Assignment-3_Apply-KNN

February 27, 2019

1 Assignment-3: Apply K-NN on Amazon Fine Food Reviews DataSet

2 1.0 Introduction

(i).The k-nearest neighbors algorithm (k-NN) is a non-parametric method used for classification and regression predictive problem.

(ii).It is more widely used in classification problems in the industry.

3 2.0 Objective

To Predict the Polarity of Amazon Fine Food Review Using K-Nearst Neighbour Algorithm.

4 3.0 Importing All Required Library

```
In [1]: %matplotlib inline
        import sqlite3
        import pandas as pd
        import numpy as np
        import nltk
        import string
        import matplotlib.pyplot as plt
        import seaborn as sns

        from sklearn.neighbors import KNeighborsClassifier
        from sklearn.model_selection import GridSearchCV
        from sklearn.feature_extraction.text import CountVectorizer
        from sklearn.metrics import accuracy_score
        from sklearn.metrics import classification_report
        from sklearn.feature_extraction.text import TfidfTransformer
        from sklearn.feature_extraction.text import TfidfVectorizer

        from sklearn.metrics import confusion_matrix
        from sklearn import metrics
        from sklearn.metrics import roc_curve, auc
        from sklearn.model_selection import cross_val_score
```

```
from gensim.models import Word2Vec
from gensim.models import KeyedVectors
import pickle

from tqdm import tqdm
import os
import warnings
warnings.filterwarnings("ignore")
```

```
C:\Users\User\Anaconda3\lib\site-packages\gensim\utils.py:1197: UserWarning: detected Windows;
  warnings.warn("detected Windows; aliasing chunkize to chunkize_serial")
```

5 4.0 Importing Amazon Fine Food Review Dataset

```
In [2]: if os.path.isfile("final.sqlite"):
            conn=sqlite3.connect("final.sqlite")
            Data=pd.read_sql_query("select * from Reviews where Score!=3",conn)
            conn.close()
        else :
            print("Error Importing the file")
```

```
In [3]: # Printing some data of DataFrame

        Data.head(2)
```

```
Out[3]:     index      Id   ProductId          UserId      ProfileName  \
        0  138706  150524  0006641040   ACITT7DI6IDDL  shari zychinski
        1  138688  150506  0006641040  A2IW4PEEKO2R0U            Tracy

           HelpfulnessNumerator  HelpfulnessDenominator  Score        Time  \
        0                     0                       0      1   939340800
        1                     1                       1      1  1194739200

                                             Summary  \
        0                     EVERY book is educational
        1  Love the book, miss the hard cover version

                                                        Text  \
        0  this witty little book makes my son laugh at l...
        1  I grew up reading these Sendak books, and watc...

                                                 CleanedText
        0  witti littl book make son laugh loud recit car...
        1  grew read sendak book watch realli rosi movi i...
```

6 5.0 Information About DataSet

```
In [4]: print("\nNumber of Reviews: ",Data["Text"].count())
        print("\nNumber of Users: ",len(Data["UserId"].unique())) # Unique returns 1-D array o
        print("\nNumber of Products: ",len(Data["ProductId"].unique()))
        print("\nShape of Data: ", Data.shape)
        print("\nColumn Name of DataSet : ",Data.columns)
        print("\n\nNumber of Attributes/Columns in data: 12")
        print("\nNumber of Positive Reviews : ", Data['Score'].value_counts()[1])
        print("\nNumber of Negative Reviews : ", Data['Score'].value_counts()[0])
```

```
Number of Reviews:  364171

Number of Users:  243414

Number of Products:  65442

Shape of Data:  (364171, 12)

Column Name of DataSet :  Index(['index', 'Id', 'ProductId', 'UserId', 'ProfileName',
       'HelpfulnessNumerator', 'HelpfulnessDenominator', 'Score', 'Time',
       'Summary', 'Text', 'CleanedText'],
      dtype='object')


Number of Attributes/Columns in data: 12

Number of Positive Reviews :  307061

Number of Negative Reviews :  57110
```

```
In [5]: print("\nNumber of Reviews: ",Data["Text"].count())
```

```
Number of Reviews:  364171
```

6.0.1 5.1 Attribute Information About DataSet

1.Id - A unique value starts from 1
2.ProductId - A unique identifier for the product
3.UserId - A unqiue identifier for the user
4.ProfileName - Name of user profile
5.HelpfulnessNumerator - Number of users who found the review helpful
6.HelpfulnessDenominator - Number of users who indicated whether they found the review helpful or not
7.Score - Rating 0 or 1

8.Time - Timestamp for the review
9.Summary - Brief summary of the review
10.Text - Text of the review
11.Cleaned Text - Text that only alphabets

6.1 6.0 Due to Limited Hardware Resource we will limit our analysis on 20000 data points only.

```
In [6]: # To randomly sample 10k points from both class

        data_pos = Data[Data["Score"] == 1].sample(n = 10000)
        data_neg = Data[Data["Score"] == 0].sample(n = 10000)
        final_20k = pd.concat([data_pos, data_neg])
        final_20k.shape
```

```
Out[6]: (20000, 12)
```

```
In [7]: Y = final_20k['Score'].values
        X = final_20k['CleanedText'].values
```

6.1.1 7.0 Splitting DataSet into Train and Test Data

```
In [8]: from sklearn.model_selection import train_test_split
        # X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.33, shuffle=Fl
        X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.33) # this is ra

        print("Shape of Train and Test Dataset")
        print(X_train.shape, y_train.shape)
        print(X_test.shape, y_test.shape)
```

```
Shape of Train and Test Dataset
(13400,) (13400,)
(6600,) (6600,)
```

7 8.0 Defining Some Function

7.0.1 8.1 Train Data Confusion Matrix Plot

```
In [9]: def trainconfusionmatrix(knn,X_train,y_train):
            print("Confusion Matrix for Train set")
            cm=confusion_matrix(y_train, knn.predict(X_train))
            class_label = ["negative", "positive"]
            df_cm = pd.DataFrame(cm, index = class_label, columns = class_label)
            sns.heatmap(df_cm, annot = True, fmt = "d")
            plt.title("Train Confusiion Matrix")
            plt.xlabel("Predicted Label")
            plt.ylabel("True Label")
            plt.show()
```

7.0.2 8.2 Test Data Confusion Matrix Plot

```
In [10]: def testconfusionmatrix(knn,X_test,y_test):
             print("Confusion Matrix for Test set")
             cm=confusion_matrix(y_test, knn.predict(X_test))
             class_label = ["negative", "positive"]
             df_cm = pd.DataFrame(cm, index = class_label, columns = class_label)
             sns.heatmap(df_cm, annot = True, fmt = "d")
             plt.title("Test Confusiion Matrix")
             plt.xlabel("Predicted Label")
             plt.ylabel("True Label")
             plt.show()
```

7.0.3 8.3 ROC-AUC Curve Plot

```
In [11]: def plot_auc_roc(knn,X_train,X_test,y_train,y_test):
             train_fpr, train_tpr, thresholds = roc_curve(y_train, neigh.predict_proba(X_train
             test_fpr, test_tpr, thresholds = roc_curve(y_test, neigh.predict_proba(X_test)[:,

             plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, train_tpr))
             plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_tpr)))
             plt.legend()
             plt.xlabel("K: hyperparameter")
             plt.ylabel("AUC")
             plt.title("ROC CURVE PLOTS")
             plt.show()
```

7.0.4 8.4 Error Plot

```
In [12]: def error_plot(neighbours,mse):
             plt.title('Error Plot')
             plt.xlabel('K')
             plt.ylabel('misscalssifiaction error')
             plt.plot(neighbours,mse)
```

7.0.5 8.5 Cross Validation Using Kd Tree Algorithm

```
In [13]: def knn_cv_kd(X_train,y_train,neighbours):

             cv_scores=[]

             for k in neighbours:
                 knn = KNeighborsClassifier(n_neighbors=k,algorithm='kd_tree')
                 scores = cross_val_score(knn, X_train, y_train, cv=10, scoring='accuracy') #
                 cv_scores.append(scores.mean())

             mse = [1-x for x in cv_scores] # calculating misscalssification_error = 1 - accur

             best_k = neighbours[mse.index(min(mse))] #returns k corresponding to minimum erro
```

```
            return mse,best_k
```

7.0.6 8.6 Cross Validation Using Brute Algorithm

```
In [14]: def knn_cv_brute(X_train,y_train,neighbours):

             cv_scores=[]

             for k in neighbours:
                 knn = KNeighborsClassifier(n_neighbors=k,algorithm='brute')
                 scores = cross_val_score(knn, X_train, y_train, cv=10, scoring='accuracy') # 
                 cv_scores.append(scores.mean())

             mse = [1-x for x in cv_scores] # calculating misscalssification_error = 1 - accura

             best_k = neighbours[mse.index(min(mse))] #returns k corresponding to minimum erro

             return mse,best_k
```

7.0.7 8.7 Accuracy

```
In [15]: def accuracy(model,X_train,Y_train,X_test,Y_test):
             prediction=model.predict(X_test)

             training_accuracy=model.score(X_train,Y_train)  # accuracy_score(y_train ,neigh.p
             training_error=1-training_accuracy

             test_accuracy=accuracy_score(Y_test,prediction)
             test_error=1-test_accuracy
             return training_accuracy,training_error,test_accuracy,test_error
```

8 9.0 Bags of Words

```
In [16]: vectorizer = CountVectorizer()
         vectorizer.fit(X_train) # fit has to happen only on train data

         # we use the fitted CountVectorizer to convert the text to vector
         X_train_bow = vectorizer.transform(X_train)
         X_test_bow = vectorizer.transform(X_test)

         print("Shape of Train , Test and Cross Validation Data After vectorizations")
         print(X_train_bow.shape, y_train.shape)
         print(X_test_bow.shape, y_test.shape)
```

```
Shape of Train , Test and Cross Validation Data After vectorizations
(13400, 15042) (13400,)
```

```
(6600, 15042) (6600,)
```

```
In [17]: type(X_train_bow)
```

```
Out[17]: scipy.sparse.csr.csr_matrix
```

8.0.1 9.1 Brute Force Algorithm

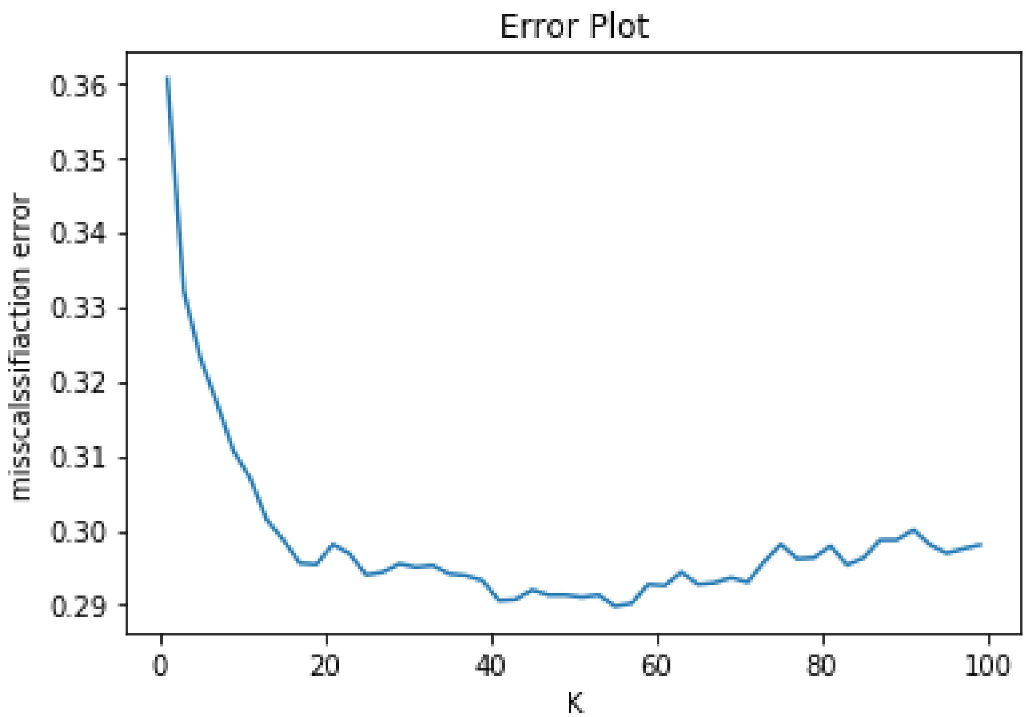
9.1.1 Finding Optimal Value of Hyperparameter(k)

```
In [18]: import numpy as np

         neighbours=np.arange(1,100,2)
         mse,best_k = knn_cv_brute(X_train_bow,y_train,neighbours)
```

```
In [19]: error_plot(neighbours,mse)
         print("Best value of K found for Brute Force Algorithm Implementaion is : ",best_k)
```

```
Best value of K found for Brute Force Algorithm Implementaion is :  55
```



9.1.2 Training the model

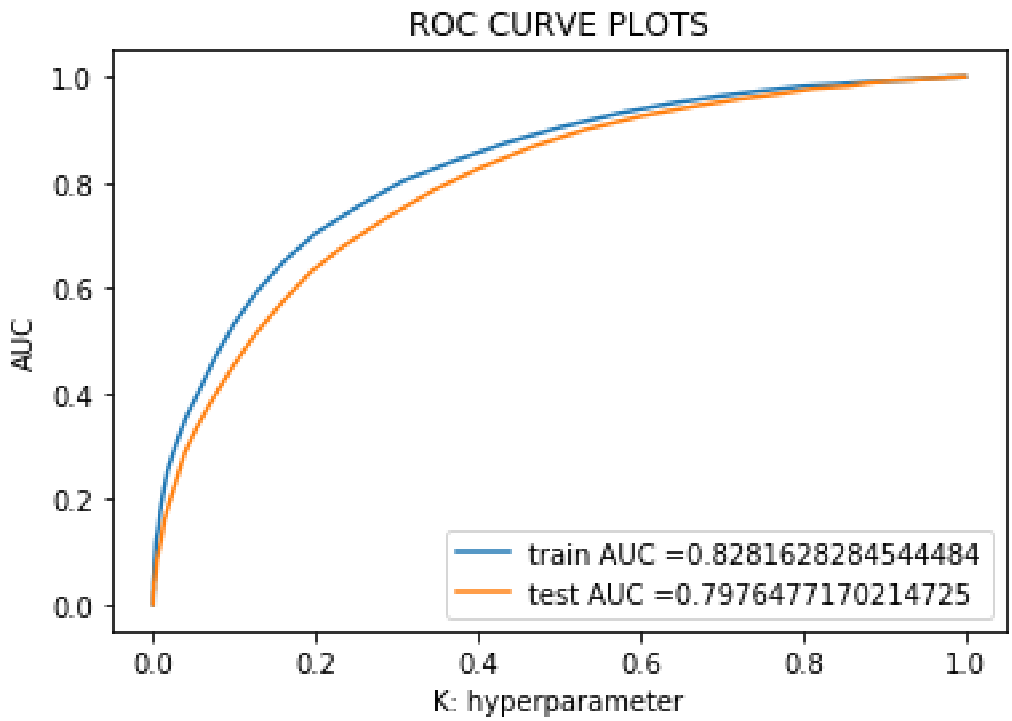
```
In [20]: neigh = KNeighborsClassifier(n_neighbors = best_k,algorithm='brute')
         neigh.fit(X_train_bow, y_train)
```

```
Out[20]: KNeighborsClassifier(algorithm='brute', leaf_size=30, metric='minkowski',
                    metric_params=None, n_jobs=None, n_neighbors=55, p=2,
                    weights='uniform')
```

9.1.3 Evaluting the performance of model

(A). Roc-Auc Plot

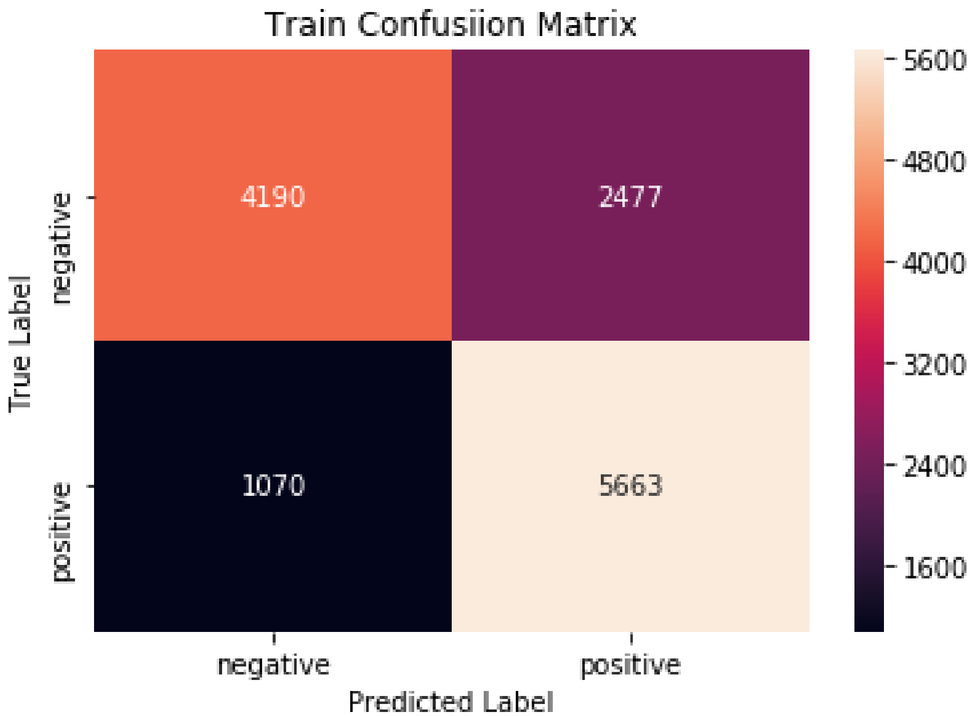
```
In [21]: plot_auc_roc(neigh,X_train_bow,X_test_bow,y_train,y_test)
```



(B). Confusion Matrix Plot on Train Data

```
In [22]: trainconfusionmatrix(neigh,X_train_bow,y_train)
```

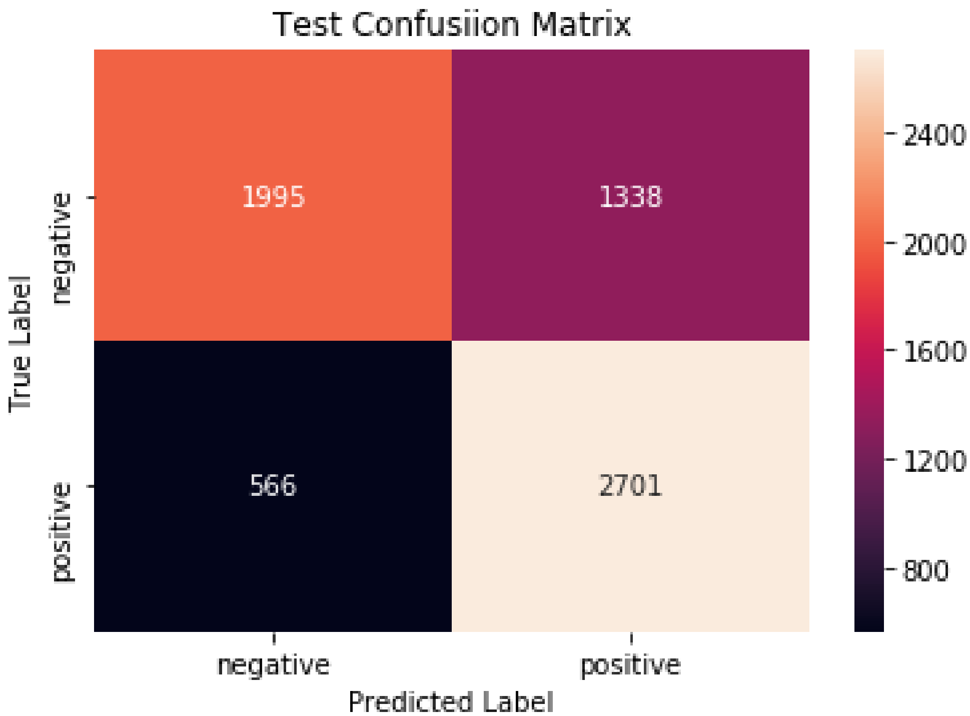
```
Confusion Matrix for Train set
```



(C). Confusion Matrix on Test Data

```
In [23]: testconfusionmatrix(neigh,X_test_bow,y_test)
```

```
Confusion Matrix for Test set
```



(D). Accuracy and Error

```
In [24]: training_accuracy,training_error,test_accuracy,test_error = accuracy(neigh,X_train_bow
         print("Training Accuracy in %: ", round(training_accuracy,2)*100)
         print("\nTrain Error in %: ", round(training_error,2)*100)
         print("\nTest Accuracy in %: ", round(test_accuracy,2)*100)
         print("\nTest Error in % : ", round(test_error,2)*100)
```

```
Training Accuracy in %:  74.0

Train Error in %:  26.0

Test Accuracy in %:  71.0

Test Error in % :  28.999999999999996
```

(E). Classification Report

```
In [25]: print("Classification Report: \n")
         prediction=neigh.predict(X_test_bow)
         print(classification_report(y_test, prediction))
```

```
Classification Report:

              precision    recall  f1-score   support

           0       0.78      0.60      0.68      3333
           1       0.67      0.83      0.74      3267

   micro avg       0.71      0.71      0.71      6600
   macro avg       0.72      0.71      0.71      6600
weighted avg       0.72      0.71      0.71      6600
```

8.0.2 9.2 KD-Tree Algorithm

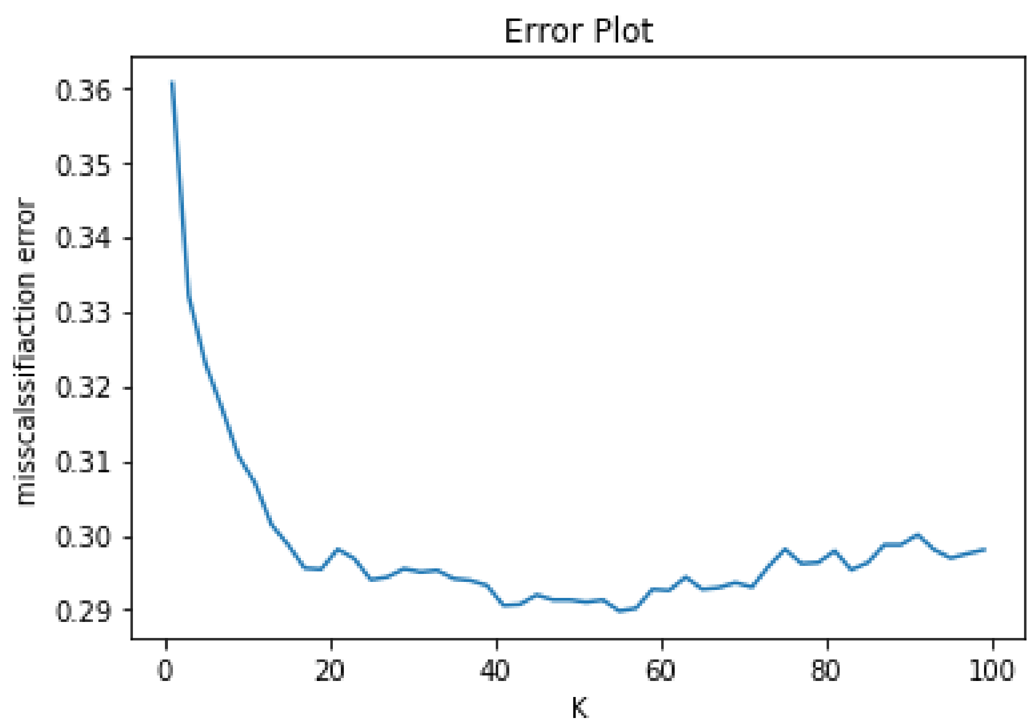
9.2.1 Finding Optimal Value of Hyperparameter(k)

In [26]:
```
import numpy as np

neighbours=np.arange(1,100,2)
mse,best_k = knn_cv_kd(X_train_bow,y_train,neighbours)
```

In [27]:
```
error_plot(neighbours,mse)
print("Best value of K found for KD Tree Algorithm Implementaion is : ",best_k)
```

```
Best value of K found for KD Tree Algorithm Implementaion is :  55
```



9.2.2 Training the model

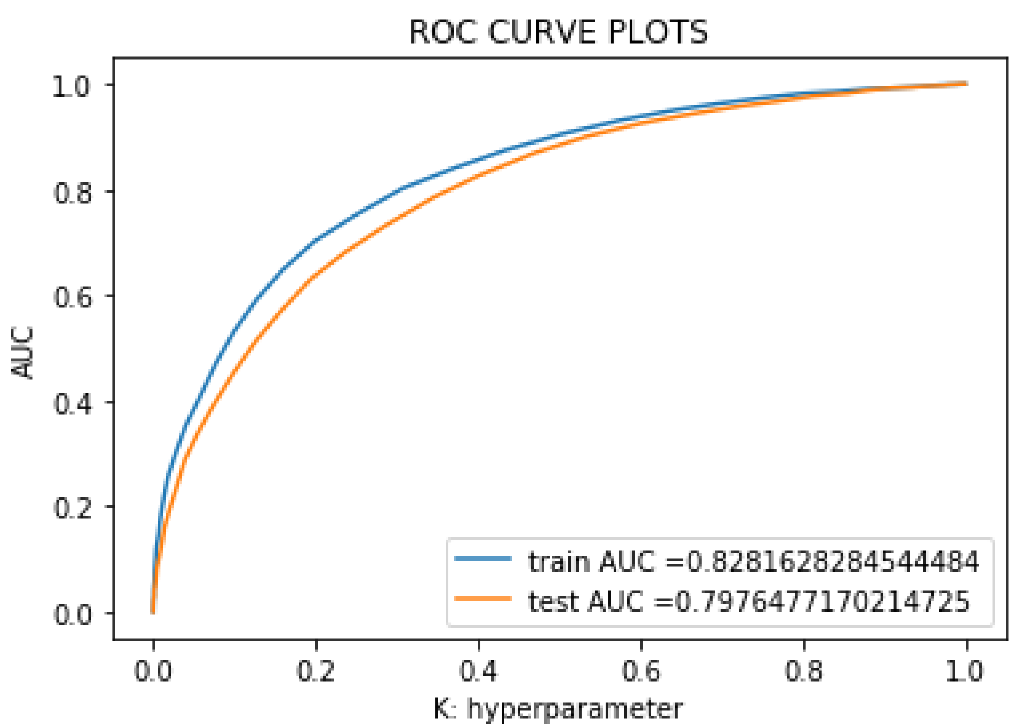
```
In [28]: neigh = KNeighborsClassifier(n_neighbors = best_k,algorithm='kd_tree')
         neigh.fit(X_train_bow, y_train)
```

```
Out[28]: KNeighborsClassifier(algorithm='kd_tree', leaf_size=30, metric='minkowski',
                    metric_params=None, n_jobs=None, n_neighbors=55, p=2,
                    weights='uniform')
```

9.2.3 Evaluting the performance of model

(A). Roc-Auc Plot

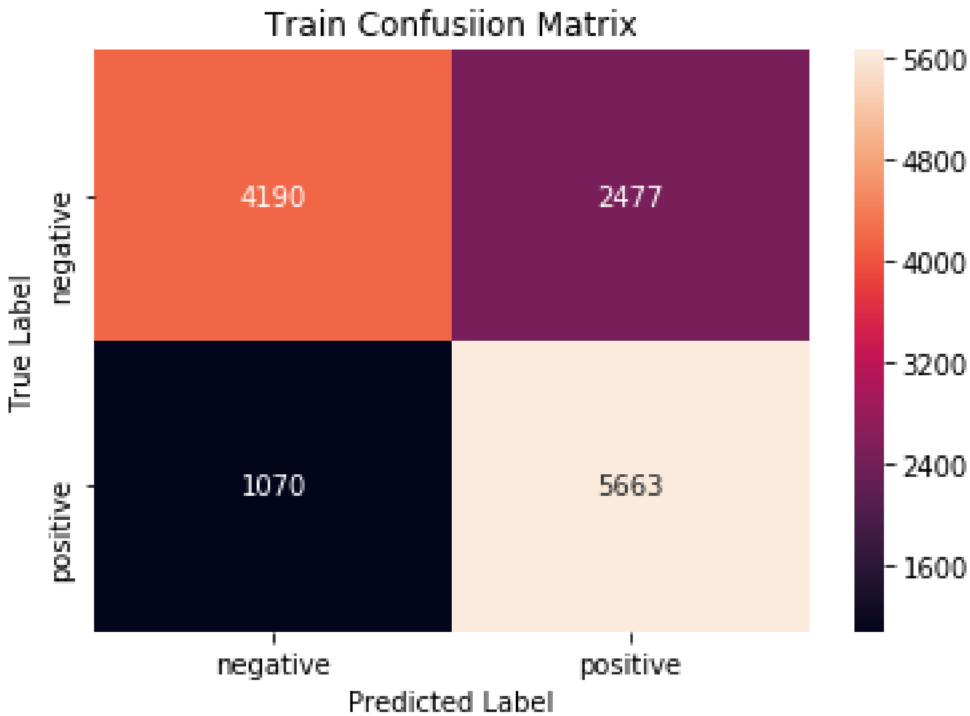
```
In [29]: plot_auc_roc(neigh,X_train_bow,X_test_bow,y_train,y_test)
```



(B). Confusion Matrix Plot on Train Data

```
In [30]: trainconfusionmatrix(neigh,X_train_bow,y_train)
```

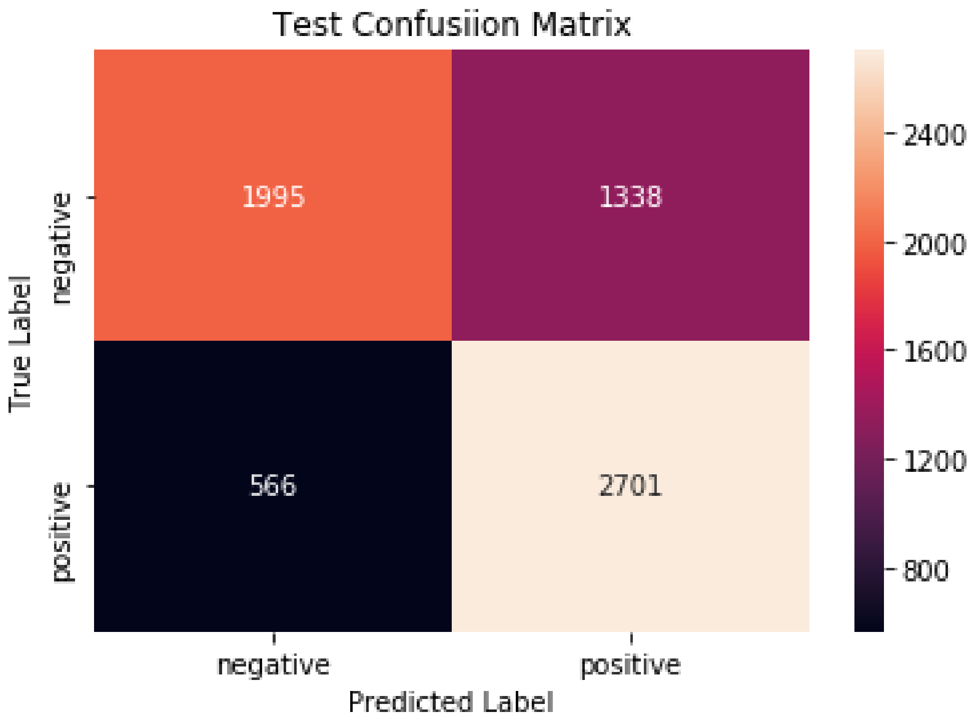
```
Confusion Matrix for Train set
```



(C). Confusion Matrix Plot on Test Data

```
In [31]: testconfusionmatrix(neigh,X_test_bow,y_test)
```

```
Confusion Matrix for Test set
```



(D). Accuracy and Error

```
In [32]: training_accuracy,training_error,test_accuracy,test_error = accuracy(neigh,X_train_bow
         print("Training Accuracy in %: ", round(training_accuracy,2)*100)
         print("\nTrain Error in %: ", round(training_error,2)*100)
         print("\nTest Accuracy in %: ", round(test_accuracy,2)*100)
         print("\nTest Error in % : ", round(test_error,2)*100)
```

```
Training Accuracy in %:  74.0

Train Error in %:  26.0

Test Accuracy in %:  71.0

Test Error in % :  28.999999999999996
```

(E). Classification Report

```
In [33]: print("Classification Report: \n")
         prediction=neigh.predict(X_test_bow)
         print(classification_report(y_test, prediction))
```

```
Classification Report:

              precision    recall  f1-score   support

           0       0.78      0.60      0.68      3333
           1       0.67      0.83      0.74      3267

   micro avg       0.71      0.71      0.71      6600
   macro avg       0.72      0.71      0.71      6600
weighted avg       0.72      0.71      0.71      6600
```

9 10.0 TF-IDF

```
In [34]: vectorizer = TfidfVectorizer(ngram_range=(1,2))
         vectorizer.fit(X_train) # fit has to happen only on train data

         # we use the fitted CountVectorizer to convert the text to vector
         X_train_TF = vectorizer.transform(X_train)
         X_test_TF = vectorizer.transform(X_test)
```

```
In [35]: print("After vectorizations")
         print(X_train_TF.shape, y_train.shape)
         print(X_test_TF.shape, y_test.shape)
```

```
After vectorizations
(13400, 304884) (13400,)
(6600, 304884) (6600,)
```

9.0.1 10.1 Brute Force Algorithm

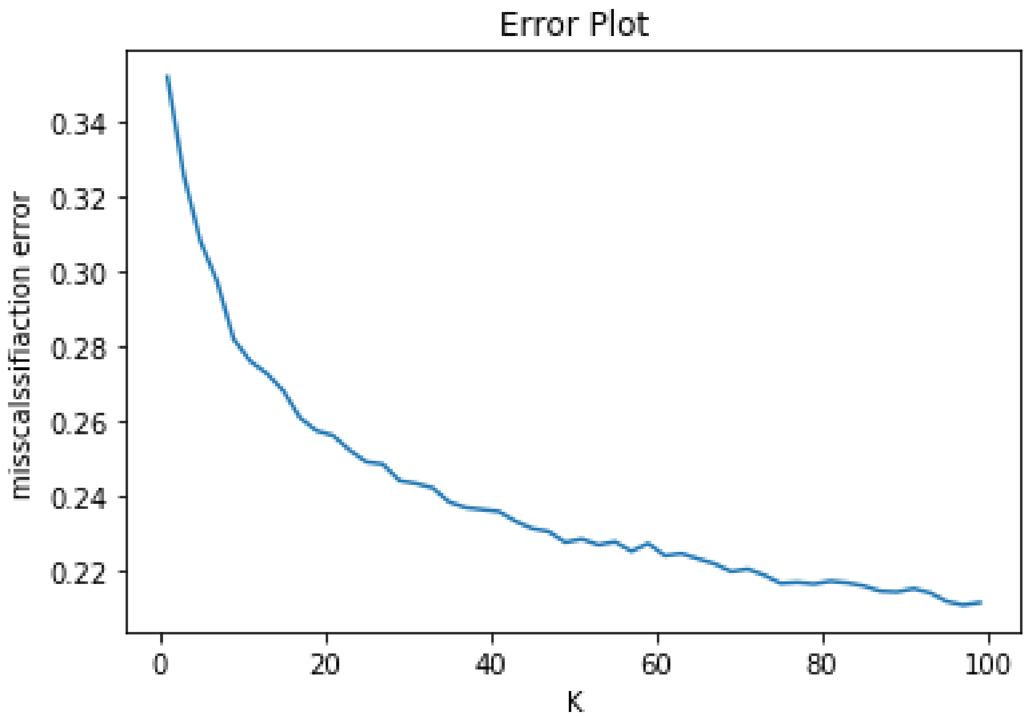
10.1.1 Finding Optimal Value of Hyperparameter(k)

```
In [36]: import numpy as np

         neighbours=np.arange(1,100,2)
         mse,best_k = knn_cv_brute(X_train_TF,y_train,neighbours)
```

```
In [37]: error_plot(neighbours,mse)
         print("Best value of K found for Brute Force Algorithm Implementaion is : ",best_k)
```

```
Best value of K found for Brute Force Algorithm Implementaion is :  97
```



10.1.2 Training the model

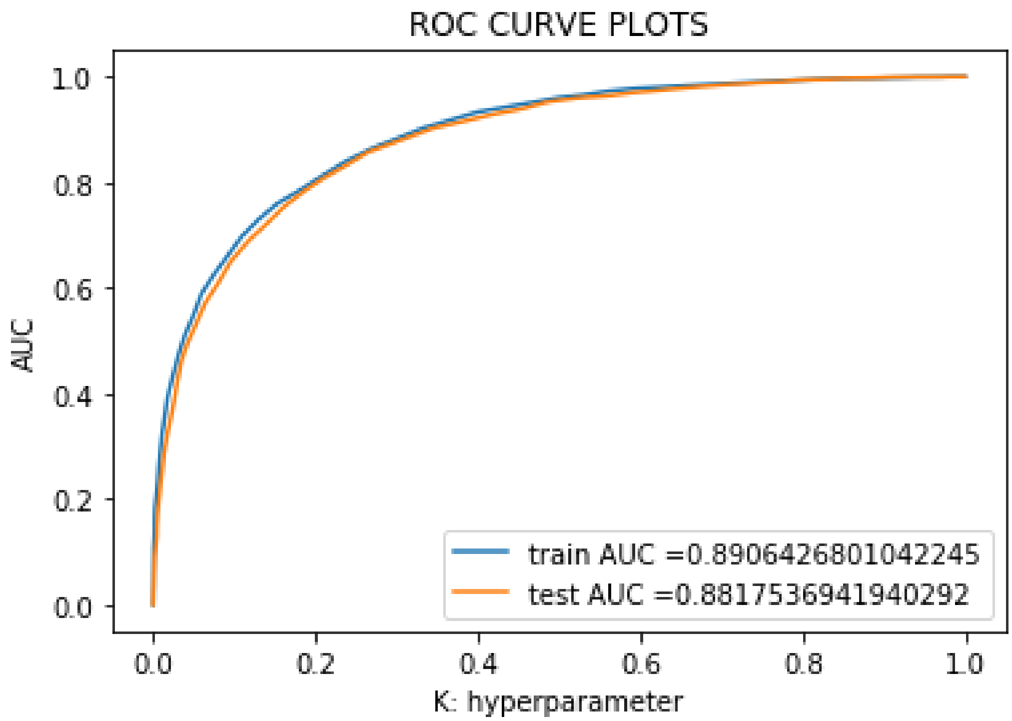
```
In [38]: neigh = KNeighborsClassifier(n_neighbors = best_k,algorithm='brute')
         neigh.fit(X_train_TF, y_train)

Out[38]: KNeighborsClassifier(algorithm='brute', leaf_size=30, metric='minkowski',
                    metric_params=None, n_jobs=None, n_neighbors=97, p=2,
                    weights='uniform')
```

10.1.3 Evaluting the performance of model

(A). Roc-Auc Plot

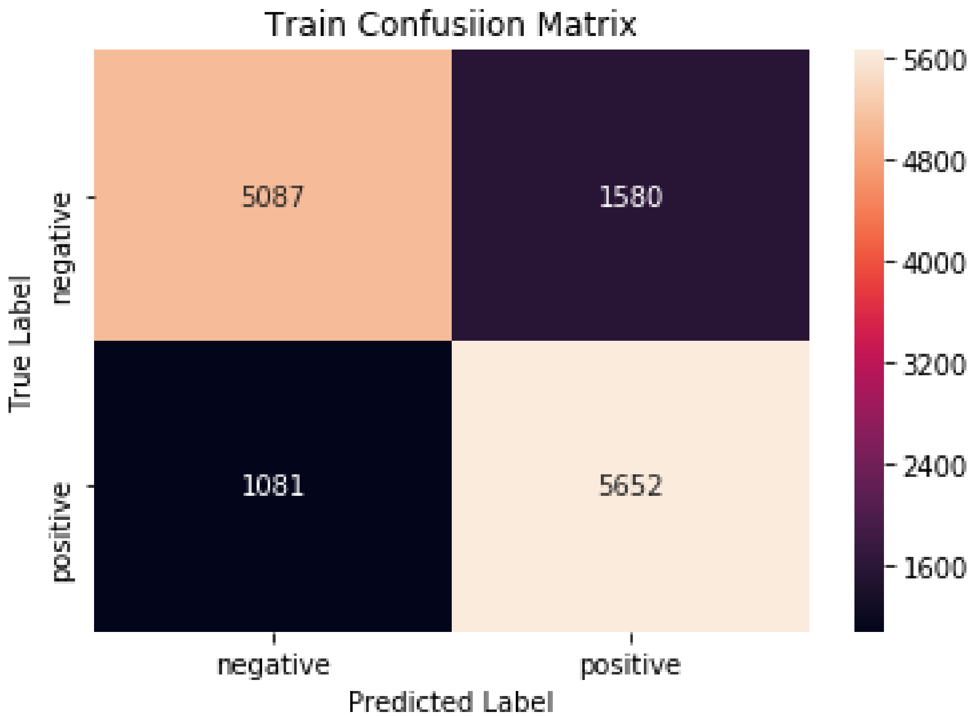
```
In [39]: plot_auc_roc(neigh,X_train_TF,X_test_TF,y_train,y_test)
```



(B). Confusion Matrix Plot on Train Data

```
In [40]: trainconfusionmatrix(neigh,X_train_TF,y_train)
```

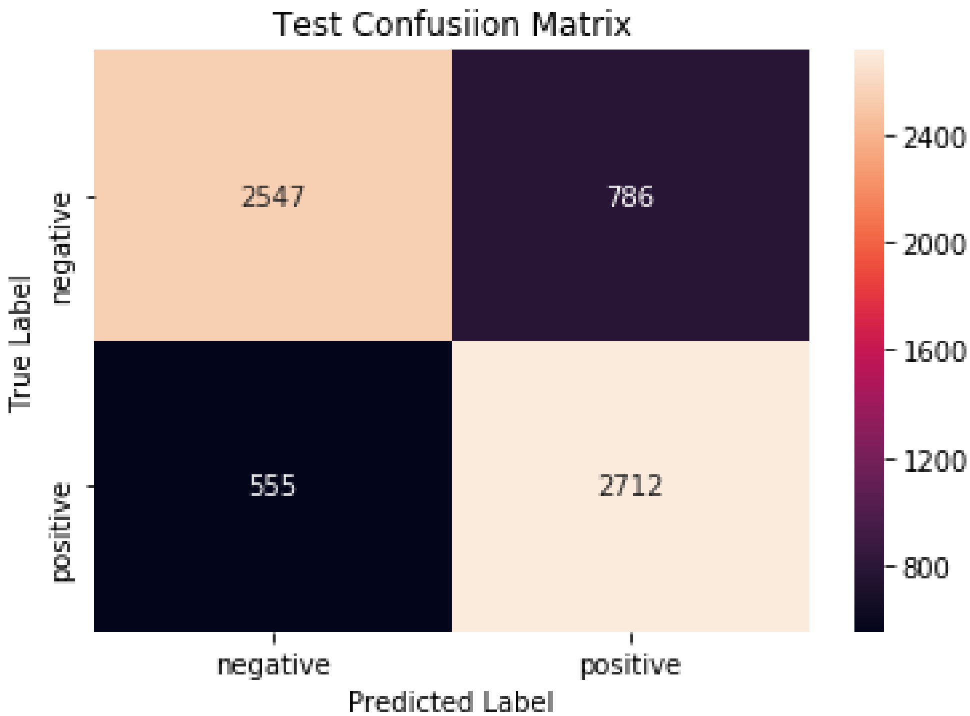
```
Confusion Matrix for Train set
```



(C). Confusion Matrix Plot on Test Data

```
In [41]: testconfusionmatrix(neigh,X_test_TF,y_test)
```

```
Confusion Matrix for Test set
```



(D). Accuracy and Error

```
In [42]: training_accuracy,training_error,test_accuracy,test_error = accuracy(neigh,X_train_TF
         print("Training Accuracy in %: ", round(training_accuracy,2)*100)
         print("\nTrain Error in %: ", round(training_error,2)*100)
         print("\nTest Accuracy in %: ", round(test_accuracy,2)*100)
         print("\nTest Error in % : ", round(test_error,2)*100)
```

```
Training Accuracy in %:  80.0

Train Error in %:  20.0

Test Accuracy in %:  80.0

Test Error in % :  20.0
```

(E). Classification Report

```
In [43]: print("Classification Report: \n")
         prediction=neigh.predict(X_test_TF)
         print(classification_report(y_test, prediction))
```

```
Classification Report:

              precision    recall  f1-score   support

           0       0.82      0.76      0.79      3333
           1       0.78      0.83      0.80      3267

   micro avg       0.80      0.80      0.80      6600
   macro avg       0.80      0.80      0.80      6600
weighted avg       0.80      0.80      0.80      6600
```

9.0.2 10.2 KD Tree Algorithm

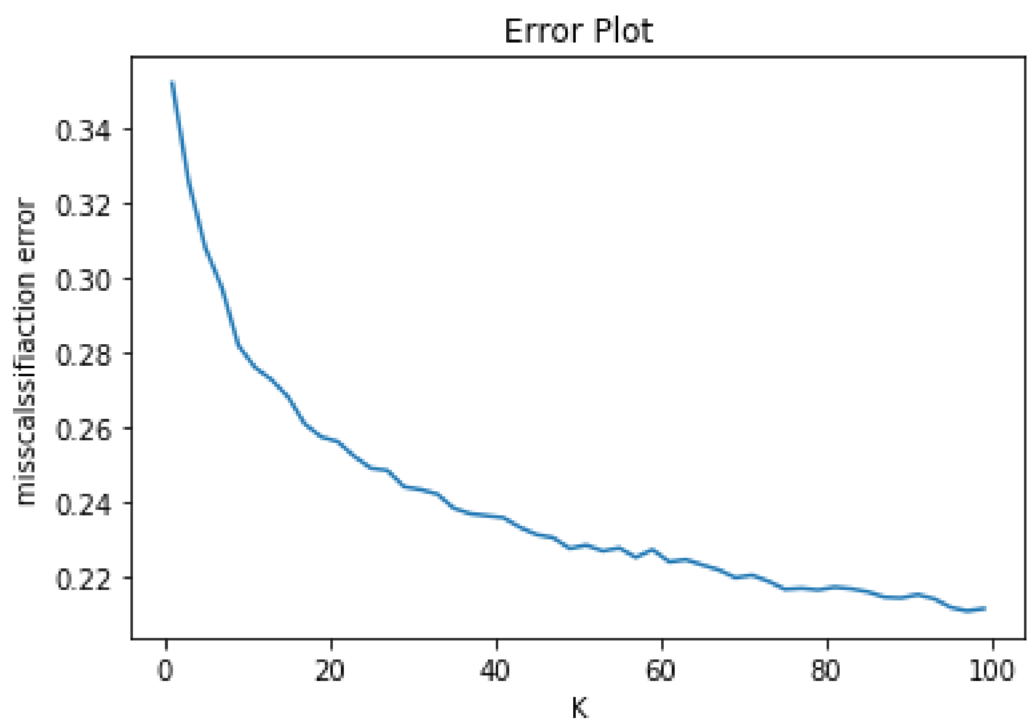
10.2.1 Finding Optimal Value of Hyperparameter(k)

In [44]:
```
import numpy as np

neighbours=np.arange(1,100,2)
mse,best_k = knn_cv_kd(X_train_TF,y_train,neighbours)
```

In [45]:
```
error_plot(neighbours,mse)
print("Best value of K found for KD Tree Algorithm Implementaion is : ",best_k)
```

```
Best value of K found for KD Tree Algorithm Implementaion is :  97
```



10.2.2 Training the model

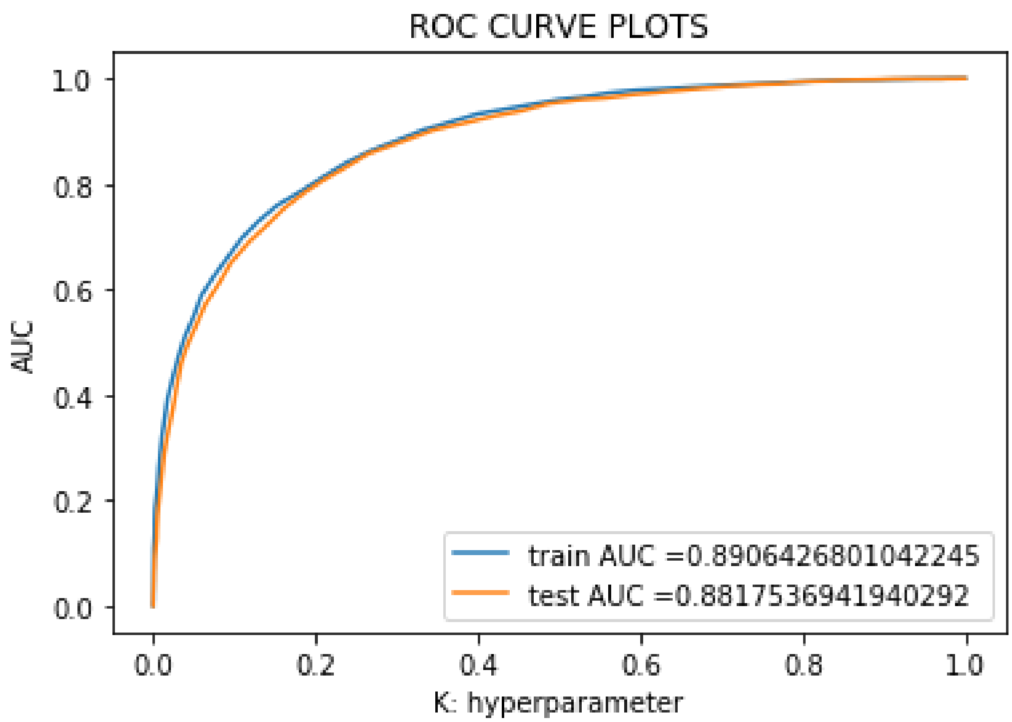
```
In [46]: neigh = KNeighborsClassifier(n_neighbors = best_k,algorithm='kd_tree')
         neigh.fit(X_train_TF, y_train)
```

```
Out[46]: KNeighborsClassifier(algorithm='kd_tree', leaf_size=30, metric='minkowski',
                    metric_params=None, n_jobs=None, n_neighbors=97, p=2,
                    weights='uniform')
```

10.2.3 Evaluting the performance of model

(A). Roc-Auc Plot

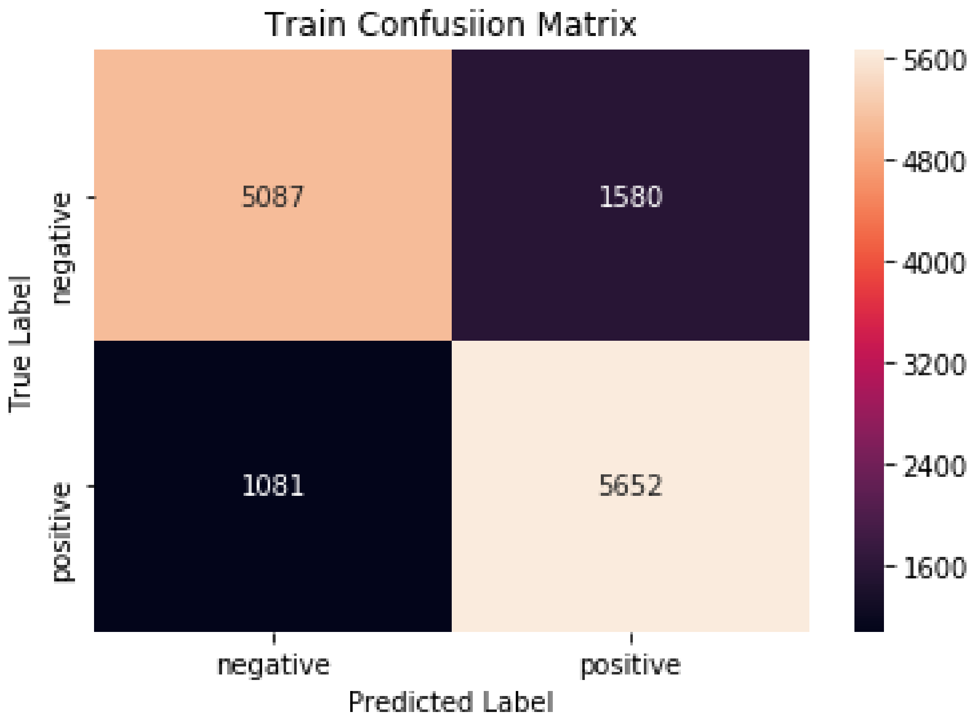
```
In [47]: plot_auc_roc(neigh,X_train_TF,X_test_TF,y_train,y_test)
```



(B). Confusion Matrix Plot on Train Data

```
In [48]: trainconfusionmatrix(neigh,X_train_TF,y_train)
```

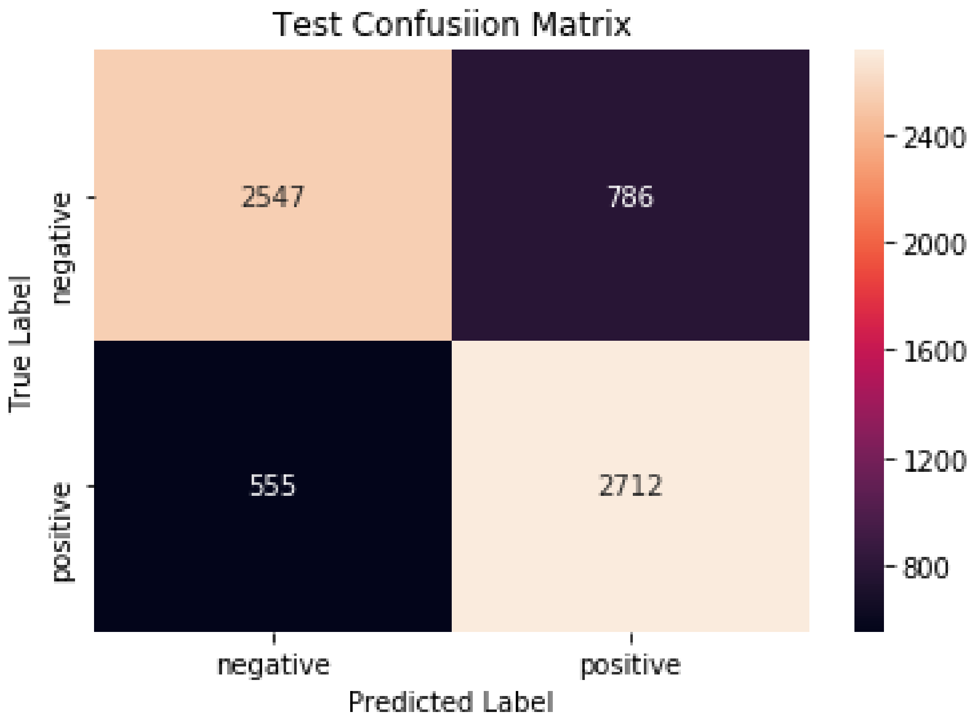
```
Confusion Matrix for Train set
```



(C). Confusion Matrix Plot on Test Data

```
In [49]: testconfusionmatrix(neigh,X_test_TF,y_test)
```

```
Confusion Matrix for Test set
```



(D). Accuracy and Error

```
In [50]: training_accuracy,training_error,test_accuracy,test_error = accuracy(neigh,X_train_TF
         print("Training Accuracy in %: ", round(training_accuracy,2)*100)
         print("\nTrain Error in %: ", round(training_error,2)*100)
         print("\nTest Accuracy in %: ", round(test_accuracy,2)*100)
         print("\nTest Error in % : ", round(test_error,2)*100)
```

```
Training Accuracy in %:  80.0

Train Error in %:  20.0

Test Accuracy in %:  80.0

Test Error in % :  20.0
```

(E). Classification Report

```
In [51]: print("Classification Report: \n")
         prediction=neigh.predict(X_test_TF)
         print(classification_report(y_test, prediction))
```

```
Classification Report:

              precision    recall  f1-score   support

           0       0.82      0.76      0.79      3333
           1       0.78      0.83      0.80      3267

   micro avg       0.80      0.80      0.80      6600
   macro avg       0.80      0.80      0.80      6600
weighted avg       0.80      0.80      0.80      6600
```

10 11.0 Word To Vector

```
In [16]: list_of_Train_sent=[]
         list_of_Test_sent=[]

         for sent in X_train:
             list_of_Train_sent.append(sent.split())

         for sent in X_test:
             list_of_Test_sent.append(sent.split())
```

```
In [17]: len(list_of_Train_sent)
```

```
Out[17]: 13400
```

```
In [18]: Train_model=Word2Vec(list_of_Train_sent,min_count=5,size=50, workers=4)
         Test_model=Word2Vec(list_of_Test_sent,min_count=5,size=50, workers=4)
```

10.0.1 11.1 Avg Word2Vec

```
In [55]: import numpy as np

         Train_vectors = []
         for sent in list_of_Train_sent:
             sent_vec = np.zeros(50)
             cnt_words = 0
             for word in sent:
                 try:
                     vec = Train_model.wv[word]
                     sent_vec += vec
                     cnt_words += 1
                 except:
                     pass
             if cnt_words!=0:
                 sent_vec /= cnt_words
```

```
            Train_vectors.append(sent_vec)
        Train_vectors = np.nan_to_num(Train_vectors)
```

```
In [56]: import numpy as np

         Test_vectors=[]
         for sent in list_of_Test_sent:
             sent_vec=np.zeros(50)
             cnt_words=0
             for word in sent:
                 try:
                     vec=Test_model.wv[word]
                     sent_vec+=vec
                     cnt_words+=1
                 except:
                     pass
             if cnt_words!=0:
                 sent_vec/=cnt_words
             Test_vectors.append(sent_vec)
         Test_vectors=np.nan_to_num(Test_vectors)
```

```
In [57]: print("Shape of Test Vectors : ",Test_vectors.shape)
```

```
Shape of Test Vectors :  (6600, 50)
```

```
In [58]: X_train_AWV = Train_vectors
         X_test_AWV = Test_vectors
```

```
In [59]: print(X_train_AWV.shape, y_train.shape)
         print(X_test_AWV.shape, y_test.shape)
```

```
(13400, 50) (13400,)
(6600, 50) (6600,)
```

10.0.2 10.2 Brute Force Algorithm

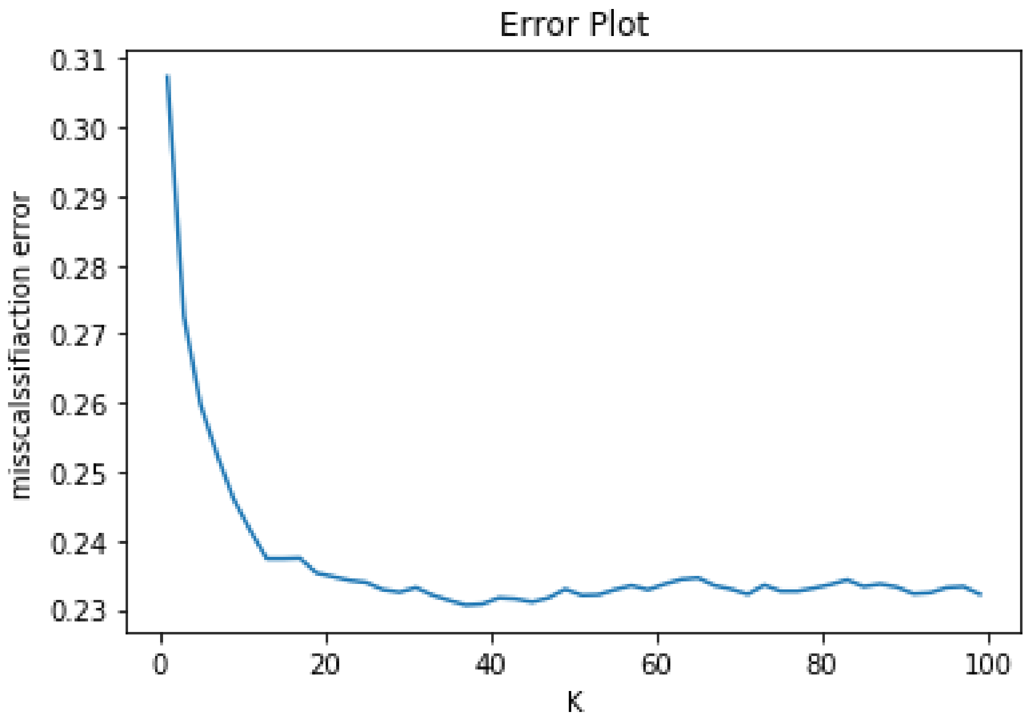
10.2.1 Finding Optimal Value of Hyperparameter(k)

```
In [60]: import numpy as np

         neighbours=np.arange(1,100,2)
         mse,best_k = knn_cv_brute(X_train_AWV,y_train,neighbours)
```

```
In [61]: error_plot(neighbours,mse)
         print("Best value of K found for Brute Force Algorithm Implementaion is : ",best_k)
```

```
Best value of K found for Brute Force Algorithm Implementaion is :  37
```



10.2.2 Training the model

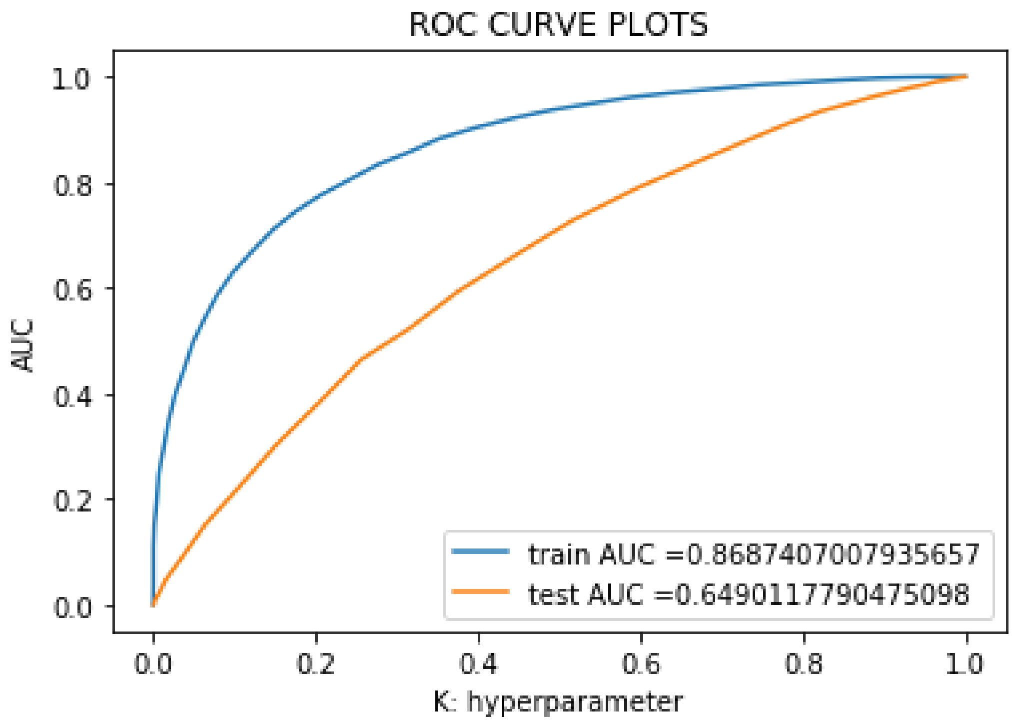
```
In [62]: neigh = KNeighborsClassifier(n_neighbors = best_k,algorithm='brute')
         neigh.fit(X_train_AWV, y_train)
```

```
Out[62]: KNeighborsClassifier(algorithm='brute', leaf_size=30, metric='minkowski',
                    metric_params=None, n_jobs=None, n_neighbors=37, p=2,
                    weights='uniform')
```

10.2.3 Evaluting the performance of model

(A). Roc-Auc Plot

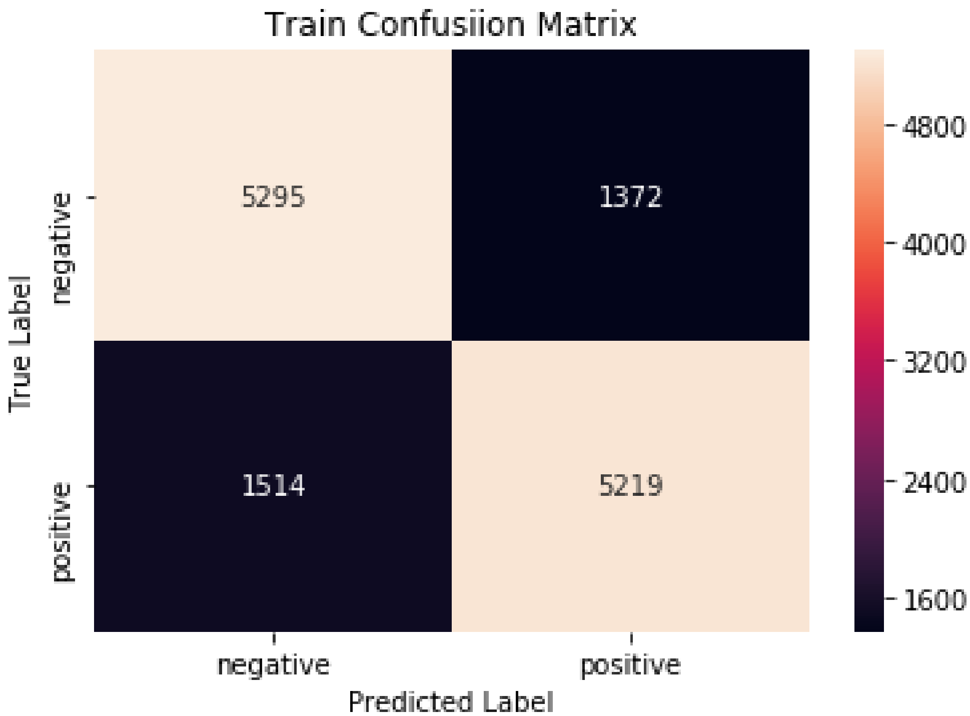
```
In [63]: plot_auc_roc(neigh,X_train_AWV,X_test_AWV,y_train,y_test)
```



(B). Confusion Matrix Plot on Train Data

In [64]:
```
trainconfusionmatrix(neigh,X_train_AWV,y_train)
```

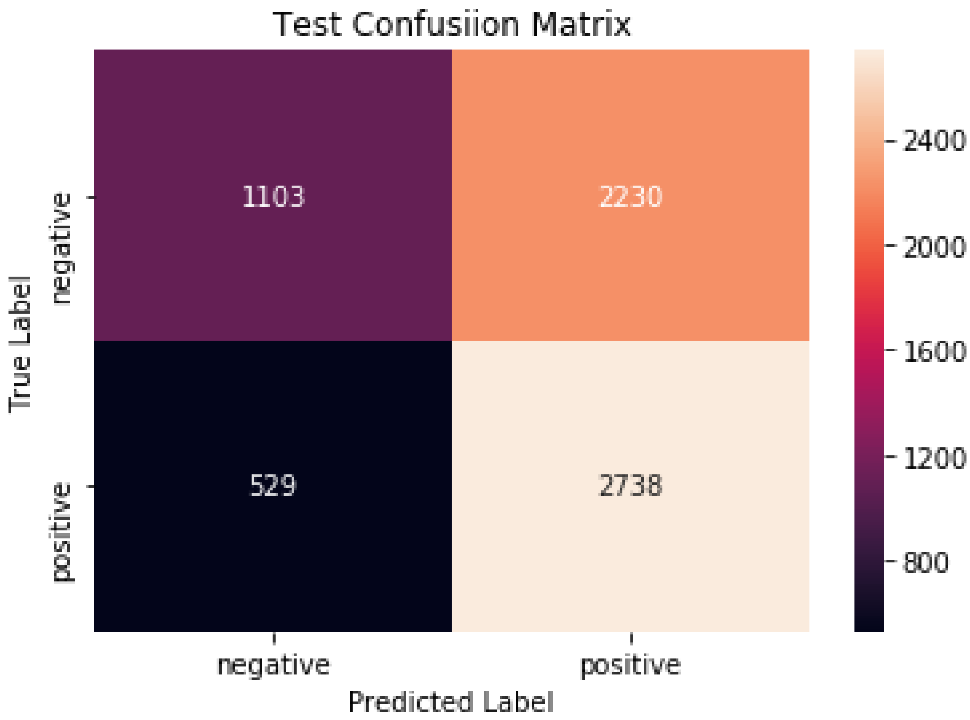
```
Confusion Matrix for Train set
```



(C). Confusion Matrix Plot on Test Data

```
In [65]: testconfusionmatrix(neigh,X_test_AWV,y_test)
```

```
Confusion Matrix for Test set
```



(D). Accuracy and Error

```
In [66]: training_accuracy,training_error,test_accuracy,test_error = accuracy(neigh,X_train_AW
         print("Training Accuracy in %: ", round(training_accuracy,2)*100)
         print("\nTrain Error in %: ", round(training_error,2)*100)
         print("\nTest Accuracy in %: ", round(test_accuracy,2)*100)
         print("\nTest Error in % : ", round(test_error,2)*100)
```

```
Training Accuracy in %:  78.0

Train Error in %:  22.0

Test Accuracy in %:  57.99999999999999

Test Error in % :  42.0
```

(E). Classification Report

```
In [67]: print("Classification Report: \n")
         prediction=neigh.predict(X_test_AWV)
         print(classification_report(y_test, prediction))
```

```
Classification Report:

              precision    recall  f1-score   support

           0       0.68      0.33      0.44      3333
           1       0.55      0.84      0.66      3267

   micro avg       0.58      0.58      0.58      6600
   macro avg       0.61      0.58      0.55      6600
weighted avg       0.61      0.58      0.55      6600
```

10.0.3 10.3 KD Tree Algorithm

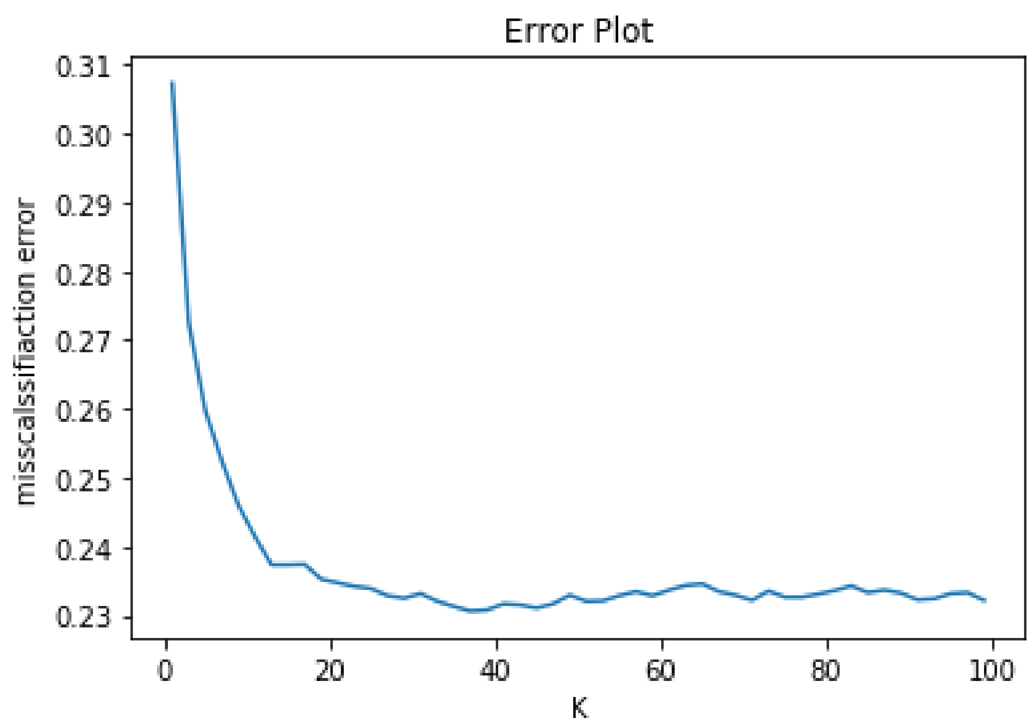
10.3.1 Finding Optimal Value of Hyperparameter(k)

```
In [68]: import numpy as np

         neighbours=np.arange(1,100,2)
         mse,best_k = knn_cv_kd(X_train_AWV,y_train,neighbours)

In [69]: error_plot(neighbours,mse)
         print("Best value of K found for KD Tree Algorithm Implementaion is : ",best_k)

Best value of K found for KD Tree Algorithm Implementaion is :  37
```



10.3.2 Training the model

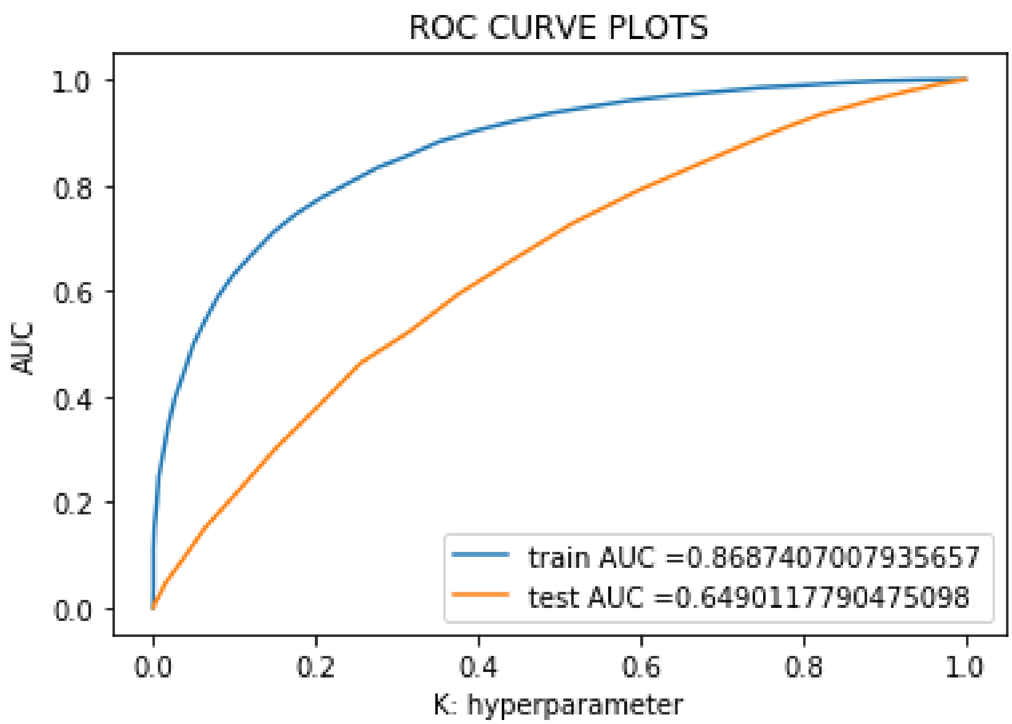
```
In [70]: neigh = KNeighborsClassifier(n_neighbors = best_k,algorithm='kd_tree')
         neigh.fit(X_train_AWV, y_train)
```

```
Out[70]: KNeighborsClassifier(algorithm='kd_tree', leaf_size=30, metric='minkowski',
                    metric_params=None, n_jobs=None, n_neighbors=37, p=2,
                    weights='uniform')
```

10.3.3 Evaluting the performance of model

(A). Roc-Auc Plot

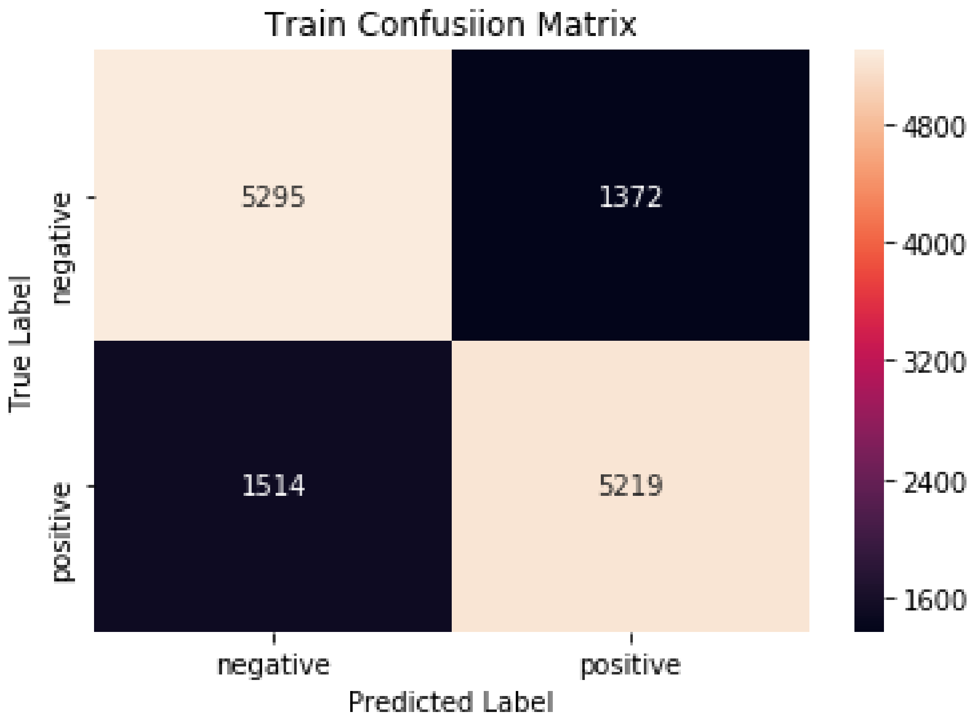
```
In [71]: plot_auc_roc(neigh,X_train_AWV,X_test_AWV,y_train,y_test)
```



(B). Confusion Matrix Plot on Train Data

```
In [72]: trainconfusionmatrix(neigh,X_train_AWV,y_train)
```

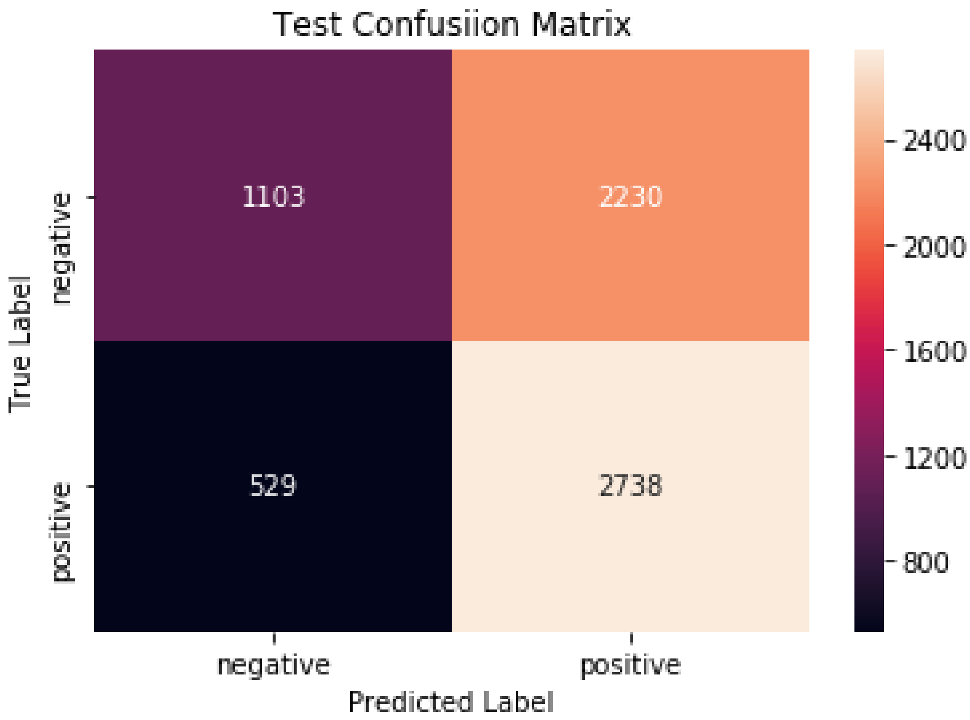
```
Confusion Matrix for Train set
```



(C). Confusion Matrix Plot on Test Data

```
In [73]: testconfusionmatrix(neigh,X_test_AWV,y_test)
```

```
Confusion Matrix for Test set
```



(D). Accuracy and Error

```
In [74]: training_accuracy,training_error,test_accuracy,test_error = accuracy(neigh,X_train_AW
         print("Training Accuracy in %: ", round(training_accuracy,2)*100)
         print("\nTrain Error in %: ", round(training_error,2)*100)
         print("\nTest Accuracy in %: ", round(test_accuracy,2)*100)
         print("\nTest Error in % : ", round(test_error,2)*100)
```

```
Training Accuracy in %:  78.0

Train Error in %:  22.0

Test Accuracy in %:  57.99999999999999

Test Error in % :  42.0
```

(E). Classification Report

```
In [75]: print("Classification Report: \n")
         prediction=neigh.predict(X_test_AWV)
         print(classification_report(y_test, prediction))
```

```
Classification Report:

              precision    recall  f1-score   support

           0       0.68      0.33      0.44      3333
           1       0.55      0.84      0.66      3267

   micro avg       0.58      0.58      0.58      6600
   macro avg       0.61      0.58      0.55      6600
weighted avg       0.61      0.58      0.55      6600
```

11 11.0 TF-IDF Word To Vector

In [19]:
```
model = TfidfVectorizer()
model.fit(X_train)
X_Train_TF = model.transform(X_train)
X_Test_TF = model.transform(X_test)
```

In [20]:
```
print("Shape of Train Data After TFIDF : ",X_Train_TF.shape)
print("Shape of Test Data After TFIDF : ",X_Test_TF.shape)
```

```
Shape of Train Data After TFIDF :  (13400, 15367)
Shape of Test Data After TFIDF :  (6600, 15367)
```

In [21]:
```
TFIDF_Feature=model.get_feature_names()
print(len(TFIDF_Feature))
print(TFIDF_Feature[0:20])
```

```
15367
['aaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaa', 'aaaaaaaaagghh', 'aaaaahhhhhhhhhhhhhhh', 'aa
```

In [22]:
```
from tqdm import tqdm
Train_TFIDF_W2V_Vectors=[]
row=0
for sent in tqdm(list_of_Train_sent):
    sent_vec=np.zeros(50)
    weight=0
    for word in sent:
        try :
            w2v_vec=Train_model.wv[word]
            tfidf_vec=X_Train_TF[row,TFIDF_Feature.index(word)]
            sent_vec+=(w2v_vec*tfidf_vec)
            weight+=tfidf_vec
```

```
            except :
                pass
        if weight!=0:
            sent_vec/=weight
        Train_TFIDF_W2V_Vectors.append(sent_vec)
        row+=1
```

100%|| 13400/13400 [02:56<00:00, 75.98it/s]

```
In [23]: Test_TFIDF_W2V_Vectors=[]
         row=0
         for sent in tqdm(list_of_Test_sent):
             sent_vec=np.zeros(50)
             weight=0

             for word in sent:
                 try:
                     w2v_vec=Test_model.wv[word]
                     tfidf_vec=X_Test_TF(row,TFIDF_Feature.index(word))
                     sent_vec+=(w2v_vec*tfidf_vec)
                     weight+=tfidf

                 except :
                     pass

             if weight!=0:
                 sent_vec/=weight
             Test_TFIDF_W2V_Vectors.append(sent_vec)
             row+=1
```

100%|| 6600/6600 [01:03<00:00, 103.35it/s]

```
In [25]: Test_tfidfw2v_vectors=np.nan_to_num(Test_TFIDF_W2V_Vectors)
         Train_tfidfw2v_vectors=np.nan_to_num(Train_TFIDF_W2V_Vectors)
```

```
In [28]: X_train_TfIdfW2v=Train_tfidfw2v_vectors
         X_test_TfIdfW2v=Test_tfidfw2v_vectors
```

11.0.1 11.1 Brute Force Algorithm

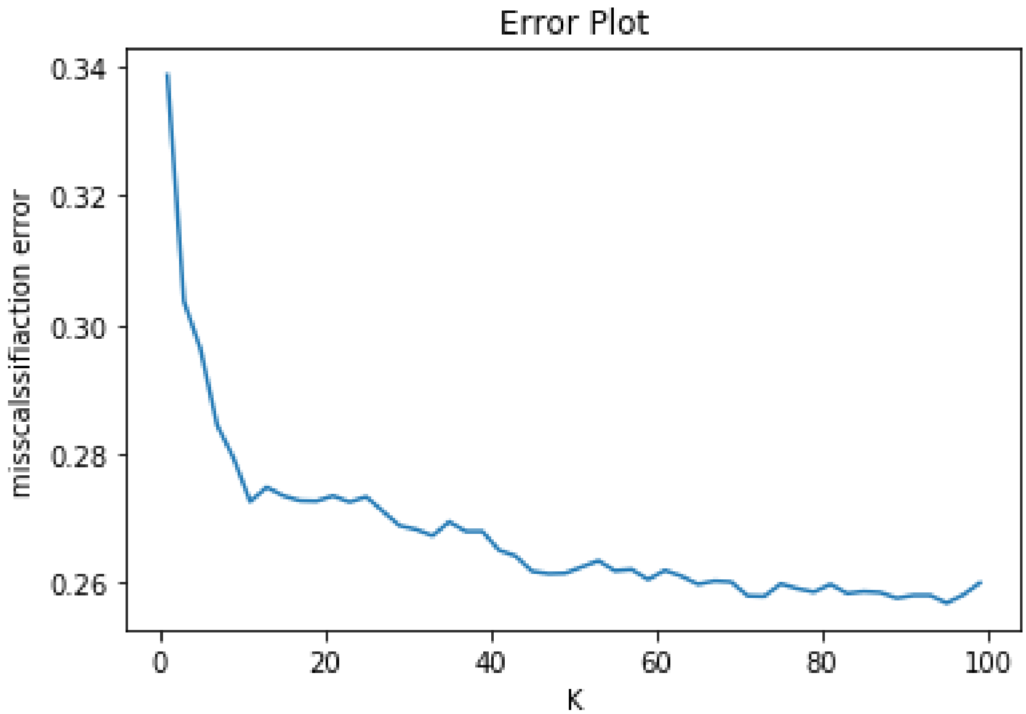
11.1.1 Finding Optimal Value of Hyperparameter(k)

```
In [29]: import numpy as np

         neighbours=np.arange(1,100,2)
         mse,best_k = knn_cv_brute(X_train_TfIdfW2v,y_train,neighbours)
```

```
In [30]: error_plot(neighbours,mse)
         print("Best value of K found for Brute Force Algorithm Implementaion is : ",best_k)
```

```
Best value of K found for Brute Force Algorithm Implementaion is :  95
```



11.1.2 Training the model

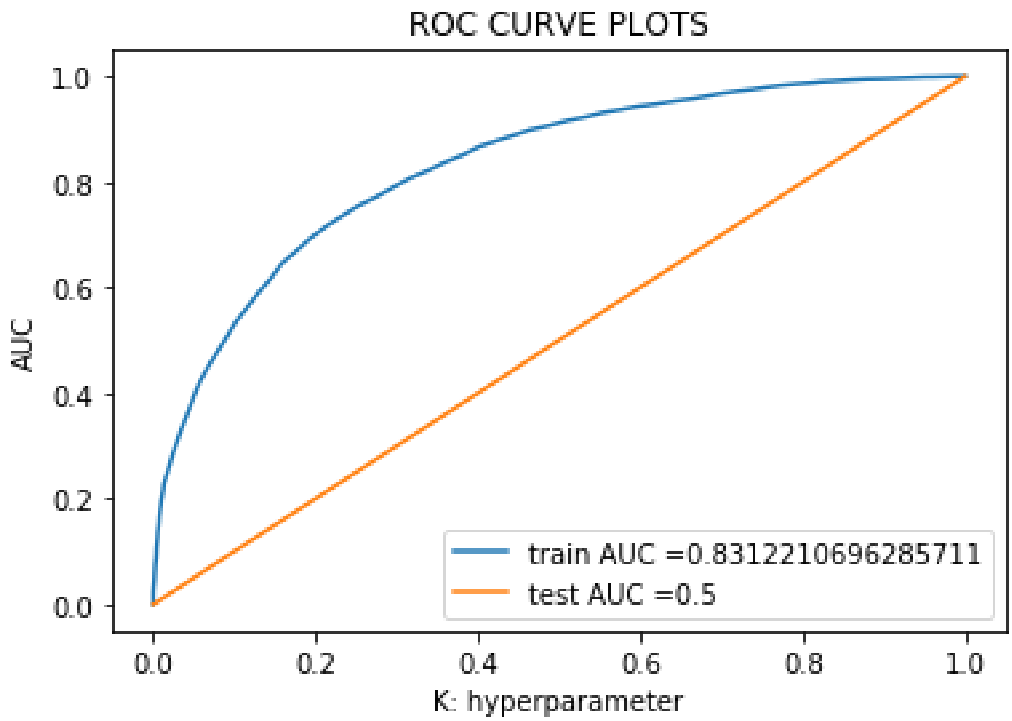
```
In [33]: neigh = KNeighborsClassifier(n_neighbors = best_k,algorithm='brute')
         neigh.fit(X_train_TfIdfW2v, y_train)
```

```
Out[33]: KNeighborsClassifier(algorithm='brute', leaf_size=30, metric='minkowski',
                    metric_params=None, n_jobs=None, n_neighbors=95, p=2,
                    weights='uniform')
```

11.1.3 Evaluting the performance of model

(A). Roc-Auc Plot

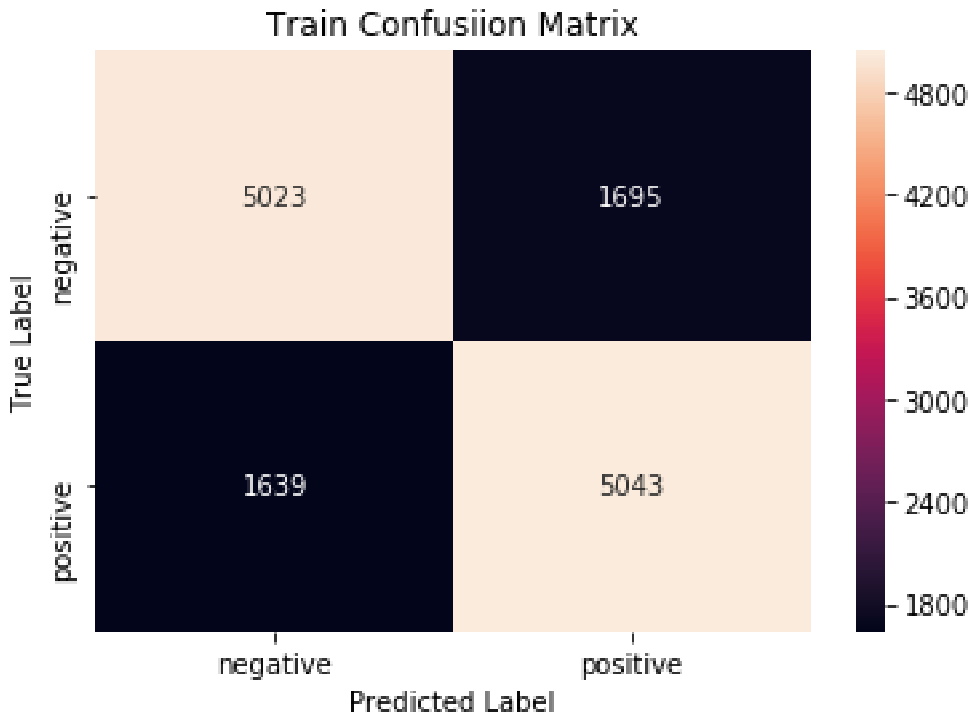
```
In [34]: plot_auc_roc(neigh,X_train_TfIdfW2v,X_test_TfIdfW2v,y_train,y_test)
```



(B). Confusion Matrix Plot on Train Data

```
In [35]: trainconfusionmatrix(neigh,X_train_TfIdfW2v,y_train)
```

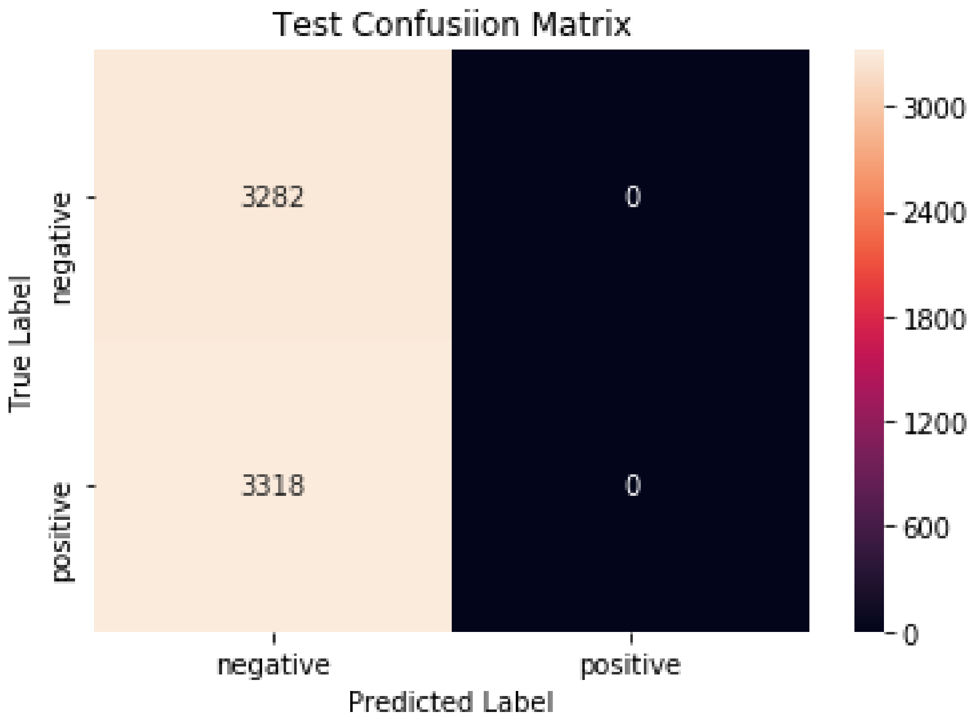
```
Confusion Matrix for Train set
```



(C). Confusion Matrix Plot on Test Data

```
In [36]: testconfusionmatrix(neigh,X_test_TfIdfW2v,y_test)
```

```
Confusion Matrix for Test set
```



(D). Accuracy and Error

```
In [37]: training_accuracy,training_error,test_accuracy,test_error = accuracy(neigh,X_train_TfI
         print("Training Accuracy in %: ", round(training_accuracy,2)*100)
         print("\nTrain Error in %: ", round(training_error,2)*100)
         print("\nTest Accuracy in %: ", round(test_accuracy,2)*100)
         print("\nTest Error in % : ", round(test_error,2)*100)
```

```
Training Accuracy in %:  75.0

Train Error in %:  25.0

Test Accuracy in %:  50.0

Test Error in % :  50.0
```

(E). Classification Report

```
In [38]: print("Classification Report: \n")
         prediction=neigh.predict(X_test_TfIdfW2v)
         print(classification_report(y_test, prediction))
```

```
Classification Report:

              precision    recall  f1-score   support

           0       0.50      1.00      0.66      3282
           1       0.00      0.00      0.00      3318

   micro avg       0.50      0.50      0.50      6600
   macro avg       0.25      0.50      0.33      6600
weighted avg       0.25      0.50      0.33      6600
```

11.0.2 11.2 KD Tree Algorithm

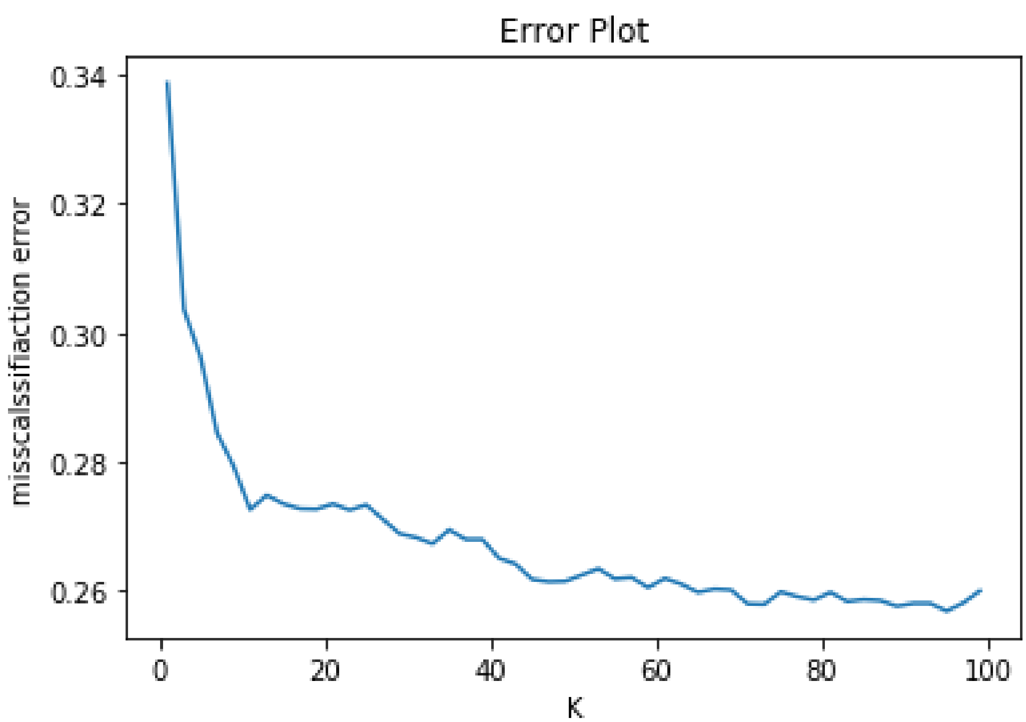
11.2.1 Finding Optimal Value of Hyperparameter(k)

In [39]:
```python
import numpy as np

neighbours=np.arange(1,100,2)
mse,best_k = knn_cv_kd(X_train_TfIdfW2v,y_train,neighbours)
```

In [40]:
```python
error_plot(neighbours,mse)
print("Best value of K found for KD Tree Algorithm Implementaion is : ",best_k)
```

```
Best value of K found for KD Tree Algorithm Implementaion is :  95
```



11.2.2 Training the model

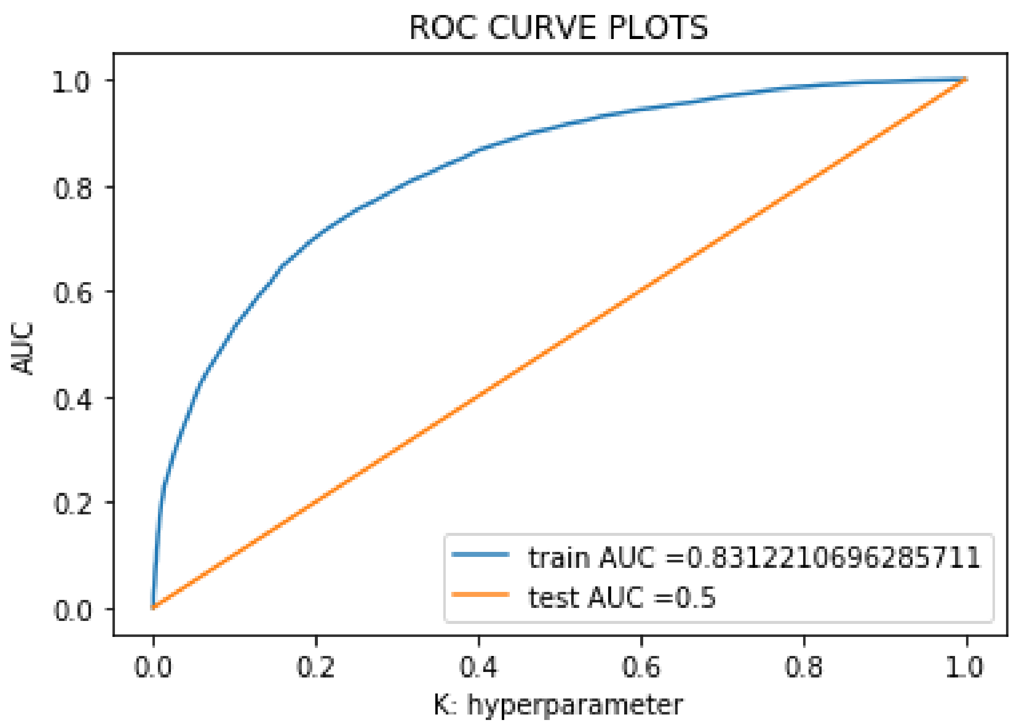
```
In [41]: neigh = KNeighborsClassifier(n_neighbors = best_k,algorithm='kd_tree')
         neigh.fit(X_train_TfIdfW2v, y_train)
```

```
Out[41]: KNeighborsClassifier(algorithm='kd_tree', leaf_size=30, metric='minkowski',
                    metric_params=None, n_jobs=None, n_neighbors=95, p=2,
                    weights='uniform')
```

11.2.3 Evaluting the performance of model

(A). Roc-Auc Plot

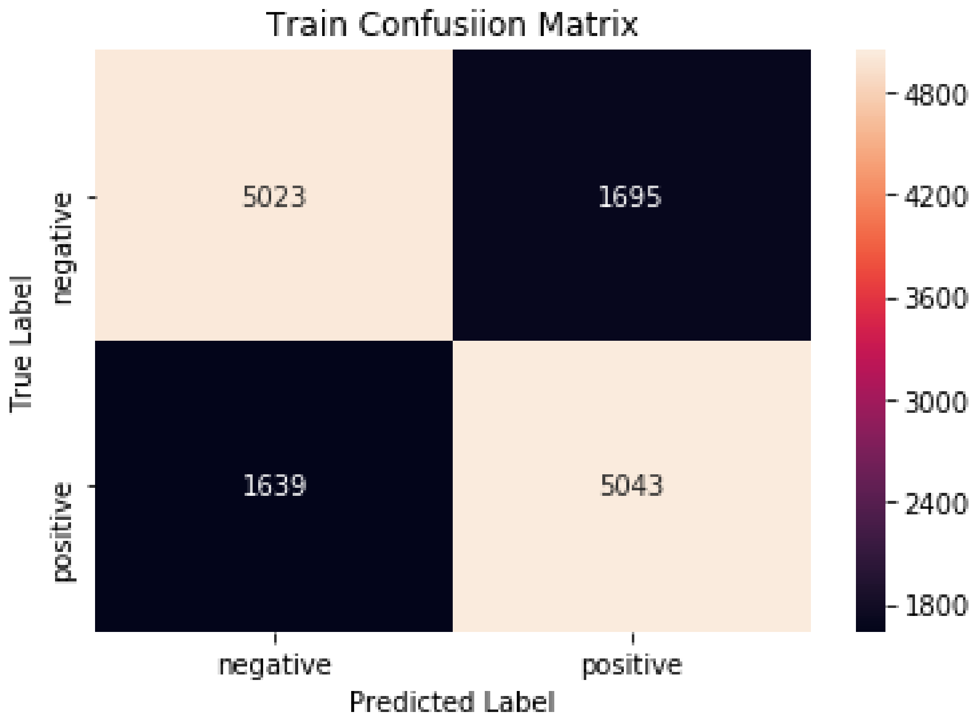
```
In [42]: plot_auc_roc(neigh,X_train_TfIdfW2v,X_test_TfIdfW2v,y_train,y_test)
```



(B). Confusion Matrix Plot on Train Data

```
In [43]: trainconfusionmatrix(neigh,X_train_TfIdfW2v,y_train)
```

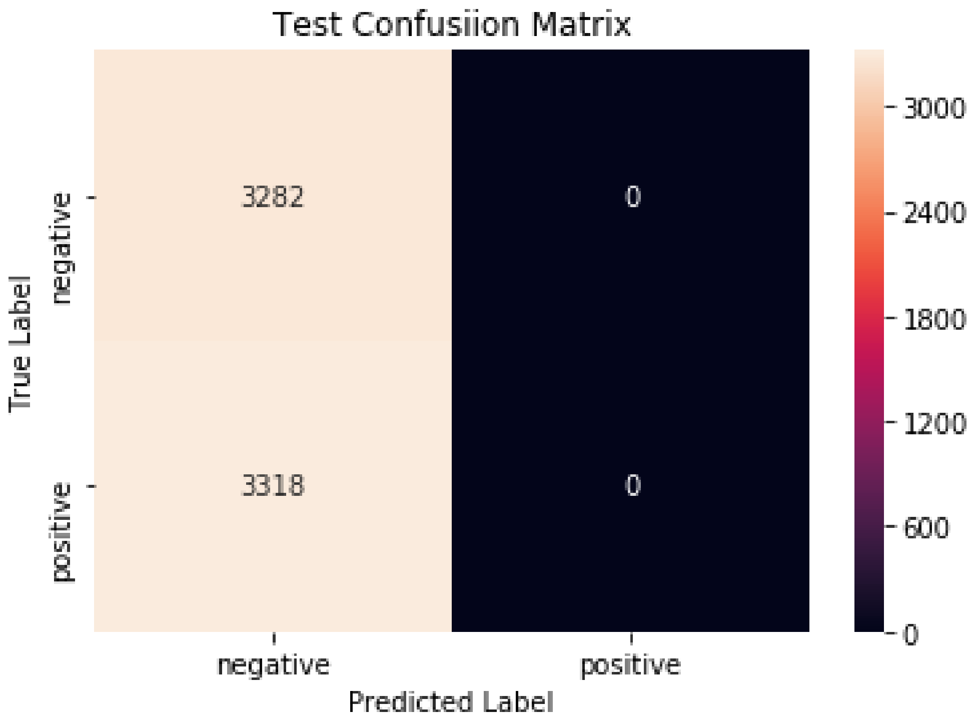
```
Confusion Matrix for Train set
```



(C). Confusion Matrix Plot on Test Data

```
In [44]: testconfusionmatrix(neigh,X_test_TfIdfW2v,y_test)
```

```
Confusion Matrix for Test set
```



(D). Accuracy and Error

```
In [45]: training_accuracy,training_error,test_accuracy,test_error = accuracy(neigh,X_train_TfI
         print("Training Accuracy in %: ", round(training_accuracy,2)*100)
         print("\nTrain Error in %: ", round(training_error,2)*100)
         print("\nTest Accuracy in %: ", round(test_accuracy,2)*100)
         print("\nTest Error in % : ", round(test_error,2)*100)
```

```
Training Accuracy in %:  75.0

Train Error in %:  25.0

Test Accuracy in %:  50.0

Test Error in % :  50.0
```

(E). Classification Report

```
In [46]: print("Classification Report: \n")
         prediction=neigh.predict(X_test_TfIdfW2v)
         print(classification_report(y_test, prediction))
```

```
Classification Report:

              precision    recall  f1-score   support

           0       0.50      1.00      0.66      3282
           1       0.00      0.00      0.00      3318

   micro avg       0.50      0.50      0.50      6600
   macro avg       0.25      0.50      0.33      6600
weighted avg       0.25      0.50      0.33      6600
```

12 12.0 Conclusion :

1. Report On Brute Force Algorithm

In [51]:
```python
from prettytable import PrettyTable

x = PrettyTable()

x.field_names = ["Vectorizer", "Hyperparameter", "AUC","Train Accuracy (%)","Test Accu

x.add_row(["BOW",55,0.79,74,71])
x.add_row(["TF-IDF", 97,0.88,80,80])
x.add_row(["W2V",37,0.64,78,57 ])
x.add_row(["TF-IDF W2V",95,0.50,75,50])
print(x)
```

```
+------------+----------------+------+--------------------+-------------------+
| Vectorizer | Hyperparameter | AUC  | Train Accuracy (%) | Test Accuracy (%) |
+------------+----------------+------+--------------------+-------------------+
|    BOW     |       55       | 0.79 |         74         |         71        |
|   TF-IDF   |       97       | 0.88 |         80         |         80        |
|    W2V     |       37       | 0.64 |         78         |         57        |
| TF-IDF W2V |       95       | 0.5  |         75         |         50        |
+------------+----------------+------+--------------------+-------------------+
```

2. Report on KD Tree Algorithm

In [52]:
```python
x = PrettyTable()

x.field_names = ["Vectorizer","Hyperparameter", "AUC","Train Accuracy (%)","Test Accu

x.add_row(["BOW",55,0.79,74,71])
x.add_row(["TF-IDF",97,0.88,80,80])
x.add_row(["W2V",37,0.64,78,57 ])
```

```python
x.add_row(["TF-IDF W2V",95,0.50,75,50])
print(x)
```

```
+------------+----------------+------+--------------------+-------------------+
| Vectorizer | Hyperparameter | AUC  | Train Accuracy (%) | Test Accuracy (%) |
+------------+----------------+------+--------------------+-------------------+
|    BOW     |       55       | 0.79 |         74         |         71        |
|   TF-IDF   |       97       | 0.88 |         80         |         80        |
|    W2V     |       37       | 0.64 |         78         |         57        |
| TF-IDF W2V |       95       | 0.5  |         75         |         50        |
+------------+----------------+------+--------------------+-------------------+
```

3. 71 % Of Accuracy is achieved by the model in case of Bag of Words.

4. 80 % Of Accuracy is achieved by the model in case of TF-IDF Vectorizer.

5. Model is overfit in case of Average Word to vector.

6. Very small subset of Data is taken but still it took more time due to large dimension and time complexity of KNN.

7. Model behaviour in TF-IDF W2V is lenint towards one class .