



Current Challenges and Recent Updates in Artificial Intelligence and Echocardiography

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Abstract

Purpose of the Review This review discusses the recent advances in automated echocardiography using artificial intelligence and machine learning (ML) techniques. Specific emphasis is placed on the potential for machine learning-based methods to improve accuracy and reproducibility of echocardiographic assessment as well as early cardiovascular disease detection and personalized risk assessment.

Recent Findings Echocardiography remains the first line imaging modality for evaluation of many cardiovascular diseases. The last few years have witnessed a rapid expansion and growth of ML-based automated analysis and interpretation of echocardiography. These ML algorithms have shown great promise for improving data reliability, accuracy, and reproducibility of echocardiographic results. We anticipate that the application of ML algorithms will further expand the indications of echocardiography to include diseases that are traditionally only diagnosed with the more advanced imaging modalities such as cardiac magnetic resonance imaging. The ability to leverage ML's robust capability for processing large and complex datasets will result in improved diagnosis of cardiovascular disease at subclinical stages, enable prediction of disease progression and prognosis, and facilitate the characterization of disease phenotypes to allow more targeted therapies.

Summary The paradigm is rapidly shifting in the field of echocardiography with the emergence of ML algorithms that are promising to improve data reliability, accuracy, reproducibility, and workflow. Current and emerging evidence suggests that these systems will undoubtedly revolutionize the diagnostic utility of echocardiography both at subclinical and clinical stages and are expected to improve personalized cardiovascular risk assessment. However, widespread implementation of this novel technology will need to overcome challenging regulatory body approval processes. At present, the technology shows promise in improving diagnostic pathways, but evidence of clinical utility is lacking. Large trials will be required to provide robust evidence of ML's prognostic value in echocardiographic assessment before its implementation in routine clinical practice.

Keywords Echocardiography · Artificial intelligence · Machine learning

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Introduction

Echocardiography remains the most indispensable cardiac imaging modality for the diagnosis, prognostication, and follow-up of various cardiovascular diseases (CVD). It allows for a rapid and comprehensive noninvasive assessment and accurate diagnosis of myocardial and structural heart diseases, provides quantifiable measurements of left and right ventricular function and pulmonary pressures, and facilitates the assessment of valvular function and intracardiac shunts [1]. Echocardiography is recommended as the first line cardiac imaging modality due to its widespread availability, low costs, versatility, acceptability, and safety profile. The demand for echocardiography is predicted to rise over the next few years due to the projected increase in the prevalence of CVD [2].

Despite its prolific utilization in clinical practice, echocardiography has some well-recognized limitations that impact its usefulness. For example, an echocardiogram generates a large volume of data that must be subjectively interpreted, resulting in significant inter-observer and intra-observer variability. Large and complex datasets generated during an echocardiogram are difficult to interpret, and a significant portion of this data remains underutilized [3]. Echocardiography is further limited by operator-dependent data acquisition, variability in instrumentation, poor image quality, and variability in data analysis and interpretation which often require expert skills.

Artificial intelligence (AI) has emerged over the last few decades as a novel technique with great potential for enhancing the diagnostic utility of cardiac imaging. AI involves the use of machine or computer systems to perform complex tasks with good and reproducible accuracy [4, 5•]. This technology has existed since the 1950s, but its application to medical diagnostics, particularly in cardiology, is relatively new and continues to evolve. AI is expected to be incorporated into all forms of cardiac imaging including echocardiography, cardiac magnetic resonance (CMR), cardiac-computed tomography angiography, single-photon emission-computed tomography, and positron emission tomography [6–10]. AI will undoubtedly have an impact on medical diagnostics, clinical decision-making, and treatment choices [11].

In echocardiography, AI is expected to improve the workflow by fully automating echocardiographic analysis and reducing the time required to provide clinically meaningful diagnostic information to the treating clinicians. Existing studies have now demonstrated that ML-based analysis of echocardiogram significantly reduce inter-observer variability and improve reproducibility [10, 12]. These algorithms have ability to analyse complex datasets and identify subtle cardiac structural and functional patterns that could easily be missed by trained observers [13, 14]. Current data suggest that the incorporation of ML algorithms into routine echocardiography may allow clinicians to expand indications for echocardiography to include a full assessment of conditions that are traditionally

diagnosed with the more advanced imaging modalities such as CMR [15•]. Furthermore, ML techniques combined with both clinical and imaging data variables will further enhance clinical decision-making by allowing for personalized cardiac risk assessment for individual patients [16]. Perhaps the greatest benefits of ML-based echocardiographic analysis could be the ability to detect CVD at subclinical stages, predict progression and prognosis of CVD, and achieve the goal of personalized medicine through characterization of disease phenotypes and subsequent targeted therapies.

This review summarizes the recent discoveries and updates in the field of ML-assisted automated echocardiography. Recent updates in the use of ML-based models in the identification of echocardiographic views, image segmentation, and image interpretation, as well as quantification of cardiac structure and function are discussed. We conclude the review by highlighting specific areas of ML-based echocardiography with the greatest potential to revolutionize modern echocardiography, such as early detection of CVD at subclinical stages, prognostication of CVD, and disease phenotyping.

The Basic Concepts of Artificial Intelligence

AI and ML are often used interchangeable although strictly speaking, ML techniques can be best described as methods for achieving AI [4]. For both AI and ML, statistical modelling and mathematical algorithms are used to seek, quantify, and interpret relationships between datasets [4]. As many reviews have previously described in great detail the basics of AI and ML and associated terminologies [4, 7, 8, 17•], our focus here is on the recent developments in the field of echocardiography and ML.

It is important, however, to appreciate the differences between the two types of ML that are commonly used to train AI models, namely “supervised learning” and “unsupervised learning”. An understanding of these two types of ML is important for the appreciation of recent advances made in the field of automated echocardiography.

Supervised ML is used to teach an AI system to rapidly, accurately, and efficiently analyze large quantities of data using computing and statistical algorithms to achieve accurate and reproducible classification of data [18]. This learning technique is commonly used in medical diagnostics, such as in the recognition of echocardiographic views and detection of cardiac abnormalities on echocardiography [5•]. The key to supervised learning is that it requires the input of pre-labelled data to train a model to enhance classification and regression of further data [19].

On the contrary, unsupervised ML focuses on discovering patterns and associations between variables and uses unlabelled datasets [4]. Unlike supervised ML, unsupervised learning does not attempt to fit data to an outcome; rather, it

identifies consistent patterns within datasets and lends itself to data exploration and generation of new hypotheses [4, 20]. As such, unsupervised ML promises to play a significant role in the unmet areas of cardiovascular imaging and practice. As an example, using an unsupervised, hierarchical cluster analysis technique, Lancaster et al. have previously demonstrated that their clustering algorithms improved the prediction of event-free survival over conventional classification for all-cause mortality and cardiac mortality in patients being evaluated for diastolic dysfunction [21]. Limited evidence also suggests that unsupervised ML techniques could identify specific characteristics and phenotypes of heart failure with preserved ejection fraction that are not visible to a human observer [22].

For both types of learning, the performance of ML programs improves as the dataset increases in size [23]. Because supervised and unsupervised learning techniques have distinctive roles, the learning technique that is utilized to train an AI model should carefully consider the intended use of the model.

Deep learning (DL) is a subset of AI inspired by the workings of the human brain, commonly referred to as an artificial neural network (ANN). The main advantage of DL is its iterative ability to continue learning and thereby improving its processing speed and diagnostic accuracy over time without explicit guidance [24–26]. There are 3 types of nodes in an ANN: input nodes, hidden nodes, and output nodes. The hidden nodes are analogous to the interneurons and perform the processing of information [26]. There can be any number of interconnected layers within the network with each layer containing any number of nodes [24]. Each layer receives inputs from previous layers and sends outputs to subsequent layers until the output layer is reached [26].

A convolutional neural network (CNN) is a subtype of ANN that mimics the visual cortex. Its main function is to process two-dimensional (2D) image-based data using multiple layers [24, 25]. Typically, a CNN is structured so that the lowest layers recognize the simplest features of the image such as the edges, with subsequent layers recognizing combinations of simple features. As such, each layer provides increasing levels of abstraction while the top layer provides the output [4, 5, 27].

DL methods play significant roles in echocardiography such as identification of echocardiographic views, and recognition of useful associations between images and pathologies [5, 9, 27]. DL has already proven itself to be of value in the fields of radiology (detecting boundaries of organs in computed tomography and magnetic resonance imaging), pathology (alerting suspicious areas of tissue biopsies), and dermatology (interpreting skin lesions as benign or malignant) [28–30]. These qualities readily translate to echocardiography and are discussed in the following sections and summarized in Table 1.

Artificial Intelligence in Echocardiography

Image Acquisition and Recognition of Views

The accuracy of transthoracic echocardiography (TTE) relies upon accurate image acquisition, traditionally achieved with the standard windows, beginning with the parasternal views (long axis and short axis) followed by apical and subcostal views. These result in the acquisition of approximately 70 unlabelled videos collected from non-consecutively acquired views [5]. The conclusion or diagnosis is achieved by integrating these acquisitions and by approximating three-dimensional (3D) objects from 2D cross-sectional images. As a result, the first step to interpretation of echocardiography is the ability to recognize and appreciate the limitations of each of the echocardiographic views [3]. Echocardiography can be limited by variability occurring during image acquisition, challenging boundary detection, as well as variability occurring during image interpretation [31]. Indeed, variability in image quality and interpretation are well-recognized limitations in echocardiography, resulting in poor reproducibility and significant controversies [31, 32].

Recent advances in state-of-the-art computer vision software and ML techniques have potential for reducing this variability and improve accuracy. Several studies have now demonstrated that using novel ML-based approaches can accurately and efficiently distinguish echocardiographic views. Khamis et al. used a multi-stage classification algorithm that employed spatio-temporal feature extraction (cuboid detector) and supervised dictionary learning (LC-KSVD) approaches to identify apical four, two, and three-chamber views with an accuracy of approximately 95% [33]. A CNN model tested by Zhang et al. had an accuracy of 84% in distinguishing between parasternal long axis, parasternal short axis, apical 2-chamber, apical 3-chamber, and apical 4-chamber views [5]. On a larger scale of images, Madani et al.'s CNN was able to classify 15 major views (12 from B-mode and 3 from pulsed-wave Doppler, continuous-wave Doppler and M-mode recordings). Using cluster analysis, this method achieved an accuracy of 97.8% on videos from patients who had a variety of pathologies, including normal variants and suboptimal views [34]. On still images, the model performed better than board-certified echocardiographers with an accuracy of 91.7% compared with 79.4%, respectively [34]. The study by Madani and colleagues further demonstrated the potential mechanisms by which the CNN is able to classify echocardiographic views [34]. By performing exclusion experiments, the authors showed that the CNN perhaps works in a similar fashion to an expert echocardiographer when classifying echocardiographic views (Fig. 1).

These studies demonstrate the ability of trained AI-based models to identify standard echocardiographic views, a first step towards echocardiographic image analysis. Importantly,

Table 1 Selected examples demonstrating application of AI in echocardiography

Author [Ref]	Aim of study	N	Mode of echocardiography	Method of AI	Results
Sengupta et al. [12]	Differentiate restrictive cardiomyopathy from constrictive pericarditis	50 (RCM), 44 (CP)	Speckle tracking Echocardiography (+ 2D echocardiography)	Associative memory classifier	AUC 89.2% (96.2% when combined with 2D echo)
Zhang et al. [5•]	Diagnosis of hypertrophic cardiomyopathy, cardiac amyloidosis, or pulmonary arterial hypertension	260 (HCM), 81 (amyloid), 104 (PAH)	2D echocardiography	CNN	AUC 0.93 (HCM) 0.87 (amyloid) 0.85 (PAH)
Narula et al. [10]	Differentiate pathologic from physiologic LV hypertrophy in athletes	77 (ATH), 62 (HCM)	2D echocardiography	Support vector machines, random forests, ANN's	Superior to early-to-late diastolic transmitral velocity ratio ($p < 0.01$, average early diastolic tissue velocity (e') ($p < 0.01$), strain ($p = 0.04$))
Mansor et al. [48]	Assessment of wall motion abnormalities	44	Stress echocardiography	Hidden Markov model	84% vs individual rest (73%) and stress (68%) sequences
Omar et al. [49]	Wall motion abnormalities	–	Dobutamine stress echocardiography	Random forest, support vector machines, CNN	Random forest 72.1% SVP 70.5% CNN 75%
Raghavendra et al. [45]	Obstructive CAD vs normal	93	2D echocardiography	DD-DTDWT	Accuracy 96.05%, sensitivity 96.12%, specificity 96.0%

AI, Artificial intelligence; 2D, 2-dimensional; RCM, restrictive cardiomyopathy; CP, constrictive pericarditis; AUC, area under the curve; CNN, convolutional neural network; HCM, hypertrophic cardiomyopathy; Amyloid, cardiac amyloidosis; PAH, pulmonary arterial hypertension; ANN, artificial neural network; LV, left ventricle; SVM, support vector machine; DD-DTDWT, double density-dual tree discrete wavelet transform; CAD, coronary artery disease002E

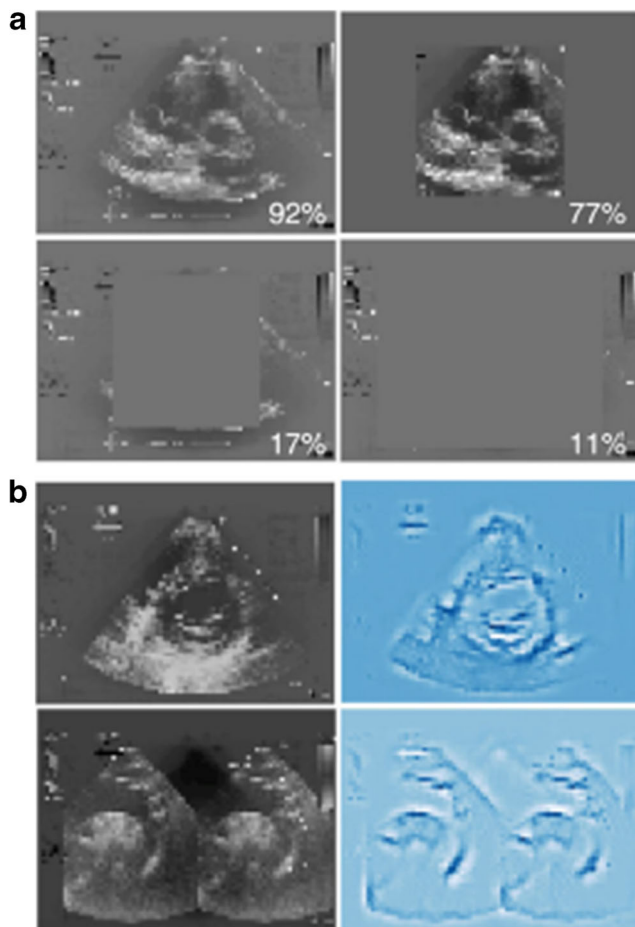


Fig. 1 Potential mechanisms of the inner workings of convoluted neural networks (CNNs). In the study performed by Madani et al., the authors sought to clarify the mechanisms by which a neural network classifies an echocardiographic view by performing occlusion experiments on test images within their CNN. **a** (short axis basal image) Stated accuracy of 92% falls significantly when the most clinically relevant structures (heart chambers, valves) are occluded, suggesting that the CNN works in a similar fashion to an expert echocardiographer when classifying views. **b** (top; suprasternal aorta/aortic arch, bottom; short axis mid/mitral input) Adds further weight to this theory. By illustrating saliency mapping, the authors demonstrated that the most important input pixels center around the same clinically relevant areas a human expert would use to classify the correct view. Reproduced from [34]

ML algorithms are able to recognize these views in less than a minute (21 ms in the case of Madani et al's model), thereby demonstrating the potential for ML to improve speed and efficiency of echocardiographic workflow. Further work is still required before these innovations are incorporated into routine clinical practice. As demonstrated by Madani and colleagues, the accuracy of most ML algorithms used for identification of echocardiographic views is highest for views that are most highly represented in the training data, and lowest for views which are closely related, e.g., apical three-chamber vs apical two-chamber views and apical four-chamber vs apical five-chamber views [34]. Furthermore, real-world data are still needed to demonstrate that the incorporation of these ML-

based view recognition algorithms into modern echocardiography translate into cost-efficient and effective strategies.

Image Analysis and Interpretation

Assessment of Left Ventricular Function

The interpretation of acquired echocardiography images requires expertise and can be challenging to a less experienced reader. The assessment of left ventricular function (both visually and quantitatively) is the most commonly performed measurement in echocardiography and has significant prognostic value [1, 32]. The assessment of left ventricular ejection function (LVEF) is subject to significant inter-observer variability and poor reproducibility [33].

There is good evidence that ML can improve the assessment of left ventricular function and reduce this variability. Knackstedt et al. demonstrated that LVEF and longitudinal strain could rapidly and reproducibly be analysed in 8 s using a ML algorithm, and this was not subject to the variability encountered when visually assessing or manually tracking [35]. Several other studies have also shown that automated software in 3D TTE can reproducibly interpret end-diastolic volume, end-systolic volume, and LVEF. Levy et al. studied 54 patients who had comprehensive 3D TTE and CMR performed on the same day and found significant correlations between CMR and ML-based 3D TTE assessment of end-diastolic volume ($r = 0.93$), end-systolic volume ($r = 0.93$), and LVEF ($r = 0.91$) [36]. Tsang et al.'s study calculated automated measurements of LVEF, left ventricular end-systolic volume, and left atrial volumes with ML-based methods and demonstrated strong agreement with CMR-derived values ($r = 0.84$ to 0.95) [37]. A similar technique for left chamber quantification in 88 patients with atrial fibrillation using single beat full-volume 3D TTE data correlated well with manual tracing while, taking significantly less time (5 min) than the manual tracing method (27 min) [38].

These data demonstrate the potential of ML techniques to revolutionize the echocardiographic assessment of cardiac function and disease detection by rapidly providing accurate and reproducible measurements with good diagnostic accuracy [4]. Furthermore, because the manual tracing required to achieve quantitative assessment of ventricular function (recommended by guidelines) is often not feasible in routine clinical practice, this rapid and reproducible assessment by ML algorithms will be increasingly important with the increasing numbers of echocardiograms being performed worldwide, both in cardiology and emergency departments.

Assessment of Right Ventricular Function

Many pathologies can cause right ventricular (RV) dysfunction, including chronic left-sided heart failure, acute coronary

syndromes, pulmonary embolism, pulmonary arterial hypertension, and congenital heart diseases. Irrespective of the aetiology, patients with RV dysfunction experience excess morbidity and mortality [39]. Because of its complex anatomical features (crescent shaped) and retrosternal position, the assessment of RV with 2D echocardiography is challenging and is associated with many limitations such as foreshortening, geometrical assumptions, cumbersome acquisition, and long post-processing times [31]. As a result, although the RV carries invaluable prognostic information, it has traditionally received less attention in echocardiographic assessment.

Accurate and reproducible quantification of the RV size and function can be achieved with 3D echocardiography. However, the existing software programs used with 3D echocardiography are time-consuming and require specialized training in image acquisition and data analysis [40]. 3D echocardiography has therefore not been widely implemented in routine clinical assessment of the RV [40]. Could AI become the answer to optimal and reproducible echocardiographic evaluation of the RV? In an unselected cohort of 56 patients with a wide range of RV sizes and function who underwent 3D echocardiography and CMR imaging on the same day, Genovese et al. recently demonstrated that the RV size and function could be evaluated with ML-based methods with excellent reproducibility [16]. In this study, accurate and fully automated measurements of the RV size and function were possible in 32% of the patients while accurate measurements were obtained in the remaining patients with minimal boundary editing.

Although more studies are needed to demonstrate the reproducibility of ML-based methods for the assessment of RV, the study by Genovese and colleagues offer very promising results. With the rapid expansion of ML algorithms, it is anticipated that incorporation of ML-based techniques into 3D echocardiography could potentially become the standard assessment of the RV.

Valvular Function

Early diagnosis and treatment of primary valvular diseases such as primary mitral and tricuspid regurgitation are associated with improved outcomes [41]. However, current analysis of valvular diseases requires manual imputation of datasets or multiple echocardiographic measurements and is subject to inter-observer variability [42]. Limited data suggest that the assessment of valvular function and identification of pathology may be amenable to ML techniques. Jeganathan and colleagues have previously shown that automated ML techniques improve reproducibility of mitral valve assessment using 3D transesophageal echocardiography [43]. ML algorithms could also be used to assess the severity of mitral regurgitation (MR) with one study demonstrating that this can be achieved with a sensitivity of 99.38% and specificity of 99.63% for differentiating between normal, moderate, and severe MR [42].

Emerging data indicate that aortic stenosis can be predicted from other echocardiographic data without the need for any left ventricular outflow tract measurements (gradients, velocity, and diameter) [44]. This would have great potential for improving efficiency and reducing study duration and cost. However, the current data for using ML-based algorithms for valvular assessment remain limited, and more studies are needed. We are yet to see quality studies demonstrating the utility of ML-assisted automated analysis and quantification of tricuspid and pulmonic valves as well as mitral stenosis. Nonetheless, the smaller number of existing studies suggests that ML-assisted valvular assessment will become a reality in the next few years.

Diagnostic Utility

Emerging data suggest that ML-based echocardiographic models may improve the diagnosis of cardiac diseases that are traditionally challenging to diagnose with echocardiography, and that often require more advanced imaging modalities, such as CMR. Narula et al. combined the techniques of support vector machines, random forests, and ANNs to accurately differentiate pathologic from physiologic cardiomyopathy in athletes [10]. This ensemble model displayed higher sensitivity and specificity when compared with the standard quantitative measurements of early-to-late diastolic transmitral velocity ratio ($p < 0.01$), average early diastolic tissue velocity (e') ($p < 0.01$), and strain ($p = 0.04$) [10]. Zhang et al. trained different CNNs to recognize the appearance of 3 chronic structural heart diseases: hypertrophic cardiomyopathy, cardiac amyloidosis, and pulmonary arterial hypertension with C statistics (area under the receiver operating characteristic curve, AUC) of 0.93, 0.87, and 0.85, respectively [5]. Finally, Raghavendra et al. deployed an unsupervised learning model (double density-dual tree discrete wavelet transform to detect 12 echocardiographic features to distinguish patients with obstructive coronary artery disease from those without disease with accuracy of 96.05%, sensitivity of 96.12%, and specificity of 96.00% [45].

Furthermore, ML-assisted strain imaging and speckle tracking echocardiography (STE) could potentially be used to differentiate between commonly mistaken conditions. Sengupta et al. found that an ML algorithm was able to differentiate between restrictive cardiomyopathy and constrictive pericarditis using 15 STE variables (AUC of 89.2%) [13]. This algorithmic approach, referred to as an associative memory classifier, achieved an AUC of 96.2% after the addition of 4 echocardiographic variables (e' , E/e' , septal, and posterior left ventricular wall thickness). Furthermore, the model was superior to commonly used echocardiographic variables such as early diastolic mitral annular longitudinal velocity and global longitudinal strain. The study demonstrated the ability of an ML algorithm to be taught and then recall key components of a complex echocardiographic evaluation, and has, as

the authors concluded, the “potential for standardizing and improving workflow in busy echocardiography laboratories” [12]. Further AI developments and improvements are expected over the next few years, and these will radically transform modern echocardiography.

Stress Echocardiography

Stress echocardiography is vulnerable to wide variations in sensitivity and specificity [46, 47]. ML techniques show promise in identifying and quantifying inducible wall motion abnormalities, thereby demonstrating an ability to overcome the limitations in accuracy. Mansor et al.’s automated model showed improved classification of wall motion abnormalities (84%) compared with individual rest (73%) and stress (68%) sequences [48]. Another study that compared random forests, support vector machines, and CNN on a 3D dobutamine stress echocardiography dataset demonstrated that these automated techniques could differentiate between normal and abnormal wall motions, and that this ability was slightly higher for deep learning approach [49].

3D Echocardiography

Despite the superior accuracy and reproducibility of 3D echocardiography compared with 2D echocardiography, widespread application of 3D echocardiography for quantitative assessment of left atrial and left ventricular volumes has not yet been implemented due to the increased time and expertise required to obtain these measurements [37]. As discussed above, current data indicate that the transition to 3D echocardiography may be hastened with incorporation of well-trained and validated ML algorithms [12, 50].

The Future of Artificial Intelligence in Echocardiography

Detection of CVD Disease at Subclinical Stage

CVD can progress at subclinical stages for many years before the onset of symptoms. Delayed diagnosis can lead to poor prognosis often related to irreversible pathophysiologic changes that occur over many years. With the increasing prevalence of obesity, hypertension, and metabolic diseases such as diabetes, there is a growing interest in the identification of disease at subclinical stages which may facilitate early interventions and improve outcomes. Many noninvasive techniques such as electrocardiograms and echocardiography, which are readily available in community settings, coupled with ML algorithms, could be used to achieve this goal [51].

LVEF has traditionally been used as a marker of LV dysfunction, with low LVEF being associated with poorer

outcomes [1]. However, LVEF is highly dependent on hemodynamic conditions and is less sensitive to minor changes occurring over time. Global longitudinal strain (GLS), a measure of myocardial deformation, is a novel and relatively newer marker of subclinical LV dysfunction and has useful prognostic value [52, 53]. The prognostic value of GLS is observed in patients with heart failure irrespective of the LVEF [53, 54]. GLS can be measured with tissue Doppler imaging or 2D stress echocardiography. However, GLS is not routinely measured in clinical practice as it requires appropriate training. Zhang et al. demonstrated that fully automated assessment of an entire echocardiogram including the evaluation of GLS is possible with ML algorithms [5•]. Once incorporated into routine echocardiography, ML-based models may improve the detection of CVD at subclinical stages by enhancing the detection of subtle changes that are not detectable or feasible with the current methods.

Furthermore, there is a highly anticipated expectation that ML technology will improve access to echocardiography in rural and less developed parts of the world. This would facilitate early detection of CVD and help to close the gap in disease outcomes between these regions and the more affluent areas. Zhang et al. postulated that AI could help detect early signs of heart disease in a cost-efficient manner by having non-experts use handheld imaging devices at point-of-care locations and subsequently uploading images to a cloud-based automated interpretation system that would allow comparison with prior studies [5•]. Such an approach would promote early detection of CVD and potentially reduce the morbidity and mortality associated with CVD [55].

Prognostication and Risk Prediction

In an era of sophisticated noninvasive cardiovascular imaging modalities, molecular profiling, and ML technologies, there is a growing interest in achieving personalized risk assessment and prognostication. LVEF is currently the most commonly used echocardiographic prognostic marker despite its limited prognostic value [52, 54]. A search for improved prognostic markers is an area where application of ML-based methods may play a substantial role in improving prognostic assessment. Samud et al. have previously demonstrated that ML-based echocardiography combined with electronic health records could significantly improve the prediction of adverse outcomes with an accuracy of 96% [56•]. Unsupervised ML techniques using clustering methods are also promising to improve the identification of at-risk patients and the prediction of cardiovascular outcomes. These techniques have been demonstrated to identify a cluster of echocardiographic phenotypes associated with an increased risk of adverse cardiovascular outcomes in patients with type 2 diabetes [57], diastolic dysfunction [21, 58], and heart failure [59]. Using guideline-recommended echocardiographic parameters for assessment of left ventricular diastolic

dysfunction, an unsupervised cluster analysis identified unique patterns that predicted outcomes better than conventional classifications recommended by the guidelines [60].

These results suggest that ML techniques may uncover as-yet unknown, but significant, echocardiographic measurements that have a real impact on clinical outcomes. Zhang et al. previously demonstrated that an ML algorithm could play a significant role in longitudinal monitoring for cardiotoxicity in cancer survivors [5]. Based on these preliminary findings, it is anticipated that ML-based techniques will improve the prognostic assessment of various cardiovascular diseases. The current and potential applications of ML algorithms in echocardiography are illustrated in Fig. 2.

Implications for Echocardiography Workforce

AI and ML algorithms are expected to radically change echocardiographic imaging practice. This has raised great concerns that “machines” may potentially replace echocardiographers in the future. This may not be the correct assumption at least based on current evidence. Instead, the echocardiographers will benefit from the support that will be offered by ML-assisted cardiac imaging. These technologies will significantly reduce the time that the imagers spend extracting and integrating the echocardiographic data and will therefore improve the workflow. The echocardiographers of the future will be expected to understand the basic principles of AI and possess abilities to integrate ML-based applications into routine echocardiography. Therefore, echocardiographers who embrace this innovative technology will stand to benefit rather than lose.

Challenges and Pitfalls

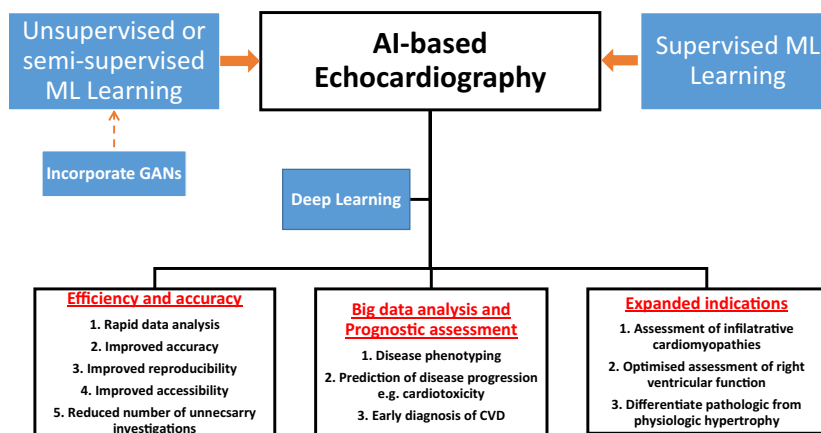
Despite the significant progress that has been made in ML-based echocardiography, there are still many challenges to overcome. First, our understanding of the inner workings of the

hidden networks of ML models, often involving thousands of interconnections, remains limited [61]. Second, the training of ML models is restricted by the availability of large datasets covering a broad range of patients and pathologies/normal variants. As demonstrated in previous studies, these large datasets are required for optimal training and validation of clinically useful ML algorithms [34]. In particular, labelling of diagnostic images, required for supervised ML, is challenging, time-consuming, and requires appropriate training and expertise. Generative adversarial networks are now being explored as potential strategies for addressing this limitation. A generative adversarial network consists of a generator which generates an image, and a discriminator that predicts whether an image is a real or generated image [17]. Generative adversarial networks were initially developed for use in unsupervised learning but can now be leveraged in semi-supervised ML to perform automated image analysis in data-limited settings [62].

A third challenge is the lack of data demonstrating clinical utility. Current studies investigating the use of ML in echocardiography have compared their results against expert readers rather than disease outcomes. For AI to be incorporated into clinical practice, it will need to prove its clinical utility beyond being diagnostically useful. Figure 3 demonstrates the stages in the development of a clinically useful AI model and highlights the limitations related to each stage. As shown in the figure, the current data demonstrate feasibility of ML-based echocardiography, with limited single-center studies suggesting potential diagnostic utility. However, there are currently no data to show that these ML-based models improve clinical outcomes. Therefore, studies evaluating the effects of ML applications on these outcomes will be required before the integration of ML into modern echocardiography practice. Linking electronic health records to existing imaging databases will perhaps be the first step towards achieving this goal, but this is yet to be fully accomplished [11, 63].

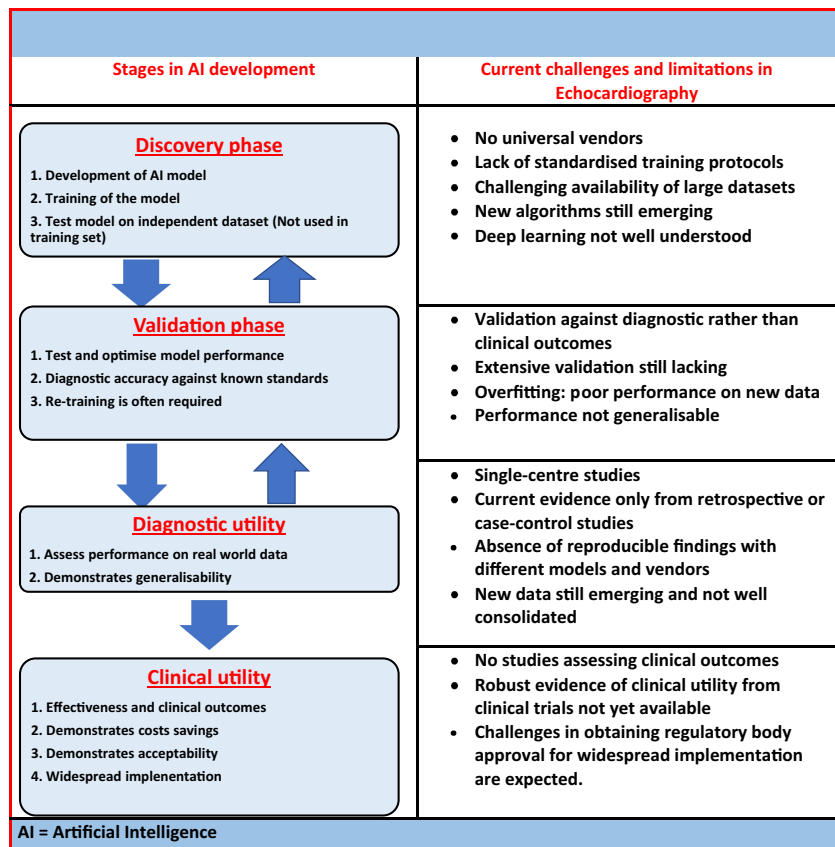
Finally, due to the potential legal liabilities and clinical governance issues, application of this technology will require

Fig. 2 Potential applications of AI-based echocardiography. AI = artificial intelligence; ML = machine learning; GANs = generative adversarial networks; CVD = cardiovascular disease



AI = artificial intelligence; ML = machine learning; GANs = generative adversarial networks; CVD = cardiovascular disease

Fig. 3 Process of developing a clinically meaningful AI model and associated challenges in echocardiography. AI = artificial intelligence



extensive validation prior to regulatory approval. The success of ML-based models in echocardiography will rest upon the ability of computer scientists, echocardiographers, and cardiologists to collaborate in order to address these limitations.

Conclusion

AI is promising to transform all forms of cardiac imaging, including echocardiography. Current and emerging data suggest that these ML algorithms are able to recognize echocardiographic views, automatically evaluate left and right ventricular function, and quantify chamber and valvular measurements. The main clinical benefits of ML algorithms in echocardiography will include reduction in time spent extracting and integrating echocardiographic data and improvement in reproducibility of echocardiographic assessments. This revolutionary approach will allow patients to obtain a more objective assessment in a timely manner. It is also expected that improvement in workflow and efficiency will reduce the costs of echocardiography imaging. Other potential benefits will include incorporation of ML into risk

prediction models and early detection of cardiovascular diseases at preclinical stages.

Although significant progress has been made over the last few years, we are currently still many steps behind the incorporation of ML technology into routine echocardiography. Clinical utility lags behind diagnostic utility as we are yet to demonstrate that ML-based diagnostic models improve clinical outcomes. Extensive validation and robust clinical benefits will need to be demonstrated before regulatory approval can be provided. Current evidence suggests we are still a long way from clinical application.

Nonetheless, the future of AI and echocardiography is bright, and with the rapidly expanding knowledge of ML algorithms, the application of ML-based echocardiography is within reach and is expected to radically transform modern echocardiography in the near future.

Compliance with Ethical Standards

Conflict of Interest All authors declare no conflict of interest.

Human and Animal Rights and Informed Consent This article does not contain any studies with human or animal subjects performed by any of the authors.

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