US 20240013802A1

(19) United States
(12) Patent Application Publication (10) Pub. No.: US 2024/0013802 A1
Federov et al. (43) Pub. Date: Jan. 11, 2024

(54) INFERRING EMOTION FROM SPEECH IN AUDIO DATA USING DEEP LEARNING

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(21) Appl. No.: **17/859,660**

(22) Filed: **Jul. 7, 2022**

Publication Classification

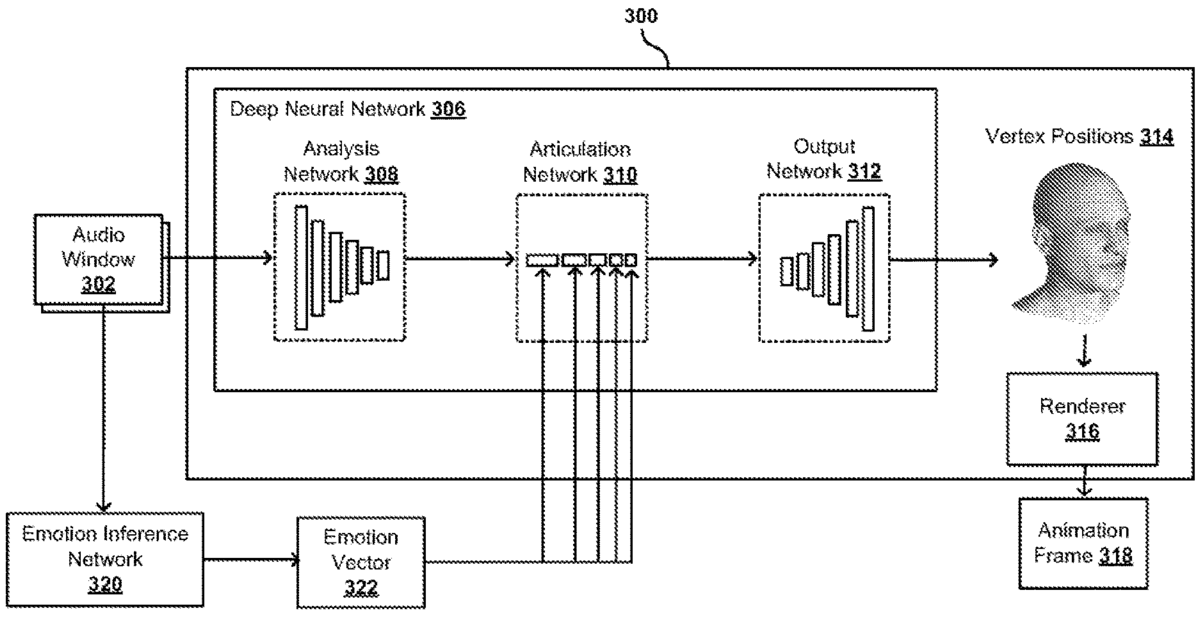
(51) **Int. Cl.**

G10L 25/63	(2006.01)
G10L 25/30	(2006.01)

(52) **U.S. Cl.**
CPC *G10L 25/63* (2013.01); *G10L 25/30* (2013.01)

(57) **ABSTRACT**

A deep neural network can be trained to infer emotion data from input audio. The network can be a transformer-based network that can infer probability values for a set of emotions or emotion classes. The emotion probability values can be modified using one or more heuristics, such as to provide for smoothing of emotion determinations over time, or via a user interface, where a user can modify emotion determinations as appropriate. A user may also provide prior emotion values to be blended with these emotion determination values. Determined emotion values can be provided as input to an emotion-based operation, such as to provide audio-driven speech animation.



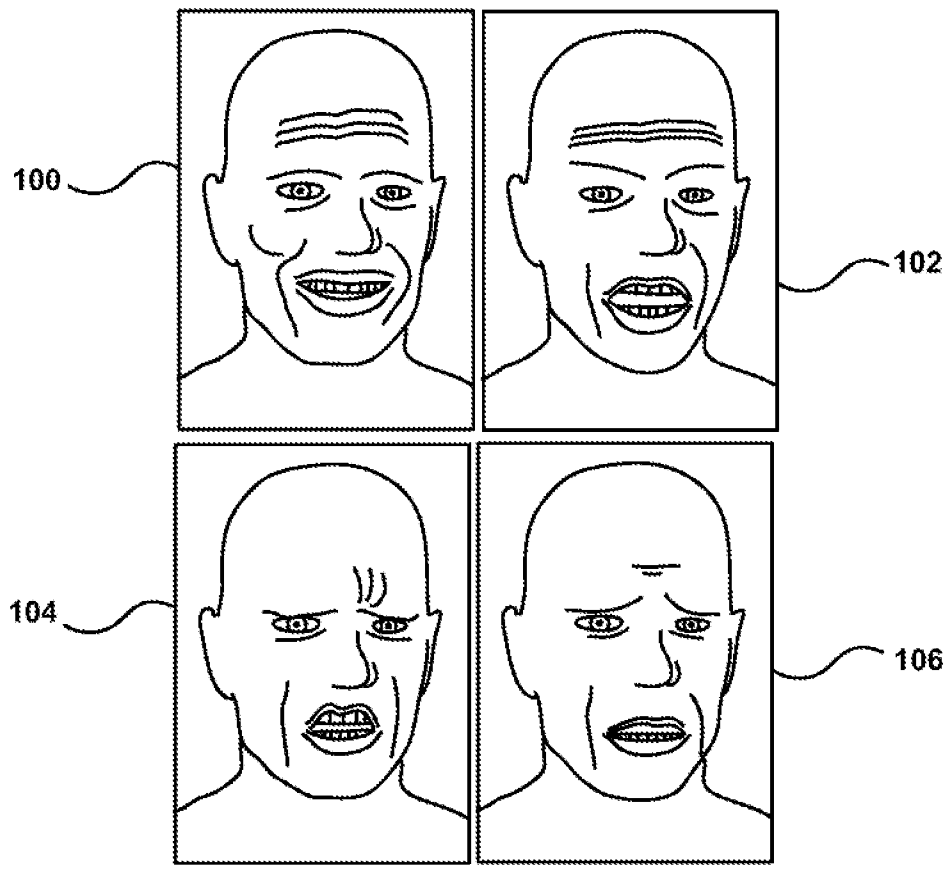


FIG. 1

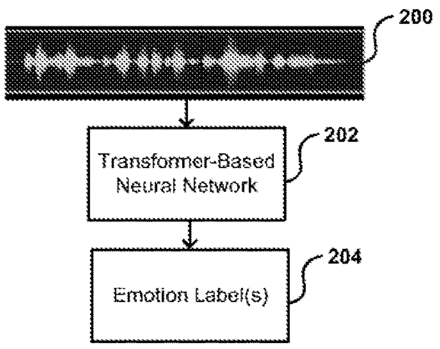

200
Transformer-Based Neural Network
202
Emotion Label(s)
204

FIG. 2A

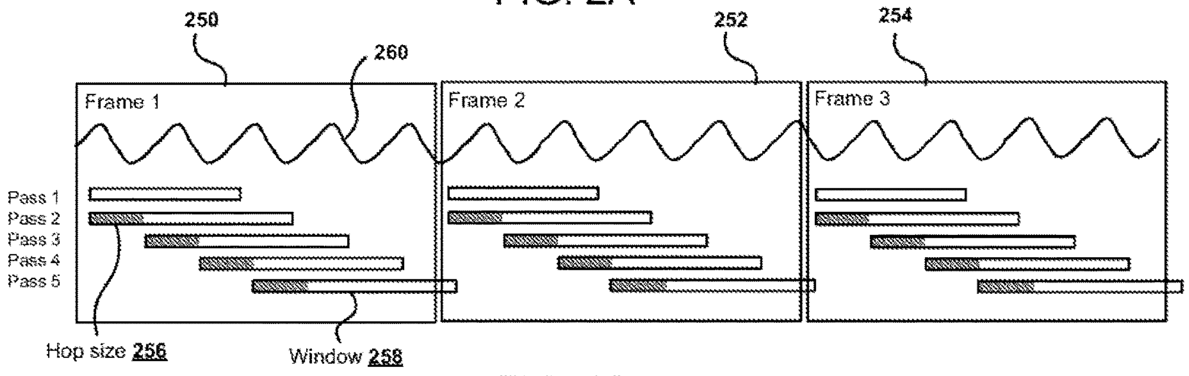

250
260
252
254
Frame 1
Frame 2
Frame 3
Pass 1
Pass 2
Pass 3
Pass 4
Pass 5
Hop size 256
Window 258

FIG. 2B

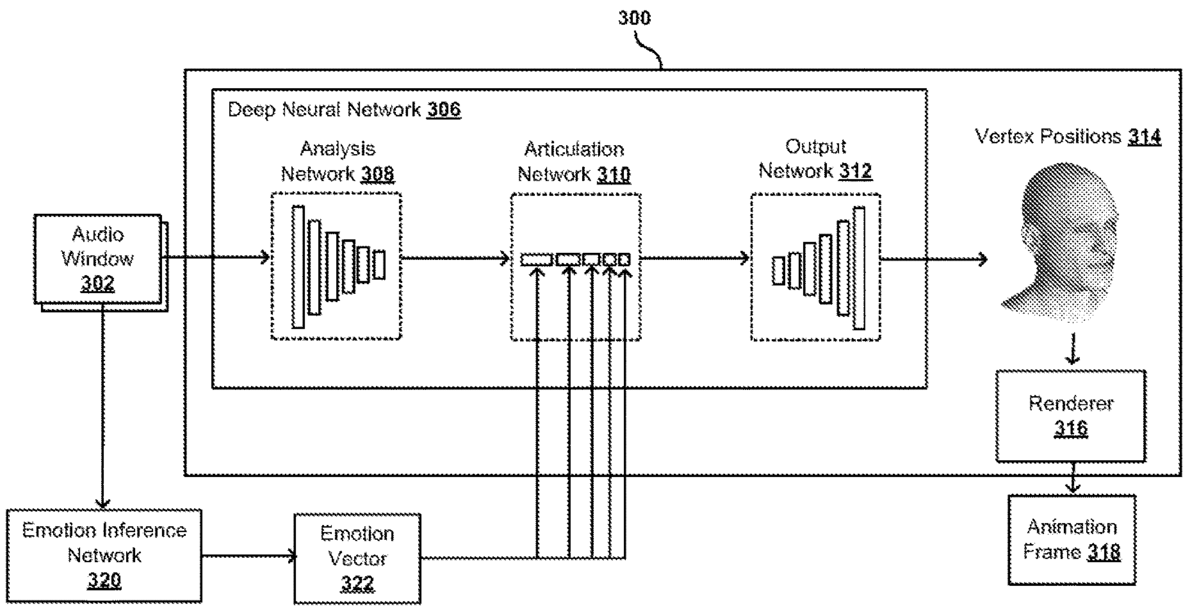
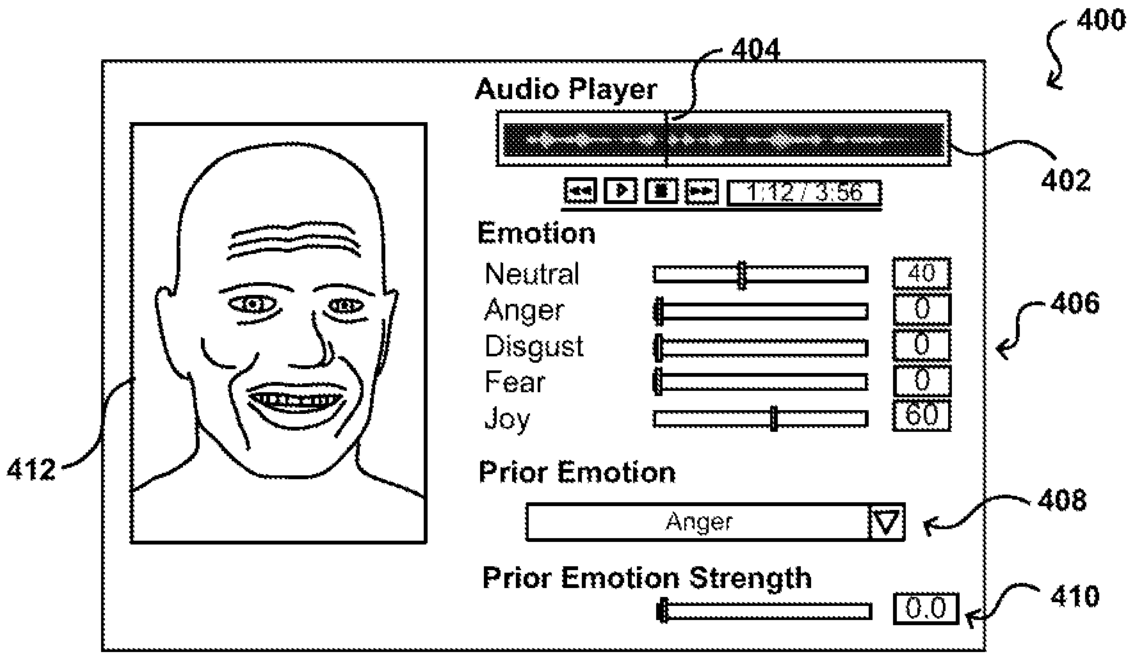

300
Deep Neural Network 306
Analysis Network 308
Articulation Network 310
Output Network 312
Vertex Positions 314
Audio Window 302
Renderer 316
Animation Frame 318
Emotion Inference Network 320
Emotion Vector 322

FIG. 3



Audio Player

1:12 / 3:56

Emotion

Neutral	40
Anger	0
Disgust	0
Fear	0
Joy	60

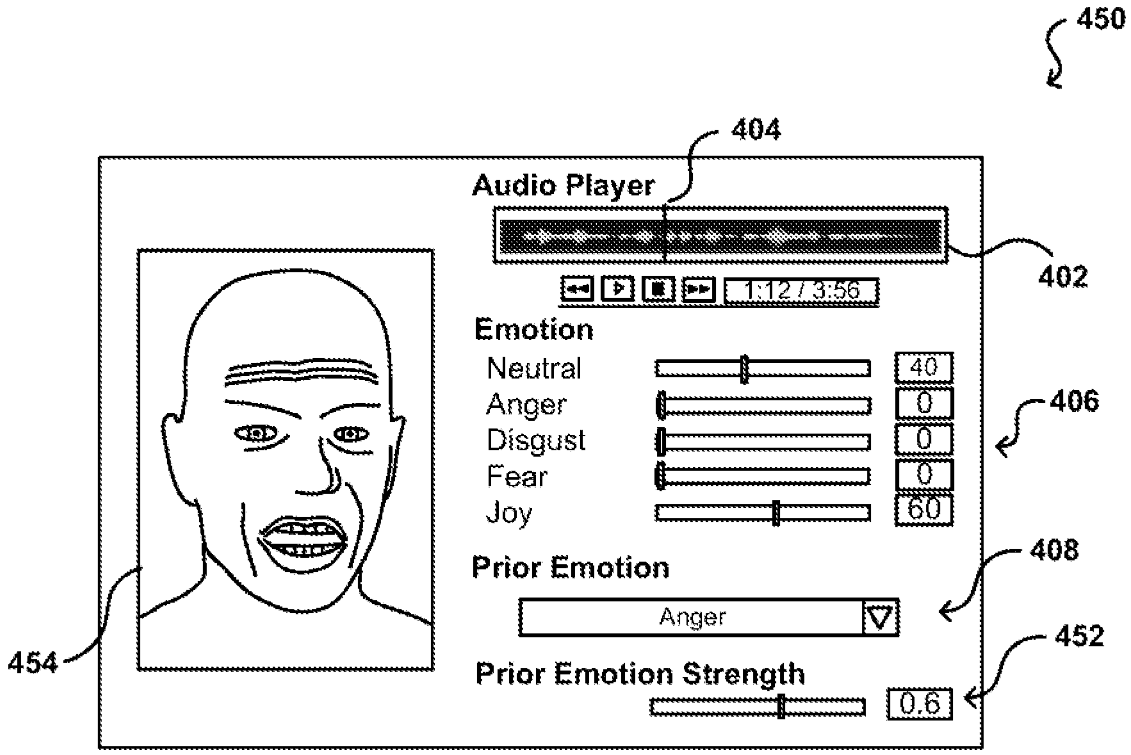
Prior Emotion

Anger

Prior Emotion Strength

0.0

FIG. 4A



Audio Player

1:12 / 3:56

Emotion

Neutral	40
Anger	0
Disgust	0
Fear	0
Joy	60

Prior Emotion

Anger

Prior Emotion Strength

0.6

FIG. 4B

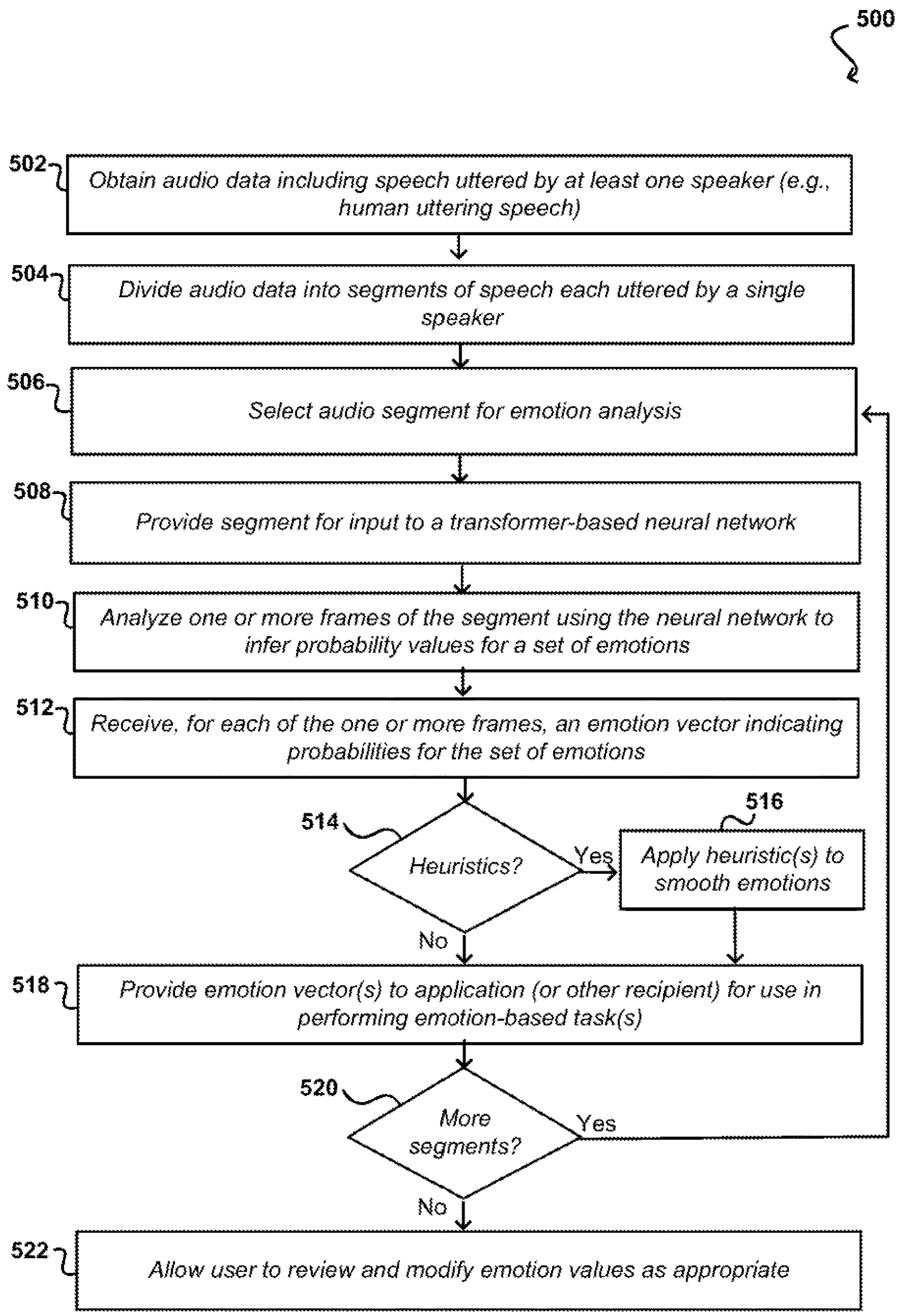

500
502
Obtain audio data including speech uttered by at least one speaker (e.g., human uttering speech)
504
Divide audio data into segments of speech each uttered by a single speaker
506
Select audio segment for emotion analysis
508
Provide segment for input to a transformer-based neural network
510
Analyze one or more frames of the segment using the neural network to infer probability values for a set of emotions
512
Receive, for each of the one or more frames, an emotion vector indicating probabilities for the set of emotions
514
Heuristics?
Yes
516
Apply heuristic(s) to smooth emotions
No
518
Provide emotion vector(s) to application (or other recipient) for use in performing emotion-based task(s)
520
More segments?
Yes
No
522
Allow user to review and modify emotion values as appropriate

FIG. 5

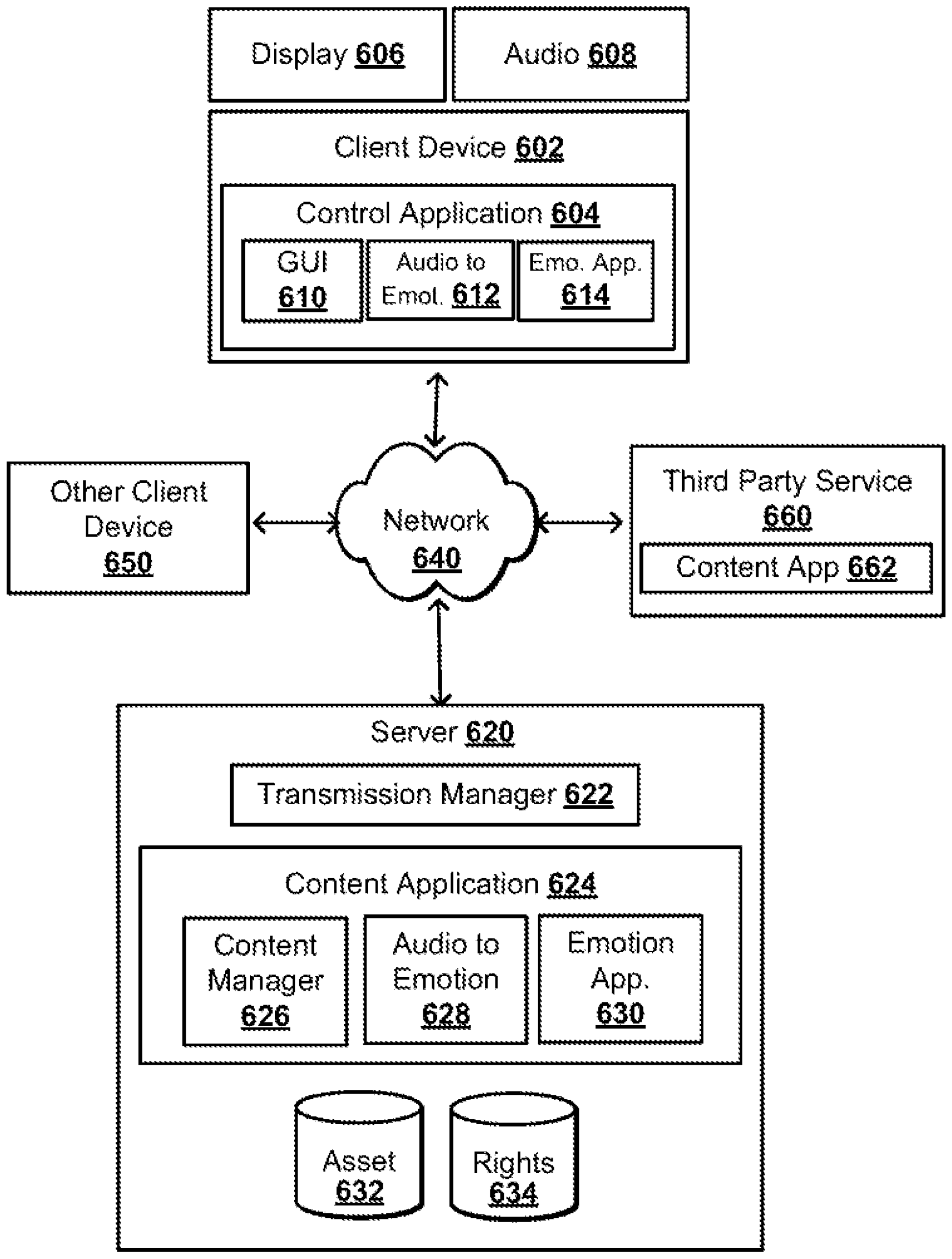

Display 606
Audio 608
Client Device 602
Control Application 604
GUI 610
Audio to Emot. 612
Emo. App. 614
Other Client Device 650
Network 640
Third Party Service 660
Content App 662
Server 620
Transmission Manager 622
Content Application 624
Content Manager 626
Audio to Emotion 628
Emotion App. 630
Asset 632
Rights 634

FIG. 6

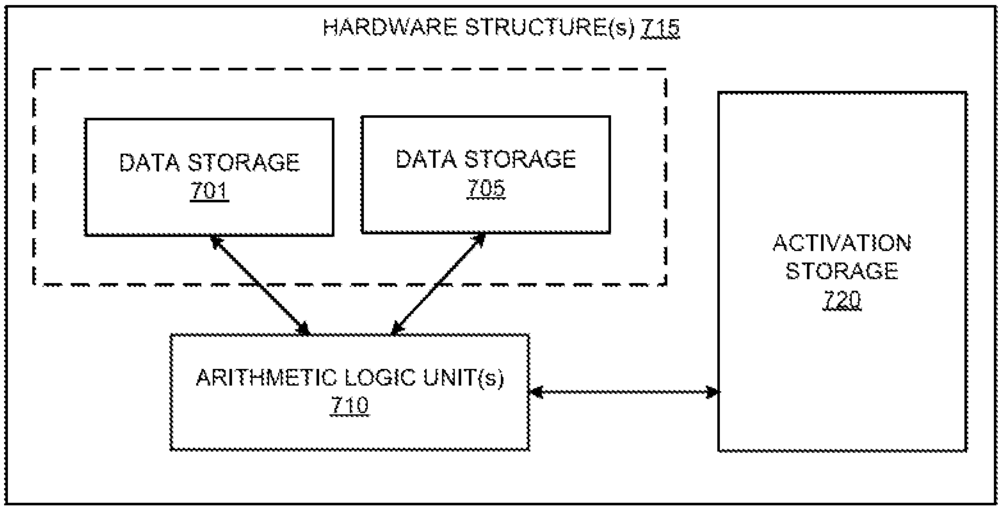

HARDWARE STRUCTURE(s) 715
DATA STORAGE 701
DATA STORAGE 705
ACTIVATION STORAGE 720
ARITHMETIC LOGIC UNIT(s) 710

FIG. 7A

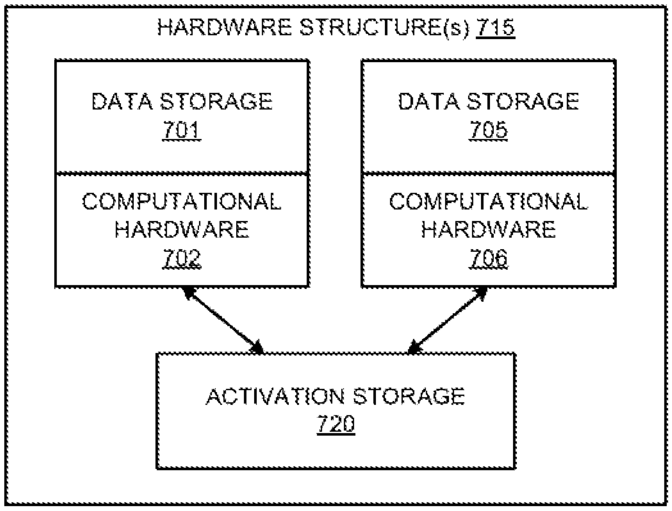

HARDWARE STRUCTURE(s) 715
DATA STORAGE 701
COMPUTATIONAL HARDWARE 702
DATA STORAGE 705
COMPUTATIONAL HARDWARE 706
ACTIVATION STORAGE 720

FIG. 7B

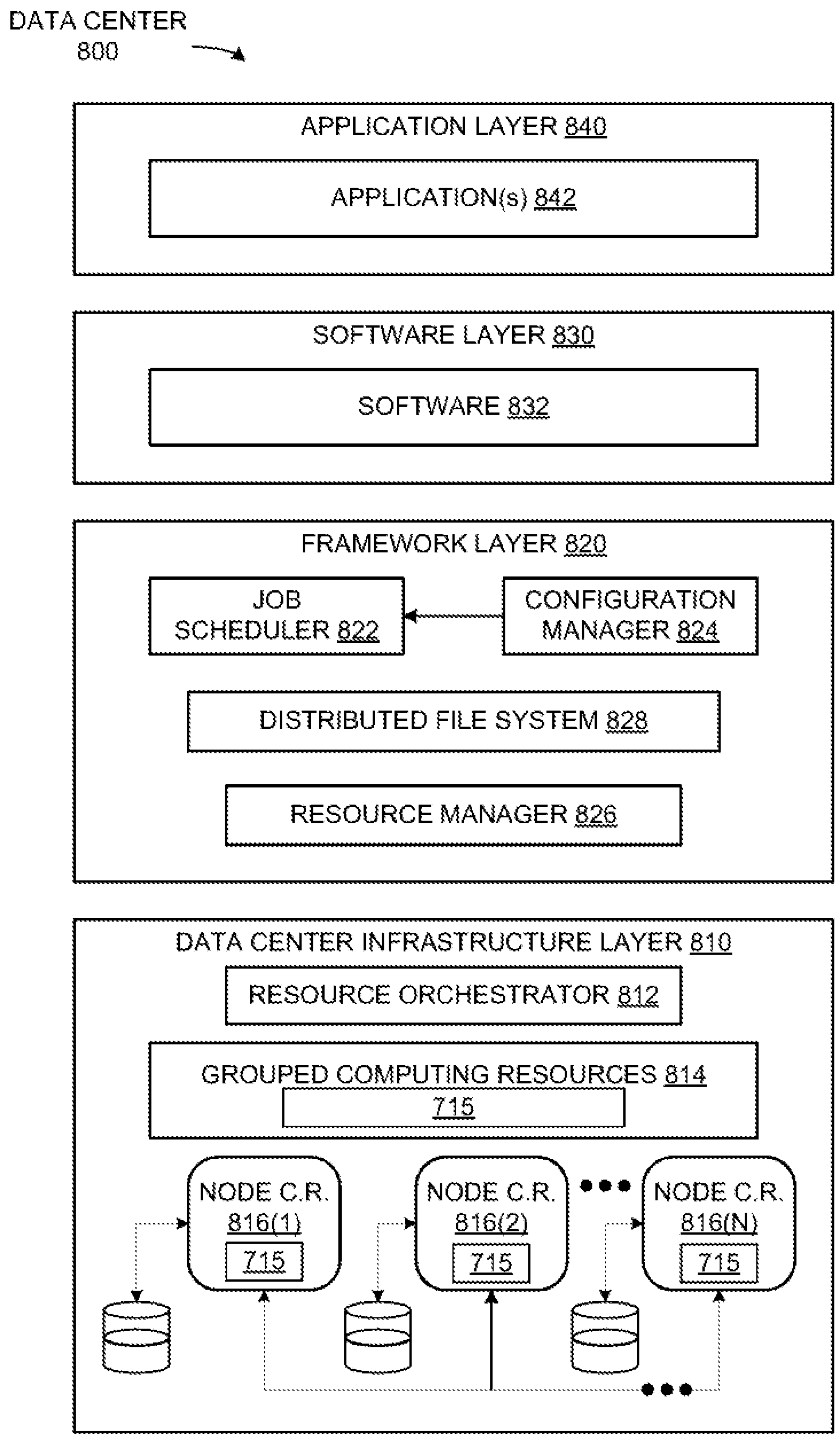

DATA CENTER
800
APPLICATION LAYER 840
APPLICATION(s) 842
SOFTWARE LAYER 830
SOFTWARE 832
FRAMEWORK LAYER 820
JOB SCHEDULER 822
CONFIGURATION MANAGER 824
DISTRIBUTED FILE SYSTEM 828
RESOURCE MANAGER 826
DATA CENTER INFRASTRUCTURE LAYER 810
RESOURCE ORCHESTRATOR 812
GROUPED COMPUTING RESOURCES 814
715
NODE C.R. 816(1)
715
NODE C.R. 816(2)
715
NODE C.R. 816(N)
715

FIG. 8

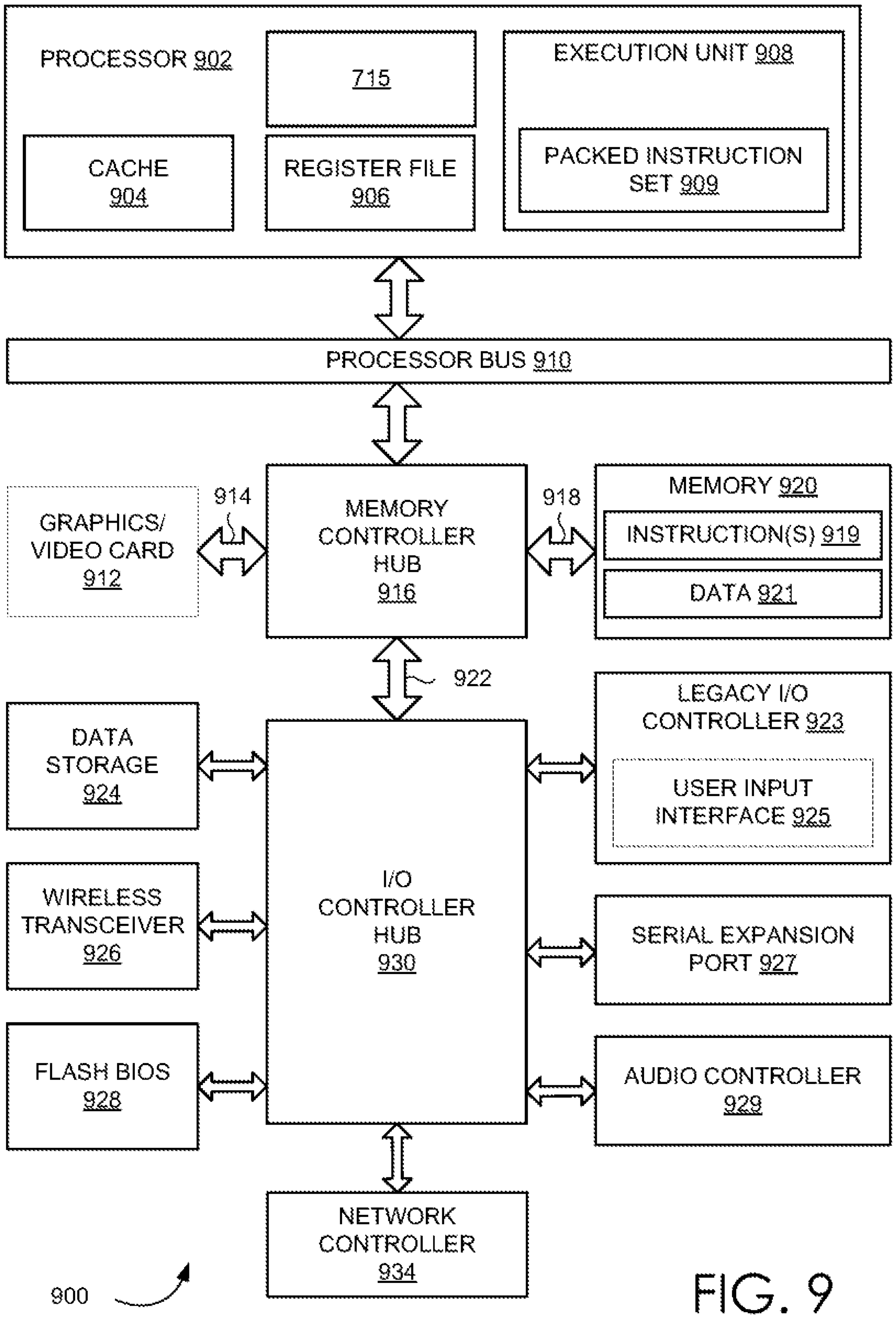

PROCESSOR 902
715
EXECUTION UNIT 908
CACHE 904
REGISTER FILE 906
PACKED INSTRUCTION SET 909
PROCESSOR BUS 910
GRAPHICS/ VIDEO CARD 912
914
MEMORY CONTROLLER HUB 916
918
MEMORY 920
INSTRUCTION(S) 919
DATA 921
922
DATA STORAGE 924
LEGACY I/O CONTROLLER 923
USER INPUT INTERFACE 925
WIRELESS TRANSCEIVER 926
I/O CONTROLLER HUB 930
SERIAL EXPANSION PORT 927
FLASH BIOS 928
AUDIO CONTROLLER 929
NETWORK CONTROLLER 934
900

FIG. 9

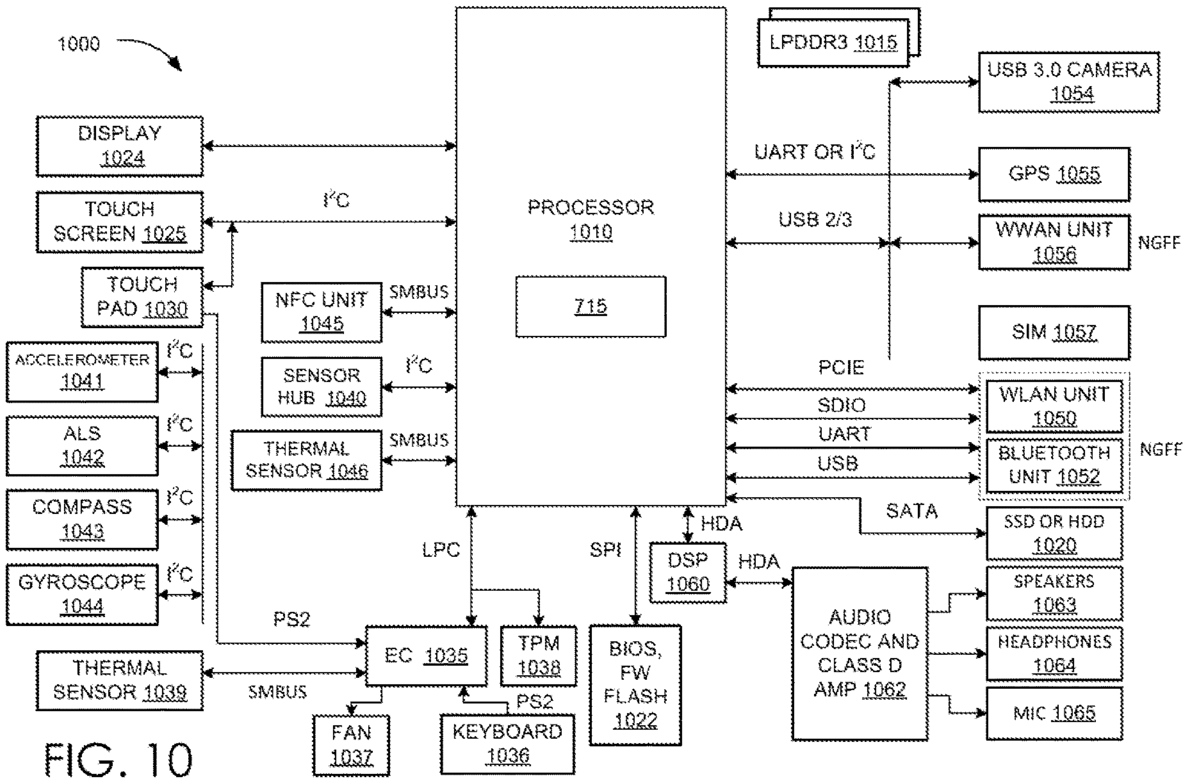

1000
PROCESSOR 1010
715
LPDDR3 1015
DISPLAY 1024
TOUCH SCREEN 1025
I²C
TOUCH PAD 1030
ACCELEROMETER 1041
ALS 1042
COMPASS 1043
GYROSCOPE 1044
I²C
NFC UNIT 1045
SMBUS
SENSOR HUB 1040
THERMAL SENSOR 1046
THERMAL SENSOR 1039
SMBUS
PS2
EC 1035
TPM 1038
FAN 1037
KEYBOARD 1036
LPC
SPI
BIOS, FW FLASH 1022
HDA
DSP 1060
AUDIO CODEC AND CLASS D AMP 1062
SPEAKERS 1063
HEADPHONES 1064
MIC 1065
USB 3.0 CAMERA 1054
UART OR I²C
GPS 1055
USB 2/3
WWAN UNIT 1056
NGFF
SIM 1057
PCIE
SDIO
UART
USB
WLAN UNIT 1050
BLUETOOTH UNIT 1052
SATA
SSD OR HDD 1020

FIG. 10

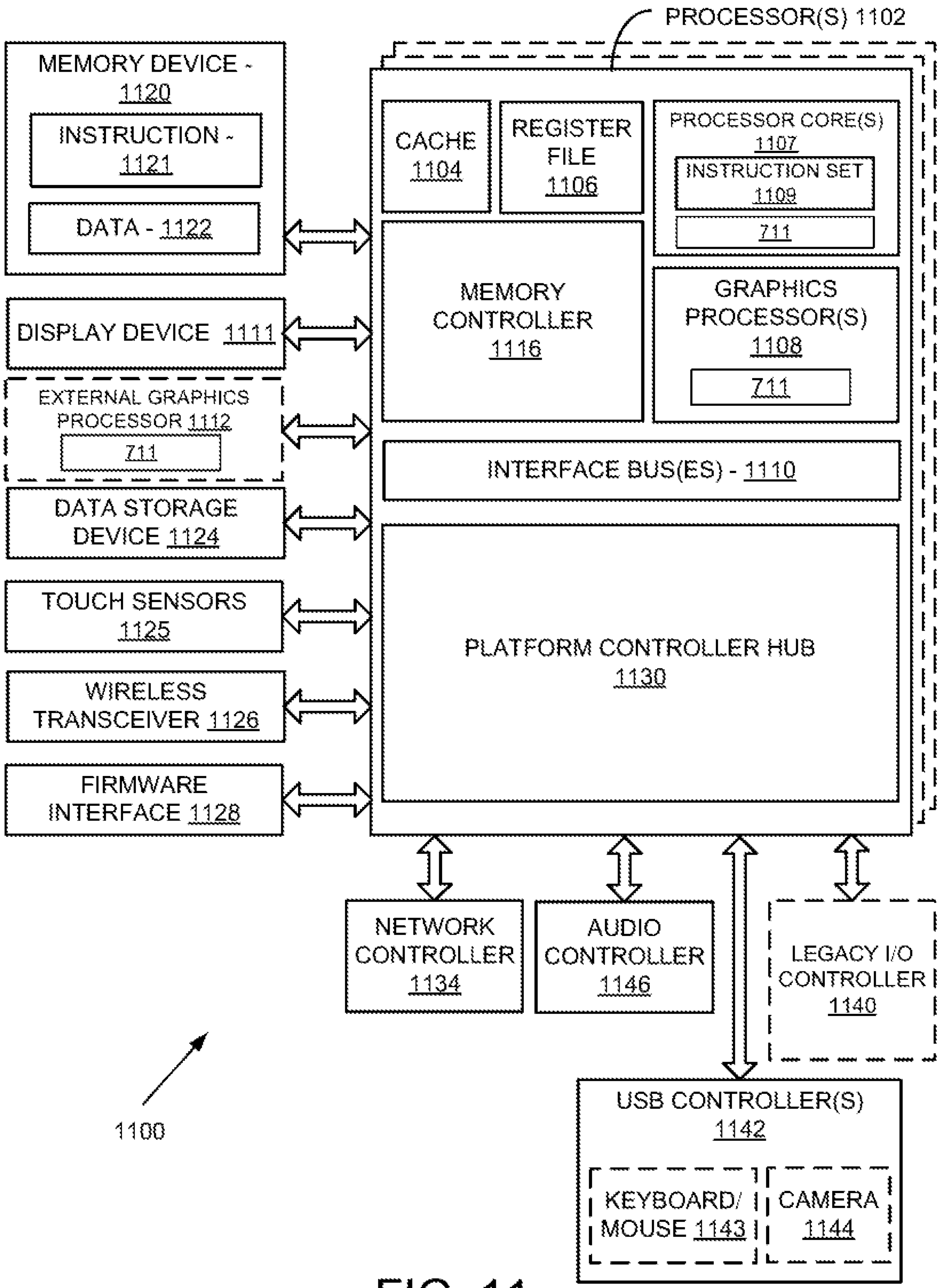

PROCESSOR(S) 1102
MEMORY DEVICE - 1120
INSTRUCTION - 1121
DATA - 1122
DISPLAY DEVICE 1111
EXTERNAL GRAPHICS PROCESSOR 1112
711
DATA STORAGE DEVICE 1124
TOUCH SENSORS 1125
WIRELESS TRANSCEIVER 1126
FIRMWARE INTERFACE 1128
CACHE 1104
REGISTER FILE 1106
PROCESSOR CORE(S) 1107
INSTRUCTION SET 1109
711
MEMORY CONTROLLER 1116
GRAPHICS PROCESSOR(S) 1108
711
INTERFACE BUS(ES) - 1110
PLATFORM CONTROLLER HUB 1130
NETWORK CONTROLLER 1134
AUDIO CONTROLLER 1146
LEGACY I/O CONTROLLER 1140
USB CONTROLLER(S) 1142
KEYBOARD/ MOUSE 1143
CAMERA 1144
1100

FIG. 11

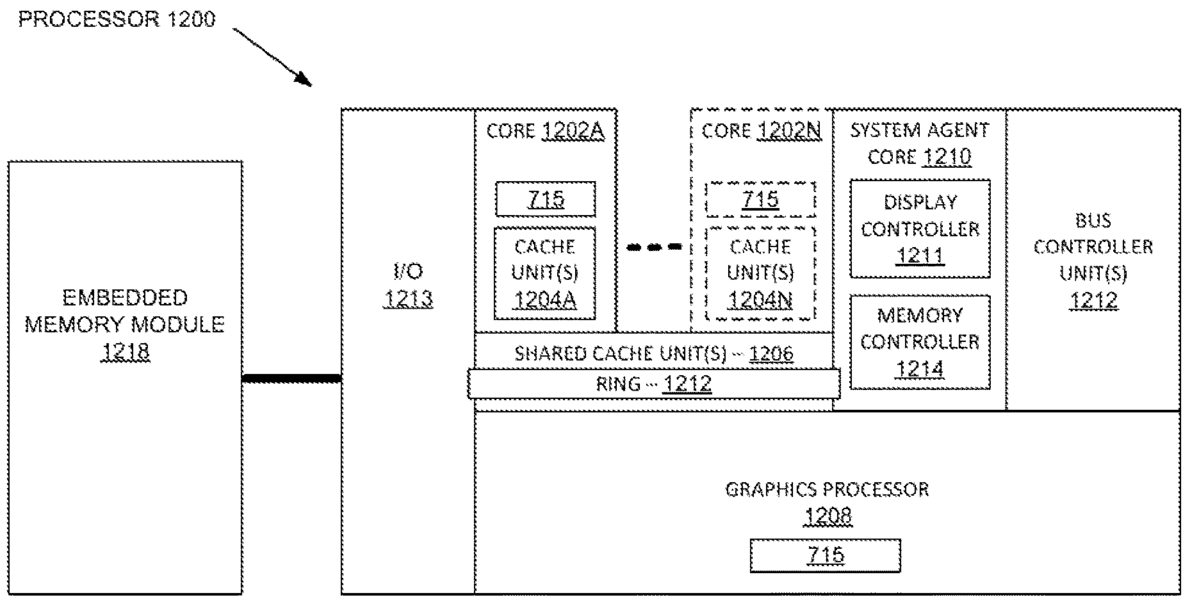

PROCESSOR 1200
EMBEDDED MEMORY MODULE 1218
I/O 1213
CORE 1202A
715
CACHE UNIT(S) 1204A
CORE 1202N
715
CACHE UNIT(S) 1204N
SYSTEM AGENT CORE 1210
DISPLAY CONTROLLER 1211
MEMORY CONTROLLER 1214
BUS CONTROLLER UNIT(S) 1212
SHARED CACHE UNIT(S) ~ 1206
RING ~ 1212
GRAPHICS PROCESSOR 1208
715

FIG. 12

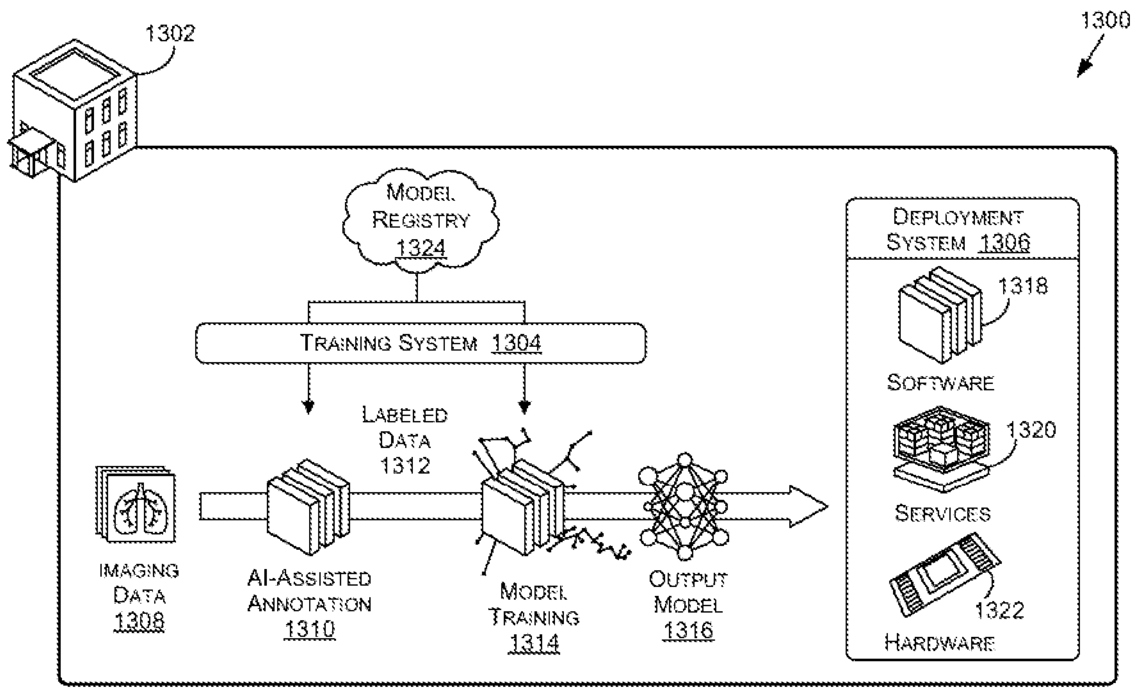

1302
1300
Model Registry 1324
Training System 1304
Deployment System 1306
1318
Software
1320
Services
1322
Hardware
Labeled Data 1312
Imaging Data 1308
AI-Assisted Annotation 1310
Model Training 1314
Output Model 1316

FIG. 13

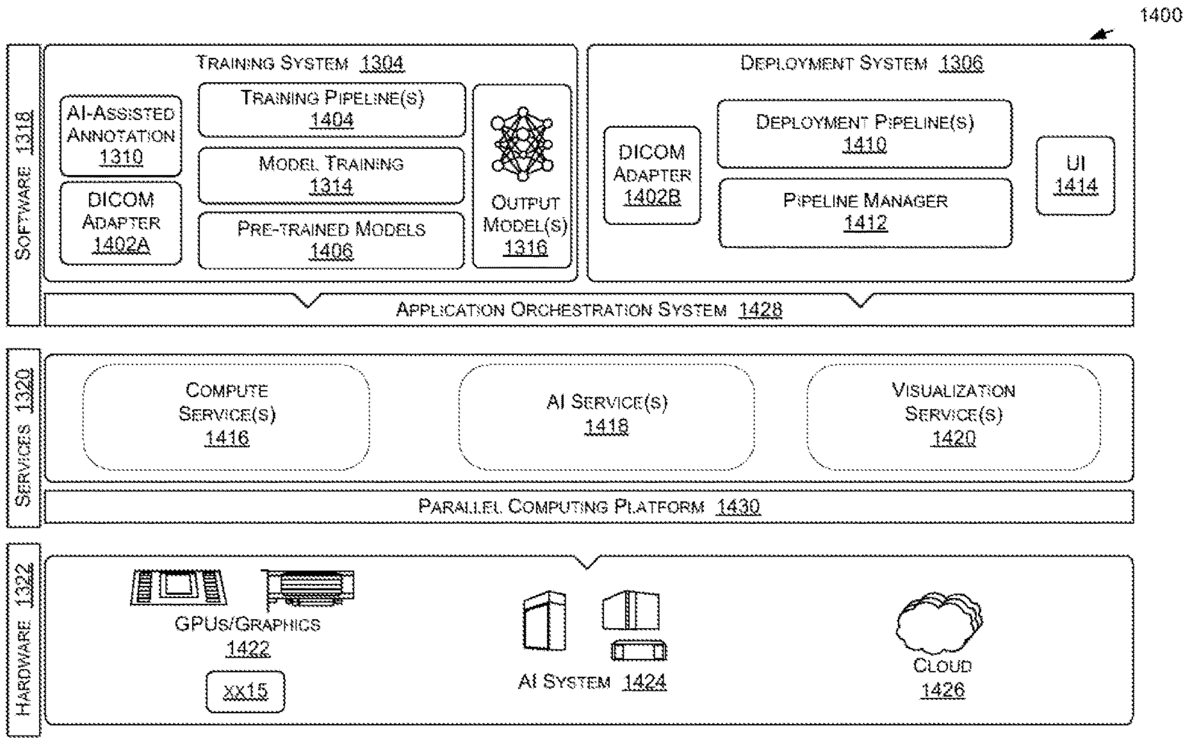

1400
Software 1318
Training System 1304
AI-Assisted Annotation 1310
DICOM Adapter 1402A
Training Pipeline(s) 1404
Model Training 1314
Pre-trained Models 1406
Output Model(s) 1316
Deployment System 1306
DICOM Adapter 1402B
Deployment Pipeline(s) 1410
Pipeline Manager 1412
UI 1414
Application Orchestration System 1428
Services 1320
Compute Service(s) 1416
AI Service(s) 1418
Visualization Service(s) 1420
Parallel Computing Platform 1430
Hardware 1322
GPUs/Graphics 1422
xx15
AI System 1424
Cloud 1426

FIG. 14

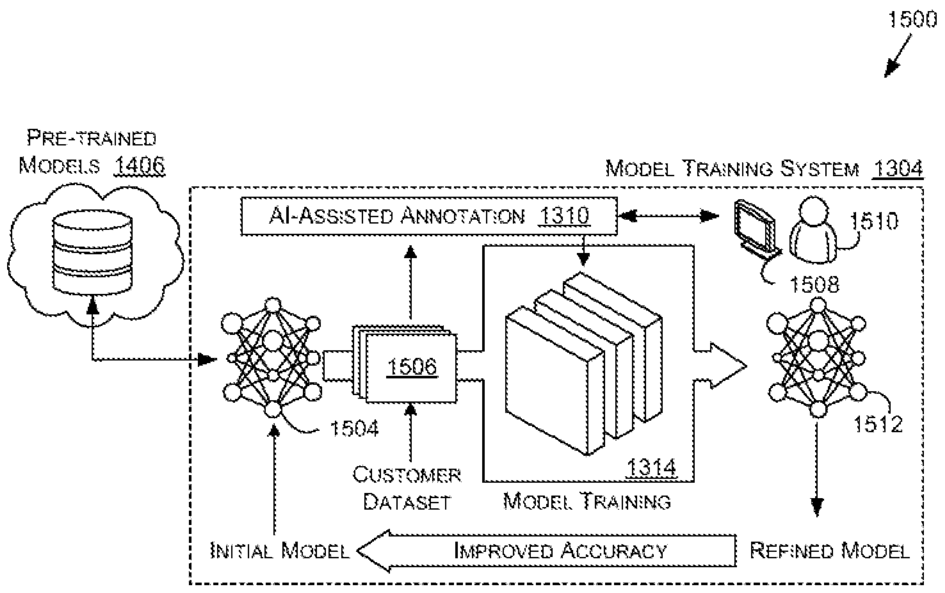

1500
Pre-trained Models 1406
Model Training System 1304
AI-Assisted Annotation 1310
1510
1508
1506
1504
1512
1314
Customer Dataset
Model Training
Initial Model
Improved Accuracy
Refined Model

FIG. 15A

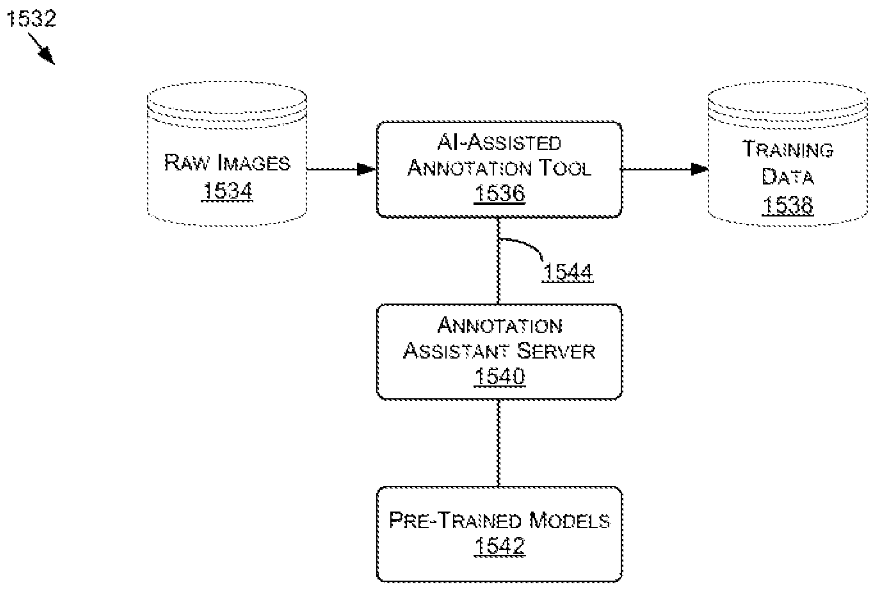

1532
Raw Images 1534
AI-Assisted Annotation Tool 1536
Training Data 1538
1544
Annotation Assistant Server 1540
Pre-Trained Models 1542

FIG. 15B

INFERRING EMOTION FROM SPEECH IN AUDIO DATA USING DEEP LEARNING

RELATED APPLICATIONS

[0001] This application relates to PCT application number ______ filed on Jul. 7, 2022, and entitled "Inferring Emotion From Speech In Audio Data Using Deep Learning," which is hereby incorporated herein in its entirety for all intents and purposes.

BACKGROUND

[0002] There are various situations where it may be desirable to determine a type of emotion exhibited by someone while uttering speech, such as speech represented by captured audio data. Certain prior approaches used machine learning to attempt to infer emotion from input audio, but these approaches were typically limited to those people or speakers for which the respective model was trained, and did not generalize well to other speakers. These networks were also typically based on spectrograms, which required conversion of the audio to a spectrogram representation that would be analyzed using image-based analysis, which did not produce optimal results. Such an approach also requires multiple models to be trained for various speakers, which can be complicated and computationally expensive, or results in varying levels of inaccuracy in the emotion inferred for any input speech. Further still, prior approaches would determine a single emotion for an entire segment of audio, which does not capture any variations in emotional state of a speaker during that segment.

BRIEF DESCRIPTION OF THE DRAWINGS

[0003] Various embodiments in accordance with the present disclosure will be described with reference to the drawings, in which:

[0004] FIG. **1** illustrates different emotions that can be exhibited by a person uttering a line of speech, in accordance with at least one embodiment;

[0005] FIG. **2**A illustrates an example pipeline for inferring emotions from input audio, in accordance with at least one embodiment;

[0006] FIG. **2**B illustrates a time window-based approach to determining emotion at specific points in an audio file or stream, according to at least one embodiment;

[0007] FIG. **3** illustrates an example character animation system that can use emotion data inferred from input audio, according to at least one embodiment;

[0008] FIGS. **4**A and **4**B illustrate interfaces for allowing specification of a prior emotion and prior emotion strength, according to at least one embodiment;

[0009] FIG. **5** illustrates an example process for inferring emotion from audio data, according to at least one embodiment;

[0010] FIG. **6** illustrates components of a distributed system that can be used to infer emotion from audio, according to at least one embodiment;

[0011] FIG. **7**A illustrates inference and/or training logic, according to at least one embodiment;

[0012] FIG. **7**B illustrates inference and/or training logic, according to at least one embodiment;

[0013] FIG. **8** illustrates an example data center system, according to at least one embodiment;

[0014] FIG. **9** illustrates a computer system, according to at least one embodiment;

[0015] FIG. **10** illustrates a computer system, according to at least one embodiment;

[0016] FIG. **11** illustrates at least portions of a graphics processor, according to one or more embodiments;

[0017] FIG. **12** illustrates at least portions of a graphics processor, according to one or more embodiments;

[0018] FIG. **13** is an example data flow diagram for an advanced computing pipeline, in accordance with at least one embodiment;

[0019] FIG. **14** is a system diagram for an example system for training, adapting, instantiating and deploying machine learning models in an advanced computing pipeline, in accordance with at least one embodiment; and

[0020] FIGS. **15**A and **15**B illustrate a data flow diagram for a process to train a machine learning model, as well as client-server architecture to enhance annotation tools with pre-trained annotation models, in accordance with at least one embodiment.

DETAILED DESCRIPTION

[0021] In the following description, various embodiments will be described. For purposes of explanation, specific configurations and details are set forth in order to provide a thorough understanding of the embodiments. However, it will also be apparent to one skilled in the art that the embodiments may be practiced without the specific details. Furthermore, well-known features may be omitted or simplified in order not to obscure the embodiment being described.

[0022] The systems and methods described herein may be used by, without limitation, non-autonomous vehicles, semi-autonomous vehicles (e.g., in one or more adaptive driver assistance systems (ADAS)), piloted and un-piloted robots or robotic platforms, warehouse vehicles, off-road vehicles, vehicles coupled to one or more trailers, flying vessels, boats, shuttles, emergency response vehicles, motorcycles, electric or motorized bicycles, aircraft, construction vehicles, underwater craft, drones, and/or other vehicle types. Further, the systems and methods described herein may be used for a variety of purposes, by way of example and without limitation, for machine control, machine locomotion, machine driving, synthetic data generation, model training, perception, augmented reality, virtual reality, mixed reality, robotics, security and surveillance, simulation and digital twinning, autonomous or semi-autonomous machine applications, deep learning, environment simulation, object or actor simulation and/or digital twinning, data center processing, conversational AI, light transport simulation (e.g., ray-tracing, path tracing, etc.), collaborative content creation for 3D assets, cloud computing, and/or any other suitable applications.

[0023] Disclosed embodiments may be comprised in a variety of different systems such as automotive systems (e.g., an infotainment or personal digital assistant system of an autonomous or semi-autonomous machine), systems implemented using a robot, aerial systems, medial systems, boating systems, smart area monitoring systems, systems for performing deep learning operations, systems for performing simulation operations, systems for performing digital twin operations, systems implemented using an edge device, systems incorporating one or more virtual machines (VMs), systems for performing synthetic data generation operations, systems implemented at least partially in a data center, systems for performing conversational AI operations, systems for performing light transport simulation, systems for performing collaborative content creation for 3D assets, systems implemented at least partially using cloud computing resources, and/or other types of systems.

[0024] Disclosed embodiments can infer emotion from speech or audio data uttered by a person, or other such speaker, that may be captured in audio data using, for example, a microphone and audio capture device that can convert a captured audio signal into digital audio data. When speaking, aspects of a person's speech may change based, at least in part, upon their emotional state, similar to how the person's facial expression may change. For example, FIG. **1** illustrates images of four example emotional states that a person might exhibit while uttering the same line of speech. This includes an image **100** showing the person to be in a happy state, an image **102** showing the person being in an angry state, an image **104** of the person being in a disgusted state, and an image **106** showing the person being in a sad state. Just as the facial expression of the person changes with emotion, there will be similar changes in vocal expression of the speech with these changes in emotion. For various operations, it can be beneficial to be able to accurately and automatically identify these emotions from captured audio data. In an example use case where the emotion data is to be used to generate facial animation, being able to accurately identify or infer emotional state of a person while uttering speech can help to ensure that the appropriate facial expressions, such as those illustrated in FIG. **1**, are used to render the animation. Emotional state data may be helpful in other contexts as well, such as to manage calls in a call center based, at least in part, upon a detected emotional state, or change in emotional state, of at least one party to a call. For example, an automatically generated prompt(s), script, or outline for a call may be dynamically updated based on detected emotional states of callers.

[0025] An emotion determination system in accordance with at least one embodiment can receive input audio data **200**, as illustrated in FIG. **2**A. This audio data **200** can contain speech uttered by at least one person, or other speaker, as may have been captured using an audio capture device. The audio data may undergo at least some amount of pre-processing, such as to reduce background noise, remove segments of silence or non-speech, or segment the audio into audio segments that each contain speech uttered by a single speaker. This audio data can then be passed as input to an emotion determination module, device, system, or process, to attempt to determine or infer an emotional state of the person uttering speech in that audio clip. In this example, the audio data **200** is passed to an algorithm that can classify the type of emotion, or emotional state, reflected in the uttered speech using a trained deep learning model or neural network, at least with respect to those emotional states or classes for which the model or network was trained. The neural network **202** can infer one or more emotion labels **204** for the input audio **200**, which can then be provided as output of the emotion determination process. This may include a single emotion label for individual portions of the audio data **200**, or one or more emotional labels or determinations for an entirety of the input audio data (as may correspond to a specific section—such as a word or sentence—of the received audio), among other such options.

[0026] In at least one embodiment, the neural network **202** can be a transformer-based network. This may include, for example, a network with a Wav2Vec2.0 or Uni Speech neural architecture. A transformer neural network can accurately and efficiently solve sequence-to-sequence tasks, including those with long-range dependencies. Such a network can take the audio data in an audio file format as input, rather than having to first convert the audio to an image-based representation or format—such as a spectrogram, or mel-spectrogram—as was required in prior approaches (which were also found to lead to less accurate results and higher instability). For example, the audio data may correspond to an audio file format such as an uncompressed audio file format (e.g., WAV, AIFF, AU, raw, etc.), a lossless compression audio file format (FLAC, WavPack, TTA, ATRAC, MPEG-4, WMA Lossless, SHN, etc.), or a lossy compression audio file format (e.g., Opus, MP3, Vorbis, Musepack, AAC, ATRAC, WMA Lossy, etc.). Using an audio file format as opposed to converting the audio file format to a non-audio file format (e.g., an image format) allows for higher accuracy and precision in predictions of the transformer-based neural network **202**, while also allowing the network **202** to be more robust to different speakers. In addition, as described, the run time of the system is reduced because post-processing of the audio data to an image or other non-audio-based format is not required.

[0027] In at least one embodiment, such a network can output a probability distribution, a confidence(s), and/or another output type indicating a likelihood of the speech represented by the input audio data corresponding to one or more of a number of emotional classes. This may include as few as two emotional classes (in which case a Boolean output may be generated by the network), or up to as many emotional classes (or combinations of classes) as can be identified and used to train the network without unduly impacting performance for a given operation, application, or use case. In at least one embodiment, such a network outputs a distribution over six emotional classes that are represented in (e.g., publicly-available) datasets that can be used for training—including anger, disgust, fear, joy, neutral (or no detectable emotion), and sadness. If other datasets are used, the set of emotions can be larger or smaller, or may include a different selection of emotions, based at least in part upon the classifications or labels used in those datasets. It can be desirable to select a variety of datasets where possible to obtain a variety of examples of expressing different emotions. In at least one embodiment, a transformer-based neural network **202** will output a vector with a value for each emotion, where that value corresponds to a probability, confidence, or other indicator of whether the speech contained in input audio (e.g., extracted from a video clip) was uttered by a person having a particular emotional state(s), or attempting to convey that emotion. These values may be normalized to values between 0 and 1 (or between 0% and 100%), that all sum to an absolute probability value such as 1.0 (or 100%—where the probability values when summed cannot exceed the maximum probability of any individual emotion). For speech that is determined to be all of a single emotion, the probability vector might have values of [1, 0, 0, 0, 0, 0], while speech determined to have equal probabilities for two different emotions might have values of [0, 0.5, 0, 0.5, 0, 0]. A typical output may have at least some probability for most or all emotions, such as may correspond to values of [0.9, 0.02, 0.01, 0.02, 0.02, 0.03]. Other such values or outputs indicative of emotional state can be provided as well within the scope of the various embodiments.

[0028] In instances where more than one emotional state may be represented, each emotion state having a probability or confidence over a threshold may be identified as an emotional class represented by the speech. Where two or more emotional state classes are determined to be present, the output values corresponding to each emotion may be used to weight the prominence of one emotion with respect to another. For example, when using the emotional states to animate a virtual actor or subject, and there is a higher confidence for anger than sadness, the virtual actor or subject may be generated to show more anger emotion than sadness emotion, which may be reflected using various facial and/or body features. Similarly, when the emotional states are used to indicate emotions of a speaker for purposes other than animation of a virtual actor or subject, the strength or confidence of different emotions may be indicated to a user or system—e.g., "The speaker is more angry than sad," or "Anger: 70%; Sadness: 30%," and/or the like.

[0029] In many instances, the emotional state of a person will not remain exactly the same while uttering more than a few words of speech, or other vocal sounds. Even if the emotional class might stay essentially the same, there may be periods where it is mixed with other emotions, or more strongly exhibits a particular emotion. In order to account for these and other such variations, an emotion determination system can attempt to determine emotional state at different points or times in input audio, even potentially within the same speech uttered by a single speaker. These "points" can correspond to emotional keyframes determined for different timestamps of the audio track. An emotion detection algorithm can then output at least one emotion classification for each emotional keyframe. An operation receiving this emotional keyframe data can then make decisions or perform actions based, at least in part, upon these changes in emotion over time.

[0030] FIG. **2**B illustrates one example approach for determining an emotion classification for a sequence of emotional keyframes that can be used in accordance with at least one embodiment. In this example, a fixed hop size **256** and window size **258** can be used to determine an emotional state for a sequence of frames **250**, **252**, **254** represented by input audio data **260**. In embodiments, a hop size (or stride) can also be thought of as a distance between stride points determined for an audio track, where stride points may be determined at regular frequency in order to obtain a desired overlap and spacing of sliding windows for an individual frame. In at least one embodiment, a source (e.g., a user, application, or operation) can specify the hop size (or stride) **256** and size of a sliding window **258** to be used to analyze the audio data. For a 16,000 Hz sample rate of input audio, example window size and stride values can be set to around 15,000, or values between 5,000 and 16,000. In this example, each frame of audio can be analyzed using a number of passes through the audio data. For each pass, the audio over a given position of a window **258** can be analyzed to determine probability values for a set of emotional classes during that window of time. In various embodiments, a window length should be long enough to represent enough audio data to generate an accurate emotional inference, while not so long as to be likely to include different emotional states that might then lead to inaccurate probability determinations over the entire window. For each pass, the sliding window **258** can be moved forward in time according to the specified hop size **256**. The hop size **256** may be set to allow for at least some overlap between window positions, in order to have at least two windows for most points in the audio to help avoid missing emotional states that might be relatively brief. The hop size **256** can also be long enough to avoid undue processing or an excess number of passes required through the audio. In at least one embodiment, a hop size can be at most half the size of the sliding window size, and at least one-tenth of the length of the window size, in order to provide for sufficient, but not excessive, overlap between window positions. Similarly, there may be thresholds or ranges set on window sizes, such as at least one-tenth of a frame size or at most nine-tenths of a frame size, where a frame can be anywhere from at least about 0.1 seconds to about 10 seconds in at least one embodiment. In at least one embodiment, probabilities can be determined for various emotional classes for each of these sliding window positions in a given frame, and then an overall probability determined for the frame by combining these probabilities. This may then be provided as an emotion vector for this emotional keyframe, which can be considered to be positioned at a start point, midpoint, or other location within an individual frame. In this example, the frames are all of the same size, such that the keyframes will be relatively regular in timing, with an emotion vector or classification output for each of these emotional keyframes.

[0031] In other embodiments, frame size and keyframe location may vary based, at least in part, on the content of the audio. In at least one embodiment, the content of the audio can be analyzed to segment that audio at least by speaker, such that an audio clip only contains speech, or primarily contains speech, uttered by a single speaker (which may include editing the audio to filter out speech from other actors). In some embodiments, this may be further broken down by, for example, sentences or words contained in the audio. Other factors may be used as well, such as pauses in speech, changes in volume, or changes in the speed of the uttered speech, among other such options. In at least some embodiments, thresholds may then be applied to determine window size and hop size, or an algorithm may be used to determine these sizes, as may depend at least in part upon the frame size. In some embodiments, audio (e.g., 16 kHz audio) may be analyzed until a change in emotion is detected, or at least a changes that meets or exceeds a change threshold (e.g., a confidence for a different emotion that is greater than a threshold confidence, a confidence for a different emotion that is greater than a current emotion confidence by more than a threshold, a confidence of a different emotion being greater than the current emotion confidence for more than a threshold number of iterations, etc.) or satisfies another selection criterion, and then a new keyframe can be started. The prior keyframe can then be analyzed using a number of passes as discussed previously to determine an emotional vector or classification for that emotional keyframe.

[0032] Emotional labels or classifications determined for individual emotional keyframes can be provided as input to a system, service, process, application, and/or operation that performs one or more tasks based at least in part upon this emotion input data. An example of one such system is an audio-driven facial animation system **300** as illustrated in FIG. **3**. This example system can provide for automated, audio-driven animation, such as full 3D facial animation, with variable emotion control. In at least one embodiment, a collection of speech performances can be captured of one or more actors uttering speech (e.g., specific sentences) with different emotions, levels of emotion, combinations of emotion, or styles of presentation, among other such options. Emotions supported by such a system can include any appropriate emotion (or similar behavior or state) that is able to be at least partially represented through character animation, image synthesis, or rendering, as may include joy, anger, amazement, sadness, pain, or fear, among others. A data collection process can include a capture of 4D data, including multi-view 3D data over at least a period of time of utterance of the speech. Reconstruction of this captured facial behavior can be performed not only for the facial skin (or such surface), but also for other articulable or controllable components, elements, or features, as may include the teeth, eyeballs, head, and tongue. The reconstruction can provide geometric deformation data in the temporal domain for each separately (or at least somewhat separately) modeled facial (or other bodily) component or region. Such reconstruction can provide a full dataset for use in training, for example, a deep neural network to perform a task such as 3D facial animation.

[0033] In at least one embodiment, a deep neural network **306** trained can be based on a U-net, generative adversarial network (GAN), or recurrent neural network (RNN)-based architecture. A sequence-to-sequence mapping can be used to obtain a sufficiently long temporal context, which can be beneficial in generating physically or behaviorally accurate animation, particularly for upper face motion. In the example system **300** of FIG. **3**, a segment of audio data—such as frames or a segment of audio within a current audio window **302**—may be provided as input to the deep neural network **306**, which can use an analysis network portion **308** to analyze the audio and encode features representative of features of the audio in the audio window **302**, as may correspond to a portion of the speech. This analysis network portion **308** may include a shared audio decoder and encoder for encoding audio features into an audio feature vector, which can be provided as input to an articulation network portion **310** of the deep neural network **306**. In this example, an emotion vector **322** (or emotion label, etc.) can be provided as input. As discussed in more detail elsewhere herein, an emotion vector **322** can be generated using an emotion inference network **320**, such as the transformer-based network **202** of FIG. 2A, which can infer emotion from input audio for respective audio frames, windows, or segments. An emotion vector **322** may correspond to an emotional keyframe to be used in determining how to render one or more frames of facial animation. An emotion vector **322** may include data (e.g., probabilities, confidences, etc.) for one or more emotions that apply to speech in audio used for training, such as an emotion that a voice actor was instructed to use when uttering the speech that was captured in the audio data. In some instances, this may include data for a single emotion label, such as “anger,” or may include data for multiple emotions, such as “anger” and “sadness,” as well as potentially relative weightings or probabilities for those two emotions.

[0034] In at least one embodiment, a style vector may also be provided as input to this network during training. A style vector can include data relating to any aspect of the animation or facial component motion that modifies how one or more points for one or more facial component should move for a given emotion or emotion vector. This may include impacting motion of specific features or facial components, or providing a style of overall animation to be used, such as “intense” or “professional.” A style vector may also be viewed as a finer-grained control over emotion, where an emotion vector provides the label(s) of the emotion(s) to use, and the style provides finer control over how the emotion(s) is expressed through the animation. Other approaches to determining style data can be used as well, such as is discussed in more detail elsewhere herein. In different implementations, a single set of emotion and style vectors may be provided for a given audio clip, a set of vectors can be provided for each frame of animation to be generated, or a set of vectors can be provided for specific points or frames of animation (e.g., emotional keyframes) where at least one emotion or style value or setting is to be modified relative to a prior frame.

[0035] In this system **300**, and without limitation, the emotion vector **322** is fed into an articulation portion **310** of the deep neural network **306** at multiple levels, including at least a beginning and an end of the network to help condition the network. The network **306** may use a shared audio encoder and multiple decoders for various facial components (e.g., face skin, jaw, tongue, eyeballs, and head). During training, an output network portion **312** of the deep neural network **306** can generate a set of vertex positions **314** and/or motion vectors (or other motions or deformations) for individual feature points of the facial components, whether for each such feature point or for only those that have changed relative to a prior frame, among other such options. During training, these vertex positions can be compared against “ground truth” data, such as the original reconstructed facial data from the 4D image capture, in order to compute an overall loss value. In at least one embodiment, a loss, such as an L2 loss, can be used for both position and velocity of feature points in an output data representation. A loss function used to determine the loss value can include terms for position, motion, and adversarial loss in at least one embodiment. This loss value can be used during back-propagation to update network parameters for the deep neural network **306**. Once the network is determined to converge or another training end criterion is satisfied (e.g., processing all training data or performing a target/maximum number of training iterations), the trained network **306** can be provided for inferencing. During inferencing, the network may receive only audio data **302** as input, and may infer a set of vertex positions **314** for various facial components (e.g., head, face, eyeballs, jaw, tongue), which can then be fed to a renderer **316** (e.g., a rendering engine of an animation or video synthesis system) in order to generate a frame of animation **318**, which may be one of a series of frames that provide the animation upon presentation or playback. The original audio data used by the deep neural network **306** may be the same as the original audio data used by the transformer-based neural network **202** of FIG. **2**A to determine the emotional state(s) or class(es) corresponding to the audio data. In various embodiments, the format of the audio data used by the DNN **306** and the transformer-based neural network **202** may differ, or may be the same. For example, both networks **306** and **202** may use the audio without conversion to an image-based format, or the network **306** may use an image-based format (e.g., a spectrogram) and the network **202** may use the audio format without conversion, as described herein.

[0036] As discussed in more detail elsewhere herein, emotion vector data may also be provided if the generated vertex positions are to be modified in some way with respect to how the deep neural network **306** would otherwise infer the vertex positions based on the audio data, such as to convey a specific style or facial behavior to be used in inferring the vertex positions **314**. In some embodiments, a deep neural network **306** may receive emotion vectors, at least when available, and use these vectors to determine how to animate a face, or use this vector in combination with its own emotion determination to attempt to provide smoother and more accurate animation. The providing of different emotional vectors for different emotional keyframes can help the emotional expression of the rendered face to change dynamically over time to correspond to the emotion conveyed in the corresponding speech data. An advantage to a transformer-based neural network **202** as described herein is that it can generalize to speech audio from many different speakers, such that an operator does not have to obtain a different model trained for each speaker, or type of speaker.

[0037] In at least one embodiment, changes in emotion during a frame or audio segment may be represented in different ways. For example, if a first emotion is detected during a first half of a segment and a second emotion is detected during a second half of that segment, then two emotion vectors might be provided that indicate the respective emotion during the respective time frame, or for a respective emotional keyframe. In another example, a single keyframe may be generated that indicates probabilities or values for both emotions over that segment, such as with substantially equal probabilities. In still other examples, the system may look at emotional values for adjacent (e.g., before and after) segments, and attempt to merge or modify segments based, at least in part, upon similarities or differences in emotion determination.

[0038] In some embodiments, all emotional classes can have a same (or no) weighting, such that determined probabilities can be used directly. In some embodiments, a user (or other source) can have an ability to specify at least one emotion label, which can then impact a weighting of at least one emotional class, or can impact an output emotion vector or value. For example, a user might specify that a given audio segment is to be associated with a “sad” emotion. During analysis, an emotion detection network might detect other emotional probabilities, such as anger or disgust. These values can be used to adjust the probabilities in an emotion vector in at least one embodiment, whether by adjusting weights applied to the various probabilities to weight a “sad” emotional state higher, or by blending or averaging determined probabilities with an overall sadness probability due to the user input, among other such options. In some embodiments, a user may also have the option of adjusting probabilities or values in a given emotion vector, in order to modify an outcome based, at least in part, on that vector.

[0039] An ability to determine emotion from speech or voice data can have various other applications or advantages in other contexts as well. For example, in a call center operation, an ability to determine emotion of call center employees on calls can help to determine whether any employees tend to exhibit specific emotions outside an expected or average range, which can help identify employees who might benefit from further training or assistance. An ability to detect a strong angry or sad emotion might also trigger a request for that employee to take a break or handle a different task, or might cause different calls to be routed to that employee which can help to improve the emotional state of the employee, or that might better match that emotional state. Emotional state data for a call can be logged as well, such that if a customer has a complaint about an employee being angry or rude on the call, the emotional state data can be analyzed to determine whether the complaint may be legitimate.

[0040] Such data can also benefit when analyzing speech of a customer or person from outside the call center. For example, if it can be determined that a caller is getting angry during a call, the call center might decide to route that call to a different employee, such as a manager or person better trained to deal with specific emotions or emotional states. Similarly, data stored for a call can help to verify an emotional state of the caller during the call, which might help with tasks such as verifying information about a complaint, or helping to train employees based at least in part upon an emotional state of a caller during a call. If emotional state can be determined through an initial menu of options that the customer navigates through voice commands, then this call can be routed initially based on the emotional state of the caller, or may provide a call center employee up front with information about the emotional state, which can help the employee better prepare for, and manage, the call. For call centers where the employees read at least a portion of their responses from a script, the emotional state might help to select a script that is more accurate for the current situation, such as to use more gentle language if a customer is inferred to be angry or more supportive language if the customer is determined to be sad, and so forth. The emotional state of a caller may also be useful where the call center uses virtual bots or assistants—at least initially—to determine where to route calls. For example, instead of continuing with a fully automated call, the call may be transferred to a live agent when the caller is determined to be upset, angry, frustrated, or the like.

[0041] In at least some embodiments, an ability to change emotional state with individual keyframes, as well as an ability to adjust the locations or frequency of those keyframes, may result in changes in emotion that may not seem natural when displayed. For example, a speaker might start a long sentence being more sad than angry, but then transition to being more angry than sad. There also may be a determination in the middle of a sentence that, for a given keyframe, the speaker has a different emotion than for the rest of the sentence. Rapid changes in emotion, however, may have jarring transitions or at least not match actual human behavior, where emotional transitions may be at least somewhat gradual. Approaches in at least some embodiments can utilize one or more of a number of heuristics, or post-processing operations, to attempt to smooth inaccurate predictions of a model, as well as to provide for more natural transitions between emotional states (e.g., a person rarely goes from 100% sad to 100% angry instantaneously in the middle of a sentence). In at least one embodiment, this may include using a sliding window approach, such as the approach discussed with respect to the audio data, except using the sliding windows with respect to keyframes determined for the audio. This can include performing smoothing for at least non-neutral emotions over a number of keyframes, where that number (e.g., 2-10) of keyframes may be able to be specified by a user or application, or may be determined based at least in part upon a number or frequency of keyframes determined for an audio clip, among other such options.

[0042] In one embodiment, a system can enable a user, application, or other such source to specify or adjust an emotion strength value. For example, a user can select a ratio from 0 to 1 that represents an emotion strength. In at least one embodiment, a larger emotional strength value corresponds to a higher level of expressiveness of the corresponding emotion. If the strength is set to 0, that can indicate that not expressiveness of that emotion is to be used. For example, an evil character in a video game may be desired to show no sadness or happiness, and a user can specify a value of 0 for the emotion strength for these emotions so that the character only is determined to express things with, for example, an angry, disgusted, or neutral emotion. If a character is to be a very happy character, then a user might set an emotional strength for a happy emotion to near 1 (e.g., 0.9) and values for other emotional strengths much lower. Such approaches can not only provide for a smoothness of emotion determination, but can also provide emotion determinations that are more appropriate for a given character.

[0043] Available heuristics may also allow for specification or adjustment relating to prior emotions. A "prior" emotion in this context does not refer to a previously determined or exhibited emotion in an audio file, but instead refers to an emotion or emotional state that was determined prior to the dynamic analysis by, for example, a transformer-based neural network **202**. This may include an emotion that was specified for a given instance of speech in audio data by, for example, a user, application, or operation. For example, where the emotion determinations are used to generate facial animation, a user might specify that the character being animated should appear sad during this speech. As mentioned, however, using only a single emotion throughout an entire instance of speech may not appear natural. A system may then allow a user (or other such source) to specify a prior emotion to use for an instance of speech, for example, but will also infer changes in emotion for various keyframes during that speech. The emotion and current emotion values can then be blended such that the character will demonstrate the prior emotion, but this emotion may be blended with different emotions at different times during the speech, such as to appear more or less sad at different times by being blended with a neutral value, or somewhat angry over a portion of the speech, and so forth. In order to allow for some control over this blending, a prior emotion strength value can also be supplied. This can function as a type of weighting to indicate how much this prior emotion value should be blended with an emotion determined by a neural network, where a prior emotional strength of 0.9 might cause the emotion value to reflect primarily the prior emotion, while a prior emotional strength of around 0.3 may cause the emotion value to at least reflect some of the prior emotion at all times during the speech, which can provide for at least some smoothing of the emotion determinations throughout the speech.

[0044] FIGS. **4**A and **4**B illustrate example states **400**, **450** of a user interface that can be used to indicate emotions for training data, as well as to provide style or modification data to emotion determination at inference time, among other such options. When specifying or modifying emotion data, an animation, rendering, or reconstruction may be displayed that is representative of one or more determined emotion probability values **406**. A user viewing this interface may then make any value adjustments that are determined to be appropriate. For example, an emotion determination may be primarily angry, but a listener may interpret the speech utterance as also sounding somewhat sad. In order to more accurately label the data, a user may adjust the label that is applied, so the network more accurately learns to interpret emotion in audio data. As illustrated, a time point **404** (e.g., a location of a keyframe) can be indicated in the audio data **402** for which these settings are to be applied. As mentioned, a single setting might be used for an audio clip or segment, but in other situations the emotional state may change during such a clip or segment, such as at various points in time or for/at specific frames of animation, which can be referred to herein as emotional keyframes. An emotional keyframe can indicate when one or more values for an emotion or style is to change, and corresponding input vectors with these values can be provided as input to a network during training in order to learn these changes.

[0045] A user of this interface can also specify a prior emotion **408** that is to be blended with the emotional determination. A user can also specify a prior emotion strength **410** that can be used to determine a blending weight for that prior emotion with respect to a determined emotion. As illustrated in FIG. **4**A, the prior emotion value of "angry" has a corresponding prior emotion strength value of 0.0. Accordingly, the emotional state illustrated in the rendered image **412** is primarily joy as determined by the determined emotion settings **406** or probabilities. As illustrated in FIG. **4**B, a user adjusting the prior emotion strength value **452** to 0.6 results in an anger emotion being blended with the joy (and neutral) emotion determinations, which results in an emotional state as illustrated in rendered image **454** that is an equal blend of joy and anger, such as where the user is happy with a result but upset with the approach that was used to obtain that result. As mentioned, an emotion strength may be provided for each individual emotion as well, and can be used to smooth emotions or modify emotional determinations, among other such options. An interface such as that illustrated in FIG. **4**A can also allow a user to adjust values for emotions and/or prior emotions, and related values, at different keyframes or points **404** in the audio. Such an interface may also allow a user to select which heuristics to apply for a given audio clip, as well as any values that may be used to modify or control a way in which those heuristics are applied.

[0046] As mentioned, such an interface can be used at inference time as a type of post process, and can also be used for continued learning in at least some embodiments. For example, a user may view generated animation playback through this interface, where animation of the character is presented. In FIG. **4**B, if the user thinks that the animation contains too much intensity for the situation, then the user can adjust the intensity style selector to reduce an intensity and have the frame(s) of animation re-rendered. If the user detects a little sadness in the character's speech that is not captured in the animation, then the user can adjust that setting as well. In some embodiments, a user may also be able to provide, as a type of style input, adjustment to specific feature points or facial components in the display. For example, the user can use a pointer to grab and move a position of the character's lip, and this information can be used as style input for re-rendering of the animation. Other changes can be provided as well, such as head movement, head tilt, eye movement or focus, or other such changes that can be conveyed through emotion or style input for re-rendering (or updated rendering or synthesis) of the animation. Various other animation control parameters can be specified through such an interface as well, which can impact the final rendering.

[0047] In some embodiments, the transformer-based neural network **202** and the deep neural network **306** may be trained in an end-to-end fashion, where outputs from the deep neural network **306** may be used to update parameters of not only the network **306**, but also the network **202**. For example, where the probability or confidence for a particular segment of audio data is determined to be very high (e.g., 0.9) for anger, but the animated character that is animated using for anger as an input to the network **306** appears to expressive, or less human-like, this feedback may be used to adjust the parameters of the network **202** to train the network **202** to instead predict lower anger confidences (e.g., 0.7) or probabilities for similar speech types. In this way, the emotional states or classes (and the confidences corresponding thereto) may be fine-tuned to aid in the network **306** generating animations that more accurately or precisely resemble emotion.

[0048] FIG. **5** illustrates an example process **500** for inferring emotion from an input audio clip that can be used in accordance with at least one embodiment. It should be understood that for this and other processes presented herein that there may be additional, fewer, or alternative steps performed in similar or alternative orders, or at least partially in parallel, within the scope of the various embodiments unless otherwise specifically stated. In this process, audio data is obtained **502** that represents speech uttered by at least one speaker, such as at least one human uttering speech during a conversation. This speech may have been captured by an audio capture device, such as at least one microphone or microphone array, then converted to digital audio data. This audio data can be divided **504** into segments of speech (e.g., sentences, paragraphs, words, or utterances between pauses) each uttered or labeled as corresponding to (e.g., where there are multiple speakers, but one speaker is prominent) a single speaker. An audio segment can be selected **506** for emotion analysis, and provided **508** as input to a transformer-based neural network, or other such emotion determination network or algorithm. One or more frames of the segment can be analyzed **510** using the neural network to infer probability (or other) values for a set of emotions. These can include a fixed set of emotions for which the neural network was trained, as well as potentially additional emotions that the network has learned through continued learning, among other such options. The number of frames in the segment can depend upon a number of factors, such as the length or content of the segment, as well as the window or stride size for the analysis. For each frame of the segment, an emotion vector can be received **512** that indicates probabilities for the set of emotions, or at least a subset of the emotions. A determination can be made **514** as to whether any heuristics are to be applied to the emotion vector(s). If so, one or more of these heuristics can be applied **516** to the vectors to perform smoothing or emotion determination adjustment, among other such options. In some embodiments, this may include adjusting the emotion probability values based on a prior emotion and/or emotion strength as discussed herein. The emotion vectors, after any heuristics, can be provided **518** to an application (or other recipient or destination) for use in performing one or more emotion-based tasks or analysis. A determination can be made **520** as to whether there are any more segments to be analyzed, and if so then this process can continue with a next segment. In some embodiments, segment analysis may be performed in parallel for at least some of the segments. After emotion vectors are provided, a user can be allowed **522** to review and modify values in these emotion vectors as appropriate, such as to perform any adjustments deemed to be appropriate by the user for a given emotion-based task.

[0049] As an example, emotional vectors can be provided to a facial animation process that attempts to generate animation with realistic behavior for various emotional states for a variety of different character types. This can include, for example, audio-driven full three-dimensional (3D) facial animation with emotion control. In such an approach, realistic animation can be generated without any manual input or post-processing required—although possible where desired. Automating such animation can help to significantly reduce the amount of time, experience, and cost needed for manual (or at least partially-manual) character animation. Audio-driven facial animation can provide an efficient way to generate facial animation compared to traditional approaches, as only audio data is needed to drive the animation of a given character.

[0050] Various systems can also support retargeting. In retargeting, motion of one character can be mapped to motion of another character, such that similar animation can be generated for similar emotions and/or style. An interface such as illustrated in FIGS. **4**A and **4**B can be further beneficial in a remapping context where different characters might express emotion or styles in slightly different ways. A user may be able to load different characters into this interface and view how a retargeted rendering would appear for that character, then can modify one or more aspects or a style of motion or behavior for that specific character, or type of character.

[0051] As discussed, aspects of various approaches presented herein can be lightweight enough to execute on a device such as a client device, such as a personal computer or gaming console, in real time or near real time. Such processing can be performed on content (e.g., a rendered version of a unique asset) that is generated on, or received by, that client device or received from an external source, such as streaming sensor data or other content received over at least one network. In some instances, the processing and/or determination of this content may be performed by one of these other devices, systems, or entities, then provided to the client device (or another such recipient) for presentation or another such use.

[0052] As an example, FIG. **6** illustrates an example network configuration **600** that can be used to provide, generate, modify, encode, and/or transmit data or other such content. In at least one embodiment, a client device **602** can generate or receive data for a session using components of a content application **604** on client device **602** and data stored locally on that client device. In at least one embodiment, a content application **624** executing on a server **620** (e.g., a cloud server or edge server) may initiate a session associated with at least client device **602**, as may use a session manager and user data stored in a user database **634**, and can cause content **632** to be determined by a content manager **626**. A content manager **626** may work with an audio-to-face module **628** or system to determine facial animation corresponding to input audio, as well as an emotion application **630** that can perform one or more tasks using determined emotion data. This may include, for example, using the audio data to generate image, video, or other visual presentation data using an asset (e.g., a character mesh) from an asset database **632**, to an extent allowable as determined by a rights manager **630** or other such component or service. At least a portion of that generated content (separate and different from the assets themselves) may be transmitted to client device **602** using an appropriate transmission manager **622** to send by download, streaming, or another such transmission channel. An encoder may be used to encode and/or compress at least some of this data before transmitting to the client device **602**. In at least one embodiment, client device **602** receiving such content can provide this content to a corresponding content application **604**, which may also or alternatively include a graphical user interface **610**, audio-to-face component **612**, and emotion application **614** for use in performing emotion-based tasks. A decoder may also be used to decode data received over the network(s) **640** for presentation via client device **602**, such as image or video content through a display **606** and audio, such as sounds and music, through at least one audio playback device **608**, such as speakers or headphones. In at least one embodiment, at least some of this content may already be stored on, rendered on, or accessible to client device **602** such that transmission over network **640** is not required for at least that portion of content, such as where that content may have been previously downloaded or stored locally on a hard drive or optical disk. In at least one embodiment, a transmission mechanism such as data streaming can be used to transfer this content from server **620**, or user database **634**, to client device **602**. In at least one embodiment, at least a portion of this content can be obtained or streamed from another source, such as a third party service **660** or other client device **650**, that may also include a content application **662** for generating or providing content. In at least one embodiment, portions of this functionality can be performed using multiple computing devices, or multiple processors within one or more computing devices, such as may include a combination of CPUs and GPUs.

[0053] In this example, these client devices can include any appropriate computing devices, as may include a desktop computer, notebook computer, set-top box, streaming device, gaming console, smartphone, tablet computer, VR/AR/MR headset, VR/AR/MR goggles, wearable computer, or a smart television. Each client device can submit a request across at least one wired or wireless network, as may include the Internet, an Ethernet, a local area network (LAN), or a cellular network, among other such options. In this example, these requests can be submitted to an address associated with a cloud provider, who may operate or control one or more electronic resources in a cloud provider environment, such as may include a data center or server farm. In at least one embodiment, the request may be received or processed by at least one edge server, that sits on a network edge and is outside at least one security layer associated with the cloud provider environment. In this way, latency can be reduced by enabling the client devices to interact with servers that are in closer proximity, while also improving security of resources in the cloud provider environment.

[0054] In at least one embodiment, such a system can be used for performing graphical rendering operations. In other embodiments, such a system can be used for other purposes, such as for providing image or video content to test or validate autonomous machine applications, or for performing deep learning operations. In at least one embodiment, such a system can be implemented using an edge device, or may incorporate one or more Virtual Machines (VMs). In at least one embodiment, such a system can be implemented at least partially in a data center or at least partially using cloud computing resources.

Inference and Training Logic

[0055] FIG. **7**A illustrates inference and/or training logic **715** used to perform inferencing and/or training operations associated with one or more embodiments. Details regarding inference and/or training logic **715** are provided below in conjunction with FIGS. **7**A and/or **7**B.

[0056] In at least one embodiment, inference and/or training logic **715** may include, without limitation, code and/or data storage **701** to store forward and/or output weight and/or input/output data, and/or other parameters to configure neurons or layers of a neural network trained and/or used for inferencing in aspects of one or more embodiments. In at least one embodiment, training logic **715** may include, or be coupled to code and/or data storage **701** to store graph code or other software to control timing and/or order, in which weight and/or other parameter information is to be loaded to configure, logic, including integer and/or floating point units (collectively, arithmetic logic units (ALUs). In at least one embodiment, code, such as graph code, loads weight or other parameter information into processor ALUs based on an architecture of a neural network to which the code corresponds. In at least one embodiment, code and/or data storage **701** stores weight parameters and/or input/output data of each layer of a neural network trained or used in conjunction with one or more embodiments during forward propagation of input/output data and/or weight parameters during training and/or inferencing using aspects of one or more embodiments. In at least one embodiment, any portion of code and/or data storage **701** may be included with other on-chip or off-chip data storage, including a processor's L1, L2, or L3 cache or system memory.

[0057] In at least one embodiment, any portion of code and/or data storage **701** may be internal or external to one or more processors or other hardware logic devices or circuits. In at least one embodiment, code and/or code and/or data storage **701** may be cache memory, dynamic randomly addressable memory ("DRAM"), static randomly addressable memory ("SRAM"), non-volatile memory (e.g., Flash memory), or other storage. In at least one embodiment, choice of whether code and/or code and/or data storage **701** is internal or external to a processor, for example, or comprised of DRAM, SRAM, Flash or some other storage type may depend on available storage on-chip versus off-chip, latency requirements of training and/or inferencing functions being performed, batch size of data used in inferencing and/or training of a neural network, or some combination of these factors.

[0058] In at least one embodiment, inference and/or training logic **715** may include, without limitation, a code and/or data storage **705** to store backward and/or output weight and/or input/output data corresponding to neurons or layers of a neural network trained and/or used for inferencing in aspects of one or more embodiments. In at least one embodiment, code and/or data storage **705** stores weight parameters and/or input/output data of each layer of a neural network trained or used in conjunction with one or more embodiments during backward propagation of input/output data and/or weight parameters during training and/or inferencing using aspects of one or more embodiments. In at least one embodiment, training logic **715** may include, or be coupled to code and/or data storage **705** to store graph code or other software to control timing and/or order, in which weight and/or other parameter information is to be loaded to configure, logic, including integer and/or floating point units (collectively, arithmetic logic units (ALUs). In at least one embodiment, code, such as graph code, loads weight or other parameter information into processor ALUs based on an architecture of a neural network to which the code corresponds. In at least one embodiment, any portion of code and/or data storage **705** may be included with other on-chip or off-chip data storage, including a processor's L1, L2, or L3 cache or system memory. In at least one embodiment, any portion of code and/or data storage **705** may be internal or external to on one or more processors or other hardware logic devices or circuits. In at least one embodiment, code and/or data storage **705** may be cache memory, DRAM, SRAM, non-volatile memory (e.g., Flash memory), or other storage. In at least one embodiment, choice of whether code and/or data storage **705** is internal or external to a processor, for example, or comprised of DRAM, SRAM, Flash or some other storage type may depend on available storage on-chip versus off-chip, latency requirements of training and/or inferencing functions being performed, batch size of data used in inferencing and/or training of a neural network, or some combination of these factors.

[0059] In at least one embodiment, code and/or data storage **701** and code and/or data storage **705** may be separate storage structures. In at least one embodiment, code and/or data storage **701** and code and/or data storage **705** may be same storage structure. In at least one embodiment, code and/or data storage **701** and code and/or data storage **705** may be partially same storage structure and partially separate storage structures. In at least one embodiment, any portion of code and/or data storage **701** and code and/or data storage **705** may be included with other on-chip or off-chip data storage, including a processor's L1, L2, or L3 cache or system memory.

[0060] In at least one embodiment, inference and/or training logic **715** may include, without limitation, one or more arithmetic logic unit(s) ("ALU(s)") **710**, including integer and/or floating point units, to perform logical and/or mathematical operations based, at least in part on, or indicated by, training and/or inference code (e.g., graph code), a result of which may produce activations (e.g., output values from layers or neurons within a neural network) stored in an activation storage **720** that are functions of input/output and/or weight parameter data stored in code and/or data storage **701** and/or code and/or data storage **705**. In at least one embodiment, activations stored in activation storage **720** are generated according to linear algebraic and or matrix-based mathematics performed by ALU(s) **710** in response to performing instructions or other code, wherein weight values stored in code and/or data storage **705** and/or code and/or data storage **701** are used as operands along with other values, such as bias values, gradient information, momentum values, or other parameters or hyperparameters, any or all of which may be stored in code and/or data storage **705** or code and/or data storage **701** or another storage on or off-chip.

[0061] In at least one embodiment, ALU(s) **710** are included within one or more processors or other hardware logic devices or circuits, whereas in another embodiment, ALU(s) **710** may be external to a processor or other hardware logic device or circuit that uses them (e.g., a co-processor). In at least one embodiment, ALUs **710** may be included within a processor's execution units or otherwise within a bank of ALUs accessible by a processor's execution units either within same processor or distributed between different processors of different types (e.g., central processing units, graphics processing units, fixed function units, etc.). In at least one embodiment, code and/or data storage **701**, code and/or data storage **705**, and activation storage **720** may be on same processor or other hardware logic device or circuit, whereas in another embodiment, they may be in different processors or other hardware logic devices or circuits, or some combination of same and different processors or other hardware logic devices or circuits. In at least one embodiment, any portion of activation storage **720** may be included with other on-chip or off-chip data storage, including a processor's L1, L2, or L3 cache or system memory. Furthermore, inferencing and/or training code may be stored with other code accessible to a processor or other hardware logic or circuit and fetched and/or processed using a processor's fetch, decode, scheduling, execution, retirement and/or other logical circuits.

[0062] In at least one embodiment, activation storage **720** may be cache memory, DRAM, SRAM, non-volatile memory (e.g., Flash memory), or other storage. In at least one embodiment, activation storage **720** may be completely or partially within or external to one or more processors or other logical circuits. In at least one embodiment, choice of whether activation storage **720** is internal or external to a processor, for example, or comprised of DRAM, SRAM, Flash or some other storage type may depend on available storage on-chip versus off-chip, latency requirements of training and/or inferencing functions being performed, batch size of data used in inferencing and/or training of a neural network, or some combination of these factors. In at least one embodiment, inference and/or training logic **715** illustrated in FIG. **7***a* may be used in conjunction with an application-specific integrated circuit ("ASIC"), such as Tensorflow® Processing Unit from Google, an inference processing unit (IPU) from Graphcore™, or a Nervana® (e.g., "Lake Crest") processor from Intel Corp. In at least one embodiment, inference and/or training logic **715** illustrated in FIG. **7***a* may be used in conjunction with central processing unit ("CPU") hardware, graphics processing unit ("GPU") hardware or other hardware, such as field programmable gate arrays ("FPGAs").

[0063] FIG. **7***b* illustrates inference and/or training logic **715**, according to at least one or more embodiments. In at least one embodiment, inference and/or training logic **715** may include, without limitation, hardware logic in which computational resources are dedicated or otherwise exclusively used in conjunction with weight values or other information corresponding to one or more layers of neurons within a neural network. In at least one embodiment, inference and/or training logic **715** illustrated in FIG. **7***b* may be used in conjunction with an application-specific integrated circuit (ASIC), such as Tensorflow® Processing Unit from

Google, an inference processing unit (IPU) from Graphcore™, or a Nervana® (e.g., "Lake Crest") processor from Intel Corp. In at least one embodiment, inference and/or training logic **715** illustrated in FIG. **7***b* may be used in conjunction with central processing unit (CPU) hardware, graphics processing unit (GPU) hardware or other hardware, such as field programmable gate arrays (FPGAs). In at least one embodiment, inference and/or training logic **715** includes, without limitation, code and/or data storage **701** and code and/or data storage **705**, which may be used to store code (e.g., graph code), weight values and/or other information, including bias values, gradient information, momentum values, and/or other parameter or hyperparameter information. In at least one embodiment illustrated in FIG. **7***b*, each of code and/or data storage **701** and code and/or data storage **705** is associated with a dedicated computational resource, such as computational hardware **702** and computational hardware **706**, respectively. In at least one embodiment, each of computational hardware **702** and computational hardware **706** comprises one or more ALUs that perform mathematical functions, such as linear algebraic functions, only on information stored in code and/or data storage **701** and code and/or data storage **705**, respectively, result of which is stored in activation storage **720**.

[0064] In at least one embodiment, each of code and/or data storage **701** and **705** and corresponding computational hardware **702** and **706**, respectively, correspond to different layers of a neural network, such that resulting activation from one "storage/computational pair **701/702**" of code and/or data storage **701** and computational hardware **702** is provided as an input to "storage/computational pair **705/706**" of code and/or data storage **705** and computational hardware **706**, in order to mirror conceptual organization of a neural network. In at least one embodiment, each of storage/computational pairs **701/702** and **705/706** may correspond to more than one neural network layer. In at least one embodiment, additional storage/computation pairs (not shown) subsequent to or in parallel with storage computation pairs **701/702** and **705/706** may be included in inference and/or training logic **715**.

Data Center

[0065] FIG. **8** illustrates an example data center **800**, in which at least one embodiment may be used. In at least one embodiment, data center **800** includes a data center infrastructure layer **810**, a framework layer **820**, a software layer **830**, and an application layer **840**.

[0066] In at least one embodiment, as shown in FIG. **8**, data center infrastructure layer **810** may include a resource orchestrator **812**, grouped computing resources **814**, and node computing resources ("node C.R.s") **816**(1)-**816**(N), where "N" represents any whole, positive integer. In at least one embodiment, node C.R.s **816**(1)-**816**(N) may include, but are not limited to, any number of central processing units ("CPUs") or other processors (including accelerators, field programmable gate arrays (FPGAs), graphics processors, etc.), memory devices (e.g., dynamic read-only memory), storage devices (e.g., solid state or disk drives), network input/output ("NW I/O") devices, network switches, virtual machines ("VMs"), power modules, and cooling modules, etc. In at least one embodiment, one or more node C.R.s from among node C.R.s **816**(1)-**816**(N) may be a server having one or more of above-mentioned computing resources.

[0067] In at least one embodiment, grouped computing resources **814** may include separate groupings of node C.R.s housed within one or more racks (not shown), or many racks housed in data centers at various geographical locations (also not shown). Separate groupings of node C.R.s within grouped computing resources **814** may include grouped compute, network, memory or storage resources that may be configured or allocated to support one or more workloads. In at least one embodiment, several node C.R.s including CPUs or processors may grouped within one or more racks to provide compute resources to support one or more workloads. In at least one embodiment, one or more racks may also include any number of power modules, cooling modules, and network switches, in any combination.

[0068] In at least one embodiment, resource orchestrator **812** may configure or otherwise control one or more node C.R.s **816**(1)-**816**(N) and/or grouped computing resources **814**. In at least one embodiment, resource orchestrator **812** may include a software design infrastructure ("SDI") management entity for data center **800**. In at least one embodiment, resource orchestrator may include hardware, software or some combination thereof

[0069] In at least one embodiment, as shown in FIG. **8**, framework layer **820** includes a job scheduler **822**, a configuration manager **824**, a resource manager **826** and a distributed file system **828**. In at least one embodiment, framework layer **820** may include a framework to support software **832** of software layer **830** and/or one or more application(s) **842** of application layer **840**. In at least one embodiment, software **832** or application(s) **842** may respectively include web-based service software or applications, such as those provided by Amazon Web Services, Google Cloud and Microsoft Azure. In at least one embodiment, framework layer **820** may be, but is not limited to, a type of free and open-source software web application framework such as Apache Spark™ (hereinafter "Spark") that may use distributed file system **828** for large-scale data processing (e.g., "big data"). In at least one embodiment, job scheduler **822** may include a Spark driver to facilitate scheduling of workloads supported by various layers of data center **800**. In at least one embodiment, configuration manager **824** may be capable of configuring different layers such as software layer **830** and framework layer **820** including Spark and distributed file system **828** for supporting large-scale data processing. In at least one embodiment, resource manager **826** may be capable of managing clustered or grouped computing resources mapped to or allocated for support of distributed file system **828** and job scheduler **822**. In at least one embodiment, clustered or grouped computing resources may include grouped computing resource **814** at data center infrastructure layer **810**. In at least one embodiment, resource manager **826** may coordinate with resource orchestrator **812** to manage these mapped or allocated computing resources.

[0070] In at least one embodiment, software **832** included in software layer **830** may include software used by at least portions of node C.R.s **816**(1)-**816**(N), grouped computing resources **814**, and/or distributed file system **828** of framework layer **820**. The one or more types of software may include, but are not limited to, Internet web page search software, e-mail virus scan software, database software, and streaming video content software.

[0071] In at least one embodiment, application(s) **842** included in application layer **840** may include one or more types of applications used by at least portions of node C.R.s **816(1)**-**816**(N), grouped computing resources **814**, and/or distributed file system **828** of framework layer **820**. One or more types of applications may include, but are not limited to, any number of a genomics application, a cognitive compute, and a machine learning application, including training or inferencing software, machine learning framework software (e.g., PyTorch, TensorFlow, Caffe, etc.) or other machine learning applications used in conjunction with one or more embodiments.

[0072] In at least one embodiment, any of configuration manager **824**, resource manager **826**, and resource orchestrator **812** may implement any number and type of self-modifying actions based on any amount and type of data acquired in any technically feasible fashion. In at least one embodiment, self-modifying actions may relieve a data center operator of data center **800** from making possibly bad configuration decisions and possibly avoiding underused and/or poor performing portions of a data center.

[0073] In at least one embodiment, data center **800** may include tools, services, software or other resources to train one or more machine learning models or predict or infer information using one or more machine learning models according to one or more embodiments described herein. For example, in at least one embodiment, a machine learning model may be trained by calculating weight parameters according to a neural network architecture using software and computing resources described above with respect to data center **800**. In at least one embodiment, trained machine learning models corresponding to one or more neural networks may be used to infer or predict information using resources described above with respect to data center **800** by using weight parameters calculated through one or more training techniques described herein.

[0074] In at least one embodiment, data center may use CPUs, application-specific integrated circuits (ASICs), GPUs, FPGAs, or other hardware to perform training and/or inferencing using above-described resources. Moreover, one or more software and/or hardware resources described above may be configured as a service to allow users to train or performing inferencing of information, such as image recognition, speech recognition, or other artificial intelligence services.

[0075] Inference and/or training logic **715** are used to perform inferencing and/or training operations associated with one or more embodiments. Details regarding inference and/or training logic **715** are provided below in conjunction with FIGS. **7**A and/or **7**B. In at least one embodiment, inference and/or training logic **715** may be used in system FIG. **8** for inferencing or predicting operations based, at least in part, on weight parameters calculated using neural network training operations, neural network functions and/or architectures, or neural network use cases described herein.

[0076] Such components can be used to determine one or more emotion values from audio data.

Computer Systems

[0077] FIG. **9** is a block diagram illustrating an exemplary computer system, which may be a system with interconnected devices and components, a system-on-a-chip (SOC) or some combination thereof **900** formed with a processor that may include execution units to execute an instruction, according to at least one embodiment. In at least one embodiment, computer system **900** may include, without limitation, a component, such as a processor **902** to employ execution units including logic to perform algorithms for process data, in accordance with present disclosure, such as in embodiment described herein. In at least one embodiment, computer system **900** may include processors, such as PENTIUM® Processor family, Xeon™, Itanium®, XScale™ and/or StrongARM™, Intel® Core™, or Intel® Nervana™ microprocessors available from Intel Corporation of Santa Clara, California, although other systems (including PCs having other microprocessors, engineering workstations, set-top boxes and like) may also be used. In at least one embodiment, computer system **900** may execute a version of WINDOWS' operating system available from Microsoft Corporation of Redmond, Wash., although other operating systems (UNIX and Linux for example), embedded software, and/or graphical user interfaces, may also be used.

[0078] Embodiments may be used in other devices such as handheld devices and embedded applications. Some examples of handheld devices include cellular phones, Internet Protocol devices, digital cameras, personal digital assistants ("PDAs"), and handheld PCs. In at least one embodiment, embedded applications may include a microcontroller, a digital signal processor ("DSP"), system on a chip, network computers ("NetPCs"), set-top boxes, network hubs, wide area network ("WAN") switches, or any other system that may perform one or more instructions in accordance with at least one embodiment.

[0079] In at least one embodiment, computer system **900** may include, without limitation, processor **902** that may include, without limitation, one or more execution units **908** to perform machine learning model training and/or inferencing according to techniques described herein. In at least one embodiment, computer system **900** is a single processor desktop or server system, but in another embodiment computer system **900** may be a multiprocessor system. In at least one embodiment, processor **902** may include, without limitation, a complex instruction set computer ("CISC") microprocessor, a reduced instruction set computing ("RISC") microprocessor, a very long instruction word ("VLIW") microprocessor, a processor implementing a combination of instruction sets, or any other processor device, such as a digital signal processor, for example. In at least one embodiment, processor **902** may be coupled to a processor bus **910** that may transmit data signals between processor **902** and other components in computer system **900**.

[0080] In at least one embodiment, processor **902** may include, without limitation, a Level 1 ("L1") internal cache memory ("cache") **904**. In at least one embodiment, processor **902** may have a single internal cache or multiple levels of internal cache. In at least one embodiment, cache memory may reside external to processor **902**. Other embodiments may also include a combination of both internal and external caches depending on particular implementation and needs. In at least one embodiment, register file **906** may store different types of data in various registers including, without limitation, integer registers, floating point registers, status registers, and instruction pointer register.

[0081] In at least one embodiment, execution unit **908**, including, without limitation, logic to perform integer and floating point operations, also resides in processor **902**. In at least one embodiment, processor **902** may also include a microcode ("ucode") read only memory ("ROM") that stores microcode for certain macro instructions. In at least one embodiment, execution unit **908** may include logic to handle a packed instruction set **909**. In at least one embodiment, by including packed instruction set **909** in an instruction set of a general-purpose processor **902**, along with associated circuitry to execute instructions, operations used by many multimedia applications may be performed using packed data in a general-purpose processor **902**. In one or more embodiments, many multimedia applications may be accelerated and executed more efficiently by using full width of a processor's data bus for performing operations on packed data, which may eliminate need to transfer smaller units of data across processor's data bus to perform one or more operations one data element at a time.

[0082] In at least one embodiment, execution unit **908** may also be used in microcontrollers, embedded processors, graphics devices, DSPs, and other types of logic circuits. In at least one embodiment, computer system **900** may include, without limitation, a memory **920**. In at least one embodiment, memory **920** may be implemented as a Dynamic Random Access Memory ("DRAM") device, a Static Random Access Memory ("SRAM") device, flash memory device, or other memory device. In at least one embodiment, memory **920** may store instruction(s) **919** and/or data **921** represented by data signals that may be executed by processor **902**.

[0083] In at least one embodiment, system logic chip may be coupled to processor bus **910** and memory **920**. In at least one embodiment, system logic chip may include, without limitation, a memory controller hub ("MCH") **916**, and processor **902** may communicate with MCH **916** via processor bus **910**. In at least one embodiment, MCH **916** may provide a high bandwidth memory path **918** to memory **920** for instruction and data storage and for storage of graphics commands, data and textures. In at least one embodiment, MCH **916** may direct data signals between processor **902**, memory **920**, and other components in computer system **900** and to bridge data signals between processor bus **910**, memory **920**, and a system I/**0** **922**. In at least one embodiment, system logic chip may provide a graphics port for coupling to a graphics controller. In at least one embodiment, MCH **916** may be coupled to memory **920** through a high bandwidth memory path **918** and graphics/video card **912** may be coupled to MCH **916** through an Accelerated Graphics Port ("AGP") interconnect **914**.

[0084] In at least one embodiment, computer system **900** may use system I/**0** **922** that is a proprietary hub interface bus to couple MCH **916** to I/O controller hub ("ICH") **930**. In at least one embodiment, ICH **930** may provide direct connections to some I/O devices via a local I/O bus. In at least one embodiment, local I/O bus may include, without limitation, a high-speed I/O bus for connecting peripherals to memory **920**, chipset, and processor **902**. Examples may include, without limitation, an audio controller **929**, a firmware hub ("flash BIOS") **928**, a wireless transceiver **926**, a data storage **924**, a legacy I/**0** controller **923** containing user input and keyboard interfaces **925**, a serial expansion port **927**, such as Universal Serial Bus ("USB"), and a network controller **934**. Data storage **924** may comprise a hard disk drive, a floppy disk drive, a CD-ROM device, a flash memory device, or other mass storage device.

[0085] In at least one embodiment, FIG. **9** illustrates a system, which includes interconnected hardware devices or "chips", whereas in other embodiments, FIG. **9** may illustrate an exemplary System on a Chip ("SoC"). In at least one embodiment, devices may be interconnected with proprietary interconnects, standardized interconnects (e.g., PCIe) or some combination thereof. In at least one embodiment, one or more components of computer system **900** are interconnected using compute express link (CXL) interconnects.

[0086] Inference and/or training logic **715** are used to perform inferencing and/or training operations associated with one or more embodiments. Details regarding inference and/or training logic **715** are provided below in conjunction with FIGS. **7**A and/or **7**B. In at least one embodiment, inference and/or training logic **715** may be used in system FIG. **9** for inferencing or predicting operations based, at least in part, on weight parameters calculated using neural network training operations, neural network functions and/or architectures, or neural network use cases described herein.

[0087] Such components can be used to determine one or more emotion values from audio data.

[0088] FIG. **10** is a block diagram illustrating an electronic device **1000** for using a processor **1010**, according to at least one embodiment. In at least one embodiment, electronic device **1000** may be, for example and without limitation, a notebook, a tower server, a rack server, a blade server, a laptop, a desktop, a tablet, a mobile device, a phone, an embedded computer, or any other suitable electronic device.

[0089] In at least one embodiment, system **1000** may include, without limitation, processor **1010** communicatively coupled to any suitable number or kind of components, peripherals, modules, or devices. In at least one embodiment, processor **1010** coupled using a bus or interface, such as a 1° C. bus, a System Management Bus ("SMBus"), a Low Pin Count (LPC) bus, a Serial Peripheral Interface ("SPI"), a High Definition Audio ("HDA") bus, a Serial Advance Technology Attachment ("SATA") bus, a Universal Serial Bus ("USB") (versions **1**, **2**, **3**), or a Universal Asynchronous Receiver/Transmitter ("UART") bus. In at least one embodiment, FIG. **10** illustrates a system, which includes interconnected hardware devices or "chips", whereas in other embodiments, FIG. **10** may illustrate an exemplary System on a Chip ("SoC"). In at least one embodiment, devices illustrated in FIG. **10** may be interconnected with proprietary interconnects, standardized interconnects (e.g., PCIe) or some combination thereof. In at least one embodiment, one or more components of FIG. **10** are interconnected using compute express link (CXL) interconnects.

[0090] In at least one embodiment, FIG. **10** may include a display **1024**, a touch screen **1025**, a touch pad **1030**, a Near Field Communications unit ("NFC") **1045**, a sensor hub **1040**, a thermal sensor **1046**, an Express Chipset ("EC") **1035**, a Trusted Platform Module ("TPM") **1038**, BIOS/firmware/flash memory ("BIOS, FW Flash") **1022**, a DSP **1060**, a drive **1020** such as a Solid State Disk ("SSD") or a Hard Disk Drive ("HDD"), a wireless local area network unit ("WLAN") **1050**, a Bluetooth unit **1052**, a Wireless Wide Area Network unit ("WWAN") **1056**, a Global Positioning System (GPS) **1055**, a camera ("USB 3.0 camera")

1054 such as a USB 3.0 camera, and/or a Low Power Double Data Rate ("LPDDR") memory unit ("LPDDR3") **1015** implemented in, for example, LPDDR3 standard. These components may each be implemented in any suitable manner.

[0091] In at least one embodiment, other components may be communicatively coupled to processor **1010** through components discussed above. In at least one embodiment, an accelerometer **1041**, Ambient Light Sensor ("ALS") **1042**, compass **1043**, and a gyroscope **1044** may be communicatively coupled to sensor hub **1040**. In at least one embodiment, thermal sensor **1039**, a fan **1037**, a keyboard **1046**, and a touch pad **1030** may be communicatively coupled to EC **1035**. In at least one embodiment, speaker **1063**, headphones **1064**, and microphone ("mic") **1065** may be communicatively coupled to an audio unit ("audio codec and class d amp") **1062**, which may in turn be communicatively coupled to DSP **1060**. In at least one embodiment, audio unit **1064** may include, for example and without limitation, an audio coder/decoder ("codec") and a class D amplifier. In at least one embodiment, SIM card ("SIM") **1057** may be communicatively coupled to WWAN unit **1056**. In at least one embodiment, components such as WLAN unit **1050** and Bluetooth unit **1052**, as well as WWAN unit **1056** may be implemented in a Next Generation Form Factor ("NGFF").

[0092] Inference and/or training logic **715** are used to perform inferencing and/or training operations associated with one or more embodiments. Details regarding inference and/or training logic **715** are provided below in conjunction with FIGS. 7*a* and/or 7*b*. In at least one embodiment, inference and/or training logic **715** may be used in system FIG. **10** for inferencing or predicting operations based, at least in part, on weight parameters calculated using neural network training operations, neural network functions and/or architectures, or neural network use cases described herein.

[0093] Such components can be used to determine one or more emotion values from audio data.

[0094] FIG. **11** is a block diagram of a processing system, according to at least one embodiment. In at least one embodiment, system **1100** includes one or more processors **1102** and one or more graphics processors **1108**, and may be a single processor desktop system, a multiprocessor workstation system, or a server system having a large number of processors **1102** or processor cores **1107**. In at least one embodiment, system **1100** is a processing platform incorporated within a system-on-a-chip (SoC) integrated circuit for use in mobile, handheld, or embedded devices.

[0095] In at least one embodiment, system **1100** can include, or be incorporated within a server-based gaming platform, a game console, including a game and media console, a mobile gaming console, a handheld game console, or an online game console. In at least one embodiment, system **1100** is a mobile phone, smart phone, tablet computing device or mobile Internet device. In at least one embodiment, processing system **1100** can also include, couple with, or be integrated within a wearable device, such as a smart watch wearable device, smart eyewear device, augmented reality device, or virtual reality device. In at least one embodiment, processing system **1100** is a television or set top box device having one or more processors **1102** and a graphical interface generated by one or more graphics processors **1108**.

[0096] In at least one embodiment, one or more processors **1102** each include one or more processor cores **1107** to process instructions which, when executed, perform operations for system and user software. In at least one embodiment, each of one or more processor cores **1107** is configured to process a specific instruction set **1109**. In at least one embodiment, instruction set **1109** may facilitate Complex Instruction Set Computing (CISC), Reduced Instruction Set Computing (RISC), or computing via a Very Long Instruction Word (VLIW). In at least one embodiment, processor cores **1107** may each process a different instruction set **1109**, which may include instructions to facilitate emulation of other instruction sets. In at least one embodiment, processor core **1107** may also include other processing devices, such a Digital Signal Processor (DSP).

[0097] In at least one embodiment, processor **1102** includes cache memory **1104**. In at least one embodiment, processor **1102** can have a single internal cache or multiple levels of internal cache. In at least one embodiment, cache memory is shared among various components of processor **1102**. In at least one embodiment, processor **1102** also uses an external cache (e.g., a Level-3 (L3) cache or Last Level Cache (LLC)) (not shown), which may be shared among processor cores **1107** using known cache coherency techniques. In at least one embodiment, register file **1106** is additionally included in processor **1102** which may include different types of registers for storing different types of data (e.g., integer registers, floating point registers, status registers, and an instruction pointer register). In at least one embodiment, register file **1106** may include general-purpose registers or other registers.

[0098] In at least one embodiment, one or more processor(s) **1102** are coupled with one or more interface bus(es) **1110** to transmit communication signals such as address, data, or control signals between processor **1102** and other components in system **1100**. In at least one embodiment, interface bus **1110**, in one embodiment, can be a processor bus, such as a version of a Direct Media Interface (DMI) bus. In at least one embodiment, interface **1110** is not limited to a DMI bus, and may include one or more Peripheral Component Interconnect buses (e.g., PCI, PCI Express), memory busses, or other types of interface busses. In at least one embodiment processor(s) **1102** include an integrated memory controller **1116** and a platform controller hub **1130**. In at least one embodiment, memory controller **1116** facilitates communication between a memory device and other components of system **1100**, while platform controller hub (PCH) **1130** provides connections to I/O devices via a local I/O bus.

[0099] In at least one embodiment, memory device **1120** can be a dynamic random access memory (DRAM) device, a static random access memory (SRAM) device, flash memory device, phase-change memory device, or some other memory device having suitable performance to serve as process memory. In at least one embodiment memory device **1120** can operate as system memory for system **1100**, to store data **1122** and instructions **1121** for use when one or more processors **1102** executes an application or process. In at least one embodiment, memory controller **1116** also couples with an optional external graphics processor **1112**, which may communicate with one or more graphics processors **1108** in processors **1102** to perform graphics and media operations. In at least one embodiment, a display device **1111** can connect to processor(s) **1102**. In at least one embodiment display device **1111** can include one or more of an internal display device, as in a mobile electronic device or a laptop device or an external display device attached via a display interface (e.g., DisplayPort, etc.). In at least one embodiment, display device **1111** can include a head mounted display (HMD) such as a stereoscopic display device for use in virtual reality (VR) applications or augmented reality (AR) applications.

[0100] In at least one embodiment, platform controller hub **1130** enables peripherals to connect to memory device **1120** and processor **1102** via a high-speed I/O bus. In at least one embodiment, I/O peripherals include, but are not limited to, an audio controller **1146**, a network controller **1134**, a firmware interface **1128**, a wireless transceiver **1126**, touch sensors **1125**, a data storage device **1124** (e.g., hard disk drive, flash memory, etc.). In at least one embodiment, data storage device **1124** can connect via a storage interface (e.g., SATA) or via a peripheral bus, such as a Peripheral Component Interconnect bus (e.g., PCI, PCI Express). In at least one embodiment, touch sensors **1125** can include touch screen sensors, pressure sensors, or fingerprint sensors. In at least one embodiment, wireless transceiver **1126** can be a Wi-Fi transceiver, a Bluetooth transceiver, or a mobile network transceiver such as a 3G, 4G, or Long Term Evolution (LTE) transceiver. In at least one embodiment, firmware interface **1128** enables communication with system firmware, and can be, for example, a unified extensible firmware interface (UEFI). In at least one embodiment, network controller **1134** can allow a network connection to a wired network. In at least one embodiment, a high-performance network controller (not shown) couples with interface bus **1110**. In at least one embodiment, audio controller **1146** is a multi-channel high definition audio controller. In at least one embodiment, system **1100** includes an optional legacy I/O controller **1140** for coupling legacy (e.g., Personal System 2 (PS/2)) devices to system. In at least one embodiment, platform controller hub **1130** can also connect to one or more Universal Serial Bus (USB) controllers **1142** connect input devices, such as keyboard and mouse **1143** combinations, a camera **1144**, or other USB input devices.

[0101] In at least one embodiment, an instance of memory controller **1116** and platform controller hub **1130** may be integrated into a discreet external graphics processor, such as external graphics processor **1112**. In at least one embodiment, platform controller hub **1130** and/or memory controller **1116** may be external to one or more processor(s) **1102**. For example, in at least one embodiment, system **1100** can include an external memory controller **1116** and platform controller hub **1130**, which may be configured as a memory controller hub and peripheral controller hub within a system chipset that is in communication with processor(s) **1102**.

[0102] Inference and/or training logic **715** are used to perform inferencing and/or training operations associated with one or more embodiments. Details regarding inference and/or training logic **715** are provided below in conjunction with FIGS. **7**A and/or **7**B. In at least one embodiment portions or all of inference and/or training logic **715** may be incorporated into graphics processor **1500**. For example, in at least one embodiment, training and/or inferencing techniques described herein may use one or more of ALUs embodied in a graphics processor. Moreover, in at least one embodiment, inferencing and/or training operations described herein may be done using logic other than logic illustrated in FIGS. **7**A or **7**B. In at least one embodiment, weight parameters may be stored in on-chip or off-chip memory and/or registers (shown or not shown) that configure ALUs of a graphics processor to perform one or more machine learning algorithms, neural network architectures, use cases, or training techniques described herein.

[0103] Such components can be used to determine one or more emotion values from audio data.

[0104] FIG. **12** is a block diagram of a processor **1200** having one or more processor cores **1202**A-**1202**N, an integrated memory controller **1214**, and an integrated graphics processor **1208**, according to at least one embodiment. In at least one embodiment, processor **1200** can include additional cores up to and including additional core **1202**N represented by dashed lined boxes. In at least one embodiment, each of processor cores **1202**A-**1202**N includes one or more internal cache units **1204**A-**1204**N. In at least one embodiment, each processor core also has access to one or more shared cached units **1206**.

[0105] In at least one embodiment, internal cache units **1204**A-**1204**N and shared cache units **1206** represent a cache memory hierarchy within processor **1200**. In at least one embodiment, cache memory units **1204**A-**1204**N may include at least one level of instruction and data cache within each processor core and one or more levels of shared mid-level cache, such as a Level 2 (L2), Level 3 (L3), Level 4 (L4), or other levels of cache, where a highest level of cache before external memory is classified as an LLC. In at least one embodiment, cache coherency logic maintains coherency between various cache units **1206** and **1204**A-**1204**N.

[0106] In at least one embodiment, processor **1200** may also include a set of one or more bus controller units **1216** and a system agent core **1210**. In at least one embodiment, one or more bus controller units **1216** manage a set of peripheral buses, such as one or more PCI or PCI express busses. In at least one embodiment, system agent core **1210** provides management functionality for various processor components. In at least one embodiment, system agent core **1210** includes one or more integrated memory controllers **1214** to manage access to various external memory devices (not shown).

[0107] In at least one embodiment, one or more of processor cores **1202**A-**1202**N include support for simultaneous multi-threading. In at least one embodiment, system agent core **1210** includes components for coordinating and operating cores **1202**A-**1202**N during multi-threaded processing. In at least one embodiment, system agent core **1210** may additionally include a power control unit (PCU), which includes logic and components to regulate one or more power states of processor cores **1202**A-**1202**N and graphics processor **1208**.

[0108] In at least one embodiment, processor **1200** additionally includes graphics processor **1208** to execute graphics processing operations. In at least one embodiment, graphics processor **1208** couples with shared cache units **1206**, and system agent core **1210**, including one or more integrated memory controllers **1214**. In at least one embodiment, system agent core **1210** also includes a display controller **1211** to drive graphics processor output to one or more coupled displays. In at least one embodiment, display controller **1211** may also be a separate module coupled with graphics processor **1208** via at least one interconnect, or may be integrated within graphics processor **1208**.

[0109] In at least one embodiment, a ring based interconnect unit **1212** is used to couple internal components of processor **1200**. In at least one embodiment, an alternative interconnect unit may be used, such as a point-to-point interconnect, a switched interconnect, or other techniques. In at least one embodiment, graphics processor **1208** couples with ring interconnect **1212** via an I/O link **1213**.

[0110] In at least one embodiment, I/O link **1213** represents at least one of multiple varieties of I/O interconnects, including an on package I/O interconnect which facilitates communication between various processor components and a high-performance embedded memory module **1218**, such as an eDRAM module. In at least one embodiment, each of processor cores **1202**A-**1202**N and graphics processor **1208** use embedded memory modules **1218** as a shared Last Level Cache.

[0111] In at least one embodiment, processor cores **1202**A-**1202**N are homogenous cores executing a common instruction set architecture. In at least one embodiment, processor cores **1202**A-**1202**N are heterogeneous in terms of instruction set architecture (ISA), where one or more of processor cores **1202**A-**1202**N execute a common instruction set, while one or more other cores of processor cores **1202**A-**1202**N executes a subset of a common instruction set or a different instruction set. In at least one embodiment, processor cores **1202**A-**1202**N are heterogeneous in terms of microarchitecture, where one or more cores having a relatively higher power consumption couple with one or more power cores having a lower power consumption. In at least one embodiment, processor **1200** can be implemented on one or more chips or as an SoC integrated circuit.

[0112] Inference and/or training logic **715** are used to perform inferencing and/or training operations associated with one or more embodiments. Details regarding inference and/or training logic **715** are provided below in conjunction with FIGS. **7***a* and/or **7***b*. In at least one embodiment portions or all of inference and/or training logic **715** may be incorporated into processor **1200**. For example, in at least one embodiment, training and/or inferencing techniques described herein may use one or more of ALUs embodied in graphics processor **1512**, graphics core(s) **1202**A-**1202**N, or other components in FIG. **12**. Moreover, in at least one embodiment, inferencing and/or training operations described herein may be done using logic other than logic illustrated in FIGS. **7**A or **7**B. In at least one embodiment, weight parameters may be stored in on-chip or off-chip memory and/or registers (shown or not shown) that configure ALUs of graphics processor **1200** to perform one or more machine learning algorithms, neural network architectures, use cases, or training techniques described herein.

[0113] Such components can be used to determine one or more emotion values from audio data.

Virtualized Computing Platform

[0114] FIG. **13** is an example data flow diagram for a process **1300** of generating and deploying an image processing and inferencing pipeline, in accordance with at least one embodiment. In at least one embodiment, process **1300** may be deployed for use with imaging devices, processing devices, and/or other device types at one or more facilities **1302**. Process **1300** may be executed within a training system **1304** and/or a deployment system **1306**. In at least one embodiment, training system **1304** may be used to perform training, deployment, and implementation of machine learning models (e.g., neural networks, object detection algorithms, computer vision algorithms, etc.) for use in deployment system **1306**. In at least one embodiment, deployment system **1306** may be configured to offload processing and compute resources among a distributed computing environment to reduce infrastructure requirements at facility **1302**. In at least one embodiment, one or more applications in a pipeline may use or call upon services (e.g., inference, visualization, compute, AI, etc.) of deployment system **1306** during execution of applications.

[0115] In at least one embodiment, some of applications used in advanced processing and inferencing pipelines may use machine learning models or other AI to perform one or more processing steps. In at least one embodiment, machine learning models may be trained at facility **1302** using data **1308** (such as imaging data) generated at facility **1302** (and stored on one or more picture archiving and communication system (PACS) servers at facility **1302**), may be trained using imaging or sequencing data **1308** from another facility (ies), or a combination thereof. In at least one embodiment, training system **1304** may be used to provide applications, services, and/or other resources for generating working, deployable machine learning models for deployment system **1306**.

[0116] In at least one embodiment, model registry **1324** may be backed by object storage that may support versioning and object metadata. In at least one embodiment, object storage may be accessible through, for example, a cloud storage (e.g., cloud **1426** of FIG. **14**) compatible application programming interface (API) from within a cloud platform. In at least one embodiment, machine learning models within model registry **1324** may uploaded, listed, modified, or deleted by developers or partners of a system interacting with an API. In at least one embodiment, an API may provide access to methods that allow users with appropriate credentials to associate models with applications, such that models may be executed as part of execution of containerized instantiations of applications.

[0117] In at least one embodiment, training pipeline **1404** (FIG. **14**) may include a scenario where facility **1302** is training their own machine learning model, or has an existing machine learning model that needs to be optimized or updated. In at least one embodiment, imaging data **1308** generated by imaging device(s), sequencing devices, and/or other device types may be received. In at least one embodiment, once imaging data **1308** is received, AI-assisted annotation **1310** may be used to aid in generating annotations corresponding to imaging data **1308** to be used as ground truth data for a machine learning model. In at least one embodiment, AI-assisted annotation **1310** may include one or more machine learning models (e.g., convolutional neural networks (CNNs)) that may be trained to generate annotations corresponding to certain types of imaging data **1308** (e.g., from certain devices). In at least one embodiment, AI-assisted annotations **1310** may then be used directly, or may be adjusted or fine-tuned using an annotation tool to generate ground truth data. In at least one embodiment, AI-assisted annotations **1310**, labeled clinic data **1312**, or a combination thereof may be used as ground truth data for training a machine learning model. In at least one embodiment, a trained machine learning model may be referred to as output model **1316**, and may be used by deployment system **1306**, as described herein.

[0118] In at least one embodiment, training pipeline **1404** (FIG. **14**) may include a scenario where facility **1302** needs a machine learning model for use in performing one or more processing tasks for one or more applications in deployment system **1306**, but facility **1302** may not currently have such a machine learning model (or may not have a model that is optimized, efficient, or effective for such purposes). In at least one embodiment, an existing machine learning model may be selected from a model registry **1324**. In at least one embodiment, model registry **1324** may include machine learning models trained to perform a variety of different inference tasks on imaging data. In at least one embodiment, machine learning models in model registry **1324** may have been trained on imaging data from different facilities than facility **1302** (e.g., facilities remotely located). In at least one embodiment, machine learning models may have been trained on imaging data from one location, two locations, or any number of locations. In at least one embodiment, when being trained on imaging data from a specific location, training may take place at that location, or at least in a manner that protects confidentiality of imaging data or restricts imaging data from being transferred off-premises. In at least one embodiment, once a model is trained—or partially trained—at one location, a machine learning model may be added to model registry **1324**. In at least one embodiment, a machine learning model may then be retrained, or updated, at any number of other facilities, and a retrained or updated model may be made available in model registry **1324**. In at least one embodiment, a machine learning model may then be selected from model registry **1324**—and referred to as output model **1316**—and may be used in deployment system **1306** to perform one or more processing tasks for one or more applications of a deployment system.

[0119] In at least one embodiment, training pipeline **1404** (FIG. **14**), a scenario may include facility **1302** requiring a machine learning model for use in performing one or more processing tasks for one or more applications in deployment system **1306**, but facility **1302** may not currently have such a machine learning model (or may not have a model that is optimized, efficient, or effective for such purposes). In at least one embodiment, a machine learning model selected from model registry **1324** may not be fine-tuned or optimized for imaging data **1308** generated at facility **1302** because of differences in populations, robustness of training data used to train a machine learning model, diversity in anomalies of training data, and/or other issues with training data. In at least one embodiment, AI-assisted annotation **1310** may be used to aid in generating annotations corresponding to imaging data **1308** to be used as ground truth data for retraining or updating a machine learning model. In at least one embodiment, labeled data **1312** may be used as ground truth data for training a machine learning model. In at least one embodiment, retraining or updating a machine learning model may be referred to as model training **1314**. In at least one embodiment, model training **1314**—e.g., AI-assisted annotations **1310**, labeled clinic data **1312**, or a combination thereof—may be used as ground truth data for retraining or updating a machine learning model. In at least one embodiment, a trained machine learning model may be referred to as output model **1316**, and may be used by deployment system **1306**, as described herein.

[0120] In at least one embodiment, deployment system **1306** may include software **1318**, services **1320**, hardware **1322**, and/or other components, features, and functionality. In at least one embodiment, deployment system **1306** may include a software "stack," such that software **1318** may be built on top of services **1320** and may use services **1320** to perform some or all of processing tasks, and services **1320** and software **1318** may be built on top of hardware **1322** and use hardware **1322** to execute processing, storage, and/or other compute tasks of deployment system **1306**. In at least one embodiment, software **1318** may include any number of different containers, where each container may execute an instantiation of an application. In at least one embodiment, each application may perform one or more processing tasks in an advanced processing and inferencing pipeline (e.g., inferencing, object detection, feature detection, segmentation, image enhancement, calibration, etc.). In at least one embodiment, an advanced processing and inferencing pipeline may be defined based on selections of different containers that are desired or required for processing imaging data **1308**, in addition to containers that receive and configure imaging data for use by each container and/or for use by facility **1302** after processing through a pipeline (e.g., to convert outputs back to a usable data type). In at least one embodiment, a combination of containers within software **1318** (e.g., that make up a pipeline) may be referred to as a virtual instrument (as described in more detail herein), and a virtual instrument may leverage services **1320** and hardware **1322** to execute some or all processing tasks of applications instantiated in containers.

[0121] In at least one embodiment, a data processing pipeline may receive input data (e.g., imaging data **1308**) in a specific format in response to an inference request (e.g., a request from a user of deployment system **1306**). In at least one embodiment, input data may be representative of one or more images, video, and/or other data representations generated by one or more imaging devices. In at least one embodiment, data may undergo pre-processing as part of data processing pipeline to prepare data for processing by one or more applications. In at least one embodiment, post-processing may be performed on an output of one or more inferencing tasks or other processing tasks of a pipeline to prepare an output data for a next application and/or to prepare output data for transmission and/or use by a user (e.g., as a response to an inference request). In at least one embodiment, inferencing tasks may be performed by one or more machine learning models, such as trained or deployed neural networks, which may include output models **1316** of training system **1304**.

[0122] In at least one embodiment, tasks of data processing pipeline may be encapsulated in a container(s) that each represents a discrete, fully functional instantiation of an application and virtualized computing environment that is able to reference machine learning models. In at least one embodiment, containers or applications may be published into a private (e.g., limited access) area of a container registry (described in more detail herein), and trained or deployed models may be stored in model registry **1324** and associated with one or more applications. In at least one embodiment, images of applications (e.g., container images) may be available in a container registry, and once selected by a user from a container registry for deployment in a pipeline, an image may be used to generate a container for an instantiation of an application for use by a user's system.

[0123] In at least one embodiment, developers (e.g., software developers, clinicians, doctors, etc.) may develop, publish, and store applications (e.g., as containers) for performing image processing and/or inferencing on supplied data. In at least one embodiment, development, publishing, and/or storing may be performed using a software development kit (SDK) associated with a system (e.g., to ensure that an application and/or container developed is compliant with or compatible with a system). In at least one embodiment, an application that is developed may be tested locally (e.g., at a first facility, on data from a first facility) with an SDK which may support at least some of services **1320** as a system (e.g., system **1400** of FIG. **14**). In at least one embodiment, because DICOM objects may contain anywhere from one to hundreds of images or other data types, and due to a variation in data, a developer may be responsible for managing (e.g., setting constructs for, building pre-processing into an application, etc.) extraction and preparation of incoming data. In at least one embodiment, once validated by system **1400** (e.g., for accuracy), an application may be available in a container registry for selection and/or implementation by a user to perform one or more processing tasks with respect to data at a facility (e.g., a second facility) of a user.

[0124] In at least one embodiment, developers may then share applications or containers through a network for access and use by users of a system (e.g., system **1400** of FIG. **14**). In at least one embodiment, completed and validated applications or containers may be stored in a container registry and associated machine learning models may be stored in model registry **1324**. In at least one embodiment, a requesting entity—who provides an inference or image processing request—may browse a container registry and/or model registry **1324** for an application, container, dataset, machine learning model, etc., select a desired combination of elements for inclusion in data processing pipeline, and submit an imaging processing request. In at least one embodiment, a request may include input data (and associated patient data, in some examples) that is necessary to perform a request, and/or may include a selection of application(s) and/or machine learning models to be executed in processing a request. In at least one embodiment, a request may then be passed to one or more components of deployment system **1306** (e.g., a cloud) to perform processing of data processing pipeline. In at least one embodiment, processing by deployment system **1306** may include referencing selected elements (e.g., applications, containers, models, etc.) from a container registry and/or model registry **1324**. In at least one embodiment, once results are generated by a pipeline, results may be returned to a user for reference (e.g., for viewing in a viewing application suite executing on a local, on-premises workstation or terminal).

[0125] In at least one embodiment, to aid in processing or execution of applications or containers in pipelines, services **1320** may be leveraged. In at least one embodiment, services **1320** may include compute services, artificial intelligence (AI) services, visualization services, and/or other service types. In at least one embodiment, services **1320** may provide functionality that is common to one or more applications in software **1318**, so functionality may be abstracted to a service that may be called upon or leveraged by applications. In at least one embodiment, functionality provided by services **1320** may run dynamically and more efficiently, while also scaling well by allowing applications to process data in parallel (e.g., using a parallel computing platform **1430** (FIG. **14**)). In at least one embodiment, rather than each application that shares a same functionality offered by a service **1320** being required to have a respective instance of service **1320**, service **1320** may be shared between and among various applications. In at least one embodiment, services may include an inference server or engine that may be used for executing detection or segmentation tasks, as non-limiting examples. In at least one embodiment, a model training service may be included that may provide machine learning model training and/or retraining capabilities. In at least one embodiment, a data augmentation service may further be included that may provide GPU accelerated data (e.g., DICOM, RIS, CIS, REST compliant, RPC, raw, etc.) extraction, resizing, scaling, and/or other augmentation. In at least one embodiment, a visualization service may be used that may add image rendering effects—such as ray-tracing, rasterization, denoising, sharpening, etc.—to add realism to two-dimensional (2D) and/or three-dimensional (3D) models. In at least one embodiment, virtual instrument services may be included that provide for beam-forming, segmentation, inferencing, imaging, and/or support for other applications within pipelines of virtual instruments.

[0126] In at least one embodiment, where a service **1320** includes an AI service (e.g., an inference service), one or more machine learning models may be executed by calling upon (e.g., as an API call) an inference service (e.g., an inference server) to execute machine learning model(s), or processing thereof, as part of application execution. In at least one embodiment, where another application includes one or more machine learning models for segmentation tasks, an application may call upon an inference service to execute machine learning models for performing one or more of processing operations associated with segmentation tasks. In at least one embodiment, software **1318** implementing advanced processing and inferencing pipeline that includes segmentation application and anomaly detection application may be streamlined because each application may call upon a same inference service to perform one or more inferencing tasks.

[0127] In at least one embodiment, hardware **1322** may include GPUs, CPUs, graphics cards, an AI/deep learning system (e.g., an AI supercomputer, such as NVIDIA's DGX), a cloud platform, or a combination thereof In at least one embodiment, different types of hardware **1322** may be used to provide efficient, purpose-built support for software **1318** and services **1320** in deployment system **1306**. In at least one embodiment, use of GPU processing may be implemented for processing locally (e.g., at facility **1302**), within an AI/deep learning system, in a cloud system, and/or in other processing components of deployment system **1306** to improve efficiency, accuracy, and efficacy of image processing and generation. In at least one embodiment, software **1318** and/or services **1320** may be optimized for GPU processing with respect to deep learning, machine learning, and/or high-performance computing, as non-limiting examples. In at least one embodiment, at least some of computing environment of deployment system **1306** and/or training system **1304** may be executed in a datacenter one or more supercomputers or high performance computing systems, with GPU optimized software (e.g., hardware and software combination of NVIDIA's DGX System). In at least one embodiment, hardware **1322** may include any number of GPUs that may be called upon to perform processing of data in parallel, as described herein. In at least one embodiment, cloud platform may further include GPU processing for GPU-optimized execution of deep learning tasks, machine learning tasks, or other computing tasks. In at least one embodiment, cloud platform (e.g., NVIDIA's NGC) may be executed using an AI/deep learning supercomputer(s) and/or GPU-optimized software (e.g., as provided on NVIDIA's DGX Systems) as a hardware abstraction and scaling platform. In at least one embodiment, cloud platform may integrate an application container clustering system or orchestration system (e.g., KUBERNETES) on multiple GPUs to allowseamless scaling and load balancing.

[0128] FIG. **14** is a system diagram for an example system **1400** for generating and deploying an imaging deployment pipeline, in accordance with at least one embodiment. In at least one embodiment, system **1400** may be used to implement process **1300** of FIG. **13** and/or other processes including advanced processing and inferencing pipelines. In at least one embodiment, system **1400** may include training system **1304** and deployment system **1306**. In at least one embodiment, training system **1304** and deployment system **1306** may be implemented using software **1318**, services **1320**, and/or hardware **1322**, as described herein.

[0129] In at least one embodiment, system **1400** (e.g., training system **1304** and/or deployment system **1306**) may implemented in a cloud computing environment (e.g., using cloud **1426**). In at least one embodiment, system **1400** may be implemented locally with respect to a healthcare services facility, or as a combination of both cloud and local computing resources. In at least one embodiment, access to APIs in cloud **1426** may be restricted to authorized users through enacted security measures or protocols. In at least one embodiment, a security protocol may include web tokens that may be signed by an authentication (e.g., AuthN, AuthZ, Gluecon, etc.) service and may carry appropriate authorization. In at least one embodiment, APIs of virtual instruments (described herein), or other instantiations of system **1400**, may be restricted to a set of public IPs that have been vetted or authorized for interaction.

[0130] In at least one embodiment, various components of system **1400** may communicate between and among one another using any of a variety of different network types, including but not limited to local area networks (LANs) and/or wide area networks (WANs) via wired and/or wireless communication protocols. In at least one embodiment, communication between facilities and components of system **1400** (e.g., for transmitting inference requests, for receiving results of inference requests, etc.) may be communicated over data bus(ses), wireless data protocols (Wi-Fi), wired data protocols (e.g., Ethernet), etc.

[0131] In at least one embodiment, training system **1304** may execute training pipelines **1404**, similar to those described herein with respect to FIG. **13**. In at least one embodiment, where one or more machine learning models are to be used in deployment pipelines **1410** by deployment system **1306**, training pipelines **1404** may be used to train or retrain one or more (e.g. pre-trained) models, and/or implement one or more of pre-trained models **1406** (e.g., without a need for retraining or updating). In at least one embodiment, as a result of training pipelines **1404**, output model(s) **1316** may be generated. In at least one embodiment, training pipelines **1404** may include any number of processing steps, such as but not limited to imaging data (or other input data) conversion or adaption In at least one embodiment, for different machine learning models used by deployment system **1306**, different training pipelines **1404** may be used. In at least one embodiment, training pipeline **1404** similar to a first example described with respect to FIG. **13** may be used for a first machine learning model, training pipeline **1404** similar to a second example described with respect to FIG. **13** may be used for a second machine learning model, and training pipeline **1404** similar to a third example described with respect to FIG. **13** may be used for a third machine learning model. In at least one embodiment, any combination of tasks within training system **1304** may be used depending on what is required for each respective machine learning model. In at least one embodiment, one or more of machine learning models may already be trained and ready for deployment so machine learning models may not undergo any processing by training system **1304**, and may be implemented by deployment system **1306**.

[0132] In at least one embodiment, output model(s) **1316** and/or pre-trained model(s) **1406** may include any types of machine learning models depending on implementation or embodiment. In at least one embodiment, and without limitation, machine learning models used by system **1400** may include machine learning model(s) using linear regression, logistic regression, decision trees, support vector machines (SVM), Naive Bayes, k-nearest neighbor (Knn), K means clustering, random forest, dimensionality reduction algorithms, gradient boosting algorithms, neural networks (e.g., auto-encoders, convolutional, recurrent, perceptrons, Long/Short Term Memory (LSTM), Hopfield, Boltzmann, deep belief, deconvolutional, generative adversarial, liquid state machine, etc.), and/or other types of machine learning models.

[0133] In at least one embodiment, training pipelines **1404** may include AI-assisted annotation, as described in more detail herein with respect to at least FIG. **15**B. In at least one embodiment, labeled data **1312** (e.g., traditional annotation) may be generated by any number of techniques. In at least one embodiment, labels or other annotations may be generated within a drawing program (e.g., an annotation program), a computer aided design (CAD) program, a labeling program, another type of program suitable for generating annotations or labels for ground truth, and/or may be hand drawn, in some examples. In at least one embodiment, ground truth data may be synthetically produced (e.g., generated from computer models or renderings), real produced (e.g., designed and produced from real-world data), machine-automated (e.g., using feature analysis and learning to extract features from data and then generate labels), human annotated (e.g., labeler, or annotation expert, defines location of labels), and/or a combination thereof. In at least one embodiment, for each instance of imaging data **1308** (or other data type used by machine learning models), there may be corresponding ground truth data generated by training system **1304**. In at least one embodiment, AI-assisted annotation may be performed as part of deployment pipelines **1410**; either in addition to, or in lieu of AI-assisted annotation included in training pipelines **1404**. In at least one embodiment, system **1400** may include a multi-layer platform that may include a software layer (e.g., software **1318**) of diagnostic applications (or other application types) that may perform one or more medical imaging and diagnostic functions. In at least one embodiment, system **1400** may be communicatively coupled to (e.g., via encrypted links) PACS server networks of one or more facilities. In at least one embodiment, system **1400** may be configured to access and referenced data from PACS servers to perform operations, such as training machine learning models, deploying machine learning models, image processing, inferencing, and/or other operations.

[0134] In at least one embodiment, a software layer may be implemented as a secure, encrypted, and/or authenticated API through which applications or containers may be invoked (e.g., called) from an external environment(s) (e.g., facility **1302**). In at least one embodiment, applications may then call or execute one or more services **1320** for performing compute, AI, or visualization tasks associated with respective applications, and software **1318** and/or services **1320** may leverage hardware **1322** to perform processing tasks in an effective and efficient manner.

[0135] In at least one embodiment, deployment system **1306** may execute deployment pipelines **1410**. In at least one embodiment, deployment pipelines **1410** may include any number of applications that may be sequentially, non-sequentially, or otherwise applied to imaging data (and/or other data types) generated by imaging devices, sequencing devices, genomics devices, etc.—including AI-assisted annotation, as described above. In at least one embodiment, as described herein, a deployment pipeline **1410** for an individual device may be referred to as a virtual instrument for a device (e.g., a virtual ultrasound instrument, a virtual CT scan instrument, a virtual sequencing instrument, etc.). In at least one embodiment, for a single device, there may be more than one deployment pipeline **1410** depending on information desired from data generated by a device. In at least one embodiment, where detections of anomalies are desired from an Mill machine, there may be a first deployment pipeline **1410**, and where image enhancement is desired from output of an Mill machine, there may be a second deployment pipeline **1410**.

[0136] In at least one embodiment, an image generation application may include a processing task that includes use of a machine learning model. In at least one embodiment, a user may desire to use their own machine learning model, or to select a machine learning model from model registry **1324**. In at least one embodiment, a user may implement their own machine learning model or select a machine learning model for inclusion in an application for performing a processing task. In at least one embodiment, applications may be selectable and customizable, and by defining constructs of applications, deployment and implementation of applications for a particular user are presented as a more seamless user experience. In at least one embodiment, by leveraging other features of system **1400**—such as services **1320** and hardware **1322**—deployment pipelines **1410** may be even more user friendly, provide for easier integration, and produce more accurate, efficient, and timely results.

[0137] In at least one embodiment, deployment system **1306** may include a user interface **1414** (e.g., a graphical user interface, a web interface, etc.) that may be used to select applications for inclusion in deployment pipeline(s) **1410**, arrange applications, modify or change applications or parameters or constructs thereof, use and interact with deployment pipeline(s) **1410** during set-up and/or deployment, and/or to otherwise interact with deployment system **1306**. In at least one embodiment, although not illustrated with respect to training system **1304**, user interface **1414** (or a different user interface) may be used for selecting models for use in deployment system **1306**, for selecting models for training, or retraining, in training system **1304**, and/or for otherwise interacting with training system **1304**.

[0138] In at least one embodiment, pipeline manager **1412** may be used, in addition to an application orchestration system **1428**, to manage interaction between applications or containers of deployment pipeline(s) **1410** and services **1320** and/or hardware **1322**. In at least one embodiment, pipeline manager **1412** may be configured to facilitate interactions from application to application, from application to service **1320**, and/or from application or service to hardware **1322**. In at least one embodiment, although illustrated as included in software **1318**, this is not intended to be limiting, and in some examples (e.g., as illustrated in FIG. **12***cc*) pipeline manager **1412** may be included in services **1320**. In at least one embodiment, application orchestration system **1428** (e.g., Kubernetes, DOCKER, etc.) may include a container orchestration system that may group applications into containers as logical units for coordination, management, scaling, and deployment. In at least one embodiment, by associating applications from deployment pipeline(s) **1410** (e.g., a reconstruction application, a segmentation application, etc.) with individual containers, each application may execute in a self-contained environment (e.g., at a kernel level) to increase speed and efficiency.

[0139] In at least one embodiment, each application and/or container (or image thereof) may be individually developed, modified, and deployed (e.g., a first user or developer may develop, modify, and deploy a first application and a second user or developer may develop, modify, and deploy a second application separate from a first user or developer), which may allow for focus on, and attention to, a task of a single application and/or container(s) without being hindered by tasks of another application(s) or container(s). In at least one embodiment, communication, and cooperation between different containers or applications may be aided by pipeline manager **1412** and application orchestration system **1428**. In at least one embodiment, so long as an expected input and/or output of each container or application is known by a system (e.g., based on constructs of applications or containers), application orchestration system **1428** and/or pipeline manager **1412** may facilitate communication among and between, and sharing of resources among and between, each of applications or containers. In at least one embodiment, because one or more of applications or containers in deployment pipeline(s) **1410** may share same services and resources, application orchestration system **1428** may orchestrate, load balance, and determine sharing of services or resources between and among various applications or containers. In at least one embodiment, a scheduler may be used to track resource requirements of applications or containers, current usage or planned usage of these resources, and resource availability. In at least one embodiment, a scheduler may thus allocate resources to different applications and distribute resources between and among applications in view of requirements and availability of a system. In some examples, a scheduler (and/or other component of application orchestration system **1428**) may determine resource availability and distribution based on constraints imposed on a system (e.g., user constraints), such as quality of service (QoS), urgency of need for data outputs (e.g., to determine whether to execute real-time processing or delayed processing), etc.

[0140] In at least one embodiment, services **1320** leveraged by and shared by applications or containers in deployment system **1306** may include compute services **1416**, AI services **1418**, visualization services **1420**, and/or other service types. In at least one embodiment, applications may call (e.g., execute) one or more of services **1320** to perform processing operations for an application. In at least one embodiment, compute services **1416** may be leveraged by applications to perform super-computing or other high-performance computing (HPC) tasks. In at least one embodiment, compute service(s) **1416** may be leveraged to perform parallel processing (e.g., using a parallel computing platform **1430**) for processing data through one or more of applications and/or one or more tasks of a single application, substantially simultaneously. In at least one embodiment, parallel computing platform **1430** (e.g., NVIDIA's CUDA) may allow general purpose computing on GPUs (GPGPU) (e.g., GPUs **1422**). In at least one embodiment, a software layer of parallel computing platform **1430** may provide access to virtual instruction sets and parallel computational elements of GPUs, for execution of compute kernels. In at least one embodiment, parallel computing platform **1430** may include memory and, in some embodiments, a memory may be shared between and among multiple containers, and/or between and among different processing tasks within a single container. In at least one embodiment, inter-process communication (IPC) calls may be generated for multiple containers and/or for multiple processes within a container to use same data from a shared segment of memory of parallel computing platform **1430** (e.g., where multiple different stages of an application or multiple applications are processing same information). In at least one embodiment, rather than making a copy of data and moving data to different locations in memory (e.g., a read/write operation), same data in same location of a memory may be used for any number of processing tasks (e.g., at a same time, at different times, etc.). In at least one embodiment, as data is used to generate new data as a result of processing, this information of a new location of data may be stored and shared between various applications. In at least one embodiment, location of data and a location of updated or modified data may be part of a definition of how a payload is understood within containers.

[0141] In at least one embodiment, AI services **1418** may be leveraged to perform inferencing services for executing machine learning model(s) associated with applications (e.g., tasked with performing one or more processing tasks of an application). In at least one embodiment, AI services **1418** may leverage AI system **1424** to execute machine learning model(s) (e.g., neural networks, such as CNNs) for segmentation, reconstruction, object detection, feature detection, classification, and/or other inferencing tasks. In at least one embodiment, applications of deployment pipeline (s) **1410** may use one or more of output models **1316** from training system **1304** and/or other models of applications to perform inference on imaging data. In at least one embodiment, two or more examples of inferencing using application orchestration system **1428** (e.g., a scheduler) may be available. In at least one embodiment, a first category may include a high priority/low latency path that may achieve higher service level agreements, such as for performing inference on urgent requests during an emergency, or for a radiologist during diagnosis. In at least one embodiment, a second category may include a standard priority path that may be used for requests that may be non-urgent or where analysis may be performed at a later time. In at least one embodiment, application orchestration system **1428** may distribute resources (e.g., services **1320** and/or hardware **1322**) based on priority paths for different inferencing tasks of AI services **1418**.

[0142] In at least one embodiment, shared storage may be mounted to AI services **1418** within system **1400**. In at least one embodiment, shared storage may operate as a cache (or other storage device type) and may be used to process inference requests from applications. In at least one embodiment, when an inference request is submitted, a request may be received by a set of API instances of deployment system **1306**, and one or more instances may be selected (e.g., for best fit, for load balancing, etc.) to process a request. In at least one embodiment, to process a request, a request may be entered into a database, a machine learning model may be located from model registry **1324** if not already in a cache, a validation step may ensure appropriate machine learning model is loaded into a cache (e.g., shared storage), and/or a copy of a model may be saved to a cache. In at least one embodiment, a scheduler (e.g., of pipeline manager **1412**) may be used to launch an application that is referenced in a request if an application is not already running or if there are not enough instances of an application. In at least one embodiment, if an inference server is not already launched to execute a model, an inference server may be launched. Any number of inference servers may be launched per model. In at least one embodiment, in a pull model, in which inference servers are clustered, models may be cached whenever load balancing is advantageous. In at least one embodiment, inference servers may be statically loaded in corresponding, distributed servers.

[0143] In at least one embodiment, inferencing may be performed using an inference server that runs in a container. In at least one embodiment, an instance of an inference server may be associated with a model (and optionally a plurality of versions of a model). In at least one embodiment, if an instance of an inference server does not exist when a request to perform inference on a model is received, a new instance may be loaded. In at least one embodiment, when starting an inference server, a model may be passed to an inference server such that a same container may be used to serve different models so long as inference server is running as a different instance.

[0144] In at least one embodiment, during application execution, an inference request for a given application may be received, and a container (e.g., hosting an instance of an inference server) may be loaded (if not already), and a start procedure may be called. In at least one embodiment, pre-processing logic in a container may load, decode, and/or perform any additional pre-processing on incoming data (e.g., using a CPU(s) and/or GPU(s)). In at least one embodiment, once data is prepared for inference, a container may perform inference as necessary on data. In at least one embodiment, this may include a single inference call on one image (e.g., a hand X-ray), or may require inference on hundreds of images (e.g., a chest CT). In at least one embodiment, an application may summarize results before completing, which may include, without limitation, a single confidence score, pixel level-segmentation, voxel-level segmentation, generating a visualization, or generating text to summarize findings. In at least one embodiment, different models or applications may be assigned different priorities. For example, some models may have a real-time (TAT<1 min) priority while others may have lower priority (e.g., TAT<10 min). In at least one embodiment, model execution times may be measured from requesting institution or entity and may include partner network traversal time, as well as execution on an inference service.

[0145] In at least one embodiment, transfer of requests between services **1320** and inference applications may be hidden behind a software development kit (SDK), and robust transport may be provide through a queue. In at least one embodiment, a request will be placed in a queue via an API for an individual application/tenant ID combination and an SDK will pull a request from a queue and give a request to an application. In at least one embodiment, a name of a queue may be provided in an environment from where an SDK will pick it up. In at least one embodiment, asynchronous communication through a queue may be useful as it may allow any instance of an application to pick up work as it becomes available. Results may be transferred back through a queue, to ensure no data is lost. In at least one embodiment, queues may also provide an ability to segment work, as highest priority work may go to a queue with most instances of an application connected to it, while lowest priority work may go to a queue with a single instance connected to it that processes tasks in an order received. In at least one embodiment, an application may run on a GPU-accelerated instance generated in cloud **1426**, and an inference service may perform inferencing on a GPU.

[0146] In at least one embodiment, visualization services **1420** may be leveraged to generate visualizations for viewing outputs of applications and/or deployment pipeline(s) **1410**. In at least one embodiment, GPUs **1422** may be leveraged by visualization services **1420** to generate visualizations. In at least one embodiment, rendering effects, such as ray-tracing, may be implemented by visualization services **1420** to generate higher quality visualizations. In at least one embodiment, visualizations may include, without limitation, 2D image renderings, 3D volume renderings, 3D volume reconstruction, 2D tomographic slices, virtual reality displays, augmented reality displays, etc. In at least one embodiment, virtualized environments may be used to generate a virtual interactive display or environment (e.g., a virtual environment) for interaction by users of a system (e.g., doctors, nurses, radiologists, etc.). In at least one embodiment, visualization services **1420** may include an internal visualizer, cinematics, and/or other rendering or image processing capabilities or functionality (e.g., ray tracing, rasterization, internal optics, etc.).

[0147] In at least one embodiment, hardware **1322** may include GPUs **1422**, AI system **1424**, cloud **1426**, and/or any other hardware used for executing training system **1304** and/or deployment system **1306**. In at least one embodiment, GPUs **1422** (e.g., NVIDIA's TESLA and/or QUADRO GPUs) may include any number of GPUs that may be used for executing processing tasks of compute services **1416**, AI services **1418**, visualization services **1420**, other services, and/or any of features or functionality of software **1318**. For example, with respect to AI services **1418**, GPUs **1422** may be used to perform pre-processing on imaging data (or other data types used by machine learning models), post-processing on outputs of machine learning models, and/or to perform inferencing (e.g., to execute machine learning models). In at least one embodiment, cloud **1426**, AI system **1424**, and/or other components of system **1400** may use GPUs **1422**. In at least one embodiment, cloud **1426** may include a GPU-optimized platform for deep learning tasks. In at least one embodiment, AI system **1424** may use GPUs, and cloud **1426** — or at least a portion tasked with deep learning or inferencing — may be executed using one or more AI systems **1424**. As such, although hardware **1322** is illustrated as discrete components, this is not intended to be limiting, and any components of hardware **1322** may be combined with, or leveraged by, any other components of hardware **1322**.

[0148] In at least one embodiment, AI system **1424** may include a purpose-built computing system (e.g., a supercomputer or an HPC) configured for inferencing, deep learning, machine learning, and/or other artificial intelligence tasks. In at least one embodiment, AI system **1424** (e.g., NVIDIA's DGX) may include GPU-optimized software (e.g., a software stack) that may be executed using a plurality of GPUs **1422**, in addition to CPUs, RAM, storage, and/or other components, features, or functionality. In at least one embodiment, one or more AI systems **1424** may be implemented in cloud **1426** (e.g., in a data center) for performing some or all of AI-based processing tasks of system **1400**.

[0149] In at least one embodiment, cloud **1426** may include a GPU-accelerated infrastructure (e.g., NVIDIA's NGC) that may provide a GPU-optimized platform for executing processing tasks of system **1400**. In at least one embodiment, cloud **1426** may include an AI system(s) **1424** for performing one or more of AI-based tasks of system **1400** (e.g., as a hardware abstraction and scaling platform). In at least one embodiment, cloud **1426** may integrate with application orchestration system **1428** leveraging multiple GPUs to allowseamless scaling and load balancing between and among applications and services **1320**. In at least one embodiment, cloud **1426** may tasked with executing at least some of services **1320** of system **1400**, including compute services **1416**, AI services **1418**, and/or visualization services **1420**, as described herein. In at least one embodiment, cloud **1426** may perform small and large batch inference (e.g., executing NVIDIA's TENSOR RT), provide an accelerated parallel computing API and platform **1430** (e.g., NVIDIA's CUDA), execute application orchestration system **1428** (e.g., KUBERNETES), provide a graphics rendering API and platform (e.g., for ray-tracing, 2D graphics, 3D graphics, and/or other rendering techniques to produce higher quality cinematics), and/or may provide other functionality for system **1400**.

[0150] FIG. **15**A illustrates a data flow diagram for a process **1500** to train, retrain, or update a machine learning model, in accordance with at least one embodiment. In at least one embodiment, process **1500** may be executed using, as a non-limiting example, system **1400** of FIG. **14**. In at least one embodiment, process **1500** may leverage services **1320** and/or hardware **1322** of system **1400**, as described herein. In at least one embodiment, refined models **1512** generated by process **1500** may be executed by deployment system **1306** for one or more containerized applications in deployment pipelines **1410**.

[0151] In at least one embodiment, model training **1314** may include retraining or updating an initial model **1504** (e.g., a pre-trained model) using new training data (e.g., new input data, such as customer dataset **1506**, and/or new ground truth data associated with input data). In at least one embodiment, to retrain, or update, initial model **1504**, output or loss layer(s) of initial model **1504** may be reset, or deleted, and/or replaced with an updated or new output or loss layer(s). In at least one embodiment, initial model **1504** may have previously fine-tuned parameters (e.g., weights and/or biases) that remain from prior training, so training or retraining **1314** may not take as long or require as much processing as training a model from scratch. In at least one embodiment, during model training **1314**, by having reset or replaced output or loss layer(s) of initial model **1504**, parameters may be updated and re-tuned for a new data set based on loss calculations associated with accuracy of output or loss layer(s) at generating predictions on new, customer dataset **1506** (e.g., image data **1308** of FIG. **13**).

[0152] In at least one embodiment, pre-trained models **1406** may be stored in a data store, or registry (e.g., model registry **1324** of FIG. **13**). In at least one embodiment, pre-trained models **1406** may have been trained, at least in part, at one or more facilities other than a facility executing process **1500**. In at least one embodiment, to protect privacy and rights of patients, subjects, or clients of different facilities, pre-trained models **1406** may have been trained, on-premise, using customer or patient data generated on-premise. In at least one embodiment, pre-trained models **1406** may be trained using cloud **1426** and/or other hardware **1322**, but confidential, privacy protected patient data may not be transferred to, used by, or accessible to any components of cloud **1426** (or other off premise hardware). In at least one embodiment, where a pre-trained model **1406** is trained at using patient data from more than one facility, pre-trained model **1406** may have been individually trained for each facility prior to being trained on patient or customer data from another facility. In at least one embodiment, such as where a customer or patient data has been released of privacy concerns (e.g., by waiver, for experimental use, etc.), or where a customer or patient data is included in a public data set, a customer or patient data from any number of facilities may be used to train pre-trained model **1406** on-premise and/or off premise, such as in a datacenter or other cloud computing infrastructure.

[0153] In at least one embodiment, when selecting applications for use in deployment pipelines **1410**, a user may also select machine learning models to be used for specific applications. In at least one embodiment, a user may not have a model for use, so a user may select a pre-trained model **1406** to use with an application. In at least one embodiment, pre-trained model **1406** may not be optimized for generating accurate results on customer dataset **1506** of a facility of a user (e.g., based on patient diversity, demographics, types of medical imaging devices used, etc.). In at least one embodiment, prior to deploying pre-trained model **1406** into deployment pipeline **1410** for use with an application(s), pre-trained model **1406** may be updated, retrained, and/or fine-tuned for use at a respective facility.

[0154] In at least one embodiment, a user may select pre-trained model **1406** that is to be updated, retrained, and/or fine-tuned, and pre-trained model **1406** may be referred to as initial model **1504** for training system **1304** within process **1500**. In at least one embodiment, customer dataset **1506** (e.g., imaging data, genomics data, sequencing data, or other data types generated by devices at a facility) may be used to perform model training **1314** (which may include, without limitation, transfer learning) on initial model **1504** to generate refined model **1512**. In at least one embodiment, ground truth data corresponding to customer dataset **1506** may be generated by training system **1304**. In at least one embodiment, ground truth data may be generated, at least in part, by clinicians, scientists, doctors, practitioners, at a facility (e.g., as labeled clinic data **1312** of FIG. **13**).

[0155] In at least one embodiment, AI-assisted annotation **1310** may be used in some examples to generate ground truth data. In at least one embodiment, AI-assisted annotation **1310** (e.g., implemented using an AI-assisted annotation SDK) may leverage machine learning models (e.g., neural networks) to generate suggested or predicted ground truth data for a customer dataset. In at least one embodiment, user **1510** may use annotation tools within a user interface (a graphical user interface (GUI)) on computing device **1508**.

[0156] In at least one embodiment, user **1510** may interact with a GUI via computing device **1508** to edit or fine-tune (auto)annotations. In at least one embodiment, a polygon editing feature may be used to move vertices of a polygon to more accurate or fine-tuned locations.

[0157] In at least one embodiment, once customer dataset **1506** has associated ground truth data, ground truth data (e.g., from AI-assisted annotation, manual labeling, etc.) may be used by during model training **1314** to generate refined model **1512**. In at least one embodiment, customer dataset **1506** may be applied to initial model **1504** any number of times, and ground truth data may be used to update parameters of initial model **1504** until an acceptable level of accuracy is attained for refined model **1512**. In at least one embodiment, once refined model **1512** is generated, refined model **1512** may be deployed within one or more deployment pipelines **1410** at a facility for performing one or more processing tasks with respect to medical imaging data.

[0158] In at least one embodiment, refined model **1512** may be uploaded to pre-trained models **1406** in model registry **1324** to be selected by another facility. In at least one embodiment, his process may be completed at any number of facilities such that refined model **1512** may be further refined on new datasets any number of times to generate a more universal model.

[0159] FIG. 15B is an example illustration of a client-server architecture **1532** to enhance annotation tools with pre-trained annotation models, in accordance with at least one embodiment. In at least one embodiment, AI-assisted annotation tools **1536** may be instantiated based on a client-server architecture **1532**. In at least one embodiment, annotation tools **1536** in imaging applications may aid radiologists, for example, identify organs and abnormalities. In at least one embodiment, imaging applications may include software tools that help user **1510** to identify, as a non-limiting example, a few extreme points on a particular organ of interest in raw images **1534** (e.g., in a 3D MRI or CT scan) and receive auto-annotated results for all 2D slices of a particular organ. In at least one embodiment, results may be stored in a data store as training data **1538** and used as (for example and without limitation) ground truth data for training. In at least one embodiment, when computing device **1508** sends extreme points for AI-assisted annotation **1310**, a deep learning model, for example, may receive this data as input and return inference results of a segmented organ or abnormality. In at least one embodiment, pre-instantiated annotation tools, such as AI-Assisted Annotation Tool **1536**B in FIG. **15**B, may be enhanced by making API calls (e.g., API Call **1544**) to a server, such as an Annotation Assistant Server **1540** that may include a set of pre-trained models **1542** stored in an annotation model registry, for example. In at least one embodiment, an annotation model registry may store pre-trained models **1542** (e.g., machine learning models, such as deep learning models) that are pre-trained to perform AI-assisted annotation on a particular organ or abnormality. These models may be further updated by using training pipelines **1404**. In at least one embodiment, pre-installed annotation tools may be improved over time as new labeled clinic data **1312** is added.

[0160] Such components can be used to determine one or more emotion values from audio data.

[0161] Other variations are within spirit of present disclosure. Thus, while disclosed techniques are susceptible to various modifications and alternative constructions, certain illustrated embodiments thereof are shown in drawings and have been described above in detail. It should be understood, however, that there is no intention to limit disclosure to specific form or forms disclosed, but on contrary, intention is to cover all modifications, alternative constructions, and equivalents falling within spirit and scope of disclosure, as defined in appended claims.

[0162] Use of terms "a" and "an" and "the" and similar referents in context of describing disclosed embodiments (especially in context of following claims) are to be construed to cover both singular and plural, unless otherwise indicated herein or clearly contradicted by context, and not as a definition of a term. Terms "comprising," "having," "including," and "containing" are to be construed as open-ended terms (meaning "including, but not limited to,") unless otherwise noted. Term "connected," when unmodified and referring to physical connections, is to be construed as partly or wholly contained within, attached to, or joined together, even if there is something intervening. Recitation of ranges of values herein are merely intended to serve as a shorthand method of referring individually to each separate value falling within range, unless otherwise indicated herein and each separate value is incorporated into specification as if it were individually recited herein. Use of term "set" (e.g., "a set of items") or "subset," unless otherwise noted or contradicted by context, is to be construed as a nonempty collection comprising one or more members. Further, unless otherwise noted or contradicted by context, term "subset" of a corresponding set does not necessarily denote a proper subset of corresponding set, but subset and corresponding set may be equal.

[0163] Conjunctive language, such as phrases of form "at least one of A, B, and C," or "at least one of A, B and C," unless specifically stated otherwise or otherwise clearly contradicted by context, is otherwise understood with context as used in general to present that an item, term, etc., may be either A or B or C, or any nonempty subset of set of A and B and C. For instance, in illustrative example of a set having three members, conjunctive phrases "at least one of A, B, and C" and "at least one of A, B and C" refer to any of following sets: {A}, {B}, {C}, {A, B}, {A, C}, {B, C}, {A, B, C}. Thus, such conjunctive language is not generally intended to imply that certain embodiments require at least one of A, at least one of B, and at least one of C each to be present. In addition, unless otherwise noted or contradicted by context, term "plurality" indicates a state of being plural (e.g., "a plurality of items" indicates multiple items). A plurality is at least two items, but can be more when so indicated either explicitly or by context. Further, unless stated otherwise or otherwise clear from context, phrase "based on" means "based at least in part on" and not "based solely on."

[0164] Operations of processes described herein can be performed in any suitable order unless otherwise indicated herein or otherwise clearly contradicted by context. In at least one embodiment, a process such as those processes described herein (or variations and/or combinations thereof) is performed under control of one or more computer systems configured with executable instructions and is implemented as code (e.g., executable instructions, one or more computer programs or one or more applications) executing collectively on one or more processors, by hardware or combinations thereof In at least one embodiment, code is stored on a computer-readable storage medium, for example, in form of a computer program comprising a plurality of instructions executable by one or more processors. In at least one embodiment, a computer-readable storage medium is a non-transitory computer-readable storage medium that excludes transitory signals (e.g., a propagating transient electric or electromagnetic transmission) but includes non-transitory data storage circuitry (e.g., buffers, cache, and queues) within transceivers of transitory signals. In at least one embodiment, code (e.g., executable code or source code) is stored on a set of one or more non-transitory computer-readable storage media having stored thereon executable instructions (or other memory to store executable instructions) that, when executed (i.e., as a result of being executed) by one or more processors of a computer system, cause computer system to perform operations described herein. A set of non-transitory computer-readable storage media, in at least one embodiment, comprises multiple non-transitory computer-readable storage media and one or more of individual non-transitory storage media of multiple non-transitory computer-readable storage media lack all of code while multiple non-transitory computer-readable storage media collectively store all of code. In at least one embodiment, executable instructions are executed such that different instructions are executed by different processors—for example, a non-transitory computer-readable storage medium store instructions and a main central processing unit ("CPU") executes some of instructions while a graphics processing unit ("GPU") executes other instructions. In at least one embodiment, different components of a computer system have separate processors and different processors execute different subsets of instructions.

[0165] Accordingly, in at least one embodiment, computer systems are configured to implement one or more services that singly or collectively perform operations of processes described herein and such computer systems are configured with applicable hardware and/or software that allow performance of operations. Further, a computer system that implements at least one embodiment of present disclosure is a single device and, in another embodiment, is a distributed computer system comprising multiple devices that operate differently such that distributed computer system performs operations described herein and such that a single device does not perform all operations.

[0166] Use of any and all examples, or exemplary language (e.g., "such as") provided herein, is intended merely to better illuminate embodiments of disclosure and does not pose a limitation on scope of disclosure unless otherwise claimed. No language in specification should be construed as indicating any non-claimed element as essential to practice of disclosure.

[0167] All references, including publications, patent applications, and patents, cited herein are hereby incorporated by reference to same extent as if each reference were individually and specifically indicated to be incorporated by reference and were set forth in its entirety herein.

[0168] In description and claims, terms "coupled" and "connected," along with their derivatives, may be used. It should be understood that these terms may be not intended as synonyms for each other. Rather, in particular examples, "connected" or "coupled" may be used to indicate that two or more elements are in direct or indirect physical or electrical contact with each other. "Coupled" may also mean that two or more elements are not in direct contact with each other, but yet still co-operate or interact with each other.

[0169] Unless specifically stated otherwise, it may be appreciated that throughout specification terms such as "processing," "computing," "calculating," "determining," or like, refer to action and/or processes of a computer or computing system, or similar electronic computing device, that manipulate and/or transform data represented as physical, such as electronic, quantities within computing system's registers and/or memories into other data similarly represented as physical quantities within computing system's memories, registers or other such information storage, transmission or display devices.

[0170] In a similar manner, term "processor" may refer to any device or portion of a device that processes electronic data from registers and/or memory and transform that electronic data into other electronic data that may be stored in registers and/or memory. As non-limiting examples, "processor" may be a CPU or a GPU. A "computing platform" may comprise one or more processors. As used herein, "software" processes may include, for example, software and/or hardware entities that perform work over time, such as tasks, threads, and intelligent agents. Also, each process may refer to multiple processes, for carrying out instructions in sequence or in parallel, continuously or intermittently. Terms "system" and "method" are used herein interchangeably insofar as system may embody one or more methods and methods may be considered a system.

[0171] In present document, references may be made to obtaining, acquiring, receiving, or inputting analog or digital data into a subsystem, computer system, or computer-implemented machine. Obtaining, acquiring, receiving, or inputting analog and digital data can be accomplished in a variety of ways such as by receiving data as a parameter of a function call or a call to an application programming interface. In some implementations, process of obtaining, acquiring, receiving, or inputting analog or digital data can be accomplished by transferring data via a serial or parallel interface. In another implementation, process of obtaining, acquiring, receiving, or inputting analog or digital data can be accomplished by transferring data via a computer network from providing entity to acquiring entity. References may also be made to providing, outputting, transmitting, sending, or presenting analog or digital data. In various examples, process of providing, outputting, transmitting, sending, or presenting analog or digital data can be accomplished by transferring data as an input or output parameter of a function call, a parameter of an application programming interface or interprocess communication mechanism.

[0172] Although discussion above sets forth example implementations of described techniques, other architectures may be used to implement described functionality, and are intended to be within scope of this disclosure. Furthermore, although specific distributions of responsibilities are defined above for purposes of discussion, various functions and responsibilities might be distributed and divided in different ways, depending on circumstances.

[0173] Furthermore, although subject matter has been described in language specific to structural features and/or methodological acts, it is to be understood that subject matter claimed in appended claims is not necessarily limited to specific features or acts described. Rather, specific features and acts are disclosed as exemplary forms of implementing the claims.

What is claimed is:

1. A computer-implemented method, comprising:

computing, using a transformer-based neural network and based at least in part on audio data representative of speech, one or more values indicative of one or more emotions;

determining, based at least in part on the one or more values, that at least one emotion of the one or more emotions corresponds to the speech; and

performing one or more operations based at least in part on the at least one emotion.

2. The computer-implemented method of claim **1**, wherein the one or more values include a respective one or more probability values for each emotion of the one or more emotions, and the one or more values are normalized and summed to an absolute value.

3. The computer-implemented method of claim **1**, wherein the one or more emotions include at least one of anger, disgust, fear, joy, sadness, or a neutral emotion.

4. The computer-implemented method of claim **1**, further comprising:

providing an interface to receive user input corresponding to one or more adjustments of the one or more values.

5. The computer-implemented method of claim **4**, further comprising:

receiving, via the interface, one or more emotion strength values for use in weighting the at least one emotion with respect to at least one other emotion of the one or more emotions determined to correspond to the speech.

6. The computer-implemented method of claim **4**, further comprising:

receiving, through the interface, one or more prior values corresponding to the one or more emotions; and

blending the one or more prior values with the one or more values to generate one or more blended values,

wherein the determining that the at least one emotion of the one or more emotions corresponds to the speech is based at least in part on the one or more blended values.

7. The computer-implemented method of claim **6**, further comprising:

receiving one or more prior emotion strength values corresponding to the one or more emotions, the one or more prior emotion strength values indicating one or more weights to be used in the blending of the one or more prior values with the one or more values.

8. The computer-implemented method of claim **1**, further comprising:

determining one or more probability values for the one or more emotions for each keyframe of a set of keyframes in the audio data, the one or more probability values being determined using a sliding window of audio data for a given audio segment.

9. The computer-implemented method of claim **8**, further comprising:

smoothing the one or more values corresponding to the one or more emotions across a plurality of iterations.

10. The computer-implemented method of claim **1**, wherein the audio data is represented using an audio file format.

11. A processor comprising:

one or more processing units to:

provide audio data in an audio file format as input to a transformer neural network;

compute, using the transformer neural network and based at least in part on the audio data, one or more values indicative of one or more emotions corresponding to the audio data; and

perform one or more operations based at least in part on a determination that at least one emotion of the one or more emotions corresponds to the audio data.

12. The processor of claim **11**, wherein the one or more emotions include a predetermined set of emotions, wherein the predetermined set of emotions includes at least anger, disgust, fear, joy, sadness, or neutral.

13. The processor of claim **11**, wherein the one or more processing units are further to:

weight the one or more values based at least in part on one or more emotion strength values corresponding to respective emotions of the one or more emotions,

wherein the one or more operations are performed based at least in part on the one or more weighted values.

14. The processor of claim **11**, wherein the one or more processing units are further to:

receive one or more prior values corresponding to the one or more emotions; and

blend the one or more prior values with the one or more values to generate one or more blended values,

wherein the determination that the at least one emotion of the one or more emotions corresponds to the audio data is based at least in part on the one or more blended values.

15. The processor of claim **11**, wherein the audio file format includes at least one of an uncompressed audio file format, a lossless compression audio file format, or a lossy compression audio file format.

16. A system comprising:

one or more processing units to:

compute, using a transformer neural network and based at least in part on audio data representative of speech, one or more first values indicating a probability that one or more emotions correspond to the speech;

compute, using a neural network and based at least in part the one or more first values and the audio data, one or more second values indicating one or more positions of one or more feature points corresponding to a virtual object; and

render the virtual object based at least in part on the one or more second values.

17. The system of claim **16**, wherein the audio data corresponds to an audio file format.

18. The system of claim **16**, wherein the audio data is processed using the transformer neural network in an audio file format and the audio data is processed using the neural network in an image file format.

19. The system of claim **16**, wherein the one or more feature points correspond to one or more facial features or one or more body features of the virtual object.

20. The system of claim **16**, wherein the system comprises at least one of:

a system for performing simulation operations;

a system for performing digital twin operations;

a system for performing light transport simulation;

a system for performing collaborative content creation for 3D assets;

a system for performing deep learning operations;

a system implemented using an edge device;

a system implemented using a robot;

a system for performing conversational AI operations;

a system for generating synthetic data;

a system incorporating one or more virtual machines (VMs);

a system implemented at least partially in a data center; or

a system implemented at least partially using cloud computing resources.

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