

```

import numpy as np
import matplotlib.pyplot as plt
from tensorflow.keras.layers import Input, Dense
from tensorflow.keras.models import Model
from tensorflow.keras.datasets import mnist

# Load the MNIST dataset
(x_train, _), (x_test, _) = mnist.load_data()

# Normalize the data to the range of [0, 1]
x_train = x_train.astype('float32') / 255.0
x_test = x_test.astype('float32') / 255.0

# Flatten the 28x28 images into vectors of size 784
x_train = x_train.reshape((x_train.shape[0], -1))
x_test = x_test.reshape((x_test.shape[0], -1))

# Define the dimensions of the autoencoder
input_dim = x_train.shape[1] # 784
encoding_dim = 32 # Dimension for the latent space

# Define the autoencoder
input_layer = Input(shape=(input_dim,))
encoded = Dense(encoding_dim, activation='relu')(input_layer)
decoded = Dense(input_dim, activation='sigmoid')(encoded)

# Build the autoencoder model
autoencoder = Model(inputs=input_layer, outputs=decoded)

# Build the encoder model
encoder = Model(inputs=input_layer, outputs=encoded)

# Compile the autoencoder
autoencoder.compile(optimizer='adam', loss='binary_crossentropy')

# Train the autoencoder
autoencoder.fit(x_train, x_train,
                epochs=50,
                batch_size=256,
                shuffle=True,
                validation_data=(x_test, x_test))

# Use the encoder to transform the test data
encoded_data = encoder.predict(x_test)

# Visualize some original and reconstructed images
decoded_images = autoencoder.predict(x_test)

n = 10 # Number of images to display
plt.figure(figsize=(10, 4))
for i in range(n):
    # Display original images
    ax = plt.subplot(2, n, i + 1)
    plt.imshow(x_test[i].reshape(28, 28), cmap='gray')
    plt.title("Original")
    plt.axis('off')

    # Display reconstructed images
    ax = plt.subplot(2, n, i + 1 + n)
    plt.imshow(decoded_images[i].reshape(28, 28), cmap='gray')
    plt.title("Reconstructed")
    plt.axis('off')

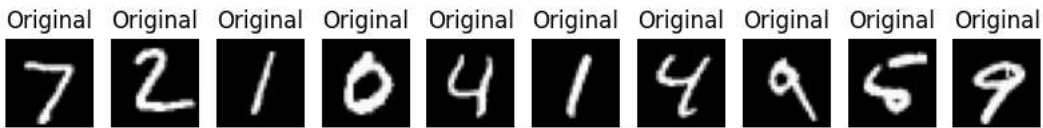
plt.show()

# Print the dimensions of the encoded data
print("Encoded data shape:", encoded_data.shape)

```

Epoch 1/50  
235/235 3s 10ms/step - loss: 0.3867 - val\_loss: 0.1921  
Epoch 2/50  
235/235 3s 13ms/step - loss: 0.1806 - val\_loss: 0.1536  
Epoch 3/50  
235/235 2s 9ms/step - loss: 0.1490 - val\_loss: 0.1337  
Epoch 4/50  
235/235 2s 9ms/step - loss: 0.1314 - val\_loss: 0.1208  
Epoch 5/50  
235/235 2s 9ms/step - loss: 0.1200 - val\_loss: 0.1128  
Epoch 6/50  
235/235 3s 9ms/step - loss: 0.1127 - val\_loss: 0.1068  
Epoch 7/50  
235/235 3s 13ms/step - loss: 0.1072 - val\_loss: 0.1027  
Epoch 8/50  
235/235 2s 9ms/step - loss: 0.1032 - val\_loss: 0.0998  
Epoch 9/50  
235/235 3s 9ms/step - loss: 0.1003 - val\_loss: 0.0975  
Epoch 10/50  
235/235 2s 9ms/step - loss: 0.0982 - val\_loss: 0.0960  
Epoch 11/50  
235/235 3s 9ms/step - loss: 0.0969 - val\_loss: 0.0949  
Epoch 12/50  
235/235 3s 13ms/step - loss: 0.0961 - val\_loss: 0.0941  
Epoch 13/50  
235/235 4s 9ms/step - loss: 0.0953 - val\_loss: 0.0936  
Epoch 14/50  
235/235 3s 9ms/step - loss: 0.0949 - val\_loss: 0.0933  
Epoch 15/50  
235/235 3s 9ms/step - loss: 0.0945 - val\_loss: 0.0930  
Epoch 16/50  
235/235 3s 12ms/step - loss: 0.0942 - val\_loss: 0.0928  
Epoch 17/50  
235/235 3s 11ms/step - loss: 0.0941 - val\_loss: 0.0926  
Epoch 18/50  
235/235 2s 9ms/step - loss: 0.0939 - val\_loss: 0.0925  
Epoch 19/50  
235/235 3s 9ms/step - loss: 0.0937 - val\_loss: 0.0924  
Epoch 20/50  
235/235 3s 9ms/step - loss: 0.0936 - val\_loss: 0.0924  
Epoch 21/50  
235/235 3s 11ms/step - loss: 0.0935 - val\_loss: 0.0922  
Epoch 22/50  
235/235 3s 13ms/step - loss: 0.0934 - val\_loss: 0.0921  
Epoch 23/50  
235/235 2s 9ms/step - loss: 0.0934 - val\_loss: 0.0921  
Epoch 24/50  
235/235 3s 9ms/step - loss: 0.0933 - val\_loss: 0.0920  
Epoch 25/50  
235/235 2s 9ms/step - loss: 0.0934 - val\_loss: 0.0920  
Epoch 26/50  
235/235 3s 9ms/step - loss: 0.0933 - val\_loss: 0.0920  
Epoch 27/50  
235/235 4s 14ms/step - loss: 0.0933 - val\_loss: 0.0919  
Epoch 28/50  
235/235 2s 9ms/step - loss: 0.0930 - val\_loss: 0.0919  
Epoch 29/50  
235/235 2s 9ms/step - loss: 0.0934 - val\_loss: 0.0920  
Epoch 30/50  
235/235 3s 9ms/step - loss: 0.0930 - val\_loss: 0.0918  
Epoch 31/50  
235/235 3s 9ms/step - loss: 0.0929 - val\_loss: 0.0918  
Epoch 32/50  
235/235 3s 13ms/step - loss: 0.0929 - val\_loss: 0.0918  
Epoch 33/50  
235/235 4s 9ms/step - loss: 0.0927 - val\_loss: 0.0918  
Epoch 34/50  
235/235 2s 9ms/step - loss: 0.0930 - val\_loss: 0.0917  
Epoch 35/50  
235/235 2s 9ms/step - loss: 0.0929 - val\_loss: 0.0918  
Epoch 36/50  
235/235 3s 11ms/step - loss: 0.0930 - val\_loss: 0.0917  
Epoch 37/50  
235/235 3s 12ms/step - loss: 0.0929 - val\_loss: 0.0917  
Epoch 38/50  
235/235 2s 9ms/step - loss: 0.0927 - val\_loss: 0.0917  
Epoch 39/50  
235/235 3s 8ms/step - loss: 0.0928 - val\_loss: 0.0917  
Epoch 40/50  
235/235 2s 9ms/step - loss: 0.0929 - val\_loss: 0.0916  
Epoch 41/50  
235/235 2s 9ms/step - loss: 0.0927 - val\_loss: 0.0917  
Epoch 42/50  
235/235 3s 13ms/step - loss: 0.0926 - val\_loss: 0.0917

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Epoch 43/50
235/235 ————— 2s 10ms/step - loss: 0.0926 - val_loss: 0.0916
Epoch 44/50
235/235 ————— 2s 9ms/step - loss: 0.0927 - val_loss: 0.0915
Epoch 45/50
235/235 ————— 2s 9ms/step - loss: 0.0927 - val_loss: 0.0916
Epoch 46/50
235/235 ————— 3s 9ms/step - loss: 0.0927 - val_loss: 0.0916
Epoch 47/50
235/235 ————— 3s 11ms/step - loss: 0.0928 - val_loss: 0.0916
Epoch 48/50
235/235 ————— 5s 9ms/step - loss: 0.0923 - val_loss: 0.0916
Epoch 49/50
235/235 ————— 2s 9ms/step - loss: 0.0927 - val_loss: 0.0916
Epoch 50/50
235/235 ————— 3s 9ms/step - loss: 0.0925 - val_loss: 0.0916
313/313 ————— 0s 1ms/step
313/313 ————— 1s 2ms/step
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Reconstructed Reconstructed Reconstructed Reconstructed Reconstructed Reconstructed Reconstructed Reconstructed Reconstructed Reconstructed



Encoded data shape: (10000, 32)