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Machine Learning based prediction of Heart Disease

*Abstract*—*cardiovascular diseases (CVDs) remain the leading cause of mortality worldwide, responsible for approximately 17.9 million deaths each year. Timely intervention coupled with early detection is crucial in minimizing heart-related diseases and cases of death arising from them. Though effective, traditional diagnostic approaches often involve invasive procedures and may consume a lot of time. Modern machine learning (ML) developments offer an alternative approach by giving non-invasive and fast diagnostics. Machine learning algorithms have the potential to completely change the way early heart disease detection is carried out through large datasets analysis and complex pattern recognition. This study aims at creating and validating a ML based system that can detect heart diseases at their earliest stage, using advanced data analytics to determine high-risk individuals before significant symptoms occur. This proposed system will employ various clinical as well as demographic factors into its predictive model hence improving the predictability power desired for better health outcomes and efficient healthcare services.*

***Keywords*** *— Diagnosis, Early heart disease detection, Machine learning, Patient Outcomes, Web development.*

# INTRODUCTION

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ardiovascular diseases (CVDs) represent the leading cause of death globally, accounting for nearly 18 million fatalities each year. The early detection of heart disease is paramount in mitigating the associated risks and reducing mortality rates. Traditional diagnostic methods, although effective, often involve invasive procedures, substantial costs, and delayed results, which can hinder timely medical intervention. here is an urgent need for more efficient, accurate, and non-invasive diagnostic tools that can facilitate early detection and enable proactive management of heart disease.

Recent advancements in machine learning (ML) have revolutionized various sectors, including healthcare. Machine learning algorithms excel in analyzing vast amounts of data, identifying intricate patterns, and making predictions with high accuracy. In the context of heart disease detection, ML offers an alternative to traditional methods by leveraging data-driven approaches to predict the onset of the disease at an early stage. This capability is particularly critical as it allows for early intervention, lifestyle modifications, and treatment adjustments that can significantly improve patient outcomes.

This research aims to develop and validate a machine learning-based system for the early detection of heart disease. By integrating diverse clinical and demographic data, the proposed system strives to achieve high predictive accuracy. The methodology involves using supervised learning algorithms trained on large datasets to identify risk factors and early indicators of heart disease. The system's ability to process and analyze complex data patterns in real-time promises to enhance the efficiency of clinical workflows and reduce the burden on healthcare professionals.

The anticipated outcomes of this project include not only improved diagnostic accuracy and earlier detection but also a more personalized approach to patient care. By providing healthcare providers with robust tools for risk assessment, this ML-based system has the potential to transform preventive cardiology. The long-term goal is to implement such systems widely in clinical settings, contributing to better healthcare delivery and ultimately saving lives through early and precise detection of heart disease.a conference, please observe the conference page limits.

# Methodology

## Flowchart/Block Diagram

Figure 1 signifies the proposed architecture of the

learning model, where different machine learning algorithms

are used to check and predict the heart disease in

the critical heart patients. In this model heart disease data

from the Kaggle web site is considered as an input

data and process the data.

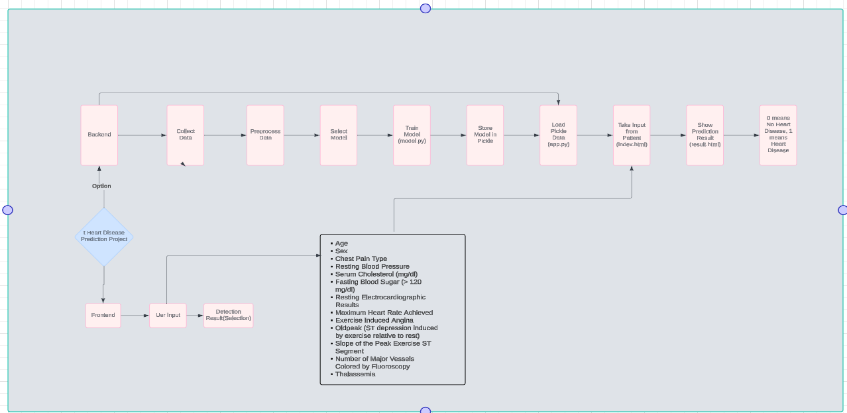


Fig1.Flowchart of proposed system

Proposed Architecture of the system explains how user inputs and how he gets expected result about his heart status.

## Data Sources

## The dataset used in this article is fetched from Kaggle website, Kaggle is a open-source database collection website. The dataset we have chosen named’heart.csv’ is a dataset consisting records of over 304 patients who suffered from heart disease or were diagnosed with it.

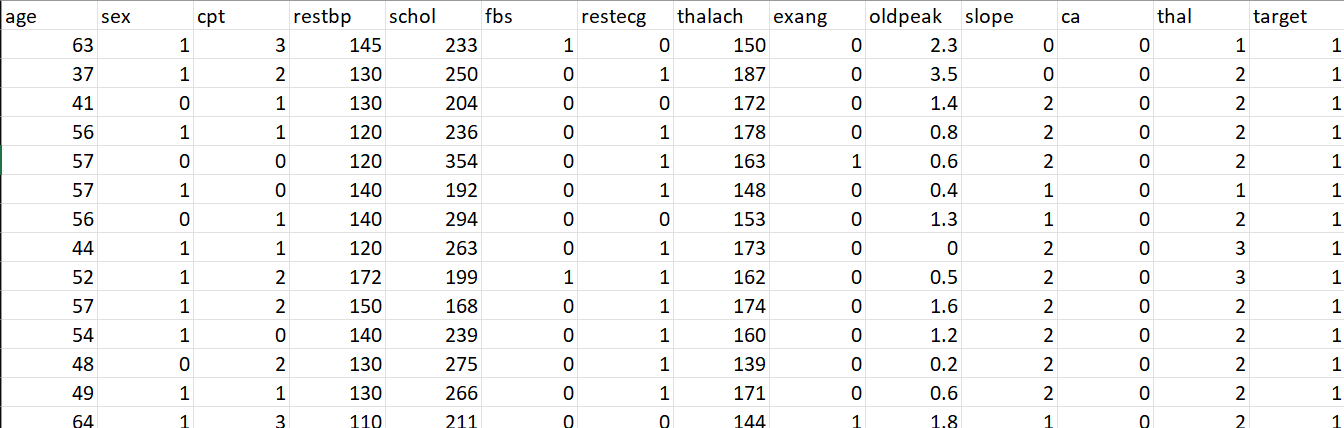


Fig2.heart.csv dataset

The Data source heart.csv accomplished with various features like, age, sex, cpt, restbp, school,fbs, restecg, thalach, etc. where these data is used to build an efficient model to classify and predict the heart disease in suffered patients shown as target value 1 in figure 2.

It is well known that high blood pressure (BP) is a significant warning sign for individuals at risk of heart disease. When the heart works excessively to pump blood throughout the body, it leads to increased stress and strain, which can damage both blood veins and vessels. Senior citizens and individuals with a family history of heart disease are particularly susceptible to chronic heart conditions. Additionally, various factors such as age, gender, poor diet, and work-related stress can contribute to the development of heart disease, even in otherwise healthy individuals. While working professionals and corporate employees have emerged as a high-risk group for heart disease due to the pressures and demands of their occupations.



Fig 3.Features of dataset

## Figure 3 illustrates a sample graph depicting heart syndrome in patients with various risk factors. Individuals engaged in highly stressful work and maintaining poor dietary habits are highly likely to develop heart disease within a short period and are potential candidates for severe coronary attacks.

## In response to this, numerous researchers and innovative medical practitioners are conducting critical analyses of heart syndrome and other chronic disease symptoms to facilitate early detection and improve patient outcomes. To enhance accuracy and efficiency in the analysis and prediction of heart syndromes, researchers are employing a variety of machine learning algorithms and techniques.

## Algorithms

Machine learning is a sophisticated computational method that enables systems to learn and improve from experience without being explicitly programmed. By training on relevant datasets, these systems can automatically adapt and enhance their performance over time. The core objective of machine learning is to develop algorithms that can autonomously analyze data and make informed decisions or predictions based on that data. These algorithms establish a framework of rules and guidelines derived from patterns and insights within the data. Throughout the training phase, diverse datasets can be employed with a single learning algorithm to generate various system models.

1. *Decision Tree Classifier:*

A Decision Tree classifier constructs a model in the form of a tree structure, where each node represents a feature, each branch represents a decision rule, and each leaf node represents the outcome. For optimal model creation, we utilized a comprehensive set of features, ranging from 1 to 30, to ensure robust and efficient predictions. The tree's hierarchical structure allows for clear visualization of the decision-making process.

1. *Support Vector Machine (SVM)*

Support Vector Machine (SVM) is a supervised learning algorithm that aims to find the optimal hyperplane that separates data points of different classes with the maximum margin. Unlike decision tree-based methods, SVM does not rely on tree structures but instead uses kernel functions to handle non-linear relationships. SVM is particularly effective in high-dimensional spaces and is designed to minimize the risk of misclassification by maximizing the margin between data points of different classes.

1. *K-Nearest Neighbours (KNN) Classifier*

The K-Nearest Neighbours (KNN) classifier determines the class of a given data point by identifying the classes of its K nearest neighbours. The classifier assigns the data point to the class most common among its nearest neighbours. To evaluate the performance of the KNN classifier, test scores can be calculated by varying the number of neighbours from 1 to 20.

1. *Random Forest Model*

The Random Forest model is an ensemble learning method that consists of multiple decision trees. Each tree in the forest makes a class prediction, and the final output is determined by majority voting among the trees. The Random Forest algorithm introduces additional randomness by using a technique called "feature bagging." Instead of selecting the best predictors greedily, it randomly samples subsets of the feature space for each tree. This approach increases model diversity and reduces variance, making the model more robust, albeit potentially at the cost of increased bias.

# IMPLEMENTATION METHODOLOGY

The machine learning algorithms were utilized to analyze this dataset and complete the implementation. Among these, the Random Forest algorithm demonstrated significantly higher accuracy compared to the other algorithms, as evidenced in the result analysis presented below.

1. ***A.*** *Dataset Over****view***

The dataset used for this study, "heart.csv," comprises various features related to heart disease. These features include age, gender, chest pain type, resting blood pressure, serum cholesterol, fasting blood sugar, resting electrocardiographic results, maximum heart rate achieved, exercise-induced angina, ST depression induced by exercise relative to rest, the slope of the peak exercise ST segment, number of major vessels coloured by fluoroscopy, and thalassemia (thal). The target variable indicates the presence or absence of heart disease.

1. *B. Data Preparation*

The dataset was first loaded into a pandas Data Frame for initial exploration and preprocessing. The features were described as follows:

1. Age
2. Gender (1: male, 0: female)
3. Chest pain type (1: typical angina, 2: atypical angina, 3: non-anginal pain, 4: asymptomatic)
4. Resting blood pressure
5. Serum cholesterol in mg/dl
6. Fasting blood sugar > 120 mg/dl
7. Resting electrocardiographic results (values 0,1,2)
8. Maximum heart rate achieved
9. Exercise-induced angina
10. Old peak = ST depression induced by exercise relative to rest
11. The slope of the peak exercise ST segment
12. Number of major vessels (0-3) coloured by fluoroscopy
13. Thalassemia (3 = normal; 6 = fixed defect; 7 = reversible defect)

The data was then split into predictors and the target variable, followed by a train-test split with an 80-20 ratio using train\_test\_split from the sklearn.model\_selection module.

*C. Machine Learning Models*

A comparison of different classification algorithms was performed to evaluate their performance on the heart disease dataset. The algorithms included Random Forest ,Logistic Regression, Naive Bayes, Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Decision Tree, and Neural Network. Each model was trained and evaluated using accuracy scores.The accuracy of each model was calculated using the accuracy\_score metric from the sklearn.metrics module.

*D. Model Evaluation and Comparison*

After training the machine learning models, their performance was evaluated using the accuracy metric. Accuracy measures the proportion of correctly classified instances out of the total instances in the test dataset. The accuracy score is calculated by comparing the predicted labels generated by the model with the actual labels in the test dataset.

Mathematically, the accuracy score is calculated using the formula:

To calculate accuracy in Python, the accuracy\_score function from the sklearn.metrics module was utilized. This function takes the actual labels and the predicted labels as input and returns the accuracy score:

* Logistic Regression: 85.25 %
* Support Vector Machine: 81.97 %
* K-Nearest Neighbors: 67.21 %
* Decision Tree: 81.97 %
* Random Forest: 90.16 %
* Neural Network: 85.25%

Among these models, the Random Forest algorithm demonstrated the highest accuracy, making it the most effective model for this dataset.The accuracy score provides valuable insight into the performance of the machine learning models. A higher accuracy score indicates better performance, while a lower accuracy score suggests poorer performance.

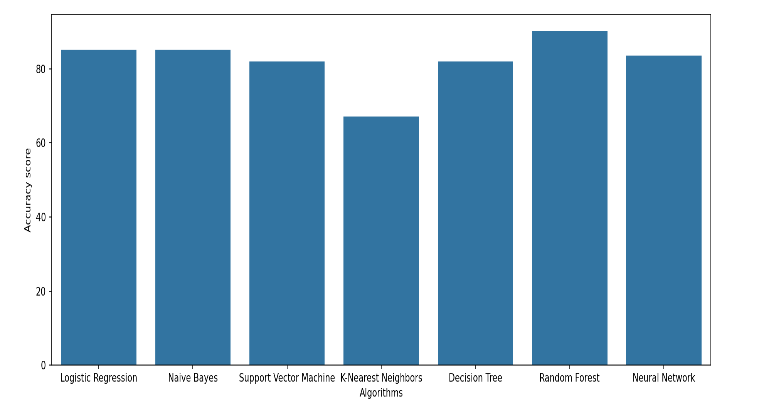


Fig4. Accuracies of different Algorithms

*E. Visualization*

A bar plot was generated using Matplotlib and Seaborn to visually compare the accuracy scores of the different algorithms. This provided a clear illustration of each model's performance.

*F. Model Deployment*

The best-performing Random Forest model was saved using Python's pickle module for future deployment and predictions. A function was also defined to predict and categorize the severity of heart disease based on input features.

Random State Tuning: Random forests are relatively robust to random state variations, so the improvement you get from tuning the random state may be marginal. However, it’s still worth trying if you want to ensure optimal performance. It performs a search over multiple random states to find the one that gives the highest accuracy for the Random Forest classifier. This approach is essentially a way of tuning the model's randomness to find the best configuration.

# RESULTS AND DISCUSSION

### Model Performance Metrics

**Precision**: Precision measures the proportion of true   
positive predictions among all positive predictions   
made by the model.

**Recall**: Recall, also known as sensitivity, measures the proportion of true positive predictions among all actual positive instances.

Cross-validation is a technique used to evaluate the performance of a machine learning model. It involves splitting the dataset into multiple subsets (folds), training the model on some of these subsets, and validating it on the remaining subsets.

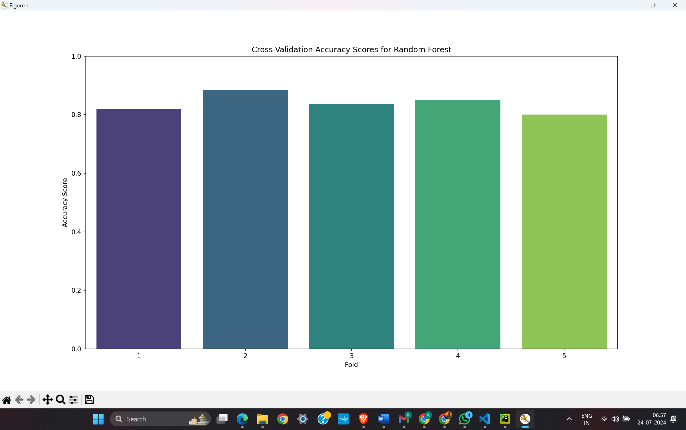


Fig 5.Cross validation Accuracy Score

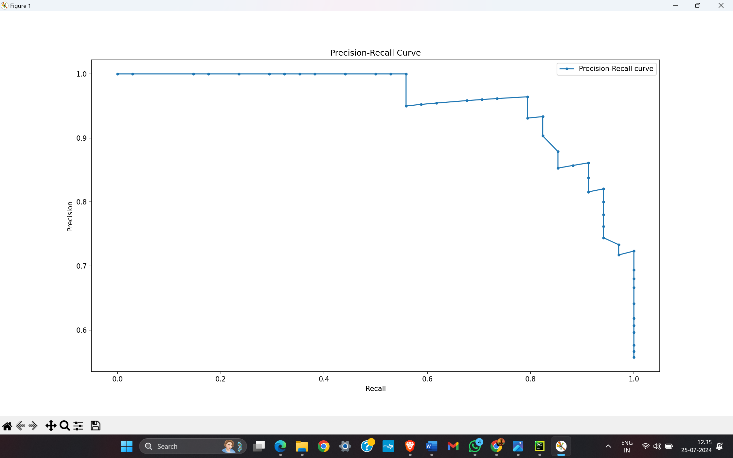


Fig 6.Bar plot of Precision-Recall Score

**Confusion Matrix**: As for each classifier Modified confusion matrices are plotted. Another important detail that the confusion matrix offers is context-specific insights into true positives, false positives, true negatives and false negatives - which enables us to assess classification performance in more details.

Significance: Confusion matrix aids in assessing the classification performance that goes past simple accuracy by showing where your model is likely to be going wrong.

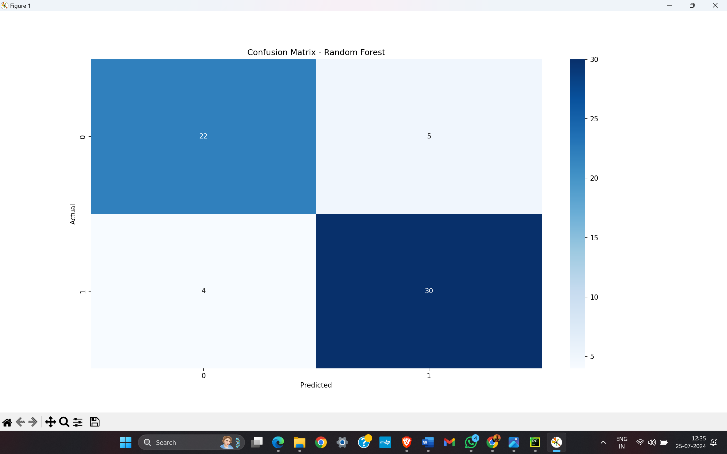


Fig7. Confusion Matrix for random Forest.

**Receiver Operating Characteristic**: ROC for models with probability predictions was plotted The ROC (Receiver Operating Characteristic) curve is a graphical representation of the trade-off between true positive rate (Sensitivity) and false positive rate(1-Specificity).

AUC (Area Under the ROC Curve): A measure that indicates how well a model is at distinguishing between classes. AUC values ranges from 0 to 1, and higher AUC means better model performance.

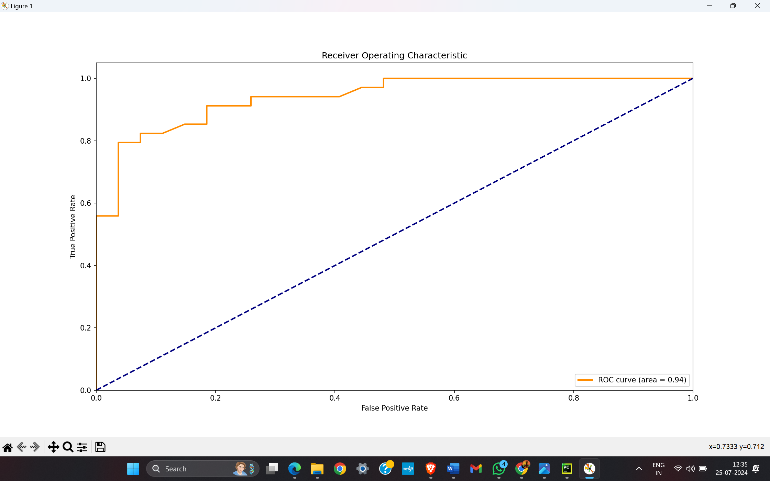


Fig8. ROC Graph plot

**Neural Network Architecture**

A simple neural network was implemented with one hidden layer to further explore the capabilities of deep learning models. The network was trained for 300 epochs using the binary cross-entropy loss function and the Adam optimizer.

* **Architecture**: The network consisted of an input layer with 13 nodes, a hidden layer with 11 nodes, and an output layer with 1 node using the sigmoid activation function.
* **Outcome**: The neural network achieved an accuracy of 88%, demonstrating competitive performance compared to other models.

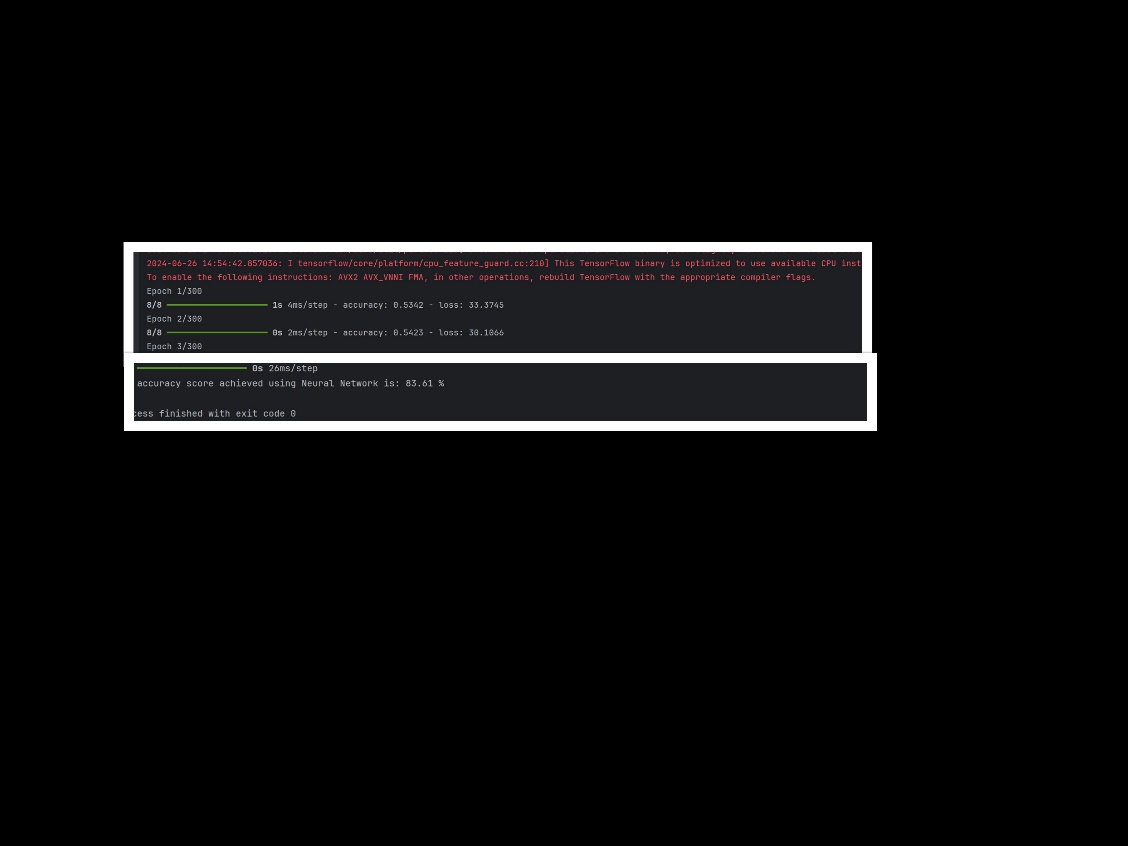


Fig9. Use of Neural Network and Accuracy

A. Feature Importance Analysis

The Random Forest model is an ensemble learning method that consists of multiple decision trees. Each tree in the forest makes a class prediction, and the final output is determined by majority voting among the trees. The Random Forest algorithm introduces additional randomness by using a technique called "feature bagging." Instead of selecting the best predictors greedily, it randomly samples subsets of the feature space for each tree. This approach increases model diversity and reduces variance, making the model more robust, albeit potentially at the cost of increased bias.

The Random Forest model was trained on the dataset, and feature importances were extracted using the feature\_importances\_ attribute provided by the trained model. These importances represent the contribution of each feature to the overall predictive performance of the classifier.

The following image presents the top 10 most important features identified by the Random Forest classifier:

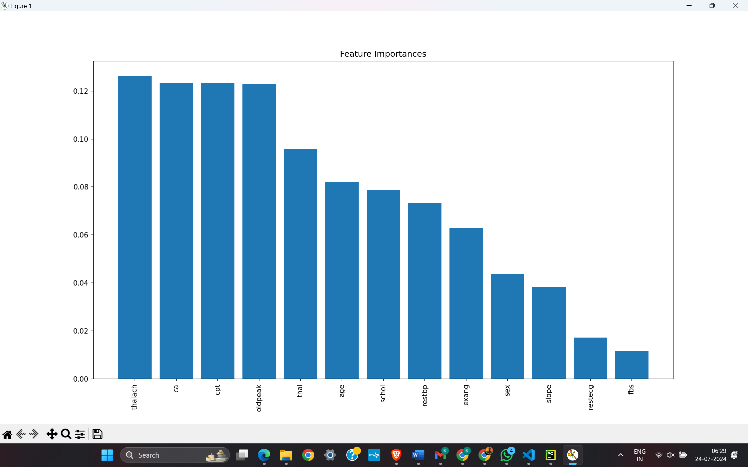


Fig Feature Importances

These results highlight the importance of certain features such as maximum heart rate achieved, serum cholesterol level, and the number of major vessels colored by fluoroscopy in predicting the presence of heart disease. Understanding the significance of these features can aid healthcare practitioners in early detection and effective management of cardiovascular conditions.

C. Model Interpretability

As illustrated in the plot, certain features exhibit higher importance values compared to others. For instance, maximum heart rate achieved, serum cholesterol level, and the number of major vessels colored by fluoroscopy emerge as key predictors of heart disease. Clinicians can leverage these insights to prioritize diagnostic tests and interventions for patients presenting with relevant risk factors.

Feature importance plots serve as intuitive tools for understanding the underlying mechanisms of machine learning models and guiding clinical decision-making. By identifying the most influential features, clinicians can tailor treatment plans and interventions to effectively manage cardiovascular conditions and improve patient outcomes

V. DISCUSSION

A. Clinical Relevance of Findings

The findings of this study hold significant clinical relevance and have profound implications for healthcare practitioners involved in the diagnosis and management of heart disease.

Early Detection and Diagnosis**:** The developed machine learning models demonstrate high accuracy in detecting the presence of heart disease based on various clinical and demographic features.

Enhanced Clinical Decision-Making**:** Moreover, the machine learning models serve as decision support tools to augment clinical decision-making processes.

Integration into Clinical Practice**:** To maximize the clinical utility of these machine learning models, integration into routine clinical practice is essential.

In conclusion, the developed machine learning models offer valuable tools for early detection, diagnosis, and personalized treatment planning for patients at risk of heart disease.

# Future Scope

Despite the promising results achieved in this study, there are several avenues for further research and improvement. Addressing these aspects can enhance the accuracy, robustness, and applicability of the heart disease detection system which includes:

Model Enhancement

1. Advanced Hyperparameter Tuning

Techniques such as Grid Search or Randomized Search can be employed to explore a wider range of hyperparameters, potentially improving model performance.

2. Ensemble Learning Techniques

Combining multiple models through ensemble methods like Stacking or Boosting could enhance predictive performance. Techniques such as Gradient Boosting Machines (GBM) or Extreme Gradient Boosting (XGBoost) can be explored to improve accuracy and generalization.

Application in Clinical Settings

1. Integration with Clinical Decision Support Systems

Integrating the model into Clinical Decision Support Systems (CDSS) can aid healthcare professionals in making informed decisions. Developing user-friendly interfaces and decision-support tools will be essential for practical implementation.

2. Impact Assessment and Cost-Benefit Analysis

Conducting impact assessments and cost-benefit analyses to evaluate the practical benefits of the predictive model in clinical settings will be valuable. This includes assessing the model's effectiveness in improving patient outcomes and reducing healthcare costs.

# Conclusion

In conclusion, this project demonstrates the significant potential of machine learning in the early detection and diagnosis of heart disease. By harnessing the power of advanced algorithms and large datasets, our system offers a non-invasive, accurate, and efficient method for identifying individuals at risk of cardiovascular diseases. The Random Forest model, after tuning the random state, achieved the highest accuracy of 90%, demonstrating its effectiveness for heart disease detection. The visualizations, including confusion matrices, ROC curves, and precision-recall curves, offered valuable insights into the models' strengths and areas for improvement. The neural network, despite being simpler, showed promising results, further validating the robustness of various machine learning approaches.. Consequent to this, the successful realization of the ML-based method does not only promise enhanced patient outcomes but also represents an innovative step into the adoption of new technologies in health. Future work is targeted at model refinement, further dataset expansion, and validation in clinical setups to ascertain its robustness and generalizability. Ultimately, this project contributes to the ongoing efforts to combat the global burden of heart disease through early detection and proactive healthcare management.

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