



```
In [ ]: import numpy as np
import matplotlib.pyplot as plt
from tensorflow.keras.datasets import mnist
from tensorflow.keras.models import Model
from tensorflow.keras.layers import Input, Dense
from tensorflow.keras.optimizers import Adam

(x_train, _), (x_test, _) = mnist.load_data()
x_train = x_train.astype('float32') / 255.
x_test = x_test.astype('float32') / 255.
x_train = x_train.reshape((len(x_train), np.prod(x_train.shape[1:])))
x_test = x_test.reshape((len(x_test), np.prod(x_test.shape[1:])))

input_img = Input(shape=(784,))
encoded = Dense(128, activation='relu')(input_img)
encoded = Dense(64, activation='relu')(encoded)
encoded = Dense(32, activation='relu')(encoded)
decoded = Dense(64, activation='relu')(encoded)
decoded = Dense(128, activation='relu')(decoded)
decoded = Dense(784, activation='sigmoid')(decoded)

autoencoder = Model(input_img, decoded)
autoencoder.compile(optimizer=Adam(), loss='binary_crossentropy')

history = autoencoder.fit(x_train, x_train,
                           epochs=50,
                           batch_size=256,
                           shuffle=True,
                           validation_data=(x_test, x_test),
                           verbose=1)

decoded_imgs = autoencoder.predict(x_test)

plt.figure(figsize=(6,4))
plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.title('Training vs Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()

n = 10
plt.figure(figsize=(20, 4))
for i in range(n):
    ax = plt.subplot(2, n, i + 1)
    plt.imshow(x_test[i].reshape(28, 28))
    plt.gray()
    ax.get_xaxis().set_visible(False)
    ax.get_yaxis().set_visible(False)
    ax = plt.subplot(2, n, i + 1 + n)
    plt.imshow(decoded_imgs[i].reshape(28, 28))
    plt.gray()
```

```
ax.get_xaxis().set_visible(False)
ax.get_yaxis().set_visible(False)
plt.show()
```

Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/mnist.npz

11490434/11490434  1s 0us/step

Epoch 1/50

235/235  8s 24ms/step - loss: 0.3364 - val_loss: 0.1626

Epoch 2/50

235/235  9s 18ms/step - loss: 0.1534 - val_loss: 0.1330

Epoch 3/50

235/235  6s 24ms/step - loss: 0.1313 - val_loss: 0.1229

Epoch 4/50

235/235  4s 18ms/step - loss: 0.1227 - val_loss: 0.1174

Epoch 5/50

235/235  4s 18ms/step - loss: 0.1173 - val_loss: 0.1130

Epoch 6/50

235/235  5s 23ms/step - loss: 0.1131 - val_loss: 0.1095

Epoch 7/50

235/235  5s 19ms/step - loss: 0.1102 - val_loss: 0.1073

Epoch 8/50

235/235  4s 18ms/step - loss: 0.1073 - val_loss: 0.1044

Epoch 9/50

235/235  6s 21ms/step - loss: 0.1053 - val_loss: 0.1021

Epoch 10/50

235/235  4s 18ms/step - loss: 0.1030 - val_loss: 0.1005

Epoch 11/50

235/235  5s 23ms/step - loss: 0.1014 - val_loss: 0.0993

Epoch 12/50

235/235  4s 17ms/step - loss: 0.0999 - val_loss: 0.0976

Epoch 13/50

235/235  4s 17ms/step - loss: 0.0984 - val_loss: 0.0964

Epoch 14/50

235/235  5s 23ms/step - loss: 0.0968 - val_loss: 0.0950

Epoch 15/50

235/235  9s 19ms/step - loss: 0.0957 - val_loss: 0.0941

Epoch 16/50

235/235  5s 22ms/step - loss: 0.0944 - val_loss: 0.0934

Epoch 17/50

235/235  4s 18ms/step - loss: 0.0938 - val_loss: 0.0926

Epoch 18/50

235/235  5s 20ms/step - loss: 0.0931 - val_loss: 0.0917

Epoch 19/50

235/235  5s 20ms/step - loss: 0.0924 - val_loss: 0.0910

Epoch 20/50

235/235  4s 17ms/step - loss: 0.0917 - val_loss: 0.0906

Epoch 21/50

235/235  5s 22ms/step - loss: 0.0914 - val_loss: 0.0902

Epoch 22/50

235/235  4s 19ms/step - loss: 0.0909 - val_loss: 0.0897

Epoch 23/50

235/235  4s 18ms/step - loss: 0.0904 - val_loss: 0.0894

Epoch 24/50

235/235  6s 24ms/step - loss: 0.0899 - val_loss: 0.0889

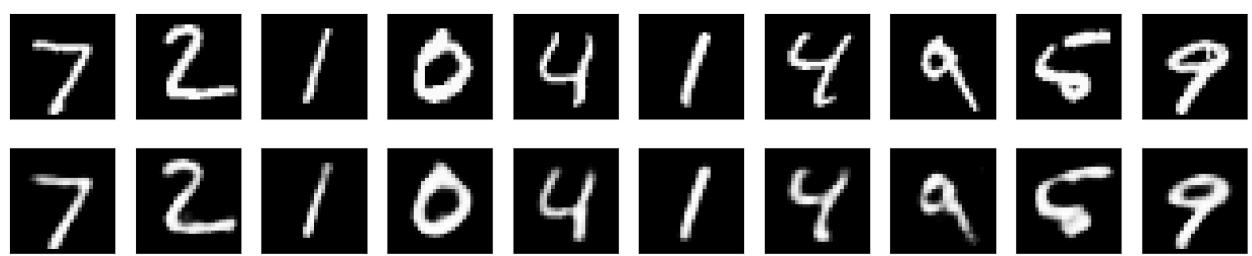
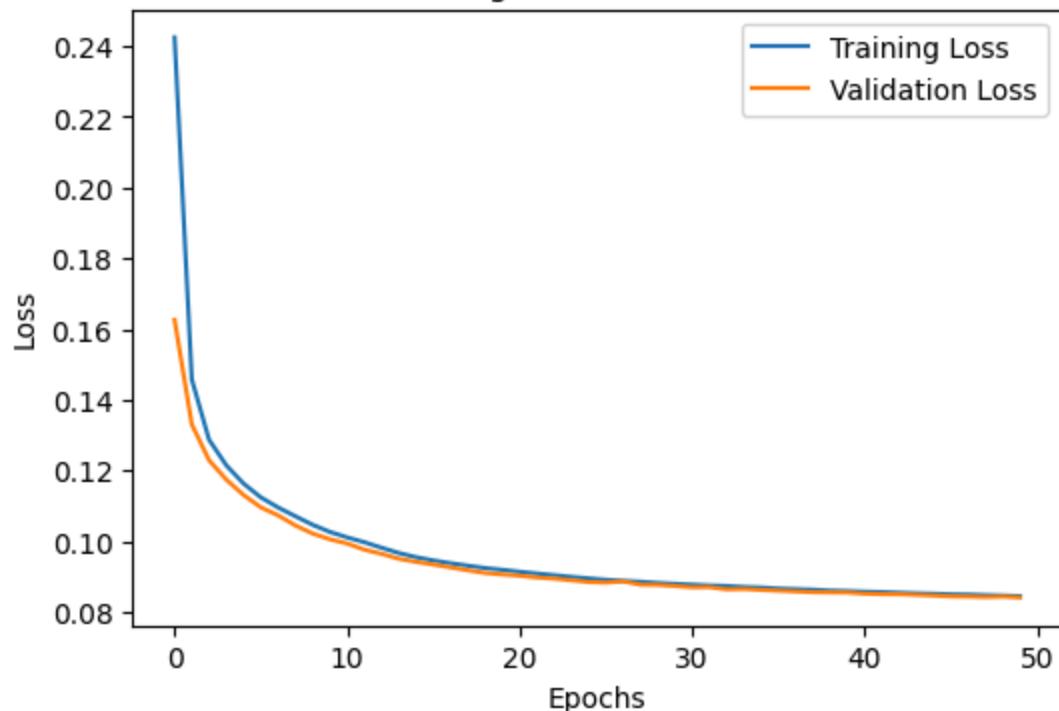
Epoch 25/50

235/235  4s 18ms/step - loss: 0.0892 - val_loss: 0.0884

Epoch 26/50

235/235 4s 17ms/step - loss: 0.0890 - val_loss: 0.0883
Epoch 27/50
235/235 5s 23ms/step - loss: 0.0887 - val_loss: 0.0886
Epoch 28/50
235/235 4s 17ms/step - loss: 0.0886 - val_loss: 0.0877
Epoch 29/50
235/235 5s 20ms/step - loss: 0.0884 - val_loss: 0.0876
Epoch 30/50
235/235 5s 21ms/step - loss: 0.0877 - val_loss: 0.0873
Epoch 31/50
235/235 4s 18ms/step - loss: 0.0877 - val_loss: 0.0869
Epoch 32/50
235/235 5s 21ms/step - loss: 0.0874 - val_loss: 0.0870
Epoch 33/50
235/235 4s 18ms/step - loss: 0.0874 - val_loss: 0.0864
Epoch 34/50
235/235 4s 17ms/step - loss: 0.0870 - val_loss: 0.0864
Epoch 35/50
235/235 6s 23ms/step - loss: 0.0870 - val_loss: 0.0862
Epoch 36/50
235/235 4s 18ms/step - loss: 0.0866 - val_loss: 0.0860
Epoch 37/50
235/235 4s 17ms/step - loss: 0.0861 - val_loss: 0.0858
Epoch 38/50
235/235 5s 23ms/step - loss: 0.0862 - val_loss: 0.0856
Epoch 39/50
235/235 4s 17ms/step - loss: 0.0861 - val_loss: 0.0855
Epoch 40/50
235/235 5s 20ms/step - loss: 0.0859 - val_loss: 0.0855
Epoch 41/50
235/235 8s 33ms/step - loss: 0.0855 - val_loss: 0.0851
Epoch 42/50
235/235 10s 30ms/step - loss: 0.0857 - val_loss: 0.0850
Epoch 43/50
235/235 8s 19ms/step - loss: 0.0853 - val_loss: 0.0850
Epoch 44/50
235/235 5s 23ms/step - loss: 0.0851 - val_loss: 0.0848
Epoch 45/50
235/235 4s 17ms/step - loss: 0.0850 - val_loss: 0.0846
Epoch 46/50
235/235 4s 18ms/step - loss: 0.0850 - val_loss: 0.0844
Epoch 47/50
235/235 5s 22ms/step - loss: 0.0850 - val_loss: 0.0843
Epoch 48/50
235/235 4s 17ms/step - loss: 0.0845 - val_loss: 0.0842
Epoch 49/50
235/235 5s 20ms/step - loss: 0.0845 - val_loss: 0.0843
Epoch 50/50
235/235 5s 22ms/step - loss: 0.0845 - val_loss: 0.0841
313/313 1s 2ms/step

Training vs Validation Loss



Exp-10: Perform compression on MNIST Dataset Using Autoencoder.

dim:

To implement an Autoencoder neural network that compresses and reconstructs handwritten digit images from the MNIST dataset, demonstrating data dimensionality reduction and unsupervised feature learning.

Description

An Autoencoder is an unsupervised neural network architecture that learns to compress data into a lower-dimensional latent space and then reconstruct it as accurately as possible. The model consists of two main components:

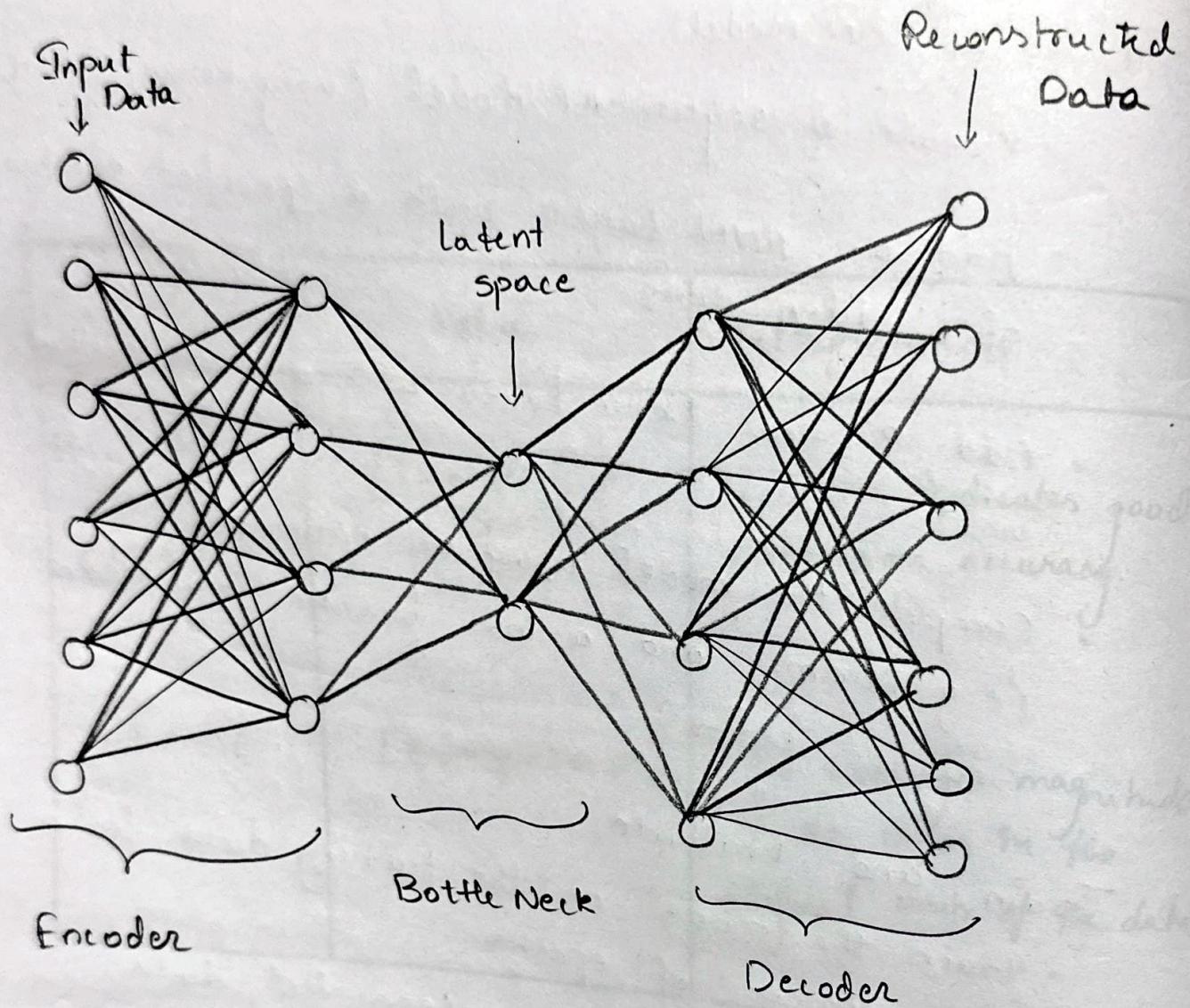
- Encoder: This part compresses the input image onto a latent-space representation by progressively reducing its dimensionality.
 - Decoder: This part reconstructs the original input from the compressed latent code, aiming to minimize the reconstruction loss.
- Mathematically, the autoencoder learns function f and g such that

$$x' = g(f(x))$$

where x is the input and x' is the reconstructed output.

The loss function (mse) is minimized to make

$$x' \approx x$$



Autoencoder Architecture



unserer Arbeit auf Basis von
einfachen Zuordnungen haben wir
die beiden Tabellen mit den
Werten 10000 und

Procedure

- 1.) Load and normalize MNIST data.
- 2.) Flatten each 28×28 image into a 784-dimensional vector.
- 3.) Define an encoder that reduces data to a small latent dimension (e.g. 32)
- 4.) Define a decoder that reconstructs the input from the latent vector.
- 5.) Compile the model using Adam optimizer and binary-crossentropy loss.
- 6.) Train for 50 epochs and visualize original vs reconstructed images.

Pseudocode

Load MNIST dataset

Normalize and Flatten Images

Build encoder ($784 \rightarrow 128 \rightarrow 64 \rightarrow 32$)

Build decoder ($32 \rightarrow 64 \rightarrow 128 \rightarrow 784$)

Compile autoencoder

Train on MNIST data

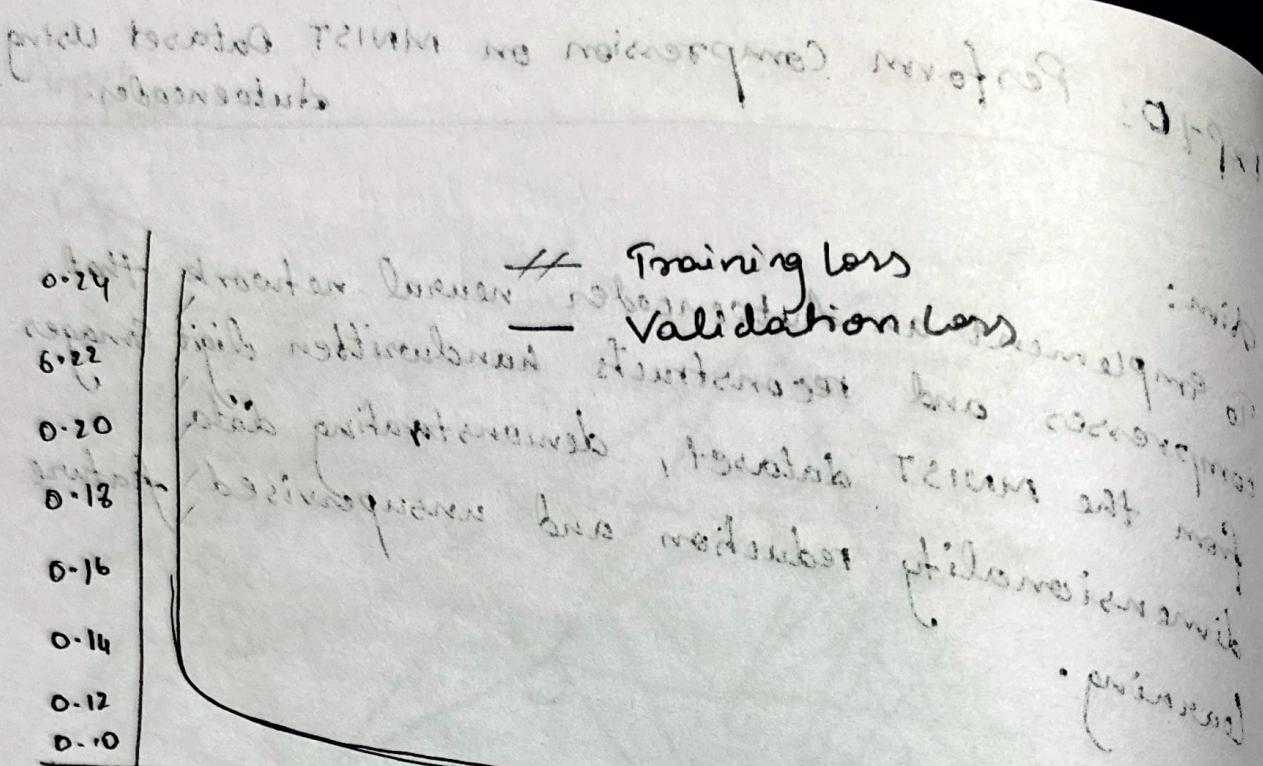
Display original and reconstructed images

~~Observation:~~

Reconstructed images are slightly blurred but preserve main digit shapes.

Result:

Autoencoder successfully compressed and reconstructed MNIST images, proving its ability to perform unsupervised feature extraction and dimensionality reduction.



Output:

Epoch [1/5], loss: 164.3796

Epoch [2/5], loss: 121.5539

Epoch [3/5], loss: 114.5693

Epoch [4/5], loss: 111.5922

Epoch [5/5], loss: 109.8722