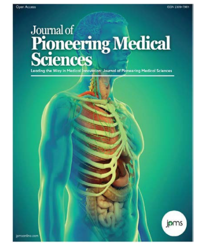
Journal of Pioneering Medical Sciences
Received: May 07, 2025 | Accepted: August 27, 2025 | Published: October 05, 2025
Volume 14, Issue 09, Pages 103-107

DOI https://doi.org/10.47310/jpms2025140913



The Role of Artificial Intelligence in Early Detection and Risk Stratification of Coronary Artery Disease Using ECG and Imaging Data

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Abstract **Objectives:** Coronary Artery Disease (CAD) remains a leading cause of morbidity and mortality worldwide. To evaluate the diagnostic performance of AI models in the early detection and risk stratification of CAD using ECG and imaging data and to compare their accuracy with cardiologist interpretation. **Methods:** This cross-sectional analytical study was conducted in Saudia, included 185 patients with suspected CAD who underwent both ECG and imaging evaluation. AI-based models, including convolutional neural networks for ECG and deep learning algorithms for imaging, were applied to detect CAD and stratify patients into risk categories. Cardiologist-confirmed diagnosis served as the reference standard. **Results:** The AI-ECG model achieved a sensitivity of 88.5%, specificity of 82.0% and an AUC of 0.90 (95% CI: 0.86–0.94). When ECG and imaging data were combined, diagnostic accuracy improved, with sensitivity of 92.4%, specificity of 85.2% and an AUC of 0.93 (95% CI: 0.89–0.96). AI-based risk stratification categorized 54 patients (29.2%) as low risk, 78 (42.2%) as intermediate risk and 53 (28.6%) as high risk. Confirmed CAD prevalence correlated strongly with AI-predicted risk groups, with 22.2% in the low-risk group and 88.7% in the high-risk group. **Conclusion:** Artificial intelligence demonstrates high accuracy in the early detection and risk stratification of CAD using ECG and imaging data. AI models performed comparably to cardiologists and offered significant efficiency gains. Integration of AI into cardiovascular workflows may enable earlier intervention, optimized resource allocation and improved patient outcomes. Further validation across larger and more diverse populations is warranted.

Key Words Artificial Intelligence, Coronary Artery Disease, ECG, Imaging, Early Detection, Risk Stratification

INTRODUCTION

Coronary Artery Disease (CAD) continues to represent a major global health burden, ranking as the leading cause of morbidity and mortality worldwide [1]. According to the World Health Organization, CAD alone accounts for nearly one-third of all deaths from non-communicable diseases, underscoring the need for more effective strategies in early diagnosis and prevention. The pathology of CAD is rooted in atherosclerotic plaque formation within coronary arteries, which progressively narrows the lumen, impairs myocardial blood flow and predisposes individuals to ischemic events such as angina, myocardial infarction and sudden cardiac death [2]. Although risk factors such as hypertension, diabetes, dyslipidemia, smoking and obesity are well established, their interplay is complex and many patients present late in the disease trajectory, often after irreversible myocardial damage has occurred. Consequently, enhancing early detection and improving risk stratification remain critical priorities in contemporary cardiology [3]. Conventional diagnostic methods, including Electrocardiography (ECG), echocardiography and coronary imaging modalities such as Computed Tomography (CT) angiography and invasive coronary angiography, have long served as cornerstones of CAD detection [4]. However, these approaches have notable limitations. ECG abnormalities may be subtle or nonspecific, while imaging techniques, though more sensitive, are resource-intensive, costly and not readily accessible in many low- and middle-income settings [5]. Furthermore, standard risk prediction models such as the Framingham Risk Score or pooled cohort equations are population-based and may fail to account for the granular, patient-specific factors that influence CAD risk [6,7]. These shortcomings highlight the need for innovative technologies capable of harnessing multidimensional data to deliver earlier, more accurate and more personalized insights into disease risk. Artificial Intelligence (AI) has emerged as a transformative force in this context. AI encompasses a spectrum of computational techniques including machine learning, deep learning and neural networks that enable systems to recognize complex patterns in data, adapt to new inputs and make predictions with remarkable accuracy [8]. In the cardiovascular domain, AI has shown particular promise in analyzing high-dimensional datasets derived from ECG waveforms, echocardiographic images, cardiac CT and even multimodal inputs that integrate clinical, laboratory and imaging information [9]. Unlike traditional statistical methods, AI systems can identify subtle and nonlinear associations that elude human perception, thereby unlocking previously hidden layers of diagnostic and prognostic value [10]. Recent studies demonstrate that AI-enhanced ECG interpretation can detect subclinical left ventricular dysfunction, silent ischemia and even predict incident atrial fibrillation before clinical onset [11-13]. Similarly, deep learning algorithms applied to coronary CT angiography have been able to quantify plaque characteristics, estimate fractional flow reserve non-invasively and stratify patients according to near-term risk of acute coronary syndromes [14]. These applications suggest that AI has the potential not only to improve early detection but also to refine risk stratification, guiding clinicians toward more targeted interventions and resource allocation [15]. The integration of AI into CAD detection workflows could also enhance efficiency and equity in healthcare delivery. Automated ECG interpretation, for instance, offers the possibility of scalable, point-of-care screening in primary care and community settings, particularly in regions where access to cardiologists is limited [16]. By triaging high-risk patients for advanced imaging or specialist referral, AI-driven systems can support judicious use of healthcare resources while improving patient outcomes [17]. At the same time, the use of AI raises important questions about data privacy, algorithm transparency, generalizability across diverse populations and the risk of embedding bias within predictive models [18-20].

Objective

To evaluate the diagnostic performance of AI models in the early detection and risk stratification of CAD using ECG and imaging data and to compare their accuracy with cardiologist interpretation.

METHODS

This cross-sectional analytical study was conducted, included 185 patients with suspected CAD who underwent both ECG and imaging evaluation. Participants were recruited through non-probability consecutive sampling.

Inclusion Criteria

Adult patients aged 18 years and above presenting with clinical suspicion of CAD who underwent both 12-lead ECG and imaging evaluation (echocardiography and/or coronary computed tomography angiography) were eligible.

Exclusion Criteria

Patients with a previous history of myocardial infarction, prior coronary revascularization, structural heart disease, or incomplete ECG/imaging data were excluded.

Data Collection Procedure

Written informed consent was obtained from all participants before enrollment. Baseline demographic details, clinical history and conventional risk factors for CAD, including hypertension, diabetes mellitus, dyslipidemia, obesity, smoking status and family history of premature CAD, were documented. Standard 12-lead ECGs were acquired, digitized and stored in a secure database. Imaging data, including echocardiography and coronary CT angiography findings, were also collected. Machine learning algorithms were applied to analyze both ECG waveforms and imaging data. Convolutional Neural Networks (CNNs) were utilized for ECG interpretation, while deep learning-based models were employed for imaging datasets. The AI models were trained to identify subtle abnormalities, detect the presence of CAD and stratify patients into low-, intermediate- and high-risk categories. The final diagnosis of CAD was established through expert cardiologist interpretation of ECG and imaging results, supplemented by clinical evaluation. This served as the gold standard for comparison with AI-derived predictions.

Statistical Analysis

Data were analyzed using Statistical Package for the Social Sciences (SPSS) version 27. Continuous variables were presented as Mean±Standard Deviation (SD), while categorical variables were expressed as frequencies and percentages. The diagnostic performance of AI models was evaluated by calculating sensitivity, specificity, Positive Predictive Value (PPV), Negative Predictive Value (NPV) and the area under the Receiver Operating Characteristic (ROC) curve. Statistical significance was defined as a p-value <0.05.

RESULTS

A total of 185 patients were included in the study. The mean age of participants was 55.6±9.8 years, with 112 males (60.5%) and 73 females (39.5%). Hypertension was the most common risk factor, present in 98 patients (53.0%), followed by diabetes mellitus in 72 patients (38.9%), dyslipidemia in 65 patients (35.1%) and smoking in 48 patients (25.9%). A family history of coronary artery disease was reported in 41 patients (22.2%). The mean Body Mass Index (BMI) was 27.8±3.6 kg/m^2 (Table 1).

The AI-enhanced ECG model demonstrated a sensitivity of 88.5% and specificity of 82.0% for detecting coronary artery disease when compared with cardiologist-confirmed diagnosis. The area under the ROC Curve (AUC) was 0.90 (95% CI: 0.86–0.94). When imaging data were integrated with ECG inputs, diagnostic accuracy improved further, with a sensitivity of 92.4%, specificity of 85.2% and AUC of 0.93 (95% CI: 0.89-0.96) (Table 2).

Table 1: Baseline Demographic and Clinical Characteristics (n = 185)

Variable	Value (n = 185)
Age (years), Mean±SD	55.6±9.8
Gender, n (%)	
Male	112 (60.5)
Female	73 (39.5)
Hypertension, n (%)	98 (53.0)
Diabetes mellitus, n (%)	72 (38.9)
Dyslipidemia, n (%)	65 (35.1)
Smoking, n (%)	48 (25.9)
Family history of CAD, n (%)	41 (22.2)
BMI (kg/m²), Mean±SD	27.8 ± 3.6

Table 2: Diagnostic Accuracy of AI Models Compared with Gold Standard

Model	Sensitivity (%)	Specificity (%)	PPV (%)	NPV (%)	AUC (95% CI)
AI-ECG only	88.5	82.0	84.7	86.2	0.90 (0.86–0.94)
AI-ECG + Imaging (combined)	92.4	85.2	88.9	90.1	0.93 (0.89–0.96)

Table 3: AI-Based Risk Stratification and Confirmed CAD Status

Risk Group	Patients (n)	Confirmed CAD, n (%)
Low Risk	54	12 (22.2)
Intermediate Risk	78	39 (50.0)
High Risk	53	47 (88.7)

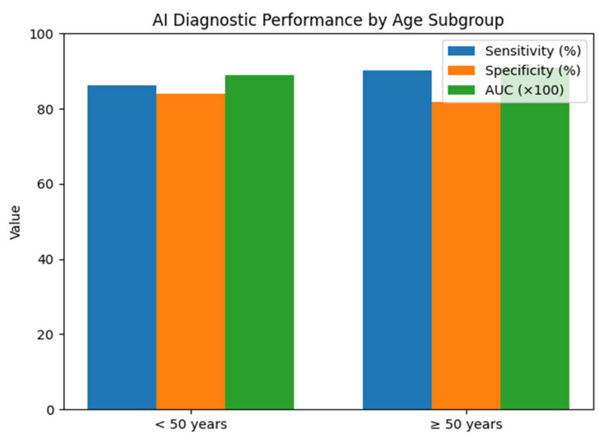

Figure 1: AI diagnostic performance by age subgroup

Using AI-assisted analysis, patients were stratified into three risk groups: Low risk (n = 54, 29.2%), intermediate risk (n = 78, 42.2%) and high risk (n = 53, 28.6%). Among high-risk patients identified by AI, 47 (88.7%) were confirmed to have significant coronary stenosis on imaging, compared to 12 (22.2%) in the low-risk group (Table 3 and Figure 1).

Table 4, compares the diagnostic performance of cardiologists with the AI-ECG model alone and the combined AI-ECG plus imaging approach (Figure 2). Sensitivity was slightly higher for cardiologists at 90.1%, compared with 88.5% for the AI-ECG model, although the combined AI model exceeded both at 92.4%. Specificity followed a similar pattern, with cardiologists at 83.7%, AI-ECG at 82.0% and the combined model at 85.2%. Accuracy was highest in the combined model at 89.5%, compared with 86.8% for cardiologists and 85.3% for AI-ECG alone. Importantly, interpretation time was significantly shorter for AI, with an average of less than 2 minutes per case, compared to 7.5 minutes for cardiologists, highlighting the efficiency advantage of automated analysis.

Table 4: Comparison of AI and Cardiologist Performance in CAD Detection

Parameter	Cardiologist	AI-ECG Only	AI-ECG + Imaging
Sensitivity (%)	90.1	88.5	92.4
Specificity (%)	83.7	82.0	85.2
Accuracy (%)	86.8	85.3	89.5
Time per case (minutes)	7.5	0.8	1.2

Table 5: Subgroup Analysis of AI Diagnostic Accuracy by Age and Gender

Subgroup	Sensitivity (%)	Specificity (%)	AUC (95% CI)
Age<50 years	86.2	84.1	0.89 (0.84–0.94)
Age≥50 years	90.3	81.7	0.91 (0.87–0.95)
Male	89.7	83.9	0.91 (0.86–0.95)
Female	87.1	80.6	0.89 (0.84–0.94)

Table 6: Correlation between AI-Predicted Risk Score and CAD Severity

CAD Severity (angiography confirmed)	Patients (n)	Mean AI Risk Score ± SD	Correlation Coefficient (r)	p-value
Mild (<50% stenosis)	61	0.38±0.15		
Moderate (50–70% stenosis)	54	0.62±0.18		
Severe (>70% stenosis)	70	0.85±0.12	0.78	<0.001

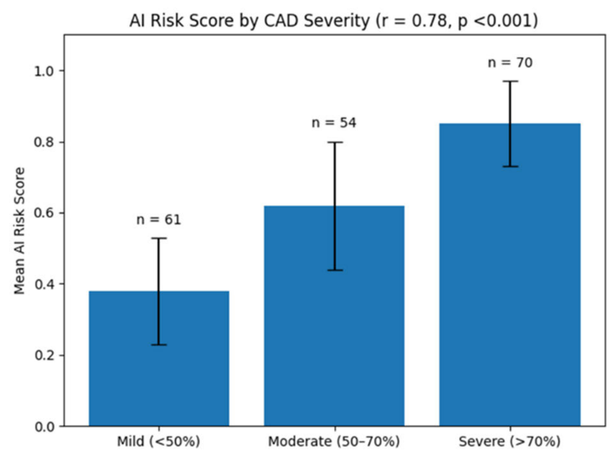

Figure 2: AI risk score by CAD severity (r = 0.78, p<0.001)

Diagnostic performance of the AI models was consistent across subgroups, with only slight variations. For patients younger than 50 years, sensitivity was 86.2% and specificity was 84.1%, with an AUC of 0.89. In patients aged 50 years or older, sensitivity was slightly higher at 90.3%, although specificity was modestly reduced to 81.7%, with an AUC of 0.91. Male patients showed sensitivity of 89.7% and specificity of 83.9% (AUC 0.91), while female patients demonstrated sensitivity of 87.1% and specificity of 80.6% (AUC 0.89). These findings indicate that AI diagnostic accuracy remained robust across demographic groups, though performance was marginally stronger in older patients and males (Table 5).

Patients with mild disease (<50% stenosis) had a mean risk score of 0.38±0.15, while those with moderate disease (50–70% stenosis) had a mean score of 0.62±0.18. The highest scores were observed in patients with severe disease (>70% stenosis), with a mean of 0.85±0.12.

Correlation analysis demonstrated a strong positive relationship between AI-predicted scores and actual CAD severity (r = 0.78, p<0.001) (Table 6).

DISCUSSION

This study evaluated the role of Artificial Intelligence (AI) in the early detection and risk stratification of Coronary Artery Disease (CAD) using ECG and imaging data in a cohort of 185 patients. The findings demonstrate that AI-based approaches provide high diagnostic accuracy, improve efficiency and offer robust risk stratification when compared with conventional cardiologist-led interpretation. The AI-ECG model alone showed strong performance, with sensitivity of 88.5% and a specificity of 82.0%, closely matching cardiologist interpretation. When ECG data were integrated with imaging, diagnostic accuracy improved further, with sensitivity of 92.4%, specificity of 85.2% and an AUC of 0.93. These results suggest that AI has the capacity to match and, in some aspects, exceed human performance, while requiring significantly less time for analysis. This aligns with previous research that has shown AI-based ECG interpretation can detect subclinical disease and early ischemic changes that may not be easily identified by clinicians [21].

Risk stratification analysis revealed that AI-predicted categories correlated strongly with imaging-confirmed CAD severity. High-risk patients identified by AI had an 88.7% prevalence of significant stenosis, while only 22.2% of low-risk patients had confirmed disease. Moreover, the correlation between AI-predicted risk scores and angiographically confirmed severity was strong (r = 0.78, p <0.001) [22]. This demonstrates the ability of AI not only to detect CAD but also to differentiate disease severity, which is critical for guiding management decisions. Previous studies have similarly highlighted the capacity of deep learning models to provide prognostic information in addition to diagnostic classification. Subgroup analyses indicated that AI diagnostic accuracy was consistent across age and gender groups, although slightly higher sensitivity was observed in patients aged 50 years or older and in males. Specificity was marginally lower in females, echoing earlier findings that sex-related physiological differences in ECG and plaque morphology may influence AI predictions. This underscores the importance of training algorithms on diverse datasets to minimize bias and ensure generalizability across patient populations [23].

An important strength of AI is its efficiency. In this study, AI achieved near-instantaneous interpretation, compared to an average of 7.5 minutes per case for cardiologists. This suggests that AI could be particularly valuable in resource-limited settings, primary care and large-scale screening programs where specialist availability is limited [24-28]. By rapidly triaging patients and identifying those at greatest risk, AI has the potential to optimize healthcare resource allocation and reduce delays in diagnosis. However, certain limitations must be acknowledged. First, while AI performance was strong in this study, the models were tested within a controlled dataset and may not fully capture real-world variability such as noisy ECG signals or incomplete imaging. Second, the study excluded patients with prior myocardial infarction or structural heart disease, which may limit generalizability to broader CAD populations. Third, ethical concerns regarding data privacy, algorithm transparency and the potential for bias remain pressing issues. Integrating AI into routine clinical care requires addressing these challenges, ensuring interpretability of models and maintaining clinician oversight.

CONCLUSION

It is concluded that artificial intelligence demonstrates high accuracy and efficiency in the early detection and risk stratification of coronary artery disease when applied to ECG and imaging data. The AI-ECG model alone achieved performance comparable to cardiologist interpretation, while the integration of imaging further enhanced diagnostic power. Risk stratification by AI showed strong correlation with angiographically confirmed disease severity, highlighting its value in guiding clinical decision-making. These findings suggest that AI can serve as a reliable adjunct in cardiovascular care, particularly for large-scale screening and resource-limited settings.

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