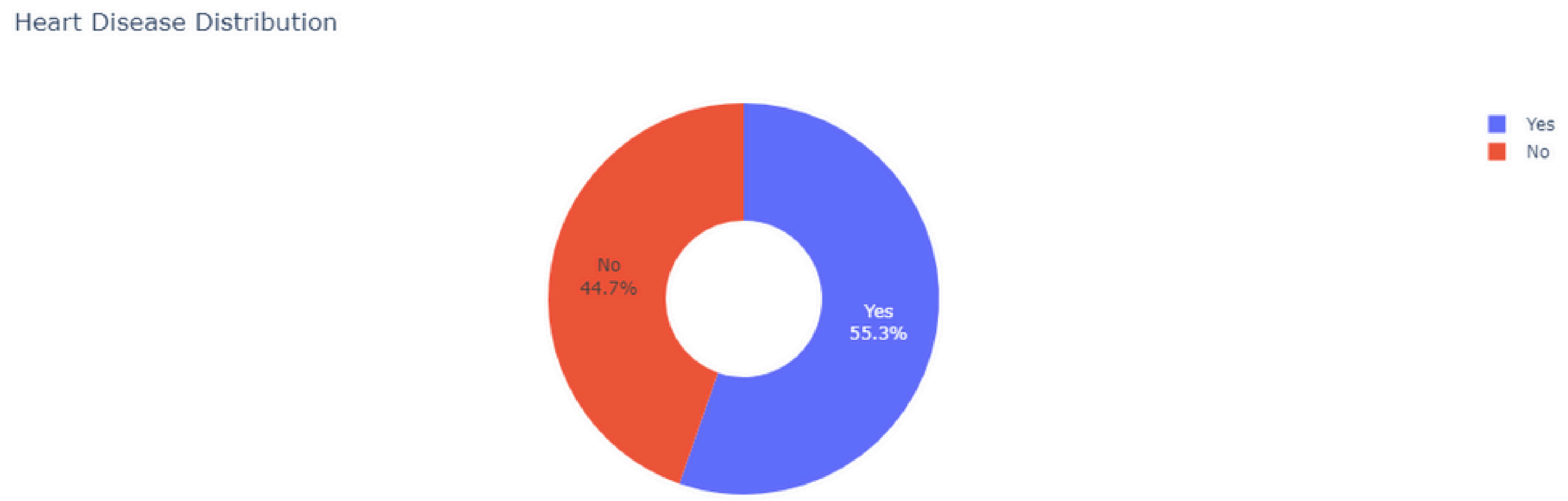
Heart Disease Risk Analysis and Prediction

Author: Fathur Rahman

Background

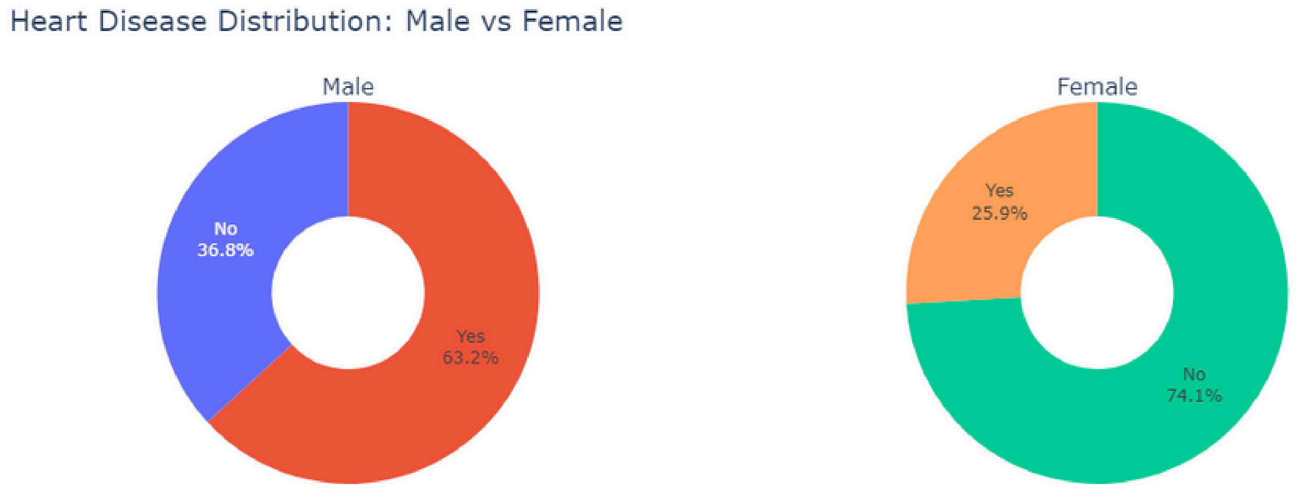
Heart disease is a critical health issue affecting millions worldwide. Patient data **provides valuable insights** into **identifying risk factors** and **predicting outcomes**. This project aims to **analyze and predict the risk of heart disease** using a multiclass classifier, leveraging patient data such as age, blood pressure, cholesterol levels, and other health metrics.

What Happened?

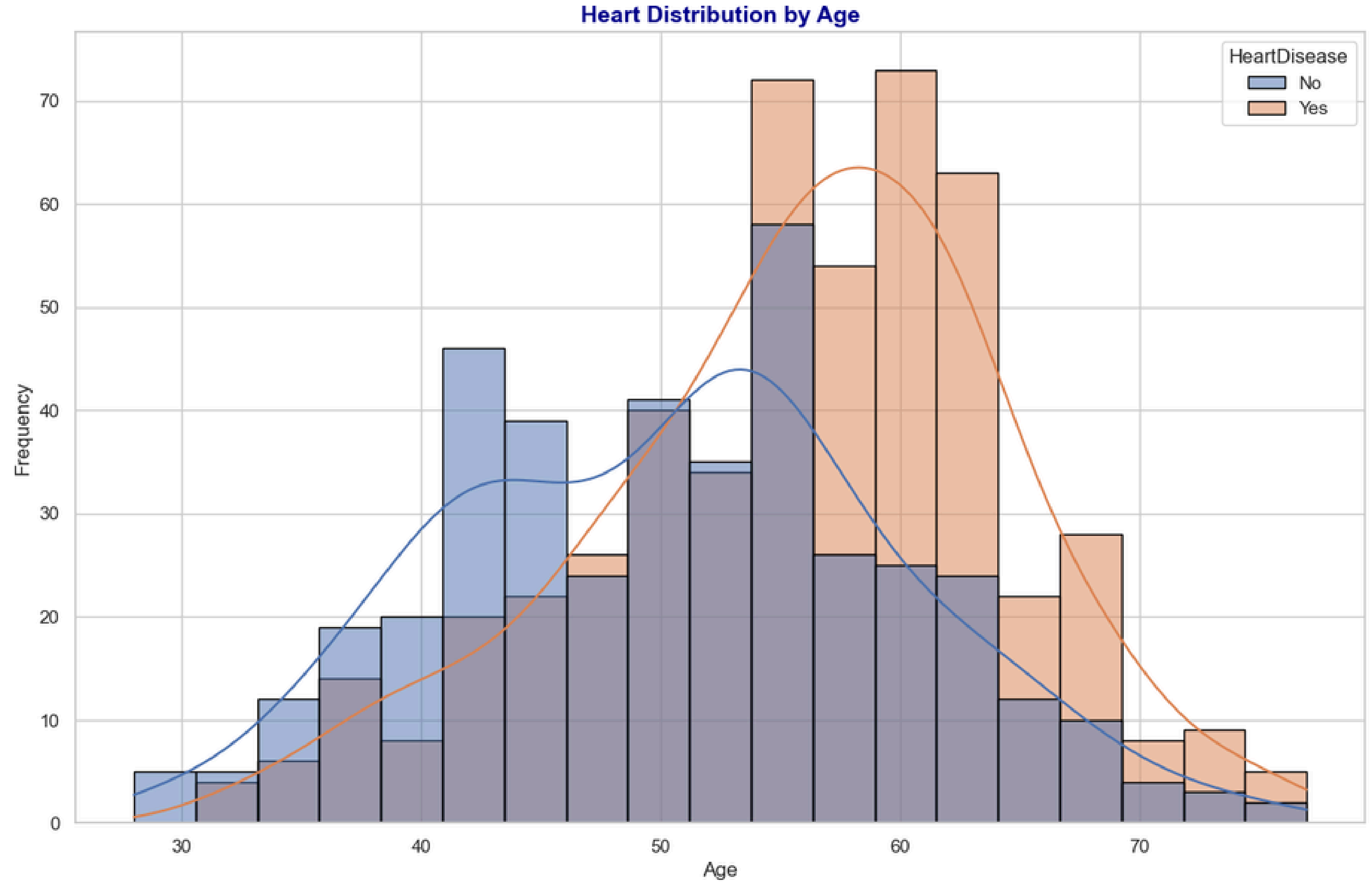


The dataset contains **508 instances (55.3%) labeled as "Heart Disease"** and **410 instances (44.7%) labeled as "No Heart Disease."**

How does the prevalence of heart disease vary by age and gender?

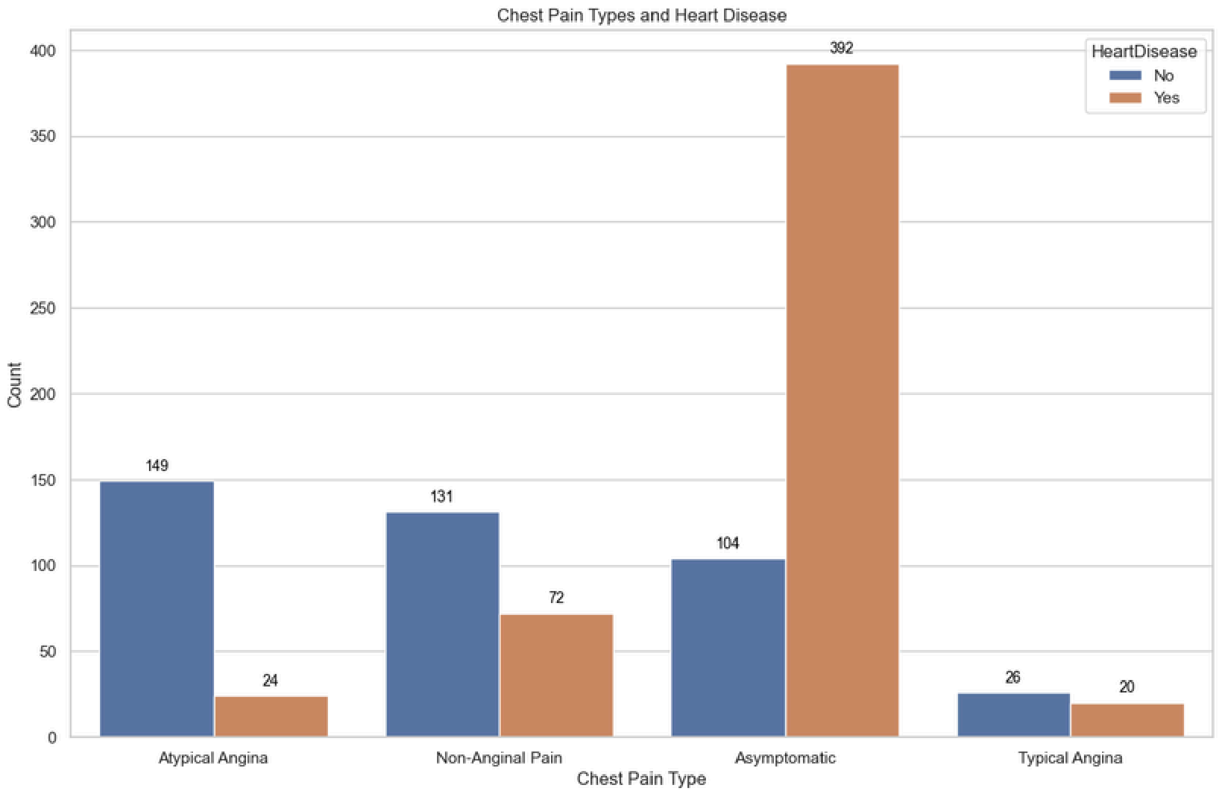


Males typically **show a higher prevalence of heart disease** compared to females.



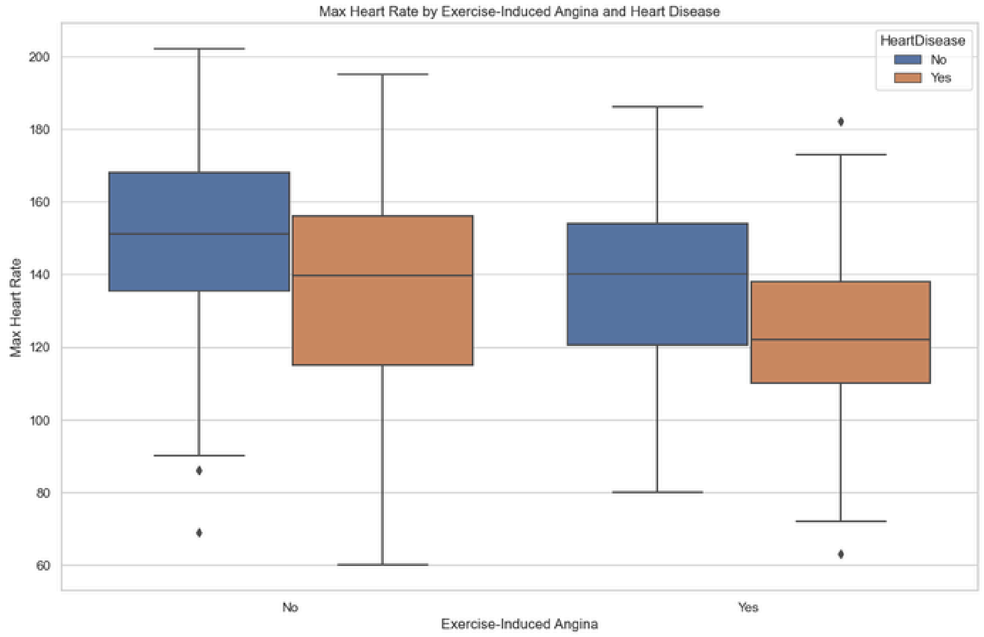
Heart disease is more prevalent among **older individuals**, with an increasing trend after age 40.

What are the most common chest pain types among patients with and without heart disease?



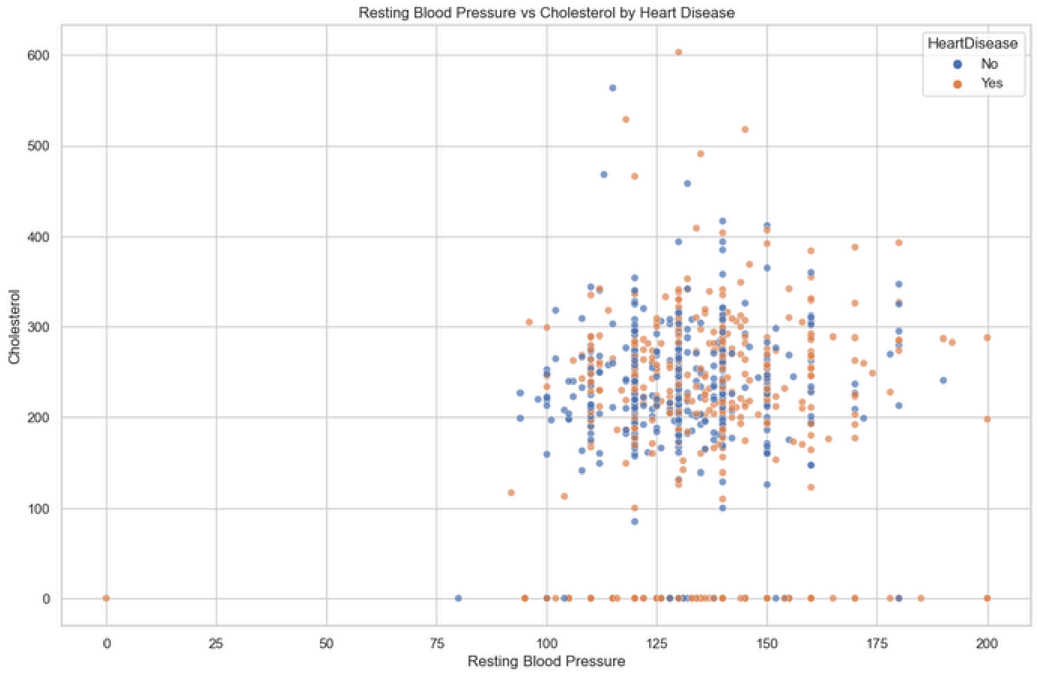
- Patients with **atypical angina, non-anginal and Typical angina** chest pain tend to have **lower rates of heart disease**.
- **asymptomatic** chest pain is often linked with **higher heart disease** prevalence.

How does the maximum heart rate achieved differ between patients with and without ExerciseAngina?



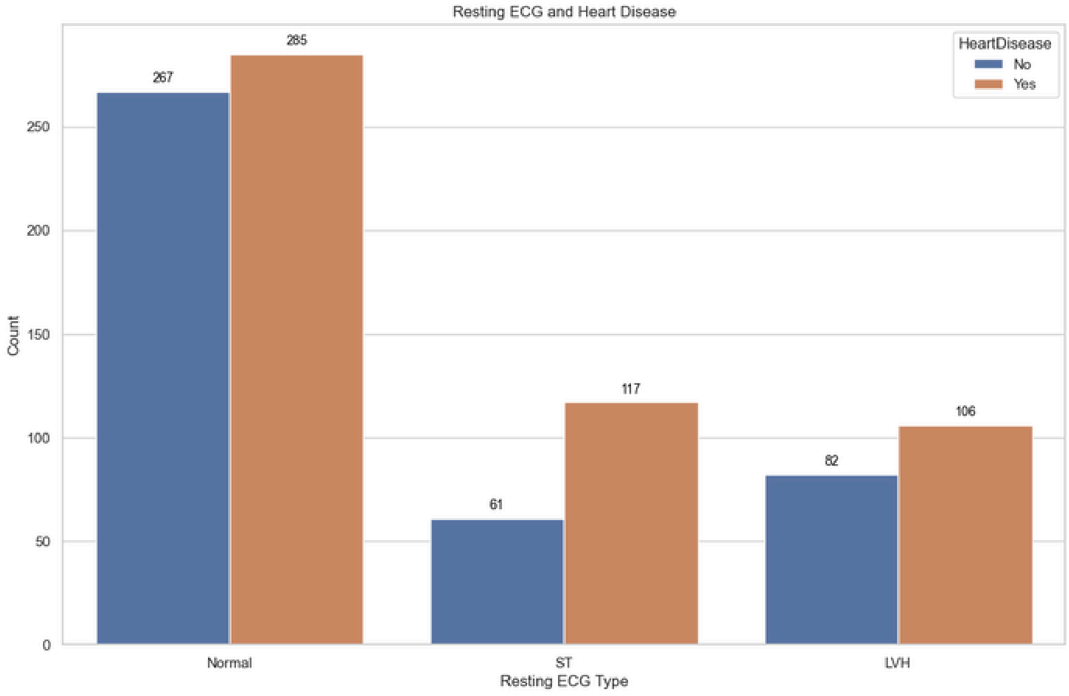
Individuals with heart disease tend to have a **lower Max Heart Rate** compared to those without heart disease, regardless of whether they experience Exercise-Induced Angina or not.

What is the relationship between resting blood pressure, cholesterol and heart disease?



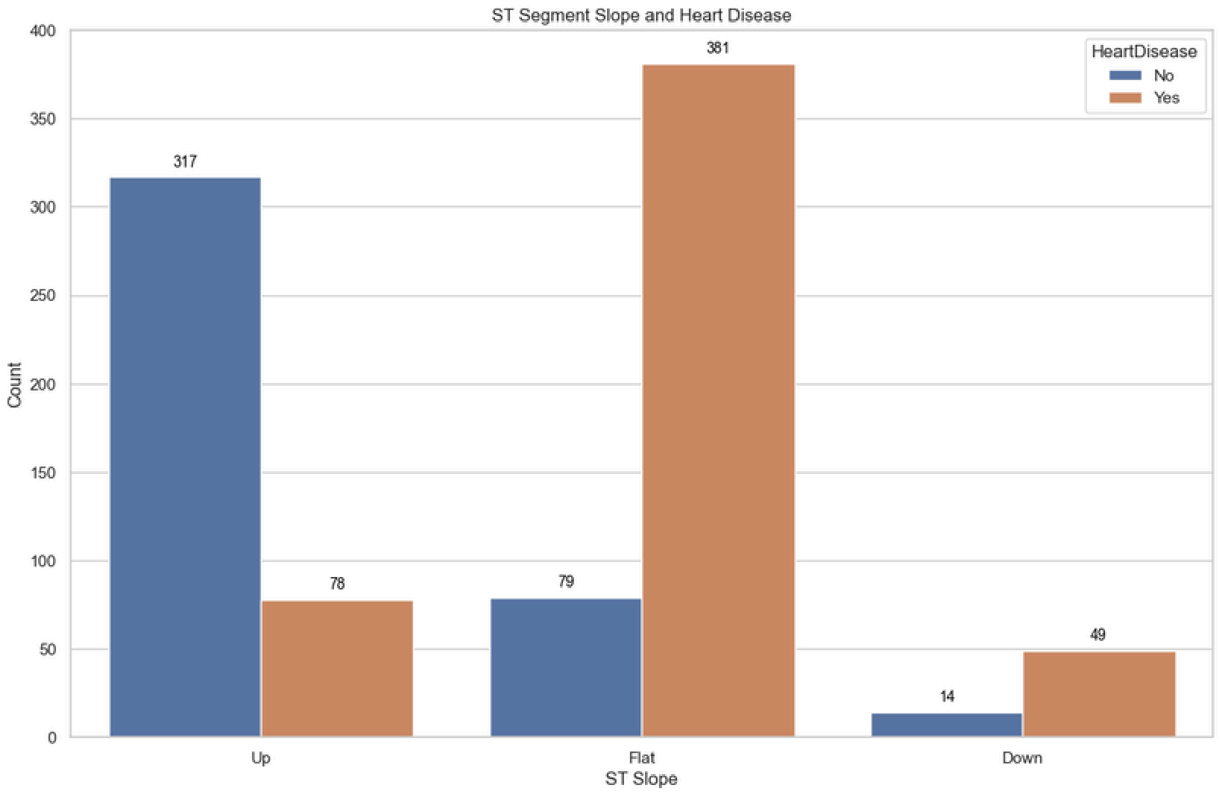
Higher cholesterol and **elevated resting blood pressure** are **associated** with **a greater likelihood of heart disease**, but the relationship may vary depending on other factors like age.

What patterns in resting ECG are associated with heart disease?



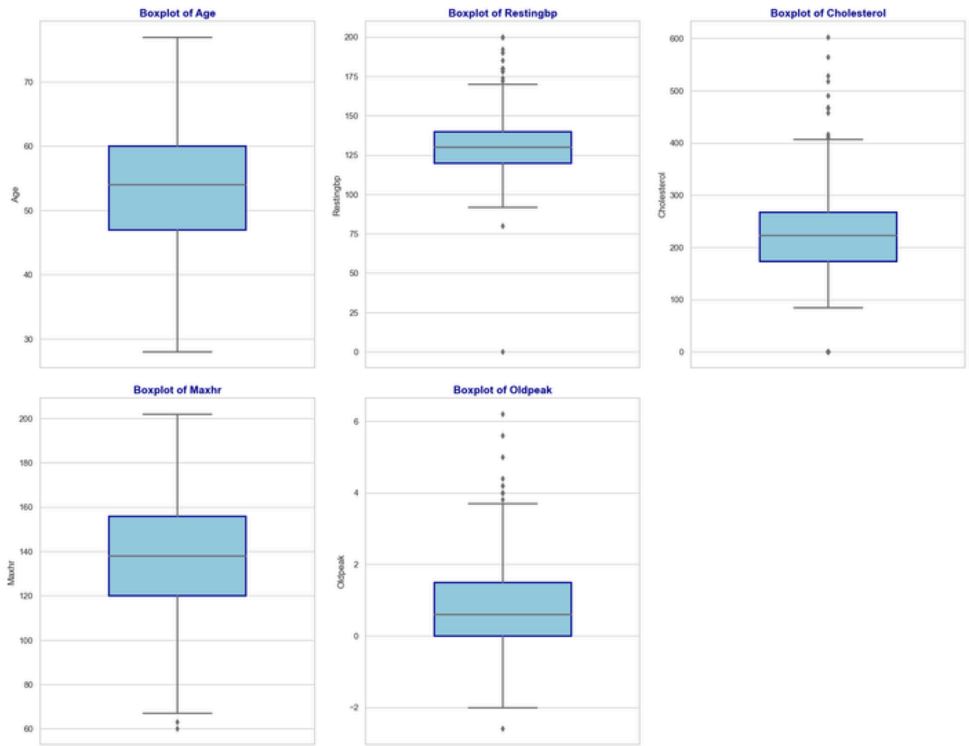
Abnormal resting ECG results are **more common** in heart disease cases.

What patterns in ST segment slope are associated with heart disease?



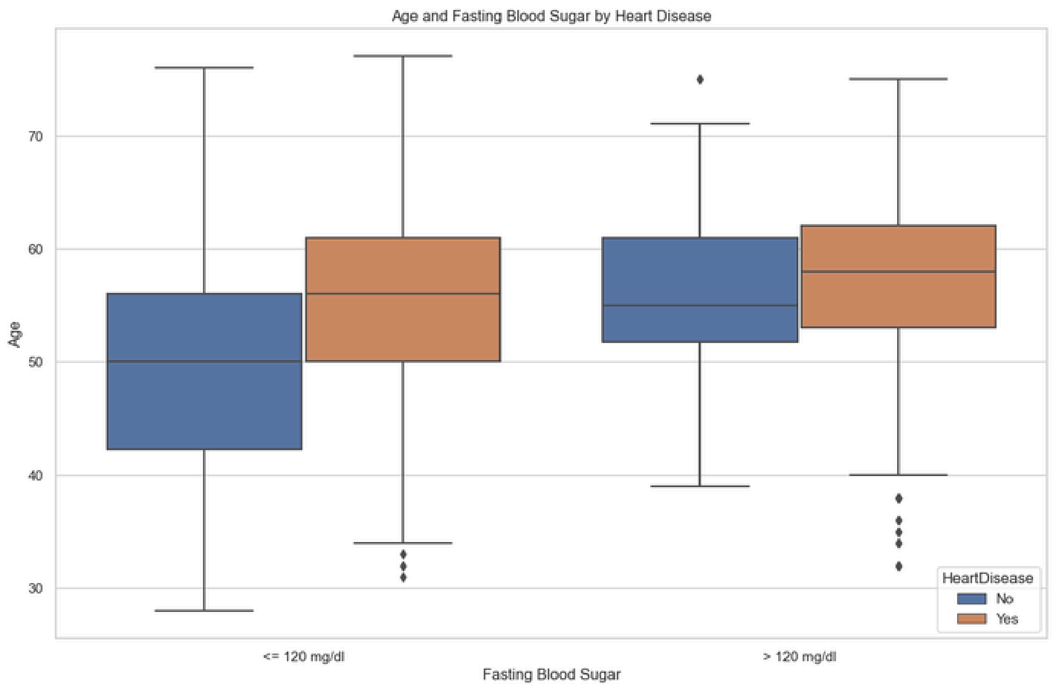
A **descending** ST segment slope is **strongly associated** with heart disease.

Are there any notable outliers in Age, RestingBP, Cholesterol, MaxHR, or Oldpeak?



Based on the boxplot, the columns **RestingBP, Cholesterol, MaxHR, and Oldpeak** contain outliers that should be removed to maintain data quality.

How do age and fasting blood sugar together influence the likelihood of heart disease?

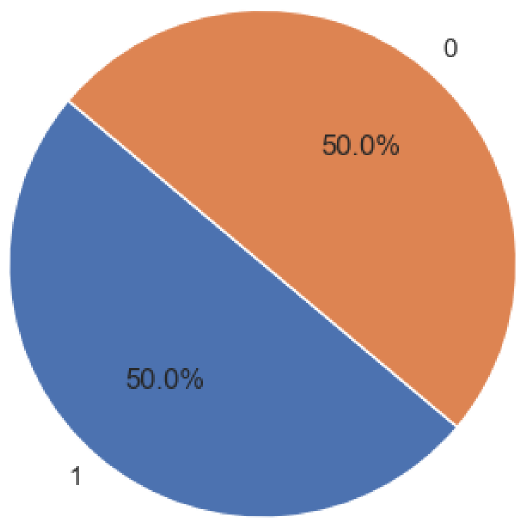


Older individuals with **fasting blood sugar > 120** mg/dl have a significantly **higher prevalence** of heart disease.

Feature Extraction

I did **Label-Encoder** and **Standard-Scaler method** on feature extraction.

Oversampling With SMOTE



This dataset is **imbalanced**, I use **SMOTE** to make it **balanced**.

Modeling

I use **Random Forest, KNeighborsClassifier (KNN)** and **Support Vector Machine (SVM)** for Model Development.

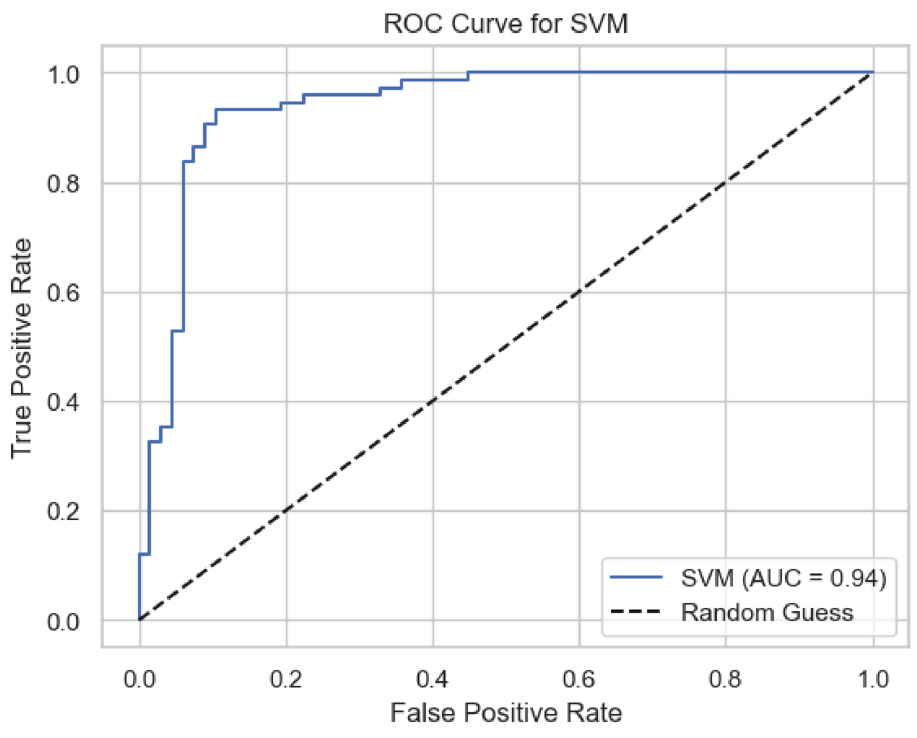
Evaluation

- I'm still **paying attention** to the **accuracy score** as well since this metric is easier to interpret.
- The model's performance was evaluated using metrics such as **precision, recall, and F1-score**.
- I'm also using **cross validation** performance to estimated accuracy score for data validation with 5-folds.
- In credit risk modeling, test performance is calculated using the **AUC metrics**.

	Model	Accuracy	F1_Score	Recall	Precisions	Cross Validation Score (5-folds)
0	KNeighborsClassifier	0.907801	0.907662	0.907801	0.908350	0.872660
1	SVM	0.900709	0.900316	0.900709	0.903238	0.886453
2	RandomForestClassifier	0.893617	0.893456	0.893617	0.894109	0.850739

Support Vector Machine (SVM) give the best performance

Click here to see my code



ROC Curve performance reach **0.94** using SVM

Deployment with Streamlit

To **deploy the Streamlit app**, I ensured all dependencies were installed, prepared a **requirements.txt** file, and **deployed via Streamlit Sharing**, linking a **GitHub repository** for **automated updates**.

Conclusion

SVM is the best model, providing a strong balance with an accuracy of **0.9007**, precision of **0.9032**, recall of **0.9007**, F1-score of **0.9003**, and cross-validation performance of **0.8865**. Its consistency across folds makes it ideal for predicting new data. The model was tested using the AUC metric, achieving an impressive **0.94**, indicating excellent performance.