Machine Learning in Cardiovascular Disease Prediction: A Comparative Study of Classification Models

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Abstract: Cardiovascular diseases (CVDs) remain the leading cause of mortality worldwide, imposing a significant burden on healthcare systems and society at large. The global impact of CVDs is profound, with millions of lives lost annually and substantial economic costs incurred due to treatment and management. Early detection and intervention are critical to improving patient outcomes and reducing the associated healthcare costs. However, traditional diagnostic methods often face challenges in identifying subtle or early-stage indicators of CVDs, highlighting the need for innovative solutions. This review paper provides a comprehensive comparative analysis of the latest machine learning (ML) models applied to cardiovascular disease (CVD) diagnosis, risk prediction, and management. By systematically evaluating state-of-the-art ML techniques. Ensemble methods like Stacking and RF provide superior generalization, making them the best choices for malware classification.

Keywords: Cardiovascular diseases; early-stage indicators; healthcar; machine learning; risk prediction

Introduction

Heart disease, which was once largely confined to men, and increasingly a problem among women in India. Women in the premenopausal group were historically thought to be relatively immune from cardiovascular diseases. Recent trends indicate an alarming increase in heart ailments like heart attacks, angina, and sudden cardiac death in young women [1]. This is motivated by the accelerating rates of risk factors such as smoking, diabetes, hypertension, high cholesterol, physical inactivity, unhealthy diet, and mental stress, which are now contracted at an earlier age. Adding to the adversity, women tend to downplay or neglect symptoms because of cultural and social expectations and thus delay diagnosis and treatment. The clinical presentation of heart disease in women can also be uncharacteristic with manifestations of unexplained tiredness, belching, or jaw or back discomfort often ignored. These issues point towards the critical importance of enhanced awareness and prompt action to deal with the growing load of heart disease in women [2].

The special difficulties in diagnosing and treating heart disease in women are compounded by underrecognition of their symptoms by both patients and physicians. Women tend to prioritize family obligations over their own health, which causes them to overlook early warning signs. The absence of typical symptoms such as chest pain and the occurrence of atypical presentations add to underdiagnosis. This delay in diagnosis usually leads to late disease development and worse results. With continuing increases in heart disease among women, it is crucial to enhance awareness, facilitate early screening, and promote changes in lifestyle in order to decrease risk factors [3].

Recent advances in artificial intelligence (AI), particularly deep learning, are revolutionizing the field of medical diagnostics. Deep learning models, such as convolutional neural networks (CNNs) and transformers, have demonstrated remarkable capabilities in analyzing diverse data modalities, including electrocardiograms (ECGs), echocardiograms, and cardiac MRIs. These models excel at detecting intricate patterns and anomalies that may be indicative of early-stage CVDs, often surpassing human expertise in accuracy and efficiency. Furthermore, the integration of explainability techniques into AI systems enhances transparency, enabling clinicians to understand the decision-making process behind predictions. This fosters trust and acceptance among healthcare professionals, paving the way for the widespread adoption of AI-driven tools in clinical practice. By leveraging these technologies, the healthcare industry can achieve earlier and more accurate diagnoses, ultimately improving patient outcomes and reducing the global burden of CVDs [4].

Cardiovascular diseases (CVDs) are the leading cause of death globally, accounting for millions of fatalities each year and placing an immense burden on healthcare systems and societies. The economic and social costs associated with CVDs are staggering, encompassing direct medical expenses, lost productivity, and reduced quality of life for patients and their families. Despite significant advancements in medical science, the prevalence of CVDs continues to rise, driven by factors such as aging populations, sedentary lifestyles, and the increasing prevalence of risk factors like obesity, diabetes, and hypertension. This underscores the urgent need for innovative approaches to improve early detection, diagnosis, and management of these conditions [5].

Early detection and intervention are pivotal in mitigating the impact of CVDs. Identifying cardiovascular issues at their nascent stages allows for timely treatment, which can significantly improve patient outcomes and reduce the progression of disease. However, traditional diagnostic methods often rely on subjective interpretations of clinical data, which can lead to variability in diagnoses and delays in treatment. Moreover, many early-stage CVDs present with subtle or atypical symptoms that are easily overlooked, further complicating the diagnostic process. Artificial intelligence (AI), particularly deep learning, has emerged as a transformative tool in addressing these challenges. By automating complex diagnostic tasks and analyzing vast amounts of data with precision, AI can enhance the accuracy and efficiency of CVD detection.

Deep learning models, such as convolutional neural networks (CNNs) and transformers, have demonstrated exceptional capabilities in analyzing diverse medical data modalities, including electrocardiograms (ECGs), echocardiograms, and cardiac MRIs. These models excel at identifying intricate patterns and anomalies that may be indicative of early-stage CVDs, often surpassing human expertise in accuracy. For instance, CNNs can process ECG signals to detect arrhythmias or ischemic changes, while transformers can analyze echocardiographic images to assess cardiac function. By leveraging these advanced techniques, AI systems can provide clinicians with actionable insights, enabling earlier and more accurate diagnoses. This not only improves patient outcomes but also reduces the likelihood of complications and hospitalizations, ultimately lowering healthcare costs.

One of the critical challenges in adopting AI in healthcare is ensuring that these systems are transparent and interpretable. Explainability techniques, such as attention mechanisms and saliency maps, play a vital role in enhancing the trustworthiness of AI models. These techniques provide insights into how the models arrive at their predictions, allowing clinicians to understand the underlying reasoning. For example, an AI system analyzing an ECG can highlight specific segments of the signal that contributed to its diagnosis, enabling clinicians to validate the findings. This transparency fosters trust and acceptance among healthcare professionals, facilitating the integration of AI-driven tools into routine clinical practice. Furthermore, explainability ensures that AI systems can be audited and refined, addressing potential biases and improving their reliability over time.

The integration of AI into cardiovascular diagnostics holds immense promise for transforming healthcare delivery. By enabling earlier and more accurate detection of CVDs, AI can help reduce the global burden of these diseases and improve patient outcomes. However, realizing this potential requires collaboration between researchers, clinicians, and policymakers to address challenges such as data privacy, regulatory approval, and equitable access to AI technologies. As these barriers are overcome, AI-driven diagnostics will become an indispensable tool in the fight against cardiovascular diseases, paving the way for a future where early detection and personalized treatment are the norm. This paradigm shift has the potential to save countless lives and significantly enhance the quality of care for patients worldwide. This article delves into the changing epidemiology, risk determinants, and diagnostic issues of cardiovascular diseases among women, and discusses the Indian context to emphasize targeted interventions and better healthcare plans.

Related work

The integration of artificial intelligence (AI) into cardiovascular disease (CVD) diagnostics has garnered significant attention in recent years, with numerous studies demonstrating its potential to enhance accuracy, efficiency, and scalability. This literature review synthesizes key findings from recent research, highlighting advancements, methodologies, advantages, and limitations of AI-driven approaches in CVD detection and management.

Alsekait et al. (2024) [6] developed a multi-modal deep learning framework, Heart-Net, which integrates MRI and ECG data for CVD diagnosis. The framework employs a 3D U-Net for MRI analysis and a Temporal Convolutional Graph Neural Network (TCGN) for ECG feature extraction, enhanced by attention mechanisms for feature integration. Heart-Net achieved high accuracy across datasets (92.56%, 93.45%, 91.89%), demonstrating its potential to reduce diagnostic errors and support personalized monitoring. However, the framework is limited by its reliance on specific datasets and the high computational resources required for multi-modal integration.

Mayourian et al. (2024) [7] focused on risk stratification for congenital heart disease (CHD) patients using AI-enhanced ECG tools. By training convolutional neural networks (CNNs) on large, diverse ECG datasets, the study outperformed traditional metrics like QRS duration and left ventricular ejection fraction. The model achieved a moderate AUC of 0.79 and was effective across various CHD lesion subgroups. While promising, the study's focus on CHD limits its applicability to other CVDs, and further validation is needed to generalize its findings.

Wang et al. (2024) [8] proposed a two-stage AI paradigm for automating cardiac magnetic resonance (CMR) interpretation to diagnose 11 types of CVD. The model achieved high AUC values for screening (0.988) and diagnosis (0.991), outperforming cardiologists in some cases. Despite its impressive performance, the reliance on specialized imaging data limits its scalability, particularly in resource-poor settings where such data may not be readily available.

Khan et al. (2024) [9] conducted a comparative analysis of AI-based methods for detecting various heart conditions, including arrhythmias and myocardial infarction. The review highlighted advancements in classification accuracy and scalability, emphasizing the potential for personalized treatment. However, the study lacked experimental results, as it was primarily a review rather than an implementation-focused work.

Bharathi et al. (2024) [10] explored the use of advanced machine learning (ML) algorithms for ECG-based CVD diagnosis. The study tested multiple algorithms for ECG signal preprocessing and classification, achieving modest accuracy (59.36%) using decision trees. While the study identified effective ML algorithms for specific conditions, it lacked the use of advanced deep learning techniques, which could potentially improve performance.

Srinivasulu et al. (2024) [11] developed a CNN-based model using SqueezeNet for ECG image-based CVD diagnosis. By applying transfer learning on pre-trained SqueezeNet, the model demonstrated high computational efficiency and superior classification performance. However, its focus on specific cardiovascular abnormalities limits its generalizability to other CVD conditions.

Brown et al. (2024) [12] utilized CNNs with attention mechanisms to detect rheumatic heart disease (RHD) from echocardiography. The model achieved high accuracy (AUC: 0.84), comparable to expert cardiologists. While effective for RHD, the model's applicability to other heart diseases remains limited, and further data is needed to enhance its generalizability.

Deepika & Jaisankar (2024) [13] proposed an enhanced CNN and ECV-3D network for detecting and classifying myocardial infarction (MI). The model achieved an AUC of 0.82 and an accuracy of 97.05%, demonstrating robustness and suitability for real-time clinical use. Its focus on MI limits its applicability to other CVD conditions.

Table 1: Highlighting advancements, methodologies, advantages, and limitations of AI-driven approaches in CVD detection and management.

Reference	Objective	Methodology	Advantages	Limitations
[6] Alsekait et al., 2024	Develop a multi-modal deep learning framework (Heart-Net) for CVD diagnosis using MRI and ECG.	Utilizes 3D U-Net for MRI analysis, Temporal Convolutional Graph Neural Network (TCGN) for ECG feature extraction, and attention mechanisms for feature integration.	Achieves high accuracy across datasets (92.56%, 93.45%, 91.89%). Reduces diagnostic errors and supports personalized monitoring.	Limited to specific datasets; requires high computational resources for multi-modal integration.
[7] Mayourian et al., 2024	Risk stratification of congenital heart disease (CHD) patients using AI-	Trained convolutional neural networks on large, diverse ECG datasets. Evaluated performance via AU	Outperforms traditional metrics like QRS duration and left ventricular ejection fraction. Effective a	Moderate AUC (0.79); focus is limited to CHD, excluding other CVDs.

	enhanced ECG tools.	C and Kaplan–Meier analysis.	cross wide CHD lesion subgroups.	
[8] Wang et al., 2024	Automate CMR interpretation for diagnosing 11 types of CVD.	Two-stage AI paradigm: cine-based screening followed by cine + gadolinium-enhanced diagnosis. Validated across internal and external datasets.	High AUC for screening (0.988) and diagnosis (0.991). Outperforms cardiologists in some cases.	Requires specialized imaging data, limiting scalability in resource-poor settings.
[9] Khan et al., 2024	Review AI methods for detecting various heart conditions, including arrhythmias and myocardial infarction.	Comparative analysis of AI-based methods. Highlights advancements in classification and accuracy improvements.	Provides insights into enhanced diagnostic accuracy, scalability, and personalized treatment.	Lack of experimental results; primarily a review rather than an implementation.
[10] Bharathi et al., 2024	Improve diagnostic accuracy and efficiency in ECG-based CVD diagnosis.	Utilizes advanced ML algorithms for ECG signal preprocessing and classification. Tested multiple algorithms for ECG analysis.	Identifies effective ML algorithms for specific conditions like arrhythmias and heart attacks.	Achieved modest accuracy (59.36%) using decision trees; lacks advanced deep learning techniques.
[11] Srinivasulu et al., 2024	Develop a CNN-based model using SqueezeNet for ECG image-based CVD diagnosis.	Transfer learning on pre-trained SqueezeNet to classify annotated ECG images for CVD conditions.	High computational efficiency with superior classification performance.	Limited focus on specific cardiovascular abnormalities.

[12] Brown et al ., 2024	Use AI for detecting rheumatic heart disease (RHD) from echocardiography.	Convolutional neural networks with attention mechanisms to localize mitral regurgitation jets.	Achieved high accuracy (AUC: 0.84). Comparable to expert cardiologists for detecting RHD.	Limited to RHD; requires more data to generalize across other heart diseases.
[13] Deepika & Jaisankar, 2024	Detect and classify myocardial infarction (MI) using enhanced CNN and ECV-3D network.	Extensive experimentation with 3D networks and echocardiogram frames. Achieved AUC of 0.82 and accuracy of 97.05%.	High accuracy and robustness in MI detection. Suitable for real-time clinical use.	Focused on MI; not generalized for other CVD conditions.

Key Contribution

This review paper provides a comprehensive comparative analysis of the latest machine learning (ML) models applied to cardiovascular disease (CVD) diagnosis, risk prediction, and management. By systematically evaluating state-of-the-art ML techniques.

Method, Experiments and Results

Dataset: This dataset appears to be related to predicting the presence or absence of heart disease based on various clinical and demographic features. The target variable is typically used as the label in supervised learning tasks, where the goal is to predict whether a patient has heart disease based on the other features.

Table 2: Dataset description

Pre-processing:

Encoding: Ensure that categorical variables (e.g., sex, chest_pain_type, etc.) are properly encoded.

Scaling/Normalization: Consider scaling or normalizing numerical features like age, resting_blood_pressure, cholesterol, etc., especially if using algorithms sensitive to feature magnitudes.

Handling Missing Values: Although the dataset currently has no missing values, it's always good practice to check for and handle any missing data in real-world scenarios.

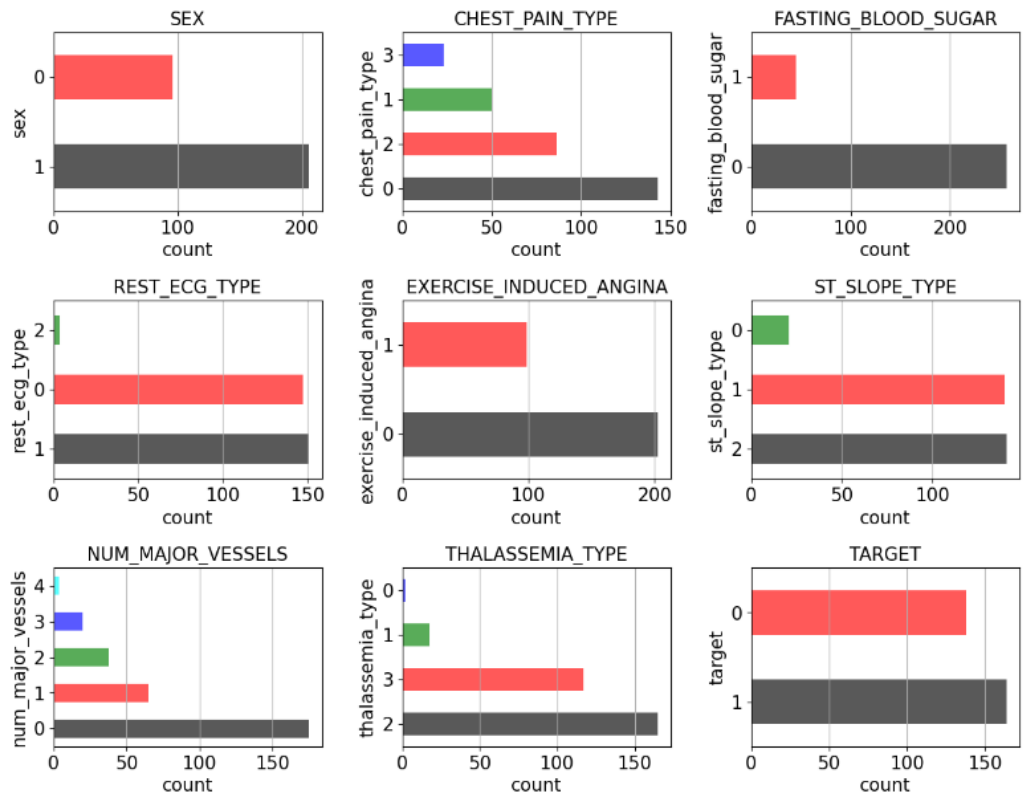

Figure 1: Dataset visualization

Different ML Models:

comparison of the K-Nearest Neighbors (KNN), Support Vector Machine with RBF Kernel (SVM_RBF), Decision Tree (DT), Random Forest (RF), and Multilayer Perceptron (MLP) algorithms in terms of their key characteristics, advantages, and limitations describe in table 3 and table 4 provides ML model performance metric.

Table 3: ML model Key characteristics, Advantage, and Limitation

Algorithm	Key Characteristics	Advantages	Limitations
	- Instance-based learning	- Simple to implement and understand	- Computationally expensive for large datasets
KNN	- Non-parametric	- No training phase	- Sensitive to irrelevant features and noise
	- Lazy learner	- Effective for small datasets	
	- Kernel-based method	- High accuracy for complex datasets	- Computationally intensive
SVM_RBF	- Effective for non-linear data	- Robust to overfitting in high-dimensional spaces	- Requires careful tuning of hyperparameters (e.g., C, gamma)
	- Margin maximization		

DT	- Tree-based model - Splits data based on feature values - Interpretable	- Easy to visualize and interpret - Handles both numerical and categorical data	- Prone to overfitting - Sensitive to small changes in data
RF	- Ensemble of decision trees - Bagging technique - Reduces overfitting	- High accuracy and robustness - Handles missing data and outliers well	- Computationally expensive - Less interpretable than single decision trees
MLP	- Feedforward neural network - Multiple layers of neurons - Non-linear mapping	- Can model complex, non-linear relationships - Scalable to large datasets	- Requires large amounts of data - Computationally expensive and hard to interpret

Table 4: ML model performance metric

Metric	**KNN**	**SVM_RBF**	**DT**	**RF**	**MLP**
Accuracy	Moderate	High	Moderate	High	High
Interpretability	Low	Low	High	Moderate	Low
Training Speed	Fast (no training)	Slow	Fast	Moderate	Slow
Scalability	Poor (large data)	Moderate	Moderate	High	High
Overfitting Risk	Low	Low	High	Low	Moderate

Result:

1. Accuracy: Measures overall correctness of the model.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

Measures the proportion of correct predictions.

2. Matthews Correlation Coefficient (MCC):

$$MCC = \frac{(TP \times TN) - (FP \times FN)}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \quad (2)$$

A balanced metric for binary classification, even when classes are imbalanced.

3. F1 Score: Balances precision & recall for better performance evaluation.

$$F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{3}$$

The harmonic mean of precision and recall, balancing false positives & false negatives.

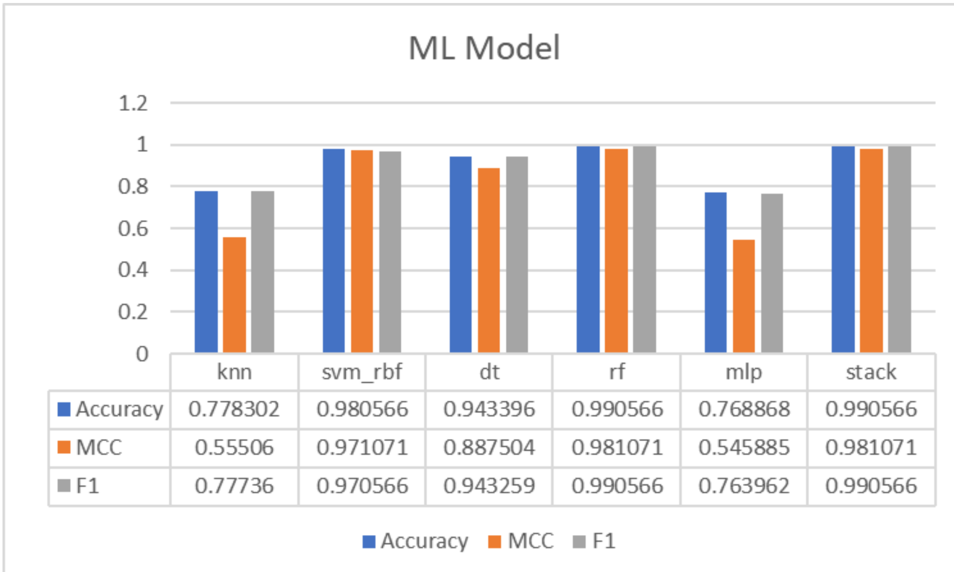

Figure 2. ML Model Performance.

Discussions

The performance comparison of machine learning models shows that Stacking and Random Forest (RF) achieve the highest accuracy (0.9906), MCC (0.9811), and F1-score (0.9906), making them the most reliable models for this dataset. SVM-RBF follows closely with strong metrics, while Decision Tree (DT) performs well but is slightly less robust. In contrast, KNN and MLP show significantly lower performance, suggesting they may struggle with the dataset's complexity or require further hyperparameter tuning. Overall, ensemble methods like Stacking and RF provide superior generalization, making them the best choices for malware classification.

Conclusions

Cardiovascular diseases (CVDs) remain the leading cause of mortality worldwide, placing a significant burden on healthcare systems and society. With millions of lives lost annually and substantial economic costs associated with treatment and management, early detection and intervention are crucial for improving patient outcomes. Traditional diagnostic methods often struggle to identify subtle or early-stage indicators of CVDs, emphasizing the need for innovative solutions. This review provides a comprehensive comparative analysis of the latest machine learning (ML) models applied to CVD diagnosis, risk prediction, and management. By systematically evaluating state-of-the-art ML techniques, this study highlights the potential of advanced algorithms—particularly ensemble methods—to enhance diagnostic accuracy, optimize predictive modeling, and improve clinical decision-making in cardiovascular healthcare.

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