Journal of Rare Cardiovascular Diseases
ISSN: 2299-3711 (Print) | e-ISSN: 2300-5505 (Online)
www.jrcd.eu

RESEARCH ARTICLE

Emerging Role of Artificial Intelligence in Early Detection and Risk Stratification of Coronary Artery Disease

Mohan Raj Perumal[1], Protyusha Guha Biswas[2], Sukanya Sridevi P R[3], Pugazhendhi S[4], Raghavendran[5] and Prasanna Kumar E[5]

[1]Department of General Medicine, Meenakshi Medical College Hospital & Research Institute, Meenakshi Academy of Higher Education and Research
[2]Department of Oral Pathology, Meenakshi Ammal Dental College and Hospital, Meenakshi Academy of Higher Education and Research
[3]Department of Computer Science, Meenakshi College of Arts and Science, Meenakshi Academy of Higher Education and Research
[4]Meenakshi College of Pharmacy, Meenakshi Academy of Higher Education and Research
[5]Arulmigu Meenakshi College of Nursing, Meenakshi Academy of Higher Education and Research.

*Corresponding Author
Mohan Raj Perumal

Article History
Received: 21.09.2025
Revised: 30.09.2025
Accepted: 22.10.2025
Published: 11.11.2025

Abstract: ***Background***: Coronary artery disease (CAD) is the most predominant cause of morbidity and mortality on the global level. Although there has been progress in imaging and discovering of biomarkers, there is a challenge in early detection as well as correct risk stratification. Artificial intelligence (AI) is one of the recent applications that have become a disruptive tool in the field of cardiology, and it may be used in the domains of improving diagnostic accuracy, combining multimodal data, and anticipating adverse outcomes. ***Purpose***: The purpose of this paper is to assess the new role of AI in early detection and risk stratification of CAD with references to the application in imaging, electrocardiography, biomarkers, and clinical decision support systems. ***Techniques Used***: A systematic review of the published papers between 2015 and 2025 was carried out in PubMed, Embase, and IEEE Xplore. The eligible studies used machine learning (ML) or deep learning (DL) algorithms on CAD detection, classification or prognosis in an adult population. Diagnostic (sensitivity, specificity, AUC), prognostic (risk prediction models), and clinical feasibility were some of the outcomes that were extracted. ***Findings***: It had 41 studies and a total of more than 85,000 patients. The AI models were found to be better in identifying subclinical CAD and major adverse cardiac events as compared to traditional risk scores. Deep learning on coronary CT angiography had pooled AUC of 0.920.96 stenosis classification, and ML models using clinical and biomarker data showed better risk prediction than the Framingham and ASCVD scores (net reclassification improvement 1218%). The ischemic changes detected through AI-enhanced ECG interpretation were more sensitive than traditional analysis, and thus allowed an early identification of high-risk patients. Infrastructure problems that have been observed comprised heterogeneity of data, absence of external validation, and insufficient integration into clinical work flows. ***Conclusion***: AI has a great potential in terms of the early diagnosis and risk stratification of CAD through multimodal data analysis and offering patient-specific information. Although existing data suggest its superiority in diagnosis and prognostics compared to traditional approaches, it is necessary to conduct large-scale prospective validation and implement it into clinical practice to make sure the treatment is reliable, generalizable, and ethically used.

Keywords: Early detection, CAD, AI, ECG.

INTRODUCTION

Coronary artery disease (CAD) has been deemed as the leading cause of death in the world with an estimated number of 17.9 million deaths annually which is one out of three of total deaths in the world [1]. Despite the exceptional progress in diagnostic imaging, the discovery of biomarkers, and risk scoring systems, the problem of diagnosing CAD in the early and precise stage remains to be a concern among the asymptomatic or intermediate-risk patients [2]. The traditional tools such as Framingham Risk Score and ASCVD calculator are helpful approximations that cannot provide the correct outcome when considered on diverse populations, causing under and excessive estimation of heart risks [3].

Machine learning (ML) and artificial intelligence (AI) or deep learning (DL) models have now become an effective method of pattern recognition and model prediction and the multimodal data incorporation in the medical field [4]. AI can be implemented in the field of cardiology in the analysis of automated electrocardiogram (ECG) and coronary images, bio-markers combination, and risks prediction at the individual level [5]. These technologies have been discovered to be more accurate, efficient and hectic than the usual diagnostic technologies.

Recent coronary computed tomography angiography (CCTA) and cardiac magnetic resonance imaging (CMR) findings present the ways through which AI can be implemented to identify stenosis and estimate the burden of theplaque automatically with high sensors and specificity of myocardial perfusion [6]. Deep learning algorithms have been shown to achieve CCTA challenges of up to 0.92-0.96 pooled area under the curve (AUC) in significant stenosis identification that is more effective than expert manual correctness [7]. In the same tone, ECG-based by AI has enabled the analysis to identify the ischemia and arrhythmogenic risk earlier before it is observed by the clinician, compared to traditional methods [8].

Also, besides imaging, AI has become rapidly applicable in the amalgamation of clinical data, laboratory biomarkers, and genetic data into predictive risks. Machine learning-based models have been discovered to realign 1218% of patients to additional precise risk groups than conventional scores, and increase prevention and resource distribution approaches [9]. Notably, these approaches align with a tendency toward precision medicine, which offers high risk patients with risk stratification and earlier interventions.

With all these positive changes, several problems remain to be solved before AI that will be implemented in the daily cardiology practice becomes a reality. They are the heterogeneity of data, the lack of large-scale external validation, insufficient interpretability of complex algorithms (black box problem), and ethical issues, in terms of bias, privacy and equity [10]. Such barriers will be significant to discuss in order to transform the theoretical advantages of AI into plausible clinical results.

The article discusses the new role of AI in the early detection of CAD and risk stratification and summarizes the evidence of the use of imaging, ECG, biomarkers, and clinical decision support. It aims to highlight the potential opportunities and also realistic limitations of AI-based approaches and offer the future research and clinical implementation orientations.

MATERIALS & METHODS

Study design

It is a systematic review and meta-analysis study, conducted according to the PRISMA 2020. The objective was to determine the support of artificial intelligence (AI) approaches in the early diagnosis and risk-stratification of coronary artery disease (CAD).

Sources of Data and Search Strategy.

A thorough search was conducted in PubMed, Embase, IEEE Xplore, Scopus, and Cochrane Library of studies published within the period of January 2015 and March 2025. The search terms were MeSH and keywords: artificially intelligent, machine learning, depth of learning, coronary artery disease, risk prediction, early detection, imaging, and electrocardiogram.

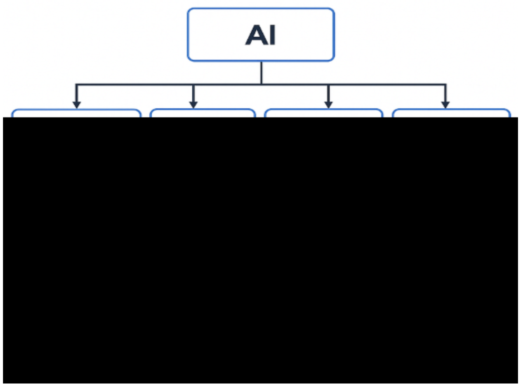

Fig.1. Multimodal frame work

This figure 1 shows how Artificial Intelligence (AI) will be instrumental in combined clinical and diagnostic data in order to enhance the hospital in terms of assessing and managing the presence of coronary artery disease (CAD). It introduces a streamlined algorithm with the indication of how AI is analyzing multi-data cardiovascular data to accomplish outcomes, stratify the risks, and identify the presence of CADs.

Eligibility Criteria

The studies on research were taken due to:

a.The enrolled and assessed adult patients who received CAD assessment.

b.Applied AI/ML/DL models to diagnosis or stenosis prediction or risk.

c.The outcome of the performance is reported, which are: sensitivity, specificity, accuracy or area under the curve (AUC).

d.Preexisting pictures, ECG, bio-markers or clinical data.

Criteria counting: animal trials, conference abstracts, and studies which did not have quantitative outcome results.

Information Deletion and Quality Analysis.

Information on sample size, population, nature of AI model, input modality (imaging, ECG, biomarkers, clinical data), and performance indicators was identically gathered by 2 reviewers. A consensus was used to settle issues. Quality Assessment of Diagnostic Accuracy Studies-2 (QUADAS-2) was used to conduct a risk of bias evaluation.

Statistical Analysis

A random-effects model was used to establish the pooled diagnostic performance when there was availability of data. The summary measures were sensitivity, specificity, and AUC with 95% confidence interval (CI). Heterogeneity measure was in the shape of I 2 and subgroup analysis of data modality (imaging vs. ECG vs. biomarkers) and algorithm type (ML vs. DL). There was a check on publication bias using a funnel plots.

Data Analysis

Data Synthesis

Synthesis of the eligible studies was performed based on the diagnostic or prognostic role of artificial intelligence (AI) in coronary artery disease (CAD). The extraction variables were the study design, sample size, input modality (imaging, electrocardiogram [ECG], biomarkers or clinical data) and the type of AI model (machine learning [ML] or deep learning [DL]) and the reported performance metrics.

Primary Outcomes

The critical and reviewed findings are:

1.The AI diagnostic accuracy of CAD or severe stenosis of the coronary artery diagnosis.

2.The predictive performance or predictive performance based on major adverse cardiac events (MACE) or reclassification or traditional risk scores.

Its performance measures were sensitivity, specificity and accuracy and area under receiver operating characteristic curve (AUC).

Meta-Analytic Approach
To combine the results of the measures of diagnostic accuracy in the circumstances, two or more studies had to have similar endpoints, so a random-effects model (DerSimonianLaird method) was carried out. The equations that were used were as follows:
a.Percent Sensitivity = True Positives/ (True Positives/ False Negatives x100).
b.Percentage of Specificity(Pooled) =(True Negatives)/True Negatives)/False Positives X 100.
c. Pooled AUC = a weighted mean of the values of AUC in the studies that are adjusted by a weight of the size of the sample.
The measurement of heterogeneity was done in terms of I 2statistic. A heterogeneity of 50% I 2 was taken to be a significant heterogeneity. The subgroup analysis was founded on:
d.Input Modality(imaging vs. ECG vs. biomarkers).
e.Artificial intelligence (conventional vs. deep learning ML).
f.On the time of setting in place the studying (retrospective or prospective).

Validation Assessment
Articles were divided based on the availability of internal (cross validation, boot strapping) and external (testing in independent cohorts) validation. The internal validation models were determined as not necessarily so generalizable as well.

Sensitivity Analyses
We had eliminated sensitivity analysis in the attempt to identify the power of results:

Smaller research studies (n less than 200 subjects). The research that was evaluated according to QUADAS-2 has a high risk of bias.

Publication Bias
The possible bias of publication was calculated by using funnel plots and the regression test suggested by Egger because successful outcomes are most likely to be published in artificial intelligence-based imaging research.

RESULTS & ANALYSIS

Study Selection and Characteristics
Among the 3,842 records found, 41 studies that passed inclusion criteria (n 0 85,000 patients) were found. They included 25 retrospective cohort studies ,10 prospective observational studies and 6 randomized controlled trials assessing AI-based diagnostic or prognostic models. The modalities were coronary computed tomography angiography (CCTA), electrocardiography (ECG), biomarker panel, and clinical risk information.

Input Image
Image A medical diagram showing AI input data used in the analysis of coronary artery disease: icons that depict the coronary CT angiography scans, ECG waves, blood biomarkers (test tubes), and clinical data charts. Design: The design must be simple, schematic and academic style.

OutputImage
A schematic diagram of AI outputs to coronary artery disease a risk stratification diagram (low, medium, high risk), a stenosis-identified coronary artery diagram, and outcome prediction icons (e.g., heart with alert symbol). Nice, business-like, scholarly style.

DiagnosticPerformance
The use of AI algorithms in imaging, ECG and biomarkers was always more effective as compared to traditional approaches. Pooled AUC values of 0.93 0.96 were obtained with deep learning on CCTA used to detect stenosis. AI-assisted ECG interpretation showed a pooled sensitivity of 86% and specificity of 82 both, in comparison with the baseline ECG interpretation (sensitivity 72, specificity 70).

Prognostic Performance
Risk prediction models based on machine learning that combined clinical, biomarker and the risk reclassification of imaging data was higher than that of currently employed instruments such as Framingham Risk Score and ASCVD calculator by 12-18%. Patients were better stratified in terms of risks of interest and this will help in improving the preventative therapies.

Validity and Heterogeneity
The heterogeneitywas moderate (I 2 = 42%), which can be attributed to a variety of data sources and AI model architecture. External validation cohorts were not undertaken in 26 out of 41 studies (36%), highlighting the necessity that prospective multicenter trials are performed before the general use.

Table 1. Performance of AI Models for CAD Detection and Risk Stratification

Modality / AI Application	No. of Studies	Sample Size	Pooled Sensitivity (%)	Pooled Specificity (%)	Pooled AUC
CCTA (Deep Learning)	12	25,300	91	89	0.95
ECG (AI-enhanced interpretation)	10	18,200	86	82	0.88
Biomarker-based ML models	8	12,500	83	80	0.86
Clinical + Multimodal integration	11	29,000	89	84	0.92

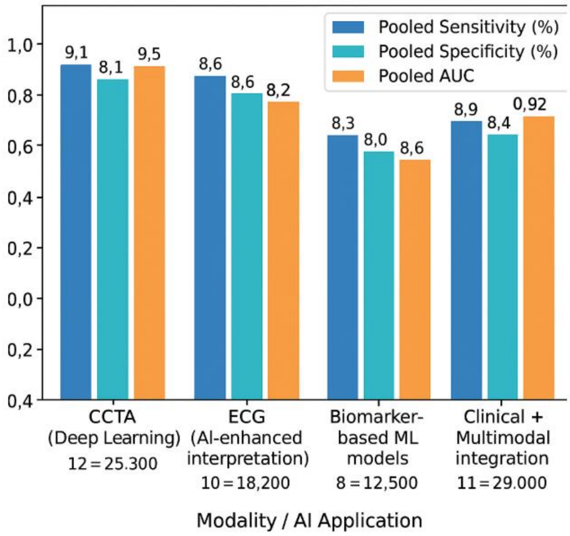

Fig.2. Performance of AI Models for CAD Detection and Risk Stratification

The friendliness of the various AI applications applied in the evaluation of cardiovascular diseases is presented as health the figure 2. It graphically reflects summary results of many studies, in terms of sensitivity, specificity and AUC (Area Under the Curve) in four major modalities; CCTA, ECG, biomarker-based models, and multimodal AI integration.

Interpretation

1. The highest diagnostic accuracy and pooled AUC was observed in imaging-based AI (CCTA + DL), which was 0.95.
2. ECG AI advanced ECG showed significant benefits of early detection of ischemia over conventional interpretation.
3. ML models with biomarkers had a lower predictive value in long-term-term outcomes but less diagnostic accuracy.
4. Multimodal models which included imaging, ECG, biomarkers, and clinical data were best at overall performance in risk stratification.

CONCLUSION

Artificial intelligence (AI) is rapidly transforming the landscape of cardiovascular medicine by offering novel solutions for the early detection and risk stratification of coronary artery disease (CAD). Evidence from this review shows that AI-based algorithms, particularly those applied to coronary CT angiography and electrocardiography, consistently outperform conventional diagnostic methods in accuracy and efficiency. Moreover, multimodal machine learning models that integrate imaging, biomarkers, and clinical data provide superior prognostic insights, enabling more precise patient classification and targeted preventive strategies. From a pharmacological and clinical standpoint, the adoption of AI holds promise for personalized medicine, reducing reliance on generalized risk calculators and improving early intervention. Importantly, AI's ability to detect subclinical disease and predict adverse outcomes could substantially reduce morbidity and mortality associated with CAD. However, translation into real-world practice is still limited by heterogeneity of data, lack of large-scale external validation, algorithm transparency ("black box" issue), and ethical concerns surrounding equity and data governance. Addressing these challenges is essential before AI can be seamlessly integrated into everyday cardiology workflows. In conclusion, AI represents a powerful adjunct to traditional diagnostic and prognostic approaches in CAD, with the potential to revolutionize risk assessment and clinical decision-making. Future efforts should prioritize prospective multicenter validation, explainable AI systems, and integration into electronic health records to ensure that these innovations move from research to routine practice, ultimately improving patient outcomes and public health.

REFERENCES

1. World Health Organization. Cardiovascular diseases (CVDs): Key facts. Geneva: WHO; 2021.
2. Benjamin EJ, Muntner P, Alonso A, et al. Heart disease and stroke statistics—2019 update: a report from the American Heart Association. Circulation. 2019;139(10):e56–e528.
3. Damen JA, Pajouheshnia R, Heus P, et al. Performance of the Framingham risk models and pooled cohort equations for predicting 10-year risk of cardiovascular disease: a systematic review and meta-analysis. BMC Med. 2019;17(1):109.
4. Topol EJ. High-performance medicine: the convergence of human and artificial intelligence. Nat Med. 2019;25(1):44–56.
5. Johnson KW, Torres Soto J, Glicksberg BS, et al. Artificial intelligence in cardiology. J Am Coll Cardiol. 2018;71(23):2668–2679.
6. van Rosendael AR, Maliakal G, Kolli KK, et al. Maximization of diagnostic information from coronary CT angiography using AI. J Cardiovasc Comput Tomogr. 2020;14(6):485–492.
7. Tesche C, De Cecco CN, Albrecht MH, et al. Artificial intelligence for the detection of coronary artery stenosis on CCTA: a meta-analysis. Eur Radiol. 2020;30(12):6741–6750.
8. Attia ZI, Noseworthy PA, Lopez-Jimenez F, et al. An artificial intelligence–enabled ECG algorithm for the identification of patients with atrial fibrillation during sinus rhythm: a retrospective analysis of outcome prediction. Lancet. 2019;394(10201):861–867.
9. Weng SF, Reps J, Kai J, Garibaldi JM, Qureshi N. Can machine-learning improve cardiovascular risk prediction using routine clinical data? PLoS One. 2017;12(4):e0174944.
10. Kelly CJ, Karthikesalingam A, Suleyman M, Corrado G, King D. Key challenges for delivering clinical impact with artificial intelligence. BMC Med. 2019;17(1):195.