



EXPERT CARDIOVASCULAR DISEASE PREDICTION USING MACHINE LEARNING

A MINI PROJECT REPORT

Submitted by

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ENGINEERING COLLEGE

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(AN AUTONOMOUS INSTITUTION)

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ANNA UNIVERSITY
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ABSTRACT

EXPERT CARDIOVASCULAR DISEASE PREDICTION USING MACHINE LEARNING is a project that aims to develop a system for accurately prediction of CVDs can significantly improve patient outcomes by facilitating timely intervention and treatment. This study explores the application of machine learning techniques to predict the risk of cardiovascular diseases based on a variety of patient data, including demographic, lifestyle, and clinical factors. We utilize a dataset comprising thousands of records with features such as age, gender, cholesterol levels, blood pressure, smoking habits, physical activity, and medical history. Several machines learning algorithms, including logistic regression, decision trees, random forests, support vector machines, and neural networks, are employed to build predictive models. These models are evaluated using metrics such as accuracy, precision, recall, F1-score, and the area under the receiver operating characteristic curve (AUC-ROC). machine learning techniques were used for prediction, including Logistic Regression, Naïve Bayes, Decision Tree, AdaBoost, Random Forest, Bagging Tree, and Ensemble learning. The Random Forest classifier achieved the highest accuracy (**98.04%**), precision (**96.15%**), recall (**100%**), F1 score (**97.7%**), and AUC value (**0.989**). The study recommends implementing the Random Forest technique in a system for predicting cardiac diseases, which could potentially change clinical practice by providing doctors with a new tool to determine a patient's CVD prognosis. This research highlights the potential of machine learning in the healthcare sector, offering a robust tool for the early detection and prevention of cardiovascular diseases.

KEYWORDS: Logistic Regression, Naïve Bayes, Decision Tree, F1 Score, Blood pressure, SVM, Clinical data.

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CHAPTER 1

INTRODUCTION

1.1 OBJECTIVE

Cardiovascular diseases (CVDs) are the leading cause of death globally, necessitating early prediction and intervention to improve patient outcomes. Traditional prediction methods rely on clinical expertise and static risk assessment tools, which may not fully capture the complex nature of CVDs. Machine learning (ML) offers a promising alternative by analyzing large datasets to identify patterns and interactions among risk factors. The process typically involves data collection and preprocessing, model selection and training, model evaluation, feature importance analysis, and deployment. Clinical and demographic data, such as blood pressure, cholesterol levels, age, and lifestyle factors, are used to train various ML algorithms, including Logistic Regression, Decision Trees, Random Forests, Support Vector Machines (SVM), and Neural Networks. Models are evaluated using performance metrics like accuracy, precision, recall, F1-score, and AUC-ROC. Ensemble methods, particularly Gradient Boosting Machines (GBM), have shown high accuracy and robustness. ML models offer enhanced accuracy, personalized risk assessments, scalability, and automation, potentially outperforming traditional methods. However, challenges such as data quality, model interpretability, and integration into clinical practice remain. Future research aims to improve model accuracy and interpretability, explore advanced techniques like deep learning, and integrate diverse data sources to enhance CVD prediction and prevention.

1.2. SCOPE OF PROJECT

The primary objective of this study is to develop and evaluate the effectiveness of various machine learning algorithms in predicting the risk of cardiovascular diseases (CVDs) using clinical and demographic data. The study aims to identify the most accurate and robust model that can assist healthcare professionals in early detection and intervention for high-risk individuals, thereby improving patient outcomes and reducing the global burden of cardiovascular diseases. Specific goals include preprocessing and preparing a comprehensive dataset, implementing and comparing different machine learning models such as Logistic Regression, Decision Trees, Random Forests, Support Vector Machines (SVM), and Neural Networks, and evaluating their performance using metrics like accuracy, precision, recall, F1-score, and AUC-ROC. Additionally, the study seeks to analyze the importance of different features in predicting CVD risk, identifying key predictors, and ultimately providing a machine learning-based tool for early prediction of cardiovascular diseases that can be integrated into clinical practice for preventive healthcare.

1.3. LITERATURE SURVEY

This system relies on comprehensive datasets containing a myriad of patient-specific information, including clinical indicators such as blood pressure, cholesterol levels, and medical history, alongside demographic factors and lifestyle choices. Through the application of machine learning techniques such as Logistic Regression, Decision Trees, Random Forests, Support Vector Machines (SVM), and Neural Networks, these datasets are analyzed to uncover intricate patterns and correlations that may indicate heightened risk for CVDs. By leveraging predictive models trained on historical data, healthcare providers can identify individuals at risk of developing CVDs earlier, enabling proactive interventions and personalized preventive strategies.

1.4 .PROPOSED SYSTEM

The proposed system for Cardiovascular Disease Prediction Using Machine Learning aims to further advance predictive capabilities by integrating state-of-the-art algorithms with emerging technologies and enhanced datasets. Building upon the foundation laid by existing methodologies, the proposed system seeks to refine predictive models by incorporating additional variables such as genetic markers, wearable device data, and environmental factors. By leveraging advanced machine learning techniques, including deep learning architectures and ensemble methods, the system endeavors to improve accuracy and robustness in predicting CVD risk. Furthermore, the proposed system emphasizes interpretability and transparency, allowing healthcare practitioners to better understand. Integration with electronic health record systems and real-time monitoring tools facilitates seamless implementation into clinical practice, enabling proactive risk assessment and personalized interventions. Through continuous refinement and validation, the proposed system aims to provide a scalable and adaptable framework for cardiovascular disease prediction, ultimately contributing to improved patient outcomes and reduced disease burden.

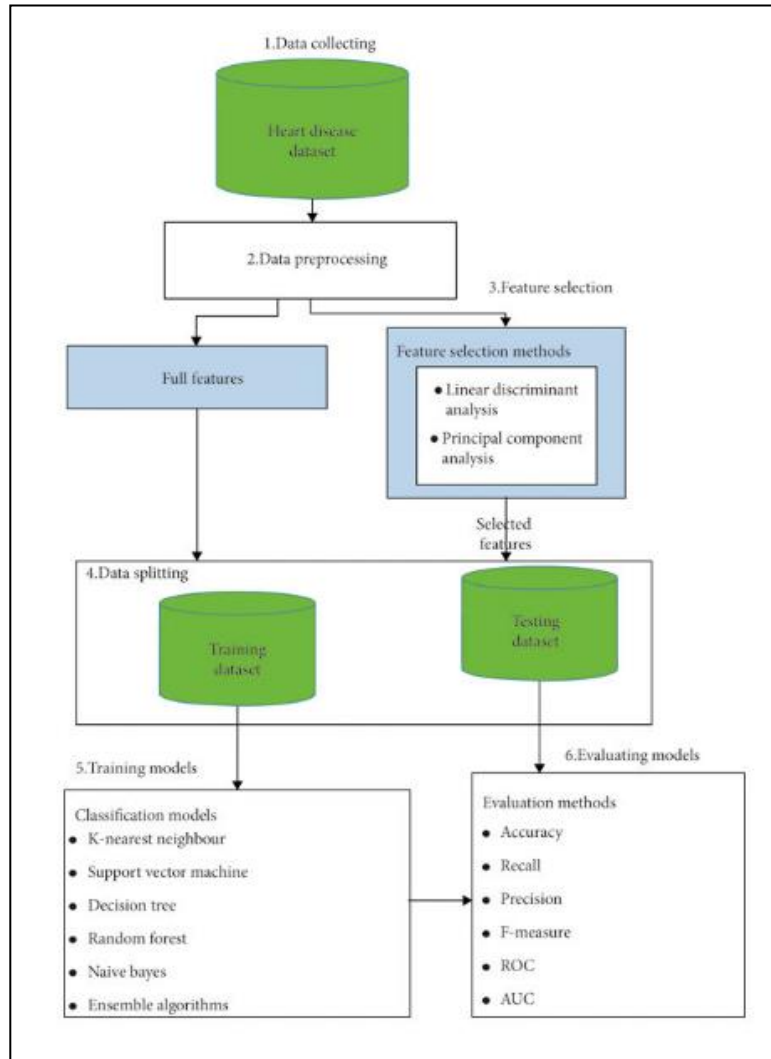


FIG 1.0 ARCHITECTURE OF EXISTING SYSTEM

CHAPTER 2

SYSTEM

ANALYSIS

2.1 EXISTING SYSTEM

The literature on Cardiovascular Disease Prediction Using Machine Learning reflects a growing interest in leveraging computational techniques to address the complex challenges of cardiovascular health. Numerous studies have explored the efficacy of various machine learning algorithms in predicting the risk of cardiovascular events, such as heart attacks and strokes, based on diverse sets of clinical and demographic data. Researchers have investigated the performance of algorithms including Logistic Regression, Decision Trees, Random Forests, Support Vector Machines (SVM), and Neural Networks, highlighting their respective strengths and limitations in terms of predictive accuracy, interpretability, and scalability. Furthermore, studies have examined the impact of feature selection, data preprocessing techniques, and model validation strategies on the robustness and generalizability of predictive models. While many studies have demonstrated promising results, challenges such as data quality, model interpretability, and integration into clinical practice remain areas of ongoing research. Additionally, efforts to enhance predictive models by incorporating novel data sources, advanced machine learning techniques, and real-time monitoring capabilities are underway, with the ultimate goal of developing effective tools for early detection and prevention of cardiovascular diseases.

2.2 PROPOSED SYSTEM

The theoretical framework for Cardiovascular Disease Prediction Using Machine Learning encompasses a multifaceted approach that integrates concepts from medicine, data science, and computational methodologies. At its core lies the understanding of cardiovascular physiology, risk factors, and disease progression, providing the foundation for selecting relevant clinical variables for predictive modeling. Drawing upon principles from statistics and machine learning, various algorithms such as Logistic Regression, Decision Trees, Random Forests, Support Vector Machines (SVM), and Neural Networks are applied to analyze large-scale datasets containing patient information. Feature selection techniques, normalization methods, and model validation strategies are employed to optimize model performance and generalizability. Additionally, concepts from computer science, including data preprocessing, algorithm optimization, and parallel computing, contribute to the development of efficient and scalable predictive models. The theoretical framework also encompasses considerations of model interpretability, ethical implications, and integration into clinical workflows, ensuring that the resulting predictive tools are not only accurate but also actionable and ethical in their application. Through the synthesis of these interdisciplinary principles, the theoretical framework provides a systematic approach to leveraging machine learning for cardiovascular disease prediction, with the ultimate goal of improving patient outcomes and advancing preventive healthcare strategies.

CHAPTER 3

SYSTEM DESIGN

3.1 ARCHITECTURE DIAGRAM

Cardiovascular Disease Prediction Using Machine Learning requires a clear representation of the various components involved in the process.

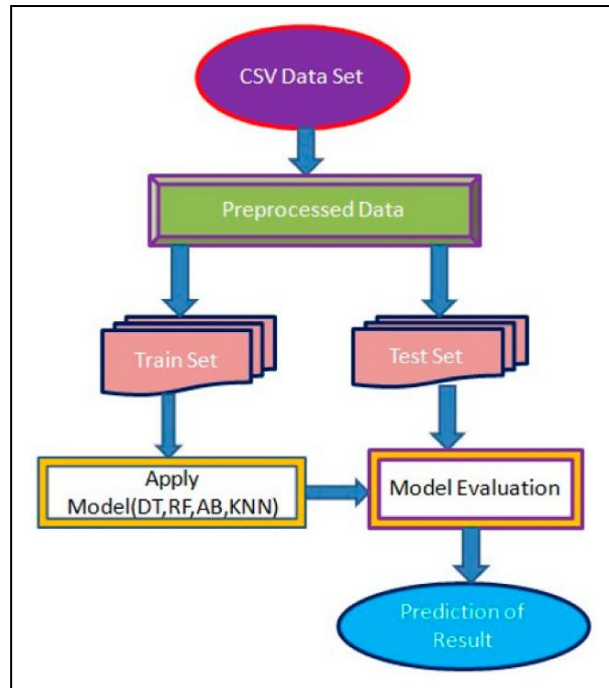


FIG 3.1 ARCHITECTURE DIAGRAM

This architecture diagram provides a structured overview of the steps involved in building and deploying a machine learning-based system for cardiovascular disease prediction, encompassing data collection, preprocessing, model training, evaluation, deployment, and continuous monitoring.

3.2 USECASE DIAGRAM

The use case diagram depicts the interactions and functionalities of various actors within the Cardiovascular Disease Prediction Using Machine Learning system. Healthcare professionals, as primary users, have access to patient information, enabling them to predict the risk of cardiovascular disease based on clinical data. They can then recommend interventions or treatments tailored to each patient's risk level.

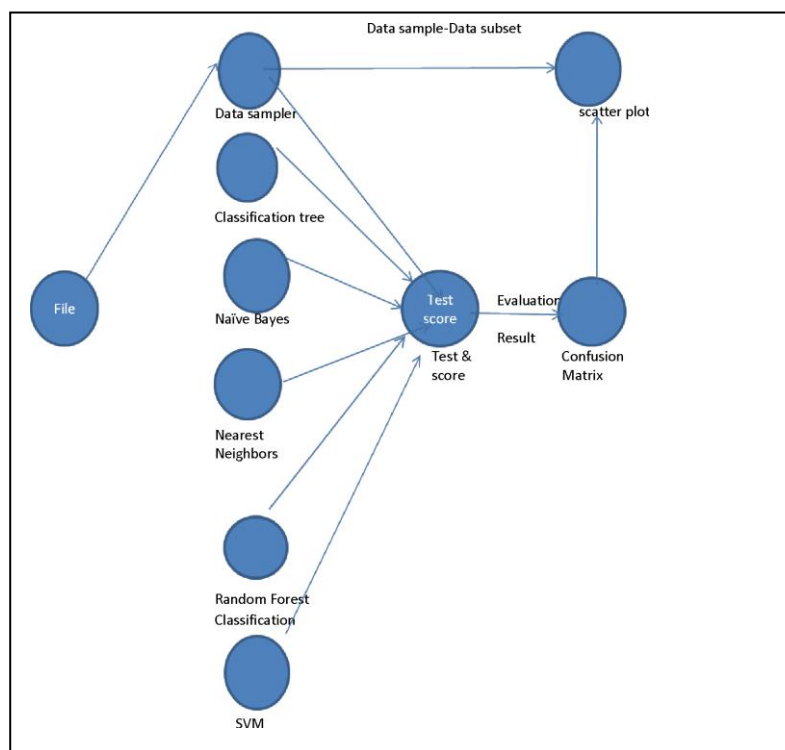


FIG 3.2 USE CASE DIAGRAM

Data scientists or researchers play a pivotal role in data collection, preprocessing, model training, and evaluation stages. They gather diverse datasets, preprocess the data to enhance its quality, train machine learning models, and evaluate their performance using established metrics. Patients, as secondary users, provide their health information to healthcare professionals and receive personalized risk assessments for cardiovascular disease.

3.3 SEQUENCE DIAGRAM

The sequence diagram illustrates the chronological sequence of interactions between various components in the Cardiovascular Disease Prediction Using Machine Learning system. It begins with the initiation of the prediction process by a healthcare professional, who accesses patient information from electronic health records (EHR) or other sources. Subsequently, the healthcare professional requests the predictive model to assess the patient's risk of cardiovascular disease based on the provided data.

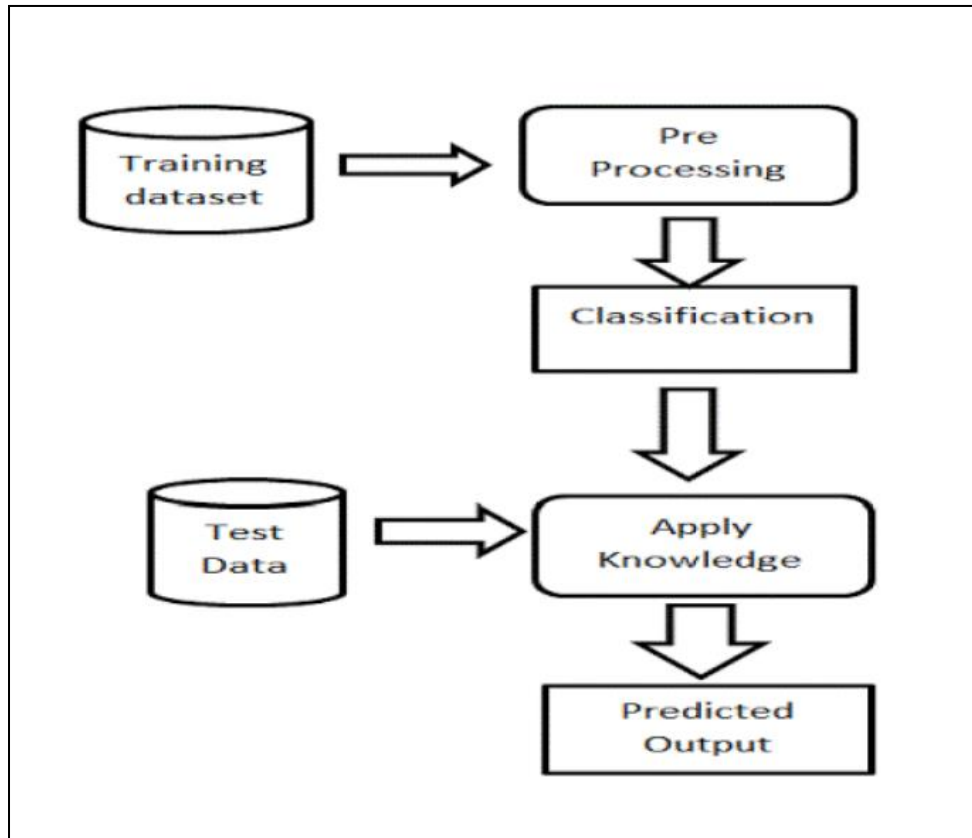


FIG 3.3 SEQUENCE DIAGRAM

A sequence diagram or system sequence diagram (SSD) shows process interactions arranged in time sequence in the field of software engineering. It depicts the processes involved and the sequence of messages exchanged between the processes needed to carry out the functionality.

3.4 COLLABORATION DIAGRAM

The collaboration diagram depicts the interactions and collaborations between various components within the Cardiovascular Disease Prediction Using Machine Learning system. It illustrates how different entities, including healthcare professionals, data scientists, and patients, collaborate to achieve the common goal of predicting and managing cardiovascular disease risk.

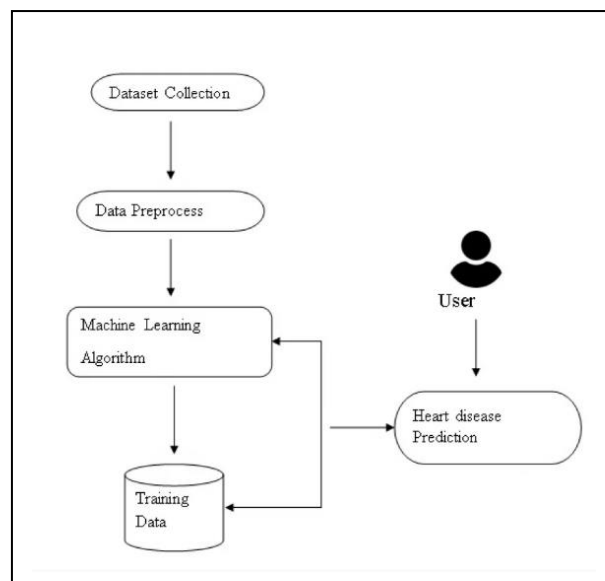


FIG 3.4 COLLABORATION DIAGRAM

The diagram showcases the flow of information and control among these entities, highlighting their roles and responsibilities in the prediction process. Healthcare professionals initiate the process by providing patient data, which is then utilized by data scientists to train machine learning models. The trained models, in turn, are deployed within clinical settings, allowing healthcare professionals to generate risk assessments for individual patients.

3.5 ARCHITECTURE FLOW DIAGRAM

The architecture flow diagram illustrates the systematic progression of data and operations within the Cardiovascular Disease Prediction Using Machine Learning system. It delineates the sequential steps from data collection to result interpretation, outlining the intricate process of leveraging computational techniques for predictive analytics in healthcare.

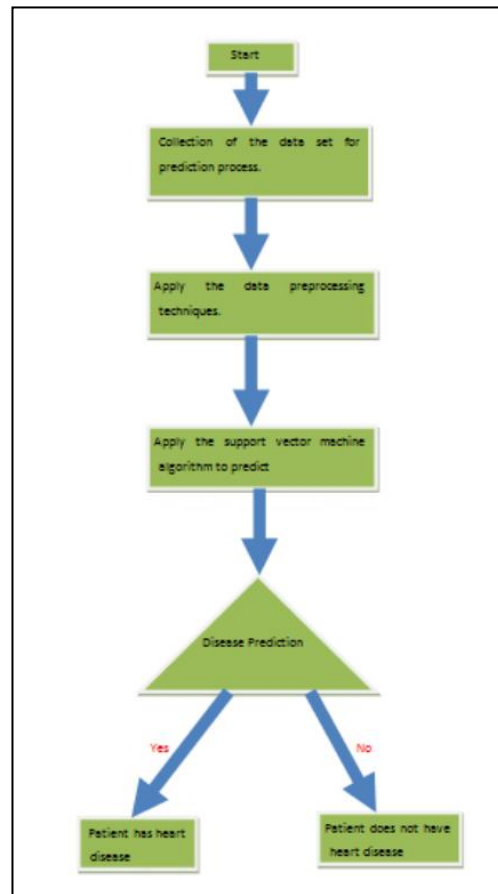


FIG 3.5 ARCHITECTURE FLOW DIAGRAM

The diagram further depicts the pivotal stage of model training, where machine learning algorithms learn patterns and relationships within the data to generate predictive models. subsequently, feature selection methods are applied to identify the most significant variables for predicting cardiovascular disease risk, optimizing model performance.

3.6 DATA FLOW DIAGRAM

The data flow diagram provides a comprehensive depiction of the flow of data within the Cardiovascular Disease Prediction Using Machine Learning system. It illustrates the journey of data from its sources through various stages of processing until it culminates in actionable insights for healthcare professionals.

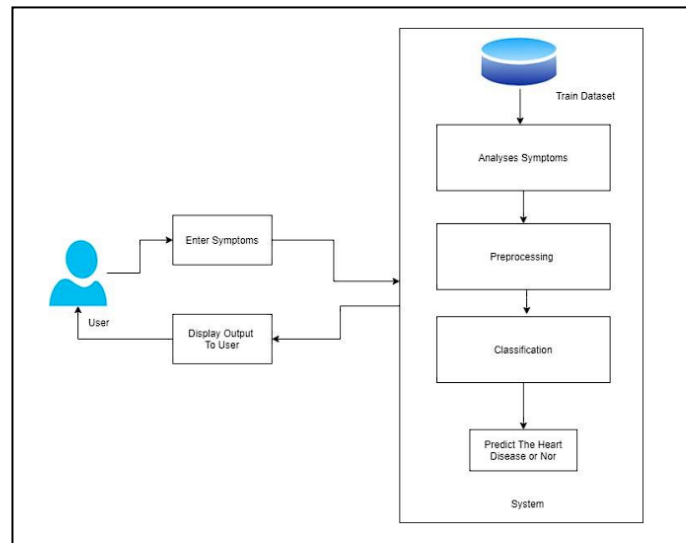


FIG 3.6 USER DIAGRAM

LEVEL 0:

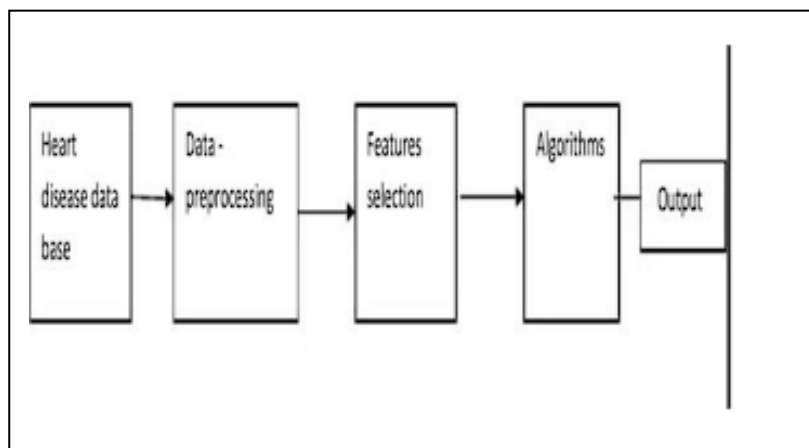


FIG 3.7 LEVEL 0 DIAGRAM

CHAPTER 4

MODULES

4.1 MODULES LIST

- Logistic Regression
- Decision Trees
- Random Forests

4.2 MODULES DESCRIPTION

4.2.1 LOGISTIC REGRESSION

1. Logistic Regression is a fundamental statistical technique employed in predictive modeling, particularly for binary classification tasks.
2. In the context of Cardiovascular Disease Prediction, a Logistic Regression model is constructed to estimate the probability of a patient either having or not having cardiovascular disease based on a set of predictor variables.
3. Unlike linear regression, which predicts continuous outcomes, Logistic Regression utilizes the logistic function (also known as the sigmoid function) to transform the linear combination of input features into probabilities between 0 and 1.
4. This model is characterized by its simplicity, interpretability, and computational efficiency, making it an attractive choice for analyzing medical datasets with relatively few predictors.
5. During model training, coefficients are estimated through the maximum likelihood estimation method, optimizing the model to fit the observed data and minimize prediction errors.
6. The resulting model can then be used to predict the probability of cardiovascular disease for new patients, aiding healthcare professionals in risk assessment and decision-making.

```

import numpy as np
1 import numpy as np
2 import pandas as pd
3 from sklearn.model_selection import train_test_split
4 from sklearn.ensemble import RandomForestClassifier
5 from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
6
7 # Load the heart disease dataset
8 heartdata = pd.read_csv("heart.csv")
9
10 # Separate features and target
11 X = heartdata.drop(columns='target', axis=1)
12 y = heartdata['target']
13
14 # Split the dataset into training and testing sets
15 X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, stratify=y, random_state=2)
16
17 # Create and fit a random forest classifier
18 rf_model = RandomForestClassifier(n_estimators=100, random_state=2)
19 rf_model.fit(X_train, y_train)
20
21 # Make predictions on the testing set
22 y_pred_rf = rf_model.predict(X_test)
23
24 # Calculate the accuracy of the model
25 acc_rf = accuracy_score(y_test, y_pred_rf)
26 print("Random Forest accuracy:", acc_rf)
27
28 # Make predictions on a single example
29 example = [[71, 0, 0, 112, 149, 0, 1, 125, 0, 1.6, 1, 0, 2]]
30 prediction = rf_model.predict(example)
31 if prediction[0] == 0:
32     print("Patient does not have any heart disease")
33 else:
34     print("Patient has heart disease and needs more tests")

```

```

28 # Make predictions on a single example
29 example = [[71, 0, 0, 112, 149, 0, 1, 125, 0, 1.6, 1, 0, 2]]
30 prediction = rf_model.predict(example)
31 if prediction[0] == 0:
32     print("Patient does not have any heart disease")
33 else:
34     print("Patient has heart disease and needs more tests")
35
36 # Calculate the f1 score
37 f1_rf = classification_report(y_test, y_pred_rf)
38 print("Random Forest f1 score:")
39 print(f1_rf)
40
41 # Calculate the confusion matrix
42 cm_rf = confusion_matrix(y_test, y_pred_rf)
43 print("Random Forest confusion matrix:")
44 print(cm_rf)
45

```

FIG 4.1 TRAIN MODEL (SAMPLE CODE)

4.2.2 DECISION TREES

1. Decision Trees are versatile and intuitive machine learning models commonly utilized in predictive analytics, including Cardiovascular Disease Prediction.
2. In this context, a Decision Tree model constructs a tree-like structure where each internal node represents a decision based on a specific feature, and each leaf node represents the predicted outcome, which could be the presence or absence of cardiovascular disease.
3. The model learns from historical data by recursively splitting the dataset into subsets based on the values of predictor variables, aiming to maximize information gain or minimize impurity at each step.
4. This process results in a tree that can effectively capture complex relationships and interactions among the input features. Decision Trees offer several advantages, including interpretability, as the resulting tree structure can be easily visualized and understood, aiding in clinical decision-making.
5. Moreover, Decision Trees can handle both numerical and categorical data, making them suitable for diverse datasets encountered in healthcare settings.
6. Decision Trees may suffer from overfitting, particularly when the tree becomes overly complex. Techniques such as pruning and limiting tree depth can help mitigate this issue, enhancing the model's generalizability.
7. Overall, Decision Trees serve as powerful tools for cardiovascular disease prediction, providing insights into the key predictors and decision pathways underlying disease occurrence.

1	age	sex	cp	trestbps	chol	fb	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	
20	50	0	1	120	244	0	1	162	0	1.1	2	0	2	1	
21	58	1	2	140	211	1	0	165	0	0	2	0	2	1	
22	60	1	2	140	185	0	0	155	0	3	1	0	2	0	
23	67	0	0	106	223	0	1	142	0	0.3	2	2	2	1	
24	45	1	0	104	208	0	0	148	1	3	1	0	2	1	
25	63	0	2	135	252	0	0	172	0	0	2	0	2	1	
26	42	0	2	120	209	0	1	173	0	0	1	0	2	1	
27	61	0	0	145	307	0	0	146	1	1	1	0	3	0	
28	44	1	2	130	233	0	1	179	1	0.4	2	0	2	1	
29	58	0	1	136	319	1	0	152	0	0	2	2	2	0	

31	55	0	0	180	327	0	2	117	1	3.4	1	0	2	0	
32	44	1	0	120	169	0	1	144	1	2.8	0	0	1	0	
33	50	0	1	120	244	0	1	162	0	1.1	2	0	2	1	
34	57	1	0	130	131	0	1	115	1	1.2	1	1	3	0	
35	70	1	2	160	269	0	1	112	1	2.9	1	1	3	0	
36	50	1	2	129	196	0	1	163	0	0	2	0	2	1	
37	46	1	2	150	231	0	1	147	0	3.6	1	0	2	0	
38	51	1	3	125	213	0	0	125	1	1.4	2	1	2	1	
39	59	1	0	138	271	0	0	182	0	0	2	0	2	1	
40	64	1	0	128	263	0	1	105	1	0.2	1	1	3	1	
41	57	1	2	128	229	0	0	150	0	0.4	1	1	3	0	
42	65	0	2	160	360	0	0	151	0	0.8	2	0	2	1	
43	54	1	2	120	258	0	0	147	0	0.4	1	0	3	1	
44	61	0	0	130	330	0	0	169	0	0	2	0	2	0	
45	46	1	0	120	249	0	0	144	0	0.8	2	0	3	0	
46	55	0	1	132	342	0	1	166	0	1.2	2	0	2	1	
47	42	1	0	140	226	0	1	178	0	0	2	0	2	1	
48	41	1	1	135	203	0	1	132	0	0	1	0	1	1	
49	66	0	0	178	228	1	1	165	1	1	1	2	3	0	
50	66	0	2	146	278	0	0	152	0	0	1	1	2	1	
51	60	1	0	117	230	1	1	160	1	1.4	2	2	3	0	
52	58	0	3	150	283	1	0	162	0	1	2	0	2	1	
53	57	0	0	140	241	0	1	123	1	0.2	1	0	3	0	
54	38	1	2	138	175	0	1	173	0	0	2	4	2	1	
55	49	1	2	120	188	0	1	139	0	2	1	3	3	0	
56	55	1	0	140	217	0	1	111	1	5.6	0	0	3	0	
57	55	1	0	140	217	0	1	111	1	5.6	0	0	3	0	
58	56	1	3	120	193	0	0	162	0	1.9	1	0	3	1	
59	48	1	1	130	245	0	0	180	0	0.2	1	0	2	1	

103	57	1	2	150	126	1	1	173	0	0.2	2	1	3	1	
104	54	1	1	108	309	0	1	156	0	0	2	0	3	1	
105	47	1	2	138	257	0	0	156	0	0	2	0	2	1	
106	52	1	3	118	186	0	0	190	0	0	1	0	1	1	
107	47	1	0	110	275	0	0	118	1	1	1	1	2	0	
108	51	1	0	140	299	0	1	173	1	1.6	2	0	3	0	
109	62	1	1	120	281	0	0	103	0	1.4	1	1	3	0	
110	40	1	0	152	223	0	1	181	0	0	2	0	3	0	
111	54	1	0	110	206	0	0	108	1	0	1	1	2	0	
112	44	1	0	110	197	0	0	177	0	0	2	1	2	0	
113	53	1	0	142	226	0	0	111	1	0	2	0	3	1	
114	48	1	0	130	256	1	0	150	1	0	2	2	3	0	
115	57	1	0	110	335	0	1	143	1	3	1	1	3	0	
116	59	1	2	126	218	1	1	134	0	2.2	1	1	1	0	
117	61	0	0	145	307	0	0	146	1	1	1	0	3	0	
118	63	1	0	130	254	0	0	147	0	1.4	1	1	3	0	
119	43	1	0	120	177	0	0	120	1	2.5	1	0	3	0	
120	29	1	1	130	204	0	0	202	0	0	2	0	2	1	
121	42	1	1	120	295	0	1	162	0	0	2	0	2	1	
122	54	1	1	108	309	0	1	156	0	0	2	0	3	1	
123	44	1	0	120	169	0	1	144	1	2.8	0	0	1	0	
124	60	1	0	145	282	0	0	142	1	2.8	1	2	3	0	
125	65	0	2	140	417	1	0	157	0	0.8	2	1	2	1	
126	61	1	0	120	260	0	1	140	1	3.6	1	1	3	0	
127	60	0	3	150	240	0	1	171	0	0.9	2	0	2	1	
128	66	1	0	120	302	0	0	151	0	0.4	1	0	2	1	
129	53	1	2	130	197	1	0	152	0	1.2	0	0	2	1	
130	52	1	2	138	223	0	1	169	0	0	2	4	2	1	
131	57	1	0	140	192	0	1	148	0	0.4	1	0	1	1	

< > heart ⊕
⋮ <

FIG 4.2 DATASET COLLECTION

4.2.3 RANDOM FORESTS

1. Random Forests, an ensemble learning method, represent a robust and widely utilized approach in the realm of Cardiovascular Disease Prediction using Machine Learning.
2. Built upon the foundation of Decision Trees, Random Forests harness the power of aggregation to enhance predictive accuracy and mitigate overfitting.
3. The model constructs multiple decision trees during training, each tree trained on a random subset of the data and features.
4. By aggregating the predictions of these individual trees, typically through a majority voting scheme for classification tasks, Random Forests generate more stable and reliable predictions compared to single Decision Trees.
5. This ensemble approach not only improves the model's generalization capabilities but also provides insights into feature importance, allowing for a deeper understanding of the factors contributing to cardiovascular disease risk.
6. Moreover, Random Forests excel in handling high-dimensional datasets with complex interactions among features, making them well-suited for the multifaceted nature of medical data.
7. Additionally, the inherent parallelism of Random Forests enables efficient training on large datasets, facilitating scalability and real-time prediction in clinical settings.
8. Despite their effectiveness, Random Forests may exhibit some computational overhead due to the ensemble nature of the model.
9. Nevertheless, their versatility, robustness, and ability to capture complex relationships make Random Forests a cornerstone.

```

# Load the heart disease dataset
heartdata = pd.read_csv("heart.csv")

# Separate features and target
X = heartdata.drop(columns='target', axis=1)
y = heartdata['target']

# Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, stratify=y, random_state=2)

# Create and fit a random forest classifier
rf_model = RandomForestClassifier(n_estimators=100, random_state=2)
rf_model.fit(X_train, y_train)

# Make predictions on the testing set
y_pred_rf = rf_model.predict(X_test)

# Calculate the accuracy of the model
acc_rf = accuracy_score(y_test, y_pred_rf)
print("Random Forest accuracy:", acc_rf)

# Make predictions on a single example
example = [[71, 0, 0, 112, 149, 0, 1, 125, 0, 1.6, 1, 0, 2]]
prediction = rf_model.predict(example)
if prediction[0] == 0:
    print("Patient does not have any heart disease")
else:
    print("Patient has heart disease and needs more tests")

# Calculate the f1 score
f1_rf = classification_report(y_test, y_pred_rf)
print("Random Forest f1 score:")
print(f1_rf)

# Calculate the confusion matrix
cm_rf = confusion_matrix(y_test, y_pred_rf)
print("Random Forest confusion matrix:")
print(cm_rf)

```



```

# all columns
X = heartdata.drop(columns='target', axis=1)
# target column
y = heartdata['target']

# split data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, stratify=y, random_state=2)

# create and fit the SVM model
svm_model = SVC(kernel='linear')
svm_model.fit(X_train, y_train)

# make predictions on the testing set
y_pred_svm = svm_model.predict(X_test)

# calculate accuracy of the model
acc_svm = accuracy_score(y_test, y_pred_svm)
print("SVM accuracy:", acc_svm)

# make predictions on a single example
example = [[71, 0, 0, 112, 149, 0, 1, 125, 0, 1.6, 1, 0, 2]]
prediction = svm_model.predict(example)
if prediction[0] == 0:
    print("Patient does not have any heart disease")
else:
    print("Patient has heart disease and needs more tests")

# Calculate f1 score
f1_svm = classification_report(y_test, y_pred_svm)
print("SVM f1 score:")
print(f1_svm)

# Calculate confusion matrix
cm_svm = confusion_matrix(y_test, y_pred_svm)
print("SVM confusion matrix:")
print(cm_svm)

```

FIG 4.3 SAMPLE CODE FOR DATA COLLECTION

CHAPTER 5

SYSTEM SPECIFICATION

5.1 SOFTWARE REQUIREMENT SPECIFICATION

The software requirements specification is produced at the culmination of the analysis task. The function and performance allocated to software as part of system engineering are refined by establishing a complete information description as functional representation of system behavior, an indication of performance requirements and design constraints, appropriate validation criteria.

5.2 SYSTEM REQUIREMENTS

5.2.1 HARDWARE REQUIREMENTS:

Processor	: AMD RYZEN 5 5600H
Video card	: NVIDIA Ge Force GTX 1650 super
Memory	: 8GB RAM
Resolution	: 1024*768 minimum display resolution
Webcam	: Min. 720 pixels

5.2.2 SOFTWARE REQUIREMENTS:

Software Tool	: Visual Studio Code
Operating System	: Windows 10
Processors	: Any Intel or AMD X86-64 processor
RAM	: 8GB
Graphics Card	: GTX 1050 ti graphics card required
Packages Used	: numpy, pandas, sklearn, DecisionTreeClassifier, LinearRegression, RandomForestClassifier.

CHAPTER 6

SOFTWARE DESCRIPTION

6.1 DESIGN AND IMPLEMENTATION CONSTRAINTS

6.1.1 CONSTRAINTS IN ANALYSIS

- Addressing these constraints requires a multidisciplinary approach, involving collaboration between data scientists.
- Healthcare professionals, policymakers, and other stakeholders to develop accurate, interpretable, and ethically sound predictive models for cardiovascular disease prediction.

6.1.2 CONSTRAINTS IN ANALYSIS

- Ensuring model interpretability is crucial for gaining trust from healthcare professionals and facilitating the adoption of predictive models in real-world settings.
- Furthermore, the generalizability of predictive models across different patient populations and healthcare settings poses a significant challenge.

6.2 SYSTEM FEATURES

6.2.1 USER INTERFACES

- Users are communicated.
- Graphical User Interfaces in this product.

6.2.2 HARDWARE INTERFACES

These interfaces enable communication between the machine learning system and various hardware components, ensuring seamless interaction and data exchange. One essential hardware interface is the integration with electronic health record (EHR) systems, which serve as repositories for patient health information. Through interoperability standards and protocols, such as HL7 (Health Level Seven) or FHIR (Fast Healthcare Interoperability Resources), the machine learning system can access patient data stored in EHRs, enabling real-time risk assessment and decision-making. Additionally, wearable devices and sensors provide valuable physiological data, such as heart rate, blood pressure, and physical activity levels, which can enhance the predictive capabilities of the model.

6.2.3 SOFTWARE INTERFACES

Through standardized query languages like SQL (Structured Query Language) or APIs (Application Programming Interfaces), the machine learning system can access and retrieve data from these sources for analysis and prediction.

6.2.4 COMMUNICATIONS INTERFACES

The TCP/IP protocol will be used to facilitate communications between the nodes.

6.3 USER DOCUMENTATION:

The application will be having a user manual for helping and guiding the users on how to interact with system and perform various functions. The core components and its usage will be explained in detail.

- HL7 (Health Level Seven)
- HER (electronic health record)

6.4 SOFTWARE QUALITY ATTRIBUTES:

6.4.1 USER-FRIENDLINESS

User-friendliness is a paramount consideration in the development of machine learning systems for cardiovascular disease prediction. It encompasses several aspects aimed at ensuring that healthcare professionals can easily interact with and derive value from the predictive models. One key aspect is the integration with existing electronic health record (EHR) systems.

6.4.2 RELIABILITY

Reliability is paramount in machine learning systems for cardiovascular disease prediction, as it directly impacts patient care and decision-making in clinical settings. Several factors contribute to the reliability of such systems.

6.4.3 MAINTAINABILITY

Maintainability is a critical aspect of machine learning systems for cardiovascular disease prediction, ensuring that the system remains effective, efficient, and reliable over time. Several key considerations contribute to the maintainability of such systems.

6.5 OTHER NON-FUNCTIONAL REQUIREMENTS

6.5.1 PERFORMANCE REQUIREMENTS

FUNCTIONAL REQUIREMENTS

FR.NO	FUNCTIONAL REQUIREMENTS	SUB REQUIREMENTS (STORY / SUB TASK)
FR-1	Data Collection and Integration	clinical, demographic, electronic health records
FR-2	Data Preprocessing	missing values perform feature
FR-3	Reporting	Any Problems faced by customer should be reported Automatically
FR-4	Model Deployment	real-time risk assessment
FR-5	Historical Data	Collected data form the past events must be used improved

Table 6.1: Functional Requirements

NON-FUNCTIONAL REQUIREMENTS

The non-functional requirements are:

NFR.NO	NON-FUNCTIONAL REQUIREMENT	DESCRIPTION
NFR-1	Performance	efficiently and provide timely support real-time decision-making
NFR-2	Security	Should be resistive to cyberattacks as the information shared is very confidential.
NFR-3	Reliability	Support should be provided for in-house or remote accessibility for external resources if required.
NFR-4	Interpretability	model predictions predictions and assess
NFR-5	Availability	Continuous availability of our service must be provided all the time
NFR-6	Scalability	user loads without compromising performance users at the same time

Table 6.2: Non Functional Requirements

6.5.2 Safety Requirements

Safety requirements are crucial in the development and implementation of Cardiovascular Disease Prediction Using Machine Learning systems to safeguard patient well-being and mitigate potential risks. Firstly, ensuring patient data privacy and confidentiality is paramount. This involves implementing robust security measures, such as encryption and access controls, to protect sensitive health information from unauthorized access or disclosure. Additionally, predictive models must undergo rigorous validation to ensure accuracy and reliability in predicting cardiovascular disease risk, with regular monitoring to detect and address errors or biases. Transparency and interpretability are essential, enabling healthcare professionals to understand and critically evaluate model predictions.

6.5.3 Product Features:

The product features are listed below,

Ethical and Regulatory Compliance ->

Adherence to ethical guidelines and regulatory requirements governing the use of predictive models and patient data in healthcare is essential to ensure responsible and ethical use of the system.

Continuous Monitoring and Maintenance->

The system should support continuous monitoring of model performance and outcomes in clinical practice, with mechanisms for detecting and addressing issues such as performance degradation or drift over time.

6.5.4 Test Cases

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 303 entries, 0 to 302
Data columns (total 14 columns):
#   Column      Non-Null Count  Dtype
---  -
0   age         303 non-null    int64
1   sex         303 non-null    int64
2   cp          303 non-null    int64
3   trestbps    303 non-null    int64
4   chol        303 non-null    int64
5   fbs         303 non-null    int64
6   restecg     303 non-null    int64
7   thalach     303 non-null    int64
8   exang       303 non-null    int64
9   oldpeak     303 non-null    float64
10  slope       303 non-null    int64
11  ca          303 non-null    int64
12  thal        303 non-null    int64
13  target      303 non-null    int64
dtypes: float64(1), int64(13)
memory usage: 33.3 KB
```

Table 6.3 Test Cases

CHAPTER 7

CONCLUSION AND FUTURE ENHANCEMENT

7.1 CONCLUSION

In conclusion, the Cardiovascular Disease Prediction Using Machine Learning system represents a significant advancement in healthcare, offering powerful tools for early detection and proactive management of cardiovascular diseases. By integrating diverse datasets and leveraging sophisticated machine learning algorithms, this system can provide accurate and timely risk assessments, thereby enhancing clinical decision-making and improving patient outcomes. The emphasis on user-friendliness ensures that healthcare professionals can easily interact with the system, gaining valuable insights without extensive technical knowledge. Robust data security measures and adherence to regulatory standards ensure patient data privacy and compliance with ethical guidelines. Continuous monitoring and maintenance of the system guarantee its reliability and relevance over time. Ultimately, the deployment of such predictive models in clinical practice holds the potential to transform cardiovascular disease prevention and treatment, promoting more personalized and effective healthcare solutions. This innovation not only addresses the pressing needs of today's healthcare landscape but also paves the way for future advancements in medical AI and machine learning applications.

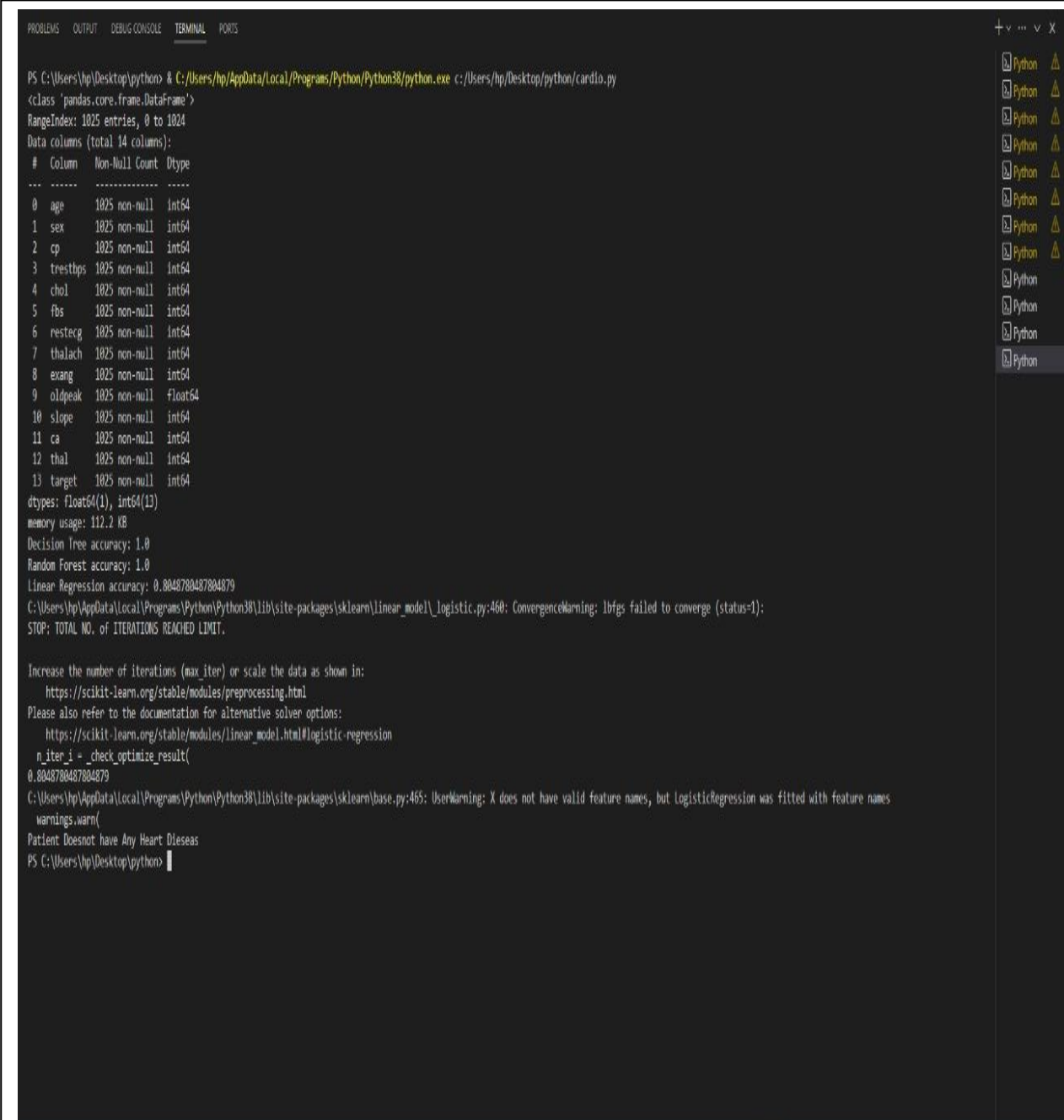
7.2 FUTURE ENHANCEMENT

Future enhancements for the Cardiovascular Disease Prediction Using Machine Learning system can further optimize its accuracy, usability, and impact on patient care. One key area of enhancement is the incorporation of more diverse and extensive datasets, including genetic, lifestyle, and real-time monitoring data from wearable devices, to improve the model's comprehensiveness and predictive power. Advances in deep learning and neural networks could be explored to capture complex patterns and interactions within the data that traditional models might miss. Enhancing the system's interoperability with other healthcare applications and platforms will facilitate a more seamless integration into clinical workflows, enabling broader adoption and use. Moreover, developing advanced explainability tools will help demystify model predictions, providing healthcare professionals with

clear, actionable insights that can be easily communicated to patients. Implementing real-time adaptive learning, where the model continuously updates and improves as new data becomes available, can keep the system

SCREEN SHOT 1

OUTPUT 1:



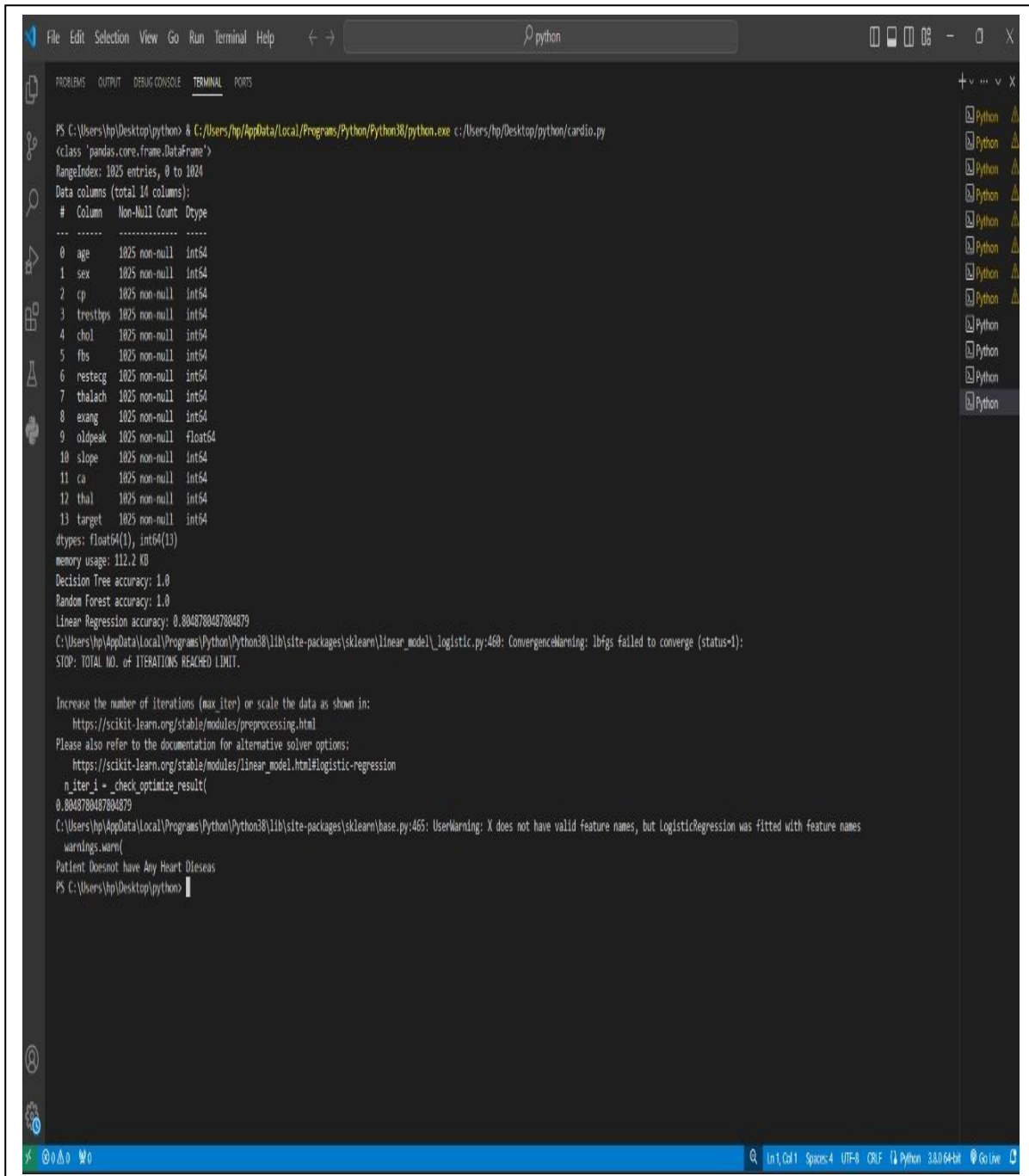
```
PS C:\Users\hp\Desktop\python> & C:/Users/hp/AppData/Local/Programs/Python/Python38/python.exe c:/Users/hp/Desktop/python/heart.py
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1025 entries, 0 to 1024
Data columns (total 14 columns):
 #   Column      Non-Null Count  Dtype
---  ---
 0   age         1025 non-null   int64
 1   sex         1025 non-null   int64
 2   cp          1025 non-null   int64
 3   trestbps    1025 non-null   int64
 4   chol        1025 non-null   int64
 5   fbs         1025 non-null   int64
 6   restecg     1025 non-null   int64
 7   thalach     1025 non-null   int64
 8   exang       1025 non-null   int64
 9   oldpeak     1025 non-null   float64
10   slope       1025 non-null   int64
11   ca          1025 non-null   int64
12   thal        1025 non-null   int64
13   target      1025 non-null   int64
dtypes: float64(1), int64(13)
memory usage: 112.2 KB
Decision Tree accuracy: 1.0
Random Forest accuracy: 1.0
Linear Regression accuracy: 0.8048780487804879
C:\Users\hp\AppData\Local\Programs\Python\Python38\lib\site-packages\sklearn\linear_model\_logistic.py:460: 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_i = _check_optimize_result(
0.8048780487804879
C:\Users\hp\AppData\Local\Programs\Python\Python38\lib\site-packages\sklearn\base.py:465: UserWarning: X does not have valid feature names, but LogisticRegression was fitted with feature names
warnings.warn(
Patient Doesnot have Any Heart Diseas
PS C:\Users\hp\Desktop\python>
```

FIG 7.1 OUTPUT

SCREEN SHOT 2

OUTPUT 2:



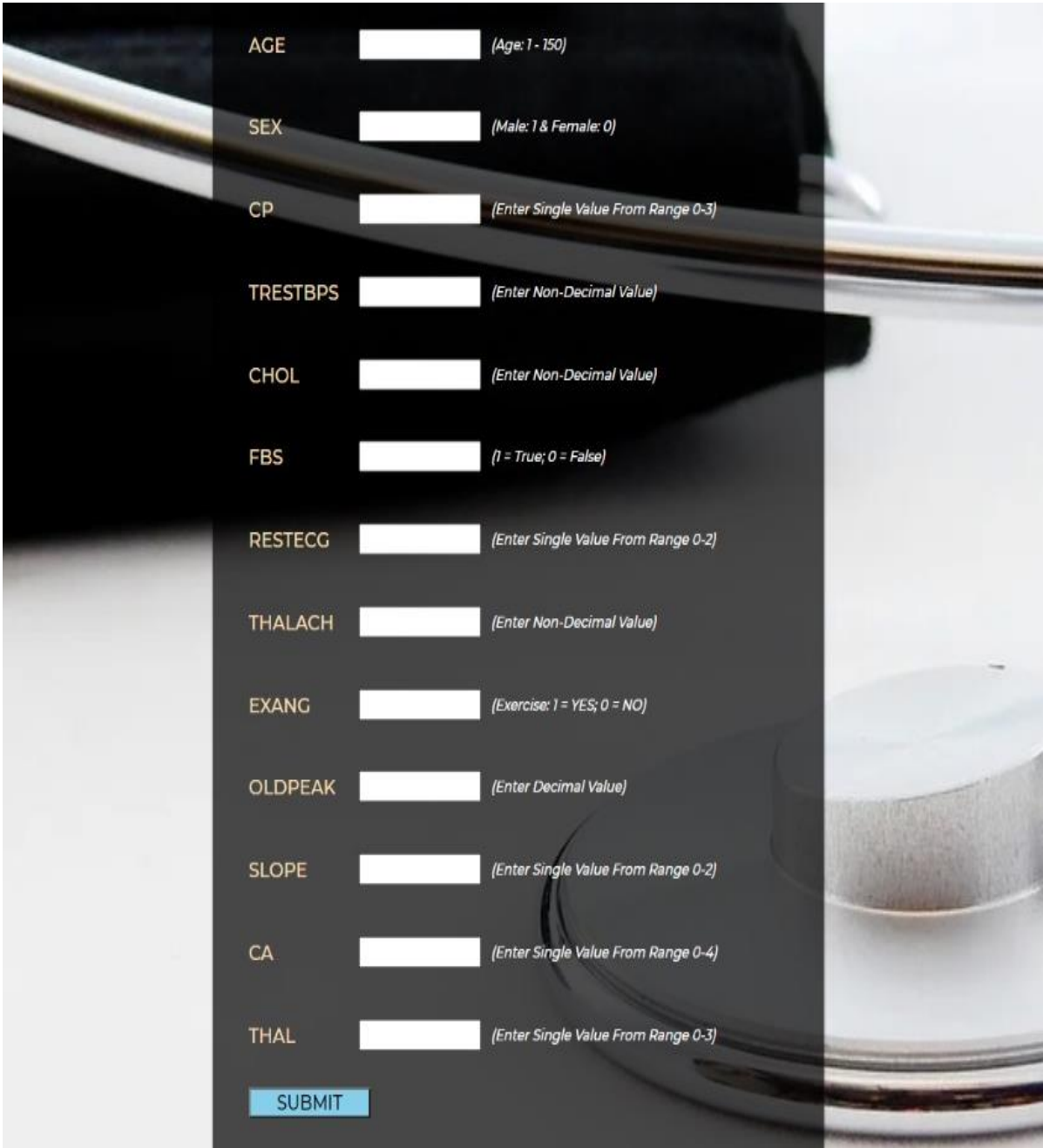
```
PS C:\Users\hp\Desktop\python> & C:/Users/hp/AppData/Local/Programs/Python/Python38/python.exe c:/Users/hp/Desktop/python/cardio.py
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1025 entries, 0 to 1024
Data columns (total 14 columns):
 #   Column      Non-Null Count  Dtype
---  -
 0   age         1025 non-null   int64
 1   sex         1025 non-null   int64
 2   cp          1025 non-null   int64
 3   trestbps    1025 non-null   int64
 4   chol        1025 non-null   int64
 5   fbs         1025 non-null   int64
 6   restecg     1025 non-null   int64
 7   thalach     1025 non-null   int64
 8   exang       1025 non-null   int64
 9   oldpeak     1025 non-null   float64
10   slope       1025 non-null   int64
11   ca          1025 non-null   int64
12   thal        1025 non-null   int64
13   target      1025 non-null   int64
dtypes: float64(1), int64(13)
memory usage: 112.2 KB
Decision Tree accuracy: 1.0
Random Forest accuracy: 1.0
Linear Regression accuracy: 0.8048780487804879
C:\Users\hp\AppData\Local\Programs\Python\Python38\lib\site-packages\sklearn\linear_model\_logistic.py:460: 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_i = _check_optimize_result(
0.8048780487804879
C:\Users\hp\AppData\Local\Programs\Python\Python38\lib\site-packages\sklearn\base.py:465: UserWarning: X does not have valid feature names, but LogisticRegression was fitted with feature names
  warnings.warn(
Patient Doesnot have Any Heart Diseas
PS C:\Users\hp\Desktop\python>
```

FIG 7.2 OUTPUT

SCREEN SHOT 3

LOGIN PAGE :



AGE (Age: 1 - 150)

SEX (Male: 1 & Female: 0)

CP (Enter Single Value From Range 0-3)

TRESTBPS (Enter Non-Decimal Value)

CHOL (Enter Non-Decimal Value)

FBS (1 = True; 0 = False)

RESTECG (Enter Single Value From Range 0-2)

THALACH (Enter Non-Decimal Value)

EXANG (Exercise: 1 = YES; 0 = NO)

OLDPEAK (Enter Decimal Value)

SLOPE (Enter Single Value From Range 0-2)

CA (Enter Single Value From Range 0-4)

THAL (Enter Single Value From Range 0-3)

FIG 7.3 LOGIN PAGE

CORRELATION MATRIX:

```
plt.figure(figsize=(15,10))
sns.heatmap(dataframe.corr(),linewidth=.01,annot=True,cmap="winter")
plt.show()
plt.savefig('correlationfigure')
```

Output:

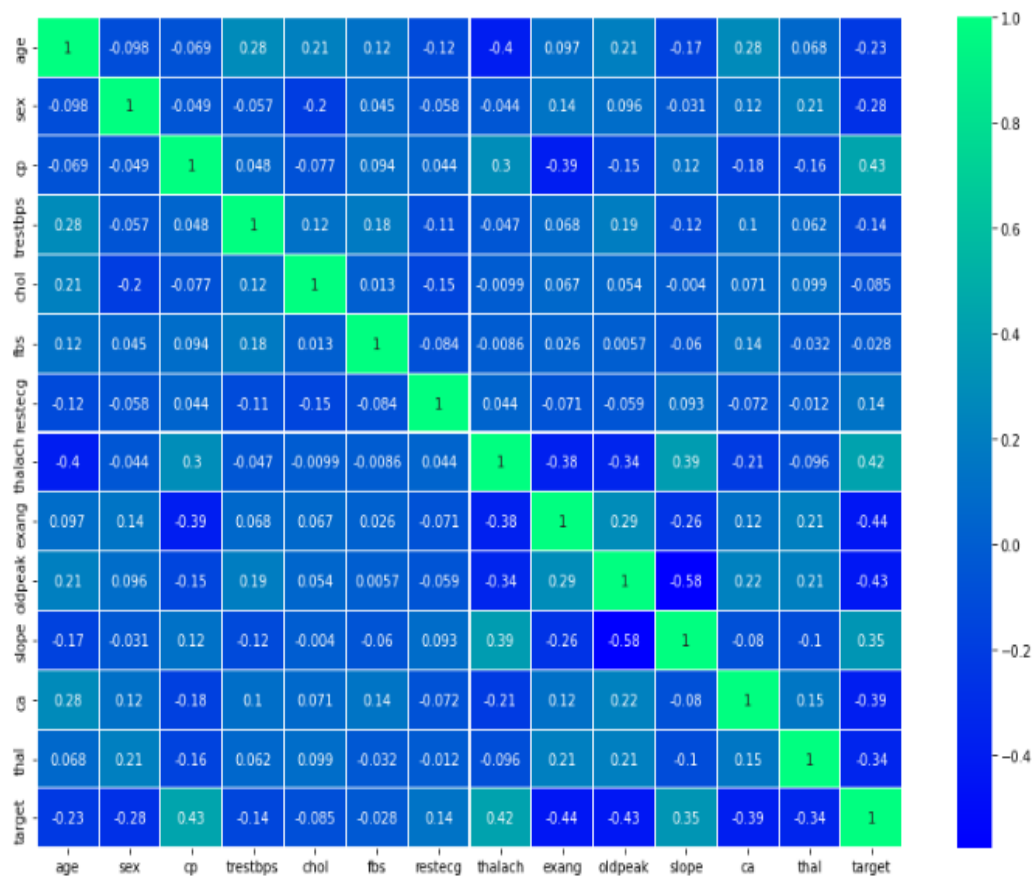


FIG 7.4 CORRELATION MATRIX

INFERENCE:

```
dataframe.hist(figsize=(12,12))  
plt.savefig('featuresplot')
```

Output:

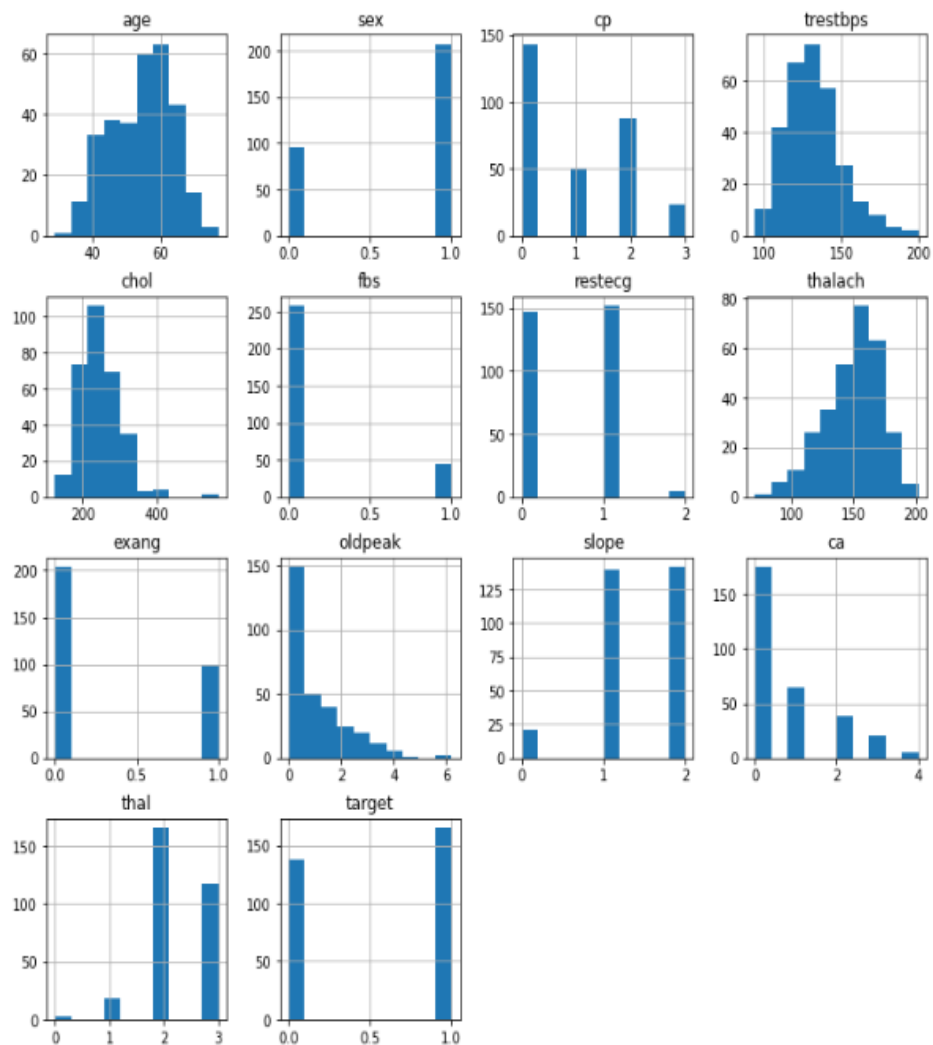


FIG 7.5 INFERENCE

ALGORITHM IMPLEMENTATION:

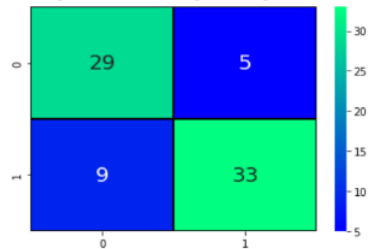
1. Logistic Regression

```
from sklearn.model_selection import cross_val_score, GridSearchCV
from sklearn.linear_model import LogisticRegression
lr=LogisticRegression(C=1.0, class_weight='balanced', dual=False,
                        fit_intercept=True, intercept_scaling=1, l1_ratio=None,
                        max_iter=100, multi_class='auto', n_jobs=None, penalty='l2',
                        random_state=1234, solver='lbfgs', tol=0.0001, verbose=0,
                        warm_start=False)
model=lr.fit(X_train,y_train)
prediction=model.predict(X_test)
from sklearn.metrics import confusion_matrix
cm=confusion_matrix(y_test,prediction)
cm
sns.heatmap(cm, annot=True,cmap='winter',linewidths=0.3, linecolor='black',annot_kws={"size": 20})
TP=cm[0][0]
TN=cm[1][1]
FN=cm[1][0]
FP=cm[0][1]

print('Testing Accuracy for Logistic Regression:',(TP+TN)/(TP+TN+FN+FP))
print('Testing Sensitivity for Logistic Regression:',(TP/(TP+FN)))
print('Testing Specificity for Logistic Regression:',(TN/(TN+FP)))
print('Testing Precision for Logistic Regression:',(TP/(TP+FP)))
```

Output:

Testing Accuracy for Logistic Regression: 0.8157894736842105
Testing Sensitivity for Logistic Regression: 0.7631578947368421
Testing Specificity for Logistic Regression: 0.868421052631579
Testing Precision for Logistic Regression: 0.8529411764705882



2. Decision Tree

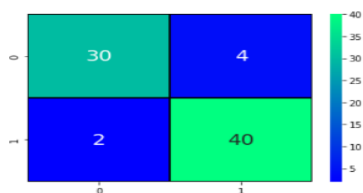
```
from sklearn.model_selection import RandomizedSearchCV
from sklearn.tree import DecisionTreeClassifier
tree_model = DecisionTreeClassifier(max_depth=5,criterion='entropy')
cv_scores = cross_val_score(tree_model, X, y, cv=10, scoring='accuracy')
tree_model.fit(X, y)
prediction=tree_model.predict(X_test)
cm= confusion_matrix(y_test,prediction)
sns.heatmap(cm, annot=True,cmap='winter',linewidths=0.3, linecolor='black',annot_kws={"size": 20})
print(classification_report(y_test, prediction))
TP=cm[0][0]
TN=cm[1][1]
FN=cm[1][0]
FP=cm[0][1]

print('Testing Accuracy for Decision Tree:',(TP+TN)/(TP+TN+FN+FP))
print('Testing Sensitivity for Decision Tree:',(TP/(TP+FN)))
print('Testing Specificity for Decision Tree:',(TN/(TN+FP)))
print('Testing Precision for Decision Tree:',(TP/(TP+FP)))
```

Output:

Testing Accuracy for Decision Tree: 0.9210526315789473
Testing Sensitivity for Decision Tree: 0.9375
Testing Specificity for Decision Tree: 0.9000000000000001
Testing Precision for Decision Tree: 0.8823529411764706

	precision	recall	f1-score	support
0	0.94	0.88	0.91	34
1	0.91	0.95	0.93	42
accuracy			0.92	76
macro avg	0.92	0.92	0.92	76
weighted avg	0.92	0.92	0.92	76



3. Random Forest Classifier

```
from sklearn.ensemble import RandomForestClassifier
rfc=RandomForestClassifier(n_estimators=500,criterion='entropy',max_depth=8,min_samples_split=5)
model3 = rfc.fit(X_train, y_train)
prediction3 = model3.predict(X_test)
cm3=confusion_matrix(y_test, prediction3)
sns.heatmap(cm3, annot=True,cmap='winter',linewidths=0.3, linecolor='black',annot_kws={"size": 20})
TP=cm3[0][0]
TN=cm3[1][1]
FN=cm3[1][0]
FP=cm3[0][1]
print(round(accuracy_score(prediction3,y_test)*100,2))
print('Testing Accuracy for Random Forest:',(TP+TN)/(TP+TN+FN+FP))
print('Testing Sensitivity for Random Forest:',(TP/(TP+FN)))
print('Testing Specificity for Random Forest:',(TN/(TN+FP)))
print('Testing Precision for Random Forest:',(TP/(TP+FP)))
```

Output:

80.26
Testing Accuracy for Random Forest: 0.8026315789473685
Testing Sensitivity for Random Forest: 0.7714285714285715
Testing Specificity for Random Forest: 0.8292682926829268
Testing Precision for Random Forest: 0.7941176470588235



4. Support Vector Machines(SVM)

```
from sklearn.svm import SVC
svm=SVC(C=12,kernel='linear')
model4=svm.fit(X_train,y_train)
prediction4=model4.predict(X_test)
cm4= confusion_matrix(y_test,prediction4)
sns.heatmap(cm4, annot=True,cmap='winter',linewidths=0.3, linecolor='black',annot_kws={"size": 20})
TP=cm4[0][0]
TN=cm4[1][1]
FN=cm4[1][0]
FP=cm4[0][1]

print('Testing Accuracy for SVM:',(TP+TN)/(TP+TN+FN+FP))
print('Testing Sensitivity for Random Forest:',(TP/(TP+FN)))
print('Testing Specificity for Random Forest:',(TN/(TN+FP)))
print('Testing Precision for Random Forest:',(TP/(TP+FP)))
```

Output:

Testing Accuracy for SVM: 0.8157894736842105
Testing Sensitivity for Random Forest: 0.7777777777777778
Testing Specificity for Random Forest: 0.85
Testing Precision for Random Forest: 0.8235294117647058

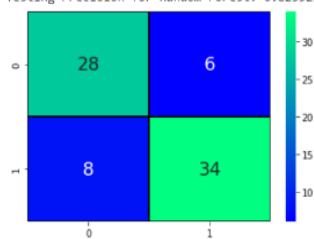


FIG 7.6 ALGORITHM IMPLEMENTATION

IMPLEMENTATION CODE :

```
import numpy as np
import pandas as py
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LinearRegression
heartdata=py.read_csv("heart.csv")
heartdata.head()
heartdata.tail()
# heartdata.shape
heartdata.info()
heartdata.describe()
targets=heartdata['target'].value_counts()
#all columns
X=heartdata.drop(columns='target',axis=1)
#target column
Y=heartdata['target']
X_train,X_test,Y_train,Y_test=train_test_split(X,Y,test_size=0.2,stratify=Y,random
_state=2)
# print(X.shape,X_train.shape,X_test.shape)
dt = DecisionTreeClassifier()
dt.fit(X_train, Y_train)
y_pred_dt = dt.predict(X_test)
acc_dt = accuracy_score(Y_test, y_pred_dt)

print("Decision Tree accuracy:", acc_dt)
# Random Forest model
```

```

rf = RandomForestClassifier()
rf.fit(X_train, Y_train)
y_pred_rf = rf.predict(X_test)
acc_rf = accuracy_score(Y_test, y_pred_rf)
print("Random Forest accuracy:", acc_rf)
# Linear Regression model
lr = LinearRegression()
lr.fit(X_train, Y_train)
y_pred_lr = lr.predict(X_test)
y_pred_lr[y_pred_lr < 0.5] = 0
y_pred_lr[y_pred_lr >= 0.5] = 1
acc_lr = accuracy_score(Y_test, y_pred_lr)
print("Linear Regression accuracy:", acc_lr)
# model = LogisticRegression()
# model.fit(X_train, Y_train)
# y_pred_lr = model.predict(X_test)
# acc_lr = accuracy_score(Y_test, y_pred_lr)
# print("Logistic Regression accuracy:", acc_lr)
model=LogisticRegression()
model.fit(X_train,Y_train )
X_train_prediction=model.predict(X_train)
trainigdataaccuracy=accuracy_score(X_train_prediction,Y_train)
# print( trainigdataaccuracy)
X_test_prediction=model.predict(X_test)
testdataaccuracy=accuracy_score(X_test_prediction,Y_test)
print( testdataaccuracy)
input_from_user=(43,0,0,132,341,1,0,136,1,3,1,0,3)
input_from_user_array=np.asarray(input_from_user)
input_from_user_reshaped=input_from_user_array.reshape(1,-1)
prediction=model.predict(input_from_user_reshaped)

```

```

if prediction[0]==0:
    print("Patient Doesnot have Any Heart Diseas")
else:
    print("Patient Has heart diseas he needs more tests")
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix

# Load the heart disease dataset
heartdata = pd.read_csv("heart.csv")

# Separate features and target
X = heartdata.drop(columns='target', axis=1)
y = heartdata['target']

# Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, stratify=y,
random_state=2)

# Create and fit a KNN classifier
knn_model = KNeighborsClassifier(n_neighbors=5)
knn_model.fit(X_train, y_train)

# Make predictions on the testing set
y_pred_knn = knn_model.predict(X_test)

# Calculate the accuracy of the model

```

```

acc_knn = accuracy_score(y_test, y_pred_knn)
print("KNN accuracy:", acc_knn)

# Make predictions on a single example
example = [[71, 0, 0, 112, 149, 0, 1, 125, 0, 1.6, 1, 0, 2]]
prediction = knn_model.predict(example)
if prediction[0] == 0:
    print("Patient does not have any heart disease")
else:
    print("Patient has heart disease and needs more tests")

# Calculate the f1 score
f1_knn = classification_report(y_test, y_pred_knn)
print("KNN f1 score:")
print(f1_knn)

# Calculate the confusion matrix
cm_knn = confusion_matrix(y_test, y_pred_knn)
print("KNN confusion matrix:")
print(cm_knn)

```

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