Dataset 2 kpca+lda

December 30, 2022

[ ]:
```
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.utils import resample
from sklearn.preprocessing  import  scale
from sklearn.decomposition  import PCA
from sklearn import metrics

from sklearn.metrics import ConfusionMatrixDisplay
from sklearn.model_selection import validation_curve
from sklearn.model_selection import KFold
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import GridSearchCV
import matplotlib.pyplot as plt
import matplotlib.colors as colors
import os
```

[ ]:
```
csv0= pd.read_csv("0.csv")
csv1= pd.read_csv("1.csv")
csv2= pd.read_csv("2.csv")
csv3= pd.read_csv("3.csv")
```

[ ]:
```
allFiles=['0.csv', '1.csv', '2.csv','3.csv']
list = []
for file in allFiles:
    read = pd.read_csv(file, header = None)
    list.append(read)
data = pd.concat(list)
```

[ ]:
```
data.info
```

[ ]:
```
<bound method DataFrame.info of          0    1    2    3     4     5      6
7     8    9   …    55  \
0     26.0  4.0  5.0  8.0  -1.0 -13.0 -109.0 -66.0  -9.0  2.0  … -28.0
1    -47.0 -6.0 -5.0 -7.0  13.0  -1.0   35.0 -10.0  10.0 -4.0  … -25.0
2    -19.0 -8.0 -8.0 -8.0 -21.0  -6.0  -79.0  12.0   0.0  5.0  … -83.0
3      2.0  3.0  0.0  2.0   0.0  22.0  106.0 -14.0 -16.0 -2.0  … -38.0
```

```
4      6.0  0.0  0.0 -2.0 -14.0  10.0  -51.0   5.0   7.0  0.0  …  38.0
…     …   …   …   …    …    …     …    …    …   …   …    …
2917  -3.0 -1.0 -1.0 -1.0 -28.0  20.0    5.0   0.0  -5.0  0.0  …  -3.0
2918 -13.0 -5.0 -4.0 -3.0  -4.0 -24.0  -10.0  -8.0  20.0  9.0  …   6.0
2919  -1.0 -3.0 -1.0  1.0  30.0  38.0   -1.0  36.0 -10.0  1.0  …  14.0
2920   1.0  4.0  4.0  5.0   9.0 -10.0    4.0   1.0  -2.0 -1.0  … -16.0
2921  -2.0  4.0  2.0 -4.0  12.0   3.0   -2.0   9.0  -8.0 -2.0  …   2.0

        56   57   58   59    60    61     62    63  64
0     61.0  4.0  8.0  5.0   4.0  -7.0  -59.0  16.0   0
1     47.0  6.0  6.0  5.0  13.0  21.0  111.0  15.0   0
2      7.0  7.0  1.0 -8.0   7.0  21.0  114.0  48.0   0
3    -11.0  4.0  7.0 11.0  33.0  39.0  119.0  43.0   0
4    -35.0 -8.0  2.0  6.0 -13.0 -24.0 -112.0 -69.0   0
…     …   …   …    …    …    …     …    …  ..
2917   1.0  4.0  3.0  4.0 -51.0 -49.0    5.0  -9.0   3
2918  -3.0 -3.0 -3.0 -5.0  -4.0 -45.0  -12.0 -15.0   3
2919  -8.0 -4.0 -4.0 -4.0 -21.0 -29.0   -5.0   0.0   3
2920  -3.0  0.0 -3.0 -5.0 -36.0 -90.0    3.0   5.0   3
2921   1.0  0.0 -1.0 -2.0 -30.0  64.0   11.0   5.0   3

[11678 rows x 65 columns]>
```

[ ]:
```python
data.isnull().sum().head
```

[ ]:
```
<bound method NDFrame.head of 0     0
1     0
2     0
3     0
4     0
     ..
60    0
61    0
62    0
63    0
64    0
Length: 65, dtype: int64>
```

[ ]:
```python
order= data[64].unique()
print(order)
```

```
[0 1 2 3]
```

[ ]:
```python
data.head()
```

[ ]:
```
     0    1    2    3    4     5      6     7     8    9  …    55    56  \
0  26.0  4.0  5.0  8.0  -1.0 -13.0 -109.0 -66.0  -9.0  2.0  … -28.0  61.0
1 -47.0 -6.0 -5.0 -7.0  13.0  -1.0   35.0 -10.0  10.0 -4.0  … -25.0  47.0
```

```
2 -19.0 -8.0 -8.0 -8.0 -21.0  -6.0  -79.0  12.0   0.0  5.0  … -83.0   7.0
3   2.0  3.0  0.0  2.0   0.0  22.0  106.0 -14.0 -16.0 -2.0  … -38.0 -11.0
4   6.0  0.0  0.0 -2.0 -14.0  10.0  -51.0   5.0   7.0  0.0  …  38.0 -35.0

    57   58   59   60   61    62   63  64
0  4.0  8.0  5.0  4.0 -7.0 -59.0 16.0   0
1  6.0  6.0  5.0 13.0 21.0 111.0 15.0   0
2  7.0  1.0 -8.0  7.0 21.0 114.0 48.0   0
3  4.0  7.0 11.0 33.0 39.0 119.0 43.0   0
4 -8.0  2.0  6.0 -13.0 -24.0 -112.0 -69.0   0

[5 rows x 65 columns]
```

[ ]:
```
y = data[64]
X= data.drop(columns=64)
```

[ ]:
```
data[64].value_counts().sort_values(ascending=False)
```

[ ]:
```
2    2943
3    2922
0    2910
1    2903
Name: 64, dtype: int64
```

[ ]:
```
X.head
```

[ ]:
```
<bound method NDFrame.head of          0    1    2    3     4     5      6     7
8    9    …      54  \
0     26.0  4.0  5.0  8.0  -1.0 -13.0 -109.0 -66.0  -9.0  2.0  …   21.0
1    -47.0 -6.0 -5.0 -7.0  13.0  -1.0   35.0 -10.0  10.0 -4.0  … -105.0
2    -19.0 -8.0 -8.0 -8.0 -21.0  -6.0  -79.0  12.0   0.0  5.0  … -128.0
3      2.0  3.0  0.0  2.0   0.0  22.0  106.0 -14.0 -16.0 -2.0  …  -54.0
4      6.0  0.0  0.0 -2.0 -14.0  10.0  -51.0   5.0   7.0  0.0  …   60.0
…      …    …    …    …     …     …      …     …     …    …  …     …
2917  -3.0 -1.0 -1.0 -1.0 -28.0  20.0    5.0   0.0  -5.0  0.0  …   -3.0
2918 -13.0 -5.0 -4.0 -3.0  -4.0 -24.0  -10.0  -8.0  20.0  9.0  …    5.0
2919  -1.0 -3.0 -1.0  1.0  30.0  38.0   -1.0  36.0 -10.0  1.0  …   12.0
2920   1.0  4.0  4.0  5.0   9.0 -10.0    4.0   1.0  -2.0 -1.0  …   -2.0
2921  -2.0  4.0  2.0 -4.0  12.0   3.0   -2.0   9.0  -8.0 -2.0  …  -10.0

        55    56   57   58   59    60    61     62    63
0    -28.0  61.0  4.0  8.0  5.0   4.0  -7.0  -59.0  16.0
1    -25.0  47.0  6.0  6.0  5.0  13.0  21.0  111.0  15.0
2    -83.0   7.0  7.0  1.0 -8.0   7.0  21.0  114.0  48.0
3    -38.0 -11.0  4.0  7.0 11.0  33.0  39.0  119.0  43.0
4     38.0 -35.0 -8.0  2.0  6.0 -13.0 -24.0 -112.0 -69.0
…      …     …    …    …    …     …     …      …     …
```

```
2917   -3.0   1.0  4.0  3.0   4.0 -51.0 -49.0   5.0  -9.0
2918    6.0  -3.0 -3.0 -3.0  -5.0  -4.0 -45.0 -12.0 -15.0
2919   14.0  -8.0 -4.0 -4.0  -4.0 -21.0 -29.0  -5.0   0.0
2920  -16.0  -3.0  0.0 -3.0  -5.0 -36.0 -90.0   3.0   5.0
2921    2.0   1.0  0.0 -1.0  -2.0 -30.0  64.0  11.0   5.0

[11678 rows x 64 columns]>
```

[ ]:
```
X.describe()
```

[ ]:
```
                  0             1             2             3             4  \
count  11678.000000  11678.000000  11678.000000  11678.000000  11678.000000
mean      -0.520380     -0.726837     -0.739082     -0.729748     -0.159103
std       18.566709     11.766878      4.989944      7.441675     17.850402
min     -116.000000   -104.000000    -33.000000    -75.000000   -121.000000
25%       -9.000000     -4.000000     -3.000000     -4.000000    -10.000000
50%       -1.000000     -1.000000     -1.000000     -1.000000      0.000000
75%        7.000000      3.000000      2.000000      3.000000     10.000000
max      111.000000     90.000000     34.000000     55.000000     92.000000

                  5             6             7             8             9  \
count  11678.000000  11678.000000  11678.000000  11678.000000  11678.000000
mean      -0.554890     -1.272649     -0.661843     -0.665953     -0.654222
std       25.809528     25.089972     15.408896     18.123854     11.841260
min     -122.000000   -128.000000   -128.000000   -110.000000   -128.000000
25%      -15.000000     -6.000000     -8.000000     -9.000000     -4.000000
50%       -1.000000     -1.000000     -1.000000     -1.000000     -1.000000
75%       13.000000      4.000000      6.000000      6.000000      3.000000
max      127.000000    127.000000    126.000000    127.000000    106.000000

       …            54            55            56            57  \
count  …  11678.000000  11678.000000  11678.000000  11678.000000
mean   …     -1.622452     -0.932694     -0.836958     -0.740623
std    …     25.293001     15.158993     18.204465     12.005206
min    …   -128.000000   -128.000000   -116.000000   -128.000000
25%    …     -6.000000     -8.000000     -9.000000     -4.000000
50%    …     -1.000000     -1.000000     -1.000000     -1.000000
75%    …      3.000000      6.000000      6.000000      3.000000
max    …    127.000000    114.000000    127.000000    105.000000

                 58            59            60            61            62  \
count  11678.000000  11678.000000  11678.000000  11678.000000  11678.000000
mean      -0.768710     -0.705343     -0.146686     -0.374807     -1.449306
std        4.969758      7.384410     17.841479     25.551082     25.259736
min      -46.000000    -74.000000   -103.000000   -128.000000   -128.000000
25%       -3.000000     -4.000000    -10.000000    -14.000000     -6.000000
50%       -1.000000     -1.000000      0.000000     -1.000000     -1.000000
```

```
75%        2.000000      3.000000     10.000000     13.000000      3.000000
max       29.000000     51.000000    110.000000    127.000000    127.000000

                 63
count  11678.000000
mean      -0.609094
std       15.530091
min     -124.000000
25%       -8.000000
50%       -1.000000
75%        6.000000
max      127.000000

[8 rows x 64 columns]
```

[ ]:
```python
X_train, X_test, y_train, y_test = train_test_split(X,y,random_state=40)
```

[ ]:
```python
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
X_scaled_train = scaler.fit_transform(X_train)
X_scaled_test = scaler.transform(X_test)
X_scaled_train =pd.DataFrame(X_scaled_train)
X_scaled_test=pd.DataFrame(X_scaled_test)
```

[ ]:
```python
X_scaled_test.head()
```

[ ]:
```
          0         1         2         3         4         5         6   \
0 -0.897962  0.223606  2.356874 -0.158795  0.349809 -0.015352  2.128207
1  0.026488 -0.374961 -1.253112 -0.556220  1.577761  0.448405 -0.070962
2 -1.441756 -0.118432  0.952990  0.503581 -0.878143 -0.672341 -0.030977
3  0.298385 -0.118432  0.150771 -0.026320  0.461441  1.298627 -0.030977
4  0.515903 -0.032923 -2.255886 -0.821171 -0.319983 -0.749634 -0.230902

          7         8         9   …         54        55        56        57  \
0 -0.413754  0.313513 -0.624990  … -1.480377 -0.196189  0.214258 -0.185965
1  1.075626  0.368848 -0.027987  …  0.055997 -0.196189  3.193393  2.106044
2 -0.478510  0.866868 -0.113273  …  0.055997 -0.196189 -0.282265  0.153592
3 -0.219488 -0.239842 -0.198559  …  0.055997 -0.065461 -0.613280 -0.525522
4 -0.413754  0.756197  2.104165  …  0.016602  0.261359  0.324596 -3.411756

          58        59        60        61        62        63
0   0.566839 -0.430394  1.484974  0.090064  2.208949  0.618095
1   2.575162  0.238175  0.061796  1.114511  0.298683  1.899496
2   0.366007  0.238175 -0.621330 -0.579766  0.219089  0.489955
3  -0.236491 -0.430394 -1.361383 -1.210194  0.020103 -0.342955
4  -0.236491  0.505602  0.346431  0.287073  0.219089 -0.150745
```

[5 rows x 64 columns]

[ ]:
```
cov_matrix = X_scaled_train.cov()
eigen_vals, eigen_vecs =np.linalg.eigh(cov_matrix)
np.sum(eigen_vals)
```

[ ]: 64.00730843896312

[ ]:
```
A = X_scaled_train.cov()
x = eigen_vecs[:, 0] # First eigenvector
LHS = np.dot(A, x) # Ax
print(LHS)
```

```
[-0.00071933 -0.00117752  0.00495437 -0.00958084  0.0111963  -0.00681954
  0.00117527  0.00129149 -0.00051435 -0.00161002  0.00965168 -0.01595066
  0.02074834 -0.01339627  0.00195487  0.0013108   0.00053154 -0.00184558
  0.01201653 -0.02024228  0.02896049 -0.01930371  0.00205734  0.00175303
  0.00042843 -0.00189969  0.01301459 -0.0214747   0.03104015 -0.02091013
  0.00225011  0.00144918  0.00082467 -0.00304437  0.01338423 -0.02178359
  0.03055792 -0.0214959   0.00311255  0.00147683  0.00170481 -0.00344283
  0.01287558 -0.01990288  0.02717143 -0.01865322  0.00176285  0.00090025
  0.00224643 -0.00370848  0.00940975 -0.01536319  0.01964771 -0.01506809
  0.00093975  0.00097418  0.00103895 -0.00270651  0.00552519 -0.00867789
  0.01036569 -0.00856539  0.00067139 -0.00021925]
```

[ ]:
```
lambda_eig = eigen_vals[0] # First eigenvalue
x = eigen_vecs[:, 0] # First eigenvector
RHS = lambda_eig * x #  x
print(RHS)
```

```
[-0.00071933 -0.00117752  0.00495437 -0.00958084  0.0111963  -0.00681954
  0.00117527  0.00129149 -0.00051435 -0.00161002  0.00965168 -0.01595066
  0.02074834 -0.01339627  0.00195487  0.0013108   0.00053154 -0.00184558
  0.01201653 -0.02024228  0.02896049 -0.01930371  0.00205734  0.00175303
  0.00042843 -0.00189969  0.01301459 -0.0214747   0.03104015 -0.02091013
  0.00225011  0.00144918  0.00082467 -0.00304437  0.01338423 -0.02178359
  0.03055792 -0.0214959   0.00311255  0.00147683  0.00170481 -0.00344283
  0.01287558 -0.01990288  0.02717143 -0.01865322  0.00176285  0.00090025
  0.00224643 -0.00370848  0.00940975 -0.01536319  0.01964771 -0.01506809
  0.00093975  0.00097418  0.00103895 -0.00270651  0.00552519 -0.00867789
  0.01036569 -0.00856539  0.00067139 -0.00021925]
```

[ ]:
```
explained_variance=[]

for i in sorted(eigen_vals,reverse=True):
  variance = (i / np.sum(eigen_vals))
  explained_variance.append(variance)
```

```
cumulative_variance_ratio = np.cumsum(explained_variance)*100
print(cumulative_variance_ratio)
```

```
[  4.70458409   9.05851929  13.01124542  16.91114022  20.66601573
  24.11699848  27.50135433  30.7106687   33.86599837  36.87929532
  39.78712524  42.46965224  45.08342903  47.65124562  50.15999691
  52.58691677  54.94842403  57.04380323  59.04692089  61.04374454
  62.97559477  64.837373    66.67903344  68.26566973  69.81758623
  71.33211173  72.74349853  74.10466444  75.43097003  76.65159236
  77.83110067  78.99758871  80.14028338  81.25562719  82.33970153
  83.40460512  84.42191333  85.41285184  86.37641944  87.33211569
  88.26160584  89.09448658  89.88205271  90.61091588  91.31954074
  92.0086025   92.68720904  93.35663384  93.98099591  94.5973542
  95.19775037  95.76188013  96.29341372  96.80876446  97.30090091
  97.7533043   98.14600186  98.50083692  98.84219798  99.14377836
  99.429229    99.65767636  99.84322373 100.        ]
```

[ ]:
```
print(explained_variance)
```

```
[0.047045840868900575, 0.04353935201222255, 0.03952726132573601,
0.038998947946944876, 0.03754875514786483, 0.03450982750431003,
0.03384355853166483, 0.0320931436554552, 0.031553296667674,
0.03013296958404461, 0.029078299182827613, 0.026825270020589445,
0.026137767889050735, 0.02567816584302076, 0.02508751295984726,
0.024269198595429805, 0.023615072576010455, 0.020953791964544076,
0.02003117661916, 0.019968236503696862, 0.01931850234868134,
0.018617782237923954, 0.01841660438951509, 0.015866362888087338,
0.015519164996488926, 0.015145255048816478, 0.014113867956005655,
0.013611659113954329, 0.013263055897155467, 0.012206223287504397,
0.011795083087986788, 0.01166488047421333, 0.011426946662708805,
0.01115343813489865, 0.010840743364865162, 0.01064903588829331,
0.010173082164622748, 0.009909385035477069, 0.009635676070379623,
0.009556962407438073, 0.009294901532381526, 0.008328807391888968,
0.007875661309277027, 0.007288631711811241, 0.0070862486286809405,
0.006890617590802156, 0.006786065419673662, 0.006694247940971714,
0.006243620736290022, 0.006163582918789114, 0.006003961685779088,
0.0056412975598951155, 0.005315335966438774, 0.005153507382075013,
0.0049213645119450195, 0.0045240338400346, 0.003926975591687665,
0.0035483506728697313, 0.0034136105161505117, 0.0030158038150721656,
0.0028545064578439873, 0.0022844735378660347, 0.0018554737128098162,
0.0015677627158603381]
```

[ ]:
```
explained_variance_ratio=[]
for i in range(64):
    e=explained_variance[i]/np.sum(explained_variance)
    explained_variance_ratio.append(e)
print(explained_variance_ratio)
```

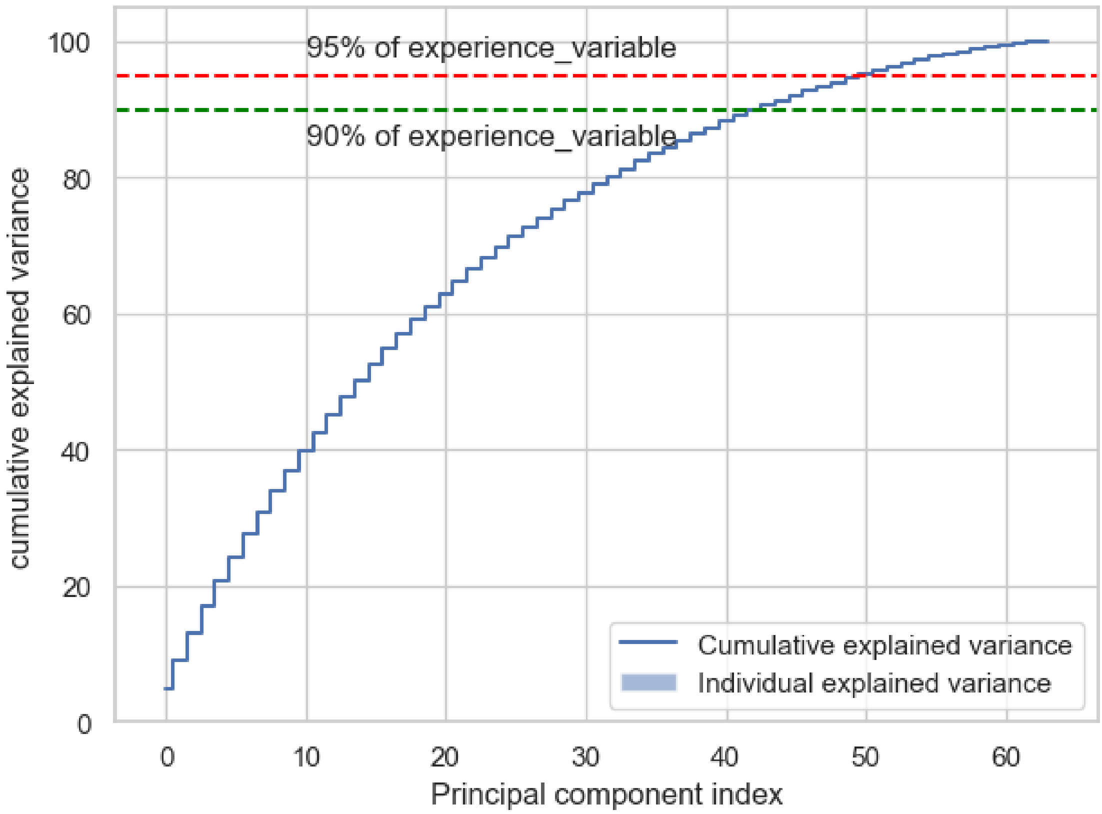
```
[0.047045840868900575, 0.04353935201222255, 0.03952726132573601,
```

```
0.038998947946944876, 0.03754875514786483, 0.03450982750431003,
0.03384355853166483, 0.03209314365545552, 0.0315532966667674,
0.03013296958404461, 0.029078299182827613, 0.026825270020589445,
0.026137767889050735, 0.02567816584302076, 0.02508751295984726,
0.024269198595429805, 0.023615072576010455, 0.020953791964544076,
0.020031176619161, 0.019968236503696862, 0.01931850234868134,
0.018617782237923954, 0.01841660438951509, 0.015866362888087338,
0.015519164996488926, 0.015145255048816478, 0.014113867956005655,
0.013611659113954329, 0.013263055897155467, 0.012206223287504397,
0.011795083087986788, 0.01166488047421333, 0.011426946662708805,
0.01115343813489865, 0.010840743364865162, 0.01064903588829331,
0.010173082164622748, 0.009909385035477069, 0.009635676070379623,
0.009556962407438073, 0.009294901532381526, 0.008328807391888968,
0.007875661309277027, 0.007288631711811241, 0.0070862486286809405,
0.006890617590802156, 0.006786065419673662, 0.006694247940971714,
0.006243620736290022, 0.006163582918789114, 0.006003961685779088,
0.0056412975598951155, 0.005315335966438774, 0.005153507382075013,
0.0049213645119450195, 0.0045240338400346, 0.003926975591687665,
0.0035483506728697313, 0.0034136105161505117, 0.0030158038150721656,
0.0028545064578439873, 0.0022844735378660347, 0.0018554737128098162,
0.0015677627158603381]
```

[ ]:
```python
cumulative_variance_ratio_df = pd.DataFrame(cumulative_variance_ratio)

len(cumulative_variance_ratio_df.loc[cumulative_variance_ratio_df[0] <= 91])
```

[ ]:
```
44
```

[ ]:
```python
plt.bar(range(0,len(explained_variance)), explained_variance, alpha=0.5,␣
 ↪align='center', label='Individual explained variance')
plt.step(range(0,len(cumulative_variance_ratio)), cumulative_variance_ratio,␣
 ↪where='mid',label='Cumulative explained variance')
plt.ylabel('Explained variance ratio')
plt.xlabel('Principal component index')
plt.legend(loc='best')
plt.axhline(y=95,c='red',linestyle='--')
plt.axhline(y=90,c='green',linestyle='--')
plt.ylabel('cumulative explained variance')
plt.annotate('95% of experience_variable',
            xy=(10, 98),fontsize=12)
plt.annotate('90% of experience_variable',
            xy=(10, 85),fontsize=12)
plt.tight_layout()
plt.show()
```



KPCA with RBF Kernel

```
[ ]: from sklearn.decomposition import KernelPCA
     import seaborn as sns
     kpca = KernelPCA(kernel='rbf', n_components=64)
     kpca=kpca.fit_transform(X_scaled_train)
     explained_variance=np.var(kpca, axis=0 )
```

```
[ ]: explained_variance_ratio=explained_variance/ np.sum(explained_variance)*100
     cumulative_variance_ratio=np.cumsum(explained_variance_ratio)
     kpca_df=pd.DataFrame()
     kpca_df['cumulative explained variance']= cumulative_variance_ratio
     kpca_df['explained_variance_ratio']= explained_variance_ratio
     display(kpca_df)
```

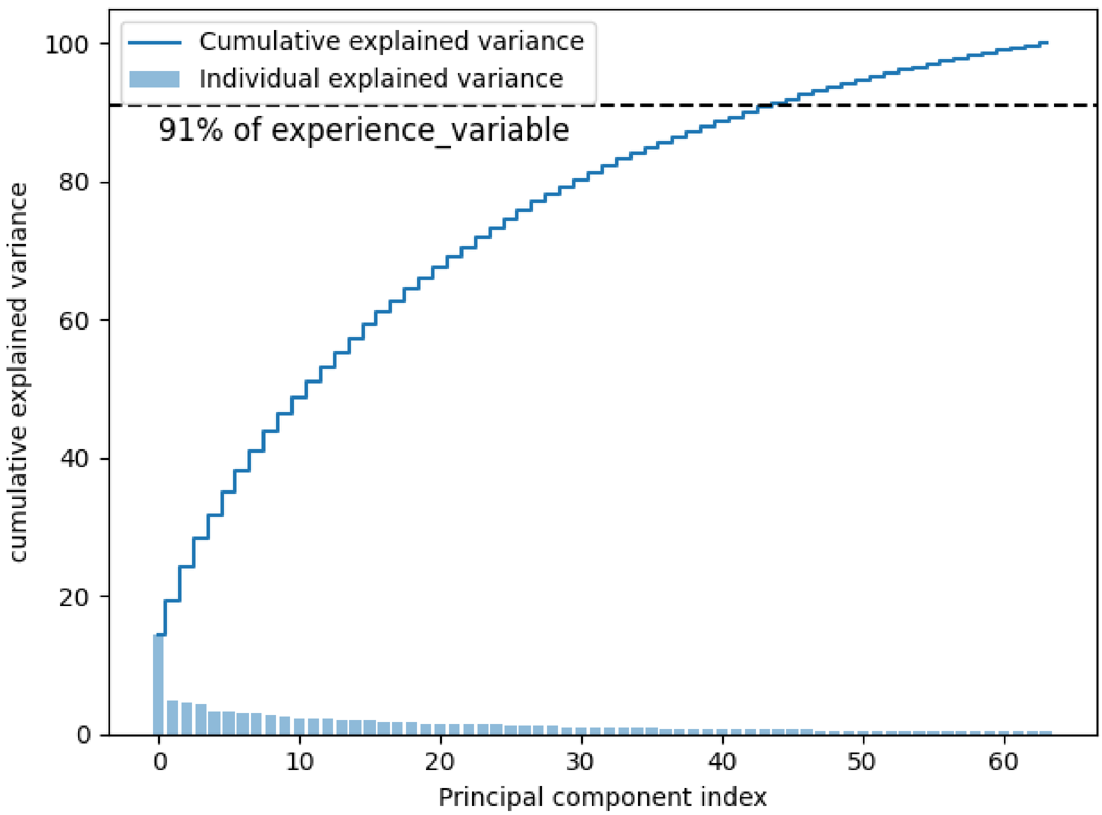
	cumulative explained variance	explained_variance_ratio
0	14.494873	14.494873
1	19.410752	4.915879
2	24.105188	4.694437
3	28.331324	4.226136
4	31.666812	3.335488
..	…	…

```
59                      98.591645                 0.385132
60                      98.975189                 0.383543
61                      99.336178                 0.360990
62                      99.671726                 0.335548
63                     100.000000                 0.328274

[64 rows x 2 columns]
```

[ ]:
```
cumulative_variance_ratio_df = pd.DataFrame(cumulative_variance_ratio)
len(cumulative_variance_ratio_df.loc[cumulative_variance_ratio_df[0] <= 91])
```

[ ]: 64

[ ]:
```
plt.bar(range(0,len(explained_variance_ratio)), explained_variance_ratio,␣
 ↪alpha=0.5, align='center', label='Individual explained variance')
plt.step(range(0,len(cumulative_variance_ratio)), cumulative_variance_ratio,␣
 ↪where='mid',label='Cumulative explained variance')
plt.xlabel('Principal component index')
plt.legend(loc='best')
plt.axhline(y=91,c='black',linestyle='--')
plt.ylabel('cumulative explained variance')
plt.annotate('91% of experience_variable',
            xy=(0, 86),fontsize=12)
plt.tight_layout()
plt.show()
```

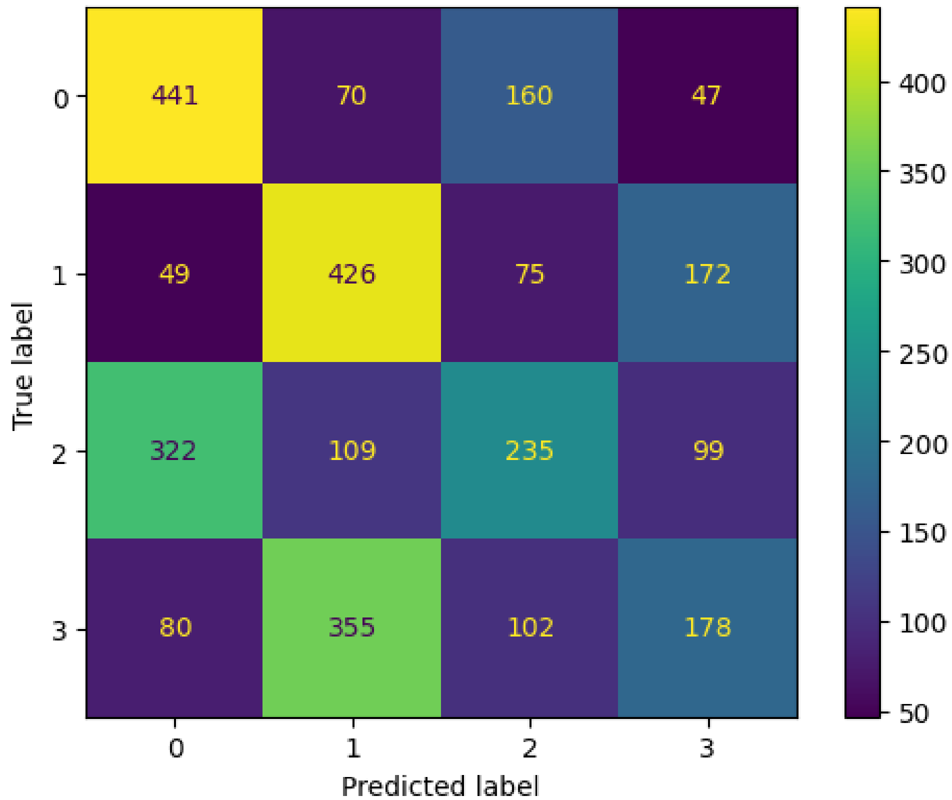



```
[ ]: from sklearn.decomposition import KernelPCA
Kernel_pca = KernelPCA(n_components = 44 ,kernel= "rbf",n_jobs=-1)# extracts 2␣
 ↪features, specify the kernel as rbf
X_train_kpca = Kernel_pca.fit_transform(X_scaled_train)
X_test_kpca= Kernel_pca.transform(X_scaled_test)

X_train_kpca=pd.DataFrame(X_train_kpca)
X_test_kpca=pd.DataFrame(X_test_kpca)
```

```
[ ]: linear_svm = SVC(kernel='linear')
linear_svm.fit(X_train_kpca, y_train)
y_pred_test = linear_svm.predict(X_test_kpca)
y_pred_train = linear_svm.predict(X_train_kpca)
print("Train accuracy:", metrics.accuracy_score(y_true=y_train,␣
 ↪y_pred=y_pred_train), "\n")
print("Test accuracy:", metrics.accuracy_score(y_true=y_test,␣
 ↪y_pred=y_pred_test), "\n")
ConfusionMatrixDisplay.from_predictions(y_test, y_pred_test)
plt.show()
```

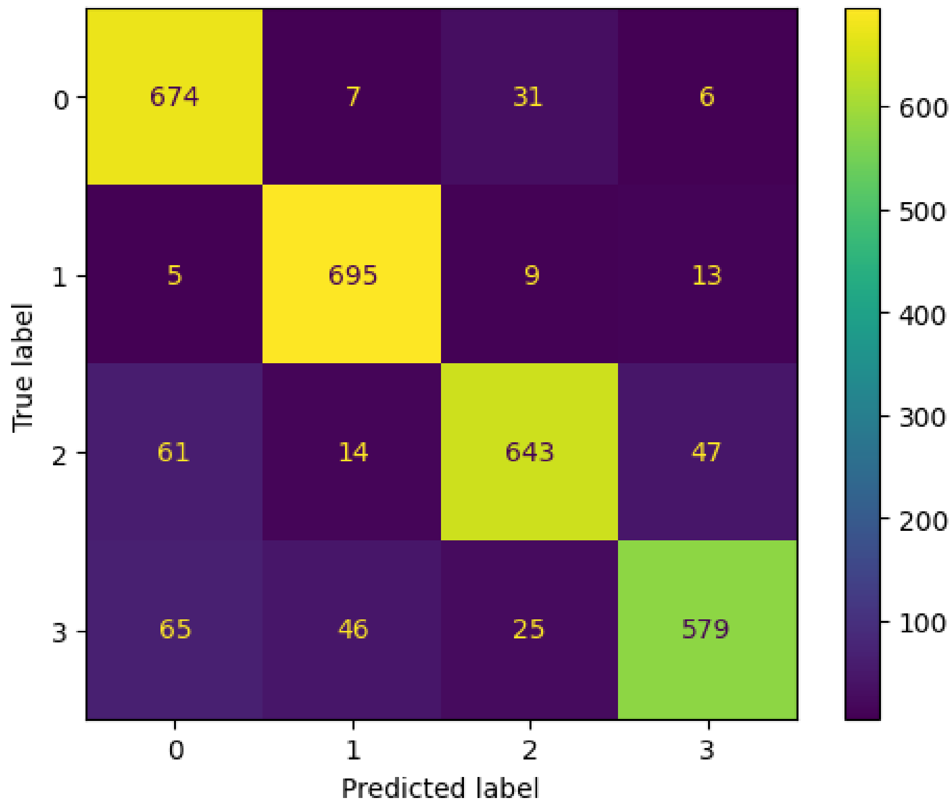
```
Train accuracy: 0.4443936971911395
```

```
Test accuracy: 0.4383561643835616
```



[ ]:
```
rbf_svm = SVC(kernel='rbf')
rbf_svm.fit(X_train_kpca, y_train)
y_pred_test = rbf_svm.predict(X_test_kpca)
y_pred_train = rbf_svm.predict(X_train_kpca)
print("Train accuracy:", metrics.accuracy_score(y_true=y_train,␣
 ↪y_pred=y_pred_train), "\n")
print("Test accuracy:", metrics.accuracy_score(y_true=y_test,␣
 ↪y_pred=y_pred_test), "\n")
ConfusionMatrixDisplay.from_predictions(y_test, y_pred_test)
plt.show()
```

```
Train accuracy: 0.9462205983101165

Test accuracy: 0.8873287671232877
```

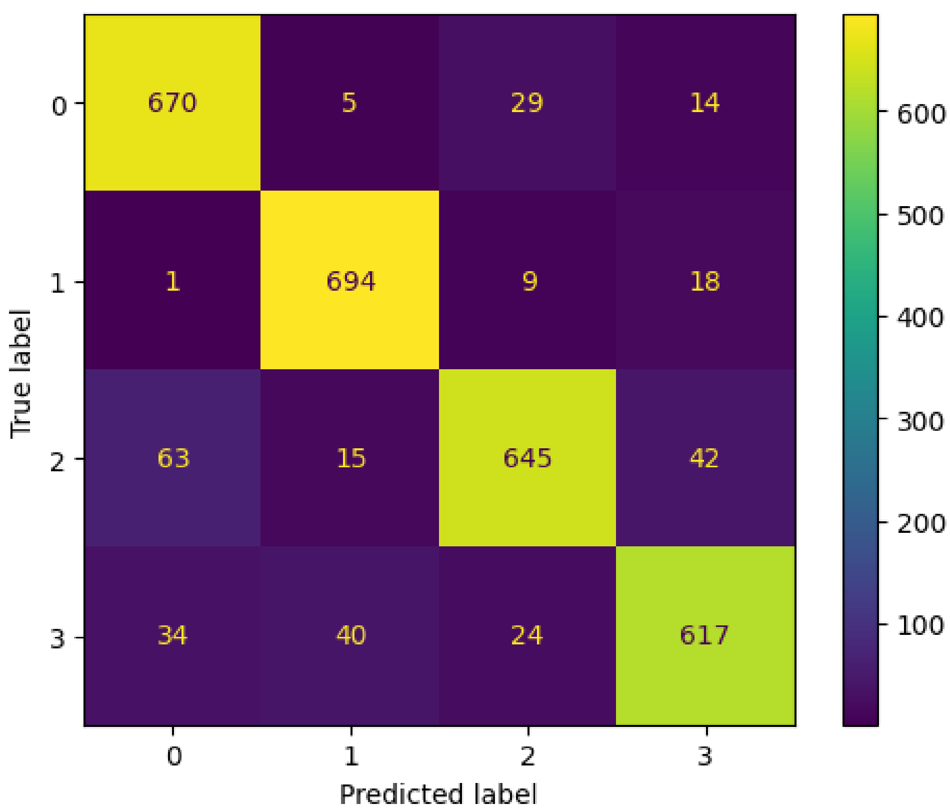


[ ]:
```
param_grid = [ {
    'C' :[4,6,10,20,25],
    "gamma" : ['scale',0.01,0.1,0.0001],
    'kernel' :['rbf']},
                ]

model = SVC(kernel="rbf")

optimal_parameters =GridSearchCV(
    model, param_grid,
    cv=5,
    scoring= 'accuracy',
    verbose=10,
    n_jobs= -5,
    return_train_score=True
)
optimal_parameters.fit(X_train_kpca,y_train)

print(optimal_parameters.best_params_)
print(optimal_parameters.best_score_)
```

```
Fitting 5 folds for each of 20 candidates, totalling 100 fits
{'C': 4, 'gamma': 'scale', 'kernel': 'rbf'}
0.8917556569109888
```

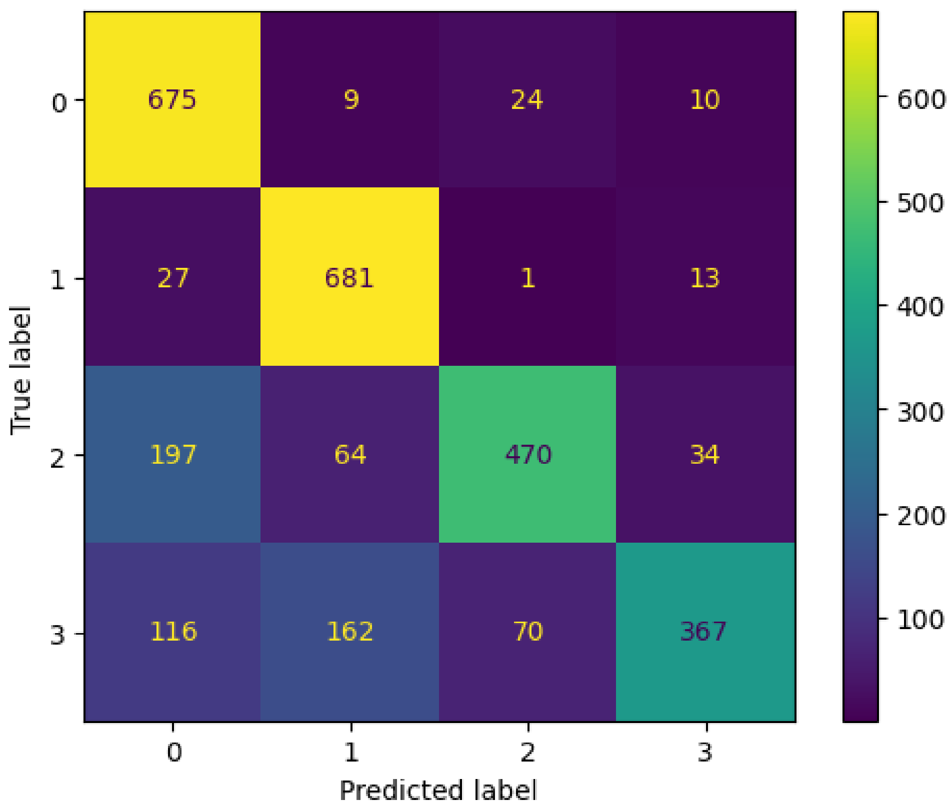
[ ]:
```python
rbf_svm_better = SVC(kernel='rbf',C = 25, gamma = 'scale')
rbf_svm_better.fit(X_train_kpca, y_train)
y_pred_test = rbf_svm_better.predict(X_test_kpca)
y_pred_train = rbf_svm_better.predict(X_train_kpca)
print("Train accuracy:", metrics.accuracy_score(y_true=y_train,␣
 ↪y_pred=y_pred_train), "\n")
print("Test accuracy:", metrics.accuracy_score(y_true=y_test,␣
 ↪y_pred=y_pred_test), "\n")
ConfusionMatrixDisplay.from_predictions(y_test, y_pred_test)
plt.show()
```

```
Train accuracy: 0.992235670244348

Test accuracy: 0.8993150684931507
```



[ ]:
```
from sklearn.neighbors import KNeighborsClassifier
knn_model =KNeighborsClassifier(n_neighbors=2)
knn_model.fit(X_train_kpca, y_train)
y_pred_test = knn_model.predict(X_test_kpca)
y_pred_train = knn_model.predict(X_train_kpca)
print("Train accuracy: ",metrics.accuracy_score(y_true=y_train,␣
 ↪y_pred=y_pred_train),"\n")
print("Test accuracy:", metrics.accuracy_score(y_true=y_test,␣
 ↪y_pred=y_pred_test), "\n")
ConfusionMatrixDisplay.from_predictions(y_test, y_pred_test)
plt.show()
```

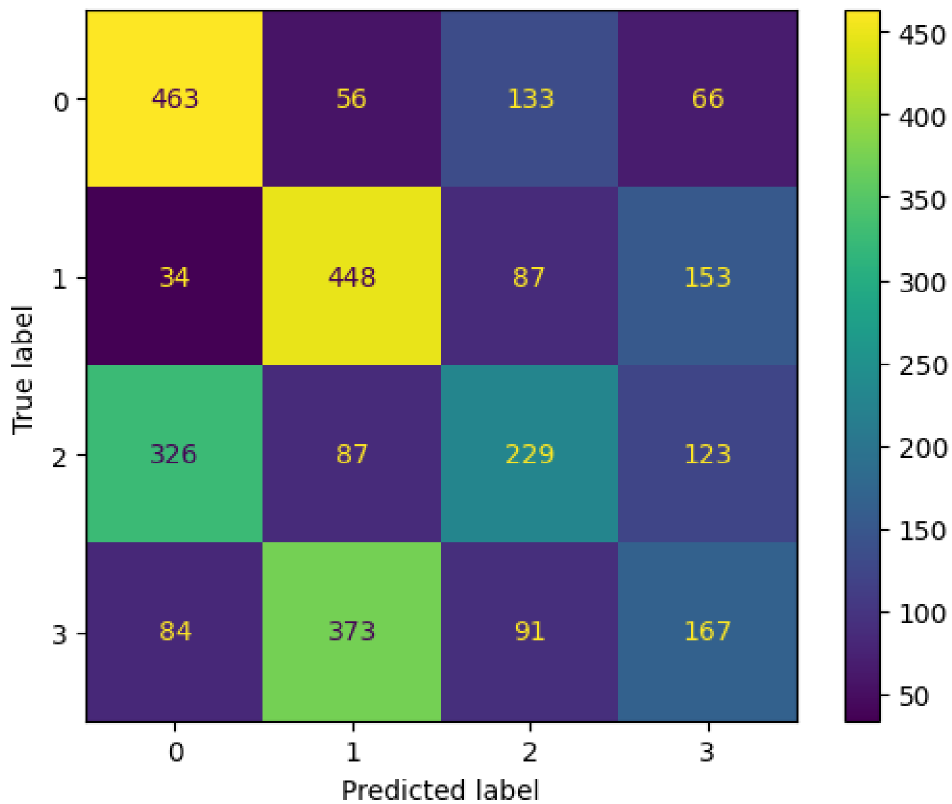
```
Train accuracy:  0.8619547841973053

Test accuracy: 0.751027397260274
```



[ ]:
```
from sklearn.neighbors import NearestCentroid

ncc_model = NearestCentroid()
ncc_model.fit(X_train_kpca, y_train)
```

```
y_pred_test = ncc_model.predict(X_test_kpca)
y_pred_train = ncc_model.predict(X_train_kpca)
print("Train accuracy: ",metrics.accuracy_score(y_true=y_train,␣
↪y_pred=y_pred_train),"\n")
print("Test accuracy:", metrics.accuracy_score(y_true=y_test,␣
↪y_pred=y_pred_test), "\n")
ConfusionMatrixDisplay.from_predictions(y_test, y_pred_test)
plt.show()
```

```
Train accuracy:  0.42943594427951587

Test accuracy: 0.4476027397260274
```



KPCA+LDA with RBF Kernel

[ ]:
```
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis as LDA

lda = LDA(n_components=None)
X_train_kpca_lda = lda.fit_transform(X_train_kpca, y_train)
```

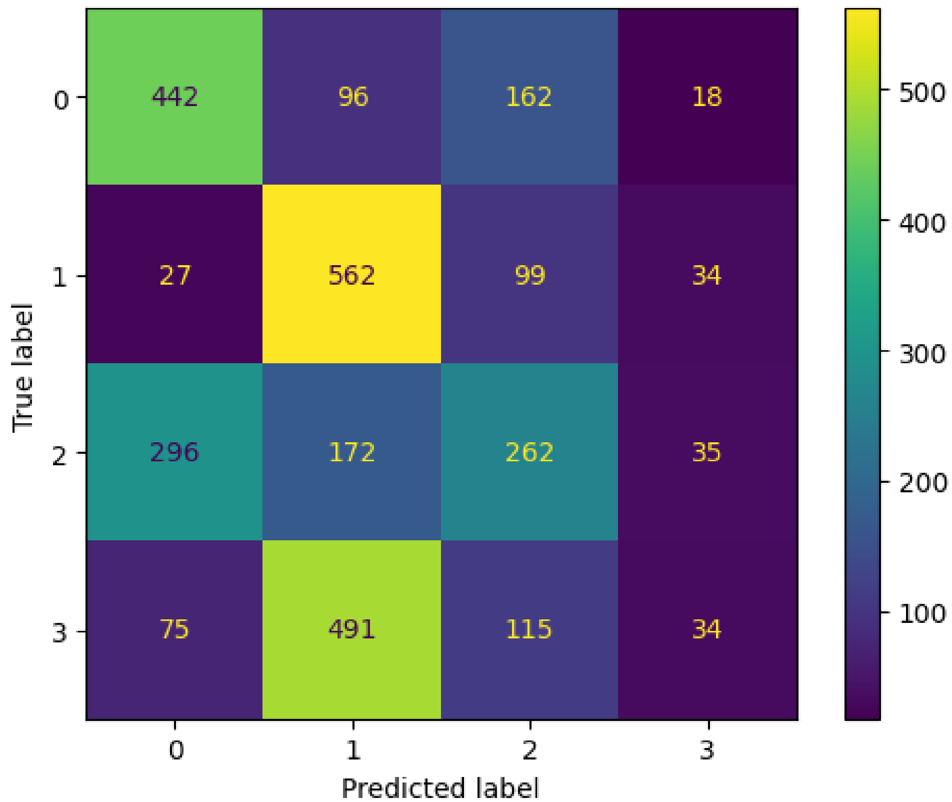
```
[ ]: # Set initial variance explained so far
total_variance = 0.0
# Set initial number of features
n_components = 0
# For the explained variance of each feature:
for explained_variance in lda.explained_variance_ratio_:
    # Add the explained variance to the total
    total_variance += explained_variance
    # Add one to the number of components
    n_components += 1

    # If we reach our goal level of explained variance
    if total_variance >= 0.91:
        break

# Return the number of components
print(n_components)
```

```
1
```

```
[ ]: lda = LDA(n_components=1)
X_train_kpca_lda = lda.fit_transform(X_train_kpca, y_train)
X_test_kpca_lda = lda.transform(X_test_kpca)
```

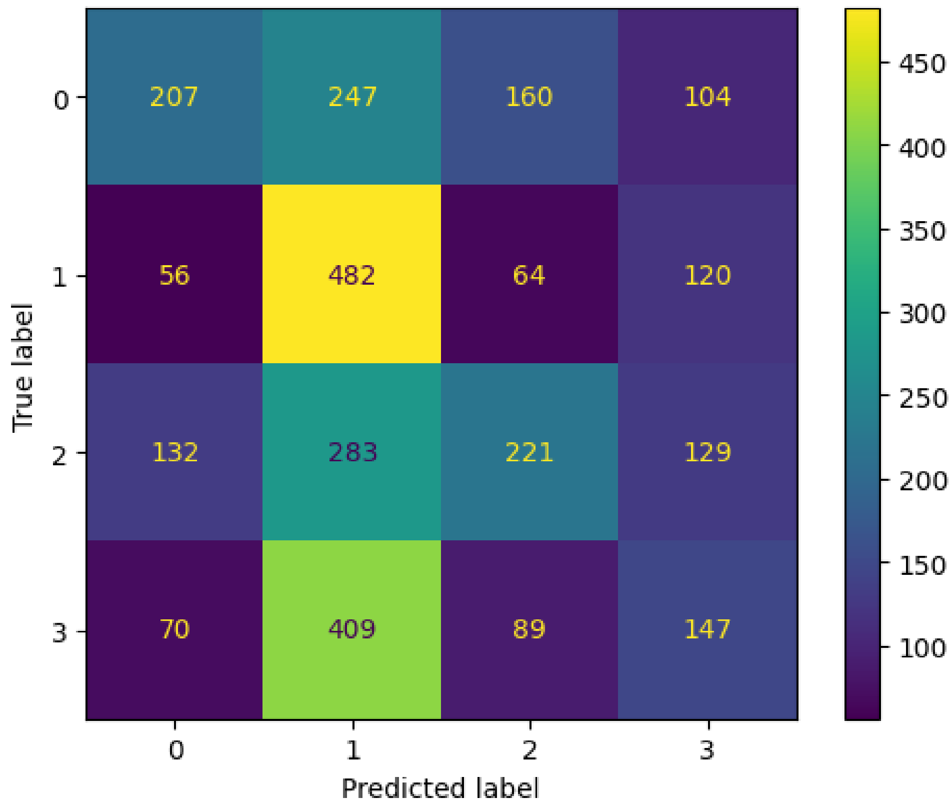
```
[ ]: linear_svm = SVC(kernel='linear')
linear_svm.fit(X_train_kpca_lda, y_train)
y_pred_test = linear_svm.predict(X_test_kpca_lda)
y_pred_train = linear_svm.predict(X_train_kpca_lda)
print("Train accuracy:", metrics.accuracy_score(y_true=y_train,␣
 ↪y_pred=y_pred_train), "\n")
print("Test accuracy:", metrics.accuracy_score(y_true=y_test,␣
 ↪y_pred=y_pred_test), "\n")
ConfusionMatrixDisplay.from_predictions(y_test, y_pred_test)
plt.show()
```

```
Train accuracy: 0.4337748344370861

Test accuracy: 0.4452054794520548
```



[ ]:
```
rbf_svm = SVC(kernel='rbf')
rbf_svm.fit(X_train_kpca_lda, y_train)
y_pred_test = rbf_svm.predict(X_test_kpca_lda)
y_pred_train = rbf_svm.predict(X_train_kpca_lda)
print("Train accuracy:", metrics.accuracy_score(y_true=y_train,
    y_pred=y_pred_train), "\n")
print("Test accuracy:", metrics.accuracy_score(y_true=y_test,
    y_pred=y_pred_test), "\n")
ConfusionMatrixDisplay.from_predictions(y_test, y_pred_test)
plt.show()
```

```
Train accuracy: 0.38661794930349397

Test accuracy: 0.36198630136986304
```

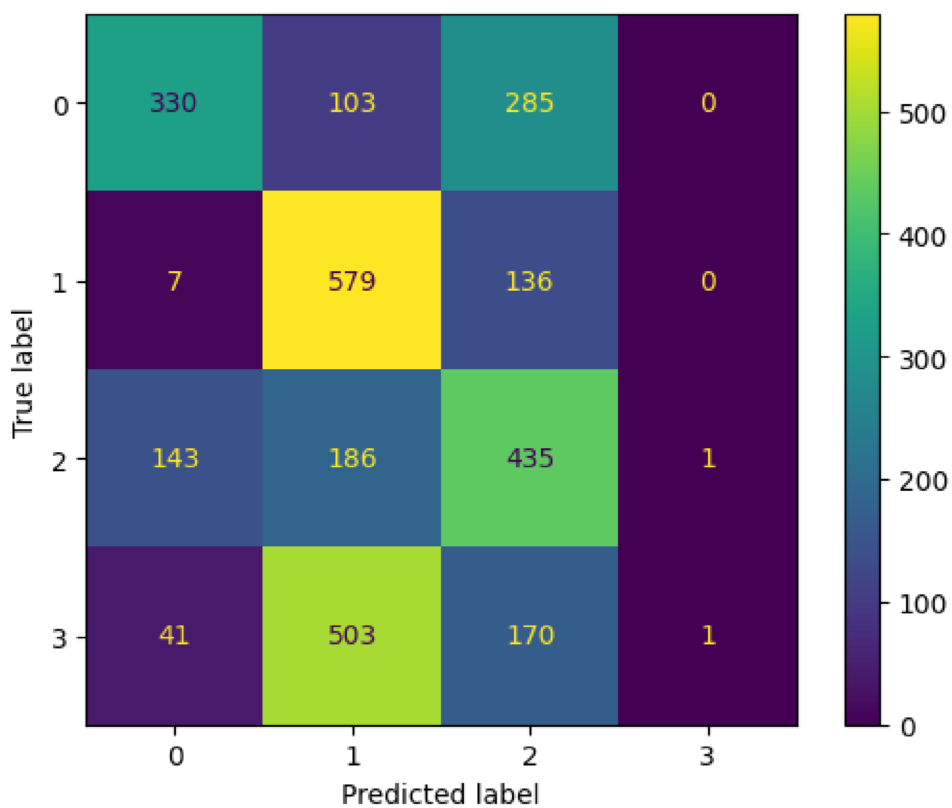


[ ]:
```
param_grid = [ {
    'C' :[4,6,10,20,25],
    "gamma" : ['scale',0.01,0.1,0.0001],
    'kernel' :['rbf']},
                ]

model = SVC(kernel="rbf")

optimal_parameters =GridSearchCV(
    model, param_grid,
    cv=5,
    scoring= 'accuracy',
    verbose=10,
    n_jobs= -5,
    return_train_score=True
)
optimal_parameters.fit(X_train_kpca_lda,y_train)

print(optimal_parameters.best_params_)
print(optimal_parameters.best_score_)
```

```
Fitting 5 folds for each of 20 candidates, totalling 100 fits
{'C': 20, 'gamma': 'scale', 'kernel': 'rbf'}
0.4456489963986659
```

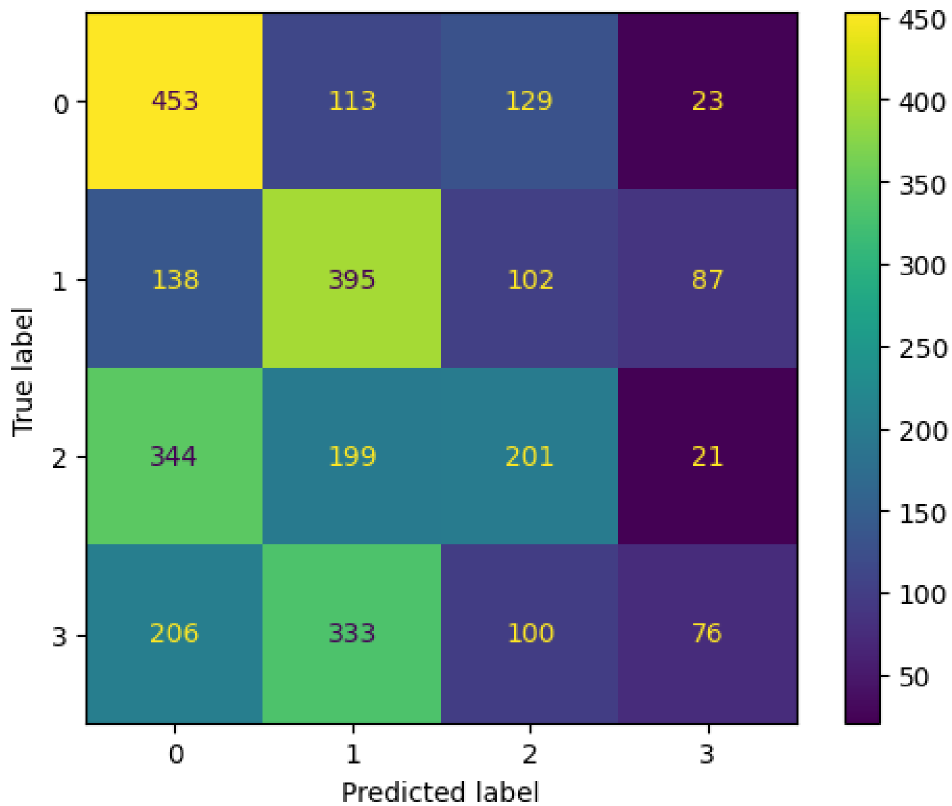
[ ]:
```
rbf_svm_better = SVC(kernel='rbf',C=20,gamma='scale')
rbf_svm_better.fit(X_train_kpca_lda, y_train)
y_pred_test = rbf_svm_better.predict(X_test_kpca_lda)
y_pred_train = rbf_svm_better.predict(X_train_kpca_lda)
print("Train accuracy:", metrics.accuracy_score(y_true=y_train,␣
 ↪y_pred=y_pred_train), "\n")
print("Test accuracy:", metrics.accuracy_score(y_true=y_test,␣
 ↪y_pred=y_pred_test), "\n")
ConfusionMatrixDisplay.from_predictions(y_test, y_pred_test)
plt.show()
```

```
Train accuracy: 0.4449646037908198

Test accuracy: 0.4606164383561644
```



[ ]:
```
from sklearn.neighbors import KNeighborsClassifier
knn_model =KNeighborsClassifier(n_neighbors=2)
knn_model.fit(X_train_kpca_lda, y_train)
y_pred_test = knn_model.predict(X_test_kpca_lda)
y_pred_train = knn_model.predict(X_train_kpca_lda)
print("Train accuracy: ",metrics.accuracy_score(y_true=y_train,␣
 ↪y_pred=y_pred_train),"\n")
print("Test accuracy:", metrics.accuracy_score(y_true=y_test,␣
 ↪y_pred=y_pred_test), "\n")
ConfusionMatrixDisplay.from_predictions(y_test, y_pred_test)
plt.show()
```

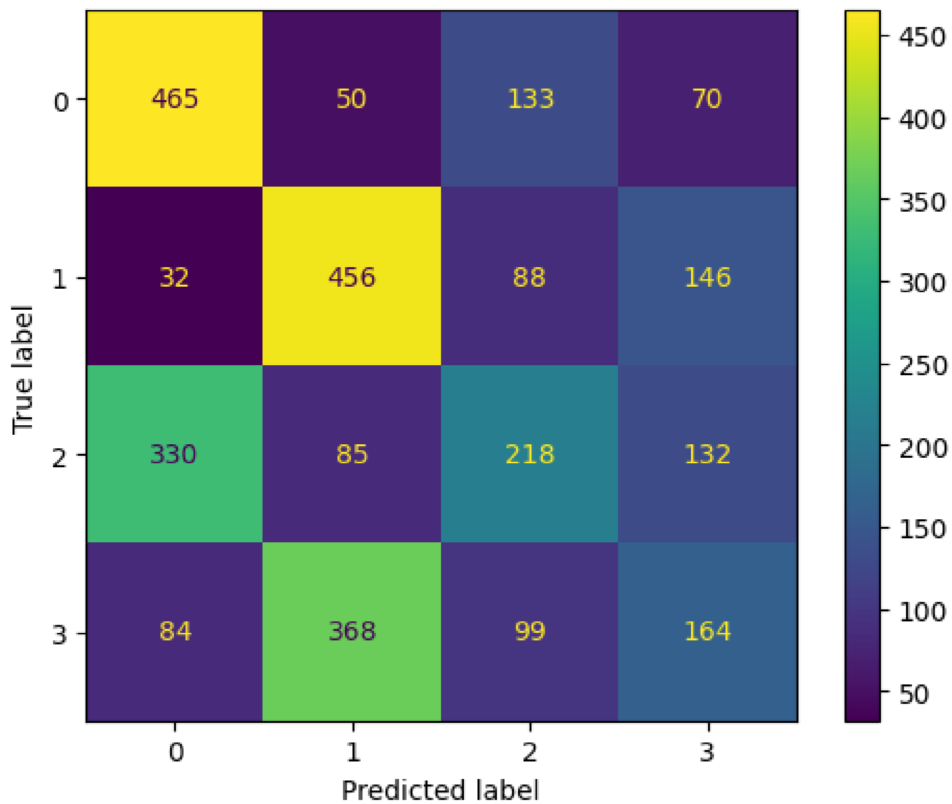
```
Train accuracy:  0.689540991093857

Test accuracy: 0.3852739726027397
```



[ ]:
```
from sklearn.neighbors import NearestCentroid

ncc_model = NearestCentroid()
ncc_model.fit(X_train_kpca_lda, y_train)
```

```
y_pred_test = ncc_model.predict(X_test_kpca_lda)
y_pred_train = ncc_model.predict(X_train_kpca_lda)
print("Train accuracy: ",metrics.accuracy_score(y_true=y_train,␣
↪y_pred=y_pred_train),"\n")
print("Test accuracy:", metrics.accuracy_score(y_true=y_test,␣
↪y_pred=y_pred_test), "\n")
ConfusionMatrixDisplay.from_predictions(y_test, y_pred_test)
plt.show()
```

```
Train accuracy:  0.42098652660424757

Test accuracy: 0.44623287671232875
```



KPCA with Sigmoid Kernel

[ ]:
```
from sklearn.decomposition import KernelPCA
import seaborn as sns
kpca = KernelPCA(kernel='sigmoid', n_components=64)
kpca=kpca.fit_transform(X_scaled_train)
explained_variance=np.var(kpca, axis=0 )
```

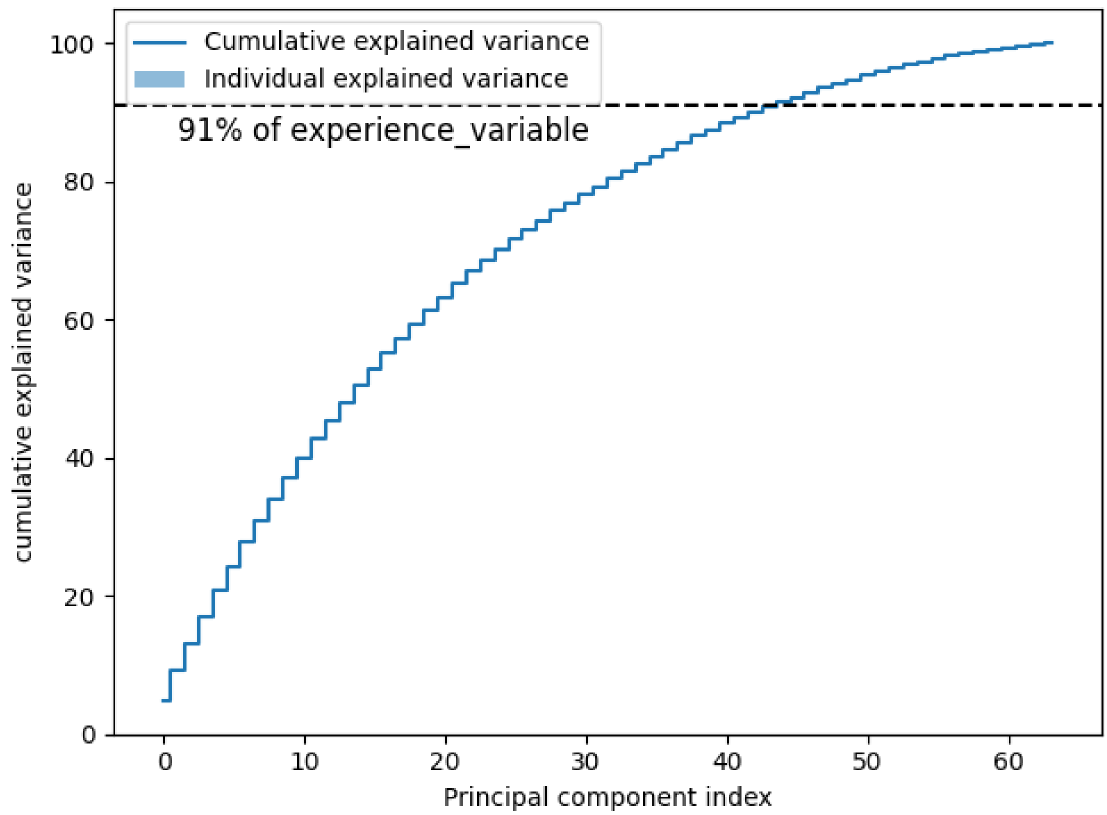
[ ]:
```
explained_variance_ratio=explained_variance/ np.sum(explained_variance)
cumulative_variance_ratio=np.cumsum(explained_variance_ratio)*100
kpca_df=pd.DataFrame()
kpca_df['cumulative explained variance']= cumulative_variance_ratio
kpca_df['explained_variance_ratio']= explained_variance_ratio*100
display(kpca_df)
```

```
    cumulative explained variance  explained_variance_ratio
0                        4.779009                  4.779009
1                        9.190418                  4.411409
2                       13.171135                  3.980717
3                       17.086425                  3.915291
4                       20.864494                  3.778069
..                            …                         …
59                      99.157272                  0.279456
60                      99.429987                  0.272715
61                      99.648334                  0.218347
62                      99.830501                  0.182167
63                     100.000000                  0.169499

[64 rows x 2 columns]
```

[ ]:
```
cumulative_variance_ratio_df = pd.DataFrame(cumulative_variance_ratio)

len(cumulative_variance_ratio_df.loc[cumulative_variance_ratio_df[0] <= 91])
```

[ ]: 44

[ ]:
```
plt.bar(range(0,len(explained_variance_ratio)), explained_variance_ratio,␣
 ↪alpha=0.5, align='center', label='Individual explained variance')
plt.step(range(0,len(cumulative_variance_ratio)), cumulative_variance_ratio,␣
 ↪where='mid',label='Cumulative explained variance')

plt.xlabel('Principal component index')
plt.legend(loc='best')
plt.axhline(y=91,c='black',linestyle='--')
plt.ylabel('cumulative explained variance')
plt.annotate('91% of experience_variable',
            xy=(1,86),fontsize=12)

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

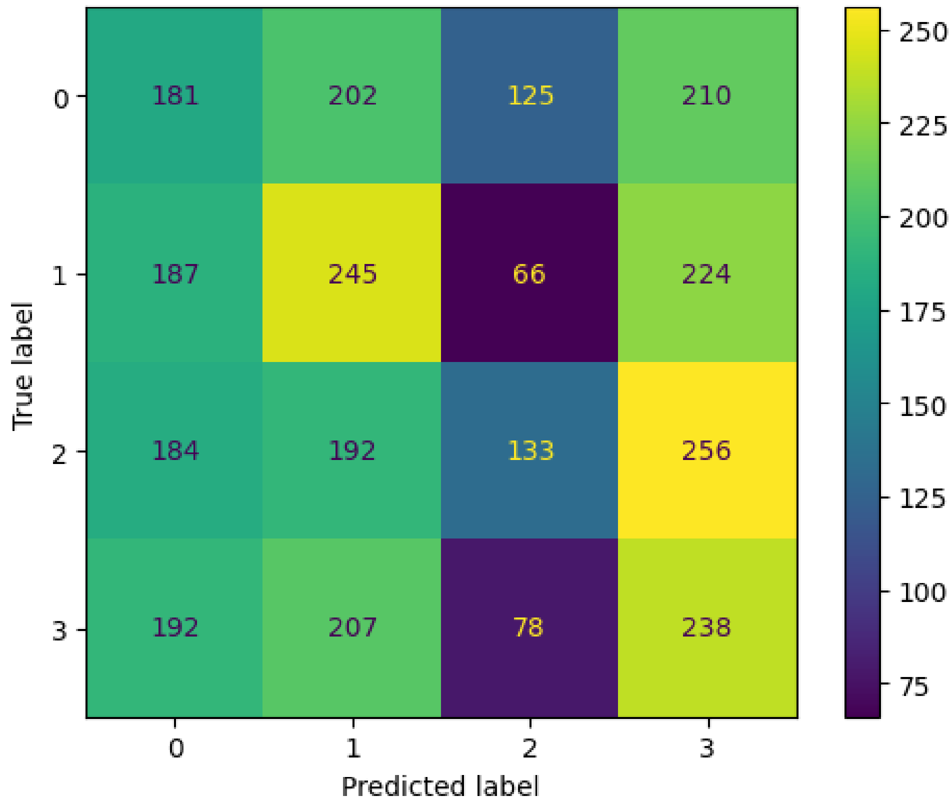


[ ]:
```
from sklearn.decomposition import KernelPCA
Kernel_pca = KernelPCA(n_components = 44 ,kernel= "sigmoid",n_jobs=-1)#␣
↪extracts 2 features, specify the kernel as rbf
X_train_kpca = Kernel_pca.fit_transform(X_scaled_train)
X_test_kpca= Kernel_pca.transform(X_scaled_test)

X_train_kpca=pd.DataFrame(X_train_kpca)
X_test_kpca=pd.DataFrame(X_test_kpca)
```

[ ]:
```
linear_svm = SVC(kernel='linear')
linear_svm.fit(X_train_kpca, y_train)
y_pred_test = linear_svm.predict(X_test_kpca)
y_pred_train = linear_svm.predict(X_train_kpca)
print("Train accuracy:", metrics.accuracy_score(y_true=y_train,␣
↪y_pred=y_pred_train), "\n")
print("Test accuracy:", metrics.accuracy_score(y_true=y_test,␣
↪y_pred=y_pred_test), "\n")
ConfusionMatrixDisplay.from_predictions(y_test, y_pred_test)
plt.show()
```

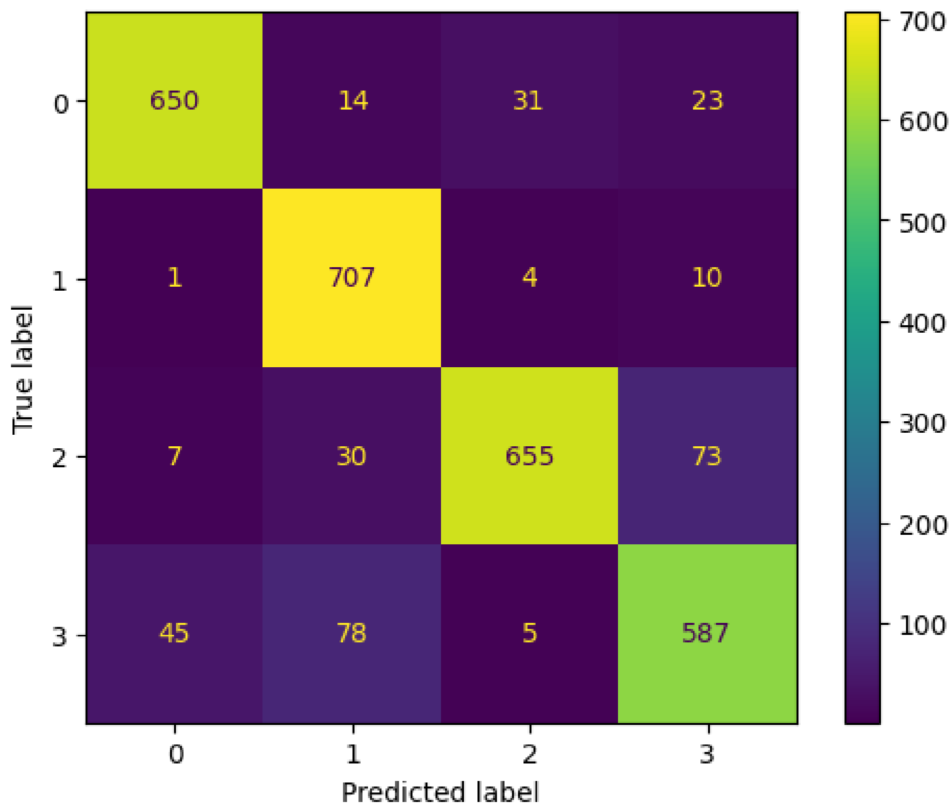
```
Train accuracy: 0.3034939483900434
```

```
Test accuracy: 0.27294520547945206
```



[ ]:
```python
rbf_svm = SVC(kernel='rbf')
rbf_svm.fit(X_train_kpca, y_train)
y_pred_test = rbf_svm.predict(X_test_kpca)
y_pred_train = rbf_svm.predict(X_train_kpca)
print("Train accuracy:", metrics.accuracy_score(y_true=y_train,␣
 ↪y_pred=y_pred_train), "\n")
print("Test accuracy:", metrics.accuracy_score(y_true=y_test,␣
 ↪y_pred=y_pred_test), "\n")
ConfusionMatrixDisplay.from_predictions(y_test, y_pred_test)
plt.show()
```

```
Train accuracy: 0.9359442795158712

Test accuracy: 0.8900684931506849
```

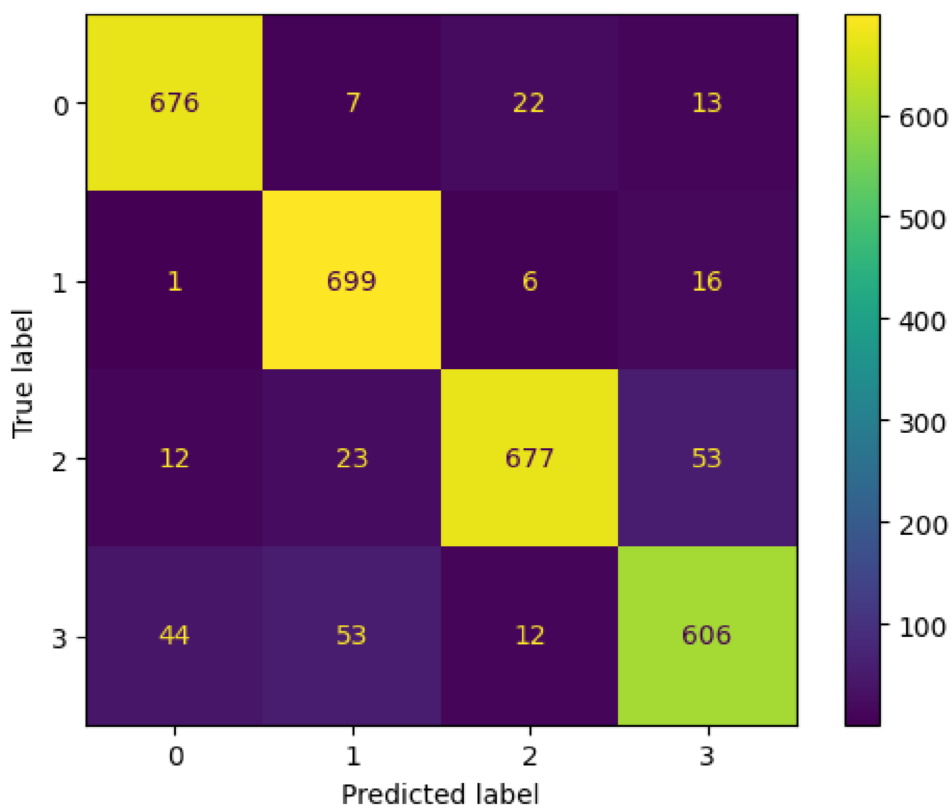


[ ]:
```
param_grid = [ {
    'C' :[4,6,10,20,25],
    "gamma" : ['scale',0.01,0.1,0.0001],
    'kernel' :['rbf']},
                ]

model = SVC(kernel="rbf")

optimal_parameters =GridSearchCV(
    model, param_grid,
    cv=5,
    scoring= 'accuracy',
    verbose=2,
    n_jobs= -5,
    return_train_score=True
)
optimal_parameters.fit(X_train_kpca,y_train)

print(optimal_parameters.best_params_)
print(optimal_parameters.best_score_)
```

```
Fitting 5 folds for each of 20 candidates, totalling 100 fits
{'C': 6, 'gamma': 'scale', 'kernel': 'rbf'}
0.8941535691281434
```

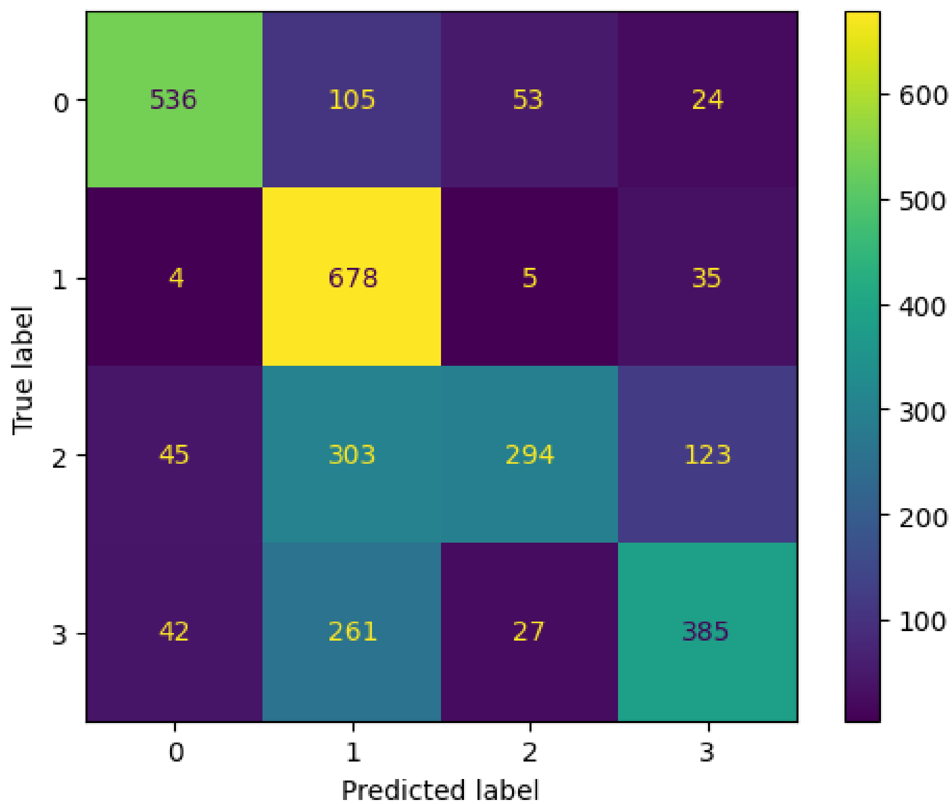
[ ]:
```
rbf_svm_better = SVC(kernel='rbf',C=6,gamma='scale')
rbf_svm_better.fit(X_train_kpca, y_train)
y_pred_test = rbf_svm_better.predict(X_test_kpca)
y_pred_train = rbf_svm_better.predict(X_train_kpca)
print("Train accuracy:", metrics.accuracy_score(y_true=y_train,␣
 ↪y_pred=y_pred_train), "\n")
print("Test accuracy:", metrics.accuracy_score(y_true=y_test,␣
 ↪y_pred=y_pred_test), "\n")
ConfusionMatrixDisplay.from_predictions(y_test, y_pred_test)
plt.show()
```

```
Train accuracy: 0.9809317195706783

Test accuracy: 0.9102739726027397
```



```
[ ]: from sklearn.neighbors import KNeighborsClassifier
knn_model =KNeighborsClassifier(n_neighbors=2)
knn_model.fit(X_train_kpca, y_train)
y_pred_test = knn_model.predict(X_test_kpca)
y_pred_train = knn_model.predict(X_train_kpca)
print("Train accuracy: ",metrics.accuracy_score(y_true=y_train,␣
 ↪y_pred=y_pred_train),"\n")
print("Test accuracy:", metrics.accuracy_score(y_true=y_test,␣
 ↪y_pred=y_pred_test), "\n")
ConfusionMatrixDisplay.from_predictions(y_test, y_pred_test)
plt.show()
```

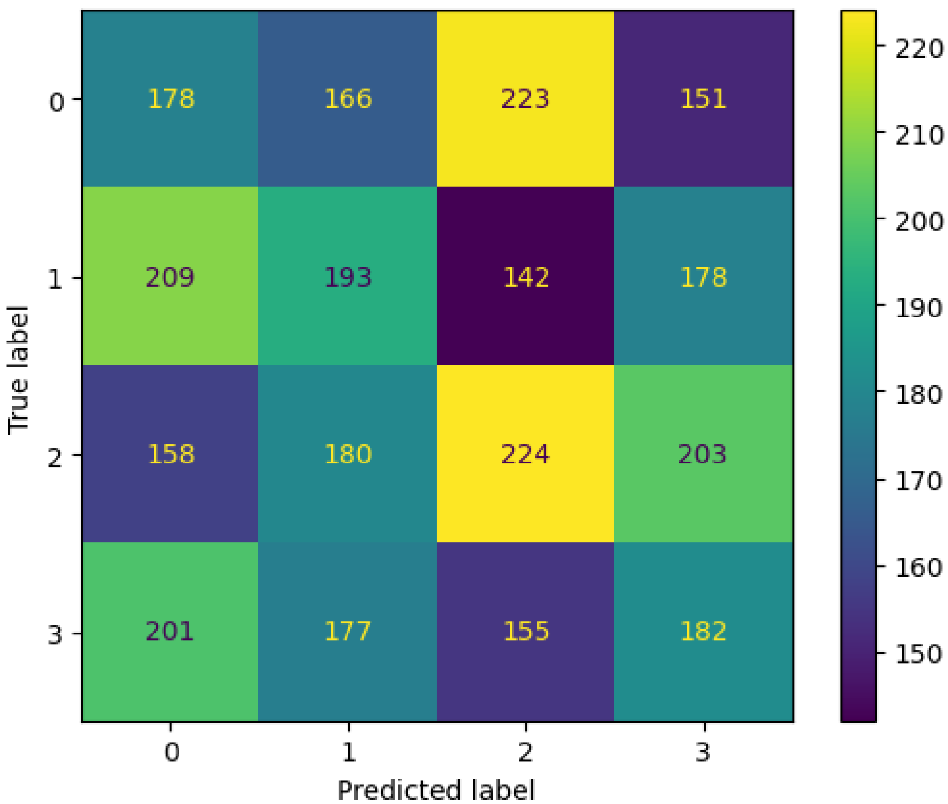
```
Train accuracy:  0.8622973281571135

Test accuracy: 0.6482876712328767
```




```
[ ]: from sklearn.neighbors import NearestCentroid

ncc_model = NearestCentroid()
ncc_model.fit(X_train_kpca, y_train)
```

```
y_pred_test = ncc_model.predict(X_test_kpca)
y_pred_train = ncc_model.predict(X_train_kpca)
print("Train accuracy: ",metrics.accuracy_score(y_true=y_train,␣
↪y_pred=y_pred_train),"\n")
print("Test accuracy:", metrics.accuracy_score(y_true=y_test,␣
↪y_pred=y_pred_test), "\n")
ConfusionMatrixDisplay.from_predictions(y_test, y_pred_test)
plt.show()
```

```
Train accuracy:  0.295957981274263544

Test accuracy: 0.2660958904109589
```



[ ]:
```
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis as LDA

lda = LDA(n_components=None)
X_train_kpca_lda = lda.fit_transform(X_train_kpca, y_train)
# Set initial variance explained so far
total_variance = 0.0
# Set initial number of features
```

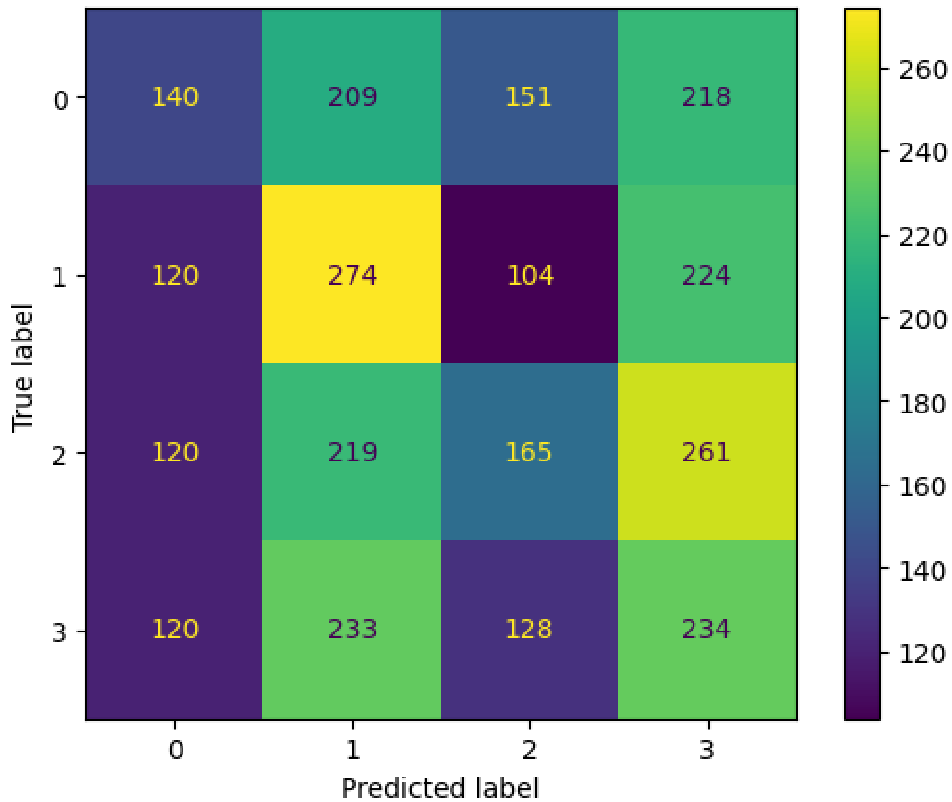
```
n_components = 0
# For the explained variance of each feature:
for explained_variance in lda.explained_variance_ratio_:
    # Add the explained variance to the total
    total_variance += explained_variance
    # Add one to the number of components
    n_components += 1

    # If we reach our goal level of explained variance
    if total_variance >= 0.95:
        break

# Return the number of components
print(n_components)
```

3

[ ]:
```
lda = LDA(n_components=3)
X_train_kpca_lda = lda.fit_transform(X_train_kpca, y_train)
X_test_kpca_lda=lda.transform(X_test_kpca)
```

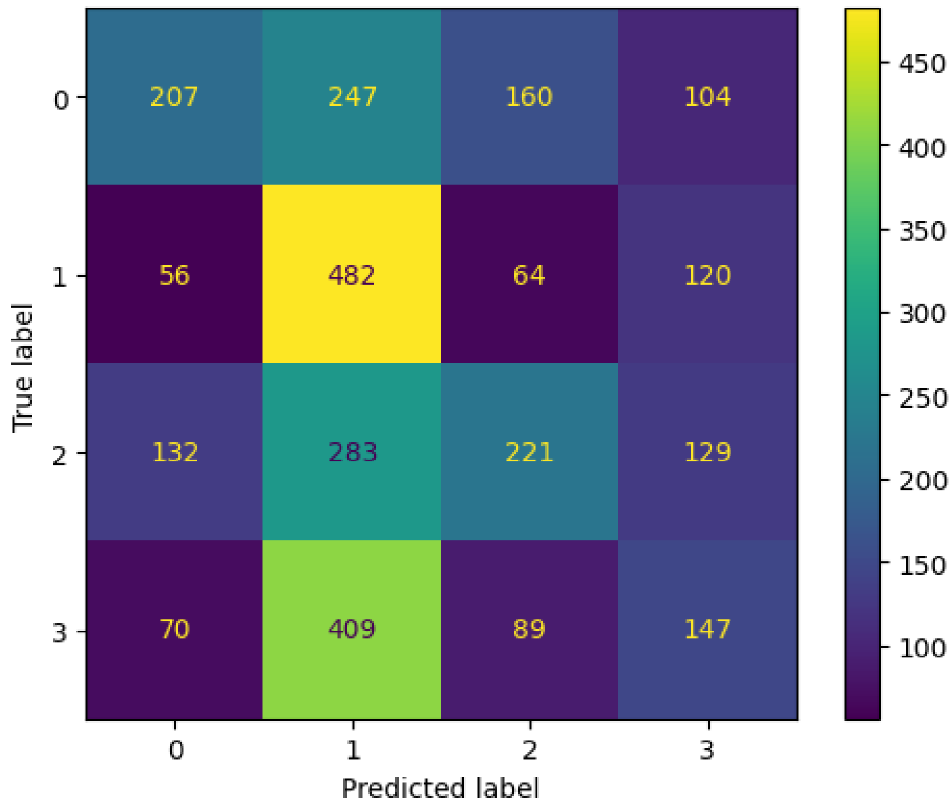
[ ]:
```
linear_svm = SVC(kernel='linear')
linear_svm.fit(X_train_kpca_lda, y_train)
y_pred_test = linear_svm.predict(X_test_kpca_lda)
y_pred_train = linear_svm.predict(X_train_kpca_lda)
print("Train accuracy:", metrics.accuracy_score(y_true=y_train,␣
 ↪y_pred=y_pred_train), "\n")
print("Test accuracy:", metrics.accuracy_score(y_true=y_test,␣
 ↪y_pred=y_pred_test), "\n")
ConfusionMatrixDisplay.from_predictions(y_test, y_pred_test)
plt.show()
```

```
Train accuracy: 0.3142269924640329

Test accuracy: 0.27842465753424656
```



[ ]:
```
rbf_svm = SVC(kernel='rbf')
rbf_svm.fit(X_train_kpca_lda, y_train)
y_pred_test = rbf_svm.predict(X_test_kpca_lda)
y_pred_train = rbf_svm.predict(X_train_kpca_lda)
print("Train accuracy:", metrics.accuracy_score(y_true=y_train,␣
  ↪y_pred=y_pred_train), "\n")
print("Test accuracy:", metrics.accuracy_score(y_true=y_test,␣
  ↪y_pred=y_pred_test), "\n")
ConfusionMatrixDisplay.from_predictions(y_test, y_pred_test)
plt.show()
```

```
Train accuracy: 0.38661794930349397

Test accuracy: 0.36198630136986304
```

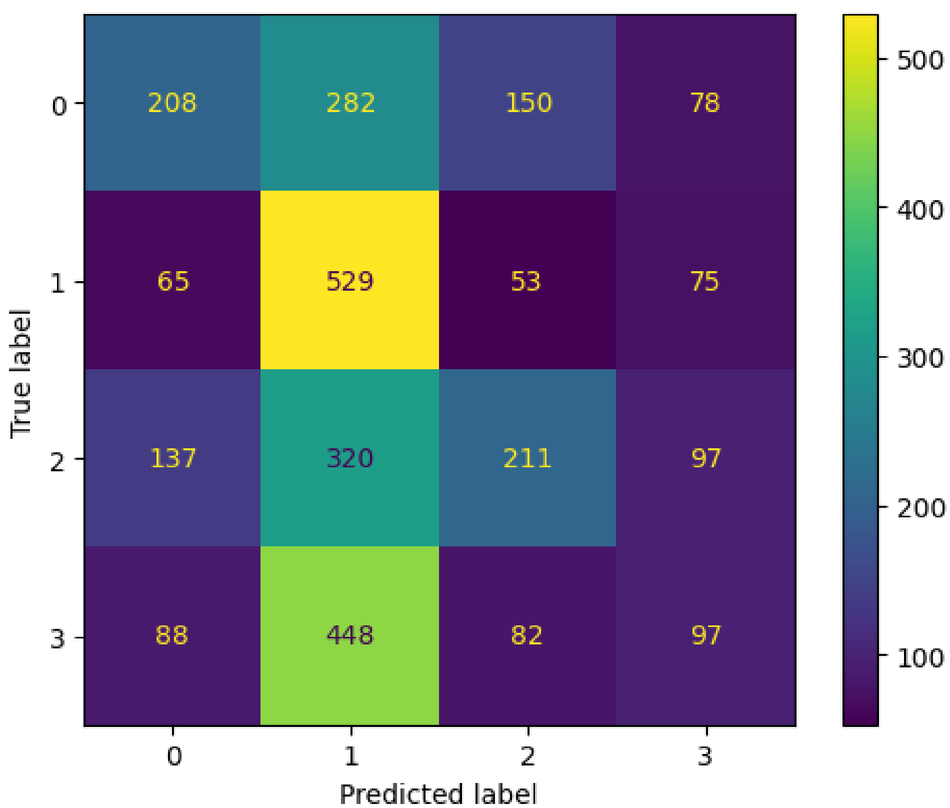


[ ]:
```
param_grid = [ {
    'C' :[4,6,10,20,25],
    "gamma" : ['scale',0.01,0.1,0.0001],
    'kernel' :['rbf']},
                ]

model = SVC(kernel="rbf")

optimal_parameters =GridSearchCV(
    model, param_grid,
    cv=5,
    scoring= 'accuracy',
    verbose=10,
    n_jobs= -5,
    return_train_score=True
)
optimal_parameters.fit(X_train_kpca_lda,y_train)

print(optimal_parameters.best_params_)
print(optimal_parameters.best_score_)
```

```
Fitting 5 folds for each of 20 candidates, totalling 100 fits
{'C': 4, 'gamma': 0.1, 'kernel': 'rbf'}
0.36777816459739904
```

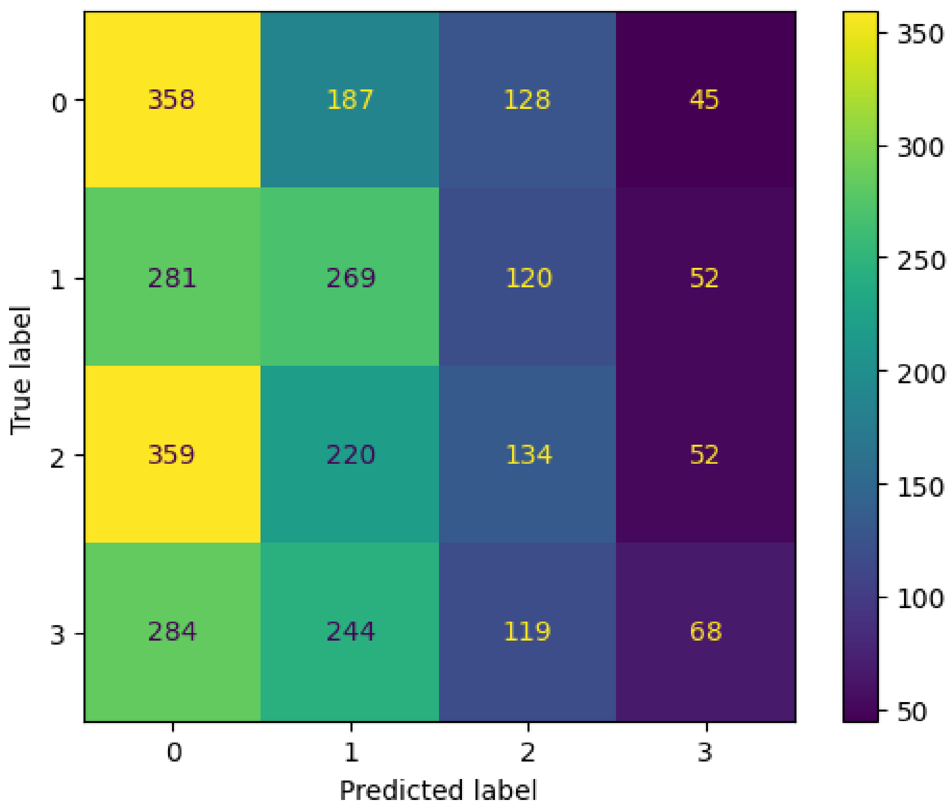
[ ]:
```
rbf_svm = SVC(kernel='rbf',C= 4, gamma= 0.1)
rbf_svm.fit(X_train_kpca_lda, y_train)
y_pred_test = rbf_svm.predict(X_test_kpca_lda)
y_pred_train = rbf_svm.predict(X_train_kpca_lda)
print("Train accuracy:", metrics.accuracy_score(y_true=y_train,␣
 ↪y_pred=y_pred_train), "\n")
print("Test accuracy:", metrics.accuracy_score(y_true=y_test,␣
 ↪y_pred=y_pred_test), "\n")
ConfusionMatrixDisplay.from_predictions(y_test, y_pred_test)
plt.show()
```

```
Train accuracy: 0.37645581182918475

Test accuracy: 0.3578767123287671
```



```
[ ]: from sklearn.neighbors import KNeighborsClassifier
knn_model =KNeighborsClassifier(n_neighbors=2)
knn_model.fit(X_train_kpca_lda, y_train)
y_pred_test = knn_model.predict(X_test_kpca_lda)
y_pred_train = knn_model.predict(X_train_kpca_lda)
print("Train accuracy: ",metrics.accuracy_score(y_true=y_train,␣
 ↪y_pred=y_pred_train),"\n")
print("Test accuracy:", metrics.accuracy_score(y_true=y_test,␣
 ↪y_pred=y_pred_test), "\n")
ConfusionMatrixDisplay.from_predictions(y_test, y_pred_test)
plt.show()
```

```
Train accuracy:  0.6493491664763644

Test accuracy: 0.2839041095890411
```




```
[ ]: from sklearn.neighbors import NearestCentroid

ncc_model = NearestCentroid()
ncc_model.fit(X_train_kpca_lda, y_train)
```

```
y_pred_test = ncc_model.predict(X_test_kpca_lda)
y_pred_train = ncc_model.predict(X_train_kpca_lda)
print("Train accuracy: ",metrics.accuracy_score(y_true=y_train,␣
↪y_pred=y_pred_train),"\n")
print("Test accuracy:", metrics.accuracy_score(y_true=y_test,␣
↪y_pred=y_pred_test), "\n")
ConfusionMatrixDisplay.from_predictions(y_test, y_pred_test)
plt.show()
```

```
Train accuracy:  0.3039506736697876

Test accuracy: 0.2684931506849315
```