```
In [1]: |#Installing the required Libraries
        !pip install seaborn
        !pip install sklearn
        Collecting seaborn
          Downloading seaborn-0.11.1-py3-none-any.whl (285 kB)
                                      285 kB 3.8 MB/s eta 0:00:01
        Collecting matplotlib>=2.2
          Downloading matplotlib-3.4.1-cp38-cp38-manylinux1 x86 64.whl (10.3 MB)
                                          | 10.3 MB 6.0 MB/s eta 0:00:01
        Collecting pandas>=0.23
          Downloading pandas-1.2.4-cp38-cp38-manylinux1_x86_64.whl (9.7 MB)
                      2.2 MB 5.5 MB/s eta 0:00:02
        Collecting scipy>=1.0
          Downloading scipy-1.6.3-cp38-cp38-manylinux1_x86_64.whl (27.2 MB)
                                      Collecting numpy>=1.15
          Downloading numpy-1.20.2-cp38-cp38-manylinux2010_x86_64.whl (15.4 MB)
                                          15.4 MB 7.1 MB/s eta 0:00:01
        Collecting pillow>=6.2.0
          Downloading Pillow-8.2.0-cp38-cp38-manylinux1_x86_64.whl (3.0 MB)
                      | 3.0 MB 4.8 MB/s eta 0:00:01
        Requirement already satisfied: python-dateutil>=2.7 in /opt/conda/lib/python
        3.8/site-packages (from matplotlib>=2.2->seaborn) (2.8.1)
        Collecting kiwisolver>=1.0.1
          Downloading kiwisolver-1.3.1-cp38-cp38-manylinux1 x86 64.whl (1.2 MB)
                         | 1.2 MB 11.1 MB/s eta 0:00:01
        Requirement already satisfied: pyparsing>=2.2.1 in /opt/conda/lib/python3.8/s
        ite-packages (from matplotlib>=2.2->seaborn) (2.4.7)
        Collecting cycler>=0.10
          Downloading cycler-0.10.0-py2.py3-none-any.whl (6.5 kB)
        Requirement already satisfied: six in /opt/conda/lib/python3.8/site-packages
        (from cycler>=0.10->matplotlib>=2.2->seaborn) (1.15.0)
        Requirement already satisfied: pytz>=2017.3 in /opt/conda/lib/python3.8/site-
        packages (from pandas>=0.23->seaborn) (2021.1)
        Installing collected packages: pillow, numpy, kiwisolver, cycler, scipy, pand
        as, matplotlib, seaborn
        Successfully installed cycler-0.10.0 kiwisolver-1.3.1 matplotlib-3.4.1 numpy-
        1.20.2 pandas-1.2.4 pillow-8.2.0 scipy-1.6.3 seaborn-0.11.1
        Collecting sklearn
          Downloading sklearn-0.0.tar.gz (1.1 kB)
        Collecting scikit-learn
          Downloading scikit learn-0.24.2-cp38-cp38-manylinux2010 x86 64.whl (24.9 M
        B)
                                      24.9 MB 9.6 MB/s eta 0:00:011
        Requirement already satisfied: numpy>=1.13.3 in /opt/conda/lib/python3.8/site
        -packages (from scikit-learn->sklearn) (1.20.2)
        Requirement already satisfied: scipy>=0.19.1 in /opt/conda/lib/python3.8/site
        -packages (from scikit-learn->sklearn) (1.6.3)
        Collecting threadpoolctl>=2.0.0
          Downloading threadpoolctl-2.1.0-py3-none-any.whl (12 kB)
        Collecting joblib>=0.11
          Downloading joblib-1.0.1-py3-none-any.whl (303 kB)
                                            | 303 kB 8.4 MB/s eta 0:00:01
        Building wheels for collected packages: sklearn
```

Building wheel for sklearn (setup.py) ... done

Created wheel for sklearn: filename=sklearn-0.0-py2.py3-none-any.whl size=1 316 sha256=d161716cd4bf6498f84b3b0718c5cae520786f78ff10bbcdbfa26d46accc5b7e

Stored in directory: /home/jovyan/.cache/pip/wheels/22/0b/40/fd3f795caaa1fb 4c6cb738bc1f56100be1e57da95849bfc897

Successfully built sklearn

Installing collected packages: threadpoolctl, joblib, scikit-learn, sklearn Successfully installed joblib-1.0.1 scikit-learn-0.24.2 sklearn-0.0 threadpoo lct1-2.1.0

In [ ]: import numpy as np import pandas as pd

from sklearn.naive bayes import GaussianNB

from sklearn.model\_selection import KFold, cross\_validate, cross\_val\_predict, val from sklearn.metrics import confusion matrix, make scorer

In [259]: #Load and print data

data = pd.read\_csv('./data/diabetes.csv')

data.head()

Out[259]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	ВМІ	DiabetesPedigreeFunction	1
0	6	148	72	35	0	33.6	0.627	
1	1	85	66	29	0	26.6	0.351	
2	8	183	64	0	0	23.3	0.672	
3	1	89	66	23	94	28.1	0.167	
4	0	137	40	35	168	43.1	2.288	
4								<b>•</b>

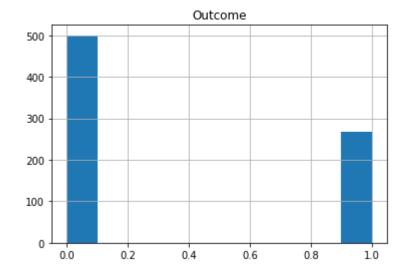
In [260]: data.describe()

Out[260]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	ВМІ	DiabetesP€
count	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	
mean	3.845052	120.894531	69.105469	20.536458	79.799479	31.992578	
std	3.369578	31.972618	19.355807	15.952218	115.244002	7.884160	
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
25%	1.000000	99.000000	62.000000	0.000000	0.000000	27.300000	
50%	3.000000	117.000000	72.000000	23.000000	30.500000	32.000000	
75%	6.000000	140.250000	80.000000	32.000000	127.250000	36.600000	
max	17.000000	199.000000	122.000000	99.000000	846.000000	67.100000	
4							<b>&gt;</b>

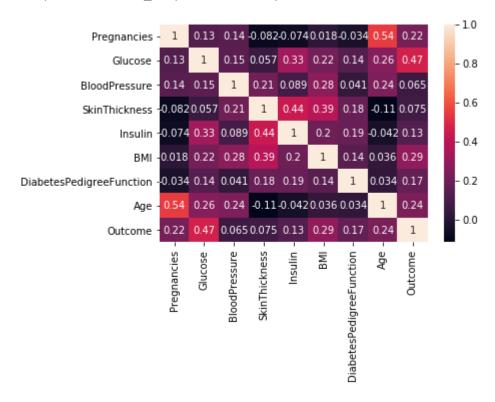
```
In [261]: for column in list(data):
              print(f'Column name: {column}, no of null : {data[column].size - data[column]
                        Pregnancies , no of null : 0
          Column name:
                        Glucose, no of null: 0
          Column name:
          Column name:
                        BloodPressure , no of null : 0
          Column name:
                        SkinThickness , no of null : 0
          Column name:
                        Insulin , no of null : 0
                        BMI, no of null: 0
          Column name:
                        DiabetesPedigreeFunction , no of null : 0
          Column name:
                        Age , no of null : 0
          Column name:
                        Outcome , no of null : 0
          Column name:
```

```
In [262]: # Diabetics.csv has 2 times non diabetic to 1 time diabetic data
data.hist(column='Outcome'))
```



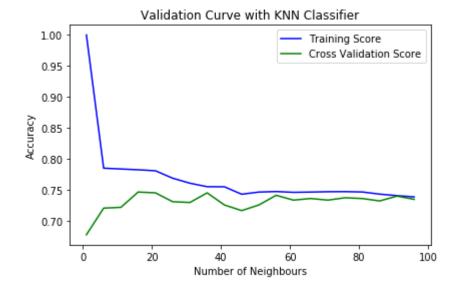
```
In [263]: sns.heatmap(data.corr(),annot=True)
# Corelation b/w fields
```

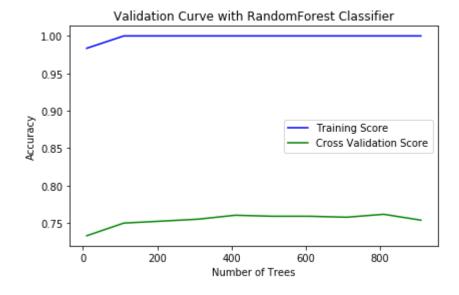
Out[263]: <matplotlib.axes.\_subplots.AxesSubplot at 0x7f306c513cc0>



```
In [264]: # features on the 'x' axis
X = data.drop("Outcome",axis = 1)
# Label in 'y' axis
y = data.Outcome
```

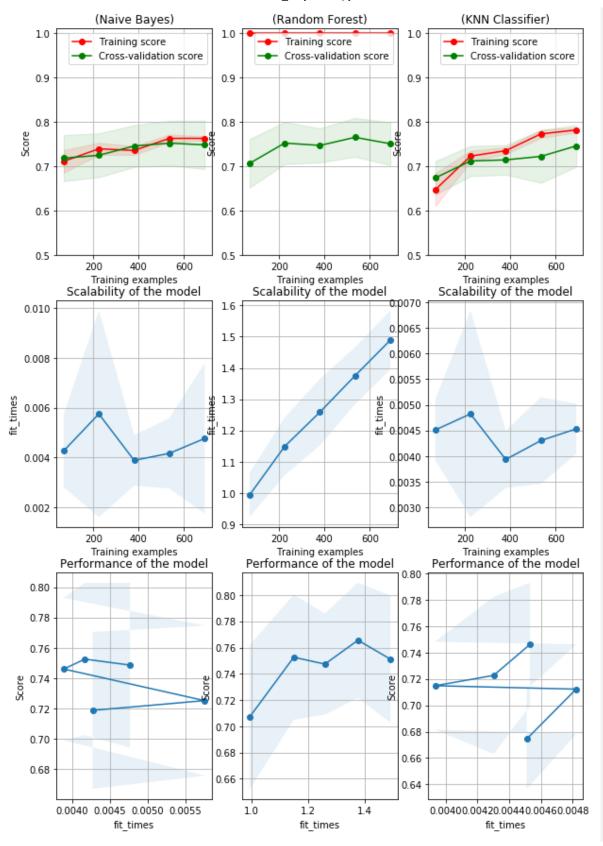
```
In [265]: X.head()
Out[265]:
                                                                      BMI DiabetesPedigreeFunction A
               Pregnancies Glucose
                                   BloodPressure
                                                 SkinThickness Insulin
            0
                                                                      33.6
                        6
                               148
                                              72
                                                           35
                                                                    0
                                                                                             0.627
                        1
                                85
                                              66
                                                           29
                                                                      26.6
                                                                                             0.351
            1
                        8
                               183
                                              64
                                                            0
                                                                     23.3
                                                                                             0.672
            2
                                                                      28.1
            3
                        1
                                89
                                                           23
                                                                                             0.167
                                              66
                                                                   94
                                                                  168 43.1
                                                                                             2.288
                        0
                               137
                                              40
                                                           35
In [266]: y.head()
Out[266]: 0
                1
                0
           1
           2
                1
           3
                0
           4
                1
           Name: Outcome, dtype: int64
In [267]: cv = KFold(n splits=10, random state=10, shuffle=True)
In [268]: def plot results(train score, test score, title, xlabel):
               #standard deviation and mean calculated for testing and training scores
               mean train score = np.mean(train score, axis = 1)
               std train score = np.std(train score, axis = 1)
               mean test score = np.mean(test score, axis = 1)
               std test score = np.std(test score, axis = 1)
               # Creating the Plot for above
               plt.plot(parameter_range, mean_train_score, label = "Training Score", color = "Training Score", color = "Training Score")
               plt.plot(parameter_range, mean_test_score, label = "Cross Validation Score",
               # values considered for algo comparison
               best_neighbor = parameter_range[np.argmax(mean_test_score)]
               # Creating the plot
               plt.title(title)
               plt.xlabel(xlabel)
               plt.ylabel("Accuracy")
               plt.tight_layout()
               plt.legend(loc = 'best')
               plt.show()
```





```
In [271]: import numpy as np
          import matplotlib.pyplot as plt
          from sklearn.model selection import learning curve
          from sklearn.model selection import ShuffleSplit
          def plot_learning_curve(estimator, title, X, y, axes=None, ylim=None, cv=None,
                                   n jobs=None, train sizes=np.linspace(.1, 1.0, 5)):
              if axes is None:
                  _, axes = plt.subplots(1, 3, figsize=(20, 5))
              axes[0].set title(title)
              if ylim is not None:
                   axes[0].set ylim(*ylim)
              axes[0].set xlabel("Training examples")
              axes[0].set_ylabel("Score")
              train_sizes, train_scores, test_scores, fit_times, _ = \
                  learning_curve(estimator, X, y, cv=cv, n_jobs=n_jobs,
                                  train sizes=train sizes,
                                  return times=True)
              train_scores_mean = np.mean(train_scores, axis=1)
              train scores std = np.std(train scores, axis=1)
              test_scores_mean = np.mean(test_scores, axis=1)
              test_scores_std = np.std(test_scores, axis=1)
              fit times mean = np.mean(fit times, axis=1)
              fit times std = np.std(fit times, axis=1)
              # Learning curve plot
              axes[0].grid()
              axes[0].fill_between(train_sizes, train_scores_mean - train_scores_std,
                                    train scores mean + train scores std, alpha=0.1,
                                    color="r")
              axes[0].fill_between(train_sizes, test_scores_mean - test_scores_std,
                                    test_scores_mean + test_scores_std, alpha=0.1,
                                    color="g")
              axes[0].plot(train_sizes, train_scores_mean, 'o-', color="r",
                            label="Training score")
              axes[0].plot(train sizes, test scores mean, 'o-', color="g",
                            label="Cross-validation score")
              axes[0].legend(loc="best")
              axes[1].grid()
              axes[1].plot(train sizes, fit times mean, 'o-')
              axes[1].fill_between(train_sizes, fit_times_mean - fit_times_std,
                                   fit_times_mean + fit_times_std, alpha=0.1)
              axes[1].set xlabel("Training examples")
              axes[1].set ylabel("fit times")
              axes[1].set_title("Scalability of the model")
              # Plot fit_time vs score
              axes[2].grid()
              axes[2].plot(fit_times_mean, test_scores_mean, 'o-')
              axes[2].fill between(fit times mean, test scores mean - test scores std,
                                   test scores mean + test scores std, alpha=0.1)
```

```
axes[2].set_xlabel("fit_times")
    axes[2].set_ylabel("Score")
    axes[2].set_title("Performance of the model")
    return plt
fig, axes = plt.subplots(3, 3, figsize=(10, 15))
# Comparison of Naive Bayes, RF and KNN algo
clf gauss = GaussianNB()
plot_learning_curve(clf_gauss, "(Naive Bayes)", X, y, axes=axes[:, 0], ylim=(0.5]
                    cv=cv, n_jobs=4)
clf_rf = RandomForestClassifier(n_estimators = best_estimator)
plot_learning_curve(clf_rf, "(Random Forest)", X, y, axes=axes[:, 1], ylim=(0.5,
                    cv=cv, n jobs=4)
clf knn = KNeighborsClassifier(n neighbors = best neighbor)
plot_learning_curve(clf_knn, "(KNN Classifier)", X, y, axes=axes[:, 2], ylim=(0.5)
                    cv=cv, n_jobs=4)
plt.show()
# Naive Bayes, RF and KNN have similar performance. Naives Bayes and KNN algorith
```



```
In [272]: def cal tn(Y test, y pred): return confusion matrix(Y test, y pred)[0,0]
          def cal_fp(Y_test, y_pred): return confusion_matrix(Y_test, y_pred)[0,1]
          def cal_fn(Y_test, y_pred): return confusion_matrix(Y_test, y_pred)[1,0]
          def cal tp(Y test, y pred): return confusion matrix(Y test, y pred)[1,1]
          def tpr(Y_test,y_pred):
              tp = cal_tp(Y_test,y_pred)
              fn = cal fn(Y test,y pred)
              return round((tp / (tp + fn)),2)
          def tnr(Y test,y pred):
              tn = cal_tn(Y_test,y_pred)
              fp = cal_fp(Y_test,y_pred)
              return round((tn / (tn + fp)),2)
          def fpr(Y_test,y_pred):
              tn = cal tn(Y test,y pred)
              fp = cal_fp(Y_test,y_pred)
              return round((fp / (tn + fp)),2)
          def fnr(Y_test,y_pred):
              tp = cal_tp(Y_test,y_pred)
              fn = cal_fn(Y_test,y_pred)
              return round((fn / (tp + fn)),2)
          def Recall(Y test,y pred):
              tp = cal_tp(Y_test,y_pred)
              fn = cal fn(Y test,y pred)
              return round((tp / (tp + fn)),2)
          def Precision(Y_test,y_pred):
              tp = cal_tp(Y_test,y_pred)
              fp = cal_fp(Y_test,y_pred)
              return round((tp / (tp + fp)),2)
          def F1Score(Y_test,y_pred):
              tp = cal_tp(Y_test,y_pred)
              fp = cal fp(Y test,y pred)
              fn = cal_fn(Y_test,y_pred)
              return round(((2*tp) / ((2*tp) + fp+fn)),2)
          def Accuracy(Y_test,y_pred):
              tn = cal_tn(Y_test,y_pred)
              tp = cal tp(Y test,y pred)
              fp = cal_fp(Y_test,y_pred)
              fn = cal_fn(Y_test,y_pred)
              return round(((tp + tn) / (tp + fp + fn + tn)),2)
          def Error(Y_test,y_pred):
              tn = cal tn(Y test,y pred)
              tp = cal_tp(Y_test,y_pred)
              fp = cal_fp(Y_test,y_pred)
              fn = cal_fn(Y_test,y_pred)
              return round(((fp + fn) / (tp + fp + fn + tn)),2)
```

```
def BACC(Y_test,y_pred):
    tn = cal_tn(Y_test,y_pred)
    tp = cal_tp(Y_test,y_pred)
    fp = cal_fp(Y_test,y_pred)
    fn = cal fn(Y test,y pred)
    return round(0.5*((tp / (tp + fn))+(tn / (fp + tn))),2)
def TSS(Y_test,y_pred):
    tn = cal_tn(Y_test,y_pred)
    tp = cal_tp(Y_test,y_pred)
    fp = cal_fp(Y_test,y_pred)
    fn = cal_fn(Y_test,y_pred)
    return round((tp / (tp + fn)) - (fp / (fp + tn)), 2)
def HSS(Y_test,y_pred):
    tn = cal_tn(Y_test,y_pred)
    tp = cal_tp(Y_test,y_pred)
    fp = cal_fp(Y_test,y_pred)
    fn = cal_fn(Y_test,y_pred)
    return round((2*((tp * tn)-(fp * fn)))/(((tp + fn)*(fn + tn))+((tp + fp)*(fp
def cal mean(dict score):
    df = pd.DataFrame.from dict(dict score, orient='index')
    df['mean'] = df.mean(axis=1)
    return df
```

In [274]: clf\_gauss\_score = cross\_validate(clf\_gauss,X,y,scoring = scoring,cv=cv)
 df\_gauss = cal\_mean(clf\_gauss\_score)
 df\_gauss.head(20)

Out[274]:

	0	1	2	3	4	5	6	
fit_time	0.011970	0.002966	0.002934	0.00289	0.004081	0.005298	0.003251	0.0028
score_time	0.029084	0.022756	0.023649	0.02103	0.024744	0.023822	0.023445	0.0204
test_tp	12.000000	20.000000	15.000000	14.00000	16.000000	14.000000	16.000000	20.0000
test_tn	43.000000	38.000000	40.000000	48.00000	45.000000	40.000000	38.000000	47.0000
test_fp	8.000000	6.000000	9.000000	9.00000	6.000000	10.000000	10.000000	4.0000
test_fn	14.000000	13.000000	13.000000	6.00000	10.000000	13.000000	13.000000	6.0000
test_tpr	0.460000	0.610000	0.540000	0.70000	0.620000	0.520000	0.550000	0.7700
test_tnr	0.840000	0.860000	0.820000	0.84000	0.880000	0.800000	0.790000	0.9200
test_fpr	0.160000	0.140000	0.180000	0.16000	0.120000	0.200000	0.210000	0.0800
test_fnr	0.540000	0.390000	0.460000	0.30000	0.380000	0.480000	0.450000	0.2300
test_recall	0.460000	0.610000	0.540000	0.70000	0.620000	0.520000	0.550000	0.7700
test_precision	0.600000	0.770000	0.620000	0.61000	0.730000	0.580000	0.620000	0.8300
test_F1Score	0.520000	0.680000	0.580000	0.65000	0.670000	0.550000	0.580000	0.8000
test_Accuracy	0.710000	0.750000	0.710000	0.81000	0.790000	0.700000	0.700000	0.8700
test_Error	0.290000	0.250000	0.290000	0.19000	0.210000	0.300000	0.300000	0.1300
test_BACC	0.650000	0.730000	0.680000	0.77000	0.750000	0.660000	0.670000	0.8500
test_TSS	0.300000	0.470000	0.350000	0.54000	0.500000	0.320000	0.340000	0.6900
test_HSS	0.320000	0.480000	0.360000	0.52000	0.520000	0.330000	0.350000	0.7000

localhost:8888/notebooks/Downloads/CS634Final\_Project.ipynb#

In [275]: clf\_rf\_score = cross\_validate(clf\_rf,X,y,scoring = scoring,cv=cv)
 df\_rf = cal\_mean(clf\_rf\_score)
 df\_rf.head(20)

Out[275]:

	0	1	2	3	4	5	6	
fit_time	1.064124	1.038974	1.030510	1.019342	1.008097	0.996995	1.021667	1.009
score_time	0.106313	0.109850	0.104925	0.102989	0.109176	0.103296	0.101269	0.104
test_tp	13.000000	19.000000	15.000000	13.000000	14.000000	16.000000	14.000000	17.000
test_tn	44.000000	40.000000	44.000000	45.000000	45.000000	43.000000	37.000000	48.000
test_fp	7.000000	4.000000	5.000000	12.000000	6.000000	7.000000	11.000000	3.000
test_fn	13.000000	14.000000	13.000000	7.000000	12.000000	11.000000	15.000000	9.000
test_tpr	0.500000	0.580000	0.540000	0.650000	0.540000	0.590000	0.480000	0.650
test_tnr	0.860000	0.910000	0.900000	0.790000	0.880000	0.860000	0.770000	0.940
test_fpr	0.140000	0.090000	0.100000	0.210000	0.120000	0.140000	0.230000	0.060
test_fnr	0.500000	0.420000	0.460000	0.350000	0.460000	0.410000	0.520000	0.350
test_recall	0.500000	0.580000	0.540000	0.650000	0.540000	0.590000	0.480000	0.650
test_precision	0.650000	0.830000	0.750000	0.520000	0.700000	0.700000	0.560000	0.850
test_F1Score	0.570000	0.680000	0.620000	0.580000	0.610000	0.640000	0.520000	0.740
test_Accuracy	0.740000	0.770000	0.770000	0.750000	0.770000	0.770000	0.660000	0.840
test_Error	0.260000	0.230000	0.230000	0.250000	0.230000	0.230000	0.340000	0.160
test_BACC	0.680000	0.740000	0.720000	0.720000	0.710000	0.730000	0.630000	0.800
test_TSS	0.360000	0.480000	0.430000	0.440000	0.420000	0.450000	0.250000	0.600
test_HSS	0.380000	0.500000	0.460000	0.410000	0.450000	0.470000	0.260000	0.630

```
In [276]: clf_knn_score = cross_validate(clf_knn,X,y,scoring = scoring,cv=cv)
df_knn = cal_mean(clf_knn_score)
df_knn.head(20)
```

## Out[276]:

	0	1	2	3	4	5	6	
fit_time	0.006313	0.00418	0.002788	0.002858	0.003150	0.002965	0.002766	0.0030
score_time	0.033054	0.03295	0.025597	0.025110	0.023521	0.024060	0.023784	0.0255
test_tp	10.000000	13.00000	14.000000	11.000000	15.000000	11.000000	14.000000	13.0000
test_tn	45.000000	38.00000	42.000000	47.000000	47.000000	46.000000	41.000000	50.0000
test_fp	6.000000	6.00000	7.000000	10.000000	4.000000	4.000000	7.000000	1.0000
test_fn	16.000000	20.00000	14.000000	9.000000	11.000000	16.000000	15.000000	13.0000
test_tpr	0.380000	0.39000	0.500000	0.550000	0.580000	0.410000	0.480000	0.5000
test_tnr	0.880000	0.86000	0.860000	0.820000	0.920000	0.920000	0.850000	0.9800
test_fpr	0.120000	0.14000	0.140000	0.180000	0.080000	0.080000	0.150000	0.0200
test_fnr	0.620000	0.61000	0.500000	0.450000	0.420000	0.590000	0.520000	0.5000
test_recall	0.380000	0.39000	0.500000	0.550000	0.580000	0.410000	0.480000	0.5000
test_precision	0.620000	0.68000	0.670000	0.520000	0.790000	0.730000	0.670000	0.9300
test_F1Score	0.480000	0.50000	0.570000	0.540000	0.670000	0.520000	0.560000	0.6500
test_Accuracy	0.710000	0.66000	0.730000	0.750000	0.810000	0.740000	0.710000	0.8200
test_Error	0.290000	0.34000	0.270000	0.250000	0.190000	0.260000	0.290000	0.1800
test_BACC	0.630000	0.63000	0.680000	0.690000	0.750000	0.660000	0.670000	0.7400
test_TSS	0.270000	0.26000	0.360000	0.370000	0.500000	0.330000	0.340000	0.4800
test_HSS	0.290000	0.27000	0.380000	0.370000	0.530000	0.360000	0.360000	0.5400

```
In [277]:
```

## Out[277]:

	Type of classifier	Test Accuracy Mean
0	KNN	0.745
1	RF	0.758
2	Gaussian NB	0.748

```
In [ ]:
```