```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.graph_objects as go
import plotly.express as px
plt.style.use('seaborn')

from collections import Counter
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split,GridSearchCV
from sklearn.metrics import
confusion_matrix,accuracy_score,roc_curve,roc_auc_score,classification_report,f1_score
from sklearn.linear_model import LogisticRegression
from sklearn.naive_bayes import GaussianNB
from xgboost import XGBClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.svm import SVC
from mlxtend.classifier import StackingCVClassifier
import itertools
from sklearn.dummy import DummyClassifier
from sklearn import metrics

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

df.head()
```

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope
0	63	1	3	145	233	1	0	150	0	2.3	0
1	37	1	2	130	250	0	1	187	0	3.5	0
2	41	0	1	130	204	0	0	172	0	1.4	2
3	56	1	1	120	236	0	1	178	0	0.8	2
4	57	0	0	120	354	0	1	163	1	0.6	2

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

df.describe()

	age	sex	cp	trestbps	chol	fbs
count	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000
mean	54.366337	0.683168	0.966997	131.623762	246.264026	0.148515
std	9.082101	0.466011	1.032052	17.538143	51.830751	0.356198
min	29.000000	0.000000	0.000000	94.000000	126.000000	0.000000
25%	47.500000	0.000000	0.000000	120.000000	211.000000	0.000000
50%	55.000000	1.000000	1.000000	130.000000	240.000000	0.000000
75%	61.000000	1.000000	2.000000	140.000000	274.500000	0.000000
max	77.000000	1.000000	3.000000	200.000000	564.000000	1.000000

	restecg	thalach	exang	oldpeak	slope	ca
count	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000
mean	0.528053	149.646865	0.326733	1.039604	1.399340	0.729373
std	0.525860	22.905161	0.469794	1.161075	0.616226	1.022606
min	0.000000	71.000000	0.000000	0.000000	0.000000	0.000000
25%	0.000000	133.500000	0.000000	0.000000	1.000000	0.000000
50%	1.000000	153.000000	0.000000	0.800000	1.000000	0.000000
75%	1.000000	166.000000	1.000000	1.600000	2.000000	1.000000
max	2.000000	202.000000	1.000000	6.200000	2.000000	4.000000

	thal	target
count	303.000000	303.000000
mean	2.313531	0.544554
std	0.612277	0.498835
min	0.000000	0.000000
25%	2.000000	0.000000
50%	2.000000	1.000000
75%	3.000000	1.000000
max	3.000000	1.000000

df.shape

(303, 14)

Variable Descriptions

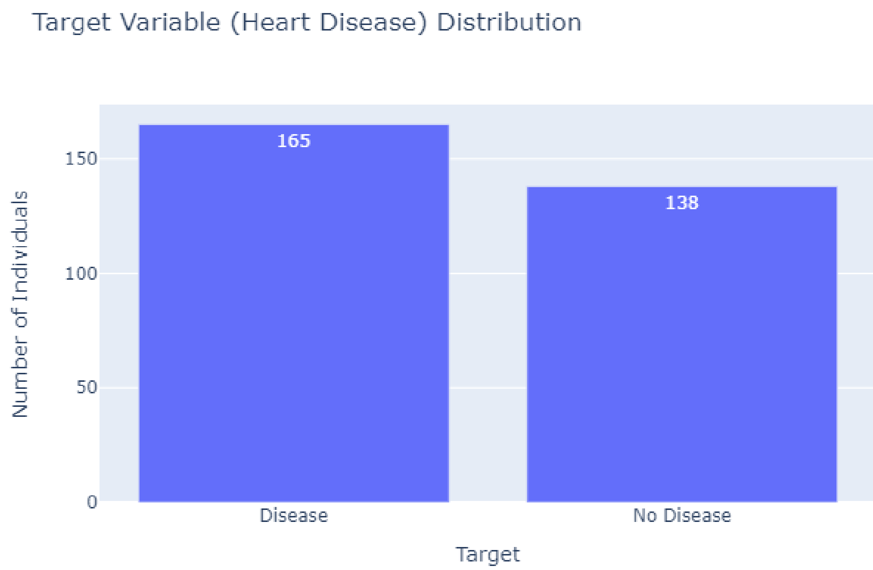
- age: age in years
- sex: sex (1 = male; 0 = female)
- cp: chest pain type - Value 1: typical angina, Value 2: atypical angina, Value 3: non-anginal pain, Value 4: asymptomatic
- trestbps: resting blood pressure (in mm Hg on admission to the hospital)
- chol: serum cholestoral in mg/dl

- fbs: (fasting blood sugar > 120 mg/dl) (1 = true; 0 = false)
- restecg: resting electrocardiographic results- Value 0: normal, Value 1: having ST-T wave abnormality (T wave inversions and/or ST elevation or depression of > 0.05 mV), Value 2: showing probable or definite left ventricular hypertrophy by Estes' criteria
- thalach: maximum heart rate achieved
- exang: exercise induced angina (1 = yes; 0 = no)
- oldpeak = ST depression induced by exercise relative to rest
- slope: the slope of the peak exercise ST segment- Value 1: upsloping, Value 2: flat, Value 3: downsloping
- ca: number of major vessels (0-3) colored by flourosopy
- thal: 3 = normal; 6 = fixed defect; 7 = reversable defect
- target: 1 = disease, 0 = no disease

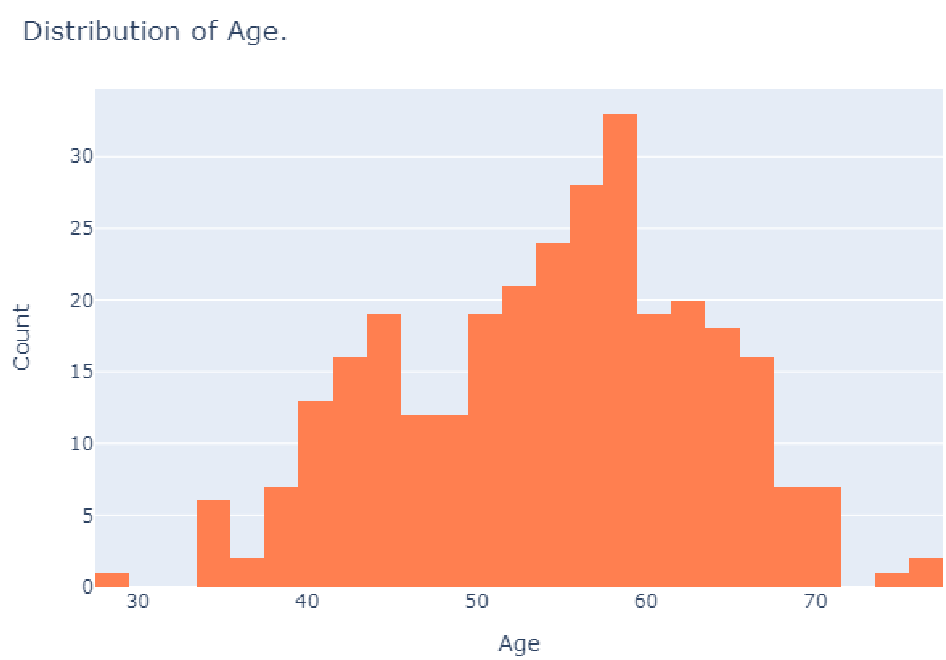
Variable Types

- Continuous - age, trestbps, chol, thalach, oldpeak
- Binary - sex, fbs, exang, target
- Categorical - cp, restecg, slope, ca, thal

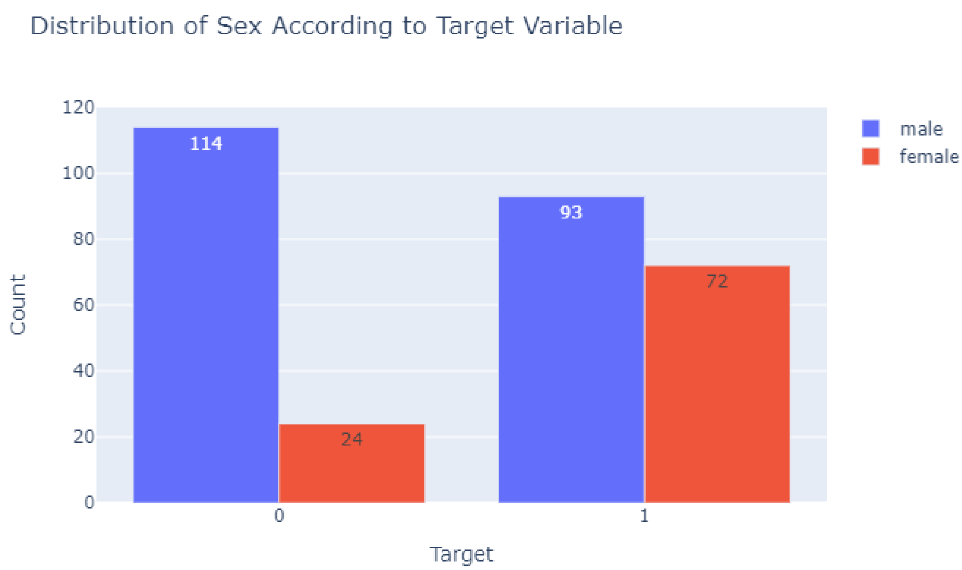
```
y = df.target.value_counts()
x = ['Disease','No Disease']

title = go.layout.Title(text='Target Variable (Heart Disease) Distribution')
layout = go.Layout(title=title)
data = go.Bar(x=x,y=y,text=y,textposition='auto')
fig = go.Figure(data=[data],layout=layout)

fig.update_xaxes(title_text='Target')
fig.update_yaxes(title_text='Number of Individuals')
fig.show()
```




```
fig = px.histogram(df,x='age',color_discrete_sequence=['coral'])
fig.update_xaxes(title_text='Age')
fig.update_yaxes(title_text='Count')
fig.update_layout(title_text='Distribution of Age.')

fig.show()
```

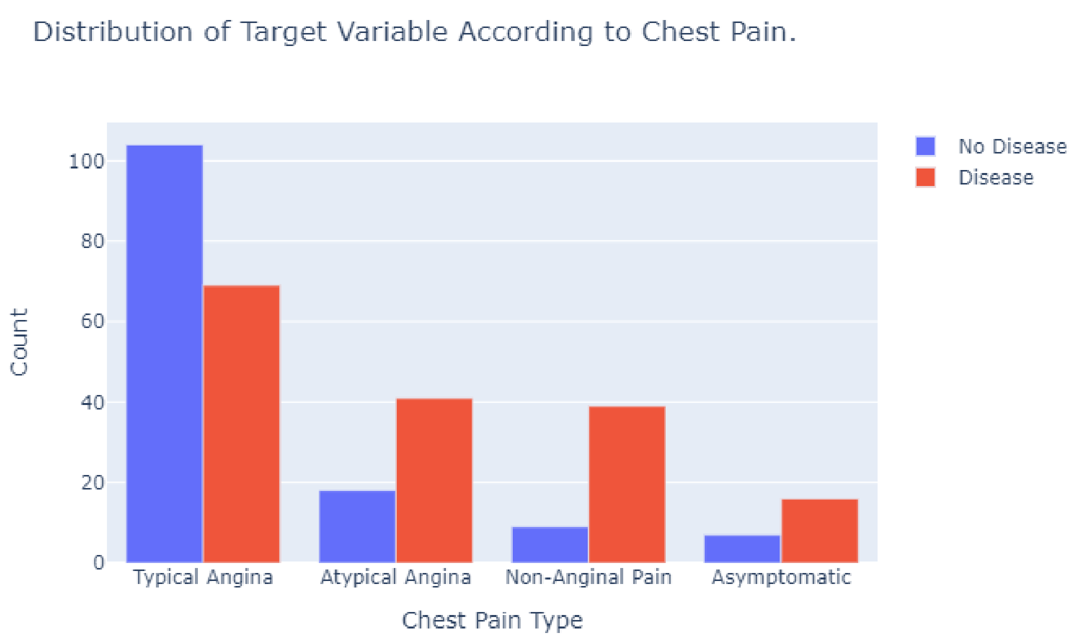


```
female = df[df['sex']==0]
female_count = female.target.value_counts()

male = df[df['sex']==1]
male_count = male.target.value_counts()


male_data =
go.Bar(name='male',x=male_count.index,y=male_count,text=male_count,textposition='auto')
female_data =
go.Bar(name='female',x=female_count.index,y=female_count,text=female_count,textposition='
auto')

fig = go.Figure(data=[male_data,female_data])

fig.update_xaxes(title_text='Target')
fig.update_yaxes(title_text='Count')
fig.update_layout(title_text='Distribution of Sex According to Target
Variable',barmode='group')
fig.show()
```




```
cp = ['Typical Angina','Atypical Angina','Non-Anginal Pain','Asymptomatic']
```

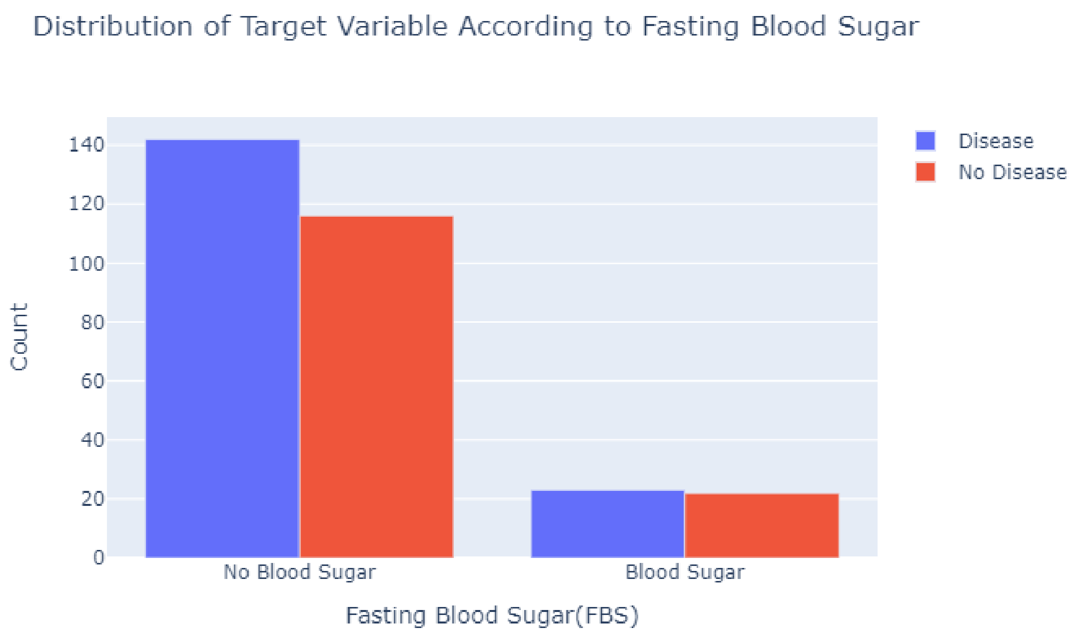
```
cp_y0 = df[df['target']==0].cp.value_counts()
cp_y1 = df[df['target']==1].cp.value_counts()

non_disease_data = go.Bar(name='No Disease',x=cp,y=cp_y0)
disease_data = go.Bar(name='Disease',x=cp,y=cp_y1)

fig = go.Figure(data=[non_disease_data,disease_data])
fig.update_xaxes(title_text='Chest Pain Type')
fig.update_yaxes(title_text='Count')
fig.update_layout(title_text='Distribution of Target Variable According to Chest
Pain.',barmode='group')

fig.show()
```



Fasting blood sugar (FBS) is a diabetes indicator with FBS >120 mg/d is considered diabetic (True). Here, we see that the number for class True, is lower compared to class False. However, if we look closely, there are higher number of heart disease patient without diabetes. This provide an indication that fbs might not be a strong feature differentiating between heart disease an non-disease patient.

```
disease_values = df[df['target']==1].fbs.value_counts()
no_disease_values = df[df['target']==0].fbs.value_counts()
```

```
x = ['No Blood Sugar','Blood Sugar']

disease_data = go.Bar(name='Disease',x=x,y=disease_values,textposition='auto')
no_disease_data = go.Bar(name='No Disease',x=x,y=no_disease_values,textposition='auto')

fig = go.Figure(data=[disease_data,no_disease_data])
fig.update_layout(title_text='Distribution of Target Variable According to Fasting Blood Sugar',barmode='group')
fig.update_xaxes(title_text='Fasting Blood Sugar(FBS)')
fig.update_yaxes(title_text='Count')

fig.show()
```




```
df.thal.value_counts()
```

```
2    166
3    117
1     18
0      2
Name: thal, dtype: int64
```

```
df[df['thal']==0] = np.NaN
```

```
df.ca.value_counts()
```

```
0.0    173
1.0     65
2.0     38
3.0     20
4.0      5
Name: ca, dtype: int64
```

```
df[df['ca']==4] = np.NaN
```

```
df = df.fillna(df.median())
```

```
# Checking For Outliers.
df.plot(kind='box',subplots=True,sharex=False,sharey=False,layout=(2,7),figsize=(20,15))
```

```
age           AxesSubplot(0.125,0.536818;0.0945122x0.343182)
sex        AxesSubplot(0.238415,0.536818;0.0945122x0.343182)
cp         AxesSubplot(0.351829,0.536818;0.0945122x0.343182)
trestbps   AxesSubplot(0.465244,0.536818;0.0945122x0.343182)
chol       AxesSubplot(0.578659,0.536818;0.0945122x0.343182)
fbs        AxesSubplot(0.692073,0.536818;0.0945122x0.343182)
restecg    AxesSubplot(0.805488,0.536818;0.0945122x0.343182)
thalach          AxesSubplot(0.125,0.125;0.0945122x0.343182)
exang         AxesSubplot(0.238415,0.125;0.0945122x0.343182)
oldpeak       AxesSubplot(0.351829,0.125;0.0945122x0.343182)
slope         AxesSubplot(0.465244,0.125;0.0945122x0.343182)
ca            AxesSubplot(0.578659,0.125;0.0945122x0.343182)
thal          AxesSubplot(0.692073,0.125;0.0945122x0.343182)
target        AxesSubplot(0.805488,0.125;0.0945122x0.343182)
dtype: object
```

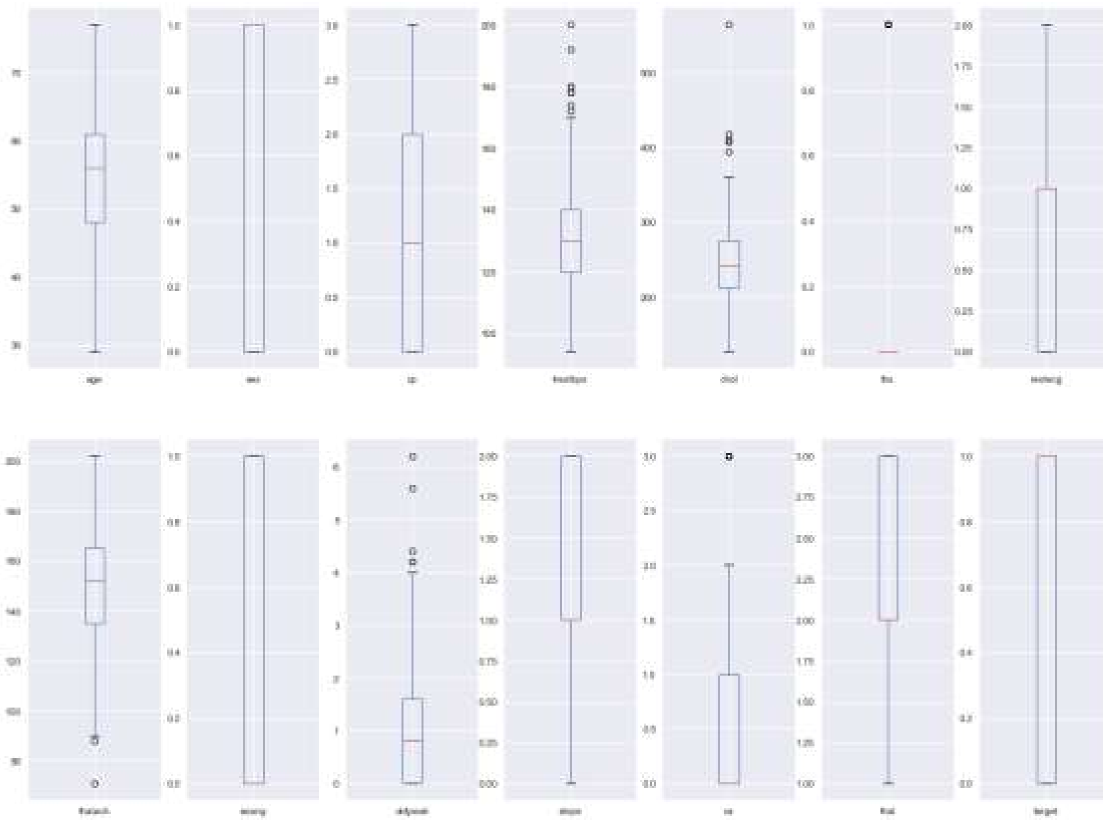
From this visualization we can see that chol has an extreme value which we will replace with its median value.

```
df.chol.describe()
```

```
count    303.000000
mean     247.047855
std       51.375873
min      126.000000
25%      212.000000
50%      242.500000
75%      274.500000
max      564.000000
Name: chol, dtype: float64
```

```
df.loc[df['chol']==df.chol.max(),'chol'] = df.chol.median()

df.chol.describe()
```

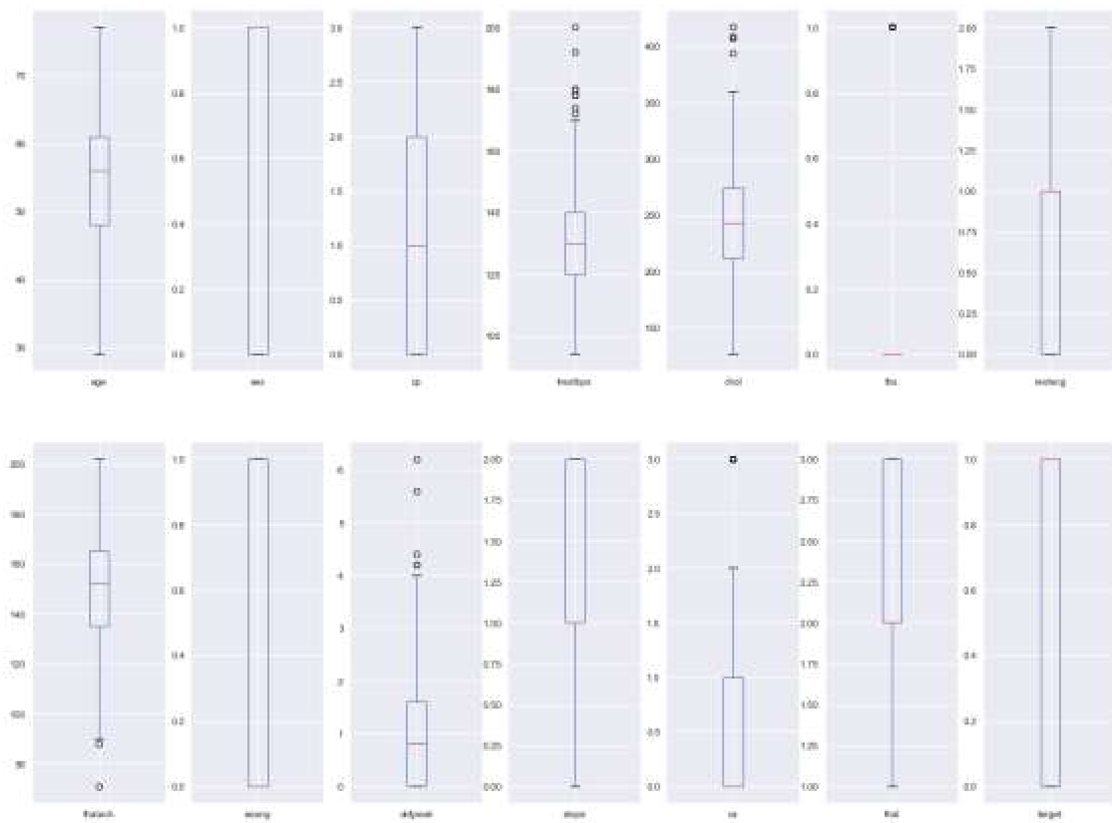
```
count    303.000000
mean     245.986799
std       48.018482
min      126.000000
25%      212.000000
```



```
50%      242.500000
75%      274.000000
max      417.000000
Name: chol, dtype: float64
```

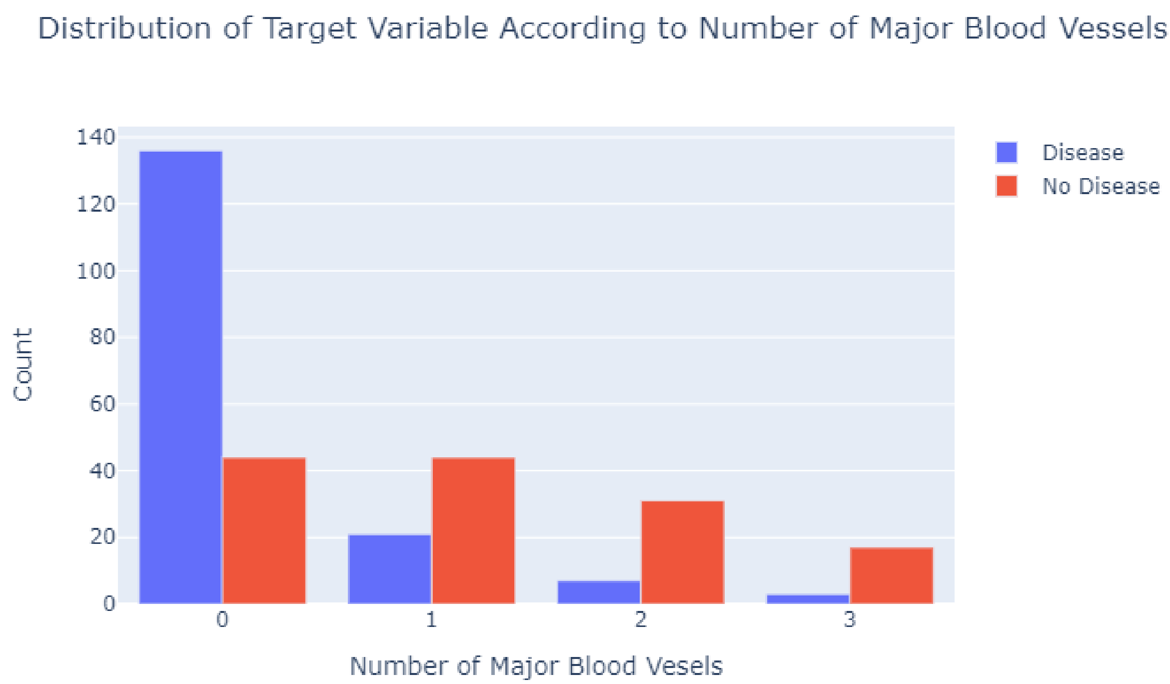
```
# Checking For Outliers.
df.plot(kind='box',subplots=True,sharex=False,sharey=False,layout=(2,7),figsize=(20,15))
```

```
age           AxesSubplot(0.125,0.536818;0.0945122x0.343182)
sex        AxesSubplot(0.238415,0.536818;0.0945122x0.343182)
cp         AxesSubplot(0.351829,0.536818;0.0945122x0.343182)
trestbps    AxesSubplot(0.465244,0.536818;0.0945122x0.343182)
chol        AxesSubplot(0.578659,0.536818;0.0945122x0.343182)
fbs         AxesSubplot(0.692073,0.536818;0.0945122x0.343182)
restecg     AxesSubplot(0.805488,0.536818;0.0945122x0.343182)
thalach          AxesSubplot(0.125,0.125;0.0945122x0.343182)
exang         AxesSubplot(0.238415,0.125;0.0945122x0.343182)
oldpeak       AxesSubplot(0.351829,0.125;0.0945122x0.343182)
slope         AxesSubplot(0.465244,0.125;0.0945122x0.343182)
ca            AxesSubplot(0.578659,0.125;0.0945122x0.343182)
thal          AxesSubplot(0.692073,0.125;0.0945122x0.343182)
target        AxesSubplot(0.805488,0.125;0.0945122x0.343182)
dtype: object
```



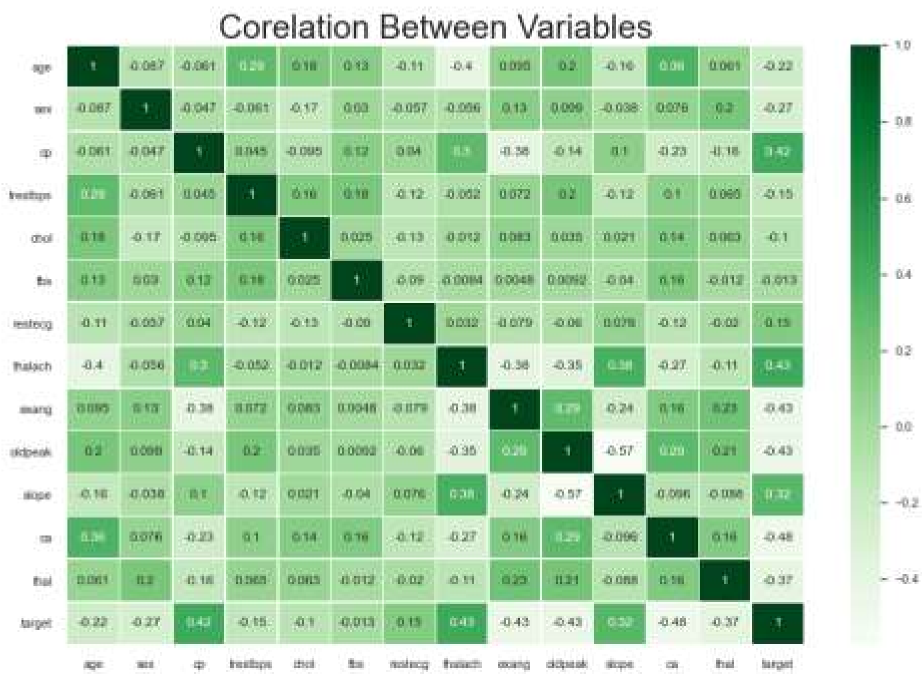
```
ca = ['0','1','2','3']
```

```
ca_y0 = df[df['target']==0].ca.value_counts()
ca_y1 = df[df['target']==1].ca.value_counts()

no_disease_data = go.Bar(name='No Disease',x=ca,y=ca_y0)
disease_data = go.Bar(name='Disease',x=ca,y=ca_y1)

fig = go.Figure(data=[disease_data,no_disease_data])
fig.update_xaxes(title_text='Number of Major Blood Vesels')
fig.update_yaxes(title_text='Count')
fig.update_layout(title_text='Distribution of Target Variable According to Number of Major
Blood Vessels',barmode='group')
fig.show()
```



Multicollinearity

```
sns.set(style='dark')
plt.figure(figsize=(15,10))
sns.heatmap(df.corr(),annot=True,linewidths=0.5,cmap='Greens')
plt.title('Corelation Between Variables',fontsize=30)
plt.show()
```




```
y = df['target']
X = df.drop('target',axis=1)
X_train,X_test,y_train,y_test = train_test_split(X,y,test_size=0.2,random_state=0)
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

```
print(X_train.shape,y_train.shape)
print(X_test.shape,y_test.shape)
```

```
(242, 13) (242,)
(61, 13) (61,)
```

Baseline Prediction

```
dummy_cls = DummyClassifier(strategy='stratified')
dummy_cls.fit(X_train,y_train)
acc = dummy_cls.score(X_test,y_test)
print("Baseline Accuracy is :",acc)
```

Baseline Accuracy is : 0.4098360655737705

```
def calculateScores(y_pred,y_test=y_test):
    acc = metrics.accuracy_score(y_test,y_pred)
    f1 = metrics.f1_score(y_test,y_pred)
    conf = confusion_matrix(y_test,y_pred)
    report = classification_report(y_test,y_pred)
    return acc,f1,conf,report

def printScores(acc,f1,conf,report):
    print("Test Accuracy Score :\n",acc,"\n")
    print("Test f1 Score :\n",f1,"\n")
    print("Confusion Matrix :\n",conf,"\n")
    print("Classification Report :\n",report,"\n")
```

Logistic Regression

```
lr = LogisticRegression()
lr.fit(X_train,y_train)
y_pred_lr = lr.predict(X_test)

acc_lr,f1_lr,conf_lr,report_lr = calculateScores(y_pred_lr)

print Scores(acc_lr,f1_lr,conf_lr,report_lr)
```

```
Test Accuracy Score :
 0.8852459016393442

Test f1 Score :
 0.8985507246376812

Confusion Matrix :
 [[23  4]
 [ 3 31]]
Classification Report:
              precision    recall f1-score   support

         0.0       0.88      0.85      0.87        27
         1.0       0.89      0.91      0.90        34

    accuracy                           0.89        61
   macro avg       0.89      0.88      0.88        61

weighted avg       0.89      0.89      0.88        61
```

K-Nearest Neighbours Classifier

```
knn = KNeighborsClassifier()
knn.fit(X_train,y_train)

y_pred_knn = knn.predict(X_test)

acc_knn,f1_knn,conf_knn,report_knn = calculateScores(y_pred_knn)

print Scores(acc_knn,f1_knn,conf_knn,report_knn)
```

```
Test Accuracy Score:
 0.819672131147541

Test f1 Score:
 0.8405797101449276

Confusion Matrix:
 [[21 6]
 [ 5 29]]

Classification Report:
              precision    recall  f1-score   support

         0.0       0.81      0.78      0.79        27
         1.0       0.83      0.85      0.84        34

    accuracy                           0.82        61
   macro avg       0.82      0.82      0.82        61
weighted avg       0.82      0.82      0.82        61
```

Decision Tree

```
des = DecisionTreeClassifier()
des.fit(X_train,y_train)

y_pred_des = des.predict(X_test)

acc_des,f1_des,conf_des,report_des = calculateScores(y_pred_des)

printScores(acc_des,f1_des,conf_des,report_des)
```

```
Test Accuracy Score:
 0.7868852459016393

Test f1 Score:
 0.7999999999999999
```

```
Confusion Matrix:
 [[22 5]
 [ 8 26]]

Classification Report:
              precision    recall f1-score   support

         0.0       0.73      0.81      0.77        27
         1.0       0.84      0.76      0.80        34

    accuracy                           0.79        61
   macro avg       0.79      0.79      0.79        61
weighted avg       0.79      0.79      0.79        61
```

```
ran = RandomForestClassifier()
ran.fit(X_train,y_train)

y_pred_ran = ran.predict(X_test)

acc_ran,f1_ran,conf_ran,report_ran = calculateScores(y_pred_ran)

printScores(acc_ran,f1_ran,conf_ran,report_ran)
```

```
Test Accuracy Score:
 0.8360655737704918

Test f1 Score:
 0.8571428571428571

Confusion Matrix :
 [[21  6]
 [ 4 30]]

Classification Report :
              precision    recall  f1-score   support

         0.0       0.84      0.78      0.81        27
         1.0       0.83      0.88      0.86        34

    accuracy                           0.84        61
   macro avg       0.84      0.83      0.83        61
weighted avg       0.84      0.84      0.84        61
```

Extreme Gradient Boosting

```
xgb = XGBClassifier(use_label_encoder=False,eval_metric='error')
xgb.fit(X_train,y_train)

y_pred_xgb = xgb.predict(X_test)

acc_xgb,f1_xgb,conf_xgb,report_xgb = calculateScores(y_pred_xgb)

printScores(acc_xgb,f1_xgb,conf_xgb,report_xgb)
```

```
Test Accuracy Score :
 0.819672131147541

Test f1 Score :
 0.8358208955223881

Confusion Matrix :
 [[22  5]
 [ 6 28]]

Classification Report :
              precision    recall  f1-score   support

         0.0       0.79      0.81      0.80        27
         1.0       0.85      0.82      0.84        34

    accuracy                           0.82        61
   macro avg       0.82      0.82      0.82        61
weighted avg       0.82      0.82      0.82        61
```

Naive Bayes

```
nb = GaussianNB()
nb.fit(X_train,y_train)
y_pred_nb = nb.predict(X_test)

acc_nb,f1_nb,conf_nb,report_nb = calculateScores(y_pred_nb)

printScores(acc_nb,f1_nb,conf_nb,report_nb)
```

```
Test Accuracy Score :
 0.8524590163934426

Test f1 Score :
 0.8732394366197184
```

```
Confusion Matrix:
[[21  6]
 [ 3 31]]

Classification Report:
              precision    recall  f1-score   support
         0.0       0.88      0.78      0.82        27
         1.0       0.84      0.91      0.87        34
    accuracy                           0.85        61
   macro avg       0.86      0.84      0.85        61
weighted avg       0.85      0.85      0.85        61
```

Support Vector Classifier

```
svc = SVC()
svc.fit(X_train,y_train)

y_pred_svc = svc.predict(X_test)

acc_svc,f1_svc,conf_svc,report_svc = calculateScores(y_pred_svc)

printScores(acc_svc,f1_svc,conf_svc,report_svc)
```

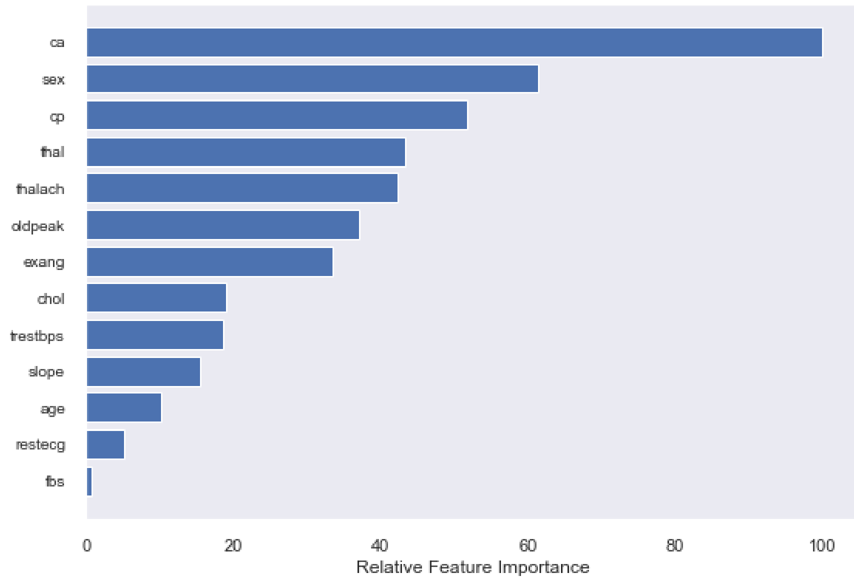
```
Test Accuracy Score:
 0.8852459016393442


Test f1 Score:
 0.9014084507042254

Confusion Matrix :
 [[22  5]
 [ 2 32]]

Classification Report :
              precision    recall  f1-score   support
         0.0       0.92      0.81      0.86        27
         1.0       0.86      0.94      0.90        34
    accuracy                           0.89        61
   macro avg       0.89      0.88      0.88        61
weighted avg       0.89      0.89      0.88        61
```

```
model_df = pd.DataFrame({'model':['Logistic Regression','Random Forest','Extreme Gradient Boost','K-Nearest Neighbour','Decision Tree','Naive Bayes','Support Vector Classifier'],

'Accuracy':[acc_lr,acc_ran,acc_xgb,acc_knn,acc_des,acc_nb,acc_svc]})
```

model_df

	model	Accuracy
0	Logistic Regression	0.885246
1	Random Forest	0.836066
2	Extreme Gradient Boost	0.819672
3	K-Nearest Neighbour	0.819672
4	Decision Tree	0.786885
5	Naive Bayes	0.852459
6	Support Vector Classifier	0.885246

```
feature_importance = abs(lr.coef_[0])
feature_importance = 100.0 *(feature_importance/feature_importance.max())
sorted_idx = np.argsort(feature_importance)
pos = np.arange(sorted_idx.shape[0]) + 0.5
featfig = plt.figure()
featax = featfig.add_subplot(1,1,1)
featax.barh(pos,feature_importance[sorted_idx],align='center')
featax.set_yticks(pos)
featax.set_yticklabels(np.array(X.columns)[sorted_idx],fontsize=10)
featax.set_xlabel('Relative Feature Importance')
plt.tight_layout()
plt.show()
```



variable ca was the most influential in predicting whether an individual had heart disease or not. Variable ca referred the the number of major vessels (0–3) colored by a flourosopy. The lower the number of major blood vessels, reduces the amount of blood flowing to the heart, increasing the presence of heart disease.

Ensembling

```
scv = StackingCVClassifier(classifiers=[lr,nb,svc],meta_classifier=nb)
scv.fit(X_train,y_train)
y_pred_scv = scv.predict(X_test)

acc_scv,f1_scv,conf_scv,report_scv = calculateScores(y_pred_scv)

printScores(acc_scv,f1_scv,conf_scv,report_scv)
```

Test Accuracy Score :
 0.8852459016393442

Test f1 Score :
 0.8985507246376812

Confusion Matrix:
 [[23 4]
 [3 31]]

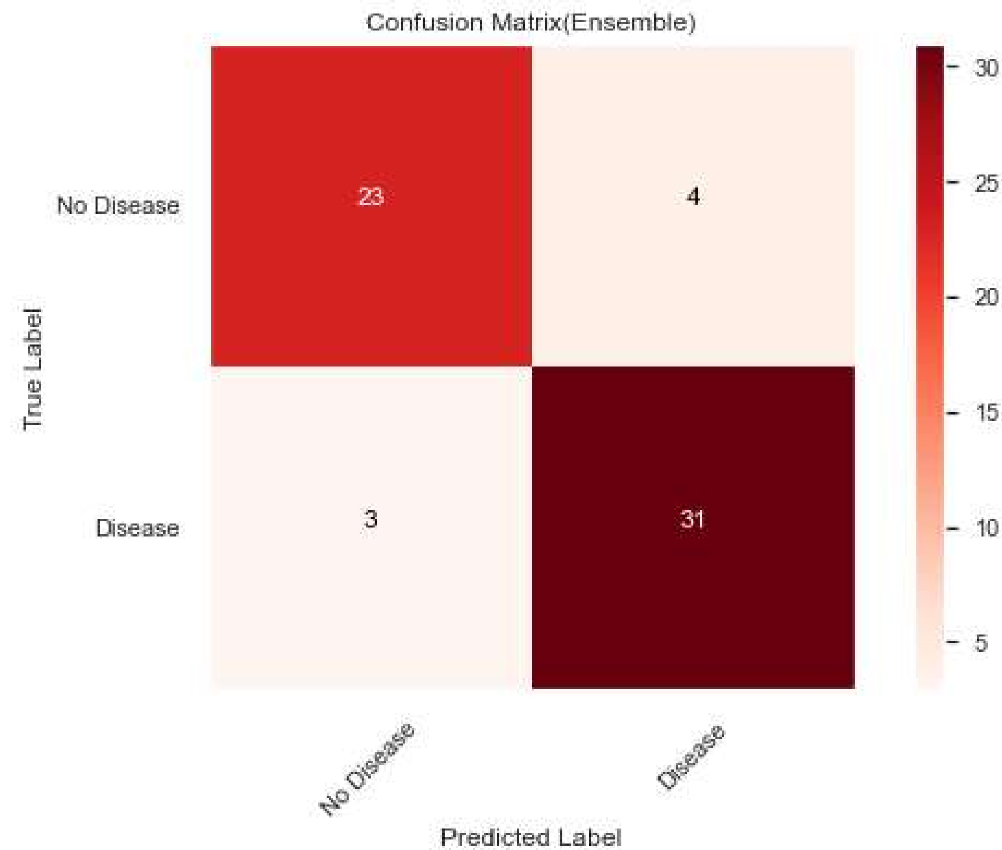
Classification Report:

	precision	recall	f1-score	support
0.0	0.88	0.85	0.87	27
1.0	0.89	0.91	0.90	34

```
   accuracy                           0.89        61
  macro avg       0.89       0.88       0.88        61
weighted avg       0.89       0.89       0.88        61
```

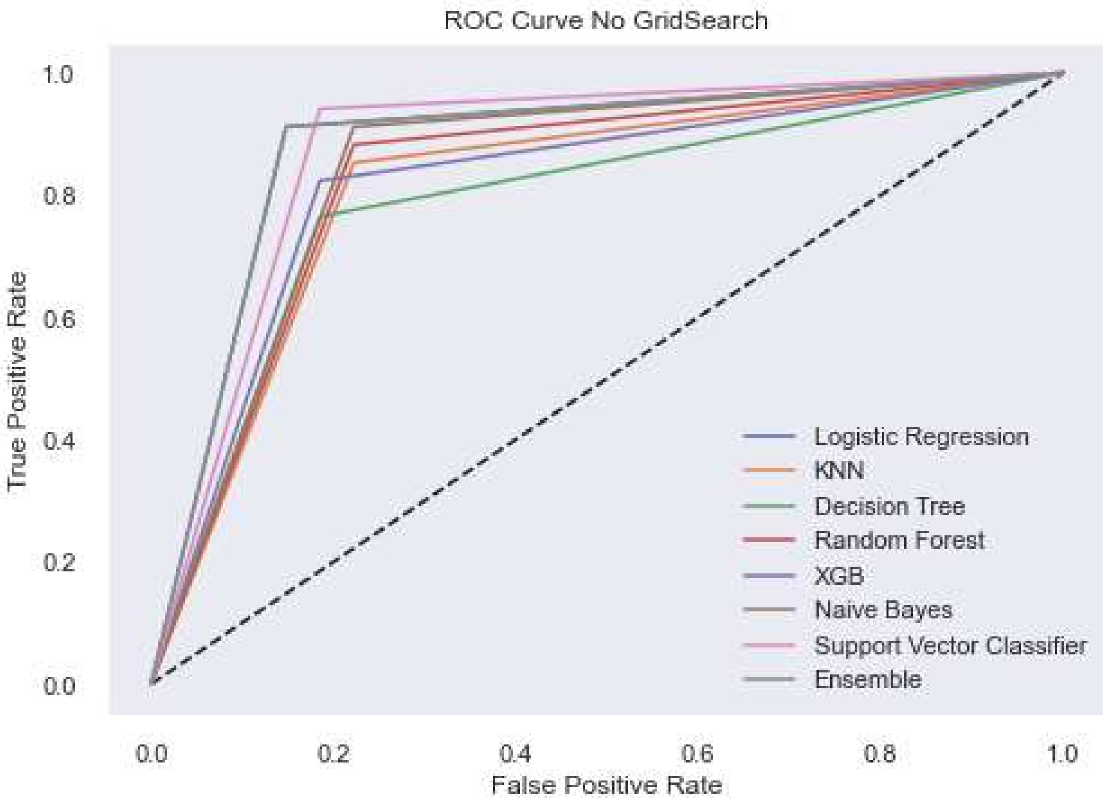
```
classes = ['No Disease','Disease']

def plot_confusion_matrix(cm,classes,normalize=False,title='Confusion
Matrix(Ensemble)',cmap=plt.cm.Reds):
    if normalize:
        cm = cm.astype('float')/cm.sum(axis=1)[:,np.newaxis]
        print("Normalized Confusion Matrix")
    else:
        print("Confusion Matrix, without Normalization")

plt.imshow(cm,interpolation='nearest',cmap=cmap)
    plt.title(title)
    plt.colorbar()
    tick_marks = np.arange(len(classes))
    plt.xticks(tick_marks,classes,rotation=45)
    plt.yticks(tick_marks,classes)
        fmt = '.2f' if normalize else 'd'
    thres = cm.max()/2.0

for i,j in itertools.product(range(cm.shape[0]),range(cm.shape[1])):
        plt.text(j,i,format(cm[i,j],fmt),horizontalalignment='center',color='white' if cm[i,j]>thres
else 'black')
    plt.tight_layout()
    plt.ylabel('True Label')
    plt.xlabel('Predicted Label')

plot_confusion_matrix(conf_scv,classes)
```

Confusion Matrix, without Normalization



Plotting ROC Curve

```
y_pred =
[y_pred_lr,y_pred_knn,y_pred_des,y_pred_ran,y_pred_xgb,y_pred_nb,y_pred_svc,y_pred_scv]
model_name = ['Logistic Regression','KNN','Decision Tree','Random Forest','XGB','Naive
Bayes','Support Vector Classifier','Ensemble']

curve = []
for y_pred_ in y_pred:
   curve.append(roc_curve(y_test,y_pred_))

plt.plot([0,1],[0,1],'k--')
for i in range(len(model_name)):
   plt.plot(curve[i][0],curve[i][1],label=model_name[i])

plt.xlabel('False Positive Rate')

plt.ylabel('True Positive Rate')
plt.legend()
plt.title('ROC Curve No GridSearch')
plt.show()
```




```
for i in range(len(model_name)):
    print("AUC ",model_name[i],":",roc_auc_score(y_test,y_pred[i]))
```

AUC Logistic Regression : 0.8818082788671023
AUC KNN : 0.815359477124183
AUC Decision Tree : 0.789760348583878
AUC Random Forest : 0.8300653594771241
AUC XGB : 0.8191721132897605
AUC Naive Bayes : 0.8447712418300652
AUC Support Vector Classifier : 0.8779956427015251
AUC Ensemble : 0.8818082788671023

GRID SEARCH CV

Logistic Regression Grid

```
param_grid_lr = {'penalty':['l1','l2'],
              'C':np.logspace(-4,4,20)}
grid_search_lr = GridSearchCV(estimator=lr,param_grid =
param_grid_lr,cv=7,scoring='accuracy',n_jobs=-1)
grid_search_lr.fit(X_train,y_train)
```

```
lr_params = grid_search_lr.best_params_
print(lr_params)
```

{'C': 0.615848211066026, 'penalty': 'l2'}

```
lr_grid = LogisticRegression(**lr_params)
lr_grid.fit(X_train,y_train)
y_pred_lr_grid = lr_grid.predict(X_test)
```

```
acc_lr_grid,f1_lr_grid,conf_lr_grid,report_lr_grid = calculateScores(y_pred_lr_grid)
```

```
printScores(acc_lr_grid,f1_lr_grid,conf_lr_grid,report_lr_grid)
```

```
Test Accuracy Score :
 0.8852459016393442

Test f1 Score :
 0.8985507246376812

Confusion Matrix :
 [[23  4]
 [ 3 31]]

Classification Report :
              precision    recall  f1-score   support
         0.0       0.88      0.85      0.87        27
         1.0       0.89      0.91      0.90        34
    accuracy                           0.89        61
   macro avg       0.89      0.88      0.88        61
weighted avg       0.89      0.89      0.88        61
```

Extreme Gradient Boosting Grid

```
param_grid_xgb = {'max_depth':[3,4,5],
              'learning_rate':[0.1,0.01,0.001],
              'n_estimators':[9,10,11,12],
              'seed':[10,20,25]}
grid_search_xgb =
GridSearchCV(estimator=xgb,param_grid=param_grid_xgb,cv=7,scoring='accuracy',n_jobs=-1)
grid_search_xgb.fit(X_train,y_train)
xgb_params = grid_search_xgb.best_params_
print(xgb_params)
```

{'learning_rate': 0.1, 'max_depth': 5, 'n_estimators': 9, 'seed': 10

```
xgb_grid = XGBClassifier(**xgb_params,use_label_encoder=False,eval_metric='error')
xgb_grid.fit(X_train,y_train)
y_pred_xgb_grid = xgb_grid.predict(X_test)

acc_xgb_grid,f1_xgb_grid,conf_xgb_grid,report_xgb_grid = calculateScores(y_pred_xgb_grid)

printScores(acc_xgb_grid,f1_xgb_grid,conf_xgb_grid,report_xgb_grid)
```

```
Test Accuracy Score:
 0.819672131147541

Test f1 Score :
 0.8405797101449276

Confusion Matrix :
 [[21  6]
 [ 5 29]]

Classification Report :
              precision    recall  f1-score   support
         0.0       0.81      0.78      0.79        27
         1.0       0.83      0.85      0.84        34
    accuracy                           0.82        61
   macro avg       0.82      0.82      0.82        61
weighted avg       0.82      0.82      0.82        61
```

Naive Bayes Grid

```
param_grid_nb = {'var_smoothing':np.logspace(0,-20,num=2)}
grid_search_nb = GridSearchCV(estimator=nb,param_grid=param_grid_nb,scoring='accuracy')
grid_search_nb.fit(X_train,y_train)
nb_params = grid_search_nb.best_params_
print(nb_params)
```

```
{'var_smoothing': 1e-20}
```

```
nb_grid = GaussianNB(**nb_params)
nb_grid.fit(X_train,y_train)
y_pred_nb_grid = nb_grid.predict(X_test)

acc_nb_grid,f1_nb_grid,conf_nb_grid,report_nb_grid = calculateScores(y_pred_nb_grid)

printScores(acc_nb_grid,f1_nb_grid,conf_nb_grid,report_nb_grid)
```

```
Test Accuracy Score :
 0.8524590163934426
```

Test f1 Score :
 0.8732394366197184

Confusion Matrix :
 [[21 6]
 [3 31]]

Classification Report :

	precision	recall	f1-score	support
0.0	0.88	0.78	0.82	27
1.0	0.84	0.91	0.87	34
accuracy			0.85	61
macro avg	0.86	0.84	0.85	61
weighted avg	0.85	0.85	0.85	61

SVC Grid

```
param_grid_svc = {'kernel':['linear','rbf','poly'],
              'C':[1,1.5,2],
              'class_weight':['balanced']
             }

grid_search_svc =

GridSearchCV(estimator=svc,param_grid=param_grid_svc,cv=7,scoring='accuracy',n_jobs=-1)
grid_search_svc.fit(X_train,y_train)
svc_params = grid_search_svc.best_params_
print(svc_params)
```

{'C': 1, 'class_weight': 'balanced', 'kernel': 'rbf'}

```
svc_grid = SVC(**svc_params,probability=True)
svc_grid.fit(X_train,y_train)
y_pred_svc_grid = svc_grid.predict(X_test)

acc_svc_grid,f1_svc_grid,conf_svc_grid,report_svc_grid = calculateScores(y_pred_svc_grid)

printScores(acc_svc_grid,f1_svc_grid,conf_svc_grid,report_svc_grid)
```

Test Accuracy Score:
 0.8852459016393442

Test f1 Score :
 0.8985507246376812

```
Confusion Matrix:
 [[23 4]
 [ 3 31]]
Classification Report:
               precision    recall  f1-score   support

         0.0       0.88      0.85      0.87        27
         1.0       0.89      0.91      0.90        34

    accuracy                           0.89        61
   macro avg       0.89      0.88      0.88        61
weighted avg       0.89      0.89      0.88        61
```

K-Nearest Neighbour Grid

```
param_grid_knn = {'n_neighbors':[5,10,15,20],
              'weights':['uniform','distance']}
grid_search_knn =
GridSearchCV(estimator=knn,param_grid=param_grid_knn,cv=3,scoring='f1',n_jobs=-1)
grid_search_knn.fit(X_train,y_train)
knn_params = grid_search_knn.best_params_
print(knn_params)
```

```
{'n_neighbors': 20, 'weights': 'uniform'}
```

```
knn_grid = KNeighborsClassifier(**knn_params)
knn_grid.fit(X_train,y_train)
y_pred_knn_grid = knn_grid.predict(X_test)

acc_knn_grid,f1_knn_grid,conf_knn_grid,report_knn_grid = calculateScores(y_pred_knn_grid)

printScores(acc_knn_grid,f1_knn_grid,conf_knn_grid,report_knn_grid)
```

```
Test Accuracy Score:
 0.819672131147541

Test f1 Score:
 0.8533333333333334

Confusion Matrix:
 [[18  9]
 [ 2 32]]
```

```
Classification Report:
              precision    recall  f1-score   support
         0.0       0.90      0.67      0.77        27
         1.0       0.78      0.94      0.85        34
    accuracy                           0.82        61
   macro avg       0.84      0.80      0.81        61
weighted avg       0.83      0.82      0.81        61
```

Decision Tree Grid

```
param_grid_des = {'criterion':['gini','entropy'],
              'max_depth':[2,3,4,5,6],
              'min_samples_leaf':[6,7,8],

              'max_leaf_nodes':[12,13,14,15],
              'max_features':['auto','sqrt','log2'],

                  'random_state':[42,52,62]
             }
grid_search_des =

GridSearchCV(estimator=des,param_grid=param_grid_des,cv=7,scoring='accuracy',n_jobs=-1)
grid_search_des.fit(X_train,y_train)
des_params = grid_search_des.best_params_
print(des_params)

{'criterion': 'gini', 'max_depth': 6, 'max_features': 'auto', 'max_leaf_nodes': 13,
'min_samples_leaf': 7, 'random_state': 52}

des_grid = DecisionTreeClassifier(**des_params)
des_grid.fit(X_train,y_train)
y_pred_des_grid = des_grid.predict(X_test)

acc_des_grid,f1_des_grid,conf_des_grid,report_des_grid = calculateScores(y_pred_des_grid)

printScores(acc_des_grid,f1_des_grid,conf_des_grid,report_des_grid)

Test Accuracy Score:
 0.7868852459016393

Test f1 Score:
 0.7868852459016393
```

Confusion Matrix:

```
[[24 3]
 [10 24]]
```

Classification Report :

```
              precision    recall  f1-score   support
         0.0       0.71      0.89      0.79        27
         1.0       0.89      0.71      0.79        34

    accuracy                           0.79        61
   macro avg       0.80      0.80      0.79        61
weighted avg       0.81      0.79      0.79        61
```

Random Forest Grid

```
param_grid_ran = {
    'criterion':['gini','entropy'],
    'max_leaf_nodes':[50,60,70],
    'max_depth':[4,5,6],
    'max_features':['auto','log2']
}
grid_search_ran =
GridSearchCV(estimator=ran,param_grid=param_grid_ran,cv=5,scoring='accuracy')
grid_search_ran.fit(X_train,y_train)
ran_params = grid_search_ran.best_params_
print(ran_params)
```

{'criterion': 'entropy', 'max_depth': 6, 'max_features': 'auto', 'max_leaf_nodes': 50}

```
ran_grid = RandomForestClassifier(**ran_params)
ran_grid.fit(X_train,y_train)
y_pred_ran_grid = ran_grid.predict(X_test)

acc_ran_grid,f1_ran_grid,conf_ran_grid,report_ran_grid = calculateScores(y_pred_ran_grid)

printScores(acc_ran_grid,f1_ran_grid,conf_ran_grid,report_ran_grid)
```

Test Accuracy Score:
 0.8524590163934426

Test f1 Score:
 0.8695652173913043

```
Confusion Matrix:
 [[22 5]
 [ 4 30]]

Classification Report:
              precision    recall  f1-score   support
         0.0       0.85      0.81      0.83        27
         1.0       0.86      0.88      0.87        34

    accuracy                           0.85        61
   macro avg       0.85      0.85      0.85        61
weighted avg       0.85      0.85      0.85        61
```

Grid Search Model Evaluation

```
model_grid_df = pd.DataFrame({'Model': ['Logistic Regression','Random Forest','Extreme Gradient Boost', 'K-Nearest Neighbour','Decision Tree','Naive Bayes', 'Support Vector Classifier'],
'Accuracy':[acc_lr_grid,acc_ran_grid,acc_xgb_grid,acc_knn_grid,acc_des_grid,acc_nb_grid,acc_svc_grid]})

model_grid_df
```

```
                       Model  Accuracy
0        Logistic Regression  0.885246
1              Random Forest  0.852459
2     Extreme Gradient Boost  0.819672
3        K-Nearest Neighbour  0.819672
4              Decision Tree  0.786885
5                Naive Bayes  0.852459
6  Support Vector Classifier  0.885246
```

```
scv_grid = StackingCVClassifier(classifiers=[lr_grid,nb_grid,svc_grid],meta_classifier=lr_grid,random_state=22)
scv_grid.fit(X_train,y_train)
y_pred_scv_grid = scv_grid.predict(X_test)

acc_scv_grid,f1_scv_grid,conf_scv_grid,report_scv_grid = calculateScores(y_pred_scv_grid)

printScores(acc_scv_grid,f1_scv_grid,conf_scv_grid,report_scv_grid)
```

```
Test Accuracy Score:
 0.8524590163934426
```

Test f1 Score:
0.8732394366197184

Confusion Matrix:
[[21 6]
[3 31]]

Classification Report:

	precision	recall	f1-score	support
0.0	0.88	0.78	0.82	27
1.0	0.84	0.91	0.87	34
accuracy			0.85	61
macro avg	0.86	0.84	0.85	61
weighted avg	0.85	0.85	0.85	61

```
plot_confusion_matrix(conf_scv_grid,classes,cmap=plt.cm.Greens)
```

Confusion Matrix, without Normalization.