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Prediction of Cardiovascular Disease on Different Parameters Using Machine Learning

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ABSTRACT

The most common serious diseases affecting human health are cardiovascular diseases (CVDs). Early diagnosis can prevent or mitigate CVDs, which can reduce the rate of death. It's a promising approach to identify risk factors using machine learning models. We wish to propose a model with different methods to effectively predict heart disease. We have employed effective data collection, data pre-processing and data transformation methods for the precise information of our training model to make our proposed model a success. A combined dataset has been used (Cleveland, Long Beach VA, Switzerland, Hungarian and Stat log). The appropriate function is selected using AASSO (Advanced Absolute Shrinkage and Selection Operator techniques) and AASSO techniques. Appropriate features are selected. New hybrids are developed with integration of the traditional bagging and boosting methods, such as Decision Tree Bagger Method (DTBM), the Random Forest Bagging Method (RFBM), the K-Nearest Neighbour Bagging method (KNNBM), the AdaBoost Boosting Method (ABBM), and the GBBM. Our machine learning algorithms, along with Negative Predictive Value (NGR, false positive rates), and false negative flow rates, also were implemented to calculate accuracy of our model, sensitivity (SEN), error rate, accuracy of the model (FRE) and the F1 score (F1) (FNR). The results are shown for comparisons separately. Based on the result analysis, our proposed model produced the highest precision, Accuracy using RFBM and relief selection methods (99.05 percent).

Keyword : AASO (Advanced Absolute Shrinkage and Selection Operator techniques), CVD (Cardio Vascular Diseases)

I. INTRODUCTION

Medical data mining has enormous potential for uncovering hidden patterns in medical data sets. These patterns can be used to make clinical diagnoses. However, the raw medical data that is currently available is widely dispersed, heterogeneous, and voluminous. These data must be gathered in an orderly fashion. This data can then be combined to form a hospital information system. Data mining technology offers a user-friendly approach to discovering novel and hidden patterns in data. The World Health Organization estimates that 12 million people die each year as a result of heart disease. Cardiovascular diseases account for half of all deaths in the United States and other developed countries. It is also the leading cause of death in a number of developing countries. Overall, it is regarded as the leading cause of adult deaths. Heart disease refers to a variety of diseases that affect the heart. Heart disease was the leading cause of death in many countries, including India. In the United States, one person dies from heart disease every 34 seconds. Heart diseases are classified into several categories, including coronary heart disease, cardiomyopathy, and cardiovascular disease. The term "cardiovascular disease" refers to a variety of conditions that affect the heart and blood vessels, as well as the way blood is pumped and circulated throughout the body. Cardiovascular disease (CVD) causes a variety of illnesses, disability, and death. Disease diagnosis is a critical and intricate task in medicine. Medical diagnosis is regarded as a critical but difficult task that must be completed accurately and efficiently. This system's automation would be extremely beneficial. Regrettably, not all doctors are experts in every subspecialty, and there is a scarcity of resource people in some areas. As a result, by bringing all of them together, an automatic medical diagnosis system would most likely be extremely beneficial. Appropriate computer-based information and/or decision support systems can help achieve clinical test results at a lower cost. A comparative study of the various techniques available is required for efficient and accurate implementation of an automated system. The purpose of this paper is to examine the various predictive/descriptive data mining techniques proposed in recent years for the diagnosis of heart disease.

II. LITERATURE REVIEW

R. Katarya and P. Srinivas proposes [1] that predicting and detecting cardiac diseases was always a vital and demanding issue for healthcare professionals. Hospitals and other clinics offer costly medicines and treatment operations for heart disease. Thus, predicting cardiovascular diseases at an early stage can help people all around the world to take critical steps before they turn serious. Heart disease has recently been a serious problem, mostly due to alcohol ingestion, tobacco and lack of physical exercise. Over the years, machine learning has demonstrated effective results in the decision-making and forecasting of a broad range of health industry data. Some of the approaches of supervised machine learning employed in this cardiovascular prediction are artificial neural networks (ANN), the decision tree (DT), the RF, the vector support maker (SVM). The performance of these algorithms is additionally summarised.

A. Gavhane, G. Kokkula, I. Pandya and K. Devadkar proposes that in order to recognise the symptoms [2] of a heart stroke at an early stage, a system needs to be put in place that is capable of preventing it. It is not possible for a common person to routinely undertake expensive tests like the ECG and so a practical method needs to be in place to predict the chances of heart disease while at the same time being dependable. Therefore, we offer an application that can forecast the vulnerability of heart disease given fundamental indicators such as age, sex, pulse rate, etc. The neural networking of the machine learning algorithm has proved to be the most precise and dependable algorithm employed in the system offered.

M. Kavitha, G. Gnaneswar, R. Dinesh, Y. R. Sai and R. S. Suraj proposes that heart disease causes a significant mortality rate around the world [3], and it has become a health threat for many people. Early prediction of heart disease may save many lives;

detecting cardiovascular diseases like heart attacks, coronary artery diseases etc., is a critical challenge by the regular clinical data analysis. Machine learning (ML) can bring an effective solution for decision making and accurate predictions. The medical industry is showing enormous development in using machine learning techniques. In the proposed work, a novel machine learning approach is proposed to predict heart disease. The proposed study used the Cleveland heart disease dataset, and data mining techniques such as regression and classification are used. Machine learning techniques Random Forest and Decision Tree are applied. The novel technique of the machine learning model is designed. In implementation, 3 machine learning algorithms are used, they are 1. Random Forest, 2. Decision Tree and 3. Hybrid model (Hybrid of random forest and decision tree). Experimental results show an accuracy level of 88.7% through the heart disease prediction model with the hybrid model. The interface is designed to get the user's input parameter to predict the heart disease, for which we used a hybrid model of Decision Tree and Random Forest.

P. Sujatha and K. Mahalakshmi proposes that the big problem [4] in the healthcare sector is recording and analysing the enormous volume of patient information. Technological innovations have revolutionised the healthcare industry. Data analytics have in recent years grown as a potential tool to solve problems and decide in medical professions. Data analysis processes data automatically to enhance the dynamic and robust healthcare system. It methodically uses and analyses healthcare data to improve low-cost therapy. Machine learning in healthcare is mostly used for the detection and diagnosis of diseases. The heart is the principal organ of the human body. Heart disease increases worldwide mortality rates. Around 90% of cardiac problems can be prevented. Machine learning plays a significant role in the prediction of heart disease in the health care industry. In this study, Decision Tree, Naive Bayes, Random Forest, Support Vector Machine, K-Nearest Neighbor and Logistic regression algorithms predict the existence of heart disease. The performance of the algorithms has been analysed with measures like accuracy, precision, AUC and F1. The experimental results show that Random Forest is more accurate than other supervised machine learning algorithms in predicting the heart disease with accuracy of 83.52%. The F1- score, the AUC score and the Random Classification Score are 84.21%, 88.24% and 88.89% correspondingly.

P. S. Kohli and S. Arora proposes that machine learning is gradually developing in the area of medical diagnosis [5]. This can mainly contribute to the advancement in the classification and identification systems used for diagnosing diseases which can give data that supports medical specialists in the early detection of fatal diseases and thus considerably increases the patient's survival rate. This paper includes multiple classification algorithms, each of which has its own benefit over three different illness databases (Heart, Breast Cancer, Diabetes) that are available for disease prediction in the UCI repository. Backward modelling with the p-value test was used to identify the feature for each dataset. The results of the study reinforce the idea of applying machine learning to early disease detection.

A. Ed-Daoudy and K. Maalmi proposes [6] that heart disease has been the most common cause of global death during the past few decades. Early detection and persistent monitoring of cardiovascular diseases can minimise mortality rates. A tremendous amount of data has been generated continually by the exponential increase of data from numerous sources, such as wearable sensor devices used in the Internet of Things health monitoring, streaming system and others. The integration of Big Data Analytics with Mechanical Learning is a technological breakthrough that can have a substantial influence on health, particularly early diagnosis of cardiac disease. This technology can be stronger and cheaper. In order to address this problem, this work proposes an Apache Spark-based real-time prediction system based on a massive distributed computing platform, which may be used successfully for the streaming of data events versus machine learning through memory computations. The system comprises of two primary sub-parts, streaming and data storage and display. The first one integrates Spark MLlib with Spark streaming and employs data classification models for cardiovascular prediction. The latter uses Apache Cassandra to store the vast volume of data created.

III. Research Methodology

A. Overview of Proposed Model

Dataset is built by a combination of Cleveland, Hungary, Switzerland, Long Beach and Statlog and various datasets. Fig. 1 illustrates the work of the models that are recommended. The combined data set is analysed during the pre-treatment process to check missing values which are then processed with the technique of imputation of K-Nearest Neighbours. Two different feature selection techniques are used to deal with problem-solving and avoid long running times: ASSO and Relief. This helps to extract the best characteristics. The performance of the classics is analysed with the features and original features selected by those techniques. The data set is then divided into two parts following the selection of the feature: training and testing. During the training phase 80% of the data and the rest 20% d are provided for the test phase, based on the model rates of learning. All ensemble models with classic models have been implemented to compare the combined data set, but the result of our model is gained in a little time. There has been a different training model for data set testing so that we are able to choose the best model for our reliable dataset. With 99.05 percent of accuracy, RFBM was the most useful process. In addition, in this diagnostic system the most appropriate features of a patient with heart disease were suggested.

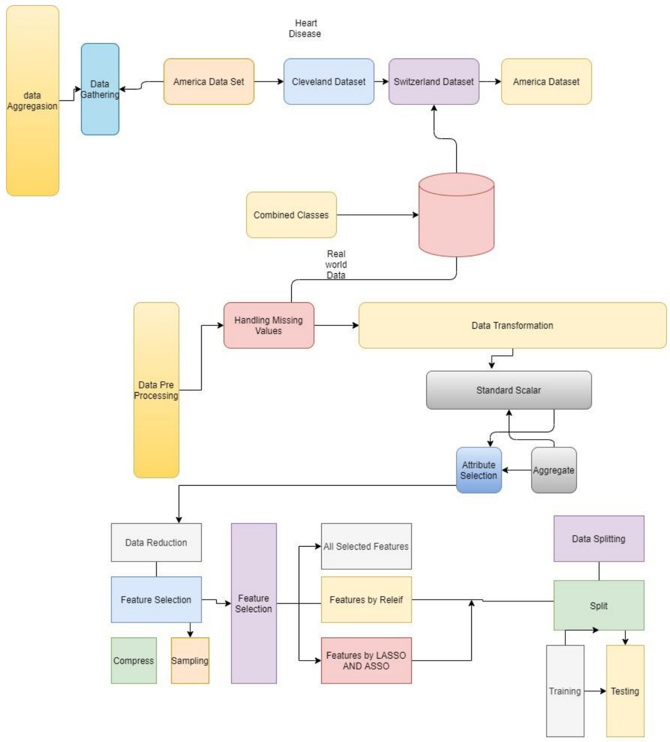

Figure 1: Flow Diagram of Proposed Model

B. Performance Measure Indices

The effectiveness and accuracy of the machine learning method can be evaluated using performance indicators. Positive classification occurs when a person is classified as having HD. When a person is not classified as having HD, he has a negative classification. The following formula from (1) to (7) has been applied to get all of this [16], [17].

TP = True Positive (when the model correctly Identified as having HD).

TN= True Negative (when the model correctly identified the opposite class, such as patients truly having no heart issues).

FP= False Positive (when the model incorrectly identified

HD patients i.e., identifying non-HD patients as HD patients)

FN = False Negative (when the model incorrectly identified the opposite class, such as HD patients as normal patients).

C. Application of the Proposed Model

Having a suitable application of the proposed model is key to the development of this unique system and will also help to deal with the real-world challenges. The process has been illustrated in this section.

IV. IMPLEMENTATION

A. Different Machine Learning Libraries

The implemented model is written in Jupiter notebook's Python programming language using simple libraries like Panda, Pyplot, and Scikit-learn .

B. Dataset

Data is considered the first and most basic aspects of using machine learning techniques to get accurate results. The applied dataset is gathered from a well-known data repository, the `UCI machine learning repository'. There are five different datasets: the Cleveland, Hungary, Switzerland, VA Long.Figure 2 below shows the actual number in data set and figure 3 actual points in data set.

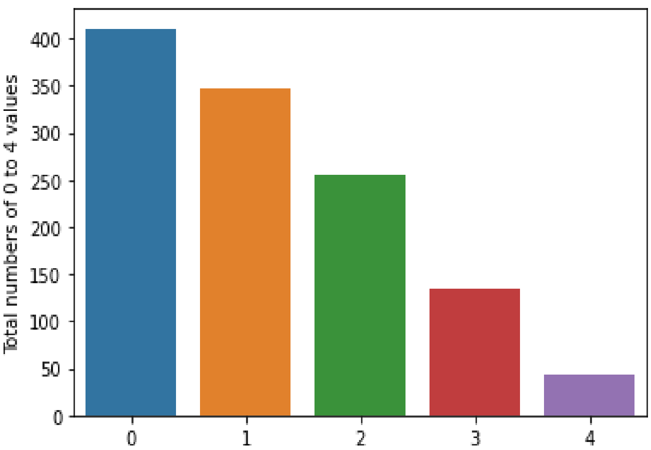

Figure 2: Actual Number in data set

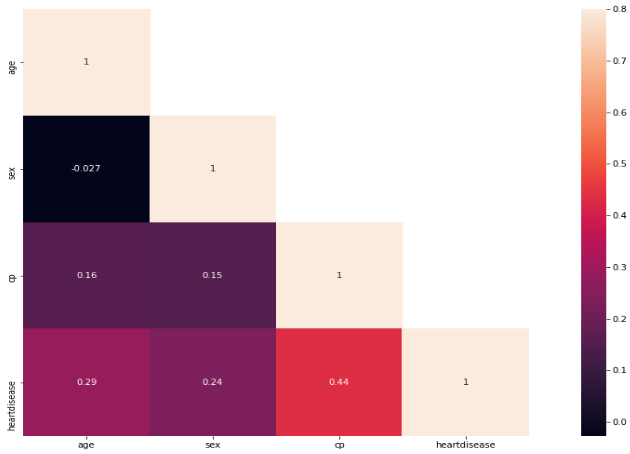

Figure 3. Actual data points in the dataset

Beach [18], and Statlog heart disease dataset [19]. Author have combined all of them in this research to obtain more accurate outcomes. More than 1190 cases are collected as a text file along with 14 special features from their database. 13 attributes of the combined datasets are taken as diagnosis inputs, whereas the 'num' attribute is selected as output. Six features which are considered relevant in medical literature were present in all or most records: age in years (age), sex (sex), resting blood pressure (trestbps), fasting blood sugar (fbs), chest pain type (cp), and resting electrocardiographic results (restecg). Table 1 describes the different attributes and the range of values.

The value of the 'num' attribute can be 0, 1, 2, 3 or 4. The predicted value '0' represents that a patient does not have heart disease and the values from 1 to 4 reflect the various stages of chronic heart disease. An overview of the total number of patients for each value of the num attribute in the combined dataset is shown in Fig. 4.

Since for the purpose of this research is to predict whether or not a patient is suffering from heart disease, we convert all values in the range of 1 to 4 to a 1. This means that the attribute now has the range of (0, 1).

C. An Overview of Data Preprocessing and Cleaning Techniques

There is a large amount of collected data in the modern world that can be gathered via the internet, surveys, and experiments, etc. Often the data to be used contain missing values, noise, and distortions, however. The combined dataset used for this research also contains missing or null values.

V. RESULTS AND DISCUSSION

A. Outcomes of Proposed Selection Processes

Relief [5], a feature selection algorithm, selects main features based on the weight of the data. The most important seven input features selected by Relief are given in Table 1. The most important feature for predicting heart disease is serum cholesterol (chol) which rank score is 0.869 according to the findings. The AASSO treats closely related features as true, and the rest as false. After applying the AASSO, chest pain (cp) had the highest rank score (0.0796), whereas maximum heart rate (thalach) had a very low score. Table 2 shows the score of the eight most essential features selected by AASSO for diagnosing heart disease.

TABLE 1. Features selected by Relief algorithms and their rankings.

Feature Name	Feature code	Score
Age in years	Age	0019
Serum cholesterol	chol	.867
Fasting blood sugar	fbs	.0233
Resting electocardiographic results	restcg	0.582
Maximum heart rate	Thalach	.543
Exercise induced angina	Exnag	0.0089
Number of major vessels	Ca	.581

B. Comparison of Various Algorithms and Hybrid Approaches on the Different features

This section compares on the outcomes of the different classification models with the different input features. First, five machine learning classifiers and five hybrid techniques were applied to all features of heart disease data set. Secondly, Least Absolute Shrinkage and Selection Operator Features Selection Algorithm (AASSO) was implemented to extract some relevant features and the same five machine learning classifiers and five hybrid techniques were applied again.

TABLE 2. Features selected by AASSO algorithms and their rankings.

Feature Name	Feature code	Score
Age in years	age	0.0012
Chest pain type	cp	0.0796
Resting blood pressure	trestbps	0.0018
Serum cholesterol	Thalach	0.0000
Maximum heart rate	Oldpeak	0.0013
ST depression induced by exercise	Oldpeak	0.0229
Slope of the peak exercise ST segment	Slope	0.0316
Thal	thal	0.0114

Finally, the most important features selected by the Relief model were used as input to the classifiers and hybrid methods. Different performance metrics are also evaluated to evaluate the predicted outcomes.
Our original dataset contains 14 individual attributes in which 13 input functions are used to generate the outcome of the disease. From these 13 features, 6 significant features of our dataset, which matched prominent medical books and guides, these are, age in years (age), gender (sex), resting blood pressure

(trestbps), fasting blood sugar (fbs), chest pain type (cp), and resting electrocardiographic results (rest ecg) [13], [14]. Some features including age, and sex are not modifiable, while risk factors associated with other features (fbs, restecg, cp and trest bps) are gradually modifiable.

After applying the Relief feature selection algorithm to the proposed dataset, 7 features: age in years (age), serum cholesterol (chol), fasting blood sugar (fbs), resting electrocardiographic results (reste cg), maximum heart rate (thalach), exercise induced angina (exang), and number of major vessels (0–3) colored by fluoroscopy (ca) have been selected based on their ranking values. Some missing attributes, present in notable medical books, were added: sex, trestbps [13], and cp [14] as it was felt that is was important that these features were included.

Eight relevant features: age, cp, trest bps, chol, thalach, oldpeak, slope, and thal were selected according to their ranking by the AASSO feature selection algorithm. Chest pain was the feature with the highest score. Some missing attributes, present in all medical records, were added: sex, fbs and restecg, so that these features were part of all three feature sets.
Different machine learning techniques were applied to the selected features. The 2 × 2 confusion matrix was generated to produce the different performance metrics and provided a comparison of all mentioned algorithms. The performance metrics Accuracy, Error rates, Sensitivity, Precision, F1-Score, Negative Predictive Value, False Positive Rate, and False Negative Rates were used to evaluate the proposed models.

1) Comparison Between Methods Based on Accuracy

Accuracy is commonly regarded as one of the most important techniques for evaluating machine learning algorithms. As previously stated, we employ five classifiers and five hybrid classifiers. We used the ten different methods on the original 13 input features, then on the eleven input features chosen by the AASSO method, and finally on the ten features chosen by the Relief method. The accuracy of the various types of classifiers, including the five hybrid classifiers, is depicted in Fig. 4.

Using 13 features, the AB Classifier produced the most accurate prediction [98] of 96.07 percent, while the accuracy of KNN is 93.97 percent. The accuracy of DT and GB are nearly identical (86.97 percent). However, the accuracy of RFBM is 92.65%, which is significantly higher than the accuracy of some of the hybrid classifiers. The RF Classifier has the lowest accuracy when only 11 features are evaluated (LASSO) (86.97 percent). With the 11 AASSO features, we get 88.6 percent, 93 percent, 90.75 percent, and 92.85 percent accuracy for the DT, KNN, AB, and GB classifiers, respectively. The other four hybrid classifiers, DTBM, RFBM, KNNBM, and ABBM, also provide good accuracy: 88.65 percent, 97.65 percent, 96.6 percent, and 90.75 percent, respectively.

In terms of accuracy with the Relief features, the Random Forest Bagging method (RFBM), a hybrid classifier, demonstrated an excellent accuracy of 99.05 percent. The results of the DT, AB, and GB hybrid models were similar to the previous results.

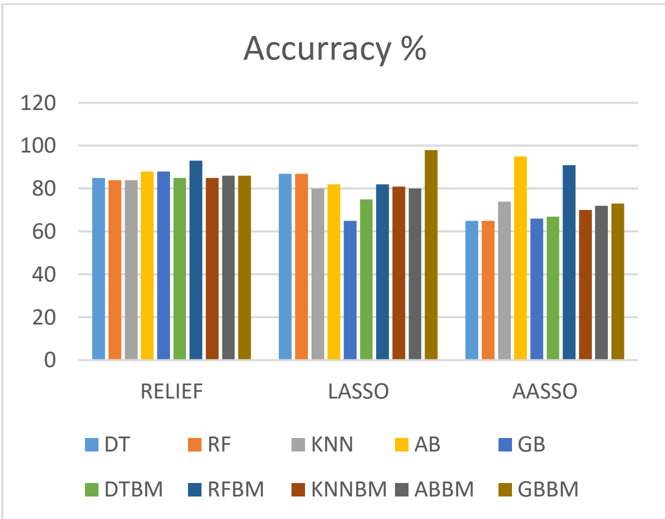

Figure 4. Accuracy

A dramatic improvement in accuracy with hybridization observed for the KNN model, from 94.11 % to more than 98 % accuracy.

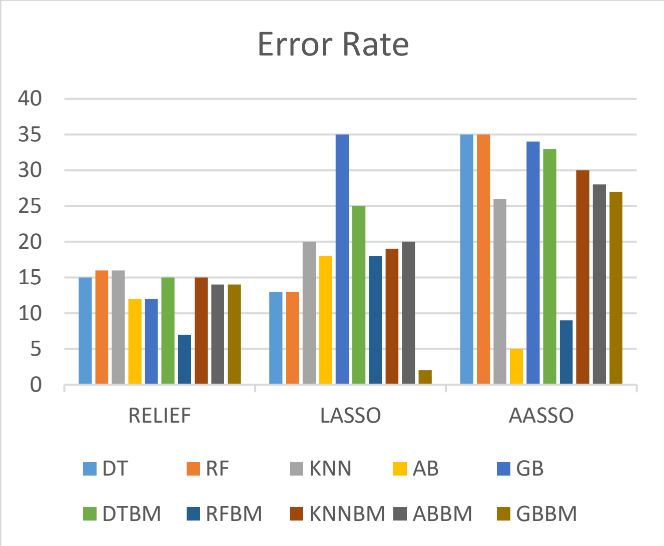

Figure 5. Error rates.

2) Comparison Between Different Methods Based on Error Rates

Error rates are also useful in understanding model performance. RFBM produces the lowest error rate, approximately 0.95 percent, on the 13 features chosen by Relief. However, for the eleven features chosen by LASSO, KNN produced the lowest error rate; just under 2.2 percent. Figure 5 clearly shows that KNN had the highest error rate (16.39 percent) for 10 features, followed by RF for 11 features (13.03 percent) and DT for ten features (10.88 percent).

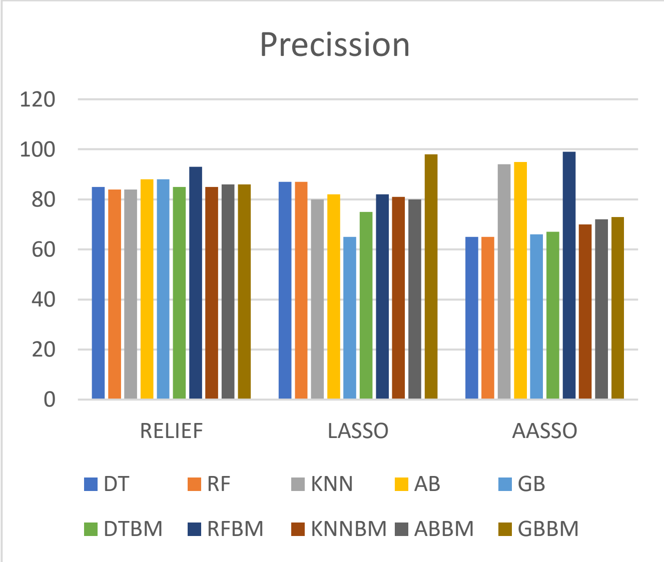

Figure 6. Precision

3) Comparison Between Different Methods Based On Precision

Other performance metrics, such as precision, have also been used to evaluate the performance of classifiers and hybrid algorithms. Using 13 input features, the RFBM model produced a significant result of more than 93% for precision. KNN had the lowest precision score (84%). Other models scored in the middle of these ranges for precision. When applied to the 11 LASSO features, the GBBM produced the highest precision (98%), while the GB classifier produced the lowest precision (98%). (84 percent). Both the Decision Tree (DT) and Random Forest (RF) classifiers had a precision score of around 87 percent. When evaluating 10 Relief features, RFBM achieved the highest precision, which was close to 99 percent. KNN also had a high precision score (94 percent). DT received the lowest score for the ten Relief features, but it still received an 89 percent. Figure 6 depicts the precision results.

V. CONCLUSION

Identifying the risk of heart disease with reasonable accuracy has the potential to have a significant impact on human long-term mortality rates, regardless of social and cultural background. Early detection is a critical step toward achieving that goal. Several studies have already attempted to use machine learning to predict heart disease. This study follows a similar path, but with a better and novel method and a larger dataset for training the model. This study shows that the Relief feature selection algorithm can generate a tightly correlated feature set that can then be used with a variety of machine learning algorithms. The study also discovered that RFBM works particularly well with high impact features (obtained through feature selection algorithms or medical literature) and produces significantly higher accuracy than related work. Furthermore, the proposed method's performance was compared to that of other well-known machine learning models as well as other methods discussed in the literature. We can safely conclude from the experimental results that the proposed diagnostic system can improve the quality of decision making during the heart disease diagnosis process.

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