Assignment-3 - Apply-KNN-On-Amazon-Review-Dataset

March 12, 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 [25]:
```
%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 precision_score
from sklearn.metrics import f1_score
from sklearn.metrics import recall_score

from sklearn.metrics import classification_report
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.model_selection import TimeSeriesSplit
```

```
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 sklearn import preprocessing

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

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

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['Score'].value_counts()
```

```
Out[3]: 1    307061
        0     57110
        Name: Score, dtype: int64
```

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 Taking 5K data for Brute Force and 2K data for KD Tree

```
In [59]: # To randomly sample 10k points from both class
         data = Data.sample(n = 50000)
         data1= Data.sample(n=20000)
```

```
In [60]: print("Number of positve and negative score in 50K Data Points")
         print(data['Score'].value_counts())
```

```
        print("\nNumber of positve and negative score in 20K Data Points")
        print(data1['Score'].value_counts())
```

```
Number of positve and negative score in 50K Data Points
1    42123
0     7877
Name: Score, dtype: int64

Number of positve and negative score in 20K Data Points
1    16882
0     3118
Name: Score, dtype: int64
```

```
In [74]: # Sorting on the basis of Time Parameter
         data.sort_values('Time',inplace=True)
         data1.sort_values('Time',inplace=True)
```

```
In [125]: data.to_csv("50K_Data.csv",index=False)
          data1.to_csv("20K_Data.csv",index=False)
```

```
In [75]: Y = data['Score'].values
         X = data['CleanedText'].values

         Y1 = data1['Score'].values
         X1 = data1['CleanedText'].values
```

6.1.1 7.0 Splitting DataSet into Train and Test Data

```
In [76]: 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=F
         X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.33) # this is r
         X1_train, X1_test, y1_train, y1_test = train_test_split(X1, Y1, test_size=0.33)

         print("Shape of Train and Test Dataset for 50k points")
         print(X_train.shape, y_train.shape)
         print(X_test.shape, y_test.shape)

         print("\nShape of Train and Test Dataset for 20k points")
         print(X1_train.shape, y1_train.shape)
         print(X1_test.shape, y1_test.shape)
```

```
Shape of Train and Test Dataset for 50k points
(33500,) (33500,)
(16500,) (16500,)

Shape of Train and Test Dataset for 20k points
(13400,) (13400,)
(6600,) (6600,)
```

7 8.0 Defining Some Function

7.0.1 8.1 Train Data Confusion Matrix Plot

```
In [77]: 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 [78]: 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 [79]: 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 [80]: 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 [81]:
```
def knn_cv_kd(X_train,y_train,neighbours):

    cv_scores=[]
    tscv = TimeSeriesSplit(n_splits=10)

    for k in neighbours:
        knn = KNeighborsClassifier(n_neighbors=k,algorithm='kd_tree')
        scores = cross_val_score(knn, X_train, y_train, cv=tscv) # returns accuracy f
        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 [82]:
```
def knn_cv_brute(X_train,y_train,neighbours):

    cv_scores=[]
    tscv = TimeSeriesSplit(n_splits=10)

    for k in neighbours:
        knn = KNeighborsClassifier(n_neighbors=k,algorithm='brute')
        scores = cross_val_score(knn, X_train, y_train, cv=tscv) # returns accuracy f
        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
```

8 9.0 Bags of Words

In [83]:
```
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_train_bow=preprocessing.normalize(X_train_bow)

X_test_bow = vectorizer.transform(X_test)
X_test_bow=preprocessing.normalize(X_test_bow)
```

```
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
(33500, 23006) (33500,)
(16500, 23006) (16500,)
```

```
In [84]: type(X_train_bow)
```

```
Out[84]: scipy.sparse.csr.csr_matrix
```

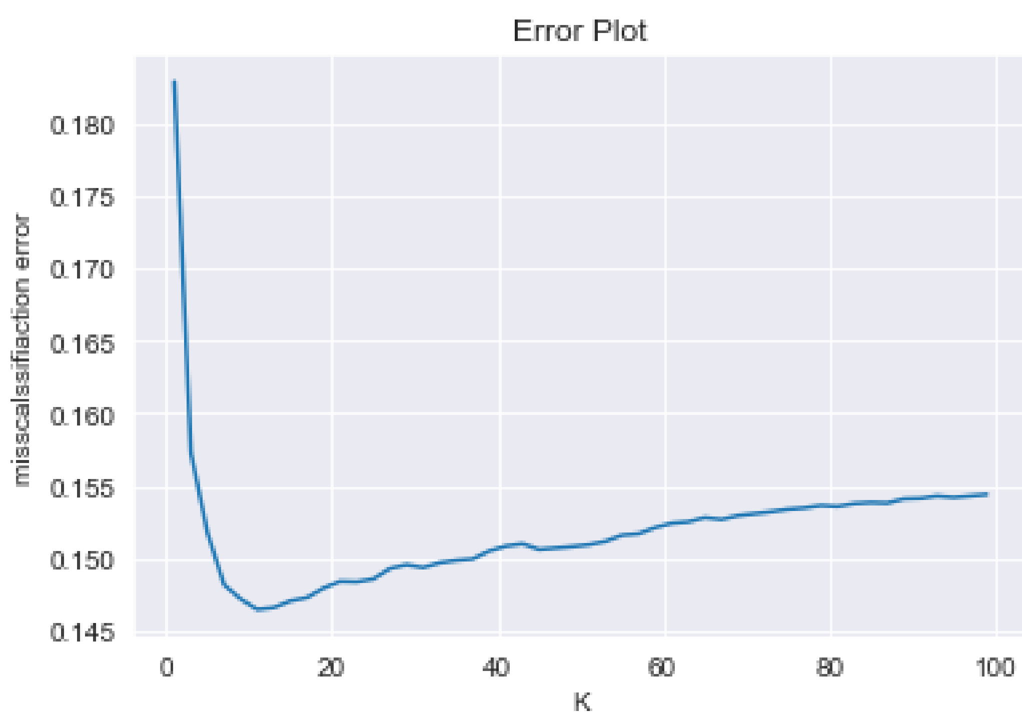
8.0.1 9.1 Brute Force Algorithm

9.1.1 Finding Optimal Value of Hyperparameter(k)

```
In [85]: import numpy as np

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

```
In [86]: 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 :  11
```



9.1.2 Training the model

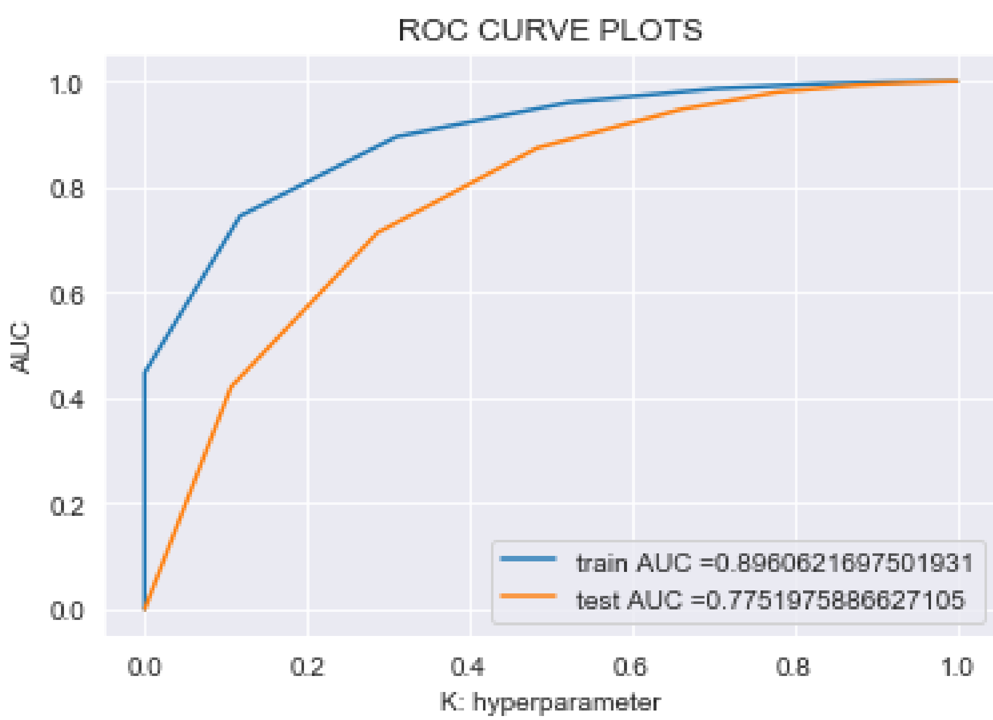
```
In [92]: neigh = KNeighborsClassifier(n_neighbors = best_k,algorithm='brute')
         neigh.fit(X_train_bow, y_train)
```

```
Out[92]: KNeighborsClassifier(algorithm='brute', leaf_size=30, metric='minkowski',
                    metric_params=None, n_jobs=None, n_neighbors=11, p=2,
                    weights='uniform')
```

9.1.3 Evaluting the performance of model

(A). Roc-Auc Plot

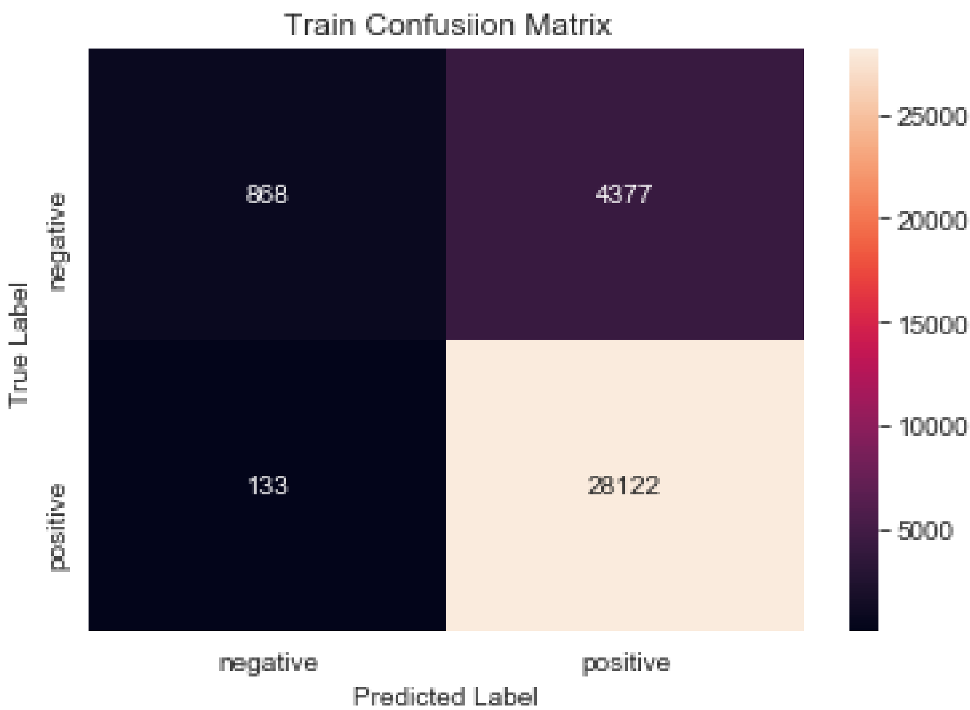
```
In [93]: plot_auc_roc(neigh,X_train_bow,X_test_bow,y_train,y_test)
```



(B). Confusion Matrix Plot on Train Data

```
In [94]: trainconfusionmatrix(neigh,X_train_bow,y_train)
```

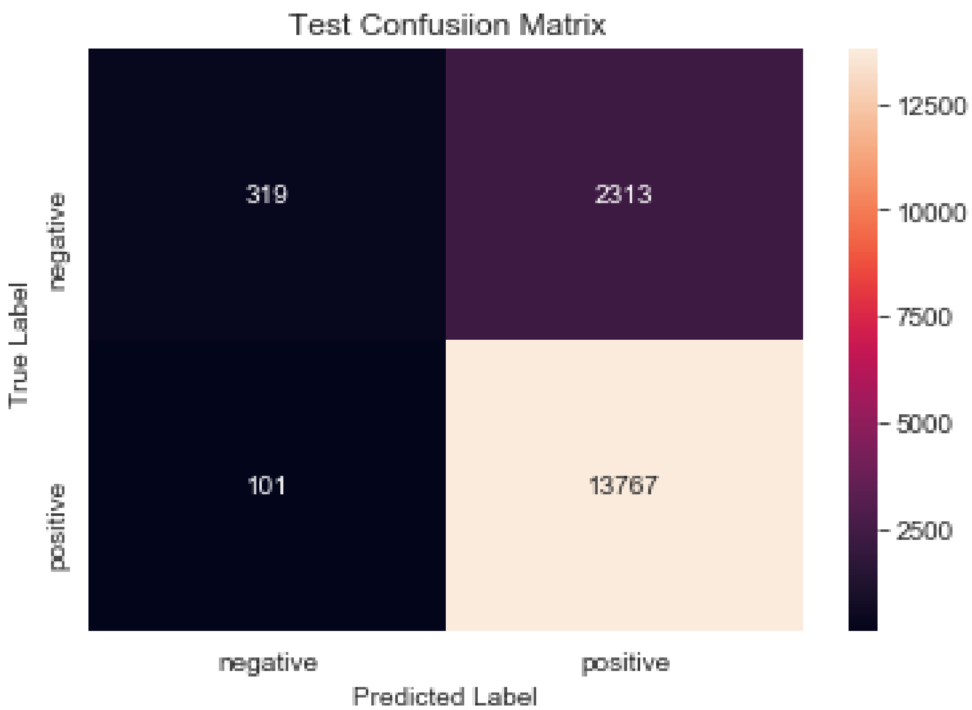
```
Confusion Matrix for Train set
```



(C). Confusion Matrix on Test Data

```
In [95]: testconfusionmatrix(neigh,X_test_bow,y_test)
```

```
Confusion Matrix for Test set
```



(D). Classification Report

```
In [99]: print("Classification Report: \n")
         y_pred=neigh.predict(X_test_bow)

         print(classification_report(y_test, y_pred))
```

```
Classification Report:

              precision    recall  f1-score   support

           0       0.76      0.12      0.21      2632
           1       0.86      0.99      0.92     13868

   micro avg       0.85      0.85      0.85     16500
   macro avg       0.81      0.56      0.56     16500
weighted avg       0.84      0.85      0.81     16500
```

8.0.2 9.2 KD-Tree Algorithm

9.2.1 Finding Optimal Value of Hyperparameter(k)

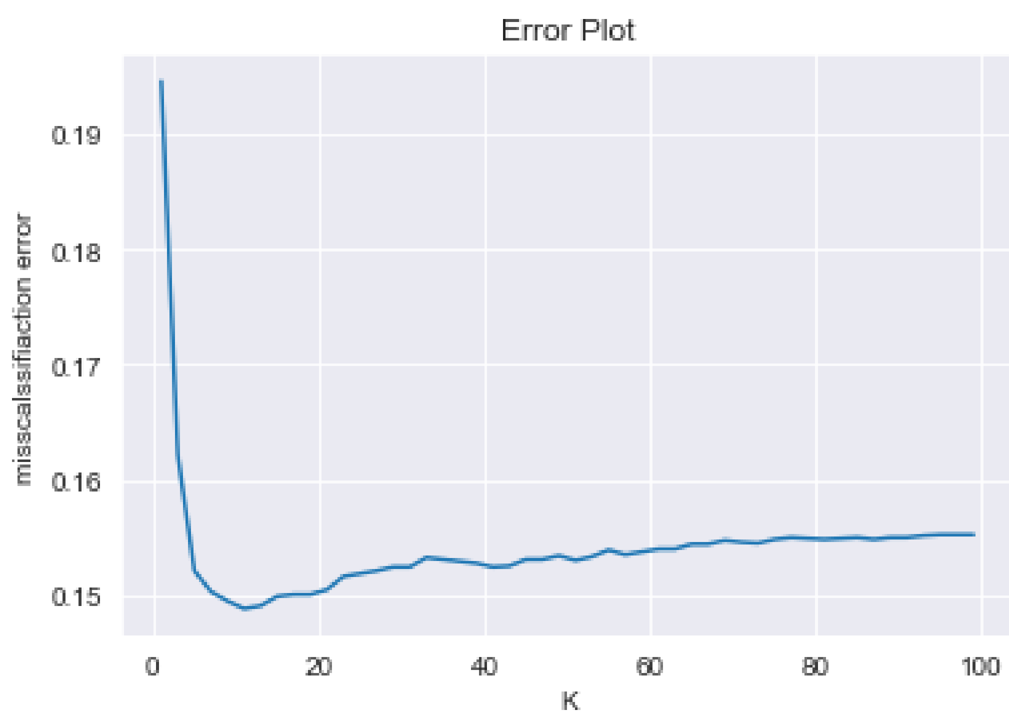
In [100]:
```
vectorizer = CountVectorizer()
vectorizer.fit(X1_train) # fit has to happen only on train data

# we use the fitted CountVectorizer to convert the text to vector
X1_train_bow = vectorizer.transform(X1_train)
X1_train_bow=preprocessing.normalize(X1_train_bow)

X1_test_bow = vectorizer.transform(X1_test)
X1_test_bow=preprocessing.normalize(X1_test_bow)

print("Shape of Train , Test and Cross Validation Data After vectorizations")
print(X1_train_bow.shape, y1_train.shape)
print(X1_test_bow.shape, y1_test.shape)
```

```
Shape of Train , Test and Cross Validation Data After vectorizations
(13400, 14961) (13400,)
(6600, 14961) (6600,)
```

In [101]:
```
import numpy as np

neighbours=np.arange(1,100,2)
mse,best_k = knn_cv_kd(X1_train_bow,y1_train,neighbours)
```

In [102]:
```
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 :  11
```



9.2.2 Training the model

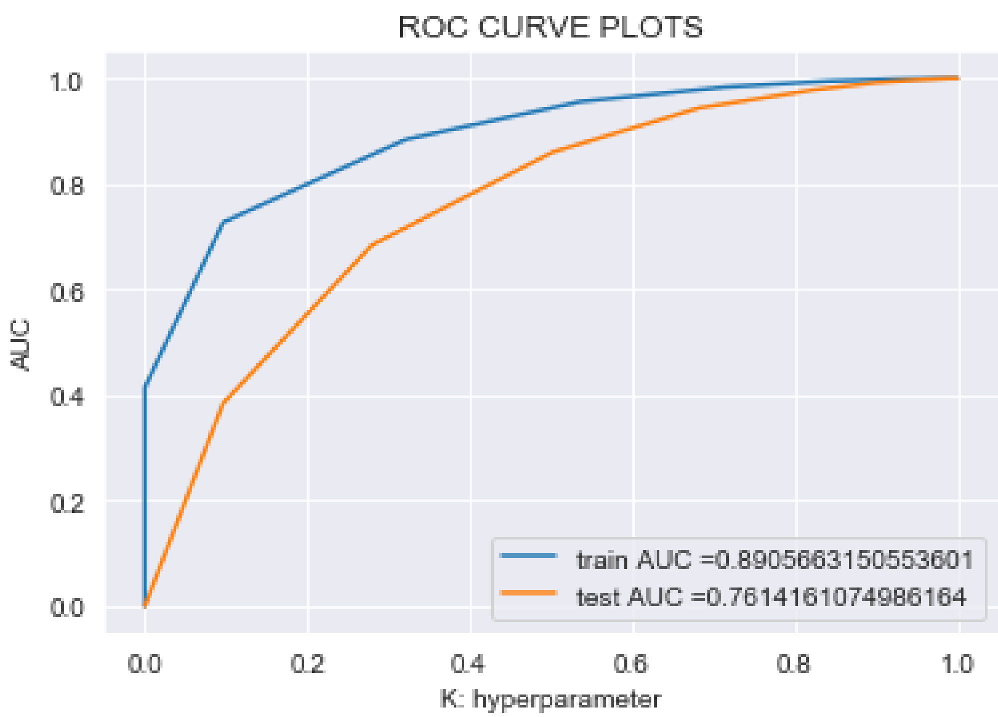
```
In [103]: neigh = KNeighborsClassifier(n_neighbors = best_k,algorithm='kd_tree')
          neigh.fit(X1_train_bow, y1_train)
```

```
Out[103]: KNeighborsClassifier(algorithm='kd_tree', leaf_size=30, metric='minkowski',
                     metric_params=None, n_jobs=None, n_neighbors=11, p=2,
                     weights='uniform')
```

9.2.3 Evaluting the performance of model

(A). Roc-Auc Plot

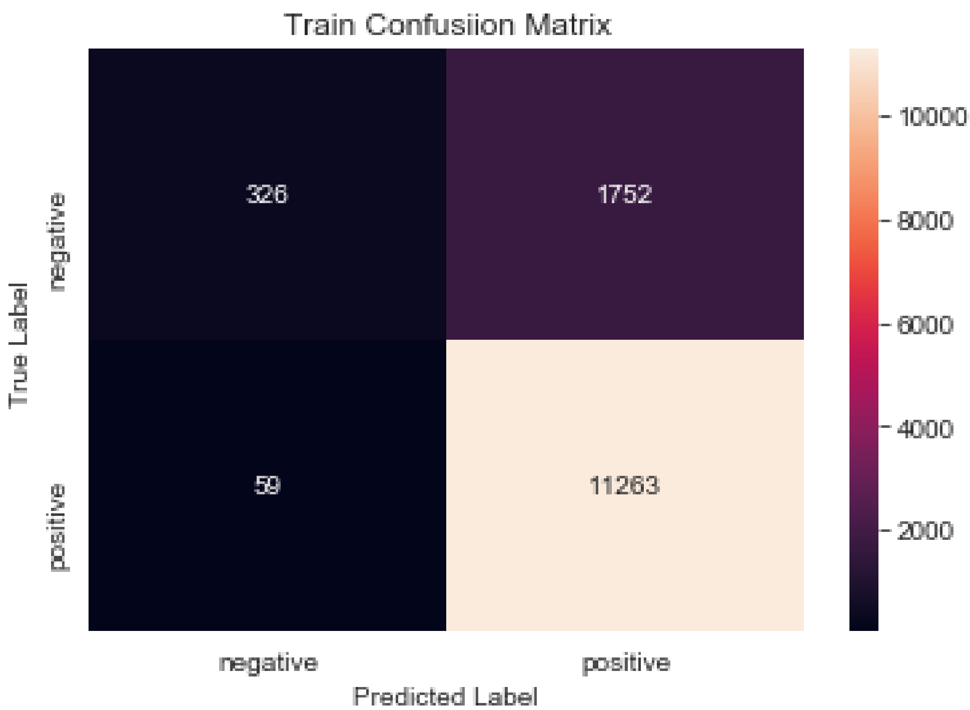
```
In [104]: plot_auc_roc(neigh,X1_train_bow,X1_test_bow,y1_train,y1_test)
```



(B). Confusion Matrix Plot on Train Data

```
In [105]: trainconfusionmatrix(neigh,X1_train_bow,y1_train)
```

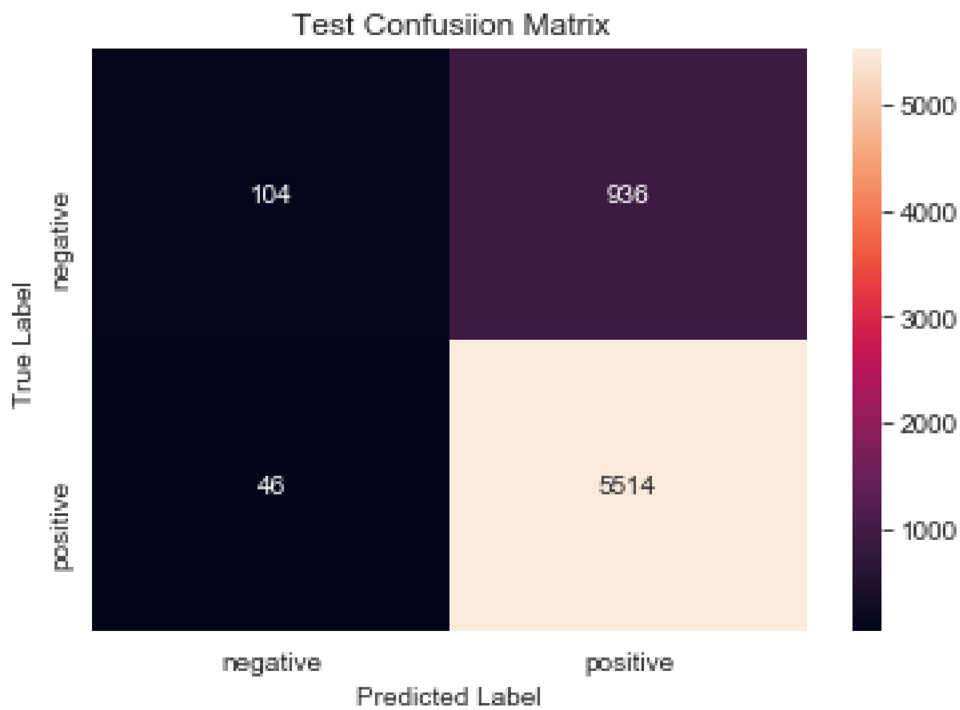
```
Confusion Matrix for Train set
```



(C). Confusion Matrix Plot on Test Data

```
In [106]: testconfusionmatrix(neigh,X1_test_bow,y1_test)
```

```
Confusion Matrix for Test set
```



(D). Classification Report

```
In [107]: print("Classification Report: \n")
          prediction=neigh.predict(X1_test_bow)
          print(classification_report(y1_test, prediction))
```

```
Classification Report:

              precision    recall  f1-score   support

           0       0.69      0.10      0.17      1040
           1       0.85      0.99      0.92      5560

   micro avg       0.85      0.85      0.85      6600
   macro avg       0.77      0.55      0.55      6600
weighted avg       0.83      0.85      0.80      6600
```

9 10.0 TF-IDF

```
In [108]: 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_train_TF= preprocessing.normalize(X_train_TF)

X_test_TF = vectorizer.transform(X_test)
X_test_TF= preprocessing.normalize(X_test_TF)
```

In [109]:
```
print("After vectorizations")
print(X_train_TF.shape, y_train.shape)
print(X_test_TF.shape, y_test.shape)
```

```
After vectorizations
(33500, 588267) (33500,)
(16500, 588267) (16500,)
```

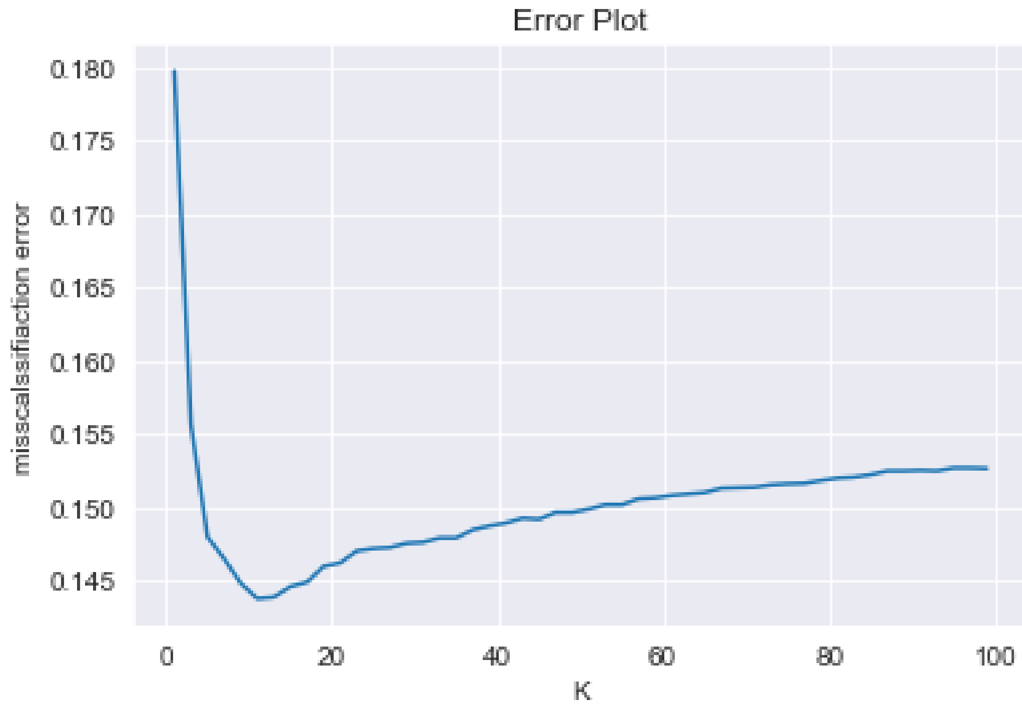
9.0.1 10.1 Brute Force Algorithm

10.1.1 Finding Optimal Value of Hyperparameter(k)

In [110]:
```
import numpy as np

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

In [111]:
```
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 :  11
```



10.1.2 Training the model

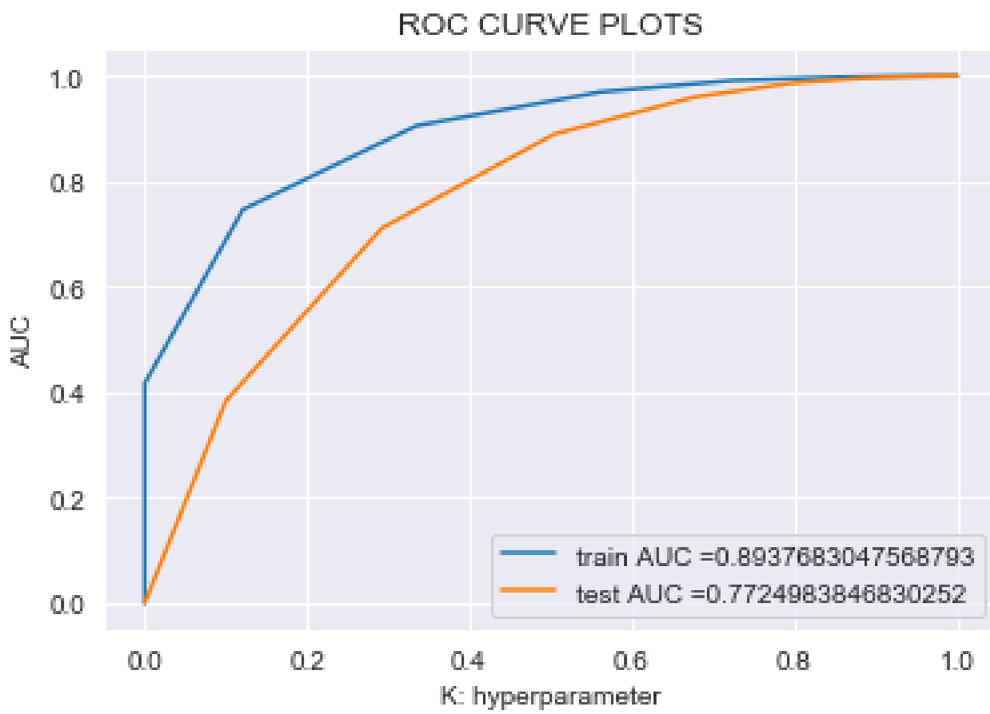
```
In [112]: neigh = KNeighborsClassifier(n_neighbors = best_k,algorithm='brute')
          neigh.fit(X_train_TF, y_train)
```

```
Out[112]: KNeighborsClassifier(algorithm='brute', leaf_size=30, metric='minkowski',
                     metric_params=None, n_jobs=None, n_neighbors=11, p=2,
                     weights='uniform')
```

10.1.3 Evaluting the performance of model

(A). Roc-Auc Plot

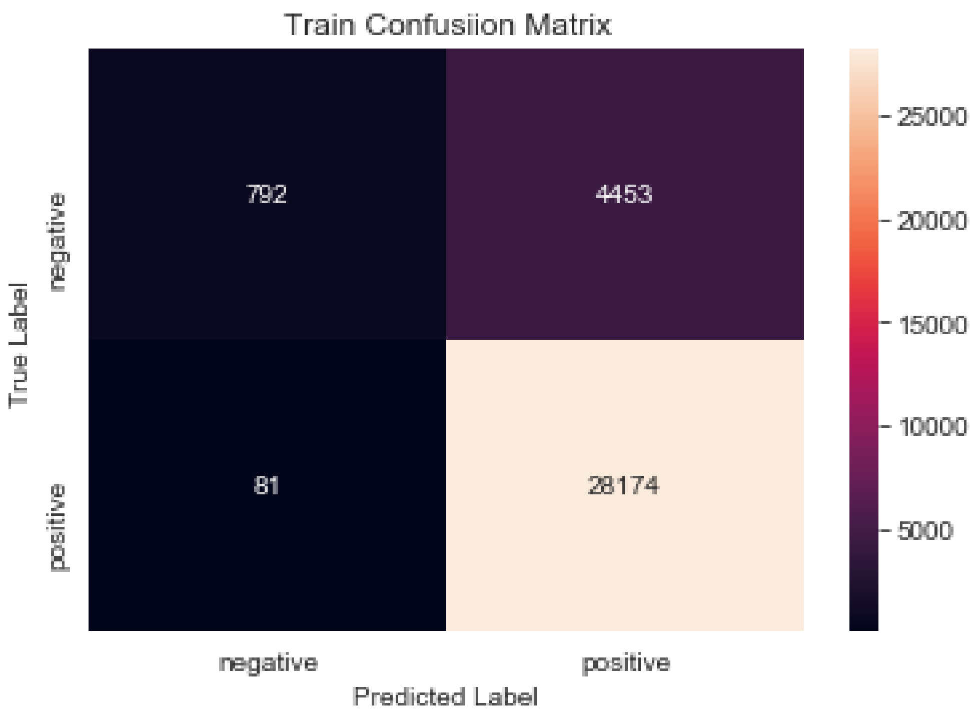
```
In [113]: plot_auc_roc(neigh,X_train_TF,X_test_TF,y_train,y_test)
```



(B). Confusion Matrix Plot on Train Data

```
In [114]: trainconfusionmatrix(neigh,X_train_TF,y_train)
```

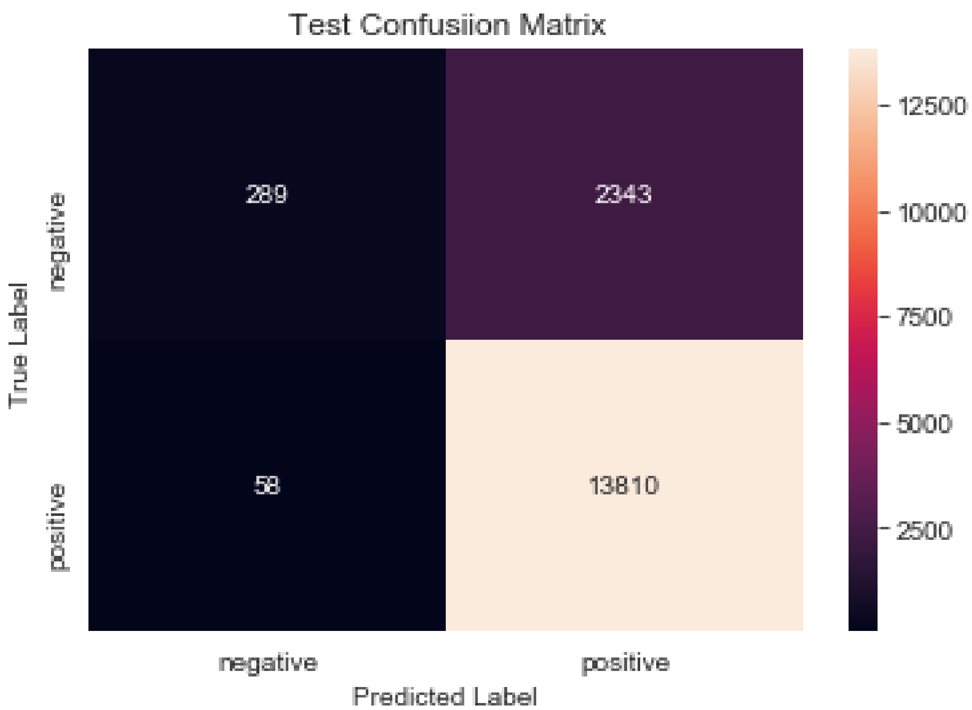
```
Confusion Matrix for Train set
```



(C). Confusion Matrix Plot on Test Data

```
In [115]: testconfusionmatrix(neigh,X_test_TF,y_test)
```

```
Confusion Matrix for Test set
```



(D). Classification Report

```
In [116]: print("Classification Report: \n")
          prediction=neigh.predict(X_test_TF)
          print(classification_report(y_test, prediction))
```

```
Classification Report:

              precision    recall  f1-score   support

           0       0.83      0.11      0.19      2632
           1       0.85      1.00      0.92     13868

   micro avg       0.85      0.85      0.85     16500
   macro avg       0.84      0.55      0.56     16500
weighted avg       0.85      0.85      0.80     16500
```

9.0.2 10.2 KD Tree Algorithm

10.2.1 Finding Optimal Value of Hyperparameter(k)

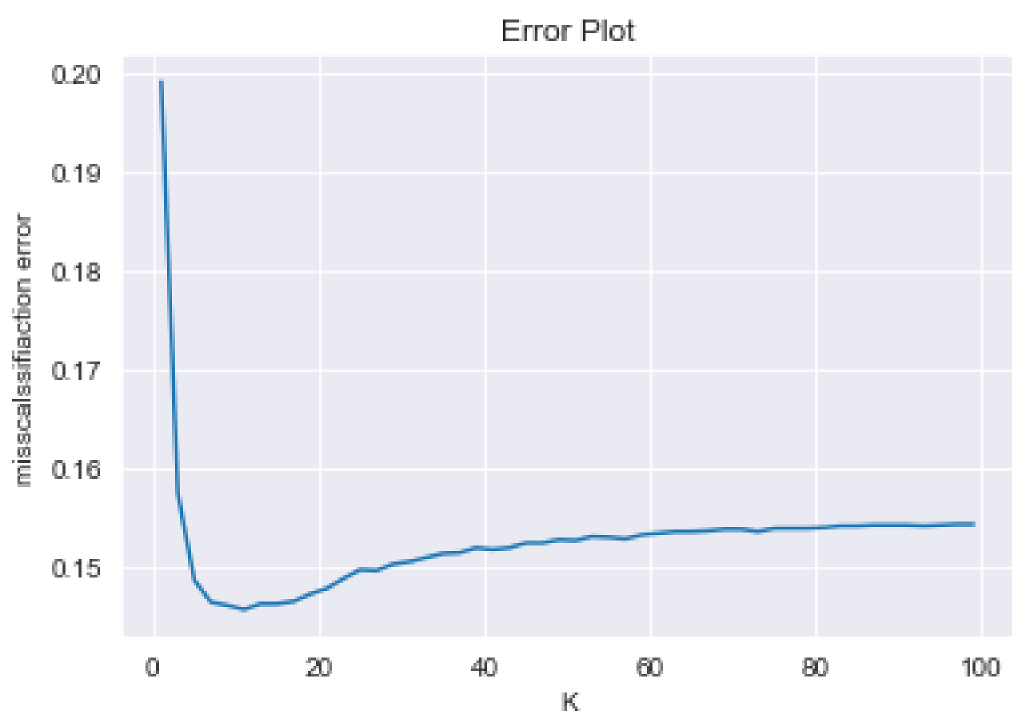
```
In [117]: vectorizer = TfidfVectorizer(ngram_range=(1,2))
          vectorizer.fit(X1_train) # fit has to happen only on train data
```

```
# we use the fitted CountVectorizer to convert the text to vector
X1_train_TF = vectorizer.transform(X1_train)
X1_train_TF= preprocessing.normalize(X1_train_TF)

X1_test_TF = vectorizer.transform(X1_test)
X1_test_TF= preprocessing.normalize(X1_test_TF)
```

In [118]:
```
import numpy as np

neighbours=np.arange(1,100,2)
mse,best_k = knn_cv_kd(X1_train_TF,y1_train,neighbours)
```

In [119]:
```
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 :  11
```



10.2.2 Training the model

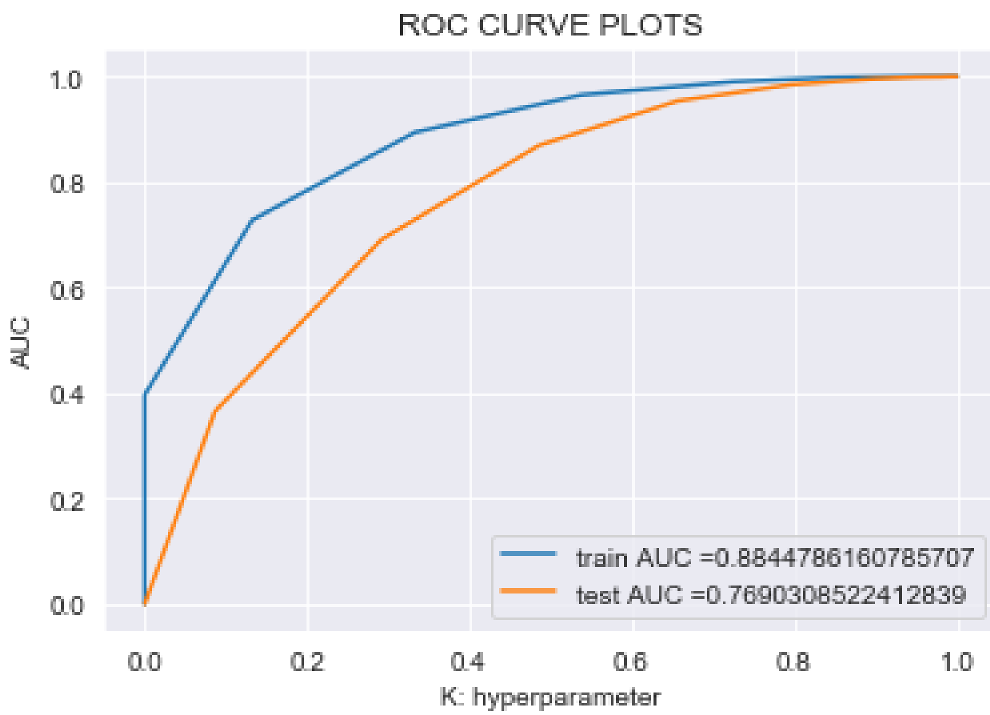
In [120]:
```
neigh = KNeighborsClassifier(n_neighbors = best_k,algorithm='kd_tree')
neigh.fit(X1_train_TF, y1_train)
```

Out[120]:
```
KNeighborsClassifier(algorithm='kd_tree', leaf_size=30, metric='minkowski',
           metric_params=None, n_jobs=None, n_neighbors=11, p=2,
           weights='uniform')
```

10.2.3 Evaluting the performance of model

(A). Roc-Auc Plot

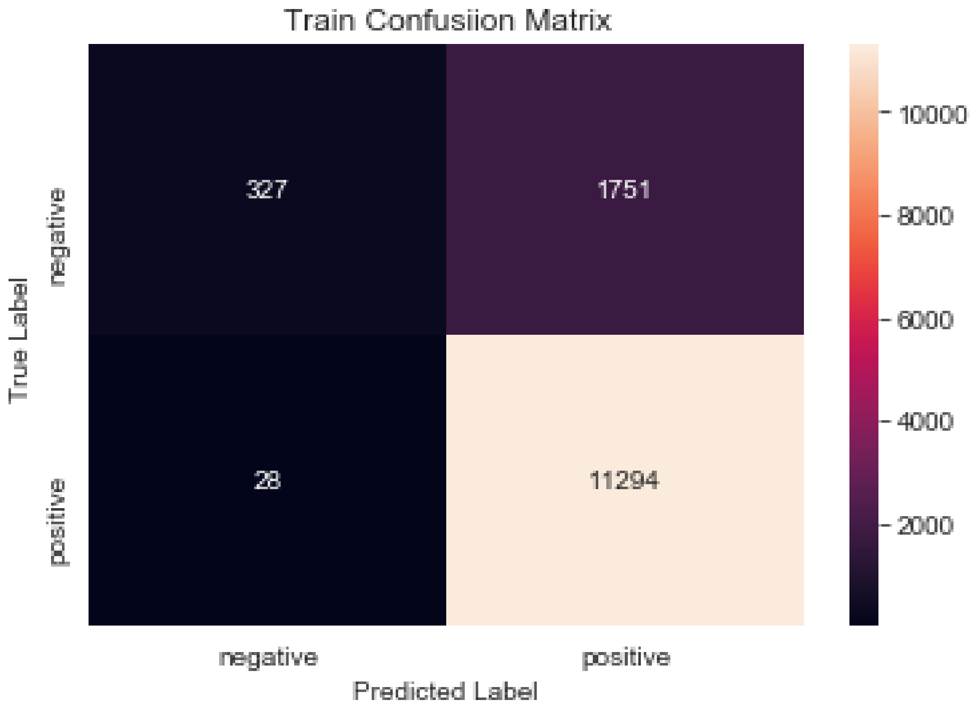
In [121]:
```
plot_auc_roc(neigh,X1_train_TF,X1_test_TF,y1_train,y1_test)
```



(B). Confusion Matrix Plot on Train Data

In [122]:
```
trainconfusionmatrix(neigh,X1_train_TF,y1_train)
```

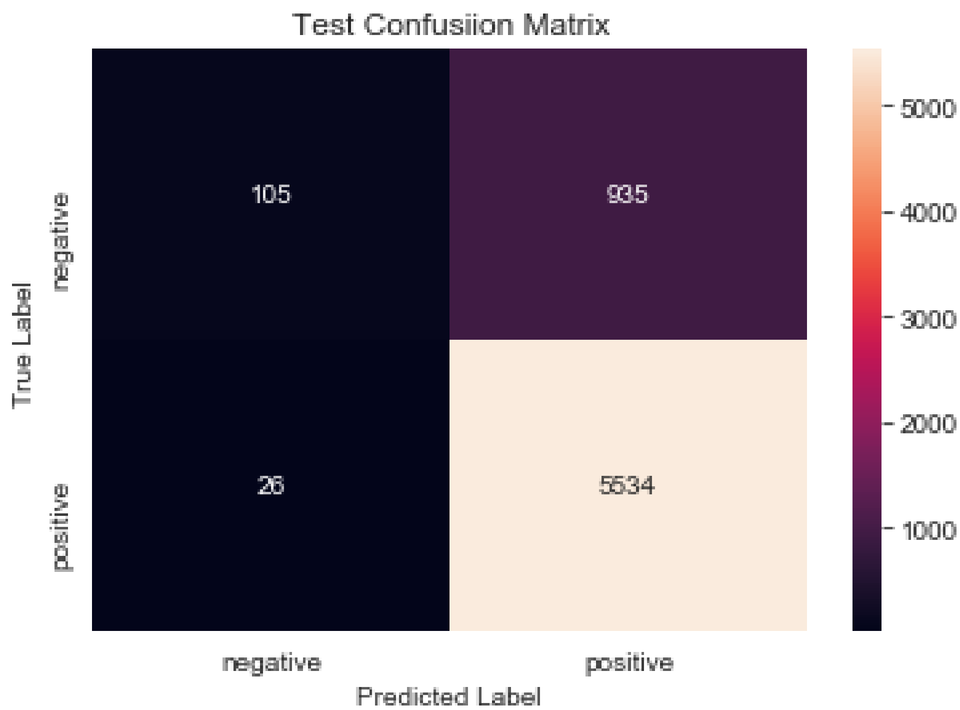
```
Confusion Matrix for Train set
```



(C). Confusion Matrix Plot on Test Data

```
In [123]: testconfusionmatrix(neigh,X1_test_TF,y1_test)
```

```
Confusion Matrix for Test set
```



(D). Classification Report

```
In [124]: print("Classification Report: \n")
          prediction=neigh.predict(X1_test_TF)
          print(classification_report(y1_test, prediction))
```

```
Classification Report: 

              precision    recall  f1-score   support

           0       0.80      0.10      0.18      1040
           1       0.86      1.00      0.92      5560

   micro avg       0.85      0.85      0.85      6600
   macro avg       0.83      0.55      0.55      6600
weighted avg       0.85      0.85      0.80      6600
```

10 11.0 Word To Vector

```
In [126]: 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 [127]:
```
len(list_of_Train_sent)
```

Out[127]: 33500

In [175]:
```
model=Word2Vec(list_of_Train_sent,min_count=5,size=50, workers=4)
```

10.0.1 11.1 Avg Word2Vec

In [176]:
```
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 = 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 [177]:
```
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=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 [178]: print("Shape of Test Vectors : ",Test_vectors.shape)
```

```
Shape of Test Vectors :  (16500, 50)
```

```
In [179]: X_train_AWV = Train_vectors
          X_test_AWV = Test_vectors
```

```
In [180]: print(X_train_AWV.shape, y_train.shape)
          print(X_test_AWV.shape, y_test.shape)
```

```
(33500, 50) (33500,)
(16500, 50) (16500,)
```

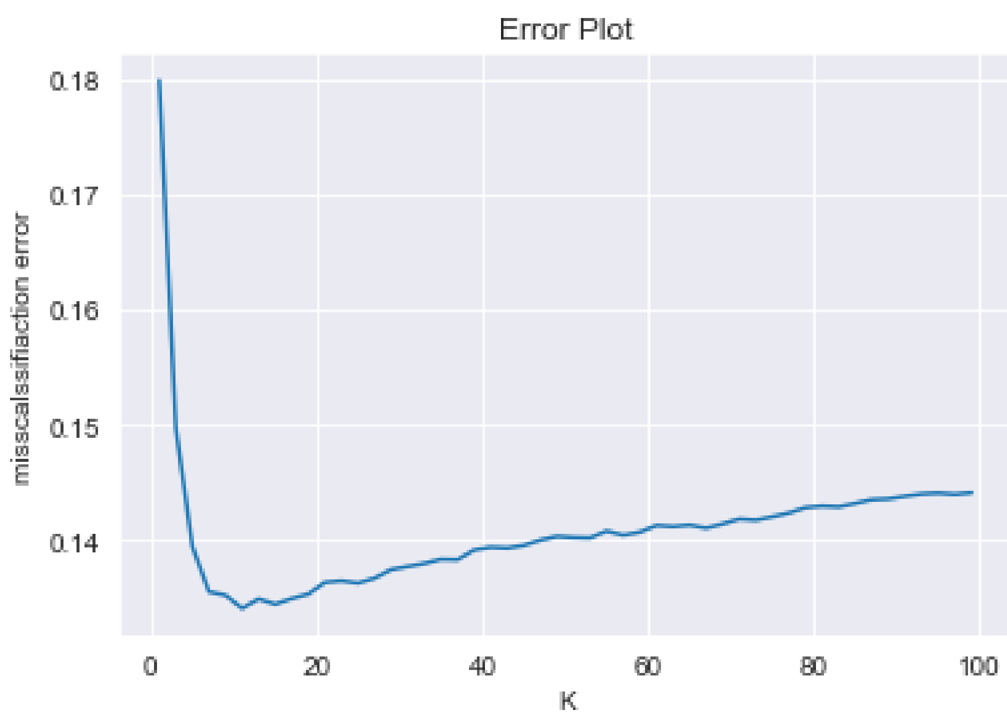
10.0.2 10.2 Brute Force Algorithm

10.2.1 Finding Optimal Value of Hyperparameter(k)

```
In [181]: import numpy as np

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

```
In [182]: 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 :  11
```



10.2.2 Training the model

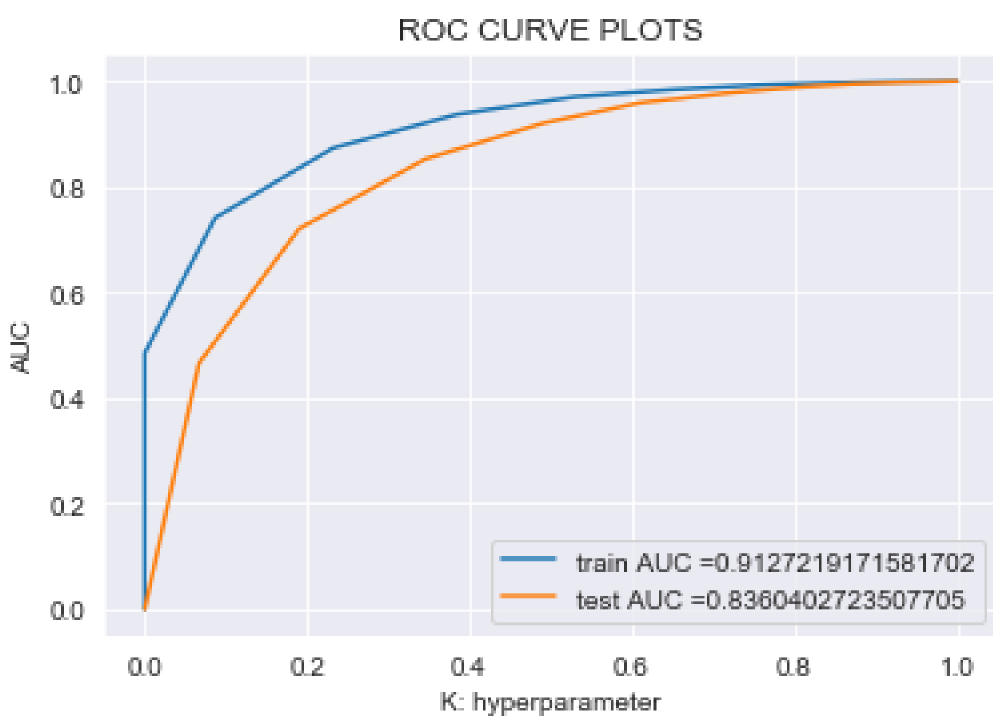
```
In [183]: neigh = KNeighborsClassifier(n_neighbors = best_k,algorithm='brute')
          neigh.fit(X_train_AWV, y_train)
```

```
Out[183]: KNeighborsClassifier(algorithm='brute', leaf_size=30, metric='minkowski',
                     metric_params=None, n_jobs=None, n_neighbors=11, p=2,
                     weights='uniform')
```

10.2.3 Evaluting the performance of model

(A). Roc-Auc Plot

```
In [184]: plot_auc_roc(neigh,X_train_AWV,X_test_AWV,y_train,y_test)
```



(B). Confusion Matrix Plot on Train Data

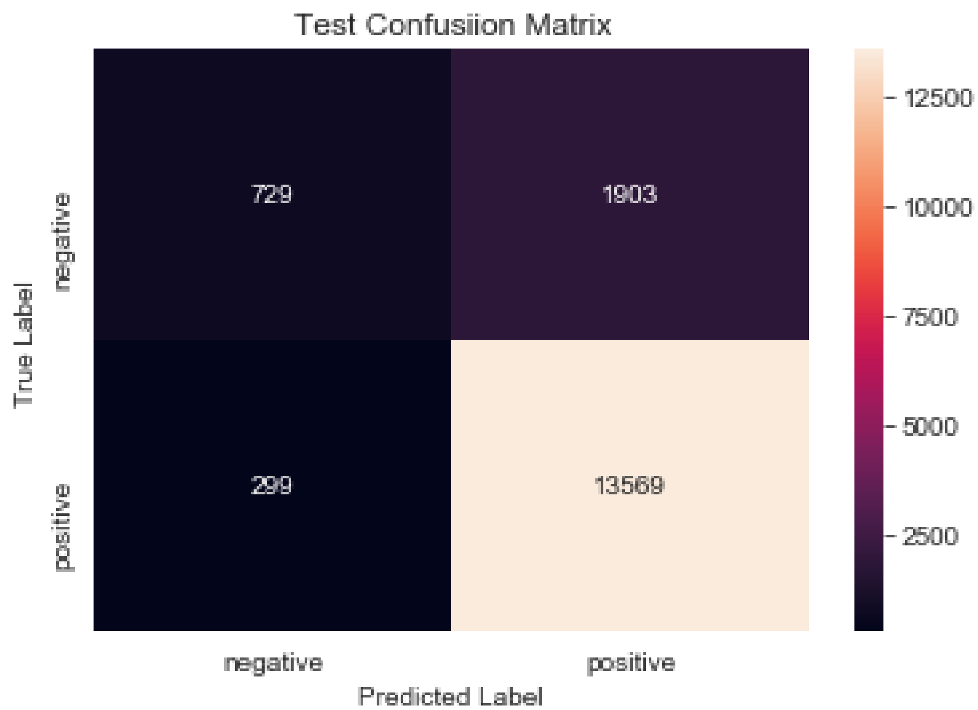
```
In [185]: trainconfusionmatrix(neigh,X_train_AWV,y_train)
```

```
Confusion Matrix for Train set
```

(C). Confusion Matrix Plot on Test Data

```
In [186]: testconfusionmatrix(neigh,X_test_AWV,y_test)
```

```
Confusion Matrix for Test set
```



(D). Classification Report

```
In [187]: print("Classification Report: \n")
          prediction=neigh.predict(X_test_AWV)
          print(classification_report(y_test, prediction))
```

```
Classification Report:

              precision    recall  f1-score   support

           0       0.71      0.28      0.40      2632
           1       0.88      0.98      0.92     13868

   micro avg       0.87      0.87      0.87     16500
   macro avg       0.79      0.63      0.66     16500
weighted avg       0.85      0.87      0.84     16500
```

10.0.3 10.3 KD Tree Algorithm

```
In [157]: list_of_Train_sent1=[]
          list_of_Test_sent1=[]
```

```
for sent in X1_train:
    list_of_Train_sent1.append(sent.split())

for sent in X1_test:
    list_of_Test_sent1.append(sent.split())
```

In [158]:
```
Train_model1=Word2Vec(list_of_Train_sent1,min_count=5,size=50, workers=4)
```

In [162]:
```
import numpy as np

Train_vectors1 = []
for sent in list_of_Train_sent1:
    sent_vec = np.zeros(50)
    cnt_words = 0
    for word in sent:
        try:
            vec = Train_model1.wv[word]
            sent_vec += vec
            cnt_words += 1
        except:
            pass
    if cnt_words!=0:
        sent_vec /= cnt_words
    Train_vectors1.append(sent_vec)
Train_vectors1 = np.nan_to_num(Train_vectors1)
```

In [163]:
```
Train_vectors1.shape
```

Out[163]:
```
(13400, 50)
```

In [164]:
```
import numpy as np

Test_vectors1=[]
for sent in list_of_Test_sent1:
    sent_vec=np.zeros(50)
    cnt_words=0
    for word in sent:
        try:
            vec=Train_model1.wv[word]
            sent_vec+=vec
            cnt_words+=1
        except:
            pass
    if cnt_words!=0:
        sent_vec/=cnt_words
    Test_vectors1.append(sent_vec)
Test_vectors1=np.nan_to_num(Test_vectors1)
```

In [165]:
```
Test_vectors1.shape
```

```
Out[165]: (6600, 50)
```

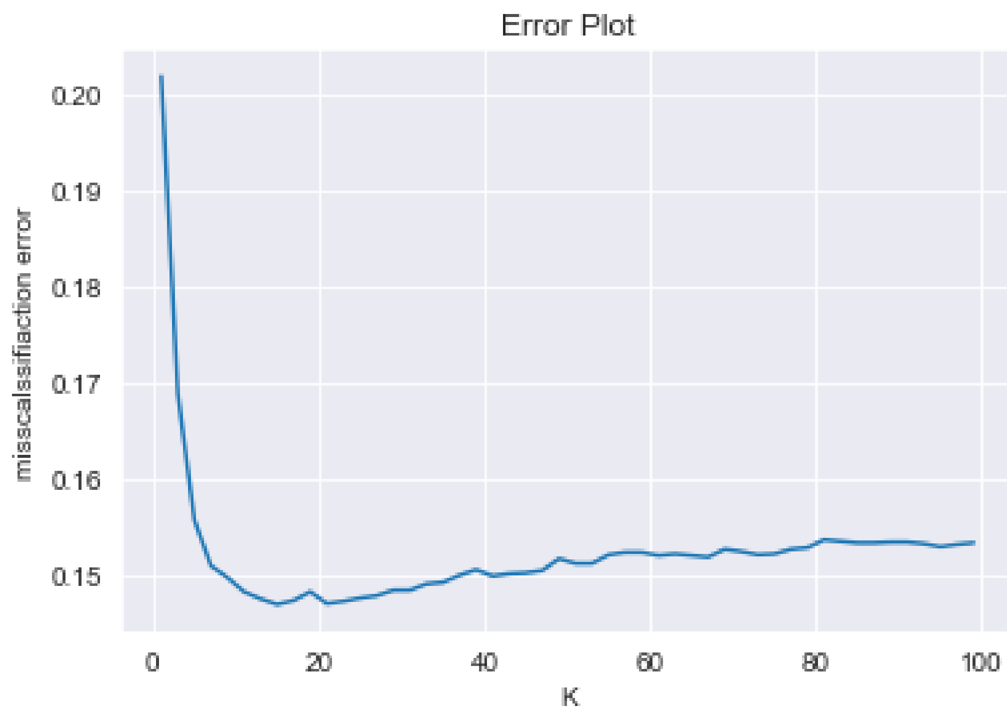
```
In [166]: X_train_AWV1 = Train_vectors1
          X_test_AWV1 = Test_vectors1
```

10.3.1 Finding Optimal Value of Hyperparameter(k)

```
In [168]: import numpy as np

          neighbours=np.arange(1,100,2)
          mse,best_k = knn_cv_kd(X_train_AWV1,y1_train,neighbours)
```

```
In [169]: 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 :  15
```



10.3.2 Training the model

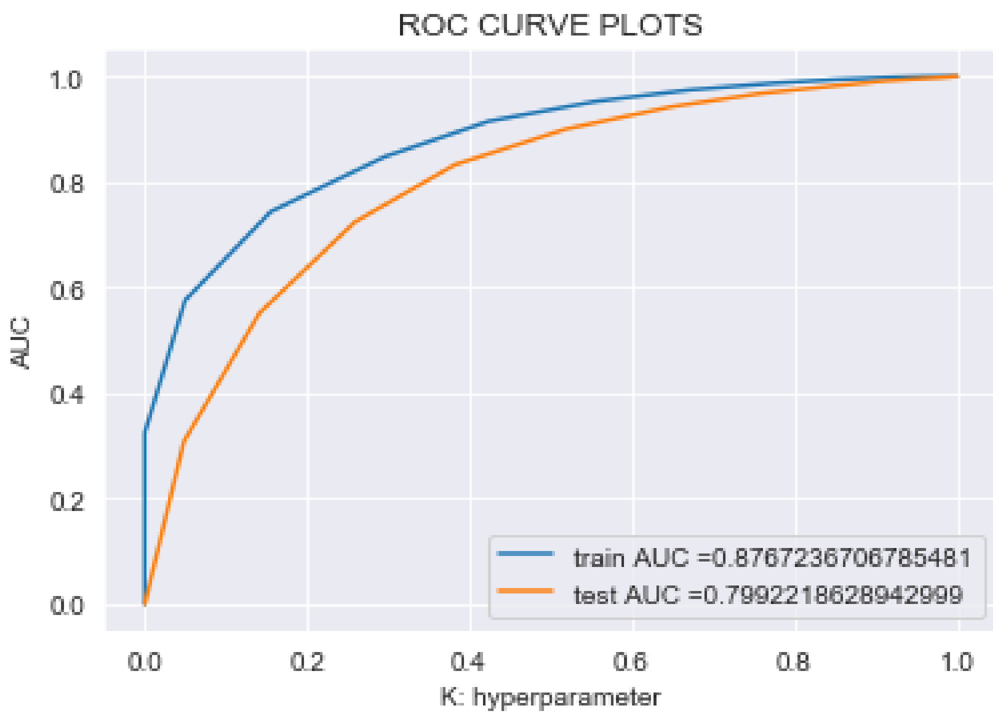
```
In [170]: neigh = KNeighborsClassifier(n_neighbors = best_k,algorithm='kd_tree')
          neigh.fit(X_train_AWV1, y1_train)
```

```
Out[170]: KNeighborsClassifier(algorithm='kd_tree', leaf_size=30, metric='minkowski',
                     metric_params=None, n_jobs=None, n_neighbors=15, p=2,
                     weights='uniform')
```

10.3.3 Evaluting the performance of model

(A). Roc-Auc Plot

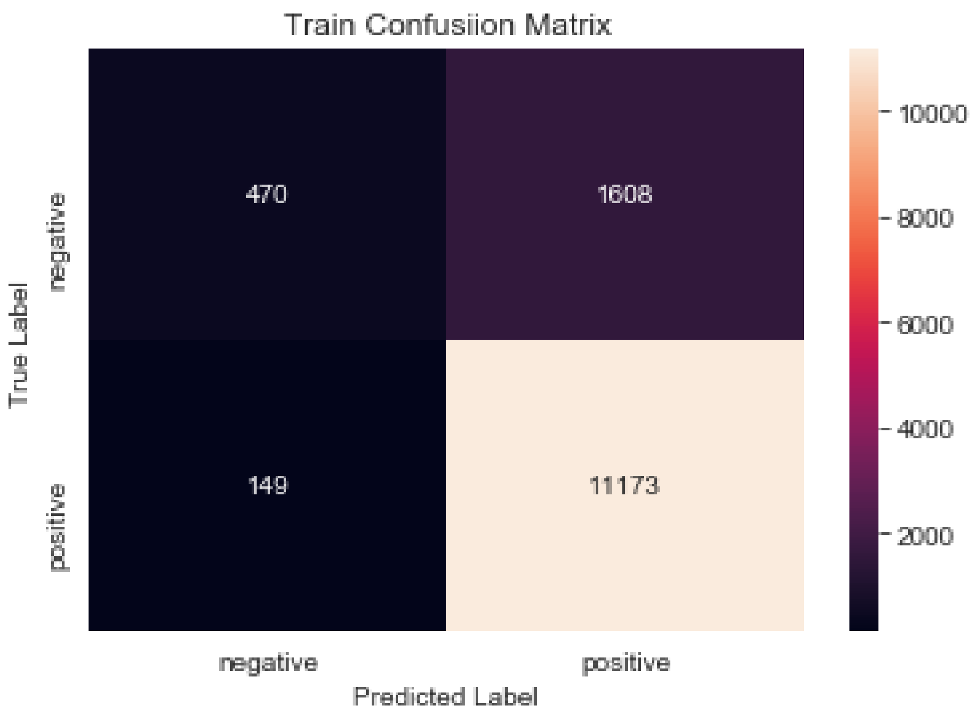
```
In [171]: plot_auc_roc(neigh,X_train_AWV1,X_test_AWV1,y1_train,y1_test)
```



(B). Confusion Matrix Plot on Train Data

```
In [172]: trainconfusionmatrix(neigh,X_train_AWV1,y1_train)
```

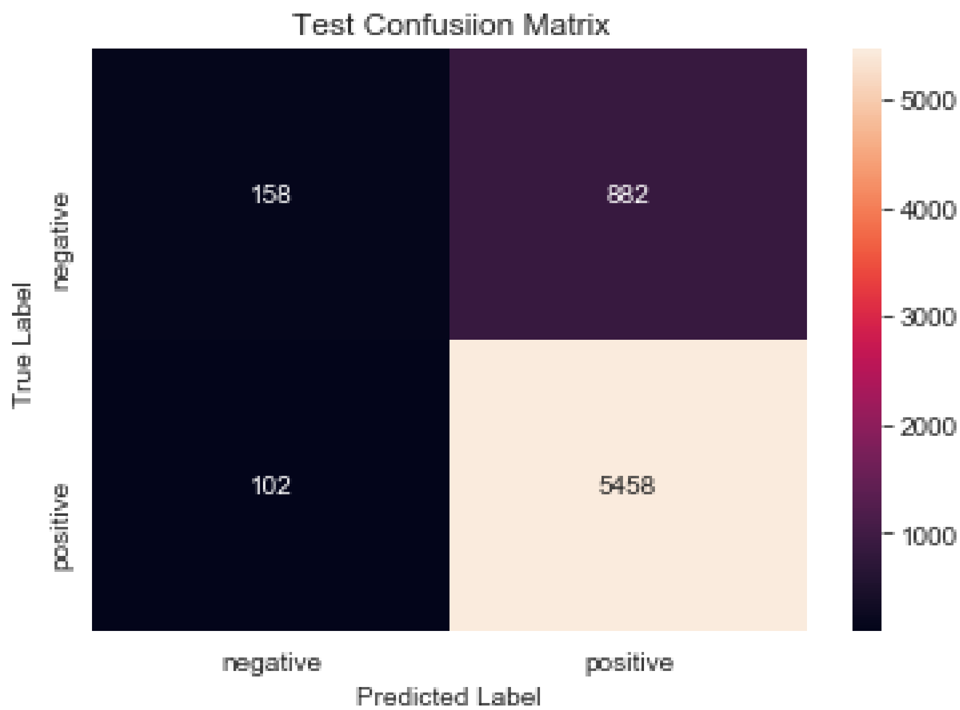
```
Confusion Matrix for Train set
```



(C). Confusion Matrix Plot on Test Data

```
In [173]: testconfusionmatrix(neigh,X_test_AWV1,y1_test)
```

```
Confusion Matrix for Test set
```



(D). Classification Report

```
In [174]: print("Classification Report: \n")
          prediction=neigh.predict(X_test_AWV1)
          print(classification_report(y1_test, prediction))
```

```
Classification Report: 

              precision    recall  f1-score   support

           0       0.61      0.15      0.24      1040
           1       0.86      0.98      0.92      5560

   micro avg       0.85      0.85      0.85      6600
   macro avg       0.73      0.57      0.58      6600
weighted avg       0.82      0.85      0.81      6600
```

11 11.0 TF-IDF Word To Vector

```
In [209]: model_TF = TfidfVectorizer()
          model_TF.fit(X_train)
```

```
X_Train_TF = model_TF.transform(X_train)
X_Test_TF = model_TF.transform(X_test)
```

In [210]:
```
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 :  (33500, 23006)
Shape of Test Data After TFIDF :  (16500, 23006)
```

In [211]:
```
TFIDF_Feature=model_TF.get_feature_names()
print(len(TFIDF_Feature))
print(TFIDF_Feature[0:20])
```

```
23006
['aa', 'aaaaawsom', 'aaf', 'aafco', 'aamzon', 'aarp', 'aarrgh', 'aauc', 'ab', 'aback', 'abamec
```

In [212]:
```
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=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%|| 33500/33500 [13:32<00:00, 36.56it/s]
```

In [213]:
```
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=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%|| 16500/16500 [05:41<00:00, 74.72it/s]
```

In [214]:
```
Test_tfidfw2v_vectors=np.nan_to_num(Test_TFIDF_W2V_Vectors)
Train_tfidfw2v_vectors=np.nan_to_num(Train_TFIDF_W2V_Vectors)
```

In [215]:
```
X_train_TfIdfW2v=Train_tfidfw2v_vectors
X_test_TfIdfW2v=Test_tfidfw2v_vectors
```

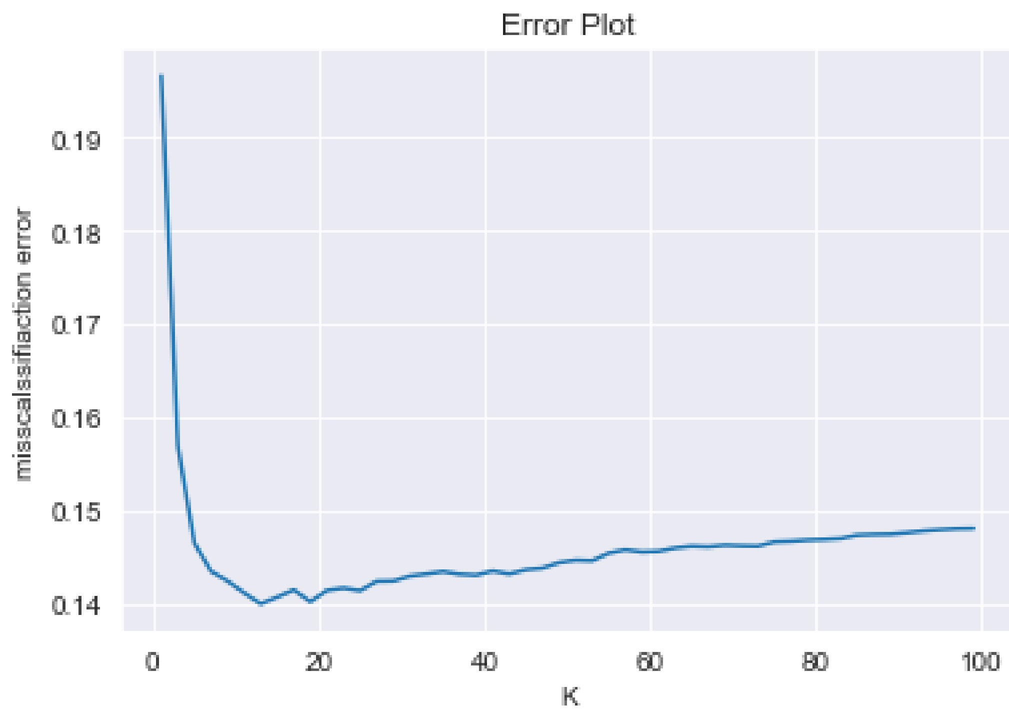
11.0.1 11.1 Brute Force Algorithm

11.1.1 Finding Optimal Value of Hyperparameter(k)

In [216]:
```
import numpy as np

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

In [217]:
```
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 :  13
```



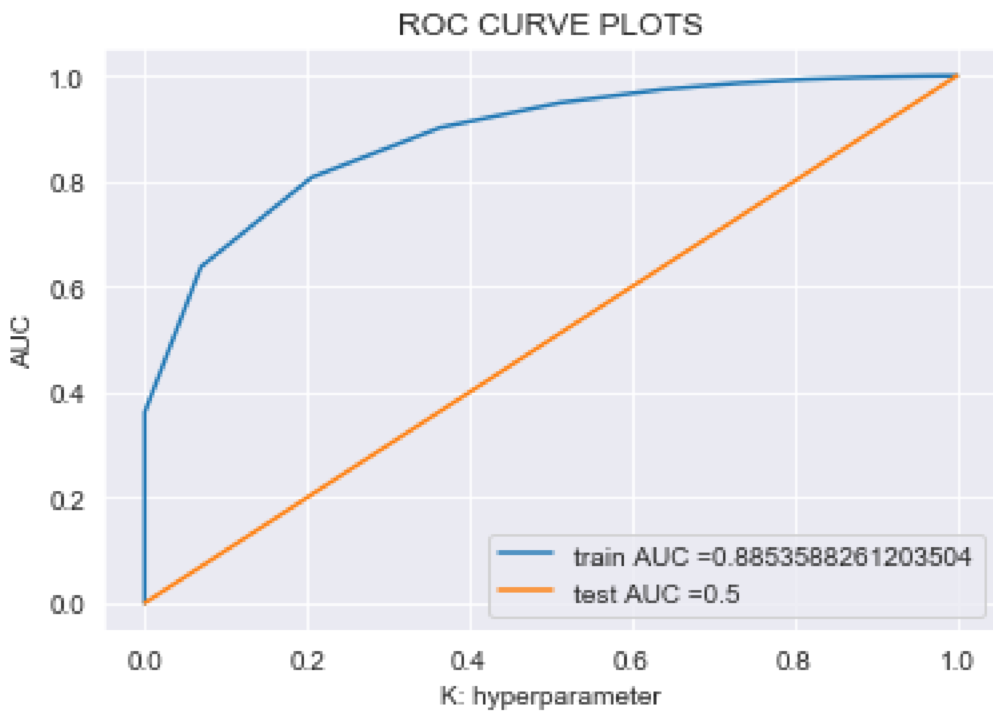
11.1.2 Training the model

```
In [218]: neigh = KNeighborsClassifier(n_neighbors = best_k,algorithm='brute')
          neigh.fit(X_train_TfIdfW2v, y_train)

Out[218]: KNeighborsClassifier(algorithm='brute', leaf_size=30, metric='minkowski',
                     metric_params=None, n_jobs=None, n_neighbors=13, p=2,
                     weights='uniform')
```

11.1.3 Evaluting the performance of model

(A). Roc-Auc Plot

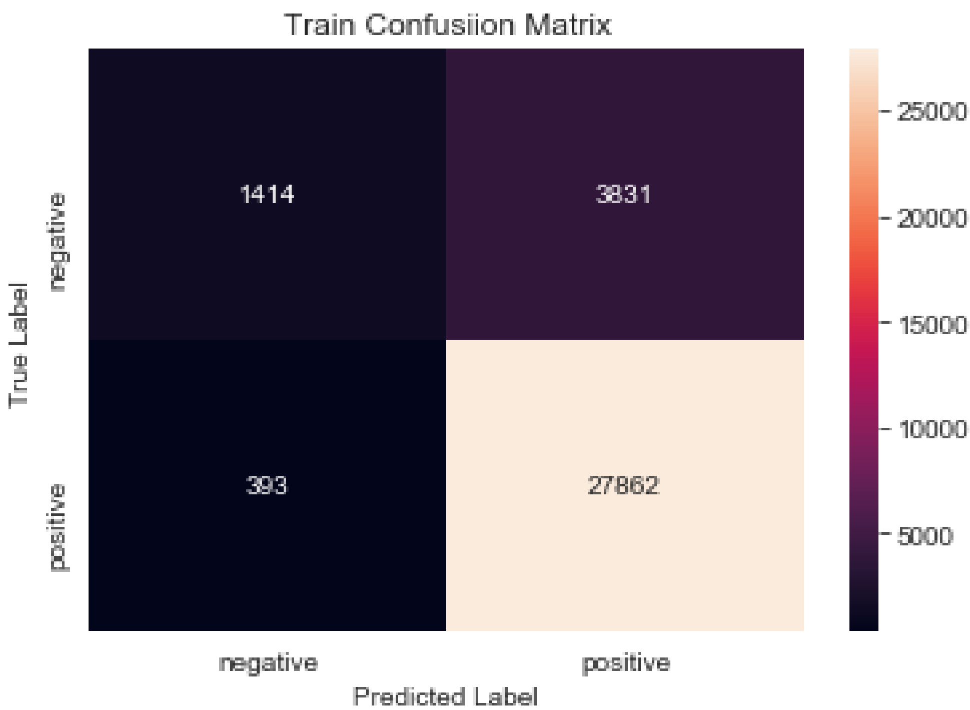
```
In [219]: plot_auc_roc(neigh,X_train_TfIdfW2v,X_test_TfIdfW2v,y_train,y_test)
```



(B). Confusion Matrix Plot on Train Data

```
In [220]: trainconfusionmatrix(neigh,X_train_TfIdfW2v,y_train)
```

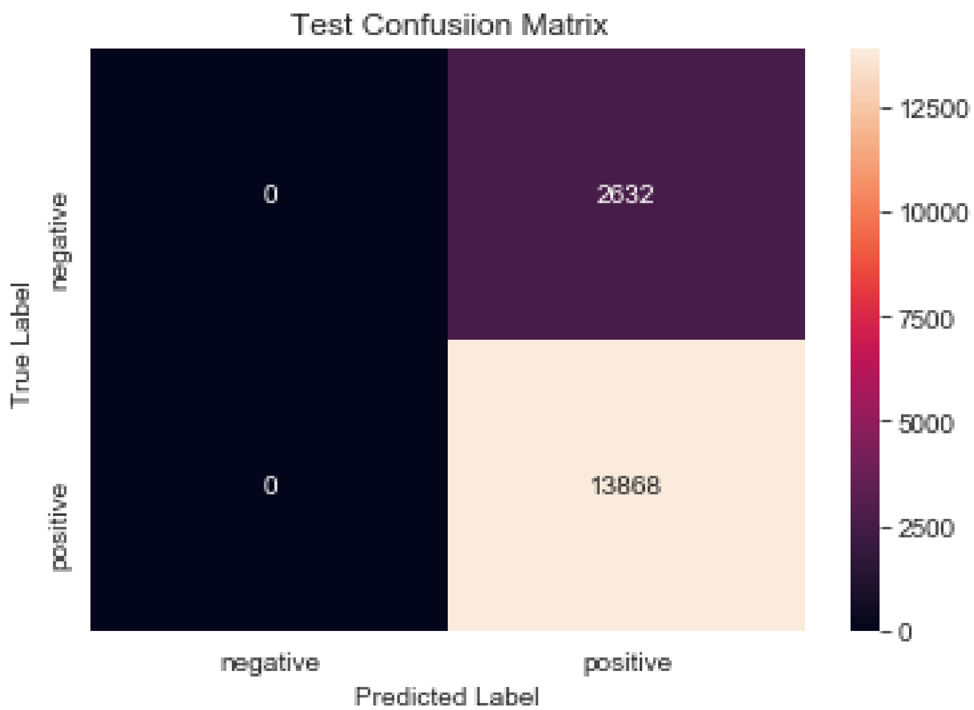
```
Confusion Matrix for Train set
```



(C). Confusion Matrix Plot on Test Data

```
In [221]: testconfusionmatrix(neigh,X_test_TfIdfW2v,y_test)
```

```
Confusion Matrix for Test set
```



(D). Classification Report

```
In [222]: print("Classification Report: \n")
          prediction=neigh.predict(X_test_TfIdfW2v)
          print(classification_report(y_test, prediction))
```

```
Classification Report:

              precision    recall  f1-score   support

           0       0.00      0.00      0.00      2632
           1       0.84      1.00      0.91     13868

   micro avg       0.84      0.84      0.84     16500
   macro avg       0.42      0.50      0.46     16500
weighted avg       0.71      0.84      0.77     16500
```

11.0.2 11.2 KD Tree Algorithm

```
In [223]: model_TF1 = TfidfVectorizer()
          model_TF1.fit(X_train)
          X_Train_TF1 = model_TF1.transform(X1_train)
          X_Test_TF1 = model_TF1.transform(X1_test)
```

```
In [224]: print("Shape of Train Data After TFIDF : ",X_Train_TF1.shape)
          print("Shape of Test Data After TFIDF : ",X_Test_TF1.shape)
```

```
Shape of Train Data After TFIDF :  (13400, 23006)
Shape of Test Data After TFIDF :  (6600, 23006)
```

```
In [225]: TFIDF_Feature1=model_TF1.get_feature_names()
          print(len(TFIDF_Feature1))
          print(TFIDF_Feature1[0:20])
```

```
23006
['aa', 'aaaaawsom', 'aaf', 'aafco', 'aamzon', 'aarp', 'aarrgh', 'aauc', 'ab', 'aback', 'abamec
```

```
In [226]: from tqdm import tqdm
          Train_TFIDF_W2V_Vectors1=[]
          row=0
          for sent in tqdm(list_of_Train_sent1):
              sent_vec=np.zeros(50)
              weight=0
              for word in sent:
                  try :
                      w2v_vec=Train_model1.wv[word]
                      tfidf_vec=X_Train_TF1[row,TFIDF_Feature1.index(word)]
                      sent_vec+=(w2v_vec*tfidf_vec)
                      weight+=tfidf_vec

                  except :
                      pass
              if weight!=0:
                  sent_vec/=weight
              Train_TFIDF_W2V_Vectors1.append(sent_vec)
              row+=1
```

```
100%|| 13400/13400 [04:57<00:00, 39.20it/s]
```

```
In [227]: Test_TFIDF_W2V_Vectors1=[]
          row=0
          for sent in tqdm(list_of_Test_sent1):
              sent_vec=np.zeros(50)
              weight=0

              for word in sent:
                  try:
                      w2v_vec=Train_model1.wv[word]
                      tfidf_vec=X_Test_TF1(row,TFIDF_Feature1.index(word))
                      sent_vec+=(w2v_vec*tfidf_vec)
```

```
                    weight+=tfidf

                except :
                    pass

            if weight!=0:
                sent_vec/=weight
            Test_TFIDF_W2V_Vectors1.append(sent_vec)
            row+=1
```

```
100%|| 6600/6600 [02:18<00:00, 47.62it/s]
```

In [228]:
```
Test_tfidfw2v_vectors1=np.nan_to_num(Test_TFIDF_W2V_Vectors1)
Train_tfidfw2v_vectors1=np.nan_to_num(Train_TFIDF_W2V_Vectors1)
```

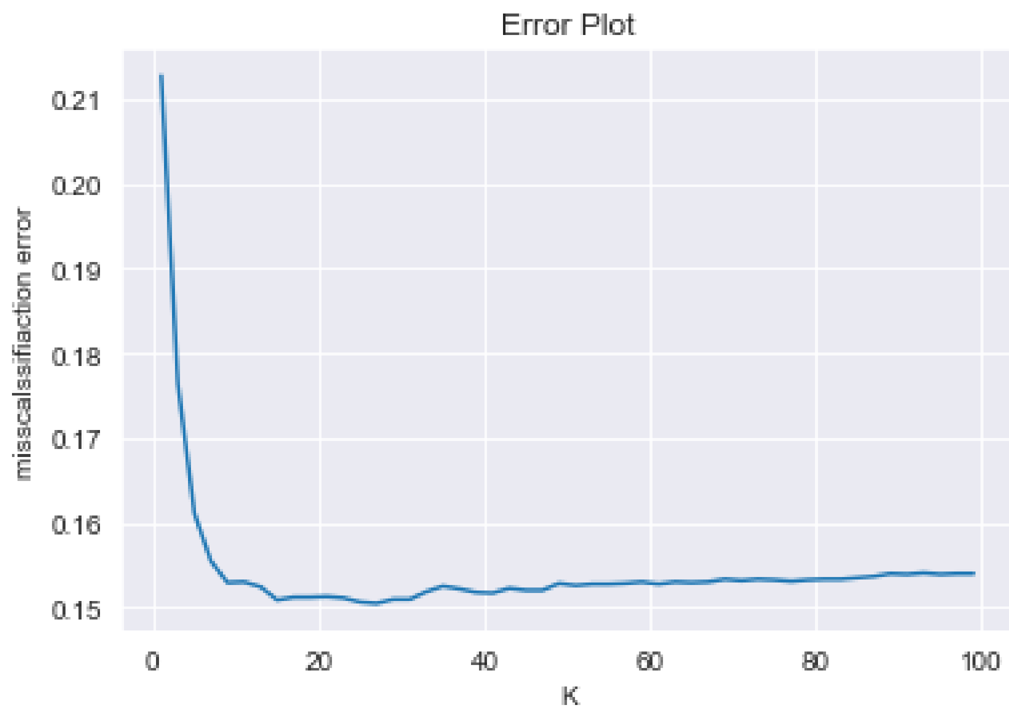
In [231]:
```
X_train_TfIdfW2v1=Train_tfidfw2v_vectors1
X_test_TfIdfW2v1=Test_tfidfw2v_vectors1
```

11.2.1 Finding Optimal Value of Hyperparameter(k)

In [232]:
```
import numpy as np

neighbours=np.arange(1,100,2)
mse,best_k = knn_cv_kd(X_train_TfIdfW2v1,y1_train,neighbours)
```

In [233]:
```
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 :  27
```



11.2.2 Training the model

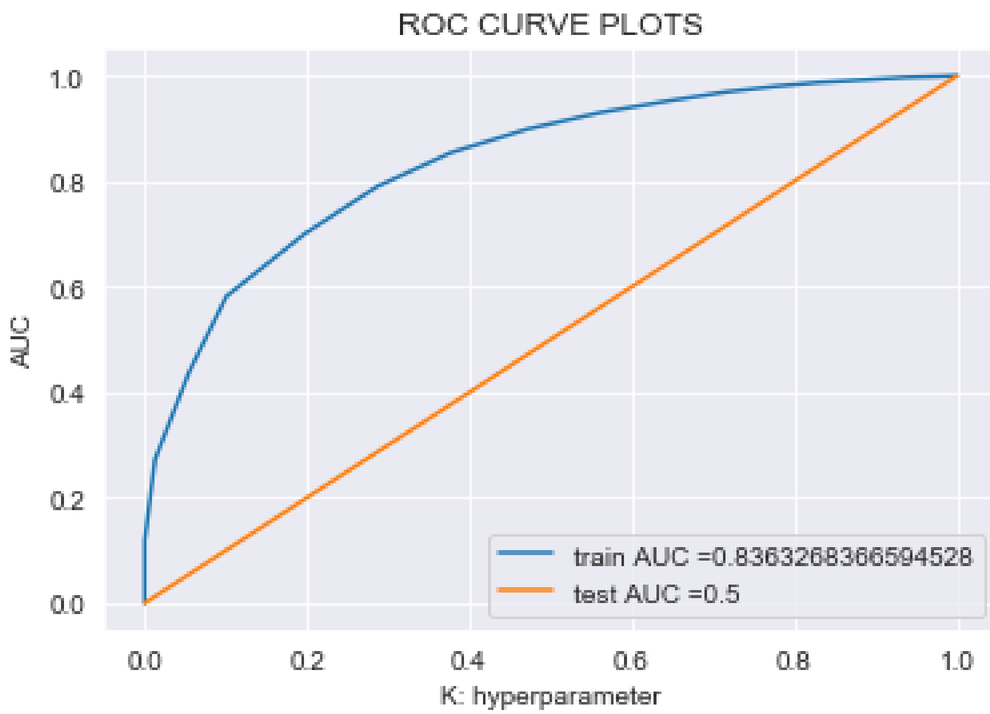
```
In [234]: neigh = KNeighborsClassifier(n_neighbors = best_k,algorithm='kd_tree')
          neigh.fit(X_train_TfIdfW2v1, y1_train)
```

```
Out[234]: KNeighborsClassifier(algorithm='kd_tree', leaf_size=30, metric='minkowski',
                     metric_params=None, n_jobs=None, n_neighbors=27, p=2,
                     weights='uniform')
```

11.2.3 Evaluting the performance of model

(A). Roc-Auc Plot

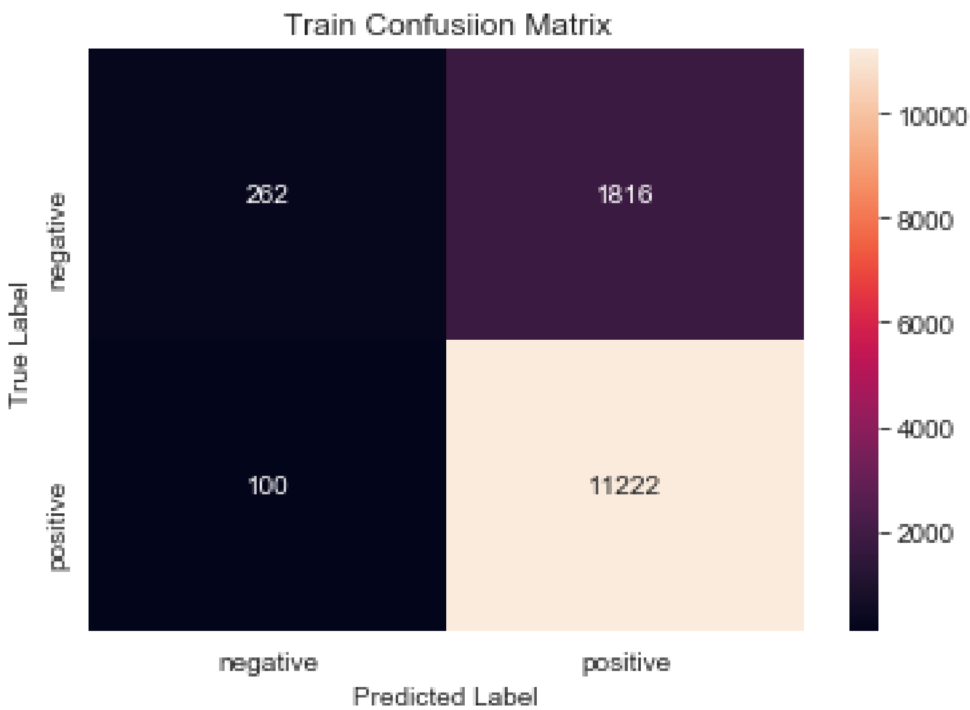
```
In [235]: plot_auc_roc(neigh,X_train_TfIdfW2v1,X_test_TfIdfW2v1,y1_train,y1_test)
```



(B). Confusion Matrix Plot on Train Data

```
In [236]: trainconfusionmatrix(neigh,X_train_TfIdfW2v1,y1_train)
```

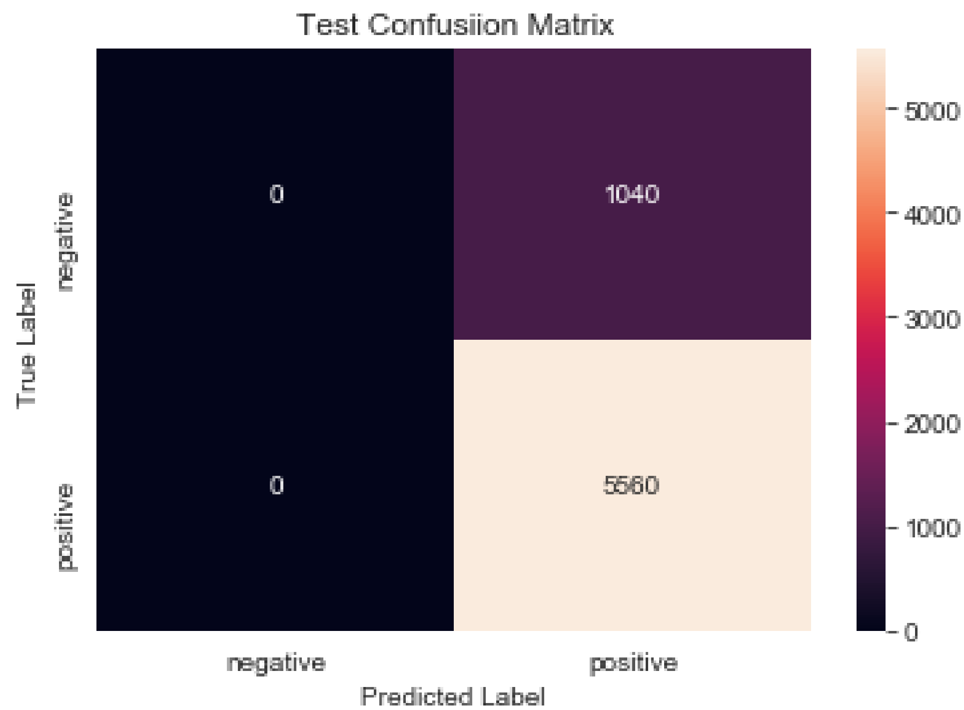
```
Confusion Matrix for Train set
```



(C). Confusion Matrix Plot on Test Data

```
In [237]: testconfusionmatrix(neigh,X_test_TfIdfW2v1,y1_test)
```

```
Confusion Matrix for Test set
```



(D). Classification Report

```
In [238]: print("Classification Report: \n")
          prediction=neigh.predict(X_test_TfIdfW2v1)
          print(classification_report(y1_test, prediction))
```

```
Classification Report:

              precision    recall  f1-score   support

           0       0.00      0.00      0.00      1040
           1       0.84      1.00      0.91      5560

   micro avg       0.84      0.84      0.84      6600
   macro avg       0.42      0.50      0.46      6600
weighted avg       0.71      0.84      0.77      6600
```

12 12.0 Conclusion :

1. Report On Brute Force Algorithm

```
In [242]: from prettytable import PrettyTable

          x = PrettyTable()

          x.field_names = ["Vectorizer", "Hyperparameter","F1-Score","Train AUC","Test AUC"]

          x.add_row(["BOW",11,0.81,0.89,0.77])
          x.add_row(["TF-IDF",11,0.80,0.89,0.77])
          x.add_row(["W2V",11,0.84,0.91,0.83])
          x.add_row(["TF-IDF W2V",13,0.77,0.88,0.50])
          print(x)
```

```
+------------+----------------+----------+-----------+----------+
| Vectorizer | Hyperparameter | F1-Score | Train AUC | Test AUC |
+------------+----------------+----------+-----------+----------+
|    BOW     |       11       |   0.81   |    0.89   |   0.77   |
|   TF-IDF   |       11       |   0.8    |    0.89   |   0.77   |
|    W2V     |       11       |   0.84   |    0.91   |   0.83   |
| TF-IDF W2V |       13       |   0.77   |    0.88   |   0.5    |
+------------+----------------+----------+-----------+----------+
```

2. Report on KD Tree Algorithm

```
In [241]: x = PrettyTable()

          x.field_names = ["Vectorizer","Hyperparameter","F1-Score","Train AUC","Test AUC"]

          x.add_row(["BOW",11,0.80,0.89,0.76])
          x.add_row(["TF-IDF",11,0.80,0.88,0.76])
          x.add_row(["W2V",15,0.81,0.87,0.79])
          x.add_row(["TF-IDF W2V",27,0.77,0.83,0.50])
          print(x)
```

```
+------------+----------------+----------+-----------+----------+
| Vectorizer | Hyperparameter | F1-Score | Train AUC | Test AUC |
+------------+----------------+----------+-----------+----------+
|    BOW     |       11       |   0.8    |    0.89   |   0.76   |
|   TF-IDF   |       11       |   0.8    |    0.88   |   0.76   |
|    W2V     |       15       |   0.81   |    0.87   |   0.79   |
| TF-IDF W2V |       27       |   0.77   |    0.83   |   0.5    |
+------------+----------------+----------+-----------+----------+
```

3. BOW and TF-IDF are giving same result of Hyperparameter,F1-Score,Train-AUC and Test-AUC.

4. Average Word To Vector is performing better than other vectorizer method.

5. The KD-Tree and Brute Force implementation of KNN gives relatively similar results.

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 .