```
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```

## Group B: Machine Learning ¶

#### Assignment B2

#### Classify the email using the binary classification method.

Email Spam detection has two states: a) Normal State – Not Spam, b) Abnormal State – Spam.

Use K-Nearest Neighbors and Support Vector Machine for classification. Analyze their performance. Dataset link: The emails.csv dataset on the Kaggle https://www.kaggle.com/datasets/balaka18/email-spam-classification-dataset-csv (https://www.kaggle.com/datasets/balaka18/email-spam-classification-dataset-csv)

In [1]:
```python
import numpy as np
import pandas as pd
```

In [2]:
```python
df = pd.read_csv("emails.csv")
```

In [3]:
```python
df.head()
```

Out[3]:

| | Email No. | the | to | ect | and | for | of | a | you | hou | ... | connevey | jay | valued | lay | infrastructure |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | Email 1 | 0 | 0 | 1 | 0 | 0 | 0 | 2 | 0 | 0 | ... | 0 | 0 | 0 | 0 | ( |
| **1** | Email 2 | 8 | 13 | 24 | 6 | 6 | 2 | 102 | 1 | 27 | ... | 0 | 0 | 0 | 0 | ( |
| **2** | Email 3 | 0 | 0 | 1 | 0 | 0 | 0 | 8 | 0 | 0 | ... | 0 | 0 | 0 | 0 | ( |
| **3** | Email 4 | 0 | 5 | 22 | 0 | 5 | 1 | 51 | 2 | 10 | ... | 0 | 0 | 0 | 0 | ( |
| **4** | Email 5 | 7 | 6 | 17 | 1 | 5 | 2 | 57 | 0 | 9 | ... | 0 | 0 | 0 | 0 | ( |

5 rows × 3002 columns

In [4]:
```python
df.columns
```

Out[4]:
```
Index(['Email No.', 'the', 'to', 'ect', 'and', 'for', 'of', 'a', 'you', 'hou',
       ...
       'connevey', 'jay', 'valued', 'lay', 'infrastructure', 'military',
       'allowing', 'ff', 'dry', 'Prediction'],
      dtype='object', length=3002)
```

In [5]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5172 entries, 0 to 5171
Columns: 3002 entries, Email No. to Prediction
dtypes: int64(3001), object(1)
memory usage: 118.5+ MB
```

In [6]:
```
df.shape
```

Out[6]: (5172, 3002)

In [7]:
```
df.duplicated().sum()
```

Out[7]: 0

In [8]:
```
df.describe()
```

Out[8]:

| | the | to | ect | and | for | of | a |
|---|---|---|---|---|---|---|---|
| **count** | 5172.000000 | 5172.000000 | 5172.000000 | 5172.000000 | 5172.000000 | 5172.000000 | 5172.000000 |
| **mean** | 6.640565 | 6.188128 | 5.143852 | 3.075599 | 3.124710 | 2.627030 | 55.517401 |
| **std** | 11.745009 | 9.534576 | 14.101142 | 6.045970 | 4.680522 | 6.229845 | 87.574172 |
| **min** | 0.000000 | 0.000000 | 1.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 |
| **25%** | 0.000000 | 1.000000 | 1.000000 | 0.000000 | 1.000000 | 0.000000 | 12.000000 |
| **50%** | 3.000000 | 3.000000 | 1.000000 | 1.000000 | 2.000000 | 1.000000 | 28.000000 |
| **75%** | 8.000000 | 7.000000 | 4.000000 | 3.000000 | 4.000000 | 2.000000 | 62.250000 |
| **max** | 210.000000 | 132.000000 | 344.000000 | 89.000000 | 47.000000 | 77.000000 | 1898.000000 |

8 rows × 3001 columns

In [9]:
```
# df.corr()
```

In [10]:
```
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score
```

In [11]:
```
df[df.isnull().any(axis=1)]
```

Out[11]:

| Email No. | the | to | ect | and | for | of | a | you | hou | ... | connevey | jay | valued | lay | infrastructure | m |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|

0 rows × 3002 columns

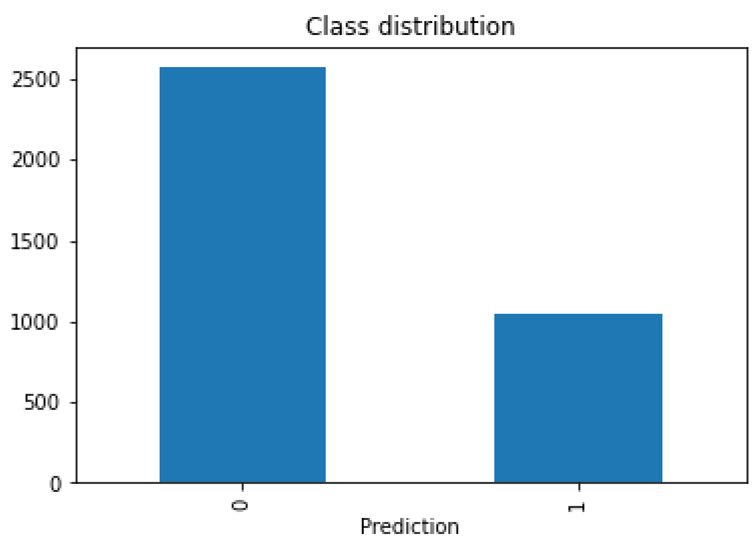
In [12]:
```
df.Prediction.value_counts()
```
Out[12]:
```
0    3672
1    1500
Name: Prediction, dtype: int64
```

In [13]:
```
train,test= train_test_split(df,test_size=0.3,stratify=df.Prediction)
```

In [14]:
```
train.shape
```
Out[14]:
```
(3620, 3002)
```

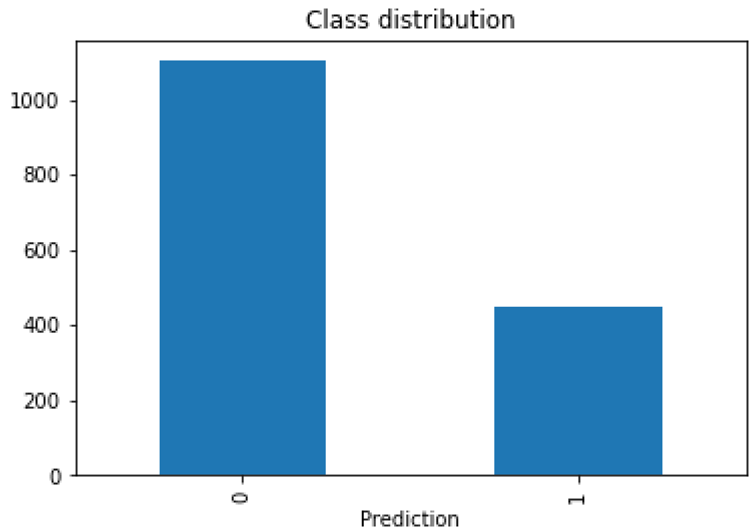
In [15]:
```
test.shape
```
Out[15]:
```
(1552, 3002)
```

In [16]:
```
train.pivot_table(index='Prediction',aggfunc='size').plot(kind='bar',title='Class
```
Out[16]:
```
<AxesSubplot:title={'center':'Class distribution'}, xlabel='Prediction'>
```



In [17]:
```
test.pivot_table(index='Prediction',aggfunc='size').plot(kind='bar',title='Class
```

Out[17]: <AxesSubplot:title={'center':'Class distribution'}, xlabel='Prediction'>




In [18]:
```
X = df.iloc[:,1:3001]
```

In [19]:
```
Y = df.iloc[:,-1].values
Y
```

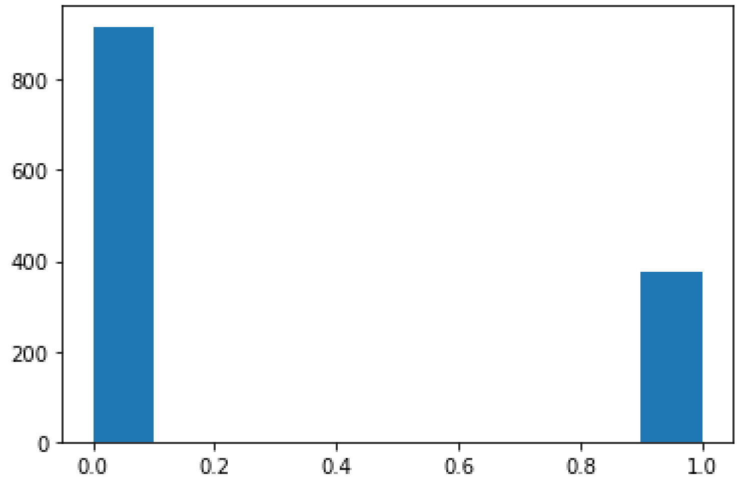
Out[19]: array([0, 0, 0, ..., 1, 1, 0], dtype=int64)

In [20]:
```
train_x,test_x,train_y,test_y = train_test_split(X,Y,test_size = 0.25,stratify =
```

In [21]:
```
plt.hist(test_y)
```

```
<IPython.core.display.Javascript object>
```

Out[21]:
```
(array([918.,   0.,   0.,   0.,   0.,   0.,   0.,   0.,   0., 375.]),
 array([0. , 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1. ]),
 <BarContainer object of 10 artists>)
```




## SVM

In [22]:
```
svc = SVC(C=1.0,kernel='rbf',gamma='auto')
# C here is the regularization parameter. Here, L2 penalty is used(default). It i
# As C increases, model overfits.
# Kernel here is the radial basis function kernel.
# gamma (only used for rbf kernel) : As gamma increases, model overfits.
svc.fit(train_x,train_y)
y_pred = svc.predict(test_x)
print("Accuracy Score for SVC : ", accuracy_score(y_pred,test_y))
```

```
Accuracy Score for SVC :  0.8963650425367363
```

In [23]:
```
acc = accuracy_score(y_pred,test_y)
acc
```

Out[23]:
```
0.8963650425367363
```

In [24]:
```
from sklearn.metrics import precision_score,recall_score,f1_score,fbeta_score,cor
```

In [25]:
```
pre = precision_score(test_y,y_pred)
pre
```

Out[25]: 0.8801261829652997

In [26]:
```
recall = recall_score(test_y,y_pred)
recall
```

Out[26]: 0.744

In [27]:
```
f1 = f1_score(test_y,y_pred)
f1
```

Out[27]: 0.8063583815028901

In [28]:
```
fbeta0_5 = fbeta_score(test_y,y_pred,beta=0.5)
fbeta0_5
```

Out[28]: 0.8490566037735849

In [29]:
```
fbeta2 = fbeta_score(test_y,y_pred,beta=2)
fbeta2
```

Out[29]: 0.7677490368739681

In [30]:
```
result = pd.DataFrame(columns=['Accuracy score','Precision','Recall','F1 Score',
result.loc['SVM'] = [acc,pre,recall,f1,fbeta0_5,fbeta2]
result
```

Out[30]:

| | Accuracy score | Precision | Recall | F1 Score | Fbeta Score(0.5) | Fbeta Score(2) |
|---|---|---|---|---|---|---|
| **SVM** | 0.896365 | 0.880126 | 0.744 | 0.806358 | 0.849057 | 0.767749 |

In [31]:
```
confusion_matrix(test_y,y_pred)
```

Out[31]:
```
array([[880,  38],
       [ 96, 279]], dtype=int64)
```

In [32]:
```
print(classification_report(test_y,y_pred))
```

```
              precision    recall  f1-score   support

           0       0.90      0.96      0.93       918
           1       0.88      0.74      0.81       375

    accuracy                           0.90      1293
   macro avg       0.89      0.85      0.87      1293
weighted avg       0.90      0.90      0.89      1293
```

## SMOTE : a powerful solution for imbalanced data

In [33]:
```
from imblearn.over_sampling import SMOTE
```

In [34]:
```
oversample = SMOTE()
```

In [35]:
```
X_sampled, Y_sampled = oversample.fit_resample(X,Y)
```

In [36]:
```
X_sampled.shape
```

Out[36]:
```
(7344, 3000)
```

In [37]:
```
Y_sampled.shape
```

Out[37]:
```
(7344,)
```

In [38]:
```
X_sampled.head()
```

Out[38]:

| | the | to | ect | and | for | of | a | you | hou | in | ... | enhancements | connevey | jay | valued | lay |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 0 | 0 | 1 | 0 | 0 | 0 | 2 | 0 | 0 | 0 | ... | 0 | 0 | 0 | 0 | 0 |
| **1** | 8 | 13 | 24 | 6 | 6 | 2 | 102 | 1 | 27 | 18 | ... | 0 | 0 | 0 | 0 | 0 |
| **2** | 0 | 0 | 1 | 0 | 0 | 0 | 8 | 0 | 0 | 4 | ... | 0 | 0 | 0 | 0 | 0 |
| **3** | 0 | 5 | 22 | 0 | 5 | 1 | 51 | 2 | 10 | 1 | ... | 0 | 0 | 0 | 0 | 0 |
| **4** | 7 | 6 | 17 | 1 | 5 | 2 | 57 | 0 | 9 | 3 | ... | 0 | 0 | 0 | 0 | 0 |

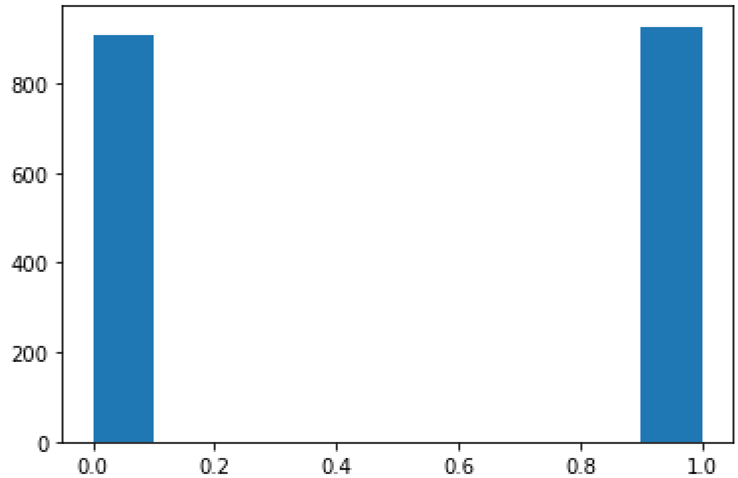
5 rows × 3000 columns

In [39]:
```
train_x1,test_x1,train_y1,test_y1 = train_test_split(X_sampled,Y_sampled,test_siz
```

In [40]:
```
plt.hist(test_y1)
```

<IPython.core.display.Javascript object>

Out[40]:
```
(array([909.,   0.,   0.,   0.,   0.,   0.,   0.,   0.,   0., 927.]),
 array([0. , 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1. ]),
 <BarContainer object of 10 artists>)
```




In [41]:
```
svc = SVC(C=1.0,kernel='rbf',gamma='auto')
# C here is the regularization parameter. Here, L2 penalty is used(default). It i
# As C increases, model overfits.
# Kernel here is the radial basis function kernel.
# gamma (only used for rbf kernel) : As gamma increases, model overfits.
svc.fit(train_x1,train_y1)
y_pred1 = svc.predict(test_x1)
print("Accuracy Score for SVC : ", accuracy_score(y_pred1,test_y1))
```

Accuracy Score for SVC :  0.9449891067538126

In [42]:
```
confusion_matrix(test_y1,y_pred1)
```

Out[42]:
```
array([[842,  67],
       [ 34, 893]], dtype=int64)
```

In [43]:
```
print(classification_report(test_y1,y_pred1))
```

```
              precision    recall  f1-score   support

           0       0.96      0.93      0.94       909
           1       0.93      0.96      0.95       927

    accuracy                           0.94      1836
   macro avg       0.95      0.94      0.94      1836
weighted avg       0.95      0.94      0.94      1836
```

In [44]:
```
acc = accuracy_score(y_pred1,test_y1)
acc
```

Out[44]: 0.9449891067538126

In [45]:
```
pre = precision_score(test_y1,y_pred1)
pre
```

Out[45]: 0.9302083333333333

In [46]:
```
recall = recall_score(test_y1,y_pred1)
recall
```

Out[46]: 0.9633225458468176

In [47]:
```
f1 = f1_score(test_y1,y_pred1)
f1
```

Out[47]: 0.9464758876523581

In [48]:
```
fbeta0_5 = fbeta_score(test_y1,y_pred1,beta=0.5)
fbeta0_5
```

Out[48]: 0.936647786868051

In [49]:
```
fbeta2 = fbeta_score(test_y1,y_pred1,beta=2)
fbeta2
```

Out[49]: 0.9565124250214223

In [50]:
```
result.loc['SVM_SMOTE'] = [acc,pre,recall,f1,fbeta0_5,fbeta2]
result
```

Out[50]:

| | Accuracy score | Precision | Recall | F1 Score | Fbeta Score(0.5) | Fbeta Score(2) |
|---|---|---|---|---|---|---|
| **SVM** | 0.896365 | 0.880126 | 0.744000 | 0.806358 | 0.849057 | 0.767749 |
| **SVM_SMOTE** | 0.944989 | 0.930208 | 0.963323 | 0.946476 | 0.936648 | 0.956512 |

In [51]:
```
from sklearn.neighbors import KNeighborsClassifier
KNN= KNeighborsClassifier(n_neighbors=3)
# Train the model using the training sets
KNN.fit(train_x,train_y)
y_pred = KNN.predict(test_x)
print("Accuracy Score for KNN : ", accuracy_score(y_pred,test_y))
```

```
Accuracy Score for KNN :  0.8476411446249034
```

In [52]:
```
acc = accuracy_score(y_pred,test_y)
acc
```

Out[52]:
```
0.8476411446249034
```

In [53]:
```
pre = precision_score(test_y,y_pred)
pre
```

Out[53]:
```
0.7099056603773585
```

In [54]:
```
recall = recall_score(test_y,y_pred)
recall
```

Out[54]:
```
0.8026666666666666
```

In [55]:
```
f1 = f1_score(test_y,y_pred)
f1
```

Out[55]:
```
0.7534418022528159
```

In [56]:
```
fbeta0_5 = fbeta_score(test_y,y_pred,beta=0.5)
fbeta0_5
```

Out[56]:
```
0.7267020762916465
```

In [57]:
```
fbeta2 = fbeta_score(test_y,y_pred,beta=2)
fbeta2
```

Out[57]:
```
0.7822245322245321
```

In [58]:
```
result.loc['KNN'] = [acc,pre,recall,f1,fbeta0_5,fbeta2]
result
```

Out[58]:

| | Accuracy score | Precision | Recall | F1 Score | Fbeta Score(0.5) | Fbeta Score(2) |
|---|---|---|---|---|---|---|
| **SVM** | 0.896365 | 0.880126 | 0.744000 | 0.806358 | 0.849057 | 0.767749 |
| **SVM_SMOTE** | 0.944989 | 0.930208 | 0.963323 | 0.946476 | 0.936648 | 0.956512 |
| **KNN** | 0.847641 | 0.709906 | 0.802667 | 0.753442 | 0.726702 | 0.782225 |

In [59]:
```
confusion_matrix(test_y,y_pred)
```

Out[59]:
```
array([[795, 123],
       [ 74, 301]], dtype=int64)
```

In [60]:
```
print(classification_report(test_y,y_pred))
```

```
              precision    recall  f1-score   support

           0       0.91      0.87      0.89       918
           1       0.71      0.80      0.75       375

    accuracy                           0.85      1293
   macro avg       0.81      0.83      0.82      1293
weighted avg       0.86      0.85      0.85      1293
```

In [61]:
```
from sklearn.neighbors import KNeighborsClassifier
KNN= KNeighborsClassifier(n_neighbors=3)
# Train the model using the training sets
KNN.fit(train_x1,train_y1)
y_pred1 = KNN.predict(test_x1)
print("Accuracy Score for KNN : ", accuracy_score(y_pred1,test_y1))
acc = accuracy_score(y_pred1,test_y1)
pre = precision_score(test_y1,y_pred1)
recall = recall_score(test_y1,y_pred1)
f1 = f1_score(test_y1,y_pred1)
fbeta0_5 = fbeta_score(test_y1,y_pred1,beta=0.5)
fbeta2 = fbeta_score(test_y1,y_pred1,beta=2)
result.loc['KNN_SMOTE'] = [acc,pre,recall,f1,fbeta0_5,fbeta2]
result
```

```
Accuracy Score for KNN :  0.8371459694989106
```

Out[61]:

| | Accuracy score | Precision | Recall | F1 Score | Fbeta Score(0.5) | Fbeta Score(2) |
|---|---|---|---|---|---|---|
| **SVM** | 0.896365 | 0.880126 | 0.744000 | 0.806358 | 0.849057 | 0.767749 |
| **SVM_SMOTE** | 0.944989 | 0.930208 | 0.963323 | 0.946476 | 0.936648 | 0.956512 |
| **KNN** | 0.847641 | 0.709906 | 0.802667 | 0.753442 | 0.726702 | 0.782225 |
| **KNN_SMOTE** | 0.837146 | 0.756956 | 0.997843 | 0.860866 | 0.795357 | 0.938134 |

In [62]:
```
confusion_matrix(test_y1,y_pred1)
```

Out[62]:
```
array([[612, 297],
       [  2, 925]], dtype=int64)
```

In [63]:
```
print(classification_report(test_y1,y_pred1))
```

```
              precision    recall  f1-score   support

           0       1.00      0.67      0.80       909
           1       0.76      1.00      0.86       927

    accuracy                           0.84      1836
   macro avg       0.88      0.84      0.83      1836
weighted avg       0.88      0.84      0.83      1836
```

## Using GridSearchCV

In [64]:
```
from sklearn.model_selection import GridSearchCV, RandomizedSearchCV
```

In [65]:
```
knn_model=KNeighborsClassifier()
```

In [66]:
```
hyperparamters = {'n_neighbors':np.arange(2,10),
                 'p':[1,2]}
rscv_model= RandomizedSearchCV(knn_model,hyperparamters,cv=5)
rscv_model.fit(train_x1,train_y1)
```

Out[66]:
```
RandomizedSearchCV(cv=5, estimator=KNeighborsClassifier(),
                   param_distributions={'n_neighbors': array([2, 3, 4, 5, 6, 7,
8, 9]),
                                        'p': [1, 2]})
```

**In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.**
**On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.**

In [67]:
```
rscv_model.best_params_
```

Out[67]:
```
{'p': 2, 'n_neighbors': 2}
```

In [70]:
```
knn_model= KNeighborsClassifier(n_neighbors=2,p=2)
# Train the model using the training sets
knn_model.fit(train_x,train_y)
y_pred = knn_model.predict(test_x)
print("Accuracy Score for KNN : ", accuracy_score(y_pred,test_y))
acc = accuracy_score(y_pred,test_y)
pre = precision_score(test_y,y_pred)
recall = recall_score(test_y,y_pred)
f1 = f1_score(test_y,y_pred)
fbeta0_5 = fbeta_score(test_y,y_pred,beta=0.5)
fbeta2 = fbeta_score(test_y,y_pred,beta=2)
result.loc['KNN_SMOTE_Hyperparameter_Tuning'] = [acc,pre,recall,f1,fbeta0_5,fbeta
result
```

```
Accuracy Score for KNN :  0.8592420726991493
```

Out[70]:

| | Accuracy score | Precision | Recall | F1 Score | Fbeta Score(0.5) | Fbeta Score(2) |
|---|---|---|---|---|---|---|
| **SVM** | 0.896365 | 0.880126 | 0.744000 | 0.806358 | 0.849057 | 0.767749 |
| **SVM_SMOTE** | 0.944989 | 0.930208 | 0.963323 | 0.946476 | 0.936648 | 0.956512 |
| **KNN** | 0.847641 | 0.709906 | 0.802667 | 0.753442 | 0.726702 | 0.782225 |
| **KNN_SMOTE** | 0.837146 | 0.756956 | 0.997843 | 0.860866 | 0.795357 | 0.938134 |
| **KNN_SMOTE_Hyperparameter_Tuning** | 0.859242 | 0.793313 | 0.696000 | 0.741477 | 0.771733 | 0.713505 |

In [71]:
```
knn_model= KNeighborsClassifier(n_neighbors=2,p=2)
# Train the model using the training sets
knn_model.fit(train_x1,train_y1)
y_pred1 = knn_model.predict(test_x1)
print("Accuracy Score for KNN : ", accuracy_score(y_pred1,test_y1))
acc = accuracy_score(y_pred1,test_y1)
pre = precision_score(test_y1,y_pred1)
recall = recall_score(test_y1,y_pred1)
f1 = f1_score(test_y1,y_pred1)
fbeta0_5 = fbeta_score(test_y1,y_pred1,beta=0.5)
fbeta2 = fbeta_score(test_y1,y_pred1,beta=2)
result.loc['KNN_SMOTE_Hyperparameter_Tuning1'] = [acc,pre,recall,f1,fbeta0_5,fbet
result
```

```
Accuracy Score for KNN :  0.8932461873638344
```

Out[71]:

| | Accuracy score | Precision | Recall | F1 Score | Fbeta Score(0.5) | Fbet Score(2 |
|---|---|---|---|---|---|---|
| **SVM** | 0.896365 | 0.880126 | 0.744000 | 0.806358 | 0.849057 | 0.76774 |
| **SVM_SMOTE** | 0.944989 | 0.930208 | 0.963323 | 0.946476 | 0.936648 | 0.95651 |
| **KNN** | 0.847641 | 0.709906 | 0.802667 | 0.753442 | 0.726702 | 0.78222 |
| **KNN_SMOTE** | 0.837146 | 0.756956 | 0.997843 | 0.860866 | 0.795357 | 0.93813 |
| **KNN_SMOTE_Hyperparameter_Tuning** | 0.859242 | 0.793313 | 0.696000 | 0.741477 | 0.771733 | 0.71350 |
| **KNN_SMOTE_Hyperparameter_Tuning1** | 0.893246 | 0.829576 | 0.992449 | 0.903733 | 0.857729 | 0.95495 |

In [ ]: