Experiment 2:

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: https://www.kaggle.com/datasets/balaka18/email-spam-classification-dataset-csv (https://www.kaggle.com/datasets/balaka18/email-spam-classification-dataset-csv (https://www.kaggle.com/datasets/balaka18/email-spam-classification-dataset-csv (https://www.kaggle.com/datasets/balaka18/email-spam-classification-dataset-csv (https://www.kaggle.com/datasets/balaka18/email-spam-classification-dataset-csv (https://www.kaggle.com/datasets/balaka18/email-spam-classification-dataset-csv (https://www.kaggle.com/dataset-csv (https://www.kaggle.com/dataset-csv (<a href="https:

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In [1]:
         import pandas as pd
         import numpy as np
         import seaborn as sns
         import matplotlib.pyplot as plt
         %matplotlib inline
         import warnings
         warnings.filterwarnings('ignore')
         from sklearn.model_selection import train_test_split
         from sklearn.svm import SVC
         from sklearn import metrics
In [2]: df=pd.read csv('emails.csv')
In [3]:
        df.head()
Out[3]:
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                       to ect and for of
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              No.
             Email
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             Email
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                    8
                      13
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             Email
                                        2
                                            57
                                                  0
                                                      9
                                                                   0
                                                                               0
                                                                                   0
                        6
                           17
                                     5
                                                                       0
         5 rows × 3002 columns
        df.columns
In [4]:
Out[4]: Index(['Email No.', 'the', 'to', 'ect', 'and', 'for', 'of', 'a', 'you', 'h
         ou',
```

'allowing', 'ff', 'dry', 'Prediction'],

dtype='object', length=3002)

'jay', 'valued', 'lay', 'infrastructure', 'military',

```
In [5]: df.isnull().sum()
Out[5]: Email No.
         the
                        0
         to
                        0
                       0
         ect
         and
         military
                       0
         allowing
                       0
         ff
                       0
         dry
                        0
         Prediction
                       0
         Length: 3002, dtype: int64
 In [6]: | df.dropna(inplace = True)
 In [7]: | df.drop(['Email No.'],axis=1,inplace=True)
         X = df.drop(['Prediction'],axis = 1)
         y = df['Prediction']
 In [8]: | from sklearn.preprocessing import scale
         X = scale(X)
         # split into train and test
         X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.3,
         KNN Classifier
 In [9]: | from sklearn.neighbors import KNeighborsClassifier
         knn = KNeighborsClassifier(n_neighbors=7)
         knn.fit(X_train, y_train)
         y_pred = knn.predict(X_test)
In [10]: |print("Prediction",y_pred)
         Prediction [0 0 1 ... 1 1 1]
In [11]: print("KNN accuracy = ",metrics.accuracy_score(y_test,y_pred))
         KNN accuracy = 0.8009020618556701
In [12]: print("Confusion matrix", metrics.confusion_matrix(y_test,y_pred))
         Confusion matrix [[804 293]
          [ 16 439]]
```

SVM Classifier