MACHINE LEARNING LAB

EXERCISE 8

Aim :

Download MNIST dataset, apply PCA from scratch.

Algorithm :

PCA is the technic of dimensionality reduction. dimensionality reduction is nothing but the reduction of n dimension data to n′ dimension data, where n > n′

MNIST dataset - contains the information of handwritten digits 0 to 9. in this dataset the information of single-digit is stored in the form of 784*1 array, where the single element of 784*1 array represents a single pixel of 28*28 image

1. **Standardize the Data:**

   - Compute the mean of each feature in the dataset.
   - Subtract the mean from each feature to center the data around the origin.
   - Optionally, divide by the standard deviation to scale the features.
2. **Compute the Covariance Matrix:**

   - Calculate the covariance matrix of the standardized data.
   - The covariance matrix represents the relationships between different features in the dataset.
3. **Eigenvalue Decomposition:**

   - Perform eigenvalue decomposition on the covariance matrix.
   - Obtain the eigenvectors and eigenvalues of the covariance matrix.
   - Sort the eigenvectors based on their corresponding eigenvalues in descending order.
   - Select the top k eigenvectors to form the principal components, where k is the desired number of dimensions in the reduced dataset.
   - Project the standardized data onto the selected eigenvectors to obtain the principal components.

Code and Output :

In [5]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [6]:
```
df=pd.read_csv(r"C:\Users\TEJU\OneDrive\Desktop\ML LAB EXERCISES\Exercise 8\train.cs
```

In [7]:
```
df.shape
```

Out[7]: (42000, 785)

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

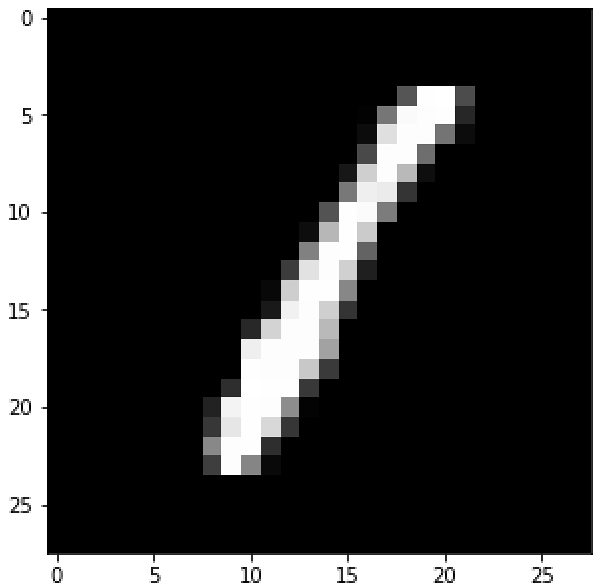
Out[8]:

	label	pixel0	pixel1	pixel2	pixel3	pixel4	pixel5	pixel6	pixel7	pixel8	...	pixel774	pixel775
0	1	0	0	0	0	0	0	0	0	0	...	0	0
1	0	0	0	0	0	0	0	0	0	0	...	0	0
2	1	0	0	0	0	0	0	0	0	0	...	0	0
3	4	0	0	0	0	0	0	0	0	0	...	0	0
4	0	0	0	0	0	0	0	0	0	0	...	0	0

5 rows × 785 columns

In [9]:
```
#extracting label column from the dataset
label=df['label']
df.drop('label',axis=1,inplace=True)
```

In [10]:
```
#generating a random index ind between 0 and 20000
#using this index to select a row from df
#converting it to a NumPy array
#reshaping it into a 28x28 grid
#displaying it as an image using plt.imshow()
ind = np.random.randint(0, 20000)
plt.figure(figsize = (20, 5))
grid_data = np.array(df.iloc[ind]).reshape(28,28)
plt.imshow(grid_data, interpolation = None, cmap = 'gray')
plt.show()
print(label[ind])
```



1

In [11]:
```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
```

```
df = scaler.fit_transform(df)
df.shape
```

Out[11]: (42000, 784)

In [12]:

```
#computes covariance matrix by taking matrix multiplication of transpose with itself
covar_mat = np.matmul(df.T, df)
covar_mat.shape
```

Out[12]: (784, 784)

In [13]:

```
#to compute eigen values and eigen vectors
from scipy.linalg import eigh
values, vectors = eigh(covar_mat, eigvals = (782, 783))
print("Dimensions of Eigen vector:", vectors.shape)
#transposes to ensure each eigen vector is a column vector
vectors = vectors.T
print("Dimensions of Eigen vector:", vectors.shape)
```

```
Dimensions of Eigen vector: (784, 2)
Dimensions of Eigen vector: (2, 784)
```

In [17]:

```
#dot product of transposed eigen vector matrix and standardised data matrix
final_df = np.matmul(vectors, df.T)
print("vectors:", vectors.shape, "\n", "std_df:", df.T.shape, "\n", "final_df:", fin
```

```
vectors: (2, 784)
 std_df: (784, 42000)
 final_df: (2, 42000)
```

In [18]:

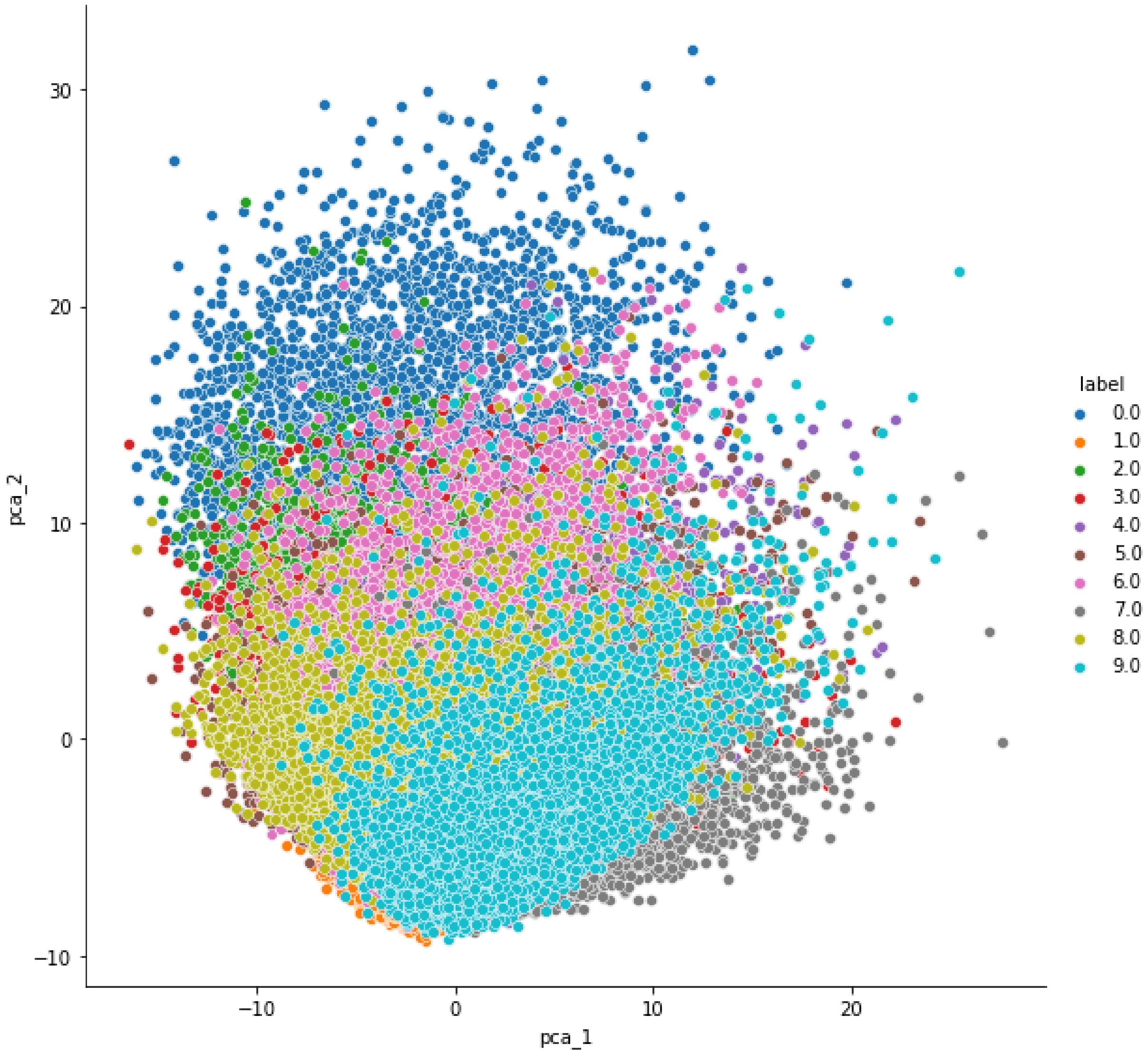
```
#combines the final_df array (which contains the transformed data after PCA) and the
final_dfT = np.vstack((final_df, label)).T
dataFrame = pd.DataFrame(final_dfT, columns = ['pca_1', 'pca_2', 'label'])
dataFrame
```

Out[18]:

	pca_1	pca_2	label
0	-5.226445	-5.140478	1.0
1	6.032996	19.292332	0.0
2	-1.705813	-7.644503	1.0
3	5.836139	-0.474207	4.0
4	6.024818	26.559574	0.0
...	...	...	...
41995	-1.350366	13.678849	0.0
41996	-1.187360	-8.869582	1.0
41997	7.076277	0.495391	7.0
41998	-4.344513	2.307240	6.0
41999	1.559121	-4.807670	9.0

42000 rows × 3 columns

In [19]:
```
#creates a FacetGrid using Seaborn, where each facet represents a unique value of th
sns.FacetGrid(dataFrame, hue='label', height=8).map(sns.scatterplot, 'pca_1', 'pca_2
plt.show()
```



Result :

Therefore, we were successfully able to implement PCA (dimensionality reduction) from scratch using the MNIST dataset