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CARDIOVASCULAR DISEASE PREDICTION USING RANDOM FOREST

Ms. V. Sarvasri Sowmya Lakshmi
Student of CSE Dept,
Sri Vasavi Engineering College (A), Pedatadepalli,
Tadepalligudem – 534101.

Mr. Y P V Satyanarayana
Student of AI&DS Dept,
Sagi Ramakrishnam Raju Engineering College(A),
Bhimavaram–534225.

Abstract: **Heart plays a vital role in living organisms. Heart disease, which is also known as coronary artery disease, is a leading cause of death globally, exacerbated by various external factors. Nowadays everything has become so simple with the upcoming technologies like machine learning. Machine learning provides a promising solution to this crisis. Machine learning, a subset of artificial intelligence, involves algorithms that help in predicting outcomes and making decisions based on large amounts of data. It has become a buzzword in almost every sector or industry due to its transformative potential. In this study, we employ the Random Forest algorithm to predict heart disease. This model achieved an accuracy of 90.16%, highlighting its potential in accurately predicting heart health status. Although there are many machine learning models available for heart disease prediction, we chose Random Forest for its robustness and reliability.**

Keywords: **Heart Disease, Machine learning, Prediction, Ensemble Learning, Random Forest, Bagging Technique, Accuracy, Health prediction, Healthcare technology.**

I. INTRODUCTION

Cardiovascular diseases (CVDs), particularly heart disease, are not only a leading cause of death but also a significant burden on healthcare systems worldwide. The economic impact of these diseases is substantial, with billions of dollars spent annually on treatment, care, and lost productivity. This underscores the urgent need for more effective diagnostic tools and preventive measures that can help reduce both the human and financial toll of heart disease. One of the challenges in diagnosing heart disease lies in the sheer variety of factors that contribute to its onset. These include traditional risk factors such as high blood pressure, high cholesterol, and smoking, as well as newer, more complex variables like genetic predispositions and environmental influences. This complexity makes it difficult for conventional diagnostic methods to accurately assess an individual's risk, leading to either over-treatment or missed diagnoses. Machine learning (ML) techniques, particularly the Random Forest algorithm, offer a powerful solution to these challenges. By leveraging large datasets and advanced computational models, Random Forest can analyse multiple variables simultaneously, uncovering patterns and relationships that might be missed by human clinicians. This ability to process and interpret vast amounts of data quickly and accurately makes it an invaluable tool in the fight against heart disease. In addition to improving diagnostic accuracy, the use of Random Forest and other ML techniques in heart disease prediction has the potential to personalize treatment plans. By identifying specific risk factors unique to each patient, healthcare providers can tailor interventions more precisely, improving outcomes and reducing the likelihood of adverse effects. This personalized approach represents a significant shift from the one-size-fits-all methods of the past, aligning with the broader trend towards precision medicine.

Furthermore, the integration of ML models like Random Forest into healthcare systems can enhance early detection efforts. Early identification of high-risk individuals allows for timely interventions, which can prevent the progression of heart disease and save lives. As these technologies continue to evolve, they hold the promise of transforming not only how we diagnose and treat heart disease but also how we understand and manage other complex conditions. In this paper, we delve into the application of the Random Forest algorithm for heart disease prediction, comparing its performance against traditional methods and exploring its potential for broader use in clinical practice. By demonstrating the efficacy of this approach, we aim to contribute to the ongoing efforts to improve cardiovascular health and reduce the global burden of heart disease.

II. LITERATURE SURVEY

Ref [1] :Kompella Sri Charan, Kolluru S S N S Mahendranath presented " Heart Disease Prediction Using Random Forest Algorithm" that represents a model of heart disease prediction that creates a Random Forest and achieves an accuracy of 92%. The approach focuses on the growing concern of cardiovascular diseases by applying machine learning techniques to patient data analysis. Different models have been compared in this study, including Decision Tree, SVM, Adaboost, and Gradient Boosting; the result reported is that Random Forest performs better than others. This research has been stressing the importance of pre-processing, feature selection, and model evaluation for the improvement in prediction accuracy. It thus emphasizes the powerful role of Random Forest in treating high complex-dimensional data and gives a very promising way for the early detection and intervention of heart disease.

Ref [2]: V V Ramalingam and Ayantan Dandapath's paper, "Heart Disease Prediction Using Machine Learning Techniques: A Survey," discusses various machine learning algorithms for predicting cardiovascular diseases. The study highlights the importance of accurate and timely diagnoses, given heart disease's status as a leading global cause of mortality. It reviews models like SVM, KNN, Naive Bayes, Decision Trees, Random Forest, and ensemble models, emphasizing the importance of dimensionality reduction for improving model efficiency. The paper also notes that while machine learning shows promise in healthcare, challenges like high-dimensional data and overfitting require further research.

Ref [3]:Aminu Bashir Suleiman, Stephen Luka and Muhammad Ibrahim -"Cardiovascular disease prediction using random forest machine learning algorithm" introduced Cardiovascular risk prediction has recently been popular with machine learning techniques, more so Random Forest. Suleiman et al. established the efficacy of RF to be 90%, where rigorous tuning of hyperparameters and data preprocessing had been done. Similarly, Jabbar et al. combined RF with feature selection methods and achieved an accuracy of 84%, thus depicting that there is a need for feature optimization. Chintan et al. (2016) compared RF with other models and proved it to be competitive with an accuracy of 87.05%. Smith et al. (2020) carried out CVD prediction using logistic regression and obtained an accuracy of 85%, therefore providing a comparative baseline. Johnson et al. (2019) combined genetic and lifestyle factors with RF to achieve 89% accuracy, thus underpinning the model's ability in handling a diversity of data types. These studies' results, therefore, overall underline the exceptionally good performance of RF in the prediction of CVD and the importance of feature selection and data integration in improving model accuracy.

Ref [4]: M.A.Jabbar, B.L.Deekshatulu and Priti Chandra - "Intelligent heart disease prediction system using random forest and evolutionary approach" on heart disease prediction explores various methods, from fuzzy logic combined with artificial immune systems to neural networks and decision trees. Researchers have used algorithms like Bayesian classifiers and decision trees, achieving accuracies between 57.85% and 97.92%. Many studies emphasize the importance of selecting the right features, often using techniques like chi-square tests or genetic algorithms, to boost prediction accuracy. These advancements highlight how crucial thoughtful feature selection and sophisticated algorithms are in diagnosing heart disease more effectively.

Ref [5]:Senthilkumar Mohan, Chandrasegar Thirumalai, Gautam Srivastava -" Effective Heart Disease Prediction Using Hybrid Machine Learning Techniques" developed a heart disease prediction tool specifically for juveniles using multilayer perceptron algorithms. They utilized the Cleveland dataset from the UCI repository, which includes 76 features like chest pain, CT scan results, and ECG data. They processed the data using Python in PyCharm. The results showed a precision of 0.92, a recall of 0.90, and a support value of 93 for positive cases, while for negative cases, the precision was 0.91, recall was 0.89, and support was 0.72.

III. METHODOLOGY

Classification:

In Random Forest, a supervised machine learning technique, classification tasks involve dividing the data into several classes, resulting in categorical outputs. By default, the square root of the total number of features is used to select the features for each decision tree in the forest. Each decision tree independently votes on the class, and the majority vote determines the final outcome.

Regression:

In Random Forest regression tasks, the results are continuous or real values. The algorithm builds an ensemble of decision trees, where each tree is constructed using a random subset of features and data points. The trees in the forest are grown to their maximum extent without pruning, and each one provides a prediction. The final prediction for regression problems is the average of all the tree predictions. Performance is typically evaluated using metrics such as root-mean-squared-error (RMSE) and mean-squared-error (MSE).

In our study, we utilized Jupyter Notebook to classify heart disease using the HEART dataset from the Kaggle repository. Our machine learning process began with data preprocessing, followed by feature selection, and then classification using the Random Forest (RF) algorithm. This iterative approach allowed us to refine both feature selection and modeling to achieve optimal accuracy. The dataset's

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attributes and data types are detailed in Tables 1 and 2. Sections A, B, C, and D provide an overview of data preprocessing, feature selection, classification, and performance evaluation, respectively.

Table – 3.1: Heart Dataset Attributes Detailed Information

Attribute	Description	Type
Age	Patient's age in completed years	Numeric
Gender	Patient's gender (male represented as 1 and female as 0)	Nominal
Cp	Type of chest pain categorized into four values: 1. Typical Angina, 2. Atypical Angina, 3. Non-anginal Pain, 4. Asymptomatic	Nominal
Trestbps	Resting blood pressure in mm/Hg at the time of admission	Numeric
Chol	Serum cholesterol in mg/dl	Numeric
FBS	Fasting blood sugar levels > 120 mg/dl (1 = true, 0 = false)	Nominal
Restecg	Resting electrocardiogram results: 0 = normal, 1 = ST-T wave abnormality, 2 = probable/definite left ventricular hypertrophy by Estes' criteria	Numeric
Thalach	Maximum heart rate achieved	Numeric
Exang	Exercise-induced angina (0 = no, 1 = yes)	Nominal
Oldpeak	ST depression induced by exercise relative to rest	Numeric
Slope	Slope of the peak exercise ST segment: 1 = upsloping, 2 = flat, 3 = downsloping	Nominal
Ca	Number of major vessels colored by fluoroscopy (0 to 3)	Numeric
Thal	Thalassemia status: 3 = normal, 6 = fixed defect, 7 = reversible defect	Nominal
Target	Heart disease diagnosis: 0 = no disease, 1 = disease present in varying degrees	Nominal

Table – 3.2: Heart Dataset Range and Datatype

Variable	Type	Range/Levels	Unique Values	Mean	Median
AGE	Numeric	29 to 77	41	54.4	56
Gender	Numeric	0 to 1	2	0.68	1
CP	Numeric	1 to 4	4	3.16	3
TESTBPS	Numeric	94 to 200	50	131.69	130
CHOL	Numeric	126 to 564	152	246.69	241
FBS	Numeric	0 to 1	2	0.15	0
RESTING	Numeric	0 to 2	3	0.99	1
THALI	Numeric	71 to 202	91	149.61	153
EXANG	Numeric	0 to 1	2	0.33	0.00
OLDPEAK	Numeric	0 to 6.20	40	1.04	0.80
SLOPE	Numeric	1 to 3	3	1.60	2
CA	Categorical	5 levels	5	-	-
THAL	Categorical	14 levels	14	-	-
TARGET	Numeric	0.00 to 4.00	5	0.94	0.00

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A. Data Pre-Processing:

The heart disease dataset undergoes pre-processing following the collection of patient records. This dataset includes 303 patient entries, all of which are complete with no missing values. For classification purposes, both multi-class and binary variables are utilized. The binary classification is employed to determine the presence or absence of heart disease in the patients. Specifically, if a patient has heart disease, their record is marked with a value of 1; otherwise, it is marked with a value of 0 to indicate no heart disease. During data pre-processing, medical records are converted into diagnostic values. After processing, the results from the 303 patient records show that 165 records are labeled with a value of 1, confirming the presence of heart disease, while the remaining 138 records are labeled with a value of 0, indicating the absence of heart disease.

B. Feature Selection:

In our dataset of 13 attributes, we use age and sex to capture basic personal details about the patient. These pieces of information help us understand the patient's background. The remaining 11 attributes are crucial because they contain important clinical information. These include things like chest pain type, blood pressure, and cholesterol levels etc. This clinical data is vital for diagnosing heart disease and figuring out how serious it might be. By examining these details, we can get a clearer picture of the patient's heart health and assess their risk more accurately. As previously mentioned in this experiment, performed using Random Forest which is a bagging technique was used to predict the heart disease using all 13 attributes.

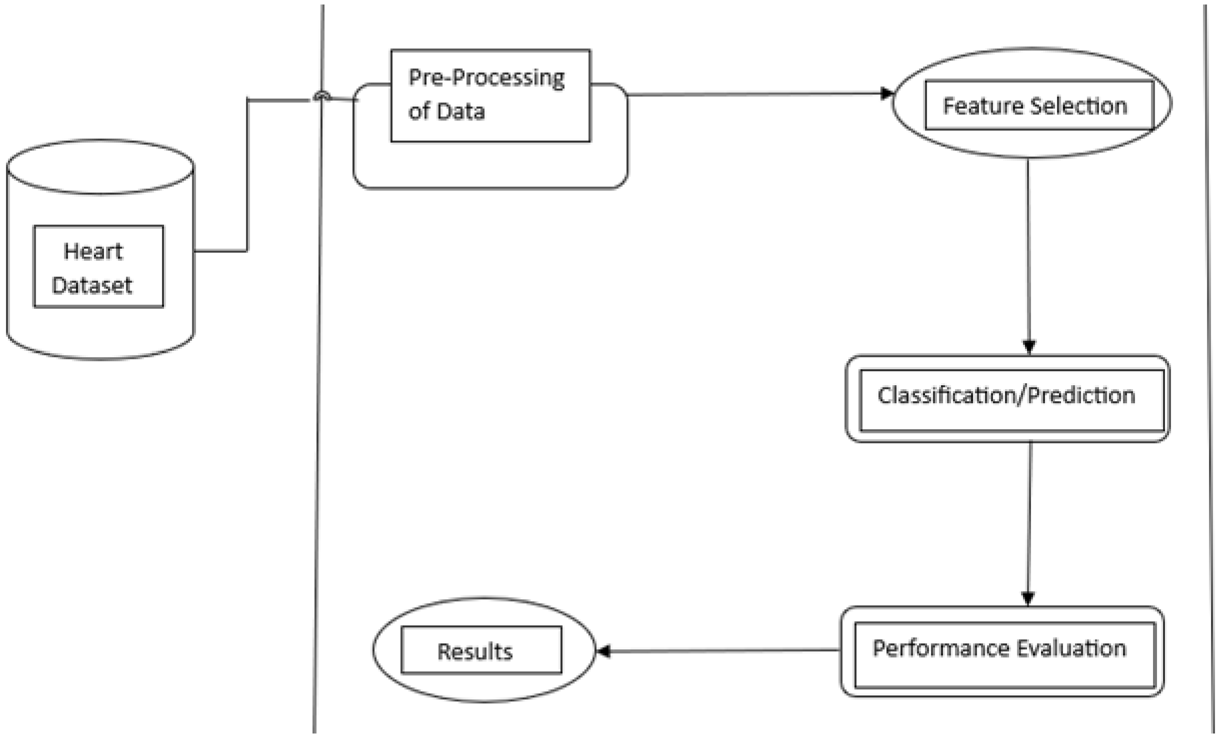

Fig-3.1 Experiment workflow with Heart dataset.

C. Classification Modeling:

We start by organizing the datasets based on the Random Forest (RF) features. Then, we apply Random Forest classifiers to each subset to see how well they perform. We pick the models that achieve the best results with the lowest error rates. To make our models even better, we focus on the RF clusters that initially showed higher errors. By fine-tuning these clusters and improving their features, we managed to boost our model's accuracy to an impressive 90.16%. This shows that our approach effectively enhances the model's performance and reliability.

- **BAGGINGTECHNIQUE**

Bagging which is known as Bootstrap Aggregating is an ensemble method. This process involves training several models separately on different random subsets of the data. Their predictions are then combined by taking a vote or averaging the results. It is a parallel approach, that every model will work with other datasets parallelly. It is a variance reduction technique (low bias, low variance).

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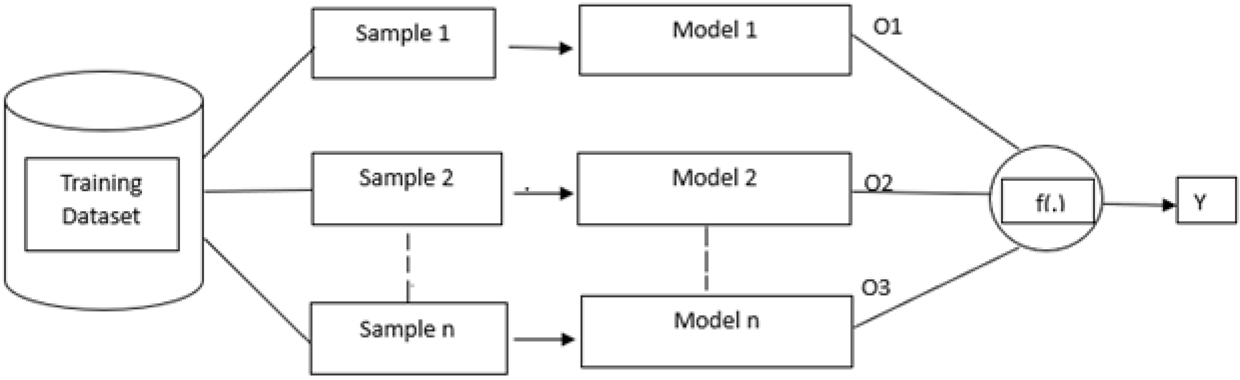

Fig-3.2 Bagging technique

- **RANDOM FOREST:**

This ensemble classifier builds several decision trees and incorporates them to gain better results. It uses the concept of Bagging. In tree learning, the technique of bootstrap aggregating, or bagging, is commonly used. For the data $X=\{x_1,x_2,x_3,\ldots,x_n\}$with responses $Y=\{x_1,x_2,x_3,\ldots,x_n\}$ which repeats the bagging from b=1 to B . The unseen samples x′ is made by averaging the predictions $\sum^{B}_{b=1} fb(x')$ from every individual tree on x'

$$j = \frac{1}{B}\sum_{b=1}^{B} fb\,(x')$$

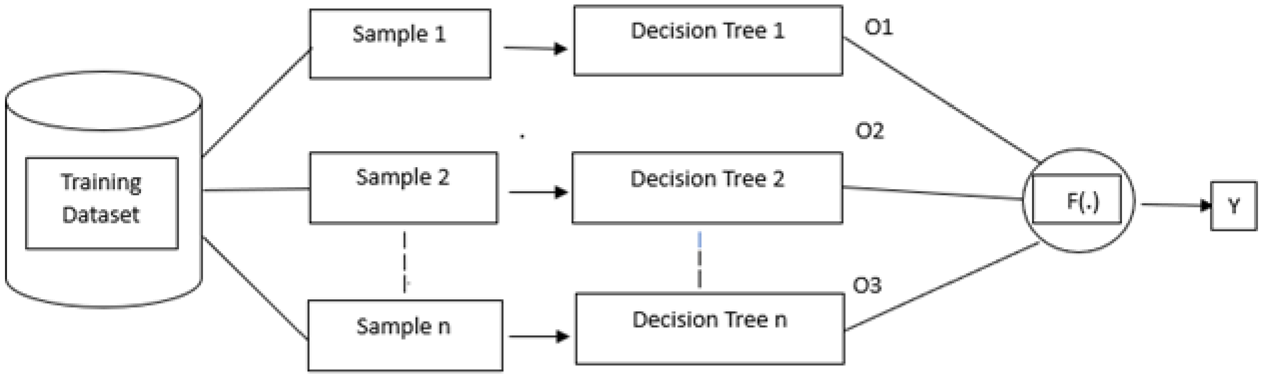

Fig-3.3 Random Forest

D. Performance Measures:

Accuracy tells us the percentage of correct predictions out of all the predictions made. For instance, if a model predicts correctly for 90 out of 100 cases, its accuracy is 90%. Precision focuses specifically on the positive predictions. It measures how many of those positive predictions are actually correct. In other words, it tells us the reliability of the model when it says a case is positive. Classification Error represents the proportion of incorrect predictions, showing how often the model gets things wrong. We use these metrics to identify which features of heart disease are most important and to understand how different combinations of features affect the model's performance. This helps us refine our approach and improve the model's predictions.

We tested several algorithms to find the best one for our heart disease prediction model. Here's how they performed:

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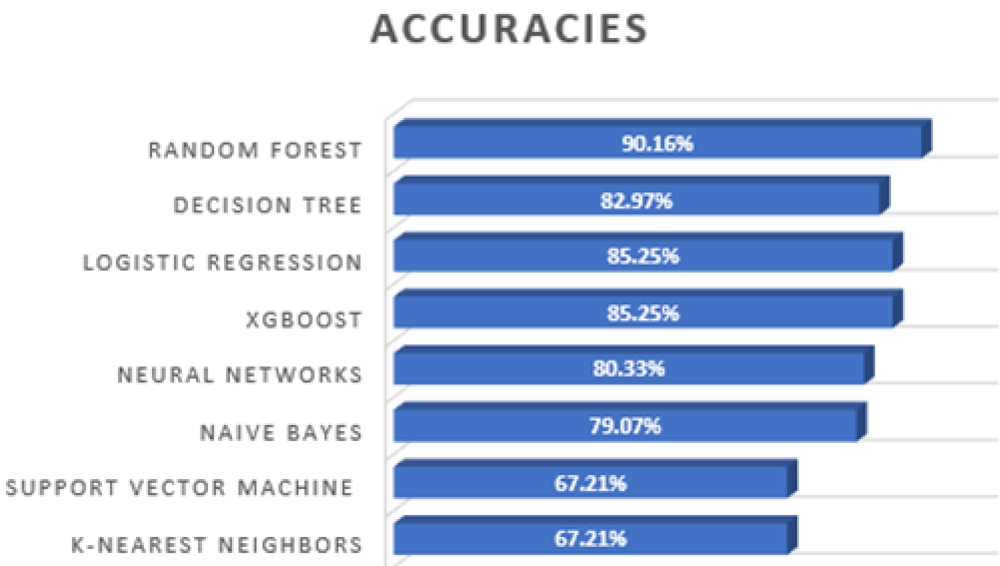

Fig-3.4 Accuracies of Different Algorithms

Among these, Random Forest stood out with the highest accuracy of 90.16%. This impressive performance indicates that Random Forest is the most effective model for predicting heart disease in our dataset, outperforming the other algorithms we tested.

- **RANDOM FOREST ALGORITHM:**

1. Initialization:
- Set the number of trees N in the forest.
- Define the number of features mmm to be randomly selected at each node.

2. For each tree ifrom 1 to N:
- Generate a bootstrap sample from the training set by randomly sampling with replacement.
- Build a decision tree using the bootstrap sample.
- At each node:

i. Randomly select m features from the total features.
ii. Compute the information gain (or Gini index) using only the selected mfeatures.
iii. Choose the feature with the best information gain (or lowest Gini index) to split the node.
iv. Continue growing the tree until it is complete or another stopping criterion is met.

3. Aggregate Predictions:
- For a given test sample, obtain predictions from each of the N trees.
- Aggregate the predictions using voting (for classification) or averaging (for regression**).**

4. Output:
- Provide the aggregated prediction as the final output.

METRICS	VALUES
Sensitivity/Recall	0.882
Specificity	0.865
Precision	0.9
True Positive Rate (TPR)	0.882
False Positive Rate (FPR)	0.118
F1 score	0.91
AUC-ROC	0.87

Table -3.3 Metrics

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IV. EXISTING SYSTEM

In this system, patient inputs are collected, and machine learning techniques are employed to generate results. The patient data, sourced from reputable medical databases, is analyzed using algorithms such as Random Forest, Logistic Regression, and K-Nearest Neighbors. The outcomes are then compared with other models, achieving an accuracy of less than 90%.

Disadvantages:
1.Complexity of Model
2.Data Quality Issues
3.High Cost of Implementation
4.Data Privacy Concerns

V. PROPOSED SYSTEM

The proposed heart disease prediction systems are designed to be user-friendly, starting with a welcoming page and guiding users through a series of input forms. Users provide personal health details like age, gender, chest pain type, blood pressure, fasting blood sugar, cholesterol levels, ECG results, maximum heart rate, exercise-induced angina, oldpeak, ST segment, fluoro-colored major vessels count, and thalassemia status. The system then uses the Random Forest algorithm, a sophisticated machine learning technique, to assess the user's heart health. If the result shows a potential issue, the system not only informs the user about their heart health but also suggests nearby hospitals based on their location. This approach integrates JavaScript, CSS, and HTML for the front-end with a Python Flask back-end, ensuring accurate predictions and practical health recommendations.

Advantages:
1.User-Friendly Interface
2.Increased Accuracy and Low time and cost-friendly
3.Comprehensive Data Collection and Advanced Predictive Model
4.Immediate Result and Localized Hospital Recommendations
5.Data Privacy and easy Accessibility

VI. RESULT AND ANALYSIS

In this research, the Random Forest (RF) model demonstrated strong predictive performance, achieving an F1 score of 0.89, an AUC of 0.91, and an overall accuracy of 90.16%. These results surpass many previous studies, emphasizing the efficacy of a structured machine-learning approach in improving heart disease prediction accuracy.

FEATURE ANALYSIS

- **Correlation Matrix:** The analysis of the correlation matrix offered critical insights into the relationships between various features. This helped refine feature selection, which, in turn, enhanced the model's performance by focusing on the most relevant attributes.

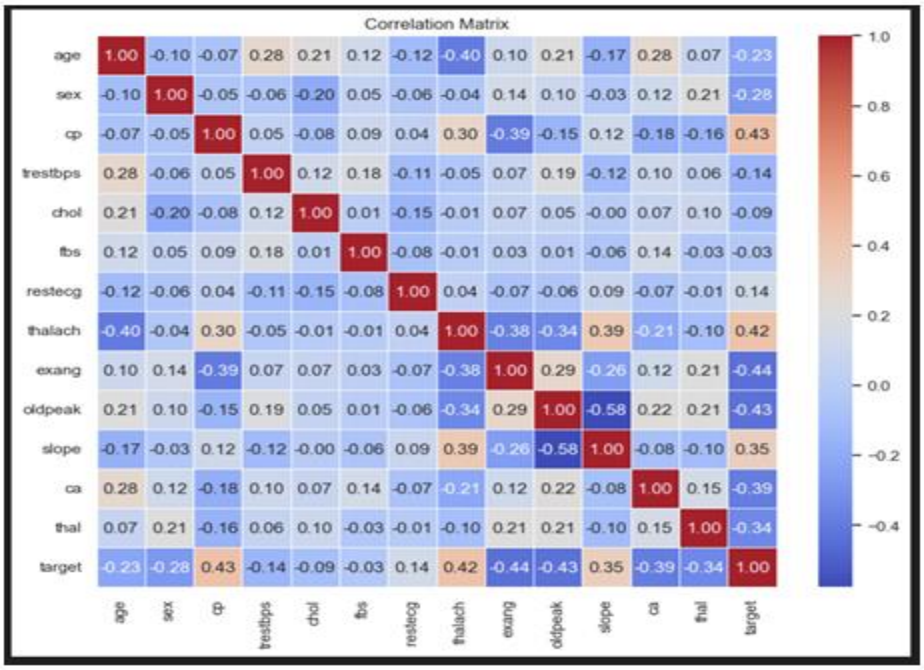

Fig 6.1: Correlation Matrix

- **Histogram Visualization:** Histograms were utilized to visualize the data distribution, aiding in the identification of categorical variables. These visual tools were crucial for understanding the data, which contributed to the model's accurate classification capabilities.

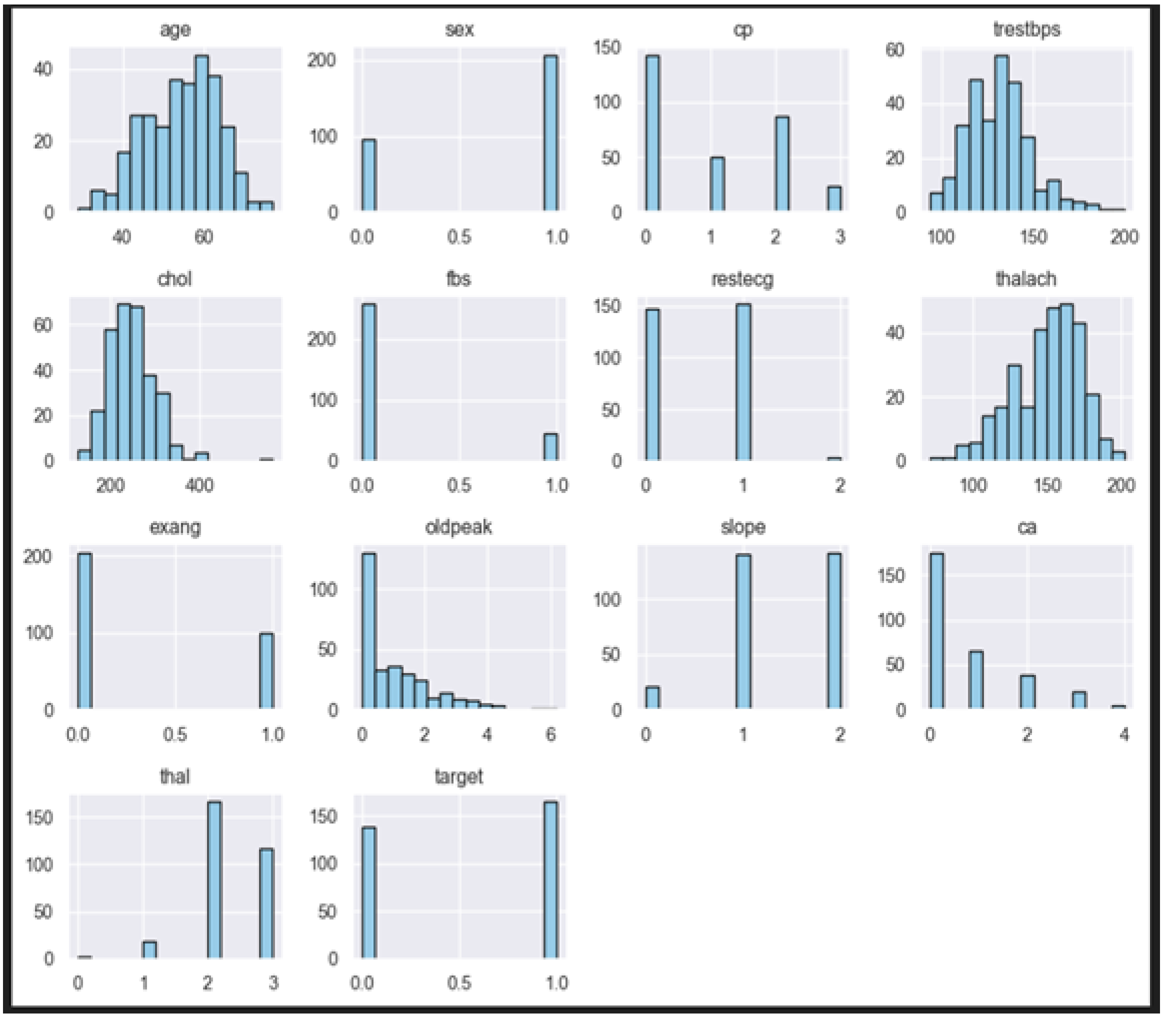

Fig.6.2 : Histogram Visualization of attributes of dataset

Result:

- **Home page: This user-friendly interface, designed with HTML and CSS, provides a welcoming gateway to the personal details section.** The inviting "Check Now" button, coupled with the intriguing question "Want to know how healthy your heart is?", sparks curiosity and encourages users to take the first step towards understanding their heart health. The thoughtful design ensures a seamless and enjoyable experience, making it easy for users to navigate the content and actively engage with their well-being. **As the first page of the project, this interface sets the tone for a positive and engaging user experience.** It invites users to explore their personal details in a friendly and informative way, while also highlighting the importance of heart health. The clear and concise language, combined with the visually appealing design, makes this page a strong foundation for the project.

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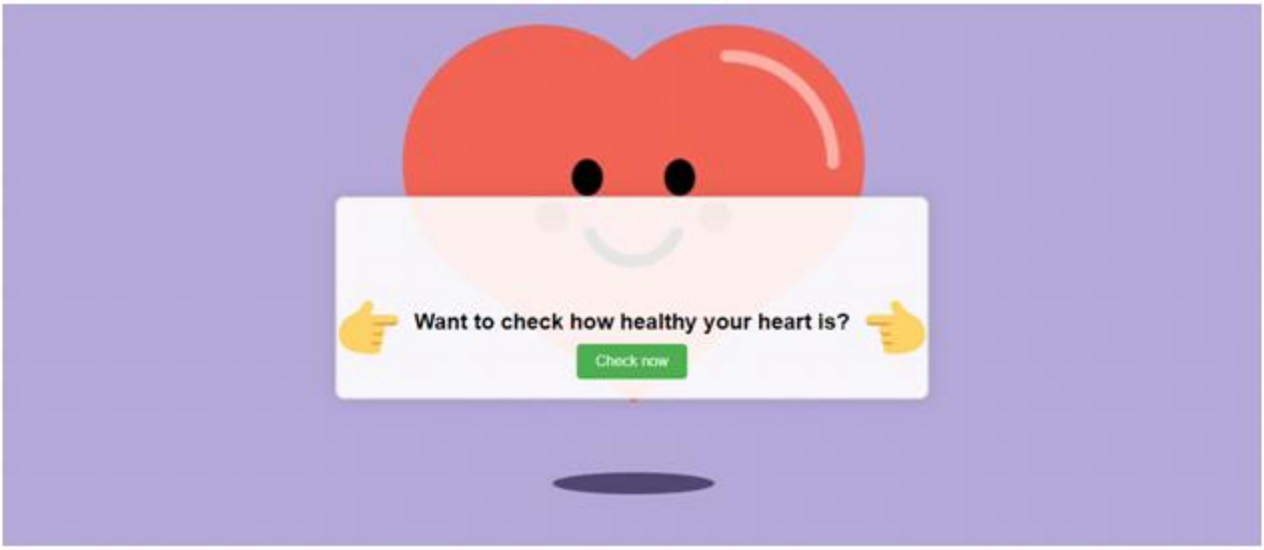

Fig.6.3 Homepage

- **Personal Details Page:** The personal details page is designed to gently guide users through entering their name, age, gender, and email. Built with care using HTML, CSS, and JavaScript, this page features a user-friendly submit button. Once clicked, it seamlessly leads users to the main heart health assessment page, ensuring a smooth and welcoming experience. The thoughtful design and clear instructions make it easy for users to provide their information confidently and proceed to the next step in their heart health journey. Additionally, the page incorporates validation checks to ensure data accuracy and prevent errors, further enhancing the user experience.

Fig.6.4 Personal Details Page

- **Heart Details:** The main page of the heart disease detection project serves as a crucial interface where users input their health information to determine the condition of their heart. This page is designed with user-friendly HTML, CSS, and JavaScript, offering a clean and intuitive layout. Users are prompted to enter essential details such as age, gender, blood pressure, and more. Each field is carefully crafted to guide the user through the process smoothly. Once all details are entered, the data is processed through a Flask backend to analyze and predict heart health, with a simple click of the submit button.

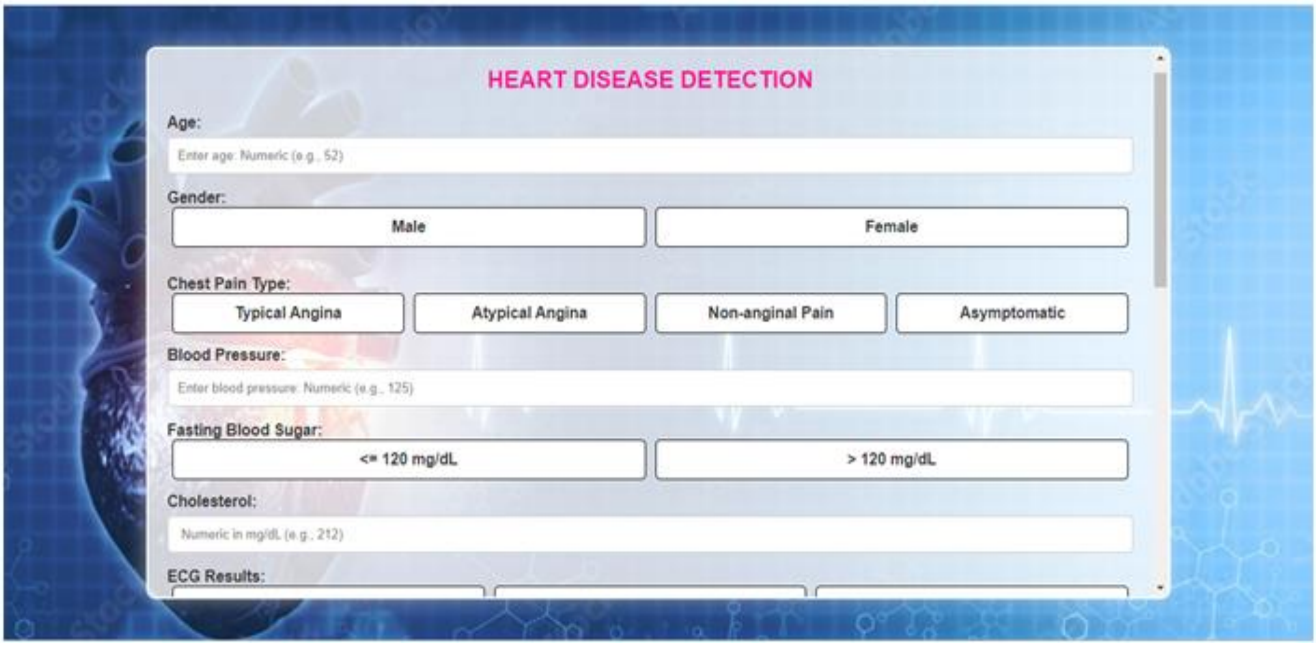

Fig.6.5 Heart Details

- **Result page:** The result page of our heart disease prediction application is designed with a user-friendly interface using HTML, CSS, and JavaScript, while the backend is managed by Flask. Based on the user's input from the previous page, the page displays a visual representation of heart health. If the prediction indicates a healthy heart, a strong heart image is shown with a message affirming the user's good health. Conversely, if the prediction suggests potential heart issues, an image of a heart with pain is displayed, accompanied by a recommendation to consult a nearby hospital. The application also provides an option to view nearby hospitals based on the user's location or to return to the home page if they choose not to seek immediate assistance. This approach ensures users receive relevant feedback and actionable advice in a clear and accessible manner.

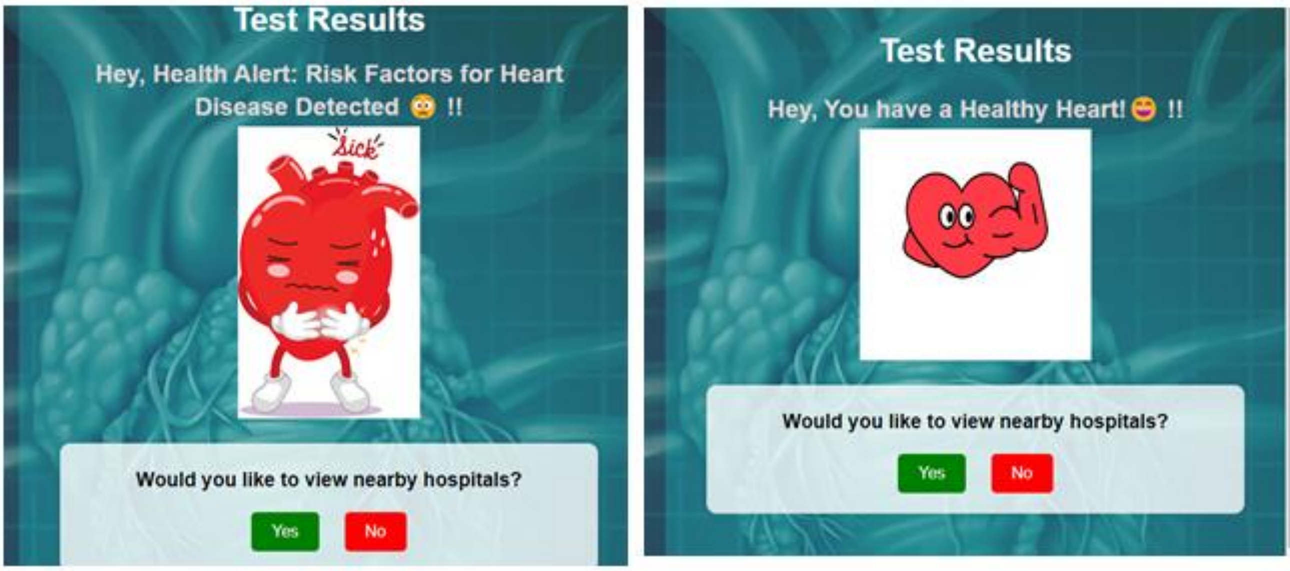

Fig.6.6 Result

VII. CONCLUSION

Accurately predicting heart disease is crucial for improving patient care and making the best use of healthcare resources. Our study shows that the Random Forest algorithm is a standout tool for this task. It effectively uncovers complex patterns in the data, leading to highly accurate predictions. What sets Random Forest apart is its robustness and ability to handle a variety of data without losing reliability. This makes it especially useful in clinical settings, where precise and timely diagnosis is key. By integrating Random Forest into healthcare, we can enhance early detection and intervention, ultimately benefiting patient outcomes. The algorithm's strong performance and reliability make it a valuable asset for heart disease prediction, with the potential for even greater impact as it continues to evolve and be applied in real-world scenarios.

VIII. FUTURE ENHANCEMENT

As part of our ongoing efforts to enhance the heart disease prediction project, several future features are being considered to further enrich the user experience and improve health outcomes. Here are some key additions that could be made:

1. **Personal Health Dashboard**: A personalized dashboard will enable users to track their health metrics over time, including predictions, actual health check-ups, and lifestyle changes. This feature will help users monitor their progress and make more informed health decisions.
2. **Predictive Analytics for Lifestyle**: The application could offer insights and recommendations on lifestyle changes based on predictive analytics. This feature aims to help users improve their heart health through personalized suggestions tailored to their specific needs and risks.
3. **Interactive Visualization**: Implementing interactive charts and graphs will enable users to visualize their health data and prediction trends more clearly. This visualization will make it easier to understand complex health information and track improvements over time.
4. **Health Risk Alerts**: Introducing a notification system that alerts users if their health metrics indicate a higher risk will prompt them to seek medical advice. These alerts will serve as an early warning system to encourage timely intervention.
5. **Patient Feedback System**: Allowing users to provide feedback on predictions and recommendations will help continuously improve the model's accuracy and relevance. This feature will ensure that the application evolves based on user experiences and needs.
6. **Telemedicine Integration**: Enabling users to book virtual consultations with healthcare professionals directly through the application will provide personalized advice based on prediction results. This feature will offer users easy access to professional medical guidance.
7. **Multi-language Support**: Expanding the application to support multiple languages will make it accessible to a broader audience globally. This feature will ensure that users from different regions can benefit from the application.
8. **Educational Resources**: Providing educational materials and resources about heart disease prevention and management will help users make informed decisions about their health. This feature will enhance user knowledge and promote proactive health management.

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