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UNITED STATES DISTRICT COURT
NORTHERN DISTRICT OF CALIFORNIA
SAN JOSE DIVISION

UNIVERSITY OF BRITISH COLUMBIA,

Plaintiff,

v.

CAPTION HEALTH, INC.,
GE HEALTHCARE TECHNOLOGIES INC.

Defendants.

Case No. 5:24-cv-03200-EKL

**FIRST AMENDED COMPLAINT FOR
PATENT INFRINGEMENT**

Judge: Hon. Eumi K. Lee

1 Plaintiff University of British Columbia (“UBC” or “Plaintiff”) files this First Amended
 2 Complaint against Caption Health, Inc. (“Caption Health”) and GE Healthcare Technologies, Inc.
 3 (“GE Healthcare”) (collectively “Defendants”) to stop Defendants’ ongoing infringement of
 4 plaintiff’s patented innovative AI-based systems and methods for evaluating cardiac ultrasound
 5 images.

6 **THE NATURE OF THE ACTION**

7 1. This is a civil action for patent infringement of United States Patent No. 11,129,591
 8 (“the ’591 patent”) and U.S. Patent No. 10,751,029 (“the ’029 patent”) (collectively, “the Patents
 9 in Suit”) under the patent laws of the United States, 35 U.S.C. § 1 et seq.

10 2. UBC seeks judgment that Defendants have infringed, and continue to infringe, the
 11 Patents in Suit based on Defendants’ commercialization of plaintiff’s patented innovative AI-based
 12 systems and methods prior to the expiration of the Patents in Suit.

13 **THE PARTIES**

14 3. UBC is a corporation continued under the University Act of British Columbia, with
 15 offices at 6328 Memorial Road, Room 240 Vancouver, B.C., Canada V6T 1Z2.

16 4. On information and belief, Caption Health is a corporation organized and existing
 17 under the laws of Delaware with its principal place of business at 500 West Monroe Street, Chicago,
 18 IL 60661.

19 5. On information and belief, GE Healthcare is a corporation organized and existing
 20 under the laws of Delaware with its principal place of business at 500 West Monroe Street, Chicago,
 21 IL 60661. On information and belief, GE Healthcare acquired Caption Health in February 2023,
 22 and Defendants work in concert in connection with the acts of infringement asserted below. GE
 23 HealthCare Form 10-Q at 14 (April 25, 2023) ([https://investor.gehealthcare.com/static-](https://investor.gehealthcare.com/static-files/900530e1-1ce0-4860-b7d0-7e2db5107f64)
 24 [files/900530e1-1ce0-4860-b7d0-7e2db5107f64](https://investor.gehealthcare.com/static-files/900530e1-1ce0-4860-b7d0-7e2db5107f64)).

25 **JURISDICTION AND VENUE**

26 6. This court has subject matter jurisdiction over the patent infringement claims
 27 asserted in this case under 28 U.S.C. §§ 1331 and 1338(a) because this action involves claims
 28 arising under the patent laws of the United States, 35 U.S.C. §§ 1 et seq.

7. This Court has personal jurisdiction over Caption Health at least because Caption Health maintains a regular and established place of business within this District and has had continuous and systematic business contacts with the State of California and this District. On information and belief, Caption Health has been registered to do business in the State of California since 2013. On information and belief, Caption Health has operated regional offices in at least San Mateo, California and Brisbane, California. *See, e.g.,* <http://captionhealth.com>; <https://web.archive.org/web/20231209012621/https://www.caption-care.com/privacy-policy>; <https://www.sbir.gov/sbc/bay-labs-inc>; <https://www.sbir.gov/sbc/bay-labs-inc>.

8. This Court has personal jurisdiction over GE Healthcare at least because GE Healthcare maintains a regular and established place of business within this District, and has had continuous and systematic business contacts with the State of California and this District. On information and belief, GE Healthcare operates regional offices in at least San Ramon, California and San Mateo, California. *See* <https://careers.gehealthcare.com/global/en/locations>; *see also, e.g.,* <https://careers.gehealthcare.com/global/en/job/R4004074/Field-Service-Engineer-San-Ramon-CA> (job listing based in San Ramon, stating “[t]his role is located in San Ramon, CA and covers the entire Bay Area.”); <https://careers.gehealthcare.com/global/en/job/R4007392/HC-Technician-1-Biomedical-HC>, <https://careers.gehealthcare.com/global/en/job/R4007236/HC-Technician-2-Biomedical-HC>, <https://careers.gehealthcare.com/global/en/job/R4003151/AI-Research-Summer-Fall-Co-op> (job listings based in San Ramon); <https://careers.gehealthcare.com/global/en/job/R4006523/Biomedical-Engineer-II-Gilroy-CA> (job listing based in San Mateo).

9. On information and belief, Caption Health and GE Healthcare have committed infringing activities in California and in this District by making, using, selling, importing, and offering for sale products and systems that infringe upon the ’591 patent and ’029 patent, or by placing such infringing products and systems into the stream of commerce with the awareness, knowledge, and intent that they would be used, offered for sale, or sold by others in this District and/or purchased by consumers in this District.

10. Venue is proper in this judicial district pursuant to 28 U.S.C. §§ 1391(b) and 1400(b) at least because a substantial part of the events or omissions giving rise to UBC's claims occurred in this District, and each of Defendants has a regular and established place of business in this District and has committed, and continues to commit, acts of infringement in this District.

FACTUAL BACKGROUND

A. UBC's Contributions to Echocardiography Research

11. UBC is one of the top research universities in the world and has created numerous innovations that benefit society. UBC has invested over \$700 million in research funding for thousands of research projects. <https://www.ubc.ca/about/facts.html>. Many of UBC's innovations have been acknowledged by patent offices throughout the world, including the United States Patent and Trademark Office.

12. Heart disease is a leading cause of death in this country and throughout the world. To diagnose the health of a heart, cardiac specialists view and analyze images of the heart created by ultrasound devices. A problem that cardiac specialists face, however, is acquiring good images of the heart.

13. Echocardiographic image analysis refers to the analysis of images of the heart created by ultrasound devices. There are numerous challenges unique to acquiring and identifying good echocardiographic images. One of the longstanding challenges is that operators need years of specialized training to properly capture and assess echocardiographic images. Slight changes in where an ultrasound transducer is placed, or the pressure applied when using the transducer, can result in significant variation in the quality and usability of an image. In most cases, the actual quality and usability of the image cannot be ascertained by the naked eye. Given the inability to discern the quality of captured echocardiographic images, operators often send inadequate or unusable images to the lab, only to learn that the procedure must be repeated. As a result, effective echocardiographic analysis can often be significantly delayed, which can delay proper treatment. Given this inefficient use of time and resources, there has long been a need for a better system and method for acquiring quality echocardiographic images.

14. Before the '591 and '029 inventions, there were many unsuccessful attempts to address these problems. Simply digitizing the assessment process, for example, proved to be deficient due to additional technical challenges. For example, the difficulty in assessing echocardiographic images is exacerbated by the fact that echocardiography involves capturing images from multiple strategic views. Different combinations of anatomical structures need to be visible from each of the various views for a proper diagnosis, and before the '591 patent and '029 patent, there was no system that could accurately assess the visibility of these anatomical structures. Additionally, unlike other medical imaging, echocardiography involves capturing the movement of the heart through sequences of images, known as echo cine series. These echo cine series include multiple images (e.g., 20 images) for each view, which further increases the number of images that are assessed. Capturing sequences of images from each of the various views increases the computational demands for assessing the echocardiographic images, especially when assessment feedback is desired quickly. Further, previous approaches were deficient in quality assessment because the anatomical variations as well as the positioning of the ultrasound transducer results in a wider distribution of echo cine series belonging to each quality group, which reasonably results in multi-modal distributions. To exacerbate the issue, echocardiography noise and artifact inference make it even more so challenging to use previous approaches. Thus, even with advances in general imaging techniques in the past few decades, there remained a need for specialized techniques for echocardiographic image analysis.

15. Recognizing this need to improve echocardiographic image analysis, UBC has invented, and continues to invent, improvements to techniques for assessing echocardiographic images. The '591 patent and '029 patent are just a few examples of UBC's innovations in the field.

B. The '591 Patent

1. Development of the '591 Invention

16. Around 2013, Dr. Tsang, an experienced cardiologist and recent winner of the Canadian Society of Echocardiography Annual Achievement Award. <https://www.ubccardio.com/canadian-cardiovascular-society-recognition-awards-2023/>, approached Dr. Abolmaesumi, another of the '591 inventors, to discuss a problem associated with

1 echocardiographic image capture and analysis. Dr. Tsang noted that while portable ultrasound
2 machines were highly capable of capturing images of the heart, the images were often inadequate
3 because the operators—typically technicians—were unable to capture usable images. Even
4 experienced operators struggled to identify and capture quality images that were acceptable for
5 analysis. Dr. Tsang had numerous patients who had to return for more imaging.

6 17. The named inventors on the '591 patent set out to address the problem. Dr.
7 Abolmaesumi and Dr. Rohling, both established professors and researchers in the field of medical
8 imaging, collaborated with Dr. Tsang about how to create a new system for determining
9 echocardiographic image quality that did not need to rely so heavily on the skill of an ultrasound
10 machine operator. They discussed how diagnoses depended on viewing images of the heart from
11 specific views, and that the quality of echocardiographic images taken from various views
12 depended on different features in the images. They determined that to analyze the three-
13 dimensional structure of the heart, a two-part process involving analyzing echocardiographic
14 images of at least two different views would be ideal. They also discussed whether neural networks
15 could be used to improve analysis of the echocardiographic images.

16 18. While the inventors recognized the benefits of neural networks, application of neural
17 networks for determining quality of echocardiographic images was not an obvious choice at the
18 time. Systems for determining echocardiographic image quality typically relied on modeling
19 techniques involving comparison to standard shapes or models. However, standard modeling
20 techniques were deficient given the complexity in determining the quality of echocardiographic
21 images of a moving heart and were not sensitive enough to distinguish small variations amongst
22 images. Along with Dr. Abdi, a former student at UBC, Dr. Abolmaesumi, Dr. Rohling, and Dr.
23 Tsang discussed how to design a neural network architecture that would make up for these
24 deficiencies. Dr. Abdi, with guidance from the other inventors, worked on several iterations of a
25 prototype of the neural network architecture to implement the team's ideas through trial and error,
26 including by updating network designs and composing parameters that provided more effective
27 image quality assessments. *See, e.g., A. H. Abdi, et. al., Automatic quality assessment of apical*
28 *four-chamber echocardiograms using deep convolutional neural networks*, Medical Imaging 2017:

1 Image Processing, 10133 (Feb. 2017); A. H. Abdi, et. al., *Automatic Quality Assessment of*
2 *Echocardiograms Using Convolutional Neural Networks: Feasibility on the Apical Four-Chamber*
3 *View*, IEEE Transactions on Medical Imaging, Vol. 36, 6:1221-1230 (June 2017); A. H. Abdi, et.
4 al., *Quality Assessment of Echocardiographic Cine Using Recurrent Neural Networks: Feasibility*
5 *on Five Standard View Planes*, Medical Image Computing and Computer Assisted Intervention
6 2017, Lecture Notes in Computer Science, 10435:302-310 (Sept. 2017). Ultimately, through
7 hundreds of hours of effort, the inventors came up with the innovations disclosed and claimed in
8 the '591 patent.

9 19. The patented system has various features. For example, a neural network is trained
10 with thousands of images from multiple views of the heart, each image being labeled with a quality
11 score. In this manner, the neural network can, for each view of the heart, create numerous
12 parameters that are relevant to the quality of an image and that can later be used to assess quality
13 of echocardiographic images. In developing a prototype, the inventors recognized that they could
14 not simply apply a neural network to echocardiographic images and expect results. As described
15 above, there are unique aspects of echocardiography that make it challenging to analyze the quality
16 of echocardiographic images, such as capturing images from various views where each view has
17 different features relating to quality. There is no one-size-fits-all approach for training and applying
18 a neural network for determining the quality of echocardiographic images—simply training a neural
19 network with a large number of echocardiographic images will not provide a system that can
20 effectively recognize quality of echocardiographic images. The inventors rectified this deficiency
21 by conceiving and designing systems and methods involving a neural network architecture that take
22 into account the view categories of images and provide assessment parameters that are specialized
23 for specific view categories. The resulting quality analysis is more accurate, reducing the need for
24 operators to retake patients' echocardiographic images and doctors to review captured images
25 multiple times.

26 20. The inventors also sought to optimize computer performance and efficiency when
27 faced with the technical issue of heavy computational resource usage typically associated with
28 neural networks. To do so, the inventors conceived of having a different assessment neural network

1 for each view of the heart, but also having such neural networks share certain layers, with the goal
2 of reducing computer processing and memory usage requirements of the computers training and
3 executing the neural network. In developing their prototype, the inventors included multiple
4 regression models that shared weights across the common shared layers and included separate
5 view-specific layers. They found that splitting the neural network into a common portion and a
6 view category specific portion facilitates more efficient training, such as by requiring fewer
7 learning parameters than would be required if using fully separate neural networks. They further
8 found that implementing the common portion reduces the amount of training performed overall,
9 decreasing computational resources directed to training and reducing the need to store and process
10 training images. The patented system thus allows for allocation of computational resources that
11 would typically be used for training, as well as storage and processing of training images to be
12 directed elsewhere. The inventors also found that their neural network architecture reduces
13 memory usage by using fewer learning parameters, for example, by facilitating data compression
14 and easier transfer of parameters to a machine.

15 21. The inventors also implemented the neural network architecture with common
16 shared layers because they recognized that training images are not easily obtainable in
17 echocardiography. While the use of neural networks in other contexts may allow outsourcing of
18 labelling of training images, labelling for echocardiographic image analysis relies on highly skilled
19 individuals, such as cardiologists, to provide their expertise. As described above, the neural
20 network architecture with common shared layers has the benefit of a reduced amount of training
21 and the need for fewer training images. Thus, the patented system did not need to rely on collection
22 of as many training images and labelling from experts.

23 22. Once they were satisfied that they had conceived and reduced to practice a system
24 that dramatically improved the capture and assessment of echocardiographic images, the inventors
25 filed a patent application disclosing their invention. The original provisional application was filed
26 on April 21, 2016.

27
28

1 **2. The Consideration and Grant of the '591 Patent**

2 23. The United States Patent Office did not take long to recognize the importance of the
3 invention. After considering over 60 references cited by UBC or the Examiner, the Examiner cited
4 one reference in an Office Action as anticipating the claims. *See* App. No. 16/095,601, May 5,
5 2021, Non-Final Rejection. However, the Examiner allowed the application shortly after UBC's
6 amendment and response upon recognizing that the Office Action had mischaracterized the cited
7 reference and that the reference did not disclose the claimed features. *See id.*, August 5, 2021,
8 Amendment/Request for Reconsideration-After Non-Final Rejection; *see id.*, August 18, 2021,
9 Notice of Allowance.

10 24. Thus, after only one Office Action rejecting the claims, the Patent Office issued a
11 "notice of allowance," acknowledging the invention was patentable, and on September 28, 2021,
12 the '591 patent, a copy of which is attached as Exhibit A, was issued.

13 **3. Caption Health's Knowledge and Infringement of the '591 Patent**

14 25. In May 2017, the inventors of the '591 patent had a teleconference with Kilian
15 Koepsell, founder and then Chief Technical Officer of Bay Labs (now Caption Health).

16 26. During the meeting, the inventors disclosed the innovations claimed in the '591
17 patent to Mr. Koepsell. The inventors and Mr. Koepsell also discussed possible collaborations
18 between the UBC and Bay Labs teams.

19 27. Shortly after the meeting, at Mr. Koepsell's request, Robert Rohling emailed Mr.
20 Koepsell papers that were discussed during the meeting. The papers sent were A. H. Abdi, et. al.,
21 *Automatic quality assessment of apical four-chamber echocardiograms using deep convolutional*
22 *neural networks*, Medical Imaging 2017: Image Processing, 10133 (Feb. 2017), and A. H. Abdi, et.
23 al., *Automatic Quality Assessment of Echocardiograms Using Convolutional Neural Networks:*
24 *Feasibility on the Apical Four-Chamber View*, IEEE Transactions on Medical Imaging, Vol. 36,
25 6:1221-1230 (June 2017). The second paper was available in preprint format on the IEEE website
26 by May 2017. A copy of the correspondence sent from Mr. Rohling to Mr. Koepsell is attached as
27 Exhibit C.
28

1 28. In early 2022, not long after the '591 patent issued, UBC and the inventors
2 discovered that Caption Health was marketing its AI-based cardiac ultrasound software that
3 practiced the claims of the '591 patent and that was remarkably close to the prototype the inventors
4 created.

5 29. UBC wrote to Caption Health and attempted to resolve this dispute without
6 litigation.

7 30. On May 5, 2022, UBC's counsel sent a letter to Steve Cashman, President and Chief
8 Executive Officer of Caption Health, bringing the infringement of the '591 patent to Caption
9 Health's attention and offering discussions to resolve the matter without litigation. A copy of the
10 May 5, 2022, letter is attached hereto as Exhibit D.

11 31. Caption Health did not respond to the letter.

12 32. Having heard no response, UBC's counsel sent another letter to Mr. Cashman on
13 May 24, 2022, attaching the original May 5, 2022, letter and requesting a response regarding the
14 '591 patent. A copy of the May 24, 2022, letter is attached hereto as Exhibit E.

15 33. On June 13, 2022, Caption Health CEO Steve Cashman sent an email
16 acknowledging receipt of the May 2022 letters and promising a prompt response following review
17 of the letters. A copy of the email is attached hereto in Exhibit F.

18 34. On June 27, 2022, Mr. Cashman sent another email alleging that the May 5 letter
19 did not include enough information to engage in a productive discussion and asking for "more
20 information..., such as detailed claim mapping and interpretation in relation to [Caption Health's]
21 current products." A copy of the email is attached hereto in Exhibit F.

22 35. In response, UBC provided the requested information, including a claim chart, in a
23 letter to Mr. Cashman on November 11, 2022, again requesting a response. A copy of the
24 November 11, 2022, letter is attached hereto as Exhibit G and incorporated herein by reference.

25 36. Caption Health never responded to the November 11, 2022, letter and has not
26 otherwise provided any substantive response to UBC.

27 37. GE Healthcare acquired Caption Health in February 2023 for about \$150 million.
28 GE HealthCare Form 10-Q at 14 (April 25, 2023) (<https://investor.gehealthcare.com/static->

1 [files/900530e1-1ce0-4860-b7d0-7e2db5107f64](https://www.businesswire.com/news/home/20230209005244/en/GE-HealthCare-to-Acquire-Caption-Health-Expanding-Ultrasound-to-Support-New-Us)); *GE HealthCare to Acquire Caption Health,*
 2 *Expanding Ultrasound to Support New Users Through FDA-Cleared, AI-Powered Image*
 3 *Guidance*, BusinessWire (Feb. 9, 2023)
 4 ([https://www.businesswire.com/news/home/20230209005244/en/GE-HealthCare-to-Acquire-](https://www.businesswire.com/news/home/20230209005244/en/GE-HealthCare-to-Acquire-Caption-Health-Expanding-Ultrasound-to-Support-New-Us)
 5 [Caption-Health-Expanding-Ultrasound-to-Support-New-Us](https://www.businesswire.com/news/home/20230209005244/en/GE-HealthCare-to-Acquire-Caption-Health-Expanding-Ultrasound-to-Support-New-Us)).

6 4. Overview of the '591 Patent

7 38. UBC owns all rights, title, and interest in the '591 patent, including those necessary
 8 to bring this action, and including the right to recover past and future damages.

9 39. The claims of the '591 patent are directed to inventions related to capturing and
 10 evaluating cardiac ultrasound images. Specifically, the claims address the problems described
 11 above of “echocardiographic systems...[that] may not assist echocardiographers in capturing high
 12 quality echocardiographic images for use in subsequent quantified clinical measurement of
 13 anatomical features.” '591 patent, 1:29-34. The claimed inventions solved this problem with new
 14 and improved methods and systems formed by training and employing neural networks for
 15 assessing the quality of echocardiographic images and providing quantitative analysis to help
 16 operators optimize the quality of such images. *See, e.g., id.*, 5:30-45, 6:13-20.

17 40. Further, the employed neural networks are trained to assess echocardiographic
 18 images of a specific view category. *See, e.g., id.*, 5:62-6:20. As described above, it is typical to
 19 capture echocardiographic images from various view or anatomical planes to allow determination
 20 of certain clinical measurements or diagnosis. *See, e.g., id.*, 5:46-49. Since the desirable
 21 characteristics for each of these different views can differ, there may be different criteria for
 22 assessing echocardiographic images based on the view they represent. *See, e.g., id.*, 5:62-67. For
 23 example, a quality assessment value for the “AP2” view category may depend on the left ventricle,
 24 left atrium, and mitral valve in the image, while a quality assessment value for the “AP3” category
 25 may depend on the aortic valve, mitral valve, left atrium, left ventricle, and septum. *See, e.g., id.*,
 26 15:28:39. As the specification explains, the employed neural networks are trained with images and
 27 their associated view category information, so that neural network parameters that are eventually
 28 used to assess image quality can evaluate quality based on criteria specific to certain view

categories. *See, e.g., id.*, 17:60-63, 18:27-35. Employment of neural networks associated with specific view categories of echocardiographic images was not known or conventional and provided an improvement over typical analyses. For example, a neural network is better able to consider in its analysis the “variability in the echocardiographic image data than when analysis of the echocardiographic image relies on an average template or atlas with average shape.” *See, id.*, 11:44-51. Applying specialized neural networks for specific view categories thus improves the system’s ability to assess echocardiographic image quality. Thus, the claims provide an improvement to a specific technology in a particular field.

41. The claimed inventions include additional technical improvements, such as the use of neural networks with common shared layers and a different set of view category specific layers. *See, e.g.*, 12:10-21, FIG. 8. The neural network architecture includes multiple regression models that share weights across the common shared layers and includes separate view-specific layers. *See, e.g.*, 12:31-35, FIG. 8. Splitting the neural network into a common portion and a view category specific portion facilitates more efficient training, such as by requiring fewer learning parameters than would be required if using fully separate neural networks. *See, e.g.*, 13:53-59. The use of fewer learning parameters also reduces memory usage, for example, by facilitating data compression and easier transfer of parameters to a machine. *See, e.g.*, 13:59-61, 24:9-10. Thus, the claims provide specific technological advances in using neural networks for analysis of echocardiographic images for the purpose of quality assessment.

C. The ’029 Patent

1. Development of the ’029 Invention

42. In addition to the inventions disclosed in the ’591 patent, the inventors also discussed and worked on other improvements relating to capture and assessment of ultrasound images. One of the problems they considered was that providing only a quality assessment value might not be ideal in certain contexts, especially when an ultrasound operator is inexperienced and is unable to recognize other contextual details about an ultrasound image. For example, for echocardiographic images, differences between certain view categories may not be apparent to an inexperienced operator and thus information about what view category is being shown in an image

1 is useful. Thus, the inventors agreed that that it would be beneficial to provide supplemental
2 information, such as an image property related to specific features or structures of an image, to the
3 operator during capture of ultrasound images.

4 43. However, designing a practical system that could determine a quality assessment
5 value and image property from ultrasound images, and provide them to an operator during
6 examination, was challenging. For example, training and deploying such a system requires a large
7 amount of computing power and resources, and processing assessment results during use could take
8 a long time. Thus, the inventors conceived of a system that combined quality assessment and image
9 property assessment, such that extracted feature representations could be used for assessment in an
10 efficient manner. For example, the inventors designed an architecture where at least some of the
11 extracted feature representations for both assessments could be extracted from a commonly defined
12 neural subnetwork. This design reduced the processing time and resources that would typically be
13 required for performing two assessments, which expanded the possibilities of implementing the
14 design on a portable device.

15 44. In addition to working on implementing a system with the combined quality
16 assessment and image property assessment to improve the capture and assessment of ultrasound
17 images, the inventors filed a patent application disclosing their invention. The original provisional
18 application leading to the '029 Patent was filed on August 31, 2018.

19 2. The Consideration and Grant of the '029 Patent

20 45. The United States Patent Office quickly recognized the importance of the claimed
21 invention. In a Non-Final Office Action, the Examiner rejected the claims for minor informalities
22 and as anticipated by Patent Publication No. 2019/0125298 ("298 publication"), the publication
23 that led to issuance of the '591 patent. *See* App. No. 16/557,261, January 8, 2020, Non-Final
24 Rejection. The Examiner allowed the application shortly thereafter upon finding the '298
25 publication was not prior art because it fell under the 102(b)(2)(C) exception. *See id.*, Mar. 19,
26 2020, Amendment/Request for Reconsideration-After Non-Final Rejection at 8-10 (describing that
27 the '298 publication and App. No. 16/557,261 were subject to an obligation of assignment to UBC);
28 *see id.*, June 25, 2020, Notice of Allowance.

1 46. Thus, finding no prior art that anticipated or rendered the claimed invention obvious,
2 the Patent Office issued a “notice of allowance” acknowledging the invention was patentable, and
3 on August 5, 2020, the ’029 patent, a copy of which is attached as Exhibit B, was issued.

4 **3. Overview of the ’029 Patent**

5 47. UBC owns all rights, title, and interest in the ’029 patent, including those necessary
6 to bring this action, and including the right to recover past and future damages.

7 48. The claims of the ’029 patent are directed to inventions related to capturing and
8 evaluating ultrasound images. Specifically, the claims address the problems relating to how
9 “[a]ccurate diagnosis in ultrasound requires high quality ultrasound images, which may need to
10 show or contain different specific features and structures depending on various properties of the
11 images,” and that recognizing such features can be especially difficult for inexperienced ultrasound
12 operators. ’029 patent, 1:22-31. The claimed inventions solved this problem with new and improved
13 methods and systems formed by training and employing an algorithm, for example using a neural
14 network, for assessing ultrasound images for quality, along with specific features or structures, to
15 facilitate more accurate analysis of the images and help operators optimize the capture of desirable
16 images. *See, e.g., id.*, 5:5-22.

17 49. The employed algorithm is trained to assess ultrasound images for quality, as well
18 as an image property that is helpful for further assessing specific features or structures captured in
19 the images. *See, e.g., id.*, 5:23-33. Since the desirable characteristics for various ultrasounds
20 images can differ, there may be different criteria for assessing ultrasound images based on their
21 context. *See, e.g., id.*, 5:5-22. For example, in addition to quality, it may be helpful for an operator
22 to know specific image properties indicating characteristics about a certain ultrasound examination
23 when capturing ultrasound images. *See, e.g., id.*, 20:50-21:30. As the specification explains, the
24 algorithm derives one or more extracted feature representations from a set of ultrasound images.
25 *See, e.g., id.*, 5:34-31. The employed algorithm combines quality assessment and image property
26 assessment to enable simultaneous determination of a quality assessment value and an image
27 category. *See, e.g., id.*, 5:34-39. With respect to echocardiography, examples of image properties
28 include the view category, left ventricular ejection fraction, and left atrial ejection fraction. *See,*

1 *e.g., id.*, 20:41-59. Thus, in one embodiment, an employed neural network can simultaneously
 2 determine a quality assessment value and view category of echocardiographic images. *Id.*
 3 Employment of such an algorithm was not known or conventional and provided an improvement
 4 over typical analyses. For example, since some “view categories for ultrasound imaging may be
 5 quite similar to an inexperienced eye and switching between them may require precise adjustments
 6 of the probe's position and orientation,” using the algorithm could “reduce the adverse effect of
 7 inter-operator variability on the quality of the acquired ultrasound images.” *See, e.g., id.*, 5:23-33.
 8 Thus, the claims provide an improvement to a specific technology in a particular field.

9 50. The claimed inventions include additional technical improvements as described in
 10 the specification. When using a neural network, for example, “the architecture of the neural
 11 network...may allow the analyzer to be implemented by a device that does not require an extremely
 12 high computing power, such as, for example an application on a mobile device or running on an
 13 off-the-shelf mobile device with the result being that the analyzer...may be portable and/or cost
 14 effective.” *See, id.*, 5:40-46. Additionally, “by combining quality assessment and another image
 15 property assessment, such as view categorization, a highly shared neural network may yield faster
 16 processing time compared to using a separate quality assessment and image property assessment.”
 17 *See, id.*, 5:46-51. Further, “by combining quality assessment and another image property
 18 assessment, such as view categorization, the joint training of the two modalities may prevent the
 19 neural network from overfitting the label from either modality.” *See, id.*, 5:51-55. Thus, the claims
 20 provide specific technological advances for analysis of ultrasound images for the purpose of quality
 21 assessment and image property assessment.

22 **D. Defendants’ Infringing Products**

23 51. On information and belief, Defendants make, use, sell, offer to sell, and/or import
 24 into the United States ultrasound products that incorporate scan guidance technology to help
 25 operators assess the quality of echocardiographic images.
 26 <https://www.gehealthcare.com/campaigns/venue-family-caption-guidance> (“Thanks to Caption
 27 Guidance™ AI-driven software on the Venue family, even new ultrasound users can capture
 28 cardiac images successfully.”); <https://www.gehealthcare.com/about/newsroom/press-releases/ge->

1 [healthcare-launches-enhanced-venue-family-point-of-care-ultrasound-systems-featuring-ai-](https://www.gehealthcare.com/about/newsroom/press-releases/ge-healthcare-launches-enhanced-venue-family-point-of-care-ultrasound-systems-featuring-ai-driven-caption-guidance?npclid=botnpclid)
 2 [driven-caption-guidance?npclid=botnpclid](https://www.gehealthcare.com/about/newsroom/press-releases/ge-healthcare-launches-enhanced-venue-family-point-of-care-ultrasound-systems-featuring-ai-driven-caption-guidance?npclid=botnpclid) (Oct. 6, 2023) (“Caption Guidance on the Venue Family
 3 point-of-care ultrasound systems is available in the United States.”).

4 52. Defendants market their infringing products as incorporating the infringing scan
 5 guidance technology under the names “Caption Guidance,” “Caption AI, ” or “Caption AI
 6 Guidance.” Caption Guidance is “a medical software tool that utilizes Artificial Intelligence (AI)
 7 for providing echocardiography.” G. Yatnalkar, *EMMA International: Caption Guidance – FDA’s*
 8 *First Authorized AI-Based Cardiac Ultrasound Software*, by Govind (Feb. 15, 2021). Caption
 9 Guidance, or Caption AI Guidance, is incorporated into a series of point-of-care ultrasound
 10 products called “the Venue Family.” *GE HealthCare Launches Enhanced Venue Family Point-of-*
 11 *Care Ultrasound Systems Featuring AI-Driven Caption Guidance*, GE Healthcare (Oct. 6, 2023),
 12 [https://www.gehealthcare.com/about/newsroom/press-releases/ge-healthcare-launches-enhanced-](https://www.gehealthcare.com/about/newsroom/press-releases/ge-healthcare-launches-enhanced-venue-family-point-of-care-ultrasound-systems-featuring-ai-driven-caption-guidance?npclid=botnpclid)
 13 [venue-family-point-of-care-ultrasound-systems-featuring-ai-driven-caption-](https://www.gehealthcare.com/about/newsroom/press-releases/ge-healthcare-launches-enhanced-venue-family-point-of-care-ultrasound-systems-featuring-ai-driven-caption-guidance?npclid=botnpclid)
 14 [guidance?npclid=botnpclid](https://www.gehealthcare.com/about/newsroom/press-releases/ge-healthcare-launches-enhanced-venue-family-point-of-care-ultrasound-systems-featuring-ai-driven-caption-guidance?npclid=botnpclid); see also [https://www.linkedin.com/posts/rolandrott_ultrasound-](https://www.linkedin.com/posts/rolandrott_ultrasound-gehealthcare-rsna-activity-7135509649302126594-J-2g/?utm_source=share&utm_medium=member_ios)
 15 [gehealthcare-rsna-activity-7135509649302126594-J-](https://www.linkedin.com/posts/rolandrott_ultrasound-gehealthcare-rsna-activity-7135509649302126594-J-2g/?utm_source=share&utm_medium=member_ios)
 16 [2g/?utm_source=share&utm_medium=member_ios](https://www.linkedin.com/posts/rolandrott_ultrasound-gehealthcare-rsna-activity-7135509649302126594-J-2g/?utm_source=share&utm_medium=member_ios) (LinkedIn post by GE HealthCare CEO,
 17 Roland Rott, marketing “the Venue Family with Caption AI Guidance”). Similarly, Caption AI
 18 “provides real-time visual guidance to prompt users on probe movements and includes a quality
 19 meter to ensure the user obtains the best possible images. Once an image is captured, the AutoEF
 20 feature automatically calculates a left ventricular ejection fraction (LVEF). In addition, users can
 21 efficiently scan with AutoCapture and Save Best Clip features to capture the best quality image
 22 from each view.” *GE HealthCare Introduces Caption AI on Vscan Air SL Wireless Handheld*
 23 *Ultrasound System to Help More Clinicians Capture Diagnostic-Quality Cardiac Images*, GE
 24 Healthcare (Apr. 3, 2024), [https://www.gehealthcare.com/about/newsroom/press-releases/ge-](https://www.gehealthcare.com/about/newsroom/press-releases/ge-healthcare-introduces-caption-ai-on-vscan-air-sl-wireless-handheld-ultrasound-system-to-help-more-clinicians-capture-diagnostic-quality-cardiac-images)
 25 [healthcare-introduces-caption-ai-on-vscan-air-sl-wireless-handheld-ultrasound-system-to-help-](https://www.gehealthcare.com/about/newsroom/press-releases/ge-healthcare-introduces-caption-ai-on-vscan-air-sl-wireless-handheld-ultrasound-system-to-help-more-clinicians-capture-diagnostic-quality-cardiac-images)
 26 [more-clinicians-capture-diagnostic-quality-cardiac-images](https://www.gehealthcare.com/about/newsroom/press-releases/ge-healthcare-introduces-caption-ai-on-vscan-air-sl-wireless-handheld-ultrasound-system-to-help-more-clinicians-capture-diagnostic-quality-cardiac-images). Caption AI is incorporated into
 27 handheld ultrasounds called “Vscan Air SL.” *Id.* While the features described below focus on
 28 Caption Guidance, on information and belief, Caption AI provides similar features. *See id.*; see

also <https://www.gehealthcare.com/products/ultrasound/handheld-ultrasound/vscan-air-caption-ai>.

Find Caption Guidance

Discover the Venue Family

Whether you're looking for an adaptable model that goes from cart to table to wall, or a console system with a large screen, there is a versatile, robust, and simple system made for your point of care.



Venue™ Point of Care Ultrasound
Designed for simplicity, speed, and precision, Venue is the premier solution of our point of care ultrasound systems.



Venue Go™ Point of Care Ultrasound
The take anywhere Venue Go adapts to your point of care and allows you to go from cart to table to wall with ease.



Venue Fit™ Point of Care Ultrasound
A simple, fast and precise way to assess a patient's medical status at the point of care, meet Venue Fit, the newest member of the Ve...

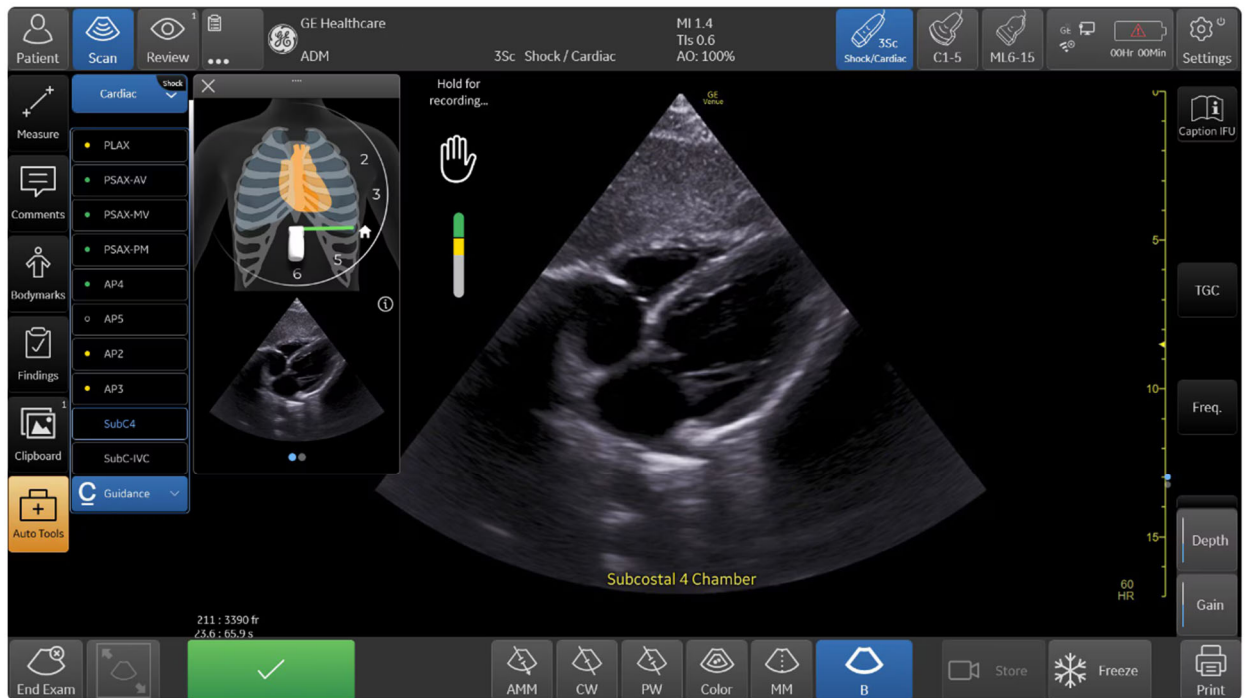
<https://www.gehealthcare.com/campaigns/venue-family-caption-guidance>.



Real-time step-by-step
scan guidance

<https://www.gehealthcare.com/products/ultrasound/handheld-ultrasound/vscan-air-caption-ai>.

53. Caption Guidance is designed to provide “[p]reliminary probe placement information [that] shows you where to place and how to orient the ultrasound probe.” *Id.* As the operator begins the exams, “a handy reference image shows [the operator] the image [they] are trying to acquire.” *Id.* During the scan, Caption Guidance further provides “prescriptive guidance...on the screen” including a “Quality Meter” that rises when the operator “get[s] closer to an image of diagnostic quality.” *Id.*

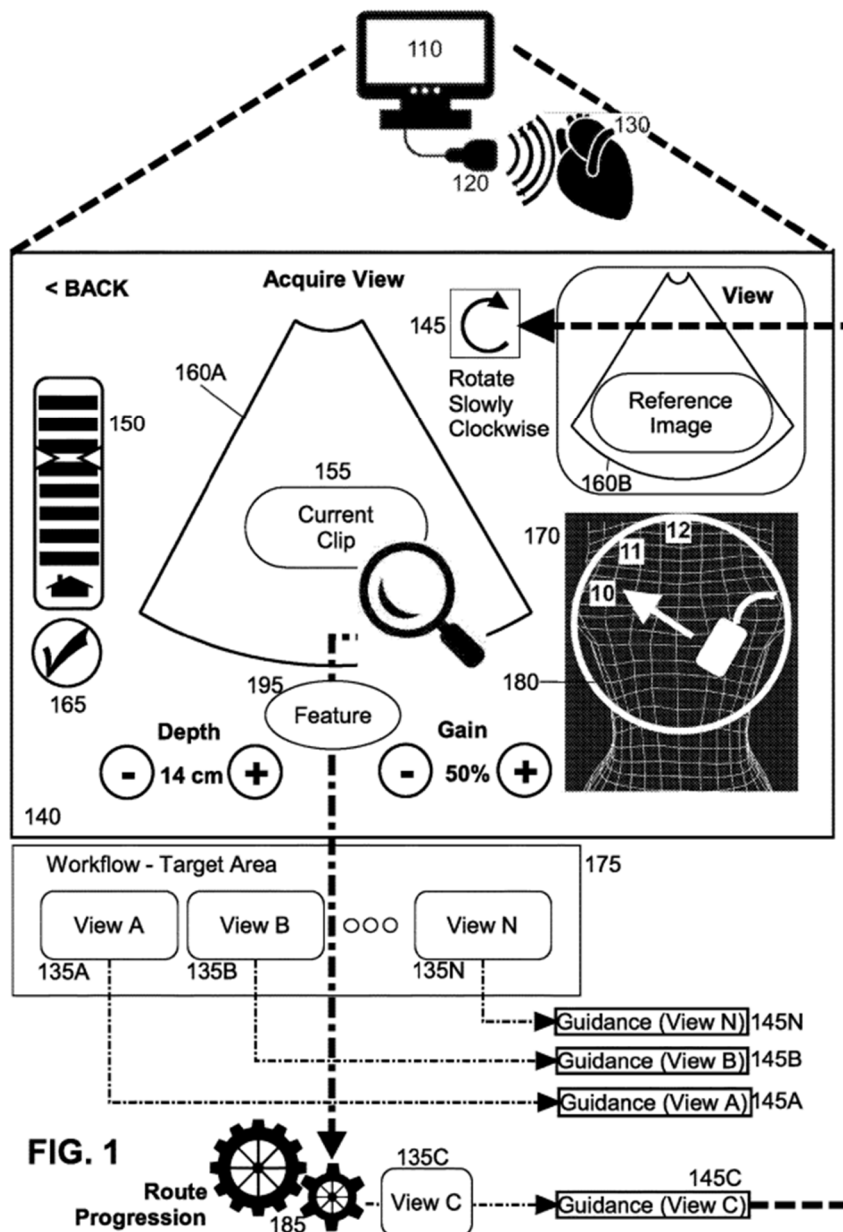


<https://www.gehealthcare.com/campaigns/venue-family-caption-guidance>.

54. On information and belief, Caption Health’s patent publication, U.S. Patent Publication No. 2021/0052253 (“the ’253 application”), describes the functionality of Caption Guidance. A copy of the ’253 application is attached hereto as Exhibit H.

55. The ’253 application is directed to ultrasound guidance dynamic progression methods and systems. The ’253 application describes “[a]n ultrasound guidance dynamic progression method [that] includes selecting a predetermined ultrasound diagnostic workflow in memory of an ultrasound diagnostic computing system.” ’253 application, Abstract. It further describes a system that comprises “at least one processor” configured to perform the method. *See, e.g., id.*, ¶¶ [0026], [0035]-[0037]. The ’253 application describes implementation of a “quality

meter” (’253 application, 150 of Fig. 1, ¶ 26), which is a feature of Caption Guidance.
<https://www.gehealthcare.com/campaigns/venue-family-caption-guidance> (“Quality Meter The
 meter rises as the image improves and gets closer to diagnostic-quality”).



Id., Fig. 1

56. The ’253 application describes that Caption Guidance is incorporated in “an ultrasound diagnostics data processing system configured for ultrasound guidance dynamic progression.” ’253 application, ¶ 26. This system is used “in connection with the imaging of a heart.” *Id.*, ¶ 20; *see also* Fig. 1 (i.e., target organ 130). Caption Guidance “provides real-time guidance during scanning to assist the user in obtaining anatomically correct images from standard

1 transthoracic echocardiographic (TTE) transducer positions.” Narang, et. al., *Utility of a Deep-*
 2 *Learning Algorithm to Guide Novices to Acquire Echocardiograms for Limited Diagnostic Use*,
 3 *JAMA Cardiology*, 6:624-632, 625 (June 2021).

4 57. Caption Guidance acquires a video clip comprising a series of echocardiographic
 5 images. ’253 application, ¶ 20 (“ultrasound imaging system 110 with ultrasound imaging probe
 6 120 conducts an ultrasound imaging operation in order to acquire a video clip as near real-time
 7 imagery 155 of a target organ 130”). The video clip is acquired by scanning using a transducer.
 8 Narang, et. al., *Utility of a Deep-Learning Algorithm to Guide Novices to Acquire*
 9 *Echocardiograms for Limited Diagnostic Use*, *JAMA Cardiology*, 6:624-632, 625 (June 2021)
 10 (“The AI-guided image acquisition software...Caption Guidance...provides real-time guidance
 11 during scanning to assist the user in obtaining anatomically correct images from standard
 12 transthoracic echocardiographic (TTE) transducer positions.”); *see also In Caption AI Product*
 13 *Demo | AI-Guided Ultrasound System*, <https://www.youtube.com/watch?v=URmb72IA4b4>.

14 58. Caption Guidance associates captured echocardiographic images with view
 15 categories. For example, the Caption Guidance workflow “includ[es] a sequence of views of a
 16 target organ” where “a first one of the views in the sequence” is selected. ’253 application, ¶ 9.
 17 Caption Guidance then “acquir[es] imagery in the computing system in association with the
 18 selected first one of the views in the sequence.” *Id.*; *see also In Caption AI Product Demo | AI-*
 19 *Guided Ultrasound System*, <https://www.youtube.com/watch?v=URmb72IA4b4>. The sequence of
 20 views includes predetermined echocardiographic image view categories, such as “a parasternal long
 21 axis view, a parasternal short axis view, an apical two, three, four or five chamber view or a
 22 subcoastal view.” *Id.*, ¶ 20.

23 59. Caption Guidance determines quality assessment values representing view category
 24 specific quality assessment of echocardiographic images. Caption Guidance implements a “quality
 25 meter” that “indicates a sliding scale of quality of the imagery...relative to a known view sought to
 26 be acquired for the target organ.” *Id.*, ¶ 22; *see also In Caption AI Product Demo | AI-Guided*
 27 *Ultrasound System*, <https://www.youtube.com/watch?v=URmb72IA4b4>. A success icon is
 28

1 displayed in connection with the quality meter if the “corresponding quality value...meets or
2 exceeds a threshold quality for the specified view.” *Id.*

3 60. Once a quality assessment value is determined for an echocardiographic image,
4 Capture Guidance automatically captures an echocardiographic image and associates the image
5 with the determined quality assessment value. For example, “[w]hen the real-time quality meter
6 exceeds a preset threshold, it automatically records a video clip (termed an *auto-capture*).” Narang,
7 et. al., *Utility of a Deep-Learning Algorithm to Guide Novices to Acquire Echocardiograms for*
8 *Limited Diagnostic Use*, JAMA Cardiology, 6:624-632, 625 (June 2021); see also H. Hong, Ph.D.,
9 *Caption Health: Flattening the Ultrasound Learning Curve with Breakthrough AI-Guided*
10 *Echocardiography System*, 4:30-4:40, <https://www.youtube.com/watch?v=NCFFAIHSPrc>
11 (“Finally, [it] recognizes when the user reaches the target and automatically captures the images in
12 diagnostic quality.”); *In Caption AI Product Demo | AI-Guided Ultrasound System*, 0:48-1:00,
13 <https://www.youtube.com/watch?v=URmb72IA4b4> (“As Sarah gets closer to the optimal view, the
14 meter rises. Once the software detects a diagnostic quality image, the meter turns green and the
15 clip is automatically recorded without having to press any buttons.”).

16 61. Caption Guidance performs the steps above for multiple echocardiographic images,
17 such as those corresponding to multiple view categories. ’253 application, ¶ 21 (“For each of the
18 views 135A, 135B, 135N, corresponding guidance 145A, 145B, 145N is determined and presented
19 in sequence of the views 135A, 135B, 135N of the workflow 175 within the user interface 140 as
20 respective graphical instructions 145. In this regard, the corresponding guidance 145A, 145B, 145N
21 includes different directives for positioning and posing the ultrasound imaging probe 120 so as to
22 produce the imagery 155 for a corresponding one of the views 135A, 135B, 135N.”); *id.*, ¶ 20 (“a
23 sequence of views...may include a parasternal long axis view, a parasternal short axis view, an
24 apical two, three, four or five chamber view or a subcoastal view.”).

25 62. On information and belief, Caption Guidance utilizes neural networks to assess the
26 quality of captured echocardiographic images. G. Yatnalkar, *Caption Guidance – FDA’s First*
27 *Authorized AI-Based Cardiac Ultrasound Software* (Feb. 15, 2021),
28 <https://emmainternational.com/fda-authorized-ai-cardiac-ultrasound-software/> (“For Caption

Guidance, the AI Algorithm used for image or video frame selection is the Deep Convolutional Neural Network (DCNN).”); Narang, et. al., *Utility of a Deep-Learning Algorithm to Guide Novices to Acquire Echocardiograms for Limited Diagnostic Use*, JAMA Cardiology, 6:624-632, 625 (June 2021) (“The AI-guided image acquisition software...Caption Guidance...provides real-time guidance during scanning to assist the user in obtaining anatomically correct images from standard transthoracic echocardiographic (TTE) transducer positions...The software monitors image quality continuously, simultaneously providing iterative prescriptive cues to improve the image via the DL algorithm.”); *FDA Authorizes Marketing of First Cardiac Ultrasound Software That Uses Artificial Intelligence to Guide User*, FDA News Release (Feb. 7, 2020), <https://www.fda.gov/news-events/press-announcements/fda-authorizes-marketing-first-cardiac-ultrasound-software-uses-artificial-intelligence-guide-user> (“The Caption Guidance software was developed using machine learning to train the software to differentiate between acceptable and unacceptable image quality.”).

63. The Caption Guidance neural networks are trained to provide quality assessment values that are specific to certain view categories. For example, “a second neural network...may be trained to characterize guidance instructions relative to contemporaneously acquired imagery of the target organ.” ’235 application, ¶ 28. The “second neural network...is trained to produce recommend[ed] guidance to achieve the optimal acquisition of generated imagery for the target organ for the particular one of the views...relative to the generated imagery contemporaneously presented in a display of the host computing system.” *Id.* The Caption Guidance “DL algorithms were trained using more than 5 million observations associating transducer orientation, the diagnostic correctness of the resulting image, and the outcome of subsequent manipulations with diagnostic quality.” Narang, et. al., *Utility of a Deep-Learning Algorithm to Guide Novices to Acquire Echocardiograms for Limited Diagnostic Use*, JAMA Cardiology, 6:624-632, 625 (June 2021). Caption Guidance’s “DL algorithm estimates image quality via a component called the quality meter, suggesting probe manipulations using prescriptive guidance.” *Id.*

64. The Caption Guidance neural networks each have an input layer configured to receive echocardiographic images and an output layer configured to output quality assessment values. Caption Guidance uses “convolutional neural networks constructed by stacking

1 computational layers, each taking input from the layer below, transforming and passing it along to
 2 the layer above.” *Id.* Caption Guidance “has several interconnected DL algorithms making 3
 3 simultaneous estimates: (1) diagnostic quality of the imagery, (2) 6-dimensional geometric distance
 4 (by position and orientation) between current probe location and the location anticipated to
 5 optimize the image, and (3) corrective probe manipulations to improve diagnostic quality.” *Id.*
 6 “[A]s the neural network...is presented with contemporaneously acquired imagery of the target
 7 organ for the particular one of the views..., the neural network produces a recommended movement
 8 or pose of the ultrasound imaging probe...in order to acquire generated imagery deemed acceptable
 9 for the particular one of the views.” ’253 application, ¶ 28.

10 65. Defendants announced plans to incorporate Caption Guidance into additional
 11 products. [https://www.gehealthcare.com/about/newsroom/press-releases/ge-healthcare-launches-](https://www.gehealthcare.com/about/newsroom/press-releases/ge-healthcare-launches-enhanced-venue-family-point-of-care-ultrasound-systems-featuring-ai-driven-caption-guidance?npclid=botnpclid)
 12 [enhanced-venue-family-point-of-care-ultrasound-systems-featuring-ai-driven-caption-](https://www.gehealthcare.com/about/newsroom/press-releases/ge-healthcare-launches-enhanced-venue-family-point-of-care-ultrasound-systems-featuring-ai-driven-caption-guidance?npclid=botnpclid)
 13 [guidance?npclid=botnpclid](https://www.gehealthcare.com/about/newsroom/press-releases/ge-healthcare-launches-enhanced-venue-family-point-of-care-ultrasound-systems-featuring-ai-driven-caption-guidance?npclid=botnpclid) (Oct. 6, 2023) (“GE HealthCare plans to integrate this innovative AI
 14 technology into other ultrasound systems, including handheld systems, helping to further expand
 15 access to diagnostic care as well as the use of ultrasound in a variety of care settings.”).

16 **COUNT I: INFRINGEMENT OF U.S. PATENT NO. 11,129,591**

17 66. UBC incorporates by reference and re-alleges all of the foregoing paragraphs of this
 18 First Amended Complaint and exhibits attached hereto as is fully set forth herein.

19 67. Defendants infringe at least claims 1 and 15 of the ’591 patent by making, using,
 20 selling, importing, offering for sale its “Venue Family” products and Vscan Air SL products that
 21 incorporate Caption Guidance or Caption AI (the “Accused Products”).

22 68. Each of the Accused Products is “[a] computer-implemented system for facilitating
 23 echocardiographic image analysis...comprising at least one processor...” and is used for “[a]
 24 computer-implemented method of facilitating echocardiographic image analysis.” *See, e.g.*, ’253
 25 application, ¶¶ [0026], [0035]-[0037]; Venue Family Caption Guidance™ product page,
 26 <https://www.gehealthcare.com/campaigns/venue-family-caption-guidance> (“Preliminary probe
 27 placement information shows you where to place and how to orient the ultrasound probe. As you
 28 begin the exam, a handy reference image shows you the image you are trying to acquire.”);

1 “prescriptive guidance [is] provided on the screen...the Quality Meter rise[s] as you get closer to
 2 an image of diagnostic quality.”); *see also* Venue Family POCUS R5 Brochure (August 2024),
 3 [https://www.gehealthcare.com/-/jssmedia/gehc/us/images/products/ultrasound/venue/feature-](https://www.gehealthcare.com/-/jssmedia/gehc/us/images/products/ultrasound/venue/feature-cards/brochure-venue-family-pocus-r5-jb29262xx.pdf?rev=-1)
 4 [cards/brochure-venue-family-pocus-r5-jb29262xx.pdf?rev=-1](https://www.gehealthcare.com/-/jssmedia/gehc/us/images/products/ultrasound/venue/feature-cards/brochure-venue-family-pocus-r5-jb29262xx.pdf?rev=-1); *see also* Vscan Air SL Product
 5 Page, [https://www.gehealthcare.com/products/ultrasound/handheld-ultrasound/vscan-air-caption-](https://www.gehealthcare.com/products/ultrasound/handheld-ultrasound/vscan-air-caption-ai)
 6 [ai](https://www.gehealthcare.com/products/ultrasound/handheld-ultrasound/vscan-air-caption-ai) (“Vscan Air SL with Caption Guidance™ software provides real-time guidance that shows you,
 7 step-by-step, how to maneuver the probe to capture diagnostic-quality standard echocardiographic
 8 views anytime, anywhere*. ... Caption AI provides handheld ultrasound users with confidence in
 9 acquiring cardiac views for rapid assessments at the point of care.”); *see also supra* ¶¶ 52-64.

10 69. The Accused Products perform “receiving signals representing a first at least one
 11 echocardiographic image.” For example, the Accused Products acquire a series of
 12 echocardiographic images when an operator scans a patient using a transducer. *See, e.g.,* ’253
 13 application, ¶ 20; Narang, et. al., *Utility of a Deep-Learning Algorithm to Guide Novices to Acquire*
 14 *Echocardiograms for Limited Diagnostic Use*, JAMA Cardiology, 6:624-632, 625 (June 2021); *see*
 15 *also* Venue Family POCUS R5 Brochure (August 2024) at 3, [https://www.gehealthcare.com/-](https://www.gehealthcare.com/-/jssmedia/gehc/us/images/products/ultrasound/venue/feature-cards/brochure-venue-family-pocus-r5-jb29262xx.pdf?rev=-1)
 16 [/jssmedia/gehc/us/images/products/ultrasound/venue/feature-cards/brochure-venue-family-pocus-](https://www.gehealthcare.com/-/jssmedia/gehc/us/images/products/ultrasound/venue/feature-cards/brochure-venue-family-pocus-r5-jb29262xx.pdf?rev=-1)
 17 [r5-jb29262xx.pdf?rev=-1](https://www.gehealthcare.com/-/jssmedia/gehc/us/images/products/ultrasound/venue/feature-cards/brochure-venue-family-pocus-r5-jb29262xx.pdf?rev=-1) (“Caption Guidance helps even new users capture diagnostic-quality
 18 images with its built-in AI-driven software”); *see also id.* at 4 (“Real-time, turn-by-turn on-screen
 19 guidance prompts your probe movements to help new POCUS users capture diagnostic-quality
 20 cardiac images.”); *In Caption AI Product Demo: AI-Guided Ultrasound System*,
 21 <https://www.youtube.com/watch?v=URmb72IA4b4>, at 0:37-0:59 (“Sarah makes specific
 22 transducer movements to optimize the image. On the left, the quality meter tells her how close she
 23 is to capturing a diagnostic quality image. As Sarah gets closer to the optimal view, the meter rises.
 24 Once the software detects a diagnostic quality image, the meter turns green and the clip is
 25 automatically recorded without having to press any buttons”); H. Hong, Ph.D., *Caption Health:*
 26 *Flattening the Ultrasound Learning Curve with Breakthrough AI-Guided Echocardiography*
 27 *System*, at 4:30-4:40 (“Finally, [it] recognizes when the user reaches the target and automatically
 28 captures the images in diagnostic quality”); *see also* Vscan Air™ Product Tutorial | Caption AI™,

1 <https://www.youtube.com/watch?v=Tbj92hMXAiU> at 2:05-2:20 (“You will see a blue box move
 2 from the bottom left of the screen to the top right, indicating a view has been captured.”); *see also*
 3 *supra* ¶¶ 55, 57.

4 70. The Accused Products perform “associating the first at least one echocardiographic
 5 image with a first view category of a plurality of predetermined echocardiographic image view
 6 categories.” *See, e.g.,* Narang et. al., *Utility of a Deep-Learning Algorithm to Guide Novices to*
 7 *Acquire Echocardiograms for Limited Diagnostic Use (Supplemental Online Content)* at 2 (“In
 8 order to help users to acquire high-quality echocardiograms, the guidance algorithm must be able
 9 to estimate the positioning of the ultrasound probe from the current imaging and provide real-time
 10 guidance based on that estimation for the user to arrive at the ideal positioning and image. It must
 11 first be able to grade the quality of the imagery and determine whether it meets diagnostic criteria.
 12 Therefore, the AI-guidance deep learning algorithm makes three simultaneous estimates: 1)
 13 diagnostic quality of the imagery, 2) six-dimensional (6D, probe position plus orientation)
 14 geometric distance between current probe location and a probe location anticipated to optimize the
 15 image, and 3) corrective probe manipulations to improve diagnostic quality. Importantly, the deep
 16 learning algorithm makes these estimates from only the ultrasound imagery; no trackers, fiducial
 17 markers, or additional sensors are needed for operation.”); *see also id.* (“Training the network: As
 18 shown in eFigure 1, the deep learning algorithm was developed to guide operators to 10 diagnostic
 19 views of the heart: parasternal long axis view (PLAX); parasternal short axis view at aortic valve
 20 level (PSAX-AV), mitral valve level (PSAX-MV), and papillary muscle level (PSAX-PM); apical
 21 2, 3, 4, 5 chamber views (Ap2, Ap3, Ap4, and Ap5); and subcostal 4 chamber (SC-4) and inferior
 22 vena cava view (SC-IVC). Fifteen (15) registered sonographers captured imagery on subjects over
 23 a range of BMI and clinical pathology to train the deep learning algorithm. This training dataset
 24 contained >5,000,000 individual data points on transducer location/orientation and observed
 25 imagery using ultrasound machines from multiple vendors. This dataset was curated and augmented
 26 with approximately 500,000 labels from expert sonographers and cardiologists annotating
 27 diagnostic quality and suggesting prescriptive guidance actions to improve the imaging (eFigure 1
 28 left). Using this dataset, the algorithm was trained to estimate the 6D distance to each of the 10

views, define 81 unique prescriptive guidance actions, and diagnostic thresholds for each of the 10 views.”); *see also supra* ¶¶ 55, 58. For example, the Accused Products receives a selection from “a sequence of views of a target organ” where “a first one of the views” in “a sequence of views of a target organ.” ’253 application, ¶ 9. The Accused Products then “acquir[es] imagery in the computing system in association with the selected first one of the views in the sequence.” *Id.* The sequence of views includes “a plurality of predetermined echocardiographic image view categories,” such as “a parasternal long axis view, a parasternal short axis view, an apical two, three, four or five chamber view or a subcoastal view.” *Id.*, ¶ 20.

71. The Accused Products perform “determining, based on the first at least one echocardiographic image and the first view category, a first quality assessment value representing a view category specific quality assessment of the first at least one echocardiographic image.” *See, e.g., Narang et. al., Utility of a Deep-Learning Algorithm to Guide Novices to Acquire Echocardiograms for Limited Diagnostic Use (Original Investigation)* at 625 (“The DL algorithms were trained using more than 5 million observations associating transducer orientation, the diagnostic correctness of the resulting image, and the outcome of subsequent manipulations with diagnostic quality. This training data set came from 15 registered sonographers via scans of individuals with a range of body mass index (BMI) values and pathological conditions, further annotated for quality by expert sonographers and cardiologists (A.N., R.P.M., R.M.L., N.J.W., and J.D.T.). eFigure 1 in the Supplement depicts the DL model training data set, expert labeling for image quality, algorithm optimization, and run-time operation during the study”); *see id.* (“The software monitors image quality continuously, simultaneously providing iterative prescriptive cues to improve the image via the DL algorithm. The guidance software used convolutional neural networks constructed by stacking computational layers, each taking input from the layer below, transforming and passing it along to the layer above. The software has several interconnected DL algorithms making 3 simultaneous estimates: (1) diagnostic quality of the imagery, (2) 6-dimensional geometric distance (by position and orientation) between current probe location and the location anticipated to optimize the image, and (3) corrective probe manipulations to improve diagnostic quality. Importantly, the algorithm makes these estimates from the ultrasonographic

imagery alone; no trackers, fiducial markers, or additional sensors are required.”); *see also* Narang et. al., *Utility of a Deep-Learning Algorithm to Guide Novices to Acquire Echocardiograms for Limited Diagnostic Use (Supplemental Online Content)* at 2 (“In order to help users to acquire high-quality echocardiograms, the guidance algorithm must be able to estimate the positioning of the ultrasound probe from the current imaging and provide real-time guidance based on that estimation for the user to arrive at the ideal positioning and image. It must first be able to grade the quality of the imagery and determine whether it meets diagnostic criteria. Therefore, the AI-guidance deep learning algorithm makes three simultaneous estimates: 1) diagnostic quality of the imagery, 2) six-dimensional (6D, probe position plus orientation) geometric distance between current probe location and a probe location anticipated to optimize the image, and 3) corrective probe manipulations to improve diagnostic quality. Importantly, the deep learning algorithm makes these estimates from only the ultrasound imagery; no trackers, fiducial markers, or additional sensors are needed for operation”); *see also supra* ¶¶ 55, 59, 70. For example, the Accused Products implement a “quality meter” that “indicates a sliding scale of quality of the imagery...relative to a known view sought to be acquired for the target organ.” ’253 application, ¶ 22. A success icon is displayed in connection with the quality meter if the “corresponding quality value...meets or exceeds a threshold quality for the specified view.” *Id.*

72. The Accused Products perform “producing signals representing the first quality assessment value for causing the first quality assessment value to be associated with the first at least one echocardiographic image.” For example, the Accused Products automatically capture an echocardiographic image and associate the image with the determined quality assessment value. “When the real-time quality meter exceeds a preset threshold, it automatically records a video clip (termed an *auto-capture*).” *See, e.g.,* Narang, et. al., *Utility of a Deep-Learning Algorithm to Guide Novices to Acquire Echocardiograms for Limited Diagnostic Use, (Original Investigation)* at 625-26 (“The DL algorithm estimates image quality via a component called the quality meter, suggesting probe manipulations using prescriptive guidance (eFigure 1 in the Supplement). When the real-time quality meter exceeds a preset threshold, it automatically records a video clip (termed an *auto-capture*). Quality is continuously monitored throughout scanning, so the operator can

1 retrospectively save the best clip observed if the auto-capture threshold is not exceeded. If auto-
 2 capture is not achieved within 2 minutes, the user may activate the option called save best clip or
 3 continue scanning to achieve auto-capture. These algorithms operate together to improve the
 4 ultrasonographic image, as in eFigure 1 in the Supplement, in which prescriptive guidance
 5 improves a parasternal long-axis view. eFigure 2 in the Supplement and Video 1 show additional
 6 detail on the user interface”); *see also* H. Hong, Ph.D., *Caption Health: Flattening the Ultrasound*
 7 *Learning Curve with Breakthrough AI-Guided Echocardiography System*,
 8 <https://www.youtube.com/watch?v=NCFFAIHSPrc>, at 4:30-4:40 (“Finally, [it] recognizes when
 9 the user reaches the target and automatically captures the images in diagnostic quality”); *see also*
 10 *In Caption AI Product Demo | AI-Guided Ultrasound System*,
 11 <https://www.youtube.com/watch?v=URmb72IA4b4>, at 0:37-0:59 (“Sarah makes specific
 12 transducer movements to optimize the image. On the left, the quality meter tells her how close she
 13 is to capturing a diagnostic quality image. As Sarah gets closer to the optimal view, the meter rises.
 14 Once the software detects a diagnostic quality image, the meter turns green and the clip is
 15 automatically recorded without having to press any buttons”); *see also supra* ¶¶ 60, 70-72.

16 73. The Accused Products perform the steps described above (*see supra* ¶¶ 69-72) for
 17 multiple echocardiographic images corresponding to multiple view categories. *See, e.g.,* ’253
 18 application, ¶ 21 (“For each of the views 135A, 135B, 135N, corresponding guidance 145A, 145B,
 19 145N is determined and presented in sequence of the views 135A, 135B, 135N of the workflow
 20 175...In this regard, the corresponding guidance 145A, 145B, 145N includes different directives
 21 for positioning and posing the ultrasound imaging probe 120 so as to produce the imagery 155 for
 22 a corresponding one of the views 135A, 135B, 135N.”); *see also supra* ¶ 61. Thus, the Accused
 23 Products perform “receiving signals representing a second at least one echocardiographic image,”
 24 “associating the second at least one echocardiographic image with a second view category of the
 25 plurality of predetermined echocardiographic image view categories, said second view category
 26 being different from the first view category,” “determining, based on the second at least one
 27 echocardiographic image and the second view category, a second quality assessment value
 28 representing a view category specific quality assessment of the second at least one

1 echocardiographic image,” and “producing signals representing the second quality assessment
2 value for causing the second quality assessment value to be associated with the second at least one
3 echocardiographic image.”

4 74. In the Accused Products, “each of the plurality of predetermined echocardiographic
5 image view categories is associated with a respective set of assessment parameters,” where “each
6 of the sets of assessment parameters being a set of neural network parameters that defines a neural
7 network having a plurality of layers including an input layer configured to receive one or more
8 echocardiographic images and an output layer configured to output one or more quality assessment
9 values.” For example, the Accused Products use neural networks with neural network parameters
10 to assess the quality of captured echocardiographic images. *See, e.g.,* G. Yatnalkar, *Caption*
11 *Guidance – FDA’s First Authorized AI-Based Cardiac Ultrasound Software* (Feb. 15, 2021),
12 <https://emmainternational.com/fda-authorized-ai-cardiac-ultrasound-software/> (“For Caption
13 Guidance, the AI Algorithm used for image or video frame selection is the Deep Convolutional
14 Neural Network (DCNN).”); *see also supra* ¶¶ 62-64.

15 75. The Accused Products use neural networks that have “a plurality of layers including
16 an input layer configured to receive one or more echocardiographic images and an output layer
17 configured to output one or more quality assessment values.” *See, e.g.,* Narang, et. al., *Utility of*
18 *a Deep-Learning Algorithm to Guide Novices to Acquire Echocardiograms for Limited Diagnostic*
19 *Use, (Original Investigation)* at 625 (“The AI-guided image acquisition software (Caption
20 Guidance [Caption Health, previously known as Bay Labs]), described in greater detail in the
21 eAppendix in the Supplement and shown schematically in eFigure 1 in the Supplement, provides
22 real-time guidance during scanning to assist the user in obtaining anatomically correct images from
23 standard transthoracic echocardiographic (TTE) transducer positions. The AI guidance is software
24 only, developed with DL to emulate sonographer expertise. ... The guidance software used
25 convolutional neural networks constructed by stacking computational layers, each taking input
26 from the layer below, transforming and passing it along to the layer above. The software monitors
27 image quality continuously, simultaneously providing iterative prescriptive cues to improve the
28 image via the DL algorithm. The guidance software used convolutional neural networks

constructed by stacking computational layers, each taking input from the layer below, transforming and passing it along to the layer above. The software has several interconnected DL algorithms making 3 simultaneous estimates: (1) diagnostic quality of the imagery, (2) 6-dimensional geometric distance (by position and orientation) between current probe location and the location anticipated to optimize the image, and (3) corrective probe manipulations to improve diagnostic quality. Importantly, the algorithm makes these estimates from the ultrasonographic imagery alone; no trackers, fiducial markers, or additional sensors are required. The DL algorithms were trained using more than 5 million observations associating transducer orientation, the diagnostic correctness of the resulting image, and the outcome of subsequent manipulations with diagnostic quality.”) *see also* Narang et. al., *Utility of a Deep-Learning Algorithm to Guide Novices to Acquire Echocardiograms for Limited Diagnostic Use (Supplemental Online Content)* at 2 (“In order to help users to acquire high-quality echocardiograms, the guidance algorithm must be able to estimate the positioning of the ultrasound probe from the current imaging and provide real-time guidance based on that estimation for the user to arrive at the ideal positioning and image. It must first be able to grade the quality of the imagery and determine whether it meets diagnostic criteria. Therefore, the AI-guidance deep learning algorithm makes three simultaneous estimates: 1) diagnostic quality of the imagery, 2) six-dimensional (6D, probe position plus orientation) geometric distance between current probe location and a probe location anticipated to optimize the image, and 3) corrective probe manipulations to improve diagnostic quality. Importantly, the deep learning algorithm makes these estimates from only the ultrasound imagery; no trackers, fiducial markers, or additional sensors are needed for operation”); *see also supra* ¶¶ 62-64. For example, when a neural network “is presented with contemporaneously acquired imagery of the target organ for the particular one of the views..., the neural network produces a recommended movement or pose of the ultrasound imaging probe...in order to acquire generated imagery deemed acceptable for the particular one of the views.” ’253 application, ¶ 28.

76. The Accused Products use neural networks that are trained to provide quality assessment values that are specific to certain view categories. For example, a “neural network...is trained to produce recommend[ed] guidance to achieve the optimal acquisition of generated

1 imagery for the target organ for the particular one of the views...relative to the generated imagery
 2 contemporaneously presented in a display of the host computing system.” ’253 application, ¶ 28;
 3 *see also* Narang et. al., *Utility of a Deep-Learning Algorithm to Guide Novices to Acquire*
 4 *Echocardiograms for Limited Diagnostic Use (Supplemental Online Content)* at 2 (“In order to
 5 help users to acquire high-quality echocardiograms, the guidance algorithm must be able to estimate
 6 the positioning of the ultrasound probe from the current imaging and provide real-time guidance
 7 based on that estimation for the user to arrive at the ideal positioning and image. It must first be
 8 able to grade the quality of the imagery and determine whether it meets diagnostic criteria.
 9 Therefore, the AI-guidance deep learning algorithm makes three simultaneous estimates: 1)
 10 diagnostic quality of the imagery, 2) six-dimensional (6D, probe position plus orientation)
 11 geometric distance between current probe location and a probe location anticipated to optimize the
 12 image, and 3) corrective probe manipulations to improve diagnostic quality. Importantly, the deep
 13 learning algorithm makes these estimates from only the ultrasound imagery; no trackers, fiducial
 14 markers, or additional sensors are needed for operation.”); *see also id.* (“Training the network: As
 15 shown in eFigure 1, the deep learning algorithm was developed to guide operators to 10 diagnostic
 16 views of the heart: parasternal long axis view (PLAX); parasternal short axis view at aortic valve
 17 level (PSAX-AV), mitral valve level (PSAX-MV), and papillary muscle level (PSAX-PM); apical
 18 2, 3, 4, 5 chamber views (Ap2, Ap3, Ap4, and Ap5); and subcostal 4 chamber (SC-4) and inferior
 19 vena cava view (SC-IVC). Fifteen (15) registered sonographers captured imagery on subjects over
 20 a range of BMI and clinical pathology to train the deep learning algorithm. This training dataset
 21 contained >5,000,000 individual data points on transducer location/orientation and observed
 22 imagery using ultrasound machines from multiple vendors. This dataset was curated and augmented
 23 with approximately 500,000 labels from expert sonographers and cardiologists annotating
 24 diagnostic quality and suggesting prescriptive guidance actions to improve the imaging (eFigure 1
 25 left). Using this dataset, the algorithm was trained to estimate the 6D distance to each of the 10
 26 views, define 81 unique prescriptive guidance actions, and diagnostic thresholds for each of the 10
 27 views.”); *see also supra* ¶¶ 59, 62-64. Each of the trained neural networks output assessment
 28

parameters, resulting in “the sets of assessment parameters being a set of neural network parameters.” *See id.*

77. To determine the “first quality assessment value,” the Accused Products perform “determining that a first set of assessment parameters of the sets of assessment parameters is associated with the first view category” and “in response to determining that the first set of assessment parameters is associated with the first view category, inputting the first at least one echocardiographic image into the neural network defined by the first set of assessment parameters.” The “neural network defined by the first set of assessment parameters” can “apply[] a first function based on the first set of assessment parameters to the first at least one echocardiographic image.” As described above (*see supra* ¶¶ 59, 62-64, 76), to determine quality assessment values, the Accused Products use neural networks that are trained to provide quality assessment values that are specific to certain view categories and that have an input layer for receiving echocardiographic images. To determine the “first quality assessment value” that is associated with “the first view category,” the Accused Products thus use assessment parameters derived from a neural network trained to provide quality assessment values specific to “the first view category.” Specifically, the Accused Products determine a first set of assessment parameters associated with the first view category, and in response input the first echocardiographic image for analysis by the determined first set assessment parameters. Similarly, to determine the “second quality assessment value” that is associated with “the second view category,” the Accused Products use assessment parameters derived from a neural network trained to provide quality assessment values specific to “the second view category.” Specifically, the Accused Products determine a second set of assessment parameters associated with the second view category, and in response input the second echocardiographic image for analysis by the determined second set of assessment parameters.

78. Defendants have also induced and continue to induce the infringement of the ’591 patent by others in violation of 35 U.S.C. § 271(b), including by selling the Accused Products to their customers and/or other end users and instructing them to practice at least claim 15 of the ’591 patent by using the Accused Products. On information and belief, Defendants are aware of the ’591 patent and are aware that when their customers and/or other end users use the Accused Products in

1 accordance with Defendants' instructions, the customers and/or other end users directly infringe at
 2 least claim 15 of the '591 patent. *See supra* ¶¶ 25-36, 82; *see also e.g., In Caption AI Product*
 3 *Demo | AI-Guided Ultrasound System*, <https://www.youtube.com/watch?v=URmb72IA4b4>. On
 4 information and belief, Defendants sell the Accused Products both directly through its own sales
 5 force and website. *See* [https://www.gehealthcare.com/about/newsroom/press-releases/ge-](https://www.gehealthcare.com/about/newsroom/press-releases/ge-healthcare-launches-enhanced-venue-family-point-of-care-ultrasound-systems-featuring-ai-driven-caption-guidance?npclid=botnpclid)
 6 [healthcare-launches-enhanced-venue-family-point-of-care-ultrasound-systems-featuring-ai-](https://www.gehealthcare.com/about/newsroom/press-releases/ge-healthcare-launches-enhanced-venue-family-point-of-care-ultrasound-systems-featuring-ai-driven-caption-guidance?npclid=botnpclid)
 7 [driven-caption-guidance?npclid=botnpclid](https://www.gehealthcare.com/about/newsroom/press-releases/ge-healthcare-launches-enhanced-venue-family-point-of-care-ultrasound-systems-featuring-ai-driven-caption-guidance?npclid=botnpclid) (Oct. 6, 2023) ("Caption Guidance on the Venue Family
 8 point-of-care ultrasound systems is available in the United States."); *see also*
 9 <https://www.gehealthcare.com/shop>; <https://www.gehealthcare.com/shop/equipment/vscan-air-sl>.

10 79. Defendants have also contributed and continue to contribute to infringement of the
 11 '591 patent in violation of 35 U.S.C. § 271(c) by selling the Accused Products to their customers
 12 and/or other end users and instructing them to practice at least claim 15 of the '591 patent by using
 13 the Accused Products. On information and belief, Defendants are aware of the '591 patent and are
 14 aware that when their customers and/or other end users use the Accused Products in accordance
 15 with Defendants' instructions, the customers and/or other end users directly infringe at least claim
 16 15 of the '591 patent. *See supra* ¶¶ 25-36, 82; *see also, e.g., In Caption AI Product Demo | AI-*
 17 *Guided Ultrasound System*, <https://www.youtube.com/watch?v=URmb72IA4b4>. The infringing
 18 Caption Guidance is a component of the Accused Products and constitutes a material part of the
 19 invention of the '591 patent. The infringing Caption Guidance has no substantial non-infringing
 20 uses and is not a staple article of commerce.

21 80. UBC has never authorized Defendants to make, use, offer to sell, or sell the Accused
 22 Products that incorporate the infringing Caption Guidance.

23 81. As a direct and proximate result of Defendants' acts of infringement, Defendants
 24 have derived and received gains, profits, and advantages. UBC has been damaged, and continues
 25 to be damaged, by Defendants' infringement in an amount yet to be determined, of at least a
 26 reasonable royalty.

27 82. Defendants' infringement has been and continues to be willful. Defendants had
 28 actual knowledge of the '591 patent at least as of May 5, 2022, the date UBC sent its initial letter

bringing the infringement of the '591 patent to Defendants' attention. *See* Exhibit D. Pursuant to 35 U.S.C. § 284, UBC is entitled to damages for Defendants' infringement acts and treble damages together with interests and costs as fixed by this Court.

83. This is an exceptional case. Pursuant to 35 U.S.C. § 285, UBC is entitled to reasonable attorneys' fees for the necessity of bringing this claim.

84. UBC further seeks any other damages to which UBC is entitled under law or in equity.

COUNT II: INFRINGEMENT OF U.S. PATENT NO. 10,751,029

85. UBC incorporates by reference and re-alleges all of the foregoing paragraphs of this First Amended Complaint and exhibits attached hereto as is fully set forth herein.

86. Defendants infringe at least claims 4 and 23 of the '029 patent by making, using, selling, importing, offering for sale its Accused Products.

87. Each of the Accused Products is "[a] system for facilitating ultrasonic image analysis comprising at least one processor..." and is used for "[a] computer-implemented method of facilitating ultrasonic image analysis of a subject." *See, e.g.*, Venue Family Caption Guidance™ product page, <https://www.gehealthcare.com/campaigns/venue-family-caption-guidance> ("Preliminary probe placement information shows you where to place and how to orient the ultrasound probe. As you begin the exam, a handy reference image shows you the image you are trying to acquire."; "prescriptive guidance [is] provided on the screen...the Quality Meter rise[s] as you get closer to an image of diagnostic quality."); *see id.* ("Thanks to Caption Guidance™ AI-driven software on the Venue family, even new ultrasound users can capture cardiac images successfully."); *see also supra* ¶¶ 52-64.

88. The Accused Products perform "receiving signals representing a set of ultrasound images of the subject." For example, the Accused Products acquire a series of echocardiographic images when an operator scans a patient using a transducer. *See, e.g.*, Venue Family POCUS R5 Brochure (August 2024), <https://www.gehealthcare.com/-/jssmedia/gehc/us/images/products/ultrasound/venue/feature-cards/brochure-venue-family-pocus-r5-jb29262xx.pdf?rev=-1>, at 3 ("Caption Guidance helps even new users capture diagnostic-quality

images with its built-in AI-driven software.”); *see also id.* at 4 (“Real-time, turn-by-turn on-screen guidance prompts your probe movements to help new POCUS users capture diagnostic-quality cardiac images.”); *see also Press Release: GE HealthCare Launches Enhanced Venue Family Point-of-Care Ultrasound Systems Featuring AI-Driven Caption Guidance*, <https://www.gehealthcare.com/about/newsroom/press-releases/ge-healthcare-launches-enhanced-venue-family-point-of-care-ultrasound-systems-featuring-ai-driven-caption-guidance?npclid=botnpclid> (“The AI-driven Caption Guidance technology gives clinicians step-by-step instructions to confidently acquire ultrasound images for cardiac assessments.”); *see also* Narang, et. al., *Utility of a Deep-Learning Algorithm to Guide Novices to Acquire Echocardiograms for Limited Diagnostic Use*, JAMA Cardiology, 6:624-632, 625 (June 2021); *see also supra* ¶¶ 55, 57.

89. The Accused Products perform “deriv[ing] one or more extracted feature representations from the set of ultrasound images.” For example, the Accused Products use neural networks to extract feature representations from and assess the set of ultrasound images. *See, e.g.,* G. Yatnalkar, *Caption Guidance – FDA’s First Authorized AI-Based Cardiac Ultrasound Software* (Feb. 15, 2021), <https://emmainternational.com/fda-authorized-ai-cardiac-ultrasound-software/> (“For Caption Guidance, the AI Algorithm used for image or video frame selection is the Deep Convolutional Neural Network (DCNN). DCNNs are the most powerful and preferred AI algorithms when it comes to imaging applications. The learning begins by training this DCNN with a massive data set of existing images and videos. When the user shifts the probe while performing an ultrasound on the patients’ body, new images or videos are generated and these are then compared with the learned data. Based on the minimal difference from image quality comparison, current images and video frames are selected.”); Narang, et. al., *Utility of a Deep-Learning Algorithm to Guide Novices to Acquire Echocardiograms for Limited Diagnostic Use*, JAMA Cardiology, 6:624-632, 625 (June 2021) (“The AI-guided image acquisition software...Caption Guidance...provides real-time guidance during scanning to assist the user in obtaining anatomically correct images from standard transthoracic echocardiographic (TTE) transducer positions...The software monitors image quality continuously, simultaneously providing iterative prescriptive cues

to improve the image via the DL algorithm.”); *FDA Authorizes Marketing of First Cardiac Ultrasound Software That Uses Artificial Intelligence to Guide User*, FDA News Release (Feb. 7, 2020), <https://www.fda.gov/news-events/press-announcements/fda-authorizes-marketing-first-cardiac-ultrasound-software-uses-artificial-intelligence-guide-user> (“The Caption Guidance software was developed using machine learning to train the software to differentiate between acceptable and unacceptable image quality.”); *see also supra* ¶¶ 62-64.

90. Examples of the “one or more extracted feature representations” may include certain patterns correlated with image quality or an image property (e.g., view category). *See e.g.*, Narang et. al., *Utility of a Deep-Learning Algorithm to Guide Novices to Acquire Echocardiograms for Limited Diagnostic Use (Supplemental Online Content)* at 2 (“Training the network: As shown in eFigure 1, the deep learning algorithm was developed to guide operators to 10 diagnostic views of the heart: parasternal long axis view (PLAX); parasternal short axis view at aortic valve level (PSAX-AV), mitral valve level (PSAX-MV), and papillary muscle level (PSAX-PM); apical 2, 3, 4, 5 chamber views (Ap2, Ap3, Ap4, and Ap5); and subcostal 4 chamber (SC-4) and inferior vena cava view (SC-IVC). Fifteen (15) registered sonographers captured imagery on subjects over a range of BMI and clinical pathology to train the deep learning algorithm. This training dataset contained >5,000,000 individual data points on transducer location/orientation and observed imagery using ultrasound machines from multiple vendors. This dataset was curated and augmented with approximately 500,000 labels from expert sonographers and cardiologists annotating diagnostic quality and suggesting prescriptive guidance actions to improve the imaging (eFigure 1 left). Using this dataset, the algorithm was trained to estimate the 6D distance to each of the 10 views, define 81 unique prescriptive guidance actions, and diagnostic thresholds for each of the 10 views.”).

91. The Accused Products perform “determin[ing], based on the derived one or more extracted feature representations, a quality assessment value representing a quality assessment of the set of ultrasound images.” For example, the Accused Products use neural networks to extract feature representations from and assess the set of ultrasound images, and then determine a quality assessment value based on the extracted feature representations. *See e.g.*, *In Caption AI Product*

1 *Demo: AI-Guided Ultrasound System*, <https://www.youtube.com/watch?v=URmb72IA4b4> at 0:37-
 2 0:59 (“Sarah makes specific transducer movements to optimize the image. On the left, the quality
 3 meter tells her how close she is to capturing a diagnostic quality image. As Sarah gets closer to the
 4 optimal view, the meter rises. Once the software detects a diagnostic quality image, the meter turns
 5 green and the clip is automatically recorded without having to press any buttons.”); H. Hong, PhD.,
 6 *Caption Health: Flattening the Ultrasound Learning Curve with Breakthrough AI-Guided*
 7 *Echocardiography System*, <https://www.youtube.com/watch?v=NCFFAIHSPrc> at 4:30-4:40
 8 (“Finally, [it] recognizes when the user reaches the target and automatically captures the images in
 9 diagnostic quality.”); Narang et. al., *Utility of a Deep-Learning Algorithm to Guide Novices to*
 10 *Acquire Echocardiograms for Limited Diagnostic Use* (Original Investigation) at 625 (“The AI-
 11 guided image acquisition software (Caption Guidance [Caption Health, previously known as Bay
 12 Labs]), described in greater detail in the eAppendix in the Supplement and shown schematically in
 13 eFigure 1 in the Supplement, provides real-time guidance during scanning to assist the user in
 14 obtaining anatomically correct images from standard transthoracic echocardiographic (TTE)
 15 transducer positions. The AI guidance is software only, developed with DL to emulate sonographer
 16 expertise. The software, designed to be compatible with multiple ultrasonography vendors, was
 17 installed on a commercially available system (uSmart 3200t Plus [Terason]). The software monitors
 18 image quality continuously, simultaneously providing iterative prescriptive cues to improve the
 19 image via the DL algorithm.”); *id.* (“The DL algorithms were trained using more than 5 million
 20 observations associating transducer orientation, the diagnostic correctness of the resulting image,
 21 and the outcome of subsequent manipulations with diagnostic quality. This training data set came
 22 from 15 registered sonographers via scans of individuals with a range of body mass index (BMI)
 23 values and pathological conditions, further annotated for quality by expert sonographers and
 24 cardiologists (A.N., R.P.M., R.M.L., N.J.W., and J.D.T.). eFigure 1 in the Supplement depicts the
 25 DL model training data set, expert labeling for image quality, algorithm optimization, and run-time
 26 operation during the study”); *see also supra* ¶¶ 59, 62-64.

27 92. The Accused Products perform “determin[ing], based on the derived one or more
 28 extracted feature representations, an image property associated with the set of ultrasound images.”

For example, the Accused Products determine a view category of the set of ultrasound images based on the extracted feature representation. *See e.g., Narang et. al., Utility of a Deep-Learning Algorithm to Guide Novices to Acquire Echocardiograms for Limited Diagnostic Use (Supplemental Online Content)* at 2 (“Training the network: As shown in eFigure 1, the deep learning algorithm was developed to guide operators to 10 diagnostic views of the heart: parasternal long axis view (PLAX); parasternal short axis view at aortic valve level (PSAX-AV), mitral valve level (PSAX-MV), and papillary muscle level (PSAX-PM); apical 2, 3, 4, 5 chamber views (Ap2, Ap3, Ap4, and Ap5); and subcostal 4 chamber (SC-4) and inferior vena cava view (SC-IVC). Fifteen (15) registered sonographers captured imagery on subjects over a range of BMI and clinical pathology to train the deep learning algorithm. This training dataset contained >5,000,000 individual data points on transducer location/orientation and observed imagery using ultrasound machines from multiple vendors. This dataset was curated and augmented with approximately 500,000 labels from expert sonographers and cardiologists annotating diagnostic quality and suggesting prescriptive guidance actions to improve the imaging (eFigure 1 left). Using this dataset, the algorithm was trained to estimate the 6D distance to each of the 10 views, define 81 unique prescriptive guidance actions, and diagnostic thresholds for each of the 10 views.”).

93. The Accused Products perform “produc[ing] signals representing the quality assessment value and the image property for causing the quality assessment value and the image property to be associated with the set of ultrasound images.” For example, the Accused Products automatically capture an echocardiographic image and associate the image with the determined quality assessment value and view category. *See e.g., Narang et. al., Utility of a Deep-Learning Algorithm to Guide Novices to Acquire Echocardiograms for Limited Diagnostic Use (Original Investigation)* at 625 (“The DL algorithm estimates image quality via a component called the quality meter, suggesting probe manipulations using prescriptive guidance (eFigure 1 in the Supplement). When the real-time quality meter exceeds a preset threshold, it automatically records a video clip (termed an auto-capture). Quality is continuously monitored throughout scanning, so the operator can retrospectively save the best clip observed if the auto-capture threshold is not exceeded. If auto-capture is not achieved within 2 minutes, the user may activate the option called

1 save best clip or continue scanning to achieve auto-capture. These algorithms operate together to
 2 improve the ultrasonographic image, as in eFigure 1 in the Supplement, in which prescriptive
 3 guidance improves a parasternal long-axis view. eFigure 2 in the Supplement and Video 1 show
 4 additional detail on the user interface.”); *see also* H. Hong, Ph.D., *Caption Health: Flattening the*
 5 *Ultrasound Learning Curve with Breakthrough AI-Guided Echocardiography System*,
 6 <https://www.youtube.com/watch?v=NCFFAIHSPrc>; *see also* *In Caption AI Product Demo | AI-*
 7 *Guided Ultrasound System*, <https://www.youtube.com/watch?v=URmb72IA4b4at> at 0:37-0:59
 8 (“Sarah makes specific transducer movements to optimize the image. On the left, the quality meter
 9 tells her how close she is to capturing a diagnostic quality image. As Sarah gets closer to the optimal
 10 view, the meter rises. Once the software detects a diagnostic quality image, the meter turns green
 11 and the clip is automatically recorded without having to press any buttons.”); *see also supra* ¶¶ 55,
 12 60.

13 94. In the Accused Products, “the image property is a view category.” For example, as
 14 described above, the Accused Products determine a view category of the set of ultrasound images
 15 based on the extracted feature representation. *See supra*, ¶¶ 89-90.

16 95. In the Accused Products, “deriving the one or more extracted feature representations
 17 from the ultrasound images comprises, for each of the ultrasound images, deriving a first feature
 18 representation associated with the ultrasound image.” For example, as described above, the
 19 Accused Products use neural networks to extract feature representations from and assess the set of
 20 ultrasound images, where one of said extracted feature representations is “a first feature
 21 representation.” *See supra*, ¶ 89. As described above, examples of the “one or more extracted
 22 feature representations” may be certain patterns correlated with image quality or an image property
 23 (e.g., view category). *See supra*, ¶ 90.

24 96. In the Accused Products, “deriving the one or more extracted feature representations
 25 comprises, for each of the ultrasound images, inputting the ultrasound image into a commonly
 26 defined first feature extracting neural subnetwork to generate the first feature representation
 27 associated with the ultrasound image.” Additionally, “the at least one processor” of the Accused
 28 Products is “configured to, for each of the ultrasound images, input the ultrasound image into a

commonly defined first feature extracting neural subnetwork to generate the first feature representation associated with the ultrasound image.” For example, on information and belief, the Accused Products use a common neural subnetwork for deriving the first feature representation. See e.g., Narang et. al., *Utility of a Deep-Learning Algorithm to Guide Novices to Acquire Echocardiograms for Limited Diagnostic Use* (Original Investigation) at 625 (“The AI-guided image acquisition software (Caption Guidance [Caption Health, previously known as Bay Labs]), described in greater detail in the eAppendix in the Supplement and shown schematically in eFigure 1 in the Supplement, provides real-time guidance during scanning to assist the user in obtaining anatomically correct images from standard transthoracic echocardiographic (TTE) transducer positions. The AI guidance is software only, developed with DL to emulate sonographer expertise. ... The guidance software used convolutional neural networks constructed by stacking computational layers, each taking input from the layer below, transforming and passing it along to the layer above. The software monitors image quality continuously, simultaneously providing iterative prescriptive cues to improve the image via the DL algorithm. The guidance software used convolutional neural networks constructed by stacking computational layers, each taking input from the layer below, transforming and passing it along to the layer above. The software has several interconnected DL algorithms making 3 simultaneous estimates: (1) diagnostic quality of the imagery, (2) 6-dimensional geometric distance (by position and orientation) between current probe location and the location anticipated to optimize the image, and (3) corrective probe manipulations to improve diagnostic quality. Importantly, the algorithm makes these estimates from the ultrasonographic imagery alone; no trackers, fiducial markers, or additional sensors are required. The DL algorithms were trained using more than 5 million observations associating transducer orientation, the diagnostic correctness of the resulting image, and the outcome of subsequent manipulations with diagnostic quality.”); see also Narang et. al., *Utility of a Deep-Learning Algorithm to Guide Novices to Acquire Echocardiograms for Limited Diagnostic Use* (Supplemental Online Content) at 2 (“Training the network: As shown in eFigure 1, the deep learning algorithm was developed to guide operators to 10 diagnostic views of the heart: parasternal long axis view (PLAX); parasternal short axis view at aortic valve level (PSAX-AV), mitral valve

level (PSAX-MV), and papillary muscle level (PSAX-PM); apical 2, 3, 4, 5 chamber views (Ap2, Ap3, Ap4, and Ap5); and subcostal 4 chamber (SC-4) and inferior vena cava view (SC-IVC). Fifteen (15) registered sonographers captured imagery on subjects over a range of BMI and clinical pathology to train the deep learning algorithm. This training dataset contained >5,000,000 individual data points on transducer location/orientation and observed imagery using ultrasound machines from multiple vendors. This dataset was curated and augmented with approximately 500,000 labels from expert sonographers and cardiologists annotating diagnostic quality and suggesting prescriptive guidance actions to improve the imaging (eFigure 1 left). Using this dataset, the algorithm was trained to estimate the 6D distance to each of the 10 views, define 81 unique prescriptive guidance actions, and diagnostic thresholds for each of the 10 views. The algorithm, consisting of more than 7,000,000 parameters, was trained using standard machine learning optimization techniques on a 31 tFLOP (trillion floating point operations per second) GPU array. Training the model took approximately 7.2 exaFLOP (1 exaFLOP is one million teraFLOPs or a quintillion (10¹⁸) 32-bit multiplication floating point operations) over two weeks (eFigure 1 center). Further information on Caption Guidance may be found in the talk, “Development and Validation of a Breakthrough AI-Guided Echocardiography System” presented at the FDA-hosted public workshop titled, “Evolving Role of Artificial Intelligence in Radiological Imaging” held in Bethesda, Maryland on February 25 and 26, 2020, with slides [<https://www.fda.gov/media/135734/download>], and video [<http://fda.yorkcast.com/webcast/Play/5ac1c24f9e48455c82011ab26837afad1d>], with the relevant portion beginning at 42:10 of the video available.”).

97. Defendants have also induced and continue to induce the infringement of the '029 patent by others in violation of 35 U.S.C. § 271(b), including by selling the Accused Products to their customers and/or other end users and instructing them to practice at least claim 4 of the '029 patent by using the Accused Products. On information and belief, Defendants are aware of the '029 patent and are aware that when their customers and/or other end users use the Accused Products in accordance with Defendants' instructions, the customers and/or other end users directly infringe at least claim 4 of the '029 patent. *See e.g., In Caption AI Product Demo | AI-Guided Ultrasound*

System, <https://www.youtube.com/watch?v=URmb72IA4b4>. On information and belief, Defendants sell the Accused Products both directly through its own sales force and website. See <https://www.gehealthcare.com/about/newsroom/press-releases/ge-healthcare-launches-enhanced-venue-family-point-of-care-ultrasound-systems-featuring-ai-driven-caption-guidance?npclid=botnpclid> (Oct. 6, 2023) (“Caption Guidance on the Venue Family point-of-care ultrasound systems is available in the United States.”); see also <https://www.gehealthcare.com/shop>; <https://www.gehealthcare.com/shop/equipment/vscan-air-sl>.

98. Defendants have also contributed and continue to contribute to infringement of the ’029 patent in violation of 35 U.S.C. § 271(c) by selling the Accused Products to their customers and/or other end users and instructing them to practice at least claim 4 of the ’029 patent by using the Accused Products. On information and belief, Defendants are aware of the ’029 patent and are aware that when their customers and/or other end users use the Accused Products in accordance with Defendants’ instructions, the customers and/or other end users directly infringe at least claim 4 of the ’029 patent. See e.g., *In Caption AI Product Demo | AI-Guided Ultrasound System*, <https://www.youtube.com/watch?v=URmb72IA4b4>. The infringing Caption Guidance is a component of the Accused Products and constitutes a material part of the invention of the ’029 patent. The infringing Caption Guidance has no substantial non-infringing uses and is not a staple article of commerce.

99. UBC has never authorized Defendants to make, use, offer to sell, or sell the Accused Products that incorporate the infringing Caption Guidance.

100. As a direct and proximate result of Defendants’ acts of infringement, Defendants have derived and received gains, profits, and advantages. UBC has been damaged, and continues to be damaged, by Defendants’ infringement in an amount yet to be determined, of at least a reasonable royalty.

101. Defendants’ infringement has been and continues to be willful. On information and belief, Defendants had actual knowledge of the ’029 patent before the filing of this First Amended Complaint. Pursuant to 35 U.S.C. § 284, UBC is entitled to damages for Defendants’ infringement acts and treble damages together with interests and costs as fixed by this Court.

1 102. This is an exceptional case. Pursuant to 35 U.S.C. § 285, UBC is entitled to
2 reasonable attorneys' fees for the necessity of bringing this claim.

3 103. UBC further seeks any other damages to which UBC is entitled under law or in
4 equity.

5 **DEMAND FOR JURY TRIAL**

6 104. UBC hereby demands a jury trial for all issues so triable.

7 **PRAYER FOR RELIEF**

8 105. WHEREFORE, UBC respectfully requests that this Court enter judgment in its
9 favor as follows:

10 A. That Judgment be entered that Defendants have infringed and continues to infringe
11 one or more claims of the '591 patent and '029 patent under 35 U.S.C. § 271;

12 B. That, in accordance with 35 U.S.C. § 283, Defendants and all their affiliates,
13 employees, agents, officers, directors, attorneys, successors, and assigns and all those acting on
14 behalf of or in active concert or participation with any of them, be preliminarily and permanently
15 enjoined from infringing the '591 patent and '029 patent;

16 C. That UBC be awarded damages sufficient to compensate UBC for Defendants'
17 infringement and enhanced damages under 35 U.S.C. § 284;

18 D. That UBC be awarded attorneys' fees and costs pursuant to 35 U.S.C. § 285 or as
19 otherwise permitted by law;
20

21 E. That UBC be awarded its costs and expenses in this action; and

22 H. Such other and further relief as the Court deems just and proper.
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1 Dated: December 20, 2024

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EXHIBIT A



US011129591B2

(12) **United States Patent**
Abolmaesumi et al.

(10) **Patent No.:** **US 11,129,591 B2**
(45) **Date of Patent:** **Sep. 28, 2021**

(54) **ECHOCARDIOGRAPHIC IMAGE ANALYSIS**

(71) Applicant: **THE UNIVERSITY OF BRITISH COLUMBIA**, Vancouver (CA)

(72) Inventors: **Purang Abolmaesumi**, Vancouver (CA); **Robert Rohling**, Vancouver (CA); **Amir H. Abdi**, Vancouver (CA); **Teresa S. M. Tsang**, Vancouver (CA)

(73) Assignee: **The University of British Columbia**, Vancouver (CA)

(*) Notice: Subject to any disclaimer, the term of this patent is extended or adjusted under 35 U.S.C. 154(b) by 500 days.

(21) Appl. No.: **16/095,601**

(22) PCT Filed: **Apr. 21, 2017**

(86) PCT No.: **PCT/CA2017/050496**

§ 371 (c)(1),

(2) Date: **Oct. 22, 2018**

(87) PCT Pub. No.: **WO2017/181288**

PCT Pub. Date: **Oct. 26, 2017**

(65) **Prior Publication Data**

US 2019/0125298 A1 May 2, 2019

Related U.S. Application Data

(60) Provisional application No. 62/325,779, filed on Apr. 21, 2016.

(51) **Int. Cl.**
G06K 9/00 (2006.01)
A61B 8/08 (2006.01)

(Continued)

(52) **U.S. Cl.**
CPC **A61B 8/0883** (2013.01); **A61B 8/4405** (2013.01); **A61B 8/463** (2013.01);
(Continued)

(58) **Field of Classification Search**

CPC A61B 8/0883; A61B 8/463; A61B 8/4405;
A61B 8/5215; G06N 3/04; G06N 3/08;
(Continued)

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(Continued)

Primary Examiner — Nan D Huynh

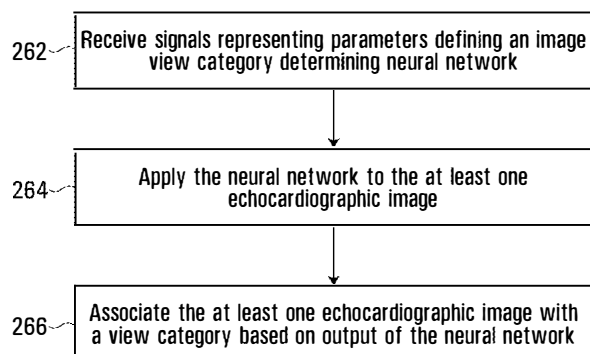
(74) *Attorney, Agent, or Firm* — Kolitch Romano LLP

(57) **ABSTRACT**

A computer-implemented system for facilitating echocardiographic image analysis is disclosed. The system includes at least one processor configured to receive signals representing a first at least one echocardiographic image, associate the image with a first view category of a plurality of predetermined view categories, determine, based on the first at least one echocardiographic image and the first view category, a first quality assessment value representing a view category specific quality assessment of the first at least one echocardiographic image, and produce signals representing the first quality assessment value for causing the first quality assessment value to be associated with the first at least one echocardiographic image. The at least one processor may

(Continued)

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also be configured to do the above steps for a second at least one echocardiographic and a second view category that is different from the first view category image. Other systems, methods, and computer-readable media are also disclosed.

20 Claims, 20 Drawing Sheets

- (51) **Int. Cl.**
A61B 8/00 (2006.01)
G06T 7/00 (2017.01)
G06N 3/04 (2006.01)
G06N 3/08 (2006.01)
- (52) **U.S. Cl.**
 CPC **G06N 3/04** (2013.01); **G06N 3/08** (2013.01); **G06T 7/0012** (2013.01); **G06N 3/082** (2013.01); **G06T 2207/10132** (2013.01); **G06T 2207/20081** (2013.01); **G06T 2207/20084** (2013.01); **G06T 2207/30048** (2013.01); **G06T 2207/30168** (2013.01)
- (58) **Field of Classification Search**
 CPC **G06N 3/082**; **G06T 7/0012**; **G06T 2207/10132**; **G06T 2207/20081**; **G06T 2207/20084**; **G06T 2207/30048**; **G06T 2207/30168**; **G16H 50/20**
 USPC 382/128
 See application file for complete search history.

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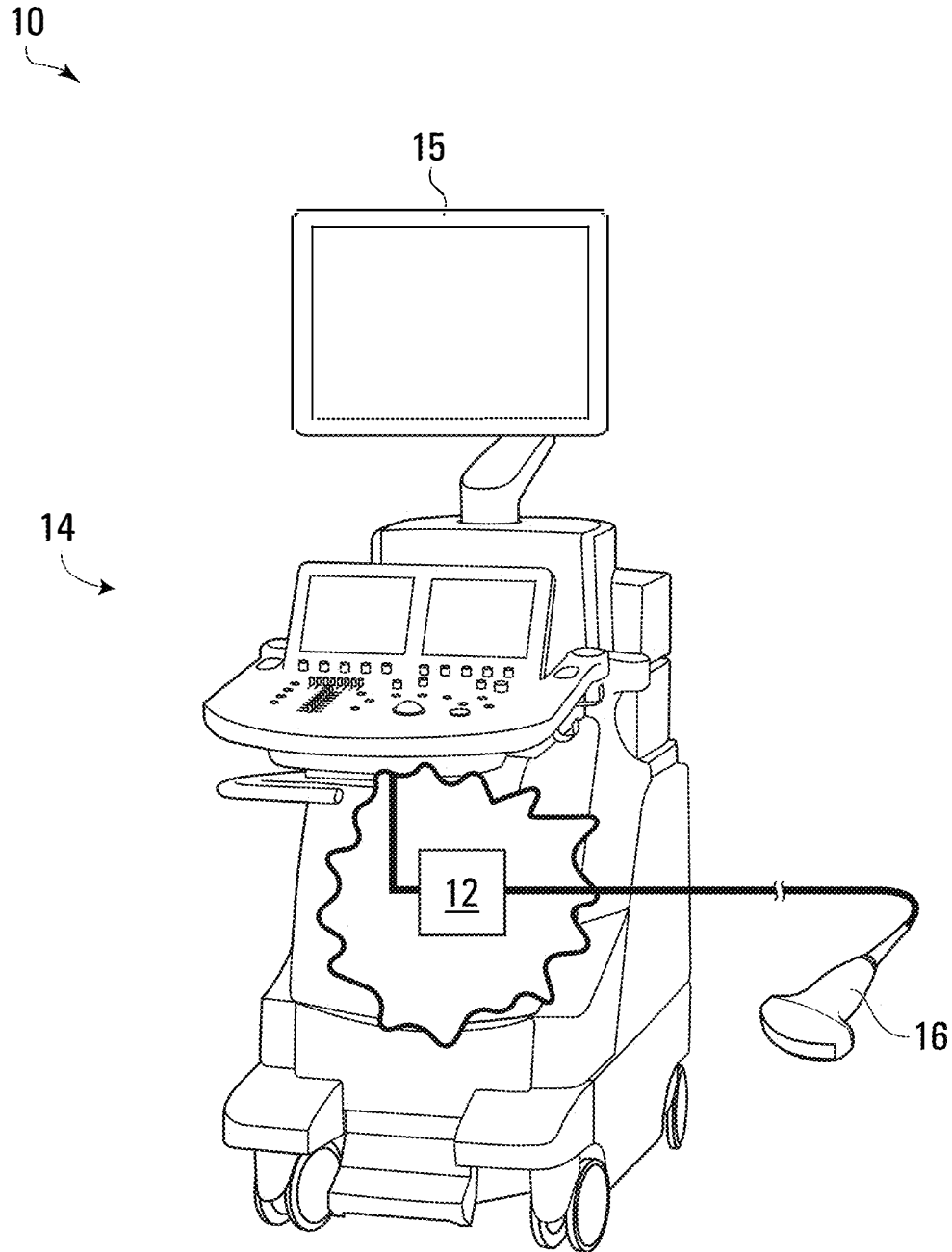


FIG. 1

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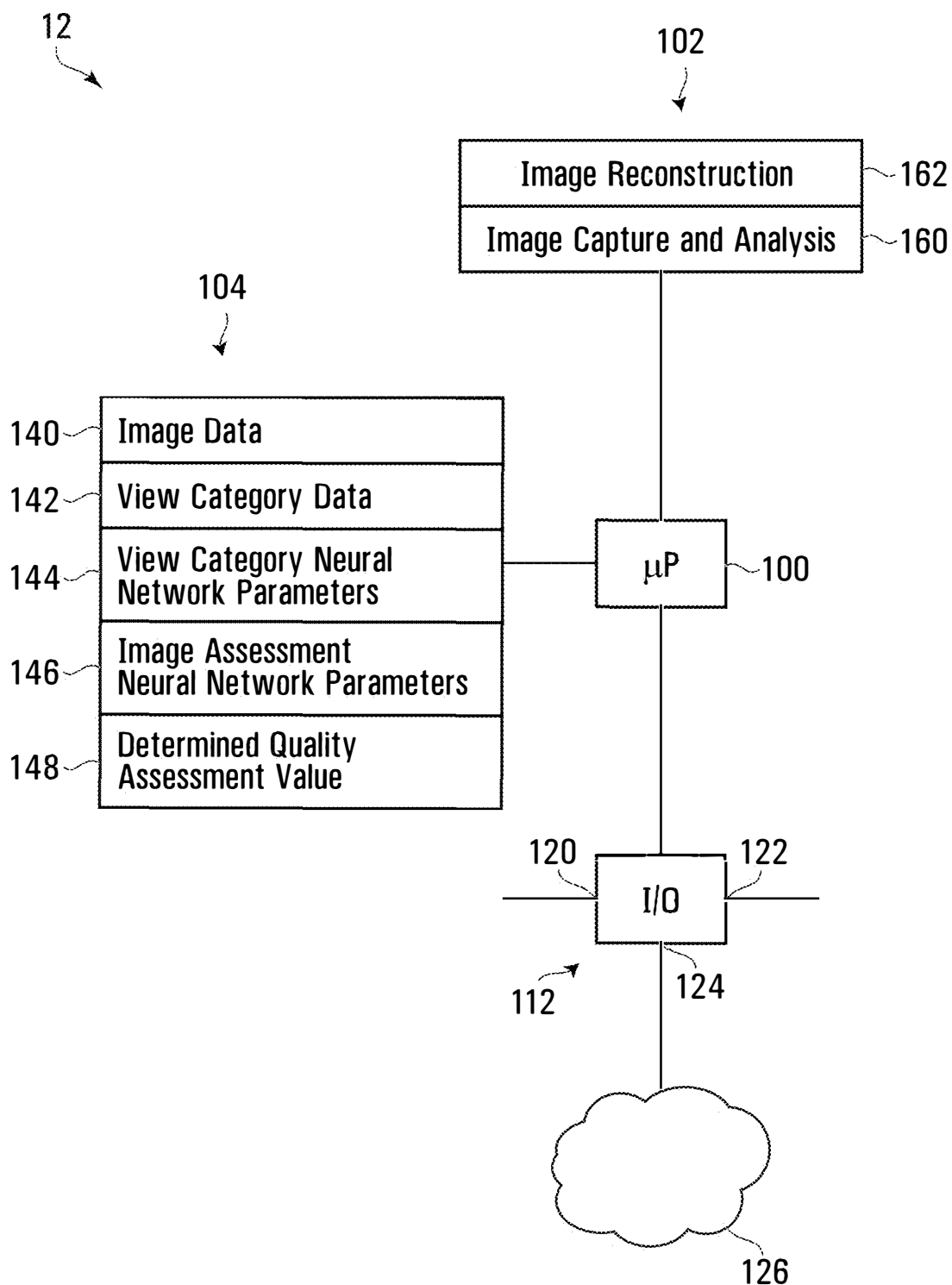


FIG. 2

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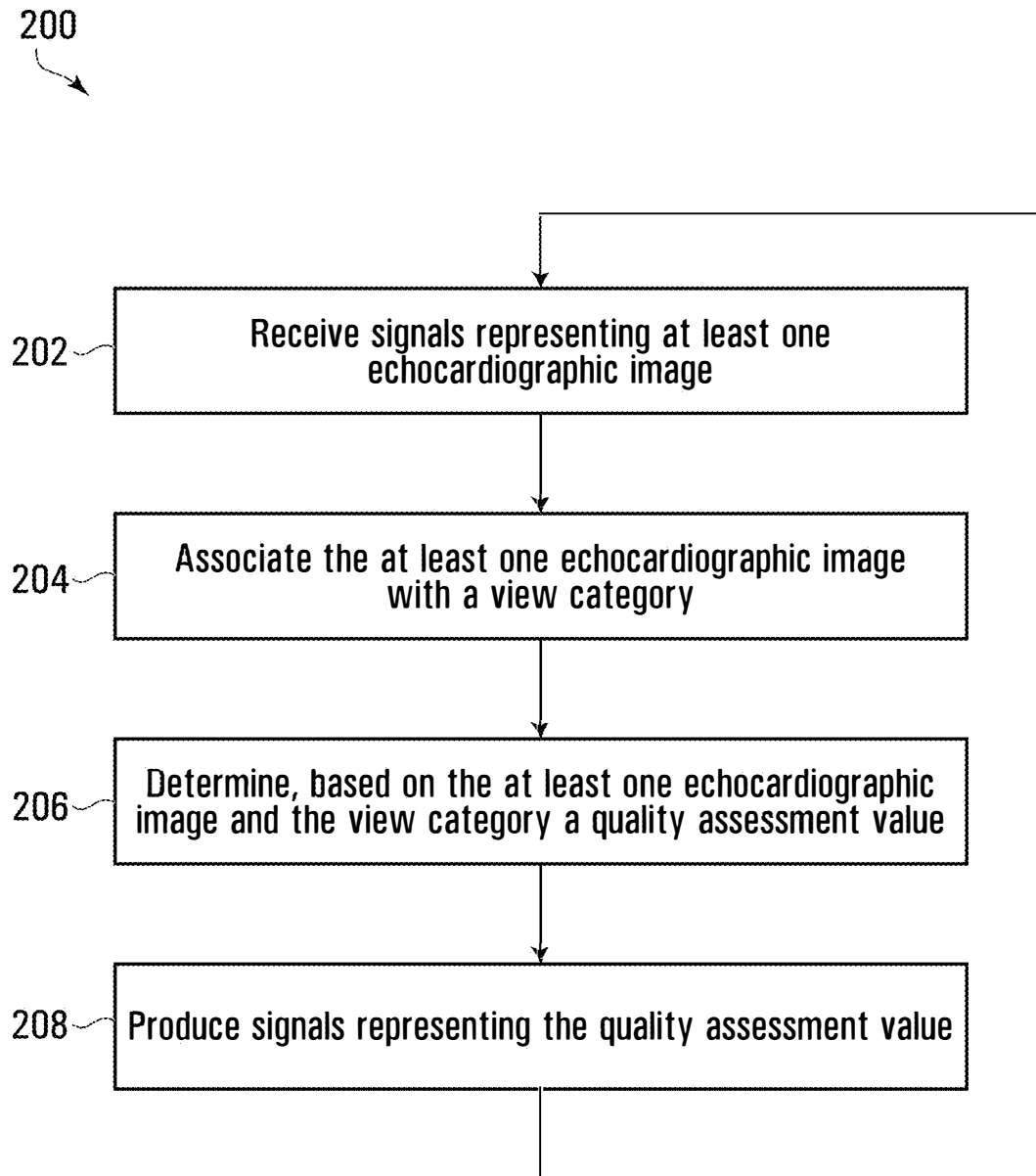


FIG. 3



FIG. 4

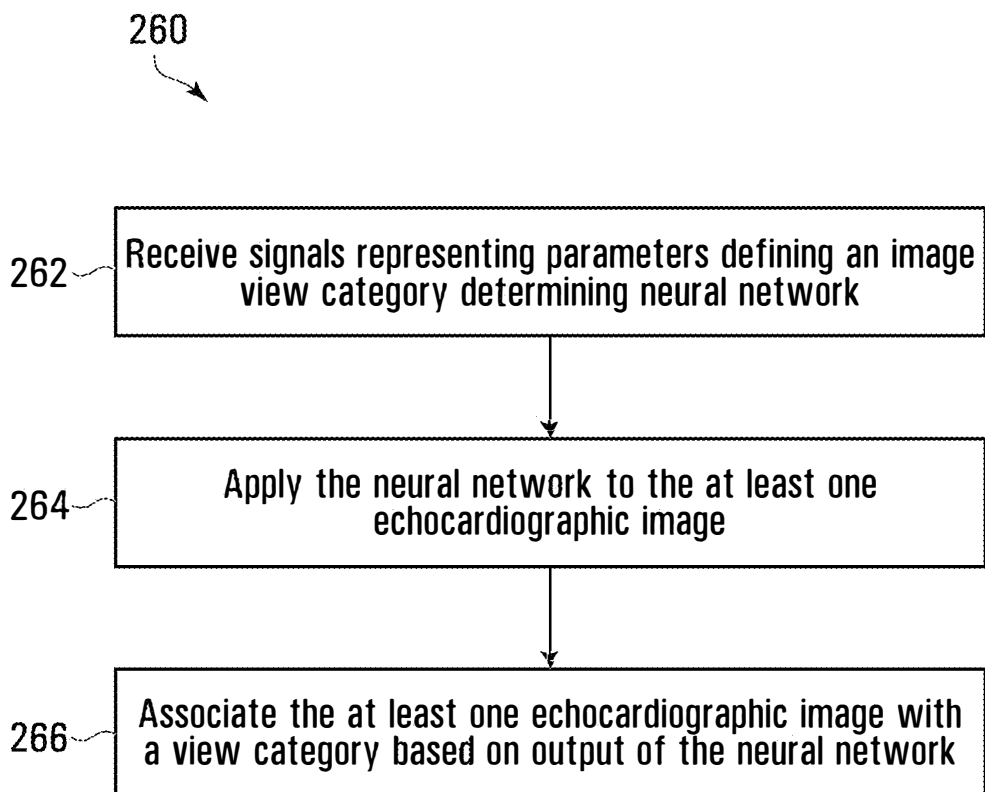


FIG. 5

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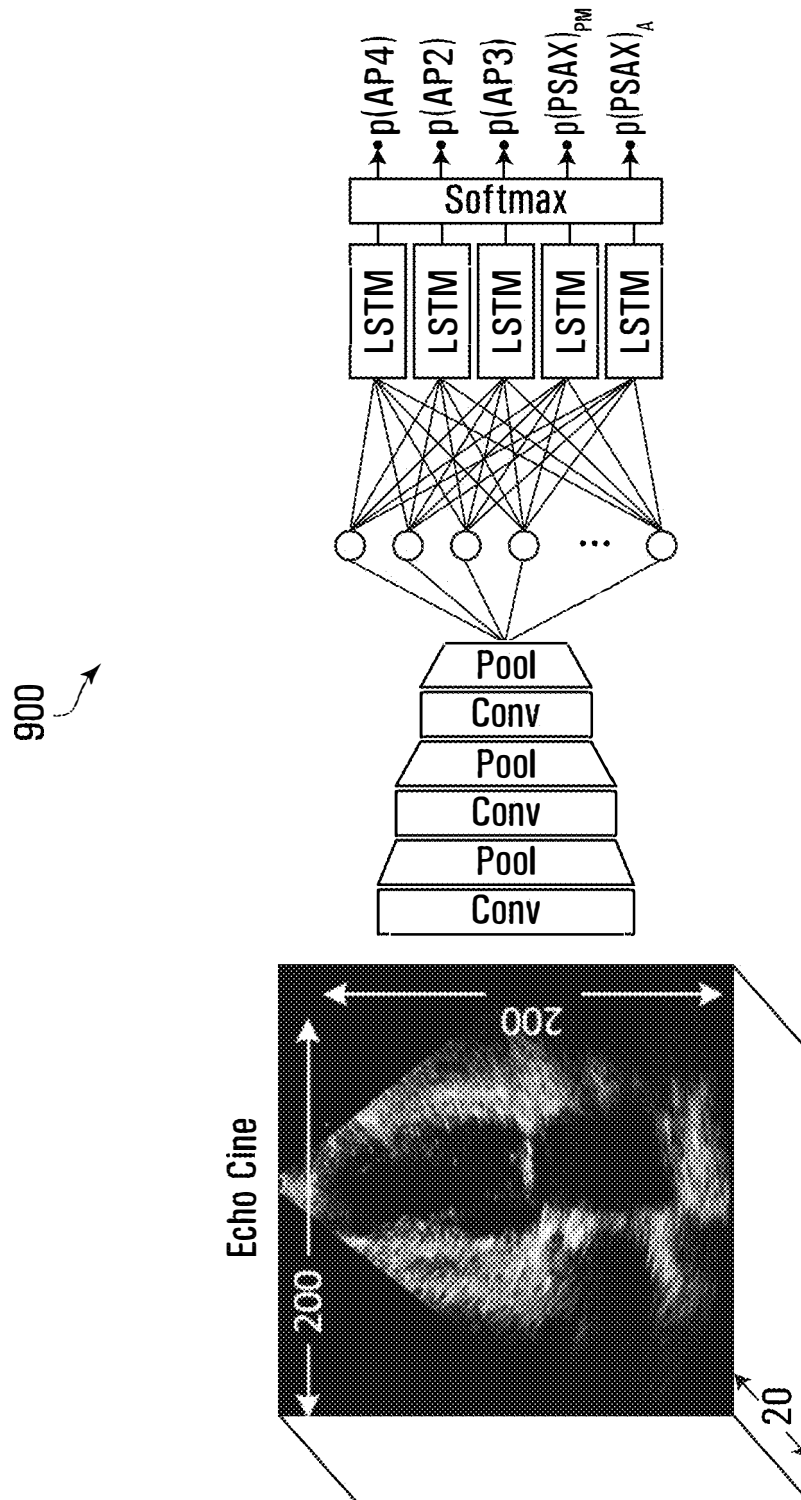


FIG. 6

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300


View category record

302	View category ID	AP4
304	Image group ID	1

FIG. 7

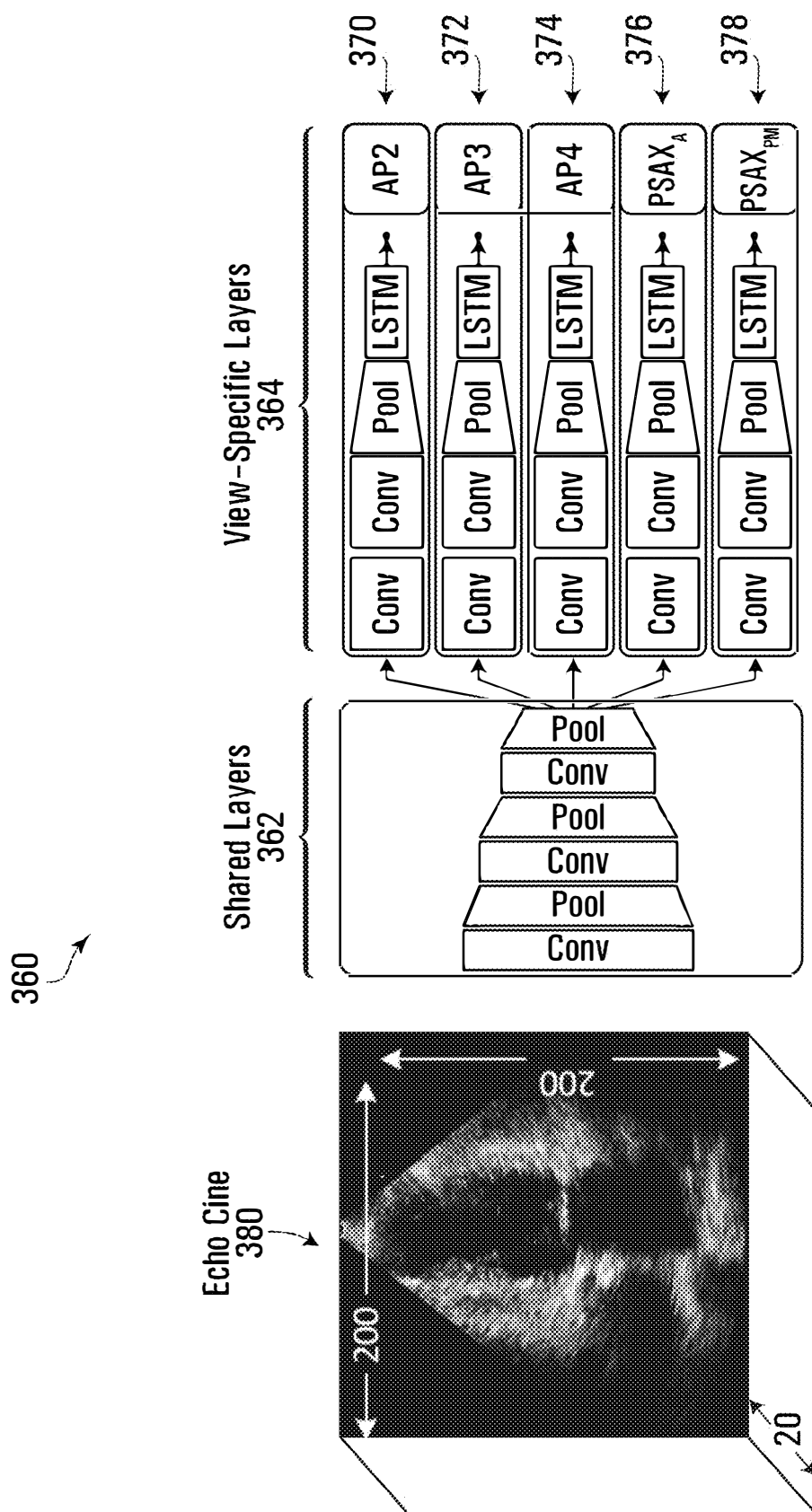


Fig. 8

320



Common neural network record

324	{	Layer number	1
		Layer type	Convolutional
		Stride	1
		Kernel 1	[...]
		...	
		Kernel 8	[...]
326	{	Layer number	2
		Layer type	Max pool
		Stride	2
		Kernel size	2x2
328	{	Layer number	3
		Layer type	Convolutional
		Stride	1
		Kernel 1	[...]
		...	
		Kernel 16	[...]
330	{	Layer number	4
		Layer type	Max pool
		Stride	2
		Kernel size	2x2
332	{	Layer number	5
		Layer type	Convolutional
		Stride	1
		Kernel 1	[...]
		...	
		Kernel 32	[...]
334	{	Layer number	6
		Layer type	Max pool
		Stride	2
		Kernel size	2x2

FIG. 9

340

View category specific neural network record

342	View category ID	AP4
	Layer number	7
	Layer type	Convolutional
344	Stride	1
	Kernel 1	[...]
	...	
	Kernel 32	[...]
	Layer number	8
	Layer type	Convolutional
346	Stride	1
	Kernel 1	[...]
	...	
	Kernel 32	[...]
	Layer number	9
348	Layer type	Max pool
	Stride	2
	Kernel size	2x2
	Layer number	10
350	Layer type	LSTM
	LSTM parameters	[...]

FIG. 10

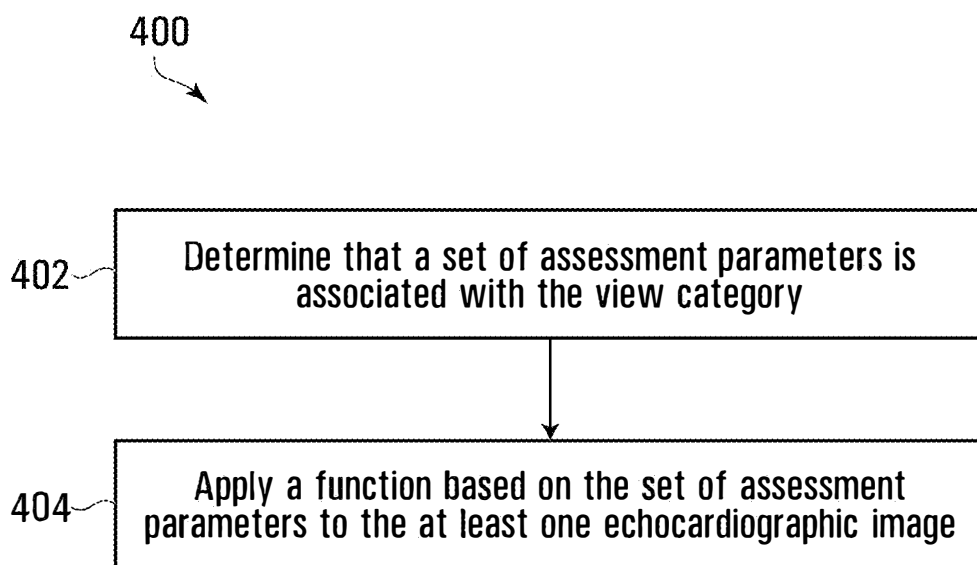


FIG. 11

420


Quality assessment record

422	Image group ID	1
424	Quality assessment	3.08

FIG. 12

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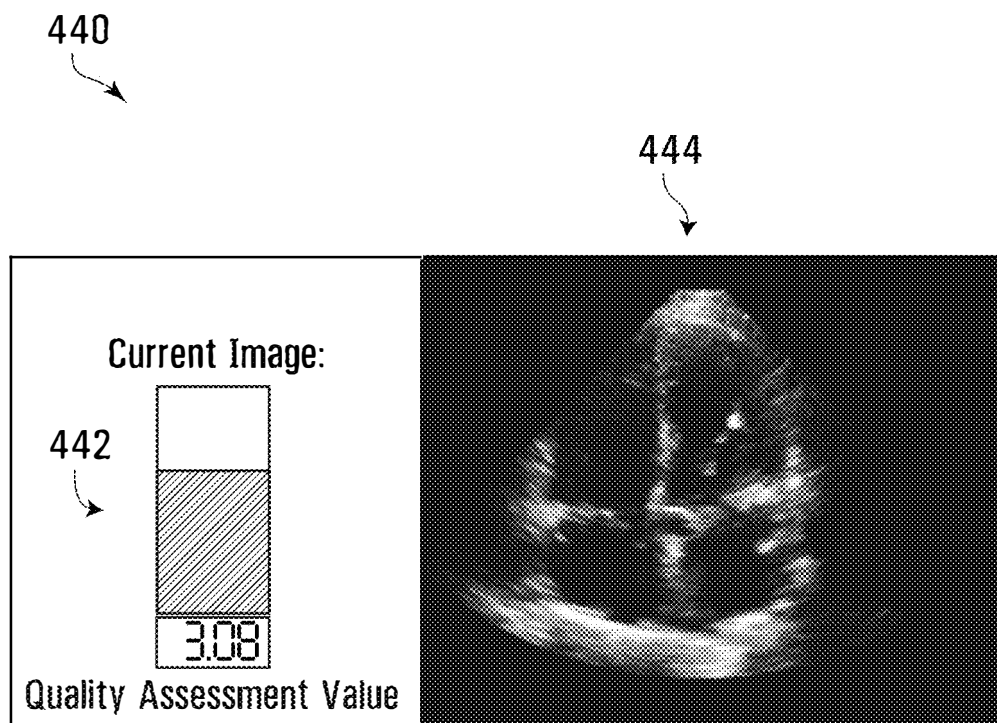


FIG. 13

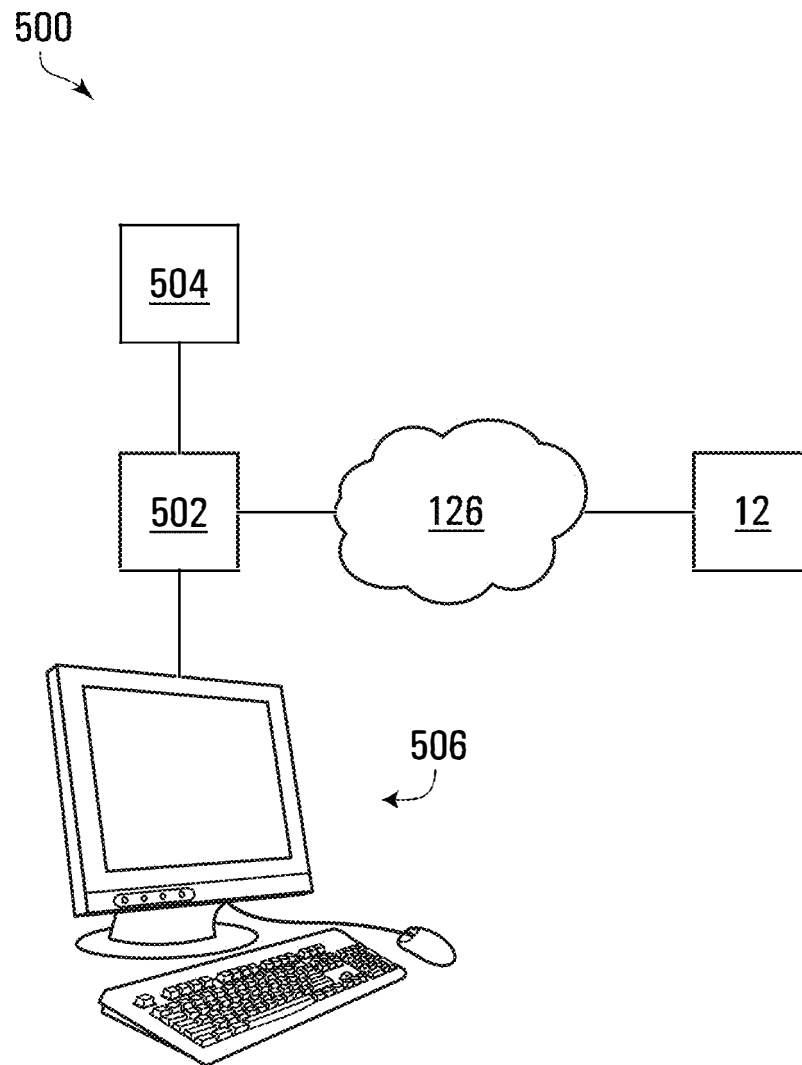
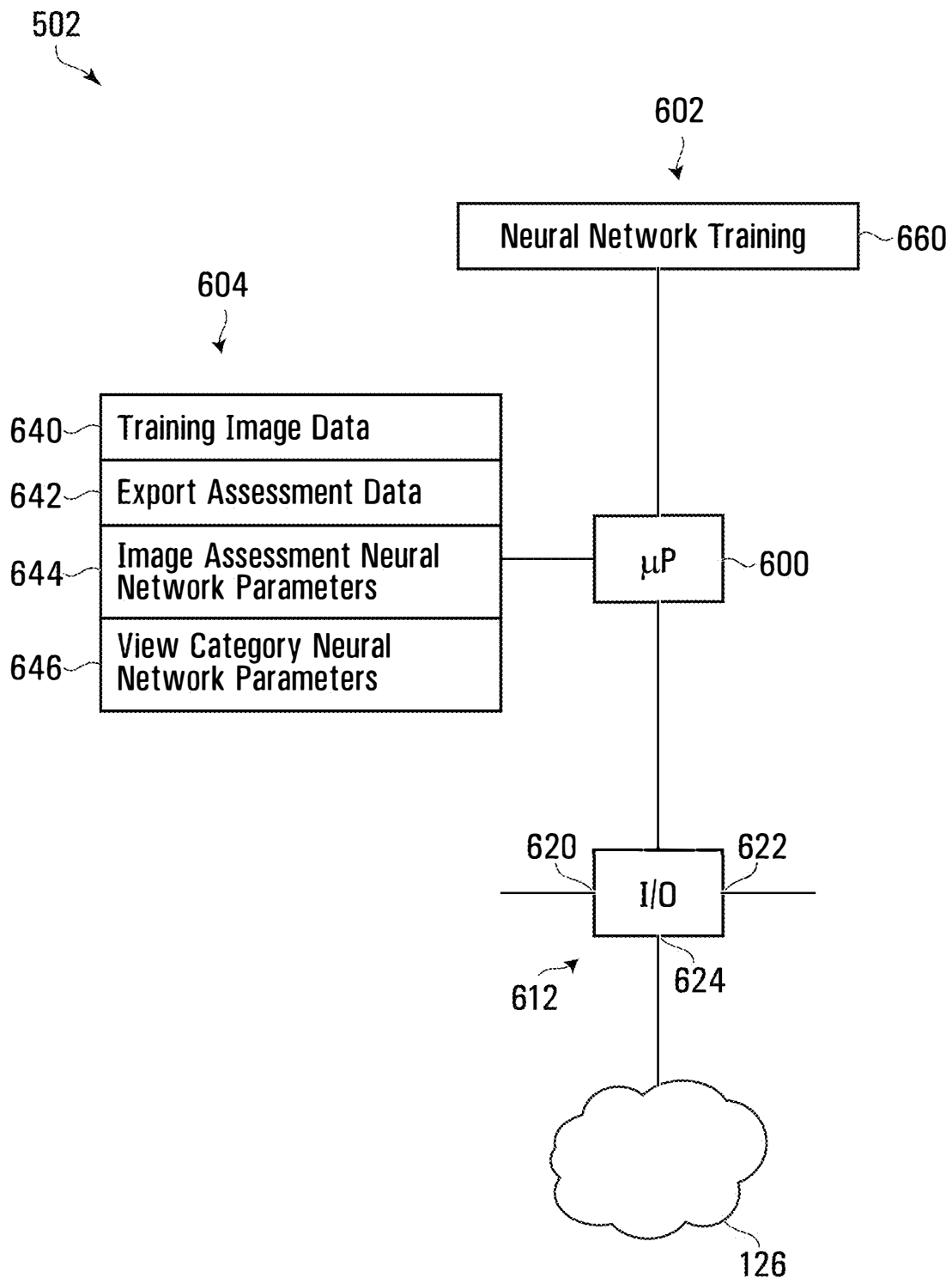


FIG. 14

**FIG. 15**

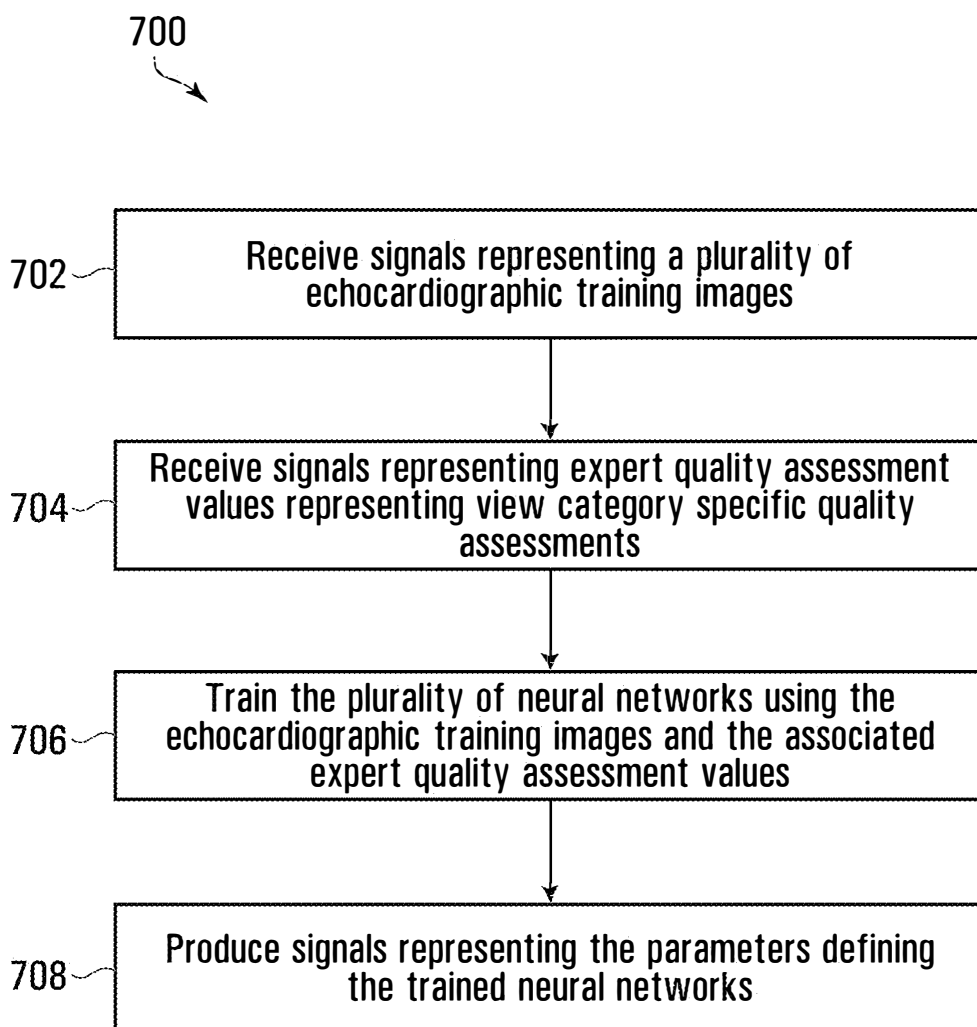


FIG. 16

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740



Training image file

742	Image ID	2015082018120000
744	Image group ID	1
746	View category ID	AP4
748	Image data	

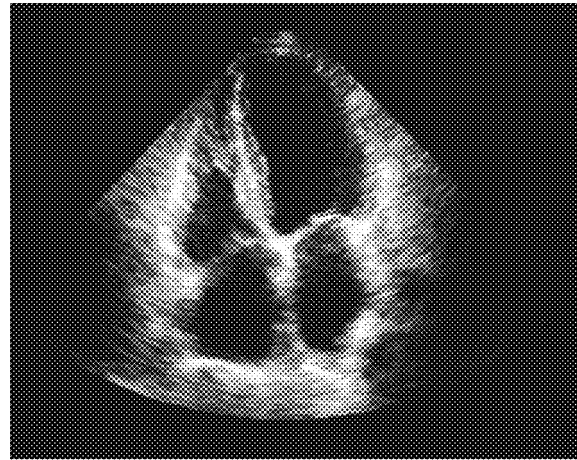


FIG. 17

780



Expert quality assessment record

782	Image group ID	1
784	Expert quality assessment	4

FIG. 18

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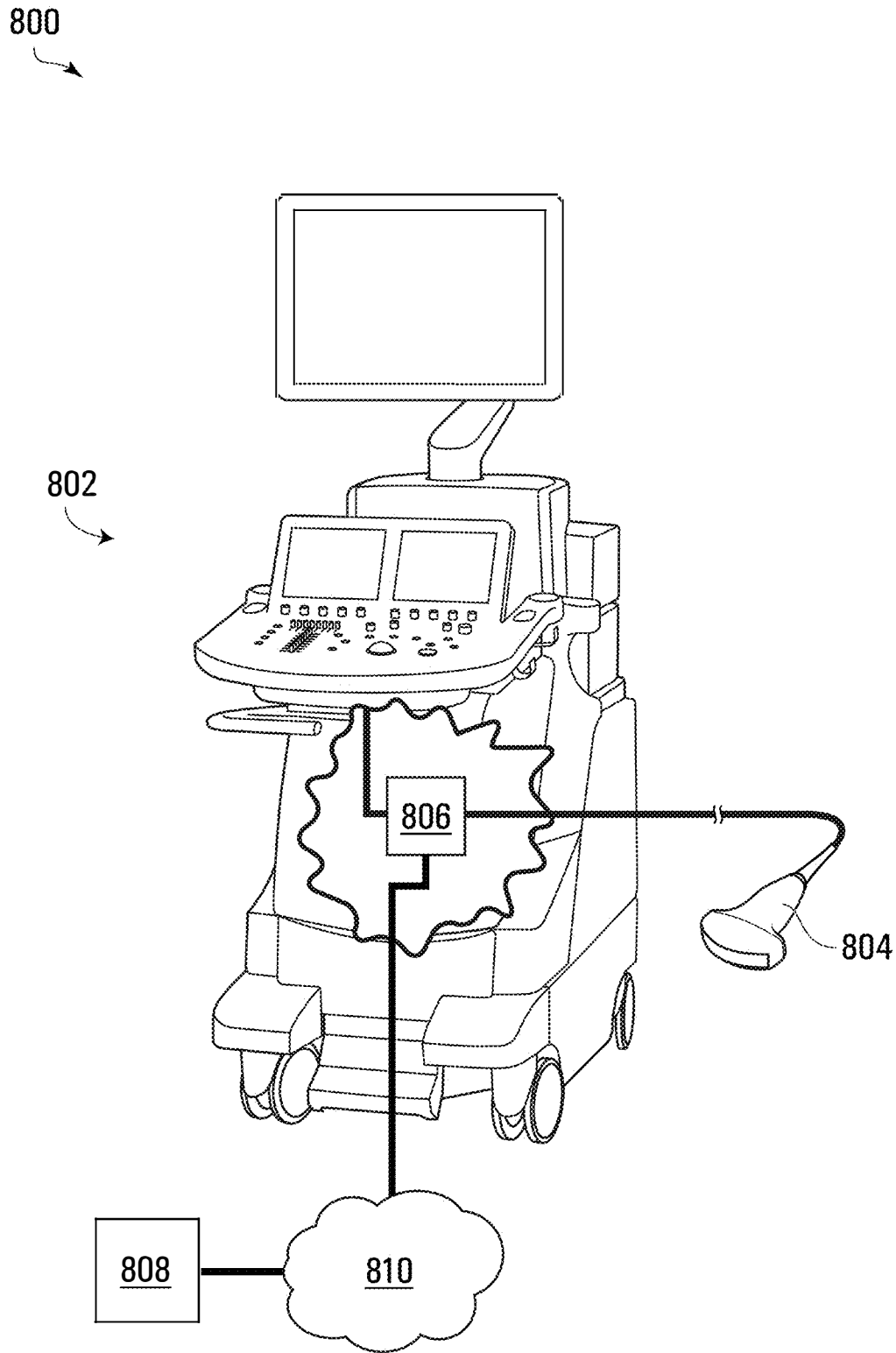


FIG. 19

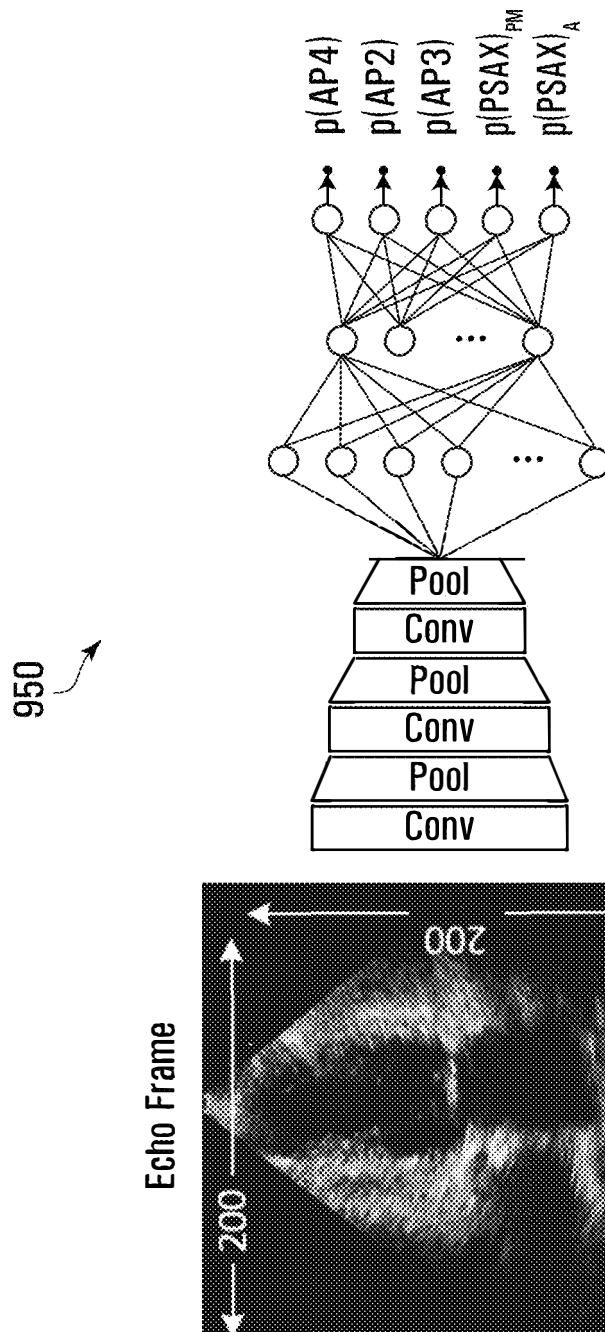


FIG. 20

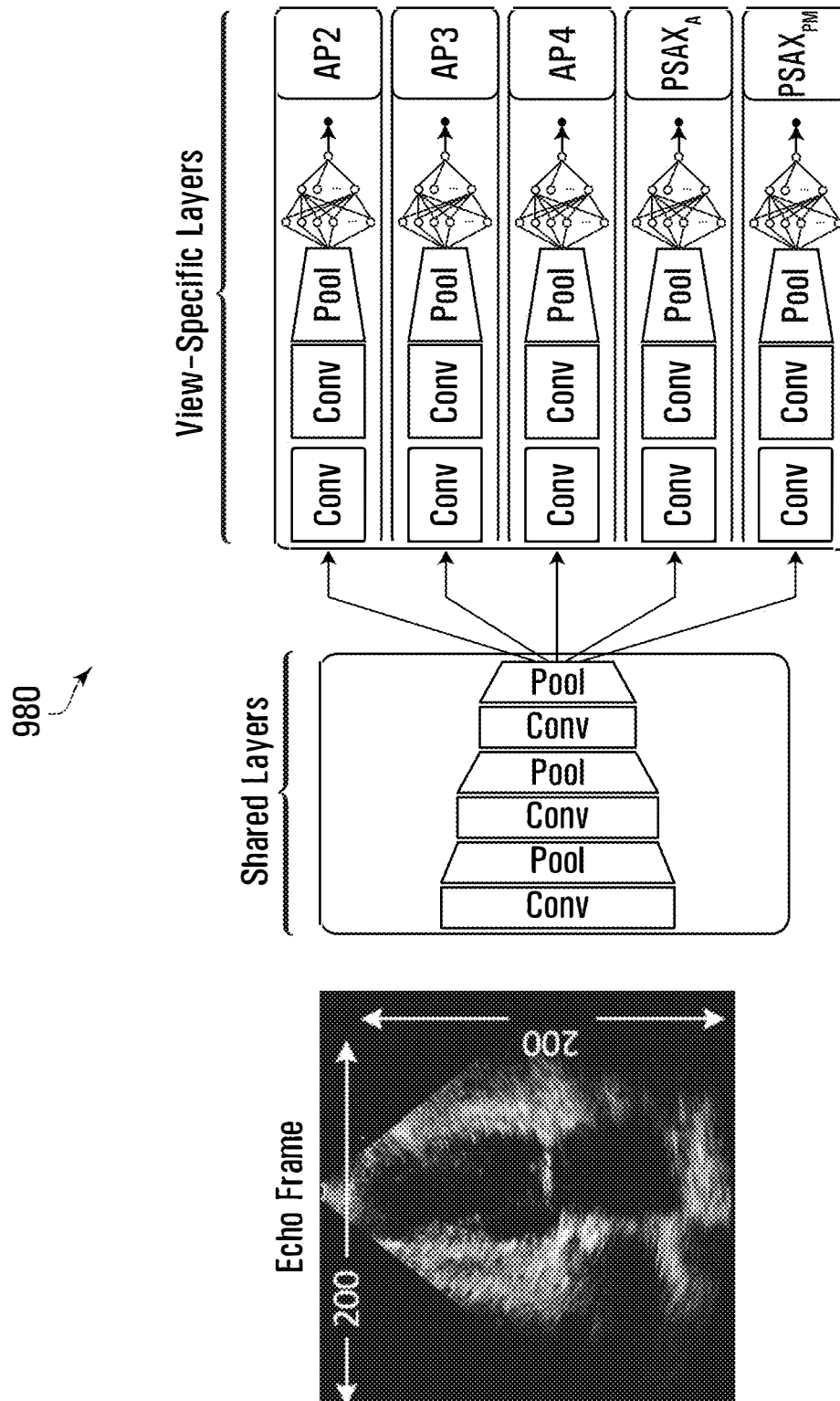


FIG. 21

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1

ECHOCARDIOGRAPHIC IMAGE ANALYSIS**RELATED APPLICATION**

This application claims the benefit of U.S. Provisional Application No. 62/325,779 entitled "PROCESS FOR IMAGING QUALITY ASSURANCE", filed on Apr. 21, 2016, which is hereby incorporated by reference herein in its entirety.

BACKGROUND**1. Field**

Embodiments of this invention relate to echocardiographic image analysis and more particularly to echocardiographic image analysis for image quality assessment.

2. Description of Related Art

Despite advances in medicine and technology, cardiovascular disease remains the leading cause of mortality worldwide. Cardiac ultrasound, better known as echocardiography (echo), is the standard method for screening, detection, and monitoring of cardiovascular disease. This noninvasive imaging modality is widely available, cost-effective, and may be used for clinical measurement of anatomical features which may then be used for evaluation of cardiac structure and/or function. Some existing echocardiographic systems may be configured to provide feedback regarding general properties of captured images. However, this feedback may not assist echocardiographers in capturing high quality echocardiographic images for use in subsequent quantified clinical measurement of anatomical features.

SUMMARY

In accordance with one embodiment, there is provided a computer-implemented system for facilitating echocardiographic image analysis. The system includes at least one processor configured to, receive signals representing a first at least one echocardiographic image, associate the first at least one echocardiographic image with a first view category of a plurality of predetermined echocardiographic image view categories, determine, based on the first at least one echocardiographic image and the first view category, a first quality assessment value representing a view category specific quality assessment of the first at least one echocardiographic image, produce signals representing the first quality assessment value for causing the first quality assessment value to be associated with the first at least one echocardiographic image, receive signals representing a second at least one echocardiographic image, associate the second at least one echocardiographic image with a second view category of the plurality of predetermined echocardiographic image view categories, said second view category being different from the first view category, determine, based on the second at least one echocardiographic image and the second view category, a second quality assessment value representing a view category specific quality assessment of the second at least one echocardiographic image, and produce signals representing the second quality assessment value for causing the second quality assessment value to be associated with the second at least one echocardiographic image.

In accordance with another embodiment, there is provided a computer-implemented system for training neural networks to facilitate echocardiographic image analysis. The

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system includes at least one processor configured to: receive signals representing a plurality of echocardiographic training images, each of the plurality of echocardiographic training images associated with one of a plurality of predetermined echocardiographic image view categories, receive signals representing expert quality assessment values representing view category specific quality assessments of the plurality of echocardiographic training images, each of the expert quality assessment values provided by an expert echocardiographer and associated with one of the plurality of echocardiographic training images, and train the neural networks using the plurality of echocardiographic training images and the associated expert quality assessment values to determine sets of neural network parameters defining the neural networks, at least a portion of each of said neural networks associated with one of the plurality of predetermined echocardiographic image view categories.

In accordance with another embodiment, there is provided a computer-implemented method of facilitating echocardiographic image analysis. The method includes receiving signals representing a first at least one echocardiographic image, associating the first at least one echocardiographic image with a first view category of a plurality of predetermined echocardiographic image view categories, determining, based on the first at least one echocardiographic image and the first view category, a first quality assessment value representing a view category specific quality assessment of the first at least one echocardiographic image, producing signals representing the first quality assessment value for causing the first quality assessment value to be associated with the first at least one echocardiographic image, receiving signals representing a second at least one echocardiographic image, associating the second at least one echocardiographic image with a second view category of the plurality of predetermined echocardiographic image view categories, said second view category being different from the first view category, determining, based on the second at least one echocardiographic image and the second view category, a second quality assessment value representing a view category specific quality assessment of the second at least one echocardiographic image, and producing signals representing the second quality assessment value for causing the second quality assessment value to be associated with the second at least one echocardiographic image.

In accordance with another embodiment, there is provided a computer-implemented method of training neural networks to facilitate echocardiographic image analysis. The method includes receiving signals representing a plurality of echocardiographic training images, each of the plurality of echocardiographic training images associated with one of a plurality of predetermined echocardiographic image view categories, receiving signals representing expert quality assessment values representing view category specific quality assessments of the plurality of echocardiographic training images, each of the expert quality assessment values provided by an expert echocardiographer and associated with one of the plurality of echocardiographic training images, and training the neural networks using the plurality of echocardiographic training images and the associated expert quality assessment values to determine sets of neural network parameters defining the neural networks, at least a portion of each of said neural networks associated with one of the plurality of predetermined echocardiographic image view categories.

In accordance with another embodiment, there is provided a computer readable medium having stored thereon codes

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which when executed by at least one processor cause the at least one processor to perform any of the above methods.

In accordance with another embodiment, there is provided a system for facilitating echocardiographic image analysis. The system includes means for receiving signals representing a first at least one echocardiographic image, means for associating the first at least one echocardiographic image with a first view category of a plurality of predetermined echocardiographic image view categories, means for determining, based on the first at least one echocardiographic image and the first view category, a first quality assessment value representing a view category specific quality assessment of the first at least one echocardiographic image, means for producing signals representing the first quality assessment value for causing the first quality assessment value to be associated with the first at least one echocardiographic image, means for receiving signals representing a second at least one echocardiographic image, means for associating the second at least one echocardiographic image with a second view category of the plurality of predetermined echocardiographic image view categories, said second view category being different from the first view category, means for determining, based on the second at least one echocardiographic image and the second view category, a second quality assessment value representing a view category specific quality assessment of the second at least one echocardiographic image, and means for producing signals representing the second quality assessment value for causing the second quality assessment value to be associated with the second at least one echocardiographic image.

In accordance with another embodiment, there is provided a system for training neural networks to facilitate echocardiographic image analysis. The system includes means for receiving signals representing a plurality of echocardiographic training images, each of the plurality of echocardiographic training images associated with one of a plurality of predetermined echocardiographic image view categories, means for receiving signals representing expert quality assessment values representing view category specific quality assessments of the plurality of echocardiographic training images, each of the expert quality assessment values provided by an expert echocardiographer and associated with one of the plurality of echocardiographic training images, and means for training the neural networks using the plurality of echocardiographic training images and the associated expert quality assessment values to determine sets of neural network parameters defining the neural networks, at least a portion of each of said neural networks associated with one of the plurality of predetermined echocardiographic image view categories. Other aspects and features of embodiments of the invention will become apparent to those ordinarily skilled in the art upon review of the following description of specific embodiments of the invention in conjunction with the accompanying figures.

BRIEF DESCRIPTION OF THE DRAWINGS

In drawings which illustrate embodiments of the invention,

FIG. 1 is a schematic view of a system for facilitating echocardiographic image analysis in accordance with various embodiments of the invention;

FIG. 2 is a schematic view of an echocardiographic image analyzer of the system of FIG. 1 including a processor circuit in accordance with various embodiments of the invention;

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

FIG. 4 is a representation of an exemplary image file that may be used in the system shown in FIG. 1;

FIG. 5 is a flowchart depicting blocks of code that may be included in the flowchart of FIG. 3 in accordance with various embodiments of the invention;

FIG. 6 is a representation of an exemplary view category determining neural network that may be used in the system shown in FIG. 1;

FIG. 7 is a representation of an exemplary view category record that may be used in the system shown in FIG. 1;

FIG. 8 is a representation of an exemplary image quality assessment neural network that may be used in the system shown in FIG. 1;

FIG. 9 is a representation of an exemplary common neural network record that may be used in the system shown in FIG. 1;

FIG. 10 is a representation of an exemplary view category specific neural network record that may be used in the system shown in FIG. 1;

FIG. 11 is a flowchart depicting blocks of code that may be included in the flowchart of FIG. 3 in accordance with various embodiments of the invention;

FIG. 12 is a representation of an exemplary quality assessment record that may be used in the system shown in FIG. 1;

FIG. 13 is a representation of a display that may be presented by a display of a user interface system included in the system shown in FIG. 1 in accordance with embodiments of the invention;

FIG. 14 is a schematic view of a system for training neural networks to facilitate echocardiographic image analysis in accordance with various embodiments of the invention;

FIG. 15 is a schematic view of a neural network trainer of the system of FIG. 1 including a processor circuit in accordance with various embodiments of the invention;

FIG. 16 is a flowchart depicting blocks of code for directing the trainer of the system of FIG. 14 to perform image assessment neural network training functions in accordance with various embodiments of the invention;

FIG. 17 is a representation of an exemplary training image file that may be used in the system shown in FIG. 1;

FIG. 18 is a representation of an exemplary expert quality assessment record that may be used in the system shown in FIG. 1;

FIG. 19 is a schematic view of a system for facilitating echocardiographic image analysis in accordance with various embodiments of the invention;

FIG. 20 is a representation of an exemplary view category determining neural network that may be used in the system shown in FIG. 1; and

FIG. 21 is a representation of an exemplary image quality assessment neural network that may be used in the system shown in FIG. 1.

DETAILED DESCRIPTION

Referring to FIG. 1, according to one embodiment of the invention, there is provided a system 10 for facilitating echocardiographic image analysis. The system 10 includes a computer-implemented echocardiographic image analyzer 12 in communication with a user interface system 14 and a transducer 16. In the embodiment shown, the analyzer 12 is also in communication with a network 126 and the user

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interface system **14** includes a display **15**. In various embodiments, the system **10** may be incorporated within an ultrasound machine or scanner. For example, in various embodiments, the system **10** may be included in an ultrasound machine generally similar to a Philips™ IE33 Ultra-

sound machine or a mobile ultrasound machine made by Clarius™. In operation, an operator of the system **10**, who may be for example, an echocardiographer, technician, or sonographer, may manipulate the transducer **16** on or around a patient, and the analyzer **12** may communicate with the transducer **16** and receive signals representing echocardiographic images of the patient. The analyzer **12** may store representations of the echocardiographic images in memory and/or output representations of the images on the display **15**. The analyzer **12** may determine a quality assessment value representing a quality assessment of at least one echocardiographic image and produce signals for causing the quality assessment value to be associated with the at least one echocardiographic image. For example, the analyzer **12** may be configured to produce signals for causing the display **15** to display a sequence of echocardiographic images captured by the analyzer **12** in near real-time, in association with the determined quality assessment value for the images. In some embodiments, the quality assessment value may be determined for a single image. In some embodiments, the quality assessment value may be determined for a sequence of images or video, which may be referred to herein as an echo-

cine. In various embodiments, this near real-time feedback to the operator may help the operator improve their skills and/or improve image quality for subsequently captured images. For example, in some embodiments, the operator may, in response to viewing a low quality assessment value on the display **15**, adjust positioning of the transducer and/or adjust image capture parameters, such as, for example, depth, focus, gain, frequency, and/or another parameter which may affect image quality in the system **10**. The operator may make such adjustments until a high quality assessment value is provided on the display **15**, for example, at which point the operator may be confident that the echocardiographic images captured are suitable for subsequent quantified clinical measurement of anatomical features and/or to assist in diagnosing a medical condition or a characteristic of the heart.

In various embodiments, the operator may wish to capture echocardiographic images for various views or anatomical planes since multiple views may be required in order to perform certain quantified clinical measurement of anatomical features and/or to assist in diagnosing a medical condition or a characteristic of the heart. In some embodiments, the views required for certain measurements or diagnoses may be chosen from standard 2D echocardiographic views. For example, the operator may wish to capture echocardiographic images of multiple standard 2D echocardiographic views to facilitate image analysis to determine ejection fraction for the patient's heart. For example, in some embodiments, a 2D Method of Simpson may be used to determine ejection fraction, which requires images from AP2 (apical 2-chamber view) and AP4 (apical 4-chamber view).

In various embodiments, some of the desirable characteristics for each of the different views may differ and so it may be desirable to determine quality assessment values for the echocardiographic images in different ways, depending on what view the echocardiographic images are meant to represent. Accordingly, the analyzer **12** may be configured to

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associate each set of echocardiographic images with a view category of a plurality of predetermined echocardiographic image view categories and to select and apply a function to the set of images to determine the quality assessment value wherein the function selected depends on the view category associated with the set of images. In some embodiments, the analyzer **12** may be configured to automatically determine the view category to associate with the set of images by analyzing the set of images. In some embodiments, the analyzer **12** may be configured to receive operator input (via the user interface system **14**, for example), which sets the view category with which to associate the image.

Applying the function to a set of images may involve inputting the set of images into a view category specific image assessment neural network which is configured to output a view category specific quality assessment value. The quality assessment value may represent an assessment of suitability of the associated set of echocardiographic images for quantified clinical measurement of anatomical features.

Image Analyzer—Processor Circuit

Referring now to FIG. 2, a schematic view of the analyzer **12** of the system **10** shown in FIG. 1 according to an embodiment is shown. As discussed above, in various embodiments, the analyzer **12** may be included in an ultrasound machine, for example.

Referring to FIG. 2, the analyzer **12** includes a processor circuit including an analyzer processor **100** and a program memory **102**, a storage memory **104**, and an input/output (I/O) interface **112**, all of which are in communication with the analyzer processor **100**. In various embodiments, the analyzer processor **100** may include one or more processing units, such as for example, a central processing unit (CPU), a graphical processing unit (GPU), and/or a field programmable gate arrays (FPGA). In some embodiments, any or all of the functionality of the analyzer **12** described herein may be implemented using one or more FPGAs.

The I/O interface **112** includes an interface **120** for communicating with the transducer **16** and an interface **122** for communicating with the user interface system **14** shown in FIG. 1. In some embodiments, the I/O interface **112** may also include an interface **124** for facilitating networked communication through the network **126**. In some embodiments, any or all of the interfaces **120**, **122**, or **124** may facilitate a wireless or wired communication.

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

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

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

Processor-executable program codes for directing the analyzer processor **100** to carry out various functions are stored in the program memory **102**. Referring to FIG. 2, the program memory **102** includes a block of codes **160** for directing the analyzer **12** to perform image capture functions and analysis functions and a block of codes **162** for directing

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the analyzer processor **100** to perform image reconstruction functions. In this specification, it may be stated that certain encoded entities such as applications or modules perform certain functions. Herein, when an application, module or encoded entity is described as taking an action, as part of, for example, a function or a method, it will be understood that at least one processor (e.g. the analyzer processor **100**) is directed to take the action by way of programmable codes or processor-executable codes or instructions defining or forming part of the application.

The storage memory **104** includes a plurality of storage locations including location **140** for storing image data, location **142** for storing view category data, location **144** for storing view category neural network parameter data, location **146** for storing image assessment neural network parameter data, and location **148** for storing determined quality assessment value data. In various embodiments, the plurality of storage locations may be stored in a database in the storage memory **104**.

In various embodiments, the blocks of codes **160** and **162** may be integrated into a single block of codes and/or each of the blocks of code **160** and **162** may include one or more blocks of code stored in one or more separate locations in program memory **102**. In various embodiments, any or all of the locations **140**, **142**, **144**, and **146** may be integrated and/or each may include one or more separate locations in the storage memory **104**.

Each of the program memory **102** and storage memory **104** may be implemented as one or more storage devices including random access memory (RAM), a hard disk drive (HDD), a solid-state drive (SSD), a network drive, flash memory, a memory stick or card, any other form of non-transitory computer-readable memory or storage medium, and/or a combination thereof. In some embodiments, the program memory **102**, the storage memory **104**, and/or any portion thereof may be included in a device separate from the analyzer **12** and in communication with the analyzer **12** via the I/O interface **112**, for example.

In various embodiments, other device components described herein, such as memory, program memory, blocks of code, storage memory, locations in memory, and/or I/O interfaces, may be implemented generally similarly to as described above for the analyzer **12**.

Image Analysis

Referring now to FIG. 3, a flowchart depicting blocks of code for directing the analyzer processor **100** shown in FIG. 2 to perform image analysis functions in accordance with one embodiment is shown generally at **200**. The blocks of code included in the flowchart **200** may be encoded in the block of codes **160** of the program memory **102** shown in FIG. 2 for example.

Referring to FIG. 3, the flowchart **200** begins with block **202** which directs the analyzer processor **100** shown in FIG. 2 to receive signals representing at least one echocardiographic image. In various embodiments, block **202** may direct the analyzer processor **100** to obtain image data via the transducer **16**. For example, block **202** may direct the analyzer processor **100** to execute blocks included in the block of codes **162** of the program memory **102**, to cause the analyzer processor **100** to receive signals representing at least one echocardiographic image from the transducer **16** shown in FIG. 1 via the interface **120** of the I/O interface. The blocks in the block of codes **162** of the program memory **102** may direct the analyzer processor **100** to interpret raw ultrasound echo waveforms received from the transducer **16** into fully formed images. The block of codes **162** may direct the analyzer processor **100** to use an image reconstruction

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algorithm to filter the waveforms, amplify the waveforms, time delay and sum the waveforms, demodulate the summed waveforms, and/or compress amplitudes of the summed waveforms. The block of codes **162** may direct the analyzer processor **100** to finally perform a scan-conversion of the waveforms to derive an image in Cartesian coordinates with pixels of known size in millimeters.

Block **202** may direct the analyzer processor **100** to store a representation of the received at least one echocardiographic image in the location **140** of the storage memory **104**.

In some embodiments, the analyzer **12** may be configured to receive and analyze respective sequences of echocardiographic images (echo cines). Accordingly, block **202** may direct the analyzer processor **100** to receive a sequence of images. Block **202** may direct the analyzer processor **100** to store a set of image files representing the sequence of images in the location **140** of the storage memory **104**. An exemplary image file which may be included in the set of image files received at block **202** is shown at **240** in FIG. 4.

Referring to FIG. 4, the image file **240** includes an image identifier field **242** for storing a unique identifier for identifying the image data stored in the image file **240**, an image group identifier field **243** for storing an identifier common to a set of image files which are to be analyzed together (e.g. frames of an echo cine), and an image data field **244** for storing information representing an image. In some embodiments, for example, the image file **240** may store a PNG file type representation of the echocardiographic image.

In some embodiments, block **202** may direct the analyzer processor **100** to receive and store a plurality of image files generally similar to the image file **240** shown in FIG. 4 in the location **140** of storage memory **104** for analysis together during execution of block **206** of the flowchart **200** shown in FIG. 3. For example, in some embodiments, the analyzer **12** may be configured to analyze a sequence of 20 images during execution of block **206** of the flowchart **200** and so block **202** may direct the analyzer processor **100** to store the received images as groups of 20 image files, each generally similar in format to the image file **240** shown in FIG. 4 and sharing a common value in their image group identifier fields.

Referring back to FIG. 4, block **204** then directs the analyzer processor **100** to associate the at least one echocardiographic image received at block **202** with a view category of a plurality of predetermined echocardiographic image view categories. In some embodiments, block **204** may direct the analyzer processor **100** to associate the at least one echocardiographic image with the view category by storing in the location **142** of the storage memory **104** a view category record that associates the view category with the received at least one echocardiographic image.

In various embodiments, associating the at least one echocardiographic image with a particular view category may assist with subsequent quality assessment of the echocardiographic images which may be performed at block **206** of the flowchart **200** shown in FIG. 3. In some embodiments, the view category that is associated with the at least one echocardiographic image may be associated with a function which can be applied to the at least one echocardiographic image to assess the quality of the at least one echocardiographic image. For example, in some embodiments, different analyses may be applied to a set of echocardiographic images, depending on which view category set of echocardiographic images falls within.

In some embodiments, the view categories with which the echocardiographic images may be associated may be chosen

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from a plurality of standard view categories. For example, the standard view categories may include the following 2D echocardiographic imaging plane views: AP2 (apical 2-chamber view), AP3 (apical 3-chamber view), AP4 (apical 4-chamber view), PSAX_A (parasternal short axis at aortic valve level view) and PSAX_{PM} (parasternal short axis at papillary muscle level view). In various embodiments, the standard view categories may include further or alternative view categories, such as, for example, any or all of the following 2D echocardiographic imaging plane view categories: parasternal long axis (PLAX), apical 5 chamber (AP5), subcostal view, aortic arch, or right parasternal. In various embodiments, with any of these views, an operator may switch the system 10 to Doppler and obtain 2D Color Doppler or Power Doppler, Continuous Wave Doppler and Duplex Doppler. In various embodiments, each view category may be associated with a different function for assessing quality of images.

In some embodiments, the block 204 may direct the analyzer processor 100 to determine which of the plurality of predetermined view categories the at least one echocardiographic image falls within before associating the image with the view category.

For example, in some embodiments, this determination may be made automatically, such as by applying a function to the received at least one echocardiographic image. Referring to FIG. 5, there is shown at 260 a flowchart representing blocks of codes which may be included in the block 204 of the flowchart 200 shown in FIG. 3, in accordance with various embodiments. The blocks of codes included in the flowchart 260 may direct the analyzer processor 100 to apply one or more view categorization functions to the at least one echocardiographic image received at block 202 to determine which of a plurality of predetermined view categories the at least one echocardiographic image falls within.

Referring to FIG. 5, the flowchart 260 begins with block 262 which directs the analyzer processor 100 to receive signals representing parameters defining an image view category determining neural network. The image view category determining neural network may be configured to take the at least one echocardiographic images received at block 202 as an input and to output an indication of what image view category should be associated with the input at least one echocardiographic image.

Block 262 may direct the analyzer processor 100 to receive parameters defining the image view category determining neural network from the location 144 of the storage memory shown in FIG. 2, for example. The parameters defining the view category determining neural network may have been previously determined during training of the neural network and stored in the location 144 of the storage memory 104.

In some embodiments, a neural network trainer (for example, as shown at 502 in FIG. 14) may have previously determined architecture and weight and bias values for the view category determining neural network. Blocks of code included in the block of codes 160 of the program memory 102 may have previously directed the analyzer processor 100 to receive signals representing the architecture and weight and bias values via the interface 124 of the I/O interface 112 and to store a view category neural network record representing the architecture and the weight and the bias values in the location 144 of the storage memory 104.

In some embodiments, the view category neural network record stored in the location 144 of the storage memory may represent a neural network having convolutional layers,

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max-pooling layers, one or more fully connected layers, one or more Long Short Term Memory (LSTM) layers, and a softmax layer acting as an output layer and having outputs which represent a likelihood that an input set of echocardiographic images falls within a particular view category. In some embodiments, the softmax outputs may indicate whether a set of echocardiographic images falls within one of the following standard 2D echocardiographic views, for example: AP2, AP3, AP4, PSAX_A, or PSAX_{PM}. An exemplary view category determining neural network that may be represented by the view category neural network record stored in the location 144 of the storage memory, in accordance with some embodiments, is shown at 900 in FIG. 6. The view category determining neural network takes as input, a sequence of 20 echocardiographic images, and outputs respective indicators that represent respective likelihoods that an input sequence of 20 echocardiographic images fall within a particular view category.

Referring back to FIG. 5, block 264 of the flowchart 260 then directs the analyzer processor 100 to apply the view category determining neural network defined by the parameters received at block 262 to the at least one echocardiographic image received at block 202 of the flowchart 200 shown in FIG. 3. Block 264 may direct the analyzer processor 100 to use the image data fields 244 of the 20 image files stored in the location 140 of the storage memory 104 at block 202 as input data for the view category determining neural network defined by the view category neural network record taken from the location 144 of the storage memory 104.

In some embodiments, the output of the neural network may be a softmax output which provides respective indicator values representing whether the set of images received at block 202 are AP2, AP3, AP4, PSAX_A, and PSAX_{PM}. In one embodiment, these indicator values may be 0.11, 0.05, 0.7, 0.11, 0.03, respectively, for example. In various embodiments, although the indicator values sum to 1.00, these values may not represent true probabilities that the at least one image received is of a particular view, as there may be a possibility that the at least one image is none of the views.

In some embodiments, block 264 of the flowchart 260 shown in FIG. 5 may direct the analyzer processor 100 to use a GPU included in the analyzer processor 100 to perform the neural network calculations. In some embodiments, use of the GPU instead of a general CPU may reduce the execution time for block 264.

Referring to FIG. 5, block 266 of the flowchart 260 then directs the analyzer processor 100 to associate the at least one echocardiographic image received at block 202 of the flowchart 200 shown in FIG. 3 with a view category based on the output of the neural network. In some embodiments, block 266 may direct the analyzer processor 100 to associate the at least one echocardiographic image with a view category that corresponds to the highest softmax output determined at block 264 of the flowchart 260 shown in FIG. 5. For example, with a softmax output which provides respective indicators for AP2, AP3, AP4, PSAX_A, and PSAX_{PM} of 0.11, 0.05, 0.7, 0.11, 0.03, block 266 may direct the analyzer processor 100 to determine which output is the largest (i.e., the AP4 view category output) and to associate the images with that output.

Block 266 may direct the analyzer processor 100 to associate the at least one echocardiographic image received at block 202 of the flowchart 200 shown in FIG. 3 with the AP4 view category by generating a view category record 300 as shown in FIG. 7 and storing the view category record 300 in the location 142 of the storage memory 104. Refer-

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ring to FIG. 7, the view category record 300 includes a view category identifier field 302 for storing an identifier for identifying the view category to be associated with the echocardiographic images and an image group identifier field 304 for storing an identifier for identifying the images with which the view category is to be associated.

In some embodiments, block 204 of the flowchart 200 shown in FIG. 3 may not include the blocks depicted in the flowchart 260, but rather an operator of the system 10 shown in FIG. 1 may input a view category by which the operator wishes to have the received echocardiographic images assessed. For example, in some embodiments, the operator may input a desired view category using an input device such as a keyboard and/or pointer or mouse of the user interface system 14. In such embodiments, block 204 may direct the analyzer processor 100 to receive operator input representing the view category via the interface 122 of the I/O interface 112 shown in FIG. 2. Block 204 may direct the analyzer processor 100 to, in response to receiving the input, generate and store a view category record in the location 142 of the storage memory 104 associating the received at least one echocardiographic image with the view category that the operator provided as input.

Referring back to FIG. 3, after block 204 has been executed, the at least one echocardiographic image received at block 202 may now be associated with a view category.

The flowchart 200 continues at block 206, which directs the analyzer processor 100 to determine, based on the at least one echocardiographic image received at block 202 and the view category associated with the echocardiographic image, a quality assessment value representing a view category specific quality assessment of the at least one echocardiographic image.

In some embodiments, each of the view categories may be associated with a function which can be applied by the analyzer to the received at least one echocardiographic image to generate the quality assessment value. In some embodiments, block 206 may direct the analyzer processor 100 to select a function to apply to the at least one echocardiographic image based on the view category associated with the received at least one echocardiographic image.

In various embodiments, applying the function may involve applying a neural network to the at least one echocardiographic image. A neural network is a non-linear model and so, in some embodiments, by using a neural network to analyze the echocardiographic images, the analyzer 12 may facilitate better functioning, for example, when there is variability in the echocardiographic image data than may be possible when analysis of the echocardiographic image relies on an average template or atlas with average shape.

Referring to FIG. 2, in various embodiments, a plurality of sets of parameters, each set defining a neural network, may be stored in the location 146 of the storage memory 104 shown in FIG. 2 and each of the sets of parameters may be associated with a view category to indicate that the set of parameters defines a neural network that is to be applied to echocardiographic images which are associated with that view category.

In some embodiments, the parameters may define neural network architectures and may include weight and bias values for the neural networks. A neural network trainer (for example, as shown at 502 in FIG. 14) may have previously determined the neural network architecture and/or the weight and bias values for each of the neural networks and provided these values to the analyzer 12. Blocks of code included in the block of codes 160 of the program memory

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102 may have previously directed the analyzer processor 100 to receive signals representing the neural network architecture and the weight and bias values via the interface 124 of the I/O interface 112, for example, and to store this information in image assessment neural network records in the location 146 of the storage memory 104.

For example, in some embodiments, the image assessment neural network records stored in the location 146 of the storage memory 104 may represent the neural network shown at 360 in FIG. 8. Referring to FIG. 8, the neural network 360 includes 5 image quality assessment neural networks, each including the same shared layers 362 but including a different set of view category specific layers 370, 372, 374, 376, and 378. In various embodiments, the shared layers 362 and the view category specific layers 370, 372, 374, 376, and 378 may each be considered neural networks and it will be understood that a neural network may include more than one neural network within. Each of the 5 image quality assessment neural networks takes as an input a sequence of 20 echocardiographic images 380 and outputs a view category specific quality assessment value.

The neural network 360 shown in FIG. 8 is a deep neural network and a regression model, consisting of convolutional (conv), pooling (pool), and Long Short Term Memory (LSTM) layers, and in various embodiments, may be simultaneously trained to estimate the quality of a sequence of 20 echocardiographic images for any of five standard 2D echocardiographic views, AP2, AP3, AP4, PSAX_A, and PSAX_{PM} by generating respective view category specific quality assessment values.

The neural network architecture, depicted in FIG. 8, represents a multi-stream network, i.e., five regression models that share weights across the first few common shared layers 362. Each stream of the network has its own view-specific layer 370, 372, 374, 376, and 378 and has been trained based on the mean absolute error loss function, via a stochastic gradient-based optimization algorithm, to minimize the absolute difference between normalized quality assessment values assigned by a trained echocardiographer to training images, as discussed further below, and the generated quality assessment values.

In the embodiment shown, all conv layers have kernels with the size of 3x3, which may, for example, follow the VGG architecture discussed in Simonyan, K., Zisserman, A.: Very Deep Convolutional Networks for Large-Scale Image Recognition. International Conference on Learning Representations (ICRL) pp. 1-14 (2015), with the number of kernels doubling for deeper conv layers, i.e., from 8 to 32 kernels. In some embodiments, the conv layers may extract hierarchical features in the image, with the first three shared layers 362 modeling high level spatial correlations, and the next two conv layers of the view category specific layers 364 focusing on view-specific quality features. In some embodiments, activation functions of the conv layers may be Rectified Linear Units (ReLUs).

Referring still to FIG. 8, in various embodiments, the pool layers of the neural network 360 may be 2x2 max-pooling with a stride of 2 to facilitate selection of superior invariant features and divide the input feature-map size in half in both dimensions to reduce feature variance and train more generalized models. The conv and pool layers are applied to each image of an input echo cine, independently.

The output feature map of the last pool layer is flattened and sent to an LSTM unit, a type of Recurrent Neural Networks (RNN) that uses a gated technique to selectively add or remove information from the cell state. Each set of view category specific layers 370, 372, 374, 376, and 378 in

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the neural network **360** shown in FIG. **8** uses a single LSTM cell to analyze 20 feature-sets corresponding to the 20 consecutive input images. The LSTM layer uses hard sigmoid functions for inner and output activations.

In some embodiments, the image assessment neural network records stored in the location **146** of the storage memory **104** which represent the neural network **360** may include a common neural network record representing the shared layers **362** and a plurality of different view category specific neural network records representing the sets of view category specific layers **370**, **372**, **374**, **376**, and **378**.

A representation of a portion of an exemplary common neural network record for storing a set of parameters defining the shared layers **362** of the neural network **360** shown in FIG. **8**, is shown at **320** in FIG. **9**. Referring to FIG. **9**, the common neural network record **320** includes first, second, third, fourth, fifth and sixth sets of fields **324**, **326**, **328**, **330**, **332**, and **334** defining the parameters for the six layers of the shared layers **362** of the neural network **360** shown in FIG. **8**. For ease of reference, not all kernel fields of the common neural network record **320** are shown in FIG. **9** and the content of the kernels is shown as [. . .], though it will be understood that there are 8 kernels in layer **1**, 16 kernels in layer **3** and 32 kernels in layer **5** and that each kernel field stores a 3x3 matrix of values.

A representation of a portion of an exemplary view category specific neural network record for storing a set of parameters defining the set of view category specific layers **374** of the neural network **360** shown in FIG. **8**, is shown at **340** in FIG. **10**. Referring to FIG. **10**, the view category specific neural network record **340** includes a view category identifier field **342** for storing a view category identifier identifying which view category the record is associated with and seventh, eighth, ninth, and tenth sets of fields **344**, **346**, **348**, and **350** for storing parameters defining the set of view category specific layers **374** of the neural network **360** shown in FIG. **8**. For ease of reference, not all kernel fields are shown in FIG. **10** and the content of the kernels and LSTM parameters are shown as [. . .], though it will be understood that there are 32 kernels in layer **7** and 32 kernels in layer **9** and that each kernel field stores a 3x3 matrix of values and the LSTM parameter fields store values defining the parameters of the LSTM.

Additional neural network records representing the sets of shared layers **370**, **372**, **376** and **378** having generally the same format as the view category specific neural network record **340** shown in FIG. **10** may also be stored in the location **146** of the storage memory **104**. Thus, each of the image view categories AP2, AP3, AP4, PSAX_A, and PSAX_{PM} may be associated with a view category specific neural network record stored in the location **146** of the storage memory **104**.

In various embodiments, splitting the neural network **360** into a common portion and view category specific portions may facilitate more efficient training of the neural networks. In some embodiments, splitting the neural network **360** into a common portion and view category specific portions may result in requiring fewer learning parameters than would be required if using fully separate neural networks, which may help facilitate easier transferring of a neural network to a new machine, and/or may reduce memory usage.

Referring now to FIG. **11**, there is shown at **400** a flowchart representing blocks of codes which may be included in the block **206** of the flowchart **200** shown in FIG. **3**, in accordance with various embodiments. The blocks included in the flowchart **400** may direct the analyzer processor **100** to determine which of the sets of quality

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assessment parameters is associated with the same view category as the at least one echocardiographic image received at block **202** and to apply a function based on that set of quality assessment parameters.

The flowchart **400** begins with block **402** which directs the analyzer processor **100** to determine that a set of assessment parameters of the sets of assessment parameters stored in the location **146** is associated with the same view category that is associated with the at least one echocardiographic image received at block **202**.

For example, in some embodiments, block **402** may direct the analyzer processor **100** to read "AP4" from the view category identifier field **302** of the view category record **300** associated with the echocardiographic image files received at block **202**. Block **402** may direct the analyzer processor **100** to read the view category specific neural network records from the location **146** of the storage memory to find a view category specific neural network record that includes the same view category identifier of "AP4" and is therefore associated with the same view category. Accordingly, block **402** may direct the analyzer processor **100** to determine that the view category specific neural network record **340** includes the view category identifier of "AP4" and is therefore associated with the same view category that is associated with the at least one echocardiographic image received at block **202**.

Block **404** then directs the analyzer processor **100** to, in response to determining that the set of assessment parameters is associated with the same view category, apply a function based on the set of assessment parameters to the at least one echocardiographic image received at block **202**. In some embodiments, block **404** may direct the analyzer processor **100** to apply the neural network defined by the parameters included in the common neural network record **320** and the view category specific neural network record **340** to the image data in the image files received at block **202**.

Block **404** may direct the analyzer processor **100** to read the image files received at block **202** from the location **140** of the storage memory **104** and to read the common neural network record **320** and the view category specific neural network record **340** from the location **146** of the storage memory, and to input the image data from the image files into a neural network that includes the shared layers **362** and the view category specific layers **374** shown in FIG. **8**, which are defined by the common neural network record **320** and the view category specific neural network record **340**, to generate or determine a view category specific quality assessment value as an output of the neural network.

In some embodiments, the quality assessment value may represent a suitability for a quantified clinical measurement. In some embodiments, the quality assessment value may represent an estimate of an expected score which would be provided by an expert to the input at least one echocardiographic image. The estimate may be based on the training of the neural network wherein an expert provided quality assessment values for various echocardiographic images.

In some embodiments, the quality assessment value may be a score with criteria and/or a range that varies depending on the view category with which the neural network is associated. In some embodiments, the expert which provided the quality assessment values with which the neural network was trained may have determined the quality assessment values as an aggregation of scores derived using semi-quantitative evaluation of component structures and parameter optimization features such as centering, depth, gain, axis, focus, frequency or another parameter optimization

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tion feature or image capture parameter. Accordingly, in various embodiments, the quality assessment value may represent an estimate of an expected aggregation of scores derived using semi-quantitative evaluation of component structures and parameter optimization features such as centering, depth, gain, axis, focus, frequency or another parameter optimization feature or image capture parameter.

For example, in some embodiments, an expert may have, for each at least one echocardiographic image that they assessed, determined for each component in the at least one echocardiographic image, a component quality score of up to 2 points based on the following observations: 0 points) the structure was not imaged or was inadequate for assessment; 1 point) the structure was adequately viewed; 2 points) the view was optimized for the structure. In some embodiments, the component score may act as a clinical plane assessment value representing an expert opinion whether the associated echocardiographic training image was taken in an anatomical plane suitable for a quantified clinical measurement of anatomical features. The expert may have, for each at least one echocardiographic image that they assessed, determined parameter optimization scores as follows: appropriate centering (1 point), correct depth setting (0.5 points), proper gain (0.5 points), correct axis (1 point), and correct depth of focus (0.5 points). In various embodiments, the quality assessment value may represent a sum of the above-noted scores.

As discussed above, in some embodiments, images for the different view categories may include a different set of components and quality assessment values may be determined using different criteria. For example, for the AP2 view category, the left ventricle (LV), left atrium (LA), and mitral valve (MV) may each be assigned a component quality score, which may be summed with scores for centering, depth, and gain to determine the quality assessment value. For the AP3 view category, the aortic valve (AV), MV, LA, LV, and septum may each be assigned a component quality score, which may be summed with scores for centering, depth, and gain to determine the quality assessment value. For the AP4 view category, the LV, right ventricle (RV), LA, right atrium (RA), MV, and TV may each be assigned a component quality score, which may be summed with scores for centering, depth, and gain to determine the quality assessment value. For the PSAX_A view category, the AV and leaflets may each be assigned a component quality score, which may be summed with scores for centering, depth, and gain to determine the quality assessment value. For the PLAX_{PM} the papillary muscles may be assigned a component quality score, which may be summed with scores for centering, depth, gain, and axis to determine the quality assessment value.

In some embodiments, the quality assessment values for all views may be normalized to the same scale, which may be, for example, between 0 and 1 or between 0 and 5.

Referring back to FIG. 11, in some embodiments, block 404 of the flowchart 400 may direct the analyzer processor 100 to apply the neural network such that the quality assessment value and associated at least one echocardiographic image may be viewed in real-time or near-real time for the operator. For example, in some embodiments, block 404 may direct the analyzer processor 100 to apply the neural network and determine a quality assessment value in less than about 3 seconds. In some embodiments, block 404 may direct the analyzer processor 100 to apply the neural network and determine a quality assessment value in less than about 1 second. In some embodiments, block 404 may direct the analyzer processor 100 to apply the neural net-

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work and determine a quality assessment value in less than about 0.33 ms. In some embodiments, for an input echo cine of 20 images of 200×200 pixels, a quality assessment value may be determined in about 10 ms, which may be suitable for real-time or near real-time deployment. In some embodiments, block 404 may direct the analyzer processor 100 to use a GPU included in the analyzer processor 100 to apply the neural network. In some embodiments, use of the GPU instead of just a general CPU may reduce the time it takes to execute the block 404 and may thus facilitate real-time or near-real time image analysis.

Referring back to FIG. 3, the flowchart 200 continues at block 208 which directs the analyzer processor 100 to produce signals representing the quality assessment value determined at block 206, for causing the quality assessment value to be associated with the at least one echocardiographic image received at block 202.

In some embodiments, block 208 may direct the analyzer processor 100 to produce signals for causing the quality assessment value to be stored in the location 148 of the storage memory 104. For example, in some embodiments, block 208 may direct the analyzer processor 100 to store a quality assessment record 420 as shown in FIG. 12 in the location 148 of the storage memory 104, wherein the quality assessment record 420 includes an image group identifier field 422 for storing the group identifier which identifies the group of images for which the quality assessment was made and a quality assessment value field 424 for storing the quality assessment that was generated at block 404 of the flowchart 400.

In some embodiments, block 208 may direct the analyzer processor 100 to produce signals for causing a representation of the quality assessment value to be transmitted to the display 15 of the user interface system 14 for causing the display to display the quality assessment value in association with the received at least one echocardiographic image. In some embodiments, this may assist one or more operators of the system 10 in capturing subsequent echocardiographic images. For example, in some embodiments, block 208 may direct the analyzer processor 100 to communicate with the user interface system 14 of the system 10 shown in FIG. 1 via the interface 122 of the I/O interface 112 shown in FIG. 2 to cause a display 440 as shown in FIG. 13 to be presented on the display 15 of the user interface system 14.

Referring to FIG. 13, the display 440 includes a representation 442 of the quality assessment value determined at block 206 shown in association with a representation 444 of the at least one echocardiographic image received at block 202.

In some embodiments, block 208 may direct the analyzer processor 100 to transmit the quality assessment value and associated at least one echocardiographic image to another device for storage and/or further analysis. For example, in various embodiments, block 208 may direct the analyzer processor 100 to transmit a representation of the image files stored at block 202 and the quality assessment record generated at block 208 to an archive device in a picture archiving and communication system (PACS) via the interface 124 and the network 126, for example.

In various embodiments, once block 208 has been executed, the analyzer processor 100 may be directed to return to block 202 to receive further echocardiographic images. In some embodiments, the flowchart 200 may be executed continuously such that the display 440 shown in FIG. 13 is updated with near real-time updates of images or image sequences and associated quality assessment values. In some embodiments, an operator may adjust image capture

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parameters of the system **10** and/or adjust positioning of the transducer until the operator sees a desired quality assessment value.

In some embodiments, the operator may make adjustments until a quality assessment value of greater than a predetermined threshold value is achieved. In some embodiments, for example, where the quality assessment value has been normalized to a possible range of 0-5 the threshold value may be about 3.0.

In some embodiments, there may be a maximum achievable quality assessment value for a given patient and the maximum achievable quality assessment value may be dependent on the patient, given their anatomy and/or echogenicity, for example. For example, in some embodiments where the quality assessment value has been normalized to a possible range of 0-5, for many patients, the maximum achievable quality assessment value for a given view category may be about 3.0. In some embodiments, the operator may make various adjustments until a near maximum achievable quality assessment value on a given patient has been achieved.

In some embodiments, after capturing images associated with a desired quality assessment value for a first view category, the operator of the system **10** may wish to capture images for a different view category and so reposition the transducer and/or reconfigure the system **10**. For example, in some embodiments, the operator may, after capturing images of the AP4 view category, wish to capture images of one or more of the AP2, AP3, PSAX_A, and PSAX_{PM} view categories to facilitate quantified clinical measurement of anatomical features and/or to assist in diagnosing a medical condition or a characteristic of the heart. For example, in some embodiments, the operator may, after capturing at least one image of the AP4 view category, wish to capture at least one image of the AP2 view category to facilitate quantified clinical measurement of anatomical features for determining an ejection fraction.

Accordingly, the operator may reposition the transducer **16** shown in FIG. **1** and/or adjust image receiving parameters to cause the flowchart **200** to be executed one or more further times, but with echocardiographic images which are of different view categories and are to be analyzed using different parameters. In various embodiments, the analyzer **12** being configured as described above to switch between analyses of varying view categories may facilitate ease of use and/or efficient capture of subsequent high quality images of different view categories.

Neural Network Trainer

As discussed above, in various embodiments, a neural network trainer may first train neural networks to determine the architecture and/or parameters to be used by the neural networks at block **204** and/or block **206** of the flowchart **200** shown in FIG. **3**. Referring to FIG. **14**, there is shown a system **500** for facilitating training of neural networks. The system includes a neural network trainer **502** in communication with a training image source **504** and a user interface system **506**. In some embodiments, the neural network trainer **502** may also be in communication with the analyzer **12** via the network **126**.

The training image source **504** stores echocardiographic images and associated view category information which indicates what view category each of the images falls within. For example, in some embodiments, the training image source **504** may include a server computer for storing and archiving medical electronic images, such as, for example, an archive device from a picture archiving and communication system (PACS).

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The neural network trainer **502** may be configured to retrieve and/or receive the echocardiographic images, which may act as echocardiographic training images, from the training image source **504**. In some embodiments, the neural network trainer **502** may, after receiving the training images, produce signals representing the echocardiographic training images and associated view categories to cause the user interface system **506** to present the echocardiographic images and the view categories to one or more experts, such as, echocardiographers or physicians trained in echocardiography.

The experts may then provide respective quality assessment values for each of the echocardiographic images. For example, in some embodiments, the neural network trainer may be configured to produce signals for causing the user interface system **506** to present the experts with a set of echocardiographic training images and an indication of what view category the set of echocardiographic training images is to be assessed as. An echocardiographer may assess the set of echocardiographic training images and provide a quality assessment value representing a suitability of the set of images for a quantified clinical measurement. The neural network trainer **502** may store the quality assessment value in memory in association with the assessed set of echocardiographic training images.

After quality assessment values have been received and associated with each set of echocardiographic training images, the neural network trainer **502** may train neural networks using the echocardiographic training images as inputs and the associated expert quality assessment values as desired outputs to determine sets of neural network parameters defining the neural networks, wherein at least a portion of each of the neural networks is associated with one of the image view categories.

In some embodiments, the neural network trainer **502** may also train a view category determining neural network to determine sets of neural network parameters defining the view category determining neural network. The view category determining neural network may be generally as described above with reference to block **262** of the flowchart **260** shown in FIG. **5**, configured to receive one or more echocardiographic images as an input, and having a softmax layer as an output layer having outputs which represent whether the input echocardiographic images fall within a particular view category.

In some embodiments, the neural network trainer **502** may produce signals representing the parameters defining the trained neural networks for causing the parameters to be provided to a system or device configured to apply the neural networks. For example, in some embodiments, the neural network trainer **502** may transmit the neural network parameters to the analyzer **12** via the network **126** shown in FIG. **14**. Alternatively, in some embodiments, the neural network trainer **502** may produce signals for causing the sets of neural network parameters to be stored in removable memory which may be provided to the analyzer **12**.

The analyzer **12** may use the sets of neural network parameters to facilitate analysis of echocardiographic images, generally as described above with reference to the flowchart **200** shown in FIG. **3**.

Neural Network Trainer—Processor Circuit

Referring now to FIG. **15**, a schematic view of the neural network trainer **502** of the system **500** shown in FIG. **14** according to an embodiment is shown. In various embodiments, the neural network trainer **502** may be incorporated in one or more computers, for example.

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Referring to FIG. 15, the neural network trainer 502 includes a processor circuit including a trainer processor 600 and a program memory 602, a storage memory 604, and an I/O interface 612, all of which are in communication with the trainer processor 600.

The I/O interface 612 includes an interface 620 for communicating with the training image source 504 and an interface 622 for communicating with the user interface system 506 shown in FIG. 14. In some embodiments, the I/O interface 612 also includes an interface 624 for facilitating networked communication with the analyzer 12 through the network 126.

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

The storage memory 604 includes a plurality of storage locations including location 640 for storing training image data, location 642 for storing expert assessment data, location 644 for storing image assessment neural network parameter data and location 646 for storing view category neural network parameter data.

Training the Neural Networks

Referring now to FIG. 16, a flowchart depicting blocks of code for directing the trainer processor 600 shown in FIG. 15 to perform image assessment neural network training functions in accordance with one embodiment is shown generally at 700. The blocks of code included in the flowchart 700 may be encoded in the block of codes 660 of the program memory 602 shown in FIG. 15 for example.

Referring to FIG. 16, the flowchart 700 begins with block 702 which directs the trainer processor 600 shown in FIG. 15 to receive signals representing a plurality of echocardiographic training images, each of the plurality of echocardiographic training images associated with one of a plurality of predetermined echocardiographic image view categories. In some embodiments, block 702 may direct the trainer processor 600 to receive echocardiographic training images from the training image source 504 shown in FIG. 14. For example, in some embodiments, block 702 may direct the trainer processor 600 to receive sets of associated image files, which may represent respective sequences of images or videos and include common image group identifiers, from the training image source 504. Each set of image files may make up an echo cine, which is associated with a view category.

An exemplary training image file that may be received at block 702 is shown at 740 in FIG. 17. The training image file 740 includes an image identifier field 742 for storing a unique identifier for identifying an image included in the file, an image group identifier field 744 for storing an identifier common to a set of image files which include images that are to be analyzed together, a view category identifier field 746 for storing an identifier for identifying the view category within which the image falls and by which the image should be analyzed, and an image data field 748 for storing information representing the image.

Block 702 may direct the trainer processor 600 to store the training image files received at block 702 in the location 640 of the storage memory 604.

After block 702 of the flowchart 700 shown in FIG. 16 has been executed, the location 640 of the storage memory 604 shown in FIG. 17 may store a large number of image files, each having generally similar format to the training image file 740 shown in FIG. 17. For example, in some embodi-

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ments, about 2,500 echo cines of about 40 images each (about 500 echo cines of each view category) may be stored in the location 640 of the storage memory 604 and therefore about 100,000 training image files generally similar to the training image file 740 shown in FIG. 17 may be stored in the location 640 of the storage memory 104.

Referring back to FIG. 16, block 704 directs the trainer processor 600 to receive signals representing expert quality assessment values representing view category specific quality assessments of the echocardiographic training images, each of the expert quality assessment values provided by an expert echocardiographer and associated with one of the received sets of echocardiographic training images.

In some embodiments, the neural network trainer 502 may cause the echocardiographic training images to be presented to an expert and the expert may provide the expert quality assessment values. For example, block 704 may direct the trainer processor 600 to transmit the training image files to the user interface system 506 via the interface 622 of the I/O interface 612 shown in FIG. 15 to cause a display of the user interface system 506 to present one or more experts with the echocardiographic images and an indication of what view category the images are to be assessed as.

In some embodiments, the echocardiographers may be directed to provide a quality assessment value representing a suitability of the images for a quantified clinical measurement. For example, the echocardiographers may be directed to provide a quality assessment value, which represents an aggregation of scores derived using semi-quantitative evaluation of component structures and parameter optimization features such as centering, depth, gain, axis, focus, frequency or another parameter optimization feature or image capture parameter, generally as described above, with reference to flowchart 400 shown in FIG. 11.

Block 704 may direct the trainer processor 600 to receive signals representing the expert quality assessment values and to store representations of the received expert quality assessment values in the location 642 of the storage memory 604. For example, in some embodiments, block 704 may direct the trainer processor 600 to receive representations of expert quality assessment records from the user interface system 506 and to store the expert quality assessment records in the location 642 of the storage memory. An exemplary expert quality assessment record that may be received at block 704 and stored in the location 642 of the storage memory 604 is shown at 780 in FIG. 18.

Referring to FIG. 18, the expert quality assessment record 780 includes an image group identifier field 782 for storing the group identifier which identifies the set of images for which the expert quality assessment was made and an expert quality assessment value field 784 for storing the view category specific expert quality assessment value provided by the expert.

Referring back to FIG. 16, the flowchart 700 continues at block 706 which directs the trainer processor 600 shown in FIG. 15 to train neural networks using the echocardiographic training images and the associated expert quality assessment values to determine sets of neural network parameters defining the neural networks, at least a portion of each of said neural networks associated with one of the plurality of predetermined echocardiographic image view categories.

In some embodiments, block 706 may direct the trainer processor 600 to train the neural network 360 shown in FIG. 8 to determine values to be included in a common neural network record and view category specific neural network

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records stored in the location **644** of the storage memory **104**. In various embodiments, the common neural network record stored in the location **644** may have a generally similar format to that of the common neural network record **320** shown in FIG. **9** and each of the view category specific neural network records stored in the location **644** of the storage memory **604** may have a generally similar format to that of the view category specific neural network record **340** shown in FIG. **10**.

In some embodiments, the sequences of images received at block **702** may include a different number of images than can be analyzed by the neural network to be applied. For example, in some embodiments, the neural network **360** shown in FIG. **8** may be configured to take as an input 20 images and the sequences of images received at block **702** may include more than 40 images each. Accordingly, in some embodiments, before training the neural networks, block **706** may direct the trainer processor **600** to split one or more groups of echocardiographic images received at block **702** into subsets.

For example, block **706** may direct the trainer processor **600** to split each sequence of images into one or more groups of 20 image files each. In order to do this, block **706** may direct the trainer processor **600** to change the value stored in the image group identifier field for each file. Block **706** may further direct the trainer processor **600** to generate and store further expert quality assessment records as necessary such that each of the new groups of images is associated with the same quality assessment value as the original sequence of images.

Due to the storage length of heart cycles and different frame acquisition rates, number of images per cardiac cycle may vary for different image sequences. Accordingly, in some embodiments the neural network may be defined to take as input a static sequence size of nearly half the average heart cycle in the echocardiographic images received at block **702** (for example, in some embodiments 20 images), to capture the quality distribution of the echo imaging view categories. In various embodiments, by choosing a static sequence size of about half the average heart cycle, images in each sequence may not be synced with the heart cycle and this may, in some embodiments, help to ensure that the estimated quality assessment value provided after training for a given input sequence may be independent of the starting phase of the cardiac data.

Block **706** may direct the trainer processor **600** to, for each 20 image sequence of images having a common group identifier value, select a set of layers of the neural network **360** shown in FIG. **8** to train, and to train those layers. For example, for a 20 image sequence associated with the AP4 view category, block **706** may direct the trainer processor **600** to train the neural network including the shared layers **362** and the AP4 view category specific layers **374**. Block **706** may direct the trainer processor **600** to use the 20 images as inputs and to use the expert quality assessment value from an associated expert quality assessment record stored in the location **642** of the storage memory **604** as the desired output.

In some embodiments, block **706** may direct the trainer processor **600** work towards optimizing network hyper-parameters by cross-validation to try to ensure that the network can sufficiently learn the distribution of all view categories without overfitting to the training data. In some embodiments, after finalizing the network architecture, the network may be trained on all of the images stored in the location **640** of the storage memory **604**.

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In various embodiments, the shared layer **362** and the view category specific layers **370**, **372**, **374**, **376**, and **378** may be trained simultaneously. In some embodiments, batch training may be used and each batch may consist of eight sequences (or groups of images) from each view, for example, wherein each sequence is a set of 20 consecutive gray-scale images of 200x200 pixels, with no preprocessing applied to the images.

In some embodiments, the neural networks may be trained using the adam optimizer with hyper-parameters as suggested by Kingma, D. P., Ba, J. L.: Adam: a Method for Stochastic Optimization, International Conference on Learning Representations 2015 pp. 1-15 (2015). The weight of the cony layers may be initialized randomly from a zero-mean Gaussian distribution. To try to prevent the neural network from overfitting on the training data, l_2 norm regularization may be added to the weights of the cony kernels. In some embodiments, Keras deep learning library with TensorFlow™ backend, may be used to train and test the models.

In some embodiments, to prevent co-adaptation of features and overfitting on the training data, a dropout layer with the dropout probability of 0.5 may be used after the third pooling layer.

After training has been completed, the sets of parameters stored in the location **646** of the storage memory **104** may represent a trained echocardiographic image quality assessment neural network that includes shared layers and a plurality of view category specific layers.

Referring back to FIG. **16**, in some embodiments, the flowchart **700** may include a further block **708** which directs the trainer processor **600** to produce signals representing the parameters defining the trained neural networks for causing the parameters to be provided to a system or device configured to apply the neural networks. In some embodiments, for example, block **708** may direct the trainer processor **600** to retrieve the neural network records from the location **644** and to produce signals representing the records for causing the records to be provided to the analyzer **12**.

For example, in some embodiments, block **708** may direct the trainer processor **600** to retrieve the common neural network record and the view category specific neural network records stored in the location **644** and transmit signals representing the records to the analyzer **12** via the interface **624** and the network **126**. Alternatively, in some embodiments, block **708** may direct the trainer processor **600** to cause the records to be stored in removable memory which may be provided to the analyzer **12**.

The analyzer **12** may be configured as described above to receive the neural network records and to perform image assessment by applying the neural networks represented thereby.

In some embodiments, the block of codes **660** of the program memory **602** shown in FIG. **16** may include a block that directs the trainer processor **600** to train a view category determining neural network that is configured to take as an input at least one echocardiographic image and to output an indication of what view category should be associated with the input at least one echocardiographic image. The block may use the image data from the training image files stored in the location **640** of the storage memory **104** as inputs and indications of the associated view categories (as determined by the view category identifiers included in the image files) as desired outputs.

The neural network may include convolutional layers, max-pooling layers, and fully connected layers, the fully connected layers including a softmax layer as an output

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layer having outputs which represent respective determinations that an input set of echocardiographic images fall within a particular view category. In some embodiments, the block may direct the trainer processor 600 to store parameters defining the trained neural network in a view category determining neural network record in the location 648 of the storage memory 604.

Embodiments Using Distributed Processing and/or Separate Devices

In some embodiments, separation of the neural network trainer 502, the training image source 504, and the analyzer 12 into different computers or systems may facilitate control of and access to information. This may be particularly desirable with the systems described herein where personal and/or confidential information may be managed. Further, in some embodiments, separation of the neural network training from the analysis, for example, may allow different or faster computers to train the neural network.

In some embodiments, the functionality of aspects of the system 10 and/or the system 500 may be further modularized and/or distributed between different devices. For example, in some embodiments, a system 800 as shown in FIG. 19 may perform generally similar functions to the system 10 shown in FIG. 1. The system 800 includes a user interface system 802 generally similar to the user interface system 14 shown in FIG. 1, and a transducer 804 generally similar to the transducer 16 shown in FIG. 1. The system 800 also includes a scanner 806 and an image analyzer 808 which are in communication with one another via a network 810 and configured to together perform generally similar functions to the analyzer 12 described above. The scanner 806 may be configured to receive signals from the transducer and generate and store echocardiographic images in memory generally as described above. The scanner 806 may be configured to send the echocardiographic images to the image analyzer 808 which is configured to receive the images from the scanner 806 and generally perform image analysis steps as described above with reference to the flowchart 200 shown in FIG. 3. The image analyzer 808 may be configured to send signals to the scanner 806 for causing the scanner 806 to cause representations of the echocardiographic images and associated quality assessment values to be displayed on the display of the user interface system 802.

In some embodiments, the functionality of any or all of the devices included in the systems 10, 500, and/or 800 as shown in FIGS. 1, 13, and 18 may be performed by multiple devices which are in communication with one another via a network. In such embodiments, the devices may be distributed in a cloud computing context, for example. For example, in some embodiments, a system that functions generally similar to the system 800 shown in FIG. 19 may include a mobile device, such as a smart phone, acting similar to the user interface system 802, in communication with a scanner generally similar to the scanner 806, via a wireless connection, for example. An image analyzer acting as the image analyzer 808 may be remotely located in comparison to the scanner and the mobile device and may be in communication with the scanner 806 and/or the mobile device via a network connection, for example, over the Internet. In some embodiments, allowing the image analyzer 808 to be remotely located and accessible via a network, may facilitate the use of low cost or fast computing resources to carry the load of intensive processing during training and/or application of the neural networks.

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In some embodiments, execution of block 206 may be performed by more than one analyzer device. For example, in some embodiments a first analyzer may apply the shared layers of an image quality assessment neural network to the received at least one echocardiographic image and then send the output of the shared layers to a second analyzer, which may apply one of the view specific layers to the received output. In such embodiments, the shared layers may act as a small neural network. In some embodiments, the shared layers may facilitate data compression. In some embodiments, the first analyzer may be in communication with the second analyzer via a network connection, such as, for example, an Internet connection. In some embodiments, the first analyzer may be implemented on a mobile device and the second analyzer may be in the cloud. In various embodiments, using a neural network with common shared layers may facilitate compressing the echocardiographic image data before sending the data to the second analyzer and may reduce the bandwidth needed to transfer data to the second analyzer.

In some embodiments, the first analyzer may use the shared layers of a neural network to generate a coarse quality score, and a finer quality score may be calculated by a larger architecture which is deployed in the cloud, for example, and uses the output of the shared layers.

Stored Image Analysis

In some embodiments, the analyzer 12 may be used to analyze stored images, rather than echocardiographic images received in real-time or near real-time. For example, in some embodiments, the analyzer 12 may be in communication with an image source, which may, for example, be implemented as a PACS. In some embodiments, the analyzer 12 may be in communication with the image source via a network, such as, the Internet, for example. In some embodiments, the analyzer 12 may be integrated with the image source as a single device.

In some embodiments where the analyzer 12 is used to analyze stored images from an image source, block 202 may direct the analyzer processor 100 to receive at least one echocardiographic image from the image source. Blocks 204 and 206 may direct the analyzer processor 100 to perform functions generally as described above. In some embodiments, block 208 may direct the analyzer processor 100 to produce signals for causing the quality assessment value to be stored in association with the at least one echocardiographic image at the image source. In some embodiments, using the analyzer 12 to analyze stored echocardiographic images from an image source may facilitate use of the previously captured echocardiographic images for later quantified clinical measurement of anatomical features and/or to assist in diagnosing a medical condition or a characteristic of the heart.

Embodiments Using Integrated Devices

In some embodiments, the functionality of some or all of the neural network trainer 502, the training image source 504 and/or the analyzer 12 of the systems 500 and 10 may be provided by a single integrated device or system, for example. By way of example, in various embodiments, aspects of the neural network trainer 502 and the analyzer 12 may be integrated, such that a single device performs the neural network training and the analysis. In some embodiments, some of the blocks of code may be altered and/or omitted to facilitate the execution of the functionality of the processes described herein by one or more integrated device or system. In some embodiments, a system including such

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integrated devices may provide advantages such as, for example, reduction in implementation and/or operating costs.

3D Representations

In some embodiments, block **202** may direct the analyzer processor **100** to receive or derive one or more 3D model representations of the patient's heart from the signals received from the scanner **16**. In such embodiments, each of the 3D model representations may represent one or more echocardiographic images which may be derived or extracted from the 3D model representation by taking slices or planar sections from the 3D model, for example. In such embodiments, the flowchart **200** may be executed to analyze echocardiographic images derived or extracted from the 3D model representation.

Various Embodiments

In some embodiments, echocardiographers may have previously provided the expert quality assessment values, and the training image source **504** may store respective expert quality assessment values in association with each of the images. In such embodiments, block **704** may direct the trainer processor **600** to receive the expert quality assessment values from the training image source **504**.

Certain embodiments of the systems **10**, **500**, and **800** have been described above, wherein a plurality of images, in some embodiments a sequence of 20 images, for example, are analyzed together to generate a single quality assessment value. In various embodiments, analyzing more than one image together may facilitate determining accurate and contextualized quality assessment values.

However, in some embodiments, the systems **10**, **500**, or **800** may be configured to analyze a single image at a time. In such embodiments, the flowchart **200** shown in FIG. 3, or a generally similar flowchart, may be executed to determine a quality assessment value for a single image received at block **202** of the flowchart **200**. In various embodiments, analyzing a single image at a time may facilitate fast processing of the flowchart **200** and/or real-time or near real-time feedback for the operator. In embodiments where a single image is analyzed at a time, the systems **10**, **500**, and/or **800** may be configured to train and/or apply functions or neural networks to the single image to determine quality assessment values of each image. In such embodiments, different neural networks from those shown in FIGS. 6 and 8, as defined by different neural network records, may be trained and applied.

For example, an exemplary view category determining neural network that may be trained and/or applied to a single echocardiographic image to determine a view category to be associated with the echocardiographic image, in accordance with some embodiments, is shown at **950** in FIG. 20. In some embodiments, the neural network **950** may be configured to take as input an image having a size of 200x200 pixels, and may include one convolutional layer with 12 kernels of each 11x11 pixels, one pooling layer with a kernel of 3x3 and stride of 2, one convolutional layer with 24 kernels of each 7x7 pixels, one pooling layer with a kernel of 3x3 and stride of 2, one convolutional layer with 48 kernels of each 3x3 pixels, one pooling layer with a kernel of 3x3 and stride of 2, a fully connected layer with 2048 outputs, a fully connected layer with 1024 outputs, and a fully connected layer with 5 outputs.

An exemplary image assessment neural network that may be trained and/or applied to a single echocardiographic image to determine a quality assessment value for the

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echocardiographic image, in accordance with some embodiments, is shown at **980** in FIG. 21.

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

The series of paragraphs below recites various illustrative combinations of features of the present disclosure. These paragraphs are intended to represent a non-limiting presentation of suitable combinations, and are alphanumerically designated for clarity and efficiency:

A0. A computer-implemented system for facilitating echocardiographic image analysis, the system comprising at least one processor configured to:

receive signals representing a first at least one echocardiographic image;

associate the first at least one echocardiographic image with a first view category of a plurality of predetermined echocardiographic image view categories;

determine, based on the first at least one echocardiographic image and the first view category, a first quality assessment value representing a view category specific quality assessment of the first at least one echocardiographic image;

produce signals representing the first quality assessment value for causing the first quality assessment value to be associated with the first at least one echocardiographic image;

receive signals representing a second at least one echocardiographic image;

associate the second at least one echocardiographic image with a second view category of the plurality of predetermined echocardiographic image view categories, said second view category being different from the first view category;

determine, based on the second at least one echocardiographic image and the second view category, a second quality assessment value representing a view category specific quality assessment of the second at least one echocardiographic image; and

produce signals representing the second quality assessment value for causing the second quality assessment value to be associated with the second at least one echocardiographic image.

A1. The system of paragraph A0 wherein the first quality assessment value represents an assessment of suitability of the first at least one echocardiographic image for quantified clinical measurement of anatomical features and wherein the second quality assessment value represents an assessment of suitability of the second at least one echocardiographic image for quantified measurement of anatomical features.

A2. The system of paragraph A0 or A1 wherein the at least one processor is configured to:

produce signals for causing a representation of the first quality assessment value to be transmitted to at least one display for causing the at least one display to display the first quality assessment value in association with the first at least one echocardiographic image, to assist one or more operators of an echocardiographic device in capturing at least one subsequent echocardiographic image; and

produce signals for causing a representation of the second quality assessment value to be transmitted to the at least one display for causing the at least one display to display the second quality assessment value in association with the second at least one echocardiographic

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image, to assist the one or more operators in capturing at least one subsequent echocardiographic image.

A3. The system of any one of paragraphs A0 to A2 wherein the at least one processor is configured to:

- apply one or more view categorization functions to the first at least one echocardiographic image to determine that the first at least one echocardiographic image falls within the first view category; and
- apply one or more view categorization functions to the second at least one echocardiographic image to determine that the second at least one echocardiographic image falls within the second view category.

A4. The system of any one of paragraphs A0 to A3 wherein the first at least one echocardiographic image comprises a plurality of echocardiographic images and wherein the at least one processor is configured to determine the first quality assessment value by determining a single quality assessment value representing a view category specific assessment of the plurality of echocardiographic images.

A5. The system of any one of paragraphs A0 to A4 wherein each of the plurality of predetermined echocardiographic image view categories is associated with a respective set of assessment parameters and wherein the at least one processor is configured to:

- determine that a first set of assessment parameters of the sets of assessment parameters is associated with the first view category;
- in response to determining that the first set of assessment parameters is associated with the first view category, apply a first function based on the first set of assessment parameters to the first at least one echocardiographic image;
- determine that a second set of assessment parameters of the sets of assessment parameters is associated with the second view category; and
- in response to determining that the second set of assessment parameters is associated with the second view category, apply a second function based on the second set of assessment parameters to the second at least one echocardiographic image.

A6. The system of paragraph A5 wherein each of the sets of assessment parameters includes:

- a set of common assessment parameters, which are common to each of the sets of assessment parameters; and
- a set of view category specific assessment parameters, which are unique to the set of assessment parameters.

A7. The system of paragraph A5 or A6 wherein each of the sets of assessment parameters is a set of neural network parameters that defines a neural network having a plurality of layers including an input layer configured to receive one or more echocardiographic images and an output layer configured to output one or more quality assessment values and wherein the at least one processor is configured to:

- apply the first function based on the first set of assessment parameters to the first at least one echocardiographic image by inputting the first at least one echocardiographic image into the neural network defined by the first set of assessment parameters; and
- apply the second function based on the second set of assessment parameters to the second at least one echocardiographic image by inputting the second at least one echocardiographic image into the neural network defined by the second set of assessment parameters.

A8. The system of paragraph A7 wherein the at least one processor is configured to train the neural networks by:

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receiving signals representing a plurality of echocardiographic training images, each of the plurality of echocardiographic training images associated with one of the plurality of predetermined echocardiographic image view categories;

receiving signals representing respective expert quality assessment values representing view category specific quality assessments of the plurality of echocardiographic training images, each of the expert quality assessment values provided by an expert echocardiographer and associated with one of the plurality of echocardiographic training images; and

training the neural networks using the plurality of echocardiographic training images as inputs and the associated expert quality assessment values as desired outputs to determine the sets of neural network parameters defining the neural networks.

A9. The system of paragraph A8 wherein each of the expert quality assessment values represents an assessment of suitability of the associated echocardiographic image for quantified clinical measurement of anatomical features.

A10. The system of paragraph A8 or A9 wherein the at least one processor is configured to derive each of the expert quality assessment values at least in part from a clinical plane assessment value representing an expert opinion whether the associated echocardiographic training image was taken in an anatomical plane suitable for quantified clinical measurement of anatomical features.

A11. The system of any one of paragraphs A8 to A10 wherein each of the sets of neural network parameters includes:

- a set of common neural network parameters, which are common to each of the sets of neural network parameters; and
- a set of view category specific neural network parameters, which are unique to the set of neural network parameters; and

wherein the at least one processor is configured to, for each echocardiographic training image:

- select one of the sets of view category specific neural network parameters based on the predetermined echocardiographic image view category associated with the echocardiographic training image; and
- using the echocardiographic training image as an input and the associated expert quality assessment values as a desired output, train a neural network defined by the set of common neural network parameters and the selected one of the sets of view category specific neural network parameters to update the set of common neural network parameters and the selected one of the sets of view category specific neural network parameters.

B0. A computer-implemented system for training neural networks to facilitate echocardiographic image analysis, the system comprising at least one processor configured to:

- receive signals representing a plurality of echocardiographic training images, each of the plurality of echocardiographic training images associated with one of a plurality of predetermined echocardiographic image view categories;
- receive signals representing expert quality assessment values representing view category specific quality assessments of the plurality of echocardiographic training images, each of the expert quality assessment values provided by an expert echocardiographer and associated with one of the plurality of echocardiographic training images; and

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train the neural networks using the plurality of echocardiographic training images and the associated expert quality assessment values to determine sets of neural network parameters defining the neural networks, at least a portion of each of said neural networks associated with one of the plurality of predetermined echocardiographic image view categories.

B1. The system of paragraph B0 wherein each of the expert quality assessment values represents an assessment of suitability of the associated echocardiographic image for quantified clinical measurement of anatomical features.

B2. The system of paragraph B0 or B1 wherein the at least one processor is configured to derive each of the expert quality assessment values at least in part from a clinical plane assessment value representing an expert opinion whether the associated echocardiographic training image was taken in an anatomical plane suitable for a quantified clinical measurement of anatomical features.

B3. The system of any one of paragraphs B0 to B2 wherein each of the sets of neural network parameters includes:

- a set of common neural network parameters, which are common to each of the sets of neural network parameters; and

- a set of view category specific neural network parameters, which are unique to the set of neural network parameters; and

wherein the at least one processor is configured to, for each echocardiographic training image:

- select one of the sets of view category specific neural network parameters based on the predetermined echocardiographic image view category associated with the echocardiographic training image; and

- using the echocardiographic training image as an input and the associated expert quality assessment value as a desired output, train a neural network defined by the set of common neural network parameters and the selected one of the sets of view category specific neural network parameters to update the set of common neural network parameters and the selected one of the sets of view category specific neural network parameters.

C0. A computer-implemented method of facilitating echocardiographic image analysis, the method comprising:

- receiving signals representing a first at least one echocardiographic image;

- associating the first at least one echocardiographic image with a first view category of a plurality of predetermined echocardiographic image view categories;

- determining, based on the first at least one echocardiographic image and the first view category, a first quality assessment value representing a view category specific quality assessment of the first at least one echocardiographic image;

- producing signals representing the first quality assessment value for causing the first quality assessment value to be associated with the first at least one echocardiographic image;

- receiving signals representing a second at least one echocardiographic image;

- associating the second at least one echocardiographic image with a second view category of the plurality of predetermined echocardiographic image view categories, said second view category being different from the first view category;

- determining, based on the second at least one echocardiographic image and the second view category, a second quality assessment value representing a view

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- category specific quality assessment of the second at least one echocardiographic image; and

- producing signals representing the second quality assessment value for causing the second quality assessment value to be associated with the second at least one echocardiographic image.

C1. The method of paragraph C0 wherein the first quality assessment value represents an assessment of suitability of the first at least one echocardiographic image for quantified clinical measurement of anatomical features and wherein the second quality assessment value represents an assessment of suitability of the second at least one echocardiographic image for quantified measurement of anatomical features.

C2. The method of paragraph C0 or C1 wherein:

- producing the signals representing the first quality assessment value comprises producing signals for causing a representation of the first quality assessment value to be transmitted to at least one display for causing the at least one display to display the first quality assessment value in association with the first at least one echocardiographic image, to assist one or more operators of an echocardiographic device in capturing at least one subsequent echocardiographic image; and

- producing the signals representing the second quality assessment value comprises producing signals for causing a representation of the second quality assessment value to be transmitted to the at least one display for causing the at least one display to display the second quality assessment value in association with the second at least one echocardiographic image, to assist the one or more operators in capturing at least one subsequent echocardiographic image.

C3. The method of any one of paragraphs C0 to C2 wherein:

- associating the first at least one echocardiographic image with the first view category comprises applying one or more view categorization functions to the first at least one echocardiographic image to determine that the first at least one echocardiographic image falls within the first view category; and

- associating the second at least one echocardiographic image with the second view category comprises applying one or more view categorization functions to the second at least one echocardiographic image to determine that the second at least one echocardiographic image falls within the second view category.

C4. The method of any one of paragraphs C0 to C3 wherein the first at least one echocardiographic image comprises a plurality of echocardiographic images and wherein determining the first quality assessment value comprises determining a single quality assessment value representing a view category specific assessment of the plurality of echocardiographic images.

C5. The method of any one of paragraphs C0 to C4 wherein each of the plurality of predetermined echocardiographic image view categories is associated with a respective set of assessment parameters and wherein:

- determining the first quality assessment value comprises:

- determining that a first set of assessment parameters of the sets of assessment parameters is associated with the first view category; and

- in response to determining that the first set of assessment parameters is associated with the first view category, applying a first function based on the first set of assessment parameters to the first at least one echocardiographic image; and

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determining the second quality assessment value comprises:

determining that a second set of assessment parameters of the sets of assessment parameters is associated with the second view category; and

in response to determining that the second set of assessment parameters is associated with the second view category, applying a second function based on the second set of assessment parameters to the second at least one echocardiographic image.

C6. The method of paragraph C5 wherein each of the sets of assessment parameters includes:

a set of common assessment parameters, which are common to each of the sets of assessment parameters; and
a set of view category specific assessment parameters, which are unique to the set of assessment parameters.

C7. The method of paragraph C5 or C6 wherein each of the sets of assessment parameters is a set of neural network parameters that defines a neural network having a plurality of layers including an input layer configured to receive one or more echocardiographic images and an output layer configured to output one or more quality assessment values and wherein:

applying the first function based on the first set of assessment parameters to the first at least one echocardiographic image comprises inputting the first at least one echocardiographic image into the neural network defined by the first set of assessment parameters; and applying the second function based on the second set of assessment parameters to the second at least one echocardiographic image comprises inputting the second at least one echocardiographic image into the neural network defined by the second set of assessment parameters.

C8. The method of paragraph C7 further comprising training the neural networks, said training comprising:

receiving signals representing a plurality of echocardiographic training images, each of the plurality of echocardiographic training images associated with one of the plurality of predetermined echocardiographic image view categories;

receiving signals representing respective expert quality assessment values representing view category specific quality assessments of the plurality of echocardiographic training images, each of the expert quality assessment values provided by an expert echocardiographer and associated with one of the plurality of echocardiographic training images; and

training the neural networks using the plurality of echocardiographic training images as inputs and the associated expert quality assessment values as desired outputs to determine the sets of neural network parameters defining the neural networks.

C9. The method of paragraph C8 wherein each of the expert quality assessment values represents an assessment of suitability of the associated echocardiographic image for quantified clinical measurement of anatomical features.

C10. The method of paragraph C8 or C9 further comprising deriving each of the expert quality assessment values at least in part from a clinical plane assessment value representing an expert opinion whether the associated echocardiographic training image was taken in an anatomical plane suitable for quantified clinical measurement of anatomical features.

C11. The method of any one of paragraphs C8 to C10 wherein each of the sets of neural network parameters includes:

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a set of common neural network parameters, which are common to each of the sets of neural network parameters; and

a set of view category specific neural network parameters, which are unique to the set of neural network parameters; and

wherein training the neural networks using the plurality of echocardiographic training images and the associated expert quality assessment values comprises, for each echocardiographic training image:

selecting one of the sets of view category specific neural network parameters based on the predetermined echocardiographic image view category associated with the echocardiographic training image; and

using the echocardiographic training image as an input and the associated expert quality assessment values as a desired output, training a neural network defined by the set of common neural network parameters and the selected one of the sets of view category specific neural network parameters to update the set of common neural network parameters and the selected one of the sets of view category specific neural network parameters.

D0. A computer-implemented method of training neural networks to facilitate echocardiographic image analysis, the method comprising:

receiving signals representing a plurality of echocardiographic training images, each of the plurality of echocardiographic training images associated with one of a plurality of predetermined echocardiographic image view categories;

receiving signals representing expert quality assessment values representing view category specific quality assessments of the plurality of echocardiographic training images, each of the expert quality assessment values provided by an expert echocardiographer and associated with one of the plurality of echocardiographic training images; and

training the neural networks using the plurality of echocardiographic training images and the associated expert quality assessment values to determine sets of neural network parameters defining the neural networks, at least a portion of each of said neural networks associated with one of the plurality of predetermined echocardiographic image view categories.

D1. The method of paragraph D0 wherein each of the expert quality assessment values represents an assessment of suitability of the associated echocardiographic image for quantified clinical measurement of anatomical features.

D2. The method of paragraph D0 or D1 further comprising deriving each of the expert quality assessment values at least in part from a clinical plane assessment value representing an expert opinion whether the associated echocardiographic training image was taken in an anatomical plane suitable for a quantified clinical measurement of anatomical features.

D3. The method of any one of paragraphs D0 to D2 wherein each of the sets of neural network parameters includes:

a set of common neural network parameters, which are common to each of the sets of neural network parameters; and

a set of view category specific neural network parameters, which are unique to the set of neural network parameters; and

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wherein training the neural networks using the plurality of echocardiographic training images and the associated expert quality assessment values comprises, for each echocardiographic training image:

selecting one of the sets of view category specific neural network parameters based on the predetermined echocardiographic image view category associated with the echocardiographic training image; and using the echocardiographic training image as an input and the associated expert quality assessment value as a desired output, training a neural network defined by the set of common neural network parameters and the selected one of the sets of view category specific neural network parameters to update the set of common neural network parameters and the selected one of the sets of view category specific neural network parameters.

D4. A computer readable medium having stored thereon codes which when executed by at least one processor cause the at least one processor to perform the method of any one of paragraphs C0 to D3.

E0. A system for facilitating echocardiographic image analysis, the system comprising:

means for receiving signals representing a first at least one echocardiographic image;

means for associating the first at least one echocardiographic image with a first view category of a plurality of predetermined echocardiographic image view categories;

means for determining, based on the first at least one echocardiographic image and the first view category, a first quality assessment value representing a view category specific quality assessment of the first at least one echocardiographic image;

means for producing signals representing the first quality assessment value for causing the first quality assessment value to be associated with the first at least one echocardiographic image;

means for receiving signals representing a second at least one echocardiographic image;

means for associating the second at least one echocardiographic image with a second view category of the plurality of predetermined echocardiographic image view categories, said second view category being different from the first view category;

means for determining, based on the second at least one echocardiographic image and the second view category, a second quality assessment value representing a view category specific quality assessment of the second at least one echocardiographic image; and

means for producing signals representing the second quality assessment value for causing the second quality assessment value to be associated with the second at least one echocardiographic image.

F0. A system for training neural networks to facilitate echocardiographic image analysis, the system comprising:

means for receiving signals representing a plurality of echocardiographic training images, each of the plurality of echocardiographic training images associated with one of a plurality of predetermined echocardiographic image view categories;

means for receiving signals representing expert quality assessment values representing view category specific quality assessments of the plurality of echocardiographic training images, each of the expert quality assessment values provided by an expert echocardiographer and associated with one of the plurality of echocardiographic training images; and

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means for training the neural networks using the plurality of echocardiographic training images and the associated expert quality assessment values to determine sets of neural network parameters defining the neural networks, at least a portion of each of said neural networks associated with one of the plurality of predetermined echocardiographic image view categories.

The invention claimed is:

1. A computer-implemented system for facilitating echocardiographic image analysis, the system comprising at least one processor configured to:

receive signals representing a first at least one echocardiographic image;

associate the first at least one echocardiographic image with a first view category of a plurality of predetermined echocardiographic image view categories;

determine, based on the first at least one echocardiographic image and the first view category, a first quality assessment value representing a view category specific quality assessment of the first at least one echocardiographic image;

produce signals representing the first quality assessment value for causing the first quality assessment value to be associated with the first at least one echocardiographic image;

receive signals representing a second at least one echocardiographic image;

associate the second at least one echocardiographic image with a second view category of the plurality of predetermined echocardiographic image view categories, said second view category being different from the first view category;

determine, based on the second at least one echocardiographic image and the second view category, a second quality assessment value representing a view category specific quality assessment of the second at least one echocardiographic image; and

produce signals representing the second quality assessment value for causing the second quality assessment value to be associated with the second at least one echocardiographic image;

wherein each of the plurality of predetermined echocardiographic image view categories is associated with a respective set of assessment parameters, each of the sets of assessment parameters being a set of neural network parameters that define a neural network having a plurality of layers including an input layer configured to receive one or more echocardiographic images and an output layer configured to output one or more quality assessment values, and wherein the at least one processor is configured to determine the first quality assessment value by:

determining that a first set of assessment parameters of the sets of assessment parameters is associated with the first view category; and

in response to determining that the first set of assessment parameters is associated with the first view category, inputting the first at least one echocardiographic image into the neural network defined by the first set of assessment parameters; and

wherein the at least one processor is configured to determine the second quality assessment value by:

determining that a second set of assessment parameters of the sets of assessment parameters is associated with the second view category; and

in response to determining that the second set of assessment parameters is associated with the second

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view category, inputting the second at least one echocardiographic image into the neural network defined by the second set of assessment parameters.

2. The system of claim 1 wherein the first quality assessment value represents an assessment of suitability of the first at least one echocardiographic image for quantified clinical measurement of anatomical features and wherein the second quality assessment value represents an assessment of suitability of the second at least one echocardiographic image for quantified measurement of anatomical features.

3. The system of claim 1 wherein the at least one processor is configured to:

produce signals for causing a representation of the first quality assessment value to be transmitted to at least one display for causing the at least one display to display the first quality assessment value in association with the first at least one echocardiographic image, to assist one or more operators of an echocardiographic device in capturing at least one subsequent echocardiographic image; and

produce signals for causing a representation of the second quality assessment value to be transmitted to the at least one display for causing the at least one display to display the second quality assessment value in association with the second at least one echocardiographic image, to assist the one or more operators in capturing at least one subsequent echocardiographic image.

4. The system of claim 1 wherein the at least one processor is configured to:

apply one or more view categorization functions to the first at least one echocardiographic image to determine that the first at least one echocardiographic image falls within the first view category; and

apply one or more view categorization functions to the second at least one echocardiographic image to determine that the second at least one echocardiographic image falls within the second view category.

5. The system of claim 1 wherein the first at least one echocardiographic image comprises a plurality of echocardiographic images and wherein the at least one processor is configured to determine the first quality assessment value by determining a single quality assessment value representing a view category specific assessment of the plurality of echocardiographic images.

6. The system of claim 1 wherein each of the sets of assessment parameters includes:

a set of common assessment parameters, which are common to each of the sets of assessment parameters; and
a set of view category specific assessment parameters, which are unique to the set of assessment parameters.

7. The system of claim 1 wherein the at least one processor is configured to train the neural networks by:

receiving signals representing a plurality of echocardiographic training images, each of the plurality of echocardiographic training images associated with one of the plurality of predetermined echocardiographic image view categories;

receiving signals representing respective expert quality assessment values representing view category specific quality assessments of the plurality of echocardiographic training images, each of the expert quality assessment values provided by an expert echocardiographer and associated with one of the plurality of echocardiographic training images; and

training the neural networks using the plurality of echocardiographic training images as inputs and the associated expert quality assessment values as desired

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outputs to determine the sets of neural network parameters defining the neural networks.

8. The system of claim 7 wherein each of the expert quality assessment values represents an assessment of suitability of the associated echocardiographic image for quantified clinical measurement of anatomical features.

9. The system of claim 7 wherein the at least one processor is configured to derive each of the expert quality assessment values at least in part from a clinical plane assessment value representing an expert opinion whether the associated echocardiographic training image was taken in an anatomical plane suitable for quantified clinical measurement of anatomical features.

10. The system of claim 7 wherein each of the sets of neural network parameters includes:

a set of common neural network parameters, which are common to each of the sets of neural network parameters; and

a set of view category specific neural network parameters, which are unique to the set of neural network parameters; and

wherein the at least one processor is configured to, for each echocardiographic training image:

select one of the sets of view category specific neural network parameters based on the predetermined echocardiographic image view category associated with the echocardiographic training image; and

using the echocardiographic training image as an input and the associated expert quality assessment values as a desired output, train a neural network defined by the set of common neural network parameters and the selected one of the sets of view category specific neural network parameters to update the set of common neural network parameters and the selected one of the sets of view category specific neural network parameters.

11. A computer-implemented system for training neural networks to facilitate echocardiographic image analysis, the system comprising at least one processor configured to:

receive signals representing a plurality of echocardiographic training images, each of the plurality of echocardiographic training images associated with one of a plurality of predetermined echocardiographic image view categories;

receive signals representing expert quality assessment values representing view category specific quality assessments of the plurality of echocardiographic training images, each of the expert quality assessment values provided by an expert echocardiographer and associated with one of the plurality of echocardiographic training images; and

train the neural networks using the plurality of echocardiographic training images and the associated expert quality assessment values to determine sets of neural network parameters defining the neural networks, at least a portion of each of said neural networks associated with one of the plurality of predetermined echocardiographic image view categories;

wherein the at least one processor is further configured to, once the neural networks are trained:

receive signals representing a first at least one echocardiographic image;

associate the first at least one echocardiographic image with a first view category of a plurality of predetermined echocardiographic image view categories;

determine, based on the first at least one echocardiographic image and the first view category, a first quality assessment value representing a view cat-

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egory specific quality assessment of the first at least one echocardiographic image;
 produce signals representing the first quality assessment value for causing the first quality assessment value to be associated with the first at least one echocardiographic image;
 receive signals representing a second at least one echocardiographic image;
 associate the second at least one echocardiographic image with a second view category of the plurality of predetermined echocardiographic image view categories, said second view category being different from the first view category;
 determine, based on the second at least one echocardiographic image and the second view category, a second quality assessment value representing a view category specific quality assessment of the second at least one echocardiographic image; and
 produce signals representing the second quality assessment value for causing the second quality assessment value to be associated with the second at least one echocardiographic image;
 wherein each of the plurality of predetermined echocardiographic image view categories is associated with a respective set of assessment parameters, each of the sets of assessment parameters being a set of neural network parameters that define a neural network having a plurality of layers including an input layer configured to receive one or more echocardiographic images and an output layer configured to output one or more quality assessment values, and wherein the at least one processor is configured to determine the first quality assessment value by:
 determining that a first set of assessment parameters of the sets of assessment parameters is associated with the first view category; and
 in response to determining that the first set of assessment parameters is associated with the first view category, inputting the first at least one echocardiographic image into the neural network defined by the first set of assessment parameters; and
 wherein the at least one processor is configured to determine the second quality assessment value by:
 determining that a second set of assessment parameters of the sets of assessment parameters is associated with the second view category; and
 in response to determining that the second set of assessment parameters is associated with the second view category, inputting the second at least one echocardiographic image into the neural network defined by the second set of assessment parameters.

12. The system of claim 11 wherein each of the expert quality assessment values represents an assessment of suitability of the associated echocardiographic image for quantified clinical measurement of anatomical features.

13. The system of claim 11 wherein the at least one processor is configured to derive each of the expert quality assessment values at least in part from a clinical plane assessment value representing an expert opinion whether the associated echocardiographic training image was taken in an anatomical plane suitable for a quantified clinical measurement of anatomical features.

14. The system of claim 11 wherein each of the sets of neural network parameters includes:

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a set of common neural network parameters, which are common to each of the sets of neural network parameters; and
 a set of view category specific neural network parameters, which are unique to the set of neural network parameters; and
 wherein the at least one processor is configured to, for each echocardiographic training image:
 select one of the sets of view category specific neural network parameters based on the predetermined echocardiographic image view category associated with the echocardiographic training image; and
 using the echocardiographic training image as an input and the associated expert quality assessment value as a desired output, train a neural network defined by the set of common neural network parameters and the selected one of the sets of view category specific neural network parameters to update the set of common neural network parameters and the selected one of the sets of view category specific neural network parameters.

15. A computer-implemented method of facilitating echocardiographic image analysis, the method comprising:
 receiving signals representing a first at least one echocardiographic image;
 associating the first at least one echocardiographic image with a first view category of a plurality of predetermined echocardiographic image view categories;
 determining, based on the first at least one echocardiographic image and the first view category, a first quality assessment value representing a view category specific quality assessment of the first at least one echocardiographic image;
 producing signals representing the first quality assessment value for causing the first quality assessment value to be associated with the first at least one echocardiographic image;
 receiving signals representing a second at least one echocardiographic image;
 associating the second at least one echocardiographic image with a second view category of the plurality of predetermined echocardiographic image view categories, said second view category being different from the first view category;
 determining, based on the second at least one echocardiographic image and the second view category, a second quality assessment value representing a view category specific quality assessment of the second at least one echocardiographic image; and
 producing signals representing the second quality assessment value for causing the second quality assessment value to be associated with the second at least one echocardiographic image;
 wherein each of the plurality of predetermined echocardiographic image view categories is associated with a respective set of assessment parameters, each of the sets of assessment parameters being a set of neural network parameters that defines a neural network having a plurality of layers including an input layer configured to receive one or more echocardiographic images and an output layer configured to output one or more quality assessment values and wherein:
 determining the first quality assessment value comprises:
 determining that a first set of assessment parameters of the sets of assessment parameters is associated with the first view category; and

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in response to determining that the first set of assessment parameters is associated with the first view category, inputting the first at least one echocardiographic image into the neural network defined by the first set of assessment parameters applying a first function based on the first set of assessment parameters to the first at least one echocardiographic image; and

determining the second quality assessment value comprises:

determining that a second set of assessment parameters of the sets of assessment parameters is associated with the second view category; and

in response to determining that the second set of assessment parameters is associated with the second view category, inputting the second at least one echocardiographic image into the neural network defined by the second set of assessment parameters.

16. The method of claim **15** wherein the first quality assessment value represents an assessment of suitability of the first at least one echocardiographic image for quantified clinical measurement of anatomical features and wherein the second quality assessment value represents an assessment of suitability of the second at least one echocardiographic image for quantified measurement of anatomical features.

17. The method of claim **15** wherein:

producing the signals representing the first quality assessment value comprises producing signals for causing a representation of the first quality assessment value to be transmitted to at least one display for causing the at least one display to display the first quality assessment value in association with the first at least one echocardiographic image, to assist one or more operators of an echocardiographic device in capturing at least one subsequent echocardiographic image; and

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producing the signals representing the second quality assessment value comprises producing signals for causing a representation of the second quality assessment value to be transmitted to the at least one display for causing the at least one display to display the second quality assessment value in association with the second at least one echocardiographic image, to assist the one or more operators in capturing at least one subsequent echocardiographic image.

18. The method of claim **15** wherein:

associating the first at least one echocardiographic image with the first view category comprises applying one or more view categorization functions to the first at least one echocardiographic image to determine that the first at least one echocardiographic image falls within the first view category; and

associating the second at least one echocardiographic image with the second view category comprises applying one or more view categorization functions to the second at least one echocardiographic image to determine that the second at least one echocardiographic image falls within the second view category.

19. The method of claim **15** wherein the first at least one echocardiographic image comprises a plurality of echocardiographic images and wherein determining the first quality assessment value comprises determining a single quality assessment value representing a view category specific assessment of the plurality of echocardiographic images.

20. The method of claim **15** wherein each of the sets of assessment parameters includes:

a set of common assessment parameters, which are common to each of the sets of assessment parameters; and
a set of view category specific assessment parameters, which are unique to the set of assessment parameters.

* * * * *

EXHIBIT B

US010751029B2

(12) **United States Patent**
Abolmaesumi et al.

(10) **Patent No.:** **US 10,751,029 B2**

(45) **Date of Patent:** **Aug. 25, 2020**

(54) **ULTRASONIC IMAGE ANALYSIS**

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Amir Abdi, Vancouver (CA)

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patent is extended or adjusted under 35
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Primary Examiner — Anand P Bhatnagar

(74) *Attorney, Agent, or Firm* — Knobbe, Martens, Olson
& Bear, LLP

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A61B 8/08 (2006.01)
A61B 8/00 (2006.01)

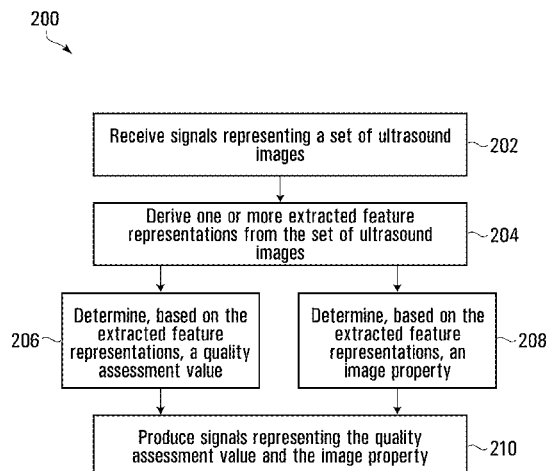
(52) **U.S. Cl.**
CPC **A61B 8/5207** (2013.01); **A61B 8/0883**
(2013.01); **A61B 8/463** (2013.01);
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(58) **Field of Classification Search**
CPC combination set(s) only.
See application file for complete search history.

(57) **ABSTRACT**

Embodiments of a computer-implemented method of facilitating ultrasonic image analysis of a subject are disclosed. The method can involve receiving signals representing a set of ultrasound images of the subject, deriving one or more extracted feature representations from the set of ultrasound images, determining, based on the derived one or more extracted feature representations, a quality assessment value representing a quality assessment of the set of ultrasound images, determining, based on the derived one or more extracted feature representations, an image property associated with the set of ultrasound images, and producing signals representing the quality assessment value and the image property for causing the quality assessment value and the image property to be associated with the set of ultrasound images. Embodiments of a computer-implemented method of training one or more neural networks to facilitate ultrasonic image analysis is also disclosed. Other apparatuses,

(Continued)



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methods, systems, and computer-readable media are also disclosed.

30 Claims, 13 Drawing Sheets

Related U.S. Application Data

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CPC *A61B 8/483* (2013.01); *A61B 8/5215*
(2013.01); *A61B 8/466* (2013.01)

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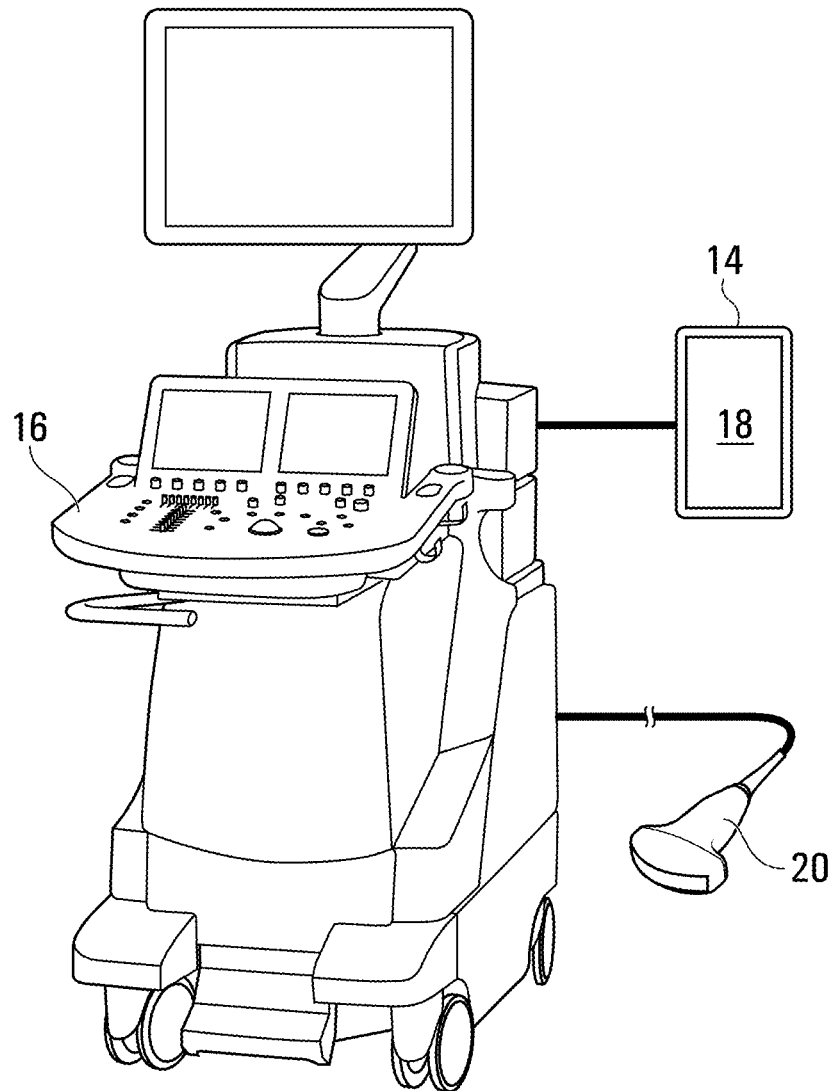
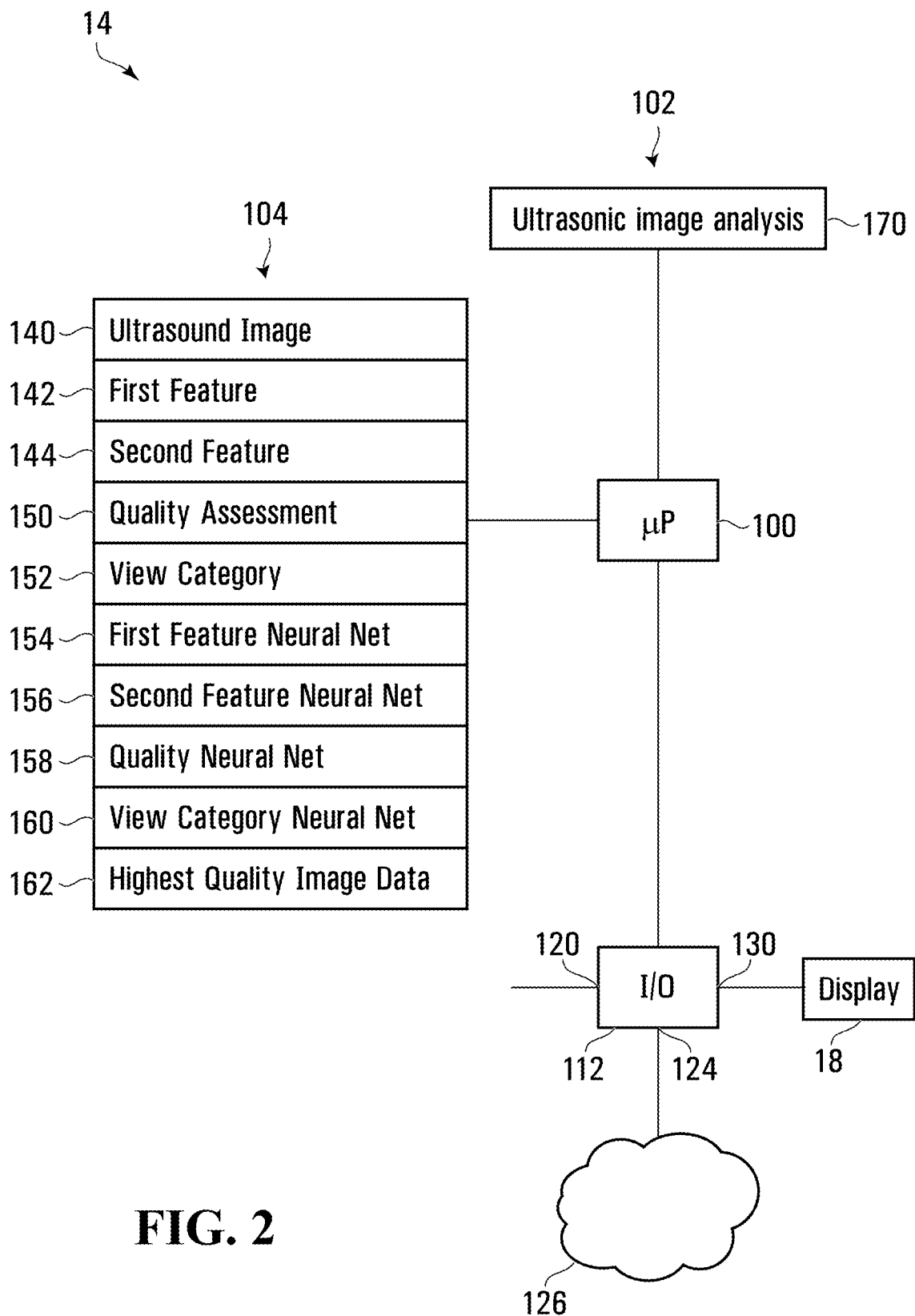


FIG. 1

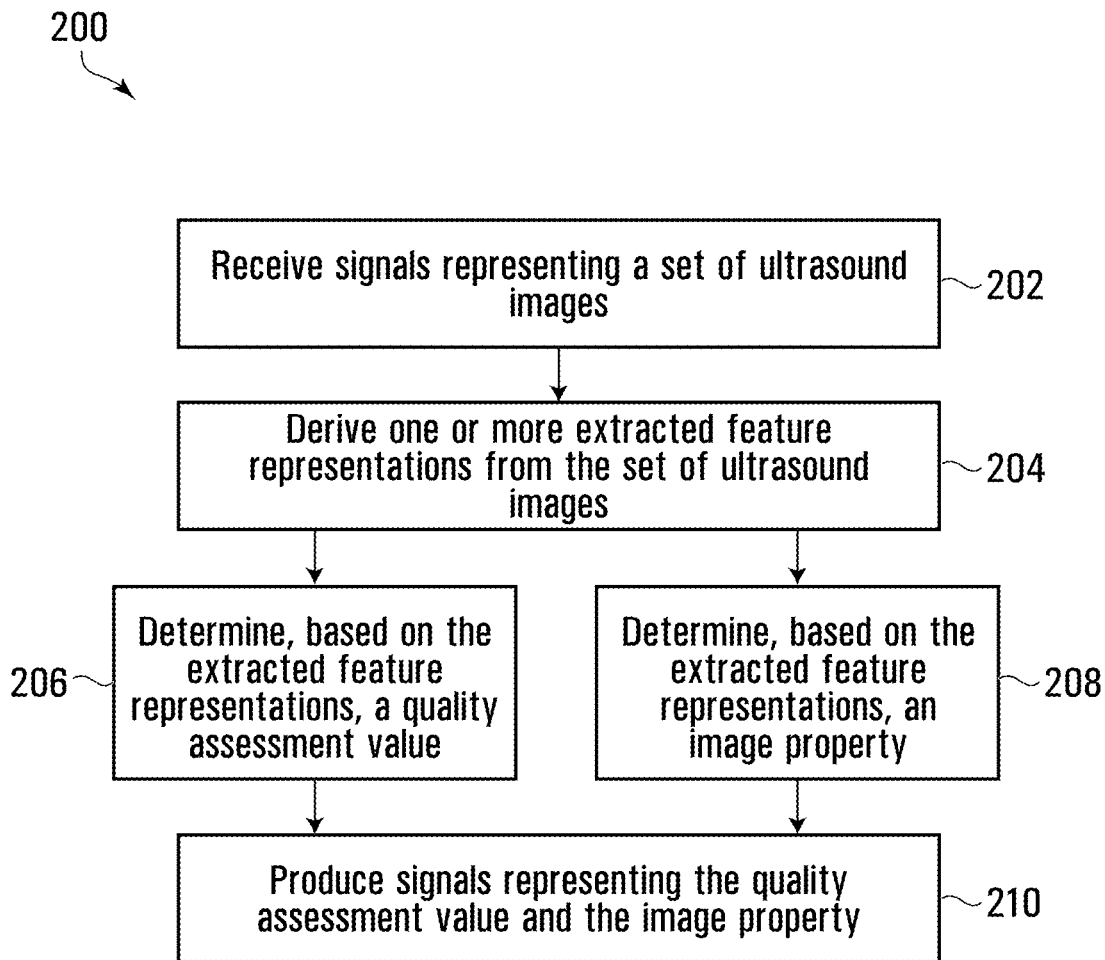
**FIG. 2**

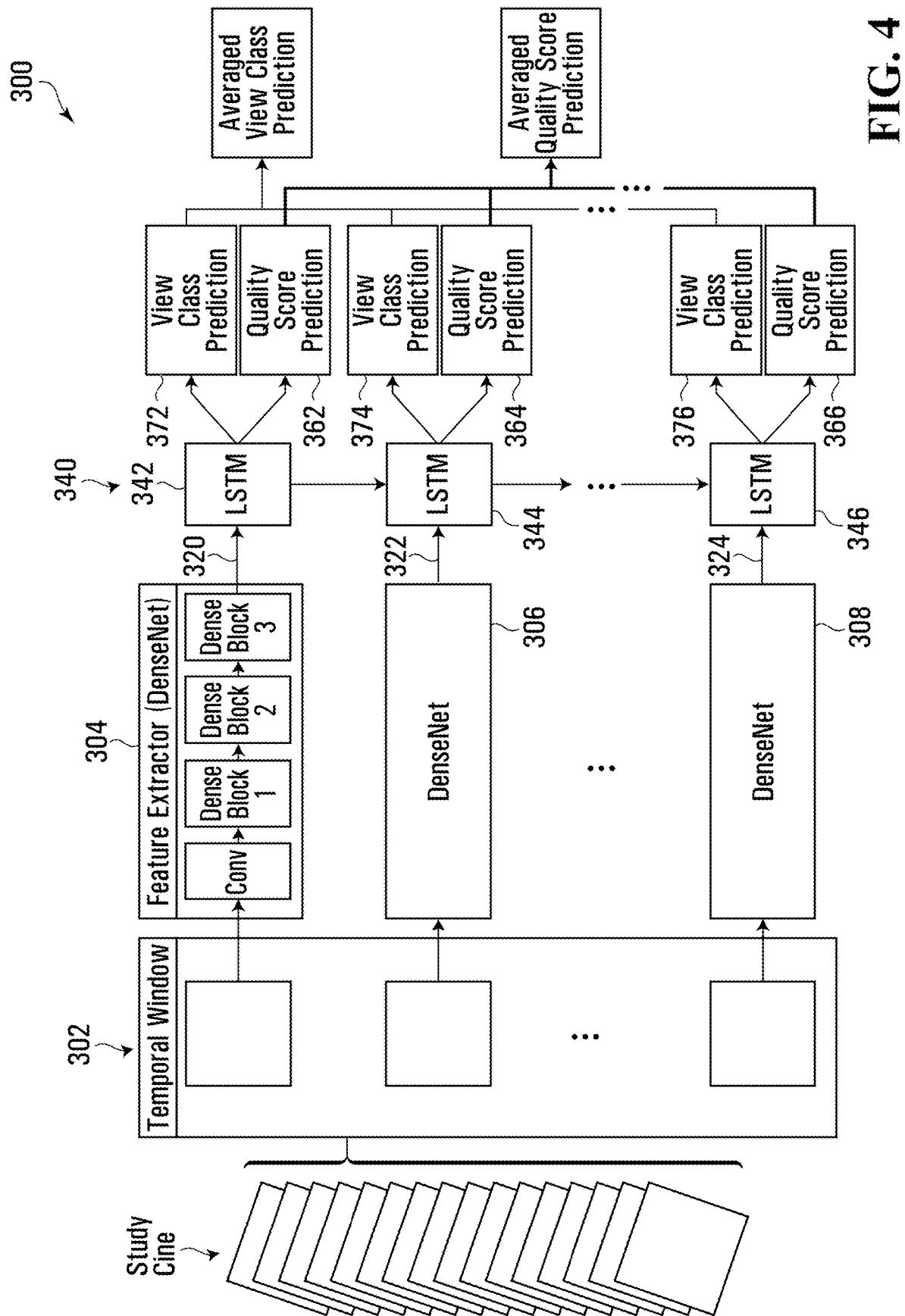
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**FIG. 3**



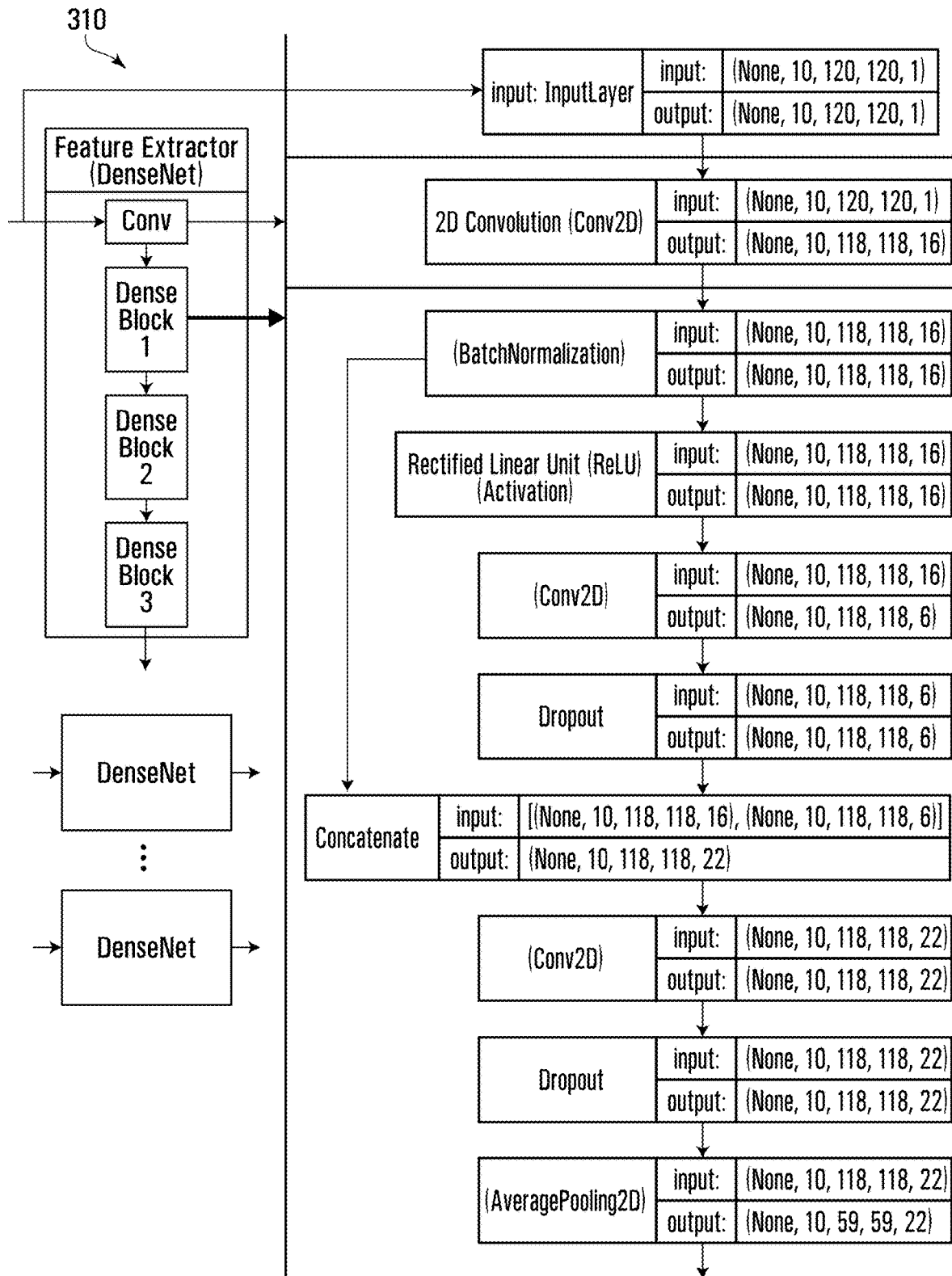


FIG. 5

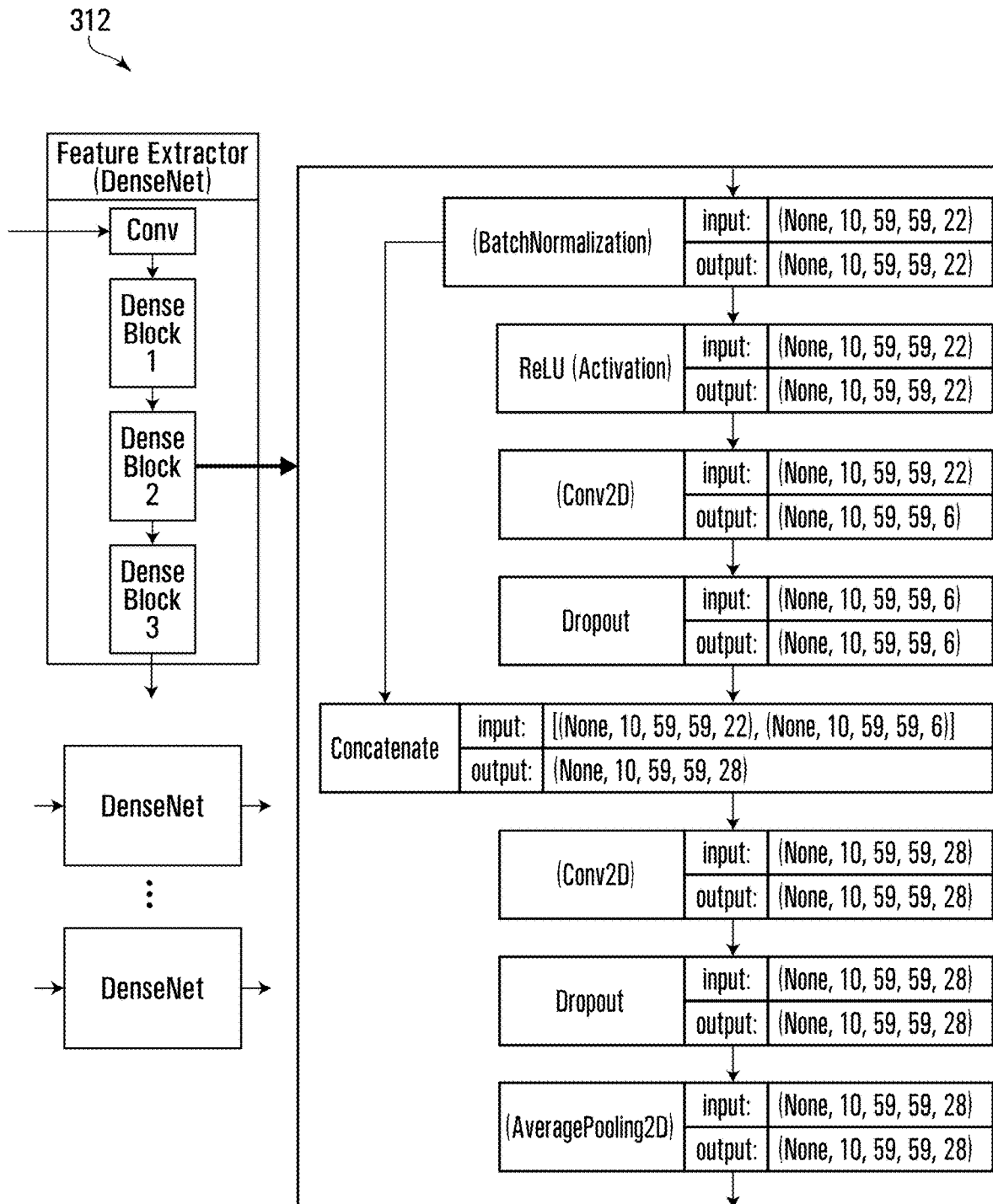


FIG. 6

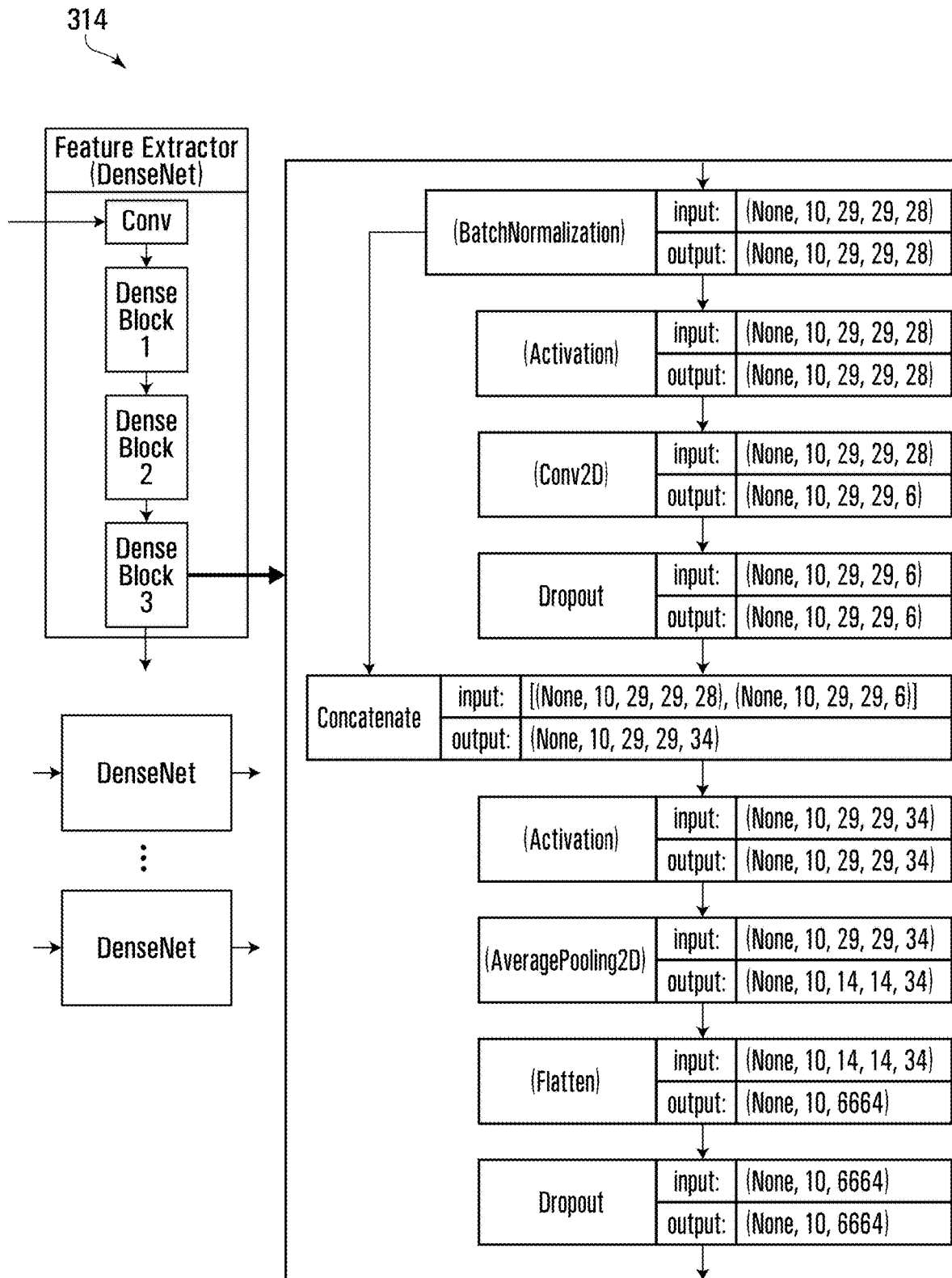


FIG. 7

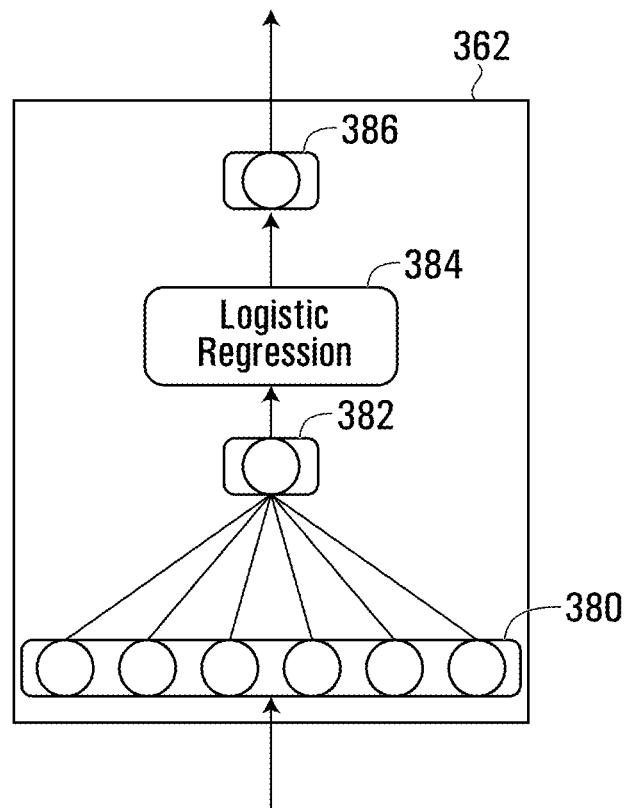


FIG. 8

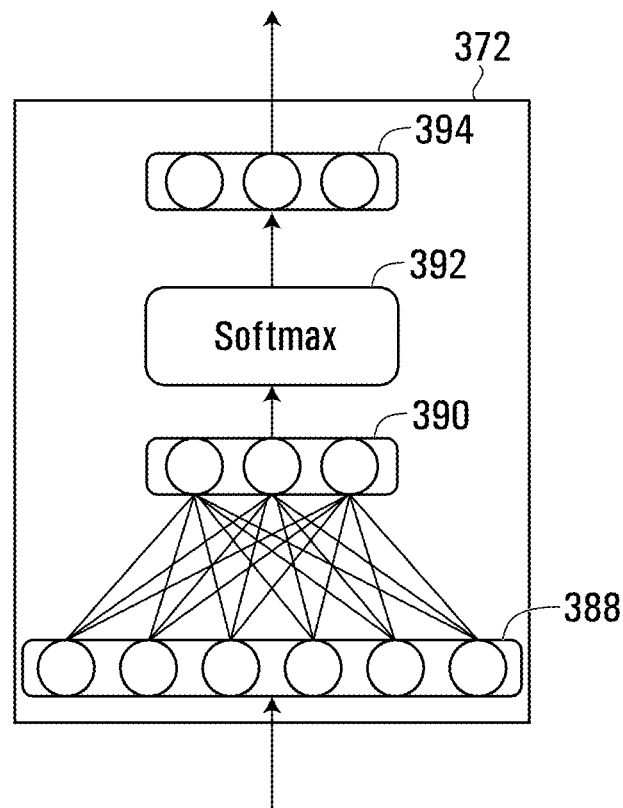


FIG. 9

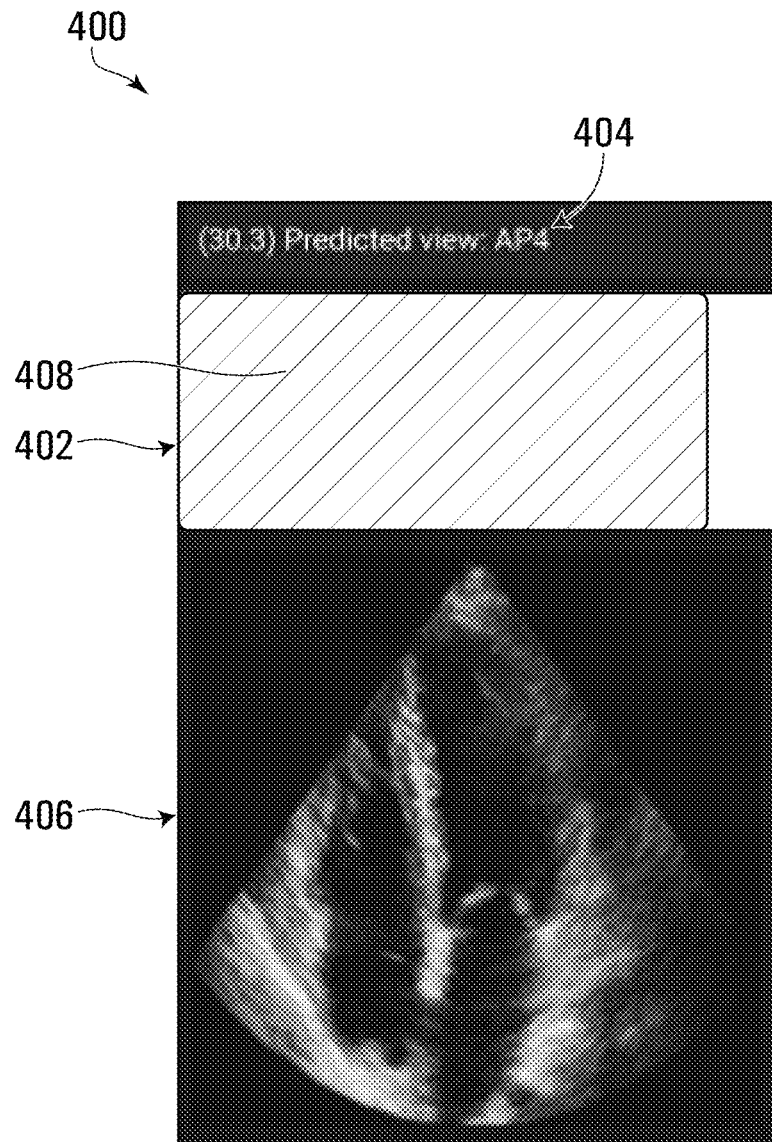
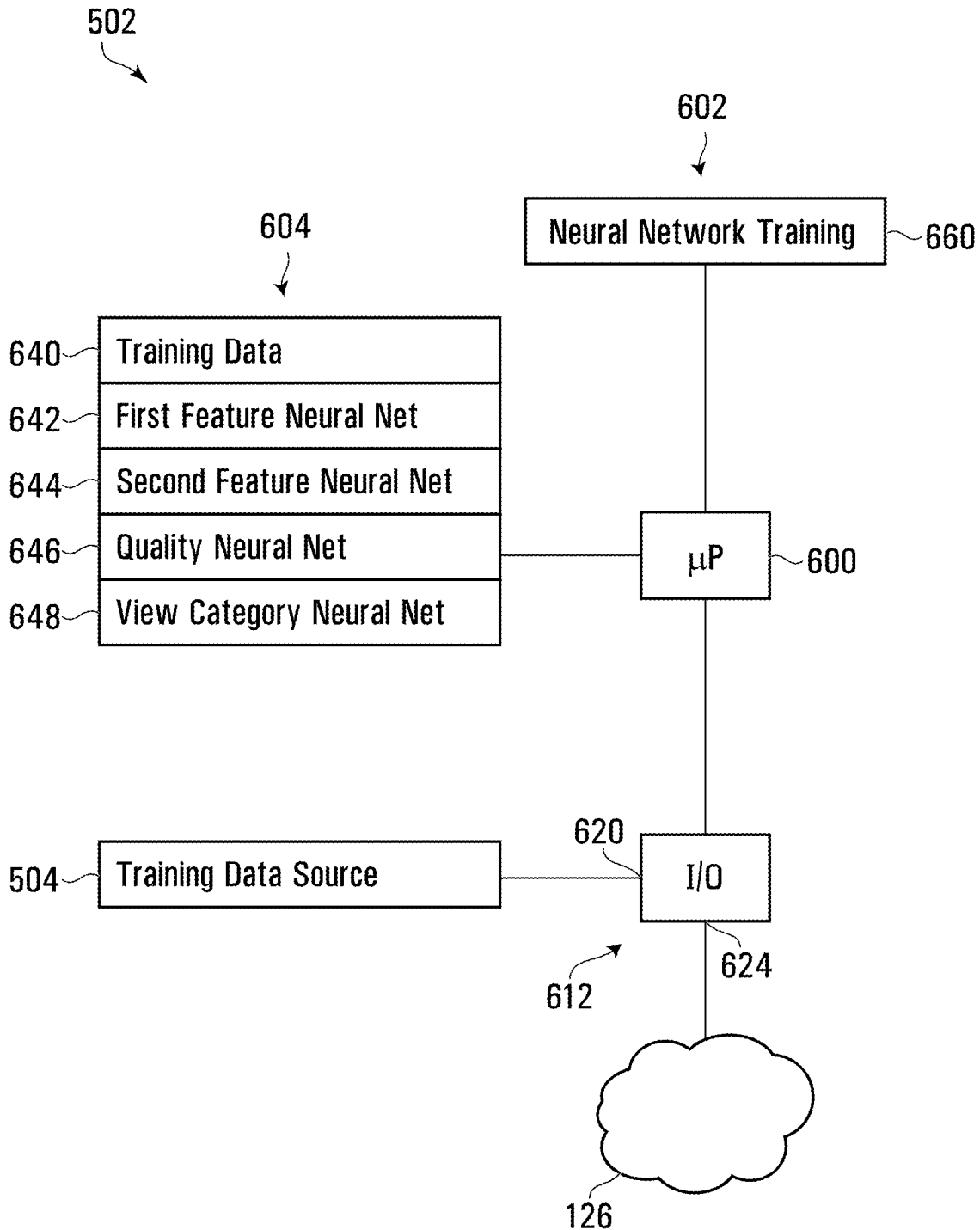


FIG. 10

**FIG. 11**

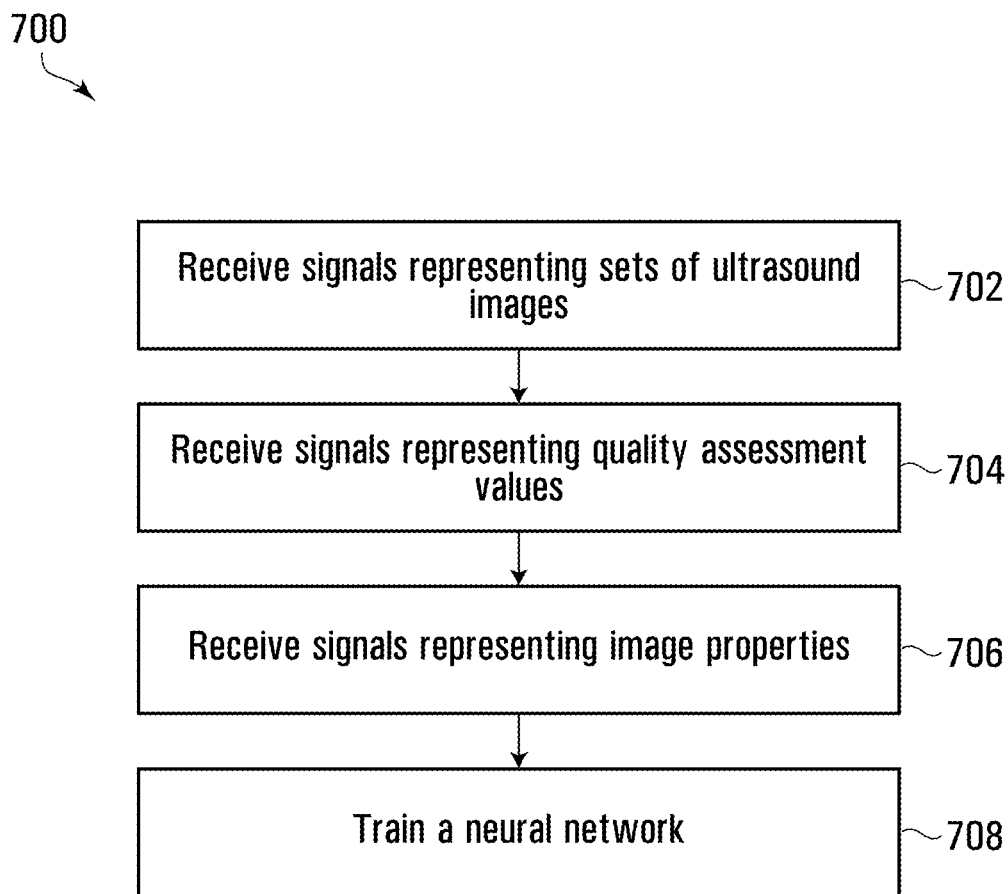


FIG. 12



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ULTRASONIC IMAGE ANALYSIS**RELATED APPLICATION**

This application is a continuation of International Application No. PCT/CA2019/051192, filed on Aug. 28, 2019, and claims the benefit of U.S. Provisional Application No. 62/725,913 entitled "ULTRASONIC IMAGE ANALYSIS", filed on Aug. 31, 2018, both of which are hereby incorporated by reference herein in their entirety.

BACKGROUND**1. Field**

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

2. Description of Related Art

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

SUMMARY

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

The image property may be a view category.

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

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

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

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

Deriving the one or more extracted feature representations may involve inputting the first feature representations into a

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

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

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

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

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

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

Each of the image properties may be a view category.

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

The feature extracting neural network may be configured to, for each of the ultrasound training images included in the

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input set of ultrasound training images, derive a first feature representation associated with the ultrasound image.

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

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

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

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

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

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

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

In accordance with various embodiments, there is provided a system for facilitating ultrasonic image analysis, the system including means for receiving signals representing a set of ultrasound images of the subject, means for deriving one or more extracted feature representations from the set of ultrasound images, means for determining, based on the derived one or more extracted feature representations, a quality assessment value representing a quality assessment of the set of ultrasound images, means for determining, based on the derived one or more extracted feature representations, an image property associated with the set of ultrasound images, and means for producing signals representing the quality assessment value and the image property for causing the quality assessment value and the image property to be associated with the set of ultrasound images. In accordance with various embodiments, there is provided a system for training one or more neural networks to facilitate ultrasonic image analysis, the system including means for receiving signals representing a plurality of sets of ultrasound training images, means for receiving signals representing quality assessment values, each of the quality assessment values associated with one of the sets of ultrasound training images and representing a quality assessment of the associated set of ultrasound training images, means for receiving signals representing image properties, each of the image properties associated with one of the sets of ultrasound training images, and means for training a neural network, the training comprising, for each set of the plurality of sets of ultrasound training images, using the set of ultrasound training images as an input to the neural network and using the quality assessment values and the image properties associated with the set of ultrasound training images as desired outputs of the neural network.

Other aspects and features of embodiments of the disclosure will become apparent to those ordinarily skilled in the

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art upon review of the following description of specific embodiments of the disclosure in conjunction with the accompanying figures.

BRIEF DESCRIPTION OF THE DRAWINGS

In drawings which illustrate embodiments of the disclosure,

FIG. 1 is a schematic view of a system for facilitating ultrasonic image analysis of a subject according to various embodiments of the disclosure;

FIG. 2 is a schematic view of an image analyzer of the system shown in FIG. 1 including a processor circuit in accordance with various embodiments of the disclosure;

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

FIG. 4 is a representation of an exemplary neural network that may be used in the system shown in FIG. 1 in accordance with various embodiments of the disclosure;

FIG. 5 is a representation of part of the neural network shown in FIG. 4 in accordance with various embodiments of the disclosure;

FIG. 6 is a representation of part of the neural network shown in FIG. 4 in accordance with various embodiments of the disclosure;

FIG. 7 is a representation of part of the neural network shown in FIG. 4 in accordance with various embodiments of the disclosure;

FIG. 8 is a representation of part of the neural network shown in FIG. 4 in accordance with various embodiments of the disclosure;

FIG. 9 is a representation of part of the neural network shown in FIG. 4 in accordance with various embodiments of the disclosure;

FIG. 10 is a representation of a display that may be provided by the system shown in FIG. 1 in accordance with various embodiments of the disclosure;

FIG. 11 is a schematic view of a neural network trainer that may be included in the system shown in FIG. 1 in accordance with various embodiments of the disclosure;

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

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

DETAILED DESCRIPTION

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

In various embodiments, the system 10 may provide feedback to an operator of the ultrasound machine 16 regarding quality of the ultrasound images being captured and other image properties. For example, in some embodiments, the system 10 may provide real-time or near real-time feedback to the operator in the form of a view category or classification and image quality estimation. In various

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embodiments, this may allow the operator to capture ultrasound images that facilitate more accurate analysis, which may in some embodiments allow more accurate diagnosis of a patient acting as the subject of the analysis.

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

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

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

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

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manipulated such that the ultrasound machine **16** produces ultrasound images of a heart of the person, for example.

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

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

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

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

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

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the view category determined by the analyzer **14** may represent the category of view represented by the set of ultrasound images.

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

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

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

Analyzer—Processor Circuit

Referring now to FIG. 2, a schematic view of the analyzer **14** of the system **10** shown in FIG. 1 according to various embodiments is shown. In various embodiments, the analyzer **14** may be implemented as a mobile device, such as a Samsung™ Galaxy S8+™ running an operating system, such as Android™, for example.

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

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

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or all of the interfaces **120**, **130**, or **124** may facilitate a wireless or wired communication.

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

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

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

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

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

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

Each of the program memory **102** and storage memory **104** may be implemented as one or more storage devices including random access memory (RAM), a hard disk drive (HDD), a solid-state drive (SSD), a network drive, flash memory, a memory stick or card, any other form of non-transitory computer-readable memory or storage medium, and/or a combination thereof. In some embodiments, the program memory **102**, the storage memory **104**, and/or any

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portion thereof may be included in a device separate from the analyzer **14** and in communication with the analyzer **14** via the I/O interface **112**, for example.

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

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

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

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

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

Referring to FIG. **3**, after block **202** has been executed, the flowchart continues to block **204**. In various embodiments, execution of blocks **204**, **206** and **208** of the flowchart **200** may result in the analyzer processor **100** being directed

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to input the received set of ultrasound images into a neural network **300** shown in FIG. **4**, to generate an output of a quality assessment value and an image property, which in some embodiments may be a view category. The parameters defining the neural network **300** may be stored in the storage memory **104** and may have been previously determined during neural network training, which is described in further detail in accordance with various embodiments below.

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

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

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

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

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814 (2010), for example), a 2D convolution layer with 3×3 filters, a dropout layer, a concatenation layer, another 2D convolution layer, another dropout layer, and an average pooling layer.

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

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

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

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

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

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

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

Block 204 may direct the analyzer processor to store the extracted first feature representations in the location 142 of the storage memory 104, for example, in a feature buffer which may be shared between all three threads. Once all of the ultrasound images included in the set of ultrasound images have been input to an instance of the commonly defined first feature extracting neural network, block 204

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may direct the analyzer processor 100 to input the stored first feature representations into a second feature extracting neural network 340 shown in FIG. 4 to generate respective second feature representations, each associated with one of the ultrasound images. In some embodiments, the second feature representations generated by the second feature extracting neural network 340 may act as the one or more extracted feature representations derived by block 204 of the flowchart 200 shown in FIG. 3.

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

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

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

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

Block 206 may direct the analyzer processor 100 to retrieve the second feature representations from the location 144 of the storage memory 104, the second feature representations acting as the one or more extracted feature representations. Block 206 may direct the analyzer processor 100 to use the second feature representations as inputs to a quality assessment value specific neural network configured to produce as an output a representation of a quality assessment value. In some embodiments, block 206 may direct the analyzer processor 100 to input each of the second

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feature representations into an implementation of a commonly defined quality assessment value specific neural subnetwork (e.g., 362, 364, and 366) to generate a quality assessment value for each of the input second feature representations. Referring to FIG. 4, in various embodiments the commonly defined quality assessment value specific neural subnetworks may each be defined by the same neural network parameters. In some embodiments, parameters defining the quality assessment value specific neural subnetworks may be stored in the location 158 of the storage memory 104 and block 206 may direct the analyzer processor 100 to retrieve the parameters from the location 158 of the storage memory 104.

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

Referring to FIG. 8, in some embodiments, the quality assessment value specific neural subnetwork 362 may include input nodes 380 for holding the output of the second feature extracting neural network 342. In some embodiments, the input nodes 380 may hold a 1x128 feature tensor, for example. In some embodiments, input nodes 364 may be connected to a feature node 382, which may, for example, hold a 1x1 feature tensor acting as an input for a logistic regression function 384. The logistic regression function 384 may be connected to an output node 386, which may include a 1x1 probability tensor holding an output of the quality assessment value specific neural subnetwork 362. In some embodiments, output node 386 may hold a value in the range of [0,1], where a value of 0 corresponds to a bad quality and a value of 1 corresponds to perfect quality.

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

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

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

In various embodiments, each of the commonly defined view category specific neural subnetworks may apply a softmax to the input second feature representations to generate a probability vector wherein each position in the vector corresponds to a view category and the value stored therein represents a probability that the ultrasound image is in the view category corresponding to the vector position. For example, where there are fourteen (14) possible view categories, the output of the view category specific neural subnetwork 372 may be a 14-element length probability vector. In various embodiments, each position in the output probability vector may represent a determined probability that the input set of ultrasound images depicts a particular view category, such as, for example, one chosen from AP2, AP3, AP4, AP5, PLAX, RVIF, PSAXA, PSAXM, PSAXPM, PSAXAP, SC4, SC5, IVC, and SUPRA. Referring to FIG. 9, there is shown a detailed representation of the view category specific neural subnetwork 372 in accordance with various embodiments. The view category specific neural subnetwork 372 shown in FIG. 9 is represented in a simplified manner as it may apply to a single cine case (i.e., for providing an output having dimension 1x14). In various embodiments, each of the commonly defined view category specific neural subnetworks may be defined by the same neural network parameters.

Referring to FIG. 9, in some embodiments, view category specific neural subnetwork 372 may include input nodes 388 for holding the output of the second feature extracting neural network 342. In some embodiments, the input nodes 388 may hold a 1x128 feature tensor, for example. In some embodiments, input nodes 388 may be connected to feature nodes 390, which may, for example, hold a 1x14 feature tensor acting as an input for a softmax function 392. The softmax function 392 may be connected to an output node 394, which may include a 1x14 probability tensor holding an output of the view category specific neural subnetwork 372. In some embodiments, output node 394 may hold values that are each in the range of [0,1] and the sum of the values may be equal to 1.

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

Referring back to FIG. 3, block 210 directs the analyzer processor 100 to produce signals representing the quality assessment value and the image property for causing the quality assessment value and the image property to be associated with the set of ultrasound images. In some embodiments, block 210 may direct the analyzer processor 100 to produce signals for causing a representation of the quality assessment value and a representation of the image property to be displayed by the display 18 in association with the set of ultrasound images. For example, in some embodiments, block 210 may direct the analyzer processor 100 to retrieve the quality assessment value from the location 150 of the storage memory 104 and to retrieve the view category from the location 152 of the storage memory 104.

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and to transmit signals to the display **18** via the interface **130** of the I/O interface **112** shown in FIG. **2**, representing the quality assessment value and the view category for causing the graphical user interface **400** shown in FIG. **10** to be displayed by the display **18**.

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

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

Neural Network Training

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

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

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

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

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

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

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

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

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

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

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

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

Block **706** then directs the trainer processor **600** to receive signals representing image properties, each of the image properties associated with one of the sets of ultrasound

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training images. In some embodiments, the image properties may each be a view category. In some embodiments, block 706 may direct the trainer processor 600 to receive signals representing view categories from the training data source 504 via the interface 620 of the I/O interface 612 shown in FIG. 11. In various embodiments, the view categories may have been previously provided to the training data source 504. For example, in some embodiments, the view categories may have been previously provided by an expert who has been trained to determine view categories for the sets of ultrasound images. For example, in some embodiments, the subject imaged in the sets of ultrasound images may be a heart and the view categories may be chosen from the following views: AP2, AP3, AP4, AP5, PLAX, RVIF, PSAXA, PSAXM, PSAXPM, PSAXAP, SC4, SC5, IVC, and SUPRA.

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

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

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

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

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

Block 708 may direct the analyzer processor 100 to feed the input tensor to the neural network 300, where each ultrasound image first goes through an instance of the commonly defined first feature extracting neural network or

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DenseNet feature extraction module. The output tensor of the commonly defined first feature extracting neural networks or DenseNet modules may be $32 \times 10 \times A \times B \times C$, where " $A \times B \times C$ " denotes the dimensionality of the output feature for each frame. In some embodiments, the output tensor may be of dimension $32 \times 10 \times 14 \times 14 \times 34$, for example.

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

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

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

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

In various embodiments the flowchart 700 may be executed many times in order to train the neural network 300 shown in FIG. 4 adequately. For example, in some embodi-

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ments, the plurality of sets of ultrasound training images may include 13400 sets or echo cine clips, and the trainer 502 may be configured to run 100 epochs where each epoch runs through the entire training with batch size 32.

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

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

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

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

Highest Quality Assessment Value

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

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

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

Upon analysis of subsequent sets of ultrasound images for the view category, The block may direct the analyzer processor 100 to, for each determined quality assessment value, determine whether the quality assessment value is higher than the quality assessment value stored in association with the ultrasound image and the same view category in the location 162 of the storage memory 104. The block may direct the analyzer processor 100 to, if the determined quality assessment value is higher than the stored quality

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assessment value, store the ultrasound image associated with the determined quality assessment in the location 162 of the storage memory 104 in association with the determined quality assessment value and the determined view category. In some embodiments, the block may direct the analyzer processor 100 to replace any previously stored quality assessment value and ultrasound image stored in the location 162 of the storage memory 104 in association with the determined view category with the determined quality assessment value and the associated ultrasound image. In various embodiments, this may facilitate storage of ultrasound images associated with the highest determined quality assessment values, for each view category, in the location 162 of the storage memory 104.

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

Various Embodiments

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

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

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

Cardiac

- Left ventricular ejection fraction (LVEF)
- Left atrial ejection fraction (LAEF)
- Strain, both local and global
- Pericardial Effusion
- Heart rate
- Cardiac phase

FAST (Emergency Medicine)

- Free Fluid
- Inferior vena cava (IVC)
- Volume Assessment

Obstetrics

- Ovarian torsion
- Endometritis
- Detection of fetal pole

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Calculation of gestational age
 Gallbladder
 Gallstones
 Pulmonary
 Pneumothorax
 Pleural Effusion
 Pneumonia/Consolidation
 Ocular
 Retinal Detachment
 Vitreous Hemorrhage
 Musculoskeletal
 Joint Effusion
 Tendon Rupture
 Fracture Identification
 Renal
 Hydronephrosis
 Nephrolithiasis
 Deep vein thrombosis (DVT)
 Aorta
 Intrauterine pregnancy
 Intrauterine Pregnancy
 Fetal Heart Rate
 Soft Tissue
 Cellulitis
 Abscess
 Foreign body
 Scrotal
 Testicular Torsion
 Hydrocele
 Epididymitis

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

Heart valve repair using transesophageal echocardiography
 Nerve blocks
 Vascular access
 Arthrocentesis
 Lumbar puncture
 Paracentesis
 Thoracentesis
 Airway

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

In various embodiments, the ultrasound machine **16** may take additional or alternative forms to the schematic representation shown in FIG. **1**. For example, in some embodiments, the ultrasound machine **16** may be implemented wherein the ultrasound machine and the transducer are one unit and the ultrasound machine produces wireless signals

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for causing a display to display the ultrasound images. For example, in some embodiments, the ultrasound machine may wirelessly transmit ultrasound data to a mobile device or phone for display. In some embodiments, the mobile device or phone displaying the ultrasound images may act as the analyzer **14** or transmit the ultrasound data to a secondary mobile device acting as the analyzer **14**, for analysis.

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

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

In various embodiments, the analyzer **14** may be implemented using an Android mobile device running a customized mobile implementation of the TensorFlow inference engine. In some embodiments, by multi-threading four TensorFlow instances together, the analyzer **14** may be able to execute the flowchart **200** shown in FIG. **3** for analyzing images being received at 30 Hz with a latency of under 0.4 seconds.

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

Referring to FIG. **13**, three first feature extracting neural network or CNN threads can be seen extracting features from ten consecutive input frames before waking a waiting RNN thread configured to run the rest of the neural network **300** shown in FIG. **4**, which then runs the LSTMs, quality assessment value and view category prediction on the buffered features extracted by the CNN threads. The target frame rate for the system may be set at 30 Hz, which can be inferred by the lines **760**, **762**, **764**, **766**, and **768** representing the arrival of input frames. In some embodiments, the mean run-time for the first feature extracting neural networks (including feeding the input, running the network, and fetching the output) may be 28.76 ms with a standard deviation of 16.42 ms and the mean run time of the rest of the neural network **300** may be 157.48 ms with a standard deviation of 21.85 ms. Therefore, the mean latency of the feedback may be 352.58 plus or minus 38.27 ms, when measured from the middle of the ten-frame sequence.

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

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

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

$$T_{max, RNN} = (\text{buffer length}) * 1 / FPS = 10 / 30 = 333.33 \text{ ms}$$

With the chosen three first feature extracting neural network threads and one thread for the rest of the neural

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network 300 configuration, in various embodiments, the application may require few threads while still providing enough tolerance to avoid frame build-up.

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

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

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

The invention claimed is:

1. A computer-implemented method of facilitating ultrasonic image analysis of a subject, the method comprising: receiving signals representing a set of ultrasound images of the subject;

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

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

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

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

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

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

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

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

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

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

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

9. The method of claim 2 wherein determining the quality assessment value comprises inputting the one or more extracted feature representations into a quality assessment value specific neural network and wherein determining the image property comprises inputting the one or more extracted feature representations into an image property specific neural network.

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

11. The method of claim 2 wherein producing signals representing the quality assessment value and the image property for causing the quality assessment value and the image property to be associated with the set of ultrasound images comprises producing signals for causing a representation of the quality assessment value and a representation of the image property to be displayed by at least one display in association with the set of ultrasound images.

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

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

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

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

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

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

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

the feature extracting neural network is configured to take an input set of the plurality of sets of ultrasound

US 10,751,029 B2

25

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

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

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

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

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

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

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

21. A system for facilitating ultrasonic image analysis comprising at least one processor configured to:

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

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

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

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

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

22. The system of claim 21 wherein the image property is a view category.

26

23. The system of claim 22 wherein the at least one processor is configured to, for each of the ultrasound images, input the ultrasound image into a commonly defined first feature extracting neural subnetwork to generate a first feature representation associated with the ultrasound image.

24. The system of claim 23 wherein the at least one processor is configured to, for each of the ultrasound images, input the ultrasound image into a commonly defined first feature extracting neural subnetwork to generate the first feature representation associated with the ultrasound image.

25. The system of claim 24 wherein the at least one processor is configured to concurrently input each of a plurality of the ultrasound images into a respective implementation of the commonly defined first feature extracting neural network.

26. The system of claim 24 wherein the at least one processor is configured to input the first feature representations into a second feature extracting neural network to generate respective second feature representations, each associated with one of the ultrasound images and wherein the one or more extracted feature representations include the second feature representations.

27. The system of claim 22 wherein the at least one processor is configured to input the one or more extracted feature representations into a quality assessment value specific neural network and to input the one or more extracted feature representations into an image property specific neural network.

28. The system of claim 27 wherein the at least one processor is configured to input each of the one or more extracted feature representations into an implementation of a commonly defined quality assessment value specific neural subnetwork and to input each of the one or more extracted feature representations into an implementation of a commonly defined image property specific neural network.

29. The system of claim 22 wherein the at least one processor is configured to produce signals for causing a representation of the quality assessment value and a representation of the image property to be displayed by at least one display in association with the set of ultrasound images.

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

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

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

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

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

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

* * * * *

EXHIBIT C

From: Robert Rohling <rohling@ece.ubc.ca>

Date: Thursday, May 25, 2017 at 9:46 AM

To: Kilian Koepsell <kilian@baylabs.io>

Cc: "Cluong@ualberta.ca" <cluong@ualberta.ca>, Purang Abolmaesumi <purang@ece.ubc.ca>, Marc Fine <marcfine@gmail.com>

Subject: Re: Introduction

Hi Kilian,

It was a pleasure speaking with a fellow “cardiac-AI” expert and I hope to continue this conversation. Here is a preprint of our latest paper in TMI, and a previous conference paper.

Rob

On May 25, 2017, at 9:09 AM, Kilian Koepsell <kilian@baylabs.io> wrote:

Rob, Christina, Purang,

Thank you all for the great first discussion yesterday!

It would be great if you could send me a digital copy of your paper on Automatic Quality Assessment of Echocardiograms. I should have access but haven’t been able to download it.

I will look at the paper and discuss possible next steps with the team.

Thank you,
Kilian

On May 24, 2017, at 8:20 AM, Rob Rohling <rohling@ece.ubc.ca> wrote:

I will also try to join in by dialling in.

Rob

Robert Rohling
Director ICICS
Professor MECH & ECE
UBC

On May 24, 2017, at 7:40 AM, Purang Abolmaesumi <purang@ece.ubc.ca> wrote:

Hi Kilian,

Thank you so much for getting back to us. Christina and I are available today at 9.30am PST. I look forward to chatting with you.

Regards,

Purang

From: Kilian Koepsell <kilian@baylabs.io>
Date: Wednesday, May 24, 2017 at 7:29 AM
To: "Cluong@ualberta.ca" <cluong@ualberta.ca>
Cc: "Purang Abolmaesumi (purang@ece.ubc.ca)" <purang@ece.ubc.ca>, Robert Rohling <rohling@ece.ubc.ca>, Amir Abdi <amirabdi@ece.ubc.ca>, "Tsang, Teresa" <t.tsang@ubc.ca>, Marc Fine <marcfine@gmail.com>
Subject: Re: Introduction

Christina,

I can meet today 9:30-10 (PST) if that is still possible.

Otherwise, we can meet Tuesday 10-10:30 PST

We can use our zoom video conference line. The dial-in information is below.

Best,
Kilian

--

Join from PC, Mac, Linux, iOS or Android: <https://zoom.us/j/2261308501>

Or iPhone one-tap (US Toll): +14086380968,2261308501# or +16465588656,2261308501#

Or Telephone:

Dial: +1 408 638 0968 (US Toll) or +1 646 558 8656 (US Toll)

Meeting ID: 226 130 8501

International numbers

available: <https://zoom.us/join?j=2261308501>

On May 23, 2017, at 2:46

PM, Cluong@ualberta.ca <cluong@ualberta.ca> wrote:

Thanks you for taking the time to meet with us.

Please let us know if one of these time slots would work for you:

Wednesday, May 24 (tomorrow) at 9:30 - 10:30 (PST)

Monday, May 29 9:00 - 10:00 (PST)

Tuesday, May 30 anytime

Thank you and look forward to speaking with you.

Sincerely,

Christina Luong on behalf of the team

Christina L. Luong MD, FRCPC
PGY 6 Cardiology
University of British Columbia

Sent from my iPhone, please excuse the brevity.

On May 22, 2017, at 17:36, Kilian Koepsell <kilian@baylabs.io> wrote:

Hi Marc, Thank you for the introduction!

Hi Christina,

Great to meet you here! It would be great to have an introductory phone call. Could you send me some days/times that would work for you this week or next?

Thank you,
Kilian

On May 18, 2017, at 12:39 AM, Christina Luong <cluong@ualberta.ca> wrote:

Thank you so much for the introduction,
Marc.

Dr. Koepsell, the team and I would love to speak with you if you have a few minutes. I know you are very busy but we would

appreciate your thoughts if you are willing to meet with us.

Thank you for your time,

Christina Luong

On Wed, May 17, 2017 at 12:10 PM, Marc Fine <marcfine@gmail.com> wrote:

Hello, Killian. I'd like to introduce you to Dr. Christina Luong. She is the clinical representative of a computer engineering research team from UBC up in Vancouver (VGH Cardiology and Drs. Abolmaesumi/Rohling).

Her group is developing a technology that will assist physicians who treat patients with cardiac symptoms. It is a tool that will be designed to add onto existing ultrasound platforms to provide real-time feedback on the quality of cardiac ultrasound images. This product is meant to improve image quality and by extension improve scanner interpretation and decrease scanning time, particularly for point of care. (Her contact info is below)

Christina, Killian Koepsell is founder and CTO of Bay Labs (www.baylabs.io) based in San Francisco. They are focused on deep learning and as it relates to cardiac (echo) scans.(See their website for more info)

Might be useful for you two to connect.

Christina L. Luong MD, FRCPC
PGY 6 Cardiology
University of British Columbia
cluong@ualberta.ca

Best regards,

Marc J. Fine

NuSonos

2679 Broadmoor Rd
Camano Island, WA 98282

Home: [360/387-5519](tel:3603875519)

Cell: [\(360\) 631-8543](tel:3606318543)

marcfine@gmail.com

skype: fine,marc

www.marcfine.com

--

Christina L. Luong, B.Sc., MD FRCPC
PGY 6 Cardiology
University of British Columbia

EXHIBIT D

Snell & Wilmer

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Jeffrey D. Morton
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jmorton@swlaw.com

May 5, 2022

Mr. Steve Cashman,
President & Chief Executive Officer
Caption Health, Inc.
2000 Sierra Point Parkway, Suite 800
Brisbane, CA 94005

*Re: Infringement of U.S. Patent No. 11,129,591, owned by
The University of British Columbia*

Dear Mr. Cashman:

We represent the University of British Columbia ("UBC"), a major research university located in Vancouver, Canada. UBC is the owner of U.S. Patent No. 11,129,591, a copy of which is enclosed for your reference.

Recently, UBC became aware of your company and its activities as summarized in the following online activities and publications:

1. <https://emmainternational.com/caption-guidance-fdas-first-authorized-ai-based-cardiac-ultrasound-software/>;
2. <https://jamanetwork.com/journals/jamacardiology/fullarticle/2776714>;
3. <https://www.jacc.org/doi/pdf/10.1016/j.jaccas.2020.12.013>; and
4. <https://www.youtube.com/watch?v=URmb72IA4b4>.

Based on a preliminary review of the above-mentioned activities and publications, UBC believes – and we agree – that such activities constitute infringement of at least one of its claims of U.S. Patent No. 11,129,591. Not surprisingly, UBC takes intellectual property misappropriation seriously and actively monitors unauthorized use of its patented inventions.

Snell & Wilmer

Mr. Steve Cashman | Caption Health, Inc.
May 5, 2022
Page 2

Notwithstanding the foregoing, UBC is – at present – willing to discuss options to resolve this matter without resorting to litigation. Accordingly, we ask that you or your counsel contact me by May 19, 2022 to discuss approaches to resolve this dispute.

Yours very truly,

SNELL & WILMER L.L.P.

A handwritten signature in black ink, appearing to read "J. Morton", with a stylized flourish extending to the right.

Per: Jeffrey D. Morton

JDM:la

Encl. U.S. Patent No. 11,129,591 (cover page)



US011129591B2

(12) **United States Patent**
Abolmaesumi et al.

(10) **Patent No.:** **US 11,129,591 B2**
(45) **Date of Patent:** **Sep. 28, 2021**

(54) **ECHOCARDIOGRAPHIC IMAGE ANALYSIS**

(71) Applicant: **THE UNIVERSITY OF BRITISH COLUMBIA**, Vancouver (CA)

(72) Inventors: **Purang Abolmaesumi**, Vancouver (CA); **Robert Rohling**, Vancouver (CA); **Amir H. Abdi**, Vancouver (CA); **Teresa S. M. Tsang**, Vancouver (CA)

(73) Assignee: **The University of British Columbia**, Vancouver (CA)

(*) Notice: Subject to any disclaimer, the term of this patent is extended or adjusted under 35 U.S.C. 154(b) by 500 days.

(21) Appl. No.: **16/095,601**

(22) PCT Filed: **Apr. 21, 2017**

(86) PCT No.: **PCT/CA2017/050496**

§ 371 (c)(1),

(2) Date: **Oct. 22, 2018**

(87) PCT Pub. No.: **WO2017/181288**

PCT Pub. Date: **Oct. 26, 2017**

(65) **Prior Publication Data**

US 2019/0125298 A1 May 2, 2019

Related U.S. Application Data

(60) Provisional application No. 62/325,779, filed on Apr. 21, 2016.

(51) **Int. Cl.**
G06K 9/00 (2006.01)
A61B 8/08 (2006.01)

(Continued)

(52) **U.S. Cl.**
CPC **A61B 8/0883** (2013.01); **A61B 8/4405** (2013.01); **A61B 8/463** (2013.01);
(Continued)

(58) **Field of Classification Search**

CPC A61B 8/0883; A61B 8/463; A61B 8/4405;
A61B 8/5215; G06N 3/04; G06N 3/08;
(Continued)

(56) **References Cited**

U.S. PATENT DOCUMENTS

5,776,063 A 7/1998 Dittrich et al.
7,672,491 B2 3/2010 Krishnan et al.
(Continued)

FOREIGN PATENT DOCUMENTS

WO 2014097090 A1 6/2014
WO 2014/155272 A1 10/2014
WO 2017181288 A1 10/2017

OTHER PUBLICATIONS

Abdi, A.H. et al., "Automatic Quality Assessment of Apical Four-Chamber Echocardiograms Using Deep Convolutional Neural Networks", SPIE Medical Imaging 2017: Image Processing, edited by Martin A. Styner, Elsa D. Angelini, Proceedings of SPIE, vol. 10133, 101330S, Feb. 2017.

(Continued)

Primary Examiner — Nan D Huynh

(74) *Attorney, Agent, or Firm* — Kolitch Romano LLP

(57) **ABSTRACT**

A computer-implemented system for facilitating echocardiographic image analysis is disclosed. The system includes at least one processor configured to receive signals representing a first at least one echocardiographic image, associate the image with a first view category of a plurality of predetermined view categories, determine, based on the first at least one echocardiographic image and the first view category, a first quality assessment value representing a view category specific quality assessment of the first at least one echocardiographic image, and produce signals representing the first quality assessment value for causing the first quality assessment value to be associated with the first at least one echocardiographic image. The at least one processor may

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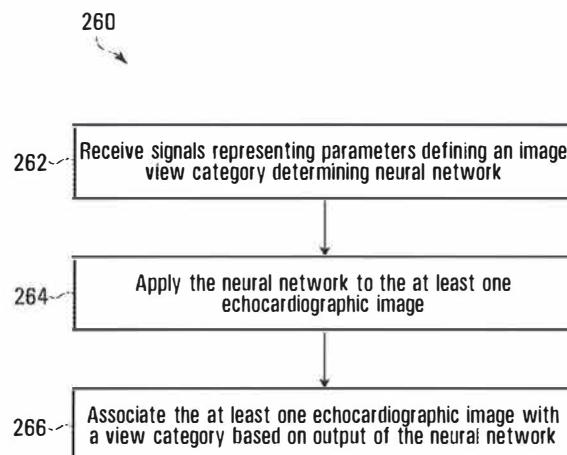


EXHIBIT E



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DEL MAR HEIGHTS
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LOS ANGELES
ORANGE COUNTY
PHOENIX
SAN DIEGO
SILICON VALLEY

May 24, 2022

VIA FEDEX

Mr. Steve Cashman
President & Chief Executive Officer
Caption Health, Inc.
2000 Sierra Point Parkway, Suite 800
Brisbane, CA 94005

Re: *Infringement of U.S. Patent No. 11,129,591, owned by The University of British Columbia*

Dear Mr. Cashman:

Further to the letter sent to you on May 5, 2022 (attached hereto as Exhibit A), I would like to inform you that I have moved my law practice to Procopio, Cory, Hargreaves & Savitch LLP, effective May 13, 2022. I have contacted my former law firm, Snell & Wilmer LLP, and they confirm that they have not received a response to the May 5, 2022 letter.

On behalf of The University of British Columbia, we ask for a substantive response to the letter of May 5, 2022 by 5:00 pm PDT on May 31, 2022. I can be reached by email (jeff.morton@procopio.com) or on my direct work line (858.720.6330). If a substantive response is not received by the requested deadline, The University of British Columbia will be provided with a full range of legal and equitable options and future action may be taken without further notice being provided.

Very truly yours,

A handwritten signature in dark ink, appearing to read 'Jeff', with a stylized flourish at the end.

Jeffrey D. Morton

Encl. Exhibit A; letter to Mr. S. Cashman, dated May 5, 2022

procopio.com

PERSONAL-1132/5937166.1

Snell & Wilmer

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Jeffrey D. Morton
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May 5, 2022

Mr. Steve Cashman,
President & Chief Executive Officer
Caption Health, Inc.
2000 Sierra Point Parkway, Suite 800
Brisbane, CA 94005

*Re: Infringement of U.S. Patent No. 11,129,591, owned by
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Dear Mr. Cashman:

We represent the University of British Columbia ("UBC"), a major research university located in Vancouver, Canada. UBC is the owner of U.S. Patent No. 11,129,591, a copy of which is enclosed for your reference.

Recently, UBC became aware of your company and its activities as summarized in the following online activities and publications:

1. <https://emmainternational.com/caption-guidance-fdas-first-authorized-ai-based-cardiac-ultrasound-software/>;
2. <https://jamanetwork.com/journals/jamacardiology/fullarticle/2776714>;
3. <https://www.jacc.org/doi/pdf/10.1016/j.jaccas.2020.12.013>; and
4. <https://www.youtube.com/watch?v=URmb72IA4b4>.

Based on a preliminary review of the above-mentioned activities and publications, UBC believes – and we agree – that such activities constitute infringement of at least one of its claims of U.S. Patent No. 11, 129,591. Not surprisingly, UBC takes intellectual property misappropriation seriously and actively monitors unauthorized use of its patented inventions.

Snell & Wilmer

Mr. Steve Cashman | Caption Health, Inc.
May 5, 2022
Page 2

Notwithstanding the foregoing, UBC is – at present – willing to discuss options to resolve this matter without resorting to litigation. Accordingly, we ask that you or your counsel contact me by May 19, 2022 to discuss approaches to resolve this dispute.

Yours very truly,

SNELL & WILMER L.L.P.

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Per: Jeffrey D. Morton

JDM:la

Encl. U.S. Patent No. 11,129,591 (cover page)



US011129591B2

(12) **United States Patent**
Abolmaesumi et al.

(10) **Patent No.:** **US 11,129,591 B2**
(45) **Date of Patent:** **Sep. 28, 2021**

(54) **ECHOCARDIOGRAPHIC IMAGE ANALYSIS**

(71) Applicant: **THE UNIVERSITY OF BRITISH COLUMBIA**, Vancouver (CA)

(72) Inventors: **Purang Abolmaesumi**, Vancouver (CA); **Robert Rohling**, Vancouver (CA); **Amir H. Abdi**, Vancouver (CA); **Teresa S. M. Tsang**, Vancouver (CA)

(73) Assignee: **The University of British Columbia**, Vancouver (CA)

(*) Notice: Subject to any disclaimer, the term of this patent is extended or adjusted under 35 U.S.C. 154(b) by 500 days.

(21) Appl. No.: **16/095,601**

(22) PCT Filed: **Apr. 21, 2017**

(86) PCT No.: **PCT/CA2017/050496**

§ 371 (c)(1),

(2) Date: **Oct. 22, 2018**

(87) PCT Pub. No.: **WO2017/181288**

PCT Pub. Date: **Oct. 26, 2017**

(65) **Prior Publication Data**

US 2019/0125298 A1 May 2, 2019

Related U.S. Application Data

(60) Provisional application No. 62/325,779, filed on Apr. 21, 2016.

(51) **Int. Cl.**
G06K 9/00 (2006.01)
A61B 8/08 (2006.01)

(Continued)

(52) **U.S. Cl.**
CPC **A61B 8/0883** (2013.01); **A61B 8/4405** (2013.01); **A61B 8/463** (2013.01);
(Continued)

(58) **Field of Classification Search**

CPC A61B 8/0883; A61B 8/463; A61B 8/4405;
A61B 8/5215; G06N 3/04; G06N 3/08;
(Continued)

(56) **References Cited**

U.S. PATENT DOCUMENTS

5,776,063 A 7/1998 Dittrich et al.
7,672,491 B2 3/2010 Krishnan et al.
(Continued)

FOREIGN PATENT DOCUMENTS

W● 2014097090 A1 6/2014
W● 2014/155272 A1 10/2014
W● 2017181288 A1 10/2017

OTHER PUBLICATIONS

Abdi, A.H. et al., "Automatic Quality Assessment of Apical Four-Chamber Echocardiograms Using Deep Convolutional Neural Networks", SPIE Medical Imaging 2017: Image Processing, edited by Martin A. Styner, Elsa D. Angelini, Proceedings of SPIE, vol. 10133, 101330S, Feb. 2017.

(Continued)

Primary Examiner — Nan D Huynh

(74) *Attorney, Agent, or Firm* — Kolitch Romano LLP

(57) **ABSTRACT**

A computer-implemented system for facilitating echocardiographic image analysis is disclosed. The system includes at least one processor configured to receive signals representing a first at least one echocardiographic image, associate the image with a first view category of a plurality of predetermined view categories, determine, based on the first at least one echocardiographic image and the first view category, a first quality assessment value representing a view category specific quality assessment of the first at least one echocardiographic image, and produce signals representing the first quality assessment value for causing the first quality assessment value to be associated with the first at least one echocardiographic image. The at least one processor may

(Continued)

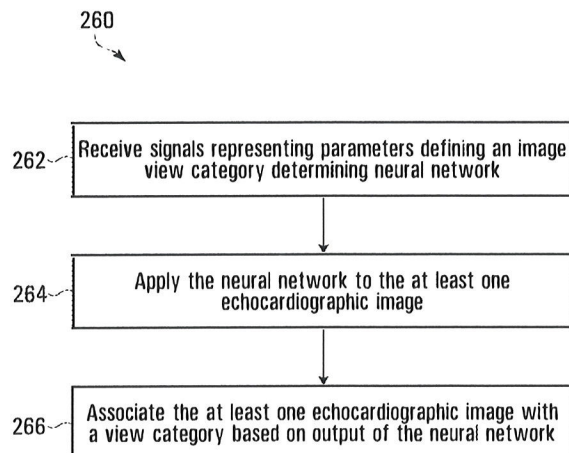


EXHIBIT F

From: Steve Cashman <steve@captionhealth.com>
Sent: Monday, June 27, 2022 1:30 PM
To: Morton, Jeff <Jeff.Morton@procopio.com>
Cc: Michael Cannon <mgc@captionhealth.com>
Subject: RE: University of British Columbia

*** EXTERNAL EMAIL - Please use Caution. ***

Dear Mr. Morton

Now that we have had a chance to read your May 5th letter more carefully, we have to tell you that we really do not see how we can respond in a thorough manner. Your letter lists a few weblinks and makes a general statement saying we infringe, but it does not provide any analysis of how our products would be covered by any of the claims in the '591 patent, and there is no interpretation of important claim language. In order to have a productive discussion we would need more information from you, such as detailed claim mapping and interpretation in relation to our current products. If you are able to provide that, please let us know.

We expect our intellectual property to be respected, and of course do the same with other's intellectual property.

Regards,

Steve

From: Morton, Jeff <Jeff.Morton@procopio.com>
Sent: Tuesday, June 14, 2022 8:41 PM
To: Steve Cashman <steve@captionhealth.com>
Cc: Michael Cannon <mgc@captionhealth.com>
Subject: RE: University of British Columbia

Dear Steve,

Thank you for your email. We acknowledge receipt and look forward to hearing from you.

Jeff

JEFFREY D. MORTON, PH.D.

PARTNER
PROCOPIO

P. 858.720.6330 | C: 858.926.9470 | F. 619.788.5588 | jeff.morton@procopio.com

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[View Profile](#) | [LinkedIn](#) | procopio.com



From: Steve Cashman <steve@captionhealth.com>

Sent: Monday, June 13, 2022 5:25 PM

To: Morton, Jeff <Jeff.Morton@procopio.com>

Cc: Michael Cannon <mgc@captionhealth.com>

Subject: University of British Columbia

*** EXTERNAL EMAIL - Please use Caution. ***

Dear Mr. Morton:

We have received your letters regarding the University of British Columbia patent but need time to review them. We will do that and respond do you shortly.

Steve



Steve Cashman
Chief Executive Officer | Caption Health

m 970-402-2255

e steve@captionhealth.com

CONFIDENTIALITY NOTICE: The information in this message, and any attachment, is intended for the sole use of the individual and entity to whom it is addressed. This information may be privileged, confidential, and protected from disclosure. If you are not the intended recipient you are hereby notified that you have received this communication in error and that any review, disclosure, dissemination, distribution or copying of it, or its contents, is strictly prohibited. If you think that you have received this message in error please notify the sender and destroy all copies of this communication and any attachments. Thank you.

Tue Jun 14 2022 17:41:03

This is an email from Procopio, Cory, Hargreaves & Savitch LLP, Attorneys at Law. This email and any attachments hereto may contain information that is confidential and/or protected by the attorney-client privilege and attorney work product doctrine. This email is not intended for transmission to, or receipt by, any unauthorized persons. Inadvertent disclosure of the contents of this email or its attachments to unintended recipients is not intended to and does not constitute a waiver of attorney-client privilege or attorney work product protections. If you have received this email in error, immediately notify the sender of the erroneous receipt and destroy this email, any attachments, and all copies of same, either electronic or printed. Any disclosure, copying, distribution, or use of the contents or information received in error is strictly prohibited.

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Tue Jun 28 2022 11:32:48

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EXHIBIT G



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November 11, 2022

Steve Cashman
President & CEO
Caption Health, Inc.
2000 Sierra Point Parkway, Suite 800
Brisbane, California 94005

Re: Caption Health, Inc.'s Infringement of U.S. Patent No. 11,129,591,
Assigned to the University of British Columbia

Dear Mr. Cashman:

I am writing to follow up on your June 27, 2022 e-mail in response to a May 5, 2022 letter from my partner, Jeffrey Morton, providing notice to Caption Health of its infringement of U.S. Patent No. 11,129,591 ("the '591 Patent"), which is assigned to the University of British Columbia ("UBC"). Please kindly let us know if Caption Health has since retained counsel in connection with UBC's assertion of the '591 Patent, so that we can communicate directly with counsel.

In your e-mail, you requested "more information ..., such as detailed claim mapping and interpretation in relation to [y]our current products," "[i]n order to have a productive discussion" regarding UBC's assertion of the '591 Patent. Pursuant to your request, please find attached a claim chart detailing how Claim 1 of the '591 Patent reads on Caption Guidance, as evidenced by statements made by Caption Health in U.S. Patent Application Pub. No. 2021/0052253 A1 and in other public forums (e.g., YouTube) regarding Caption Guidance. For convenience of reference, I have attached this published patent application and the '591 Patent again.

Now that we have provided the requested information, we look forward to a productive discussion regarding UBC's assertion of the '591 Patent against Caption Health to see whether this matter may be resolved without resort to litigation. In view of the intervening Thanksgiving holiday, we request your substantive response by December 2, 2022. Thank you.



Sincerely,

A handwritten signature in blue ink that reads "Rayl Chan".

Raymond Chan

Enclosure

cc: Steve Cashman (steve@captionhealth.com)
Michael Cannon (mgc@captionhealth.com)
Jeffrey D. Morton (jeffrey.morton@procopio.com)
Dave Deonarine (dave.deonarine@procopio.com)

U.S. Patent No. 11,129,591 / Caption Guidance

Claim 1

P	A computer-implemented system for facilitating echocardiographic image analysis,	To the extent that the preamble is limiting: - US 2021/0052253 A1 describes “an ultrasound diagnostics data processing system configured for ultrasound guidance dynamic progression.” ¶ [0026]. This system is used “in connection with the imaging of a heart.” ¶ [0020]; <i>see also</i> Fig. 1 (i.e., target organ 130). - Caption Guidance is “a medical software tool that utilizes Artificial Intelligence (AI) for providing echocardiography.” EMMA International: Caption Guidance – FDA’s First Authorized AI-Based Cardiac Ultrasound Software, by Govind Yatnalkar, Feb. 15, 2021.
1[a]	the system comprising at least one processor configured to:	Caption Guidance is described in a published U.S. patent application as a system which comprises at least one processor. The system includes a host computing system 210 that includes a computer with at least one processor, memory and a display. US 2021/0052253 A1, Abstract.
1[b]	receive signals representing a first at least one echocardiographic image;	Caption Guidance acquires a video clip comprising a series of echocardiographic images. ... an ultrasound imaging system 110 with ultrasound imaging probe 120 conducts an ultrasound imaging operation in order to acquire a video clip as near real-time imagery 155 of a target organ 130. US 2021/0052253 A1, ¶ [0020].

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1[c]	associate the first at least one echocardiographic image with a first view category of a plurality of predetermined echocardiographic image view categories;	Caption Guidance associates the first at least one echocardiographic image with a first view category. ... an ultrasound guidance dynamic progression method includes selecting a predetermined ultrasound diagnostic workflow in memory of an ultrasound diagnostic computing system, the workflow including <u>a sequence of views</u> of a target organ. The method further includes selecting <u>a first one of the views in the sequence</u> and presenting guidance, such as visual guidance, in a display of the computing system for the selected first one of the views. The method yet further includes acquiring imagery in the computing system <u>in association with</u> the selected first one of the views in the sequence, and ... US 2021/0052253 A1, ¶ [0009] (“Brief Summary of the Invention”) (underlining added). The above first view category is one of a plurality of predetermined echocardiographic image view categories. In conducting the ultrasound imaging operation, a workflow 175 of the target organ 130 is selected that includes <u>a sequence of views 135A, 135B, 135N</u>. For example, in connection with the imaging of a heart, the views 135A, 135B, 135N may include a parasternal long axis view, a parasternal short axis view, an apical two, three, four or five chamber view or a subcoastal view, ... US 2021/0052253 A1, ¶ [0020] (underlining added).
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1[d]	determine, based on the first at least one echocardiographic image and the first view category, a first quality assessment value representing a view category specific quality assessment of the first at least one echocardiographic image;	Caption Guidance determines a first quality assessment value representing a <u>view category specific</u> quality assessment of the first at least one echocardiographic image. A quality meter 150 is disposed in the user interface 140 and indicates a sliding scale of quality of the imagery 155 in the contemporaneous display 160A <u>relative to a known view</u> sought to be acquired for the target organ 130. To the extent that the imagery 155 is determined to have a corresponding quality value that meets or exceeds a threshold quality <u>for the specified view</u>, a success icon 165 is displayed in connection with the quality meter 150. US 2021/0052253 A1, ¶ [0022] (underlining added); Fig. 1.
1[e]	produce signals representing the first quality assessment value for causing the first quality assessment value to be associated with the first at least one echocardiographic image;	Please see Element 1[d] above. Caption Guidance automatically captures the first at least one echocardiographic image and associates it with the first quality assessment value. In a presentation titled <u>Caption Health: Flattening the Ultrasound Learning Curve with Breakthrough AI-Guided Echocardiography System</u>, Ha Hong, Ph.D., a founding team member of Caption Health, the machine learning lead of Caption Guidance, and an inventor listed on the published patent application, described the system as follows: Finally, [it] recognizes when the user reaches the target and automatically captures the images in diagnostic quality. https://www.youtube.com/watch?v=NCFFAIHSPrc (at 4:30-4:40). In Caption AI Product Demo AI-Guided Ultrasound System: As Sarah gets closer to the optimal view, the meter rises. Once the software detects a diagnostic quality image, the meter turns

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		green and the clip is automatically recorded without having to press any buttons. https://www.youtube.com/watch?v=URmb72IA4b4 (at 0:48-1:00).
1[f]	receive signals representing a second at least one echocardiographic image;	Caption Guidance repeats the above steps for a second at least one echocardiographic image. For each of the views 135A, 135B, 135N, corresponding guidance 145A, 145B, 145N is determined and presented in sequence of the views 135A, 135B, 135N of the workflow 175 within the user interface 140 as respective graphical instructions 145. In this regard, the corresponding guidance 145A, 145B, 145N includes different directives for positioning and posing the ultrasound imaging probe 120 so as to produce the imagery 155 for a corresponding one of the views 135A, 135B, 135N. US 2021/0052253 A1, ¶ [0021] Please see Element 1[b] above.
1[g]	associate the second at least one echocardiographic image with a second view category of the plurality of predetermined echocardiographic image view categories,	Please see Elements 1[c] and 1[f] above.
1[g][1]	said second view category being different from the first view category;	Caption Guidance acquires a second echo-CG image under a second view category which is different from the first view category. In conducting the ultrasound imaging operation, a workflow 175 of the target organ 130 is selected that includes a sequence of views 135A, 135B, 135N. For example, in connection with the imaging of a heart, the views 135A, 135B, 135N may include a parasternal long axis view, a parasternal short axis view, an apical two, three, four or five chamber view or a subcoastal view,”

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		US 2021/0052253 A1, ¶ [0020]; Fig. 1. For each of the views 135A, 135B, 135N, corresponding guidance 145A, 145B, 145N is determined and presented in sequence of the views 135A, 135B, 135N of the workflow 175 within the user interface 140 as respective graphical instructions 145. In this regard, the corresponding guidance 145A, 145B, 145N includes different directives for positioning and posing the ultrasound imaging probe 120 so as to produce the imagery 155 for a corresponding one of the views 135A, 135B, 135N. US 2021/0052253 A1, ¶ [0021].
1[h]	determine, based on the second at least one echocardiographic image and the second view category, a second quality assessment value representing a view category specific quality assessment of the second at least one echocardiographic image; and	Please see Element 1[d] above.
1[i]	produce signals representing the second quality assessment value for causing the second quality assessment value to be associated with the second at least one echocardiographic image;	Please see Element 1[e] above.
1[j]	wherein each of the plurality of predetermined echocardiographic image view categories is associated with a respective set of assessment parameters,	Each of the plurality of predetermined echocardiographic image view categories is associated with a respective set of assessment parameters. To the extent that the imagery 155 is determined to have a corresponding quality value that meets or exceeds a threshold quality <u>for the specified view</u>, a success icon 165 is displayed in connection with the quality meter 150.

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		US 2021/0052253 A1, ¶ [0022] (underlining added).
1[j][1]	each of the sets of assessment parameters being a set of neural network parameters that define a neural network having a plurality of layers including an input layer configured to receive one or more echocardiographic images and an output layer configured to output one or more quality assessment values,	As discussed above in Elements 1[d] and 1[h] above, Caption Guidance outputs a view category specific quality assessment value. This assessment is done via a second neural network 270. ... a second neural network 270 may be trained to characterize guidance instructions relative to contemporaneously acquired imagery of the target organ. ... as the neural network 270 is presented with contemporaneously acquired imagery of the target organ for the particular one of the views 290, the neural network produces a recommended movement or pose of the ultrasound imaging probe 230 in order to acquire generated imagery deemed acceptable for the particular one of the views 290. US 2021/0052253 A1, ¶ [0028]. Caption Guidance assesses the quality of the echocardiographic image in order to provide guidance on the position and orientation of the ultrasound probe. For example: In order to help users to acquire high-quality echocardiograms, the guidance algorithm must be able to estimate the positioning of the ultrasound probe from the current imaging and provide real-time guidance based on that estimation for the user to arrive at the ideal positioning and image. <u>It must first be able to grade the quality of the imagery and determine whether it meets diagnostic criteria.</u> JAMA Supplement (Feb. 18, 2021)¹ (underlining added).

¹ <https://jamanetwork.com/journals/jamacardiology/fullarticle/2776714#note-HOI210005-1>

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1[k]	and wherein the at least one processor is configured to determine the first quality assessment value by:	See below.
1[k][1]	determining that a first set of assessment parameters of the sets of assessment parameters is associated with the first view category; and	In Caption Guidance, each set of assessment parameters is associated with a corresponding view category. <i>See Element 1[d] above (describing quality assessment of echocardiographic image “relative to a known view” and “for the specified view”); see Element 1[j][1] above (describing guidance to acquire images “acceptable for the particular one of the views”).</i>
1[k][2]	in response to determining that the first set of assessment parameters is associated with the first view category, inputting the first at least one echocardiographic image into the neural network defined by the first set of assessment parameters; and	See Element 1[j][1].
1[l]	wherein the at least one processor is configured to determine the second quality assessment value by:	See below.
1[l][1]	determining that a second set of assessment parameters of the sets of assessment parameters is associated with the second view category; and	See Element 1[k][1].
1[l][2]	in response to determining that the second set of assessment parameters is associated with the second view category, inputting the second at least one echocardiographic image into the neural network defined by the second set of assessment parameters.	See Element 1[k][2].

EXHIBIT H

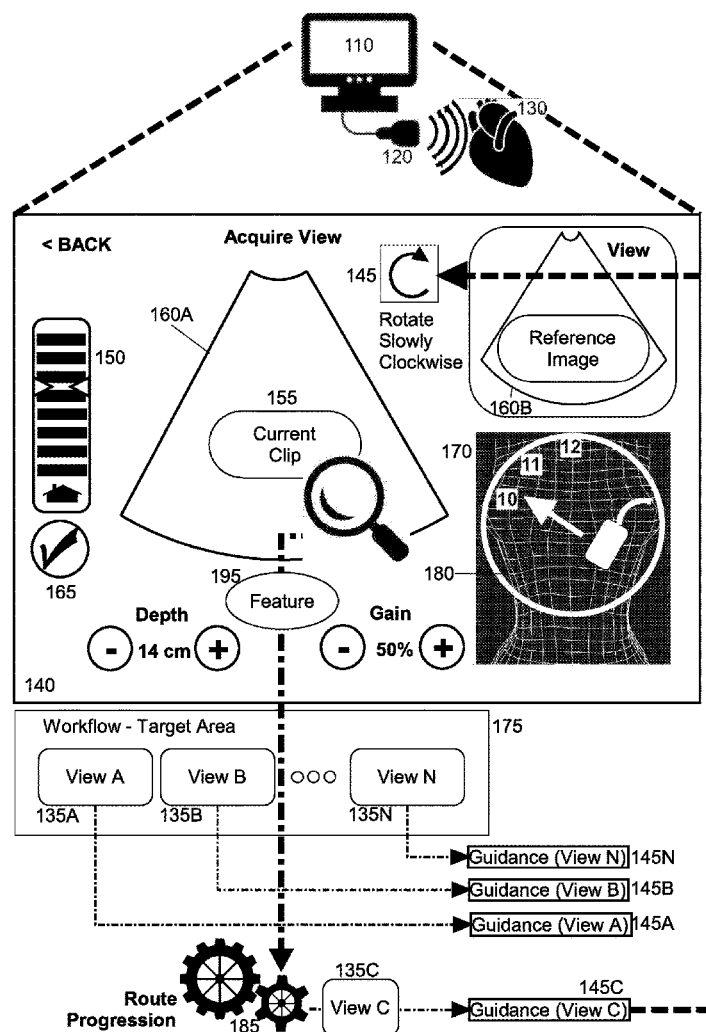
US 20210052253A1

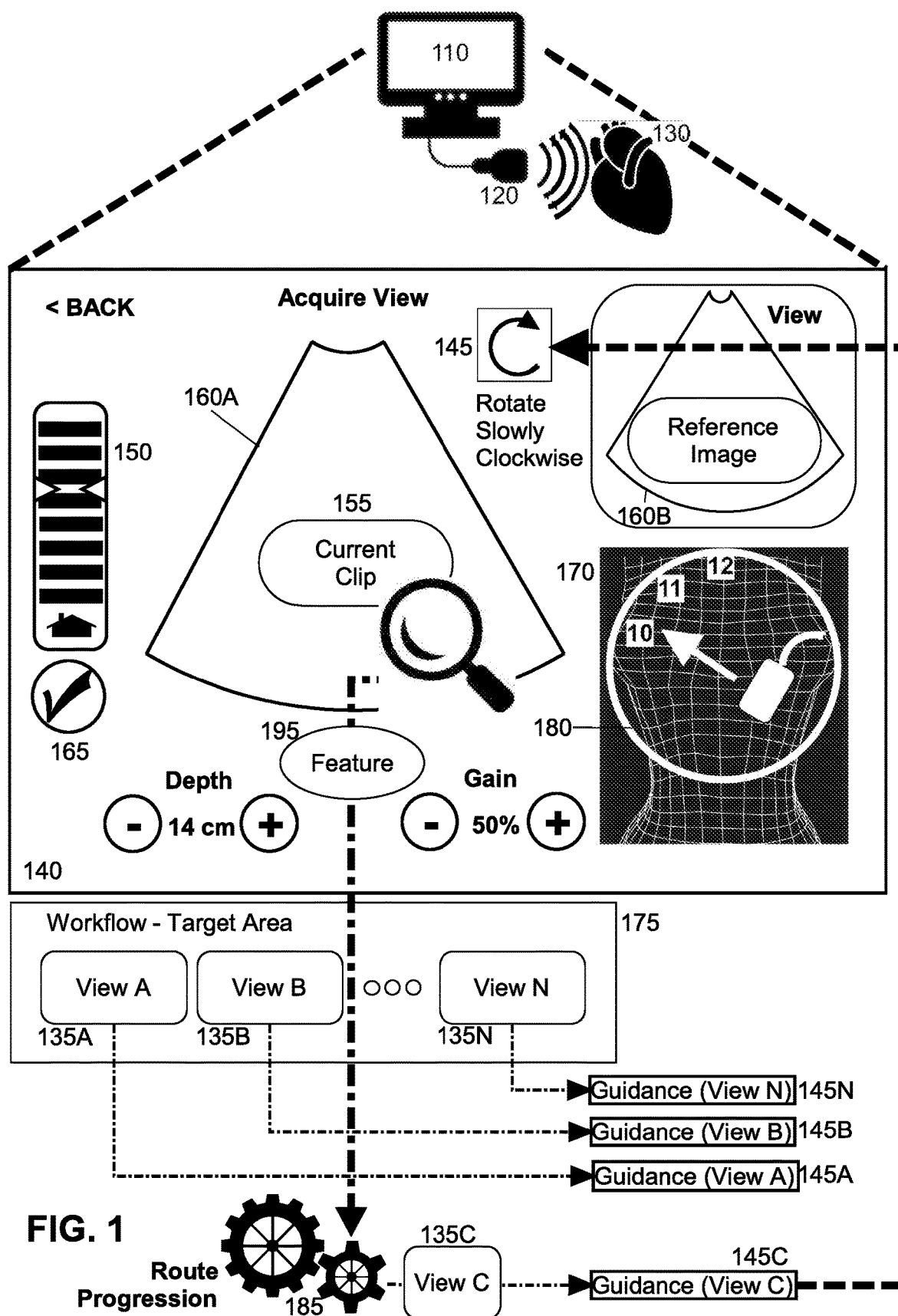
(19) **United States**(12) **Patent Application Publication**
Cadieu et al.(10) **Pub. No.: US 2021/0052253 A1**(43) **Pub. Date: Feb. 25, 2021**(54) **MID-PROCEDURE VIEW CHANGE FOR
ULTRASOUND DIAGNOSTICS**(52) **U.S. Cl.**CPC *A61B 8/5223* (2013.01); *A61B 8/08*
(2013.01); *A61B 5/055* (2013.01); *G06T*
7/0012 (2013.01); *A61B 8/463* (2013.01)(71) Applicant: **Bay Labs, Inc.**, San Francisco, CA
(US)(72) Inventors: **Charles Cadieu**, Menlo Park, CA (US);
Michael G. Cannon, Haverford, PA
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CA (US); **Ha Hong**, San Ramon, CA
(US); **Kilian Koepsell**, San Francisco,
CA (US); **Nripesh Parajuli**, Millbrae,
CA (US); **Nicolas Poilvert**, Seattle, WA
(US)(21) Appl. No.: **16/544,582**(22) Filed: **Aug. 19, 2019****Publication Classification**(51) **Int. Cl.***A61B 8/08* (2006.01)*A61B 8/00* (2006.01)*G06T 7/00* (2006.01)

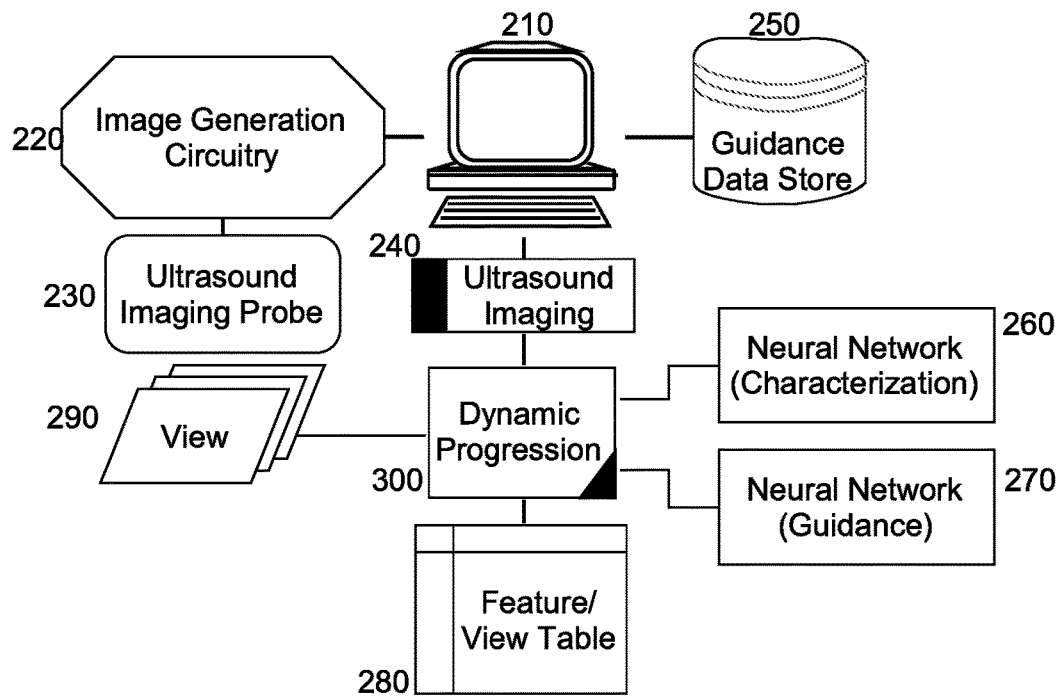
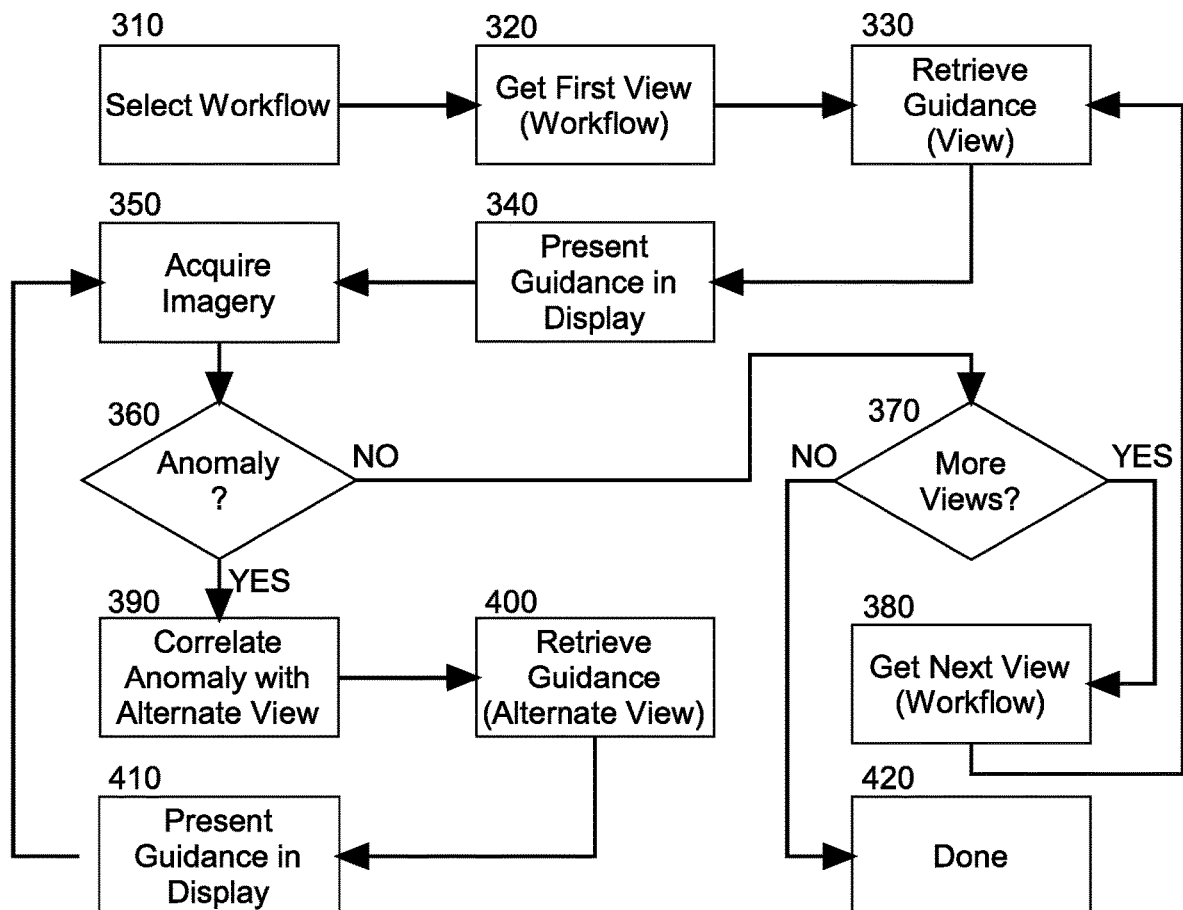
(57)

ABSTRACT

An ultrasound guidance dynamic progression method includes selecting a predetermined ultrasound diagnostic workflow in memory of an ultrasound diagnostic computing system, the workflow including a sequence of views of a target organ. The method further includes selecting a first view in the sequence and presenting guidance in a display of the computing system for the first view, for instance visual, audible or haptic feedback. The method yet further includes acquiring imagery in the computing system in association with the first view, and detecting an anomalous feature of the acquired imagery. Finally, the method includes selecting a different view in the sequence as a substitute for a next one of the views in the sequence in response to having detected the anomalous feature, and further presenting different guidance in the display for the different view in lieu of guidance for the next one of the views.





**FIG. 2****FIG. 3**

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MID-PROCEDURE VIEW CHANGE FOR ULTRASOUND DIAGNOSTICS

BACKGROUND OF THE INVENTION

Field of the Invention

[0001] The present invention relates to ultrasound imaging and more particularly to ultrasound image acquisition.

Description of the Related Art

[0002] Medical imaging refers to the process of creating a visual representation of an interior portion of a mammalian body for the purpose of clinical analysis and medical intervention. Medical imaging seeks to reveal internal structures hidden by the exterior of the body so as to facilitate the diagnosis and treatment of disease. Medical imaging incorporates several different image acquisition methodologies and corresponding radiological devices technologies. Common techniques include X-ray radiography including computerized tomography (CT), magnetic resonance imaging (MRI), medical ultrasonography or ultrasound, endoscopy, elastography, tactile imaging, thermography, medical photography and nuclear medicine functional imaging techniques as positron emission tomography (PET) and Single-photon emission computed tomography (SPECT). Depending upon the desired use of the imagery for the purpose of a medical diagnosis or the targeting of specific tissue or a particular organ or portion of an organ, different techniques and devices for different imagery may be preferred.

[0003] Ultrasound imaging, also known as sonography, is a medical imaging technique that employs high-frequency sound waves to view three-dimensional structures inside the body of a living being. Because ultrasound images are captured in real-time, ultrasound images also show movement of the internal organs of the body as well as blood flowing through the blood vessels of the human body and the stiffness of tissue. Unlike x-ray imaging, ultrasound imaging does not involve ionizing radiation thereby allowing prolonged usage of ultrasound imaging without threatening tissue and internal organ damage from prolonged radiation exposure.

[0004] To acquire ultrasound imagery, during an ultrasound exam, a transducer, commonly referred to as a probe, is placed directly on the skin or inside a body opening. The probe is coupled to image generation circuitry that includes circuitry adapted to transmit and receive signals to and from the probe, and may include a beamformer, though synthetic aperture imaging systems may use retrospective image formation reducing the need for beamforming and scan conversion functions. A thin layer of gel is applied to the skin so that the ultrasound waves are transmitted from the probe through the medium of the gel into the body. The ultrasound image is produced based upon a measurement of the reflection of the ultrasound waves off the body structures. The strength of the ultrasound signal, measured as the amplitude of the detected sound wave reflection, and the time taken for the sound wave to travel through the body provide the information necessary to compute an image of target structures of the body. As well, the “Doppler” effect may be used in ultrasound imagery to measure the velocity and direction of fluid flow within the structures of the body (namely, blood).

[0005] Compared to other prominent methods of medical imaging, ultrasound presents several advantages to the diagnostician and patient. First and foremost, ultrasound imaging provides images in real-time. As well, ultrasound imaging requires equipment that is portable and can be brought to the bedside of the patient. Further, as a practical matter, the ultrasound imaging equipment is substantially lower in cost than other medical imaging equipment, and as noted, does not use harmful ionizing radiation. Even still, ultrasound imagery is not without challenge.

[0006] For example, in some instances, an attempted view of a target organ may be incomplete omitting key features of the target organ from the view due to anatomical limitations or an improper placement of the imaging sensor. In this regard, as to the term “view”, the ultrasound imaging of a target area of the body may be achieved from many different “views” utilizing the ultrasound probe. Each view may be achieved through a combination of position and pose of the probe such that the angle and approach of the ultrasound probe generally results in a different perspective “view” of the target area. Generally, a particular view of the target area presented in an ultrasound image may be preferred depending upon the desired use of the imagery for the purpose of a medical diagnosis or the targeting of specific tissue or a particular organ or portion thereof. More to the point, different views of the same target area produce imagery with emphasis on different anatomical features such that some views are known to have the highest probability of producing imagery of a feature of interest. As well, different views can also be required in order to perform measurements that are used for diagnostic purposes.

[0007] Thus, depending upon the particular feature of interest, the operator must first know the desired view to best image the feature of interest and then, with respect to the portion of the body selected for imaging and the desired view, the skilled operator must know where to initially place the ultrasound probe on the body. Then, the skilled operator must know how to spatially orient the probe and finally, the skilled operator must know where to move the probe so as to acquire the desired imagery, including acquiring additional views. Generally, the ultrasound operator is guided in the initial placement, orientation and movement of the probe based upon the visual feedback provided by the imagery produced during the ultrasound. As it will be recognized, then, essentially, the navigation of the probe is a manual process consisting of iterative trial and error and requires specialized knowledge and expertise on the part of the ultrasound operator—especially in the selection of a route of views through which the probe must move in order to produce a complete exam.

[0008] Importantly, given the nature of conventional ultrasound imaging, the resultant images of a target area of the body may vary in quality. That is to say, depending upon the operator, the clarity and focal point of a medical image may vary. As well, external factors such as the anatomical features of the body may inhibit clarity of key features of the target organ despite proper placement of the imaging sensor. Yet, whereas certain anatomical features may inhibit a quality image of a target area in one view, a different view of the same target area or even a slightly different target area may provide higher quality imagery of the anatomical feature sought for imaging by the practitioner. Thus, the operator must know through experience to shift efforts from acquiring imagery of the target area through one view to

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another view when the quality of imagery through the first view is substandard or when a particular structure of the target area is only partially viewable within the first view but desirable in light of the determination from the first view that an abnormality or anomalous condition justifies clearer visualization of the particular structure through a presentation of a different view than the first view more likely to produce the clearer visualization. As can be seen, then, the production of quality ultrasound images remains highly dependent upon a skilled operator.

BRIEF SUMMARY OF THE INVENTION

[0009] Embodiments of the present invention address deficiencies of the art in respect to ultrasound imaging and provide a novel and non-obvious method, system and computer program product for route diversion during ultrasound diagnostics. In an embodiment of the invention, an ultrasound guidance dynamic progression method includes selecting a predetermined ultrasound diagnostic workflow in memory of an ultrasound diagnostic computing system, the workflow including a sequence of views of a target organ. The method further includes selecting a first one of the views in the sequence and presenting guidance, such as visual guidance, in a display of the computing system for the selected first one of the views. The method yet further includes acquiring imagery in the computing system in association with the selected first one of the views in the sequence, and detecting an anomalous feature of the target organ. Finally, the method includes selecting a different one of the views in the sequence as a substitute for a next one of the views responsive to the detection and further presenting different guidance in the display for the different one of the views in lieu of guidance for the next one of the views.

[0010] In one aspect of the embodiment, the method additionally includes identifying a measurement to be performed based on the detection of an anomalous feature of the target organ. In response, a different one of the views in the sequence is identified in association with the identified measurement. The different one of the views is then presented as a substitute for a next one of the views in order to perform the identified measurement. An exemplary measurement includes a measurement of fluid velocity—namely blood velocity in proximity to the target organ.

[0011] In another aspect of the embodiment, the anomalous feature is a presence of a visible feature in the acquired imagery. Conversely, in yet another aspect of the embodiment, the anomalous feature is an absence of a visible feature in the acquired imagery. In even yet another aspect of the embodiment, the visible feature is correlated in memory of the computing system with a disease. As well, in even yet another aspect of the embodiment, the visible feature is an irregular characteristic of a structure of the target organ. Finally, in even yet another aspect of the embodiment, the visible feature is extraneous material on a structure of the target organ.

[0012] In another embodiment of the invention, a data processing system is configured for ultrasound guidance dynamic progression. The system includes a computer with memory and at least one processor, a display coupled to the computer, image generation circuitry coupled to the computer and the display and an ultrasound imaging probe comprising a transducer connected to the image generation circuitry. The system also includes an ultrasound guidance dynamic progression module executing in the memory of the

computer. The module includes program code enabled upon execution by the processor of the computer to select a predetermined ultrasound diagnostic workflow in memory of the computer, to select a first one of the views in the sequence and to present visual guidance in a display of the computer for the selected first one of the views. The program instructions further are enabled to acquire imagery in the computer in association with the selected first one of the views in the sequence, to detect an anomalous feature of the target organ and to select a different one of the views in the sequence as a substitute for a next one of the views responsive to the detection and further presenting different visual guidance in the display for the different one of the views in lieu of visual guidance for the next one of the views.

[0013] Additional aspects of the invention will be set forth in part in the description which follows, and in part will be obvious from the description, or may be learned by practice of the invention. The aspects of the invention will be realized and attained by means of the elements and combinations particularly pointed out in the appended claims. It is to be understood that both the foregoing general description and the following detailed description are exemplary and explanatory only and are not restrictive of the invention, as claimed.

BRIEF DESCRIPTION OF THE SEVERAL VIEWS OF THE DRAWINGS

[0014] The accompanying drawings, which are incorporated in and constitute part of this specification, illustrate embodiments of the invention and together with the description, serve to explain the principles of the invention. The embodiments illustrated herein are presently preferred, it being understood, however, that the invention is not limited to the precise arrangements and instrumentalities shown, wherein:

[0015] FIG. 1 is pictorial illustration of a process for ultrasound guidance dynamic progression;

[0016] FIG. 2 is a schematic illustration of an ultrasound diagnostics data processing system configured for ultrasound guidance dynamic progression; and,

[0017] FIG. 3 is a flow chart illustrating a process for ultrasound guidance dynamic progression.

DETAILED DESCRIPTION OF THE INVENTION

[0018] Embodiments of the invention provide for ultrasound guidance dynamic progression. In accordance with an embodiment of the invention, a workflow is defined within an ultrasound diagnostic computing system for the ultrasound imaging of a target area of a body. In this regard, the workflow is defined to include multiple different views of the target area to be performed in a particular sequence. Then, upon commencing ultrasound imaging of the target area according to the workflow, guidance for a first one of the views is presented in a display of the ultrasound diagnostic computing system, and ultrasound imagery is acquired in association with the selected first view of the sequence.

[0019] In response to the acquired imagery, an association between the acquired imagery and a visible feature of the target area is detected, for instance the presence of a particular feature not expected to be visible within the imagery, or in the alternative, the absence of a particular feature

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expected to be visible within the imagery. Consequently, a different one of the views in the sequence is selected as a substitute for a next one of the views and different guidance is then presented in the display for the different one of the views in lieu of guidance for the next one of the views. In this way, the operator of the ultrasound diagnostic computing system deviates from the original planned sequence of the workflow mid procedure to provoke the acquisition of a more optimal view of the target area in consequence of the detected association.

[0020] FIG. 1 is pictorial illustration of a process for ultrasound guidance dynamic progression. As shown in FIG. 1, an ultrasound imaging system 110 with ultrasound imaging probe 120 conducts an ultrasound imaging operation in order to acquire a video clip as near real-time imagery 155 of a target organ 130. In conducting the ultrasound imaging operation, a workflow 175 of the target organ 130 is selected that includes a sequence of views 135A, 135B, 135N. For example, in connection with the imaging of a heart, the views 135A, 135B, 135N may include a parasternal long axis view, a parasternal short axis view, an apical two, three, four or five chamber view or a subcoastal view, to name a few examples.

[0021] For each of the views 135A, 135B, 135N, corresponding guidance 145A, 145B, 145N is determined and presented in sequence of the views 135A, 135B, 135N of the workflow 175 within the user interface 140 as respective graphical instructions 145. In this regard, the corresponding guidance 145A, 145B, 145N includes different directives for positioning and posing the ultrasound imaging probe 120 so as to produce the imagery 155 for a corresponding one of the views 135A, 135B, 135N. Exemplary guidance includes include, by way of example, the rotation of the ultrasound imaging probe 120 either in a clockwise or counter-clockwise direction, the movement of the ultrasound imaging probe 120 laterally away from the sternum, or medially towards the sternum, and the aiming of the imaging beam downwards or upwards by tilting the tail of the ultrasound imaging probe 120 upwards or downwards, respectively, slide downward, rock towards the indicator, rock away from the indicator, tilting the tail medially, or tilting the tail laterally, to name only a few examples.

[0022] To that end, a user interface 140 to the ultrasound imaging system 110 presents a contemporaneous display 160A of the imagery 155 acquired by the ultrasound imaging probe 120 of the target organ 130. A quality meter 150 is disposed in the user interface 140 and indicates a sliding scale of quality of the imagery 155 in the contemporaneous display 160A relative to a known view sought to be acquired for the target organ 130. To the extent that the imagery 155 is determined to have a corresponding quality value that meets or exceeds a threshold quality for the specified view, a success icon 165 is displayed in connection with the quality meter 150. As well, a previously acquired, ideal, reference image 160B of the target organ 130 according to the known view is displayed in the user interface 140.

[0023] Optionally, an additional portion 170 of the user interface 140 may be provided displaying an iconic image of a portion of a body in which the target organ 130 resides and a recommended movement of the ultrasound imaging probe 120 relative to the iconic image in order to achieve the specified view for the target organ 130. The additional portion of the user interface 170 includes a spatial orientation indicator 180 superimposed upon the iconic image of

the portion of the body in which the target organ 130 resides, arranged as a clock angle indicator with twelve angularly equidistant positions. In this regard, only a relevant number of the clock angle positions are shown, as can be seen in FIG. 1, which positions are selected as a range towards which the ultrasound imaging probe 120 is known to move in order to acquire imagery of the specified view for the target organ 130. In this way, the combination of the recommended movement and the spatial orientation indicator 180 provide quick visual guidance to the operator of the ultrasound imaging system 110 in order to achieve a real-time image of sufficient quality for the selected view.

[0024] Of note, route progression logic 185 monitors the imagery 155 for each of the views 135A, 135B, 135N. In monitoring each imagery 155 for each of the views 135A, 135B, 135N, the route progression logic 185 may detect an anomalous feature 195. In this regard, the anomalous feature 195 can include imagery of structure not expected to be visible within the imagery 155. As well, the anomalous feature can include features related to the movement of fluids within the structure or through the structure or around the structure, for example, blood flow. Examples of the anomalous feature 195 include an irregular characteristic of a structure of the target organ 130, or extraneous material on a structure of the target organ 130. Either may be indicative of disease of the target organ 130. Alternatively, the anomalous feature 195 can include an absence of structure visible in the imagery 155, the absence of the structure also indicating disease of the target organ 130.

[0025] The route progression logic 185, upon detecting the anomalous feature 195, correlates the detected anomalous feature 195 with a different view 135C previously determined to provide for optimal imaging of the indicated disease, the different view 135C differing from the views 135A, 135B, 135N of the workflow 175. Consequently, guidance 145C for the different view 135C is presented as the respective graphical instruction 145 in the user interface 140 in lieu of the guidance 145A, 145B, 145N correlating to the next one of the views 135A, 135B, 135N of the workflow 175. In this way, the workflow 175 of views 135A, 135B, 135N can change dynamically mid-procedure responsive to the detection of the anomalous feature 195.

[0026] The process described in connection with FIG. 1 can be implemented within an ultrasound diagnostics data processing system. In further illustration, FIG. 2 schematically shows an ultrasound diagnostics data processing system configured for ultrasound guidance dynamic progression. The system includes a host computing system 210 that includes a computer with at least one processor, memory and a display. The host computing system 210 also includes a data store 250. The host computing system 210 yet further is coupled to an ultrasound imaging system 240 adapted to generate ultrasound imagery acquired through the placement of an imaging wand 230 proximate to a target organ of interest in a mammalian subject by operation of image generation circuitry 220. The host computing system 210 is communicatively coupled to fixed storage (not shown), either locally or remotely ("in the cloud") storing therein one or more neural networks 260 and a programmatic interface to the neural networks 260.

[0027] The neural network 260 is trained to characterize one or more features of the target organ, for example an ejection fraction value of a heart, or the presence or absence of aortic stenosis, or the presence or absence of a structural

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feature of the target organ. To do so, generated imagery of a specified view of the target organ acquired by the ultrasound imaging system **240** is provided to the neural network **260** which in turn accesses the programmatic interface so that the neural network **260** may then output the characterization for the generated imagery along with an indication of confidence in that characterization. The ultrasound imaging system **240** in turn renders on the display of the host computing system **210** not only the generated imagery, but also the characterization and optionally, the indication of confidence in that characterization.

[0028] As well, a second neural network **270** may be trained to characterize guidance instructions relative to contemporaneously acquired imagery of the target organ. In this regard, with respect to a particular one of the views **290**, the second neural network **270** is trained to produce recommend guidance to achieve the optimal acquisition of generated imagery for the target organ for the particular one of the views **290**, relative to the generated imagery contemporaneously presented in a display of the host computing system **210**. To that end, as the neural network **270** is presented with contemporaneously acquired imagery of the target organ for the particular one of the views **290**, the neural network produces a recommended movement or pose of the ultrasound imaging probe **230** in order to acquire generated imagery deemed acceptable for the particular one of the views **290**.

[0029] Importantly, a dynamic progression module **300** is coupled to the ultrasound imaging system **240**. The dynamic progression module **300** includes computer program instructions that when executing in the memory of the host computing system **210**, are enabled to group together a sequence of different views **290** as a workflow and, for each of the views **290** in the sequence, retrieve from the data store **250** guidance instructions necessary to optimally acquire generated imagery for the selected one of the views **290**. The program instructions are further enabled to receive from the neural network **260** in characterizing acquired generated imagery for a selected one of the views **250** of a workflow, an indication of an anomalous feature, such as the presence of an unexpected structural feature, or the absence of an expected structural feature.

[0030] The program instructions of the module **300** then are adapted to correlate the anomalous feature with a particular one of the views **290** in a table **280**, whether included as part of the contemporaneous workflow or otherwise. Finally, the program instructions of the module **300** are enabled to retrieve guidance from the data store **250** for the correlated one of the views **290** and to display the retrieved guidance in a display of the host computing system **210** in lieu of guidance for a next one of the views **290** in the contemporaneous workflow.

[0031] In even yet further illustration of the operation of the dynamic progression module **300**, FIG. 3 is a flow chart illustrating a process for ultrasound guidance dynamic progression. Beginning in block **310**, a workflow is selected including a multiplicity of different views of a target organ. In block **320**, a first one of the views is selected for acquiring generated imagery of the target organ and in block **330**, guidance instructions for the first view are retrieved into memory for display in a user interface to the ultrasound imaging system. In this regard, the guidance instructions may be retrieved from a fixed data store irrespective of any contemporaneous imagery acquired for the first view, or the

guidance instructions may be selected based upon the output of a neural network trained to produce guidance instructions for a particular view based upon the content of contemporaneous imagery acquired for the first view. In either circumstance, in block **340**, the guidance instructions are displayed in the user interface to the ultrasound imaging system.

[0032] In block **350**, imagery is acquired in the ultrasound imaging system for the target organ. In decision block **360**, it is determined whether or not an anomalous feature exists in connection with the acquired imagery. For instance, the imagery may be submitted to a neural network trained to classify anomalous features such as the presence or absence of structural elements of a target organ. If no anomalous features are determined to exist in the acquired imagery, in decision block **370** it is determined if additional views remain to be processed in the workflow. If so, a next view of the workflow is selected and the process repeats in block **330**. Otherwise, the process proceeds to block **390**.

[0033] In block **390**, responsive to a determination that an anomalous feature has been detected in connection with the acquired imagery, the anomalous feature is correlated with an alternate view. In this regard, the anomalous feature of the target organ is a presence of a visible feature in the acquired imagery the absence of a visible feature in the acquired imagery, a visible feature correlated with a disease, an irregular characteristic of a structure of the target organ, or extraneous material on a structure of the target organ. As it will be understood, the anomalous feature may be correlated with a particular measurement helpful in better understanding the anomalous feature, such as the measurement of fluid flow in respect to a structure of the target organ. Such measurements may include, by way of example, the measurement of the velocity of blood flow through the structure of the target organ.

[0034] In block **400**, guidance for the alternate view is retrieved. Finally, in block **410** the guidance for the alternate view is presented in the user interface for the ultrasound imaging system so as to provoke a dynamic change in the views of the workflow in response to having detected the anomalous feature of the acquired imagery. Thereafter, the process returns to decision block **350** in which new imagery is acquired and in decision block **360** it is determined if additional anomalous features are detected in the newly acquired imagery. Thereafter, in decision block **370**, if it is determined that no additional views remain to be processed in the workflow, the process ends in block **420**.

[0035] The present invention may be embodied within a system, a method, a computer program product or any combination thereof. The computer program product may include a computer readable storage medium or media having computer readable program instructions thereon for causing a processor to carry out aspects of the present invention. The computer readable storage medium can be a tangible device that can retain and store instructions for use by an instruction execution device. The computer readable storage medium may be, for example, but is not limited to, an electronic storage device, a magnetic storage device, an optical storage device, an electromagnetic storage device, a semiconductor storage device, or any suitable combination of the foregoing.

[0036] Computer readable program instructions described herein can be downloaded to respective computing/processing devices from a computer readable storage medium or to

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an external computer or external storage device via a network. The computer readable program instructions may execute entirely on the user's computer, partly on the user's computer, as a stand-alone software package, partly on the user's computer and partly on a remote computer or entirely on the remote computer or server. Aspects of the present invention are described herein with reference to flowchart illustrations and/or block diagrams of methods, apparatus (systems), and computer program products according to embodiments of the invention. It will be understood that each block of the flowchart illustrations and/or block diagrams, and combinations of blocks in the flowchart illustrations and/or block diagrams, can be implemented by computer readable program instructions.

[0037] These computer readable program instructions may be provided to a processor of a general purpose computer, special purpose computer, or other programmable data processing apparatus to produce a machine, such that the instructions, which execute via the processor of the computer or other programmable data processing apparatus, create means for implementing the functions/acts specified in the flowchart and/or block diagram block or blocks. These computer readable program instructions may also be stored in a computer readable storage medium that can direct a computer, a programmable data processing apparatus, and/or other devices to function in a particular manner, such that the computer readable storage medium having instructions stored therein includes an article of manufacture including instructions which implement aspects of the function/act specified in the flowchart and/or block diagram block or blocks.

[0038] The computer readable program instructions may also be loaded onto a computer, other programmable data processing apparatus, or other device to cause a series of operational steps to be performed on the computer, other programmable apparatus or other device to produce a computer implemented process, such that the instructions which execute on the computer, other programmable apparatus, or other device implement the functions/acts specified in the flowchart and/or block diagram block or blocks.

[0039] The flowchart and block diagrams in the Figures illustrate the architecture, functionality, and operation of possible implementations of systems, methods, and computer program products according to various embodiments of the present invention. In this regard, each block in the flowchart or block diagrams may represent a module, segment, or portion of instructions, which includes one or more executable instructions for implementing the specified logical function(s). In some alternative implementations, the functions noted in the block may occur out of the order noted in the figures. For example, two blocks shown in succession may, in fact, be executed substantially concurrently, or the blocks may sometimes be executed in the reverse order, depending upon the functionality involved. It will also be noted that each block of the block diagrams and/or flowchart illustration, and combinations of blocks in the block diagrams and/or flowchart illustration, can be implemented by special purpose hardware-based systems that perform the specified functions or acts or carry out combinations of special purpose hardware and computer instructions.

[0040] Finally, the terminology used herein is for the purpose of describing particular embodiments only and is not intended to be limiting of the invention. As used herein, the singular forms "a", "an" and "the" are intended to

include the plural forms as well, unless the context clearly indicates otherwise. It will be further understood that the terms "includes" and/or "including," when used in this specification, specify the presence of stated features, integers, steps, operations, elements, and/or components, but do not preclude the presence or addition of one or more other features, integers, steps, operations, elements, components, and/or groups thereof.

[0041] The corresponding structures, materials, acts, and equivalents of all means or step plus function elements in the claims below are intended to include any structure, material, or act for performing the function in combination with other claimed elements as specifically claimed. The description of the present invention has been presented for purposes of illustration and description, but is not intended to be exhaustive or limited to the invention in the form disclosed. Many modifications and variations will be apparent to those of ordinary skill in the art without departing from the scope and spirit of the invention. The embodiment was chosen and described in order to best explain the principles of the invention and the practical application, and to enable others of ordinary skill in the art to understand the invention for various embodiments with various modifications as are suited to the particular use contemplated.

[0042] Having thus described the invention of the present application in detail and by reference to embodiments thereof, it will be apparent that modifications and variations are possible without departing from the scope of the invention defined in the appended claims as follows:

We claim:

1. An ultrasound guidance dynamic progression method comprising:

selecting a predetermined ultrasound diagnostic workflow in memory of an ultrasound diagnostic computing system, the workflow comprising a sequence of views of a target organ;

selecting a first one of the views in the sequence and presenting guidance in a display of the computing system for the selected first one of the views;

acquiring imagery in the computing system in association with the selected first one of the views in the sequence;

detecting an anomalous feature of the target organ; and,

selecting a different one of the views in the sequence as a substitute for a next one of the views responsive to the detection and further presenting different guidance in the display for the different one of the views in lieu of guidance for the next one of the views.

2. The method of claim 1, wherein the selection of the different one of the views comprises:

identifying a measurement to be performed based upon the detection of the anomalous feature of the target organ; and,

selecting the different one of the views in the sequence based upon an association with the identified measurement as a substitute for a next one of the views; and, presenting the different one of the views as a substitute for the next one of the views in order to perform the identified measurement and presenting different guidance in the display for the different one of the views in lieu of guidance for the next one of the views.

3. The method of claim 1, wherein the anomalous feature of the target organ is a presence of a visible feature in the acquired imagery.

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4. The method of claim 1, wherein the anomalous feature is an absence of a visible feature in the acquired imagery.

5. The method of claim 3, wherein the visible feature is correlated in memory of the computing system with a disease.

6. The method of claim 3, wherein the visible feature is an irregular characteristic of a structure of the target organ.

7. The method of claim 3, wherein the visible feature is extraneous material on a structure of the target organ.

8. A data processing system configured for ultrasound guidance dynamic progression, the system comprising:

a computer with memory and at least one processor;
a display coupled to the computer;
image generation circuitry coupled to the computer and the display;

an ultrasound imaging probe comprising a transducer connected to the image generation circuitry; and,

an ultrasound guidance dynamic progression module executing in the memory of the computer, the module comprising program code enabled upon execution by the processor of the computer to perform:

selecting a predetermined ultrasound diagnostic workflow in memory of the computer, the workflow comprising a sequence of views of a target organ;

selecting a first one of the views in the sequence and presenting guidance in a display of the computer for the selected first one of the views;

acquiring imagery in the computer in association with the selected first one of the views in the sequence; detecting an anomalous feature of the target organ; and, selecting a different one of the views in the sequence as a substitute for a next one of the views responsive to the detection and further presenting different visual guidance in the display for the different one of the views in lieu of visual guidance for the next one of the views.

9. The system of claim 8, wherein the anomalous feature is a presence of the visible feature in the acquired imagery.

10. The system of claim 8, wherein the anomalous feature is an absence of the visible feature in the acquired imagery.

11. The system of claim 9, wherein the visible feature is correlated in memory of the computing system with a disease.

12. The system of claim 9, wherein the visible feature is an irregular characteristic of a structure of the target organ.

13. The system of claim 9, wherein the visible feature is extraneous material on a structure of the target organ.

14. A computer program product for ultrasound guidance dynamic progression, the computer program product including a computer readable storage medium having program

instructions embodied therewith, the program instructions executable by a device to cause the device to perform a method including:

selecting a predetermined ultrasound diagnostic workflow in memory of an ultrasound diagnostic computing system, the workflow comprising a sequence of views of a target organ;

selecting a first one of the views in the sequence and presenting guidance in a display of the computing system for the selected first one of the views;

acquiring imagery in the computing system in association with the selected first one of the views in the sequence;

detecting an anomalous feature of the target organ; and,

selecting a different one of the views in the sequence as a substitute for a next one of the views responsive to the detection and further presenting different guidance in the display for the different one of the views in lieu of guidance for the next one of the views.

15. The computer program product of claim 14, wherein the selection of the different one of the views comprises:

identifying a measurement to be performed based upon the detection of the anomalous feature of the target organ; and,

selecting the different one of the views in the sequence based upon an association with the identified measurement as a substitute for a next one of the views; and,

presenting the different one of the views as a substitute for the next one of the views in order to perform the identified measurement and presenting different guidance in the display for the different one of the views in lieu of guidance for the next one of the views.

16. The computer program product of claim 14, wherein the anomalous feature is a presence of a visible feature in the acquired imagery.

17. The computer program product of claim 14, wherein the anomalous feature is an absence of a visible feature in the acquired imagery.

18. The computer program product of claim 16, wherein the visible feature is correlated in memory of the computing system with a disease.

19. The computer program product of claim 16, wherein the visible feature is an irregular characteristic of a structure of the target organ.

20. The computer program product of claim 16, wherein the visible feature is extraneous material on a structure of the target organ.

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