alogrithms

December 4, 2022

[1]:
```
#importing Core-Libraries & Exploratory Data Analysis
import pandas as pd
import pandas as pd
import matplotlib.pyplot as plt
import plotly.express as px
import plotly.graph_objects as go
import plotly.express as px
from plotly.subplots import make_subplots

#importing pre-processing libraries
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split

#importing machine learning libraries
from sklearn.naive_bayes import GaussianNB
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier

#performance metrics libraries
from sklearn.feature_selection import chi2
from sklearn.metrics import confusion_matrix, classification_report,␣
 ↪roc_auc_score, RocCurveDisplay
```

All libraries imported successfully

[2]:
```
#importing & reading dataset

data = pd.read_csv('heart.csv')
data.head()
```

[2]:
```
   Age Sex ChestPainType  RestingBP  Cholesterol  FastingBS RestingECG  MaxHR  \
0   40   M           ATA        140          289          0     Normal    172
1   49   F           NAP        160          180          0     Normal    156
2   37   M           ATA        130          283          0         ST     98
3   48   F           ASY        138          214          0     Normal    108
4   54   M           NAP        150          195          0     Normal    122

  ExerciseAngina  Oldpeak ST_Slope  HeartDisease
```

```
0              N       0.0        Up            0
1              N       1.0      Flat            1
2              N       0.0        Up            0
3              Y       1.5      Flat            1
4              N       0.0        Up            0
```

Only first 5 rows of the dataset displayed

[3]:
```python
#checking missing data

data.info()
```

```
<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
```

There is no missing values out of 918 rows in the dataset

[4]:
```python
#checking data description

data.describe()
```

[4]:
```
              Age   RestingBP  Cholesterol   FastingBS       MaxHR  \
count  918.000000  918.000000   918.000000  918.000000  918.000000
mean    53.510893  132.396514   198.799564    0.233115  136.809368
std      9.432617   18.514154   109.384145    0.423046   25.460334
min     28.000000    0.000000     0.000000    0.000000   60.000000
25%     47.000000  120.000000   173.250000    0.000000  120.000000
50%     54.000000  130.000000   223.000000    0.000000  138.000000
75%     60.000000  140.000000   267.000000    0.000000  156.000000
max     77.000000  200.000000   603.000000    1.000000  202.000000

          Oldpeak  HeartDisease
```

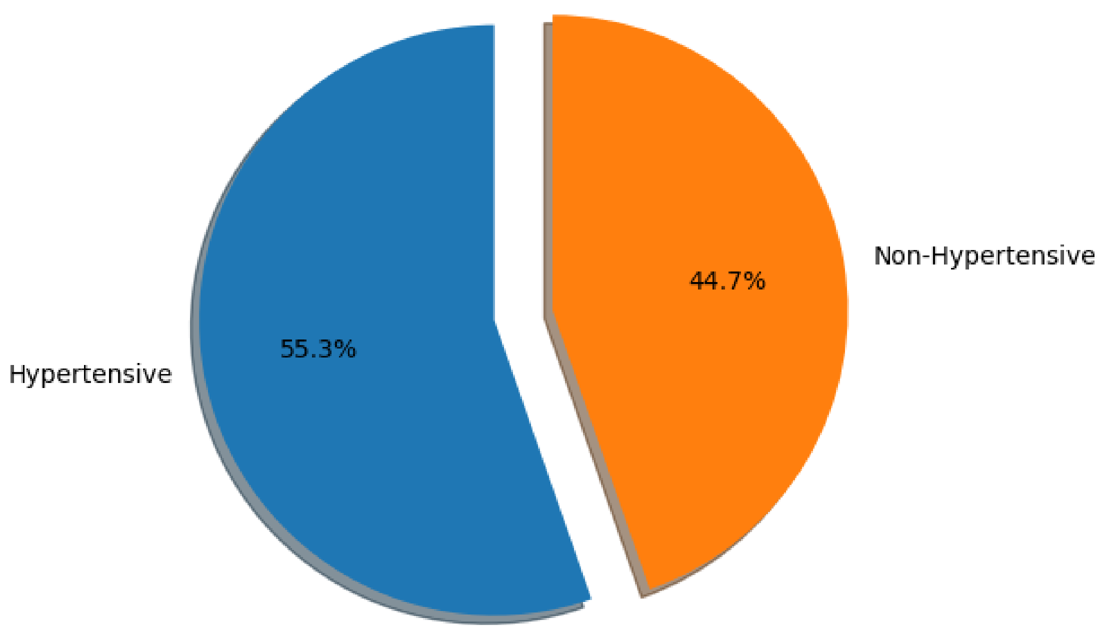
```
count   918.000000    918.000000
mean      0.887364      0.553377
std       1.066570      0.497414
min      -2.600000      0.000000
25%       0.000000      0.000000
50%       0.600000      1.000000
75%       1.500000      1.000000
max       6.200000      1.000000
```

There is data irregularities. It is not possible for a living being to have: *0 RestingBP*, *0 Cholesterol*, *0 FastingBS*

Therefore, we need to perform EDA to understand the data in a better sense.

EXPLORATORY DATA ANALYSIS

[5]:
```
#percentage of heart disease

heart_counts = data['HeartDisease'].value_counts()
labels = 'Hypertensive', 'Non-Hypertensive'
explode = (0.1,0.1)

ax = plt.subplot()
ax.pie(heart_counts, explode=explode, labels=labels, autopct='%1.1f%%',␣
 ↪shadow=True, startangle=90)
ax.axis('equal')
plt.show()
```



Morethan 55% of the patients in the dataset are heart disease (hypertensive)

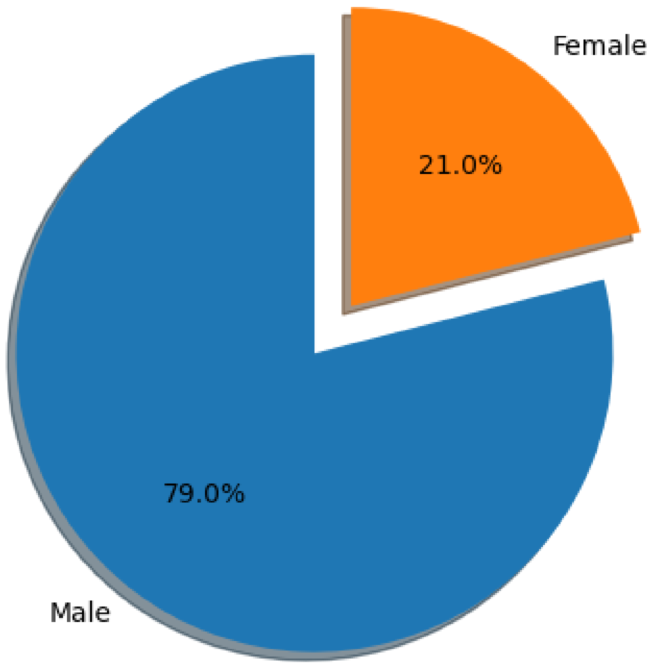
[6]:
```
#Checking the Distribution of Age

age_his = px.histogram(data, x='Age', marginal='box',␣
↪color_discrete_sequence=['#C147E9'])
age_his.update_layout(title='Age Distribution')
age_his.show()
```

Distribution of Ages shown that most of the patient are between 42 - 65 Years of age.

[7]:
```
#distribution of Age as per heart disease

cls = 'HeartDisease'
mrg = 'box'
hst = 'density'
cdm = {0:'#C147E9',1:'#F06292'}

age_hds = px.histogram(data, x='Age', color=cls, marginal=mrg, histnorm=hst,␣
↪color_discrete_map=cdm)
age_hds.show()
```

This is suggesting that the higher the ages of the patients, the higher the chances of having heart disease

[8]:
```
#distrubtion of sex

sex_counts = data['Sex'].value_counts()
labels = 'Male', 'Female'
explode = (0.1,0.1)

ax = plt.subplot()
ax.pie(sex_counts, explode=explode, labels=labels, autopct='%1.1f%%',␣
↪shadow=True, startangle=90)
ax.axis('equal')
plt.show()
```



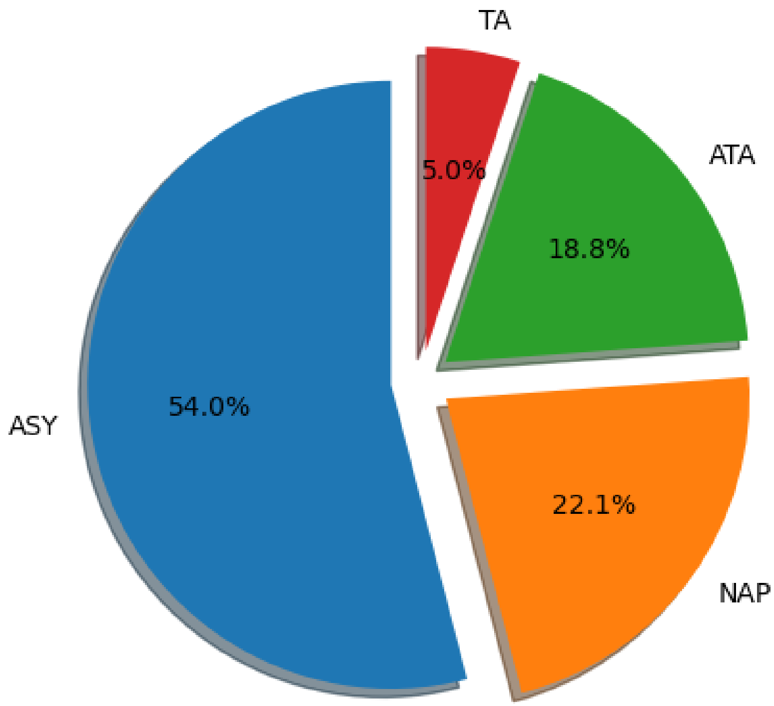
About of 80% of the patients are male.

[9]:
```
#sex distribution on heart disease

x='Sex'
cdm = {0:'#C147E9',1:'#F06292'}
clr='HeartDisease'

bar_sex_hd = px.histogram(data, x=x,color=clr, barmode='group',␣
 ↪color_discrete_map=cdm)
bar_sex_hd.show()
```

The output suggested that Male are more likely to have Heart Disease than Female

[10]:
```
#percentage distrubtion of chest pain

chest_counts = data['ChestPainType'].value_counts()
labels = 'ASY', 'NAP', 'ATA', 'TA'
explode = (0.1,0.1,0.1,0.1)

ax = plt.subplot()
ax.pie(chest_counts, explode=explode, labels=labels, autopct='%1.1f%%',␣
 ↪shadow=True, startangle=90)
ax.axis('equal')
```

```
plt.show()
```



Most of the patients are Asymptomatic with highest scores of 54%.

[11]:
```
#chest pain type distribution on heart disease

x='ChestPainType'
clr='HeartDisease'
cdm = {0:'#C147E9',1:'#F06292'}

bar_chest_hd = px.histogram(data, x=x,color=clr, barmode='group',␣
 ↪color_discrete_map=cdm)
bar_chest_hd.show()
```

This is indicating that majority of heart diseased patients are asymptomatic and having chest pain may not necessarily results to a heart disease or may not be due to a heart disease.

[12]:
```
#Checking the Distribution of resting Blood Pressure

rbp_his = px.histogram(data, x='RestingBP', marginal='box',␣
 ↪color_discrete_sequence=['#C147E9'])
rbp_his.update_layout(title='Resting Blood Pressure')
rbp_his.show()
```

Majority of the patients have a Resting Blood Pressure between 110 - 150

[13]:
```
#distribution of RestingBP as per heart disease

cls = 'HeartDisease'
x = 'RestingBP'
mrg = 'box'
hst = 'density'
cdm = {0:'#C147E9',1:'#F06292'}

rbp_hds = px.histogram(data, x=x, color=cls, marginal=mrg, histnorm=hst,␣
 ↪color_discrete_map=cdm)
rbp_hds.show()
```

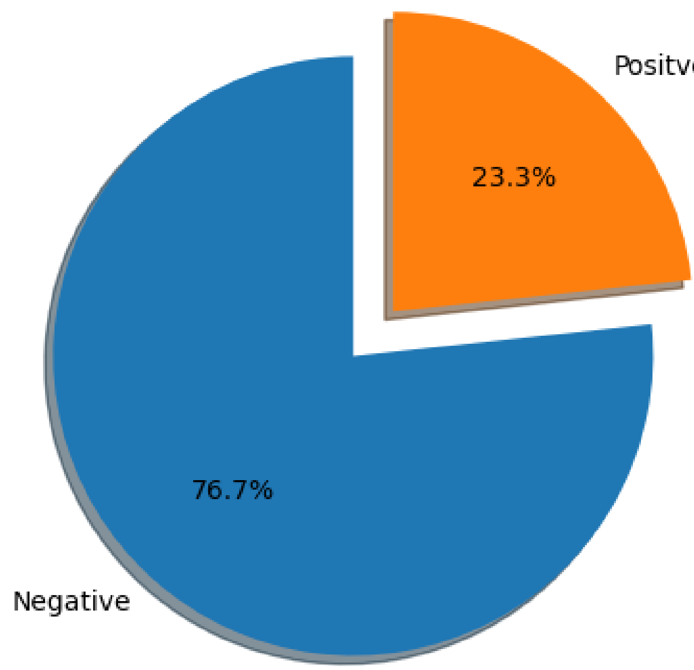
The distribution shown that patient with higher restingBP have more chances of heart disease.

[14]:
```
#Checking the Distribution of Cholesterol

cls_his = px.histogram(data, x='Cholesterol', marginal='box',␣
 ↪color_discrete_sequence=['#C147E9'] )
cls_his.update_layout(title='Cholesterol')
cls_his.show()
```

A number of patients have considerable high colesterol. There is huge outlier in this distribtion

[15]:
```
#distribution of Cholesterol as per heart disease

cls = 'HeartDisease'
x = 'Cholesterol'
mrg = 'box'
hst = 'density'
cdm = {0:'#C147E9',1:'#F06292'}

cls_hds = px.histogram(data, x=x, color=cls, marginal=mrg, histnorm=hst,␣
 ↪color_discrete_map=cdm)
cls_hds.show()
```

[16]:
```
#percentage distrubtion of fasting blood sugar

fbs_counts = data['FastingBS'].value_counts()
labels = 'Negative', 'Positve'
explode = (0.1,0.1)

ax = plt.subplot()
ax.pie(fbs_counts, explode=explode, labels=labels, autopct='%1.1f%%',␣
 ↪shadow=True, startangle=90)
ax.axis('equal')
plt.show()
```



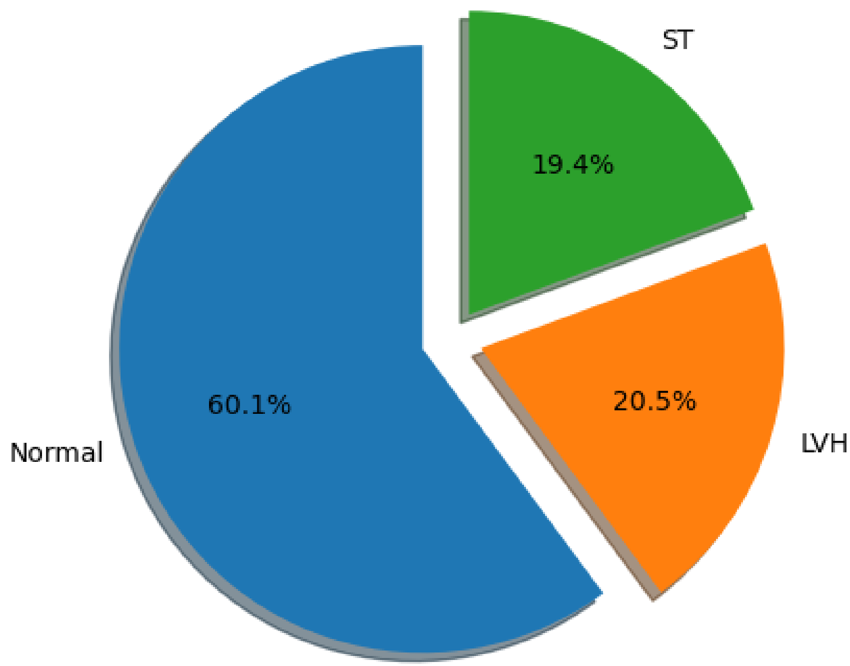
Only 23% of the patients have Fasting Blood Sugar

[17]:
```
#Fasting Blood Sugar type distribution on heart disease

x='FastingBS'
clr='HeartDisease'
cdm = {0:'#C147E9',1:'#F06292'}

fbs_chest_hd = px.histogram(data, x=x,color=clr, barmode='group',␣
 ↪color_discrete_map=cdm)
fbs_chest_hd.show()
```

Patients with Fasting Blood Sugar have a high chances of heart disease

[18]:
```
#percentage distrubtion of Resting ECG

fbs_counts = data['RestingECG'].value_counts()
labels = 'Normal', 'LVH', 'ST'
explode = (0.1,0.1,0.1)

ax = plt.subplot()
ax.pie(fbs_counts, explode=explode, labels=labels, autopct='%1.1f%%',␣
 ↪shadow=True, startangle=90)
ax.axis('equal')
```

```
plt.show()
```




```
[19]: #RestingECG Sugar type distribution on heart disease

x='RestingECG'
clr='HeartDisease'
cdm = {0:'#C147E9',1:'#F06292'}

fbs_chest_hd = px.histogram(data, x=x,color=clr, barmode='group',␣
  ↪color_discrete_map=cdm)
fbs_chest_hd.show()
```

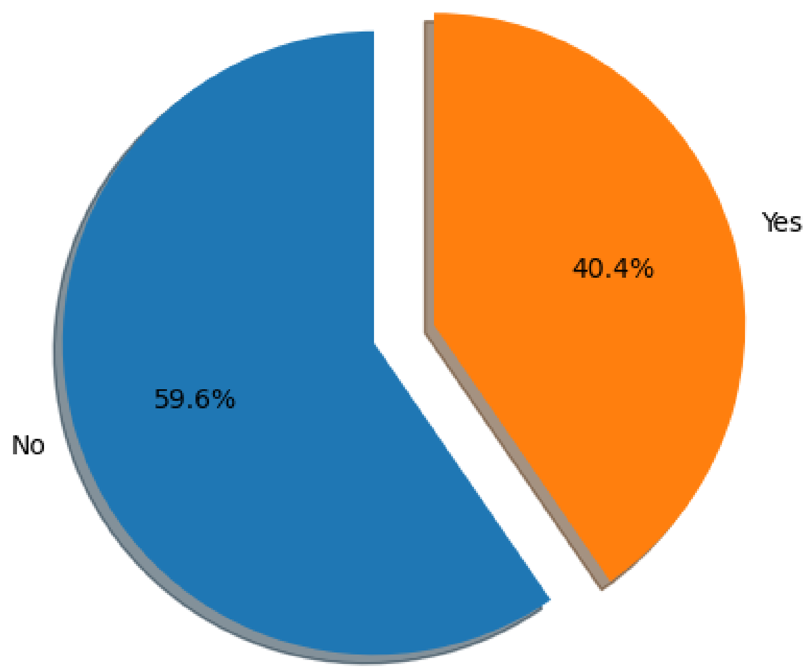
Have no clear information from this distribution.

```
[20]: #Checking the Distribution of MaxHR

mhr_his = px.histogram(data, x='MaxHR', marginal='box',␣
  ↪color_discrete_sequence=['#C147E9'] )
mhr_his.update_layout(title='Max HR')
mhr_his.show()
```

```
[21]: #distribution of MaxHR as per heart disease
```

```
cls = 'HeartDisease'
x = 'MaxHR'
mrg = 'box'
hst = 'density'
cdm = {0:'#C147E9',1:'#F06292'}

mhr_hds = px.histogram(data, x=x, color=cls, marginal=mrg, histnorm=hst,␣
 ↪color_discrete_map=cdm)
mhr_hds.show()
```

[22]:
```
#percentage distrubtion of Exercise Agina

exg_counts = data['ExerciseAngina'].value_counts()
labels = 'No', 'Yes'
explode = (0.1,0.1)

ax = plt.subplot()
ax.pie(exg_counts, explode=explode, labels=labels, autopct='%1.1f%%',␣
 ↪shadow=True, startangle=90)
ax.axis('equal')
plt.show()
```



[23]:
```
#ExerciseAngina type distribution on heart disease

x='ExerciseAngina'
clr='HeartDisease'
cdm = {0:'#C147E9',1:'#F06292'}

exg_chest_hd = px.histogram(data, x=x,color=clr, barmode='group',␣
 ↪color_discrete_map=cdm)
exg_chest_hd.show()
```

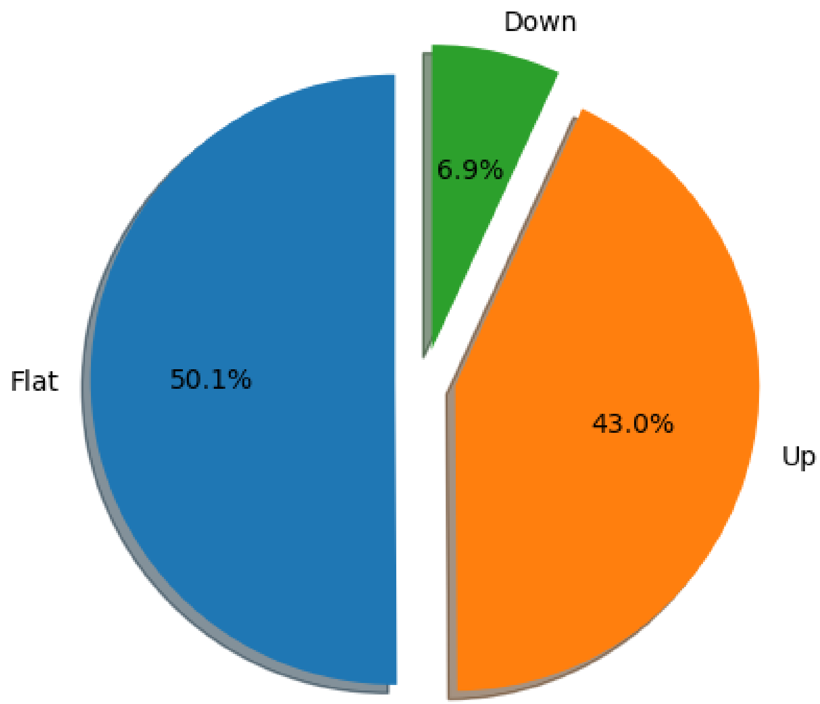
Patients with Angina are more likely to have heart disease, than those without.

[24]:
```
#Checking the Distribution of Oldpeak

olp_his = px.histogram(data, x='Oldpeak', marginal='box',␣
 ↪color_discrete_sequence=['#C147E9'] )
olp_his.update_layout(title='Oldpeak')
olp_his.show()
```

[25]:
```
#distribution of MaxHR as per heart disease

cls = 'HeartDisease'
x = 'Oldpeak'
mrg = 'box'
hst = 'density'
cdm = {0:'#C147E9',1:'#F06292'}

olp_hds = px.histogram(data, x=x, color=cls, marginal=mrg, histnorm=hst,␣
 ↪color_discrete_map=cdm)
olp_hds.show()
```

Patients with oldPeak of 1.0 and above, have higher chances of heart disease

[26]:
```
#percentage distrubtion of ST_Slope

sts_counts = data['ST_Slope'].value_counts()
labels = 'Flat', 'Up', 'Down'
explode = (0.1,0.1,0.1)

ax = plt.subplot()
ax.pie(sts_counts, explode=explode, labels=labels, autopct='%1.1f%%',␣
 ↪shadow=True, startangle=90)
ax.axis('equal')
plt.show()
```



[27]:
```
#ST_Slope type distribution on heart disease

x='ST_Slope'
clr='HeartDisease'
cdm = {0:'#C147E9',1:'#F06292'}

sts_hd = px.histogram(data, x=x,color=clr, barmode='group',␣
 ↪color_discrete_map=cdm)
sts_hd.show()
```

Patient with flat and down-slopping are more likely to have heart disease than patient with up-slopping

[28]:
```
#voerall data distribtion

data_columns = ['Age', 'RestingBP', 'Cholesterol', 'MaxHR', 'Oldpeak']
check = go.Figure()
for i in data_columns:
    check.add_trace(go.Box(y=data[i], name=i))
check.show()
```

Age and MaxHR are the only perfect candidate here without outliers. RestingBP, Cholesterol and Oldpeak have significant outliers but may be meaningful to the predictions based on the nature of the dataset. However, all the three (3) variables have some inputs with zero (0) which rendered them invalid because, the values cannot be zero (0). Therefore, all the rows with zero (0) data will be removed!!!.

DATA PRE-PROCESSING

[29]:
```
data = data[data['RestingBP'] != 0]
data = data[data['Cholesterol'] != 0]
#data = data[data['Oldpeak'] != 0]
```

[30]:
```
data
```

[30]:
```
     Age Sex ChestPainType  RestingBP  Cholesterol  FastingBS RestingECG  \
0     40   M           ATA        140          289          0     Normal
1     49   F           NAP        160          180          0     Normal
2     37   M           ATA        130          283          0         ST
3     48   F           ASY        138          214          0     Normal
4     54   M           NAP        150          195          0     Normal
..   …  ..           …        …          …        …        …
913   45   M            TA        110          264          0     Normal
914   68   M           ASY        144          193          1     Normal
915   57   M           ASY        130          131          0     Normal
916   57   F           ATA        130          236          0        LVH
917   38   M           NAP        138          175          0     Normal

     MaxHR ExerciseAngina  Oldpeak ST_Slope  HeartDisease
0      172              N      0.0       Up             0
1      156              N      1.0     Flat             1
2       98              N      0.0       Up             0
3      108              Y      1.5     Flat             1
4      122              N      0.0       Up             0
..     …            …    …      …           …
913    132              N      1.2     Flat             1
914    141              N      3.4     Flat             1
915    115              Y      1.2     Flat             1
916    174              N      0.0     Flat             1
917    173              N      0.0       Up             0

[746 rows x 12 columns]
```

Since morethan half of Oldpeak data have zero (0). Removing the values may significantly affect the performance of the machine learning. So it was left.

[31]:
```
#Chaning strings to numeric for Scaling

#for sex
sex_c = []

for value in data.Sex.values:
    if value == 'M':
```

```
        sex_c.append(1)
    else:
        sex_c.append(0)

data['Sex'] = sex_c

#for Chestpain
chest = []

for value in data.ChestPainType.values:
    if value == 'ATA':
        chest.append(1)
    elif value == 'TA':
        chest.append(2)
    elif value == 'NAP':
        chest.append(3)
    else:
        chest.append(4)

data['ChestPainType'] = chest

#restingECG
ecg = []

for value in data.RestingECG.values:
    if value == 'ST':
        ecg.append(1)
    elif value == 'LVH':
        ecg.append(2)
    else:
        ecg.append(3)

data['RestingECG'] = ecg

#for excercise agina
exg = []

for value in data.ExerciseAngina.values:
    if value == 'Y':
        exg.append(1)
    else:
        exg.append(0)

data['ExerciseAngina'] = exg

#for ST_Slope
slope = []
```

```
for value in data.ST_Slope.values:
    if value == 'Up':
        slope.append(1)
    elif value == 'Flat':
        slope.append(2)
    else:
        slope.append(3)

data['ST_Slope'] = slope
data
```

[31]:
```
     Age  Sex  ChestPainType  RestingBP  Cholesterol  FastingBS  RestingECG  \
0     40    1              1        140          289          0           3
1     49    0              3        160          180          0           3
2     37    1              1        130          283          0           1
3     48    0              4        138          214          0           3
4     54    1              3        150          195          0           3
..   ...  ...            ...        ...          ...        ...
913   45    1              2        110          264          0           3
914   68    1              4        144          193          1           3
915   57    1              4        130          131          0           3
916   57    0              1        130          236          0           2
917   38    1              3        138          175          0           3

     MaxHR  ExerciseAngina  Oldpeak  ST_Slope  HeartDisease
0      172               0      0.0         1             0
1      156               0      1.0         2             1
2       98               0      0.0         1             0
3      108               1      1.5         2             1
4      122               0      0.0         1             0
..     ...             ...      ...       ...
913    132               0      1.2         2             1
914    141               0      3.4         2             1
915    115               1      1.2         2             1
916    174               0      0.0         2             1
917    173               0      0.0         1             0

[746 rows x 12 columns]
```

[32]:
```
#declaring dependent and indepndent variables

X = data.iloc[:,:-1].values
y = data.iloc[:,-1].values
```

[33]:
```
#preprocessing with standardScaler
```

```
sc = StandardScaler()
X = sc.fit_transform(X)
```

[34]:
```
#splitting data into training and testing sets

X_train, X_test,  y_train, y_test = train_test_split(X,y, test_size=0.2,␣
↪random_state=42)
```

Machine Learning

[35]:
```
#training with K-Nearest Nieghboors
kn_classifier=KNeighborsClassifier(n_neighbors=5,metric='minkowski',p=2)
kn_classifier.fit(X_train,y_train)

#training with Decision Tree
dt_classifier = DecisionTreeClassifier()
dt_classifier.fit(X_train, y_train)

#training with Naive Bayes
nb_classifier=GaussianNB()
nb_classifier.fit(X_train, y_train)
```

[35]:
```
GaussianNB()
```

PERFORMANCE EVALUATION

[36]:
```
#Predictions Performance Scores

kn_score = kn_classifier.score(X_test, y_test)
dt_score = dt_classifier.score(X_test, y_test)
nb_score = nb_classifier.score(X_test, y_test)

print('---------Prediction Scores------')

print('K-Nearest Classifier Prediction Score is', kn_score*100,'%')
print('Decision Tree Classifier Prediction Score is', dt_score*100,'%')
print('Naive Bayes Prediction Score is', nb_score*100,'%')
```

```
---------Prediction Scores------
K-Nearest Classifier Prediction Score is 89.33333333333333 %
Decision Tree Classifier Prediction Score is 84.66666666666667 %
Naive Bayes Prediction Score is 86.66666666666667 %
```

All the algorithms have a very good performance of above 80% but K-Nearest has outperformed the rest with 4.0% and 2.7% respectively.

[37]:
```
#determining the precision,recall and f1-score
ykn = kn_classifier.predict(X_test)
ydt = dt_classifier.predict(X_test)
```

```python
ynb = nb_classifier.predict(X_test)

KN_report=classification_report(y_test,ykn)
DT_report=classification_report(y_test, ydt)
NB_report=classification_report(y_test,ynb)
```

[38]:
```python
print('K-Nearest Classifier Report:')
print(KN_report)
```

```
K-Nearest Classifier Report:
              precision    recall  f1-score   support

           0       0.88      0.90      0.89        71
           1       0.91      0.89      0.90        79

    accuracy                           0.89       150
   macro avg       0.89      0.89      0.89       150
weighted avg       0.89      0.89      0.89       150
```

[39]:
```python
print('Decision Tree Classifier Report:')
print(DT_report)
```

```
Decision Tree Classifier Report:
              precision    recall  f1-score   support

           0       0.81      0.89      0.85        71
           1       0.89      0.81      0.85        79

    accuracy                           0.85       150
   macro avg       0.85      0.85      0.85       150
weighted avg       0.85      0.85      0.85       150
```

[40]:
```python
print('Naive Bayes Classifier Report:')
print(NB_report)
```

```
Naive Bayes Classifier Report:
              precision    recall  f1-score   support

           0       0.84      0.89      0.86        71
           1       0.89      0.85      0.87        79

    accuracy                           0.87       150
   macro avg       0.87      0.87      0.87       150
weighted avg       0.87      0.87      0.87       150
```

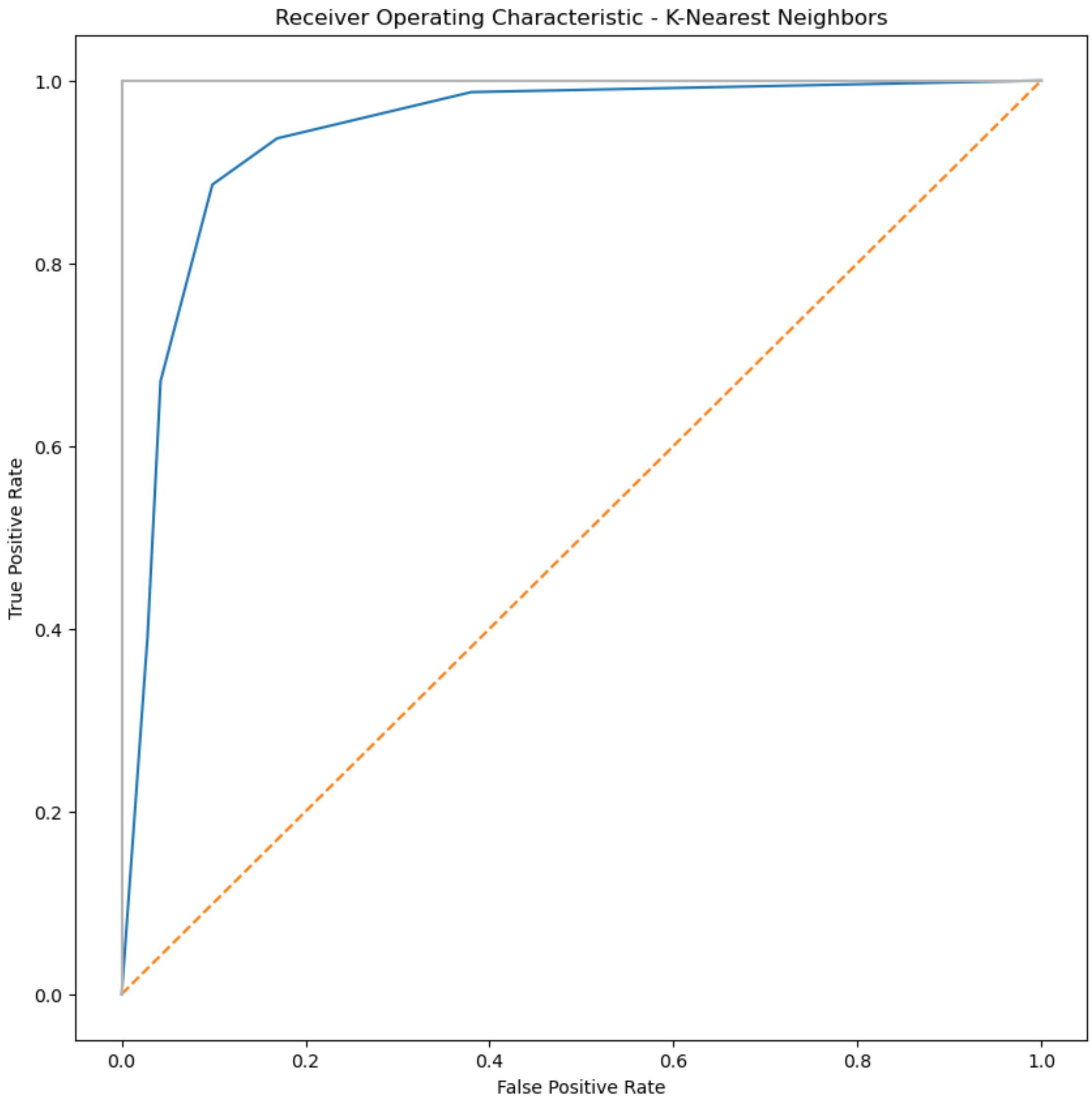
```
[41]: #ROC Curve
kn_score = kn_classifier.predict_proba(X_test)[:,1]
dt_score = dt_classifier.predict_proba(X_test)[:,1]
nb_score = nb_classifier.predict_proba(X_test)[:,1]

from sklearn.metrics import roc_curve, roc_auc_score

false_positive_rate1, true_positive_rate1, threshold1 = roc_curve(y_test,␣
 ↪kn_score)
false_positive_rate2, true_positive_rate2, threshold2 = roc_curve(y_test,␣
 ↪dt_score)
false_positive_rate3, true_positive_rate3, threshold3 = roc_curve(y_test,␣
 ↪nb_score)

print('roc_auc_score for K-Nearest Neighbors: ', roc_auc_score(y_test,␣
 ↪kn_score))
print('roc_auc_score for DecisionTree: ', roc_auc_score(y_test, dt_score))
print('roc_auc_score for Naive Bayes: ', roc_auc_score(y_test, nb_score))
```

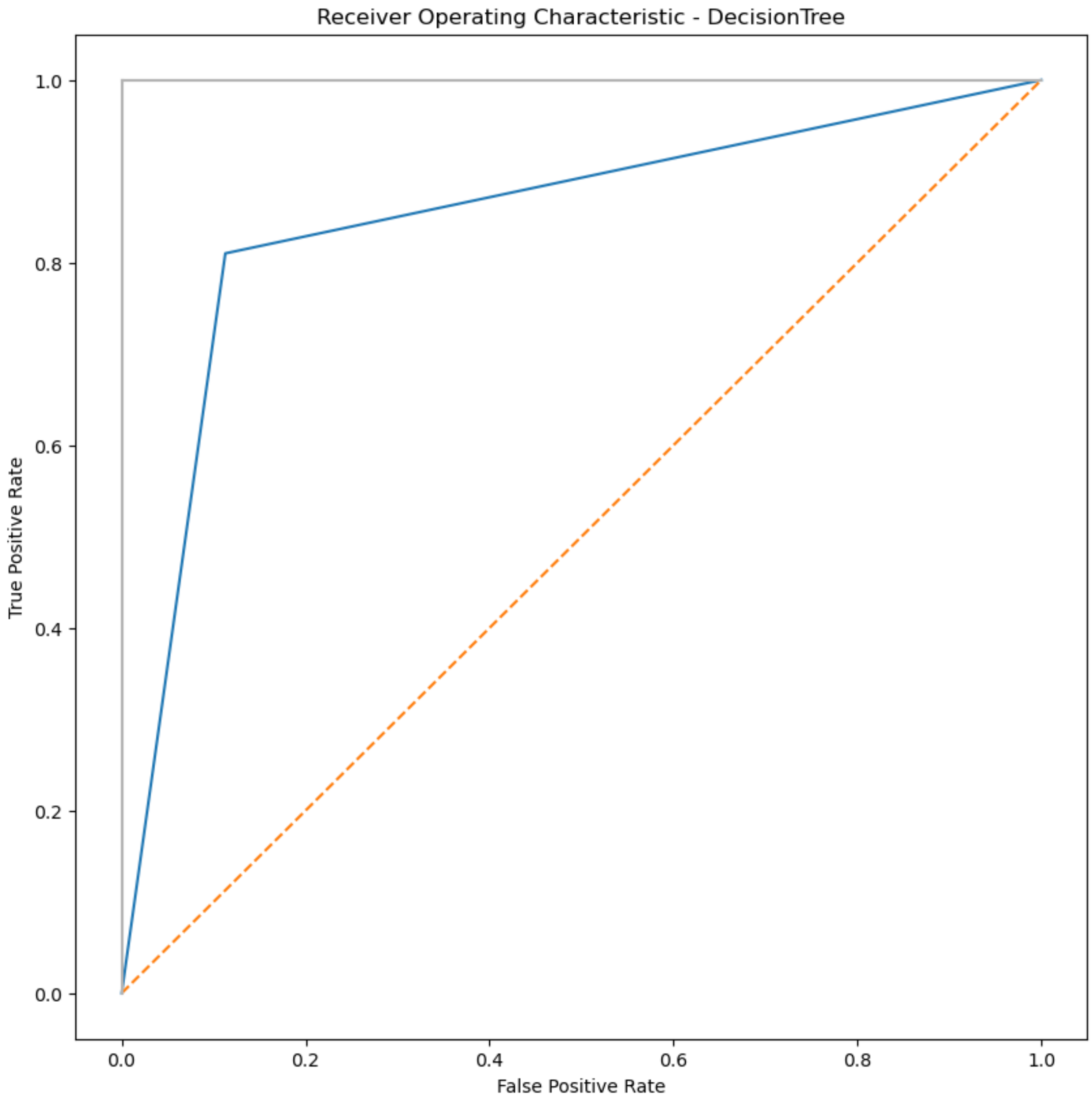
```
roc_auc_score for K-Nearest Neighbors:  0.9400962738456053
roc_auc_score for DecisionTree:  0.8487252629702264
roc_auc_score for Naive Bayes:  0.9424139775361027
```

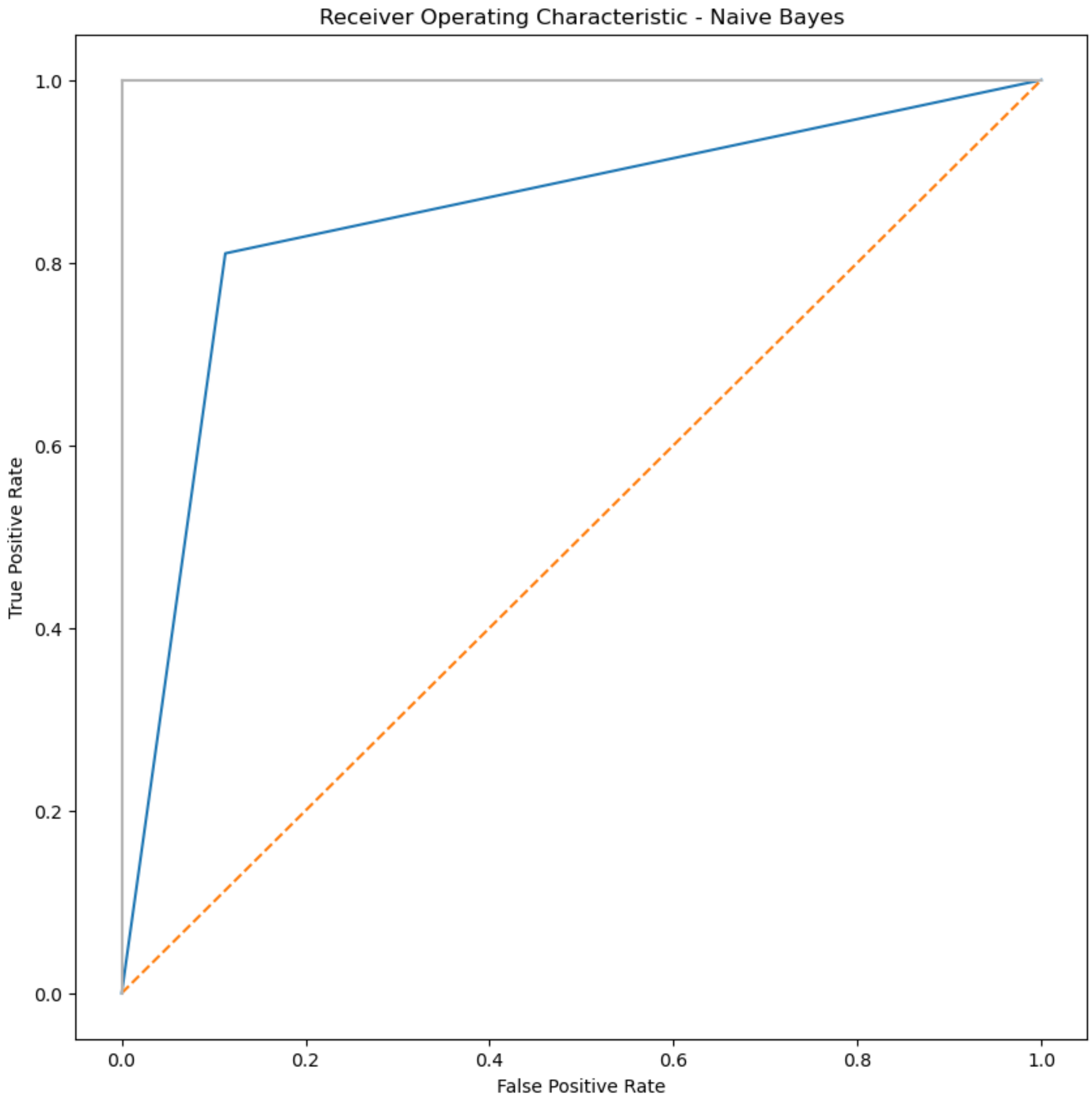
KNN and NB have similar ROC Score.

```
[42]: plt.subplots(1, figsize=(10,10))
plt.title('Receiver Operating Characteristic - K-Nearest Neighbors')
plt.plot(false_positive_rate1, true_positive_rate1)
plt.plot([0, 1], ls="--")
plt.plot([0, 0], [1, 0] , c=".7"), plt.plot([1, 1] , c=".7")
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()

plt.subplots(1, figsize=(10,10))
plt.title('Receiver Operating Characteristic - DecisionTree')
plt.plot(false_positive_rate2, true_positive_rate2)
plt.plot([0, 1], ls="--")
plt.plot([0, 0], [1, 0] , c=".7"), plt.plot([1, 1] , c=".7")
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()

plt.subplots(1, figsize=(10,10))
plt.title('Receiver Operating Characteristic - Naive Bayes')
plt.plot(false_positive_rate2, true_positive_rate2)
plt.plot([0, 1], ls="--")
plt.plot([0, 0], [1, 0] , c=".7"), plt.plot([1, 1] , c=".7")
```

```python
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```




Receiver Operating Characteristic - DecisionTree
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
0.0
0.2
0.4
0.6
0.8
1.0



All the algorithms have a very strong positive rates. Though KNN has outperformed the rest.