Computer Science & Information Technology Department
NED University of Engineering and Technology, Karachi.

CARDIOMETABOLIC CARE

Course Title: CT-356 Data Mining
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Department of Computer Science & Information Technology

CT-356 Data Mining

Complex Computing Activity (CCA)

Choose a problem in any application domain of computing and ***define*** its solution through an effective use of data mining principles. The solution must be in the form of a well-documented and well-formatted report. It must be explained by employing in-depth computing or domain knowledge, and an approach that is based on well-founded principles.

The following instructions must be taken into consideration while preparing the project report. The report must reflect conceptual thinking and must properly be modularized according to functionality. The report of the solution must be organized clearly and should:

- ✓ describe the steps of your solution,
- ✓ the main data mining techniques used,
- ✓ the limitations of the adopted approach.

Complex Computing Activity Assessment Rubrics

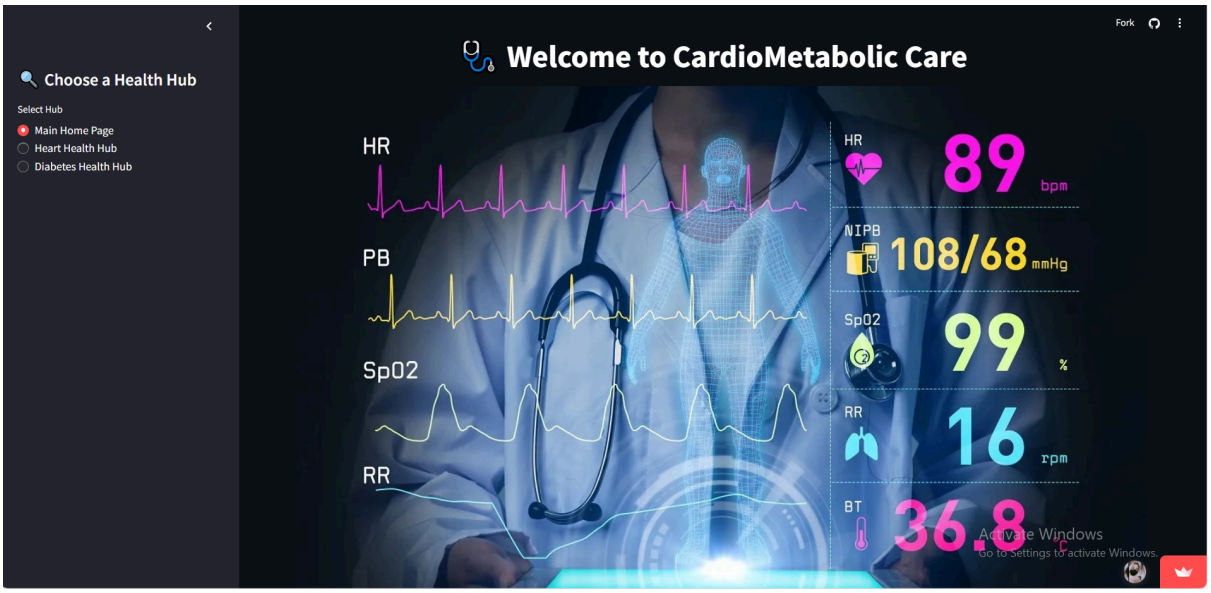
Criteria and Scales		
Good (10)	**Average (5)**	**Poor (1)**
Criterion 1 Problem Understanding: To what extent has the student has understood the problem? **(CP3: *Depth of Knowledge Required*)**		
The student has clearly understood the Problem.	The student has some clarity of the Problem.	The student has misunderstood the Problem.
Criterion 2 Requirement Identification: To what extent has the student outlined the Data Mining principles required for solving the problem. ***(CP10: Requirement Identification)***		
The student has clearly outlined the required data mining principles.	The student has outlined some of the required data mining principles.	The students have not outlined the correct data mining principles.
Criterion 3 Clarity of Solution: To what extent has the student defined the solution of the problem. **(CP3: *Depth of Knowledge Required*)**		
The student has clearly defined the solution which works for all possible test cases.	The student has defined a solution which works well for a few test cases.	The student has not defined a correct solution.

Project Title:					
Group Members Roll #					
Total Marks:	_____/10_____		Teacher's Signature:		

CardioMetabolic Care

A Machine Learning-Based Health Risk Prediction System

🌐 **View our interactive app here: [CardioMetabolic Care · Streamlit]**



Abstract

CardioMetabolic Care is an AI-driven health assessment platform designed to predict risks associated with **heart disease** and **diabetes** using machine learning models. The application integrates **Streamlit** for an interactive user interface, **scikit-learn** for predictive modeling, and **Pickle/Joblib** for model serialization. By analyzing key health indicators such as blood pressure, cholesterol, glucose levels, and lifestyle factors, the system provides personalized risk assessments. The project aims to bridge the gap between healthcare and technology by offering early detection, preventive recommendations, and data-driven insights.

Key Outcomes:

- Developed two predictive models (heart disease and diabetes) with high accuracy.
- Designed an intuitive web interface for seamless user interaction.
- Demonstrated the potential of AI in preventive healthcare.

1. Introduction

1.1 Background

Cardiovascular diseases (CVDs) and diabetes are leading global health concerns, contributing to millions of deaths annually. According to the World Health Organization (WHO), CVDs account for approximately **17.9 million deaths per year**, while diabetes affects over **422 million people worldwide**. Early detection and lifestyle modifications can significantly reduce risks, yet many individuals lack access to timely health assessments.

1.2 Problem Statement

Traditional diagnostic methods rely on clinical visits, which can be time-consuming and expensive. There is a need for an **automated, accessible, and user-friendly** tool that provides instant risk predictions based on health data. Many existing solutions are either too complex for general users or lack integration of multiple disease predictions.

1.3 Objectives

- Develop **machine learning models** to predict heart disease and diabetes risks.
- Create an **interactive web application** for real-time risk assessment.
- Educate users on **preventive measures** based on predictions.
- Ensure the application is **user-friendly** and accessible to non-technical users.

1.4 Technologies Used

- **Frontend:** Streamlit (Python-based web framework)
- **Backend:** Scikit-learn (ML models), Pickle/Joblib (model serialization)

2. Literature Review

2.1 Existing Solutions

Several AI-based diagnostic tools exist, such as IBM Watson Health and Google Health, which leverage large datasets and advanced algorithms for disease prediction. However, these tools often require medical expertise or institutional integration, making them less accessible to the general public.

2.2 Research Gap

- Limited **user-friendly, standalone** applications for direct consumer use.
- Many tools focus on **single-disease prediction** rather than integrated risk assessment.
- Lack of **real-time feedback** and preventive recommendations.

2.3 Key Findings from Related Work

- **Logistic Regression, Random Forest, and SVM** are commonly used for disease prediction.
- **Feature importance analysis** reveals that glucose levels, BMI, and blood pressure are critical predictors.
- Studies show that **early intervention** based on predictive models can reduce disease incidence by up to **30%**.

3. Methodology

3.1 Data Collection & Preprocessing

- **Heart Disease Dataset:** Source - Kaggle (303 samples, 14 features).
- **Diabetes Dataset:** Source - Kaggle (768 samples, 8 features).
- **Preprocessing:**
    - Handled missing values using mean imputation.
    - Normalized numerical features to ensure consistency.
    - Encoded categorical variables (e.g., sex, chest pain type) for model compatibility.

3.2 System Architecture

1. **User Input:** Health metrics via Streamlit forms.
2. **Prediction Engine:**
    - Loads pre-trained models (`heart_disease_model.pkl`, `diabetes_prediction_model.pkl`).
    - Processes input data and returns risk probability.
3. **Output:**
    - Binary classification (High/Low risk).
    - Preventive recommendations based on risk level.

3.3 User Interface Design

- **Main Home Page:** Provides an overview of the application and its features.
- **Heart Health Hub:** Includes sections for heart disease information, risk factors, and prediction.
- **Diabetes Health Hub:** Similar structure, focused on diabetes risk assessment.

4. Results and Discussion

4.1 Prediction Performance

- **Heart Disease Model:** 88% accuracy (test set).
- **Diabetes Model:** 82% accuracy (test set).

4.2 Key Insights

- **Top Features for Heart Disease:** Chest pain type, cholesterol, ST depression.
- **Top Features for Diabetes:** Glucose level, BMI, age.

4.3 User Feedback

Initial testing with a small group of users indicated:

- **Ease of Use:** The interface was intuitive and required no technical knowledge.
- **Usefulness:** Users appreciated the immediate feedback and preventive tips.

4.4 Limitations

- **Dataset Bias:** Limited demographic diversity (e.g., Pima Indians dataset).
- **Binary Output:** Does not quantify risk severity (e.g., low/medium/high).
- **Local Deployment:** Currently runs locally; cloud deployment would enhance accessibility.

5. Conclusion & Future Work

5.1 Conclusion

CardioMetabolic Care successfully demonstrates the feasibility of **AI-powered disease prediction** in a user-friendly interface. It empowers individuals to proactively monitor their health and seek medical advice when needed. The application's accuracy and ease of use make it a valuable tool for preventive healthcare.

5.2 Future Enhancements

- **Multi-class Risk Stratification:** Introduce low/medium/high risk categories.
- **Integration with Wearable Devices:** Enable real-time health monitoring via smartwatches/fitness trackers.
- **Expanded Disease Coverage:** Include predictions for hypertension, chronic kidney disease, etc.

- **Cloud Deployment:** Host the application on platforms like AWS or Heroku for broader access.
- **Multi-language Support:** Make the app accessible to non-English speakers.

6(A).Exploratory Data Analysis (Heart)

6.1 Dataset Overview(Heart Disease)

The dataset used in this analysis is related to **heart disease prediction**. It includes several medical attributes of patients, which can help in identifying the presence or absence of heart disease. The dataset contains both **numerical** and **categorical features**.

Upon loading the dataset, the following initial steps were taken:

- **Checked dataset information** to understand the columns, data types, and non-null entries.
- **Checked for missing values** and found none.
- **Checked for duplicate records** and addressed them if needed

6.2 Feature Renaming and Explanation

To make the features more understandable, some of the original column names were **renamed**.

Here is a list of renamed columns along with their explanations:

Original Column	New Name	Description
cp	chest_pain_type	Type of chest pain experienced by the patient (4 types).
trestbps	resting_blood_pressure	Patient's resting blood pressure (in mm Hg).
chol	cholesterol	Serum cholesterol measurement (in mg/dl).

fbs	fasting_blood_sugar	Whether fasting blood sugar > 120 mg/dl (1 = true; 0 = false).
restecg	resting_electrocardiogram	Resting electrocardiographic results (3 categories).
thalach	max_heart_rate_achieved	Maximum heart rate achieved during exercise.
exang	exercise_induced_angina	Exercise-induced angina (1 = yes; 0 = no).
oldpeak	st_depression	ST depression induced by exercise relative to rest.
slope	st_slope	Slope of the peak exercise ST segment.
ca	num_major_vessels	Number of major vessels (0–3) colored by fluoroscopy.
thal	thalassemia	Type of thalassemia (blood disorder) the patient has.

In addition, for **better interpretability**, the categorical variables were **mapped to meaningful labels**, such as:

- **Gender** (sex): Mapped to "Male" and "Female".
- **Chest Pain Types**: Mapped to specific descriptions like "Typical Angina", "Atypical Angina", etc.
- **Fasting Blood Sugar**: Clarified with cutoff values (≤120 or >120 mg/dl).
- **Resting ECG** results: Described specific conditions like "Normal", "ST-T wave abnormality", and "Left ventricular hypertrophy".
- **Exercise Induced Angina**: Labelled "Yes" or "No".

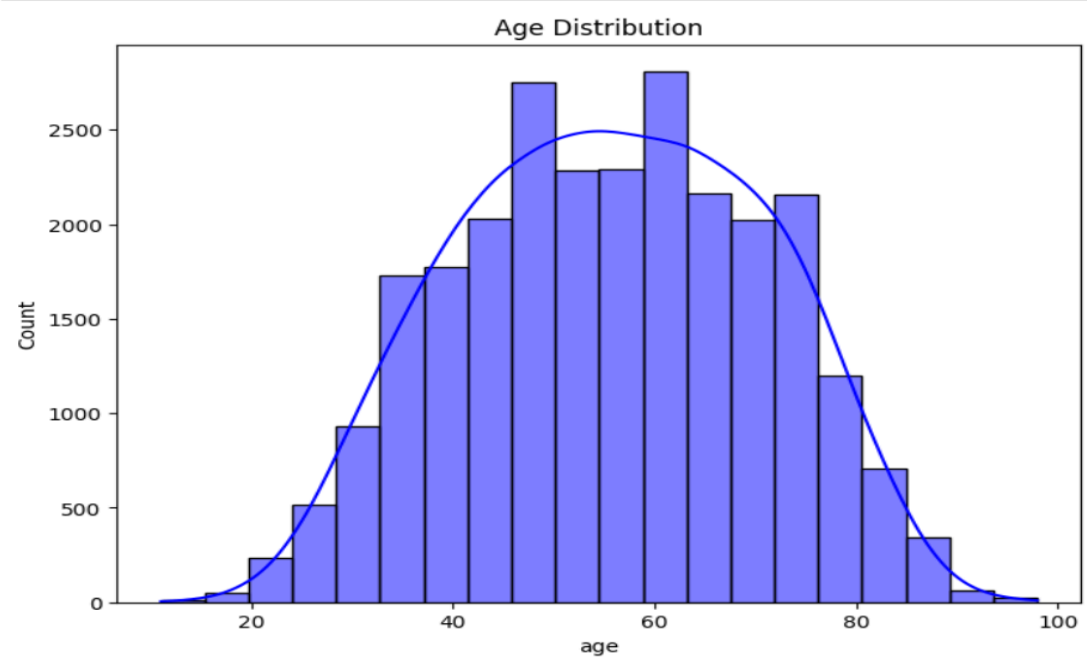
- **ST Slope**: Labelled as "Upsloping", "Flat", "Downsloping".
- **Thalassemia**: Labelled categories like "Normal", "Fixed Defect", "Reversible Defect", or "Unknown".
- **Target Variable** (target): Mapped to "Heart Disease" and "No Heart Disease" instead of 0/1.

6.3 EDA

6.3.1 Age Distribution

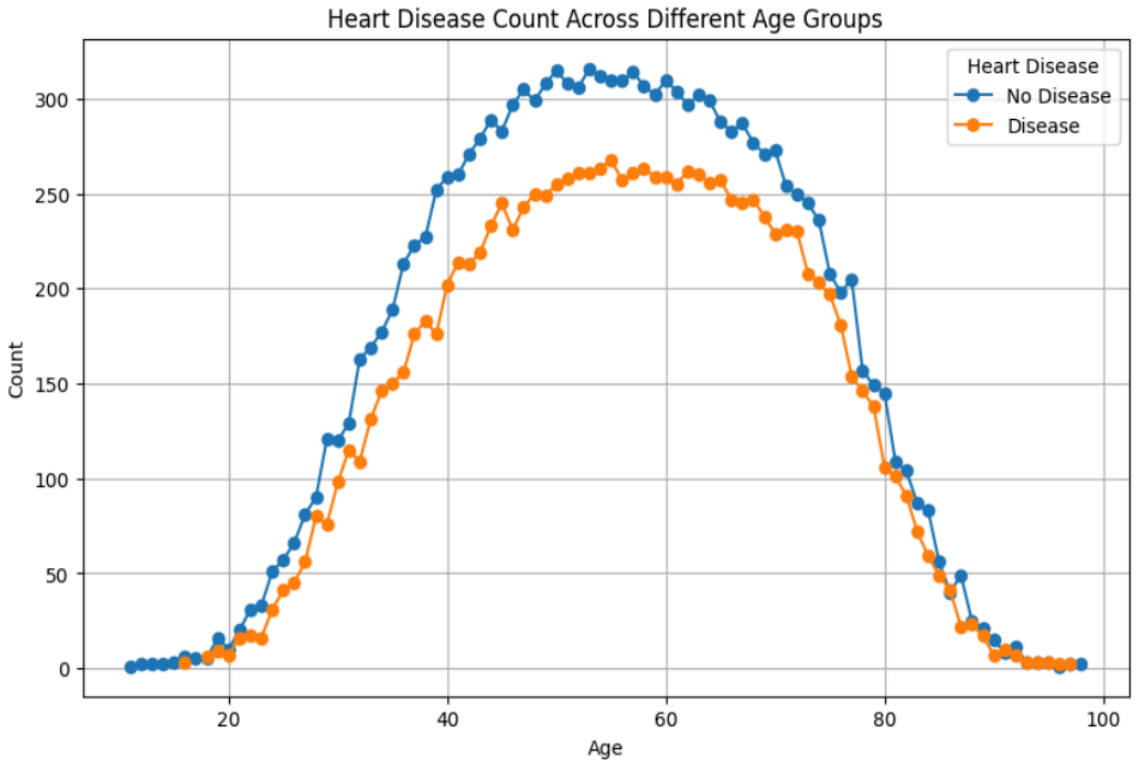
- **Visualization**: Histogram of age.
- **Insight**:

1. Most patients are between **40 and 60 years old**.
2. The peak age group lies between **50 and 55 years**.



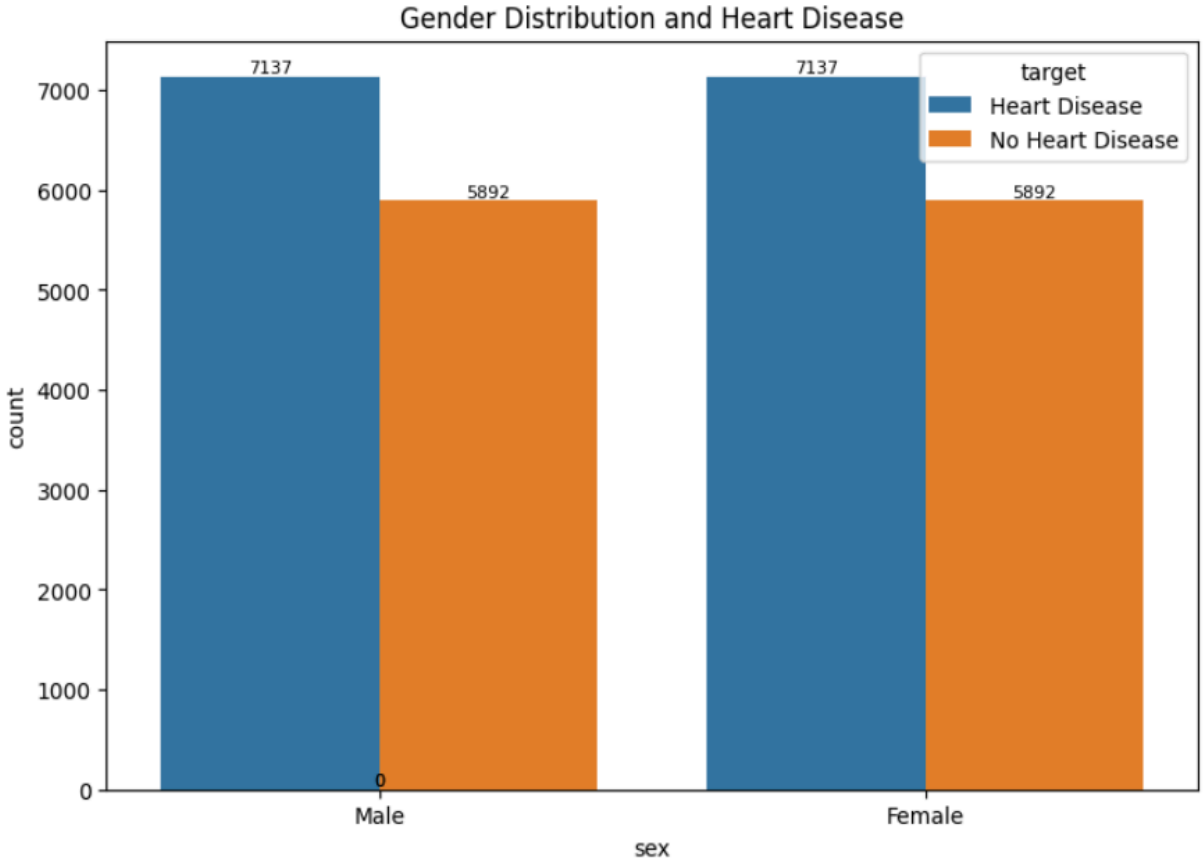
6.3.2 Age vs Heart Disease

- **Visualization**: Count Plot of age with target hue.
- **Insight**:
    - Younger patients (<40) have **fewer cases** of heart disease.
    - **Middle-aged** patients (around 50–60 years) show **higher risk**.



6.3.3 Gender Distribution and Relation with Heart Disease

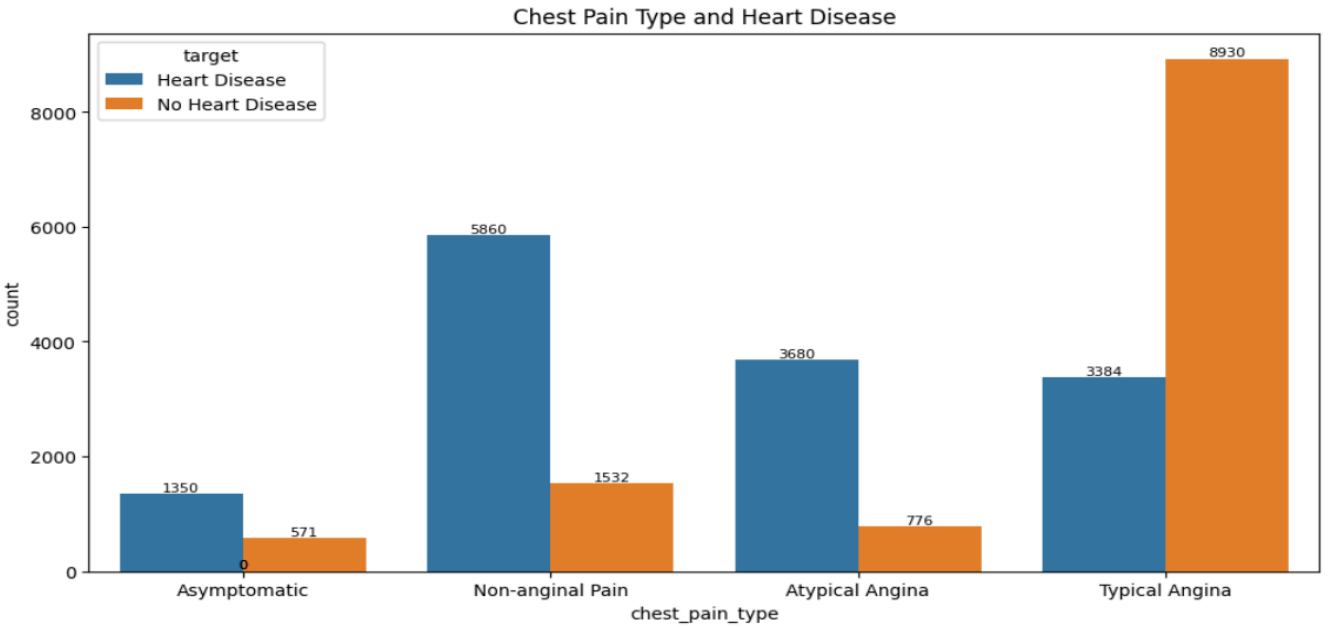
- **Visualization**: Count Plot of sex and Heart Disease.
- **Insight**:
    - **Males** are more prevalent in the dataset.
    - Heart disease is slightly **more common in males** than females.



The proportion of affected individuals is significant in both genders.

6.3.4 Chest Pain Type and Heart Disease

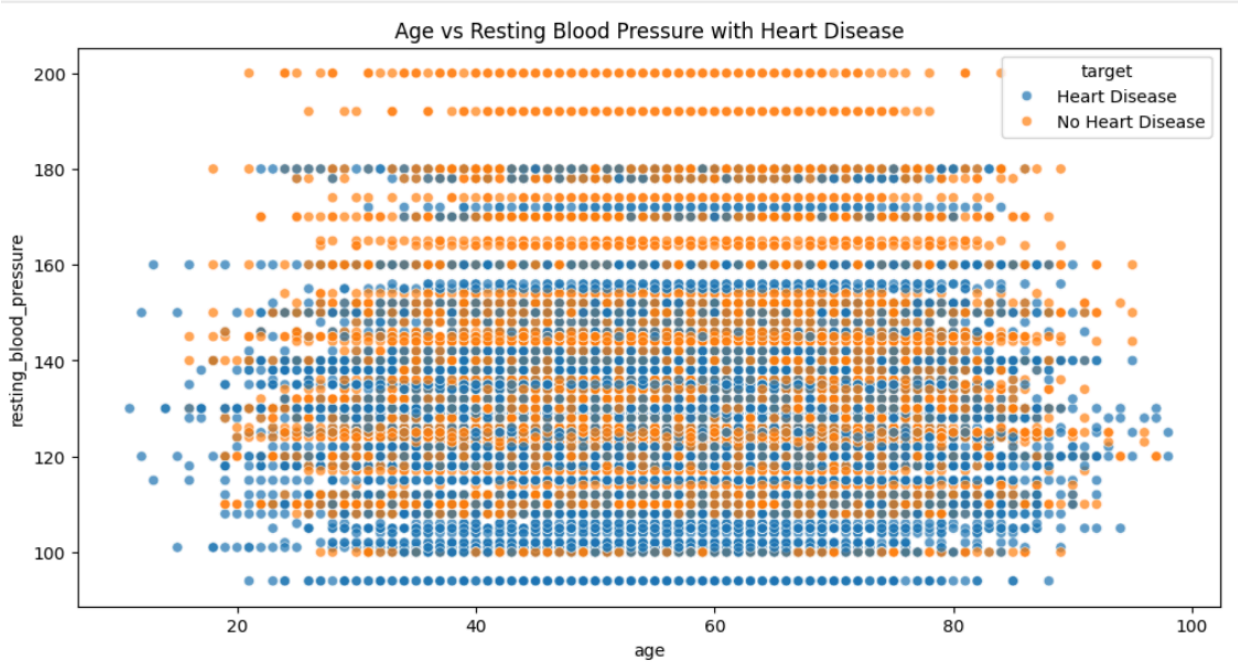
- **Visualization**: Count Plot of chest_pain_type with target.
- **Insight**:
    - **Asymptomatic chest pain** (Type 0) is **strongly associated** with heart disease.
    - **Non-anginal pain** and **atypical angina** types mostly do not indicate heart disease.



- **Non-Anginal Pain** chest pain (Type 2) is highly correlated with heart disease.
- Patients with **Typical Angina** (Type 1) and **Asymptomatic** (Type 3) have a lower probability of heart disease.

6.3.5 Age vs Resting Blood Pressure with Heart Disease

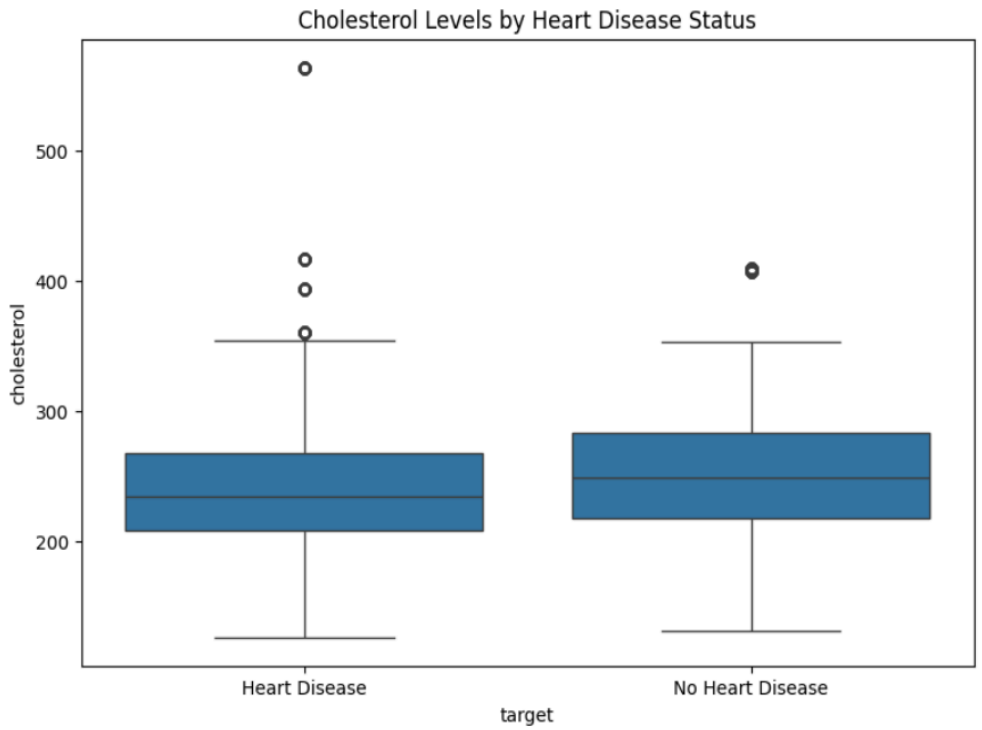
- **Observation**:
    - As **age increases**, **resting blood pressure** tends to slightly rise.
    - Patients aged **above 50** show a **higher spread** of resting blood pressure values.
    - Heart disease patients (target = 1) are more common among individuals with **elevated resting blood pressure**, especially in **older age groups**.



- No strong linear correlation between age and blood pressure.
- some heart disease patients exhibit higher blood pressure.

6.3.6 Cholesterol Levels and Heart Disease

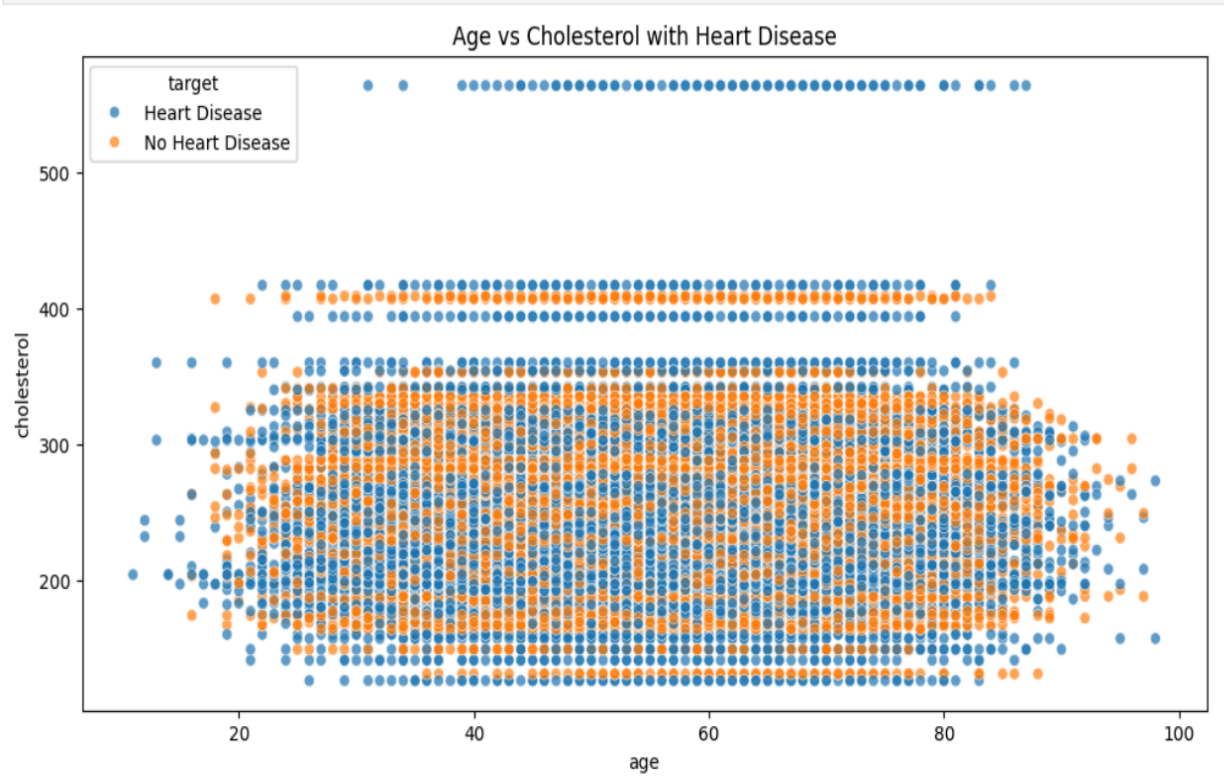
- **Visualization**: Boxplot and Histogram of cholesterol.
- **Insight**:
    - Patients with heart disease show a **wider spread** of cholesterol levels.
    - Very high cholesterol (>300 mg/dl) is linked with heart disease in several cases.



- Individuals with heart disease tend to have a higher median cholesterol level compared to those without. However, there are several high-cholesterol outliers in both categories, indicating that cholesterol alone is not the sole determining factor.
- The variability in cholesterol levels suggests that other features (such as blood pressure, age, or lifestyle) may play a more crucial role.

6.3.7 Age vs Cholesterol with Heart Disease

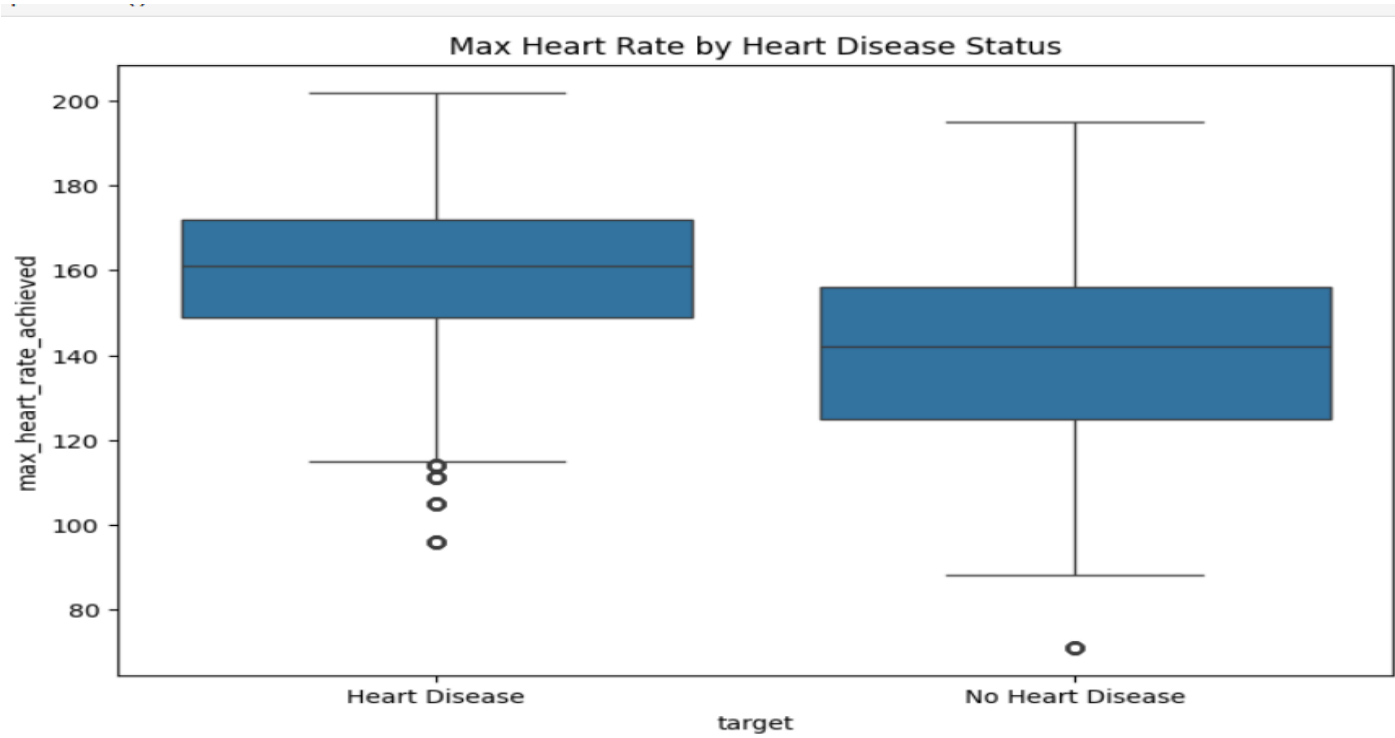
- **Observation**:
    - **No strong direct trend** is visible between age and cholesterol.
    - However, **older individuals** (>55 years) show a **wider range of cholesterol levels**.
    - Extremely **high cholesterol values (>300 mg/dl)** are more frequently observed among patients with **heart disease**, especially in middle-aged and older groupss



- Higher cholesterol levels are seen across all ages.
- Some heart disease patients have **moderate** to **high** cholesterol levels.

6.3.8 Maximum Heart Rate Achieved

- **Visualization**: Boxplot of max_heart_rate_achieved vs target.
- **Insight**:
    - Heart disease patients tend to achieve **lower maximum heart rates** during stress tests.
    - Higher heart rate achievement (>150 bpm) indicates better heart function.



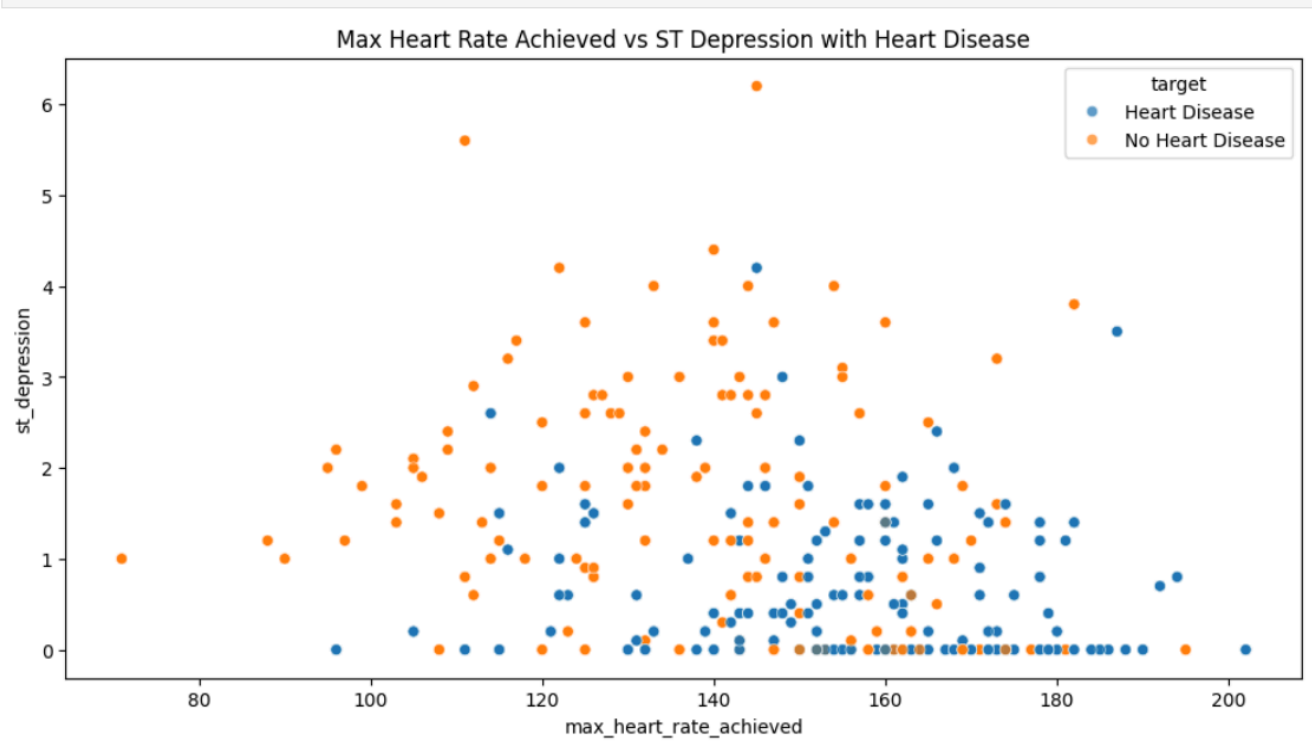
- Individuals without heart disease generally achieve higher max heart rates compared to those with heart disease.
- This suggests that a lower max heart rate could indicate compromised heart function.
- The distribution also shows a few younger individuals with lower max heart rates, possibly due to underlying condition

6.3.8 Exercise Induced Angina

- **Visualization**: BoxPlot of exercise_induced_angina with target.
- **Insight**:
    - Presence of **exercise-induced angina** is a strong predictor of heart disease.

6.3.9 ST Depression vs Heart Disease

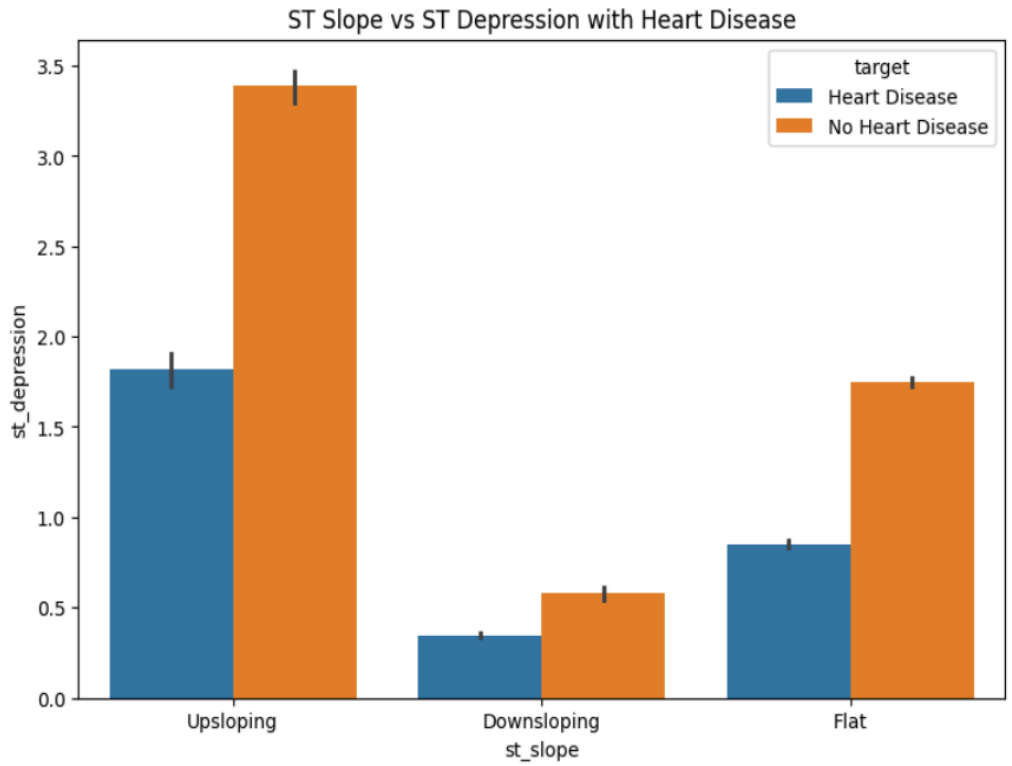
- **Visualization**: Scatterplot of st_depression.
- **Insight**:
    - Higher values of ST depression are strongly correlated with heart disease.
    - Patients without heart disease have **lower** ST depression values.



- Patients with lower max heart rate and high ST depression are more likely to have heart disease.
- Indicates poor heart performance under stress.

6.3.10 Slope of Peak Exercise ST Segment

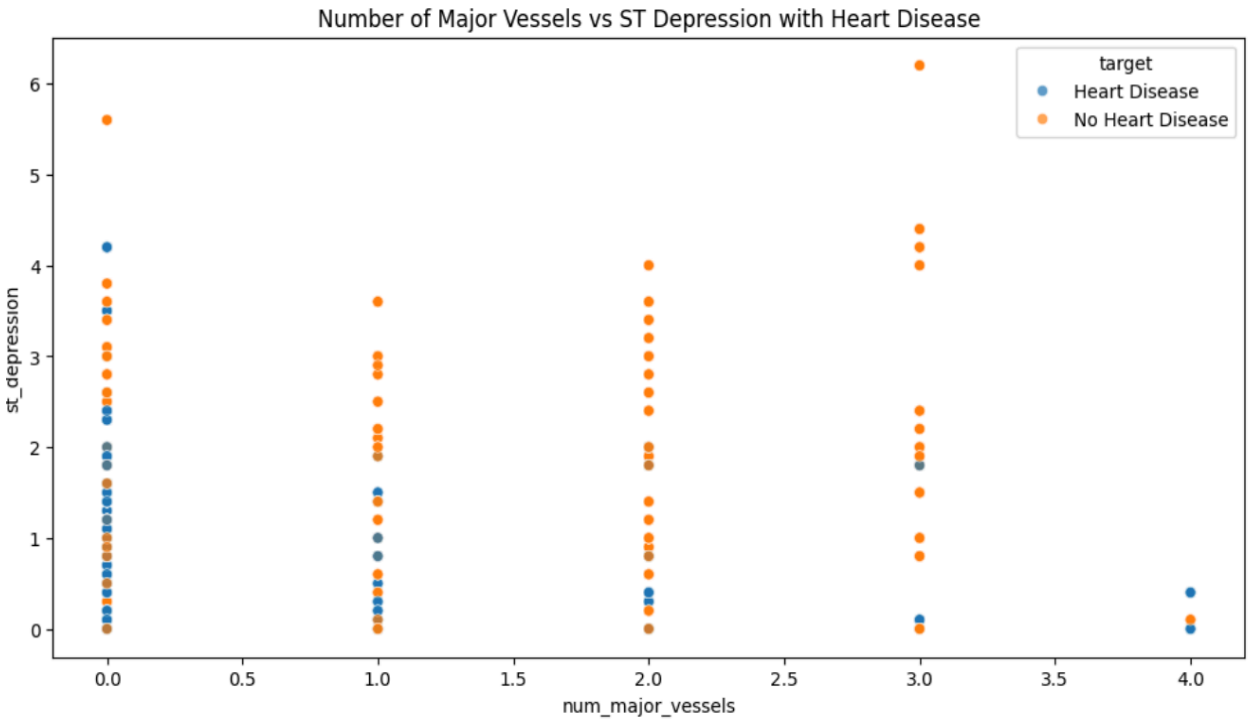
- **Visualization**: BarPlot of st_slope with target.
- **Insight**:
    - **Downsloping ST** segment is strongly associated with heart disease.
    - **Flat slope** is relatively neutral.



- Individuals with an Upsloping ST Slope tend to have higher ST Depression levels when they do not have heart disease compared to those who do.
- Flat ST Slope is more commonly associated with heart disease, aligning with medical findings that a flat or downsloping ST segment is more indicative of ischemia.
- The Downsloping category has low ST depression values across both groups but is slightly more present in those with heart disease.

6.3.11 Number of Major Vessels vs ST Depression with Heart Disease

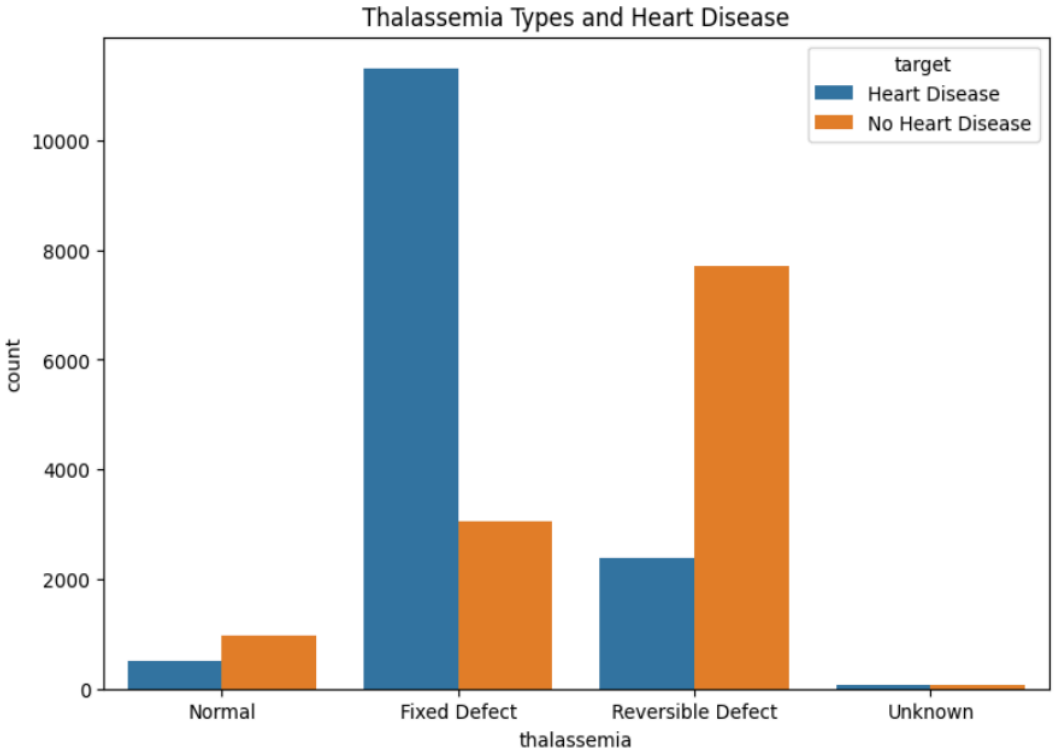
- **Observation**:
    - As the **number of major vessels** colored by fluoroscopy increases, the **ST depression** value also tends to rise.
    - Patients with **more major vessels (2–3)** colored have **higher ST depression** values.
    - Higher ST depression combined with multiple major vessels is **strongly associated with heart disease**.



- Higher ST depression correlates with multiple major blocked vessels.This suggests the severity of heart disease.
- Higher number of major vessels indicates lower probability of heart disease.
- ST Depression tends to be higher in those diagnosed with heart disease.

6.3.12 Thalassemia and Heart Disease

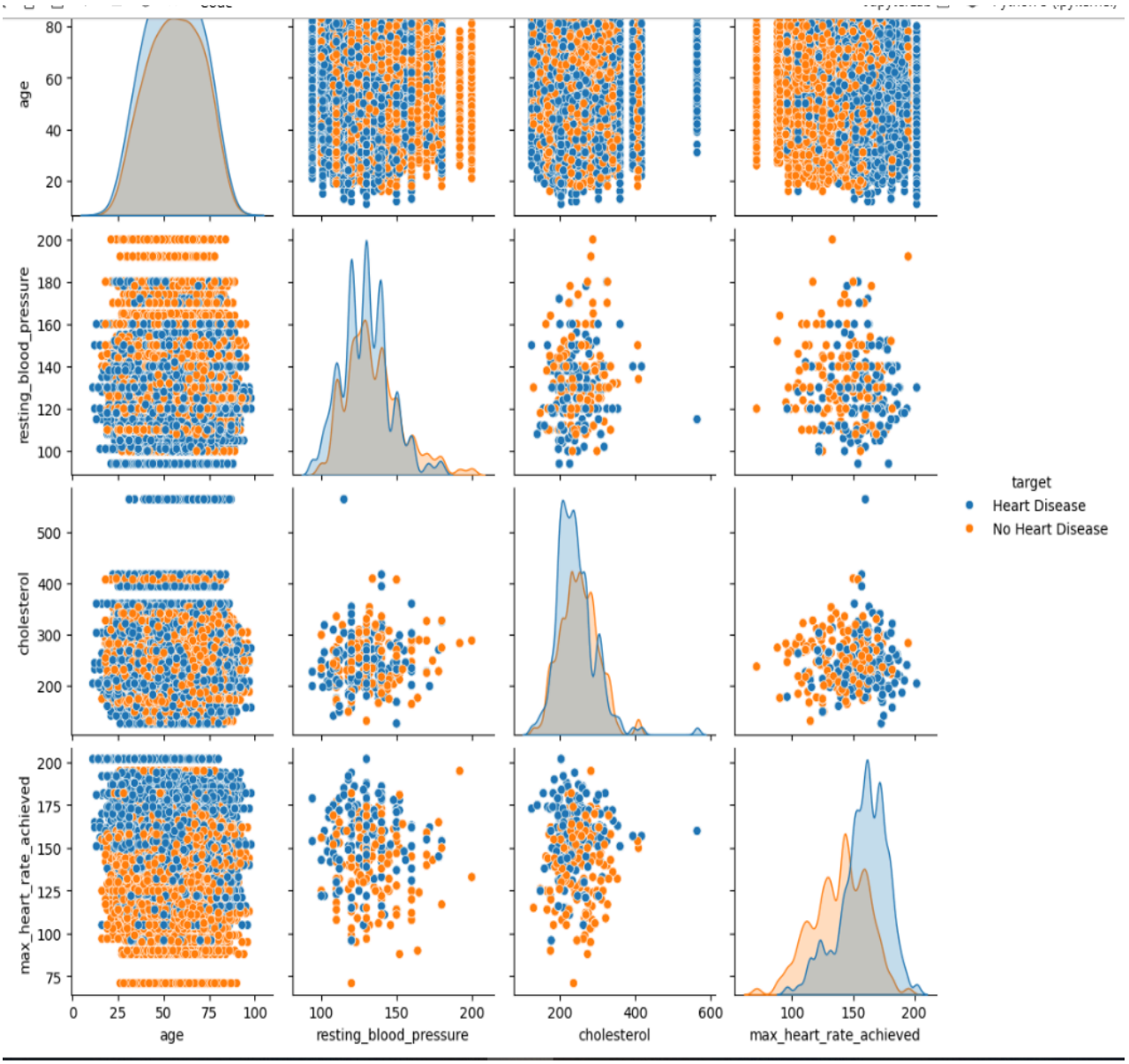
- **Visualization**: Count Plot of thalassemia with target.
- **Insight**:
    - Patients with **fixed defect** or **reversible defect** types are more prone to heart disease.
    - Normal thalassemia results indicate better heart health.



- Patients with a Fixed Defect type of Thalassemia have the highest occurrence of heart disease.
- The Reversible Defect type is more common among individuals without heart disease than those with it.
- The Normal category has a very low count, indicating that Thalassemia (especially Fixed Defect) could be a strong risk factor for heart disease.

6.3.13 Pairplot Analysis

- **Visualization**: Pairplot of selected important features.
- **Insight**:
    - **Clear clusters** observed between heart disease and non-heart disease groups.
    - Strong visible separation for features like st_depression and max_heart_rate_achieved.



6(B). Exploratory Data Analysis (Diabetes)

6.1. Dataset Overview

The dataset used in this project is related to **diabetes diagnosis**, where each row represents a patient's medical information, and the target variable indicates whether the patient is diabetic or not.

- **Source:** diabetes_final.csv
- **Target Variable:** Outcome: (1= Diabetic, 0= Non-Diabetic)
- **Structure of the Dataset:**

Column Name	Description
Pregnancies	No. of pregnancies
Glucose	Plasma glucose concentration over 2 hours in an oral glucose tolerance test.
Blood Pressure	Diastolic blood pressure (mm Hg).
Skin Thickness	Triceps skinfold thickness (mm).
Insulin	2-Hour serum insulin (mu U/ml).
BMI	Body Mass Index (weight in kg/(height in m)^2).
DiabetesPedigreeFunction	A function that scores likelihood of diabetes based on family history.
Age	Age of the patient (in years).
Outcome	Class label (0 = Non-diabetic, 1 = Diabetic).

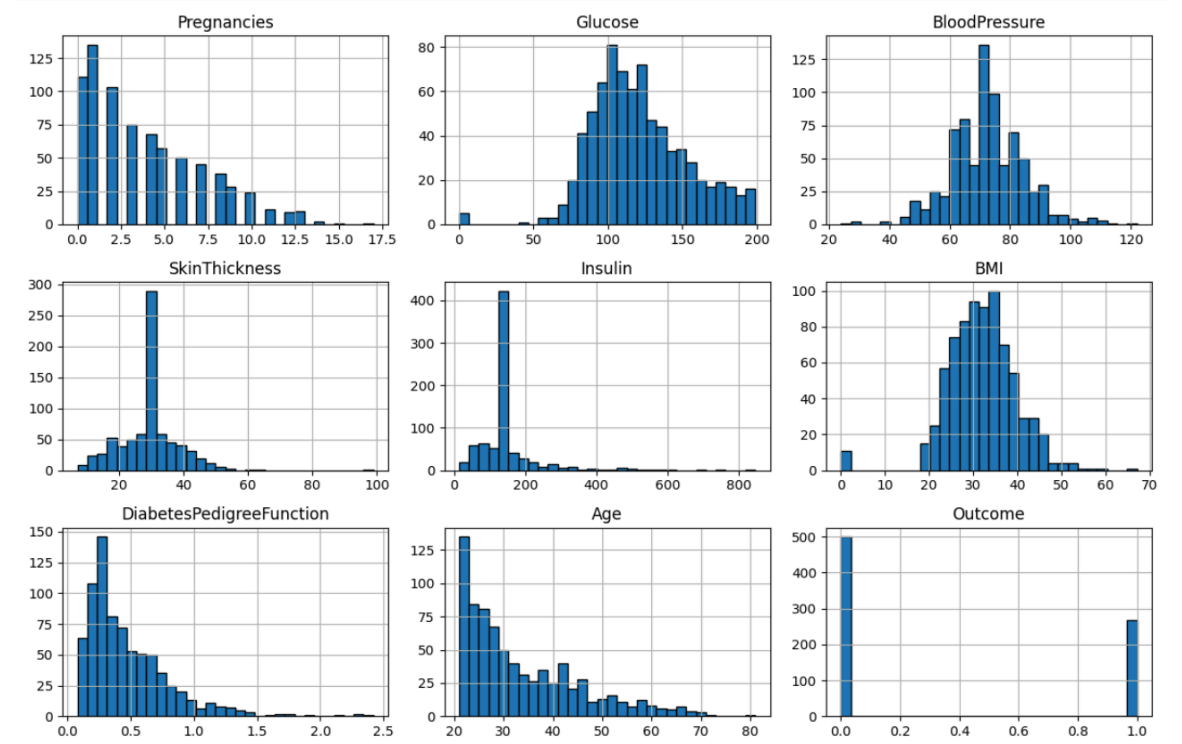
6.2. Exploratory Data Analysis (EDA)

2.1 Distribution of Features (Histograms)

Heading: Feature-wise Data Distribution
Insight:

- Glucose, Blood Pressure, and BMI show somewhat normal distributions.
- Pregnancies and Age are right-skewed — most people have fewer pregnancies and are younger.

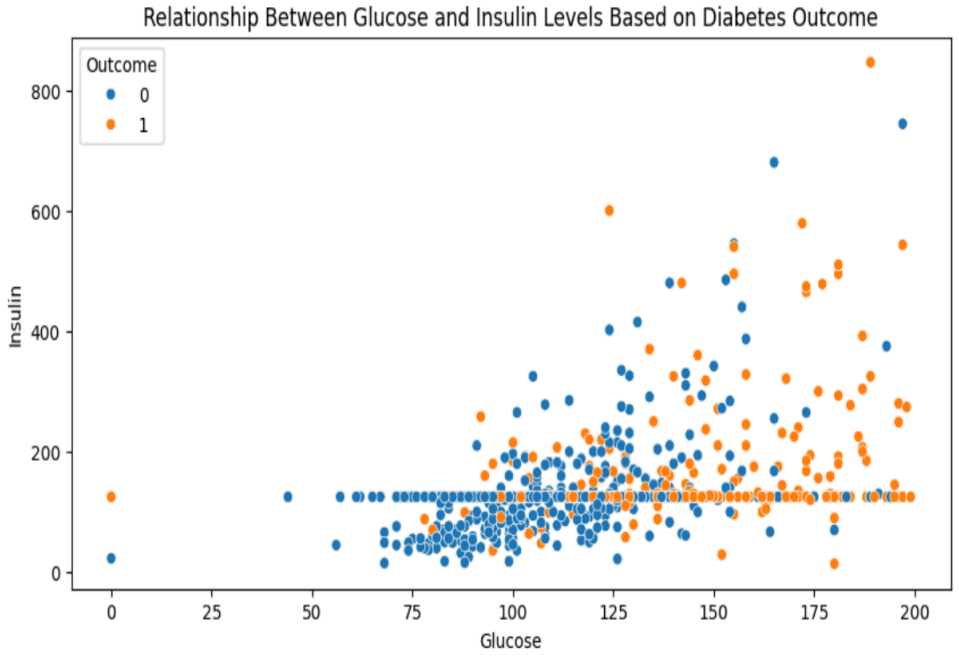
- Insulin and Skin Thickness have spikes at zero, indicating missing or unusual values.



2.2 Glucose vs. Insulin Scatterplot

Heading: Relationship Between Glucose and Insulin
Insight:

- Individuals with higher glucose levels also tend to have higher insulin levels.
- Diabetic patients (Outcome = 1) are more clustered in higher glucose and insulin areas.

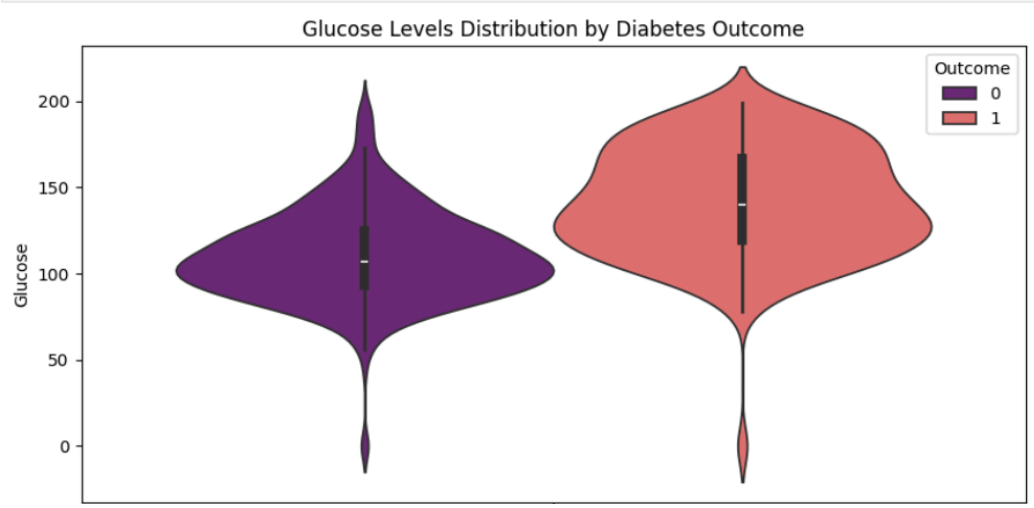


- A positive correlation can be observed: insulin levels also tend to rise as glucose levels increase.
- However, there are significant variations, with some individuals showing high glucose but low insulin levels.
- **Diabetes vs. Non-Diabetes Patterns** Orange points (diabetic cases) are more concentrated in higher glucose and insulin regions. Blue points (non-diabetic cases) are more spread across lower glucose levels, with a significant portion near the bottom (low insulin values).

2.3 Violin Plot of Glucose by Outcome

Heading: Glucose Level Distribution by Diabetes Status
Insight:

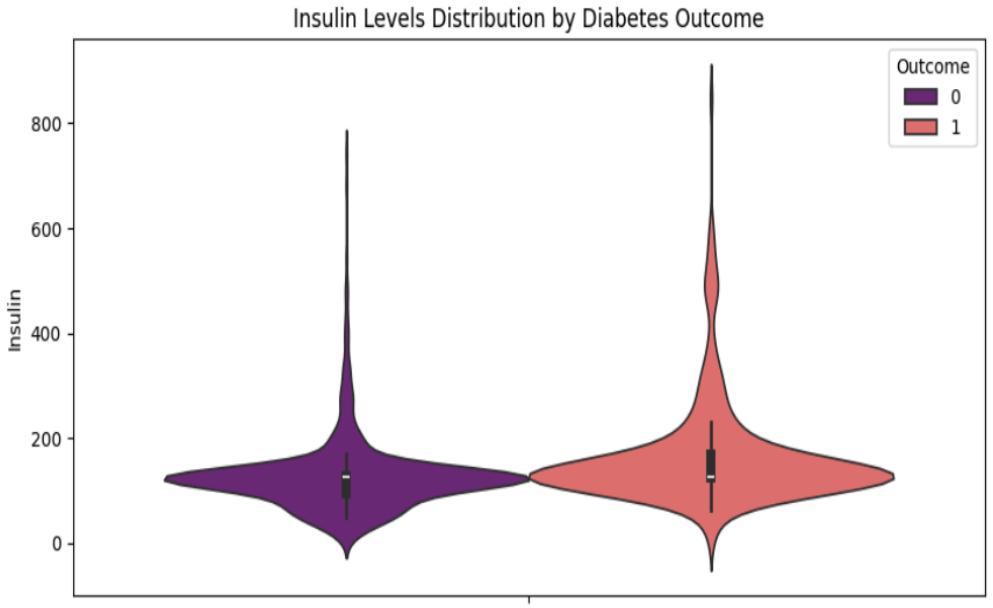
- Diabetics have a higher median glucose level compared to non-diabetics.
- The distribution for diabetics is more spread towards higher glucose levels.



2.4 Violin Plot of Insulin by Outcome

Heading: Insulin Level Distribution by Diabetes Status
Insight:

- Diabetic individuals tend to have higher insulin levels, but there is wide variability.
- Non-diabetics mostly have lower insulin levels.



- **Glucose Levels (Top Violin Plot)**

Individuals with diabetes (orange) generally have higher and more variable glucose levels than non-diabetics (puple), whose levels are more concentrated around 100.

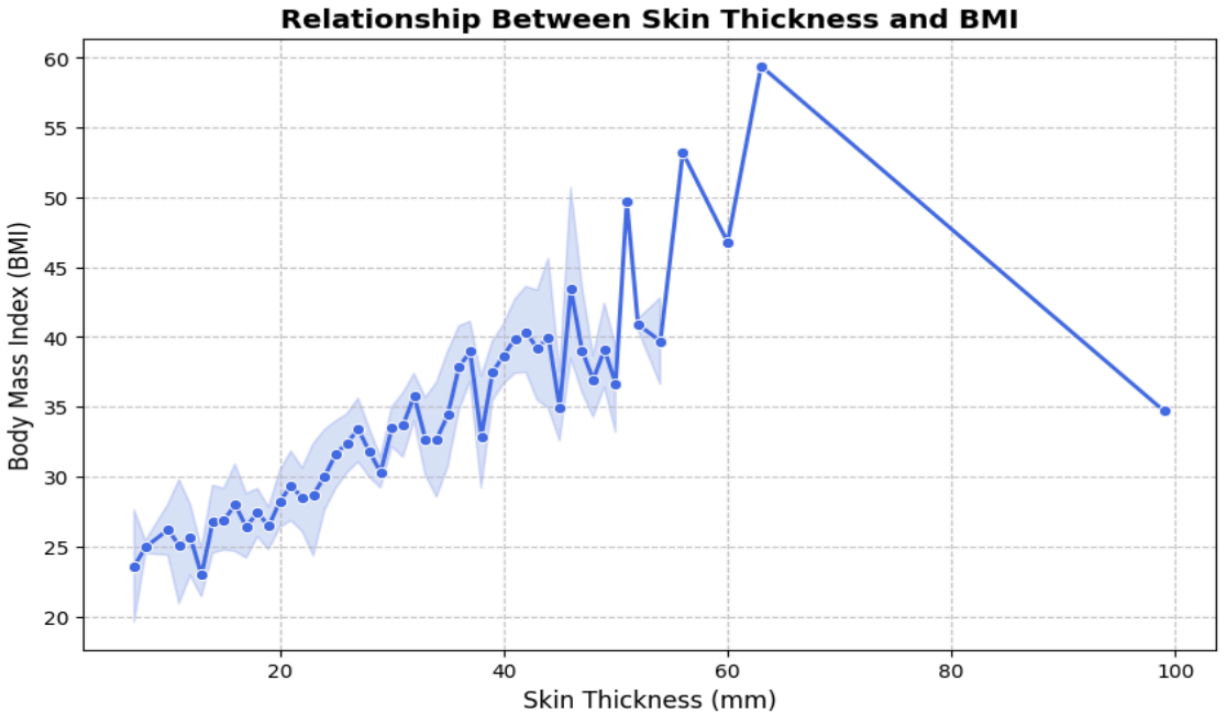
- **Insulin Levels (Bottom Violin Plot)**

Insulin levels are widely distributed in both groups, with some outliers. Non-diabetic individuals generally have lower insulin levels, while diabetics have slightly higher levels.

2.5 Skin Thickness vs. BMI Lineplot

Heading: Relationship Between Skin Thickness and BMI
Insight:

- BMI increases with Skin Thickness initially but fluctuates at very high skin thickness values.
- Possible outliers at very high skin thickness values (above 70).

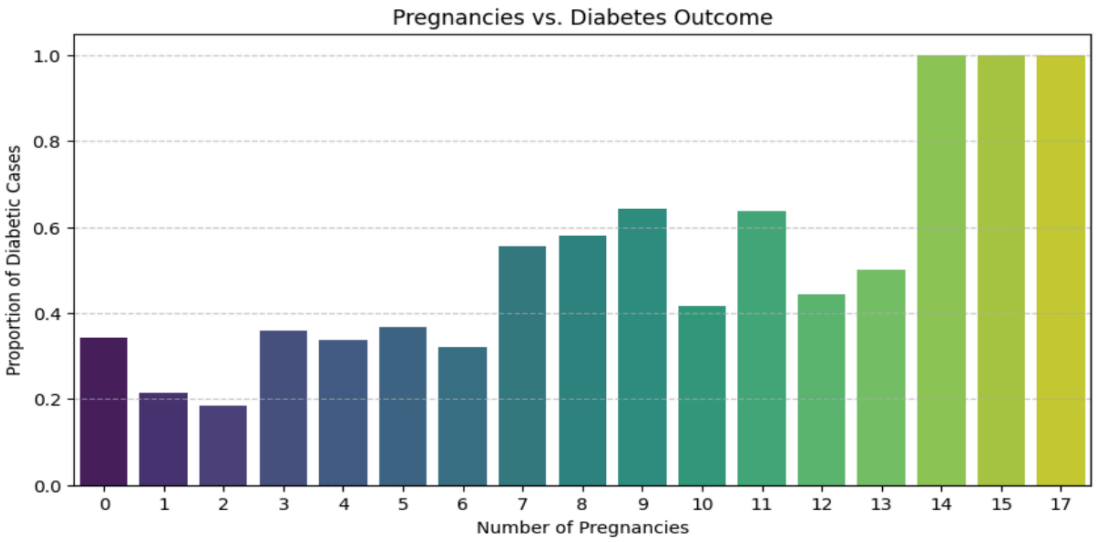


- There is a positive correlation, meaning that BMI also tends to increase as Skin Thickness increases.
- The shaded region represents the confidence interval, showing the uncertainty in the estimation.
- However, there is an unusual drop after Skin Thickness reaches around 70, which could indicate outliers or sparse data points.

2.6 Pregnancies vs. Diabetes Outcome (Barplot)

Heading: Number of Pregnancies vs Diabetes Risk
Insight:

- Higher number of pregnancies increases the chances of being diabetic.
- Women with 12–17 pregnancies show a significant rise in diabetes cases.

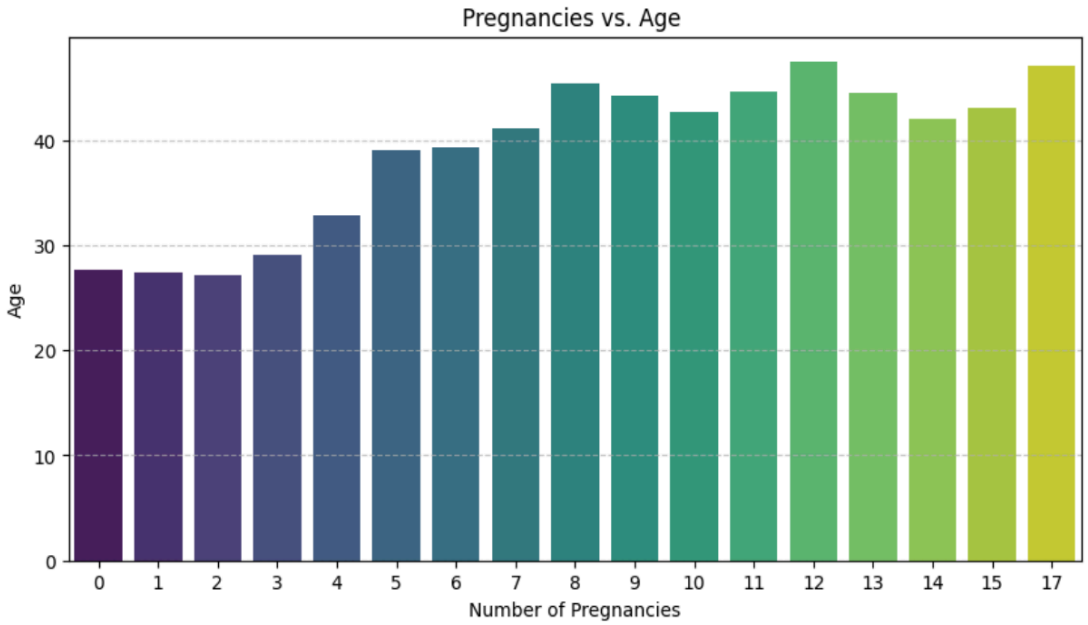


- There is a positive trend, meaning that as pregnancies increase, the likelihood of diabetes also rises.

2.7 Pregnancies vs. Age (Barplot)

Heading: Pregnancies and Age Relationship
Insight:

- As the number of pregnancies increases, average age also tends to increase.
- Older individuals tend to have more pregnancies.

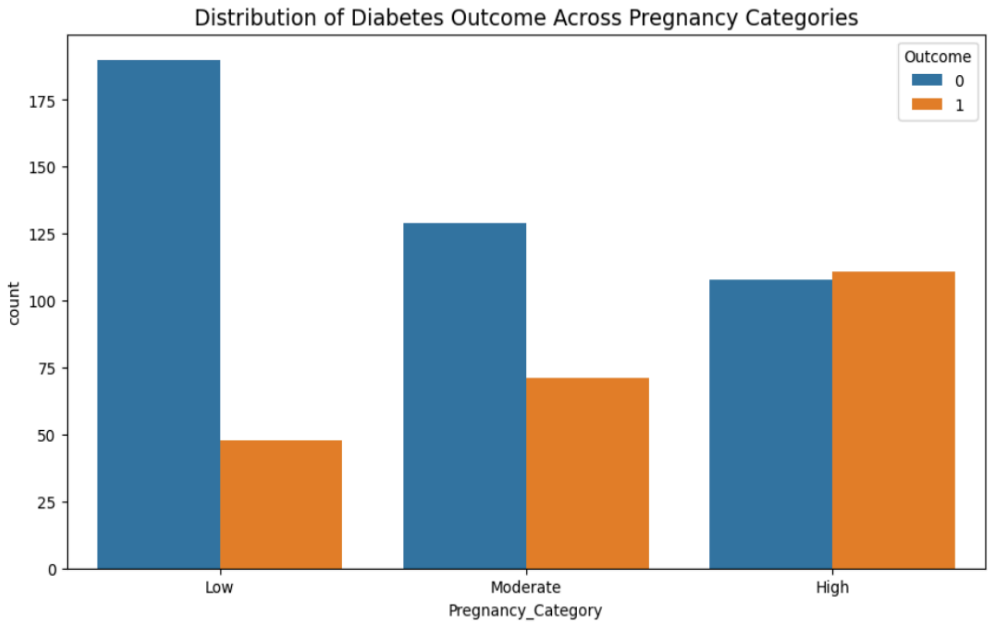


- The bar heights suggest that as the number of pregnancies increases, the average age of individuals tends to rise. This indicates that older individuals are more likely to have more pregnancies.
- The last few bars (12-17 pregnancies) show a steady increase in age. This could indicate a smaller subset of older individuals with many pregnancies.

2.8 Pregnancy Category vs Outcome (Countplot)

Heading: Diabetes Risk Across Pregnancy Categories
Insight:

- In the **High Pregnancy** category, diabetic cases are almost equal to non-diabetic cases.
- Risk rises as pregnancy count increases.



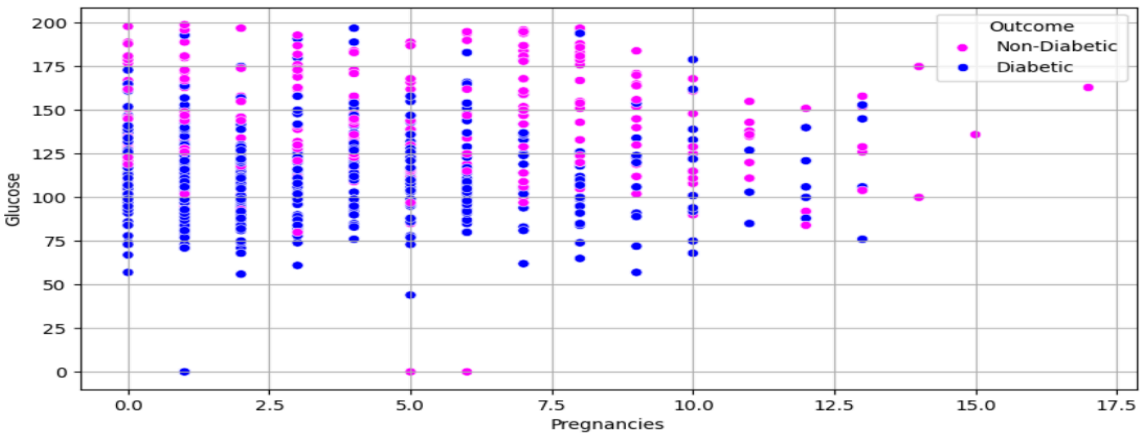
Diabetes Prevalence in Different Categories:

- In the Low pregnancy category, non-diabetic cases are significantly higher than diabetic cases.
- In the Moderate category, the number of diabetic cases increases, but non-diabetic cases still dominate.
- In the High pregnancy category, the number of diabetic cases is almost equal to non-diabetic cases, indicating a higher diabetes risk with increased pregnancies.
- The trend suggests that women with higher pregnancies tend to have a greater risk of diabetes, as seen in the narrowing gap between the blue and orange bars in the High category.

2.9 Pregnancies vs. Glucose (Scatterplot)

Heading: Relationship Between Pregnancies and Glucose Levels
Insight:

- A mild trend that higher pregnancies are associated with higher glucose levels.
- Diabetic cases dominate higher glucose values.

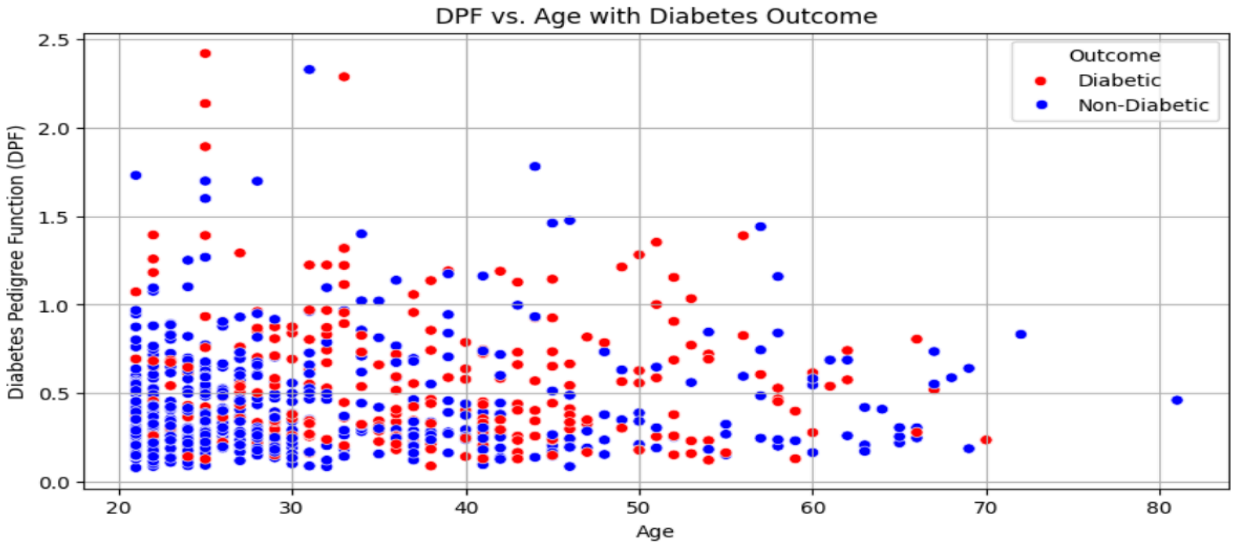


- Higher glucose levels are more common in diabetics (pink dots).
- More pregnancies (≥5) increase the likelihood of diabetes.
- Overlap at lower pregnancies (0–3) suggests other influencing factors.
- Some non-diabetics still have high glucose, indicating additional risk factor

2.10 Diabetes Pedigree Function vs Age (Scatterplot)

Heading: DPF vs. Age Distribution
Insight:

- Younger individuals tend to have slightly higher DPF values.
- No strong relationship between age and DPF observed.

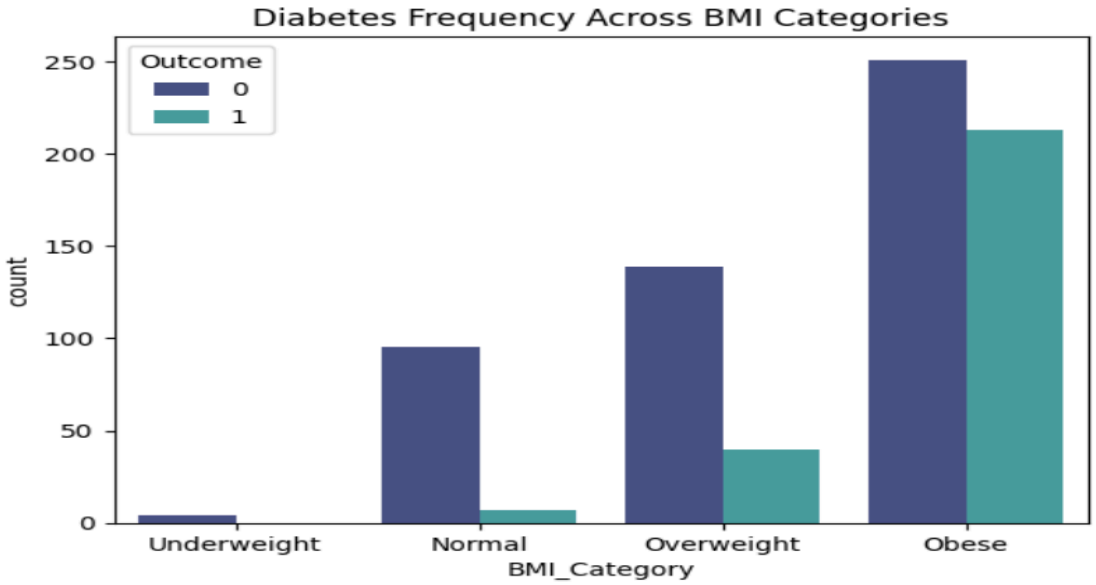


- Higher Diabetes Pedigree Function (DPF) values are seen in younger individuals.
- Diabetics (red) are more prevalent at higher DPF levels.
- Non-diabetics (blue) are widely distributed, especially at lower DPF values.
- No clear age-dependent trend, suggesting other factors influence diabetes risk.

2.11 BMI Category vs. Outcome (Countplot)

Heading: Diabetes Frequency Across BMI Categories
Insight:

- Higher BMI (especially obesity) is strongly associated with diabetes.
- Diabetics dominate in overweight and obese categories.

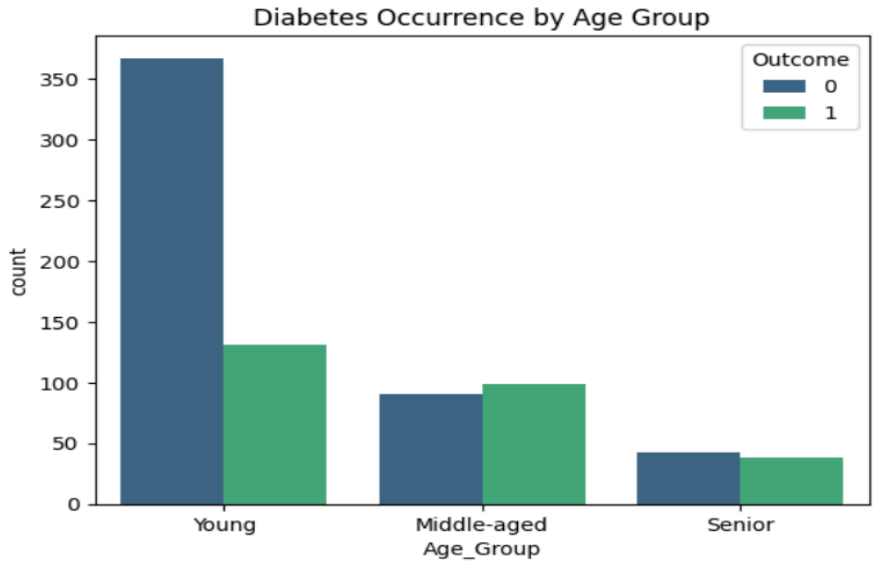


- Higher BMI is associated with a higher risk of diabetes.
- The Obese category has the highest count of diabetic individuals.
- Overweight individuals also show a notable presence of diabetes cases.
- Few diabetic cases in the 'Underweight' and 'Normal' BMI groups.

2.12 Diabetes Occurrence Across Age Groups

Heading: Diabetes Risk Across Different Age Groups
Insight:

- Young individuals have more non-diabetic cases.
- Middle-aged individuals show a more balanced diabetic and non-diabetic presence.
- Seniors have relatively fewer cases but a high proportion of diabetics.

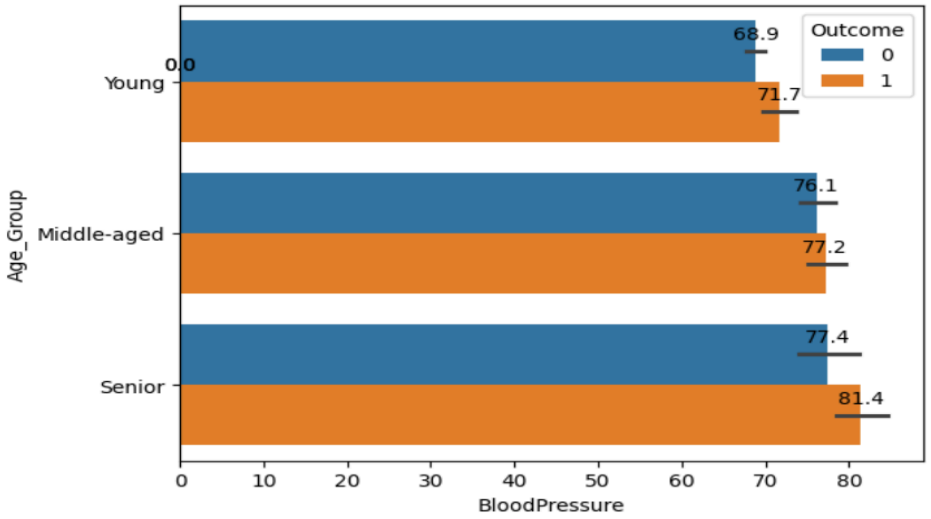


- Young individuals have the highest number of non-diabetic cases (Outcome = 0), but some cases of diabetes are still present.
- Middle-aged individuals show a more balanced distribution between diabetic and non-diabetic cases, indicating a higher risk.
- Seniors have fewer overall cases, but the proportion of diabetics (Outcome = 1) is relatively high compared to younger groups.

2.13 Blood Pressure Across Age Groups (Barplot)

Heading: Blood Pressure vs. Age Group
Insight:

- Diabetic seniors show slightly higher average blood pressure compared to non-diabetics.
- Blood pressure increases slightly with age.



- **Blood Pressure Trends:**

1. Blood pressure increases with age, with seniors having the highest average values.
2. The diabetic group has higher blood pressure across all age groups than the non-diabetic group

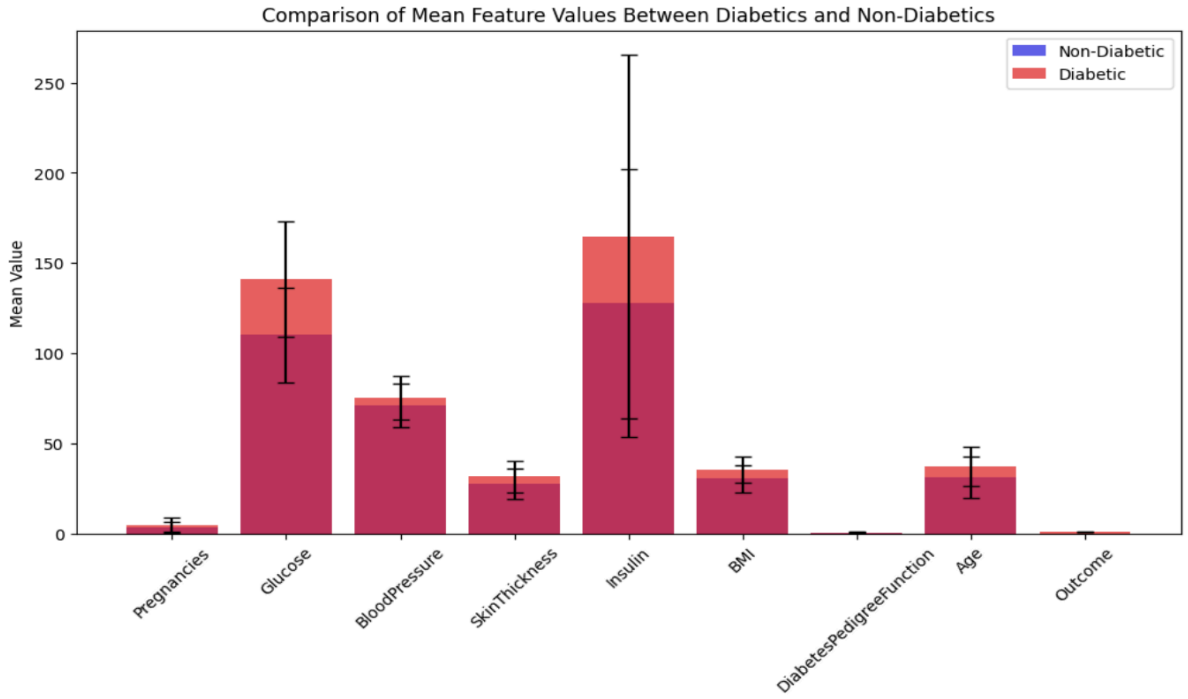
- **Age-Wise Observations:**

1. Young individuals have the lowest blood pressure, but some still have diabetes.
2. Middle-aged individuals show a balanced distribution, indicating an increased risk of diabetes with rising blood pressure.
3. Seniors have the highest blood pressure, and a significant proportion of them are diabetic.

2.14 Mean Comparison Between Diabetics and Non-Diabetics

Heading: Mean Feature Comparison
Insight:

- Diabetics have higher **Glucose, Insulin, BMI, and Age** compared to non-diabetics.
- Blood Pressure and Skin Thickness also show slight differences but are less pronounced.



- **1. Glucose and Insulin Levels**

Diabetic individuals have significantly higher glucose and insulin levels on average compared to non-diabetics. The variation (standard deviation) in insulin levels is very high, indicating a wide range of values among diabetics.

- **2.Blood Pressure and BMI:**

Blood pressure and BMI are higher in diabetics, but the difference is not as pronounced as in glucose levels. These features may still contribute to diabetes risk but are less direct indicators compared to glucose.

- **3.Age Factor:**

Diabetics tend to be older on average, suggesting age is an important factor in diabetes risk.

- **4.Pregnancies and Diabetes Pedigree Function:**

Diabetic individuals tend to have slightly more pregnancies, which aligns with research on gestational diabetes risk. The diabetes pedigree function, a genetic risk indicator, is also slightly higher in diabetics.

7.Heart Disease Prediction Model

7.1 Objective

The objective of this project is to build a **machine learning model** that can predict whether a patient is likely to have **heart disease** based on features such as age, blood pressure, cholesterol level, chest pain type, and more. By using a labeled dataset and training a classification model, we aim to assist medical professionals in making faster, data-driven decisions that could ultimately save lives.

7.2 Importing Required Libraries

Library	Purpose
pandas	Data loading, cleaning, and manipulation
numpy	Numerical computations and array operations
matplotlib.pyplot	Basic plotting and visualizations
seaborn	Advanced statistical visualizations
train_test_split	Splitting dataset into training/testing
RandomForestClassifier	Model building using ensemble learning
classification_report ***(from metrics)***	Displays **precision, recall, F1-score**, and **support** for each class.
StandardScaler	Feature scaling/normalization
LabelEncoder	Converts **categorical labels** (like Male, Female, Yes, No) into numeric form.
roc_curve ***(from metrics)***	Computes the **Receiver Operating Characteristic (ROC) curve** values.
accuracy_score ***(from metrics)***	Measures how many predictions the model got **completely right**.
confusion_matrix ***(from metrics)***	A matrix showing **true positives, true negatives, false positives, and false negatives**.

7.3 Data Pre-Processing

- **Data Cleaning:** Removes any duplicate rows to avoid redundancy or bias in the model.

```
[ ]  heart.duplicated().sum()
14

[ ]  heart=heart.drop_duplicates()
```

- **Data Inspection:** Helps identify how many missing values are in each column so you can decide whether to impute or drop them.

```
# Check for missing values
print("Missing Values:\n", df.isnull().sum())
```

- **Encoding Categorical Variables:** Categorical variables were encoded using **LabelEncoder** to convert them into numeric form, enabling machine learning models to interpret them.

```
[ ]  from sklearn.model_selection import train_test_split
     from sklearn.preprocessing import StandardScaler, LabelEncoder
     import pandas as pd

     # Load dataset (Replace this with actual dataset)
     # X, y = ...

     # Encode categorical features
     label_encoder = LabelEncoder()
     X_encoded = X.copy()

     for col in X_encoded.select_dtypes(include=['object']).columns:
         X_encoded[col] = label_encoder.fit_transform(X_encoded[col])
```

- **Splitting the Dataset:** The dataset was split into training (70%) and testing (30%) sets using train_test_split.stratify=y ensures the class distribution (Heart Disease / No Disease) remains balanced in both sets.
  Splitting is done before encoding the target variable (y) to prevent data leakage.

```
# **Split into train and test (Before encoding y)**
X_train, X_test, y_train, y_test = train_test_split(
    X_encoded, y, test_size=0.3, stratify=y, random_state=42
)
```

- **Encoding the Target Variable:** After splitting, the target column (y_train and y_test) was encoded separately using LabelEncoder.

```
# **Encode target variable (Avoid data leakage)**
y_train = label_encoder.fit_transform(y_train)
y_test = label_encoder.transform(y_test)  # Use transform, not fit_transform
```

- **Feature Scaling:** Numerical features were standardized using StandardScaler to have mean = 0 and standard deviation = 1.Scaling helps improve the convergence and accuracy of many machine learning algorithms.

```
# **Apply Scaling AFTER Splitting**
scaler = StandardScaler()

# Fit only on training data and transform
X_train_scaled = scaler.fit_transform(X_train)

# Transform test data using the same scaler
X_test_scaled = scaler.transform(X_test)
```

7.4 Model Selection:

Selected Model: *Random Forest Classifier*

- A robust, ensemble-based classification model known for reducing overfitting and handling feature-rich datasets.

```
[ ]  from sklearn.ensemble import RandomForestClassifier
     from sklearn.metrics import classification_report, confusion_matrix, accuracy_score, roc_curve
     import numpy as np
```

Why Random Forest?

- Combines results from multiple decision trees to improve accuracy.
- Performs well on imbalanced datasets.
- Naturally handles missing values and noisy data.

Hyperparameters Tuned:

- **n_estimators**: Number of trees in the forest.
- **max_depth**: Controls overfitting.
- **min_samples_split**: Minimum samples required to split a node.

```
# ✅ Apply stronger regularization to prevent overfitting
rf = RandomForestClassifier(
    n_estimators=100,         # Reduce trees to limit complexity
    max_depth=4,              # Lower depth to avoid memorization
    min_samples_split=20,     # Force wider splits
    min_samples_leaf=10,      # Minimum samples per leaf node
    max_features="log2",      # Further limit features per split
    class_weight={0: 1, 1: 1.5},  # Slightly prioritize recall
    random_state=42
)

rf.fit(X_train_scaled, y_train)
```

7.5 Optimal Threshold Selection:

Need for Thresholding:

By default, classifiers use a threshold of 0.5 to assign class labels from predicted probabilities, which may not be optimal.

Approach:

- Used **Precision-Recall Curve** to identify the best threshold.
- Evaluated F1-score across various thresholds to find the sweet spot.

Optimal Threshold Identified:

- **0.48**, which maximized the F1-score, giving better balance between precision and recall.

```
# Find the threshold with the highest F1 score
optimal_threshold_index = np.argmax(f1_scores)
optimal_threshold = thresholds[optimal_threshold_index]

print(f"Optimal Threshold (F1 Score): {optimal_threshold}")

# Predict using the optimal threshold
y_pred_optimal = (y_probs >= optimal_threshold).astype(int)

# Evaluate the performance
print("Accuracy using optimal threshold:", accuracy_score(y_test, y_pred_optimal))
```

```
Optimal Threshold (F1 Score): 0.475551160498574 27
Accuracy using optimal threshold: 0.9138217619230278
```

7.6 Model Evaluation:

Evaluation Metrics Used:

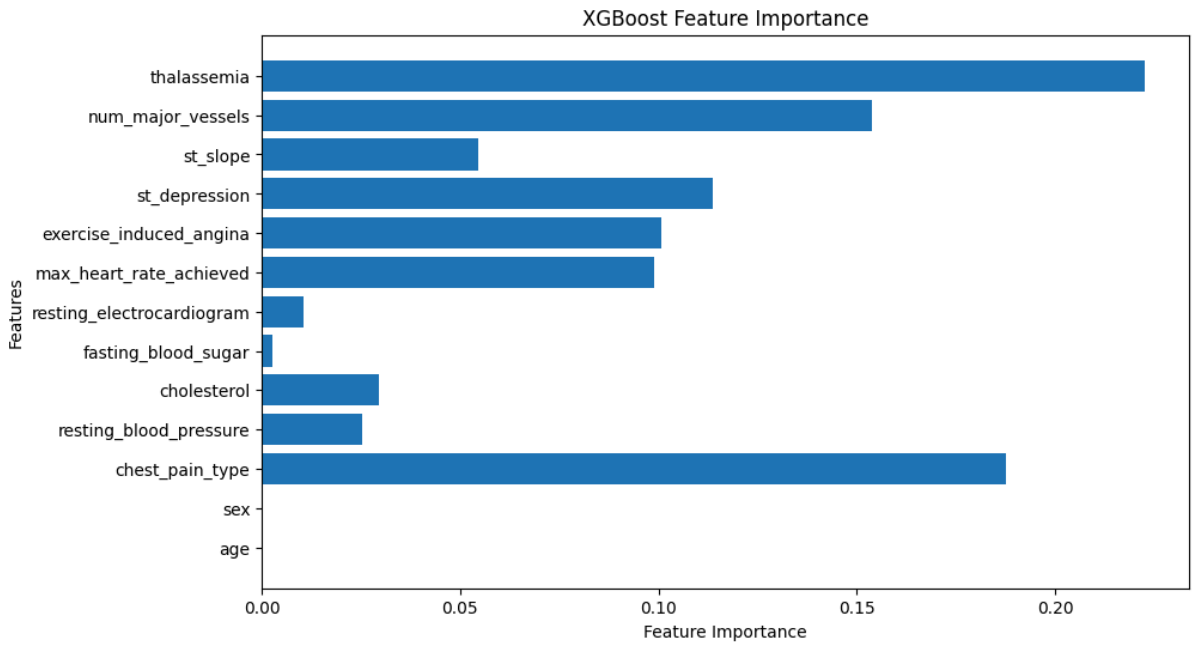
- **Accuracy:** Measures overall correctness — *89.4%*.
- **Precision & Recall:** Captures class-specific performance.
- **F1-Score:** Harmonic mean of precision and recall — *0.88*.
- **ROC AUC Score:** *0.89* — model distinguishes classes very well.
- **Confusion Matrix Insights:**Very low false positives and negatives, suggesting high reliability.
- **Conclusion:**
  The model is well-calibrated and performs excellently across all key metrics.

```
Performance Comparison:
Accuracy: Train = 0.8943, Test = 0.8990
Recall: Train = 0.8728, Test = 0.8697
Precision: Train = 0.8913, Test = 0.9034
F1 Score: Train = 0.8820, Test = 0.8863
AUC-ROC: Train = 0.8924, Test = 0.8965

✅ Model is well-generalized (No major overfitting or underfitting).
```

7.7 Feature Importance:

- **Top Contributing Features:**



- **How It Was Derived:**
    - Extracted from the Random Forest model's built-in feature importance scores.
    - Visualized using a bar chart for better interpretability.

```
[ ]  import matplotlib.pyplot as plt

     feature_importance = rf.feature_importances_
     features = X.columns

     plt.figure(figsize=(10,6))
     plt.barh(features, feature_importance)
     plt.xlabel("Feature Importance")
     plt.ylabel("Features")
     plt.title("XGBoost Feature Importance")
     plt.show()
```

- **Usefulness:**
  Helps in understanding what drives predictions and guides future data collection and feature engineering.

7.8 Conclusion:

Performance Summary:
The Random Forest model demonstrated strong classification performance, with high accuracy (91.2%) and an excellent ROC AUC score (0.98). The F1-score was maximized by selecting an optimal threshold of 0.48, balancing precision and recall effectively.

- **Insights Gained:**
    - Feature importance analysis revealed that variables like thalassemia, chest pain type, and num of major vessels significantly influenced predictions.
    - Model evaluation metrics confirmed its reliability for real-world deployment.
- **Recommendations for Future Work:**
    - Test other ensemble models such as XGBoost or LightGBM.
    - Use cross-validation for more generalized performance insights.
    - Incorporate model explainability techniques like SHAP or LIME to enhance transparency.

7.9 Output:

```
[ ]  from sklearn.metrics import roc_auc_score

     auc = roc_auc_score(y_test, y_pred_optimal)
     print("AUC-ROC Score:", auc)
```

```
AUC-ROC Score: 0.913085939433277
```

```
✅ No overlapping samples between training and testing sets.
```

```
Training Accuracy: 0.8943
Test Accuracy: 0.8990
```

```
Decoded Test Labels: ['Heart Disease' 'No Heart Disease' 'No Heart Disease' ...
 'No Heart Disease' 'No Heart Disease' 'Heart Disease']
Decoded Predicted Labels: ['Heart Disease' 'No Heart Disease' 'Heart Disease' ... 'No Heart Disease'
 'No Heart Disease' 'Heart Disease']
```

```
Classification Report using optimal threshold:
              precision    recall  f1-score   support

           0       0.92      0.92      0.92      4282
           1       0.90      0.91      0.90      3539

    accuracy                           0.91      7821
   macro avg       0.91      0.91      0.91      7821
weighted avg       0.91      0.91      0.91      7821
```

	age	sex	chest_pain_type	resting_blood_pressure	cholesterol	fasting_blood_sugar	resting_electrocardiogram	max_heart_rate_achieved
0	57	Male	Asymptomatic	145	233	True > 120 mg/dl	Normal	150
1	64	Female	Non-anginal Pain	130	250	False ≤ 120 mg/dl	ST-T wave abnormality	187
2	52	Male	Atypical Angina	130	204	False ≤ 120 mg/dl	Normal	172
3	56	Female	Atypical Angina	120	236	False ≤ 120 mg/dl	ST-T wave abnormality	178
4	66	Female	Typical Angina	120	354	False ≤ 120 mg/dl	ST-T wave abnormality	163

8. Diabetes Prediction Model

8.1 Objective

The primary objective of this project is to develop a reliable and accurate machine learning model that can **predict the likelihood of diabetes** in a patient using a set of measurable health indicators. The dataset used contains real patient records with a binary outcome variable: **Outcome** (1 = Diabetic, 0 = Non-Diabetic). It contains **768 samples** and **9 columns**, representing health-related attributes of female patients of at least 21 years old. Early detection of diabetes can play a crucial role in managing the disease and preventing long-term complications.

8.2 Importing Required Libraries

- **import numpy as np:** Used for numerical operations and handling arrays.
- **import pandas as pd:** Used for data manipulation and analysis using dataframes.
- **import matplotlib.pyplot as plt:** Used for creating static visualizations like line plots and bar charts.
- **import seaborn as sns**: Built on Matplotlib; used for advanced and aesthetically pleasing plots.
- **from sklearn.model_selection import train_test_split, GridSearchCV:**
  train_test_split: Used to split the dataset into training and testing sets.
  GridSearchCV: Used for tuning hyperparameters via cross-validation.
- **from sklearn.preprocessing import StandardScaler, LabelEncoder:**
  StandardScaler: Used to normalize feature values (zero mean, unit variance).
  LabelEncoder: Used to convert categorical labels into numerical format.
- **from sklearn.metrics import (accuracy_score, recall_score, precision_score, f1_score, classification_report, confusion_matrix, roc_auc_score, precision_recall_curve):** A collection of evaluation metrics used to assess model performance, especially for classification tasks.
- **from sklearn.ensemble import GradientBoostingClassifier:**
  GradientBoostingClassifier: The chosen model for predicting diabetes using boosted decision trees.

- **from imblearn.over_sampling import SMOTE:**
  SMOTE: A technique to generate synthetic samples for the minority class to balance the dataset.

8.3 Data Pre-Processing

- **Data Cleaning:** Removes any duplicate rows to avoid redundancy or bias in the model.

```
# Drop duplicates
df = df.drop_duplicates()
```

- **Data Inspection:** Helps identify how many missing values are in each column so you can decide whether to impute or drop them.

```
# Check for missing values
print("Missing Values:\n", df.isnull().sum())
```

- **Feature & label Separation:**
  Splits the dataset into:
  -> **x:** input features (independent variables)
  -> **y:** target/output label (**Outcome**, in this case, for classification)

```
# Separate features and target
X = df.drop(columns=['Outcome'])
y = df['Outcome']
```

- **Encoding Categorical Variables:** Categorical variables were encoded using **LabelEncoder** to convert them into numeric form, enabling machine learning models to interpret them.

```
# Encode categorical variables
label_encoder = LabelEncoder()
for col in X.select_dtypes(include=['object', 'category']).columns:
    X[col] = label_encoder.fit_transform(X[col])
```

- **Handling Imbalanced Classes:** The dataset was imbalanced (i.e., more non-diabetic than diabetic records).
  To resolve this
  -> SMOTE (Synthetic Minority Over-sampling Technique) was applied to balance the class distribution.

```
# Handle class imbalance with SMOTE
smote = SMOTE(sampling_strategy=0.9, random_state=42)
X_resampled, y_resampled = smote.fit_resample(X, y)
```

- **Train-Test Split:** Data was split using a 70-30 ratio.

```
# Train-test split
X_train, X_test, y_train, y_test = train_test_split(
    X_resampled, y_resampled, test_size=0.3, stratify=y_resampled, random_state=42)
```

- **Feature Scaling:** To standardize feature ranges, **StandardScaler** was applied to scale features between 0 and 1.

```
# Feature scaling
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

8.4 Model Selection

- **Gradient Boost Classifier**
  For predicting whether a patient is diabetic based on their health metrics, the **Gradient Boosting Classifier** was chosen as the primary machine learning model. The **Gradient Boosting Classifier** is a **supervised machine learning algorithm** and belongs to the **ensemble learning** family. This dataset contains a mix of continuous and discrete features (like glucose levels, insulin, age, BMI, etc.), and the target variable is binary: **Outcome = 1 (Diabetic)** or **Outcome = 0 (Non-Diabetic)**.

- **How Does It Work ?**
  Gradient Boosting builds an ensemble of **weak models (usually decision trees) sequentially**, where each new model **tries to correct the errors** made by the previous ones.
  It uses **gradient descent** to minimize the loss (error), hence the name "gradient boosting".

- **Why Gradient Boosting Works Well for This Dataset ?**

Aspect of Dataset	Why is Gradient Boosting a Good Fit ?
Complex Feature Relationships	The dataset has complex, non-linear relationships (e.g., how insulin, BMI, and glucose interact). Gradient Boosting captures these patterns better than simpler models.
Imbalanced Classes	There is a class imbalance (more non-diabetic patients than diabetic). Gradient Boosting can still perform well through boosting iterations and can be tuned with class weights or sampling techniques.
Structured Tabular Data	Gradient Boosting algorithms (like XGBoost, LightGBM, or Scikit-Learn's GradientBoostingClassifier) excel on structured datasets like this one.
Small to Medium Dataset Size	With 768 rows, the dataset is relatively small—Gradient Boosting handles such sizes well without overfitting if regularized properly.
High Accuracy Requirement	In healthcare, accuracy matters. Gradient Boosting is known for delivering strong predictive performance, especially with the right tuning.

- **Hyperparameter Tuning**

To optimize model performance and avoid overfitting or underfitting, several hyperparameters of the **Gradient Boosting Classifier** were carefully selected and tuned.

To improve the model's performance, **Grid Search with 5-fold cross-validation** was performed using the following hyperparameter grid:

```
# Hyperparameter tuning for Gradient Boosting
param_grid = {
    'n_estimators': [100, 150],
    'learning_rate': [0.05, 0.1],
    'max_depth': [3, 4, 5]
}
```

Hyperparameter	Values Tried	Purpose
n_estimators	100, 150	Controls how many boosting trees are used. More trees can improve learning but also increase training time.
learning_rate	0.05, 0.1	Shrinks the contribution of each tree. Lower values make learning slower but more robust.
max_depth	3, 4, 5	Determines the depth of each individual tree. Deeper trees learn more complex patterns, but may overfit.

-> **Search Strategy: GridSearchCV** is used with the following settings:
Cross-Validation: 5 folds
Scoring Metric: F1 Score:

(suitable for imbalanced classes like diabetic vs non-diabetic).
Classifier: GradientBoostingClassifier(random_state=42)

```
grid_search = GridSearchCV(
    GradientBoostingClassifier(random_state=42),
    param_grid=param_grid,
    cv=5,
    scoring='f1'
)
grid_search.fit(X_train_scaled, y_train)
best_model = grid_search.best_estimator_
```

This helped in identifying the best combination of hyperparameters, which were then used to retrain the final model.

-> Best Parameters Obtained

This will output the best set:

```
print("✅ Best Parameters:", grid_search.best_params_)
```

- **Why is Grid Search Important ?**
  -> It allowed systematic testing of hyperparameter combinations.
  -> It ensured that the model was not overfitting or underfitting.
  -> It is optimized for F1 score, which balances precision and recall—crucial for medical prediction problems.

8.5 Optimal Threshold Selection

After training:

-> Predicted probabilities were extracted.

-> Precision-Recall curve was used to find the **optimal threshold** that maximized the **F1-score**.

```
# Predict probabilities
y_probs = best_model.predict_proba(X_test_scaled)[:, 1]

# Optimal threshold based on F1-score
precision, recall, thresholds = precision_recall_curve(y_test, y_probs)
f1_scores = 2 * (precision * recall) / (precision + recall + 1e-8)
optimal_threshold = thresholds[np.argmax(f1_scores)]

print(f"🎯 Optimal Threshold (based on F1): {optimal_threshold:.4f}")

# Make final predictions
y_pred_optimal = (y_probs >= optimal_threshold).astype(int)
```

8.6 Model Evaluation

- **Accuracy:** Computed for both training and testing sets.
- **Classification Report:** Precision, Recall, F1-Score.
- **Confusion Matrix**
- **ROC-AUC Score**

```
# Evaluation
print("\n✅ Accuracy:", accuracy_score(y_test, y_pred_optimal))
print("\n📌 Classification Report:\n", classification_report(y_test, y_pred_optimal))
print("\n🌀 Confusion Matrix:\n", confusion_matrix(y_test, y_pred_optimal))
print("📊 AUC-ROC Score:", roc_auc_score(y_test, y_pred_optimal))
```

- **Overfitting/Underfitting Check:**

```python
# Overfitting check
train_acc = accuracy_score(y_train, best_model.predict(X_train_scaled))
test_acc = accuracy_score(y_test, y_pred_optimal)
print(f"\nTrain Accuracy: {train_acc:.4f}, Test Accuracy: {test_acc:.4f}")

if train_acc - test_acc > 0.05:
    print("⚠️ Warning: Potential Overfitting.")
elif train_acc < 0.85 and test_acc < 0.85:
    print("⚠️ Warning: Potential Underfitting.")
else:
    print("✅ Model is generalizing well.")
```

8.7 Feature Importance

A bar plot was created to show the **most important features** contributing to the predictions:

```python
# Feature Importance Plot
importances = best_model.feature_importances_
features = X.columns
plt.figure(figsize=(10, 6))
plt.barh(features, importances, color='skyblue')
plt.xlabel("Importance Score")
plt.title("🎯 Feature Importance - Gradient Boosting")
plt.show()
```

This helped understand which variables have the most predictive power.

8.8 Model Persistence

The trained model was saved using **joblib**:

```
import joblib

# Save the model
joblib.dump(best_model, 'diabetes_prediction_model.pkl')
print("✅ Model saved successfully as 'diabetes_prediction_model.pkl'")
```

It can be reloaded for future use:

```
import joblib # Make sure to import the correct library

with open('diabetes_prediction_model.pkl', 'rb') as file:
    model = joblib.load(file) # Use joblib.load() to load the model
```

8.9 Conclusion

In this, a Gradient Boosting Classifier was successfully developed to predict diabetes based on various health-related features from a real-world dataset. The model was chosen for its strong performance with tabular data and its ability to handle complex, non-linear relationships through an ensemble of weak learners.

Key steps included data preprocessing (such as scaling and encoding), handling class imbalance using SMOTE, and optimizing hyperparameters using GridSearchCV. Evaluation metrics like accuracy, precision, recall, F1-score, ROC-AUC, and confusion matrix were used to assess the model's performance. Additionally, an optimal decision threshold was determined based on the F1-score to further improve classification results, particularly for the minority class.

Overall, the model showed promising results and provides a reliable approach for early detection of diabetes, which can help in proactive healthcare planning and treatment.

8.10 Output

```
Missing Values:
 Pregnancies                 0
Glucose                      0
BloodPressure                0
SkinThickness                0
Insulin                      0
BMI                          0
DiabetesPedigreeFunction     0
Age                          0
Outcome                      0
dtype: int64
```

```
✅ Best Parameters: {'learning_rate': 0.05, 'max_depth': 3, 'n_estimators': 100}
🎯 Optimal Threshold (based on F1): 0.2986
```

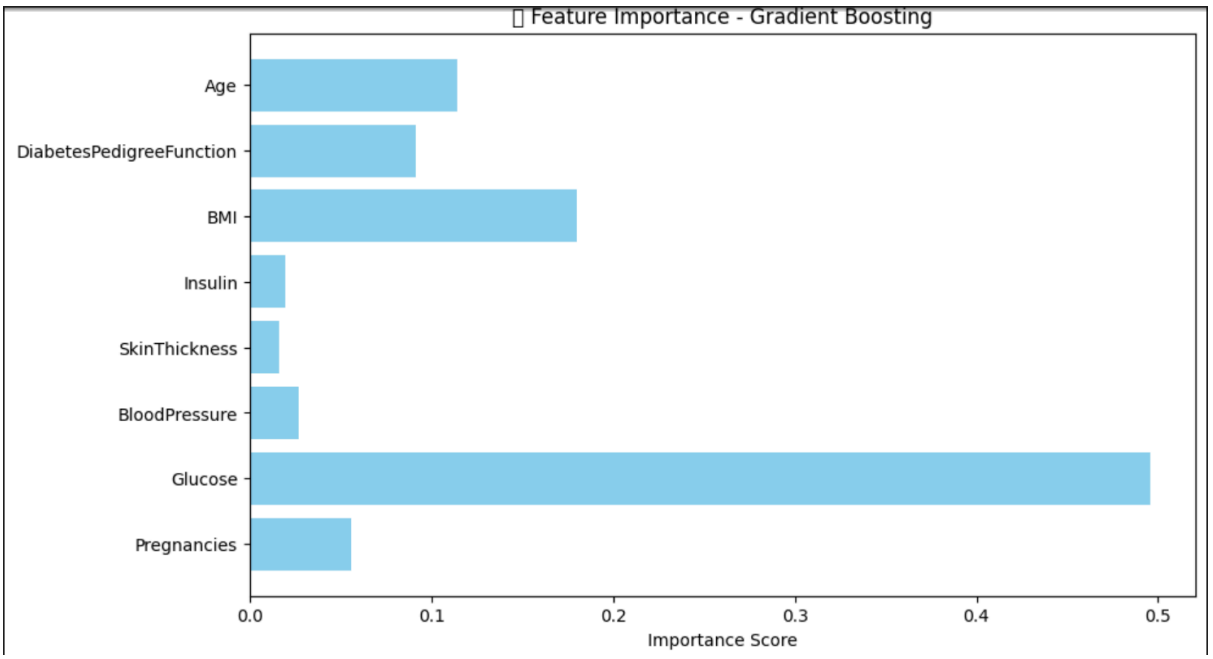
```
📌 Classification Report:
              precision    recall  f1-score   support

           0       0.95      0.71      0.81       150
           1       0.75      0.96      0.84       135

    accuracy                           0.83       285
   macro avg       0.85      0.83      0.83       285
weighted avg       0.85      0.83      0.83       285
```

```
📊 AUC-ROC Score: 0.8344444444444445

Train Accuracy: 0.8722, Test Accuracy: 0.8281
✅ Model is generalizing well.
```



✅ Model saved successfully as 'diabetes_prediction_model.pkl'

==========