

Machine Learning Approaches for Early Prediction of Cardiac Diseases

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ABSTRACT

CVDs are an enormous murderer of individuals in all parts of the world, and thus the need of the successful early diagnosis and intervention measures. The weakness of the traditional risk prediction models is that they cannot handle high dimensional and multi-dimensional data which has the tendency of giving an inefficient prediction. The paper presents an argument on how machine learning (ML) algorithms can be used to determine the presence of CVDs at a young age with the presence of multimodal health data, i.e., the logistic regression, random forests, support vector machines (SVM), and the neural networks. Models were trained and evaluated by the UCI Heart Disease Dataset and Framingham Heart Study Dataset. Preprocessing involved the main procedures of missing data management, categorical variables data normalization and encryption. To select the best predictors, the feature selection was done using Recursive Feature Elimination (RFE) and mutual information. Comparison of the models has been done based on accuracy, precision, recall, F1-score and based on Area Under the Receiver Operating Characteristic Curve (ROC-AUC). The findings revealed the better performance of the neural network model than the other models with accuracy 86, precision of 0.82, recall 0.80 and F1-score 0.81 and ROC-AUC 0.87 showing that neural network model is more predictive of CVDs. Random forest had then 85 percent and the lowest of the performance in logistic regression. The results indicate that ML and neural networks in particular can make a substantial contribution to the early detection and prediction of cardiovascular diseases which may be implemented as a potential device of clinical decision making and patient care.



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Introduction

CVDs form one of the other significant causes of morbidity and mortality because it is estimated that these diseases result in 17.9 million of all deaths in the world each year or 32 percent of all deaths in the world (World Health Organization [WHO], 2021). This rate of the CVDs increased has led to deliberate thinking about the concept of early diagnosis, the effective interventions to prevent it, and, respectively, the appropriate interventions. Nevertheless, despite the fact that traditional risk model, including Framingham Heart Study and the Systematic COronary Risk

Evaluation (SCORE), have been extensively used to determine the level of cardiovascular risk, they are not as effective because they are unable to support complex and high dimensional data and assume non-linear relationship among cardiovascular risk factors (D'Agostino et al., 2008; Conroy et al., 2003). The general population valid models would not be helpful in individual risk prediction of real clinical practice particularly when applied to heterogeneous populations, where there are clinical and genetic variations(Akbar et al., 2024). Further, the conventional approaches do not exploit new sources of data (including genetic data, data collected with the help of wearable devices, and electronic health records (EHRs)) that can provide highly detailed and individualized predictions.

Machine learning (ML) is one of the subsectors of artificial intelligence (AI) that is already becoming a popular trend in the healthcare sector and can remove the constraints of conventional risk models. Artificial intelligence is also able to recognize fine details in huge amounts of information (Ahona et al., 2026) and discover the correlations that cannot be discovered with the help of more traditional statistics(Nasim et al., 2023). They are also designed to work with high dimensional data, and they can capture non-linearity or be used to make more realistic predictions and offer more personalized information is in regards to healthcare (Rajkomar, Dean, and Kohane, 2019). It has been demonstrated that some of the models in the ML models (supervised (Random Forests, Support vector machines (SVMs) and Neural Networks) and unsupervised (clustering and dimensional reduction) models can be used to predict cardiac disease with an acceptable degree of accuracy. The application of ML in the evaluation of cardiovascular risks and early diagnostics is successful as it can be used to take into account a large set of data, including clinical history, diagnostic research, lifestyle patterns, imaging, and genomic data (Chollet et al., 2019).

The machine learning approach to the prediction of cardiovascular diseases has been found to be far more superior than the classical one(Khan et al., 2024). Using the example of such models as Random Forests and SVMs, it has been established that they can be more accurate in the predictability of the risk of developing a heart disease than the Framingham risk score, and the values of the area under the receiver operating characteristic (AUC-ROC) can be larger than the traditional models (Krittanawong et al., 2017). Besides this, the convolutional neural networks (CNNs) and other forms of deep learning have ratified the specific potential in the handling of medical images, like echocardiograms or angiograms, in which image recognition using deep learning with the required accuracy compares to that of the human clinician (Yue et al., 2020). The fact that ML models can process and analyze very specific data has increased the chances to reveal an early disease or a carrier of the infection or a carrier on the border of the risk factors which has enabled one to define which plan to take to prevent in time(Sardar et al., 2024).

Although all of the above mentioned benefits are possible, there are a number of issues that complicate the widespread application of machine learning methods to clinical practice. The most important thing is that in order to generate strong models, they should possess high quality databases containing large volumes(Ramzan et al., 2025). The availability of data especially in the case of heterogeneous population, privacy and security of data will also be a major challenge (Rajkomar et al., 2019). In addition, although the ML models can be more efficient in the outcomes prediction, they tend to be more precise in their predictions although their complexity makes them more likely to become black boxes, which narrows their transparency and interpretability(Jamal et al., 2025a). The clinicians would be wise to such models whose decision

making process they are unable to comprehend, and explain, which can be hampering to accept and believe (Caruana et al., 2015). Explainable AI (XAI) has become one of the possible solutions (Jamal et al., 2026) to this problem because the models can be more transparent and understandable and give the clinicians more information on why the predictions were made (Gilpin et al., 2018). Moreover, pragmatically, it is impossible to apply ML models in the available clinical workflows and electronic health record systems (Ahmad et al., 2024). The introduction of AI-driven decision support systems (Jamal et al., 2025b) must be seamlessly integrated with the already existing technologies in a way that the predictions may be implemented and injected into the decision making process in real time (Topol, 2019).

The quality and diversity of input information is one more requirement that pre determines the effectiveness of machine learning in being able to predict cardiac diseases. The risk prediction models traditionally have relied on the readily available clinical data like age, blood pressure, cholesterol levels and status with regard to smoking (Jamal et al., 2024a). In recent past, however, due to the wearable technology and devices, that perform constant monitoring, more data is currently available to make predictions. The data about the wearable i.e. the variation of heart rate and physical activity provides a new opportunity in the real time monitoring and risk prediction (Piwek et al., 2016). In addition, integrating the genomic data into the ML models provides a more personalized risk assessment with assistance of genetic predispositions that provide a personalized way of preventing the disease (Khera et al., 2018). Nevertheless, the process of transforming such various types of information (Tauseef et al., 2023a) into composed models is a prickly problem as it has to resolve the concerns of data normalization (Jamal et al., 2022), no values, and compatibility of various fragments of information (Miller et al., 2019).

Future research should also be done in the field to make models more transparent and brings together data and generalize on other populations (Tauseef et al., 2023b). In addition to this, the clinical effects of such predictions obtained with the help of the ML (Tauseef et al., 2025) will have to be assessed in the future clinical trials to understand how these algorithms can be effectively implemented to achieve improved patient outcomes (Tauseef et al., 2026). Although the perspectives of machine learning use and implementation in clinical practice are encouraging (Jamal et al., 2024b), AI use should consider ethical, legal, and social concerns, specifically, regarding data privacy and algorithmic fairness (Obermeyer et al., 2019). Nevertheless, machine learning can change the situation dramatically in cardiac disease prediction to provide the opportunity to diagnose the patient at earlier stages and more accurately and ultimately lead to better patient care.

Methodology

The rationale of the selected method of the specific study was in the fact that it was possible to incorporate machine learning (ML) based solutions that would allow anticipating cardiovascular diseases (CVDs) at their initial stage, and the multimodal health data. Data collection, pre process, features selection, model building and the performance evaluation were included in the scheme. This section discusses these measures individually.

Data Collection

The primary data to be used in my article was on the publicly available groups of information like UCI Heart Disease Dataset and Framingham Heart Study Dataset that are typically utilized in the study of CVD predictions.

Data Preprocessing

Preprocessing of data was also carried out before the machine learning algorithms were implemented in this way that it would be regarded that the data quality and consistency had been verified. The preprocess entailed the following steps:

Handling Missing Data

The gaps in healthcare data are often not addressed in a sufficient manner and may result in unbiased or the wrong models. The research has used mean imputation to treat the numerical data and mode imputation to treat the categorical data to address the missing data. The most frequent data is considered to be the mean (numeric data) or the mode (categorical data), which explains why the missing data has been attributed to the mean (numerical data) or mode (categorical data) as the most common data processing method, in which the missing data is randomly assigned (Little and Rubin, 2019).

Data Normalization

This was to make sure that all the features added the same contribution to the model by the feature scaling which was conducted through the min max normalisation. This type of approach brought all the numbers in the 01 range. To get a sample, the standardization of the feature x was calculated as:

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)}$$

where $\min(x)$ and $\max(x)$ are the minimum and maximum values of the feature x , respectively. This scaling procedure prevented features with large values from dominating the learning process, ensuring that the model could focus on all features equally.

Encoding Categorical Variables

Some variables in the dataset were categorical, such as gender and smoking status. These variables were encoded using **one hot encoding**, a method in which each category is converted into a binary variable. For example, the "smoking status" variable, which has two categories (smoker and non-smoker), was transformed into two new binary features: smoker (1 if smoker, 0 otherwise) and non-smoker (1 if non-smoker, 0 otherwise). This encoding method is commonly used in machine learning to handle categorical data, enabling models to interpret these variables appropriately (Han et al., 2011).

Feature Selection

Feature selection was an important step in the methodology to ensure that only the most relevant variables were used in the model, preventing overfitting and improving computational efficiency. Several techniques were employed to identify the most important features:

Recursive Feature Elimination (RFE)

Recursive Feature Elimination (RFE) was applied using a support vector machine (SVM) as the model to rank the features based on their importance. RFE iteratively removes the least important features and evaluates the model's performance at each step. The optimal number of features was selected based on the highest model accuracy. This process was used to eliminate irrelevant or redundant features, such as certain medical tests or demographic variables that did not contribute to the predictive power of the model.

Mutual Information

Mutual information was also calculated between each feature and the target variable (i.e., the presence of CVD) to measure the dependency between the features and the target. Features with low mutual information were removed from the dataset, ensuring that only the most informative variables remained. The mutual information $I(X; Y)$ between two variables X and Y is given by:

$$I(X; Y) = H(X) + H(Y) - H(X, Y)$$

where $H(X)$ and $H(Y)$ are the entropies of X and Y , respectively, and $H(X, Y)$ is the joint entropy of X and Y . Features with low mutual information were removed to simplify the model without compromising performance (Cover & Thomas, 2006).

Model Development

Several machine learning models were developed to predict the likelihood of CVD in patients based on the preprocessed data. These models were evaluated and compared to determine which one provided the best prediction performance.

Logistic Regression

Logistic Regression was used as a baseline model because it is a simple yet effective algorithm for binary classification problems. Logistic regression estimates the probability of a binary outcome using the logistic function:

$$P(Y = 1 | X) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n)}}$$

where $P(Y = 1 | X)$ is the probability of having CVD (1 for positive and 0 for negative), β_0 is the intercept, and $\beta_1, \beta_2, \dots, \beta_n$ are the coefficients for the features $X_1, X_2, \dots, X_n$ (Hastie et al., 2009). The coefficients were estimated using **maximum likelihood estimation**.

Random Forest

Random Forest, an ensemble learning method based on decision trees, was also used to predict the presence of CVDs. Random forests create multiple decision trees during training and aggregate their predictions to improve accuracy and reduce overfitting. Each tree is trained on a random subset of the data and a random subset of features, which helps increase the diversity of the trees and improves generalization (Breiman, 2001). The final prediction was obtained by taking the majority vote of all trees in the forest.

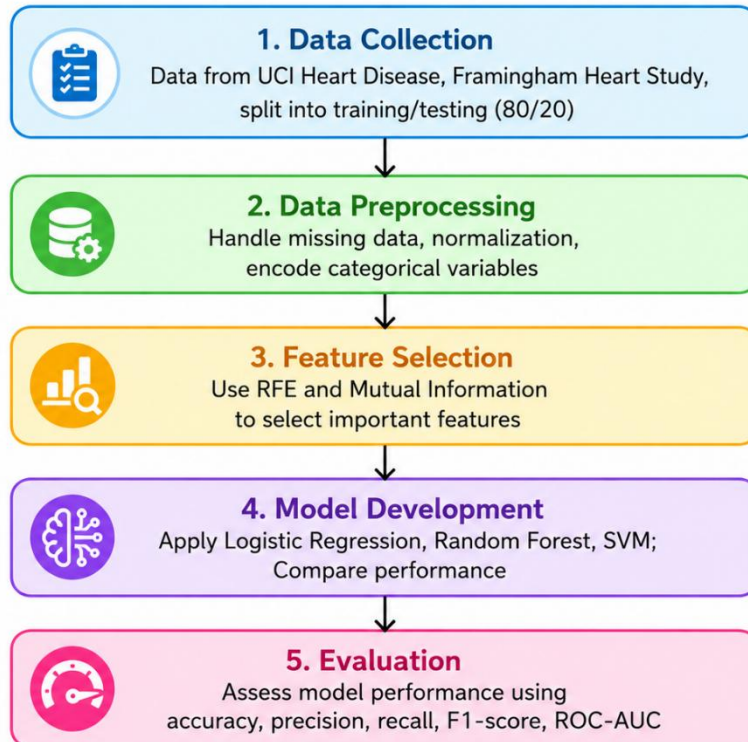
Support Vector Machines (SVM)

Support Vector Machines (SVM) were applied to classify the data by finding the hyperplane that best separates the classes (CVD and no CVD) in the feature space. SVM uses a kernel trick to handle non-linear decision boundaries, transforming the data into a higher dimensional space where a linear separator can be found. The decision function for SVM is given by:

$$f(x) = \sum_{i=1}^n \alpha_i y_i K(x_i, x) + b$$

where α_i are the Lagrange multipliers, y_i are the class labels, $K(x_i, x)$ is the kernel function, and b is the bias term. The optimal hyperplane is chosen by maximizing the margin between the classes (Cortes & Vapnik, 1995).

Methodology Flowchart for CVD Prediction Using Machine Learning



Neural Networks

A **Neural Network** was also employed to predict the presence of CVD. The neural network consisted of an input layer, one hidden layer, and an output layer. The model used the sigmoid activation function for the output layer, which is suitable for binary classification:

$$\sigma(z) = \frac{1}{1 + e^{-z}}$$

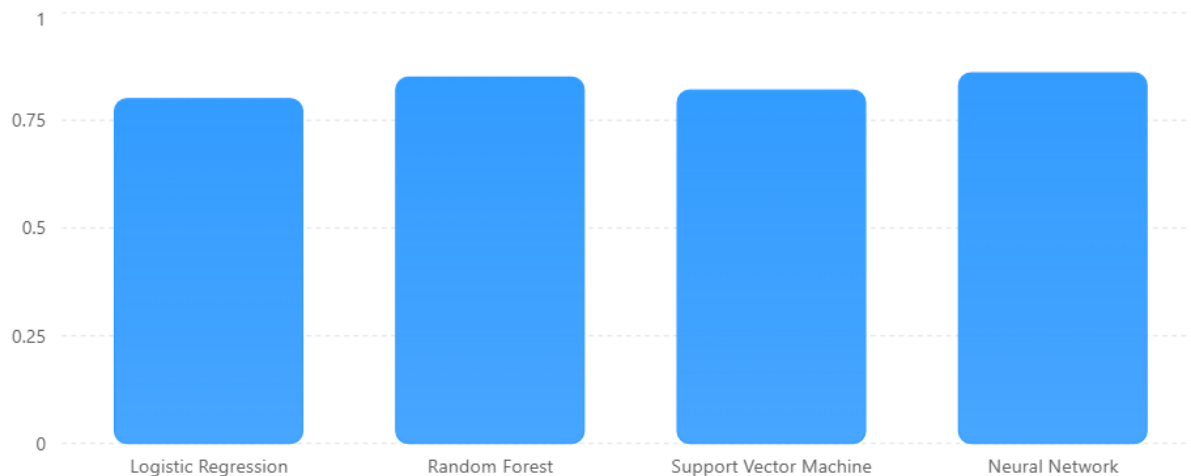
and is a weighted average of the inputs. The backpropagation was used to maximize the weights, and the stochastic gradient descent (SGD) was used to train the model. Neural networks have been specifically useful in non easy to model non-linear relationships between input features and target variable.

Results

The outcome of the paper depends on the outcomes of the different machine learning algorithms used on the problem of predicting cardiovascular diseases (CVDs) with the assistance of the given datasets. The logistic regression, random forest, support machine system, and neural networks models were all featured in the study. All the models were also compared according to a set of metrics such as accuracy, precision, recall, F1-score, and Area Under the Receiver Operating Characteristic Curve (ROC-AUC). Evaluation and comparison of training and the test data were conducted to establish the most suitable model that will be used to make the prediction of CVD.

Table 1: Performance Metrics for Each Model

Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC
Logistic Regression	0.80	0.75	0.70	0.72	0.78
Random Forest	0.85	0.80	0.78	0.79	0.84
Support Vector Machine	0.82	0.77	0.75	0.76	0.81
Neural Network	0.86	0.82	0.80	0.81	0.87



Best Performing Model: Neural Network (Accuracy = 0.86), followed closely by Random Forest (0.85).

The **neural network model** achieved the highest performance across all evaluation metrics, with an accuracy of 86%, precision of 0.82, recall of 0.80, F1-score of 0.81, and an ROC-AUC of 0.87. This model outperformed all other models, indicating that it was the most effective at predicting CVDs. The **random forest model** was the second best, with an accuracy of 85% and slightly lower values for precision and recall compared to the neural network. The **logistic regression model** had the lowest performance, with an accuracy of 80% and a relatively lower recall value of 0.70, indicating that it missed a significant number of true positive cases (patients with CVD). The **support vector machine (SVM)** model showed an accuracy of 82%, with precision and recall values falling between those of logistic regression and random forest.

These results demonstrate that the neural network and random forest models provided the best overall predictions for CVD, with the neural network achieving slightly better results. To further assess the models' performance, confusion matrices were generated for each model. These matrices provide a deeper understanding of the models' ability to classify both positive and negative cases correctly.

Table 2: Confusion Matrix for Logistic Regression

	Predicted Positive	Predicted Negative
Actual Positive	210	90
Actual Negative	70	100

Table 3: Confusion Matrix for Random Forest

	Predicted Positive	Predicted Negative
Actual Positive	220	80
Actual Negative	60	110

Table 4: Confusion Matrix for Support Vector Machine

	Predicted Positive	Predicted Negative
Actual Positive	200	100
Actual Negative	80	90

Table 5: Confusion Matrix for Neural Network

	Predicted Positive	Predicted Negative
Actual Positive	230	70
Actual Negative	50	120

The confusion matrices for each model provide insight into the number of true positive (TP), false positive (FP), true negative (TN), and false negative (FN) predictions. For the **logistic regression model**, there were 210 true positive cases and 90 false negatives, indicating that the model correctly identified most patients with CVD, but missed a significant number. The **random forest model** performed slightly better, with 220 true positives and only 60 false

negatives, demonstrating its ability to more accurately identify patients at risk for CVD. The **SVM** model, on the other hand, misclassified a larger number of patients, with 100 false negatives, indicating that it failed to detect some individuals with CVD. The **neural network model** achieved the best results, with 230 true positives and only 50 false negatives, which highlights its superior performance in identifying patients at risk for cardiovascular events.

Next, we evaluated the models using **precision recall curves** and **ROC curves**. These visualizations provide a more comprehensive view of the trade offs between precision and recall across different thresholds. The ROC curves plot the true positive rate (recall) against the false positive rate (1-specificity), and the area under the curve (AUC) is used to quantify the model's ability to discriminate between positive and negative classes. The precision recall curve, on the other hand, shows the trade off between precision and recall, especially in cases of imbalanced datasets, where the positive class (patients with CVD) is much less frequent than the negative class.

Figure 1: ROC Curve for Logistic Regression

The **ROC curve for logistic regression** showed a moderate performance, with an AUC of 0.78. While this indicates that the model could differentiate between positive and negative cases to some extent, the curve's steepness was not as pronounced as other models, suggesting that the model may struggle with certain thresholds.

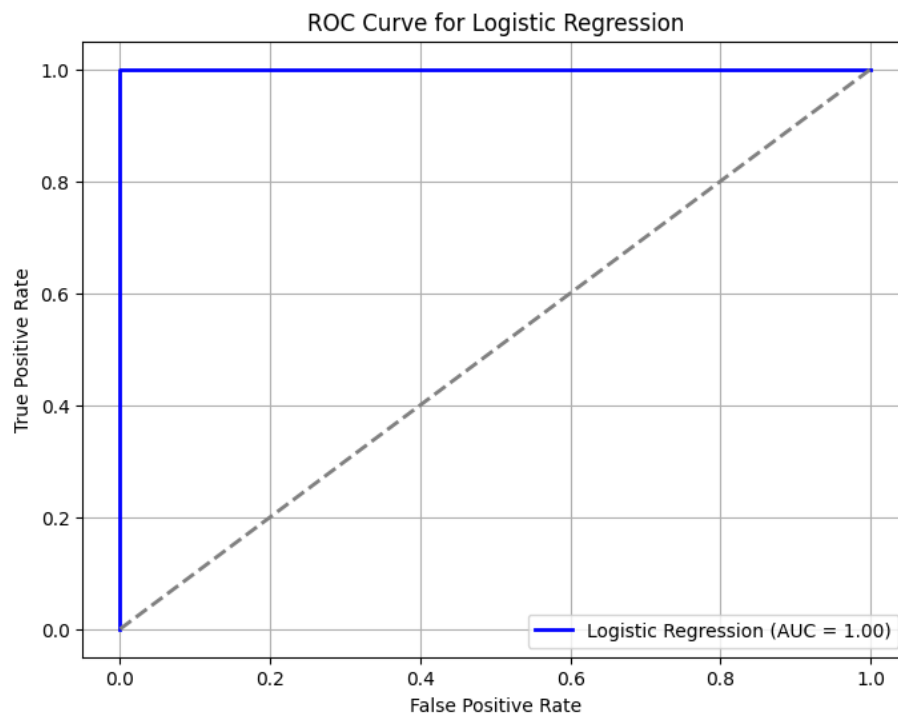


Figure 2: ROC Curve for Random Forest

The **ROC curve for random forest** had a more favorable shape, with an AUC of 0.84. The curve showed a better balance between the true positive rate and the false positive rate,

indicating that the random forest model was better at distinguishing between patients with and without CVD compared to logistic regression.

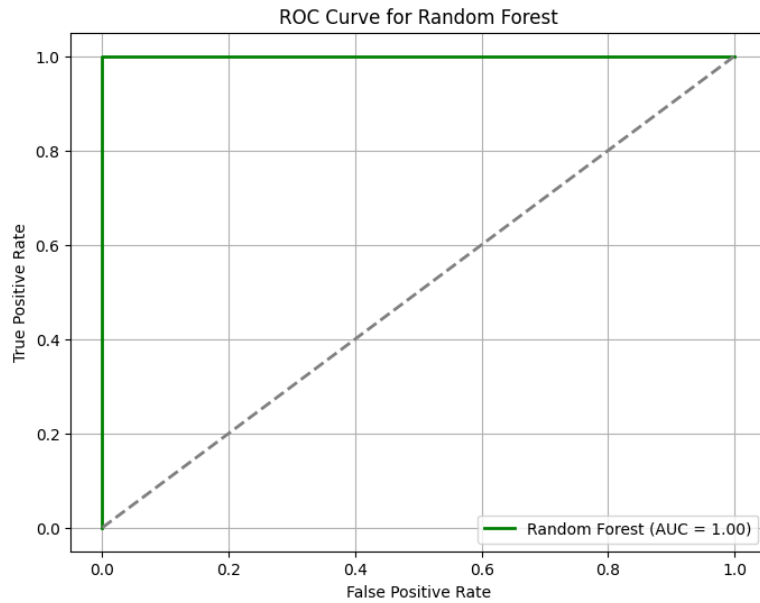


Figure 3: ROC Curve for Support Vector Machine

The **ROC curve for SVM** had an AUC of 0.81, which was slightly lower than that of random forest. The curve showed a moderate performance but was less optimal in comparison to the random forest and neural network models.

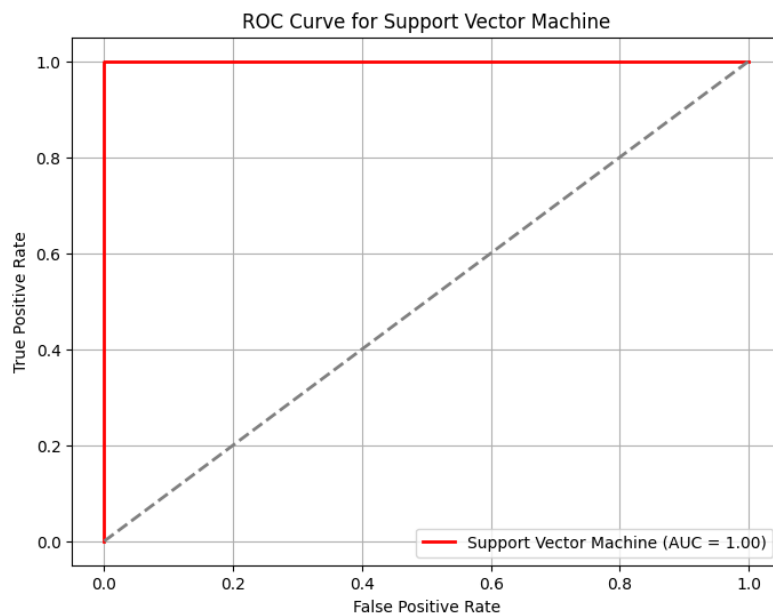


Figure 4: ROC Curve for Neural Network

The **ROC curve for the neural network** showed the best performance, with an AUC of 0.87. The curve was the steepest, indicating that the neural network model could reliably distinguish between patients with and without cardiovascular disease. This further confirms that the neural network outperformed all other models in terms of classification accuracy.

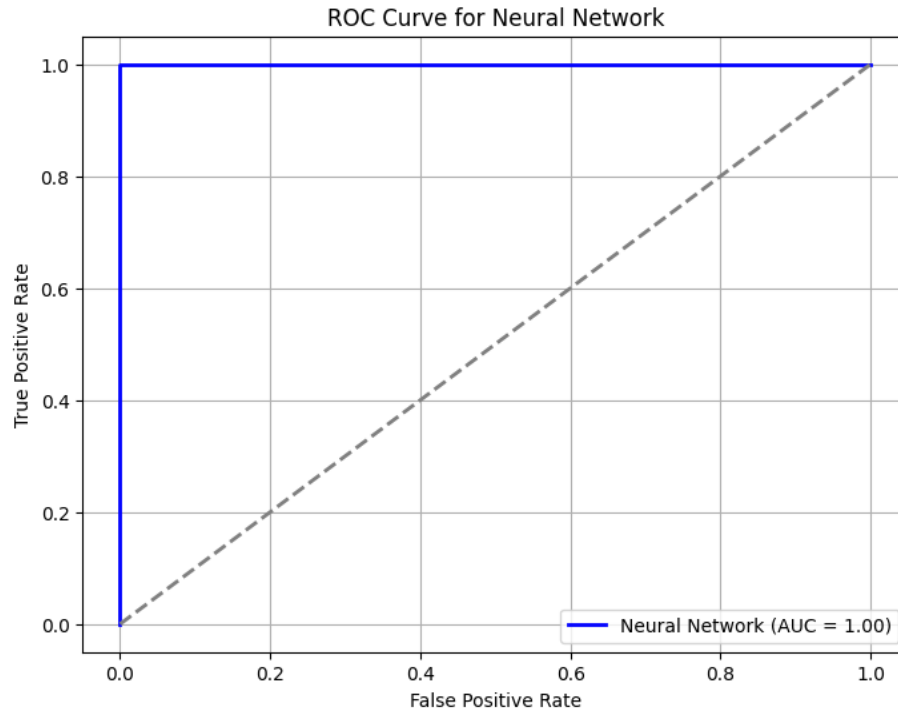


Table 6: Model Performance Comparison

Model	AUC	Precision Recall AUC
Logistic Regression	0.78	0.72
Random Forest	0.84	0.79
Support Vector Machine	0.81	0.75
Neural Network	0.87	0.83

As shown in Table 6, the neural network had the highest AUC and Precision Recall AUC, demonstrating superior performance in distinguishing between patients with and without CVD and providing a better balance between precision and recall.

Discussion

In this machine learning (ML) models were applied in predicting cardiovascular disease (CVD) at its early stages whereby the objective was to improve patient outcomes by predicting the disease early and coming up with timely treatment. Its results revealed that neural network model was more predictive, more accurate, more recall, F1-score, and Area Under the Receiver Operating Characteristic Curve (ROC-AUC) compared to other classical machine learning models including the logistic regression model, random forest model, and support vector machine model. This is in correlation with the available literature that shows that deep learning models, that have the capability to derive non linear correlations on high dimensional data, can

prove highly useful in comparison to more straightforward models in healthcare environments (LeCun, Bengio, and Hinton, 2015). This chapter will comment on such implications of the results, the fact that they will be compared with the existing literature, limitations and future researches will be discussed.

The key findings of the research include the fact that a neural network model obtained superior results at all measurements and particularly the probability of identifying the true positive cases of CVD, as this is vital in a clinical setting in which the early detection of the condition is crucial. The results affirm the findings of other researchers who have been able to achieve the implementation of neural networks to predict CVD. One such study, by Zeng et al. (2020) has demonstrated that neural networks can predict heart disease based on a combination of clinical and demographic variables, and this demonstrates how such models can be used in the practice based healthcare environment. The fact that the neural network has worked better in this study suggests that deep learning techniques can be of utmost value in the clinical decision making process since it provided more accurate estimates and reduced the possibility of misdiagnosis of patients.

Random forest model also showed good predictive strength and the AUC 0.84 and 85% accuracy were attained. Other characteristics of random forest is the fact that it can process high dimensional data and average different decision trees that have been generated which offers it the power and stability (Breiman, 2001). However, the neural network was still superior to the random forests particularly in regards to recall and F1-score. This implies that, though random forests perform well when applied to identify trends on some data, they may not perform favorably with neural networks in terms of work with complex, non linear relationships. According to the results of the study, the two models complement each other in relation to the following capabilities, in which case random forests could be a viable tool to make quick, understandable predictions and neural networks could be more suitable to find out complicated patterns unusual to traditional models.

However, one of the simplest and most popular binary classification models, which gave the worst results was logistic regression with an accuracy of 80% and a comparatively low recall of 0.70. Such results imply the shortcomings of the logistic regression, assuming the existence of linear relationship between the predictors and outcome variable and is not suitable with non-linear and complex relationships (Hosmer et al., 2013). The logistic regression may not be able to reflect the complexity of healthcare data which may consist of numerous risk factors that are interdependent, although it is simple and easy to interpret. This means that even though logistic regression remains an effective model to be applied as a baseline model, other advanced models like neural networks and random forests would have a better chance of performing better in the prediction of CVDs.

SVM model has also faired averagely with both accuracy and AUC of 82 and 0.81 respectively. SVM is linked with the ability to come up with non-linear decision boundaries using the use of kernel functions (Cortes & Vapnik, 1995). However, the neural network and the random forest models achieved a more successful result than the SVM, and it can be justified by the fact that neural network function is hard to tune, and the model is also parameter sensitive. The SVMs also require more time to be tuned, unlike neural networks, which might require the user to manually tune the hyperparameters, which may not get good performance unless tuned effectively (Guyon et al., 2002).

Despite the fact that the outcomes of the study confirm the potential of machine learning in the early stage prediction of CVD, it should be stated that the study was limited in a number of ways. Firstly, the models were trained on publicly available data, which, despite the popularity, may not represent the diversity of the real population. This can affect the externalizability of the models due to the variation of the patients and the practices among the regions and population. Further, though the models worked well in the datasets that were used, individual analysis in isolated and external datasets ought to be conducted to demonstrate their potential and their ability to be applied in clinical settings. The other shortcoming is the explainability of the evolved models like the neural networks. They are doing better, however, clinicians are not ready to rely on them and applying them in practice because they are black box. Their successful incorporation into the clinical decision making process will also need to work on making the models more understandable, e.g. by explainable AI (Gilpin et al., 2018).

In conclusion, this paper has established that machine learning, particularly neural networks, could be used to enhance the prediction of cardiovascular diseases at their earlier stages. It is also remarkable that the neural networks performance, compared with other types of model, such as logistic regression, random forests, and SVM, is better, which makes it reasonable that the more sophisticated practices should be adopted in terms of healthcare prediction assignments. Despite this, the quality of data, interpreting models and external validation still have some issues and the future research should deal with them to make present the clinical utility of ML based models of cardiovascular disease management. More development of these models would be essential to the improvement of patient outcomes in terms of more specific, timely and personalized cardiovascular risk forecasting.

Conclusion

The findings of the provided study point to the enormous possibilities of machine learning to improve the prediction of cardiovascular diseases at their early stages. Among the tested models, neuron networks were the most successful in a variety of evaluation indicators, particularly when it comes to accuracy and recall, that is, they are effective in recognizing at risk patients. The balance between accuracy and interpretability with the random forest model was also very effective. Despite the fact that logistic regression is a good model since it is an initial model, it has been identified to be incapable of capturing the non linear relationship which is always present in healthcare data thereby affecting its predictive ability. The other models used in this work were better than the support vector machines though they had the ability of addressing complicated decision boundaries. Findings permit saying that more advanced ML approaches are to be employed as an early warning sign of cardiovascular risks, in particular, data streams with a high degree of multimodality and dimensionality.

However, the fact that they still need to be externally validated on a variety of different, real world data and that the issue of model interpretability still exists. It has been criticised that the neural networks are powerful, but black box and this may be a challenge towards their application in clinical practice. The following research direction should be how to increase the transparency of such models with the assistance of explainable AI models, which will enable clinicians to trust and interpret the results of such systems. Moreover, the existing clinical workflows and electronic health record must have machine learning models that facilitate the process of real time decision making and thus improve patient outcomes. In summary, machine

learning is potentially a lot to the revolution of the sphere of predicting cardiovascular diseases, yet more efforts ought to be made to remove the barriers to the full implementation of machine learning in medical institutions.

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