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(71) Applicant: **CARDIOSENSE, INC.** [US/US]; 400 N Aberdeen Street, Suite 900, Chicago, Illinois 60642 (US).

(72) Inventors; and
(71) Applicants: **CAREK, Andrew M.** [US/US]; c/o Cardiosense, Inc., 400 N Aberdeen Street, Suite 900, Chicago, Illinois 60642 (US). **GANTI, Venu G.** [US/US]; c/o Cardiosense, Inc., 400 N Aberdeen Street, Suite 900, Chicago, Illinois 60642 (US). **ETEMADI, Mozziyar** [US/US]; c/o Cardiosense, Inc., 400 N Aberdeen Street, Suite 900, Chicago, Illinois 60642 (US). **INAN, Omer T.** [US/US]; c/o Cardiosense, Inc., 400 N Aberdeen Street, Suite 900, Chicago, Illinois 60642 (US). **SONI, Priyanka B.** [IN/IN]; c/o Cardiosense, Inc., 400 N Aberdeen Street, Suite 900, Chicago, Illinois 60642 (US). **JETHVA, Mineshbhai A.** [IN/IN]; c/o Cardiosense, Inc., 400 N Aberdeen Street, Suite 900, Chicago, Illinois 60642 (US).

(74) Agent: **TALBOT, C. Scott** et al.; Cooley LLP, 1299 Pennsylvania Avenue NW, Suite 700, Washington, District of Columbia 20004 (US).

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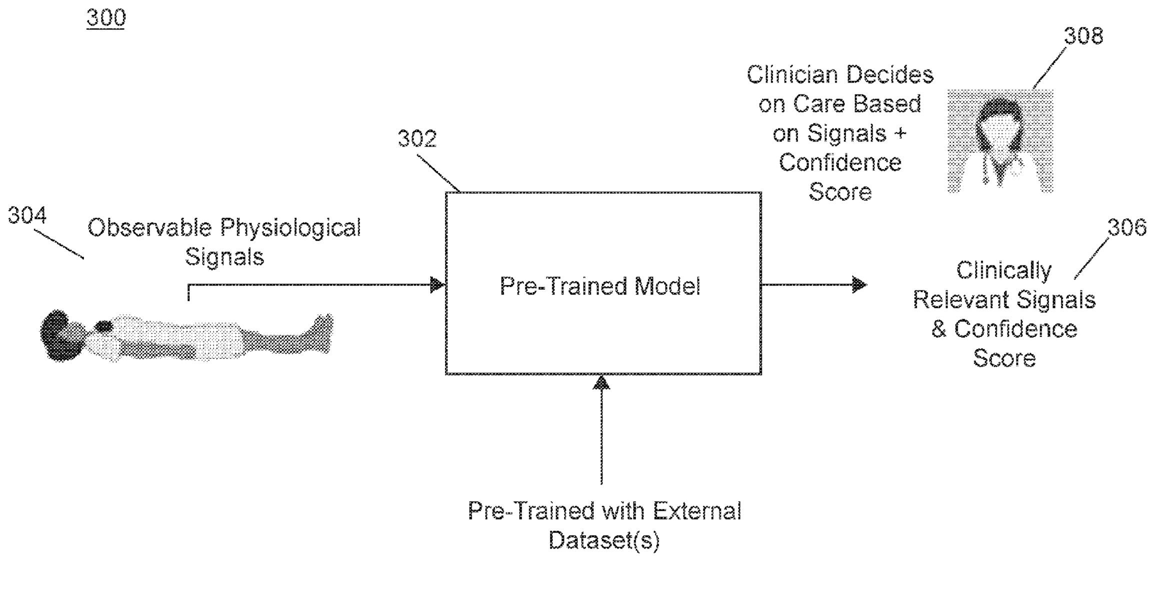

FIG. 3

(57) **Abstract:** Devices, systems, and methods herein relate to determining physiological information. In some embodiments, a method includes receiving, from at least one of a sensing device or a database, at least one signal associated with a physiological variable of a patient. The method includes generating a waveform based on the at least one signal, the waveform representing the physiological variable. The method includes generating a confidence score indicative of a reliability of the waveform.

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SYSTEMS, DEVICES, AND METHODS FOR ANALYZING AND PRESENTING PHYSIOLOGICAL INFORMATION

TECHNICAL FIELD

[0001] This application claims priority to and benefit of U.S. Provisional Patent Application No. 63/612,815, titled, "SYSTEMS, DEVICES, AND METHODS FOR ANALYZING AND PRESENTING PHYSIOLOGICAL INFORMATION," filed December 20, 2023, the disclosure of which is incorporated herein by reference.

TECHNICAL FIELD

[0002] Devices, systems, and methods disclosed herein relate to analyzing and presenting physiological information, including physiological information based on signals measured using one or more wearable devices on a patient's body.

BACKGROUND

[0003] Wearable devices may provide a convenient way to capture physiological signals or characteristics of a user. Signals from sensors used to measure physiological characteristics, such as photoplethysmography (PPG) sensors, electrocardiogram (ECG) sensors, and/or seismocardiogram (SCG) sensors, can often include noise associated with the sensor (e.g., high frequency noise, noise from movement, noise due to improperly positioned sensors, etc.). Because of the noise, physicians, when using sensor measurements to support decisions, often are not confident in the measurements from the sensors.

[0004] Current methods for providing decision support using wearable technology provide limited information and may be unreliable. Current methods may also be difficult to generate across multiple types of data and/or sensors because small differences in data collection approach, dataset demographic differences, and ground truth collection methods can impact the datasets and therefore outputs or inferences derived from the datasets.

[0005] Thus, there is a need for devices and methods that can process and analyze physiological information, provide insights into reliability of such information or analysis, and/or present more robust or comprehensive information associated with such information or analysis.

SUMMARY

[0006] Described here are systems, devices, and methods for processing and/or analyzing physiological information, and presenting such information in a usable format for a user or physician.

[0007] In some embodiments, a method includes: receiving, from at least one of a sensing device, at least one signal associated with a physiological characteristic of a patient. The method includes processing at least one signal using a language model to output a clinically relevant physiological signal and a confidence score indicative of a reliability of the physiological signal. In some embodiments, the method includes transforming the at least one sensor signal into a formal suitable for processing using a language model (e.g., a text-based format). In some embodiments, the method includes processes for training the model, e.g., training using auxiliary tasks, dictionary learning, etc. In some embodiments, the model can be a multi-output model that can be trained to generate multiple different clinical signal outputs.

[0008] In some embodiments, an apparatus includes: a sensing device configured to measure an observable physiological characteristic of a patient; a display; and a processor operatively coupled to the sensing device and the display, the processor configured to: receive, from the sensing device, at least one signal indicative of the observable physiological characteristic of the patient; transform the at least one signal to an input format associated with a language model; generate, using the language model, an output associated with a physiological variable; generate an output waveform for the physiological variable based on the output; and present, via the display, the output waveform.

BRIEF DESCRIPTION OF THE DRAWINGS

[0009] FIG. 1A is a block diagram of a system for capturing and processing and/or presenting physiological data, according to an embodiment.

[0010] FIG. 1B is a block diagram of a compute device of the system of FIG. 1A, according to an embodiment.

[0011] FIG. 2 is a block diagram of a network of devices for processing and/or presenting physiological data, according to an embodiment.

[0012] FIG. 3 schematically depicts the flow of inputs into and outputs from systems and devices for processing physiological data, according to an embodiment.

[0013] FIG. 4 is a flow chart illustrating the flow of information through systems and devices for processing physiological data, according to an embodiment.

[0014] FIG. 5 is a flow chart illustrating a method for processing physiological data, according to an embodiment.

[0015] FIG. 6 is a flow chart illustrating a method for training a language model to generate one or more physiological signals, according to an embodiment.

DETAILED DESCRIPTION

[0016] Systems, apparatuses, and methods for processing and analyzing observable physiological signals and outputting clinically relevant physiological signals are described herein. In some embodiments, systems and devices described herein can be configured to receive observable patient information (e.g., physiological signals collected by sensing device, such as a pulse oximeter, an ECG device, a PPG device, a SCG device, an arterial line, etc.). The observable patient information may be captured by a wearable device (e.g., a smart watch, a patch, etc.), and/or may have been pre-collected in a home or clinical setting and stored in a database. The observable patient information may be associated with a physiological variable or characteristic of a patient. The systems and devices described herein may process and/or analyze the observable patient information, e.g., using pre-processing algorithms and/or trained models, and output a clinically relevant physiological signal. In some embodiments, other information may also be outputted with the clinically relevant physiological signal, e.g., including a confidence score indicative of the reliability of the output and/or information indicative of one or more health conditions of a user. In some embodiments, the clinically relevant physiological signal, the confidence score, and/or other information associated therewith can be used to support clinical decisions.

[0017] Conventional systems, devices, and/or methods for using wearable technology to provide decision support include certain limitations. Many of these systems rely on a dedicated dataset, which includes the wearable signals together with ground truth (e.g., clinical variables such as blood pressure including diastolic blood pressure, systolic blood pressure, etc.). The dataset is typically split into training and testing groups, from which a model is formed using the training set to relate the signals measured with the wearable to low-dimensional variables of clinical interest. Such systems fail to provide information on the reliability of the variable that is estimated. Moreover, any trained models or other algorithms used in such systems are typically difficult to generalize across multiple datasets, since small differences in the collection approach, dataset demographics, and ground truth collection methods can have a significant influence on the performance of the models.

[0018] Systems, devices, and methods described herein are designed to overcome these limitations by providing more comprehensive information associated with a physiological variable of interest. In particular, systems, devices, and methods described herein use a trained model to output a waveform associated with a clinically relevant physiological variable, instead of a single value output. The full output waveform can be configured to provide more meaningful information to a clinician over single values associated with a variable. For example, for a model that is designed to assist clinicians in deciding how to control a person's hemodynamic state, rather than outputting a limited number of values for blood pressure (e.g., 120 / 80 mmHg), systems, devices, and methods described herein are configured to output the full blood pressure waveform (e.g., multiple time points per section of blood pressure values, including, for example, hundreds of time points per second of blood pressure values). This has multiple advantages – first, the clinician is able to see the entire waveform rather than the two values alone, and thus there is more insight into the details of the predicted output and ability to verify the data that is presented; second, the full waveform output can be used by the models described herein to further train the models; third, by predicting the output waveform and not low dimensional values (e.g., 120 / 80 mmHg), the model is configured to learn inherent information that is deeply embedded in the waveform output and not necessarily obvious at the surface of the waveform itself, which allows the model to be more accurate and more generalizable across different datasets and conditions. In some embodiments, systems, devices, and methods described herein can also provide a confidence score or other information indicative of a reliability of the waveform output.

[0019] FIG. 1A is a block diagram of a system 100 for capturing and/or analyzing physiological information of a user, according to embodiments. The system includes a sensing device 110 operably coupled to a compute device 120. In some embodiments, the sensing device 110 and the compute device 120 can be implemented as separate or different devices, which can be operatively coupled to one another. In some embodiments, the sensing device 110 and the compute device 120 can be implemented on the same device.

[0020] The sensing device 110 can be configured to collect information about a user. For example, the sensing device 110 can be configured to capture observable physiological information of a user. The captured data can be in the form of signals, e.g., associated with one or more sensor(s) 116. In some embodiments, the sensing device 110 can be, or included in, a wearable device, such as a smart watch, a sleeve, a band, a patch, or the like.

[0021] In some embodiments, the sensing device 110 can be a wearable device that can have an external structure or housing that includes a first side (e.g., a first portion) and a second side (e.g., a second portion). The first side and second side can be connectable and separable structures. The first side and second side can be generally round in shape and connectable to create a generally puck-like shape. Alternatively, or in addition, the first side and the second side can have other shapes (e.g., square, rectangular, oblong, etc.). The wearable device can include electronics for carrying out the various operations of the sensing device 110. For example, the electronics (e.g., processor 112, memory 114, etc.) can be located inside the wearable device 110 between the first side and second side.

[0022] The first side can be configured to face away from the body of a user (e.g., distal the heart). The first side can include an alignment marker. For example, the alignment can be an arrow for indicating a direction that the sensing device 110 should be oriented when worn by a user (e.g., arrow should face towards head of user). In some embodiments, the first side is configured to be worn on the chest of the user below the suprasternal notch of the user.

[0023] The second side can be configured to face the body of a user (e.g., proximal the heart). The first side and/or second side can be a flat surface. In some embodiments, the second side can include connectors, e.g., for connecting to one or more electrodes and/or other sensors. For example, the connectors can connect to the first sensor. In an embodiment, the first sensor can include one or more electrodes that can be stuck on the body of the user and the connectors can connect the second side to the one or more electrodes. In doing so, the wearable device can be affixed to the user by the one or more electrodes of the first sensor being stuck to the user and the other portions of the sensing device 110 (e.g., second sensor, first side, second side, and electronics) being connected to the one or more electrodes by the connectors. The connectors can be any connector such as, including, but not limited to buttons, snap buttons, press buttons, adhesive, hook and loop, and the like, or any combination thereof. In some embodiments, a set of one or more sensors can be disposed on the first and/or second side of the device. For example, one or more sensors can be disposed on the flat surface of the sensing device facing the user such that the sensors can be in contact with the user's skin while the sensing device is being worn. In some embodiments, a set of one or more sensors can be disposed within the external structure of the sensing device (e.g., within the space formed by the first and second sides).

[0024] In some embodiments, the sensing device 110 can include a plug. The plug can be configured to provide power to the sensing device 110. For example, the plug can be connected to a power source to directly power the sensing device 110 and/or charge a battery of the sensing device 110. Alternatively, or in addition, the plug can be configured to connect (e.g., send and receive data) with an external device. For example, the plug can allow for the wearable device to be connected to an external computer, tablet, mobile phone, other processor, and the like, to send and receive data. The plug can be a USB connector. The sensing device 110 can include a power source. For example, the power source can be a battery for powering the components of the wearable device (e.g., sensor, processor, transceiver).

[0025] In some embodiments, the sensing device 110 can be configured to measure signals associated with one or more of volume changes, electrical activity, cardiac vibrations, ECG, heart rate, pulse rate, PPG, blood pressure, blood flow, SCG, muscle electrical potential, nerve electrical potential, temperature, brain waves, motion, measures of activity, number of steps taken, location, acceleration, pace, distance, altitude, direction, velocity, speed, time elapsed, time left, and/or the like. In some embodiments, the sensing device 110 can be configured to collect data of the user at predetermined times and/or time intervals. In some embodiments, the sensing device 110 can be configured to collect data of the user during predetermined activities (e.g., during rest and/or sleep, or other times when a user may be less likely to be moving). The sensing device 110 includes a processor 112, a memory 114, a sensor(s) 116, an input/output (I/O) device 118, and a communications interface 119 (or a multiplicity of such components), each operatively coupled to one another (e.g., via a system bus, a network, etc.).

[0026] The processor 112 can be, for example, a hardware based integrated circuit (IC), or any other suitable processing device configured to run and/or execute a set of instructions or code. For example, the processor 112 can be a general-purpose processor, a central processing unit (CPU), an accelerated processing unit (APU), an application specific integrated circuit (ASIC), a field programmable gate array (FPGA), a programmable logic array (PLA), a complex programmable logic device (CPLD), a programmable logic controller (PLC) and/or the like. The processor 112 can be operatively coupled to the memory 114, the I/O device, and/or the communications interface 119, e.g., through a system bus (for example, address bus, data bus and/or control bus).

[0027] The memory 114 can be, for example, a random-access memory (RAM), a memory buffer, a hard drive, a flash memory, a read-only memory (ROM), an erasable programmable read-only memory (EPROM), and/or the like. In some instances, the memory 114 can store, for example, one or more software programs and/or code that can include instructions to cause the processor 112 to perform one or more processes, functions, and/or the like. In some implementations, the memory 114 can be a portable memory (for example, a flash drive, a portable hard disk, and/or the like) that can be operatively coupled to the processor 102. In some instances, the memory 114 can be operatively coupled to the sensing device 110 and/or another compute device (e.g., compute device 120, database, etc.). For example, in some embodiments, the memory 114 can be coupled to a remote server or database, e.g., for sending and/or receiving information therefrom. In some embodiments, the memory 114 and processor 112 may be implemented on a single chip. In other embodiments, the memory 114 and processor 112 may be implemented on separate chips.

[0028] The sensor(s) 116 can include one or more sensor(s) configured to measure an observable or measurable characteristic of a user (e.g., ECG, PPG, SCG, electrodermal activity (EDA), blood pressure, heart rate, skin temperature, etc.). The sensor(s) 116 can send a signal indicative of the measured characteristic to the processor 112, memory 114, and/or other components of the sensing device 110. For example, the sensor(s) 116 can measure and output one or more of a SCG waveform, a PPG waveform, an ECG waveform, etc. In some embodiments, the data from the sensor(s) 116 is stored in the memory 114. In some embodiments, the processor 112 can be configured to control the operation of the sensor(s) 116. For example, the processor 112 can be configured to activate the sensor(s) 116 and/or change one or more operational parameters (e.g., light wavelengths, length intensity, sampling frequency, etc.) of the sensor(s) 116. The sensor(s) 116 can be configured to operate continuously, sporadically, and/or periodically.

[0029] In some embodiments, the sensor(s) 116 can include one or more electrodes placed on the body of the user. For example, the sensor(s) 116 can include one or more electrodes that can be placed on the body of the user. For example, the one or more electrodes can be stuck to the skin of the user. In some embodiments, the one or more electrodes being stuck to the skin of the user can further affix the sensing device 110 to the user. In some embodiments, the sensor(s) 116 can include one or more sensors can be configured to measure environmental parameters. For example, the sensor(s) 116 can be configured to measure one or more of temperature, humidity, altitude, and the like, or any combination thereof. In some embodiments, the sensor(s) 116 can be configured to measure a photoplethysmography signal of the user. The sensor(s) 116 can be configured to measure cardiogenic vibrations of the user. For example, the sensor(s) 116 can be configured to measure a SCG signal of the user. The sensor(s) 116 can be configured to measure tri-axial SCG signals. For example, tri-axial SCG signals can include the DV, Lat, and/or HtoF axis. In some embodiments, the sensor(s) 116 can be configured to measure a gyrocardiogram signal of the user.

[0030] The I/O device 118 can include an input device and/or an output device, such as, for example, a display (e.g., Cathode Ray tube (CRT) display, Liquid Crystal Display (LCD), Light Emitting Diode (LED) display, Organic Light Emitting Diode (OLED) display, and/or the like), mouse, keyboard, microphone, touch screen, speaker, scanner, headset, printer, camera, and/or the like. For example, the I/O device 118 may include an input device for a user to input information or instructions and/or an output device for a user to receive an output (e.g., SCG readings, ECG readings, PPG readings, etc.). In some embodiments, the I/O device 118 can be used to provide alerts to a user, e.g., to indicate to a user that there is too much movement for sensor data capture, to indicate to the user a possible issue with the sensor (e.g., sensor placement due to a wearable being worn too loosely, or sensor defect), etc. In some embodiments, the I/O device 118 can instruct a user to perform certain activities (e.g., to lay down or to minimize movement), e.g., to facilitate cleaner data capture by sensor(s) 116. In some embodiments, the I/O device 118 can display information received from the compute device 120. This information can include, for example, physiological information derived using a model, a confidence score or another reliability indication, etc., as further described herein.

[0031] The communications interface 119 of the sensing device 110 can be configured to receive information and/or send information to other devices (e.g., compute device 120). The communications interface 119 can be a wired or wireless communications interface. The communications interface 119 can, for example, be configured to send information captured by the sensor(s) 116 to the compute device 120. In some embodiments, the communications interface 119 can receive data, signals, and/or instructions from the compute device 120.

[0032] The compute device 120 can be configured to process and/or analyze sensor data, e.g., received from the sensing device 110, and/or other data, e.g., received from a user, a database, or other source. For example, the compute device 120 can be configured to filter, rectify, differentiate, integrate, enhance, pre-process, and/or combine the sensor data. In some embodiments, the compute device 120 can be configured to receive sensor data from more than one sensing device 110. In some embodiments, the compute device 120 can be nearby the sensing device 110, such as, for example, a local computer, laptop, mobile device, tablet, etc. In some embodiments, the compute device 120 can be a server that is remote from the sensing device 110 but can communicate with the sensing device 110, e.g., via a network (as depicted in FIG. 2). In some embodiments, the sensing device 110 can be configured to transmit sensor data to a nearby device (e.g., a user device such as a mobile device) via a wireless network (e.g., Wi-Fi, Bluetooth, etc.), and then that device can be configured to transmit the sensor data to the compute device 120 for further processing and/or analysis. In some embodiments, the compute device 120 is implemented as or includes a user device.

[0033] The compute device 120 can include a processor 122, a memory 124, an I/O device 128, and a communications interface 128 (or a multiplicity of such components). The memory 124 can be, for example, a random access memory (RAM), a memory buffer, a hard drive, a flash memory, a database, an erasable programmable read-only memory (EPROM), an electrically erasable read-only memory (EEPROM), a read-only memory (ROM), and/or so forth. In some embodiments, the memory 124 stores instructions that cause processor 122 to execute modules, processes, and/or functions associated with processing and/or analyzing sensor data from sensing device 110. In some instances, the memory 124 can be operatively coupled to other compute devices (e.g., as depicted in FIG. 2). In some embodiments, the memory 124 stores information associated with more than one user. For example, compute device 120 can be a household account, a medical provider account, and/or the like, and the memory 124 can be configured to store information associated with one or more users associated with that account. The administrator account can be utilized to allow one or more users (e.g., healthcare professionals, caretakers, etc.) to access information during operation.

[0034] The processor 122 of compute device 120 can be any suitable processing device configured to run and/or execute functions associated with processing and/or analyzing sensor data from the sensing device 110. The processor 122 can be a general purpose processor, microcontroller, a Field Programmable Gate Array (FPGA), an Application Specific Integrated Circuit (ASIC), a Digital Signal Processor (DSP), and/or the like. In some embodiments where the sensing device 110 and the compute device 120 are implemented as one device, the processor 122 and the processor 112 can be the same processor.

[0035] In some embodiments, the compute device 120 can be configured to process a signal from the sensor(s) 116 and/or other sensed information, e.g., to determine physiological information and/or a confidence score associated with the physiological information. The sensed information can include, for example, one or more of raw sensor signal information, processed sensor signal information, timestamp information, time window information, contextual information, and/or the like. In some embodiments, the sensed information can indicate a time period during which the sensed information was obtained and/or collected. In some embodiments, the compute device 120 can be configured to send instructions to the sensing device 110 to cause the sensing device 110 to operate according to one or more parameters. For example, the processor 122 can be configured to send instructions to the sensing device 110 to take measurements at predetermined times and/or intervals.

[0036] Generally, to generate physiological information and/or a confidence score, the compute device 120 is configured to process the sensor data received from the sensing device 110 using a model trained to predict or infer the physiological information based on the sensor data. For example, the sensor data, before or after pre-processing, can be input into a trained model, which in response can output clinically relevant physiological information. In some embodiments, the compute device 120 can be configured to use multinomial sampling to determine a confidence score associated with the predicted physiological information. For example, the sensor data may be input into the model multiple times to obtain a distribution of outputs. The compute device 120 can then analyze the distribution of outputs (e.g., by analyzing the variability of the outputs) to determine a confidence score associated with the predicted physiological information. In some implementations, the compute device 120 can be configured to generate an output including a waveform of a physiological variable of interest. The output waveform can be used by a clinician or other user to gain insight into the patient's health.

[0037] In some embodiments, the compute device 120 is configured to transform the signals or data received from the sensing device 110, such that the signals are suitable for processing by a model or other algorithm. For example, the compute device can transform the signals from the sensing device 110 from a first format (e.g., time-domain signal) to a second format (e.g., text-based signal or frequency-domain signal). In some embodiments, the model used by the compute device 120 can be a language model. The such embodiments, the compute device 120 can be configured to transform a signal or waveform from the sensing device 110 into language or text-based data (e.g., a string, text, etc.). The compute device 120 can then process the transformed data using the model to generate an output. The compute device 120 can then transform the output into a suitable format for presentation to a user. For example, the compute device 120 can transform the output back into a time-domain signal waveform. In some embodiments, the compute device 120 is configured to implement an encoder and decoder architecture (e.g., an encoder-decoder model) to transform or convert the input data into a suitable format for the model, and to revert the output data back to an initial format. Moreover, because language models and other types of models are transformer-based models, the compute device can use multinomial sampling to generate a distribution of outputs based on the input data. As such, in some embodiments, the compute device 120 can be configured to generate a distribution of outputs based on the input data and to determine a confidence score or reliability of the outputs, e.g., based on a variability of the outputs. The outputs from the model can be associated with at least one physiological variable (e.g., heart rate, blood pressure, etc.). In some implementations, the outputs can be predictions of the at least one physiological variable generated by the model.

[0038] FIG. 1B provides a more detailed view of the compute device 120. The memory 124 can store processor-executable instructions that, when executed by a processor (e.g., processor 122, causes the processor to implement data/waveform processing 124a, data transformation or encoding-decoding 124b, an inference model 124c, and/or a physiological variable determination 124e. Optionally, in some embodiments, the memory 124 can store instructions that cause the processor to implement a confidence score determination 124d. In some implementations, the memory 124 can include additional instructions for operating the compute device 120 and/or instructions for operating the sensing device 110.

[0039] The data/waveform processing 124a includes pre-processing of data received from the sensing device 110 and/or stored in a database (e.g., functionally and/or structurally similar to the database(s) 260 of FIG. 2). The data can include data associated with physiological signals measured using the sensing device 110. The pre-processing can include filtering, augmenting, normalization, cleaning, cropping, averaging, and/or combining the data, and/or the like. In some embodiments, the pre-processing can implement one or more rules to assess the quality of an input signal and discard input signals that have a signal-to-noise ratio that is above a predetermined threshold.

[0040] The data transformation 124b includes transforming the data from a first format (e.g., type, domain, etc.) into a second format that is different from the first format. In some embodiments, the data transformation 124b includes implementing an encoder-decoder architecture. In particular, the data transformation 124b can include encoding the input data (e.g., data from the sensor(s)) into a format for processing by a model (e.g., inference model 124c), and the data transformation can include decoding the output data (e.g., data generated by the inference model 124c) back into an original format. In other words, the data transformation 124b can include processing the input data (e.g., signal) using an encoder-decoder model (e.g., a first model) to generate an output (e.g., encoded output) that can be input into a language model (e.g., a second model), and processing output data from the language model using the encoder-decoder model to decode the output data. The decoded data can include clinically relevant physiological information (e.g., waveforms of physiological variable(s) of interest), which can be presented to a clinical to evaluate and/or assess a user's health. In some implementations, the data transformation 124b include transforming sensor data into a format suitable for processing by a language model (e.g., a string, text, etc.). In some implementations, the data transformation 124b can be configured to transform multiple signal types (e.g., different types of sensor data) into an input suitable for processing by a language model.

[0041] The inference model 124c includes generating one or more outputs associated with one or more physiological variables. In some implementations, such as when the inference model 124c is a multi-output model, the one or more outputs can include multiple different clinical signal outputs. As such, in some implementations, the inference model 124c can be configured to generate multiple signal outputs at the same time. The inference model 124c can be configured to learn shared, embedded characteristics of the different outputs that may not be obvious at a surface level that is observable but is shared at a level that the model can access. By learning multiple outputs at the same time, the model can focus on the underlying key characteristics of the output that are shared, as well as the nuances of each individual output signal that defines them. This type of learning can be analogous to language models being trained to learn different dialects of the same language and thus better understand the salient characteristics of the language itself.

[0042] In some implementations, the inference model l24c can be a machine learning model. In some implementations, the inference model 124c includes a language model (e.g., natural language model, etc.). The output of such a model can be text-based. In some implementations, the inference model 124c includes a convolutional neural network. The model can be trained to identify and extract key features that can be used to determine or predict values associated with a physiological parameter of interest.

[0043] In some embodiments, the inference model 124c can be a model that uses self-attention to generate or predict outputs. Self-attention involves using already predicted values to predict the net values in a sequence. For example, in the case of waveform prediction, if the model has predicted a first portion of a waveform (e.g., a first second of a waveform), then the first portion can be used as an input to predict the next portion(s) of the waveform. The inference model 124c, by implementing self-attention, can learn from previous predictions and more accurately predict future values. This is different from traditional models that predict values based on fixed input sizes and/or are static. In some embodiments, the model is configured to predict sequences of output data points that are inherently related rather than individual data points or low-level variables. In other words, the model is configured to predict a sequence of data points where each data point in the sequence following an earlier data point is predicted based on the earlier data point. This is analogous to a language model predicting words rather than individual letters, or sentences rather than letter and/or words. The use of such language models for physiological signals provides more accurate predictions. This approach is further leveraged in the self-attention methodology, by which the model is configured to correct itself dynamically based on the outputs it generates by assessing the viability of the sequences of these outputs as being realistic based on types of signals it has previously observed or predicted.

[0044] In some embodiments, the inference model 124c is trained using one or more datasets, including datasets with observable physiological signals, clinically relevant signals, ground truth signals, and/or other types of signals. In some embodiments, when the inference model 124c is a language model, the model can be trained using dictionary learning on physiological signals to capture one or more essential or key characteristics of such signals, which may be non-obvious at the surface level but are deeply embedded information within the signals. Such characteristics may be shared across different signals and different datasets, allowing for training based on and learning of different signals and datasets. In some embodiments, the inference model 124c can also be trained using auxiliary tasks, e.g., tasks which do not directly relate to the main task at hand. While these tasks in and of themselves are less relevant from a clinical standpoint, they are easier to administer and require little to no ground truth domain expertise to conduct. Further details on the training of an inference model 124c, as described herein, are provided with reference to FIG. 6.

[0045] In some embodiments, the inference model 124c can be used to generate a distribution of outputs that are associated with a physiological variable of interest. The output can vary, depending on the reliability of the input data. Multinomial sampling allows the model to generate multiple predictions from the same input to give distributions of outputs. This differs from conventional models with fixed weights, which produce the same output from the same input data, and thus the reliability of the underlying data cannot be derived from and/or quantified based on the output of the model.

[0046] Multinomial sampling may be used to provide insight on the accuracy of the physiological variable prediction. For example, the more the distribution of outputs differ, the potential error in the input data may be higher. Optionally, in some embodiments, confidence score determination 124d can be implemented. The confidence score determination 124d can include determining a confidence score associated with the output of the inference model 124c. Taking the distribution of outputs generated by the inference model 124c, the confidence score determination 124d can analyze the variability of the distribution and/or other characteristic of the distribution and output a confidence score. The confidence score can quantify for a user the reliability or accuracy of output of the inference model 124c. Such reliability or accuracy may be affected by signal quality, sensor placement, movement, and/or the like. In some implementations, the confidence score can be determined by determining the standard deviation of the output distribution. If the standard deviation is higher (indicating greater variability), then the confidence score may indicate a lower confidence or reliability in the data. Conversely, if the standard deviation is lower (indicating lower variability), the confidence score may indicate a higher confidence or reliability in the data. In contrast to traditional approaches that may only use a pre-processing step to assess a signal quality of inputs based on rules, such as, for example, signal-to-noise ratio, and discard ones that are beyond a certain threshold, the confidence score determination 124d evaluates the inference model 124c's understanding and familiarity with the input data and provides a confidence score indicative of the model's ability to produce an accurate output based on its understanding of the inputs.

[0047] The physiological variable determination 124e includes determining at least one physiological variable based on the output of the inference model 124c. In some implementations, the physiological variable determination 124e includes transforming the output generated by the inference model 124c to a waveform, e.g., a clinically relevant physiological waveform such as a blood pressure waveform. In some implementations, transforming can include using a decoder (as described above) to decode the output from the inference model 124c to a waveform data type. In some embodiments, the decode decodes the output back to an original format. In some implementations, the physiological variable determination 124e can include taking an average (e.g., mean, median, mode), maximum, minimum, and/or the like of the output to determine the physiological variable. For example, if a distribution of outputs was generated for each second (or time period), the physiological variable determination 124e can involve averaging or otherwise combining the values from the distribution to arrive at a combined value for that second (or time period). The values over time can then be presented together to a user, e.g., as a waveform. For example, the values for the time periods can be combined together to construct a time-domain waveform for the physiological variable.

[0048] The I/O device 128 of the compute device 120 can be similar to the I/O device 118 of the sensing device 110. For example, the I/O device 128 can include an input device for receiving one or more inputs and/or commands from a user and/or an output device for presenting information to a user. The I/O device 128 can include any type of peripherals, such as an input device, an output device, a mouse, keyboard, microphone, touch screen, speaker, scanner, headset, printer, camera, and/or the like. In some embodiments, the I/O device 128 can be used by a user to view the processed data. For example, if the system 100 processes PPG, ECG, or SCG data, the I/O device 128 can be utilized to display physiological data metrics (e.g., heart metrics) and/or a confidence score derived from the data to the user.

[0049] The communications interface 129 of the compute device 120 can be configured to receive information and/or send information to other devices (e.g., sensing device 110, and/or other compute devices as depicted in FIG. 2). The communications interface 128 can be a wired or wireless communications interface. In some embodiments, the communications interface

129 can be configured to receive data from the sensing device 110, including the data associated with the sensor(s) 116.

[0050] FIG. 2 is a block diagram of a network of devices, including systems and devices for determining clinically relevant physiological information and/or a confidence level associated with such information, according to an embodiment. Such systems and devices can be configured to process signals to generate a physiological data waveform and/or a confidence score associated with the physiological data outputs. In some embodiments, the systems and devices can include a sensing device 210 (e.g., functionally and/or structurally similar to the sensing device 110 of FIG. 1A) and/or a compute device 220 (e.g., functionally and/or structurally similar to the compute device 120 of FIGS. 1A-1B). The sensing device 210 and/or the compute device 220 can be operatively coupled to one or more other compute devices, including, for example, a server 250, a database 260, and/or optionally, one or more other device(s) 290, via one or more network(s) 202. The device(s) 290 can include, for example, additional sensing device(s) (e.g., functionally and/or structurally similar to the sensing device 110 of FIG. 1A) and/or additional compute device(s) (e.g., functionally and/or structurally similar to the compute device 120 of FIGS. 1A-1B). In some embodiments, the other device(s) 290 can include compute devices that are associated with one or more third parties, such as, for example, an administrator, a physician or healthcare provider, a hospital, a caretaker, etc.

[0051] The network 202 can be any type of network implemented as a wired network and/or wireless network and used to operatively couple the sensing device 210, the compute device 220, the server 250, the database 260, and/or other device(s) 290 to one another. The communication may or may not be encrypted. A wireless network may refer to any type of digital network that is not connected by cables of any kind. Examples of wireless communication in a wireless network include, but are not limited to cellular, near-field communication, radio, satellite, and microwave communication. However, a wireless network may connect to a wired network in order to interface with the Internet, other carrier voice and data networks, business networks, and personal networks. A wired network is typically carried over copper twisted pair, coaxial cable and/or fiber optic cables. There are many different types of wired networks including wide area networks (WAN), metropolitan area networks (MAN), local area networks (LAN), Internet area networks (IAN), campus area networks (CAN), global area networks (GAN), like the Internet, and virtual private networks (VPN).

[0052] The network 202 may include or be coupled to the server 250 and the database 260 for processing and/or storage. The database 260 can be any device configured to store data, e.g., received from other devices. For example, the database 260 can include instructions for storing signal data (e.g., signals captured by sensor(s) 116 of a sensing device 110), processed signal data, signal repositories, and/or the like. In some embodiments, the database 260 can store the final outputs from processing the signals, such as, for example, the clinically relevant physiological data waveforms and/or confidence scores associated therewith. In some embodiments, the database 260 can be configured to store other patient information, e.g., historical physiological characteristic information, patient demographic information, patient health history, etc. The server 250 can be any device configured to process signals and/or data received from the sensing device 210 and/or the compute device 220. In some embodiments, the server 250 can be configured to execute some or all of the processes of the sensing device 210 and/or the compute device 220, as described above with reference to FIGS. 1A and 1B.

[0053] Similar to other sensing devices described above, the sensing device 210 can be operatively coupled to the compute device 220. For example, the sensing device 210 can be operatively coupled to the compute device 220 via near-field communication, a wireless connection (e.g., Wi-Fi, Bluetooth, etc.), and/or a wired connection. Optionally, the sensing device 210 can be coupled to the network(s) 202 and/or other compute devices (e.g., server 250, database 260, other device(s) 290). The sensing device 210 can be operatively coupled to the compute device 220 and/or one or more other compute devices such that the sensing device 210 can send information (e.g., sensor signals) to and/or receive information (e.g., instructions for monitoring a patient or subject, parameters for operation, etc.) from one or more such devices.

[0054] FIG. 3 is a flow 300 of information being inputted into and outputted by a pre-trained model 302, according to embodiments. The flow 300 can be implemented, for example, by a compute device such as the compute device 120 of FIGS. 1A-1B and/or the compute device 220 of FIG. 2.

[0055] The pre-trained model 302 can be structurally and/or functionally similar to the inference model 124c, as described above with reference to FIG. 1B. In some embodiments, the pre-trained model 302 may have been trained using dataset(s) that can be from database(s), such as, for example, the database(s) 260 of FIG. 2. The dataset(s) can include observable signals (e.g., those measured by a sensing device such as a sensing device 110 of FIG. 1A and/or the sensing device 210 of FIG. 2) and/or other information collected of a patient. In some implementations, the observable signals may be associated with ground truth data, e.g., data collected of one or more clinically relevant physiological variables using established measurement methods. For example, ground truth data for blood pressure may be captured using tonometry, a blood pressure cuff, etc. In some implementations, the pre-trained model 302 may have been trained using auxiliary tasks and data associated therewith.

[0056] The pre-trained model 302 can receive observable physiological signals 304 that are associated with a patient. The observable physiological signals may be measured by a sensing device (e.g., structurally and/or functionally similar to the sensing device 110 of FIG. 1A and/or the sensing device 210 of FIG. 2). The pre-trained model 302, by processing the observable physiological signals 304, can generate an output 306. The output 306 can include clinically relevant signals (e.g., physiological signals) which can include signals, waveforms, and/or the like related to information desired by a clinician to make a decision associated with the health of the patient. Additionally, the output may include a confidence score associated with the output. The confidence score indicates how likely the clinically relevant signals are representative of the actual characteristics of the patient. In some embodiments, a clinician 308 can receive the output 306 and decide on care based on the clinically relevant signals and the confidence score. The output 306 allows the clinician to more confidently make a decision for a patient that may bring about a desired outcome as the signals may be directly related to the care and the confidence score can indicate if the signals are reliable and should be considered by the clinician. For example, if the confidence score is below a predetermined threshold (or a threshold set by the clinician), the clinician may capture additional data from the user, e.g., after adjusting or reorienting the sensing device, or use other information to decide on care.

[0057] FIG. 4 is a flow 400 illustrating a process of analyzing patient data (e.g., observable physiological data, patient records, etc.) and generating physiological waveform data, according to an embodiment. The flow chart 400 includes a sensing device 410 (e.g., structurally and/or functionally similar to the sensing device 110 of FIG. 1A and/or the sensing device 210 of FIG. 2) and a compute device 420 (e.g., structurally and/or functionally similar to the compute device 120 of FIG. 1B and/or the compute device 220 of FIG. 2), and optionally database(s) 460 (e.g., functionally and/or structurally similar to the database(s) 260 of FIG. 2) and/or other device(s) 490 (e.g. functionally and/or structurally similar to the other device(s) 290 of FIG. 2).

[0058] The compute device 420 includes data processing 424a (e.g., structurally and/or functionally similar to the data/waveform processing 124a of FIG. 1B), a data transformation 424b (e.g., structurally and/or functionally similar to the data transformation 124b of FIG. 1B), an inference model 424c (e.g., functionally and/or structurally similar to the inference model 124c of FIG. 1B and the pre-trained model of FIG. 3), a confidence score determination 424d (e.g., functionally and/or structurally similar to the confidence score determination 124d of

FIG. 1B), and a physiological variable determination 424e (e.g., structurally and/or functionally similar to the physiological variable determination 124e of FIG. 1B). In some implementations, the data processing 424a and the confidence score determination 424d are optional.

[0059] The data processing 424a receives inputs from the sensing device 410. Optionally, the data processing 424a receives inputs from the database(s) 460. The inputs can include observable physiological data measured by the sensing device 410 and/or stored in the database(s) 460. In some embodiments, the inputs can include historical patient data, patient demographic information, and/or other information associated with a patient. In some embodiments, where data was collected using a sensing device implemented as a wearable device (e.g., a PPG sensor, a SCG sensor, an ECG sensor, etc.), the inputs can include information associated with the wearable and/or sensor(s) thereof (e.g., type of device and/or operational parameters associated with the device). The data processing 424a can be configured to pre-process the inputs. For example, the data processing 424a can include one or more of filtering, normalizing, cropping, segmenting, etc.

[0060] The data transformation 424b receives the observable physiological data and/or other patient data, e.g., directly from sensor(s) or after the data has been pre-processed via data processing 424a. The data transformation 424b transforms the waveforms from a first format to a second format, where the second format is suitable for processing using the inference model 424c. For example, the observable physiological data and/or other patient data can be transformed into a text-based or language-based format including text, phrases, and/or the like. In some implementations, the data transformation 424b can include implementing encoding.

[0061] The inference model 424c receives as inputs the transformed or encoded data. In some embodiments, the inference model 424c is a natural language model. The inference model 424c processes the inputs and generates outputs, including, for example, generated predictions of a physiological variable. In some implementations, the output can include a distribution of outputs, e.g., generated using multinomial sampling. In some implementations, the inference model 424c can be configured to use self-attention, whereby the model uses already predicted outputs to predict the next outputs in a sequence.

[0062] The physiological variable determination 424e receives the output from the inference model 424c and generates an output waveform (or multiple output waveforms), e.g., by decoding or transforming the output back into its original format. In some implementations, where a distribution of outputs was generated, the output for each time period (e.g., each millisecond, second, etc.) can be determined based on an average, median, mode, maximum, minimum, and/or the like of the output for that time period. In some implementations, the physiological variable determination 424e receives additional information associated with a patient from the database(s) 460. The additional patient information can be used when determining the physiological variables or output waveform and/or to associate the physiological variables or output waveform with a particular patient. In some implementations, the physiological variable determination 424e can send the output waveform to other device(s) 490, e.g., for review by one or more users (e.g., a clinician).

[0063] Optionally, a confidence score determination 424d receives a distribution of outputs from the inference model 424c and determines a confidence score based on the distribution of outputs. In some implementations, the confidence score is determined based on a variability, standard deviation, and/or the like of the distribution of outputs. For example, if the output is found to have higher variability or a greater standard deviation, the confidence score can indicate that there is lower confidence in the determined value for a physiological variable. In some implementations, the confidence score determination 424d can receive the values for the physiological variable from the physiological variable determination 424e and use those values to determine the confidence score. In some implementations, the confidence score can be sent to the other device(s) 490, e.g., for review by one or more users.

[0064] FIG. 5 is a flow chart illustrating a method 500 for determining physiological data, according to an embodiment. The method can be executed by any of the systems and devices described herein, for example, any of the compute devices or sensing devices described in FIGS. 1A-3.

[0065] At 502, the method 500 includes receiving, from a sensing device and/or database, at least one signal associated with an observable physiological characteristic of a patient and/or other patient information. At least one signal can be associated with a SCG waveform, PPG waveform, ECG waveform, heart rate, blood pressure, and/or the like. In some implementations, the other patient information can include information such as age, weight, expected blood pressure, resting heart rate, activity level, and/or the like.

[0066] At 508, the method 500 includes transforming the at least one signal into an input format for an inference model such as, for example, a language model. In some implementations, the input format can be a text-based format, a string format, and/or the like. In some implementations, transforming to the input format associated with the language model can include using an encoder to encode at least one signal. In some implementations, other patient information can also be transformed into a format associated with the language model.

[0067] At 510, the method 500 includes generating, using the language model, an output. In some implementations, the output can include at least one prediction of a physiological variable. The output can include distributions of outputs for multiple periods of time (e.g., millisecond, seconds, etc.). Each distribution can include a set of predicted physiological variables. In some implementations, generating the output includes self-attention. Self-attention can include using generated outputs as inputs to generating additional outputs, thus increasing the accuracy of future outputs. In some implementations, generating the output can be based on the other patient information. For example, a patient’s age can indicate an expected range of a physiological variable for that patient.

[0068] At 512, the method 500 optionally includes determining a confidence score based on the output. Determining the confidence score can be based on the variability of the output, a standard deviation of the output, and/or the like. The confidence score can indicate a level of potential inaccuracy and/or reliability in the outputs generated by the model at 510.

[0069] At 514, the method 500 includes determining one or more measures or values associated with a physiological variable based on the output. In some implementations, 514 can include transforming the output from the language model into an output waveform. Where a distribution of outputs was generated for each time period in an output waveform, the individual values of the distribution can be determined by determining an average, a median, a mode, a maximum, and/or the like of the distribution. At 516, the method 500 optionally includes sending, to the display of a user device, the measure and/or the confidence score. A user can then review the displayed measure and/or the confidence score to aid in determining care for a patient.

[0070] FIG. 6 is a flow chart illustrating a method 600 for training at least one machine learning model, according to an embodiment. The method can be executed by any of the systems and devices described herein, for example, the system 100 of FIG. 1A, the network environment 200 of FIG. 2, and/or the one or more compute devices described in FIGS. 1A-2.

[0071] At 602, the method 600 includes receiving, from a database, data associated with at least one physiological signal type or physiological variable. The at least one physiological signal type can include signals from various sources of various types (e.g., waveform, values, array, etc.). The physiological variables can include heart rate, PPG, ECG, blood pressure, blood flow, and/or the like. In some implementations, the data can include additional health information such as weight, age, and/or the like associated with the data associated with at least one physiological signal type or physiological variable.

[0072] At 604, the method 600 includes training at least one machine learning model based on the data. The at least one machine learning model can, in some implementations, include a language model (e.g., natural language model, etc.). At least one machine learning model is trained to include dictionary learning on physiological signals to determine characteristics which may be embedded within the signals. In some implementations, the machine learning model can be trained to recognize the characteristics across different signals and different datasets. At least one machine learning model is trained to recognize and utilize various types of inputs. In some implementations, at least one machine learning model includes a multi-output model that can learn multiple different physiological outputs at the same time. by learning multiple outputs at the same time, the at least one machine learning model can determine characteristics of the outputs that are shared. The at least one machine learning model can be trained to generate outputs that are clinically desirable (e.g., desired by a clinic) and/or confidence scores.

[0073] At 606, the method 600 optionally includes training at least one machine learning model using auxiliary tasks. The auxiliary tasks can be tasks that are not directly related to the primary function of the at least one machine learning model, however, can still aid in generated output signals that are clinically relevant outputs and/or confidence scores. The auxiliary tasks can aid in a more accurate output of the machine learning model without increasing complexity as the auxiliary tasks may not need ground truth domain expertise to conduct. In some implementations, the auxiliary tasks can include pretraining the at least one machine learning model to predict ambulatory blood pressure (ABP) and/or pulmonary artery pressure (PAP). For example, the auxiliary tasks can include predicting ABP using ECG and PPG, classifying ECG arrhythmias, predicting ECG, PPG and/or SCG using signals such as ECG and PPG, SCG, PPG, and SCG, ECG, etc., and/or the like. In some implementations, the auxiliary tasks can include unmasking portion of signal.

[0074] At 608, the method 600 includes generating, using at least one machine learning model, an output. The output is generated as described in reference to 510 of FIG. 5. The output can be a distribution based off of an input from a sensing device. The output can include a prediction, distribution of prediction, and/or the like. At 610, the method 600 includes training the at least one machine learning model based on the output. Training the at least one machine learning model based on the output allows the at least one machine learning model to learn from previous predictions and more accurately predict future values.

[0075] At 612, the method 600 includes a decision to continue training. If it is still desirable for the at least one machine learning model to generate additional outputs, the method 600 can continue down the "YES" path to return to 602 to continue training the at least one machine learning model. If it is not desirable for the at least one machine learning model to generate additional outputs, the method 600 can continue down the "NO" path to 614. At 614, the method 600 includes terminating training of the at least one machine learning model. In some implementations, the at least one machine learning model can be used for generating outputs. In some implementations, training can restart when the at least one machine learning model generates additional models.

[0076] It should be understood that the disclosed embodiments are not intended to be exhaustive, and functional, logical, operational, organizational, structural and/or topological modifications can be made without departing from the scope of the disclosure. As such, all examples and/or embodiments are deemed to be non-limiting throughout this disclosure.

[0077] All definitions, as defined and used herein, should be understood to control over dictionary definitions, definitions in documents incorporated by reference, and/or ordinary meanings of the defined terms.

[0078] Examples of computer code include, but are not limited to, micro-code or micro-instructions, machine instructions, such as produced by a compiler, code used to produce a web service, and files containing higher-level instructions that are executed by a computer using an interpreter. For example, embodiments can be implemented using Python, Java, JavaScript, C++, and/or other programming languages and development tools. Additional examples of computer code include, but are not limited to, control signals, encrypted code, and compressed code.

[0079] The drawings primarily are for illustrative purposes and are not intended to limit the scope of the subject matter described herein. The drawings are not necessarily to scale; in some instances, various aspects of the subject matter disclosed herein can be shown exaggerated or enlarged in the drawings to facilitate an understanding of different features. In the drawings, like reference characters generally refer to like features (e.g., functionally similar and/or structurally similar elements).

[0080] The acts performed as part of a disclosed method(s) can be ordered in any suitable way. Accordingly, embodiments can be constructed in which processes or steps are executed in an order different than illustrated, which can include performing some steps or processes simultaneously, even though shown as sequential acts in illustrative embodiments. Put differently, it is to be understood that such features can not necessarily be limited to a particular order of execution, but rather, any number of threads, processes, services, servers, and/or the like that can execute serially, asynchronously, concurrently, in parallel, simultaneously, synchronously, and/or the like in a manner consistent with the disclosure. As such, some of these features can be mutually contradictory, in that they cannot be simultaneously present in a single embodiment. Similarly, some features are applicable to one aspect of the innovations, and inapplicable to others.

[0081] Where a range of values is provided, it is understood that each intervening value, to the tenth of the unit of the lower limit unless the context clearly dictates otherwise, between the upper and lower limit of that range and any other stated or intervening value in that stated range is encompassed within the disclosure. That the upper and lower limits of these smaller ranges can independently be included in the smaller ranges is also encompassed within the disclosure, subject to any specifically excluded limit in the stated range. Where the stated range includes one or both of the limits, ranges excluding either or both of those included limits are also included in the disclosure.

[0082] The phrase "and/or," as used herein in the specification and in the embodiments, should be understood to mean "either or both" of the elements so conjoined, i.e., elements that are conjunctively present in some cases and disjunctively present in other cases. Multiple elements listed with "and/or" should be construed in the same fashion, i.e., "one or more" of the elements so conjoined. Other elements can optionally be present other than the elements specifically identified by the "and/or" clause, whether related or unrelated to those elements specifically identified. Thus, as a non-limiting example, a reference to "A and/or B", when used in conjunction with open-ended language such as "comprising" can refer, in one embodiment, to A only (optionally including elements other than B); in another embodiment, to B only (optionally including elements other than A); in yet another embodiment, to both A and B (optionally including other elements); etc.

[0083] As used herein in the specification and in the embodiments, "or" should be understood to have the same meaning as "and/or" as defined above. For example, when separating items in a list, "or" or "and/or" shall be interpreted as being inclusive, i.e., the inclusion of at least one, but also including more than one of a number or list of elements, and, optionally, additional unlisted items. Only terms clearly indicated to the contrary, such as "only one of" or "exactly one of," or, when used in the embodiments, "consisting of," will refer to the inclusion of exactly one element of a number or list of elements. In general, the term "or" as used herein shall only be interpreted as indicating exclusive alternatives (i.e., "one or the other but not both") when preceded by terms of exclusivity, such as "either," "one of," "only one of," or "exactly one of." "Consisting essentially of," when used in the embodiments, shall have its ordinary meaning as used in the field of patent law.

[0084] As used herein in the specification and in the embodiments, the phrase “at least one,” in reference to a list of one or more elements, should be understood to mean at least one element selected from any one or more of the elements in the list of elements, but not necessarily including at least one of each and every element specifically listed within the list of elements and not excluding any combinations of elements in the list of elements. This definition also allows that elements can optionally be present other than the elements specifically identified within the list of elements to which the phrase “at least one” refers, whether related or unrelated to those elements specifically identified. Thus, as a non-limiting example, “at least one of A and B” (or, equivalently, “at least one of A or B,” or, equivalently “at least one of A and/or B”) can refer, in one embodiment, to at least one, optionally including more than one, A, with no B present (and optionally including elements other than B); in another embodiment, to at least one, optionally including more than one, B, with no A present (and optionally including elements other than A); in yet another embodiment, to at least one, optionally including more than one, A, and at least one, optionally including more than one, B (and optionally including other elements); etc.

[0085] In the embodiments, as well as in the specification above, all transitional phrases such as “comprising,” “including,” “carrying,” “having,” “containing,” “involving,” “holding,” “composed of,” and the like are to be understood to be open-ended, i.e., to mean including but not limited to. Only the transitional phrases “consisting of” and “consisting essentially of” shall be closed or semi-closed transitional phrases, respectively, as set forth in the United States Patent Office Manual of Patent Examining Procedures, Section 2111.03.

[0086] Some embodiments described herein relate to a computer storage product with a non-transitory computer-readable medium (also can be referred to as a non-transitory processor-readable medium) having instructions or computer code thereon for performing various computer-implemented operations. The computer-readable medium (or processor-readable medium) is non-transitory in the sense that it does not include transitory propagating signals per se (e.g., a propagating electromagnetic wave carrying information on a transmission medium such as space or a cable). The media and computer code (also can be referred to as code) can be those designed and constructed for the specific purpose or purposes. Examples of non-transitory computer-readable media include, but are not limited to, magnetic storage media such as hard disks, floppy disks, and magnetic tape; optical storage media such as Compact Disc/Digital Video Discs (CD/DVDs), Compact Disc-Read Only Memories (CD-ROMs), and holographic devices; magneto-optical storage media such as optical disks; carrier wave signal processing modules; and hardware devices that are specially configured to store and execute program code, such as Application-Specific Integrated Circuits (ASICs), Programmable Logic Devices (PLDs), Read-Only Memory (ROM) and Random-Access Memory (RAM) devices. Other embodiments described herein relate to a computer program product, which can include, for example, the instructions and/or computer code discussed herein.

[0087] Some embodiments and/or methods described herein can be performed by software (executed on hardware), hardware, or a combination thereof. Hardware modules can include, for example, a processor, a field programmable gate array (FPGA), and/or an application specific integrated circuit (ASIC). Software modules (executed on hardware) can include instructions stored in a memory that is operably coupled to a processor and can be expressed in a variety of software languages (e.g., computer code), including C, C++, Java™, Ruby, Visual Basic™, and/or other object-oriented, procedural, or other programming language and development tools. Examples of computer code include, but are not limited to, micro-code or micro-instructions, machine instructions, such as produced by a compiler, code used to produce a web service, and files containing higher-level instructions that are executed by a computer using an interpreter. For example, embodiments can be implemented using imperative programming languages (e.g., C, Fortran, etc.), functional programming languages (Haskell, Erlang, etc.), logical programming languages (e.g., Prolog), object-oriented programming languages (e.g., Java, C++, etc.) or other suitable programming languages and/or development tools. Additional examples of computer code include, but are not limited to, control signals, encrypted code, and compressed code.

CLAIMS

We claim:

1. A method, comprising:

receiving, from a sensing device, at least one signal in a first format of observable characteristics measured by sensors of the sensing device;

transforming the signal from the first format into a second format different from the first format, the second format associated with a language model;

inputting, after transforming the signal, the signal into the language model to generate an output associated with a physiological variable; and

generating, based on the output, a time-domain waveform showing values of the physiological variable over time.

2. The method of claim 1, further comprising:

inputting the signal in the second format into the language model a plurality of times to obtain a distribution of outputs; and

generating a confidence score based on a measure of a variability of the distribution of outputs.

3. The method of claim 1, wherein the signal in the first format includes a time-domain waveform of the observable characteristics.

4. The method of claim 3, wherein the signal in the second format includes text-based data indicative of the observable characteristics.

5. The method of claim 1, wherein the observable characteristics include at least one of: a seismocardiogram (SCG) waveform, a photothermography (PPG) waveform, or an electrocardiogram (ECG) waveform.

6. The method of claim 1, wherein the output includes text-based data indicative of the physiological variable, and the method further comprises:

generating the time-domain waveform by transforming the text-based data into time-domain data.

7. The method of claim 1, further comprising:

inputting the signal in the second format into the language model a plurality of times to obtain a distribution of outputs, wherein generating the time-domain waveform includes:

determining, for each time period of a plurality of time periods associated with the time-domain waveform, a value for that time period based on the distribution of outputs; and

constructing the time-domain waveform from the values determined for the plurality of time periods.

8. A method, comprising:

receiving, from a sensing device, at least one signal associated with an observable characteristic of a user, the signal being in a first format;

transforming, using a first model, the signal from the first format into a second format suitable for inputting into a second model, the second model being a language model;

generating, using the second model and the signal in the second format, a first portion of an output associated with a physiological variable;

generating, using the second model, the signal in the second format, and the first portion of the output, a second portion of the output, the output including the first and second portions being in the second format; and

transforming, using the first model, the output from the second format into the first format.

9. The method of claim 8, further comprising:

generating, using the second model, a distribution of outputs; and

determining a confidence score based on a measure of a variability of the distribution of outputs.

10. The method of claim 8, wherein the signal in the first format includes a time-domain waveform of the observable characteristics.

11. The method of claim 10, wherein the signal in the second format includes text-based data indicative of the observable characteristics.

12. The method of claim 10, wherein the output in the first format includes a time-domain waveform showing values of the physiological variable over time.

13. The method of claim 8, further comprising:

training the second model using dictionary learning on signals of observable characteristics associated with known data of the physiological parameter.

14. The method of claim 8, wherein the sensing devices is a wearable device including at least one of: a smart watch, a sleeve, a band, or a patch.

15. An apparatus, comprising:

a sensing device configured to be worn on a body of a user, the sensing device including:

a housing having a flat surface configured to face the body of the user when the sensing device is worn by the user;

a first set of one or more sensors disposed on the flat surface and configured to be in contact with skin of the user when the sensing device is worn by the user; and

a second set of one or more sensors disposed in the housing, the first and second sets of sensors configured to measure observable characteristics of the user; and

a processor and a memory operatively coupled to the sensing device, the processor configured to execute instructions stored in the memory to:

receive, from the first and second sets of sensors, at least one signal in a first format of the observable characteristics measured by the first and second sets of sensors;

transform the signal from the first format into a second format different from the first format, the second format associated with a language model;

input, after transforming the signal, the signal into the language model to generate an output associated with a physiological variable; and

generate, based on the output, a time-domain waveform showing values of the physiological variable over time.

16. The apparatus of claim 15, wherein the processor is further configured to execute instructions stored in the memory to:

input the signal in the second format into the language model a plurality of times to obtain a distribution of outputs; and

generate a confidence score based on a measure of a variability of the distribution of outputs.

17. The apparatus of claim 15, wherein the signal in the first format includes a time-domain waveform of the observable characteristics.

18. The apparatus of claim 17, wherein the signal in the second format includes text-based data indicative of the observable characteristics.

19. The apparatus of claim 15, wherein the observable characteristics include at least one of: a seismocardiogram (SCG) waveform, a photothermography (PPG) waveform, or an electrocardiogram (ECG) waveform.

20. The apparatus of claim 15, wherein the output includes text-based data indicative of the physiological variable, and the processor is configured to generate the time-domain waveform by transforming the text-based data into time-domain data.

21. The apparatus of claim 15, wherein the processor is further configured to execute instructions stored in the memory to:

input the signal in the second format into the language model a plurality of times to obtain a distribution of outputs,

the processor configured to generate the time-domain waveform by:

determining, for each time period of a plurality of time periods associated with the time-domain waveform, a value for that time period based on the distribution of outputs; and

constructing the time-domain waveform from the values determined for the plurality of time periods.

22. The apparatus of claim 15, wherein the processor is configured to transform the signal from the first format into the second format using an encoder of an encoder-decoder model, and

the processor is configured to generate the time-domain waveform by using a decoder of the encoder-decoder model.

23. A method, comprising:

receiving, from at least one of a sensing device or a database, at least one signal associated with an observable physiological characteristic of a patient;

transforming the at least one signal to an input format associated with a language model;

generating, using the language model, an output associated with a physiological variable; and

generating an output waveform for the physiological variable based on the output.

24. The method of claim 23, wherein the language model is trained based on dictionary learning on physiological signals.

25. The method of claim 23, wherein the language model is a natural language model.

26. The method of claim 23, wherein the input format includes at least one of a text-based format or a string format.

27. The method of claim 23, furthering comprising:

sending, to a display of an external device, an output including a representation of the waveform.

28. The method of claim 23, wherein generating the output includes generating a distribution of outputs, and the method further comprising:

generating a confidence score based on at least one of the distribution of outputs, output variability, and a standard deviation associated with the output.

29. The method of claim 28, further comprising:

sending, to a display of an external device, the confidence score.

30. The method of claim 23, wherein the sensing device is a wearable device configured to measure at least one of: a seismocardiogram (SCG) signal, a photothermography (PPG) signal, or an electrocardiogram (ECG) signal.

31. The method of claim 30, wherein the wearable device is at least one of a smart watch, a sleeve, a band, or a patch.

32. An apparatus, comprising:

a sensing device configured to measure an observable physiological characteristic of a patient;

a display;

a memory; and

a processor operatively coupled to the sensing device and the display, the processor configured to execute instructions stored in the memory to:

receive, from the sensing device, at least one signal indicative of the observable physiological characteristic of the patient;

transform the at least one signal to an input format associated with a language model;

generate, using the language model, an output associated with a physiological variable;

generate an output waveform for the physiological variable based on the output; and

present, via the display, the output waveform.

33. The apparatus of claim 32, wherein the processor is configured to generate the output by generating a distribution of outputs, and the processor further configured to:

generate a confidence score based on at least one of the distribution of outputs, output variability, and a standard deviation associated with the output; and

present, via the display, the confidence score.

34. The apparatus of claim 32, wherein the sensing device is a wearable device configured to measure at least one of: a seismocardiogram (SCG) signal, a photothermography (PPG) signal, or an electrocardiogram (ECG) signal.

35. The apparatus of claim 32, wherein transforming the at least one signal includes transforming the at least one signal from a first format to the input format, wherein the first format is a time-domain signal.

36. The apparatus of claim 32, wherein the input signal is at least one of a text-based signal or a frequency-domain signal.

37. The apparatus of claim 32, wherein transforming includes using an encoder/decoder architecture.

38. The apparatus of claim 32, wherein the language model is a convolutional neural network.

39. The apparatus of claim 32, wherein the input format includes at least one of a text-based format or a string format.

40. A method, comprising:

receiving, from at least one of a sensing device or a database, at least one signal associated with an observable physiological characteristic of a patient;

encoding the at least one signal into a format associated with a language model;

generating, using the language model, an output associated with a physiological variable;

decoding the output from the format associated with the language model into a waveform format; and

generating an output waveform for the physiological variable based on the output.

41. The method of claim 40, wherein the at least one signal includes a plurality of signals and the output is associated with underlying characteristics shared by the plurality of signals.

42. The method of claim 41, wherein the language model is trained based on a plurality of types of signals.

43. The method of claim 40, wherein the language model is a convolutional neural network.

44. The method of claim 40, wherein the language model is trained to identify and extract features associated with the physiological variable.

45. The method of claim 40, wherein the language model using self-attention to generate the output.

46. The method of claim 40, wherein self-attention includes using generated portions of the output to generate subsequent portions of the output.

47 The method of claim 40, wherein the language model is trained on auxiliary tasks.

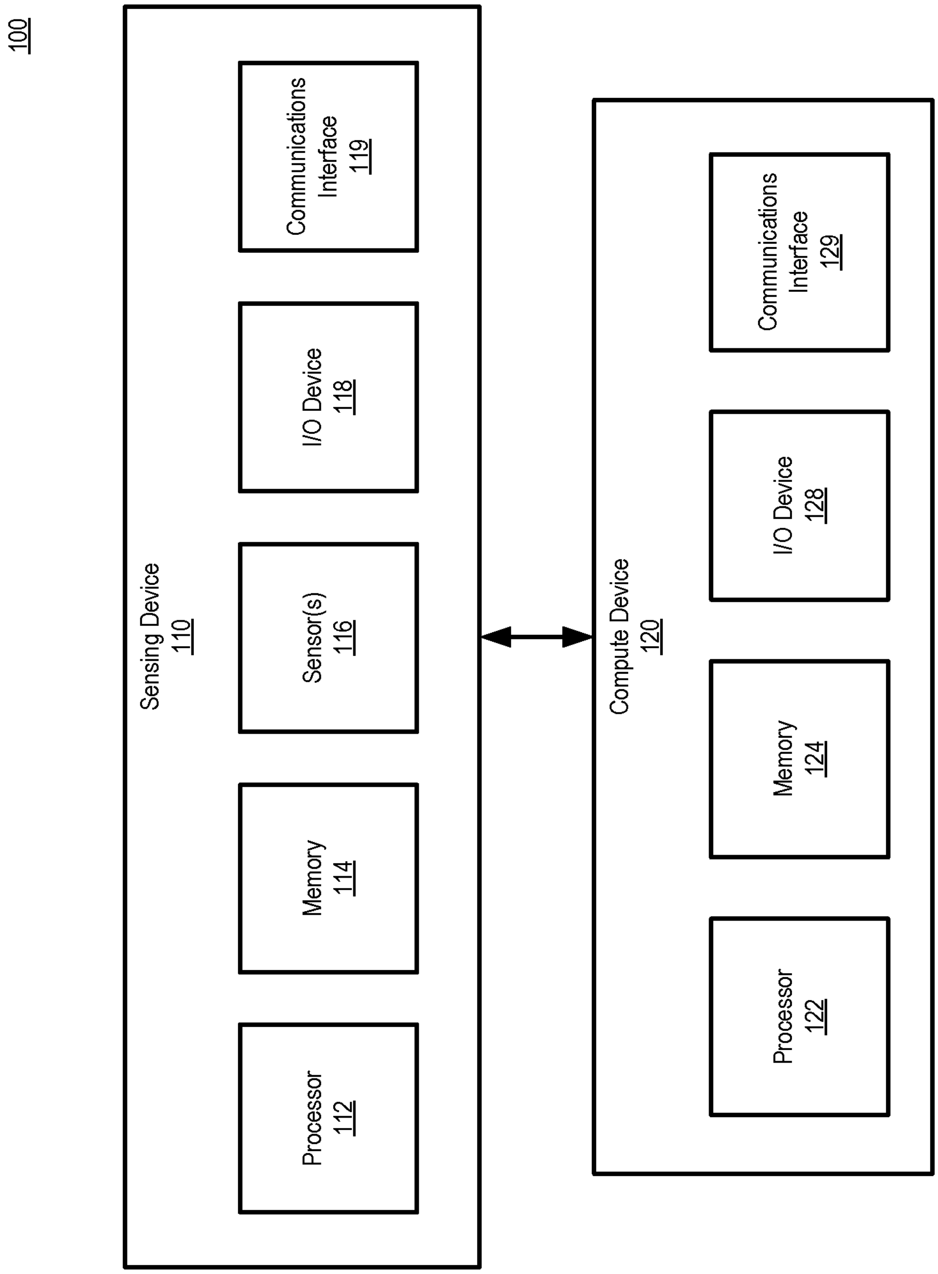
100
Sensing Device
110
Processor
112
Memory
114
Sensor(s)
116
I/O Device
118
Communications
Interface
119
Compute Device
120
Processor
122
Memory
124
I/O Device
128
Communications
Interface
129

FIG. 1A

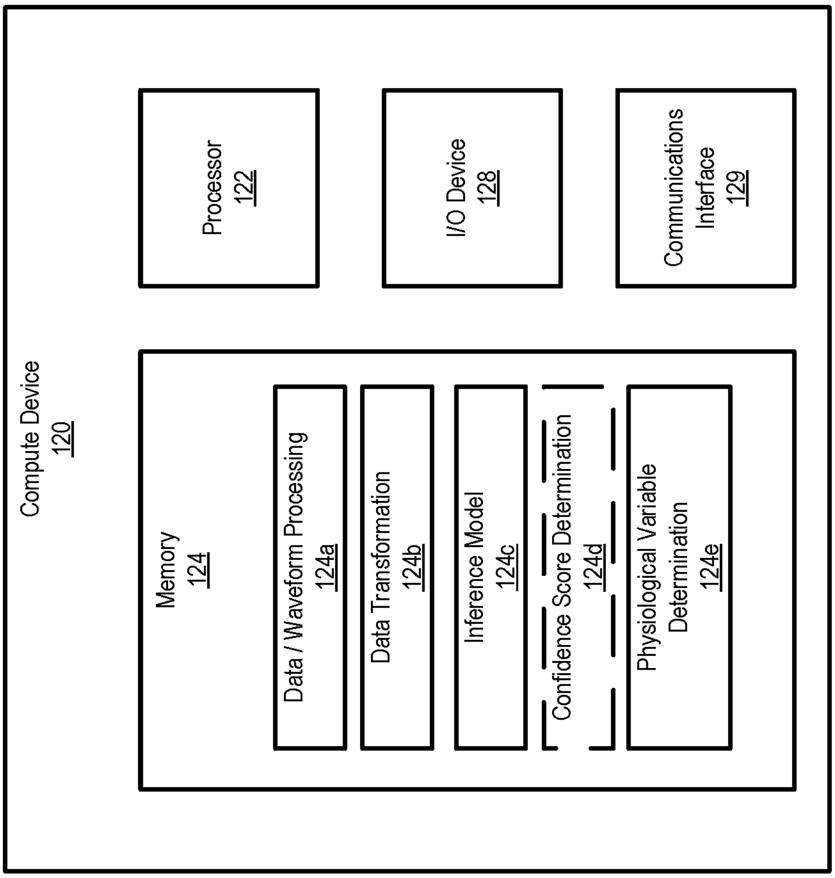
Compute Device
120
Processor
122
I/O Device
128
Communications
Interface
129
Memory
124
Data / Waveform Processing
124a
Data Transformation
124b
Inference Model
124c
Confidence Score Determination
124d
Physiological Variable
Determination
124e

FIG. 1B

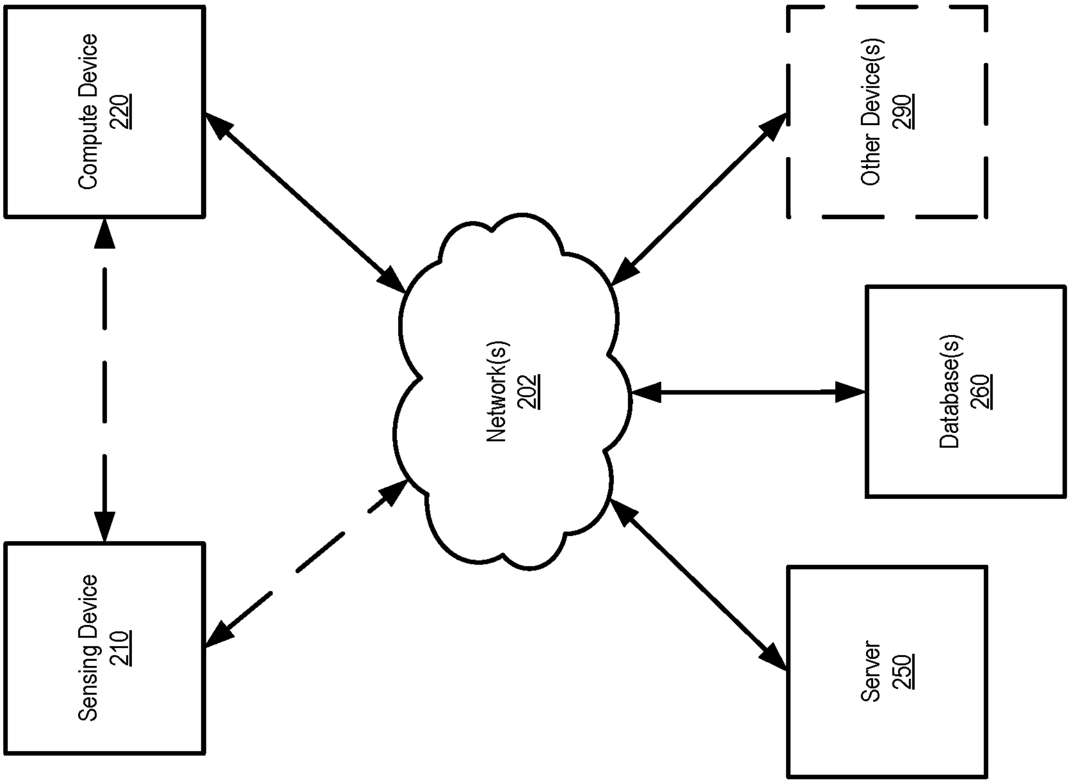
Compute Device
220
Other Device(s)
290
Network(s)
202
Database(s)
260
Sensing Device
210
Server
250

FIG. 2

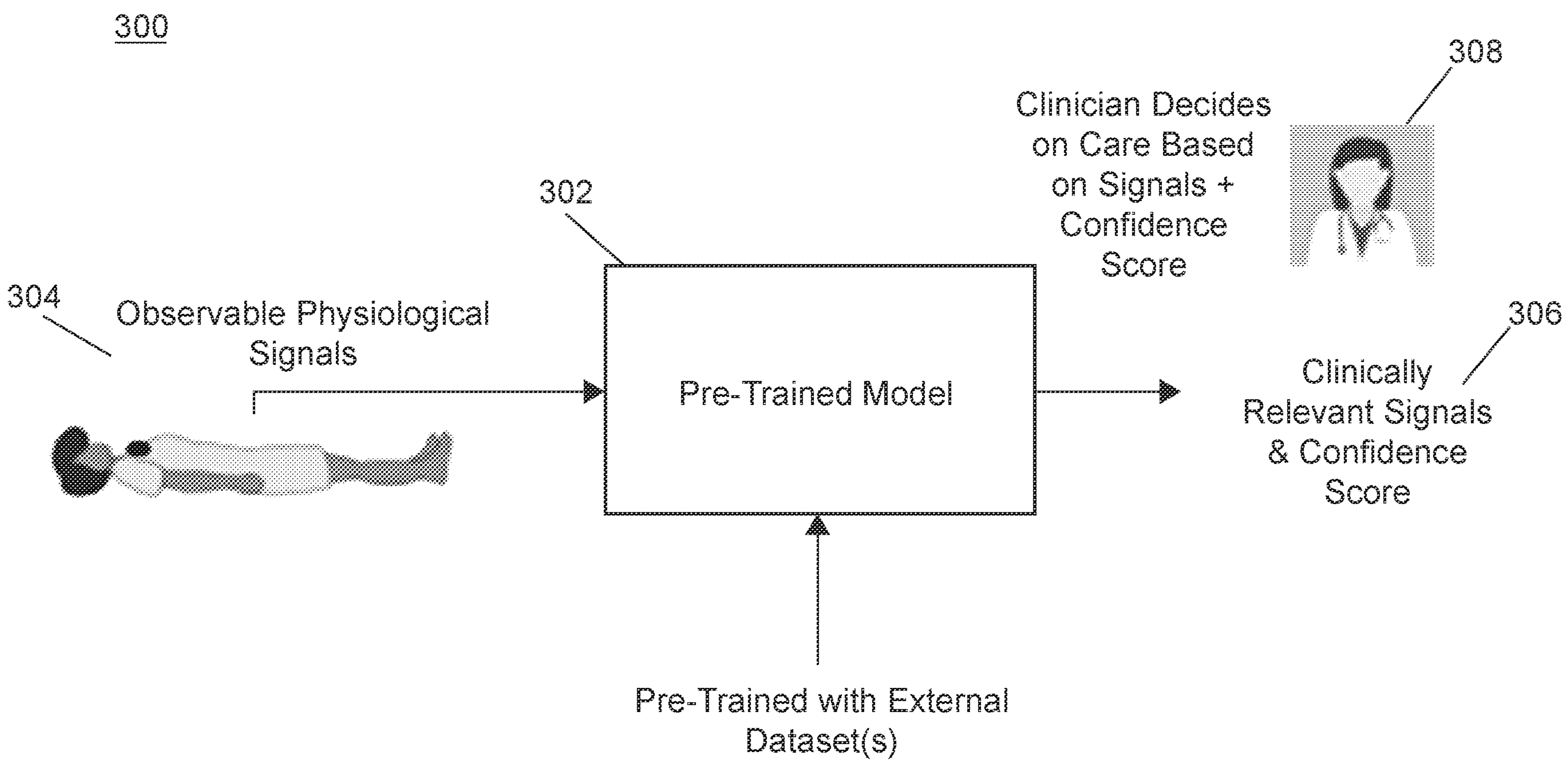
300
304
Observable Physiological Signals
302
Pre-Trained Model
Pre-Trained with External Dataset(s)
Clinician Decides on Care Based on Signals + Confidence Score
308
306
Clinically Relevant Signals & Confidence Score

FIG. 3

400

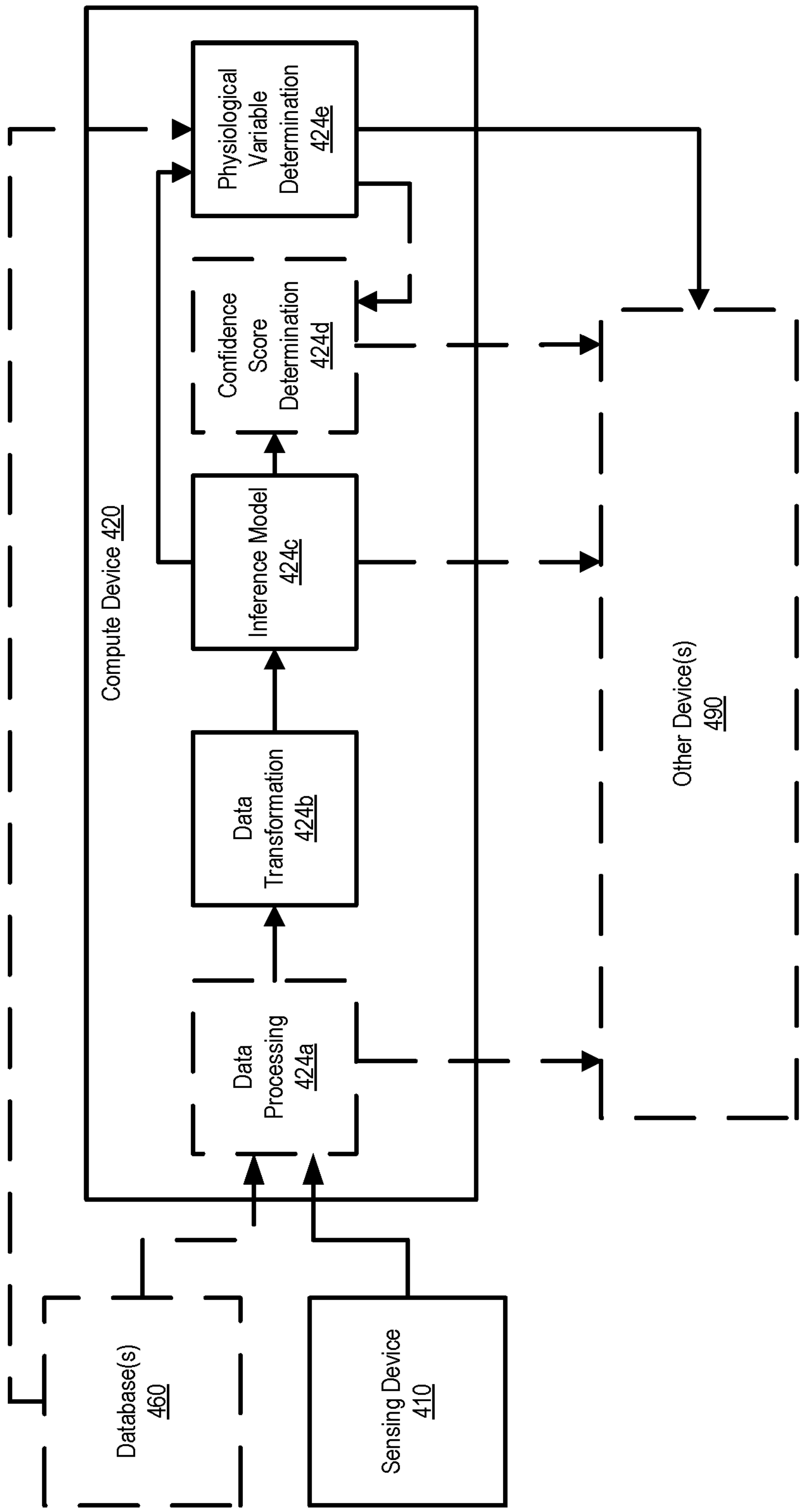
Compute Device 420
Data Processing 424a
Data Transformation 424b
Inference Model 424c
Confidence Score Determination 424d
Physiological Variable Determination 424e
Database(s) 460
Sensing Device 410
Other Device(s) 490

FIG. 4

500

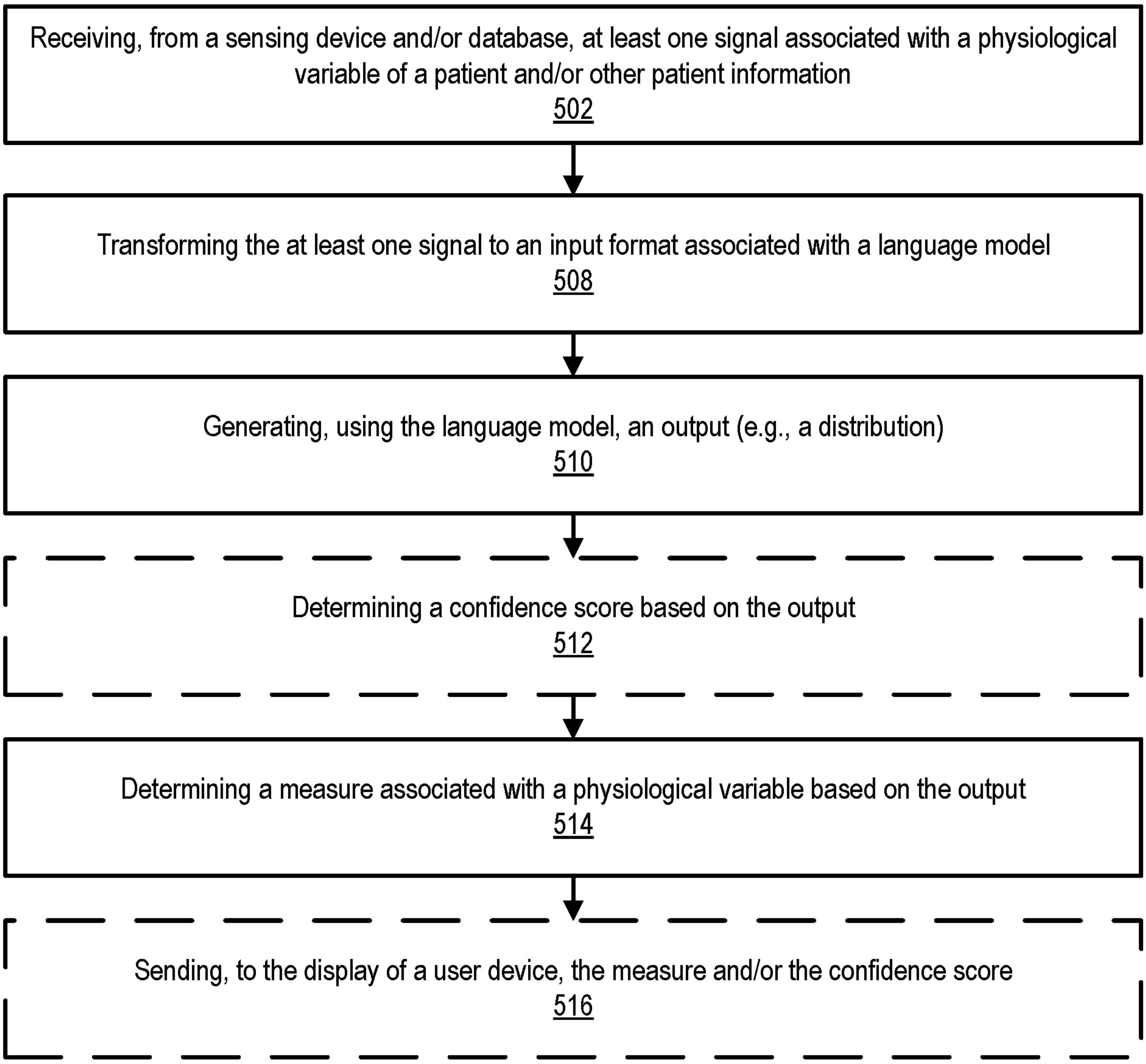
Receiving, from a sensing device and/or database, at least one signal associated with a physiological variable of a patient and/or other patient information
502
Transforming the at least one signal to an input format associated with a language model
508
Generating, using the language model, an output (e.g., a distribution)
510
Determining a confidence score based on the output
512
Determining a measure associated with a physiological variable based on the output
514
Sending, to the display of a user device, the measure and/or the confidence score
516

FIG. 5

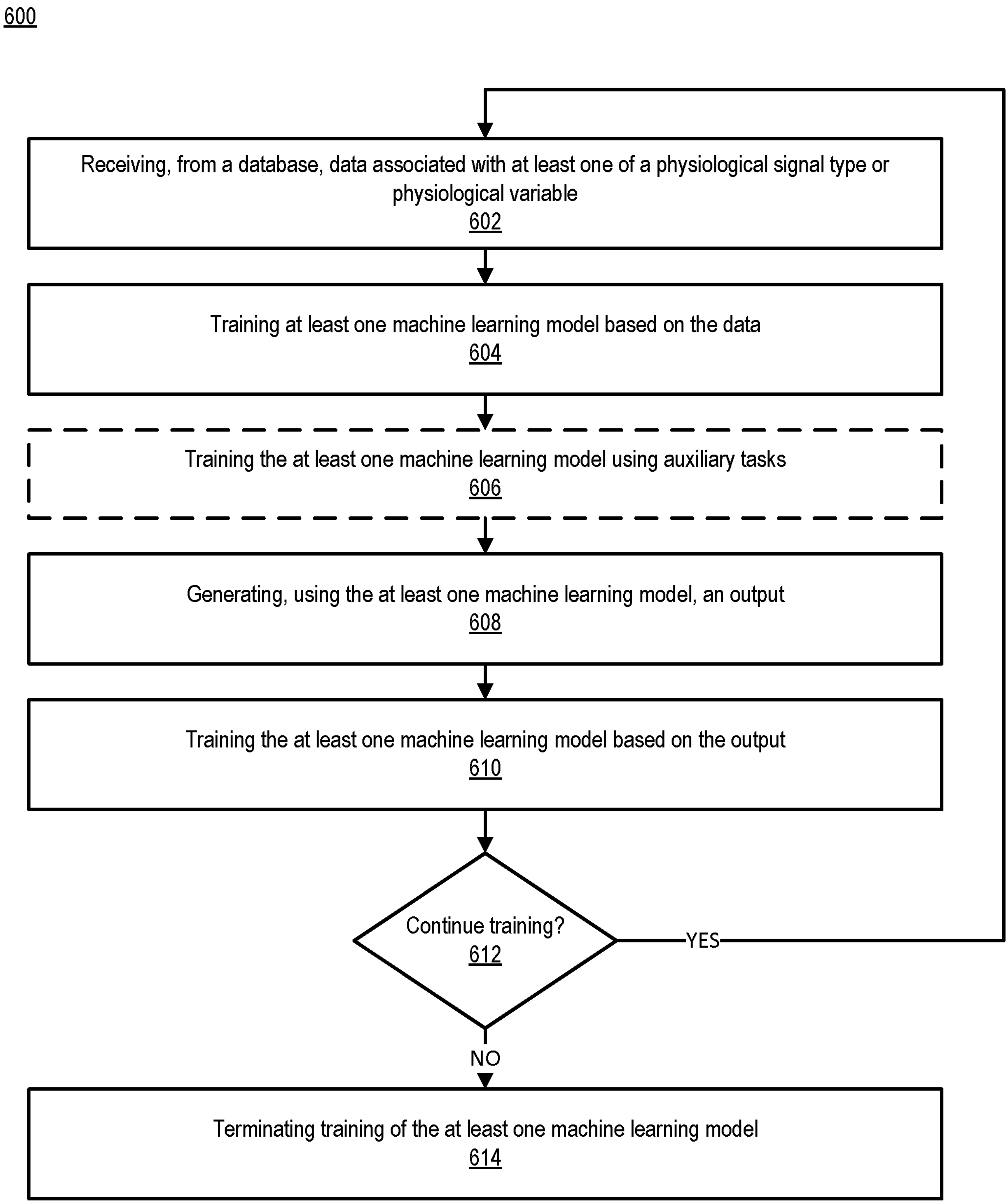
600
Receiving, from a database, data associated with at least one of a physiological signal type or physiological variable
602
Training at least one machine learning model based on the data
604
Training the at least one machine learning model using auxiliary tasks
606
Generating, using the at least one machine learning model, an output
608
Training the at least one machine learning model based on the output
610
Continue training?
612
YES
NO
Terminating training of the at least one machine learning model
614

FIG. 6

INTERNATIONAL SEARCH REPORT

International application No
PCT/US2024/061541

A. CLASSIFICATION OF SUBJECT MATTER
INV. A61B5/024 A61B5/318 A61B5/00 G06F40/20
ADD.

According to International Patent Classification (IPC) or to both national classification and IPC

B. FIELDS SEARCHED

Minimum documentation searched (classification system followed by classification symbols)
A61B

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

Electronic data base consulted during the international search (name of data base and, where practicable, search terms used)

EPO-Internal

C. DOCUMENTS CONSIDERED TO BE RELEVANT

Category*	Citation of document, with indication, where appropriate, of the relevant passages	Relevant to claim No.
X	SEOKMIN CHOI ET AL: "ECGBERT: Understanding Hidden Language of ECGs with Self-Supervised Representation Learning", ARXIV.ORG, CORNELL UNIVERSITY LIBRARY, 201 OLIN LIBRARY CORNELL UNIVERSITY ITHACA, NY 14853, 10 June 2023 (2023-06-10), XP091535179,	1-7, 15-47
A	page 4 - page 5 page 8 figure 2 abstract -----	8-14

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[x] Further documents are listed in the continuation of Box C. [x] See patent family annex.

* Special categories of cited documents :

"A" document defining the general state of the art which is not considered to be of particular relevance

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"L" document which may throw doubts on priority claim(s) or which is cited to establish the publication date of another citation or other special reason (as specified)

"O" document referring to an oral disclosure, use, exhibition or other means

"P" document published prior to the international filing date but later than the priority date claimed

"T" later document published after the international filing date or priority date and not in conflict with the application but cited to understand the principle or theory underlying the invention

"X" document of particular relevance;; the claimed invention cannot be considered novel or cannot be considered to involve an inventive step when the document is taken alone

"Y" document of particular relevance;; the claimed invention cannot be considered to involve an inventive step when the document is combined with one or more other such documents, such combination being obvious to a person skilled in the art

"&" document member of the same patent family

Date of the actual completion of the international search	Date of mailing of the international search report
3 April 2025	17/04/2025

Name and mailing address of the ISA/
European Patent Office, P.B. 5818 Patentlaan 2
NL - 2280 HV Rijswijk
Tel. (+31-70) 340-2040,
Fax: (+31-70) 340-3016

Authorized officer

Costa Angeli, M

C(Continuation). DOCUMENTS CONSIDERED TO BE RELEVANT

Category*	Citation of document, with indication, where appropriate, of the relevant passages	Relevant to claim No.
A	KATADA SHUN ET AL: "Transformer-Based Physiological Feature Learning for Multimodal Analysis of Self-Reported Sentiment", PROCEEDINGS OF THE 34TH ACM SYMPOSIUM ON PARALLELISM IN ALGORITHMS AND ARCHITECTURES, ACMPUB27, NEW YORK, NY, USA, 7 November 2022 (2022-11-07), pages 349-358, XP059270703, DOI: 10.1145/3536221.3556576 ISBN: 978-1-4503-9408-6 page 5 figure 4 -----	1-47
X	Liu Chunyu ET AL: "BioSignal Copilot: Leveraging the power of LLMs in drafting reports for biomedical signals", medRxiv, 6 July 2023 (2023-07-06), XP093215724, DOI: 10.1101/2023.06.28.23291916 Retrieved from the Internet: URL:https://www.medrxiv.org/content/10.1101/2023.06.28.23291916v1.full.pdf [retrieved on 2025-03-10] page 3 page 5 - page 6 figures 2, 4 -----	1-47
A	US 2023/008809 A1 (FORGER DANIEL [US] ET AL) 12 January 2023 (2023-01-12) figure 1A -----	1-47
A	Singhal Vanika ET AL: "<mark>How to Train Your Deep Neural Network with Dictionary Learning</mark>", arXiv.org, 22 December 2016 (2016-12-22), XP093258425, Retrieved from the Internet: URL:https://arxiv.org/pdf/1612.07454 [retrieved on 2025-03-10] abstract -----	1-47

INTERNATIONAL SEARCH REPORT

Information on patent family members

International application No
PCT/US2024/061541

Patent document cited in search report	Publication date	Patent family member(s)	Publication date
US 2023008809 A1	12-01-2023	NONE	