Analysis and Prediction of Cardio Vascular Disease using Machine Learning Classifiers

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Abstract
Cardiovascular disease (CVD) often refers to illnesses characterized by narrowed or clogged veins, which may lead to cardiovascular events such as heart attacks, chest pain (angina), or strokes. The machine learning classifier uses the patient's reported adverse effects to make a diagnosis. Cardiovascular disease (CVD) prediction using machine learning tree classifiers is the focus of this research. The accuracy and area under the curve (AUC) scores were used to categorize several machine learning tree classifiers, such as Decision Tree, Random Forest, Logistic Regression, Support Vector Machine (SVM), and K-nearest neighbors (KNN). This study of cardiovascular disease prediction found that the Random woodland machine learning classifier achieved an improved accuracy of 85%, an area under the curve (ROC) score of 0.8675, and a runtime of 1.09 seconds.
Keywords—Accuracy, Classifiers, Cardiovascular disease, Prediction.

INTRODUCTION

Worldwide, cardiovascular disease (CVD) is the most recognizable and dangerous infectious disease; more people die from CVD each year than any other cause. In 2016, 17.9 million people died from cardiovascular disease (CVD), accounting for 31% of all deaths globally [1]. Heart attacks and cardiac arrest account for 85 percent of these fatalities. Depressed yield countries account for about 75% of all fatalities from cardiovascular disease. The majority of the 17 million less-than-ideal closures (those younger than 70) in 2015 were caused by cardiovascular disease (CVD) (37%), with 82% occurring in countries with a low fertility rate) [2]. Treating identifiable risk factors, such as cigarette smoking, unhealthy eating habits and obesity, physical inactivity, and harmful alcohol consumption, may eliminate the majority of cardiovascular disease (CVD) cases. Early introduction and management using brief prescriptions are necessary for individuals with Cardio Vascular Disease (CVD) or who are at high cardiovascular risk (due to the presence of at least one risk factor, such as hypertension, diabetes, hyperlipidemia, or effectively settled illness), as specified. The accumulation of lipids [3] inside the arteries (atherosclerosis) and the formation of blood clots are the last stages of cardiovascular disease (CVD). Additionally, it may be associated with damage to pathways in organs including the eyes, kidneys, heart, and brain. Cardiovascular disease (CVD) is a leading cause of mortality and disability in the United Kingdom [4], yet it is often greatly preventable by leading a healthy lifestyle. A blockage that prevents blood from reaching the heart or brain is the most common cause of both coronary episodes and strokes, which are usually caused by severe events. The most common explanation for this is the accumulation of lipids along the inner walls of veins. In most cases, a combination of risk factors, such as a sedentary lifestyle, being overweight, and tobacco use, is the immediate cause of cardiovascular failure and stroke.

RELATED WORK

Research into the use of machine learning classifiers for the prediction of persistent and infectious diseases is an active topic in this field. Juan [5] used decision trees, random forests, support vector machines, neural networks, and logistic regression to evaluate the validity and accuracy of machine learning classifiers for clinical use. In a study that looked at the heart failure rate using a variety of tools, including a distance distribution matrix, a convolutional neural network model, and support vector machine learning models, the results showed that support vector machine performed better than all of the classifiers. In [7], a method for automatically diagnosing dilated cardiomyopathy (DCM) and atrial septal defect (ASD) using directed machine learning classifiers was suggested. The distinct features are organized with the use of a controlled support vector machine technique, Omar[8] investigated how to deconstruct the system's performance on the local device by feeding the combined data into a support vector machine, and then he used that data to identify patterns of critical signals in the context of mobile phone clinical databases (SVM) Future sensors may be able to classify patients as "proceeded with hazard" or "no longer in danger" based on a mobile machine learning model for cardiovascular disease. Patients with severe DCM were anticipated to have their cardiovascular events predicted using Machine Learning (ML) in the study published in [9]. 32 key points derived from clinical data were an addition to Information Gain (IG) selected the major highlights that were highly relevant to the cardiovascular events using the ML algorithm. Predicting cardiac problems with the use of a hybrid machine learning strategy was detailed in [10]. Using a combination of a basic k-means algorithm and an arbitrary random forest classifier, a hybrid technique is suggested for the prediction of cardiac disease. The following results were attained by means of a random forest classifier, and the accompanying confusion matrix illustrates the method's resilience. Research by Dinesh Kumar [11] into early methods for predicting cardiovascular illnesses led to decisions for the developments that should have occurred in high-risk people, reducing their risks. This forecast's data pre-processing makes use of methods including eliminating noise, removing missing data, changing default values as needed, and combining characteristics for prediction at different levels, among others. In order to demonstrate an accurate model for predicting cardiovascular diseases, these advancements are completed by comparing the accuracy of rule applications with individual outcomes of classifiers like logistic regression, naive Bayes, support vector machine, random forest, and gradient boosting applied to a dataset extracted from a district. Research on medication-induced worsening of cardiovascular diseases was conducted in [12]. Two machine learning approaches were used and incorporated into the foundation of Fisiologiab Clinica's thinking to achieve this goal. The second procedure was used to an American dataset provided by the National Institute of Diabetes and Digestive and Kidney Diseases (NIDDK) vault. In [13], a method for dealing with the characterization and prediction of atherosclerosis illnesses using machine learning algorithms was described. The classifiers used in this approach for predicting the presence or absence of atherosclerosis infection were K-nearest neighbours (KNN) and artificial neural networks (ANN). Diabetes and cardiovascular disease management was suggested by Berina [14] using machine learning methods. For this task, the most common classifiers used were ANNs and Bayesian Networks (BNs). Using an Artificial Neural Network, the authors of [15] foresaw cases of cardiac infections. The goal is to treat cardiac conditions by using pattern matching and machine learning. In [16], a method for handling the ordering of cardiovascular risk forecasts based on retinal vessel investigations using machine learning was mentioned. A reliable individual risk prediction based on Retinal Vessel Analysis (RVA) was achieved by the use of oversampling and cutting-edge techniques. The results indicated that the RVA-based models for cardiovascular disease prediction are more aggressive than the well-established Framingham and Qrisk-based models. Using a plethora of machine learning classifiers, Martin [17] predicted the Constant Cardiovascular breakdown detection from cardiac sounds. The methods used for prediction include machine learning, segmentation, filtering, and feature extraction. For severe cardiovascular patients, the authors of the aforementioned study devised a system for dynamic death prediction using machine learning techniques [18]. Demands for critical information to improve have been met, and educated basic leadership has been used. Hemoglobin (HGB), red blood cell count (RBC), alanine transaminase (ALT), aspartate transaminase (AST), glucose, platelet count (PLT), and creatinine levels were used as indicators in the basic lab tests. In order to assess the potential for complications after a coronary medicine eluting stent procedure, Balasubramanian [19] developed conformal indicators based on vector machines. A novel conformal expectation system based on support vector machines (SVMs) has been used in this approach. Consequently, these predictive model risks categorize a patient for complications after DES. According to the research in [20], machine learning can make coronary supply route disease diagnostic methods more accurate. One machine learning strategy that was used was the Naive Bayesian classifier. In [21], the authors provide a machine learning-based prediction of cardiovascular events for percutaneous coronary intervention using algorithms such as support vector machines, neural networks, and extreme gradient boosting and light boosting machines. A structural model for the prediction of cardiovascular diseases has been put out by Manpreet [22]. This approach makes use of structural equation modeling (SEM) and fuzzy cognitive mapping (FCN). In [23], an approach for prediction of cardiovascular disease risk using computerized machine learning is provided. Data imputation, feature processing, and a calibration technique are all components of an ML modeling pipeline that has been chosen and implemented using an algorithmic tool that infers the model via auto prognosis. Cardiovascular illness is a complicated and varied clinical framework, and Karman [24] suggested a new cosmology and machine learning to help visualize it. This approach makes use of methods from machine learning and ontology. As a result, it demonstrates a practical cardiovascular option to aid tool for addressing errors in the clinical risk assessment of patients with chest pain and aids clinicians in appropriately distinguishing between patients with severe angina and heart chest pain and those with other causes of chest pain. The article [25] provided an additional machine learning approach for the accurate diagnosis of coronary artery disease. This methodology also included a new advancement method called the N2 Genetic optimizer agent, which is another kind of genetic preparation. These results are aggressive and quite similar to the field's best. The authors of the study used machine learning to predict cardiovascular events in individuals with severely enlarged cardiomyopathy one year from the date of diagnosis [26]. We built a Naive Bayes classifier and tested its predictive performance using 10-overlap cross-approval, which measures the area under the curve of the beneficiary's working characteristics. According to Bhuvaneswari [27], a heart infection expectation framework utilizing a genetic algorithm and neural network. A generic-based neural network is utilized for preparing the framework. The work in [28] gave the continuous arrhythmia heartbeats classification algorithm. The strategies utilized in this procedure are Parallel Delta Modulations and Rotated Linear-Kernel Support Vector Machines. Photonic crystal enhanced fluorescence imaging [29] provided an immunoassay for evaluating biomarkers of cardiovascular disease using machine learning. This investigation makes use of principal component analysis (PCA), partial least squares regression (PLSR) techniques, support vector machine characterisation, and sophisticated machine learning algorithms. Datasets, test sizes, highlights, regions of data collection, execution measures, and applied ML are the fundamental approaches that have been deconstructed in this methodology, which was discussed in relation to machine learning-based coronary artery disease conclusions in [30]. Consequently, the major challenges and shortcomings of ML-based CAD diagnosis are finally discussed. In a study that used machine learning classifiers to predict the spread of hepatitis, the authors found that the random forest classifier performed better than all of the other classifiers tested. The use of machine learning classifiers for the prediction of chronic and infectious diseases has been realized in a number of contexts, including non-small cell lung cancer ensemble multi-model techniques for chronic kidney disease [32], diabetes mellitus [33], Optimized random forest for diabetes mellitus [34], and hybrid machine learning classifier [35] [36].

PROPOSED METHODOLOGY

Table I shows the 304 occurrences of the ten variables included in the heart disease dataset that we got from the repository at the University of California, Irvine (UCI). These attributes were age, sex, cp, trestbps, cho, fbs, restecg, thalach, ca, and target. Data integration, data transformation, data reduction, and data cleaning inside the pandas tool are some of the preprocessing approaches used to clean and prepare the dataset at the first level. In Fig. 1 we can see the suggested structure. The visualization included 304 patient records in total. When a data scientist uses data visualization tools, they may better grasp the dataset's viability. The link between the desired qualities and sex is shown in Fig. 2 as a box plot. Figures 3 and 4 showed the correlation matrix and histogram, respectively. Figure 5 displays the seaborn plot, which shows the attribute statistics. In Figures 6 and 7, we can see the scatter plot and matrices. We use five machine learning classifiers—Logistic Regression (LR), Support Vector Machine (SVM), Decision Tree (DT), Random Forest (RF), and K-Nearest Neighbors (KNN)—after dividing the cleaned data into 60% training and 40% test sets, according to the split criteria. The confusion matrix was used to determine the classifiers' accuracy. It is possible to identify the top classifier by looking at which one achieves the greatest accuracy.

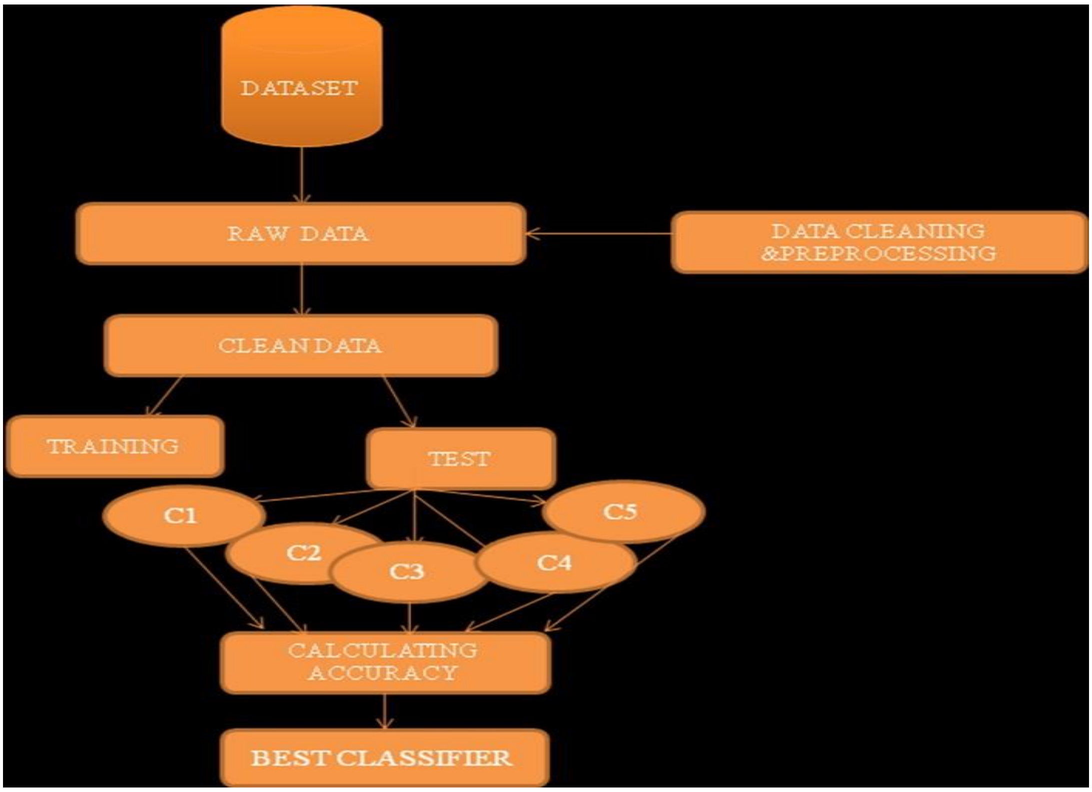

Fig. 1. Proposed Framework

TABLE I. DESCRIPTION OF THE DATASET

S.No	Attributes	Value type
1.	age	Numerical
2.	sex	Nominal
3.	cp	Nominal
4.	trestbps	Numerical
5.	cho	Numerical
6.	fbs	Nominal
7.	restecg	Nominal
8.	thalach	Numerical
9.	ca	Nominal
10.	target	Nominal

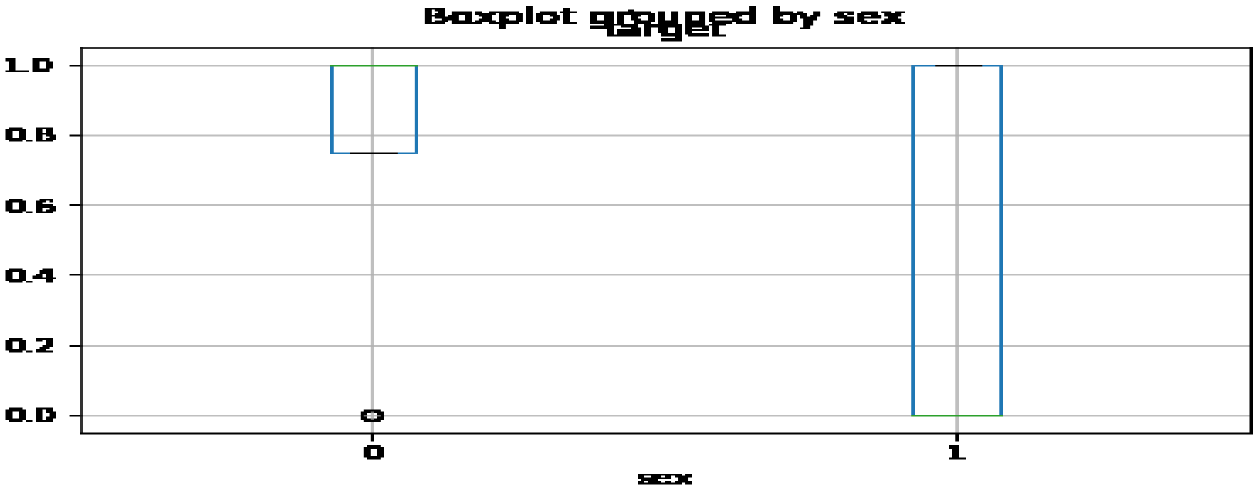

Fig. 2. Box plot

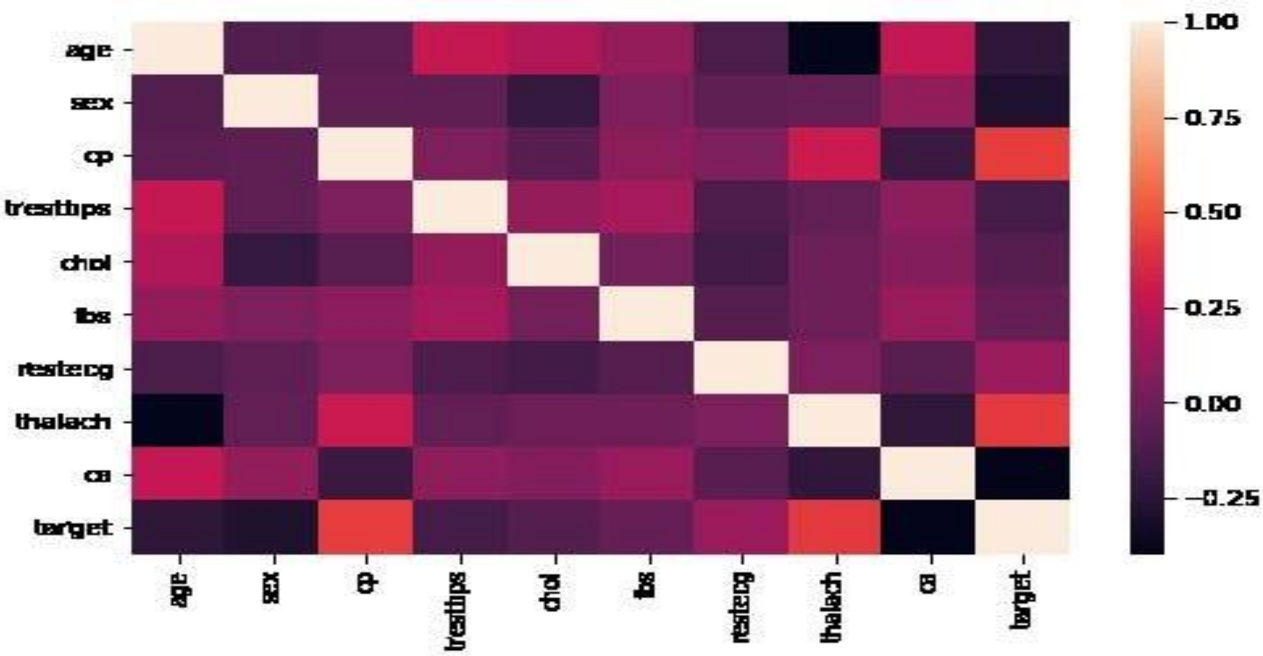

Fig. 3. Correlation matrix

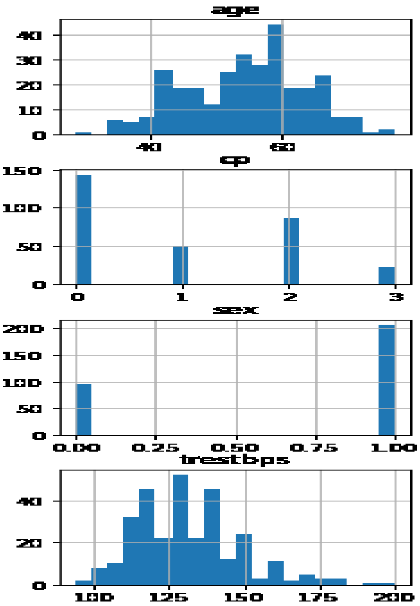

Fig. 4. Histogram

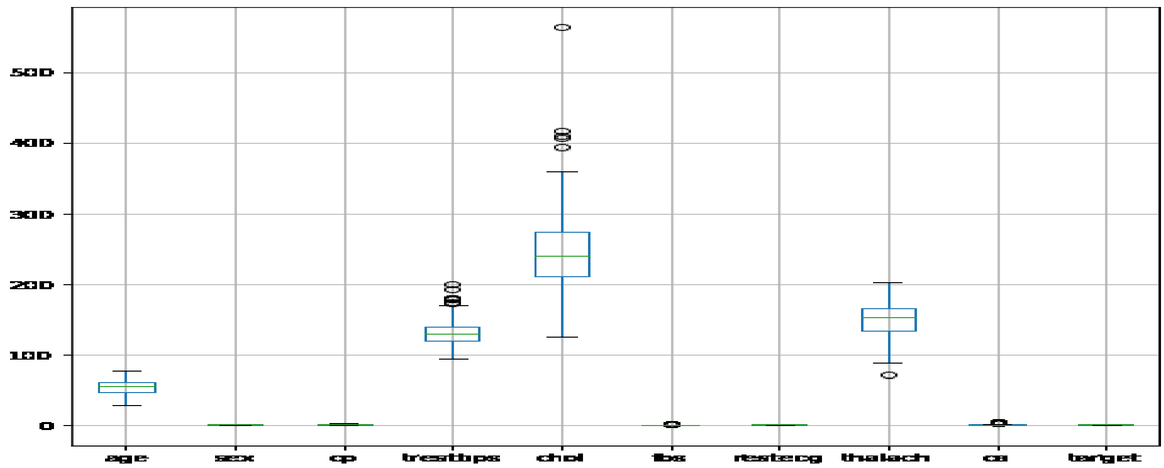

Fig. 6. Scatter matrix

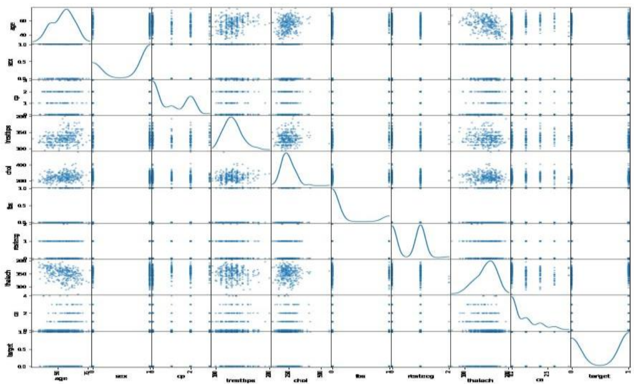

Fig. 7. Subplot

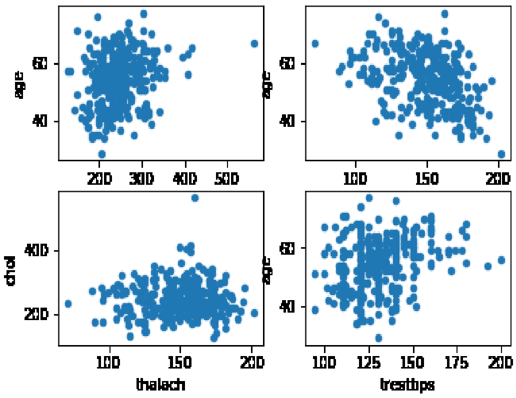

Fig. 5. Sea born

EXPERIMENTAL ANALYSIS AND FINDINGS

The experimental results and analysis of cardiovascular disease prediction are presented in this part. Jupyter was utilized in an environment with a quad-core i5 processor, 6 GB of RAM, pandas, Ipython, SciPy, StatsModels, and Matplotlib software packages. First, we use the pandas tool to clean up the dataset. Then, we run five machine learning classifiers on the cleaned up dataset to see how well they predict cardiovascular illness. This is the second step of our experimental research. Figures 8, 9, 10, 11, and 12 demonstrate the classifier's execution with its accuracy, in that order. Figure 13 displays the comparison as a whole.

```
In [50]: #Random Forest Classifier
         from sklearn.ensemble import RandomForestClassifier
         from sklearn.metrics import confusion_matrix
         import warnings
         warnings.simplefilter('ignore')
         clf=RandomForestClassifier(n_estimators=30)
         clf.fit(X_train,y_train)
         y_pred=clf.predict(X_test)
         print("Accuracy score {}".format(accuracy_score(y_test,y_pred)))
         print("ROC AUC score {}".format(roc_auc_score(y_test,y_pred)))
         #pd.DataFrame(data={"Y_Actual":y_test,"Y_Predict":y_pred})
         cm=confusion_matrix(y_test,y_pred)
         cm

         Accuracy score 0.8571428571428571
         ROC AUC score 0.8675213675213675

Out[50]: array([[ 8,  1],
                [ 4, 22]], dtype=int64)
```

Fig. 8. Accuracy and ROC AUC of Random Forest

```
In [49]: #Decision tree classifier
         from sklearn.tree import DecisionTreeClassifier
         from sklearn.metrics import confusion_matrix
         import warnings
         warnings.simplefilter('ignore')
         clf = DecisionTreeClassifier().fit(X_train, y_train)
         clf.fit(X_train,y_train)
         y_pred=clf.predict(X_test)
         print("Accuracy score {}".format(accuracy_score(y_test,y_pred)))
         print("ROC AUC score {}".format(roc_auc_score(y_test,y_pred)))
         #pd.DataFrame(data={"Y_Actual":y_test,"Y_Predict":y_pred})
         cm=confusion_matrix(y_test,y_pred)
         cm

         Accuracy score 0.7428571428571429
         ROC AUC score 0.717948717948718

Out[49]: array([[ 6,  3],
                [ 6, 20]], dtype=int64)
```

Fig. 9. Accuracy and ROC AUC of Decision Tree

```
In [47]: #Logistic regression
         from sklearn.linear_model import LogisticRegression
         from sklearn.metrics import accuracy_score,roc_auc_score
         from sklearn.metrics import confusion_matrix
         import warnings
         warnings.simplefilter('ignore')
         clf=LogisticRegression()
         clf.fit(X_train,y_train)
         y_pred=clf.predict(X_test)
         print("Accuracy score {}".format(accuracy_score(y_test,y_pred)))
         print("ROC AUC score {}".format(roc_auc_score(y_test,y_pred)))
         #pd.DataFrame(data={"Y_Actual":y_test,"Y_Predict":y_pred})
         cm=confusion_matrix(y_test,y_pred)
         cm

         Accuracy score 0.7428571428571429
         ROC AUC score 0.7542735042735043

Out[47]: array([[ 7,  2],
                [ 7, 19]], dtype=int64)
```

Fig. 10. Accuracy and ROC AUC of Logistic Regression

```
In [48]: #Support Vector Machine Classifier
         from sklearn.svm import SVC
         from sklearn.metrics import confusion_matrix
         import warnings
         warnings.simplefilter('ignore')
         clf=SVC(kernel='linear',gamma='scale')
         clf.fit(X_train,y_train)
         y_pred=clf.predict(X_test)
         print("Accuracy score {}".format(accuracy_score(y_test,y_pred)))
         print("ROC AUC score {}".format(roc_auc_score(y_test,y_pred)))
         #pd.DataFrame(data={"Y_Actual":y_test,"Y_Predict":y_pred})
         cm=confusion_matrix(y_test,y_pred)
         cm

         Accuracy score 0.7714285714285715
         ROC AUC score 0.7371794871794872

Out[48]: array([[ 6,  3],
                [ 5, 21]], dtype=int64)
```

Fig. 11. Accuracy and ROC AUC of Support Vector Machine

```
In [52]: #KNN
         from sklearn.neighbors import KNeighborsClassifier
         from sklearn.metrics import confusion_matrix
         import warnings
         warnings.simplefilter('ignore')
         clf=KNeighborsClassifier(n_neighbors=11)
         clf.fit(X_train,y_train)
         y_pred=clf.predict(X_test)
         print("Accuracy score {}".format(accuracy_score(y_test,y_pred)))
         print("ROC AUC score {}".format(roc_auc_score(y_test,y_pred)))
         #pd.DataFrame(data={"Y_Actual":y_test,"Y_Predict":y_pred})
         cm=confusion_matrix(y_test,y_pred)
         cm

         Accuracy score 0.6857142857142857
         ROC AUC score 0.6431623931623931

Out[52]: array([[ 5,  4],
                [ 7, 19]], dtype=int64)
```

Fig. 12. Accuracy and ROC AUC of K Neighbor

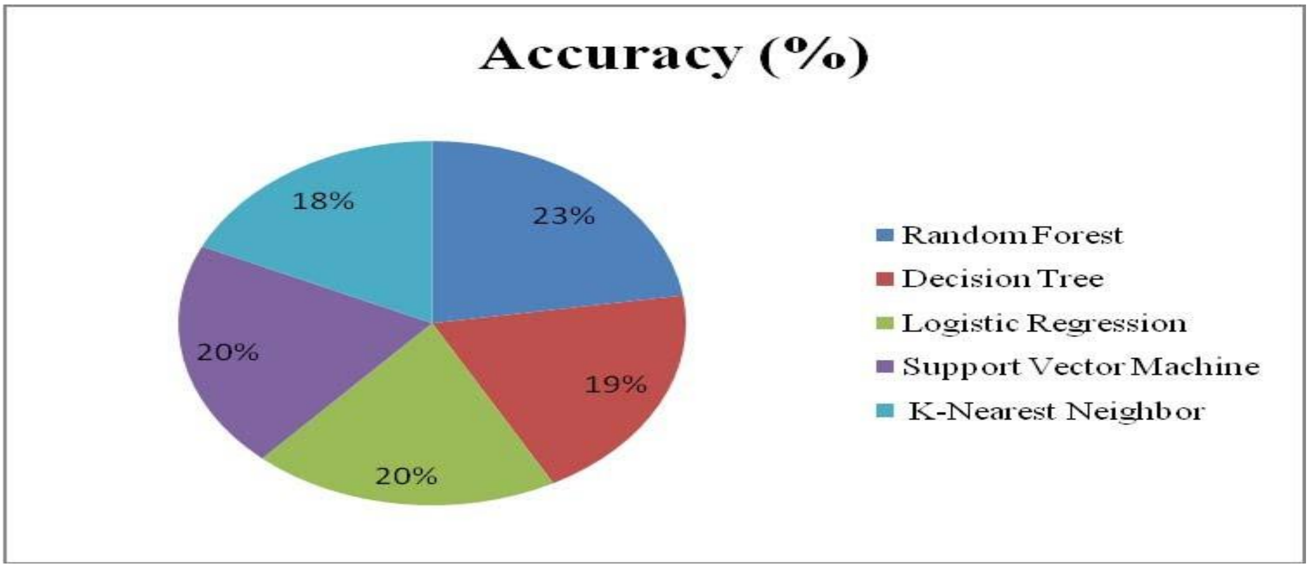

TABLE II. ACCURACY OF THE CLASSIFIERS

Classifier	Accuracy (%)	Inaccuracy (%)
Random Forest	85.71	14.29
Decision Tree	74.28	25.72
Logistic Regression	74.28	25.72
Support Vector Machine	77.14	22.86
K-Nearest Neighbor	68.57	31.43

Fig. 13. Accuracy of the classifiers

TABLE III. ROC AUC OF THE CLASSIFIERS

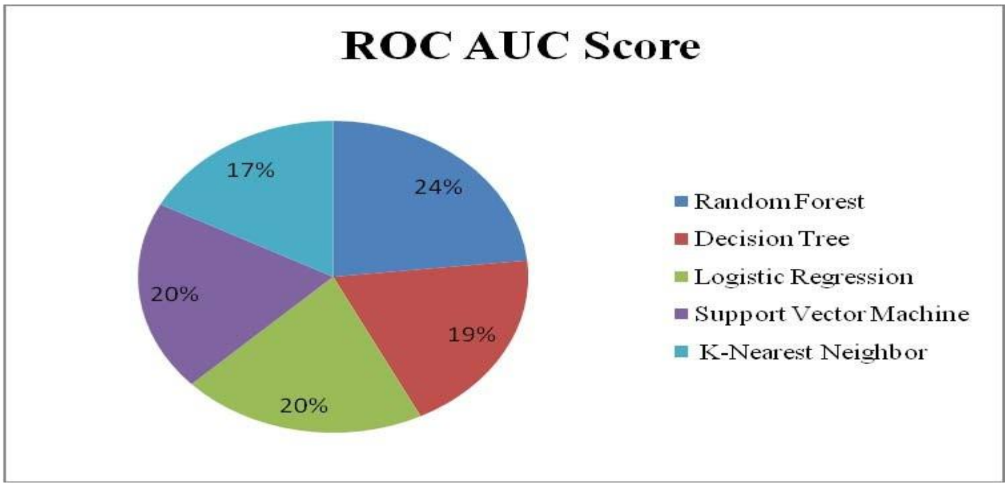

Fig. 14. ROC AUC of the classifiers

Among the classifiers tested, a random forest classifier outperformed the others with an accuracy of 85.71% when it came to misclassifying cases. When it came to instance classification, the decision tree was just as accurate as logistic regression at 74.28%. The two classifiers with the lowest scores were Support Vector Machine (SVM) at 77.14% and K-Nearest Neighbor (KNN) at 68.57%. Compared to the logistic regression classifier, whose ROC AUC was 0.7542, the random forest classifier attained a superior value of 0.8675. In that order, the decision tree had a ROC AUC of 0.7179, the logistic regression 0.7542, the support vector machine 0.7371, and K-Nearest Neighbor 0.6431. We can see this in the ROC AUC and accuracy of

Classifier	ROC AUC Score
Random Forest	0.8675
Decision Tree	0.7179
Logistic Regression	0.7542
Support Vector Machine	0.7371
K-Nearest Neighbor	0.6431

the classifiers were shown in Fig. 13 and Fig. 14 respectively.

CONCLUSION AND FUTURE DIRECTIONS

Cardiovascular disease (CVD) prediction in this study made use of ML classifiers including Random Forest, Decision Tree, Logistic Regression, Support Vector Machine (SVM), and K-nearest neighbors (KNN). With a ROC AUC score of 0.8675 and an accuracy of 85.71%, the suggested strategy utilizing a random forest machine learning classifier surpassed all of the classifiers that were analyzed for the purpose of categorizing patients with cardiovascular disease.

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