

```
In [1]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import sklearn

from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import cross_val_score, KFold, train_test_split
from sklearn.preprocessing import StandardScaler, MinMaxScaler, RobustScaler, LabelEncoder
from sklearn.datasets import make_classification, make_regression
from sklearn.model_selection import train_test_split, StratifiedKFold
from sklearn.neighbors import KNeighborsClassifier, KNeighborsRegressor
from sklearn.metrics import accuracy_score, confusion_matrix, ConfusionMatrixDisplay,
from sklearn.dummy import DummyClassifier, DummyRegressor
from mlxtend.plotting import plot_decision_regions
```

```
In [2]: df=pd.read_csv(r"C:\Users\pavan\Downloads\Dry_Bean_Dataset.csv")
```

```
In [3]: df
```

```
Out[3]:
```

	Area	Perimeter	MajorAxisLength	MinorAxisLength	AspectRation	Eccentricity	C
0	28395	610.291	208.178117	173.888747	1.197191	0.549812	
1	28734	638.018	200.524796	182.734419	1.097356	0.411785	
2	29380	624.110	212.826130	175.931143	1.209713	0.562727	
3	30008	645.884	210.557999	182.516516	1.153638	0.498616	
4	30140	620.134	201.847882	190.279279	1.060798	0.333680	
...	...	...	...	...	...	...	...
13606	42097	759.696	288.721612	185.944705	1.552728	0.765002	
13607	42101	757.499	281.576392	190.713136	1.476439	0.735702	
13608	42139	759.321	281.539928	191.187979	1.472582	0.734065	
13609	42147	763.779	283.382636	190.275731	1.489326	0.741055	
13610	42159	772.237	295.142741	182.204716	1.619841	0.786693	

13611 rows × 17 columns

```
In [4]: df.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

```

```
In [5]: df.isna().sum()
```

```

Out[5]: 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

```

```
In [6]: df.describe()
```

Out[6]:		Area	Perimeter	MajorAxisLength	MinorAxisLength	AspectRation	Ec
	<b>count</b>	13611.000000	13611.000000	13611.000000	13611.000000	13611.000000	136
	<b>mean</b>	53048.284549	855.283459	320.141867	202.270714	1.583242	
	<b>std</b>	29324.095717	214.289696	85.694186	44.970091	0.246678	
	<b>min</b>	20420.000000	524.736000	183.601165	122.512653	1.024868	
	<b>25%</b>	36328.000000	703.523500	253.303633	175.848170	1.432307	
	<b>50%</b>	44652.000000	794.941000	296.883367	192.431733	1.551124	
	<b>75%</b>	61332.000000	977.213000	376.495012	217.031741	1.707109	
	<b>max</b>	254616.000000	1985.370000	738.860154	460.198497	2.430306	

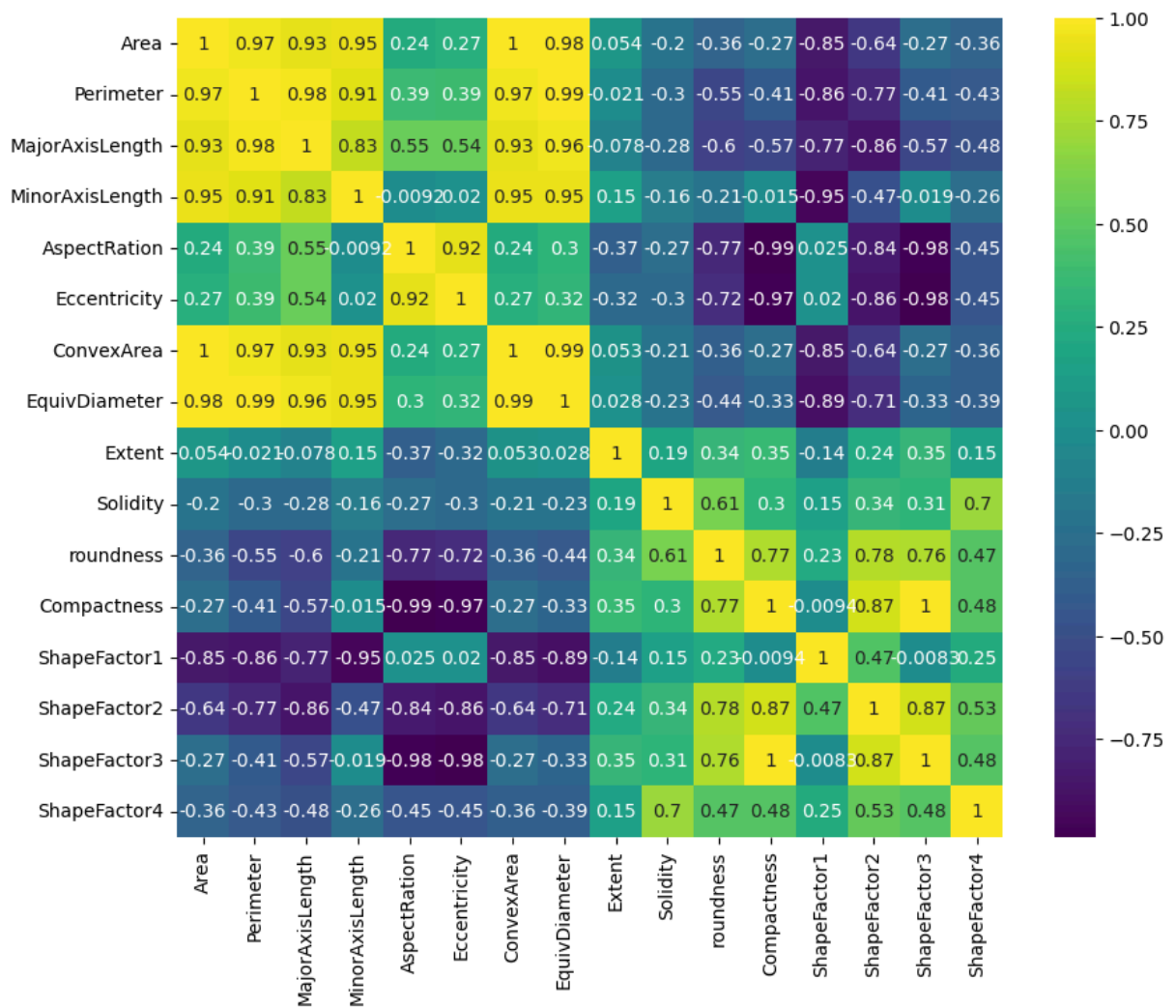
```
In [7]: df.describe(include="object")
```

Out[7]:	Class
<b>count</b>	13611
<b>unique</b>	7
<b>top</b>	DERMASON
<b>freq</b>	3546

```
In [8]: df.head()
```

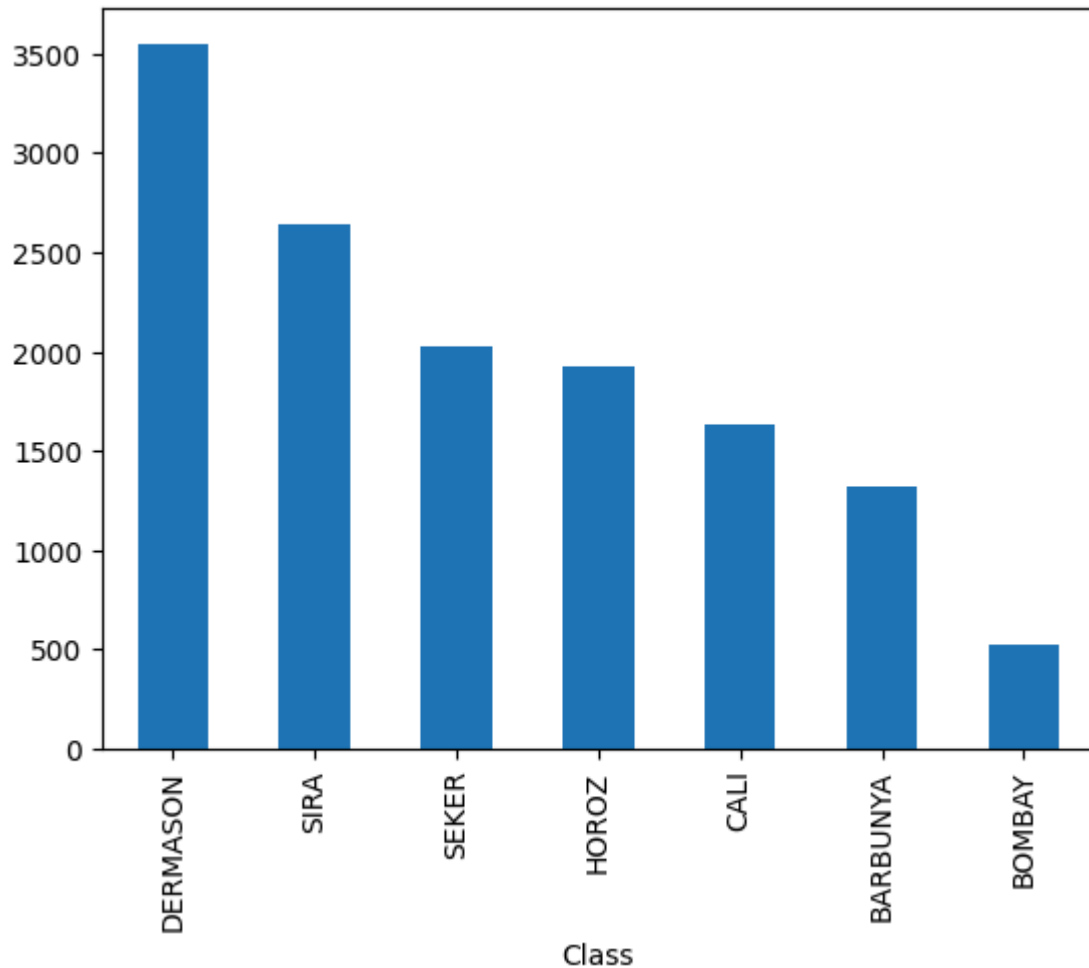
Out[8]:		Area	Perimeter	MajorAxisLength	MinorAxisLength	AspectRation	Eccentricity	Conve
	<b>0</b>	28395	610.291	208.178117	173.888747	1.197191	0.549812	
	<b>1</b>	28734	638.018	200.524796	182.734419	1.097356	0.411785	
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	<b>4</b>	30140	620.134	201.847882	190.279279	1.060798	0.333680	

```
In [9]: plt.figure(figsize=(10,8))
sns.heatmap(df.corr(numeric_only=True),annot=True,cmap='viridis')
plt.show()
```



```
In [10]: df["Class"].value_counts().plot.bar()
```

```
Out[10]: <Axes: xlabel='Class'>
```



```
In [11]: import seaborn as sns
import matplotlib.pyplot as plt

# Assuming 'df' is your DataFrame
for column in df.columns[:-1]:
    plt.figure(figsize=(8, 6))

    # Using sns.distplot for combined histogram and KDE plot
    sns.distplot(df[column], bins=10, hist_kws={'color': 'blue', 'edgecolor': 'black'})

    plt.title(f'Combined Histogram and KDE Plot for {column}')
    plt.xlabel(column)
    plt.ylabel('Frequency/Density')
    plt.legend()

    plt.show()
```

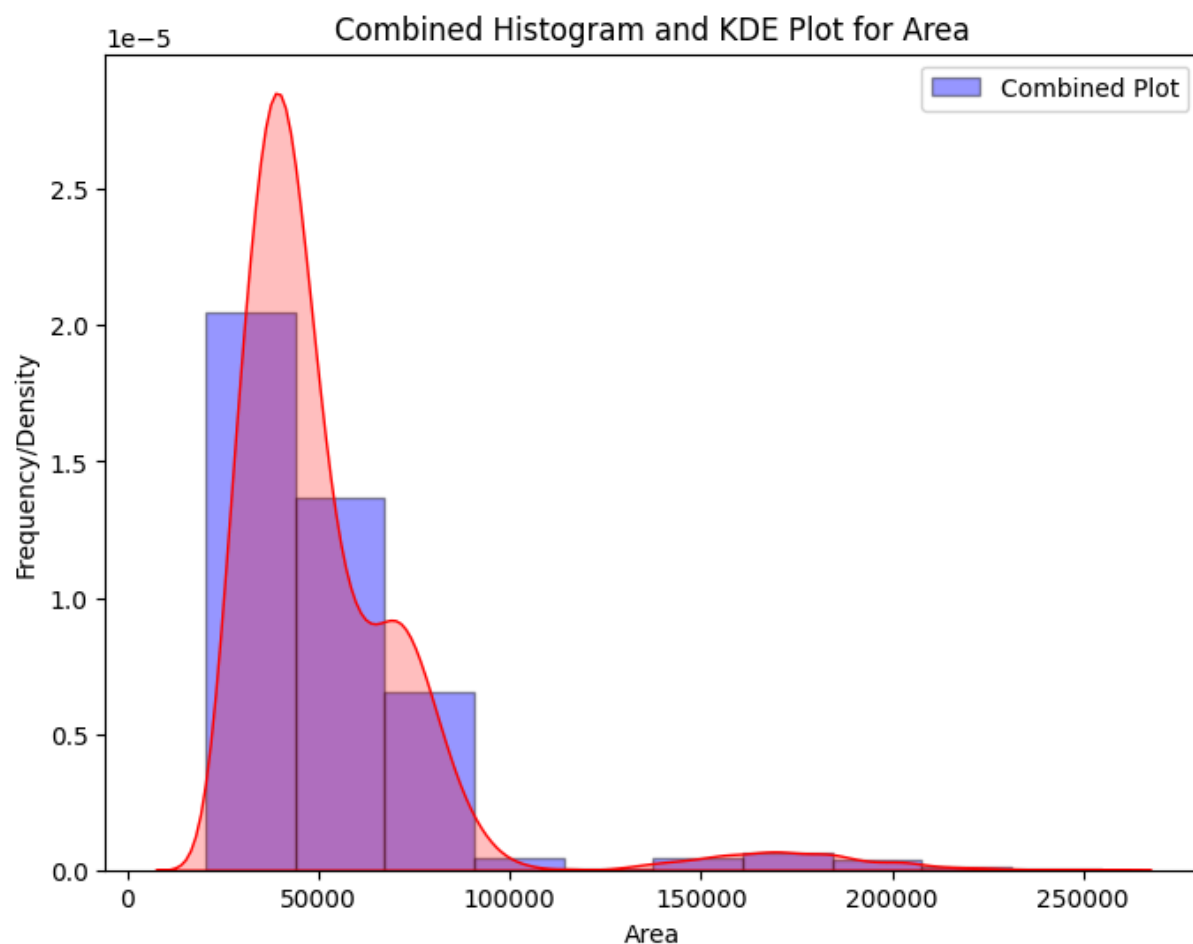
C:\Users\pavan\AppData\Local\Temp\ipykernel\_14488\2934260078.py:9: UserWarning:

``distplot`` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either ``displot`` (a figure-level function with similar flexibility) or ``histplot`` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see <https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751>

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sns.distplot(df[column], bins=10, hist_kws={'color': 'blue', 'edgecolor': 'black'}, kde_kws={'color': 'red', 'fill': True}, label='Combined Plot')
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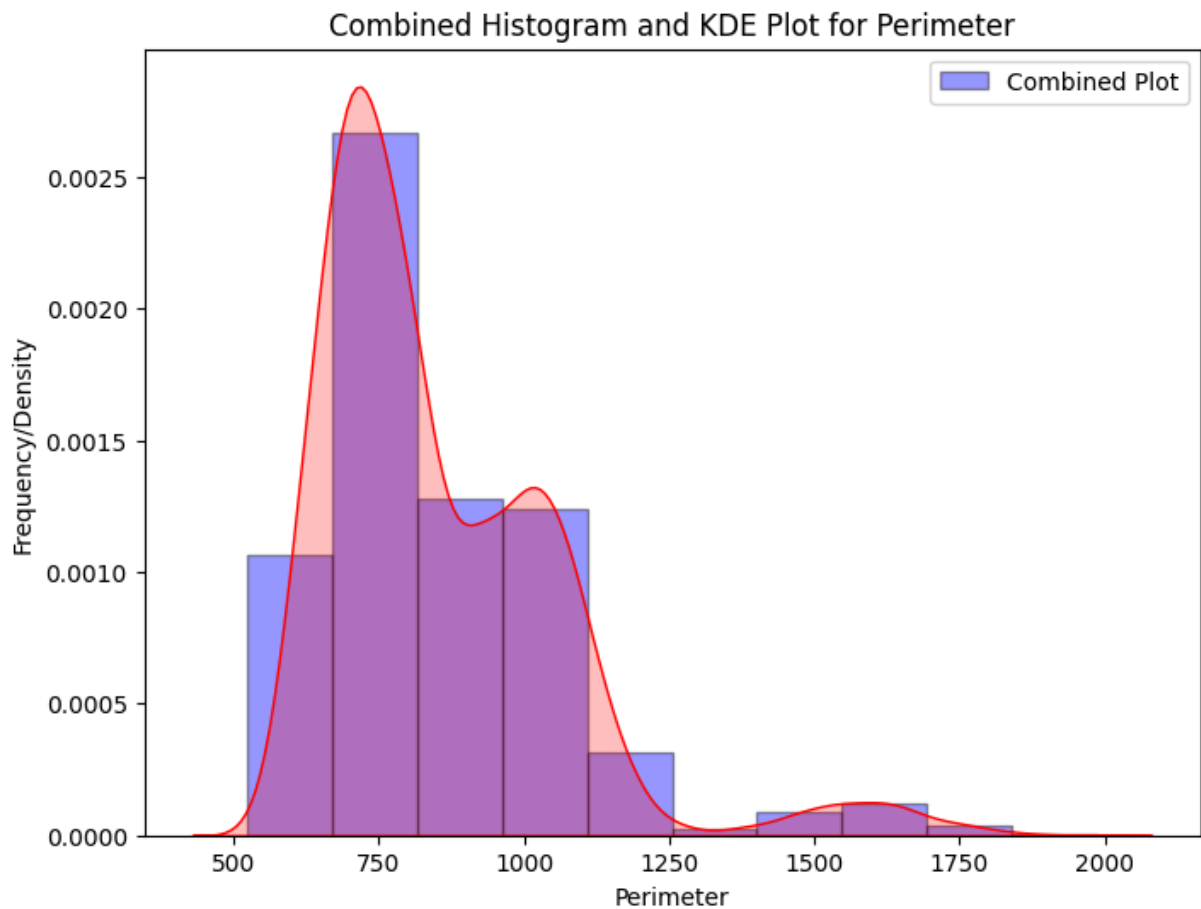
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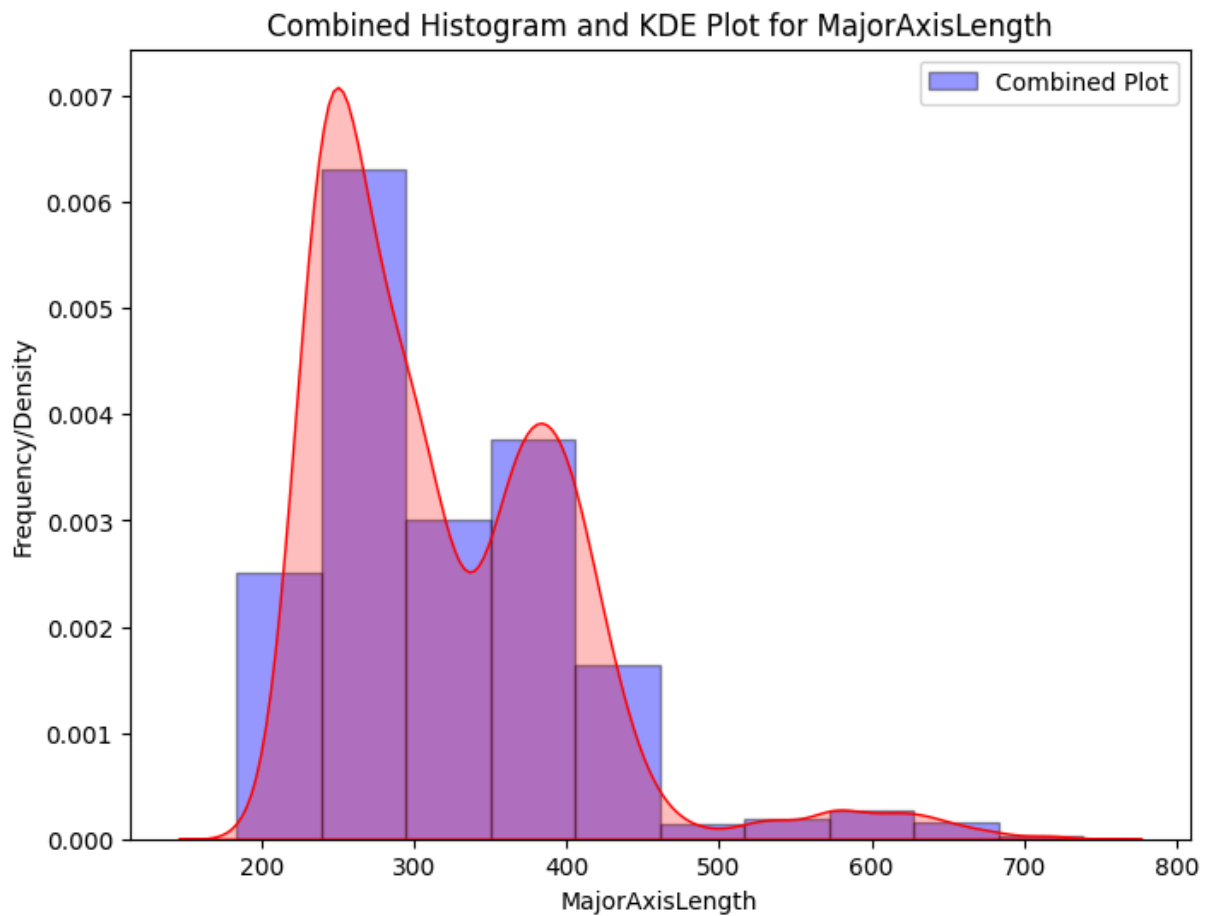
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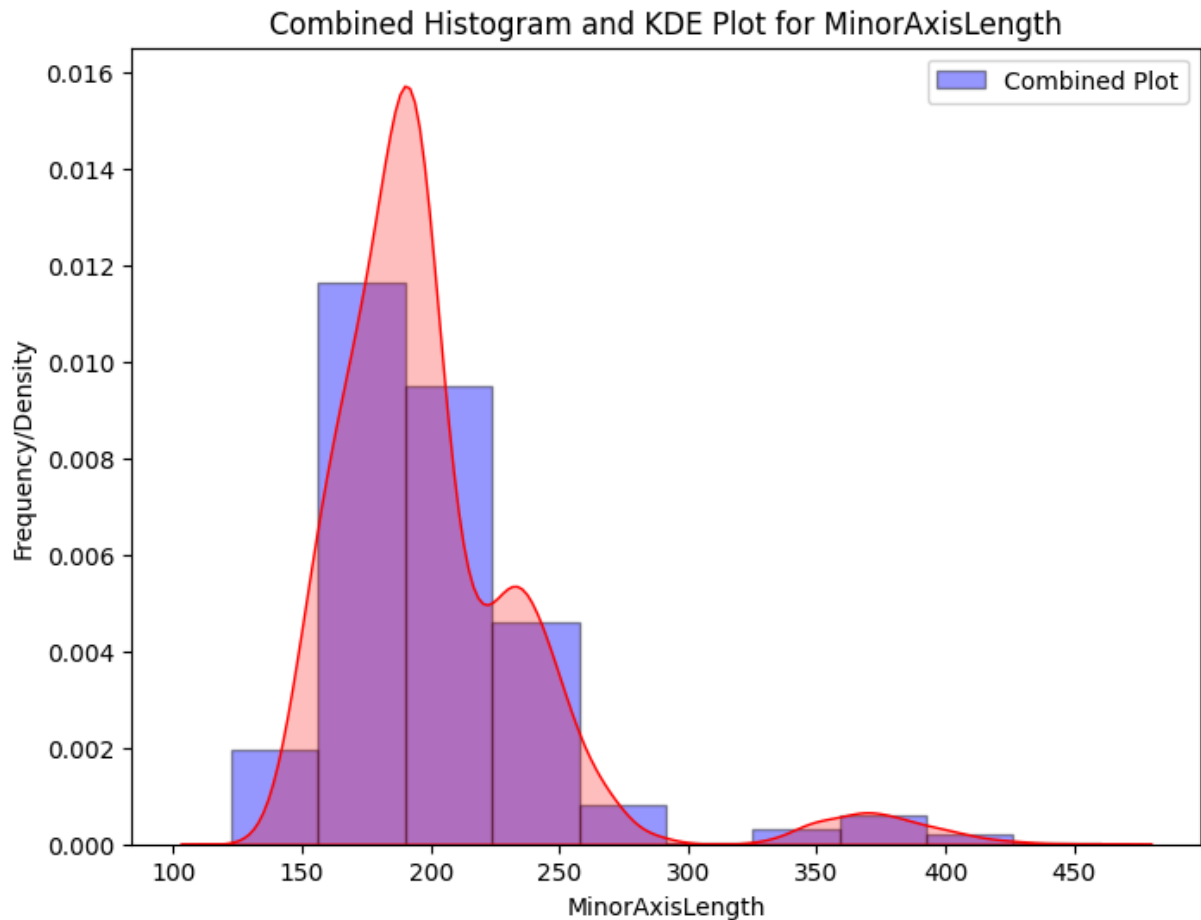
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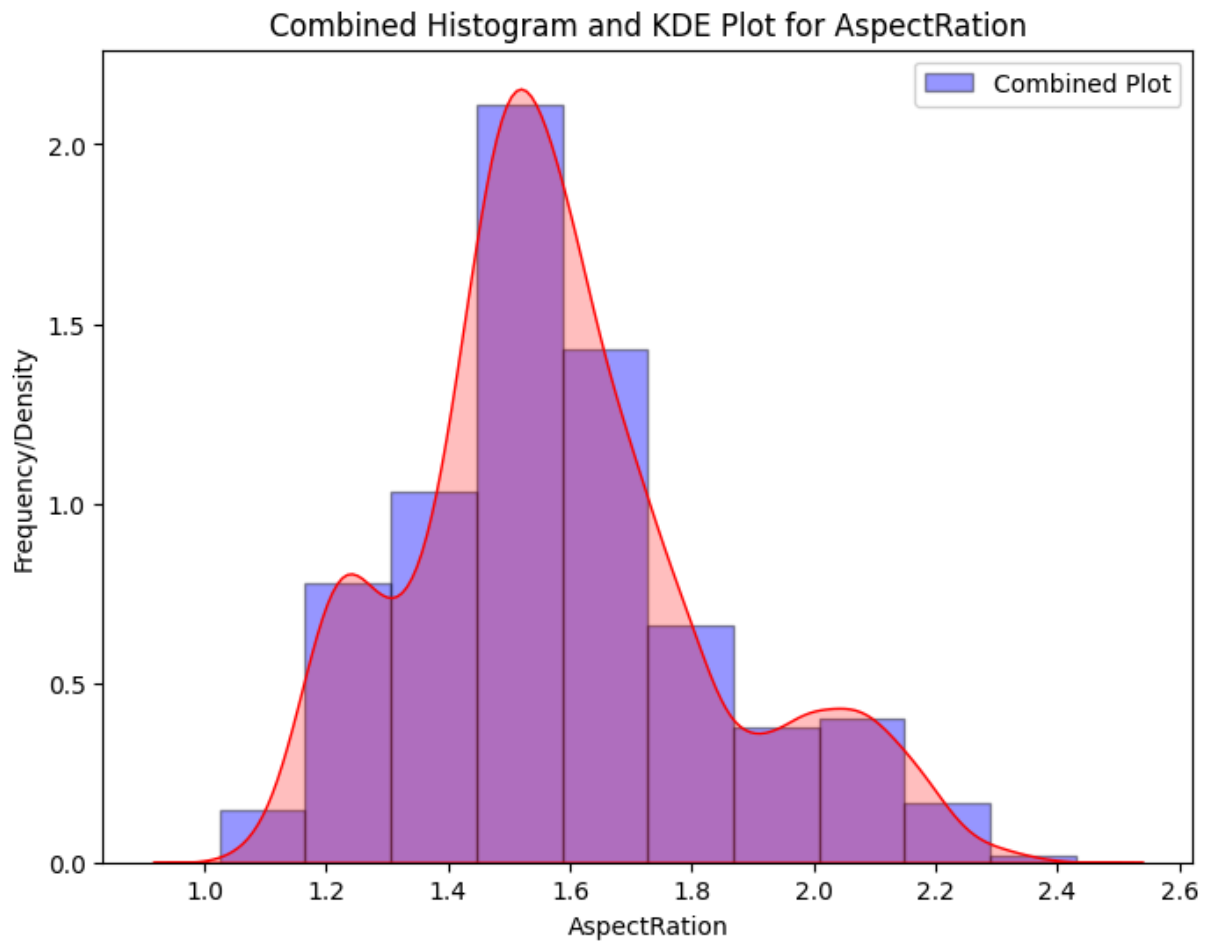
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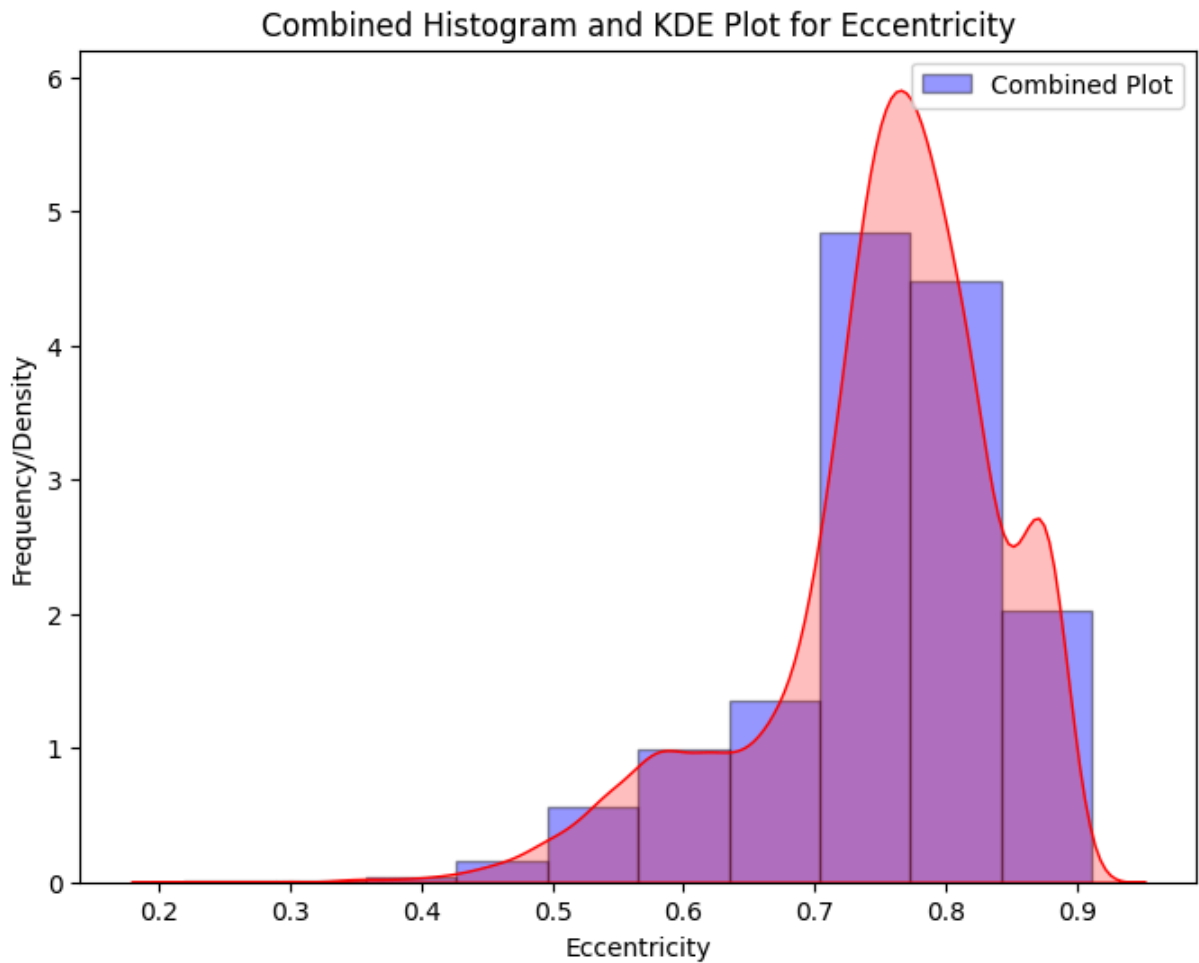
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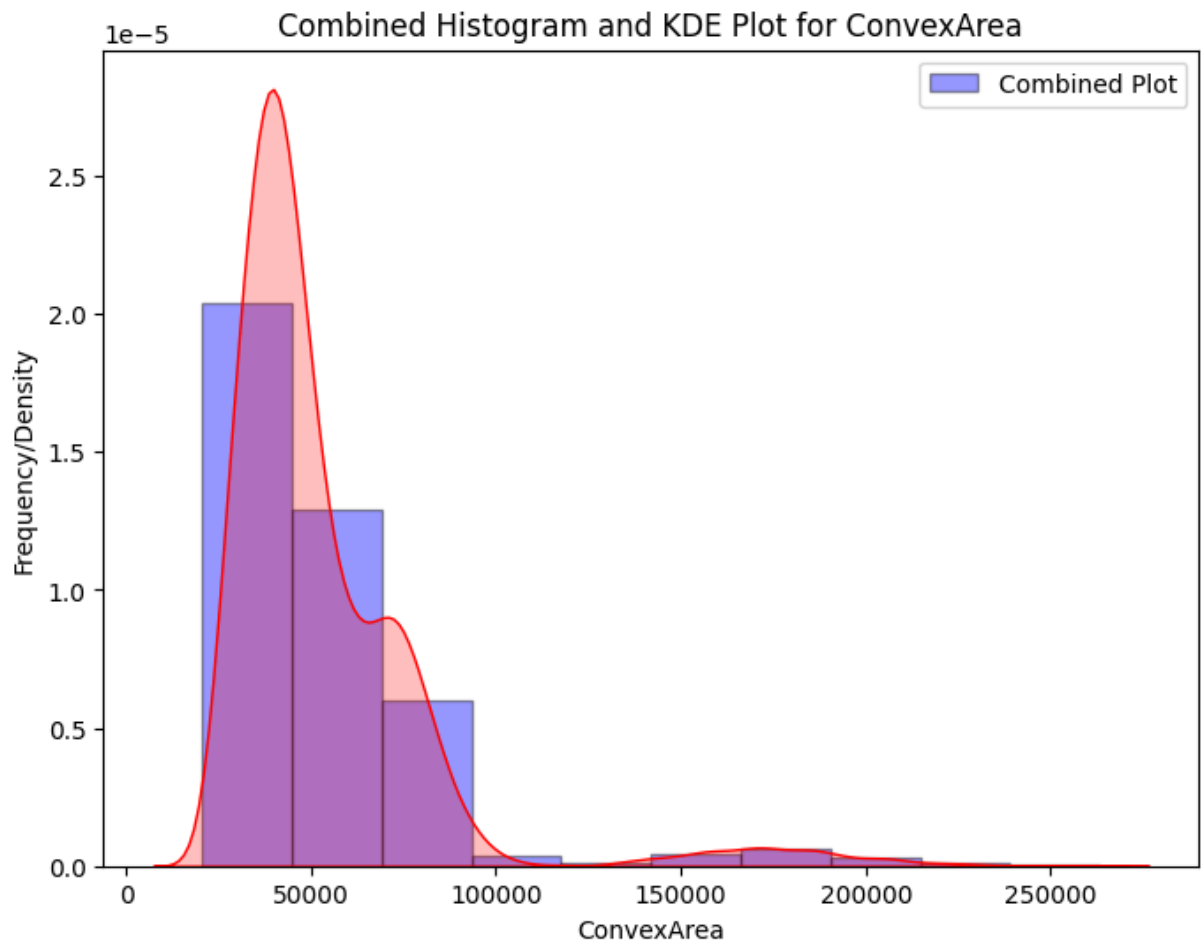
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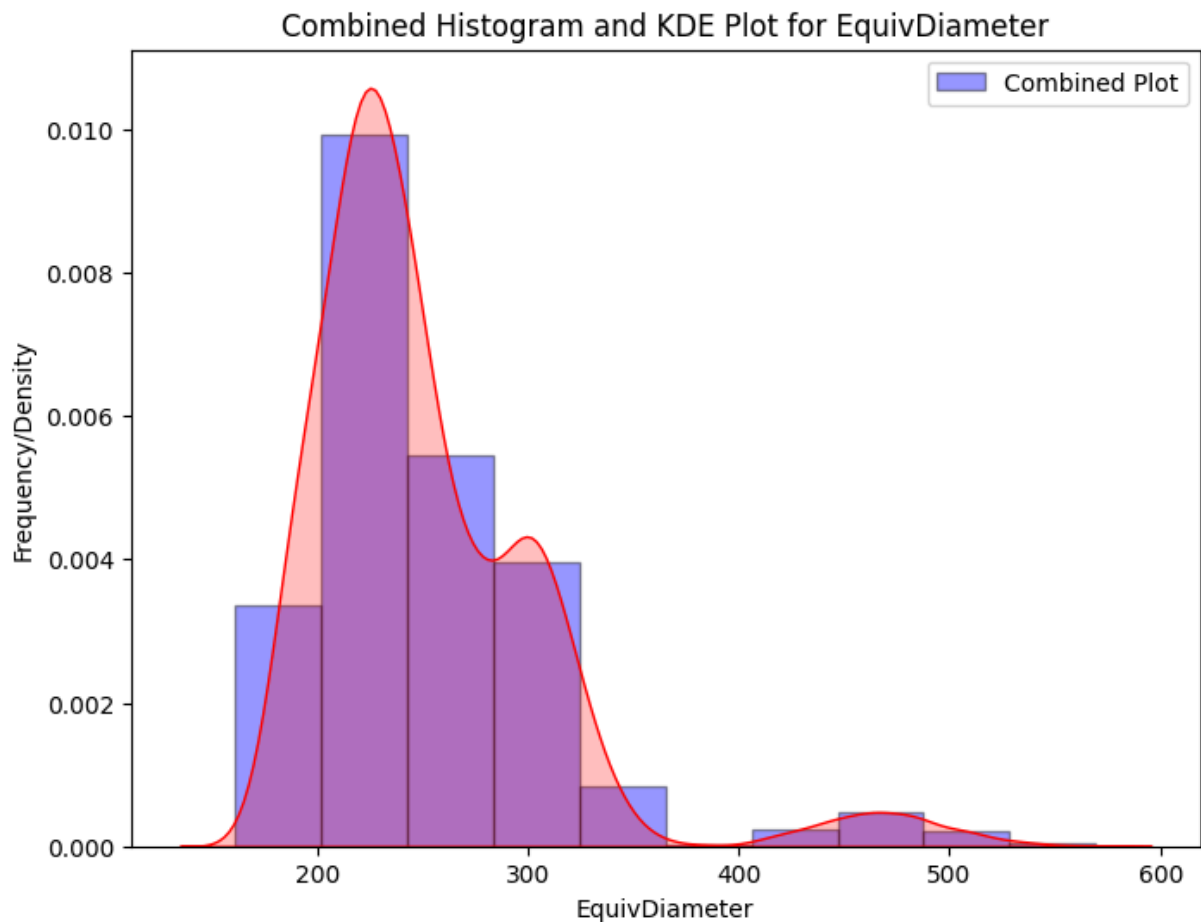
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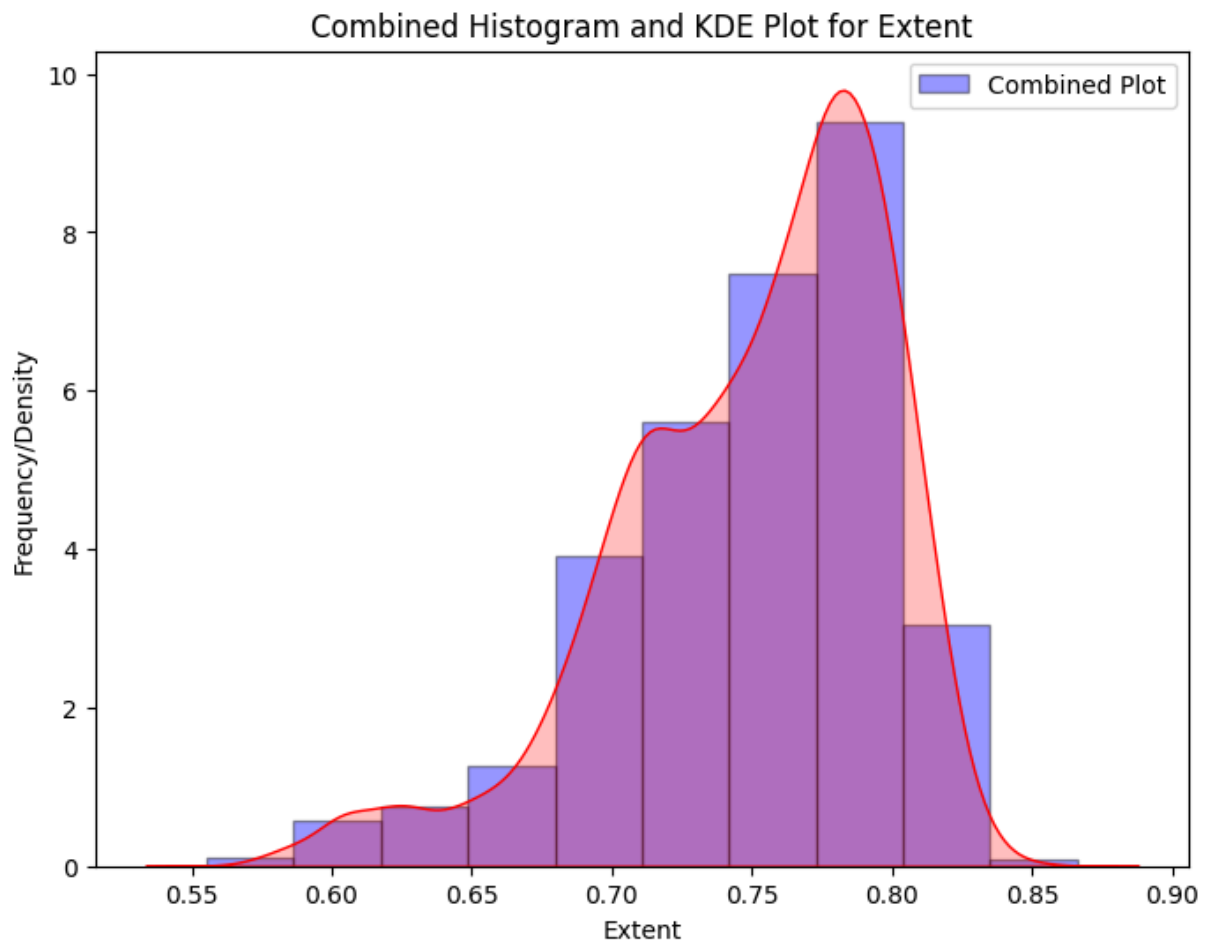
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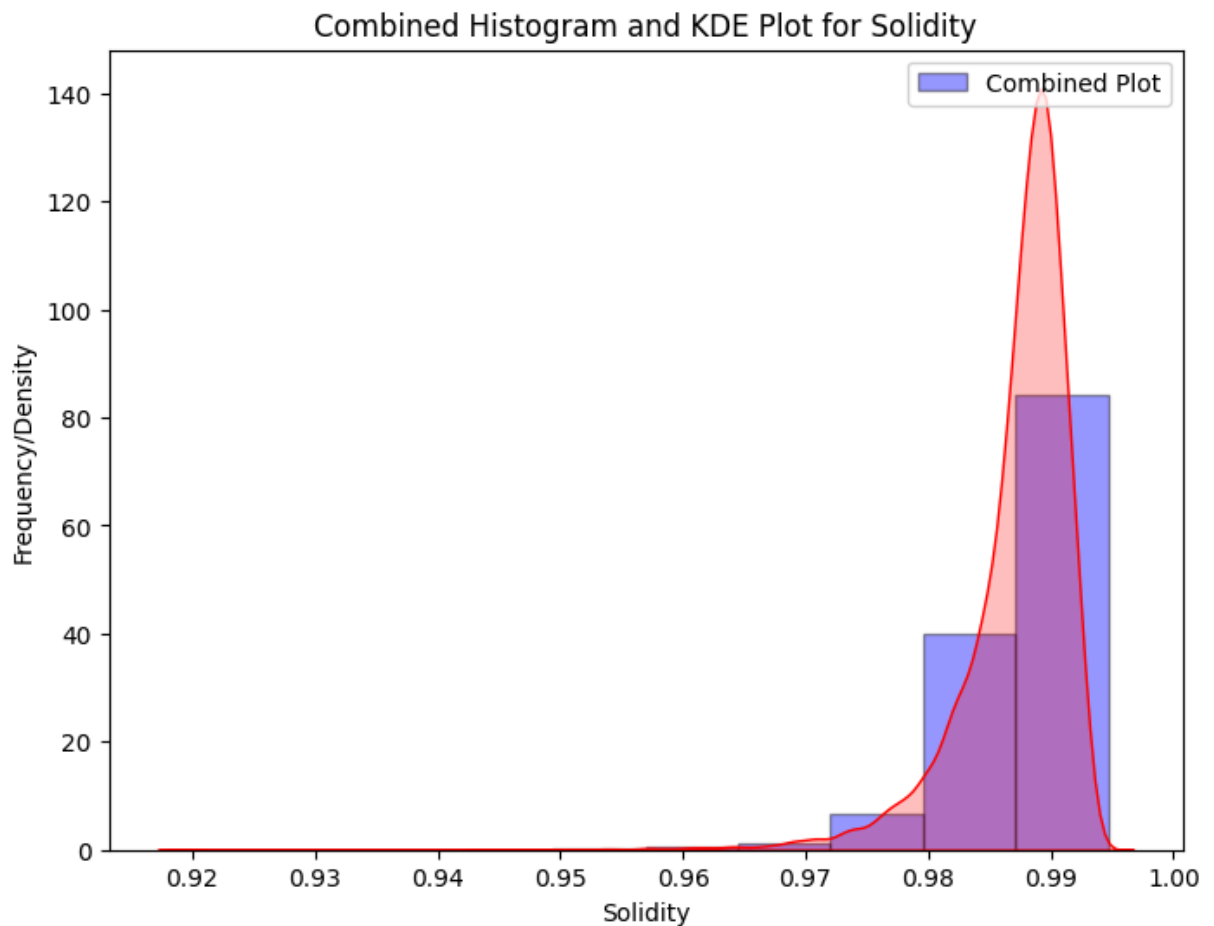
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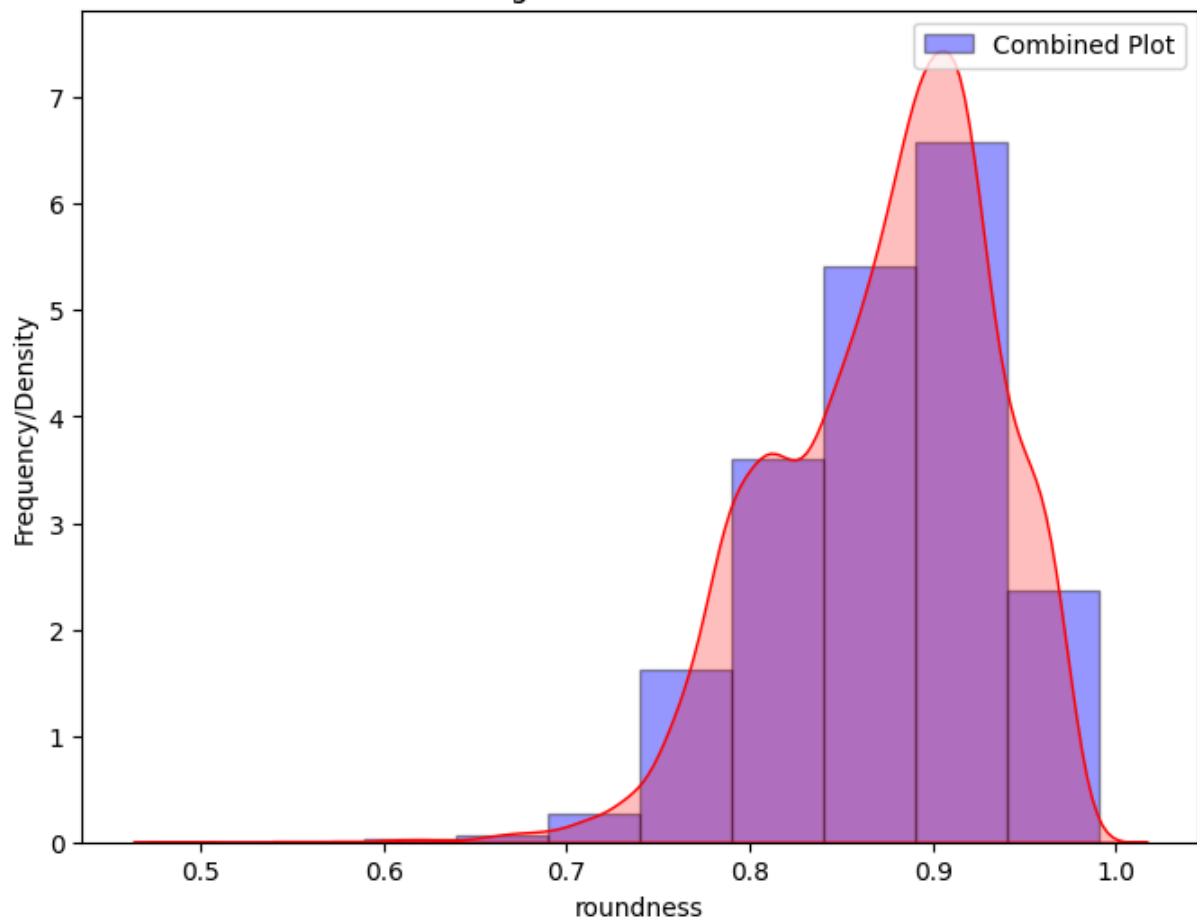
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```

Combined Histogram and KDE Plot for roundness



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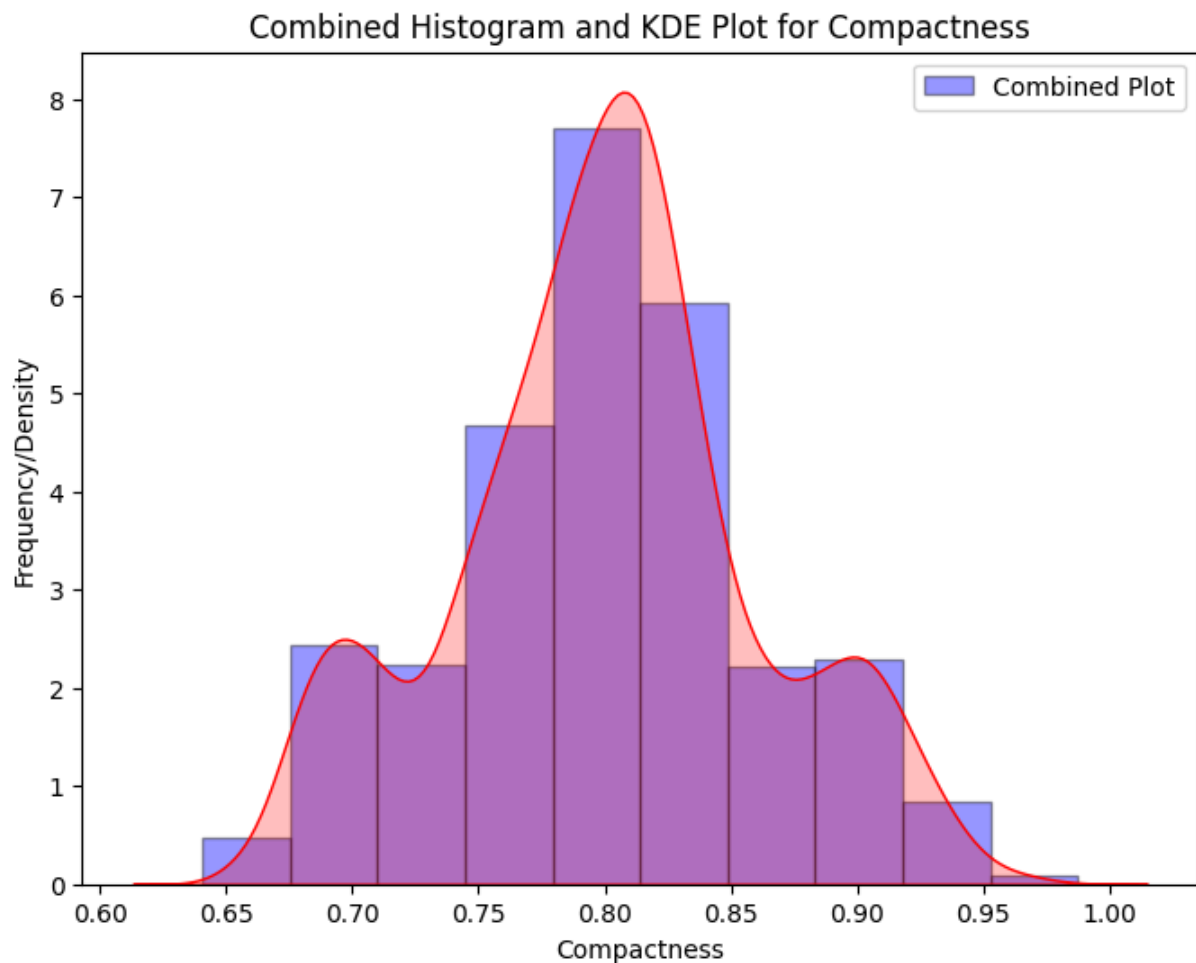
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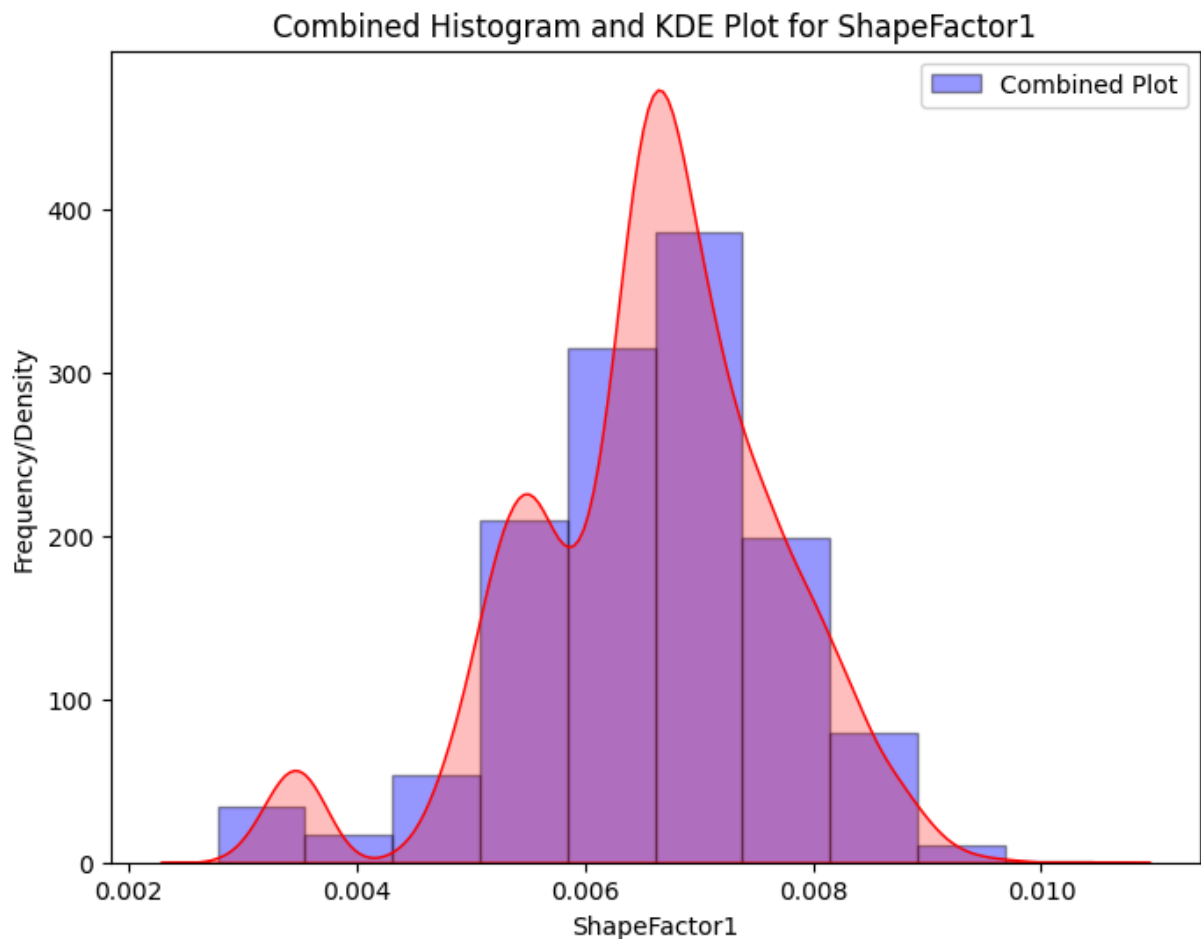
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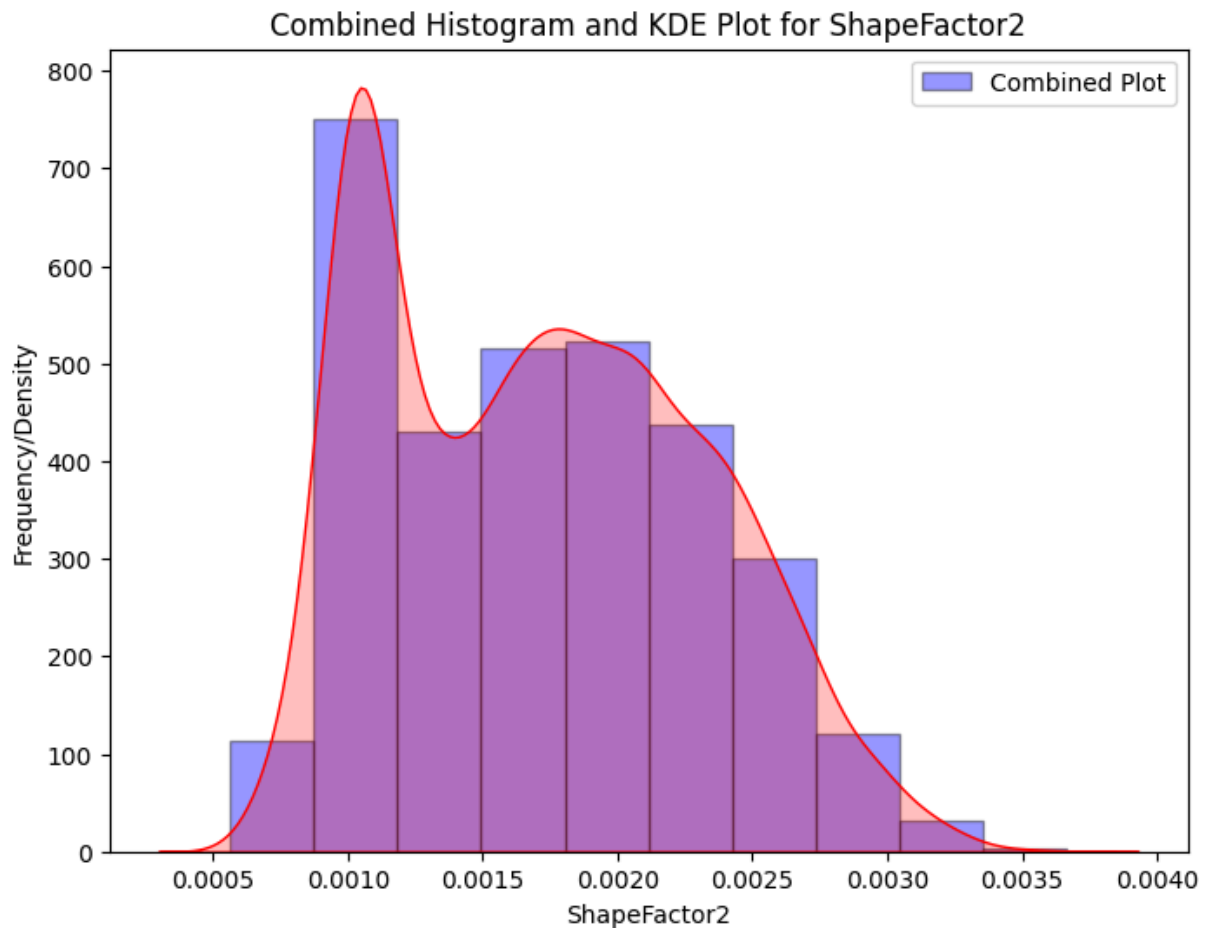
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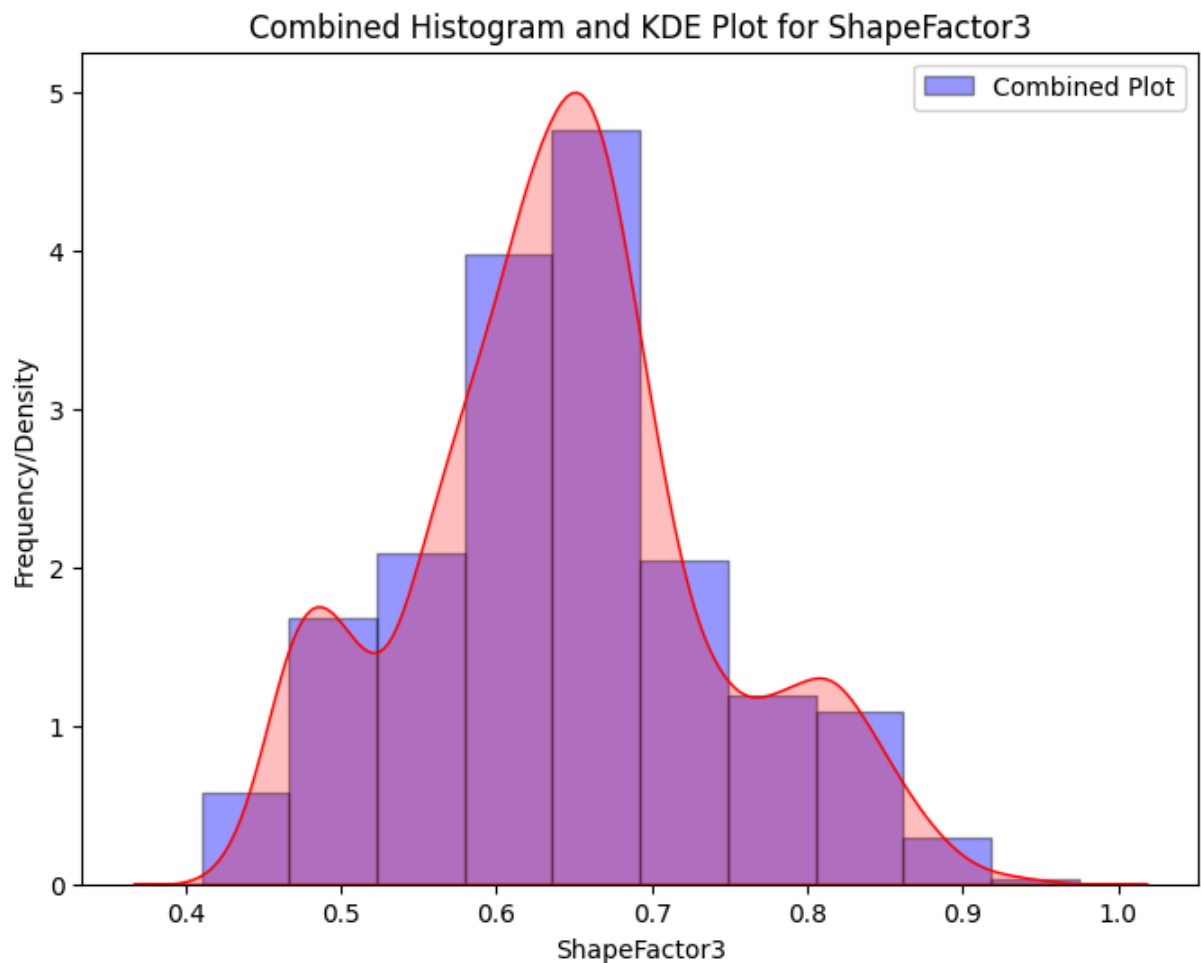
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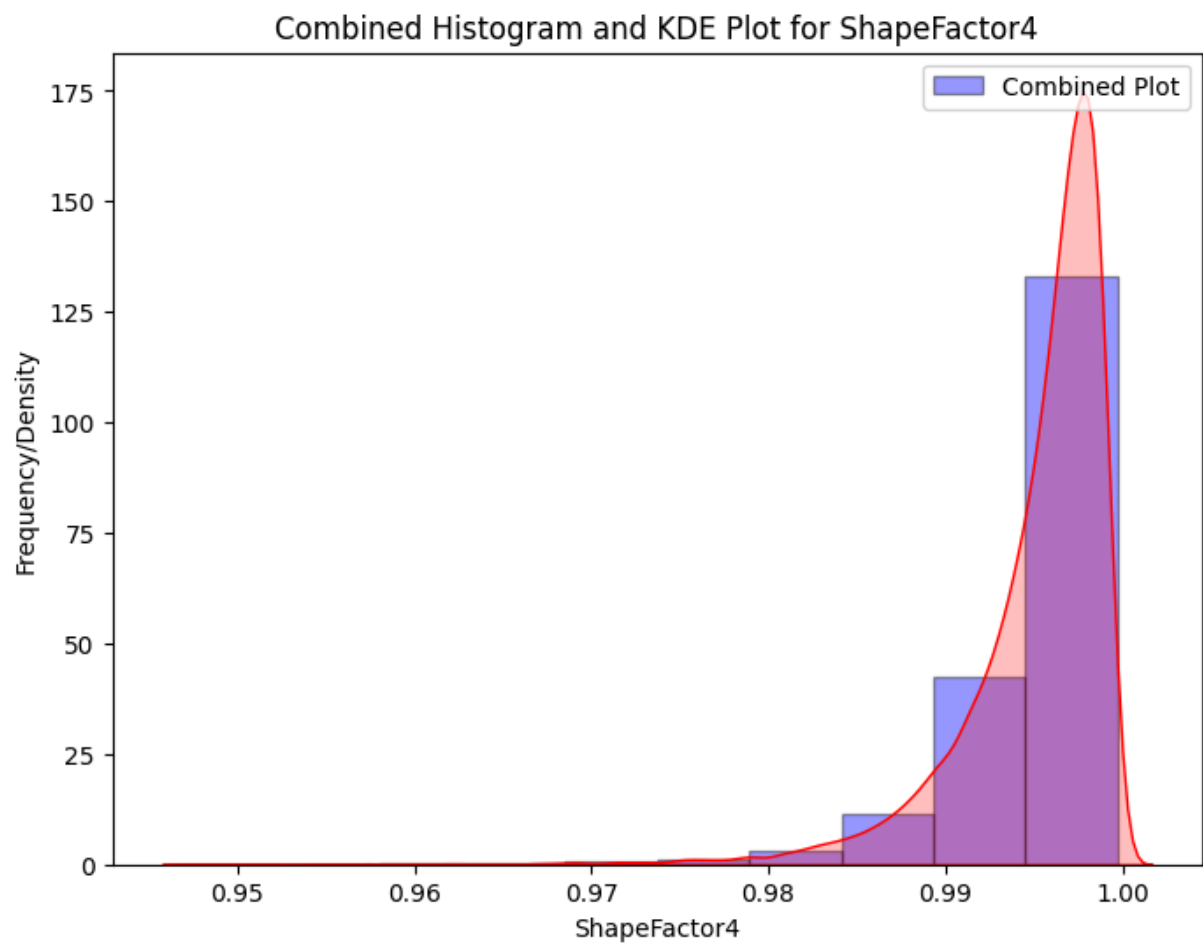
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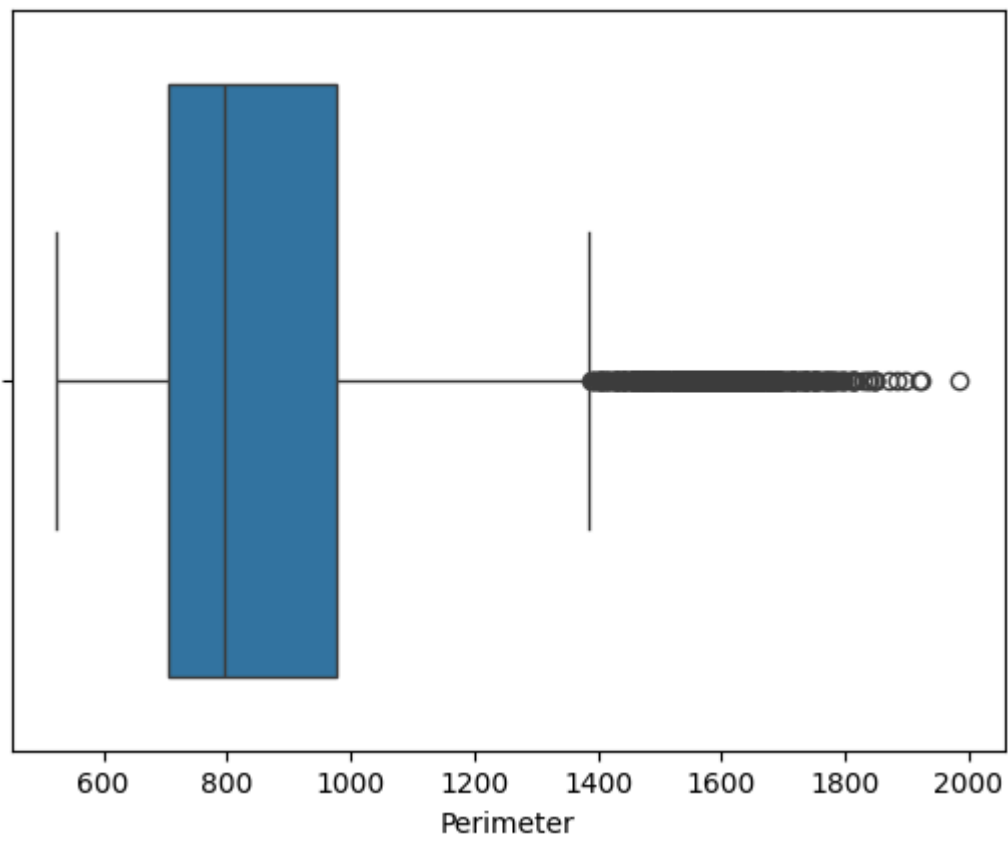
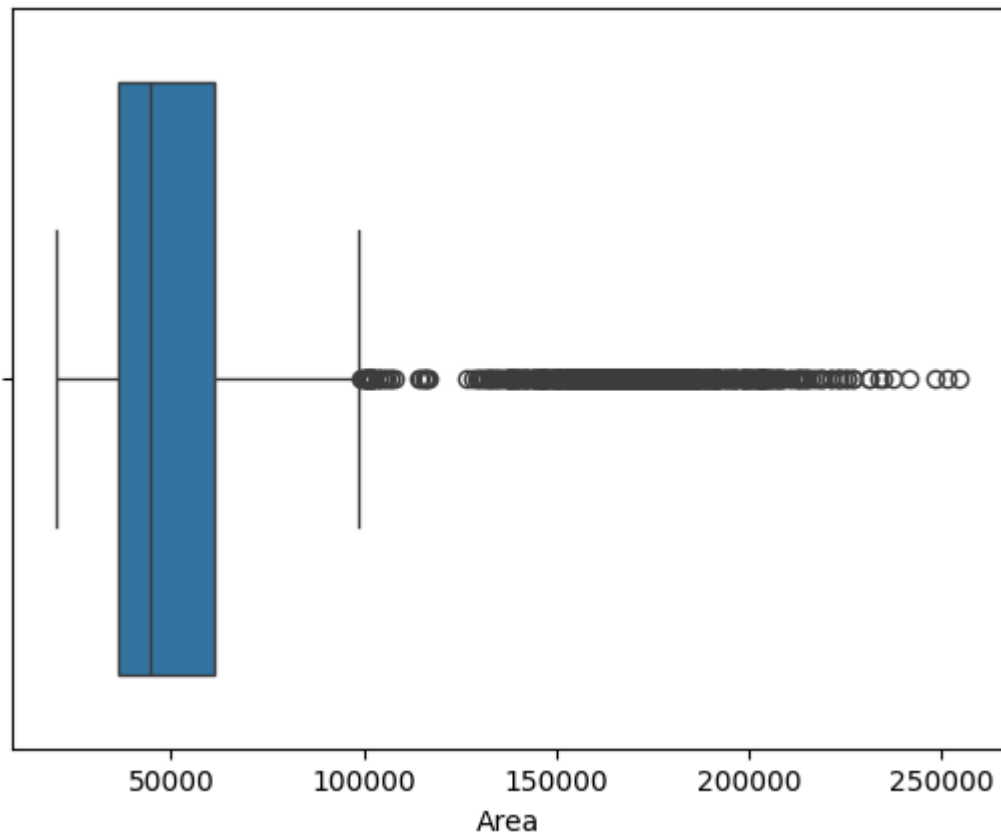
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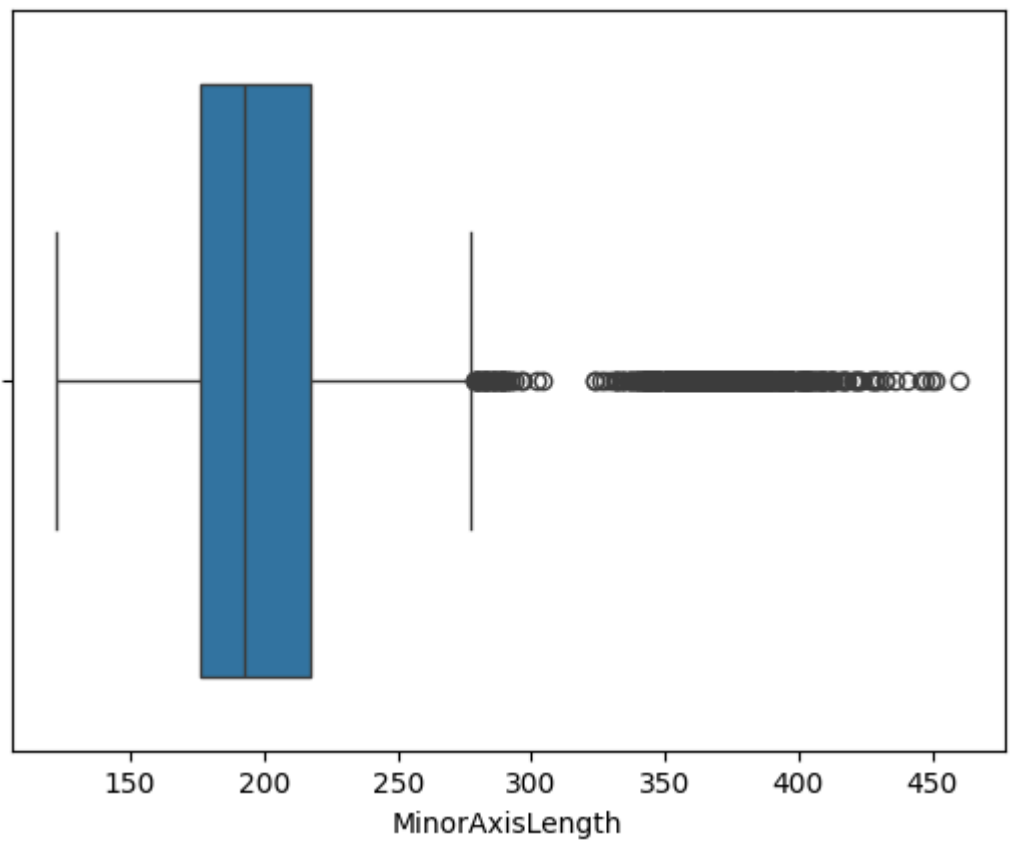
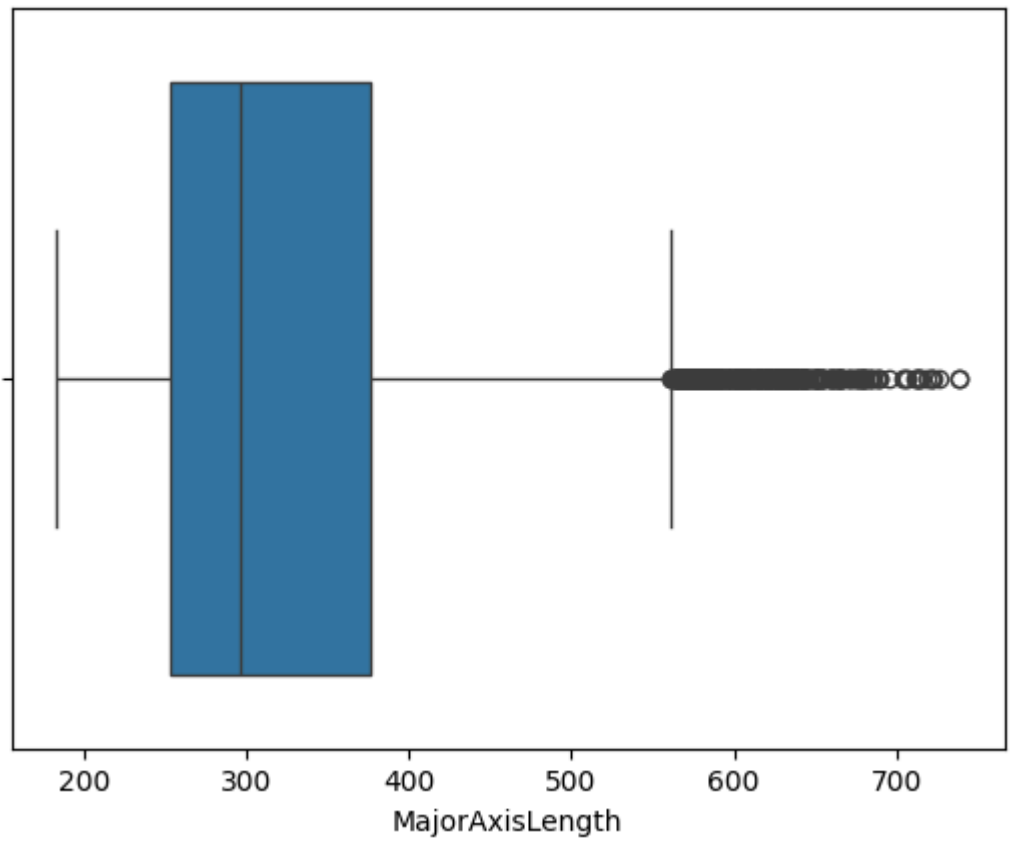
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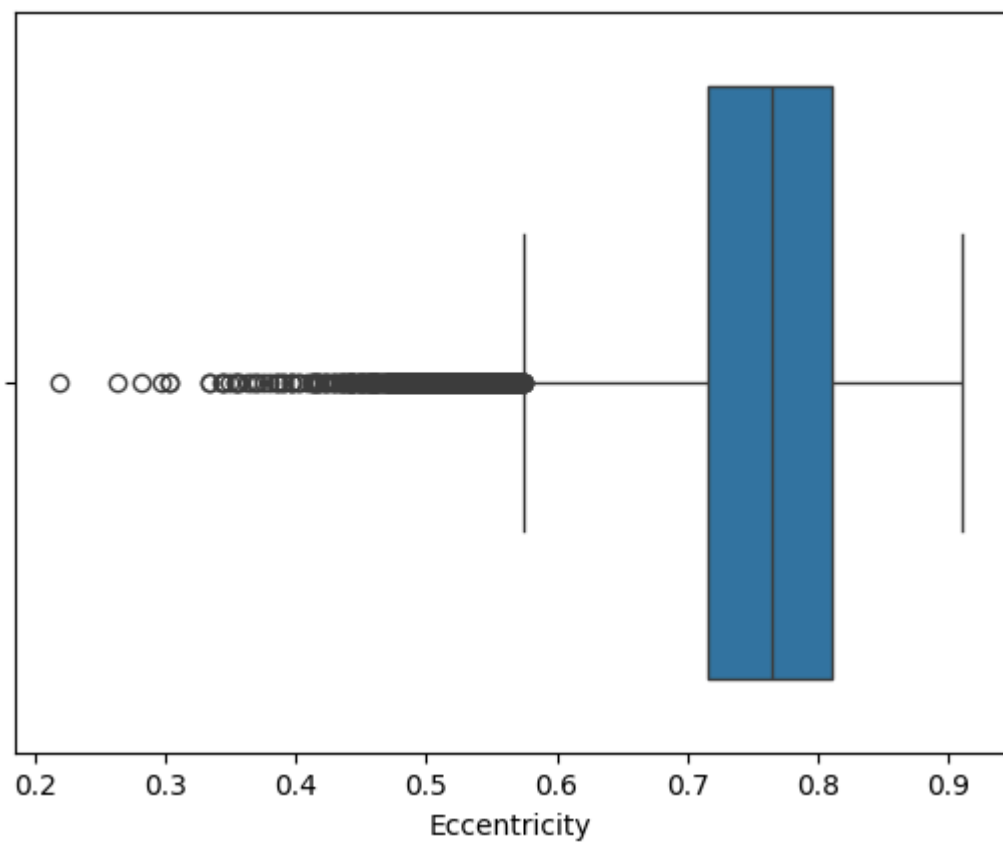
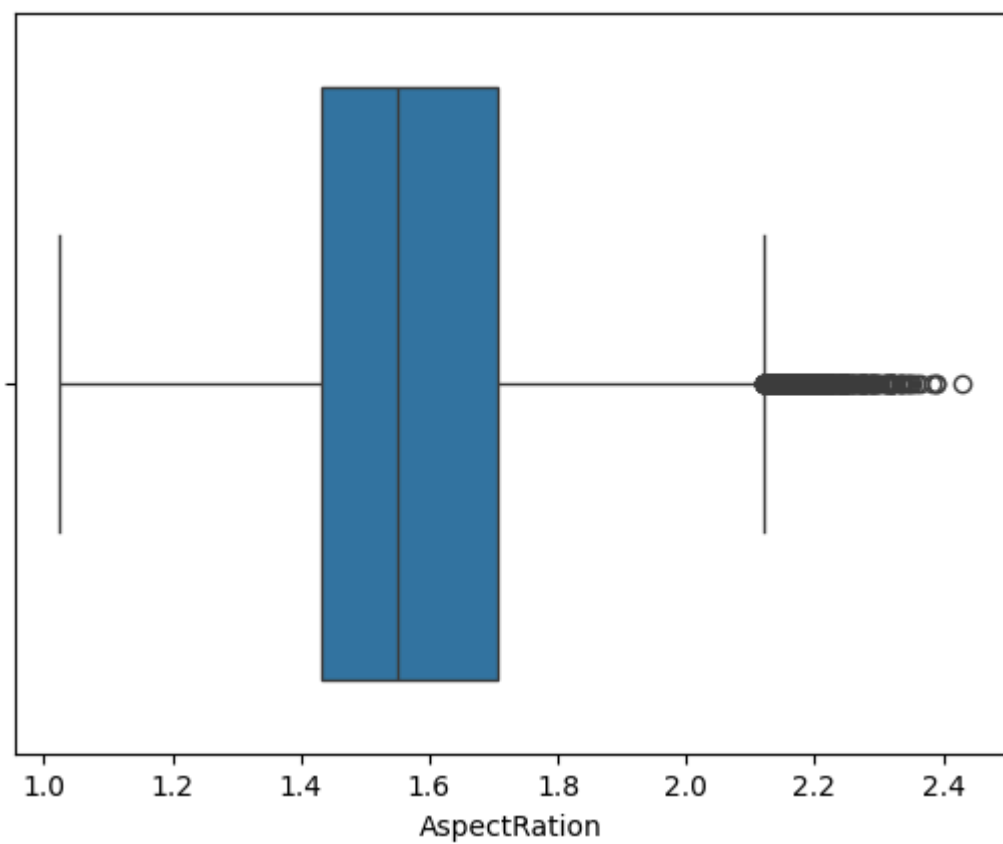
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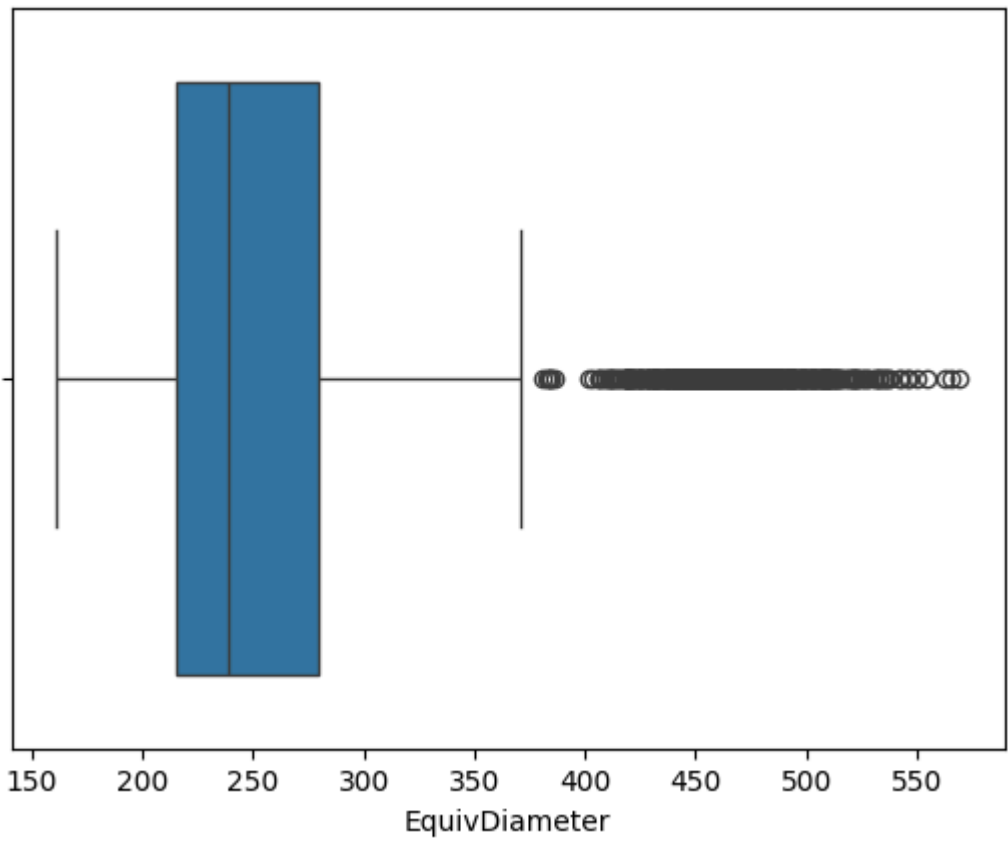
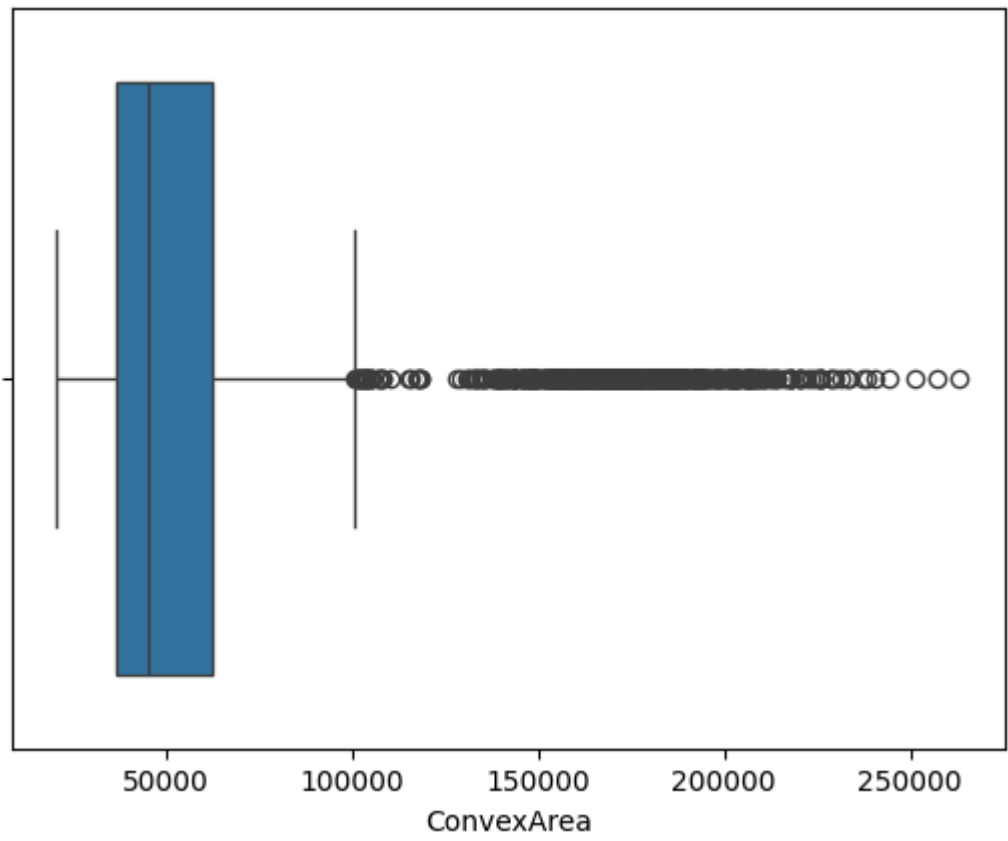
```
In [12]: for i in df.columns[:-1]:  
          sns.boxplot(data=df, x=df[i])  
          plt.show()
```

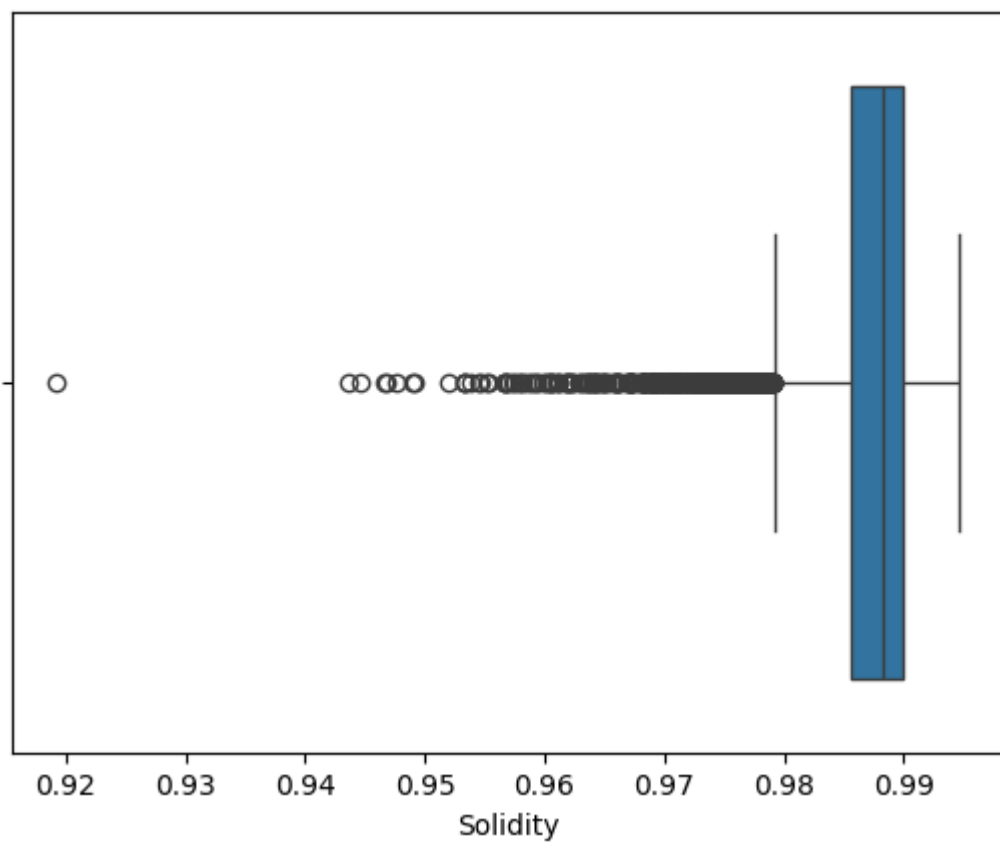
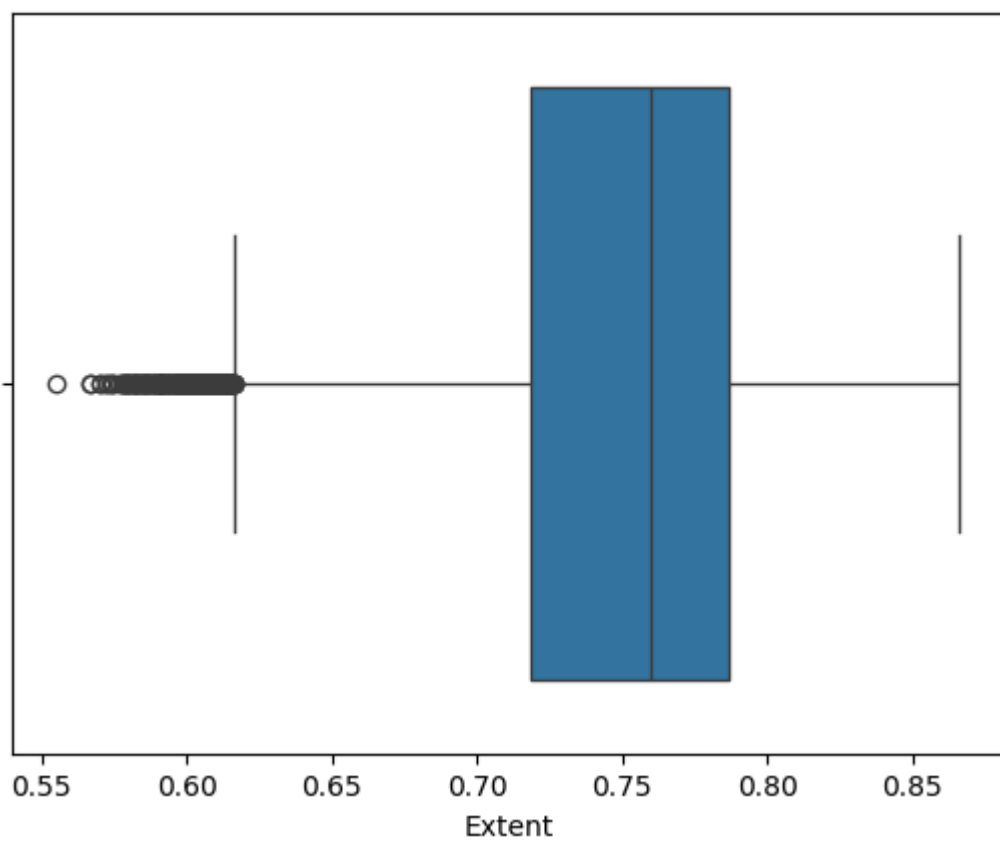


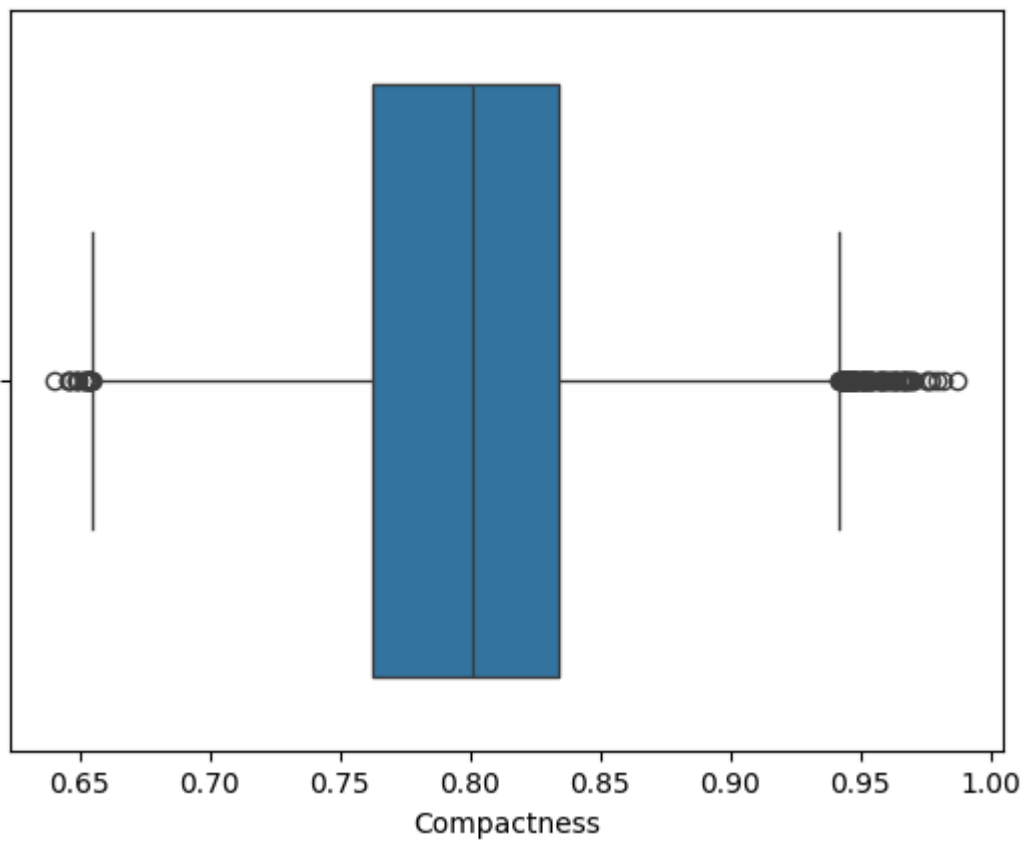
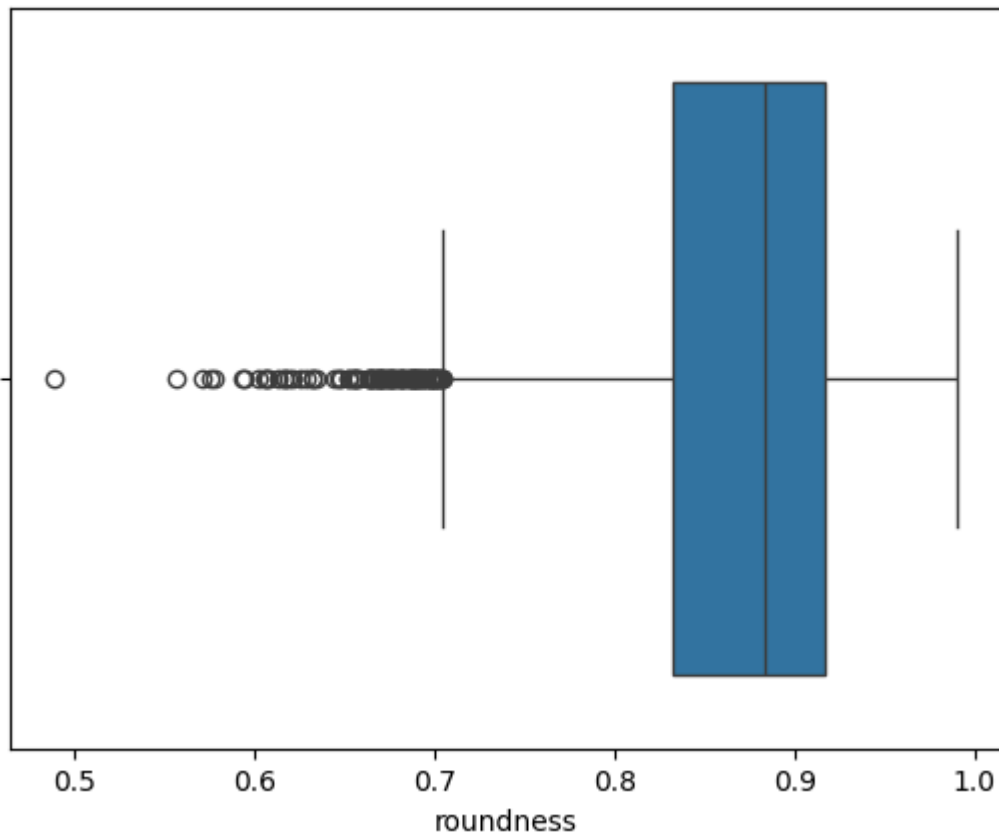


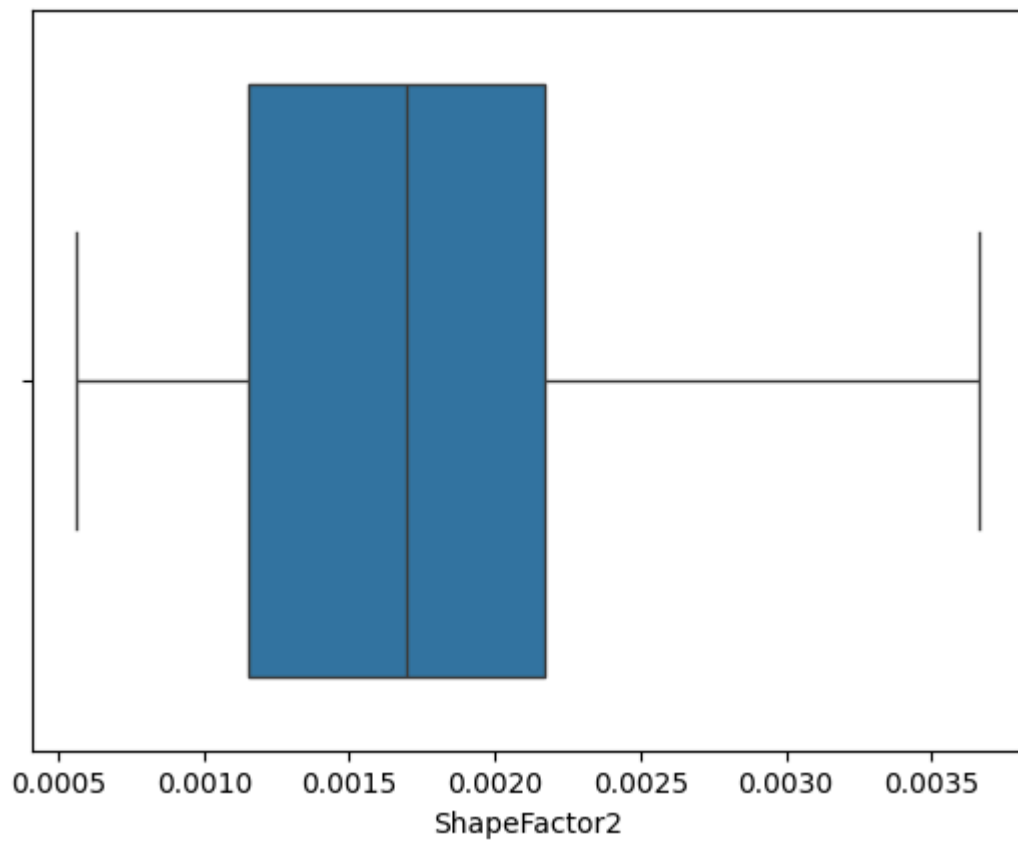
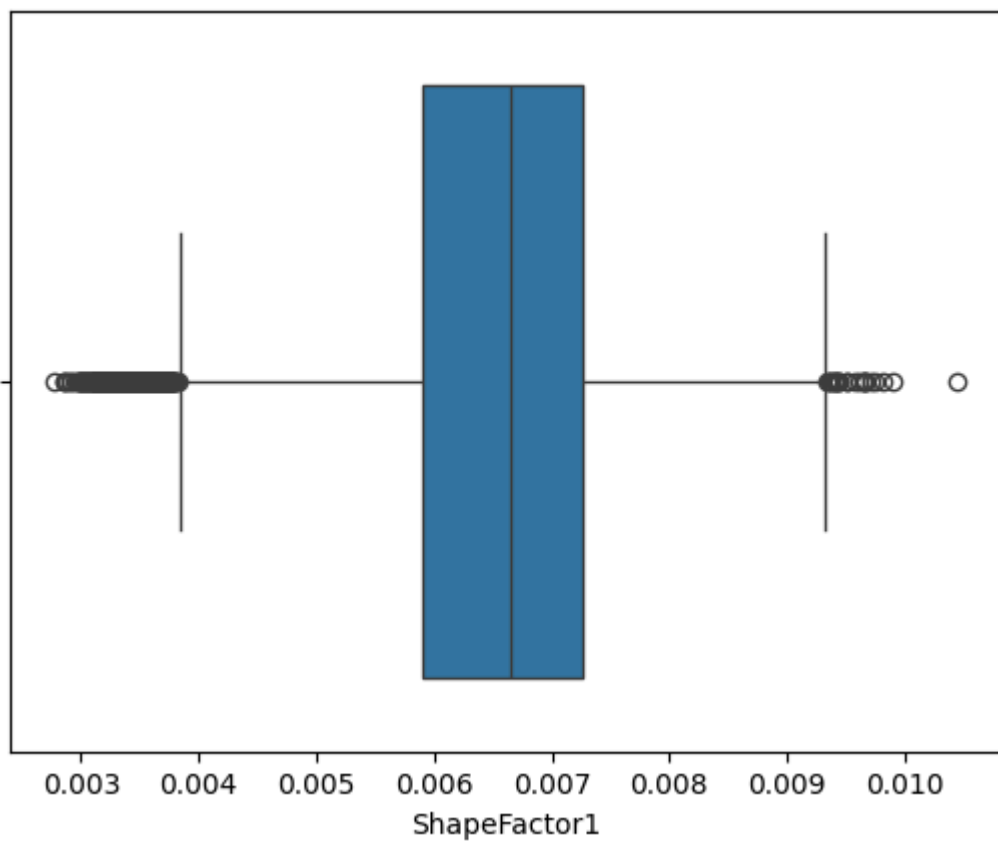


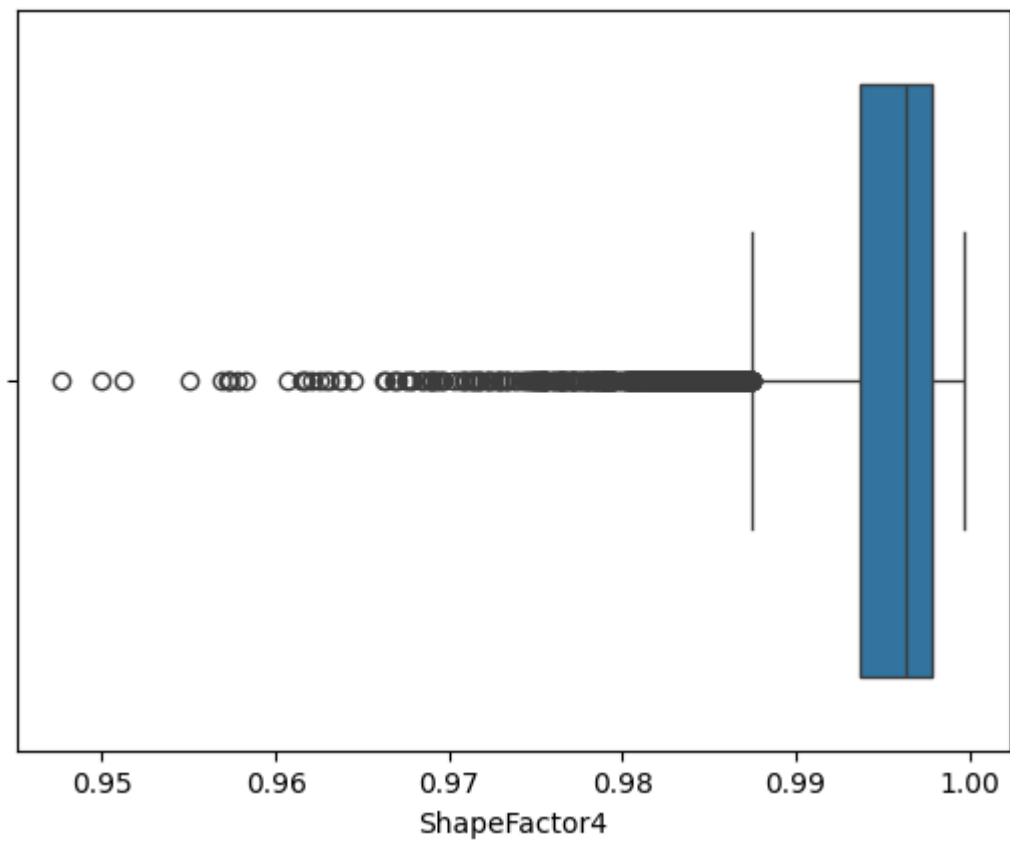
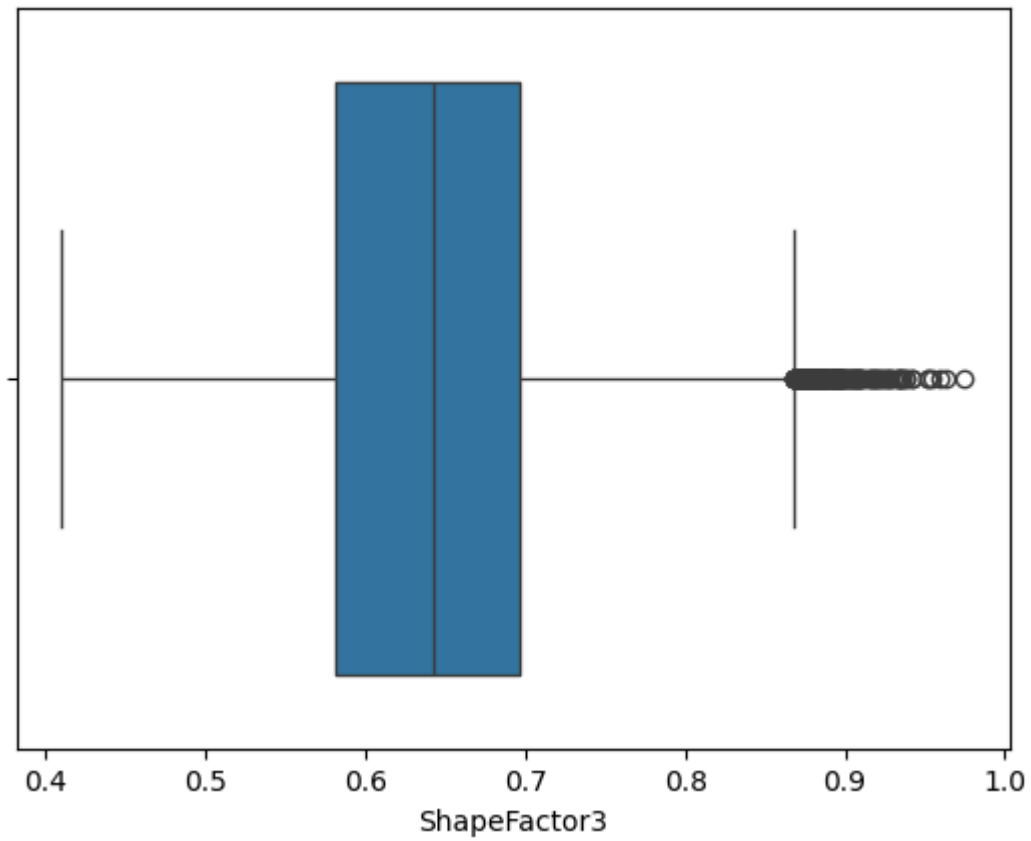












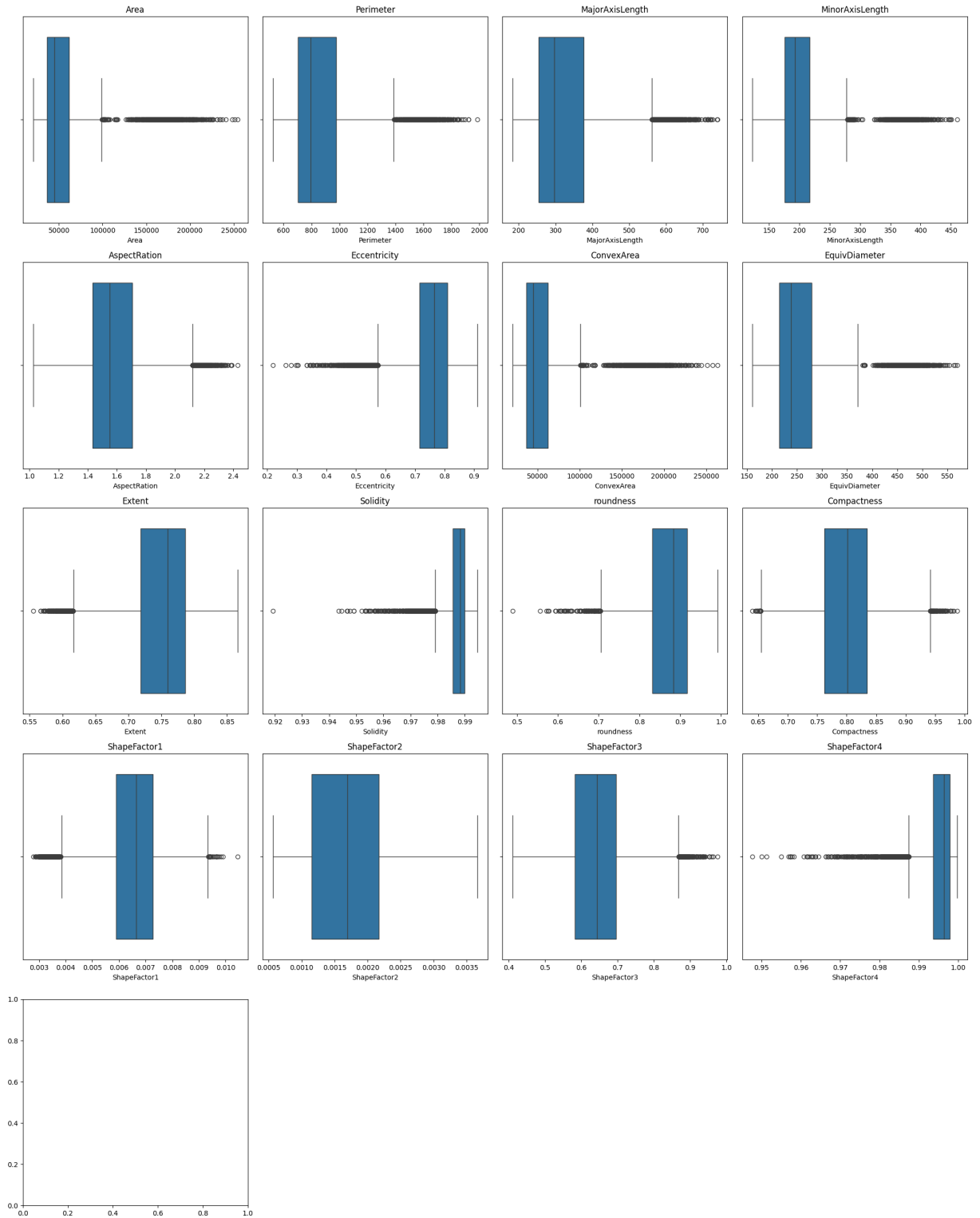
```
In [14]: num_plots = len(df.columns)
num_cols = 4
num_rows = (num_plots + num_cols - 1) // num_cols
```

```
# Create subplots
fig, axes = plt.subplots(nrows=num_rows, ncols=num_cols, figsize=(20, 5*num_rows))

# Loop through each column (excluding the last column)
for i, column in enumerate(df.columns[:-1]):
    row_idx = i // num_cols
    col_idx = i % num_cols
    sns.boxplot(data=df, x=column, ax=axes[row_idx, col_idx])
    axes[row_idx, col_idx].set_title(column)

# Hide empty subplots
for i in range(num_plots, num_rows * num_cols):
    row_idx = i // num_cols
    col_idx = i % num_cols
    fig.delaxes(axes[row_idx, col_idx])

plt.tight_layout()
plt.show()
```



```
In [15]: num_plots = 16
num_cols = 4
num_rows = (num_plots + num_cols - 1) // num_cols

# Create subplots
fig, axes = plt.subplots(nrows=num_rows, ncols=num_cols, figsize=(20, 5*num_rows))

# Loop through each column and create boxplots
for i, column in enumerate(df.columns[:-1]):
    row_idx = i // num_cols
```

```
col_idx = i % num_cols
IQR = df[column].quantile(0.75) - df[column].quantile(0.25)
upper_limit = df[column].quantile(0.75) + 1.5 * IQR
lower_limit = df[column].quantile(0.25) - 1.5 * IQR
df[column] = np.clip(df[column], lower_limit, upper_limit)
```

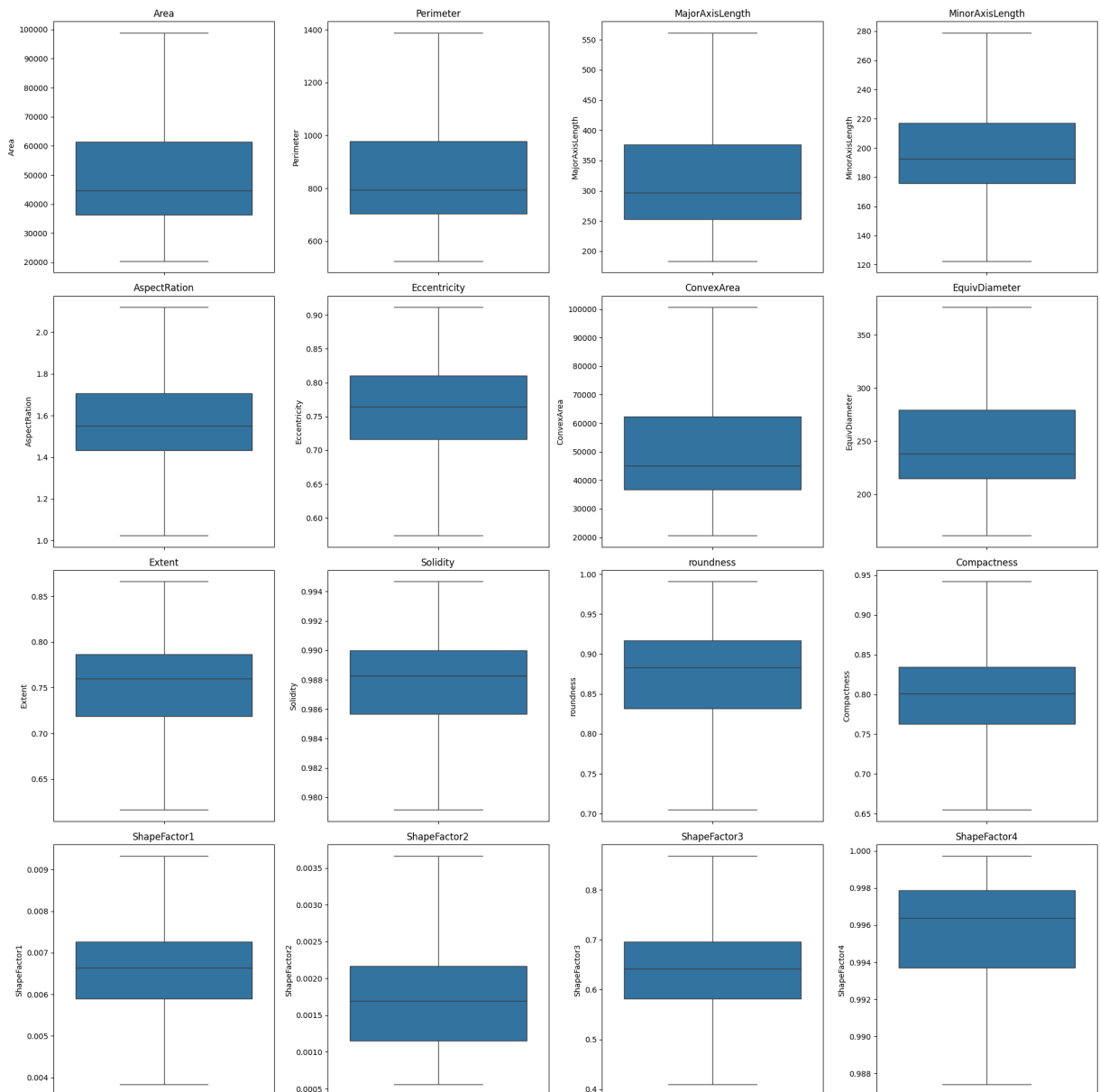
```
# Plot boxplot
```

```
sns.boxplot(df[column], ax=axes[row_idx, col_idx])
axes[row_idx, col_idx].set_title(column)
```

```
# Hide empty subplots
```

```
for i in range(num_plots, num_rows * num_cols):
    row_idx = i // num_cols
    col_idx = i % num_cols
    fig.delaxes(axes[row_idx, col_idx])
```

```
plt.tight_layout()
plt.show()
```





```
In [16]: df
```

```
Out[16]:
```

	Area	Perimeter	MajorAxisLength	MinorAxisLength	AspectRatio	Eccentricity	C
0	28395	610.291	208.178117	173.888747	1.197191	0.574120	
1	28734	638.018	200.524796	182.734419	1.097356	0.574120	
2	29380	624.110	212.826130	175.931143	1.209713	0.574120	
3	30008	645.884	210.557999	182.516516	1.153638	0.574120	
4	30140	620.134	201.847882	190.279279	1.060798	0.574120	
...	...	...	...	...	...	...	...
13606	42097	759.696	288.721612	185.944705	1.552728	0.765002	
13607	42101	757.499	281.576392	190.713136	1.476439	0.735702	
13608	42139	759.321	281.539928	191.187979	1.472582	0.734065	
13609	42147	763.779	283.382636	190.275731	1.489326	0.741055	
13610	42159	772.237	295.142741	182.204716	1.619841	0.786693	

13611 rows × 7 columns

```
In [17]: label=LabelEncoder()  
a=label.fit_transform(df["Class"])
```

```
In [18]: df["Class"]=a
```

## feature selection

from the above heat map i can see that area is directly to the convex area so we can remove the convex area

i can see that from the descriptive staistics the solidity range for all the beans are same

i can see that equdiameter is directly corelated to the area

```
In [19]: df
```

Out[19]:

	Area	Perimeter	MajorAxisLength	MinorAxisLength	AspectRation	Eccentricity	C
0	28395	610.291	208.178117	173.888747	1.197191	0.574120	
1	28734	638.018	200.524796	182.734419	1.097356	0.574120	
2	29380	624.110	212.826130	175.931143	1.209713	0.574120	
3	30008	645.884	210.557999	182.516516	1.153638	0.574120	
4	30140	620.134	201.847882	190.279279	1.060798	0.574120	
...	...	...	...	...	...	...	...
13606	42097	759.696	288.721612	185.944705	1.552728	0.765002	
13607	42101	757.499	281.576392	190.713136	1.476439	0.735702	
13608	42139	759.321	281.539928	191.187979	1.472582	0.734065	
13609	42147	763.779	283.382636	190.275731	1.489326	0.741055	
13610	42159	772.237	295.142741	182.204716	1.619841	0.786693	

13611 rows × 17 columns

In [20]:

```
df.drop(["ConvexArea", "Solidity", "EquivDiameter", "Compactness"],axis=1,inplace=True)
```

In [21]:

```
df
```

Out[21]:

	Area	Perimeter	MajorAxisLength	MinorAxisLength	AspectRation	Eccentricity	
0	28395	610.291	208.178117	173.888747	1.197191	0.574120	0
1	28734	638.018	200.524796	182.734419	1.097356	0.574120	0
2	29380	624.110	212.826130	175.931143	1.209713	0.574120	0
3	30008	645.884	210.557999	182.516516	1.153638	0.574120	0
4	30140	620.134	201.847882	190.279279	1.060798	0.574120	0
...	...	...	...	...	...	...	...
13606	42097	759.696	288.721612	185.944705	1.552728	0.765002	0
13607	42101	757.499	281.576392	190.713136	1.476439	0.735702	0
13608	42139	759.321	281.539928	191.187979	1.472582	0.734065	0
13609	42147	763.779	283.382636	190.275731	1.489326	0.741055	0
13610	42159	772.237	295.142741	182.204716	1.619841	0.786693	0

13611 rows × 13 columns

## Splitting the data into the feature variable and the class variable

```
In [22]: fv=df.iloc[:, :-1]
         cv=df.iloc[:, -1]
```

```
In [23]: fv
```

```
Out[23]:
```

	Area	Perimeter	MajorAxisLength	MinorAxisLength	AspectRation	Eccentricity	
0	28395	610.291	208.178117	173.888747	1.197191	0.574120	0
1	28734	638.018	200.524796	182.734419	1.097356	0.574120	0
2	29380	624.110	212.826130	175.931143	1.209713	0.574120	0
3	30008	645.884	210.557999	182.516516	1.153638	0.574120	0
4	30140	620.134	201.847882	190.279279	1.060798	0.574120	0
...	...	...	...	...	...	...	...
13606	42097	759.696	288.721612	185.944705	1.552728	0.765002	0
13607	42101	757.499	281.576392	190.713136	1.476439	0.735702	0
13608	42139	759.321	281.539928	191.187979	1.472582	0.734065	0
13609	42147	763.779	283.382636	190.275731	1.489326	0.741055	0
13610	42159	772.237	295.142741	182.204716	1.619841	0.786693	0

13611 rows × 12 columns

```
In [24]: cv
```

```
Out[24]:
```

0	5
1	5
2	5
3	5
4	5
...	...
13606	3
13607	3
13608	3
13609	3
13610	3

Name: Class, Length: 13611, dtype: int32

```
In [25]: x_train,x_test,y_train,y_test=train_test_split(fv,cv,test_size=0.1,random_state=10,
```

```
In [26]: x_trainf,x_cv,y_trainf,y_cv=train_test_split(x_train,y_train,test_size=0.1,random_s
```

## Feature Scaling in Machine Learning: StandardScaler

```
In [27]: std=StandardScaler()
px_train=std.fit_transform(x_trainf)
px_cv=std.transform(x_cv)
px_test=std.transform(x_test)
```

## Finding the k value based on the dtrainf and d\_cv

```
In [28]: k=[]
a=[]
a_train=[]
e=[]
p=[]
r=[]
l=[]
l_d=[]
for i in range(1,30,2):
    knn=KNeighborsClassifier(n_neighbors=i)
    model=knn.fit(x_trainf,y_trainf)
    predict_train=model.predict(x_trainf)
    a_train.append(accuracy_score(y_trainf,predict_train))

    predicted=model.predict(x_cv)
    print("no of neighbours :",i)
    print(" ")
    k.append(i)
    print("accuaracy train :",accuracy_score(y_trainf,predict_train))
    print("")
    a.append(accuracy_score(y_cv,predicted))
    print("accuaracy :",accuracy_score(y_cv,predicted))
    print(" ")
    print("")
    e.append(1-accuracy_score(y_cv,predicted))
    print("error :",1-accuracy_score(y_cv,predicted))
    print(" ")
    cm=ConfusionMatrixDisplay(confusion_matrix(y_cv,predicted,labels=model.classes_))
    cm.plot()
    plt.show()
    print(" ")
    p.append(precision_score(y_cv,predicted,average=None))
    print("precision_score :",precision_score(y_cv,predicted,average=None))
    print(" ")
    r.append(recall_score(y_cv,predicted,average=None))
    print("recall_score :",recall_score(y_cv,predicted,average=None))
    print(" ")
    print(classification_report(y_cv,predicted))
    print(" ")
    predicted_probablity=model.predict_proba(x_cv)
    l.append(log_loss(y_cv,predicted_probablity))
    print("logloss :",log_loss(y_cv,predicted_probablity))
    print(" ")
    dc=DummyClassifier()
```

```

dc_model=dc.fit(x_train,y_train)
dc_predit=dc_model.predict_proba(x_cv)
l_d.append(log_loss(y_cv,dc_predit))
print(" ")
print("log_loss dummy :",log_loss(y_cv,dc_predit))
print(" ")
print("***100)
print("")

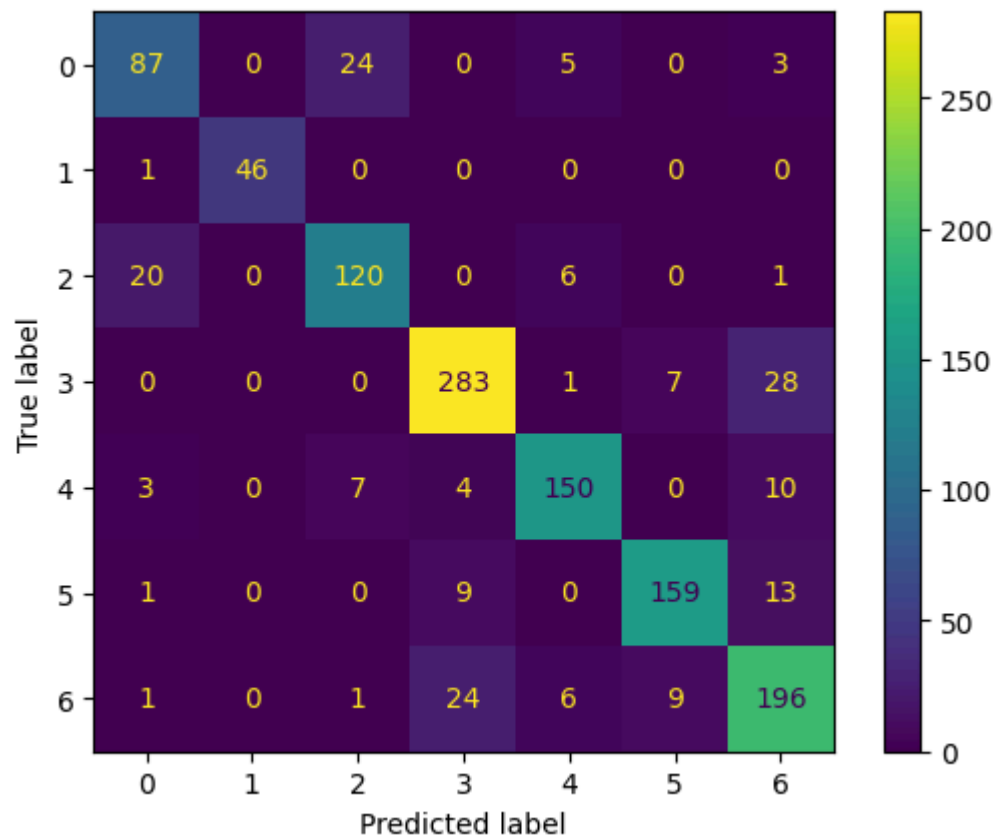
```

no of neighbours : 1

accuaracy train : 1.0

accuaracy : 0.8497959183673469

error : 0.15020408163265309



precision\_score : [0.7699115 1. 0.78947368 0.884375 0.89285714 0.90857143  
0.78087649]

recall\_score : [0.73109244 0.9787234 0.81632653 0.88714734 0.86206897 0.87362637  
0.82700422]

	precision	recall	f1-score	support
0	0.77	0.73	0.75	119
1	1.00	0.98	0.99	47
2	0.79	0.82	0.80	147
3	0.88	0.89	0.89	319
4	0.89	0.86	0.88	174
5	0.91	0.87	0.89	182
6	0.78	0.83	0.80	237
accuracy			0.85	1225
macro avg	0.86	0.85	0.86	1225
weighted avg	0.85	0.85	0.85	1225

logloss : 5.413903855998007

log\_loss dummy : 1.8346996197876575

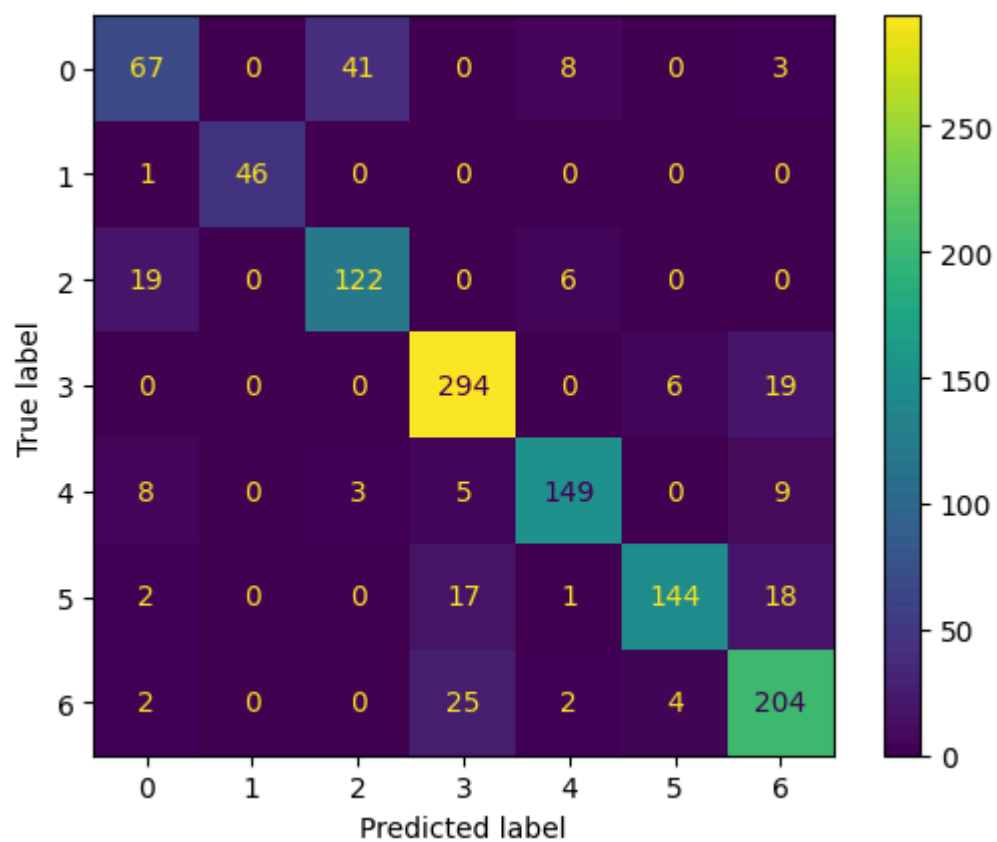
\*\*\*\*\*  
\*\*\*\*\*

no of neighbours : 3

accuaracy train : 0.9093795355587808

accuaracy : 0.8375510204081633

error : 0.16244897959183668



precision\_score : [0.67676768 1. 0.73493976 0.86217009 0.89759036 0.93506494  
0.80632411]

recall\_score : [0.56302521 0.9787234 0.82993197 0.92163009 0.85632184 0.79120879  
0.86075949]

	precision	recall	f1-score	support
0	0.68	0.56	0.61	119
1	1.00	0.98	0.99	47
2	0.73	0.83	0.78	147
3	0.86	0.92	0.89	319
4	0.90	0.86	0.88	174
5	0.94	0.79	0.86	182
6	0.81	0.86	0.83	237
accuracy			0.84	1225
macro avg	0.84	0.83	0.83	1225
weighted avg	0.84	0.84	0.84	1225

logloss : 2.3252825844788947

log\_loss dummy : 1.8346996197876575

\*\*\*\*\*  
\*\*\*\*\*

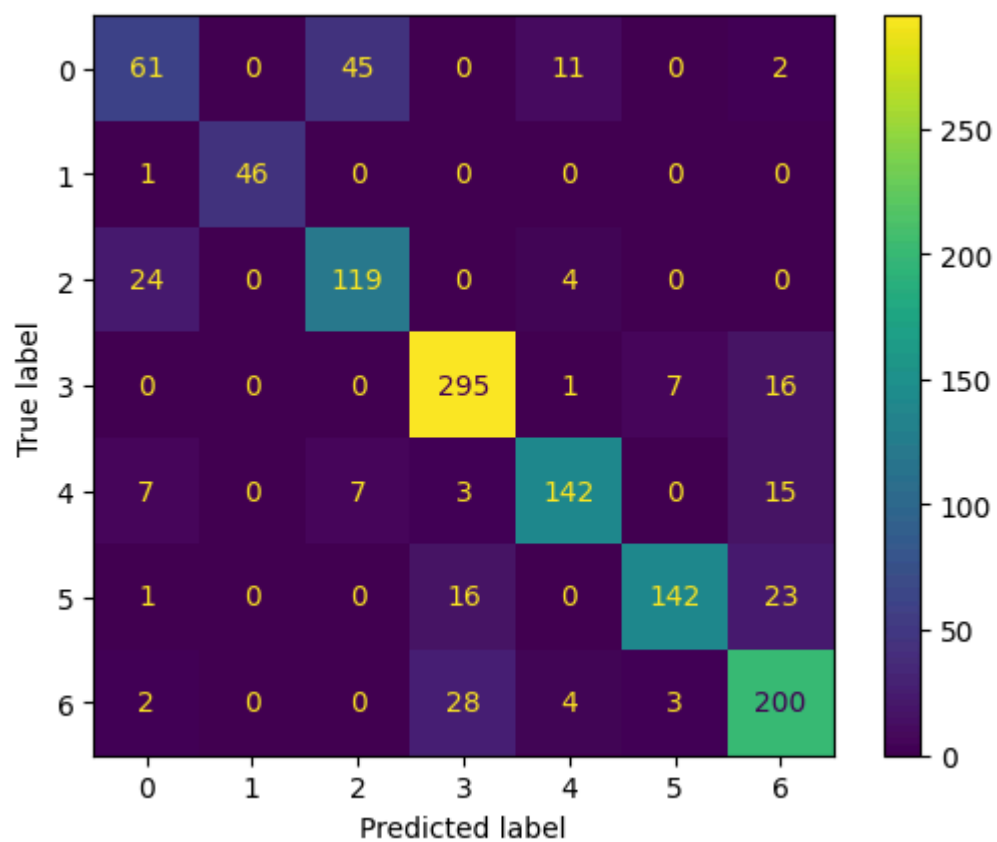
no of neighbours : 5

accuaracy train : 0.8780841799709724

accuaracy : 0.8204081632653061

error : 0.17959183673469392





precision\_score : [0.63541667 1. 0.69590643 0.8625731 0.87654321 0.93421053  
0.78125 ]

recall\_score : [0.51260504 0.9787234 0.80952381 0.92476489 0.81609195 0.78021978  
0.84388186]

	precision	recall	f1-score	support
0	0.64	0.51	0.57	119
1	1.00	0.98	0.99	47
2	0.70	0.81	0.75	147
3	0.86	0.92	0.89	319
4	0.88	0.82	0.85	174
5	0.93	0.78	0.85	182
6	0.78	0.84	0.81	237
accuracy			0.82	1225
macro avg	0.83	0.81	0.81	1225
weighted avg	0.82	0.82	0.82	1225

logloss : 1.683962528050476

log\_loss dummy : 1.8346996197876575

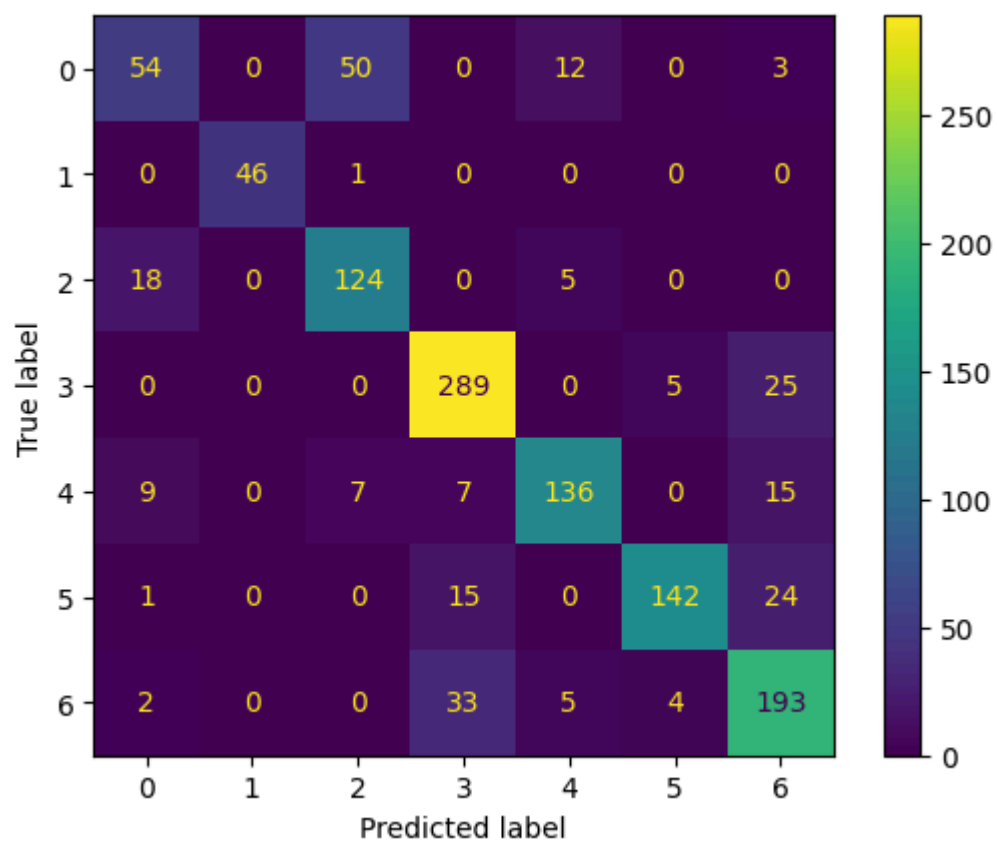
\*\*\*\*\*  
\*\*\*\*\*

no of neighbours : 7

accuaracy train : 0.8489658925979681

accuaracy : 0.803265306122449

error : 0.19673469387755105



precision\_score : [0.64285714 1. 0.68131868 0.84011628 0.86075949 0.94039735  
0.74230769]

recall\_score : [0.45378151 0.9787234 0.84353741 0.90595611 0.7816092 0.78021978  
0.81434599]

	precision	recall	f1-score	support
0	0.64	0.45	0.53	119
1	1.00	0.98	0.99	47
2	0.68	0.84	0.75	147
3	0.84	0.91	0.87	319
4	0.86	0.78	0.82	174
5	0.94	0.78	0.85	182
6	0.74	0.81	0.78	237
accuracy			0.80	1225
macro avg	0.82	0.79	0.80	1225
weighted avg	0.81	0.80	0.80	1225

logloss : 1.4498288060971456

log\_loss dummy : 1.8346996197876575

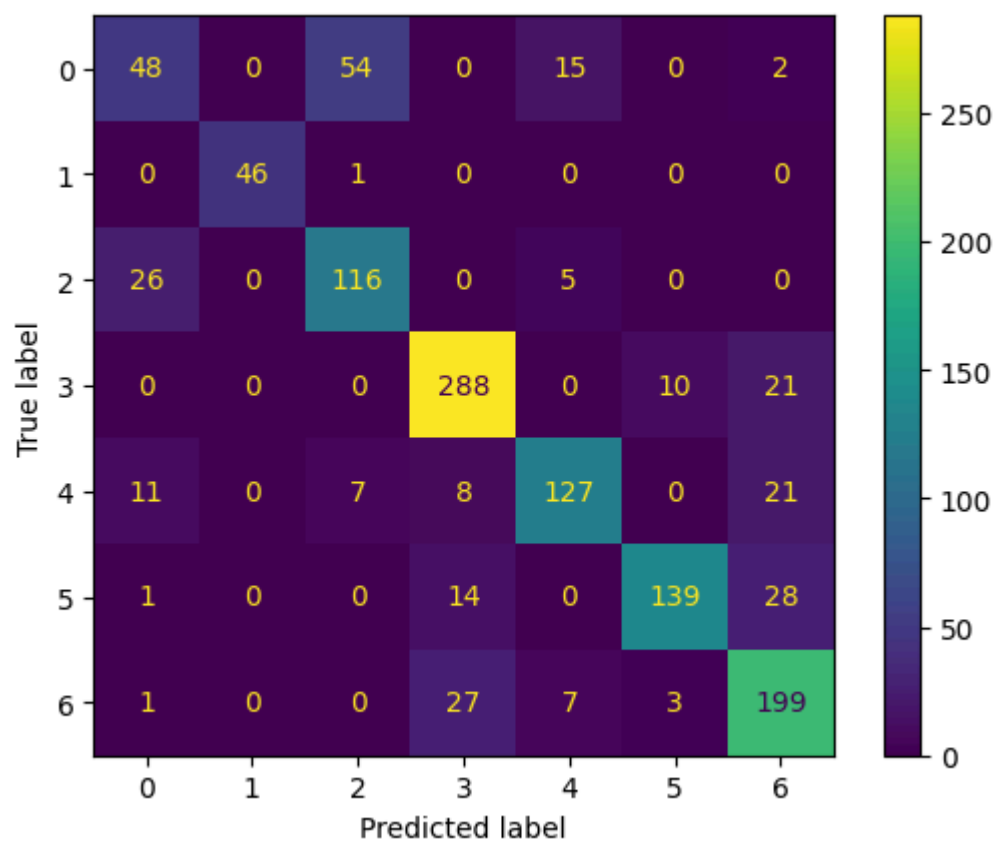
\*\*\*\*\*  
\*\*\*\*\*

no of neighbours : 9

accuaracy train : 0.8290094339622641

accuaracy : 0.7861224489795918

error : 0.21387755102040817



precision\_score : [0.55172414 1. 0.65168539 0.85459941 0.82467532 0.91447368  
0.73431734]

recall\_score : [0.40336134 0.9787234 0.78911565 0.90282132 0.72988506 0.76373626  
0.83966245]

	precision	recall	f1-score	support
0	0.55	0.40	0.47	119
1	1.00	0.98	0.99	47
2	0.65	0.79	0.71	147
3	0.85	0.90	0.88	319
4	0.82	0.73	0.77	174
5	0.91	0.76	0.83	182
6	0.73	0.84	0.78	237
accuracy			0.79	1225
macro avg	0.79	0.77	0.78	1225
weighted avg	0.79	0.79	0.78	1225

logloss : 1.1320083797295186

log\_loss dummy : 1.8346996197876575

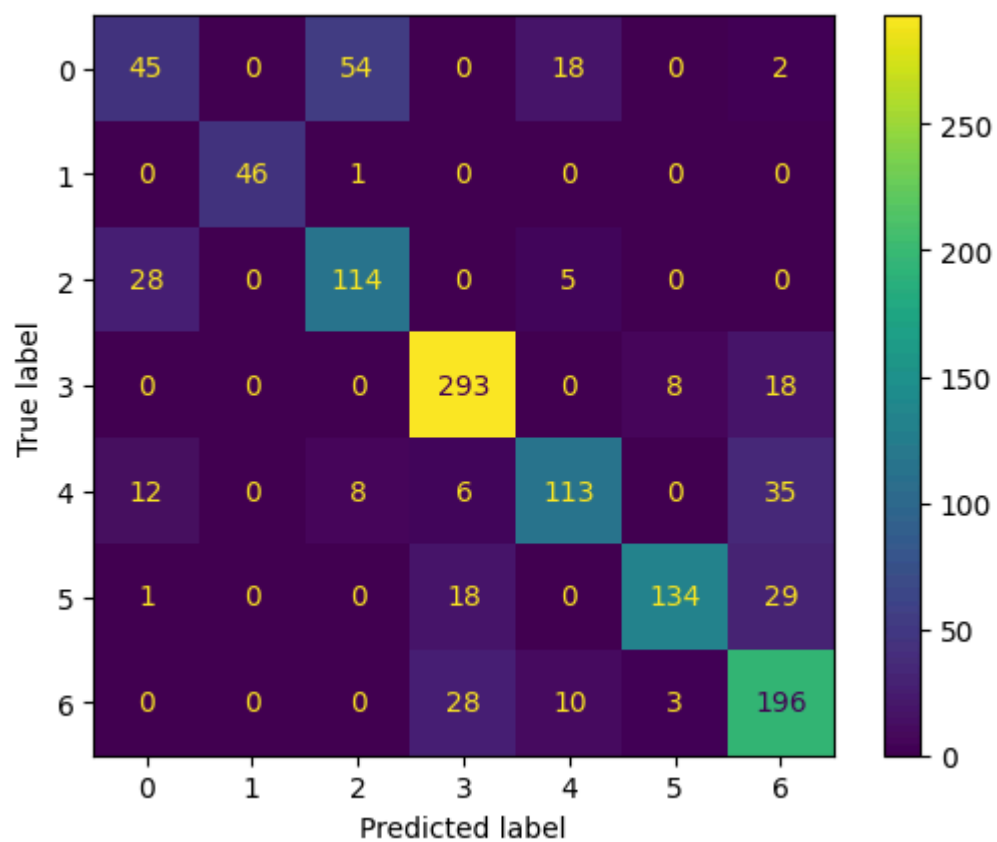
\*\*\*\*\*  
\*\*\*\*\*

no of neighbours : 11

accuaracy train : 0.8099600870827286

accuaracy : 0.7681632653061224

error : 0.23183673469387756



precision\_score : [0.52325581 1. 0.6440678 0.84927536 0.7739726 0.92413793  
0.7 ]

recall\_score : [0.37815126 0.9787234 0.7755102 0.9184953 0.64942529 0.73626374  
0.82700422]

	precision	recall	f1-score	support
0	0.52	0.38	0.44	119
1	1.00	0.98	0.99	47
2	0.64	0.78	0.70	147
3	0.85	0.92	0.88	319
4	0.77	0.65	0.71	174
5	0.92	0.74	0.82	182
6	0.70	0.83	0.76	237
accuracy			0.77	1225
macro avg	0.77	0.75	0.76	1225
weighted avg	0.77	0.77	0.76	1225

logloss : 1.026101687139419

log\_loss dummy : 1.8346996197876575

\*\*\*\*\*  
\*\*\*\*\*

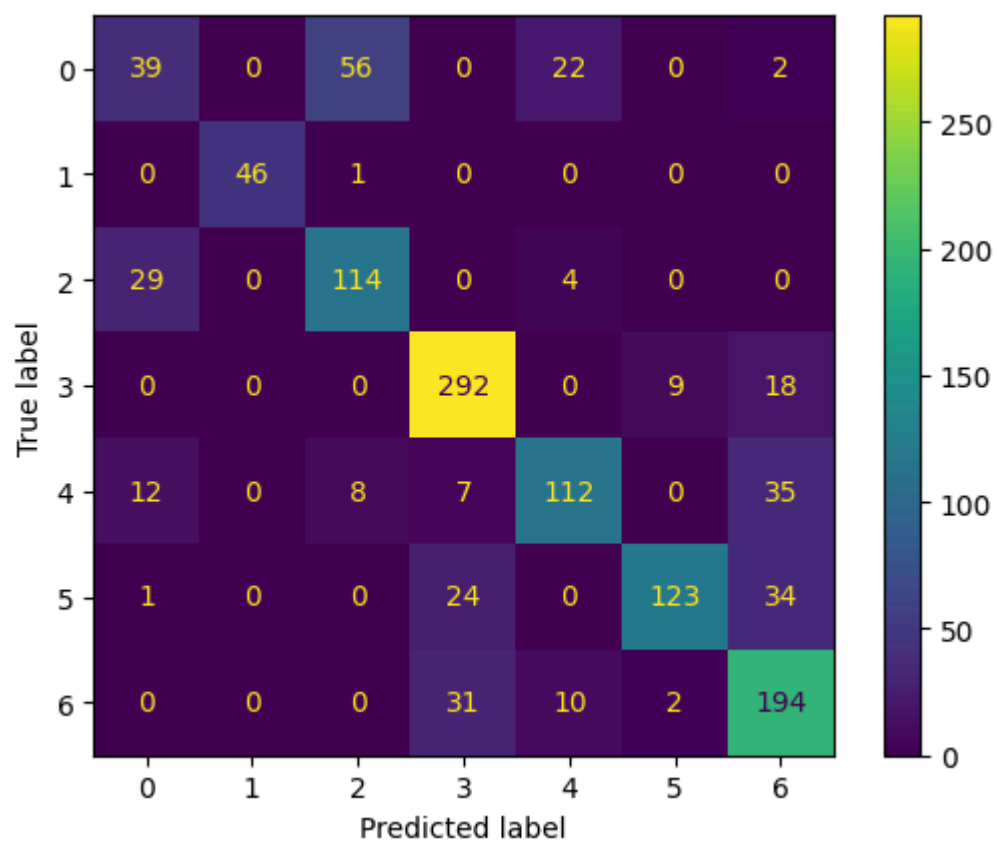
no of neighbours : 13

accuaracy train : 0.7891872278664731

accuaracy : 0.7510204081632653

error : 0.24897959183673468





precision\_score : [0.48148148 1. 0.63687151 0.82485876 0.75675676 0.91791045  
0.68551237]

recall\_score : [0.32773109 0.9787234 0.7755102 0.9153605 0.64367816 0.67582418  
0.8185654 ]

	precision	recall	f1-score	support
0	0.48	0.33	0.39	119
1	1.00	0.98	0.99	47
2	0.64	0.78	0.70	147
3	0.82	0.92	0.87	319
4	0.76	0.64	0.70	174
5	0.92	0.68	0.78	182
6	0.69	0.82	0.75	237
accuracy			0.75	1225
macro avg	0.76	0.73	0.74	1225
weighted avg	0.75	0.75	0.74	1225

logloss : 0.945905538216687

log\_loss dummy : 1.8346996197876575

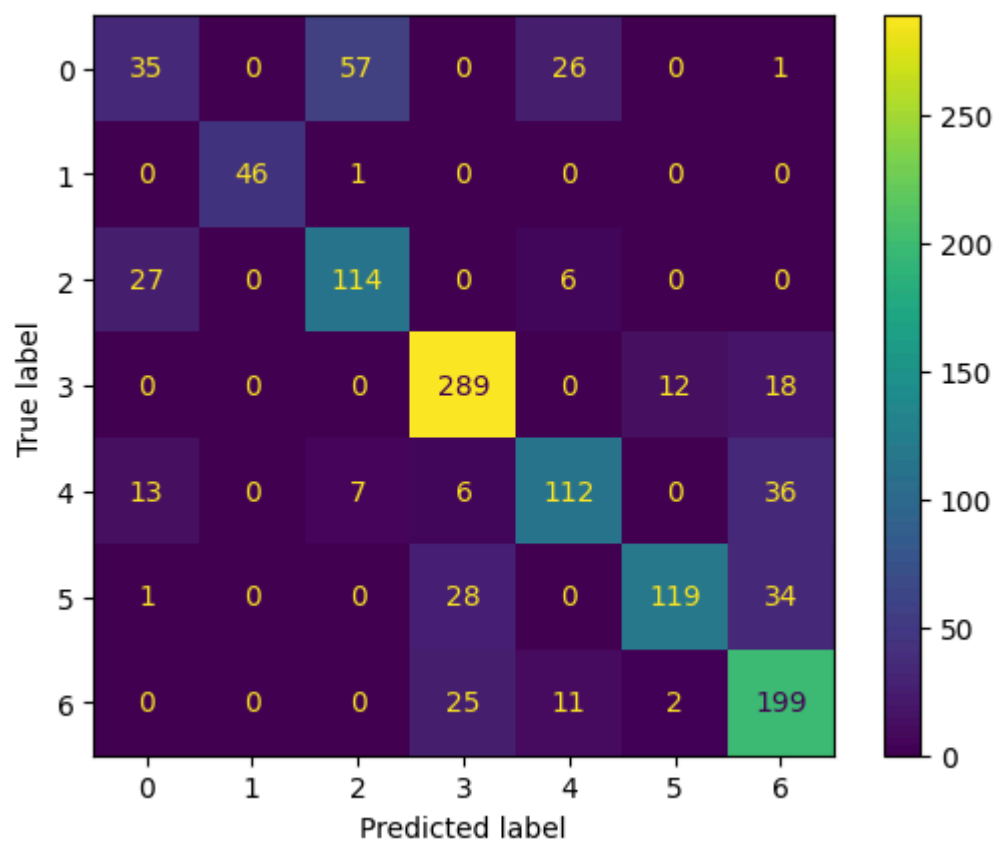
\*\*\*\*\*  
\*\*\*\*\*

no of neighbours : 15

accuaracy train : 0.7759433962264151

accuaracy : 0.7461224489795918

error : 0.2538775510204082



precision\_score : [0.46052632 1. 0.63687151 0.83045977 0.72258065 0.89473684  
0.69097222]

recall\_score : [0.29411765 0.9787234 0.7755102 0.90595611 0.64367816 0.65384615  
0.83966245]

	precision	recall	f1-score	support
0	0.46	0.29	0.36	119
1	1.00	0.98	0.99	47
2	0.64	0.78	0.70	147
3	0.83	0.91	0.87	319
4	0.72	0.64	0.68	174
5	0.89	0.65	0.76	182
6	0.69	0.84	0.76	237
accuracy			0.75	1225
macro avg	0.75	0.73	0.73	1225
weighted avg	0.75	0.75	0.74	1225

logloss : 0.9446509212406085

log\_loss dummy : 1.8346996197876575

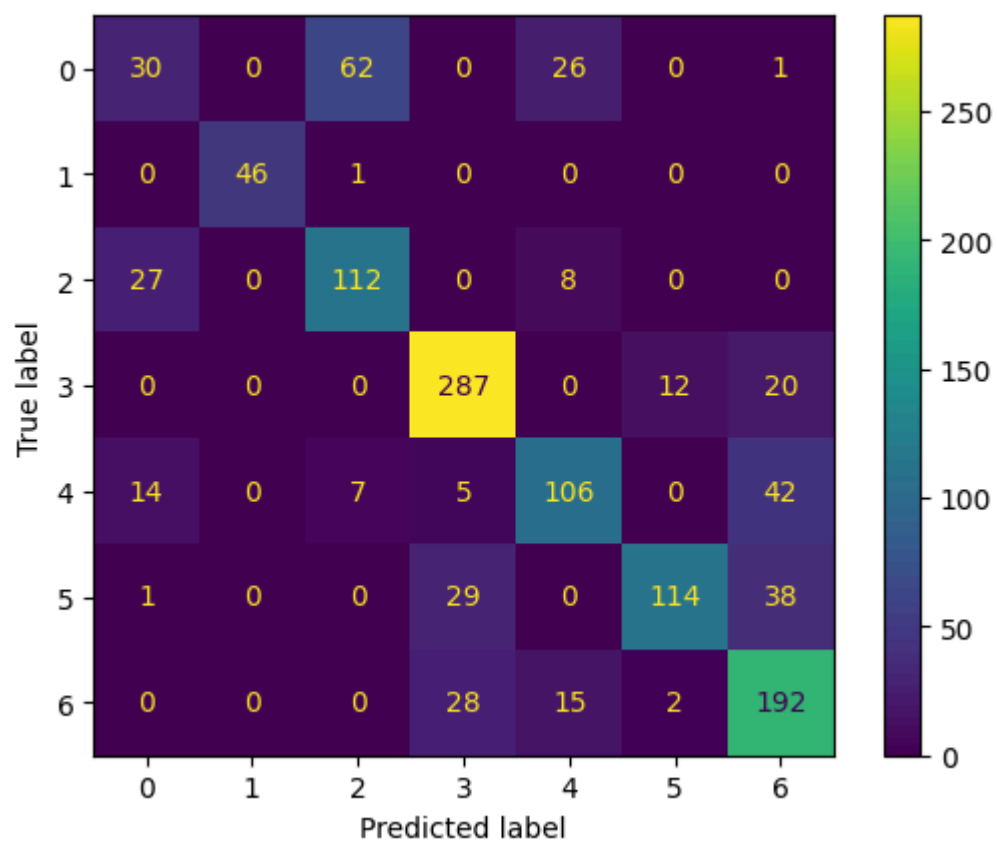
\*\*\*\*\*  
\*\*\*\*\*

no of neighbours : 17

accuaracy train : 0.7644230769230769

accuaracy : 0.7240816326530612

error : 0.27591836734693875



precision\_score : [0.41666667 1. 0.61538462 0.82234957 0.68387097 0.890625  
0.6552901 ]

recall\_score : [0.25210084 0.9787234 0.76190476 0.89968652 0.6091954 0.62637363  
0.81012658]

	precision	recall	f1-score	support
0	0.42	0.25	0.31	119
1	1.00	0.98	0.99	47
2	0.62	0.76	0.68	147
3	0.82	0.90	0.86	319
4	0.68	0.61	0.64	174
5	0.89	0.63	0.74	182
6	0.66	0.81	0.72	237
accuracy			0.72	1225
macro avg	0.73	0.71	0.71	1225
weighted avg	0.72	0.72	0.71	1225

logloss : 0.9400443138405687

log\_loss dummy : 1.8346996197876575

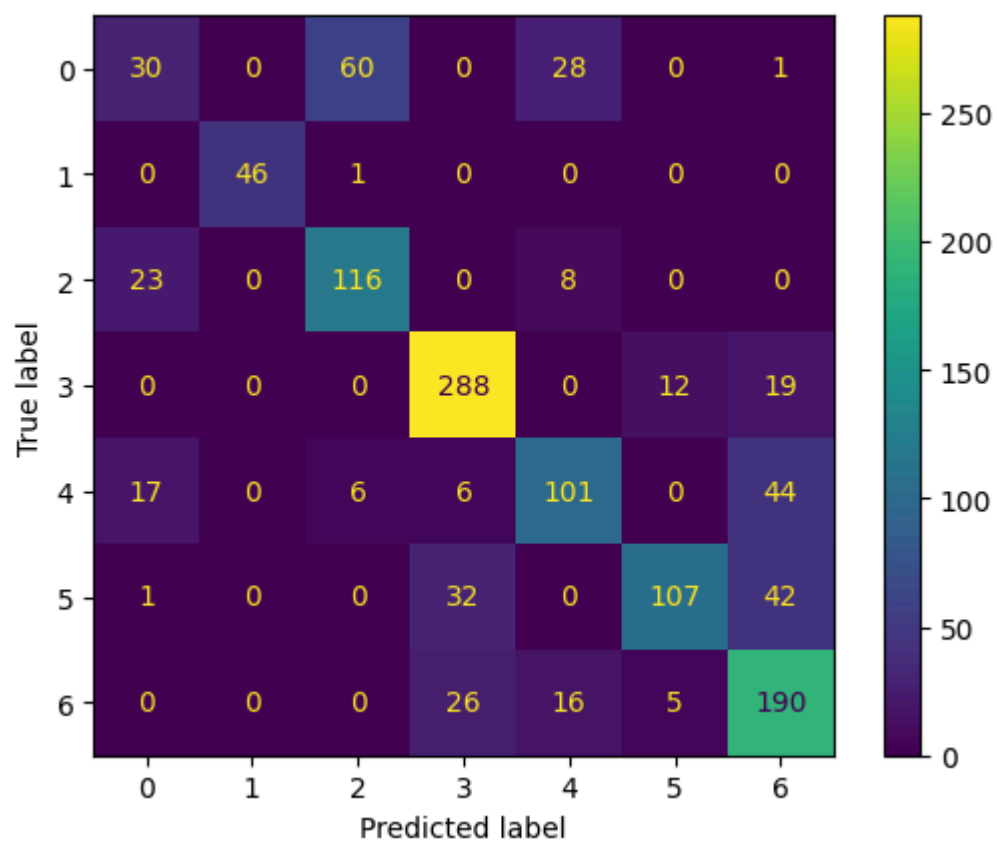
\*\*\*\*\*  
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no of neighbours : 19

accuaracy train : 0.752177068214804

accuaracy : 0.7167346938775511

error : 0.28326530612244893



precision\_score : [0.42253521 1. 0.63387978 0.81818182 0.66013072 0.86290323  
0.64189189]

recall\_score : [0.25210084 0.9787234 0.78911565 0.90282132 0.58045977 0.58791209  
0.80168776]

	precision	recall	f1-score	support
0	0.42	0.25	0.32	119
1	1.00	0.98	0.99	47
2	0.63	0.79	0.70	147
3	0.82	0.90	0.86	319
4	0.66	0.58	0.62	174
5	0.86	0.59	0.70	182
6	0.64	0.80	0.71	237
accuracy			0.72	1225
macro avg	0.72	0.70	0.70	1225
weighted avg	0.71	0.72	0.71	1225

logloss : 0.9097212388371554

log\_loss dummy : 1.8346996197876575

\*\*\*\*\*  
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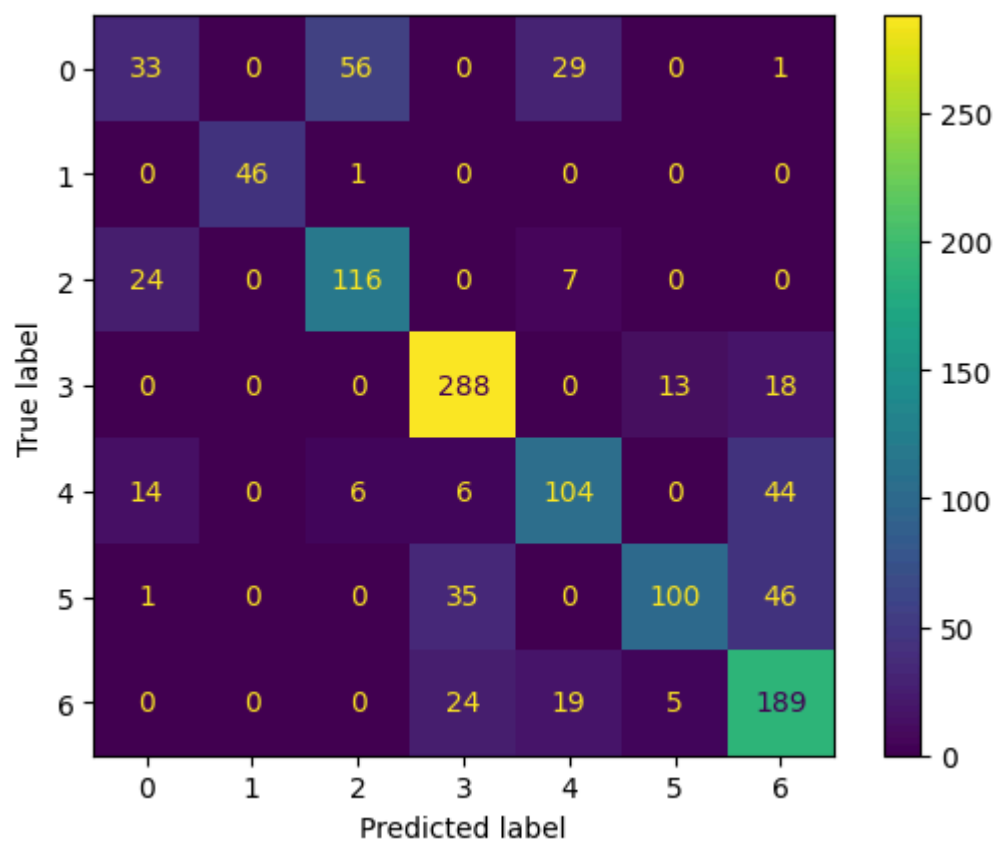
no of neighbours : 21

accuaracy train : 0.7434687953555879

accuaracy : 0.7151020408163266

error : 0.28489795918367344





precision\_score : [0.45833333 1. 0.64804469 0.81586402 0.65408805 0.84745763  
0.63422819]

recall\_score : [0.27731092 0.9787234 0.78911565 0.90282132 0.59770115 0.54945055  
0.79746835]

	precision	recall	f1-score	support
0	0.46	0.28	0.35	119
1	1.00	0.98	0.99	47
2	0.65	0.79	0.71	147
3	0.82	0.90	0.86	319
4	0.65	0.60	0.62	174
5	0.85	0.55	0.67	182
6	0.63	0.80	0.71	237
accuracy			0.72	1225
macro avg	0.72	0.70	0.70	1225
weighted avg	0.71	0.72	0.70	1225

logloss : 0.9038109390872345

log\_loss dummy : 1.8346996197876575

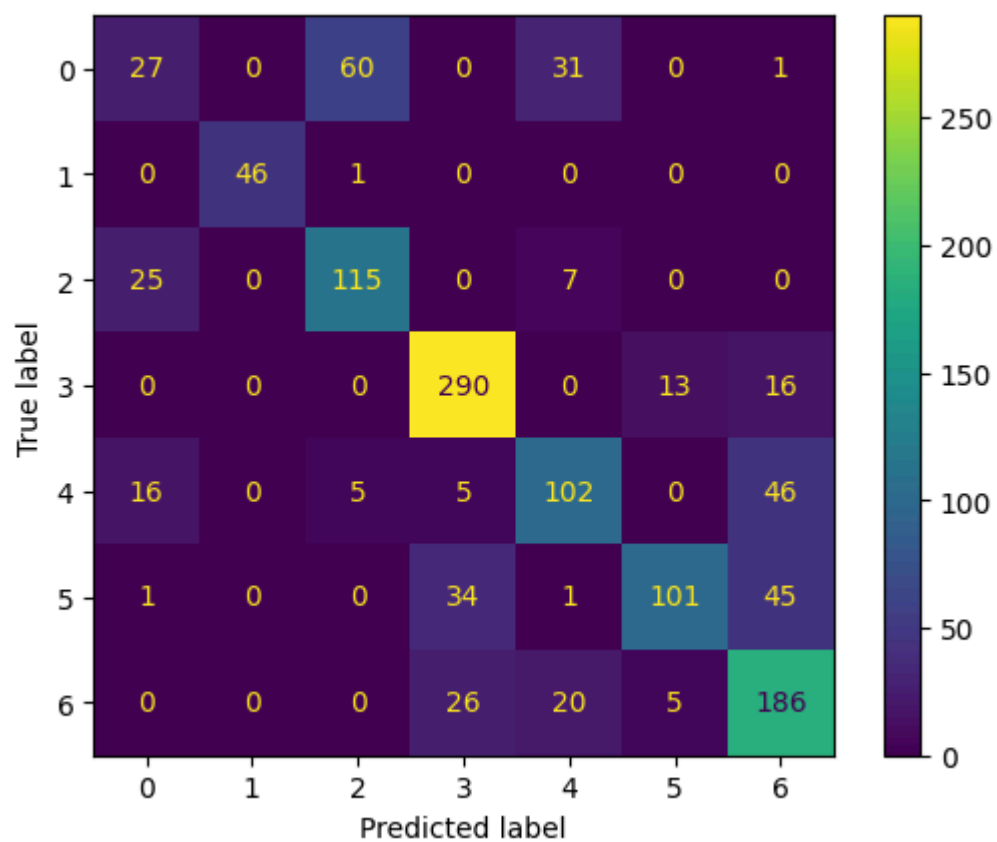
\*\*\*\*\*  
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no of neighbours : 23

accuaracy train : 0.7327648766328012

accuaracy : 0.7077551020408164

error : 0.2922448979591836



precision\_score : [0.39130435 1. 0.63535912 0.81690141 0.63354037 0.8487395  
0.63265306]

recall\_score : [0.22689076 0.9787234 0.78231293 0.90909091 0.5862069 0.55494505  
0.78481013]

	precision	recall	f1-score	support
0	0.39	0.23	0.29	119
1	1.00	0.98	0.99	47
2	0.64	0.78	0.70	147
3	0.82	0.91	0.86	319
4	0.63	0.59	0.61	174
5	0.85	0.55	0.67	182
6	0.63	0.78	0.70	237
accuracy			0.71	1225
macro avg	0.71	0.69	0.69	1225
weighted avg	0.70	0.71	0.70	1225

logloss : 0.8924082359316066

log\_loss dummy : 1.8346996197876575

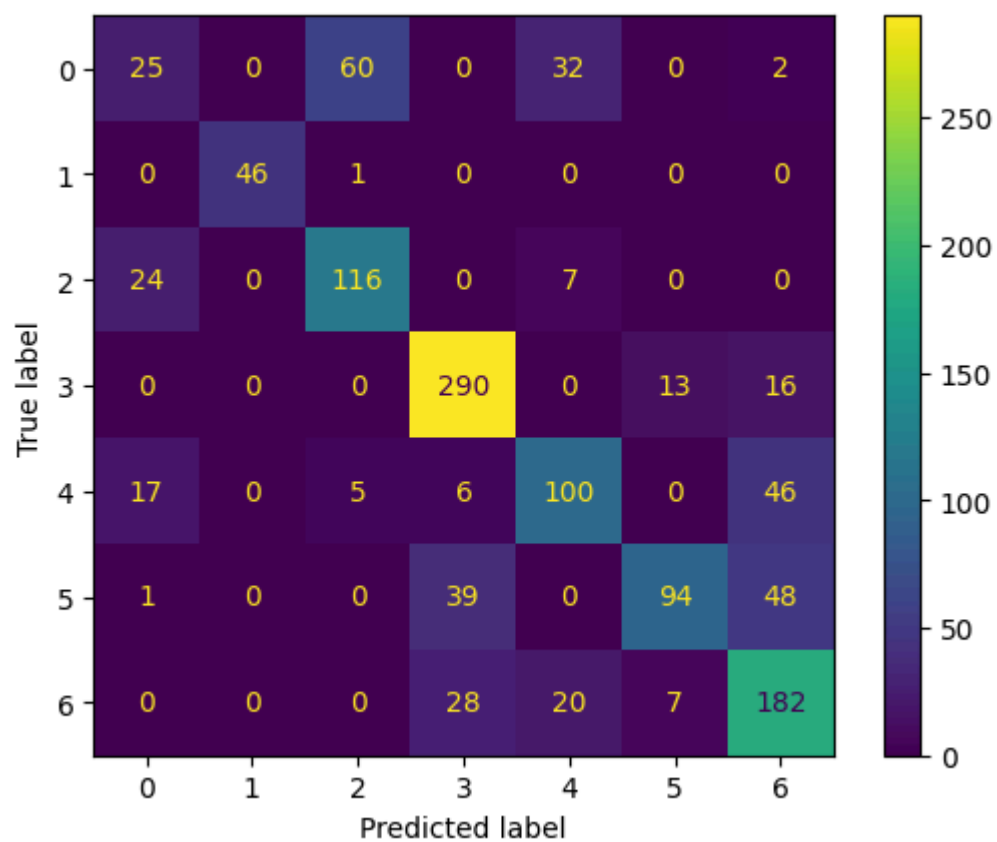
\*\*\*\*\*  
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no of neighbours : 25

accuaracy train : 0.726233671988389

accuaracy : 0.6963265306122449

error : 0.3036734693877551



precision\_score : [0.37313433 1. 0.63736264 0.79889807 0.62893082 0.8245614  
0.61904762]

recall\_score : [0.21008403 0.9787234 0.78911565 0.90909091 0.57471264 0.51648352  
0.76793249]

	precision	recall	f1-score	support
0	0.37	0.21	0.27	119
1	1.00	0.98	0.99	47
2	0.64	0.79	0.71	147
3	0.80	0.91	0.85	319
4	0.63	0.57	0.60	174
5	0.82	0.52	0.64	182
6	0.62	0.77	0.69	237
accuracy			0.70	1225
macro avg	0.70	0.68	0.68	1225
weighted avg	0.69	0.70	0.68	1225

logloss : 0.8794946369586336

log\_loss dummy : 1.8346996197876575

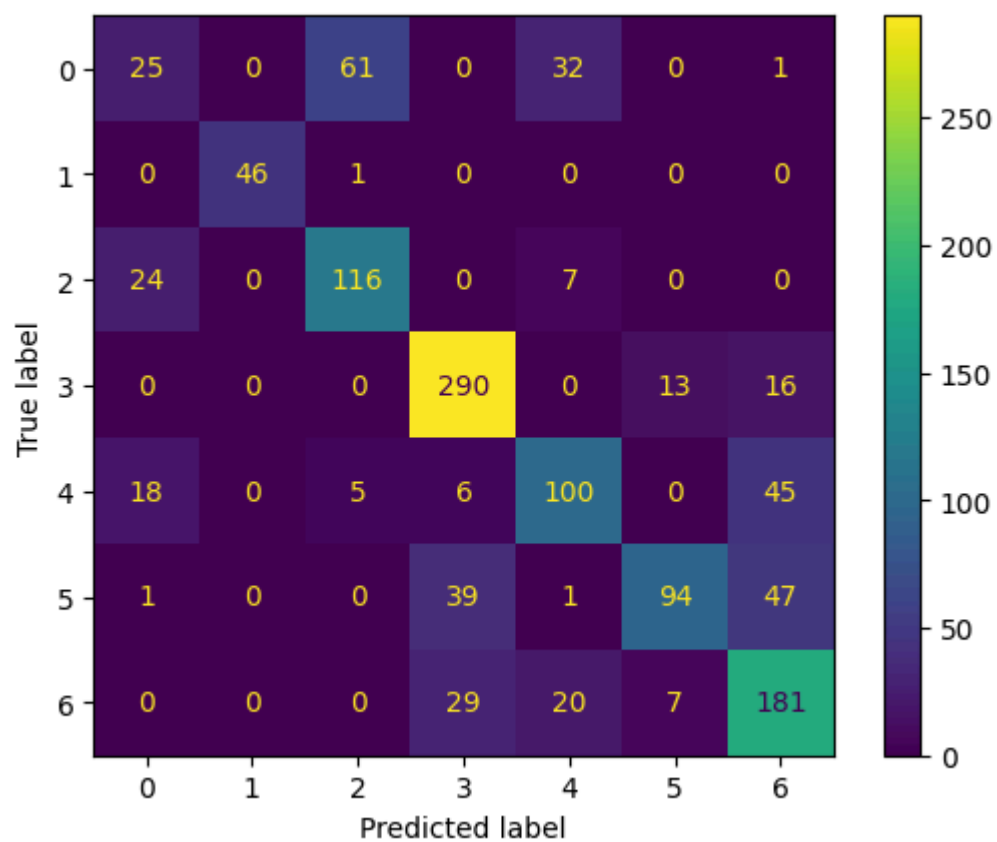
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no of neighbours : 27

accuaracy train : 0.7197024673439768

accuaracy : 0.6955102040816327

error : 0.30448979591836733



precision\_score : [0.36764706 1. 0.63387978 0.7967033 0.625 0.8245614  
0.62413793]

recall\_score : [0.21008403 0.9787234 0.78911565 0.90909091 0.57471264 0.51648352  
0.76371308]

	precision	recall	f1-score	support
0	0.37	0.21	0.27	119
1	1.00	0.98	0.99	47
2	0.63	0.79	0.70	147
3	0.80	0.91	0.85	319
4	0.62	0.57	0.60	174
5	0.82	0.52	0.64	182
6	0.62	0.76	0.69	237
accuracy			0.70	1225
macro avg	0.70	0.68	0.68	1225
weighted avg	0.69	0.70	0.68	1225

logloss : 0.8901366984225116

log\_loss dummy : 1.8346996197876575

\*\*\*\*\*  
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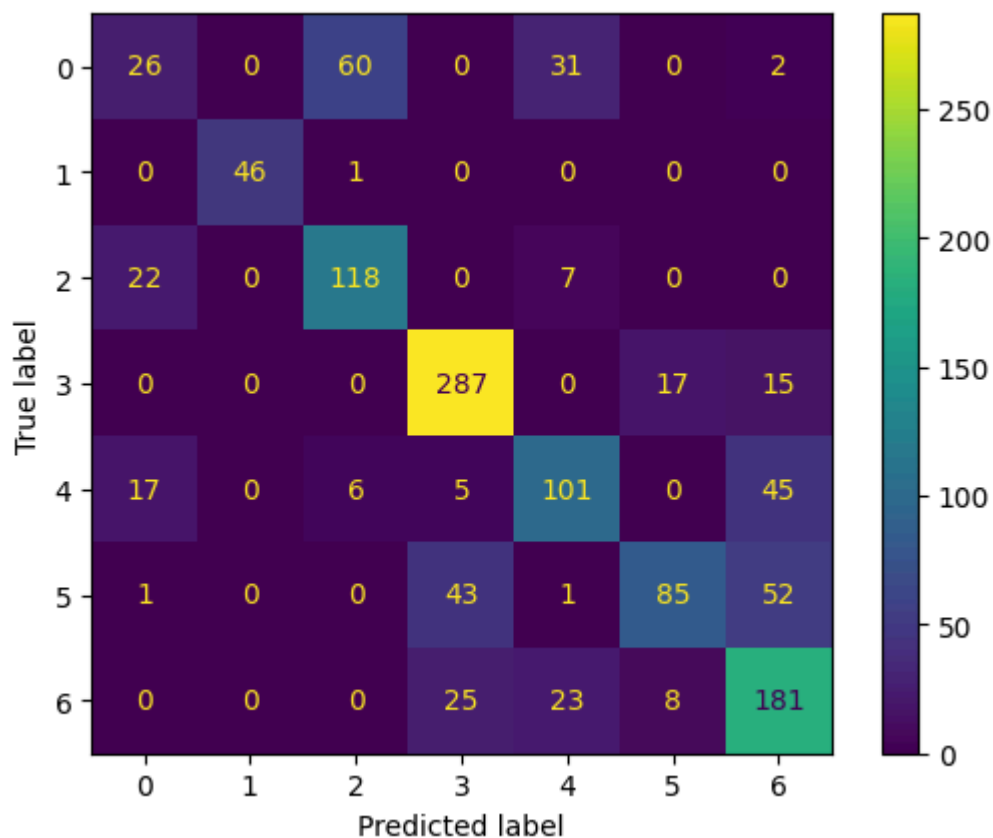
no of neighbours : 29

accuaracy train : 0.7120827285921626

accuaracy : 0.6889795918367347

error : 0.31102040816326526





```
precision_score : [0.39393939 1.          0.63783784 0.79722222 0.6196319  0.77272727
0.61355932]
```

```
recall_score : [0.21848739 0.9787234  0.80272109 0.89968652 0.58045977 0.46703297
0.76371308]
```

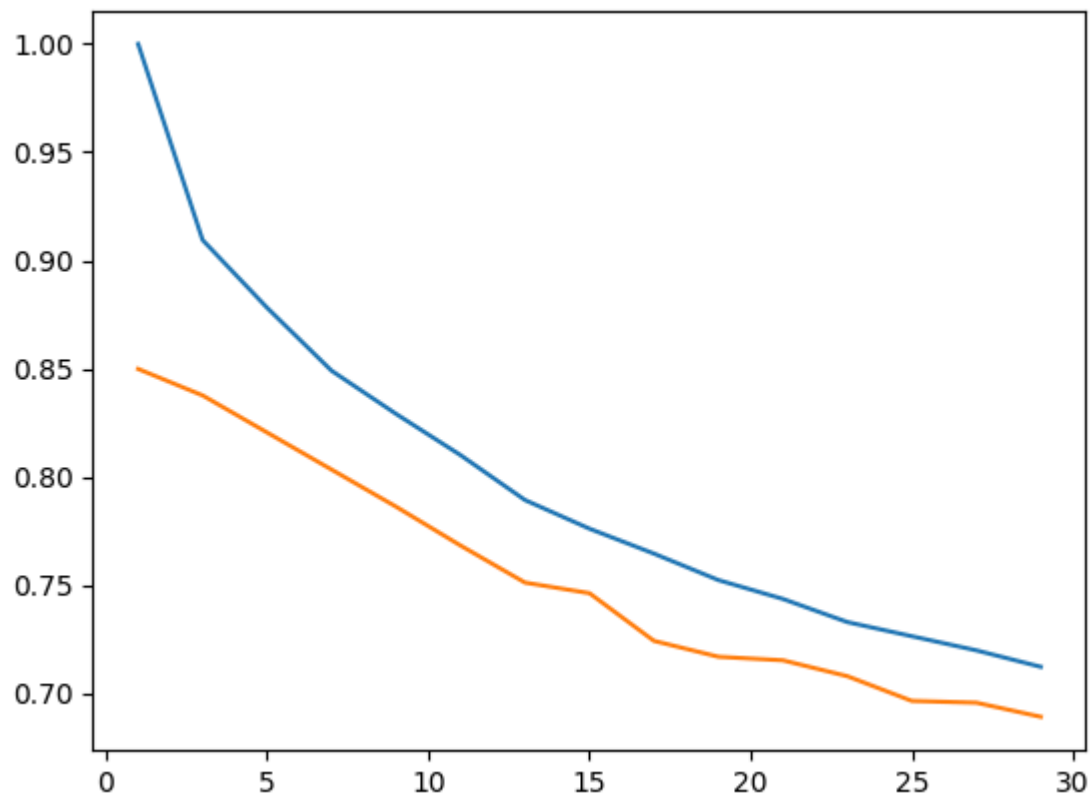
	precision	recall	f1-score	support
0	0.39	0.22	0.28	119
1	1.00	0.98	0.99	47
2	0.64	0.80	0.71	147
3	0.80	0.90	0.85	319
4	0.62	0.58	0.60	174
5	0.77	0.47	0.58	182
6	0.61	0.76	0.68	237
accuracy			0.69	1225
macro avg	0.69	0.67	0.67	1225
weighted avg	0.68	0.69	0.67	1225

```
logloss : 0.8769737559218076
```

```
log_loss dummy : 1.8346996197876575
```

```
*****
*****
```

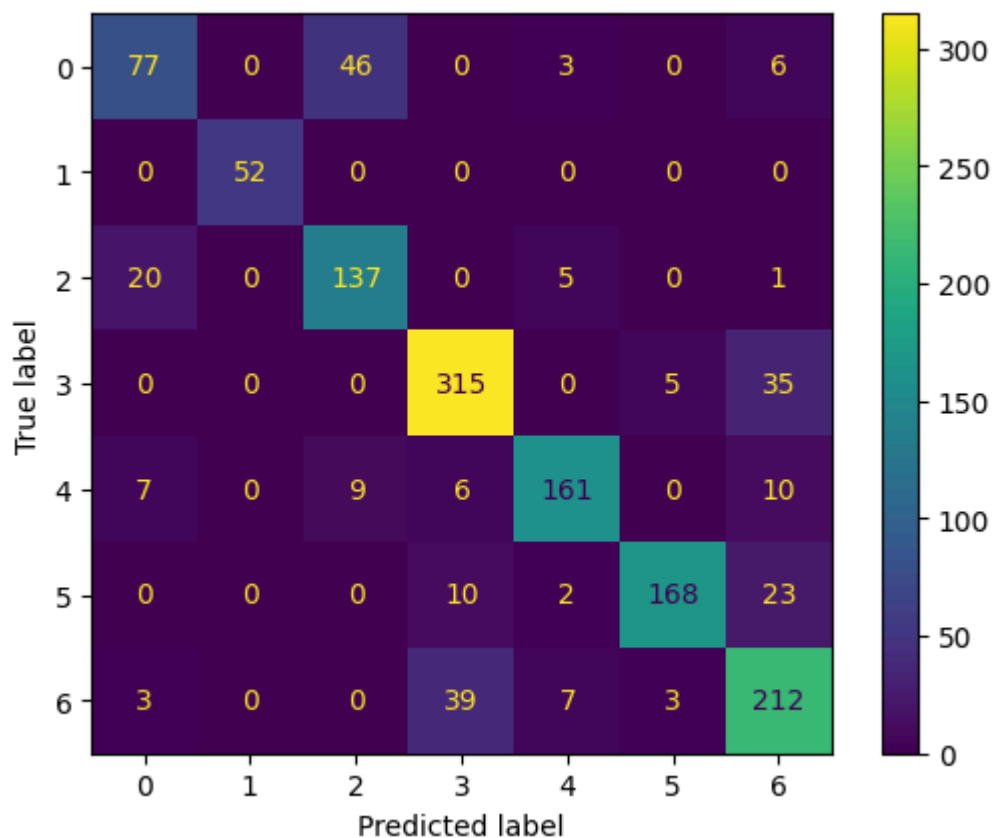
```
In [29]: plt.plot(k,a_train)
plt.plot(k,a)
plt.show()
```



```
In [30]: knn=KNeighborsClassifier(n_neighbors=3)
model=knn.fit(x_trainf,y_trainf)
predicted=model.predict(x_test)
print("accuracy score : ",accuracy_score(y_test,predicted))
print("")
print("error score :",1-accuracy_score(y_test,predicted))
print("")
cm=ConfusionMatrixDisplay(confusion_matrix(y_test,predicted,labels=model.classes_))
cm.plot()
plt.show()
print("recall score",recall_score(y_test,predicted,average=None))
print("")
print("precision score :",precision_score(y_test,predicted,average=None))
print("")
print(classification_report(y_test,predicted))
predicted=model.predict_proba(x_test)
print("precision score :",log_loss(y_test,predicted))
```

accuracy score : 0.8237885462555066

error score : 0.17621145374449343



```
recall score [0.58333333 1.          0.8404908  0.88732394 0.83419689 0.82758621
 0.8030303 ]
```

```
precision score : [0.71962617 1.          0.71354167 0.85135135 0.90449438 0.95454545
 0.73867596]
```

	precision	recall	f1-score	support
0	0.72	0.58	0.64	132
1	1.00	1.00	1.00	52
2	0.71	0.84	0.77	163
3	0.85	0.89	0.87	355
4	0.90	0.83	0.87	193
5	0.95	0.83	0.89	203
6	0.74	0.80	0.77	264
accuracy			0.82	1362
macro avg	0.84	0.83	0.83	1362
weighted avg	0.83	0.82	0.82	1362

```
precision score : 2.9284165675745806
```

```
In [31]: kf=KFold(n_splits=3)
```

```
In [32]: acc_train=[]
acc_cv=[]
k_values=[]
for i in range(1,30,2):
    acc=[]
    acc_train=[]
```

```

err=[]
conf=[]
recall=[]
prec=[]
k=[]
logloss=[]
logloss_dummy=[]
for train_index,cv_index in kf.split(x_train,y_train):
    x_trainf,x_cv,y_trainf,y_cv=x_train.iloc[train_index],x_train.iloc[cv_index]
    knn=KNeighborsClassifier(n_neighbors=i)
    model=knn.fit(x_trainf,y_trainf)
    predicted_train=model.predict(x_trainf)
    acc_train.append(accuracy_score(y_trainf,predicted_train))
    predicted=model.predict(x_cv)
    acc.append(accuracy_score(y_cv,predicted))
    err.append(1-accuracy_score(y_cv,predicted))
    conf.append(confusion_matrix(y_cv,predicted,labels=model.classes_))
    recall.append(recall_score(y_cv,predicted,average=None))
    prec.append(precision_score(y_cv,predicted,average=None))
    predicted=model.predict_proba(x_cv)
    logloss.append(log_loss(y_cv,predicted))
    dc=DummyClassifier()
    dc_model=dc.fit(x_trainf,y_trainf)
    dc_predit=dc_model.predict_proba(x_test)
    logloss_dummy.append(log_loss(y_test,dc_predit))

print("K_value",i)
print("")
acc_train
print("")
acc_cv.append(np.mean(acc))
print("avg_accuracy : ",np.mean(acc))
print("")
print("avg_err : ",np.mean(err))
print(" ")

plt.figure(figsize=(20,8))
cm=ConfusionMatrixDisplay(np.int64(np.round((conf[0]+conf[1]+conf[2])/3)))
cm.plot()
plt.show()
print(" ")
print("recall_score : ",np.mean(recall))
print(" ")
print("precision Score : ",np.mean(prec))
print(" ")
print("log loss : ",np.mean(logloss))
print(" ")
print("log loss_dummy : ",np.mean(logloss_dummy))
print(" ")
print("*100)
k_values.append(i)

print(" ")

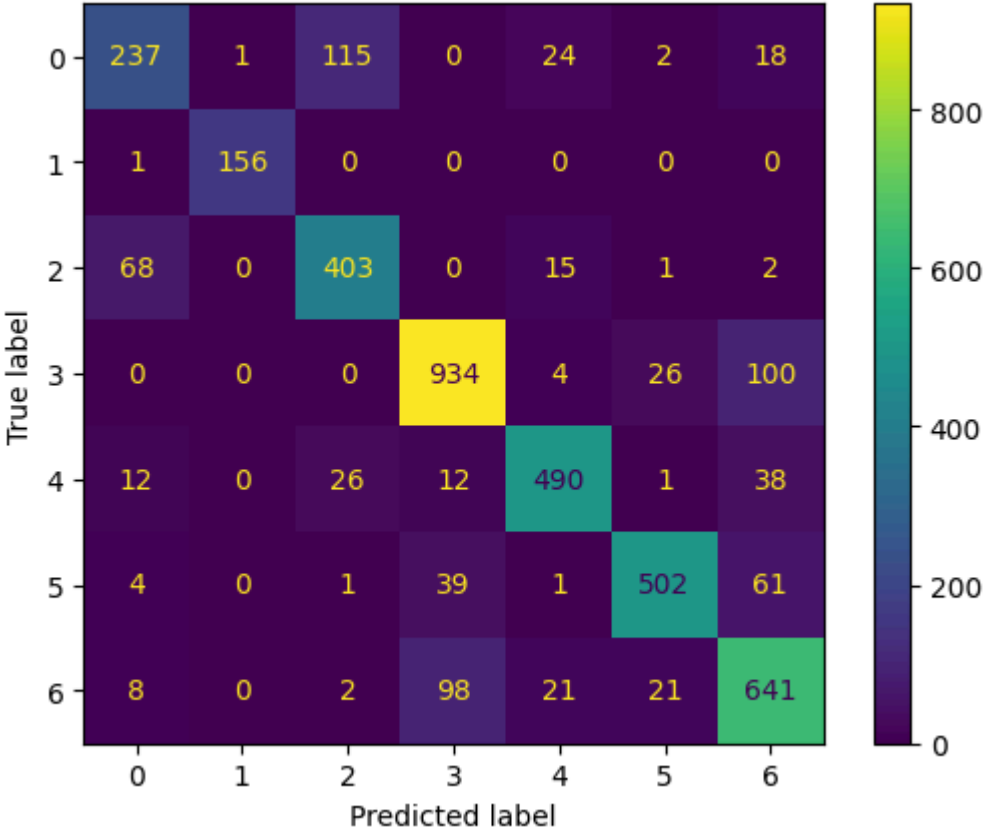
```

K\_value 1

avg\_accuracy : 0.8234141562576537

avg\_err : 0.17658584374234632

<Figure size 2000x800 with 0 Axes>



recall\_score : 0.8251404425874777

precision Score : 0.8357553113955363

log loss : 6.364798945273935

log loss\_dummy : 1.834217157999518

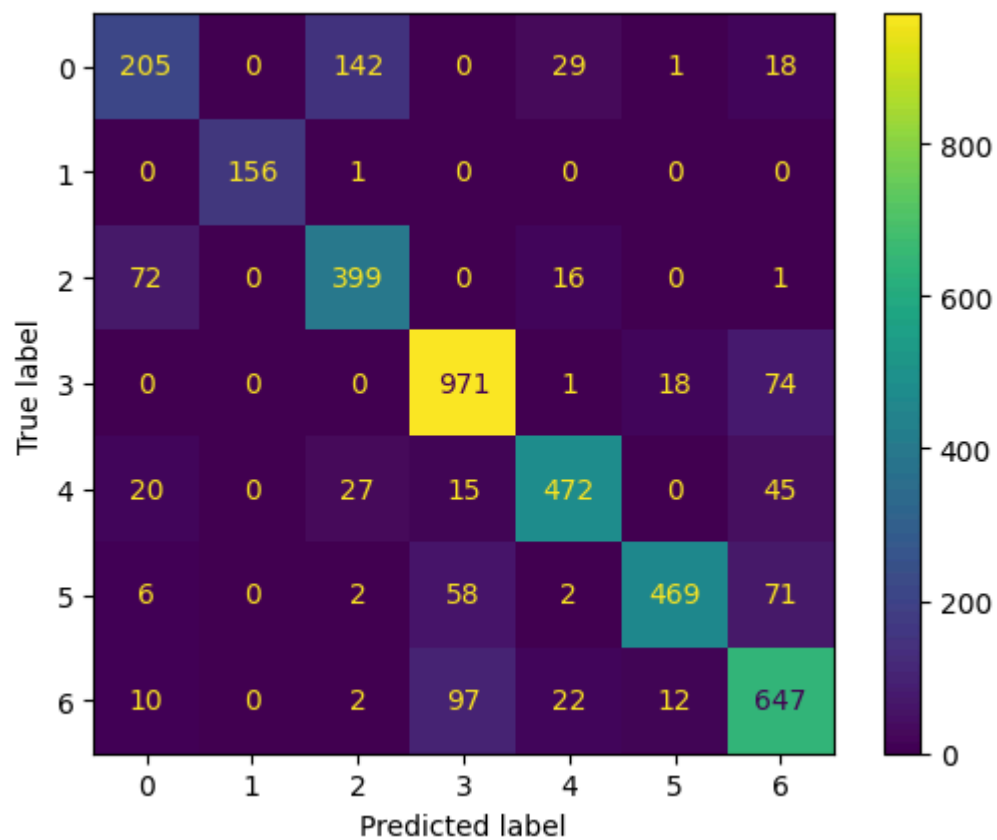
\*\*\*\*\*  
\*\*\*\*\*

K\_value 3

avg\_accuracy : 0.8126377663482733

avg\_err : 0.18736223365172666

<Figure size 2000x800 with 0 Axes>



recall\_score : 0.8063116220104359

precision Score : 0.822837318654935

log loss : 2.9567680815923403

log loss\_dummy : 1.834217157999518

\*\*\*\*\*

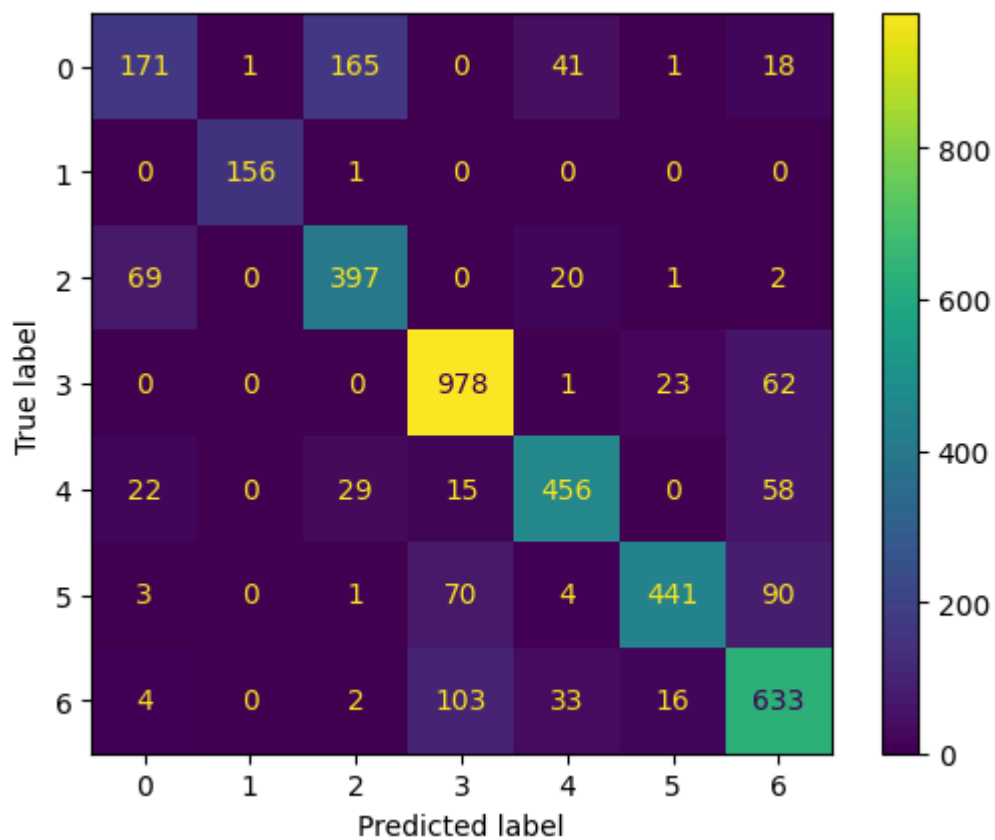
\*\*\*\*\*

K\_value 5

avg\_accuracy : 0.7913299044819985

avg\_err : 0.20867009551800145

<Figure size 2000x800 with 0 Axes>



recall\_score : 0.7811994173128243

precision Score : 0.8016457200759577

log loss : 2.1476688325288786

log loss\_dummy : 1.834217157999518

\*\*\*\*\*

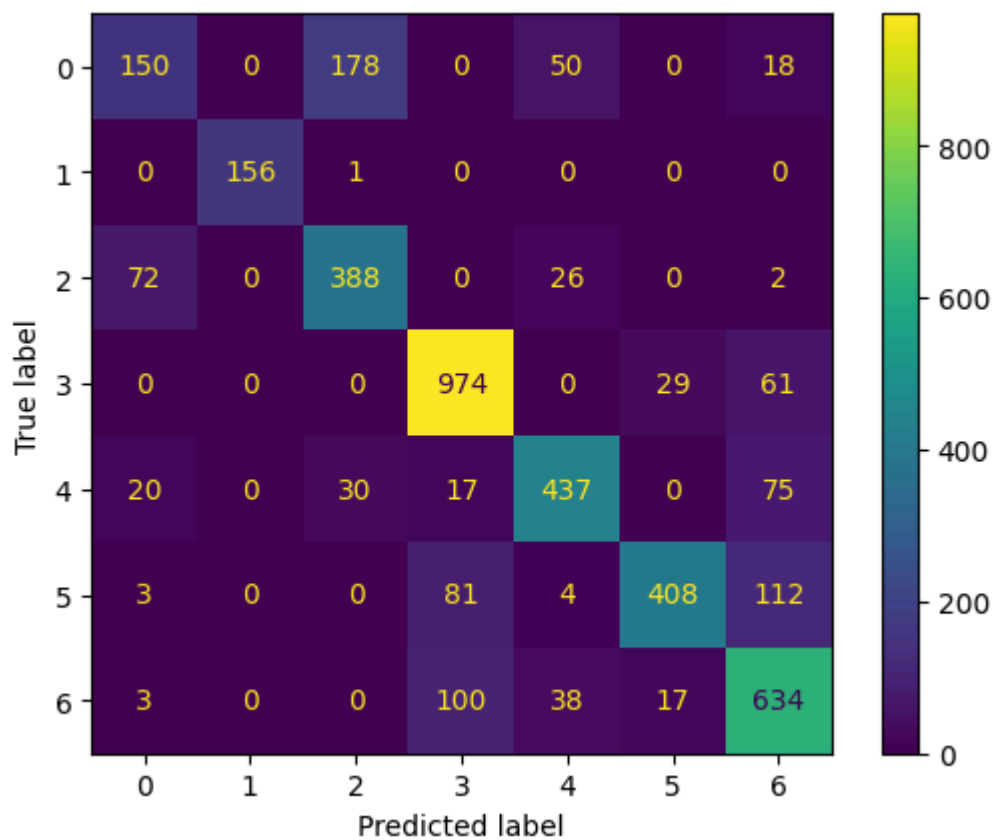
\*\*\*\*\*

K\_value 7

avg\_accuracy : 0.7704302392032002

avg\_err : 0.22956976079679972

<Figure size 2000x800 with 0 Axes>



recall\_score : 0.7586233970709605

precision Score : 0.7813774339257245

log loss : 1.769392442446806

log loss\_dummy : 1.834217157999518

\*\*\*\*\*

\*\*\*\*\*

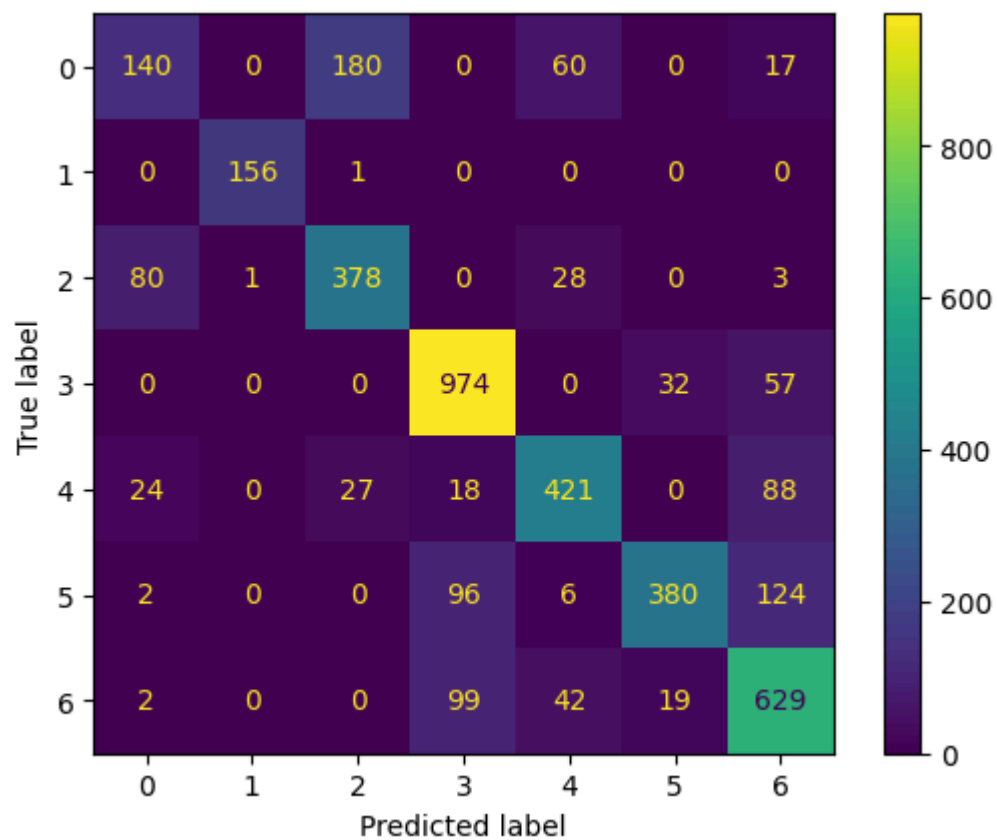
K\_value 9

avg\_accuracy : 0.7538574577516531

avg\_err : 0.24614254224834684

<Figure size 2000x800 with 0 Axes>





recall\_score : 0.7408418559540463

precision Score : 0.763939091867034

log loss : 1.524297957776321

log loss\_dummy : 1.834217157999518

\*\*\*\*\*

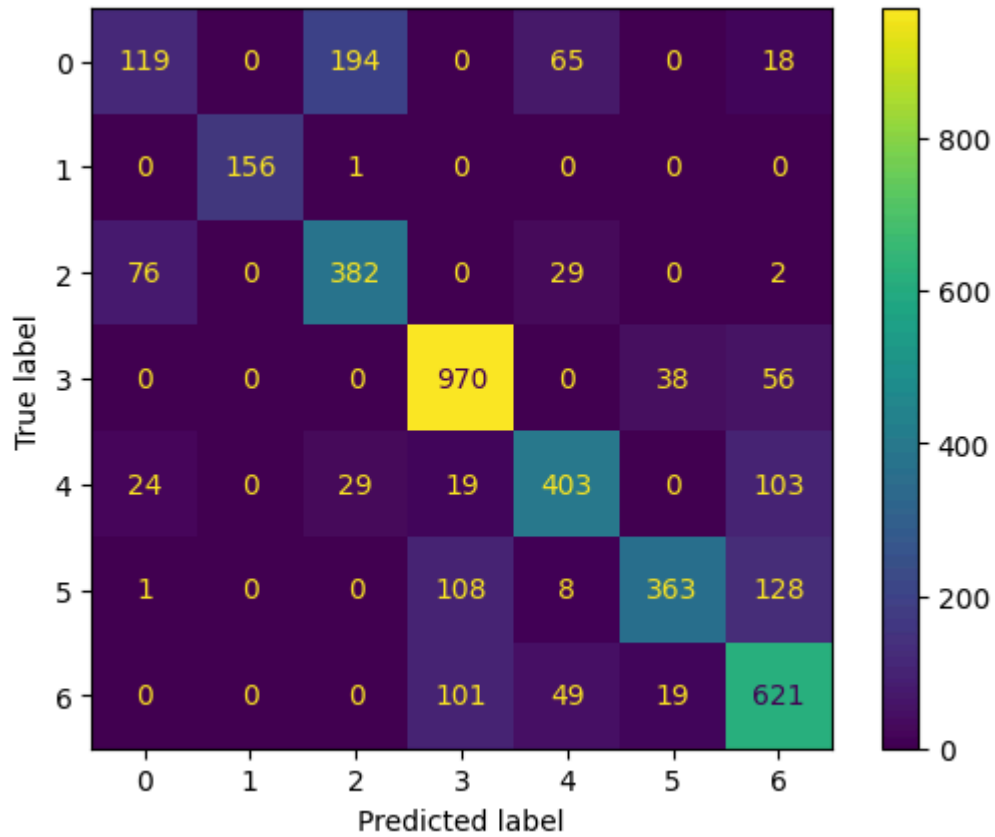
\*\*\*\*\*

K\_value 11

avg\_accuracy : 0.7382643481100498

avg\_err : 0.2617356518899502

<Figure size 2000x800 with 0 Axes>



recall\_score : 0.7242331156637712

precision Score : 0.7483810055833919

log loss : 1.3938582795179772

log loss\_dummy : 1.834217157999518

\*\*\*\*\*

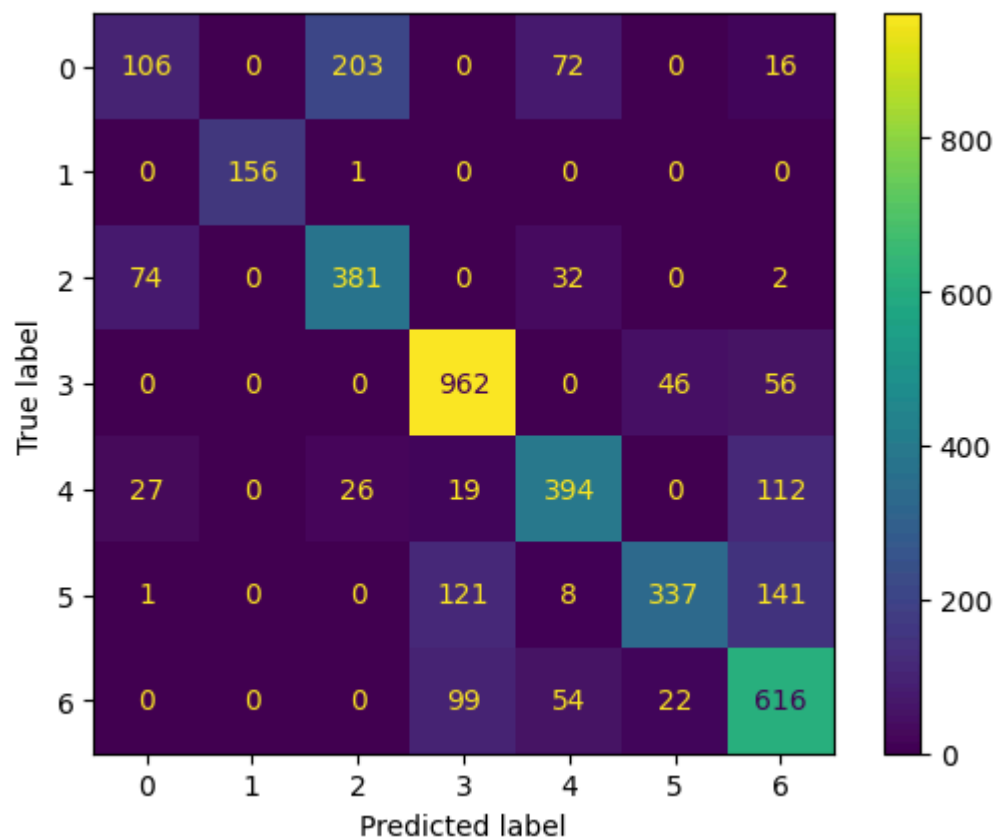
\*\*\*\*\*

K\_value 13

avg\_accuracy : 0.7229977957384276

avg\_err : 0.27700220426157235

<Figure size 2000x800 with 0 Axes>



recall\_score : 0.7088690776668566

precision Score : 0.7315705712896279

log loss : 1.314407970762016

log loss\_dummy : 1.834217157999518

\*\*\*\*\*

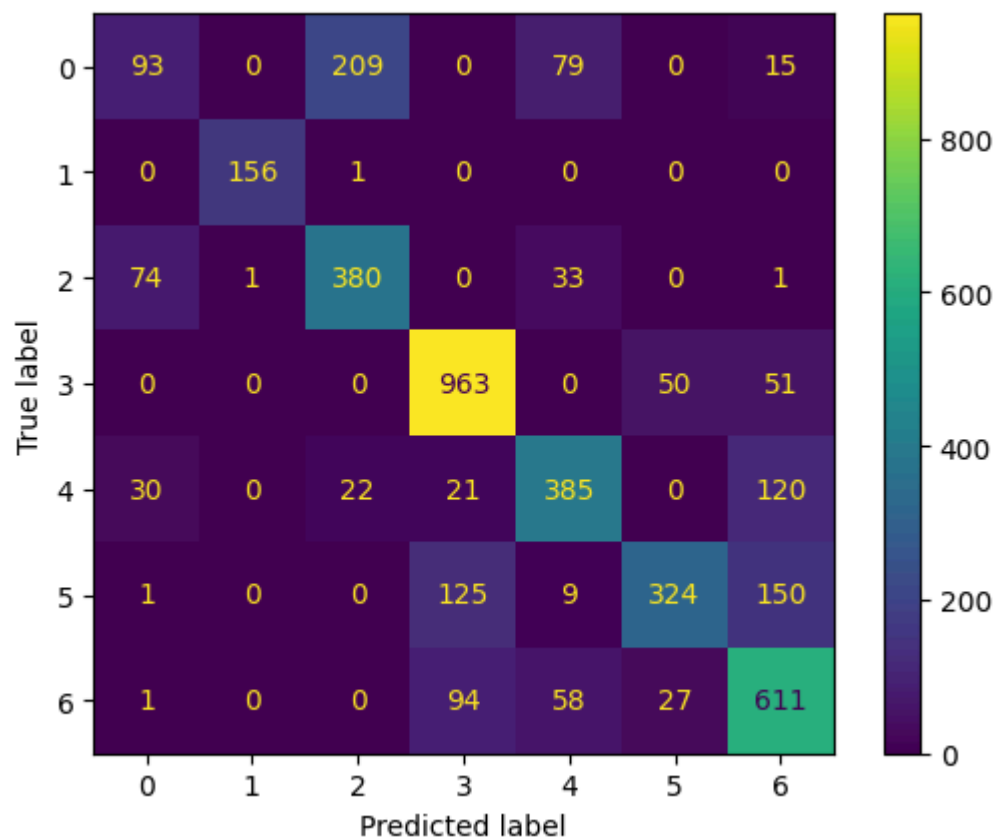
\*\*\*\*\*

K\_value 15

avg\_accuracy : 0.7132827169564863

avg\_err : 0.28671728304351374

<Figure size 2000x800 with 0 Axes>



recall\_score : 0.6978126778560305

precision Score : 0.7171294355020862

log loss : 1.2567635565850492

log loss\_dummy : 1.834217157999518

\*\*\*\*\*

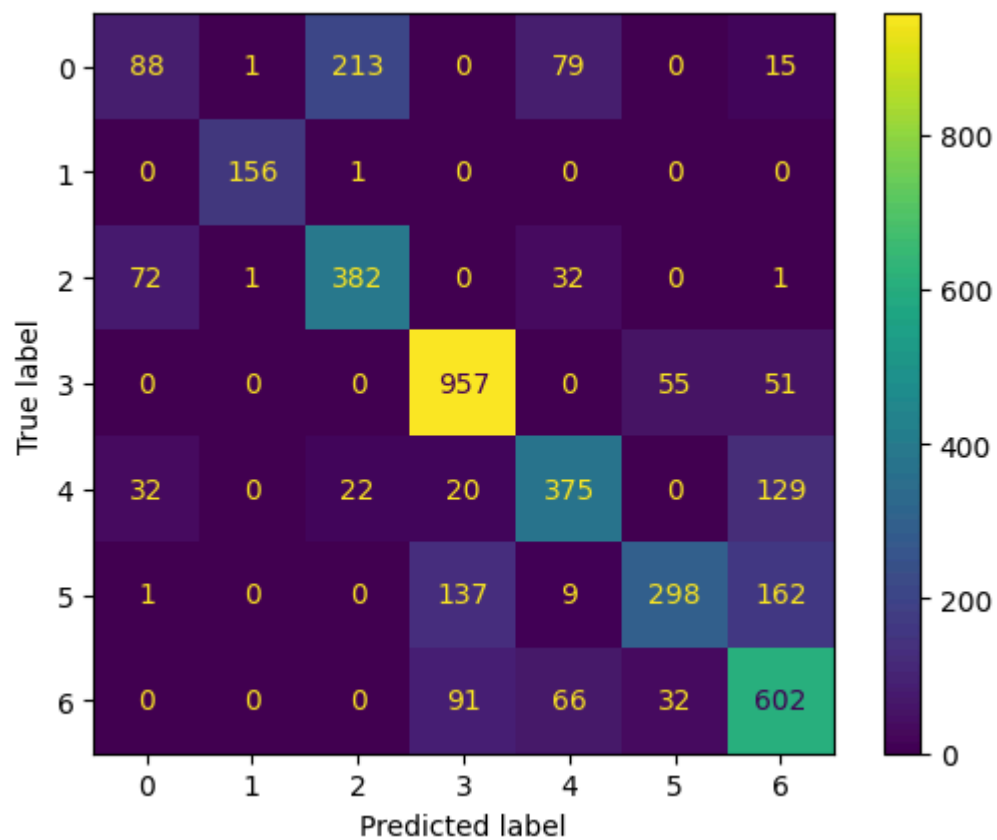
\*\*\*\*\*

K\_value 17

avg\_accuracy : 0.7000571475222467

avg\_err : 0.2999428524777533

<Figure size 2000x800 with 0 Axes>



recall\_score : 0.6855606495824125

precision Score : 0.7029346670766715

log loss : 1.2208601145888027

log loss\_dummy : 1.834217157999518

\*\*\*\*\*

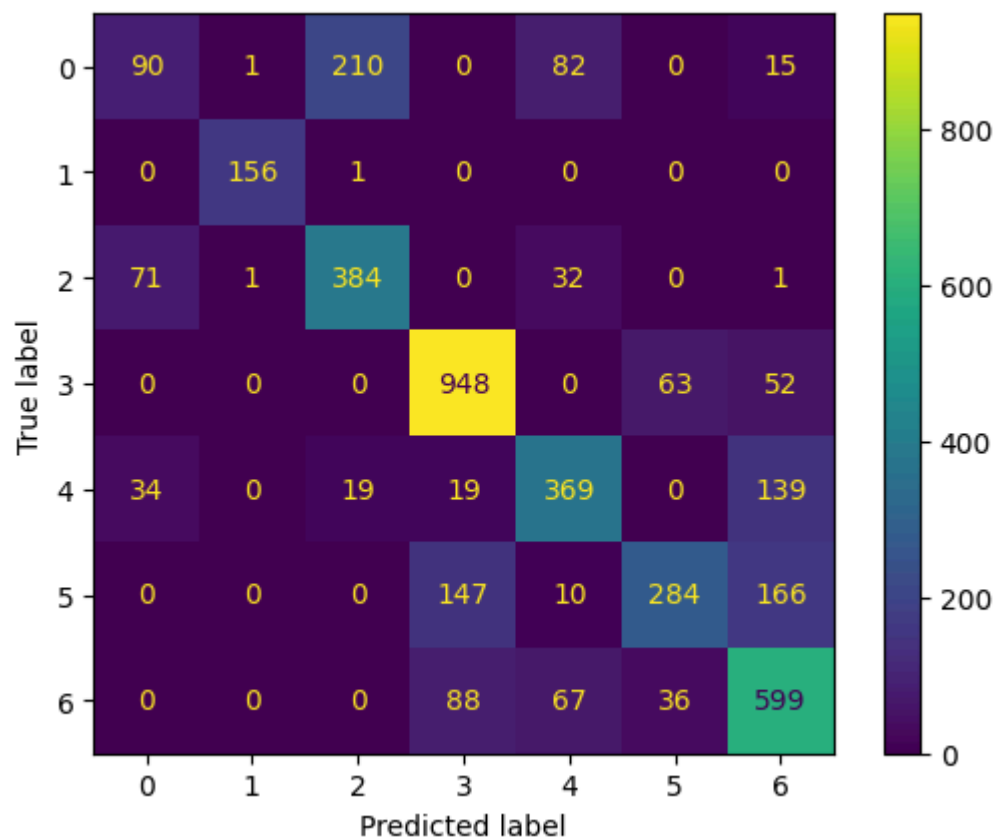
\*\*\*\*\*

K\_value 19

avg\_accuracy : 0.6930361662176504

avg\_err : 0.3069638337823496

<Figure size 2000x800 with 0 Axes>



recall\_score : 0.6801200749920688

precision Score : 0.6969371596130948

log loss : 1.1911573583137398

log loss\_dummy : 1.834217157999518

\*\*\*\*\*

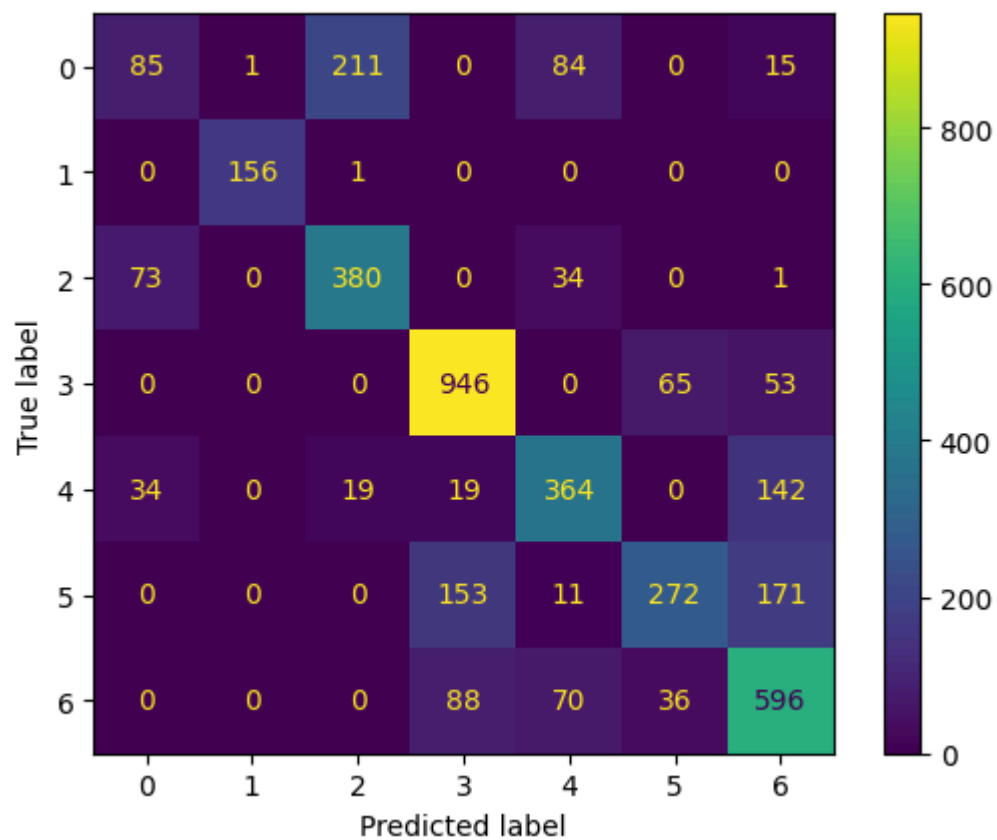
\*\*\*\*\*

K\_value 21

avg\_accuracy : 0.6860151849130541

avg\_err : 0.31398481508694587

<Figure size 2000x800 with 0 Axes>



recall\_score : 0.6729986106003335

precision Score : 0.6896463663523

log loss : 1.1769580436364786

log loss\_dummy : 1.834217157999518

\*\*\*\*\*

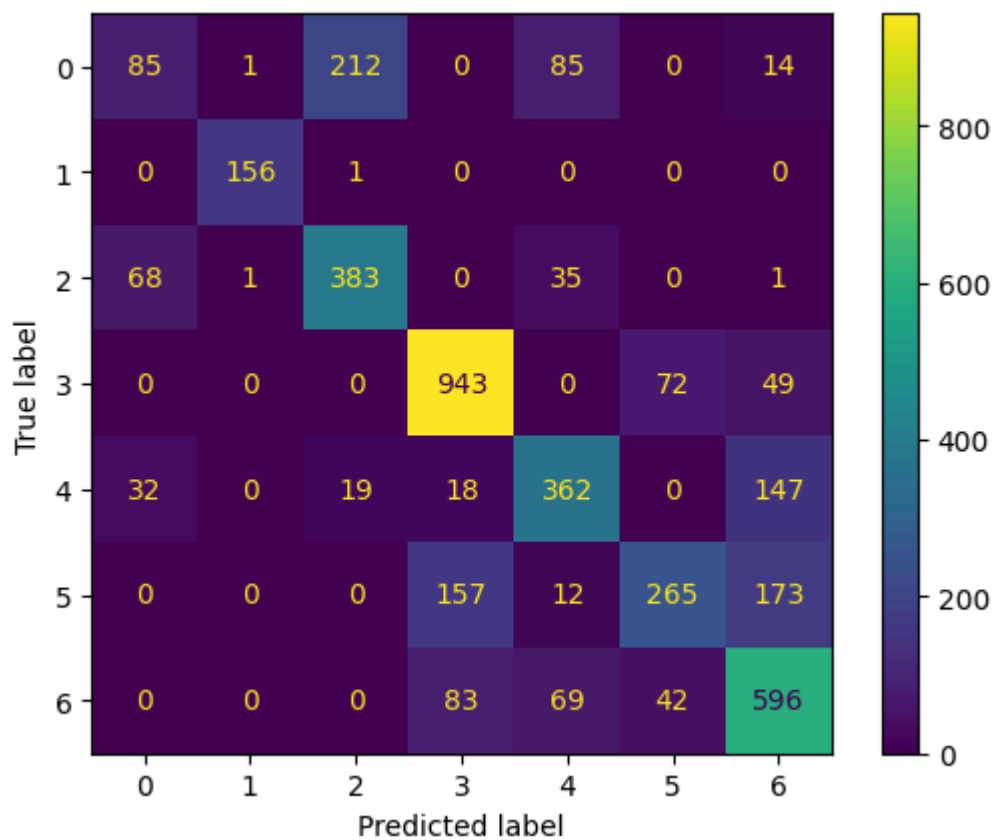
\*\*\*\*\*

K\_value 23

avg\_accuracy : 0.6831578088007184

avg\_err : 0.31684219119928153

<Figure size 2000x800 with 0 Axes>



recall\_score : 0.6706807614682132

precision Score : 0.6862081033493774

log loss : 1.1395032154701266

log loss\_dummy : 1.834217157999518

\*\*\*\*\*

\*\*\*\*\*

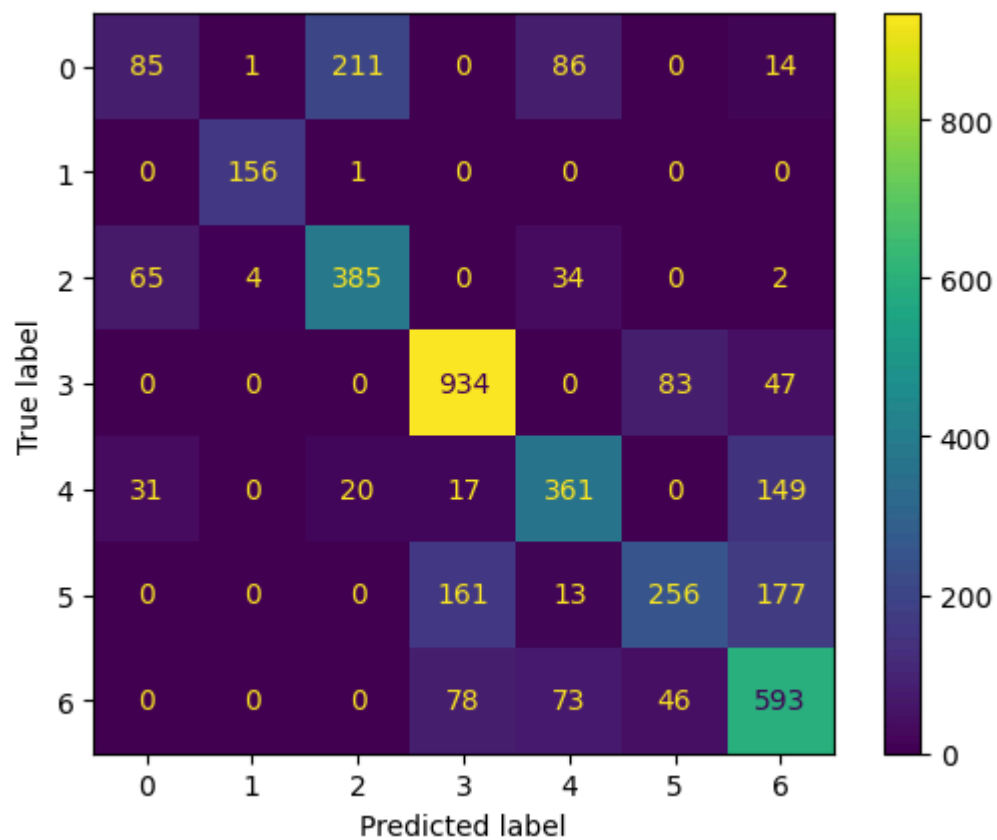
K\_value 25

avg\_accuracy : 0.6783410890684953

avg\_err : 0.3216589109315046

<Figure size 2000x800 with 0 Axes>





recall\_score : 0.667242208283678

precision Score : 0.6794791869624268

log loss : 1.1123471075252038

log loss\_dummy : 1.834217157999518

\*\*\*\*\*

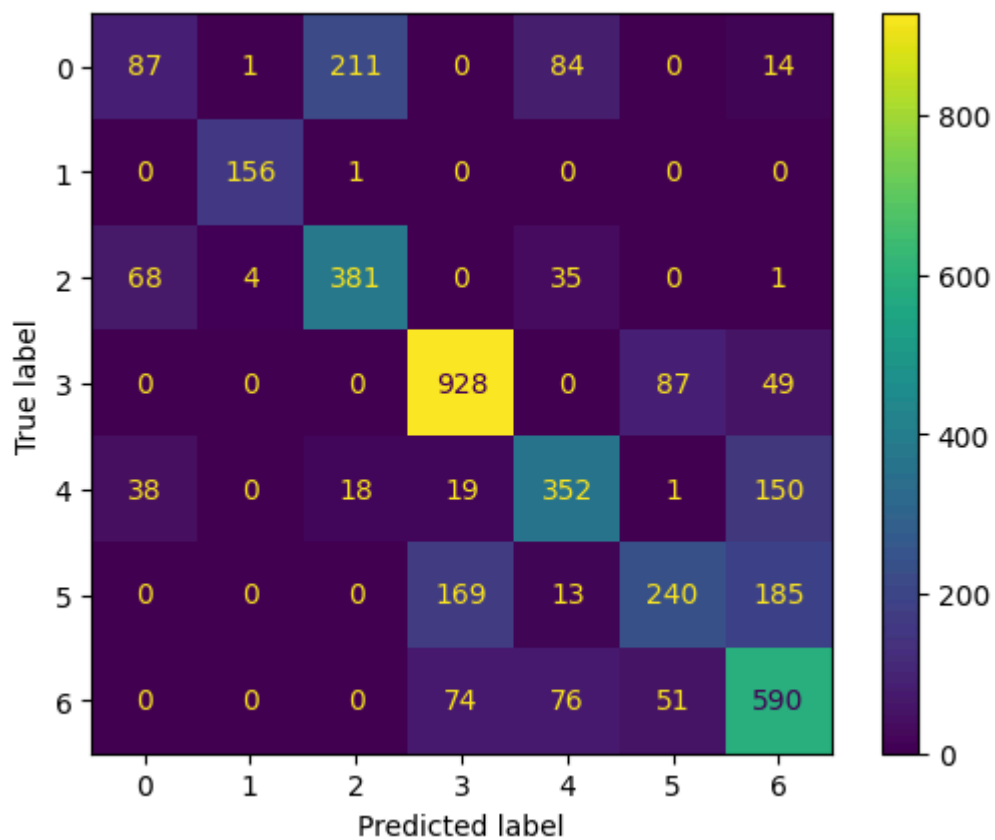
\*\*\*\*\*

K\_value 27

avg\_accuracy : 0.6697689607314882

avg\_err : 0.3302310392685118

<Figure size 2000x800 with 0 Axes>



recall\_score : 0.659779921987875

precision Score : 0.6696309007696621

log loss : 1.0923289685809705

log loss\_dummy : 1.834217157999518

\*\*\*\*\*

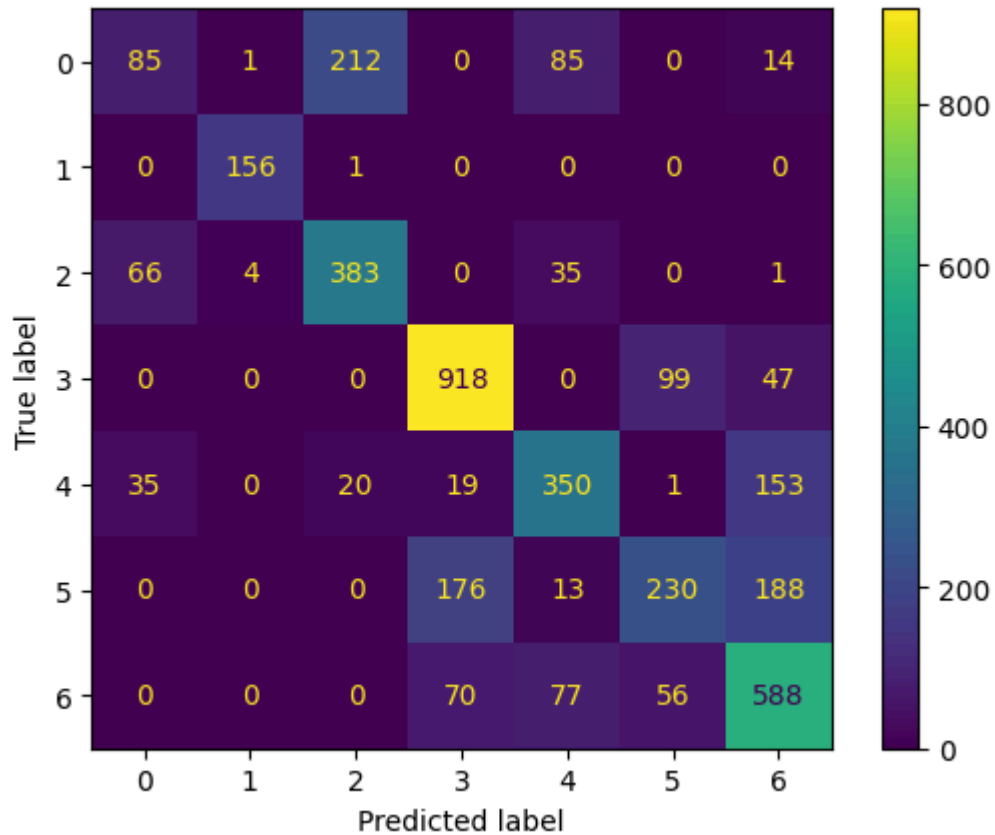
\*\*\*\*\*

K\_value 29

avg\_accuracy : 0.6638909298718263

avg\_err : 0.33610907012817376

<Figure size 2000x800 with 0 Axes>



recall\_score : 0.6551124126542112

precision Score : 0.6632301874609948

log loss : 1.0738462342454322

log loss\_dummy : 1.834217157999518

\*\*\*\*\*  
\*\*\*\*\*

```
In [33]: sf=StratifiedKFold(n_splits=3)
```

```
In [34]: import matplotlib.pyplot as plt
no_of_splits=3
k=[]
avg_training_accuracy=[]
avg_accuracy=[]
avg_error=[]
avg_recall_score=[]
avg_log_loss=[]
avg_precision_score=[]
avg_f1_score=[]
avg_log_loss_dummy=[]
for i in range(1, 60, 2):
    acc = []
    acc_train = []
    err = []
```

```

conf = []
recall = []
prec = []
k = []
logloss = []
logloss_dummy = []
Classification_report=[]
f1_score=[]
for train_index, cv_index in kf.split(x_train, y_train):
    x_trainf, x_cv, y_trainf, y_cv = x_train.iloc[train_index], x_train.iloc[cv_index]
    #Training the model
    knn = KNeighborsClassifier(n_neighbors=i)
    model = knn.fit(x_trainf, y_trainf)
    # Predicting the Model
    predicted_train = model.predict(x_trainf)
    # training accuracy of an model
    acc_train.append(accuracy_score(y_trainf, predicted_train))
    predicted = model.predict(x_cv)
    acc.append(accuracy_score(y_cv, predicted))
    err.append(1 - accuracy_score(y_cv, predicted))
    conf.append(confusion_matrix(y_cv, predicted, labels=model.classes_))
    recall.append(recall_score(y_cv, predicted, average=None))
    prec.append(precision_score(y_cv, predicted, average=None))
    f1_score_.append(f1_score(y_cv, predicted, average=None))
    Classification_report.append(classification_report(y_cv,predicted))
    predicted = model.predict_proba(x_cv)
    logloss.append(log_loss(y_cv, predicted))
    dc = DummyClassifier()
    dc_model = dc.fit(x_trainf, y_trainf)
    dc_predit = dc_model.predict_proba(x_test)
    logloss_dummy.append(log_loss(y_test, dc_predit))
a = np.mean(acc_train)
b = np.mean(acc)

print("K_value", i)
k.append(i)
print("")

avg_training_accuracy.append(np.mean(acc_train))
print("avg_accuracy train : ", np.mean(acc_train))
print("")

avg_accuracy.append(np.mean(acc))
print("avg_accuracy : ", np.mean(acc))
print("")

avg_error.append(np.mean(err))
print("avg_err : ", np.mean(err))
print(" ")

print(np.round(sum(conf) / no_of_splits))
print(" ")

plt.figure(figsize=(20, 8))
cm = ConfusionMatrixDisplay(np.int64(np.round((conf[0] + conf[1] + conf[2]) / 3

```

```

cm.plot()
plt.show()
print(" ")

avg_recall_score.append( np.mean(recall))
print("recall_score : ", np.mean(recall))
print(" ")

avg_precision_score.append(np.mean(prec))
print("precision Score : ", np.mean(prec))
print(" ")

avg_f1_score.append(np.mean(f1_score_))
print("f1_score :", np.mean(f1_score_))
print("")

avg_log_loss.append(np.mean(logloss))
print("log loss : ", np.mean(logloss))
print(" ")

avg_log_loss_dummy.append(np.mean(logloss_dummy))
print("log loss dummy : ", np.mean(logloss_dummy))
print(" ")
print(" *" * 100)

print(" ")

```

K\_value 1

avg\_accuracy train : 1.0

avg\_accuracy : 0.8234141562576537

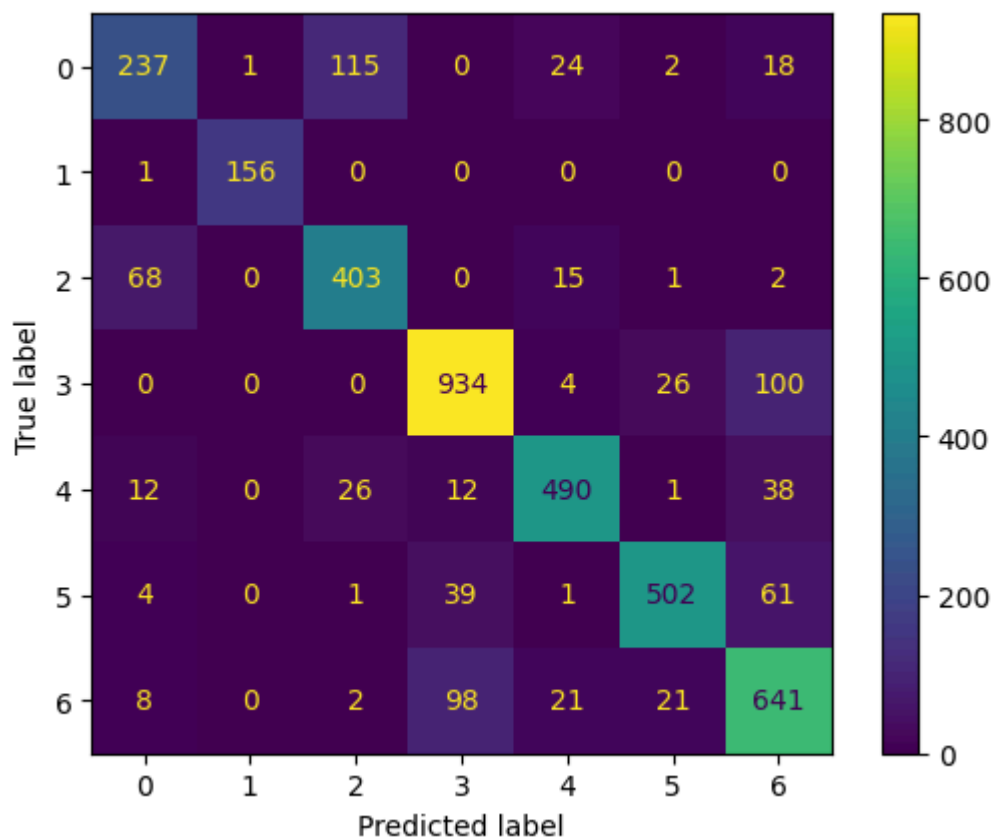
avg\_err : 0.17658584374234632

```

[[237.  1. 115.  0. 24.  2. 18.]
 [  1. 156.  0.  0.  0.  0.  0.]
 [ 68.  0. 403.  0. 15.  1.  2.]
 [  0.  0.  0. 934.  4. 26. 100.]
 [ 12.  0. 26. 12. 490.  1. 38.]
 [  4.  0.  1. 39.  1. 502. 61.]
 [  8.  0.  2. 98. 21. 21. 641.]]

```

<Figure size 2000x800 with 0 Axes>



recall\_score : 0.8251404425874777

precision Score : 0.8357553113955363

f1\_score : 0.828681686307948

log loss : 6.364798945273935

log loss dummy : 1.834217157999518

\*\*\*\*\*  
\*\*\*\*\*

K\_value 3

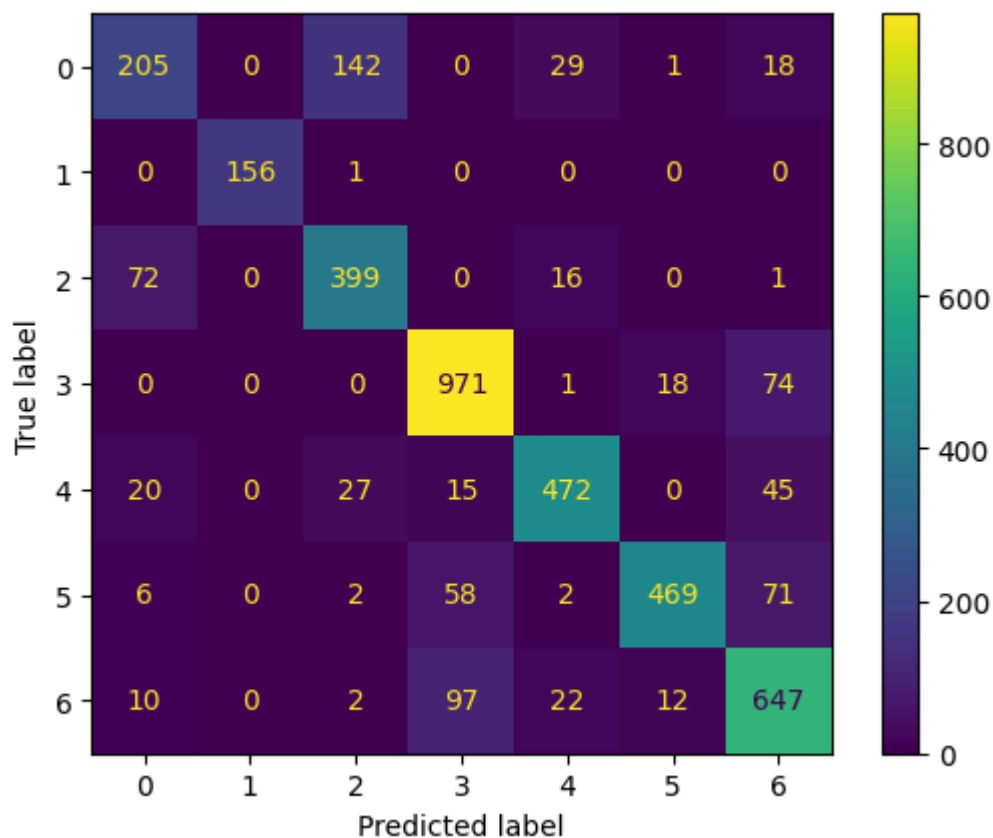
avg\_accuracy train : 0.9013388848069231

avg\_accuracy : 0.8126377663482733

avg\_err : 0.18736223365172666

```
[[205.  0. 142.  0. 29.  1. 18.]
 [ 0. 156.  1.  0.  0.  0.  0.]
 [ 72.  0. 399.  0. 16.  0.  1.]
 [  0.  0.  0. 971.  1. 18. 74.]
 [ 20.  0. 27. 15. 472.  0. 45.]
 [  6.  0.  2. 58.  2. 469. 71.]
 [ 10.  0.  2. 97. 22. 12. 647.]]
```

<Figure size 2000x800 with 0 Axes>



recall\_score : 0.8063116220104359

precision Score : 0.822837318654935

f1\_score : 0.811074974923937

log loss : 2.9567680815923403

log loss dummy : 1.834217157999518

\*\*\*\*\*  
\*\*\*\*\*

K\_value 5

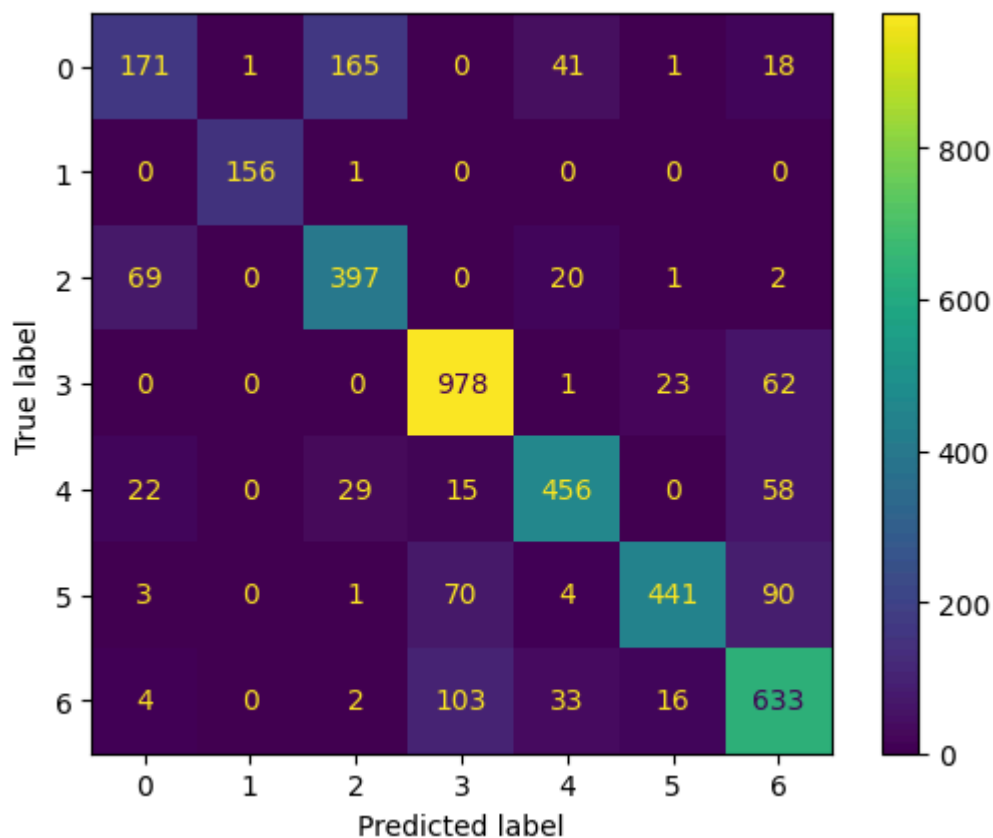
avg\_accuracy train : 0.8632133235366153

avg\_accuracy : 0.7913299044819985

avg\_err : 0.20867009551800145

```
[[171.  1. 165.  0. 41.  1. 18.]
 [ 0. 156.  1.  0.  0.  0.  0.]
 [ 69.  0. 397.  0. 20.  1.  2.]
 [ 0.  0.  0. 978.  1. 23. 62.]
 [ 22.  0. 29. 15. 456.  0. 58.]
 [ 3.  0.  1. 70.  4. 441. 90.]
 [ 4.  0.  2. 103. 33. 16. 633.]]
```

<Figure size 2000x800 with 0 Axes>



recall\_score : 0.7811994173128243

precision Score : 0.8016457200759577

f1\_score : 0.7853433841465789

log loss : 2.1476688325288786

log loss dummy : 1.834217157999518

\*\*\*\*\*  
\*\*\*\*\*

K\_value 7

avg\_accuracy train : 0.8300269409747734

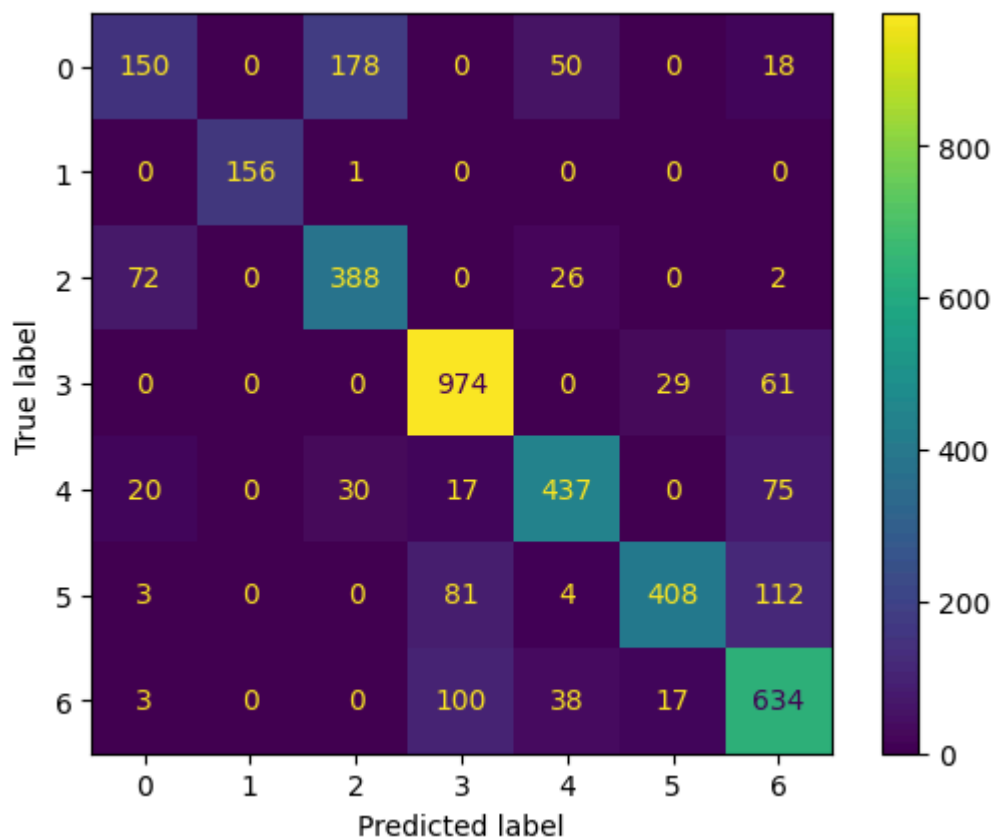
avg\_accuracy : 0.7704302392032002

avg\_err : 0.22956976079679972

```
[[150.  0. 178.  0.  50.  0.  18.]
 [  0. 156.  1.  0.  0.  0.  0.]
 [ 72.  0. 388.  0.  26.  0.  2.]
 [  0.  0.  0. 974.  0.  29. 61.]
 [ 20.  0.  30. 17. 437.  0.  75.]
 [  3.  0.  0.  81.  4. 408. 112.]
 [  3.  0.  0. 100. 38. 17. 634.]]
```

<Figure size 2000x800 with 0 Axes>





recall\_score : 0.7586233970709605

precision Score : 0.7813774339257245

f1\_score : 0.7620720991566718

log loss : 1.769392442446806

log loss dummy : 1.834217157999518

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K\_value 9

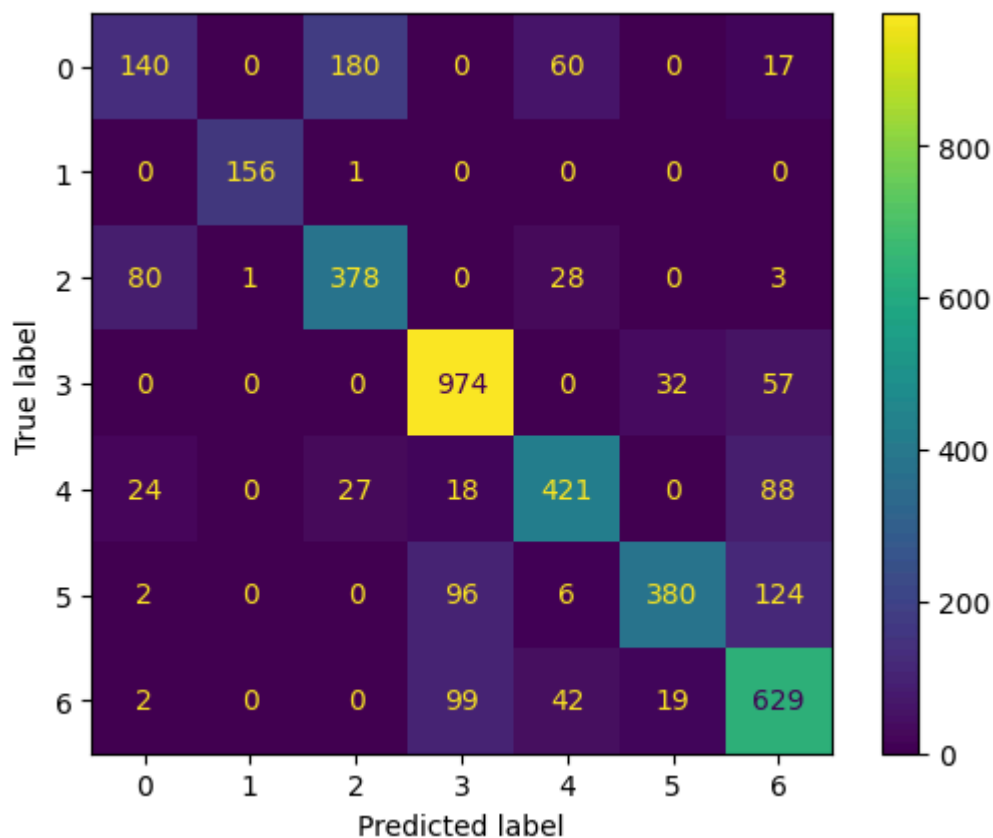
avg\_accuracy train : 0.8052902277736959

avg\_accuracy : 0.7538574577516531

avg\_err : 0.24614254224834684

```
[[140.  0. 180.  0.  60.  0. 17.]
 [  0. 156.  1.  0.  0.  0.  0.]
 [ 80.  1. 378.  0. 28.  0.  3.]
 [  0.  0.  0. 974.  0. 32. 57.]
 [ 24.  0. 27. 18. 421.  0. 88.]
 [  2.  0.  0. 96.  6. 380. 124.]
 [  2.  0.  0. 99. 42. 19. 629.]]
```

<Figure size 2000x800 with 0 Axes>



recall\_score : 0.7408418559540463

precision Score : 0.763939091867034

f1\_score : 0.7438963440368104

log loss : 1.524297957776321

log loss dummy : 1.834217157999518

\*\*\*\*\*  
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K\_value 11

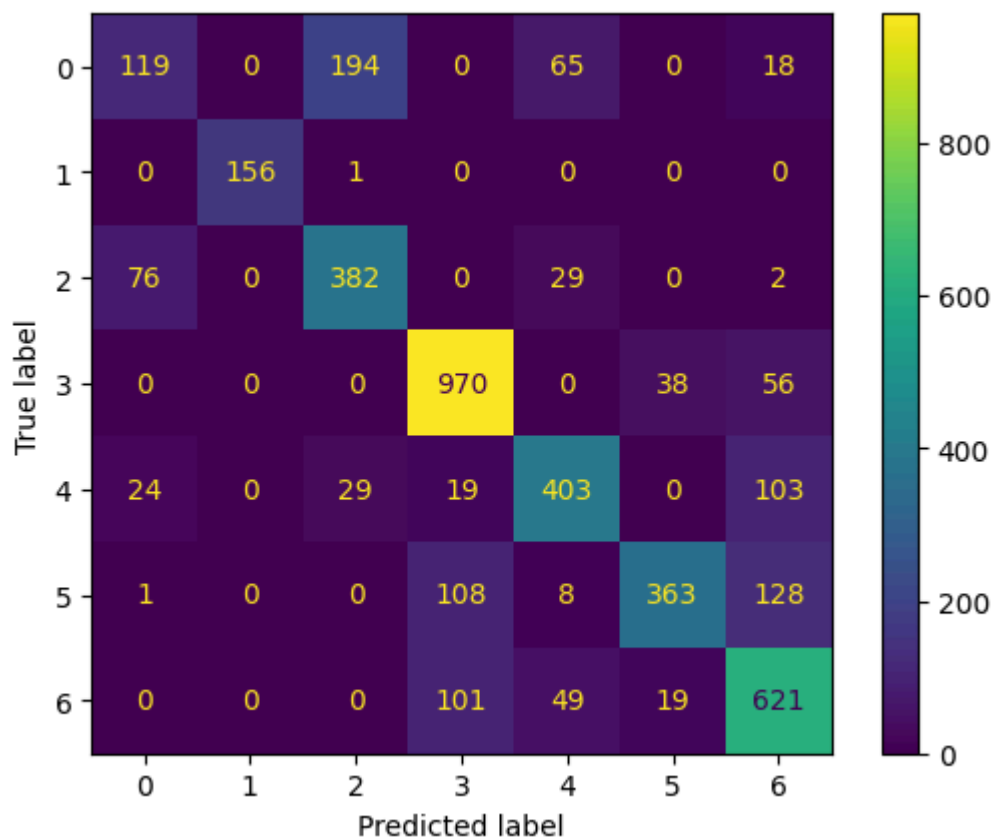
avg\_accuracy train : 0.7862682667972895

avg\_accuracy : 0.7382643481100498

avg\_err : 0.2617356518899502

```
[[119.  0. 194.  0.  65.  0. 18.]
 [  0. 156.  1.  0.  0.  0.  0.]
 [ 76.  0. 382.  0.  29.  0.  2.]
 [  0.  0.  0. 970.  0.  38. 56.]
 [ 24.  0.  29. 19. 403.  0. 103.]
 [  1.  0.  0. 108.  8. 363. 128.]
 [  0.  0.  0. 101. 49. 19. 621.]]
```

<Figure size 2000x800 with 0 Axes>



recall\_score : 0.7242331156637712

precision Score : 0.7483810055833919

f1\_score : 0.7254363532284891

log loss : 1.3938582795179772

log loss dummy : 1.834217157999518

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K\_value 13

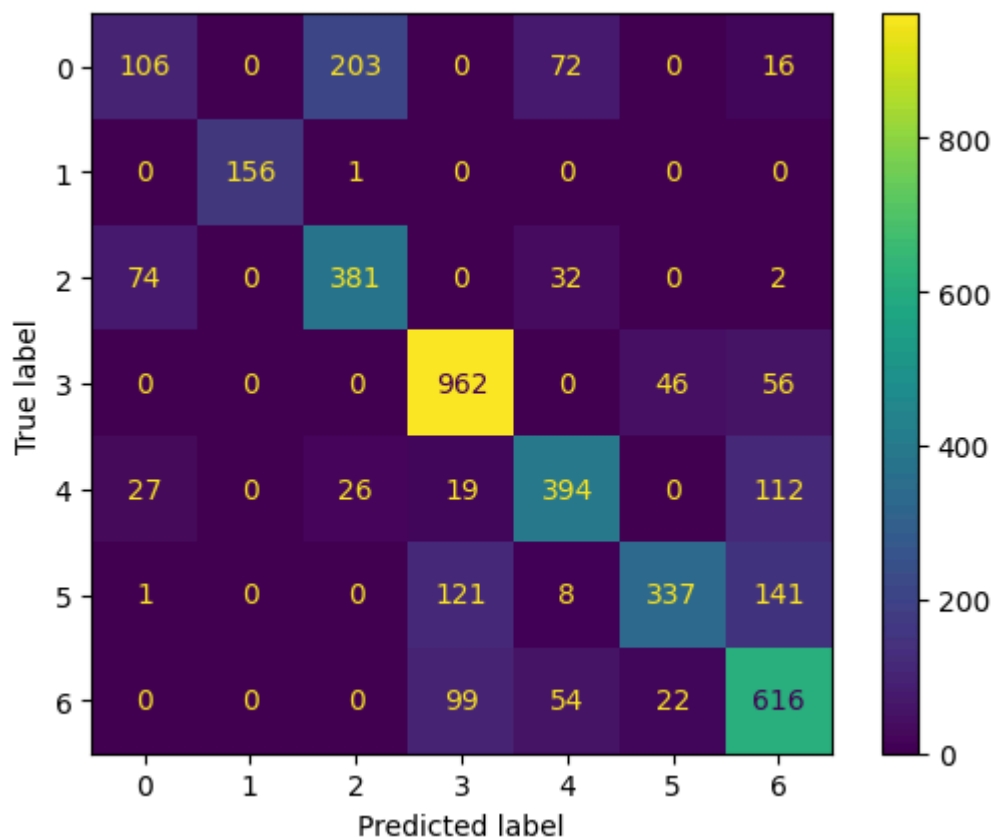
avg\_accuracy train : 0.7658176177647155

avg\_accuracy : 0.7229977957384276

avg\_err : 0.27700220426157235

```
[[106.  0. 203.  0.  72.  0.  16.]
 [  0. 156.  1.  0.  0.  0.  0.]
 [ 74.  0. 381.  0.  32.  0.  2.]
 [  0.  0.  0. 962.  0.  46.  56.]
 [ 27.  0.  26.  19. 394.  0. 112.]
 [  1.  0.  0. 121.  8. 337. 141.]
 [  0.  0.  0.  99.  54.  22. 616.]]
```

<Figure size 2000x800 with 0 Axes>



recall\_score : 0.7088690776668566

precision Score : 0.7315705712896279

f1\_score : 0.7081288161923693

log loss : 1.314407970762016

log loss dummy : 1.834217157999518

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K\_value 15

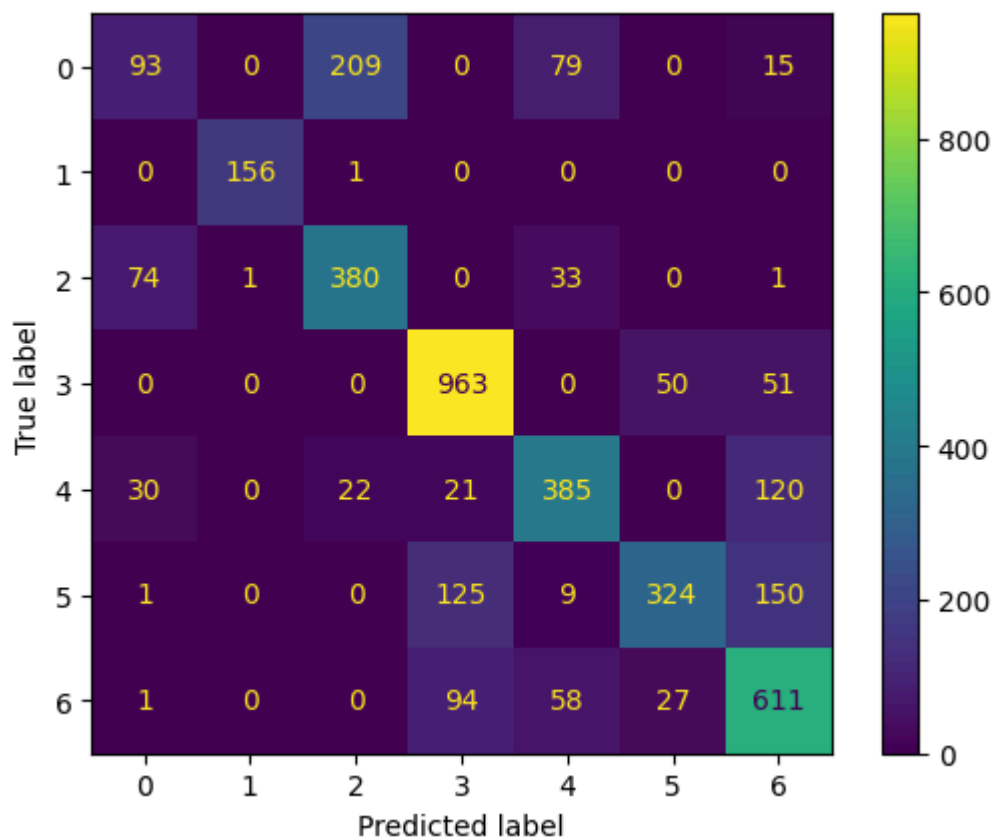
avg\_accuracy train : 0.7484284431382154

avg\_accuracy : 0.7132827169564863

avg\_err : 0.28671728304351374

```
[[ 93.  0. 209.  0.  79.  0.  15.]
 [  0. 156.  1.  0.  0.  0.  0.]
 [ 74.  1. 380.  0.  33.  0.  1.]
 [  0.  0.  0. 963.  0.  50.  51.]
 [ 30.  0.  22.  21. 385.  0. 120.]
 [  1.  0.  0. 125.  9. 324. 150.]
 [  1.  0.  0.  94.  58.  27. 611.]]
```

<Figure size 2000x800 with 0 Axes>



recall\_score : 0.6978126778560305

precision Score : 0.7171294355020862

f1\_score : 0.695131629455029

log loss : 1.2567635565850492

log loss dummy : 1.834217157999518

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K\_value 17

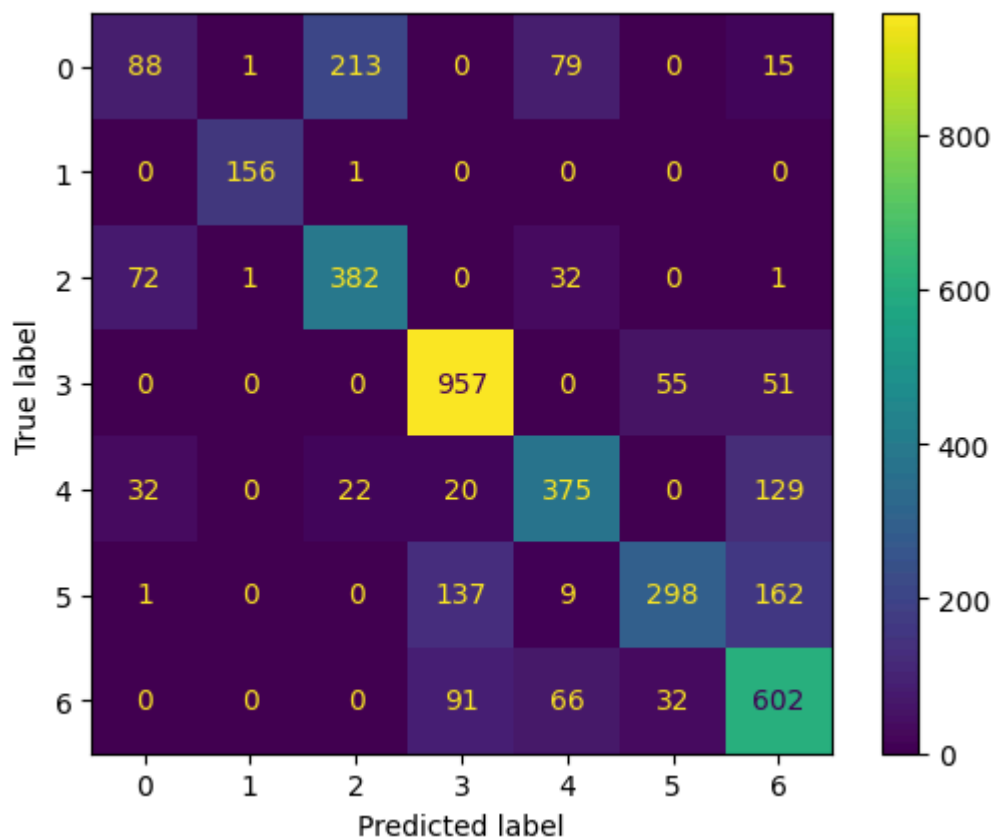
avg\_accuracy train : 0.734835496775247

avg\_accuracy : 0.7000571475222467

avg\_err : 0.2999428524777533

```
[[ 88.   1. 213.   0.  79.   0.  15.]
 [  0. 156.   1.   0.   0.   0.   0.]
 [ 72.   1. 382.   0.  32.   0.   1.]
 [  0.   0.   0. 957.   0.  55.  51.]
 [ 32.   0.  22.  20. 375.   0. 129.]
 [  1.   0.   0. 137.   9. 298. 162.]
 [  0.   0.   0.  91.  66.  32. 602.]]
```

<Figure size 2000x800 with 0 Axes>



recall\_score : 0.6855606495824125

precision Score : 0.7029346670766715

f1\_score : 0.6811068252814495

log loss : 1.2208601145888027

log loss dummy : 1.834217157999518

\*\*\*\*\*  
\*\*\*\*\*

K\_value 19

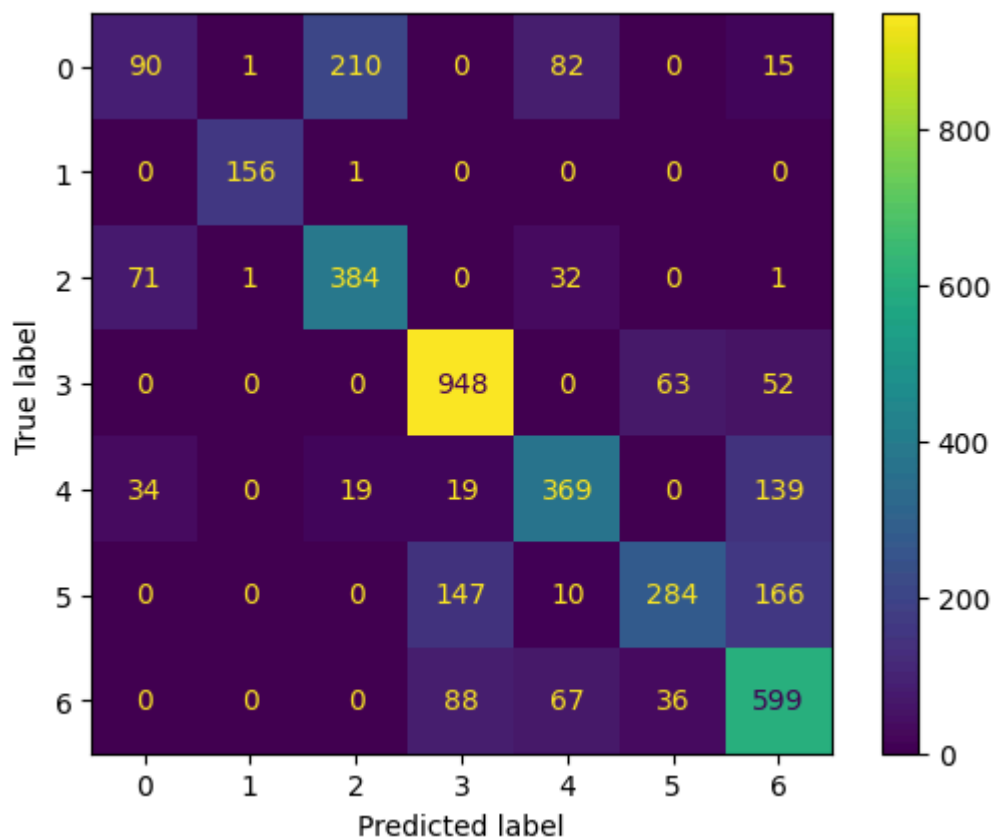
avg\_accuracy train : 0.7271614009306883

avg\_accuracy : 0.6930361662176504

avg\_err : 0.3069638337823496

```
[[ 90.   1. 210.   0.  82.   0.  15.]
 [  0. 156.   1.   0.   0.   0.   0.]
 [ 71.   1. 384.   0.  32.   0.   1.]
 [  0.   0.   0. 948.   0.  63.  52.]
 [ 34.   0.  19.  19. 369.   0. 139.]
 [  0.   0.   0. 147.  10. 284. 166.]
 [  0.   0.   0.  88.  67.  36. 599.]]
```

<Figure size 2000x800 with 0 Axes>



recall\_score : 0.6801200749920688

precision Score : 0.6969371596130948

f1\_score : 0.6754019426843676

log loss : 1.1911573583137398

log loss dummy : 1.834217157999518

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\*\*\*\*\*

K\_value 21

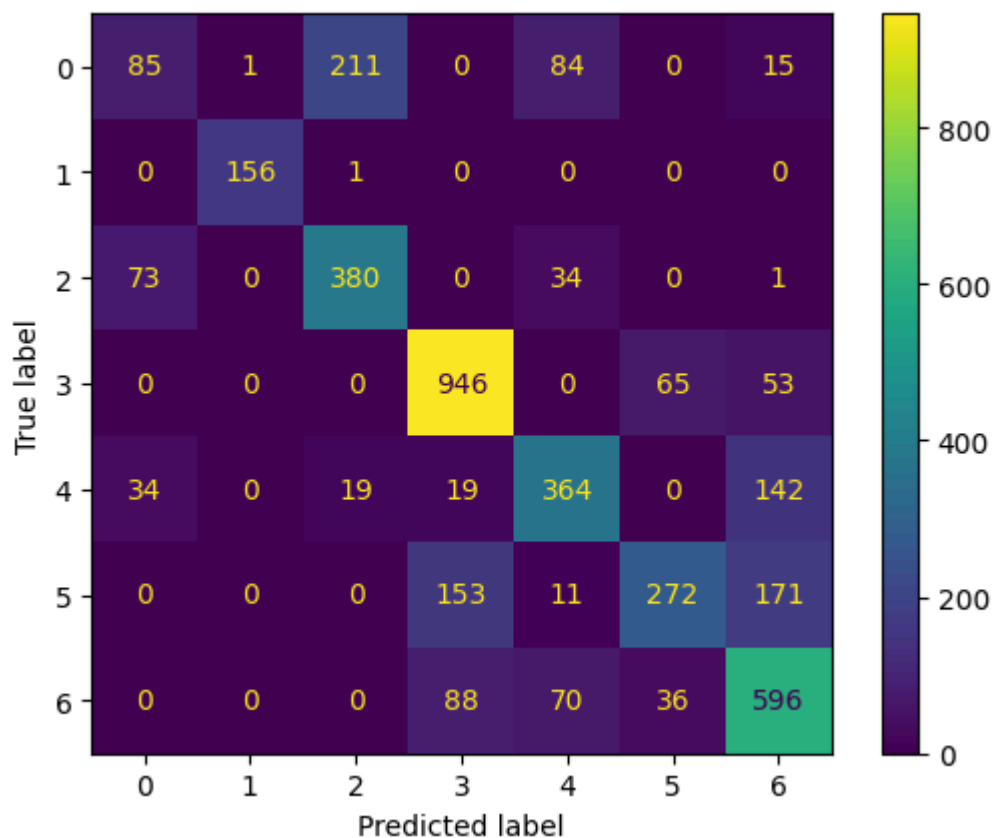
avg\_accuracy train : 0.7160992734100743

avg\_accuracy : 0.6860151849130541

avg\_err : 0.31398481508694587

```
[[ 85.   1. 211.   0.  84.   0.  15.]
 [  0. 156.   1.   0.   0.   0.   0.]
 [ 73.   0. 380.   0.  34.   0.   1.]
 [  0.   0.   0. 946.   0.  65.  53.]
 [ 34.   0.  19.  19. 364.   0. 142.]
 [  0.   0.   0. 153.  11. 272. 171.]
 [  0.   0.   0.  88.  70.  36. 596.]]
```

<Figure size 2000x800 with 0 Axes>



recall\_score : 0.6729986106003335

precision Score : 0.6896463663523

f1\_score : 0.6678059688116427

log loss : 1.1769580436364786

log loss dummy : 1.834217157999518

\*\*\*\*\*  
\*\*\*\*\*

K\_value 23

avg\_accuracy train : 0.7080578006367867

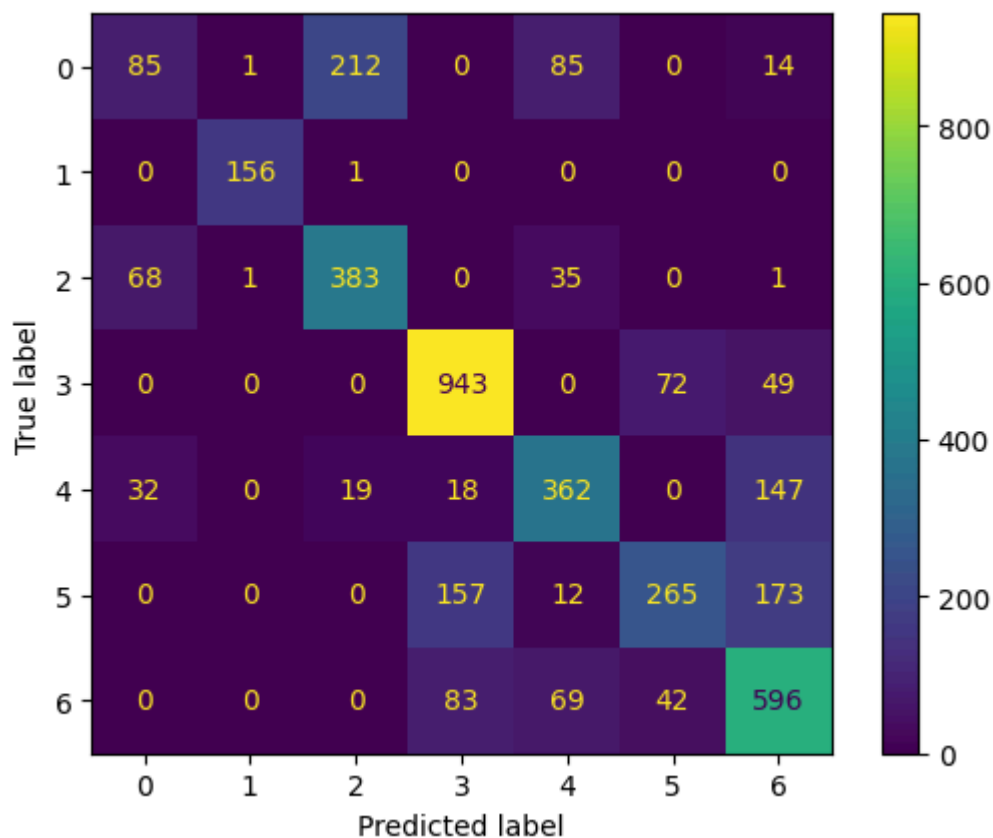
avg\_accuracy : 0.6831578088007184

avg\_err : 0.31684219119928153

```
[[ 85.   1. 212.   0.  85.   0.  14.]
 [  0. 156.   1.   0.   0.   0.   0.]
 [ 68.   1. 383.   0.  35.   0.   1.]
 [  0.   0.   0. 943.   0.  72.  49.]
 [ 32.   0.  19.  18. 362.   0. 147.]
 [  0.   0.   0. 157.  12. 265. 173.]
 [  0.   0.   0.  83.  69.  42. 596.]]
```

<Figure size 2000x800 with 0 Axes>





recall\_score : 0.6706807614682132

precision Score : 0.6862081033493774

f1\_score : 0.6644808967324396

log loss : 1.1395032154701266

log loss dummy : 1.834217157999518

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K\_value 25

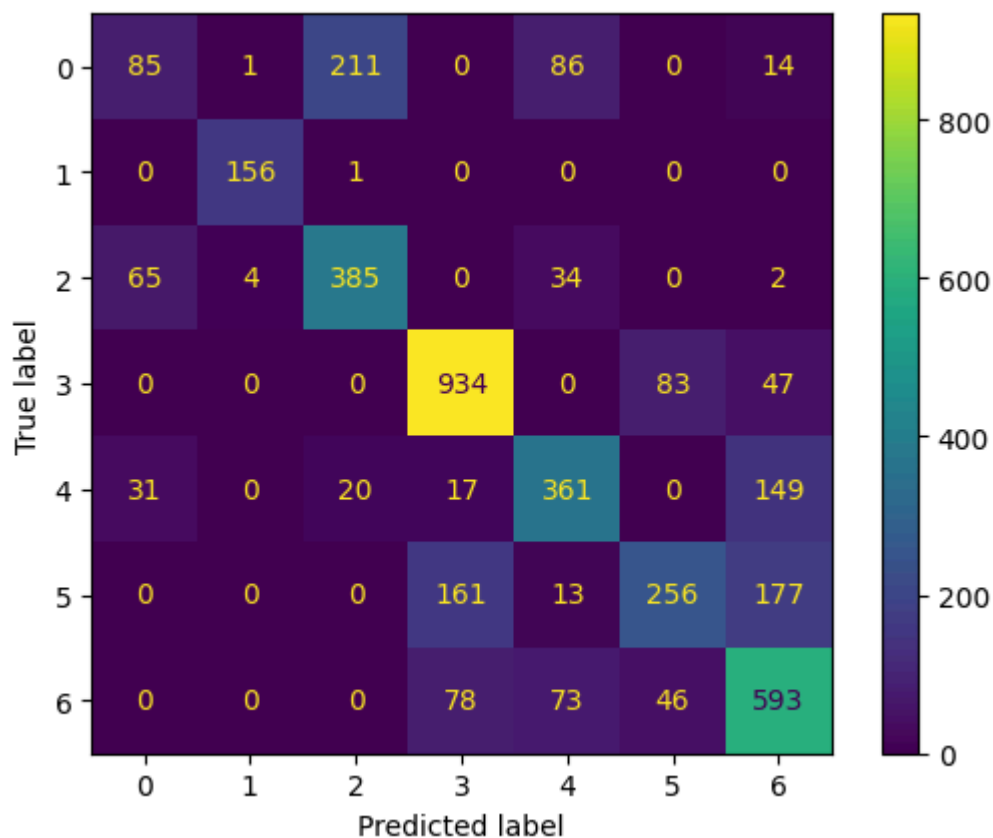
avg\_accuracy train : 0.7004245244509756

avg\_accuracy : 0.6783410890684953

avg\_err : 0.3216589109315046

```
[[ 85.   1. 211.   0.  86.   0.  14.]
 [  0. 156.   1.   0.   0.   0.   0.]
 [ 65.   4. 385.   0.  34.   0.   2.]
 [  0.   0.   0. 934.   0.  83.  47.]
 [ 31.   0.  20.  17. 361.   0. 149.]
 [  0.   0.   0. 161.  13. 256. 177.]
 [  0.   0.   0.  78.  73.  46. 593.]]
```

<Figure size 2000x800 with 0 Axes>



recall\_score : 0.667242208283678

precision Score : 0.6794791869624268

f1\_score : 0.6593124104698246

log loss : 1.1123471075252038

log loss dummy : 1.834217157999518

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K\_value 27

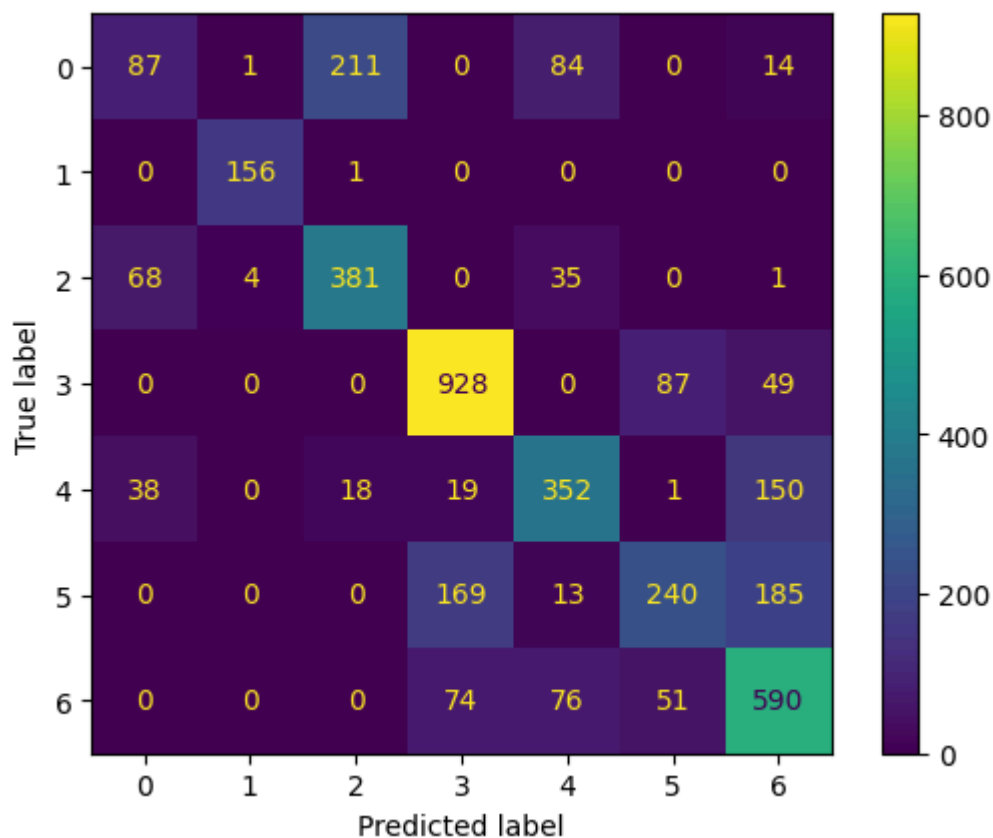
avg\_accuracy train : 0.6933627234876316

avg\_accuracy : 0.6697689607314882

avg\_err : 0.3302310392685118

```
[[ 87.   1. 211.   0.  84.   0.  14.]
 [  0. 156.   1.   0.   0.   0.   0.]
 [ 68.   4. 381.   0.  35.   0.   1.]
 [  0.   0.   0. 928.   0.  87.  49.]
 [ 38.   0.  18.  19. 352.   1. 150.]
 [  0.   0.   0. 169.  13. 240. 185.]
 [  0.   0.   0.  74.  76.  51. 590.]]
```

<Figure size 2000x800 with 0 Axes>



recall\_score : 0.659779921987875

precision Score : 0.6696309007696621

f1\_score : 0.651723684157035

log loss : 1.0923289685809705

log loss dummy : 1.834217157999518

\*\*\*\*\*  
\*\*\*\*\*

K\_value 29

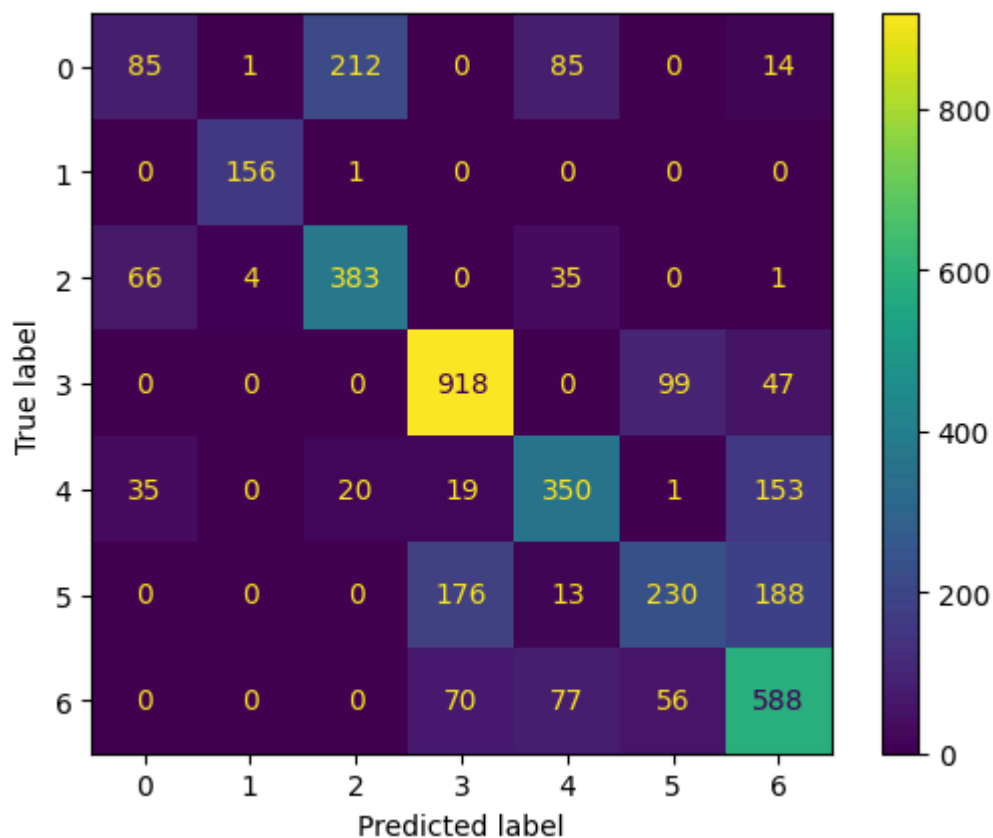
avg\_accuracy train : 0.6895664952241

avg\_accuracy : 0.6638909298718263

avg\_err : 0.33610907012817376

```
[[ 85.   1. 212.   0.  85.   0.  14.]
 [  0. 156.   1.   0.   0.   0.   0.]
 [ 66.   4. 383.   0.  35.   0.   1.]
 [  0.   0.   0. 918.   0.  99.  47.]
 [ 35.   0.  20.  19. 350.   1. 153.]
 [  0.   0.   0. 176.  13. 230. 188.]
 [  0.   0.   0.  70.  77.  56. 588.]]
```

<Figure size 2000x800 with 0 Axes>



recall\_score : 0.6551124126542112

precision Score : 0.6632301874609948

f1\_score : 0.6461410179732751

log loss : 1.0738462342454322

log loss dummy : 1.834217157999518

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K\_value 31

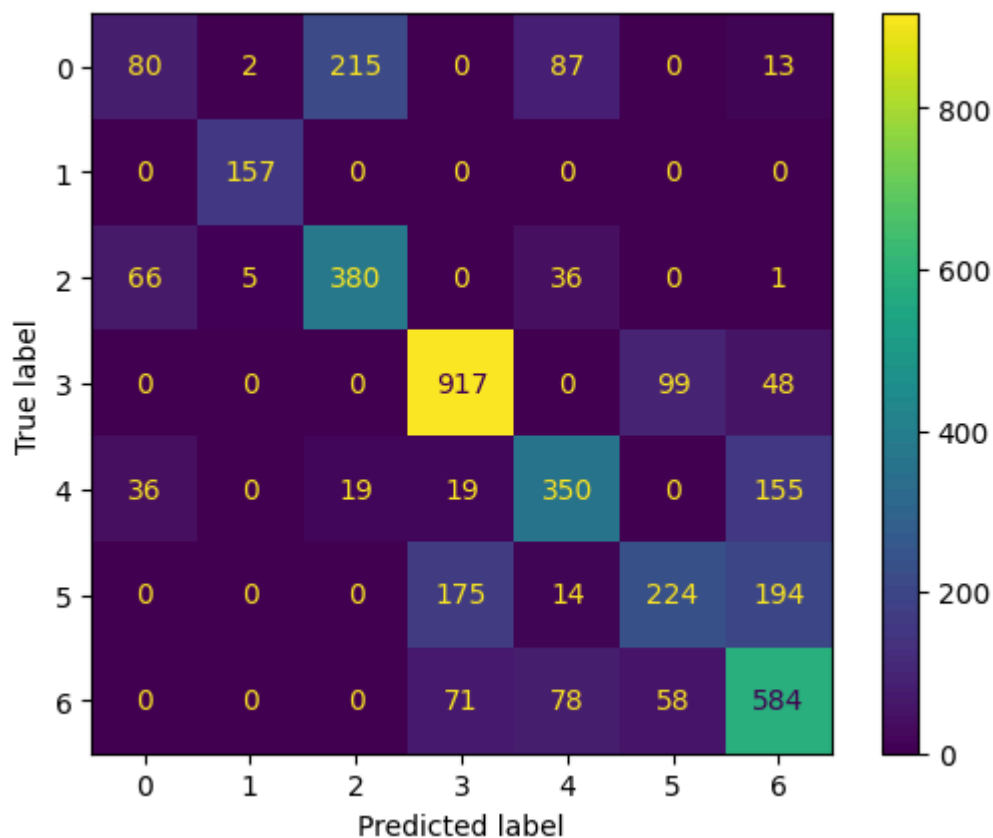
avg\_accuracy train : 0.6840558412931669

avg\_accuracy : 0.6592374887745939

avg\_err : 0.3407625112254061

```
[[ 80.  2. 215.  0. 87.  0. 13.]
 [  0. 157.  0.  0.  0.  0.  0.]
 [ 66.  5. 380.  0. 36.  0.  1.]
 [  0.  0.  0. 917.  0. 99. 48.]
 [ 36.  0. 19. 19. 350.  0. 155.]
 [  0.  0.  0. 175. 14. 224. 194.]
 [  0.  0.  0. 71. 78. 58. 584.]]
```

<Figure size 2000x800 with 0 Axes>



recall\_score : 0.6506448213100685

precision Score : 0.6551323134349727

f1\_score : 0.6396230474617453

log loss : 1.0489821898598921

log loss dummy : 1.834217157999518

\*\*\*\*\*  
\*\*\*\*\*

K\_value 33

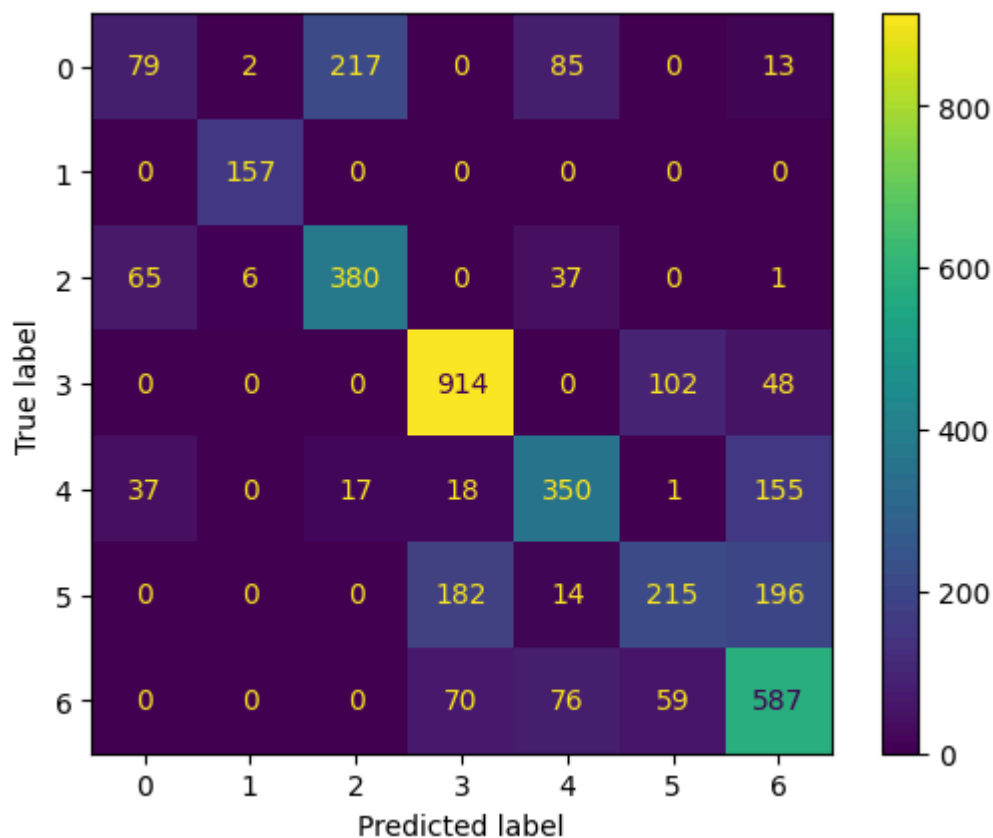
avg\_accuracy train : 0.680626989958364

avg\_accuracy : 0.6567066699322394

avg\_err : 0.3432933300677606

```
[[ 79.   2. 217.   0.  85.   0.  13.]
 [  0. 157.   0.   0.   0.   0.   0.]
 [ 65.   6. 380.   0.  37.   0.   1.]
 [  0.   0.   0. 914.   0. 102.  48.]
 [ 37.   0.  17.  18. 350.   1. 155.]
 [  0.   0.   0. 182.  14. 215. 196.]
 [  0.   0.   0.  70.  76.  59. 587.]]
```

<Figure size 2000x800 with 0 Axes>



recall\_score : 0.6483806411632825

precision Score : 0.6517579371697899

f1\_score : 0.636558234734546

log loss : 1.0415956994443434

log loss dummy : 1.834217157999518

\*\*\*\*\*  
\*\*\*\*\*

K\_value 35

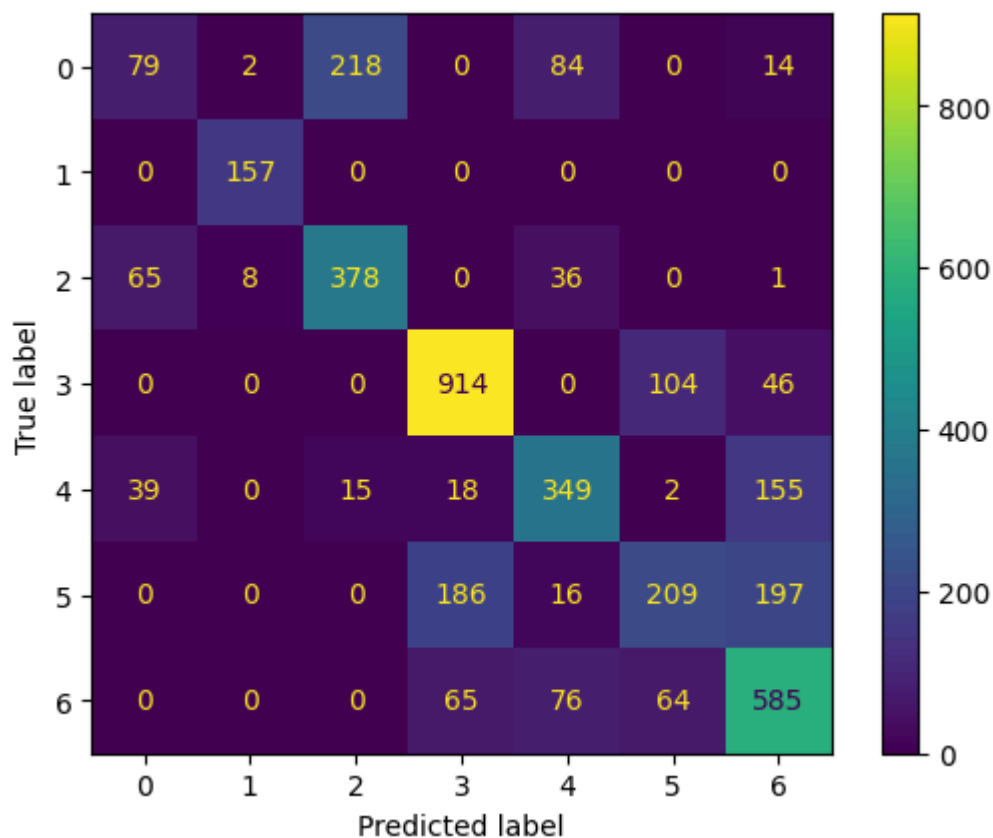
avg\_accuracy train : 0.6747081394399542

avg\_accuracy : 0.6543391297248754

avg\_err : 0.3456608702751245

```
[[ 79.   2. 218.   0.  84.   0.  14.]
 [  0. 157.   0.   0.   0.   0.   0.]
 [ 65.   8. 378.   0.  36.   0.   1.]
 [  0.   0.   0. 914.   0. 104.  46.]
 [ 39.   0.  15.  18. 349.   2. 155.]
 [  0.   0.   0. 186.  16. 209. 197.]
 [  0.   0.   0.  65.  76.  64. 585.]]
```

<Figure size 2000x800 with 0 Axes>



recall\_score : 0.6459984436177825

precision Score : 0.6467299038481672

f1\_score : 0.6333214908549667

log loss : 1.0221148597310428

log loss dummy : 1.834217157999518

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K\_value 37

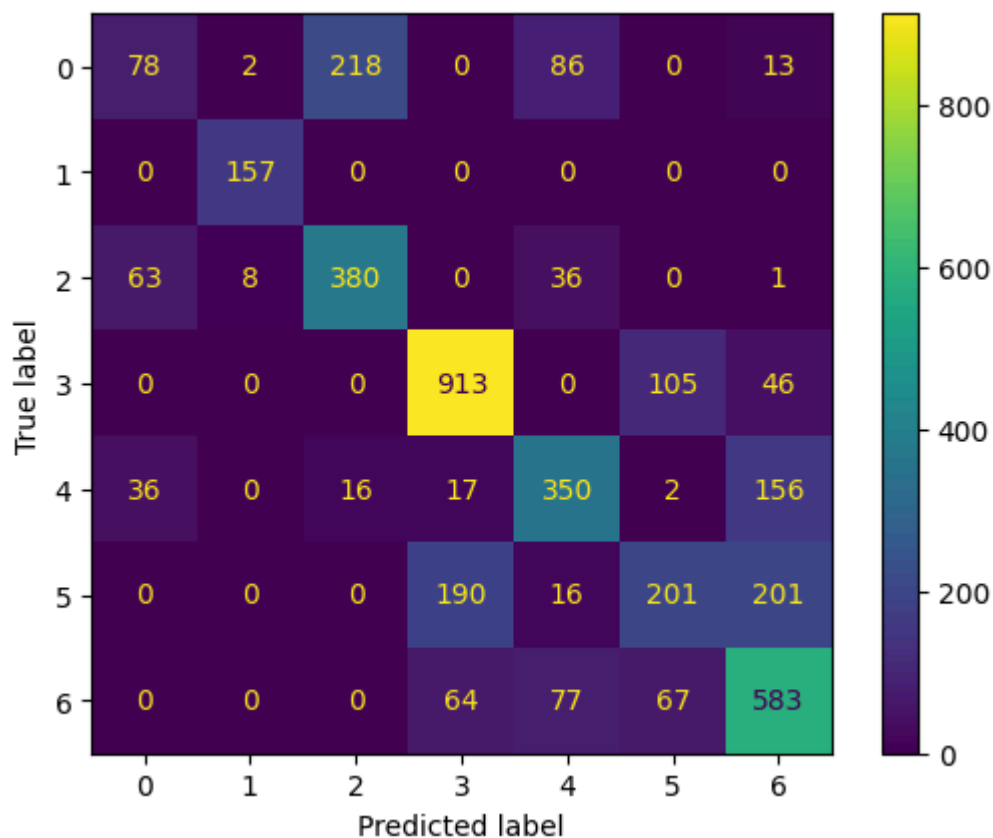
avg\_accuracy train : 0.6698506000489836

avg\_accuracy : 0.6518899502000164

avg\_err : 0.34811004979998367

```
[[ 78.   2. 218.   0.  86.   0.  13.]
 [  0. 157.   0.   0.   0.   0.   0.]
 [ 63.   8. 380.   0.  36.   0.   1.]
 [  0.   0.   0. 913.   0. 105.  46.]
 [ 36.   0.  16.  17. 350.   2. 156.]
 [  0.   0.   0. 190.  16. 201. 201.]
 [  0.   0.   0.  64.  77.  67. 583.]]
```

<Figure size 2000x800 with 0 Axes>



recall\_score : 0.6438036546126459

precision Score : 0.6442329604248503

f1\_score : 0.6304061303331268

log loss : 1.016053551737408

log loss dummy : 1.834217157999518

\*\*\*\*\*  
\*\*\*\*\*

K\_value 39

avg\_accuracy train : 0.6663809290554331

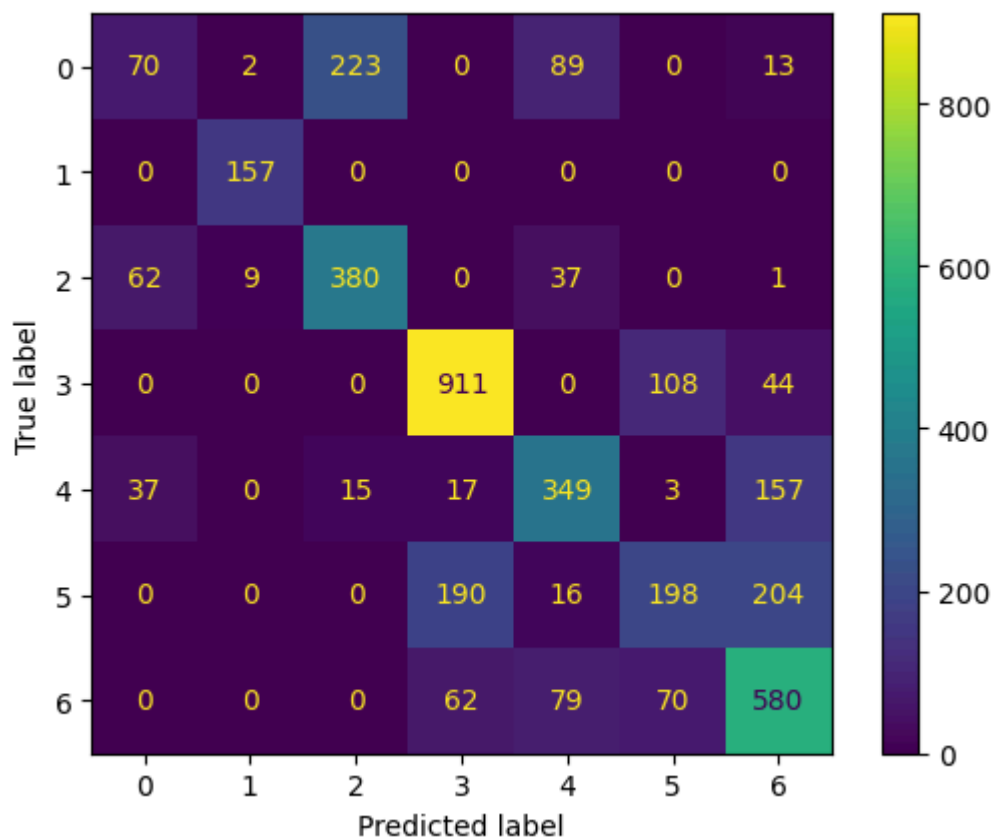
avg\_accuracy : 0.6476447056902604

avg\_err : 0.3523552943097396

```
[[ 70.   2. 223.   0.  89.   0.  13.]
 [  0. 157.   0.   0.   0.   0.   0.]
 [ 62.   9. 380.   0.  37.   0.   1.]
 [  0.   0.   0. 911.   0. 108.  44.]
 [ 37.   0.  15.  17. 349.   3. 157.]
 [  0.   0.   0. 190.  16. 198. 204.]
 [  0.   0.   0.  62.  79.  70. 580.]]
```

<Figure size 2000x800 with 0 Axes>





recall\_score : 0.6390721481134259

precision Score : 0.6363644041565057

f1\_score : 0.6240778107253575

log loss : 1.0103154546435167

log loss dummy : 1.834217157999518

\*\*\*\*\*  
\*\*\*\*\*

K\_value 41

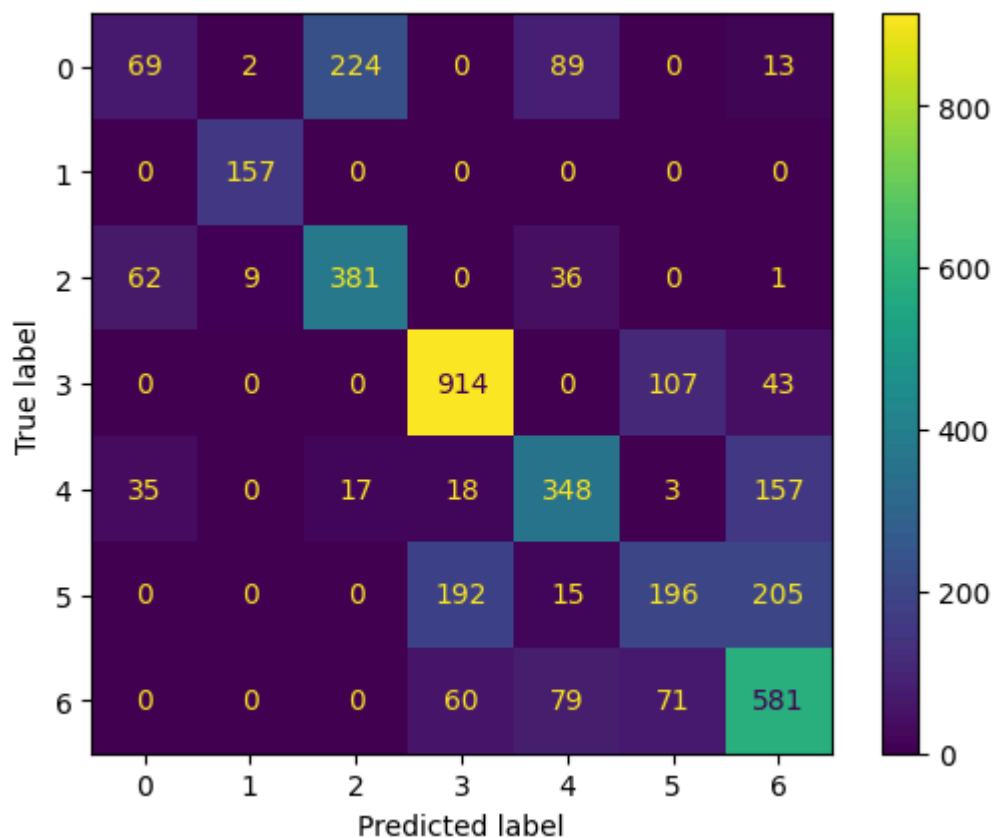
avg\_accuracy train : 0.664625683729284

avg\_accuracy : 0.6478896236427464

avg\_err : 0.3521103763572537

```
[[ 69.  2. 224.  0.  89.  0.  13.]
 [  0. 157.  0.  0.  0.  0.  0.]
 [ 62.  9. 381.  0.  36.  0.  1.]
 [  0.  0.  0. 914.  0. 107.  43.]
 [ 35.  0.  17.  18. 348.  3. 157.]
 [  0.  0.  0. 192. 15. 196. 205.]
 [  0.  0.  0.  60. 79.  71. 581.]]
```

<Figure size 2000x800 with 0 Axes>



recall\_score : 0.6388148939711963

precision Score : 0.635697910841138

f1\_score : 0.6233967886700015

log loss : 1.000404867317704

log loss dummy : 1.834217157999518

\*\*\*\*\*  
\*\*\*\*\*

K\_value 43

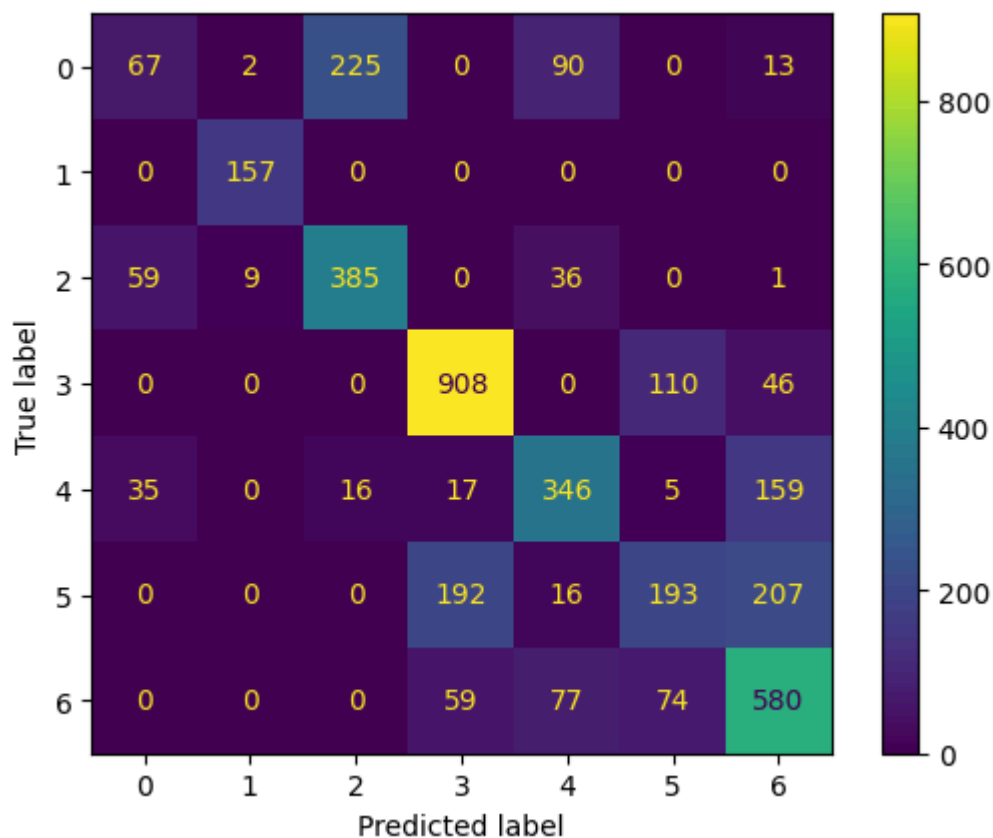
avg\_accuracy train : 0.6623806024981631

avg\_accuracy : 0.6454404441178873

avg\_err : 0.35455955588211285

```
[[ 67.   2. 225.   0.  90.   0.  13.]
 [  0. 157.   0.   0.   0.   0.   0.]
 [ 59.   9. 385.   0.  36.   0.   1.]
 [  0.   0.   0. 908.   0. 110.  46.]
 [ 35.   0.  16.  17. 346.   5. 159.]
 [  0.   0.   0. 192.  16. 193. 207.]
 [  0.   0.   0.  59.  77.  74. 580.]]
```

<Figure size 2000x800 with 0 Axes>



recall\_score : 0.6369617563429409

precision Score : 0.6334310226649885

f1\_score : 0.6209181393571244

log loss : 0.9796900619479331

log loss dummy : 1.834217157999518

\*\*\*\*\*  
\*\*\*\*\*

K\_value 45

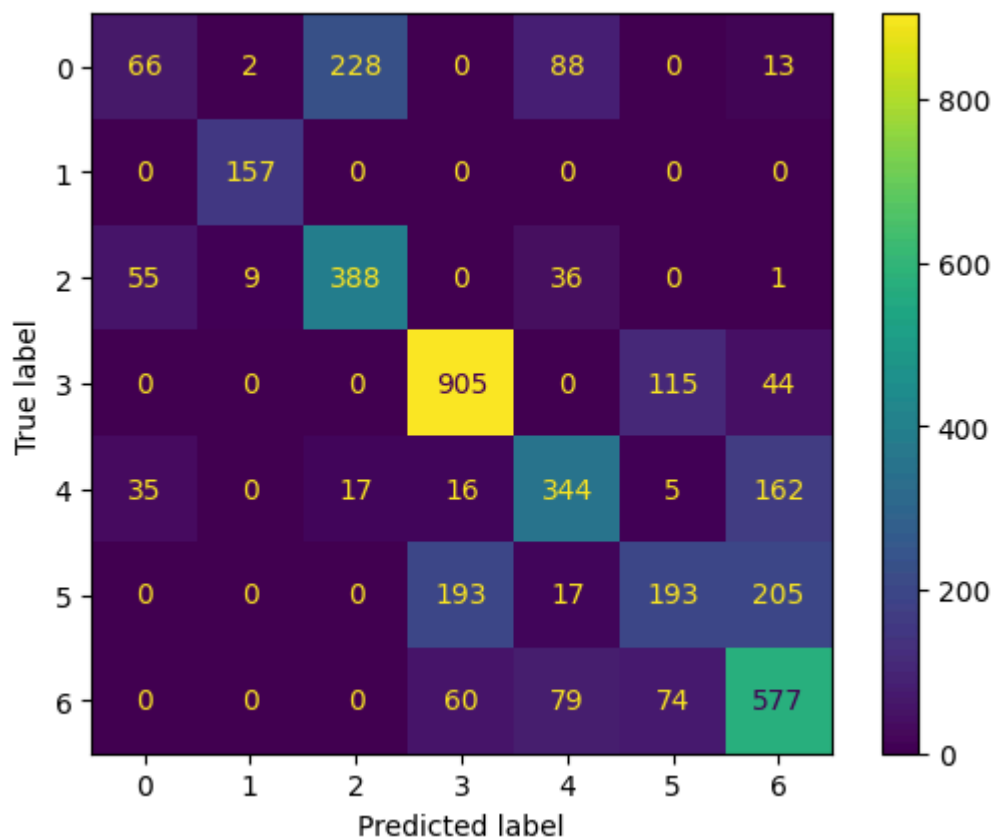
avg\_accuracy train : 0.6602171605845375

avg\_accuracy : 0.6439709364029716

avg\_err : 0.3560290635970283

```
[[ 66.   2. 228.   0.  88.   0.  13.]
 [  0. 157.   0.   0.   0.   0.   0.]
 [ 55.   9. 388.   0.  36.   0.   1.]
 [  0.   0.   0. 905.   0. 115.  44.]
 [ 35.   0.  17.  16. 344.   5. 162.]
 [  0.   0.   0. 193.  17. 193. 205.]
 [  0.   0.   0.  60.  79.  74. 577.]]
```

<Figure size 2000x800 with 0 Axes>



recall\_score : 0.6359570694264588

precision Score : 0.6330678882552664

f1\_score : 0.6196707734332383

log loss : 0.9764736235884156

log loss dummy : 1.834217157999518

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K\_value 47

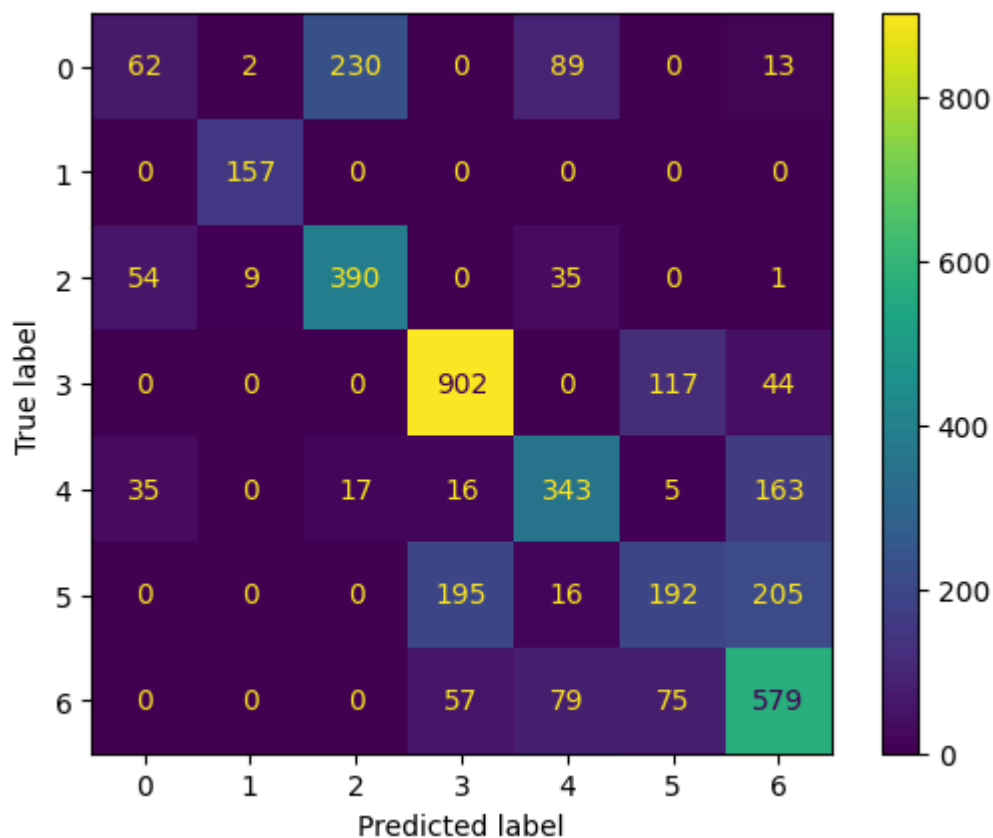
avg\_accuracy train : 0.6575230631071926

avg\_accuracy : 0.6427463466405421

avg\_err : 0.3572536533594579

```
[[ 62.   2. 230.   0.  89.   0.  13.]
 [  0. 157.   0.   0.   0.   0.   0.]
 [ 54.   9. 390.   0.  35.   0.   1.]
 [  0.   0.   0. 902.   0. 117.  44.]
 [ 35.   0.  17.  16. 343.   5. 163.]
 [  0.   0.   0. 195.  16. 192. 205.]
 [  0.   0.   0.  57.  79.  75. 579.]]
```

<Figure size 2000x800 with 0 Axes>



recall\_score : 0.6345906596165608

precision Score : 0.6301794233537474

f1\_score : 0.6171233892272939

log loss : 0.9709063532226181

log loss dummy : 1.834217157999518

\*\*\*\*\*  
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K\_value 49

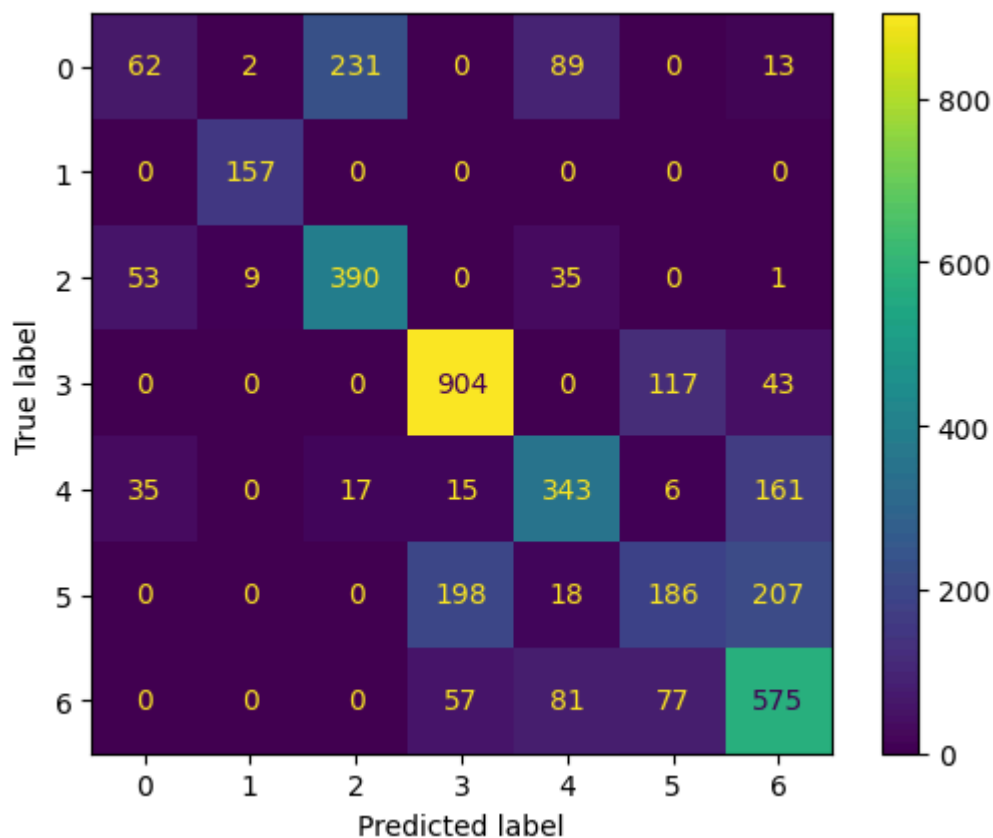
avg\_accuracy train : 0.6567066699322394

avg\_accuracy : 0.64086864233815

avg\_err : 0.35913135766185

```
[[ 62.   2. 231.   0.  89.   0.  13.]
 [  0. 157.   0.   0.   0.   0.   0.]
 [ 53.   9. 390.   0.  35.   0.   1.]
 [  0.   0.   0. 904.   0. 117.  43.]
 [ 35.   0.  17.  15. 343.   6. 161.]
 [  0.   0.   0. 198.  18. 186. 207.]
 [  0.   0.   0.  57.  81.  77. 575.]]
```

<Figure size 2000x800 with 0 Axes>



recall\_score : 0.6328590509492654

precision Score : 0.6279035564125378

f1\_score : 0.6153198606540268

log loss : 0.9721187720960208

log loss dummy : 1.834217157999518

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K\_value 51

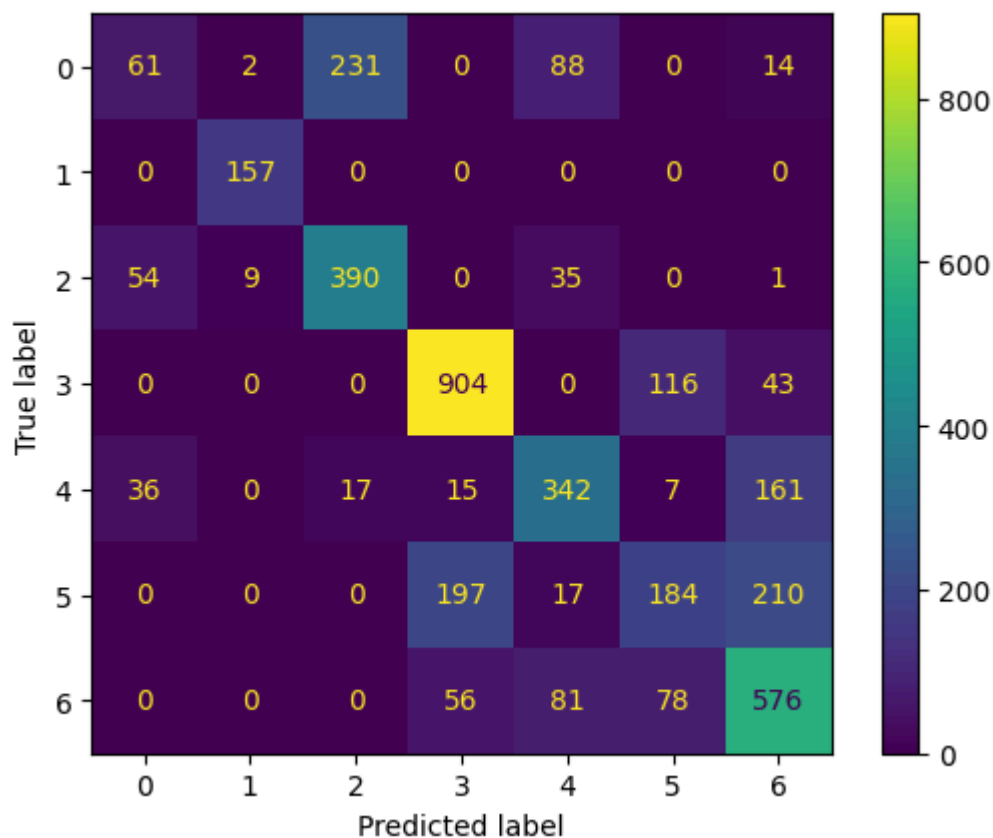
avg\_accuracy train : 0.6546656869948567

avg\_accuracy : 0.6404604457506734

avg\_err : 0.3595395542493265

```
[[ 61.   2. 231.   0.  88.   0.  14.]
 [  0. 157.   0.   0.   0.   0.   0.]
 [ 54.   9. 390.   0.  35.   0.   1.]
 [  0.   0.   0. 904.   0. 116.  43.]
 [ 36.   0.  17.  15. 342.   7. 161.]
 [  0.   0.   0. 197.  17. 184. 210.]
 [  0.   0.   0.  56.  81.  78. 576.]]
```

<Figure size 2000x800 with 0 Axes>



recall\_score : 0.6322355837648513

precision Score : 0.6265542218179357

f1\_score : 0.614471411261527

log loss : 0.9659145265944966

log loss dummy : 1.834217157999518

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K\_value 53

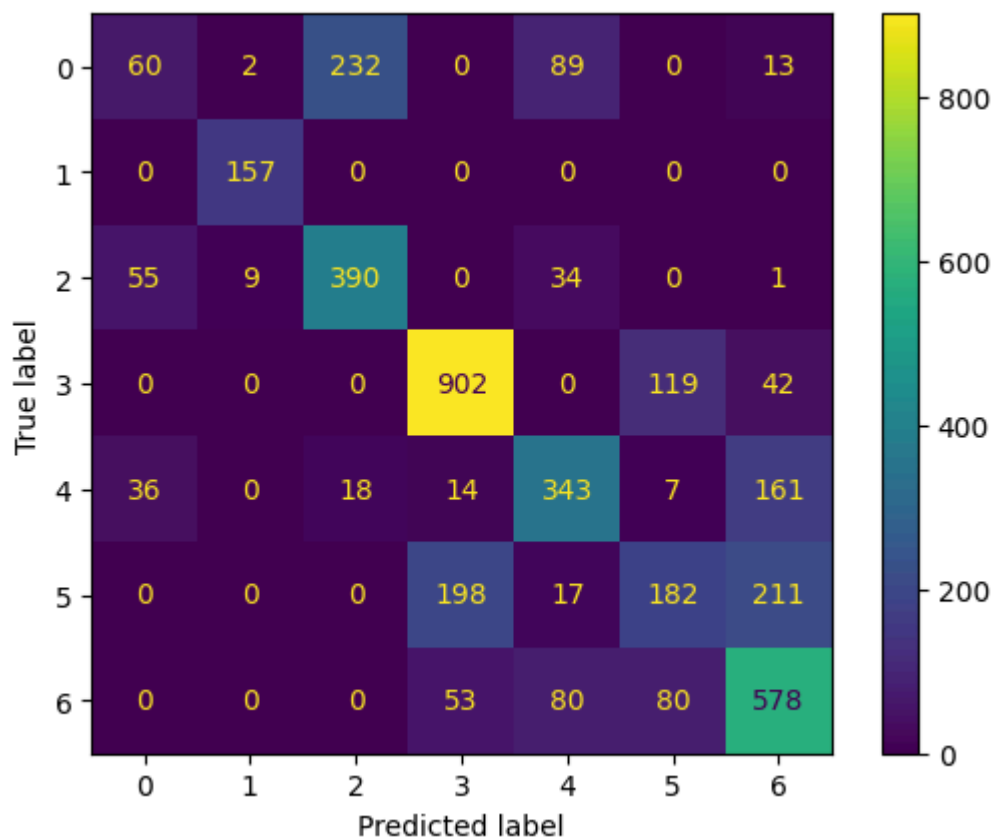
avg\_accuracy train : 0.6527879826924646

avg\_accuracy : 0.6395624132582252

avg\_err : 0.36043758674177484

```
[[ 60.  2. 232.  0.  89.  0.  13.]
 [  0. 157.  0.  0.  0.  0.  0.]
 [ 55.  9. 390.  0.  34.  0.  1.]
 [  0.  0.  0. 902.  0. 119.  42.]
 [ 36.  0.  18.  14. 343.  7. 161.]
 [  0.  0.  0. 198. 17. 182. 211.]
 [  0.  0.  0.  53.  80.  80. 578.]]
```

<Figure size 2000x800 with 0 Axes>



recall\_score : 0.6313124565733746

precision Score : 0.6245725733516974

f1\_score : 0.6131909269200325

log loss : 0.9593635130580211

log loss dummy : 1.834217157999518

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K\_value 55

avg\_accuracy train : 0.6510327373663157

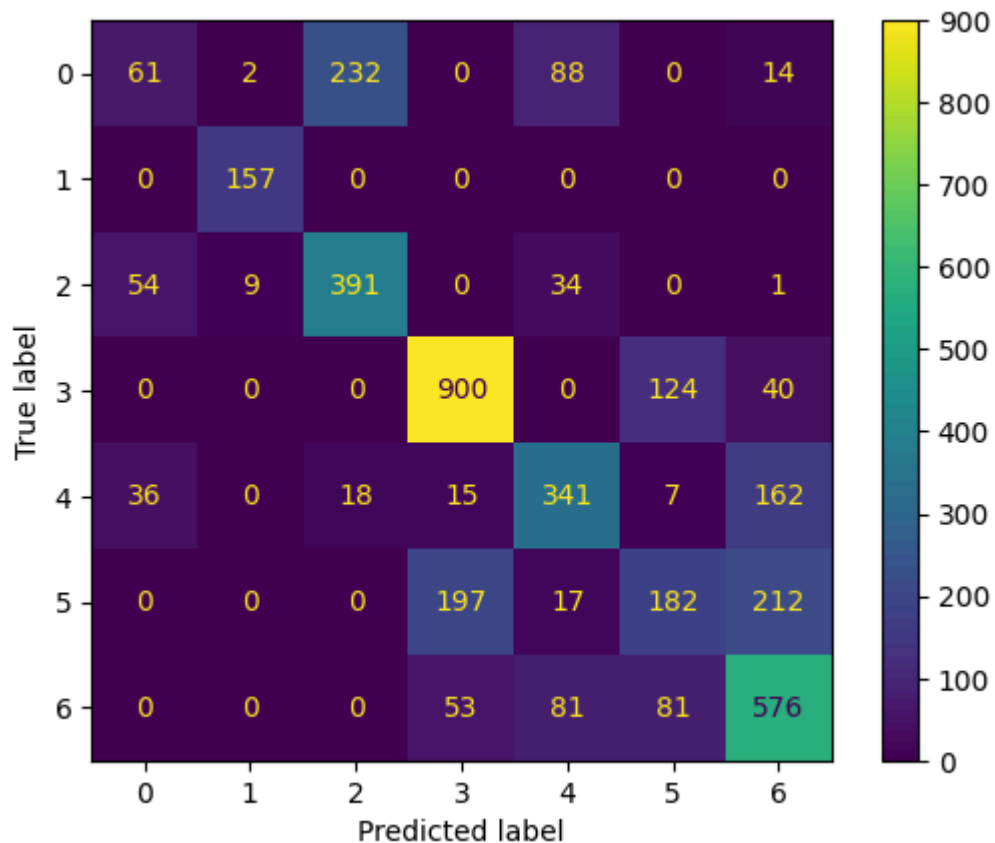
avg\_accuracy : 0.638419462813291

avg\_err : 0.36158053718670913

```
[[ 61.   2. 232.   0.  88.   0.  14.]
 [  0. 157.   0.   0.   0.   0.   0.]
 [ 54.   9. 391.   0.  34.   0.   1.]
 [  0.   0.   0. 900.   0. 124.  40.]
 [ 36.   0.  18.  15. 341.   7. 162.]
 [  0.   0.   0. 197.  17. 182. 212.]
 [  0.   0.   0.  53.  81.  81. 576.]]
```

<Figure size 2000x800 with 0 Axes>





recall\_score : 0.6307217381214544

precision Score : 0.6247054826618869

f1\_score : 0.6128400322601802

log loss : 0.9475245414406479

log loss dummy : 1.834217157999518

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K\_value 57

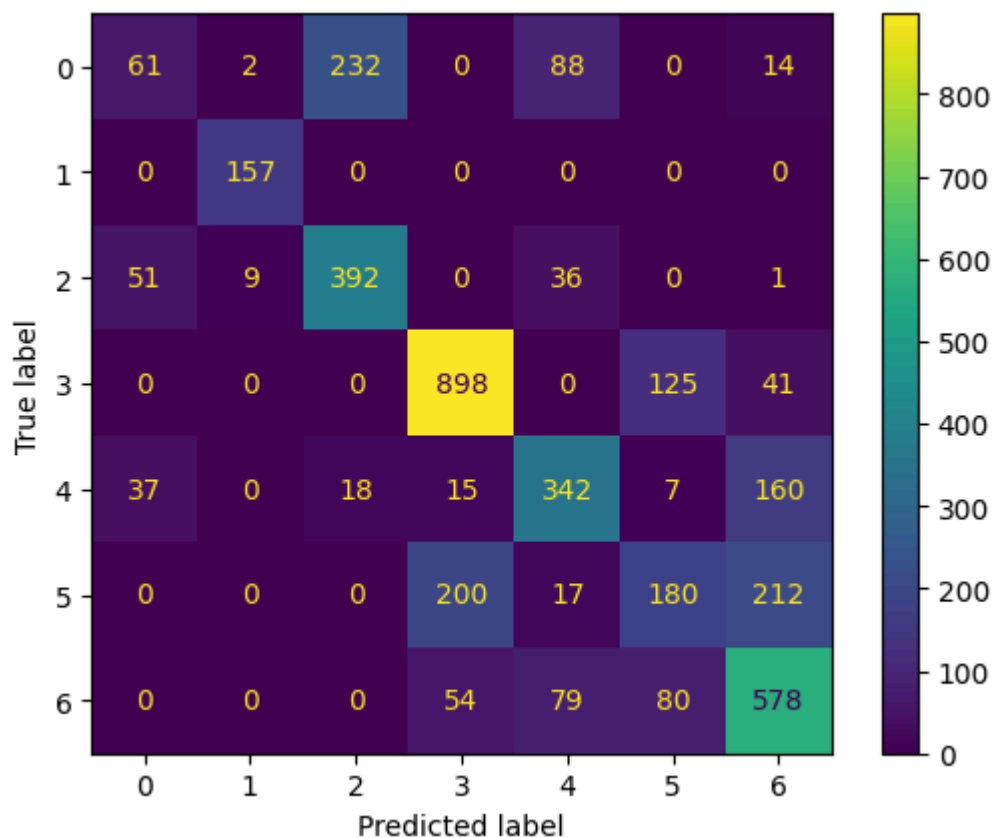
avg\_accuracy train : 0.6497673279451384

avg\_accuracy : 0.6385011021307861

avg\_err : 0.36149889786921374

```
[[ 61.  2. 232.  0.  88.  0.  14.]
 [  0. 157.  0.  0.  0.  0.  0.]
 [ 51.  9. 392.  0.  36.  0.  1.]
 [  0.  0.  0. 898.  0. 125. 41.]
 [ 37.  0.  18.  15. 342.  7. 160.]
 [  0.  0.  0. 200.  17. 180. 212.]
 [  0.  0.  0.  54.  79.  80. 578.]]
```

<Figure size 2000x800 with 0 Axes>



recall\_score : 0.6309196818816623

precision Score : 0.6247460363894447

f1\_score : 0.6125886298297468

log loss : 0.9440356312797133

log loss dummy : 1.834217157999518

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K\_value 59

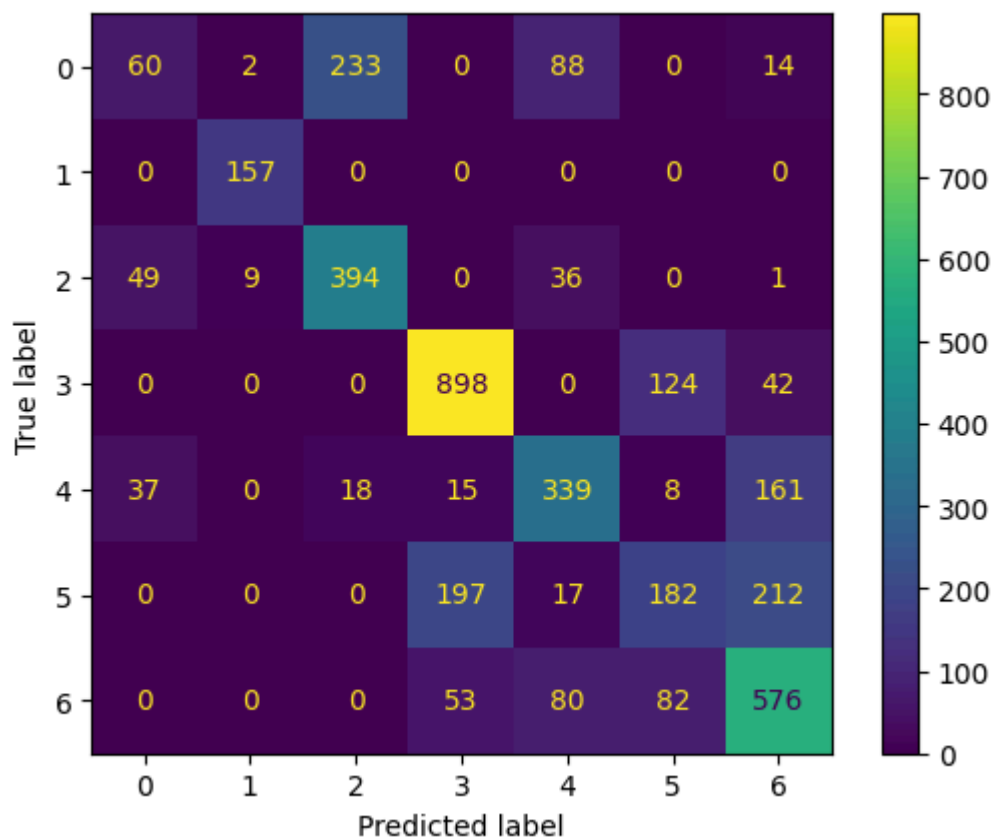
avg\_accuracy train : 0.6496856886276431

avg\_accuracy : 0.6382561841783003

avg\_err : 0.36174381582169973

```
[[ 60.   2. 233.   0.  88.   0.  14.]
 [  0. 157.   0.   0.   0.   0.   0.]
 [ 49.   9. 394.   0.  36.   0.   1.]
 [  0.   0.   0. 898.   0. 124.  42.]
 [ 37.   0.  18.  15. 339.   8. 161.]
 [  0.   0.   0. 197.  17. 182. 212.]
 [  0.   0.   0.  53.  80.  82. 576.]]
```

<Figure size 2000x800 with 0 Axes>



recall\_score : 0.6307509965379721

precision Score : 0.6248313044665244

f1\_score : 0.612371688598355

log loss : 0.9406680830670627

log loss dummy : 1.834217157999518

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```
In [35]: import matplotlib.pyplot as plt
no_of_splits=3
k=[]
avg_training_accuracy=[]
avg_accuracy=[]
avg_error=[]
avg_recall_score=[]
avg_log_loss=[]
avg_precision_score=[]
avg_f1_score=[]
avg_log_loss_dummy=[]
for i in range(1, 30, 2):
    acc = []
    acc_train = []
    err = []
```

```

conf = []
recall = []
prec = []
k = []
logloss = []
logloss_dummy = []
Classification_report=[]
f1_score=[]
for train_index, cv_index in sf.split(x_train, y_train):
    x_trainf, x_cv, y_trainf, y_cv = x_train.iloc[train_index], x_train.iloc[cv_index]
    #Training the model
    knn = KNeighborsClassifier(n_neighbors=i)
    model = knn.fit(x_trainf, y_trainf)
    # Predicting the Model
    predicted_train = model.predict(x_trainf)
    # training accuracy of an model

    acc_train.append(accuracy_score(y_trainf, predicted_train))
    predicted = model.predict(x_cv)
    #accuracy score
    acc.append(accuracy_score(y_cv, predicted))
    # error score
    err.append(1 - accuracy_score(y_cv, predicted))
    # confusion matrix
    conf.append(confusion_matrix(y_cv, predicted, labels=model.classes_))
    # recall score
    recall.append(recall_score(y_cv, predicted, average=None))
    # precision score
    prec.append(precision_score(y_cv, predicted, average=None))
    # f1 score
    f1_score_.append(f1_score(y_cv, predicted, average=None))
    Classification_report.append(classification_report(y_cv,predicted))
    predicted = model.predict_proba(x_cv)
    # log Loss score
    logloss.append(log_loss(y_cv, predicted))
    dc = DummyClassifier()
    dc_model = dc.fit(x_trainf, y_trainf)
    dc_predit = dc_model.predict_proba(x_test)
    logloss_dummy.append(log_loss(y_test, dc_predit))
a = np.mean(acc_train)
b = np.mean(acc)

print("K_value", i)
k.append(i)
print("")

avg_training_accuracy.append(np.mean(acc_train))
print("avg_accuracy train : ", np.mean(acc_train))
print("")

avg_accuracy.append(np.mean(acc))
print("avg_accuracy : ", np.mean(acc))
print("")

avg_error.append(np.mean(err))
print("avg_err : ", np.mean(err))

```

```

print(" ")

plt.figure(figsize=(20, 8))
cm = ConfusionMatrixDisplay(np.int64(np.round(sum(conf) / no_of_splits)))
cm.plot()
plt.show()
print(" ")

avg_recall_score.append( np.mean(recall))
print("recall_score : ", np.mean(recall))
print(" ")

avg_precision_score.append(np.mean(prec))
print("precision Score : ", np.mean(prec))
print(" ")

avg_f1_score.append(np.mean(f1_score_))
print("f1_score :", np.mean(f1_score_))
print("")

avg_log_loss.append(np.mean(logloss))
print("log loss : ", np.mean(logloss))
print(" ")

avg_log_loss_dummy.append(np.mean(logloss_dummy))
print("log loss dummy : ", np.mean(logloss_dummy))
print(" ")
print("*" * 100)

print(" ")

```

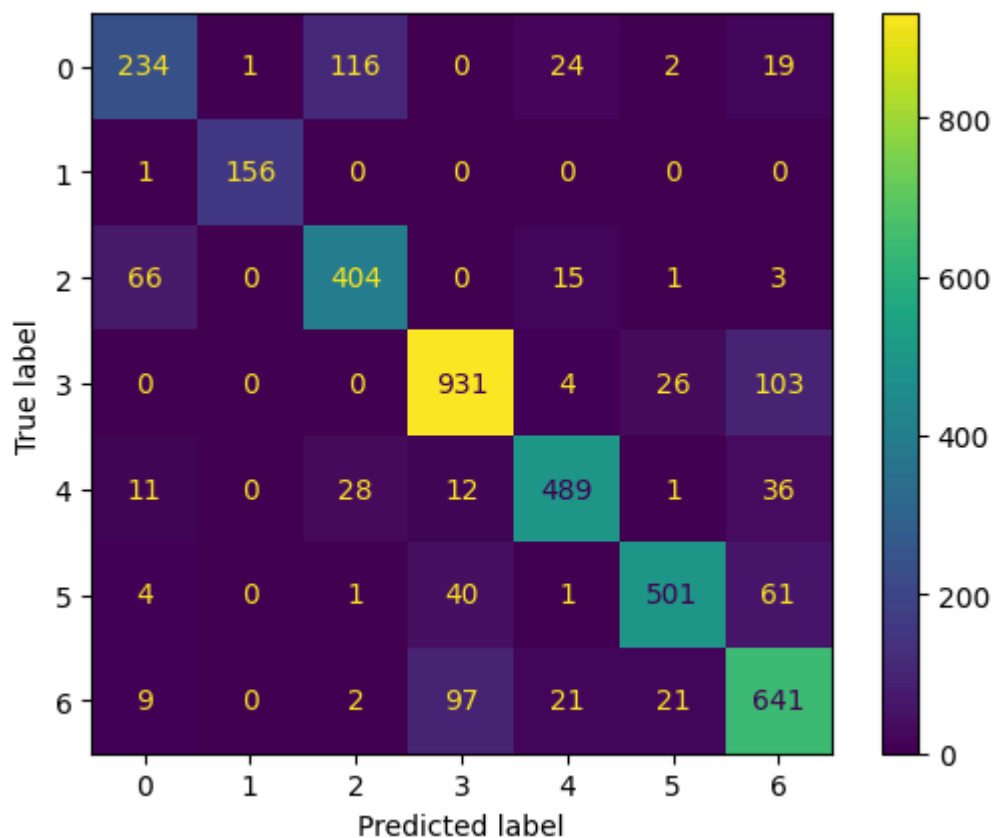
K\_value 1

avg\_accuracy train : 1.0

avg\_accuracy : 0.8220262878602335

avg\_err : 0.17797371213976654

<Figure size 2000x800 with 0 Axes>



recall\_score : 0.8238485889207074

precision Score : 0.8348899763571325

f1\_score : 0.8273762562276636

log loss : 6.4148227927402575

log loss dummy : 1.8340319962763019

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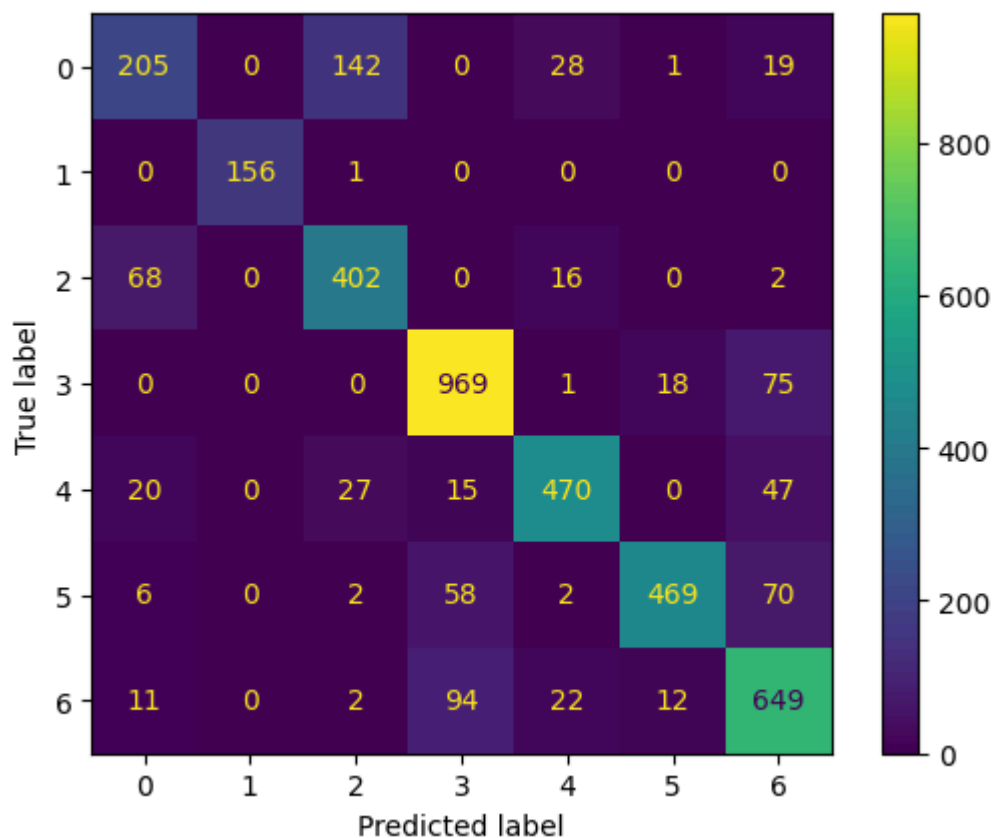
K\_value 3

avg\_accuracy train : 0.9010123275369418

avg\_accuracy : 0.8134541595232264

avg\_err : 0.1865458404767736

<Figure size 2000x800 with 0 Axes>



recall\_score : 0.8073358514619703

precision Score : 0.8242825572146922

f1\_score : 0.8121106004695948

log loss : 2.9505199085223723

log loss dummy : 1.8340319962763019

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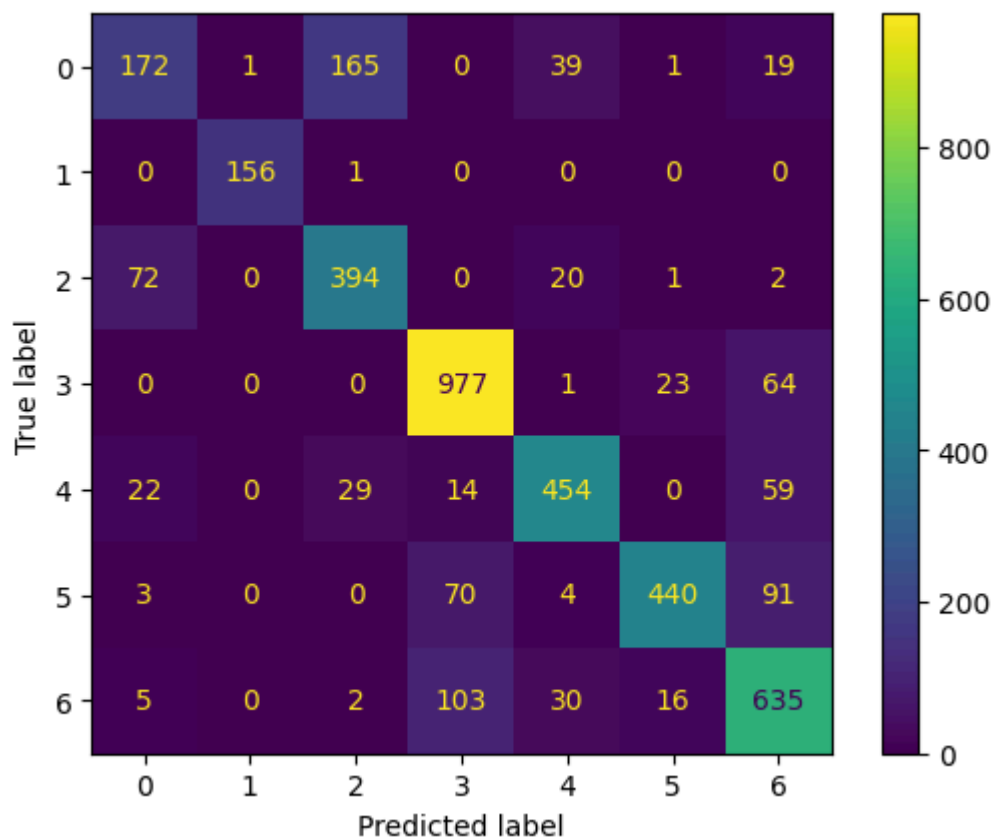
K\_value 5

avg\_accuracy train : 0.8626826679728957

avg\_accuracy : 0.7905135113070454

avg\_err : 0.20948648869295453

<Figure size 2000x800 with 0 Axes>



recall\_score : 0.780539433194088

precision Score : 0.800753237752061

f1\_score : 0.7848984921538916

log loss : 2.1663681559792987

log loss dummy : 1.8340319962763019

\*\*\*\*\*  
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K\_value 7

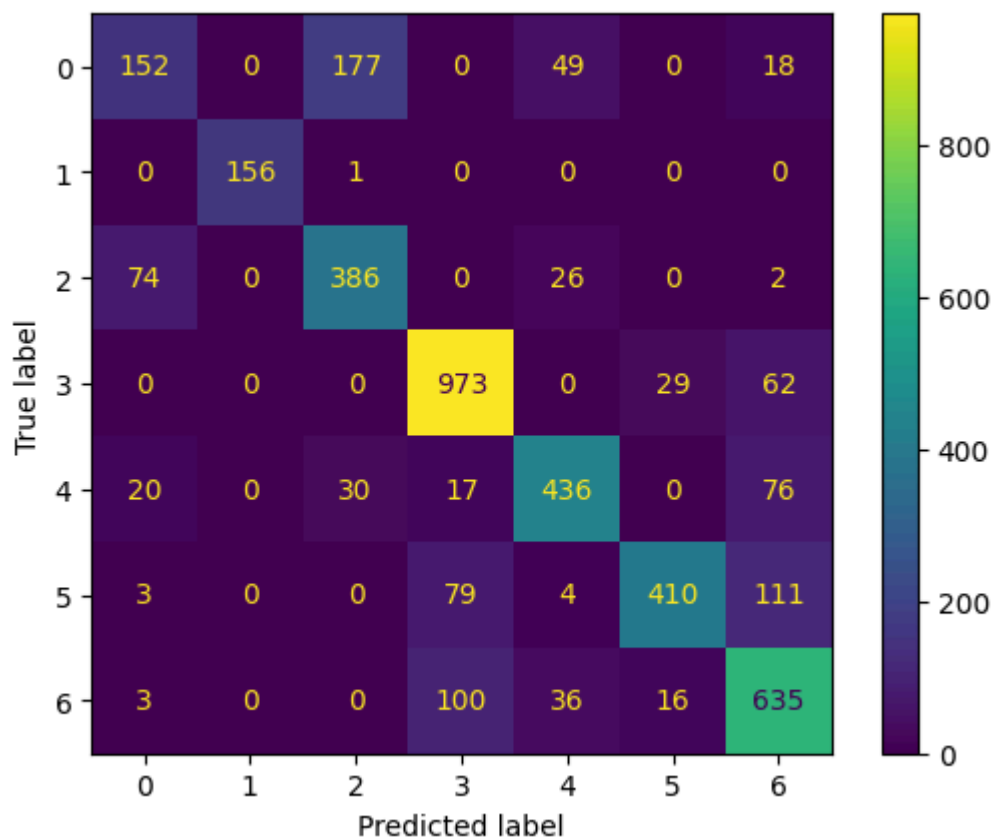
avg\_accuracy train : 0.8306392358559883

avg\_accuracy : 0.7710017144256675

avg\_err : 0.22899828557433258

<Figure size 2000x800 with 0 Axes>





recall\_score : 0.7591642708117672

precision Score : 0.78211042999781

f1\_score : 0.7629061350360529

log loss : 1.7600900612959673

log loss dummy : 1.8340319962763019

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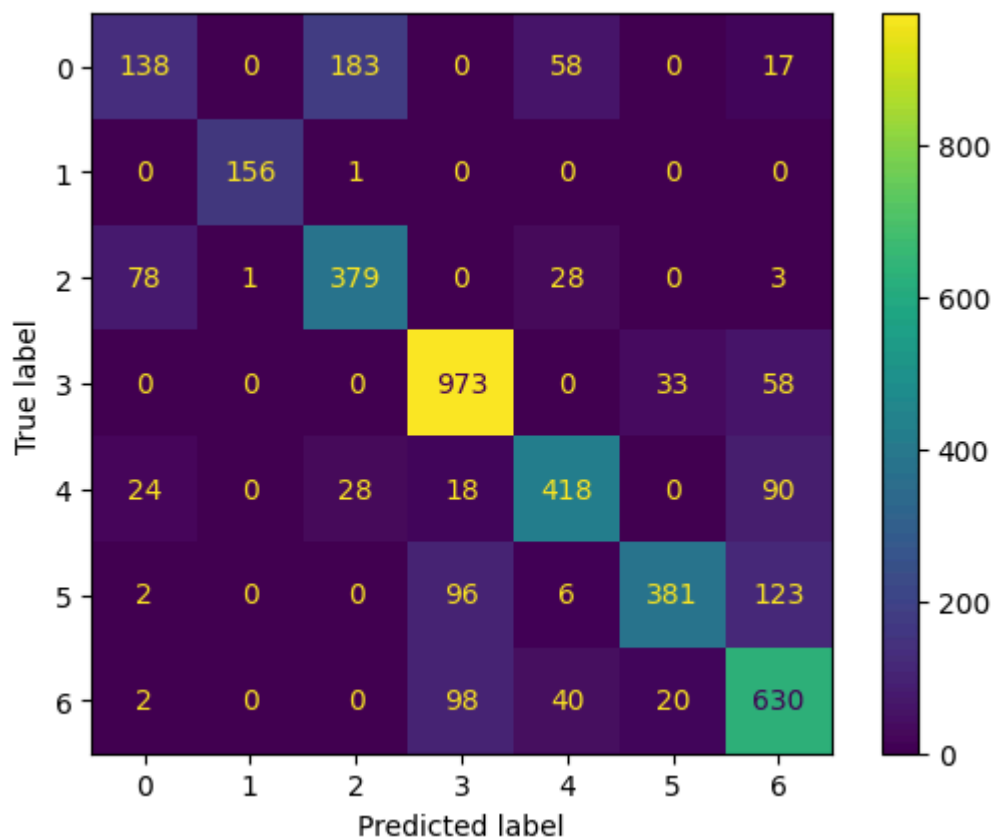
K\_value 9

avg\_accuracy train : 0.804922850844967

avg\_accuracy : 0.7533676218466813

avg\_err : 0.24663237815331865

<Figure size 2000x800 with 0 Axes>



recall\_score : 0.7401503491396053

precision Score : 0.7635529744523277

f1\_score : 0.7431312808871307

log loss : 1.548729464547853

log loss dummy : 1.8340319962763019

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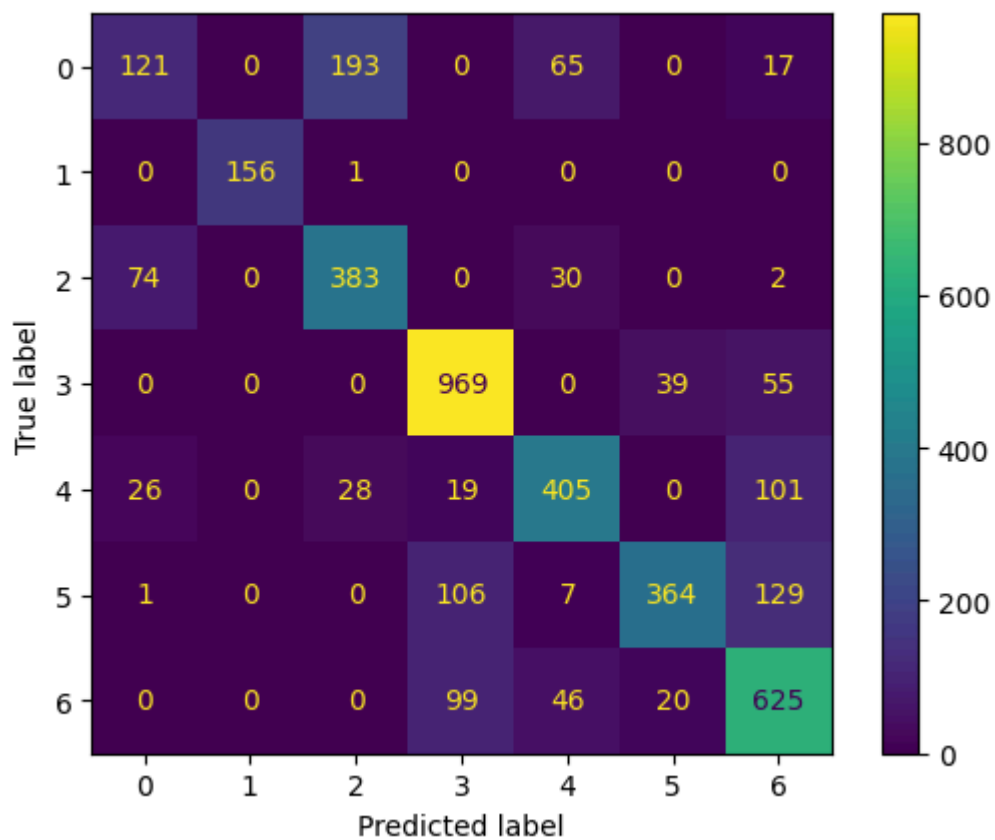
K\_value 11

avg\_accuracy train : 0.7864315454322801

avg\_accuracy : 0.7404686096824231

avg\_err : 0.25953139031757694

<Figure size 2000x800 with 0 Axes>



recall\_score : 0.7263913996240478

precision Score : 0.7501824543785461

f1\_score : 0.7277558166963308

log loss : 1.4205287953655974

log loss dummy : 1.8340319962763019

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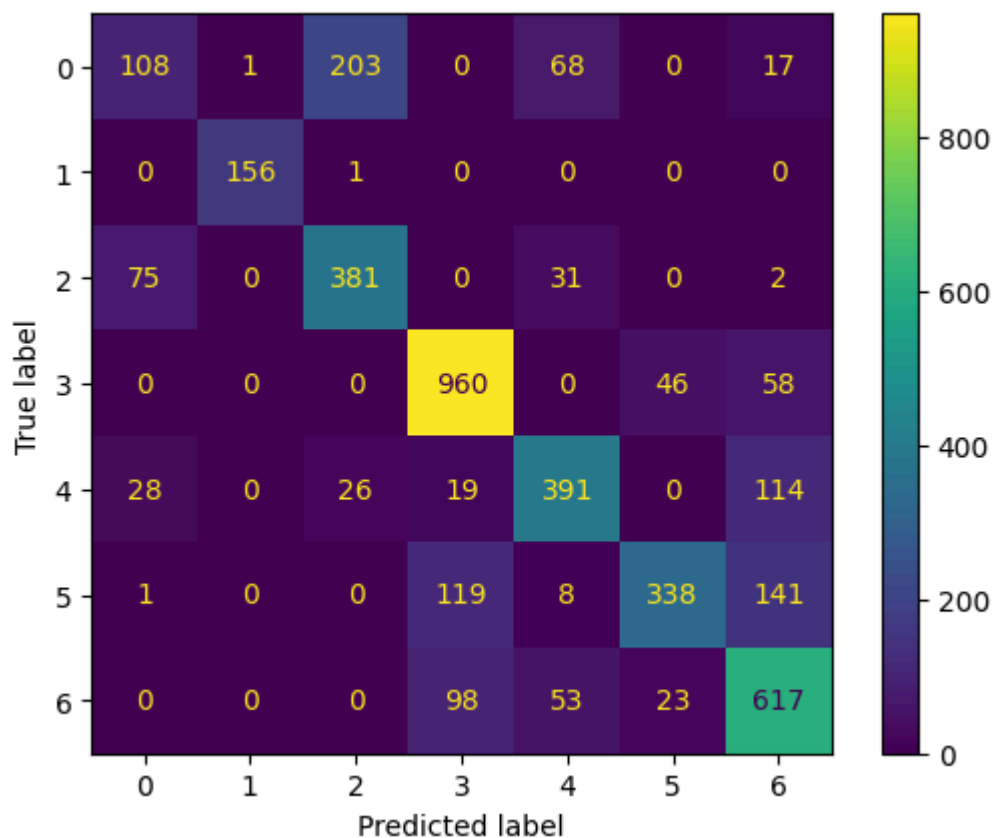
K\_value 13

avg\_accuracy train : 0.765858437423463

avg\_accuracy : 0.7227528777859417

avg\_err : 0.2772471222140583

<Figure size 2000x800 with 0 Axes>



recall\_score : 0.7088421714004566

precision Score : 0.7313505056126378

f1\_score : 0.7084442897668649

log loss : 1.3447841013341415

log loss dummy : 1.8340319962763019

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\*\*\*\*\*

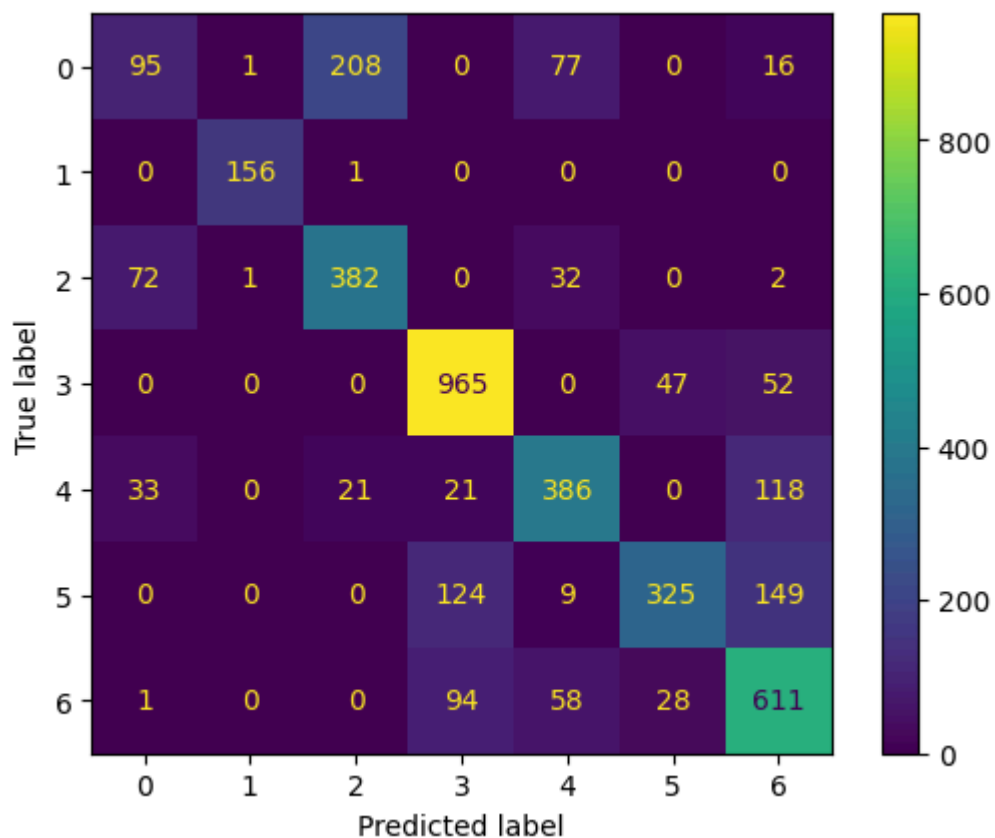
K\_value 15

avg\_accuracy train : 0.7487550004081966

avg\_accuracy : 0.7149971426238876

avg\_err : 0.28500285737611236

<Figure size 2000x800 with 0 Axes>



recall\_score : 0.6996611001173868

precision Score : 0.7191260658094757

f1\_score : 0.6972136292980365

log loss : 1.2845361923385195

log loss dummy : 1.8340319962763019

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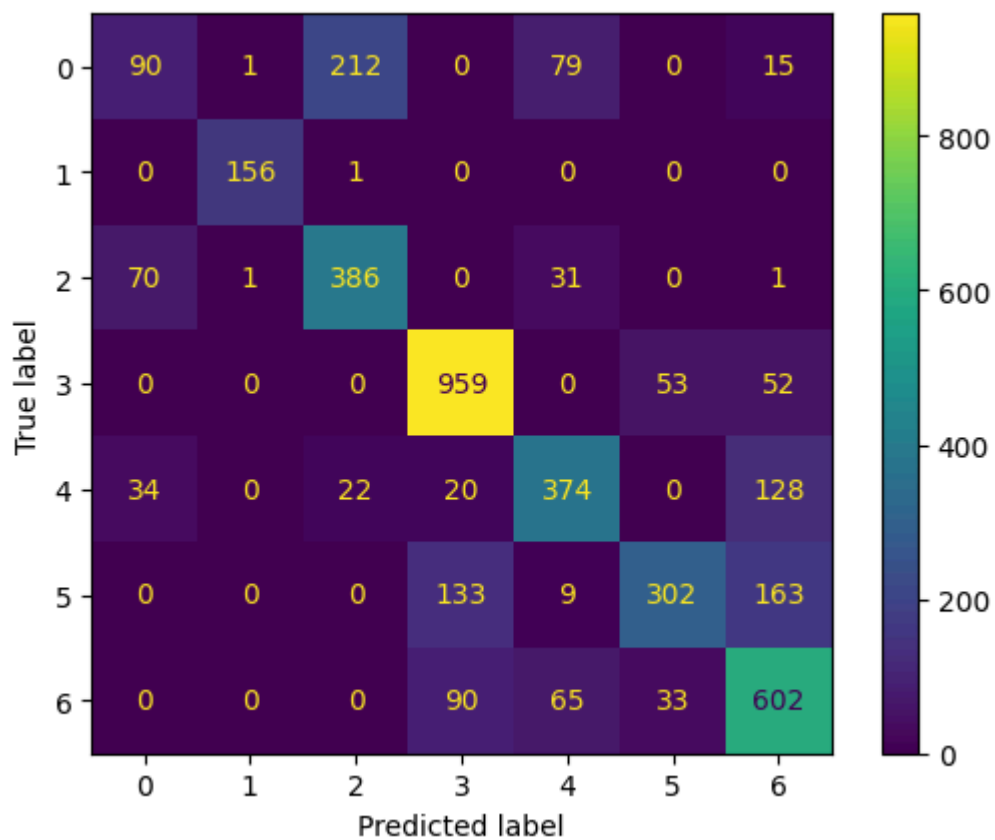
K\_value 17

avg\_accuracy train : 0.7361009061964242

avg\_accuracy : 0.7025063270471059

avg\_err : 0.29749367295289414

<Figure size 2000x800 with 0 Axes>



recall\_score : 0.6881142719698091

precision Score : 0.7060903909261003

f1\_score : 0.6839980569728477

log loss : 1.2428411843410867

log loss dummy : 1.8340319962763019

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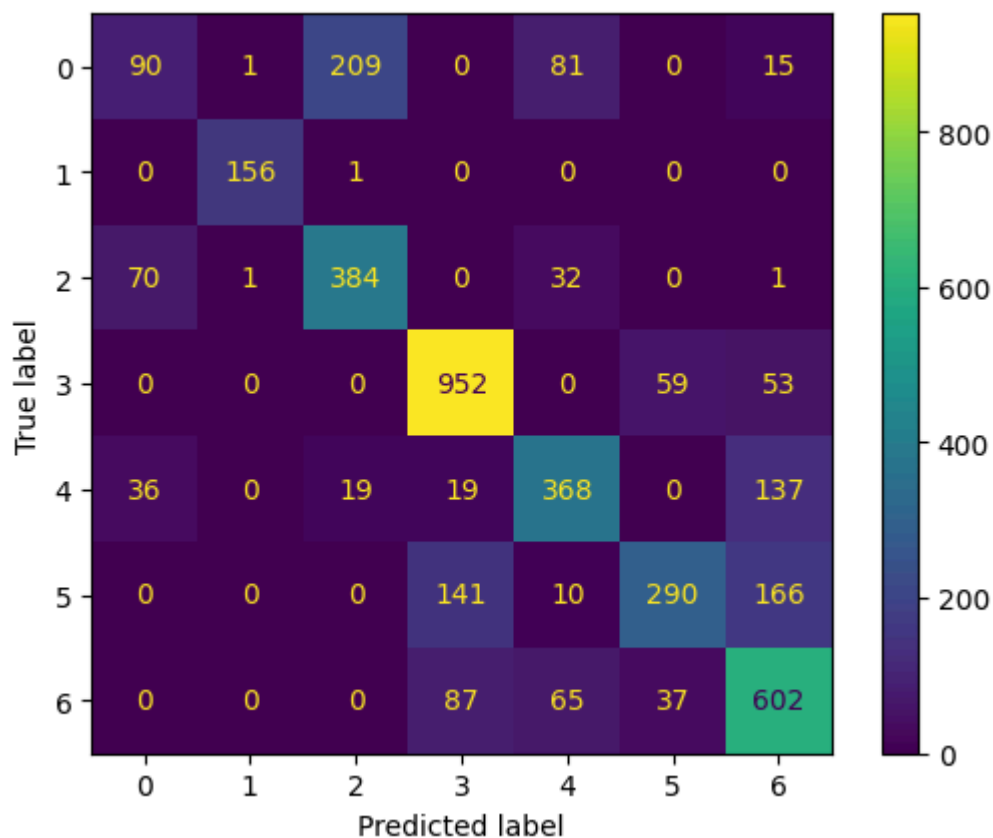
K\_value 19

avg\_accuracy train : 0.7271614009306883

avg\_accuracy : 0.6961384602824721

avg\_err : 0.30386153971752794

<Figure size 2000x800 with 0 Axes>



recall\_score : 0.6826687346778583

precision Score : 0.700111209098076

f1\_score : 0.6784962691870055

log loss : 1.2155430714965823

log loss dummy : 1.8340319962763019

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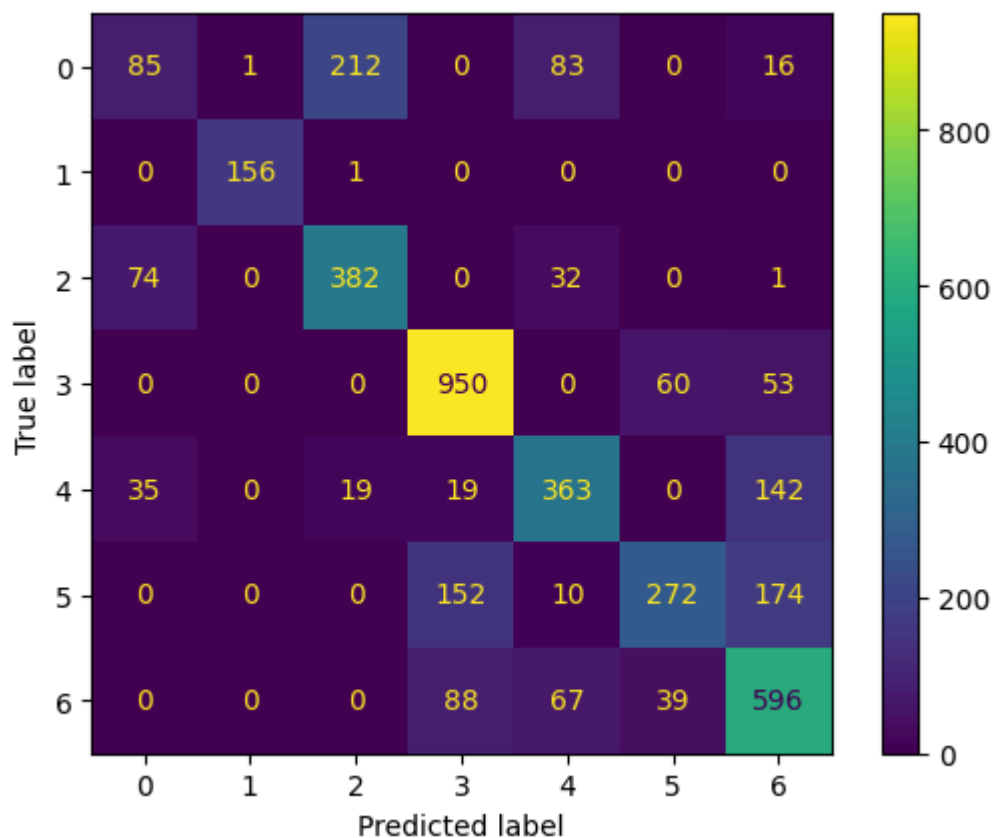
K\_value 21

avg\_accuracy train : 0.7163441913625602

avg\_accuracy : 0.6869132174055025

avg\_err : 0.31308678259449746

<Figure size 2000x800 with 0 Axes>



recall\_score : 0.673443372919309

precision Score : 0.6906040194404961

f1\_score : 0.6685735320506557

log loss : 1.193369762932856

log loss dummy : 1.8340319962763019

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K\_value 23

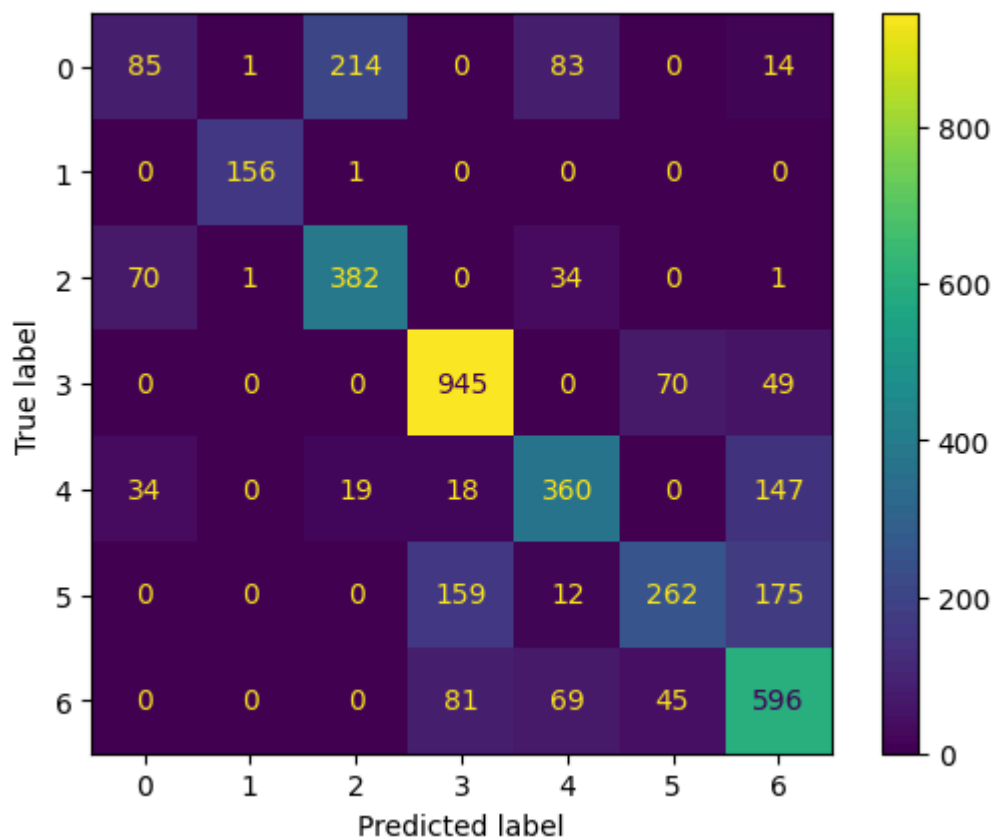
avg\_accuracy train : 0.7081802596130297

avg\_accuracy : 0.6822597763082702

avg\_err : 0.31774022369172994

<Figure size 2000x800 with 0 Axes>





recall\_score : 0.6695440801131809

precision Score : 0.6847725913939391

f1\_score : 0.6635885191477676

log loss : 1.1687553739812981

log loss dummy : 1.8340319962763019

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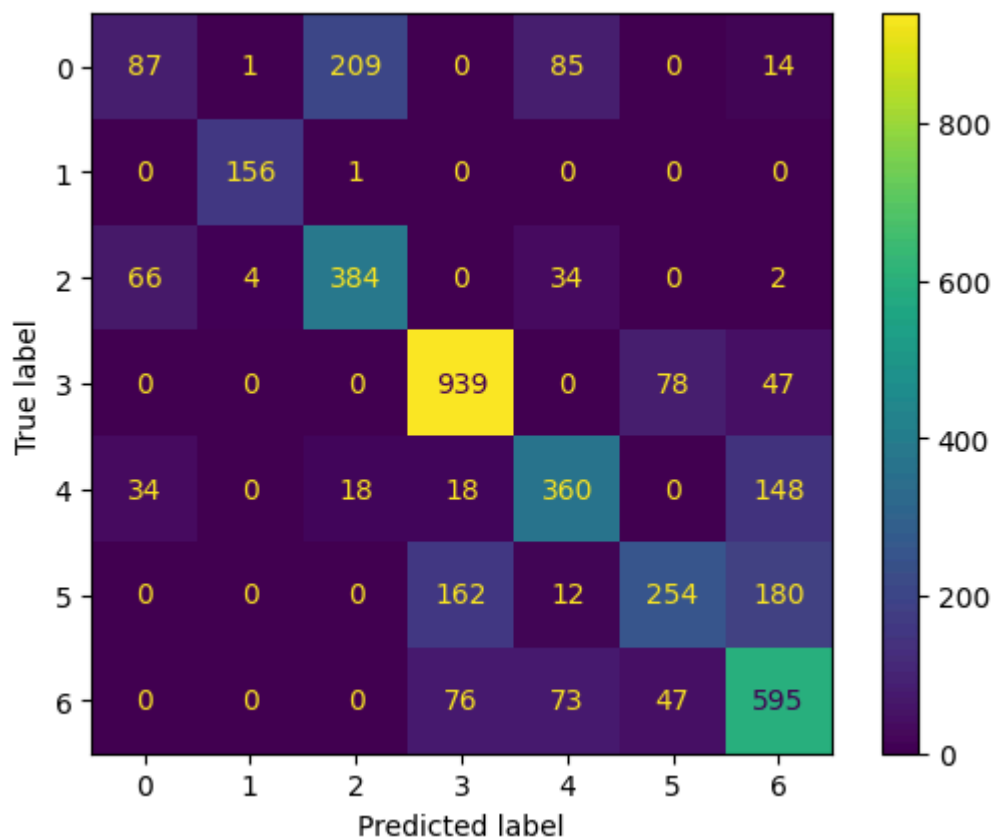
K\_value 25

avg\_accuracy train : 0.7016491142134051

avg\_accuracy : 0.6793207608784391

avg\_err : 0.32067923912156093

<Figure size 2000x800 with 0 Axes>



recall\_score : 0.6677444904431725

precision Score : 0.6806547957756115

f1\_score : 0.6605295744189509

log loss : 1.1395065900992185

log loss dummy : 1.8340319962763019

\*\*\*\*\*  
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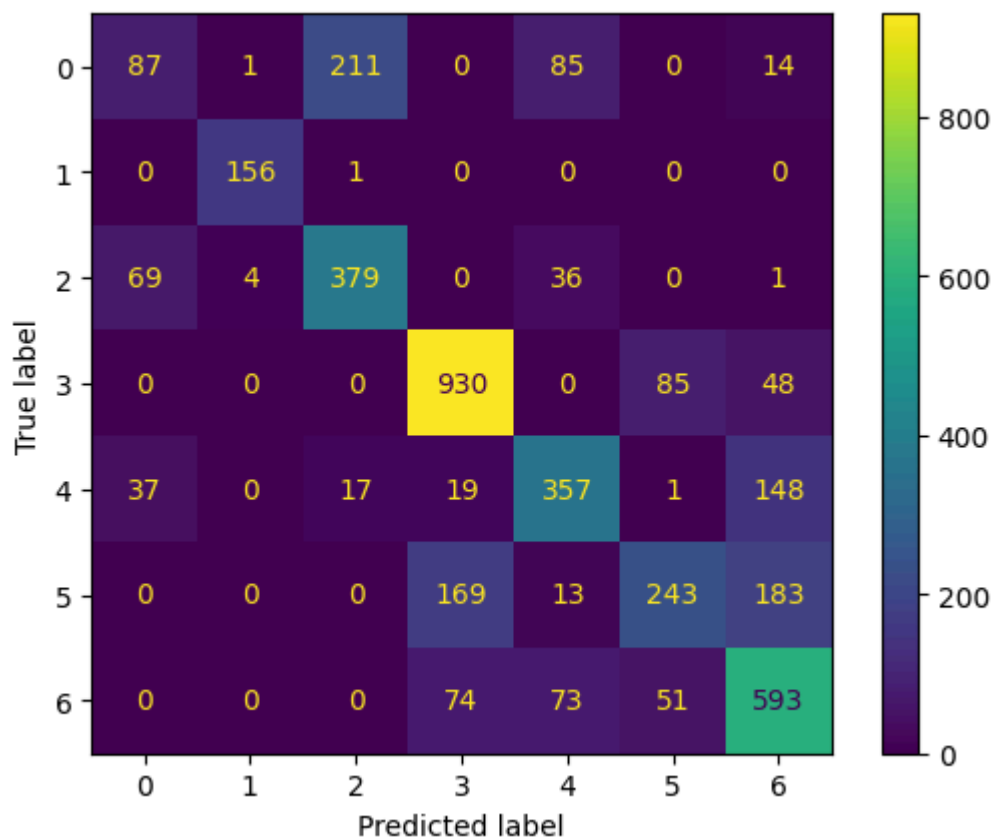
K\_value 27

avg\_accuracy train : 0.694383214956323

avg\_accuracy : 0.6720548616213567

avg\_err : 0.3279451383786432

<Figure size 2000x800 with 0 Axes>



recall\_score : 0.6612964468923967

precision Score : 0.6714308701403982

f1\_score : 0.653685021143487

log loss : 1.108588442932277

log loss dummy : 1.8340319962763019

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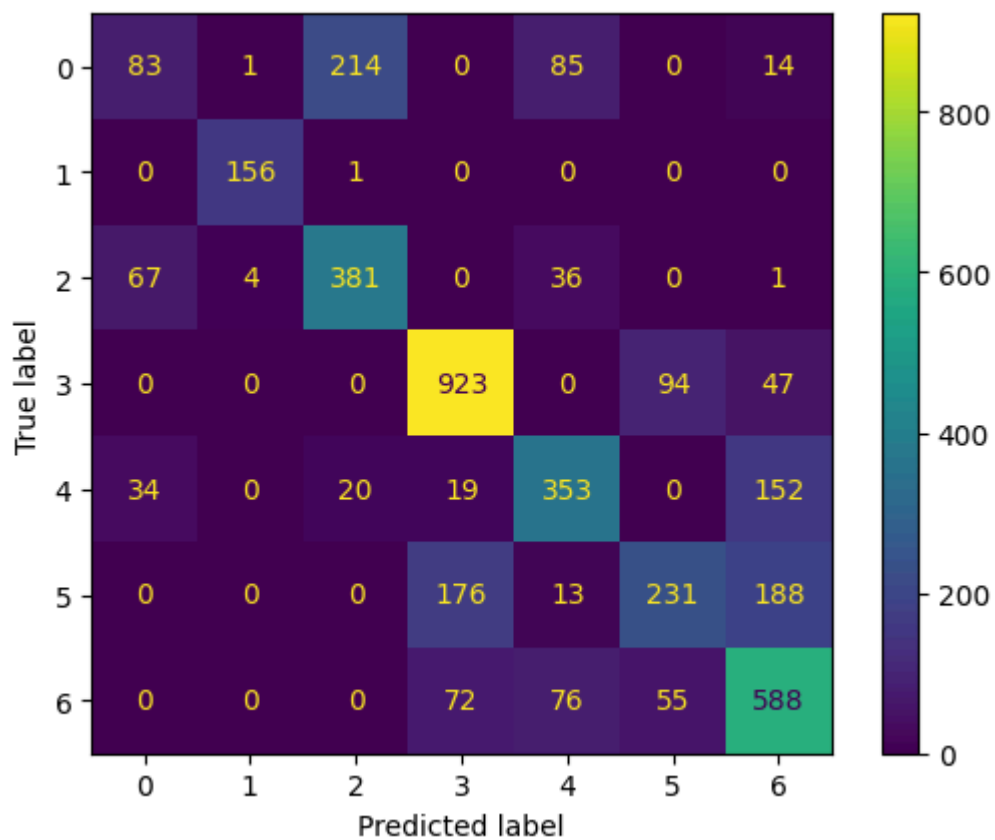
K\_value 29

avg\_accuracy train : 0.6899338721528289

avg\_accuracy : 0.6648706016817699

avg\_err : 0.33512939831823

<Figure size 2000x800 with 0 Axes>



recall\_score : 0.6549915090368369

precision Score : 0.6636007741162344

f1\_score : 0.6461978024475789

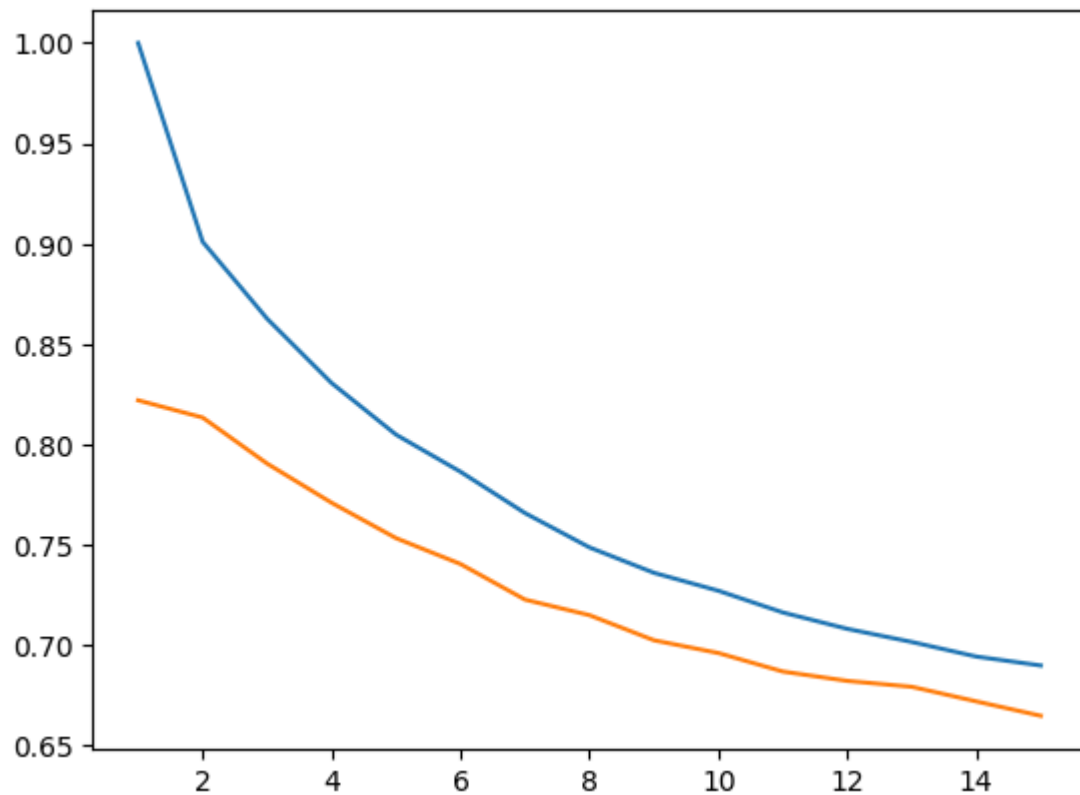
log loss : 1.095352221114359

log loss dummy : 1.8340319962763019

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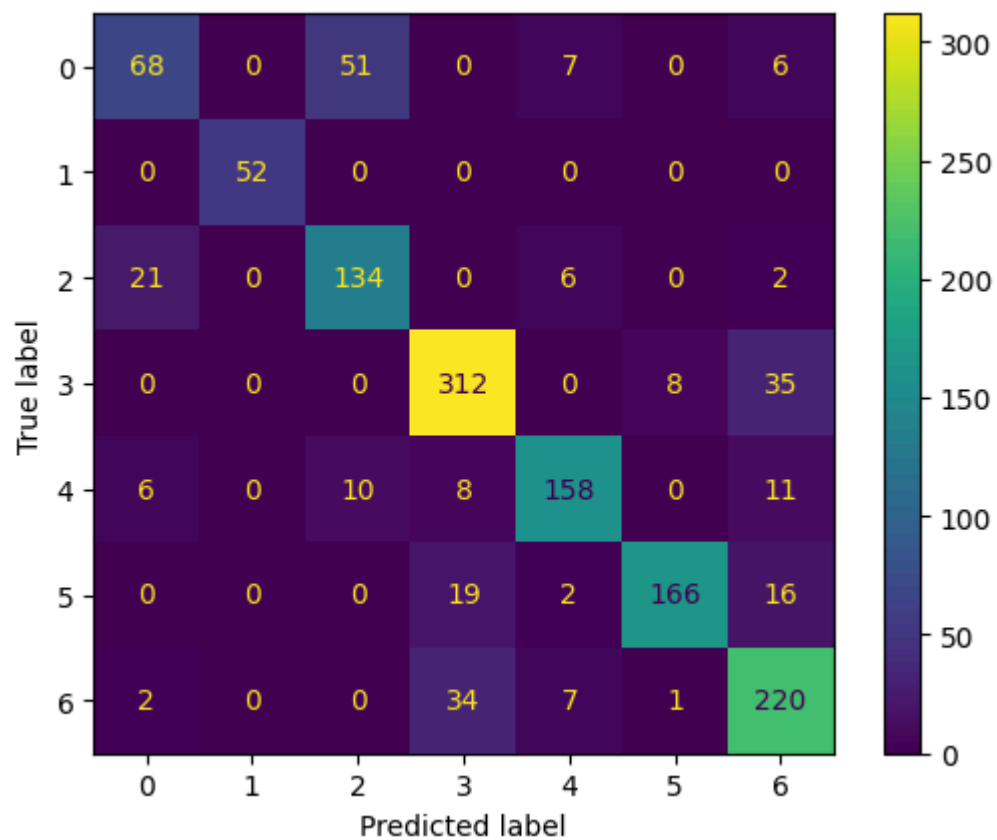
In [36]: k=range(1,16)

In [37]: plt.plot(k,avg\_training\_accuracy)  
plt.plot(k,avg\_accuracy)  
plt.show()



```
In [39]: knn=KNeighborsClassifier(n_neighbors=3)
model=knn.fit(x_trainf,y_trainf)
predicted=model.predict(x_test)
print("accuracy score :",accuracy_score(y_test,predicted))
print("")
cm=ConfusionMatrixDisplay(confusion_matrix(y_test,predicted))
cm.plot()
plt.show()
print("")
print("precision_score",np.mean(precision_score(y_test,predicted,average=None)))
print("")
print("recall score",np.mean(recall_score(y_test,predicted,average=None)))
print("")
print("f1 score",np.mean(f1_score(y_test,predicted,average=None)))
```

accuracy score : 0.8149779735682819



precision\_score 0.8299487767177541

recall score 0.8122615453401051

f1 score 0.8170497662281592

In [40]: !pip install "nbconvert[webpdf]"

Requirement already satisfied: nbconvert[webpdf] in c:\users\pavan\anaconda3\envs\gpavan\lib\site-packages (7.11.0)

Requirement already satisfied: beautifulsoup4 in c:\users\pavan\anaconda3\envs\gpavan\lib\site-packages (from nbconvert[webpdf]) (4.12.2)

Requirement already satisfied: bleach!=5.0.0 in c:\users\pavan\anaconda3\envs\gpavan\lib\site-packages (from nbconvert[webpdf]) (6.1.0)

Requirement already satisfied: defusedxml in c:\users\pavan\anaconda3\envs\gpavan\lib\site-packages (from nbconvert[webpdf]) (0.7.1)

Requirement already satisfied: Jinja2>=3.0 in c:\users\pavan\anaconda3\envs\gpavan\lib\site-packages (from nbconvert[webpdf]) (3.1.2)

Requirement already satisfied: jupyter-core>=4.7 in c:\users\pavan\anaconda3\envs\gpavan\lib\site-packages (from nbconvert[webpdf]) (5.5.0)

Requirement already satisfied: jupyterlab-pygments in c:\users\pavan\anaconda3\envs\gpavan\lib\site-packages (from nbconvert[webpdf]) (0.2.2)

Requirement already satisfied: MarkupSafe>=2.0 in c:\users\pavan\anaconda3\envs\gpavan\lib\site-packages (from nbconvert[webpdf]) (2.1.3)

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Requirement already satisfied: nbclient>=0.5.0 in c:\users\pavan\anaconda3\envs\gpavan\lib\site-packages (from nbconvert[webpdf]) (0.9.0)

Requirement already satisfied: nbformat>=5.7 in c:\users\pavan\anaconda3\envs\gpavan\lib\site-packages (from nbconvert[webpdf]) (5.9.2)

Requirement already satisfied: packaging in c:\users\pavan\anaconda3\envs\gpavan\lib\site-packages (from nbconvert[webpdf]) (23.2)

Requirement already satisfied: pandocfilters>=1.4.1 in c:\users\pavan\anaconda3\envs\gpavan\lib\site-packages (from nbconvert[webpdf]) (1.5.0)

Requirement already satisfied: pygments>=2.4.1 in c:\users\pavan\anaconda3\envs\gpavan\lib\site-packages (from nbconvert[webpdf]) (2.16.1)

Requirement already satisfied: tinycss2 in c:\users\pavan\anaconda3\envs\gpavan\lib\site-packages (from nbconvert[webpdf]) (1.2.1)

Requirement already satisfied: traitlets>=5.1 in c:\users\pavan\anaconda3\envs\gpavan\lib\site-packages (from nbconvert[webpdf]) (5.13.0)

Collecting playwright (from nbconvert[webpdf])

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Requirement already satisfied: six>=1.9.0 in c:\users\pavan\anaconda3\envs\gpavan\lib\site-packages (from bleach!=5.0.0->nbconvert[webpdf]) (1.16.0)

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Requirement already satisfied: pywin32>=300 in c:\users\pavan\anaconda3\envs\gpavan\lib\site-packages (from jupyter-core>=4.7->nbconvert[webpdf]) (306)

Requirement already satisfied: jupyter-client>=6.1.12 in c:\users\pavan\anaconda3\envs\gpavan\lib\site-packages (from nbclient>=0.5.0->nbconvert[webpdf]) (8.6.0)

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Collecting pyee==11.0.1 (from playwright->nbconvert[webpdf])

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Collecting typing-extensions (from pyee==11.0.1->playwright->nbconvert[webpdf])

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----- 29.4/29.4 MB 3.9 MB/s eta 0:00:01
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```

Downloading greenlet-3.0.3-cp312-cp312-win\_amd64.whl (293 kB)

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----- 0.0/293.6 kB ? eta -:--:--
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----- 286.7/293.6 kB 8.6 MB/s eta 0:00:01
----- 293.6/293.6 kB 4.5 MB/s eta 0:00:00
Downloading pyee-11.0.1-py3-none-any.whl (15 kB)
Downloading typing_extensions-4.10.0-py3-none-any.whl (33 kB)
Installing collected packages: typing-extensions, greenlet, pyee, playwright
Successfully installed greenlet-3.0.3 playwright-1.42.0 pyee-11.0.1 typing-extension
s-4.10.0
```

In [42]: `!playwright install chromium`

Downloading Chromium 123.0.6312.4 (playwright build v1105) from <https://playwright.azureedge.net/builds/chromium/1105/chromium-win64.zip>

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| 10% of 122.2 MiB
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| 20% of 122.2 MiB
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| 100% of 1
22.2 MiB
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Chromium 123.0.6312.4 (playwright build v1105) downloaded to C:\Users\pavan\AppData\Local\ms-playwright\chromium-1105

Downloading FFMPEG playwright build v1009 from <https://playwright.azureedge.net/builds/ffmpeg/1009/ffmpeg-win64.zip>

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| 10% of 1.4 MiB
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| 20% of 1.4 MiB
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| 30% of 1.4 MiB
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In [ ]: