In [1]:
```
import warnings
warnings.filterwarnings('ignore')
# data wrangling & pre-processing
import pandas as pd
import numpy as np
# data visualization
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
from sklearn.model_selection import train_test_split
#model validation
from sklearn.metrics import log_loss,roc_auc_score,precision_score,f1_score,recall_score,roc_curve,auc
from sklearn.metrics import classification_report, confusion_matrix,accuracy_score,fbeta_score,matthews_corrcoef
from sklearn import metrics
# cross validation
from sklearn.model_selection import StratifiedKFold
# machine learning algorithms
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier,VotingClassifier,AdaBoostClassifier,GradientBoostingClassifi
from sklearn.neural_network import MLPClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.linear_model import SGDClassifier
from sklearn.svm import SVC
import xgboost as xgb
from scipy import stats
from sklearn.neighbors import KNeighborsClassifier
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.naive_bayes import GaussianNB
```

Loading Dataset

In [2]:
```
dataset=pd.read_csv("C:/Users/Harshini/Downloads/Heart_Disease_Prediction (2).csv")
df=pd.DataFrame(dataset)
df
```

Out[2]:

	Age	Sex	Chest pain type	BP	Cholesterol	FBS over 120	EKG results	Max HR	Exercise angina	ST depression	Slope of ST	Number of vessels fluro	Thallium	Heart Disease
0	70	1	4	130	322	0	2	109	0	2.4	2	3	3	Presence
1	67	0	3	115	564	0	2	160	0	1.6	2	0	7	Absence
2	57	1	2	124	261	0	0	141	0	0.3	1	0	7	Presence
3	64	1	4	128	263	0	0	105	1	0.2	2	1	7	Absence
4	74	0	2	120	269	0	2	121	1	0.2	1	1	3	Absence
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
265	52	1	3	172	199	1	0	162	0	0.5	1	0	7	Absence
266	44	1	2	120	263	0	0	173	0	0.0	1	0	7	Absence
267	56	0	2	140	294	0	2	153	0	1.3	2	0	3	Absence
268	57	1	4	140	192	0	0	148	0	0.4	2	0	6	Absence
269	67	1	4	160	286	0	2	108	1	1.5	2	3	3	Presence

270 rows × 14 columns

Data Cleaning & Preprocessing

In [3]:
```
df['Chest pain type'][df['Chest pain type'] == 1] = 'typical angina'
df['Chest pain type'][df['Chest pain type'] == 2] = 'atypical angina'
df['Chest pain type'][df['Chest pain type'] == 3] = 'non-anginal pain'
df['Chest pain type'][df['Chest pain type'] == 4] = 'asymptomatic'
```

In [4]:
```
df['EKG results'][df['EKG results'] == 0] = 'normal'
df['EKG results'][df['EKG results'] == 1] = 'ST-T wave abnormality'
df['EKG results'][df['EKG results'] == 2] = 'left ventricular hypertrophy'
```

In [5]:
```
df['Slope of ST'][df['Slope of ST'] == 1] = 'upsloping'
df['Slope of ST'][df['Slope of ST'] == 2] = 'flat'
df['Slope of ST'][df['Slope of ST'] == 3] = 'downsloping'
```

In [6]:
```
df["Sex"] = df.Sex.apply(lambda  x:'male' if x==1 else 'female')
```

In [7]:
```
df['Chest pain type'].value_counts()
```

Out[7]:
```
asymptomatic        129
non-anginal pain     79
atypical angina      42
typical angina       20
Name: Chest pain type, dtype: int64
```

In [8]:
```
df['EKG results'].value_counts()
```

Out[8]:
```
left ventricular hypertrophy    137
normal                          131
ST-T wave abnormality             2
Name: EKG results, dtype: int64
```

In [9]:
```
df['Slope of ST'].value_counts()
```

Out[9]:
```
upsloping      130
flat           122
downsloping     18
Name: Slope of ST, dtype: int64
```

In [10]:
```
df.head()
```

Out[10]:

	Age	Sex	Chest pain type	BP	Cholesterol	FBS over 120	EKG results	Max HR	Exercise angina	ST depression	Slope of ST	Number of vessels fluro	Thallium	Heart Disease
0	70	male	asymptomatic	130	322	0	left ventricular hypertrophy	109	0	2.4	flat	3	3	Presence
1	67	female	non-anginal pain	115	564	0	left ventricular hypertrophy	160	0	1.6	flat	0	7	Absence
2	57	male	atypical angina	124	261	0	normal	141	0	0.3	upsloping	0	7	Presence
3	64	male	asymptomatic	128	263	0	normal	105	1	0.2	flat	1	7	Absence
4	74	female	atypical angina	120	269	0	left ventricular hypertrophy	121	1	0.2	upsloping	1	3	Absence

In [11]:
```
df.tail()
```

Out[11]:

	Age	Sex	Chest pain type	BP	Cholesterol	FBS over 120	EKG results	Max HR	Exercise angina	ST depression	Slope of ST	Number of vessels fluro	Thallium	Heart Disease
265	52	male	non-anginal pain	172	199	1	normal	162	0	0.5	upsloping	0	7	Absence
266	44	male	atypical angina	120	263	0	normal	173	0	0.0	upsloping	0	7	Absence
267	56	female	atypical angina	140	294	0	left ventricular hypertrophy	153	0	1.3	flat	0	3	Absence
268	57	male	asymptomatic	140	192	0	normal	148	0	0.4	flat	0	6	Absence
269	67	male	asymptomatic	160	286	0	left ventricular hypertrophy	108	1	1.5	flat	3	3	Presence

In [12]:
```
df.isna().sum()
```

Out[12]:
```
Age                        0
Sex                        0
Chest pain type            0
BP                         0
Cholesterol                0
FBS over 120               0
EKG results                0
Max HR                     0
Exercise angina            0
ST depression              0
Slope of ST                0
Number of vessels fluro    0
Thallium                   0
Heart Disease              0
dtype: int64
```

In [13]:
```
df.shape
```

Out[13]:
```
(270, 14)
```

In [14]:
```
df.columns
```

Out[14]:
```
Index(['Age', 'Sex', 'Chest pain type', 'BP', 'Cholesterol', 'FBS over 120',
       'EKG results', 'Max HR', 'Exercise angina', 'ST depression',
       'Slope of ST', 'Number of vessels fluro', 'Thallium', 'Heart Disease'],
      dtype='object')
```

In [15]:
```
df.describe(include =[np.number])
```

Out[15]:

	Age	BP	Cholesterol	FBS over 120	Max HR	Exercise angina	ST depression	Number of vessels fluro	Thallium
count	270.000000	270.000000	270.000000	270.000000	270.000000	270.000000	270.00000	270.000000	270.000000
mean	54.433333	131.344444	249.659259	0.148148	149.677778	0.329630	1.05000	0.670370	4.696296
std	9.109067	17.861608	51.686237	0.355906	23.165717	0.470952	1.14521	0.943896	1.940659
min	29.000000	94.000000	126.000000	0.000000	71.000000	0.000000	0.00000	0.000000	3.000000
25%	48.000000	120.000000	213.000000	0.000000	133.000000	0.000000	0.00000	0.000000	3.000000
50%	55.000000	130.000000	245.000000	0.000000	153.500000	0.000000	0.80000	0.000000	3.000000
75%	61.000000	140.000000	280.000000	0.000000	166.000000	1.000000	1.60000	1.000000	7.000000
max	77.000000	200.000000	564.000000	1.000000	202.000000	1.000000	6.20000	3.000000	7.000000

In [16]:
```
df.describe(include =[np.object])
```

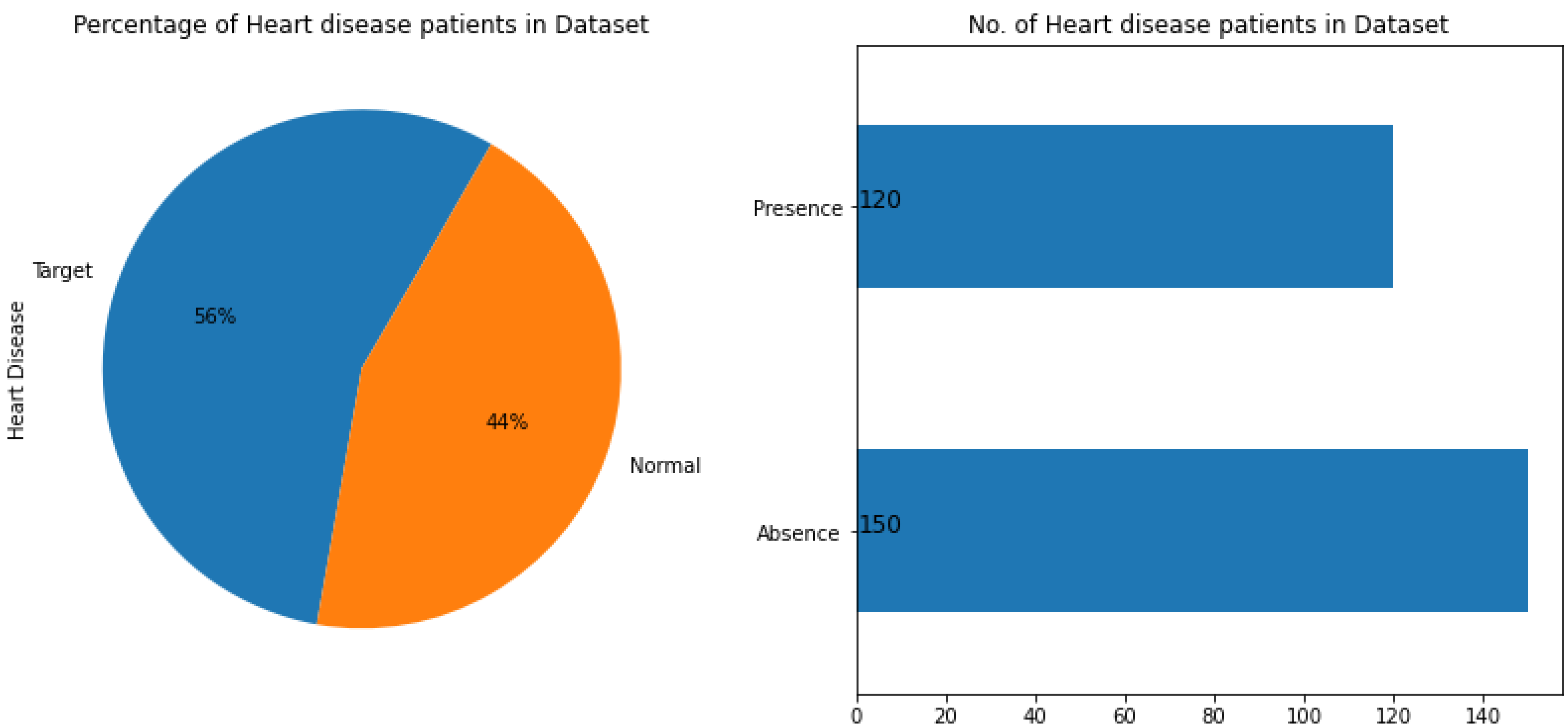
Out[16]:

	Sex	Chest pain type	EKG results	Slope of ST	Heart Disease
count	270	270	270	270	270
unique	2	4	3	3	2
top	male	asymptomatic	left ventricular hypertrophy	upsloping	Absence
freq	183	129	137	130	150

Distribution of Heart Disease

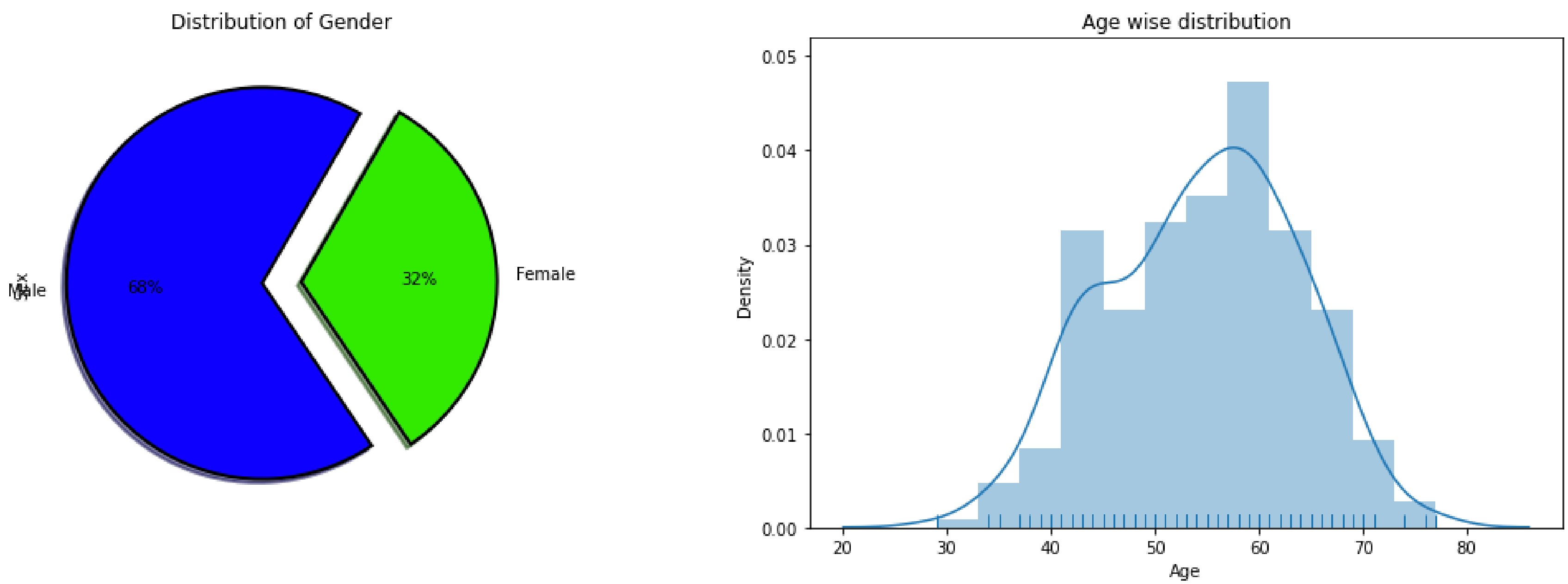
In [17]:
```
fig, (ax1, ax2) = plt.subplots(nrows=1, ncols=2, sharey=False, figsize=(14,6))

ax1 = df['Heart Disease'].value_counts().plot.pie( x="Target" ,y ='no.of patients',
                   autopct = "%1.0f%%",labels=["Target","Normal"], startangle = 60,ax=ax1);
ax1.set(title = 'Percentage of Heart disease patients in Dataset')

ax2 = df["Heart Disease"].value_counts().plot(kind="barh" ,ax =ax2)
for i,j in enumerate(df['Heart Disease'].value_counts().values):
    ax2.text(.5,i,j,fontsize=12)
ax2.set(title = 'No. of Heart disease patients in Dataset')
```

Out[17]:
```
[Text(0.5, 1.0, 'No. of Heart disease patients in Dataset')]
```

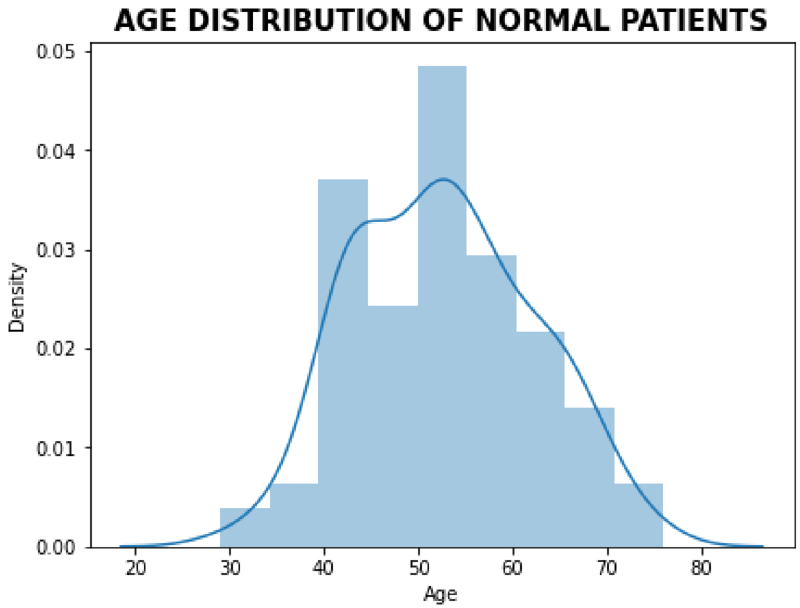


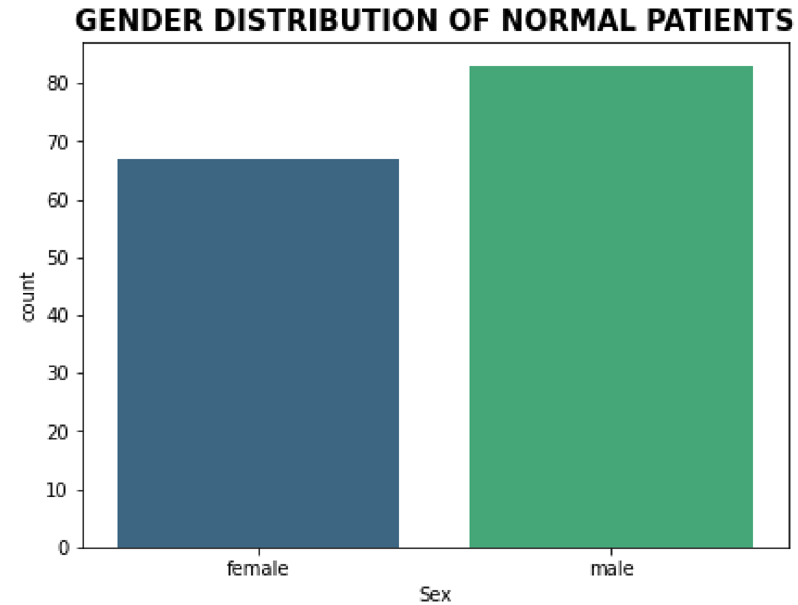
Gender and Age wise Distribution

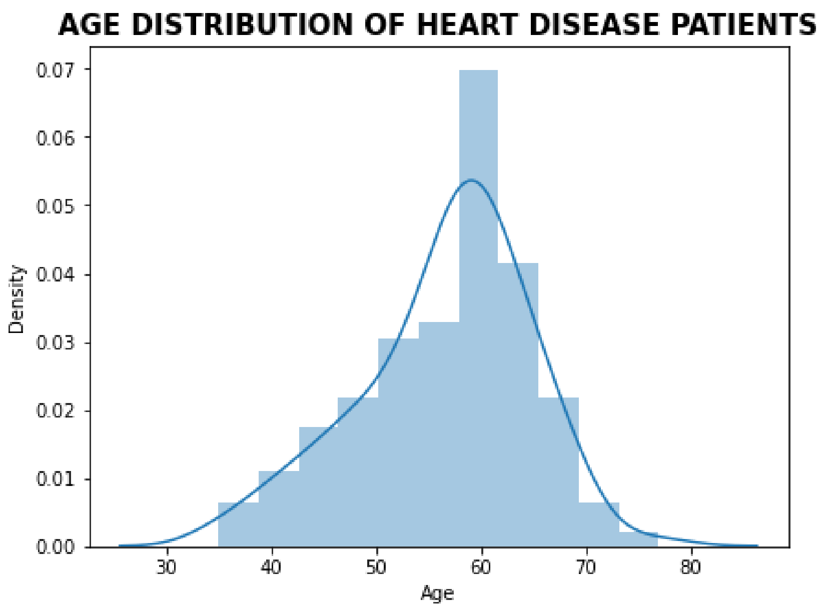
In [18]:
```
plt.figure(figsize=(18,12))
plt.subplot(221)
df["Sex"].value_counts().plot.pie(autopct = "%1.0f%%",colors = sns.color_palette("prism",5),startangle = 60,labe
wedgeprops={"linewidth":2,"edgecolor":"k"},explode=[.1,.1],shadow =True)
plt.title("Distribution of Gender")
plt.subplot(222)
ax= sns.distplot(df['Age'], rug=True)
plt.title("Age wise distribution")
plt.show()
```

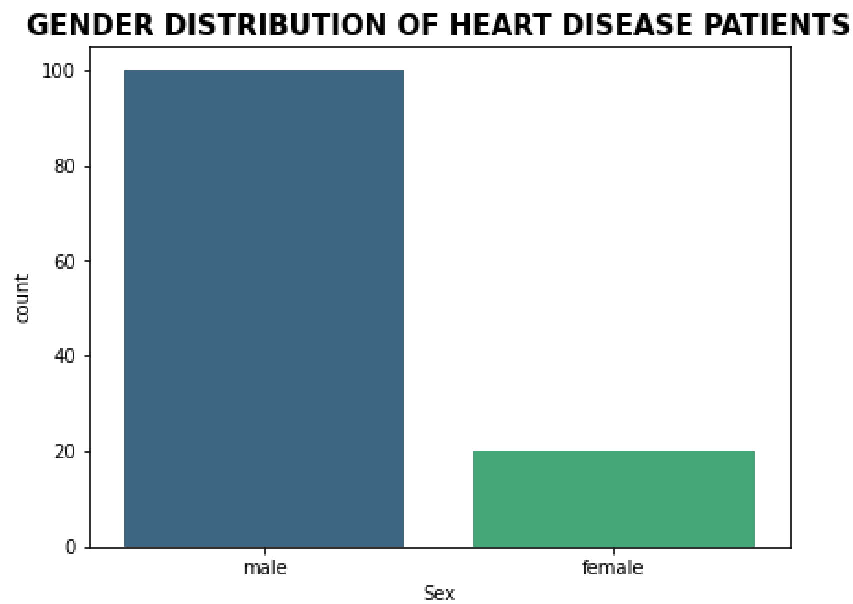


In [19]:
```
attr_1=df[df['Heart Disease']=='Presence']

attr_0=df[df['Heart Disease']=='Absence']

# plotting normal patients
fig = plt.figure(figsize=(15,5))
ax1 = plt.subplot2grid((1,2),(0,0))
sns.distplot(attr_0['Age'])
plt.title('AGE DISTRIBUTION OF NORMAL PATIENTS', fontsize=15, weight='bold')

ax1 = plt.subplot2grid((1,2),(0,1))
sns.countplot(attr_0['Sex'], palette='viridis')
plt.title('GENDER DISTRIBUTION OF NORMAL PATIENTS', fontsize=15, weight='bold' )
plt.show()

#plotting heart patients

fig = plt.figure(figsize=(15,5))
ax1 = plt.subplot2grid((1,2),(0,0))
sns.distplot(attr_1['Age'])
plt.title('AGE DISTRIBUTION OF HEART DISEASE PATIENTS', fontsize=15, weight='bold')

ax1 = plt.subplot2grid((1,2),(0,1))
sns.countplot(attr_1['Sex'], palette='viridis')
plt.title('GENDER DISTRIBUTION OF HEART DISEASE PATIENTS', fontsize=15, weight='bold' )
plt.show()
```


AGE DISTRIBUTION OF NORMAL PATIENTS
Density
Age
0.00
0.01
0.02
0.03
0.04
0.05
20
30
40
50
60
70
80

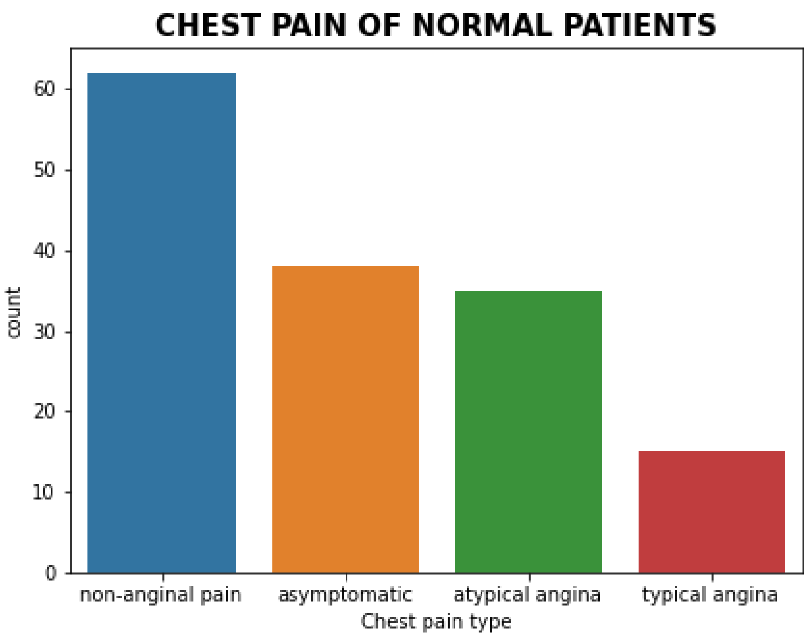

GENDER DISTRIBUTION OF NORMAL PATIENTS
count
Sex
female
male
0
10
20
30
40
50
60
70
80

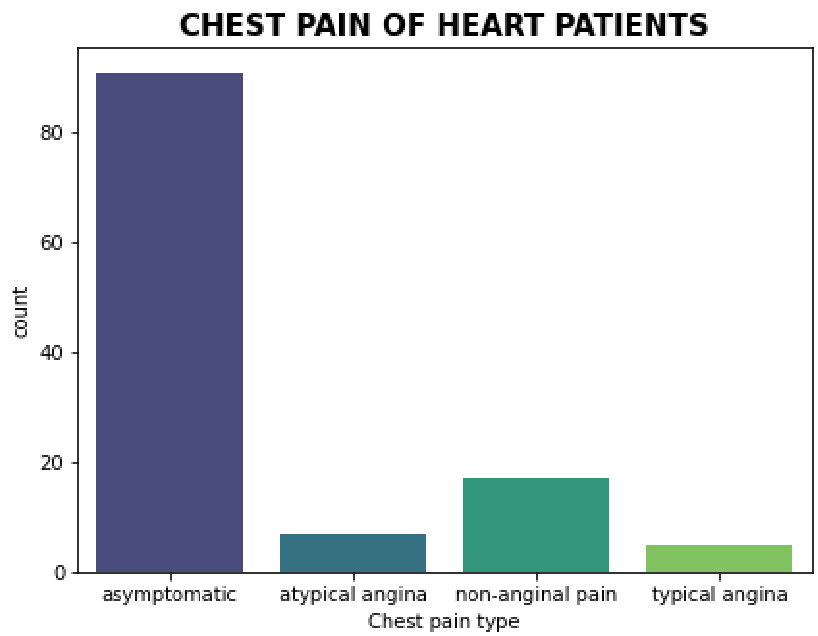

AGE DISTRIBUTION OF HEART DISEASE PATIENTS
Density
Age
0.00
0.01
0.02
0.03
0.04
0.05
0.06
0.07
30
40
50
60
70
80


GENDER DISTRIBUTION OF HEART DISEASE PATIENTS
count
Sex
male
female
0
20
40
60
80
100

Distribution of Chest pain type

In [20]:
```
fig = plt.figure(figsize=(15,5))
ax1 = plt.subplot2grid((1,2),(0,0))
sns.countplot(attr_0['Chest pain type'])
plt.title('CHEST PAIN OF NORMAL PATIENTS', fontsize=15, weight='bold')

#plotting heart patients
ax1 = plt.subplot2grid((1,2),(0,1))
sns.countplot(attr_1['Chest pain type'], palette='viridis')
plt.title('CHEST PAIN OF HEART PATIENTS', fontsize=15, weight='bold' )
plt.show()
```





In [21]:

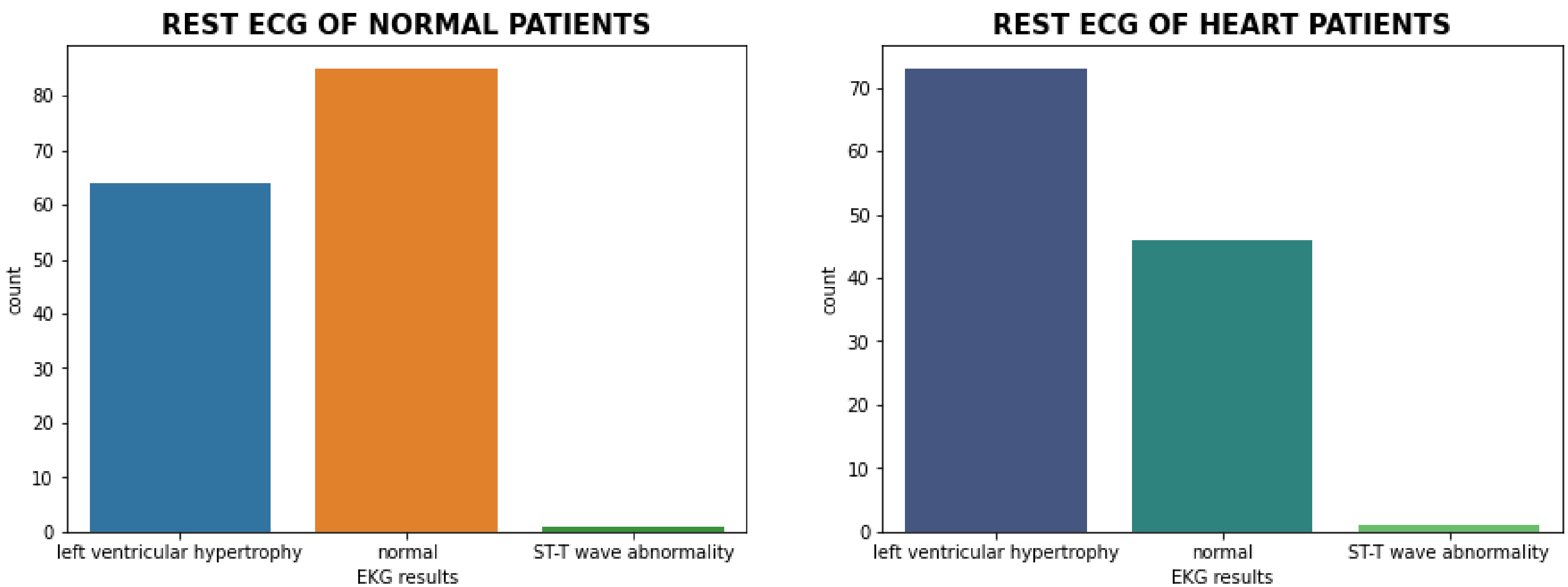
```
plot_criteria= ['Chest pain type', 'Heart Disease']
cm = sns.light_palette("red", as_cmap=True)
(round(pd.crosstab(df[plot_criteria[0]], df[plot_criteria[1]], normalize='columns') * 100,2)).style.background_g
```

Out[21]:

Heart Disease	Absence	Presence
Chest pain type		
asymptomatic	25.330000	75.830000
atypical angina	23.330000	5.830000
non-anginal pain	41.330000	14.170000
typical angina	10.000000	4.170000

Distribution of Rest ECG

In [22]:
```
fig = plt.figure(figsize=(15,5))
ax1 = plt.subplot2grid((1,2),(0,0))
sns.countplot(attr_0['EKG results'])
plt.title('REST ECG OF NORMAL PATIENTS', fontsize=15, weight='bold')

#plotting heart patients
ax1 = plt.subplot2grid((1,2),(0,1))
sns.countplot(attr_1['EKG results'], palette='viridis')
plt.title('REST ECG OF HEART PATIENTS', fontsize=15, weight='bold' )
plt.show()
```



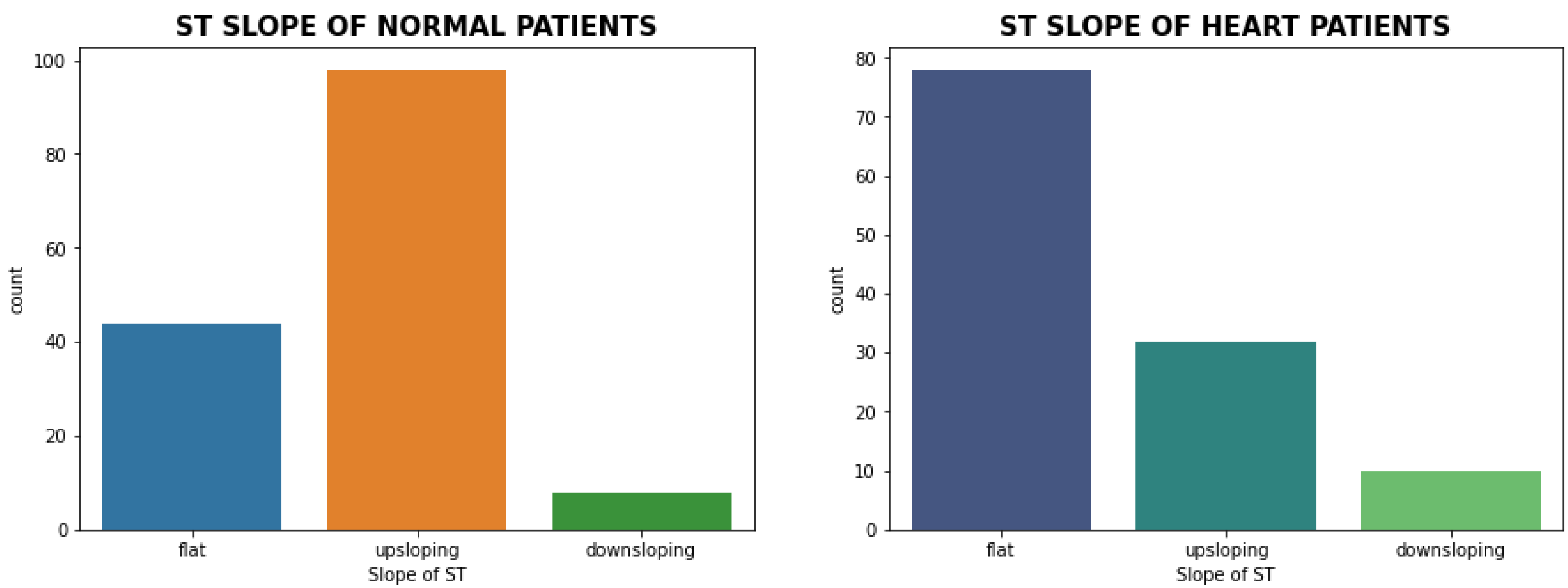
In [23]:
```
plot_criteria= ['EKG results', 'Heart Disease']
cm = sns.light_palette("red", as_cmap=True)
(round(pd.crosstab(df[plot_criteria[0]], df[plot_criteria[1]], normalize='columns') * 100,2)).style.background_g
```

Out[23]:

Heart Disease	Absence	Presence
EKG results		
ST-T wave abnormality	0.670000	0.830000
left ventricular hypertrophy	42.670000	60.830000
normal	56.670000	38.330000

In [58]:
```
fig = plt.figure(figsize=(15,5))
ax1 = plt.subplot2grid((1,2),(0,0))
sns.countplot(attr_0['Slope of ST'])
plt.title('ST SLOPE OF NORMAL PATIENTS', fontsize=15, weight='bold')

#plotting heart patients
ax1 = plt.subplot2grid((1,2),(0,1))
sns.countplot(attr_1['Slope of ST'], palette='viridis')
plt.title('ST SLOPE OF HEART PATIENTS', fontsize=15, weight='bold' )
```

Out[58]:
```
Text(0.5, 1.0, 'ST SLOPE OF HEART PATIENTS')
```



In [60]:
```
plot_criteria= ['Slope of ST', 'Heart Disease']
cm = sns.light_palette("red", as_cmap=True)
(round(pd.crosstab(df[plot_criteria[0]], df[plot_criteria[1]], normalize='columns') * 100,2)).style.background_g
```

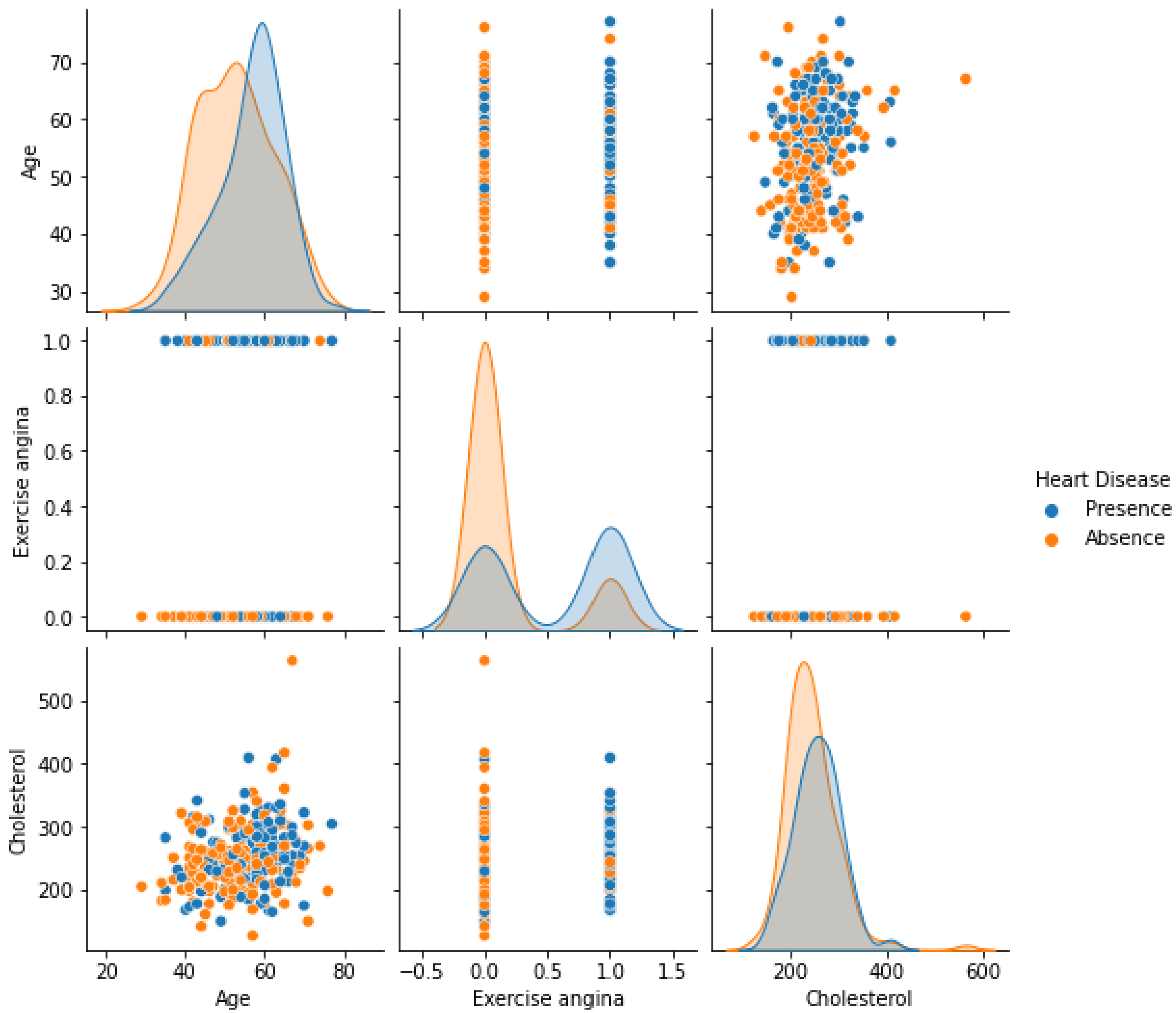
Out[60]:

Heart Disease	Absence	Presence
Slope of ST		
downsloping	5.330000	8.330000
flat	29.330000	65.000000
upsloping	65.330000	26.670000

Distribution of numerical feature

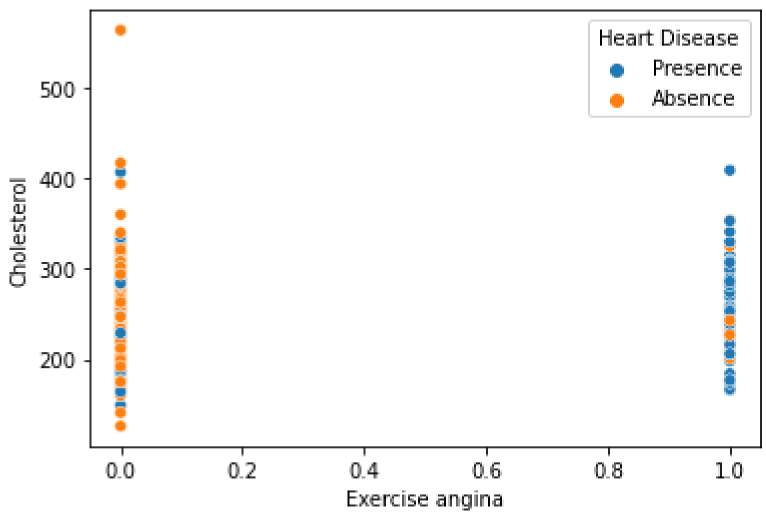
In [24]:
```
sns.pairplot(df, hue = 'Heart Disease', vars = ['Age', 'Exercise angina', 'Cholesterol'] )
```

Out[24]: <seaborn.axisgrid.PairGrid at 0x10fd89b2400>



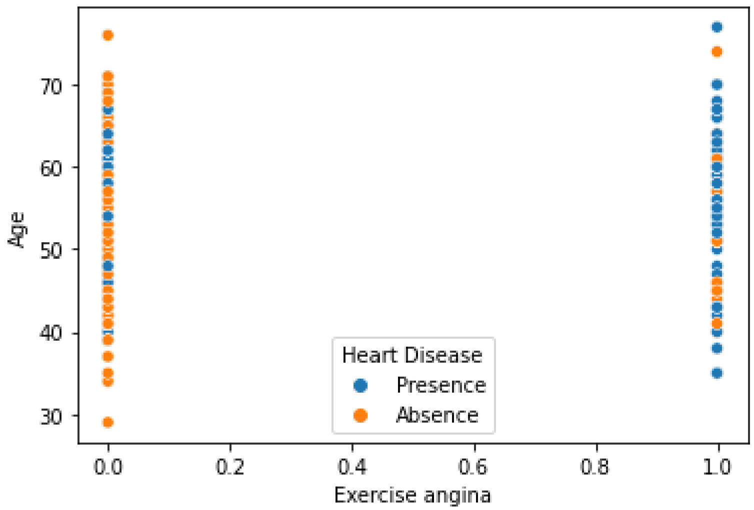
In [63]:
```
sns.scatterplot(x = 'Exercise angina', y = 'Cholesterol', hue = 'Heart Disease', data = df)
```

Out[63]:
```
<AxesSubplot:xlabel='Exercise angina', ylabel='Cholesterol'>
```



In [66]:
```
sns.scatterplot(x = 'Exercise angina', y = 'Age', hue = 'Heart Disease', data = df)
```

Out[66]: <AxesSubplot:xlabel='Exercise angina', ylabel='Age'>



Outlier Detection and Removal

In [25]:
```
df_numeric = df[['Age','Exercise angina','Cholesterol','Max HR']]
```

In [26]:
```
df_numeric.head()
```

Out[26]:

	Age	Exercise angina	Cholesterol	Max HR
0	70	0	322	109
1	67	0	564	160
2	57	0	261	141
3	64	1	263	105
4	74	1	269	121

In [27]:
```
z = np.abs(stats.zscore(df_numeric))
print(z)
```

```
          Age  Exercise angina  Cholesterol    Max HR
0    1.712094         0.701222     1.402212  1.759208
1    1.382140         0.701222     6.093004  0.446409
2    0.282294         0.701222     0.219823  0.375291
3    1.052186         1.426081     0.258589  1.932198
4    2.152032         1.426081     0.374890  1.240239
..        ...              ...          ...       ...
265  0.267629         0.701222     0.981951  0.532904
266  1.147506         0.701222     0.258589  1.008625
267  0.172309         0.701222     0.859476  0.143677
268  0.282294         0.701222     1.117635  0.072560
269  1.382140         1.426081     0.704409  1.802456

[270 rows x 4 columns]
```

In [28]:
```
threshold = 3
print(np.where(z > 3))
```

```
(array([  1,   9,  52, 101, 181], dtype=int64), array([2, 2, 2, 3, 2], dtype=int64))
```

In [29]:
```
df = df[(z < 3).all(axis=1)]
```

In [30]:
```
df.shape
```

Out[30]:
```
(265, 14)
```

In [31]:
```
df = pd.get_dummies(df, drop_first=True)

df.head()
```

Out[31]:

	Age	BP	Cholesterol	FBS over 120	Max HR	Exercise angina	ST depression	Number of vessels fluro	Thallium	Sex_male	Chest pain type_atypical angina	Chest pain type_non-anginal pain	Chest pain type_typical angina	results ventric hypertro
0	70	130	322	0	109	0	2.4	3	3	1	0	0	0	
2	57	124	261	0	141	0	0.3	0	7	1	1	0	0	
3	64	128	263	0	105	1	0.2	1	7	1	0	0	0	
4	74	120	269	0	121	1	0.2	1	3	0	1	0	0	
5	65	120	177	0	140	0	0.4	0	7	1	0	0	0	

In [32]:
```
df.shape
```

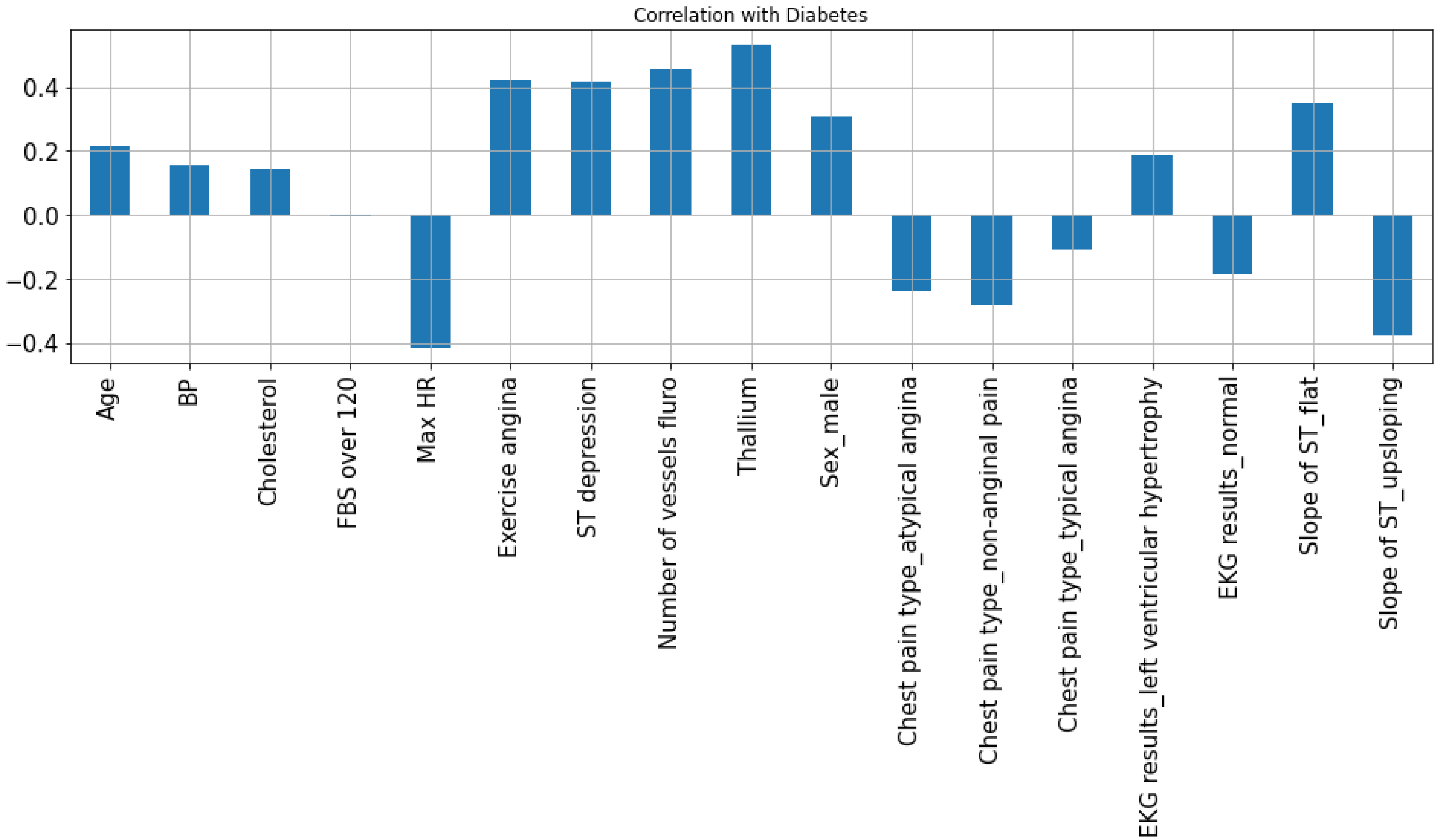
Out[32]: (265, 18)

In [33]:
```
X = df.drop(['Heart Disease_Presence'],axis=1)
y = df['Heart Disease_Presence']
```

Checking Correlation

In [34]:
```
X.corrwith(y).plot.bar(
        figsize = (16, 4), title = "Correlation with Diabetes", fontsize = 15,
        rot = 90, grid = True)
```

Out[34]: <AxesSubplot:title={'center':'Correlation with Diabetes'}>



Train Test split

In [35]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, stratify=y, test_size=0.2,shuffle=True, random_state=5
```

In [36]:
```
print('Distribution of target variable in training set')
print(y_train.value_counts())

print('Distribution of target variable in test set')
print(y_test.value_counts())
```

```
Distribution of traget variable in training set
0    118
1     94
Name: Heart Disease_Presence, dtype: int64
Distribution of traget variable in test set
0    30
1    23
Name: Heart Disease_Presence, dtype: int64
```

In [37]:
```
print('------------Training Set-----------------')
print(X_train.shape)
print(y_train.shape)

print('------------Test Set------------------')
print(X_test.shape)
print(y_test.shape)
```

```
------------Training Set-----------------
(212, 17)
(212,)
------------Test Set------------------
(53, 17)
(53,)
```

In [38]:
```
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
X_train[['Age','EKG results_normal','Cholesterol','Max HR','Slope of ST_flat']] = scaler.fit_transform(X_train[[
X_train.head()
```

Out[38]:

	Age	BP	Cholesterol	FBS over 120	Max HR	Exercise angina	ST depression	Number of vessels fluro	Thallium	Sex_male	Chest pain type_atypical angina	Chest pain type_non-anginal pain	Chest pa type_typic angi
182	0.250000	110	0.171642	0	0.584906	0	0.0	0	7	1	0	0	
140	0.729167	145	0.320896	0	0.339623	0	2.0	2	6	1	0	0	
193	0.125000	126	0.582090	0	0.566038	1	0.0	0	7	1	0	0	
200	0.812500	118	0.563433	0	0.518868	0	1.0	1	7	1	0	1	
206	0.645833	102	0.716418	0	0.603774	0	0.0	1	3	0	0	1	

In [39]:
```
X_test[['Age','EKG results_normal','Cholesterol','Max HR','Slope of ST_flat']] = scaler.transform(X_test[['Age',
X_test.head()
```

Out[39]:

	Age	BP	Cholesterol	FBS over 120	Max HR	Exercise angina	ST depression	Number of vessels fluro	Thallium	Sex_male	Chest pain type_atypical angina	Chest pain type_non-anginal pain	Chest pa type_typic angi
58	0.625000	174	0.458955	0	0.443396	1	0.0	0	3	0	0	0	
219	0.312500	120	0.350746	0	0.698113	0	0.0	0	3	1	1	0	
53	0.708333	140	0.257463	0	0.783019	0	0.0	2	3	0	1	0	
2	0.583333	124	0.503731	0	0.424528	0	0.3	0	7	1	1	0	
47	0.312500	110	0.264925	0	0.764151	0	0.0	1	3	1	0	0	

In [40]:
```
from sklearn import model_selection
from sklearn.model_selection import cross_val_score
import xgboost as xgb
# function initializing baseline machine learning models
def GetBasedModel():
    basedModels = []
    basedModels.append(('LR_L2'   , LogisticRegression(penalty='l2')))
    basedModels.append(('LDA'   , LinearDiscriminantAnalysis()))
    basedModels.append(('KNN7'   , KNeighborsClassifier(7)))
    basedModels.append(('KNN5'   , KNeighborsClassifier(5)))
    basedModels.append(('KNN9'   , KNeighborsClassifier(9)))
    basedModels.append(('KNN11'   , KNeighborsClassifier(11)))
    basedModels.append(('CART' , DecisionTreeClassifier()))
    basedModels.append(('NB'   , GaussianNB()))
    basedModels.append(('SVM Linear'  , SVC(kernel='linear',gamma='auto',probability=True)))
    basedModels.append(('SVM RBF'  , SVC(kernel='rbf',gamma='auto',probability=True)))
    basedModels.append(('AB'   , AdaBoostClassifier()))
    basedModels.append(('GBM'  , GradientBoostingClassifier(n_estimators=100,max_features='sqrt')))
    basedModels.append(('RF_Ent100'   , RandomForestClassifier(criterion='entropy',n_estimators=100)))
    basedModels.append(('RF_Gini100'   , RandomForestClassifier(criterion='gini',n_estimators=100)))
    basedModels.append(('ET100'   , ExtraTreesClassifier(n_estimators= 100)))
    basedModels.append(('ET500'   , ExtraTreesClassifier(n_estimators= 500)))
    basedModels.append(('MLP', MLPClassifier()))
    basedModels.append(('SGD3000', SGDClassifier(max_iter=1000, tol=1e-4)))
    basedModels.append(('XGB_2000', xgb.XGBClassifier(n_estimators= 2000)))
    basedModels.append(('XGB_500', xgb.XGBClassifier(n_estimators= 500)))
    basedModels.append(('XGB_100', xgb.XGBClassifier(n_estimators= 100)))
    basedModels.append(('XGB_1000', xgb.XGBClassifier(n_estimators= 1000)))
    basedModels.append(('ET1000'   , ExtraTreesClassifier(n_estimators= 1000)))

    return basedModels

# function for performing 10-fold cross validation of all the baseline models
def BasedLine2(X_train, y_train,models):
    # Test options and evaluation metric
    num_folds = 10
    scoring = 'accuracy'
    seed = 7
    results = []
    names = []
    for name, model in models:
        kfold = model_selection.KFold(n_splits=10, random_state=None)
```

```
        cv_results = model_selection.cross_val_score(model, X_train, y_train, cv=kfold, scoring=scoring)
        results.append(cv_results)
        names.append(name)
        msg = "%s: %f (%f)" % (name, cv_results.mean(), cv_results.std())
        print(msg)

    return results,msg
```

In [41]:
```
models = GetBasedModel()
names,results = BasedLine2(X_train, y_train,models)
```

```
LR_L2: 0.858874 (0.045985)
LDA: 0.854113 (0.052426)
KNN7: 0.777922 (0.087742)
KNN5: 0.749567 (0.097254)
KNN9: 0.777922 (0.085119)
KNN11: 0.749567 (0.099558)
CART: 0.731169 (0.063378)
NB: 0.839610 (0.057009)
SVM Linear: 0.840043 (0.051116)
SVM RBF: 0.763853 (0.102216)
AB: 0.783333 (0.061148)
GBM: 0.802165 (0.074146)
RF_Ent100: 0.830087 (0.056553)
RF_Gini100: 0.820779 (0.049480)
ET100: 0.820130 (0.067026)
ET500: 0.810606 (0.067851)
MLP: 0.741991 (0.191860)
SGD3000: 0.674675 (0.118784)
XGB_2000: 0.792641 (0.050455)
XGB_500: 0.797403 (0.049569)
XGB_100: 0.816017 (0.044422)
XGB_1000: 0.792641 (0.054765)
ET1000: 0.820130 (0.063553)
```

Model Building

Random forest classifier

In [42]:
```
rf_ent = RandomForestClassifier(criterion='entropy',n_estimators=100)
rf_ent.fit(X_train, y_train)
y_pred_rfe = rf_ent.predict(X_test)
```

Multi Layer Perceptron

In [43]:
```
mlp = MLPClassifier()
mlp.fit(X_train,y_train)
y_pred_mlp = mlp.predict(X_test)
```

K-Nearest Neighbour

In [44]:
```
knn = KNeighborsClassifier(9)
knn.fit(X_train,y_train)
y_pred_knn = knn.predict(X_test)
```

Extre Tree Classifier

In [45]:
```
et_100 = ExtraTreesClassifier(n_estimators= 100)
et_100.fit(X_train,y_train)
y_pred_et_100 = et_100.predict(X_test)
```

XGBoost

In [46]:
```
import xgboost as xgb
xgb = xgb.XGBClassifier(n_estimators= 500)
xgb.fit(X_train,y_train)
y_pred_xgb = xgb.predict(X_test)
```

Support Vector Classifier

In [47]:
```
svc = SVC(kernel='linear',gamma='auto',probability=True)
svc.fit(X_train,y_train)
y_pred_svc = svc.predict(X_test)
```

Stochastic Gradient Descent

In [48]:
```
sgd = SGDClassifier(max_iter=1000, tol=1e-4)
sgd.fit(X_train,y_train)
y_pred_sgd = sgd.predict(X_test)
```

Adaboost Classifier

In [49]:
```
ada = AdaBoostClassifier()
ada.fit(X_train,y_train)
y_pred_ada = ada.predict(X_test)
```

Decision Tree Classifier

In [50]:
```
decc = DecisionTreeClassifier()
decc.fit(X_train,y_train)
y_pred_decc = decc.predict(X_test)
```

Gradient Boosting Machine

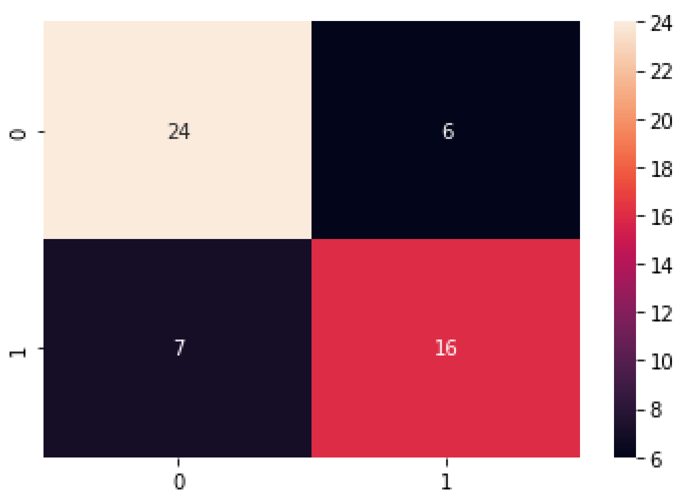
In [51]:
```
gbm = GradientBoostingClassifier(n_estimators=100,max_features='sqrt')
gbm.fit(X_train,y_train)
y_pred_gbm = gbm.predict(X_test)
```

In [53]:

```
CM=confusion_matrix(y_test,y_pred_rfe)
sns.heatmap(CM, annot=True)

TN = CM[0][0]
FN = CM[1][0]
TP = CM[1][1]
FP = CM[0][1]
specificity = TN/(TN+FP)
loss_log = log_loss(y_test, y_pred_rfe)
acc= accuracy_score(y_test, y_pred_rfe)
roc=roc_auc_score(y_test, y_pred_rfe)
prec = precision_score(y_test, y_pred_rfe)
rec = recall_score(y_test, y_pred_rfe)
f1 = f1_score(y_test, y_pred_rfe)

mathew = matthews_corrcoef(y_test, y_pred_rfe)
model_results =pd.DataFrame([['Random Forest',acc, prec,rec,specificity, f1,roc, loss_log,mathew]],
               columns = ['Model', 'Accuracy','Precision', 'Sensitivity','Specificity', 'F1 Score','ROC','Log_Lo

model_results
```

Out[53]:

	Model	Accuracy	Precision	Sensitivity	Specificity	F1 Score	ROC	Log_Loss	mathew_corrcoef
0	Random Forest	0.754717	0.727273	0.695652	0.8	0.711111	0.747826	8.471866	0.498551



In [54]:

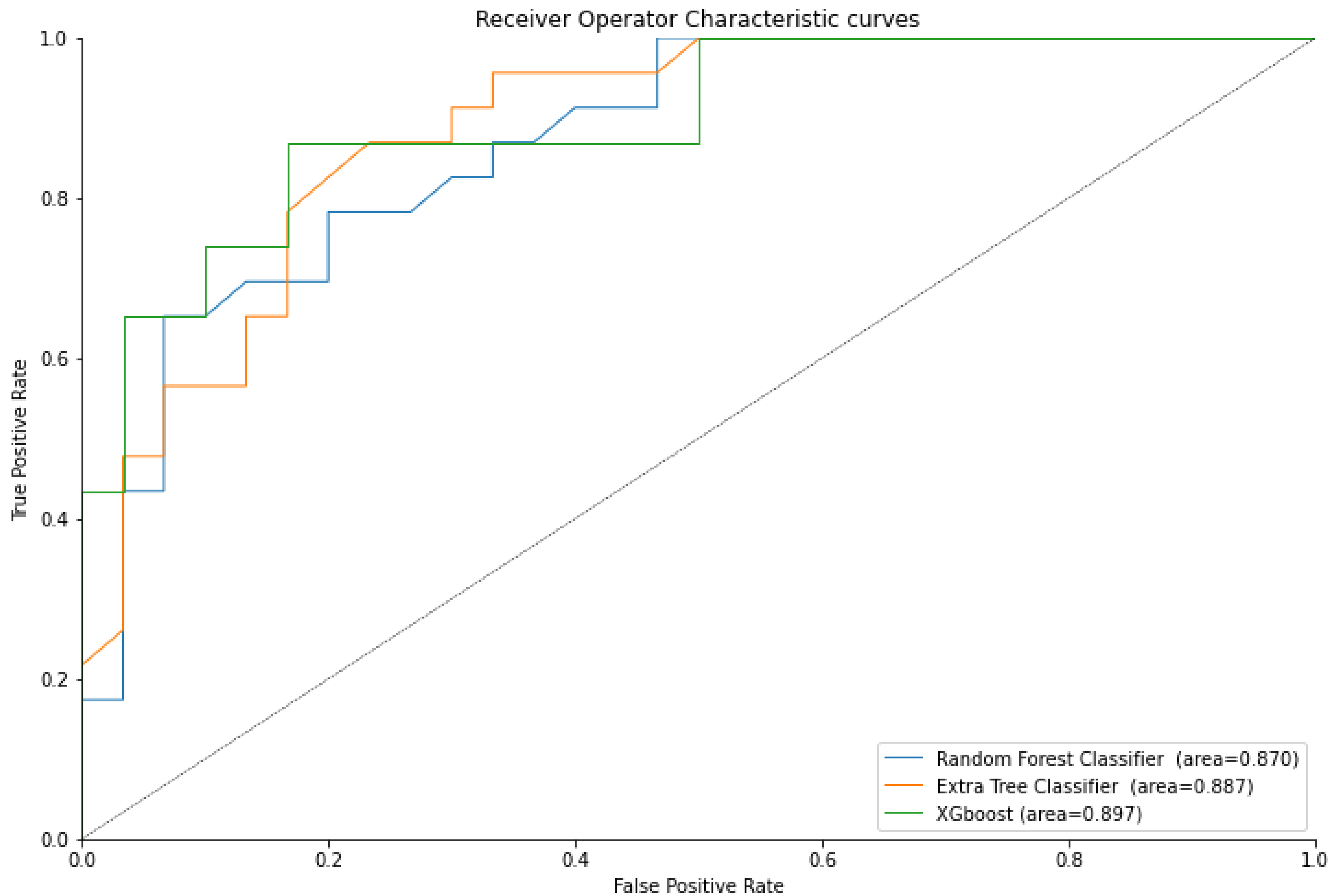
```
data = {        'MLP': y_pred_mlp,
                'KNN': y_pred_knn,
                'EXtra tree classifier': y_pred_et_100,
                'XGB': y_pred_xgb,
                'SVC': y_pred_svc,
                'SGD': y_pred_sgd,
                'Adaboost': y_pred_ada,
                'CART': y_pred_decc,
                'GBM': y_pred_gbm }

models = pd.DataFrame(data)

for column in models:
    CM=confusion_matrix(y_test,models[column])

    TN = CM[0][0]
    FN = CM[1][0]
    TP = CM[1][1]
    FP = CM[0][1]
    specificity = TN/(TN+FP)
    loss_log = log_loss(y_test, models[column])
    acc= accuracy_score(y_test, models[column])
    roc=roc_auc_score(y_test, models[column])
    prec = precision_score(y_test, models[column])
    rec = recall_score(y_test, models[column])
    f1 = f1_score(y_test, models[column])

    mathew = matthews_corrcoef(y_test, models[column])
    results =pd.DataFrame([[column,acc, prec,rec,specificity, f1,roc, loss_log,mathew]],
               columns = ['Model', 'Accuracy','Precision', 'Sensitivity','Specificity', 'F1 Score','ROC','Log_Lo
    model_results = model_results.append(results, ignore_index = True)

model_results
```

Out[54]:

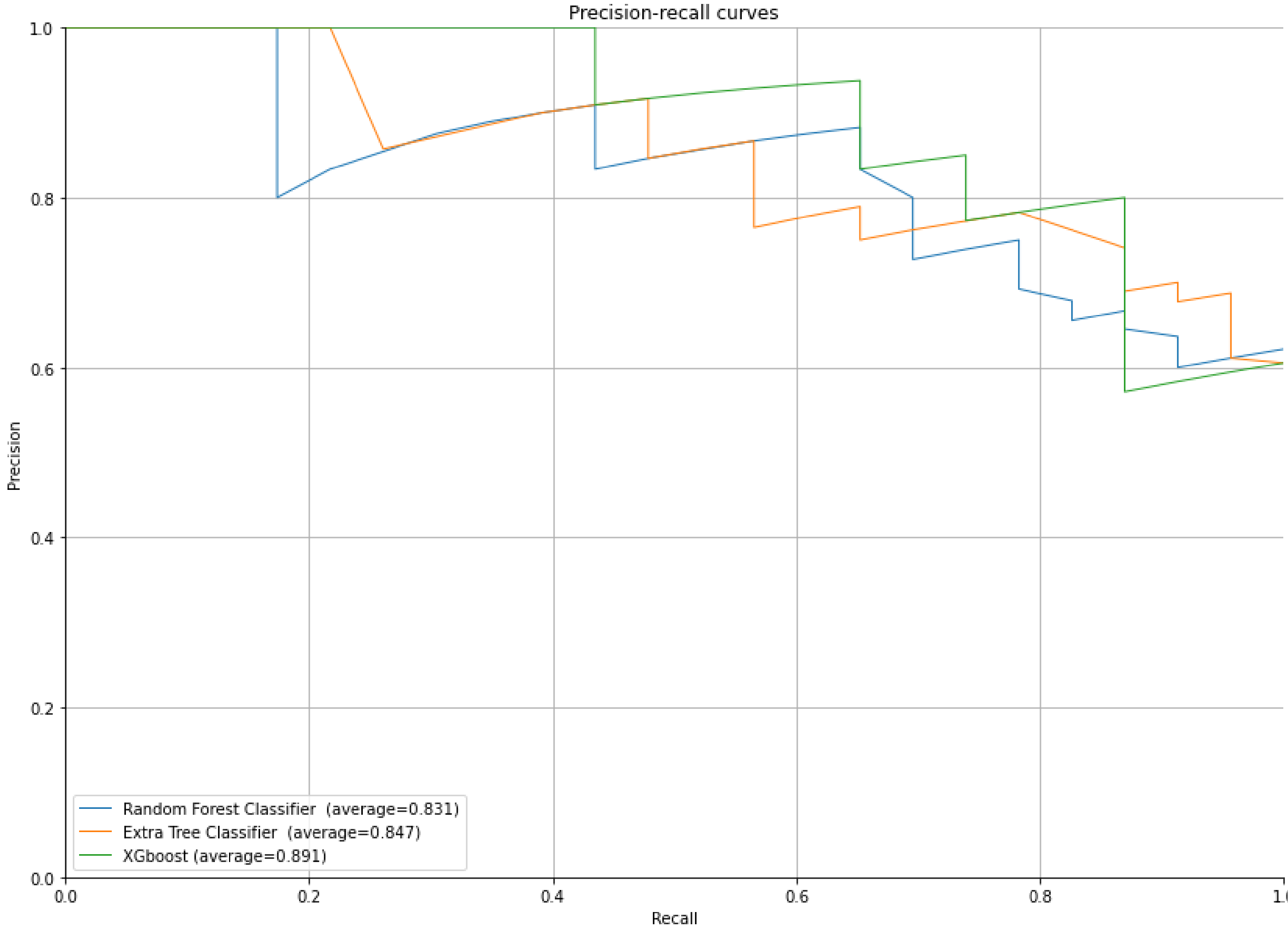
	Model	Accuracy	Precision	Sensitivity	Specificity	F1 Score	ROC	Log_Loss	mathew_corrcoef
0	Random Forest	0.754717	0.727273	0.695652	0.800000	0.711111	0.747826	8.471866	0.498551
1	MLP	0.792453	0.772727	0.739130	0.833333	0.755556	0.786232	7.168501	0.575812
2	KNN	0.792453	0.772727	0.739130	0.833333	0.755556	0.786232	7.168501	0.575812

	Model	Accuracy	Precision	Sensitivity	Specificity	F1 Score	ROC	Log_Loss	mathew_corrcoef
3	EXtra tree classifier	0.773585	0.761905	0.695652	0.833333	0.727273	0.764493	7.820176	0.536023
4	XGB	0.811321	0.782609	0.782609	0.833333	0.782609	0.807971	6.516826	0.615942
5	SVC	0.811321	0.809524	0.739130	0.866667	0.772727	0.802899	6.516811	0.613857
6	SGD	0.433962	0.433962	1.000000	0.000000	0.605263	0.500000	19.550703	0.000000
7	Adaboost	0.735849	0.695652	0.695652	0.766667	0.695652	0.731159	9.123556	0.462319
8	CART	0.792453	0.750000	0.782609	0.800000	0.765957	0.791304	7.168516	0.580092
9	GBM	0.773585	0.720000	0.782609	0.766667	0.750000	0.774638	7.820206	0.545338

In [55]:
```
def roc_auc_plot(y_true, y_proba, label=' ', l='-', lw=1.0):
    from sklearn.metrics import roc_curve, roc_auc_score
    fpr, tpr, _ = roc_curve(y_true, y_proba[:,1])
    ax.plot(fpr, tpr, linestyle=l, linewidth=lw,
            label="%s (area=%.3f)"%(label,roc_auc_score(y_true, y_proba[:,1])))

f, ax = plt.subplots(figsize=(12,8))


roc_auc_plot(y_test,rf_ent.predict_proba(X_test),label='Random Forest Classifier ',l='-')
roc_auc_plot(y_test,et_100.predict_proba(X_test),label='Extra Tree Classifier ',l='-')
roc_auc_plot(y_test,xgb.predict_proba(X_test),label='XGboost',l='-')

ax.plot([0,1], [0,1], color='k', linewidth=0.5, linestyle='--',
        )
ax.legend(loc="lower right")
ax.set_xlabel('False Positive Rate')
ax.set_ylabel('True Positive Rate')
ax.set_xlim([0, 1])
ax.set_ylim([0, 1])
ax.set_title('Receiver Operator Characteristic curves')
sns.despine()
```

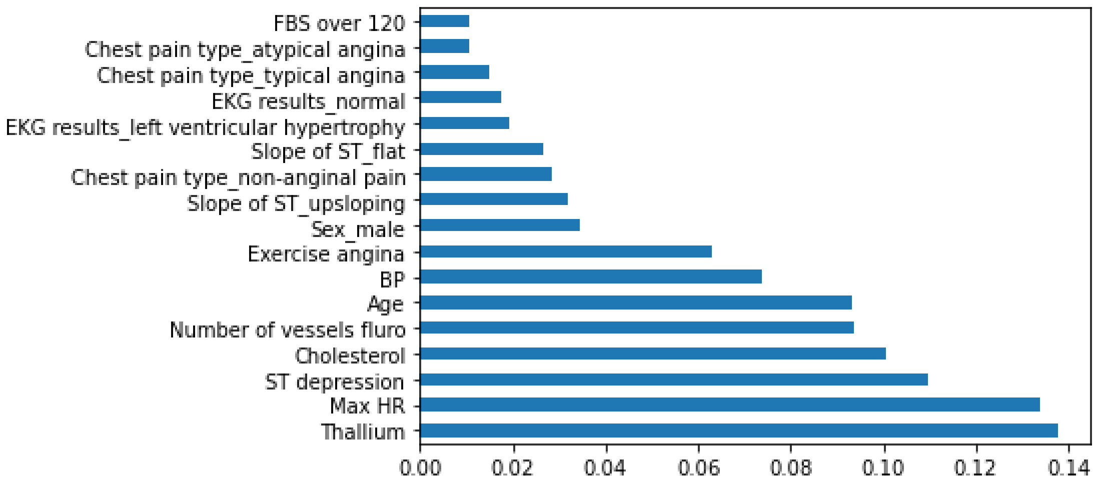

Receiver Operator Characteristic curves
1.0
0.8
0.6
0.4
0.2
0.0
True Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
False Positive Rate
Random Forest Classifier (area=0.870)
Extra Tree Classifier (area=0.887)
XGboost (area=0.897)

In [56]:
```
def precision_recall_plot(y_true, y_proba, label=' ', l='-', lw=1.0):
    from sklearn.metrics import precision_recall_curve, average_precision_score
    precision, recall, _ = precision_recall_curve(y_test,
                                                  y_proba[:,1])
    average_precision = average_precision_score(y_test, y_proba[:,1],
                                                     average="micro")
    ax.plot(recall, precision, label='%s (average=%.3f)'%(label,average_precision),
            linestyle=l, linewidth=lw)

f, ax = plt.subplots(figsize=(14,10))

precision_recall_plot(y_test,rf_ent.predict_proba(X_test),label='Random Forest Classifier ',l='-')
precision_recall_plot(y_test,et_100.predict_proba(X_test),label='Extra Tree Classifier ',l='-')
precision_recall_plot(y_test,xgb.predict_proba(X_test),label='XGboost',l='-')
ax.set_xlabel('Recall')
ax.set_ylabel('Precision')
ax.legend(loc="lower left")
ax.grid(True)
ax.set_xlim([0, 1])
ax.set_ylim([0, 1])
ax.set_title('Precision-recall curves')
sns.despine()
```


Precision-recall curves
1.0
0.8
0.6
0.4
0.2
0.0
Precision
0.0
0.2
0.4
0.6
0.8
1.0
Recall
Random Forest Classifier (average=0.831)
Extra Tree Classifier (average=0.847)
XGboost (average=0.891)

In [61]:
```
feat_importances = pd.Series(rf_ent.feature_importances_, index=X_train.columns)
feat_importances.nlargest(20).plot(kind='barh')
```

Out[61]: <AxesSubplot:>



In [67]:
```
Y={0.584906,0.320896,0.458955,1.14521}
if(Y==1):
    print("The Person having a data diseases")
else:
    print("The person not having a heart diseases")
```

```
The person not having a heart diseases
```

From above model we can predict accuracy of 85% by using a logistic regression algorthim. Compare to all the algorithm logistic regression is best to predict the heart diseases with high accuracy