



## LAB EXPERIMENT NO. 8

### AIM :

Compare the performance of PCA and Autoencoders on a given dataset

### THEORY:

#### What is Dimensionality Reduction?

In machine learning classification problems, there are often too many factors on the basis of which the final classification is done. These factors are basically variables called features. The higher the number of features, the harder it gets to visualize the training set and then work on it. Sometimes, most of these features are correlated, and hence redundant. This is where dimensionality reduction algorithms come into play. Dimensionality reduction is the process of reducing the number of random variables under consideration, by obtaining a set of principal variables. It can be divided into feature selection and feature extraction.

#### Principle Component Analysis

Principle Component Analysis is an unsupervised technique where the original data is projected to the direction of high variance. These directions of high variance are orthogonal to each other resulting in very low or almost close to 0 correlation in the projected data. These features transformation is linear and the methodology to do it is:

**Step 1:** Calculate the Correlation matrix data consisting of  $n$  dimensions. The Correlation matrix will be of shape  $n \times n$ .

**Step 2:** Calculate the Eigenvectors and Eigenvalues of this matrix.

**Step 3:** Take the first  $k$ -eigenvectors with the highest eigenvalues.

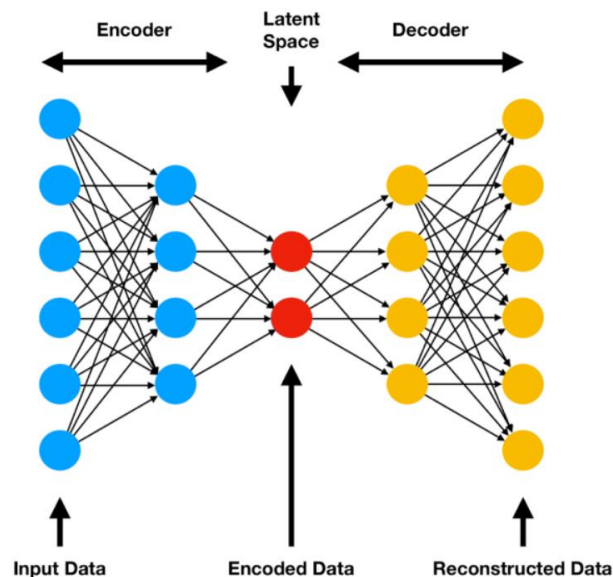
**Step 4:** Project the original dataset into these  $k$  eigenvectors resulting in  $k$  dimensions where  $k \leq n$ .

#### Autoencoders

Autoencoder is an unsupervised artificial neural network that compresses the data to lower dimension and then reconstructs the input back. Autoencoder finds the representation of the data in



a lower dimension by focusing more on the important features getting rid of noise and redundancy. It's based on Encoder-Decoder architecture, where encoder encodes the high-dimensional data to lower-dimension and decoder takes the lower-dimensional data and tries to reconstruct the original high-dimensional data.



#### Tasks to be performed:

1. Use the Iris Dataset present in the scikit-learn library
2. Create an Auto Encoder and fit it with our data using 3 neurons in the dense layer
3. Use encoded layer to encode the training input
4. Plot loss for different encoders [PCA, Linear Autoencoder, Sigmoid based Non-Linear Autoencoder, ReLU based Non-Linear Auto encoder]

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3 LAB 8

4 Step 1: Load the Iris Dataset

```
[19]: from sklearn.datasets import load_iris
      from sklearn.preprocessing import StandardScaler
      import numpy as np

      data = load_iris()
      X = data['data']
      y = data['target']

      scaler = StandardScaler()
      X_scaled = scaler.fit_transform(X)
```

5 Step 2: Implement PCA

```
[20]: from sklearn.decomposition import PCA

      pca = PCA(n_components=3)
      X_pca = pca.fit_transform(X_scaled)
```

6 Step 3: Implement Autoencoders (Linear, Sigmoid, and ReLU based)

Linear Autoencoder

```
[21]: import tensorflow as tf
      from tensorflow.keras import layers, models

      input_dim = X_scaled.shape[1]
```

```

encoding_dim = 3

linear_autoencoder = models.Sequential([
    layers.Dense(encoding_dim, input_shape=(input_dim,), activation='linear'),
    layers.Dense(input_dim, activation='linear')
])

linear_autoencoder.compile(optimizer='adam', loss='mse')
history_linear = linear_autoencoder.fit(X_scaled, X_scaled, epochs=100,
    ↪batch_size=8, verbose=0)

```

/usr/local/lib/python3.10/dist-packages/keras/src/layers/core/dense.py:87:  
 UserWarning: Do not pass an `input\_shape`/`input\_dim` argument to a layer. When  
 using Sequential models, prefer using an `Input(shape)` object as the first  
 layer in the model instead.

```

super().__init__(activity_regularizer=activity_regularizer, **kwargs)

```

### Sigmoid-based Non-Linear Autoencoder

```

[22]: sigmoid_autoencoder = models.Sequential([
    layers.Dense(encoding_dim, input_shape=(input_dim,), activation='sigmoid'),
    layers.Dense(input_dim, activation='sigmoid')
])

sigmoid_autoencoder.compile(optimizer='adam', loss='mse')
history_sigmoid = sigmoid_autoencoder.fit(X_scaled, X_scaled, epochs=100,
    ↪batch_size=8, verbose=0)

```

### ReLU-based Non-Linear Autoencoder

```

[23]: relu_autoencoder = models.Sequential([
    layers.Dense(encoding_dim, input_shape=(input_dim,), activation='relu'),
    layers.Dense(input_dim, activation='relu')
])

relu_autoencoder.compile(optimizer='adam', loss='mse')
history_relu = relu_autoencoder.fit(X_scaled, X_scaled, epochs=100,
    ↪batch_size=8, verbose=0)

```

## 7 Step 4: Encode the Input Data Using Autoencoders

```

[24]: linear_autoencoder.compile(optimizer='adam', loss='mse')
linear_autoencoder.fit(X_scaled, X_scaled, epochs=50, batch_size=16,
    ↪shuffle=True, validation_split=0.2)

sigmoid_autoencoder.compile(optimizer='adam', loss='mse')

```

```
sigmoid_autoencoder.fit(X_scaled, X_scaled, epochs=50, batch_size=16,
↳shuffle=True, validation_split=0.2)

relu_autoencoder.compile(optimizer='adam', loss='mse')
relu_autoencoder.fit(X_scaled, X_scaled, epochs=50, batch_size=16,
↳shuffle=True, validation_split=0.2)
```

```
Epoch 1/50
8/8          1s 23ms/step - loss:
0.0525 - val_loss: 0.0741
Epoch 2/50
8/8          0s 6ms/step - loss:
0.0483 - val_loss: 0.0746
Epoch 3/50
8/8          0s 7ms/step - loss:
0.0429 - val_loss: 0.0746
Epoch 4/50
8/8          0s 6ms/step - loss:
0.0404 - val_loss: 0.0738
Epoch 5/50
8/8          0s 6ms/step - loss:
0.0434 - val_loss: 0.0737
Epoch 6/50
8/8          0s 5ms/step - loss:
0.0457 - val_loss: 0.0729
Epoch 7/50
8/8          0s 5ms/step - loss:
0.0454 - val_loss: 0.0725
Epoch 8/50
8/8          0s 9ms/step - loss:
0.0390 - val_loss: 0.0722
Epoch 9/50
8/8          0s 8ms/step - loss:
0.0416 - val_loss: 0.0719
Epoch 10/50
8/8          0s 10ms/step - loss:
0.0368 - val_loss: 0.0712
Epoch 11/50
8/8          0s 8ms/step - loss:
0.0376 - val_loss: 0.0706
Epoch 12/50
8/8          0s 7ms/step - loss:
0.0398 - val_loss: 0.0702
Epoch 13/50
8/8          0s 12ms/step - loss:
0.0408 - val_loss: 0.0700
```

Epoch 14/50  
8/8 0s 10ms/step - loss:  
0.0395 - val\_loss: 0.0694  
Epoch 15/50  
8/8 0s 10ms/step - loss:  
0.0408 - val\_loss: 0.0692  
Epoch 16/50  
8/8 0s 10ms/step - loss:  
0.0376 - val\_loss: 0.0687  
Epoch 17/50  
8/8 0s 10ms/step - loss:  
0.0346 - val\_loss: 0.0679  
Epoch 18/50  
8/8 0s 11ms/step - loss:  
0.0335 - val\_loss: 0.0675  
Epoch 19/50  
8/8 0s 11ms/step - loss:  
0.0466 - val\_loss: 0.0671  
Epoch 20/50  
8/8 0s 11ms/step - loss:  
0.0346 - val\_loss: 0.0667  
Epoch 21/50  
8/8 0s 11ms/step - loss:  
0.0401 - val\_loss: 0.0663  
Epoch 22/50  
8/8 0s 11ms/step - loss:  
0.0405 - val\_loss: 0.0657  
Epoch 23/50  
8/8 0s 8ms/step - loss:  
0.0371 - val\_loss: 0.0654  
Epoch 24/50  
8/8 0s 8ms/step - loss:  
0.0353 - val\_loss: 0.0655  
Epoch 25/50  
8/8 0s 8ms/step - loss:  
0.0303 - val\_loss: 0.0651  
Epoch 26/50  
8/8 0s 14ms/step - loss:  
0.0375 - val\_loss: 0.0642  
Epoch 27/50  
8/8 0s 7ms/step - loss:  
0.0322 - val\_loss: 0.0638  
Epoch 28/50  
8/8 0s 8ms/step - loss:  
0.0300 - val\_loss: 0.0635  
Epoch 29/50  
8/8 0s 5ms/step - loss:  
0.0363 - val\_loss: 0.0631

Epoch 30/50  
8/8 0s 6ms/step - loss:  
0.0400 - val\_loss: 0.0628  
Epoch 31/50  
8/8 0s 8ms/step - loss:  
0.0362 - val\_loss: 0.0625  
Epoch 32/50  
8/8 0s 5ms/step - loss:  
0.0383 - val\_loss: 0.0624  
Epoch 33/50  
8/8 0s 6ms/step - loss:  
0.0371 - val\_loss: 0.0619  
Epoch 34/50  
8/8 0s 6ms/step - loss:  
0.0364 - val\_loss: 0.0617  
Epoch 35/50  
8/8 0s 7ms/step - loss:  
0.0333 - val\_loss: 0.0612  
Epoch 36/50  
8/8 0s 7ms/step - loss:  
0.0380 - val\_loss: 0.0607  
Epoch 37/50  
8/8 0s 6ms/step - loss:  
0.0347 - val\_loss: 0.0605  
Epoch 38/50  
8/8 0s 6ms/step - loss:  
0.0358 - val\_loss: 0.0598  
Epoch 39/50  
8/8 0s 5ms/step - loss:  
0.0317 - val\_loss: 0.0596  
Epoch 40/50  
8/8 0s 6ms/step - loss:  
0.0296 - val\_loss: 0.0594  
Epoch 41/50  
8/8 0s 5ms/step - loss:  
0.0291 - val\_loss: 0.0593  
Epoch 42/50  
8/8 0s 8ms/step - loss:  
0.0317 - val\_loss: 0.0587  
Epoch 43/50  
8/8 0s 5ms/step - loss:  
0.0299 - val\_loss: 0.0583  
Epoch 44/50  
8/8 0s 9ms/step - loss:  
0.0277 - val\_loss: 0.0578  
Epoch 45/50  
8/8 0s 10ms/step - loss:  
0.0300 - val\_loss: 0.0574

Epoch 46/50  
8/8 0s 8ms/step - loss:  
0.0281 - val\_loss: 0.0571  
Epoch 47/50  
8/8 0s 6ms/step - loss:  
0.0316 - val\_loss: 0.0567  
Epoch 48/50  
8/8 0s 8ms/step - loss:  
0.0374 - val\_loss: 0.0562  
Epoch 49/50  
8/8 0s 8ms/step - loss:  
0.0283 - val\_loss: 0.0563  
Epoch 50/50  
8/8 0s 8ms/step - loss:  
0.0316 - val\_loss: 0.0559  
Epoch 1/50  
8/8 1s 23ms/step - loss:  
0.8354 - val\_loss: 0.4930  
Epoch 2/50  
8/8 0s 6ms/step - loss:  
0.9238 - val\_loss: 0.4927  
Epoch 3/50  
8/8 0s 5ms/step - loss:  
0.8260 - val\_loss: 0.4925  
Epoch 4/50  
8/8 0s 7ms/step - loss:  
0.8763 - val\_loss: 0.4919  
Epoch 5/50  
8/8 0s 6ms/step - loss:  
0.8378 - val\_loss: 0.4914  
Epoch 6/50  
8/8 0s 6ms/step - loss:  
0.9062 - val\_loss: 0.4907  
Epoch 7/50  
8/8 0s 5ms/step - loss:  
0.8601 - val\_loss: 0.4901  
Epoch 8/50  
8/8 0s 5ms/step - loss:  
0.9499 - val\_loss: 0.4896  
Epoch 9/50  
8/8 0s 6ms/step - loss:  
0.8981 - val\_loss: 0.4889  
Epoch 10/50  
8/8 0s 5ms/step - loss:  
0.9054 - val\_loss: 0.4883  
Epoch 11/50  
8/8 0s 6ms/step - loss:  
0.8681 - val\_loss: 0.4877



Epoch 12/50  
8/8 0s 5ms/step - loss:  
0.9075 - val\_loss: 0.4869  
Epoch 13/50  
8/8 0s 7ms/step - loss:  
0.8791 - val\_loss: 0.4861  
Epoch 14/50  
8/8 0s 7ms/step - loss:  
0.8398 - val\_loss: 0.4855  
Epoch 15/50  
8/8 0s 6ms/step - loss:  
0.8755 - val\_loss: 0.4847  
Epoch 16/50  
8/8 0s 10ms/step - loss:  
0.8527 - val\_loss: 0.4843  
Epoch 17/50  
8/8 0s 8ms/step - loss:  
0.8915 - val\_loss: 0.4835  
Epoch 18/50  
8/8 0s 7ms/step - loss:  
0.8399 - val\_loss: 0.4826  
Epoch 19/50  
8/8 0s 6ms/step - loss:  
0.8097 - val\_loss: 0.4817  
Epoch 20/50  
8/8 0s 9ms/step - loss:  
0.8751 - val\_loss: 0.4808  
Epoch 21/50  
8/8 0s 5ms/step - loss:  
0.8905 - val\_loss: 0.4799  
Epoch 22/50  
8/8 0s 6ms/step - loss:  
0.9536 - val\_loss: 0.4791  
Epoch 23/50  
8/8 0s 9ms/step - loss:  
0.8604 - val\_loss: 0.4781  
Epoch 24/50  
8/8 0s 7ms/step - loss:  
0.8528 - val\_loss: 0.4773  
Epoch 25/50  
8/8 0s 5ms/step - loss:  
0.8627 - val\_loss: 0.4766  
Epoch 26/50  
8/8 0s 8ms/step - loss:  
0.8458 - val\_loss: 0.4759  
Epoch 27/50  
8/8 0s 8ms/step - loss:  
0.9006 - val\_loss: 0.4752

Epoch 28/50  
8/8 0s 6ms/step - loss:  
0.8409 - val\_loss: 0.4741  
Epoch 29/50  
8/8 0s 8ms/step - loss:  
0.9425 - val\_loss: 0.4732  
Epoch 30/50  
8/8 0s 6ms/step - loss:  
0.8807 - val\_loss: 0.4722  
Epoch 31/50  
8/8 0s 6ms/step - loss:  
0.8526 - val\_loss: 0.4714  
Epoch 32/50  
8/8 0s 7ms/step - loss:  
0.7871 - val\_loss: 0.4705  
Epoch 33/50  
8/8 0s 6ms/step - loss:  
0.9123 - val\_loss: 0.4695  
Epoch 34/50  
8/8 0s 6ms/step - loss:  
0.8833 - val\_loss: 0.4686  
Epoch 35/50  
8/8 0s 7ms/step - loss:  
0.8498 - val\_loss: 0.4677  
Epoch 36/50  
8/8 0s 6ms/step - loss:  
0.7922 - val\_loss: 0.4668  
Epoch 37/50  
8/8 0s 6ms/step - loss:  
0.8785 - val\_loss: 0.4661  
Epoch 38/50  
8/8 0s 6ms/step - loss:  
0.9586 - val\_loss: 0.4654  
Epoch 39/50  
8/8 0s 5ms/step - loss:  
0.8832 - val\_loss: 0.4645  
Epoch 40/50  
8/8 0s 6ms/step - loss:  
0.9342 - val\_loss: 0.4635  
Epoch 41/50  
8/8 0s 8ms/step - loss:  
0.8449 - val\_loss: 0.4626  
Epoch 42/50  
8/8 0s 7ms/step - loss:  
0.8853 - val\_loss: 0.4617  
Epoch 43/50  
8/8 0s 6ms/step - loss:  
0.8962 - val\_loss: 0.4608

Epoch 44/50  
8/8 0s 6ms/step - loss:  
0.9268 - val\_loss: 0.4599  
Epoch 45/50  
8/8 0s 10ms/step - loss:  
0.9273 - val\_loss: 0.4590  
Epoch 46/50  
8/8 0s 6ms/step - loss:  
0.9082 - val\_loss: 0.4582  
Epoch 47/50  
8/8 0s 6ms/step - loss:  
0.9476 - val\_loss: 0.4574  
Epoch 48/50  
8/8 0s 6ms/step - loss:  
0.8505 - val\_loss: 0.4565  
Epoch 49/50  
8/8 0s 6ms/step - loss:  
0.8344 - val\_loss: 0.4558  
Epoch 50/50  
8/8 0s 7ms/step - loss:  
0.9327 - val\_loss: 0.4549  
Epoch 1/50  
8/8 1s 26ms/step - loss:  
0.8619 - val\_loss: 0.7541  
Epoch 2/50  
8/8 0s 8ms/step - loss:  
0.9813 - val\_loss: 0.7540  
Epoch 3/50  
8/8 0s 10ms/step - loss:  
0.9485 - val\_loss: 0.7540  
Epoch 4/50  
8/8 0s 10ms/step - loss:  
0.9410 - val\_loss: 0.7539  
Epoch 5/50  
8/8 0s 10ms/step - loss:  
1.0033 - val\_loss: 0.7538  
Epoch 6/50  
8/8 0s 10ms/step - loss:  
0.9873 - val\_loss: 0.7537  
Epoch 7/50  
8/8 0s 7ms/step - loss:  
0.8637 - val\_loss: 0.7536  
Epoch 8/50  
8/8 0s 13ms/step - loss:  
0.9366 - val\_loss: 0.7535  
Epoch 9/50  
8/8 0s 11ms/step - loss:  
0.9182 - val\_loss: 0.7536

Epoch 10/50  
8/8 0s 7ms/step - loss:  
0.9187 - val\_loss: 0.7534  
Epoch 11/50  
8/8 0s 8ms/step - loss:  
0.9899 - val\_loss: 0.7533  
Epoch 12/50  
8/8 0s 10ms/step - loss:  
0.8495 - val\_loss: 0.7532  
Epoch 13/50  
8/8 0s 10ms/step - loss:  
0.9535 - val\_loss: 0.7532  
Epoch 14/50  
8/8 0s 11ms/step - loss:  
0.9451 - val\_loss: 0.7532  
Epoch 15/50  
8/8 0s 12ms/step - loss:  
0.8759 - val\_loss: 0.7531  
Epoch 16/50  
8/8 0s 11ms/step - loss:  
0.8876 - val\_loss: 0.7529  
Epoch 17/50  
8/8 0s 11ms/step - loss:  
0.8519 - val\_loss: 0.7529  
Epoch 18/50  
8/8 0s 11ms/step - loss:  
0.9378 - val\_loss: 0.7528  
Epoch 19/50  
8/8 0s 11ms/step - loss:  
0.9979 - val\_loss: 0.7529  
Epoch 20/50  
8/8 0s 9ms/step - loss:  
0.9144 - val\_loss: 0.7527  
Epoch 21/50  
8/8 0s 9ms/step - loss:  
0.8945 - val\_loss: 0.7527  
Epoch 22/50  
8/8 0s 11ms/step - loss:  
0.9197 - val\_loss: 0.7526  
Epoch 23/50  
8/8 0s 9ms/step - loss:  
0.9597 - val\_loss: 0.7526  
Epoch 24/50  
8/8 0s 6ms/step - loss:  
0.9252 - val\_loss: 0.7526  
Epoch 25/50  
8/8 0s 6ms/step - loss:  
0.9710 - val\_loss: 0.7524

Epoch 26/50  
8/8 0s 6ms/step - loss:  
0.9248 - val\_loss: 0.7524  
Epoch 27/50  
8/8 0s 6ms/step - loss:  
0.9112 - val\_loss: 0.7523  
Epoch 28/50  
8/8 0s 6ms/step - loss:  
0.8992 - val\_loss: 0.7523  
Epoch 29/50  
8/8 0s 9ms/step - loss:  
0.8946 - val\_loss: 0.7522  
Epoch 30/50  
8/8 0s 6ms/step - loss:  
1.0203 - val\_loss: 0.7522  
Epoch 31/50  
8/8 0s 6ms/step - loss:  
0.8728 - val\_loss: 0.7520  
Epoch 32/50  
8/8 0s 6ms/step - loss:  
0.8110 - val\_loss: 0.7520  
Epoch 33/50  
8/8 0s 6ms/step - loss:  
0.8673 - val\_loss: 0.7520  
Epoch 34/50  
8/8 0s 7ms/step - loss:  
0.8636 - val\_loss: 0.7519  
Epoch 35/50  
8/8 0s 6ms/step - loss:  
0.9693 - val\_loss: 0.7518  
Epoch 36/50  
8/8 0s 5ms/step - loss:  
0.9046 - val\_loss: 0.7517  
Epoch 37/50  
8/8 0s 6ms/step - loss:  
0.8757 - val\_loss: 0.7517  
Epoch 38/50  
8/8 0s 8ms/step - loss:  
0.9743 - val\_loss: 0.7516  
Epoch 39/50  
8/8 0s 8ms/step - loss:  
0.9430 - val\_loss: 0.7515  
Epoch 40/50  
8/8 0s 6ms/step - loss:  
0.9207 - val\_loss: 0.7515  
Epoch 41/50  
8/8 0s 6ms/step - loss:  
0.9226 - val\_loss: 0.7514

```

Epoch 42/50
8/8          0s 8ms/step - loss:
0.9655 - val_loss: 0.7514
Epoch 43/50
8/8          0s 7ms/step - loss:
0.9571 - val_loss: 0.7513
Epoch 44/50
8/8          0s 7ms/step - loss:
0.9359 - val_loss: 0.7514
Epoch 45/50
8/8          0s 6ms/step - loss:
0.9372 - val_loss: 0.7513
Epoch 46/50
8/8          0s 6ms/step - loss:
0.9059 - val_loss: 0.7512
Epoch 47/50
8/8          0s 6ms/step - loss:
0.9200 - val_loss: 0.7511
Epoch 48/50
8/8          0s 6ms/step - loss:
0.8775 - val_loss: 0.7511
Epoch 49/50
8/8          0s 7ms/step - loss:
0.8561 - val_loss: 0.7510
Epoch 50/50
8/8          0s 8ms/step - loss:
0.8462 - val_loss: 0.7510

```

[24]: <keras.src.callbacks.history.History at 0x787ecdee7490>

```

[25]: from keras import models
      from keras import layers
      import pandas as pd
      import matplotlib.pyplot as plt
      import seaborn as sns

      input_dim = X_scaled.shape[1]
      input_layer = layers.Input(shape=(input_dim,))
      encoded = layers.Dense(3, activation='linear')(input_layer)
      decoded = layers.Dense(input_dim, activation='linear')(encoded)

      linear_autoencoder = models.Model(inputs=input_layer, outputs=decoded)
      linear_autoencoder.compile(optimizer='adam', loss='mse')
      linear_autoencoder.fit(X_scaled, X_scaled, epochs=50, batch_size=16)

      encoder_layer_linear = models.Model(inputs=input_layer, outputs=encoded)

```

```

X_encoded_linear = encoder_layer_linear.predict(X_scaled)

input_layer_sigmoid = layers.Input(shape=(input_dim,))
encoded_sigmoid = layers.Dense(3, activation='sigmoid')(input_layer_sigmoid)
decoded_sigmoid = layers.Dense(input_dim, activation='sigmoid')(encoded_sigmoid)

sigmoid_autoencoder = models.Model(inputs=input_layer_sigmoid,
    ↪ outputs=decoded_sigmoid)
sigmoid_autoencoder.compile(optimizer='adam', loss='mse')
sigmoid_autoencoder.fit(X_scaled, X_scaled, epochs=50, batch_size=16)

encoder_layer_sigmoid = models.Model(inputs=input_layer_sigmoid,
    ↪ outputs=encoded_sigmoid)
X_encoded_sigmoid = encoder_layer_sigmoid.predict(X_scaled)

input_layer_relu = layers.Input(shape=(input_dim,))
encoded_relu = layers.Dense(3, activation='relu')(input_layer_relu)
decoded_relu = layers.Dense(input_dim, activation='linear')(encoded_relu)

relu_autoencoder = models.Model(inputs=input_layer_relu, outputs=decoded_relu)
relu_autoencoder.compile(optimizer='adam', loss='mse')
relu_autoencoder.fit(X_scaled, X_scaled, epochs=50, batch_size=16)

encoder_layer_relu = models.Model(inputs=input_layer_relu, outputs=encoded_relu)
X_encoded_relu = encoder_layer_relu.predict(X_scaled)

```

```

Epoch 1/50
10/10          1s 3ms/step - loss:
0.8825
Epoch 2/50
10/10          0s 2ms/step - loss:
0.7532
Epoch 3/50
10/10          0s 2ms/step - loss:
0.7949
Epoch 4/50
10/10          0s 2ms/step - loss:
0.7949
Epoch 5/50
10/10          0s 2ms/step - loss:
0.6385
Epoch 6/50
10/10          0s 2ms/step - loss:
0.6170
Epoch 7/50
10/10          0s 2ms/step - loss:

```

```

0.5868
Epoch 8/50
10/10      0s 2ms/step - loss:
0.5507
Epoch 9/50
10/10      0s 2ms/step - loss:
0.5294
Epoch 10/50
10/10      0s 2ms/step - loss:
0.5479
Epoch 11/50
10/10      0s 2ms/step - loss:
0.4529
Epoch 12/50
10/10      0s 2ms/step - loss:
0.4731
Epoch 13/50
10/10      0s 2ms/step - loss:
0.4791
Epoch 14/50
10/10      0s 2ms/step - loss:
0.4131
Epoch 15/50
10/10      0s 2ms/step - loss:
0.3644
Epoch 16/50
10/10      0s 2ms/step - loss:
0.4153
Epoch 17/50
10/10      0s 2ms/step - loss:
0.3436
Epoch 18/50
10/10      0s 2ms/step - loss:
0.3940
Epoch 19/50
10/10      0s 2ms/step - loss:
0.3101
Epoch 20/50
10/10      0s 2ms/step - loss:
0.3273
Epoch 21/50
10/10      0s 2ms/step - loss:
0.3208
Epoch 22/50
10/10      0s 2ms/step - loss:
0.2800
Epoch 23/50
10/10      0s 2ms/step - loss:

```



```

0.3073
Epoch 24/50
10/10      0s 3ms/step - loss:
0.2809
Epoch 25/50
10/10      0s 3ms/step - loss:
0.2297
Epoch 26/50
10/10      0s 2ms/step - loss:
0.2794
Epoch 27/50
10/10      0s 2ms/step - loss:
0.2773
Epoch 28/50
10/10      0s 2ms/step - loss:
0.2180
Epoch 29/50
10/10      0s 3ms/step - loss:
0.2429
Epoch 30/50
10/10      0s 2ms/step - loss:
0.2400
Epoch 31/50
10/10      0s 2ms/step - loss:
0.2093
Epoch 32/50
10/10      0s 2ms/step - loss:
0.1985
Epoch 33/50
10/10      0s 2ms/step - loss:
0.2246
Epoch 34/50
10/10      0s 2ms/step - loss:
0.1908
Epoch 35/50
10/10      0s 2ms/step - loss:
0.1893
Epoch 36/50
10/10      0s 2ms/step - loss:
0.1869
Epoch 37/50
10/10      0s 2ms/step - loss:
0.1981
Epoch 38/50
10/10      0s 2ms/step - loss:
0.1978
Epoch 39/50
10/10      0s 2ms/step - loss:

```

```

0.1920
Epoch 40/50
10/10      0s 2ms/step - loss:
0.1816
Epoch 41/50
10/10      0s 3ms/step - loss:
0.1566
Epoch 42/50
10/10      0s 2ms/step - loss:
0.1859
Epoch 43/50
10/10      0s 2ms/step - loss:
0.1720
Epoch 44/50
10/10      0s 2ms/step - loss:
0.1608
Epoch 45/50
10/10      0s 2ms/step - loss:
0.1481
Epoch 46/50
10/10      0s 2ms/step - loss:
0.1448
Epoch 47/50
10/10      0s 2ms/step - loss:
0.1260
Epoch 48/50
10/10      0s 2ms/step - loss:
0.1383
Epoch 49/50
10/10      0s 2ms/step - loss:
0.1357
Epoch 50/50
10/10      0s 2ms/step - loss:
0.1174
5/5        0s 6ms/step
Epoch 1/50
10/10      1s 2ms/step - loss:
1.2957
Epoch 2/50
10/10      0s 2ms/step - loss:
1.1582
Epoch 3/50
10/10      0s 2ms/step - loss:
1.2765
Epoch 4/50
10/10      0s 3ms/step - loss:
1.2421
Epoch 5/50

```

10/10	0s 2ms/step - loss:
1.1575	
Epoch 6/50	
10/10	0s 2ms/step - loss:
1.2048	
Epoch 7/50	
10/10	0s 2ms/step - loss:
1.2590	
Epoch 8/50	
10/10	0s 2ms/step - loss:
1.1627	
Epoch 9/50	
10/10	0s 2ms/step - loss:
1.1686	
Epoch 10/50	
10/10	0s 2ms/step - loss:
1.2294	
Epoch 11/50	
10/10	0s 2ms/step - loss:
1.2406	
Epoch 12/50	
10/10	0s 2ms/step - loss:
1.1399	
Epoch 13/50	
10/10	0s 2ms/step - loss:
1.1635	
Epoch 14/50	
10/10	0s 2ms/step - loss:
1.1685	
Epoch 15/50	
10/10	0s 2ms/step - loss:
1.1014	
Epoch 16/50	
10/10	0s 2ms/step - loss:
1.0911	
Epoch 17/50	
10/10	0s 2ms/step - loss:
1.1609	
Epoch 18/50	
10/10	0s 2ms/step - loss:
1.1093	
Epoch 19/50	
10/10	0s 2ms/step - loss:
1.1625	
Epoch 20/50	
10/10	0s 2ms/step - loss:
1.1179	
Epoch 21/50	

10/10	0s 2ms/step - loss:
1.1833	
Epoch 22/50	
10/10	0s 3ms/step - loss:
1.1511	
Epoch 23/50	
10/10	0s 2ms/step - loss:
1.0332	
Epoch 24/50	
10/10	0s 2ms/step - loss:
1.0837	
Epoch 25/50	
10/10	0s 2ms/step - loss:
1.2054	
Epoch 26/50	
10/10	0s 2ms/step - loss:
1.1081	
Epoch 27/50	
10/10	0s 2ms/step - loss:
1.1029	
Epoch 28/50	
10/10	0s 2ms/step - loss:
1.1255	
Epoch 29/50	
10/10	0s 2ms/step - loss:
1.1455	
Epoch 30/50	
10/10	0s 2ms/step - loss:
1.0649	
Epoch 31/50	
10/10	0s 2ms/step - loss:
1.1287	
Epoch 32/50	
10/10	0s 2ms/step - loss:
1.0376	
Epoch 33/50	
10/10	0s 2ms/step - loss:
1.0842	
Epoch 34/50	
10/10	0s 2ms/step - loss:
1.0224	
Epoch 35/50	
10/10	0s 2ms/step - loss:
1.0524	
Epoch 36/50	
10/10	0s 2ms/step - loss:
1.0651	
Epoch 37/50	

10/10	0s 2ms/step - loss:
1.0845	
Epoch 38/50	
10/10	0s 2ms/step - loss:
1.0749	
Epoch 39/50	
10/10	0s 2ms/step - loss:
1.0166	
Epoch 40/50	
10/10	0s 3ms/step - loss:
1.0485	
Epoch 41/50	
10/10	0s 3ms/step - loss:
1.0537	
Epoch 42/50	
10/10	0s 3ms/step - loss:
1.0731	
Epoch 43/50	
10/10	0s 2ms/step - loss:
1.0189	
Epoch 44/50	
10/10	0s 3ms/step - loss:
1.0640	
Epoch 45/50	
10/10	0s 3ms/step - loss:
0.9899	
Epoch 46/50	
10/10	0s 2ms/step - loss:
1.0546	
Epoch 47/50	
10/10	0s 2ms/step - loss:
1.0259	
Epoch 48/50	
10/10	0s 2ms/step - loss:
1.0287	
Epoch 49/50	
10/10	0s 3ms/step - loss:
0.9786	
Epoch 50/50	
10/10	0s 4ms/step - loss:
0.9310	
5/5	0s 9ms/step
Epoch 1/50	
10/10	1s 3ms/step - loss:
1.1037	
Epoch 2/50	
10/10	0s 3ms/step - loss:
1.1091	

Epoch 3/50	
10/10	0s 3ms/step - loss:
1.0180	
Epoch 4/50	
10/10	0s 3ms/step - loss:
0.9229	
Epoch 5/50	
10/10	0s 3ms/step - loss:
0.9816	
Epoch 6/50	
10/10	0s 2ms/step - loss:
1.0011	
Epoch 7/50	
10/10	0s 2ms/step - loss:
0.9376	
Epoch 8/50	
10/10	0s 2ms/step - loss:
0.9339	
Epoch 9/50	
10/10	0s 2ms/step - loss:
0.8256	
Epoch 10/50	
10/10	0s 2ms/step - loss:
0.8554	
Epoch 11/50	
10/10	0s 2ms/step - loss:
0.8201	
Epoch 12/50	
10/10	0s 2ms/step - loss:
0.8510	
Epoch 13/50	
10/10	0s 2ms/step - loss:
0.8417	
Epoch 14/50	
10/10	0s 2ms/step - loss:
0.7874	
Epoch 15/50	
10/10	0s 2ms/step - loss:
0.7293	
Epoch 16/50	
10/10	0s 2ms/step - loss:
0.7833	
Epoch 17/50	
10/10	0s 2ms/step - loss:
0.7373	
Epoch 18/50	
10/10	0s 2ms/step - loss:
0.7357	

Epoch 19/50	
10/10	0s 2ms/step - loss:
0.6885	
Epoch 20/50	
10/10	0s 3ms/step - loss:
0.6775	
Epoch 21/50	
10/10	0s 2ms/step - loss:
0.6395	
Epoch 22/50	
10/10	0s 2ms/step - loss:
0.6582	
Epoch 23/50	
10/10	0s 2ms/step - loss:
0.6728	
Epoch 24/50	
10/10	0s 2ms/step - loss:
0.5835	
Epoch 25/50	
10/10	0s 2ms/step - loss:
0.5819	
Epoch 26/50	
10/10	0s 2ms/step - loss:
0.5971	
Epoch 27/50	
10/10	0s 2ms/step - loss:
0.5796	
Epoch 28/50	
10/10	0s 2ms/step - loss:
0.4946	
Epoch 29/50	
10/10	0s 2ms/step - loss:
0.5212	
Epoch 30/50	
10/10	0s 2ms/step - loss:
0.4571	
Epoch 31/50	
10/10	0s 2ms/step - loss:
0.4249	
Epoch 32/50	
10/10	0s 2ms/step - loss:
0.4468	
Epoch 33/50	
10/10	0s 2ms/step - loss:
0.4785	
Epoch 34/50	
10/10	0s 2ms/step - loss:
0.5011	

Epoch 35/50	
10/10	0s 2ms/step - loss:
0.4946	
Epoch 36/50	
10/10	0s 2ms/step - loss:
0.3920	
Epoch 37/50	
10/10	0s 4ms/step - loss:
0.3943	
Epoch 38/50	
10/10	0s 2ms/step - loss:
0.4277	
Epoch 39/50	
10/10	0s 2ms/step - loss:
0.4415	
Epoch 40/50	
10/10	0s 2ms/step - loss:
0.4317	
Epoch 41/50	
10/10	0s 2ms/step - loss:
0.3893	
Epoch 42/50	
10/10	0s 2ms/step - loss:
0.3525	
Epoch 43/50	
10/10	0s 2ms/step - loss:
0.3236	
Epoch 44/50	
10/10	0s 2ms/step - loss:
0.3720	
Epoch 45/50	
10/10	0s 2ms/step - loss:
0.3494	
Epoch 46/50	
10/10	0s 2ms/step - loss:
0.3462	
Epoch 47/50	
10/10	0s 2ms/step - loss:
0.3661	
Epoch 48/50	
10/10	0s 2ms/step - loss:
0.3382	
Epoch 49/50	
10/10	0s 2ms/step - loss:
0.3552	
Epoch 50/50	
10/10	0s 2ms/step - loss:
0.2879	



## 8 PCA Implementation

```
[26]: # Visualization
plt.figure(figsize=(15, 10))

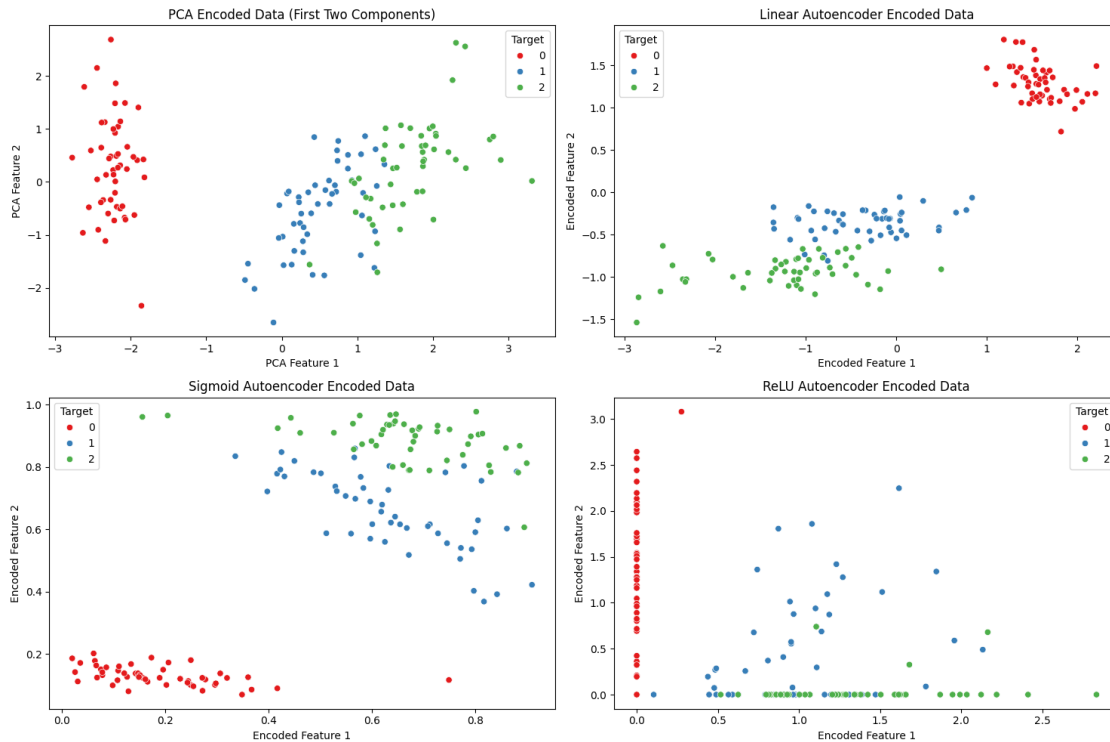
# PCA
plt.subplot(2, 2, 1)
sns.scatterplot(data=pd.DataFrame(X_encoded_pca, columns=['PCA Feature 1', 'PCA_
↳Feature 2', 'PCA Feature 3']).assign(Target=y),
                x='PCA Feature 1', y='PCA Feature 2', hue='Target',
↳palette='Set1')
plt.title('PCA Encoded Data (First Two Components)')

# Linear Autoencoder
plt.subplot(2, 2, 2)
sns.scatterplot(data=pd.DataFrame(X_encoded_linear, columns=['Encoded Feature_
↳1', 'Encoded Feature 2', 'Encoded Feature 3']).assign(Target=y),
                x='Encoded Feature 1', y='Encoded Feature 2', hue='Target',
↳palette='Set1')
plt.title('Linear Autoencoder Encoded Data')

# Sigmoid Autoencoder
plt.subplot(2, 2, 3)
sns.scatterplot(data=pd.DataFrame(X_encoded_sigmoid, columns=['Encoded Feature_
↳1', 'Encoded Feature 2', 'Encoded Feature 3']).assign(Target=y),
                x='Encoded Feature 1', y='Encoded Feature 2', hue='Target',
↳palette='Set1')
plt.title('Sigmoid Autoencoder Encoded Data')

# ReLU Autoencoder
plt.subplot(2, 2, 4)
sns.scatterplot(data=pd.DataFrame(X_encoded_relu, columns=['Encoded Feature 1',
↳'Encoded Feature 2', 'Encoded Feature 3']).assign(Target=y),
                x='Encoded Feature 1', y='Encoded Feature 2', hue='Target',
↳palette='Set1')
plt.title('ReLU Autoencoder Encoded Data')

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



```
[27]: import matplotlib.pyplot as plt

losses = {
    "PCA": [],
    "Linear Autoencoder": [],
    "Sigmoid Autoencoder": [],
    "ReLU Autoencoder": []
}

linear_autoencoder.fit(X_scaled, X_scaled, epochs=50, batch_size=16)
losses["Linear Autoencoder"] = linear_autoencoder.history.history['loss']

sigmoid_autoencoder.fit(X_scaled, X_scaled, epochs=50, batch_size=16)
losses["Sigmoid Autoencoder"] = sigmoid_autoencoder.history.history['loss']

relu_autoencoder.fit(X_scaled, X_scaled, epochs=50, batch_size=16)
losses["ReLU Autoencoder"] = relu_autoencoder.history.history['loss']

losses["PCA"] = [0] * len(losses["Linear Autoencoder"])

plt.figure(figsize=(10, 6))
for encoder, loss in losses.items():
    plt.plot(loss, label=encoder)
```

```
plt.title('Loss for Different Encoders')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()
```

```
Epoch 1/50
10/10          0s 4ms/step - loss:
0.1284
Epoch 2/50
10/10          0s 3ms/step - loss:
0.1233
Epoch 3/50
10/10          0s 3ms/step - loss:
0.1241
Epoch 4/50
10/10          0s 3ms/step - loss:
0.1153
Epoch 5/50
10/10          0s 4ms/step - loss:
0.1191
Epoch 6/50
10/10          0s 3ms/step - loss:
0.1112
Epoch 7/50
10/10          0s 3ms/step - loss:
0.1150
Epoch 8/50
10/10          0s 3ms/step - loss:
0.1050
Epoch 9/50
10/10          0s 3ms/step - loss:
0.1020
Epoch 10/50
10/10          0s 3ms/step - loss:
0.1014
Epoch 11/50
10/10          0s 5ms/step - loss:
0.1072
Epoch 12/50
10/10          0s 5ms/step - loss:
0.0876
Epoch 13/50
10/10          0s 7ms/step - loss:
0.0906
Epoch 14/50
```

10/10	0s 4ms/step - loss:
0.1007	
Epoch 15/50	
10/10	0s 4ms/step - loss:
0.0971	
Epoch 16/50	
10/10	0s 3ms/step - loss:
0.0794	
Epoch 17/50	
10/10	0s 3ms/step - loss:
0.0857	
Epoch 18/50	
10/10	0s 3ms/step - loss:
0.0730	
Epoch 19/50	
10/10	0s 3ms/step - loss:
0.0855	
Epoch 20/50	
10/10	0s 3ms/step - loss:
0.0841	
Epoch 21/50	
10/10	0s 3ms/step - loss:
0.0730	
Epoch 22/50	
10/10	0s 3ms/step - loss:
0.0621	
Epoch 23/50	
10/10	0s 3ms/step - loss:
0.0696	
Epoch 24/50	
10/10	0s 3ms/step - loss:
0.0725	
Epoch 25/50	
10/10	0s 3ms/step - loss:
0.0736	
Epoch 26/50	
10/10	0s 3ms/step - loss:
0.0659	
Epoch 27/50	
10/10	0s 4ms/step - loss:
0.0748	
Epoch 28/50	
10/10	0s 2ms/step - loss:
0.0692	
Epoch 29/50	
10/10	0s 2ms/step - loss:
0.0655	
Epoch 30/50	

10/10	0s 2ms/step - loss:
0.0647	
Epoch 31/50	
10/10	0s 2ms/step - loss:
0.0599	
Epoch 32/50	
10/10	0s 2ms/step - loss:
0.0650	
Epoch 33/50	
10/10	0s 2ms/step - loss:
0.0554	
Epoch 34/50	
10/10	0s 3ms/step - loss:
0.0630	
Epoch 35/50	
10/10	0s 2ms/step - loss:
0.0632	
Epoch 36/50	
10/10	0s 2ms/step - loss:
0.0601	
Epoch 37/50	
10/10	0s 2ms/step - loss:
0.0635	
Epoch 38/50	
10/10	0s 2ms/step - loss:
0.0644	
Epoch 39/50	
10/10	0s 2ms/step - loss:
0.0592	
Epoch 40/50	
10/10	0s 2ms/step - loss:
0.0553	
Epoch 41/50	
10/10	0s 2ms/step - loss:
0.0605	
Epoch 42/50	
10/10	0s 3ms/step - loss:
0.0538	
Epoch 43/50	
10/10	0s 2ms/step - loss:
0.0508	
Epoch 44/50	
10/10	0s 2ms/step - loss:
0.0594	
Epoch 45/50	
10/10	0s 2ms/step - loss:
0.0546	
Epoch 46/50	

10/10	0s 2ms/step - loss:
0.0575	
Epoch 47/50	
10/10	0s 2ms/step - loss:
0.0574	
Epoch 48/50	
10/10	0s 2ms/step - loss:
0.0491	
Epoch 49/50	
10/10	0s 2ms/step - loss:
0.0484	
Epoch 50/50	
10/10	0s 2ms/step - loss:
0.0559	
Epoch 1/50	
10/10	0s 2ms/step - loss:
1.0063	
Epoch 2/50	
10/10	0s 2ms/step - loss:
0.9512	
Epoch 3/50	
10/10	0s 2ms/step - loss:
1.0700	
Epoch 4/50	
10/10	0s 2ms/step - loss:
0.9992	
Epoch 5/50	
10/10	0s 3ms/step - loss:
0.9045	
Epoch 6/50	
10/10	0s 2ms/step - loss:
1.0700	
Epoch 7/50	
10/10	0s 2ms/step - loss:
0.9887	
Epoch 8/50	
10/10	0s 2ms/step - loss:
0.9059	
Epoch 9/50	
10/10	0s 2ms/step - loss:
0.9681	
Epoch 10/50	
10/10	0s 2ms/step - loss:
1.0340	
Epoch 11/50	
10/10	0s 2ms/step - loss:
0.9953	
Epoch 12/50	

10/10	0s 3ms/step - loss:
0.8987	
Epoch 13/50	
10/10	0s 2ms/step - loss:
0.9718	
Epoch 14/50	
10/10	0s 2ms/step - loss:
1.0029	
Epoch 15/50	
10/10	0s 2ms/step - loss:
0.9040	
Epoch 16/50	
10/10	0s 2ms/step - loss:
0.9139	
Epoch 17/50	
10/10	0s 2ms/step - loss:
0.8853	
Epoch 18/50	
10/10	0s 2ms/step - loss:
0.8706	
Epoch 19/50	
10/10	0s 2ms/step - loss:
0.9792	
Epoch 20/50	
10/10	0s 2ms/step - loss:
0.9511	
Epoch 21/50	
10/10	0s 2ms/step - loss:
0.8829	
Epoch 22/50	
10/10	0s 2ms/step - loss:
0.9552	
Epoch 23/50	
10/10	0s 2ms/step - loss:
0.8769	
Epoch 24/50	
10/10	0s 2ms/step - loss:
0.9523	
Epoch 25/50	
10/10	0s 2ms/step - loss:
0.8935	
Epoch 26/50	
10/10	0s 2ms/step - loss:
0.9496	
Epoch 27/50	
10/10	0s 3ms/step - loss:
0.8485	
Epoch 28/50	

10/10	0s 2ms/step - loss:
1.0229	
Epoch 29/50	
10/10	0s 2ms/step - loss:
0.8583	
Epoch 30/50	
10/10	0s 2ms/step - loss:
0.8616	
Epoch 31/50	
10/10	0s 2ms/step - loss:
0.8343	
Epoch 32/50	
10/10	0s 2ms/step - loss:
0.9231	
Epoch 33/50	
10/10	0s 3ms/step - loss:
0.9357	
Epoch 34/50	
10/10	0s 2ms/step - loss:
0.8755	
Epoch 35/50	
10/10	0s 3ms/step - loss:
0.9271	
Epoch 36/50	
10/10	0s 2ms/step - loss:
0.9404	
Epoch 37/50	
10/10	0s 2ms/step - loss:
0.8352	
Epoch 38/50	
10/10	0s 2ms/step - loss:
0.8679	
Epoch 39/50	
10/10	0s 2ms/step - loss:
0.9442	
Epoch 40/50	
10/10	0s 2ms/step - loss:
0.8982	
Epoch 41/50	
10/10	0s 2ms/step - loss:
0.9067	
Epoch 42/50	
10/10	0s 2ms/step - loss:
0.8566	
Epoch 43/50	
10/10	0s 2ms/step - loss:
0.8628	
Epoch 44/50	



10/10	0s 2ms/step - loss:
0.8752	
Epoch 45/50	
10/10	0s 2ms/step - loss:
0.8722	
Epoch 46/50	
10/10	0s 2ms/step - loss:
0.9514	
Epoch 47/50	
10/10	0s 2ms/step - loss:
0.8571	
Epoch 48/50	
10/10	0s 2ms/step - loss:
0.8732	
Epoch 49/50	
10/10	0s 3ms/step - loss:
0.8262	
Epoch 50/50	
10/10	0s 2ms/step - loss:
0.9147	
Epoch 1/50	
10/10	0s 2ms/step - loss:
0.2872	
Epoch 2/50	
10/10	0s 2ms/step - loss:
0.3752	
Epoch 3/50	
10/10	0s 2ms/step - loss:
0.3089	
Epoch 4/50	
10/10	0s 2ms/step - loss:
0.3229	
Epoch 5/50	
10/10	0s 2ms/step - loss:
0.3621	
Epoch 6/50	
10/10	0s 2ms/step - loss:
0.3377	
Epoch 7/50	
10/10	0s 2ms/step - loss:
0.3156	
Epoch 8/50	
10/10	0s 2ms/step - loss:
0.2801	
Epoch 9/50	
10/10	0s 2ms/step - loss:
0.2798	
Epoch 10/50	

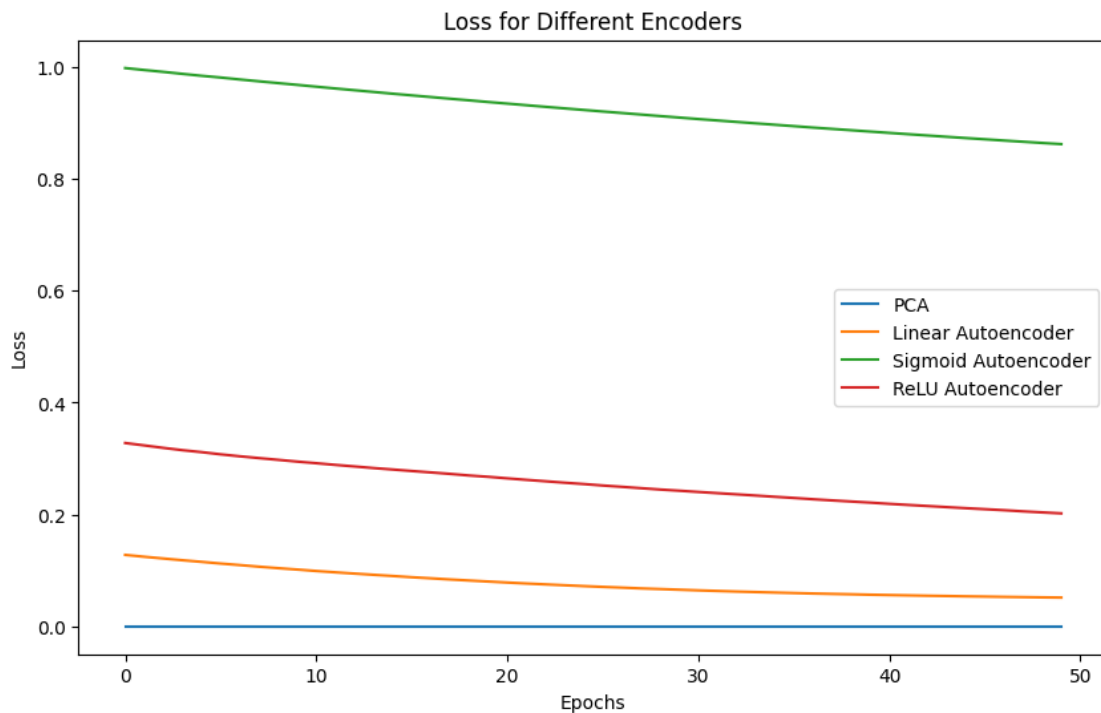
10/10	0s 2ms/step - loss:
0.3233	
Epoch 11/50	
10/10	0s 2ms/step - loss:
0.2780	
Epoch 12/50	
10/10	0s 3ms/step - loss:
0.2957	
Epoch 13/50	
10/10	0s 2ms/step - loss:
0.3312	
Epoch 14/50	
10/10	0s 2ms/step - loss:
0.2448	
Epoch 15/50	
10/10	0s 2ms/step - loss:
0.2689	
Epoch 16/50	
10/10	0s 2ms/step - loss:
0.2795	
Epoch 17/50	
10/10	0s 2ms/step - loss:
0.2877	
Epoch 18/50	
10/10	0s 2ms/step - loss:
0.2996	
Epoch 19/50	
10/10	0s 2ms/step - loss:
0.2099	
Epoch 20/50	
10/10	0s 2ms/step - loss:
0.3453	
Epoch 21/50	
10/10	0s 2ms/step - loss:
0.2880	
Epoch 22/50	
10/10	0s 2ms/step - loss:
0.2892	
Epoch 23/50	
10/10	0s 2ms/step - loss:
0.2610	
Epoch 24/50	
10/10	0s 2ms/step - loss:
0.2322	
Epoch 25/50	
10/10	0s 3ms/step - loss:
0.2938	
Epoch 26/50	

10/10	0s 3ms/step - loss:
0.2402	
Epoch 27/50	
10/10	0s 3ms/step - loss:
0.2647	
Epoch 28/50	
10/10	0s 2ms/step - loss:
0.2801	
Epoch 29/50	
10/10	0s 2ms/step - loss:
0.2426	
Epoch 30/50	
10/10	0s 2ms/step - loss:
0.2219	
Epoch 31/50	
10/10	0s 2ms/step - loss:
0.2423	
Epoch 32/50	
10/10	0s 2ms/step - loss:
0.2170	
Epoch 33/50	
10/10	0s 2ms/step - loss:
0.2249	
Epoch 34/50	
10/10	0s 2ms/step - loss:
0.2473	
Epoch 35/50	
10/10	0s 2ms/step - loss:
0.2191	
Epoch 36/50	
10/10	0s 3ms/step - loss:
0.1978	
Epoch 37/50	
10/10	0s 2ms/step - loss:
0.2021	
Epoch 38/50	
10/10	0s 3ms/step - loss:
0.2068	
Epoch 39/50	
10/10	0s 2ms/step - loss:
0.2308	
Epoch 40/50	
10/10	0s 2ms/step - loss:
0.2465	
Epoch 41/50	
10/10	0s 2ms/step - loss:
0.2697	
Epoch 42/50	

```

10/10          0s 2ms/step - loss:
0.2011
Epoch 43/50
10/10          0s 2ms/step - loss:
0.2227
Epoch 44/50
10/10          0s 2ms/step - loss:
0.2213
Epoch 45/50
10/10          0s 2ms/step - loss:
0.1785
Epoch 46/50
10/10          0s 2ms/step - loss:
0.2224
Epoch 47/50
10/10          0s 2ms/step - loss:
0.2523
Epoch 48/50
10/10          0s 2ms/step - loss:
0.2210
Epoch 49/50
10/10          0s 3ms/step - loss:
0.1844
Epoch 50/50
10/10          0s 2ms/step - loss:
0.2033

```



[ ]: