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Review Article

Artificial Intelligence in Echocardiography: Where Do We Stand?

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ABSTRACT

Artificial intelligence (AI) has been expanding exponentially in the field of health care. AI not only simplifies disease interpretation but also improves the efficiency of patient management. The novel machine learning algorithms, and deep learning models are expanding the boundaries in the arena of echocardiography. The automated assessment of the biventricular function, atrio-ventricular coupling, Integrating novel approaches like speckle tracking may aid in the identification, classification, diagnosis, and prognostication of cardiovascular abnormalities. Moreover, AI integration reduces the time of interpretation, inter as well as intra-observer variability and provides a rapid, non-invasive and accurate result. AI stands at the pinnacle of echocardiography. Therefore, the index article aims to review the existing and upcoming AI integration modalities in echocardiography with regard to the technique, advantages, limitations, and its clinical application.

Keywords: Artificial intelligence, Cardiovascular abnormalities, Deep learning, Echocardiography, Machine learning

INTRODUCTION

Artificial intelligence (AI) has ushered in a new era of echocardiography. Integration of AI datasets aids in unmatched efficiency and reproducibility in the arena of echocardiography, making an invaluable modality for meeting increased demand. The contribution of novel machine learning (ML) models, and deep learning (DL) algorithms are transformative, as these can improve and generate new prognostication modalities for various cardiac as well as cardiovascular abnormalities.

Echocardiography provides non-invasive, accurate, and immediate characterization of cardiac anatomy, evaluation of biventricular function, atrioventricular coupling, valvular function, delineation of the pulmonary vasculature, and congenital abnormalities.[1] Its availability all around, minimal price, and better safety profile made it a necessary tool for all clinicians, including cardiologists and perioperative cardiac anesthesiologists.[2] Transesophageal echocardiography not only confirms the diagnosis but also delineates the anatomy and guides surgical repair. AI integration further minimizes the time of acquisition, and automated border tracking enables accurate assessment of cardiac function in a time constraint perioperative period and, therefore, considered as a modern stethoscope in the armamentarium of cardiac anesthesiologists. AI integration can also provide additional information which the human eye fails to detect.

In echocardiography, the interpretation of cardiac function highly depends on the subjective knowledge and level of experience of the interpreter as compared to other imaging techniques

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such as nuclear imaging, computed tomography, and magnetic resonance imaging. This limitation can be overcome by AI technologies that offer produce automated, and more consistent interpretations of echocardiography.[3,4] Furthermore, AI has been used in educating and training novice doctors for image acquisition and interpretation.[5,6]

AI: THE INNOVATION

AI defines the application of machines to simulate the human brain and carry out multiple activities with limited participation or supervision.[7] ML is a subfield of AI which allows analysis of wide datasets through computing and various statistical algorithms. Furthermore, ML models can provide predictions and prognostication on the basis of unseen datasets.[8]

ML technique is categorized into three major groups, unsupervised, supervised, and reinforcement learning. Unsupervised learning mainly uses unlabeled datasets and focuses on devising new patterns and linkage among variables, whereas supervised learning "taught" machine to group the data by providing labeled data. Furthermore, the reinforcement learning model uses algorithms that are obtained through a trial and error method with only given dataset to optimize the result [Figure 1].

DL algorithm is a subcategory of ML model which consists of networks of nodes which simulate the human brain and neural networking, therefore, called artificial neural networks. Commonly, DL model constitutes convolutional neural networks (CNN) and recurrent neural networks. CNN can able to process two-dimensional (2D) image on the basis of multi-layered datasets, whereas recurrent neural networks are utilized for sequential datasets which, therefore, can be used for the interpretation of language and speech recognition.

AI INTEGRATED ECHOCARDIOGRAPHY: THE TIME IS NOW

Echocardiographic views acquisition and interpretation

AI algorithms in integration with commercially accessible software play a key role in acquisition and interpretation of echocardiographic views. These AI integrated models provide clear instructions for image acquisition, with proper probe manipulation, recognizing and warning about the image quality, thus facilitating training as well as self-improvement [Table 1]. In 2021, Narang *et al.*[5] expressed the use of DL model in training nurses for the acquisition of echocardiograms and these nurses have no prior exposure to echocardiography. Same year, Schneider *et al.*[6] trained 1st year medical students about the acquisition of diagnostic echocardiographic views using ML model; furthermore, this ML algorithm calculates left ventricle ejection fraction (LVEF) from the acquired datasets. Madani *et al.*[9] applied CNN for developing AI algorithm to classify 15 classical views on the basis of 267 labeled trials with a clinical variation. Their model can classify the images with 97.8% accuracy. More importantly, the interpretation is rapid with an average of 21 milliseconds per image. Zhang *et al.*[10] also trained and validated CNN models for multi-tasking in echocardiography that includes classification of 23 standard views.

ECHOCARDIOGRAPHIC IMAGE ANALYSIS AND INTERPRETATION

Left ventricular systolic function (LVSF)

LVSF is one of the primary echocardiographic derivative, which has significant prognostic value. Systolic and diastolic function is the two horizon of heart failure, the determination

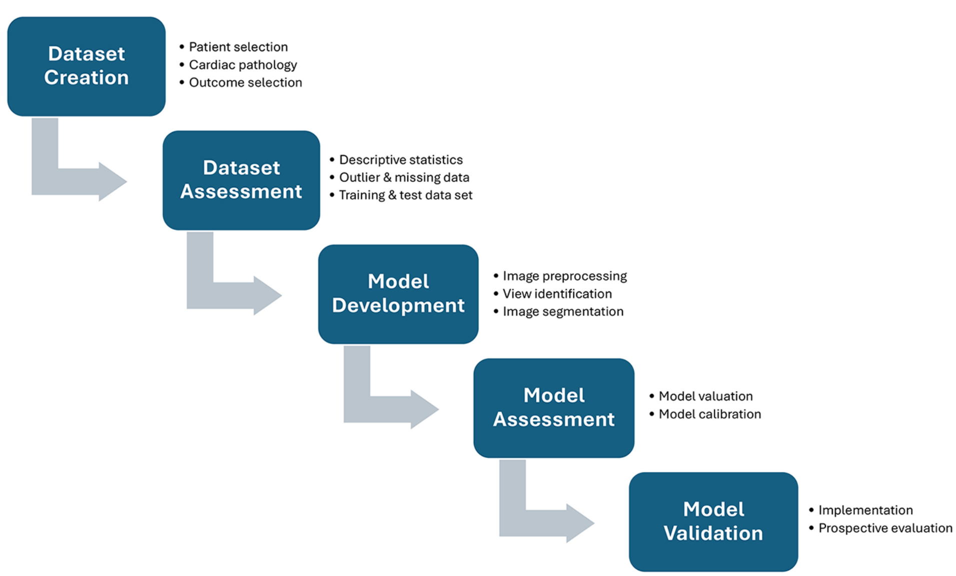

Figure 1: Deep learning workflow in automated image analysis.

of which comprises high inter- as well as intra-observer variability and poor reproducibility. The most commonly used modified Simpson's biplane method for calculation of LVEF required manual tracing of end-systolic and end-diastolic border of the LV in the orthogonal views such as four-chamber and two-chamber views. It is challenging at times as it depends on good quality images, time consuming for manual tracing and has interobserver variability.

Leclerc *et al*.[11] trained an encoder decoder-based CNN and DL model for segmentation and analysis of 500 echocardiography with four- and two-chamber views and able to measure end-systolic, end-diastolic volumes, and LVEF. Its reproducibility was superior with regard to inter-observer variability than conventional methods. Similarly, Ouyang *et al*.[12] developed another CNN model with 10030 apical four chamber echocardiographic loops, which can predict LVEF with a mean absolute error of 4.1% and much faster rate, that is, 1.6 s per cardiac cycle [Figure 2 and 3].

LV Strain

Salte *et al*.[13] developed a DL-based algorithm to estimate global longitudinal strain (GLS) using traditional 2D echocardiography. The DL model effectively accomplished automatic segmentation and estimations of GLS across a wide range of cardiac abnormalities, with little variation of 1.8% between the methods [Figure 4]. The evaluation was rapid and takes hardly 15 s time per assessment as compared to 5–10 min by traditional technique to determine GLS.

LV Diastolic function

Assessment of diastolic function is extremely difficult, with multiple echocardiographic parameters, numerous complex flow charts, and critical appraisal with guidelines. The novice AI technology enables easy diagnosis and interpretation of diastolic dysfunction. Salem *et al*.[14] used speckle tracking echocardiographic measurements to create an AI model that can precisely predict increased left atrial pressure, the key variable of diastolic dysfunction. Pandey *et al*.[15] emphasized ML-based algorithm for identifying individuals with high left atrial pressure in comparison to the American Society of Echocardiography 2016 diastolic guidelines grading system.

Right ventricle (RV) function

Evaluation of RV function is laborious and is affected by congenital malformation, left ventricular failure, valvular abnormalities, pulmonary arterial hypertension, and coronary artery disease (CAD). Moreover, precise evaluation of RV dysfunction may be tough due to its crescent shape, poor echocardiographic delineation of the RV, and discrepancy in RV functional analysis. However, with the advancement of AI technology, RV function can be assessed accurately and in a faster time. Zhu *et al*.[16] formulate an AI-based 3D echocardiographic algorithm to evaluate RV function accurately. The AI model showed excellent diagnostic accuracy being cut off ejection fraction of 43% with sensitivity and specificity of 94% and 67%, respectively, in comparison to cardiac magnetic resonance 0imaging

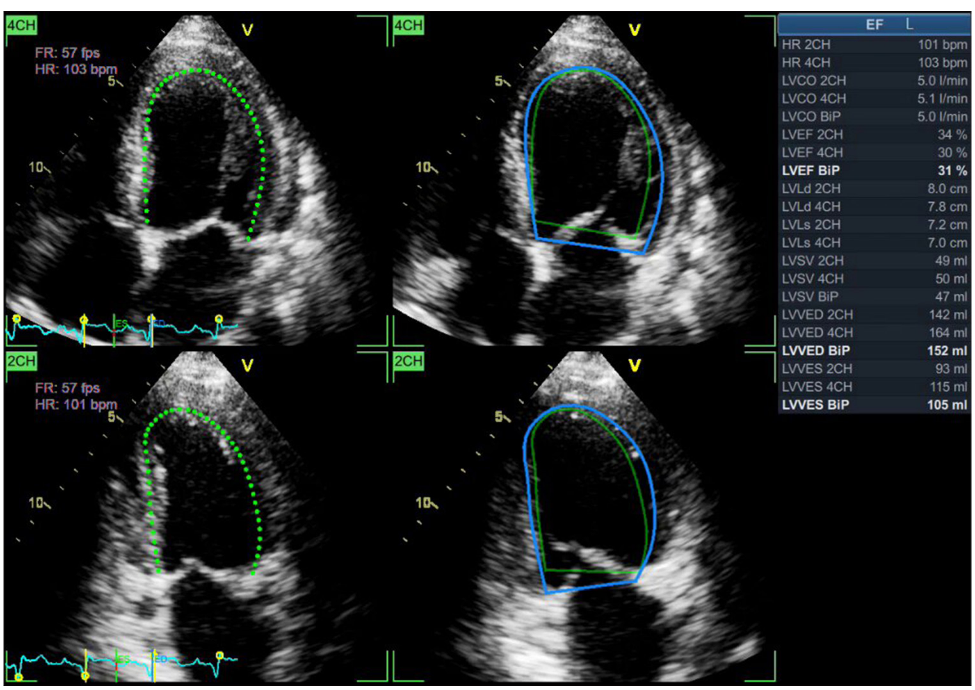

Figure 2: Artificial intelligence integrated calculation of ejection fraction by automated border tracking. Green dots represents the endo-myocardial border whereas green and blue solid lines denote end-systolic and end-diastolic border respectively.

[Figure 5]. Following LV assist device implantation, RV dysfunction is common but difficult to predict on the basis of existing echocardiographic parameters. However, Shad *et al.*[17] used video-based DL to forecast the development of RV failure following device implantation utilizing 2D echocardiographic dataset.

Valvular function

Echocardiographic evaluation of valvular morphology and function is a tedious process which requires proper imaging and precise measurements for the feasibility of repair. Moghaddasi and Nourian[18] used ML model for the assessment of mitral regurgitation on the basis of image

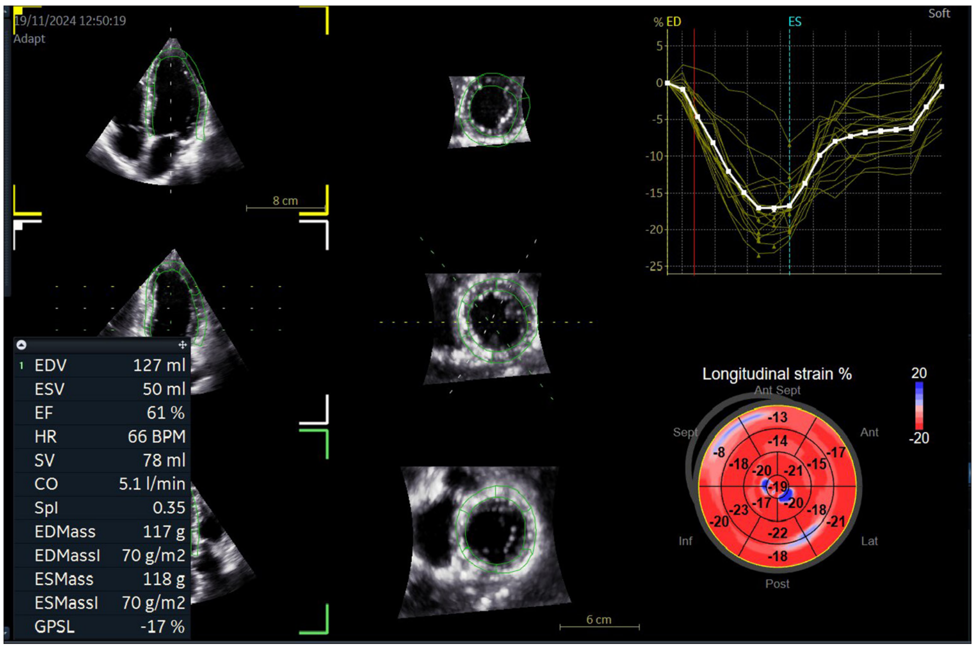

Figure 3: Artificial intelligence integrated three-dimensional quantification of left ventricular function.

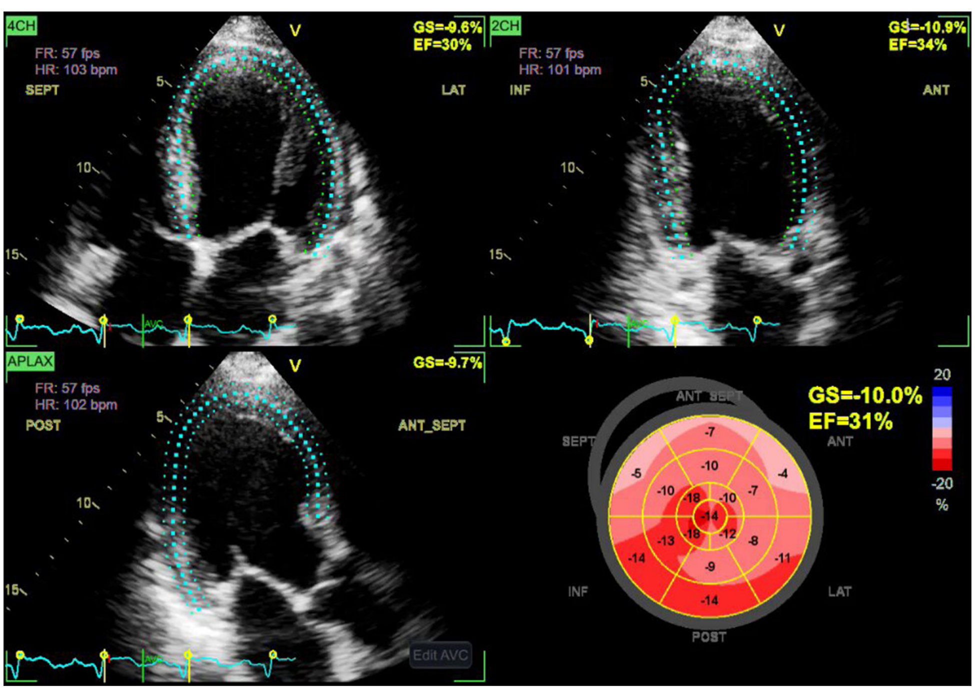

Figure 4: Artificial intelligence integrated measurements of global longitudinal strain by automatic speckle tracking. Blue dots indicate "speckles".

Figure 5: Artificial intelligence integrated three-dimensional quantification of right ventricular function.

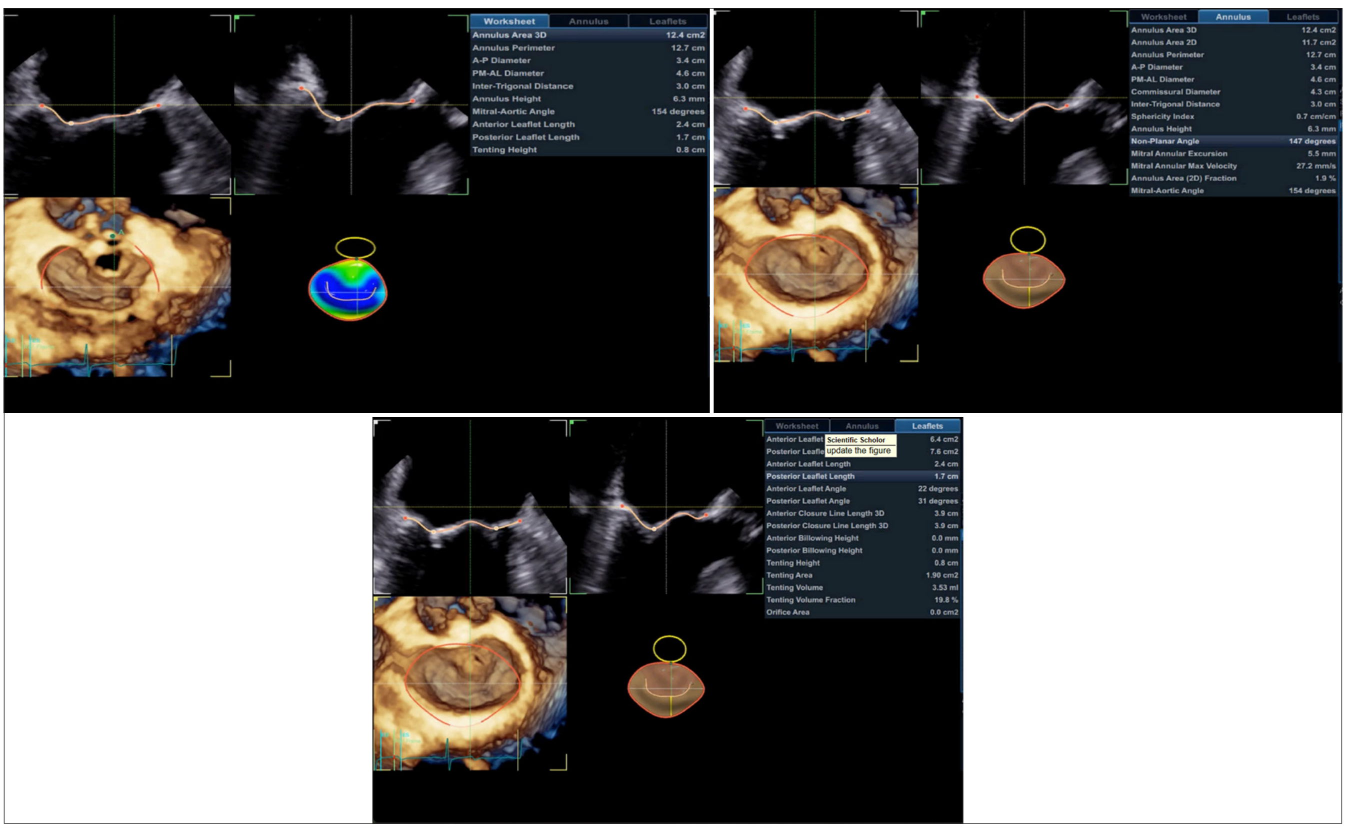

Figure 6: Artificial intelligence integrated three-dimensional quantification of mitral valve.

processing and micro-patterns of 2D echocardiography [Figure 6[. Prihadi *et al.*[19] innovate a AI based 3D transesophageal echocardiographic technique for precise measurement of aortic root and annular dimensions. Similar findings were also demonstrated by Queiros *et al.*[20] but using a different AI model for assessment of aortic valve evaluation in transcatheter aortic valve replacement.

Stress echocardiography

Stress echocardiography is a convenient technique for the detection of CAD, but requires a substantial learning with persistent inter-observer variability. Omar *et al.*[21] confirmed the effectiveness of DL-based algorithm, which can be used for analyzing strain of stress echocardiographs. Upton *et al.*[22] did a multi-centric,

Table 1: Artificial intelligence-driven algorithms in echocardiography and cardiac abnormalities.

S. No.	Authors	Type of AI algorithm	Description
1.	Narang *et al.*[5]	DL algorithm	Guidance on image acquisition
2.	Schneider *et al.*[6]	ML algorithm	Guidance for acquiring diagnostic echocardiography images
3.	Madani *et al.*[9]	CNN model	Classification of 15 standard views
4.	Zhang *et al.*[10]	CNN models	Classification of 23 standard views and segmentation
5.	Leclerc *et al.*[11]	CNN DL model	Segmentation and analysis of apical four and two chamber views to measure LV EDV, ESV, and EF
6.	Ouyang *et al.*[12]	CNN model	Prediction of EF
7.	Salte *et al.*[13]	DL model	Automated segmentation and measurement of GLS
8.	Salem Omar *et al.*[14]	AI model	Prediction of increased LV filling pressure
9.	Pandey *et al.*[15]	ML model	Prediction of elevated LV filling pressure
10.	Zhu *et al.*[16]	AI algorithm	Assessment of RV function using 3D echocardiography
11.	Shad *et al.*[17]	Video-based DL model	Development of RV failure
12.	Moghaddasi and Nourian[18]	ML model	Assessment of mitral regurgitation
13.	Prihadi *et al.*[19]	3D AI model	Measurement of aortic annulus and root dimensions
14.	Queiros *et al.*[20]	AI algorithm	Aortic valve assessment for TAVR
15.	Omar *et al.*[21]	DL based algorithm	Strain analysis for stress echocardiograms
16.	Upton *et al.*[22]	CNN model	Prognostication of coronary artery disease on stress echocardiograms
17.	Ghorbani *et al.*[23]	CNN model	Diagnosing pacemaker leads, left atrial enlargement, and LV hypertrophy
18.	Kusunose *et al.*[24]	CNN model	Detection of regional wall motion abnormality
19.	Strzelecki *et al.*[25]	AI-derived algorithm	Automatic identification of intracardiac tumor and thrombi
20.	Sun *et al.*[26]	Computer-aided diagnostic algorithm	Left atrial and left atrial appendage thrombi
21.	Samad *et al.*[27]	Non-linear ML model	Prediction of survival from tricuspid regurgitation velocity than EF

AI: Artificial intelligence, DL: Deep learning, ML: Machine learning, CNN: Convolutional neural networks, LV: Left ventricle, RV: Right ventricle, ESV: End-systolic volume, EDV: End-diastolic volume, EF: Ejection fraction, GLS: Global longitudinal strain, TAVR: Transcatheter aortic valve replacement, 3D: Three-dimensional

multi-vendor trial using a CNN model that can recognize angiographically confirmed CAD on stress echocardiograms.

Other utilities

Zhang *et al.*[10] used a CNN-based model to develop a fully automated echocardiographic modality, including image recognition and segmentation to diagnose hypertrophic obstructive cardiomyopathy, amyloidosis, and pulmonary hypertension. Ghorbani *et al.*[23] invented a novice CNN algorithm to identify pacemaker leads, left atrial enlargement, and LV hypertrophy. Omar *et al.*[21] customized a CNN technique for the automatic assessment of regional wall motion abnormality by analyzing strain during dobutamine stress echocardiograms to diagnose CAD. Similarly, Kusunose *et al.*[24] developed CNN algorithm for distinguishing regional wall motion abnormality. Strzelecki *et al.*[25] validated an AI-derived model for automatic recognition of various intracardiac tumor and mass using 2D echocardiography. This AI model demonstrates better accuracies, sensitivities, and specificities than conventional echocardiography. Sun *et al.*[26] developed a computer-aided diagnostic model from transesophageal echocardiographic images to detect left atrial and left atrial appendage thrombi. AI models can be integrated into hemodynamic measurements in less time. ML models trained to calculate systemic vascular resistance (SVR), pulmonary vascular resistance (PVR), and cardiac output (CO). Furthermore, AI-enhanced Doppler echocardiography can refine the TR jet, can integrate cardiac MRI, and catheterization data for accurate estimation of PVR. Similarly, AI-driven algorithms can predict SVR in real time, enabling vasopressor and fluid titration.

Disease prognostication

Samad *et al.*[27] developed a non-linear ML algorithm for the prediction of survival by utilizing clinical parameters and echocardiographic datasets. They have concluded that the tricuspid regurgitation velocity was more reliable echocardiographic parameter for survival than LVEF. Furthermore, Omar *et al*.[21] utilized unsupervised cluster analysis techniques for the evaluation of diastolic function and found two phenotypic categories of diastolic failure. Zhang *et al*.[10] used AI-derived echocardiographic paraments for the assessment of GLS in individuals treated with cardiotoxic chemotherapeutic agents and even prognostication of the patients.

AI-BASED TRAINING

AI has made immense development in the training for the acquisition, interpretation, and diagnosis of cardiovascular abnormalities by echocardiography. The major issue is to train how to operate the machine as well as the probe. Arbeille *et al*.[28] first revealed the efficient control of robots with a teleoperated motorized echocardiography probe by trained echocardiographers. Later on, Narang *et al*.[5] and Schneider *et al*.[6] used AI-based technology to train nurses and 1st year medical students, respectively.

OVERCOMING CHALLENGES: THE FUTURE PROSPECTS

Despite of huge development of AI in echocardiography, there are certain challenges for its globalization. Firstly, legal and ethical issues incurred with AI integration on echocardiography are the major hurdle; therefore, extensive validation study should be carried out before seeking approval of regulatory bodies.[29]

Furthermore, the internal network of DL algorithms is difficult to understand, therefore, often considered as a "black box" that makes hesitancy in adoption by clinicians. Although challenging and time-consuming, extensive training with larger training data sets with regard to acquisition, labeling, and interpretation can overcome the hesitancy hurdle.[30]

The most important limitation is the requirement of huge data banks constituting high quality training datasets to train the algorithm. If the algorithm is trained with sub-optimal real world imaging, it will give impaired view recognition and interpretation, which can hamper the quality of results. The solution is to continue continuous training of models with real world datasets to ascertain improved effectuality and safety.[31-33]

Another limitation is paucity of clinical trials on AI. Evidence of robust clinical outcomes should be required before the integration of AI into echocardiographic practice. Moreover, more clinical trials are required to validate AI in multiple demographic locations and various vendor-dependent setups. AI-enabled systems are costlier to set up; however, carrying out repetitive, simple tasks more accurately and substantially faster without medical errors make it cost effective.

AI models trained primarily on normal sinus rhythm patients and may not generalize well to patients with arrhythmias unless explicitly trained with diverse dataset. However, AI can analyze thousands of beats quickly and provide trend analysis rather than relying on single cycle measurement. Future AI models may integrate real-time electrocardiogram and respiratory monitoring to adjust these variations dynamically.

AI is continuously evolving and therefore, a multidisciplinary approach with engineers, computer scientists, and echocardiographers is inevitable for the fruitful integration of AI in echocardiography. This novice innovation expanded its boundaries and paved the pathway for huge clinical studies as well as multicentric trials.

CONCLUSION

Transforming potential of AI has led its integration with echocardiography. Starting from training echocardiographers, AI integration culminate improvement in image acquisition, recognition, and interpretation of echocardiographic views. The major perk of AI integration is incomparable effectiveness and reproducibility. Despite of considerable impediments, the future of AI in echocardiography cannot be challenged and has the potential to revolutionize modern echocardiography.

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