

Lab Report

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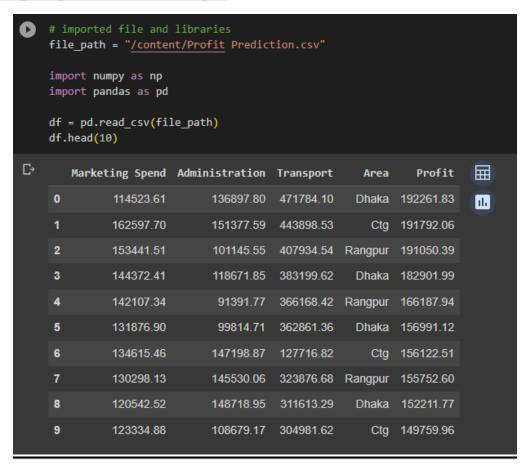
ID: 213-15-4278

Section: 60_B

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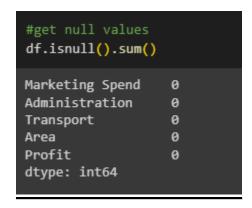
Check data

Checking original data and shape:



#get row and column of the data df.shape
(50, 5)

Check null:



Get information of data:

<pre>#gives a brief description of data df.describe()</pre>										
	Marketing Spend	Administration	Transport	Profit						
count	50.000000	50.000000	50.000000	50.000000	111					
mean	73721.615600	121344.639600	211025.097800	112012.639200						
std	45902.256482	28017.802755	122290.310726	40306.180338						
min	0.000000	51283.140000	0.000000	14681.400000						
25%	39936.370000	103730.875000	129300.132500	90138.902500						
50%	73051.080000	122699.795000	212716.240000	107978.190000						
75%	101602.800000	144842.180000	299469.085000	139765.977500						
max	165349.200000	182645.560000	471784.100000	192261.830000						

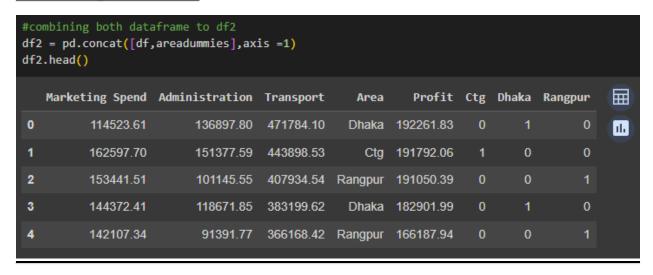
```
#gives information about the data
#we can see that we have an object type data
df.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 50 entries, 0 to 49
Data columns (total 5 columns):
                    Non-Null Count Dtype
# Column
0 Marketing Spend 50 non-null
                                   float64
1 Administration 50 non-null
                                   float64
2 Transport 50 non-null
                                   float64
3 Area
                   50 non-null
                                   object
                                   float64
4 Profit
                   50 non-null
dtypes: float64(4), object(1)
memory usage: 2.1+ KB
```

Dividing dataframe

Encoding object:



Combining dataframe:



Dividing input and output:

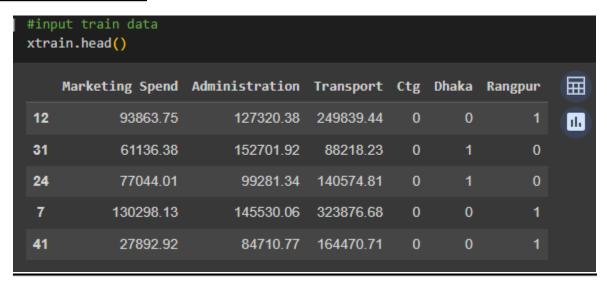
```
# we need to seperate given data and the value we want to find
# we put given data in x and result data in y
#obj data Area is encoded with onehotencoder
#deleting obj data and result data to get pure given data
x = df2.drop(['Area', 'Profit'],axis=1)
# result data goes to y
y = df2['Profit']
x.head()
   Marketing Spend Administration Transport Ctg Dhaka Rangpur
                                                                     翩
0
          114523.61
                          136897.80 471784.10
                                                                     II.
          162597.70
                          151377.59 443898.53
                                                                 0
2
         153441.51
                          101145.55 407934.54
          144372.41
                          118671.85 383199.62
                                                                 0
                                                 0
          142107.34
                           91391.77 366168.42
                                                        0
```

Splitting data:

```
# splitting into train and test data
# defined the ratio of test:train as 20%:80%

from sklearn.model_selection import train_test_split
xtrain,xtest,ytrain,ytest = train_test_split(x,y,test_size = 0.2)
```

Show divided data:



```
#output train data
ytrain.head()

12  141585.52
31  97483.56
24  108552.04
7  155752.60
41  77798.83
Name: Profit, dtype: float64
```

	<pre>#input test data xtest.head()</pre>									
	Marketing Spend	Administration	Transport	Ctg	Dhaka	Rangpur				
4	142107.34	91391.77	366168.42	0	0	1	11.			
21	78389.47	153773.43	299737.29	0	1	0				
36	28663.76	127056.21	201126.82	0	0	1				
46	1315.46	115816.21	297114.46	0	0	1				
40	28754.33	118546.05	172795.67	1	0	0				

	t test data .head()	
4 21 36 46 40 Name:	166187.94 111313.02 90708.19 49490.75 78239.91 Profit, dtype:	float64

Scaling data

Scaling from 0 to 1:

```
#scaled the input data (0 to 1)
from sklearn.preprocessing import MinMaxScaler
mms = MinMaxScaler()
mms.fit(xtrain)
xtrain mms = mms.transform(xtrain)
xtest mms = mms.transform(xtest)
print(xtrain mms)
            0.57883556 0.52956308 0.
                                              0.
[[0.577276
                                                         1.
[0.37599782 0.77205322 0.18698856 0.
                                              1.
                                                         0.
[0.4738321 0.3653876 0.29796428 0.
                                              1.
                                                         0.
 [0.80135285 0.71745725 0.68649342 0.
                                              0.
                                                         1.
[0.1715456 0.25446874 0.34861436 0.
                                              0.
                                                         1.
[0.94368807 0.37957895 0.8646636 0.
                                                         1.
[0.6191475 0.30836422 0.52936195 1.
                                                         0.
[0.00615156 0.5547241 0.0040356 0.
                                                         0.
                                              1.
[0.23714056 0.24130912 0.3709309 1.
                                              0.
                                                         0.
[0.53149399 0.77823604 0.
                                              1.
                                                         0.
 [0.46328374 0.70684477 0.28413435 0.
                                              0.
                                                         1.
[0.45507753 0.54429273 0.64291963 0.
                                              0.
                                                         1.
[0.40348344 0.77456642 0.22709197 0.
                                                         0.
[0.58215559 0.71401273 0.59894835 0.
                                              1.
                                                         0.
[0.28552722 0.81005496 0.44680961 1.
                                              0.
                                                         0.
[0.81106252 0.3694479 0.76912588 0.
                                             1.
                                                         0.
[0.75852783 0.43692884 0.64644319 1.
                                             0.
                                                         0.
 [0.47979221 0.53527036 0.56031151 1.
                                              0.
                                                         0.
 [0.88791176 0.51299839 0.81223513 0.
                                              1.
                                                         0.
 [0.56576686 0.64106561 0.53555202 1.
[0.44347245 0.58297807 0.74861321 0.
                                                         0.
[0.82790507 0.73016111 0.27071031 1.
                                              0.
                                                         0.
            0.76197173 0.94089337 1.
                                                         0.
                                              0.
[0.13639639 0.78807166 0.06005866 1.
                                              0.
                                                         0.
 [0.40622666 1.
                       0.25042853 0.
                                              0.
[0.14539523 0.34185188 0.31370517 1.
                                              0.
                                                         0.
            0.50014806 0.09574943 1.
                                              0.
                                                         0.
[0.73766874 0.8013272 0.54370828 0.
                                              0.
                                                         1.
[0.00333369 0.00350184 0.
                                   0.
                                              1.
                                                         0.
[0.70433721 0.65174393 1.
                                   0.
                                                         0.
```

Creating new DataFrame:

#add	#added columns to create dataframe										
xtes	xtrain_mms_df = pd.DataFrame(xtrain_mms,columns=xtrain.columns) xtest_mms_df = pd.DataFrame(xtest_mms,columns=xtest.columns) xtrain_mms_df										
	Marketing Spend	Administration	Transport	Ctg	Dhaka	Rangpur					
0	0.577276	0.578836	0.529563	0.0	0.0	1.0	11				
1	0.375998	0.772053	0.186989	0.0	1.0	0.0					
2	0.473832	0.365388	0.297964	0.0	1.0	0.0					
3	0.801353	0.717457	0.686493	0.0	0.0	1.0					
4	0.171546	0.254469	0.348614	0.0	0.0	1.0					
5	0.943688	0.379579	0.864664	0.0	0.0	1.0					
6	0.619148	0.308364	0.529362	1.0	0.0	0.0					
7	0.006152	0.554724	0.004036	0.0	1.0	0.0					
8	0.237141	0.241309	0.370931	1.0	0.0	0.0					
9	0.531494	0.778236	0.000000	0.0	1.0	0.0					
10	0.463284	0.706845	0.284134	0.0	0.0	1.0					
11	0.455078	0.544293	0.642920	0.0	0.0	1.0					
12	0.403483	0.774566	0.227092	0.0	1.0	0.0					
13	0.582156	0.714013	0.598948	0.0	1.0	0.0					
14	0.285527	0.810055	0.446810	1.0	0.0	0.0					
15	0.811063	0.369448	0.769126	0.0	1.0	0.0					
16	0.758528	0.436929	0.646443	1.0	0.0	0.0					

LInearRegression Model

Insert in model:

```
#inserting the data in linear regression model
from sklearn.linear_model import LinearRegression
model_linear = LinearRegression()
model_linear.fit(xtrain_mms_df,ytrain)

* LinearRegression
LinearRegression()
```

Check accuracy:

```
#predicted result is 62% close to real result
model_linear.score(xtest_mms_df,ytest)

0.6216500003260639
```

Predict data:

```
#show first test
xtest.head(1)
   Marketing Spend Administration Transport Ctg Dhaka Rangpur
                                                                   屇
         142107.34
                          91391.77 366168.42 0
                                                      0
                                                                    Ш
#predicting the result of first test
model linear.predict(xtest mms df.head(1))
array([171551.76658782])
#predict for all test
model_linear.predict(xtest_mms_df)
array([171551.76658782, 126765.31390141, 75160.80566426, 59618.80934177,
       75459.08817672, 132824.28709055, 96023.04190476, 94415.22177388,
      190626.87325536, 159803.9315159 ])
```

Error calculation

Error:

```
#finding error

from sklearn import metrics
test_pred = model_linear.predict(xtest_mms_df)
mae = metrics.mean_absolute_error(ytest,test_pred)
mse = metrics.mean_squared_error(ytest,test_pred)
mse = np.sqrt(metrics.mean_squared_error(ytest,test_pred))
print ('MAE ',mae)
print ('RMSE ',mse)

MAE 13369.220999207924
RMSE 21317.97594757009
```

Ridge Regression model

```
# inserting data into ridge regression model
from sklearn.linear_model import Ridge
model_Ridge = Ridge()
model_Ridge.fit(xtrain_mms_df,ytrain)
test_pred = model_Ridge.predict(xtest_mms_df)
mae = metrics.mean_absolute_error(ytest, test_pred)
mse = metrics.mean_squared_error(ytest, test_pred)
mse = np.sqrt(metrics.mean_squared_error(ytest, test_pred))
print('MAE:', mae)
print('MSE:', mse)
MAE: 31800.027104984445
MSE: 43308.800218347846
```

Lasso Regression model

```
#inserting data into lasso regression model
from sklearn.linear_model import Lasso
model_Lasso = Lasso()
model_Lasso.fit(xtrain_mms_df,ytrain)
test_pred = model_Lasso.predict(xtest_mms_df)
mae = metrics.mean_absolute_error(ytest, test_pred)
mse = metrics.mean_squared_error(ytest, test_pred)
mse = np.sqrt(metrics.mean_squared_error(ytest, test_pred))
print('MAE: ', mae)
print('MSE:', mse)
MAE: 33650.65420351333
MSE: 47032.709140628154
```

Check second data

Checking original data and shape:

```
file_path = "/content/breast_cancer_dataframe.csv"
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
df = pd.read_csv(file_path)
df.head(10)
                                                                              mean
                                                                                                   mean
              mean
                         mean
                                mean
                                             mean
                                                          mean
                                                                     mean
                                                                                        mean
                                                                          concave
                                                                                                fractal ...
   radius texture perimeter
                                area smoothness compactness concavity
                                                                                    symmetry
                                                                                             dimension
                                                                            points
    17.99
              10.38
                        122.80 1001.0
                                          0.11840
                                                       0.27760
                                                                  0.30010 0.14710
                                                                                      0.2419
                                                                                                0.07871
     20.57
                        132.90 1326.0
                                          0.08474
                                                       0.07864
                                                                  0.08690 0.07017
              17.77
                                                                                      0.1812
                                                                                                0.05667
     19.69
             21.25
                        130.00 1203.0
                                          0.10960
                                                       0.15990
                                                                  0.19740 0.12790
                                                                                      0.2069
                                                                                                0.05999
2
3
     11.42
              20.38
                         77.58
                               386.1
                                          0.14250
                                                       0.28390
                                                                  0.24140 0.10520
                                                                                      0.2597
                                                                                                0.09744
     20.29
                        135.10 1297.0
                                          0.10030
                                                                  0.19800 0.10430
4
              14.34
                                                       0.13280
                                                                                      0.1809
                                                                                                0.05883
5
    12.45
              15.70
                                          0.12780
                                                       0.17000
                                                                  0.15780 0.08089
                                                                                      0.2087
                                                                                                0.07613
     18.25
              19.98
                        119.60 1040.0
                                          0.09463
                                                       0.10900
                                                                  0.11270 0.07400
                                                                                      0.1794
                                                                                                0.05742
     13.71
             20.83
                               577.9
                                          0.11890
                                                       0.16450
                                                                  0.09366 0.05985
                         90.20
                                                                                      0.2196
                                                                                                0.07451
     13.00
                         87.50
                                519.8
                                          0.12730
                                                       0.19320
                                                                  0.18590 0.09353
                                                                                      0.2350
8
              21.82
                                                                                                0.07389
                         83.97
     12.46
              24 04
                                          0.11860
                                                       0.23960
                                                                  0.22730 0.08543
                                                                                      0.2030
                                                                                                0.08243
10 rows × 31 columns
```

```
#get row and column of the data df.shape

(569, 31)
```

Check null:

#get null values	
<pre>df.isnull().sum()</pre>	
mean radius	0
mean texture	0
mean perimeter	0
mean area	0
mean smoothness	0
mean compactness	0
mean concavity	0
mean concave points	0
mean symmetry	0
mean fractal dimension	0
radius error	0
texture error	0
perimeter error	0
area error	0
smoothness error	0
compactness error	0
concavity error	0
concave points error	0
symmetry error	0
fractal dimension error	0
worst radius	0
worst texture	0
worst perimeter	0
worst area	0
worst smoothness	0
worst compactness	0
worst concavity	0
worst concave points	0
worst symmetry	0
worst fractal dimension	0
target	0
dtype: int64	

Get information of data:

_	<pre>#gives a brief description of data df.describe()</pre>									
	mean radius	mean texture	mean perimeter	mean area	mean smoothness	mean compactness	mean concavity	mean concave points	m symme	
count	569.000000	569.000000	569.000000	569.000000	569.000000	569.000000	569.000000	569.000000	569.000	
mean	14.127292	19.289649	91.969033	654.889104	0.096360	0.104341	0.088799	0.048919	0.181	
std	3.524049	4.301036	24.298981	351.914129	0.014064	0.052813	0.079720	0.038803	0.027	
min	6.981000	9.710000	43.790000	143.500000	0.052630	0.019380	0.000000	0.000000	0.106	
25%	11.700000	16.170000	75.170000	420.300000	0.086370	0.064920	0.029560	0.020310	0.161	
50%	13.370000	18.840000	86.240000	551.100000	0.095870	0.092630	0.061540	0.033500	0.179	
75%	15.780000	21.800000	104.100000	782.700000	0.105300	0.130400	0.130700	0.074000	0.195	
max	28.110000	39.280000	188.500000	2501.000000	0.163400	0.345400	0.426800	0.201200	0.304	
8 rows ×	31 columns									

#gives information about the data
#we can see that we dont have any object data
df.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 569 entries, 0 to 568
Data columns (total 31 columns):
    Column
                             Non-Null Count Dtype
    mean radius
0
                             569 non-null
                                             float64
    mean texture
                             569 non-null
                                             float64
1
2
    mean perimeter
                             569 non-null
                                             float64
    mean area
                             569 non-null
                                            float64
    mean smoothness
4
                             569 non-null
                                            float64
    mean compactness
                             569 non-null
                                            float64
6
    mean concavity
                             569 non-null
                                             float64
    mean concave points
                             569 non-null
                                            float64
8
    mean symmetry
                             569 non-null
                                            float64
    mean fractal dimension
                                            float64
9
                             569 non-null
10 radius error
                             569 non-null
                                            float64
11 texture error
                             569 non-null
                                             float64
                             569 non-null
                                            float64
12 perimeter error
13 area error
                             569 non-null
                                             float64
14 smoothness error
                             569 non-null
                                            float64
15 compactness error
                             569 non-null
                                             float64
16 concavity error
                             569 non-null
                                            float64
17 concave points error
                             569 non-null
                                            float64
                             569 non-null
                                            float64
18 symmetry error
19 fractal dimension error 569 non-null
                                             float64
20 worst radius
                             569 non-null
                                            float64
 21 worst texture
                             569 non-null
                                             float64
22 worst perimeter
                             569 non-null
                                            float64
 23 worst area
                             569 non-null
                                             float64
24 worst smoothness
                             569 non-null
                                            float64
 25 worst compactness
                             569 non-null
                                            float64
                                            float64
26 worst concavity
                             569 non-null
                             569 non-null
27 worst concave points
                                            float64
28 worst symmetry
                             569 non-null
                                            float64
29 worst fractal dimension 569 non-null
                                            float64
                             569 non-null
30 target
                                             int64
dtypes: float64(30), int64(1)
memory usage: 137.9 KB
```

Dividing dataframe

Dividing input and output:

```
x=df.drop ([ 'target' ], axis = 1)
x.head (10)
                                                                                                  fractal ...
                                                                            concave
    radius texture perimeter
                                 area smoothness compactness concavity
                                                                                     symmetry
                                                                             points
                                                                                               dimension
     17.99
              10.38
                        122.80 1001.0
                                           0.11840
                                                         0.27760
                                                                    0.30010 0.14710
                                                                                        0.2419
                                                                                                  0.07871
                                           0.08474
                                                                    0.08690 0.07017
     20.57
              17.77
                        132.90 1326.0
                                                         0.07864
                                                                                        0.1812
                                                                                                  0.05667
     19.69
                        130.00 1203.0
                                           0.10960
                                                        0.15990
                                                                    0.19740 0.12790
                                                                                        0.2069
                                                                                                  0.05999
2
              21.25
 3
     11.42
              20.38
                         77.58
                                 386.1
                                           0.14250
                                                        0.28390
                                                                    0.24140 0.10520
                                                                                        0.2597
                                                                                                  0.09744
     20.29
                        135.10 1297.0
                                           0.10030
                                                                    0.19800 0.10430
              14.34
                                                         0.13280
                                                                                        0.1809
                                                                                                  0.05883
5
     12.45
              15.70
                         82.57
                                 477.1
                                           0.12780
                                                         0.17000
                                                                    0.15780 0.08089
                                                                                        0.2087
                                                                                                  0.07613
     18.25
              19.98
                        119.60 1040.0
                                           0.09463
                                                         0.10900
                                                                    0.11270 0.07400
                                                                                                  0.05742
                                                                                        0.1794
     13.71
              20.83
                         90.20
                                 577.9
                                           0.11890
                                                        0.16450
                                                                    0.09366 0.05985
                                                                                        0.2196
                                                                                                  0.07451
     13.00
              21.82
                         87.50
                                 519.8
                                           0.12730
                                                         0.19320
                                                                    0.18590 0.09353
                                                                                        0.2350
                                                                                                  0.07389
 9
     12.46
              24.04
                         83.97
                                 475.9
                                                        0.23960
                                                                    0.22730 0.08543
                                                                                        0.2030
                                                                                                  0.08243
                                           0.11860
10 rows × 30 columns
```

```
#output data
y=df['target']
y.head (10)
0
     0
1
     0
2
     0
     0
4
     0
     0
6
     0
     0
8
     0
9
     0
Name: target, dtype: int64
```

Splitting data:

```
# splitting into train and test data
# defined the ratio of test:train as 20%:80%

from sklearn.model_selection import train_test_split
xtrain,xtest,ytrain,ytest = train_test_split(x,y,test_size = 0.2)
```

Standard Scaling

Scaling:

```
# standard scaling input data
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
xtrain_sc = sc.fit_transform (xtrain )
xtest_sc = sc.transform (xtest )
```

Non-Scaled Accuracy:

```
#accuracy without standard scaling
#used classification model
from sklearn.metrics import confusion_matrix, classification_report , accuracy_score
from sklearn.svm import SVC
svc_classifier = SVC ()
svc_classifier.fit (xtrain,ytrain )
y_pred_scv = svc_classifier.predict (xtest )
accuracy_score (ytest,y_pred_scv)

0.9122807017543859
```

Scaled Accuracy:

```
#accuracy with standard scaling
svc_classifier2 = SVC ()
svc_classifier2.fit (xtrain_sc,ytrain )
y_pred_svc_sc = svc_classifier2.predict (xtest_sc )
accuracy_score (ytest , y_pred_svc_sc )

0.9824561403508771
```

KNeighborsClassifier Model

```
#accuracy with KNeighborsClassifier model
from sklearn.neighbors import KNeighborsClassifier
knn_classifier = KNeighborsClassifier ()
knn_classifier.fit (xtrain ,ytrain )
y_pred_knn = knn_classifier.predict (xtest )
accuracy_score (ytest , y_pred_knn )

0.956140350877193
```

GaussianNB Model

```
#accuracy with GaussianNB model
from sklearn.naive_bayes import GaussianNB
nb_classifier = GaussianNB ()
nb_classifier.fit (xtrain ,ytrain )
y_pred_nb = nb_classifier.predict (xtest )
accuracy_score (ytest, y_pred_nb )

0.9385964912280702
```

DecisionTreeClassifier Model

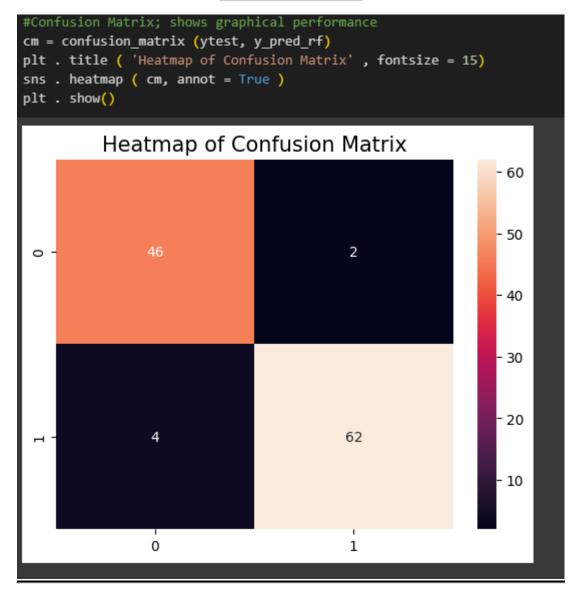
```
#accuracy with DecisionTreeClassifier model
from sklearn.tree import DecisionTreeClassifier
dt_classifier = DecisionTreeClassifier()
dt_classifier.fit (xtrain , ytrain )
y_pred_dt = dt_classifier.predict (xtest )
accuracy_score (ytest, y_pred_dt )

0.9122807017543859
```

RandomForestClassifier Model

```
#accuracy with RandomForestClassifier model
from sklearn.ensemble import RandomForestClassifier
rf_classifier = RandomForestClassifier ()
rf_classifier.fit (xtrain, ytrain )
y_pred_rf = rf_classifier.predict (xtest )
accuracy_score (ytest, y_pred_rf)
0.9473684210526315
```

Confusion Matrix



Evaluation

Report:

<pre>#report on the prediction print (classification_report (ytest , y_pred_rf))</pre>										
precision recall f1-score support										
0	0.92	0.96	0.94	48						
1	0.97	0.94	0.95	66						
accuracy			0.95	114						
macro avg	0.94	0.95	0.95	114						
weighted avg	0.95	0.95	0.95	114						

Cross Validation:

Other evaluation:

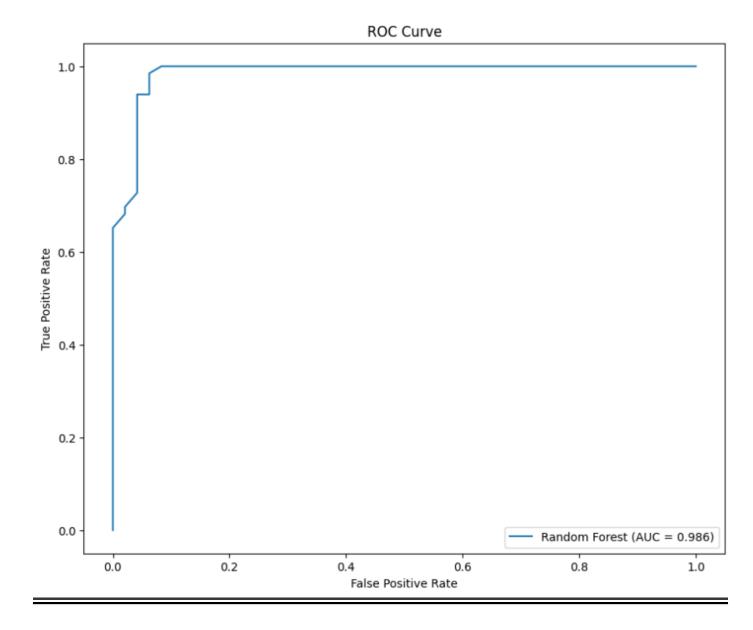
```
#evaluation of the model
from sklearn.metrics import f1_score
from sklearn.metrics import precision_score
from sklearn.metrics import recall_score
from sklearn.metrics import roc_auc_score
from sklearn.metrics import roc_curve , roc_auc_score , auc
print ("F1 Score :" , f1_score (ytest , rf_classifier . predict (xtest ), average='macro' ))
print ("Precision :" , precision_score (ytest , rf_classifier . predict (xtest ), average='macro' ))
print ("Recall :" , recall_score (ytest , rf_classifier . predict (xtest ), average='macro' ))
F1 Score : 0.9463108320251178
Precision : 0.9488636363636565
```

AUC evaluation:

```
#AUC evaluation
from sklearn import metrics
probs = rf_classifier.predict_proba (xtest)
probs = probs [ :, 1]
auc = roc_auc_score (ytest, probs)
fpr , tpr, _ = roc_curve (ytest, probs)
aucl= metrics . auc (fpr , tpr)
print ( "AUC : " , aucl )
AUC : 0.9856376262626262
```

ROC Curve

```
#Showing ROC curve
import matplotlib.pyplot as plt
plt . figure (figsize=(10, 8))
plt . plot (fpr , tpr, label='Random Forest (AUC = %0.3f)' % aucl )
plt . title ( 'ROC Curve' )
plt . xlabel ( 'False Positive Rate' )
plt . ylabel ( 'True Positive Rate' )
plt . legend ()
plt . grid (False)
plt . show()
```



Saving

Model saving:

```
#saving model
import pickle
pickle . dump ( rf_classifier, open ( 'breast_cancer_detector.pickle' , 'wb' ))
```

Using model:

```
# using the model

breast_cancer_detector_model = pickle.load (open ( 'breast_cancer_detector.pickle' , 'rb' ))
y_pred = breast_cancer_detector_model . predict (xtest )
print ( 'Confusion matrix of XGBoost model: \n' , confusion_matrix (ytest , y_pred ), '\n' )
print ( 'Accuracy of XGBoost model= ' , accuracy_score (ytest , y_pred ))

Confusion matrix of XGBoost model:
[[46 2]
[ 4 62]]

Accuracy of XGBoost model= 0.9473684210526315
```