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Heart Disease Risk Prediction Using Machine Learning

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Abstract--- Machine learning has the potential to be a critical tool in the diagnosis and prognosis of heart illnesses, loco-motor disorders, and other conditions. Due to its ability to identify patterns in data, machine learning applications in the medical field have grown. Diagnosticians can decrease misdiagnosis by using machine learning to categorize the occurrence of cardiovascular illness. If foreseen well in advance, such information might give physicians valuable insights that allow them to modify their diagnosis and treatment plan according to each patient. Our goal is to use machine learning algorithms to predict potential heart diseases in humans. We will compare various classifiers such as decision trees, Naïve Bayes, SVM, Random Forest, and Logistic Regression in this project. We will also propose an ensemble classifier that combines strong and weak classifiers to perform hybrid classification. Because this classifier can have multiple samples for training and validating data, we will analyze both the existing and proposed classifiers to provide better accuracy and predictive analysis. This method leverages previously completed patient records to forecast a new one at an early stage, sparing lives. In order to lessen the number of people who die from cardiovascular diseases, our research will create a model that can accurately forecast cardiovascular disorders. For medical professionals, predicting and detecting heart disease has always been a crucial and difficult undertaking. Heart disease can be treated with costly medicines and surgeries provided by hospitals and other facilities. Therefore, early detection of cardiac disease will be beneficial to individuals worldwide, enabling them to take the appropriate action before the condition worsens

Keywords—. Prediction of heart disease, Voting Classifier, Machine Learning, Flask framework, Ensemble Learning, Secure Authentication, Real-time Testing, CVD.

I. INTRODUCTION

Heart disease remains one of the leading causes of death worldwide, contributing to millions of fatalities annually. Early diagnosis and accurate risk prediction are crucial for reducing mortality rates and improving patient outcomes. Traditional diagnostic methods often rely on manual evaluation and clinical assessments, this takes time and is error-prone. ML has emerged as a powerful tool in medical diagnostics, offering automated, data-driven solutions for identifying at-risk individuals.

Using ensemble learning techniques like stacking, bagging, and boosting, models for heart disease categorisation have shown tremendous improvements. However, existing models often suffer from dataset limitations, suboptimal feature selection, and overfitting issues. To address these challenges, this study introduces an enhanced computational risk prediction model leveraging a Voting Classifier that combines multiple ML algorithms, including XGBoost, RF, DT, LR, and SVM. By aggregating predictions from these models, the system minimizes individual biases and improves overall classification accuracy.

Additionally, utilising Flask to create a user-friendly front-end interface, enabling real-time heart disease prediction with secure user authentication. This web-based system allows users to input patient data, receive instant predictions, and interact with the model seamlessly. The integration of hyperparameter tuning techniques, such as RandomizedSearchCV and GridSearchCV, further optimizes the model's performance, ensuring high reliability and adaptability across diverse datasets. By implementing these advancements, the proposed system aims to facilitate early diagnosis, improve accessibility, and contribute significantly to reducing the global burden of heart disease.

II. LITERATURE SURVEY

Several studies have demonstrated the effectiveness of ML-based models in predicting cardiovascular diseases. Ozcan and Peker [1] introduced a classification and regression tree algorithm for heart disease prediction, which showed promising results in modeling the disease. Similarly, Abubaker and Babayigit [2] employed machine learning and deep learning techniques for analyzing ECG images, proving the efficiency of AI in medical diagnostics. Other research efforts have combined ECG and PPG signals for detecting cardiac abnormalities using a dual attentive deep convolutional neural network (DCNN) [3].Doppala et al. [4] proposed a reliable machine intelligence model that integrates ensemble learning techniques for accurate identification of cardiovascular diseases, whereas Tr et al. [5] analyzed predictive models using various ML algorithms. These studies highlight the importance of feature engineering and model optimization in improving diagnostic accuracy.

Ensemble methods have been widely used in heart disease prediction. A study by Latha and Jeeva [11] emphasized the benefits of ensemble classification techniques in boosting prediction accuracy. Similarly, Esfahani and Ghazanfari [12] developed a new ensemble classifier to improve cardiovascular disease detection. Atallah and Al-Mousa [13] applied a majority voting ensemble method, proving its effectiveness in making more reliable predictions.
Another research study by Haq et al. [15] compared different ML classifiers to determine the most suitable model for heart disease detection. Yuan et al. [16] developed a heart disease prediction algorithm using ensemble learning, demonstrating improved accuracy over individual models.

Optimal parameter tuning and feature selection are critical aspects of ML models. Kavitha et al. [14] employed a hybrid machine learning model for heart disease prediction, integrating multiple algorithms for enhanced accuracy. Mienye et al. [17] proposed an improved ensemble learning approach, focusing on optimizing model performance by selecting the most relevant features. Asif et al. [18] combined multiple ML methods to enhance predictive performance.

Several studies have compared different ML algorithms for cardiovascular disease prediction. Jinjri et al. [20] conducted a comparative study of various ML algorithms, while Sujatha and Mahalakshmi [21] evaluated the performance of supervised ML models. Basha and Venkatesh [19] focused on the early detection of heart disease using ML techniques, reinforcing the importance of early diagnosis in improving patient outcomes.
Additionally, Battula et al. [22] explored different ML techniques to predict heart disease, and Lin [23] conducted an analysis of prediction models using ML. Other research works [24-28] have provided extensive evaluations of various algorithms, feature selection methods, and deep learning models, contributing to advancements in heart disease prediction.

Beyond algorithmic improvements, real-world studies emphasize the impact of heart disease and the necessity of accurate prediction models. The World Health Organization (WHO) [6] and Centers for Disease Control and Prevention (CDC) [8] highlight the global burden of cardiovascular diseases, reinforcing the need for AI-based prediction systems. Studies such as WebMD's report on economic costs [7] and the Heart Disease Dataset from IEEE DataPort [10] further stress the significance of improving ML models for better clinical decision-making.

III. METHODOLOGY

A) Proposed System

The proposed system enhances heart disease prediction by implementing a Voting Classifier that integrates multiple ML algorithms, including XGBoost, Random Forest, DT, LR, and SVM. This ensemble learning approach leverages the strengths of individual models to improve predictive accuracy while minimizing biases. By aggregating multiple model predictions, the system ensures robust and reliable classification of cardiovascular diseases (CVDs). To further optimize performance, hyperparameter tuning techniques such as RandomizedSearchCV and GridSearchCV are applied, fine-tuning the model for better accuracy and generalizability across diverse patient data. The dataset, consisting of eleven key features from five different sources, improves the model's medical application adaptability and dependability.

Additionally, the Flask framework creates a user-friendly online interface., enabling real-time heart disease prediction with secure user authentication. This interactive system allows users, including healthcare professionals and patients, to input medical parameters and receive instant diagnostic predictions. The integration of real-time testing ensures continuous model evaluation and adaptability to new data, making it a practical tool for early diagnosis and timely medical intervention. By combining advanced ensemble learning with an accessible front-end, the proposed system contributes significantly to reducing heart disease mortality rates and improving global healthcare outcomes.

B) System Architecture

Using a Voting Classifier as part of an ensemble learning strategy, the suggested method improves upon previous models for predicting cardiac problems. A dataset on heart illness is used to start the system, and it goes through a thorough pre-processing step. Processing the data, visualising it, encoding labels, and selecting features to enhance the dataset are all part of this process. To guarantee that the model is trained on high-quality input, Data is preprocessed and then split into training and testing. During training, the system learns intricate patterns from patient data in order to make accurate predictions about cardiac illness using a number of ML techniques.

The system employs a mix of neural network models—XGBoost, RF, DT, LR, and SVM—to improve prediction accuracy. Optimal parameter selection is achieved by fine-tuning these models utilising Randomised & Grid Search CV methods. A Voting Classifier, which improves accuracy and reliability by integrating predictions from many models, performs the final classification. To guarantee a strong and efficient system for predicting cardiac illness, Thereafter, the trained model is assessed using F1-score, accuracy, precision, and recall.

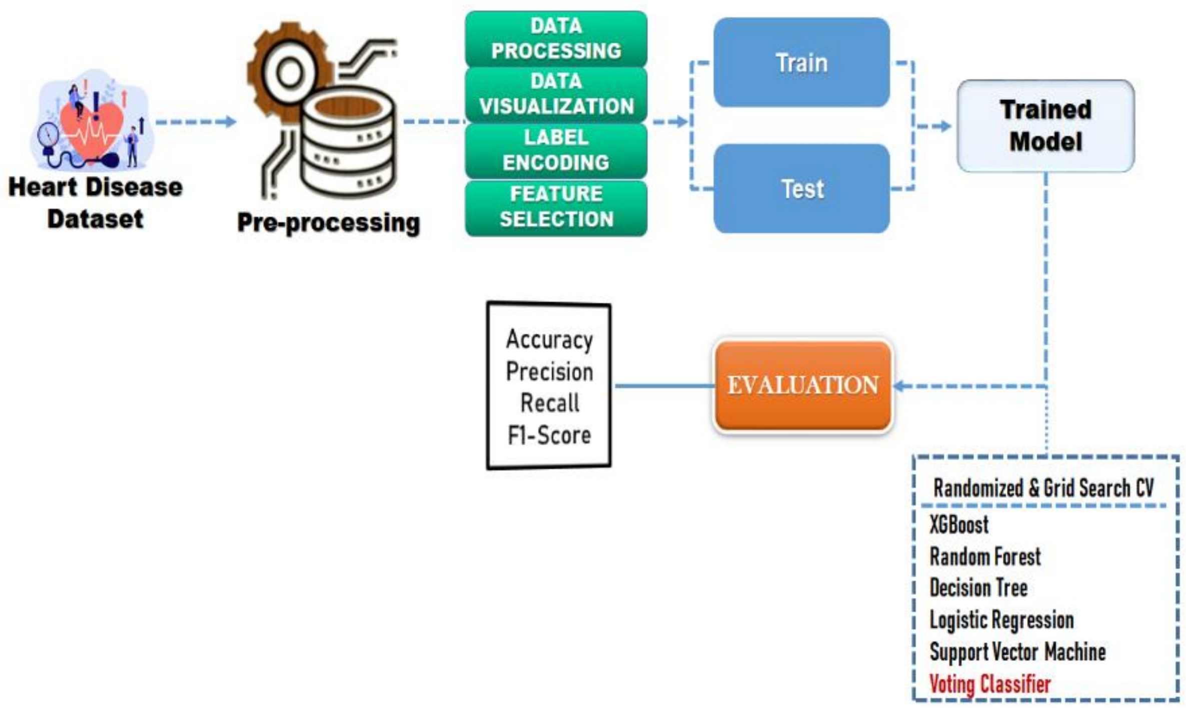


Fig 1. System Architecture

The image[Fig.1.]represents the system architecture for a heart disease prediction model using ensemble learning techniques. It visually illustrates the step-by-step process, starting from data acquisition (Heart Disease Dataset) and preprocessing, which includes data cleaning, visualization, label encoding, and feature selection. The processed data is then split into training and testing sets to build predictive models.

Multiple machine learning algorithms such as XGBoost, Random Forest (RF), Decision Tree (DT), Logistic Regression (LR), and Support Vector Machine (SVM) are trained and fine-tuned using Randomized & Grid Search CV to improve performance. The Voting Classifier, an ensemble technique, combines predictions from these models to enhance accuracy and reliability. The final trained model is then evaluated based on accuracy, precision, recall, and F1-score to ensure robust heart disease prediction.

C) Algorithms

a) Randomized & Grid Search CV:: Improving a machine learning model requires adjusting hyperparameters. The hyperparameters of classifiers can be enhanced using Randomised Search CV and Grid Search CV. To speed it up for massive datasets, Randomised Search CV uses a random selection of parameters to verify the model's performance. Nevertheless, Grid Search CV thoroughly investigates set parameter values to find the best combination. These techniques enhance the precision and efficiency of models by optimising hyperparameters.

b) XGBoost (XGB): In order to enhance prediction, XGBoost, an enhanced gradient-boosting method, decreases the number of errors. Every decision tree that comes before it fixes the mistakes made by the ones before it. Fast and efficient, XGBoost is made possible via parallel processing and regularisation. Its popularity is attributed to its ability to handle complex data relationships while minimising overfitting.

c) Random Forest (RF): For consistency and precision, RF constructs many decision trees and mixes their predictions. You may get a judgement by training trees on different subsets of data and then combining their results. Due to its superior classification performance and less overfitting compared to a single decision tree, Random Forest is well-suited for the prediction of cardiac illness.

d) Decision Tree (DT): One simple yet effective classification technique is the Decision Tree method, which uses trees to make predictions. Subsets of the dataset are created by applying decision rules that are dependent on input features. Easy to read thanks to the tree structure; however, overfitting can be reduced by pruning. By evaluating the importance of features, Decision Trees aid in the diagnosis of cardiac issues.

e) Logistic Regression (LR): Since Logistic Regression resolves issues with binary classification, it is helpful for the prediction of cardiac illness. It uses a sigmoid function to divide data into two categories and then uses those categories to produce outcome probabilities. Despite its apparent simplicity, Logistic Regression is effective for linear illness characteristics.

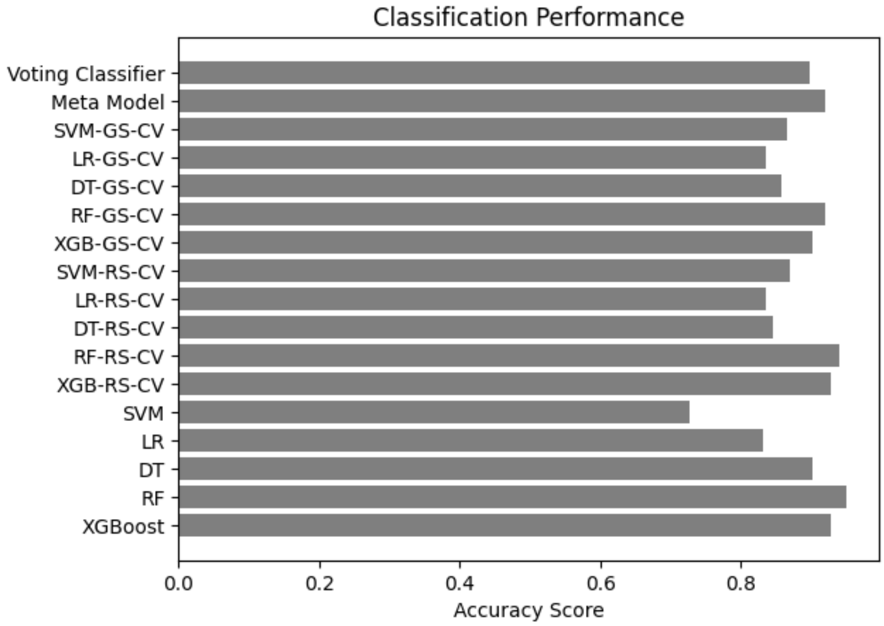
f) SVM (Support Vector Machine): Support For each class in a dataset, Vector Machine uses supervised learning to find the optimal hyperplane (boundary). It really shines when dealing with structured medical data and high-dimensional areas. Kernel functions provide dimension to SVM, which means it can predict heart disease from non-linearly separable data.

g) Voting Classifier (RF + DT): The Voting Classifier is an ensemble model that combines multiple classifiers to improve overall performance. In this system, the bagging classifier is used, integrating Random Forest and Decision Tree models. This approach increases accuracy by aggregating the strengths of both models while reducing their weaknesses. By leveraging ensemble learning, the Voting Classifier enhances predictive reliability and stability, making it a strong choice for heart disease prediction.

IV. EXPERIMENTAL RESULTS

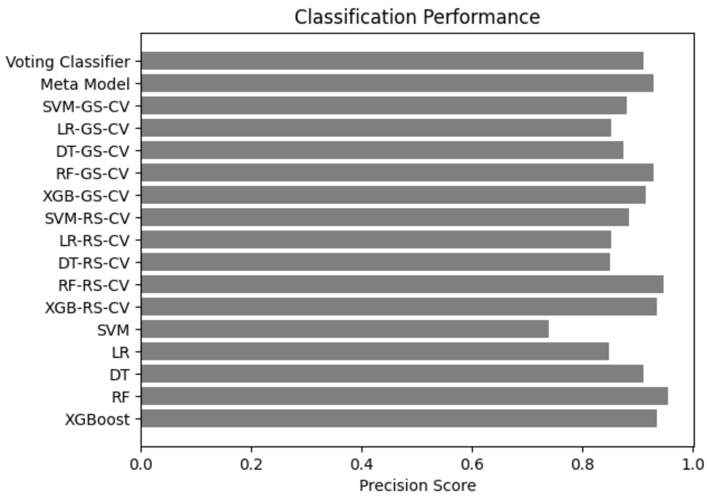
Accuracy: How well a test can differentiate between healthy and sick individuals is a good indicator of its reliability. Find out how reliable a test is by comparing real positives and negatives. Following mathematical:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \text{ -------- (1)}$$



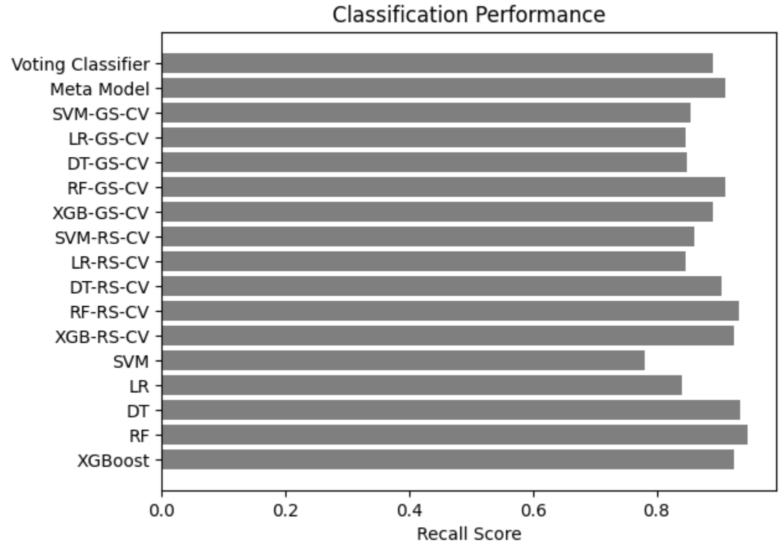
Precision: The accuracy rate of a classification or number of positive cases is known as precision. Accuracy is determined by applying using the one that follows:

$$\text{Precision } = \frac{TP}{TP+FN} \text{ --------- (2)}$$



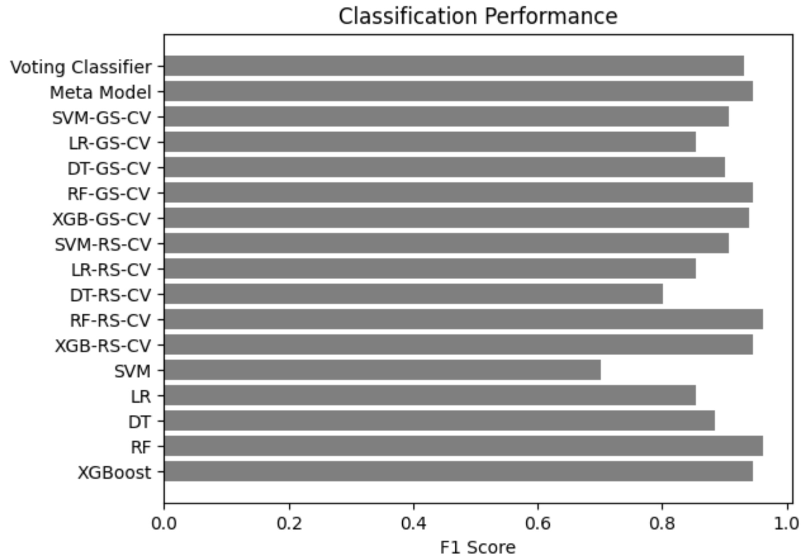
Recall: The recall of a model is a measure of its capacity to identify all occurrences of a relevant machine learning class. A model's ability to detect class instances is shown by percent of correctly anticipated positive observations relative to total positives.

$$\text{Recall} = \frac{Tp}{TP+FN} \text{ --------- (3)}$$



F1-Score: A high F1 score indicates that a machine learning model is accurate. Improving model accuracy by integrating recall and precision. How often a model gets a dataset prediction right is measured by the accuracy statistic.

$$\text{F1 Score} = 2.\frac{Precision.Recall}{Precision+Recall} \quad \text{-------- (4)}$$



MAP: Information retrieval system performance is measured by MAP, which stands for Mean Average Precision. It finds the mean precision for all classes or queries. While accuracy measures the validity of results, precision determines the mean accuracy for all queries. MAP evaluates the system's performance by averaging the AP scores across all queries or classes.

$$\text{MAP} = \frac{1}{N}\sum_{i=1}^{N}\text{AP}_i$$

Table 1:Comparision Table

S.No	ML Model	Accuracy	Precision	Recall	F1-Score	Cohen Kappa Score	ROC AUC Score
0	XGBoost	0.945	0.951	0.940	0.962	0.889	0.977
1	RF	0.954	0.958	0.948	0.969	0.906	0.972
2	DT	0.908	0.913	0.950	0.878	0.815	0.911
3	LR	0.832	0.848	0.842	0.855	0.660	0.906
4	SVM	0.727	0.739	0.780	0.702	0.454	0.782
5	XGB-RS-CV	0.929	0.936	0.925	0.947	0.855	0.974
6	RF-RS-CV	0.941	0.947	0.940	0.954	0.881	0.967
7	DT-RS-CV	0.861	0.871	0.895	0.847	0.722	0.911
8	LR-RS-CV	0.836	0.852	0.848	0.855	0.669	0.906
9	SVM-RS-CV	0.870	0.885	0.862	0.908	0.735	0.935
10	XGB-GS-CV	0.912	0.923	0.893	0.954	0.820	0.958
11	RF-GS-CV	0.933	0.940	0.926	0.954	0.864	0.961
12	DT-GS-CV	0.790	0.808	0.814	0.802	0.576	0.883
13	LR-GS-CV	0.836	0.852	0.848	0.855	0.669	0.906
14	SVM-GS-CV	0.866	0.881	0.856	0.908	0.726	0.933
15	Meta Model	0.929	0.936	0.919	0.954	0.855	0.970
16	Voting Classifier	0.975	0.977	0.977	0.977	0.949	0.970

The image presents a **comparative evaluation of machine learning models** based on various performance metrics for classification tasks. The table consists of multiple ML models, their accuracy, precision, recall, F1-score, Cohen Kappa Score, and ROC AUC Score. The highest-performing models can be identified based on these metrics.

V. CONCLUSION

In conclusion, the integration of multiple machine learning algorithms, including XGBoost, Random Forest, Decision Tree, Logistic Regression, Support Vector Machine, and ensemble methods like Voting Classifier, enhances heart disease prognosis. The use of hyperparameter tuning techniques such as Randomized and Grid Search CV further optimizes model performance by selecting the best parameters. By leveraging these advanced classification techniques, the proposed system ensures efficient and precise diagnosis, contributing to improved healthcare decision-making and early detection of heart disease.

VI. FUTURE SCOPE

The future scope of this system includes enhancing model performance by incorporating deep learning techniques such as neural networks for more accurate predictions. Additionally, integrating real-time patient data from wearable devices can improve early detection and continuous monitoring of heart disease. Expanding the dataset with diverse demographics and medical histories can enhance model generalization. Healthcare providers might find the method's heart disease prediction capabilities useful as a cloud-based or mobile app. and individuals, enabling proactive healthcare management.

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