EFFICACY OF ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING ALGORITHMS IN THE EARLY DIAGNOSIS OF CARDIOVASCULAR DISEASES

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Abstract. Cardiovascular diseases (CVDs) remain the leading contributor to premature mortality and global disease burden. Early detection at the subclinical, asymptomatic stage is critical for timely therapeutic interventions and secondary prevention. This study provides an in-depth empirical evaluation of artificial intelligence (AI) and machine learning (ML) algorithms in early CVD detection utilizing digitized 12-lead electrocardiograms (ECGs) and multi-parametric clinical-biochemical biomarkers. We comparatively assessed Support Vector Machine (SVM), Random Forest (RF), eXtreme Gradient Boosting (XGBoost), and deep Convolutional Neural Networks (1D-CNN and ResNet architectures). The empirical results demonstrate that deep learning models achieve a remarkable diagnostic accuracy of 98.4% with an area under the receiver operating characteristic curve (AUC-ROC) of 0.992 in classifying complex cardiac arrhythmias. Furthermore, the ensemble XGBoost model surpassed traditional risk scoring systems (Framingham and SCORE2) by 11.4% in long-term cardiovascular risk stratification. Integrating these AI models into clinical decision support systems (CDSS) provides an objective, scalable, and highly accurate methodology for primary healthcare screening.

Keywords*: artificial intelligence, machine learning, cardiovascular diseases, electrocardiography, convolutional neural networks, early diagnosis, XGBoost, clinical decision support system, risk stratification.*

1. INTRODUCTION AND BACKGROUND

Cardiovascular diseases (CVDs) represent the most formidable public health challenge of the twenty-first century. According to the World Health Organization (WHO), CVDs claim approximately 17.9 million lives each year, accounting for nearly 32% of all global deaths. Of these fatalities, over 85% are precipitated by acute myocardial infarction and cerebrovascular stroke. In the Republic of Uzbekistan, circulatory system disorders similarly constitute the primary cause of adult morbidity, premature mortality, and permanent disability, posing substantial socioeconomic burdens on national healthcare infrastructure.

The clinical prognosis of cardiovascular conditions relies heavily on early detection. Pathological cascades—such as coronary atherosclerosis, myocardial remodeling,

microvascular ischemia, and occult paroxysmal arrhythmias—frequently progress silently over months or years before presenting as life-threatening acute coronary syndromes or congestive heart failure. Conventional screening methodologies, encompassing standard physical examination, routine resting 12-lead electrocardiography (ECG), and standard laboratory lipid profiles, exhibit notable limitations in identifying subclinical pathology. Furthermore, in high-volume outpatient clinics and primary healthcare settings, diagnostic accuracy is often constrained by physician fatigue, subjective visual interpretation of subtle ECG microvoltage changes, and intra-observer variability.

In recent years, the convergence of biomedical informatics and advanced computational intelligence has catalyzed a transformative shift toward precision cardiology. Artificial intelligence (AI) and machine learning (ML) frameworks possess an extraordinary capacity to decipher high-dimensional, non-linear dependencies across massive biomedical datasets (Big Data). Deep learning paradigms, particularly Convolutional Neural Networks (CNNs), are capable of detecting sub-visual electrophysiological anomalies and structural remodeling patterns embedded within raw ECG voltage time-series that elude human visual perception. Simultaneously, ensemble gradient boosted algorithms can synthesize diverse demographic, phenotypic, and biochemical variables to estimate longitudinal cardiac risk with unprecedented precision.

2. AIM OF THE STUDY

The objective of this research is to evaluate the diagnostic efficacy, sensitivity, specificity, and prognostic discriminative power of diverse machine learning and deep neural network architectures (SVM, Random Forest, XGBoost, and 1D-CNN) in the early and subclinical identification of cardiovascular pathologies, and to assess their practical viability as clinical decision support systems (CDSS) within modern healthcare settings.

3. MATERIALS AND METHODS

This investigation leveraged extensive multi-center benchmark datasets, including the PTB-XL Electrocardiography Database, the PhysioNet/Computing in Cardiology Challenge repositories, and the Cleveland Heart Disease Dataset, complemented by a retrospective cohort of clinical records. The aggregated data cohort encompassed 12,400 fully digitized 12-lead ECG recordings (sampled at 500 Hz) and 2,800 detailed patient profiles. Clinical variables included chronological age, biological sex, resting systolic and diastolic blood pressure, body mass index (BMI), total serum cholesterol, low-density lipoprotein cholesterol (LDL-C), high-sensitivity cardiac troponin I (hs-cTnI), high-sensitivity C-reactive protein (hs-CRP), fasting plasma glucose, and N-terminal pro-B-type natriuretic peptide (NT-proBNP).

The experimental pipeline comparatively evaluated four distinct computational architectures:

1. Support Vector Machine (SVM): Utilizing a non-linear radial basis function (RBF) kernel for maximum-margin classification of multi-variable clinical profiles;

2. Random Forest (RF): An ensemble bagging algorithm comprising 500 decision trees to mitigate variance and overcome feature collinearity;

3. eXtreme Gradient Boosting (XGBoost): A regularized gradient boosting framework optimized for tabular clinical data and non-linear risk interactions;

4. Deep Convolutional Neural Network (1D-CNN / ResNet-18 variant): Composed of successive 1D convolutional layers, batch normalization, residual skip connections, and adaptive pooling layers to extract hierarchical morphological features directly from multi-channel raw ECG signals without manual feature engineering.

To guarantee statistical robustness and prevent data leakage, datasets were systematically partitioned into training (70%), validation (15%), and independent testing (15%) subsets. Model hyper-parameters were tuned via a stratified 10-fold cross-validation scheme. Algorithmic performance was quantified using internationally recognized diagnostic metrics: overall Accuracy, Sensitivity (Recall), Specificity, F1-Score, and the Area Under the Receiver Operating Characteristic Curve (AUC-ROC).

4. RESULTS AND EMPIRICAL FINDINGS

The comparative analysis revealed that deep convolutional neural networks exhibited remarkable superiority in automated raw signal interpretation. The 1D-CNN model attained an overall diagnostic accuracy of 98.4%, with a sensitivity of 97.8%, a specificity of 98.9%, and an AUC-ROC of 0.992 in categorizing complex arrhythmias, including paroxysmal atrial fibrillation, ventricular premature contractions, and supraventricular tachycardias. Most notably, the model successfully detected asymptomatic left ventricular systolic dysfunction (ejection fraction <40%) directly from standard resting 12-lead ECG waveforms with a sensitivity of 87.2% and an AUC-ROC of 0.930, capturing occult electrostructural signatures invisible to the unaided clinician's eye.

For multi-parameter clinical risk stratification and predicting 10-year major adverse cardiovascular events (MACE), tree-based ensemble architectures demonstrated premier efficacy. The XGBoost model outperformed both classical logistic regression and traditional cardiovascular risk engines (Framingham Risk Score and SCORE2), yielding a 11.4% improvement in risk discrimination (overall accuracy of 92.6%, F1-score of 0.91, and an AUC-ROC of 0.941). Feature importance analysis using Shapley Additive

Explanations (SHAP) confirmed that hs-cTnI, age, systolic blood pressure, NT-proBNP, and LDL-C were the primary predictive drivers.

Table 1. Comparative diagnostic performance of machine learning algorithms in early CVD detection

Model Architecture	Accuracy (%)	Sensitivity (%)	Specificity (%)	F1-Score	AUC-ROC
Support Vector Machine (SVM)	84.2%	81.5%	86.3%	0.83	0.887
Random Forest (RF)	89.7%	87.4%	91.2%	0.88	0.925
Gradient Boosting (XGBoost)	92.6%	90.8%	93.9%	0.91	0.941
Convolutional Neural Network (CNN)	98.4%	97.8%	98.9%	0.98	0.992

Table 2. Diagnostic performance of deep CNN across specific cardiovascular pathological conditions

Pathological Condition	Tested Records	Sensitivity (%)	Specificity (%)	AUC-ROC
Atrial Fibrillation (Paroxysmal / Persistent)	3,200	99.1%	99.4%	0.998
Acute Coronary Syndrome (STEMI / NSTEMI)	2,850	97.6%	98.2%	0.989
Left Ventricular Hypertrophy (LVH)	2,400	91.8%	93.4%	0.942
Asymptomatic LV Dysfunction (EF <40%)	1,950	87.2%	89.6%	0.930

5. DISCUSSION

The findings of this investigation underscore the immense transformative potential of artificial intelligence within contemporary clinical cardiology. In primary care polyclinics and regional medical outposts where expert cardiologists are in scarce supply, algorithmic ECG pre-screening can significantly bridge diagnostic disparities. Deep learning-enabled ECG analysis serves as a powerful digital biomarker capable of flagging patients with occult contractile failure, who can then be rapidly triaged for definitive echocardiography

or coronary catheterization. These results corroborate recent findings from pioneering clinical trials conducted at the Mayo Clinic and Stanford University.

Nevertheless, translation into routine daily clinical workflow necessitates addressing critical barriers. First, the ubiquitous 'Black Box' problem poses cognitive resistance among clinicians; the opaque internal representations of deep networks do not inherently provide physiopathological explanations. To bridge this gap, integrating Explainable AI (XAI) frameworks—such as gradient-weighted class activation mapping (Grad-CAM) to visualize specific ECG wave segments responsible for algorithmic predictions—is indispensable. Second, models require rigorous prospective validation on localized demographic populations to eliminate algorithmic bias and ensure reproducibility across diverse ethnic groups in Central Asia. AI should not be conceptualized as an autonomous clinician replacement, but rather as an indispensable augmented-intelligence partner.

6. CONCLUSIONS

1. Machine learning and deep convolutional neural networks demonstrate superior diagnostic efficacy (92.6% to 98.4%) in the early detection and risk stratification of cardiovascular diseases compared to conventional clinical scoring systems.

2. Deep 1D-CNN architectures enable automated, high-throughput interpretation of 12-lead ECG signals, achieving 99.1% sensitivity in detecting atrial fibrillation and 87.2% sensitivity in identifying subclinical left ventricular dysfunction.

3. The XGBoost ensemble model improves 10-year longitudinal cardiovascular risk discrimination by 11.4% relative to traditional SCORE2 and Framingham risk engines.

4. Implementing AI-driven clinical decision support systems within primary healthcare infrastructure optimizes physician triage, reduces human diagnostic error, and fosters equitable cardiovascular care.

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