Title: Diagnostic Accuracy of Artificial intelligence -Enabled Electrocardiography for Detection of Valvular Heart Disease , A Systematic Review and Metaanalysis

Abstract

Background :
Valvular heart diseases (VHD) contribute significantly to mortality, yet early detection remains challenging. Artificial intelligence (AI) applied to ECG has emerged as a promising screening tool.

Study aim:This study evaluates the diagnostic accuracy of AI-based ECG algorithms for detecting VHD. Secondary objectives include assessing the effect of disease severity on diagnostic performance, comparing between Deep Learning (DL) and Traditional Machine Learning (ML) models, and evaluating 12-lead modality versus single-lead ECG modality.

Methods:We retrieved 1030 cardiology-related records from PubMed, Scopus, and Web of Science, and selected 19 studies focusing on VHD for full-text review. After applying exclusion criteria and adding four studies from reference mining, 17 studies were reviewed, but only 11 studies have been entered in the quantitative analysis. The primary outcome is the pooled Area Under the Curve (AUC).

Results: The pooled AUC was 0.85 for Aortic Stenosis and Mitral Regurgitation, and 0.80 for Aortic Regurgitation. Severe AR was detected with higher accuracy (AUC 0.88) than moderate-to-severe AR (AUC 0.78). DL models outperformed ML models (AUC 0.87 vs 0.72), and 12-lead ECGs performed better than single-lead recordings.

Conclusion : AI-enabled ECG can reliably screen for significant VHD, particularly severe cases. Integrating these algorithms into primary care may allow earlier referrals and improve patient outcomes.

key words : (modern technology, deep learning, ECG, Electrocardiogram, Cardiology).

Introduction

Valvular heart diseases (VHD) are significant causes of death [1]. However, early detection remains challenging [2,3]. Recent advancements in applying artificial intelligence (AI) to ECG interpretation have been emerged as a valuable screening tool[4].Valvular heart disease (VHD) incidence is increasing with age, affecting over 13% of Americans aged 75 or more, according to (2024 Heart Disease and Stroke Statistics) [5]. Furthermore, with longer life expectancy, the global burden of significant VHD will be expected to double by 2040[6]. However, many cases go undiagnosed until advanced stage .

Current physical exams have limited sensitivity, making early VHD detection challenging. However, Echocardiography remains the primary diagnostic modality and is considered a gold standard for VHD detection. it is resource-intensive and requires specialized expertise, making it impractical for widespread screening [7]. Reliance on clinical auscultation is limited by high inter-observer variability and unreliability, as many moderate-to-severe cases lack a detectable murmur[4]. So, there is a need for a scalable, cost-effective screening tool.

Artificial intelligence has turned 12-lead ECG into a powerful marker of structural heart disease. Deep learning models can detect subtle waveform patterns related to cardiac remodeling that will be missed by human interpretation[8,9]. Early studies show that AI-ECG can identify cardiac dysfunction and valvular disease even in asymptomatic individuals, so help in bridging the gap between screening and diagnosis [9].

However, the effect of disease severity and model architecture on diagnostic performance remains unclear. Our study has been designed to assess the accuracy of AI-ECG in detecting valvular heart diseases by examining pooled diagnostic yield for each valvular lesion , investigating severity gap by comparing model performance in severe versus moderate lesions and compare effectiveness of Deep Learning versus traditional Machine Learning models.

Method

This systematic review and Meta-analysis analysis study has been conducted following the PRISMA 2020 framework .

The study protocol had been designed to evaluate the diagnostic accuracy of artificial intelligence (AI) algorithms using electrocardiography (ECG) for the detection of valvular heart diseases (VHD).

Search strategy:

Through searching three high impact databases: PubMed, Web of Science and Scopus, searching from database inception until November; 2025.The search strategy had been based on the following key words :(Artificial intelligence, modern technology, deep learning, ECG, Electrocardiogram, Cardiology).

Selection Criteria

Initially, a broad search strategy was employed to include the impact of AI on electrocardiography in cardiology. 1,911 records have been identified after removing duplicates, relevant articles have been screened by title / abstract, During the title and abstract screening phase of 1,911 records, studies have been categorized/labeled into subdomains (e.g., Arrhythmia, Ischemia, Heart Failure, and Valvular Heart Disease…).Upon reviewing the landscape of current literature, we decided to focus on VHD to fulfill the research gap.

Therefore, 1,030 cardiology-related records have been identified, from which 19 specific studies focusing on VHD have been selected for full-text retrieval, according to exclusion criteria 6 records have been excluded. Also, by manual searching the references mentioned in narrative and systematic reviews, 4 studies have been added to our study. Finally, 17 studies have been reviewed ,but 11 studies have been included in quantitative assessment. The main pooled estimate for our study is Area Under the Curve (AUC).

ELIGIBILITY CRITERIA: Population :adults (≥18 years) undergoing ECG testing for any cardiac condition. Intervention(s) : AI-enabled algorithms applied to ECG interpretation, including machine learning (ML) and deep learning (DL) models, regardless of device type (single-lead, 12-lead, and wearable) . Eligible studies compared AI-ECG performance against echocardiography and reported diagnostic accuracy metrics, particularly AUC. Only English-language studies with available full text have been included. Reviews have been used only for reference mining. We have been excluding records outside the selected databases, non-English publications, duplicate or incomplete records, outside the scope of AI in cardiology, without full-text access, non-journal publications, and studies that did not address the research question or report diagnostic accuracy outcome.

Data extraction

From each eligible study, we extracted the following data: first author and year, country, sample size, type and severity of valvular lesion, participant age, model used, algorithm class, ECG modality, reference standard, and the AUC.

Quality assessment test

Methodological quality has been assessed using the QUADAS-2 tool, evaluating risk of bias across four domains: patient selection, index test, reference standard, and flow and timing .

Statistical Analysis
All statistical analyses have been performed using R software (version 4.x.x),

Pooled Analysis: the pooled Area Under the Curve (AUC) for each valvular lesion has been calculated using the Generic Inverse Variance method. Due to anticipated clinical and methodological diversity, a Random-Effects Model (REML) has been employed for all meta-analyses.

Heterogeneity: to assess heterogeneity we used I2 statistics and Cochran's Q test, where I2>50% indicated substantial heterogeneity.

Subgroup & Sensitivity Analysis: subgroup analyses have been done based on disease severity (Severe vs. Moderate-to-Severe), algorithm type (Deep Learning vs. Machine Learning), and ECG modality (12-Lead vs. Single-Lead). Sensitivity analysis has been performed by excluding high-risk or small-sample studies to assess the strength of our results.

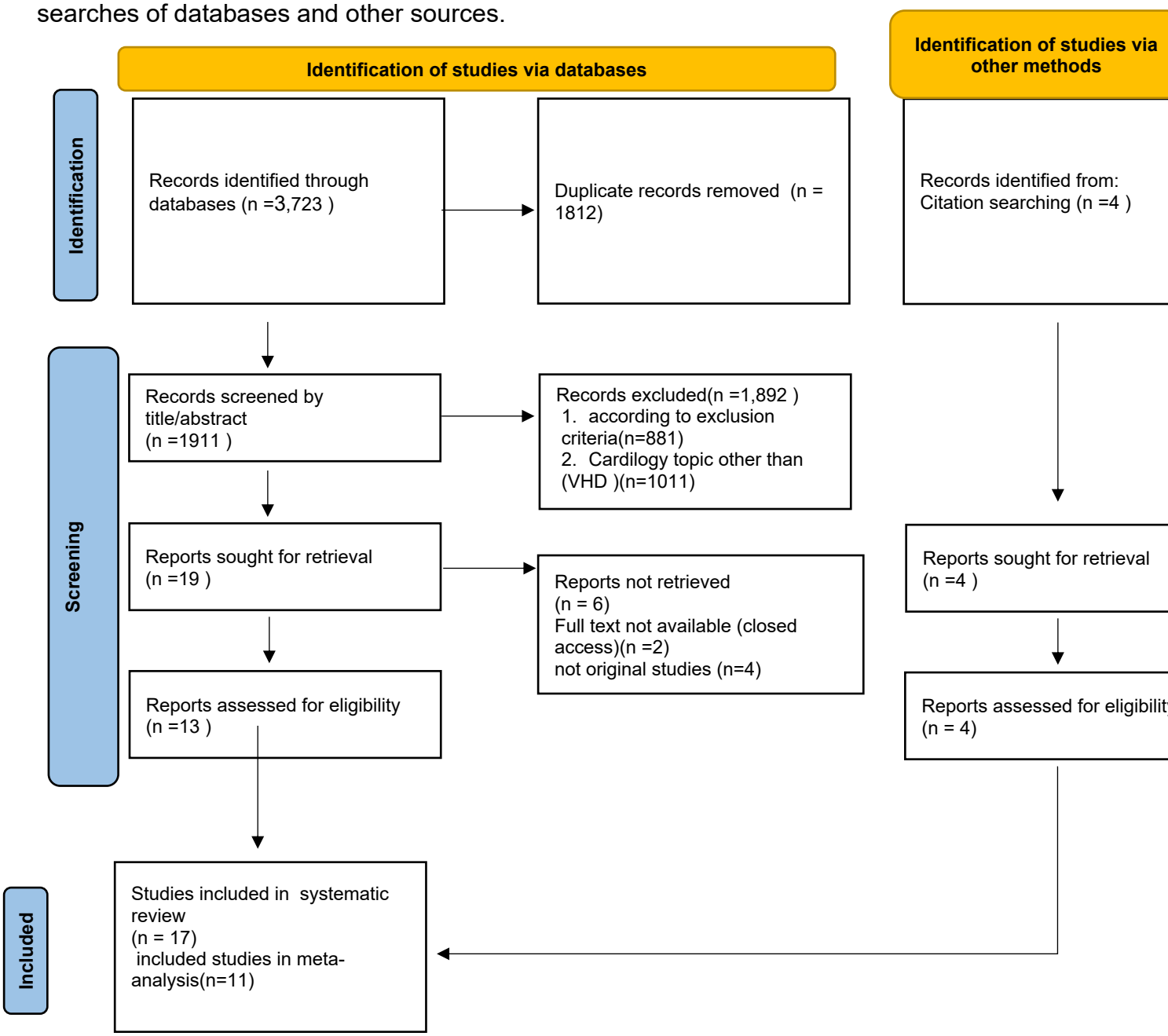
Publication Bias: Wehave been assessed publication bias both visually, using funnel plots, and statistically, with Egger's regression test, considering a P-value < 0.05 as significant.

Result

Identification of Studies

A total of 3723 records were identified through database searching. After removing duplicates and screening titles/abstracts, 17 full-text articles had been assessed for eligibility.Another 4 articles had been added through manual reference searching of the Systematic or narrative reviews, Finally,17 studies met the inclusion criteria and were included in the systematic review but only 11 studies included in meta-analysis. The selection process is detailed in the PRISMA flow diagram **(Figure 1)**

(Figure 1) PRISMA 2020 flow diagram for new systematic reviews which included searches of databases and other sources.



- **Total excluded from quantitative synthesis: n = 6 Reasons**: Overlapping populations (**n = 2**) *(Vaid*[10]*, Ito*[11]*)*. Ineligible outcome measures (**n = 4**) *(Tison*[12]*, Hu*[13]*, Li*[14]*,Attia*[9]*)*.

Characteristics of the Studies included in meta-analysis.

Our study includes seventeen studies that have been published between 2020 and 2025, covering five regions: the USA, South Korea, Taiwan, China, and Japan. Validation sample sizes vary widely, ranging from 103 to 102,926 participants. Most studies are focused on moderate-to-severe valvular heart disease, some of them providing subgroup analyses for severe lesions (e.g., Lin et al.[8], Shiraga et al.[15]). The main valvular conditions observed are Aortic Stenosis (AS), Mitral Regurgitation (MR), and Aortic Regurgitation (AR). Participants' mean ages range from 61 to 75 years.

Regading Ecg modality and AI-model , most studies relied on standard 12-lead ECG raw waveforms as input and Deep Learning (DL), particularly Convolutional Neural Networks (CNNs) algorithms . (e.g., Cohen-Shelly[7], Ulloa-Cerna[4], Lin[8]). Only 3 studies compared these to traditional Machine Learning models (e.g., Random Forest, XGBoost) (Shiraga et al.[15], Sawano et al.[16], and Kwon et al.[2]). The diagnostic performance of single-lead ECG inputs, mimicking wearable devices, was evaluated in three cohorts (Aminorroaya et al. and Kwon et al. [2,3][both AS and MR studies]). The primary outcome measure retrieved for quantitative synthesis was the Area Under the Receiver Operating Characteristic Curve (AUC). The characteristics of studies in meta-analysis of our study have been summarized in Table 1.

Table 1:**Baseline Characteristics and Diagnostic Performance of Studies Included in the Meta-Analysis**

Study ID	Country	Sample Size (N)	Valve Lesion	Severity	Age (Mean)	Model Used	Algorithm Class	ECG Modality	Ref. Standard	AUC
Cohen-Shelly et al., 2021	USA	102,926	AS	Mod-Severe	62.9 ± 16	CNN	DL	12-Lead	TTE	0.85

Ulloa-Cerna et al., 2022	USA	43,422	AS,MR, AR,	Mod-Severe	68 ± 15	ResNet	DL	12-Lead	TTE	AS:0.908 MR: 0.91 AR: 0.846
Lin et al., 2024	Taiwan	11,800	AS, MR, AR	Severe	65.8± 18	CNN	DL	12-Lead	TTE	AS: 0.87 MR: 0.90 AR: 0.88
Liang et al., 2025	China/USA	34,214	MR, AR, TR	Mod-Severe	62.2 ± 16	ResNet	DL	12-Lead	TTE	MR: 0.78 AR: 0.75
Elias et al., 2022	USA	21,048	MR, AR	Mod-Severe	61.5 ± 17	ValveNet	DL	12-Lead	TTE	MR: 0.83 AR: 0.77
Kwon et al., 2020 (AS)	S. Korea	10,865	AS	Mod-Severe	73.2 ± 12	Ensemble(CNN and MLP),MLP,CNN,RF / Ensemble	DL/ML	12-Lead/ Single lead	TTE	0.86, 0.8, 0.82,0.8 / 0.82
Kwon et al., 2020 (MR)	S. Korea	10,865	MR	Mod-Severe	68.3 ± 14	CNN	DL	12-Lead/ single lead	TTE	0.877/ 0.85
D. Kim et al., 2025	S. Korea	5,425	AS	Mod-Severe	74.5 ± 7	CNN	DL	12-Lead	TTE	0.85
Aminorroaya et al., 2023	USA	3,733	AS	Mod-Severe	61(IQR)	CNN/Ensemble(XGBoost)	DL/ML	Single lead	TTE	0.755/ 0.83
Sawano et al., 2021	Japan	3,269	AR	Mod-Severe	62.9 ± 17	CNN,MLP /lightGBM/ RF	DL /ML	12-Lead	TTE	0.73 ,0.73(DL)/0.75 0.66 (ML)
Shiraga et al., 2023	Japan	103	AS, MR	Severe	67 ± 15	CNN/RF /XGBoot	DL /ML	12-Lead	TTE	AS: 0.78,/0.79 /0.756 MR:0.678/ 0.695/0.65

Note:

Abbreviations: AS: Aortic Stenosis; MR: Mitral Regurgitation; AR: Aortic Regurgitation; TR: Tricuspid Regurgitation; TTE: Transthoracic Echocardiography; CNN: Convolutional Neural Network; MLP: Multi-Layer Perceptron., RF: Random forest ,XGBoost ; extreme gradient boosting , GBM; gradient boosted machine.

Excluded Studies: Six additional studies (e.g., Vaid et al., Attia et al.) were reviewed qualitatively but excluded from this table and the meta-analysis due to overlapping patient populations or ineligible outcome measures.

Qualitative Synthesis of Additional Studies

- In addition to the 11 studies included in quantitative meta-analysis, six other original studies met our inclusion criteria but were excluded from pooling to ensure statistical independence and homogeneity. Two studies (Vaid et al[10]. and Ito et al[11].) utilized patient cohorts that overlapped with larger datasets included in our analysis (Ulloa-Cerna et al[4]. and Cohen-Shelly et al[7].).
- Four studies defined ineligible outcome measures (Tison et al[12]., Hu et al[13]., Li et al[14]. and Attia et al[9].), as they focused on (arrythmogenic MVP ,hemodynamically significant AR ,mortality prediction, and cardiac contractile dysfunction respectively),rather than diagnostic accuracy for VHD .

Quality Assessment

Risk of bias assessment using the QUADAS-2 tool indicated that most included studies had a minimal risk of bias and high applicability. However, one study (Shiraga et al.[15]) was classified as having an elevated risk of bias inpatient selection domain and the index test domain due to small sample size and potential overfitting. One study unclears (swano, as its information not fully detailed .

Data Analysis

Diagnostic Accuracy for Valvular Heart Disease

. Aortic Stenosis (AS)

The pooled analysis of studies evaluating aortic stenosis showed excellent diagnostic accuracy, with an overall AUC of 0.85 (95% CI: 0.84–0.86). Subgroup analyses by disease severity demonstrated consistently powerful performance across both severe and moderate-to-severe aortic stenosis **(Figure 2).**

. Aortic Regurgitation (AR)

The overall pooled AUC for Aortic Regurgitation was 0.80 (95% CI: 0.74–0.86). Notably, disease severity significantly impacted diagnostic accuracy (P=0.003for subgroup difference). The model detected Severe AR with higher accuracy (AUC = 0.88) compared to Moderate-to-Severe AR (AUC = 0.78), suggesting that AI performance improves with advanced disease stages **(Figure 3).**

. Mitral Regurgitation (MR)

For Mitral Regurgitation, the AI-ECG models achieved a pooled AUC of 0.85 (95% CI: 0.79–0.90). Subgroup

analysis indicated that disease severity did not significantly influence the diagnostic performance in this cohort. **(Figure 4).**

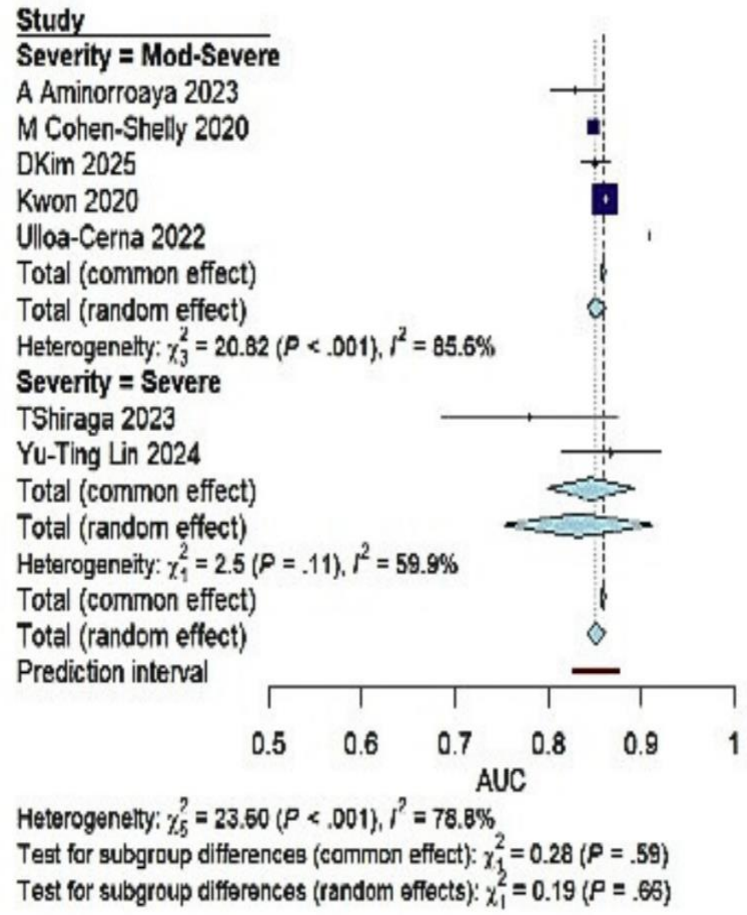


Figure 2 : Diagnostic accuracy for Aortic stenosis (AS).

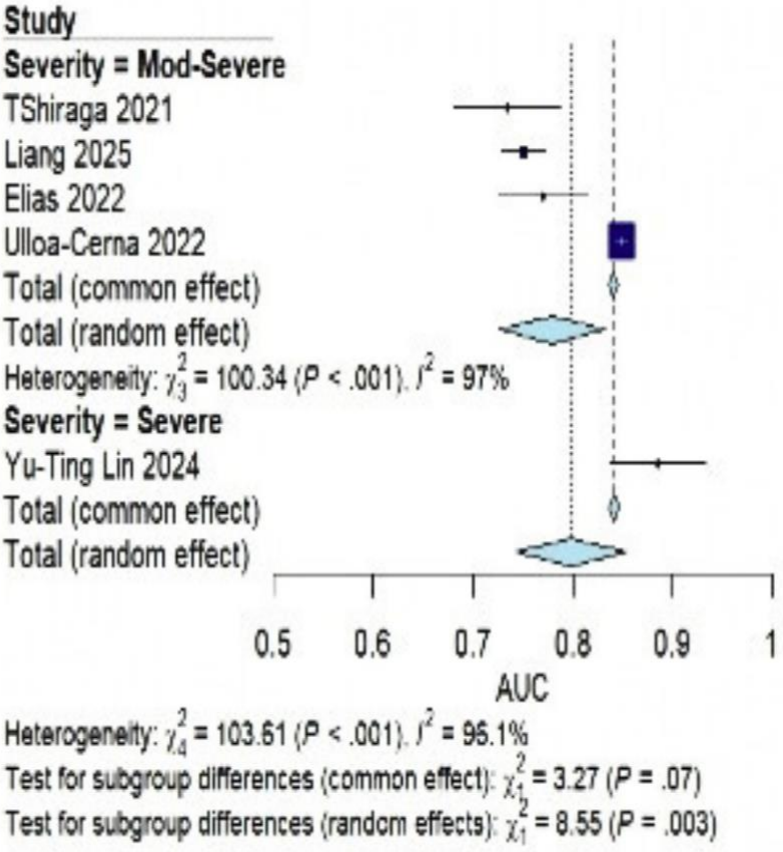


Figure 3: Diagnostic accuracy for Aortic Regurge (AR)

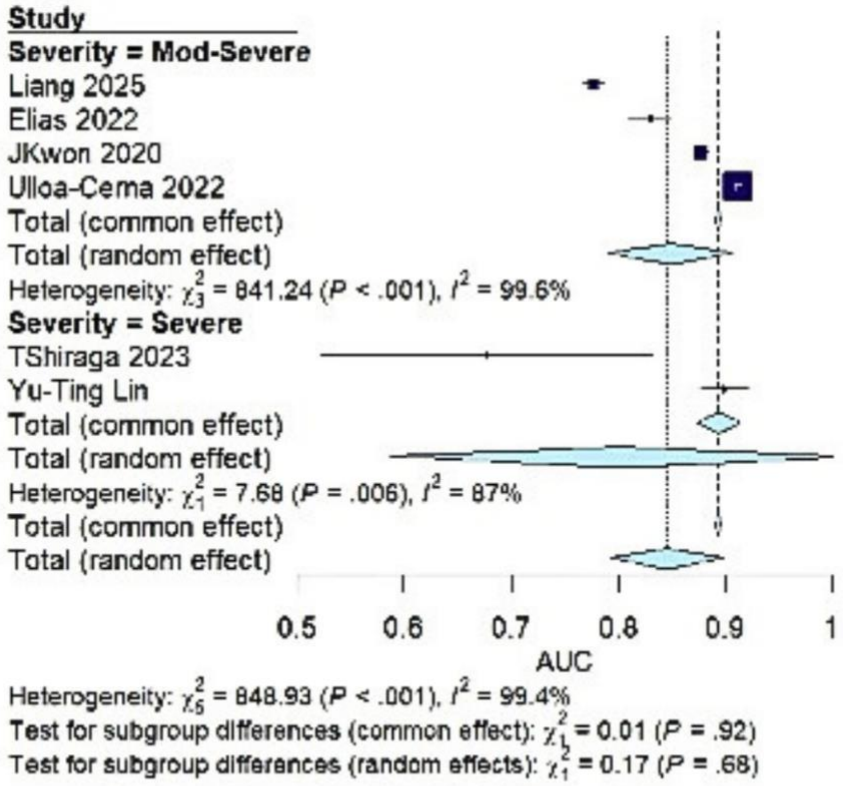


Figure 4: Diagnostic accuracy for Mitral Regurge (MR).

. Sensitivity Analysis

sensitivity analyses have done by excluding studies with elevated risk or small sample sizes (e.g., Shiraga et al.[15]). Removing these studies reduced heterogeneity and provided more precise pooled estimates, supporting the reliability of our main findings .

For Aortic Stenosis (AS), the pooled AUC is steady at 0.85 (95% CI: 0.84–0.86), with a slight reduction in heterogeneity (I^2 = 80.9%) and there are no significant differences between severity subgroups (P = 0.57).

For Mitral Regurgitation (MR), the pooled AUC also stayed high at 0.85; but , with high heterogeneity (I^2 = 99.5) even after removing the small study, and there are no significant differences between severity subgroups (P = 0.11).

. Subgroup Comparisons: Model & Modality

. Deep Learning (DL) models outperformed traditional Machine Learning (ML), with pooled AUCs of 0.87 vs. 0.72, showing a borderline significant difference (P = 0.054). This reflects DL's ability to extract complex features from raw ECG data.

. 12-Lead vs. Single-Lead ECG
Models using 12-lead ECGs achieved higher pooled AUCs (0.89) than single-lead models (0.81). The difference was not statistically significant (P = 0.26), due to the small number of single-lead studies (k = 3) which reduces the statistical power to detect a significant difference .

A hybrid approach (ECG + Demographics)

A qualitative review of the included studies shows the value of demographic integration. Specifically, studies by (Vaid et al. [10]and Lin et al[8]) demonstrated that adding age and sex to the AI model results in a modest but significant improvement in AUC, compared to ECG-only models.

. Publication Bias

The following funnel plots for aortic stenosis, mitral regurgitation, and aortic regurgitation show symmetrical distribution of studies. These observations were supported by Egger's regression test, which found no significant evidence of publication bias across the analyzed groups (P > 0.05 for all). However, these findings should be interpreted with caution owing to the limited number of included studies (**Figure 5 (a-c))**

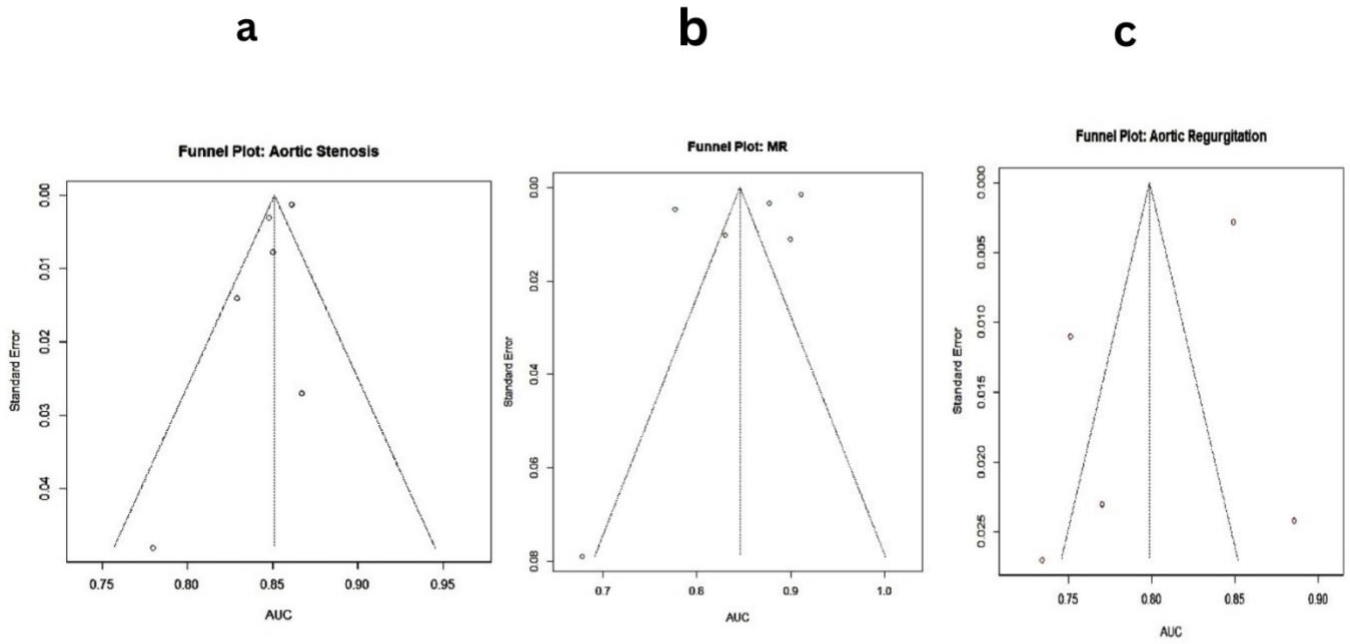


Figure 5 (a-c) : Funnel plots for aortic stenosis, mitral regurgitation, and aortic regurgitation show symmetrical distribution of studies.

Discussion

our results show that AI-ECG is effective in detecting valvulalar heart diseases especially in Aortic Stenosis (AS) and Mitral Regurgitation (MR), compared to Aortic Rgurgitation[4,7].

The variability in diagnostic accuracy across different valvular lesions owing to their hemodynamic and electrophysiological consequences.

Aortic Stenosis leads to a chronic pressure overload on the left ventricle, leading to increased wall tension,concentric hypertrophy (LVH). So, repolarization abnormalities (e.g., strain patterns) [7]. These structural changes create a strong, consistent electrical signature that is easily detected by AI algorithms, even in the absence of overt criteria for LVH.
In contrast, Aortic and Mitral Regurgitation induce volume overload, leading to eccentric hypertrophy and chamber dilatation [1]. The electrical changes of diffuse dilatation are often more subtle and heterogeneous compared to the distinct hypertrophy of pressure overload, what explains the slightly lower sensitivity observed in AR and MR compared to AS.

The AI models detected Severe AR with higher accuracy than Moderate-to-Severe cases [8]. This supports the hypothesis that deep learning models do not detect the valve defect itself, but rather the cumulative myocardial remodeling caused by the disease. As severity progresses, the structural and electrical "footprint" of the disease becomes more pronounced, enhancing the algorithm's discrimination capability[7,8].

Our subgroup analysis shows that deep learning(DL) outperforms traditional machine learning approaches .

Deep learning (DL) models, such as Convolutional Neural Networks (CNNs) used by Lin et al[8]. and Cohen-Shelly et al.[7], and Multi-Layer Perceptrons (MLP) used by Kwon et al.[2], analyze raw waveform data. This allows them to automatically learn a vast number of complexes, non-linear features, capturing subtle alterations in depolarization and repolarization that are not discernible to the human eye.

Traditional Machine Learning models(e. g:Random Forest and XGBoost) used by Shiraga et al.[15] and Sawano et al.[16], show lower accuracy (AUC ~0.65–0.75). Owing to ML relies on "hand-crafted" features (e.g., QRS duration, QT interval), which may fail to capture the full complexity of the structural remodeling associated with VHD.

Our study concentrated on the ECG signal's raw diagnostic power; however, a hybrid approach that combines AI-ECG characteristics with patient's demographics will be a better screening model[8,10].

Comparison with Previous Studies

The findings of this meta-analysis are consistent with the results reported in major individual validation cohorts, supporting the generalizability of AI-ECG across different populations.

Aortic Stenosis Consistency:

Our results show the pooled AUC of 0.85 for aortic stenosis mirrors the findings with Cohen-Shelly et al[7]. study (AUC 0.85) and the independent validation by Kwon et al[3]. (AUC 0.86). This consistency across US and Asian cohorts suggests that the ECG features of AS (e.g., pressure overload patterns) are strong enough and can be reliably detected by AI models regardless of patient ethnicity.

Resolving Discrepancies in Mitral Regurgitation:

In contrast, for mitral regurgitation, there is variability in results among studies , with Ulloa-Cerna et al[4]. Shows a high AUC of 0.91, while smaller studies like Shiraga et al[15]. Shows significantly lower performance (AUC ~0.68). Our pooled analysis clarifies this discrepancy (AUC = 0.85) which suggests that while AI is highly effective for MR, its performance is more sensitive to sample size and training data quality than for AS.

The "Severity Gap" Novelty:
Most individual studies have analyzed valvular disease as a binary outcome (Present/Absent). A unique contribution of our review is systematic stratification by severity. While Lin et al[8]. individually noted better performance in severe cases, our meta-analysis generalizes this finding, confirming statistically (P=0.003for AR) that AI models are significantly more sensitive to the structural remodeling associated with severe disease compared to moderate forms.

Architecture Comparison:

Through subgroup analysis results confirm the superiority of Deep Learning (AUC 0.87) over Machine Learning (AUC 0.72). This finding is consistent with the hypothesis proposed by Kwon et al[2].and lin et al.[8], who suggested that hand-crafted features (used in ML) fail to capture the rich, non-linear complexity of the raw ECG signal that CNNs can extract.

Although 12-lead ECGs offer higher sensitivity through more comprehensive spatial information, single-lead models still show good accuracy (AUC ≈ 0.81). This supports the use of wearable single-lead devices as practical first-line screening tools in the community[2,8], identifying high-risk individuals for confirmatory 12-lead ECG and echocardiography[7,17].

Strengths and Limitations.

With respect to publication bias, there's no significant asymmetry across our results for the tested all three valvular lesions, supporting the validity of it . However, cautions should be taken for these results because of the limited number of studies available for each subgroup analysis.

Conclusion

AI-enabled ECG will be a powerful, low-cost screening tool for valvular heart disease[2,16], especially for sever lesion, more especially for severe aortic stenosis[3]. Deep learning algorithms based on 12-lead ECGs models with highest performance in comparison to screening tests used in other medical disciplines[3,7]. Future efforts should focus on hybrid models incorporating patient demographics and validate these approaches in the community settings to create early referral for echocardiography.

Conflict of interest : Non to declare

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