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Neural Networks & Deep Learning – Assignment - 8

Github link: https://github.com/ShaikRumana301/Neural-Network-DL-Assignment-8.git

Video Link:
https://drive.google.com/file/d/1vyNwjGHVu_lZANuy3AK2WESaBa_flCRa/view?usp=sharing

- **In class programming:**

1. Add one more hidden layer to autoencoder

```
[1] from keras.layers import Input, Dense
    from keras.models import Model

    # this is the size of our encoded representations
    encoding_dim = 32  # 32 floats -> compression of factor 24.5, assuming the input is 784 floats

    # 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)
    # "decoded" is the lossy reconstruction of the input
    decoded = Dense(784, activation='sigmoid')(encoded)
    # this model maps an input to its reconstruction
    autoencoder = Model(input_img, decoded)
    # this model maps an input to its encoded representation
    autoencoder.compile(optimizer='adadelta', loss='binary_crossentropy')
    from keras.datasets import mnist, fashion_mnist
    import numpy as np
    (x_train, y_train), (x_test, y_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:])))

    autoencoder.fit(x_train, x_train,
                    epochs=5,
                    batch_size=256,
                    shuffle=True,
                    validation_data=(x_test, x_test))
```

```
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 [==============================] - 2s 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 [==============================] - 1s 0us/step
Epoch 1/5
235/235 [==============================] - 4s 15ms/step - loss: 0.6972 - val_loss: 0.6970
Epoch 2/5
235/235 [==============================] - 2s 10ms/step - loss: 0.6968 - val_loss: 0.6966
Epoch 3/5
235/235 [==============================] - 4s 15ms/step - loss: 0.6964 - val_loss: 0.6962
Epoch 4/5
235/235 [==============================] - 2s 10ms/step - loss: 0.6960 - val_loss: 0.6958
Epoch 5/5
235/235 [==============================] - 2s 10ms/step - loss: 0.6957 - val_loss: 0.6955
<keras.src.callbacks.History at 0x7f3c3e93e230>
```

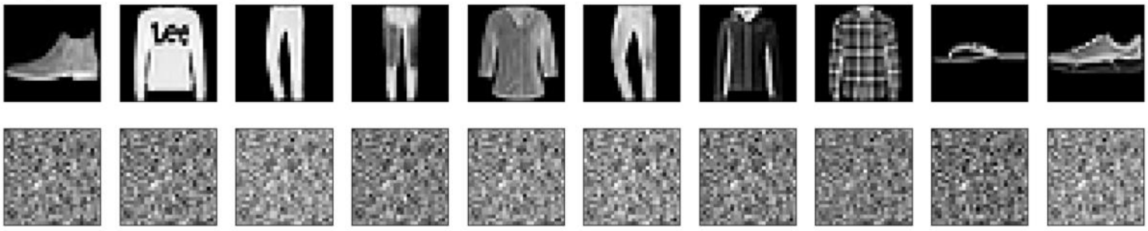
2. Do the prediction on the test data and then visualize one of the reconstructed version of that test data. Also, visualize the same test data before reconstruction using Matplotlib

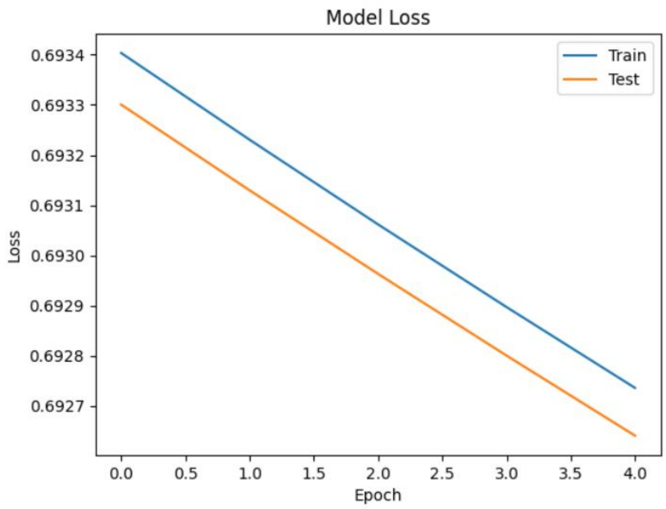
```python
from keras.layers import Input, Dense
from keras.models import Model
from keras.datasets import mnist, fashion_mnist
import numpy as np
import matplotlib.pyplot as plt

encoding_dim = 32

input_img = Input(shape=(784,))

hidden_1 = Dense(256, activation='relu')(input_img)

encoded = Dense(encoding_dim, activation='relu')(hidden_1)

hidden_2 = Dense(256, activation='relu')(encoded)

# Define the output layer
decoded = Dense(784, activation='sigmoid')(hidden_2)

# Define the autoencoder model
autoencoder = Model(input_img, decoded)

# Compile the model
autoencoder.compile(optimizer='adadelta', loss='binary_crossentropy',metrics=['accuracy'])

# Load the fashion MNIST dataset
(x_train, _), (x_test, _) = fashion_mnist.load_data()

x_train = x_train.astype('float32') / 255.
x_test = x_test.astype('float32') / 255.
```

```python
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:])))

history = autoencoder.fit(x_train, x_train,
                epochs=5,
                batch_size=256,
                shuffle=True,
                validation_data=(x_test, x_test))

decoded_imgs = autoencoder.predict(x_test)

# Visualize one of the reconstructed images
n = 10  # number of images to display
plt.figure(figsize=(20, 4))
for i in range(n):
    # Display original test image
    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 reconstructed test image
    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()

plt.plot(history.history['loss'])
```

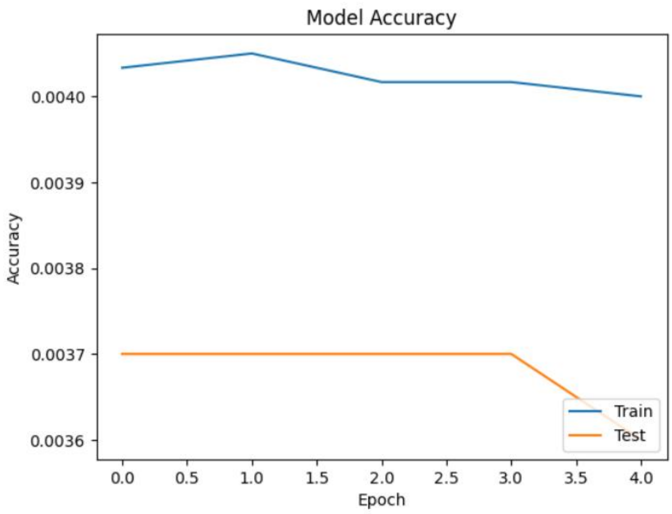
```
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('Model Loss')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(['Train', 'Test'], loc='upper right')
plt.show()

plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('Model Accuracy')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend(['Train', 'Test'], loc='lower right')
plt.show()
```

```
Epoch 1/5
235/235 [==============================] - 8s 31ms/step - loss: 0.6934 - accuracy: 0.0040 - val_loss: 0.6933 - val_accuracy: 0.0037
Epoch 2/5
235/235 [==============================] - 6s 25ms/step - loss: 0.6932 - accuracy: 0.0041 - val_loss: 0.6931 - val_accuracy: 0.0037
Epoch 3/5
235/235 [==============================] - 6s 27ms/step - loss: 0.6931 - accuracy: 0.0040 - val_loss: 0.6930 - val_accuracy: 0.0037
Epoch 4/5
235/235 [==============================] - 6s 26ms/step - loss: 0.6929 - accuracy: 0.0040 - val_loss: 0.6928 - val_accuracy: 0.0037
Epoch 5/5
235/235 [==============================] - 8s 32ms/step - loss: 0.6927 - accuracy: 0.0040 - val_loss: 0.6926 - val_accuracy: 0.0036
313/313 [==============================] - 1s 3ms/step
```





38s [10]



3. Repeat the question 2 on the denoisening autoencoder

```
[11] from keras.layers import Input, Dense
     from keras.models import Model

     encoding_dim = 32  # 32 floats -> compression of factor 24.5, assuming the input is 784 floats

     input_img = Input(shape=(784,))
     encoded = Dense(encoding_dim, activation='relu')(input_img)
     # "decoded" is the lossy reconstruction of the input
     decoded = Dense(784, activation='sigmoid')(encoded)
     autoencoder = Model(input_img, decoded)
     # this model maps an input to its encoded representation
     autoencoder.compile(optimizer='adadelta', loss='binary_crossentropy')
     from keras.datasets import fashion_mnist
     import numpy as np
     (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:])))

     noise_factor = 0.5
     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)

     autoencoder.fit(x_train_noisy, x_train,
                     epochs=10,
                     batch_size=256,
                     shuffle=True,
                     validation_data=(x_test_noisy, x_test_noisy))
```

```
Epoch 1/10
235/235 [==============================] - 4s 14ms/step - loss: 0.6965 - val_loss: 0.6965
Epoch 2/10
235/235 [==============================] - 2s 10ms/step - loss: 0.6963 - val_loss: 0.6962
Epoch 3/10
235/235 [==============================] - 3s 11ms/step - loss: 0.6960 - val_loss: 0.6960
Epoch 4/10
235/235 [==============================] - 2s 10ms/step - loss: 0.6958 - val_loss: 0.6958
Epoch 5/10
235/235 [==============================] - 3s 12ms/step - loss: 0.6956 - val_loss: 0.6955
Epoch 6/10
235/235 [==============================] - 3s 13ms/step - loss: 0.6953 - val_loss: 0.6953
Epoch 7/10
235/235 [==============================] - 2s 10ms/step - loss: 0.6951 - val_loss: 0.6951
Epoch 8/10
235/235 [==============================] - 2s 10ms/step - loss: 0.6949 - val_loss: 0.6949
Epoch 9/10
235/235 [==============================] - 2s 11ms/step - loss: 0.6947 - val_loss: 0.6947
Epoch 10/10
235/235 [==============================] - 3s 13ms/step - loss: 0.6945 - val_loss: 0.6945
<keras.src.callbacks.History at 0x7f3c2a33ec80>
```

4. plot loss and accuracy using the history object

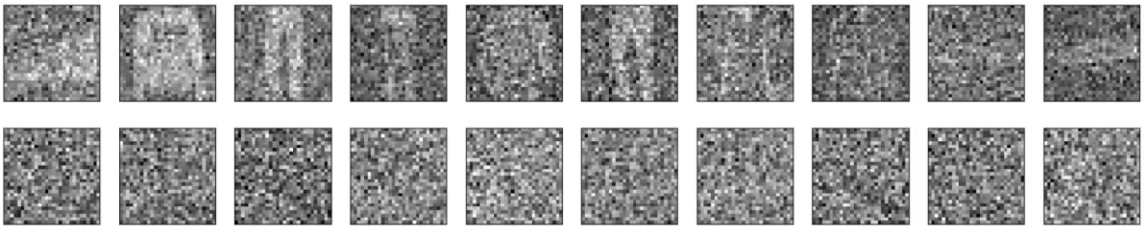
```python
from keras.layers import Input, Dense
from keras.models import Model
from keras.datasets import fashion_mnist
import numpy as np
import matplotlib.pyplot as plt

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)

# Compile the model
autoencoder.compile(optimizer='adadelta', loss='binary_crossentropy',metrics=['accuracy'])

# Load the fashion MNIST dataset
(x_train, _), (x_test, _) = fashion_mnist.load_data()

# Normalize the data and flatten the images
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:])))

noise_factor = 0.5
x_test_noisy = x_test + noise_factor * np.random.normal(loc=0.0, scale=1.0, size=x_test.shape)
```

[12]

```python
x_test_noisy = x_test + noise_factor * np.random.normal(loc=0.0, scale=1.0, size=x_test.shape)

history = autoencoder.fit(x_train_noisy, x_train,
                epochs=10,
                batch_size=256,
                shuffle=True,
                validation_data=(x_test_noisy, x_test_noisy))

decoded_imgs = autoencoder.predict(x_test_noisy)

# Visualize one of the noisy test images
plt.figure(figsize=(20, 4))
n = 10
for i in range(n):
    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)

# Visualize one of the reconstructed test images
for i in range(n):
    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()

plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
```

```
plt.show()

plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('Model Loss')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(['Train', 'Test'], loc='upper right')
plt.show()

plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('Model Accuracy')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend(['Train', 'Test'], loc='lower right')
plt.show()
```

```
Epoch 1/10
235/235 [==============================] - 4s 13ms/step - loss: 0.6980 - accuracy: 0.0014 - val_loss: 0.6977 - val_accuracy: 0.0012
Epoch 2/10
235/235 [==============================] - 3s 13ms/step - loss: 0.6977 - accuracy: 0.0013 - val_loss: 0.6974 - val_accuracy: 0.0011
Epoch 3/10
235/235 [==============================] - 3s 11ms/step - loss: 0.6974 - accuracy: 0.0013 - val_loss: 0.6971 - val_accuracy: 0.0011
Epoch 4/10
235/235 [==============================] - 3s 11ms/step - loss: 0.6971 - accuracy: 0.0013 - val_loss: 0.6968 - val_accuracy: 0.0011
Epoch 5/10
235/235 [==============================] - 3s 11ms/step - loss: 0.6968 - accuracy: 0.0013 - val_loss: 0.6966 - val_accuracy: 0.0012
Epoch 6/10
235/235 [==============================] - 4s 15ms/step - loss: 0.6966 - accuracy: 0.0013 - val_loss: 0.6963 - val_accuracy: 0.0012
Epoch 7/10
```



Model Loss