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Gupta et al.

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(54) **MULTI-DEVICE SPEECH PROCESSING**

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G10L 15/22 (2006.01)
G10L 15/16 (2006.01)

(52) **U.S. Cl.**
CPC ***G10L 15/16*** (2013.01); ***G10L 15/22*** (2013.01)

(58) **Field of Classification Search**
CPC G10L 15/18; G10L 15/22; G10L 15/30
See application file for complete search history.

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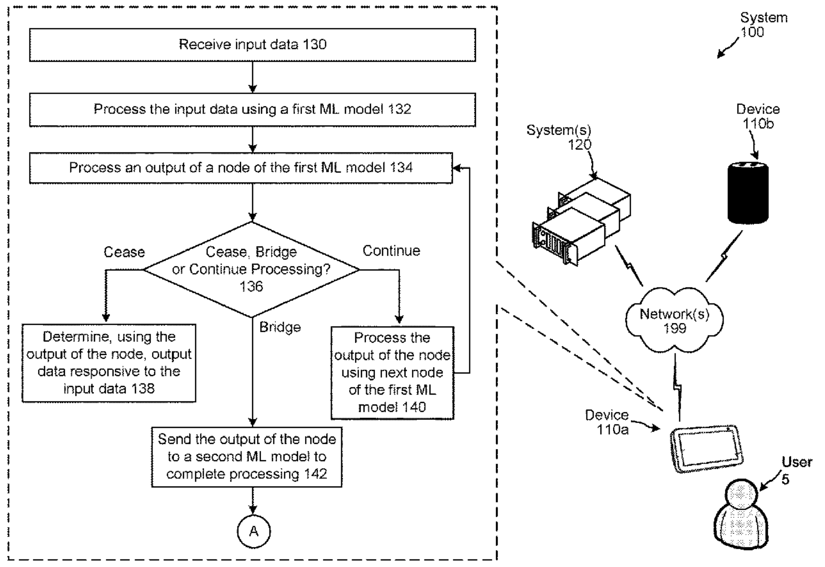
(74) *Attorney, Agent, or Firm* — Pierce Atwood LLP

(57) **ABSTRACT**

Techniques for partially processing an input on a device and completing processing at a remote system are provided. The device may process an input using an on-device machine learning (ML) model, and determine to cease processing at an intermediary node of the (ML) model based on the output of the intermediary node. Based on the output of the intermediary node satisfying a condition, the device may use the output of the intermediary node to generate an output responsive to the input. Conversely, if the output of the intermediary node does not satisfy a condition, the device may send the output of the intermediary node to the remote system, so the remote system can use another machine learning model to complete processing with respect to the input.

20 Claims, 14 Drawing Sheets



Receive input data 130
Process the input data using a first ML model 132
Process an output of a node of the first ML model 134
Cease
Cease, Bridge or Continue Processing? 136
Continue
Bridge
Determine, using the output of the node, output data responsive to the input data 138
Process the output of the node using next node of the first ML model 140
Send the output of the node to a second ML model to complete processing 142
A
System 100
System(s) 120
Device 110b
Network(s) 199
Device 110a
User 5

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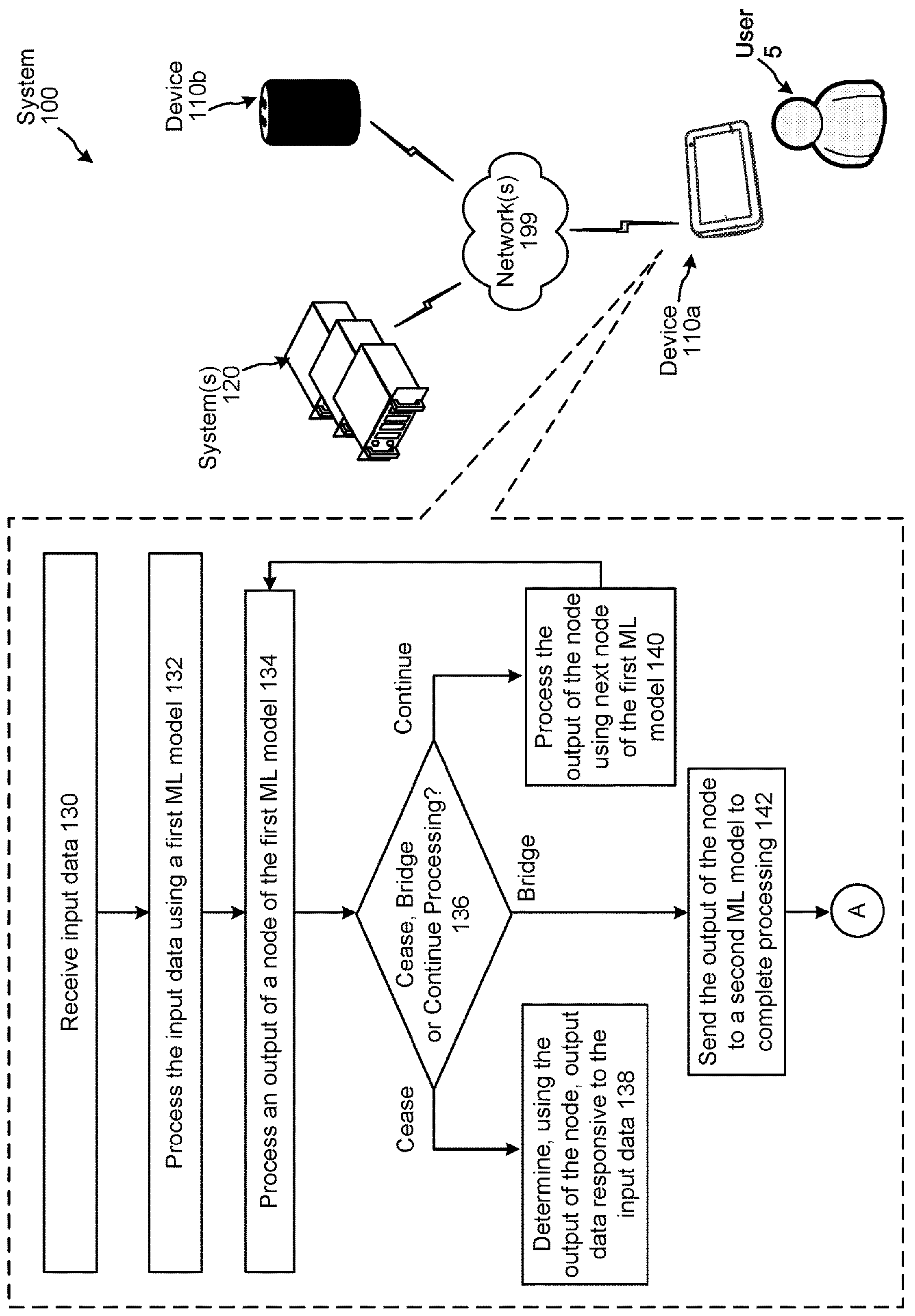
System 100
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System(s) 120
Network(s) 199
Device 110a
User 5
Receive input data 130
Process the input data using a first ML model 132
Process an output of a node of the first ML model 134
Cease, Bridge or Continue Processing? 136
Cease
Bridge
Continue
Determine, using the output of the node, output data responsive to the input data 138
Process the output of the node using next node of the first ML model 140
Send the output of the node to a second ML model to complete processing 142
A

FIG. 1A

FIG. 1B

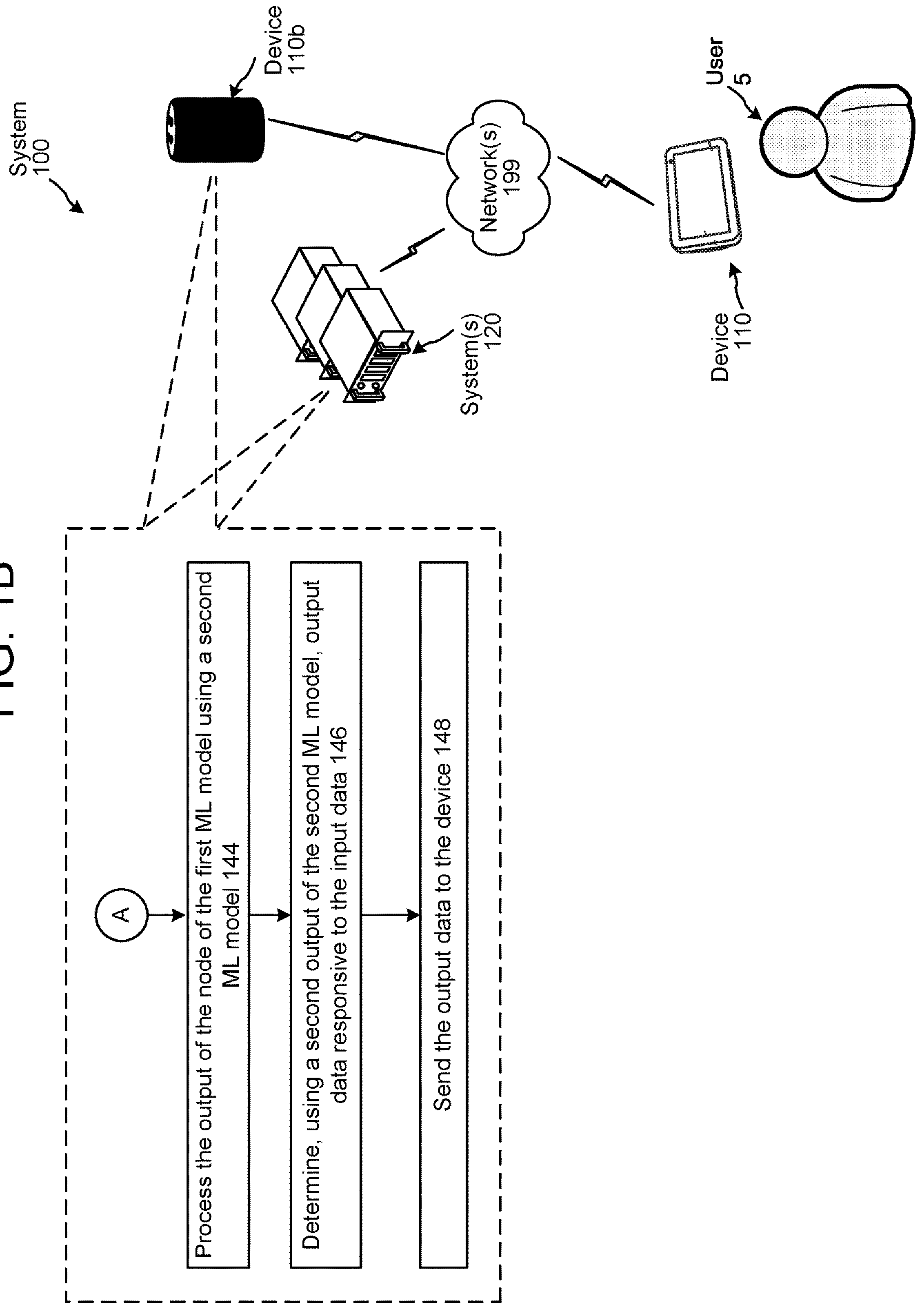

System 100
Device 110b
Network(s) 199
System(s) 120
Device 110
User 5
A
Process the output of the node of the first ML model using a second ML model 144
Determine, using a second output of the second ML model, output data responsive to the input data 146
Send the output data to the device 148

FIG. 2

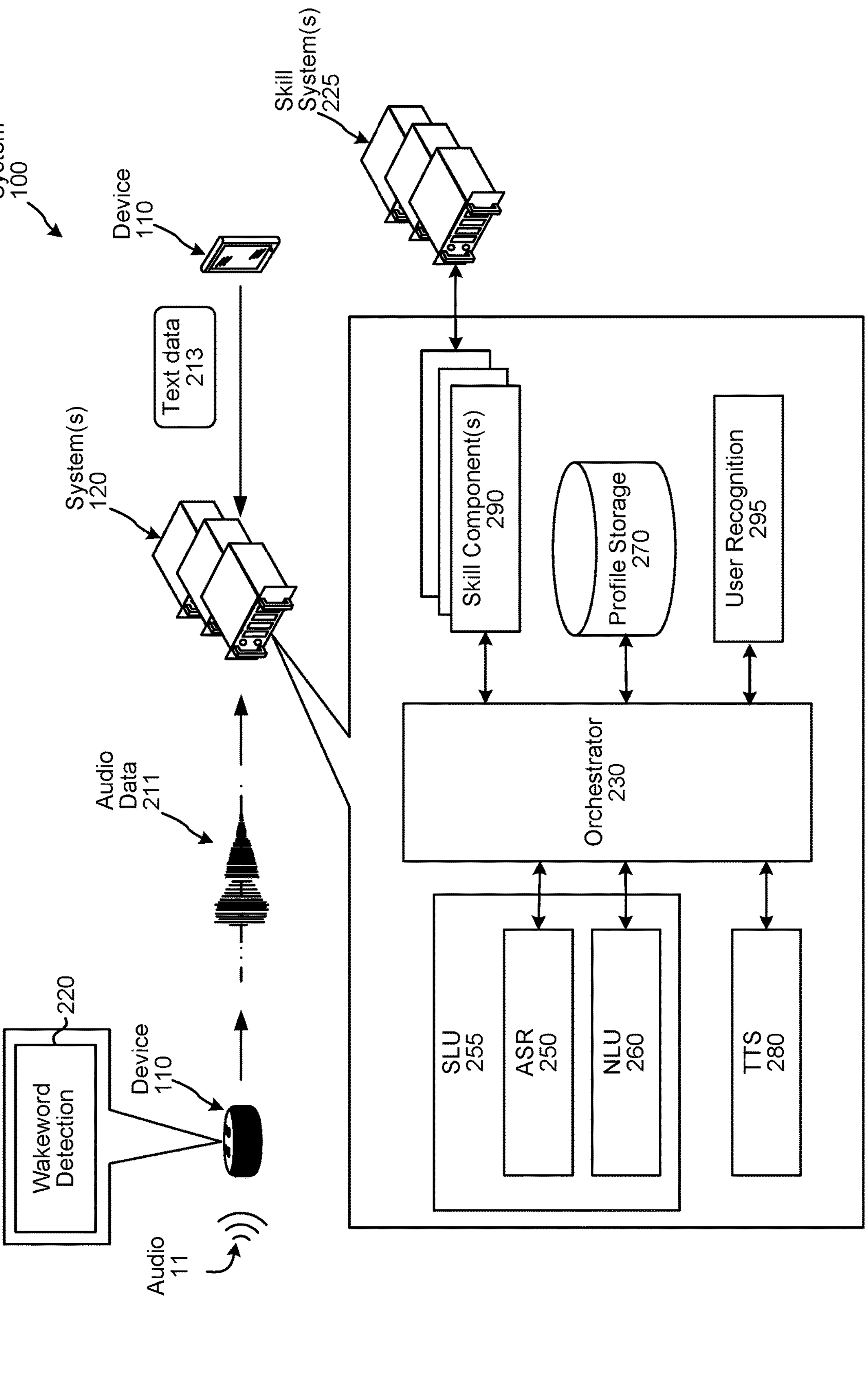

System 100
Device 110
Text data 213
Skill System(s) 225
System(s) 120
Skill Component(s) 290
Profile Storage 270
User Recognition 295
Orchestrator 230
Audio Data 211
SLU 255
ASR 250
NLU 260
TTS 280
220
Wakeword Detection
Device 110
Audio 11

FIG. 3

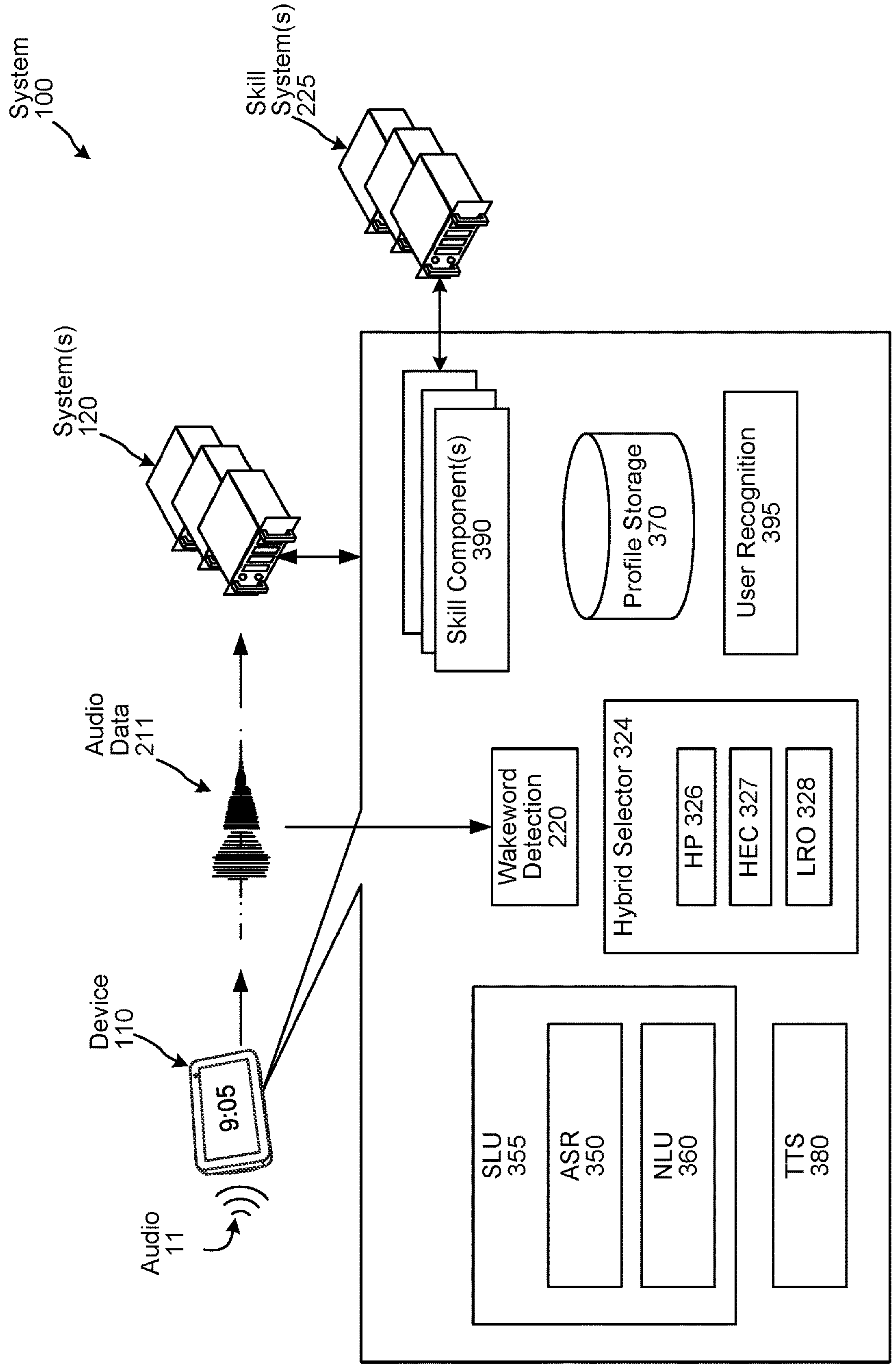

System 100
Skill System(s) 225
System(s) 120
Audio Data 211
Device 110
9:05
Audio 11
Skill Component(s) 390
Profile Storage 370
User Recognition 395
Wakeword Detection 220
Hybrid Selector 324
HP 326
HEC 327
LRO 328
SLU 355
ASR 350
NLU 360
TTS 380

FIG. 4

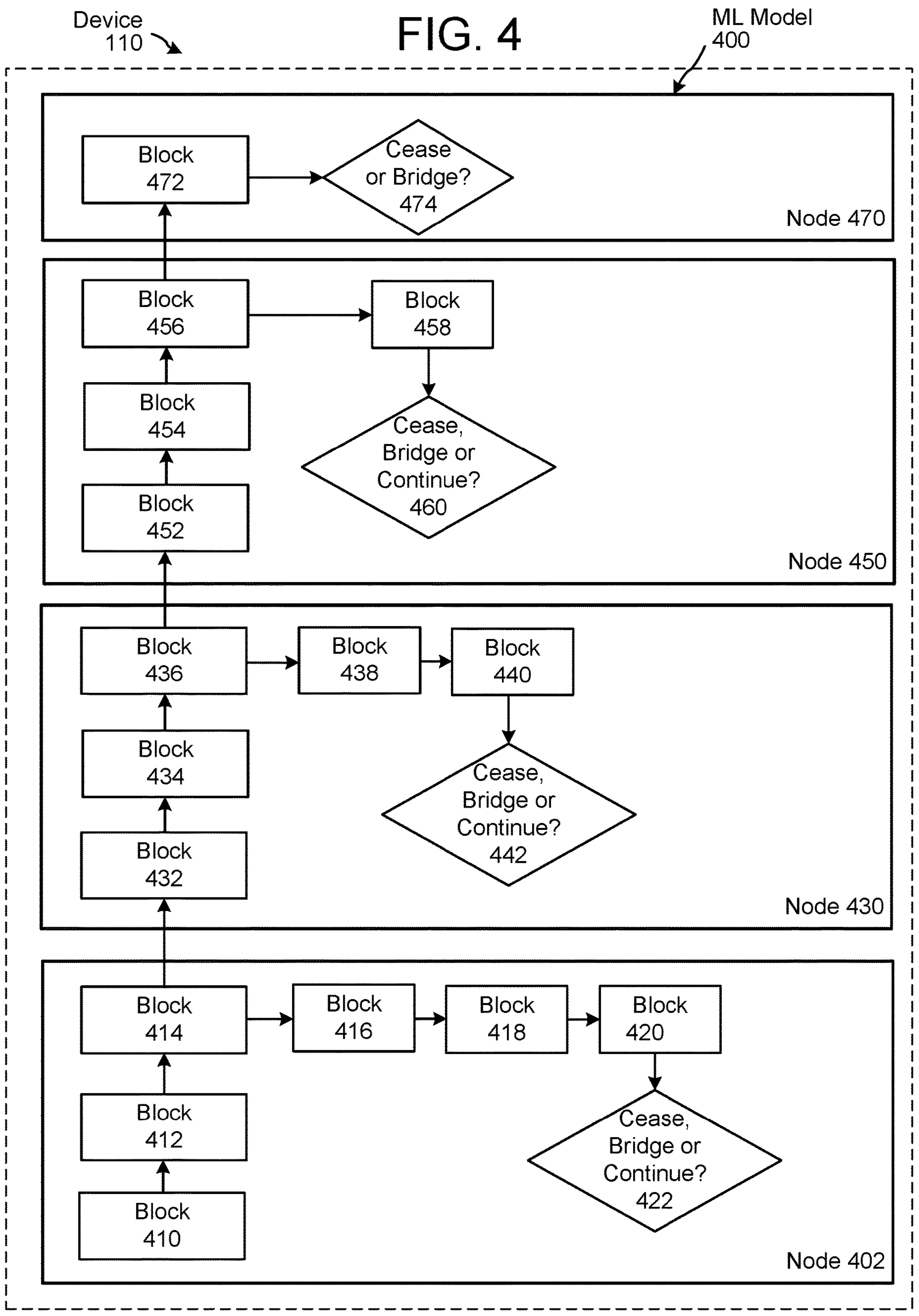

Device 110
ML Model 400
Block 472
Cease or Bridge? 474
Node 470
Block 456
Block 458
Block 454
Cease, Bridge or Continue? 460
Block 452
Node 450
Block 436
Block 438
Block 440
Block 434
Cease, Bridge or Continue? 442
Block 432
Node 430
Block 414
Block 416
Block 418
Block 420
Block 412
Cease, Bridge or Continue? 422
Block 410
Node 402

FIG. 5

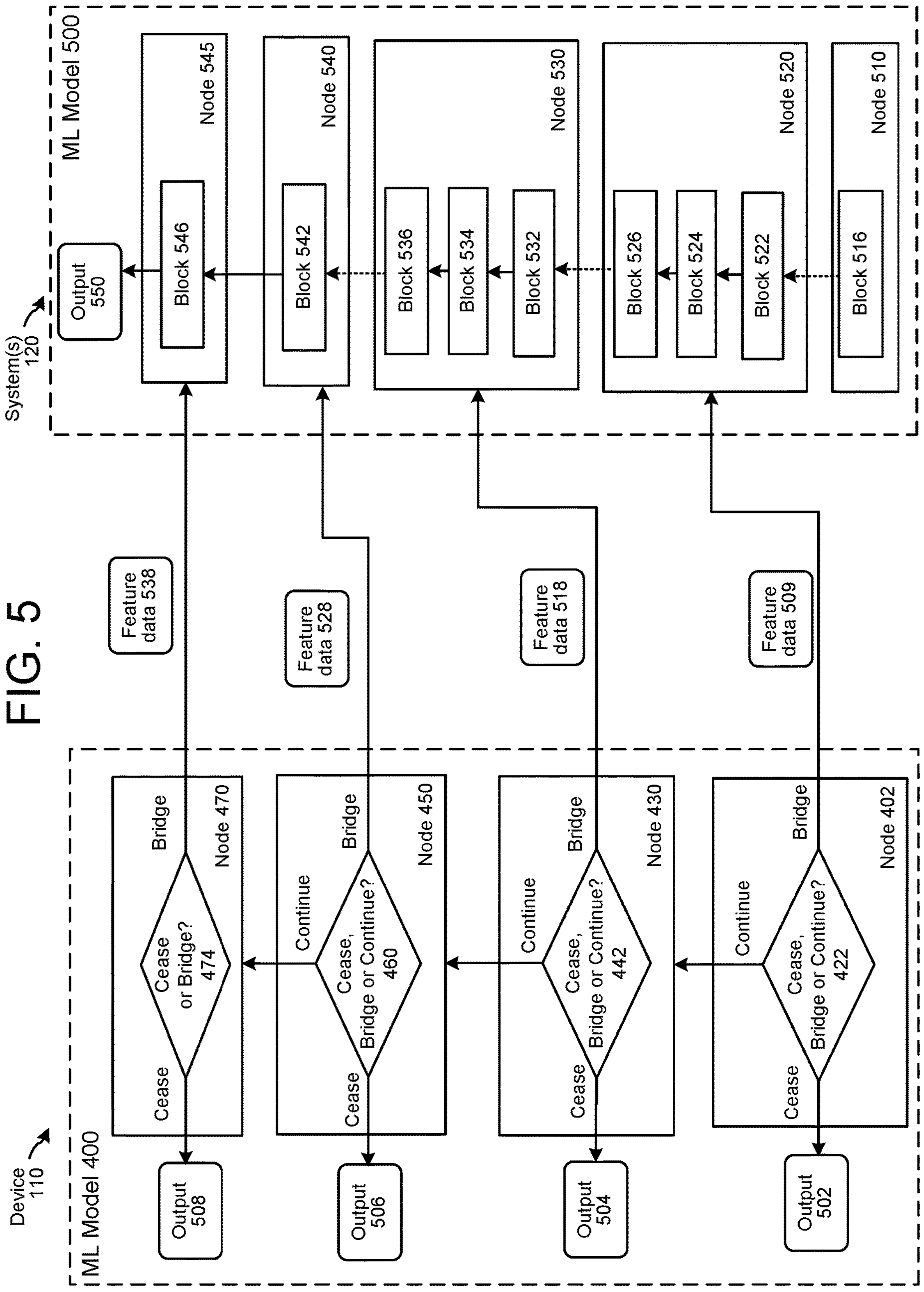

System(s) 120
ML Model 500
Output 550
Node 545
Block 546
Node 540
Block 542
Node 530
Block 536
Block 534
Block 532
Node 520
Block 526
Block 524
Block 522
Node 510
Block 516
Feature data 538
Feature data 528
Feature data 518
Feature data 509
Device 110
ML Model 400
Node 470
Cease or Bridge? 474
Bridge
Cease
Node 450
Cease, Bridge or Continue? 460
Continue
Bridge
Cease
Node 430
Cease, Bridge or Continue? 442
Continue
Bridge
Cease
Node 402
Cease, Bridge or Continue? 422
Continue
Bridge
Cease
Output 508
Output 506
Output 504
Output 502

FIG. 6A

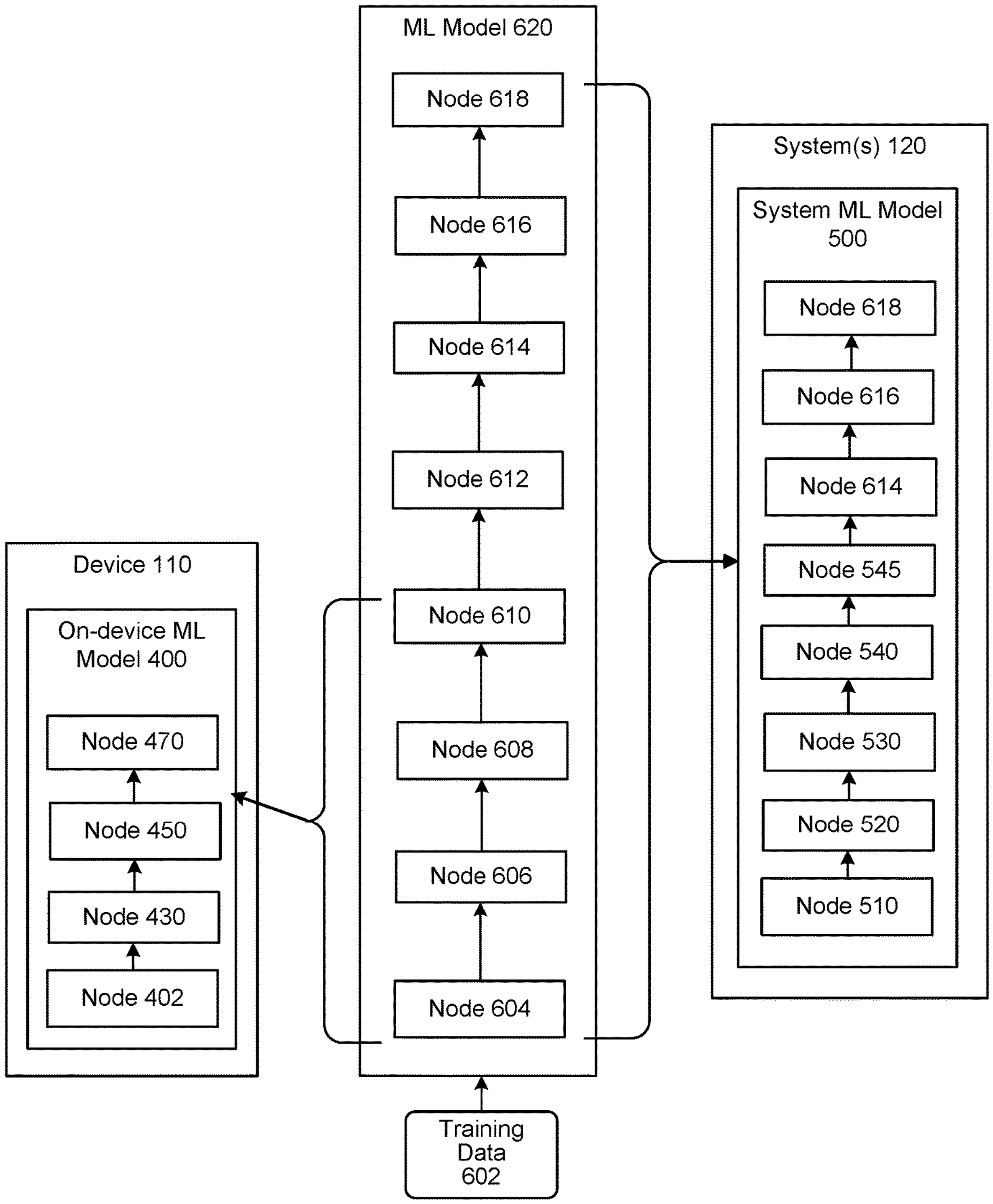
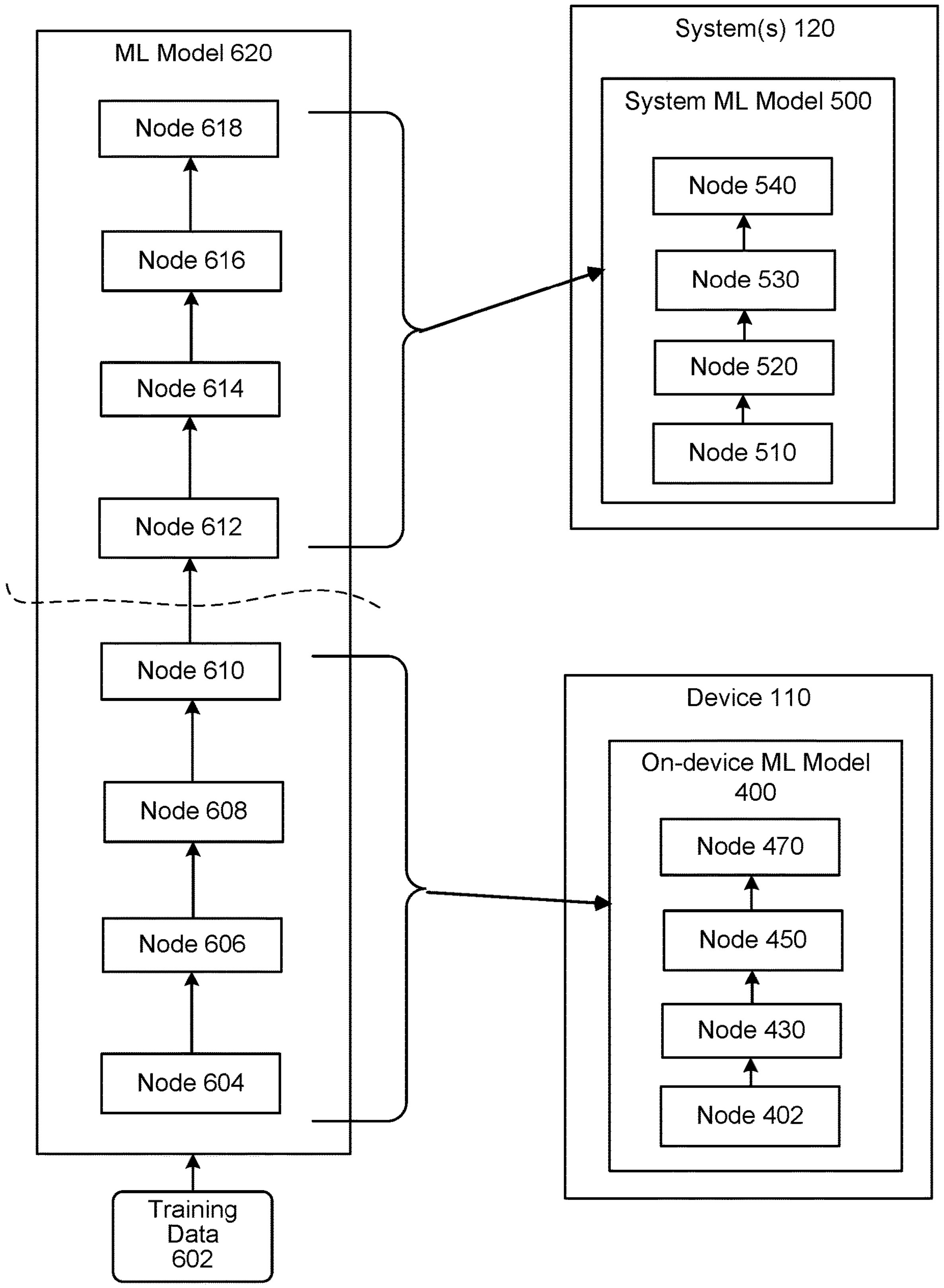

ML Model 620
Node 618
Node 616
Node 614
Node 612
Node 610
Node 608
Node 606
Node 604
Training Data 602
System(s) 120
System ML Model 500
Node 618
Node 616
Node 614
Node 545
Node 540
Node 530
Node 520
Node 510
Device 110
On-device ML Model 400
Node 470
Node 450
Node 430
Node 402

FIG. 6B



ML Model 620
Node 618
Node 616
Node 614
Node 612
Node 610
Node 608
Node 606
Node 604
Training Data 602
System(s) 120
System ML Model 500
Node 540
Node 530
Node 520
Node 510
Device 110
On-device ML Model 400
Node 470
Node 450
Node 430
Node 402

FIG. 6C

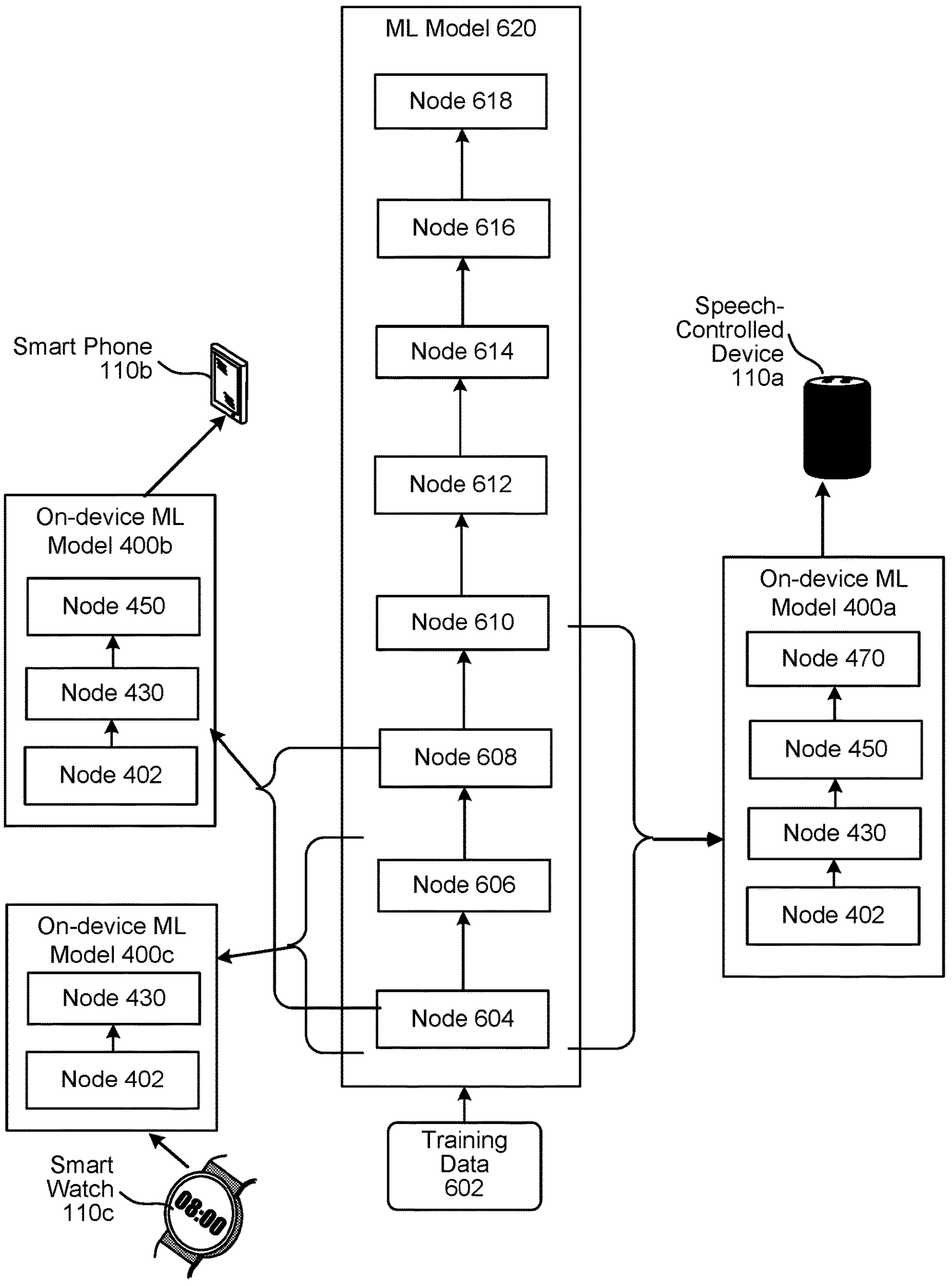

ML Model 620
Node 618
Node 616
Node 614
Node 612
Node 610
Node 608
Node 606
Node 604
Training Data 602
Smart Phone 110b
On-device ML Model 400b
Node 450
Node 430
Node 402
On-device ML Model 400c
Node 430
Node 402
Smart Watch 110c
08:00
Speech-Controlled Device 110a
On-device ML Model 400a
Node 470
Node 450
Node 430
Node 402

FIG. 7

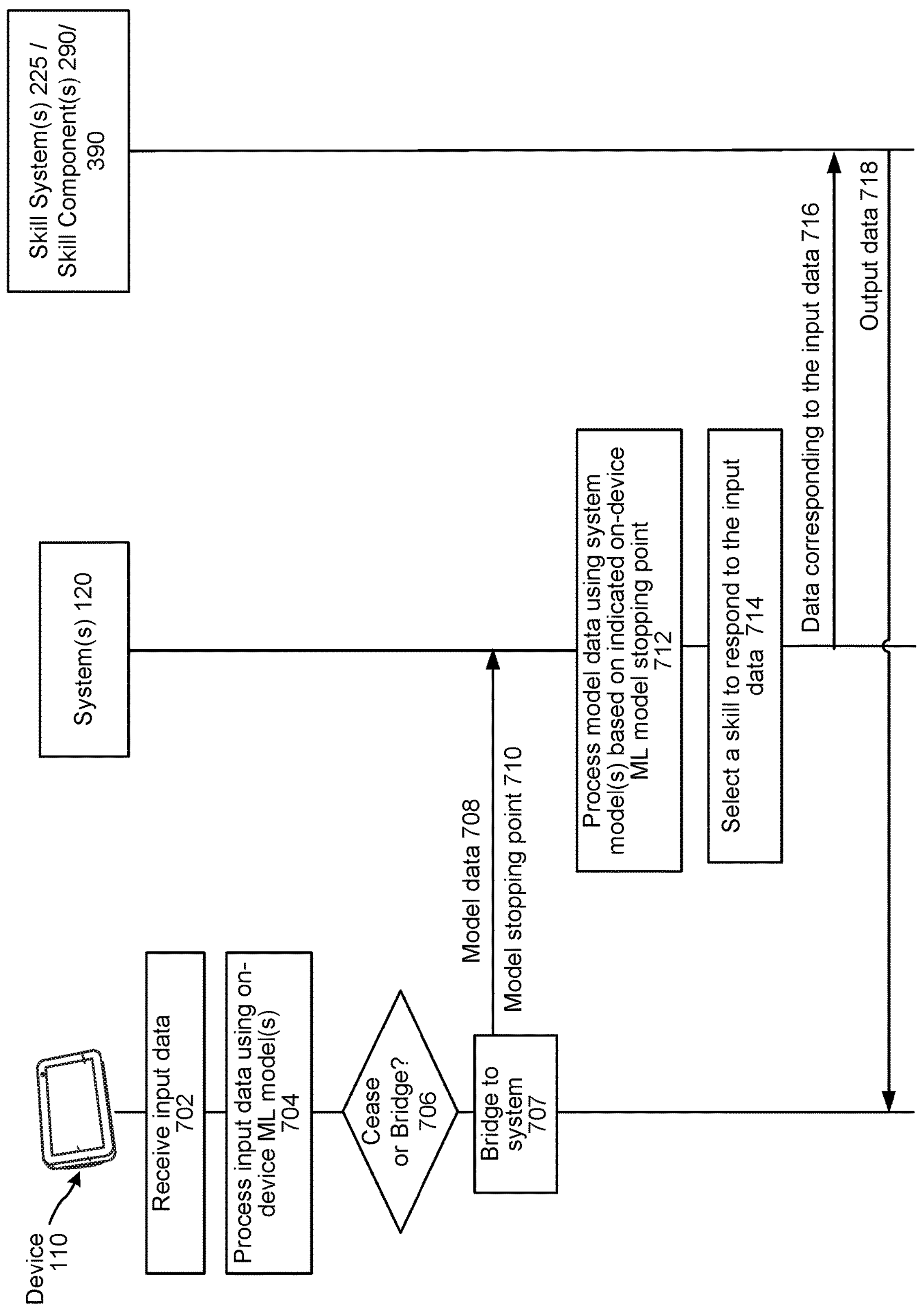

Device 110
System(s) 120
Skill System(s) 225 / Skill Component(s) 290/ 390
Receive input data 702
Process input data using on-device ML model(s) 704
Cease or Bridge? 706
Bridge to system 707
Model data 708
Model stopping point 710
Process model data using system model(s) based on indicated on-device ML model stopping point 712
Select a skill to respond to the input data 714
Data corresponding to the input data 716
Output data 718

FIG. 8

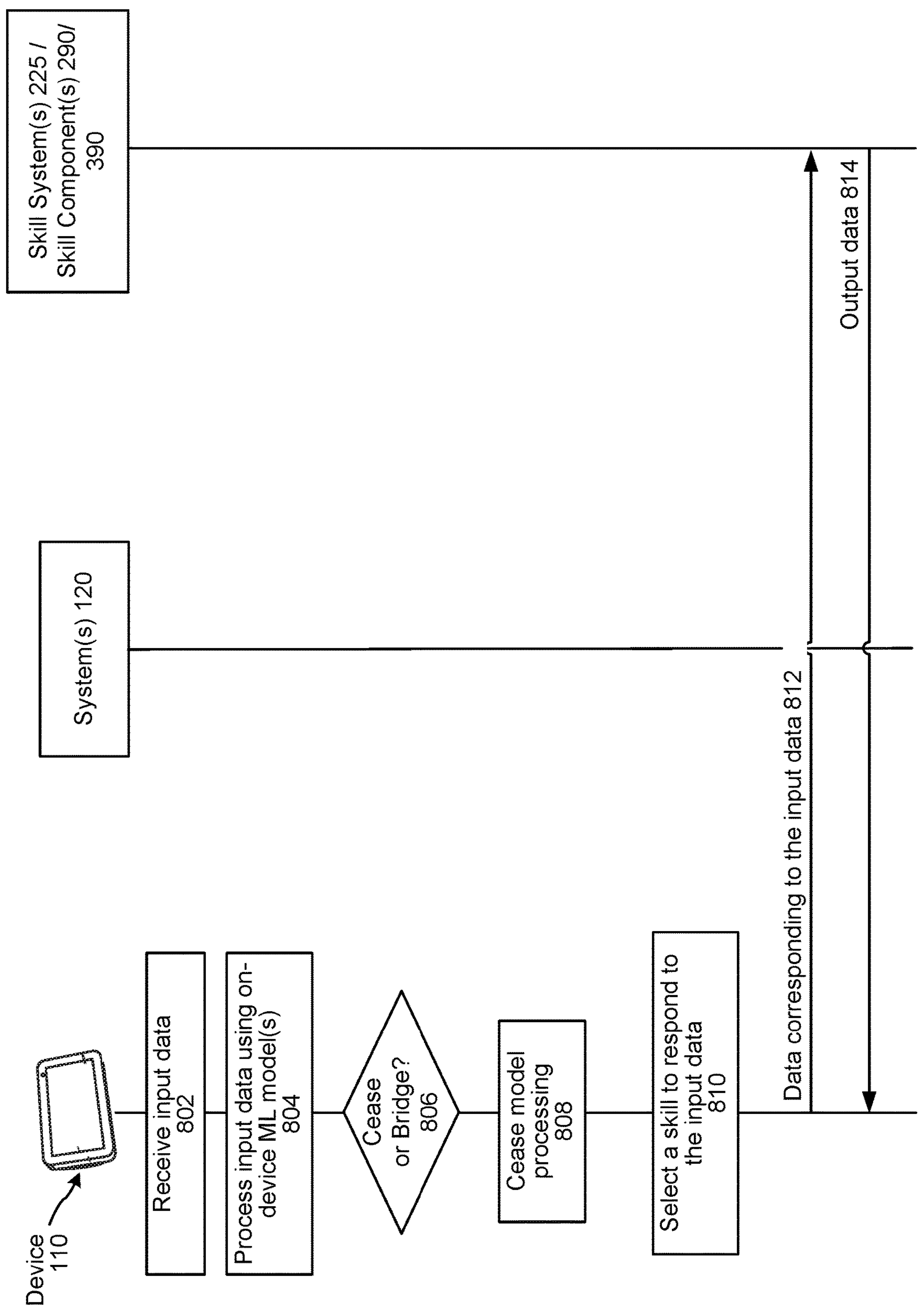

Device 110
System(s) 120
Skill System(s) 225 / Skill Component(s) 290/ 390
Receive input data 802
Process input data using on-device ML model(s) 804
Cease or Bridge? 806
Cease model processing 808
Select a skill to respond to the input data 810
Data corresponding to the input data 812
Output data 814

FIG. 9

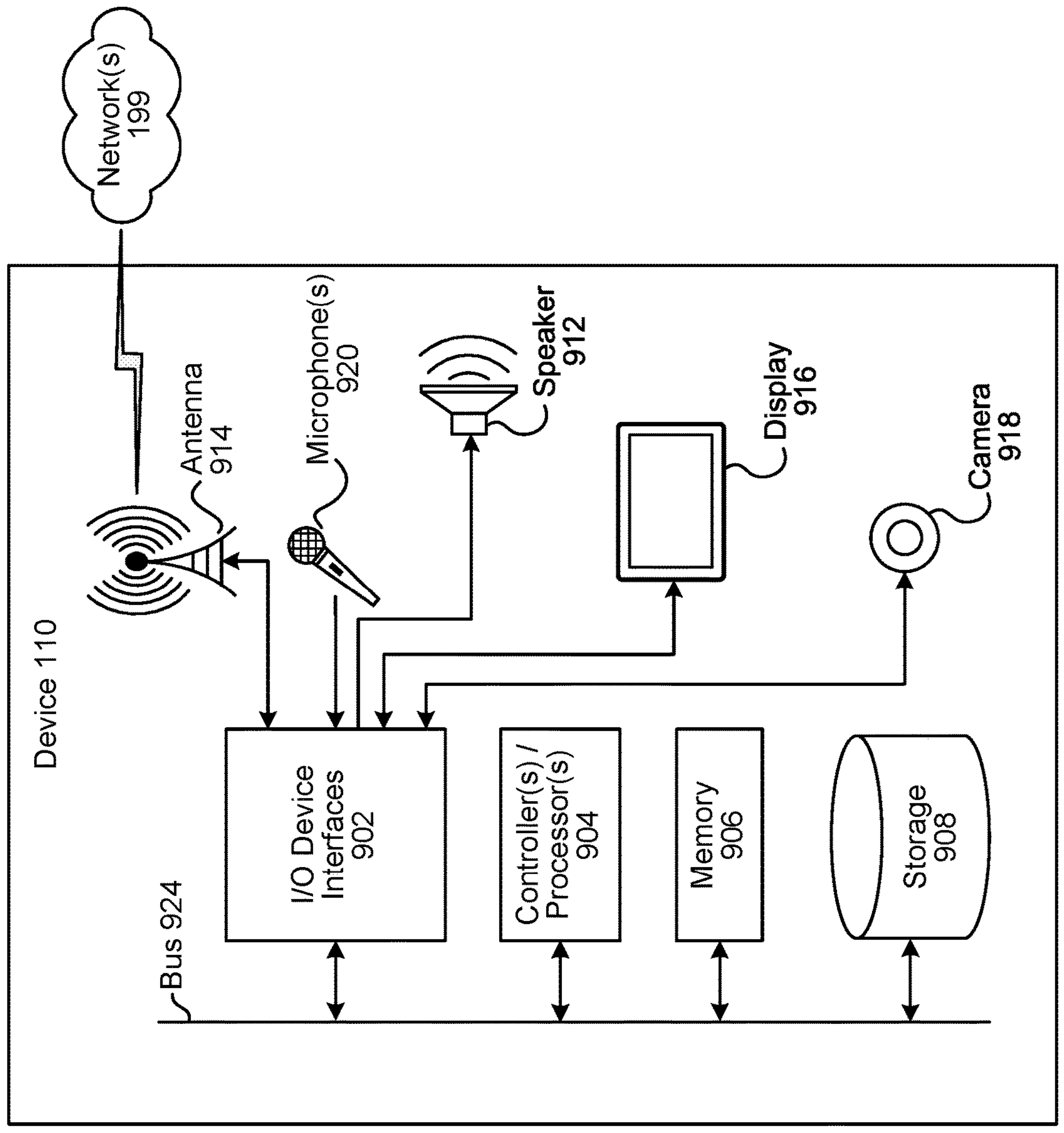

Network(s) 199
Device 110
Antenna 914
Microphone(s) 920
Speaker 912
Display 916
Camera 918
I/O Device Interfaces 902
Controller(s) / Processor(s) 904
Memory 906
Storage 908
Bus 924

FIG. 10

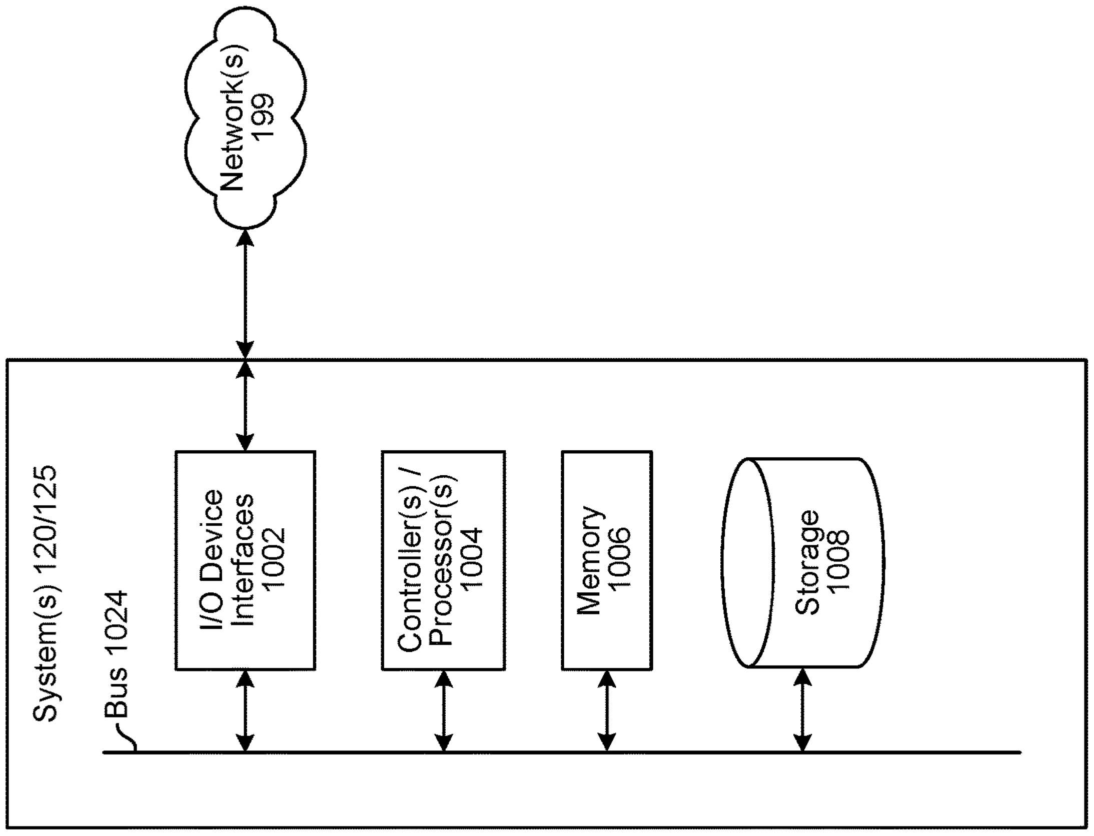
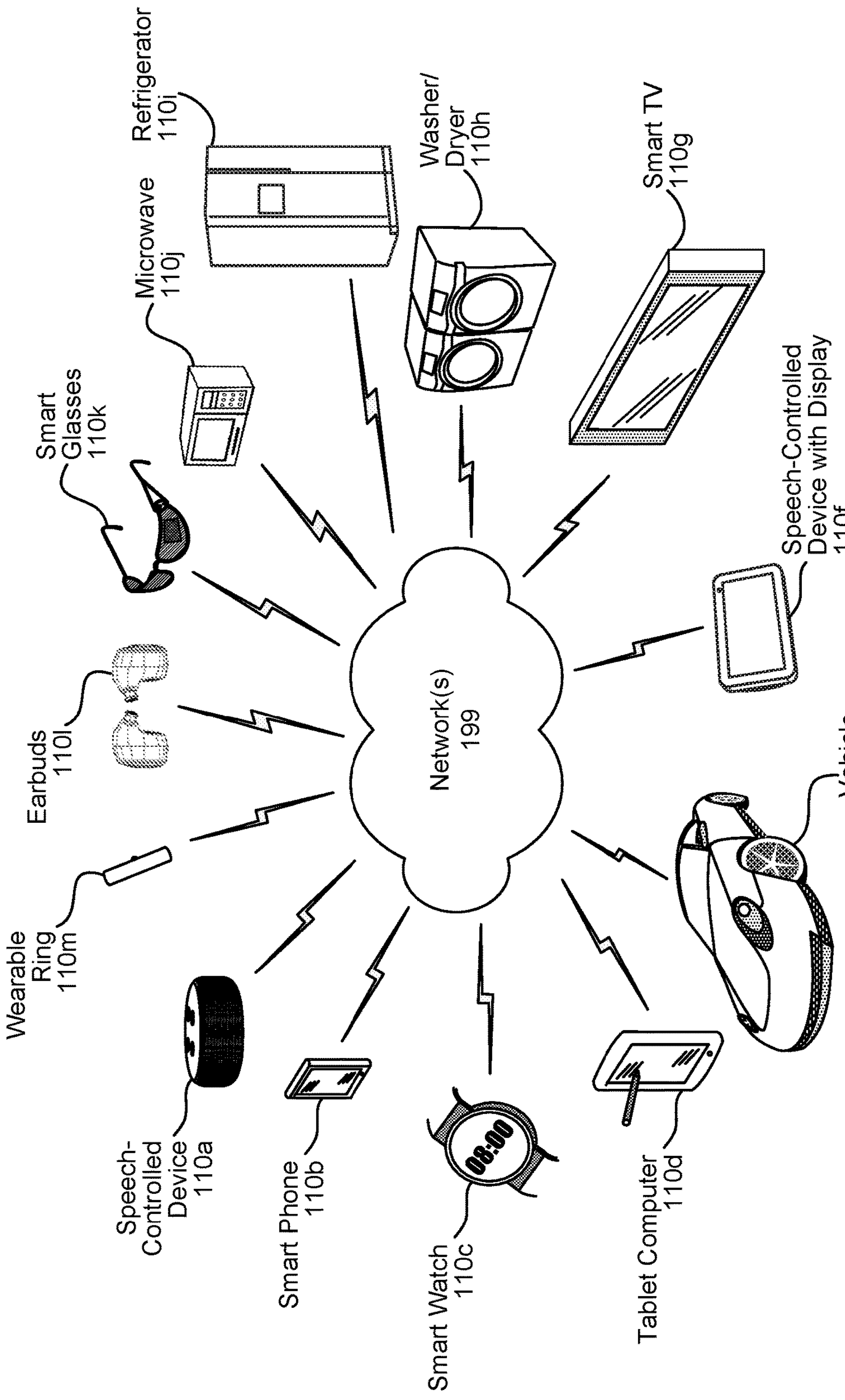

Network(s) 199
System(s) 120/125
Bus 1024
I/O Device Interfaces 1002
Controller(s) / Processor(s) 1004
Memory 1006
Storage 1008

FIG. 11



Network(s) 199
Speech-Controlled Device 110a
Smart Phone 110b
Smart Watch 110c
Tablet Computer 110d
Vehicle 110e
Speech-Controlled Device with Display 110f
Smart TV 110g
Washer/ Dryer 110h
Refrigerator 110i
Microwave 110j
Smart Glasses 110k
Earbuds 110l
Wearable Ring 110m
08:00

MULTI-DEVICE SPEECH PROCESSING

BACKGROUND

Natural language processing systems have progressed to the point where humans can interact with computing devices using their voices and natural language textual inputs. Such systems employ techniques to identify the words spoken and typed by a human user based on the various qualities of received input data. Speech recognition combined with natural language understanding processing techniques enable speech-based user control of computing devices to perform tasks based on the user's spoken inputs. Speech recognition and natural language understanding processing techniques may be referred to collectively or separately herein as spoken language understanding (SLU) processing. SLU processing may be used by computers, hand-held devices, telephone computer systems, kiosks, and a wide variety of other devices to improve human-computer interactions.

BRIEF DESCRIPTION OF DRAWINGS

For a more complete understanding of the present disclosure, reference is now made to the following description taken in conjunction with the accompanying drawings.

FIGS. **1**A-**1**B are conceptual diagrams illustrating a system configured to perform processing partially on a device and partially by a system, according to embodiments of the present disclosure.

FIG. **2** is a conceptual diagram of components of a system, according to embodiments of the present disclosure.

FIG. **3** is a conceptual diagram illustrating components that may be included in a device, according to embodiments of the present disclosure.

FIG. **4** is a conceptual diagram of a machine learning model, implemented by a device, with branches to determine further processing strategy, according to embodiments of the present disclosure.

FIG. **5** is a conceptual diagram illustrating how an on-device machine learning model can bridge to a machine learning model, on a system, to perform further processing, according to embodiments of the present disclosure.

FIGS. **6**A, **6**B and **6**C are conceptual diagrams illustrating how a machine learning model may be split, according to embodiments of the present disclosure.

FIG. **7** is a signal flow diagram illustrating how input data may be processed by a device and a system, according to embodiments of the present disclosure.

FIG. **8** is a signal flow diagram illustrating how input data may be processed by a device and a system, according to embodiments of the present disclosure.

FIG. **9** is a block diagram conceptually illustrating example components of a device, according to embodiments of the present disclosure.

FIG. **10** is a block diagram conceptually illustrating example components of a system, according to embodiments of the present disclosure.

FIG. **11** illustrates an example of a computer network for use with the overall system, according to embodiments of the present disclosure.

DETAILED DESCRIPTION

Automatic speech recognition (ASR) is a field of computer science, artificial intelligence, and linguistics concerned with transforming audio data associated with speech into a token(s) or other textual representation of that speech. Natural language understanding (NLU) is a field of computer science, artificial intelligence, and linguistics concerned with enabling computers to derive meaning from natural language user inputs (such as spoken inputs). ASR and NLU are often used together as part of a spoken language understanding (SLU) processing component of a system. Text-to-speech (TTS) is a field of computer science, artificial intelligence, and linguistics concerned with transforming text and/or other data into audio data synthesized to resemble human speech.

Certain systems may be configured to perform actions responsive to user inputs. For example, for the user input of "Alexa, play music by <Artist>," a system may output music sung by the indicated artist. For further example, for the user input of "Alexa, turn on the lights," a system may turn on lights based on where the user is located. In another example, for the user input of "Alexa, find flights to Miami," a system may search, using another system, for flights from the user's location to Miami, and present the available flights to the user for selection.

In some cases, a system may be configured so that speech processing (i.e., ASR processing, and NLU processing, or SLU processing) of a user input is wholly performed by a device. In other cases, a system may be configured so that speech processing of a user input is wholly performed by a system separate and remote from the device (e.g., the cloud). In such cases, the device may receive a user input and send the user input to the system for speech processing.

The present disclosure relates to techniques for partial processing of a user input at a device and partial processing of the user input at a remote system, when appropriate. In particular, the present disclosure describes techniques for processing data using an on-device component, including a machine learning (ML) model(s), and determining to complete processing using a component at the remote system when the on-device component is not able to complete the processing. In some embodiments, the device is capable of making dynamic decisions regarding when to cease processing at the device and when to bridge to the remote system to complete processing. As used herein, "bridge processing" refers to when a device requests a remote system or another device to complete processing of data that the device may have (partially) processed already or may not have processed. The on-device component may include multiple egress points at different nodes of processing, where the device determines to cease processing or bridge processing. In some embodiments, the decision to cease processing or bridge processing may be based on the output of the corresponding node, the processing time spent by the device, the processing time that may still need to be spent by the device to complete processing, the computational resources of the device, the complexity of the user input, and/or other factors.

In some embodiments, the component on the remote system, including a ML model(s), may pick up processing of the user input where the device left off. When the device determines to bridge processing to the remote system, the device may send (to the remote system) data corresponding to the processing performed by the device thus far, and the remote system may initiate processing using that data. Data sent between the device and the remote system may be sent using privacy preserving techniques, such as encryption, addition of noise to the data, etc.

In some cases, the device of the present disclosure may determine to complete processing at the device, when possible, and may only request the remote system to complete processing of the user input when the device is not capable of doing so (with a certain level of confidence, for example).

The techniques of the present disclosure may provide an improved user experience and an improved system for processing user inputs. For example, the techniques described herein may improve preservation of privacy as only user inputs that the device is not capable of processing may be sent to the remote system for processing. Allowing a device to bridge processing per the techniques described herein also improves accuracy and decreases user-perceived latency with respect to processing of user inputs. Also, the need to compress a full ML model(s) to include on the device is minimized, as the device can bridge processing to the remote system when needed.

A system according to the present disclosure may be configured to incorporate user permissions and may only perform activities disclosed herein if approved by a user. As such, the systems, devices, components, and techniques described herein would be typically configured to restrict processing where appropriate and only process user data in a manner that ensures compliance with all appropriate laws, regulations, standards, and the like. The systems, devices, components, and techniques can be implemented on a geographic basis to ensure compliance with laws in various jurisdictions and entities in which the components of the systems, devices, components, and/or user are located.

FIGS. **1A**-**1B** illustrate a system **100** configured to perform processing using a device **110***a*, a device **110***b* and a system(s) **120**. Although the figures and discussion of the present disclosure illustrate certain steps in a particular order, the steps described may be performed in a different order (as well as certain steps removed or added) without departing from the present disclosure. As shown in FIGS. **1A**-**1B**, the system **100** may include the devices **110***a*, **110***b* (local to a user **5**) and the system(s) **120** in communication across a network(s) **199**. The network(s) **199** may include a local-area network(s) (LAN(s)), a wireless local-area network(s) (WLAN(s)), a Metropolitan Area Network(s), a Wide Area Network(s), a Campus Area Network(s), a mobile carrier system(s), and/or the like.

Referring to FIG. **1A**, the device **110***a* receives (**130**) input data representing an input provided by the user **5** to the device **110***a*. In some cases, the input data may be audio data representing a spoken natural language input. In some cases, the input data may be text data representing a text-based natural language input. In other cases, the input data may be a sequence of images, captured by a camera of the device **110***a*, representing the user **5** performing a gesture, or facial expressions of the user **5**. The input data may be motion sensor data captured by a motion sensor of the device **110***a*. The input data may represent an input received via a button on the device **110** or a touchscreen of the device **110***a*.

The device **110***a* processes (**132**) the input data using a first machine learning (ML) model. The first ML model may be considered an on-device ML model. The first ML model may be configured to process data of the same type as the input data, and generate a prediction corresponding to the input data. For example, in the case the input data is a spoken input, the first ML model may be configured to process audio data representing spoken inputs and perform SLU processing. In another example, in the case the input data is a natural language text input, the first ML model may be configured to process text data representing natural language inputs and perform NLU processing. In yet another example, in the case the input data is an image(s) representing facial expressions of the user **5**, the first ML model may be configured to process image data and perform sentiment detection. In

some cases, where the input data is audio data representing a spoken input or other data representing a natural language input, the first ML model may be configured to perform spoken language understanding (SLU) processing or natural language understanding (NLU) processing with respect to the input data. The first ML model may include multiple processing nodes that may be invoked in a sequential manner to process the input data. The first ML model may include at least an initial node, one or more intermediary nodes, and a final node. Each node of the first ML model may generate an output based on the processing performed by the node. The output may represent the features learned by the node.

The device **110***a* processes (**134**) an (first) output of a (first) node of the first ML model. The first node may be the initial node or an intermediary node of the first ML model. The first output may be the features determined by the first node during processing of the input data. The device **110***a* may process the first output using one or more processing blocks. The processing blocks may be a convolutional layer, a softmax layer, or other types of layers used in a deep learning model. By processing the first output using the processing blocks, the device **110***a* may derive a prediction from the first output and determine a confidence value corresponding to the prediction.

Based on processing the first output, the device **110***a* determines (**136**) whether to exit, bridge or continue processing at the first ML model. If processing of the first output indicates that the first ML model is confident in its prediction of the first node, then the device **110***a* ceases processing at the first ML model, and the device **110***a* determines (**138**), using the first output, output data responsive to the input data. The device **110***a* may determine a confidence value/score associated with the first output and/or derived from processing the first output, and if the confidence value/score meets a threshold confidence value/score then the device **110***a* may determine that the first ML model is confident in its prediction of the first node. In this scenario, the device **110***a* uses a prediction of an initial or intermediary node of the first ML model, rather than the prediction of the final node, to generate output data responsive to the input data. This may reduce latency in responding to the user **5**.

If processing of the first output indicates that the first ML model is not confident in its prediction of the first node but that the first ML model is capable of generating a high confidence prediction (or the first ML model is confident at the first node that the next node is capable of generating a high confidence prediction), then the device **110** continues processing at the first ML model, and the device **110** processes (**140**) the first output using the next (second) node of the first ML model. The device **110***a* may determine a confidence value/score associated with the first output and/or derived from processing the first output, and if the confidence value/score does not meet a threshold confidence value/score then the device **110***a* may determine that the first ML model is not confident in its prediction of the first node.

In continuing processing at the first ML model, the device **110***a* may process an (second) output of the second node of the first ML model (per the step **134**), and may determine, based on processing the second output of the second node, whether to cease, bridge or continue processing at the first ML model (per the step **136**).

If the processing of the first output indicates that first ML model is not confident in the prediction of the first node and that further processing by the first ML model will not result in a high confidence prediction, then the device **110** bridges processing to the system(s) **120**, and the device **110***a* sends

(**142**) the first output to a second ML model to complete processing. The second ML model may be included at the system(s) **120** or the device **110***b*. Thus, in this scenario, the device **110***a* uses a prediction of an initial or intermediary node of the first ML model to determine that the first ML model will not generate an accurate prediction (a prediction with high confidence), and then requests the system(s) **120** or the device **110***b* to complete processing instead. This may improve accuracy in generating output data responsive to the input data. This may also reduce latency because the device **110***a*, in some cases, does not wait for the first ML model to complete processing to then determine that the first ML model prediction has low confidence, and then send the input data to the system(s) **120** or the device **110***b* to perform processing. The system(s) **120** and the device **110***b* picks up processing where the device **110***a* left off.

Referring to FIG. **1**B, the system(s) **120** or the device **110***b* processes (**144**) the first output, of the node of the first ML model, using a second ML model. The second ML model may be configured to perform the same type of processing as the first ML model. For example, the first ML model and the second ML model may be configured to perform SLU processing. In another example, the first ML model and the second ML model may be configured to perform NLU processing. In yet another example, the first ML model and the second ML model may be configured to perform sentiment detection. Using the first output, the second ML model may pick up processing where the first ML model left off. Thus, the second ML model may not relearn/re-determine the features that the first ML model already learned/determined. The second ML model may complete processing with respect to the input data, and may generate a second output. The system(s) **120** or the device **110***b* determines (**146**), using the third output of the second ML model, output data responsive to the input data. The third output may be an output of a final node of the second ML model. In some embodiments, the third output may be an output of an initial node or intermediary node of the second ML model. After determining the output data, the system(s) **120** or the device **110***b* sends (**148**) the output data to the device **110***a* for output to the user **5**.

In some embodiments, the device **110***a* may determine to continue processing at the decision block **136** based on a network signal quality or network connection quality between the device **110***a* and the system(s) **120** or the device **110***b*. For example, if the network connection quality is low/poor between the device **110***a* and the system(s) **120**, then the device **110***a* may continue processing per the step **140**. Thus, instead of risking the system(s) **120** not receiving the output of the node (as done in step **142**), the device **110***a* may continue processing at the first ML model. Once the network connection improves, the device **110***a* may bridge processing to the system(s) **120**. Similarly, the device **110***a* may determine to continue processing at the decision block **136** if the network connection quality is low/poor between the device **110***a* and the device **110***b*. In some embodiments, the device **110***a* may determine to continue processing at the decision block **136** based on the device **110***b* being presently engaged in performing other operations, such as processing a user input, received at the device **110***b*, from the user **5** or another user.

The system **100** may operate using various components as illustrated in FIG. **2**. The various components may be located on a same or different physical devices. Communication between various components may occur directly or across a network(s) **199**.

A microphone or array of microphones (of or otherwise associated with a device **110**) may capture audio **11**. The device **110** processes audio data, representing the audio **11**, to determine whether speech is detected. The device **110** may use various techniques to determine whether audio data includes speech. In some examples, the device **110** may apply voice activity detection (VAD) techniques. Such techniques may determine whether speech is present in audio data based on various quantitative aspects of the audio data, such as the spectral slope between one or more frames of the audio data, the energy levels of the audio data in one or more spectral bands, the signal-to-noise ratios of the audio data in one or more spectral bands, or other quantitative aspects. In other examples, the device **110** may implement a classifier configured to distinguish speech from background noise. The classifier may be implemented by techniques such as linear classifiers, support vector machines, and decision trees. In still other examples, the device **110** may apply Hidden Markov Model (HMM) or Gaussian Mixture Model (GMM) techniques to compare the audio data to one or more acoustic models in storage, which acoustic models may include models corresponding to speech, noise (e.g., environmental noise or background noise), or silence. Still other techniques may be used to determine whether speech is present in audio data.

Once speech is detected in audio data representing the audio **11**, the device **110** may determine if the speech is directed at the device **110**/system **120**. In at least some embodiments, such determination may be made using a wakeword detection component **220**. The wakeword detection component **220** may be configured to detect various wakewords. In at least some examples, each wakeword may correspond to a name of a different digital assistant. An example wakeword/digital assistant name is "Alexa."

Wakeword detection is typically performed without performing linguistic analysis, textual analysis, or semantic analysis. Instead, the audio data, representing the audio **11**, is analyzed to determine if specific characteristics of the audio data match preconfigured acoustic waveforms, audio signatures, or other data corresponding to a wakeword.

Thus, the wakeword detection component **220** may compare audio data to stored data to detect a wakeword. One approach for wakeword detection applies general large vocabulary continuous speech recognition (LVCSR) systems to decode audio signals, with wakeword searching being conducted in the resulting lattices or confusion networks. Another approach for wakeword detection builds HMMs for each wakeword and non-wakeword speech signals, respectively. The non-wakeword speech includes other spoken words, background noise, etc. There can be one or more HMMs built to model the non-wakeword speech characteristics, which are named filler models. Viterbi decoding is used to search the best path in the decoding graph, and the decoding output is further processed to make the decision on wakeword presence. This approach can be extended to include discriminative information by incorporating a hybrid DNN-HMM decoding framework. In another example, the wakeword detection component **220** may be built on deep neural network (DNN)/recursive neural network (RNN) structures directly, without HMM being involved. Such an architecture may estimate the posteriors of wakewords with context data, either by stacking frames within a context window for DNN, or using RNN. Follow-on posterior threshold tuning or smoothing is applied for decision making. Other techniques for wakeword detection, such as those known in the art, may also be used.

Once the wakeword detection component **220** detects a wakeword, the device **110** may "wake" and begin transmitting audio data **211**, representing the audio **11**, to the system **120**. The audio data **211** may include data corresponding to the detected wakeword, or the device **110** may remove the portion of the audio corresponding to the detected wakeword prior to sending the audio data **211** to the system **120**.

The system **120** may include an orchestrator component **230** configured to, among other things, coordinate data transmissions between components of the system **120**. The orchestrator component **230** may receive the audio data **211** from the device **110**, and send the audio data **211** to an ASR component **250**.

The ASR component **250** transcribes the audio data **211** into ASR output data including one or more ASR hypotheses. An ASR hypothesis may be configured as a textual interpretation of the speech, or may be configured in another manner, such as one or more tokens. Each ASR hypothesis may represent a different likely interpretation of the speech in the audio data **211**. Each ASR hypothesis may be associated with a score representing a confidence of ASR processing performed to determine the ASR hypothesis with which the score is associated.

The ASR component **250** interprets the speech in the audio data **211** based on a similarity between the audio data **211** and pre-established language models. For example, the ASR component **250** may compare the audio data **211** with models for sounds (e.g., subword units, such as phonemes, etc.) and sequences of sounds to identify words that match the sequence of sounds of the speech represented in the audio data **211**.

In at least some instances, instead of the device **110** receiving audio **11**, the device **110** may receive a text-based (e.g., typed) natural language user input. The device **110** may determine text data **213** representing the typed natural language user input, and may send the text data **213** to the system **120**, wherein the text data **213** is received by the orchestrator component **230**.

The orchestrator component **230** may send the text data **213** or ASR output data output, depending on the type of natural language user input received, to a NLU component **260**. The NLU component **260** processes the ASR output data or text data to determine one or more NLU hypotheses embodied in NLU output data. The NLU component **260** may perform intent classification (IC) processing on the ASR output data or text data to determine an intent of the natural language user input. An intent corresponds to an action to be performed that is responsive to the natural language user input. To perform IC processing, the NLU component **260** may communicate with a database of words linked to intents. For example, a music intent database may link words and phrases such as "quiet," "volume off," and "mute" to a <Mute> intent. The NLU component **260** identifies potential intents by comparing words and phrases in ASR output data or text data to the words and phrases in an intents database. In at least some embodiments, the NLU component **260** may communicate with multiple intents databases, with each intents database corresponding to one or more intents associated with a particular skill.

For example, IC processing of the natural language user input "play my workout playlist" may determine an intent of <PlayMusic>. For further example, IC processing of the natural language user input "call mom" may determine an intent of <Call>. In another example, IC processing of the natural language user input "call mom using video" may determine an intent of <VideoCall>. In yet another example, IC processing of the natural language user input "what is today's weather" may determine an intent of <OutputWeather>.

The NLU component **260** may also perform named entity recognition (NER) processing on the ASR output data or text data to determine one or more portions (which may be referred to as one or more slots) of the natural language user input that may be needed for post-NLU processing (e.g., processing performed by a skill). For example, NER processing of the natural language user input "play [song name]" may determine a slot corresponding to "SongName: [song name]." For further example, NER processing of the natural language user input "call mom" may determine a slot corresponding to "Recipient: Mom." In another example, NER processing of the natural language user input "what is today's weather" may determine a slot corresponding to "Date: Today."

In at least some embodiments, the intents identifiable by the NLU component **260** may be linked to one or more grammar frameworks with "slots" to be filled. Each slot of a grammar framework corresponds to a portion of ASR output data or text data that the NLU component **260** believes corresponds to an entity. For example, a grammar framework corresponding to a <PlayMusic> intent may correspond to sentence structures such as "Play {Artist Name}," "Play {Album Name}," "Play {Song name}," "Play {Song name} by {Artist Name}," etc.

For example, the NLU component **260** may perform NER processing to identify words in ASR output data or text data as subject, object, verb, preposition, etc. based on grammar rules and/or models. Then, the NLU component **260** may perform IC processing that involves using the identified verb to identify an intent. Thereafter, the NLU component **260** may again perform NER processing to determine a grammar model associated with the identified intent. For example, a grammar model for a <PlayMusic> intent may specify a list of slots applicable to play the identified "object" and any object modifier (e.g., a prepositional phrase), such as {Artist Name}, {Album Name}, {Song name}, etc. The NER processing may then involve searching corresponding fields in a lexicon, attempting to match words and phrases in the ASR output data that NER processing previously tagged as a grammatical object or object modifier with those identified in the lexicon.

NER processing may include semantic tagging, which is the labeling of a word or combination of words according to their type/semantic meaning. NER processing may include parsing ASR output data or text data using heuristic grammar rules, or a model may be constructed using techniques such as hidden Markov models, maximum entropy models, log linear models, conditional random fields (CRF), and the like. For example, NER processing with respect to a music skill may include parsing and tagging ASR output data or text data corresponding to "play mother's little helper by the rolling stones" as {Verb}: "Play," {Object}: "mother's little helper," {Object Preposition}: "by," and {Object Modifier}: "the rolling stones." The NER processing may identify "Play" as a verb based on a word database associated with the music skill, which IC processing determines corresponds to a <PlayMusic> intent.

The NLU component **260** may generate NLU output data including one or more NLU hypotheses, with each NLU hypothesis including the intent and slot(s) determined from IC processing and NER processing of the ASR output data or text data. In at least some embodiments, the NLU component **260** may perform IC processing and NLU processing with respect to different skills. One skill may support the same or different intents than another skill. Thus, the NLU output data may include multiple NLU hypotheses, with each NLU hypothesis corresponding to IC processing and NER processing performed on the ASR output or text data with respect to a different skill.

As described above, the system **120** may perform speech processing using two different components (e.g., the ASR component **250** and the NLU component **260**). In at least some embodiments, the system **120** may implement a spoken language understanding (SLU) component **255** configured to process audio data **211** to determine NLU output data.

The SLU component **255** may be equivalent to a combination of the ASR component **250** and the NLU component **260**. Yet, the SLU component **255** may process audio data **211** and directly determine the NLU output data, without an intermediate step of generating ASR output data. As such, the SLU component **255** may take audio data **211** representing speech and attempt to make a semantic interpretation of the speech. That is, the SLU component **255** may determine a meaning associated with the speech and then implement that meaning. For example, the SLU component **255** may interpret audio data **211** representing speech from the user **5** in order to derive a desired action. The SLU component **255** may output a most likely NLU hypothesis, or multiple NLU hypotheses associated with respective confidence or other scores (such as probability scores, etc.).

The NLU component **260** (or the SLU component **255** depending on configuration of the system **120**) may send the NLU output data to the orchestrator component **230**. The orchestrator component **230** may send the top-scoring NLU hypothesis (in the NLU output data) to a skill associated with the NLU hypothesis.

The system **120** may include one or more skill components **290** and/or may communicate with one or more skill systems **225** via one or more skill components **290**. As used herein, a "skill" may refer to a skill component **290**, a skill system **225**, or a combination of a skill component **290** and a skill system **225**. A skill may be configured to execute with respect to NLU output data. For example, for an NLU hypothesis including a <GetWeather> intent, the system **120** (and more particularly the orchestrator component **230**) may invoke a weather skill to determine and output weather information for a geographic location represented in a user profile or corresponding to a location of the device **110** that captured the corresponding natural language user input. For further example, for an NLU hypothesis including a <BookRide> intent, the system **120** (and more particularly the orchestrator component **230**) may invoke a taxi skill to book a requested ride. In another example, for an NLU hypothesis including a <BuyPizza> intent, the system **120** (and more particularly the orchestrator component **230**) may invoke a restaurant skill to place an order for a pizza. A skill may operate in conjunction between the system **120** and other devices, such as the device **110**, restaurant electronic ordering systems, taxi electronic booking systems, etc. in order to complete certain functions. Inputs to a skill may come from speech processing interactions or through other interactions or input sources.

A skill may be associated with a domain, a non-limiting list of which includes a smart home domain, a music domain, a video domain, a weather domain, a communications domain, a flash briefing domain, a shopping domain, and a custom domain.

The system **120** may include a TTS component **280** that determine audio data (e.g., synthesized speech) from text data using one or more different methods. Text data input to

the TTS component **280** may come from a skill, the orchestrator component **230**, or another component of the system **120**.

In one method of synthesis called unit selection, the TTS component **280** matches text data against a database of recorded speech. The TTS component **280** selects matching units of recorded speech and concatenates the units together to form audio data. In another method of synthesis called parametric synthesis, the TTS component **280** varies parameters such as frequency, volume, and noise to determine audio data including an artificial speech waveform. Parametric synthesis uses a computerized voice generator, sometimes called a vocoder.

The system **120** may include a user recognition component **295**. The user recognition component **295** may recognize one or more users using various data. The user recognition component **295** may take as input the audio data **211**. The user recognition component **295** may perform user recognition by comparing speech characteristics, in the audio data **211**, to stored speech characteristics of users (e.g., stored speech characteristics associated with user profile identifiers associated with the device **110** that determined the audio data **211**). The user recognition component **295** may additionally or alternatively perform user recognition by comparing biometric data (e.g., fingerprint data, iris data, retina data, etc.), received by the system **120** in correlation with a natural language user input, to stored biometric data of users (e.g., stored biometric data associated with user profile identifiers associated with the device **110** that determined the audio data **211** or otherwise captured a user input). The user recognition component **295** may additionally or alternatively perform user recognition by comparing image data (e.g., including a representation of at least a feature of a user), received by the system **120** in correlation with a natural language user input, with stored image data including representations of features of different users (e.g., stored image data associated with user profile identifiers associated with the device **110** that determined the audio data **211** or otherwise captured a user input). The user recognition component **295** may perform other or additional user recognition processes, including those known in the art. For a particular user input, the user recognition component **295** may perform processing with respect to stored data of users associated with the device **110** that captured the user input.

The user recognition component **295** determines whether a user input originated from a particular user. For example, the user recognition component **295** may determine a first value representing a likelihood that a user input originated from a first user, a second value representing a likelihood that user input originated from a second user, etc. The user recognition component **295** may also determine an overall confidence regarding the accuracy of user recognition processing.

The user recognition component **295** may output a single user profile identifier corresponding to the most likely user that originated the user input. Alternatively, the user recognition component **295** may output multiple user profile identifiers (e.g., in the form of an N-best list) with respective values representing likelihoods of respective users originating the user input. The output of the user recognition component **295** may be used to inform NLU processing, processing performed by a skill, as well as processing performed by other components of the system **120** and/or other systems.

The system **120** may include profile storage **270**. The profile storage **270** may include a variety of data related to individual users, groups of users, devices, etc. that interact with the system **120**. As used herein, a "profile" refers to a set of data associated with a user, group of users, device, etc. The data of a profile may include preferences specific to the user, group of users, device, etc.; input and output capabilities of one or more devices; internet connectivity data; user bibliographic data; subscription data; as well as other data.

The profile storage **270** may include one or more user profiles. Each user profile may be associated with a different user profile identifier. Each user profile may include various user identifying data. Each user profile may also include preferences of the user. Each user profile may include one or more device identifiers, representing one or more devices registered to the user. Each user profile may include identifiers of skills that the user has enabled. When a user enables a skill, the user is providing the system **120** with permission to allow the skill to execute with respect to the user's natural language user inputs. If a user does not enable a skill, the system **120** may not invoke the skill to execute with respect to the user's natural language user inputs.

The profile storage **270** may include one or more group profiles. Each group profile may be associated with a different group profile identifier. A group profile may be specific to a group of users. That is, a group profile may be associated with two or more individual user profiles. For example, a group profile may be a household profile that is associated with user profiles associated with multiple users of a single household. A group profile may include preferences shared by all the user profiles associated therewith. Each user profile associated with a group profile may additionally include preferences specific to the user associated therewith. That is, a user profile may include preferences unique from one or more other user profiles associated with the same group profile. A user profile may be a stand-alone profile or may be associated with a group profile. A group profile may be associated with (or include) one or more device profiles corresponding to one or more devices associated with the group profile.

The profile storage **270** may include one or more device profiles. Each device profile may be associated with a different device identifier/device profile identifier. A device profile may include various device identifying data, input/output characteristics, networking characteristics, etc. A device profile may also include one or more user profile identifiers, corresponding to one or more user profiles associated with the device profile. For example, a household device's profile may include the user profile identifiers of users of the household.

The foregoing describes illustrative components and processing of the system **120**. In at least some embodiments, the device **110** may be configured to include some or all of the components, and perform some or all of the processing, of the system **120** described above. FIG. **3** illustrates such a configured device **110**.

In at least some embodiments, the system **120** may receive the audio data **211** from the device **110**, to recognize speech corresponding to a spoken input in the received audio data **211**, and to perform functions in response to the recognized speech. In at least some embodiments, these functions involve sending directives (e.g., commands), from the system **120** to the device **110** (and/or other devices **110**) to cause the device **110** to perform an action, such as output an audible response to the spoken input via a loudspeaker(s), and/or control secondary devices in the environment by sending a control command to the secondary devices.

Thus, when the device **110** is able to communicate with the system **120** over the network(s) **199**, some or all of the functions capable of being performed by the system **120** may be performed by sending one or more directives over the network(s) **199** to the device **110**, which, in turn, may process the directive(s) and perform one or more corresponding actions. For example, the system **120**, using a remote directive that is included in response data (e.g., a remote response), may instruct the device **110** to output an audible response (e.g., using TTS processing performed by an on-device TTS component **380**) to a user's question via a loudspeaker(s) of (or otherwise associated with) the device **110**, to output content (e.g., music) via the loudspeaker(s) of (or otherwise associated with) the device **110**, to display content on a display of (or otherwise associated with) the device **110**, and/or to send a directive to a secondary device (e.g., a directive to turn on a smart light). It is to be appreciated that the system **120** may be configured to provide other functions in addition to those discussed herein, such as, without limitation, providing step-by-step directions for navigating from an origin location to a destination location, conducting an electronic commerce transaction on behalf of the user **5** as part of a shopping function, establishing a communication session (e.g., a video call) between the user **5** and another user, and so on.

As noted with respect to FIG. **2**, the device **110** may include a wakeword detection component **220** configured to compare the audio data **211** to stored models used to detect a wakeword (e.g., "Alexa") that indicates to the device **110** that the audio data **211** is to be processed for determining NLU output data (e.g., slot data that corresponds to a named entity, label data, and/or intent data, etc.). In at least some embodiments, a hybrid selector **324**, of the device **110**, may send the audio data **211** to the wakeword detection component **220**. If the wakeword detection component **220** detects a wakeword in the audio data **211**, the wakeword detection component **220** may send an indication of such detection to the hybrid selector **324**. In response to receiving the indication, the hybrid selector **324** may send the audio data **211** to the system **120** and/or the ASR component **350**. The wakeword detection component **220** may also send an indication, to the hybrid selector **324**, representing a wakeword was not detected. In response to receiving such an indication, the hybrid selector **324** may refrain from sending the audio data **211** to the system **120**, and may prevent the ASR component **350** from further processing the audio data **211**. In this situation, the audio data **211** can be discarded.

The device **110** may conduct its own speech processing using on-device language processing components, such as an SLU component **355** (an ASR component **350** and an NLU **360**), similar to the manner discussed above with respect to the SLU component **255** (or ASR component **250** and the NLU component **260**) of the system **120**. The device **110** may also internally include, or otherwise have access to, other components such as one or more skill components **390** capable of executing commands based on NLU output data or other results determined by the device **110**/system **120**, a user recognition component **395** (configured to process in a similar manner to that discussed above with respect to the user recognition component **295** of the system **120**), profile storage **370** (configured to store similar profile data to that discussed above with respect to the profile storage **270** of the system **120**), or other components. In at least some embodiments, the profile storage **370** may only store profile data for a user or group of users specifically associated with the device **110**. Similar to as described above with respect to FIG. **2**, a skill component **390** may communicate with a skill system(s) **225**.

In at least some embodiments, the on-device language processing components may not have the same capabilities as the language processing components of the system **120**. For example, the on-device language processing components may be configured to handle only a subset of the natural language user inputs that may be handled by the system **120**. For example, such subset of natural language user inputs may correspond to local-type natural language user inputs, such as those controlling devices or components associated with a user's home. In such circumstances the on-device language processing components may be able to more quickly interpret and respond to a local-type natural language user input, for example, than processing that involves the system **120**. If the device **110** attempts to process a natural language user input for which the on-device language processing components are not necessarily best suited, the language processing results determined by the device **110** may indicate a low confidence or other metric indicating that the processing by the device **110** may not be as accurate as the processing done by the system **120**.

The hybrid selector **324**, of the device **110**, may include a hybrid proxy (HP) **326** configured to proxy traffic to/from the system **120**. For example, the HP **326** may be configured to send messages to/from a hybrid execution controller (HEC) **327** of the hybrid selector **324**. For example, command/directive data received from the system **120** can be sent to the HEC **327** using the HP **326**. The HP **326** may also be configured to allow the audio data **211** to pass to the system **120** while also receiving (e.g., intercepting) this audio data **211** and sending the audio data **211** to the HEC **327**.

In at least some embodiments, the hybrid selector **324** may further include a local request orchestrator (LRO) **328** configured to notify the ASR component **350** about the availability of new audio data **211** that represents user speech, and to otherwise initiate the operations of on-device language processing when new audio data **211** becomes available. In general, the hybrid selector **324** may control execution of on-device language processing, such as by sending "execute" and "terminate" events/instructions. An "execute" event may instruct a component to continue any suspended execution (e.g., by instructing the component to execute on a previously-determined intent in order to determine a directive). Meanwhile, a "terminate" event may instruct a component to terminate further execution, such as when the device **110** receives directive data from the system **120** and chooses to use that remotely-determined directive data.

Thus, when the audio data **211** is received, the HP **326** may allow the audio data **211** to pass through to the system **120** and the HP **326** may also input the audio data **211** to the on-device ASR component **350** by routing the audio data **211** through the HEC **327** of the hybrid selector **324**, whereby the LRO **328** notifies the ASR component **350** of the audio data **211**. At this point, the hybrid selector **324** may wait for response data from either or both of the system **120** or the on-device language processing components. However, the disclosure is not limited thereto, and in some examples the hybrid selector **324** may send the audio data **211** only to the on-device ASR component **350** without departing from the disclosure. For example, the device **110** may process the audio data **211** on-device without sending the audio data **211** to the system **120**.

The on-device ASR component **350** is configured to receive the audio data **211** from the hybrid selector **324**, and to recognize speech in the audio data **211**, and the on-device NLU component **360** is configured to determine a user intent from the recognized speech, and to determine how to act on the user intent by generating NLU output data which may

include directive data (e.g., instructing a component to perform an action). Such NLU output data may take a form similar to that as determined by the NLU component **260** of the system **120**. In some cases, a directive may include a description of the intent (e.g., an intent to turn off {device A}). In some cases, a directive may include (e.g., encode) an identifier of a second device(s), such as kitchen lights, and an operation to be performed at the second device(s). Directive data may be formatted using Java, such as JavaScript syntax, or JavaScript-based syntax. This may include formatting the directive using JSON. In at least some embodiments, a device-determined directive may be serialized, much like how remotely-determined directives may be serialized for transmission in data packets over the network(s) **199**. In at least some embodiments, a device-determined directive may be formatted as a programmatic API call with a same logical operation as a remotely-determined directive. In other words, a device-determined directive may mimic a remotely-determined directive by using a same, or a similar, format as the remotely-determined directive.

An NLU hypothesis (output by the NLU component **360**) may be selected as usable to respond to a natural language user input, and local response data may be sent (e.g., local NLU output data, local knowledge base information, internet search results, and/or local directive data) to the hybrid selector **324**, such as a "ReadyToExecute" response. The hybrid selector **324** may then determine whether to use directive data from the on-device components to respond to the natural language user input, to use directive data received from the system **120**, assuming a remote response is even received (e.g., when the device **110** is able to access the system **120** over the network(s) **199**), or to determine output audio requesting additional information from the user **5**.

The device **110** and/or the system **120** may associate a unique identifier with each natural language user input. The device **110** may include the unique identifier when sending the audio data **211** to the system **120**, and the response data from the system **120** may include the unique identifier to identify which natural language user input the response data corresponds.

In at least some embodiments, the device **110** may include, or be configured to use, one or more skill components **390** that may work similarly to the skill component(s) **290** implemented by the system **120**. The skill component(s) **390** may correspond to one or more domains that are used in order to determine how to act on a spoken input in a particular way, such as by outputting a directive that corresponds to the determined intent, and which can be processed to implement the desired operation. The skill component(s) **390** installed on the device **110** may include, without limitation, a smart home skill component (or smart home domain) and/or a device control skill component (or device control domain) to execute in response to spoken inputs corresponding to an intent to control a second device(s) in an environment, a music skill component (or music domain) to execute in response to spoken inputs corresponding to a intent to play music, a navigation skill component (or a navigation domain) to execute in response to spoken input corresponding to an intent to get directions, a shopping skill component (or shopping domain) to execute in response to spoken inputs corresponding to an intent to buy an item from an electronic marketplace, and/or the like.

Additionally or alternatively, the device **110** may be in communication with one or more skill systems **225**. For example, a skill system **225** may be located in a remote environment (e.g., separate location) such that the device

110 may only communicate with the skill system **225** via the network(s) **199**. However, the disclosure is not limited thereto. For example, in at least some embodiments, a skill system **225** may be configured in a local environment (e.g., home server and/or the like) such that the device **110** may communicate with the skill system **225** via a private network, such as a local area network (LAN).

As used herein, a "skill" may refer to a skill component **390**, a skill system **225**, or a combination of a skill component **390** and a skill system **225**.

Machine learning (ML) is a valuable computing technique that allows computing systems to learn techniques for solving complex problems without needing an explicit algorithm for the computing system to follow. ML may use a trained model that consists of internally configured operations that can manipulate a particular type of input data to determine a desired result. Trained models are used in many computing tasks such as computer vision, speech processing, predictive analyses, and many more.

Trained models come in a variety of forms including trained classifiers, Support Vector Machines (SVMs), neural networks (such as deep neural networks (DNNs), recurrent neural networks (RNNs), or convolutional neural networks (CNNs)), random forests, isolation forests, and others. As an example, a neural network typically includes an input layer, an output layer and one or more intermediate hidden layers where the input layer is configured to take in a certain kind of data and the output layer is configured to output the desired kind of data resulting from the network and the hidden layer(s) perform a variety of functions to generate output data from the input data.

Various techniques may be used to train ML models including backpropagation, statistical learning, supervised learning, semi-supervised learning, stochastic learning, or other known techniques. In supervised learning a model may be configured to infer a function from labeled training data. Thus a computing system may use training data in the form of training examples that provide examples of the kinds of input data the model will be configured to process at runtime as well as an accompanying "ground truth" for each training example. The ground truth provides the correct response for the respective training example, thus providing a complete example that can be used to train the model. Other data that may be used to train a model may include training parameters such as error functions, weights or other data that can be used to guide the training of a model.

One or more of the components described in relation to FIGS. **2** and **3** may employ one or more ML models to perform the described functionalities. For example, the SLU component **255/355** may employ one or more deep neural networks (DNNs) or other type of deep ML models to process audio data **211** (representing speech from the user **5**) and determine NLU output data, representing an intent and one or more entities indicated in the audio data **211**. Described below are techniques for processing input data (such as the audio data **211**) using an on-device ML model (for example, included in the SLU component **355**), and sending feature data to the system(s) **120**, when needed/appropriate, to enable the system(s) **120** (for example, using a ML model included in the SLU component **255**) to complete processing with respect to the input data.

The improved performance of additional layers in a DNN may come at the cost of added latency and energy usage. As networks continue to get deeper and larger, these costs become more prohibitive for real-time and energy-sensitive applications. To address this issue, the ML model(s) on the device may be augmented with additional side branch classifiers. The architecture shown in FIG. **4** may allow the device to cease processing by the ML model(s) early when the prediction for the input data can already be inferred with high confidence. The architecture may also allow the device to bridge processing to the system **120** when the prediction for the input data cannot be inferred with high confidence. In some cases, features determined at an early node/layer of a ML model may be sufficient to make a prediction with respect to certain input data, in which case, the device may determine to cease processing. In some cases, based on the features learned at an early node/layer of the ML model, the device may be able to determine that the network is not capable of making a prediction with high confidence, in which case the device may determine to bridge processing. In other cases, the device may determine to continue processing using the remaining nodes/layers of the on-device ML model. Using such techniques can improve accuracy and reduce the time it takes to process input data.

In some embodiments, an existing ML model (e.g., a DNN) may be modified to include branches at various egress points, as shown in FIG. **4**. For example, the existing ML model may include blocks **410**, **412**, **414**, **432**, **434**, **436**, **452**, **454**, **456**, and **472**. The blocks **414**, **436**, **456** and **472** may be considered egress points, and the blocks **416**, **418**, **420**, **422**, **438**, **440**, **442**, **458**, **460** and **474** may be considered branches. In some embodiments, after each node the ML model **400** makes a prediction and decides whether to go to the next node or to stop and return the prediction. During training a loss is computed at each egress point (after each node) and the training objective is to optimize a weighted sum of the losses. An ML model, including the processing nodes and processing blocks, may be stored as software in a memory of a device or computing system.

A ML model with branches as described herein, may consist of one entry point (at the first node of the ML model that receives input data) and multiple egress points. A branch may be a subset of the network containing contiguous layers, which do not overlap other branches, followed by an egress point. The main branch may be considered as the existing ML model (the original network) before the side branches are added.

The modified ML model architecture may promote faster inference via early egress points from branches. Through the branching structures and egress point criteria as well as joint optimization of loss functions for all egress points, the ML model may be able to leverage the insight that many data points can be correctly classified early and therefore do not need the later model layers/nodes.

FIG. **4** is a conceptual diagram of a ML model **400**, included at the device **110**, with branches to determine a strategy with respect to further processing the input data. In some embodiments, the ML model **400** may be a deep learning model, such as a DNN. The ML model **400** may include one or more processing nodes, such as, node **402**, node **430**, node **450** and node **470** (which may also be referred to as layers of a ML model). Each of the nodes **402**, **430**, **450** and **470** may include one or more processing blocks. In some embodiments, the processing blocks may be configured to perform convolutions. Each of the nodes **402**, **430**, **450** and **470** may also include a processing strategy decision block configured to determine whether the device **110** should cease processing, bridge processing to the system(s) **120** or continue processing at the device **110**. Each processing node/layer may be a collection of processing blocks operating together at a specific depth within a neural network type ML model **400**.

The first node, for example node **402**, may be an input node/layer that processes raw input data. The intermediary nodes, for example nodes **430** and **450**, may be hidden nodes/layers of a neural network type ML model **400**, where each node is attempting to learn different aspects/features about the input data by minimizing an error/cost function. In the example embodiment where the ML model **400** is configured for facial recognition in images, the intermediary node **430** may perform edge detection in the image data, the intermediary node **450** may detect eyes, the next intermediary node (not shown) may detect a nose, etc. The final node/layer, for example node **470**, may be an output node/layer that may consist of a single output for classification problems.

In some embodiments, the node **402** may be the first node of the ML model **400** on the device **110**, and may receive the input data (such as, audio data **211**) for processing. The node **402** may include a (first) block **410** configured to process the input data and provide output data to a (second) block **412**, where the output data from the block **410** may be features learned from processing the input data. The block **412** may process the output data from the block **410** and provide output data to a (third) block **414**, where the output data from the block **412** may be features learned from processing the output data from the block **410**. The blocks **410**, **412** and **414** may perform convolutional operations of a DNN.

In an example embodiment, the device **110**, using the decision block **422**, may determine to cease processing (cease processing) at the node **402** with respect to the input data, bridge processing at the node **402** to the system(s) **120** with respect to the input data, or continue processing the input data using the ML model **400**. The data evaluated by the decision block **422** may be features or model output data determined by the block **414**. The features or model output data determined by the block **414** may be further processed using one or more processing blocks, such as blocks **416**, **418** and **420**. Each of the blocks **416**, **418** and **420** may perform convolution operations on the output of the block **414**, thus, rendering the output of the block **414** into a form that may be evaluated by the decision block **422**.

In some embodiments, the device **110** may cease processing at a particular node of the ML model **400** if the device **110** determines that the ML model **400** is capable of outputting a prediction with respect to the input data based on the processing performed at the node, and that processing by the remaining nodes of the ML model **400** will not result in a different prediction. The decision to cease processing by the device **110** may be based on a confidence score(s) derived from the output of the last processing block of the node. For example, in the node **402** the decision to cease processing may be based on the confidence score(s) derived from the output of the block **414** and determined by the blocks **416**, **418** and **420**. If the confidence score(s) satisfies a threshold confidence score/level, then the device **110** may determine to cease processing.

In some embodiments, the device **110** may bridge processing at a particular node of the ML model **400** if the device **110** determines that the ML model **400** on the device **110** is not capable of outputting a prediction with respect to the input data based on the processing performed at the node, and that processing by the remaining nodes of the ML model **400** will not result in a prediction either. In this case, the device **110** may bridge processing to a ML model **400** included in the system(s) **120**, such that, processing with respect to the input data is completed by the system(s) **120**. Further details on how bridge processing is performed are described with respect to FIG. **5**. The decision to bridge processing by the device **110** may be based on a confidence score(s) derived from the output of the last processing block of the node. For example, in the node **402** the decision to bridge processing may be based on the confidence score(s) derived from the output of the block **414** and determined by the blocks **416**, **418** and **420**. If the confidence score(s) fails to satisfy a threshold confidence score/level, then the device **110** may determine to bridge processing.

In some embodiments, the device **110** may continue processing at the ML model **400** if the device **110** determines that the ML model **400** on the device **110** is capable of outputting a prediction with respect to the input data if processing is continued. In some embodiments, the device **110** may continue processing at the ML model **400** if the device **110** determines to not cease processing and determines to not bridge processing to the system(s) **120**. The decision to continue processing by the device **110** may be based on a confidence score(s) derived from the output of the last processing block of the node. For example, in the node **402** the decision to continue processing may be based on the confidence score(s) derived from the output of the block **414** and determined by the blocks **416**, **418** and **420**. If the confidence score(s) satisfy a first threshold confidence score/value and fails to satisfy a second threshold confidence score/value, then the device **110** may determine to continue processing.

In some embodiments, the decision block **422** may evaluate binned representations of the confidence score(s) to determine whether to cease processing, bridge processing or continue processing. For example, the decision block **422** may determine to cease processing if the confidence score(s) is a high score, may determine to bridge processing if the confidence score(s) is a low score, and may determine to continue processing if the confidence score(s) is a medium score.

If the device **110** determines to continue processing at decision block **422**, then the output of the block **414** may be provided to a block **432** (the first block) of the next node **430** of the ML model **400**, so that the ML model **400** may continue processing with respect to the input data. The node **430** may include a (first) block **432** configured to process the output data from the block **414** and provide output data to a (second) block **434**, where the output data from the block **432** may be features learned from processing the output data from the block **414**. The block **434** may process the output data from the block **432** and provide output data to a (third) block **436**, where the output data from the block **434** may be features learned from processing the output data from the block **432**. The blocks **432**, **434** and **436** may perform convolutional operations of the DNN.

In an example embodiment, the device **110**, using the decision block **442**, may determine to cease processing (cease processing) at the node **430** with respect to the input data, bridge processing at the node **430** to the system(s) **120** with respect to the input data, or continue processing the input data using the ML model **400**. The data evaluated by the decision block **442** may be features or model output data determined by the block **436**. The features or model output data determined by the block **436** may be further processed using one or more processing blocks, such as blocks **438** and **440**. Each of the blocks **438** and **440** may perform convolution operations on the output of the block **436**, thus, rendering the output of the block **436** into a form that may be evaluated by the decision block **442**.

In the node **430** the decision to cease processing, bridge processing, or continue processing may be based on the confidence score(s) derived from the output of the block **436** and determined by the blocks **438** and **440**. If the confidence score(s) satisfies a first threshold confidence score/level, then the device **110** may determine to cease processing at the node **430**. If the confidence score(s) fails to satisfy a second (lower) threshold confidence score/level, then the device **110** may determine to bridge processing at the node **430**. If the confidence score(s) satisfies the second (lower) threshold confidence score/level and fails to satisfy the first (higher) threshold confidence score/level, then the device **110** may determine to continue processing at the ML model **400**.

In some embodiments, the decision block **442** may evaluate binned representations of the confidence score(s) to determine whether to cease processing, bridge processing or continue processing. For example, the decision block **442** may determine to cease processing at the node **430** if the confidence score(s) is a high score, may determine to bridge processing at the node **430** if the confidence score(s) is a low score, and may determine to continue processing if the confidence score(s) is a medium score.

If the device **110** determines to continue processing at decision block **442**, then the output of the block **436** may be provided to a block **452** (the first block) of the next node **450** of the ML model **400**, so that the ML model **400** may continue processing with respect to the input data. The node **450** may include a (first) block **452** configured to process the output data from the block **436** and provide output data to a (second) block **454**, where the output data from the block **452** may be features learned from processing the output data from the block **436**. The block **454** may process the output data from the block **452** and provide output data to a (third) block **456**, where the output data from the block **454** may be features learned from processing the output data from the block **452**. The blocks **452**, **454** and **456** may perform convolutional operations of the DNN. In some embodiments, the block **456** may be perform pooling operations of the DNN.

In an example embodiment, the device **110**, using the decision block **460**, may determine to cease processing (exit processing) at the node **450** with respect to the input data, bridge processing at the node **450** to the system(s) **120** with respect to the input data, or continue processing the input data using the ML model **400**. The data evaluated by the decision block **460** may be features or model output data determined by the block **456**. The features or model output data determined by the block **456** may be further processed using one or more processing blocks, such as block **458**. The block **458** may perform convolution operations on the output of the block **456**, thus, rendering the output of the block **456** into a form that may be evaluated by the decision block **460**.

In the node **450** the decision to cease processing, bridge processing, or continue processing may be based on the confidence score(s) derived from the output of the block **456** and determined by the block **458**. If the confidence score(s) satisfies a first threshold confidence score/level, then the device **110** may determine to cease processing at the node **450**. If the confidence score(s) fails to satisfy a second (lower) threshold confidence score/level, then the device **110** may determine to bridge processing at the node **450**. If the confidence score(s) satisfies the second (lower) threshold confidence score/level and fails to satisfy the first (higher) threshold confidence score/level, then the device **110** may determine to continue processing at the ML model **400**.

In some embodiments, the decision block **460** may evaluate binned representations of the confidence score(s) to determine whether to cease processing, bridge processing or continue processing. For example, the decision block **460** may determine to cease processing at the node **450** if the confidence score(s) is a high score, may determine to bridge processing at the node **450** if the confidence score(s) is a low score, and may determine to continue processing if the confidence score(s) is a medium score.

If the device **110** determines to continue processing at decision block **460**, then the output of the block **456** may be provided to a block **472** of the next node **470** of the ML model **400**, so that the ML model **400** may continue processing with respect to the input data. The block **472** may be the last processing block of the ML model **400**. In some embodiments, the block **472** may be an activation layer, and may employ a rectified linear activation function (ReLu). In some embodiments, the block **472** may be a pooling layer. In some embodiments, the block **472** may be a softmax layer. In some cases, with the block **472** being the last processing block of the ML model **400**, the output of the block **472** may be the prediction of the ML model **400** with respect to the input data.

In some embodiments, the device **110** may determine, at decision block **474**, to cease processing or bridge processing at the node **470**. The decision block **474** may evaluate the output of the block **472**, which may be a confidence score(s) corresponding to the processing performed by the entire ML model **400**. In this case, since the node **470** is the final processing node of the ML model **400**, when the device **110** determines to cease processing, the device **110** is determining to use the prediction of the on-device ML model **400**. In other words, the device **110** may determine that the prediction/output of the on-device ML model **400** with respect to the input data satisfies a threshold confidence score/level, and may be used by downstream components (as described with respect to FIGS. **2** and **3**) to perform further processing of the input data. At decision block **474**, if the device **110** determines to bridge processing to the system(s) **120**, since the node **470** is the final processing node of the ML model **400**, the device **110** is determining that the prediction/output of the on-device ML model **400** with respect to the input data does not satisfy a threshold confidence score/level, and may not be used by downstream components to perform further processing of the input data.

In some embodiments, the device **110** may consider other factors/data at the decision blocks **422**, **442**, **460** and **474** in determining whether to cease processing, bridge processing or continue processing. The factors may relate to and affect the latency in processing the input data and providing a responsive output to the user. The data may include time spent by the ML model **400** in processing the input data till the egress point, estimated time that the ML model **400** will spend if processing continues, the number of nodes and/or blocks of the ML model **400** that have processed the input data, the number of nodes and/or blocks remaining in the ML model **400** that can process the input data, the time elapsed since the device **110** received the input data, etc. The decision blocks **422**, **442**, **460** and **474** may also consider the number of iterations/computations/operations already performed by the ML model **400** in processing the input data till the egress point, and the number of iterations/computations/operations that may have to be performed if processing continues at ML model **400**. The decision blocks **422**, **442**, **460**, and **474** may also consider a divergence in the features determined by the respective node. In some embodiments, the decision blocks **422**, **442**, **460** and **474** may also consider the complexity of the input data in terms of the amount of data received, the quality of data received, etc. For example, if the input data is audio data **211**, the length of the audio data **211** may be considered, the noise to signal ratio may be considered; if the input data is a natural language input, then the number of words in the input data may be considered. In some embodiments, the decision blocks **422**, **442**, **460** and **474** may consider the quality of the network connection between the device **110** and the system(s) **120**. If the network connection is low/poor, then the system(s) **120** may not receive data sent by the device **110** or may be delayed in receiving the data sent by the device **110**. In this case, the device **110** may determine to continue processing at the device **110** using the ML model **400**, and reduce latency in processing the input data.

It should be understood that the ML model **400** may include fewer or more processing nodes than shown in FIG. **4**. Each of the nodes may include fewer or more processing blocks than shown in FIG. **4**. The architecture of the ML model **400** may vary from what is illustrated based on system configurations and ML model configurations.

The ML model **400**, in some embodiments, may be trained by solving a joint optimization problem on the weighted sum of the loss functions associated with the egress points. The blocks **414**, **436**, **456** and **472**, for example, may be considered as egress points. Once the ML model **400** is trained, the device **110** utilizes the egress points to determine whether to cease processing, bridge processing or continue processing, as described above, thus reducing the cost (time and resources-wise) of processing input data.

At each egress point, the device **110** may use the entropy of a classification result (e.g., output of a softmax layer at blocks **420**, **440**, **458** and **472**) as a measure of confidence in the prediction. If the entropy is below a threshold value, meaning that the ML model **400** is confident in the prediction, the device **110** may cease processing, and the remaining nodes of the ML model **400** do not process the input data. If the entropy value is above a threshold value, then the ML model **400** is deemed not confident, and the device **110** may continue to the next nodes in the ML model **400**. In some embodiments, if the entropy is below another threshold value, meaning that the ML model **400** is not capable of making a prediction with a high confidence, even if processing continues, then the device **110** may determine to bridge processing to the system(s) **120**.

In some embodiments, if the entropy is below the threshold value and certain other conditions exist, then the device **110** may determine to bridge processing to the system(s) **120**, to reduce latency in processing the input data and to increase accuracy in processing the input data. These other conditions may include, but are not limited to, the processing time already spent by the ML model **400** in processing the input data when the ML model **400** reached the egress point, the time since the input data was received by the device **110**, the number of nodes remaining in the ML model **400** to process the input data, the number of nodes in the ML model **400** that already processed the input data, and others. In some embodiments, the device **110** may also compare a previous entropy (or previous confidence score) of the prediction at a previous egress point (e.g., the block **420**) with the instant entropy (or instant confidence score) of the prediction at an instant egress point (e.g., the block **440**) to determine whether there is positive or negative change in the entropy (or confidence score). If there is an increase in the instant entropy from the previous entropy (or a decrease in the instant confidence score from the previous confidence score) then the likelihood of the ML model **400** generating an accurate prediction may be low. That is, continued processing by the ML model **400** is not likely to result in an accurate prediction. In this case, the device **110** may determine to bridge processing to the system(s) **120** to complete

processing. In this manner, the device **110** may not waste time by continuing to process at the device **110** when the ML model **400** is not going to be able to make a high confidence prediction.

In training the blocks in the branches, network regularization and mitigation of vanishing gradients in backpropagation may also be considered. For the former, the branches may provide regularization on the existing ML model. For the latter, a relatively shallower branch (with fewer blocks) at a lower layer may provide more immediate gradient signal in backpropagation, resulting in discriminative features in lower nodes of the ML model **400**, thus improving its accuracy.

In some embodiments, there may be fewer egress points than illustrated in FIG. **4**. Each node of the ML model **400** may not have an egress point. For example, the first node **402** may not have an egress point because it may not be beneficial (time-wise and resource-wise) to evaluate the prediction made by the first node of the ML model **400**, as the features learned at the first node may not be valuable for making a prediction. In other embodiments, there may be more than one egress point in a node of the ML model **400**. In some embodiments, there may be fewer blocks in a branch for an egress point. For example, at node **402**, there may only be block **416** (and no blocks **418** and **420**).

In some embodiments, a node of the ML model **400** may include a combination of convolutional layers and fully-connected layers after the convolutional layers, enabling both local and global features to be combined at a node level, which may be used to make a decision at the egress point. The number of blocks in a first egress point branch may be less than the number of blocks in a second/next egress point branch, thus, lessening the amount of computation needed at a later egress point. Earlier egress points may include more processing blocks than later egress points. The blocks in the egress point branches may include a combination of convolutional layers and fully-connected layers.

The device **110** may base its decision at the egress points on the observation that lower and intermediate nodes of the ML model **400** may suffice to classify certain input data or determine that the ML model **400** is not going to be able to classify the input data.

Each of the processing blocks **410**, **412**, **414**, **416**, **418**, **420**, **432**, **434**, **436**, **438**, **440**, **452**, **454**, **456**, **458**, and **472** may be configured to perform one or more operations of a ML model, for example, including but not limited to, a convolutional layer, a recurrent layer, a LSTM layer, a pooling layer, an averaging layer, a rectified linear activation function, a softmax layer, or other operations/layers of a ML model.

As the input data is processed by the nodes of ML model, the dimensions of the features determined by a node decreases, based on which later occurring egress branches may have fewer processing blocks. For example, the egress branch for node **450** may have one processing block **458** in the egress branch because the dimension of the feature vector outputted at block **456** may be smaller than dimension of the feature vector outputted by the block **414**, where the egress branch has three blocks, **416**, **418** and **420**, for the node **402**.

The system(s) **120** (or another device **110**) may include one or more ML models (e.g., ML model **500** of FIG. **5**) to perform the same type of processing performed by the ML model **400**. The ML model **500** may include, in some embodiments, the same number of processing nodes as the on-device ML model **400**. In some embodiments, the sequential nodes of the ML model **500** may correspond to the sequential nodes of the ML model **400**. For example, the node **402** may be an initial/first node of the ML model **400**, while node **510** may be an initial/first node of the ML model **500**. FIG. **5** is a conceptual diagram illustrating how the on-device ML model **400** can bridge to a ML model **500** on the system(s) **120** to perform processing with respect to input data. As described in relation to FIG. **4**, the device **110** may determine, at each processing node, whether to bridge processing to the system(s) **120**.

At the decision block **422**, the device **110** may determine to cease processing at the node **402**, in response to which, the node **402** may provide output data **502** (e.g., the output of the block **414**). The device **110** may use the output data **502** as the prediction of the ML model **400**, and may provide the output data **502** to downstream components to perform further processing of the input data.

At decision block **422**, the device **110** may determine to bridge processing at the node **402**, in response to which, the device **110** may send feature data **509** to the system(s) **120**. The feature data **509** may be the output of the block **414**. In some embodiments, the feature data **509** may be embeddings determined based on processing by the block **414**. In some embodiments, the feature data **509** may be token data determined based on processing by the block **414**. In some embodiments, the device **110** may also provide data, to the system(s) **120**, indicating where within the ML model **400** the device **110** decided to bridge processing. Such data may indicate a processing node and a processing block within the processing node, using a node identifier and a block identifier. The ML model **500** may pick up processing where the ML model **400** left off. The ML model **500** may do so using the node and block indicated by the device **110**. As such, the system(s) **120** may not re-perform processing that the device **110** has already performed, thus, reducing latency.

At decision block **422**, the device **110** may determine to continue processing at the ML model **400**, in response to which, the output of the node **402** may be provided to the next node **430** of the ML model **400**.

As shown in FIG. **5**, at the nodes **430** and **450**, the device **110**, similarly to the decision block **422**, may determine to cease processing, bridge processing or continue processing, via the decision blocks **442** and **460**. Output data **504** may be provided by the node **430** if the device **110** determines to cease processing at the node **430**. Feature data **518** may be provided to the system(s) **120** if the device **110** determines to bridge processing at the node **430**. Output data **506** may be provided by the node **450** if the device **110** determines to cease processing at the node **450**. Feature data **528** may be provided to the system(s) **120** if the device **110** determines to bridge processing at the node **450**.

At the node **470**, which may be the final processing node of the ML model **400**, the device **110** may determine to cease processing and may send output data **508** generated by the node **470** to downstream components to perform further processing of the input data. In this case, the device **110** may determine to use the prediction of the on-device ML model **400**. The device **110**, at node **470**, may determine to bridge processing to the system(s) **120**, and may send feature data **538** to the system(s) **120**. In this case, the device **110** may determine that the on-device ML model **400** is not confident enough in its processing of the input data, and therefore, the device **110** may request the system(s) **120** to complete processing with respect to the input data.

The ML model **500** may be a ML model included in the SLU component **255**. As shown in FIG. **5**, the ML model **500** of the system(s) **120** may include multiple processing nodes, such as nodes **510**, **520**, **530**, **540**, **545**. Each of the processing nodes may include one or more processing blocks, such as, blocks **516**, **522**, **524**, **526**, **532**, **534**, **536**, **542** and **546**. The system(s) **120** may initiate processing at the ML model **500** based on where the device **110** left off. For example, the system(s) **120** may begin processing at the node **520** if the device **110** bridged processing at the node **402**, where the node **520** in the ML model **500** may be the second node. Thus, the ML model **500** may not perform processing by the first node **510** that may be already performed by the first node **402** of the ML model **400**. In this case, the system(s) **120** may continue processing at the ML model **500** via the nodes **520**, **530**, **540** and **545**.

The node **545** may be the final processing node of the ML model **500**, and may determine output data **550** representing a prediction of the ML model **500** on the system(s) **120** with respect to the input data. If the device **110** determines to bridge processing to the system(s) **120**, then the output data **550** may be used as the prediction for the input data, and the output data **550** may be sent to downstream components (of the system **120**) to perform further processing of the input data.

In some embodiments, the system ML model **500** may also include exit points (similar to the egress points of the ML model **400**). At these exit points, the system(s) **120** may determine to cease processing or continue processing, based on the confidence level of the prediction generated by the corresponding node.

The feature data **509**, **518**, **528** and **538** may be the output of the last block in the corresponding node. In some embodiments, the feature data **509**, **518**, **528** and **538** may be embeddings determined based on processing by the corresponding node. In some embodiments, the feature data **509**, **518**, **528** and **538** may be token data determined based on processing by the corresponding node. In some embodiments, the device **110** may also send other data to the system(s) **120** along with the feature data **509**, **518**, **528** and **538**. The other data may include, but is not limited to, context data corresponding to the input data, the input data, user profile data associated with the user that provided the input data, and other data. The context data may include device information (device type, device model, version number, device input/output capabilities) for the device **110** that received the input data, location information (user location, device **110** location), time information (when the input data was received), and other context information. The device **110** may encrypt the data sent to the system(s) **120**, and the system(s) **120** may decrypt the received data prior to processing (such encryption and description may be performed using art-known/industry-known techniques). The device **110** may add noise to the data prior to sending the data to the system(s) **120**, and the system(s) **120** may remove the noise or process the data with the noise. The added noise may be such that it may not impact the processing results.

In some embodiments, the ML model **400** may be included in the SLU component **355** and configured to process audio data **211** to determine NLU output data, and the ML model **500** may be included in the SLU component **255** and configured to process audio data **211** to determine NLU output data. In other embodiments, the ML model **400** may be included in the NLU component **360** and may be configured to process ASR output data to determine NLU output data, and the ML model **500** may be included in the NLU component **260** configured to process ASR output data to determine NLU output data. In yet other embodiments, the ML model **400** and the ML model **500** may be configured to process other types of data.

In some embodiments, the ML model **500** may be included in another device **110**, and the ML model **400** may bridge processing to the ML model **500** on the device **110** (e.g., the device **110***b*). The device **110***b* may be associated with the device **110***a* (that includes the ML model **400**) with respect to a user profile identifier—as in the device **110***a* and the device **110***b* may be associated with the same user **5**. The device **110***a* and the device **110***b* may be associated with the same household (office, vehicle, hotel, building, etc.). The device **110***b* may have higher/better processing capabilities in terms of a processor and a memory included in the device **110***b* as compared to the processing capabilities of the device **110***a*.

Given the size of some of the ML models, it may be difficult to compress an entire ML model to include in the device **110**. Instead, splitting an ML model across environments may enable optimization of operations performed on the device **110**. The modular structure of the ML models described herein may allow for the processing to be spilt across environments, as a subset of the processing nodes can reside on a user device and the remainder of the processing nodes (or the entire ML model) can reside on a system (e.g., a server, in the cloud, etc.) or on another device. FIGS. **6**A, **6**B and **6**C are conceptual diagrams illustrating how a ML model **620** may be split, according to embodiments of the present disclosure. In some embodiments, a system(s) may train/configure the ML model **620** using training data **602**. In the case that the ML model is to be used by the SLU components **255** and **355**, the training data **602** may include annotated audio data. In the case that the ML model is to be used by the NLU components **260** and **360**, the training data **602** may include annotated ASR output data. In the case that the ML model **620** is to be used for image processing, object recognition, and computer vision tasks, the training data **602** may include annotated image data and video data. In the case that the ML model **620** is to be used to detect sentiment from audio data, the training data **602** may include audio data labeled with a sentiment category. Using the training data **602**, the system(s) may configure the ML model **620**. In some embodiments, the ML model **620** may include multiple sequential processing nodes, such as, nodes **604**, **606**, **608**, **610**, **612**, **614**, **616** and **618**.

As shown in FIG. **6**A, in some embodiments, the ML model **620** may be spilt (divided) to generate the on-device ML model **400**. In some embodiments, the on-device ML model **400** may include a set of processing nodes from the ML model **620** that correspond to the bottom processing nodes (sequentially first processing nodes) of the ML model **620**. For example, the nodes **402**, **430**, **450** and **470** of the on-device ML model **400** may correspond respectively to the nodes **604**, **606**, **608** and **610** of the ML model **620**. In this example embodiment, the ML model **500** of the system(s) **120** may include all of the processing nodes of ML model **620**. In some embodiments, the system(s) **120** may use the training data **602** to configure the ML model **620**, store the configured ML model **620** as the ML model **500**, and then send data corresponding to the bottom set of the processing nodes of the ML model **620** to the device **110** to be stored as the ML model **400** at the device **110**.

As shown in FIG. **6**B, in some embodiments, the ML model **620** may be split (divided) to generate the on-device ML model **400** and the system ML model **500**. In some embodiments, the on-device ML model **400** may include a set of the processing nodes from the ML model **620** that correspond to the bottom processing nodes (sequentially first processing nodes) of the ML model **620**, while the system ML model **500** may include a set of the processing nodes from the ML model **620** that correspond to the top processing nodes (sequentially last processing nodes) of the ML model **620**. For example, the nodes **402**, **430**, **450** and **470** of the on-device ML model **400** may correspond respectively to the nodes **604**, **606**, **608** and **610** of the ML model **620**. The nodes **510**, **520**, **530** and **540** of the system ML model **500** may correspond respectively to the nodes **612**, **614**, **616** and **618** of the ML model **620**.

Different devices **110** may include a different set or number of processing nodes from the ML model **620**. Which nodes and the number of nodes included in the device **110** may be based on the processing capabilities (at least with respect to a processor and a memory) of the device **110**. FIG. **6**C shows how different devices **110** may include a different set of processing nodes. For example, as shown in FIG. **6**C, the device **110***a* may include an on-device ML model **400***a* with four processing nodes corresponding to the bottom/first four processing nodes of the ML model **620**, while the device **110***b* may include an on-device ML model **400***b* including three processing nodes corresponding to the bottom/first three processing nodes of the ML model **620**, and the device **110***c* may include an on-device ML model **400***c* including two processing nodes corresponding to the bottom/first two processing nodes of the ML model **620**. The system ML model **500** (not shown in FIG. **6**C) may include all of the processing nodes of the ML model **620** (as shown in FIG. **6**A). As described herein, the device **110**, when bridging processing to the system(s) **120** or to another device **110**, may send data representing a node where the on-device ML model **400** stopped processing, so that the system(s) **120** or the other device **110** may pick up processing at that point.

In splitting the ML model **620** and generating the on-device ML model **400**, one or more final processing nodes may be added to the set of nodes for the on-device ML model **400**, so that the on-device ML model **400** may be a fully functional ML model capable of outputting a prediction for input data. For example, a pooling layer or softmax layer may be added after the bottom set of nodes from the ML model **620**.

In some embodiments, one or more compression techniques may be applied to the on-device ML model(s) **400** for storing at the device **110**. These compression techniques may include reducing the total number of model parameters of the ML model(s) **400**, thus reducing the amount of computations required to generate the prediction. The compression techniques may also include pruning the ML model **400** by removing one or more network connections with small contributions towards the prediction. The compression techniques may also include quantizing the processing nodes. In some embodiments, a neural architecture search model/algorithm may be used to automatically determine where, within the ML model **400**, to insert branches and egress points, and which nodes/branches/egress points should be deployed to the device **110** based on the device's capabilities.

In some embodiments, the on-device ML model **400** and the system ML model **500** may be trained/configured separately, rather than split from a larger ML model. In some cases, the on-device ML model **400** may configured to perform a light (lite) version of processing as compared to the system ML model **500**. In embodiments where the ML models are configured for SLU processing, the on-device ML model **400** may have reduced capabilities as compared to the system ML model **500**, for example, the on-device ML model **400** may be able to process certain simple natural language inputs (e.g., "stop," "turn on the lights," "play music," etc.), while the system ML model **500** may be able to process the simple natural language inputs as well as complex natural language inputs (e.g., "find flights to Miami and book one that gets me there in time for my meeting"). A natural language input may be simple or complex based on the number of words in the input, the number of entities in the input, the number of verbs and/or nouns in the input, the number of requests in the input, the number of skills that may invoked to respond to the input, etc.

In some embodiments, the ML model **400** outputs within the same label space at each processing node **402**, **430**, **450** and **470**. For example, each processing node, the ML model **400** is able to make a prediction from the same domain labels and intent labels.

In other embodiments, the ML model **400** outputs in different label spaces at different processing nodes **402**, **430**, **450** and **470**. For example, at processing node **402**, the ML model **400** may be able to make a prediction from a first subset of domains and intents, while at processing node **430** the ML model **400** may be able to make a prediction from a second subset of domains and intents, where the first subset may be different than the second subset or the first subset may be included in the second subset. For domains and intents that are not supported by the ML model **400**, the device **110** may bridge processing to the system ML model **500**.

In some embodiments, the device **110** may include a ML model, for example, a binary classifier, configured to determine whether the device **110** is able to generate a prediction for the input data (with a high confidence). In some embodiments, the device **110** may process the input data using the binary classifier, before sending the input data to the ML model **400** for processing. If the binary classifier determines that the ML model **400** will not be able to make a prediction with high confidence, then the device **110** may send the input data to the system(s) **120** for processing, and may not perform any processing of the input data at the device **110**, and the system(s) **120** may start processing the input data at the first node **510** of the ML model **500**. If the binary classifier determines that the ML model **400** will be able to make a prediction with high confidence, then the device **110** may send the input data to the ML model **400** for processing. In some embodiments, the decision blocks **422**, **442**, **460** and **474** may employ the binary classifier.

In some embodiments, where the ML models are configured for SLU processing, the binary classifier, may be configured using a training dataset that includes a first portion of data (of the same type as the input data) labeled as "simple" and a second portion of data labeled as "complex." If the input data corresponds to the "simple" category, then device **110** may process the input data, and if the input data corresponds to the "complex" category, then the device **110** may send the input data to the system(s) **120** for processing.

In some embodiments, the binary classifier may be configured using a training dataset that includes data (same type as the input data) labeled with a value/identifier indicating at which egress point the ML model **400** ceased processing for that data point. For example, the training dataset may include a first natural language input "stop" and the corresponding label may be "egress point 1" or "1" indicating that the ML model **400** exited processing at the first egress point (and used the prediction of the first node). In another example, the training dataset may include a second natural language input "turn off the lights in the bedroom" and the corresponding label may be "egress point 4" or "4" indicating that the ML model **400** exited processing at the fourth/final egress point, indicating that all nodes of the ML model **400** had to be used to generate a prediction for this data point. In yet another example, the training dataset may include a third natural language input "play music" and the corresponding label may be "egress point 2" or "2" indicating that the ML model **400** exited processing at the second egress point (and used the prediction of the second node). Using the binary classifier, the device **110** may estimate which egress point the input data may have to be processed until. When that estimated egress point is reached, and other conditions exist (such as the data considered at the decision blocks **422**, **442**, **460** and **474**), the device **110** may determine to cease processing or bridge processing, instead of continuing processing.

In some embodiments, the device **110** may process the input data using the entire ML model **400** (without checking the egress points), may send the processing results of the ML model **400** to the system(s) **120**, and the system ML model **500** may complete processing of the input data based on the processing results of the ML model **400**.

In some embodiments, the ML models **400** and **500** may be configured to perform SLU processing as described above. In other embodiments, the ML models **400** and **500** may be configured to process image data and video data for various tasks, such as, object recognition, facial recognition, gesture recognition, text recognition, computer vision tasks, etc. In yet other embodiments, the ML models **400** and **500** may be configured to process other types of data (e.g., motion sensor data, text data, non-speech audio data, etc.) to perform other tasks, such as, predictive analysis, classification analysis, user activity detection, etc.

FIG. **7** is a signal flow diagram illustrating how input data may be processed by the device **110** and the system(s) **120**. The device **110** may receive (**702**) input data, for example audio data **211** or text data **213**, and the device **110** may process (**704**) the input data using an on-device ML model(s). At decision block **706**, the device **110** may determine to cease processing or bridge processing with respect to the input data being processed by the on-device ML model(s). In this example case, the device **110** may bridge (**707**) processing to the system(s) **120**. The device **110**, in this case, may send (**708**) feature data to the system(s) **120**, where the feature data is determined by or generated by the on-device ML model(s) when processing the input data. The device **110** may also send (**710**) a model stopping point to the system(s) **120**, where the model stopping point may represent the point (a processing node and/or a processing block) within the on-device ML model(s) up to which the on-device ML model(s) completed processing with respect to the input data.

The system(s) **120** may process (**712**) the feature data using a system ML model(s) based on the model stopping point. The system(s) **120** may pick up processing where the on-device ML model(s) left off with respect to the input data. As such, the system(s) **120** may use the feature data, provided by the device **110**, to initialize a processing node of the system ML model(s). The system(s) **120** may determine which processing node to initialize based on the model stopping point.

The system(s) **120** may process the input data, as described in relation to FIG. **2**, and may select (**714**) a skill to respond to the input data. The system(s) **120** may send (**716**) data corresponding to the input data to a skill system(s) **225**/skill component(s) **290**/**390** associated with the selected skill. The skill system **225** may send (**718**) output data to the device **110**, where the output data is responsive to the input data received at step **702**. Alternatively, the skill system **225** may send the output data to the system(s) **120**, which sends the output data to the device **110**.

In this manner, an on-device ML model(s) may process input data, but may not complete the processing of the input data or may not be confident in its processing of the input data, and may send data to the system(s) **120** to enable the system(s) **120** to complete processing with respect to the input data.

FIG. **8** is a signal flow diagram illustrating how input data may be processed by the device **110**. The device **110** may receive (**802**) input data, for example, audio data **211** or text data **213**, and the device **110** may process (**804**) the input data using an on-device ML model(s). At decision block **806**, the device **110** may determine to cease processing or bridge processing with respect to the input data being processed by the on-device ML model(s). In this example case, the device **110** may cease (**808**) processing at the on-device ML model(s). Using the output of the on-device ML model(s), the device **110** may perform further processing as described in relation to FIG. **3**. The device **110** may select (**810**) a skill to respond to the input data. The system(s) **120** may send (**812**) data corresponding to the input data to a skill system(s) **225**/skill component(s) **290/390** associated with the selected skill. The skill system **225** may send (**814**) output data to the device **110**, where the output data is responsive to the input data received at step **802**. In this manner, the device **110** may complete processing with respect to the input data at the device **110**, without requesting the system(s) **120** to perform some processing.

FIG. **9** is a block diagram conceptually illustrating example components of a device **110** according to the present disclosure. FIG. **10** is a block diagram conceptually illustrating example components of a system, such as the system **120** or a skill system **225**. A system (**120/225**) may include one or more servers. A "server" as used herein may refer to a traditional server as understood in a server/client computing structure but may also refer to a number of different computing components that may assist with the operations discussed herein. For example, a server may include one or more physical computing components (such as a rack server) that are connected to other devices/components either physically and/or over a network and is capable of performing computing operations. A server may also include one or more virtual machines that emulates a computer system and is run on one or across multiple devices. A server may also include other combinations of hardware, software, firmware, or the like to perform operations discussed herein. The system **120** may be configured to operate using one or more of a client-server model, a computer bureau model, grid computing techniques, fog computing techniques, mainframe techniques, utility computing techniques, a peer-to-peer model, sandbox techniques, or other computing techniques.

Multiple systems (**120/225**) may be included in the system **100** of the present disclosure, such as one or more systems **120** for performing ASR processing, one or more systems **120** for performing NLU processing, and one or more skill systems **225**, etc. In operation, each of these systems may include computer-readable and computer-executable instructions that reside on the respective device (**120/225**), as will be discussed further below.

Each of these devices (**110/120/225**) may include one or more controllers/processors (**904/1004**), which may each include a central processing unit (CPU) for processing data and computer-readable instructions, and a memory (**906/1006**) for storing data and instructions of the respective device. The memories (**906/1006**) may individually include volatile random access memory (RAM), non-volatile read only memory (ROM), non-volatile magnetoresistive memory (MRAM), and/or other types of memory. Each device (**110/120/225**) may also include a data storage component (**908/1008**) for storing data and controller/processor-executable instructions. Each data storage component (**908/1008**) may individually include one or more non-volatile storage types such as magnetic storage, optical storage, solid-state storage, etc. Each device (**110/120/225**) may also be connected to removable or external non-volatile memory and/or storage (such as a removable memory card, memory key drive, networked storage, etc.) through respective input/output device interfaces (**902/1002**).

Computer instructions for operating each device (**110/120/225**) and its various components may be executed by the respective device's controller(s)/processor(s) (**904/1004**), using the memory (**906/1006**) as temporary "working" storage at runtime. A device's computer instructions may be stored in a non-transitory manner in non-volatile memory (**906/1006**), storage (**908/1008**), or an external device(s). Alternatively, some or all of the executable instructions may be embedded in hardware or firmware on the respective device in addition to or instead of software.

Each device (**110/120/225**) includes input/output device interfaces (**902/1002**). A variety of components may be connected through the input/output device interfaces (**902/1002**), as will be discussed further below. Additionally, each device (**110/120/225**) may include an address/data bus (**924/1024**) for conveying data among components of the respective device. Each component within a device (**110/120/225**) may also be directly connected to other components in addition to (or instead of) being connected to other components across the bus (**924/1024**).

Referring to FIG. **9**, the device **110** may include input/output device interfaces **902** that connect to a variety of components such as an audio output component such as a speaker **912**, a wired headset or a wireless headset (not illustrated), or other component capable of outputting audio. The device **110** may also include an audio capture component. The audio capture component may be, for example, a microphone **920** or array of microphones, a wired headset or a wireless headset (not illustrated), etc. If an array of microphones is included, approximate distance to a sound's point of origin may be determined by acoustic localization based on time and amplitude differences between sounds captured by different microphones of the array. The device **110** may additionally include a display **916** for displaying content. The device **110** may further include a camera **918**.

Via antenna(s) **914**, the input/output device interfaces **902** may connect to a network(s) **199** via a wireless local area network (WLAN) (such as WiFi) radio, Bluetooth, and/or wireless network radio, such as a radio capable of communication with a wireless communication network such as a Long Term Evolution (LTE) network, WiMAX network, 3G network, 4G network, 5G network, etc. A wired connection such as Ethernet may also be supported. Through the network(s) **199**, the system may be distributed across a networked environment. The I/O device interface (**902/1002**) may also include communication components that allow data to be exchanged between devices such as different physical servers in a collection of servers or other components.

The components of the device **110**, the system **120**, and/or a skill system **225** may include their own dedicated processors, memory, and/or storage. Alternatively, one or more of the components of the device **110**, the system **120**, and/or a skill system **225** may utilize the I/O interfaces (**902/1002**), processor(s) (**904**/**1004**), memory (**906**/**1006**), and/or storage (**908**/**1008**) of the device(s) **110**, system **120**, or the skill system **225**, respectively. Thus, the ASR component **250** may have its own I/O interface(s), processor(s), memory, and/or storage; the NLU component **260** may have its own I/O interface(s), processor(s), memory, and/or storage; and so forth for the various components discussed herein.

As noted above, multiple devices may be employed in a single system. In such a multi-device system, each of the devices may include different components for performing different aspects of the system's processing. The multiple devices may include overlapping components. The components of the device **110**, the system **120**, and a skill system **225**, as described herein, are illustrative, and may be located as a stand-alone device or may be included, in whole or in part, as a component of a larger device or system.

As illustrated in FIG. **11**, multiple devices (**110***a*-**110***l*) may process as part of the system **100**. The network(s) **199** may include a local or private network or may include a wide network such as the Internet. Devices may be connected to the network(s) **199** through either wired or wireless connections. For example, the system **100** may include a speech-controlled device(s) **110***a*, a smart phone(s) **110***b*, a smart watch(s) **110***c*, a tablet computer(s) **110***d*, a vehicle(s) **110***e*, a speech-controlled display device(s) with a display **110***f*, a smart television(s) **110***g*, a washer(s)/dryer(s) **110***h*, a refrigerator(s) **110***i*, a microwave(s) **110***j*, smart glasses **110***k*, earbuds **110***l*, and/or a wearable ring(s) **110***m*.

The concepts disclosed herein may be applied within a number of different devices and computer systems, including, for example, general-purpose computing systems, speech processing systems, and distributed computing environments.

The above aspects of the present disclosure are meant to be illustrative. They were chosen to explain the principles and application of the disclosure and are not intended to be exhaustive or to limit the disclosure. Many modifications and variations of the disclosed aspects may be apparent to those of skill in the art. Persons having ordinary skill in the field of computers and speech processing should recognize that components and process steps described herein may be interchangeable with other components or steps, or combinations of components or steps, and still achieve the benefits and advantages of the present disclosure. Moreover, it should be apparent to one skilled in the art, that the disclosure may be practiced without some or all of the specific details and steps disclosed herein.

Aspects of the disclosed system may be implemented as a computer method or as an article of manufacture such as a memory device or non-transitory computer readable storage medium. The computer readable storage medium may be readable by a computer and may comprise instructions for causing a computer or other device to perform processes described in the present disclosure. The computer readable storage medium may be implemented by a volatile computer memory, non-volatile computer memory, hard drive, solid-state memory, flash drive, removable disk, and/or other media. In addition, components of system may be implemented as in firmware or hardware, such as an acoustic front end (AFE), which comprises, among other things, analog and/or digital filters (e.g., filters configured as firmware to a digital signal processor (DSP)).

Conditional language used herein, such as, among others, "can," "could," "might," "may," "e.g.," and the like, unless specifically stated otherwise, or otherwise understood within the context as used, is generally intended to convey that certain embodiments include, while other embodiments do

not include, certain features, elements and/or steps. Thus, such conditional language is not generally intended to imply that features, elements, and/or steps are in any way required for one or more embodiments or that one or more embodiments necessarily include logic for deciding, with or without other input or prompting, whether these features, elements, and/or steps are included or are to be performed in any particular embodiment. The terms "comprising," "including," "having," and the like are synonymous and are used inclusively, in an open-ended fashion, and do not exclude additional elements, features, acts, operations, and so forth. Also, the term "or" is used in its inclusive sense (and not in its exclusive sense) so that when used, for example, to connect a list of elements, the term "or" means one, some, or all of the elements in the list.

Disjunctive language such as the phrase "at least one of X, Y, Z," unless specifically stated otherwise, is understood with the context as used in general to present that an item, term, etc., may be either X, Y, or Z, or any combination thereof (e.g., X, Y, and/or Z). Thus, such disjunctive language is not generally intended to, and should not, imply that certain embodiments require at least one of X, at least one of Y, or at least one of Z to each be present.

As used in this disclosure, the term "a" or "one" may include one or more items unless specifically stated otherwise. Further, the phrase "based on" is intended to mean "based at least in part on" unless specifically stated otherwise.

What is claimed is:

1. A system comprising:

a first component including at least a first processor and at least a first memory, wherein the first component is a user device; and

a second component including at least a second processor and at least a second memory, wherein the second component is a second device that uses a network connection to communicate with the first component,

the at least first memory including first instructions that, when executed by the at least first processor, cause the first component to:

receive first audio data representing a first spoken user input;

using a first node of a first machine learning (ML) model, the first ML model configured to perform spoken language understanding (SLU) processing, process a first portion of the first audio data to determine embedding data representing a partial speech recognition output of the first node;

determine, based on the embedding data, the second component is to process to generate a SLU output; and

in response to determining the second component is to process to generate the SLU output, and prior to processing the embedding data using a second node of the first ML model, send the embedding data to the second component,

the at least second memory including second instructions that, when executed by the at least second processor, cause the second component to:

process the embedding data using a second ML model to complete the SLU processing of the first audio data;

determine, using the second ML model, a first SLU output;

determine, using the first SLU output, a first output responsive to the first spoken user input; and

send the first output to the first component.

2. The system of claim **1**, wherein the first instructions, when executed by the at least first processor, further cause the first component to:

Send, to the second component, a node identifier corresponding to the first node of the first ML model;

send, to the second component, a device identifier corresponding to the user device;

process the first audio data to perform user recognition and determine a profile identifier corresponding to the first audio data; and

send, to the second component, the profile identifier.

3. The system of claim **1**, wherein the first instructions, when executed by the at least first processor, further cause the first component to:

receive second audio data representing a second spoken user input;

using a classifier, process the second audio data to determine a confidence value representing a likelihood of the first ML model being able to process the second audio data;

based on the confidence value failing to meet a threshold, determine that the second audio data is to be sent to the second component to generate a second SLU output; and

send the second audio data to the second component to perform SLU processing.

4. A computer-implemented method comprising:

receiving, at a first device, first input data corresponding to a first input;

processing, at the first device, a first portion of the first input data using a second portion of a first machine learning (ML) model, wherein the second portion of the first ML model comprises a first node of the first ML model;

determining, at the first device and based at least in part on processing the first portion of the first input data using the second portion of the first ML model, first embedding data representing a partial speech recognition output of the second portion of the first ML model;

determining, based on the first embedding data, a second device is to complete the processing of the first input data; and

in response to determining the second device is to complete the processing of the first input data, and prior to processing the first embedding data using a third portion of the first ML model, sending the first embedding data to the second device to complete the processing of the first input data using a second ML model, wherein:

the third portion of the first ML model comprises a second node of the first ML model,

the first ML model and the second ML model are configured to perform a first type of processing, and

sending the first embedding data to the second device causes the second device to complete the first type of processing of the first input data using the second ML model to determine a response to the first input.

5. The computer-implemented method of claim **4**, wherein the first embedding data is determined by the first node of the second portion of the first ML model, and the method further comprises:

processing, at the first device, the first embedding data using the second node of the third portion of the first ML model;

determining, at the first device, second embedding data output by the second node;

processing the first embedding data with respect to the second embedding data; and

sending the second embedding data to the second device based at least in part on the processing of the first embedding data with respect to the second embedding data.

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

receiving the first input data comprises receiving audio data representing a spoken input, and

processing the first portion of the first input data using the second portion of the first ML model comprises processing a fourth portion of the audio data using the second portion of the first ML model, wherein the first ML model is configured for spoken language understanding (SLU) processing, and wherein the second ML model is configured for SLU processing.

7. The computer-implemented method of claim **4** wherein:

receiving the first input data comprises receiving image data representing an object, and

processing the first portion of the first input data using the second portion of the first ML model comprises processing a fourth portion of the image data using the second portion of the first ML model, wherein the first ML model is configured for object recognition, and wherein the second ML model is configured for object recognition.

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

receiving second input data corresponding to a second input;

processing a fourth portion of the second input data using the first node of the second portion of the first ML model;

determining second embedding data output by the first node;

processing the second embedding data to determine an entropy value corresponding to the second embedding data;

determining the entropy value satisfies a threshold value; and

based on the entropy value satisfying the threshold value, determining, using the second embedding data, first output data responsive to the second input.

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

receiving second input data corresponding to a second input;

using a classifier, processing the second input data to determine a likelihood that the first ML model is able to process the second input data to generate a first output;

based on the likelihood failing to meet a threshold, determining to send the second input data to the second device for processing; and

sending the second input data to the second device to generate the first output responsive to the second input.

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

receiving second input data corresponding to a second input;

using the first node of the second portion of the first ML model, processing a fourth portion of the second input data to determine second embedding data;

determining the second embedding data satisfies a first threshold condition;

using the second node of the third portion of the first ML model, processing the second embedding data to determine third embedding data;

determining the third embedding data satisfies a second threshold condition; and

sending the third embedding data to the second device to perform processing using the second ML model.

11. The computer-implemented method of claim **10**, further comprising:

processing, at the second device using the second ML model, the second embedding data to determine fourth embedding data;

determining, at the second device and using the fourth embedding data, a first output responsive to the second input; and

sending, from the second device to the first device, the first output.

12. The computer-implemented method of claim **4**, wherein:

the first ML model includes a first plurality of nodes,

the second ML model includes a second plurality of nodes,

the first embedding data is determined based on processing the first portion of the first input data using the first node of the second portion of the first ML model, and

the method further comprises:

receiving, at the second device from the first device, an indication representing the first node of the first ML model,

wherein the processing of the first embedding data at the second device is performed by a third node of the second ML model instead of a fourth node of the second ML model based on the indication.

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

configuring, using training data, the second ML model to perform the first type of processing, the second ML model comprising a plurality of nodes;

storing, at the first device, a first set of nodes, from the plurality of nodes, as the first ML model, wherein the first set is based on a processing capacity of the first device;

storing, at a third device, a second set of nodes, from the plurality of nodes, as a third ML model, wherein the second set is based on a processing capacity of the third device; and

storing, at the second device, the second ML model.

14. A system comprising:

a first device including at least one processor, and at least one memory including instructions that, when executed by the at least one processor, cause the first device to:

receive first input data corresponding to a first input;

process a first portion of the first input data using a second portion of a first machine learning (ML) model, wherein the second portion of the first ML model comprises a first node of the first ML model;

determine, based at least in part on processing the first portion of the first input data using the second portion of the first ML model, first embedding data representing a partial speech recognition output of the second portion of the first ML model;

determine, based at least in part on the first embedding data, a second device is to complete the processing of the first input data; and

in response to determining the second device is to complete the processing of the first input data, and prior to processing the first embedding data using a

third portion of the first ML model, send the first embedding data to the second device to complete the processing of the first input data using a second ML model, wherein:

the third portion of the first ML model comprises a second node of the first ML model,

the first ML model and the second ML model are configured to perform a first type of processing, and

sending the first embedding data to the second device causes the second device to complete the first type of processing of the first input data using the second ML model to determine a response to the first input.

15. The system of claim **14**, wherein the first embedding data is determined by the first node of the second portion of the first ML model, and the instructions that, when executed by the at least one processor, further cause the first device to:

process the first embedding data using the second node of the third portion of the first ML model;

determine second embedding data output by the second node;

process the first embedding data with respect to the second embedding data; and

send the second embedding data to the second device based at least in part on processing the first embedding data with respect to the second embedding data.

16. The system of claim **14**, wherein:

the first input data comprises audio data representing a spoken input, and

the first ML model and the second ML model are configured for SLU processing.

17. The system of claim **14**, wherein:

the first input data comprises image data representing an object, and

the first ML model and the second ML model are configured for object recognition.

18. The system of claim **14**, wherein the instructions that, when executed by the at least one processor, further cause the first device to:

receive second input data corresponding to a second input;

process a fourth portion of the second input data using the first node of the second portion of the first ML model;

determine second embedding data output by the first node;

processing the second embedding data to determine an entropy value corresponding to the second embedding data;

determine the entropy value satisfies a threshold value; and

based on the entropy value satisfying the threshold value, determine, using the second embedding data, first output data responsive to the second input.

19. The system of claim **14**, wherein the instructions that, when executed by the at least one processor, further cause the first device to:

receive second input data corresponding to a second input;

using a classifier, process the second input data to determine a likelihood that the first ML model is able to process the second input data to generate a first output;

based on the likelihood failing to meet a threshold, determine to send the second input data to the second device for processing; and

send the second input data to the second device to generate the first output responsive to the second input.

20. The system of claim **14**, wherein the instructions that, when executed by the at least one processor, further cause the first device to:

receive second input data;

using the first node of the second portion of the first ML model, process a fourth portion of the second input data to determine second embedding data;

determine the second embedding data satisfies a first threshold condition;

using the second node of the second portion of the first ML model, process the second embedding data to determine third embedding data;

determine the third embedding data satisfies a second threshold condition; and

send the third embedding data to the second device to perform processing using the second ML model.

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