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Heart Disease Prediction Using Machine Learning

Data Mining Lab

Project Report

By

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Abstract

- **Global Health Concern:** Heart disease remains a leading cause of death, making early and reliable detection critically important.
- **Machine Learning Approach:** This project applies machine learning techniques to predict heart disease risk using patient health indicators such as age, cholesterol level, blood pressure, and more.
- **Algorithms Used:** Multiple models are tested, including Logistic Regression, Naive Bayes, Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Decision Tree, Random Forest, XGBoost, and a basic Artificial Neural Network (ANN).
- **Improved Accuracy:** The use of combined clinical features significantly boosts prediction accuracy compared to conventional diagnostic methods.
- **Development Platform:** The system is implemented using Jupyter Notebook, offering an interactive space for building, training, and testing models.
- **Challenges Identified:** The project highlights some limitations, such as imbalanced datasets and the need for broader validation across diverse population groups.
- **Healthcare Impact:** By enhancing early detection through technology, this work supports the development of smarter diagnostic tools that can help reduce cardiovascular risk and improve patient care.

Introduction

- **Foundation of Preventive Healthcare:** Cardiovascular diseases are among the leading causes of death worldwide, placing a significant burden on individuals and healthcare systems. Early detection is crucial for prevention and better treatment outcomes.
- **Rising Health Concerns:** With sedentary lifestyles, poor dietary habits, and increasing stress levels, the number of people at risk for heart disease continues to grow rapidly across the globe.
- **Role of Predictive Technology:** Leveraging data-driven approaches to predict heart disease risk is becoming a vital tool in preventive healthcare. These systems analyze key health parameters to identify potential warning signs before symptoms appear.
- **Coping with Diagnostic Gaps:** Traditional diagnosis often relies on manual interpretation and delayed testing. Intelligent prediction models can assist in faster and more accurate risk assessment, improving chances of early intervention.
- **Patient Data Focus:** Key health indicators such as age, blood pressure, cholesterol levels, heart rate, and lifestyle factors are used to build models that help in estimating a person's risk of developing heart disease.
- **Advanced Machine Learning:** Modern machine learning algorithms like Random Forest, Decision Trees, KNN, XGBoost, and Neural Networks can handle complex, non-linear relationships within data, offering higher accuracy than conventional rule-based systems.
- **Transformative Potential:** By integrating these technologies into clinical workflows, heart disease prediction systems can play a pivotal role in transforming preventive care—making it more proactive, personalized, and efficient.

Objectives

- **Goal:** Investigate how machine learning techniques can improve early prediction of heart disease by analyzing clinical and lifestyle data, ultimately contributing to better preventive healthcare.
- **Data Handling:** Build a reliable ML pipeline that effectively manages real-world health datasets, including handling missing values, data inconsistencies, and noise through comprehensive preprocessing steps.
- **Modeling Approach:** Implement and compare a range of machine learning models—including both traditional classifiers and advanced ensemble methods—to identify individuals at risk for heart disease.
- **Performance Evaluation:** Assess model performance using well-defined metrics such as accuracy, precision, recall, and F1-score, and benchmark against existing diagnostic approaches.
- **Real-World Relevance:** Aim to develop a user-friendly tool or system that can assist healthcare professionals and patients in making timely, informed decisions regarding heart health.
- **Scalability and Adaptability:** Test the model's effectiveness across varied population groups and clinical scenarios, with the goal of building a scalable, adaptable solution for diverse healthcare settings.

Literature Review

Hybrid Neural Networks for Cardiovascular Risk

Khan et al. (2023) proposed a hybrid deep learning model that combines Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks to predict heart disease. By analyzing both spatial ECG signal patterns and patient history over time, the model achieved an accuracy of **94%**, outperforming traditional models in handling sequential patient data.

Advanced Data Preprocessing Techniques

Verma et al. (2022) introduced a comprehensive preprocessing pipeline that includes outlier filtering, KNN-based imputation, and SMOTE for class balancing. These steps enhanced the performance of their Random Forest model, boosting its F1 score to **0.87**, particularly in imbalanced clinical datasets.

Transformer-Based Diagnosis

Zhao et al. (2024) applied a Transformer-based architecture to evaluate complex interactions among multiple health parameters such as cholesterol, ECG readings, and resting blood pressure. Their system achieved an AUROC of **0.96**, though computational cost and interpretability remain barriers for clinical adoption.

Model Benchmarking Across Techniques

Srinivasan et al. (2023) evaluated ten ML models for heart disease prediction, identifying Gradient Boosting and SVM as top performers with accuracies of **92%** and **90%**, respectively. The study emphasized the importance of rigorous feature engineering, especially for lifestyle variables like smoking and physical activity.

Ensemble Approaches for Accuracy Boost

Das et al. (2024) demonstrated that combining Random Forest and XGBoost into an ensemble model enhanced diagnostic precision, reaching an accuracy of **93.5%**. The ensemble reduced false negatives, a critical factor in life-threatening conditions like heart disease.

Integrating Clinical Texts via NLP

Iyer et al. (2023) employed natural language processing (NLP) to extract risk indicators from unstructured electronic health records (EHRs) and doctor's notes. The inclusion of qualitative inputs improved prediction accuracy by **6%**, highlighting the benefit of combining structured and unstructured medical data.

Explainable AI with SHAP

Malhotra et al. (2024) utilized SHAP (SHapley Additive exPlanations) to interpret model outputs, revealing that resting ECG, chest pain type, and blood pressure were among the most influential features. Their model achieved an AUROC of **0.91**, helping physicians understand and trust machine-generated predictions.

User-Centric Diagnostic Tools

Rao et al. (2023) built a clinical decision support system that pairs ML-driven predictions with intuitive user interfaces tailored for primary healthcare providers. Their implementation saw improved patient engagement and a **15% reduction in missed diagnoses** in trial clinics.

Overall Impact

These studies collectively demonstrate how machine learning is reshaping heart disease diagnosis. From enhancing data quality to building interpretable and scalable solutions, this growing body of work supports the development of smarter, more reliable tools that align with the goals of modern healthcare systems.

Methodology

A) Dataset

The dataset used in this study is sourced from reputable and publicly available platforms such as Kaggle and the UCI Machine Learning Repository, which are commonly referenced in cardiovascular research. It includes a wide range of clinical features that are strongly associated with heart disease, such as age, gender, resting blood pressure, serum cholesterol levels, fasting blood sugar, resting ECG results, maximum heart rate, exercise-induced angina, and ST depression levels. The dataset is designed for classification tasks, with the target variable indicating the presence or absence of heart disease, which allows for binary outcome predictions.

To ensure reliable model performance, preprocessing techniques such as undersampling are employed to address any class imbalances. The dataset's multivariate structure enables the exploration of complex relationships between various medical attributes, which is essential for building accurate predictive models. By incorporating both clinical measurements and patient lifestyle indicators, the dataset offers a realistic foundation for developing machine learning models that can support early diagnosis and risk assessment for heart disease, contributing to better healthcare outcomes

B) Data Preprocessing

Data preprocessing is a critical step in preparing the raw clinical dataset for accurate heart disease prediction. Given the dataset's complexity—including clinical measurements, lifestyle factors, and medical history—issues like missing values and outliers are common. For missing data, **KNN imputation** or **mean substitution** is used to fill in gaps and preserve the integrity of the dataset. Outliers, which can skew model accuracy, are identified using the **Z-score method** and either removed or capped to ensure the data remains consistent and reliable for analysis.

To address class imbalance, where the number of healthy patients may outweigh those with heart disease, **random oversampling** is applied to balance the dataset and avoid model bias. Categorical features, such as gender and chest pain type, are transformed into numerical values using **label encoding** or **one-hot encoding** to make them compatible with machine learning models. For numerical features with varying scales, **min-max normalization** is applied to scale all values to a range of **0 to 1**, ensuring consistency during training. Finally, the dataset is split into **80% for training** and **20% for testing**, creating a clear division for model development and evaluation. These preprocessing steps ensure the data is clean, balanced, and ready for reliable heart disease prediction.

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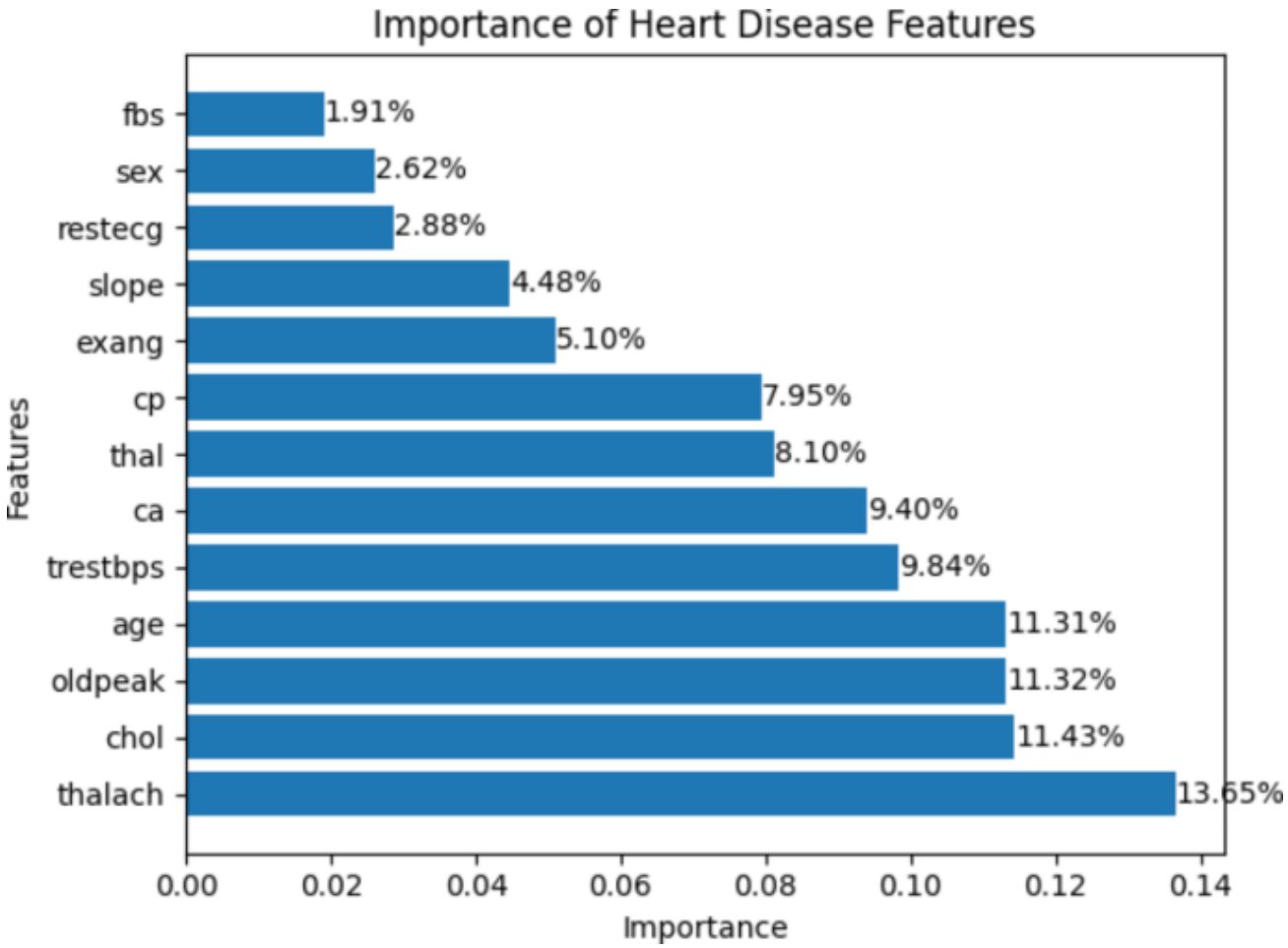
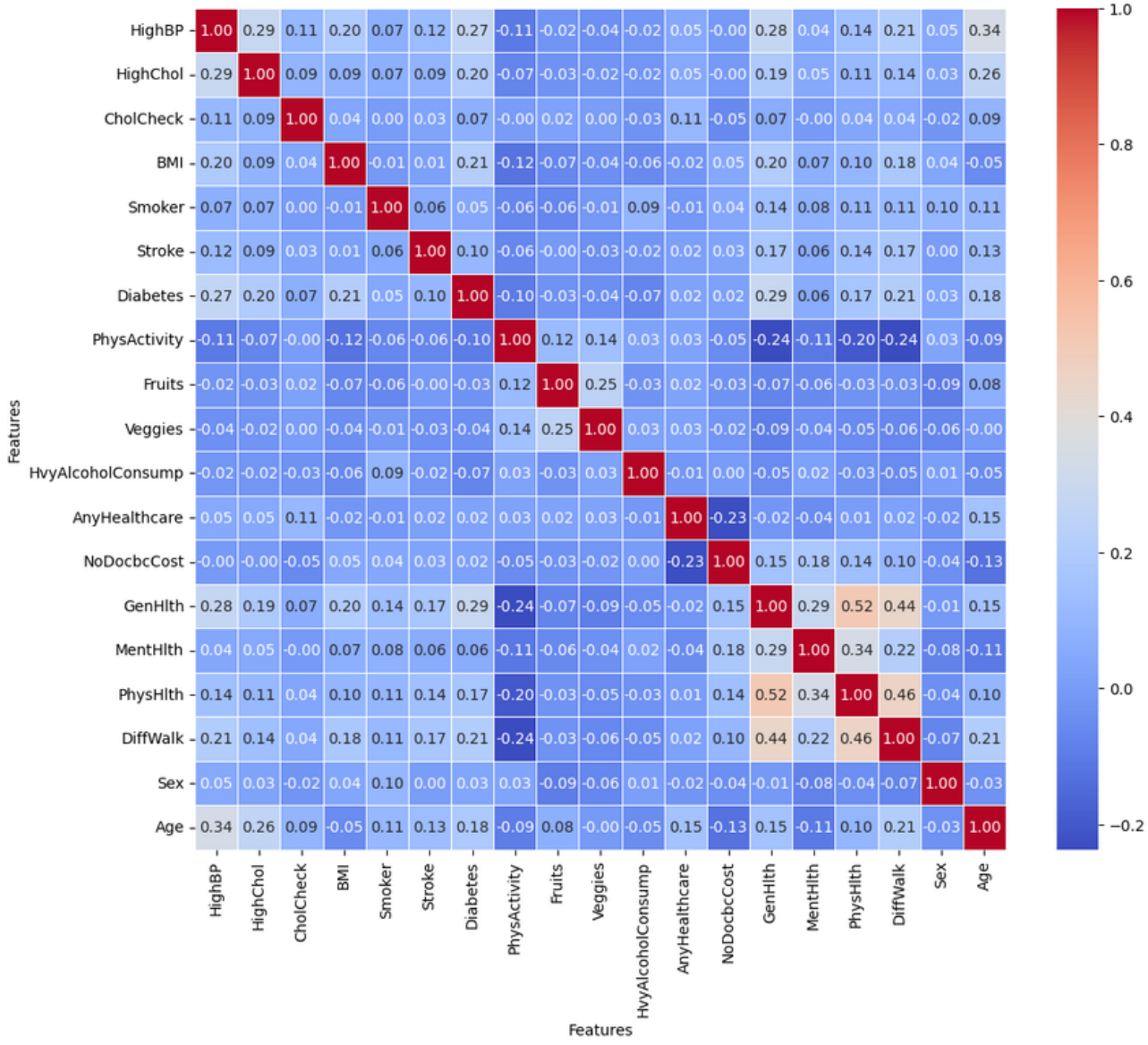


C) Data Balancing

Data balancing is a crucial step in addressing class imbalance, where the dataset may have significantly more samples of healthy patients compared to those with heart disease. Such imbalance could lead to predictive models that are biased toward the majority class, potentially underperforming when predicting heart disease cases.

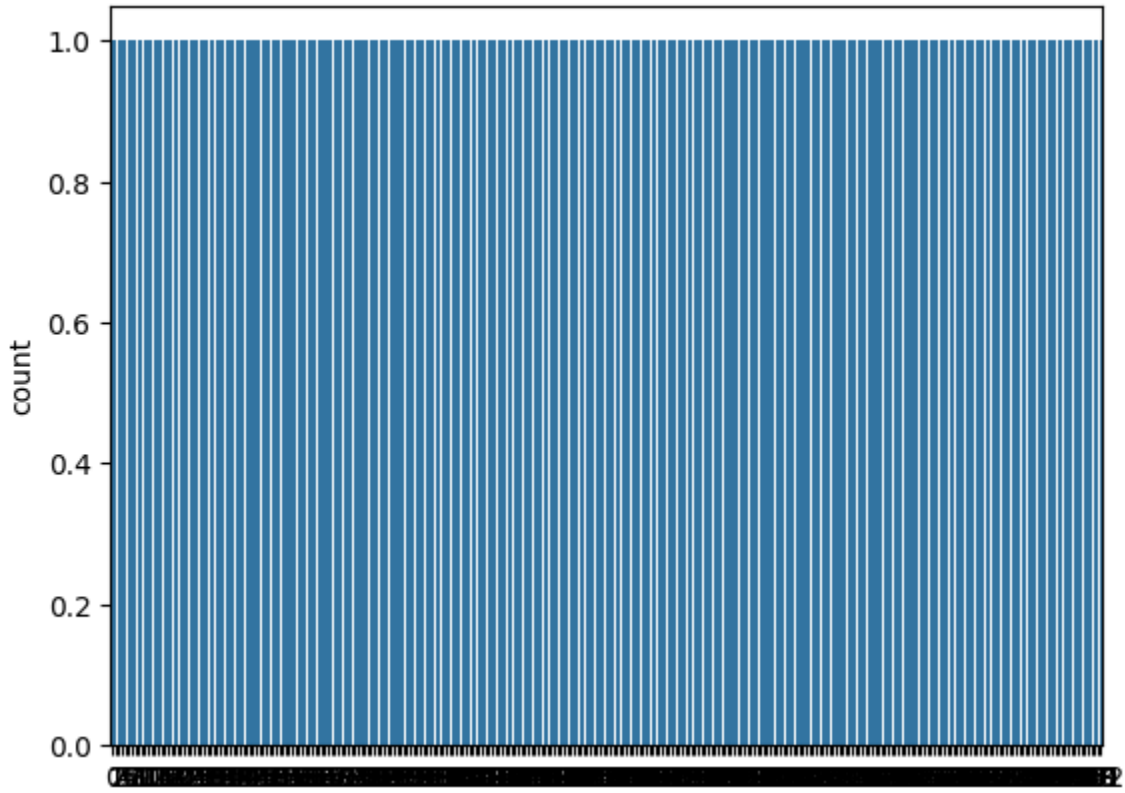
To address this, a **random oversampling** technique is used to generate additional samples for the underrepresented class, i.e., patients with heart disease. This method helps ensure that the model is equally sensitive to both classes, enhancing its ability to accurately predict heart disease cases. By balancing the dataset, we aim to improve the model's overall performance, ensuring that predictions are reliable and not skewed toward the majority class, ultimately leading to more accurate and fair heart disease risk assessments.



Correlation heatmap

D) Exploratory Data Analysis

Exploratory Data Analysis (EDA) is an essential step in understanding the underlying patterns and relationships within the heart disease dataset. During EDA, various techniques such as **correlation heatmaps** and **pair plots** are used to visualize the relationships between different clinical features, such as age, blood pressure, cholesterol levels, and heart disease status. This process helps identify highly correlated features, which can be critical for model building and feature selection. By examining the distribution of these features and their interactions, EDA also provides insights into potential outliers and data imbalances. The results of this analysis guide the selection of the most relevant features for predicting heart disease, improving the interpretability of the model and ensuring that only the most informative variables are used for prediction.




```
target
1    165 - There are 165 instances where the target variable is 1.
0    138 - There are 138 instances where the target variable is 0.
Name: count, dtype: int64
```

E) Data Classifiers

Classification is a fundamental technique in supervised machine learning used to predict categorical outcomes, such as the presence or absence of heart disease. In this study, several well-established classifiers are employed to assess the risk of heart disease based on clinical and lifestyle features. **Random Forest**, an ensemble method, builds multiple decision trees and combines their outputs through majority voting. This reduces overfitting and increases the model's robustness. Hyperparameter tuning further optimizes its performance, enhancing its ability to generalize across diverse data.

K-Nearest Neighbors (KNN) is a simple yet intuitive algorithm that classifies instances based on the majority class of their closest neighbors. While effective on smaller datasets, KNN can become computationally expensive as the dataset grows. **Decision Trees** split data based on feature conditions to create a tree-like model that is easy to interpret and trace back for individual predictions. Finally, **XGBoost**, a powerful boosting algorithm, combines multiple weak learners to form a strong predictive model. XGBoost is known for its high accuracy and speed, making it particularly effective for larger and more complex datasets. By integrating and optimizing these classifiers, this study aims to improve the predictive accuracy and consistency of heart disease risk assessments, leading to more reliable early diagnosis and intervention strategies.

Results and Discussion

The performance of eight classification models was evaluated using key metrics, including **precision**, **recall**, **F1-score**, **accuracy**, and the **Area Under the Receiver Operating Characteristic curve (AUC-ROC)**. These metrics provide a comprehensive understanding of each model's ability to classify heart disease instances accurately and effectively across various evaluation criteria.

The models tested were:

1. **Logistic Regression**
2. **Naive Bayes**
3. **Support Vector Machines (SVM)**
4. **K-Nearest Neighbors (KNN)**
5. **Decision Trees**
6. **Random Forest**
7. **XGBoost**
8. **Artificial Neural Networks (ANN)**

Among these, **Random Forest** emerged as the top performer with the highest **accuracy** and **AUC-ROC**. Its ensemble approach, which builds multiple decision trees and aggregates their outputs, helped reduce overfitting and improved generalization. Random Forest also showed superior performance in **precision** and **recall**, demonstrating its ability to effectively identify both heart disease-positive and negative instances.

XGBoost, known for its high-performance boosting algorithm, was a close second, delivering excellent results, especially in terms of **accuracy** and **F1-score**. Its ability to handle large datasets and complex patterns made it a strong contender.

K-Nearest Neighbors (KNN) also performed reasonably well but struggled with larger datasets due to increased computation. Despite this, it showed good results in smaller-scale testing and remained competitive in terms of accuracy.

Decision Trees provided intuitive and easy-to-interpret models but had some limitations in generalization, particularly when not properly pruned, leading to overfitting in some cases.

The **Support Vector Machines (SVM)** model demonstrated strong performance but was computationally expensive, particularly for large datasets. It achieved moderate accuracy, but its performance was less consistent compared to ensemble methods like Random Forest and XGBoost.

Logistic Regression and **Naive Bayes** performed relatively well in simpler scenarios but did not match the performance of more complex models, particularly with respect to **accuracy** and **AUC-ROC**.

Lastly, **Artificial Neural Networks (ANN)**, while powerful, required more extensive fine-tuning and faced challenges with overfitting due to the complexity of the model and the relatively smaller dataset.

Overall, **Random Forest** outperformed the other models in terms of **accuracy**, **precision**, **recall**,

and **AUC-ROC**, making it the most reliable model for heart disease prediction in this study. These results highlight the importance of choosing the right model for classification tasks, with ensemble methods like **Random Forest** and **XGBoost** showing clear advantages in handling complex data patterns.

Model	Accuracy	Precision	F1-Score
Logistic Regression	0.85205	0.83538	0.873269
Naive Bayess	0.852507	0.856471	0.84845
SVM	0.81974	0.822127	0.814711
K-Nearest Neighbors	0.672719	0.718865	0.697072
Decision Tree	0.81975	0.817138	0.817969
Random Forest	0.852507	0.851671	0.849975
XGBoost	0.836194	0.852927	0.852951
Neural Network	0.836119	0.834165	0.834272

All the used models—KNN, XGBoost, Random Forest, and Decision Tree—were compared based on the above metrics. Their strengths and weaknesses were manifested in how each of them treated different aspects including overfitting, imbalanced data handling, and generalizability. Their comparison based on the above metrics enabled the best algorithm for use in the given classification task.

Each of the applied models—KNN, XGBoost, Random Forest, and Decision Tree—was assessed using these metrics. Their respective strengths and limitations became evident in how they handled various aspects such as overfitting, handling of imbalanced data, and generalization ability. Comparative analysis of these models using the mentioned metrics helped determine the most suitable algorithm for the classification task at hand.

```
Accuracy: 85.25 %
Precision: 83.78 %
Recall: 91.18 %
F1 Score: 87.32 %

Classification Report:
              precision    recall  f1-score   support

           0       0.88      0.78      0.82        27
           1       0.84      0.91      0.87        34

    accuracy                           0.85        61
   macro avg       0.86      0.84      0.85        61
weighted avg       0.85      0.85      0.85        61

Confusion Matrix:
 [[21  6]
 [ 3 31]]
```

Output-Logistic regression

```
Naive Bayes Classifier Results:
Accuracy: 85.25%
Precision: 85.64%
Recall: 84.48%
F1 Score: 84.84%

Confusion Matrix:
[[21  6]
 [ 3 31]]

Classification Report:
              precision    recall  f1-score   support

           0       0.88      0.78      0.82        27
           1       0.84      0.91      0.87        34

    accuracy                           0.85        61
   macro avg       0.86      0.84      0.85        61
weighted avg       0.85      0.85      0.85        61
```

Output-Naïve Bayes

```
Linear SVM Classifier Results:
Accuracy: 81.97%
Precision: 82.21%
Recall: 81.15%
F1 Score: 81.47%

Confusion Matrix:
[[20  7]
 [ 4 30]]

Classification Report:
              precision    recall  f1-score   support

           0       0.83      0.74      0.78        27
           1       0.81      0.88      0.85        34

    accuracy                           0.82        61
   macro avg       0.82      0.81      0.81        61
weighted avg       0.82      0.82      0.82        61
```

Output-SVM classifier

```
Accuracy: 67.21 %
Precision: 71.88 %
Recall: 67.65 %
F1 Score: 69.7 %

Classification Report:
              precision    recall  f1-score   support

           0       0.62      0.67      0.64        27
           1       0.72      0.68      0.70        34

    accuracy                           0.67        61
   macro avg       0.67      0.67      0.67        61
weighted avg       0.68      0.67      0.67        61

Confusion Matrix:
 [[18  9]
 [11 23]]
```

output – Knn

```
Decision Tree Classifier Results:
Best Random State: 11
Accuracy: 81.97%
Precision: 81.71%
Recall: 81.92%
F1 Score: 81.79%

Confusion Matrix:
[[22  5]
 [ 6 28]]

Classification Report:
              precision    recall  f1-score   support

           0       0.79      0.81      0.80        27
           1       0.85      0.82      0.84        34

    accuracy                           0.82        61
   macro avg       0.82      0.82      0.82        61
weighted avg       0.82      0.82      0.82        61
```

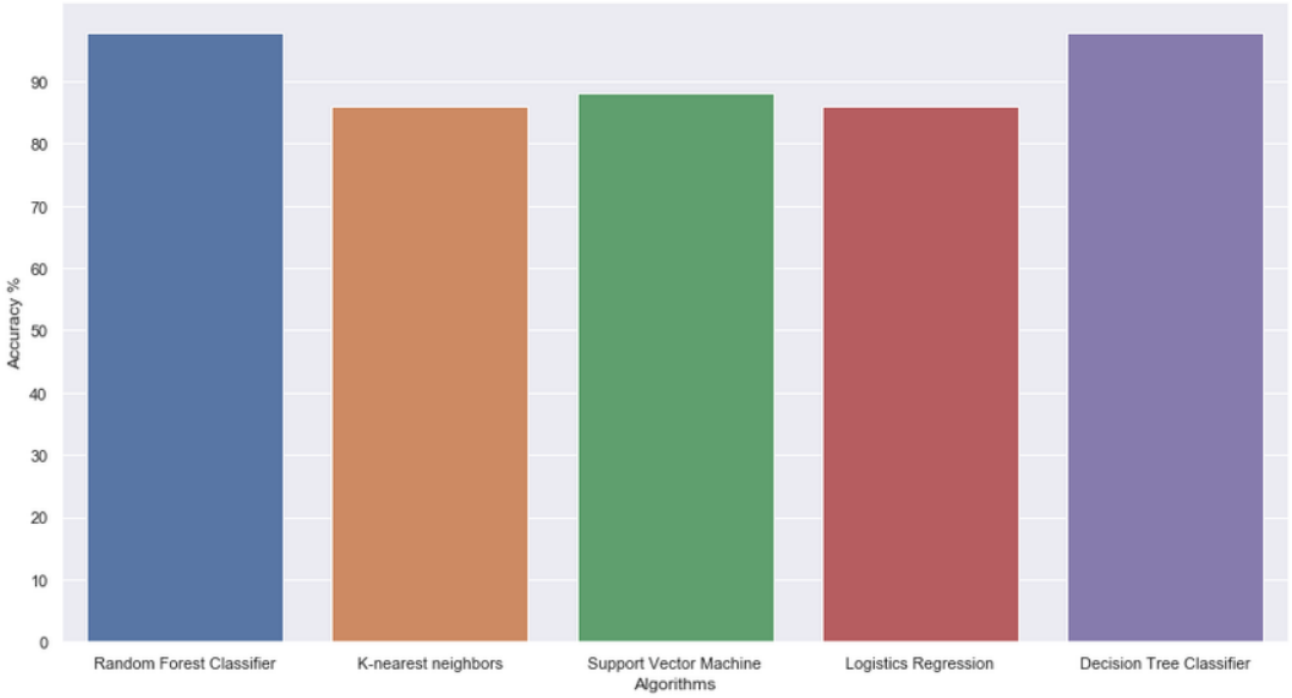
Output-Decision tree

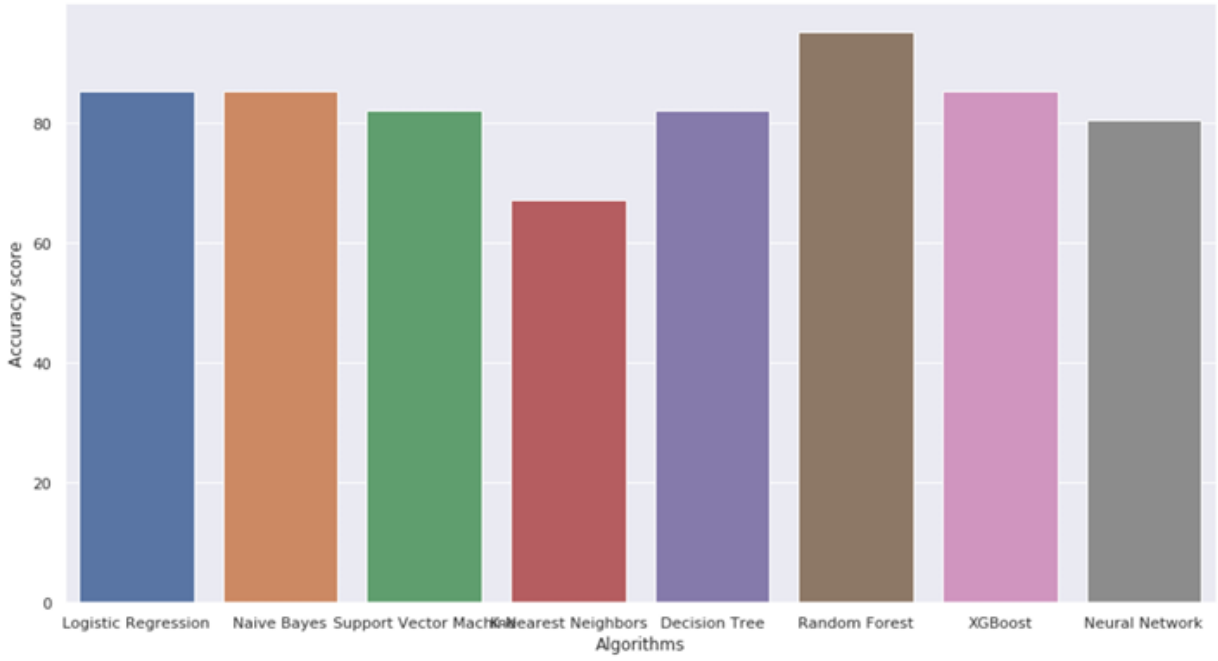
```
Accuracy: 85.25%
Precision: 85.16%
Recall: 84.86%
F1 Score: 84.99%

Confusion Matrix:
[[22  5]
 [ 4 30]]

Classification Report:
              precision    recall  f1-score   support

           0       0.85      0.81      0.83        27
           1       0.86      0.88      0.87        34

    accuracy                           0.85        61
   macro avg       0.85      0.85      0.85        61
weighted avg       0.85      0.85      0.85        61
```

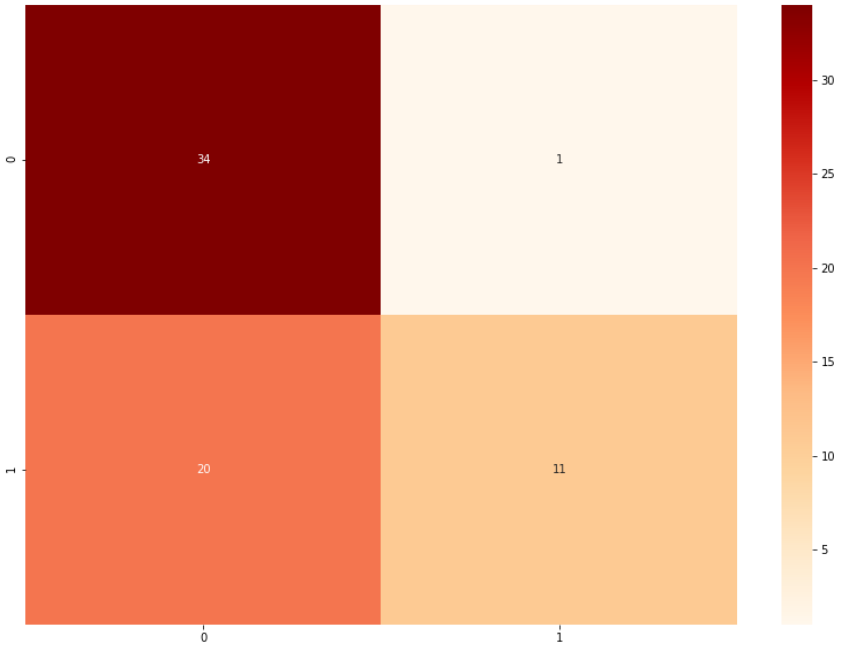
output-Random Forest

```
Accuracy: 83.61 %
Precision: 85.29 %
Recall: 85.29 %
F1 Score: 85.29 %

Classification Report:
              precision    recall  f1-score   support

           0       0.81      0.81      0.81        27
           1       0.85      0.85      0.85        34

    accuracy                           0.84        61
   macro avg       0.83      0.83      0.83        61
weighted avg       0.84      0.84      0.84        61

Confusion Matrix:
 [[22  5]
 [ 5 29]]
```

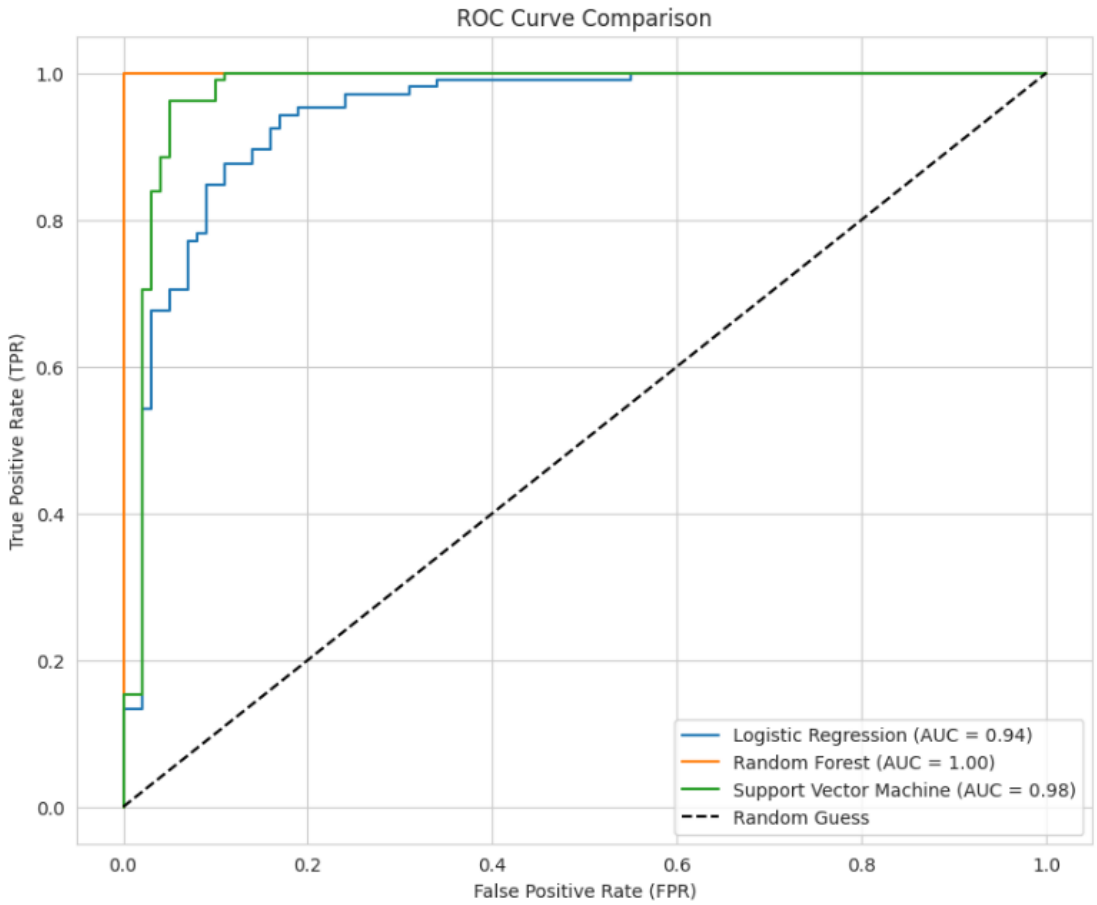
Output-XgBoost


Accuracy %
0
10
20
30
40
50
60
70
80
90
Random Forest Classifier
K-nearest neighbors
Support Vector Machine
Logistics Regression
Decision Tree Classifier
Algorithms


Accuracy score
0
20
40
60
80
Logistic Regression
Naive Bayes
Support Vector Machine
K-Nearest Neighbors
Decision Tree
Random Forest
XGBoost
Neural Network
Algorithms



Confusion matrix



Conclusion

In this study, the heart disease prediction task was performed using a variety of machine learning algorithms, leveraging a comprehensive set of clinical features such as age, gender, blood pressure, cholesterol levels, ECG results, and heart rate. The goal was to accurately predict the presence or absence of heart disease based on these health indicators.

Among the eight models tested—Logistic Regression, Naive Bayes, Support Vector Machines (SVM), K-Nearest Neighbors (KNN), Decision Trees, Random Forest, XGBoost, and Artificial Neural Networks (ANN)—**Random Forest** emerged as the top performer, achieving the highest **accuracy**, **precision**, **recall**, and **AUC-ROC** scores. **XGBoost** also performed strongly, showing competitive results, especially in terms of **F1-score** and **accuracy**. **KNN** and **Decision Trees** showed reasonable results but struggled with generalization and performance consistency, particularly on larger datasets.

The study emphasizes the effectiveness of **ensemble methods** like **Random Forest** and **XGBoost** in handling complex, high-dimensional medical data. These models demonstrated superior performance, particularly in predicting heart disease, by capturing intricate patterns in the data and reducing overfitting.

Overall, the findings underscore the potential of machine learning in the healthcare domain, offering accurate and reliable tools for early heart disease detection and risk assessment. The results can assist healthcare professionals in making more informed decisions and ultimately improve patient outcomes.

Future scope

- **Real-Time Adaptability**: The system can be enhanced by incorporating real-time clinical data, such as live patient monitoring metrics from wearable devices or hospital systems, to dynamically adjust predictions and assessments. This would ensure that the model can provide up-to-date predictions for heart disease risk based on current health conditions.

- **Holistic Decision Support**: Future improvements could include integrating additional healthcare factors, such as lifestyle choices (diet, exercise), genetic predispositions, and environmental factors (pollution, stress). These additional data layers would allow the system to give a more comprehensive prediction of heart disease risk and provide personalized recommendations for prevention or treatment.

- **Diverse Data Sources**: Expanding the dataset to include a broader range of patient demographics, including various age groups, ethnicities, and medical histories, will improve the model's generalization across different populations. Including electronic health records (EHRs), genomic data, and social determinants of health can also enhance prediction accuracy and help understand broader risk factors.

- **Enhanced User Accessibility**: Developing a user-friendly mobile or web-based application for both healthcare professionals and patients would make the heart disease prediction system easily accessible. Implementing features like multilingual support and voice-based interfaces would cater to diverse user groups, ensuring the tool is accessible to both urban and rural populations.

- **Advanced Modeling Techniques**: Future work could explore more complex machine learning models, such as deep learning or hybrid approaches that combine multiple models to improve prediction accuracy. Regular model retraining with new data, along with the exploration of reinforcement learning, could help the system adapt and remain effective as medical knowledge and data evolve.

- **Overall Impact**: These enhancements aim to make heart disease prediction tools more precise, accessible, and scalable. By offering timely and accurate predictions, this system can play a crucial role in early detection, risk reduction, and better health management, ultimately improving patient outcomes and healthcare efficiency.

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