iml554-classification-assignment02

August 21, 2024

1 Case Study:

Let's assume you are a data scientist, and you have been tasked with a classification problem of a Dry Bean

About the dataset:

Seven different types of dry beans were used in this research, taking into account the features such as form, shape, type, and structure by the market situation. A computer vision system was developed to distinguish seven different registered varieties of dry beans with similar features in order to obtain uniform seed classification. For the classification model, images of 13,611 grains of 7 different registered dry beans were taken with a high-resolution camera. Bean images obtained by computer vision system were subjected to segmentation and feature extraction stages, and a total of 16 features; 12 dimensions and 4 shape forms, were obtained from the grains.

1.1 Task 1:- Perform data loading, preprocessing by dropping any rows with 'NaN' values in the 'Class' column. [1M]

1.1.1 Libraries Import

[219]:
```
# Importing required packages
import numpy as np
import pandas as pd
import warnings as war
war.filterwarnings("ignore")
```

1.1.2 Load & Read Dataset

[220]:
```
# Defining dataset excelsheet Path
dataSetPath="C:\\Users\ASUS\\jupyterworkspace\\Assignment & Mini␣
↪Project\\Module_03_Classification\\Assignment\\02_Train Naive bayes and␣
↪logistic regression\\Dry_Bean_Dataset (1).xlsx"
# Loading dataSet
dataSetRead=pd.read_excel(dataSetPath)
```

[221]:
```
# Displaying first 5 records to confirming data loading
print("**************************************************Displaying below␣
↪first 5 records********************************************************")
dataSetRead.head()
```

```
*****************************************************Displaying below first 5
records**********************************************************
```

[221]:

	Area	Perimeter	MajorAxisLength	MinorAxisLength	AspectRation
0	28395	610.291	208.178117	173.888747	1.197191
1	28734	638.018	200.524796	182.734419	1.097356
2	29380	624.110	212.826130	175.931143	1.209713
3	30008	645.884	210.557999	182.516516	1.153638
4	30140	620.134	201.847882	190.279279	1.060798

	Eccentricity	ConvexArea	EquivDiameter	Extent	Solidity	roundness
0	0.549812	28715	190.141097	0.763923	0.988856	0.958027
1	0.411785	29172	191.272750	0.783968	0.984986	0.887034
2	0.562727	29690	193.410904	0.778113	0.989559	0.947849
3	0.498616	30724	195.467062	0.782681	0.976696	0.903936
4	0.333680	30417	195.896503	0.773098	0.990893	0.984877

	Compactness	ShapeFactor1	ShapeFactor2	ShapeFactor3	ShapeFactor4	Class
0	0.913358	0.007332	0.003147	0.834222	0.998724	SEKER
1	0.953861	0.006979	0.003564	0.909851	0.998430	SEKER
2	0.908774	0.007244	0.003048	0.825871	0.999066	SEKER
3	0.928329	0.007017	0.003215	0.861794	0.994199	SEKER
4	0.970516	0.006697	0.003665	0.941900	0.999166	SEKER

[222]:

```python
# Displaying last 5 records to confirming data loading
print("*****************************************************Displaying below␣
↪first 5 records**********************************************************")
dataSetRead.tail()
```

```
*****************************************************Displaying below first 5
records**********************************************************
```

[222]:

	Area	Perimeter	MajorAxisLength	MinorAxisLength	AspectRation
13606	42097	759.696	288.721612	185.944705	1.552728
13607	42101	757.499	281.576392	190.713136	1.476439
13608	42139	759.321	281.539928	191.187979	1.472582
13609	42147	763.779	283.382636	190.275731	1.489326
13610	42159	772.237	295.142741	182.204716	1.619841

	Eccentricity	ConvexArea	EquivDiameter	Extent	Solidity	roundness
13606	0.765002	42508	231.515799	0.714574	0.990331	0.916603
13607	0.735702	42494	231.526798	0.799943	0.990752	0.922015
13608	0.734065	42569	231.631261	0.729932	0.989899	0.918424
13609	0.741055	42667	231.653248	0.705389	0.987813	0.907906
13610	0.786693	42600	231.686223	0.788962	0.989648	0.888380

```
       Compactness  ShapeFactor1  ShapeFactor2  ShapeFactor3  ShapeFactor4  \
```

```
13606     0.801865      0.006858      0.001749      0.642988      0.998385
13607     0.822252      0.006688      0.001886      0.676099      0.998219
13608     0.822730      0.006681      0.001888      0.676884      0.996767
13609     0.817457      0.006724      0.001852      0.668237      0.995222
13610     0.784997      0.007001      0.001640      0.616221      0.998180

          Class
13606  DERMASON
13607  DERMASON
13608  DERMASON
13609  DERMASON
13610  DERMASON
```

[223]:

```
# Displaying dimension of dataSet
print("Dimention of Dataset:- {}".format(dataSetRead.shape[0:2]))
print("Total number of rows in Dataset:- {}".format(dataSetRead.shape[0]))
print("Total number of columns in Dataset:- {}".format(dataSetRead.shape[1]))
```

```
Dimention of Dataset:- (13611, 17)
Total number of rows in Dataset:- 13611
Total number of columns in Dataset:- 17
```

[224]:

```
# Displaying the description and statistical summary of the data
dataSetRead.describe().T
```

[224]:

```
                   count          mean           std           min  \
Area             13611.0  53048.284549  29324.095717  20420.000000
Perimeter        13611.0    855.283459    214.289696    524.736000
MajorAxisLength  13611.0    320.141867     85.694186    183.601165
MinorAxisLength  13611.0    202.270714     44.970091    122.512653
AspectRation     13611.0      1.583242      0.246678      1.024868
Eccentricity     13611.0      0.750895      0.092002      0.218951
ConvexArea       13611.0  53768.200206  29774.915817  20684.000000
EquivDiameter    13611.0    253.064220     59.177120    161.243764
Extent           13611.0      0.749733      0.049086      0.555315
Solidity         13611.0      0.987143      0.004660      0.919246
roundness        13611.0      0.873282      0.059520      0.489618
Compactness      13611.0      0.799864      0.061713      0.640577
ShapeFactor1     13611.0      0.006564      0.001128      0.002778
ShapeFactor2     13611.0      0.001716      0.000596      0.000564
ShapeFactor3     13611.0      0.643590      0.098996      0.410339
ShapeFactor4     13611.0      0.995063      0.004366      0.947687

                          25%           50%           75%            max
Area             36328.000000  44652.000000  61332.000000  254616.000000
Perimeter          703.523500    794.941000    977.213000    1985.370000
MajorAxisLength    253.303633    296.883367    376.495012     738.860153
```

```
MinorAxisLength    175.848170    192.431733    217.031741    460.198497
AspectRation         1.432307      1.551124      1.707109      2.430306
Eccentricity         0.715928      0.764441      0.810466      0.911423
ConvexArea       36714.500000  45178.000000  62294.000000  263261.000000
EquivDiameter      215.068003    238.438026    279.446467    569.374358
Extent               0.718634      0.759859      0.786851      0.866195
Solidity             0.985670      0.988283      0.990013      0.994677
roundness            0.832096      0.883157      0.916869      0.990685
Compactness          0.762469      0.801277      0.834270      0.987303
ShapeFactor1         0.005900      0.006645      0.007271      0.010451
ShapeFactor2         0.001154      0.001694      0.002170      0.003665
ShapeFactor3         0.581359      0.642044      0.696006      0.974767
ShapeFactor4         0.993703      0.996386      0.997883      0.999733
```

[225]:
```python
# Displaying the columns and their respective data types
dataSetRead.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 13611 entries, 0 to 13610
Data columns (total 17 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   Area             13611 non-null  int64
 1   Perimeter        13611 non-null  float64
 2   MajorAxisLength  13611 non-null  float64
 3   MinorAxisLength  13611 non-null  float64
 4   AspectRation     13611 non-null  float64
 5   Eccentricity     13611 non-null  float64
 6   ConvexArea       13611 non-null  int64
 7   EquivDiameter    13611 non-null  float64
 8   Extent           13611 non-null  float64
 9   Solidity         13611 non-null  float64
 10  roundness        13611 non-null  float64
 11  Compactness      13611 non-null  float64
 12  ShapeFactor1     13611 non-null  float64
 13  ShapeFactor2     13611 non-null  float64
 14  ShapeFactor3     13611 non-null  float64
 15  ShapeFactor4     13611 non-null  float64
 16  Class            13611 non-null  object
dtypes: float64(14), int64(2), object(1)
memory usage: 1.8+ MB
```

[226]:
```python
# Checking total no. of missing values for attributes specific
missingValue_Count=dataSetRead.isnull().sum()
print(missingValue_Count)
```

```
Area               0
Perimeter          0
```

```
MajorAxisLength    0
MinorAxisLength    0
AspectRation       0
Eccentricity       0
ConvexArea         0
EquivDiameter      0
Extent             0
Solidity           0
roundness          0
Compactness        0
ShapeFactor1       0
ShapeFactor2       0
ShapeFactor3       0
ShapeFactor4       0
Class              0
dtype: int64
```

[227]:
```python
# Checking duplicate values in dataSet
duplicatevalue_Count=dataSetRead.duplicated().sum()
print("Total duplicates values in dataSet:- {}".format(duplicatevalue_Count))
```

```
Total duplicates values in dataSet:- 68
```

[228]:
```python
# Removing duplicates values in dataSet
dataSetRead=dataSetRead.drop_duplicates(subset=None,keep='first')
```

[229]:
```python
# Displaying dimension of dataSet after removing duplicates values
print("Dimention of Dataset:- {}".format(dataSetRead.shape[0:2]))
print("Total number of unique rows in Dataset:- {}".format(dataSetRead.
 ↪shape[0]))
print("Total number of columns in Dataset:- {}".format(dataSetRead.shape[1]))
```

```
Dimention of Dataset:- (13543, 17)
Total number of unique rows in Dataset:- 13543
Total number of columns in Dataset:- 17
```

[230]:
```python
# Checking percentagewise distiribution for "Class" target variable
dataSetRead['Class'].value_counts(normalize=True).mul(100).round(2)
```

[230]:
```
Class
DERMASON    26.18
SIRA        19.46
SEKER       14.97
HOROZ       13.73
CALI        12.04
BARBUNYA     9.76
BOMBAY       3.85
Name: proportion, dtype: float64
```

[231]:
```
# Checking countwise distiribution for "Class" target variable
dataSetRead['Class'].value_counts()
```

[231]:
```
Class
DERMASON    3546
SIRA        2636
SEKER       2027
HOROZ       1860
CALI        1630
BARBUNYA    1322
BOMBAY       522
Name: count, dtype: int64
```

Analysis:- Above distribution operation shows that the dataset is unbalnaced hence SMOTE technique to be implmented for the over sampling

[232]:
```
# Dropping target variable
X=dataSetRead.drop('Class',axis=1)
# Taking target variavle
y=dataSetRead['Class']
```

[233]:
```
# Importing SMOTE module from imblearn library
from imblearn.over_sampling import SMOTE
# Importing Counter module from collections library
from collections import Counter
counter = Counter(y)
print('Before oversampling', counter)
# Oversampling the dataset using SMOTE
smt = SMOTE(random_state = 2)
X_res, y_res = smt.fit_resample(X, y.ravel())
counter = Counter(y_res)
print('After oversampling', counter)
```

```
Before oversampling Counter({'DERMASON': 3546, 'SIRA': 2636, 'SEKER': 2027,
'HOROZ': 1860, 'CALI': 1630, 'BARBUNYA': 1322, 'BOMBAY': 522})
After oversampling Counter({'SEKER': 3546, 'BARBUNYA': 3546, 'BOMBAY': 3546,
'CALI': 3546, 'HOROZ': 3546, 'SIRA': 3546, 'DERMASON': 3546})
```

1.2 Task 2:- Split the dataset into features (X) and the target variable (y), and further divide into training and test sets. [Consider test_size=0.2] [1M]

1.2.1 Split data in to features & target

[234]:
```
# Importing train_test_split package
from sklearn.model_selection import train_test_split
```

[235]:
```python
# Printing oversampling dataset witout target variable
X_res
```

[235]:
```
        Area   Perimeter  MajorAxisLength  MinorAxisLength  AspectRation  \
0      28395  610.291000       208.178117       173.888747      1.197191
1      28734  638.018000       200.524796       182.734419      1.097356
2      29380  624.110000       212.826130       175.931143      1.209713
3      30008  645.884000       210.557999       182.516516      1.153638
4      30140  620.134000       201.847882       190.279279      1.060798
…        …         …              …                …             …
24817  53569  880.253331       337.553023       203.621165      1.658148
24818  39072  741.455454       274.092716       182.229010      1.504613
24819  50806  847.574851       316.894424       205.483287      1.544764
24820  40310  760.238931       287.386392       179.663073      1.601752
24821  41699  773.085596       288.422067       184.790362      1.560825

       Eccentricity  ConvexArea  EquivDiameter    Extent  Solidity  roundness  \
0          0.549812       28715     190.141097  0.763923  0.988856   0.958027
1          0.411785       29172     191.272750  0.783968  0.984986   0.887034
2          0.562727       29690     193.410904  0.778113  0.989559   0.947849
3          0.498616       30724     195.467062  0.782681  0.976696   0.903936
4          0.333680       30417     195.896503  0.773098  0.990893   0.984877
…               …          …             …         …         …         …
24817      0.797243       54137     261.165044  0.753328  0.989505   0.868802
24818      0.746414       39633     223.044599  0.797245  0.985855   0.893511
24819      0.758764       51377     254.339651  0.783406  0.988884   0.889169
24820      0.778282       40877     226.548769  0.770890  0.986109   0.876587
24821      0.767784       42264     230.419395  0.734819  0.986615   0.876778

       Compactness  ShapeFactor1  ShapeFactor2  ShapeFactor3  ShapeFactor4
0         0.913358      0.007332      0.003147      0.834222      0.998724
1         0.953861      0.006979      0.003564      0.909851      0.998430
2         0.908774      0.007244      0.003048      0.825871      0.999066
3         0.928329      0.007017      0.003215      0.861794      0.994199
4         0.970516      0.006697      0.003665      0.941900      0.999166
…              …            …            …            …            …
24817     0.773819      0.006301      0.001394      0.598886      0.992484
24818     0.813890      0.007015      0.001899      0.662530      0.996186
24819     0.803308      0.006237      0.001605      0.645870      0.994271
24820     0.788884      0.007129      0.001706      0.622823      0.994733
24821     0.798899      0.006917      0.001738      0.638241      0.996168

[24822 rows x 16 columns]
```

[236]:
```python
# Displaying type of y_res
type(y_res)
```

[236]: numpy.ndarray

[237]:
```
# Converting a NumPy array to Pandas dataframe
y_res=pd.DataFrame(y_res,columns=['Class'])
# Printing oversampling dataframe of target variable
print(y_res)
```

```
       Class
0      SEKER
1      SEKER
2      SEKER
3      SEKER
4      SEKER
…      …
24817   SIRA
24818   SIRA
24819   SIRA
24820   SIRA
24821   SIRA

[24822 rows x 1 columns]
```

[238]:
```
# Splitting train & test data
X_train,X_test,y_train,y_test=train_test_split(X_res,y_res,test_size=0.
 ↪2,random_state=42,stratify=y_res)
```

[239]:
```
# Displaying dimenstion of train & test dataset
print('Shape of X_train = ', X_train.shape)
print('Shape of y_train = ', y_train.shape)
print('Shape of X_test = ', X_test.shape)
print('Shape of y_test = ', y_test.shape)
```

```
Shape of X_train =  (19857, 16)
Shape of y_train =  (19857, 1)
Shape of X_test =  (4965, 16)
Shape of y_test =  (4965, 1)
```

[240]:
```
# Checking distiribution for "Class" target variable in Y_train
y_train.value_counts()
```

[240]:
```
Class
BARBUNYA    2837
BOMBAY      2837
CALI        2837
HOROZ       2837
SEKER       2837
DERMASON    2836
```

```
SIRA        2836
Name: count, dtype: int64
```

[241]:
```python
# Checking distiribution for "Class" target variable in Y_test
y_test.value_counts()
```

[241]:
```
Class
DERMASON    710
SIRA        710
BARBUNYA    709
BOMBAY      709
CALI        709
HOROZ       709
SEKER       709
Name: count, dtype: int64
```

1.3 Task 3:- Perform data scaling and modelling. [1M]

1.3.1 Data scaling

[242]:
```python
# importing required package
# MinMax Scaler is used to perform feature scalling
from sklearn.preprocessing import MinMaxScaler
scalling=MinMaxScaler()
scalling.fit(X_train)
```

[242]:
```
MinMaxScaler()
```

[243]:
```python
X_train_scalling=scalling.transform(X_train)
X_test_scalling=scalling.transform(X_test)
```

[244]:
```python
X_train_scalling
```

[244]:
```
array([[0.14270645, 0.28115446, 0.35594759, …, 0.13112294, 0.10828791,
        0.58689491],
       [0.59331545, 0.67384644, 0.64922538, …, 0.1393321 , 0.4915265 ,
        0.92599022],
       [0.17322508, 0.30750345, 0.34622427, …, 0.18803977, 0.24628834,
        0.8526562 ],
       …,
       [0.03446052, 0.06991895, 0.09257644, …, 0.52406776, 0.43518305,
        0.95644806],
       [0.53953842, 0.64154451, 0.6518136 , …, 0.10964016, 0.38556336,
        0.92359037],
       [0.07892736, 0.13247946, 0.10436721, …, 0.70559719, 0.77462088,
        0.98085773]])
```

[245]:
```
X_test_scalling
```

[245]:
```
array([[0.10625577, 0.18312527, 0.19692738, …, 0.39799217, 0.46253546,
        0.92078002],
       [0.09231183, 0.17687182, 0.19509935, …, 0.36185769, 0.38455981,
        0.84551881],
       [0.24955157, 0.38464237, 0.41623691, …, 0.17438083, 0.30696353,
        0.91148264],
       …,
       [0.21997677, 0.38671015, 0.40001887, …, 0.16505286, 0.25827008,
        0.75019787],
       [0.12693464, 0.25104715, 0.28076253, …, 0.23072029, 0.2537147 ,
        0.85338992],
       [0.09071885, 0.16722327, 0.18626795, …, 0.38508826, 0.41260767,
        0.88714452]])
```

1.4 Task 4:-Train Naive bayes and logistic regression [2 M]

[264]:
```
# Importing library of Gaussian Navie Bayes Model
from sklearn.naive_bayes import GaussianNB
# Creating a Gaussian Navie Bayes classifier
Classifiermodel_GNB = GaussianNB()
```

[265]:
```
# Training the Naive Bayes model using training data set
Classifiermodel_GNB.fit(X_train_scalling, y_train)
```

[265]:
```
GaussianNB()
```

[266]:
```
# Importing library of logistic regression
from sklearn.linear_model import LogisticRegression
# Creating a  Logistic regression classifier
Classifiermodel_LOR = LogisticRegression()
```

[267]:
```
# Training the logistic regression model using training data set
Classifiermodel_LOR.fit(X_train_scalling, y_train)
```

[267]:
```
LogisticRegression()
```

1.5 Task 5:- Evaluate the model performance using a classification report and accuracy score and compare both the models [2M]

[250]:
```
# Importing Library of classification_report, accuracy_score
from sklearn.metrics import classification_report, accuracy_score
```

[251]:
```
# Prediction on test data for Navie Bayes Model
y_prediction_GNB=Classifiermodel_GNB.predict(X_test_scalling)
```

[252]:
```python
# Evaluating the accuracy of Navie Bayes Model
accuracy_GNB=accuracy_score(y_test,y_prediction_GNB)
print("Gaussian Navie Bayes Model Accuracy: {}".format(round(accuracy_GNB,2)))
```

```
Gaussian Navie Bayes Model Accuracy: 0.92
```

[253]:
```python
# Displaying classfication report for Navie Bayes Model
report_GNB=classification_report(y_test,y_prediction_GNB)
print(report_GNB)
```

```
              precision    recall  f1-score   support

    BARBUNYA       0.93      0.84      0.88       709
      BOMBAY       1.00      1.00      1.00       709
        CALI       0.88      0.93      0.91       709
    DERMASON       0.90      0.87      0.89       710
       HOROZ       0.96      0.96      0.96       709
       SEKER       0.95      0.96      0.96       709
        SIRA       0.82      0.87      0.85       710

    accuracy                           0.92      4965
   macro avg       0.92      0.92      0.92      4965
weighted avg       0.92      0.92      0.92      4965
```

[254]:
```python
# Prediction on test data for Logistic Regression Model
y_prediction_LOR=Classifiermodel_LOR.predict(X_test_scalling)
```

[255]:
```python
# Evaluating the accuracy of Logistic Regression Model
accuracy_LOR=accuracy_score(y_test,y_prediction_LOR)
print("Logistic Regression Model Accuracy: {}".format(round(accuracy_LOR,2)))
```

```
Logistic Regression Model Accuracy: 0.94
```

[256]:
```python
# Displaying classfication report for Logistic Regression Model
report_LOR=classification_report(y_test,y_prediction_LOR)
print(report_LOR)
```

```
              precision    recall  f1-score   support

    BARBUNYA       0.97      0.92      0.94       709
      BOMBAY       1.00      1.00      1.00       709
        CALI       0.94      0.96      0.95       709
    DERMASON       0.91      0.87      0.89       710
       HOROZ       0.96      0.96      0.96       709
       SEKER       0.95      0.97      0.96       709
        SIRA       0.83      0.88      0.85       710
```

```
    accuracy                           0.94      4965
   macro avg       0.94      0.94      0.94      4965
weighted avg       0.94      0.94      0.94      4965
```

1.6 Task 6:- Plot a confusion matrix as a heatmap, offering a visual representation of the model's performance, illustrating True Positives, True Negatives, False Positives, and False Negatives for both models. [2M]

[257]:
```
# Importing required packages
from sklearn.metrics import confusion_matrix
import matplotlib.pyplot as plt
import seaborn as sbn
```

[258]:
```
#Confusion matrix for Navie Bayes Model
conf_matrix_GNB=confusion_matrix(y_test,y_prediction_GNB)
print(conf_matrix_GNB)
```

```
[[599   0  75   0   2   6  27]
 [  0 709   0   0   0   0   0]
 [ 38   3 658   0   9   0   1]
 [  1   0   0 619   0  17  73]
 [  0   0   7   9 680   0  13]
 [  3   0   0   5   0 680  21]
 [  4   0   4  55  17  11 619]]
```

[259]:
```
falsePositive = conf_matrix_GNB.sum(axis=0) - np.diag(conf_matrix_GNB)
falseNegative = conf_matrix_GNB.sum(axis=1) - np.diag(conf_matrix_GNB)
truePositive = np.diag(conf_matrix_GNB)
trueNegative = conf_matrix_GNB.sum() - (falsePositive1 + falseNegative1 +
 ↪truePositive1)
print('************* Gaussian Navie Bayes *************')
for i in range(len(truePositive)):
    print(f"Class {i}:")
    print(f"truePositive: {truePositive[i]}, falsePositive: {falsePositive[i]},
 ↪falseNegative: {falseNegative[i]}, trueNegative: {trueNegative[i]}")
    print()
```

```
************* Gaussian Navie Bayes *************
Class 0:
truePositive: 599, falsePositive: 46, falseNegative: 110, trueNegative: 4236

Class 1:
truePositive: 709, falsePositive: 3, falseNegative: 0, trueNegative: 4256

Class 2:
truePositive: 658, falsePositive: 86, falseNegative: 51, trueNegative: 4213
```

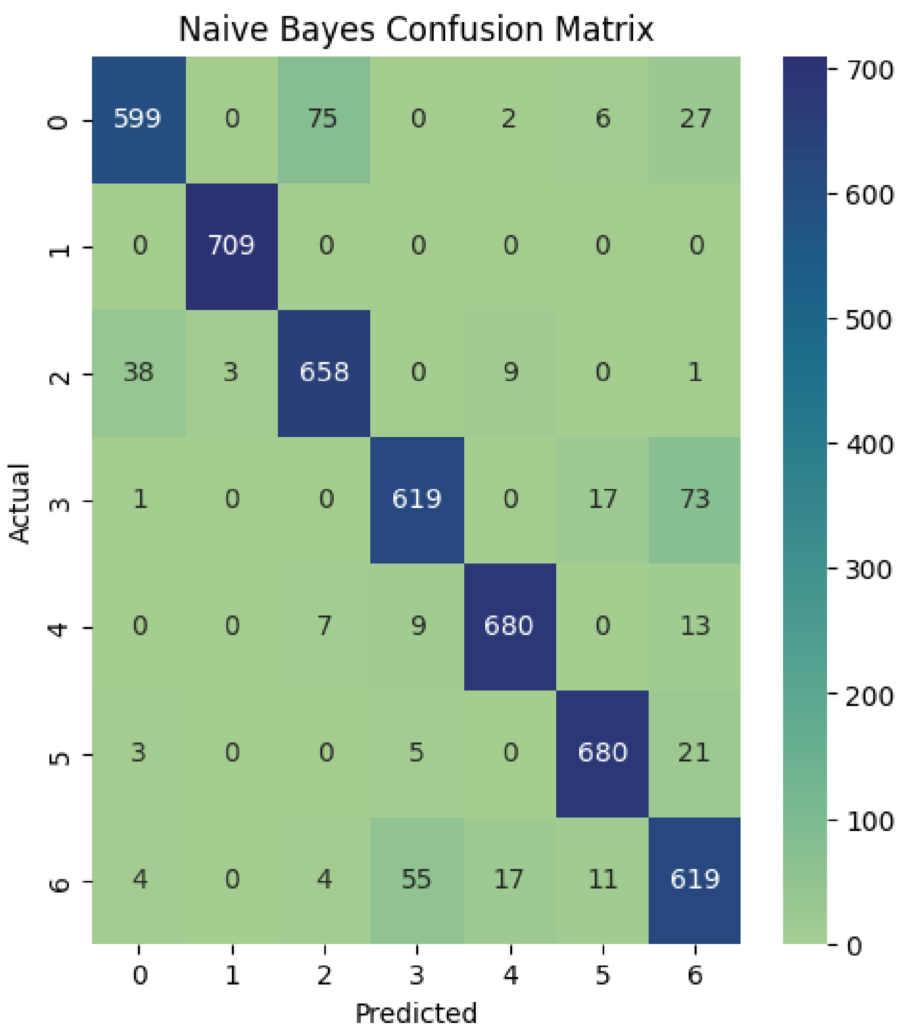
```
Class 3:
truePositive: 619, falsePositive: 69, falseNegative: 91, trueNegative: 4190

Class 4:
truePositive: 680, falsePositive: 28, falseNegative: 29, trueNegative: 4229

Class 5:
truePositive: 680, falsePositive: 34, falseNegative: 29, trueNegative: 4221

Class 6:
truePositive: 619, falsePositive: 135, falseNegative: 91, trueNegative: 4129
```

[260]:

```python
# Plotting the confusion matrix for Naive Bayes Model
plt.figure(figsize=(12, 6))
plt.subplot(1, 2, 1)
sbn.heatmap(conf_matrix_GNB, annot=True, fmt='d', cmap='crest')
plt.title('Naive Bayes Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('Actual')
```

[260]:

```
Text(120.72222222222221, 0.5, 'Actual')
```



[261]:
```
#Confusion matrix for logistic regression Model
conf_matrix_LOR=confusion_matrix(y_test,y_prediction_LOR)
print(conf_matrix_LOR)
```

```
[[651   0  32   0   1   6  19]
 [  0 709   0   0   0   0   0]
 [ 13   0 681   0   9   0   6]
 [  1   0   0 620   1  15  73]
 [  0   0  10   8 679   0  12]
 [  4   0   0   4   0 685  16]
 [  2   0   1  53  16  14 624]]
```

[262]:
```
falsePositive1 = conf_matrix_LOR.sum(axis=0) - np.diag(conf_matrix_LOR)
falseNegative1 = conf_matrix_LOR.sum(axis=1) - np.diag(conf_matrix_LOR)
truePositive1 = np.diag(conf_matrix_LOR)
```

```
trueNegative1 = conf_matrix_LOR.sum() - (falsePositive1 + falseNegative1 +␣
 ↪truePositive1)
print('************* Logistic Regression *************')
for i in range(len(truePositive1)):
    print(f"Class {i}:")
    print(f"truePositive: {truePositive1[i]}, falsePositive:␣
 ↪{falsePositive1[i]}, falseNegative: {falseNegative1[i]}, trueNegative:␣
 ↪{trueNegative1[i]}")
    print()
```

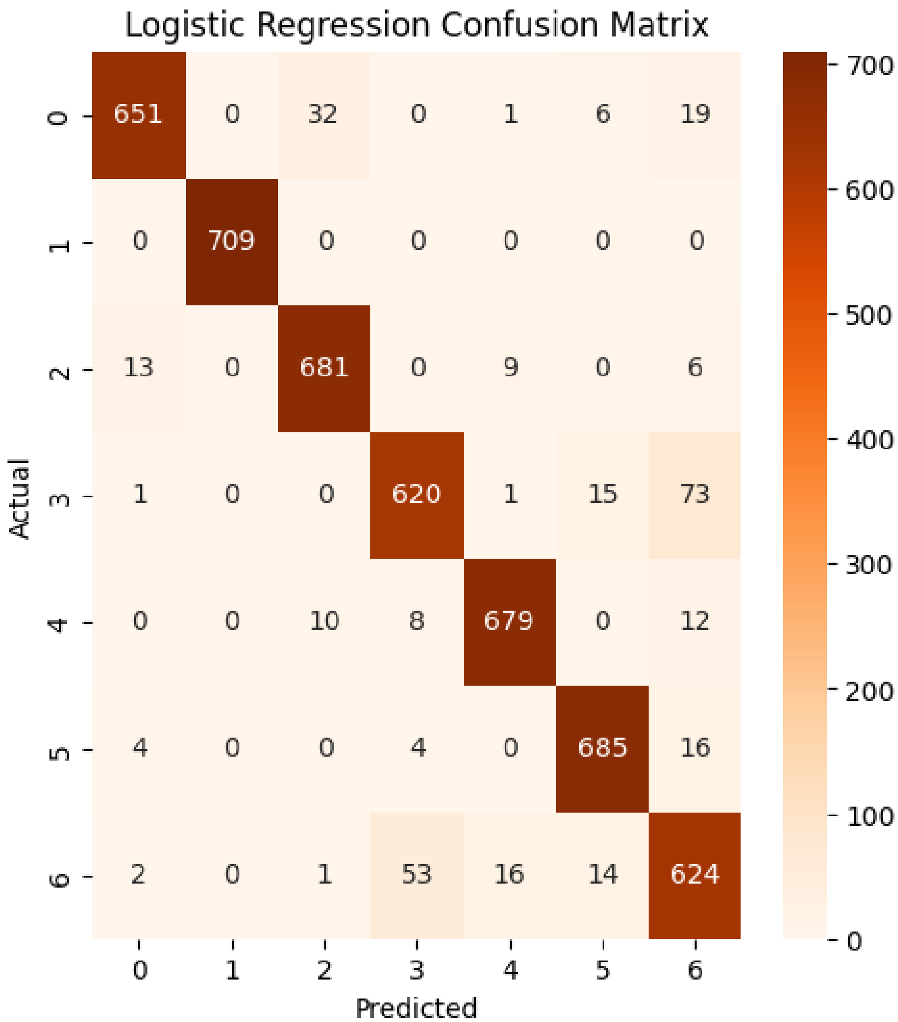
```
************* Logistic Regression *************
Class 0:
truePositive: 651, falsePositive: 20, falseNegative: 58, trueNegative: 4236

Class 1:
truePositive: 709, falsePositive: 0, falseNegative: 0, trueNegative: 4256

Class 2:
truePositive: 681, falsePositive: 43, falseNegative: 28, trueNegative: 4213

Class 3:
truePositive: 620, falsePositive: 65, falseNegative: 90, trueNegative: 4190

Class 4:
truePositive: 679, falsePositive: 27, falseNegative: 30, trueNegative: 4229

Class 5:
truePositive: 685, falsePositive: 35, falseNegative: 24, trueNegative: 4221

Class 6:
truePositive: 624, falsePositive: 126, falseNegative: 86, trueNegative: 4129
```

[263]:

```
# Plot the confusion matrix for Logistic Regression
plt.figure(figsize=(12, 6))
plt.subplot(1, 2, 1)
sbn.heatmap(conf_matrix_LOR, annot=True, fmt='d', cmap='Oranges')
plt.title('Logistic Regression Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('Actual')
```

[263]:

```
Text(120.72222222222221, 0.5, 'Actual')
```



1.7 Task 7:- Write some conclusion commenting which model is better and why ? [1M]

Conclusion: Between the two models, Logistic Regression outperforms Naive Bayes based on the analysis of the confusion matrices and key metrics.

Reasons why Logistic Regression is better: Higher True Positive Rates: Logistic Regression consistently shows higher true positive counts across most classes. This indicates that it is more effective at correctly identifying positive instances.

Lower False Positive and False Negative Rates: Logistic Regression typically has fewer false positives and false negatives, which means it makes fewer mistakes in classifying instances as positive or negative. This contributes to better precision and recall.

Better Precision and Recall: With fewer classification errors (both false positives and false negatives), Logistic Regression achieves higher precision and recall, which are crucial for tasks where correct classification is important.

Consistency Across Classes: Logistic Regression shows consistent performance improvements across nearly all classes, making it a more reliable model overall.

Summary:

Logistic Regression is the better model because it provides more accurate and reliable classifications with fewer errors, making it more suitable for this particular task. Its superior performance in terms of true positives, precision, and recall indicates that it will generally provide more dependable results compared to Naive Bayes.