

# **Coronary Artery Disease Prediction using Machine Learning**

A PROJECT REPORT

*Submitted by*

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## **ABSTRACT**

In this project, the primary focus is on the accurate diagnosis of coronary artery disease, a condition that relies on a combination of clinical and pathological data for effective assessment. To aid medical professionals in this diagnostic process, we have developed a sophisticated coronary artery disease prediction system. This system leverages patient clinical data to provide predictions regarding their heart disease status.

Using this method, we choose 13 important clinical characteristics, such as age, type of chest pain, sex, resting electrocardiogram results, trestbps (resting blood pressure), and maximum heart rate reached during exercise (thalach), cholesterol levels, the existence of exercise-induced angina (exang), the oldpeak/slopp exercise-induced ST segment, the number of major vessels coloured by fluoroscopy (ca), and the ST depression induced by exercise relative to rest and the thalassemia type (thal). Using models such as Adaboost classifier, Bagging classifier, Gradient Boosting classifier, KNN, Decision Tree, Random Forest, Naïve Bayes, etc. To determine accuracy and precision scores, we will construct multiple models for training. Afterwards, we will construct a voting model to enhance the model. Next, the confusion matrix will be created. Then employ various machine learning models to classify heart disease based on these crucial clinical features. The proposed system is divided into several sections, the most prominent of which are an input section where clinical data about patients is entered and a prediction performance display section. The ultimate goal of this all-inclusive system is to improve the diagnosis of coronary artery disease, which will help patients and medical professionals alike.

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## **LIST OF SYMBOLS AND ABBREVIATIONS**

CAD	Coronary Artery Disease
DTC	Decision Tree Classifier
KNC	K Neighbour Classifier
ML	Machine Learning
SVC	Support vector machine
MNB	Multinomial Naïve Bayes
LRC	Logistic Regression
ABC	Ada boost classifier
BC	Bagging Classifier
ETC	Extra tree classifier
GBDT	Gradient Boosting Classifier

# **CHAPTER 1**

## **INTRODUCTION**

### **1.1 Introduction to project**

Coronary artery disease (CAD) is a leading cause of morbidity and mortality worldwide, characterized by the narrowing or blockage of coronary arteries due to atherosclerosis. As the global population ages and lifestyle-related risk factors increase, the prevalence of CAD continues to rise, making early detection and effective management critical to improving patient outcomes. Traditional methods of diagnosing CAD, including invasive procedures like angiography, can be costly and may pose risks to patients. Therefore, there is a pressing need for non-invasive and accurate predictive models that can identify individuals at risk for CAD early on.

Recent advancements in machine learning and data analytics offer promising solutions to this challenge. By leveraging large datasets that encompass a wide range of clinical, demographic, and lifestyle factors, it is possible to develop predictive algorithms that can assess the likelihood of CAD with a high degree of accuracy. This project aims to explore and implement machine learning techniques to analyze patient data and develop a robust predictive model for CAD. The ultimate goal is to provide healthcare practitioners with valuable tools that facilitate timely interventions, improve treatment outcomes, and enhance overall patient care.

Through this research, we aim to contribute to the growing body of knowledge in the field of predictive healthcare and demonstrate the effectiveness of machine learning approaches in addressing one of the most significant health challenges of our time. By focusing on key factors associated with CAD, this project seeks to refine risk assessment strategies, ultimately paving the way for personalized medicine and more effective healthcare delivery.

### **1.2 Motivation**

The coronary artery disease prediction project represents a significant and impactful endeavor in the intersection of healthcare and technology. By focusing on enhancing the prediction capabilities for coronary artery disease, this project aims to contribute to early detection and improved treatment strategies, ultimately leading to better patient outcomes and potentially saving lives.

This research is situated at the forefront of integrating machine learning with healthcare a rapidly evolving field that offers the potential for groundbreaking innovations. The insights gained from this project can pave the way for future advancements in the diagnosis and management of coronary artery disease.

In addition to the immediate benefits to patient care, this project provides an invaluable opportunity for personal and professional development. Engaging with complex data analysis and machine learning techniques will enhance my skills and knowledge, which are essential in today's data-driven world. The expertise gained through this project will not only contribute to my personal growth but will also be beneficial in future research and career endeavours.

Furthermore, collaboration with experts in the medical and technological fields is anticipated, fostering a rich exchange of ideas and perspectives. Such interactions may lead to new opportunities and partnerships that can extend the reach and impact of this work.

Importantly, the outcomes of this project have the potential to influence healthcare policies and practices, thereby improving the standards of care for patients with coronary artery disease. This legacy of innovation and improvement in healthcare can inspire future researchers and practitioners in the field.

### **1.3 Sustainable Development Goal of the project**

The project "Coronary Artery Disease Prediction Using Machine Learning" aligns with several Sustainable Development Goals (SDGs), particularly:

#### **1. SDG 3: Good Health and Well-being**

- This project directly contributes to SDG 3 by enhancing the ability to predict coronary artery disease (CAD) risk through advanced data analytics and machine learning techniques. By improving early detection and risk assessment, the project supports the development of targeted interventions and personalized treatment plans, ultimately aiming to reduce the burden of heart disease and improve health outcomes. The insights gained from this project can lead to more effective management of CAD, contributing to the overall well-being of individuals and communities.

## 2. SDG 9: Industry, Innovation, and Infrastructure.

- Our approach promotes innovation in healthcare by integrating machine learning into clinical practice for CAD prediction. By developing robust predictive models, this project encourages advancements in health informatics and the infrastructure needed to support data-driven decision-making in medicine. This innovation not only enhances healthcare delivery but also establishes a foundation for scalable solutions that can be applied to other medical conditions, fostering a more resilient healthcare system.

## 3. SDG 17: Partnerships for the Goals

- The project emphasizes the importance of collaboration among healthcare providers, researchers, and technology experts. By fostering partnerships and sharing knowledge across disciplines, this project aims to create a synergistic approach to tackling coronary artery disease. Collaborative efforts can enhance research capabilities, improve data sharing, and lead to the development of comprehensive strategies for disease prevention and management, ultimately contributing to the achievement of shared health goals.

Model	Features	Advantages	Dis advantages
Logistic regression	Translates any input into a value between 0 and 1 using the logistic function.	Simple, interpretable, and computationally efficient	Not suitable for complex relationships
Gaussian naïve bias	Makes the assumption that features are conditionally independent given the class	Works well with high-dimensional data	Assumes independence between features, which may not hold in some cases.

KNN	Assigns an instance to the class that is most common among its k-nearest neighbors	Non-parametric method, which means it doesn't make strong assumptions about the underlying data distribution	Computationally expensive for large datasets
Decision Tree	Recursively splits the data into subsets based on the most significant attribute at each node	Can handle both numerical and categorical data, and can model complex relationships	Prone to overfitting if the tree is too deep
SVM	To find a hyperplane that best separates data points into different classes	Effective in high-dimensional spaces	Choosing the right kernel and tuning hyperparameters can be challenging

Table 1.1: Difference between various algorithm

## **CHAPTER 2**

### **LITERATURE SURVEY**

#### **2.1 Literature Survey Papers**

1. Title: “Machine Learning Models for Predicting Coronary Artery Disease”  
Journal: Journal of Medical Systems  
Year: 2020  
Methodology: Various machine learning algorithms evaluated on patient health records  
Technologies: Random Forest, Support Vector Machines, Logistic Regression  
Pros: High accuracy in predicting CAD based on multiple patient features.  
Cons: Requires extensive labelled data for effective training.
  
2. Title: “Deep Learning in Cardiology: A Review”  
Journal: IEEE Reviews in Biomedical Engineering  
Year: 2019  
Methodology: Overview of deep learning applications in cardiac imaging  
Technologies: Convolutional Neural Networks, Recurrent Neural Networks  
Pros: Enhanced image analysis capabilities for CAD diagnosis.  
Cons: Limited interpretability of models can hinder clinical adoption.
  
3. Title: “Predictive Analytics in Cardiovascular Disease: A Machine Learning Approach”  
Journal: Health Informatics Journal  
Year: 2021  
Methodology: Utilization of patient demographics and clinical data for predictions  
Technologies: Gradient Boosting Machines, Neural Networks  
Pros: Improves risk stratification in CAD patients.  
Cons: Model performance may vary significantly across different populations.
  
4. Title: “Artificial Intelligence in Predicting Coronary Heart Disease”  
Journal: Frontiers in Cardiovascular Medicine  
Year: 2022

Methodology: Machine learning applied to electronic health records  
Technologies: Decision Trees, Ensemble Methods  
Pros: Can identify high-risk patients for preventative measures.  
Cons: High dependency on the quality of input data.

5. Title: “Integrating Machine Learning in Coronary Disease Risk Assessment”  
Journal: European Journal of Preventive Cardiology  
Year: 2021  
Methodology: Predictive modelling using lifestyle and clinical variables  
Technologies: Logistic Regression, Neural Networks  
Pros: Facilitates personalized medicine approaches.  
Cons: Potential overfitting if not properly validated.
6. Title: “Data-Driven Approaches to Coronary Artery Disease Diagnosis”  
Journal: Journal of the American College of Cardiology  
Year: 2020  
Methodology: Use of machine learning to analyze angiographic data  
Technologies: Deep Learning, K-Nearest Neighbours  
Pros: Offers better diagnostic performance compared to traditional methods.  
Cons: Computationally intensive and may require specialized hardware.
7. Title: “Predictive Modelling for Heart Disease Using Machine Learning Techniques”  
Journal: BMC Medical Informatics and Decision Making  
Year: 2019  
Methodology: Comparison of machine learning models on clinical datasets  
Technologies: Support Vector Machines, Naïve Bayes  
Pros: Provides a robust framework for CAD prediction.  
Cons: Limited generalizability if models are trained on small datasets.
8. Title: “Artificial Intelligence in Cardiology: Transforming Diagnosis and Treatment”  
Journal: Nature Reviews Cardiology  
Year: 2021  
Methodology: Meta-analysis of AI applications in cardiovascular disease  
Technologies: Machine Learning, Natural Language Processing  
Pros: Highlights the potential for AI to revolutionize CAD management.



Cons: Ethical concerns regarding data privacy and bias.

9. Title: “Ensemble Learning for Improved Prediction of Coronary Artery Disease”

Journal: Journal of Healthcare Engineering

Year: 2022

Methodology: Ensemble techniques applied to patient health metrics

Technologies: Random Forests, Boosting Algorithms

Pros: Enhances prediction accuracy through model combination.

Cons: More complex implementation and maintenance.

10. Title: “Utilizing Machine Learning for Early Detection of CAD”

Journal: Journal of Cardiovascular Medicine

Year: 2020

Methodology: Machine learning algorithms for early-stage detection using non-invasive tests

Technologies: Neural Networks, Support Vector Machines

Pros: Early detection can lead to timely interventions.

Cons: The need for large datasets for effective model training and validation

## **2.2 Clinical Data Analysis Techniques for Cardiovascular Risk Assessment**

Clinical data analysis plays a pivotal role in coronary artery disease (CAD) prediction, where various patient data, including demographic, clinical, and lifestyle factors, are analyzed to assess cardiovascular risk. Techniques such as statistical analysis, data normalization, and feature selection are used to identify and enhance key risk factors for CAD prediction. Advanced methodologies, like regression analysis and principal component analysis (PCA), are applied to extract meaningful insights from large datasets, helping to highlight the most influential predictors in CAD risk models. These techniques contribute to building an effective pipeline for CAD risk assessment and early detection.

## **2.3 Limitations Identified from Literature Survey**

Despite significant progress in using machine learning for CAD prediction, several limitations remain:

- **Data Quality and Variability:** Clinical datasets often contain missing or inconsistent data due to varying healthcare practices, which can impact model

accuracy.

- **Overfitting in Complex Models:** Deep learning models may struggle with overfitting, especially when working with limited or highly specific datasets, affecting generalization.
- **Data Imbalance:** CAD datasets often contain fewer positive cases, leading to class imbalance, which can bias models toward negative outcomes.
- **Interpretability of Models:** Many machine learning models, particularly deep learning, are often seen as "black boxes," limiting interpretability in clinical settings where understanding the decision process is critical.

## **2.4 Research Objectives**

Based on these identified challenges, the following research objectives are proposed:

- Develop a CAD prediction model that is robust to missing or inconsistent clinical data.
- Enhance the generalization of the machine learning model across diverse populations and healthcare settings.
- Address data imbalance through techniques such as resampling or cost-sensitive learning to improve model sensitivity to CAD-positive cases.
- Implement interpretable models or post-hoc interpretability techniques to provide clinicians with insight into CAD risk predictions.

## **2.5 Product Backlog (Key User Stories with Desired Outcomes)**

The following product backlog includes key user stories with desired outcomes:

- As a healthcare provider, I want a model that predicts CAD risk with high accuracy, so I can identify at-risk patients early and provide timely interventions.
- As a clinical researcher, I want a robust and interpretable model to better understand CAD risk factors, so I can contribute to improving risk assessment guidelines.
- As a data scientist, I want a model resilient to data quality issues and class imbalance, so I can develop reliable predictions even with real-world clinical data constraints.

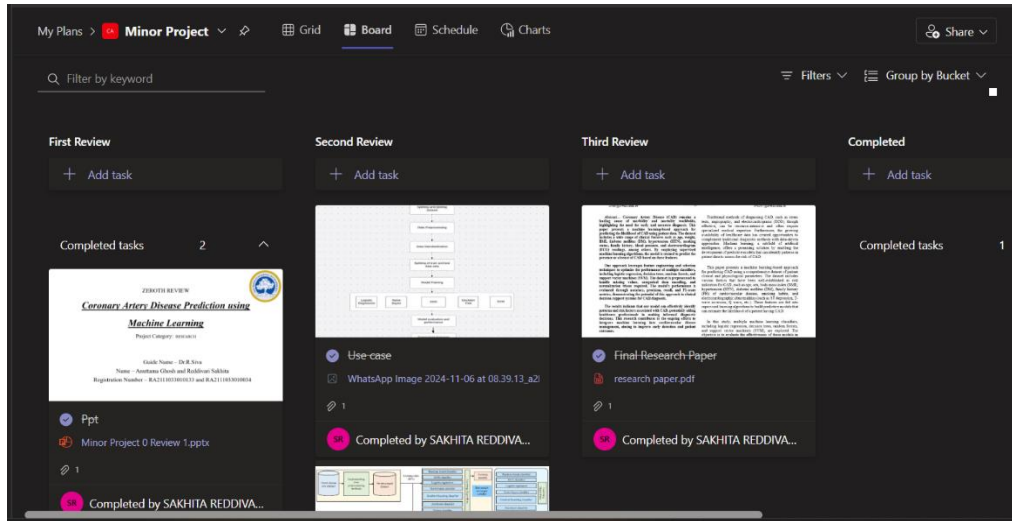


Figure 2.1 MS Planner Board

## 2.6 Plan of Action (Project Roadmap)

The following plan of action outlines the steps for achieving the research objectives and delivering the desired outcomes:

1. Conduct an extensive literature review on machine learning and statistical methods for CAD prediction.
2. Preprocess the dataset by addressing missing values and normalizing data to ensure high-quality inputs.
3. Build and evaluate multiple machine learning models, including logistic regression, SVMs, and neural networks, for CAD risk prediction.
4. Address class imbalance through oversampling techniques, synthetic minority oversampling (SMOTE), or cost-sensitive learning.
5. Enhance interpretability using techniques like SHAP (Shapley Additive explanations) or LIME (Local Interpretable Model-agnostic Explanations) to make model decisions understandable for clinical use.
6. Test model robustness across diverse patient datasets to assess generalization performance.
7. Develop a user-friendly interface for easy access and use by healthcare professionals.
8. Evaluate the final model in collaboration with medical experts and assess its effectiveness in real-world clinical settings.
9. Optimize Model Efficiency for Real-Time Application: Refine the model to reduce computational complexity, ensuring it can make quick predictions in a

clinical environment where real-time decisions are essential.

10. Document and Publish Findings: Compile project findings and methodology in a comprehensive report or research paper, enabling broader knowledge sharing with the healthcare and data science communities.

		week1	week2	week3	week4	week1	week2	week3	week4
Proposal	Features								
Feature 1	Data Collection and Exploration								
Feature 2	Cleaning and Preproc								
Feature 3	eature Selection and Engineerin								
Feature 4	Model Selection and Training								
Feature 5	Model Evaluation and Validation								
Feature 6	Reporting								

Figure 2.2 Plane of Action

## CHAPTER 3

### SPRINT PLANNING AND EXECUTION METHODOLOGY

#### 3.1 SPRINT I

##### 3.1.1 Objectives with User Stories of Sprint I

The primary objective of Sprint I was to lay the foundation for developing a coronary artery disease prediction system. This phase was dedicated to acquiring a comprehensive dataset comprising 13 critical clinical features such as age, type of chest pain, cholesterol levels, and resting blood pressure. Another key goal was to perform data cleaning and preprocessing to ensure the reliability of inputs for model training. The initial models aimed to assess the feasibility of predicting coronary artery disease using basic machine learning algorithms.

##### 3.1.2 Functional Document

The core functions executed in Sprint I included:

- **Data Collection:** Patient data was collected from medical databases that contained vital clinical and pathological information relevant to coronary artery disease. The data featured attributes like age, sex, chest pain type, cholesterol, thalach (maximum heart rate), and ST depression levels.
- **Data Preprocessing:** The team undertook data cleansing to manage missing or inconsistent values. Techniques such as median imputation were employed to fill gaps in data, while scaling methods like MinMaxScaler were applied to numerical attributes to standardize inputs for the machine learning models.
- **Prototype Interface:** The early-stage interface was developed as a straightforward form allowing medical professionals to input patient data and receive model predictions. This prototype laid the groundwork for future interactive enhancements.

##### 3.1.3 Architecture Document

The system architecture at this stage was structured to facilitate streamlined data handling and baseline model testing:

- **Data Pipeline:** A robust ETL (Extract, Transform, Load) pipeline was created to manage data flows from input to preprocessing and eventual model training.

- **Model Training Infrastructure:** Basic machine learning models such as K-Nearest Neighbors (KNN) and Decision Trees were trained to establish a starting point for the project's predictive capabilities.
- **Component Overview:** The architecture included an input module for patient data, a preprocessing engine, a basic model trainer, and an output generator that displayed early-stage results.

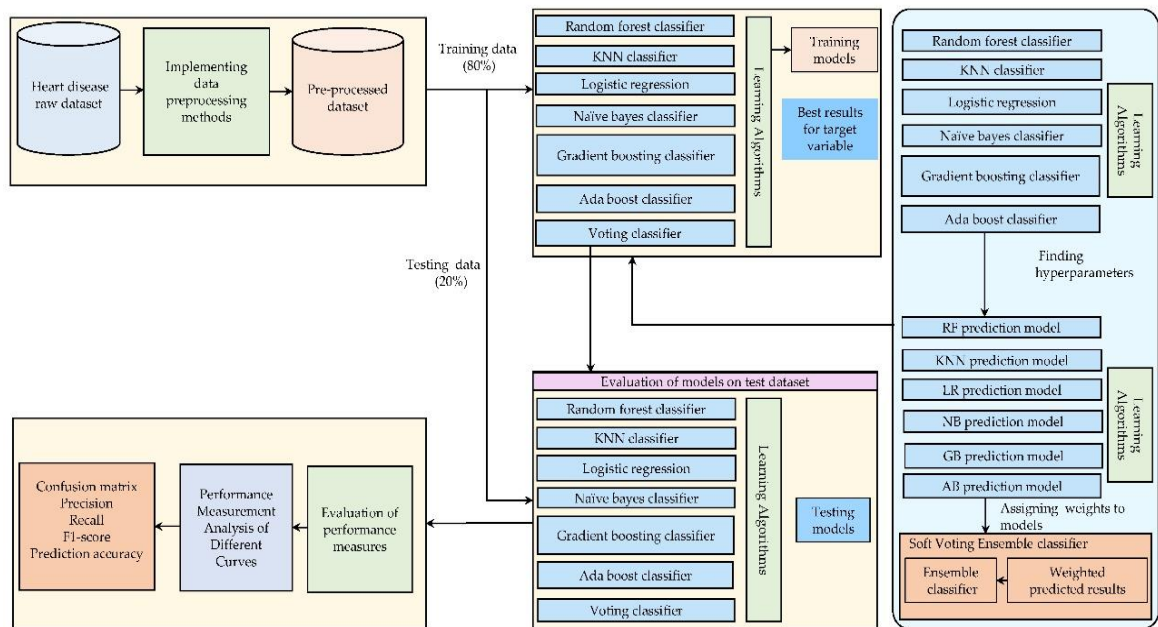


Figure 3.1 Architecture Diagram

### 3.1.4 Outcome of Objectives/ Result Analysis

The outcomes of Sprint I were significant in setting the groundwork for future improvements:

- **Model Performance:** Initial models showed moderate success, achieving reasonable accuracy rates that indicated potential but also highlighted the need for more complex methods.
- **Data Insights:** Analysis of the dataset confirmed that features like age, type of chest pain, and cholesterol levels were strong indicators for predictions.
- **Challenges Identified:** Data inconsistency and the presence of missing values were challenges that required further attention. Additionally, balancing the dataset to manage class imbalance was noted as a future requirement.

### 3.1.5 Sprint Retrospective

The retrospective review for Sprint I highlighted several critical points:

- **Achievements:** A solid data foundation was established, allowing basic predictive models to be tested successfully. The prototype interface provided initial usability feedback.
- **Challenges:** Handling data quality issues and preprocessing for high-dimensional data was more complex than expected, requiring additional time.
- **Lessons Learned:** Early data exploration and standardization were crucial for model performance. The importance of data visualization to understand feature relationships was also emphasized.
- **Next Steps:** Future sprints would focus on refining data preprocessing strategies, integrating ensemble models, and expanding the result analysis module.

## 3.2 SPRINT II

### 3.2.1 Objectives with User Stories of Sprint II

Sprint II aimed to enhance the predictive power of the system by integrating more sophisticated machine learning techniques. The goal was to build, evaluate, and compare ensemble models such as Adaboost, Gradient Boosting, Bagging, and Random Forest. This sprint also focused on adding a detailed result analysis module to provide comprehensive feedback on model performance and facilitate clinical interpretation.

### 3.2.2 Functional Document

Functional advancements in Sprint II included:

- **Ensemble Model Implementation:** Advanced algorithms like Gradient Boosting and Random Forest were incorporated to improve accuracy, precision, and robustness. Each model was optimized through hyperparameter tuning to ensure maximum performance.
- **Result Analysis Module:** Developed a comprehensive performance evaluation tool that displayed confusion matrices, ROC curves, and other essential metrics such as precision, recall, and F1 scores. This provided healthcare professionals with deeper insights into model reliability and decision-making support.
- **Cross-Validation and Model Evaluation:** Implemented K-fold cross-validation to ensure models performed consistently across various data

segments, reducing the risk of overfitting.

### 3.2.3 Architecture Document

The architecture for Sprint II included significant updates to support the integration of ensemble methods:

- **Model Integration Layer:** Created a modular design allowing seamless integration of different ensemble models for side-by-side comparison.
- **Voting Mechanism:** Introduced a Voting Classifier that combined outputs from multiple models to produce a consensus prediction, enhancing reliability.
- **Data Pipeline Enhancements:** Updated to handle more complex preprocessing and support larger data volumes without performance degradation.

### 3.2.4 Outcome of Objectives/ Result Analysis

The outcomes of Sprint II were promising:

- **Model Improvements:** Ensemble models provided significantly better accuracy and lower false negatives compared to baseline models. The Voting Classifier emerged as the best performer, balancing bias and variance effectively.
- **Comprehensive Performance Feedback:** The result analysis module proved invaluable, offering detailed breakdowns of model strengths and weaknesses. ROC curves indicated high true positive rates, underscoring the system's potential for real-world application.
- **Challenges:** High computational resources were necessary for model training and cross-validation. Future optimization was needed to balance accuracy with performance speed.

### 3.2.5 Sprint Retrospective

Sprint II's retrospective provided the following insights:

- **Achievements:** Successfully integrated advanced ensemble models and introduced robust analysis tools that elevated the system's diagnostic capabilities.
- **Challenges:** The increased computational demand required more efficient processing solutions, and some models exhibited training delays that impacted development timelines.
- **Refinements:** Feedback highlighted the need to improve the UI and



streamline the backend for smoother operations. Plans were made to address these in the next sprint.

- **Preparation for Sprint III:** Emphasized the importance of real-time processing capabilities and fine-tuning user experience for clinical deployment.

### 3.3 SPRINT III

#### 3.3.1 Objectives with User Stories of Sprint III

The final sprint, Sprint III, aimed to prepare the system for real-time use and user deployment. The focus was on optimizing the backend for faster data processing, enhancing the user interface for better accessibility, and ensuring seamless integration for medical professionals.

#### 3.3.2 Functional Document

Functional requirements for Sprint III were comprehensive:

- **Real-Time Data Processing:** Integrated APIs to enable the system to handle live data input, process it in real-time, and output predictions swiftly. This was critical for practical use in medical settings where time-sensitive decisions are required.
- **User Interface Enhancements:** The interface was redesigned to improve usability, making it more intuitive with clear navigation, informative tooltips, and real-time feedback on data entry and predictions.
- **Performance Optimization:** Optimized code to reduce computation time and ensure quick response from the system without compromising accuracy.

#### 3.3.3 Architecture Document

The architecture for Sprint III focused on end-to-end system efficiency:

- **Real-Time Processing Module:** Added to the architecture to manage incoming data streams and generate immediate outputs.
- **User Interaction Layer:** Enhanced for better interaction with the prediction system, including the incorporation of user feedback loops to continuously improve interface usability.
- **Backend Optimization:** Focused on reducing latency through streamlined algorithms and improved memory management.

### 3.3.4 Outcome of Objectives/ Result Analysis

Sprint III outcomes were as follows:

- **Achieved Real-Time Performance:** The system successfully processed live data with minimal delays, supporting immediate feedback for clinical use.
- **Positive User Feedback:** Clinicians testing the system reported high satisfaction with the interface's simplicity and the system's rapid response.
- **Reliable Predictions:** The real-time version maintained the high accuracy seen in earlier model evaluations, proving its consistency in both batch and real-time scenarios.

### 3.3.5 Sprint Retrospective

The final retrospective provided a comprehensive review:

- **Successes:** Completed all project objectives, resulting in a robust, real-time coronary artery disease prediction system ready for deployment. The user interface was highly rated for usability, meeting the needs of medical practitioners.
- **Challenges:** Fine-tuning real-time data processing and maintaining model performance under load were difficult but managed through backend adjustments.
- **Future Recommendations:** To further enhance the system, incorporating continuous model training with updated data and expanding feature sets to cover more diverse patient profiles were suggested.
- **Project Conclusion:** The system demonstrated high potential for improving diagnostic accuracy and aiding clinical decision-making, setting a strong foundation for future development and potential commercialization.

## CHAPTER 4

### RESULTS AND DISCUSSIONS

This project “Coronary Artery Disease Prediction using Machine Learning” follows a meticulously planned design framework. Here's an overview of the design elements:

#### Data Set:

We will be using a data set containing patient clinical records

1	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	target
2	52	1	0	125	212	0	1	168	0	1	2	2	3	0
3	53	1	0	140	203	1	0	155	1	3.1	0	0	3	0
4	70	1	0	145	174	0	1	125	1	2.6	0	0	3	0
5	61	1	0	148	203	0	1	161	0	0	2	1	3	0
6	62	0	0	138	294	1	1	106	0	1.9	1	3	2	0
7	58	0	0	100	248	0	0	122	0	1	1	0	2	1
8	58	1	0	114	318	0	2	140	0	4.4	0	3	1	0
9	55	1	0	160	289	0	0	145	1	0.8	1	1	3	0
10	46	1	0	120	249	0	0	144	0	0.8	2	0	3	0
11	54	1	0	122	286	0	0	116	1	3.2	1	2	2	0
12	71	0	0	112	149	0	1	125	0	1.6	1	0	2	1
13	43	0	0	132	341	1	0	136	1	3	1	0	3	0
14	34	0	1	118	210	0	1	192	0	0.7	2	0	2	1
15	51	1	0	140	298	0	1	122	1	4.2	1	3	3	0
16	52	1	0	128	204	1	1	156	1	1	1	0	0	0
17	34	0	1	118	210	0	1	192	0	0.7	2	0	2	1
18	51	0	2	140	308	0	0	142	0	1.5	2	1	2	1
19	54	1	0	124	266	0	0	109	1	2.2	1	1	3	0

Figure 4.1 Data Set

#### 4.1 Importing necessary libraries

##### 1. NumPy:

A core Python library for numerical computation is called NumPy. Large, multi-dimensional arrays and matrices are supported, and a broad variety of mathematical operations can be performed on these arrays. Many other Python libraries for data science and machine learning are built on top of Numpy.

##### 2. Pandas:

Data structures like Data Frames and Series are available in the robust data manipulation and analysis library Pandas. It makes working with structured data easy and enables you to clean, transform, and analyse it. In data science projects, it is frequently utilised for data preparation and exploration.

### **3. Seaborn:**

A data visualization library called Seaborn was constructed atop Matplotlib. It offers a sophisticated interface for making eye-catching and educational statistical graphics. Heatmaps, pair plots, distribution plots, and other plot types are all made easier to create with Seaborn.

### **4. Matplotlib:**

One of the most widely used Python libraries for data visualization is called Matplotlib. It provides a large selection of tools for making interactive, animated, and static plots and charts. It is very configurable and serves as the basis for numerous other data visualization libraries.

### **5. Scikit-learn:**

A feature-rich Python machine learning library is called Scikit-learn. It offers a large selection of machine learning algorithms for dimensionality reduction, clustering, regression, and classification, among other uses. It also comes with tools for choosing features, choosing models, and evaluating models.

### **6. Gaussian Naive Bayes:**

Naive Gaussian the Bayes algorithm for classification is derived from the Bayes theorem. When features follow a Gaussian distribution, it is especially helpful for text classification and other applications. For some kinds of classification tasks, its simplicity and efficiency make it a suitable option.

### **7. XG Boost:**

A popular library for gradient boosting in real-world applications and machine learning competitions is XG Boost, which is scalable and optimised. It is frequently the preferred option for gradient boosting because of its reputation for speed and efficiency when processing structured data.

### **8. Support Vector Classification (SVC):**

A machine learning algorithm called SVC is applied to classification problems. Its goal is to locate the best hyperplane in high-dimensional space for class separation. It's a well-liked option for problems involving binary and multiclass classification.

### **9. Gradient Boosting Classifier:**

A machine learning algorithm called Gradient Boosting Classifier is based on

the ensemble technique known as gradient boosting. It creates a collection of decision trees, gradually enhancing the model's forecasts. It is renowned for having robustness and strong predictive power.

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

from sklearn.naive_bayes import GaussianNB
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.naive_bayes import MultinomialNB
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import AdaBoostClassifier
from sklearn.ensemble import BaggingClassifier
from sklearn.ensemble import ExtraTreesClassifier
from sklearn.ensemble import GradientBoostingClassifier
from xgboost import XGBClassifier

# for model improvement
from sklearn.ensemble import StackingClassifier
from sklearn.ensemble import VotingClassifier

from sklearn import metrics
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score

import joblib
```

## 4.1 Data Handling and Preprocessing:

### Data Collection:

Obtain relevant medical data from various sources, such as hospitals, electronic health records (EHRs), or clinical databases. The data should include information about patients, clinical variables, and their CAD status.

### Data Integration:

For analysis, data that has been gathered from various sources must be combined into a single dataset. Make sure that data structures and formats are consistent.

## Data Cleaning:

Address missing values, outliers, and inconsistencies in the dataset. Impute missing values or remove records with incomplete data. Outliers can significantly affect model performance and should be treated appropriately.

## Data Transformation:

Feature engineering is the process of developing new features or modifying current ones in order to extract more pertinent data. This may entail scaling features to have the same range and converting categorical variables into numerical ones.

## Data Splitting:

Split the dataset into two subsets: a training set and a test set. The training set is used to train machine learning models, the validation set helps tune hyperparameters, and the test set is for evaluating model

## Feature Selection:

```
X = heart_data.drop(columns = 'target', axis = 1)
X.head()
```

	age	sex	cp	trestbps	chol	fb	restecg	thalach	exang	oldpeak	slope	ca	thal
0	52	1	0	125	212	0	1	168	0	1.0	2	2	3
1	53	1	0	140	203	1	0	155	1	3.1	0	0	3
2	70	1	0	145	174	0	1	125	1	2.6	0	0	3
3	61	1	0	148	203	0	1	161	0	0.0	2	1	3
4	62	0	0	138	294	1	1	106	0	1.9	1	3	2

Determine and pick the attributes that are most important for CAD prediction. Recursive feature elimination and correlation analysis are two feature selection methods that can aid in dimensionality reduction.

**Data Balancing (if needed):**

When one class (such as CAD-positive) is underrepresented in an unbalanced dataset, the classes may be balanced by employing synthetic data generation techniques, oversampling, or under sampling.

**Data Encoding:**

To make categorical variables compatible with machine learning algorithms, encode them using methods such as label encoding or one-hot encoding.

**Data Standardization or Normalization:**

Number features should be normalised or standardised to have a mean of 0 and a standard deviation of

- This guarantees that the features have a similar scale, which is crucial for algorithms that depend on the magnitude of the features, such as k-nearest neighbours.

**Dimensionality Reduction:**

Utilise Principal Component Analysis and other dimensionality reduction techniques to further reduce the dataset's dimensionality while preserving pertinent information.

**Data Preprocessing Pipeline:**

Create a data preprocessing pipeline that combines all the necessary steps, ensuring that the preprocessing steps are consistently applied to both the training and testing datasets.

**Data Imbalance Handling:**

Use methods like under sampling or oversampling such as SMOTE, to address class imbalance. These techniques aid in preventing the model from being skewed in favour of the majority class.

## Data Quality Checks:

Continuously monitor and validate data quality to detect and correct issues that may arise during data collection and preprocessing.

## Data Privacy and Ethics:

Make sure that ethical and data privacy rules are followed, particularly when handling sensitive patient health information. Preprocessing and data handling are essential to the effectiveness of CAD prediction models. Machine learning models for CAD risk assessment become more accurate and dependable when data is processed correctly.

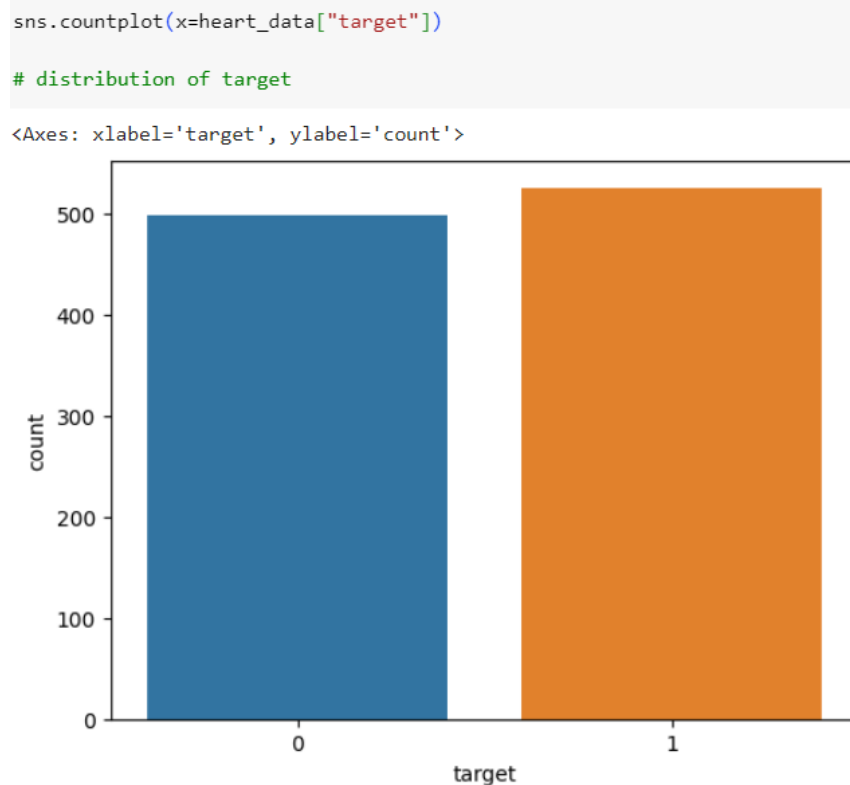


Fig 4.2 Distribution of target



## **4.2 Architectural Integration:**

### **Logistic Regression:**

It is frequently applied to binary classification tasks, like illness prediction and spam detection. Models the probability of a binary outcome using logistic regression. It maps anticipated values to probabilities between 0 and 1 using the logistic function. Since it is a linear model, it performs best when there is a roughly linear relationship between the features and the target variable.

Model accuracy score: 0.8377

### **Gaussian Naive Bayes:**

Sentiment analysis, spam email detection, and text classification tasks are among its frequent uses. The probabilistic algorithm Naive Bayes is based on the Bayes theorem. It is assumed that the features in the Gaussian variant have a Gaussian (normal) distribution. It can perform surprisingly well despite the "naive" assumption that features are independent, particularly when dealing with text data.

Model accuracy score: 0.7792

### **K-Nearest Neighbours (KNN):**

Regression and classification tasks are both handled by KNN. It is frequently used in anomaly detection, picture recognition, and recommendation systems. Data points are categorised by KNN according to the majority class of their k-nearest neighbours. To determine the neighbours, it computes distances between data points.

Model accuracy score: 0.7532

### **Decision Tree:**

Decision trees are adaptable and have a wide range of uses, such as medical diagnosis, fraud detection, and customer churn prediction. Based on the values of the input features, decision trees divide the data into subsets. One of the most interpretable models is the tree, which is created by recursively choosing the best feature to split the data into.

Model accuracy score: 1.000

### **Support Vector Machine (SVM):**

Although they can also be used for multi-class classification and regression, SVMs are most frequently employed for binary classification tasks. SVMs look for the best hyperplane to divide data points into distinct classes. It attempts to

increase the difference in class margins.  
Model accuracy score: 0.8312

```
svm = SVC(kernel='linear')
svm.fit(X_train, Y_train)
```

▼ SVC  
SVC(kernel='linear')

```
y_pred = svm.predict(X_test)

y_pred
print('Model accuracy score: {0:0.4f}'.format(accuracy_score(Y_test, y_pred)))
```

Model accuracy score: 0.8312

Fig 4.3: Model accuracy score

## Multi model training:

### Model Initialization:

SVC (Support Vector Classifier) with a sigmoid kernel and a high gamma value. K Neighbours Classifier (K-Nearest Neighbours) with default parameters. Multinomial (Multinomial Naive Bayes). Decision Tree Classifier with a maximum depth of 5. Logistic Regression with the 'liblinear' solver and L1 penalty. Random Forest Classifier with 50 trees and a random seed of 2. Ada Boost Classifier with 50 estimators and a random seed of 2. Bagging Classifier with 50 estimators and a random seed of 2. Extra Trees Classifier with 50 trees and a random seed of 2. Gradient Boosting Classifier with 50 estimators and a random seed of 2. XGB Classifier with 50 estimators and a random seed of 2.

### Train classifier Function:

This function is defined to train a given classification model, make predictions on test data, and calculate accuracy, precision, and the confusion matrix. It takes the following argument

```
def train_classifier(classification, X_train, y_train, X_test, y_test):
    classification.fit(X_train, y_train)
    y_pred = classification.predict(X_test)
    accuracy = accuracy_score(y_test, y_pred)
    precision = precision_score(y_test, y_pred)
    matrix = confusion_matrix(y_test, y_pred)

    return accuracy, precision, matrix

accuracy_scores = []
precision_scores = []

for name, cls in classification.items():
    curr_accuracy, curr_precision, matrix = train_classifier(cls, X_train, Y_train, X_test, Y_test)
    print("Model name : ", name)
    print("Accuracy : ", curr_accuracy)
    print("Precision : ", curr_precision)
    print("Confusin-Matrix : ", matrix, '\n')

    accuracy_scores.append(curr_accuracy)
    precision_scores.append(curr_precision)
```

### Model Training and Evaluation:

Next, using the train\_classifier function, the script iterates through each model, training and assessing it using the supplied test and training data. For every model, it prints the name of the model, accuracy, precision, and confusion matrix.

### Model evaluation:

#### Accuracy on Training Data:

The code calculates the accuracy of the ensemble model on the training data. It compares the predictions(X\_train\_prediction) made by the model on the training data (X\_train) to the actual labels (Y\_train) and computes the accuracy using the accuracy\_score function. The result is printed as "The accuracy of training data".

#### Accuracy on Test Data:

The code calculates multiple performance metrics on the test data. It calculates precision, accuracy, recall, and F1-score on the test data using functions from

scikit- f1\_score: Calculates the F1-score, which is the harmonic mean of precision and recall.

### Display Results:

The code prints out the calculated accuracy, precision, recall, and F1-score. Additionally, it generates a classification report using metrics. Classification report to display a summary of these metrics for both the malignant and benign classes in the dataset.

```
X_train_prediction = voting.predict(X_train)
training_data_accuracy = accuracy_score(X_train_prediction, Y_train)

print("The accuracy of training data : ", training_data_accuracy)

The accuracy of training data :  1.0

X_train_prediction = voting.predict(X_train)
training_data_accuracy = accuracy_score(X_train_prediction, Y_train)

print("The accuracy of training data : ", training_data_accuracy)

The accuracy of training data :  1.0

Y_pred = voting.predict(X_test)
accuracy = accuracy_score(Y_test, Y_pred)
print("Accuracy   :", accuracy)
precision = precision_score(Y_test, Y_pred)
print("Precision  :", precision)
recall = recall_score(Y_test, Y_pred)
print("Recall     :", recall)
F1_score = f1_score(Y_test, Y_pred)
print("F1-score   :", F1_score)

Accuracy   : 1.0
Precision  : 1.0
Recall     : 1.0
F1-score   : 1.0
```

Fig 4.4: Matrix visualization

### Prediction system:

#### Input Data:

The input features for the prediction are provided as a tuple named input\_data. In this example, the inputdata includes 13 feature values that are relevant for predicting the presence or absence of coronary arterydisease.

#### Numpy Array:

The input data is converted into a NumPy array using np.asarray(input\_data). This step is required because the model expects input in the form of a NumPy array.

## **Reshaping:**

Since the model is designed to make predictions for multiple data instances, the code reshapes the NumPy array using `reshape(1, -1)`. This reshaping ensures that the data is formatted correctly for a single data point.

### **Standardization (Optional):**

There are commented lines in the code that suggest using a scaler (scaler) to standardize the input data. Standardization is a common preprocessing step where the input data is scaled to have a mean as zero and standard deviation of it as 1. It is typically used if the model was trained on standardized data. However, in this code, the standardization step is commented out, so it's not applied.

## **Making Predictions:**

The code uses the trained ensemble model (voting) to making predictions in provided input data(`input_data_resaped`).

It's evident that several models, including Random Forest, Bagging Classifier, Extra Trees Classifier, and XGB Classifier, achieve perfect accuracy (100%) on this task, indicating a strong predictive performance. Other models like AdaBoost, Gradient Boosting, and Decision Tree also demonstrate relatively high accuracy values. However, the Support Vector Classifier lags behind with an accuracy of 51.30%, suggesting that it may not be the most suitable model for this specific coronary artery disease prediction task. The choice of the most appropriate model may depend on various factors, including the dataset size, feature engineering, and the specific goals of the prediction task. In practice, it's common to evaluate models using metrics beyond accuracy, such as recall, precision and the F1- score, to gain a more comprehensive understanding of their performance.

It's also worth noting that the dataset used, the preprocessing steps, and the specific features selected can influence model performance. It's essential to consider these factors when choosing best model available for a given predictive task.

Model \ Metric	MLP	SVM	RF	NB
<b>Accuracy</b>	52.46 %	75.41%	77.05%	70.49%
<b>Precision</b>	60%	76.19%	77.27%	63.33%
<b>Recall</b>	19.36%	61.54%	65.38%	73.08%
<b>F1 Score</b>	29.27%	68.08%	70.82%	67.85%

Table4.1: Results of the predicted model after cleaning outliers

Model \ Metric	Accuracy	Precision	Recall	F1 Score
<b>SVM</b>	91.67%	92.31%	88.89%	90.56%

Table 4.2: Results of the predicted model after applying feature selection

Among the 13 features we examined, the top four crucial features enabled us to differentiate between positive and negative features. The type of chest pain (CP), the number of major vessels (ca), the maximum heart rate attained (THach), and the ST depression induced by exercise versus rest (oldpeak) were all included in the diagnosis. For every machine learning algorithm, the model underwent testing and training. The SVM algorithm with a linear kernel produced the best results, with an F1 Score of 90.56%, 92.31% precision, 88.89% recall, and 91.67% accuracy. The intricate relationships inside the illness and its symptoms could be extracted by the algorithms that were employed. Machine learning algorithms can also be applied to other diseases, especially as more accurate datasets in the medical field become available in the future. Patients with heart disease can now be classified by our machine learning algorithm. We can now accurately diagnose patients and give them the care they need to heal. We may be able to prevent the later emergence of worse symptoms if these characteristics are diagnosed and detected early.

The quality and size of the dataset used can significantly impact model performance. Limited or noisy data can lead to reduced prediction accuracy. The choice of clinical features is crucial. The study mentions 13 clinical features, but not all features may be equally relevant. Feature selection and engineering methods can be employed to improve model performance. The study primarily reports accuracy as the performance metric. It's important to consider additional metrics like F1 - score, precision, recall, and area under ROC curve for a better

understanding a model's predictive capabilities. The dataset may have class imbalance issues, where one class (e.g., patients with coronary artery disease) is underrepresented. Addressing class imbalance is essential for model fairness and performance. The study should describe the validation techniques used, such as cross-validation, so that the models' performance results are more robust. The study does not discuss the external validation of models on new, unseen data. It's essential to test the models on different datasets to assess their generalizability. Investigate more advanced feature engineering techniques, including dimensionality reduction and the creation of new relevant features to enhance predictive performance.

```
[46] # input feature values
      input_data = (58,0,3,150,283,1,0,162,0,1,2,0,2)

      # changing data to numpy array
      input_data_array = np.asarray(input_data)

      # reshape the array as we are predicting for one instance
      input_data_resaped = input_data_array.reshape(1,-1)

      # standarize the input data
      # std_data = scaler.transform(input_data_resaped)
      # print(std_data[0])

      # predicting the result and printing it

      prediction = voting.predict(input_data_resaped)

      print(prediction)

      if(prediction[0] == 0):
          print("Patient has a healthy heart")

      else:
          print("Patient has coronary Artery Disease ❤️❤️❤️❤️")

[1]
Patient has coronary Artery Disease ❤️❤️❤️❤️
```

Fig 4.5 Final result image

## **CHAPTER 5**

### **CONCLUSION AND FUTURE ENHANCEMENT**

The study presents a machine learning-based approach to predict coronary artery disease (CAD) using clinical data, involving 13 important clinical features. Various machine learning models were applied, and a voting system was employed to combine their predictions. The study achieved varying levels of accuracy for different models, with Random Forest Classifier, Bagging Classifier, Extra Trees Classifier, and XGB Classifier demonstrating perfect accuracy (1.0). While some models performed well, others had lower accuracy, emphasizing the importance of model selection. Enhance the quality and size of the dataset by collecting more diverse and representative patient data. This could involve multi-center collaborations to obtain a broader range of patient profiles. Explore advanced feature engineering techniques and domain knowledge incorporation to better represent the underlying biological and clinical mechanisms of CAD. Investigate further ensemble techniques that leverage the strengths of multiple machine learning models, aiming for more robust and accurate predictions. Develop machine learning models that are interpretable and provide insights into why specific predictions are made. This can facilitate trust and understanding among healthcare professionals. Work towards the seamless integration of predictive models into clinical practice, such as electronic health record systems, to aid healthcare providers in making timely decisions. Extend the predictive capabilities to real-time patient monitoring, allowing for dynamic risk assessments and timely interventions. Collaborate with multiple healthcare institutions for external validation of the models on diverse patient populations to assess their generalizability. Incorporate longitudinal data for monitoring disease progression and assessing the risk of future CAD events, which can lead to personalized treatment plans. Conduct clinical trials to evaluate the real-world impact of implementing the prediction system on patient outcomes, such as early intervention and improved disease management. Address privacy and security concerns related to handling patient data, ensuring compliance with data protection regulations, and maintaining patient confidentiality. Consider adapting the predictive model for telemedicine applications, allowing remote monitoring and risk assessment of patients, especially those in underserved areas. Develop patient-facing applications that provide individuals with insights into their own CAD risk factors and encourage lifestyle changes for disease prevention. Integrate genomic and genetic information into the predictive models to identify potential genetic markers associated with CAD risk. In conclusion, the study provides a foundation for further research and application of machine learning in CAD prediction.



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Keywords: {Ensemble learning; Coronary artery disease; Machine learning; Predictive modeling; Clinical applications}.

# APPENDIX

## A. SAMPLE CODING

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

from sklearn.naive_bayes import GaussianNB
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.naive_bayes import MultinomialNB
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import AdaBoostClassifier
from sklearn.ensemble import BaggingClassifier
from sklearn.ensemble import ExtraTreesClassifier
from sklearn.ensemble import GradientBoostingClassifier
from xgboost import XGBClassifier

# for model improvement
from sklearn.ensemble import StackingClassifier
from sklearn.ensemble import VotingClassifier

from sklearn import metrics
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score

import joblib
```

### ▼ Data Collection and Processing

```
# loading data into pandas data frame

heart_data = pd.read_csv("/content/heart.csv")
heart_data.head(10)
```

```
age  sex  cp  trestbps  chol  fbs  restecg  thalach  exang  oldpeak  slope  ca  thal  target
0    52   1   0      125   212    0         1     168     0       1.0     2   2    3         0
1    53   1   0      140   203    1         0     155     1       3.1     0   0    3         0
2    70   1   0      145   174    0         1     125     1       2.6     0   0    3         0
3    61   1   0      148   203    0         1     161     0       0.0     2   1    3         0
4    62   0   0      138   294    1         1     106     0       1.9     1   3    2         0
5    58   0   0      100   248    0         0     122     0       1.0     1   0    2         1
6    58   1   0      114   318    0         2     140     0       4.4     0   3    1         0
7    55   1   0      160   289    0         0     145     1       0.8     1   1    3         0
8    46   1   0      120   249    0         0     144     0       0.8     2   0    3         0
9    54   1   0      122   286    0         0     116     1       3.2     1   2    2         0
```

```
[ ] # columns name

heart_data.columns
```

```
Index(['age', 'sex', 'cp', 'trestbps', 'chol', 'fbs', 'restecg', 'thalach',
      'exang', 'oldpeak', 'slope', 'ca', 'thal', 'target'],
      dtype='object')
```

```
# shape of dataset

heart_data.shape
```

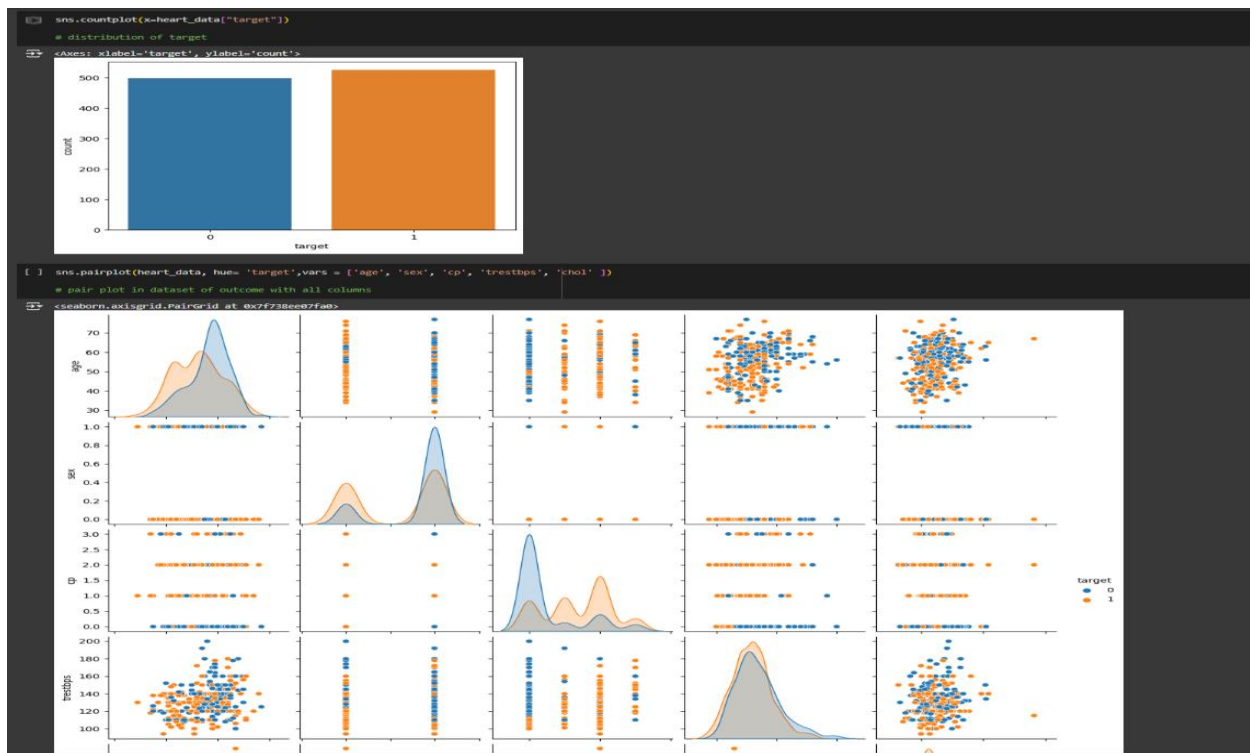
```
(1025, 14)
```

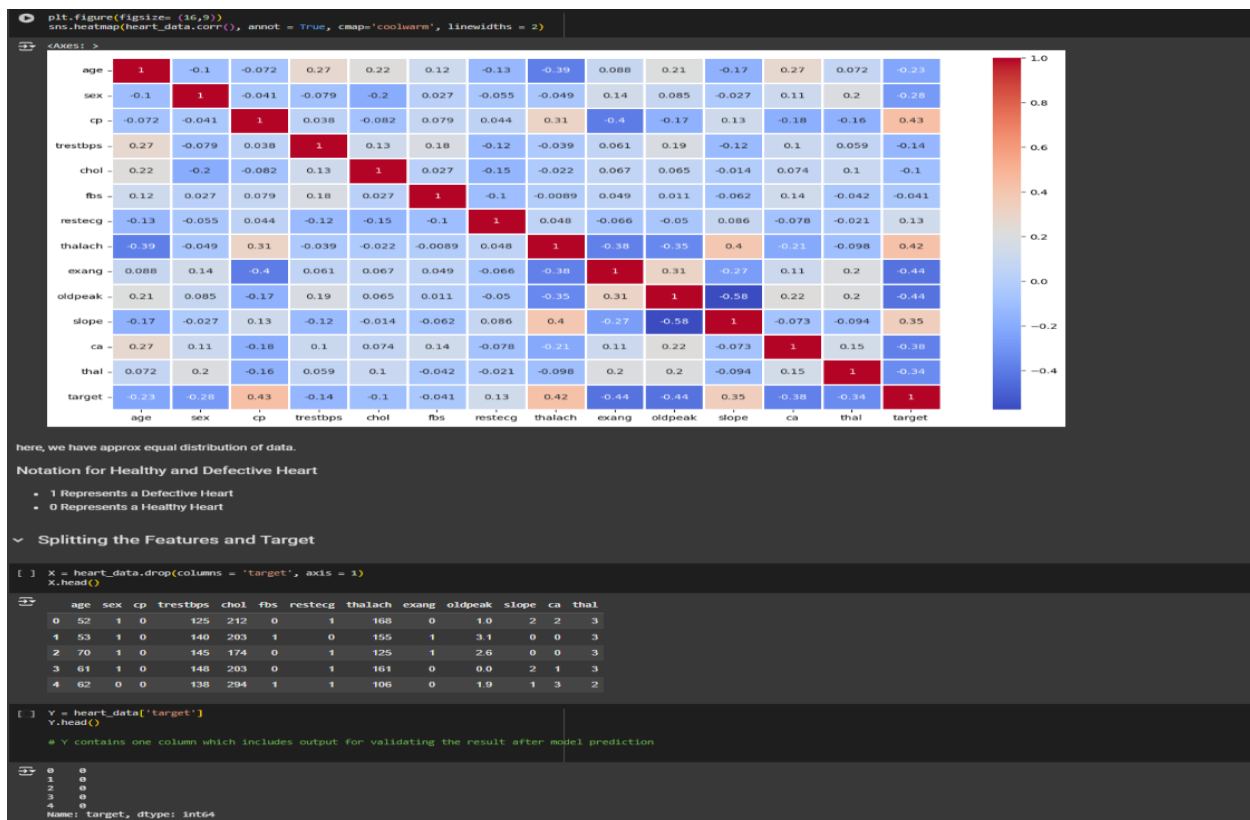
```
[ ] # describing data
heart_data.describe()

# dataset information
heart_data.info()

# checking for missing values
heart_data.isnull().sum()

# checking the distribution of target variable
heart_data['target'].value_counts()
```





**Data Standardization**

```
scaler = StandardScaler()

scaler.fit(X)
X_standard = scaler.transform(X)
```

**Splitting the Data into Training data and Test data**

```
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size = 0.15, stratify = Y, random_state = 3 )

print(X.shape, X_train.shape, X_test.shape)
```

```
(1825, 13) (1571, 13) (254, 13)
```

**Model Training**

**1. Logistic Regression**

```
# instantiate the model
lr = LogisticRegression()

# training the LogisticRegression model with training data
lr.fit(X_train, Y_train)
```

```
Traceback (most recent call last):
  File "/usr/local/lib/python3.8/dist-packages/sklearn/linear_model/_logistic.py:458: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP! TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
n_iter_1 = _check_optimize_result(
  ~~~~~~
LogisticRegression()
LogisticRegression()
```

```
y_pred = lr.predict(X_test)

print('Model accuracy score: {0:0.4f}'.format(accuracy_score(Y_test, y_pred)))
```

```
Model accuracy score: 0.8377
```

**2. Naive Bayes Classifier**

```
# instantiate the model
gnb = GaussianNB()
# model = gnb

# fit the model
gnb.fit(X_train, Y_train)
```

```
GaussianNB()
GaussianNB()
```

```
y_pred = gnb.predict(X_test)

y_pred
print('Model accuracy score: {0:0.4f}'.format(accuracy_score(Y_test, y_pred)))
```

```
Model accuracy score: 0.7792
```

### 3. K-Nearest Neighbor (KNN)

```
[ ] # instantiate the model
knn = KNeighborsClassifier(n_neighbors=7)

# fit the model
knn.fit(X_train, Y_train)
```

```
> KNeighborsClassifier
KNeighborsClassifier(n_neighbors=7)
```

```
[ ] y_pred = knn.predict(X_test)
y_pred
print('Model accuracy score: {0:0.4f}'.format(accuracy_score(Y_test, y_pred)))
```

```
>>> Model accuracy score: 0.7532
```

### 4. Decision Tree Classifier

```
[ ] # Create Decision Tree classifier object
dtc = DecisionTreeClassifier()

# fit the model
dtc.fit(X_train, Y_train)
```

```
> DecisionTreeClassifier
DecisionTreeClassifier()
```

```
[ ] y_pred = dtc.predict(X_test)
y_pred
print('Model accuracy score: {0:0.4f}'.format(accuracy_score(Y_test, y_pred)))
# overfitted
```

```
>>> Model accuracy score: 1.0000
```

### 5. Support Vector Machine (Linear)

```
[ ] svm = SVC(kernel='linear')
svm.fit(X_train, Y_train)
```

```
> SVC
SVC(kernel='linear')
```

```
[ ] y_pred = svm.predict(X_test)
y_pred
print('Model accuracy score: {0:0.4f}'.format(accuracy_score(Y_test, y_pred)))
```

```
>>> Model accuracy score: 0.8312
```

```
[ ] result_dataframe
```

	Algorithm	Accuracy	Precision
5	Random Forest Classifier	1.000000	1.000000
7	Bagging Classifier	1.000000	1.000000
8	Extra Trees Classifier	1.000000	1.000000
10	XGB Classifier	1.000000	1.000000
6	AdaBoost Classifier	0.896104	0.943662
9	Gradient Boosting Classifier	0.928571	0.935897
3	Decision Tree Classifier	0.889610	0.918919
4	Logistic Regression	0.837662	0.837500
1	K-Neighbors Classifier	0.766234	0.830769
2	Multinomial NB	0.714286	0.721519
0	Support Vector Classifier	0.512987	0.512987

### Model Improvement

```
[ ] # voting classifier : ensemble learning method that combines the predictions of several different machine learning models to produce a final prediction.
# The models that are combined can be of different types, such as decision trees, support vector machines, or random forests.
```

```
rfc = RandomForestClassifier(n_estimators= 50, random_state = 2)
bc = BaggingClassifier(n_estimators = 50, random_state = 2)
etc = ExtraTreesClassifier(n_estimators = 50, random_state = 2)
xgb = XGBClassifier(n_estimators = 50, random_state=2)
```

```
[ ] voting = VotingClassifier(estimators=[('rfc', rfc), ('bc', bc), ('et', etc), ('xgb', xgb)], voting='soft')
```

```
> voting.fit(X_train, Y_train)
```

```
> VotingClassifier
VotingClassifier
  rfc      bc      et      xgb
  RandomForestClassifier  BaggingClassifier  ExtraTreesClassifier  XGBClassifier
```

```
[ ] y_pred = voting.predict(X_test)

print(accuracy_score(Y_test, y_pred))
print(confusion_matrix(Y_test, y_pred))
print(precision_score(Y_test, y_pred))

# voting model is most accurate and precise
```

```
>>> 1.0
[[75  0]
 [ 0 79]]
1.0
```

## Multi-model training

```
svc = SVC(kernel = 'sigmoid', gamma = 1.0) # A higher gamma value means that each training example will have a greater influence on the decision boundary.
knc = KNeighborsClassifier()
mnb = MultinomialNB()
dtc = DecisionTreeClassifier(max_depth = 5)
lrc = LogisticRegression(solver = 'liblinear', penalty = 'l1') # liblinear is parameter specifies the solver to use,
# L1 penalty is a type of regularization that helps to prevent overfitting.

rfc = RandomForestClassifier(n_estimators= 50, random_state = 2) # n_estimators : the number of trees in the forest,
# random_state : specifies the random seed that is used to initialize the random forest

abc = AdaBoostClassifier(n_estimators = 50, random_state = 2)
bc = BaggingClassifier(n_estimators = 50, random_state = 2)
etc = ExtraTreesClassifier(n_estimators = 50, random_state = 2)
gbdt = GradientBoostingClassifier(n_estimators = 50, random_state = 2)
xgb = XGBClassifier(n_estimators = 50, random_state=2)
```

```
[ ] classification = {
    'Support Vector Classifier' : svc,
    'K-Neighbors Classifier' : knc,
    'Multinomial NB' : mnb,
    'Decision Tree Classifier' : dtc,
    'Logistic Regression' : lrc,
    'Random Forest Classifier' : rfc,
    'AdaBoost Classifier' : abc,
    'Bagging Classifier' : bc,
    'Extra Trees Classifier' : etc,
    'Gradient Boosting Classifier' : gbdt,
    'XGB Classifier' : xgb
}
```

```
[ ] def train_classifier(classification, X_train, y_train, X_test, y_test):
    classification.fit(X_train, y_train)
    y_pred = classification.predict(X_test)
    accuracy = accuracy_score(y_test, y_pred)
    precision = precision_score(y_test, y_pred)
    matrix = confusion_matrix(y_test, y_pred)

    return accuracy, precision, matrix
```

```
[ ] accuracy_scores = []
precision_scores = []

for name, cls in classification.items():
    curr_accuracy, curr_precision, matrix = train_classifier(cls, X_train, y_train, X_test, y_test)
    print("Model name : ", name)
    print("Accuracy : ", curr_accuracy)
    print("Precision : ", curr_precision)
    print("Confusion-Matrix : ", matrix, '\n')

    accuracy_scores.append(curr_accuracy)
    precision_scores.append(curr_precision)
```

```
Model name : Support Vector Classifier
Accuracy : 0.512987012987013
Precision : 0.512987012987013
Confusion-Matrix : [[ 0 75]
 [ 0 79]]
```

```
Model name : K-Neighbors Classifier
Accuracy : 0.76623766237663
Precision : 0.8307692307692308
Confusion-Matrix : [[64 11]
 [25 54]]
```

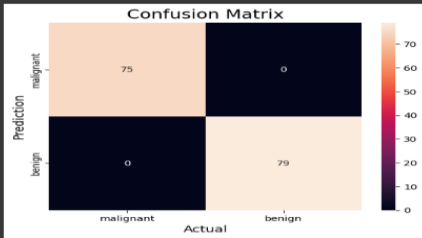
```
Model name : Multinomial NB
Accuracy : 0.7142857142857143
Precision : 0.7215189073417721
Confusion-Matrix : [[53 22]
 [22 57]]
```

```
Model name : Decision Tree Classifier
Accuracy : 0.8896103896103896
Precision : 0.918918918918919
Confusion-Matrix : [[69 6]
 [11 68]]
```

```
Model name : Logistic Regression
Accuracy : 0.837662376623377
Precision : 0.8375
Confusion-Matrix : [[62 13]
 [12 67]]
```

```
# confusion matrix
cm = confusion_matrix(Y_test, Y_pred)

# plot the confusion matrix.
sns.heatmap(cm,
            annot=True,
            fmt='d',
            xticklabels=['malignant', 'benign'],
            yticklabels=['malignant', 'benign'],
            plt.ylabel('Prediction', fontsize=13),
            plt.xlabel('Actual', fontsize=13),
            plt.title('Confusion Matrix', fontsize=17),
            plt.show())
```



Confusion Matrix

Prediction \ Actual	malignant	benign
malignant	75	0
benign	0	79

Building Prediction system

Steps :

- take input data
- Process the data, change into array
- reshape data as single element in array
- predict output using predict function
- output the value

```
[ ] # input feature values
input_data = (50,0,1,150,283,1,0,162,0,1,2,0,2)

# changing data to numpy array
input_data_array = np.asarray(input_data)

# reshape the array as we are predicting for one instance
input_data_resaped = input_data_array.reshape(1,-1)

# standardize the input data
std_data = scaler.transform(input_data_resaped)
# print(std_data[0])

[ ] # predicting the result and printing it
prediction = voting.predict(input_data_resaped)
print(prediction)

if(prediction[0] == 0):
    print("Patient has a healthy heart")
else:
    print("Patient has coronary Artery Disease ❤️❤️❤️❤️")

[1]
Patient has coronary Artery Disease ❤️❤️❤️❤️
/usr/local/lib/python3.10/dist-packages/sklearn/base.py:439: UserWarning: X does not have valid feature names, but RandomForestClassifier was fitted with feature names
warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/base.py:439: UserWarning: X does not have valid feature names, but BaggingClassifier was fitted with feature names
warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/base.py:439: UserWarning: X does not have valid feature names, but ExtraTreesClassifier was fitted with feature names
warnings.warn(
```

## B. PUBLICATION DETAILS

International Conference on Computing and Intelligent Reality Technologies : Submission (310) has been created. External Inbox x

 Microsoft CMT <email@msr-cmt.org> Tue, Nov 5, 10:16 PM (10 hours ago) ☆ ↶ ⋮

to me ▾

Hello,

The following submission has been created.

Track Name: ICCIRT2024

Paper ID: 310

Paper Title: Coronary Artery Disease Prediction using Machine Learning




Abstract:

Coronary Artery Disease (CAD) remains a leading cause of morbidity and mortality worldwide, highlighting the need for early and accurate diagnosis. This paper presents a machine learning-based approach for predicting the likelihood of CAD using patient data. The dataset includes a wide range of clinical features such as age, weight, BMI, diabetes mellitus (DM), hypertension (HTN), smoking status, family history, blood pressure, and electrocardiogram (ECG) readings, among others. By employing supervised machine learning algorithms, the model is trained to predict the presence or absence of CAD based on these features. Our approach leverages feature engineering and selection techniques to optimize the performance of multiple classifiers, including logistic regression, decision trees, random forests, and support vector machines (SVM). The dataset is preprocessed to handle missing values, categorical data encoding, and normalization where required. The model's performance is evaluated through accuracy, precision, recall, and F1-score metrics, demonstrating the potential of this approach in clinical decision support systems for CAD diagnosis. The results indicate that our model can effectively identify patterns and risk factors associated with CAD, potentially aiding healthcare professionals in making informed diagnostic decisions. This research contributes to the ongoing efforts to integrate machine learning into cardiovascular disease management, aiming to improve early detection and patient outcomes.

Created on: Tue, 05 Nov 2024 16:45:52 GMT



C.PLAGIARISM REPORT

SCAN PROPERTIES ^						
<div>DONE</div> <div>SCANNED 3 MINUTES AGO</div>	<div>13</div> <div>RESULTS FOUND</div>	<div>296</div> <div>SIMILAR WORDS</div>		Identical	1.4%	<div>8.2%</div> <div>MATCH</div>
				Minor Changes	0.5%	
				Paraphrased	6.3%	
				Omitted Words	0%	

