Classification based on heart.csv

In [32]:

```
#import
import numpy as np
import pandas as pd
import seaborn as sn
from sklearn.preprocessing import LabelEncoder
import matplotlib.pyplot as plt
from sklearn import metrics
# to plot fusion matrix

plt.rcParams["figure.figsize"] = (10,6)
df=pd.read_csv("heart.csv")
```

In [33]:

```
df.head()
```

Out[33]:

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	target
0	52	1	0	125	212	0	1	168	0	1.0	2	2	3	0
1	53	1	0	140	203	1	0	155	1	3.1	0	0	3	0
2	70	1	0	145	174	0	1	125	1	2.6	0	0	3	0
3	61	1	0	148	203	0	1	161	0	0.0	2	1	3	0
4	62	0	0	138	294	1	1	106	0	1.9	1	3	2	0

In [34]:

```
df.describe()
```

Out[34]:

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang
count	1025.000000	1025.000000	1025.000000	1025.000000	1025.00000	1025.000000	1025.000000	1025.000000	1025.000000
mean	54.434146	0.695610	0.942439	131.611707	246.00000	0.149268	0.529756	149.114146	0.336585
std	9.072290	0.460373	1.029641	17.516718	51.59251	0.356527	0.527878	23.005724	0.472772
min	29.000000	0.000000	0.000000	94.000000	126.00000	0.000000	0.000000	71.000000	0.000000
25%	48.000000	0.000000	0.000000	120.000000	211.00000	0.000000	0.000000	132.000000	0.000000
50%	56.000000	1.000000	1.000000	130.000000	240.00000	0.000000	1.000000	152.000000	0.000000
75%	61.000000	1.000000	2.000000	140.000000	275.00000	0.000000	1.000000	166.000000	1.000000
max	77.000000	1.000000	3.000000	200.000000	564.00000	1.000000	2.000000	202.000000	1.000000

In [35]:

```
df.isna().sum()
```

Out[35]:

```
age         0
sex         0
cp          0
trestbps    0
chol        0
fbs         0
```

```
restecg     0
thalach     0
exang       0
oldpeak     0
slope       0
ca          0
thal        0
target      0
dtype: int64
```

In [36]:

```
df.nunique()
```

Out[36]:

```
age          41
sex           2
cp            4
trestbps     49
chol        152
fbs           2
restecg       3
thalach      91
exang         2
oldpeak      40
slope         3
ca            5
thal          4
target        2
dtype: int64
```

correlation matrix

In [37]:

```
#correlation matrix
corrMatrix = df.corr()
sn.heatmap(corrMatrix, annot=True)
plt.show()
```

PREPROCESSING

duplicates....

In [38]:

```
#dropping duplicate rows...
df.drop(axis="rows", labels=df.index[df.duplicated()], inplace=True)
```

In [39]:

```
df.duplicated().sum()
len(df)
```

Out[39]:

```
302
```

Fuction to calculate f1 score

In [40]:

```
#function for caluculating f1 score, accuracy , precision , recall
def f1(actual, predicted, label):
    tp = np.sum((actual==label) & (predicted==label)) # true - true
    fp = np.sum((actual!=label) & (predicted==label)) #
    fn = np.sum((predicted!=label) & (actual==label))
    tn = np.sum((predicted!=label) & (actual!=label))

    accu=(tp+tn)/(tp+fp+tn+fn)
    print("accuracy:",accu)
    precision = tp/(tp+fp)
    print("Precision:", precision)
    recall = tp/(tp+fn)
    print("recall:",recall)
    f1 = 2 * (precision * recall) / (precision + recall)
    print("f1 score:", f1)
```

In [41]:

```
df.info()
df.describe()
df.shape[1]
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 302 entries, 0 to 878
Data columns (total 14 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   age       302 non-null    int64
 1   sex       302 non-null    int64
 2   cp        302 non-null    int64
 3   trestbps  302 non-null    int64
 4   chol      302 non-null    int64
 5   fbs       302 non-null    int64
 6   restecg   302 non-null    int64
 7   thalach   302 non-null    int64
 8   exang     302 non-null    int64
 9   oldpeak   302 non-null    float64
 10  slope     302 non-null    int64
 11  ca        302 non-null    int64
 12  thal      302 non-null    int64
 13  target    302 non-null    int64
dtypes: float64(1), int64(13)
memory usage: 35.4 KB
```

Out[41]:

Splitting data.... standardizzzzzee.....

X as set of features...... Y as target column.......

In [42]:

```
from random import random

df.apply(pd.to_numeric, errors='ignore')
X = df.iloc[:,0:df.shape[1]-1]
Y = df.iloc[:,df.shape[1]-1]

# standardize the data
X=(X-X.mean())/X.std()
# add a columns of 1 at the end
X.insert(df.shape[1]-1, "Const", [1]*len(X), True)

arr_rand = np.random.rand(X.shape[0])
split = arr_rand < np.percentile(arr_rand, 85)
# spliting data into train and split
X_train = X[split]
Y_train = Y[split]
X_test =  X[~split]
Y_test = Y[~split]
#print(X_test)
```

In [43]:

```
#sigmoid function....
def sigmoid(x):
    return 1/(1+np.exp(-x))
```

Logistic Regression : univariate

preparing data for univariate

In [44]:

```
lr=0.01
W=np.random.uniform(low=0,high=1,size=2)
X_uni = df.iloc[:,[0]]
X_uni = (X_uni - X_uni.mean())/X_uni.std()
X_uni.insert(1, "Const", [1]*len(X_uni), True)
#print(X_uni)

X_uni_tr=X_uni[split]
X_uni_te=X_uni[~split]
```

Using gradient descent,calculating best probable graph..

In [45]:

```
#gradient descent
#decreasing the error gradualy
for i in range(5000):
    p=sigmoid(X_uni_tr@W)
    grad=X_uni_tr.T@(Y_train-p)
    W+=lr*grad

break_point=np.array(sigmoid(X_uni_te@W))
c0=0
c1=0
```

above 0.5 probability as 1....

In [46]:

```
# margin probability as 0.5
for i in range(len(break_point)):
    if(break_point[i]>=0.5):
        c1=c1+1
        break_point[i]=1
    else:
         c0=c0+1
         break_point[i]=0
```

In [47]:

```
f1(Y_test,break_point,1)
```

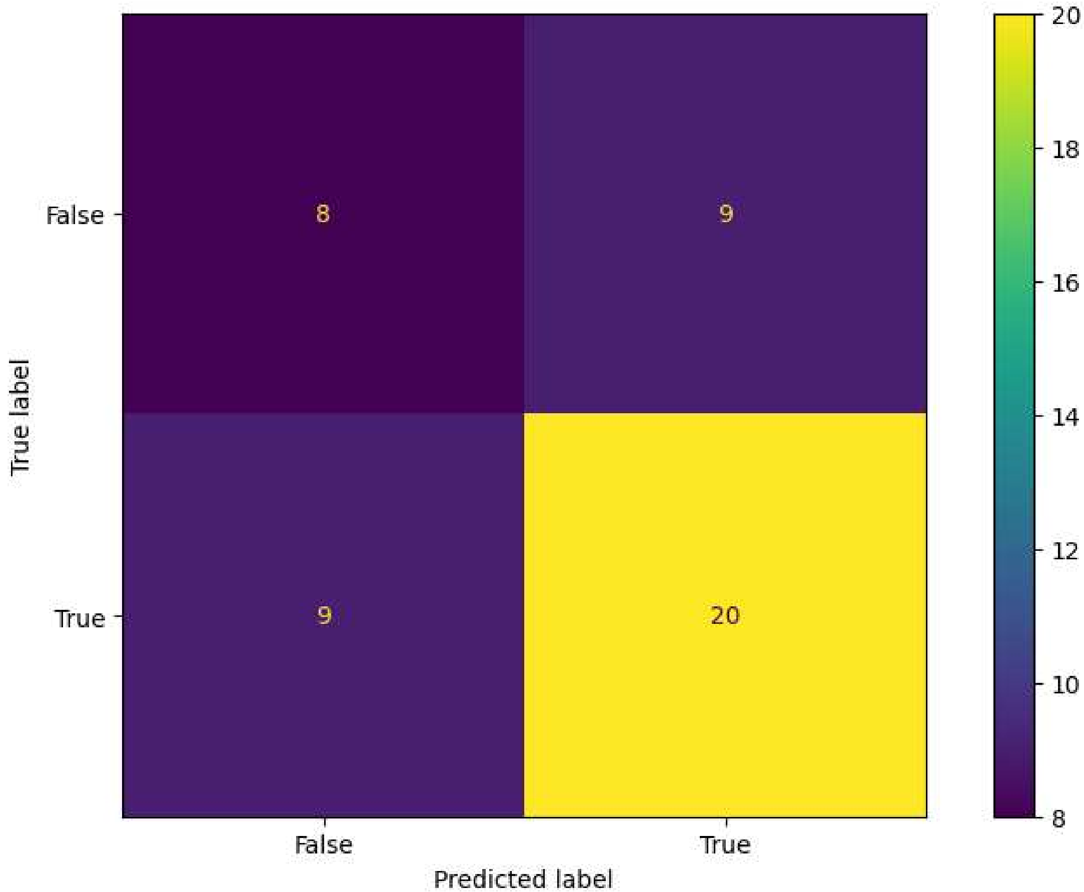
```
accuracy: 0.6086956521739131
Precision: 0.6896551724137931
recall: 0.6896551724137931
f1 score: 0.6896551724137931
```

In [48]:

```
#fusion
confusion_matrix = metrics.confusion_matrix(Y_test,break_point)
cm_display = metrics.ConfusionMatrixDisplay(confusion_matrix = confusion_matrix, display
_labels = [False, True])
cm_display.plot()
```

Out[48]:

```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x1ce27d43be0>
```



Logistic Regression: Multivariate

In [49]:

```
#learning rate and generating a matrix of size based on the size.
lr=0.01
W=np.random.uniform(low=0,high=1,size=df.shape[1])

for i in range(5000):
    pa=sigmoid(X_train@W)
    grad=X_train.T@(Y_train-pa)
    W+=lr*grad

break_point=np.array(sigmoid(X_test@W))
c0=0
c1=0
```

In [50]:

```
for i in range(len(break_point)):
    if(break_point[i]>=0.5):
        c1=c1+1
        break_point[i]=1
    else:
        c0=c0+1
        break_point[i]=0

#print(c0)
#print(c1)
```

In [51]:

```
f1(Y_test,break_point,1)
```

```
accuracy: 0.8913043478260869
Precision: 0.9285714285714286
recall: 0.896551724137931
f1 score: 0.912280701754386
```

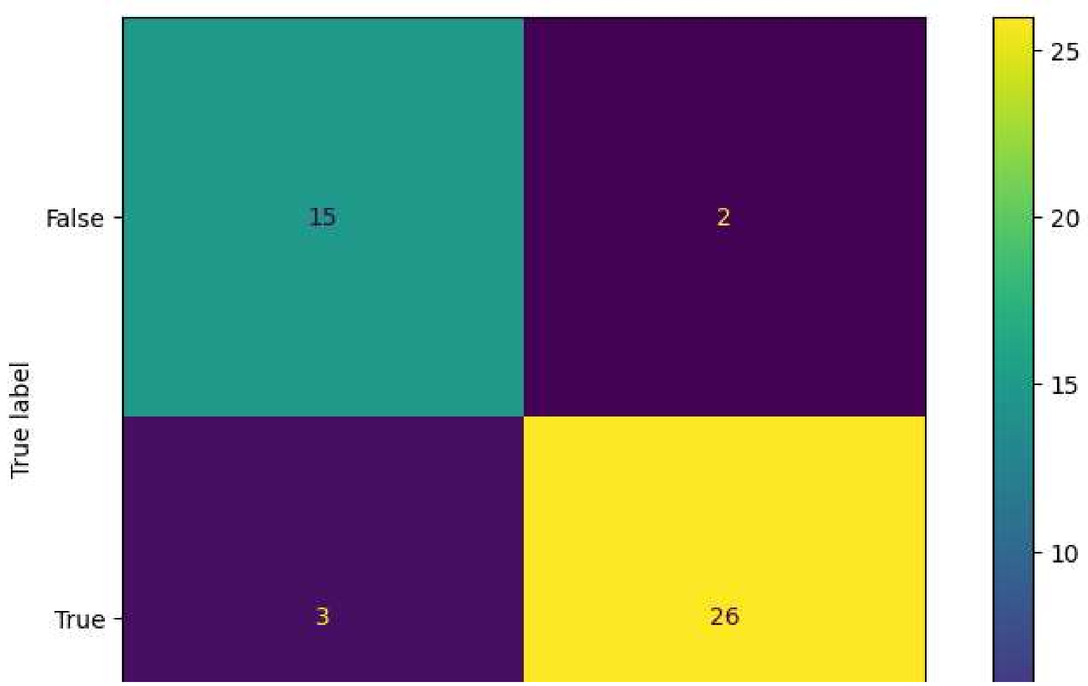
In [52]:

```
from sklearn import metrics

confusion_matrix = metrics.confusion_matrix(Y_test,break_point)
cm_display = metrics.ConfusionMatrixDisplay(confusion_matrix = confusion_matrix, display
_labels = [False, True])
cm_display.plot()
```

Out[52]:

```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x1ce2a19f1c0>
```



Naive Bayes

def for calculating probablitiy..

In [53]:

```
#definition to calculate probability using mean and std
def calc_prob(mu, sigma, x):
    return 1/(sigma * np.sqrt(2 * np.pi)) * np.exp( - (x - mu)**2 / (2 * sigma**2))
#df.shape[0]
```

Modifying data

In [54]:

```
#one hot encoding fot target column
df2=pd.get_dummies(df, columns=["target"])
X = df2.iloc[:,]
#X=(X-X.mean())/X.std()

arr_rand = np.random.rand(X.shape[0])
split = arr_rand < np.percentile(arr_rand, 90)
#split data
X_train = X[split]
Y_train = Y[split]
X_test =  X[~split]
Y_test = Y[~split]

#splitting rows into 2 set of rows based on the value of target column
Y_1=X_train.loc[X_train.iloc[:,14]==1]
Y_0=X_train.loc[X_train.iloc[:,14]==0]
print(len(Y_test))
#print(X_test)
```

```
31
```

Naive Bayes:Univariate

In [55]:

```
#mean and std of both the sets
mean_0=np.mean(Y_0.iloc[:,0])
std_0=np.std(Y_0.iloc[:,0])
std_1=np.std(Y_1.iloc[:,0])
mean_1=np.mean(Y_1.iloc[:,0])
#print(mean_0)
#print(mean_1)

#predicted probability set
pre_prob=np.zeros(Y_test.shape[0])
```

In [56]:

```
for i in range(X_test.shape[0]):
    p_0=mean_0
    p_1=mean_1
    x=X.iat[i,0]
```

```
    p_0=calc_prob(mean_0,std_0,x)
    p_1=calc_prob(mean_1,std_1,x)
    if(p_0>p_1):
        pre_prob[i]=1
    else:
        pre_prob[i]=0
```

In [57]:

```
#accuracy and fusion matrix
f1(Y_test,pre_prob,1)
```

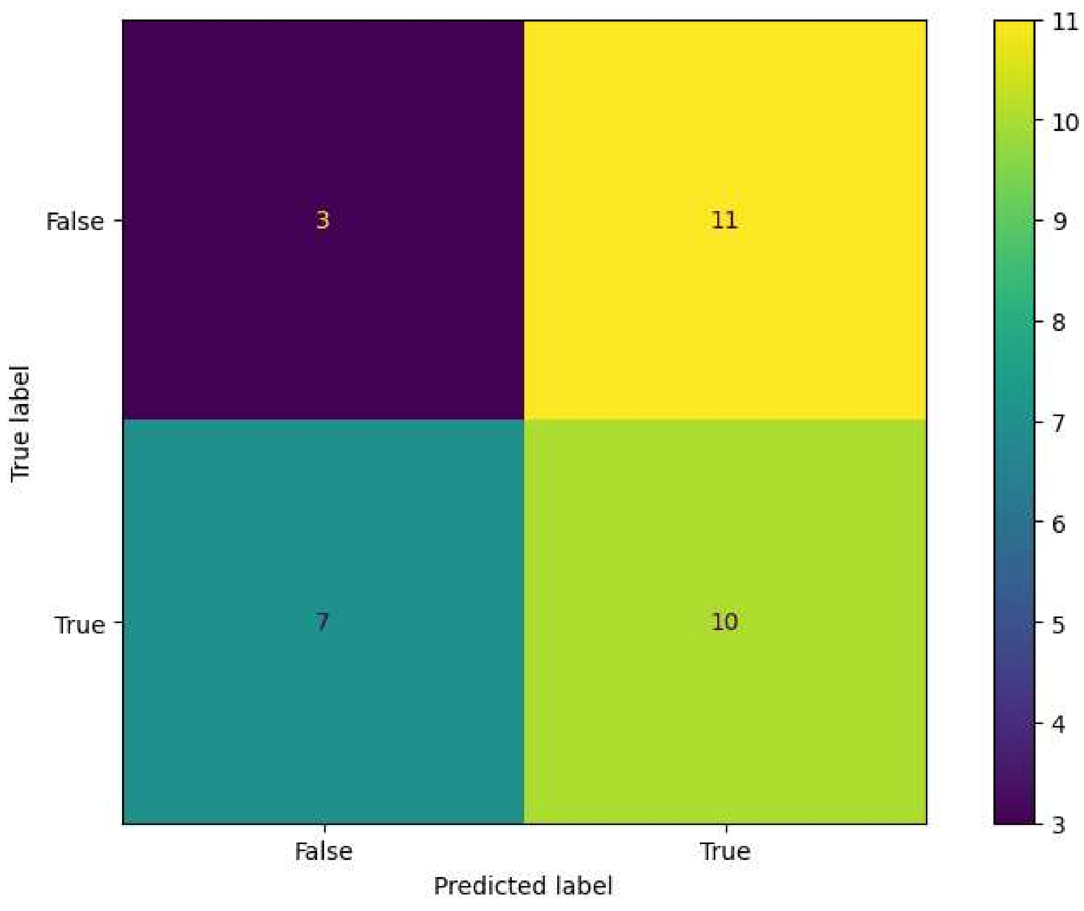
```
accuracy: 0.41935483870967744
Precision: 0.47619047619047616
recall: 0.5882352941176471
f1 score: 0.5263157894736842
```

In [58]:

```
confusion_matrix = metrics.confusion_matrix(Y_test,pre_prob)
cm_display = metrics.ConfusionMatrixDisplay(confusion_matrix = confusion_matrix, display
_labels = [False, True])
cm_display.plot()
```

Out[58]:

```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x1ce2ad5f430>
```



Naive bayes: multivariate

In [59]:

```
#set of all columns mean and std
mean_00=[]
mean_11=[]
std_00=[]
std_11=[]
```

```python
#mean of all features
for i in range(Y_0.shape[1]):
    mean_00.append(np.mean(Y_0.iloc[:,i]))
    std_00.append(np.std(Y_0.iloc[:,i]))

#std of all features
for i in range(Y_1.shape[1]):
    mean_11.append(np.mean(Y_1.iloc[:,i]))
    std_11.append(np.std(Y_1.iloc[:,i]))
```

In [60]:

```python
#Assuming that all features are independent to each other


y_pred=np.zeros(Y_test.shape[0])
for i in range(X_test.shape[0]):
    p_0=mean_0
    p_1=mean_1


#for a particular row, caluclate probability of both 0 and 1. select the max one
    for j in range(X_test.shape[1]-2):
        x=X_test.iat[i,j]
        p_0*=calc_prob(mean_00[j],std_00[j],x)
        p_1*=calc_prob(mean_11[j],std_11[j],x)

    if(p_0>p_1):
        y_pred[i]=0
    else:
        y_pred[i]=1
```

In [61]:

```python
f1(Y_test,y_pred,1)
```

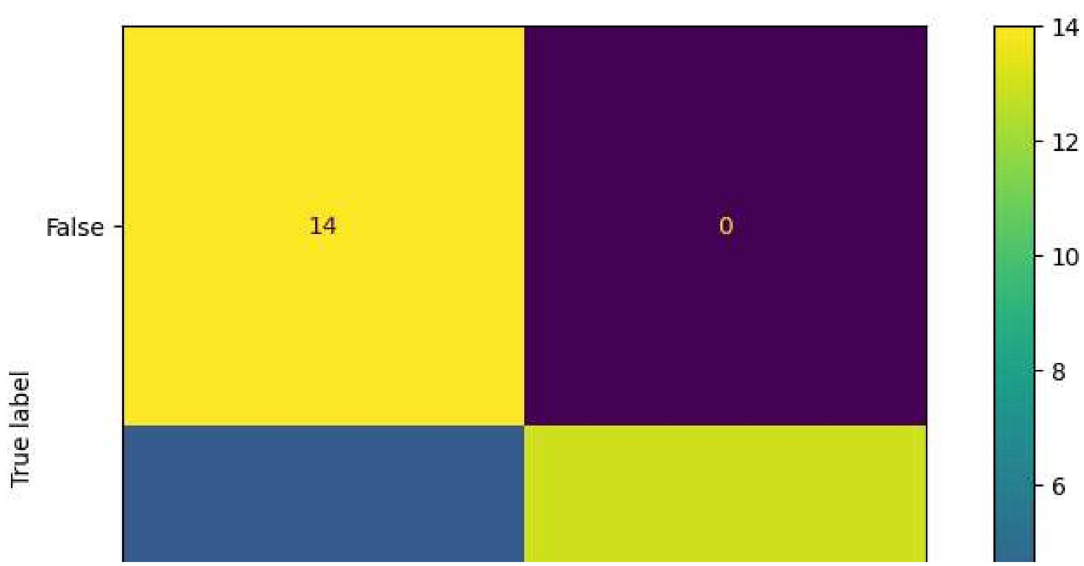
```
accuracy: 0.8709677419354839
Precision: 1.0
recall: 0.7647058823529411
f1 score: 0.8666666666666666
```

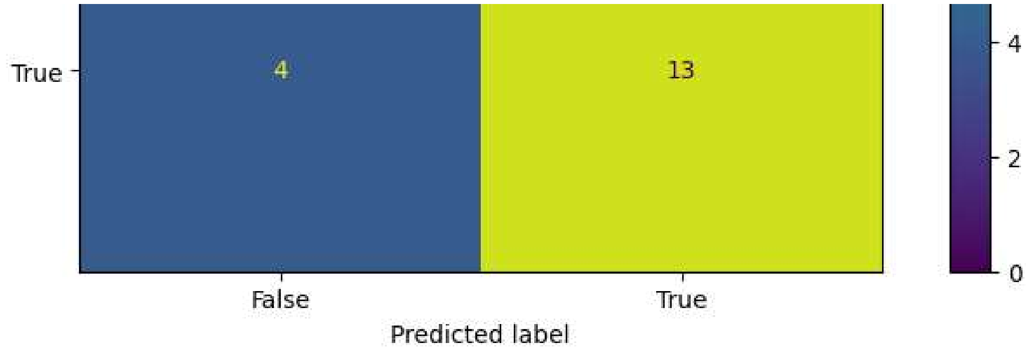
In [62]:

```python
confusion_matrix = metrics.confusion_matrix(Y_test, y_pred)
cm_display = metrics.ConfusionMatrixDisplay(confusion_matrix = confusion_matrix, display
_labels = [False, True])
cm_display.plot()
```

Out[62]:

```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x1ce2a31abc0>
```





If the features are dependent... then we have to use some columns which have good correaltion between that column and target..

for this data set..I choose ["cp","thalach","exchang","oldpeak"] these columns as they have co-relation>0.4. (plotted correlation matrix above)