Dataset 1 kpca+lda

December 29, 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
```

1 Data Preperation

[ ]:
```
data = pd.read_csv(r"C:\Users\vaasimak\Desktop\CI-SL\dataset\dataset1.csv")␣
↪#reading the csv files using pandas
```

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

[ ]:
```
   label  pixel0  pixel1  pixel2  pixel3  pixel4  pixel5  pixel6  pixel7  \
0      1       0       0       0       0       0       0       0       0
1      0       0       0       0       0       0       0       0       0
2      1       0       0       0       0       0       0       0       0
3      4       0       0       0       0       0       0       0       0
4      0       0       0       0       0       0       0       0       0

   pixel8  …  pixel774  pixel775  pixel776  pixel777  pixel778  pixel779  \
0       0  …         0         0         0         0         0         0
1       0  …         0         0         0         0         0         0
2       0  …         0         0         0         0         0         0
3       0  …         0         0         0         0         0         0
4       0  …         0         0         0         0         0         0
```

```
   pixel780  pixel781  pixel782  pixel783
0         0         0         0         0
1         0         0         0         0
2         0         0         0         0
3         0         0         0         0
4         0         0         0         0

[5 rows x 785 columns]
```

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

[ ]:
```
<bound method NDFrame.head of label       0
pixel0      0
pixel1      0
pixel2      0
pixel3      0
           ..
pixel779    0
pixel780    0
pixel781    0
pixel782    0
pixel783    0
Length: 785, dtype: int64>
```

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

[ ]:
```
              label   pixel0   pixel1   pixel2   pixel3   pixel4   pixel5  \
count  42000.000000  42000.0  42000.0  42000.0  42000.0  42000.0  42000.0
mean       4.456643      0.0      0.0      0.0      0.0      0.0      0.0
std        2.887730      0.0      0.0      0.0      0.0      0.0      0.0
min        0.000000      0.0      0.0      0.0      0.0      0.0      0.0
25%        2.000000      0.0      0.0      0.0      0.0      0.0      0.0
50%        4.000000      0.0      0.0      0.0      0.0      0.0      0.0
75%        7.000000      0.0      0.0      0.0      0.0      0.0      0.0
max        9.000000      0.0      0.0      0.0      0.0      0.0      0.0

        pixel6   pixel7   pixel8  …      pixel774      pixel775  \
count  42000.0  42000.0  42000.0  …  42000.000000  42000.000000
mean       0.0      0.0      0.0  …      0.219286      0.117095
std        0.0      0.0      0.0  …      6.312890      4.633819
min        0.0      0.0      0.0  …      0.000000      0.000000
25%        0.0      0.0      0.0  …      0.000000      0.000000
50%        0.0      0.0      0.0  …      0.000000      0.000000
75%        0.0      0.0      0.0  …      0.000000      0.000000
max        0.0      0.0      0.0  …    254.000000    254.000000
```

```
         pixel776     pixel777      pixel778      pixel779  pixel780  \
count  42000.000000  42000.00000  42000.000000  42000.000000   42000.0
mean       0.059024      0.02019      0.017238      0.002857       0.0
std        3.274488      1.75987      1.894498      0.414264       0.0
min        0.000000      0.00000      0.000000      0.000000       0.0
25%        0.000000      0.00000      0.000000      0.000000       0.0
50%        0.000000      0.00000      0.000000      0.000000       0.0
75%        0.000000      0.00000      0.000000      0.000000       0.0
max      253.000000    253.00000    254.000000     62.000000       0.0

       pixel781  pixel782  pixel783
count   42000.0   42000.0   42000.0
mean        0.0       0.0       0.0
std         0.0       0.0       0.0
min         0.0       0.0       0.0
25%         0.0       0.0       0.0
50%         0.0       0.0       0.0
75%         0.0       0.0       0.0
max         0.0       0.0       0.0

[8 rows x 785 columns]
```

[ ]:
```
len(data)
```

[ ]: 42000

1.1 Seperate the dataset to X , y

[ ]:
```
y = data['label']
X = data.drop(columns='label')
X=pd.DataFrame(X)
```

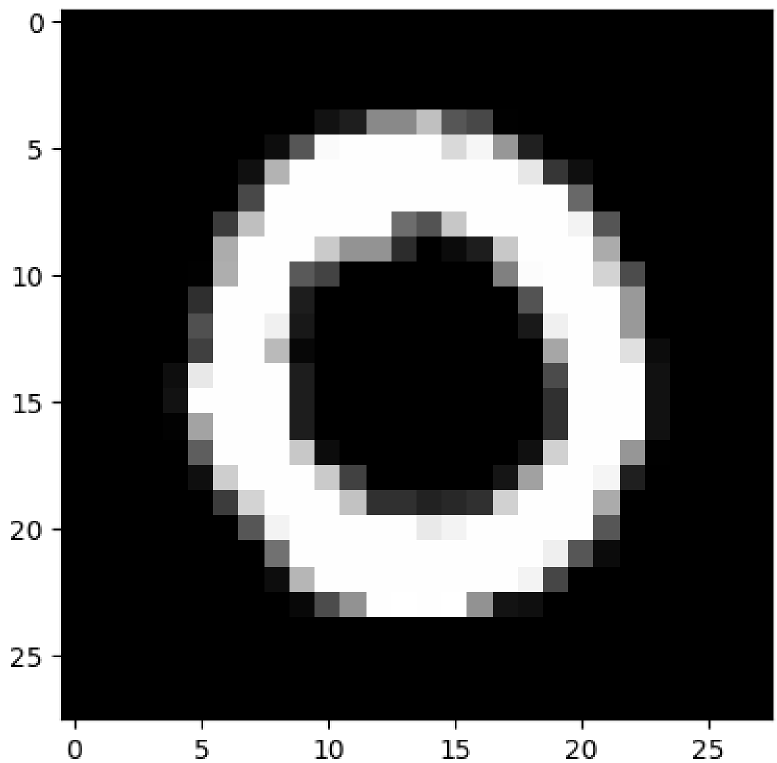
[ ]:
```
len(y)
```

[ ]: 42000

[ ]:
```
x_np =X.to_numpy()
```

[ ]:
```
plt.imshow(x_np[1].reshape(28,28),cmap ='gray')
```

[ ]: <matplotlib.image.AxesImage at 0x1532119eb50>



1.2 Downsampling X, y

[ ]:
```
X_downsampled=resample(
    X,
    replace=False,
    n_samples=10000,
    random_state=42)
```

[ ]:
```
X_downsampled.shape
```

[ ]:
```
(10000, 784)
```

[ ]:
```
y_downsampled=resample(
    y,
    replace=False,
    n_samples=10000,
    random_state=42)
```

[ ]:
```
y_downsampled.shape
```

[ ]:
```
(10000,)
```

1.3 Split and Scale the data

[ ]:
```
X_train, X_test, y_train, y_test =␣
↪train_test_split(X_downsampled,y_downsampled,random_state=40)
```

[ ]:
```
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler(feature_range=(0, 1))
X_train_minmaxcale = scaler.fit_transform(X_train)
X_test_minmaxcale = scaler.fit_transform(X_test)
X_scaled_train = scale(X_train_minmaxcale)
X_scaled_test = scale(X_test_minmaxcale)
X_scaled_train =pd.DataFrame(X_scaled_train)
X_scaled_test=pd.DataFrame(X_scaled_test)
```

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

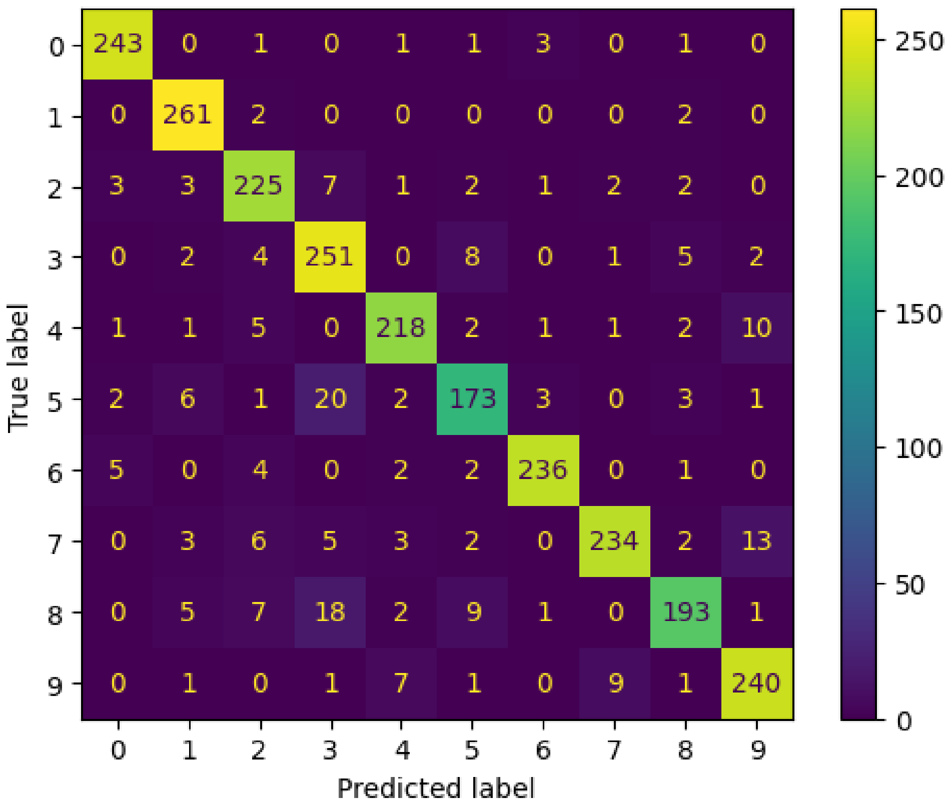
[ ]:
```
            0       1       2       3       4       5       6       7       8   \
count  7500.0  7500.0  7500.0  7500.0  7500.0  7500.0  7500.0  7500.0  7500.0
mean      0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
std       0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
min       0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
25%       0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
50%       0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
75%       0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
max       0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0

            9   …           774           775           776     777     778  \
count  7500.0  …  7.500000e+03  7.500000e+03  7.500000e+03  7500.0  7500.0
mean      0.0  …  9.000208e-18 -9.473903e-19 -1.421085e-18     0.0     0.0
std       0.0  …  1.000067e+00  1.000067e+00  1.000067e+00     0.0     0.0
min       0.0  … -3.470053e-02 -2.205782e-02 -1.633211e-02     0.0     0.0
25%       0.0  … -3.470053e-02 -2.205782e-02 -1.633211e-02     0.0     0.0
50%       0.0  … -3.470053e-02 -2.205782e-02 -1.633211e-02     0.0     0.0
75%       0.0  … -3.470053e-02 -2.205782e-02 -1.633211e-02     0.0     0.0
max       0.0  …  4.802680e+01  5.046613e+01  6.122908e+01     0.0     0.0

          779     780     781     782     783
count  7500.0  7500.0  7500.0  7500.0  7500.0
mean      0.0     0.0     0.0     0.0     0.0
std       0.0     0.0     0.0     0.0     0.0
min       0.0     0.0     0.0     0.0     0.0
25%       0.0     0.0     0.0     0.0     0.0
50%       0.0     0.0     0.0     0.0     0.0
75%       0.0     0.0     0.0     0.0     0.0
max       0.0     0.0     0.0     0.0     0.0

[8 rows x 784 columns]
```

2 Train SVM (linear, rbf) Models before KCPA and LDA

2.1 Linear SVM

[ ]:
```
linear_svm = SVC(kernel='linear')
linear_svm.fit(X_scaled_train, y_train)
y_pred_test = linear_svm.predict(X_scaled_test)
y_pred_train = linear_svm.predict(X_scaled_train)
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()
```

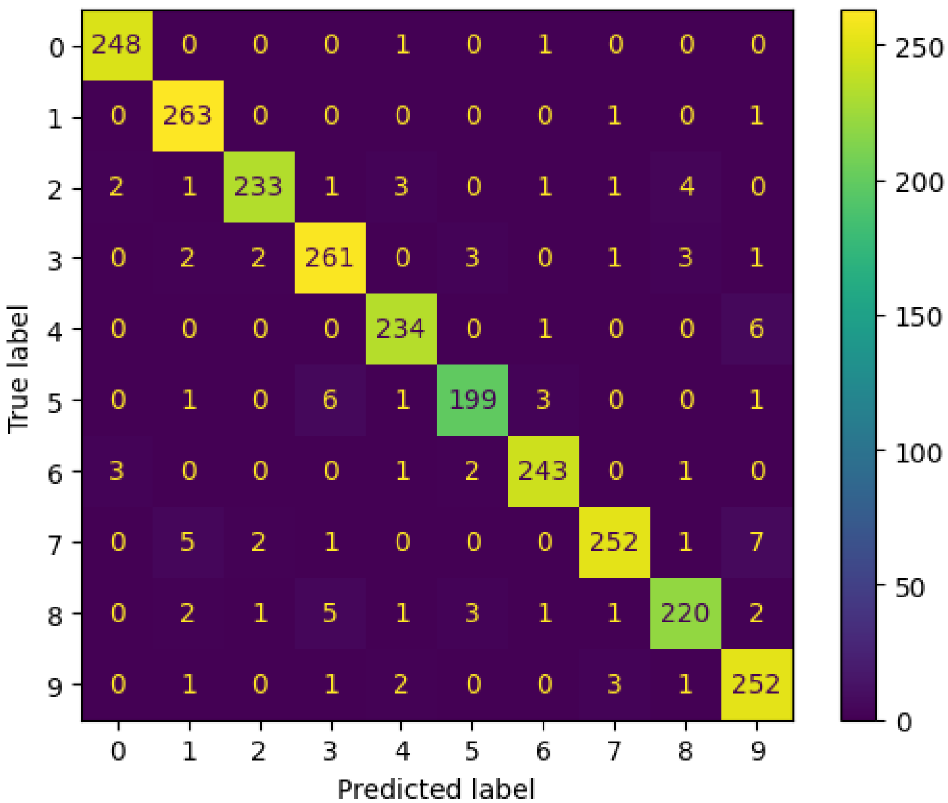
```
train accuracy:  1.0

test accuracy: 0.9096
```



2.2 RBF SVM

[ ]:
```
rbf_svm = SVC(kernel='rbf')
rbf_svm.fit(X_train, y_train)
y_pred_test = rbf_svm.predict(X_test)
y_pred_train = rbf_svm.predict(X_train)
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:  0.9857333333333334

 test accuracy: 0.962
```



3 KPCA with RBF Kernel

3.1 Visualise KPCA to find the number of principal components

[ ]:
```
from sklearn.decomposition import KernelPCA
import seaborn as sns
kpca = KernelPCA(kernel='rbf', n_components=784)
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)
```

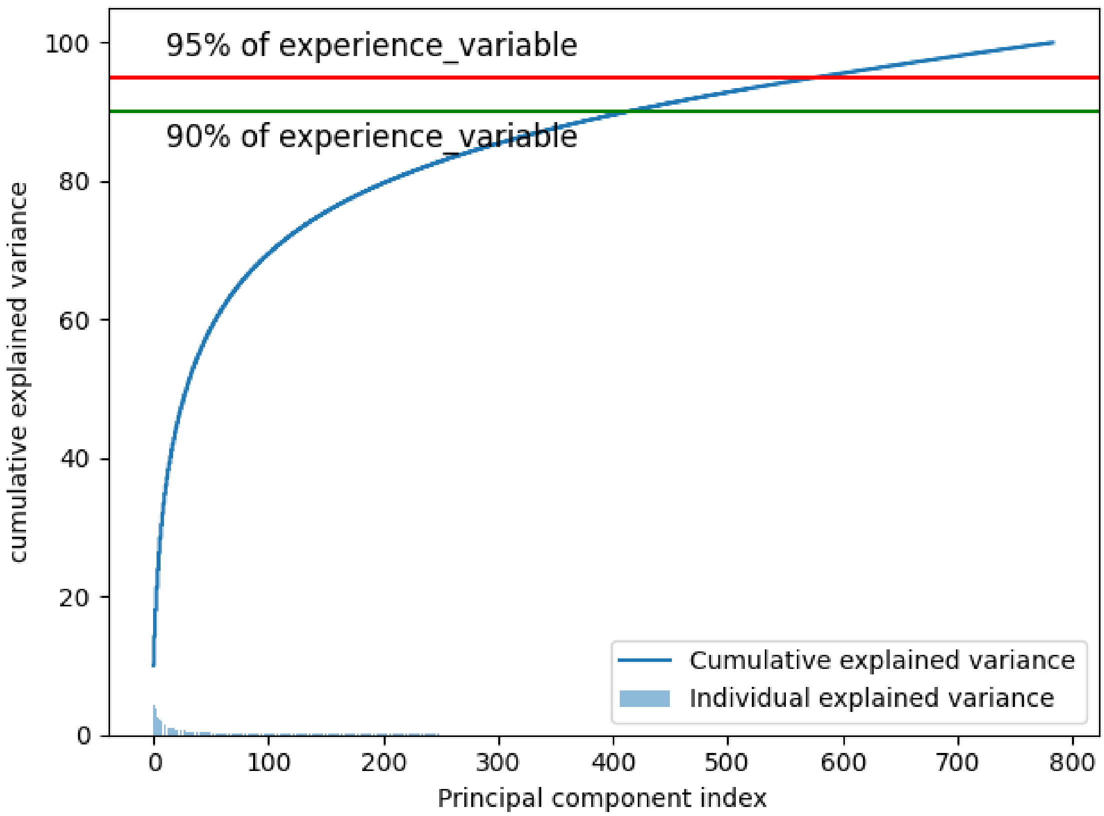
```
     cumulative explained variance  explained_variance_ratio
0                        10.010179                 10.010179
1                        14.274098                  4.263919
2                        18.031954                  3.757856
3                        21.286833                  3.254878
4                        23.920424                  2.633592
..                             …                        …
779                      99.910117                  0.022519
780                      99.932621                  0.022504
781                      99.955104                  0.022483
782                      99.977569                  0.022465
783                     100.000000                  0.022431

[784 rows x 2 columns]
```

[ ]:
```
cumulative_variance_ratio_df = pd.DataFrame(cumulative_variance_ratio)
len(cumulative_variance_ratio_df.loc[cumulative_variance_ratio_df[0] <= 95])
```

[ ]: 579

[ ]:
```
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.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()
```



3.2 Building KPCA with the right principal components

[ ]:
```
from sklearn.decomposition import KernelPCA
Kernel_pca = KernelPCA(n_components = 579 ,kernel=␣
 ↪"rbf",n_jobs=-1,fit_inverse_transform=True)
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)
```

[ ]:
```
X_train_kpca.shape
```

[ ]:
```
(7500, 579)
```

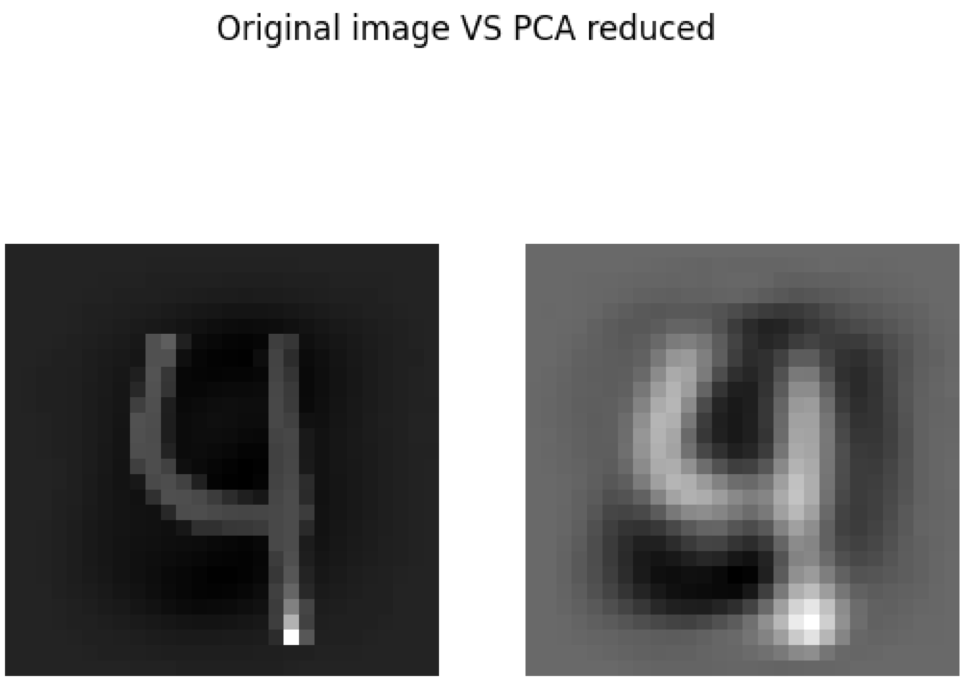
[ ]:
```
X_scaled_test.shape
```

[ ]: (2500, 784)

[ ]:
```
X_train_reduced = Kernel_pca.inverse_transform(X_train_kpca)
X_train_unscaled = scaler.inverse_transform(X_scaled_train)
```

3.2.1 Visualize the difference between the original image and the image after KPCA

[ ]:
```
fig, (ax1, ax2) = plt.subplots(1,2)
ax1.matshow(X_train_unscaled[1].reshape(28,28), cmap='gray')
ax2.matshow(X_train_reduced[1].reshape(28,28), cmap='gray')
ax1.set_axis_off()
ax2.set_axis_off()
fig.suptitle("Original image VS PCA reduced".format(y_train[1]))
plt.show()
```



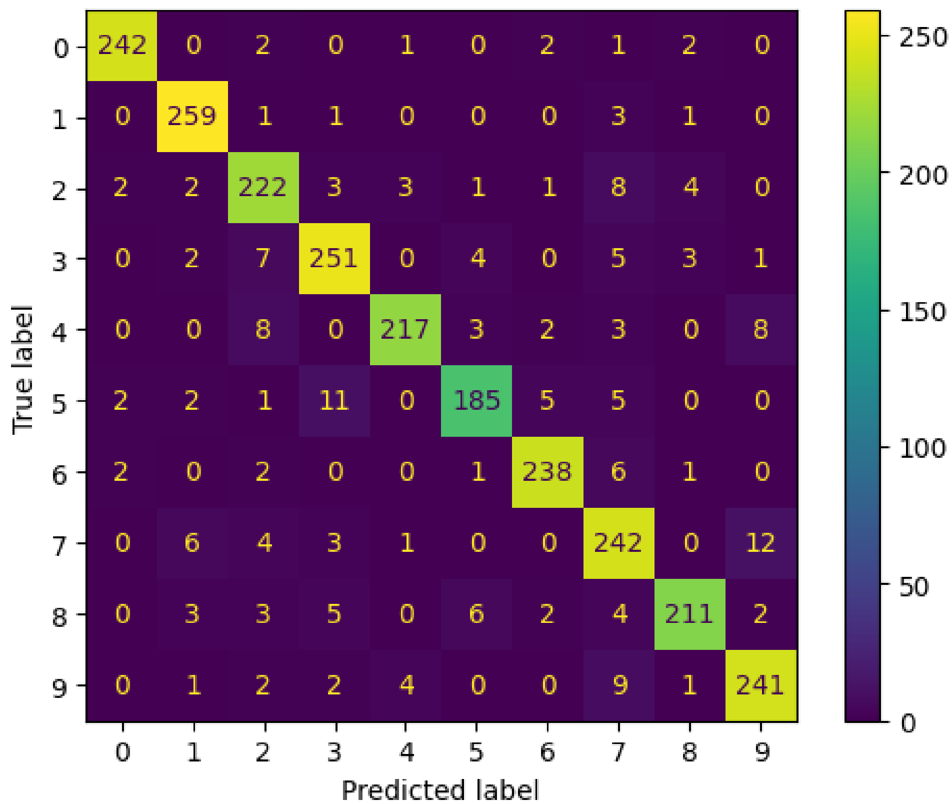
3.3 Training SVM (linear, rbf) Models

3.3.1 Linear Model

[ ]:
```
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:  0.9484

test accuracy: 0.9232
```

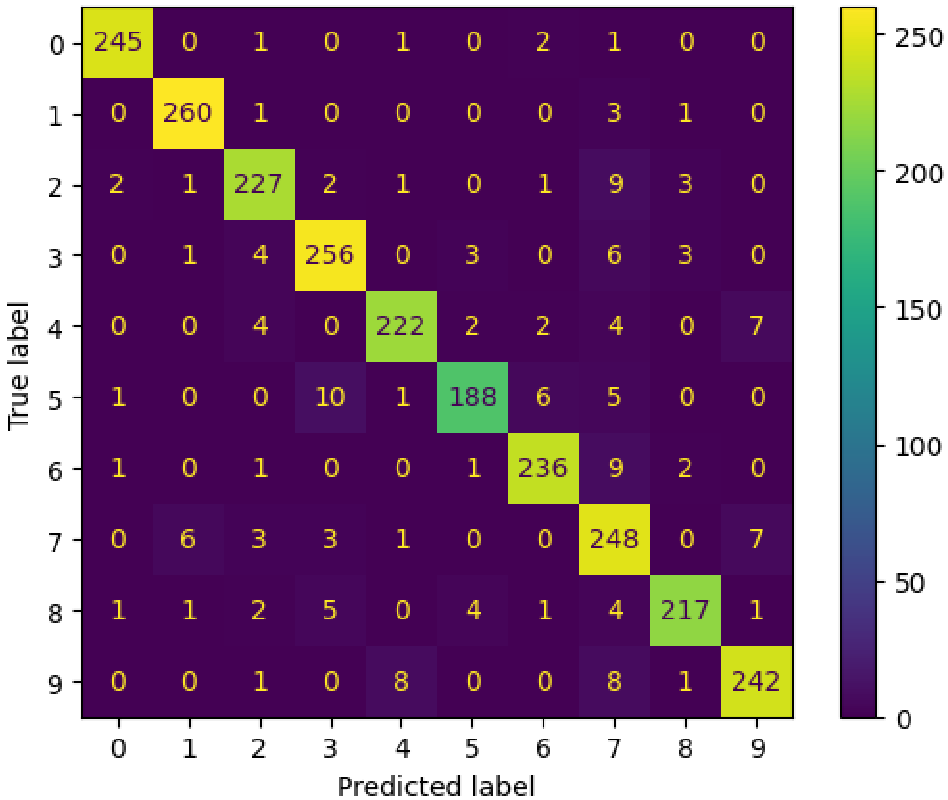


3.3.2 RBF Model

```
[ ]: 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:  0.9797333333333333

 test accuracy: 0.9364
```



4 KPCA+LDA with RBF Kernel

4.1 Searching the best component for the LDA

[ ]:
```
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)
```

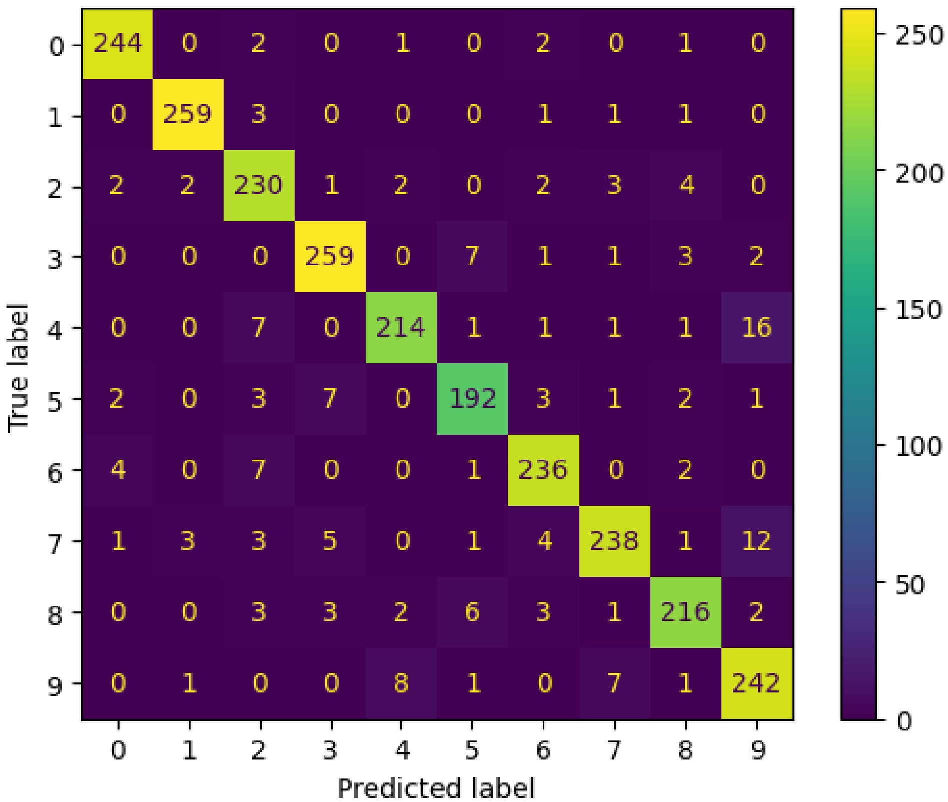
```
8
```

4.2 Building LDA with the right component

[ ]:
```
lda = LDA(n_components=8)
X_train_kpca_lda = lda.fit_transform(X_train_kpca, y_train)
X_test_kpca_lda=lda.transform(X_test_kpca)
```

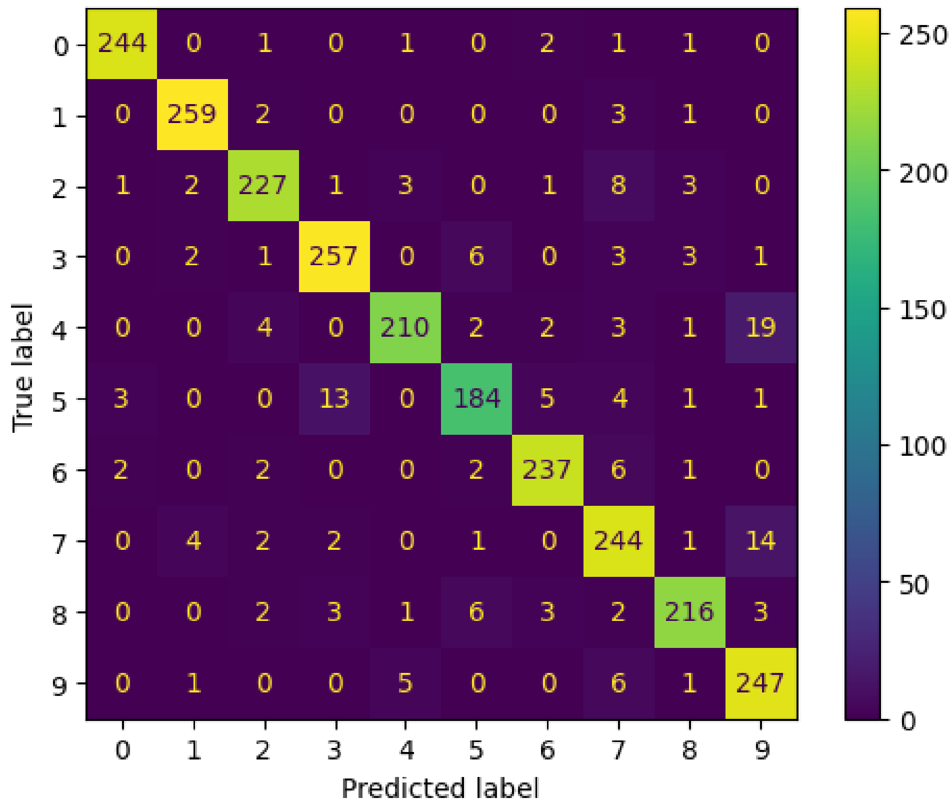
[ ]:
```
linear_svm = SVC(kernel='linear')
linear_svm.fit(X_train_kpca_lda, y_train)
y_pred_test = linear_svm.predict(X_test_kpca_lda)
y_pred_train = linear_svm.predict(X_train_kpca_lda)
print("Train accuracy:", metrics.accuracy_score(y_true=y_train,␣
 ↪y_pred=y_pred_train), "\n")
print("Test accuracy:", 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: 0.958

Test accuracy: 0.932
```



[ ]:
```
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: 0.9548

Test accuracy: 0.93
```



4.3 KPCA with Sigmoid Kernel

```
[ ]: from sklearn.decomposition import KernelPCA
import seaborn as sns
kpca = KernelPCA(kernel='sigmoid', n_components=784)
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)
```

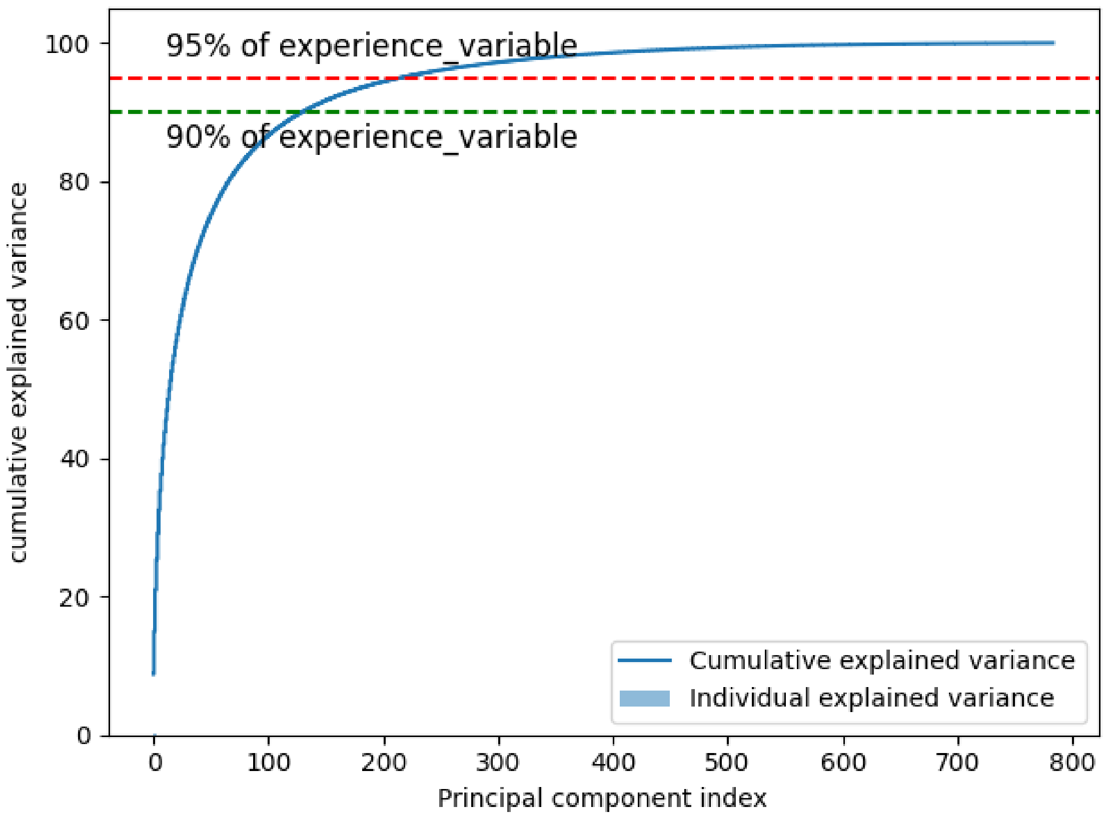
	cumulative explained variance	explained_variance_ratio
0	8.800310	8.800310
1	15.019349	6.219040
2	20.951083	5.931733
3	25.401624	4.450541
4	29.183188	3.781565

```
..                         …                  …
779                99.997237           0.000700
780                99.997936           0.000699
781                99.998629           0.000693
782                99.999315           0.000687
783               100.000000           0.000685

[784 rows x 2 columns]
```

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

len(cumulative_variance_ratio_df.loc[cumulative_variance_ratio_df[0] <= 95])
```

[ ]:
```
216
```

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

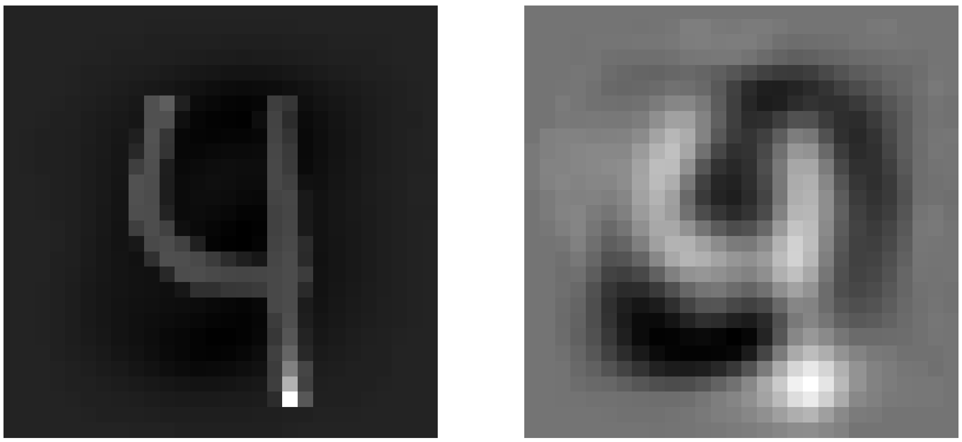


[ ]:
```
from sklearn.decomposition import KernelPCA
Kernel_pca = KernelPCA(n_components = 216 ,kernel=␣
 ↪"sigmoid",n_jobs=-1,fit_inverse_transform=True)# extracts 2 features,␣
 ↪specify the kernel as rbf
X_train_kpca = Kernel_pca.fit_transform(X_scaled_train)
X_test_kpca= Kernel_pca.transform(X_scaled_test)

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

[ ]:
```
X_train_reduced = Kernel_pca.inverse_transform(X_train_kpca)
X_train_unscaled = scaler.inverse_transform(X_scaled_train)
```

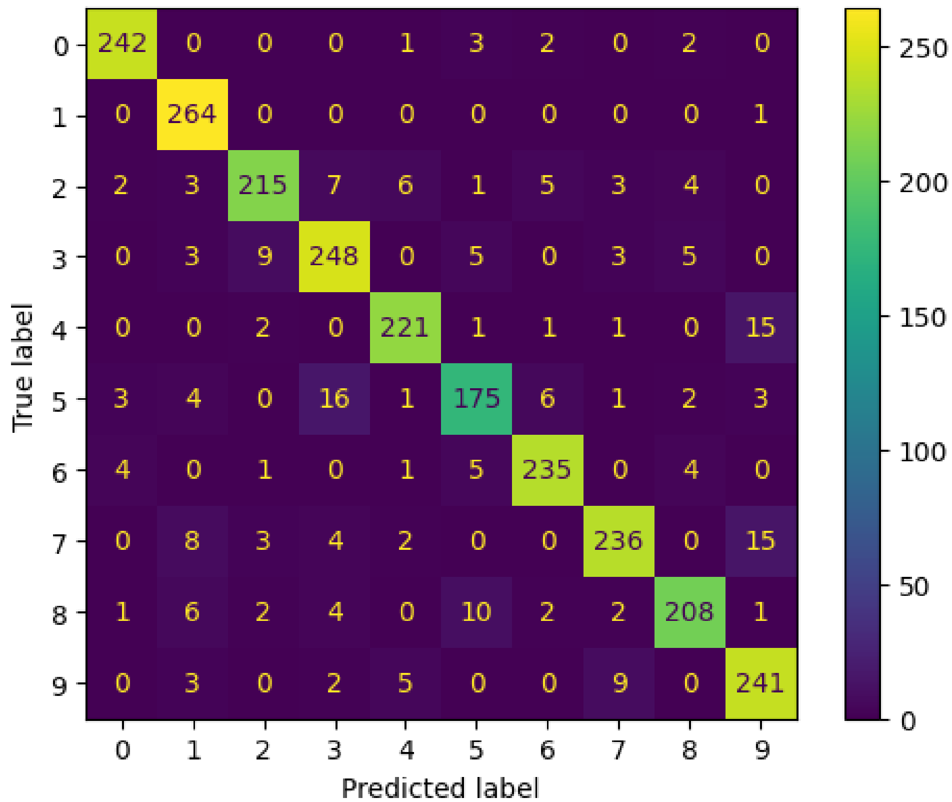
[ ]:
```
fig, (ax1, ax2) = plt.subplots(1,2)
ax1.matshow(X_train_unscaled[1].reshape(28,28), cmap='gray')
ax2.matshow(X_train_reduced[1].reshape(28,28), cmap='gray')
ax1.set_axis_off()
ax2.set_axis_off()
fig.suptitle("Original image VS PCA reduced".format(y_train[1]))
plt.show()
```

Original image VS PCA reduced



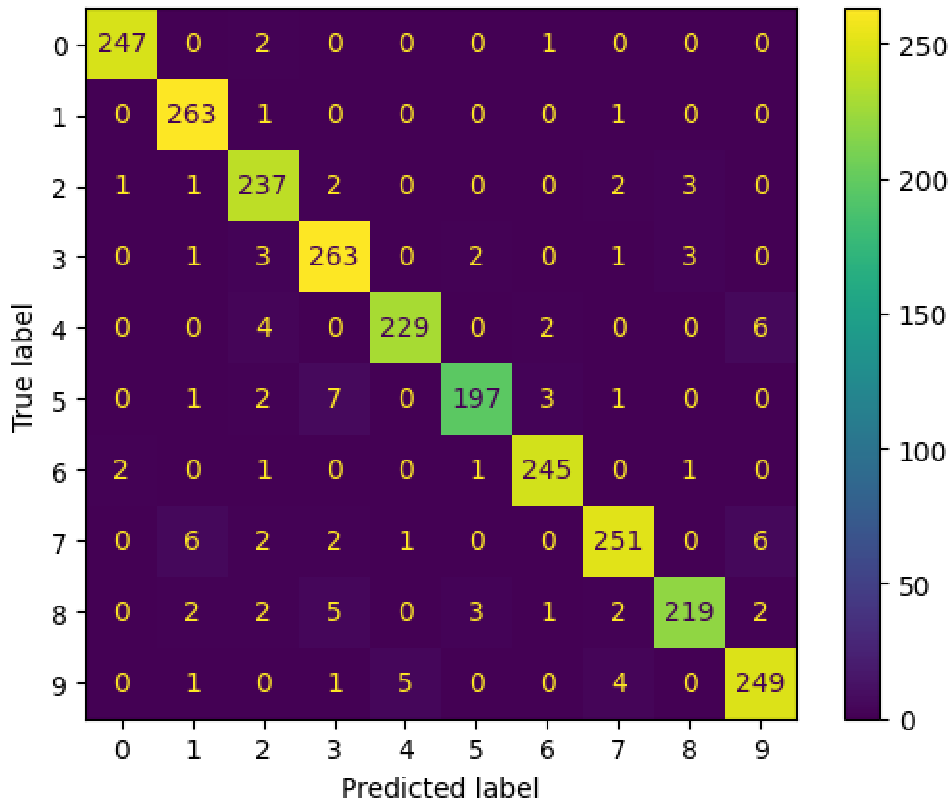
```
[ ]: linear_svm = SVC(kernel='linear')
     linear_svm.fit(X_train_kpca, y_train)
     y_pred_test = linear_svm.predict(X_test_kpca)
     y_pred_train = linear_svm.predict(X_train_kpca)
     print("train accuracy: ",metrics.
       ↪accuracy_score(y_true=y_train,y_pred=y_pred_train),"\n")
     print("test 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:  0.9265333333333333

test accuracy: 0.914
```



[ ]:
```
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:  0.9917333333333334

 test accuracy: 0.96
```



4.4 KPCA+LDA with Sigmoid 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 >= 0.95:
        break
```

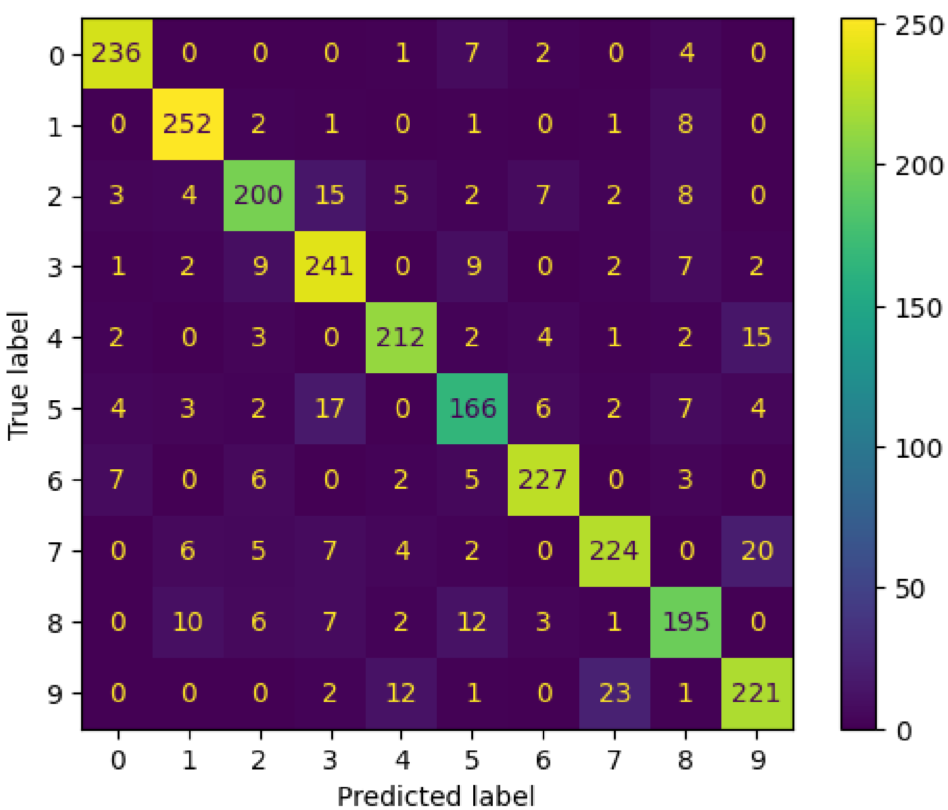
```
# Return the number of components
print(n_components)
```

```
8
```

[ ]:
```
lda = LDA(n_components=8)
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: 0.8932

Test accuracy: 0.8696
```



[ ]:
```
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: 0.9146666666666666

Test accuracy: 0.89
```