heart-deases-predication-1

February 24, 2025

[ ]:
```python
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from collections import Counter
from xgboost import XGBClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import confusion_matrix, accuracy_score,␣
↪classification_report
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import cross_val_score
```

[ ]:
```python
data=pd.read_csv("/content/heart.csv")
```

[ ]:
```python
data.head()
```

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

   ca  thal  target
0   2     3       0
1   0     3       0
2   0     3       0
3   1     3       0
4   3     2       0
```

This dataset appears to be related to heart disease prediction, with various medical and demographic features :

1. **age** – Age of the individual (numerical).

2. **sex** – Gender of the individual (1 = Male, 0 = Female).
3. **cp (Chest Pain Type)** – Types of chest pain experienced:
   - 0 = Typical angina
   - 1 = Atypical angina
   - 2 = Non-anginal pain
   - 3 = Asymptomatic
4. **trestbps (Resting Blood Pressure)** – Blood pressure in mm Hg when the patient is at rest.
5. **chol (Serum Cholesterol)** – Cholesterol level in mg/dl.
6. **fbs (Fasting Blood Sugar)** – Whether fasting blood sugar is > 120 mg/dl (1 = True, 0 = False).
7. **restecg (Resting Electrocardiographic Results)** – Results of ECG at rest:
   - 0 = Normal
   - 1 = Having ST-T wave abnormality
   - 2 = Showing probable or definite left ventricular hypertrophy
8. **thalach (Maximum Heart Rate Achieved)** – Maximum heart rate recorded during a stress test.
9. **exang (Exercise-Induced Angina)** – Whether the patient experiences angina (chest pain) during exercise (1 = Yes, 0 = No).
10. **oldpeak (ST Depression Induced by Exercise)** – ST depression measured from rest to peak exercise, indicating ischemia.
11. **slope (Slope of the Peak Exercise ST Segment)** – Describes the shape of the ST segment in ECG:

- 0 = Upsloping
- 1 = Flat
- 2 = Downsloping

12. **ca (Number of Major Vessels Colored by Fluoroscopy)** – Number of major vessels (0-3) detected.

13. **thal (Thalassemia Test Result)** –

- 1 = Normal
- 2 = Fixed defect (no proper blood flow in some part of the heart)
- 3 = Reversible defect (a blood flow issue that can be corrected)

14. **target (Heart Disease Presence)** – The output label:

- 1 = Heart disease present
- 0 = No heart disease

[ ]:
```
data.shape
```

[ ]:
```
(1025, 14)
```

The dataset have 1025 rows and 14 clinical column

[ ]:
```
data.isnull().sum()
```

[ ]:
```
age         0
sex         0
cp          0
trestbps    0
chol        0
fbs         0
restecg     0
thalach     0
exang       0
oldpeak     0
slope       0
ca          0
thal        0
target      0
dtype: int64
```

[ ]:
```
data.describe()
```

[ ]:
```
               age          sex           cp     trestbps        chol  \
count  1025.000000  1025.000000  1025.000000  1025.000000  1025.00000
mean     54.434146     0.695610     0.942439   131.611707   246.00000
std       9.072290     0.460373     1.029641    17.516718    51.59251
min      29.000000     0.000000     0.000000    94.000000   126.00000
25%      48.000000     0.000000     0.000000   120.000000   211.00000
50%      56.000000     1.000000     1.000000   130.000000   240.00000
```

```
75%      61.000000     1.000000     2.000000   140.000000   275.00000
max      77.000000     1.000000     3.000000   200.000000   564.00000

               fbs      restecg      thalach        exang      oldpeak  \
count  1025.000000  1025.000000  1025.000000  1025.000000  1025.000000
mean      0.149268     0.529756   149.114146     0.336585     1.071512
std       0.356527     0.527878    23.005724     0.472772     1.175053
min       0.000000     0.000000    71.000000     0.000000     0.000000
25%       0.000000     0.000000   132.000000     0.000000     0.000000
50%       0.000000     1.000000   152.000000     0.000000     0.800000
75%       0.000000     1.000000   166.000000     1.000000     1.800000
max       1.000000     2.000000   202.000000     1.000000     6.200000

             slope           ca         thal       target
count  1025.000000  1025.000000  1025.000000  1025.000000
mean      1.385366     0.754146     2.323902     0.513171
std       0.617755     1.030798     0.620660     0.500070
min       0.000000     0.000000     0.000000     0.000000
25%       1.000000     0.000000     2.000000     0.000000
50%       1.000000     0.000000     2.000000     1.000000
75%       2.000000     1.000000     3.000000     1.000000
max       2.000000     4.000000     3.000000     1.000000
```

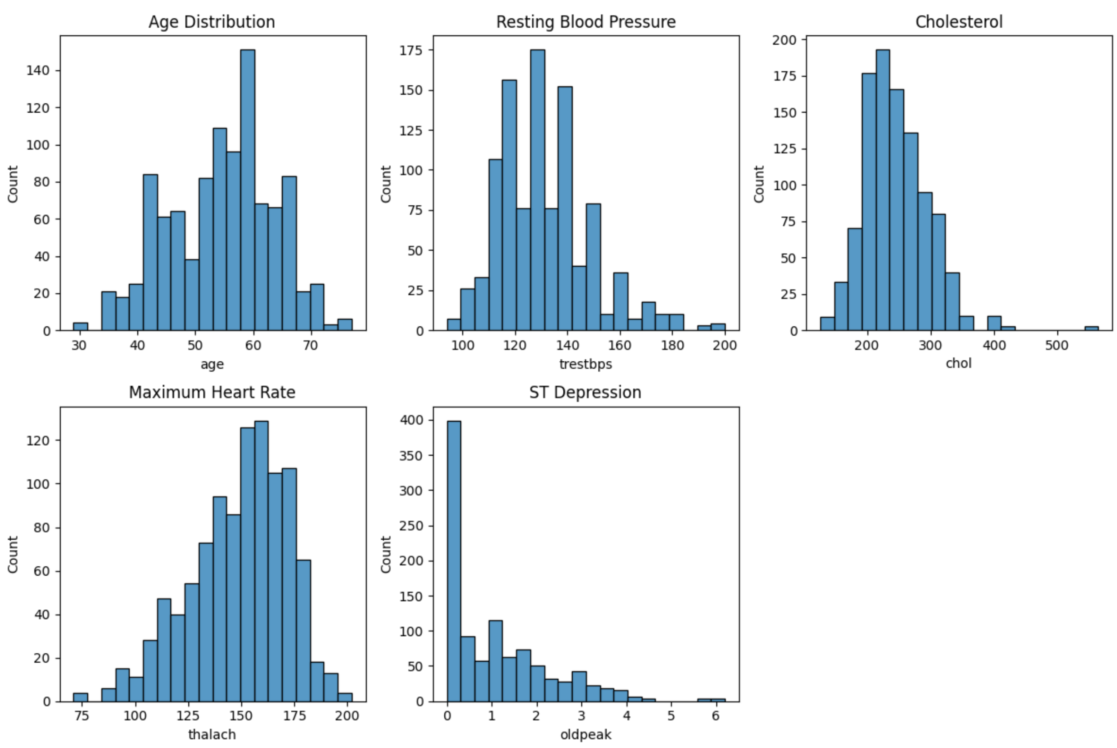
[ ]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1025 entries, 0 to 1024
Data columns (total 14 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   age       1025 non-null   int64
 1   sex       1025 non-null   int64
 2   cp        1025 non-null   int64
 3   trestbps  1025 non-null   int64
 4   chol      1025 non-null   int64
 5   fbs       1025 non-null   int64
 6   restecg   1025 non-null   int64
 7   thalach   1025 non-null   int64
 8   exang     1025 non-null   int64
 9   oldpeak   1025 non-null   float64
 10  slope     1025 non-null   int64
 11  ca        1025 non-null   int64
 12  thal      1025 non-null   int64
 13  target    1025 non-null   int64
dtypes: float64(1), int64(13)
memory usage: 112.2 KB
```

Univariate Analysis

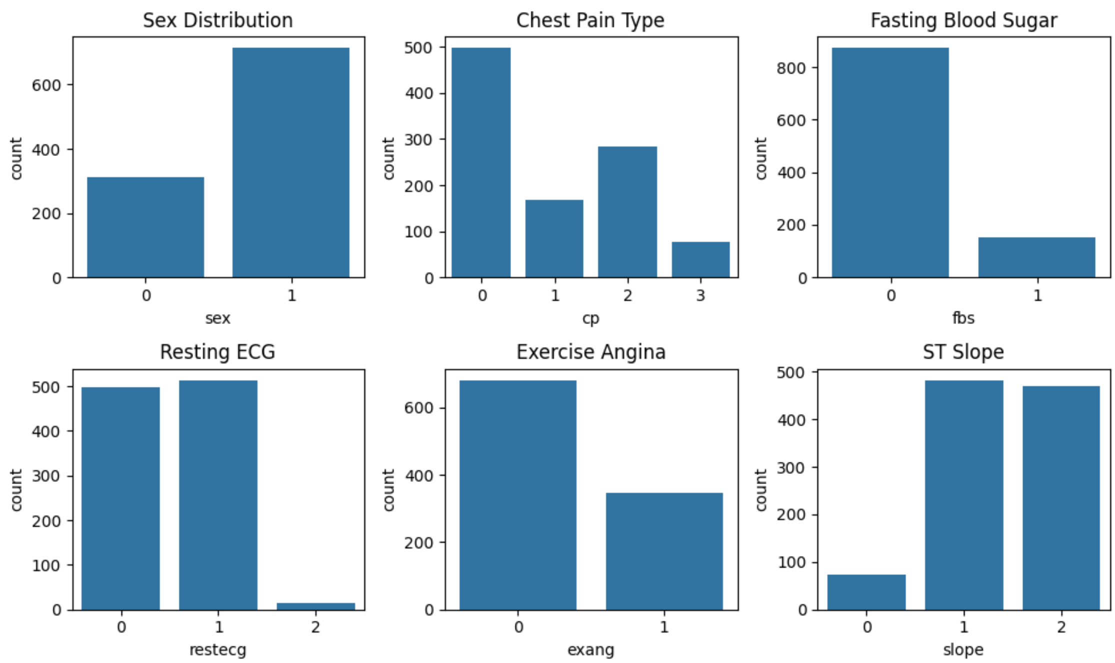
[ ]:

```
plt.figure(figsize=(12, 8))
plt.subplot(2, 3, 1)
sns.histplot(data['age'], bins=20)
plt.title('Age Distribution')

plt.subplot(2, 3, 2)
sns.histplot(data['trestbps'], bins=20)
plt.title('Resting Blood Pressure')

plt.subplot(2, 3, 3)
sns.histplot(data['chol'], bins=20)
plt.title('Cholesterol')

plt.subplot(2, 3, 4)
sns.histplot(data['thalach'], bins=20)
plt.title('Maximum Heart Rate')

plt.subplot(2, 3, 5)
sns.histplot(data['oldpeak'], bins=20)
plt.title('ST Depression')

plt.tight_layout()
plt.show()
```



Visualize the distribution of categorical variables:

```
[ ]: plt.figure(figsize=(10, 6))
plt.subplot(2, 3, 1)
sns.countplot(x='sex', data=data)
plt.title('Sex Distribution')

plt.subplot(2, 3, 2)
sns.countplot(x='cp', data=data)
plt.title('Chest Pain Type')

plt.subplot(2, 3, 3)
sns.countplot(x='fbs', data=data)
plt.title('Fasting Blood Sugar')

plt.subplot(2, 3, 4)
sns.countplot(x='restecg', data=data)
plt.title('Resting ECG')

plt.subplot(2, 3, 5)
sns.countplot(x='exang', data=data)
plt.title('Exercise Angina')

plt.subplot(2, 3, 6)
sns.countplot(x='slope', data=data)
plt.title('ST Slope')

plt.tight_layout()
plt.show()
```

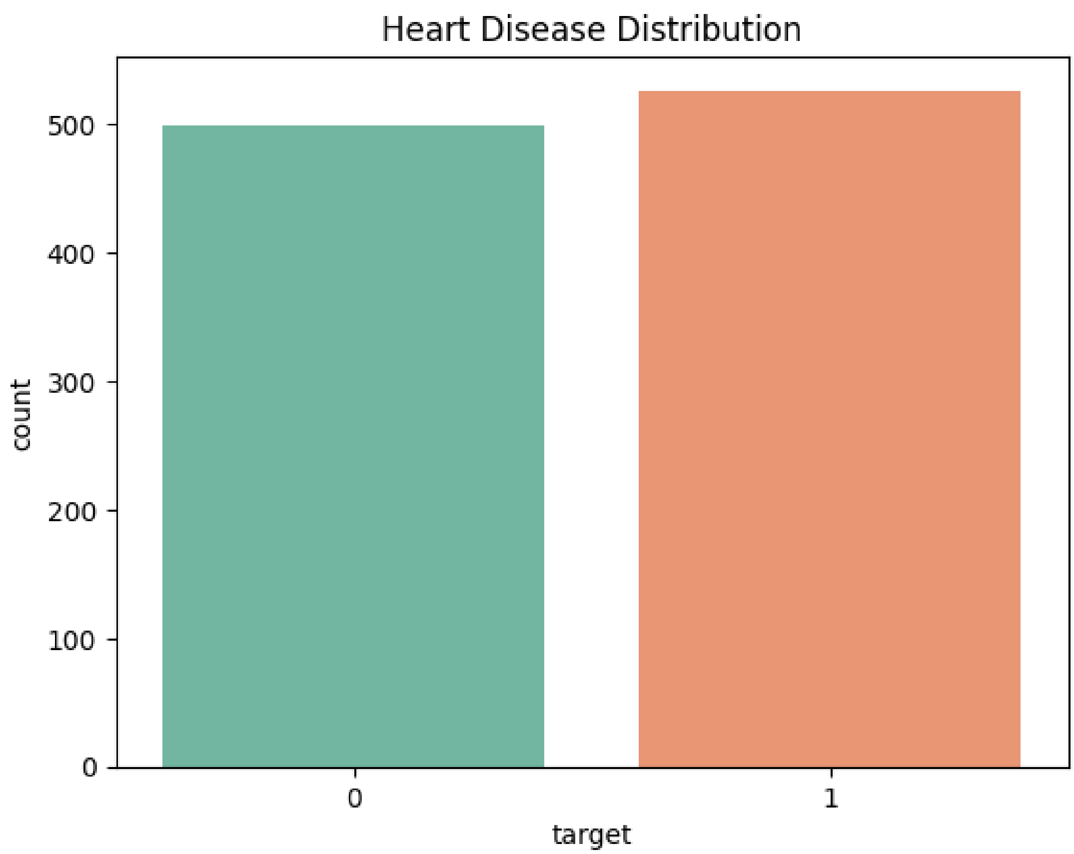



```
[ ]:
```

Visualize the target variable:

```
[ ]: sns.countplot(x='target', data=data,palette='Set2')
plt.title('Heart Disease Distribution')
plt.show()
```

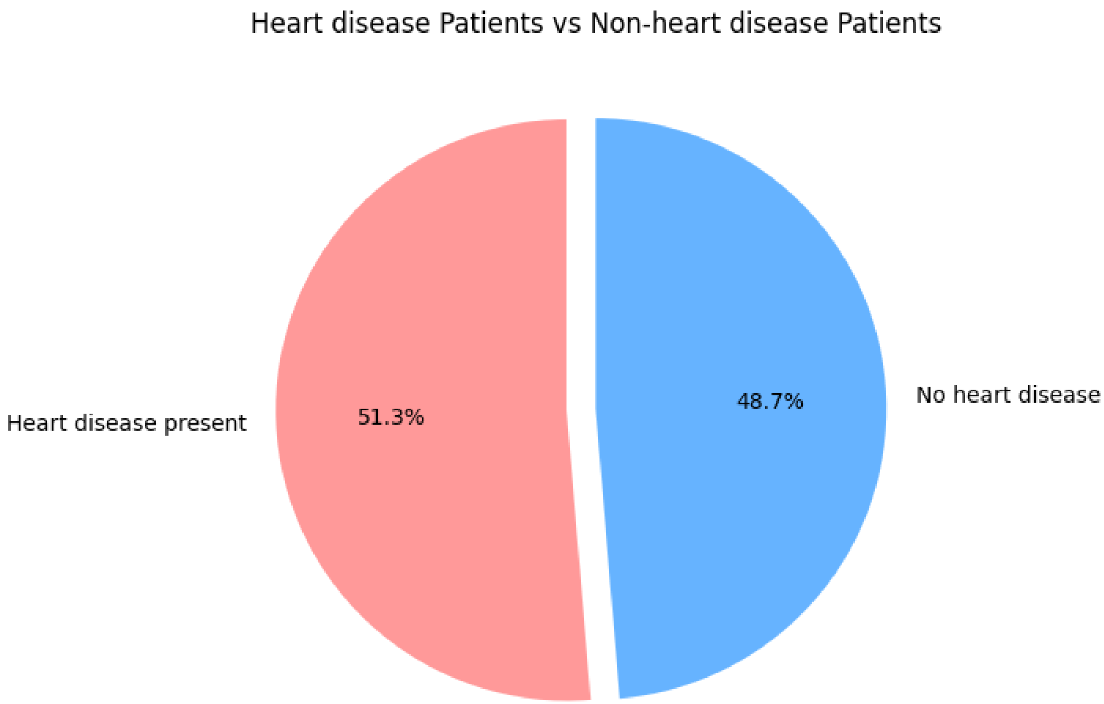
```
<ipython-input-10-67cfcc2798e9>:1: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.countplot(x='target', data=data,palette='Set2')
```




```
[ ]: # bivariate
```

```
[ ]: Heart_disease_present = data['target'].value_counts().get(1, 0)  # Get count␣
      ↪for target = 1, default to 0 if not found
     No_heart_disease = data['target'].value_counts().get(0, 0)  # Get count for␣
      ↪target = 0, default to 0 if not found
```

```
[ ]: # Data for the pie chart
     labels = ['Heart disease present', 'No heart disease']
     sizes = [Heart_disease_present, No_heart_disease]
     colors = ['#ff9999', '#66b3ff']  # Color scheme
     explode = (0.1, 0)  # To slightly separate the heart patients slice

     # Create Pie Chart
     plt.figure(figsize=(6,6))
     plt.pie(sizes, labels=labels, autopct='%1.1f%%', colors=colors,␣
      ↪explode=explode, startangle=90)
     plt.title("Heart disease Patients vs Non-heart disease Patients")
     plt.show()
```

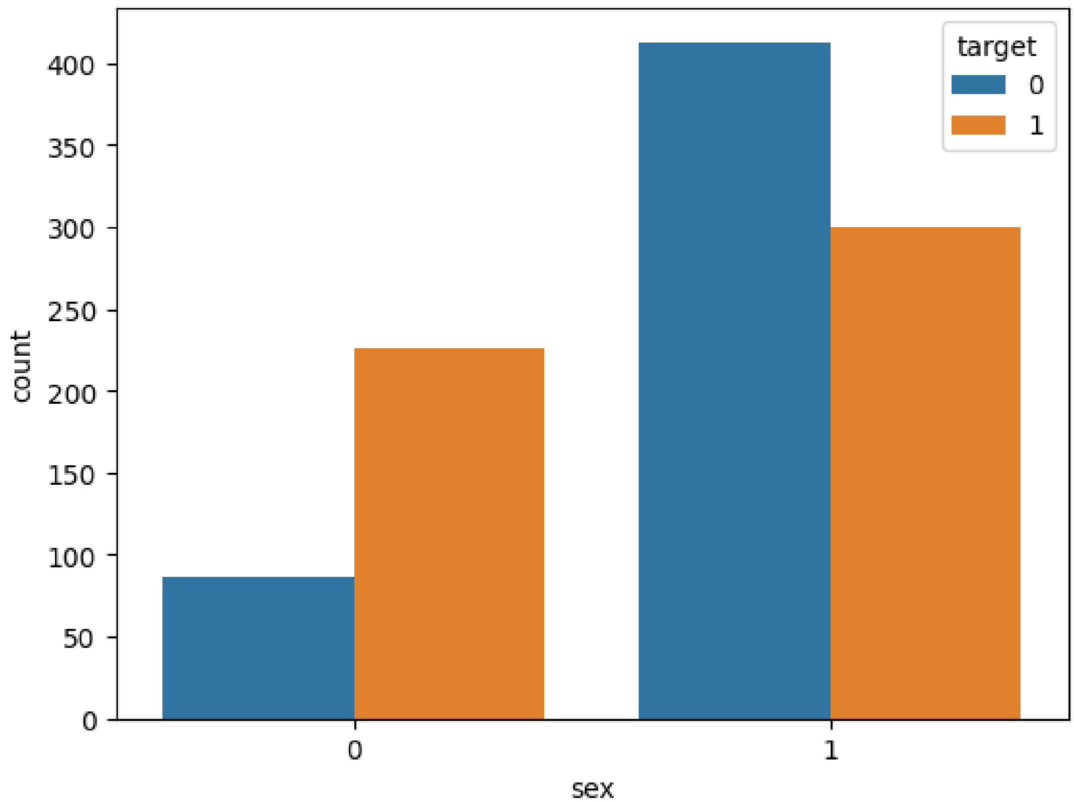


It is observed that from the given dataset, 51.3 % of the data belongs to heart_disease_patients whereas 48.7 % belongs to No_heart_disease Patients.

[ ]:
```
data['target'].value_counts()
```

[ ]:
```
target
1    526
0    499
Name: count, dtype: int64
```

[ ]:
```
sns.countplot(data=data,x='sex', hue='target')
plt.show()
```



[ ]:
```
print(data['sex'].value_counts())
```

```
sex
1    713
0    312
Name: count, dtype: int64
```

[ ]:
```
Femalepatients = data[(data.sex == 0) & (data.target == 1)]
Femalepatients
```

[ ]:

```
      age  sex  cp  trestbps  chol  fbs  restecg  thalach  exang  oldpeak  \
5      58    0   0       100   248    0        0      122      0      1.0
10     71    0   0       112   149    0        1      125      0      1.6
12     34    0   1       118   210    0        1      192      0      0.7
15     34    0   1       118   210    0        1      192      0      0.7
16     51    0   2       140   308    0        0      142      0      1.5
…     …    …  ..     …    …   …      …       …      …       …
989    71    0   1       160   302    0        1      162      0      0.4
992    50    0   0       110   254    0        0      159      0      0.0
1004   51    0   2       140   308    0        0      142      0      1.5
1014   44    0   2       108   141    0        1      175      0      0.6
```

```
1023   50    0   0       110   254    0        0      159       0       0.0

      slope  ca  thal  target
5         1   0     2       1
10        1   0     2       1
12        2   0     2       1
15        2   0     2       1
16        2   1     2       1
…      …  ..    …     …
989       2   2     2       1
992       2   0     2       1
1004      2   1     2       1
1014      1   0     2       1
1023      2   0     2       1

[226 rows x 14 columns]
```

Number of female heart patients are 226 out of 312 Females

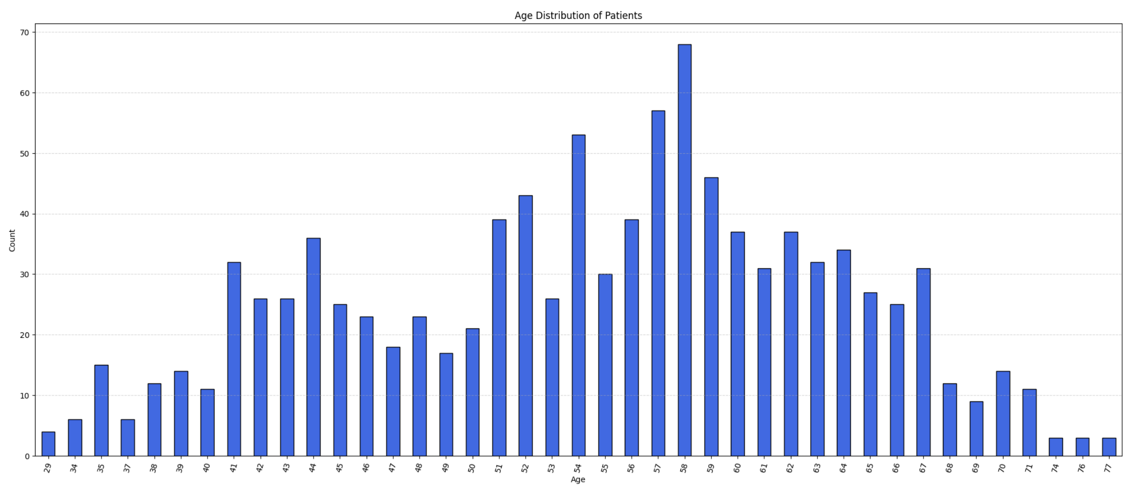
[ ]:
```python
Male_patients = data[(data.sex == 1) & (data.target == 1)]
Male_patients
```

[ ]:
```
      age  sex  cp  trestbps  chol  fbs  restecg  thalach  exang  oldpeak  \
19     58    1   2       140   211    1        0      165      0      0.0
22     45    1   0       104   208    0        0      148      1      3.0
26     44    1   2       130   233    0        1      179      1      0.4
34     50    1   2       129   196    0        1      163      0      0.0
36     51    1   3       125   213    0        0      125      1      1.4
…    …   …  ..      …   …   …      …      …     …      …
1007   56    1   3       120   193    0        0      162      0      1.9
1008   42    1   1       120   295    0        1      162      0      0.0
1011   45    1   1       128   308    0        0      170      0      0.0
1019   47    1   0       112   204    0        1      143      0      0.1
1020   59    1   1       140   221    0        1      164      1      0.0

      slope  ca  thal  target
19        2   0     2       1
22        1   0     2       1
26        2   0     2       1
34        2   0     2       1
36        2   1     2       1
…      …  ..    …     …
1007      1   0     3       1
1008      2   0     2       1
1011      2   0     2       1
1019      2   0     2       1
1020      2   0     2       1
```

```
[300 rows x 14 columns]
```

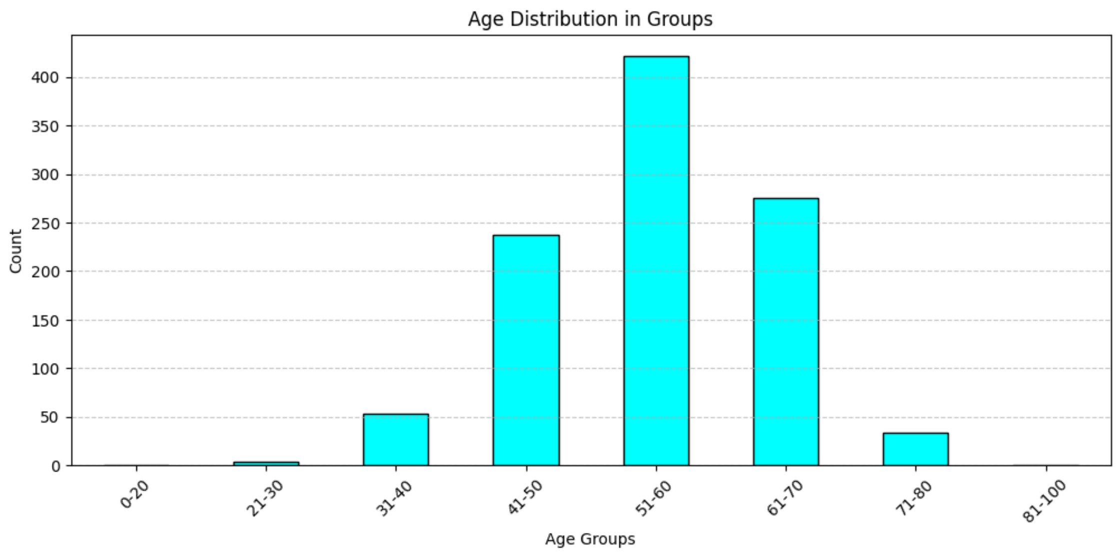
Number of male heart patients are 300 out of 713 males

[ ]:
```python
# Plot the age group distribution
plt.figure(figsize=(25,10))
data['age'].value_counts().sort_index().plot(kind='bar', color='royalblue', edgecolor='black')
plt.xlabel("Age")
plt.ylabel("Count")
plt.title("Age Distribution of Patients")
plt.xticks(rotation=75)  # Rotating labels to prevent overlap
plt.grid(axis='y', linestyle="--", alpha=0.5)
plt.show()
```



[ ]:
```python
# Define age bins
bins = [0, 20, 30, 40, 50, 60, 70, 80, 100]  # Customize as needed
labels = ['0-20', '21-30', '31-40', '41-50', '51-60', '61-70', '71-80', '81-100']

# Create a new column for age groups
data['age_group'] = pd.cut(data['age'], bins=bins, labels=labels, right=False)

# Plot the age group distribution
plt.figure(figsize=(12,5))
data['age_group'].value_counts().sort_index().plot(kind='bar', color='Cyan', edgecolor='black')
plt.xlabel("Age Groups")
plt.ylabel("Count")
plt.title("Age Distribution in Groups")
```

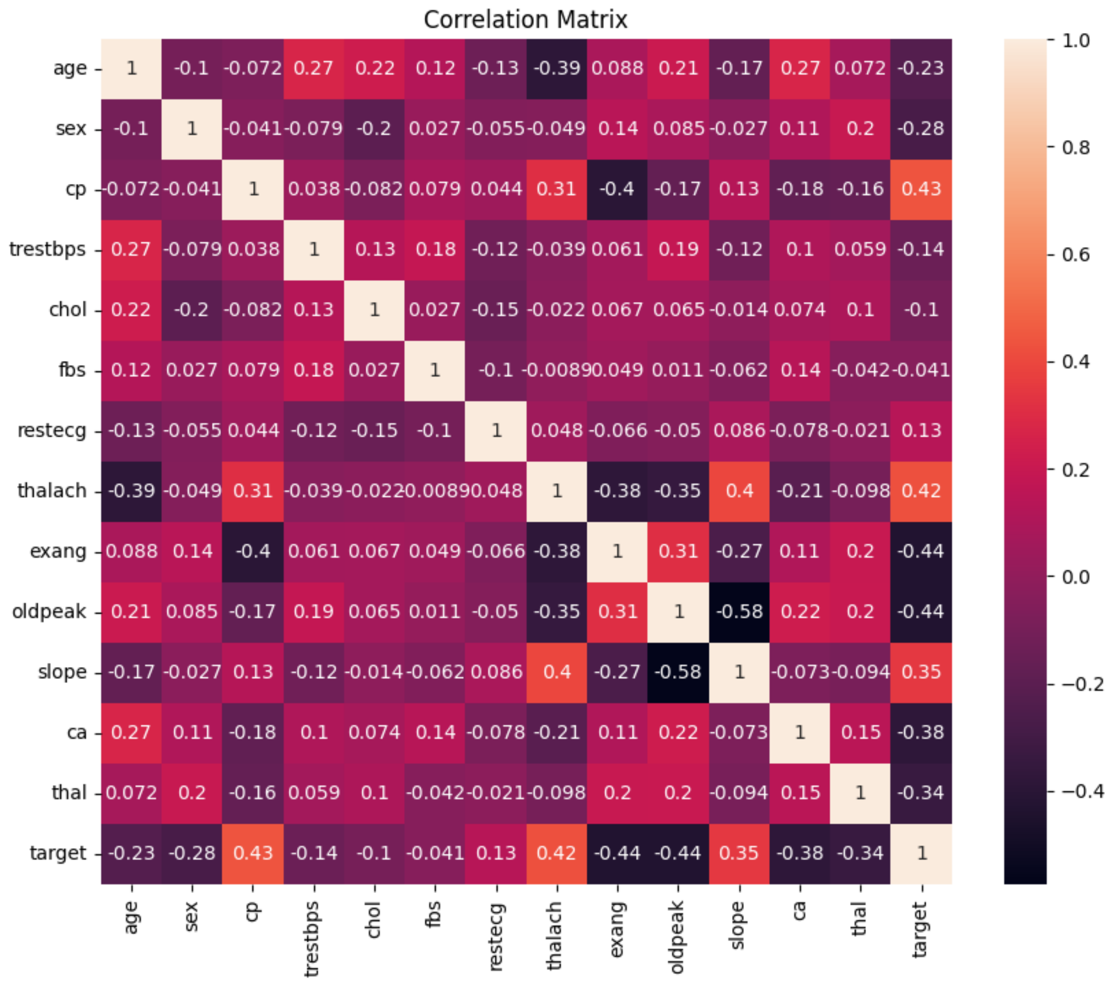
```
plt.xticks(rotation=45)
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.show()
```



[ ]:
```
data.drop(['age_group'],inplace = True , axis =1)
```

Bivariate Analysis

[ ]:
```
correlation_matrix = data.corr()
plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True)
plt.title('Correlation Matrix')
plt.show()
```

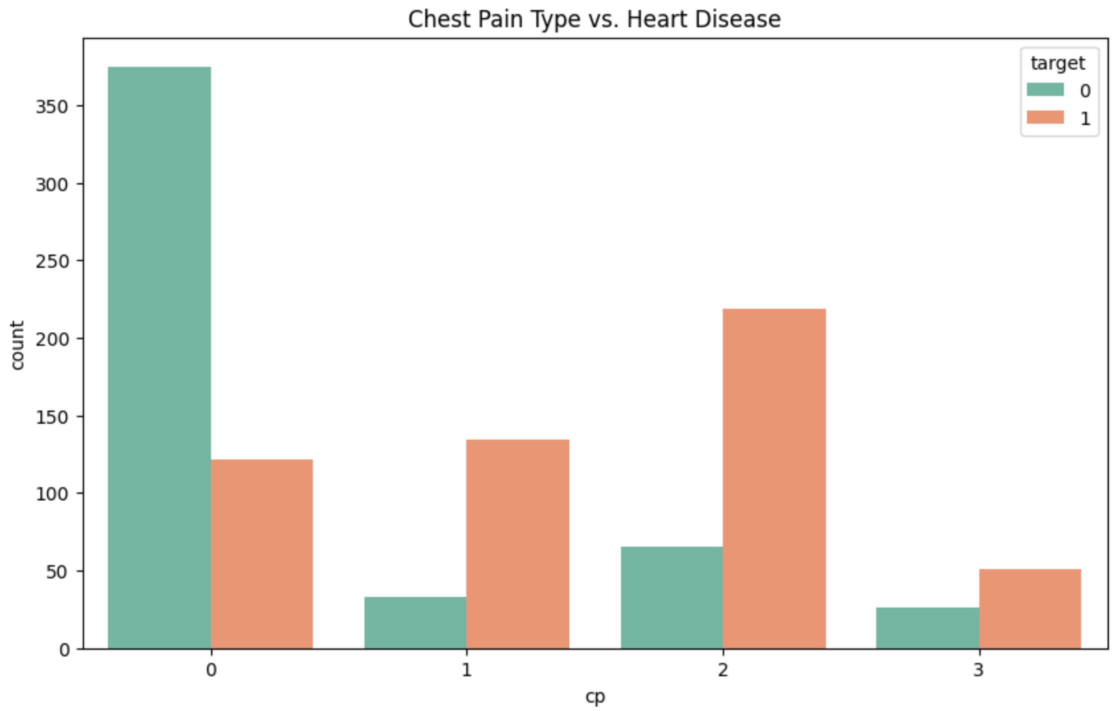


Relationship between age and maximum heart rate:

```
[ ]: sns.scatterplot(x='age', y='thalach', data=data, hue='target',palette='Set2')
     plt.title('Age vs. Maximum Heart Rate')
     plt.show()
```

Relationship between chest pain type and heart disease:

```
[ ]: plt.figure(figsize=(10, 6))
sns.countplot(x='cp', hue='target', data=data,palette='Set2')
plt.title('Chest Pain Type vs. Heart Disease')
plt.show()
```



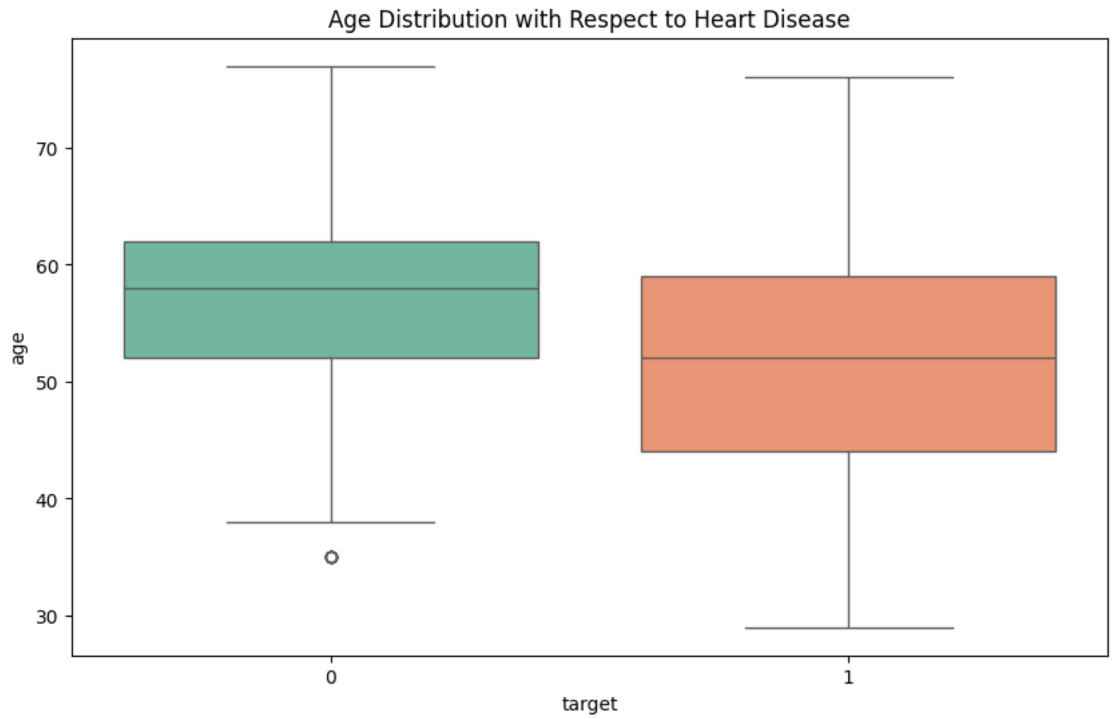

```
[ ]: data['ca'].value_counts()
```

```
[ ]: ca
0    578
1    226
2    134
3     69
4     18
Name: count, dtype: int64
```

Interaction between Age and Target (Heart Disease Presence):

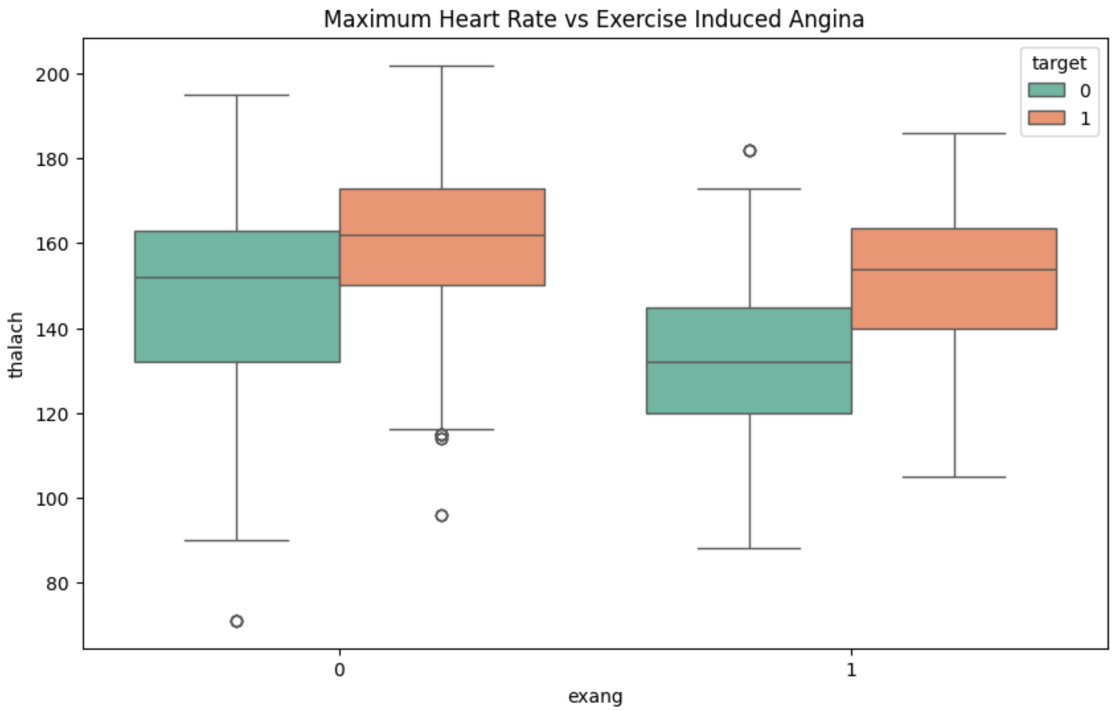
```
[ ]: plt.figure(figsize=(10, 6))
sns.boxplot(x='target', y='age', data=data, palette='Set2')
plt.title('Age Distribution with Respect to Heart Disease')
plt.show()
```

```
<ipython-input-26-ffb02d68012b>:2: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.boxplot(x='target', y='age', data=data, palette='Set2')
```



Maximum Heart Rate (thalach) vs Exercise Induced Angina (exang):

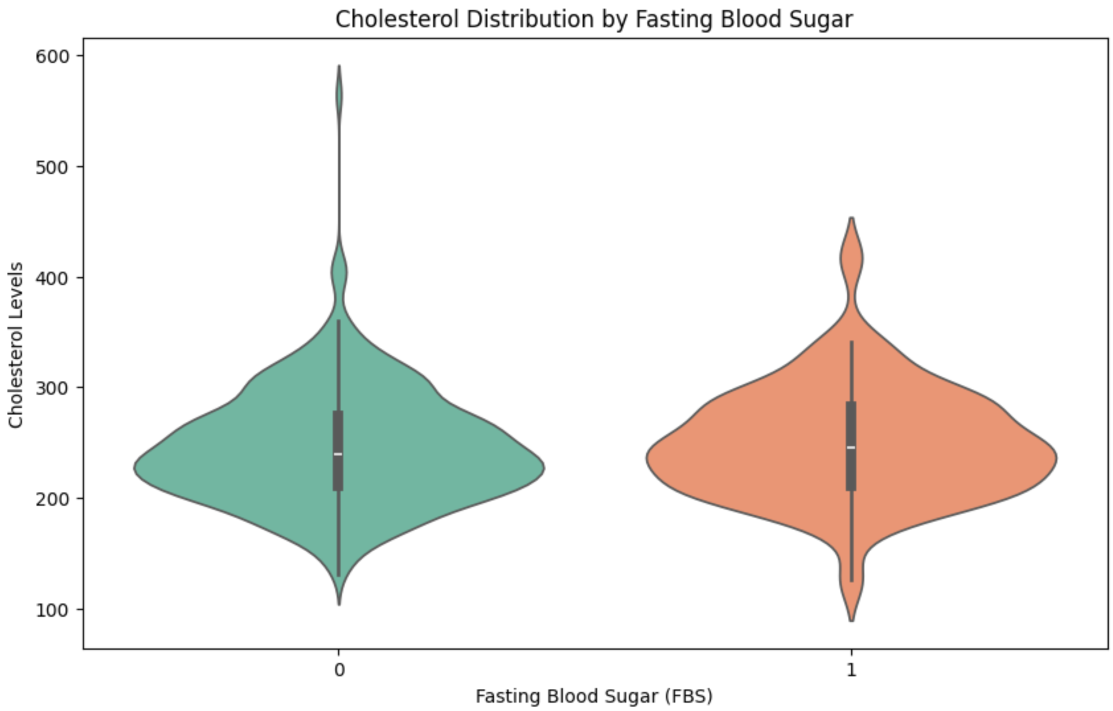
[ ]:
```
plt.figure(figsize=(10, 6))
sns.boxplot(x='exang', y='thalach', hue='target', data=data, palette='Set2')
plt.title('Maximum Heart Rate vs Exercise Induced Angina')
plt.show()
```



Cholesterol vs Fasting Blood Sugar (fbs):

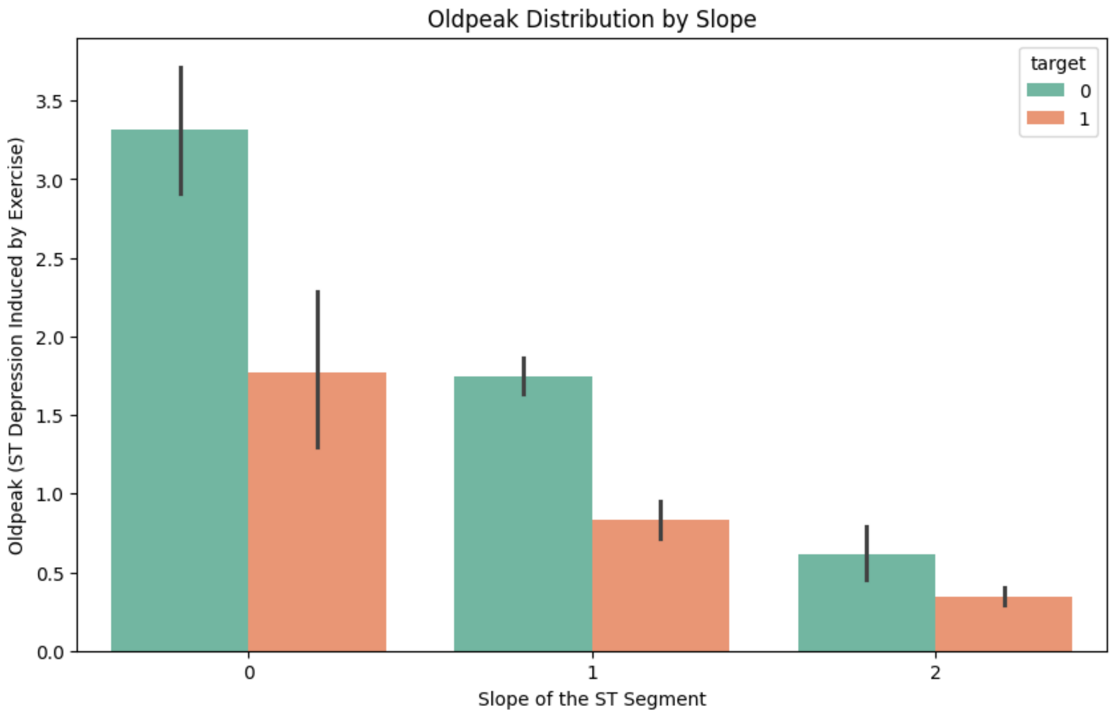
```
[ ]: plt.figure(figsize=(10, 6))
sns.violinplot(x='fbs', y='chol', data=data, palette='Set2')
plt.title('Cholesterol Distribution by Fasting Blood Sugar')
plt.xlabel('Fasting Blood Sugar (FBS)')
plt.ylabel('Cholesterol Levels')
plt.show()
```

```
<ipython-input-28-58dbc364bfe7>:2: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.violinplot(x='fbs', y='chol', data=data, palette='Set2')
```

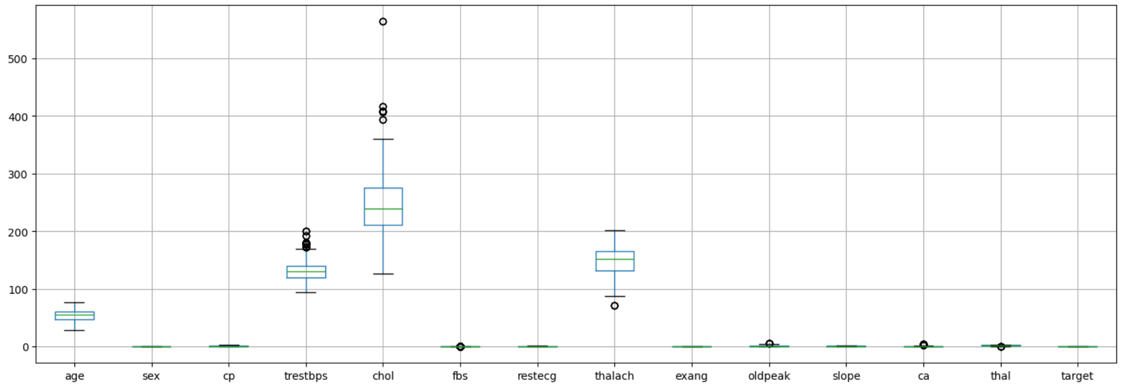


Oldpeak vs Slope

```
[ ]: plt.figure(figsize=(10, 6))
     sns.barplot(x='slope', y='oldpeak', hue='target', data=data, palette='Set2')
     plt.title('Oldpeak Distribution by Slope')
     plt.xlabel('Slope of the ST Segment')
     plt.ylabel('Oldpeak (ST Depression Induced by Exercise)')
     plt.show()
```




```
[ ]: #cheking the outliers
     plt.figure(figsize=(18, 6))
     data.boxplot()
     plt.show()
```

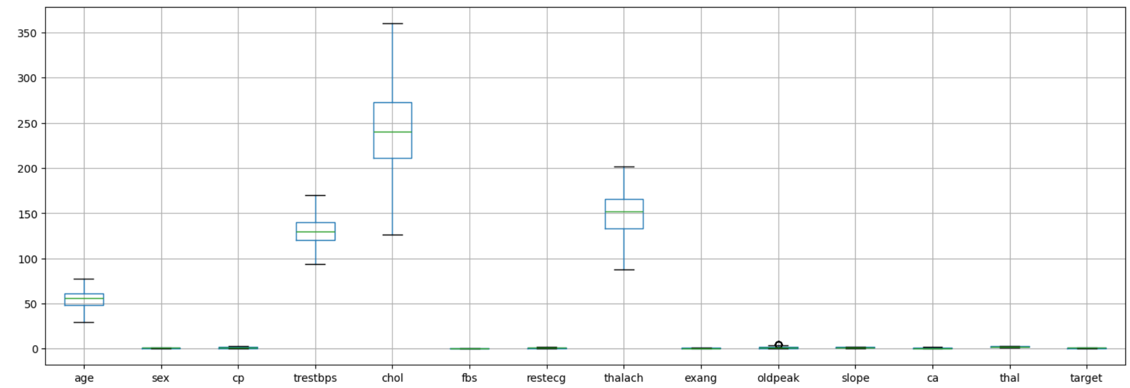



```
[ ]: #Treating the outlier

     def ot(data,col):
       Q3=data[col].quantile(0.75)
       Q1=data[col].quantile(0.25)
```

```
    IQR=Q3-Q1
    UB=Q3+1.5*IQR
    LB=Q1-1.5*IQR
    upper_ot=data[col]>UB
    lower_ot=data[col]<LB
    data.loc[upper_ot,col]=data[col].median()
    data.loc[lower_ot,col]=data[col].median()
    return data
```

[ ]:
```
for i in data.select_dtypes(include=['int64','float64']):
    ot(data,i)
```

[ ]:
```
#cheking the outliers
plt.figure(figsize=(18, 6))
data.boxplot()
plt.show()
```



[ ]:
```
#checking skewness
data.skew()
```

[ ]:
```
age        -0.248866
sex        -0.851449
cp          0.529455
trestbps    0.265765
chol        0.203290
fbs         0.000000
restecg     0.180440
thalach    -0.428708
exang       0.692655
oldpeak     0.985010
slope      -0.479134
ca          1.138307
thal       -0.261968
```

```
target      -0.052778
dtype: float64
```

[ ]:
```
data['oldpeak'] = np.log1p(data['oldpeak'])
```

[ ]:
```
data.skew()
```

[ ]:
```
age         -0.248866
sex         -0.851449
cp           0.529455
trestbps     0.265765
chol         0.203290
fbs          0.000000
restecg      0.180440
thalach     -0.428708
exang        0.692655
oldpeak      0.315959
slope       -0.479134
ca           1.138307
thal        -0.261968
target      -0.052778
dtype: float64
```

0.0.1 Model prepration

[ ]:
```
y = data["target"]
X = data.drop('target',axis=1)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.20,␣
 ↪random_state = 0)
```

[ ]:
```
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

Before applying algorithm we should check whether the data is equally splitted or not, because if data is not splitted equally it will cause for data imbalacing problem

[ ]:
```
print(y_test.unique())
Counter(y_train)
```

```
[1 0]
```

[ ]:
```
Counter({1: 419, 0: 401})
```

[ ]:
```
m1 = 'Logistic Regression'
lr = LogisticRegression()
model = lr.fit(X_train, y_train)
```

```
lr_predict = lr.predict(X_test)
lr_conf_matrix = confusion_matrix(y_test, lr_predict)
lr_acc_score = accuracy_score(y_test, lr_predict)
print("confussion matrix")
print(lr_conf_matrix)
print("\n")
print("Accuracy of Logistic Regression:",lr_acc_score*100,'\n')
print(classification_report(y_test,lr_predict))
```

```
confussion matrix
[[82 16]
 [ 9 98]]


Accuracy of Logistic Regression: 87.8048780487805

              precision    recall  f1-score   support

           0       0.90      0.84      0.87        98
           1       0.86      0.92      0.89       107

    accuracy                           0.88       205
   macro avg       0.88      0.88      0.88       205
weighted avg       0.88      0.88      0.88       205
```

[ ]:
```
m2 = 'Random Forest Classfier'
rf = RandomForestClassifier(n_estimators=20, random_state=2,max_depth=5)
rf.fit(X_train,y_train)
rf_predicted = rf.predict(X_test)
rf_conf_matrix = confusion_matrix(y_test, rf_predicted)
rf_acc_score = accuracy_score(y_test, rf_predicted)
print("confussion matrix")
print(rf_conf_matrix)
print("\n")
print("Accuracy of Random Forest:",rf_acc_score*100,'\n')
print(classification_report(y_test,rf_predicted))
```

```
confussion matrix
[[ 90   8]
 [  2 105]]


Accuracy of Random Forest: 95.1219512195122

              precision    recall  f1-score   support

           0       0.98      0.92      0.95        98
```

```
           1       0.93      0.98      0.95       107

    accuracy                           0.95       205
   macro avg       0.95      0.95      0.95       205
weighted avg       0.95      0.95      0.95       205
```

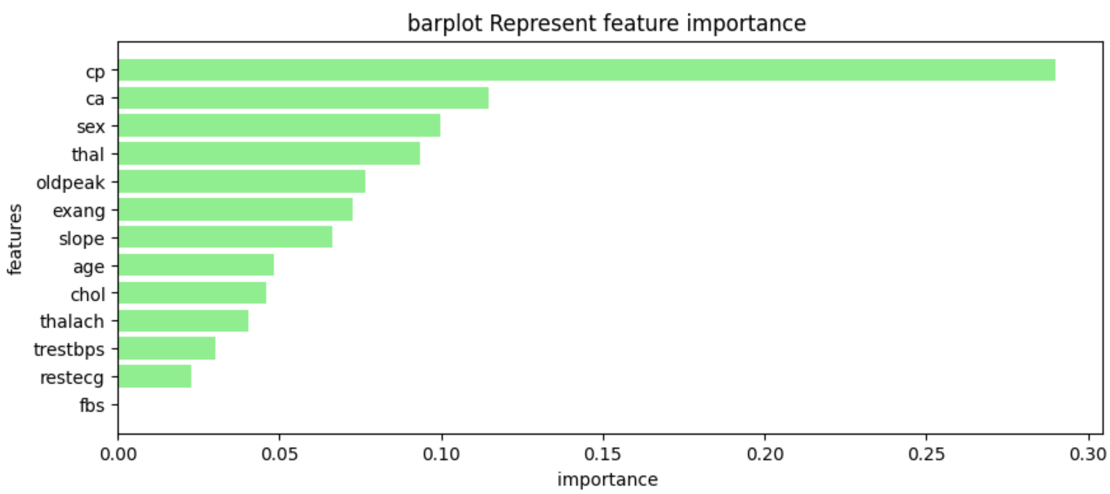
[ ]:
```
m3 = 'K-NeighborsClassifier'
knn = KNeighborsClassifier(n_neighbors=10)
knn.fit(X_train, y_train)
knn_predicted = knn.predict(X_test)
knn_conf_matrix = confusion_matrix(y_test, knn_predicted)
knn_acc_score = accuracy_score(y_test, knn_predicted)
print("confussion matrix")
print(knn_conf_matrix)
print("\n")
print("Accuracy of K-NeighborsClassifier:",knn_acc_score*100,'\n')
print(classification_report(y_test,knn_predicted))
```

```
confussion matrix
[[85 13]
 [ 8 99]]


Accuracy of K-NeighborsClassifier: 89.75609756097562

              precision    recall  f1-score   support

           0       0.91      0.87      0.89        98
           1       0.88      0.93      0.90       107

    accuracy                           0.90       205
   macro avg       0.90      0.90      0.90       205
weighted avg       0.90      0.90      0.90       205
```

[ ]:
```
m4 = 'DecisionTreeClassifier'
dt = DecisionTreeClassifier(criterion = 'entropy',random_state=0,max_depth = 6)
dt.fit(X_train, y_train)
dt_predicted = dt.predict(X_test)
dt_conf_matrix = confusion_matrix(y_test, dt_predicted)
dt_acc_score = accuracy_score(y_test, dt_predicted)
print("confussion matrix")
print(dt_conf_matrix)
print("\n")
print("Accuracy of DecisionTreeClassifier:",dt_acc_score*100,'\n')
print(classification_report(y_test,dt_predicted))
```

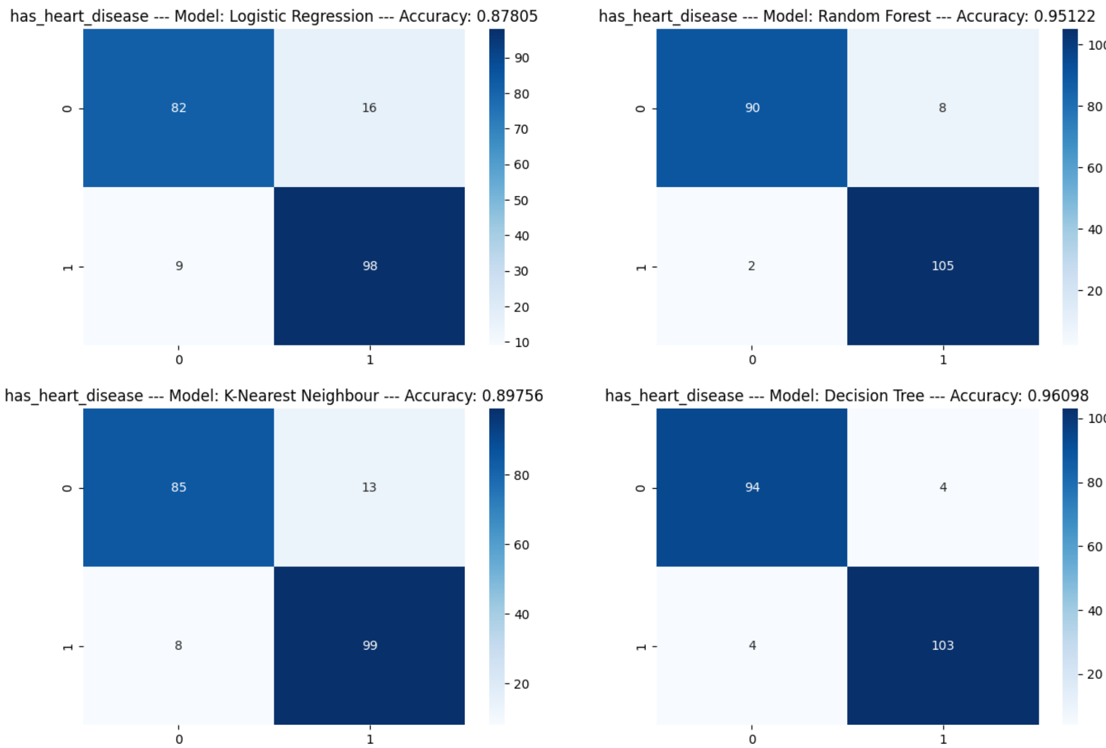
```
confussion matrix
[[ 94   4]
 [  4 103]]


Accuracy of DecisionTreeClassifier: 96.09756097560975

              precision    recall  f1-score   support

           0       0.96      0.96      0.96        98
           1       0.96      0.96      0.96       107

    accuracy                           0.96       205
   macro avg       0.96      0.96      0.96       205
weighted avg       0.96      0.96      0.96       205
```

[ ]:
```
xgb=XGBClassifier()
xgb.fit(X_train,y_train)
imp_feature = pd.DataFrame({'Feature': ['age', 'sex', 'cp', 'trestbps', 'chol',␣
 ↪'fbs', 'restecg', 'thalach',
       'exang', 'oldpeak', 'slope', 'ca', 'thal'], 'Importance': xgb.
 ↪feature_importances_})

imp_feature = imp_feature.sort_values(by='Importance', ascending=True)
plt.figure(figsize=(10,4))
plt.title("barplot Represent feature importance ")
plt.xlabel("importance ")
plt.ylabel("features")
plt.barh(imp_feature['Feature'],imp_feature['Importance'],color="lightgreen")
plt.show()
```



[ ]:
```
plt.figure(figsize=(15,10))

# Logistic Regression
plt.subplot(2, 2, 1)
plt.title(f'has_heart_disease --- Model: Logistic Regression --- Accuracy:␣
↪{lr_acc_score:.5f}')
sns.heatmap(lr_conf_matrix, annot=True, cmap="Blues", fmt="d")

# Random Forest
plt.subplot(2, 2, 2)
plt.title(f'has_heart_disease --- Model: Random Forest --- Accuracy:␣
↪{rf_acc_score:.5f}')
sns.heatmap(rf_conf_matrix, annot=True, cmap="Blues", fmt="d")

# K-Nearest Neighbor
plt.subplot(2, 2, 3)
plt.title(f'has_heart_disease --- Model: K-Nearest Neighbour --- Accuracy:␣
↪{knn_acc_score:.5f}')
sns.heatmap(knn_conf_matrix, annot=True, cmap="Blues", fmt="d")

# Decision Tree
plt.subplot(2, 2, 4)
plt.title(f'has_heart_disease --- Model: Decision Tree --- Accuracy:␣
↪{dt_acc_score:.5f}')
sns.heatmap(dt_conf_matrix, annot=True, cmap="Blues", fmt="d")
```

[ ]:
```
<Axes: title={'center': 'has_heart_disease --- Model: Decision Tree ---
Accuracy: 0.96098'}>
```



0.0.2 Model Evaluation

[ ]:
```
model_ev = pd.DataFrame(
    {'Model': ['Logistic Regression','Random Forest','K-Nearest Neighbour','Decision Tree'],
     'Accuracy': [lr_acc_score*100,rf_acc_score*100,knn_acc_score*100,dt_acc_score*100]
     })
```

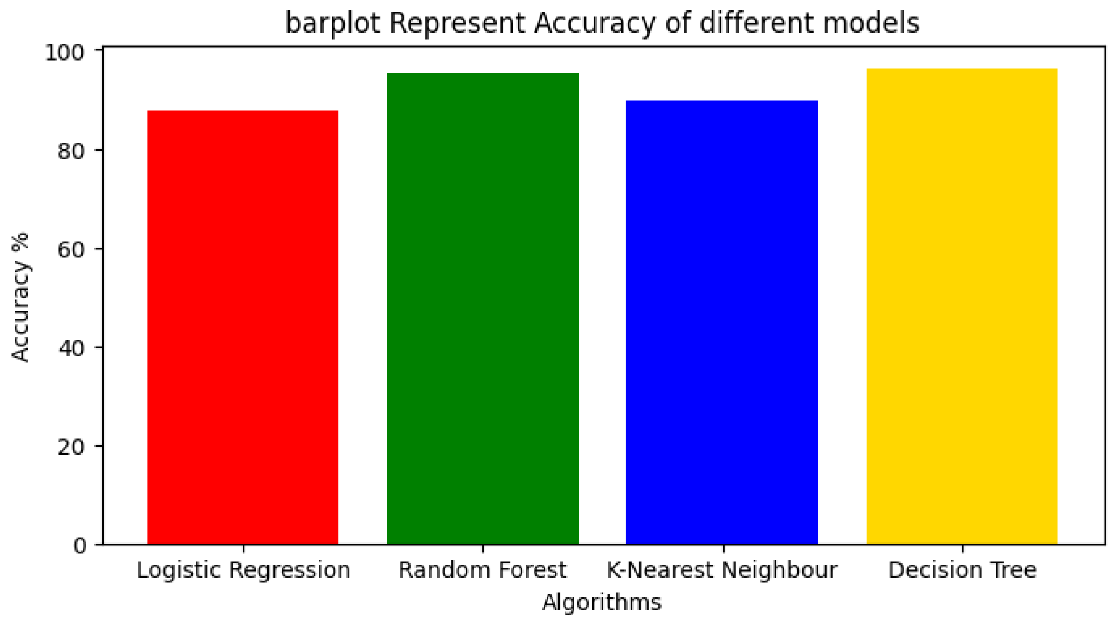
[ ]:
```
model_ev
```

[ ]:

	Model	Accuracy
0	Logistic Regression	87.804878
1	Random Forest	95.121951
2	K-Nearest Neighbour	89.756098
3	Decision Tree	96.097561

[ ]:
```
colors = ['red','green','blue','gold','silver','yellow','orange',]
plt.figure(figsize=(8,4))
plt.title("barplot Represent Accuracy of different models")
plt.ylabel("Accuracy %")
plt.xlabel("Algorithms")
plt.bar(model_ev['Model'],model_ev['Accuracy'],color = colors)
```

```
plt.show()
```



Cross Validation score

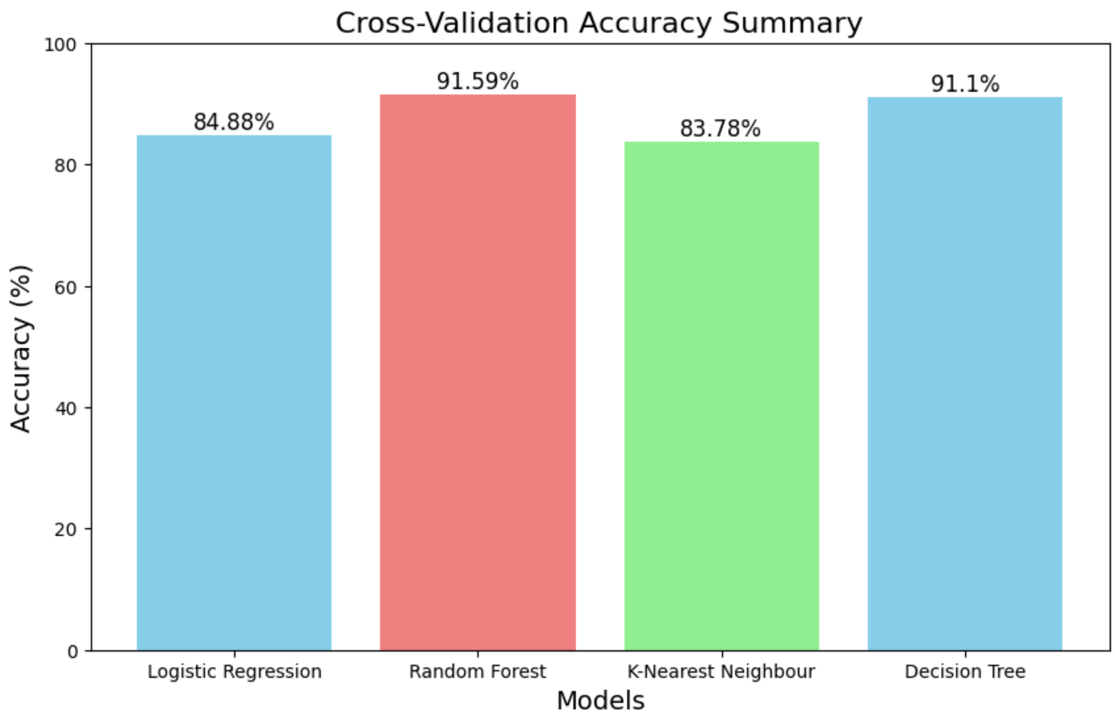
```
[ ]: LR_Validation=cross_val_score(lr,X_train,y_train,cv=5).mean()
RF_Validation=cross_val_score(rf,X_train,y_train,cv=5).mean()
KNN_Validation=cross_val_score(knn,X_train,y_train,cv=5).mean()
DT_Validation=cross_val_score(dt,X_train,y_train,cv=5).mean()
```

```
[ ]: print("Cross validation Score Summary:")
print("Logistic Regression Accuracy: ",LR_Validation*100)
print("Random Forest Accuracy: ",RF_Validation*100)
print("KNN Accuracy: ",KNN_Validation*100)
print("Decision Tree Accuracy: ",DT_Validation*100)
```

```
Cross validation Score Summary:
Logistic Regression Accuracy:  84.87804878048782
Random Forest Accuracy:  91.58536585365853
KNN Accuracy:  83.78048780487805
Decision Tree Accuracy:  91.09756097560975
```

```
[ ]: CVD_Accuracies =␣
  ↪[LR_Validation*100,RF_Validation*100,KNN_Validation*100,DT_Validation*100]

plt.figure(figsize=(10, 6))
plt.bar(model_ev['Model'], CVD_Accuracies, color=['skyblue', 'lightcoral',␣
  ↪'lightgreen'])
```

```
plt.title('Cross-Validation Accuracy Summary', fontsize=16)
plt.ylabel('Accuracy (%)', fontsize=14)
plt.xlabel('Models', fontsize=14)
plt.ylim(0, 100)  # Set y-axis limit to 100%

for i, v in enumerate(CVD_Accuracies):
    plt.text(i, v + 1, str(round(v, 2)) + '%', ha='center', fontsize=12)

plt.show()
```



0.0.3 Conclusion

1. Extreme Random Forest gives the best Accuracy compared to other models
2. Exercise induced angina,Chest pain is major symptoms of heart attack.

In summary:

- **Overall Performance**: All models (Logistic Regression, Random Forest, K-Nearest Neighbors, and Decision Tree) have high accuracy, ranging from 83.7% to 91.5%, indicating they are good at predicting heart disease.
- **Model Observations**:
  - **Logistic Regression**: 84.8% accuracy, with some misclassifications.
  - **Random Forest**: 91.5% accuracy, the most accurate model with few misclassifications.
  - **K-Nearest Neighbors**: 83.7% accuracy, with slightly more false negatives.
  - **Decision Tree**: 91.1% accuracy, similar to Random Forest with low misclassifications.

Key Takeaways: - **Chest Pain Type (cp)** is the most important feature for predicting heart disease. - **Number of Major Vessels (ca)** is the second most important feature. - **Thallium Stress Test Result (thal)** is also a key feature. - Other important features include **oldpeak**, **exang**, **sex**, and **slope**.

Confusion Matrix terms: - **True Positives**: Correctly predicted heart disease. - **True Negatives**: Correctly predicted no heart disease. - **False Positives**: Incorrectly predicted heart disease. - **False Negatives**: Incorrectly predicted no heart disease.

dataset_link : "https://drive.google.com/file/d/1E_FY_vrz21zYnR4MJ0sSKfU-QERDCzki/view?usp=sharing"

project_file_link : "https://colab.research.google.com/drive/1Qrhc7YEUgDNquOMexM5woweC_5C_LeLR?usp