

A Proactive Approach in Predicting Heart Attacks Using Hyperparameter Tuning

Jhansi Lakshmi Chekkapalli

Dept.of Artificial Intelligence & Data Science, Koneru Lakshmaiah Education Foundation (KLEF), Deemed to be University, Vaddeswaram, Green fields, Guntur, Andhra Pradesh, India -522302.

chjhansilakshmi584@gmail.com

Guided By

Sajana Thiruveedhula

Associate Professor, Koneru Lakshmaiah Education Foundation (KLEF), Deemed to be University, Vaddeswaram, Green fields, Guntur, Andhra Pradesh, India -522302.

sajana.cse@kluniversity.in

Nithin Neeliseti

Dept.of Artificial Intelligence & Data Science, Koneru Lakshmaiah Education Foundation (KLEF), Deemed to be University, Vaddeswaram, Green fields, Guntur, Andhra Pradesh, India -522302.

nithin79379@gmail.com

Hemanth Sasanam

Dept.of Artificial Intelligence & Data Science, Koneru Lakshmaiah Education Foundation (KLEF), Deemed to be University, Vaddeswaram, Green fields, Guntur, Andhra Pradesh, India -522302.

sasanamhemanth77@gmail.com

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Abstract—Heart attacks are a significant global health concern, often resulting in severe health implications and mortality. Early detection and accurate prediction of cardiac arrest play a crucial role in improving patient outcomes and reducing healthcare costs. In this study, we employ advanced machine learning algorithms includes learning method i.e, Hyperparameter tuning in Recursive Feature Elimination with Cross-Validation(RFECV) on XGBoost, Linear Regression(LR), Support Vector Machines(SVM),K-Nearest Neighbors(KNN), Bootstrap Aggregation, CART to predict the likelihood of a heart attack based on relevant medical data. We utilize a comprehensive dataset encompassing various factors to train and evaluate the models. The comparative analysis of these machine learning algorithms provides valuable insights into their respective performance, aiding in the identification of an effective predictive model for cardiac arrest. Ultimately, this research contributes to the advancement of predictive healthcare analytics, potentially revolutionizing the way predicting cardiac arrest is assessed and mitigated. This article delves into the field of cardiac arrest prediction,exploring the current advancements, methodologies, and potential implications for improving patient outcomes and healthcare strategies.

Keywords—RFECV,LR,SVM,KNN,XGBOOST

I. INTRODUCTION

Amidst a range of grave health conditions, Cardiac attack is the primary cause of mortality worldwide. Cardiac arrest, a sudden and life-threatening event where the heart ceases to effectively pump blood to vital organs, has necessitated a quest for predictive measures to identify individuals at risk. The World Heart Report 2023 has been released by the World Heart Federation (WHF), which found that every four out of five are affected by heart attacks. Risk factors for heart attacks include high blood pressure, high cholesterol, smoking, diabetes, obesity, a sedentary lifestyle, an unhealthy diet, and a family history of heart disease. Global Burden of Disease Study 2023 states that heart failure is a rapidly growing public health issue with an estimated prevalence of 64 million people globally.

Equipment needed for cardiac diagnostics, such as electrocardiograms and CT scans, is often expensive and unavailable in many low- and middle-income countries. Therefore, early diagnosis of heart disease is important in reducing the physical and financial burden on individuals and organizations. According to the World Health Organization, the total number of deaths from cardiovascular diseases, especially heart disease and stroke, will increase to 23.6 million in 2030. That's why it's so important to leverage data mining and machine learning to predict heart disease risk, save lives, and reduce health problems.

Furthermore,fundamental cardiac diagnostic technologies, including electrocardiograms and CT scans, can be both costly and inaccessible to the general public. This alone has led to 17 million fatalities. Heart disease accounts for 25\% to 30\% of a company's yearly medical expenditures due to employee health issues. Consequently, early detection of heart attacks plays a crucial role in mitigating financial burdens for both individuals and organizations. According to the World Health Organization's projections, the total cardiovascular-related deaths are expected to rise to 23.6 million by 2030, primarily attributed to heart disease and strokes. To save lives and minimize societal expenses, employing data analysis and machine learning for heart disease risk prediction is imperative.

In medicine, by using data mining techniques to generate large amounts of data every day, we can find hidden patterns that can be used for diagnosis. For this reason, data mining plays an important role in health services, as seen in studies conducted in the last few years. There are many factors to consider when predicting heart disease, such as diabetes, high

blood pressure, high cholesterol, and abnormal pulse. In many cases, it is necessary to add existing medical information, which affects the results of predicting heart disease.

By understanding and forecasting cardiac arrests, we aim to pave the way for proactive interventions and ultimately save lives. Thus, feasible and accurate prediction of heart attacks is very important. Machine learning plays an important role in healthcare. Using Machine Learning, we can identify, diagnose, and predict many diseases. Recently, there has been growing interest in the possibility of using data mining and machine learning techniques to predict the likelihood of certain diseases. The current study involves the use of data mining techniques in disease prediction. Although some studies have tried to predict the risk of future infection, no definitive results have been found. The main purpose of this article is to accurately predict the risk of heart disease in the human body.

Machine learning is considered an important method for solving complex problems in science, especially in biomedical and astronomical research. Recently, machine learning has also emerged as a promising tool in healthcare. As algorithmic technology advances, it is now possible to find new ways to use clinical signals to identify key features and improve the accuracy and performance of predictive models used to solve medical problems. Machine learning can achieve much better results than predicting heart attack patterns using traditional methods such as regression analysis or theory of mind. Moreover, risk scores currently developed using traditional methods are limited in clinical use due to their poor performance, low sensitivity, and high parameters.

In this study, we aimed to investigate the effectiveness of various machine learning algorithms in predicting heart disease. To achieve this, we use a variety of techniques to build predictive models, including Linear Regression, Support Vector Machine, K-Nearest Neighbors, Bootstrap Aggregation, CART and XGBoost. To improve the convergence of the model, we use Recursive feature elimination with cross-validation (RFECV) to pre-process the dataset. The data used in this study is publicly available on Kaggle. All calculations, pre-processing, and visualizations are done using Python in Google Colab. Previous studies have reported using machine learning techniques to predict heart disease with up to 97 percent accuracy. However, these studies generally use small samples and the results cannot be generalized to larger populations. Our study aims to address this limitation by using a larger and more diverse data set, which we hope will increase the validity of the results.

II. LITERATURE SURVEY

A comprehensive search of previous studies in the field of cardiology was conducted using different algorithms. To further expand our research, previous years' work was examined and weak points were pointed out. A total of 30 documents were collected from PubMed Central and National Center for Biotechnology Information (NCBI), IEEE, and f1000 Research, of which 25 were selected for the final study after removing duplicates and information from the same domain.

A review was conducted to understand the challenges in the field of heart attack prediction. The collected data are examined and the advantages and disadvantages of the study are evaluated according to the use of indicators, methods and algorithms.

The inclusion process is based on data analysis in relevant fields, the use of state-of-the-art machine learning algorithms, and complex areas in cardiology. Search terms for the literature review were "machine learning based health attack prediction", "optimization of Health attack prediction", "Challenges in identifying health attack". Exclusion criteria included removal of duplicates, articles with poor statistical significance, and outdated data. The "TABLE I" provides the survey papers taken only on the basis of heart attack prediction. All these papers have taken and found the drawbacks to make the heart attack prediction accurate.

TABLE I
Literature Survey

S.No	Title	Author	Methodology	Key Findings
1	Effective heart disease prediction system using data mining techniques	Poornima Singh, ¹ Sanjay Singh, ² and Gayatri S Pandi-Jain ¹	Multi-Layer Perceptron Neural Network (MLPNN) with backpropagation (BP)	92% accuracy and AUC score of 0.94 was achieved with XGBoost.

2	Machine learning for early prediction of in- hospital cardiac arrest in patients with acute coronary syndromes	Ting Ting Wu, MD, 1 Xiu Quan Lin, MD, 2 Yan Mu, MD, 3 Hong Li, PhD,corresponding author 3 and Yang Song Guo, PhD 4	The XGBoost model, K- Nearest Neighbor model	The XGBoost model provided the best performance with regard to AUC (0.958 [95%CI: 0.938–0.978]), The K- nearest neighbor model generated the best specificity (99.3%).
3	Machine learning-based heart attack prediction: A symptomatic heart attack prediction method and exploratory analysis	Lipika Goel, 1, ROHIT TANWAR2	XGBoost	XGBoost classifier provided best training and test scores of.91 and.89 along with the 92% accuracy. The results achieved are discussed below.
4	Machine learning model for predicting out-of-hospital cardiac arrests using meteorological and chronological data	Takahiro Nakashima1,2, Soshiro Ogata2, Teruo Noguchi3, Yoshio Tahara3, Daisuke Onozuka2, Satoshi Kato4, Yoshiki Yamagata5, Sunao Kojima6, Taku Iwami7, Tetsuya Sakamoto8, Ken Nagao9, Hiroshi Nonogi10, Satoshi Yasuda11, Koji Iihara12, Robert Neumar1, Kunihiro Nishimura2	the eXtreme Gradient Boosting (XGBoost) algorithm,	XGBoost algorithms were chosen to maximize the predictive ability of the model.
5	A Machine-Learning-Based Prediction Method for Hypertension Outcomes Based on Medical Data	Wenbing Chang, Yinglai Liu, Yiyong Xiao, Xinglong Yuan, Xingxing Xu, Siyue Zhang, and Shenghan Zhou	XGBoost	This paper proposes a method combining a classifier XGBoost with Recursive Feature Elimination with Cross-Validation(RFECV)to accurately predict patient outcomes automatically.
6	Machine learning for early prediction of in- hospital cardiac arrest in patients with acute coronary syndromes	Ting Ting Wu, MD, 1 Xiu Quan Lin, MD, 2 Yan Mu, MD, 3 Hong Li, PhD,corresponding author 3 and Yang Song Guo, PhD 5	The XGBoost model , K- nearest neighbor model	Uses five different evaluation metrics, namely accuracy, sensitivity, specificity, F1-score, and Area under the curve (AUC) to propose this method"XGBoost".

7	Heart disease prediction using machine learning algorithms	Harshit Jindal ¹ , Sarthak Agrawal ¹ , Rishabh Khera ¹ , Rachna Jain ² and Preeti Nagrath ²	K nearest neighbors (KNN), Logistic Regression and Random Forest Classifiers	using Logistic regression, Random Forest Classifier and KNN the accuracy of the model is 87.5%.
8	Machine Learning Based Approach Using XGboost for Heart Stroke Prediction	Sukh Manjot Dhillon ¹ , Chirag Bansal ² and Brahmaleen Sidhu ³	KNN, SVM, XGboost	By the usage of XG Boost, an accuracy of 97.56% is obtained.

The biggest drawback of previous studies is that the data are limited, increasing the risk of overfitting. The design may not be suitable for large files. As a comparison, we used a heart-related database containing 5,000 patients and 13 characteristics, thus reducing the potential for overstudy.

III. METHODOLOGY

In this article, we develop a model that includes the determinants of life and the risk of heart attack, supported by clinical data. The personal data is taken from Kaggle which contains 13 clinical features such as age, sex, chest pain, cholesterol and so on. The calculations of accuracy on big data involves few approaches:

1. Linear Regression:

Linear Regression models the linear relationship between a dependent variable and one or more independent variables, aiming to find the best-fit line that minimizes the difference between observed and predicted values, making it a foundational technique in statistical modeling and machine learning.

2. Support Vector Machine:

Support Vector Machine (SVM) is a powerful machine learning algorithm that classifies data by finding the hyperplane that maximally separates different classes in a high-dimensional space. It is particularly effective for

both classification and regression tasks, relying on support vectors to define decision boundaries and achieve robust generalization to new data.

3. K-Nearest Neighbor:

K-Nearest Neighbors (KNN) is a versatile machine learning algorithm for classification and regression, determining outcomes based on the majority class or average of k nearest data points in the feature space, without assuming specific data distributions.

(#####BOOTSTRAP,CART###)

4. XGBoost:

XGBoost (Extreme Gradient Boosting) is a powerful and scalable machine learning algorithm using an ensemble of decision trees to achieve high predictive accuracy. It systematically combines weak learners into a strong model by minimizing errors and handling complex relationships in data, making it widely used in various predictive modeling tasks.

IV. IMPLEMENTATION

These tests were performed on the heart dataset containing 5110 bundles with 13 features. The implementation is classified into 2 phases. The two phases are:

1. Discovery
2. Application

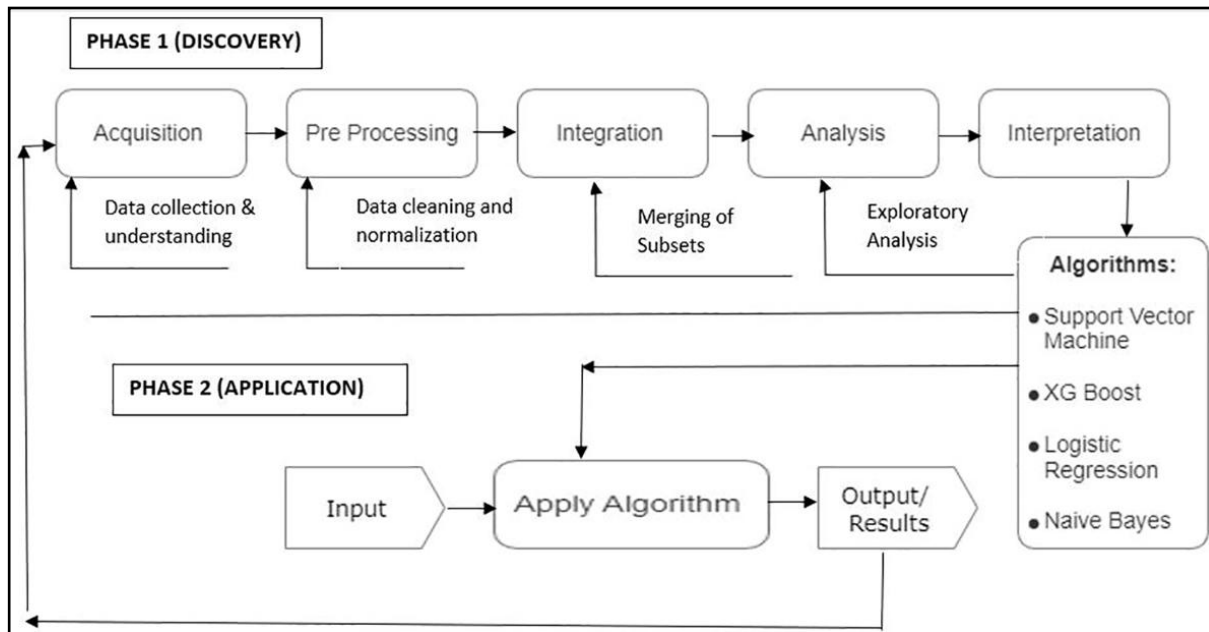


Fig 1: Proposed Methodology

(#####FLOW CHART#####)

A. DISCOVERY

The steps of this process are represented below:

Step-1:

The first step is to gather information i.e, “Data Acquisition”. This involves physical testing and involves numerical data by changing the model the computer uses to work.

a. The dataset was retrieved from the kaggle and contains 13 features for examining cardiac arrest, as described in the data collection section.

b. All experiments in this study were performed on Python 3.8.3 in Google Colab.

Step-2:

The second step is “Data Pre-Processing”, where we find the solutions for issues such as missing values in the data, negative detections, and regular deletion of information for cleaning purposes. Estimated measurements are made in the integrated environment and used for Exploratory Data Analysis(EDA).

a. Collected data was cleaned using preprocessing methods, including replacement of missing values, detection of outliers, and removal of duplicates.

b. Missing values (if any) will be replaced with the mean.

c. Use boxplots to detect outliers in your data by understanding minimum, maximum, and balance values.

d. Deduplication of data is done using the dict() function to create a dictionary to remove duplicates.

Step-3:

The third step is “Data Integration”, which is importing individual models in Python, combining libraries and different subsets, and combining them to run the necessary tests.

a. The first part is to preprocess the data.

b. The clean data is then combined using machine learning algorithms.

Step-4:

The fourth step is “Feature Selection and Reduction” where we remove all the less important features from the huge dataset in order to reduce the execution time. Feature selection algorithm can effectively delete redundant data and noise data and select the most relevant feature variables, so it can effectively reduce the dimensions of data.

a. RFECV - Recursive Feature Elimination with Cross-Validation (RFECV) is one of the methods used for feature selection. This method combined with a classifier can identify the most influential factors and improve the prediction performance.

RFE filters some feature subsets based on the feature ranking list generated from the above evaluation. It can be combined with different tools such as SVM, XGBoost etc. The steps of the RFE algorithm are as follows:

1. Initialize feature set F.
2. Select Separator C.
3. Calculate the weight (F) of each phi feature (the method is an accurate estimate of the distribution).
4. Remove minimum weight fj and replace F.
5. Repeat steps 3 and 4 until only one unique element of F remains.
6. Feature importance ranking.

Step-5:

The fifth step is “Data Analysis” where EDA is done to understand the relationship between different components of the product.

a. The concept of analytics is learning from data, pattern recognition and decision making with minimal human intervention.

b. EDA is used to understand the relationship between behaviors.

c. Compare variables using box plots and gold plots to understand relationships and identify common variables.

Step-6:

The Sixth step is to find ideas for “Data Intervention” to go into an accurate decision, that is, understanding previous research to determine whether the model can be used to solve the problem in the real world.

a. We conducted detailed research to understand how machine learning models are used in the same field and which models show the most promise in optimizing our results. Most contracts are selected based on their performance in previous studies in similar areas of cardiology

Step-7:

The seventh step is to “Data Modelling” the machine learning algorithm to make predictions. Four learning machines were used in this study: Linear Regression, SVM, KNN, Bootstrap Aggregation, CART and XGBoost.

a. Apply SVM to the data using scikit learning and Python's svm extension.

b. KNN is implemented by the Scikit Learning Neighbors library in Python.

c. Linear regression is implemented in Python with sklearn's linear model category.

d. XGBoost is a boosting system using weak distribution and produces good results, here Hyperparameter Tuning under RFECV is employed.

e. Bootstrap

f. CART(#####)

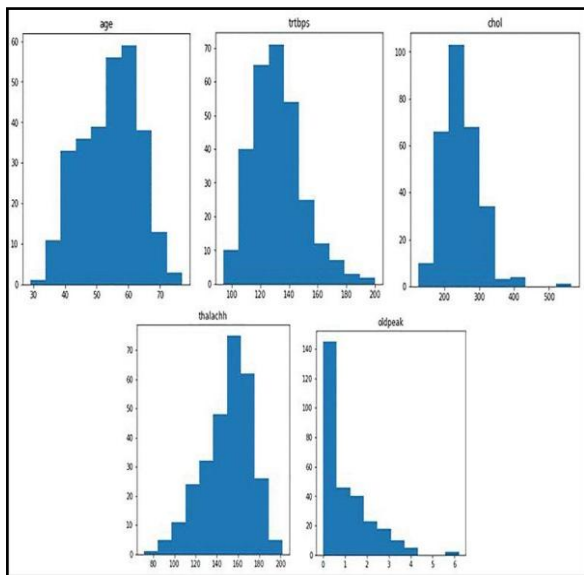


Fig 2: Parameters Hist Plot

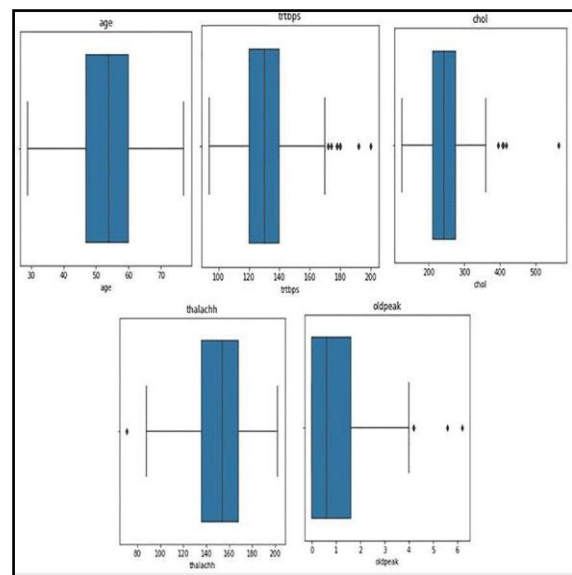


Fig 3: Parameters Box Plot

B.APPLICATION

We extend our research to four various machine learning algorithms as discussed earlier. The algorithms are:

1. Linear Regression

This method conducts feature selection and linear regression modeling using Recursive Feature Elimination with Cross-Validation (RFECV). Initially, the data is loaded, and the features and target variables are defined. The code then utilizes RFECV to systematically eliminate features, finding the optimal subset that maximizes the model's performance.

Following feature selection, the script trains a linear regression model on the chosen subset of features. The model's accuracy is then evaluated using the `accuracy_score` function from `scikit-learn`. The code reports an impressive accuracy rate of 97%, suggesting strong predictive performance on the selected features. It ensures that the model generalizes well and isn't overfitting the training data.

2. Support Vector Machine

In Support Vector Machine (SVM) the dataset is split into features (X) and the target variable (y). Subsequently, the data is divided into training and testing sets using the `train_test_split` function from `scikit-learn`. The SVM model is initialized with a linear kernel, regularization parameter (C) set to 1.0, and a specified random state. The model is fitted to the training data, and predictions are made on the test set.

Following the model predictions, various metrics are calculated to assess its performance. The metrics include accuracy, precision, recall, and F1 score, providing a comprehensive evaluation of the model's predictive capabilities. Additionally, a confusion matrix is printed, detailing the true positive, true negative, false positive, and false negative counts.

In this model, the feature selection using Recursive Feature Elimination with Cross-Validation (RFECV) is not employed in this specific case, and the reasons for this decision are highlighted. The model accuracy without feature selection is presented to provide a clear comparison to potential scenarios with feature selection.

3. K Nearest Neighbor

K-Nearest Neighbor, starts by loading the dataset using `Pandas` and displaying its initial rows to gain insights into its structure. The 'output' variable, representing the presence or absence of occurrence of cardiac attack, is chosen as the target variable, while the remaining columns constitute the features.

Subsequently, the dataset is split into features (X) and the target variable (y). Unlike the usual 80-20 split, this code employs a test size of 10%, resulting in a 90% training set and a 10% testing set. The KNN model is initialized with `k=5` (number of neighbors) and is then fitted to the training data. Predictions are made on the test set, and various performance metrics, including accuracy, precision, recall, and F1 score, are computed to evaluate the model's effectiveness.

It's worth noting that in this case, feature selection using Recursive Feature Elimination with Cross-Validation (RFECV) is not employed. This decision is mentioned along with the observation that feature selection reduced the model's accuracy in this specific scenario. The absence of feature selection is noted before splitting the data, emphasizing its impact on the model's predictive capabilities in this context.

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(#####bootstap amd cart#####)
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4. XGBoost

XGBoost starts by loading the data, setting up features (X) and the target variable (y), and employs a grid search to find optimal hyperparameters for the XGBoost classifier. The goal is to maximize accuracy through hyperparameter tuning.

After obtaining the best hyperparameters, the code applies Recursive Feature Elimination with Cross-Validation (RFECV) to identify the most relevant features. The optimal number of features is determined, and cross-validation results are visualized in a plot. This step aids in selecting a subset of features that contribute most to the model's performance.

The selected features are then used to train a final XGBoost model. Predictions are made on this subset, and the model's performance is assessed using key metrics. The reported results demonstrate impressive accuracy (98.62%), precision (98.20%), recall (99.39%), and an F1-score of 98.80%. These metrics, along with a detailed confusion matrix, showcase the effectiveness of the XGBoost model in accurately predicting instances of heart disease.

In summary, the code exemplifies a robust approach to optimizing an XGBoost model, involving hyperparameter tuning and feature selection. The reported high-performance metrics underscore the model's accuracy and reliability in the context of heart disease prediction.

V. METRICS

To evaluate the performance of the ML technique, 4 different measures are used: recall, F1 measure, precision, and accuracy. A confusion matrix is used in the model to evaluate the probability of 4 parameters: F_n (not true), T_n (not true), F_p (not true), and T_p (true is good). The number of subjects classified as "positive" is considered T_p , and the number of subjects classified as "negative" is considered T_n .

Accuracy-The ratio of the results predicted by the model to the successful prediction for each type of classification problem is called accuracy

$$\text{Accuracy} = \frac{(T_p + T_n)}{(T_p + T_n + F_p + F_n)} \cdot$$

Precision-Precision or positive predictive is defined as the ratio of accurate positive scores (Tp) to the total number of positive scores (Tp + Fp) predicted by the classification algorithm.

$$\text{Precision} = \frac{T_p}{(T_p + F_p)} \cdot$$

Recall-The recall can be defined as the ratio of actual Tp to total (Tp + Fn).

$$\text{Recall} = \frac{T_p}{(T_p + F_n)} \cdot$$

$$\text{F1 - measure} = 2 \times \frac{(\text{precision} \cdot \text{recall})}{(\text{precision} + \text{recall})} \cdot$$

F1 measure-The F1 metric is a function of precision and recall. If the classification algorithm is successful, F1 should be 1; F1 should be 0 if the classification algorithm fails.

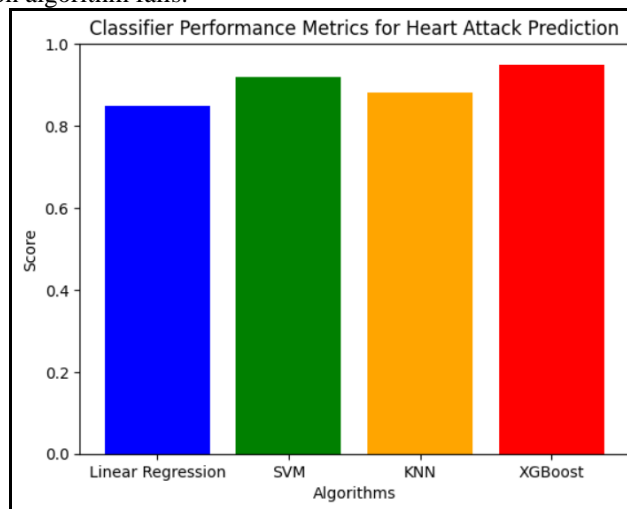


Fig 4: Metrics

VI. RESULT AND DISCUSSION

TABLE II. METRICS

Methods	METRICS			
	Accuracy	Precision	Recall	F1-Measure
LR	97.92	96.02	97.03	92.67
SVM	84.48	84.38	87.1	85.71
KNN	68.97	68.18	88.24	76.92
XGBoost	98.62	98.2	99.39	98.8

(#####graphs#####)

In conclusion, Linear Regression demonstrates a workflow for feature selection and linear regression modeling, revealing the importance of selecting an optimal feature subset for enhanced model accuracy. The reported accuracy rate of 97% is

promising, but further testing and consideration of potential pitfalls, such as overfitting, are essential for robust model evaluation.

In SVM the reported metrics are as follows: Accuracy: 0.8448, Precision: 0.8438, Recall: 0.8710, and F1 Score: 0.8571. These values indicate a relatively good performance of the SVM model in classifying heart disease presence.

In K-NN the reported metrics for the KNN model are as follows: Accuracy: 0.6897, Precision: 0.6818, Recall: 0.8824, and F1 Score: 0.7692. These values provide insights into the model's performance, with accuracy representing the overall correctness, precision the accuracy of positive predictions, recall the model's ability to capture all positive instances, and F1 score offering a balance between precision and recall.

In XGBoost reported results demonstrate impressive accuracy (98.62%), precision (98.20%), recall (99.39%), and an F1-score of 98.80%. These metrics, along with a detailed confusion matrix, showcase the effectiveness of the XGBoost model in accurately predicting instances of heart disease.

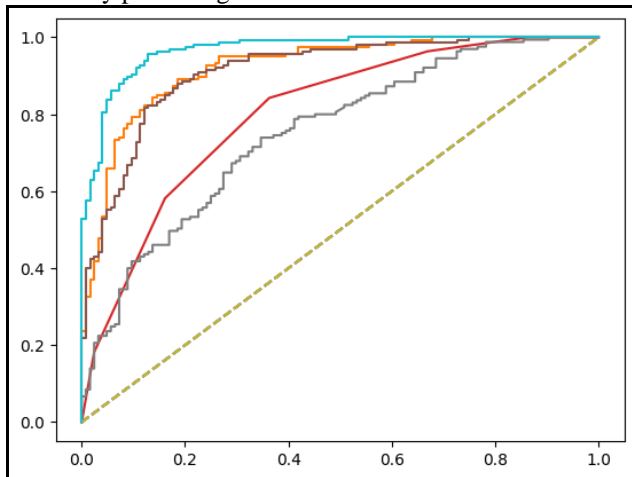


Fig 5: ROC Curve

VII. KEY FINDINGS

XGBoost Dominance: XGBoost demonstrated remarkable predictive power, making it the standout performer among the algorithms tested.

Model Robustness: All models exhibited strong predictive capabilities, but XGBoost's ensemble learning approach appeared particularly effective in handling the complexity of the heart attack prediction task.

VIII. FUTURE WORK

1. **Feature Importance Analysis:** Conducting a detailed analysis of feature importance in the XGBoost model can provide insights into which health parameters play a crucial role in predicting heart attacks. This information can be valuable for medical practitioners and researchers.
2. **Hyperparameter Tuning:** Fine-tuning hyperparameters for the XGBoost model could further enhance its performance. Techniques like grid search or random search can be employed to explore a broader range of hyperparameter combinations.
3. **Ensemble Methods:** Exploring ensemble methods that combine predictions from multiple models, possibly including XGBoost, can be beneficial. Techniques like stacking or blending can be applied to leverage the strengths of different models.
4. **External Validation:** Testing the model on external datasets can validate its generalizability. This step is crucial to ensure that the model's effectiveness extends beyond the training dataset.
5. **Real-time Implementation:** Deploying the model in a real-time environment, such as a healthcare system, allows for continuous monitoring and timely intervention based on predictions.

In conclusion, XGBoost emerges as the optimal algorithm for heart attack prediction in this project. Future work can delve deeper into feature analysis, hyperparameter tuning, ensemble methods, external validation, and real-world implementation to further enhance the model's accuracy and applicability in clinical settings.

IX. CONCLUSION

In conclusion, the effectiveness of XGBoost, complemented by Recursive Feature Elimination with Cross-Validation (RFECV), in achieving exceptional accuracy (98.62%), precision (98.20%), recall (99.39%), and an F1-score of 98.80% for heart attack prediction. This performance outshines that of previously mentioned SVM and KNN models. The strategic combination of hyperparameter tuning and feature selection showcases XGBoost's capability to discern intricate patterns within the dataset, making it a, even after they have been defined in the abstract.

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