# Project Report on
# Heart Disease Prediction


Submitted by:

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# Abstract

The Cardiovascular Disease Prediction project aims to utilize data-driven methodologies for a thorough analysis of predicting heart diseases, with a primary focus on employing statistical techniques, exploratory data analysis, time series analysis, and machine learning models. This project seeks to unravel intricate patterns, trends, and contributing factors associated with cardiovascular health.

# Acknowledgement

At this juncture of our journey, we wish to express our heartfelt gratitude to all those who have contributed to the creation and success of **"Heart Disease Predication".** This project has been a labor of passion and dedication, and it would not have been possible without the unwavering support and guidance we have received.

First and foremost, we offer our thanks to the boundless creativity and inspiration that flows from the universe. We are grateful for the opportunity to embark on this venture.

We extend our sincerest appreciation to our mentors, **Mrs. Mala Mishra & Ms. Ankita Shukla**, whose wisdom and guidance have been instrumental in shaping the vision of **"Heart Disease Predication".** Your support at every crucial turn has illuminated our path and fueled our determination to create a meaningful platform.

To our dedicated team of developers, designers, and content creators, we extend our deepest gratitude. Your tireless efforts, innovation, and creativity have breathed life into **"Heart**

**Disease Predication".** It is your collective dedication that has made this project a reality.

Our appreciation also goes to our colleagues and friends who provided invaluable insights and feedback during the development process. Your input has been instrumental in refining our ideas and enhancing the user experience.

We acknowledge the contributions of the broader IT community, whose open-source ethos has been a wellspring of knowledge and inspiration. The collaborative spirit of this community has been a guiding light.

Last but not least, we owe a debt of gratitude to our families and friends who have stood by us throughout this journey. Your unwavering support, encouragement, and belief in our vision have been our constant motivation.

## ADVANCE DIPLOMA IN IT NETWORKING & CLOUD COMPUTING

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The Advanced Diploma in IT Networking and Cloud Computing program offered by NSTI (W) Noida in collaboration with Edunet Foundation is a comprehensive course designed to equip students with advanced skills in information technology and cloud computing. This program covers a wide range of topics, including Computer Networking, Database Management, Virtualization, Cloud Technologies, and Cybersecurity. Students will gain hands-on experience through practical labs, workshops, and real-world projects, enabling them to excel in the rapidly evolving IT industry. Upon completion of the program, Graduates will have a strong foundation in both IT Fundamentals and Cloud Computing, making them highly sought-after professionals in the field.

## Project Requirements

| **Project Name** | **Heart Disease Predication** |
|---|---|
| **Languages Used** | **Python** |
| **Editor** | **Jupyter Notebook, Google Colab** |
| **Web Browser** | **Google Chrome, Microsoft Edge** |

## Team Composition and Workload Division

| | |
|---|---|
| Kumkum | Research and Data Analysis |
| Varsha | Data Analysis, Synopsis |

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# 1. Introduction to Problem

The escalating challenges associated with heart disease have become a cause for concern amid rapid urbanization and industrialization. This surge in heart-related issues has been negatively influenced by factors such as air and water quality, compounded by the lack of robust data analysis tools. This project is specifically tailored to address this critical gap through an extensive analysis of heart disease data. It aims to identify key contributors and formulate effective strategies for prediction and mitigation. The overarching objective is to provide actionable insights to policymakers and communities, facilitating informed decision-making to foster a healthier environment and reduce the prevalence of heart disease.

# 2. Requirements

### 3.1 Technology Stack

**Python:** High-level programming language used for server-side scripting.

**Jupyter Notebook:** Jupyter Notebook is an open-source web application that allows you to create and share documents containing live code, equations, visualizations, and narrative text, providing an interactive and collaborative environment for data science and analysis.

### 3.2 Hardware

Laptop/ Computer

### 3.3 Software

Operating System (OS)

Version Control System

Text Editors and Integrated Development Environments (IDEs)

# 3. Overview

The Heart Disease Prediction project aims to investigate and derive meaningful insights from a specific dataset related to heart health. It involves collecting, cleaning, and processing raw data to uncover patterns, trends, and correlations specifically within the context of cardiovascular health. Using statistical methods and visualization tools, the project seeks to provide a comprehensive understanding of the data, enabling informed decision-making in the prediction of heart diseases. The analysis may involve exploring relationships between variables, identifying outliers, and creating predictive models tailored to cardiovascular outcomes. Throughout the project, a systematic approach is followed, including hypothesis testing and validation of results. The ultimate goal is to offer actionable recommendations or conclusions based on the data findings in the realm of heart disease prediction. The project typically employs programming languages such as Python or R, along with tools like Jupyter Notebooks, to facilitate a transparent and reproducible analytical workflow. Overall, the Heart Disease Prediction project serves to extract valuable insights, enhance understanding, and support evidence-based decision-making in the field of cardiovascular health.

# 4. Project Module

1. Import the required libraries.

2. Load/ Read the Dataset

3. Prepare EDA

# 6 Sample Screenshots

## Import the Required Libraries

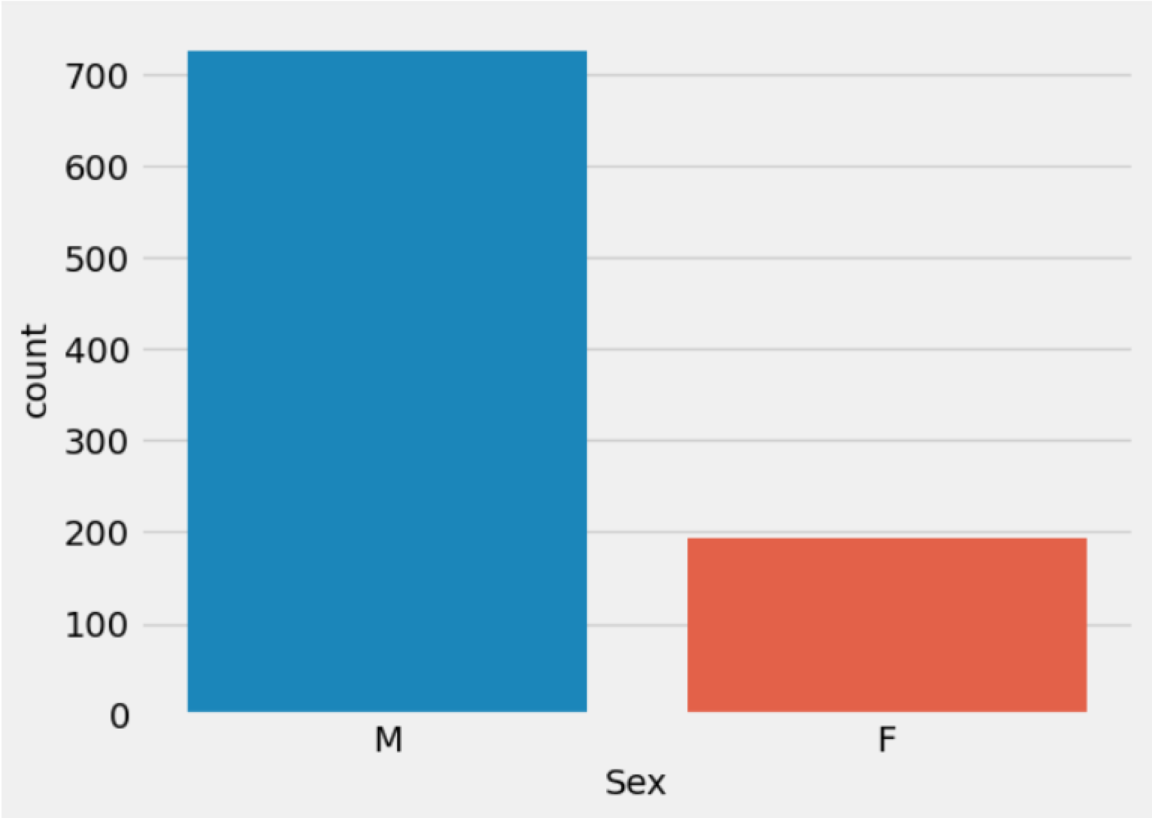
In [1]:

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
from sklearn.neighbors import KNeighborsClassifier
from sklearn.preprocessing import StandardScaler
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn import datasets, linear_model, metrics
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
from sklearn.model_selection import train_test_split
from sklearn.datasets import make_classification
import warnings
warnings.filterwarnings('ignore')
```

## 1. Import the Dataset

In [2]:

```
df = pd.read_csv('heart.csv')
df
```




# 7. Source Code

- **Import the Required Libraries**

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
from sklearn.neighbors import KNeighborsClassifier
from sklearn.preprocessing import StandardScaler
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn import datasets, linear_model, metrics
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
from sklearn.model_selection import train_test_split
from sklearn.datasets import make_classification
import warnings
warnings.filterwarnings('ignore')
```

- **Read the CSV File**

```
df = pd.read_csv('heart.csv')
df
```

- **Show the first 5 row**

```
df.head()
```

- **Show the last 5 row**

```
df.tail()
```

- **Dataset Description**

```
df.describe()
```

- **Short info of the dataframe**

```
df.info() #short info of the dataframe
```

- **Show the total column and row**

```
df.shape
```

- **Show the all size**

```
df.size
```

- **Find unique value**

```
#find unique value
df.apply(lambda x: len(x.unique()))
```

- **Checking the null values present in the DataFrame**

```
df.isnull().sum() #checking the null values present in the DataFrame
```

- **Unique values found in the DataFrame of each column**

```
df.nunique() #unique values found in the DataFrame of each column
```

- **Show the dtype**

```
df.dtypes
```

- **It's show mean, median, mode**

```
df.describe().T
```

- ## Show the duplicated

```
df.duplicated().sum()
```

```
df.corr()
```

```
df.skew()
```

- ## Exploratory Data Analysis

```
plt.plot()
```

```
res=sns.barplot(df)
```

```
res=sns.barplot(df,x='HeartDisease',y='Age')
```

```
res=sns.boxplot(df,x='HeartDisease',y='Age')
```

```
res=sns.boxplot(df,x='RestingBP',y='Age')
```

- ## Dist plot for RestingBP

```
#Dist plot for RestingBP
plt.style.use('fivethirtyeight')
plt.figure(figsize=(12,8))
sns.distplot(df['RestingBP'], bins=25)
```

- ## Distribution of numerical variable

```
#Distribution of numerical variable
sns.countplot(data=df, x='Sex')
```

```
sns.countplot(data=df, x='Age')
```

```
sns.countplot(data=df, x='FastingBS')
```

```
sns.countplot(data=df, x='MaxHR')
```

```
sns.countplot(data=df, x='HeartDisease')
```

- **Bivariate analysis**

```
#bivariate analysis
age_plot = df.pivot_table(index='Age', values='HeartDisease', aggfunc=np.mean)
age_plot.plot(kind='bar', figsize=(13, 7))
plt.xlabel('Age')
plt.ylabel("HeartDisease")
plt.title("Age and HeartDisease Analysis")
plt.xticks(rotation=0)
plt.show()
```

```
old_plot = df.pivot_table(index='Age', values='Oldpeak', aggfunc=np.mean)
old_plot.plot(kind='bar', figsize=(13, 7))
plt.xlabel('Age')
plt.ylabel("Oldpeak")
plt.title("Age and oldpeak Analysis")
plt.xticks(rotation=0)
plt.show()
```

```
MaxHR_plot = df.pivot_table(index='MaxHR', values='HeartDisease', aggfunc=np.mean)
MaxHR_plot.plot(kind='bar', figsize=(13, 7))
plt.xlabel('MaxHR')
plt.ylabel("HeartDisease")
plt.title("MaxHR and HeartDisease Analysis")
plt.xticks(rotation=0)
plt.show()
```

```
Sex_plot = df.pivot_table(index='Sex', values='HeartDisease', aggfunc=np.mean)
Sex_plot.plot(kind='bar', figsize=(13, 7))
plt.xlabel('Sex')
plt.ylabel("HeartDisease")
plt.title("Sex and HeartDisease Analysis")
plt.xticks(rotation=0)
plt.show()
```

```
plt.figure(figsize=(18,18))
plt.subplot(3,2,1)
plt.style.use('seaborn')
plt.tight_layout()
sns.set_context('talk')
sns.histplot(data=df, x='Age', hue="HeartDisease",multiple="stack",palette='magma')
plt.title('Age vs HeartDisease')

plt.subplot(3,2,2)
plt.style.use('seaborn')
plt.tight_layout()
sns.set_context('talk')
sns.histplot(data=df, x='RestingBP', hue="HeartDisease",multiple="stack",palette='magma')
plt.title('RestingBP vs HeartDisease')

plt.subplot(3,2,3)
plt.style.use('seaborn')
plt.tight_layout()
sns.set_context('talk')
sns.histplot(data=df, x='Cholesterol', hue="HeartDisease",multiple="stack",palette='magma')
plt.title('Cholesterol vs HeartDisease')

plt.subplot(3,2,4)
plt.style.use('seaborn')
plt.tight_layout()
sns.set_context('talk')
sns.histplot(data=df, x='FastingBS', hue="HeartDisease",multiple="stack",palette='magma')
plt.title('FastingBS vs HeartDisease')

plt.subplot(3,2,5)
plt.style.use('seaborn')
plt.tight_layout()
sns.set_context('talk')
sns.histplot(data=df, x='MaxHR', hue="HeartDisease",multiple="stack",palette='magma')
plt.title('MaxHR vs HeartDisease')

plt.subplot(3,2,6)
plt.style.use('seaborn')
plt.tight_layout()
sns.set_context('talk')
sns.histplot(data=df, x='Oldpeak', hue="HeartDisease",multiple="stack",palette='magma')
plt.title('Oldpeak vs HeartDisease')
plt.show()
```

- g = sns.FacetGrid(tips, col="time")
- g.map(sns.histplot, "tip")

```
#g = sns.FacetGrid(tips, col="time")
#g.map(sns.histplot, "tip")
sns.set()
df.hist(figsize=(10,10))
plt.show()
```

```
sns.pairplot(df,hue='HeartDisease')
```

- Average age is same for both male and female

```
dff= df.groupby('Sex').agg({'Age' : 'mean', "ChestPainType":'count','RestingBP':'mean','Cholesterol':'mean',
                            'FastingBS':'sum','RestingECG':'count','MaxHR':'mean','ExerciseAngina':'count','Oldpeak':'mean',
                            'ST_Slope':'count','HeartDisease':'sum'})
dff
# average age is same for both male and female
```

```
import plotly.express as px
px.bar(data_frame=dff, barmode='group', title = "Gender wise Analyzing",template="plotly_dark")
```

# Data Preprocessing

- Check for null values

```
#Check for null values
dff.isnull().sum()
```

- To improve the metric use one hot encoding
- Label encoding

```
# to improve the metric use one hot encoding
# label encoding
cols = ['Sex', 'MaxHR', 'HeartDisease']
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
for col in cols:
    df[col] = le.fit_transform(df[col])
df.head()
```

# Corelation Matrix

```
corr = df.corr()
plt.figure(figsize=(14,7))
sns.heatmap(corr, annot=True, cmap='coolwarm')
```

```
df.head()
```

```
X = df.drop(columns=['ExerciseAngina', 'FastingBS', 'ST_Slope'])
y = df['ST_Slope']
```

```
print('Mean: ',df['Cholesterol'].mean())
print('Median: ',df['Cholesterol'].median())
```

```
mc=df[df['Cholesterol']>0].Cholesterol.mean() #mean value of Cholesterol without including the cholesterol=0
print('Mean of Cholesterol>0: ',mc)
```

```
df.describe().T
```

## One Hot Encoding

```
df.describe().columns.to_list()
```

## Feature Scaling

```
# altering the DataFrame
df = df[['Age',
 'RestingBP',
 'Cholesterol',
 'FastingBS',
 'MaxHR',
 'Oldpeak',
 'Sex',
 'HeartDisease',]]

# printing the altered DataFrame
df.head(5)
```

```
scaler = StandardScaler()
scaler.fit(df.drop('HeartDisease',axis = 1))
```

```
scaled_features = scaler.transform(df.drop('HeartDisease',axis = 1))
df_feat = pd.DataFrame(scaled_features,columns = df.columns[:-1])
df_feat.head()
```

```
df.head(5)
```

## Feature Selection

```
col=df.describe().columns.to_list()
print(col)
```

```python
X = df_feat
y = df['HeartDisease']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, random_state=20)
print(X, y)
```

# Model Selection

## 10-Fold Cross validation and model comparision

```python
from sklearn.model_selection import KFold
from sklearn.model_selection import cross_val_score
from sklearn.svm import SVC
cv = KFold(n_splits=10, random_state=100, shuffle=True)
model = KNeighborsClassifier(n_neighbors=36)
scores = cross_val_score(model, X, y, scoring='accuracy', cv=cv, n_jobs=-1)
print('Accuracy of KNN: %.3f (%.3f)' % (np.mean(scores), np.std(scores)))
model = SVC(kernel='rbf')
scores = cross_val_score(model, X, y, scoring='accuracy', cv=cv, n_jobs=-1)
print('Accuracy of SVC: %.3f (%.3f)' % (np.mean(scores), np.std(scores)))
model=RandomForestClassifier(n_estimators =40,random_state=100)
scores = cross_val_score(model, X, y, scoring='accuracy', cv=cv, n_jobs=-1)
print('Accuracy of RandomForest: %.3f (%.3f)' % (np.mean(scores), np.std(scores)))
```

# K value estimation

```python
from matplotlib import pyplot
error_rate= []
for i in range(1,40):
    knn = KNeighborsClassifier(n_neighbors = i)
    knn.fit(X_train,y_train)
    pred_i = knn.predict(X_test)
    error_rate.append(np.mean(pred_i != y_test))
    print(i,np.mean(pred_i != y_test))
```

```python
plt.figure(figsize = (10,6))
plt.plot(range(1,40),error_rate,color = 'black',linestyle = '--',marker = '*',markerfacecolor='red',markersize = 8)
plt.title('Error Rate vs K')
plt.xlabel('K')
plt.ylabel('Error Rate')
```

# KNN model

```python
classifier = KNeighborsClassifier(n_neighbors=45)
classifier.fit(X_train, y_train)
y_pred = classifier.predict(X_test)
print(classification_report(y_test, y_pred))
print('Confusion Matrix')
kn = confusion_matrix(y_test, y_pred)
print(kn)
plt.figure(figsize=(8, 6))
sns.heatmap(kn, annot=True, fmt="d", cmap="binary", cbar=False)
plt.title('Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.grid(False)
plt.show()
```

# Support Vector Classifier

```
classifier = SVC(kernel='rbf', random_state=100)
classifier.fit(X_train, y_train)
y_pred = classifier.predict(X_test)
print(classification_report(y_test, y_pred))
print('Confusion Matrix')
print(confusion_matrix(y_test, y_pred))
sp = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(8, 6))
sns.heatmap(sp, annot=True, fmt="d", cmap="binary", cbar=False)
plt.title('Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.grid(False)
plt.show()
```

# Parameter selectikon for Random Forest Classifier

```
from sklearn.model_selection import RandomizedSearchCV
n_estimators = [int(x) for x in np.linspace(start = 103, stop = 300, num = 10)]
max_features = ['auto', 'sqrt']
max_depth = [int(x) for x in np.linspace(10, 110, num = 11)]
max_depth.append(None)
min_samples_split = [2, 5, 10]
min_samples_leaf = [1, 2, 4]
bootstrap = [True, False]
random_grid = {'n_estimators': n_estimators,
               'max_features': max_features,
               'max_depth': max_depth,
               'min_samples_split': min_samples_split,
               'min_samples_leaf': min_samples_leaf,
               'bootstrap': bootstrap}
```

```
rf = RandomForestClassifier()
forest = RandomizedSearchCV(estimator = rf, param_distributions = random_grid, n_iter
= 100, cv = 3, verbose=2, random_state=42, n_jobs = -1)
forest.fit(X_train,y_train)
```

```
forest.best_params_
```

# Random Forest Classifier

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, random_state=0)
clf=RandomForestClassifier(n_estimators=124,min_samples_split= 2,
                           min_samples_leaf= 1,max_features='sqrt',max_depth=None, bootstrap=False)
clf.fit(X_train,y_train)
y_pred=clf.predict(X_test)
import warnings
warnings.filterwarnings("ignore")
print(classification_report(y_test, y_pred))
print('Confusion Matrix')
#print(confusion_matrix(y_test, y_pred))
kn = confusion_matrix(y_test, y_pred)
print(kn)
plt.figure(figsize=(8, 6))
sns.heatmap(kn, annot=True, fmt="d", cmap="binary", cbar=False)
plt.title('Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.grid(False)
plt.show()
```

# Gradient Boosting Classifier

```
from sklearn.ensemble import GradientBoostingClassifier
clff = GradientBoostingClassifier(n_estimators=100, learning_rate=0.2, max_depth=1, random_state=23)
clff.fit(X_train, y_train)
y_pred=clff.predict(X_test)
print(classification_report(y_test, y_pred))
print('Confusion Matrix')
print(confusion_matrix(y_test, y_pred))
#cl = confusion_matrix(y_test, y_pred)
#print(cl)
plt.figure(figsize=(5, 8))
sns.heatmap(cl, annot=True, fmt="d", cmap="binary", cbar=False)
plt.title('Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.grid(False)
plt.show()
```

# Conclusion

```
KNN model gives the accuracy of                  : 89%
Random forest givea the accuracy of              : 89%
Suport Vector Classifier gives the accuracy of   : 88%
Gradient Boosting Classifier gives the accuracy of: 86%
```

# Outputs:-

- **Show the all dataset**

| | Age | Sex | ChestPainType | RestingBP | Cholesterol | FastingBS | RestingECG | MaxHR | ExerciseAngina | Oldpeak | ST_Slope | HeartDisease |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 40 | M | ATA | 140 | 289 | 0 | Normal | 172 | N | 0.0 | Up | 0 |
| **1** | 49 | F | NAP | 160 | 180 | 0 | Normal | 156 | N | 1.0 | Flat | 1 |
| **2** | 37 | M | ATA | 130 | 283 | 0 | ST | 98 | N | 0.0 | Up | 0 |
| **3** | 48 | F | ASY | 138 | 214 | 0 | Normal | 108 | Y | 1.5 | Flat | 1 |
| **4** | 54 | M | NAP | 150 | 195 | 0 | Normal | 122 | N | 0.0 | Up | 0 |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| **913** | 45 | M | TA | 110 | 264 | 0 | Normal | 132 | N | 1.2 | Flat | 1 |
| **914** | 68 | M | ASY | 144 | 193 | 1 | Normal | 141 | N | 3.4 | Flat | 1 |
| **915** | 57 | M | ASY | 130 | 131 | 0 | Normal | 115 | Y | 1.2 | Flat | 1 |
| **916** | 57 | F | ATA | 130 | 236 | 0 | LVH | 174 | N | 0.0 | Flat | 1 |
| **917** | 38 | M | NAP | 138 | 175 | 0 | Normal | 173 | N | 0.0 | Up | 0 |

918 rows × 12 columns

- **Show the first 5 row**

| | Age | Sex | ChestPainType | RestingBP | Cholesterol | FastingBS | RestingECG | MaxHR | ExerciseAngina | Oldpeak | ST_Slope | HeartDisease |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 40 | M | ATA | 140 | 289 | 0 | Normal | 172 | N | 0.0 | Up | 0 |
| **1** | 49 | F | NAP | 160 | 180 | 0 | Normal | 156 | N | 1.0 | Flat | 1 |
| **2** | 37 | M | ATA | 130 | 283 | 0 | ST | 98 | N | 0.0 | Up | 0 |
| **3** | 48 | F | ASY | 138 | 214 | 0 | Normal | 108 | Y | 1.5 | Flat | 1 |
| **4** | 54 | M | NAP | 150 | 195 | 0 | Normal | 122 | N | 0.0 | Up | 0 |

- **Show the last 5 row**

| | Age | Sex | ChestPainType | RestingBP | Cholesterol | FastingBS | RestingECG | MaxHR | ExerciseAngina | Oldpeak | ST_Slope | HeartDisease |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **913** | 45 | M | TA | 110 | 264 | 0 | Normal | 132 | N | 1.2 | Flat | 1 |
| **914** | 68 | M | ASY | 144 | 193 | 1 | Normal | 141 | N | 3.4 | Flat | 1 |
| **915** | 57 | M | ASY | 130 | 131 | 0 | Normal | 115 | Y | 1.2 | Flat | 1 |
| **916** | 57 | F | ATA | 130 | 236 | 0 | LVH | 174 | N | 0.0 | Flat | 1 |
| **917** | 38 | M | NAP | 138 | 175 | 0 | Normal | 173 | N | 0.0 | Up | 0 |

- **Describe the dataset**

| | Age | RestingBP | Cholesterol | FastingBS | MaxHR | Oldpeak | HeartDisease |
|---|---|---|---|---|---|---|---|
| **count** | 918.000000 | 918.000000 | 918.000000 | 918.000000 | 918.000000 | 918.000000 | 918.000000 |
| **mean** | 53.510893 | 132.396514 | 198.799564 | 0.233115 | 136.809368 | 0.887364 | 0.553377 |
| **std** | 9.432617 | 18.514154 | 109.384145 | 0.423046 | 25.460334 | 1.066570 | 0.497414 |
| **min** | 28.000000 | 0.000000 | 0.000000 | 0.000000 | 60.000000 | -2.600000 | 0.000000 |
| **25%** | 47.000000 | 120.000000 | 173.250000 | 0.000000 | 120.000000 | 0.000000 | 0.000000 |
| **50%** | 54.000000 | 130.000000 | 223.000000 | 0.000000 | 138.000000 | 0.600000 | 1.000000 |
| **75%** | 60.000000 | 140.000000 | 267.000000 | 0.000000 | 156.000000 | 1.500000 | 1.000000 |
| **max** | 77.000000 | 200.000000 | 603.000000 | 1.000000 | 202.000000 | 6.200000 | 1.000000 |

| Attribute | Description |
|---|---|
| **Age** | Age of a patient [years] |
| **Sex** | Gender of the patient [M: Male, F: Female] |
| **ChestPain** | chest pain type [TA: Typical Angina, ATA: Atypical Angina, NAP: Non-Anginal Pain, ASY: Asymptomatic] |
| **RestingBP** | Blood pressure in Hg (Normal blood pressure - 120/80 Hg) |
| **Cholesterol** | Serum cholestrol level in blood (Normal cholesterol level below for adults 200mg/dL) |
| **FastingBS** | Fasting Blood Sugar (Normal less than 100mg/dL for non diabetes for diabetes 100-125mg/dL) |
| **RestingECG** | resting electrocardiogram results [Normal: Normal, ST: having ST-T wave abnormality (T wave inversions and/or ST elevation or depression of > 0.05 mV), LVH: showing probable or definite left ventricular hypertrophy by Estes' criteria] |
| **MaxHR** | maximum heart rate achieved [Numeric value between 60 and 202] |
| **ExerciseAngina** | exercise-induced angina [Y: Yes, N: No] |
| **Oldpeak** | oldpeak = ST [Numeric value measured in depression] |
| **ST_Slope** | the slope of the peak exercise ST segment [Up: upsloping, Flat: flat, Down: downsloping] |
| **HeartDisease** | output class [1: heart disease, 0: Normal] |

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 918 entries, 0 to 917
Data columns (total 12 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   Age             918 non-null    int64
 1   Sex             918 non-null    object
 2   ChestPainType   918 non-null    object
 3   RestingBP       918 non-null    int64
 4   Cholesterol     918 non-null    int64
 5   FastingBS       918 non-null    int64
 6   RestingECG      918 non-null    object
 7   MaxHR           918 non-null    int64
 8   ExerciseAngina  918 non-null    object
 9   Oldpeak         918 non-null    float64
 10  ST_Slope        918 non-null    object
 11  HeartDisease    918 non-null    int64
dtypes: float64(1), int64(6), object(5)
memory usage: 86.2+ KB
```

```
(918, 12)
```

```
11016
```

```
Age                50
Sex                 2
ChestPainType       4
RestingBP          67
Cholesterol       222
FastingBS           2
RestingECG          3
MaxHR             119
ExerciseAngina      2
Oldpeak            53
ST_Slope            3
HeartDisease        2
dtype: int64
```

```
Age               0
Sex               0
ChestPainType     0
RestingBP         0
Cholesterol       0
FastingBS         0
RestingECG        0
MaxHR             0
ExerciseAngina    0
Oldpeak           0
ST_Slope          0
HeartDisease      0
dtype: int64
```


```
Age                50
Sex                 2
ChestPainType       4
RestingBP          67
Cholesterol       222
FastingBS           2
RestingECG          3
MaxHR             119
ExerciseAngina      2
Oldpeak            53
ST_Slope            3
HeartDisease        2
dtype: int64
```


```
Age                 int64
Sex                object
ChestPainType      object
RestingBP           int64
Cholesterol         int64
FastingBS           int64
RestingECG         object
MaxHR               int64
ExerciseAngina     object
Oldpeak           float64
ST_Slope           object
HeartDisease        int64
dtype: object
```

| | count | mean | std | min | 25% | 50% | 75% | max |
|---|---|---|---|---|---|---|---|---|
| **Age** | 918.0 | 53.510893 | 9.432617 | 28.0 | 47.00 | 54.0 | 60.0 | 77.0 |
| **RestingBP** | 918.0 | 132.396514 | 18.514154 | 0.0 | 120.00 | 130.0 | 140.0 | 200.0 |
| **Cholesterol** | 918.0 | 198.799564 | 109.384145 | 0.0 | 173.25 | 223.0 | 267.0 | 603.0 |
| **FastingBS** | 918.0 | 0.233115 | 0.423046 | 0.0 | 0.00 | 0.0 | 0.0 | 1.0 |
| **MaxHR** | 918.0 | 136.809368 | 25.460334 | 60.0 | 120.00 | 138.0 | 156.0 | 202.0 |
| **Oldpeak** | 918.0 | 0.887364 | 1.066570 | -2.6 | 0.00 | 0.6 | 1.5 | 6.2 |
| **HeartDisease** | 918.0 | 0.553377 | 0.497414 | 0.0 | 0.00 | 1.0 | 1.0 | 1.0 |

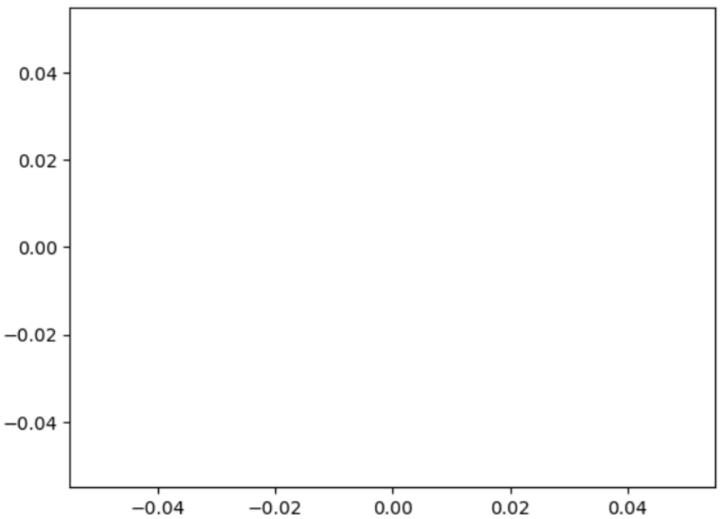
```
0
```

| | Age | RestingBP | Cholesterol | FastingBS | MaxHR | Oldpeak | HeartDisease |
|---|---|---|---|---|---|---|---|
| **Age** | 1.000000 | 0.254399 | -0.095282 | 0.198039 | -0.382045 | 0.258612 | 0.282039 |
| **RestingBP** | 0.254399 | 1.000000 | 0.100893 | 0.070193 | -0.112135 | 0.164803 | 0.107589 |
| **Cholesterol** | -0.095282 | 0.100893 | 1.000000 | -0.260974 | 0.235792 | 0.050148 | -0.232741 |
| **FastingBS** | 0.198039 | 0.070193 | -0.260974 | 1.000000 | -0.131438 | 0.052698 | 0.267291 |
| **MaxHR** | -0.382045 | -0.112135 | 0.235792 | -0.131438 | 1.000000 | -0.160691 | -0.400421 |
| **Oldpeak** | 0.258612 | 0.164803 | 0.050148 | 0.052698 | -0.160691 | 1.000000 | 0.403951 |
| **HeartDisease** | 0.282039 | 0.107589 | -0.232741 | 0.267291 | -0.400421 | 0.403951 | 1.000000 |

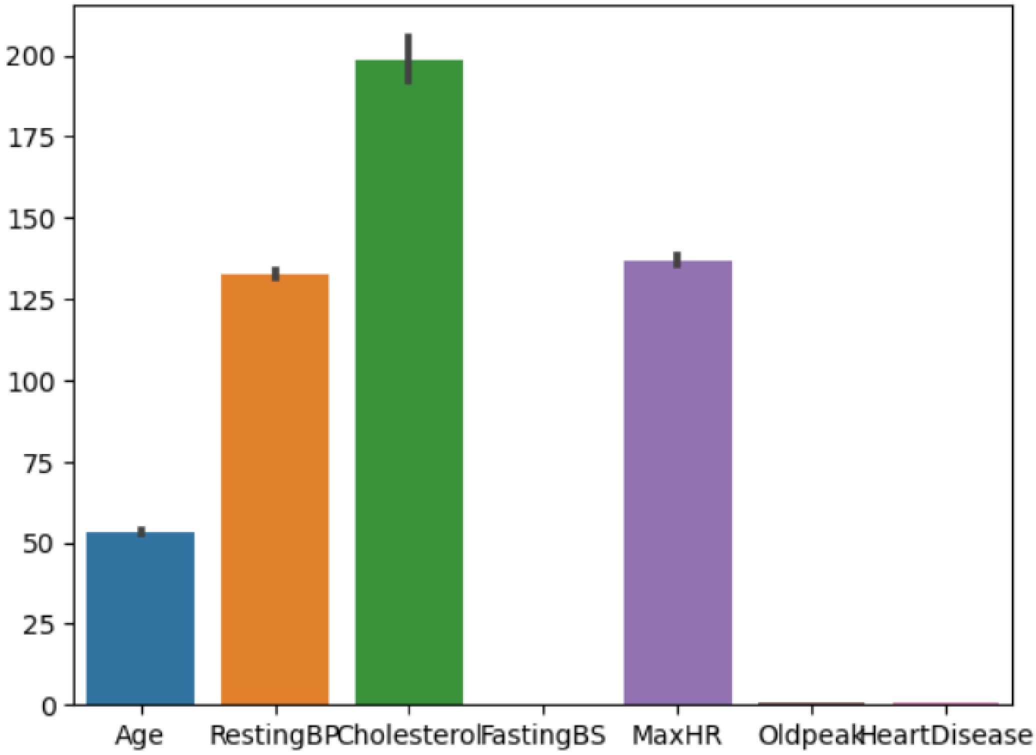
```
Age            -0.195933
RestingBP       0.179839
Cholesterol    -0.610086
FastingBS       1.264484
MaxHR          -0.144359
Oldpeak         1.022872
HeartDisease   -0.215086
dtype: float64
```

# Data Visualizations:

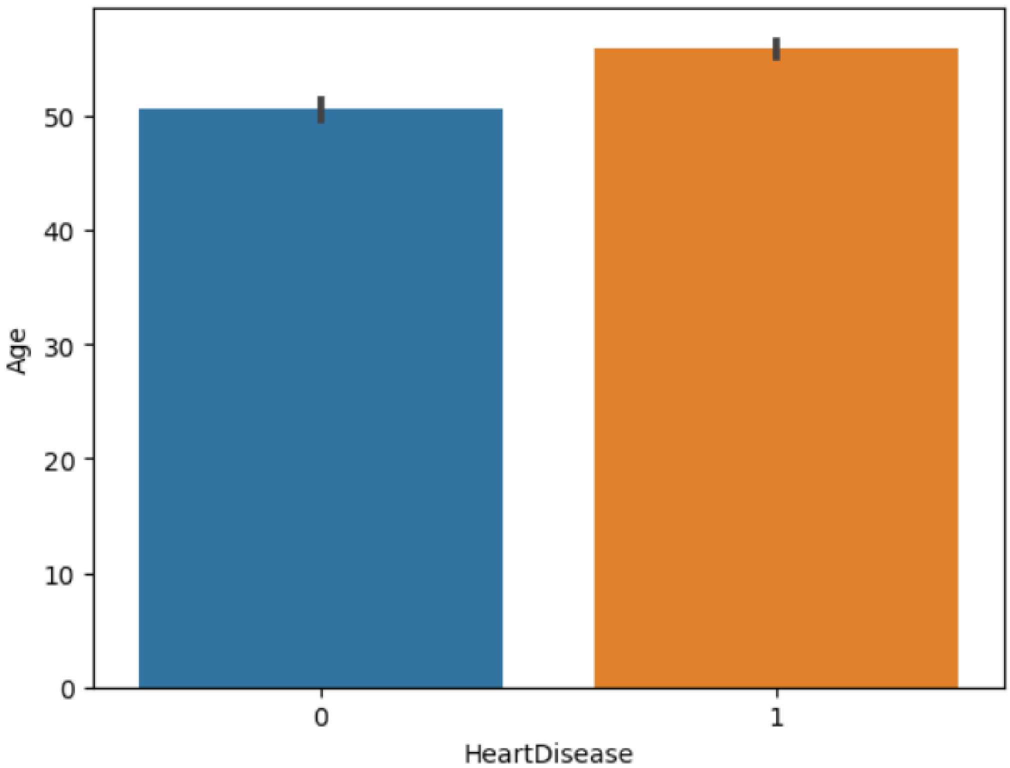
```
[]
```



## Bar plot:

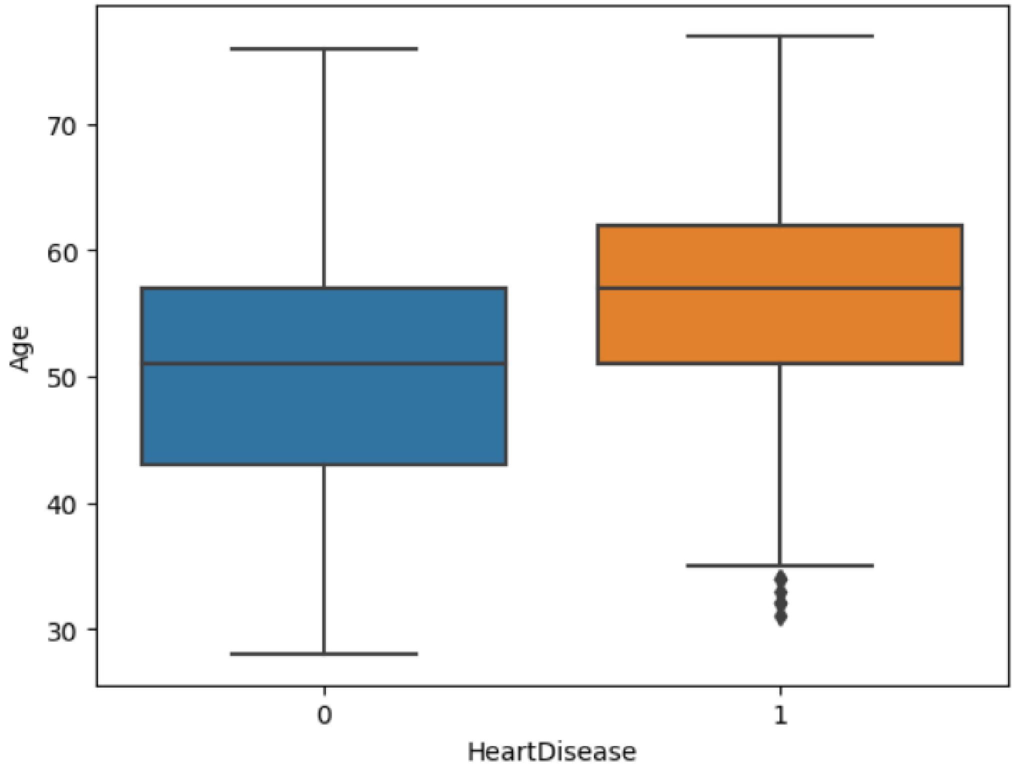


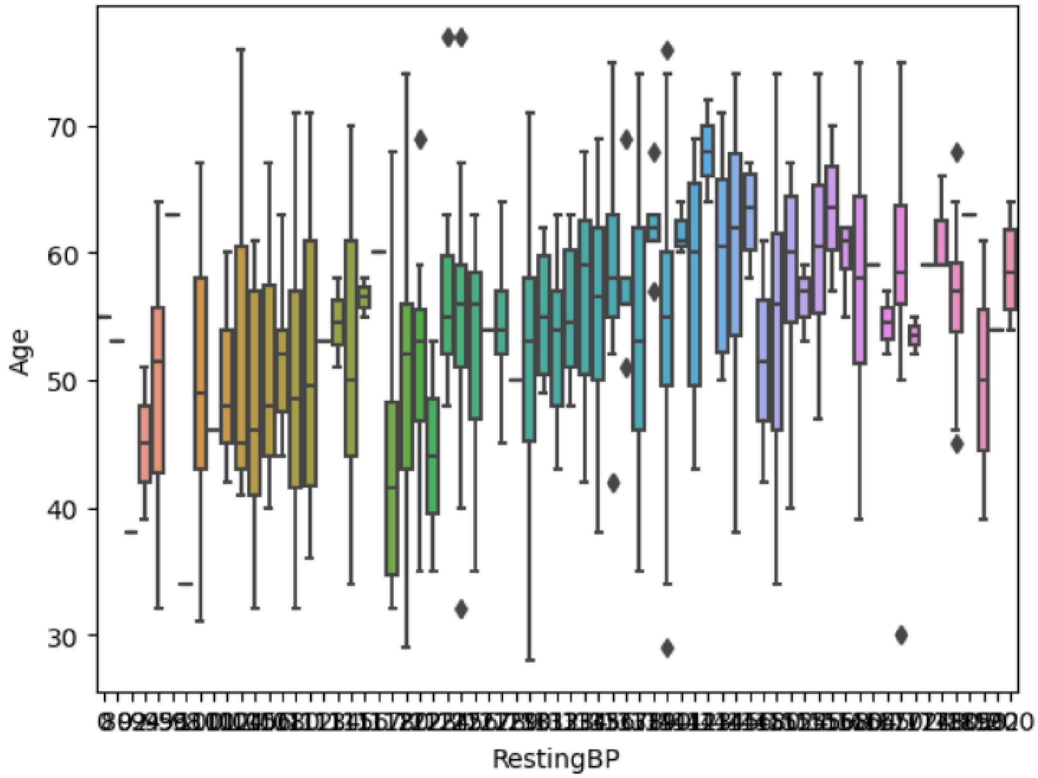
200
175
150
125
100
75
50
25
0
Age
RestingBP
Cholesterol
FastingBS
MaxHR
Oldpeak
HeartDisease

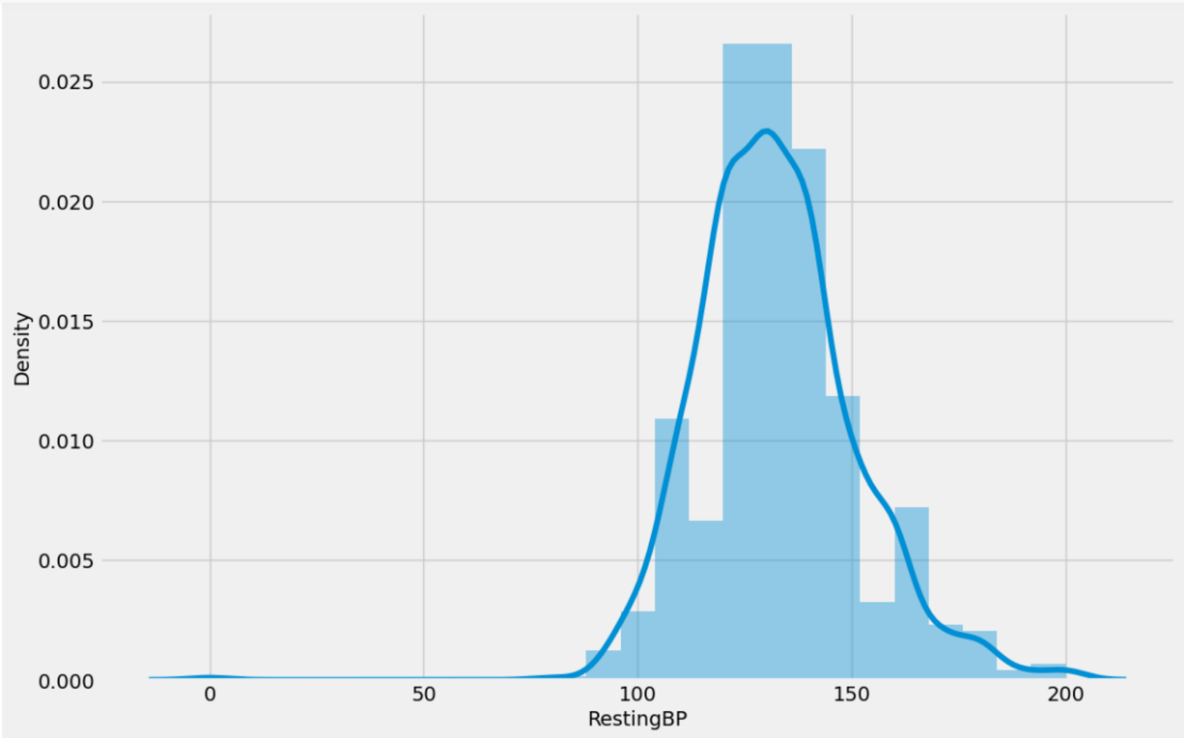
Age
50
40
30
20
10
0
0
1
HeartDisease

## Box plot:



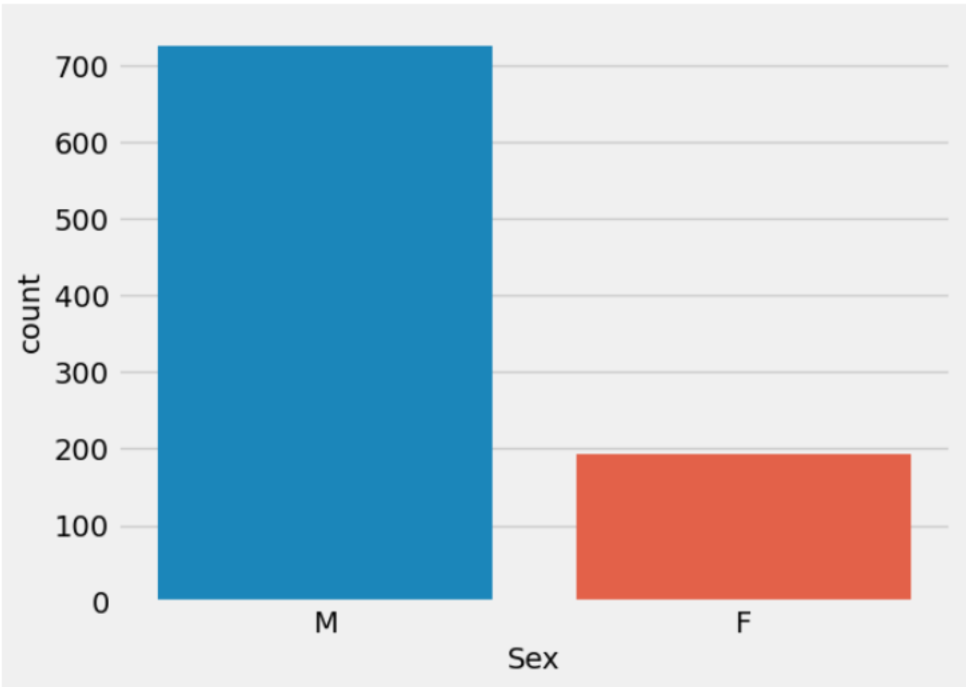



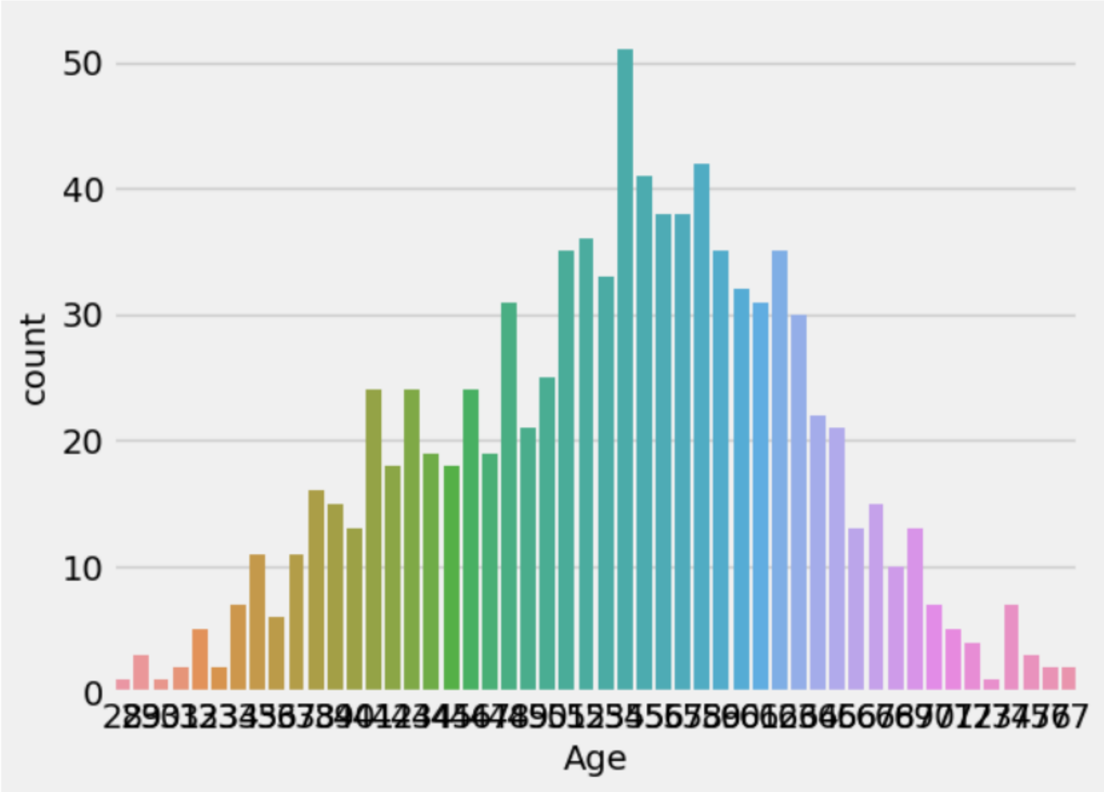
## Dist plot:

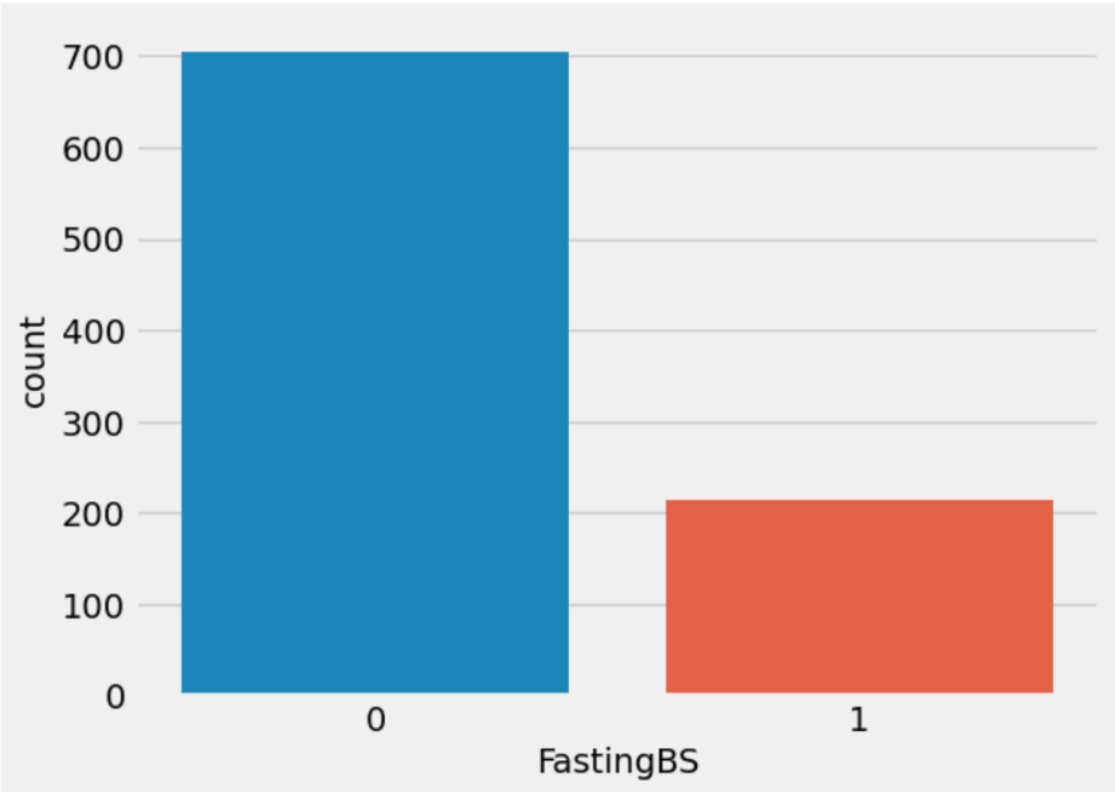


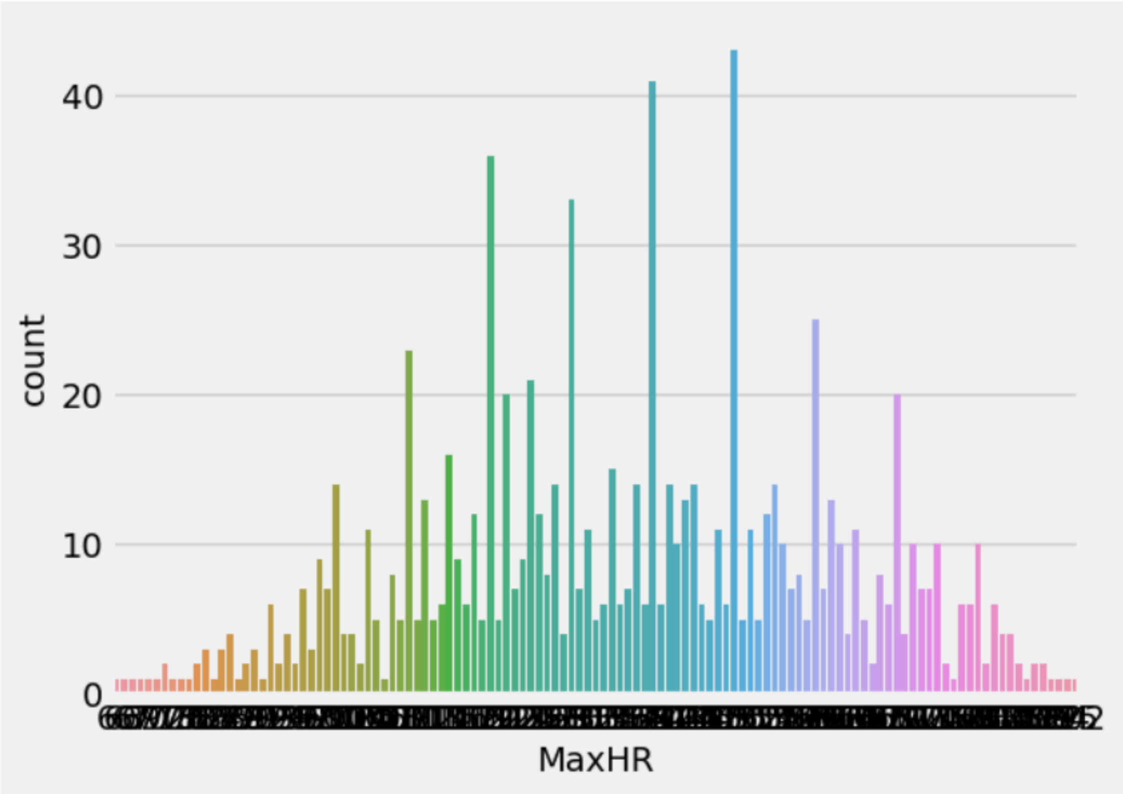

## Count plot:

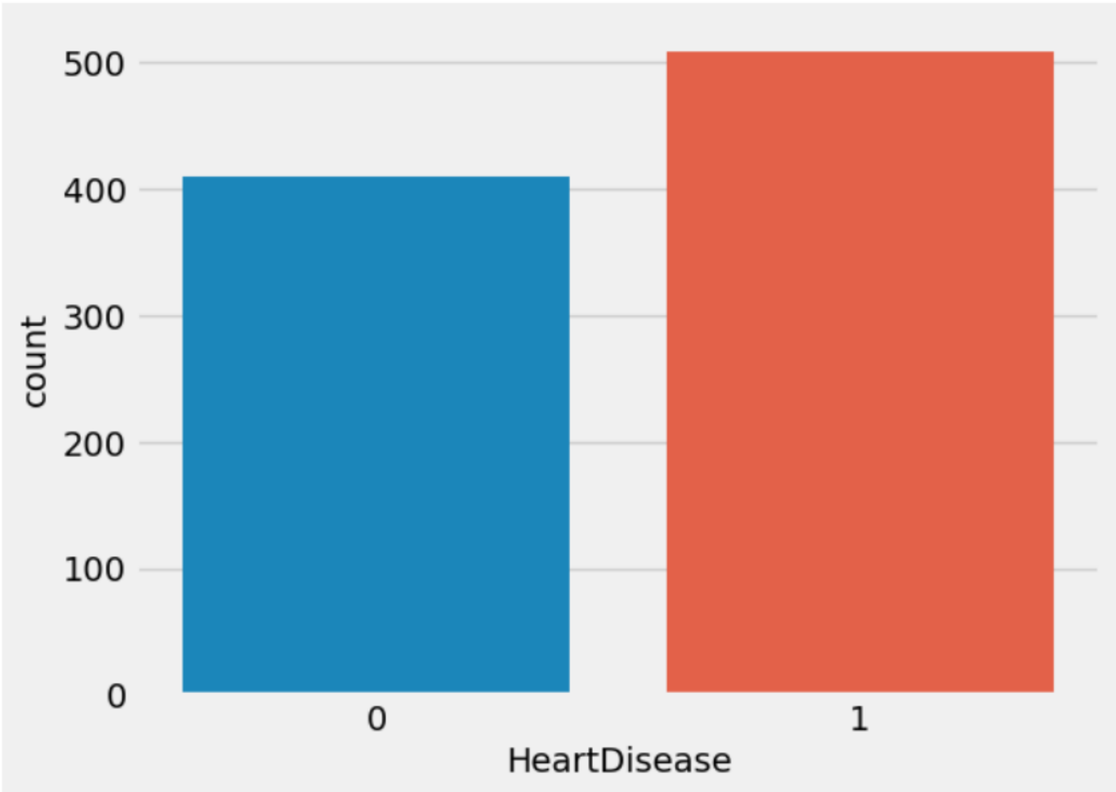
<Axes: xlabel='Sex', ylabel='count'>

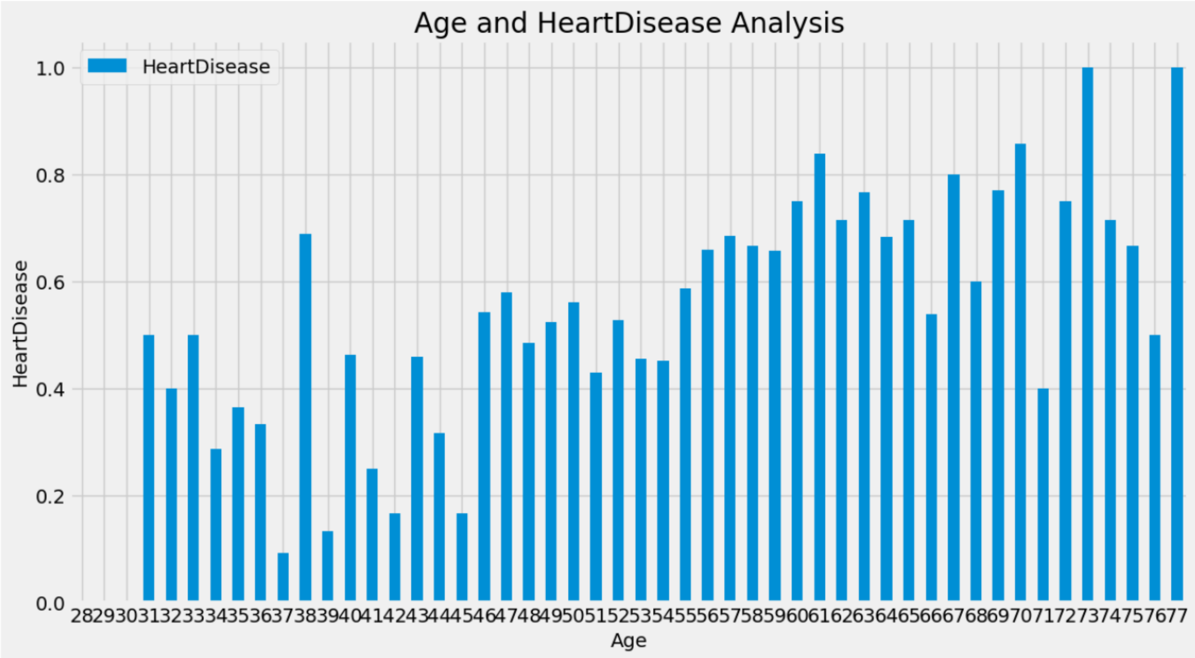


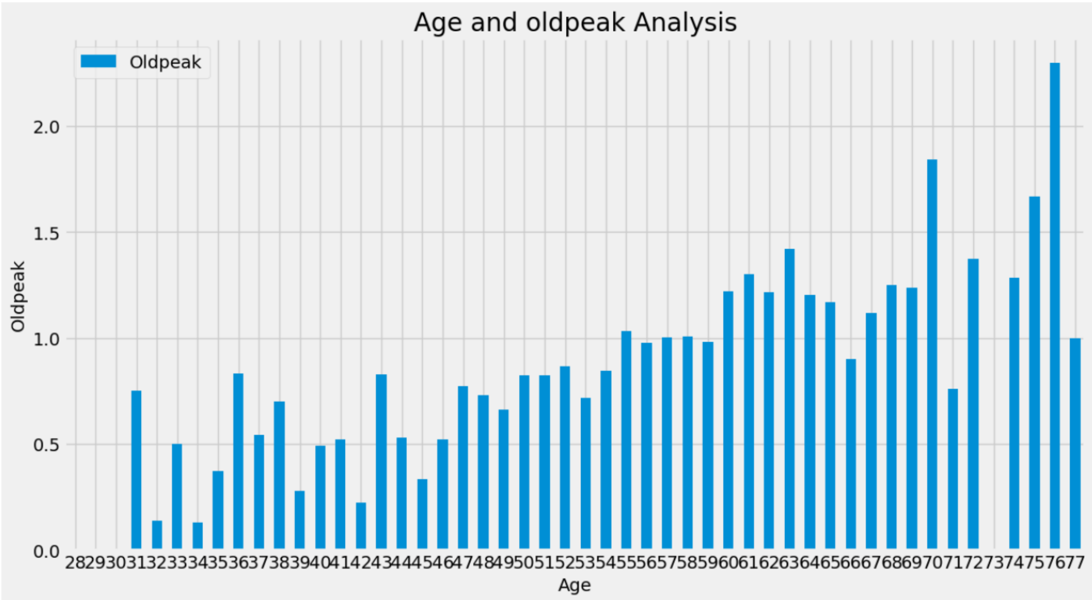

50
40
30
20
10
0
count
Age

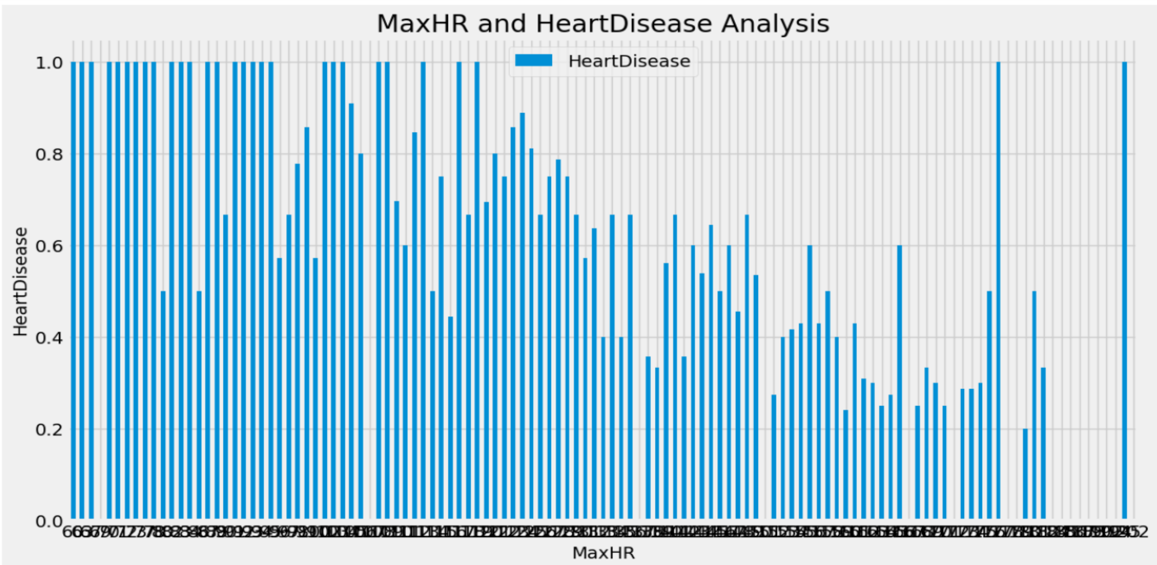

700
600
500
400
300
200
100
0
count
0
1
FastingBS

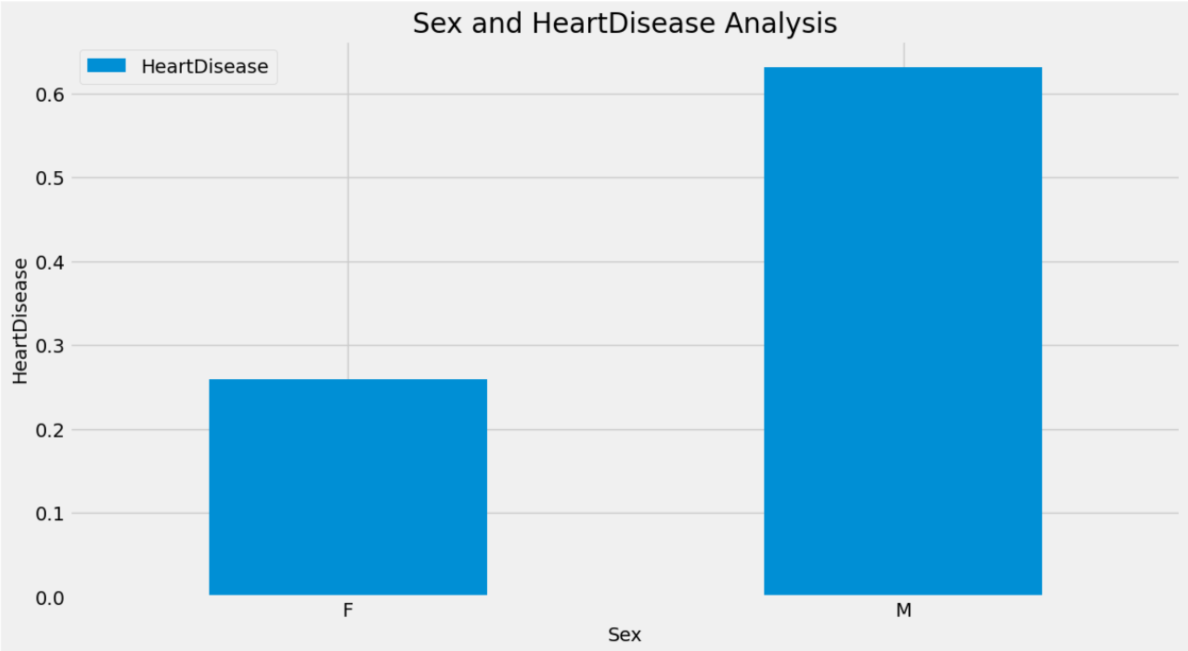

count
40
30
20
10
0
MaxHR


count
500
400
300
200
100
0
0
1
HeartDisease

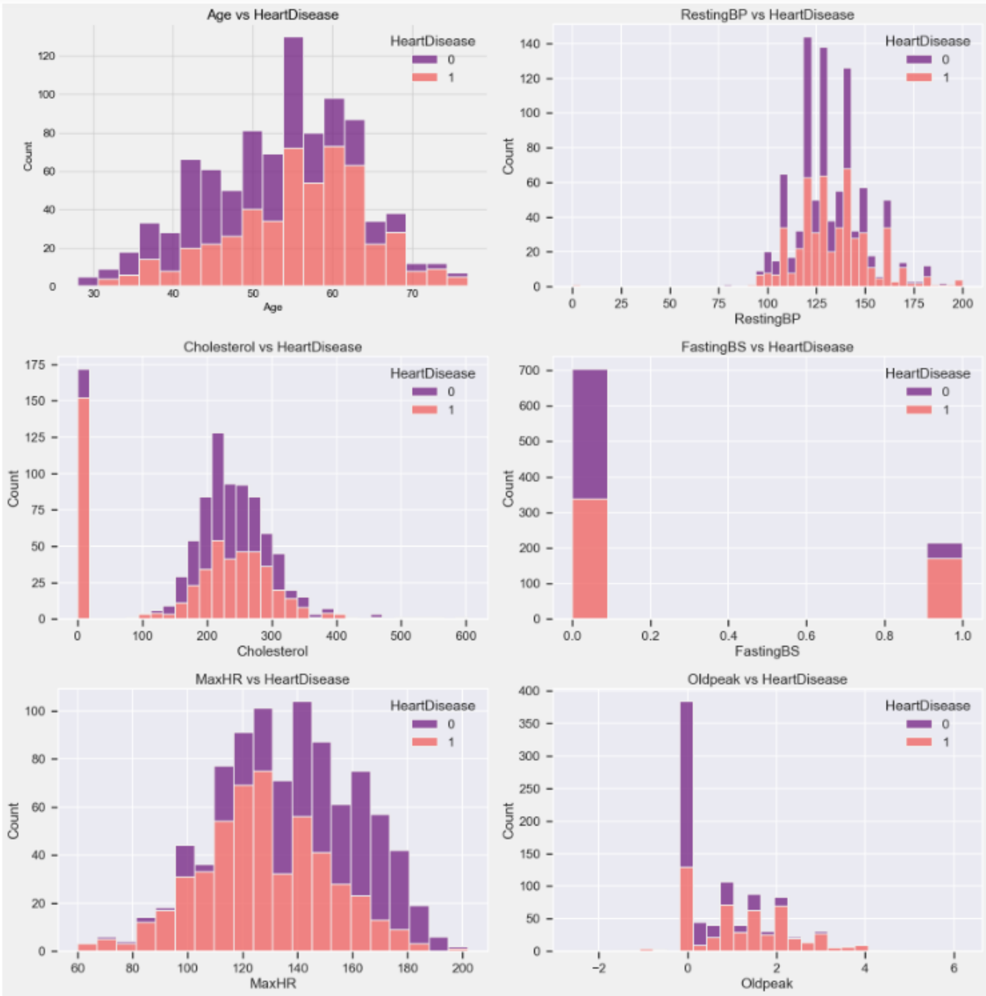

Age and HeartDisease Analysis
HeartDisease
1.0
0.8
0.6
0.4
0.2
0.0
HeartDisease
Age


Age and oldpeak Analysis
Oldpeak
2.0
1.5
1.0
0.5
0.0
Oldpeak
Age

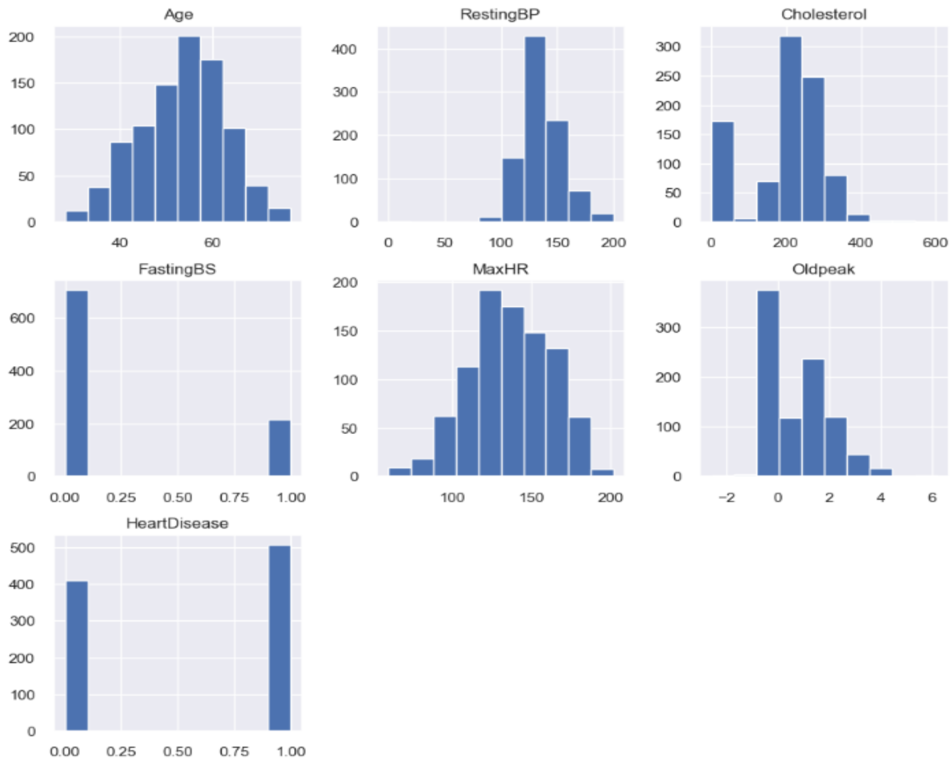

MaxHR and HeartDisease Analysis
HeartDisease
1.0
0.8
0.6
0.4
0.2
0.0
HeartDisease
MaxHR

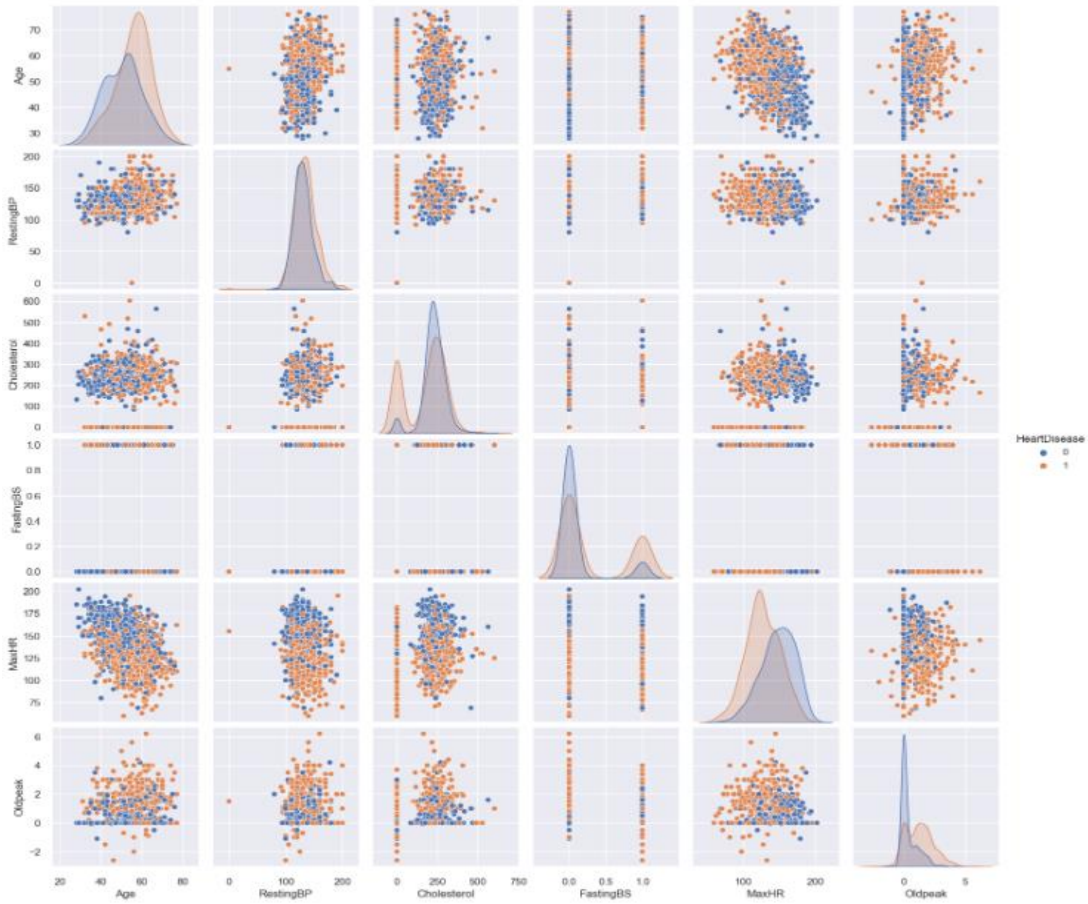



## Subplots:



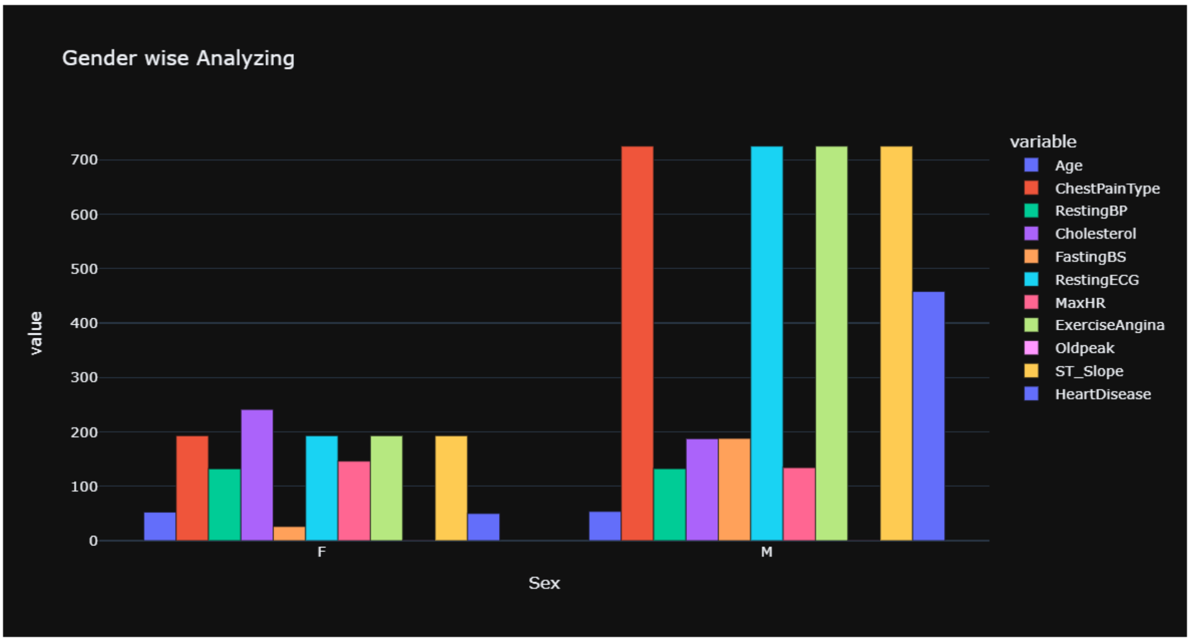

## Pairplot:


Age
RestingBP
Cholesterol
FastingBS
MaxHR
Oldpeak
HeartDisease


Age
RestingBP
Cholesterol
FastingBS
MaxHR
Oldpeak
HeartDisease

| Sex | Age | ChestPainType | RestingBP | Cholesterol | FastingBS | RestingECG | MaxHR | ExerciseAngina | Oldpeak | ST_Slope | HeartDisease |
|---|---|---|---|---|---|---|---|---|---|---|---|
| F | 52.492228 | 193 | 132.212435 | 241.196891 | 26 | 193 | 146.139896 | 193 | 0.668912 | 193 | 50 |
| M | 53.782069 | 725 | 132.445517 | 187.513103 | 188 | 725 | 134.325517 | 725 | 0.945517 | 725 | 458 |

# Plotly chart:

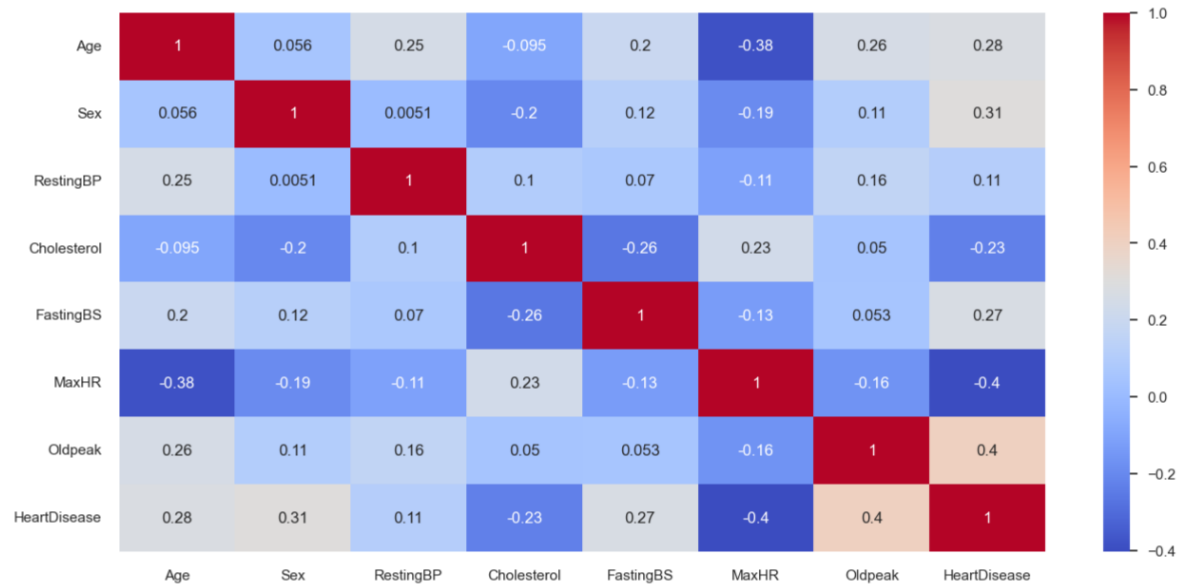



```
Age               0
ChestPainType     0
RestingBP         0
Cholesterol       0
FastingBS         0
RestingECG        0
MaxHR             0
ExerciseAngina    0
Oldpeak           0
ST_Slope          0
HeartDisease      0
dtype: int64
```

| | Age | Sex | ChestPainType | RestingBP | Cholesterol | FastingBS | RestingECG | MaxHR | ExerciseAngina | Oldpeak | ST_Slope | HeartDisease |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 40 | 1 | ATA | 140 | 289 | 0 | Normal | 98 | N | 0.0 | Up | 0 |
| 1 | 49 | 0 | NAP | 160 | 180 | 0 | Normal | 82 | N | 1.0 | Flat | 1 |
| 2 | 37 | 1 | ATA | 130 | 283 | 0 | ST | 25 | N | 0.0 | Up | 0 |
| 3 | 48 | 0 | ASY | 138 | 214 | 0 | Normal | 34 | Y | 1.5 | Flat | 1 |
| 4 | 54 | 1 | NAP | 150 | 195 | 0 | Normal | 48 | N | 0.0 | Up | 0 |

# Heatmap:

<Axes: >




| | Age | Sex | ChestPainType | RestingBP | Cholesterol | FastingBS | RestingECG | MaxHR | ExerciseAngina | Oldpeak | ST_Slope | HeartDisease |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 40 | 1 | ATA | 140 | 289 | 0 | Normal | 98 | N | 0.0 | Up | 0 |
| **1** | 49 | 0 | NAP | 160 | 180 | 0 | Normal | 82 | N | 1.0 | Flat | 1 |
| **2** | 37 | 1 | ATA | 130 | 283 | 0 | ST | 25 | N | 0.0 | Up | 0 |
| **3** | 48 | 0 | ASY | 138 | 214 | 0 | Normal | 34 | Y | 1.5 | Flat | 1 |
| **4** | 54 | 1 | NAP | 150 | 195 | 0 | Normal | 48 | N | 0.0 | Up | 0 |

# Display mean, median, mod:

```
Mean:  198.7995642701525
Median:  223.0
```

```
Mean of Cholesterol>0:  244.6353887399464
```

| | count | mean | std | min | 25% | 50% | 75% | max |
|---|---|---|---|---|---|---|---|---|
| **Age** | 918.0 | 53.510893 | 9.432617 | 28.0 | 47.00 | 54.0 | 60.0 | 77.0 |
| **Sex** | 918.0 | 0.789760 | 0.407701 | 0.0 | 1.00 | 1.0 | 1.0 | 1.0 |
| **RestingBP** | 918.0 | 132.396514 | 18.514154 | 0.0 | 120.00 | 130.0 | 140.0 | 200.0 |
| **Cholesterol** | 918.0 | 198.799564 | 109.384145 | 0.0 | 173.25 | 223.0 | 267.0 | 603.0 |
| **FastingBS** | 918.0 | 0.233115 | 0.423046 | 0.0 | 0.00 | 0.0 | 0.0 | 1.0 |
| **MaxHR** | 918.0 | 62.979303 | 24.919644 | 0.0 | 46.00 | 64.0 | 82.0 | 118.0 |
| **Oldpeak** | 918.0 | 0.887364 | 1.066570 | -2.6 | 0.00 | 0.6 | 1.5 | 6.2 |
| **HeartDisease** | 918.0 | 0.553377 | 0.497414 | 0.0 | 0.00 | 1.0 | 1.0 | 1.0 |

```
['Age',
 'Sex',
 'RestingBP',
 'Cholesterol',
 'FastingBS',
 'MaxHR',
 'Oldpeak',
 'HeartDisease']
```

| | Age | RestingBP | Cholesterol | FastingBS | MaxHR | Oldpeak | Sex | HeartDisease |
|---|---|---|---|---|---|---|---|---|
| **0** | 40 | 140 | 289 | 0 | 98 | 0.0 | 1 | 0 |
| **1** | 49 | 160 | 180 | 0 | 82 | 1.0 | 0 | 1 |
| **2** | 37 | 130 | 283 | 0 | 25 | 0.0 | 1 | 0 |
| **3** | 48 | 138 | 214 | 0 | 34 | 1.5 | 0 | 1 |
| **4** | 54 | 150 | 195 | 0 | 48 | 0.0 | 1 | 0 |

```
StandardScaler()
```

**In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.**
**On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.**

| | Age | RestingBP | Cholesterol | FastingBS | MaxHR | Oldpeak | Sex |
|---|---|---|---|---|---|---|---|
| **0** | -1.433140 | 0.410909 | 0.825070 | -0.551341 | 1.406111 | -0.832432 | 0.515952 |
| **1** | -0.478484 | 1.491752 | -0.171961 | -0.551341 | 0.763697 | 0.105664 | -1.938163 |
| **2** | -1.751359 | -0.129513 | 0.770188 | -0.551341 | -1.524902 | -0.832432 | 0.515952 |
| **3** | -0.584556 | 0.302825 | 0.139040 | -0.551341 | -1.163544 | 0.574711 | -1.938163 |
| **4** | 0.051881 | 0.951331 | -0.034755 | -0.551341 | -0.601432 | -0.832432 | 0.515952 |

| | Age | RestingBP | Cholesterol | FastingBS | MaxHR | Oldpeak | Sex | HeartDisease |
|---|---|---|---|---|---|---|---|---|
| **0** | 40 | 140 | 289 | 0 | 98 | 0.0 | 1 | 0 |
| **1** | 49 | 160 | 180 | 0 | 82 | 1.0 | 0 | 1 |
| **2** | 37 | 130 | 283 | 0 | 25 | 0.0 | 1 | 0 |
| **3** | 48 | 138 | 214 | 0 | 34 | 1.5 | 0 | 1 |
| **4** | 54 | 150 | 195 | 0 | 48 | 0.0 | 1 | 0 |

```
['Age', 'RestingBP', 'Cholesterol', 'FastingBS', 'MaxHR', 'Oldpeak', 'Sex', 'HeartDisease']
```

feature = pd.Series(forest.feature_importances_, index =).sort_values(ascending = False) print(feature)

## Display accuracy of dataset:

```
          Age  RestingBP  Cholesterol  FastingBS     MaxHR   Oldpeak       Sex
0   -1.433140   0.410909     0.825070  -0.551341  1.406111 -0.832432  0.515952
1   -0.478484   1.491752    -0.171961  -0.551341  0.763697  0.105664 -1.938163
2   -1.751359  -0.129513     0.770188  -0.551341 -1.524902 -0.832432  0.515952
3   -0.584556   0.302825     0.139040  -0.551341 -1.163544  0.574711 -1.938163
4    0.051881   0.951331    -0.034755  -0.551341 -0.601432 -0.832432  0.515952
..        ...        ...          ...        ...       ...       ...       ...
913 -0.902775  -1.210356     0.596393  -0.551341 -0.199923  0.293283  0.515952
914  1.536902   0.627078    -0.053049   1.813758  0.161434  2.357094  0.515952
915  0.370100  -0.129513    -0.620168  -0.551341 -0.882488  0.293283  0.515952
916  0.370100  -0.129513     0.340275  -0.551341  1.486413 -0.832432 -1.938163
917 -1.645286   0.302825    -0.217696  -0.551341  1.446262 -0.832432  0.515952

[918 rows x 7 columns] 0      0
1      1
2      0
3      1
4      0
      ..
913    1
914    1
915    1
916    1
917    0
Name: HeartDisease, Length: 918, dtype: int64
```

```
Accuracy of KNN: 0.781 (0.046)
Accuracy of SVC: 0.786 (0.040)
Accuracy of RandomForest: 0.782 (0.030)
```

```
1 0.23043478260869565
2 0.2391304347826087
3 0.2217391304347826
4 0.21304347826086956
5 0.20434782608695654
6 0.19130434782608696
7 0.18695652173913044
8 0.2
9 0.2
10 0.18695652173913044
11 0.19130434782608696
12 0.18695652173913044
13 0.2
14 0.1956521739130435
15 0.2
16 0.19130434782608696
17 0.1956521739130435
18 0.1956521739130435
19 0.2
20 0.2
21 0.20869565217391303
22 0.2
23 0.21304347826086956
24 0.20434782608695654
25 0.1956521739130435
26 0.19130434782608696
27 0.20434782608695654
28 0.2
29 0.21304347826086956
30 0.2
31 0.20869565217391303
32 0.20434782608695654
33 0.21739130434782608
34 0.21304347826086956
35 0.21739130434782608
36 0.2217391304347826
37 0.2217391304347826
38 0.2217391304347826
39 0.21739130434782608
```

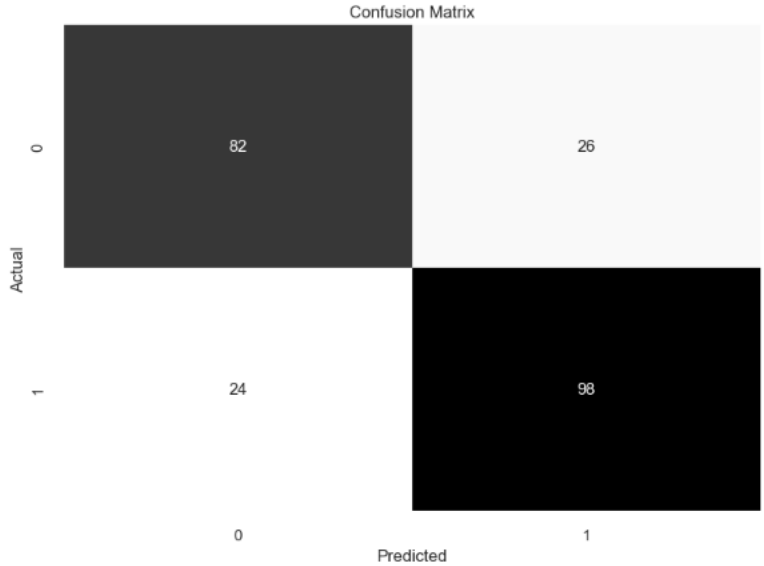
# Confusion matrix with different types of models:

```
              precision    recall  f1-score   support

           0       0.77      0.76      0.77       108
           1       0.79      0.80      0.80       122

    accuracy                           0.78       230
   macro avg       0.78      0.78      0.78       230
weighted avg       0.78      0.78      0.78       230

Confusion Matrix
[[82 26]
 [24 98]]
```

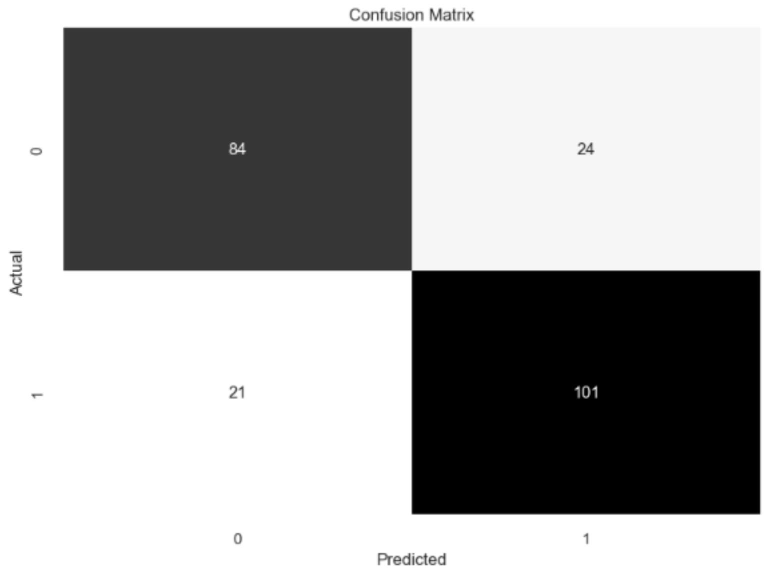



```
              precision    recall  f1-score   support

           0       0.80      0.78      0.79       108
           1       0.81      0.83      0.82       122

    accuracy                           0.80       230
   macro avg       0.80      0.80      0.80       230
weighted avg       0.80      0.80      0.80       230

Confusion Matrix
[[ 84  24]
 [ 21 101]]
```



```
Fitting 3 folds for each of 100 candidates, totalling 300 fits

RandomizedSearchCV(cv=3, estimator=RandomForestClassifier(), n_iter=100,
                   n_jobs=-1,
                   param_distributions={'bootstrap': [True, False],
                                        'max_depth': [10, 20, 30, 40, 50, 60,
                                                      70, 80, 90, 100, 110,
                                                      None],
                                        'max_features': ['auto', 'sqrt'],
                                        'min_samples_leaf': [1, 2, 4],
                                        'min_samples_split': [2, 5, 10],
                                        'n_estimators': [103, 124, 146, 168,
                                                         190, 212, 234, 256,
                                                         278, 300]},
                   random_state=42, verbose=2)
```

**In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.**
**On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.**

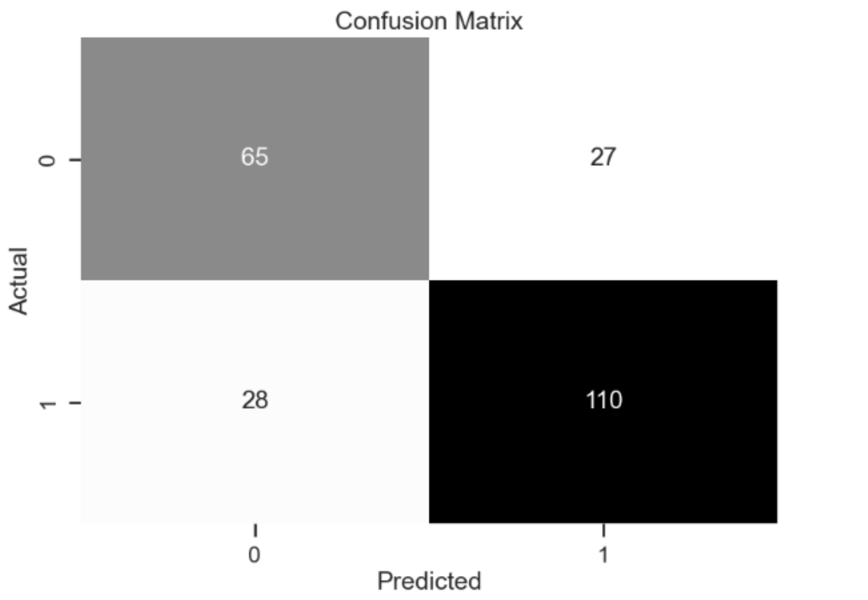
```
{'n_estimators': 168,
 'min_samples_split': 10,
 'min_samples_leaf': 4,
 'max_features': 'sqrt',
 'max_depth': 100,
 'bootstrap': True}
```

```
              precision    recall  f1-score   support

           0       0.70      0.71      0.70        92
           1       0.80      0.80      0.80       138

    accuracy                           0.76       230
   macro avg       0.75      0.75      0.75       230
weighted avg       0.76      0.76      0.76       230

Confusion Matrix
[[ 65  27]
 [ 28 110]]
```

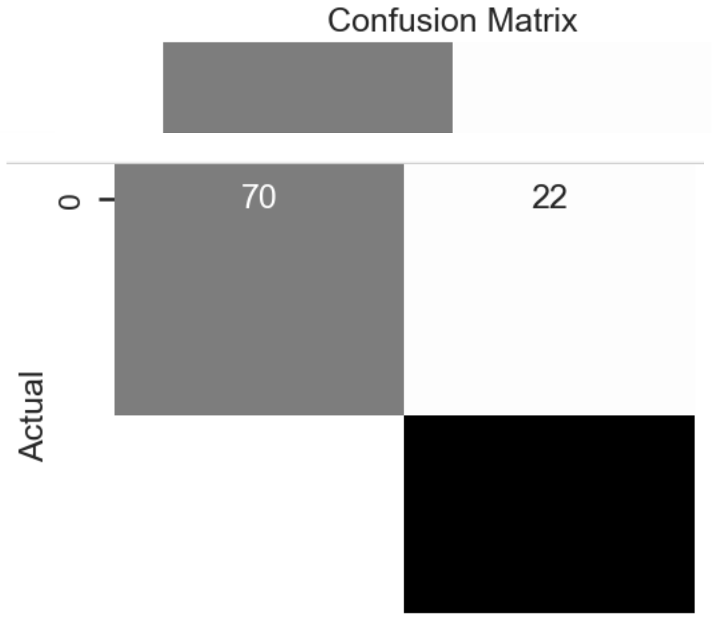


```
              precision    recall  f1-score   support

           0       0.77      0.76      0.77        92
           1       0.84      0.85      0.84       138

    accuracy                           0.81       230
   macro avg       0.81      0.80      0.80       230
weighted avg       0.81      0.81      0.81       230

Confusion Matrix
[[ 70  22]
 [ 21 117]]
```




### Conclusion

```
KNN model gives the accuracy of                  : 89%
Random forest givea the accuracy of              : 89%
Suport Vector Classifier gives the accuracy of   : 88%
Gradient Boosting Classifier gives the accuracy of: 86%
```

# 8. Future Scope

With the increasing volume and variety of data generated, the future will likely see a greater emphasis on big data analytics, exploring large datasets to extract meaningful patterns and insights. As the need for instant insights grows, real-time data analysis will become more prominent, especially in industries like finance, healthcare, and IoT (Internet of Things).

In the context of the Heart Disease Prediction project, the future scope involves leveraging advancements in big data analytics and real-time data processing. This includes exploring larger and more diverse datasets related to cardiovascular health, incorporating real-time monitoring and analysis for more accurate and timely predictions. The project envisions contributing to the evolving landscape of healthcare analytics, where predictive models for heart disease can provide rapid and actionable insights, ultimately enhancing preventive and personalized healthcare strategies.

# 9. Conclusion

In conclusion, this Heart Disease Prediction project has successfully unveiled valuable insights, revealing patterns and trends within the dataset specific to heart health. The systematic exploration of relationships between variables has provided a deeper understanding of the underlying dynamics in cardiovascular health. The findings offer a foundation for informed decision-making, guiding future strategies and actions in the realm of predicting heart diseases. The project's use of advanced analytical tools and methodologies showcases the evolving landscape of data science within the context of cardiovascular research. Moving forward, continuous advancements in machine learning, artificial intelligence, and big data analytics will shape the future of predicting heart diseases. Ethical considerations must remain at the forefront to ensure responsible data usage and unbiased results, especially when dealing with sensitive health information. Collaboration between data scientists and domain experts in cardiology will further refine analyses, tailoring predictive models to specific aspects of cardiovascular health. The project highlights the importance of transparency and reproducibility in analytical workflows for fostering trust in results, critical in the healthcare domain. As we embrace emerging technologies, the scope for data analysis in cardiovascular health remains expansive, promising innovative solutions to complex challenges in preventing and managing heart diseases.

**THANK YOU**