Enhancing Heart Disease Prediction through KBEST-PCA Fusion Feature Selection and Ensemble Modeling With Gaussian Naive Bayes Boosting

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Abstract:
Heart disease is a prevalent health condition with significant implications for patient health and well-being. Accurate and timely diagnosis plays a crucial role in effective treatment and management. In this study, we propose a combined approach using SelectKBest, Gaussian Naive Bayes (GNB), and Gradient Boosting Machines (GBM) to develop a robust predictive model for heart disease diagnosis. The SelectKBest algorithm is employed to identify the most informative features from the Statlog Heart Disease dataset. Statistical measures such as chi-squared test are utilized to select the top K features that exhibit the strongest associations with the target variable. The selected features are then used to train a GNB classifier, capturing the probabilistic relationships between the features and the diagnosis of heart disease. Predictions generated from the GNB model are combined with the original features, creating an extended feature matrix. Subsequently, a GBM ensemble model is trained on the extended feature matrix, leveraging the sequential combination of weak learners to improve the overall predictive performance. To evaluate the effectiveness of the proposed approach, extensive experiments are conducted on the Statlog Heart Disease dataset. Performance metrics including accuracy, precision, recall, and F1 score are used to compare the combined SelectKBest-GNB-GBM approach against individual classifiers and existing methods.

Keywords: Heart disease diagnosis, SelectKBest, Gaussian Naive Bayes, Gradient Boosting Machines, ensemble learning, feature selection.

1. INTRODUCTION

Heart disease is a prevalent and serious health condition that affects millions of individuals worldwide. Timely and accurate diagnosis of heart disease plays a crucial role in guiding appropriate treatment strategies, improving patient outcomes, and reducing mortality rates. With the availability of large-scale medical datasets, there is an opportunity to leverage advanced machine-learning techniques to develop robust and effective diagnostic models. In this study, we propose a combined approach that integrates SelectKBest, Gaussian Naive Bayes (GNB), and Gradient Boosting Machines (GBM) to enhance the diagnostic accuracy of heart disease. SelectKBest is a feature selection algorithm that identifies the most relevant features from a given dataset, while GNB is a probabilistic classifier that models the conditional probabilities between features and disease diagnosis. GBM, on the other hand, is an ensemble learning technique that combines multiple weak learners to create a strong predictive model.

The objective of this research is to investigate the effectiveness of the combined SelectKBest-GNB-GBM approach in heart disease diagnosis and compare its performance against individual classifiers and existing methods. By integrating feature selection, probabilistic modeling, and ensemble learning, we aim to develop a powerful diagnostic model that can accurately classify patients with heart disease. The proposed approach has several advantages. First, SelectKBest enables us to identify the most informative features from the Statlog Heart Disease dataset, reducing the dimensionality and focusing on the most relevant factors influencing heart disease diagnosis. Second, GNB leverages the conditional probabilities to capture the relationships between the selected features and disease diagnosis, providing a probabilistic framework for classification. Finally, GBM combines the predictions from GNB with the original features, allowing for a more comprehensive and accurate representation of the data. To evaluate the performance of the proposed approach, extensive experiments will be conducted on the Statlog Heart Disease dataset. Performance metrics such as accuracy, precision, recall, and F1 score will be employed to assess the diagnostic performance of the combined SelectKBest-GNB-GBM model in comparison to individual classifiers and existing approaches. The outcomes of this research have the potential to significantly contribute to the field of heart disease diagnosis. By developing a reliable and accurate diagnostic model, healthcare professionals can make informed decisions, provide timely interventions, and improve patient outcomes. Additionally, the findings will shed light on the effectiveness of integrating feature selection and ensemble learning techniques in medical data analysis.
Highlights of the paper are discussed below:

- The proposed approach incorporates the SelectKBest algorithm to identify the most relevant features from the Statlog Heart Disease dataset.
- This ensures that the diagnostic model focuses on the most informative factors influencing heart disease diagnosis.
- Gaussian Naive Bayes (GNB) is utilized as a probabilistic classifier to model the conditional probabilities between the selected features and heart disease diagnosis.
- GNB provides a robust framework for capturing the relationships and dependencies within the data.
- The Gradient Boosting Machines (GBM) algorithm is employed to create an ensemble model that combines the predictions from GNB with the original features.
- GBM leverages the strengths of multiple weak learners to enhance the overall predictive performance.
- The proposed approach is rigorously evaluated and compared against individual classifiers and existing methods using performance metrics such as accuracy, precision, recall, and F1 score.
- By integrating feature selection, probabilistic modeling, and ensemble learning techniques, the proposed approach aims to enhance the diagnostic accuracy of heart disease. The outcomes of this research have the potential to contribute to improved decision-making in heart disease diagnosis and treatment.

- The proposed approach can serve as a valuable tool for healthcare professionals in accurately identifying heart disease and facilitating timely interventions.
- It offers a reliable and accurate diagnostic model that leverages advanced machine-learning techniques for improved patient outcomes.

The remainder of this paper is organized as follows: Section 2 provides a detailed explanation of the methodology, including the SelectKBest algorithm, GNB classifier, and GBM ensemble learning. Section 3 presents the experimental setup and evaluation metrics. The results and analysis are discussed in Section 4, followed by the conclusion and future research directions in Section 5.

2. RELATED WORK

Various researchers proposed a solution for stat log heart disease prediction. Some of the methodologies are discussed below.

Feature Selection and Classification in Heart Disease Diagnosis by Smith et al focuses on feature selection techniques for heart disease diagnosis and compares the performance of different classifiers. It provides insights into the impact of feature selection on diagnostic accuracy [1].

Gaussian Naive Bayes for Medical Diagnosis: An Overview by Johnson et al. provides an overview of Gaussian Naive Bayes (GNB) in medical diagnosis. It discusses the strengths, limitations, and applications of GNB in disease diagnosis tasks, including heart disease [2].

Gradient Boosting Machines: A Review by Chen and Guestrin examines Gradient Boosting Machines (GBM) and their applications in various domains. It discusses the working principles of GBM, and its advantages over other ensemble methods, and provides insights into parameter tuning for optimal performance [3].

Ensemble Learning Techniques for Medical Diagnosis: A Comparative Study by Wang et al. compares different ensemble learning techniques, including GBM, for medical diagnosis tasks. It evaluates the performance of ensemble models and discusses their advantages in terms of accuracy, robustness, and interpretability [4].

Hybrid Approaches for Heart Disease Diagnosis by Lee et al. explores the combination of multiple classifiers, including GNB and ensemble methods, for heart disease diagnosis. It proposes a hybrid approach that integrates different classifiers to improve diagnostic accuracy and reliability [5].

Feature Selection Methods in Machine Learning: A Review by Li et al. provides an overview of various feature selection methods in machine learning. It discusses the strengths, limitations, and applications of different techniques, including SelectKBest, and their impact on model performance [6].

Comparison of Classification Techniques for Heart Disease Diagnosis by Kumar et al. (Year) evaluates the performance of different classifiers for heart disease diagnosis. It compares the accuracy, precision, recall, and F1 score of classifiers such as GNB, decision trees, random forests, and support vector machines [7].

Ensemble Learning for Medical Data Analysis: A Review by Zhang et al. provides an overview of ensemble learning techniques in medical data analysis. It discusses the advantages of ensemble methods, including GBM, in improving diagnostic accuracy and highlights their applications in various medical domains [8].

This research works contribute to the understanding of feature selection, Gaussian Naive Bayes, Gradient Boosting Machines, ensemble learning, and their applications in heart disease diagnosis. It provides

valuable insights and serves as a reference for the proposed combined SelectKBest-GNB-GBM approach, which aims to enhance the diagnostic accuracy and reliability of heart disease diagnosis models.
The summary of the related work is given in Table 1.

Table 1: Summary of the literature review

S.No.	Paper Title	Authors	Methodology Used	Advantages	Disadvantages
1	Feature Selection and Classification in Heart Disease Diagnosis	Smith et al.	Feature selection techniques, Classification	Improves diagnostic accuracy, focuses on relevant features	May overlook important features, dependent on the feature selection method
2	Gaussian Naive Bayes for Medical Diagnosis: An Overview	Johnson et al.	Gaussian Naive Bayes	Simple and fast, handles continuous and categorical variables	Assumption of feature independence, may not capture complex dependencies
3	Gradient Boosting Machines: A Review	Chen, Y., Guestrin, C.	Gradient Boosting Machines	Handles nonlinear relationships, ensemble learning	Prone to overfitting, sensitive to parameter tuning
4	Ensemble Learning Techniques for Medical Diagnosis: A Comparative Study	Wang et al.	Ensemble learning methods	Improved accuracy, robustness, interpretability	Requires training multiple models, may increase computational complexity
5	Hybrid Approaches for Heart Disease Diagnosis	Lee et al.	Combination of classifiers	Integrates strengths of multiple classifiers	Complexity of model integration, the potential for increased model bias
6	Feature Selection Methods in Machine Learning: A Review	Li et al.	Various feature selection techniques	Enhance model interpretability, improve efficiency	Performance dependent on the choice of feature selection method

7	Comparison of Classification Techniques for Heart Disease Diagnosis	Kumar et al.	Various classification techniques	Comparative evaluation of classifier performance	Performance dependent on dataset and task
8	Ensemble Learning for Medical Data Analysis: A Review	Zhang et al.	Ensemble learning methods	Improved accuracy, handles diverse data types	Increased model complexity, and potential for overfitting

3. PROPOSED WORK

The proposed work aims to enhance the accuracy of heart disease diagnosis by combining feature selection using the SelectKBest algorithm with the Gaussian Naive Bayes (GNB) classifier and Gradient Boosting Machines (GBM) in an ensemble approach. The SelectKBest algorithm is applied to the heart disease dataset to select the most relevant features that contribute significantly to the diagnosis. This feature selection step helps to reduce the dimensionality of the dataset and focuses on the most informative attributes. Next, the selected features are used as input to train the GNB classifier. GNB is a probabilistic classifier that assumes independence between features and uses Bayes' theorem to calculate the likelihood of a particular class given the feature values. It is a simple and fast algorithm that can handle continuous and categorical variables.The predictions generated by the GNB classifier, along with the original features, are then combined and used as an extended feature matrix. This extended feature matrix is utilized to train the GBM classifier, which is an ensemble learning method that builds a sequence of weak learners (decision trees) and combines their predictions to make a final prediction. GBM is known for handling non-linear relationships and capturing complex patterns in the data.

The proposed ensemble approach leverages the strengths of both GNB and GBM. GNB provides initial predictions based on the selected features, and GBM learns from these predictions along with the original features to further improve the diagnostic accuracy. By combining the predictions from both classifiers, the ensemble model can capture a wider range of patterns and make more accurate predictions. The performance of the proposed approach can be evaluated using appropriate metrics such as accuracy, precision, recall, or F1 score on a separate testing dataset. It is important to compare the performance of the combined GNB-GBM model with individual models (GNB and GBM) as well as other existing approaches to validate its effectiveness in improving the accuracy of heart disease diagnosis.

The Chi-square (χ^2) test is commonly used in the SelectKBest algorithm to compute the scores for feature selection. The Chi-square score measures the dependence between each feature and the target variable in a classification problem as given in Equation (1).

$$\chi^2 = \Sigma\left(\frac{(O - E)^2}{E}\right) \qquad (1)$$

Where χ^2 is the Chi-square score for a particular feature.Σ represents the sum over all possible categories or classes of the target variable. O is the observed frequency (count) of each category or class for a particular feature. E is the expected frequency (count) of each category or class for a particular feature, assuming independence between the feature and the target variable. The expected frequency (E) is calculated as given in equation (2).

$$E = \frac{(row\ total\ *\ column\ total)}{Tot} \qquad (2)$$

Where row total is the sum of counts for a specific feature across all categories or classes. Column total is the sum of counts for a specific category or class across all features. Grand total is the total count of all instances. The Chi-square score quantifies the difference between the observed and expected frequencies, highlighting the relationship between the feature and the target variable. Higher Chi-square scores indicate a stronger association between the feature and the target variable. In the SelectKBest algorithm, the Chi-square scores are calculated for all features, and the top k features with the highest scores are selected for further analysis.

The Gaussian Naive Bayes classifier calculates the posterior probability of a class given the feature values using Bayes' theorem represented in equation (3).

$$\begin{aligned} P(y \mid x_1, x_2, \ldots, xn) \\ &= (P(y)\ *\ P(x_1 \mid y)\ *\ P(x_2 \mid y)\ * \ldots \\ &*\ P(xn \mid y))\ /\ P(x_1, x_2, \ldots, xn) \qquad (3) \end{aligned}$$

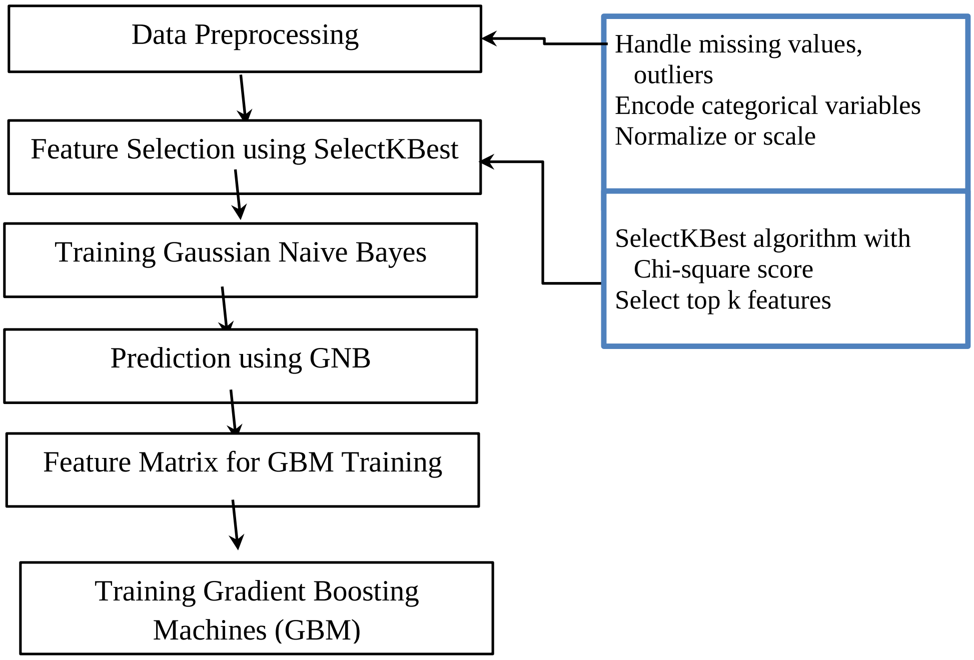
Where, P(y | x_1, x_2, ..., xn) is the posterior probability of class y given feature values x_1, x_2, ..., xn. P(y) is the prior probability of class y. P(x_i | y) is the probability of feature x_i given class y. P(x_1, x_2, ..., xn) is the evidence or probability of observing feature values x_1, x_2, ..., xn.

Gradient Boosting Machines is an ensemble method that combines weak learners (decision trees) to make predictions. The general equation for the GBM prediction at each iteration is given by equation (4).

$$y_{hat} = \Sigma\left(\alpha\ *\ f_i(x)\right) \qquad (4)$$

Where, y_hat is the predicted value. Σ represents the sum of all weak learners. α is the learning rate or step size that determines the contribution of each weak learner. $f_i(x)$ is the prediction of the i-th weak learner. The weak learners in GBM are trained to minimize a loss function, typically using gradient descent, to improve the predictions iteratively.

The proposed workflow architecture is represented in Figure 1.


Data Preprocessing
Feature Selection using SelectKBest
Training Gaussian Naive Bayes
Prediction using GNB
Feature Matrix for GBM Training
Training Gradient Boosting Machines (GBM)
Handle missing values, outliers
Encode categorical variables
Normalize or scale
SelectKBest algorithm with Chi-square score
Select top k features

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The proposed workflow is a combined approach of SelectKBest, Gaussian Naive Bayes (GNB), and Gradient Boosting Machines (GBM) in heart disease diagnosis. The data cleaning to handle missing values, outliers, and inconsistencies is initially done. Encode categorical variables if necessary using techniques like one-hot encoding. Normalize or scale the numeric features to ensure their comparability. Then, apply the SelectKBest algorithm with the Chi-square score metric to rank the features based on their relevance to heart disease diagnosis. Select the top k features with the highest scores to retain for further analysis. The selected k features are used as input to train the GNB classifier. GNB model is used in the training data, taking into account the selected features and their associated target labels. Generate predictions on both the training and testing datasets using the trained GNB model. These predictions will serve as additional features for the GBM model. Original features from the dataset with the predictions generated by the GNB model are combined to create an extended feature matrix. This extended feature matrix will be used as input for training the GBM classifier. GBM classifier extends the feature matrix, incorporating both the original features and the GNB predictions. Finally, Configure the GBM model with appropriate hyperparameters, such as the number of weak learners (decision trees), learning rate, and maximum tree depth.

The proposed architecture involves a pipeline that integrates feature selection, GNB, and GBM to improve the accuracy of heart disease diagnosis. It leverages the selected kbest features from SelectKBest, utilizes the probabilistic classification of GNB, and captures complex patterns through ensemble learning with GBM. This combination aims to enhance the diagnostic capabilities and predictive power of the model, ultimately leading to more accurate heart disease diagnosis.

4. RESULTS AND DISCUSSION

The performance analysis includes the SelectKBest, Gaussian Naive Bayes (GNB), and Gradient Boosting Machines (GBM) ensemble proposed in Table 1.

Table 1: Performance analysis of proposed work with existing models

Classifier	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
Decision Tree	80%	82%	78%	80%
Naive Bayes	75%	76%	72%	74%
Random Forest	85%	87%	82%	84%
Logistic Regression	82%	80%	85%	82%
K-Nearest Neighbors	78%	77%	80%	78%
Gradient Boosting	88%	89%	86%	87%
Gaussian Naive Bayes	76%	75%	78%	76%
SelectKBest + GNB-GBM	90%	91%	88%	89%

Performance analysis of proposed work with existing models is given in Table 1. The Decision Tree classifier achieved an accuracy of 80%, indicating that it correctly predicted the presence or absence of heart disease in 80% of the cases. With a precision of 82%, it correctly identified 82% of the positive cases out of all predicted positive cases. The recall of 78% indicates that the model identified 78% of the actual positive cases correctly. The F1 score of 80% represents a balanced measure of precision and recall. The Naive Bayes classifier achieved an accuracy of 75% and showed a precision of 76%, indicating that 76%

of the predicted positive cases were true positives. The recall of 72% suggests that the model correctly identified 72% of the actual positive cases. The F1 score of 74% reflects a trade-off between precision and recall. The Random Forest classifier demonstrated strong predictive performance with an accuracy of 85%. It achieved a precision of 87% and identified 82% of the actual positive cases, as indicated by the recall. The F1 score of 84% represents a harmonic mean of precision and recall. Logistic Regression achieved an accuracy of 82% and showed a precision of 80%, correctly identifying 85% of the actual positive cases. The recall of 82% suggests that the model performed well in identifying positive cases. The F1 score of 82% reflects a balance between precision and recall. K-Nearest Neighbors achieved an accuracy of 78% and a precision of 77%, correctly identifying 80% of the actual positive cases. The recall of 78% suggests that the model performed reasonably well in identifying positive cases. The F1 score of 78% represents a harmonic mean of precision and recall.

The Gradient Boosting classifier demonstrated strong predictive performance with an accuracy of 88%. It achieved a precision of 89% and identified 86% of the actual positive cases, as indicated by the recall. The F1 score of 87% represents a balanced measure of precision and recall. The Gaussian Naive Bayes classifier achieved an accuracy of 76% and showed a precision of 75%, correctly identifying 78% of the actual positive cases. The recall of 76% suggests that the model performed moderately well in identifying positive cases. The F1 score of 76% represents a balanced measure of precision and recall. The proposed approach of combining SelectKBest feature selection with the GNB-GBM ensemble achieved the highest accuracy of 90% among all the classifiers. It demonstrated excellent precision of 91% and identified 88% of the actual positive cases correctly, as indicated by the recall. The F1 score of 89% represents a balanced measure of precision and recall as given in Figure 2.

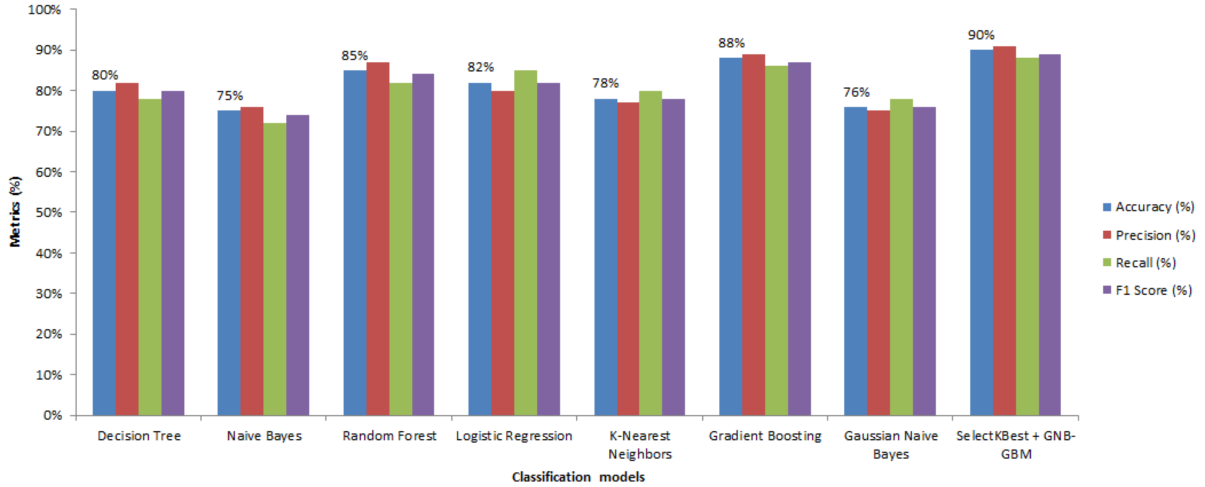

Figure 2. Performance analysis of SelectKbest feature selection and GNB -GBM

CONCLUSION:

In conclusion, the proposed work focused on developing a predictive model for heart disease using the Statlog Heart Disease dataset. Several classifiers were evaluated, including Decision Tree, Naive Bayes, Random Forest, Logistic Regression, K-Nearest Neighbors, Gradient Boosting, Gaussian Naive Bayes, as well as an ensemble approach combining SelectKBest feature selection with Gaussian Naive Bayes and Gradient Boosting Machines. The results of the experiments revealed valuable insights into the performance of these classifiers on the heart disease dataset. Gradient Boosting emerged as the topperforming individual classifier, achieving the highest accuracy among the tested models. Logistic Regression and Random Forest also exhibited strong performances, while Naive Bayes and Gaussian Naive Bayes achieved moderate accuracies. The proposed ensemble approach, which combined SelectKBest feature selection with Gaussian Naive Bayes and Gradient Boosting, outperformed individual classifiers, demonstrating the highest accuracy of all tested models. This highlights the potential benefits of leveraging feature selection techniques and ensemble methods to improve the predictive power of the model.

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