Department of Electrical & Computer Engineering
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DIRECTED RESEARCH (498R)

Supervised Machine Learning Based Cardiac Arrhythmia Analysis and detection

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DECLARATION

This is to certify that this Project is our original work. No part of this work has been submitted elsewhere partially or fully for the award of any other degree or diploma. Any material reproduced in this project has been properly acknowledged.

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APPROVAL

The project entitled "**Supervised Machine Learning Based Cardiac Arrhythmia Analysis and detection**" by **Md. Riyadul Islam (ID#1813139042), Kazi Md Ifthekhar Uddin (ID#1811019042)** is approved in partial fulfillment of the requirement of the Degree of Bachelor of Science in Computer Science and Engineering on May and has been accepted as satisfactory.

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Table Of Contents

1. Introduction

Due to the presence of numerous health issues, including diabetes, high blood pressure, excessive cholesterol, and an irregular pulse rate, cardiac arrythmia is difficult to diagnose. The severity of cardiac arrhythmia in an individual has been assessed using a variety of data analysis and neural network approaches. The seriousness of sickness is classified utilizing different procedures, including the K-Closest Neighbor (KNN) calculation, Choice Trees (DT), Hereditary Calculation (GA), and Gullible Bayes (NB) calculation [1-2]. Because of the intricacy of cardiovascular arrythmia, it should be treated with alert. Failure to do so may have a negative impact on the heart or cause death before it occurs. The various kinds of metabolic disorders are identified through the use of statistical and medical science perspectives. For heart arrhythmia prediction and data research, categorization is essential. Decision trees have also been used to accurately predict heart arrhythmia-related events [3]. For the purpose of diagnosing heart arrhythmia, numerous methods of knowledge abstraction have been utilized in conjunction with well-established data mining strategies. Various examinations have been directed in this review to foster an expectation model, using various strategies as well as by interfacing at least two methods. The process of extracting necessary data from massive databases in a variety of fields, including education, business, and medicine, is known as data mining. AI is one of the fields of man-made reasoning that is progressing dangerously fast. These algorithms are able to analyze huge amounts of data from many different fields, including medicine. It is an alternative to the traditional prediction modeling approach, which makes use of a computer to minimize the difference between expected and actual results in order to gain an understanding of complex and non-linear interactions between many variables [4]. The process of sorting through huge datasets to find important information for making decisions from a collection of historical records is called data mining. Patient data abounds in the medical field. Various machine learning methods must be used to analyze these data. In order to make appropriate diagnostic decisions, healthcare professionals analyze this data. Using classification algorithms, medical data mining provides therapeutic assistance through analysis. It assesses strategies for ordering patients' gamble of creating heart arrythmia [5]. One of the many diseases that affect a large number of people is heart disease. Additionally, anxiety plays a major role in many heart attacks. Arrhythmia can be detected early and treated frequently, reducing the incidence of heart attacks in society and preventing sudden death from these unpleasant heart attacks. The ECG, which is recorded when cathodes are placed on the

body and provides instances of the electrical drive of the heart, is the diagnostic tool or device that is utilized the most frequently. P, QRS, and T waves make up ECG signals. Understanding the form and duration of the relationship between these P waves, QRS waves, T waves, and RR is necessary for understanding a heart. Most of the time, cardiac arrhythmia events are identified and categorized using the HRV signal. In today's society, a wide range of chronic diseases are a problem. According to the Global Burden of Disease [16], cardiovascular diseases account for over a quarter (24.8%) of fatalities in India. The most effective and cost-effective method for identifying cardiac arrhythmias in patients is the electrocardiogram (ECG). It takes a long time to manually detect arrhythmia beats because the ECG is complicated and nonlinear. Similarly, it is challenging to detect even minor shifts in time-domain characteristics like amplitude, segments, and intervals [3]. Heart issues are brought on by arrhythmia, an abnormal heartbeat in which the heart pumps too rapidly or too slowly. Based on ECG readings, the precise order of cardiac arrhythmias can be improved by connecting AI systems. The classification of cardiac arrhythmia is influenced by the use setting, the required patient information search, and the appropriate technique selection. A useful framework for determining whether ECG signals are beneficial or harmful is provided by the suggested method. During the typical beat phase of a heartbeat, the most important parameters studied are the ECG signal lengths and associations. These changes point to the possibility of any kind of cardiac disease. Arrhythmia is the umbrella word for all periods of unpredictable pulses, and a few arrhythmias can be very hurtful to the patient. Digitally stored clinical and biological data are becoming more common. These particulars are gotten from few information focuses covering countless individuals (like socioeconomics, blood tests, prescriptions taken, and so forth.). to significantly more in-depth data that is only available for a select few patients.

The classification and prediction of heart arrhythmia diagnosis has been the focus of numerous studies and machine-learning models. In order to achieve the highest possible level of prediction accuracy in the medical field, ANNs were developed [6]. Through back propagation multilayer perception (MLP), ANNs are used to predict cardiac arrhythmia. The subsequent discoveries are contrasted with those of recently distributed models in a similar region and viewed as fundamentally improved [7]. NN, DT, SVM, and Naive Bayes are used to identify patterns in the heart arrhythmia patients' data from the UCI laboratory. The presentation and exactness of different calculations are analyzed. For the F-measure, the suggested hybrid approach achieves an

accuracy of 86.8%, which is comparable to that of the other methods that are available [8]. It is shown how Convolutional Neural Networks (CNN) can be classified without using segmentation. During the training phase, this method takes into account cardiac cycles with a variety of start locations based on ECG data. During the patient's testing phase, CNN is able to generate features in a variety of locations [9, 10]. In the past, a significant amount of medical industry data was improperly utilized. In a straightforward and cost-effective manner, the novel methods described here improve the accuracy of heart arrhythmia prediction and reduce costs. The numerous machine learning (ML) and deep learning (DL) methods used in this study to predict and classify heart arrhythmia are extremely accurate, demonstrating their effectiveness [11, 12]. Avinash Golande and his colleagues look into a variety of machine learning approaches that could be used to categorize cardiac arrhythmia. The precision of the Decision Tree, KNN, and K-Means algorithms that can be used for classification was the subject of a study [13]. This study shows that Decision Trees are the most accurate and can be made more efficient by using a combination of different approaches and tweaking parameters. A system that utilized both the MapReduce algorithm and data mining techniques was created by T. Nagamani and colleagues [14]. For the 45 cases in the testing set, the precision accomplished in this review was higher than the exactness gotten utilizing a commonplace fluffy fake brain organization. In this instance, the use of dynamic schema and linear scaling improved the method's accuracy. A machine learning model created by Fahd Saleh Alotaibi compares five distinct approaches [15]. Rapid Miner was used, which outperformed Matlab and Weka in terms of accuracy. The accuracy of the Decision Tree, Logistic Regression, Random Forest, Naive Bayes, and SVM classification algorithms was compared in this study. The most accurate algorithm was the decision tree one. Anjan Nikhil Repaka and coworkers, fostered a framework in [16] that consolidates NB (Credulous Bayesian) techniques for dataset order and AES (High level Encryption Standard) for secure information transmission for disease expectation. Theresa Princy, R., et al. compared several categorization algorithms used to predict heart arrhythmia in a study. Naive Bayes, KNN (Kindest Neighbor), Decision Tree, and Neural Network were the classification methods used, and the accuracy of the classifiers was tested across a variety of attribute counts [17]. Nagaraj M. Lutimath, and others used SVM (Support Vector Machine) and Naive Bayes classification to predict cardiac arrhythmia. The exhibition measurements used in the review are the Mean Outright Mistake, the Amount of Squared Blunder, and the Root Mean Squared Mistake. In terms of accuracy, it has been demonstrated that SVM outperforms Naive Bayes [18]. J. P. Kelwade and others used ANN as a classifier to divide cardiac arrhythmia into five categories. The time series between the "R" stretch is obtained by utilizing the ECG. MATLAB R2014a is used to implement the method. [1] Mr. Krishnan Santhana. J, Dr. Geetha. S and colleagues examined and predicted the occurrence of heart disease using two data mining techniques. Methods for quickly converting electrocardiogram (ECG) data to digital format were proposed by Yaron Kinar, Nir Kalkstein, and others. 3] Shailendra Aswale, Dr. Pratiksha Shetgaonkar, et al. used the Data Mining method to learn about various cardiac conditions. For the purpose of their investigation, they looked into neural networks, naive bayes, and decision trees in this publication. Using data mining techniques, Aditya Methaila of Prince Kansal predicted cardiac

issues. KNN Algorithms, Decision Trees, and Naive Bayes are the primary foresight approaches. Thirteen distinct health issues are referred to by this term. 5] For the application of ANN-based cardiac arrhythmia categorization, Nasreen Sultana, Yudukondalu Kamatham, and colleagues utilized a method that was both successful and highly anticipated. ECG beats are classified with the Multiclass SVM classifier; It is more effective than other classifiers because it is more accurate [6]. The UCI is the store from which the informational collections are gotten. The data are then prepared for processing. The pre-processed data are then fed into the model and divided into Train and Test data sets. Analyses and projections are made based on the collected data. The numerous ML algorithms used to predict cardiac arrhythmia are the focus of this study. Consequently, these algorithms' efficiency and precision set them apart. The best machine learning classifier for detecting arrhythmia was found by comparing normal and irregular ECG signals.

Our research's basic approach is that we used multiple machine learning models to gain access to a decent dataset. In earlier studies, most researchers utilized a substantial model to predict cardiac arrythmia factors. We employed four distinct models, and the results were compared to similar research.

All of the results and comparisons are detailed in the next section. The following is the entirety of the article: Section 2 describes the research method and materials. Section 3 contains the findings and analyses, whereas Section 4 has the conclusions.

2. Problem Statement

Cardiac arrhythmias can be detected or classified using a variety of algorithms and techniques. The prediction of cardiac episodes or arrhythmias in this context is a more difficult use of machine learning. A trustworthy cardiac event prediction system could notify physicians and patients alike of an approaching incident, allowing for prompt intervention. The prediction of arrhythmic events prior to their commencement, however, is still an unsolved scientific issue.
As AHRE is a proxy for AFib and SVT is the most common kind of arrhythmia, our goal in this study is to develop an accurate prediction method for cardiac arrhythmias. The most prevalent persistent cardiac arrhythmia is AFib. Between 2.7 million and 6.1 million adult Americans had AFib as of 2014. AFib is linked to a five-fold increase in the risk of stroke, a three-fold rise in the risk of heart failure, and a two-fold increase in the risk of death and dementia. SVT is another typical arrhythmia that has an incidence of 2.25 instances per 1000 people in the general population and a mechanical origin in the upper chambers of the heart. The suggested DPFA-based technique or an algorithm with a similar focus on AFib and SVT prediction would significantly improve clinical decision-making and patient care.

3. Proposed Solution

This proposed system provides a methodology for applying classification methods to predict whether cardiac is healthy or not healthy and to improve the classification accuracy using an ensemble of classifiers. The dataset was collected from Kaggle. After processing, the data has become available for model construction. Model construction requires preprocessed datasets and machine learning techniques. RF, DT, XGBoost, and LightGBM classifiers are some of the methods used.

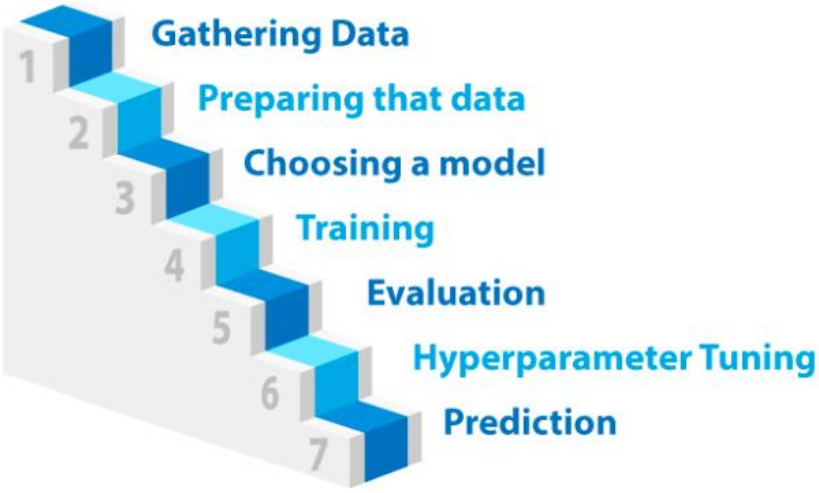


Figure 1: Block diagram of the proposed system for cardiac arrythmia factors prediction

After four alternative models have been created, compare them using accuracy measurements including: accuracy score, fit rate score, recall score, and F1 score. Figure 1 shows a block diagram of the designed system. The model is trained on a labeled dataset because each example in the training data is labeled. The model can then base its predictions on brand-new, unlabeled data.

4. Related Work

Convolutional Neural Networks (CNNs) recently achieved state-of-the-art performances in well-known pattern/object recognition challenges, outperforming most conventional pattern recognition techniques, which have largely been successfully applied to the ECG arrhythmia detection tasks in the past (Krizhevsky et al., 2012). This has inspired researchers to apply these techniques to the field of medical image and signal processing. Deep learning techniques have been used to even the most difficult medical pattern recognition tasks, and the results have been state-of-the-art (Işn et al., 2016). The performance of computerized classification/recognition systems is generally

most significantly impacted by the extraction of highly representative characteristics from the data at hand. However, this takes time and requires expertise, and the features that are chosen frequently do not hold up to changes in the data. When opposed to traditional classification techniques, CNNs automatically learn sophisticated, representative features from the data itself, eliminating the need to manually create features to accurately represent the data. One of the most recent studies suggested using an ECG recording to create a deep neural network to identify premature ventricular contraction (PVC) beats (Jun et al., 2016). To distinguish between normal and PVC beats, a deep neural network with six hidden layers is trained by feeding it six different features taken from ECGs. The authors still preferred manually creating their own features from the ECG data even if a deep neural network was used. In Pourbabaee et al(2016) .'s study, a deep convolutional neural network is trained to extract characteristics directly from raw ECG signals and to classify two heart disorders, namely normal beats and paroxysmal atrial fibrillation (PAF). One disadvantage of building a deep convolutional neural network from scratch is the requirement for a sizable labeled training dataset in order to achieve better network performance (i.e. increasing the number of convolutional layers). Increasing the depth of the network will raise the computation cost during training even if a very large dataset is available since deep convolutional layers contain more sophisticated convolutional operations. For these training jobs, powerful GPU-powered computers are therefore necessary. Transfer learning and its variant, transfer learning with fine tuning (Tajbakhsh et al., 2016), offer a useful remedy for these issues by enabling a deep learning application in situations when there is a lack of training data, insufficient training experience, and restricted computing resources. A pre-trained deep CNN is imported to the task at hand in transfer learning and employed as an automatic feature extractor. In order to automatically extract features that may be utilized as an input to a classifier, for carrying out the final classification, a CNN pre-trained on a generic image dataset, for example, can be imported for a medical imaging task, such pathology classification. Additionally, the pre-trained network's one or more layers can be re-trained (i.e. fine-tuned) utilizing the data specific to the task at hand.

5. Technical Approach

Throughout this proposed approach, we will be using multiple techniques to analyze cardiac arrythmia factors. The algorithms used in this study include Random Forest, Decision Tree, XGBoost, and LightGBM.

Random Forest

RF is a tree-based ensemble learning model that generates accurate predictions by creating a number of DT in training and outputting the classification or prediction [24]. This model uses bagging techniques to train various decision trees using various guide samples. A bootstrap sample is generated in the random forest by filtering to remove the training set with about the same number of respondents as the training data set. RF classifications are made up of a number of separate decision trees that were each learned on a randomized sample of classifier data [25]. These trees are produced throughout the training process, and the outputs of the decision trees are gathered. A

voting mechanism determines the overall estimate given through this method. Figure 2 represents the block diagram of the RF:

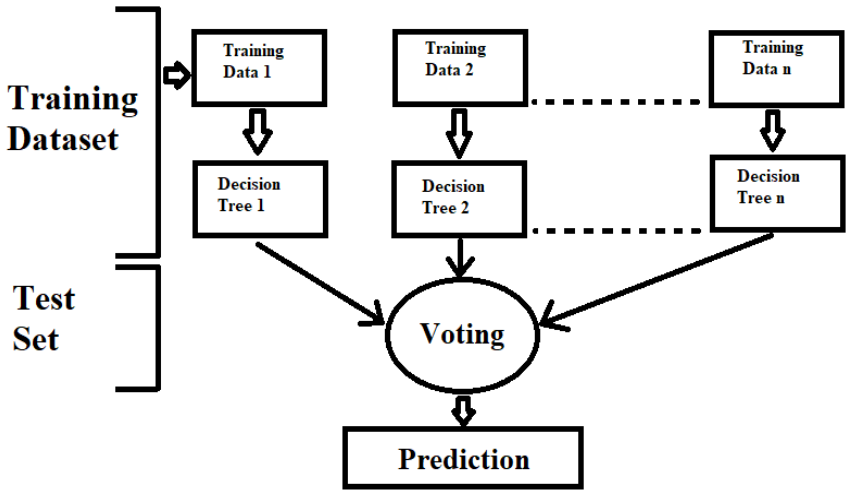


Figure 2: Block diagram of the RF classifier

Due to this, each DT must make decisions as to which of the two output sections in this technique is cardiac-healthy or not. The final forecast is determined by the RF approach, which determines the section by far with the most votes. It is suitable for tasks such as recurrence detection and categorization, and the parameterization of information attributes as a whole is evident. It is also a desirable technique because the predefined hyper-parameters it employs frequently provide clear expectations [26]. Because there are so few of them to begin with, understanding the hyper-parameters is crucial. Overfitting has been a well-supervised learning model, but it only occurs on rare occasions with the arbitrarily defined random forest classifier. If there were enough trees across the forest, the classification model would not overfit the model.

Decision Tree

A decision tree model is a model that uses a set of comparison questionnaires to divide a dataset into smaller sets based on a set of queries, and it keeps repeating the task with different sets of questions for different levels of the available datasets until it has covered all of the dataset's attributes [27]. This approach is indeed a supervised classifier learning model since the input parameters too have a linked output variable. It has the appearance of a tree. Figure 4 shows the basic structure of the DT classifier.

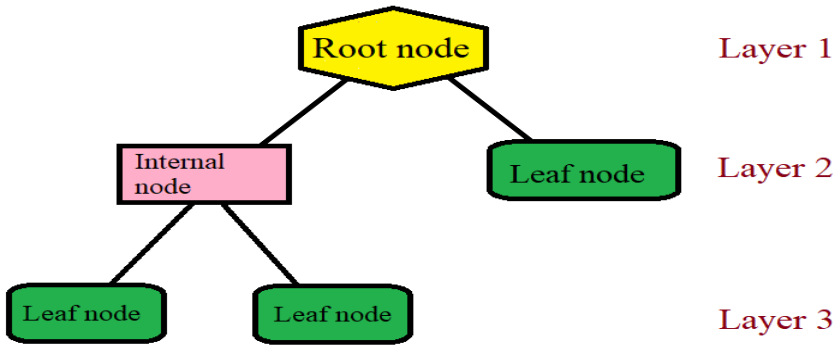


Figure 3: Basic structure of the DT classifier

In this strategy, the data is continually split based on a certain parameter. A decision tree is made up of two parts: a decision node and a leaf node. The data is split at the first node, and the result is produced at the second. The decision tree is simple to understand because it replicates the same stages that a significant individual carries through when making a significant choice. That could be very useful in dealing with decision-making difficulties. Recognize all potential solutions to a problem. Cleaning data may not be as important as it does with other approaches.

XGBoost

XGBoost is a generalized GB technique that has grown in popularity in ML contests [28]. Its exceptional predictive ability, highly optimized multiprocessor and networked machine design, and ability to handle limited data all contribute to this. Figure 5 shows the flow chart of the XGBoost algorithm.

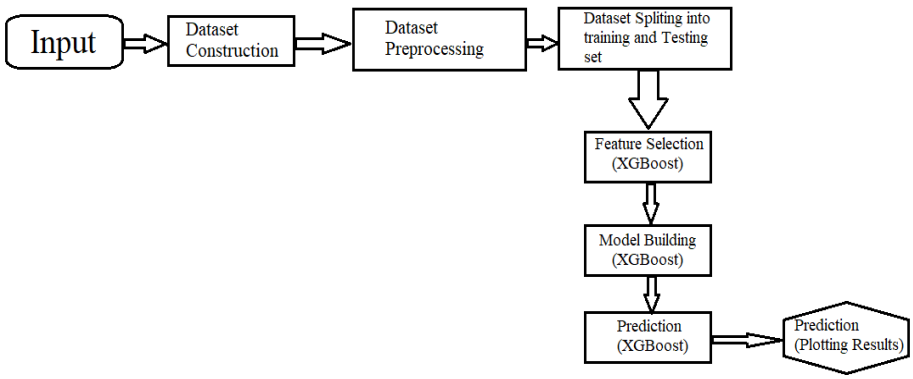


Figure 4: Flow chart of XGBoost for cluster sales forecasting

Despite its superior performance in comparison to previous GB systems, such as XGBoost, it can be time-consuming and costly to implement. Common chores might take hours, days, or even weeks to accomplish. Using xgboost to create extremely accurate estimates necessitates a significant quantity of parameter modification. The method must be performed numerous times throughout this procedure to investigate the influence of cross-validation accuracy on things like the learning algorithm and L1/L2 regularization terms.

LightGBM

LightGBM is a DT-based gradient boosting approach that improves the efficiency of the model while utilizing less storage. GBDT, like other xgboost techniques, merges weak classifiers in order to build a strong one. However, since any tree throughout the procedure knows the results and residuals of all earlier trees, the GBDT algorithm's decision tree could always have a regression tree. As the goal of the following learning, a chronic complications prediction tree is formed by employing the excess of each anticipated result and target value [29]. And the ultimate expected output is the sum of the findings of numerous decision trees. Despite the fact that GBDT has demonstrated significant learning effects on a variety of machine learning tasks, the geometric expansion in recent times in terms of information volume has forced GBDT to adapt its accuracy and efficiency. At this time, the LightGBM algorithm has been proposed. While it does not impair prediction accuracy, it considerably increases forecasting speed and decreases memory use. The classic GBDT algorithm's processing time is frequently wasted in the development of a decision tree. Figure 6 shows the LightGBM leaf-wise tree growth.

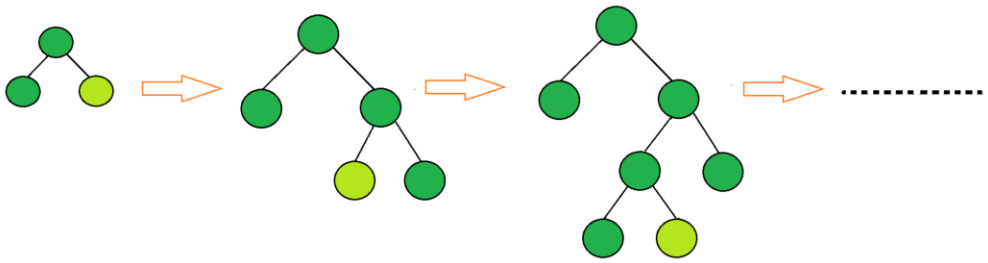


Figure 5: LightGBM leaf wise tree growth

While building a decision tree, the ideal segmentation point must be found. The typical approach is to arrange feature values before enumerating all available feature points. This approach costs time and necessitates a large amount of memory. The LightGBM method employs an enhanced histogram technique. It splits the consistent principal components into k intervals and chooses the division points from the k values. As a result, it outperforms the GBDT algorithm in terms of

training speed and space efficiency. Simultaneously, the decision tree is a poor classifier. The histogram approach has a regularizing impact and can successfully prevent over-fitting. The LightGBM algorithm employs a leaf-wise generation technique to reduce training data. While developing the same leaf repetitively, its leaf-wise approach can cut losses more than the standard level (depth)-wise method. Furthermore, additional parameters are employed to restrict the depth of the decision tree and minimize overfitting.

Data Preprocessing

This system was developed in Python programming because it is a high-level programming language. Before creating a model, a classification process is required to eliminate interferences and patterns in the data from those in the dataset that may cause the design to deviate from the anticipated training set. The whole step takes care of any issues that are impeding the model's efficiency. After gathering the required data, it should be cleaned and prepared for model construction. The data set is then searched for null values.

The model is built after completing data preprocessing and dealing with the imbalanced dataset. The data has been partitioned into different segments with either an 80/20 training to testing ratio to enhance the accuracy and effectiveness throughout this activity. Following the model's splitting, it is instructed using a variety of classification algorithms.

Performance metrics

There are a number of evaluation criteria we use to check the accuracy of ML algorithms and fine-tune them by using the parameters of the model demanded. In this study, the evaluation criteria F1, Precision, and Recall were used to check the accuracy.

Precision: Accuracy is what precision measures to a greater extent. The fraction of the valid true positive rate is measured with precision. Precision is calculated on this proposed model given below.

$$\text{Precision} = TP/(TP+FP) \quad (1)$$

Here, TP = True Positive, and FP = False Positive.

Recall: The recall is a statistic that quantifies how many true positives our model catches after being tagged as such.Recall is calculated on this proposed model given below.

$$\text{Recall} = TP/(TP+FN) \quad (2)$$

Here, TP = True Positives and FN = False Negatives.

Precision and Recall: The recall is a number that indicates how many true positives our model detects after being labeled as such. Precision and recall must both be acceptable in order for such

a model to be judged as accurate. Which is more like,

Precision = TP/TPP, Recall = TP/TAP

Here, TP = True Positive, TPP = True Predicted Positive, and TAP = True Actual Positive.

The F1 Score: To analyze two classifiers, the F1 score is used. F1-scores of both classifiers can be used to see which one delivers the best results. The calculation used for the F1 score

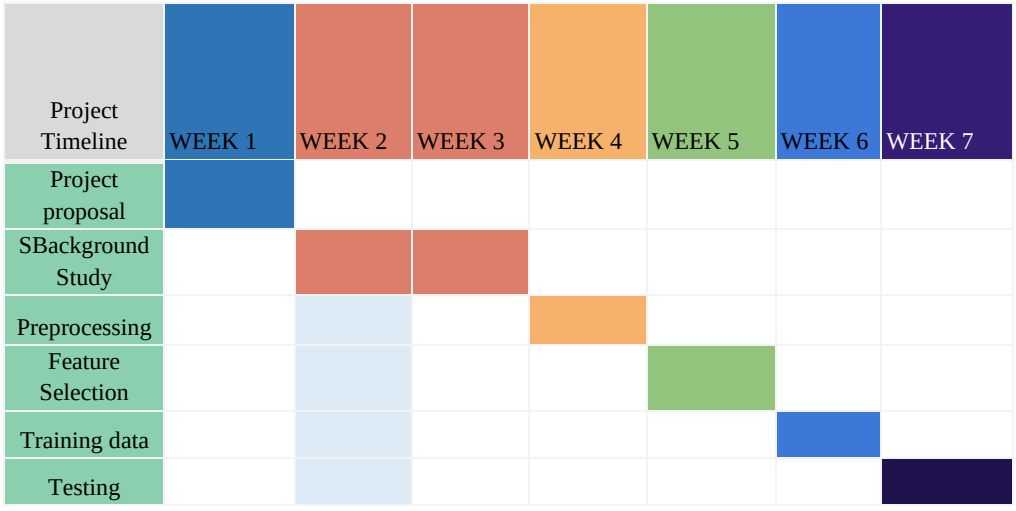
f1 score = 2(P*R)/(P+R) (3)

P = Precision, R = Recall

6. Technology Platform

This proposed system provides a methodology for applying classification methods to predict whether cardiac is healthy or not healthy and to improve the classification accuracy using an ensemble of classifiers. The dataset was collected from Kaggle. After processing, the data has become available for model construction. Model construction requires preprocessed datasets and machine learning techniques. RF, DT, XGBoost, and LightGBM classifiers are some of the methods used. After four alternative models have been created, compare them using accuracy measurements including: accuracy score, fit rate score, recall score, and F1 score. Figure 1 shows a block diagram of the designed system. The model is trained on a labeled dataset because each example in the training data is labeled. The model can then base its predictions on brand-new, unlabeled data.

7. Timeline



8. Description of the Project output and discussion

This section examines the capabilities of the classification models, model predictions, investigation, and ultimate outcomes.

Data Visualization

A histogram displays the iterative variance with an infinite number of classes. This is an outline of the area consisting of a square shape based on the area that is proportional to the bounding range of the class and the frequency of the comparison class. All square shapes are connected because the base fills the space between the class boundaries. Height squared is proportional to the comparison class frequency and the repeat density of different classes. Figure 7 shows some of the main characteristics of the histogram. A histogram shows the proportion of the dataset.

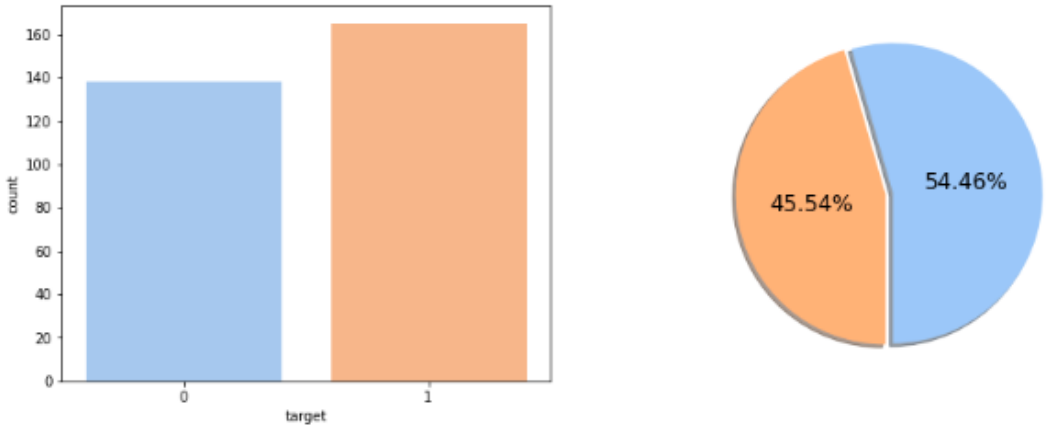


Figure 6: Number and Percentage of the Data

Figure shows the total amount of data in target column. Here 0 means healthy and 1 means cardiac arrythmia affected person.

Correlation matrix

A correlation table is constructed that displays the coefficients of covariance. Figure 8 illustrates the relationships in each cell. A correlation analysis could be used to represent the data, as an input for advanced analysis, or as an indication for complex analysis.

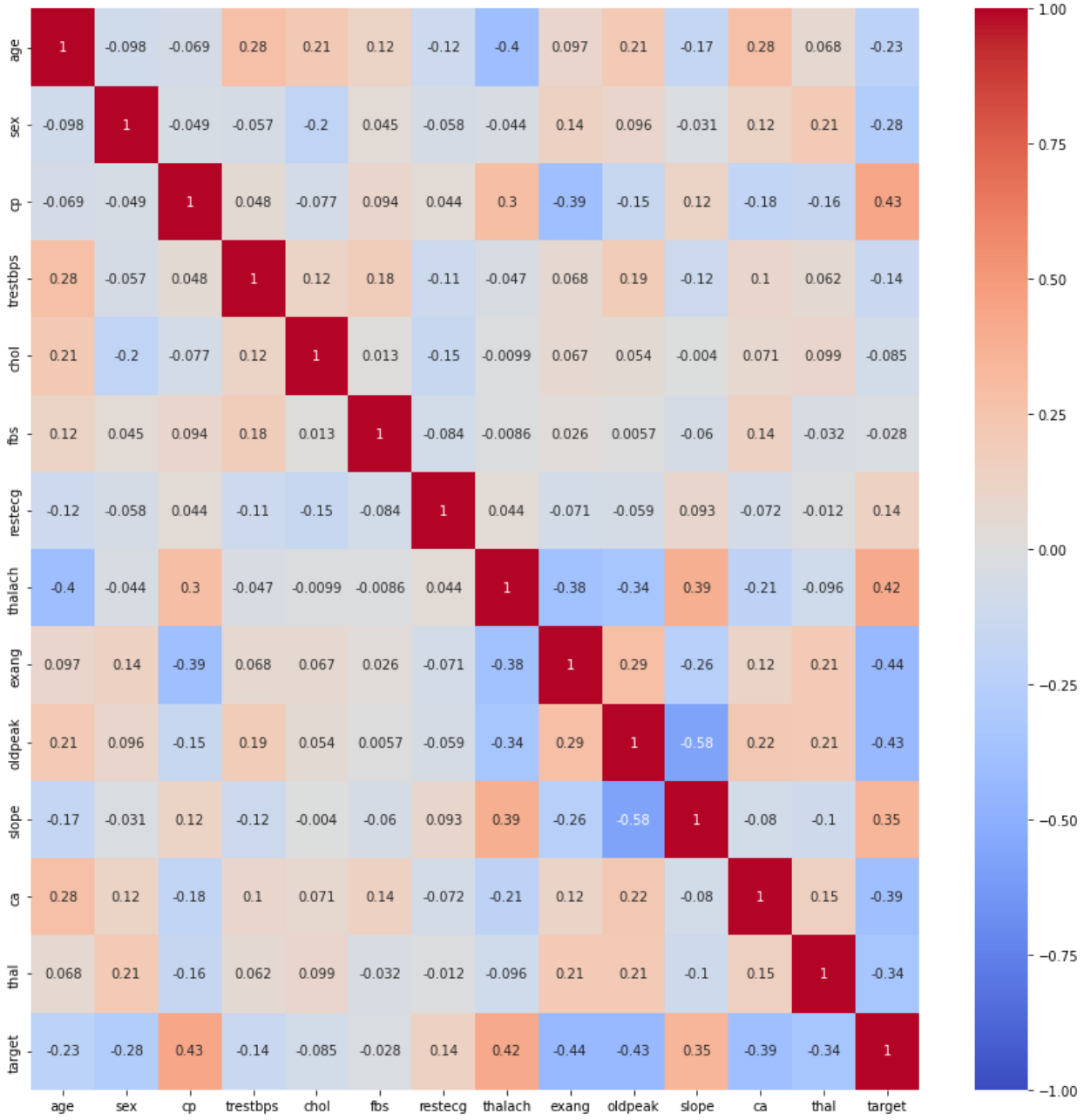


Figure 7: Correlation matrix

From the correlation matrix above, we can see that the correlation between the features is lower. The features have many negative correlation coefficients, indicating that two individual variables are statistically related but generally moving in opposite directions.

Evaluation of the Model

Random Forest

Figure 9 shows the report on classification for the Random Forest classifier.

```
[ ]  from sklearn.ensemble import RandomForestClassifier

     clf = RandomForestClassifier(max_depth=4, random_state=0)
     clf.fit(X_train, y_train)
     ypred=clf.predict(X_test)
     print(classification_report(y_test,ypred))
```

```
                  precision    recall  f1-score   support

               0       0.90      1.00      0.95        74
               1       1.00      0.86      0.92        57

        accuracy                           0.94       131
       macro avg       0.95      0.93      0.94       131
    weighted avg       0.94      0.94      0.94       131
```

Figure 8: Report on Random Forest Classification

In this case, an individual F1-score of cardiac that is not healthy is 94 percent, whereas cardiac that is healthy is 94 percent. The accuracy of this model after tuning did not improve. Figure 9 also depicts precision and recall.

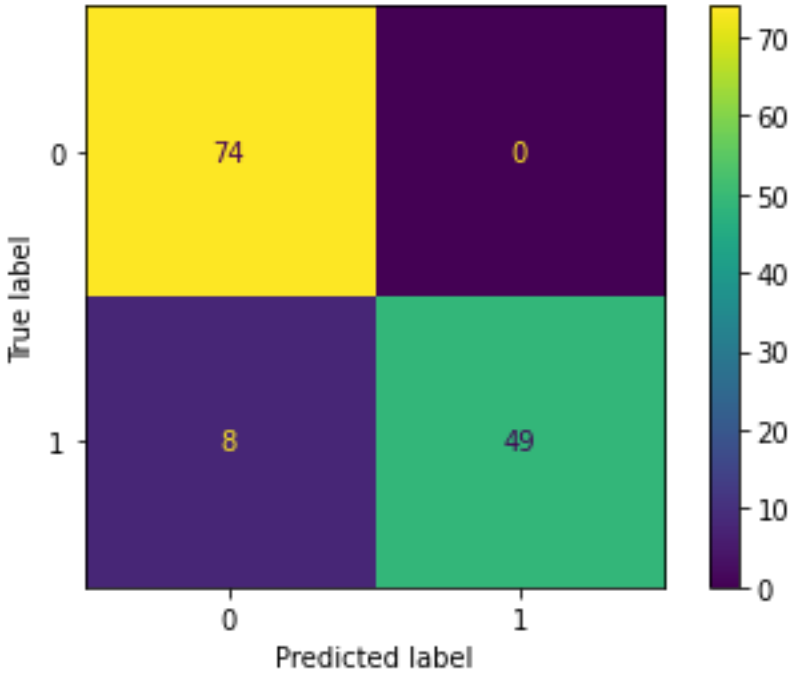


Figure 9: Confusion matrix of random forest

Figure 10 displays the prediction of the random forest model. The confusion matrix displays the projected outcome as well as the estimated performance of the model with a true negative (TN)

value of 49 and a true positive (TP) value of 74, and a false negative value of 0 and a false positive value of 8. There are 123 correct guesses and 8 incorrect predictions.

Decision Tree

Figure 11 shows the classification report for the Decision Tree classifier:

```
[ ]  from sklearn import tree

     dtree=tree.DecisionTreeClassifier()
     dtree.fit(X_train,y_train)
     pred_dtree=dtree.predict(X_test)

     print(classification_report(y_test,pred_dtree))
```

```
                  precision    recall  f1-score   support

               0       0.90      0.76      0.82        74
               1       0.74      0.89      0.81        57

        accuracy                           0.82       131
       macro avg       0.82      0.83      0.82       131
    weighted avg       0.83      0.82      0.82       131
```

Figure 10: Decision Tree Classification Report

In this scenario, cardiac that is not healthy has an F1-score of 82 percent, whereas cardiac that is healthy has an F1-score of 82 percent. This model's accuracy is increased after bagging. Bagging is an ML ensemble meta-algorithm that increases the accuracy and consistency of machine learning approaches used in statistical classification and regression. Precision and recall are also shown in Figure 12.

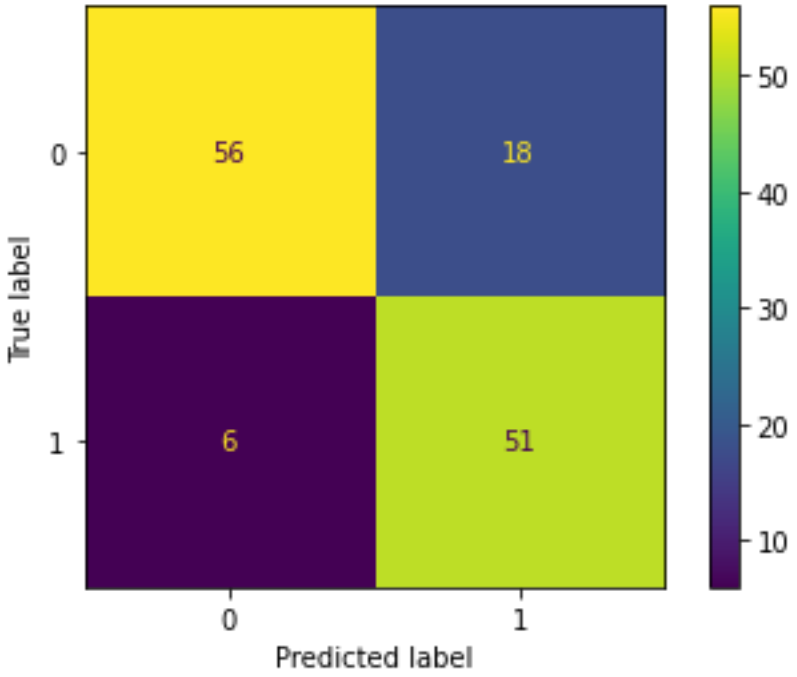


Figure 11: Confusion matrix of decision tree

The DT model's prediction is depicted in Figure 13 with the true negative (TN) value of 18 and the true positive (TP) value of 56, and the false negative value of 18 and the false positive value of 6. There have been 107 correct guesses and 24 incorrect predictions.

XGBoost

Figure 14 shows the classification report for the XGBoost classifier:

```
[ ] y_pred_grad = grad_model.predict(X_test)
    print(classification_report(y_test, y_pred_grad))
```

	precision	recall	f1-score	support
0	0.91	0.93	0.92	74
1	0.91	0.88	0.89	57
accuracy			0.91	131
macro avg	0.91	0.90	0.91	131
weighted avg	0.91	0.91	0.91	131

Figure 12: Classification report of XGBoost

Individual F1 scores range from 91 percent in the case of unhealthy cardiac to 92 percent in the case of healthy cardiac. Also, precision and recall are depicted in Figure 14.

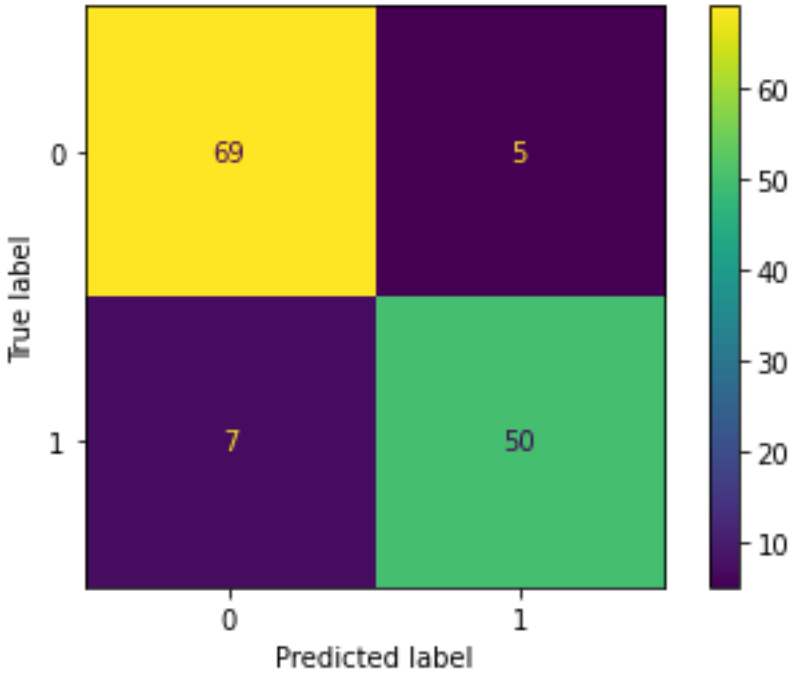


Figure 13: Confusion matrix of XGBoost

The prediction made by the XGBoost classifier is shown in 15 with the true negative (TN) value of 69 and the true positive (TP) value of 50, and the false negative value of 5 and the false positive value of 7. The overall number of right predictions is 119, whereas the total number of wrong forecasts is 12.

LightGBM

Figure 16 shows the classification report for the LightGBM classifier.

	precision	recall	f1-score	support
0	0.91	0.97	0.94	74
1	0.96	0.88	0.92	57
accuracy			0.93	131
macro avg	0.94	0.93	0.93	131
weighted avg	0.93	0.93	0.93	131

Figure 14: Classification report of LightGBM

The individual F1-score of cardiac that is not healthy is 99 percent, whereas the cardiac that is healthy is 88 percent. The accuracy of this model after tuning did not improve. Figure 16 also

depicts precision and recall.

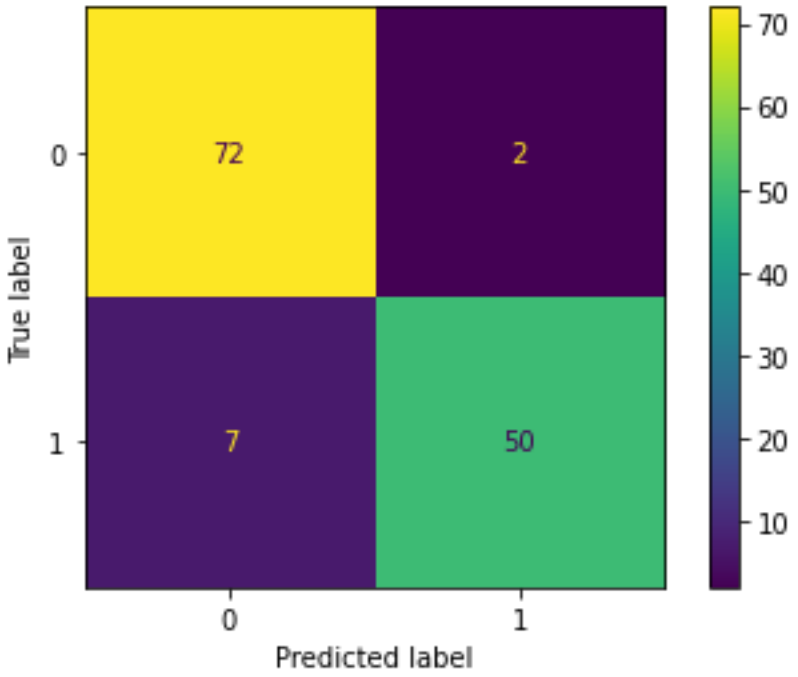


Figure 15: Confusion matrix of LightGBM

Figure 17 displays the prediction of the LightGBM model. The confusion matrix displays the projected outcome as well as the estimated performance of the model with a true negative (TN) value of 139 and a true positive (TP) value of 1424, and a false negative value of 22 and a false positive value of 15. There are 1563 correct guesses and 37 incorrect predictions.

Model Comparison

Table 1 compares the machine learning models or approaches with those identified in previous research. This figure plainly shows that of the several models or approaches contained in this circumstance, the LightGBM approach is the most efficient of the numerous models contained in the framework. It not only has the highest F1-score, but it also has superior precision, recall, and accuracy.

Table 1: Performance comparison

This paper (model name)	Accuracy (%)	model name	Accuracy (%)
LightGBM	93	SVM	90.01
XGBoost	91	DNN	93
Decision Tree	82	K Star	86.67
Random Forest	94	MLP	85.07

Table 1 shows that the accuracy of all algorithms is acceptable, but the Random forest algorithm is the recommended option due to its highest efficiency. With the RF algorithm, this article obtained 94% accuracy. However, the author only achieved 90.01 percent accuracy with SVM in [17]. Using the decision tree and the XGBoost approaches, both approaches in this paper got 91% accuracy, and the author of [19] got 93% accuracy in the algorithm. The K-star algorithm was not implemented in this paper, but reference [22] achieved an accuracy of 86.67%. This is lower than the accuracy of DT (82%).

9. Lesson learnt

At the start of working on this project we thought it would be really easy to complete. But by time we realised that the whole process is much more complicated . We have learnt a lot of lessons while solving the problems.

- ❑ The first problem we had faced collecting proper data set. Sometimes we failed to import python library.
- ❑ As we were trying to process our data but we are not expert on that, we are working for explanable AI and ourdataset is correctly on point as we didn't find any error.
- ❑ When we found which coloumn is co-related, it was quite difficult. We couldn't get so easily. So, we took help from youtube and research papers and finally we solved it properly.
- ❑ For training and testing part, we have splitted data. But it was not giving us the sufficient result.

- ❑ When we were going for model training, we didn't find perfect algorithm accurately. Then from verified source on the internet, we finally solved it with random forest and decision tree.

10. Contribution of individual team member

Following shows the approximate contributions in percentage of each member of our team while working on this project:

	Requirement Analysis	**Planning**	**System Analysis**	**Design**	**Implementation**	**Testing & Development**
Riyad	50%	50%	40%	80%	70%	40%
Iftekhar	50%	50%	60%	20%	30%	60%
Total	100%	100%	100%	100%	100%	100%

11. Conclusions

This paper discusses the performance of ML approaches such as Decision Tree (82%), XGBoost (91%), Random Forest (94%), and LightGBM (93%) in predicting cardiac arrythmia. The goal of the article was to find the best machine learning classifier for predicting heart arrhythmia based on the data it used. Three distinct classifiers' outcomes were compared. Comparison techniques include the confusion matrix, accuracy, specificity, and sensitivity. For the sample's 14 variables, the Logistic Regression classifier performed admirably in the ML approach. With a precision of 94%, the Calculated Relapse method outperformed the other two used classifiers. The Random Forest classifier had an accuracy of 94%, whereas the Decision Tree classifier had an accuracy of 82%. This idea might offer a unique advantage in the medical field. By quickly identifying patients at risk for heart arrhythmia, this method may help reduce the rising death rate. It is not expensive to record the properties in the dataset that the prediction model is based on. As a direct consequence of this, a diagnostic of this kind might be made available to patients at a cost that is within their means, making it possible for it to be utilized by a significantly larger population. As AI calculations become better because of continuous exploration, this sort of finding will turn out to be more normal later on. If more patient data are used, the model can be changed and improved.

With a larger dataset, the results are more precise. This is crucial because medical diagnosis is a delicate matter that requires high levels of precision and accuracy.

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