

# NEURAL NETWORK DEEP LEARNING

## ICP 6

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### GitHub:

Repository URL for the source code:

<https://github.com/saikumarreddyMandha/Assignment-6>

### Video Link:

[https://drive.google.com/file/d/1q1zHUeda\\_FuybVgnOwEO\\_j8beHwvWwWw/view?usp=drive\\_link](https://drive.google.com/file/d/1q1zHUeda_FuybVgnOwEO_j8beHwvWwWw/view?usp=drive_link)

## 1. Adding hidden layer to Autoencoder

```
1. Adding hidden layer to Autoencoder

from keras.layers import Input, Dense
from keras.models import Model
from keras.datasets import mnist, fashion_mnist
import numpy as np

# this is the size of our encoded representations
encoding_dim = 32
# this is our input placeholder
input_img = Input(shape=(784,))
# "encoded" is the encoded representation of the input
encoded = Dense(encoding_dim, activation='relu')(input_img)
# Adding an additional hidden layer
hidden_layer_dim = 64
hidden_layer = Dense(hidden_layer_dim, activation='relu')(encoded)
# "decoded" is the lossy reconstruction of the input, now connected to the hidden layer instead of 'encoded'
decoded = Dense(784, activation='sigmoid')(hidden_layer)
# this model maps an input to its reconstruction
autoencoder = Model(input_img, decoded)
# this model maps an input to its encoded representation
```

```
x_test = x_test.reshape((len(x_test), np.prod(x_test.shape[1:])))

# Train the model
autoencoder.fit(x_train, x_train,
               epochs=5,
               batch_size=256,
               shuffle=True,
               validation_data=(x_test, x_test))

Epoch 1/5
235/235 — 4s 13ms/step - loss: 0.6946 - val_loss: 0.6945
Epoch 2/5
235/235 — 6s 17ms/step - loss: 0.6945 - val_loss: 0.6943
Epoch 3/5
235/235 — 4s 12ms/step - loss: 0.6943 - val_loss: 0.6942
Epoch 4/5
235/235 — 4s 15ms/step - loss: 0.6942 - val_loss: 0.6941
Epoch 5/5
235/235 — 6s 19ms/step - loss: 0.6940 - val_loss: 0.6940
<keras.src.callbacks.history.History at 0x7c74c8675c90>
```

2. 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

```
[3] from keras.layers import Input, Dense
    from keras.models import Model
    from keras.datasets import mnist, fashion_mnist
    import numpy as np
    import matplotlib.pyplot as plt

    # Define the model architecture
    encoding_dim = 32
    hidden_layer_dim = 64

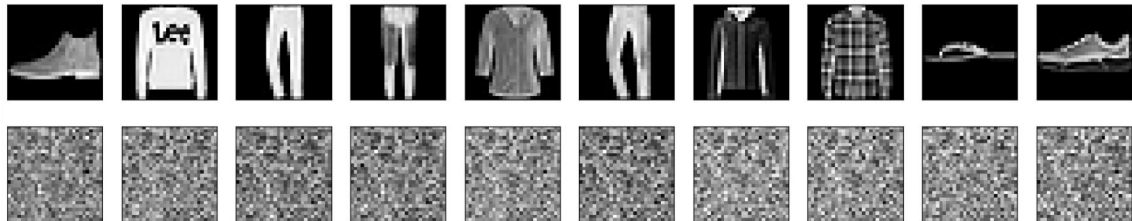
    input_img = Input(shape=(784,))
    encoded = Dense(encoding_dim, activation='relu')(input_img)
    hidden_layer = Dense(hidden_layer_dim, activation='relu')(encoded) # Additional hidden layer
    decoded = Dense(784, activation='sigmoid')(hidden_layer)

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

    # Load and prepare data
    (x_train, _), (x_test, _) = fashion_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:])))
```

```
plt.show()

Epoch 1/5
235/235 — 4s 12ms/step - loss: 0.6959 - val_loss: 0.6957
Epoch 2/5
235/235 — 5s 12ms/step - loss: 0.6956 - val_loss: 0.6954
Epoch 3/5
235/235 — 4s 18ms/step - loss: 0.6953 - val_loss: 0.6951
Epoch 4/5
235/235 — 4s 12ms/step - loss: 0.6950 - val_loss: 0.6948
Epoch 5/5
235/235 — 6s 15ms/step - loss: 0.6948 - val_loss: 0.6946
313/313 — 1s 2ms/step
```



3. Denoising Autoencoder - 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
from keras.models import Model
from keras.datasets import fashion_mnist
import numpy as np
import matplotlib.pyplot as plt

# Define the model architecture
encoding_dim = 32

input_img = Input(shape=(784,))
encoded = Dense(encoding_dim, activation='relu')(input_img)
decoded = Dense(784, activation='sigmoid')(encoded)

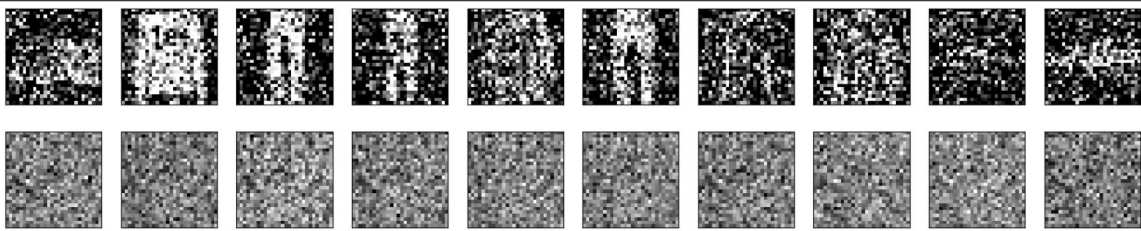
autoencoder = Model(input_img, decoded)
autoencoder.compile(optimizer='adadelta', loss='binary_crossentropy')

# Load data
(x_train, _), (x_test, _) = fashion_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:])))
# Introducing noise
```

```
# 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()
```

```
Epoch 1/20
235/235 — 3s 11ms/step - loss: 0.6963 - val_loss: 0.6960
Epoch 2/20
235/235 — 5s 11ms/step - loss: 0.6960 - val_loss: 0.6958
Epoch 3/20
235/235 — 5s 11ms/step - loss: 0.6957 - val_loss: 0.6955
Epoch 4/20
235/235 — 2s 10ms/step - loss: 0.6955 - val_loss: 0.6953
Epoch 5/20
235/235 — 2s 10ms/step - loss: 0.6952 - val_loss: 0.6950
Epoch 6/20
235/235 — 3s 12ms/step - loss: 0.6950 - val_loss: 0.6948
Epoch 7/20
235/235 — 4s 15ms/step - loss: 0.6947 - val_loss: 0.6946
Epoch 8/20
235/235 — 4s 11ms/step - loss: 0.6945 - val_loss: 0.6944
Epoch 9/20
235/235 — 3s 11ms/step - loss: 0.6943 - val_loss: 0.6942
Epoch 10/20
235/235 — 2s 10ms/step - loss: 0.6941 - val_loss: 0.6940
Epoch 11/20
235/235 — 4s 17ms/step - loss: 0.6939 - val_loss: 0.6938
```

```
[4] Epoch 15/20
235/235 — 3s 13ms/step - loss: 0.6932 - val_loss: 0.6931
Epoch 16/20
235/235 — 5s 11ms/step - loss: 0.6930 - val_loss: 0.6929
Epoch 17/20
235/235 — 5s 10ms/step - loss: 0.6928 - val_loss: 0.6927
Epoch 18/20
235/235 — 3s 14ms/step - loss: 0.6927 - val_loss: 0.6926
Epoch 19/20
235/235 — 3s 14ms/step - loss: 0.6925 - val_loss: 0.6924
Epoch 20/20
235/235 — 5s 13ms/step - loss: 0.6924 - val_loss: 0.6922
313/313 — 1s 2ms/step
```



#### 4. 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'])
```

```
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()
```

```
Epoch 1/10
235/235 — 3s 7ms/step - accuracy: 0.7185 - loss: 0.8426 - val_accuracy: 0.8283 - val_loss: 0.4965
Epoch 2/10
235/235 — 2s 6ms/step - accuracy: 0.8500 - loss: 0.4343 - val_accuracy: 0.8524 - val_loss: 0.4266
Epoch 3/10
235/235 — 3s 6ms/step - accuracy: 0.8652 - loss: 0.3853 - val_accuracy: 0.8607 - val_loss: 0.3955
Epoch 4/10
235/235 — 3s 10ms/step - accuracy: 0.8712 - loss: 0.3647 - val_accuracy: 0.8534 - val_loss: 0.4032
Epoch 5/10
235/235 — 2s 7ms/step - accuracy: 0.8813 - loss: 0.3394 - val_accuracy: 0.8654 - val_loss: 0.3798
Epoch 6/10
235/235 — 2s 7ms/step - accuracy: 0.8846 - loss: 0.3226 - val_accuracy: 0.8665 - val_loss: 0.3677
Epoch 7/10
235/235 — 2s 6ms/step - accuracy: 0.8900 - loss: 0.3061 - val_accuracy: 0.8719 - val_loss: 0.3612
Epoch 8/10
235/235 — 3s 6ms/step - accuracy: 0.8919 - loss: 0.2978 - val_accuracy: 0.8725 - val_loss: 0.3539
Epoch 9/10
235/235 — 3s 7ms/step - accuracy: 0.8954 - loss: 0.2897 - val_accuracy: 0.8742 - val_loss: 0.3509
Epoch 10/10
235/235 — 3s 11ms/step - accuracy: 0.9000 - loss: 0.2799 - val_accuracy: 0.8742 - val_loss: 0.3474
```

