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(54) **METHODS AND APPARATUS TO ADAPT MEDICAL IMAGE INTERFACES BASED ON LEARNING**

(71) Applicant: **General Electric Company**, Schenectady, NY (US)

(72) Inventor: **Manuel Joy**, Chicago, IL (US)

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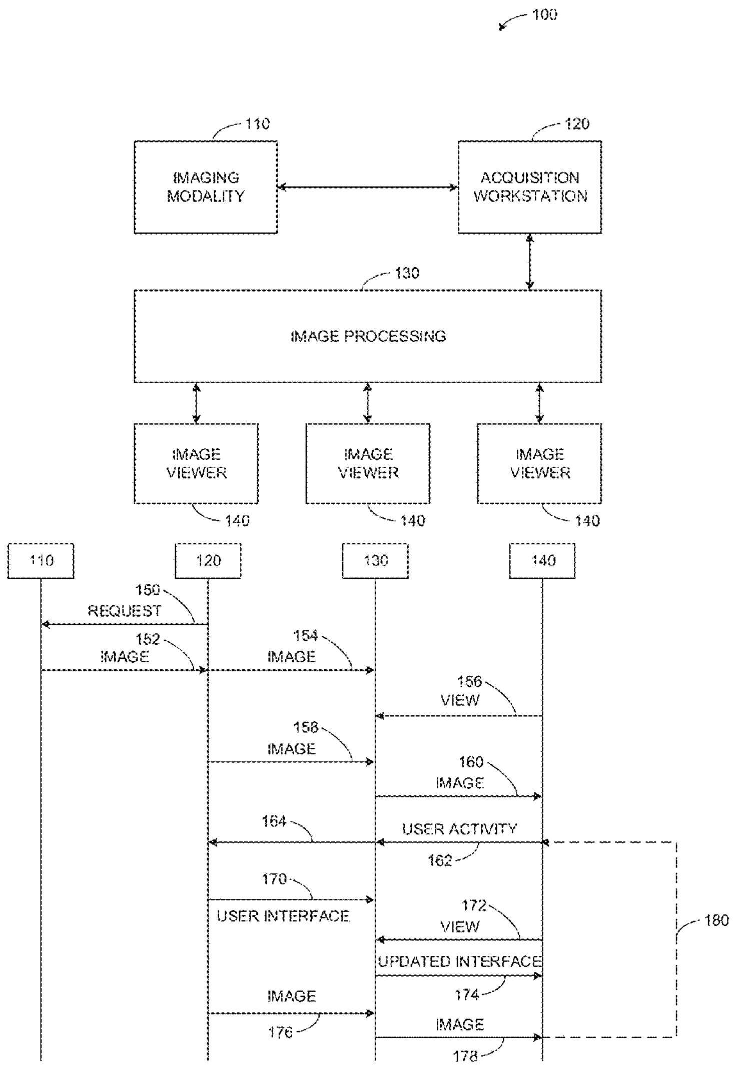
(57) **ABSTRACT**

Methods and apparatus to adapt medical imaging interfaces based on learning are disclosed. An example apparatus includes a use monitor to monitor, in a first session, user actions and medical content data pertaining to operation of a clinical image display, a learning device including a processor to implement a learning network to develop a model for a subsequent session based on the user actions in relationship to a context of the medical content data. The model developed by defining contextual patterns of the user actions based on the context and the medical content data. The learning device is to update, prior to or during a second session subsequent the first session, a user interface based on the model.



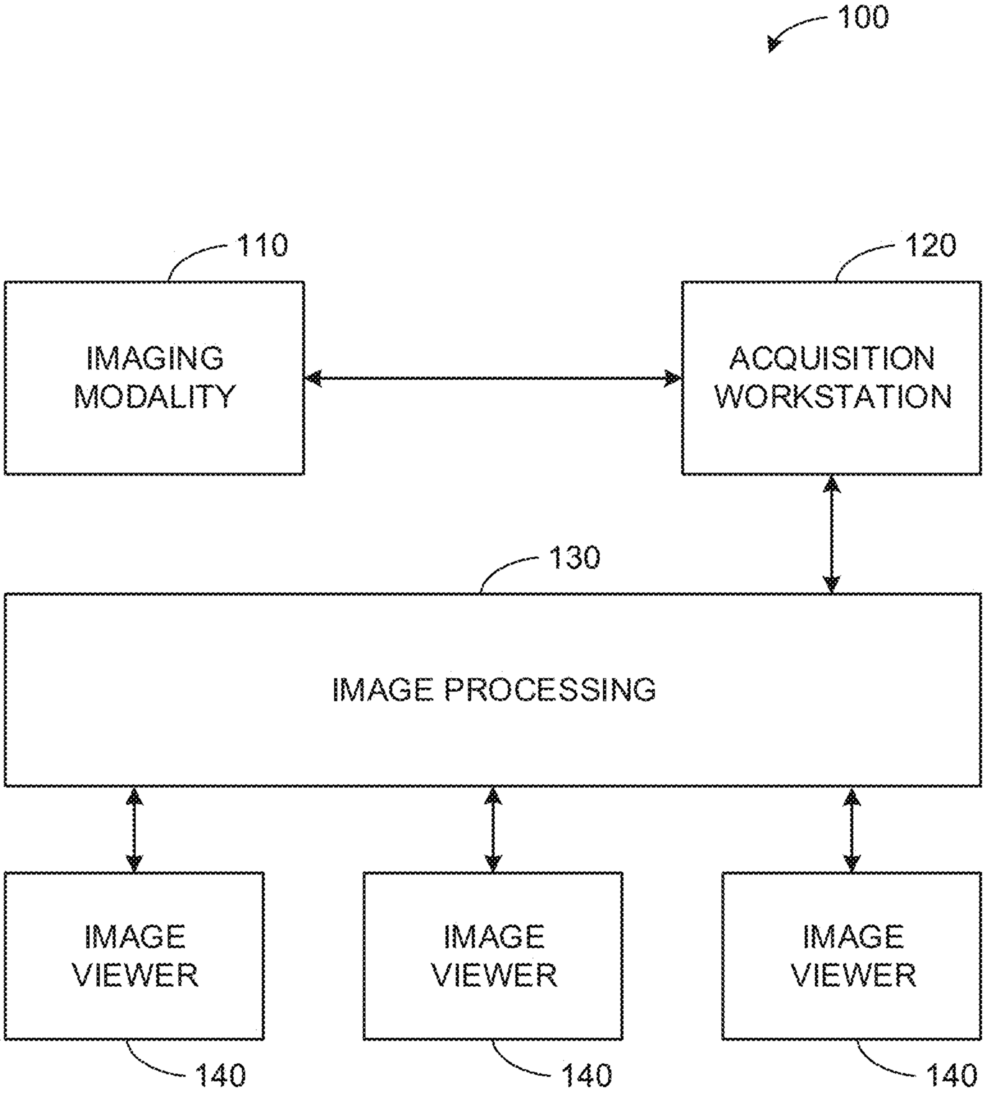

100
110
IMAGING MODALITY
120
ACQUISITION WORKSTATION
130
IMAGE PROCESSING
IMAGE VIEWER
IMAGE VIEWER
IMAGE VIEWER
140
140
140

FIG. 1A

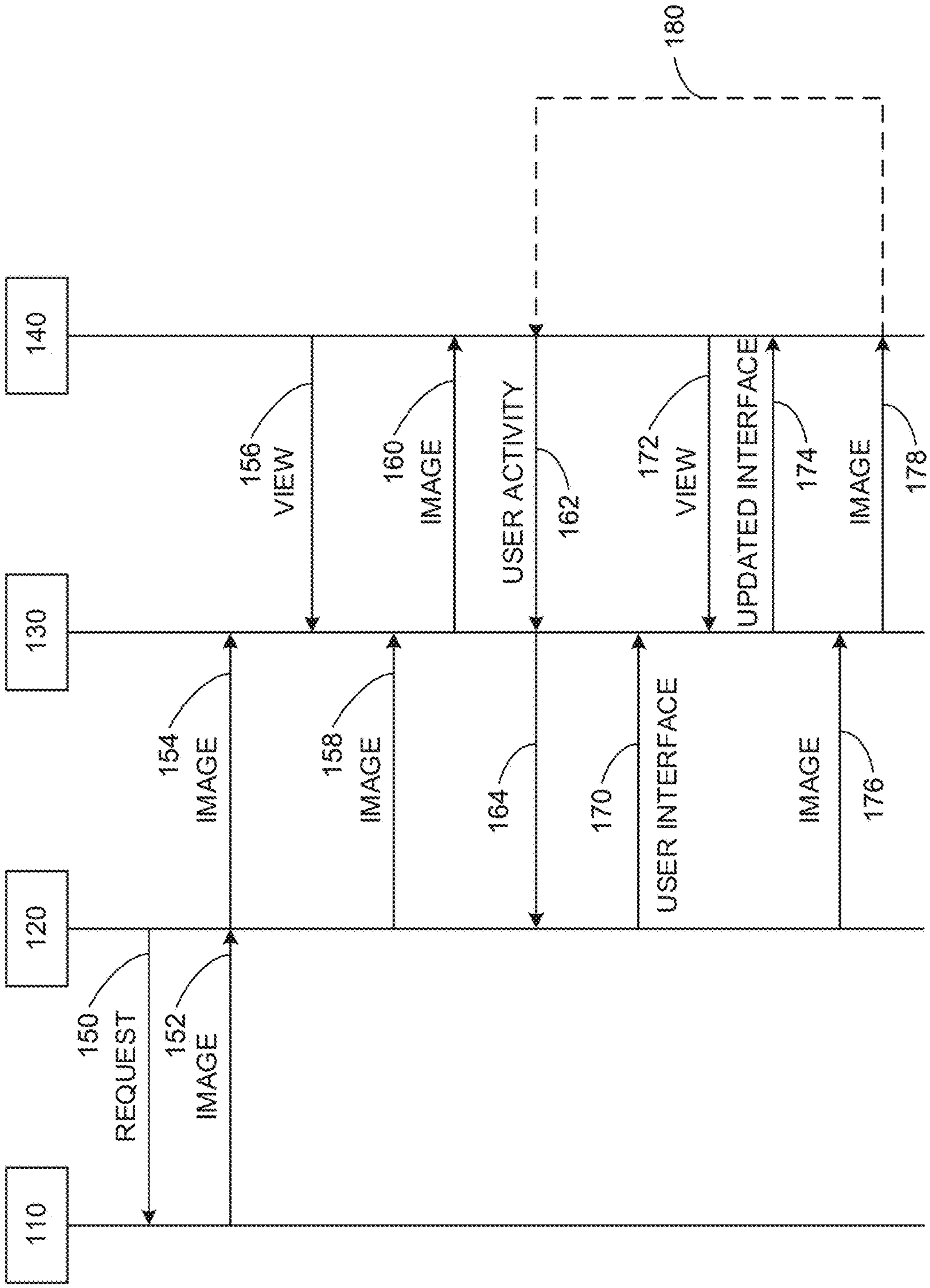

110
120
130
140
150
REQUEST
152
IMAGE
154
IMAGE
156
VIEW
158
IMAGE
160
IMAGE
USER ACTIVITY
162
164
170
USER INTERFACE
172
VIEW
UPDATED INTERFACE
174
IMAGE
176
IMAGE
178
180

FIG. 1B

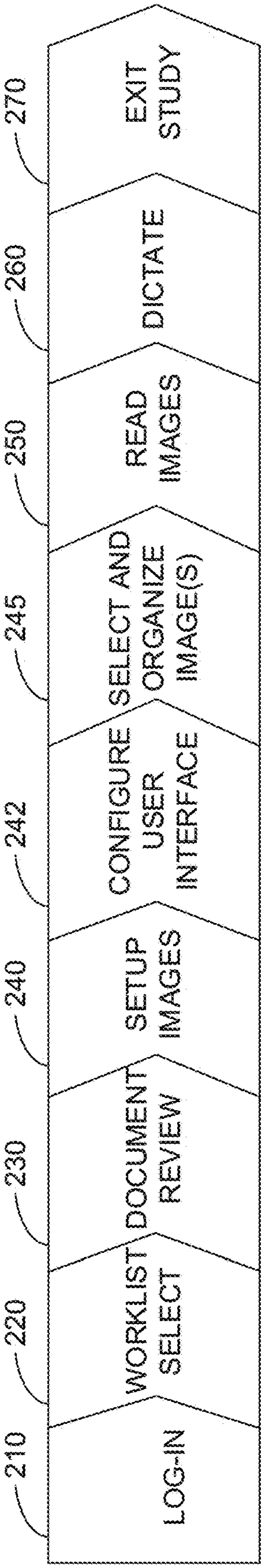

210
LOG-IN
220
WORKLIST SELECT
230
DOCUMENT REVIEW
240
SETUP IMAGES
242
CONFIGURE USER INTERFACE
245
SELECT AND ORGANIZE IMAGE(S)
250
READ IMAGES
260
DICTATE
270
EXIT STUDY

FIG. 2

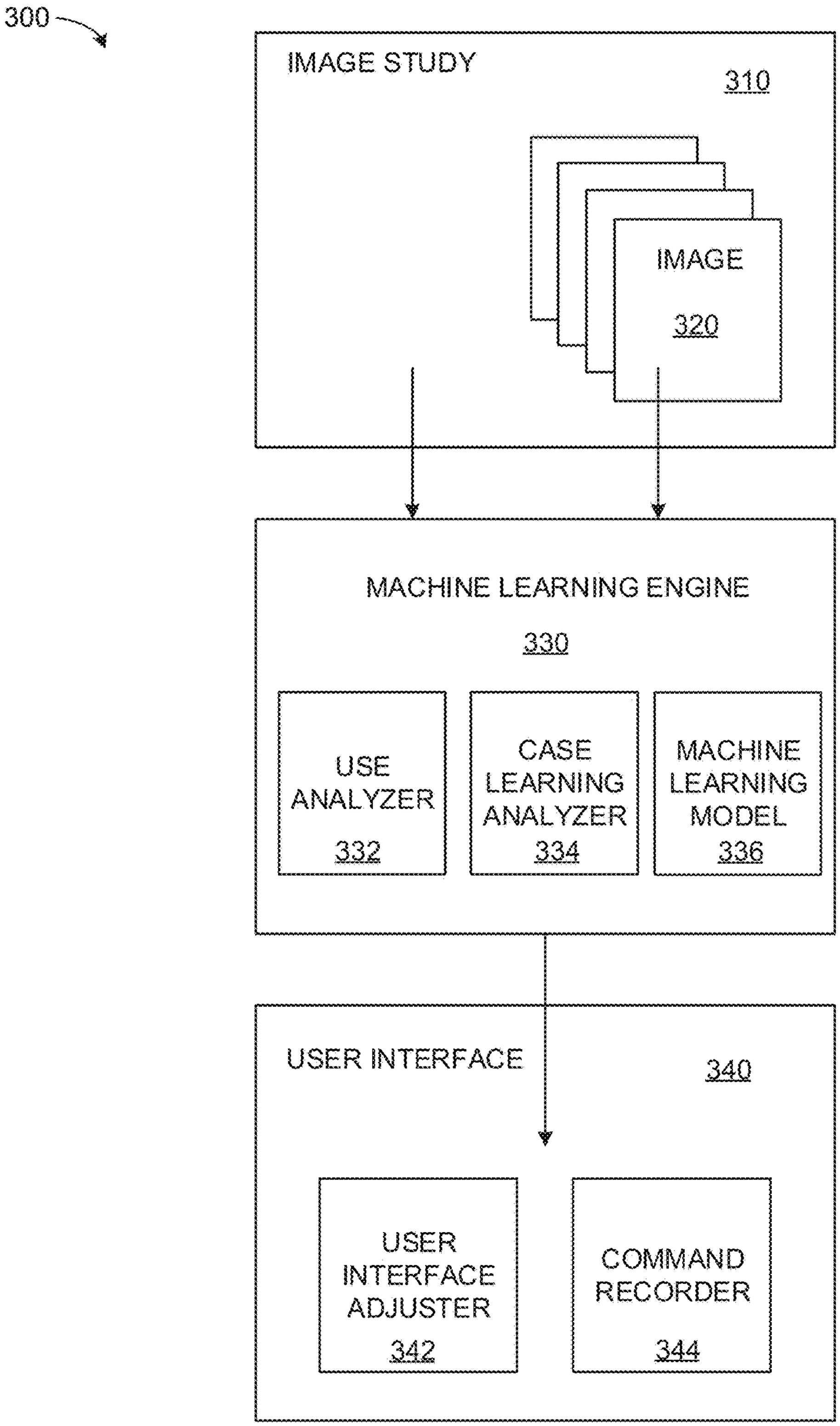

300
IMAGE STUDY
310
IMAGE
320
MACHINE LEARNING ENGINE
330
USE ANALYZER
332
CASE LEARNING ANALYZER
334
MACHINE LEARNING MODEL
336
USER INTERFACE
340
USER INTERFACE ADJUSTER
342
COMMAND RECORDER
344

FIG. 3

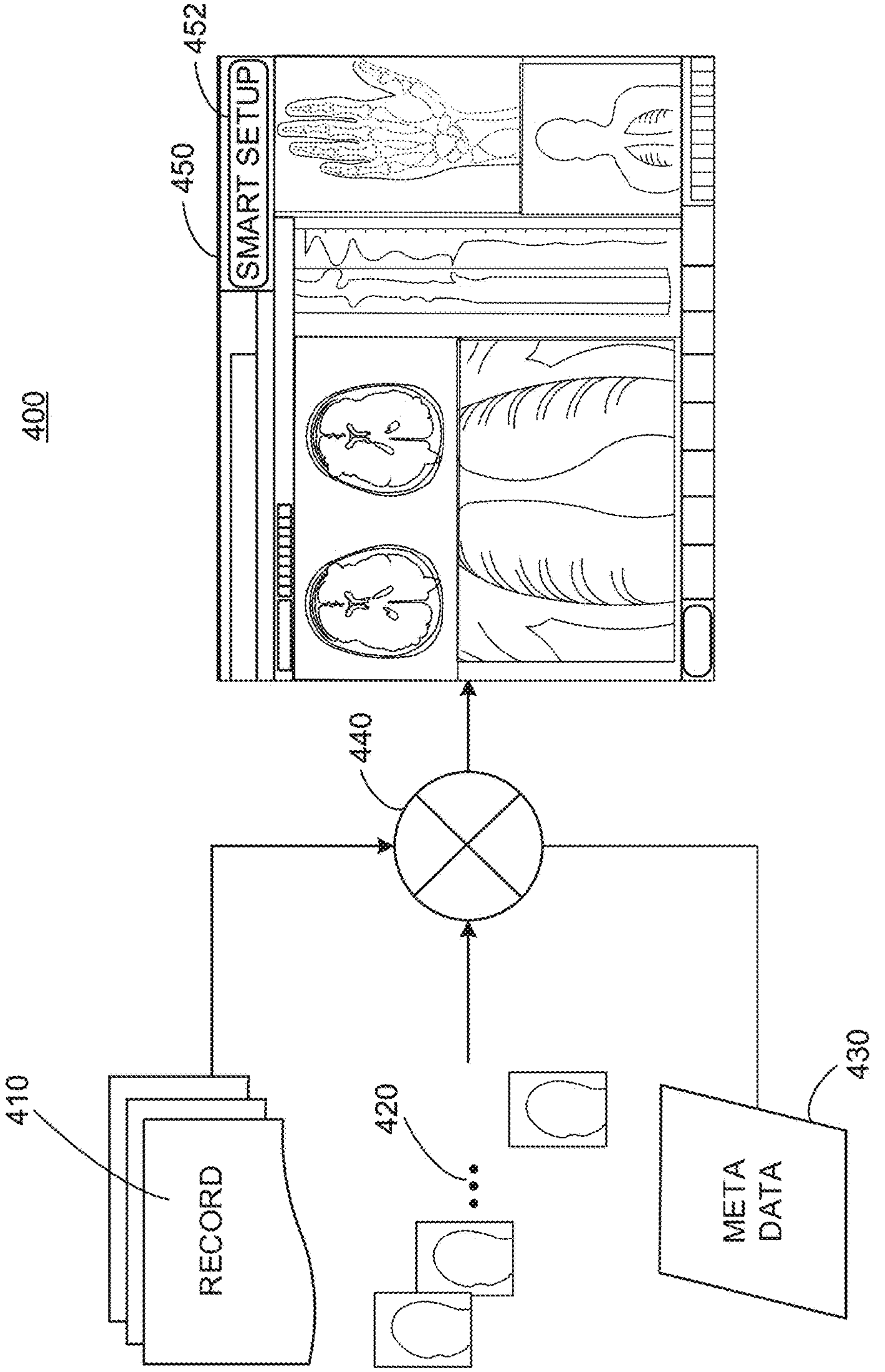


FIG. 4

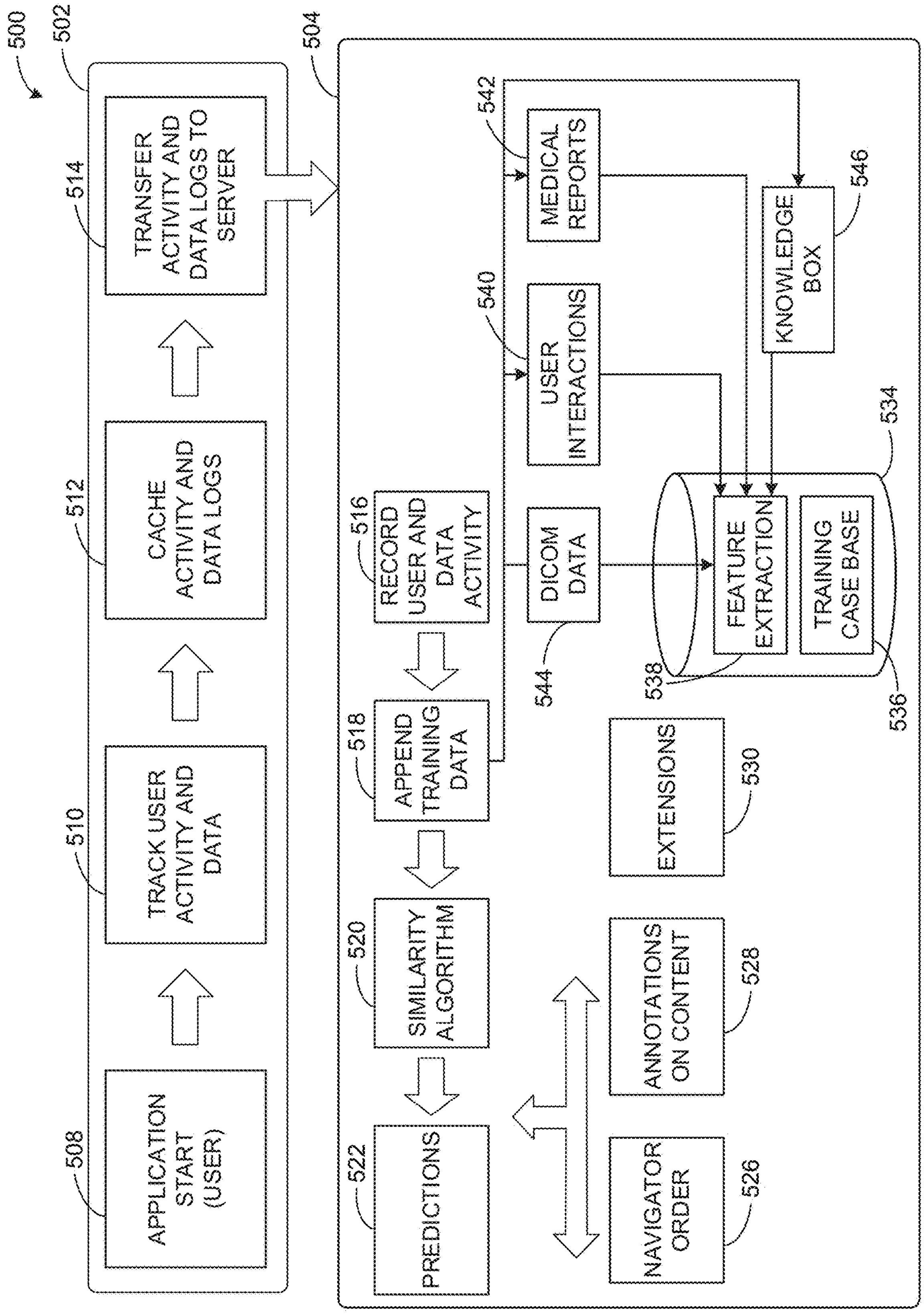

500
502
APPLICATION START (USER)
508
TRACK USER ACTIVITY AND DATA
510
CACHE ACTIVITY AND DATA LOGS
512
TRANSFER ACTIVITY AND DATA LOGS TO SERVER
514
504
PREDICTIONS
522
SIMILARITY ALGORITHM
520
APPEND TRAINING DATA
518
RECORD USER AND DATA ACTIVITY
516
DICOM DATA
544
USER INTERACTIONS
540
MEDICAL REPORTS
542
NAVIGATOR ORDER
526
ANNOTATIONS ON CONTENT
528
EXTENSIONS
530
FEATURE EXTRACTION
538
TRAINING CASE BASE
536
534
KNOWLEDGE BOX
546

FIG. 5

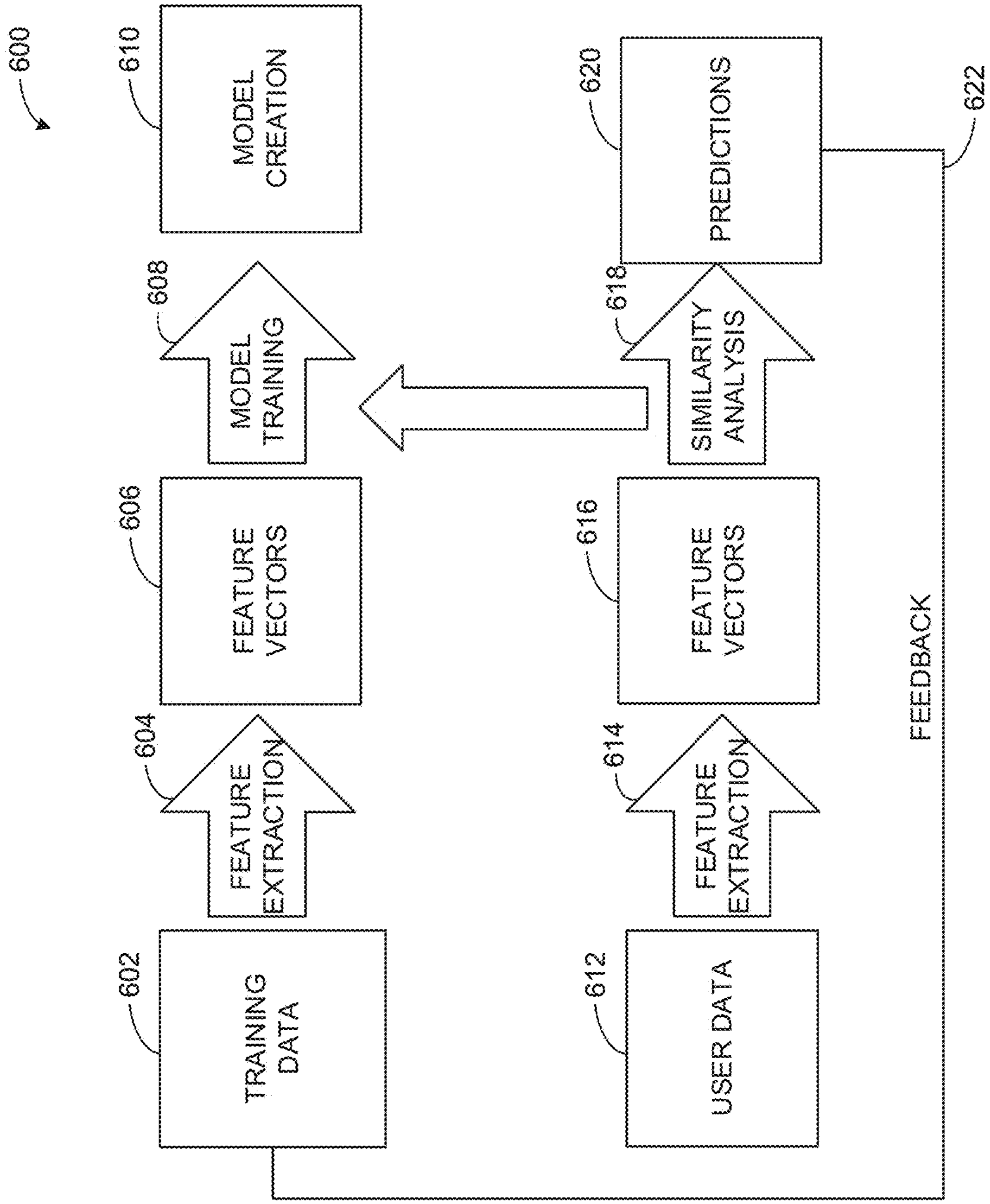

600
602
TRAINING DATA
604
FEATURE EXTRACTION
606
FEATURE VECTORS
608
MODEL TRAINING
610
MODEL CREATION
612
USER DATA
614
FEATURE EXTRACTION
616
FEATURE VECTORS
618
SIMILARITY ANALYSIS
620
PREDICTIONS
622
FEEDBACK

FIG. 6

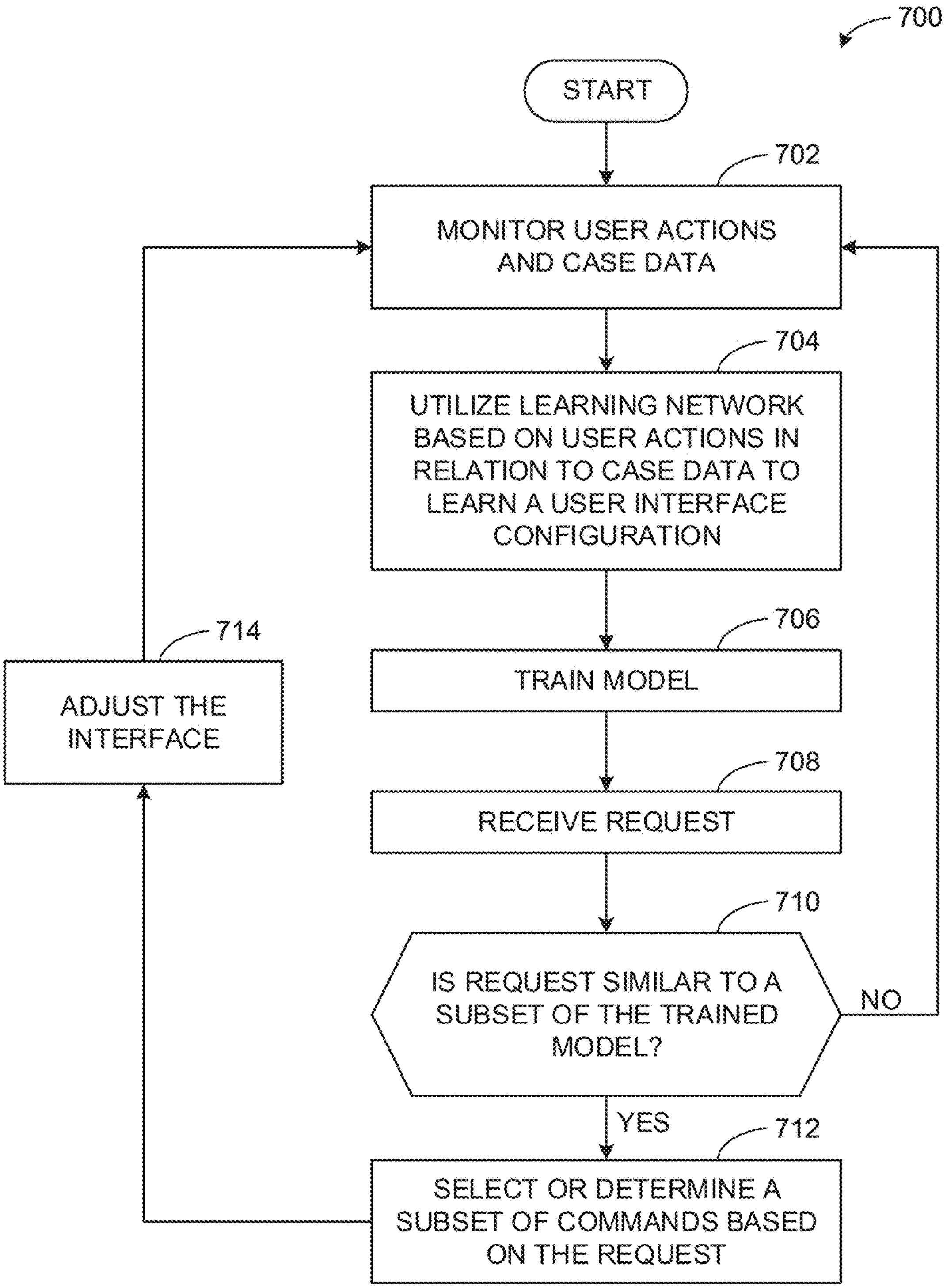

700
START
702
MONITOR USER ACTIONS AND CASE DATA
704
UTILIZE LEARNING NETWORK BASED ON USER ACTIONS IN RELATION TO CASE DATA TO LEARN A USER INTERFACE CONFIGURATION
706
TRAIN MODEL
708
RECEIVE REQUEST
710
IS REQUEST SIMILAR TO A SUBSET OF THE TRAINED MODEL?
NO
YES
712
SELECT OR DETERMINE A SUBSET OF COMMANDS BASED ON THE REQUEST
714
ADJUST THE INTERFACE

FIG. 7

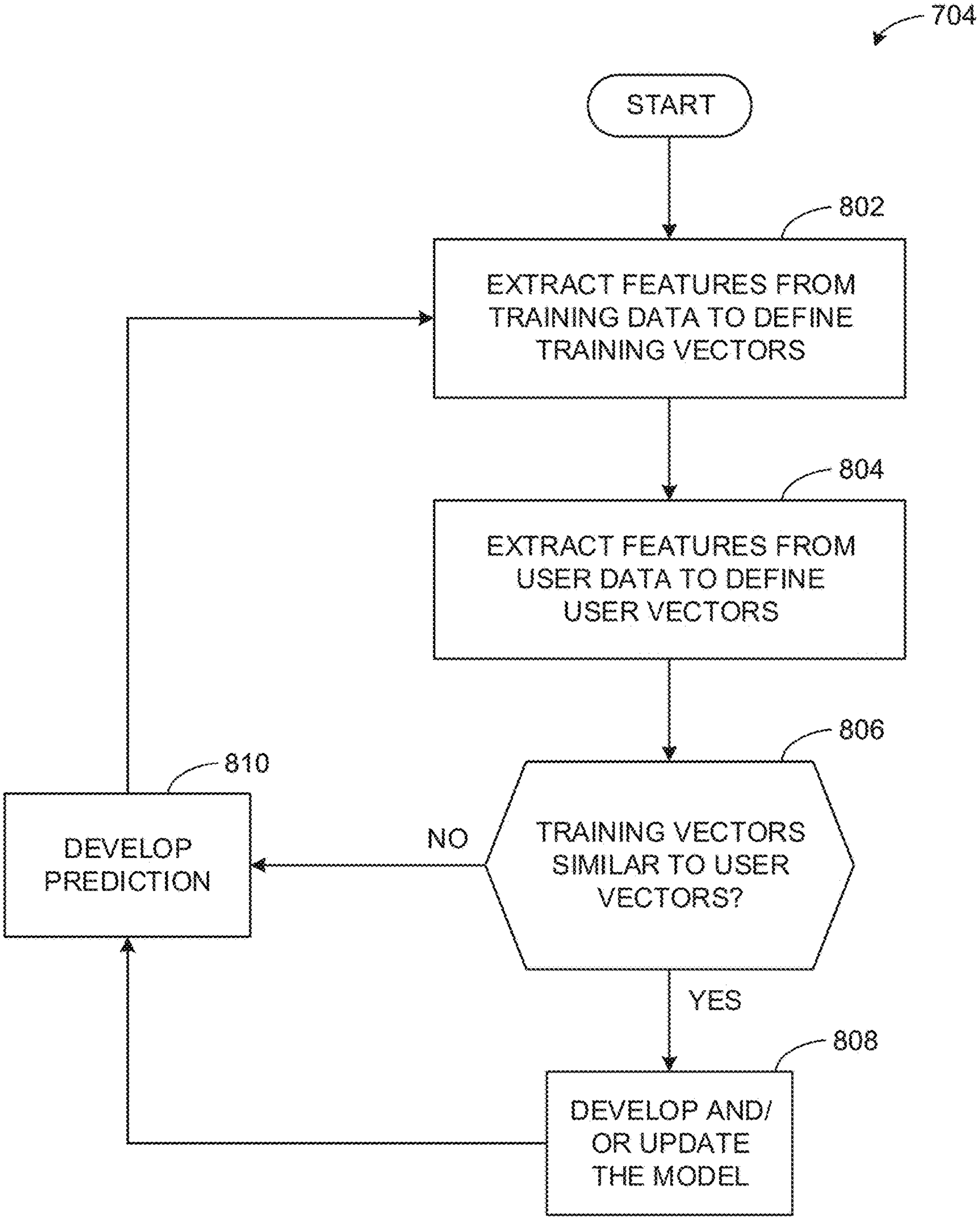
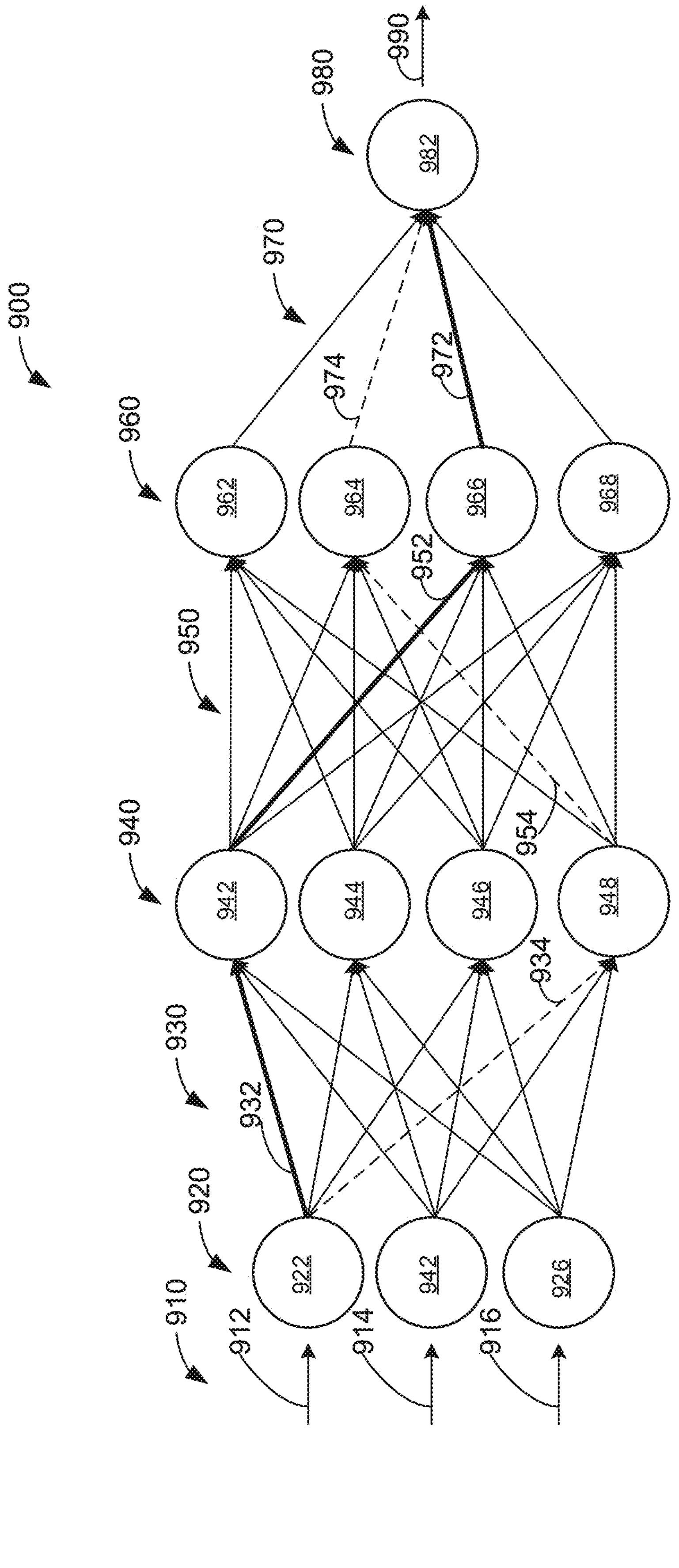

704
START
802
EXTRACT FEATURES FROM TRAINING DATA TO DEFINE TRAINING VECTORS
804
EXTRACT FEATURES FROM USER DATA TO DEFINE USER VECTORS
806
TRAINING VECTORS SIMILAR TO USER VECTORS?
NO
YES
810
DEVELOP PREDICTION
808
DEVELOP AND/ OR UPDATE THE MODEL

FIG. 8


900
910
912
914
916
920
922
942
926
930
932
934
940
942
944
946
948
950
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954
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962
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968
970
972
974
980
982
990

FIG. 9

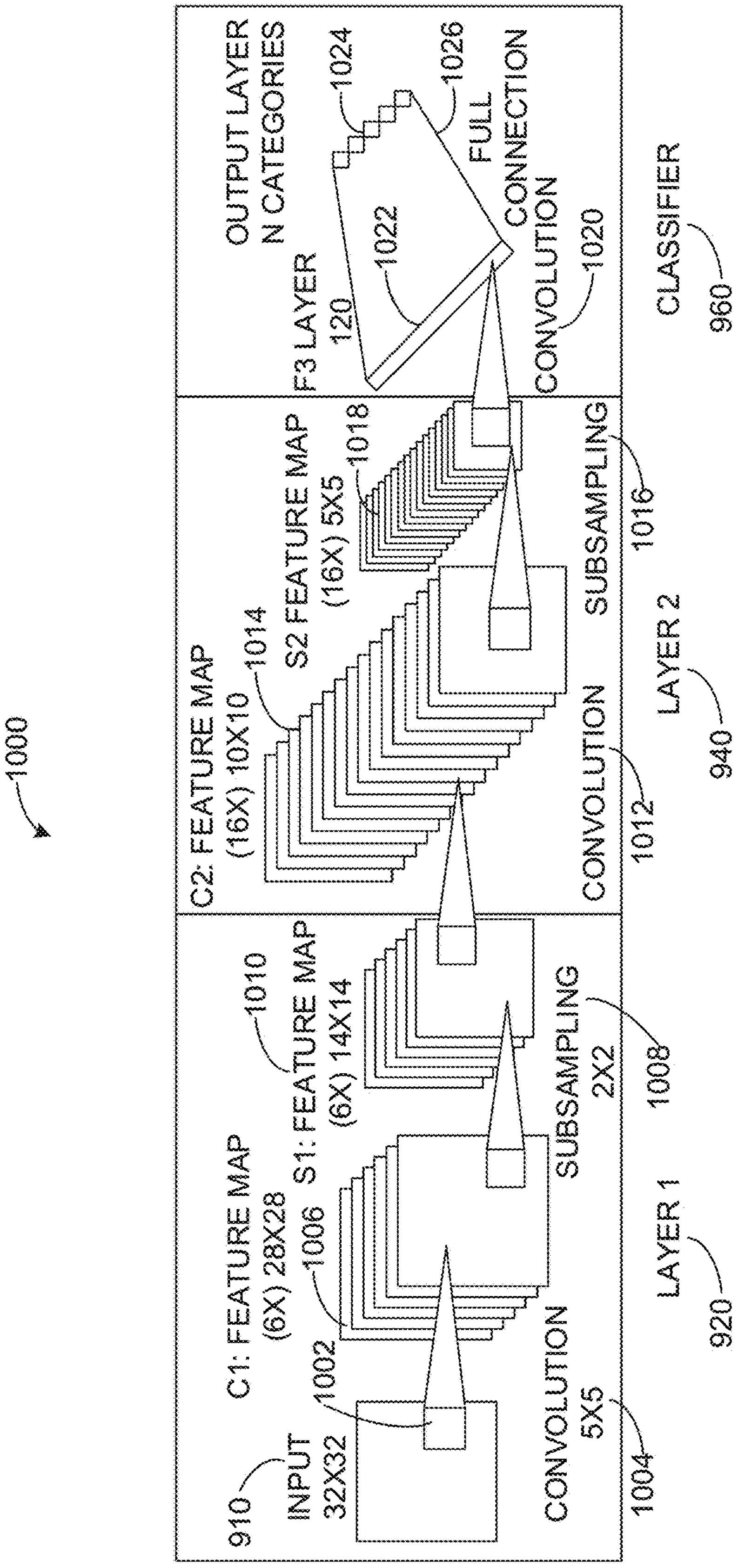
1000
910
INPUT
32X32
1002
CONVOLUTION
5X5
1004
C1: FEATURE MAP
(6X) 28X28
1006
SUBSAMPLING
S1: FEATURE MAP
(6X) 14X14
1010
SUBSAMPLING
2X2
1008
LAYER 1
920
C2: FEATURE MAP
(16X) 10X10
1014
CONVOLUTION
1012
S2 FEATURE MAP
(16X) 5X5
1018
SUBSAMPLING
1016
LAYER 2
940
F3 LAYER
120
1022
CONVOLUTION
1020
OUTPUT LAYER
N CATEGORIES
1024
1026
FULL
CONNECTION
CONVOLUTION
CLASSIFIER
960

FIG. 10

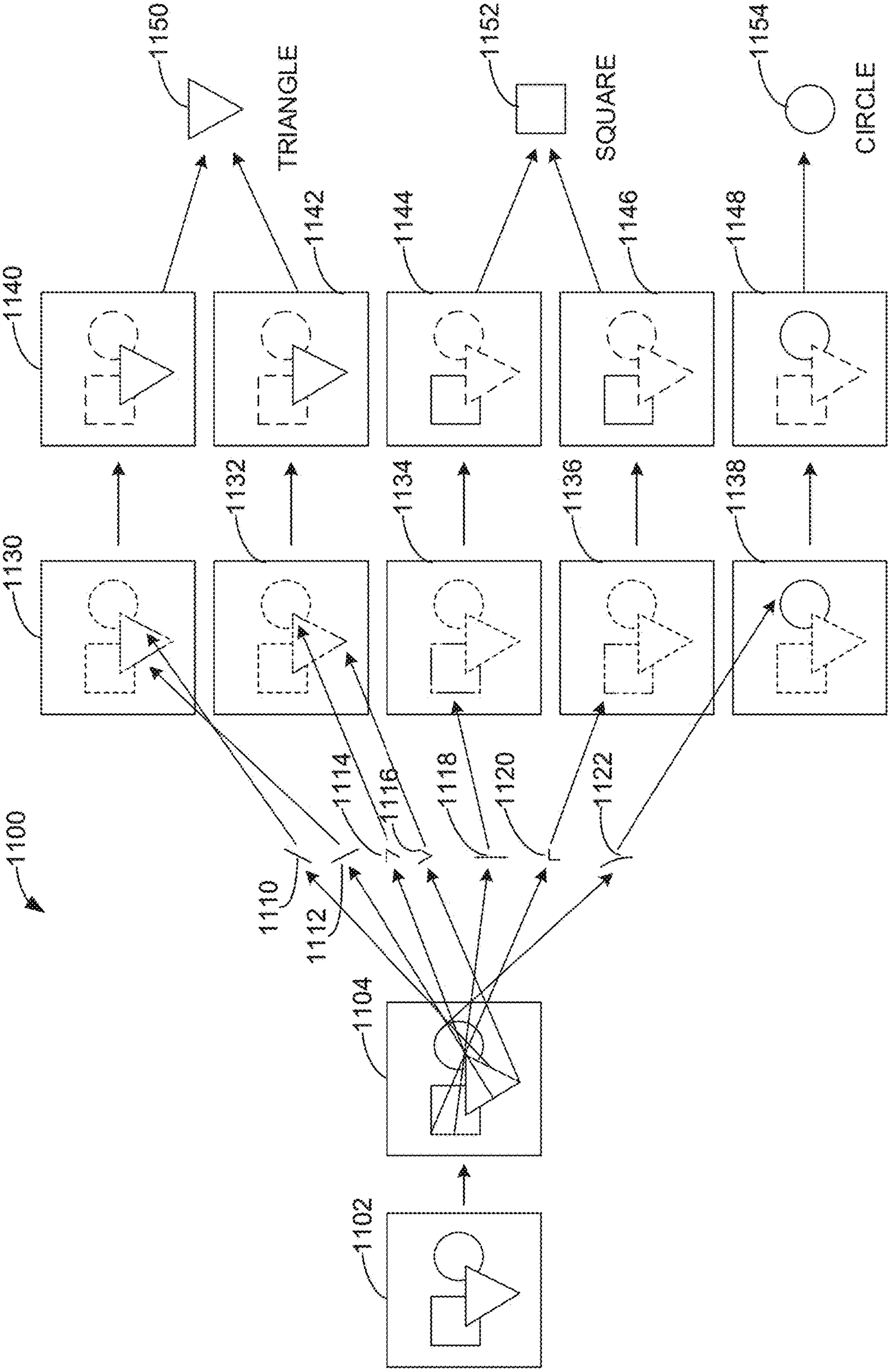
1100
1102
1104
1110
1112
1114
1116
1118
1120
1122
1130
1132
1134
1136
1138
1140
1142
1144
1146
1148
1150
TRIANGLE
1152
SQUARE
1154
CIRCLE

FIG. 11

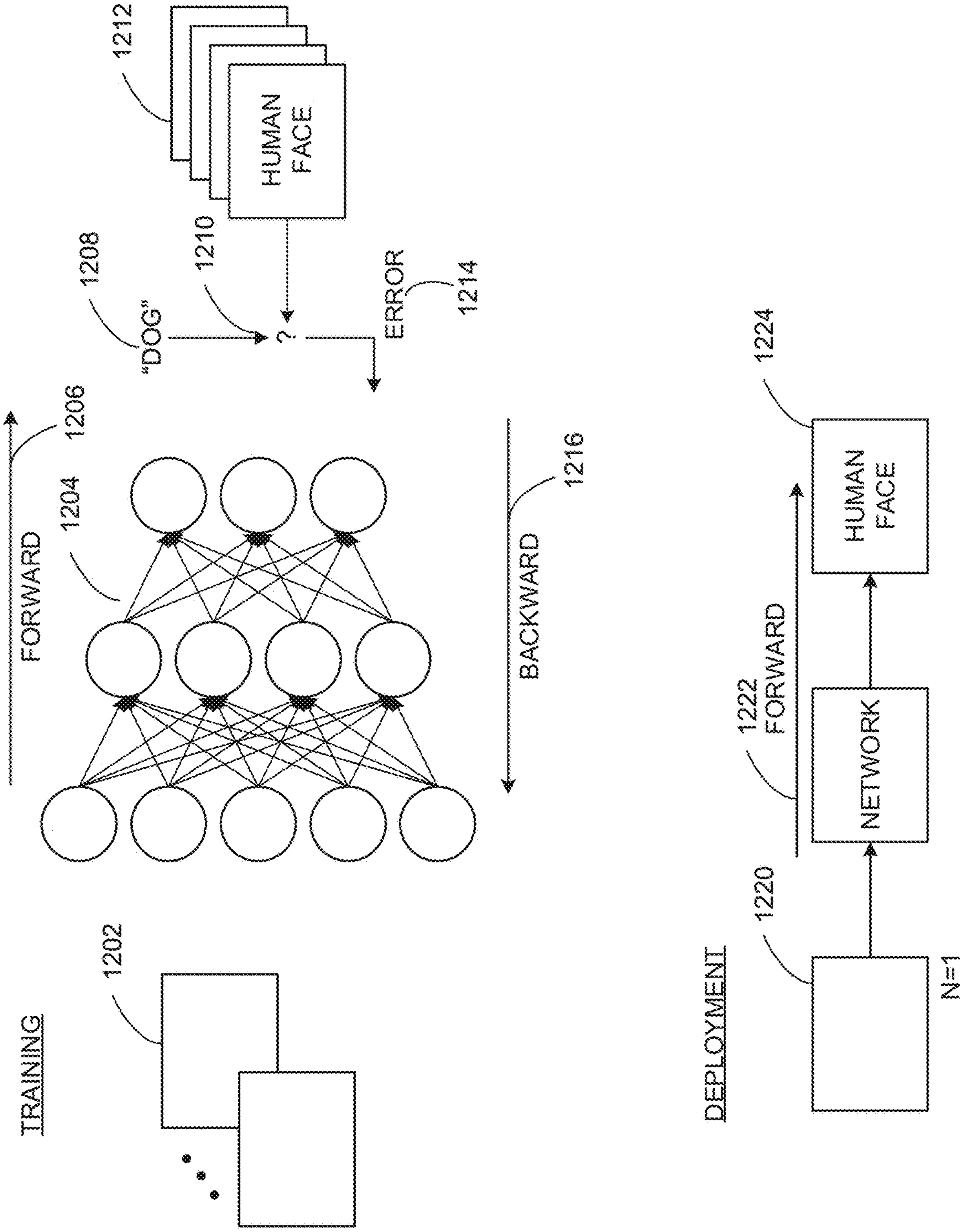
TRAINING
1202
FORWARD
1206
1204
"DOG"
1208
1210
?
ERROR
1214
1212
HUMAN FACE
BACKWARD
1216
DEPLOYMENT
1220
N=1
NETWORK
1222
FORWARD
HUMAN FACE
1224

FIG. 12

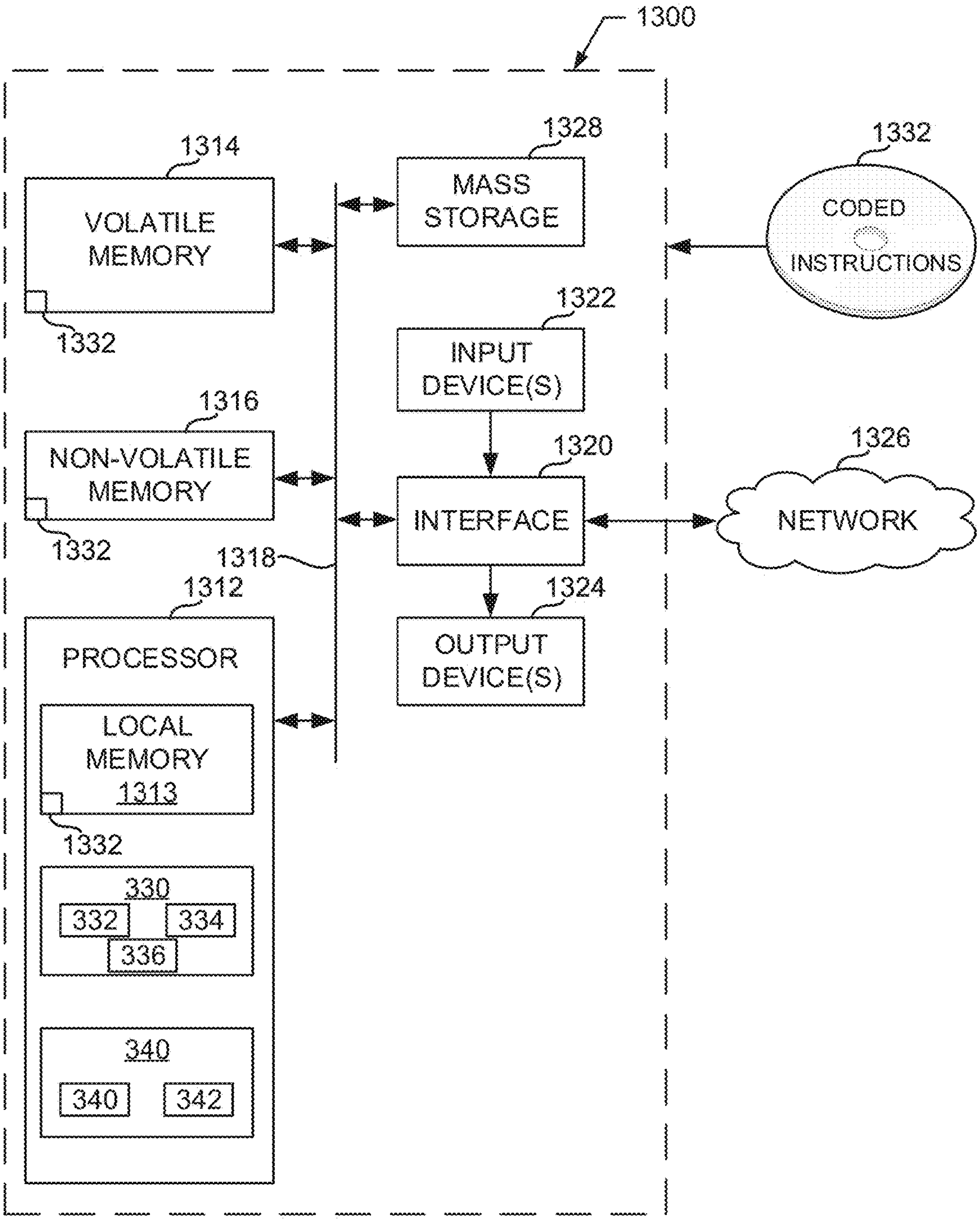
1300
1314
VOLATILE MEMORY
1332
1316
NON-VOLATILE MEMORY
1332
1318
1312
PROCESSOR
LOCAL MEMORY 1313
1332
330
332
334
336
340
340
342
1328
MASS STORAGE
1322
INPUT DEVICE(S)
1320
INTERFACE
1324
OUTPUT DEVICE(S)
1332
CODED INSTRUCTIONS
1326
NETWORK

FIG. 13

METHODS AND APPARATUS TO ADAPT MEDICAL IMAGE INTERFACES BASED ON LEARNING

FIELD OF THE DISCLOSURE

[0001] This disclosure relates generally to medical imaging systems, and, more particularly, to methods and apparatus to adapt medical imaging interfaces based on learning.

BACKGROUND

[0002] Healthcare environments, such as hospitals or clinics, include clinical information systems. Information stored on these systems may include patient medical histories, imaging data, test results, diagnosis information, management information, and/or scheduling information. The information may be centrally stored or divided at a plurality of locations. Healthcare practitioners access patient information or other information at various points in a healthcare workflow.

[0003] A reading, such as a radiology or cardiology procedure reading, typically involves a healthcare practitioner, such as a radiologist or a cardiologist, viewing digital images of a patient. In particular, the practitioner performs a diagnosis based on a content of the diagnostic images and reports on the results. Some examples of other tools are prior and related prior exams and their results, laboratory exams, allergies, pathology results, medication, alerts, document images, and other tools.

[0004] Typically, a medical imaging system is implemented to provide one or more medical images for examination by a medical professional. For example, the medical imaging system can provide a series of x-ray or MRI images to a display workstation where the images are displayed by a radiologist to perform a diagnostic examination. Based on viewing these images, the radiologist can provide a diagnosis.

SUMMARY

[0005] An example apparatus includes a use monitor to monitor, in a first session, user actions and medical content data pertaining to operation of a clinical image display, a learning device including a processor to implement a learning network to develop a model for a subsequent session based on the user actions in relationship to a context of the medical content data. The model developed by defining contextual patterns of the user actions based on the context and the medical content data. The learning device is to update, prior to or during a second session subsequent the first session, a user interface based on the model.

[0006] An example method includes to adapt a user interface configuration pertaining to a clinical image display includes monitoring, by executing instructions with a processor, user actions and medical content data during a first session of the clinical image display to define training data. The example method also includes developing, by executing instructions with the processor, a model for a subsequent session based on the user actions in relation to a context of the medical content data with a learning network. The model is developed by defining contextual patterns of the user actions based on the context and the medical content data. The example method also includes adjusting, by executing instructions with the processor, a user interface based on the model prior to or during a second session subsequent the first session.

[0007] An example tangible machine readable medium comprising instructions, which when executed, cause a processor to at least define training data based on monitored user actions in relationship to a context of medical content data during operation of a clinical image display in a first session. The example tangible machine readable medium also causes the processor to develop, by a training network, a model for a subsequent session based on the training data. The model is developed by defining contextual patterns of the user actions based on the context and the medical content data. The example tangible machine readable medium also causes the processor to adjust a user interface of the clinical image display based on the model for a second session subsequent the first session.

BRIEF DESCRIPTION OF THE DRAWINGS

[0008] FIG. **1**A illustrates an example medical imaging system in which examples disclosed herein can be implemented.

[0009] FIG. **1**B illustrates an example data transfer sequence that can be implemented in the example imaging system of FIG. **1**A.

[0010] FIG. **2** illustrates an example radiology workflow in which examples disclosed herein can be implemented.

[0011] FIG. **3** depicts an example learning system to adjust a user interface of a medical imaging device in accordance with teachings of this disclosure.

[0012] FIG. **4** provides an example visualization of image data information that may be analyzed in examples disclosed herein.

[0013] FIG. **5** depicts a high level data flow for an example machine learning algorithm.

[0014] FIG. **6** depicts a high level data flow of an example model learning and prediction algorithm.

[0015] FIG. **7** is a flowchart representative of machine readable instructions which may be executed to implement the example system **300** of FIG. **3**.

[0016] FIG. **8** is a flowchart of an example subroutine of the machine readable instructions of FIG. **7**.

[0017] FIG. **9** is a representation of an example deep learning neural network that can be implemented in examples disclosed herein.

[0018] FIG. **10** illustrates a particular implementation of the example neural network of FIG. **9** as a convolutional neural network.

[0019] FIG. **11** is a representation of an example image analysis convolutional neural network that can be implemented in examples disclosed herein.

[0020] FIG. **12** illustrates example training and deployment phases of a deep learning network.

[0021] FIG. **13** is a block diagram of an example processor system that may be used to implement the systems, apparatus and methods described herein.

[0022] The figures are not to scale. In general, the same reference numbers will be used throughout the drawing(s) and accompanying written description to refer to the same or like parts.

DETAILED DESCRIPTION

[0023] Methods and apparatus to adapt medical imaging interfaces based on learning are disclosed. Some known medical imaging interfaces typically require repeated and frequent adjustment of settings and/or image placement by practitioners, such as radiologists or cardiologists. These adjustments can take significant time, thereby increasing costs associated with clinical readings of the images.

[0024] Examples disclosed herein utilize machine learning techniques with a learning network to adapt user interfaces to facilitate use of clinical imaging devices. In particular, a learning network is utilized to monitor user actions along with a context of medical content data (e.g., medical case data including image data, patient history data, patient vital signs data, laboratory data, exam data including reason for examination, etc.) to learn a user interface configuration that facilitates use of the clinical imaging device by a clinical practitioner. In other words, the aforementioned learning network is used to analyze the context of the medical content data in view of monitored user actions and the medical content data itself to learn user interface configurations that can be helpful to medical practitioners, thereby saving time for the medical practitioners. Further, examples disclosed herein can streamline imaging viewing by the practitioners (e.g., by caching predicted commands and/or images) to reduce computing resources needed by predicting user commands and/or caching relevant data (e.g., predicted data).

[0025] In some examples, image similarity between clinical images of different cases are used to develop a predictive model and/or define a context between user inputs and medical images associated with a medical case history. In some examples, the learned user interface configuration is deployed to a remote viewing display (e.g., the learned user interface is generated at a central server, but deployed to multiple remote viewing workstations). In some examples, a symbol is displayed on a clinical imaging device to represent at least one command (e.g., a batch of commands, viewing setups, etc.) of a learned user interface configuration.

[0026] As used herein, the term "context" refers to a contextual relationship (e.g., contextual meaning, contextual commonality, etc.) between medical content data and user inputs or actions (e.g., commands, image arrangements, etc.). As used herein, the term "medical content data" can refer to, but is not limited to, medical files, medical case histories, metadata, diagnoses, patient data, medical image data, medical image types, medical image similarities, key terms, etc. As used herein, the terms "user interface" and "user interface configuration" can refer to icons, a collection of icons, a spatial arrangement of icons, a spatial arrangement of menu items, menu items hierarchies, menu organization, a sequence of commands and/or batched commands, etc.

[0027] FIG. **1**A illustrates an example imaging system **100** that can be implemented with examples disclosed herein. The imaging system **100** includes an imaging modality **110**, an acquisition workstation **120**, an image processing server **130**, and one or more image viewers (e.g., imaging devices including tablets, computers, workstations, mobile phones, remote viewing displays, etc.) **140**. The imaging system **100** can include any number of the imaging modalities **110**, acquisition workstations **120**, the image processing servers **130** and the image viewers **140** and is not in any way limited to the example system **100** illustrated in FIG. **1**A. The components of the system **100** can communicate via wired and/or wireless communication, for example, and can be separate systems and/or integrated to varying degrees, for example.

[0028] In operation, the example imaging modality **110** obtains one or more images of a patient anatomy. The imaging modality **110** can include any device capable of capturing an image of a patient anatomy, such as a medical diagnostic imaging device, or a server to store images taken by the medical diagnostic imaging device. For example, the imaging modality **110** includes an X-ray imager, ultrasound scanner, magnetic resonance imager, or the like. In this example, image data representative of the image(s) is communicated between the imaging modality **110** and the acquisition workstation **120**. The image data is communicated electronically over a wired or wireless connection, for example.

[0029] In some examples, the acquisition workstation **120** applies one or more preprocessing functions, for example, to the image data to prepare the image for viewing on an image viewer **140**. For example, the acquisition workstation **120** converts raw image data into a Digital Imaging and

[0030] Communications in Medicine (DICOM) standard format or attach a DICOM header.

[0031] The image data is then communicated between the acquisition workstation **120** and the image processing server **130**. The image data can be communicated electronically over a wired or wireless connection, for example.

[0032] The image viewers **140** can retrieve or receive image data from the image processing server **130** for display to one or more users. For example, one of the image viewers **140** retrieves or receives image data representative of a computed radiography ("CR") image of a patient's chest. A radiologist or user can then examine the image for any objects of interest, such as tumors, lesions, etc., for example.

[0033] Healthcare information systems, such as a Hospital Information System (HIS), Radiology Information System (RIS), Cardio-Vascular Information System (CVIS) and/or Picture Archiving and Communication System (PACS), for example, can be implemented in conjunction with examples disclosed herein. The example imaging system **100** and/or PACS stores images from different modalities, such as X-ray, Computed Tomography (CT), Magnetic Resonance (MR), ultrasound, positron emission tomography (PET), etc., while a RIS, CIS or HIS contains non-image information, such as physician reports, disease history, and/or other patient associated data. In order to make a conclusion regarding a reviewed case, a clinician organizes relevant data in a certain order on a set of monitors, for example. In some examples, this order can depend on a plurality of parameters, such as an imaging modality of the exam under review, existence of historical images and number of historical images, previous reports, and/or list of prescribed medications, etc. In some examples, the imaging system **100**, PACS, RIS, CIS, and/or HIS can be combined into a single integrated system for easier storing, organizing, searching, correlating, and analysis of data.

[0034] FIG. **1**B illustrates an example data transfer sequence (e.g., a sequence of communication and data transfers) that can be implemented in the example medical imaging system **100** of FIG. **1**A. According to the illustrated example, the acquisition workstation **120** requests images from the imaging modality **110** at **150**. As a result, the acquisition workstation **120** is provided with at least one image from the imaging modality **110** at **152** which, in turn, is forwarded from the acquisition workstation **120** to the image processing system **130** at **154**.

[0035] At **156**, the image viewer **140** makes a request to view the aforementioned image. As a result, the image is provided to the image processing system **130** at **158** and to the image viewer **140** at **160**.

[0036] According to the illustrated example, user activity (e.g., commands, and/or image arrangements) are logged or recorded and provided to the image processing system **130** at **162**. In some examples, the user activity is also forwarded to the acquisition workstation **120** and the imaging modality **130** at **164**. In this example, the acquisition workstation **120** generates, via a learning network associated with a learning process, a user interface configuration based on the user activity in relationship to a context of medical content data (e.g., medical case data, medical case history, medical metadata, etc.) and forwards the generated user interface configuration to the image processing server **130** at **170**. In other examples, the image processing server **130** generates the user interface configuration. As will be discussed in greater detail below in connection with FIGS. **2-13**, the user interface configuration is generated or adapted based on machine learning techniques (e.g., deep learning techniques) of the user's (or multiple users) manipulation of a viewing interface and/or the user's manipulation of images in relationship to the aforementioned context (subsequent to an initial hang being presented). The generated user interface configuration is then forwarded to the imaging processing system **130** at **170**.

[0037] In this example, the image viewer **140** sends a request to the image processing server **130** for an additional image at **172**. As a result, a user interface of the image viewer **140** is updated based on the generated user interface configuration. Images from the image acquisition workstation **120** are forwarded to the image viewer **140** via the image processing system **130** at **176**, **178**. In other words, the later forwarded image is viewed with the updated user interface at **174** in this example. According to the illustrated example of FIG. **1**B, an arrow **180** indicates how the learning process in examples disclosed herein can be repeated to (continuously and/or periodically) refine and/or adapt user interface models based on the recorded user input.

[0038] FIG. **2** illustrates an example radiology workflow in which examples disclosed herein can be implemented. A radiologist logs into an imaging system (block **210**), reviews his/her worklist (block **220**), and selects a study to review (block **230**). In some medical imaging systems, imaging data is opened in an initial setup (block **240**). Further, a reviewing physician configures settings, interface items (e.g., interface buttons, etc.) (block **242**) and selects and organized images (block **245**), depending on a type of case he/she is reviewing (block **250**). During or after image reading (block **250**), the reviewing physician can dictate findings, notes, instructions, etc. (block **260**), and then exit the study (block **270**).

[0039] According to some known examples, the reviewing physician will sometimes re-adjust images (e.g., zoom, pan and/or reorder the images) and/or adjust a user interface based on individual preferences. In such known examples, often the reviewing physician will need to manually set the user interface preferences and move and/or select images according to his/her preferences. The adjustment of the user interface can be time consuming and also computationally intensive.

[0040] Examples disclosed herein utilize training data to develop models used to predict preferences, sequences and/or image organization to save time and/or effort on the part of the reviewing physician or other practitioner. In particular, examples disclosed herein use machine learning to adapt a user interface based on a context of medical contend data to enable more efficient utilization of image data, thereby saving time and costs associated with time wasted configuring a user interface. Examples disclosed herein also enable more efficient utilization of processor/computing resources by streamlining user experiences. In particular, some examples disclosed herein can reduce processing associated with reconfiguring a user interface by caching predicted interface adjustments or images, or enabling streamlined data transfers based on predicted user commands (e.g., predicted based on learning techniques).

[0041] FIG. **3** depicts an example of a learning system **300** to adjust a user interface based on learning (e.g., deep learning techniques) in accordance with teachings of this disclosure. The example learning system **300** of the illustrated example includes an image study **310** including study information, one or more individual images **320** including image DICOM header information, a machine learning engine **330** that includes a use analyzer (e.g., a use monitor) **332**, a case learning analyzer (e.g., a medical content data analyzer) **334**, and a machine learning model (e.g., an artificial neural network) **336**. The example learning system **300** also includes a user interface **340** with a user interface adjuster **342** and a command recorder **344**. The components of the learning system **300** can be implemented in software, hardware, and/or firmware, for example.

[0042] In operation, the study **310** information and individual image **320** information are extracted from an image study and provided or otherwise made accessible to the machine learning engine **330**. Based on user input and user commands (e.g., a sequence of multiple user commands), the machine learning engine **330** generates a configuration of the user interface **340** (e.g., a configuration generated by the user interface adjuster **342**). For example, an artificial neural network and/or other adaptive processing model can be used by the machine learning engine **330** to select or generate a user interface configuration based on commands and/or user input recorded by the command recorder **344**. In some examples, the medical content data can include case data, case histories, case study information, diagnoses, medical report information, case metadata, case terms, etc.

[0043] To analyze user commands and/or monitored user actions, the use analyzer **332** analyzes user inputs representing actions performed during viewing of images at a clinical display. In other words, the use analyzer **332** develops and/or trains models based on monitored user actions.

[0044] According to the illustrated example, the case learning analyzer **334** is used to analyze and/or determine a context of medical content data. For example, the case learning analyzer **334** develops training data and/or models associated with metadata or case histories of medical cases. The case learning analyzer **334** can utilize key terms, image content, diagnoses, image classifications and/or individual case histories. In some examples, the case learning analyzer **334** performs a similarity analysis by analyzing similarities between images of different medical cases (e.g., in conjunction with user commands or inputs).

[0045] In some examples, the machine learning engine **330** implements a machine learning model **336**, which is an artificial neural network and/or other machine or deep learning construct to determine or generate a user interface configuration. In some examples, context based algorithms can use DICOM header elements to associate medical content data with user input. In some examples, as the user issues various input commands over time, the artificial neural network nodes are updated by the machine learning model **336**, and the nodes continue to evolve. Although artificial neural networks are discussed above, other forms of artificial intelligence, such as fuzzy logic, Boltzmann machine, Bayesian network, etc., can be used as machine learning techniques to determine an applicable user input configuration.

[0046] The machine learning engine **330** and/or the machine learning model **336** is used to analyze image similarities between different medical cases so that images and/or their associated data can be correlated to user inputs so that subsequently encountered similar images can be correlated or tied to the user inputs. By correlating images with user input, application settings and/or user interface configuration settings, the machine learning model **336** learns a context that matches and/or correlates the user input/commands with the content of the images, which can include associated data and/or metadata. In other words, the example machine learning model **336** determines patterns (e.g., contextual patterns) between a context/situation and resulting user interface application configurations (e.g., interface configuration changes) that have been applied by a user. As an example, instead of simply correlating a situation to a user interface configuration, the machine learning model **336** can determine similarities in situations (e.g., similarities in context and/or images, etc.) and/or a degree of similarity without necessarily requiring an exact situation, thereby resulting in great adaptability in learning and application of the modified user interface configurations. Additionally or alternatively, in some examples, the application is executed is modified or adjusted (e.g., a sequence of hierarchy of when different modules or executables are run, etc.) by the machine learning model **336**.

[0047] FIG. **4** provides an example visualization of image data information **400** that can be analyzed in examples disclosed herein. According to the illustrated example, records (e.g., medical records) **410** are associated with medical images **420**. As can also be seen in the example of FIG. **4**, metadata **430** is associated with the records **410** and/or the images **420**. According to the illustrated example of FIG. **4**, a user configuration mapper **440** displays a user interface (e.g., a user display) **450** based on learned user interface configuration data developed by the machine learning engine **330**.

[0048] Examples disclosed herein can generate and/or modify a user interface and/or other application configuration by utilizing learning based on context of any of the records **410** or the images **420** in combination with recorded user actions and/or commands. In particular, learning techniques, such as those described below in connection with FIGS. **5-12**, can be implemented to develop user interface training models based on a context of the images **420**, the records **410** and/or the metadata **430** in relationship to the recorded user actions, clinical context, observed results, etc. For example, contextual patterns, which can be used to associate different or similar situations encountered, can be learned based on the user inputs in reference to contextual information. In some examples, the user interface **450** is provided with an icon or symbol **452** to represent a user interface configuration (e.g., a batched command, rearranged menu items or icons, shifted or rearranged menu item hierarchies, etc.).

[0049] FIG. **5** depicts a high level data flow **500** for an example machine learning algorithm to generate a user interface configuration. The high level data flow can be implemented by the machine learning engine **300** and/or the machine learning model **336**. In this example, the high level data flow **500** is used to develop predictions (e.g., user computer behavior models, interface use models, application modification predictions, etc.) so that a user interface configuration can be generated or modified to better suit practitioner viewing needs. In particular, the user interface configuration can be adapted for more time-efficient use by avoiding common user interface setup steps and/or image arrangements. According to the illustrated example of FIG. **5**, steps **502** represent activities that can be performed on the image viewer **140** while steps **504** represent server-based activities (e.g., the image processing server **130**, for example.

[0050] At block **508**, a user (e.g., a reviewing physician) starts work on an application associated with an image viewer **140** by opening a study on the image viewer **140**. In this example, the user activity (e.g., commands, sequences, inputs, image arrangement, etc.) are tracked or recorded at block **510**. Further, the user activity is cached into data logs at block **512**. In this example, the user activity and data logs are cached and transferred to a server (e.g., the image processing server **130** and/or the data acquisition workstation **120**) (block **514**).

[0051] At block **516**, user and data are recorded and/or forwarded to the image processing server **130** and/or the data acquisition workstation **120**. In some examples, data and/or metadata related to medical content data is also forwarded along with the user data. In this example, the aforementioned user and data activity are used to append training data at block **518**. In other words, the training data is utilized so that the machine learning engine **330** can develop or modify (e.g., refine) user interface configuration (s).

[0052] The machine learning engine **330** of the illustrated example executes a similarity algorithm **520** of the appended training data to develop predictions **522**. According to the illustrated example, user commands are analyzed in conjunction with medical content data and/or its associated metadata to develop the predictions **522**. In this example, the predictions **522** are refined and/or modified as the aforementioned training data is appended or corrected.

[0053] In some examples, the similarity algorithm **520** utilizes a similarity-based classification model to estimate a class label of an incoming study based on a degree of similarity between the incoming data and a set of training data samples and/or pairwise similarities between the training samples. Accordingly, similarity calculation can be done based on feature vectors extracted from training data and an incoming study. For example, a similarity score is calculated by a summation of Euclidian distance measurement(s) of individual features. In some such examples, the nearest neighbors are calculated and recommended to the users using a learning and/or analytics engine. For example, a Euclidian distance measurement on a high dimensional space can be calculated using equation 1 below, where Xi and Yi represent numeric quantifications of individual feature vectors in n dimensional space:

$$D=\mathrm{Sqrt}\ (\Sigma_{i=0}^{n}\ (Xi-Yi)\hat{}2) \tag{1}$$

[0054] In this example, a minimal distance value directly translates to higher similarity. For features with string values, comparisons done and appropriate numeric value weightage is associated for exact match and approximate match to be later used for a similarity calculation.

[0055] As a result of developing the predictions **522**, a user interface configuration and/or a user interface displaced on the image viewer **140** is adjusted. In particular, any of a navigation order **526**, annotations on content **528**, or extensions (e.g., extensions to menu icons and/or shortcuts on a user interface, etc.) **530** can be adjusted based on the predictions **522**.

[0056] In some examples, training data is stored on a training data storage **534**. The example training data storage **534** includes a training case base **536** and feature extraction data **538**. In this example, at least one of user interactions (e.g., user commands, user input sequences, user rearrangement of elements of a user interface, etc.) **540**, medical reports data **542**, DICOM data **544** or knowledge data (e.g., knowledge base data, anatomy data, physiology data, etc.) **546** are incorporated into training data associated with machine learning and stored in the training data storage **534**. In some examples, the training data is developed for a later session (e.g., user commands/inputs in the context of content data are learned in a first reading session and then a user interface is adjusted prior or during a second reading session that is subsequent to the first session). In some other examples, the training data is updated during a session.

[0057] FIG. **6** depicts a high level data flow of an example model learning and prediction algorithm **600**. The example of FIG. **6** illustrates a data flow in which training and model data is updated, corrected and/or appended based on machine learning performed by the machine learning engine **330** of FIG. **3**. In this example, the machine learning engine **330** generates, modifies and/or appends training data **602**. In particular, the machine learning engine **330** extracts features **604** to define feature vectors **606**. In turn, the feature vectors **606** are utilized in a model training process **608** to define a model **610**.

[0058] In this example, user data **612** undergoes feature extraction **614** to define feature vectors **616**. To develop the model **610**, the feature vectors **606** are compared to the feature vectors **616** in a similarity analysis **618**, thereby generating predictions **622**. In this example, the predictions **622** provide feedback **622** to the training data **602**. In other words, the predictions **622** are used to refine, improve and/or augment the training data **602** in this example. In some examples, vectors associated with a single user are extracted. In such examples, the vectors can be used to generate a model tailored to an individual (e.g., individual preferences). Additionally or alternatively, vectors associated with multiple users are utilized to develop a model for multiple users. In some such examples, the vectors based on multiple users are used to generate a user interface configuration (e.g., an aggregate user interface configuration) that is forwarded to multiple ones of the display viewers **140**.

[0059] While an example manner of implementing the example learning system **300** of FIG. **3** is illustrated in FIG. **3**, one or more of the elements, processes and/or devices illustrated in FIG. **3** may be combined, divided, re-arranged, omitted, eliminated and/or implemented in any other way. Further, the example machine learning engine **330**, the example use analyzer **332**, the example case learning analyzer **334**, the machine learning model **336**, the example user interface **340**, the example user interface adjuster **340**, the example command recorder **344** and/or, more generally, the example learning system **300** of FIG. **3** may be implemented by hardware, software, firmware and/or any combination of hardware, software and/or firmware. Thus, for example, any of the example machine learning engine **330**, the example use analyzer **332**, the example case learning analyzer **334**, the machine learning model **336**, the example user interface **340**, the example user interface adjuster **340**, the example user interface adjuster **342**, the example command recorder **344** and/or, more generally, the example learning system **300** could be implemented by one or more analog or digital circuit(s), logic circuits, programmable processor(s), programmable controller(s), graphics processing unit(s) (GPU (s)), digital signal processor(s) (DSP(s)), application specific integrated circuit(s) (ASIC(s)), programmable logic device (s) (PLD(s)) and/or field programmable logic device(s) (FPLD(s)). When reading any of the apparatus or system claims of this patent to cover a purely software and/or firmware implementation, at least one of the example machine learning engine **330**, the example use analyzer **332**, the example case learning analyzer **334**, the machine learning model **336**, the example user interface **340**, the example user interface adjuster **340**, the example user interface adjuster **342** and/or the example the example command recorder **344** is/are hereby expressly defined to include a non-transitory computer readable storage device or storage disk such as a memory, a digital versatile disk (DVD), a compact disk (CD), a Blu-ray disk, etc. including the software and/or firmware. Further still, the example learning system **300** of FIG. **3** may include one or more elements, processes and/or devices in addition to, or instead of, those illustrated in FIG. **3**, and/or may include more than one of any or all of the illustrated elements, processes and devices. As used herein, the phrase "in communication," including variations thereof, encompasses direct communication and/or indirect communication through one or more intermediary components, and does not require direct physical (e.g., wired) communication and/or constant communication, but rather additionally includes selective communication at periodic intervals, scheduled intervals, aperiodic intervals, and/or one-time events.

[0060] Flowcharts representative of example hardware logic, machine readable instructions, hardware implemented state machines, and/or any combination thereof for implementing the learning system **300** of FIG. **3** are shown in FIGS. **7** and **8**. The machine readable instructions may be an executable program or portion of an executable program for execution by a computer processor such as the processor **1312** shown in the example processor platform **1300** discussed below in connection with FIG. **13**. The program may be embodied in software stored on a non-transitory computer readable storage medium such as a CD-ROM, a floppy disk, a hard drive, a DVD, a Blu-ray disk, or a memory associated with the processor **1312**, but the entire program and/or parts thereof could alternatively be executed by a device other than the processor **1312** and/or embodied in firmware or dedicated hardware. Further, although the example programs described with reference to the flowcharts illustrated in FIGS. **7** and **8**, many other methods of implementing the example learning system **300** may alternatively be used. For example, the order of execution of the blocks may be changed, and/or some of the blocks described may be changed, eliminated, or combined. Additionally or alternatively, any or all of the blocks may be implemented by one or more hardware circuits (e.g., discrete and/or integrated analog and/or digital circuitry, an FPGA, an ASIC, a comparator, an operational-amplifier (op-amp), a logic circuit, etc.) structured to perform the corresponding operation without executing software or firmware.

[0061] As mentioned above, the example processes of FIGS. **7** and **8** may be implemented using executable instructions (e.g., computer and/or machine readable instructions) stored on a non-transitory computer and/or machine readable medium such as a hard disk drive, a flash memory, a read-only memory, a compact disk, a digital versatile disk, a cache, a random-access memory and/or any other storage device or storage disk in which information is stored for any duration (e.g., for extended time periods, permanently, for brief instances, for temporarily buffering, and/or for caching of the information). As used herein, the term non-transitory computer readable medium is expressly defined to include any type of computer readable storage device and/or storage disk and to exclude propagating signals and to exclude transmission media.

[0062] "Including" and "comprising" (and all forms and tenses thereof) are used herein to be open ended terms. Thus, whenever a claim employs any form of "include" or "comprise" (e.g., comprises, includes, comprising, including, having, etc.) as a preamble or within a claim recitation of any kind, it is to be understood that additional elements, terms, etc. may be present without falling outside the scope of the corresponding claim or recitation. As used herein, when the phrase "at least" is used as the transition term in, for example, a preamble of a claim, it is open-ended in the same manner as the term "comprising" and "including" are open ended. The term "and/or" when used, for example, in a form such as A, B, and/or C refers to any combination or subset of A, B, C such as (1) A alone, (2) B alone, (3) C alone, (4) A with B, (5) A with C, (6) B with C, and (7) A with B and with C.

[0063] An example method **700** of FIG. **7** begins as a user (e.g., a reviewing physician) is to utilize a medical imaging interface. In this example, the user will access images during multiple sessions (e.g., multiple sessions defining different medical cases) on the image viewer **140**.

[0064] According to the illustrated example, the command recorder **344** monitors user actions and case data (block **702**). In this example, the user actions (e.g., commands, settings, image manipulation) are monitored in conjunction with medical content data.

[0065] The machine learning engine **330** utilizes a learning network to learn a user interface configuration based on the user actions in relationship to content of the medical content data (e.g., based on monitored user actions in relationship to a context of the medical content data) (block **704**). In some examples, case metadata is also analyzed. Additionally or alternatively, image data (e.g., image similarity data) is utilized by the machine learning engine **330** to learn the user configuration.

[0066] In this example, the model is trained by the use analyzer **332**, the machine learning model **336** and/or the case learning analyzer **334** (block **706**). In particular, feature vectors associated with a training module as well feature vectors associated with user input data are utilized to train the model.

[0067] Next, in some examples, a request is received from a user (block **708**). In particular, the request can include information of a new incoming medical case to be viewed and/or specifically requested parameters provided from a user.

[0068] In some examples, the request is compared to a subset of the trained model for similarity (block **710**). If the request is not similar to the subset (e.g., the trained model does not have a relevant user interface configuration based on the request), control of the process proceeds to block **702**. Otherwise, control of the process proceeds to block **712**.

[0069] At block **712**, the user interface adjuster **342** selects or determines a subset of commands from the trained model based on the request. In particular, the example user interface adjuster **342** defines a group of commands and/or user interface adjustments from the trained model based on the request. In other words, the user interface adjuster **342** provides a user interface configuration based on the request being similar to at least one subset of the trained model.

[0070] At block **714**, the user interface adjuster **342** adjusts and/or modifies a user interface of the image viewer **140** (e.g., applies the user interface configuration to the image viewer **140**) and control of the process returns to block **702**. In some examples, menu items of a user interface are adjusted. Additionally or alternatively, an icon, symbol or button representing a learned command or set of commands is shown on the image viewer **140**.

[0071] Turning to FIG. **8**, a flowchart representative of the example subroutine **704** of FIG. **7** is shown. The example subroutine **704** begins as features are extracted from training data to define training vectors by the user analyzer **332**, the machine learning model **336** and/or the case learning analyzer **334** (block **802**).

[0072] According to the illustrated example, features are extracted from user data to define user vectors by the user analyzer **334** and/or the machine learning model **336** (block **804**). For example, the features can be related to translation, zooming, panning or annotations of medical case images.

[0073] It is then determined if the training vectors are similar to the user vectors (block **806**). In particular, a degree of similarity between the training vectors and the user vectors is determined. If the training vectors are similar to the user vectors based on the degree of similarity (block **806**), control of the process proceeds to block **808**. Otherwise, control of the process proceeds to block **810**.

[0074] At block **808**, the model is developed and/or updated by the machine learning engine **330**. For example, a pre-defined condition (e.g., a case history or potential diagnosis) can be linked a user interface configuration.

[0075] At block **810**, a prediction is developed and/or updated. In this example, the prediction developed and/or updated based on the comparison of the training vectors to the user vectors. Subsequently, control of the process returns to block **802**.

[0076] FIGS. **9-12** illustrate example learning techniques and methods that can be implemented in examples disclosed herein. The examples of FIGS. **9-12** can be implemented by the machine learning model **336**, for example, to create a user interface model that associated user interactions with user identifications, data context and/or data content (e.g., case information). In particular, the examples of FIGS. **9-12**

can be implemented to learn a user interface in the context of user patterns, user preferences, individual preferences, image similarity, case histories, case types, metadata, etc. FIG. **9** is a representation of an example deep learning neural network **900** that can be implemented in examples disclosed herein. The example neural network **900** includes layers **920**, **940**, **960**, and **980**. The layers **920** and **940** are connected with neural connections **930**. The layers **940** and **960** are connected with neural connections **950**. The layers **960** and **980** are connected with neural connections **970**. Data flows forward via inputs **912**, **914**, **916** from the input layer **920** to the output layer **980** and to an output **990**.

[0077] The layer **920** is an input layer that, in the example of FIG. **9**, includes a plurality of nodes **922**, **924**, **926**. The layers **940** and **960** are hidden layers and include, the example of FIG. **9**, nodes **942**, **944**, **946**, **948**, **962**, **964**, **966**, **968**. The neural network **900** can include more or less hidden layers **940** and **160** than shown. The layer **980** is an output layer and includes, in the example of FIG. **9**, a node **982** with an output **990**. Each input **912-916** corresponds to a node **922-126** of the input layer **920**, and each node **922-926** of the input layer **920** has a connection **930** to each node **942-948** of the hidden layer **940**. Each node **942-948** of the hidden layer **940** has a connection **950** to each node **962-968** of the hidden layer **960**. Each node **962-968** of the hidden layer **960** has a connection **970** to the output layer **980**. The output layer **980** has an output **990** to provide an output from the example neural network **900**.

[0078] Of connections **930**, **950**, and **970** certain example connections **932**, **952**, **972** can be given added weight while other example connections **934**, **954**, **974** are given less weight in the neural network **900**. Input nodes **922-926** are activated through receipt of input data via inputs **912-916**, for example. Nodes **942-948** and **962-968** of hidden layers **940** and **960** are activated through the forward flow of data through the network **900** via the connections **930** and **950**, respectively. Node **982** of the output layer **980** is activated after data processed in hidden layers **940** and **960** is sent via connections **970**. When the output node **982** of the output layer **980** is activated, the node **982** outputs an appropriate value based on processing accomplished in hidden layers **940** and **160** of the neural network **900**.

[0079] FIG. **10** illustrates a particular implementation of the example neural network **900** as a convolutional neural network **1000**. As shown in the example of FIG. **10**, an input **910** is provided to the first layer **920** which processes and propagates the input **910** to the second layer **940**. The input **910** is further processed in the second layer **940** and propagated to the third layer **960**. The third layer **960** categorizes data to be provided to the output layer **980**. More specifically, as shown in the example of FIG. **10**, a convolution **1004** (e.g., a 5×5 convolution, etc.) is applied to a portion or window (also referred to as a "receptive field") **1002** of the input **910** (e.g., a 32×32 data input, etc.) in the first layer **920** to provide a feature map **1006** (e.g., a (6×) 28×28 feature map, etc.). The convolution **1004** maps the elements from the input **910** to the feature map **1006**. The first layer **920** also provides subsampling (e.g., 2×2 subsampling, etc.) to generate a reduced feature map **1010** (e.g., a (6×) 14×14 feature map, etc.). The feature map **1010** undergoes a convolution **1012** and is propagated from the first layer **920** to the second layer **940**, where the feature map **1010** becomes an expanded feature map **1014** (e.g., a (16×) 10×10 feature map, etc.). After subsampling **1016** in the second layer **940**, the feature map **1014** becomes a reduced feature map **1018** (e.g., a (16×) 4×5 feature map, etc.). The feature map **1018** undergoes a convolution **1020** and is propagated to the third layer **960**, where the feature map **1018** becomes a classification layer **1022** forming an output layer of N categories **1024** with connection **1026** to the convoluted layer **1022**, for example.

[0080] FIG. **11** is a representation of an example image analysis convolutional neural network **1100** that can be implemented in examples disclosed herein. In particular, the example image analysis of FIG. **11** can be implemented to analyze similarities in medical images between cases (e.g., to develop training models based on medical case images). The convolutional neural network **1100** receives an input image **1102** and abstracts the image in a convolution layer **1104** to identify learned features **1110-1122**. In a second convolution layer **1130**, the image is transformed into a plurality of images **1130-1138** in which the learned features **1110-1122** are each accentuated in a respective sub-image **1130-1138**. The images **1130-1138** are further processed to focus on the features of interest **1110-1122** in images **1140-1148**. The resulting images **1140-1148** are then processed through a pooling layer which reduces the size of the images **1140-1148** to isolate portions **1150-1154** of the images **1140-1148** including the features of interest **1110-1122**. Outputs **1150-1154** of the convolutional neural network **1100** receive values from the last non-output layer and classify the image based on the data received from the last non-output layer. In certain examples, the convolutional neural network **1100** can contain many different variations of convolution layers, pooling layers, learned features, and outputs, etc.

[0081] FIG. **12** illustrates example training and deployment phases of a deep learning network that can be implemented in examples disclosed herein. As shown in the example of FIG. **12**, in the training phase, a set of inputs **1202** is provided to a network **1204** for processing. In this example, the set of inputs **1202** can include facial features of an image to be identified. The network **1204** processes the input **1202** in a forward direction **1206** to associate data elements and identify patterns. The network **1204** determines that the input **1202** represents a dog **1208**. In training, the network result **1208** is compared **1210** to a known outcome **1212**. In this example, the known outcome **1212** is a human face (e.g., the input data set **1202** represents a human face, not a dog face). Since the determination **1208** of the network **1204** does not match **1210** the known outcome **1212**, an error **1214** is generated. The error **1214** triggers an analysis of the known outcome **1212** and associated data **1202** in reverse along a backward pass **1216** through the network **1204**. Thus, the training network **1204** learns from forward **1206** and backward **1216** passes with data **1202**, **1212** through a communication network.

[0082] Once the comparison of network output **1208** to known output **1212** matches **1210** according to a certain criterion or threshold (e.g., matches n times, matches greater than x percent, etc.), the training network **1204** can be used to generate a network for deployment with an external system. Once deployed, a single input **1220** is provided to a deployed deep learning network **1222** to generate an output **1224**. In this case, based on the training network **1204**, the deployed network **1222** determines that the input **1220** is an image of a human face **1224**.

[0083] Accordingly, an analysis similar to the face example shown in FIG. **12** can be performed with respect to medical images in examples disclosed herein. For example, multiple images associated with different cases can be analyzed or learned, via machine learning processes, for similarity in conjunction with medical data (e.g., medical history information, diagnoses, metadata, key words, etc.) to develop a context associated with user inputs/commands to adapt a user interface configuration.

[0084] In some examples, DICOM metadata (e.g., a DICOM header) analysis leverages medical content metadata to do an approximate fuzzy match between clinical images rather than a literal pixel-by-pixel (2D) or voxel-by-voxel (3D) or literal image content match. In some examples, learning is transferred to apply lessons learned in one domain to another domain.

[0085] Additionally or alternatively, labels, indicators, identification numbers, etc., are extracted from DICOM headers associated with images and other clinical content. As a result, the images and clinical content are matched based on an assumption from the DICOM header content. In particular, it can be assumed that because headers have similar words, indicators, labels, etc., two or more items (or any appropriate number of items) have a relationship.

[0086] FIG. **13** is a block diagram of an example processor platform **1300** structured to execute the instructions of FIGS. **7** and **8** to implement the learning system **300** of FIG. **3**. The processor platform **1300** can be, for example, a server, a personal computer, a workstation, a self-learning machine (e.g., a neural network), a mobile device (e.g., a cell phone, a smart phone, a tablet such as an iPad™), a personal digital assistant (PDA), an Internet appliance, a DVD player, a CD player, a digital video recorder, a Blu-ray player, a gaming console, a personal video recorder, a set top box, a headset or other wearable device, or any other type of computing device.

[0087] The processor platform **1300** of the illustrated example includes a processor **1312**. The processor **1312** of the illustrated example is hardware. For example, the processor **1312** can be implemented by one or more integrated circuits, logic circuits, microprocessors, GPUs, DSPs, or controllers from any desired family or manufacturer. The hardware processor may be a semiconductor based (e.g., silicon based) device. In this example, the processor implements the example machine learning engine **330**, the example use analyzer **332**, the example case learning analyzer **334**, the machine learning model **336**, the example user interface **340**, the example user interface adjuster **340**, the example user interface adjuster **342** and the example command recorder **344**.

[0088] The processor **1312** of the illustrated example includes a local memory **1313** (e.g., a cache). The processor **1312** of the illustrated example is in communication with a main memory including a volatile memory **1314** and a non-volatile memory **1316** via a bus **1318**. The volatile memory **1314** may be implemented by Synchronous Dynamic Random Access Memory (SDRAM), Dynamic Random Access Memory (DRAM), RAMBUS® Dynamic Random Access Memory (RDRAM®) and/or any other type of random access memory device. The non-volatile memory **1316** may be implemented by flash memory and/or any other desired type of memory device. Access to the main memory **1314**, **1316** is controlled by a memory controller.

[0089] The processor platform **1300** of the illustrated example also includes an interface circuit **1320**. The interface circuit **1320** may be implemented by any type of interface standard, such as an Ethernet interface, a universal serial bus (USB), a Bluetooth® interface, a near field communication (NFC) interface, and/or a PCI express interface.

[0090] In the illustrated example, one or more input devices **1322** are connected to the interface circuit **1320**. The input device(s) **1322** permit(s) a user to enter data and/or commands into the processor **1312**. The input device(s) can be implemented by, for example, an audio sensor, a microphone, a camera (still or video), a keyboard, a button, a mouse, a touchscreen, a track-pad, a trackball, isopoint and/or a voice recognition system.

[0091] One or more output devices **1324** are also connected to the interface circuit **1320** of the illustrated example. The output devices **1024** can be implemented, for example, by display devices (e.g., a light emitting diode (LED), an organic light emitting diode (OLED), a liquid crystal display (LCD), a cathode ray tube display (CRT), an in-place switching (IPS) display, a touchscreen, etc.), a tactile output device, a printer and/or speaker. The interface circuit **1320** of the illustrated example, thus, typically includes a graphics driver card, a graphics driver chip and/or a graphics driver processor.

[0092] The interface circuit **1320** of the illustrated example also includes a communication device such as a transmitter, a receiver, a transceiver, a modem, a residential gateway, a wireless access point, and/or a network interface to facilitate exchange of data with external machines (e.g., computing devices of any kind) via a network **1326**. The communication can be via, for example, an Ethernet connection, a digital subscriber line (DSL) connection, a telephone line connection, a coaxial cable system, a satellite system, a line-of-site wireless system, a cellular telephone system, etc.

[0093] The processor platform **1300** of the illustrated example also includes one or more mass storage devices **1328** for storing software and/or data. Examples of such mass storage devices **1328** include floppy disk drives, hard drive disks, compact disk drives, Blu-ray disk drives, redundant array of independent disks (RAID) systems, and digital versatile disk (DVD) drives.

[0094] The machine executable instructions **1332** of FIGS. **7** and **8** may be stored in the mass storage device **1328**, in the volatile memory **1314**, in the non-volatile memory **1316**, and/or on a removable non-transitory computer readable storage medium such as a CD or DVD.

[0095] From the foregoing, it will be appreciated that example methods, apparatus and articles of manufacture have been disclosed that enable adjustment of user interfaces based on machine learning techniques to save user time. In particular, examples disclosed herein can be implemented to save time for a reviewing physician that views medical images. Some examples disclosed herein enable more computationally efficient transfers of image data and/or files associated with user interfaces by utilizing models to predict user commands based on data context (e.g., learned contextual associations). As opposed to known user interface adjustments, which mainly develop an initial image hang or arrangement, examples disclosed herein learn and train models that encompass learning of a large extent of user/application behavior/interaction to examine an initial setup and subsequent interaction to provide a comprehensive model affecting operation of the whole application and not just the initial user interface setup. In other words, examples disclosed herein greatly improve the user interface by continuously adjusting the user interface setup based on contextual learning of medical data.

[0096] Although certain example methods, apparatus and articles of manufacture have been disclosed herein, the scope of coverage of this patent is not limited thereto. On the contrary, this patent covers all methods, apparatus and articles of manufacture fairly falling within the scope of the claims of this patent. While examples disclosed herein are shown in relation to clinical imaging system, the examples can be implemented with any appropriate user interface application or user-interface driven data system.

What is claimed is:

1. An apparatus comprising:

a use monitor including a processor to monitor, in a first session, user actions and medical content data pertaining to operation of a clinical image display to define training data; and

a learning device including a processor to implement a learning network to develop a model for a subsequent session based on the training data in relationship to a context of the medical content data, the model developed by defining contextual patterns of the user actions based on the context and the medical content data, the learning device to update, prior to or during a second session subsequent the first session, a user interface based on the model.

2. The apparatus as defined in claim **1**, wherein the learning device is to define the context at least partially based on an image similarity analysis.

3. The apparatus as defined in claim **1**, wherein the learning device is to modify an execution of an application associated with the clinical image display based on the model.

4. The apparatus as defined in claim **1**, wherein the learning network includes a convolutional neural network or a deep learning network.

5. The apparatus as defined in claim **4**, wherein the learning network is to analyze similarities of images of different medical cases in relationship to medical case data.

6. The apparatus as defined in claim **1**, wherein the clinical image display is to display a symbol on a screen of the clinical image display, the symbol representing at least one command of the model.

7. The apparatus as defined in claim **1**, wherein the content data includes at least one of metadata or histories associated with a respective medical case.

8. The apparatus as defined in claim **1**, wherein the user actions include at least one of translation, zooming, panning or annotations of case images.

9. The apparatus as defined in claim **1**, wherein updating the user interface includes deploying a user interface configuration to a remote image display.

10. A method to adapt a user interface configuration pertaining to a clinical image display, the method comprising:

monitoring, by executing instructions with a processor, user actions and medical content data during a first session of the clinical image display to define training data;

developing, by executing instructions with the processor, a model for a subsequent session based on the user actions in relation to a context of the medical content data with a learning network, the model developed by defining contextual patterns of the user actions based on the context and the medical content data; and

adjusting, by executing instructions with the processor, a user interface based on the model prior to or during a second session subsequent the first session.

11. The method as defined in claim **10**, further including modifying, by executing instructions with the processor, an execution of an application associated with the clinical image display based on the model.

12. The method as defined in claim **10**, further including comparing first vectors associated with training data of the model with second vectors associated with the user actions to determine a similarity between the training data and the model.

13. The method as defined in claim **10**, further including performing a similarity analysis of medical images of different medical cases in relationship to medical case data to analyze the context of the medical content data.

14. The method as defined in claim **10**, wherein the content data includes metadata or case histories associated with multiple medical cases.

15. The method as defined in claim **10**, further including displaying a symbol that represents a command of the adjusted user interface configuration.

16. A tangible machine readable medium comprising instructions, which when executed, cause a processor to at least:

define training data based on monitored user actions in relationship to a context of medical content data during operation of a clinical image display in a first session;

develop, by a training network, a model for a subsequent session based on the training data, the model developed by defining contextual patterns of the user actions based on the context and the medical content data; and

adjust a user interface of the clinical image display based on the model for a second session subsequent the first session.

17. The tangible machine readable medium as defined in claim **16**, wherein the processor is further caused to perform a similarity analysis of medical images of different medical cases in relationship to medical case data to analyze the context of the medical content data.

18. The tangible machine readable medium as defined in claim **17**, wherein the processor is further caused to compare first vectors associated with the training data with second vectors associated with the user actions to determine a degree of similarity between the training data and the model, wherein predictions of user commands are generated or updated based on the degree of similarity.

19. The tangible machine readable medium as defined in claim **16**, wherein the processor is further caused to display a symbol of a command of a learned user interface configuration developed from the model, the symbol to represent a sequence of user commands.

20. The tangible machine readable medium as defined in claim **16**, wherein the processor is further caused to modify an execution of an application associated with the clinical image display based on the model.

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