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Original Article

Role of AI-Based Echocardiography in Early Detection of Subclinical Heart Failure

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ABSTRACT

Background: Subclinical left ventricular dysfunction may precede symptomatic heart failure, while conventional echocardiographic interpretation can be affected by operator dependence and measurement variability. Artificial intelligence (AI)-assisted echocardiography may facilitate more standardized recognition of subtle abnormalities in ventricular function. Objective: To evaluate the diagnostic accuracy of an AI-based echocardiography model for detecting subclinical left ventricular dysfunction compared with conventional echocardiographic assessment. Methods: This diagnostic accuracy study included 212 adults undergoing echocardiographic evaluation at a cardiac care facility in Faisalabad, Pakistan. Standard transthoracic echocardiography served as the reference assessment, and stored echocardiographic images and video clips were independently analyzed using an AI-based model. Diagnostic performance was assessed using sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV), overall accuracy, and receiver operating characteristic analysis. Results: Conventional echocardiography identified subclinical left ventricular dysfunction in 58 of 212 participants (27.4%). Based on the internally reconciled classification counts, the AI model correctly identified 54 participants with dysfunction and 146 without dysfunction, with 4 false-negative and 8 false-positive classifications. Sensitivity was 93.1%, specificity 94.8%, PPV 87.1%, NPV 97.3%, and overall accuracy 94.3%. The area under the receiver operating characteristic curve was 0.95 (95% CI: 0.91–0.98), indicating excellent discrimination. Conclusion: AI-based echocardiography demonstrated high diagnostic accuracy for identifying subclinical left ventricular dysfunction in this single-center sample. The findings support its potential as an adjunct to conventional echocardiographic interpretation, while broader validation is required before routine clinical implementation. Keywords: Artificial Intelligence; Echocardiography; Left Ventricular Dysfunction; Diagnostic Accuracy; Heart Failure; Cardiac Imaging.

INTRODUCTION

Subclinical left ventricular dysfunction represents an early stage of myocardial impairment in which abnormalities of ventricular structure, motion, deformation, or contractile performance may be present before clinically overt heart failure develops. Conventional assessment of ventricular function relies substantially on left ventricular ejection fraction (LVEF), chamber dimensions, wall-motion assessment, Doppler measurements, and, where available, myocardial deformation imaging. However, LVEF may remain within a preserved range despite early myocardial dysfunction, while global longitudinal strain (GLS) and more detailed assessment of ventricular mechanics may identify abnormalities at an earlier stage (1,2). Early recognition of such dysfunction is clinically relevant because it may identify individuals who require closer cardiovascular evaluation before progression to symptomatic disease.

Transthoracic echocardiography remains a principal non-invasive modality for evaluating cardiac structure and function, but its interpretation is influenced by image quality, acquisition technique, operator experience, and interobserver variability. Standardization of chamber quantification has improved reproducibility, although manual measurement and visual interpretation remain important components of routine practice (2). These limitations are particularly relevant when the abnormality is subtle and diagnostic decisions depend on small differences in ventricular dimensions, wall motion, or systolic function.

Artificial intelligence (AI), particularly deep-learning approaches, has increasingly been applied to echocardiographic image acquisition, view recognition, chamber segmentation, measurement, functional assessment, and diagnostic classification. Ouyang et al. demonstrated that deep-learning analysis of echocardiographic video could quantify cardiac function on a beat-to-beat basis, while Ghorbani et al. showed that deep-learning systems could extract clinically relevant information from echocardiographic examinations (3,4). Fully automated echocardiographic analysis has also demonstrated the feasibility of obtaining multiple cardiac measurements with reduced dependence on manual interpretation (5). Collectively, these findings support the potential role of AI as an adjunct to conventional echocardiographic assessment.

The potential value of AI is particularly relevant for early ventricular dysfunction, in which clinically meaningful abnormalities may be difficult to identify from conventional measurements alone. AI-based phenotyping can integrate complex spatial and temporal imaging information and may recognize patterns of ventricular dysfunction that are not readily captured by isolated conventional parameters (1,6). Automated view classification and AI-guided image acquisition have further demonstrated that machine-learning approaches can contribute to multiple stages of the echocardiographic workflow, potentially improving standardization and supporting less-experienced operators (7,8).

The clinical relevance of scalable diagnostic support is considerable in healthcare systems where cardiovascular disease is common and access to specialist cardiac imaging expertise may be uneven. Pakistan faces a substantial burden of cardiovascular disease and associated risk factors, including hypertension, diabetes mellitus, smoking, and other metabolic and lifestyle-related factors (9–11). In such settings, technologies capable of supporting consistent echocardiographic interpretation may have particular value, provided that their diagnostic performance is established in the population in which they are intended to be used.

Despite rapid progress in AI-assisted cardiovascular imaging, diagnostic performance may vary according to population characteristics, disease spectrum, image quality, acquisition protocols, and model development conditions. Local validation is therefore necessary before performance estimates derived from one healthcare setting are assumed to generalize to another. Evidence regarding AI-assisted echocardiographic detection of subclinical left ventricular dysfunction in Pakistani clinical populations remains limited. Accordingly, this study aimed to evaluate the diagnostic accuracy of an AI-powered echocardiography model for detecting subclinical left ventricular dysfunction compared with conventional echocardiographic assessment among adults undergoing cardiac evaluation in Faisalabad, Pakistan.

MATERIALS AND METHODS

This diagnostic accuracy study evaluated the performance of an AI-based echocardiography model for detecting subclinical left ventricular dysfunction, using conventional echocardiographic assessment as the reference standard. The study was conducted at a cardiac care facility in Faisalabad, Pakistan and was structured in accordance with principles applicable to diagnostic-accuracy research and the Standards for Reporting Diagnostic Accuracy Studies (STARD) framework (12).

Adult patients aged 18 years or older who presented to the echocardiography unit for cardiac evaluation were assessed for eligibility. Eligible participants had cardiovascular risk factors or clinical suspicion of early cardiac dysfunction but did not have established symptomatic heart failure. Patients with known severe heart failure, previous major cardiac surgery, significant valvular heart disease, congenital heart disease, acute myocardial infarction, uncontrolled arrhythmias, or echocardiographic images of inadequate quality were excluded. Patients unable to provide consent or with incomplete clinical information were also excluded. Consecutive sampling was used to enroll eligible patients presenting during the study period, thereby reducing discretionary participant selection. Written informed consent was obtained before enrollment.

All enrolled participants underwent standard transthoracic echocardiographic assessment using routine clinical protocols. Examinations were performed by trained cardiologists or experienced echocardiographers who were unaware of the AI-derived classification. Conventional assessment included LVEF, cardiac chamber dimensions, wall-motion evaluation, and Doppler-based measurements. GLS was additionally recorded when available. Standardization of ventricular chamber measurements is important for reproducible echocardiographic assessment of cardiac structure and function (2).

The final conventional echocardiographic interpretation served as the reference standard for classification of participants according to the presence or absence of subclinical left ventricular dysfunction. Echocardiographic examinations were reviewed by the clinical assessors, and disagreements in conventional interpretation were resolved through discussion with a senior cardiologist. The reference-standard assessment was completed independently of the AI-generated result.

For the index test, stored echocardiographic images and video clips were analyzed using an AI-powered echocardiography model employing deep-learning algorithms. The system automatically identified cardiac views, evaluated myocardial motion, generated measurements related to left ventricular function, and classified each participant according to the presence or absence of subclinical left ventricular dysfunction. AI-generated results were recorded independently and were not manually modified by the operator. The primary diagnostic outcome was the ability of the AI model to correctly classify subclinical left ventricular dysfunction relative to the conventional echocardiographic reference assessment.

A structured data-collection form was used to record demographic, cardiovascular risk, and imaging information. Collected variables included age, sex, body mass index, hypertension, diabetes mellitus, smoking history, family history of cardiovascular disease, and other clinically relevant cardiovascular risk factors. Echocardiographic findings obtained through conventional and AI-based assessment were recorded for diagnostic comparison. Study information was coded and entered into a secure database to maintain confidentiality.

Diagnostic classification was summarized in a 2×2 contingency table comprising true-positive, false-positive, true-negative, and false-negative results. Sensitivity was calculated as the proportion of reference-positive participants correctly classified by the AI model, whereas specificity represented the proportion of reference-negative participants correctly classified as negative. Positive predictive value (PPV), negative predictive value (NPV), and overall diagnostic accuracy were also calculated. Diagnostic discrimination was evaluated using receiver operating characteristic (ROC) analysis, with the area under the ROC curve (AUC) used to quantify the ability of the AI model to distinguish participants with and without subclinical left ventricular dysfunction. Diagnostic proportions were reported with 95% confidence intervals.

Continuous variables were summarized using mean and standard deviation or median and interquartile range according to the distribution of the data, while categorical variables were summarized as frequencies and percentages. For the reported diagnostic classification counts, 95% confidence intervals for sensitivity, specificity, predictive values, and accuracy were calculated using binomial proportion estimates. A two-sided p-value below 0.05 was considered statistically significant for inferential analyses where applicable. ROC analysis was used to characterize discriminatory performance of the AI-based assessment.

Standardized echocardiographic procedures were maintained throughout data collection, and the same AI software version was used for analysis of all participants. Image quality and data recording were checked during the study to support consistency of the diagnostic comparison.

RESULTS

A total of 250 patients were assessed for eligibility. After application of the eligibility criteria, 212 participants were included in the final diagnostic analysis, corresponding to 84.8% of those initially assessed. The mean age of the analyzed participants was 54.6 ± 10.8 years. Of the 212 participants, 128 (60.4%) were male and 84 (39.6%) were female. Hypertension was present in 119 (56.1%), diabetes mellitus in 86 (40.6%), and a history of smoking in 72 (34.0%). Conventional echocardiographic assessment identified subclinical left ventricular dysfunction in 58 participants (27.4%), whereas 154 (72.6%) were classified as having preserved left ventricular function (Table 1).

Table 1. Baseline Characteristics of Study Participants

Characteristic	Total Participants (n = 212)
Age, years, mean ± SD	54.6 ± 10.8
Male sex, n (%)	128 (60.4)
Female sex, n (%)	84 (39.6)
Hypertension, n (%)	119 (56.1)
Diabetes mellitus, n (%)	86 (40.6)
Smoking history, n (%)	72 (34.0)
Subclinical LV dysfunction, n (%)	58 (27.4)
Preserved LV function, n (%)	154 (72.6)

The AI-based assessment correctly identified 54 of the 58 participants classified by conventional echocardiography as having subclinical left ventricular dysfunction, resulting in four false-negative classifications. Among the 154 participants with preserved ventricular function on conventional assessment, 146 were correctly classified as negative and eight were classified as false positive. Accordingly, the internally reconciled diagnostic contingency table comprised 54 true-positive, 8 false-positive, 146 true-negative, and 4 false-negative results. The AI model therefore classified 62 participants as positive and 150 as negative (Table 2).

Table 2. Cross-Classification of AI-Based Echocardiography Against the Conventional Echocardiographic Reference Assessment

AI-Based Classification	Subclinical LV Dysfunction Present	Subclinical LV Dysfunction Absent	Total
Positive	54	8	62
Negative	4	146	150
Total	58	154	212

Based on these classification counts, the AI model demonstrated a sensitivity of 93.1% (95% CI: 83.6–97.3%) and specificity of 94.8% (95% CI: 90.1–97.3%). The PPV was 87.1% (95% CI: 76.6–93.3%), while the NPV was 97.3% (95% CI: 93.3–99.0%). Overall diagnostic accuracy was 94.3% (95% CI: 90.4–96.7%) (Table 3).

Table 3. Diagnostic Performance of AI-Based Echocardiography

Diagnostic Measure	Estimate	95% CI
Sensitivity	93.1%	83.6–97.3%
Specificity	94.8%	90.1–97.3%
Positive predictive value	87.1%	76.6–93.3%

Diagnostic Measure	Estimate	95% CI
Negative predictive value	97.3%	93.3–99.0%
Overall accuracy	94.3%	90.4–96.7%
Area under the ROC curve	0.95	0.91–0.98

ROC analysis showed an AUC of 0.95 (95% CI: 0.91–0.98), demonstrating excellent discrimination between participants with and without subclinical left ventricular dysfunction (Figure 1). The diagnostic classification counts similarly showed close concordance between AI-based and conventional echocardiographic classification, with 200 of 212 participants receiving concordant classifications and 12 receiving discordant classifications.

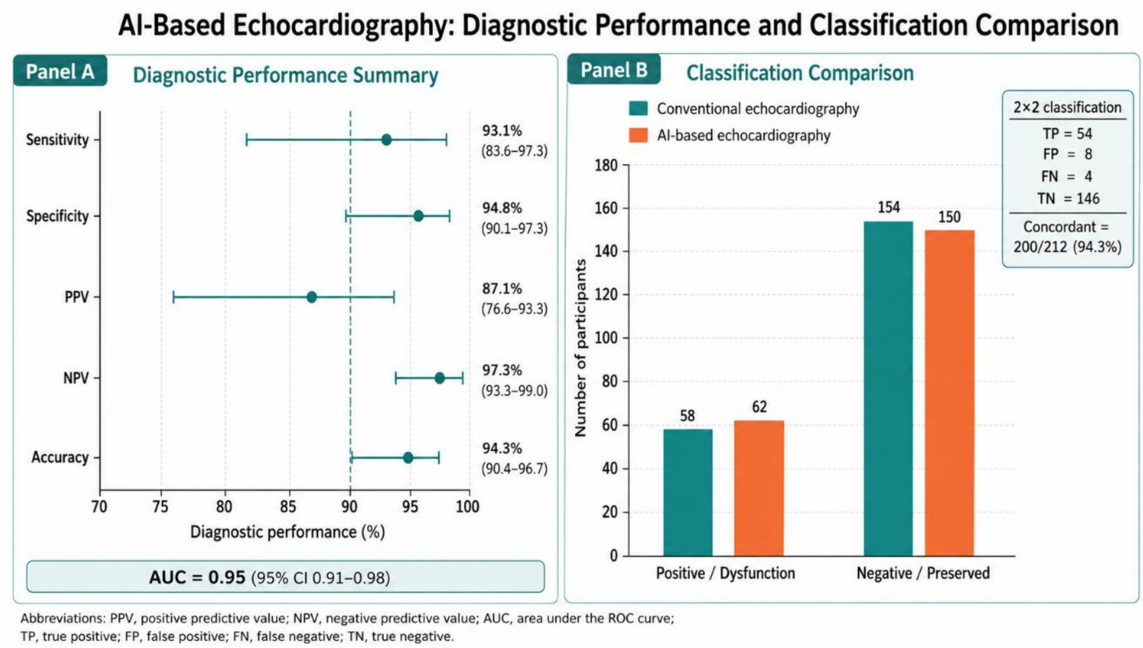

Figure 1. Diagnostic Performance and Classification Comparison of AI-Based Echocardiography. Panel A presents the diagnostic performance of AI-based echocardiography for detecting subclinical left ventricular dysfunction, showing sensitivity, specificity, positive predictive value, negative predictive value, and overall accuracy with corresponding 95% confidence intervals. Receiver operating characteristic analysis demonstrated excellent discrimination, with an area under the curve (AUC) of 0.95 (95% CI: 0.91–0.98). Panel B compares AI-based classification with conventional echocardiographic assessment. Conventional echocardiography classified 58 participants as having subclinical left ventricular dysfunction and 154 as having preserved ventricular function, whereas AI-based assessment classified 62 participants as positive and 150 as negative. The reconciled 2 × 2 classification comprised 54 true positives, 8 false positives, 4 false negatives, and 146 true negatives, with overall concordance of 200/212 (94.3%). Abbreviations: AUC, area under the receiver operating characteristic curve; PPV, positive predictive value; NPV, negative predictive value; TP, true positive; FP, false positive; FN, false negative; TN, true negative.

DISCUSSION

This diagnostic accuracy study demonstrated strong performance of AI-based echocardiographic assessment for identifying subclinical left ventricular dysfunction. Among 212 participants, the AI model correctly classified 54 of 58 participants with dysfunction and 146 of 154 participants without dysfunction, yielding a sensitivity of 93.1%, specificity of 94.8%, PPV of 87.1%, NPV of 97.3%, and overall accuracy of 94.3%. The AUC of 0.95 further demonstrated excellent discrimination between participants with and without subclinical left ventricular dysfunction. Taken together, these findings indicate that automated echocardiographic analysis can distinguish abnormal from preserved ventricular function with a low proportion of discordant classifications in the studied population.

The observed diagnostic performance is consistent with the growing evidence supporting deep-learning applications in echocardiography. Ouyang et al. demonstrated that video-based deep learning could quantify cardiac function directly from echocardiographic recordings and achieve performance comparable with expert assessment (3). Ghorbani et al. similarly showed that deep-learning models could extract clinically relevant cardiac information from echocardiographic images, while Zhang et al.

demonstrated the feasibility of fully automated echocardiographic interpretation across several routinely assessed cardiac parameters (4,5). These studies support the principle that AI systems can automate components of cardiac image interpretation while maintaining clinically meaningful diagnostic performance.

The sensitivity of 93.1% observed in the present study indicates that relatively few participants classified as having subclinical left ventricular dysfunction by the reference assessment were missed by the AI model. The NPV of 97.3% is particularly relevant when considering an AI system as an adjunctive screening or triage tool because a negative automated assessment was rarely associated with reference-standard dysfunction in this sample. Nevertheless, predictive values are influenced by the prevalence of the target condition; therefore, the PPV and NPV obtained in this population should not be assumed to remain unchanged in populations with substantially different disease prevalence. AI-based echocardiographic phenotyping has shown potential for recognizing ventricular dysfunction beyond conventional manual measurements, but diagnostic performance requires validation within the populations and clinical settings in which the technology is intended to be used (2,6,7).

The findings are also relevant to the limitations of conventional ventricular assessment. Standard echocardiographic evaluation relies on measures such as LVEF, chamber dimensions, wall-motion assessment, Doppler parameters, and, when available, myocardial strain. Although LVEF remains central to ventricular assessment, subtle myocardial dysfunction may occur before overt reductions in ejection fraction become apparent. Standardized chamber quantification and deformation-based assessment can improve recognition of such abnormalities, while automated image analysis may further reduce measurement variability and facilitate reproducible assessment (1,2,6). Accordingly, the value of AI in this context lies primarily in complementing established echocardiographic measurements rather than replacing clinically validated reference assessment.

The excellent AUC observed in this study is consistent with previous work showing that machine-learning approaches can discriminate between clinically relevant patterns of ventricular structure and function. Narula et al. demonstrated that machine-learning analysis of echocardiographic variables could distinguish different patterns of left ventricular remodeling and functional abnormality (12). Importantly, however, an AUC represents discriminatory ability rather than agreement between two measurement methods. The present AUC of 0.95 therefore indicates a high probability that the AI model can correctly differentiate participants with and without the target condition, whereas assessment of measurement agreement would require additional analyses specifically designed for that purpose.

AI may also improve the operational efficiency of echocardiography. Automated recognition of standard cardiac views is a prerequisite for scalable image-analysis workflows, and Madani et al. demonstrated that deep-learning algorithms can accurately classify echocardiographic views (13). AI-guided approaches have additionally been evaluated as a means of supporting less-experienced operators in acquiring diagnostically useful cardiac images, suggesting potential applications where access to expert echocardiography personnel is limited (14). Such systems are therefore most appropriately conceptualized as decision-support and workflow-enhancement technologies rather than independent substitutes for cardiovascular specialists, consistent with broader models of human-AI collaboration in clinical medicine (15,16).

The potential application of such technology is particularly relevant in healthcare environments where cardiovascular disease burden is high and specialist diagnostic resources may be unevenly distributed. Cardiovascular risk factors and coronary disease represent substantial clinical challenges in Pakistan, with hypertension, diabetes, smoking, obesity, and related metabolic risks contributing to cardiovascular morbidity (8–10). In such settings, automated echocardiographic analysis could potentially support standardized interpretation and prioritization of patients requiring specialist review. However, the present findings demonstrate diagnostic performance under the conditions of this study and do not establish that AI implementation will independently reduce cardiovascular morbidity, healthcare costs, or progression to symptomatic heart failure.

The broader cardiovascular-imaging literature similarly emphasizes that AI applications should be evaluated not only according to technical accuracy but also according to reproducibility, transportability, integration into clinical workflows, and performance across diverse populations and imaging environments (7,17,18). Differences in equipment, acquisition technique, image quality, patient characteristics, and model-training populations can affect model performance. Consequently, high accuracy within one clinical dataset does not by itself establish external validity. Local and multicenter evaluation remains important before implementation across substantially different healthcare settings.

Several limitations should therefore be considered. The study was conducted at a single center and included 212 participants, which restricts the extent to which the observed diagnostic estimates can be generalized to other institutions or patient populations. The investigation was cross-sectional from a diagnostic perspective and did not include longitudinal follow-up; consequently, it cannot determine whether AI-detected abnormalities predict subsequent symptomatic heart failure, hospitalization, cardiovascular events, or mortality. The analysis also evaluated diagnostic classification rather than downstream clinical outcomes, and the findings should therefore be interpreted as evidence of diagnostic performance rather than clinical effectiveness. Furthermore, the observed predictive values are specific to the prevalence of subclinical left ventricular dysfunction in the studied sample. These considerations reinforce the need for external validation in larger and clinically diverse populations.

Overall, the study adds to evidence suggesting that AI-assisted echocardiography can provide accurate and reproducible support for assessment of ventricular function. Contemporary reviews of cardiovascular imaging have emphasized the potential of machine learning to enhance image interpretation, workflow efficiency, phenotyping, and clinical decision support while maintaining an important role for physician oversight (7,17–19). The present findings extend this concept to the detection of subclinical left ventricular dysfunction in a Pakistani clinical setting, but implementation should be guided by external validation, transparent model characterization, and evaluation within the intended clinical workflow.

CONCLUSION

AI-based echocardiography demonstrated high diagnostic accuracy for identifying subclinical left ventricular dysfunction in this single-center sample, with high sensitivity, specificity, negative predictive value, overall accuracy, and excellent discriminatory performance. These findings support the potential use of AI-assisted analysis as an adjunct to conventional echocardiographic interpretation for recognizing early ventricular dysfunction. However, the results establish diagnostic performance rather than improved clinical outcomes, and larger multicenter studies with external validation and longitudinal follow-up are required before routine implementation can be justified.

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