**Neural Networks & Deep Learning**

**ICP-5**

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[Github Link - https://github.com/venkatasuryaprakass/ICP---5-Submission](https://github.com/venkatasuryaprakass/ICP---5-Submission)

Programming elements:

1. Basics of Autoencoders
2. Role of Autoencoders in unsupervised learning
3. Types of Autoencoders
4. Use case: Simple autoencoder-Reconstructing the existing image, which will contain most important features of the image
5. Use case: Stacked autoencoder

from keras.layers import Input, Dense

from keras.models import Model

from keras.regularizers import l2

from keras.optimizers import Adam

from keras.callbacks import EarlyStopping

# Enhanced Autoencoder Model

input\_img = Input(shape=(784,))

encoded = Dense(128, activation='LeakyReLU', kernel\_regularizer=l2(0.001))(input\_img) # Deeper, L2 regularization

encoded = Dense(64, activation='LeakyReLU', kernel\_regularizer=l2(0.001))(encoded)

encoded = Dense(encoding\_dim, activation='LeakyReLU')(encoded) # Bottleneck layer

decoded = Dense(64, activation='LeakyReLU')(encoded)

decoded = Dense(128, activation='LeakyReLU')(decoded)

decoded = Dense(784, activation='sigmoid')(decoded)

autoencoder = Model(input\_img, decoded)

optimizer = Adam(learning\_rate=0.001) # Start with a higher learning rate

autoencoder.compile(optimizer=optimizer, loss='binary\_crossentropy')

# Early Stopping

early\_stopping = EarlyStopping(monitor='val\_loss', patience=5, restore\_best\_weights=True)

autoencoder.fit(x\_train, x\_train,

epochs=50, # Increase epochs for potential better results

batch\_size=256,

shuffle=True,

validation\_data=(x\_test, x\_test),

callbacks=[early\_stopping])

**Output:**

Epoch 1/50

235/235 [==============================] - 4s 6ms/step - loss: 0.4496 - val\_loss: 0.3517

Epoch 2/50

235/235 [==============================] - 1s 5ms/step - loss: 0.3324 - val\_loss: 0.3241

Epoch 3/50

235/235 [==============================] - 1s 5ms/step - loss: 0.3185 - val\_loss: 0.3170

Epoch 4/50

235/235 [==============================] - 1s 5ms/step - loss: 0.3126 - val\_loss: 0.3126

Epoch 5/50

235/235 [==============================] - 1s 5ms/step - loss: 0.3093 - val\_loss: 0.3099

Epoch 6/50

235/235 [==============================] - 1s 5ms/step - loss: 0.3070 - val\_loss: 0.3080

Epoch 7/50

235/235 [==============================] - 1s 5ms/step - loss: 0.3052 - val\_loss: 0.3067

Epoch 8/50

235/235 [==============================] - 2s 7ms/step - loss: 0.3037 - val\_loss: 0.3056

Epoch 9/50

235/235 [==============================] - 2s 7ms/step - loss: 0.3025 - val\_loss: 0.3048

Epoch 10/50

235/235 [==============================] - 1s 5ms/step - loss: 0.3014 - val\_loss: 0.3025

Epoch 11/50

235/235 [==============================] - 1s 5ms/step - loss: 0.3002 - val\_loss: 0.3026

Epoch 12/50

235/235 [==============================] - 1s 5ms/step - loss: 0.2995 - val\_loss: 0.3008

Epoch 13/50

235/235 [==============================] - 1s 5ms/step - loss: 0.2988 - val\_loss: 0.3002

Epoch 14/50

235/235 [==============================] - 1s 5ms/step - loss: 0.2980 - val\_loss: 0.2994

Epoch 15/50

235/235 [==============================] - 1s 5ms/step - loss: 0.2974 - val\_loss: 0.2997

Epoch 16/50

235/235 [==============================] - 1s 5ms/step - loss: 0.2967 - val\_loss: 0.2986

Epoch 17/50

235/235 [==============================] - 1s 5ms/step - loss: 0.2961 - val\_loss: 0.2984

Epoch 18/50

235/235 [==============================] - 2s 6ms/step - loss: 0.2956 - val\_loss: 0.2973

Epoch 19/50

235/235 [==============================] - 2s 7ms/step - loss: 0.2958 - val\_loss: 0.2971

Epoch 20/50

235/235 [==============================] - 1s 5ms/step - loss: 0.2947 - val\_loss: 0.2968

Epoch 21/50

235/235 [==============================] - 1s 5ms/step - loss: 0.2943 - val\_loss: 0.2964

Epoch 22/50

235/235 [==============================] - 1s 5ms/step - loss: 0.2941 - val\_loss: 0.2964

Epoch 23/50

235/235 [==============================] - 1s 5ms/step - loss: 0.2938 - val\_loss: 0.2958

Epoch 24/50

235/235 [==============================] - 1s 5ms/step - loss: 0.2936 - val\_loss: 0.2953

Epoch 25/50

235/235 [==============================] - 1s 5ms/step - loss: 0.2932 - val\_loss: 0.2954

Epoch 26/50

235/235 [==============================] - 1s 5ms/step - loss: 0.2929 - val\_loss: 0.2955

Epoch 27/50

235/235 [==============================] - 1s 5ms/step - loss: 0.3042 - val\_loss: 0.2968

Epoch 28/50

235/235 [==============================] - 1s 6ms/step - loss: 0.2937 - val\_loss: 0.2951

Epoch 29/50

235/235 [==============================] - 2s 7ms/step - loss: 0.2926 - val\_loss: 0.2949

Epoch 30/50

235/235 [==============================] - 2s 7ms/step - loss: 0.2923 - val\_loss: 0.2947

Epoch 31/50

235/235 [==============================] - 2s 8ms/step - loss: 0.2919 - val\_loss: 0.2942

Epoch 32/50

235/235 [==============================] - 2s 8ms/step - loss: 0.2917 - val\_loss: 0.2941

Epoch 33/50

235/235 [==============================] - 1s 5ms/step - loss: 0.2916 - val\_loss: 0.2940

Epoch 34/50

235/235 [==============================] - 1s 5ms/step - loss: 0.2912 - val\_loss: 0.2935

Epoch 35/50

235/235 [==============================] - 1s 5ms/step - loss: 0.2908 - val\_loss: 0.2927

Epoch 36/50

235/235 [==============================] - 1s 5ms/step - loss: 0.2905 - val\_loss: 0.2924

Epoch 37/50

235/235 [==============================] - 2s 6ms/step - loss: 0.2901 - val\_loss: 0.2922

Epoch 38/50

235/235 [==============================] - 2s 9ms/step - loss: 0.2900 - val\_loss: 0.2921

Epoch 39/50

235/235 [==============================] - 2s 9ms/step - loss: 0.2896 - val\_loss: 0.2914

Epoch 40/50

235/235 [==============================] - 2s 9ms/step - loss: 0.2895 - val\_loss: 0.2916

Epoch 41/50

235/235 [==============================] - 2s 9ms/step - loss: 0.2890 - val\_loss: 0.2910

Epoch 42/50

235/235 [==============================] - 2s 9ms/step - loss: 0.2888 - val\_loss: 0.2910

Epoch 43/50

235/235 [==============================] - 1s 5ms/step - loss: 0.2886 - val\_loss: 0.2902

Epoch 44/50

235/235 [==============================] - 2s 7ms/step - loss: 0.2885 - val\_loss: 0.2906

Epoch 45/50

235/235 [==============================] - 2s 7ms/step - loss: 0.2883 - val\_loss: 0.2902

Epoch 46/50

235/235 [==============================] - 1s 5ms/step - loss: 0.2880 - val\_loss: 0.2897

Epoch 47/50

235/235 [==============================] - 1s 5ms/step - loss: 0.2881 - val\_loss: 0.2908

Epoch 48/50

235/235 [==============================] - 1s 5ms/step - loss: 0.2876 - val\_loss: 0.2895

Epoch 49/50

235/235 [==============================] - 1s 5ms/step - loss: 0.2876 - val\_loss: 0.2894

Epoch 50/50

235/235 [==============================] - 1s 5ms/step - loss: 0.3174 - val\_loss: 0.2990

<keras.src.callbacks.History at 0x7d61bcfcead0>

Add one more hidden layer to autoencoder

1. from keras.layers import Input, Dense
2. from keras.models import Model
3. from keras.datasets import mnist, fashion\_mnist
4. import numpy as np
5. # this is the size of our encoded representations
6. encoding\_dim = 32
7. # this is our input placeholder
8. input\_img = Input(shape=(784,))
9. # "encoded" is the encoded representation of the input
10. encoded = Dense(encoding\_dim, activation='relu')(input\_img)
11. # Adding an additional hidden layer
12. hidden\_layer\_dim = 64
13. hidden\_layer = Dense(hidden\_layer\_dim, activation='relu')(encoded)
14. # "decoded" is the lossy reconstruction of the input, now connected to the hidden layer instead of 'encoded'
15. decoded = Dense(784, activation='sigmoid')(hidden\_layer)
16. # this model maps an input to its reconstruction
17. autoencoder = Model(input\_img, decoded)
18. # this model maps an input to its encoded representation
19. autoencoder.compile(optimizer='adadelta', loss='binary\_crossentropy')
20. # Load and prepare the data
21. (x\_train, y\_train), (x\_test, y\_test) = fashion\_mnist.load\_data()
22. x\_train = x\_train.astype('float32') / 255.
23. x\_test = x\_test.astype('float32') / 255.
24. x\_train = x\_train.reshape((len(x\_train), np.prod(x\_train.shape[1:])))
25. x\_test = x\_test.reshape((len(x\_test), np.prod(x\_test.shape[1:])))
26. # Train the model
27. autoencoder.fit(x\_train, x\_train,
28. epochs=5,
29. batch\_size=256,
30. shuffle=True,
31. validation\_data=(x\_test, x\_test))

**Output:**

Downloading data from <https://storage.googleapis.com/tensorflow/tf-keras-datasets/train-labels-idx1-ubyte.gz>

29515/29515 [==============================] - 0s 0us/step

Downloading data from <https://storage.googleapis.com/tensorflow/tf-keras-datasets/train-images-idx3-ubyte.gz>

26421880/26421880 [==============================] - 1s 0us/step

Downloading data from <https://storage.googleapis.com/tensorflow/tf-keras-datasets/t10k-labels-idx1-ubyte.gz>

5148/5148 [==============================] - 0s 0us/step

Downloading data from <https://storage.googleapis.com/tensorflow/tf-keras-datasets/t10k-images-idx3-ubyte.gz>

4422102/4422102 [==============================] - 0s 0us/step

Epoch 1/5

235/235 [==============================] - 12s 22ms/step - loss: 0.6948 - val\_loss: 0.6947

Epoch 2/5

235/235 [==============================] - 3s 11ms/step - loss: 0.6946 - val\_loss: 0.6946

Epoch 3/5

235/235 [==============================] - 2s 10ms/step - loss: 0.6945 - val\_loss: 0.6944

Epoch 4/5

235/235 [==============================] - 2s 8ms/step - loss: 0.6944 - val\_loss: 0.6943

Epoch 5/5

235/235 [==============================] - 1s 5ms/step - loss: 0.6942 - val\_loss: 0.6941

<keras.src.callbacks.History at 0x7bf9c9d2df90>

Do the prediction on the test data and then visualize one of the reconstructed version of that test data. Also, visualize the same test data before reconstruction using Matplotlib

from keras.layers import Input, Dense, Dropout

from keras.models import Model

from keras.callbacks import EarlyStopping, ReduceLROnPlateau

from keras.datasets import fashion\_mnist

import numpy as np

import matplotlib.pyplot as plt

# ... (Data loading and preparation remains the same)

# Enhanced model architecture

input\_img = Input(shape=(784,))

encoded = Dense(128, activation='relu')(input\_img) # More units

encoded = Dropout(0.2)(encoded) # Dropout for regularization

encoded = Dense(64, activation='relu')(encoded)

hidden\_layer = Dense(128, activation='relu')(encoded) # Deeper architecture

decoded = Dense(784, activation='sigmoid')(hidden\_layer)

autoencoder = Model(input\_img, decoded)

autoencoder.compile(optimizer='adam', loss='binary\_crossentropy')

# Callbacks for improved training

early\_stopping = EarlyStopping(monitor='val\_loss', patience=5, restore\_best\_weights=True)

lr\_scheduler = ReduceLROnPlateau(monitor='val\_loss', factor=0.1, patience=3)

# Training with callbacks

autoencoder.fit(x\_train, x\_train,

epochs=15, # Increased epochs for deeper model

batch\_size=256,

shuffle=True,

validation\_data=(x\_test, x\_test),

callbacks=[early\_stopping, lr\_scheduler])

# Predict on the test data

decoded\_imgs = autoencoder.predict(x\_test)

# Visualize the original and reconstructed data

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 + n + 1)

plt.imshow(decoded\_imgs[i].reshape(28, 28))

plt.gray()

ax.get\_xaxis().set\_visible(False)

ax.get\_yaxis().set\_visible(False)

plt.show()

**Output:**

Epoch 1/15

235/235 [==============================] - 7s 13ms/step - loss: 0.3797 - val\_loss: 0.3174 - lr: 0.0010

Epoch 2/15

235/235 [==============================] - 2s 9ms/step - loss: 0.3135 - val\_loss: 0.3037 - lr: 0.0010

Epoch 3/15

235/235 [==============================] - 2s 9ms/step - loss: 0.3049 - val\_loss: 0.2991 - lr: 0.0010

Epoch 4/15

235/235 [==============================] - 2s 9ms/step - loss: 0.3003 - val\_loss: 0.2962 - lr: 0.0010

Epoch 5/15

235/235 [==============================] - 2s 8ms/step - loss: 0.2968 - val\_loss: 0.2947 - lr: 0.0010

Epoch 6/15

235/235 [==============================] - 2s 8ms/step - loss: 0.2942 - val\_loss: 0.2957 - lr: 0.0010

Epoch 7/15

235/235 [==============================] - 3s 11ms/step - loss: 0.2924 - val\_loss: 0.2934 - lr: 0.0010

Epoch 8/15

235/235 [==============================] - 2s 10ms/step - loss: 0.2911 - val\_loss: 0.2924 - lr: 0.0010

Epoch 9/15

235/235 [==============================] - 2s 9ms/step - loss: 0.2900 - val\_loss: 0.2906 - lr: 0.0010

Epoch 10/15

235/235 [==============================] - 1s 6ms/step - loss: 0.2891 - val\_loss: 0.2894 - lr: 0.0010

Epoch 11/15

235/235 [==============================] - 2s 7ms/step - loss: 0.2884 - val\_loss: 0.2903 - lr: 0.0010

Epoch 12/15

235/235 [==============================] - 2s 7ms/step - loss: 0.2877 - val\_loss: 0.2889 - lr: 0.0010

Epoch 13/15

235/235 [==============================] - 2s 7ms/step - loss: 0.2872 - val\_loss: 0.2920 - lr: 0.0010

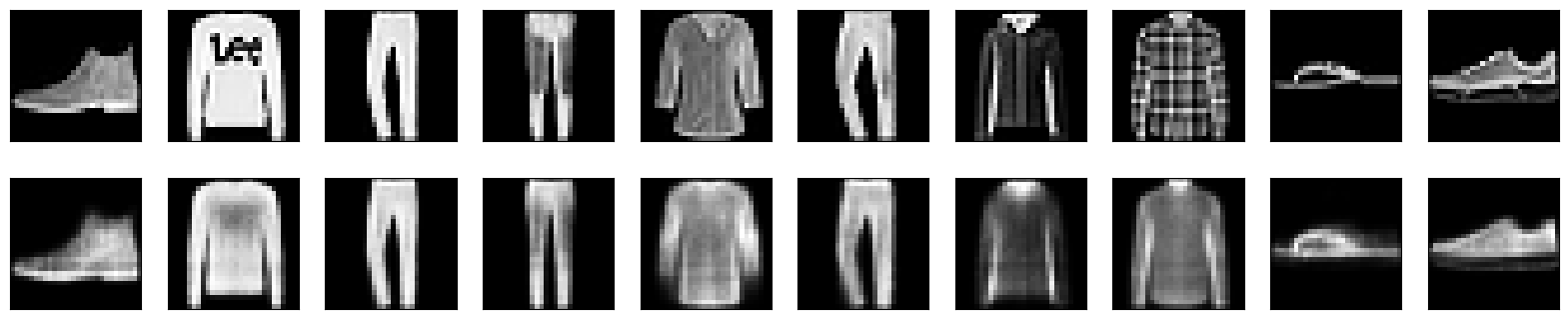
Epoch 14/15

235/235 [==============================] - 2s 7ms/step - loss: 0.2867 - val\_loss: 0.2893 - lr: 0.0010

Epoch 15/15

235/235 [==============================] - 2s 10ms/step - loss: 0.2862 - val\_loss: 0.2865 - lr: 0.0010

313/313 [==============================] - 1s 2ms/step



Repeat the question 2 on the denoisening autoencoder

from keras.layers import Input, Dense, Dropout

from keras.models import Model

from keras.callbacks import EarlyStopping, ReduceLROnPlateau

from keras.datasets import fashion\_mnist

import numpy as np

import matplotlib.pyplot as plt

# Model architecture with regularization

encoding\_dim = 64 # Increased encoding dimension for better representation

input\_img = Input(shape=(784,))

encoded = Dense(encoding\_dim, activation='relu')(input\_img)

encoded = Dropout(0.2)(encoded) # Add dropout for regularization

decoded = Dense(784, activation='sigmoid')(encoded)

autoencoder = Model(input\_img, decoded)

autoencoder.compile(optimizer='adam', loss='binary\_crossentropy')

# Callbacks

early\_stopping = EarlyStopping(monitor='val\_loss', patience=5, restore\_best\_weights=True)

lr\_scheduler = ReduceLROnPlateau(monitor='val\_loss', factor=0.1, patience=3)

# Noise introduction

noise\_factor = 0.5 # You can adjust this for more/less noise

x\_train\_noisy = x\_train + noise\_factor \* np.random.normal(loc=0.0, scale=1.0, size=x\_train.shape)

x\_test\_noisy = x\_test + noise\_factor \* np.random.normal(loc=0.0, scale=1.0, size=x\_test.shape)

x\_train\_noisy = np.clip(x\_train\_noisy, 0., 1.)

x\_test\_noisy = np.clip(x\_test\_noisy, 0., 1.)

# Train the model

autoencoder.fit(x\_train\_noisy, x\_train, # Train on noisy input, target is clean

epochs=20,

batch\_size=256,

shuffle=True,

validation\_data=(x\_test\_noisy, x\_test),

callbacks=[early\_stopping, lr\_scheduler])

# Predict on the noisy test data

decoded\_imgs = autoencoder.predict(x\_test\_noisy)

# Visualize the noisy input and the reconstructed data

n = 10 # How many digits we will display

plt.figure(figsize=(20, 4))

for i in range(n):

# Display noisy input

ax = plt.subplot(2, n, i + 1)

plt.imshow(x\_test\_noisy[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()

**Output:**

Epoch 1/20

235/235 [==============================] - 3s 5ms/step - loss: 0.4210 - val\_loss: 0.3453 - lr: 0.0010

Epoch 2/20

235/235 [==============================] - 1s 4ms/step - loss: 0.3433 - val\_loss: 0.3300 - lr: 0.0010

Epoch 3/20

235/235 [==============================] - 1s 5ms/step - loss: 0.3331 - val\_loss: 0.3238 - lr: 0.0010

Epoch 4/20

235/235 [==============================] - 1s 5ms/step - loss: 0.3275 - val\_loss: 0.3195 - lr: 0.0010

Epoch 5/20

235/235 [==============================] - 1s 5ms/step - loss: 0.3241 - val\_loss: 0.3163 - lr: 0.0010

Epoch 6/20

235/235 [==============================] - 1s 5ms/step - loss: 0.3217 - val\_loss: 0.3141 - lr: 0.0010

Epoch 7/20

235/235 [==============================] - 1s 5ms/step - loss: 0.3197 - val\_loss: 0.3122 - lr: 0.0010

Epoch 8/20

235/235 [==============================] - 1s 5ms/step - loss: 0.3184 - val\_loss: 0.3110 - lr: 0.0010

Epoch 9/20

235/235 [==============================] - 2s 7ms/step - loss: 0.3171 - val\_loss: 0.3098 - lr: 0.0010

Epoch 10/20

235/235 [==============================] - 2s 7ms/step - loss: 0.3161 - val\_loss: 0.3088 - lr: 0.0010

Epoch 11/20

235/235 [==============================] - 1s 5ms/step - loss: 0.3153 - val\_loss: 0.3079 - lr: 0.0010

Epoch 12/20

235/235 [==============================] - 1s 5ms/step - loss: 0.3146 - val\_loss: 0.3074 - lr: 0.0010

Epoch 13/20

235/235 [==============================] - 1s 5ms/step - loss: 0.3139 - val\_loss: 0.3063 - lr: 0.0010

Epoch 14/20

235/235 [==============================] - 1s 5ms/step - loss: 0.3134 - val\_loss: 0.3061 - lr: 0.0010

Epoch 15/20

235/235 [==============================] - 1s 5ms/step - loss: 0.3129 - val\_loss: 0.3052 - lr: 0.0010

Epoch 16/20

235/235 [==============================] - 1s 5ms/step - loss: 0.3125 - val\_loss: 0.3047 - lr: 0.0010

Epoch 17/20

235/235 [==============================] - 1s 5ms/step - loss: 0.3119 - val\_loss: 0.3046 - lr: 0.0010

Epoch 18/20

235/235 [==============================] - 1s 5ms/step - loss: 0.3116 - val\_loss: 0.3040 - lr: 0.0010

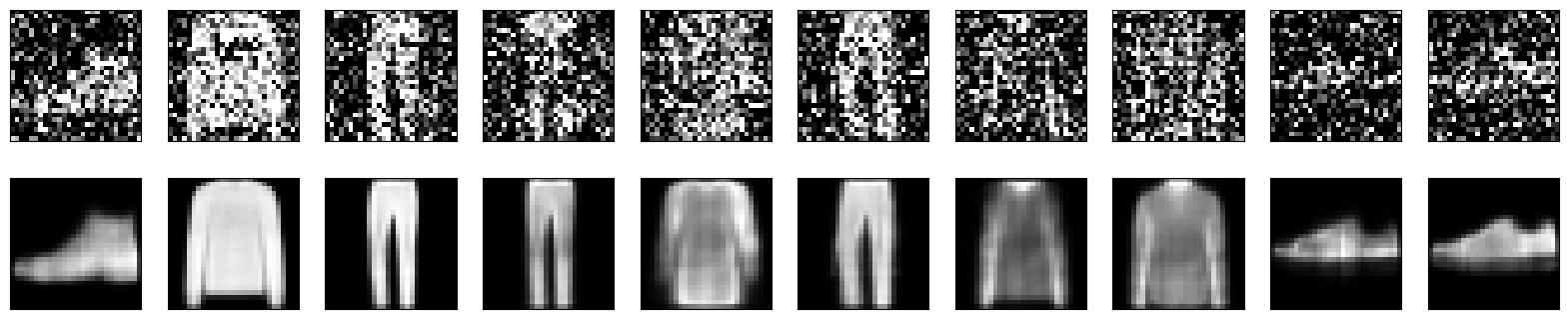
Epoch 19/20

235/235 [==============================] - 1s 5ms/step - loss: 0.3111 - val\_loss: 0.3038 - lr: 0.0010

Epoch 20/20

235/235 [==============================] - 2s 7ms/step - loss: 0.3109 - val\_loss: 0.3034 - lr: 0.0010

313/313 [==============================] - 1s 3ms/step



plot loss and accuracy using the history object

from keras.layers import Input, Dense

from keras.models import Model

from keras.datasets import fashion\_mnist

from keras.utils import to\_categorical

import numpy as np

import matplotlib.pyplot as plt

from keras.optimizers import Adam

# Load and prepare the Fashion MNIST data

(x\_train, y\_train), (x\_test, y\_test) = fashion\_mnist.load\_data()

x\_train = x\_train.reshape(-1, 784).astype('float32') / 255

x\_test = x\_test.reshape(-1, 784).astype('float32') / 255

# Convert labels to one-hot encoding

num\_classes = 10

y\_train = to\_categorical(y\_train, num\_classes)

y\_test = to\_categorical(y\_test, num\_classes)

# Model architecture

input\_img = Input(shape=(784,))

encoded = Dense(128, activation='relu')(input\_img)

decoded = Dense(10, activation='softmax')(encoded) # Classification layer

model = Model(input\_img, decoded)

model.compile(optimizer=Adam(learning\_rate=0.001), loss='categorical\_crossentropy', metrics=['accuracy'])

# Train the model

history = model.fit(x\_train, y\_train,

epochs=10,

batch\_size=256,

shuffle=True,

validation\_data=(x\_test, y\_test))

# Plotting the training and validation loss

plt.figure(figsize=(10, 5))

# Plotting training and validation accuracy

plt.subplot(1, 2, 1)

plt.plot(history.history['accuracy'], label='Training Accuracy')

plt.plot(history.history['val\_accuracy'], label='Validation Accuracy')

plt.title('Training and Validation Accuracy')

plt.xlabel('Epoch')

plt.ylabel('Accuracy')

plt.legend()

# Plotting training and validation loss

plt.subplot(1, 2, 2)

plt.plot(history.history['loss'], label='Training Loss')

plt.plot(history.history['val\_loss'], label='Validation Loss')

plt.title('Training and Validation Loss')

plt.xlabel('Epoch')

plt.ylabel('Loss')

plt.legend()

plt.tight\_layout()

plt.show()

**Output:**

Epoch 1/10

235/235 [==============================] - 2s 6ms/step - loss: 0.6263 - accuracy: 0.7865 - val\_loss: 0.4995 - val\_accuracy: 0.8282

Epoch 2/10

235/235 [==============================] - 2s 7ms/step - loss: 0.4339 - accuracy: 0.8517 - val\_loss: 0.4470 - val\_accuracy: 0.8445

Epoch 3/10

235/235 [==============================] - 1s 4ms/step - loss: 0.3932 - accuracy: 0.8637 - val\_loss: 0.4276 - val\_accuracy: 0.8493

Epoch 4/10

235/235 [==============================] - 1s 4ms/step - loss: 0.3675 - accuracy: 0.8704 - val\_loss: 0.3909 - val\_accuracy: 0.8621

Epoch 5/10

235/235 [==============================] - 1s 4ms/step - loss: 0.3457 - accuracy: 0.8774 - val\_loss: 0.3841 - val\_accuracy: 0.8650

Epoch 6/10

235/235 [==============================] - 1s 4ms/step - loss: 0.3290 - accuracy: 0.8833 - val\_loss: 0.3816 - val\_accuracy: 0.8607

Epoch 7/10

235/235 [==============================] - 1s 6ms/step - loss: 0.3173 - accuracy: 0.8873 - val\_loss: 0.3644 - val\_accuracy: 0.8716

Epoch 8/10

235/235 [==============================] - 1s 6ms/step - loss: 0.3048 - accuracy: 0.8910 - val\_loss: 0.3528 - val\_accuracy: 0.8756

Epoch 9/10

235/235 [==============================] - 1s 5ms/step - loss: 0.2947 - accuracy: 0.8938 - val\_loss: 0.3535 - val\_accuracy: 0.8749

Epoch 10/10

235/235 [==============================] - 1s 4ms/step - loss: 0.2876 - accuracy: 0.8969 - val\_loss: 0.3580 - val\_accuracy: 0.8724

