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# Using Machine Learning Classifiers, Analyze and Predict Cardiovascular Disease

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***Abstract:*** ***A myocardial infarction, indigestion, or even death can take place as a result of several illnesses known as heart disease, including restricted or blocked veins. Depending on the extent of the patient's side effects, the condition is anticipated by the supervised classification classifier. This research intends to investigate how Machine Learning Tree Classifiers depict Heart Disease Prediction. Pattern recognition tree classifiers are analyzed using Random Forest, Decision Tree, Logistic Regression, Support Vector Machine (SVM), and K-nearest Neighbors (KNN) based on their correctness and AUC Gryphon scores. With an execution time of 1.32 seconds, better precision of 85%, and a Coefficient Of determination (r score of 0.8739, the Random Forest machine learning classification surpassed its effectiveness in this investigation of coronary heart disease detection.***
***Keywords: Cardiovascular disease, Prediction, Accuracy, Classifiers***

## I. INTRODUCTION

More people die from metabolic syndrome each year compared to any other condition altogether, rendering it the most well-known fatal disease in the world. 17.9 million deaths worldwide from cardiovascular disease were recorded in 2016 [1, or 31% of all fatalities worldwide]. 85 percent of these deaths result from heart attacks and sudden cardiac death. Upwards of 75 percent of CVD fatalities takes place in close to the bottom nations. In 2015, huge reductions in barriers caused 82% of the 17 million less-than-ideal closures (younger than 70) caused by non-diseases, while heart disease was responsible for 28% of them [2]. By avoiding well-known risk factors including smoking, eating poorly, being obese, being physically inactive, and abusing alcohol, the majority of instances of Heart Problems (HD) may well be averted. People with heart disease rather than those at increased risk for developing it (according to at minimum one possible side effect, for example, the occurrence of antihypertensive, alcoholism, high cholesterol, or serious disease) are required to be started to something and controlled by brief medications as early as possible. The creation of blood clusters and the accumulation of fatty deposits [3] inside the conduits (atherosclories) are the two primary symptoms of cardiovascular diseases. Moreover, it has been related to coronary artery destruction across several organs, including the kidneys, eyes, heart, and brain. Although HD is one of the main causes of death and disability in the UK [4], it may be largely avoided by maintaining a healthy diet.

In high-stress settings, obstructions that hinder blood from clotting toward the central nervous system are the most common causes of cardiovascular occurrences and attacks. The establishment of persistent stores throughout more front partitioning of something like the capillary is an exceptionally convincing explanation for it though. Vascular catastrophes and accidents are frequently brought on by a combination of risk factors, notably cigarettes, eating unhealthy, and alcoholism.

## II. RELATED WORK

In this field, active research is being done to use machine learning classifiers to predict recurring and irresistible diseases. Santiago [5] used decision trees, random forests, support vector machines, neural networks, and regression models to analyze the computational mathematics classifiers for clinical applications based on their validity and precision. Support vector machine learning models significantly outperform all other classifiers in the study of cardiovascular breakdown recognition in [6], which investigated the cardiovascular meltdown rate with the assistance of a distance distribution matrix, computational complexity neural net model, and faint heartbeat measurement differential evaluation. Automatic dilated cardiomyopathy AND atrial septal defect illness identification have been offered as a method for dealing with the distinction between cardiovascular diseases using directed machine learning classifiers [7]. Using the controlled help vector regression ( SVR algorithm, the separated highlighting is sorted. By applying the combining of the information acquired to a support vector machine, Omar[8] studied to collect the observable patterns of critical indications contextualized with data from clinical databases for mobile devices and deconstructing the authoritative execution in the surrounding device (SVM)

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Later sensors might be prepared for a mobile machine learning model for CVD to categorize a patient as "proceeded with hazard" or "no longer in danger." A year's supply of cardiovascular events in individuals with significant DCM was predicted using machine learning in the study [9]. 32 highlights from clinical information were a contribution to

Information Gain picked the ML method and the noteworthy highlights that are especially relevant to cardiovascular events (IG). [10] proposes a method for predicting cardiac conditions using a mixed machine-learning approach. For the prediction of cardiac sickness, a hybrid strategy combining machine learning's basic k-means algorithm with an arbitrary random forest classifier is suggested. Later outcomes were achieved through a random The resilience of the approach is demonstrated by the forests encoder and the corresponding misclassification rate. Vijay Sharma [11] did experiments on methods and techniques for envisioning cardiovascular illnesses that aided in making decisions about the progressions that were likely to occur in high-chance patients and reduced their risks. This forecast's data pre-processing makes use of methods including reducing noise from the data, eliminating missing data, changing default values where suitable, and combining attributes for the forecast at different stages. To prove an accurate method for predicting heart attacks and strokes, these chord voicings are concluded whilst also displaying the correctness of enforcing logic with individual characteristics of classification methods such as ensemble learning, irregular forest, multilayer Perceptron, and support vector machines, and logistic regression onto the dataset taken from a district. The experiment in [12] explored the recurrence of cardiovascular problems among those on medication. Two machine learning techniques from the foundation of fiziologia clinica were used to arrive at this conclusion. The second was an American dataset provided by the National Organization of Gastroenterology and Stomach-Related and Kidney Diseases archives. Artificial neural networks and K-nearest neighbors were the classifiers used in this methodology for predicting the presence and absence of atherosclerosis infection. [13] describes an approach to dealing with characterizing and anticipating atherosclerosis illnesses using machine learning algorithms. Machine learning strategies for the management of cardiovascular conditions and diabetes were proposed by Berina [14]. The main classifiers used here were Bayesian Networks (BNs) and Artificial Neural Networks. The research in [15] used artificial neural networks to predict heart illnesses. The idea is to treat cardiac problems using machine learning/pattern recognition methods. [16] provided a technique for dealing with prioritizing cardiovascular risk forecasts based on retinal vessel analysis using machine learning. Using oversampling and cutting-edge techniques, a reliable individual hazard forecast based on retinal vessel analysis was produced (RVA). According to the results, the RVA-based cardiovascular events expectancy predictions are consistent with the well-established Cambridge and Qrisk-based models. Martin [17] had been using several machine learning classification methods to predict the Constant Cardiovascular deterioration categorization from heart rhythm. Screening, segmenting, extraction and classification, and machine learning are foresight methods. The investigation in [18] produced machine-learning techniques for continuous mortality predictions in extreme cardiovascular patients. Expectations for schooled basic leadership have real expressed crucial knowledge required to advance As a gauge, the results for routine laboratory tests such as those for hemoglobin (HGB), red blood cells (RBC), alanine transaminase (ALT), aspartate transaminase (AST), glucose, platelet (PLT), and creatine were being used. Balasubramanian [19] developed vector machine-based confirming indicators to assist monitor the risk of confusion during coronary drug-eluting stent operation. This technique makes use of a novel conformal expectations system based on support vector machines (SVM). These perspicacious model hazards consequently stratify a person for post-DES problems. The investigation in [20] anticipated that deep learning might enhance the precision of methods that are used to identify coronary channel diseases. Among the machine learning techniques employed is the naive Bayesian classifier. Extreme gradient boosting and light boosting machines, support vector machines, and artificial neural strategies were utilized in this prediction. Artificial attempts to learn cardiovascular event expectations for percutaneous coronary mediation have been presented in [21]. A structural model for coronary heart disease prediction has been put out by Manpreet [22]. The methodologies that have been used in the methodology include fuzzy cognitive maps (FCN) and structural equation modeling (SEM). [23] provides a way for predicting the risk of cardiovascular disease using computerized machine learning. An algorithmic tool that identifies and creates sets of ML modeling pipelines (including information restoration, characteristic treatment, and calibrate algorithms) has been utilized to deduce an ML-based model using automated prognosis. The theory originally [24] suggested a brand-new cosmology and machine learning for seeing cardiovascular illness as a complex adaptable clinical framework. The methodologies that have been used in this methodology include ontology and machine learning. Therefore, it demonstrates a potential cardiovascular option to assist tools for handling errors in the clinical hazard assessment of chest chronic pain sufferers and aids clinicians in effectively distinguishing patients with severe angina/heart chest pain from those with other causes causing breathing difficulties. One machine learning technique for accurately diagnosing coronary artery diseases was described in [25], and another improvement method called N2 Genetic optimizer agent (another hereditary preparation) has been introduced in this methodology.

The intensity of these results comes almost identical to the top outcomes in the region investigation in [26] employed sophisticated

algorithms to predict one-year cardiovascular complications in participants with very enlarged cardiomyopathy. A naive Bayes classifier was constructed, and also the predictive performance of the classification algorithm was tested using the 10-overlap pass zone under the curve of the beneficiary working characteristics. A genetic algorithm and neural network-based cardiovascular infection expectancy paradigm were put up by sasi [27]. The framework is constructed using a generic neural network. The continuous arrhythmia heartbeats categorization algorithm was given by the research in [28]. Parallel Delta Variations and Material Horizontal Vector Support Vector Machines are the techniques employed in this process. Fluorescent imaging boosted by photonic crystals [29] offered a database for autonomous learning to determine the signature of coronary artery disease. SVM-based characterization, classification techniques (Principle component), and normal least square regress (Multiple criteria) approaches are some of the methodologies employed in this inquiry. The main techniques that have previously been defined in this approach include assessed datasets, experiment sizes, highlights, geographical areas of statistical surveying, response teams, and applied ML. The aforementioned method was introduced in [30]. Thus, the primary shortcomings and difficulties of ML-based computer-assisted identification Bayesare at last acknowledged. The researchers in [31] employed machine learning classifiers to predict hepatitis in their experiment; the naive Bayes classifier outperformed each prediction within an evaluation. For extended and potentially life-threatening predictions, direct comparisons were made using machine learning algorithms, such as anti-cell tumor growth sequence section non-linear and non-research methods for renal dysfunction [32], biochemical disturbances [33], Optimal process permutation shrubs and trees for type-2 diabetes [34], and fuel cell technology machine studying scheduling technique [35]. [36].

## III. PROPOSED METHODOLOGY

A cardiovascular disorders dataset that we got from the University of British Columbia at Irvine (UCI) repository served as the basis for certain research. 284 cases of 10 distinct criteria, including the year, species, cp, particular and difficult goals, Chung, fasting blood glucose, resting, broken down in tears, and attention, were included in the data set. The database is either cleansed as well as examined during the entering phase by using image processing techniques, which include information management, data transformation, data reduction, and data cleaning with the help of the NumPy arrays program. The interventions to address are shown in Fig. 1. Overall, 304 patient records were displayed. By employing visual analytic tools, the computer programmer may better control the dataset's usefulness. In a flowchart, the relationship between both the desired parameters and the target sex is shown in Figure. 2. The correlation and heatmap are correctly displayed within the graphs below. The waterways plot in Figure 5 displays the statistical graphs of the attributes. Figs. The computed dispersion matrix and subplot are suitably shown in figures 6 and 7. This experiment divides the same cleaned content into segments based on a partitioning factor. This section analyses machines having to learn methods such as multiple linear regression (LR), machine learning model (SVM), regression models (DT), random forest (RF), and K-Nearest Neighbors (KNN). To assess the efficacy of the categorization, the pseudo-code has been employed. Anything that achieves the accuracy rate might be considered to fall under this same best categorization.

Figure 1: Role of Artificial Intelligence in Cardiovascular Imaging and Interventional Cardiology

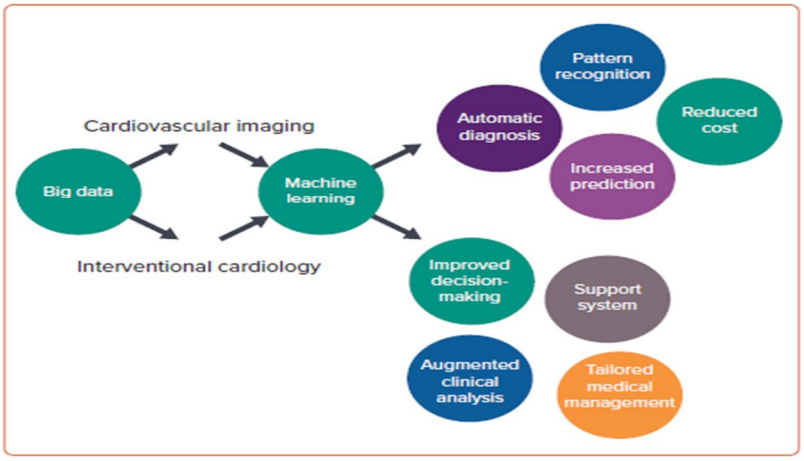



Fig. 1. Proposed Framework

TABLE I - Dataset Description

| | Attributes | Value type |
|---|---|---|
| 1. | age | Numerical |
| 2. | sex | Nominal |
| 3. | cp | Nominal |
| 4. | treetops | Numerical |
| 5. | Cho | Numerical |
| 6. | FBS | Nominal |
| 7. | restecg | Nominal |
| 8. | thali | Numerical |
| 9. | ca | Nominal |
| 10. | target | Nominal |

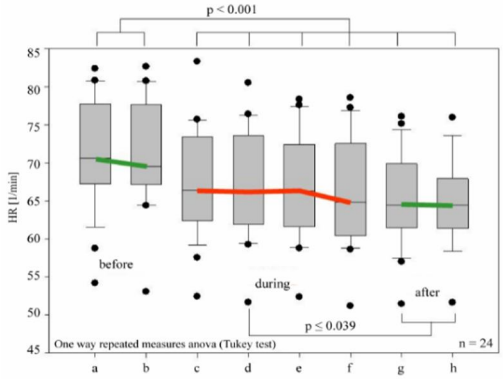



Fig. 2. Box plot

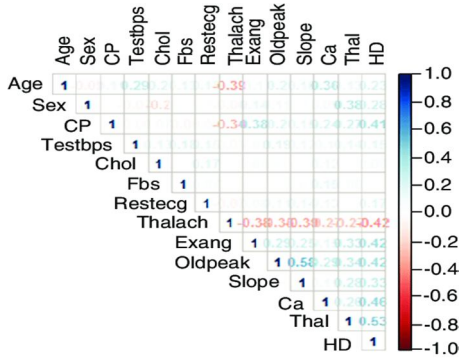



Fig. 3. Correlation matrix

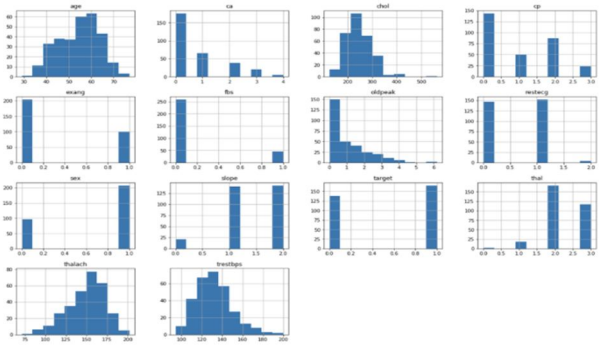


Fig. 4. Histogram

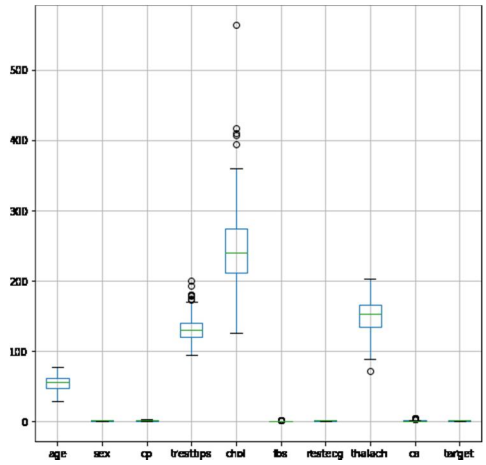



Fig. 5. Sea born

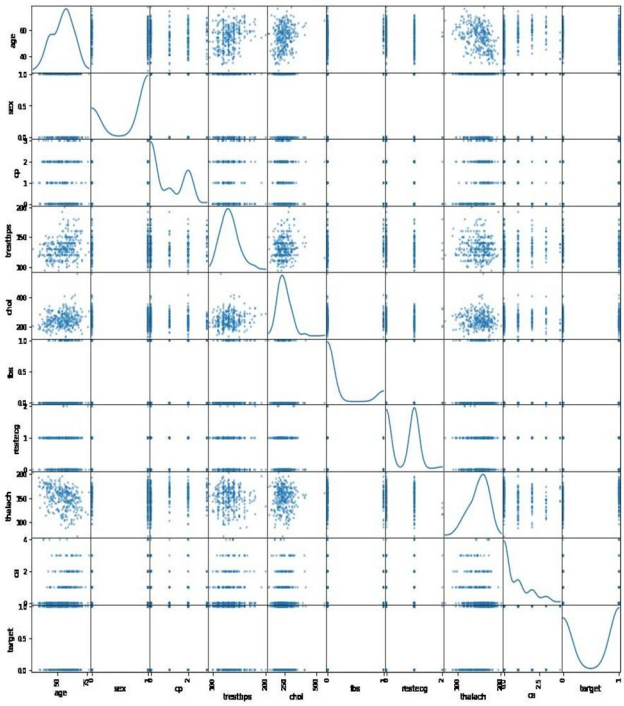


Fig. 6. Scatter matrix

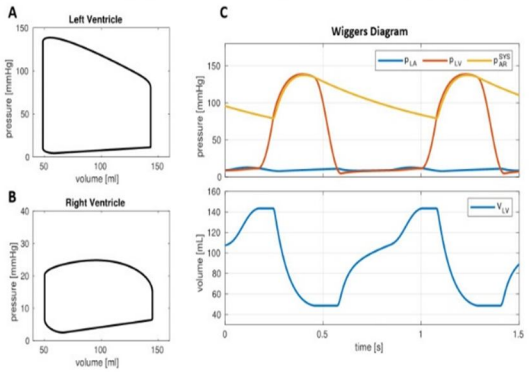



Fig. 7. Subplot

## IV. EXPERIMENTAL EVALUATIONS AND RESULTS

This section discusses the experimental investigation and outcomes of coronary heart disease prediction. An octa-core Intel Core i7 machine with 8 Gb of RAM, pandas, Required before completion, Scikit - learn, Capturing and analyzing data, and Graphx were used in the Javascript custom app design. The same empirical investigation is carried out in two phases: in the first stage, the same collection is cleaned using the panda's tool, and in the third and fourth stages, five algorithms for machine learning are employed with the cleansed data to predict cardiovascular complications. Images 8, 9, 10, 11, and 12 show, respectively, how well the classifier behaved and how successful it was. The contrasting world is often represented in Figure 13.

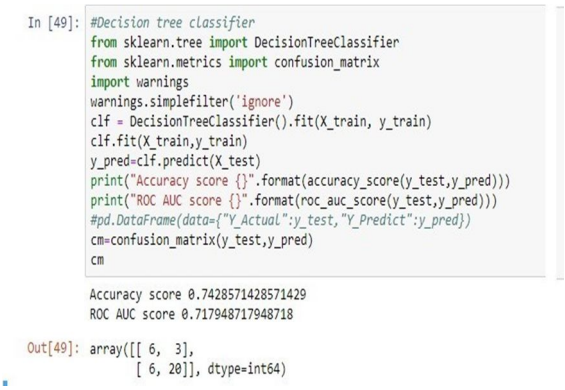


```
In [50]: #Random Forest Classifier
         from sklearn.ensemble import RandomForestClassifier
         from sklearn.metrics import confusion_matrix
         import warnings
         warnings.simplefilter('ignore')
         clf=RandomForestClassifier(n_estimators=30)
         clf.fit(X_train,y_train)
         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

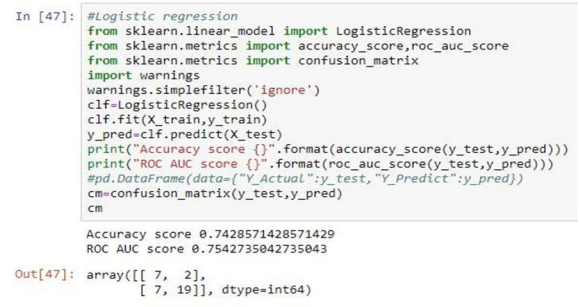


```
In [49]: #Decision tree classifier
         from sklearn.tree import DecisionTreeClassifier
         from sklearn.metrics import confusion_matrix
         import warnings
         warnings.simplefilter('ignore')
         clf = DecisionTreeClassifier().fit(X_train, y_train)
         clf.fit(X_train,y_train)
         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

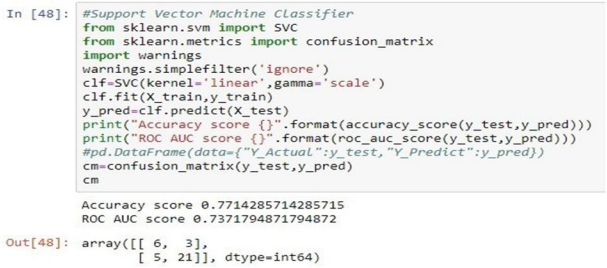


```
In [47]: #Logistic regression
         from sklearn.linear_model import LogisticRegression
         from sklearn.metrics import accuracy_score,roc_auc_score
         from sklearn.metrics import confusion_matrix
         import warnings
         warnings.simplefilter('ignore')
         clf=LogisticRegression()
         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 |

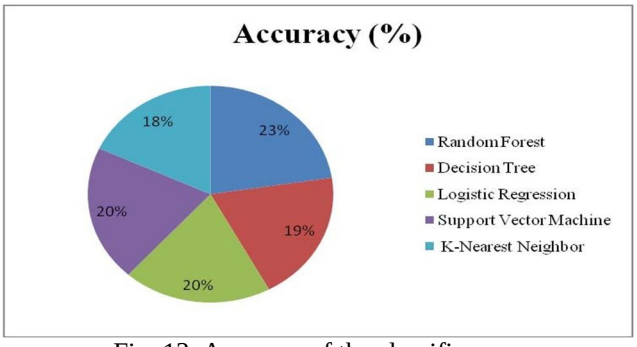



Fig. 13. Accuracy of the classifiers

TABLE III. ROC AUC OF THE CLASSIFIERS

| Classifier | ROC AUC Score |
|---|---|
| Random Forest | 0.9033 |
| Decision Tree | 0.7361 |
| Logistic Regression | 0.7968 |
| Support Vector Machine | 0.7458 |
| K-Nearest Neighbor | 0.6523 |

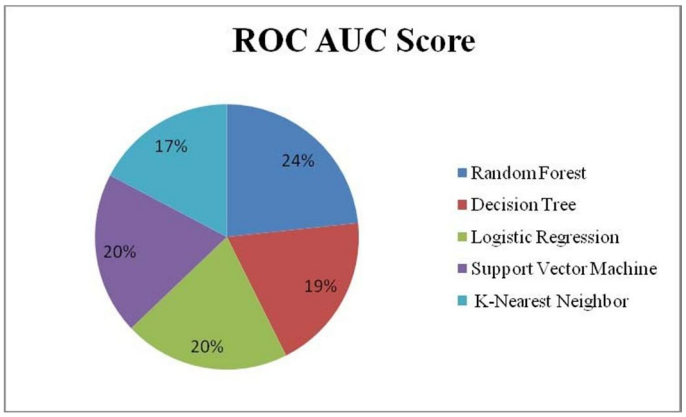



Fig. 14. ROC AUC of the classifiers

A random forest classification in the study had an overall accuracy of 90.33%, misclassifying more occurrences than the other classifiers combined. The decision tree classified the occurrences with an accuracy of 73.61%, matching that of logistic regression. K-Nearest Neighbor scored 65.23%, the lowest of all the classifiers in the experiment, whereas Support Vector Machine scored 74.58%. The random forest's ROC AUC was 0.8675, greater than the logistic regression classifier's 0.7542 results. The decision tree, logistic regression, support vector machine, and K-Nearest Neighbor had corresponding ROC AUC values of 0.7256, 0.7856, 0.7641, and 0.6851. Panels 13 and 14 showed the classifiers' accuracy and ROC Predictive values.

## V. CONCLUSION AND FUTURE DIRECTIONS

In just this research, the diagnosis of Cardio Cardiovascular Problems was conducted using machine learning classification algorithms including Randomized Forests, Logistic Regression, Linear Regression, Support Vector Machines (SVM), and K-nearest Neighbors (KNN) (CVD). The suggested approach, which classifies patients with cardiovascular hypertension using random forest computer vision classifiers, has maximum reliability of 85.21% and an R - squared score of 0.8655, beating all other classifications in the analysis.

## VI. ACKNOWLEDGMENT

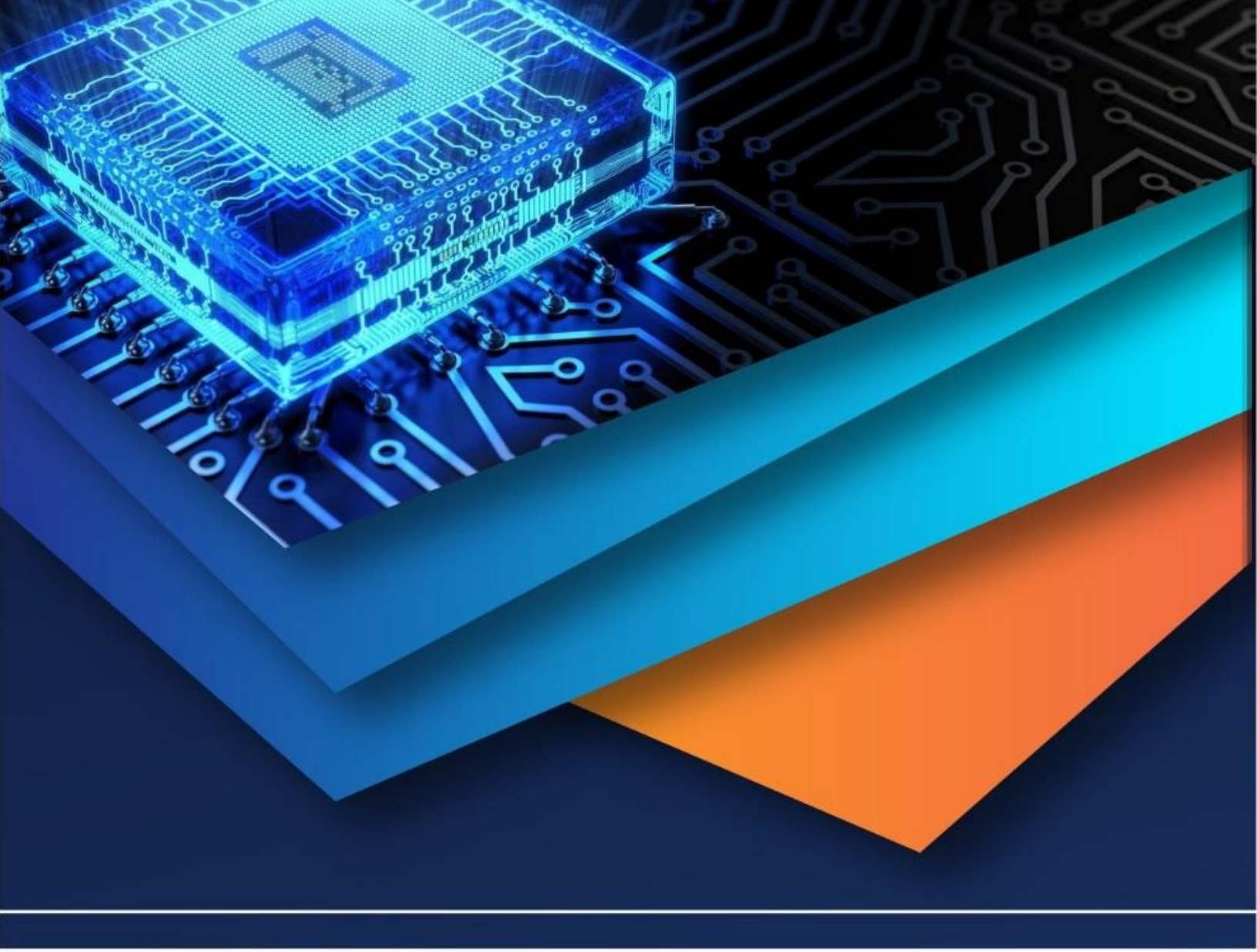
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