Heart Failure Model

November 25, 2021

0.1 Class Assignment

1 Heart Failure Model

[1]:
```
#importing libraries for EDA

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

from IPython.display import clear_output
```

[2]:
```
heart_df = pd.read_csv("Heart Failure Dataset.csv")
```

[3]:
```
heart_df.head()
```

[3]:
```
    age  anaemia  creatinine_phosphokinase  diabetes  ejection_fraction  \
0  75.0        0                       582         0                 20
1  55.0        0                      7861         0                 38
2  65.0        0                       146         0                 20
3  50.0        1                       111         0                 20
4  65.0        1                       160         1                 20

   high_blood_pressure  platelets  serum_creatinine  serum_sodium  sex  \
0                    1  265000.00               1.9           130    1
1                    0  263358.03               1.1           136    1
2                    0  162000.00               1.3           129    1
3                    0  210000.00               1.9           137    1
4                    0  327000.00               2.7           116    0

   smoking  time  DEATH_EVENT
0        0     4            1
1        0     6            1
2        1     7            1
3        0     7            1
4        0     8            1
```

[4]:
```
heart_df.tail()
```

[4]:
```
      age  anaemia  creatinine_phosphokinase  diabetes  ejection_fraction  \
294  62.0        0                        61         1                 38
295  55.0        0                      1820         0                 38
296  45.0        0                      2060         1                 60
297  45.0        0                      2413         0                 38
298  50.0        0                       196         0                 45

     high_blood_pressure  platelets  serum_creatinine  serum_sodium  sex  \
294                    1   155000.0               1.1           143    1
295                    0   270000.0               1.2           139    0
296                    0   742000.0               0.8           138    0
297                    0   140000.0               1.4           140    1
298                    0   395000.0               1.6           136    1

     smoking  time  DEATH_EVENT
294        1   270            0
295        0   271            0
296        0   278            0
297        1   280            0
298        1   285            0
```

[5]:
```
heart_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 299 entries, 0 to 298
Data columns (total 13 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   age                       299 non-null    float64
 1   anaemia                   299 non-null    int64
 2   creatinine_phosphokinase  299 non-null    int64
 3   diabetes                  299 non-null    int64
 4   ejection_fraction         299 non-null    int64
 5   high_blood_pressure       299 non-null    int64
 6   platelets                 299 non-null    float64
 7   serum_creatinine          299 non-null    float64
 8   serum_sodium              299 non-null    int64
 9   sex                       299 non-null    int64
 10  smoking                   299 non-null    int64
 11  time                      299 non-null    int64
 12  DEATH_EVENT               299 non-null    int64
dtypes: float64(3), int64(10)
memory usage: 30.5 KB
```

2 EDA (Exploratory Data Analysis)

[6]:
```
heart_df.shape
```

[6]:
```
(299, 13)
```

[7]:
```
heart_df.describe()
```

[7]:
```
              age     anaemia  creatinine_phosphokinase    diabetes  \
count  299.000000  299.000000                299.000000  299.000000
mean    60.833893    0.431438                581.839465    0.418060
std     11.894809    0.496107                970.287881    0.494067
min     40.000000    0.000000                 23.000000    0.000000
25%     51.000000    0.000000                116.500000    0.000000
50%     60.000000    0.000000                250.000000    0.000000
75%     70.000000    1.000000                582.000000    1.000000
max     95.000000    1.000000               7861.000000    1.000000

       ejection_fraction  high_blood_pressure      platelets  \
count         299.000000           299.000000     299.000000
mean           38.083612             0.351171  263358.029264
std            11.834841             0.478136   97804.236869
min            14.000000             0.000000   25100.000000
25%            30.000000             0.000000  212500.000000
50%            38.000000             0.000000  262000.000000
75%            45.000000             1.000000  303500.000000
max            80.000000             1.000000  850000.000000

       serum_creatinine  serum_sodium         sex    smoking        time  \
count         299.00000    299.000000  299.000000  299.00000  299.000000
mean            1.39388    136.625418    0.648829    0.32107  130.260870
std             1.03451      4.412477    0.478136    0.46767   77.614208
min             0.50000    113.000000    0.000000    0.00000    4.000000
25%             0.90000    134.000000    0.000000    0.00000   73.000000
50%             1.10000    137.000000    1.000000    0.00000  115.000000
75%             1.40000    140.000000    1.000000    1.00000  203.000000
max             9.40000    148.000000    1.000000    1.00000  285.000000

       DEATH_EVENT
count    299.00000
mean       0.32107
std        0.46767
min        0.00000
25%        0.00000
50%        0.00000
75%        1.00000
max        1.00000
```

[8]:
```
heart_df.columns
```

[8]:
```
Index(['age', 'anaemia', 'creatinine_phosphokinase', 'diabetes',
       'ejection_fraction', 'high_blood_pressure', 'platelets',
       'serum_creatinine', 'serum_sodium', 'sex', 'smoking', 'time',
       'DEATH_EVENT'],
      dtype='object')
```

3 Dataset description (understanding the dataset)

from above columns we can identify that there are 12 attributes and 1 target column (death_event)

1. Age - age of the individual.
2. anaemia - a condition in which you lack enough healthy red blood cells to carry adequate oxygen to your body's tissues(False-0, true-1)
3. creatinine_phosphokinase - level of the CPK enzyme in the blood (mcg/L)
4. diabetes - If the person has diabetes or not (0- False , 1- True)
5. ejection_fraction - refers to how well your left ventricle (or right ventricle) pumps blood with each heartbeat (percentage)
6. high blood pressure: if the patient has hypertension (0- false, 1-True)
7. platelets: platelets in the blood (kiloplatelets/mL)
8. serum creatinine: level of serum creatinine in the blood (mg/dL)
9. serum sodium: level of serum sodium in the blood (mEq/L)
10. sex: 0-Female, 1- Male
11. smoking: 0-False, 1-True
12. time: follow-up period (days)
13. [target column] Death: do the person dies during the followup period.

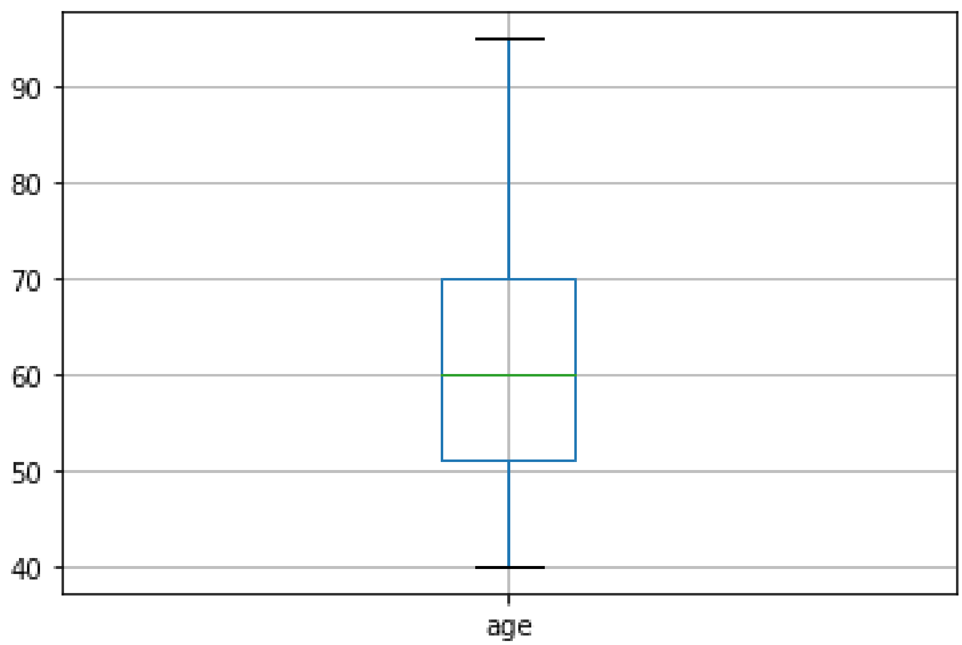
the Objective here is to find out the solution or the behavior changes to be taken care to prevent the individual from suffering death from the top-most reason for the death(heart failure).

Dataset has no null values we can start with the analysis

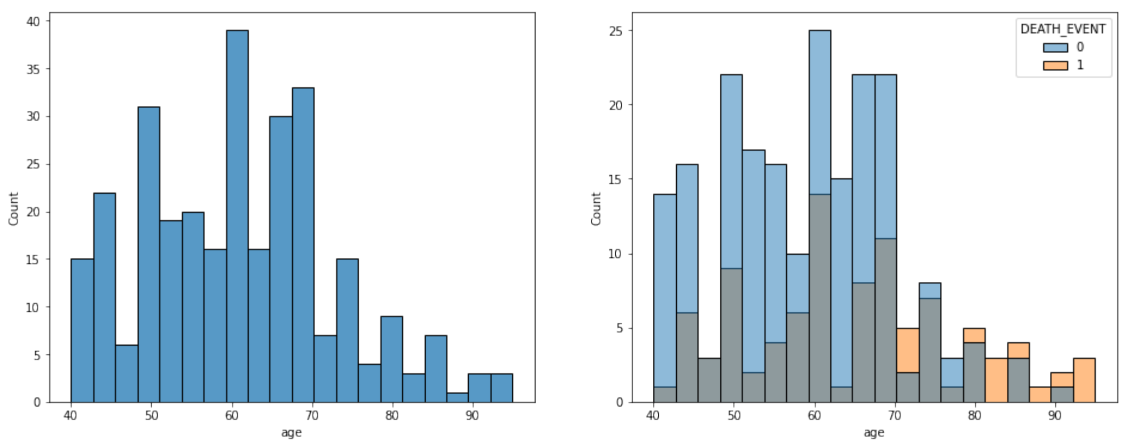
Lets start with the Age

[9]:
```
heart_df.boxplot('age')
```

[9]:
```
<AxesSubplot:>
```




```
[10]: fig,axes = plt.subplots(1,2,figsize=[16,6])
      sns.histplot(ax=axes[0],x='age',data=heart_df,bins=20)
      sns.histplot(ax=axes[1],x='age',data=heart_df,bins=20,hue="DEATH_EVENT")
      plt.show()
```

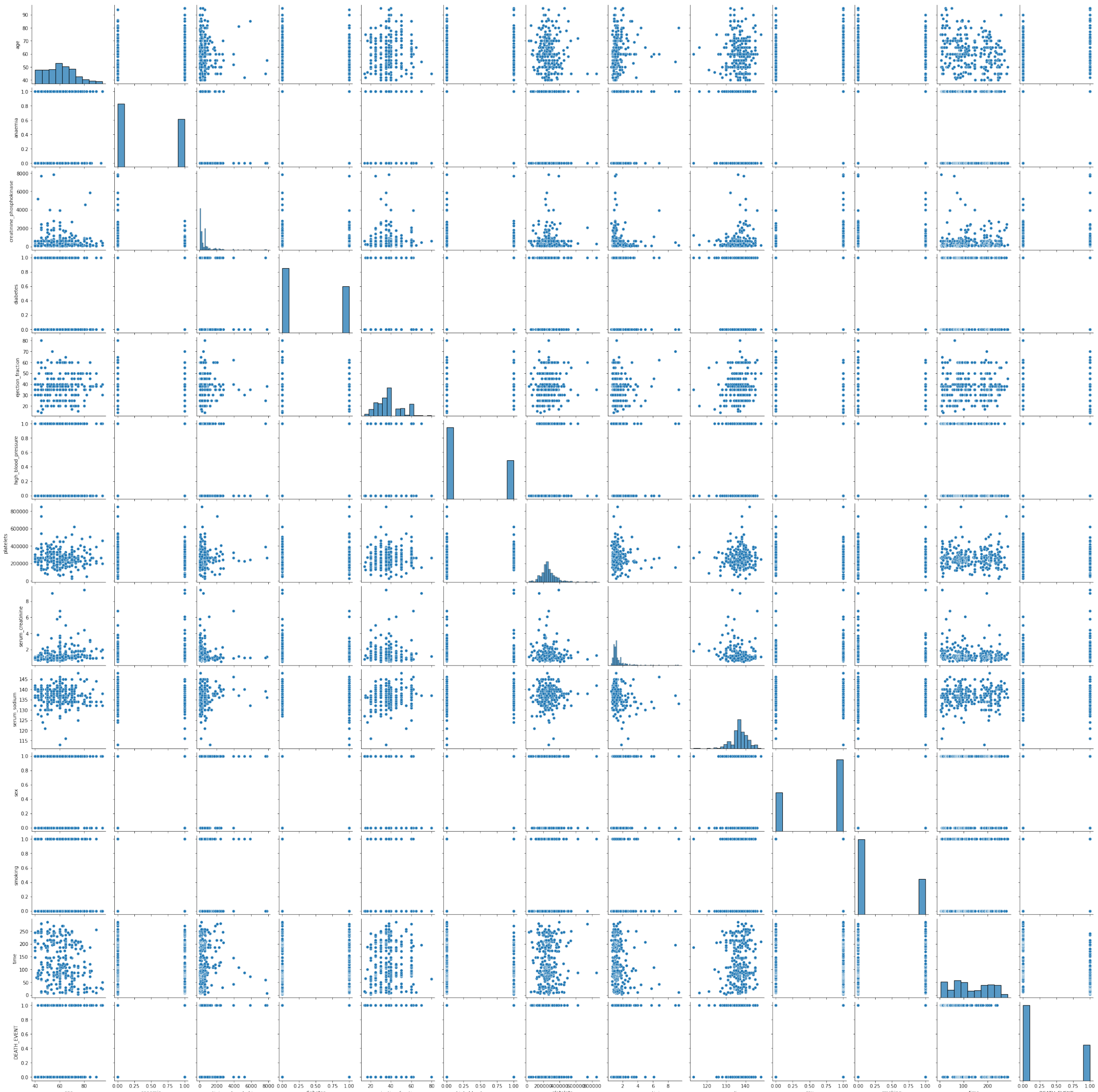


we can see that the most common age to identify the problem is around 60 - 70 also has the most deaths too, but can't be said that deaths are dependent on the Age.

Lets check lets check the relation of every feature using pair plot.

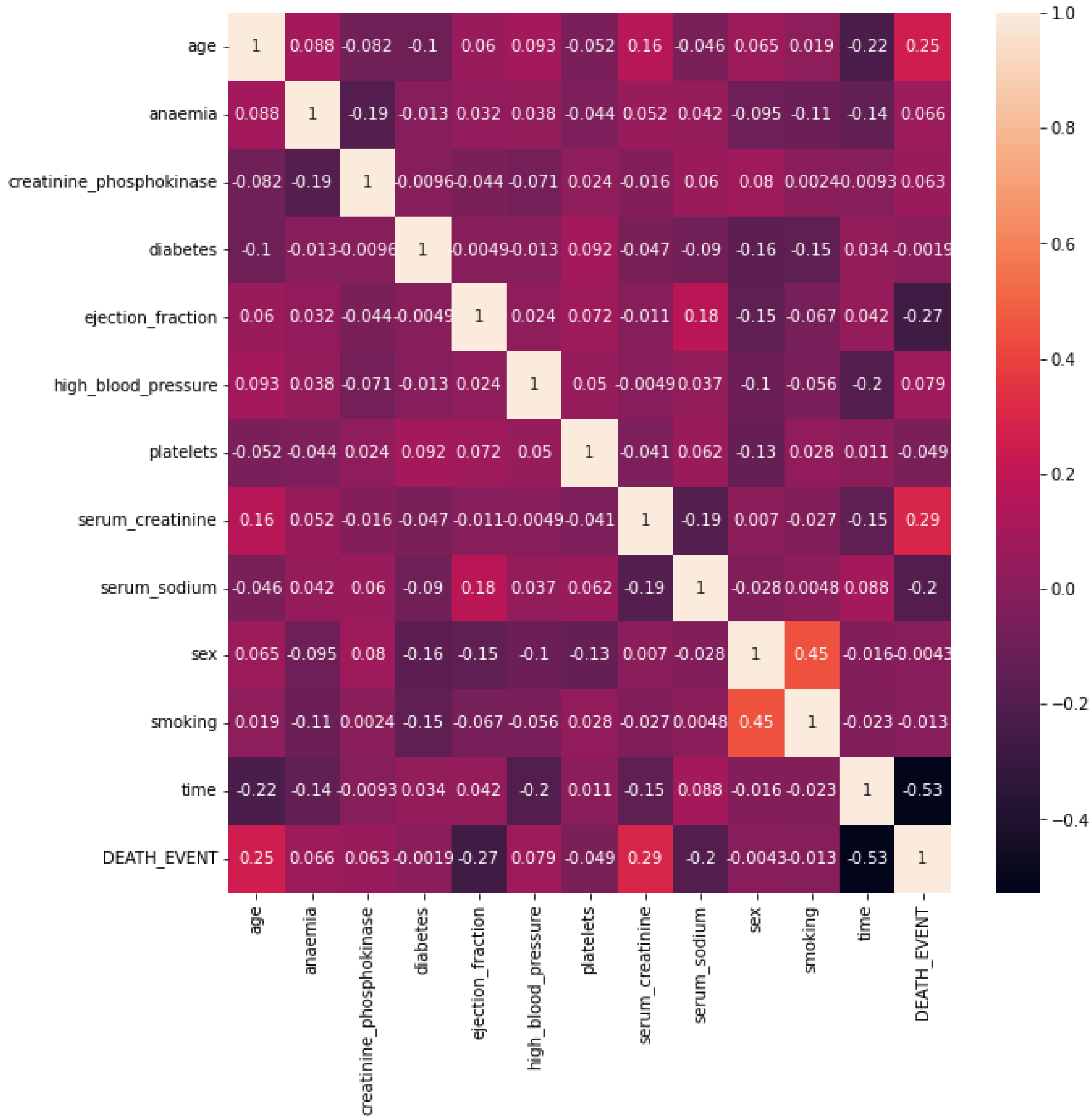
```
[11]: sns.pairplot(data=heart_df)
```

[11]: <seaborn.axisgrid.PairGrid at 0x1e0f643af40>



Plotting to see the correlation.

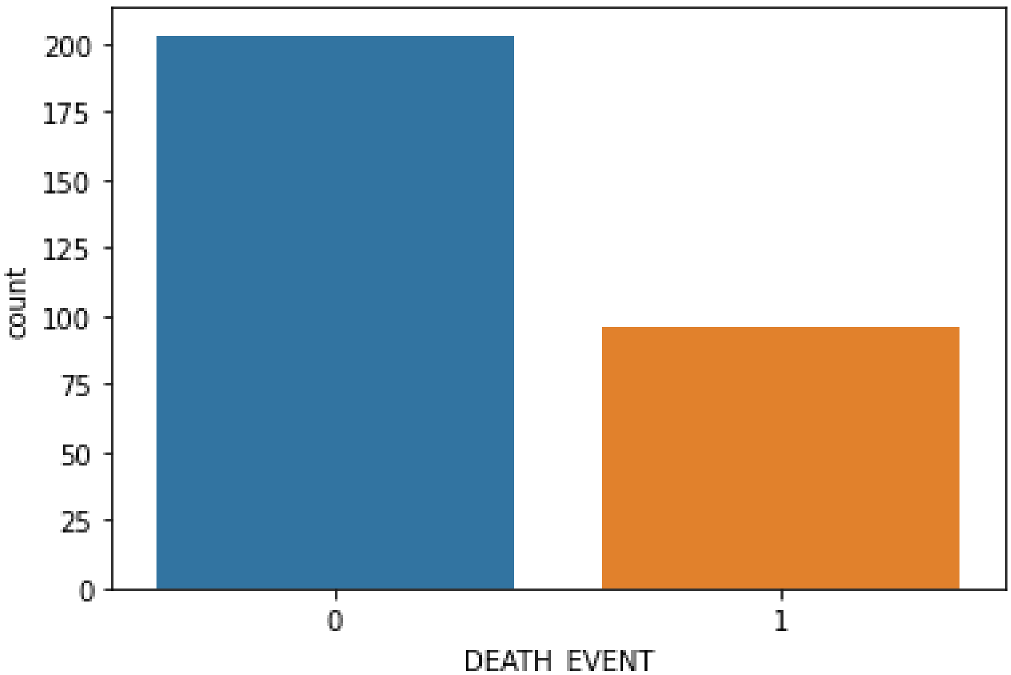
[12]:
```
plt.figure(figsize=[10,10])
sns.heatmap(data=heart_df.corr(),annot=True)
plt.show()
```



To see if data is well balanced

[38]:
```
sns.countplot(x="DEATH_EVENT",data=heart_df)
```

[38]: <AxesSubplot:xlabel='DEATH_EVENT', ylabel='count'>



4 Building a model

we can see that data is imbalanced we have to take into consideration while splitting of the data

importing libraries for model creation

[106]:
```
from sklearn.preprocessing import StandardScaler # for the feature engineering
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix,plot_confusion_matrix

#classification libraries

from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.ensemble import AdaBoostClassifier
from xgboost import XGBClassifier
```

Seperating the target and dependent variable

[14]:
```
X = heart_df.drop(columns="DEATH_EVENT")

y = heart_df.DEATH_EVENT
```

4.1 Splitting the data

lets check for the ratio

[39]:
```
sum(y)/len(y)
```

[39]:
```
0.3210702341137124
```

[40]:
```
X_train,X_test,y_train,y_test = train_test_split(X,y,test_size=.
↪15,random_state=42,stratify=y)

print(f'Shape of the data:\n Shape of X_train = {X_train.shape}, Shape of␣
↪X_test = {X_test.shape},\n Shape of y_train = {y_train.shape}, Shape of␣
↪y_test = {y_test.shape}')
```

```
Shape of the data:
 Shape of X_train = (254, 12), Shape of X_test = (45, 12),
 Shape of y_train = (254,), Shape of y_test = (45,)
```

Let's check the ratio again

[41]:
```
sum(y_test)/len(y_test)
```

[41]:
```
0.3111111111111111
```

[42]:
```
sum(y_train)/len(y_train)
```

[42]:
```
0.3228346456692913
```

Data is well distributed

4.2 Feature Scalling

[43]:
```
scale = StandardScaler(with_std=True)

X_scale_train = scale.fit_transform(X_train)

X_scale_test = scale.transform(X_test)
```

5 KNN Classification

finding optimal neighbours

[44]:
```
fin_score= 0
for i in range(1,255):
  model = KNeighborsClassifier(i)
  model.fit(X_scale_train,y_train)
  score = model.score(X_scale_test,y_test)

  if fin_score < score:
```

```
    fin_score = score
    neigh = i

print(f'Neighbours: {neigh}, best score:{fin_score}')
```

```
Neighbours: 1, best score:0.7555555555555555
```

6 Decision Tree

[45]:
```
dt_model = DecisionTreeClassifier(random_state=42)

dt_model.fit(X_scale_train,y_train)

print(f"Decision tree score : {dt_model.score(X_scale_test,y_test)}")
```

```
Decision tree score : 0.7333333333333333
```

[46]:
```
print(f"Decision tree train score : {dt_model.score(X_scale_train,y_train)}")
```

```
Decision tree train score : 1.0
```

7 Random Forest Classifier

[61]:
```
def optimal_trees(Xtrain,Xtest,ytrain, ytest,trees):
    score_df = pd.DataFrame(columns=["trees","score","train_score"])
    for estimator in trees:
        rf_model =␣
↪RandomForestClassifier(n_estimators=estimator,random_state=42)
        rf_model.fit(Xtrain,ytrain)
        score_df = score_df.append({"trees":estimator,"score":rf_model.
↪score(Xtest,ytest),"train_score":rf_model.
↪score(Xtrain,ytrain)},ignore_index=True)
        print ("+",end="")
    print("Complete")
    return score_df
```

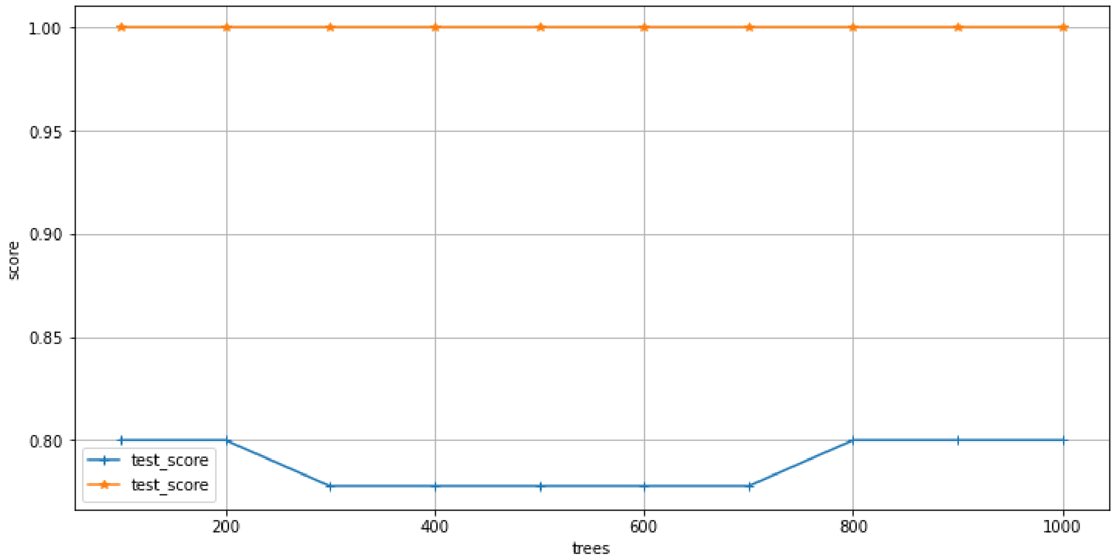
[62]:
```
trees = [100,200,300,400,500,600,700, 800,900,1000]

df = optimal_trees(X_scale_train,X_scale_test,y_train,y_test,trees)
```

```
++++++++++Complete
```

[64]:
```
plt.figure(figsize=[12,6])
plt.plot(df.trees,df.score,marker='+',label="test_score")
plt.plot(df.trees,df.train_score,marker='*',label="test_score")
plt.xlabel("trees")
plt.ylabel("score")
plt.legend()
```

```
plt.grid()
plt.show()
```

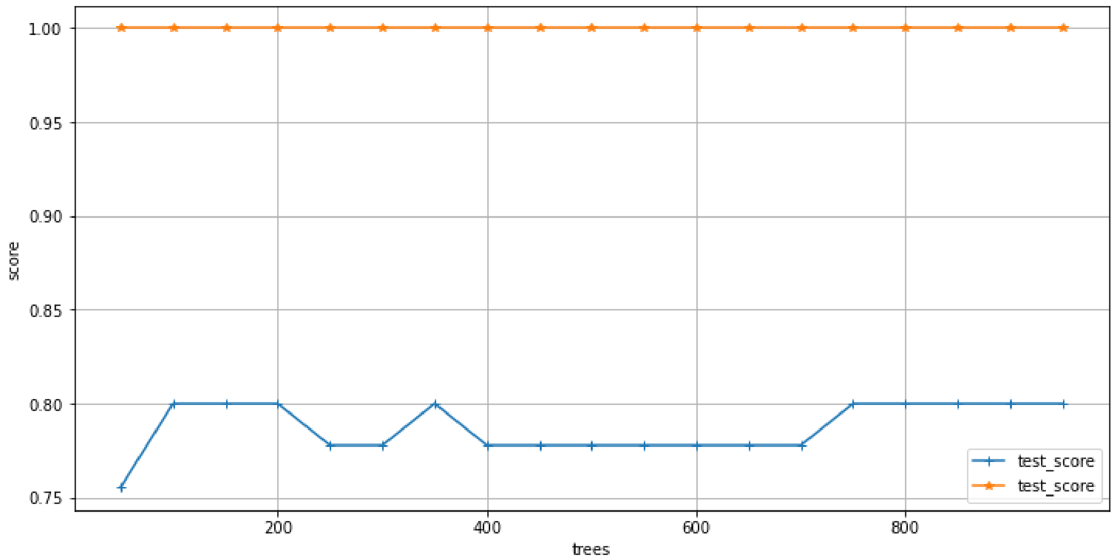


Lets try with iteration of 50

[65]:
```
df = optimal_trees(X_scale_train,X_scale_test,y_train,y_test,range(50,1000,50))

plt.figure(figsize=[12,6])
plt.plot(df.trees,df.score,marker='+',label="test_score")
plt.plot(df.trees,df.train_score,marker='*',label="test_score")
plt.xlabel("trees")
plt.ylabel("score")
plt.legend()
plt.grid()
plt.show()
```

```
++++++++++++++++++Complete
```



100 seems to be optimum estimator for the Random forest algoritm

Making Random forest model with 100 n_estimators

[66]:
```
rf_model = RandomForestClassifier(n_estimators=100,random_state=42)
rf_model.fit(X_scale_train,y_train)
print("Score of the Random Forest classifier: ",rf_model.
 ↪score(X_scale_test,y_test))
```

```
Score of the Random Forest classifier:  0.8
```

[67]:
```
print(f"Random Forest train score : {rf_model.score(X_scale_train,y_train)}")
```

```
Random Forest train score : 1.0
```

8 Gradient Boosting Classifier

Selecting hyper parameters

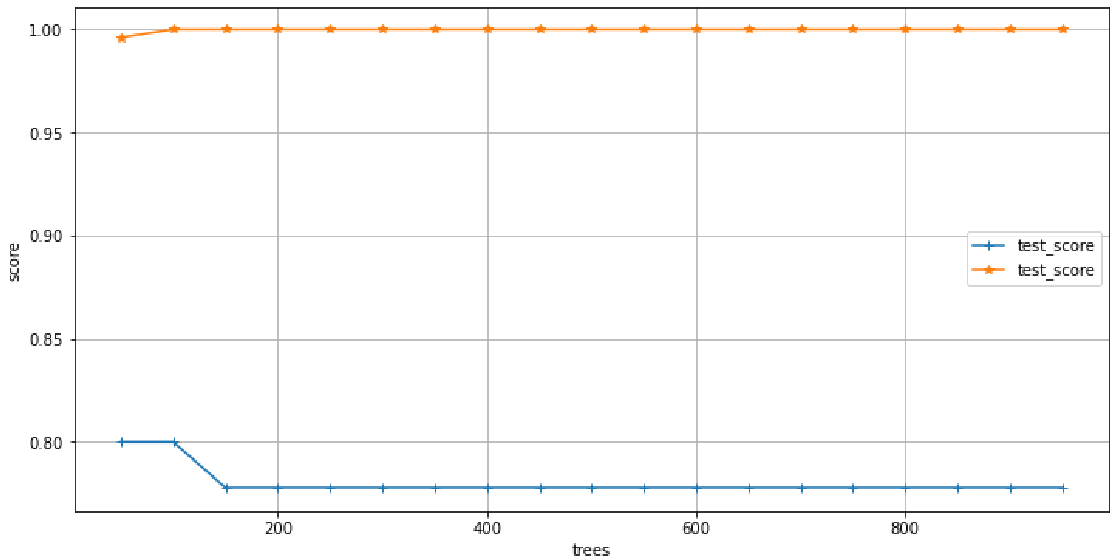
[68]:
```
def gb_optimal_trees(Xtrain,Xtest,ytrain, ytest,trees):
    score_df = pd.DataFrame(columns=["trees","score","train_score"])
    for estimator in trees:
        gb_model =␣
 ↪GradientBoostingClassifier(n_estimators=estimator,random_state=42)
        gb_model.fit(Xtrain,ytrain)
        score_df = score_df.append({"trees":estimator,"score":gb_model.
 ↪score(Xtest,ytest),"train_score":gb_model.
 ↪score(Xtrain,ytrain)},ignore_index=True)
        print ("+",end="")
```

```
    print("Complete")
    return score_df
```

[69]:
```
df =␣
↪gb_optimal_trees(X_scale_train,X_scale_test,y_train,y_test,range(50,1000,50))
```

```
++++++++++++++++++Complete
```

[70]:
```
plt.figure(figsize=[12,6])
plt.plot(df.trees,df.score,marker='+',label="test_score")
plt.plot(df.trees,df.train_score,marker='*',label="test_score")
plt.xlabel("trees")
plt.ylabel("score")
plt.grid()
plt.legend()
plt.show()
```



Above figure shows 50 as optimum amount of estimator

Building a model with 50 estimators

[71]:
```
lists = [50]

df = gb_optimal_trees(X_scale_train,X_scale_test,y_train,y_test,lists)

clear_output(wait=True)
print(f"Score of the gradient boosting classifier: {df.score[0]} \nScore of the␣
↪gradient boosting classifier: {df.train_score[0]}")
```

```
Score of the gradient boosting classifier: 0.8
Score of the gradient boosting classifier: 0.9960629921259843
```

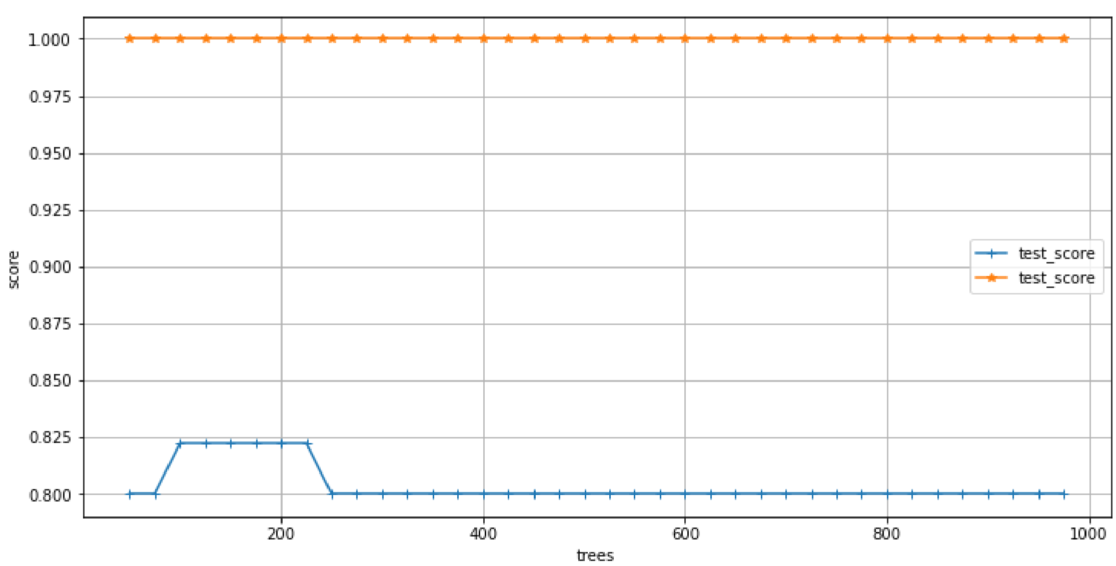
9 XGBClassifier model

[89]:
```python
def xg_optimal_estimator(Xtrain,Xtest,ytrain, ytest,trees):
    score_df = pd.DataFrame(columns=["trees","score","train_score"])
    for estimator in trees:
        xg_model =␣
 ↪XGBClassifier(n_estimators=estimator,use_label_encoder=False,random_state=42)
        xg_model.fit(Xtrain,ytrain,eval_metric='aucpr')
        score_df = score_df.append({"trees":estimator,"score":xg_model.
 ↪score(Xtest,ytest),"train_score":xg_model.
 ↪score(Xtrain,ytrain)},ignore_index=True)
        print ("+",end="")
    print("Complete")
    return score_df
```

[90]:
```python
df =␣
 ↪xg_optimal_estimator(X_scale_train,X_scale_test,y_train,y_test,range(50,1000,25))
```

```
++++++++++++++++++++++++++++++++++++++Complete
```

[91]:
```python
plt.figure(figsize=[12,6])
plt.plot(df.trees,df.score,marker='+',label="test_score")
plt.plot(df.trees,df.train_score,marker='*',label="test_score")
plt.xlabel("trees")
plt.ylabel("score")
plt.grid()
plt.legend()
plt.show()
```



[87]:
```
xg_model =␣
↪XGBClassifier(use_label_encoder=False,random_state=42,n_estimator=100)

xg_model.fit(X_scale_train,y_train,eval_metric='aucpr')
```

[87]:
```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, enable_categorical=False,
              gamma=0, gpu_id=-1, importance_type=None,
              interaction_constraints='', learning_rate=0.300000012,
              max_delta_step=0, max_depth=6, min_child_weight=1, missing=nan,
              monotone_constraints='()', n_estimators=100, n_jobs=2,
              num_parallel_tree=1, predictor='auto', random_state=42,
              reg_alpha=0, reg_lambda=1, scale_pos_weight=1, subsample=1,
              tree_method='exact', use_label_encoder=False,
              validate_parameters=1, verbosity=None)
```

[88]:
```
xg_model.score(X_scale_test,y_test)
```

[88]:
```
0.8222222222222222
```

10 Adaboost

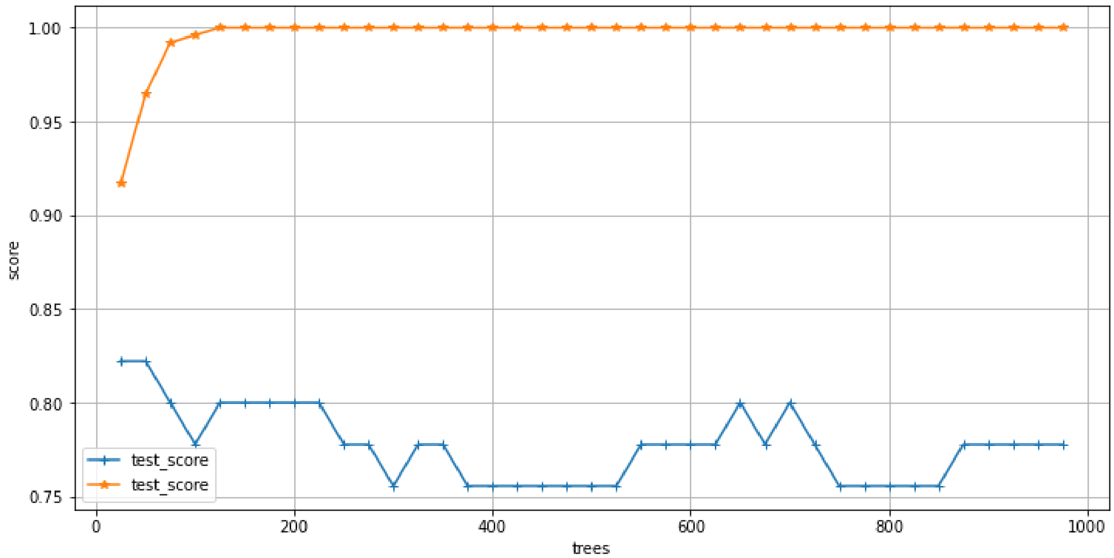
[92]:
```
def ad_optimal_estimator(Xtrain,Xtest,ytrain, ytest,trees):
    score_df = pd.DataFrame(columns=["trees","score","train_score"])
    for estimator in trees:
        ad_model = AdaBoostClassifier(n_estimators=estimator,random_state=42)
        ad_model.fit(Xtrain,ytrain)
        score_df = score_df.append({"trees":estimator,"score":ad_model.
↪score(Xtest,ytest),"train_score":ad_model.
↪score(Xtrain,ytrain)},ignore_index=True)
        print ("+",end="")
    print("Complete")
    return score_df
```

[95]:
```
df =␣
↪ad_optimal_estimator(X_scale_train,X_scale_test,y_train,y_test,range(25,1000,25))
```

```
+++++++++++++++++++++++++++++++++++++++Complete
```

[96]:
```
plt.figure(figsize=[12,6])
plt.plot(df.trees,df.score,marker='+',label="test_score")
plt.plot(df.trees,df.train_score,marker='*',label="test_score")
plt.xlabel("trees")
plt.ylabel("score")
plt.grid()
```

```
plt.legend()
plt.show()
```



Building with 50 estimators

[102]:
```
ad_model = AdaBoostClassifier(n_estimators=50,random_state=42)

ad_model.fit(X_scale_train,y_train)
```

[102]:
```
AdaBoostClassifier(random_state=42)
```

[103]:
```
train_score = ad_model.score(X_scale_train,y_train)

test_score = ad_model.score(X_scale_test,y_test)

print(f"Score of the Adaboost classifier: {test_score} \nTraining Score of the␣
↪Adaboost classifier: {train_score}")
```

```
Score of the Adaboost classifier: 0.8222222222222222
Training Score of the Adaboost classifier: 0.9645669291338582
```

From all the build models we can clearly see Xg boosting algorithm and Adaboost algorithm gives us highest score of **82%** but we can select to go with the Adaboost algorithm with the found parameter as it prevents overfiting

Let’s built the model with the found parameters with Adaboost

10.0.1 confusion matrix for the Adaboost

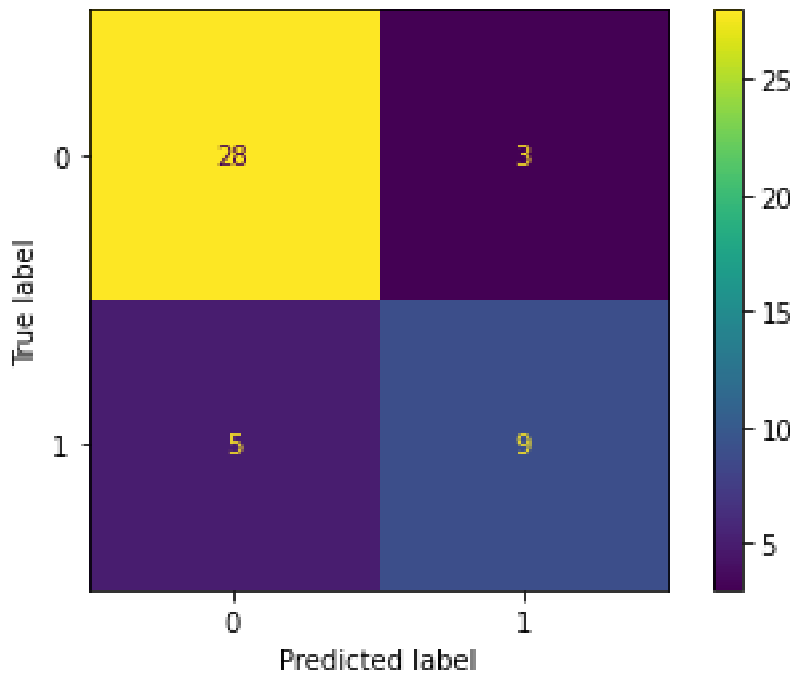
[104]:
```
pred_y = ad_model.predict(X_scale_test)
```

[105]:
```
confusion_matrix(y_test,pred_y)
```

[105]:
```
array([[28,  3],
       [ 5,  9]], dtype=int64)
```

[113]:
```
plot_confusion_matrix(estimator=ad_model,X=X_scale_test,y_true=y_test)
```

[113]: <sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x1e0846eeaf0>



[116]:
```
precision = 28/(28+3)
print(f"the precision of the model is: {precision}")
```

```
the precision of the model is: 0.9032258064516129
```

[117]:
```
recall = 28/(28+5)
print(f"the recall of the model is: {recall}")
```

```
the recall of the model is: 0.8484848484848485
```

[118]:
```
print("F1 score for the model: ",2*precision*recall/(precision+recall))
```

```
F1 score for the model:  0.875
```

10.0.2 Scalling model

[99]:
```
X_scale = scale.transform(X)
```

10.0.3 Building Final model

[100]:
```
final_model = ad_model.fit(X_scale,y)

print("Model created sucessfully")
```

```
Model created sucessfully
```

10.0.4 Model is ready to deploy