

```
import numpy as np
import matplotlib.pyplot as plt
import tensorflow as tf
from tensorflow.keras import layers, losses
from tensorflow.keras.datasets import mnist
from tensorflow.keras.models import Model

(x_train, _), (x_test, _) = tf.keras.datasets.mnist.load_data()
# declaring a variable with ( _ ) as we dont require labels from
#dataset ( _ )is a dummy variable

x_train = x_train.astype('float32') / 255.
# type casting the data and rescaling it will 255 to 0-1 values
x_test = x_test.astype('float32') / 255.

print(x_train.shape)
print(x_test.shape)

(60000, 28, 28)
(10000, 28, 28)

latent_dim = 64 # input dimension for the model

class Autoencoder(Model): # creating a class for Autoencoder
    def __init__(self, latent_dim): # initilizing the class with required objects of the model
        super(Autoencoder, self).__init__() # creating a super class object to directly initilize the object
        self.latent_dim = latent_dim # creating aclass attribute for future reference and local utili;
        # here the model is split into 2 pares of encoder and decoder for

        self.encoder = tf.keras.Sequential([
            layers.Flatten(),
            layers.Dense(latent_dim, activation='relu')

        ])
# creating an attribute to store encoder part of the model using the
# sequential api from keras
# flatern the input and then pass it to a dense node and output
# the data to decoder
        self.decoder = tf.keras.Sequential([
            layers.Dense(784, activation='sigmoid'),
            layers.Reshape((28,28))

        ]) # creating an attribute to store decoder part of the model using
        # connect the input from encoder to the same no one nodes when fl

    def call(self, x): # defining the class function of the class
        encoded = self.encoder(x) # calling the encoder part and sending the input into it :: i/f
        decoded = self.decoder(encoded) # calling the decoder part and sending the encoder output as input
        return decoded # return only the decoder output as it contains the reconstructed

autoencoder = Autoencoder(latent_dim) # initilizing the class object

autoencoder.compile(optimizer='adam', loss=losses.MeanSquaredError())
# compiling the model with required loss function and optimizer

# here we train the model with same data for input and target as we need to reconstruct
# the same image so X_train,Y_train = X_train and same follows for the validation set also

autoencoder.fit(x_train, x_train, epochs=10, shuffle=True, validation_data=(x_test, x_test))

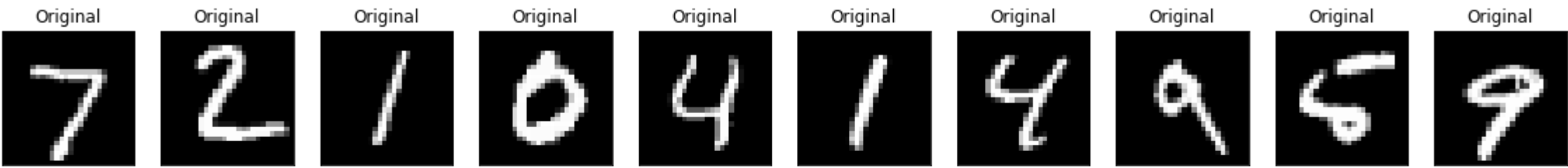
Epoch 1/10
1875/1875 [=====] - 4s 2ms/step - loss: 0.0243 - val_loss: 0.0094
Epoch 2/10
1875/1875 [=====] - 3s 2ms/step - loss: 0.0070 - val_loss: 0.0054
Epoch 3/10
1875/1875 [=====] - 3s 2ms/step - loss: 0.0050 - val_loss: 0.0045
Epoch 4/10
1875/1875 [=====] - 3s 2ms/step - loss: 0.0046 - val_loss: 0.0043
Epoch 5/10
1875/1875 [=====] - 3s 2ms/step - loss: 0.0044 - val_loss: 0.0042
Epoch 6/10
1875/1875 [=====] - 3s 2ms/step - loss: 0.0042 - val_loss: 0.0041
Epoch 7/10
1875/1875 [=====] - 3s 2ms/step - loss: 0.0042 - val_loss: 0.0040
Epoch 8/10
1875/1875 [=====] - 3s 2ms/step - loss: 0.0041 - val_loss: 0.0040
Epoch 9/10
1875/1875 [=====] - 3s 2ms/step - loss: 0.0040 - val_loss: 0.0039
Epoch 10/10
1875/1875 [=====] - 3s 2ms/step - loss: 0.0040 - val_loss: 0.0039
<tensorflow.python.keras.callbacks.History at 0x7f532ef91ed0>

# applying the model to new data
encoded_imgs = autoencoder.encoder(x_test).numpy() # calling the attributes of model to encode new data
decoded_imgs = autoencoder.decoder(encoded_imgs).numpy() # calling the attributes of model to decode new encoded data

# plotting the images for comparision between original and reconstructed data
n = 10 # plotting only first 10 images
plt.figure(figsize=(20, 4)) # initilizing the figure size for plot
for i in range(n):
    ax = plt.subplot(2, n, i + 1) # creating subplot rules for 1st row in the plot of original images
    plt.imshow(x_test[i]) # plotting the original images
    plt.title("Original")
    plt.gray() # The gray() function is used to set the colormap to “gray”.
    ax.get_xaxis().set_visible(False) # removing the visiblity of grid lines in plot
    ax.get_yaxis().set_visible(False)

    ax = plt.subplot(2, n, i + 1 + n) # creating subplot rules for 2nd row in the plot of original images
    plt.imshow(decoded_imgs[i]) # plotting the original images
    plt.title("Reconstructed")
    plt.gray() # The gray() function is used to set the colormap to “gray”.
    ax.get_xaxis().set_visible(False) # removing the visiblity of grid lines in plot
    ax.get_yaxis().set_visible(False)

plt.show()
```



autoencoder.summary()

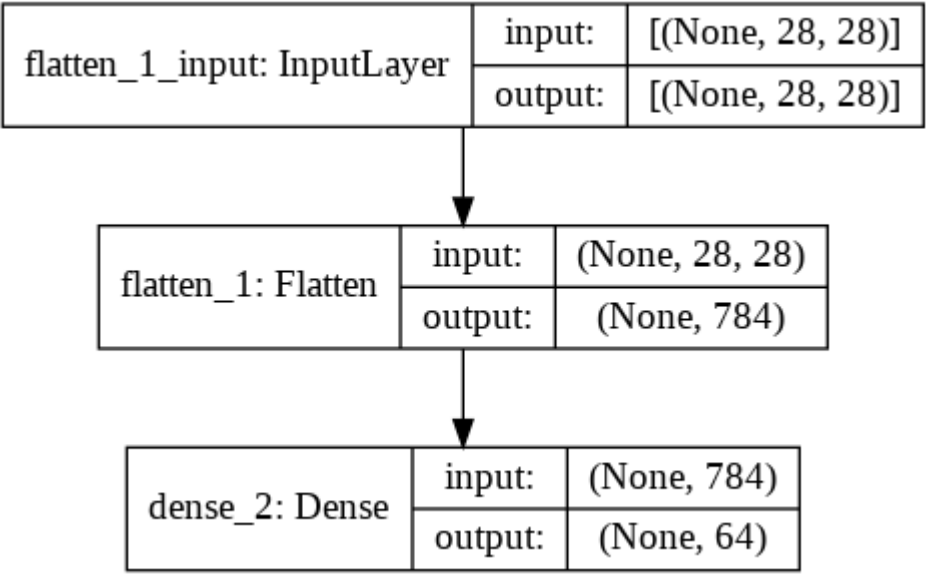
# print the model summary to understand the layers present

Model: "autoencoder\_1"

Layer (type)	Output Shape	Param #
=====		
sequential_2 (Sequential)	(None, 64)	50240
=====		
sequential_3 (Sequential)	(None, 28, 28)	50960
=====		
Total params: 101,200		
Trainable params: 101,200		
Non-trainable params: 0		

tf.keras.utils.plot\_model(autoencoder.encoder, show\_shapes=True)

# plotting the encoder part of the model



tf.keras.utils.plot\_model(autoencoder.decoder, show\_shapes=True)

# plotting the decoder part of the model

