Heart Disease UCI

November 21, 2021

1 IBM Machine Learning: Classification Capstone Project

by Marwan Khalil

1.1 Introduction

The heart is an amazing organ. It continuously pumps oxygen and nutrient-rich blood throughout your body to sustain life. This fist-sized powerhouse beats (expands and contracts) 100,000 times per day pumping 23,000 liters (5,000 gallons) of blood every day. To work properly, the heart (just like any other muscle) needs a good blood supply.

A heart attack (also known as myocardial infarction; MI) is defined as the sudden blockage of blood flow to a portion of the heart. Some of the heart muscle begins to die during a heart attack, and without early medical treatment, the loss of the muscle could be permanent.

Conditions such as high blood pressure, high blood cholesterol, obesity, and diabetes can raise the risk of a heart attack. Behaviors such as an unhealthy diet, low levels of physical activity, smoking, and excessive alcohol consumption can contribute to the conditions that can cause heart attacks. Some factors, such as age and family history of heart disease, cannot be modified but are associated with a higher risk of a heart attack.

1.2 Dataset

For the exploration of the risk a person has to develop a heart attack (**prediction** analysis), the Heart Attack Analysis & Prediction Dataset from *kaggle.com* was utilized. It consists of:

- Age of the patient (age in years)
- Sex of the patient (sex; 1 = male, 0 = female)
- Exercise induced angina (exng; 1 = yes, 0 = no)
- Number of major vessels (ca; 0-3)
- Chest pain type (cp; Value 1: typical angina, Value 2: atypical angina, Value 3: non-anginal pain, Value 4: asymptomatic)
- Resting blood pressure (trestpbs; in mm/Hg on admission to the hospital)
- Cholesterol levels (chol; in mg/dl)
- Fasting blood sugar (fbs; if > 120 mg/dl, 1 = true; 0 = false)
- Resting electrocardiographic results (rest_ecg; 0 = normal, 1 = having ST-T wave abnormality, 2 = showing probable or definite left ventricular hypertrophy by Estes' criteria)
- Maximum heart rate achieved (thalach)
- Chance of heart attack (target: Heart disease)

- A blood disorder called thalassemia (thall; 1 = normal; 2 = fixed defect; 3 = reversable defect)
- Previous peak (oldpeak; ST depression induced by exercise relative to rest - 'ST' relates to positions on the ECG plot)
- Slope (slp; the slope of the peak exercise ST segment, Value 1: upsloping, Value 2: flat, Value 3: downsloping)

1.2.1 Acknowledgements

Creators:

```
Hungarian Institute of Cardiology. Budapest: Andras Janosi, M.D.
University Hospital, Zurich, Switzerland: William Steinbrunn, M.D.
University Hospital, Basel, Switzerland: Matthias Pfisterer, M.D.
V.A. Medical Center, Long Beach and Cleveland Clinic Foundation: Robert Detrano, M.D., Ph.D.
```


[1]:
```
# Importing libraries

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

from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.neighbors import KNeighborsClassifier
from sklearn.preprocessing import MinMaxScaler
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import ExtraTreesClassifier
from sklearn.ensemble import BaggingClassifier
from sklearn.ensemble import AdaBoostClassifier
from sklearn.ensemble import GradientBoostingClassifier

from sklearn.metrics import confusion_matrix, accuracy_score
from sklearn.metrics import precision_recall_curve
from sklearn.metrics import average_precision_score
from sklearn.metrics import roc_curve
from sklearn.metrics import auc
from sklearn.model_selection import cross_val_score
from sklearn.metrics import f1_score
from sklearn.metrics import classification_report

%matplotlib inline
```

[2]:
```
import warnings
warnings.filterwarnings('ignore')
```

[3]:
```
sns.set()
```

[4]:
```
heart = pd.read_csv('heart.csv')
```

[5]:
```
heart.head()
```

[5]:
```
   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
```

1.3 Feature Engineering

[6]:
```
heart.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 303 entries, 0 to 302
Data columns (total 14 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   age       303 non-null    int64
 1   sex       303 non-null    int64
 2   cp        303 non-null    int64
 3   trestbps  303 non-null    int64
 4   chol      303 non-null    int64
 5   fbs       303 non-null    int64
 6   restecg   303 non-null    int64
 7   thalach   303 non-null    int64
 8   exang     303 non-null    int64
 9   oldpeak   303 non-null    float64
 10  slope     303 non-null    int64
 11  ca        303 non-null    int64
 12  thal      303 non-null    int64
 13  target    303 non-null    int64
dtypes: float64(1), int64(13)
memory usage: 33.3 KB
```

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

[7]:

	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

[8]:
```
duplicate=heart[heart.duplicated()]
print("Duplicate Rows :")
duplicate
```

Duplicate Rows :

[8]:

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	\
164	38	1	2	138	175	0	1	173	0	0.0	

	slope	ca	thal	target
164	2	4	2	1

[9]:
```
heart_attack = heart.drop_duplicates()
```

[10]:
```
heart_attack['target'].value_counts(normalize=True)
```

[10]:
```
1    0.543046
0    0.456954
```

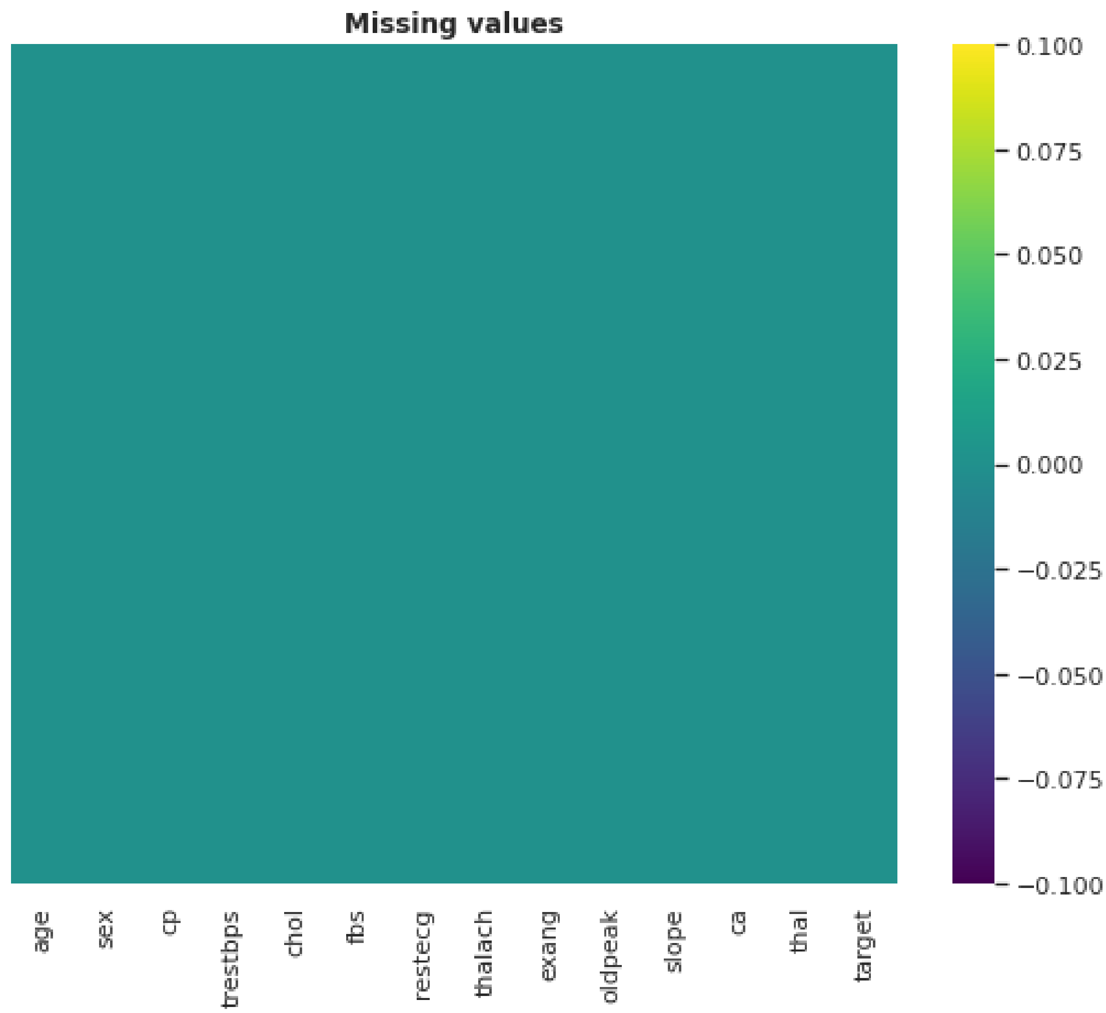
```
Name: target, dtype: float64
```

[11]:
```
heart_attack.describe()
```

[11]:
```
              age         sex          cp    trestbps        chol         fbs  \
count  302.00000  302.000000  302.000000  302.000000  302.000000  302.000000
mean    54.42053    0.682119    0.963576  131.602649  246.500000    0.149007
std      9.04797    0.466426    1.032044   17.563394   51.753489    0.356686
min     29.00000    0.000000    0.000000   94.000000  126.000000    0.000000
25%     48.00000    0.000000    0.000000  120.000000  211.000000    0.000000
50%     55.50000    1.000000    1.000000  130.000000  240.500000    0.000000
75%     61.00000    1.000000    2.000000  140.000000  274.750000    0.000000
max     77.00000    1.000000    3.000000  200.000000  564.000000    1.000000

          restecg     thalach       exang     oldpeak       slope          ca  \
count  302.000000  302.000000  302.000000  302.000000  302.000000  302.000000
mean     0.526490  149.569536    0.327815    1.043046    1.397351    0.718543
std      0.526027   22.903527    0.470196    1.161452    0.616274    1.006748
min      0.000000   71.000000    0.000000    0.000000    0.000000    0.000000
25%      0.000000  133.250000    0.000000    0.000000    1.000000    0.000000
50%      1.000000  152.500000    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  302.000000  302.000000
mean     2.314570    0.543046
std      0.613026    0.498970
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
```

[12]:
```
heart_attack = heart_attack.reset_index(drop=True)
```

[13]:
```
plt.figure(figsize=(9,7))
plt.title('Missing values', fontweight='bold')

ax = sns.heatmap(heart.isnull(),yticklabels=False,cbar='viridis',cmap='viridis')

plt.show()
```



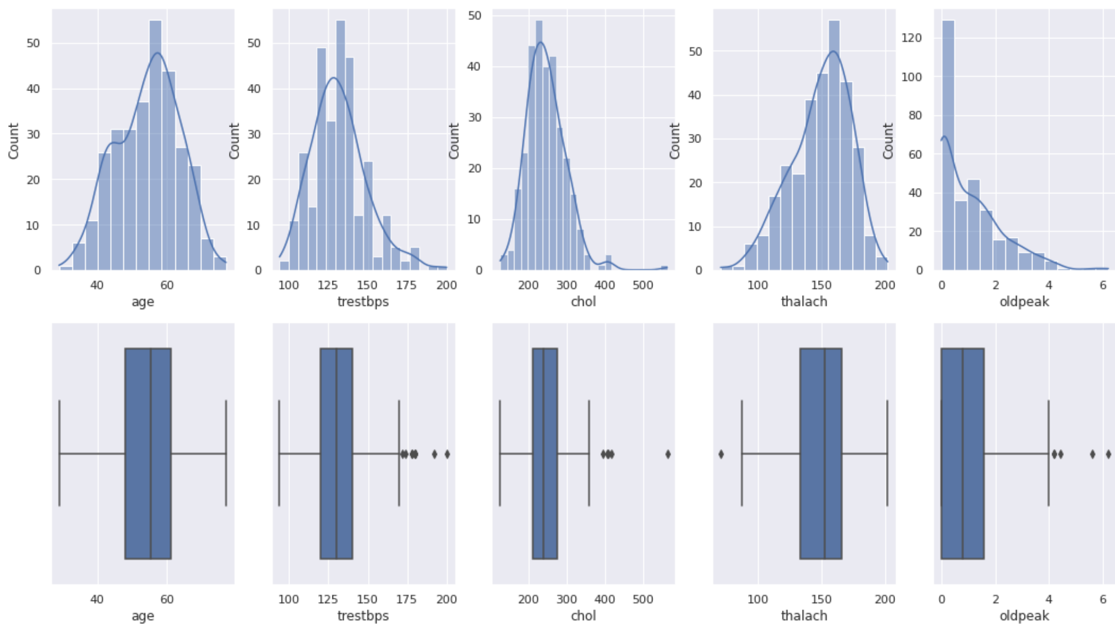
Categorical: Cp, fbs, restecg, exang, slope, ca, thal, sex

Numerical: Age, trestbps, chol, thalach, oldpeak

[14]:

```
# FInding outliers and plotting histograms for all numerical features

plt.figure(figsize=(18,10))
plt.subplot(2,5,1)
sns.histplot(heart_attack['age'],kde=True)
plt.subplot(2,5,6)
sns.boxplot(heart_attack['age'])
plt.subplot(2,5,2)
sns.histplot(heart_attack['trestbps'],kde=True)
plt.subplot(2,5,7)
sns.boxplot(heart_attack['trestbps'])
plt.subplot(2,5,3)
```

```
sns.histplot(heart_attack['chol'],kde=True)
plt.subplot(2,5,8)
sns.boxplot(heart_attack['chol'])
plt.subplot(2,5,4)
sns.histplot(heart_attack['thalach'],kde=True)
plt.subplot(2,5,9)
sns.boxplot(heart_attack['thalach'])
plt.subplot(2,5,5)
sns.histplot(heart_attack['oldpeak'],kde=True)
plt.subplot(2,5,10)
sns.boxplot(heart_attack['oldpeak']);
```



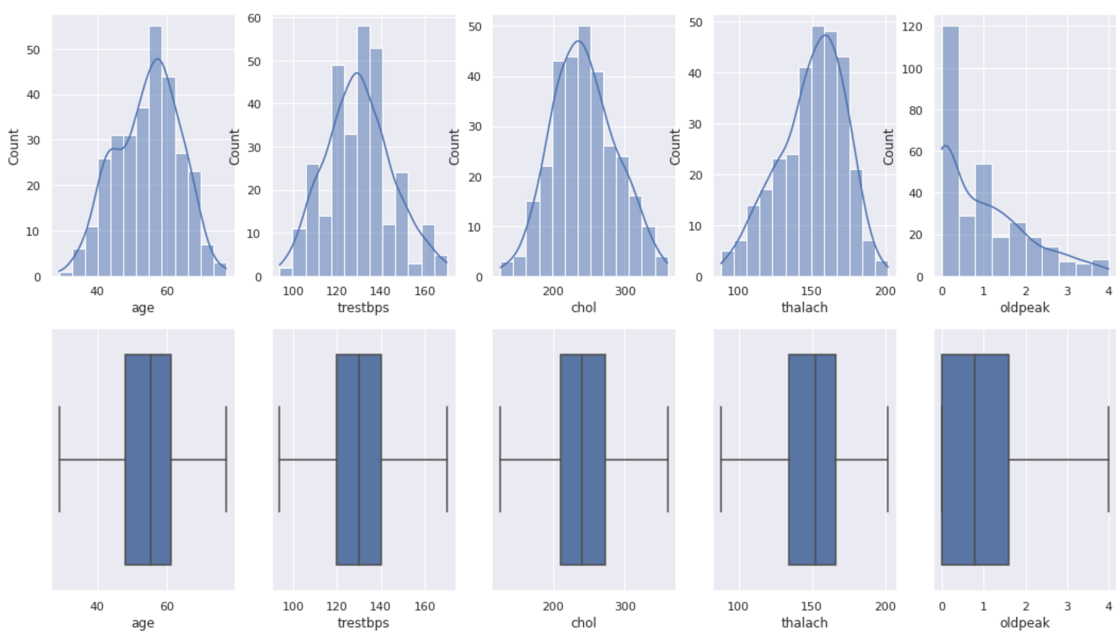
1.3.1 Removing the outliers

[15]:
```
for col in ['trestbps', 'chol', 'oldpeak']:

    Q1 = heart_attack[col].quantile(0.25)
    Q3 = heart_attack[col].quantile(0.75)
    IQR = Q3 - Q1

    heart_attack.loc[heart_attack[col] > Q3 + 1.5 * IQR, col] = heart_attack.
 ↪describe().loc['50%'][col]
```

[16]:
```
Q1 = heart_attack['thalach'].quantile(0.25)
Q3 = heart_attack['thalach'].quantile(0.75)
IQR = Q3 - Q1
```

```
min_thalach = Q1 - 1.5 * IQR

median_thalach = heart_attack.describe().loc['50%']['thalach']
heart_attack.loc[heart_attack['thalach'] < min_thalach, 'thalach'] =␣
↪median_thalach
```

[17]:
```
plt.figure(figsize=(18,10))
plt.subplot(2,5,1)
sns.histplot(heart_attack['age'],kde=True)
plt.subplot(2,5,6)
sns.boxplot(heart_attack['age'])
plt.subplot(2,5,2)
sns.histplot(heart_attack['trestbps'],kde=True)
plt.subplot(2,5,7)
sns.boxplot(heart_attack['trestbps'])
plt.subplot(2,5,3)
sns.histplot(heart_attack['chol'],kde=True)
plt.subplot(2,5,8)
sns.boxplot(heart_attack['chol'])
plt.subplot(2,5,4)
sns.histplot(heart_attack['thalach'],kde=True)
plt.subplot(2,5,9)
sns.boxplot(heart_attack['thalach'])
plt.subplot(2,5,5)
sns.histplot(heart_attack['oldpeak'],kde=True)
plt.subplot(2,5,10)
sns.boxplot(heart_attack['oldpeak']);
```



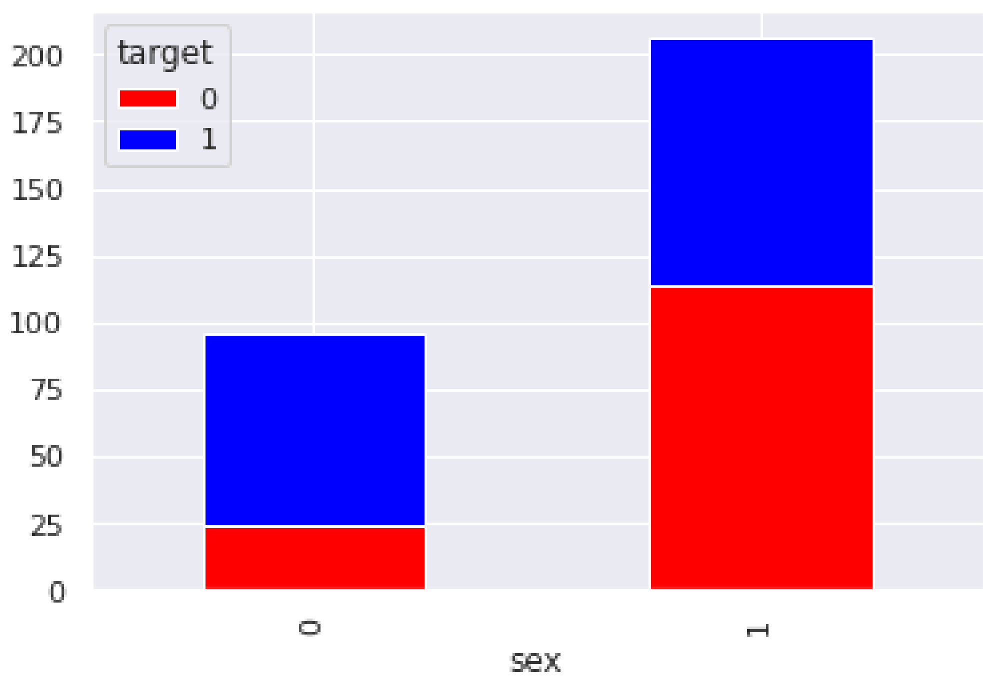
[18]:
```
for col in heart_attack.columns:
    print(col,":",heart_attack[col].unique().size)
```

```
age : 41
sex : 2
cp : 4
trestbps : 43
chol : 148
fbs : 2
restecg : 3
thalach : 91
exang : 2
oldpeak : 36
slope : 3
ca : 5
thal : 4
target : 2
```

1.4 Exploratory Data Analysis

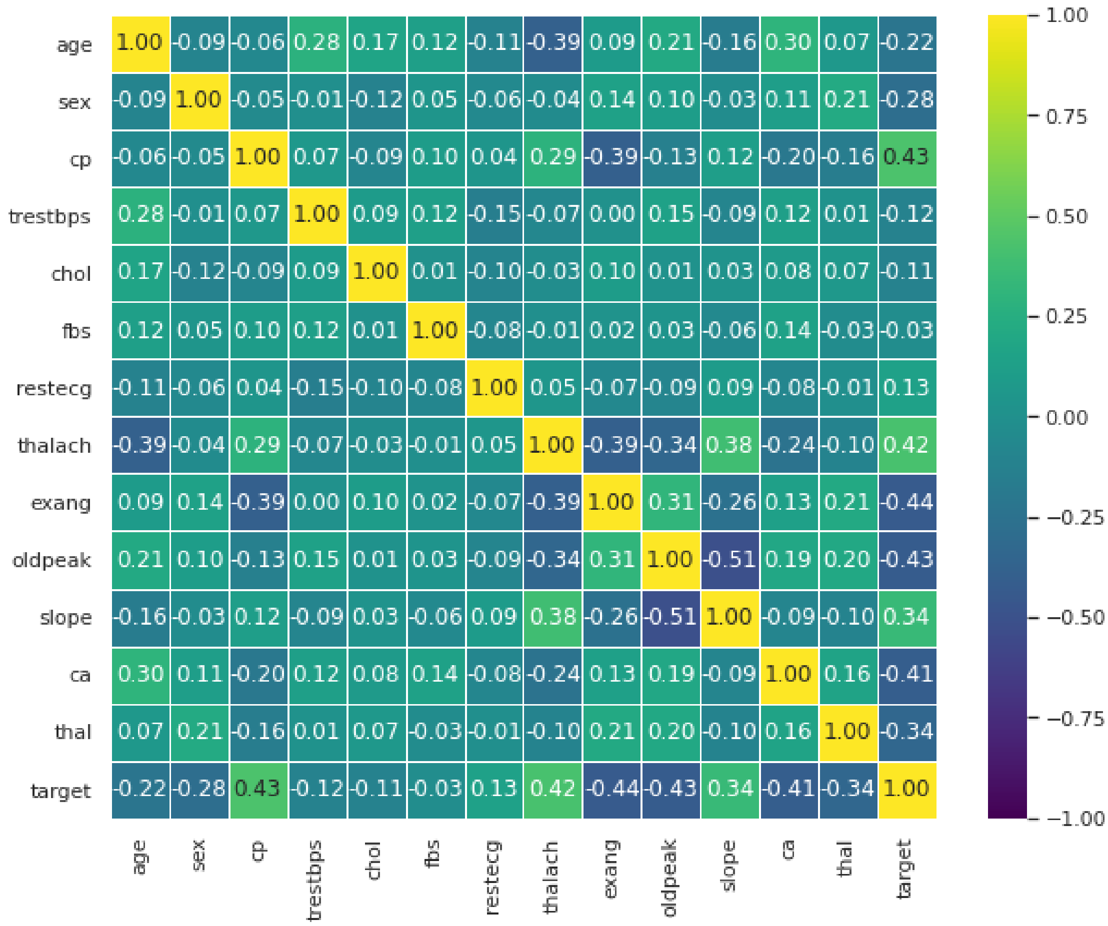
[19]:
```
ha_plot = heart_attack.groupby(['sex','target']).size().reset_index().
 ↪pivot(columns='target', index='sex', values=0)
ha_plot.plot(kind='bar', stacked=True, color=['red','blue'])
```

[19]: <AxesSubplot:xlabel='sex'>



[20]:

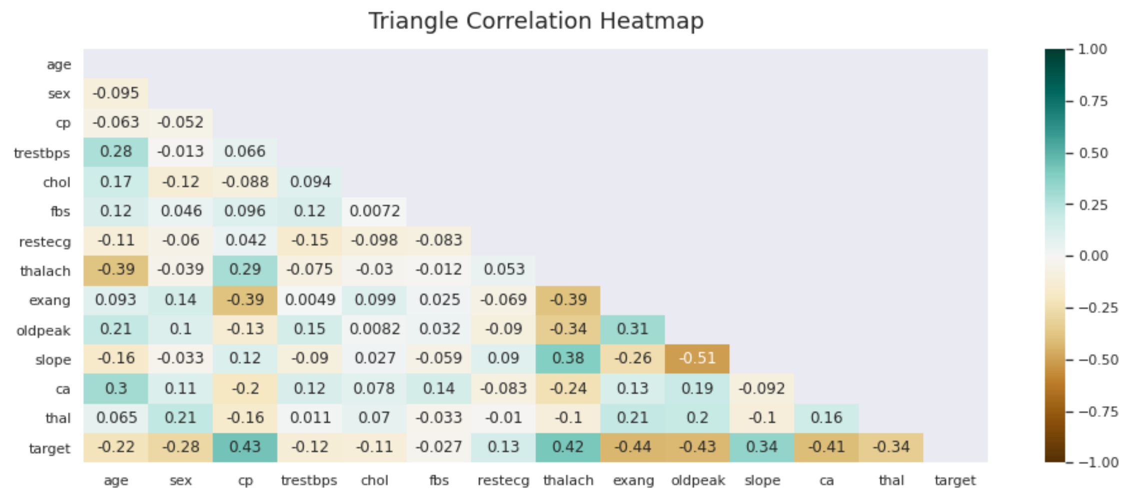
```
corrPearson = heart_attack.corr(method="pearson")

figure = plt.figure(figsize=(10,8))

cm = sns.heatmap(corrPearson,
                 annot=True,
                 fmt=".2f",
                 linewidth=.5,
                 cmap='viridis',
                 vmin=-1, vmax=+1
                 #cbar_pos=(1., .25, .03, .5)
                    )
```



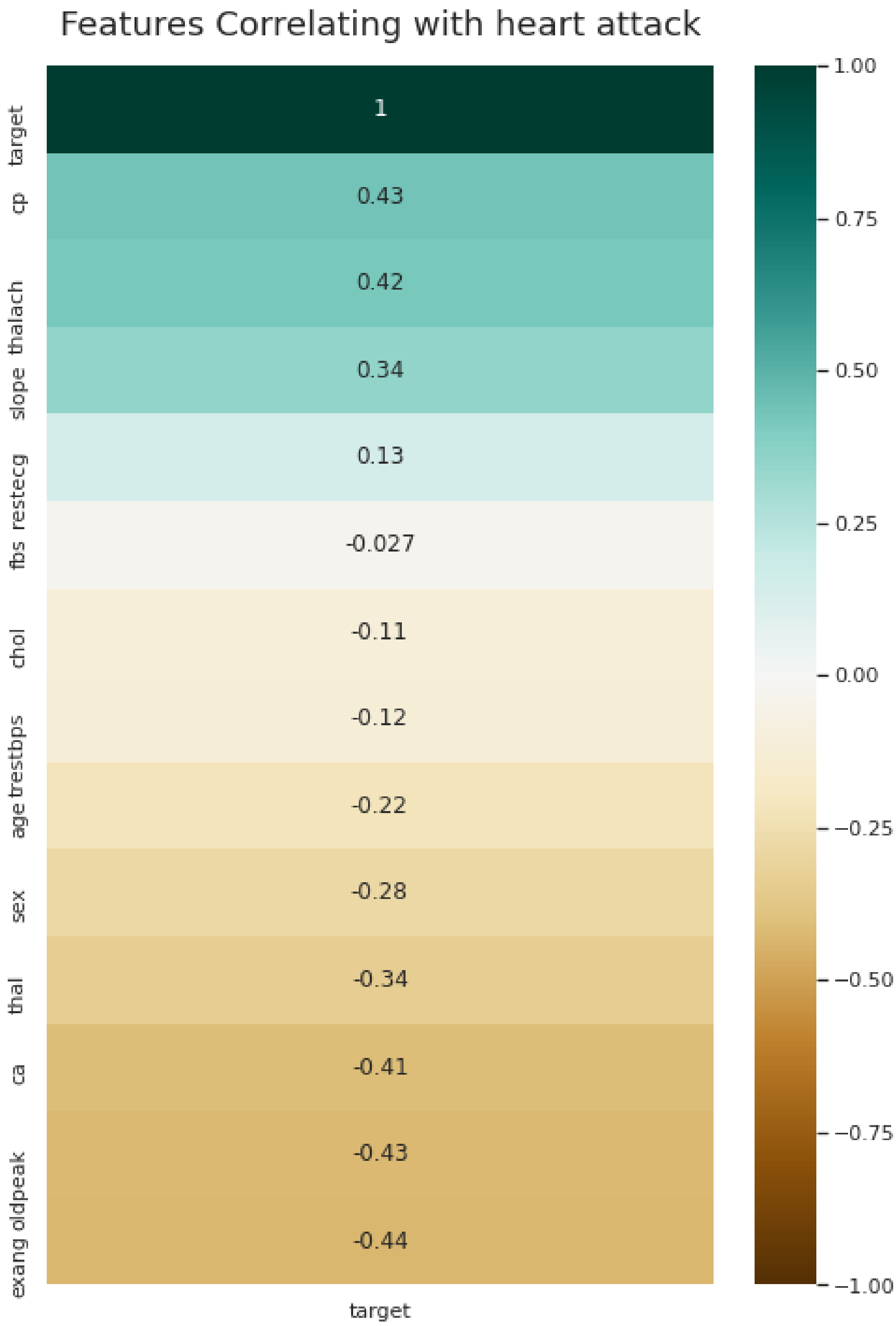
[21]:

```
plt.figure(figsize=(16,6))
```

```
mask = np.triu(np.ones_like(corrPearson, dtype=np.bool))

heatmap = sns.heatmap(corrPearson, mask=mask, vmin=-1, vmax=1, annot=True,␣
 ↪cmap='BrBG')

heatmap.set_title('Triangle Correlation Heatmap', fontdict={'fontsize':18},␣
 ↪pad=16);
```



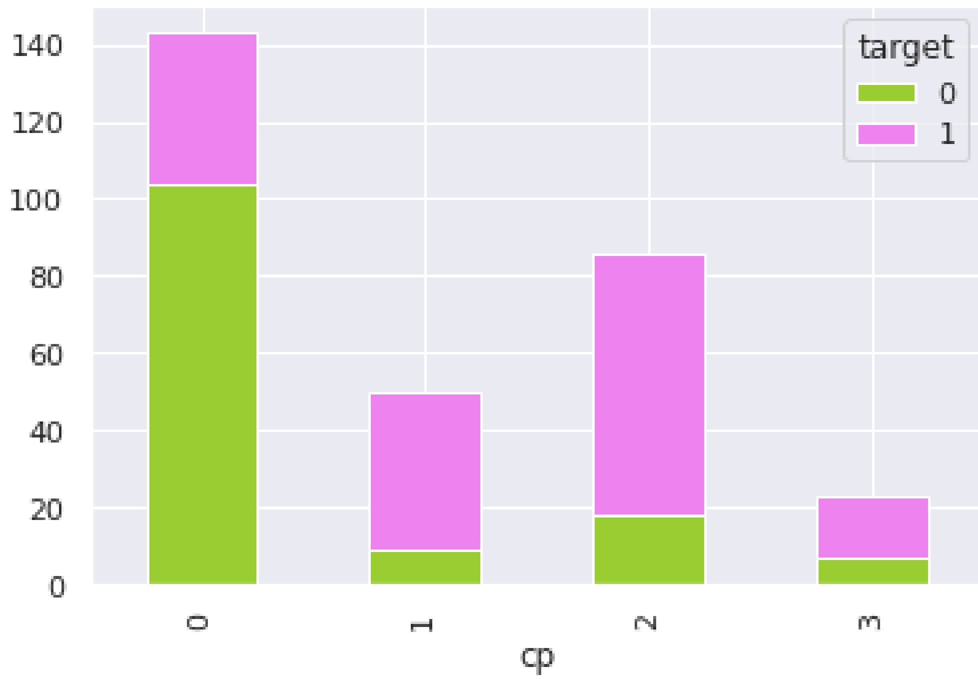
[22]:
```
plt.figure(figsize=(8, 12))
heatmap = sns.heatmap(corrPearson[['target']].sort_values(by='target',␣
 ↪ascending=False), vmin=-1, vmax=1, annot=True, cmap='BrBG')
heatmap.set_title('Features Correlating with heart attack',␣
 ↪fontdict={'fontsize':18}, pad=16);
```



Features Correlating with heart attack
target
cp
thalach
slope
restecg
fbs
chol
trestbps
age
sex
thal
ca
oldpeak
exang
1
0.43
0.42
0.34
0.13
-0.027
-0.11
-0.12
-0.22
-0.28
-0.34
-0.41
-0.43
-0.44
target
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00

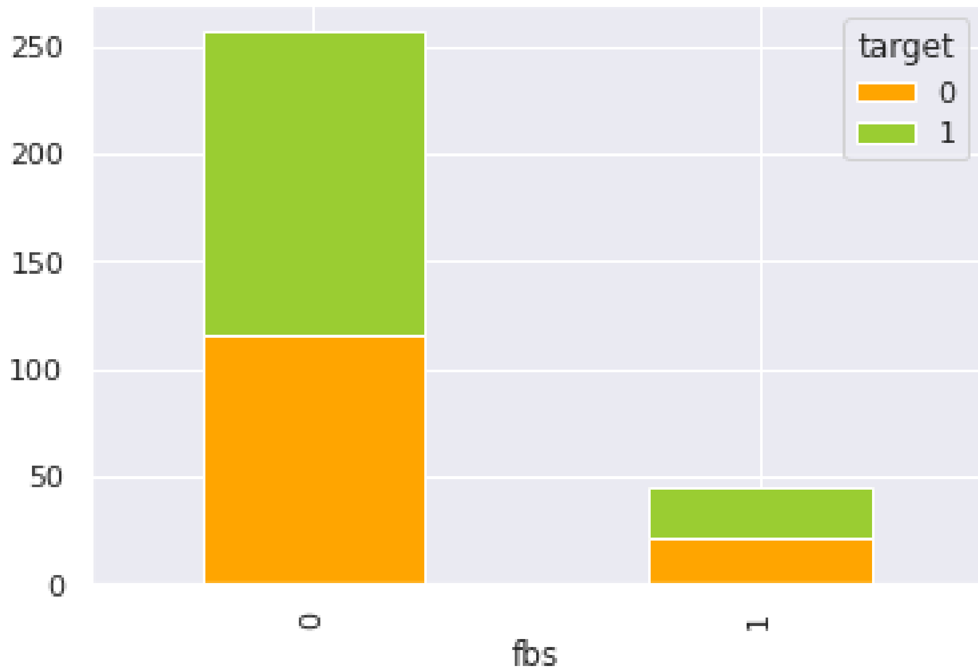
[23]:
```
ha_plot = heart_attack.groupby(['target', 'cp']).size().reset_index().
 ↪pivot(columns='target', index='cp', values=0)
ha_plot.plot(kind='bar', stacked=True, color=['yellowgreen','violet'])
```

[23]: <AxesSubplot:xlabel='cp'>



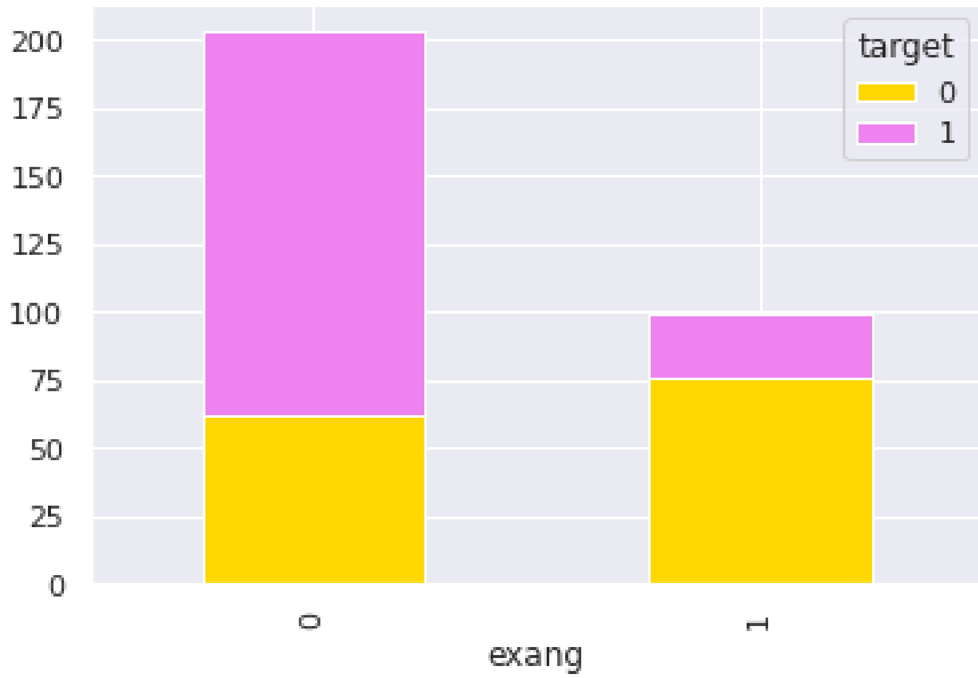
[24]:
```
ha_plot = heart_attack.groupby(['target', 'fbs']).size().reset_index().
 ↪pivot(columns='target', index='fbs', values=0)
ha_plot.plot(kind='bar', stacked=True, color=['orange', 'yellowgreen'])
```

[24]: <AxesSubplot:xlabel='fbs'>



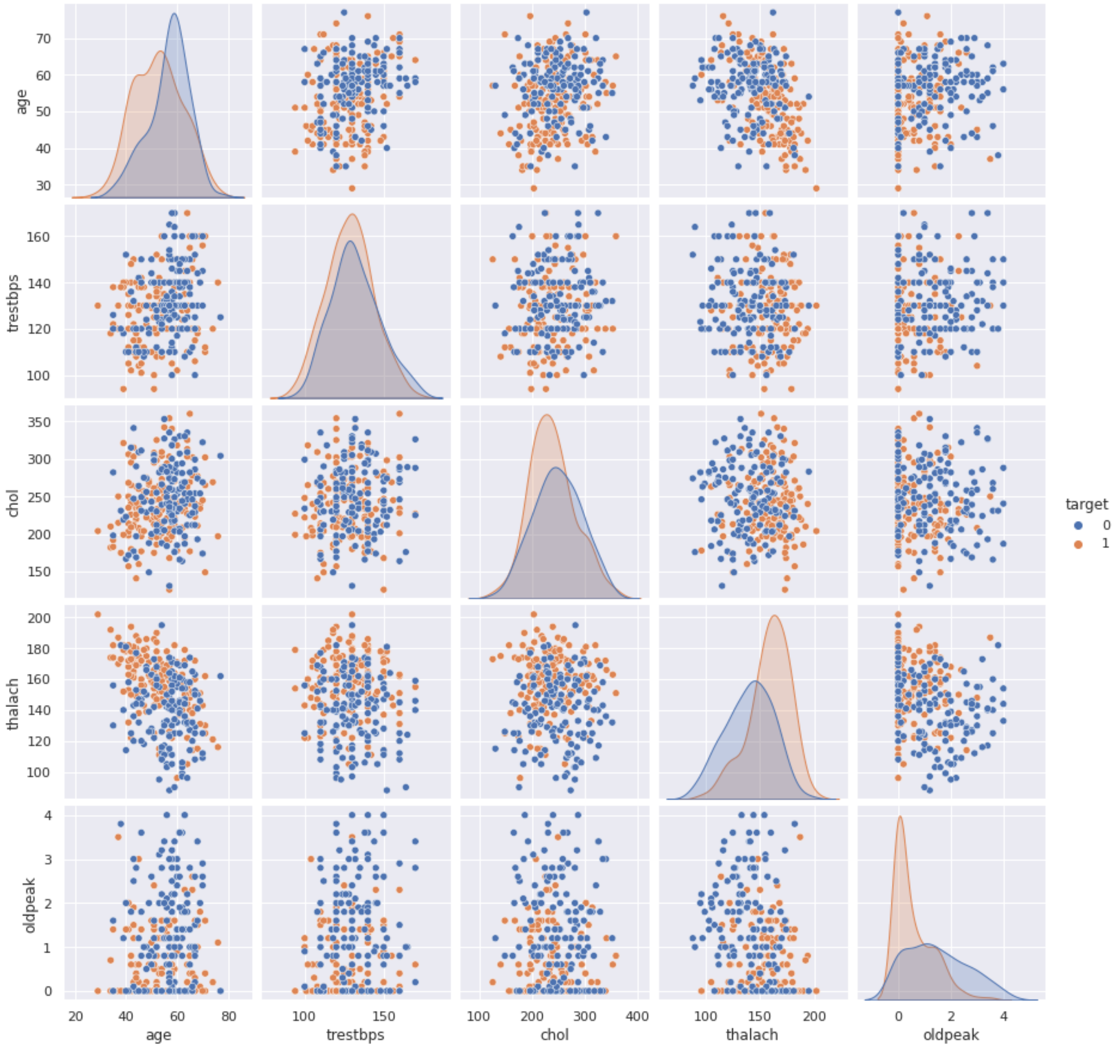
[25]:
```
ha_plot = heart_attack.groupby(['target', 'exang']).size().reset_index().
 ↪pivot(columns='target', index='exang', values=0)
ha_plot.plot(kind='bar', stacked=True, color=['gold', 'violet'])
```

[25]: `<AxesSubplot:xlabel='exang'>`



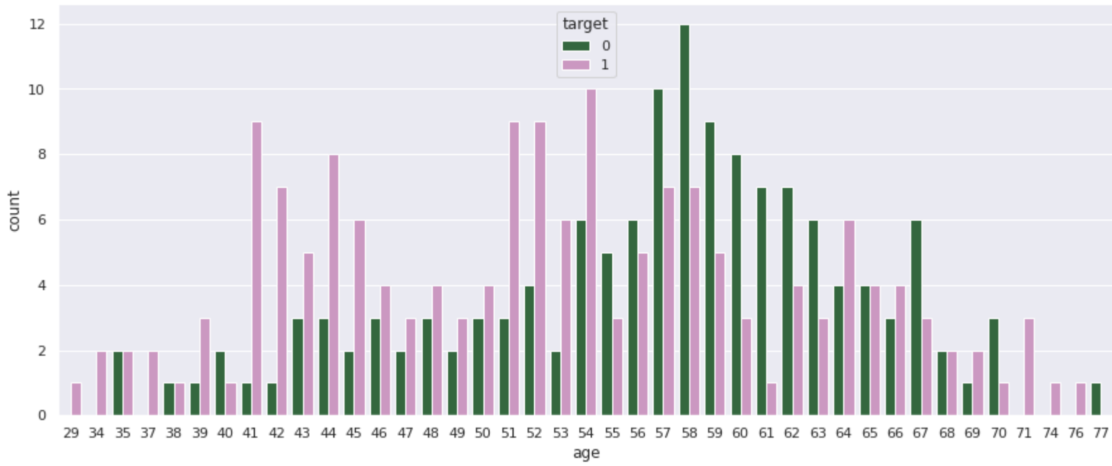
[26]:
```
sns.pairplot(heart_attack[['age','trestbps','chol',
                   'thalach','oldpeak','target']],hue='target')
```

[26]: <seaborn.axisgrid.PairGrid at 0x7ff42cb83d90>

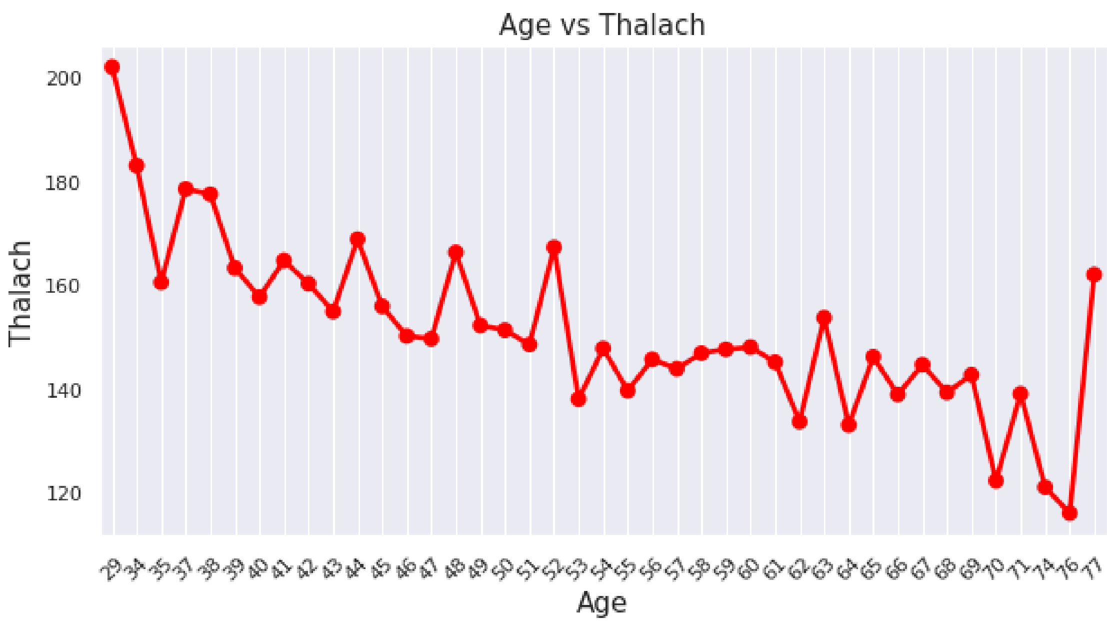


[27]:
```
plt.figure(figsize=(15,6))
sns.countplot(x='age',data = heart_attack, hue = 'target',palette='cubehelix')
```

[27]: <AxesSubplot:xlabel='age', ylabel='count'>



[29]:
```
age_unique=sorted(heart_attack.age.unique())
age_thalach_values=heart_attack.groupby('age')['thalach'].count().values
mean_thalach=[]
for i,age in enumerate(age_unique):
    mean_thalach.append(sum(heart_attack[heart_attack['age']==age].thalach)/
 ↪age_thalach_values[i])

plt.figure(figsize=(10,5))
sns.pointplot(x=age_unique,y=mean_thalach,color='red',alpha=0.8)
plt.xlabel('Age',fontsize = 15)
plt.xticks(rotation=45)
plt.ylabel('Thalach',fontsize = 15)
plt.title('Age vs Thalach',fontsize = 15)
plt.grid()
plt.show()
```



1.5 Machine learning models

1.5.1 Creating Dummy variables

[30]:
```python
# Since 'cp', 'thal', 'fbs', 'restecg', 'ca'. 'exang' and 'slope' are categorical variables we'll turn them into dummy variables.
sex_dummy = pd.get_dummies(heart_attack['sex'], prefix = "sex")
cp_dummy = pd.get_dummies(heart_attack['cp'], prefix = "cp")
thal_dummy = pd.get_dummies(heart_attack['thal'], prefix = "thal")
slope_dummy = pd.get_dummies(heart_attack['slope'], prefix = "slope")
fbs_dummy = pd.get_dummies(heart_attack['fbs'], prefix = "fbs")
restecg_dummy = pd.get_dummies(heart_attack['restecg'], prefix = "restecg")
ca_dummy = pd.get_dummies(heart_attack['ca'], prefix = "ca")
exang_dummy = pd.get_dummies(heart_attack['exang'], prefix = "exang")

frames = [heart_attack, cp_dummy, thal_dummy, slope_dummy, fbs_dummy, restecg_dummy, ca_dummy, exang_dummy]
heart_attack = pd.concat(frames, axis = 1)

heart_attack = heart_attack.drop(columns = ['sex', 'cp', 'thal', 'slope', 'fbs', 'restecg', 'ca', 'exang'])
heart_attack.head()
```

[30]:
```
   age  trestbps   chol  thalach  oldpeak  target  cp_0  cp_1  cp_2  cp_3  \
0   63     145.0  233.0    150.0      2.3       1     0     0     0     1
1   37     130.0  250.0    187.0      3.5       1     0     0     1     0
```

```
2   41     130.0  204.0    172.0       1.4         1      0      1      0      0
3   56     120.0  236.0    178.0       0.8         1      0      1      0      0
4   57     120.0  354.0    163.0       0.6         1      1      0      0      0

   …  restecg_0  restecg_1  restecg_2  ca_0  ca_1  ca_2  ca_3  ca_4  \
0  …          1          0          0     1     0     0     0     0
1  …          0          1          0     1     0     0     0     0
2  …          1          0          0     1     0     0     0     0
3  …          0          1          0     1     0     0     0     0
4  …          0          1          0     1     0     0     0     0

   exang_0  exang_1
0        1        0
1        1        0
2        1        0
3        1        0
4        0        1

[5 rows x 29 columns]
```

[31]:
```python
heart_attack.columns
```

[31]:
```
Index(['age', 'trestbps', 'chol', 'thalach', 'oldpeak', 'target', 'cp_0',
       'cp_1', 'cp_2', 'cp_3', 'thal_0', 'thal_1', 'thal_2', 'thal_3',
       'slope_0', 'slope_1', 'slope_2', 'fbs_0', 'fbs_1', 'restecg_0',
       'restecg_1', 'restecg_2', 'ca_0', 'ca_1', 'ca_2', 'ca_3', 'ca_4',
       'exang_0', 'exang_1'],
      dtype='object')
```

[32]:
```python
scaler = MinMaxScaler()

heart_scaled=scaler.fit_transform(heart_attack)
heart_scaled=pd.DataFrame(data=heart_scaled, columns=heart_attack.columns)
```

[33]:
```python
heart_scaled.head()
```

[33]:
```
        age  trestbps      chol   thalach  oldpeak  target  cp_0  cp_1  cp_2  \
0  0.708333  0.671053  0.457265  0.543860    0.575     1.0   0.0   0.0   0.0
1  0.166667  0.473684  0.529915  0.868421    0.875     1.0   0.0   0.0   1.0
2  0.250000  0.473684  0.333333  0.736842    0.350     1.0   0.0   1.0   0.0
3  0.562500  0.342105  0.470085  0.789474    0.200     1.0   0.0   1.0   0.0
4  0.583333  0.342105  0.974359  0.657895    0.150     1.0   1.0   0.0   0.0

   cp_3  …  restecg_0  restecg_1  restecg_2  ca_0  ca_1  ca_2  ca_3  ca_4  \
0   1.0  …        1.0        0.0        0.0   1.0   0.0   0.0   0.0   0.0
1   0.0  …        0.0        1.0        0.0   1.0   0.0   0.0   0.0   0.0
2   0.0  …        1.0        0.0        0.0   1.0   0.0   0.0   0.0   0.0
```

```
3   0.0  …         0.0         1.0         0.0    1.0    0.0    0.0    0.0    0.0
4   0.0  …         0.0         1.0         0.0    1.0    0.0    0.0    0.0    0.0

   exang_0  exang_1
0      1.0      0.0
1      1.0      0.0
2      1.0      0.0
3      1.0      0.0
4      0.0      1.0

[5 rows x 29 columns]
```

[34]:
```
y = heart_scaled['target']
X = heart_scaled.drop(columns = ['target'])

X_train, X_test, y_train, y_test = train_test_split(X,
                                                    y,
                                                    test_size=0.2,
                                                    random_state = 0
                                                   )
```

1.5.2 Logistic Regression with GridSearch

[35]:
```
params = {"C": np.logspace(-4, 4, 20),
          "solver": ["liblinear"]}

lr_clf = LogisticRegression()

lr_cv = GridSearchCV(lr_clf, params, scoring="accuracy", n_jobs=-1, verbose=1,␣
 ↪cv=5)
lr_cv.fit(X_train, y_train)
best_params = lr_cv.best_params_
print(f"Best parameters: {best_params}")
lr_clf = LogisticRegression(**best_params)

score_lr=np.mean(cross_val_score(lr_clf, X_train, y_train, cv=3,␣
 ↪scoring='accuracy'))
print("Accuracy is : ",score_lr)

lr_clf.fit(X_train, y_train)
```

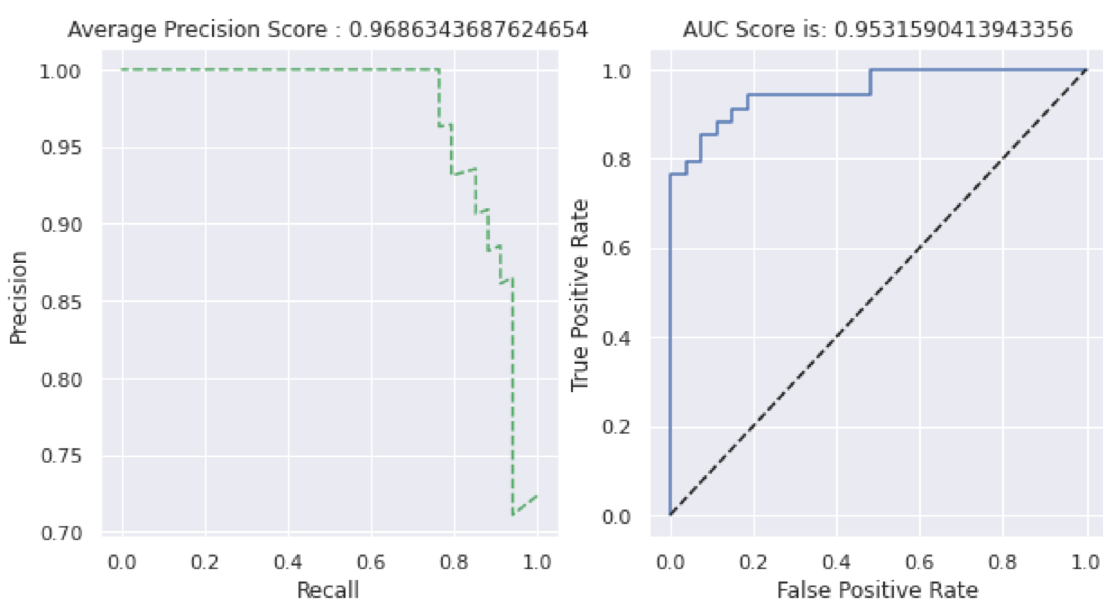
```
Fitting 5 folds for each of 20 candidates, totalling 100 fits
Best parameters: {'C': 0.615848211066026, 'solver': 'liblinear'}
Accuracy is :  0.8382716049382717
```

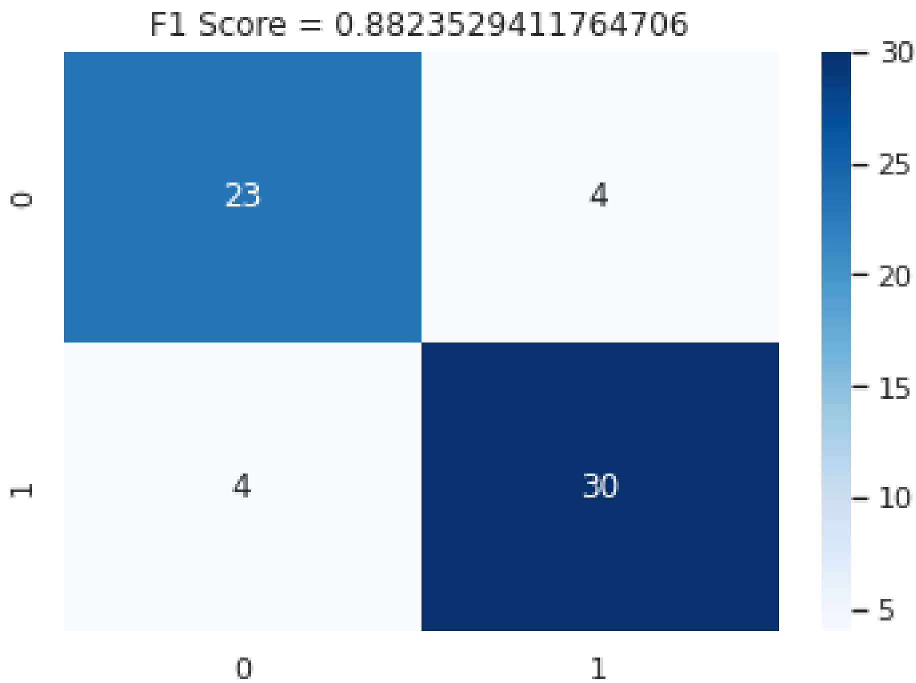
[35]:
```
LogisticRegression(C=0.615848211066026, solver='liblinear')
```

[36]:
```
def plotting(true,pred):
    fig,ax=plt.subplots(1,2,figsize=(10,5))
    precision,recall,threshold = precision_recall_curve(true,pred[:,1])
    ax[0].plot(recall,precision,'g--')
    ax[0].set_xlabel('Recall')
    ax[0].set_ylabel('Precision')
    ax[0].set_title("Average Precision Score : {}".
 ↪format(average_precision_score(true,pred[:,1])))
    fpr,tpr,threshold = roc_curve(true,pred[:,1])
    ax[1].plot(fpr,tpr)
    ax[1].set_title("AUC Score is: {}".format(auc(fpr,tpr)))
    ax[1].plot([0,1],[0,1],'k--')
    ax[1].set_xlabel('False Positive Rate')
    ax[1].set_ylabel('True Positive Rate')
```

[37]:
```
plotting(y_test,lr_clf.predict_proba(X_test))

fig=plt.figure()
sns.heatmap(confusion_matrix(y_test,lr_clf.predict(X_test)), annot= True,␣
 ↪cmap='Blues')
lr_f1=f1_score(y_test,lr_clf.predict(X_test))
plt.title('F1 Score = {}'.format(lr_f1))
```

[37]:
```
Text(0.5, 1.0, 'F1 Score = 0.8823529411764706')
```






```
[38]: test_score = accuracy_score(y_test, lr_clf.predict(X_test)) * 100
      train_score = accuracy_score(y_train, lr_clf.predict(X_train)) * 100

      tuning_results_df = pd.DataFrame(data=[["Tuned Logistic Regression",␣
       ↪train_score, test_score]],
                                   columns=['Model', 'Training Accuracy %', 'Testing␣
       ↪Accuracy %'])
```

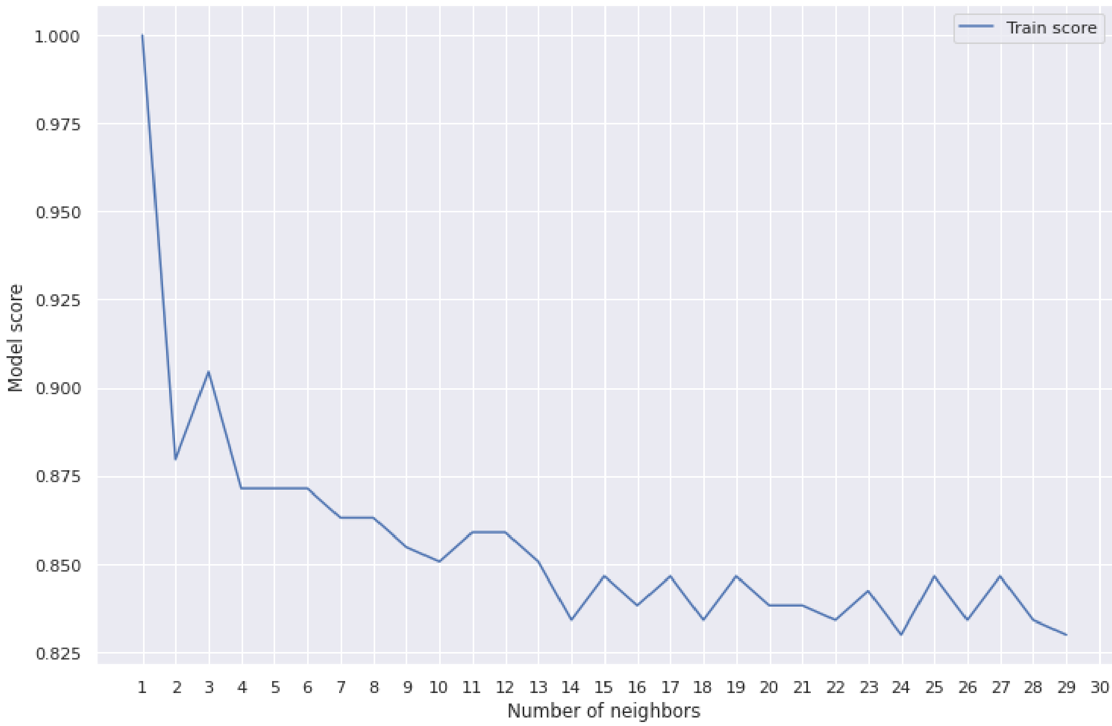
1.5.3 K Nearest Neighbors searching through a range of neighbors

```
[39]: train_score = []
      test_score = []
      neighbors = range(1, 30)

      for k in neighbors:
          model = KNeighborsClassifier(n_neighbors=k)
          model.fit(X_train, y_train)
          train_score.append(accuracy_score(y_train, model.predict(X_train)))
      #     test_score.append(accuracy_score(y_test, model.predict(X_test)))
```

```
[40]: plt.figure(figsize=(12, 8))

      plt.plot(neighbors, train_score, label="Train score")
      # plt.plot(neighbors, test_score, label="Test score")
```

```
plt.xticks(np.arange(1, 31, 1))
plt.xlabel("Number of neighbors")
plt.ylabel("Model score")
plt.legend()

print(f"Maximum KNN score on the test data: {max(train_score)*100:.2f}%")
```

Maximum KNN score on the test data: 100.00%



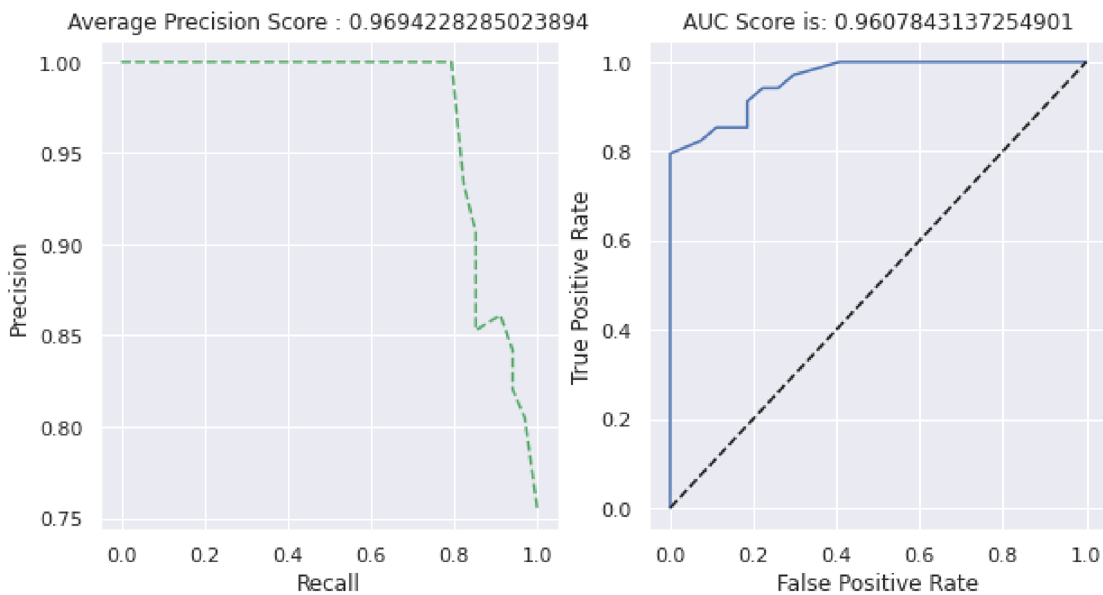
[41]:
```
knn_clf = KNeighborsClassifier(n_neighbors=24)
knn_clf.fit(X_train, y_train)

score_k=np.mean(cross_val_score(knn_clf, X_train, y_train, cv=3,␣
↪scoring='accuracy'))
print("Accuracy is : ",score_k)
```

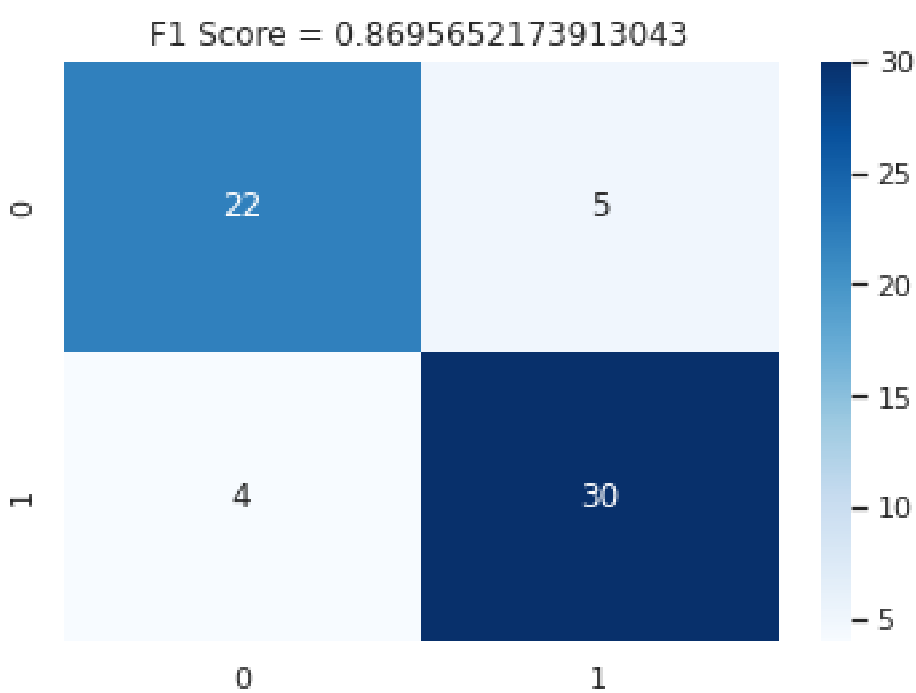
Accuracy is : 0.8423868312757202

[42]:
```
plotting(y_test,knn_clf.predict_proba(X_test))

fig=plt.figure()
sns.heatmap(confusion_matrix(y_test,knn_clf.predict(X_test)), annot= True,␣
↪cmap='Blues')
knn_f1=f1_score(y_test,knn_clf.predict(X_test))
```

```
plt.title('F1 Score = {}'.format(knn_f1))
```

[42]: Text(0.5, 1.0, 'F1 Score = 0.8695652173913043')





[43]:
```
test_score = accuracy_score(y_test, knn_clf.predict(X_test)) * 100
train_score = accuracy_score(y_train, knn_clf.predict(X_train)) * 100

results_df_2 = pd.DataFrame(data=[["Tuned K-nearest neighbors", train_score,␣
↪test_score]],
                          columns=['Model', 'Training Accuracy %', 'Testing␣
↪Accuracy %'])
tuning_results_df = tuning_results_df.append(results_df_2, ignore_index=True)
```

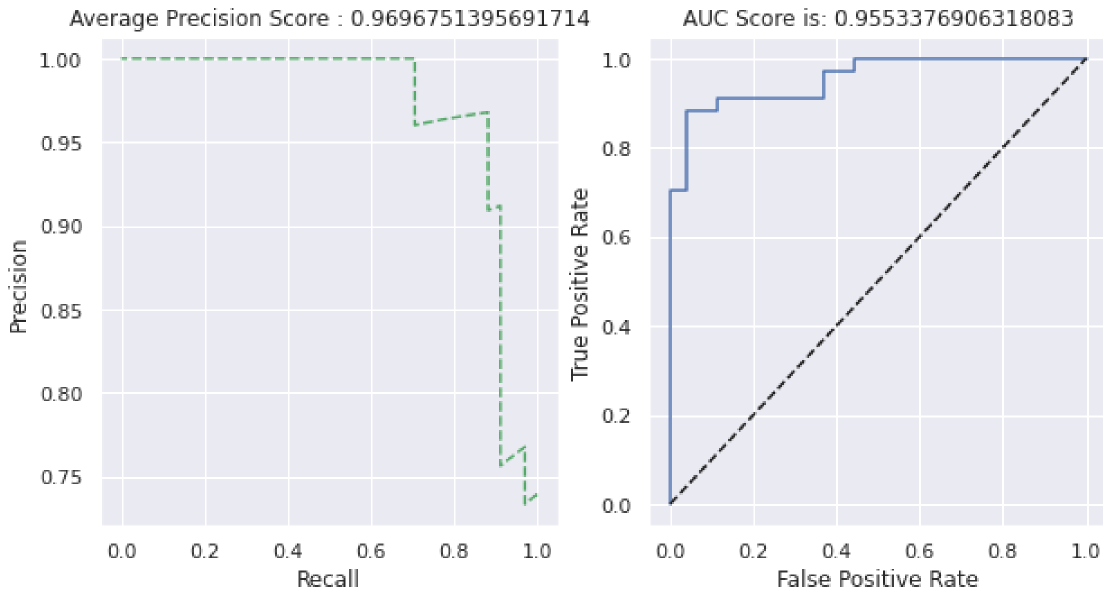
1.5.4 Support Vector Machine

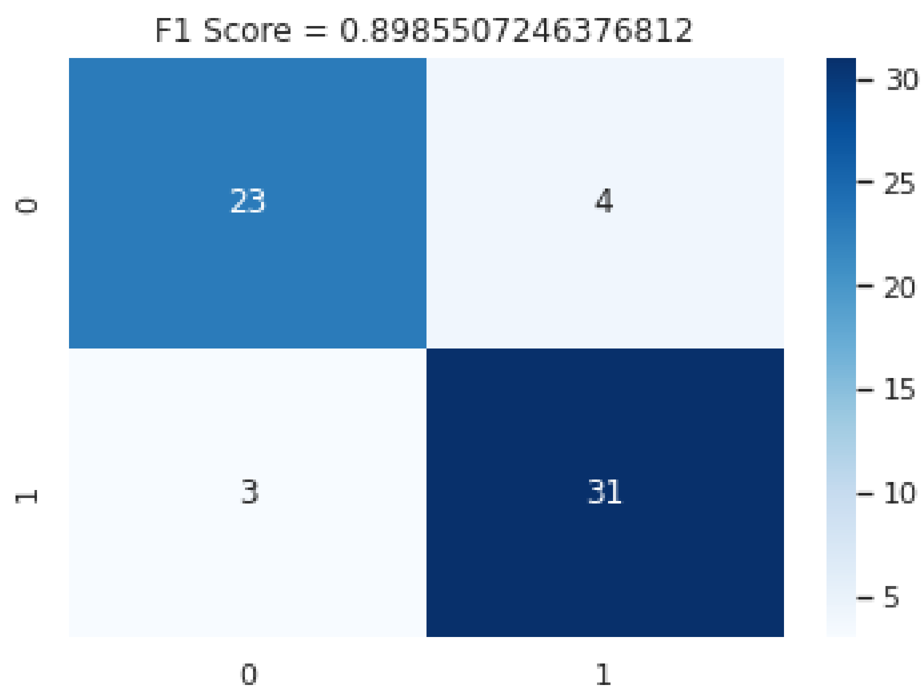
[44]:
```
svm_clf = SVC(C= 2, gamma= 0.1, kernel= 'rbf',probability=True)

# params = {"C":(0.1, 0.5, 1, 2, 5, 10, 20),
#           "gamma":(0.001, 0.01, 0.1, 0.25, 0.5, 0.75, 1),
#           "kernel":('linear', 'poly', 'rbf'),
#          }

# svm_cv = GridSearchCV(svm_clf, params, n_jobs=-1, cv=5, verbose=1,␣
↪scoring="accuracy")
# svm_cv.fit(X_train, y_train)
# best_params = svm_cv.best_params_
# print(f"Best params: {best_params}")

# svm_clf = SVC(**best_params)

svm_clf.fit(X_train, y_train)

score_svm=np.mean(cross_val_score(svm_clf, X_train, y_train, cv=3,␣
↪scoring='accuracy'))
print("Accuracy is : ",score_svm)
```

```
Accuracy is :  0.8507201646090534
```

[45]:
```
plotting(y_test,svm_clf.predict_proba(X_test))

fig=plt.figure()
sns.heatmap(confusion_matrix(y_test,svm_clf.predict(X_test)), annot= True,␣
↪cmap='Blues')
svm_f1=f1_score(y_test,svm_clf.predict(X_test))
plt.title('F1 Score = {}'.format(svm_f1))
```

[45]:
```
Text(0.5, 1.0, 'F1 Score = 0.8985507246376812')
```





[46]:

```
test_score = accuracy_score(y_test, svm_clf.predict(X_test)) * 100
train_score = accuracy_score(y_train, svm_clf.predict(X_train)) * 100
```

```
results_df_2 = pd.DataFrame(data=[["Support Vector Machine", train_score,␣
 ↪test_score]],
                          columns=['Model', 'Training Accuracy %', 'Testing␣
 ↪Accuracy %'])
tuning_results_df = tuning_results_df.append(results_df_2, ignore_index=True)
```

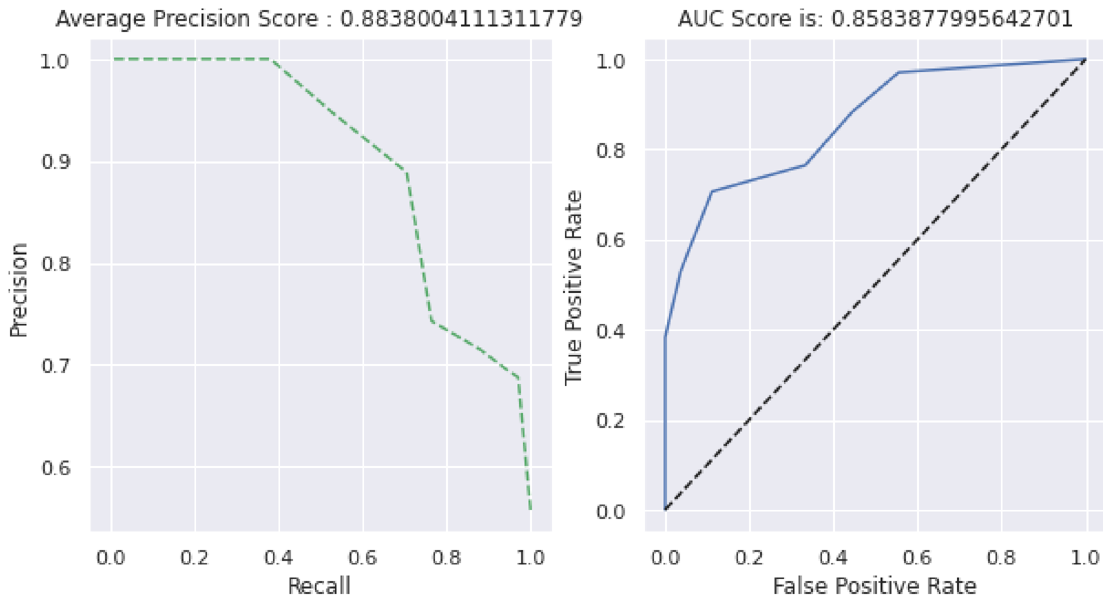
1.5.5 Decision Tree Classifier with GridSearch

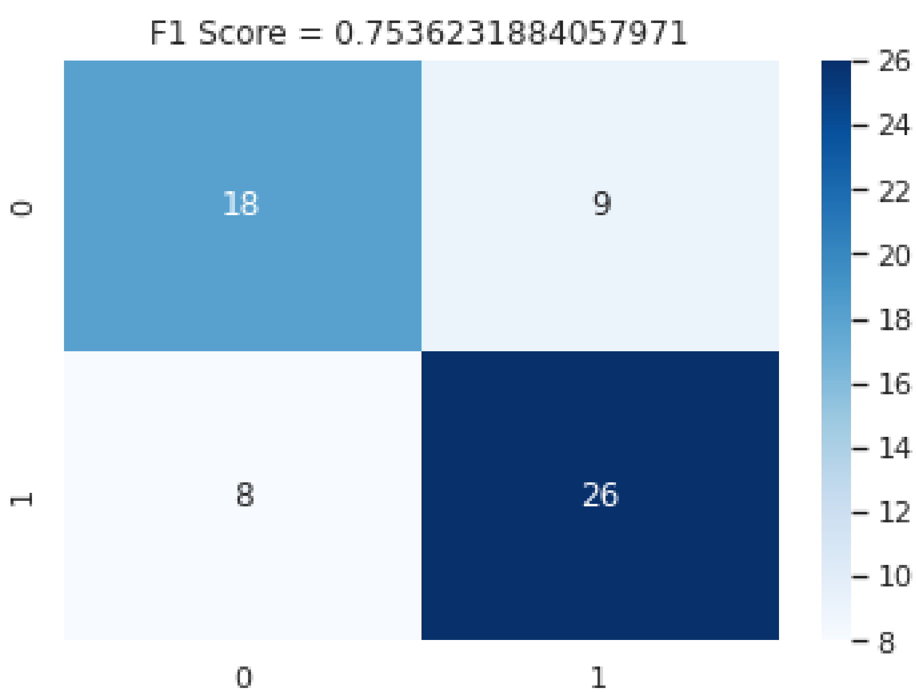
[47]:
```
params = {"criterion":("gini", "entropy"),
          "splitter":("best", "random"),
          "max_depth":(list(range(1, 20))),
          "min_samples_split":[2, 3, 4],
          "min_samples_leaf":list(range(1, 20))
          }

tree_clf = DecisionTreeClassifier(random_state=42)
tree_cv = GridSearchCV(tree_clf, params, scoring="accuracy", n_jobs=-1,␣
 ↪verbose=1, cv=3)
tree_cv.fit(X_train, y_train)
best_params = tree_cv.best_params_
print(f'Best_params: {best_params}')

tree_clf = DecisionTreeClassifier(**best_params)
tree_clf.fit(X_train, y_train)

score_tree=np.mean(cross_val_score(tree_clf, X_train, y_train, cv=3,␣
 ↪scoring='accuracy'))
print("Accuracy is : ",score_tree)
```

```
Fitting 3 folds for each of 4332 candidates, totalling 12996 fits
Best_params: {'criterion': 'gini', 'max_depth': 3, 'min_samples_leaf': 11,
'min_samples_split': 2, 'splitter': 'random'}
Accuracy is :  0.854783950617284
```

[48]:
```
plotting(y_test,tree_clf.predict_proba(X_test))

fig=plt.figure()
sns.heatmap(confusion_matrix(y_test,tree_clf.predict(X_test)), annot= True,␣
 ↪cmap='Blues')
tree_f1=f1_score(y_test,tree_clf.predict(X_test))
plt.title('F1 Score = {}'.format(tree_f1))
```

[48]:
```
Text(0.5, 1.0, 'F1 Score = 0.7536231884057971')
```






```
[49]: test_score = accuracy_score(y_test, tree_clf.predict(X_test)) * 100
      train_score = accuracy_score(y_train, tree_clf.predict(X_train)) * 100
```

```
results_df_2 = pd.DataFrame(data=[["Tuned Decision Tree Classifier",␣
↪train_score, test_score]],
                          columns=['Model', 'Training Accuracy %', 'Testing␣
↪Accuracy %'])
tuning_results_df = tuning_results_df.append(results_df_2, ignore_index=True)
```

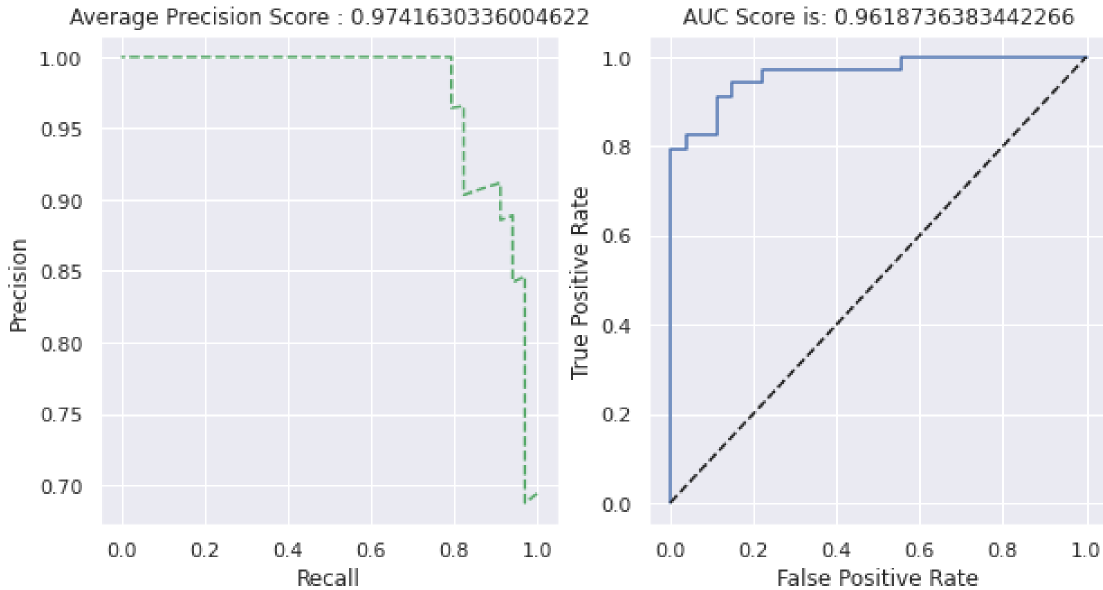
1.5.6 Random Forest with GridSearch

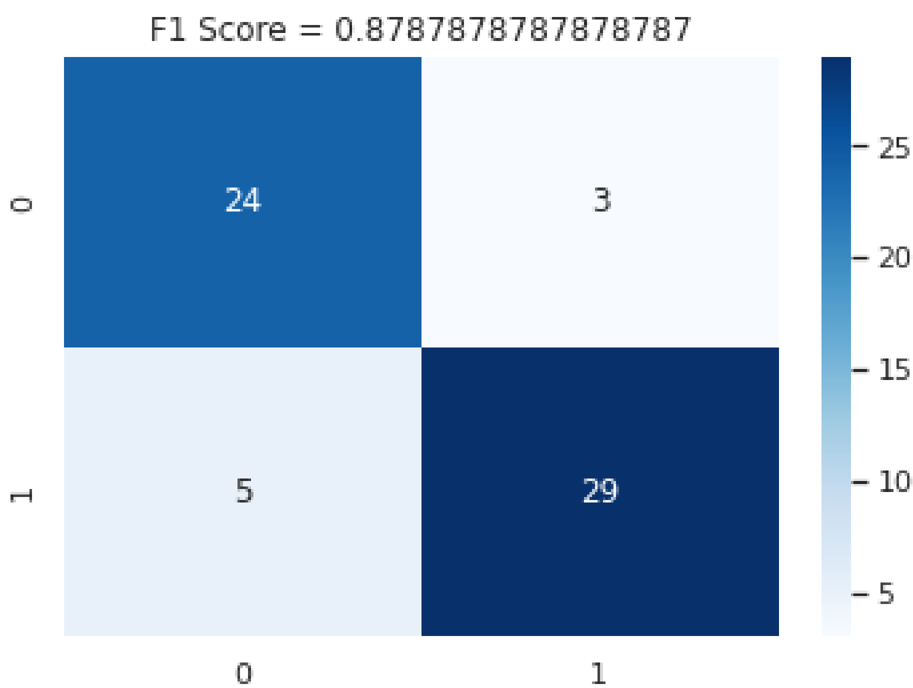
[50]:
```
# Create the parameter grid based on the results of random search
params_grid = {
    'bootstrap': [True],
    'max_depth': [80, 90, 100, 110],
    'max_features': [2, 3],
    'min_samples_leaf': [3, 4, 5],
    'min_samples_split': [8, 10, 12],
    'n_estimators': [100, 200, 300, 1000]
}

rf_clf = RandomForestClassifier(random_state=42)

rf_cv = GridSearchCV(rf_clf, params_grid, scoring="accuracy", cv=3, verbose=2,␣
↪n_jobs=-1)


rf_cv.fit(X_train, y_train)
best_params = rf_cv.best_params_
print(f"Best parameters: {best_params}")

rf_clf = RandomForestClassifier(**best_params)
rf_clf.fit(X_train, y_train)

score_rf=np.mean(cross_val_score(rf_clf, X_train, y_train, cv=3,␣
↪scoring='accuracy'))
print("Accuracy is : ",score_rf)
```

```
Fitting 3 folds for each of 288 candidates, totalling 864 fits
Best parameters: {'bootstrap': True, 'max_depth': 80, 'max_features': 3,
'min_samples_leaf': 3, 'min_samples_split': 8, 'n_estimators': 200}
Accuracy is :  0.8258744855967078
```

[51]:
```
plotting(y_test,rf_clf.predict_proba(X_test))

fig=plt.figure()
sns.heatmap(confusion_matrix(y_test,rf_clf.predict(X_test)), annot= True,␣
↪cmap='Blues')
rf_f1=f1_score(y_test,rf_clf.predict(X_test))
plt.title('F1 Score = {}'.format(rf_f1))
```

[51]: Text(0.5, 1.0, 'F1 Score = 0.8787878787878787')






```
[52]: test_score = accuracy_score(y_test, rf_clf.predict(X_test)) * 100
      train_score = accuracy_score(y_train, rf_clf.predict(X_train)) * 100
```

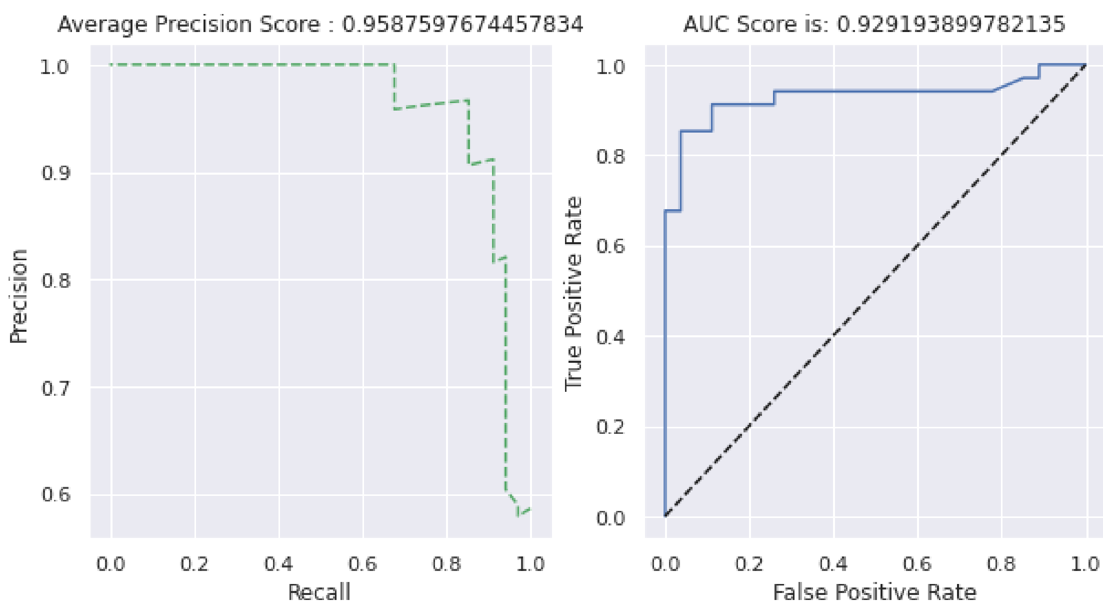
```
results_df_2 = pd.DataFrame(data=[["Tuned Random Forest Classifier",␣
↪train_score, test_score]],
                          columns=['Model', 'Training Accuracy %', 'Testing␣
↪Accuracy %'])
tuning_results_df = tuning_results_df.append(results_df_2, ignore_index=True)
```

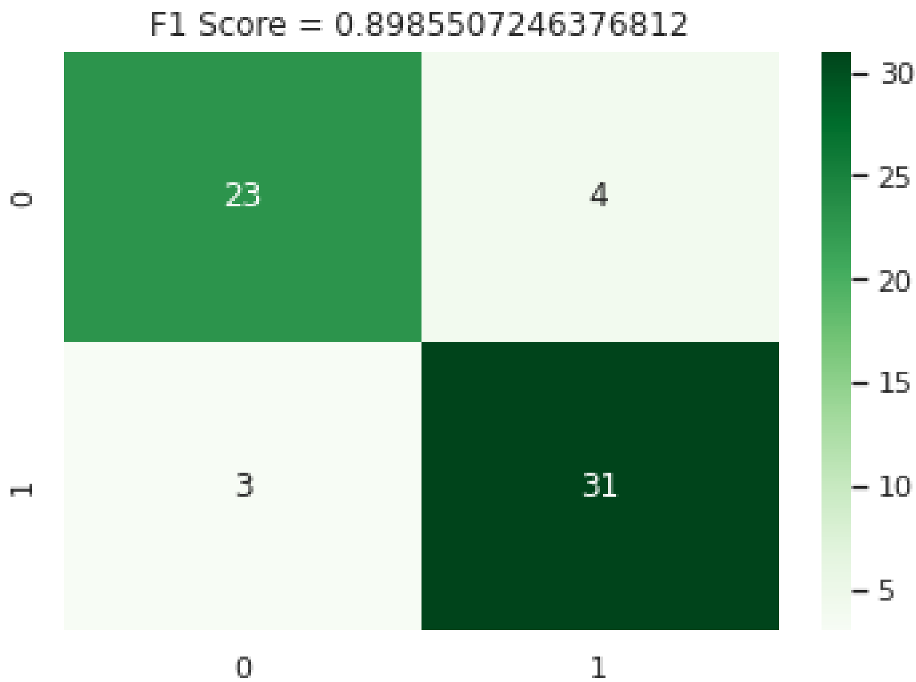
1.5.7 Extra Trees Classifier

[53]:
```
etc=ExtraTreesClassifier(n_estimators=200, n_jobs=-1, random_state=2)

etc.fit(X_train,y_train)

score_etc=np.mean(cross_val_score(etc, X_train, y_train, cv=3,␣
↪scoring='accuracy'))
print("Accuracy is : ",score_etc)

plotting(y_test,etc.predict_proba(X_test))

fig=plt.figure()
sns.heatmap(confusion_matrix(y_test,etc.predict(X_test)), annot= True,␣
↪cmap='Greens')

etc_f1=f1_score(y_test,etc.predict(X_test))
plt.title('F1 Score = {}'.format(etc_f1))
```

```
Accuracy is :  0.8049897119341564
```

[53]:
```
Text(0.5, 1.0, 'F1 Score = 0.8985507246376812')
```





[54]:
```
test_score = accuracy_score(y_test, etc.predict(X_test)) * 100
train_score = accuracy_score(y_train, etc.predict(X_train)) * 100

results_df_2 = pd.DataFrame(data=[["Extra Trees Classifier", train_score,␣
↪test_score]],
                          columns=['Model', 'Training Accuracy %', 'Testing␣
↪Accuracy %'])
tuning_results_df = tuning_results_df.append(results_df_2, ignore_index=True)
```

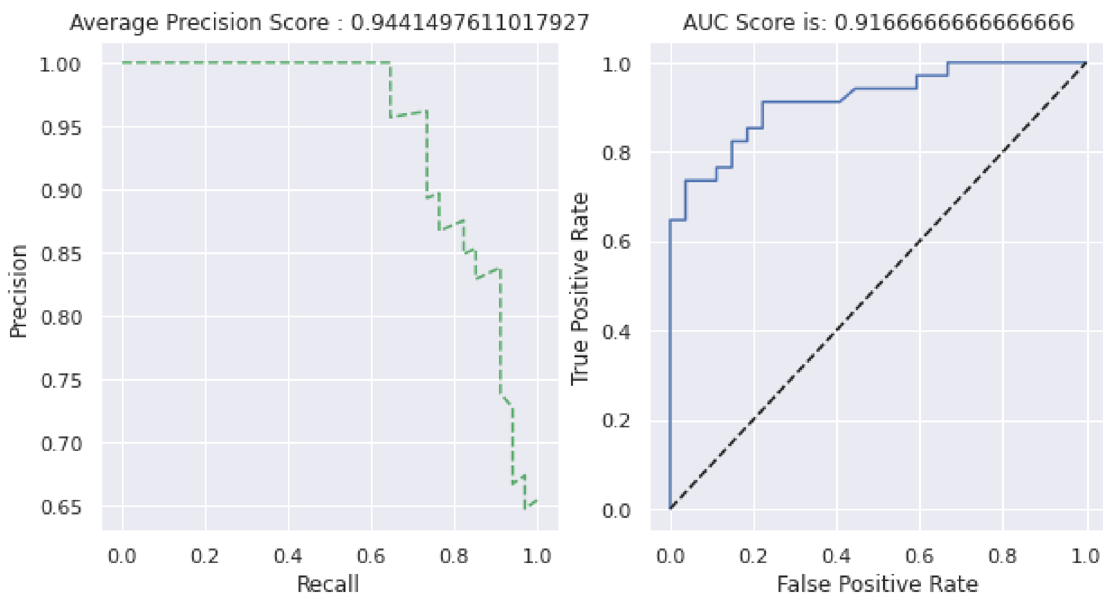
1.5.8 Gradient Boosting Classfier

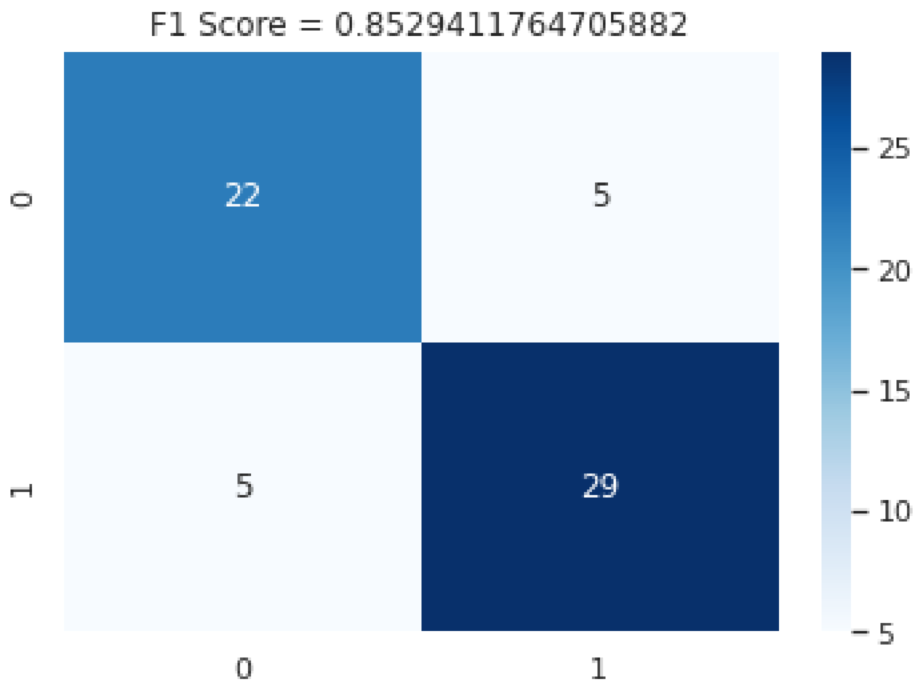
[55]:
```
gbc=GradientBoostingClassifier(n_estimators=100, random_state=43, learning_rate␣
↪= 0.01)

gbc.fit(X_train,y_train)

score_gbc=np.mean(cross_val_score(gbc, X_train, y_train, cv=3,␣
↪scoring='accuracy'))
print("Accuracy is : ",score_gbc)

plotting(y_test,gbc.predict_proba(X_test))
```

```
fig=plt.figure()
sns.heatmap(confusion_matrix(y_test,gbc.predict(X_test)), annot= True,␣
 ↪cmap='Blues')

gbc_f1=f1_score(y_test,gbc.predict(X_test))
plt.title('F1 Score = {}'.format(gbc_f1))
```

```
Accuracy is :  0.8217592592592592
```

[55]:
```
Text(0.5, 1.0, 'F1 Score = 0.8529411764705882')
```






```
[56]: test_score = accuracy_score(y_test, gbc.predict(X_test)) * 100
train_score = accuracy_score(y_train, gbc.predict(X_train)) * 100

results_df_2 = pd.DataFrame(data=[["Gradient Boosting Classifier", train_score,␣
↪test_score]],
                          columns=['Model', 'Training Accuracy %', 'Testing␣
↪Accuracy %'])
tuning_results_df = tuning_results_df.append(results_df_2, ignore_index=True)
```

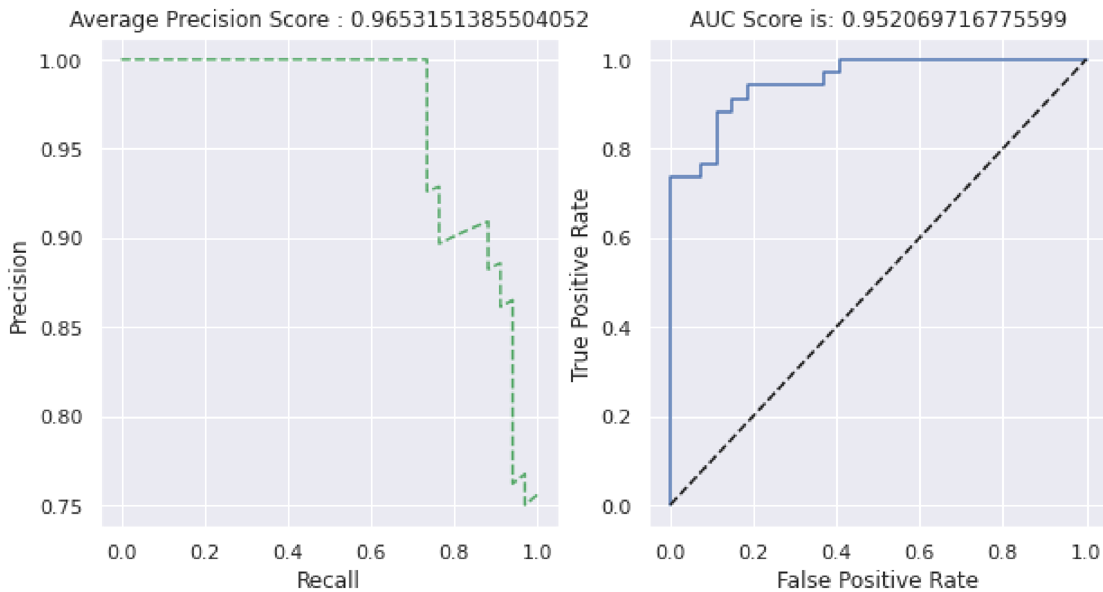
1.5.9 Bagging Classifier

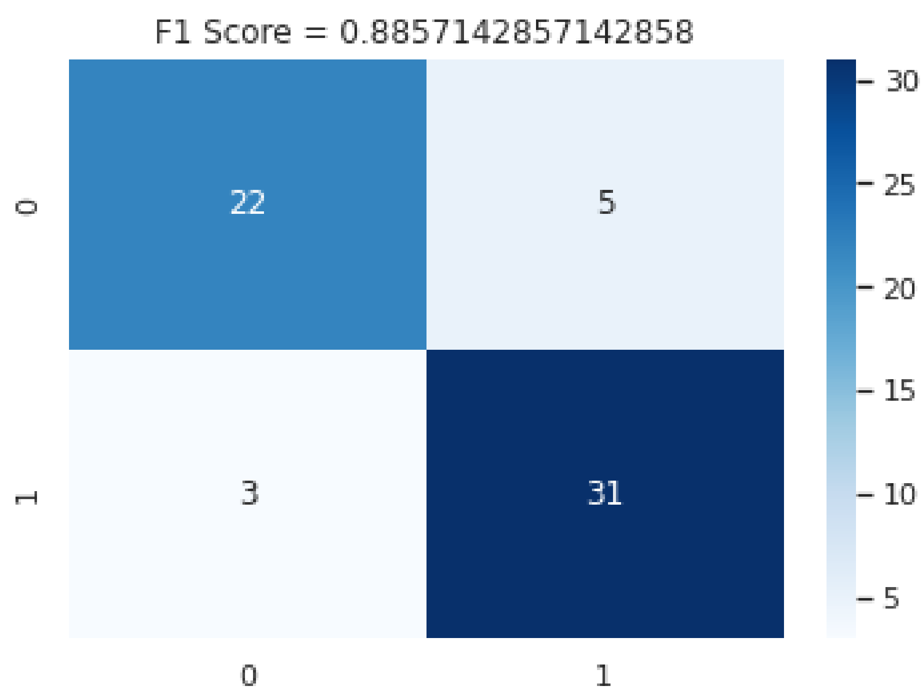
```
[57]: bc=BaggingClassifier(lr_clf,max_samples=23, bootstrap=True, n_jobs= -1)

bc.fit(X_train,y_train)

score_bc=np.mean(cross_val_score(bc, X_train, y_train, cv=3,␣
↪scoring='accuracy'))
print("Accuracy is : ",score_bc)

plotting(y_test,bc.predict_proba(X_test))

fig=plt.figure()
sns.heatmap(confusion_matrix(y_test,bc.predict(X_test)), annot= True,␣
↪cmap='Blues')
```

```
bc_f1=f1_score(y_test,bc.predict(X_test))
plt.title('F1 Score = {}'.format(bc_f1))
```

```
Accuracy is :  0.8425411522633744
```

```
[57]: Text(0.5, 1.0, 'F1 Score = 0.8857142857142858')
```

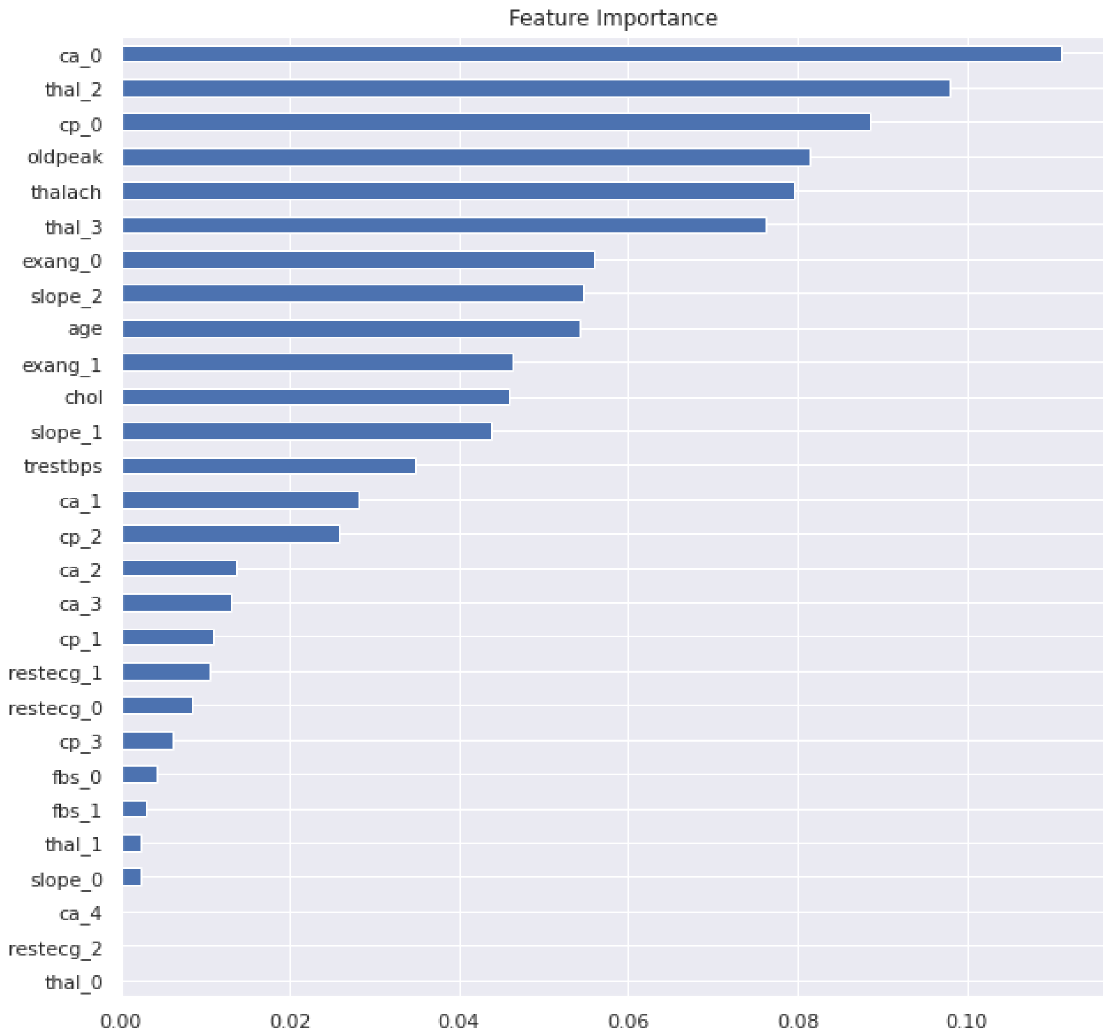




[58]:
```
test_score = accuracy_score(y_test, bc.predict(X_test)) * 100
train_score = accuracy_score(y_train, bc.predict(X_train)) * 100

results_df_2 = pd.DataFrame(data=[["Bagging Classifier", train_score,␣
↪test_score]],
                          columns=['Model', 'Training Accuracy %', 'Testing␣
↪Accuracy %'])
tuning_results_df = tuning_results_df.append(results_df_2, ignore_index=True)
```

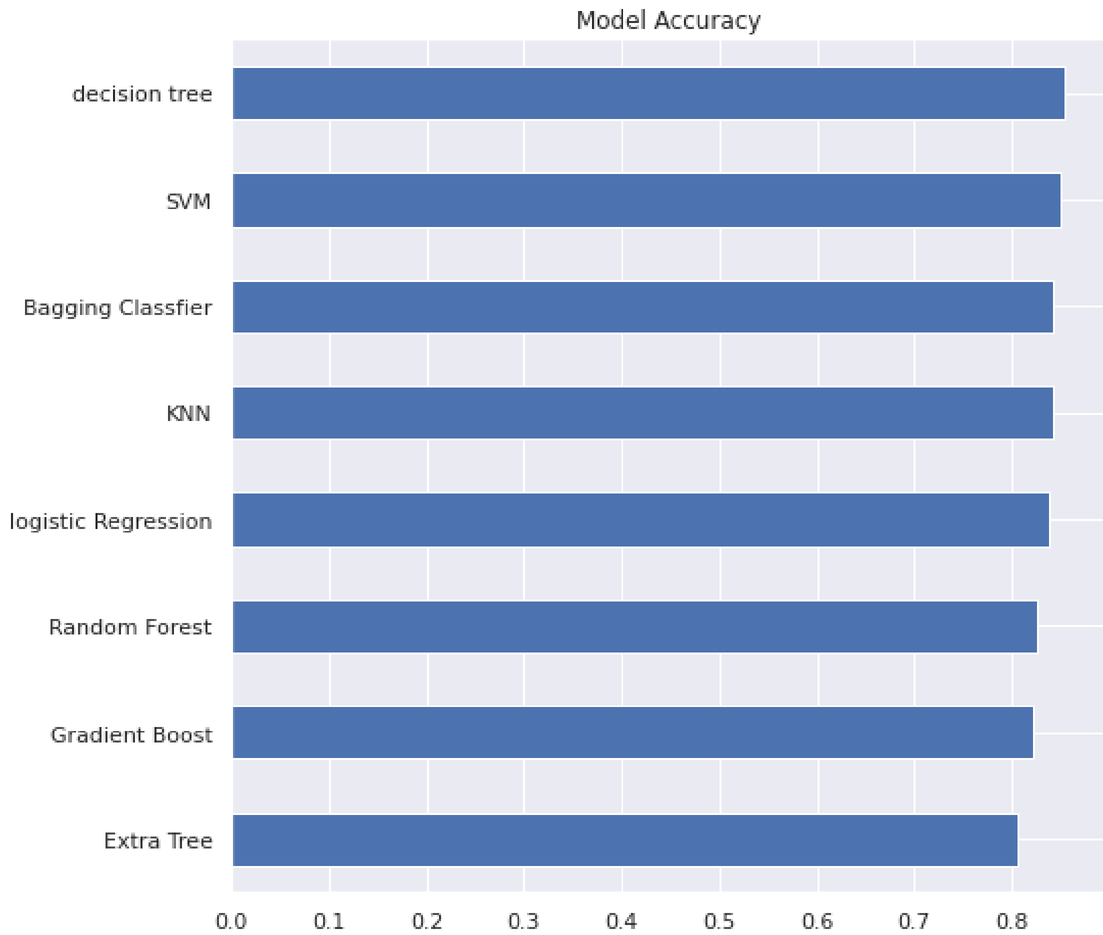
[59]:
```
## Feature Importance

fig= plt.figure(figsize=(10,10))
important=pd.Series(rf_clf.feature_importances_, index= X_train.columns)
important.sort_values().plot.barh()
plt.title('Feature Importance')
```

[59]: Text(0.5, 1.0, 'Feature Importance')



[60]:
```
model_accuracy = pd.Series(data=[score_k, score_lr, score_tree, score_svm,␣
 ↪score_rf, score_etc,
                                score_gbc, score_bc],
                               index=['KNN','logistic Regression','decision tree',␣
 ↪'SVM', 'Random Forest',
                                'Extra Tree',  'Gradient Boost','Bagging␣
 ↪Classfier'])
fig= plt.figure(figsize=(8,8))
model_accuracy.sort_values().plot.barh()
plt.title('Model Accuracy')
```

[60]: Text(0.5, 1.0, 'Model Accuracy')

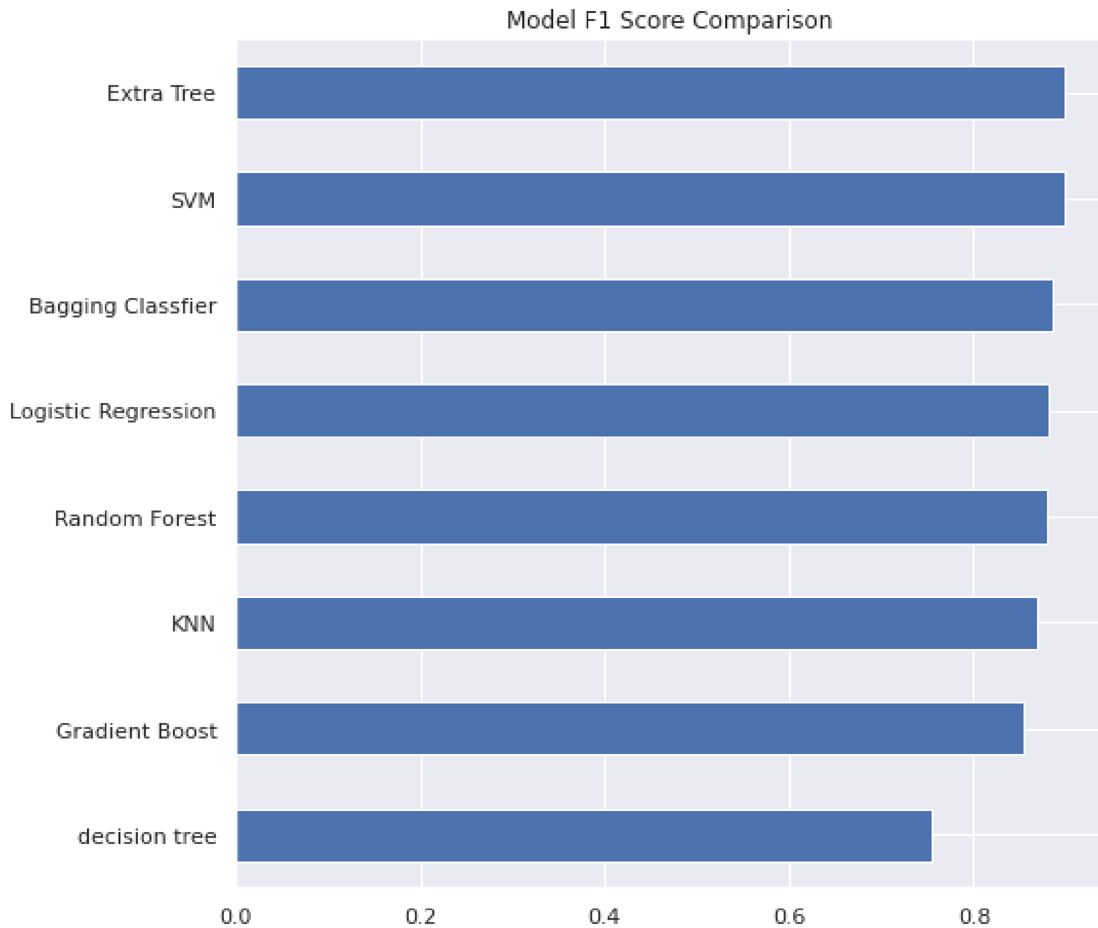


[61]:

```
model_f1_score = pd.Series(data=[knn_f1, lr_f1, tree_f1, svm_f1, rf_f1, etc_f1,
                           gbc_f1, bc_f1],
                           index=['KNN','Logistic Regression','decision tree',␣
 ↪'SVM', 'Random Forest',
                                 'Extra Tree', 'Gradient Boost', 'Bagging␣
 ↪Classfier'])
fig= plt.figure(figsize=(8,8))
model_f1_score.sort_values().plot.barh()
plt.title('Model F1 Score Comparison')
```

[61]:

```
Text(0.5, 1.0, 'Model F1 Score Comparison')
```



[62]:
```
tuning_results_df
```

[62]:

	Model	Training Accuracy %	Testing Accuracy %
0	Tuned Logistic Regression	87.136929	86.885246
1	Tuned K-nearest neighbors	82.987552	85.245902
2	Support Vector Machine	89.626556	88.524590
3	Tuned Decision Tree Classifier	85.892116	72.131148
4	Tuned Random Forest Classifier	91.286307	86.885246
5	Extra Trees Classifier	100.000000	88.524590
6	Gradient Boosting Classifier	89.211618	83.606557
7	Bagging Classifier	85.892116	86.885246

1.6 Conclusion

In this report, the heart attack dataset from UCI was explored to find the most suitable ML algorithm for the prediction of a possible myocardial infarction (**classification task**)

After some feature engineering of the acquired dataset, and the removal of both duplicate and outlier values, some numerical variables were explored by creating their corresponding plots.

Overall, the dataset didn't require a lot of change and is of good quality. Nonetheless, it would be beneficial if there were more than 302 observations. Further suggestions for improving the quality of this dataset are to add features that are responsible for myocardial infarctions, like the diet, smoking information of the patient, and type of diabetes (if eligible).

A correlation heatmap was then created to find which variables are correlated, to what degree, in which direction, while furthermore, it is useful for observing any multicollinearity problems.

Next, the dataset was preprocessed by creating dummy variables and scaling the numerical features before the creation of the ML models. In particular, 8 models were instantiated, a logistic regression, a k-nearest neighbors, a support vector machine, a decision tree classifier, a random forest classifier, an extra trees classifier, a gradient boosting classifier, and a bagging classifier model. Four of those (i.e. logistic regression, k-nearest neighbors, decision tree, and random forest classifier) were explored further, for tuning their hyperparameters by using grid-search.

Based on the models' accuracy findings, the most suitable algorithms are the decision tree classifier (~0.855 accuracy), the support vector machine (with approximately 0.85 accuracy score), and third, being bagging classifier model (0.84 accuracy). However, the comparison between the f1 scores shows that the best model is the extra tree classifier. Considering that all accuracy metrics and f1 scores of the best models are very similar, here the **Support Vector Machine model** was selected as the most suitable in our case.

1.6.1 Next Steps

Next to our exploration would be the creation of a voting classifier model by combining the Support Vector Machine, the Extra tree classifier, and the bagging classifier model. For even better results, one could create a stacking model.