```
In [14]: import keras
         from keras import layers
         # This is the size of our encoded representations
         encoding dim = 32 # 32 floats -> compression of factor 24.5, assuming the
         # This is our input image
         input img = keras.Input(shape=(784,))
         # "encoded" is the encoded representation of the input
         encoded = layers.Dense(encoding_dim, activation='relu')(input_img)
         # "decoded" is the lossy reconstruction of the input
         decoded = layers.Dense(784, activation='sigmoid')(encoded)
         # This model maps an input to its reconstruction
         autoencoder = keras.Model(input img, decoded)
In [15]: encoder = keras.Model(input img, encoded)
In [16]: # This is our encoded (32-dimensional) input
         encoded input = keras.Input(shape=(encoding dim,))
         # Retrieve the last layer of the autoencoder model
         decoder_layer = autoencoder.layers[-1]
         # Create the decoder model
         decoder = keras.Model(encoded input, decoder layer(encoded input))
In [17]: autoencoder.compile(optimizer='adam', loss='binary_crossentropy')
In [18]: from keras.datasets import mnist
         import numpy as np
         (x_train, _), (x_test, _) = mnist.load_data()
In [19]: 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:])))
         print(x_train.shape)
         print(x_test.shape)
        (60000, 784)
        (10000, 784)
In [20]: autoencoder.fit(x_train, x_train,
          epochs=50,
          batch_size=256,
          shuffle=True,
          validation_data=(x_test, x_test))
```

```
Epoch 1/50
235/235
                            - 4s 9ms/step - loss: 0.3861 - val loss: 0.1938
Epoch 2/50
235/235 -
                             2s 8ms/step - loss: 0.1835 - val_loss: 0.1558
Epoch 3/50
                            - 2s 10ms/step - loss: 0.1512 - val loss: 0.1348
235/235 -
Epoch 4/50
                            3s 12ms/step - loss: 0.1327 - val_loss: 0.1221
235/235 -
Epoch 5/50
235/235
                             2s 9ms/step - loss: 0.1214 - val loss: 0.1137
Epoch 6/50
235/235 -
                             2s 9ms/step - loss: 0.1137 - val loss: 0.1077
Epoch 7/50
                             2s 8ms/step - loss: 0.1080 - val_loss: 0.1031
235/235 -
Epoch 8/50
                             2s 9ms/step - loss: 0.1035 - val loss: 0.0998
235/235 -
Epoch 9/50
                            - 3s 12ms/step - loss: 0.1002 - val loss: 0.0975
235/235 -
Epoch 10/50
                             2s 9ms/step - loss: 0.0982 - val_loss: 0.0958
235/235 •
Epoch 11/50
                             2s 9ms/step - loss: 0.0968 - val_loss: 0.0947
235/235
Epoch 12/50
                             3s 12ms/step - loss: 0.0957 - val loss: 0.0940
235/235 -
Epoch 13/50
                             2s 10ms/step - loss: 0.0950 - val_loss: 0.0935
235/235 -
Epoch 14/50
                             2s 9ms/step - loss: 0.0947 - val_loss: 0.0932
235/235 -
Epoch 15/50
                            3s 11ms/step - loss: 0.0945 - val_loss: 0.0929
235/235 -
Epoch 16/50
235/235 -
                             2s 9ms/step - loss: 0.0940 - val_loss: 0.0927
Epoch 17/50
235/235
                             2s 9ms/step - loss: 0.0939 - val_loss: 0.0926
Epoch 18/50
                             2s 10ms/step - loss: 0.0939 - val_loss: 0.0926
235/235 -
Epoch 19/50
                            - 2s 10ms/step - loss: 0.0936 - val_loss: 0.0924
235/235 -
Epoch 20/50
                             2s 9ms/step - loss: 0.0937 - val_loss: 0.0923
235/235 -
Epoch 21/50
235/235 -
                             2s 9ms/step - loss: 0.0936 - val_loss: 0.0923
Epoch 22/50
235/235 -
                            - 2s 9ms/step - loss: 0.0931 - val_loss: 0.0922
Epoch 23/50
235/235
                             2s 9ms/step - loss: 0.0932 - val loss: 0.0921
Epoch 24/50
235/235 -
                             2s 8ms/step - loss: 0.0932 - val_loss: 0.0920
Epoch 25/50
                             2s 9ms/step - loss: 0.0932 - val loss: 0.0921
235/235
Epoch 26/50
235/235 -
                             3s 12ms/step - loss: 0.0931 - val_loss: 0.0920
Epoch 27/50
235/235 -
                            - 2s 10ms/step - loss: 0.0932 - val_loss: 0.0920
Epoch 28/50
235/235 -
                            - 2s 9ms/step - loss: 0.0932 - val_loss: 0.0919
```

```
Epoch 29/50
        235/235 -
                                    - 2s 9ms/step - loss: 0.0931 - val loss: 0.0919
        Epoch 30/50
        235/235 -
                                    - 2s 9ms/step - loss: 0.0930 - val_loss: 0.0919
        Epoch 31/50
                                    - 2s 9ms/step - loss: 0.0930 - val loss: 0.0919
        235/235 -
        Epoch 32/50
                                    - 3s 10ms/step - loss: 0.0930 - val_loss: 0.0920
        235/235 -
        Epoch 33/50
                                    - 3s 11ms/step - loss: 0.0930 - val loss: 0.0918
        235/235 -
        Epoch 34/50
        235/235 -
                                    - 2s 10ms/step - loss: 0.0930 - val_loss: 0.0919
        Epoch 35/50
                                     • 2s 8ms/step - loss: 0.0928 - val_loss: 0.0918
        235/235 -
        Epoch 36/50
                                    - 2s 9ms/step - loss: 0.0930 - val loss: 0.0918
        235/235 -
        Epoch 37/50
                                    - 2s 10ms/step - loss: 0.0928 - val loss: 0.0918
        235/235 -
        Epoch 38/50
                                    - 2s 9ms/step - loss: 0.0929 - val_loss: 0.0918
        235/235 -
        Epoch 39/50
                                     2s 8ms/step - loss: 0.0932 - val_loss: 0.0918
        235/235 •
        Epoch 40/50
                                    - 2s 10ms/step - loss: 0.0928 - val loss: 0.0917
        235/235 -
        Epoch 41/50
                                    - 3s 11ms/step - loss: 0.0928 - val_loss: 0.0918
        235/235 -
        Epoch 42/50
                                    - 5s 9ms/step - loss: 0.0928 - val_loss: 0.0917
        235/235 -
        Epoch 43/50
                                    - 2s 8ms/step - loss: 0.0928 - val_loss: 0.0917
        235/235 -
        Epoch 44/50
        235/235 -
                                    - 2s 10ms/step - loss: 0.0928 - val_loss: 0.0917
        Epoch 45/50
        235/235 -
                                    - 2s 8ms/step - loss: 0.0927 - val_loss: 0.0917
        Epoch 46/50
                                    - 2s 8ms/step - loss: 0.0927 - val_loss: 0.0917
        235/235 -
        Epoch 47/50
                                    - 2s 8ms/step - loss: 0.0926 - val_loss: 0.0917
        235/235 -
        Epoch 48/50
                                    - 2s 8ms/step - loss: 0.0927 - val_loss: 0.0917
        235/235 -
        Epoch 49/50
        235/235 -
                                    - 2s 8ms/step - loss: 0.0927 - val_loss: 0.0917
        Epoch 50/50
        235/235 -
                                    - 2s 8ms/step - loss: 0.0926 - val_loss: 0.0917
Out[20]: <keras.src.callbacks.history.History at 0x22345ebc310>
In [21]: encoded imgs = encoder.predict(x test)
          decoded_imgs = decoder.predict(encoded_imgs)
        313/313 -
                                    - 1s 2ms/step
        313/313 -
                                    - 1s 2ms/step
In [23]: # Display original and reconstructed images
         import matplotlib.pyplot as plt
```

```
In [24]: n = 10 # How many digits we will display
        plt.figure(figsize=(20, 4))
        for i in range(n):
           # Display original
           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)
           # Display reconstruction
           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()
       7210414959
      7210414359
In [25]: from keras import regularizers
        encoding_dim = 32
In [26]: input_img = keras.Input(shape=(784,))
        # Add a Dense layer with a L1 activity regularizer
        encoded = layers.Dense(encoding_dim, activation='relu',
                      activity_regularizer=regularizers.11(10e-5))(input_img)
        decoded = layers.Dense(784, activation='sigmoid')(encoded)
        autoencoder = keras.Model(input_img, decoded)
In [28]: autoencoder.compile(optimizer='adam', loss='binary_crossentropy')
In [29]: autoencoder.fit(x_train, x_train,
         epochs=50,
         batch_size=256,
         shuffle=True,
         validation_data=(x_test, x_test))
```

5 h 1/50								
Epoch 1/50 235/235 ————————————————————————————————————	4 c	7ms/sten	_	loss	0 6803	_	val_loss:	0 6155
Epoch 2/50	.5	, 3, 3 ccp		1055.	0.0003		·u1_1033.	0.0133
235/235	25	7ms/step	_	loss:	0.5987	_	val loss:	0.5535
Epoch 3/50		, г						
235/235	2s	9ms/step	_	loss:	0.5398	_	val loss:	0.5038
Epoch 4/50							_	
235/235	2s	9ms/step	-	loss:	0.4928	-	<pre>val_loss:</pre>	0.4638
Epoch 5/50								
	2 s	9ms/step	-	loss:	0.4548	-	<pre>val_loss:</pre>	0.4314
Epoch 6/50				_				
	3s	9ms/step	-	loss:	0.4241	-	<pre>val_loss:</pre>	0.4050
Epoch 7/50 235/235 ————————————————————————————————————	26	Omc/ston		1000	0 2006		val_loss:	0 2024
Epoch 8/50	25	ollis/step	_	1055.	0.3960	_	va1_1055.	0.3634
-	25	8ms/sten	_	1055.	0.3784	_	val_loss:	0.3656
Epoch 9/50		ошэ, эсер		1055.	0.5701		.41_1033.	0.3030
•	2s	8ms/step	_	loss:	0.3611	_	val_loss:	0.3508
Epoch 10/50							_	
235/235 —————	2s	9ms/step	-	loss:	0.3472	-	<pre>val_loss:</pre>	0.3385
Epoch 11/50								
235/235	2 s	9ms/step	-	loss:	0.3355	-	val_loss:	0.3281
Epoch 12/50				_				
	2 s	9ms/step	-	loss:	0.3257	-	val_loss:	0.3194
Epoch 13/50 235/235	26	Ome/ston		10001	0 2172		val loss.	0 2120
Epoch 14/50	25	ollis/step	_	1055.	0.31/3	-	val_loss:	0.3120
•	25	9ms/sten	_	loss:	0.3104	_	val_loss:	0.3056
Epoch 15/50		эшэ, эсер		1055.	0.3101		·u1_1033.	0.3030
·	2 s	9ms/step	_	loss:	0.3043	_	val_loss:	0.3002
Epoch 16/50							_	
235/235 —————	2s	8ms/step	-	loss:	0.2988	-	<pre>val_loss:</pre>	0.2955
Epoch 17/50								
235/235	2 s	8ms/step	-	loss:	0.2949	-	val_loss:	0.2915
Epoch 18/50				-				
235/235 ————————————————————————————————————	25	9ms/step	-	loss:	0.2905	-	val_loss:	0.2880
Epoch 19/50 235/235 ————————————————————————————————————	26	Qmc/stan		1000	0 2873	_	val_loss:	0 2850
Epoch 20/50	23	Jiii3/3Cep	_	1033.	0.2075	_	va1_1033.	0.2030
	2s	9ms/step	_	loss:	0.2843	_	val_loss:	0.2823
Epoch 21/50		,						
235/235	2s	9ms/step	-	loss:	0.2819	-	<pre>val_loss:</pre>	0.2800
Epoch 22/50								
	2 s	9ms/step	-	loss:	0.2798	-	<pre>val_loss:</pre>	0.2780
Epoch 23/50		_ , .		_				
	2s	8ms/step	-	loss:	0.2776	-	val_loss:	0.2762
Epoch 24/50 235/235 ————————————————————————————————————	26	Omc/ston		1000	0 2761		val locci	0 2747
Epoch 25/50	25	ollis/step	_	1055.	0.2761	-	val_loss:	0.2/4/
·	25	9ms/sten	_	loss:	0.2743	_	val_loss:	0.2733
Epoch 26/50		эшэ, эсер		1055.	0.2713		·u1_1033.	0.2/33
•	2s	9ms/step	_	loss:	0.2734	-	val_loss:	0.2721
Epoch 27/50							_	
	2s	9ms/step	-	loss:	0.2720	-	<pre>val_loss:</pre>	0.2710
Epoch 28/50								
235/235 ————————————————————————————————————	2s	9ms/step	-	loss:	0.2710	-	val_loss:	0.2700

```
Epoch 29/50
        235/235 -
                                    - 2s 8ms/step - loss: 0.2701 - val loss: 0.2692
        Epoch 30/50
        235/235 -
                                     2s 9ms/step - loss: 0.2694 - val_loss: 0.2685
        Epoch 31/50
                                    - 2s 8ms/step - loss: 0.2682 - val loss: 0.2678
        235/235 -
        Epoch 32/50
                                    - 2s 8ms/step - loss: 0.2676 - val_loss: 0.2672
        235/235 -
        Epoch 33/50
                                     2s 9ms/step - loss: 0.2675 - val loss: 0.2667
        235/235
        Epoch 34/50
        235/235 -
                                     2s 9ms/step - loss: 0.2670 - val loss: 0.2663
        Epoch 35/50
                                     2s 10ms/step - loss: 0.2668 - val_loss: 0.2658
        235/235 -
        Epoch 36/50
                                     2s 9ms/step - loss: 0.2658 - val loss: 0.2655
        235/235 -
        Epoch 37/50
                                    - 2s 9ms/step - loss: 0.2656 - val loss: 0.2652
        235/235 -
        Epoch 38/50
                                    • 2s 8ms/step - loss: 0.2650 - val_loss: 0.2649
        235/235 •
        Epoch 39/50
                                     2s 8ms/step - loss: 0.2649 - val_loss: 0.2646
        235/235 •
        Epoch 40/50
                                     2s 8ms/step - loss: 0.2648 - val loss: 0.2644
        235/235 -
        Epoch 41/50
                                    • 2s 9ms/step - loss: 0.2642 - val_loss: 0.2642
        235/235 -
        Epoch 42/50
                                     2s 9ms/step - loss: 0.2642 - val_loss: 0.2640
        235/235 -
        Epoch 43/50
                                    - 2s 10ms/step - loss: 0.2647 - val_loss: 0.2638
        235/235 -
        Epoch 44/50
        235/235 -
                                    - 2s 9ms/step - loss: 0.2637 - val_loss: 0.2637
        Epoch 45/50
        235/235 -
                                     2s 8ms/step - loss: 0.2641 - val_loss: 0.2636
        Epoch 46/50
                                    - 2s 8ms/step - loss: 0.2641 - val_loss: 0.2635
        235/235 -
        Epoch 47/50
                                    - 2s 8ms/step - loss: 0.2635 - val_loss: 0.2634
        235/235 -
        Epoch 48/50
                                    - 2s 9ms/step - loss: 0.2632 - val_loss: 0.2633
        235/235 -
        Epoch 49/50
        235/235 -
                                     2s 9ms/step - loss: 0.2639 - val_loss: 0.2632
        Epoch 50/50
        235/235 -
                                    - 2s 9ms/step - loss: 0.2632 - val_loss: 0.2631
Out[29]: <keras.src.callbacks.history.History at 0x2232f28c310>
In [33]: decoded imgs = autoencoder.predict(x test)
          # Set the number of images you want to display
          n = 10
          plt.figure(figsize=(20, 4))
         for i in range(n):
             # Display original images
              ax = plt.subplot(2, n, i + 1)
```

```
plt.imshow(x_test[i].reshape(28, 28)) # Assuming x_test is reshaped to (28, 28)
     plt.gray()
     ax.get_xaxis().set_visible(False)
     ax.get_yaxis().set_visible(False)
     # Display reconstructed images
     ax = plt.subplot(2, n, i + 1 + n)
     plt.imshow(decoded_imgs[i].reshape(28, 28)) # Reshape decoded images to (28, 2
     plt.gray()
     ax.get_xaxis().set_visible(False)
     ax.get_yaxis().set_visible(False)
 # Adding labels for the two rows
 plt.text(-10, 30, 'Original Images', fontsize=14, ha='center', va='top')
 plt.text(-10, -5, 'Reconstructed Images', fontsize=14, ha='center', va='top')
 plt.show()
313/313 -
                             1s 2ms/step
```

In []: