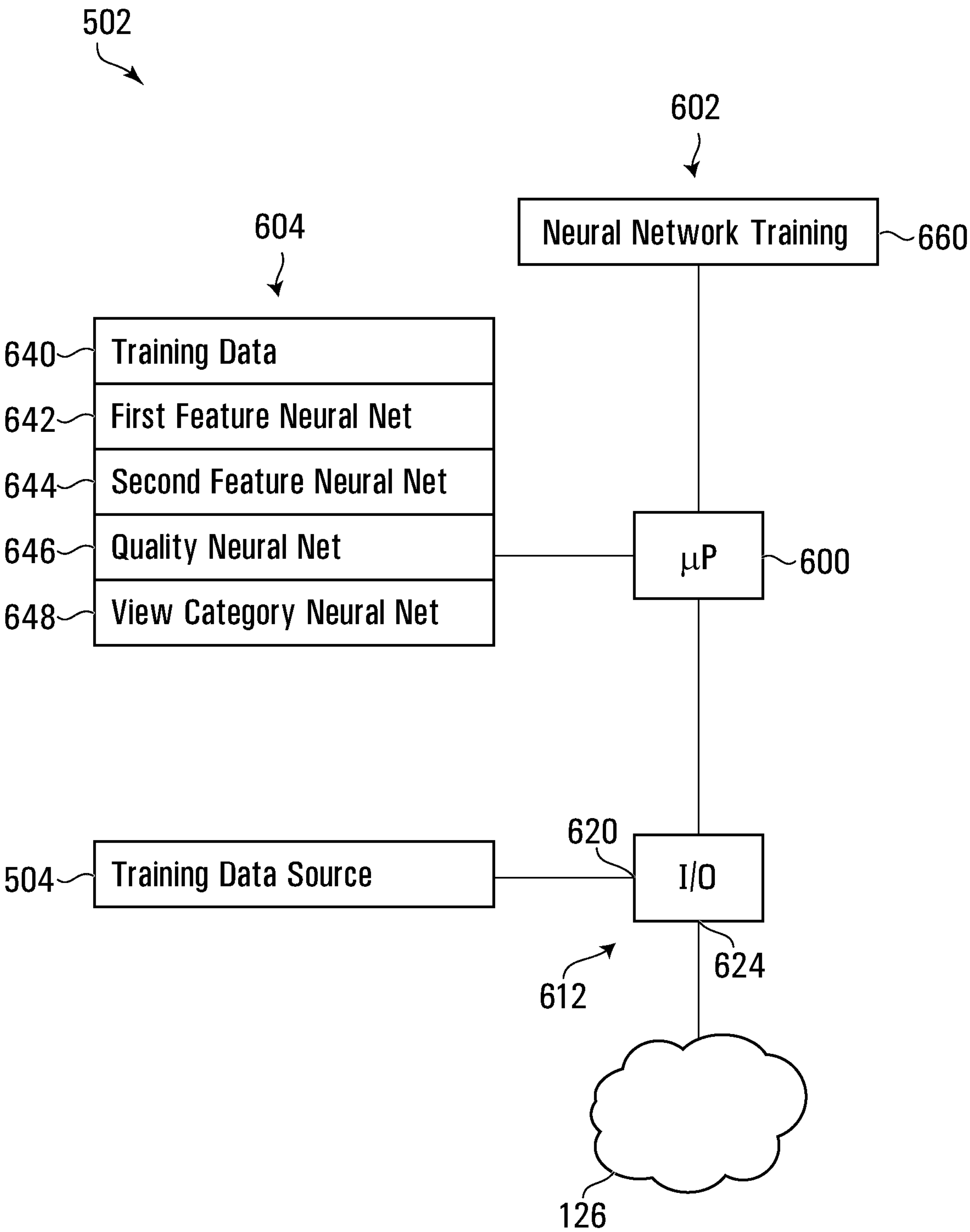
502
602
Neural Network Training
660
604
640
Training Data
642
First Feature Neural Net
644
Second Feature Neural Net
646
Quality Neural Net
648
View Category Neural Net
μP
600
620
504
Training Data Source
I/O
612
624
126

FIG. 11

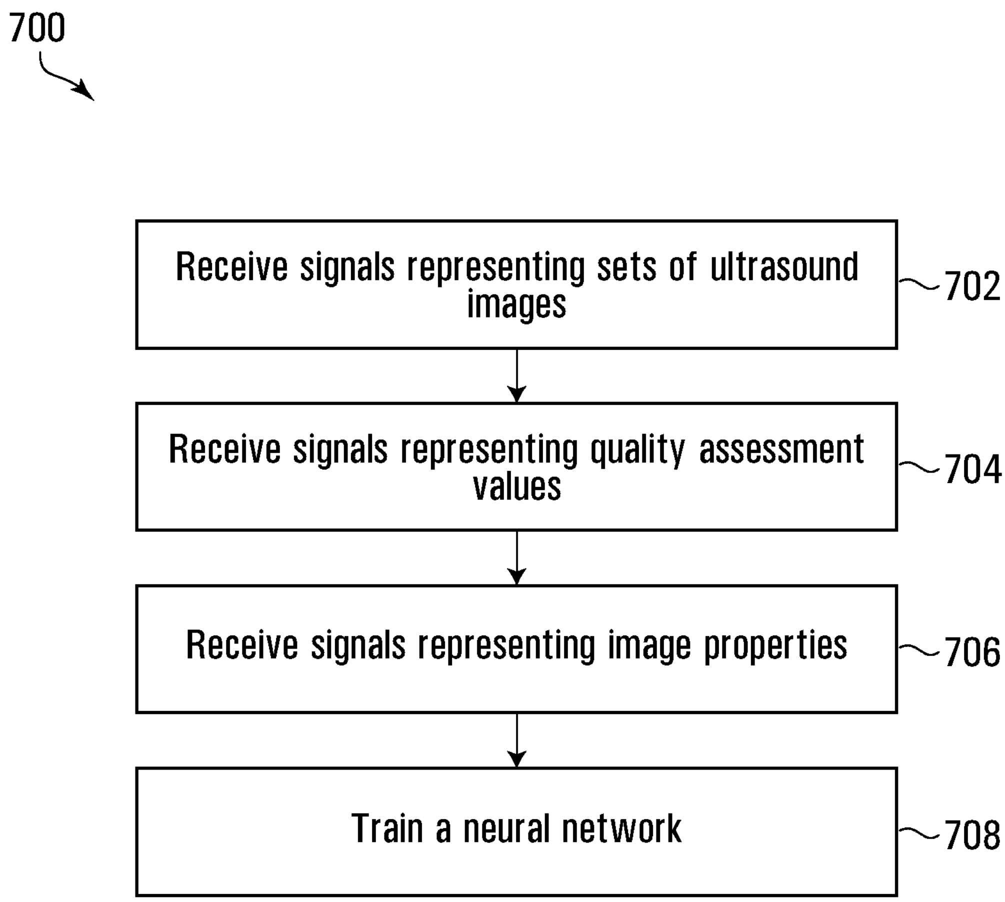
700
Receive signals representing sets of ultrasound images
702
Receive signals representing quality assessment values
704
Receive signals representing image properties
706
Train a neural network
708

FIG. 12

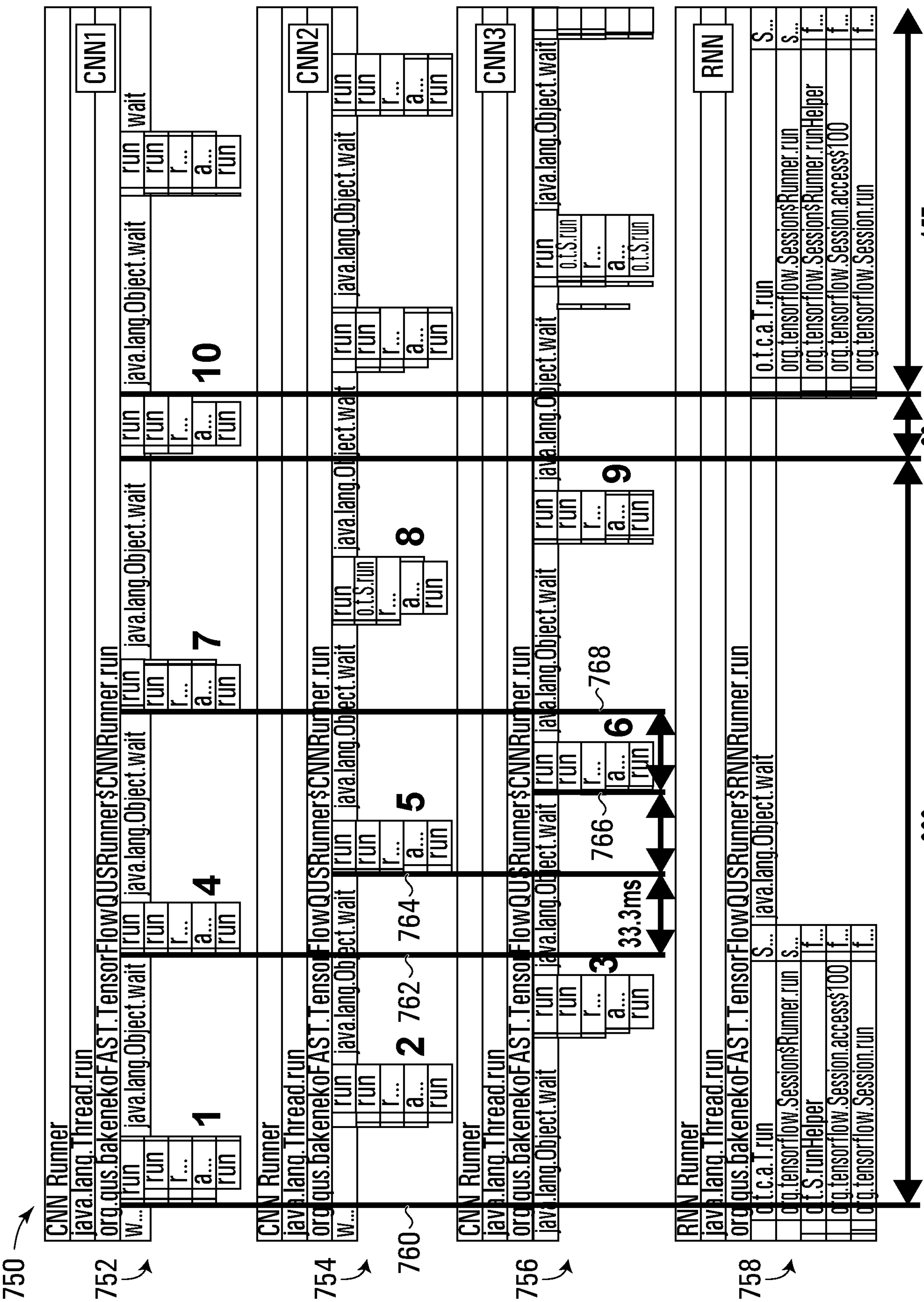
750
752
754
756
758
760
762
764
766
768
CNN Runner
java.lang.Thread.run
org.qus.bakenekoFAST.TensorFlowQUSRunner$CNNRunner.run
java.lang.Object.wait
CNN1
CNN2
CNN3
RNN Runner
org.qus.bakenekoFAST.TensorFlowQUSRunner$RNNRunner.run
RNN
o.t.c.a.T.run
org.tensorflow.Session$Runner.run
org.tensorflow.Session$Runner.runHelper
org.tensorflow.Session.access$100
org.tensorflow.Session.run
o.t.S.run
o.t.S.runHelper
1
2
3
4
5
6
7
8
9
10
33.3ms
333ms
~29ms
~157ms

FIG. 13

INTERNATIONAL SEARCH REPORT

International application No.
PCT/CA2019/051192

A. CLASSIFICATION OF SUBJECT MATTER
IPC: ***G06T 7/00*** (2017.01) , ***A61B 8/13*** (2006.01) , ***G06N 3/08*** (2006.01) , ***G06T 1/40*** (2006.01)

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)
IPC: ***G06T 7/00*** (2017.01) , ***A61B 8/13*** (2006.01) , ***G06N 3/08*** (2006.01) , ***G06T 1/40*** (2006.01)

Documentation searched other than minimum documentation to the extent that such documents are included in the fields searched

Electronic database(s) consulted during the international search (name of database(s) and, where practicable, search terms used)
Databases searched: QuestelOrbit, USPTO, Esp@cenet, PatentScope®, IEEE Xplore® Digital Library, Canadian Patent Database.
Keywords: image, analysis, feature, representation, quality assessment, property, ultrasound, view, category, neural, network, classification, training, convolutional, analyzer, processor, and related terms.

C. DOCUMENTS CONSIDERED TO BE RELEVANT

Category*	Citation of document, with indication, where appropriate, of the relevant passages	Relevant to claim No.
X	WO 2017/181288 Al (THE UNIVERSITY OF BRITISH COLUMBIA), 26 October 2017 (26.10.2017). **Entire document.**	1 to 24
A	US 2006/0147107 A1 (Microsoft Corporation), 06 July 2006 (06.07.2006). **Entire document.**	1 to 24
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☐ Further documents are listed in the continuation of Box C.

☑ See patent family annex.

*	Special categories of cited documents:	"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
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Date of the actual completion of the international search	Date of mailing of the international search report
08 November 2019 (08-11-2019)	08 November 2019 (08-11-2019)

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