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Enhancing Accuracy & Efficiency Analysis for Heart Disease Prediction using Machine Learning Algorithm

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KEYWORDS

Machine Learning,

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ABSTRACT: Cardiovascular diseases remain a leading cause of mortality worldwide, emphasizing the importance of accurate and efficient methods for early detection and prediction. This study focuses on enhancing the accuracy and efficiency of heart disease prediction by employing advanced machine learning algorithms. Traditional risk assessment methods often lack the precision required for early intervention, making the integration of machine learning an essential component in modern healthcare. The proposed research leverages a comprehensive dataset containing diverse patient information, including demographic details, lifestyle factors, and medical history. A multi-faceted approach combines feature engineering, data preprocessing techniques, and state-of-the-art machine learning algorithms to develop a robust predictive model.

To enhance accuracy, the study explores ensemble learning techniques, including Random Forests, Gradient Boosting, and stacking methods. The ensemble approach leverages the strengths of individual models, resulting in a more robust and accurate prediction model. Furthermore, deep learning algorithms such as neural networks are employed to capture intricate patterns and dependencies within the data. Efficiency is addressed through optimization strategies, including model hyper parameter tuning and dimensionality reduction techniques. The goal is to streamline the computational requirements without compromising predictive performance. The study investigates the trade-offs between model complexity and efficiency, ensuring practical implementation in real-world healthcare settings. The performance of the proposed model is rigorously evaluated using cross-validation techniques and compared against existing heart disease prediction models.

The outcomes of this research have the potential to revolutionize heart disease prediction, offering healthcare practitioners a reliable tool for early identification of at-risk individuals. By leveraging the power of advanced machine learning algorithms, this study contributes to the on-going efforts to enhance preventive healthcare strategies and reduce the global burden of cardiovascular diseases.

1. Introduction

Cardiovascular diseases (CVDs) continue to be a leading cause of morbidity and mortality globally, underscoring the critical need for accurate and efficient predictive tools. Timely identification of individuals at risk of heart disease is pivotal for implementing preventive interventions and improving patient outcomes. In recent years, the integration of machine learning algorithms into healthcare has shown immense promise, offering a paradigm shift in the precision and efficiency of disease prediction.

This research aims to advance the field of heart disease prediction by focusing on two crucial aspects: accuracy and efficiency. Improving accuracy involves developing a predictive model that can discern subtle patterns and nuances within the data, enabling early identification of

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individuals at risk. Concurrently, optimizing efficiency ensures that the developed model is practical for real-world implementation, considering computational resources and time constraints commonly present in clinical settings.

The methodology employed in this study integrates advanced machine learning algorithms, leveraging a comprehensive dataset encompassing a wide range of patient information. By utilizing ensemble learning techniques, such as Random Forests, Gradient Boosting, and stacking methods, the study seeks to combine the strengths of individual models, ultimately enhancing the robustness and accuracy of the predictive model. Furthermore, the exploration of deep learning algorithms, such as neural networks, aims to capture intricate patterns and nonlinear relationships inherent in complex healthcare data

Efficiency considerations are addressed through thoughtful model optimization, including hyper parameter tuning and dimensionality reduction techniques. Striking the right balance between model complexity and computational efficiency is crucial for ensuring the practicality of the developed predictive tool in real-world healthcare applications.

The significance of this research lies in its potential to revolutionize heart disease prediction, offering healthcare practitioners a more accurate and efficient means of identifying at-risk individuals. As we delve into the era of precision medicine, the integration of advanced machine learning algorithms in cardiovascular risk assessment stands at the forefront, promising to usher in a new era of proactive and personalized healthcare.

2. Objectives

The main objective of this research to advance the field of heart disease prediction by focusing on two crucial aspects: accuracy and efficiency.

3. Literature Review

[1] This research article conducts a comprehensive examination of various techniques employed in predicting heart disease. Recognizing the diverse manifestations of heart conditions, the study explores a range of prediction methods. Factors such as R-Blood Pressure, S-Cholesterol, F-Blood Sugar, R-ECG, Thalach, Ex-Ang, Number of major Vessels blocked, and Thallium Scan are considered as crucial contributors to heart disease prediction. The research employs sophisticated techniques like Naive Bayes, Decision Tree, and K-nearest neighbor from the realm of data mining. The central objective is to scrutinize the efficacy of these techniques in identifying and predicting heart disease. By reviewing existing models, the research aims to provide insights into their strengths and limitations. The article concludes by highlighting key areas for improvement and future exploration, offering valuable directions for enhancing heart disease prediction methodologies.

[2] [3] [4] Heart failure has been predicted using a variety of supervised learning algorithms, of which KNN and SVM are just two examples [28, 29]. The authors go into great detail about the supervised machine learning models they use in [30]. This study uses five machine learning algorithms to examine statistics related to cancer and heart disease. The authors have demonstrated the accuracy of this approach in predicting various diseases, including breast cancer. Additionally, the fundamental causes of these illnesses are being looked into. Principal component regression (PCR) and random forest (RF) are the most effective methods for analysing data related to breast cancer. The authors contend that machine learning can be used to predict cardiac illness [31]. Several decision tree categorization techniques were contrasted and compared using WEKA. Numerous algorithms have been studied, such as logistic model tree (J48) and random forest. The Cleveland Heartland Registry is used by UCI researchers to screen for and confirm heart disease in patients. The information types listed below are included in this dataset. Next, a recommendation for the best algorithm for large-scale classification will be made. In order to provide patients with more precise diagnoses, data mining can be used to identify correlations between patient data and heart disease risk factors.

[5] This research paper presents a comprehensive meta-analysis on the application of machine learning (ML) techniques in predicting cardiovascular diseases (CVD). With the increasing prevalence of CVD and the growing availability of health data, ML has emerged as a promising tool for improving risk assessment and early detection in this critical domain.The meta-analysis synthesizes findings from a diverse set of studies,

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JCHR (2024) 14(2), 1375-1384 | ISSN:2251-6727

encompassing various ML algorithms and datasets related to CVD prediction. The paper systematically reviews the performance of different ML models in terms of accuracy, sensitivity, specificity, and area under the receiver operating characteristic curve (AUC-ROC). Additionally, it explores the impact of different features, data sources, and preprocessing techniques on the predictive capabilities of the models.Key findings highlight the overall efficacy of ML in predicting cardiovascular events, showcasing its potential to outperform traditional risk assessment methods. The paper also identifies specific ML algorithms that consistently demonstrate superior performance across multiple studies. Furthermore, it discusses the challenges and limitations associated with implementing ML models in clinical practice, including issues related to data privacy, interpretability, and generalizability.

The meta-analysis contributes valuable insights to the ongoing efforts in leveraging ML for CVD prediction, providing a synthesized overview of the current state of research in this area. The findings underscore the need for further research to address existing challenges and promote the integration of ML-based predictive models into clinical decision-making processes for cardiovascular risk management.

[6] The research focuses on the design and implementation of a sophisticated computational model that utilizes artificial intelligence (AI) and machine learning algorithms. By leveraging a diverse set of patient data, including clinical parameters, imaging results, and possibly genetic information, the model aims to achieve improved accuracy in predicting and diagnosing various heart diseases. The paper provides a comprehensive overview of the model architecture, detailing the selection and optimization of algorithms, as well as the integration of relevant features and data sources.

Key findings highlight the model's performance in terms of sensitivity, specificity, and overall accuracy, demonstrating its potential to outperform traditional diagnostic methods. The study also discusses the interpretability and transparency of the model's decision-making process, addressing concerns related to the integration of computational models in clinical settings.

[7] The research begins by exploring a diverse set of machine learning algorithms, including decision trees, support vector machines, and neural networks. The key innovation lies in the construction of an ensemble model that combines the strengths of these individual algorithms, leveraging their complementary features to enhance overall predictive performance. The optimization process involves thorough algorithm selection based on dataset characteristics and subsequent parameter tuning to maximize accuracy. Feature engineering and selection are also emphasized to ensure the inclusion of relevant clinical and demographic variables in the prediction model.

The ensemble model's effectiveness is evaluated through rigorous validation techniques, such as cross-validation, to assess its performance across diverse datasets. The study showcases improvements in accuracy, sensitivity, and specificity, demonstrating the superiority of the ensemble approach over individual algorithms.

[8] The research begins by delving into the selection and construction of deep learning architectures, exploring various neural network configurations such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and hybrid models. The paper emphasizes the importance of feature representation and extraction in these models, highlighting how deep learning algorithms can automatically learn hierarchical features from raw data. Dataset selection and preprocessing are integral components of the empirical analysis, with researchers considering diverse sources of patient data including clinical records, imaging, and potentially genetic information. The study also discusses the challenges associated with the scarcity and quality of labeled data in healthcare, offering insights into strategies for overcoming these limitations.

[9] The research commences with the identification and selection of diverse machine learning algorithms, including decision trees, support vector machines, and neural networks. The innovative aspect lies in the hybridization of these models, combining their unique features to create a comprehensive predictive framework. The integration is carefully optimized to leverage the synergies between algorithms, aiming for improved performance in terms of sensitivity, specificity, and overall accuracy.

Journal of Chemical Health Risks

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Feature engineering and selection are given due attention in the study, ensuring that relevant clinical and demographic variables are incorporated into the hybrid model. The researchers address the challenges associated with dataset variability and noise, employing preprocessing techniques to enhance the quality of input data.The evaluation of the hybrid model involves a thorough validation process, employing metrics such as precision, recall, and F1 score to assess its performance. Comparative analyses against individual machine learning models and traditional risk assessment methods provide insights into the superiority of the hybrid approach.

[10] The research begins with the implementation of a BPNN, a popular neural network architecture, for heart disease prediction. The paper then introduces the Butterfly Optimization algorithm, a metaheuristic optimization technique inspired by the foraging behaviour of butterflies, and integrates it into the training phase of the neural network.

The synergy between the BPNN and Butterfly Optimization is examined to improve the model's convergence speed, robustness, and overall predictive accuracy. The study emphasizes the significance of feature selection and data preprocessing in optimizing the training process, ensuring that relevant clinical and demographic variables are effectively utilized.

To evaluate the proposed approach, the research employs standard metrics such as accuracy, sensitivity, specificity, and area under the curve (AUC) of the receiver operating characteristic (ROC) curve. Comparative analyses against traditional neural network models and other optimization techniques provide insights into the effectiveness of the BPNN with Butterfly Optimization for heart disease prediction.

The paper also discusses the interpretability of the model, addressing the need for transparency in complex machine learning applications for healthcare. By elucidating the decision-making process of the BPNN with Butterfly Optimization, the study aims to enhance the trustworthiness and applicability of the proposed predictive model in clinical settings.

3.1 Comparative Analysis Based on Datasets

Reference	Dataset	Techniques	Accuracy
11	The dataset from the UCI Machine Learning repository was uesd	Machine Learning Algorithm	82.6%
12	The UCI machine learning repository provide the HF Indian heart attack dataset	Post hod technique	-
13	Telemonitoring HE,1653 patients	Logistic Regression	83.2%
14	Data heart disease patient from medical records	SVM	-
15	It is necessary to make use of a vast number of disparate electronic datasets.	Cardio magnetic resonance(CMR)	-
16	Data from the repository of patient related data is maintained on monthly basis	ANN	56.7%
18	Self created dataset	Logistics regression & KNN	78%
17	UCI machine learning repository	KNN	72.9%
19	Self created dataset with 44 prior feature	Decision tree	84.3%
20	Medical database	SVM	67.2%
21	Prepare data from hospital	Machine learning algorithm	-
22	Dataset with 8 different feature	Naïve Bayes	62%
24	Massive clinical data	Machine learning Technique	-
23	UCI machine learning repository	Deep learning	86%

4. Block Diagram

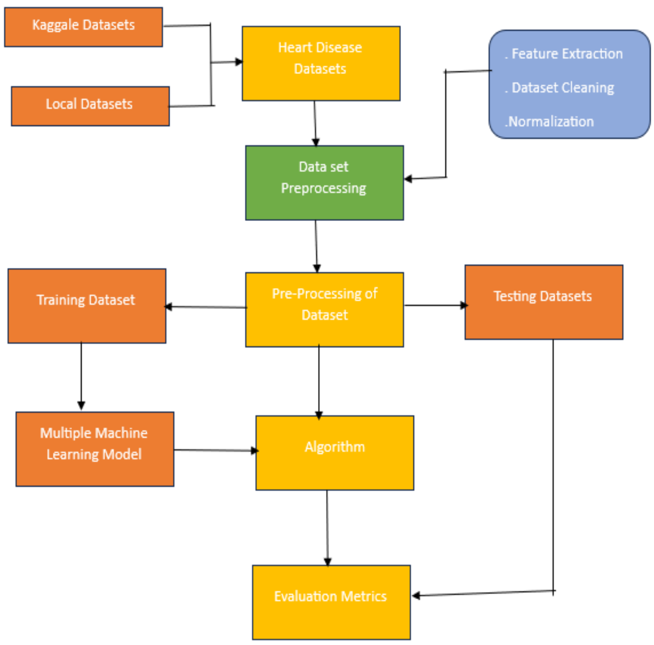

Fig. 4.1 Block Diagram

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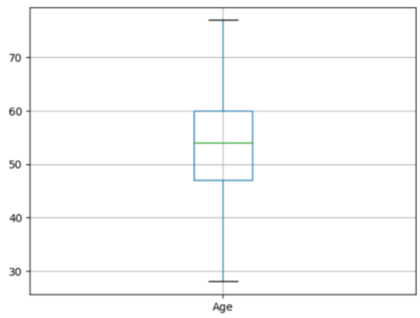
JCHR (2024) 14(2), 1375-1384 | ISSN:2251-6727

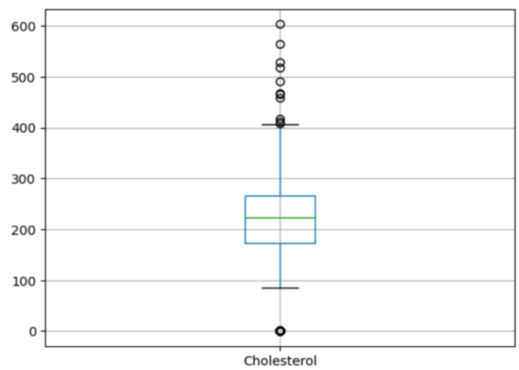
Feature	Values	Description
Age	Age Values	Different age value
Sex	(1=male, 0=female)	Gender Patient
Chest Pain Type	(0=ASY,1= ATA, 2= NAP,3=TA)	Chest Pain type
Resting BP	Values of BP	Values of BP
Cholestrol	Cholesterol Different Values	Cholesterol Values
Fasting BS	(0=no,1=yes)	Fasting or not
Resting ECG	(1=Normal,2=ST)	ECG normal or not
Max HR	Heart rate Values	Heart rate Values
Exercise Angina	0=no, 1=yes	Exercise or not
Old-Peak	Old_peak Values	Higher old_peak values Less Chances to Heart Disaese
ST-Slope	(1=Flat,2=UP)	Slope flat or up
Heart Disease	0=no, 1=yes	Heart disease or not

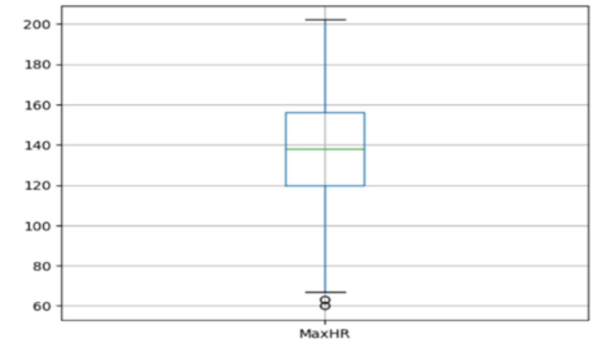
Table 4.1 Data Attribute

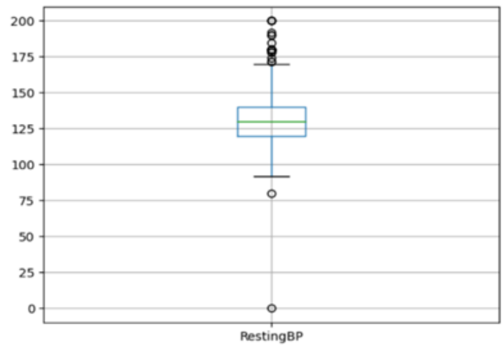
Feature	Values	Description
Age	Age Values	Different age value
Sex	(1=male, 0=female)	Gender Patient
Chest Pain Type	(0=ASY,1= ATA, 2= NAP,3=TA)	Chest Pain type
Resting BP	Values of BP	Values of BP
Cholestrol	Cholesterol Different Values	Cholesterol Values
Fasting BS	(0=no,1=yes)	Fasting or not
Resting ECG	(1=Normal,2=ST)	ECG normal or not
Max HR	Heart rate Values	Heart rate Values
Exercise Angina	0=no, 1=yes	Exercise or not
Old-Peak	Old_peak Values	Higher old_peak values Chances to Heart Disa
ST-Slope	(1=Flat,2=UP)	Slope flat or up
Heart Disease	0=no, 1=yes	Heart disease or not

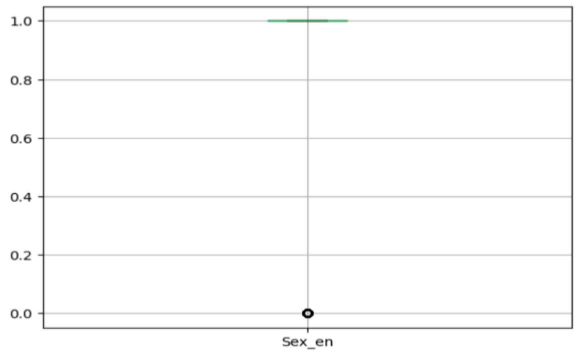
Table 4.2 : Data Attribute dataset (local)

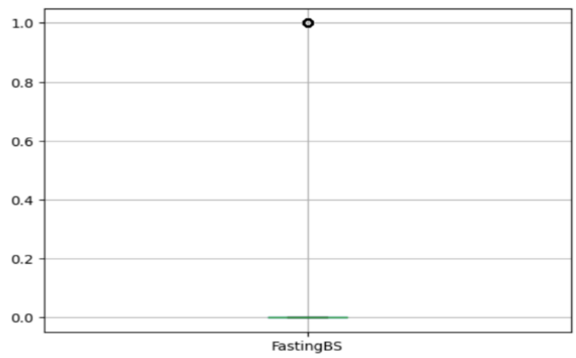












Journal of Chemical Health Risks
www.jchr.org
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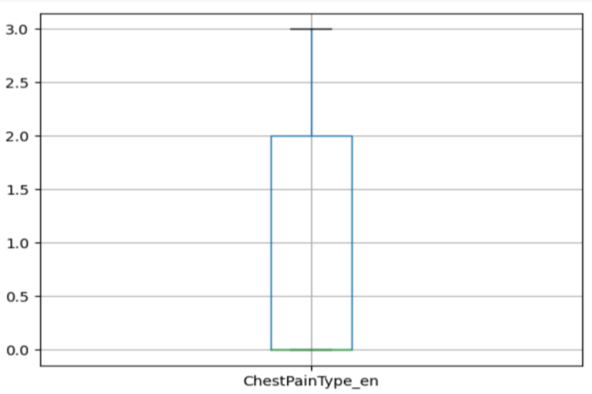


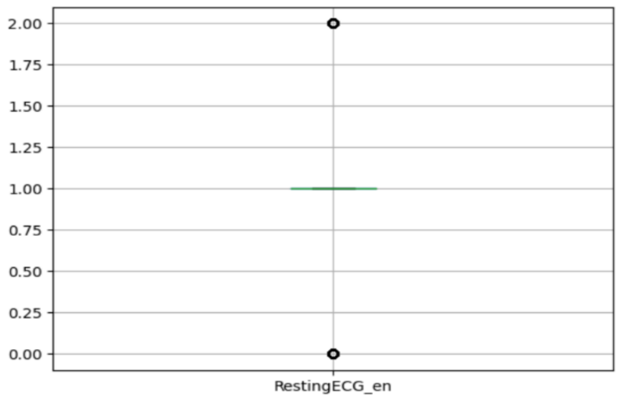
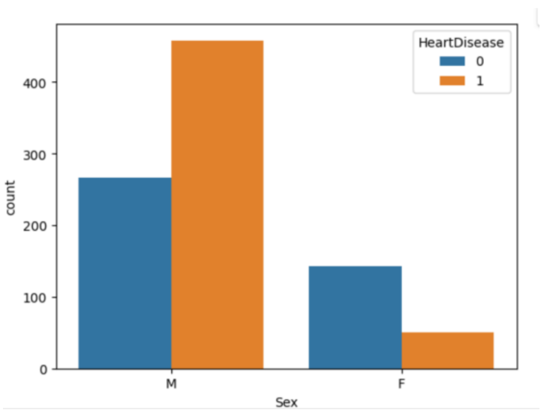
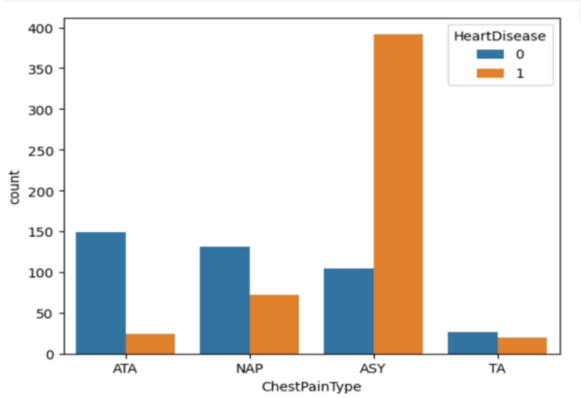


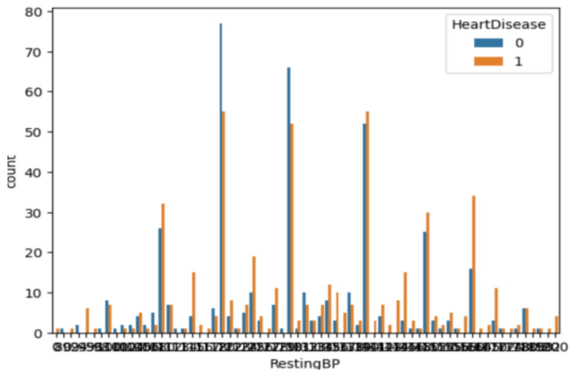
Fig 4.2.BoxPlot of Each Attribute

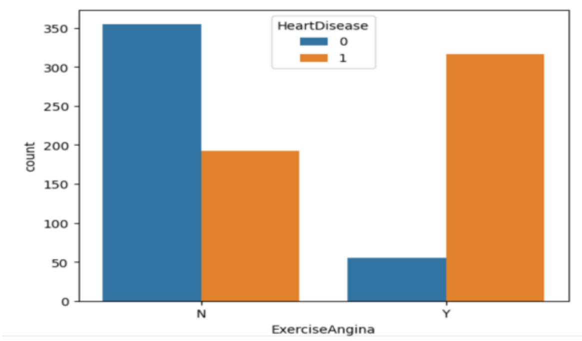
5. Methodology

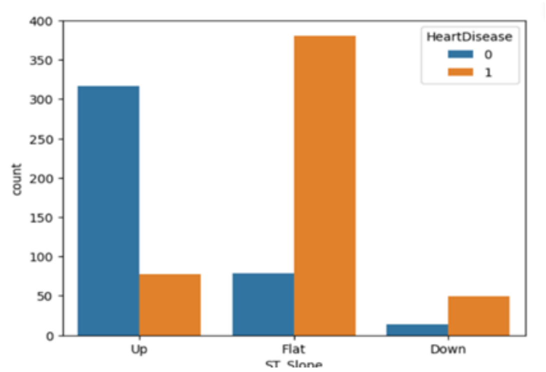
Here, we describe the methodology we used for the study. The collection, description, and analysis of datasets is the work involved in feature engineering, model building, and performance assessment. A flowchart depicting the study's overall development can be found in Figure 4.1.











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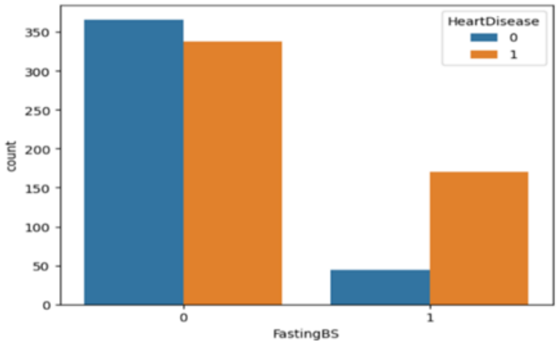

Fig 5.1: Data about Heart disease from Each Attribute

Information regarding the block diagram can be found as follows:

(i) Data from the heart failure dataset was used to create a comma-separated values (.csv) file.
(ii) During preprocessing, outliers were eliminated and the data was normalized. The outcomes of the application of cross-validation have been verified. Machine learning models have been employed.
(iii) After selecting the best classification models, ensemble learning techniques have been implemented.

On Kaggle, the prediction dataset is openly accessible. These data were gathered by the American Heart Failure Institute. The dataset consists of a large number of unrelated independent variables and one dependent variable. Table 3 contains a list of all available datasets. Items in the dataset include The local dataset is thought to include approximately 500 patients with left ventricular systolic dysfunction. The next 12 columns, heart failure, describe specific patient characteristics. The data attributes dataset (local) is displayed in Table 4.

Data about Heart disease from Each Attribute is shown in the following Figure 5.1.

The HF dataset must be used to test and assess the recommended method's efficacy. The HF dataset includes diseases from a wide range of real-world categories. We utilize the CSV file format for initial processing and feature extraction on unprocessed data.

5.1. Data Cleaning: We were able to obtain raw data access through Kaggle. Several techniques were used to eliminate redundant data, null values, and other superfluous information. This clinical data was collected using wearables, including blood pressure monitors, thermometers, pulse oximeters, and electrocardiogram (ECG) monitors. These sensors collected blood pressure, temperature, and electrocardiogram (ECG) data when they were worn on an individual. We were able to gather and store the data in the cloud thanks to the Internet of Things.

5.2. Data Preprocessing: This process of converting unstructured data into a more readable format is the foundation of data mining. Real-world information is occasionally incomplete, inaccurate, or otherwise useless. The preprocessing techniques mentioned above are a few. Accurate prediction models cannot be developed due to imprecise categorization. Almost all machine learning techniques categorize data with roughly the same number of examples in each class.

5.3. Feature Engineering: Functions that learning algorithms can use are created using data from a particular domain. Creating a machine learning representation starts with extracting and processing raw data. In this investigation, it is used to determine how closely related things are to one another. Alternatively stated, a correlation matrix is simply a covariance matrix with a fancy name. The correlation coefficient yields a numerical value that can be used to summarize the strength of a linear relationship.

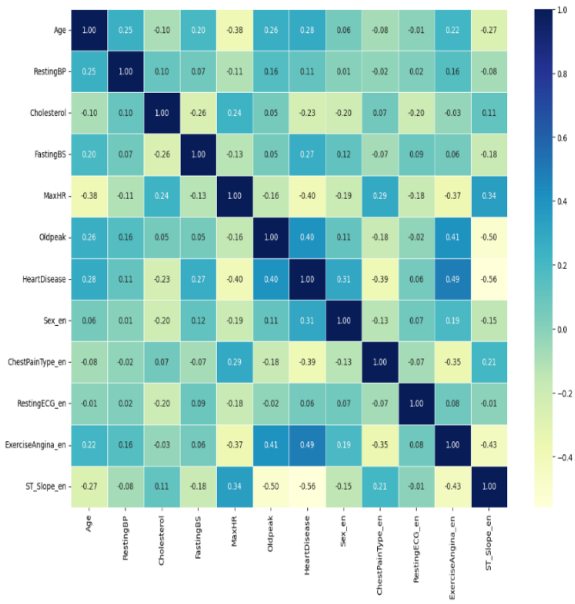

Fig 5.2: Correlation matrices Heart disease dataset

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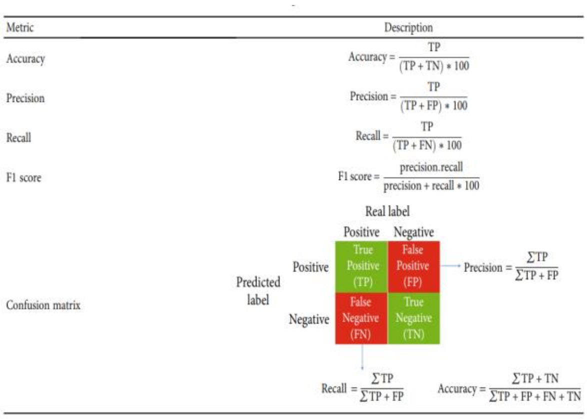

Metric	Description
Accuracy	$\text{Accuracy} = \frac{TP}{(TP+TN)*100}$
Precision	$\text{Precision} = \frac{TP}{(TP+FP)*100}$
Recall	$\text{Recall} = \frac{TP}{(TP+FN)*100}$
F1 score	$\text{F1 score} = \frac{\text{precision.recall}}{\text{precision}+\text{recall}*100}$
Confusion matrix	Real label: Positive / Negative; Predicted label: Positive: True Positive (TP), False Positive (FP); Negative: False Negative (FN), True Negative (TN). $\text{Precision} = \frac{\Sigma TP}{\Sigma TP+FP}$ $\text{Recall} = \frac{\Sigma TP}{\Sigma TP+FP}$ $\text{Accuracy} = \frac{\Sigma TP+TN}{\Sigma TP+FP+FN+TN}$

Table 5.1: Description Matrix

Architecture diagram of Proposed method:

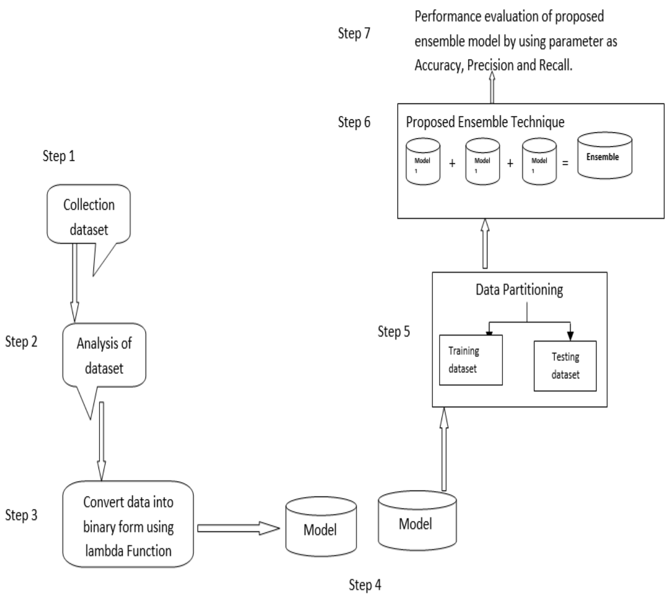

Fig 5.3: Architecture diagram of Proposed method

Step 1. Read the dataset from UCI machinery repository.

Step 2. In this step, Analysis of data is complete which means preprocessed of data is done Such as check duplicate of data , check the null value of dataset.

Step 3. Now, the whole dataset is convert into Binary form using label encoder.

Step 4. Then importance of each feature is calculated using important_feature in python. This process enhances the accuracy of prediction as explained.

Step 5. After complete Step 4, whole dataset is divided into two parts i.e. Training and Testing dataset with 70-30 ratio.

Step 6. In the this step, Different machine learning algorithms are used to get proposed model.

Step 7. After complete all the step as mention above, performance of the proposed ensemble model has been evaluated on various parameters such as Precision, sensitivity and accuracy. To analyze the robustness of the model, repeated k-fold cross-validation is used. Finally, results have been analyzed to conclude the effectiveness of the proposed ensemble model.

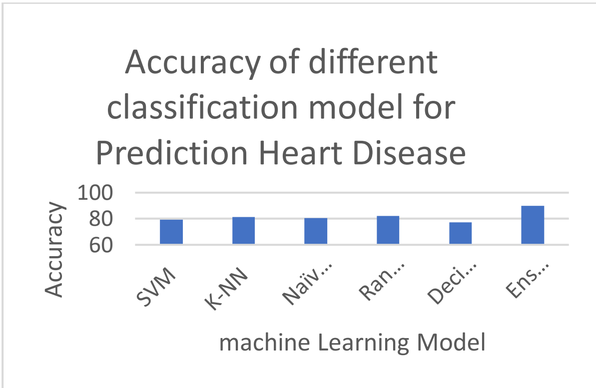

Fig 5.4: Machine Learning Classification model performance

6. Experimental Result

The heart failure dataset, which is derived from the kaggle database, is tested in this section. The training and testing portions of the dataset are separated into 60-40 and 70-30 ratios. Each run's accuracy is measured, and the average is then determined for the entire run. The findings are presented appropriately.

S.No.	Classifier name	Accuracy (%)	
		70-30	60-40
1	SVM	79.35	75.4
2	K-NN	81.25	79.23
3	Naïve Bayes	80.5	79.35
4	Random Forest	82.34	80.45
5	Decision Tree	77.17	75.61
6	Ensemble Classifier	89.9	88.7

Table 6.1: Accuracy of Different classification models for Prediction Heart Disease

Journal of Chemical Health Risks
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In table 6.1, the result shows of the proposed approach for the Heart disease dataset, we determine the performance of the proposed approach in terms of Accuracy. By using the ensemble classifier maximum accuracy is recorded for 60-40 partition is 88.7% and 70-30 partition is 89.9% for the heart disease dataset.

7. Conclusion

In the modern era, heart disease is a common disease that can be fatal. Globally, an estimated 26 million people become infected each year. It is difficult to predict when a patient may develop heart disease in cardiology and surgery. Because they show potential uses for medical data, classification and prediction models are helpful to the medical industry. Utilizing cardiovascular disease data, machine learning techniques will be applied to predict the occurrence of heart disease in a medical database, thereby improving the accuracy of HD projections. Based on the latest findings and comparative evaluations, heart disease can now be predicted with greater accuracy. In this work, we present a machine learning method that can be applied to enhance heart disease prediction for any condition, not only HD. With an accuracy rating of 82.34 percent or higher, SVM, KNN, GNB, Decision tree, and Random forest are the four most accurate linear models. The accuracy (89.97%) of ensemble learning models, like GBC and ABC. By utilizing the HD dataset, this research can be improved in subsequent studies to predict patient survival.

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