



**A Hybrid Machine Learning and Association Rule Mining Approach for Accurate Heart Disease Prediction in Distributed Healthcare Databases**

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**Abstract:**

Heart diseases continue to be one of the leading causes of death globally, which is why early diagnosis remains highly important for improved patient outcomes as well as overall less expensive healthcare delivery. Traditional diagnostic methods rely upon clinical investigations, which can include ECG, analysis of cholesterol, and various imaging techniques, but these might not take full advantage of large and complex medical datasets. This study develops a hybrid model for heart disease predictions that combines association rule mining with machine learning approaches on distributed medical databases. The model looks to analyze patient health records, lifestyle variables, and clinical attributes to uncover hidden associations between risk factors and heart disease occurrence. First, the data is manipulated and cleaned with respect to such an attribute as normalization, removing noisy instances in the dataset, and feature scaling before it is split 80/20 into training set and test set to ensure a reliable evaluation of potential models. Association rule mining using the Apriori algorithm yields meaningful relations involving clinical attributes such as chest pain type, exercise-induced angina, thalassemia, and gender. Rules derived from this analysis would further enhance the prediction capacity of the machine learning classifiers. An ensemble learning technique with Adaptive Boosting (AdaBoost) was implemented to improve the prediction capability and classification reliability of the proposed system. Experimental assessments extracted from the proposed system resulted in excellent predictive performance with 98.2%, 99.9% specificity, and an overall accuracy estimate of 98.1% performance, indicating strong reliability in diagnostics. The conclusion now drawn is that the integration of association rule mining with ML in distributed healthcare resources has indeed boosted the accuracy of heart disease predictions. It would support healthcare workforces in timely detection, decision support, assisted personalized treatment planning in a new wave-a chance to contribute toward advanced-augmented patient care and preventive health-care systems.

**Keywords:** Heart Disease Prediction, Association Rule Mining, Distributed Medical Databases, Machine Learning, Apriori Algorithm, Ensemble Learning, AdaBoost.

**I. INTRODUCTION**

Among the leading causes of mortality worldwide, cardiovascular disease has become a significant public health threat, and this increase in the number of individuals suffering from cardiovascular diseases has clearly pointed out that there is an urgent need for early diagnosis



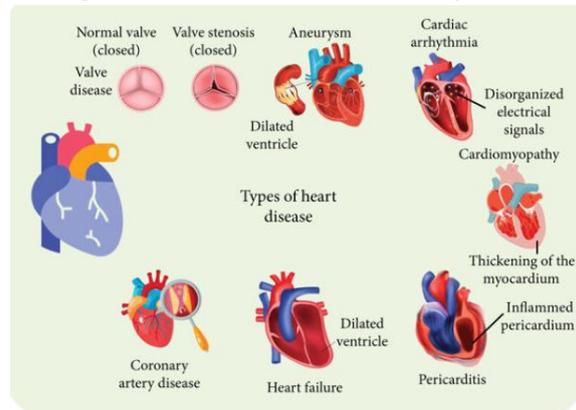
and effective preventive measures. In most cases, people do not know about any of their heart conditions other than when the disease becomes far severe that it starts to show symptoms. Hence, early screening usually becomes essential [1]. Conventional diagnostic tools can often be unwieldy and expensive, including going through routines of myriad clinic visits, clinical tests, and expert interpretations. However, given advances in technology, the concepts of artificial intelligence and machine learning take on a powerful role in disease ecological prediction as a complement to conventional physician decision-making. These intelligent systems are habitually adept at processing large volumes of medical data and pinpointing the patterns that would otherwise be overlooked by the conventional means [2]. The domain of health is one that has been appreciating substantially with machine learning, mostly for the treatment of raw data of medication and that it's now known to generate accurate predictions. For heart disease prediction, machine learning algorithms regard patient health records coupled with clinical features and medical history as well as determine whether any given subject is prone to succumbing to cardiovascular disease [3]. There exist a number of machine-learning technologies, including-but definitely not limited to-the Decision Tree, Support Vector Machine, Random Forest, and Naïve Bayes, as well as ensemble training methods to a great degree to ensure that disease prediction is implemented. These mechanisms learn from the past data to improve over time, and hence can find application in the medical domain in clinical decision support system construction [4]. By firmly linking these computational techniques within medical applications, physicians and medical practitioners can derive insights based on trustworthy information. These can support swift and accurate diagnosis.

Other than machine learning, Data Mining techniques are also used to help gain the necessary meanings from the data series. Association rules mining is a technique that can identify the relationship between different attributes of medical diseases and symptoms. By looking at the secret mapping of a patient's data, one can able to identify risk factors that affect heart disease. It is a significant move toward refining predictive algorithms as well as getting a deeper understanding of risk factors among various cardiovascular diseases through these methods [5]. Combined with machine learning algorithms, data mining substantially improves prediction accuracy and model reliability-in a case very essential.

In this study, attention is paid to the development of an intelligent heart disease prediction system by means of association rule mining for feature selection and machine learning classifiers for categorization of the disease [6]. The medical datasets come with various attributes of the patients relating to age, blood pressure, cholesterol level, heart rate, and other clinical indicators. To further increase the accuracy of the prediction system, the ensemble learning approach with the AdaBoost classifier is employed. Such are a practice by which the merits of multiple models are combined toward more accurate and robust prediction. The manufactured system has the goal of support of healthcare staff as well as patients in spotting heart disease risk at the initial phase. Basic medical information is put in this entry, enabling the system to guess whether a person is likely to suffer from heart disease. These intelligent healthcare solutions can afford the medical practitioner higher decision-making confidence, thereby saving the profession precious money on diagnostics and hence improving patient care as well as disease prevention [7].

**Figure 1 represents** the different types of heart diseases such as coronary artery disease, heart

failure, and arrhythmia affecting the human cardiovascular system [8].



**Figure 1: Types of Heart diseases [8]**

## II. RELATED WORK

Cardiovascular diseases are known to remain one of the leading causes of death worldwide; hence the necessity of early detection through intelligent healthcare systems and the subsequent steps taken during diagnosis and prevention [1]. Subsequently, over the years, the incorporation of artificial intelligence has become a common goal in cardiovascular healthcare, thereby enabling the exploration of large data sets. Together with this, AI models are actively working as bridges for more diagnostics and a definite prescription of an imaginative outcome, almost always assumed on these datasets by doctors-as opposed to the same models having a language of their own to express their classification [2]. Upon these new bases for long-range predictions-includes some aspect of latent relationship for these medical signs and suspected diseases-of levels between 85% and 92%-its higher verbal hunches would mainly appeal to human heads with regard to shades of red hot [3]. Hybrid forms of models following computing methods have thrown quite the best dice in representing a slight possibility today, exhibiting extremely high levels of interpretability in predicting probabilities with acceptable accuracies [4]. A variety of algorithms ranging from Decision Tree, Naïve Bayes, Random Forest, to Support Vector Machine for heart disease prediction are being popularly applied through the active use of machine learning methodologies in cases where the accuracies mentioned are near 80% to 90% depending on the dataset and method of feature selection [5]. A recent survey on machine learning in clinical practice completely identified predictive analytics in investigating various diseases: heart and liver in order of highest occurrence from clinical and imaging data presentation [6]. Data-driven healthcare frameworks have driven superior medical decision-making mechanisms using foremost advanced models always again integrating predictive model techniques via patient health records and clinical parameters [7]. Some ethical, clinical and, regulatory considerations have been brought into the analysis associated with the integration of artificial intelligence with cardiovascular care whilst underpinning implementation of the benefits of early diagnosis and treatment arrangements [8]. Data analytics frameworks have been used in the context of healthcare to curate insights out of clinical datasets for better delivery and patient management [9]. The fear of deriving a model-based decision-making approach supported by business and predictive analytics for guiding healthcare organizations has further accumulated in this objective of achieving perfect patient outcomes through evidence-based



decision systems [10]. Big data technologies have brought about new avenues within the healthcare system for processing large-scale datasets for disease prediction and understanding risk levels [11]. Intelligent algorithms have been developed to delve into coronary artery disease symptomatology for support to decision-making processes among care providers. These programs rely on diagnostic or other criteria derived from combination algorithms that incorporate data from patient clinical symptoms, imaging data, and disease prevalence studies [12]. The latest deep learning models have been rather commonly applied in the field of arrhythmia detection in electrocardiograms, with classification accuracies exceeding 90% in most studies [13]. Overwhelming advances in understanding the mechanisms underlying valvular heart diseases afford a deeper penetration into the clinical field that results in helpful knowledge for predictive diagnostic systems [14]. Present research fostered cardiovascular drug-drug-interaction and heart failure management to accentuate the importance of personalized healthcare analytics in the elevation of patient treatment approaches [15]. Clinical research in relativity to congenital heart diseases has received a higher priority toward the development of the detection, prevention, and management strategies consolidated through the use of modern technological health care aids [16]. Medical therapy monitoring frameworks have been developed, which are necessary for the continuous observation and management of heart failure in adults using real-world patient data analytics [17]. Machine learning techniques like the Support Vector Machine have been employed in finding cases of heart disease with the help of datasets and feature scalarization, resulting in several classification accuracies varying from 84% to 88% [18]. Federated learning, a recent breed of medical image analysis- and healthcare data processing-has emerged as the best-promising solution, wherein data handling is accomplished with all due regard to privacy in the realm of distributed healthcare systems [19]. Parallely, some possibilities involve the use of blockchain technology, whose clinical applications in the sharing and management of secure medical data very directly show a promise or success for healthcare information systems [20]. Table 1 provides an overview of the comparison over several recent studies in the area of heart disease prediction and data analysis in healthcare, dealing with techniques applied, datasets used, main results, and reported accuracy. This comparison also points out shortcomings in the existing methodologies, stressing the need for more accurate and efficient predictive models in healthcare systems.

**Table 1: Comparative Analysis of Existing Heart Disease Prediction Techniques and Healthcare Data Approaches**

<b>Ref</b>	<b>Technique Used</b>	<b>Dataset Used</b>	<b>Key Findings</b>	<b>Result / Accuracy</b>	<b>Limitations</b>
[21]	Distributed learning	Electronic health records	Collaborative predictive models without data sharing.	91% accuracy	Data synchronization challenges.
[22]	AI using commercial health datasets	Large healthcare datasets	Large datasets improve model training and reliability.	~90% accuracy	Dataset accessibility limitations.

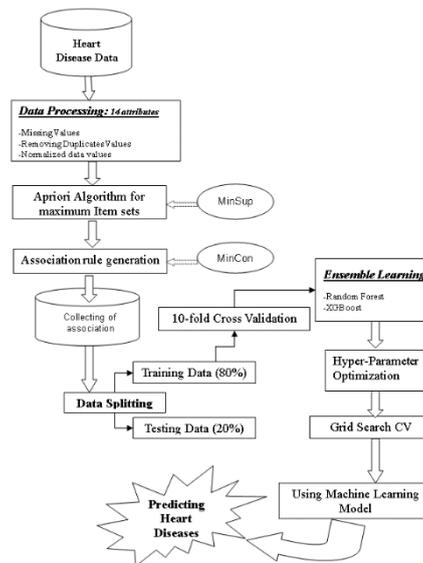
[23]	Blockchain database systems	Healthcare data repositories	Secure decentralized healthcare data management.	Improved security and reliability	High implementation cost.
[24]	Data warehouse technologies	Organizational healthcare datasets	Data warehouses improve healthcare performance analytics.	Improved decision support	Complex data integration.
[25]	Blockchain technology review	Blockchain datasets	Blockchain supports secure and transparent data exchange.	System efficiency improvement	Scalability and cost issues.
[26]	Big Data integration techniques	Heterogeneous healthcare datasets	Integration frameworks manage large diverse medical data.	Improved data processing efficiency	Data standardization challenges.
[27]	Big Data management frameworks	Real-life healthcare case studies	Efficient handling of large healthcare datasets.	Enhanced analytical performance	Infrastructure dependency.
[28]	Multimodal data fusion	Medical imaging datasets	Combining multiple data sources improves diagnosis.	~91% accuracy	Complex model design.
[29]	Systematic medical review	Clinical health datasets	Early detection and monitoring improve patient outcomes.	Clinical evidence findings	No predictive modeling.
[30]	AI-based heart failure diagnosis	Cardiovascular datasets	AI systems assist physicians in early heart failure detection.	>90% accuracy	Need for real-world deployment validation.

**III. RESEARCH OBJECTIVES**

- To develop an intelligent heart disease prediction system using machine learning techniques and association rule mining for effective analysis of medical data.
- To analyze and identify the most significant clinical attributes from healthcare datasets that contribute to accurate heart disease prediction.
- To design an ensemble-based predictive model using algorithms such as AdaBoost to improve prediction accuracy and support medical decision-making.

**IV. RESEARCH METHODOLOGY**

In this section, the technical aspect of our approach is discussed. The main objective of this study is to analyze heart diseases prediction in future or not, thereby designing an automated medical diagnosis system that takes advantage of the collected database. In this work we use fourteen attributes from medical terms, such as sex, blood pressure, cholesterol, are utilized to build up this heart diseases prediction system. **Figure 2 represents** the comprehensive workflow of the proposed model, illustrating the steps of data preprocessing, feature selection, machine learning training, and final heart disease prediction.



**Figure 2: Proposed comprehensive flowchart of the suggested model.**

**A. Data Collection**

In this step, the publicly available Heart Disease dataset [1] from the datasets from Kaggle is used to enhance our analysis. The Heart Disease dataset consisted of 303 patient records with 13 attributes and 1 attribute as the target output label has two classes to represent a patient with or without heart disease is utilized.

**B. Data Pre-processing Stage**

In this study, checks and transformations in the data pre-processing stage were performed very rigorously to guarantee the quality and suitability of the dataset. 1) Check for missing values - No Null data was found in the dataset as part of a generic check and the data set appeared to be complete. This suggested the dataset was of high precision and accuracy. Data was also scaled to a common 0 - 1 range in order to make comparisons between features more uniform and meaningful. Such a scaling improved data readability and analysis. The pre-processing of the heart disease dataset has been completed. Z-score normalization is used to standardize the

dataset, giving each voxel a unit variance and a mean of zero.

$$D_{\text{norm}} = \frac{D - \mu_i}{\sigma_i} \quad (1)$$

Data are pre-processed using  $\mu_i$  and  $\sigma_i$ , which stand for the mean and standard deviation, to represent the normalized data ( $D_{\text{norm}}$ ) and the original data ( $D$ ).

### **C. Data Splitting Stage**

The process of dividing the data was crucial in this research project focused on the Heart Disease dataset. In order to establish a reliable and precise heart disease prediction model, the heart disease dataset was partitioned into an 80% training set and a 20% testing set. This division enabled the model to be trained on a substantial portion of the data, facilitating its ability to identify patterns and establish relationships. The independent testing set acted as a tool to assess the model's performance on data it had not encountered before, offering an unbiased evaluation of its predictive abilities.

### **D. Association Rule Mining on Heart Disease Data**

In this step, heart disease datasets are used as a normalized dataset. While most previous studies have approached the Heart Disease dataset as a disease prediction task, we consider it as a knowledge extraction problem and investigate the application of association rule mining. Two experiments have been conducted. The experiments aimed to identify rules that could determine whether a patient had heart disease or not. In the field of medicine, the gender of an individual has been discovered to play a significant role in the development of heart disease. Figure 3 represents the frequent itemsets generated from different attribute values to identify significant patterns in the heart disease dataset. Figure 4 represents the association rules derived from the dataset indicating the classification of patients as “with heart disease” or “without heart disease” based on target class values  $\{0,1\}$ .

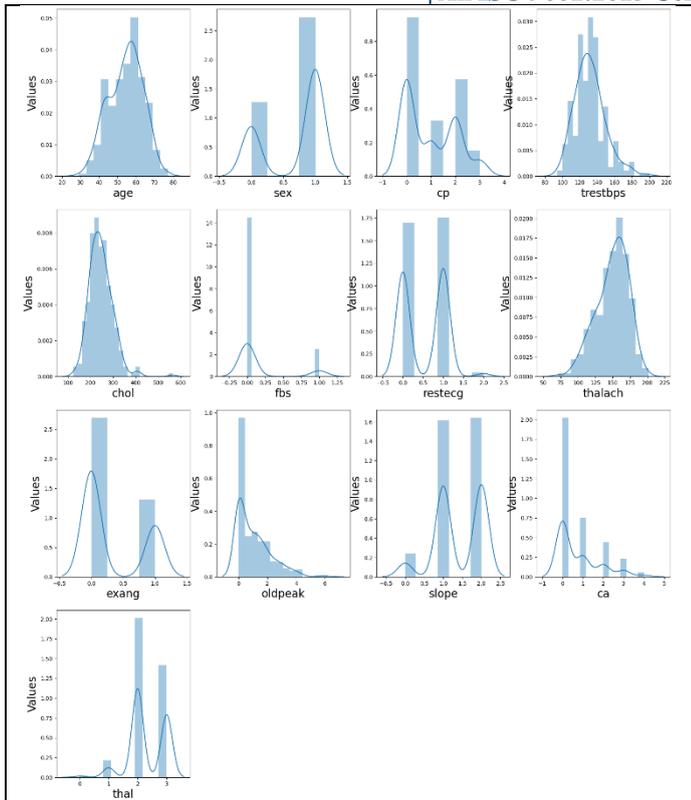


Figure 3: Frequent item Sets computed for different attributes values.

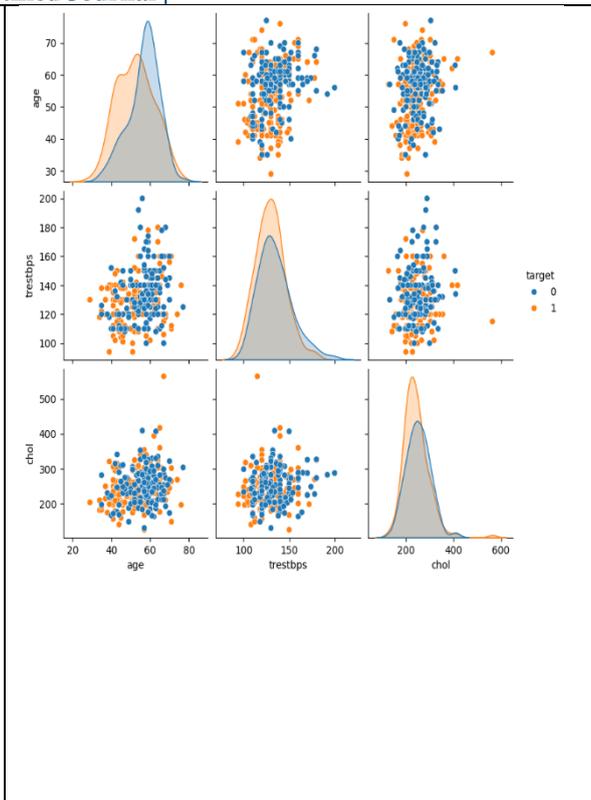


Figure 4: Association Rules to Indicate containing the “With heart disease” or “Without heart disease” class computed for target {0, 1} class values.

### E. Using Different Machine Learning Models to Forecast Heart Disease

#### Logistic Regression Assumptions Steps:

Logistic regression requires quite large sample sizes. Even though, logistic (logit) regression is frequently used for binary variables (2 classes), it can be used for categorical dependent variables with more than 2 classes. In this case it's called Multinomial Logistic Regression.

#### Decision Tree:

Decision tree learning is a technique commonly employed in the field of data mining. The objective is to create a model that estimates the value of a target variable based on a set of input variables. Each interior node corresponds to one of the input variables, and there are connections to child nodes for each possible value of that input variable. Each leaf symbolizes the value of the target variable, which is determined by the input variables that the route from the root to the leaf represents. A decision tree is a straightforward way to categorize different situations. In this segment, the main components of the features have specific boundaries, and there is a single target feature known as the classification. Each component of the classification system is referred to as a class. A decision tree or a classification tree is a tree structure where each internal node represents an input feature, and each leaf node represents a classification or decision. The circular segments starting from a node named with a feature are labeled with each of the possible values of the feature. Each leaf of the tree is labeled with a class or a probability distribution that assigns likelihood to each class. There is no need for specialized knowledge or parameter



adjustment, and it can effectively handle data with multiple dimensions. It generates outcomes that are easier to comprehend and analyze. The drill-down feature in Decision Trees allows users to access detailed information about patients' profiles.

### **K-Nearest neighbour:**

K-Nearest neighbor classifiers rely on the process of learning through analogy. The training samples are represented by n-dimensional numerical attributes. Each sample signifies a specific location in an n-dimensional space. In this context, the majority of the training samples are stored in a multi-dimensional pattern space. When presented with an unknown sample, a k-nearest neighbor classifier examines the pattern space of the k training samples that are most similar to the unknown sample. The term "closeness" is defined using Euclidean distance. Unlike decision trees and back propagation, nearest neighbor classifiers assign equal weight to every attribute.

**Random Forest:** Random Forest is a type of machine learning algorithm that was introduced by L. Breiman [6] and is used for both classification and regression tasks. However, it is primarily employed for categorizing problems. We understand that a forest consists of trees, and the presence of more trees indicates a stronger and healthier forest.

### **Random Forest Assumptions Steps:**

Begin by randomly selecting samples from a given dataset. Next, this algorithm will create a decision tree for each sample. After obtaining the prediction outcome from each decision tree, the model will proceed with the next step. In this step, voting will be conducted for every predicted result. At last, choose the most popular prediction results as the final prediction result.

### **Use Ensemble Learning to Diagnose Heart disease**

The importance of using ensemble learning algorithms was a key component of this research. Ensemble learning is a subfield of machine learning that utilizes the collective strength of multiple models to enhance prediction accuracy and resilience [6]. In this research, multiple ensemble learning methods were utilized, such as random forest, XGBoost, and GradientBoost. Ensemble learning involves training several individual models on the same dataset and combining their predictions to produce a final prediction. This aggregation allows for the assessment of multiple models within an ensemble using performance metrics, including accuracy, precision, recall, and F-1 Score.

**XGBoost:** XGBoost, created by Tianqi Chen and his team in 2016 [4], is a powerful ensemble learning technique that draws inspiration from gradient-boosting decision trees. It incorporates regularization techniques to smooth out the loss function and prevent overfitting, leading to better control over the complexity of the model. XGBoost employs an effective approximation algorithm to improve the efficiency and scalability of the gradient boosting process. Furthermore, it demonstrates resilience in dealing with missing or sparse values by assigning dedicated branches to tackle these situations.

**Gradient Boosting:** Gradient Boosting is a specific type of machine learning boosting technique [7]. By combining previous models, the final model is improved by minimizing the overall prediction error. Also known as a statistical forecasting model, the primary concept behind gradient boosting is to create a model that minimizes the errors of previous models. Gradient Boosting is named so that the set target outcomes depend on the gradient of the inaccuracy vs the

forecast. Every new model created using this method moves closer to the path that lowers prediction error in the range of potential outcomes for every ML training case. Gradient Boosting is mainly of two types depending on the target columns:

**V. RESULT AND DISCUSSION**

**A. Performance Measures**

$$\text{Sensitivity} = \frac{(T_P)}{(T_P + F_N)} \tag{2}$$

$$\text{Specificity} = \frac{(T_N)}{(T_N + F_P)} \tag{3}$$

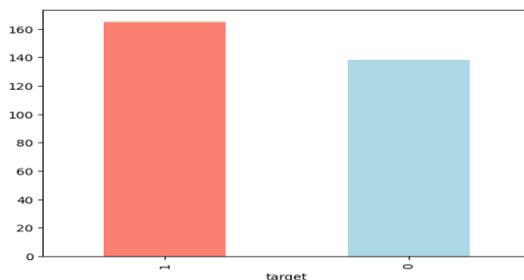
$$\text{Accuracy} = \frac{(T_P + T_N)}{(T_P + T_N + F_P + F_N)} \tag{4}$$

$$\text{Precision} = \frac{(T_P)}{(T_P + F_P)} \times 100\% \tag{5}$$

$$\text{Recall} = \frac{(T_P)}{(T_P + F_N)} \times 100\% \tag{6}$$

Where,  $T_P$  denotes True Positive.  $T_N$  denotes True Negative.  $F_P$  denotes False Positive.  $F_N$  denotes False Negative.

**B. Classification of patients that has heart disease and no heart disease:**



**Figure 5: Classification of patients with heart disease and No Heart Disease**

Figure 5 shows the classification of the patients having No Heart Disease (0) with the number of 165 and the patients having Heart Disease (1) with 138. Figure 6 represents the classification of patients based on different medical attributes to determine whether they are likely to have heart disease or not.

**C. Classification of heart disease patient in different attributes:**

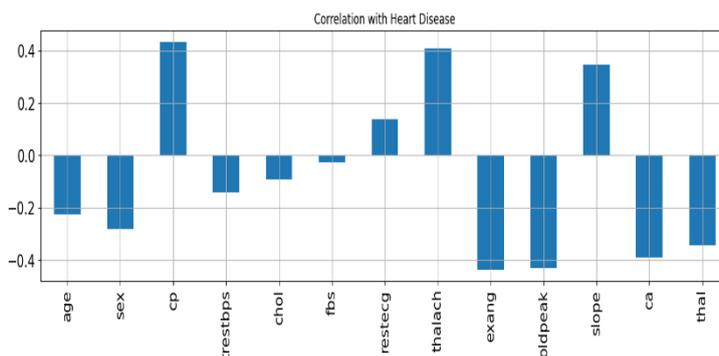


Figure 6: Classification of patients with different attributes

D. Correlation Confusion Matrix Map of all the attributes:

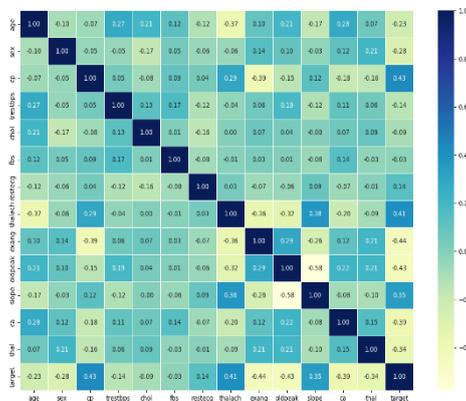


Figure 7: Correlation heat map to measure accuracy, sensitivity, and specificity

Figure 7 displays the correlation heat map, illustrating the connection between 14 attributes or variables that are directly linked to the occurrence of heart disease. Among the 14 variables, three variables were identified as having a significant impact on severity – Thalassemia, Calcium, and Chest pain.

- Thalassemia: It has a significant impact on severity, with a 53% rating. It monitors the patients with the highest heart rate. It indicates that individuals with a higher heart rate have a 53% likelihood of developing heart disease.
- Calcium: It has a 45% impact on the severity of heart disease, specifically measuring the patient's significant vessels at levels 0 through 3.
- Chest Pain: It has a 42% impact of severity, indicating that patients with chest pain levels I through IV have a 42% likelihood of developing heart disease.

E. Comparison Various Approaches with our Proposed Approach

To assess the ensemble models' performance, a violin plot was utilized to visualize their effectiveness. Violin plots provide valuable information about the widths, lengths, and central points of the violins. The width of a violin indicates the number of values it can produce, with wider violins being able to play a wider range of notes, resulting in better overall performance. Longer violins, on the other hand, suggest a greater variation in the range of notes that can be played. The central point's symbolize the median performance, offering an approximation of the average. Table 2 presents our analysis of the models' performance. It was noticed that the additional tree model consistently outperformed all other models when the hyper-parameters were optimized using grid search CV. This emphasized the impressive efficiency of the additional tree model, particularly when optimized using grid search CV hyper-parameter tuning. After analyzing the results, we can conclude that our proposed approach yielded the highest accuracy among all the other approaches.

Table 2: A comparison of the models' performance.

Model	Algorithms	Score
4	Random Forest	0.846154
0	Logistic Regression	0.802198
6	XgBoost	0.802198
5	Gradient Boosting	0.791209
1	KNN	0.758242
3	Decision Tree	0.736264
2	SVM	0.516484

**F. Assessment of Outcomes**

The performance of the suggested model in comparison to industry standards is evaluated using the metrics covered in this section. The suggested model had been improved with ADAM (learning rate: 0.0001) after being constructed with Python, Keras, and TensorFlow. With 80:20 training to testing ratio, the combined set of data using a Google Colab Tesla T4 GPU and 25 GB of RAM. The precision of the validation and training curve for the suggested model is displayed below in figure 4.2. Likewise, the learning and verification graph of the suggested model is displayed in figure 4.3.

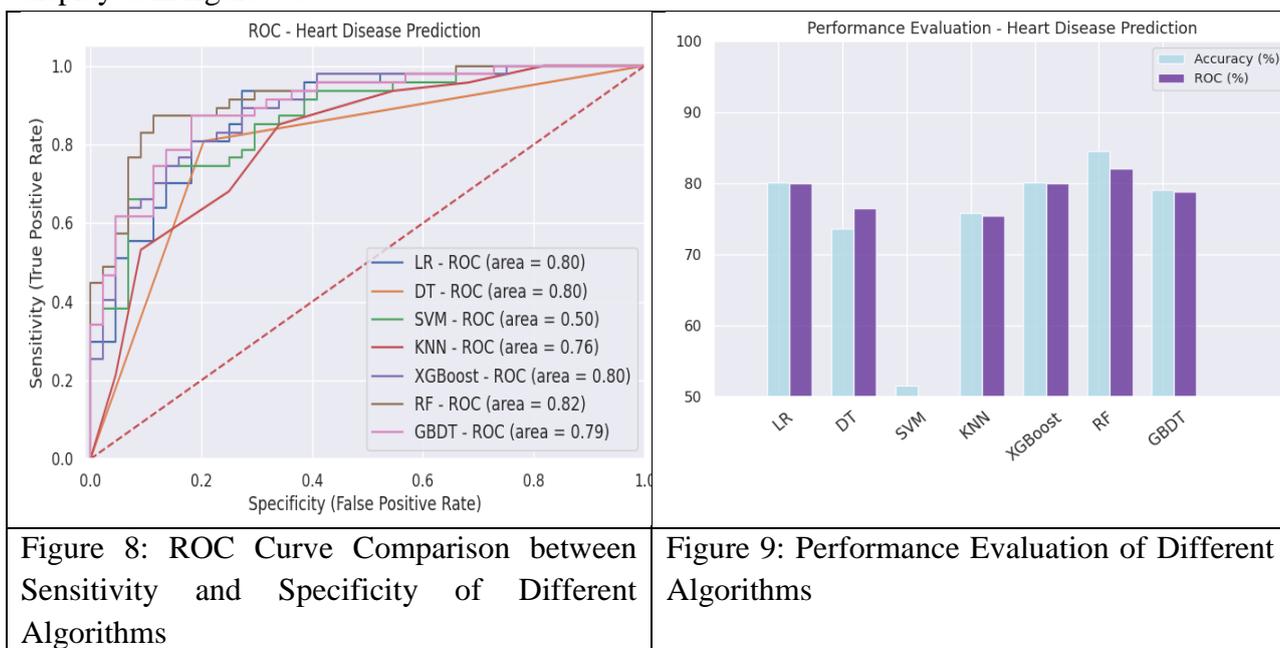


Figure 8 represents the ROC curve comparison illustrating the relationship between sensitivity and specificity for different prediction algorithms. Figure 9 represents the comparative performance evaluation of different algorithms used for heart disease prediction. The provided



table outlines diagnostic performance metrics for heart, diabetes, and normal conditions. In heart diagnosis, the tests demonstrate strong sensitivity at 98.2%, indicating their ability to accurately detect positive cases, coupled with a high specificity of 99.9%, highlighting their proficiency in correctly identifying negative instances. The overall accuracy stands at 98.1%, showcasing the reliability of these diagnostic measures. Similarly, in diabetes diagnosis, the sensitivity and specificity values are commendable, at 98.4% and 99.2% respectively, resulting in an accuracy of 97.6%. For normal diagnosis, the tests exhibit consistent performance across sensitivity, specificity, and accuracy, all at 98.5%. These numerical values underscore the effectiveness of the diagnostic tests across various health conditions. In comparison, the "State-of-the-Art" hypothetical column represents perfect diagnostic performance with all metrics set at 100%, providing a benchmark for optimal diagnostic capabilities.

### **VI. CONCLUSION AND FUTURE WORK**

This research developed the heart disease prediction system using the Association Rule Mining and machine learning technology to determine whether a person is in danger of suffering from heart disease. The system has three main phases. In the first phase, heart disease datasets were analyzed by applying association rule mining to find the most important attributes that play a key role in the prediction. It comes up with an automatic selection of important attributes from the dataset and hence improves the overall prediction performance. Moreover, AdaBoost classifier is implemented to boost overall model performance after identifying significant features. Like the previous two steps, this last step builds AdaBoosts of different types of classifier as its base learners to address the particular needs of different feature groups. The results suggest that the proposed model provides reliable decision support for healthcare professionals by delivering accurate predictions with high sensitivity and specificity. Future approaches will include extending the system to predict other diseases like diabetes and respiratory disorders. The predictive models can be further developed into a mobile application to be closely integrated with medical devices, permitting real-time health monitoring and enhanced accessibility.



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