AUTOMATIC CLINICAL WORKFLOW THAT RECOGNIZES AND ANALYZES 2D AND DOPPLER MODALITY ECHOCARDIOGRAM IMAGES FOR AUTOMATED CARDIAC MEASUREMENTS AND THE DIAGNOSIS, PREDICTION AND PROGNOSIS OF HEART DISEASE

BACKGROUND

[001] The present invention relates to image classification for disease prediction, and more specifically, to an automatic clinical workflow that recognizes and analyzes 2D and Doppler modality echocardiogram images for automated measurements and the diagnosis, prediction and prognosis of heart disease.

[002] Cardiovascular disease including heart failure is a major health problem accounting for about 30% of human deaths worldwide. Heart failure is also the leading cause of hospitalization in adults over the age of 65 years. Echocardiography is an important diagnostic aid in cardiology for the morphological and functional assessment of the heart. In a typical patient echocardiogram (echo) examination, a clinician called a sonographer places an ultrasound device against the patient's chest to capture a number of 2D images/videos of the patients' heart. Reflected sound waves reveal the inner structure of the heart walls and the velocities of blood flows. The ultrasound device position is varied during an echo exam to capture different anatomical sections as 2D slices of the heart from different viewpoints or views. The clinician has the option of adding to these 2D images a waveform captured from various possible modalities including continuous wave Doppler, m-mode, pulsed wave Doppler and pulsed wave tissue Doppler. The 2D images/videos and Doppler modality images are typically saved in DICOM (Digital Imaging and Communications in Medicine) formatted files. Although the type of modality is partially indicated in the metadata of the DICOM file, the ultrasound

device position in both the modality and 2D views, which is the final determinant of which cardiac structure has been imaged, is not.

[003] After the patient examination, a clinician/technician goes through the DICOM files, manually annotates heart chambers and structures like the left ventricle (LV) and takes measurements of those structures. The process is reliant on the clinicians' training to recognize the view in each image and make the appropriate measurements. In a follow up examination, a cardiologist reviews the DICOM images and measurements, compares them to memorized guideline values and make a diagnosis based on the interpretation made from the echocardiogram.

[004] The current workflow process for analyzing DICOM images, measuring cardiac structures in the images and determining, predicting and prognosticating heart disease is highly manual, time-consuming and error-prone.

[005] There has been a recent proposal for automated cardiac image interpretation to enable low cost assessment of cardiac function by non-experts. Although the proposed automated system holds the promise of improved performance compared to the manual process, the system has several shortfalls. One shortfall is that the system only recognizes 2D images. In addition, although the proposed system may distinguish between a normal heart and a diseased heart, the proposed system is incapable of distinguishing hearts having similar-looking diseases. Consequently, the number of heart diseases identified by the proposed system is very limited and requires manual intervention to identify other types of heart diseases.

[006] For example, heart failure has been traditionally viewed as a failure of contractile function and left ventricular ejection fraction (LVEF) has been widely used to

define systolic function, assess prognosis and select patients for therapeutic interventions. However, it is recognized that heart failure can occur in the presence of normal or near-normal EF: so-called "heart failure with preserved ejection fraction (HFPEF)" which accounts for a substantial proportion of clinical cases of heart failure. Heart failure with severe dilation and/or markedly reduced EF: so-called "heart failure with reduced ejection fraction (HFREF)" is the best understood type of heart failure in terms of pathophysiology and treatment**.** The symptoms of heart failure may develop suddenly' acute heart failure' leading to hospital admission, but they can also develop gradually. Timely diagnosis, categorization of heart failure subtype-HFREF or HFPEF, and improved risk stratification are critical for the management and treatment of heart failure, but the proposed system does not address this.

[007] The proposed system is also incapable of generating a prognosis based on the identified heart disease, and would instead require a cardiologist to manually form the prognosis.

[008] Accordingly, there is a need for an improved and fully automatic clinical workflow that recognizes and analyzes both 2D and Doppler modality echocardiographic images for automated measurements and the diagnosis, prediction and prognosis of heart disease.

BRIEF SUMMARY

[009] The exemplary embodiments provide methods and systems for an automated workflow performed by a software component executing at least one processor. Aspects of exemplary embodiment include receiving a patient study comprising a plurality of echocardiographic images taken by an ultrasound device of a patient heart. A first filter

separates the plurality of echocardiographic images according to 2D images and Doppler modality images based on analyzing image metadata. A first neural network classifies the 2D images by view type, and a second neural network classifies the Doppler modality images by view type. A third neural network segments cardiac chambers in the 2D images and a fourth neural network segments the Doppler modality images to generate waveform traces, thereby producing segmented 2D images and segmented Doppler modality images. Using both the segmented 2D images and the segmented Doppler modality images, the software component calculates for the patient study measurements of cardiac features for both left and right sides of the heart. Conclusions are then generated by comparing the calculated measurements with international cardiac guidelines, and a report is generated and output highlighting values among the calculated measurements that fall outside of the International guidelines.

[0010] According to the method and system disclosed herein, the disclosed embodiments use machine learning to recognize and analyze both 2D and Doppler modality Echocardiographic images for automated measurements and the diagnosis, prediction and prognosis of heart disease, and the system can be deployed in workstation or mobile-based ultrasound point-of-care systems

BRIEF DESCRIPTION OF SEVERAL VIEWS OF THE DRAWINGS

[0011] Figures 1A-1C are diagrams illustrating embodiments of a system for implementing an automated clinical workflow that recognizes and analyzes both 2D and Doppler modality Echocardiographic images for automated measurements and the diagnosis, prediction and prognosis of heart disease.

[0012] Figure 2 illustrates architectural layers of the echo workflow engine.

[0013] Figure 3 is a flow diagram illustrating one embodiment of a process for performed by the echo workflow engine to automatically recognize and analyze both 2D and Doppler modality echo images to perform automated measurements and the diagnosis, prediction and prognosis of heart disease.

[0014] Figure 4A is a flow diagram illustrating details of the process for automatically recognizing and analyze both 2D and Doppler modality echo images to perform automated measurements and the diagnosis, prediction and prognosis of heart disease according to one embodiment.

[0015] Figure 4B is a flow diagram illustrating advanced functions of the echo workflow engine.

[0016] Figure 5A is diagram illustrating an example 2D echo image.

[017] Figure 5B is diagram illustrating an example Doppler modality image.

[018] Figures 6A-6K are diagrams illustrating some example view types automatically classified by the echo workflow engine.

[019] Figure 7 is a diagram illustrating an example 2D image segmented to produce annotations indicating cardiac chambers, and an example Doppler modality image segmented to produce a mask and trace waveform

[020] Figures 8A and 8B are diagrams illustrating examples of finding systolic/diastolic end points.

[021] Figures 9A and 9B are diagrams illustrating processing of an imaging window in a 2D echo image and the automated detection of out of sector annotations.

[022] Figures 10A and 10B are diagrams graphically illustrating structural measurements automatically generated from annotations of cardiac chambers in a 2D

image, and velocity measurements automatically generated from annotations of waveforms in a Doppler modality.

[023] Figure 11 is a diagram graphically illustrating measurements of global longitudinal strain that were automatically generated from the annotations of cardiac chambers in 2D images.

[024] Figure 12A is a diagram graphically illustrating an example set of best measurement data based on largest volume cardiac chambers and the saving of the best measurement data to a repository.

[025] Figure 12B is a diagram graphically illustrating the input of automatically derived measurements from a patient with normal LV EF measurements into a set of rules to determine a conclusion that the patient has normal diastolic function, diastolic dysfunction, or indeterminate.

[026] Figure 13 is a diagram graphically illustrating the output of classification, annotation and measurement data to an example JSON file.

[027] Figure 14 is a diagram illustrating a portion of an example report showing highlighting values that are outside the range of International guidelines.

[028] Figure 15 is a diagram illustrating a portion of an example report of Main Findings that may be printed and/or displayed by the user.

[029] Figure 16A is a diagram showing a graph A plotting PCWP and HFpEF scores.

[030] Figure 16B is a diagram showing a graph B plotting CV mortality or hospitalization for HF.

DETAILED DESCRIPTION

[031] The exemplary embodiments relate to an automatic clinical workflow that recognizes and analyzes 2D and Doppler modality Echocardiographic images for automated measurements and the diagnosis, prediction and prognosis of heart disease. The following description is presented to enable one of ordinary skill in the art to make and use the invention and is provided in the context of a patent application and its requirements. Various modifications to the exemplary embodiments and the generic principles and features described herein will be readily apparent. The exemplary embodiments are mainly described in terms of particular methods and systems provided in particular implementations. However, the methods and systems will operate effectively in other implementations. Phrases such as "exemplary embodiment", "one embodiment" and "another embodiment" may refer to the same or different embodiments. The embodiments will be described with respect to systems and/or devices having certain components. However, the systems and/or devices may include more or less components than those shown, and variations in the arrangement and type of the components may be made without departing from the scope of the invention. The exemplary embodiments will also be described in the context of particular methods having certain steps. However, the method and system operate effectively for other methods having different and/or additional steps and steps in different orders that are not inconsistent with the exemplary embodiments. Thus, the present invention is not intended to be limited to the embodiments shown, but is to be accorded the widest scope consistent with the principles and features described herein.

[032] The disclosed embodiments provide method and system for implementing a software-based automatic clinical workflow using machine learning that recognizes and

analyzes both 2D and Doppler modality Echocardiographic images for automated measurements and the diagnosis, prediction and prognosis of heart disease, and which can be deployed in workstation or mobile-based ultrasound point-of-care systems.

[033] Figures 1A-1C are diagrams illustrating embodiments of a system for implementing an automated clinical workflow that recognizes and analyzes both 2D and Doppler modality Echocardiographic images for automated measurements and the diagnosis, prediction and prognosis of heart disease. Figure 1A shows a basic standalone configuration for the automated clinical workflow system 10A. The automated clinical workflow 10A is primarily implemented as a software application, referred to as echo workflow engine 12, that executes on a computer 14 operating in a standalone setting, disconnected from other devices on network 26. The computer 14 may be implemented in any form factor including a workstation, desktop, notebook, laptop server or tablet capable of running an operating system, such as Microsoft Windows® (e.g., Windows 7®, Windows 10®), Apple macOS®, Linux®, Apple iOS®, Android®, and the like.

[034] The computer 14 may include typical hardware components (not shown) including a processor, input devices (e.g., keyboard, pointing device, microphone for voice commands, buttons, touchscreen, etc.), output devices (e.g., a display device, speakers, and the like), and wired or wireless network communication interfaces (not shown) for communication. The computer 14 may include internal computer-readable media, such as memory (not shown) containing computer instructions comprising the echo workflow engine 12, which implements the functionality disclosed herein when executed by one or more computer processors.

[035] The computer 14 may further include local internal storage for storing one or more databases 16 and an image file archive 18. In one embodiment, the contents of the image file archive 18 include echocardiogram image files (also referred to herein as echo images), which in some embodiments may be stored in DICOM (Digital Imaging and Communications in Medicine) format.

[036] In one embodiment, the computer 14 is in communication with peripheral devices such an ultrasound imaging device 24 that captures echocardiogram images of a patient's organ (e.g., a heart), which may then be stored as a patient study using the database 16 and image file archive 18. For example, the computer 14 may be located in a hospital or clinical lab environment where Echocardiography is performed as a diagnostic aid in cardiology for the morphological and functional assessment of the heart. During a typical patient echocardiogram exam (referred to as a study), a sonographer or technician places the ultrasound imaging device 24 against the patient's chest to capture 2D echo images/videos of the heart to help diagnose the particular heart ailment. Measurements of the structure and blood flows are typically made using 2D slices of the heart and the position of the ultrasound imaging device 24 is varied during an echo exam to capture different anatomical sections of the heart from different viewpoints. The technician has the option of adding to these 2D echo images a waveform captured from various possible modalities including: continuous wave Doppler, m-mode, pulsed wave Doppler and pulsed wave tissue Doppler. The 2D images and Doppler waveform images may be saved as DICOM files. Although the type of modality is sometimes indicated in the metadata of the DICOM file, the 2D view is not.

[037] The computer 14 may further include removable storage devices such as an optical disk 20 and/or a flash memory 22 and the like for storage of the echo images. In some embodiments, the removable storage devices may be used as an import source of echo images and related data structures into the internal image file archive 18, rather than or in addition to, the ultrasound imaging device 24. The removable storage devices may also be used as an archive for electrocardiogram data stored in the database 16 and/or the image file archive 18.

[038] In an advanced embodiment referred to as connected configuration 10B, the computer 14 may be connected through the network 26 and router 28 to other DICOM based devices, such as DICOM servers 30, network file share devices 32, Echo workstations 34, and/or cloud storage services 36 hosting DICOM files. In the connected configuration 10B, several possible interactions with the database 16 and the image file archive 18 are possible, as described below.

[039] One possible interaction is to use the cloud storage services 36 as an internal archive. In case of very large archives consisting of large amounts of DICOM files, the computer 14 may not have sufficient storage to host all files and the echo workflow engine 12 may be configured to use external network storage of the cloud storage services 36 for file storage.

[040] Another possible interaction is to use the cloud storage services 36 as an import source by i) selecting a DICOM file set or patient study, which includes the DICOM and Doppler waveforms images and patient data and examination information. The patient study may also be selected by a reserved DICOMDIR file instance, from which the patient, exams and image files are read.

[041] Yet a further possible interaction is to use the DICOM servers 30, the network file share devices 32, echo workstations 34, and/or DICOM clients (of Figure 1C) acting as DICOM servers (workstations with modalities CFind, CMove and CStore) in order to retrieve patients, exams and images by performing a CFind operation, followed by a CMove operation, to request the remote device to send the images resulting from the CFind operation.

[042] Referring now to Figure 1B, a handheld configuration 10C for the automated clinical workflow system is shown. In this embodiment, the computer 14 of Figure 1A is implemented as a handheld device 14', such as a tablet or a mobile phone, connected to a wired or wireless portable ultrasound scanner probe 24' that transmits echo images to the handheld device 14'. In such embodiments, the echo workflow engine 12 may be implemented as an application executed by the handheld device 14'.

[043] Figure 1C illustrates a software as a service (SaaS) configuration 10D for the automated clinical workflow. In this embodiment, the echo workflow engine 12 is run on a server 40 that is in communication over the network 26 with a plurality of client devices 42. In this embodiment, the server 42 and the echo workflow engine 12 may be part of a third-party service that provides automated measurements and the diagnosis, prediction and prognosis of heart disease to client devices (e.g., hospital, clinic, or doctor computers) over the Internet. It should be understood that although the server 40 is shown as a single computer, it should be understood that the functions of server 40 may be distributed over more than one server. In an alternative embodiment, the server 40 and the echo workflow engine 12 of Figure 1C may be implemented as a virtual entity whose functions are distributed over multiple client devices 42. Likewise, it should be understood

that although the echo workflow engine 12 is shown as a single component in each embodiment, the functionality of the echo workflow engine 12 may be separated into a greater number of modules/components.

[044] Conventionally, after a patient examination where echo images are captured stored, a clinician/technician goes through the DICOM files, manually annotates heart chambers and structures and takes measurements, which are presented in a report. In a follow up examination, a doctor will review the DICOM images and measurements, compare them to memorized guideline values and make a diagnosis. Such a process is reliant on the clinicians' training to recognize the view and make the appropriate measurements so that a proper diagnosis can be made. Such a process is error-prone and time consuming.

[045] According to the disclosed embodiments, the echo workflow engine 12 mimics the standard clinical practice, processing DICOM files of a patient by using a combination of machine learning, image processing, and DICOM workflow techniques to derive clinical measurements, diagnose specific diseases, and prognosticate patient outcomes, as described below. While an automated solution to echo image interpretation using machine learning has been previously proposed, the solution only analyzes 2D echo images and not Doppler modality waveform images. The solution also mentions disease prediction, but only attempts to handle two diseases (hypertrophic cardiomyopathy and cardiac amyloidosis) and the control only compares normal patients to diseased patients.

[046] The echo workflow engine 12 of the disclosed embodiments, however, improves on the automated solution by utilizing machine learning to automatically recognize and analyze not only 2D echo images but also Doppler modality waveform

images. The echo workflow engine 12 is also capable of comparing patients having similar-looking heart diseases (rather than comparing normal patients to diseased patients), and automatically identifies additional diseases, including both heart failure with reduced ejection fraction (HFrEF) and heart failure with preserved ejection fraction (HFpEF). HFrEF is known as heart failure due to left ventricular systolic dysfunction or systolic heart failure and occurs when the ejection fraction is less than 40%. HFpEF is a form of congestive heart failure where in the amount of blood pumped from the heart's left ventricle with each beat (ejection fraction) is greater than 50%. Finally, unlike the proposed automated solution, the echo workflow engine 12 automatically generates a report with the results of the analysis for medical decision support.

[047] Figure 2 illustrates architectural layers of the echo workflow engine 12. In one embodiment, the echo workflow engine 12 may include a number of servers that are packaged together in one software application. For example, the echo workflow engine 12 may include a machine learning layer 200, a presentation layer 202, and a database layer 204.

[048] The machine learning layer 200 comprises several neural networks to process incoming echo images and corresponding metadata. In one embodiment, machine learning layer 200 utilizes a set of one or more classification convolutional neural networks (CNNs) 200A for view classification, a set of one or more segmentation CNNs 200B for chamber segmentation and waveform mask/trace, a set of one or more prediction CNNs 200C for disease prediction and optionally a set of one or more prognosis CNNs 200D for disease prognosis.

[049] In machine learning, a CNN is a class of deep, feed-forward artificial neural network typically use for analyzing visual imagery. Each CNN comprises an input and an output layer, as well as multiple hidden layers. In neural networks, each node or neuron receives an input from some number of locations in the previous layer. Each neuron computes an output value by applying some function to the input values coming from the previous layer. The function that is applied to the input values is specified by a vector of weights and a bias (typically real numbers). Learning in a neural network progresses by making incremental adjustments to the biases and weights. The vector of weights and the bias are called a filter and represents some feature of the input (e.g., a particular shape).

[050] The machine learning layer 200 operates in a training mode to train each of the CNNs 200A-200D prior to the echo workflow engine 12 being placed in an analysis mode to automatically recognize and analyze echo images in patient studies. In one embodiment, the CNNs 200A-200D may be trained to recognize and segment the various echo image views using thousands of echo images from an online public or private echocardiogram DICOM database.

[051] The presentation layer 202 is used to format and present information to a user. In one embodiment, the presentation layer is written in HTML 5, Angular 4 and/or JavaScript. The presentation layer 202 may include a Windows Presentation Foundation (WPF) graphical subsystem 202A for implementing a light weight browser-based user interface that displays reports and allows a user (e.g., doctor/technician) to edit the reports. The presentation layer 202 may also include an image viewer 202B (e.g., a DICOM viewer) for viewing echo images, and a python server 202C for running the CNN

algorithms and generating a file of the results in JavaScript Object Notation (JSON) format, for example.

[052] The database layer 204 in one embodiment comprises a SQL database 204A and other external services that the system may use. The SQL database 204A stores patient study information for individual patient studies input to the system. In some embodiments, the database layer 204 may also include the image file archive 18 of Figure 1.

[053] Figure 3 is a flow diagram illustrating one embodiment of a process for performed by the echo workflow engine 12 to automatically recognize and analyze both 2D and Doppler modality echo images to perform automated measurements and the diagnosis, prediction and prognosis of heart disease. The process occurs once the echo workflow engine 12 is trained and placed in analysis mode.

[054] The process may begin by the echo workflow engine 12 receiving from a memory one or more patient studies comprising a plurality of echocardiogram images taken by an ultrasound device of a patient organ, such as a heart (block 300). In one embodiment, the patient study may include 70-90 images and videos.

[055] A first filter of the echo workflow engine 12 is used to separate the plurality of echocardiogram images according to 2D images and Doppler modality images based on analyzing image metadata (block 302). The filter analyzes the DICOM tags, or metadata, incorporated in the image, and runs an algorithm based upon the tag information to distinguish between 2D and modality images, and then separate the modality images into either pulse wave, continuous wave, PWTDI or m-mode groupings.

[056] Because sonographers do not label the view types in the echo images, one or more of the CNNs 200 are used classify the echo images by view type. In one embodiment, a first neural network is used by the echo workflow engine 12 to classify the 2D images by view type (block 304); and a second neural network is used by the echo workflow engine 12 to classify, the Doppler modality images by view type (block 306). As shown, the processing of 2D images is separate from the processing of Doppler modality images. In one embodiment, the first and second neural networks may implemented using the set of classification convolutional neural networks (CNNs) 200A. In one specific embodiment, a five class CNN may be used to classify the 2D images by view type and an 11 class CNN may be used to classify the Doppler modality images by view type. In an alternative embodiment, the first and second neural networks may be combined into one neural network.

[057] In one embodiment, the echo workflow engine 12 is trained to classify many different view types. For example, the echo workflow engine 12 may classify at least 11 different view types including parasternal long axis (PLAX), apical 2-, 3-, and 4-chamber (A2C, A3C, and A4C), A4C plus pulse wave of the mitral valve, A4C plus pulse wave tissue Doppler on the septal side, A4C plus pulse wave tissue Doppler on the lateral side, A4C plus pulse wave tissue Doppler on the tricuspid side, A5C plus continuous wave of the aortic valve, A4C + Mmode (TrV), A5C + PW (LVOT).

[058] Based on the classified images, a third neural network is used by the echo workflow engine 12 to segment regions of interest (e.g., cardiac chambers) in the 2D images to produce annotated or segmented 2D images (block 308). A fourth neural network is used by the echo workflow engine 12 to generate waveform traces for the

Doppler modality images to generate annotated or segmented Doppler modality images (block 309). The process of segmentation includes determining locations where each of the cardiac chambers begin and end to generate outlines of structures of the heart (e.g., cardiac chambers) depicted in each image and/or video. Segmentation can also be used to trace the outline of the waveform depicting the velocity of blood flow in a Doppler modality. In one embodiment, the third and fourth neural networks may be implemented using the set of one or more segmentation CNNs 200B. The choice of segmentation CNN used is determined by the view type of the image, which makes the prior correct classification of view type a crucial step.

[059] Using both the segmented 2D images and the segmented Doppler modality images, the echo workflow engine 12 calculates for the patient study, measurements of cardiac features for both left and right sides of the heart (block 310).

[060] The echo workflow engine 12 then generates conclusions by comparing the calculated measurements with international cardiac guidelines (block 312). The echo workflow engine 12 further outputs a report to a user highlighting ones of the calculated measurements that fall outside of the International guidelines (block 314). In one embodiment, the report may be electronically displayed to a doctor and/or a patient on a display of an electronic device and/or as a paper report. In some embodiments, the electronic report may be editable by the user per rule or role based permissions, e.g., a cardiologist may be allowed to modify the report, but a patient may have only view privileges.

[061] Figure 4A is a flow diagram illustrating further details of the process for automatically recognizing and analyze both 2D and Doppler modality echo images to

perform automated measurements and the diagnosis, prediction and prognosis of heart disease according to one embodiment.

[062] The process may begin with receiving one or more patient studies (Fig. 3 block 300), which comprises blocks 400-4010. In one embodiment, echo images from each of the patient studies are automatically downloaded into the image file archive 18 (block 400). The echo images may be received from a local or remote storage source of the computer 14. The local storage sources may include internal/external storage of the computer 14 including removable storage devices. The remote storage sources may include the ultrasound imaging device 24, the DICOM servers 30, the network file share devices 32, the echo workstations 34, and/or the cloud storage services 36 (see Figure 1). In one embodiment, the echo workflow engine 12 includes functions for operating as a picture archiving and communication server (PACS), which is capable of handling images from multiple modalities (source machine types, one of which is the ultrasound imaging device 24). The echo workflow engine 12 uses PACS to download and store the echo images into the image file archive 18 and provides the echo workflow engine 12 with access to the echo images during the automated workflow. The format for PACS image storage and transfer is DICOM (Digital Imaging and Communications in Medicine).

[063] Patient information from each of the patient studies is extracted and stored in the database 16 (block 402). Non-image patient data may include metadata embedded within the DICOM images and/or scanned documents, which may be incorporated using consumer industry standard formats such as PDF (Portable Document Format), once encapsulated in DICOM. In one embodiment, received patient studies are placed in a processing queue for future processing, and during the processing of each patient study,

the echo workflow engine 12 queues and checks for unprocessed echo images (block 404). The echo workflow engine 12 monitors the status of patient studies, and keeps track of them in a queue to determine which have been processed and which are still pending. In one embodiment, prioritization of the patient studies in the queue may be configured by a user. For example, the patient studies may be prioritized in the queue for processing according to the date of the echo exam, the time of receipt of the patient study or by estimated severity of the patient's heart disease.

[064] Any unprocessed echo images are then filtered for having a valid DICOM image format and non DICOM files in an echo study are discarded (block 406). In one embodiment, the echo images are filtered for having a particular type of format, for example, a valid DICOM file format, and any other file formats may be ignored. Filtering the echo images for having a valid image file format enhances the reliability of the echo workflow engine 12 by rejecting invalid DICOM images for processing.

[065] Any unprocessed valid echo images are then opened and processed in the memory of the computer 14 (block 408). Opening of the echo images for the patient study in memory of the computer 14 is done to enhance processing speed by echo workflow engine 12. This is in contrast to an approach of opening the echo files as sub-processes, saving the echo files to disk, and then reopening each echo image during processing, which could significantly slow processing speed.

[066] The echo workflow engine 12 then extracts and stores the metadata from the echo images and then anonymizes the images by blacking out the images and overwriting the metadata in order to protect patient data privacy by covering personal information written on the image (block 410). As an example, DICOM formatted image files include

metadata referred to as DICOM tags that may be used to store a wide variety of information such as patient information, Doctor information, ultrasound manufacture information, study information, and so on. In one embodiment, the extracted metadata may be stored in the database 16 and the metadata in image files is over written for privacy.

[067] After receipt and processing of the patient studies, the echo workflow engine 12 separates 2D images from Doppler modality images so the two different image types can be processed by different pipeline flows, described below. In one embodiment, the separating of the images (Fig, 3 block 302) may comprise blocks 412-414. First, the 2D images are separated from the Doppler modality images by analyzing the metadata (block 412).

[068] Figures 5A and 5B are diagrams illustrating an example 2D echo image 500 and an example Doppler modality image 502 including a waveform, respectively. The echo workflow engine 12 may determine the image type by examining metadata/DICOM tags. In one embodiment, information within the DICOM tags may be extracted in order to group the images into one of the following four classes: 2D only, pulsed-wave (PW), continuous wave (CW), and m-mode. Similarly, the transducer frequency of the ultrasound imaging device 24 in the metadata may be used to further separate some of the PW images into a fifth class: pulsed-wave tissue doppler imaging (PWTDI).

[069] Referring again to Figure 4A, the echo workflow engine 12 may also filter out images with a zoomed view, which may also be determined by analyzing the metadata (block 414). Any of the echo images that has been zoomed during image capture are not processed through the pipeline because when zooming, useful information is necessarily

left out of the image, meaning the original image would have to be referenced for the missing data, which is a duplication of effort that slows processing speed. Accordingly, rather than potentially slowing the process in such a manner, the echo workflow engine 12 filters out or discards the zoomed images to save processing time. In an alternative embodiment, filtering out zoomed images in block 414 may be performed prior to separating the images in block 412.

[070] After separating the 2D images from the Doppler modality images, the echo workflow engine 12 extracts and converts the image data from each echo image into numerical arrays 416 (block 416). For the echo images that are 2D only, the pixel data comprises a series of image frames played in sequence to create a video. Because the image frames are unlabeled, the view angle needs to be determined. For the Doppler modality images that include waveform modalities, there are two images in the DICOM file that may be used for subsequent view identification, a waveform image and an echo image of the heart. The pixel data is extracted from the DICOM file and tags in the DICOM file determine the coordinates to crop the images. The cropped pixel data is stored in numerical arrays for further processing. In one embodiment, blocks 412, 414 and 416 may correspond to the separating images block 302 of Figure 3.

[071] After separating images, the echo workflow engine 12 attempts to classify each of the echo images by view type. In one embodiment, view classification (Fig. 3 blocks 304 and 306) correspond to blocks 418-422.

[072] According to the disclosed embodiments, the echo workflow engine 12 attempts to classify each of the echo images by view type by utilizing parallel pipeline flows. The parallel pipeline includes a 2D image pipeline and a Doppler modality image

pipeline. The 2D pipeline flow begins by classifying, by a first CNN, the 2D images by view type (block 418), corresponding to block 304 from Figure 3. The Doppler modality image pipeline flow begins by classifying, by a second CNN, the Doppler modality images by view type (block 420), corresponding to block 306 from Figure 3.

[073] Figures 6A-6K are diagrams illustrating some example view types automatically classified by the echo workflow engine 12. As stated previously, example view types may include parasternal long axis (PLAX), apical 2-, 3-, and 4-chamber (A2C, A3C, and A4C), A4C plus pulse wave of the mitral valve, A4C plus pulse wave tissue Doppler on the septal side, A4C plus pulse wave tissue Doppler on the lateral side, A4C plus pulse wave tissue Doppler on the tricuspid side, A5C plus continuous wave of the aortic valve, A4C + Mmode (TrV), A5C + PW (LVOT).

[074] Referring again to Figure 4A, in one embodiment, 2D image classification is performed as follows. If the DICOM file contains video frames from a 2D view, only a small subset of the video frames are analyzed to determine 2D view classification for more efficient processing. In one embodiment, the subset of the video frames may range approximately 8-12 video frames, but preferably 10 frames are input into one of the CNNs 200A trained for 2D to determine the actual view. In an alternative embodiment, subset a video frames may be randomly selected from the video file. In one embodiment, the CNNs 200A classify each of the analyzed video frames as one of: A2C, A3C, A4C, A5C, PLAX Modified, PLAX, PSAX AoV level, PSAX Mid-level, Subcostal Ao, Subcostal Hep vein, Subcostal IVC, Subcostal LAX, Subcostal SAX, Suprasternal and Other.

[075] Doppler modality images comprise two images, an echocardiogram image of the heart and a corresponding waveform, both of which are extracted from the echo file

for image processing. In one embodiment, Doppler modality image classification of continuous wave (CW), pulsed-wave (PW), and M-mode images is performed as follows. If the DICOM file contains a waveform modality (CW, PW, PWTDI, M-mode), the two extracted images are input to one of the CNNs 200A trained for CW, PW, PWTDI and M-mode view classification to further classify the echo images as one of: CW (AoV), CW (TrV), CW Other, PW (LVOT), PW (MV), PW Other, PWTDI (lateral), PWTDI (septal), PWTDI (tricuspid), M-mode (TrV) and M-mode Other.

[076] There are many more potential classifications available for modalities, but the present embodiments strategically select the classes above, while grouping the remaining potential classes into “Other”, in order to maximize processing efficiency, while identifying the most clinically important images for further processing and quantification. Customization of the CNNs 200A occurs in the desired number of layers used and the quantity of filters within each layer. During the training phase, the correct size of the CNNs may be determined through repeated training and adjustments until optimal performance levels are reached.

[077] During view classification, the echo workflow engine 12 maintains classification confidence scores that indicate a confidence level that the view classifications are correct. The echo workflow engine 12 filters out the echo images having classification confidence scores that fail to meet a threshold, i.e., low classification confidence scores (block 422). Multiple algorithms may be employed to derive classification confidence scores depending upon the view in question. Anomalies detected in cardiac structure annotations, image quality, cardiac cycles detected and the presence of image artifacts

may all serve to decrease the classification confidence score and discard an echo image out of the automated echo workflow.

[078] With respect to the confidence scores, the echo workflow engine 12 generates and analyzes several different types of confidence scores at different stages of processing, including classification, annotation, and measurements (e.g., blocks 422, 434 and 442). For example, poor quality annotations or classifications, which may be due to substandard image quality, are filtered out by filtering the classification confidence scores. In another example, in a patient study the same view may be acquired more than once, in which case the best measurements are chosen by filtering out low measurement confidence scores as described further below in block 442. Any data having a confidence score that meets a predetermined threshold continues through the workflow. Should there be a duplication of measurements both with high confidence, the most clinically relevant measurement may be chosen.

[079] Next the echo workflow engine 12 performs image segmentation to define regions of interest (ROI). In computer vision, image segmentation is the process of partitioning a digital image into multiple segments (sets of pixels) to locate and boundaries (lines, curves, and the like) of objects. Typically, annotations are a series of boundary lines overlaying overlaid on the image to highlight segment boundaries/edges. In one embodiment, the segmentation to define ROI (Fig. 3 block 308) corresponds to blocks 426-436.

[080] In one embodiment, the 2D image pipeline annotates, by a third CNN, regions of interests, such as cardiac chambers in the 2D images, to produce annotated 2D images (block 426). An annotation post process then erodes the annotations to reduce their

dimensions, spline fits outlines of cardiac structures and adjusts locations of the boundary lines closer to the region of interest (ROIs) (block 427). The 2D image pipeline continues with analyzing the ROIs (e.g., cardiac chambers) in the annotated 2D images to estimate volumes and determine key points in the cardiac cycle by finding systolic/diastolic end points (block 430). For 2D only views, measurements are taken at the systolic or diastolic phase of the cardiac cycle, i.e. when the left ventricle reaches the smallest volume (systole) or the largest volume (diastole). From the 2D video images, it must be determined which end points are systolic and which are diastolic based on the size of the estimated volumes of the left ventricle. For example a significantly large left ventricle may indicate a dystonic end point, while a significantly small volume may indicate a systolic end point. Every video frame is annotated and the volume of the left ventricle is calculated throughout the whole cardiac cycle. The frames with minimum and maximum volumes are detected with a peak detection algorithm.

[081] The Doppler modality pipeline analyzes the Doppler modality images and generates, by a fourth CNN, a mask and a waveform trace in the Doppler modality images to produce annotated Doppler modality images (block 431).

[082] Figure 7 is a diagram illustrating an example 2D image segmented in block 426 to produce annotations 700 indicating cardiac chambers, and an example Doppler modality image segmented in block 431 to produce a mask and waveform trace 702.

[083] In one embodiment, the third and fourth CNNs may correspond to segmentation CNNs 200B. In one embodiment, each of the CNNs 200B used to segment the 2D images and Doppler modality images may be implemented as U-Net CNN, which is convolutional neural network developed for biomedical image segmentation. Multiple

U-Nets may be used. For example, for 2D images, a first U-Net CNN can be trained to annotate ventricles and atria of the heart from the A2C, A3C, A4C views. A second U- net CNN can be trained to annotate the chambers in the PLAX views. For M-mode views, a third U-Net CNN can be trained to segment the waveform, remove small pieces of the segments to find likely candidates for the region of interest, and then reconnect the segments to provide a full trace of the movement of the mitral valve. For CW views, a fourth U-net CNN can be trained to annotate and trace blood flow. For PW views, a fifth U-net CNN trained to annotate and trace the blood flow. For PWTDI views, a sixth U-net CNN can be trained to annotate and trace movement of the tissues structures (lateral/septal/ tricuspid valve).

[084] Referring again to Figure 4A, the Doppler modality pipeline continues by processing the annotated Doppler modality images with a sliding window to identify cycles, peaks are measured in the cycles, and key points in the cardiac cycle are determined by finding systolic/diastolic end points (block 432). Typically a Doppler modality video may capture three heart cycles and the sliding window is adjusted in size to block out two of the cycles so that only one selected cycle is analyzed. Within the selected cycle, the sliding window is used to identify cycles, peaks are measured in the cycles, and key points in the cardiac cycle are determined by finding systolic/diastolic end points.

[085] Figures 8A and 8B are diagrams illustrating examples of finding systolic/diastolic end points in the cardiac cycle, for both 2D and Doppler modalities, respectively, which are key points in order to take accurate cardiac measurements

[086] Referring again to Figure 4A, in one embodiment, the echo workflow engine 12 maintains annotation confidence scores corresponding to the estimated volumes, systolic/diastolic end points, identified cycles and measured peaks. The echo workflow engine 12 filters out annotated images having annotation confidence scores that fail to meet a threshold, i.e., low annotated confidence scores (block 434). Examples of low confidence annotations may include annotated images having one or more of: excessively small areas/volumes, sudden width changes, out of proportion sectors, partial heart cycles, and insufficient heart cycles.

[087] After images having low annotation confidence scores are filtered out, the echo workflow engine 12 defines an imaging window for each image, and filters out annotations that lie outside of the imaging window (block 435).

[088] Figures 9A and 9B are diagrams illustrating processing of an imaging window in a 2D echo image 900. In Figure 9A, a shaded ROI 902 is shown having unshaded regions or holes 904 therein. Open CV morphology transformations are used to fill the holes 904 inside the ROI, as shown in In Figure 9B. Thereafter, a Hough line transformation may be used to find an imaging window border 906. As is well known, a Hough transform is a feature extraction technique used in digital image processing to find imperfect instances of objects within a certain class of shapes. After an imaging window border is are found, a pixel account of annotations beyond the imaging window border is made. Annotations 908 with a significant number of pixels outside the border of the imaging window are then discarded.

[089] Referring again to Figure 4A, in the handheld configuration for the automated clinical workflow system 10C (See Figure 1B), the patient studies may not include Doppler

modality images. According to a further aspect, the disclosed embodiments accommodate for such handheld configurations by using the 2D images to simulate Doppler modality measurements by using Left Ventricular (LV) and Left Atrial (LA) volume measurements to derive E, e' and A (e.g., early and late diastolic transmittal flow and early/mean diastolic tissue velocity) measurements (block 436). In one embodiment, simulating the Doppler modality measurements may be optional and may be invoked based on a software setting indicating the presence of a handheld configuration and/or absence of Doppler modality images for the current patient study.

[090] Referring again to Figure 4A, in one embodiment, once cardiac features are annotated during segmentation, the cardiac features are then measured during a measurement process (block 310 of Figure 3), which in one embodiment may comprises block 438-448. The process of measuring cardiac features may begin by quantifying a plurality of measurements using the annotations. First, the 2D pipeline measures for the 2D images left/right ventricle, left/right atriums, left ventricular outflow (LVOT) and pericardium (block 438). For the Doppler modality images, the Doppler modality image pipeline measures blood flow velocities (block 440).

[091] More specifically, for A2C, A3C, and A4C image views, volumetric measurements of chamber size are conducted on the systolic and diastolic frames of the video, and image processing techniques mimic a trained clinician at measuring the volume using the method of disks (MOD). For 2D Plax image views, linear measurements of chamber size and inter-chamber distances are conducted on the systolic and diastolic frames of the video using image processing techniques to mimic the trained clinician. For M-mode image views, from the annotated segments of the movement of the Mitral valve,

a center line is extracted and smoothed, and then the peaks and valleys are measured in order to determine the minimum and maximum deviations over the cardiac cycle. For PW image views, from the annotations of the blood flow, a mask is created to isolate parts of the waveform. A sliding window is then run across the trace to identify one full heart cycle, in combination with heart rate data from the DICOM tags, to use as a template. This template is then used to identify all other heart cycles in the image. Peak detection is then performed on each cycle and then run through an algorithm to identify which part of the heart cycle each peak represents. For CW image views, from the annotations of the trace of the blood flow, curve fitting is performed on the annotation to then quantify the desired measurements. For PWTDI image views, from the annotations of the movement of the tissue, a mask is created to isolate parts of the waveform. A sliding window is then run across the trace to identify one full heart cycle, in combination with heart rate data from the DICOM tags, to use as a template. This template is then used to identify all other heart cycles in the image. Peak detection is then performed on each cycle and then run through an algorithm to identify which part of the heart cycle each peak represents.

[092] Figures 10A and 10B are diagrams graphically illustrating structural measurements automatically generated from annotations of cardiac chambers in a 2D image, and velocity measurements automatically generated from annotations of waveforms in a Doppler modality, respectively.

[093] The measurement table below list the measurements that may be compiled by the echo workflow engine 12 according to one embodiment.

[094] Measurement Table

Measurement Name	Measurement Description
LAESV MOD A2C	Left Atrial End Systolic Volume in A2C calculation based on Method Of Discs
LAESVi MOD A2C	Left Atrial End Systolic Volume in A2C calculation based on Method Of Discs indexed to BSA
LAL A2C	Left Atrial End Sysolic Length measured in A2C
LVEDV MOD A2C	Left Ventricular End Diastolic Volume in A2C calculation based on Method Of Discs
LVEDVi MOD A2C	Left Ventricular End Diastolic Volume in A2C calculation based on Method Of Discs indexed to BSA
LVEF MOD A2C	Left Ventricular Ejection Fraction in A2C based on Method Of Discs
LVESV MOD A2C	Left Ventricular End Systolic Volume in A2C calculation based on Method Of Discs
LVESVi MOD A2C	Left Ventricular End Systolic Volume in A2C calculation based on Method Of Discs indexed to BSA
LV length A2C	Left Ventricular Length measured in A2C
LAESV MOD A4C	Left Atrial End Systolic Volume in A4C calculation based on Method Of Discs
LAESVi MOD A4C	Left Atrial End Systolic Volume in A4C calculation base on Method Of Discs indexed to BSA
LAL A4C	Left Atrial End Systolic Length measured in A4C
LAW A4C	Left Atrial End Systolic Width measurement in A4C
LA area A4C	Left Atrial Area measured in A4C
LAESV A-L A4C	Left Atrial End Systolic Volume in A4C calculation based on Area-Length method
LVEDV MOD A4C	Left Ventricular End Diastolic Volume in A4C calculation based on Method Of Discs
LVEDVi MOD A4C	Left Ventricular End Diastolic Volume in A4C calculation based on Method Of Discs indexed to BSA
LVEF MOD A4C	Left Ventricular Ejection Fraction in A4C based on Method Of Discs
LVESV MOD A4C	Left Ventricular End Systolic Volume in A4C calculation based on Method Of Discs
LVESVi MOD A4C	Left Ventricular End Systolic Volume in A4C calculation based on Method Of Discs indexed to BSA
LV length A4C	Left Ventricular Length measured in A4C
LVAd A4C	Left Ventricular Area measured at end diastole in A4C

TAPSE	Tricuspid Annular Plane Systolic Excursion
DecT	Deceleration Time of early diastolic MV transmitral flow
E/A ratio	Ratio of early and late diastolic transmitral flow
MV-A	Late diastolic transmitral flow
MV-Adur	Duration of late diastolic transmitral flow
MV-E	Early diastolic transmitral flow
e' lateral	Early diastolic tissue velocity taken from the lateral region
e' mean	Mean early diastolic tissue velocity (mean of lateral and septal region)
e' septal	Early diastolic tissue velocity taken from the septal region
E/e' lateral	Ratio of early transmitral flow and early diastolic tissue velocity taken form the lateral region
E/e' septal	Ratio of early transmitral flow and early diastolic tissue velocity taken form the septal region
E/e' mean	Ratio of early transmitral flow and mean diastolic tissue velocity
a' lateral	Late diastolic tissue velocity taken from the lateral region
a' septal	Late diastolic tissue velocity taken from the septal region
s' lateral	Systolic tissue velocity taken from the lateral region
s' septal	Systolic tissue velocity taken from the septal region
LAESV A-L biplane	Left Atrial End Systolic Volume biplane calculation based on Area-Length method
LAESV MOD biplane	Left Atrial End Systolic Volume biplane calculation based on Method Of Discs
LAESVi MOD biplane	Left Atrial End Systolic Volume biplane calculation based on Method Of Discs indexed to BSA
LAESVi A-L biplane	Left Atrial End Systolic Volume biplane calculation based on Area-Length method indexed to BSA
LVCO MOD biplane	Left Ventricular Cardiac Output biplane calculation based on Method Of Discs
LVEDV MOD biplane	Left Ventricular End Diastolic Volume biplane calculation based on Method Of Discs
LVEDVi MOD biplane	Left Ventricular End Diastolic Volume biplane calculation based on Method Of Discs indexed to BSA
LVEF MOD biplane	Left Ventricular Ejection Fraction biplane based on Method Of Discs
LVESV MOD biplane	Left Ventricular End Systolic Volume biplane calculation based on Method Of Discs
LVESVi MOD biplane	Left Ventricular End Systolic Volume biplane calculation based on Method Of Discs indexed to BSA

LVSV MOD biplane	Left Ventricular Stroke Volume biplane calculation based on Method of Disks
AoV Vmax	Aortic Valve maximum Velocity
AoV Vmean	Aortic Valve mean Velocity
AoV Pmax	Aortic Valve maximum Pressure gradient
LVOT Vmax	Left Ventricular Outflow Tract maximum Velocity
LVOT Vmean	Left Ventricular Outflow Tract mean Velocity
IVSd	Inter Ventricular Septal thickness measured end diastolic
LV mass	Left Ventricular mass
LVIDd	Left Ventricular internal Diameter measured at end diastole
LVIDd index	Left Ventricular internal Diameter measured at end diastole indexed to BSA
LVIDs	Left Ventricular internal Diameter measured at end systole
LVIDs index	Left Ventricular internal Diameter measured at end systole indexed to BSA
LVMi	Left Ventricular Mass indexed to BSA
LVOT	Left Ventricular Outflow Tract diameter
LVPWd	Left Ventricular Posterior Wall thickness measured end diastolic
RWT	Relative Wall Thickness
LA area A2C	Left Atrial Area measured in A2C
LAESV A-L A2C	Left Atrial End Systolic Volume in A2C calculation based on Area-Length method
LVAd A2C	Left Ventricular Area measured at end diastole in A2C
LVAs A2C	Left Ventricular Area measured at end systole in A2C
LVAs A4C	Left Ventricular Area measured at end systole in A4C
RAL	Right Atrial End Systolic Length
RAW	Right Atrial End Systolic Width
RAESV MOD A4C	Right Atrial end systolic Volume in A4C calculation based on Method Of Discs
RAESV A-L A4C	Right Atrial end systolic Volume in A4C calculation based on Area-Length method
RAESVi MOD A4C	Right Atrial end systolic Volume in A4C calculation based on Method Of Discs indexed to BSA
RA area	Right Atrial area
RVIDd	Right Ventricular End Diastolic Internal Diameter
RV area (d)	Right Ventricular Area (measured at end-diastole)
RV area (s)	Right Ventricular Area (measured at end systole)
LVOT Pmax	Left Ventricular Outflow Tract max pressure gradient
LVOT Pmean	Left Ventricular Outflow Tract mean pressure gradient
LVSV (Doppler)	Left Ventricular Stroke Volume based on Doppler
LVOT VTI	Left Ventricular Outflow Tract Velocity Time Integral

LVCO (Doppler)	Left Ventricular Cardiac Output (based on Doppler)
LVCOi (Doppler)	Left Ventricular Cardiac Output (based on Doppler) indexed to Body Surface Area
LVSVi (Doppler)	Left Ventricular Stroke Volume (based on Doppler) indexed to Body Surface Area
TR Vmax	Tricuspid Regurgitation maximum velocity
CSA LVOT	Crossectional Area of the LVOT
Sinotub J	Sinotubular junction diameter
Sinus valsalva	Sinus valsalva diameter
Asc. Ao	Ascending Aorta diameter
Asc. Ao index	Ascending Aorta diameter index
Sinus valsalva index	Sinus valsalva diameter indexed to BSA
IVC max	Inferior Vena Cava maximum diameter
IVC min	Inferior Vena Cava minimum diameter
IVC Collaps	Inferior Vena Cava collaps
RVIDd mid	Right Ventricular Internal Diameter at mid level (measured end diastole)
RVOT prox	Right Ventricular Outflow Tract proximal diameter
RVOT dist	Right Ventricular Outflow Tract distal diameter
RV FAC	Right Ventricular Fractional Area Change
TEI index	
RVAWT	Right Ventricular Anterior Wall Thickness
TrV-E	Tricuspid valve E wave
TrV-A	Tricuspid valve A wave
TrV E/A	Tricuspid valve E/A ratio
TrV DecT	Tricuspid valve deceleration time
MV Vmax	Mitral valve maximum velocity
MV Vmean	Mitral valve mean velocity
MV VTI	Mitral valve velocity time intergal
MV PHT	Mitral valve pressure half time
MVA (by PHT)	Mitral valve area (by pressure half time)
RV e'	Early diastolic tissue velocity taken from the right ventricular free wall region
RV a'	Late diastolic tissue velocity taken from the right ventricular free wall region
RV s'	Systolic tissue velocity taken from the right ventricular free wall region
RVCO	Right Ventricular Cardiac Output
ULS	Unidimensional Longitudinal Strain
Ao-arch	Aortic arch diameter
Descending Ao	Descending Aortic diameter
Ao-arch index	Aortic arch diameter indexed to BSA
Descending Ao index	Descending Aortic diameter indexed to BSA
LA GLS (reservoir) (A4C)	Left Atrial strain during systole measured in A4C
LA GLS (conduit) (A4C)	Left Atrial strain during early diastole measured in A4C

LA GLS (booster) (A4C)	Left Atrial strain during pre atrial contraction measured in A4C
LA GLS (reservoir) (A2C)	Left Atrial strain during systole measured in A2C
LA GLS (conduit) (A2C)	Left Atrial strain during early diastole measured in A2C
LA GLS (booster) (A2C)	Left Atrial strain during pre atrial contraction measured in A2C
LA GLS (reservoir)	Left Atrial strain during systole
LA GLS (conduit)	Left Atrial strain during early diastole
LA GLS (booster)	Left Atrial strain during pre atrial contraction
LVSr-e (A4C)	Left Ventricular strain rate during early diastole measured in A4C
LVSr-a (A4C)	Left Ventricular strain rate during late diastole measured in A4C
LVSr-s (A4C)	Left Ventricular strain rate during systole measured in A4C
LVSr-e (A2C)	Left Ventricular strain rate during early diastole measured in A2C
LVSr-a (A2C)	Left Ventricular strain rate during late diastole measured in A2C
LVSr-s (A2C)	Left Ventricular strain rate during systole measured in A2C
LVSr-e	Left Ventricular strain rate during early diastole
LVSr-a	Left Ventricular strain rate during late diastole
LVSr-s	Left Ventricular strain rate during systole
LASr-e (A4C)	Left Atrial strain rate during early diastole
LASr-a (A4C)	Left Atrial strain rate during late diastole
LASr-s (A4C)	Left Atrial strain rate during systole
LASr-e (A2C)	Left Atrial strain rate during early diastole
LASr-a (A2C)	Left Atrial strain rate during late diastole
LASr-s (A2C)	Left Atrial strain rate during systole
LASr-e	Left Atrial strain rate during early diastole
LASr-a	Left Atrial strain rate during late diastole
LASr-s	Left Atrial strain rate during systole
AV-S (A4C)	Atrio Ventricular strain measured in A4C
AV-S (A2C)	Atrio Ventricular strain measured in A2C
AV-S	Atrio Ventricular strain
Sr-Sav (A4C)	Atrio Ventricular strain rate during systole measured in A4C
Sr-Eav (A4C)	Atrio Ventricular strain rate during early diastole measured in A4C
Sr-Aav (A4C)	Atrio Ventricular strain rate during late diastole measured in A4C
Sr-Sav (A2C)	Atrio Ventricular strain rate during systole measured in A2C

Sr-Eav(A2C)	Atrio Ventricular strain rate during early diastole measured in A2C
Sr-Aav (A2C)	Atrio Ventricular strain rate during late diastole measured in A2C
Sr-Sav	Atrio Ventricular strain rate during systole
Sr-Eav	Atrio Ventricular strain rate during early diastole
Sr-Aav	Atrio Ventricular strain rate during late diastole
LVVr-e (A4C)	Left Ventricular volume rate during early diastole measured in A4C
LVVr-a (A4C)	Left Ventricular volume rate during late diastole measured in A4C
LVVr-s (A4C)	Left Ventricular volumerate during systole measured in A4C
LVVr-e (A2C)	Left Ventricular volume rate during early diastole measured in A2C
LVVr-a (A2C)	Left Ventricular volume rate during late diastole measured in A2C
LVVr-s (A2C)	Left Ventricular volumerate during systole measured in A2C
LVVr-e	Left Ventricular volume rate during early diastole
LVVr-a	Left Ventricular volume rate during late diastole
LVVr-s	Left Ventricular volumerate during systole
LAVr-e (A4C)	Left Atrial volume rate during early diastole measured in A4C
LAVr-a (A4C)	Left Atrial volume rate during late diastole measured in A4C
LAVr-s (A4C)	Left Atrial volumerate during systole measured in A4C
LAVr-e (A2C)	Left Atrial volume rate during early diastole measured in A2C
LAVr-a (A2C)	Left Atrial volume rate during late diastole measured in A2C
LAVr-s (A2C)	Left Atrial volumerate during systole measured in A2C
LAVr-e	Left Atrial volume rate during early diastole
LAVr-a	Left Atrial volume rate during late diastole
LAVr-s	Left Atrial volumerate during systole
TLVd	Total Left heart volume end-diastolic
TLVs	Total Left heart volume end-systolic
TLVd (A4C)	Total Left heart volume end-diastolic measured in A4C
TLVs (A4C)	Total Left heart volume end-systolic measured in A4C
TLVd (A2C)	Total Left heart volume end-diastolic measured in A2C
TLVs (A2C)	Total Left heart volume end-systolic measured in A2C
Ar	Pulmonary vein Atrial reversal flow
Ardur	Pulmonary vein Atrial reversal flow duration
D	Pulmonary vein diastolic flow velocity
S	Pulmonary vein systolic flow velocity

S/D ratio	Ratio of Pulmonary vein systolic- and diastolic flow Vel.
RV GLS	Right Ventricular Global Longitudinal Strain (mean)
RV GLS (A4C)	Right Ventricular Global Longitudinal Strain measured in A4C
RV GLS (A2C)	Right Ventricular Global Longitudinal Strain measured in A2C
RV GLS (A3C)	Right Ventricular Global Longitudinal Strain measured in A3C
LA GLS	Left Atrial Global Longitudinal Strain (mean)
LA GLS (A4C)	Left Atrial Global Longitudinal Strain measured in A4C
LA GLS (A2C)	Left Atrial Global Longitudinal Strain measured in A2C
LA GLS (A3C)	Left Atrial Global Longitudinal Strain measured in A3C
RA GLS	Right Atrial Global Longitudinal Strain (mean)
RA GLS (A4C)	Right Atrial Global Longitudinal Strain measured in A4C
RA GLS (A2C)	Right Atrial Global Longitudinal Strain measured in A2C
RA GLS (A3C)	Right Atrial Global Longitudinal Strain measured in A3C
PV Vmax	Pulmonary Valve maximum Velocity
PV Vmean	Pulmonary Valve mean Velocity
PV Pmax	Pulmonary Valve maximum Pressure gradient
PV Pmean	Pulmonary Valve mean Pressure gradient
PV VTI	Pulmonary Valve Velocity Time Integral
MV-Adur - Ardur	Difference between late diastolic transmitral flow and pulmonary vein atrial reversal flow duration
Mean % WT A2C	Mean percentual Wall Thickening of 6 segments in A2C
AA-%WT	Percentile wall thickening of apical anterior segment
AA-WTd	Wall thickness of apical anterior segment in diastole
AA-WTs	Wall thickness of apical anterior segment in systole
AI-%WT	Percentile wall thickening of apical inferior segment
AI-WTd	Wall thickness of apical inferior segment in diastole
AI-WTs	Wall thickness of apical inferior segment in systole
BA-%WT	Percentile wall thickening of basal anterior segment
BA-WTd	Wall thickness of basal anterior segment in diastole
BA-WTs	Wall thickness of basal anterior segment in systole
BI-%WT	Percentile wall thickening of basal interior segment
BI-WTd	Wall thickness of basal interior segment in diastole
BI-WTs	Wall thickness of basal interior segment in systole
MA-%WT	Percentile wall thickening of mid anterior segment
MA-WTd	Wall thickness of mid anterior segment in diastole
MA-WTs	Wall thickness of mid anterior segment in systole
MI-%WT	Percentile wall thickening of mid inferior segment
MI-WTd	Wall thickness of mid inferior segment in diastole

MI-WTs	Wall thickness of mid inferior segment in systole
Pericardial effusion	Pericardial effusion
Mean % WT A3C	Mean percentual Wall Thickening of 6 segments in A3C
AAS-%WT	Percentile wall thickening of apical antero-septal segment
AAS-WTd	Wall thickness of apical antero-septal segment in diastole
AAS-WTs	Wall thickness of apical antero-septal segment in systole
AP-%WT	Percentile wall thickening of apical posterior segment
AP-WTd	Wall thickness of apical posterior segment in diastole
AP-WTs	Wall thickness of apical posterior segment in systole
BAS-%WT	Percentile wall thickening of basal antero-septal segment
BAS-WTd	Wall thickness of basal antero-septal segment in diastole
BAS-WTs	Wall thickness of basal antero-septal segment in systole
BP-%WT	Percentile wall thickening of basal posterior segment
BP-WTd	Wall thickness of basal posterior segment in diastole
BP-WTs	Wall thickness of basal posterior segment in systole
MAS-%WT	Percentile wall thickening of mid antero-septal segment
MAS-WTd	Wall thickness of mid antero-septal segment in diastole
MAS-WTs	Wall thickness of mid antero-septal segment in systole
MP-%WT	Percentile wall thickening of mid posterior segment
MP-WTd	Wall thickness of mid posterior segment in diastole
MP-WTs	Wall thickness of mid posterior segment in systole
Mean % WT A4C	Mean percentual Wall Thickening of 6 segments in A4C
AL-%WT	Percentile wall thickening of apical lateral segment
AL-WTd	Wall thickness of apical lateral segment in diastole
AL-WTs	Wall thickness of apical lateral segment in systole
AS-%WT	Percentile wall thickening of apical septal segment
AS-WTd	Wall thickness of apical septal segment in diastole
AS-WTs	Wall thickness of apical septal segment in systole
BL-%WT	Percentile wall thickening of basal lateral segment
BL-WTd	Wall thickness of basal lateral segment in diastole
BL-WTs	Wall thickness of basal lateral segment in systole
BS-%WT	Percentile wall thickening of basal septal segment
BS-WTd	Wall thickness of basal septal segment in diastole
BS-WTs	Wall thickness of basal septal segment in systole
ML-%WT	Percentile wall thickening of mid lateral segment
ML-WTd	Wall thickness of mid lateral segment in diastole
ML-WTs	Wall thickness of mid lateral segment in systole

MS-%WT	Percentile wall thickening of mid septal segment
MS-WTd	Wall thickness of mid septal segment in diastole
MS-WTs	Wall thickness of mid septal segment in systole
Global % WT	Global percentual Wall Thickening of the Left Ventricle
AoV Vmean	Aortic Valve mean Velocity
AoV Pmean	Aortic Valve mean Pressure gradient
AoV VTI	Aortic Valve Velocity Time Integral
AVA Vmax	Aortic Valve Area (measured by max Vel.)
AVA VTI	Aortic valve Area (measured by Velocity Time Integral)
AVAi Vmax	Aortic Valve Area (measured by maximum Velocity) indexed to Body Surface Area
AVAi VTI	Aortic valve Area (measured by Velocity Time Integral) indexed to Body Surface Area
ivrt	IsoVolumic Relaxation Time
LV GLS (A4C)	Left Ventricular Global Longitudinal Strain measured in A4C
LV GLS (A2C)	Left Ventricular Global Longitudinal Strain measured in A2C
LV GLS (A3C)	Left Ventricular Global Longitudinal Strain measured in A3C
LV GLS	Left Ventricular Global Longitudinal Strain (mean)

[095] Referring again to Figure 4A, in one embodiment, the echo workflow engine 12 maintains measurement confidence scores corresponding to the measured left/right ventricles, left/right atriums, LVOTs, pericardiums and measured velocities. The echo workflow engine 12 filters out echo images having measurement confidence scores that fail to meet a threshold, i.e., low measurement confidence scores (block 442).

[096] Measurement of cardiac features continues with calculating longitudinal strain graphs using the annotations generated by the CNNs (block 444). Thereafter, a fifth CNN detects pericardial effusion 446.

[097] Figure 11 is a diagram graphically illustrating measurements of global longitudinal strain that were automatically generated from the annotations of cardiac chambers in 2D images.

[098] Referring again to Figure 4A, for all remaining non-filtered out data, the echo workflow engine 12 selects as best measurement data the measurements associated with cardiac chambers with the largest volumes, and saves with the best measurement data, image location, classification, annotation and other measurement data associated with the best measurements (block 447).

[099] Figure 12A is a diagram graphically illustrating an example set of best measurement data 1200 based on largest volume cardiac chambers and the saving of the best measurement data 1200 to a repository, such as database 16 of Figure 1.

[0100] Referring again to Figure 4A, the echo workflow engine 12 then generates conclusions by inputting the best measurement data 1200 to a set of rules based on international measurement guidelines to generate conclusions for medical decisions support (block 448).

[0101] Figure 12B is a diagram graphically illustrating the input of normal LV EF measurements into a set of rules to determine a conclusion that the patient has normal diastolic function, diastolic dysfunction, or indeterminate.

[0102] Referring again to Figure 4A, after the conclusions are generated, a report is generated and output (Fig. 3 block 314), which may comprise blocks 450-456. Report generation may begin by the echo workflow engine 12 outputting the best measurement data 1200 to a JSON file for flexibility of export to other applications (block 450).

[0103] Figure 13 is a diagram graphically illustrating the output of classification, annotation and measurement data to an example JSON file.

[0104] Referring again to Figure 4A, a lightweight browser-based user interface (UI) displayed showing a report that visualizes the best measurement data 1200 from the JSON file and that is editable by a user (e.g., doctor/technician) for human verification (block 452). As is well known, a lightweight web browser is a web browser that is optimize to reduce consumption of system resources, particularly to minimize memory footprint, and by sacrificing some of the features of a mainstream web browser. In one embodiment, any edits made to the data are stored in the database 16 and displayed in the UI.

[0105] In order to make clinically relevant suggestion to the user, measurements associated with the best measurement data 1200 are automatically compared to current International guideline values and any out of range values are highlighted for the user (block 454).

[0106] Figure 14 is a diagram illustrating a portion of an example report showing highlighting values that are outside the range of International guidelines.

[0107] Referring again to Figure 4A, the user is provided with an option of generating a printable report showing an automated summary of Main Findings (i.e., a conclusion reached after examination) and underlining measurements of the patient's health (block 456).

[0108] Figure 15 is a diagram illustrating a portion of an example report of Main Findings that may be printed and/or displayed by the user.

[0109] In one embodiment, the automated workflow of the echo workflow engine 12 may end at block 456. However, in further aspects of the disclosed embodiments, the process may continue with advance functions, as described below.

[0110] Figure 4B is a flow diagram illustrating advanced functions of the echo workflow engine. According to this embodiment, the echo workflow engine 12, takes as inputs values of specific measurements that were automatically derived using machine learning (see block 310), and analyzes the specific measurements to determine disease diagnosis/prediction/prognosis versus both disease and matched controls and normal patient controls (block 460). In one embodiment, the echo workflow engine 12 may use the disease predictions to perform diagnosis of any combination of: cardiac amyloidosis, hypertrophic cardiomyopathy, restrictive pericarditis, cardiotoxity, early diastolic dysfunction and Doppler free diastolic dysfunction assessment (block 462). A prognosis in the form of an automated score may then be generated to predict mortality and hospitalizations in the future (block 464).

[0111] Echocardiography is key for the diagnosis of heart failure with preserved ejection fraction (HFpEF). However, existing guidelines are mixed in their

recommendations for echocardiogram criteria and none of the available guidelines have been validated against gold-standard invasive hemodynamic measurements in HFpEF.

[0112] According to one embodiment, the echo workflow engine 12 further generates a diagnostic score for understanding predictions (block 466). Using machine learning, the echo workflow engine 12 validates the diagnostic score against invasively measured pulmonary capillary wedge pressure (PCWP), and determines the prognostic utility of the score in a large HFpEF cohort.

[0113] In one embodiment, the echo workflow engine 12, takes as the inputs values of specific measurements that were automatically derived using machine learning workflow, and analyzes the input values using an HFpEF algorithm to compute the HFpEF diagnostic score.

[0114] Recognizing that hypertensive heart disease is the most common precursor to HFpEF and has overlapping echocardiogram characteristics with HFpEF, echocardiogram features of 233 patients with HFpEF (LVEF ≥50%) was compared to 273 hypertensive controls with normal ejection fraction but no heart failure. An agnostic model was developed using penalized logistic regression model and Classification and Regression Tree (CART) analysis. The association of the derived echocardiogram score with invasively measured PCWP was investigated in a separate cohort of 96 patients. The association of the score with the combined clinical outcomes of cardiovascular mortality of HF hospitalization was investigated in 653 patients with HFpEF from the Americas echocardiogram sub study of the TOPCAT trial.

[0115] According to one embodiment, left ventricular ejection fraction (LVEF<60%), peak TR velocity (>2.3 m/s), relative wall thickness (RWT>0.39 mm),

interventricular septal thickness (>12.2 mm) and E wave (>1 m/s) are selected as the most parsimonious combination of variables to identify HFpEF from hypertensive controls. A weighted score (range 0-9) based on these 5 echocardiogram variables had a combined area under the curve of 0.9 for identifying HFpEF from hypertensive controls.

[0116] Figures 16A and 16B are diagrams showing a graph A plotting PCWP and HFpEF scores, and a graph B plotting CV mortality or hospitalization for HF, respectively. Graph A shows that in the independent cohort, the HFpEF score was significantly associated with PCWP in patients with HFpEF (R^2= 0.22, P= 0.034). Graph B shows that a one-point increase was associated with a 12% increase in risk (hazard ratio [HR] 1.12; 95%CI 1.02-1.23, P= 0.015) for the combined outcome after multivariable correction.

[0117] According to the disclosed embodiments, the echocardiographic score can distinguish HFpEF from hypertensive controls and is associated with objective measurements of severity and outcomes in HFpEF.

[0118] A method and system for implementing a software-based automatic clinical workflow using machine learning that recognizes and analyzes both 2D and Doppler modality Echocardiographic images for automated measurements and the diagnosis, prediction and prognosis of heart disease, and which can be deployed in workstation or mobile-based ultrasound point-of-care systems has been disclosed. The present invention has been described in accordance with the embodiments shown, and there could be variations to the embodiments, and any variations would be within the spirit and scope of the present invention. For example, the exemplary embodiment can be implemented using hardware, software, a computer readable medium containing program

instructions, or a combination thereof. Software written according to the present invention is to be either stored in some form of computer-readable medium such as a memory, a hard disk, or a optical-ROM and is to be executed by a processor. Accordingly, many modifications may be made by one of ordinary skill in the art without departing from the spirit and scope of the appended claims.