KNN Algorithm implementation over Amazon fine food reviews dataset

In [2]:
```
%matplotlib inline

import warnings
warnings.filterwarnings("ignore")

from datetime import datetime
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.feature_extraction.text import TfidfTransformer
from sklearn.feature_extraction.text import TfidfVectorizer

from sklearn.feature_extraction.text import CountVectorizer
from sklearn.metrics import confusion_matrix
from sklearn import metrics

from sklearn.cross_validation import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score
from sklearn.cross_validation import cross_val_score
from collections import Counter
from sklearn.metrics import accuracy_score
from sklearn import cross_validation
from sklearn.model_selection import train_test_split
from imblearn.over_sampling import SMOTE
from prettytable import PrettyTable
```

Connecting to the Preprocessed SQLite database__

In [3]:
```
#Connecting to the SQL table
con = sqlite3.connect('final.sqlite')

#Reading data from the database

Data = pd.read_sql_query("""
SELECT *
FROM Reviews """,con)
Data.shape
```

Out[3]:
```
(364171, 12)
```

In [4]:
```
# Drop index column
Data.drop(columns=['index'],inplace=True)
```

In [5]:
```
Data["Time"]=pd.to_datetime(Data.Time)
Data.head(5)
```

Out[5]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	
0	150524	0006641040	ACITT7DI6IDDL	shari zychinski	0	0	positive	1970- 00:00:00.9393
1	150506	0006641040	A2IW4PEEKO2R0U	Tracy	1	1	positive	1970- 00:00:01.1947
2	150507	0006641040	A1S4A3IQ2MU7V4	sally sue "sally sue"	1	1	positive	1970- 00:00:01.1914
3	150508	0006641040	AZGXZ2UUK6X	Catherine Hallberg " (Kate)"	1	1	positive	1970- 00:00:01.0760
4	150509	0006641040	A3CMRKGE0P909G	Teresa	3	4	positive	1970- 00:00:01.0183

In [6]:

```
#Setting Time column as index of the dataframe
Data.set_index("Time",inplace=True)

#Sampling the above data
Sorted=Data.sort_index()
```

In [7]:

```
Sorted.head()
```

Out[7]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Sc
Time							
1970-01-01 00:00:00.939340800	150524	0006641040	ACITT7DI6IDDL	shari zychinski	0	0	posit
1970-01-01 00:00:00.940809600	150501	0006641040	AJ46FKXOVC7NR	Nicholas A Mesiano	2	2	posit
1970-01-01 00:00:00.944092800	451856	B00004CXX9	AIUWLEQ1ADEG5	Elizabeth Medina	0	0	posit
1970-01-01 00:00:00.944438400	374359	B00004CI84	A344SMIA5JECGM	Vincent P. Ross	1	2	posit
1970-01-01 00:00:00.946857600	451855	B00004CXX9	AJH6LUC1UT1ON	The Phantom of the Opera	0	0	posit

In [8]:

```
#Sampling the above data

Sampled_data=Sorted.sample(n=20000,replace='False')
Sample_sort=Sampled_data.sort_index()
Sample_sort.shape
```

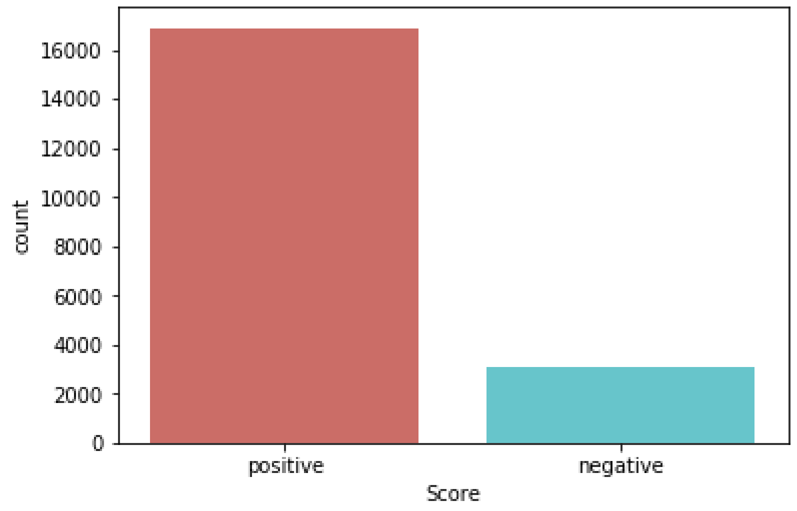
Out[8]: (20000, 10)

In [9]:

```
sampled_data=Sorted.sample(n=5000,replace='False')
mini_sort=sampled_data.sort_index()
mini_sort.shape
```

Out[9]: (5000, 10)

In [10]:
```
label=mini_sort["Score"]
Class=Sample_sort["Score"]
sns.countplot(x="Score",data=Sample_sort,palette="hls")
plt.show()
plt.savefig("count_plot")
```




```
<Figure size 432x288 with 0 Axes>
```

In [11]:
```
#Dropping the Score column which are the actual class labels of the dataset
mini_sort.drop(columns=['Score'],inplace=True)
mini_sort.shape
```

Out[11]: (5000, 9)

In [12]:
```
#Dropping the Score column from the sampled_set which are the actual class labels of the dataset
Sample_sort.drop(columns=['Score'],inplace=True)
Sample_sort.shape
```

Out[12]: (20000, 9)

Observations

- Here after all the text-preprocesing and the data-cleaning only 364k datapoints remained.
- I have taken a sample size of 20k out of the total population for the purpose of analyzing and studying the behaviour of the data by applying the K-nearest neighbour algorithm.
- First I took the "TIME" column and set as the index of the new sampled dataframe and then sorted accordingly in ascending order since the data has a temporal nature.
- By setting the "SCORE" column as a class label for classifying the reviews as a positive and negative.
- By observing the above bar plot it is clear that the above dataset is highly imbalanced and this may cause problems in the future analysis.

Splitting the data into 80:20 partitions sets

In [13]:
```
def data_split(x,y):
    #Splitting the model into 80:30 split of Training and test split
    X_tr, X_test, y_tr, y_test = train_test_split(X, Y, test_size=0.2,shuffle=False,random_state=None)


    return X_tr,y_tr,X_test,y_test
```

Preparing the data for further use

In [14]:
```
X=Sample_sort
Y=Class

X_tr,y_tr,X_test,y_test=data_split(X,Y)

print("The shape of x_train is:",X_tr.shape)
print("the shape of y_train is:",y_tr.shape)
print("the shape of x_test is:",X_test.shape)
print("the shape of y_test is:",y_test.shape)
```

```
The shape of x_train is: (16000, 9)
the shape of y_train is: (16000,)
the shape of x_test is: (4000, 9)
the shape of y_test is: (4000,)
```

Preparing the data for applying the kd-tree approach

In [25]:
```python
X_1=mini_sort
Y_1=label

X_train,X_Test,y_train,y_Test=train_test_split(X_1, Y_1, test_size=0.2,shuffle=False,random_state=None
)

print("The shape of x_train is:",X_train.shape)
print("the shape of y_train is:",y_train.shape)
print("the shape of x_test is:",X_Test.shape)
print("the shape of y_test is:",y_Test.shape)
```

```
The shape of x_train is: (4000, 9)
the shape of y_train is: (4000,)
the shape of x_test is: (1000, 9)
the shape of y_test is: (1000,)
```

Utility functions for training the models

In [37]:
```
#Function for Training the model

def train (X_tr,y_tr,X_test,y_test,algo):

    for i in range(1,30,2):
    # instantiate learning model (k = 30)
        knn = KNeighborsClassifier(n_neighbors=i,algorithm=algo,n_jobs= -1)

    # fitting the model on crossvalidation train
        knn.fit(X_tr, y_tr)

    # predict the response on the crossvalidation train
        pred = knn.predict(X_test)

    # evaluate CV accuracy
        acc = accuracy_score(y_test, pred, normalize=True) * float(100)
        print('\n The train accuracy for k = %d is %d%%' % (i, acc))


#########################################################################################

#Function for performing the crossvalidation technique
# creating odd list of K for KNN
def crossval(X_tr,y_tr,alg="auto"):
    myList = list(range(0,50))
    neighbors = list(filter(lambda x: x % 2 != 0, myList))

# empty list that will hold cv scores
    cv_scores = []

# perform 10-fold cross validation
    for k in neighbors:
        knn = KNeighborsClassifier(n_neighbors=k,algorithm=alg,n_jobs= -1)
        scores = cross_val_score(knn, X_tr, y_tr, cv=10, scoring='accuracy')
        cv_scores.append(scores.mean())
    return cv_scores,neighbors

###################################################################################################


#Function for plotting the error plot

def errorplot(cv_scores,neighbors):

# changing to misclassification error
    MSE = [1 - x for x in cv_scores]

# determining best k
    optimal_k1 = neighbors[MSE.index(min(MSE))]
    print('\nThe optimal number of neighbors is %d.' % optimal_k1)

# plot misclassification error vs k
    plt.plot(neighbors, MSE)

    for xy in zip(neighbors, np.round(MSE,3)):
        plt.annotate('(%s, %s)' % xy, xy=xy, textcoords='data')

    plt.xlabel('Number of Neighbors K')
    plt.ylabel('Misclassification Error')
    plt.show()
    print("the misclassification error for each k value is : ", np.round(MSE,3))
    return optimal_k1

#######################################################################################################
########

#Function for finding the Test accuracy using the best k vaue

def Optimal_test(X_train,y_train,X_test,y_test,optimal_k,alg="auto"):
# instantiate learning model k = optimal_k
    knn_optimal = KNeighborsClassifier(n_neighbors=optimal_k,algorithm=alg,n_jobs= -1)

# fitting the model
    knn_optimal.fit(X_train, y_train)

# predict the response
    pred = knn_optimal.predict(X_test)

# evaluate accuracy
    acc = accuracy_score(y_test, pred) * 100
    print('\nThe accuracy of the knn classifier for k = %d is %f%%' % (optimal_k, acc))
    return pred,acc
```

Utility functions for plotting the confusion matrix

In [19]:

```python
from sklearn.metrics import confusion_matrix
def Confusion_metric(y_test,y_pred,acc):
    print(metrics.confusion_matrix(y_test,y_pred))
    confusion=metrics.confusion_matrix(y_test,y_pred)

    plt.figure(figsize=(9,9))
    sns.heatmap(confusion, annot=True, fmt=".3f", linewidths=.5, square = True, cmap = 'Blues_r');
    plt.ylabel('Predicted label');
    plt.xlabel('Actual label');
    all_sample_title = 'Accuracy Score: {0}'.format( acc)
    plt.title(all_sample_title, size = 15);
    plt.show()

#Storing the values of the confusion matrix
    TN=confusion[0,0]
    FP=confusion[0,1]
    FN=confusion[1,0]
    TP=confusion[1,1]

# use float to perform true division, not integer division
    Class_acc=((TP + TN) / float(TP + TN + FP + FN))*100

#Code for classification error

    classification_error = ((FP + FN) / float(TP + TN + FP + FN))*100


#Code for finding the TPR,FPR,TNR,FNR

    TPR = (TP / float(FN + TP))*100

    FNR = (FN / float(FN + TP))*100

    TNR=(TN / float(TN + FP))*100

    FPR=(FP / float(TN + FP))*100

#Code for finding the Precision,Recall & F1_score

    precision = (TP/float(TP+FP))*100

    recall= (TP / float(FN + TP))*100

    F1_s= ((float(precision*recall)/float(precision+recall))*2)

    print()

    ptable=PrettyTable()
    ptable.title="The performance metrics of the above model are as follows: "
    ptable.field_names=["Metrics","Scores"]
    ptable.add_row(["Classification_accuracy",Class_acc])
    ptable.add_row(["Classification_error",classification_error])
    ptable.add_row(["True positive",TP])
    ptable.add_row(["False positive",FP])
    ptable.add_row(["True negative",TN])
    ptable.add_row(["False negative",FN])
    ptable.add_row(["True positive rate",TPR])
    ptable.add_row(["False negative rate",FNR])
    ptable.add_row(["True negative rate",TNR])
    ptable.add_row(["False positive rate",FPR])
    ptable.add_row(["Precision value",precision])
    ptable.add_row(["Recall value",recall])
    ptable.add_row(["f1_score value",F1_s])

    print(ptable)
```

Utilty functions for vectorizing the data

In [20]:
```python
#Function for vectorizing the train data
from sklearn.preprocessing import StandardScaler
scaler=StandardScaler(with_mean=False)


def vec_train(vect,X_tr):
    import warnings
    warnings.filterwarnings("ignore")

    count_vect = vect #in scikit-learn
    BOW = count_vect.fit_transform(X_tr.values)

#Standardizing the vectorized data
    standardized_data = scaler.fit_transform(BOW)
    standardized_data.shape
    return count_vect,standardized_data


#Function for vectorizing the CV data

def vec_cv(count,X_cv):
    cv=count.transform(X_cv.values)
    cv.get_shape()

    std_cv=scaler.transform(cv)
    std_cv.shape
    return std_cv


#Function for vectorizing the test data

def vec_test(count,X_test):
    test=count.transform(X_test.values)
    test.get_shape()

    std_data=scaler.transform(test)
    std_data.shape
    return std_data

#Funtion for printing the total number of top features
def top_tfidf_feats(name,row, features, top_n=25):
    ''' Get top n tfidf values in row and return them with their corresponding feature names.'''
    topn_ids = np.argsort(row)[::-1][:top_n]
    top_feats = [(features[i], row[i]) for i in topn_ids]
    df = pd.DataFrame(top_feats)
    df.columns = ['feature', name]
    return df
```

Bag of words implementation of the data

In [21]:
```python
#Initializing the count vectorizer
Count_vect=CountVectorizer(binary=True)

#vectorizing the X_train set
count,x_tr=vec_train(Count_vect,X_tr["CleanedText"])

print("The shape of the X_train is: ",x_tr.shape)

#Vectorizing the X_test set
x_test=vec_test(count,X_test["CleanedText"])
print("The shape of the X_test is: ",x_test.shape)


#Printing the total length of the features
print("\nTop 25 feaures acording to the Bow score are as follows")
features = Count_vect.get_feature_names()
len(features)


top_Bow = top_tfidf_feats("bow",x_tr[1,:].toarray()[0],features,25)
top_Bow
```

```
The shape of the X_train is:  (16000, 15959)
The shape of the X_test is:  (4000, 15959)

Top 25 feaures acording to the Bow score are as follows
```

Out[21]:

	feature	bow
0	efect	126.495059
1	winona	73.036522
2	ryder	63.253460
3	cartoon	56.577383
4	hilari	56.577383
5	film	33.820970
6	danc	33.820970
7	shown	19.315686
8	hey	18.477783
9	funni	17.740594
10	movi	16.932743
11	older	16.226488
12	apart	12.948849
13	known	12.384973
14	short	10.481069
15	watch	9.868942
16	special	8.063242
17	wrong	7.864681
18	night	7.820951
19	fan	7.067569
20	mayb	6.601307
21	end	6.405126
22	fact	6.204687
23	decid	6.190605
24	big	5.080342

Training the KNN model over BOW implemented data

In [40]:
```
##Preparing the data

train(x_tr,y_tr,x_test,y_test,"brute")
```

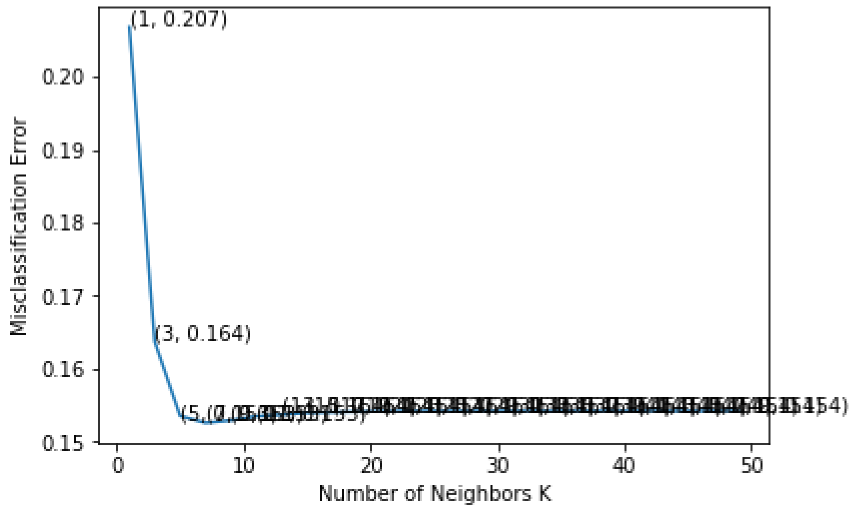
```
The train accuracy for k = 1 is 78%

The train accuracy for k = 3 is 81%

The train accuracy for k = 5 is 82%

The train accuracy for k = 7 is 82%

The train accuracy for k = 9 is 82%

The train accuracy for k = 11 is 82%

The train accuracy for k = 13 is 82%

The train accuracy for k = 15 is 82%

The train accuracy for k = 17 is 82%

The train accuracy for k = 19 is 82%

The train accuracy for k = 21 is 82%

The train accuracy for k = 23 is 82%

The train accuracy for k = 25 is 82%

The train accuracy for k = 27 is 82%

The train accuracy for k = 29 is 82%
```

Finding the best Hyperparameter using the Cross-validation technique_

In [49]:
```
#FINDING THE 10 FOLD ACCURACY OVER THE CROSS-VALIDATION SET
cv,neigh=crossval(x_tr,y_tr,"brute")
```

In [50]:
```
#FINDING THE OPTIMAL VALUE
Optimal_k= errorplot(cv,neigh)
```

```
The optimal number of neighbors is 7.
```




```
the misclassification error for each k value is :  [0.207 0.164 0.153 0.153 0.153 0.153 0.154 0.154 0.
154 0.154 0.154 0.154
 0.154 0.154 0.154 0.154 0.154 0.154 0.154 0.154 0.154 0.154 0.154 0.154
 0.154]
```

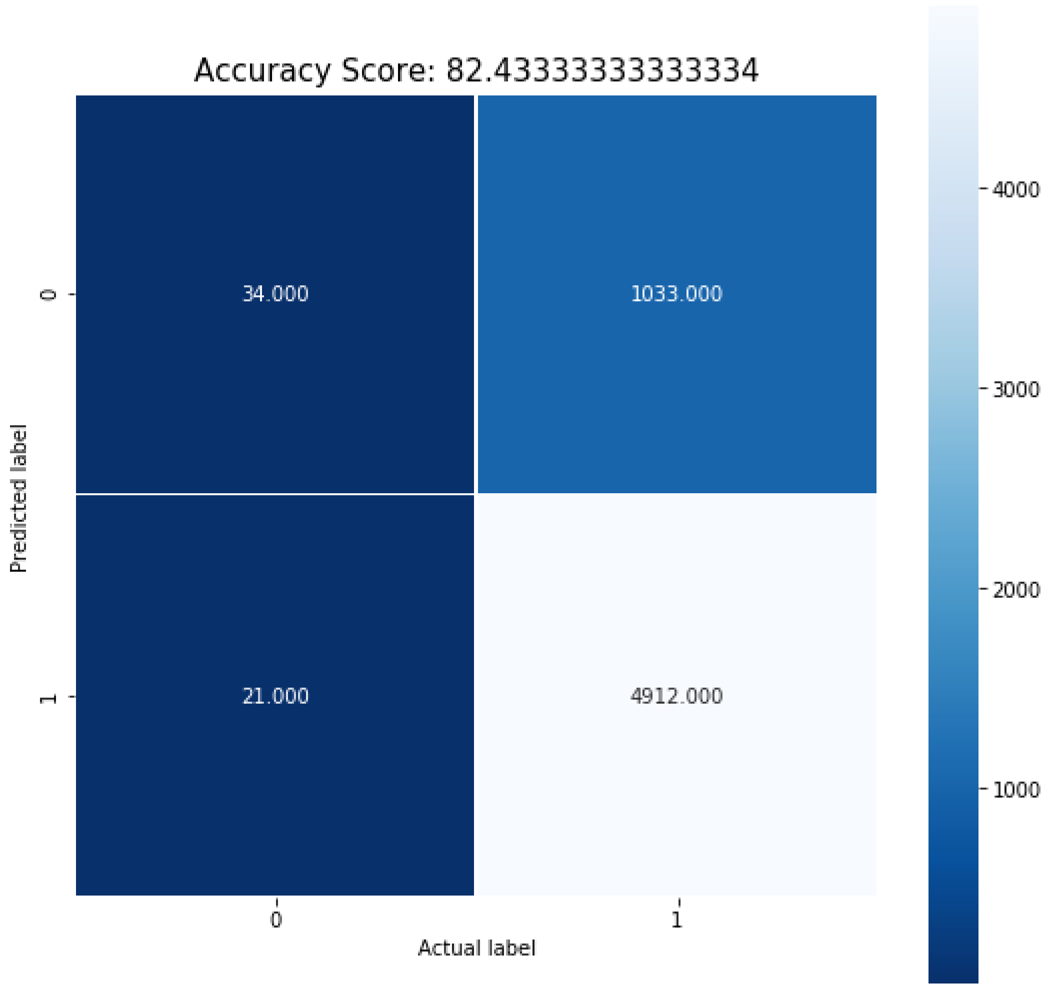
Finding the Test accuracy using the best K value

In [51]:
```
y_Pre,Acc=Optimal_test(x_tr,y_tr,x_test,y_test,Optimal_k,"brute")
```

```
The accuracy of the knn classifier for k = 7 is 82.433333%
```

In [52]:
```
Confusion_metric(y_test,y_Pre,Acc)
```

```
[[  34 1033]
 [  21 4912]]
```



```
+-----------------------------------------------------------+
| The performance metrics of the above model are as follows:  |
+-------------------------------+---------------------------+
|            Metrics            |           Scores          |
+-------------------------------+---------------------------+
|     Classification_accuracy   |      82.43333333333334    |
|      Classification_error     |      17.566666666666666   |
|         True positive         |            4912           |
|         False positive        |            1033           |
|         True negative         |             34            |
|         False negative        |             21            |
|       True positive rate      |      99.57429556051085    |
|      False negative rate      |     0.42570443948915465   |
|       True negative rate      |      3.1865042174320526   |
|      False positive rate      |      96.81349578256795    |
|        Precision value        |      82.62405382674515    |
|          Recall value         |      99.57429556051085    |
|         f1_score value        |      90.31071888214746    |
+-------------------------------+---------------------------+
```

Observations

- The train accuracy of the above model is 82% at 7 as a optimal value.
- But after analyzing the confusion matrix the model is not sensible at all because the True positive value is dominating so as the TPR values as compared to the other metrics.
- The True negative and the False negative rates are very miniscule which leads to decreased TNR and increased FNR which is very bad for a classification model.
- The model is not at all clssiffying the negative reviews and the model is really dumb.
- The model is facing a very heavy bias problem and underfitting a lot.
- So accuracy as a metric cannot be trusted in a imbalanced dataset, the model's performance may improve if we use another approach such as:-
    - 1)KD-tree approach.
    - 2)Oversampling techniques.

Implementing the count vectorizer for applying kd-tree method

In [26]:

```
#Initializing the count vectorizer
Count_vect=CountVectorizer(binary=True)

#vectorizing the X_train set
Coun,bow_tra=vec_train(Count_vect,X_train["CleanedText"])

print("The shape of the X_train is: ",bow_tra.shape)

#Vectorizing the X_test set
bow_tes=vec_test(Coun,X_Test["CleanedText"])
print("The shape of the X_test is: ",bow_tes.shape)


#Printing the total length of the features
print("\nTop 25 feaures acording to the Bow score are as follows")
feature = Count_vect.get_feature_names()
len(feature)


Top_Bow = top_tfidf_feats("bow",bow_tra[1,:].toarray()[0],feature,25)
Top_Bow
```

```
The shape of the X_train is:  (4000, 8720)
The shape of the X_test is:  (1000, 8720)

Top 25 feaures acording to the Bow score are as follows
```

Out[26]:

	feature	bow
0	melitta	31.638600
1	overpow	11.055335
2	lemon	9.481575
3	hint	9.183979
4	life	7.969709
5	recent	6.974274
6	addit	6.343647
7	instead	5.792413
8	expect	5.517877
9	green	5.149618
10	varieti	5.133963
11	far	4.689622
12	perfect	4.227291
13	mani	4.115854
14	favorit	3.868653
15	bought	3.712667
16	tea	3.289919
17	coffe	3.125734
18	flavor	2.310944
19	love	2.283376
20	tast	2.145066
21	fleshi	0.000000
22	fluke	0.000000
23	flyaway	0.000000
24	flushabl	0.000000

KD-TREE implementation of the KNN-model

In [27]:
```
#Creating the dense representation of the Train and Test sets

Dense_tr=bow_tra.todense(order="C")
Dense_te=bow_tes.todense(order="C")
```

Training the model using the kd-tree approach

In [29]:
```
train(Dense_tr,y_train,Dense_te,y_Test,"kd_tree")
```

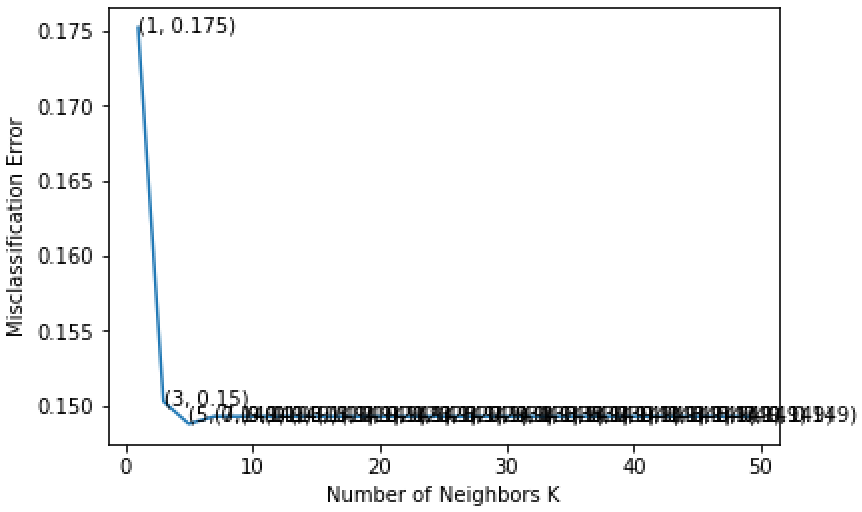
```
The train accuracy for k = 1 is 79%

The train accuracy for k = 3 is 81%

The train accuracy for k = 5 is 81%

The train accuracy for k = 7 is 82%

The train accuracy for k = 9 is 82%

The train accuracy for k = 11 is 82%

The train accuracy for k = 13 is 82%

The train accuracy for k = 15 is 82%

The train accuracy for k = 17 is 82%

The train accuracy for k = 19 is 82%

The train accuracy for k = 21 is 82%

The train accuracy for k = 23 is 82%

The train accuracy for k = 25 is 82%

The train accuracy for k = 27 is 82%

The train accuracy for k = 29 is 82%
```

Hyperparameter tuning & plotting error metric the above model for finding the right K

In [30]:
```
#FINDING THE 10 FOLD ACCURACY OVER THE CROSS-VALIDATION SET
kdcv,kdneigh=crossval(Dense_tr,y_train,"kd_tree")
```

In [31]:
```
#FINDING THE OPTIMAL VALUE
Kd_Optimal_k= errorplot(kdcv,kdneigh)
```

```
The optimal number of neighbors is 5.
```




```
the misclassification error for each k value is :  [0.175 0.15  0.149 0.149 0.149 0.149 0.149 0.149 0.
149 0.149 0.149 0.149
 0.149 0.149 0.149 0.149 0.149 0.149 0.149 0.149 0.149 0.149 0.149 0.149
 0.149]
```

Testing the above model over the test set

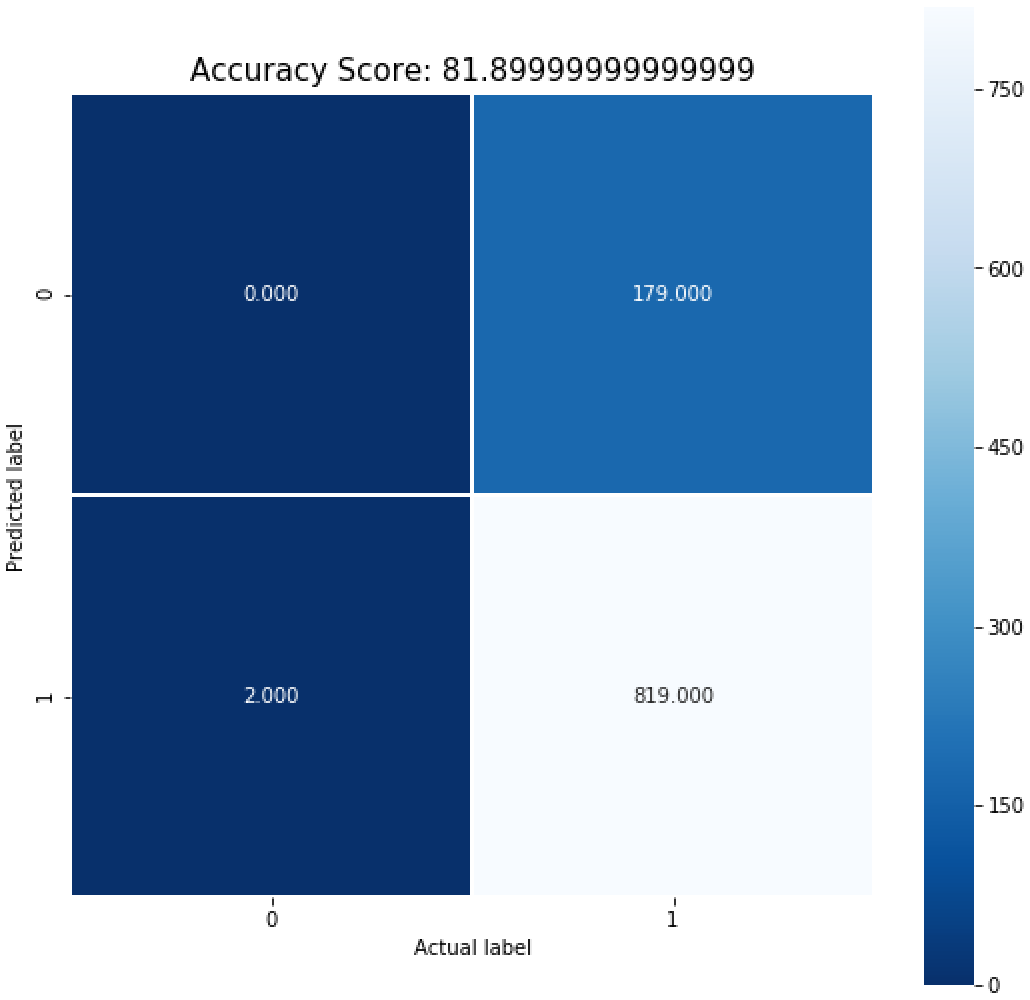
In [33]:
```
kd_y_Pre,kd_Acc=Optimal_test(Dense_tr,y_train,Dense_te,y_Test,Kd_Optimal_k,"kd_tree")
```

```
The accuracy of the knn classifier for k = 5 is 81.900000%
```

Confusion matrix of the above model

In [34]:
```
Confusion_metric(y_Test,kd_y_Pre,kd_Acc)
```

```
[[  0 179]
 [  2 819]]
```



```
+-------------------------------------------------------------+
| The performance metrics of the above model are as follows:  |
+----------------------------------+--------------------------+
|             Metrics              |          Scores          |
+----------------------------------+--------------------------+
|     Classification_accuracy      |     81.89999999999999    |
|       Classification_error       |    18.099999999999998    |
|          True positive           |           819            |
|          False positive          |           179            |
|          True negative           |            0             |
|          False negative          |            2             |
|        True positive rate        |     99.7563946406821     |
|       False negative rate        |   0.24360535931790497    |
|        True negative rate        |           0.0            |
|       False positive rate        |          100.0           |
|         Precision value          |    82.06412825651303     |
|           Recall value           |     99.7563946406821     |
|          f1_score value          |    90.04947773501925     |
+----------------------------------+--------------------------+
```

Observations

- First I took a small sample of points(5K)for the implementation of kd_tree and converted the sparse representation to dense because Kd-tree works on dense matrix.
- Even after applying the Kd-tree approach and tuning the hyperparameter the model's accuracy and performance didn't changed and the model still underfitts
- Lets try Oversampling the data and try to run all the model diagnostics to see model improvements in terms of stability and accuracy.

function for Oversampling the data by using the Synthetic minority oversampling technique (SMOTE).

In [51]:
```
#FUNCTION FOR IMPLEMENTING THE SYNTHETIC MINORITY OVERSAMPLING TECHNIQUE
from imblearn.over_sampling import SMOTE

def Bal_train (X_tr, y_tr,X_test,y_test,algo="auto"):

    sm = SMOTE()
    X_Train_res, y_Train_res = sm.fit_sample(X_tr, y_tr)

    X_Test_res,y_Test_res=sm.fit_sample(X_test,y_test)


    for i in range(1,30,2):
    # instantiate learning model (k = 30)
        knn = KNeighborsClassifier(n_neighbors=i,algorithm=algo,n_jobs= -1)

    # fitting the model on crossvalidation train
        knn.fit(X_Train_res,y_Train_res)

    # predict the response on the crossvalidation train
        pred = knn.predict( X_Test_res)

    # evaluate CV accuracy
        acc = accuracy_score(y_Test_res, pred, normalize=True) * float(100)
        print('\n The train accuracy for k = %d is %d%%' % (i, acc))


    return X_Train_res, y_Train_res,X_Test_res,y_Test_res
```

Training the KNN model over the Oversampled data.

In [59]:
```
X_btr,y_btr,X_btest,y_btest=Bal_train(x_tr,y_tr,x_test,y_test,"brute")
```

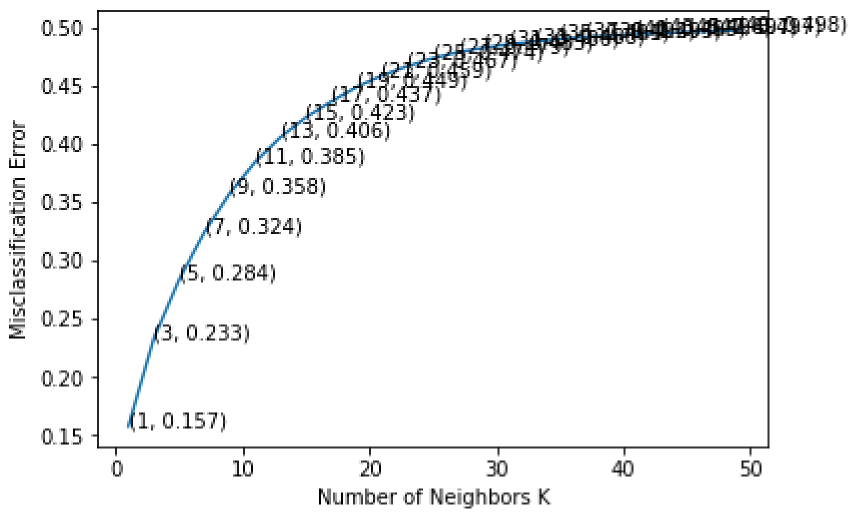
```
The train accuracy for k = 1 is 66%

The train accuracy for k = 3 is 66%

The train accuracy for k = 5 is 67%

The train accuracy for k = 7 is 65%

The train accuracy for k = 9 is 63%

The train accuracy for k = 11 is 61%

The train accuracy for k = 13 is 59%

The train accuracy for k = 15 is 58%

The train accuracy for k = 17 is 57%

The train accuracy for k = 19 is 55%

The train accuracy for k = 21 is 54%

The train accuracy for k = 23 is 53%

The train accuracy for k = 25 is 53%

The train accuracy for k = 27 is 52%

The train accuracy for k = 29 is 52%
```

Hyperparameter tuning the above model for finding the optimal K

In [60]:
```
#FINDING THE 10 FOLD ACCURACY OVER THE CROSS-VALIDATION SET
balcv,balneigh=crossval(X_btr,y_btr,"brute")
```

In [61]:
```
#FINDING THE OPTIMAL VALUE
Bal_Optimal_k= errorplot(balcv,balneigh)
```

```
The optimal number of neighbors is 1.
```




```
the misclassification error for each k value is :  [0.157 0.233 0.284 0.324 0.358 0.385 0.406 0.423 0.
437 0.449 0.459 0.467
 0.474 0.479 0.483 0.486 0.488 0.491 0.492 0.493 0.495 0.496 0.497 0.497
 0.498]
```

Testing the model over the test data

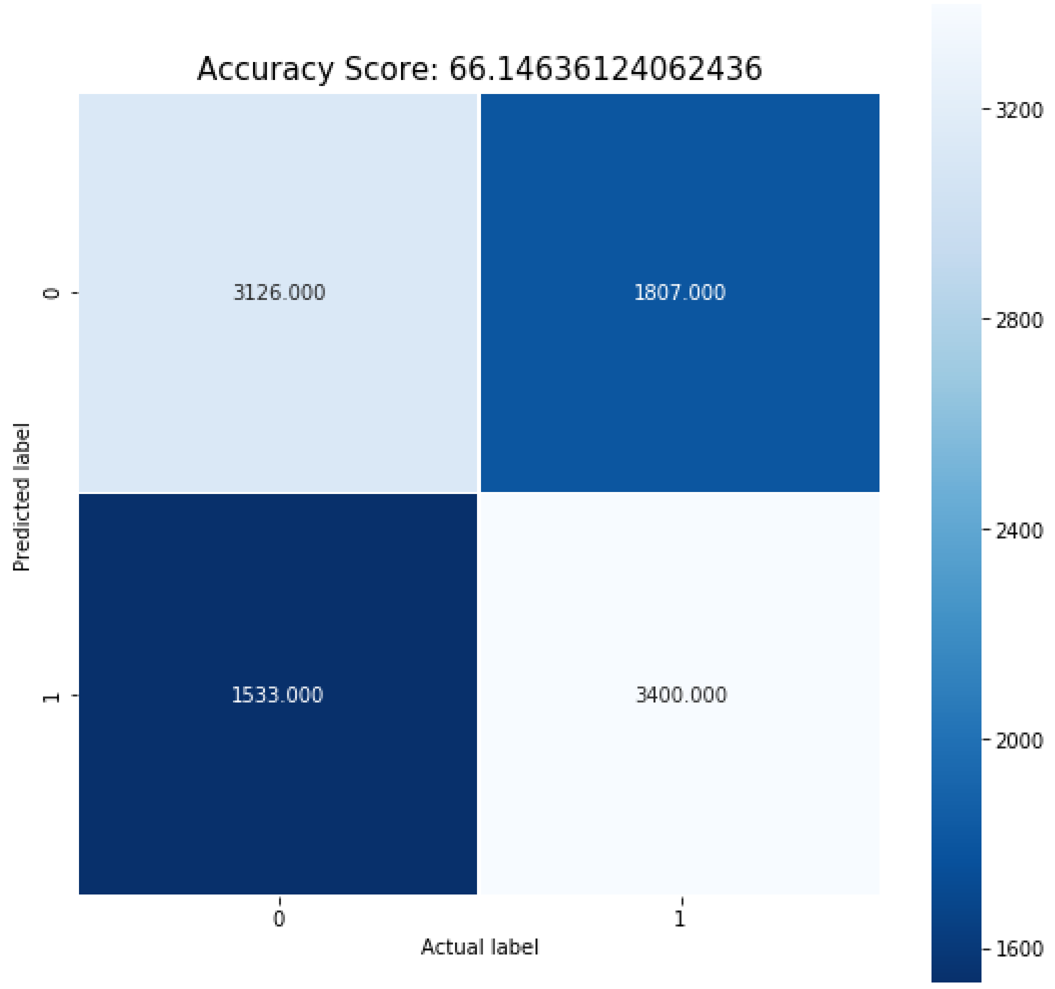
In [63]:
```
bal_y_Pre,bal_Acc=Optimal_test(X_btr,y_btr,X_btest,y_btest,Bal_Optimal_k,"brute")
```

```
The accuracy of the knn classifier for k = 1 is 66.146361%
```

Confusion matrix of the above model

In [67]:
```
Confusion_metric(y_btest,bal_y_Pre,bal_Acc)
```

```
[[3126 1807]
 [1533 3400]]
```




```
+-------------------------------------------------------------+
| The performance metrics of the above model are as follows:  |
+---------------------------------+---------------------------+
|             Metrics             |           Scores          |
+---------------------------------+---------------------------+
|     Classification_accuracy     |     66.14636124062436     |
|       Classification_error      |     33.853638759375634    |
|          True positive          |            3400           |
|          False positive         |            1807           |
|          True negative          |            3126           |
|          False negative         |            1533           |
|        True positive rate       |     68.92357591729171     |
|       False negative rate       |     31.076424082708293    |
|        True negative rate       |     63.369146563957024    |
|       False positive rate       |     36.630853436042976    |
|         Precision value         |     65.29671595928558     |
|           Recall value          |     68.92357591729171     |
|          f1_score value         |     67.06114398422092     |
+---------------------------------+---------------------------+
```

Observations

- The Test accuracy of the model is around 66.14% which is quite low for a classification model.
- The optimal K value is 1 which means the model overfitts which reduces the model performance.
- The Performance metrics are quite good as compared to the previous unbalanced model inspite of the low accuracy of the classification model.
- The True Positive and the True negative values are good as compared to the other 2 values
- The main reason the low accuracy is because of considerable FNR and FPR values which is quite alarming.
- Here the model is overfitting but still the model is stable as compared to the previous models

Implementing Tf-idf vectorization technique and finding the top 25 features

In [18]:
```
#Initializing the count vectorizer
TF_vect=TfidfVectorizer(ngram_range=(1,2),binary=True)

#vectorizing the X_train set
TF_count,X_tra=vec_train(TF_vect,X_tr["CleanedText"])

print("The shape of the X_train is: ",X_tra.shape)


#Vectorizing the X_test set
X_tes=vec_test(TF_count,X_test["CleanedText"])
print("The shape of the X_test is: ",X_tes.shape)


#Printing the total length of the features
print("\nTop 25 feaures acording to the Bow score are as follows")
Features = TF_vect.get_feature_names()
len(Features)


top_tfidf = top_tfidf_feats("tfidf",X_tra[1,:].toarray()[0],Features,25)
top_tfidf
```

```
The shape of the X_train is:  (24000, 446329)
The shape of the X_test is:  (6000, 446329)

Top 25 feaures acording to the Bow score are as follows
```

Out[18]:

	feature	tfidf
0	especi fun	154.922561
1	season cooki	154.922561
2	event birthday	154.922561
3	shade ice	154.922561
4	fun event	154.922561
5	tabl decor	154.922561
6	ice martha	154.922561
7	event past	154.922561
8	easili blend	154.922561
9	tea event	154.922561
10	cake especi	154.922561
11	intens easili	154.922561
12	color must	154.922561
13	wonder tabl	154.922561
14	time show	154.922561
15	simpl ice	154.922561
16	excit color	154.922561
17	wonder season	154.922561
18	frost cooki	154.922561
19	kid contest	154.922561
20	cooki parti	154.922561
21	dessert parti	154.922561
22	parti cake	154.922561
23	parti tea	154.922561
24	contest fun	154.922561

KNN (Brute force) implementation of the above data

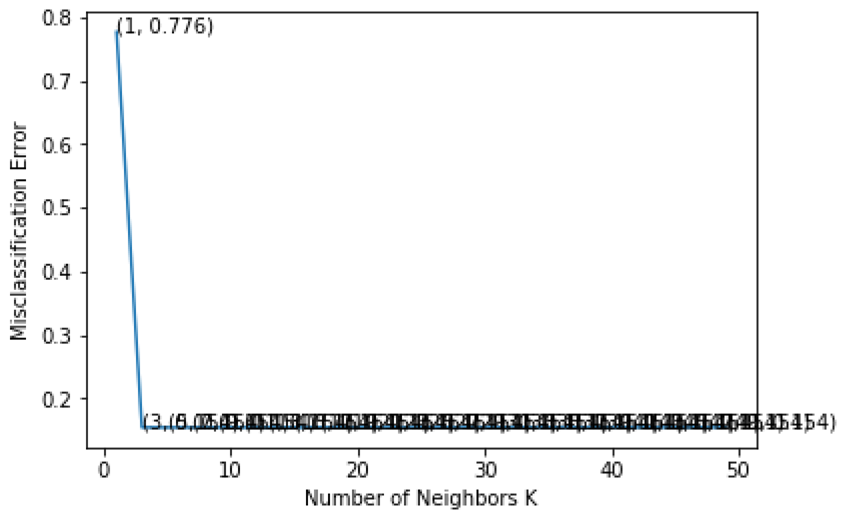
In [83]:
```
train(X_tr,y_tr,X_test,y_test,"brute")
```

```
The train accuracy for k = 1 is 17%

The train accuracy for k = 3 is 82%

The train accuracy for k = 5 is 82%

The train accuracy for k = 7 is 82%

The train accuracy for k = 9 is 82%

The train accuracy for k = 11 is 82%

The train accuracy for k = 13 is 82%

The train accuracy for k = 15 is 82%

The train accuracy for k = 17 is 82%

The train accuracy for k = 19 is 82%

The train accuracy for k = 21 is 82%

The train accuracy for k = 23 is 82%

The train accuracy for k = 25 is 82%

The train accuracy for k = 27 is 82%

The train accuracy for k = 29 is 82%
```

In [84]:
```
#FINDING THE 10 FOLD ACCURACY OVER THE CROSS-VALIDATION SET
TFcv,TFneigh=crossval(X_tr,y_tr,"brute")
```

In [85]:
```
#FINDING THE OPTIMAL VALUE
TF_Optimal_k= errorplot(TFcv,TFneigh)
```

```
The optimal number of neighbors is 5.
```




```
the misclassification error for each k value is :  [0.776 0.154 0.154 0.154 0.154 0.154 0.154 0.154 0.
154 0.154 0.154 0.154
 0.154 0.154 0.154 0.154 0.154 0.154 0.154 0.154 0.154 0.154 0.154 0.154
 0.154]
```

Testing the model over the test data

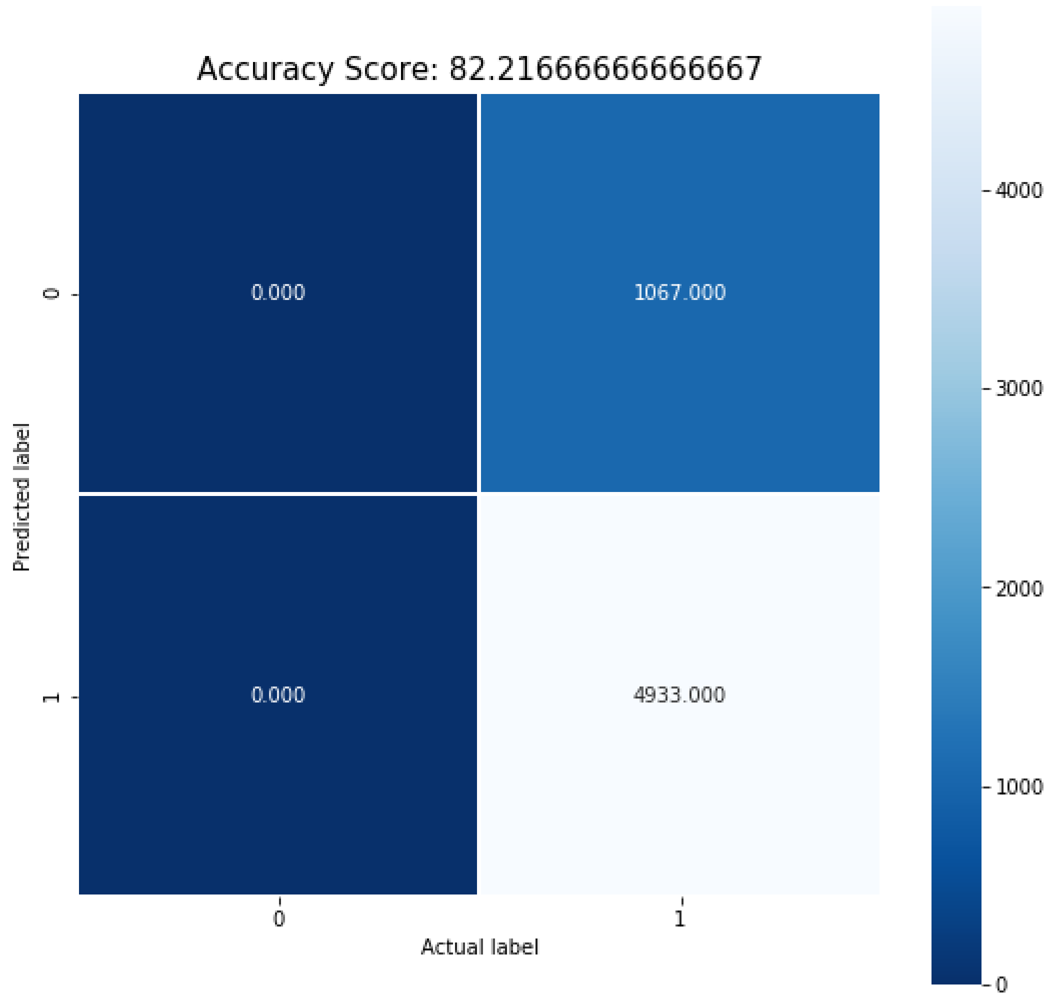
In [86]:
```
TF_y_Pre,TF_Acc=Optimal_test(X_tr,y_tr,X_test,y_test,TF_Optimal_k,"brute")
```

```
The accuracy of the knn classifier for k = 5 is 82.216667%
```

Confusion matrix of the above model

In [87]:
```
Confusion_metric(y_test,TF_y_Pre,TF_Acc)
```

```
[[    0 1067]
 [    0 4933]]
```



The performance metrics of the above model are as follows:

Metrics	Scores
Classification_accuracy	82.21666666666667
Classification_error	17.783333333333335
True positive	4933
False positive	1067
True negative	0
False negative	0
True positive rate	100.0
False negative rate	0.0
True negative rate	0.0
False positive rate	100.0
Precision value	82.21666666666667
Recall value	100.0
f1_score value	90.24055611451568

Observation

- The above model has a accuracy of 82.21% but still the model is completely dumb.
- By studying the confusion matrix it is clear that the model has a very severe bias problem.
- Only the positive class labels are dominating and we can see a FPR equal to 100% so the model is clearly neglecting or missclassiffying the negative reviews.
- Lets explore other techniques in which the performance of the model may improve.

Implementing the Tf-idf vectorizer for applying the kd-tree method

In [36]:
```
#Initializing the count vectorizer
Tf_vect=TfidfVectorizer(ngram_range=(1,2),binary=True)

#vectorizing the X_train set
TF_coun,tfidf_tra=vec_train(Tf_vect,X_train["CleanedText"])

print("The shape of the X_train is: ",tfidf_tra.shape)


#Vectorizing the X_test set
tfidf_tes=vec_test(TF_coun,X_Test["CleanedText"])
print("The shape of the X_test is: ",tfidf_tes.shape)


#Printing the total length of the features
print("\nTop 25 feaures acording to the Bow score are as follows")
TF_Features = Tf_vect.get_feature_names()
len(TF_Features)


Top_tfidf = top_tfidf_feats("tfidf",tfidf_tra[1,:].toarray()[0],TF_Features,25)
Top_tfidf
```

```
The shape of the X_train is:  (4000, 114026)
The shape of the X_test is:  (1000, 114026)

Top 25 feaures acording to the Bow score are as follows
```

Out[36]:

	feature	tfidf
0	coffe instead	63.253460
1	expect love	63.253460
2	life far	63.253460
3	perfect addit	63.253460
4	bought melitta	63.253460
5	melitta expect	63.253460
6	lemon perfect	63.253460
7	favorit hint	63.253460
8	instead love	63.253460
9	hint lemon	55.595564
10	tea life	54.688301
11	addit flavor	53.200657
12	melitta	48.741124
13	varieti green	46.939181
14	mani varieti	44.858687
15	flavor overpow	44.274599
16	tast mani	40.208815
17	recent bought	37.002712
18	far favorit	24.695543
19	overpow	15.021774
20	love coffe	13.226892
21	tea tast	13.089876
22	lemon	12.835398
23	hint	12.520443
24	love tea	12.400434

Creating dense matrix representation of the tf-idf vectorized data.

In [58]:
```
Dense_tra=tfidf_tra.todense(order="C")
Dense_tes=tfidf_tes.todense(order="C")
```

KD-TREE implementation of the KNN-model

In [59]:
```
train(Dense_tra,y_train,Dense_tes,y_Test,"kd_tree")
```

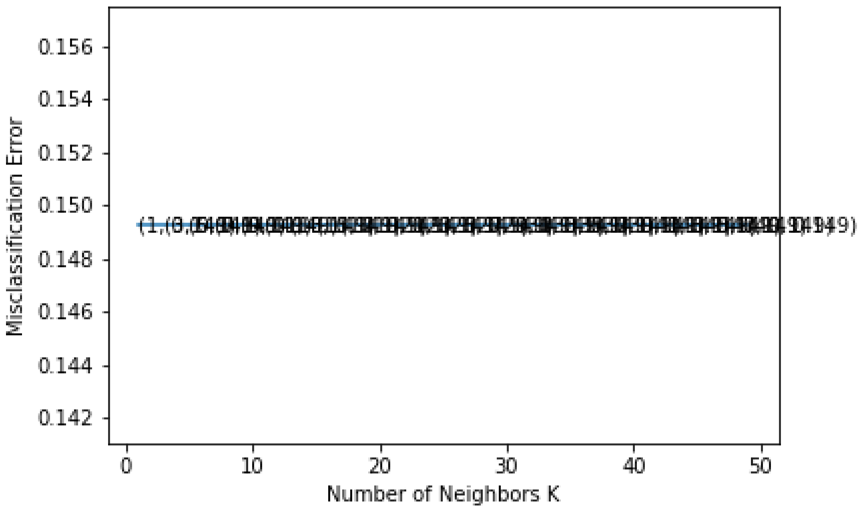
```
The train accuracy for k = 1 is 82%

The train accuracy for k = 3 is 82%

The train accuracy for k = 5 is 82%

The train accuracy for k = 7 is 82%

The train accuracy for k = 9 is 82%

The train accuracy for k = 11 is 82%

The train accuracy for k = 13 is 82%

The train accuracy for k = 15 is 82%

The train accuracy for k = 17 is 82%

The train accuracy for k = 19 is 82%

The train accuracy for k = 21 is 82%

The train accuracy for k = 23 is 82%

The train accuracy for k = 25 is 82%

The train accuracy for k = 27 is 82%

The train accuracy for k = 29 is 82%
```

In [60]:
```
TFkdcv,TFkdneigh=crossval(Dense_tra,y_train,"kd_tree")
```

Hyperparameter tuning for finding the optimal k

In [61]:
```
#FINDING THE OPTIMAL VALUE
TFkd_Optimal_k= errorplot(TFkdcv,TFkdneigh)
```

```
The optimal number of neighbors is 1.
```




```
the misclassification error for each k value is :  [0.149 0.149 0.149 0.149 0.149 0.149 0.149 0.149 0.
149 0.149 0.149 0.149
 0.149 0.149 0.149 0.149 0.149 0.149 0.149 0.149 0.149 0.149 0.149 0.149
 0.149]
```

Testing the model over the test data

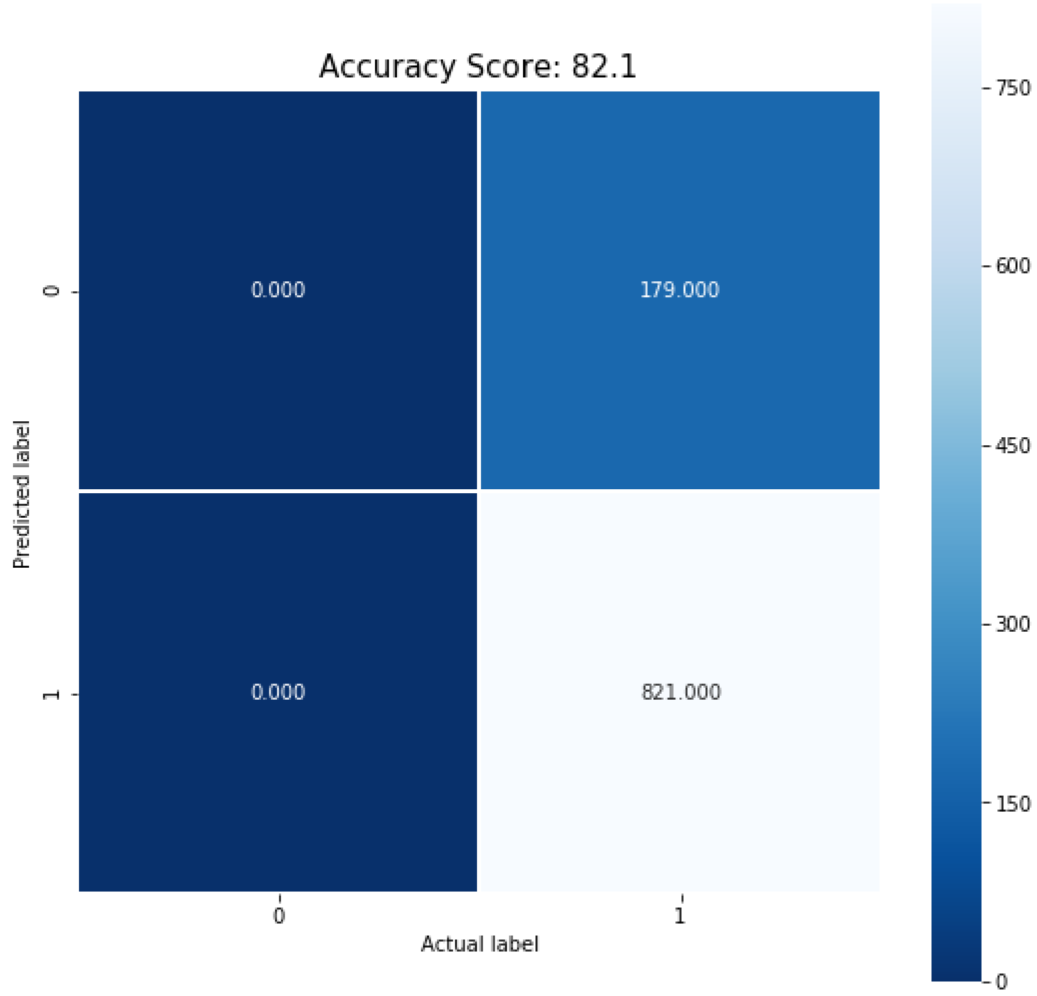
In [62]:
```
TFkd_y_Pre,TFkd_Acc=Optimal_test(Dense_tra,y_train,Dense_tes,y_Test,TFkd_Optimal_k,"kd_tree")
```

```
The accuracy of the knn classifier for k = 1 is 82.100000%
```

Confusion matrix of the above model

In [63]:
```
Confusion_metric(y_Test,TFkd_y_Pre,TFkd_Acc)
```

```
[[  0 179]
 [  0 821]]
```




```
+-----------------------------------------------------------+
| The performance metrics of the above model are as follows: |
+--------------------------------+--------------------------+
|            Metrics             |          Scores          |
+--------------------------------+--------------------------+
|    Classification_accuracy     |           82.1           |
|      Classification_error      |           17.9           |
|         True positive          |           821            |
|         False positive         |           179            |
|         True negative          |            0             |
|         False negative         |            0             |
|       True positive rate       |          100.0           |
|      False negative rate       |           0.0            |
|       True negative rate       |           0.0            |
|      False positive rate       |          100.0           |
|        Precision value         |           82.1           |
|          Recall value          |          100.0           |
|         f1_score value         |    90.17023613399232     |
+--------------------------------+--------------------------+
```

Observations

- To implement the Kd_tree approch it took me about (17-Hrs) to complete it on 5K points since the matrix was dense and this approach is very computationally expensive.
- The model is still dumb and no differnce is seen in this approach so this technique do not add any value to the model.
- Bias problem is still there and the model is still underfitting and lets try to solve the problem by oversampling it.
- Since the kd_tree was implemented on 5k datapoints and still it gave the same performance of the 20K points(Brute) approach so if the Kd_tree(KNN) model is trained over larger datapoints the perrformance might increase.
- In the Tf-idf vectorized KNN model the effect of Curse of dimensionality is seen.

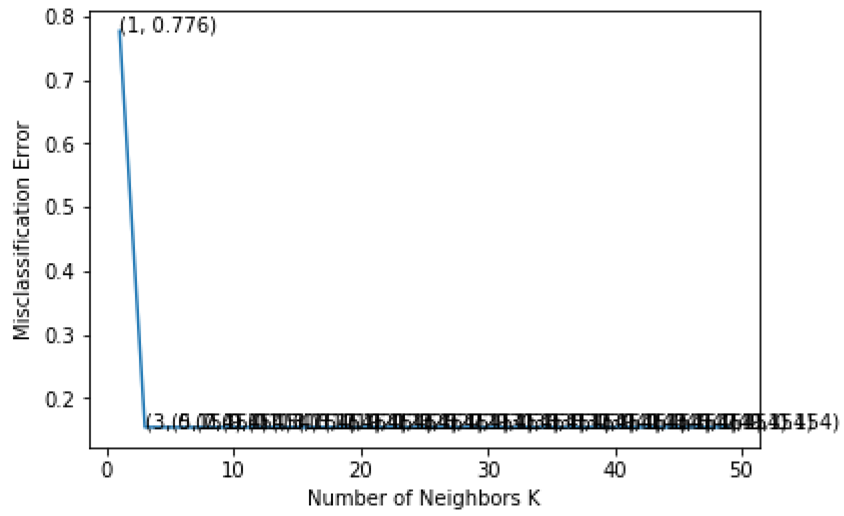
Oversampling the data by using the Synthetic minority oversampling technique (SMOTE).

In [94]:
```
X_Btr,y_Btr,X_Btest,y_Btest=Bal_train(Dense_tra,y_tr,x_test,y_test,"brute")
```

```
The train accuracy for k = 1 is 67%

The train accuracy for k = 3 is 67%

The train accuracy for k = 5 is 67%

The train accuracy for k = 7 is 65%

The train accuracy for k = 9 is 63%

The train accuracy for k = 11 is 61%

The train accuracy for k = 13 is 59%

The train accuracy for k = 15 is 58%

The train accuracy for k = 17 is 56%

The train accuracy for k = 19 is 55%

The train accuracy for k = 21 is 54%

The train accuracy for k = 23 is 53%

The train accuracy for k = 25 is 53%

The train accuracy for k = 27 is 52%

The train accuracy for k = 29 is 52%
```

In [96]:
```
#FINDING THE OPTIMAL VALUE
TFB_Optimal_k= errorplot(TFBcv,TFBneigh)
```

```
The optimal number of neighbors is 5.
```




```
the misclassification error for each k value is :  [0.776 0.154 0.154 0.154 0.154 0.154 0.154 0.154 0.
154 0.154 0.154 0.154
 0.154 0.154 0.154 0.154 0.154 0.154 0.154 0.154 0.154 0.154 0.154 0.154
 0.154]
```

Testing the model over the test data

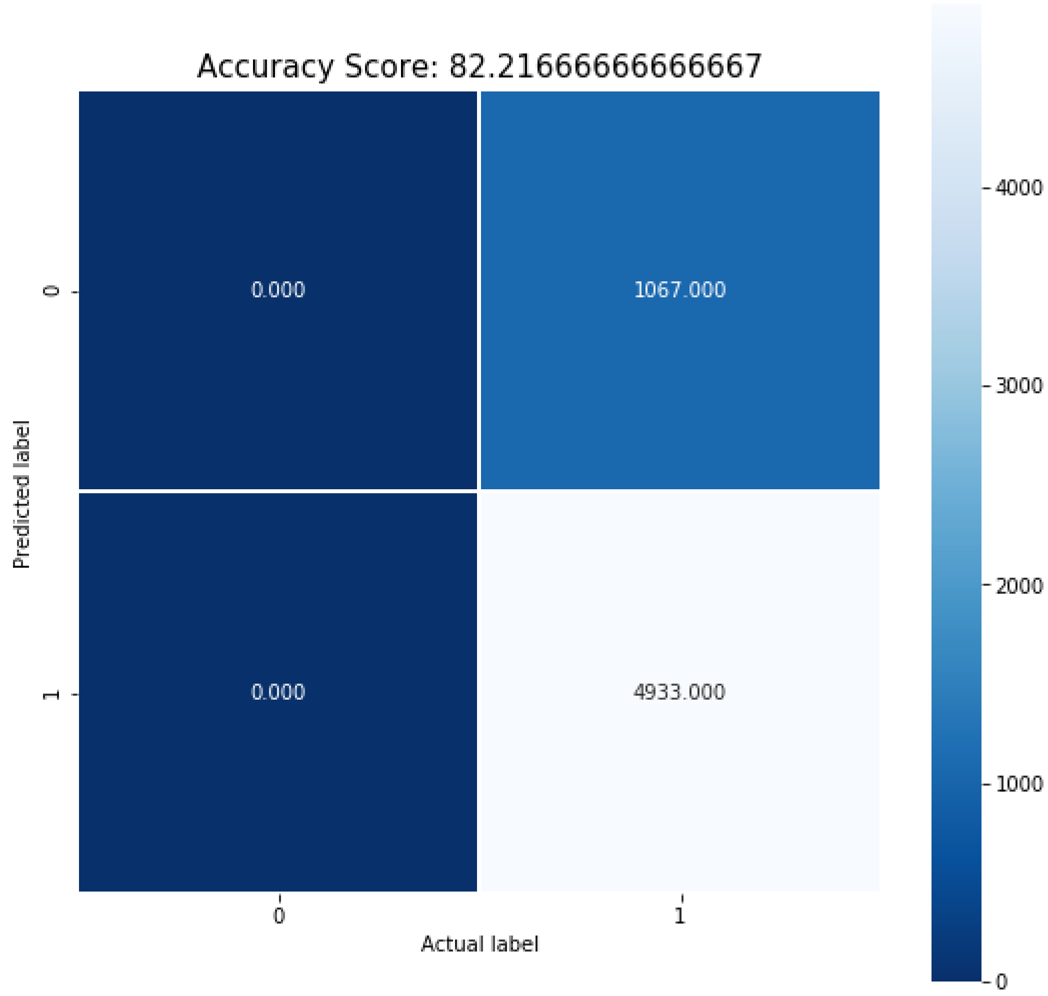
In [97]:
```
TFB_y_Pre,TFB_Acc=Optimal_test(X_tr,y_tr,X_test,y_test,TFB_Optimal_k,"brute")
```

```
The accuracy of the knn classifier for k = 5 is 82.216667%
```

Confusion matrix of the above model

In [98]:
```
Confusion_metric(y_test,TFB_y_Pre,TFB_Acc)
```

```
[[    0 1067]
 [    0 4933]]
```



The performance metrics of the above model are as follows:	
Metrics	Scores
Classification_accuracy	82.21666666666667
Classification_error	17.783333333333335
True positive	4933
False positive	1067
True negative	0
False negative	0
True positive rate	100.0
False negative rate	0.0
True negative rate	0.0
False positive rate	100.0
Precision value	82.21666666666667
Recall value	100.0
f1_score value	90.24055611451568

Observations

- Even after oversampling the datapoints there is no improvements seen in the model and still it is dumb.
-
- Since the Tf-idf vectorizer has high dimensions and KNN-Algorithm do not work well with this type of data so may be there is a problem of "Curse of dimensionality".
- Let's try two other vectorization techniques which are:-

  1. Avg W2V technique.
  2. Tf-idf weighted W2V technique

Implementing the Average word to vectorization technique.

In [19]:
```python
start = datetime.now()
import gensim

# Train our own Word2Vec model using text corpus
list_of_sentence_vec=[]
for sentence in Sample_sort['CleanedText'].values:
    list_of_sentence_vec.append(sentence.split())
# Generate model.
w2v_Model = gensim.models.Word2Vec(list_of_sentence_vec,min_count=5,size=50, workers=6)

w2v_Words = list(w2v_Model.wv.vocab)
print("number of words that occured minimum 5 times is ",len(w2v_Words))


#code for finding the avg w2v
# average Word2Vec
# compute average word2vec for each review.
sent_vectors = []; # the avg-w2v for each sentence/review is stored in this list
for sent in list_of_sentence_vec: # for each review/sentence
    sent_vec = np.zeros(50) # as word vectors are of zero length
    cnt_words =0; # num of words with a valid vector in the sentence/review
    for word in sent: # for each word in a review/sentence
        try:
            vec = w2v_Model.wv[word]
            sent_vec += vec
            cnt_words += 1
        except:
            pass
    sent_vec /= cnt_words
    #print(np.isnan(np.sum(sent_vec)))
    sent_vectors.append(sent_vec)
print(len(sent_vectors))
print(len(sent_vectors[0]))

print('Time taken :', datetime.now() - start)
```

```
number of words that occured minimum 5 times is  7526
30000
50
Time taken : 0:00:08.588583
```

Training the K-NN model by using Avg-Word to vector.

In [20]:
```python
X=sent_vectors
Y=Class

X_w2vtr, X_w2vtes, y_w2vtr, y_w2vtes = train_test_split(X, Y, test_size=0.2,shuffle=False,random_state
=None)
```

In [21]:
```python
train(X_w2vtr,y_w2vtr,X_w2vtes,y_w2vtes,"brute")
```

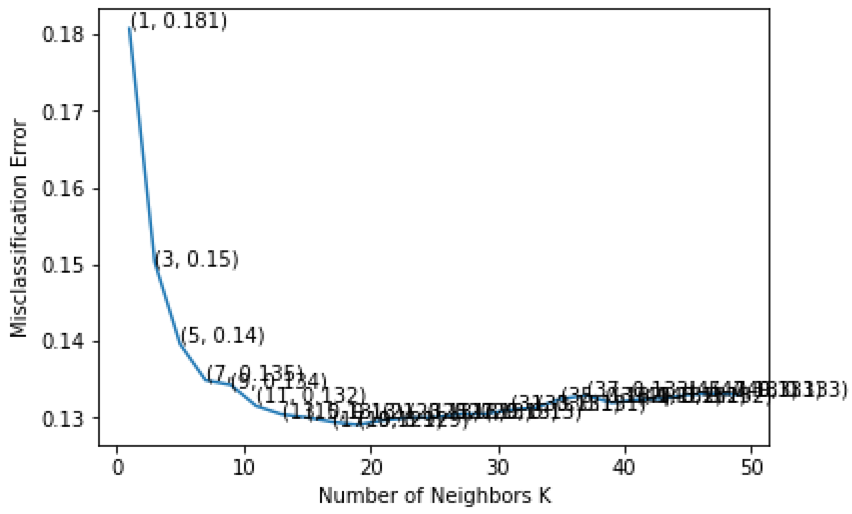
```
 The train accuracy for k = 1 is 81%

 The train accuracy for k = 3 is 84%

 The train accuracy for k = 5 is 84%

 The train accuracy for k = 7 is 85%

 The train accuracy for k = 9 is 85%

 The train accuracy for k = 11 is 85%

 The train accuracy for k = 13 is 85%

 The train accuracy for k = 15 is 85%

 The train accuracy for k = 17 is 85%

 The train accuracy for k = 19 is 85%

 The train accuracy for k = 21 is 85%

 The train accuracy for k = 23 is 85%

 The train accuracy for k = 25 is 85%

 The train accuracy for k = 27 is 85%

 The train accuracy for k = 29 is 85%
```

Hyperparameter tuning the above model to find the right k.

In [22]:
```
w2vcv,w2vneigh=crossval(X_w2vtr,y_w2vtr,"brute")
```

In [23]:
```
#FINDING THE OPTIMAL VALUE
w2v_Optimal_k= errorplot(w2vcv,w2vneigh)
```

The optimal number of neighbors is 19.




```
the misclassification error for each k value is :  [0.181 0.15  0.14  0.135 0.134 0.132 0.13  0.13  0.
129 0.129 0.13  0.13
 0.13  0.13  0.13  0.131 0.131 0.132 0.133 0.132 0.132 0.132 0.133 0.133
 0.133]
```

Testing the model over the test set

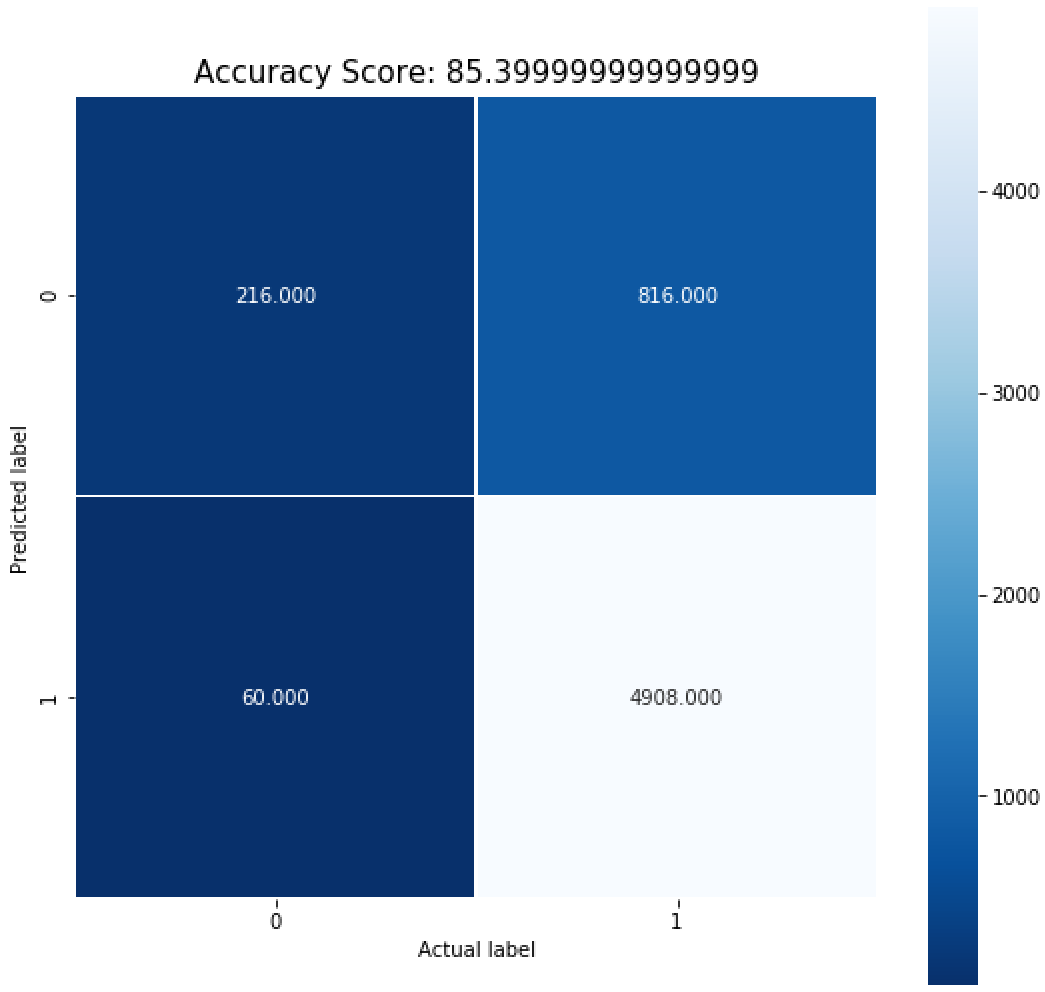
In [24]:
```
w2v_y_Pre,w2v_Acc=Optimal_test(X_w2vtr,y_w2vtr,X_w2vtes,y_w2vtes ,w2v_Optimal_k,"brute")
```

The accuracy of the knn classifier for k = 19 is 85.400000%

Plotting the confusion matrix of the above model

In [25]:
```
Confusion_metric(y_w2vtes,w2v_y_Pre,w2v_Acc)
```

```
[[ 216  816]
 [  60 4908]]
```



```
+-----------------------------------------------------------+
| The performance metrics of the above model are as follows: |
+----------------------------------+-------------------------+
|              Metrics             |          Scores         |
+----------------------------------+-------------------------+
|     Classification_accuracy      |     85.39999999999999   |
|       Classification_error       |           14.6          |
|          True positive           |           4908          |
|          False positive          |           816           |
|          True negative           |           216           |
|          False negative          |            60           |
|        True positive rate        |     98.79227053140096   |
|       False negative rate        |     1.2077294685990339  |
|        True negative rate        |     20.930232558139537  |
|       False positive rate        |     79.06976744186046   |
|         Precision value          |     85.74423480083857   |
|           Recall value           |     98.79227053140096   |
|          f1_score value          |     91.80695847362513   |
+----------------------------------+-------------------------+
```

Observation

- The train accuracy of the above model is 85.39% at 19 as a optimal value.
- But after analyzing the confusion matrix the model is not sensible at all because the True positive value is dominating so as the TPR values as compared to the other metrics.
- The True negative and the False negative rates are very miniscule which leads to decreased TNR and increased FNR which is very bad for a classification model.
- The model is classifying the negative reviews very badly and the model is really dumb.
- The model is facing a very heavy bias problem and underfitting a lot.
- So accuracy as a metric cannot be trusted in a imbalanced dataset, the model's performance may improve if we use another approach such as:-
  - 1)KD-tree approach.
  - 2)Oversampling techniques.

  </ul

Oversampling the data by using the Synthetic minority oversampling technique (SMOTE).

In [27]:
```
train_X,train_Y,test_X,test_Y=Bal_train (X_w2vtr,y_w2vtr,X_w2vtes,y_w2vtes,"brute")
```

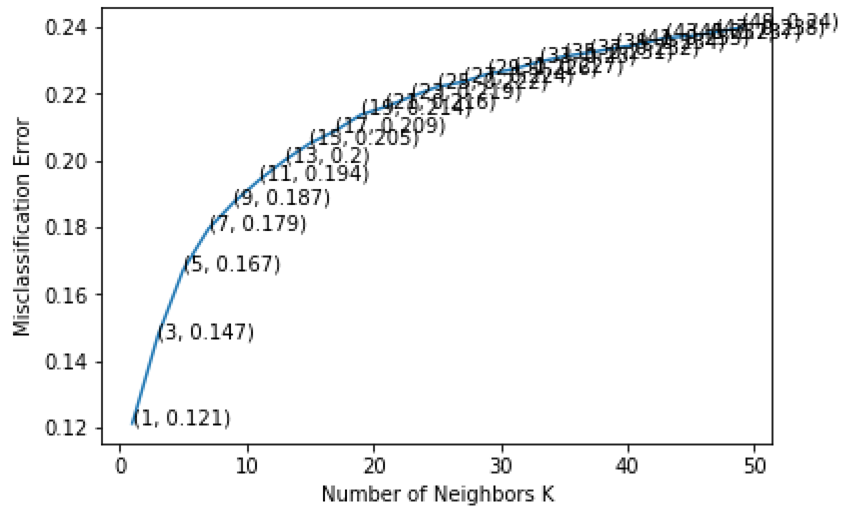
```
The train accuracy for k = 1 is 72%

The train accuracy for k = 3 is 73%

The train accuracy for k = 5 is 74%

The train accuracy for k = 7 is 74%

The train accuracy for k = 9 is 74%

The train accuracy for k = 11 is 74%

The train accuracy for k = 13 is 75%

The train accuracy for k = 15 is 75%

The train accuracy for k = 17 is 75%

The train accuracy for k = 19 is 75%

The train accuracy for k = 21 is 75%

The train accuracy for k = 23 is 75%

The train accuracy for k = 25 is 75%

The train accuracy for k = 27 is 75%

The train accuracy for k = 29 is 75%
```

Hyperparameter tuning the above model to find the right k.

In [28]:
```
W2vcv,W2vneigh=crossval(train_X,train_Y,"brute")
```

In [29]:
```
#FINDING THE OPTIMAL VALUE
W2v_Optimal_k= errorplot(W2vcv,W2vneigh)
```

```
The optimal number of neighbors is 1.
```




```
the misclassification error for each k value is :  [0.121 0.147 0.167 0.179 0.187 0.194 0.2   0.205 0.
209 0.214 0.216 0.219
 0.222 0.224 0.226 0.227 0.23  0.231 0.232 0.234 0.235 0.237 0.237 0.238
 0.24 ]
```

Testing the model over the test set

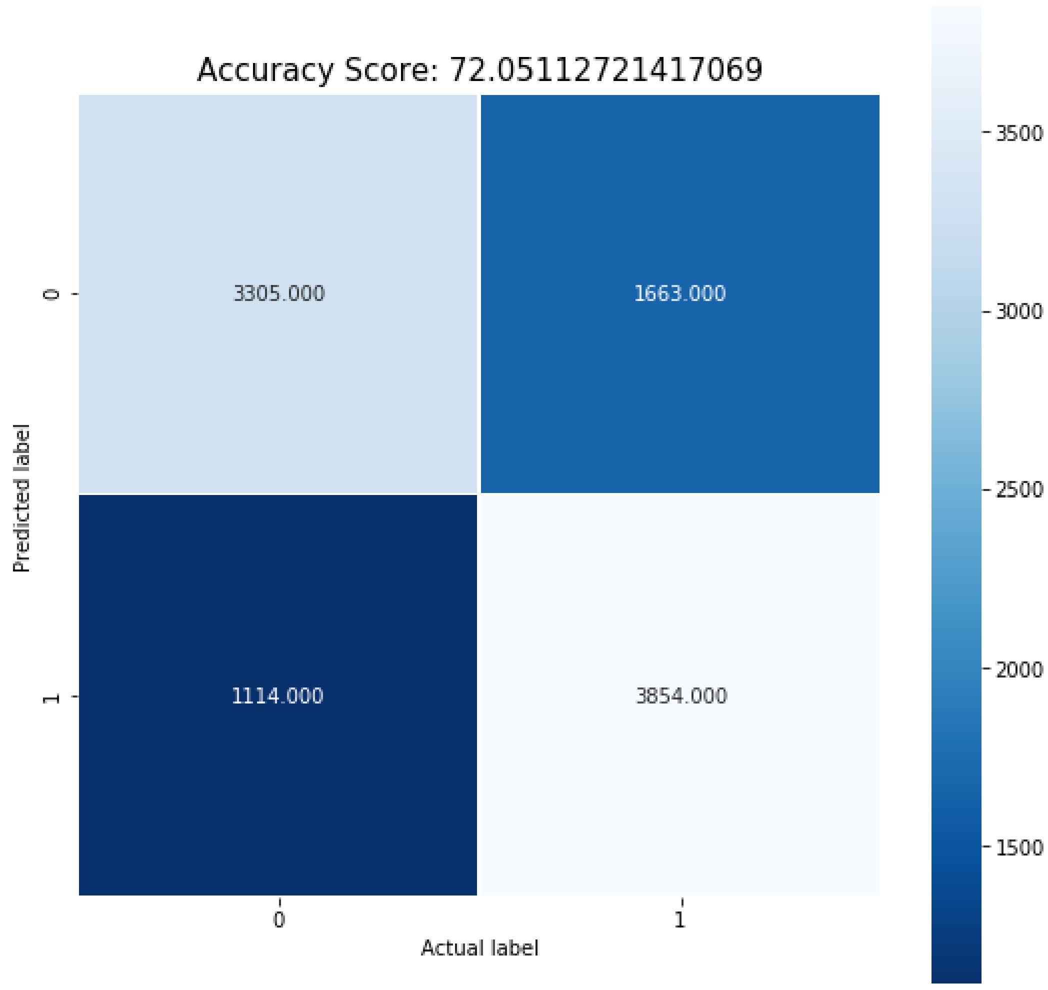
In [31]:
```
W2v_y_Pre,W2v_Acc=Optimal_test(train_X,train_Y,test_X,test_Y,W2v_Optimal_k,"brute")
```

```
The accuracy of the knn classifier for k = 1 is 72.051127%
```

Confusion matrix of the above model

In [32]:
```
Confusion_metric(test_Y,W2v_y_Pre,W2v_Acc)
```

```
[[3305 1663]
 [1114 3854]]
```



```
+-----------------------------------------------------------+
| The performance metrics of the above model are as follows: |
+------------------------------+--------------------------+
|           Metrics            |          Scores          |
+------------------------------+--------------------------+
|   Classification_accuracy    |    72.05112721417069     |
|     Classification_error     |    27.94887278582931     |
|        True positive         |           3854           |
|        False positive        |           1663           |
|        True negative         |           3305           |
|        False negative        |           1114           |
|      True positive rate      |    77.57648953301127     |
|     False negative rate      |    22.423510466988727    |
|      True negative rate      |    66.52576489533011     |
|     False positive rate      |    33.47423510466989     |
|       Precision value        |     69.8568062352728     |
|         Recall value         |    77.57648953301127     |
|        f1_score value        |    73.51454458750597     |
+------------------------------+--------------------------+
```

Observations

- The Test accuracy of the model is around 72.05% which is quite low for a classification model.
- The optimal K value is 1 which means the model overfitts which reduces the model performance.
- The Performance metrics are quite good as compared to the previous unbalanced model inspite of the low accuracy of the classification model.
- The True Positive value is good as compared to the True negative
- The main reason the low accuracy is because of considerable FNR and FPR values which is quite alarming.
- Here the model is overfitting but still the model is stable as compared to the previous models

Implementing Tf-idf weighted word to vector technique

In [51]:
```
start = datetime.now()

Tfidf_vector=TfidfVectorizer()
Tf_model=Tfidf_vector.fit_transform(Sample_sort["CleanedText"].values)

Dimension=Tfidf_vector.get_feature_names()

LIST_VECTOR=[]
row=0
for sentence in list_of_sentence_vec:
    word_2_vec=np.zeros(50)
    weight_tf_sum=0
    for word in sentence:
        try:
            vec=w2v_Model.wv[word]
            tfidf_value=Tf_model[row,Dimension.index(word)]
            word_2_vec += (vec* tfidf_value)
            weight_tf_sum += tfidf_value
        except:
            pass
    if weight_tf_sum !=0:
        word_2_vec /=weight_tf_sum
    LIST_VECTOR.append(word_2_vec)
    row += 1

print('Time taken :', datetime.now() - start)
```

```
Time taken : 0:03:34.863762
```

Training the knn model over the TF-idf weighted W2V implemented vector

In [35]:
```
X1=LIST_VECTOR
Y1=Class

X_tfw2v, X_tfw2vtes, y_tfw2vtr, y_tfw2vtes = train_test_split(X1, Y1, test_size=0.2,shuffle=False,rand
om_state=None)
```

In [39]:
```
train(X_tfw2v,y_tfw2vtr, X_tfw2vtes,y_tfw2vtes ,"brute")
```

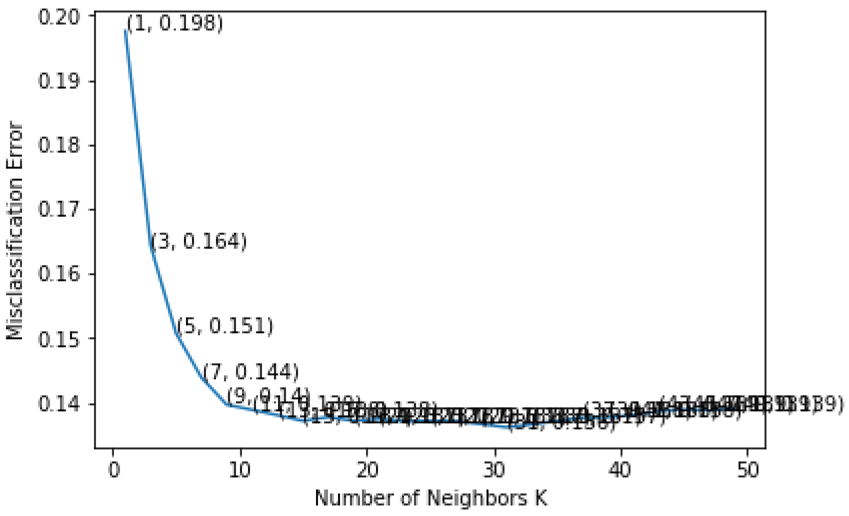
```
The train accuracy for k = 1 is 79%

The train accuracy for k = 3 is 82%

The train accuracy for k = 5 is 83%

The train accuracy for k = 7 is 84%

The train accuracy for k = 9 is 84%

The train accuracy for k = 11 is 84%

The train accuracy for k = 13 is 84%

The train accuracy for k = 15 is 84%

The train accuracy for k = 17 is 84%

The train accuracy for k = 19 is 84%

The train accuracy for k = 21 is 84%

The train accuracy for k = 23 is 84%

The train accuracy for k = 25 is 84%

The train accuracy for k = 27 is 84%

The train accuracy for k = 29 is 84%
```

Hyperparameter tuning the above model to find the right k.

In [40]:
```
tfw2vcv,tfw2vneigh=crossval(X_tfw2v,y_tfw2vtr,"brute")
```

In [41]:
```
#FINDING THE OPTIMAL VALUE
tfw2v_Optimal_k= errorplot(tfw2vcv,tfw2vneigh)
```

```
The optimal number of neighbors is 31.
```




```
the misclassification error for each k value is :  [0.198 0.164 0.151 0.144 0.14  0.139 0.138 0.137 0.
138 0.137 0.137 0.137
 0.137 0.137 0.137 0.136 0.137 0.137 0.138 0.138 0.138 0.139 0.139 0.139
 0.139]
```

Testing the model over the test set

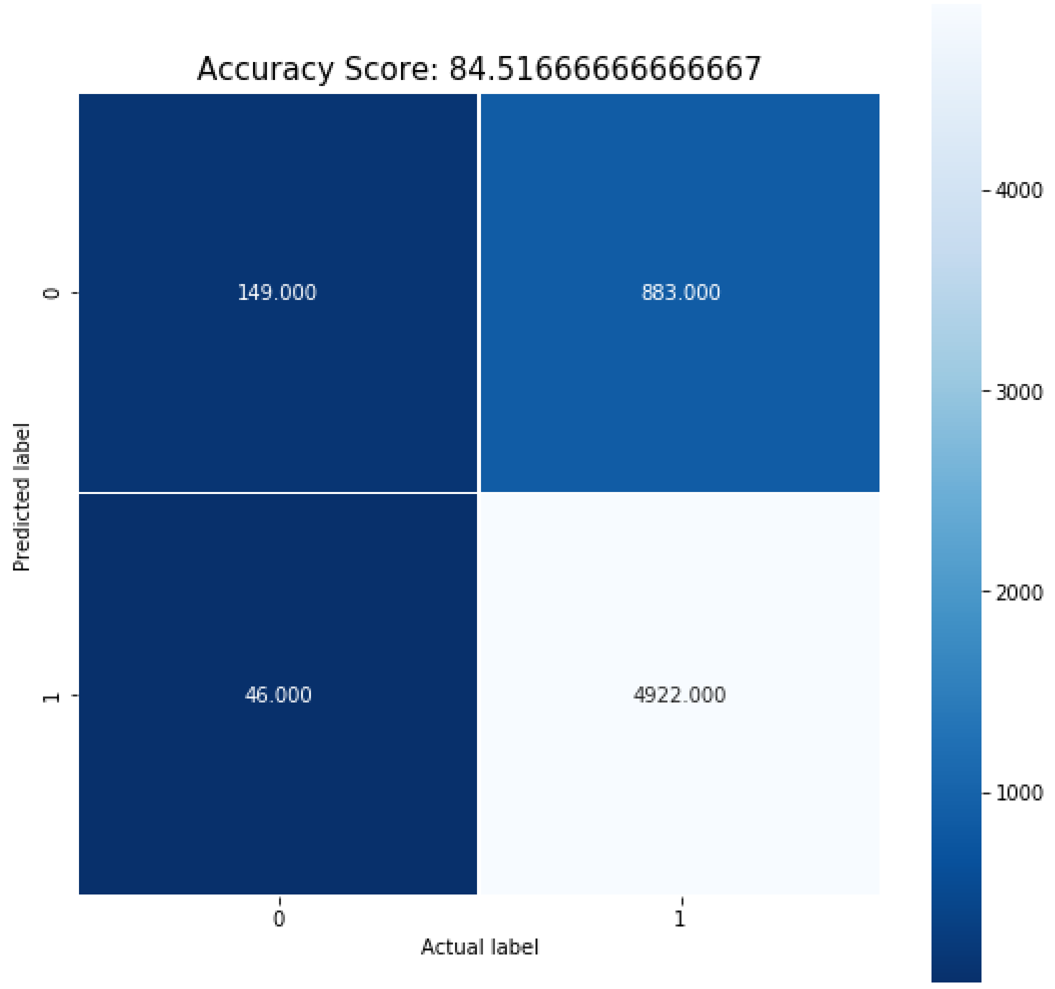
In [42]:
```
tfw2v_y_Pre,tfw2v_Acc=Optimal_test(X_tfw2v,y_tfw2vtr, X_tfw2vtes,y_tfw2vtes,tfw2v_Optimal_k,"brute")
```

```
The accuracy of the knn classifier for k = 31 is 84.516667%
```

Confusion matrix of the above model

In [43]:
```
Confusion_metric(y_tfw2vtes,tfw2v_y_Pre,tfw2v_Acc)
```

```
[[ 149  883]
 [  46 4922]]
```




```
+-------------------------------------------------------------+
| The performance metrics of the above model are as follows:  |
+--------------------------------+----------------------------+
|            Metrics             |           Scores           |
+--------------------------------+----------------------------+
|    Classification_accuracy     |     84.51666666666667      |
|      Classification_error      |     15.483333333333333     |
|         True positive          |            4922            |
|         False positive         |            883             |
|         True negative          |            149             |
|         False negative         |             46             |
|       True positive rate       |     99.07407407407408      |
|      False negative rate       |     0.9259259259259258     |
|       True negative rate       |     14.437984496124031     |
|      False positive rate       |     85.56201550387597      |
|        Precision value         |     84.78897502153316      |
|          Recall value          |     99.07407407407408      |
|         f1_score value         |     91.37658962220367      |
+--------------------------------+----------------------------+
```

Observations

- The train accuracy of the above model is 84.51% at 31 as a optimal value.
- But after analyzing the confusion matrix the model is not sensible at all because the True positive value is dominating so as the TPR values as compared to the other metrics.
- The True negative and the False negative rates are very miniscule which leads to decreased TNR which is very bad for a classification model.
- The model is not at all classiffying the negative reviews and the model is really dumb.
- The model is facing a very heavy bias problem and underfitting a lot since the optimal k value is 31.
- So accuracy as a metric cannot be trusted in a imbalanced dataset, the model's performance may improve if we use another approach such as:-
  - 1)KD-tree approach.
  - 2)Oversampling techniques.

  </ul

Oversampling the datapoints by using the SMOTE technique.

In [44]:
```
Train_x,Train_y,Test_x,Test_y=Bal_train (X_tfw2v,y_tfw2vtr, X_tfw2vtes,y_tfw2vtes,"brute")
```

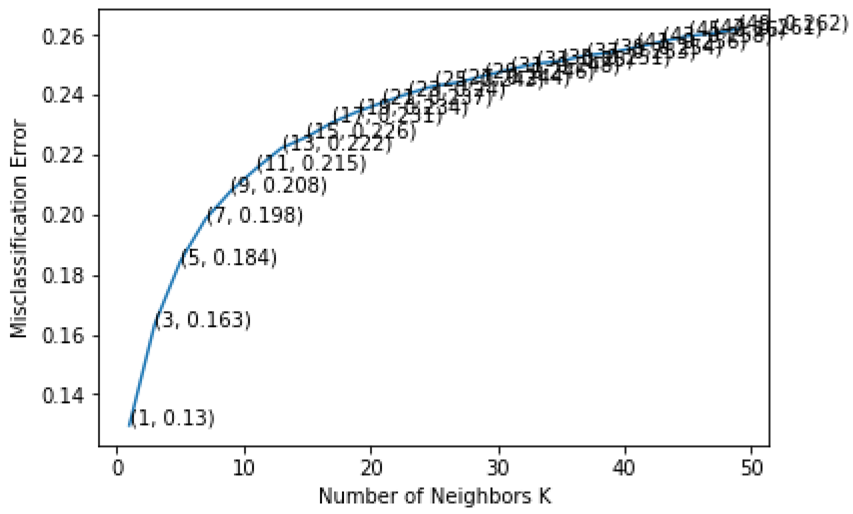
```
The train accuracy for k = 1 is 68%

The train accuracy for k = 3 is 71%

The train accuracy for k = 5 is 72%

The train accuracy for k = 7 is 72%

The train accuracy for k = 9 is 72%

The train accuracy for k = 11 is 72%

The train accuracy for k = 13 is 72%

The train accuracy for k = 15 is 72%

The train accuracy for k = 17 is 72%

The train accuracy for k = 19 is 72%

The train accuracy for k = 21 is 72%

The train accuracy for k = 23 is 72%

The train accuracy for k = 25 is 72%

The train accuracy for k = 27 is 72%

The train accuracy for k = 29 is 72%
```

Hyperparameter tuning the above model to find the right k.

In [46]:
```
TFW2vcv,TFW2vneigh=crossval(Train_x,Train_y,"brute")
```

In [47]:
```
#FINDING THE OPTIMAL VALUE
TFW2v_Optimal_k= errorplot(TFW2vcv,TFW2vneigh)
```

```
The optimal number of neighbors is 1.
```




```
the misclassification error for each k value is :  [0.13  0.163 0.184 0.198 0.208 0.215 0.222 0.226 0.
231 0.234 0.237 0.24
 0.243 0.244 0.246 0.248 0.25  0.251 0.253 0.254 0.256 0.258 0.26  0.261
 0.262]
```

Testing the model over the test set

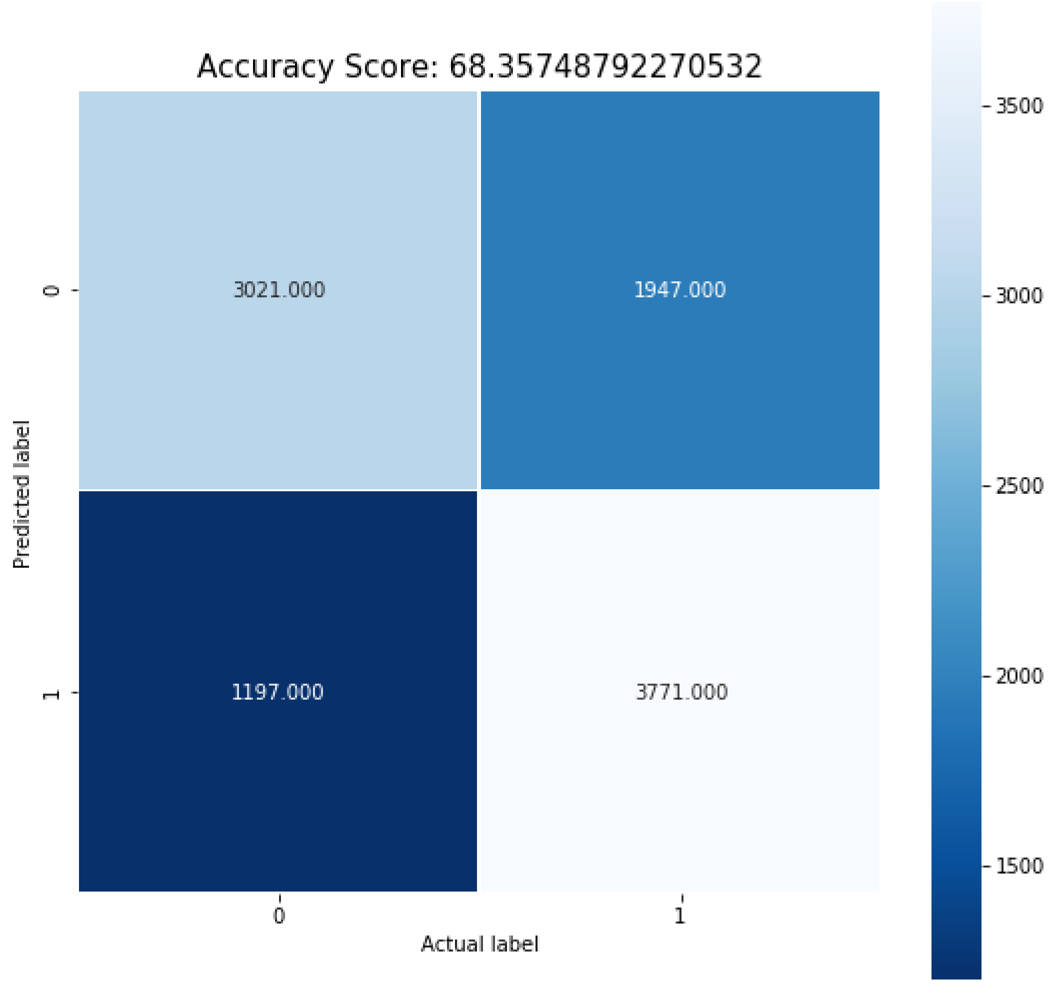
In [48]:
```
TFW2v_y_Pre,TFW2v_Acc=Optimal_test(Train_x,Train_y,Test_x,Test_y,W2v_Optimal_k,"brute")
```

```
The accuracy of the knn classifier for k = 1 is 68.357488%
```

Confusion matrix of the above model

In [50]:
```
Confusion_metric(Test_y,TFW2v_y_Pre,TFW2v_Acc)
```

```
[[3021 1947]
 [1197 3771]]
```




```
+-----------------------------------------------------------+
| The performance metrics of the above model are as follows: |
+--------------------------------+--------------------------+
|            Metrics             |          Scores          |
+--------------------------------+--------------------------+
|    Classification_accuracy     |    68.35748792270532     |
|      Classification_error      |    31.642512077294686    |
|         True positive          |           3771           |
|         False positive         |           1947           |
|         True negative          |           3021           |
|         False negative         |           1197           |
|       True positive rate       |    75.90579710144928     |
|      False negative rate       |    24.094202898550723    |
|       True negative rate       |    60.809178743961354    |
|      False positive rate       |    39.190821256038646    |
|        Precision value         |    65.94963273871983     |
|          Recall value          |    75.90579710144928     |
|         f1_score value         |    70.57832678270634     |
+--------------------------------+--------------------------+
```

Observations

- The Test accuracy of the model is around 68.35% which is quite low for a classification model.
- The optimal K value is 1 which means the model overfitts which reduces the model performance.
- The Performance metrics are quite good as compared to the previous unbalanced model inspite of the low accuracy of the classification model.
- The True Positive value is good as compared to the True negative.
- The main reason the low accuracy is because of considerable FNR and FPR values which is quite alarming.
- Here the model is overfitting but still the model is stable and sensible as compared to the previous models.

Conclusion:-

- So by implementing all the four techniques of vectorization I have come to these conclusions:-

  1. The results in both the approachs with Kd-tree and Brute are not that much similar and the Kd_tree method may yield better results if trained on larger datapoints.
  2. The Knn-algorithm suffers from curse of dimensionality specially with tf-idf vectorization technique and Dense Kd_tree implementation.
  3. The KNN-model overfits and underfitts easily if the model is trained over an Imbalanced datasets and accuracy as a metric cannot be trusted completely.
  4. The Kd_tree approach is very much computationally expensive and time consuming.
  5. The usage of Synthetic minority oversampling technique (SMOTE) is usefull in imbalanced text data as it made the models stable as compared to the imbalanced datasets but it overfitts easily.
  6. From my observations I can conclude that KNN-algorithm does not work well with the text data due to high dimensions.