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Github Link: https://github.com/Sandeep2982/ICP-5/blob/main/IPC_5.ipynb

1. Add one more hidden layer to autoencoder

In [5]:

```
from keras.layers import Input, Dense
from keras.models import Model


encoding_dim = 32

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))
```

```
Epoch 1/5
235/235 [==============================] - 3s 12ms/step - loss: 0.6941 - val_loss: 0.6940
Epoch 2/5
```

```
235/235 [==============================] - 3s 12ms/step - loss: 0.6941 - val_loss: 0.6940
Epoch 2/5
235/235 [==============================] - 4s 17ms/step - loss: 0.6939 - val_loss: 0.6938
Epoch 3/5
235/235 [==============================] - 3s 12ms/step - loss: 0.6937 - val_loss: 0.6936
Epoch 4/5
235/235 [==============================] - 3s 12ms/step - loss: 0.6935 - val_loss: 0.6934
Epoch 5/5
235/235 [==============================] - 3s 12ms/step - loss: 0.6933 - val_loss: 0.6932
```

Out[5]:
```
<keras.src.callbacks.History at 0x7b60bfb7e980>
```

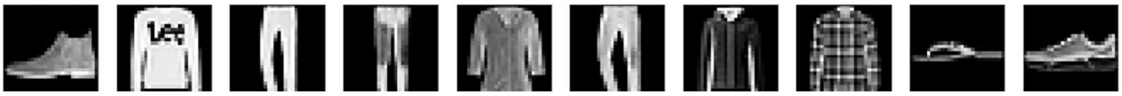
2. Do the prediction on the test data and then visualize one of the reconstructed version of that test data. Also, visualize the same test data before reconstruction using Matplotlib

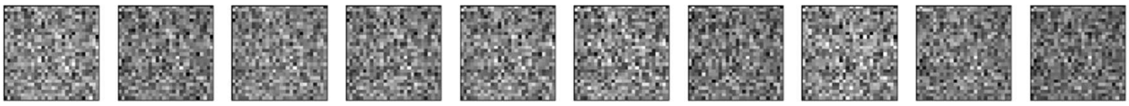
In [6]:
```python
from keras.layers import Input, Dense
from keras.models import Model
from keras.datasets import mnist, fashion_mnist
import numpy as np
import matplotlib.pyplot as plt

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)
```

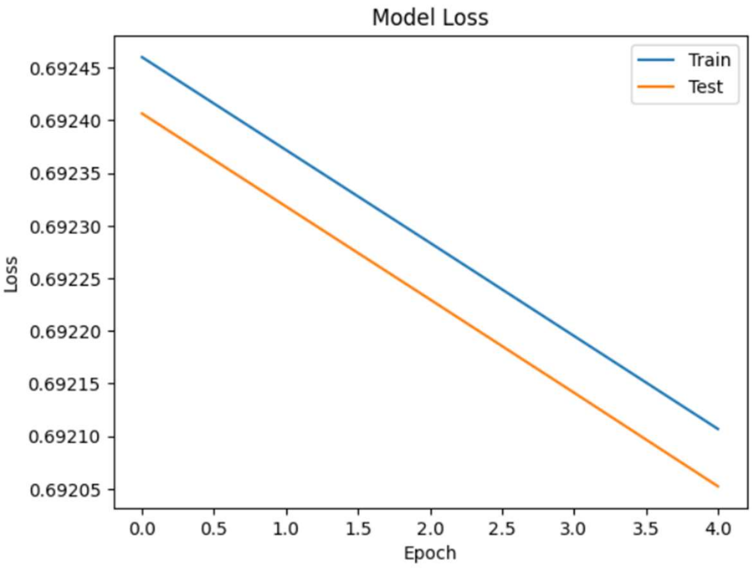
```python
# Compile the model
autoencoder.compile(optimizer='adadelta', loss='binary_crossentropy',metrics=['accuracy'])

# 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.
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()
```

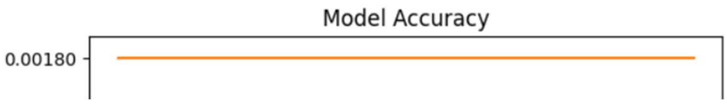
```
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('Model Loss')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(['Train', 'Test'], loc='upper right')
plt.show()

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()
```

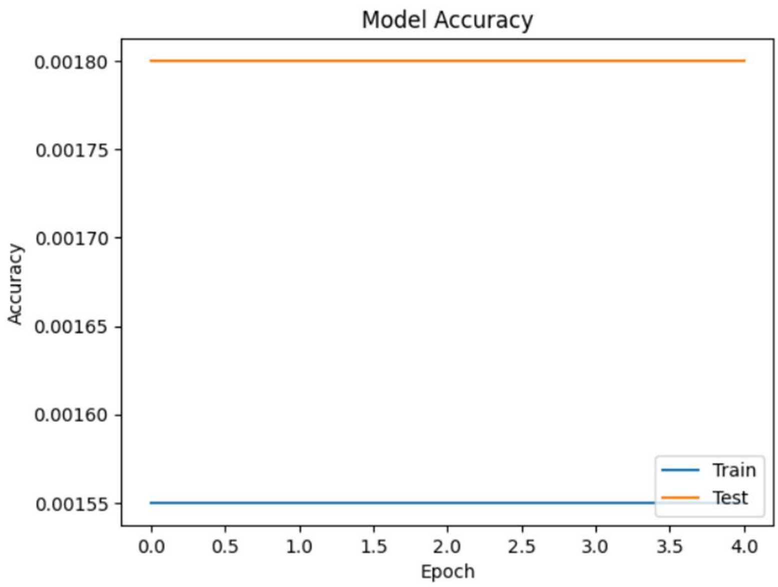
```
Epoch 1/5
235/235 [==============================] - 8s 29ms/step - loss: 0.6925 - accuracy: 0.0016 - val_loss: 0.6924 - val_accurac
y: 0.0018
Epoch 2/5
235/235 [==============================] - 7s 29ms/step - loss: 0.6924 - accuracy: 0.0016 - val_loss: 0.6923 - val_accurac
y: 0.0018
Epoch 3/5
235/235 [==============================] - 7s 29ms/step - loss: 0.6923 - accuracy: 0.0016 - val_loss: 0.6922 - val_accurac
y: 0.0018
Epoch 4/5
235/235 [==============================] - 7s 29ms/step - loss: 0.6922 - accuracy: 0.0016 - val_loss: 0.6921 - val_accurac
y: 0.0018
Epoch 5/5
235/235 [==============================] - 7s 31ms/step - loss: 0.6921 - accuracy: 0.0016 - val_loss: 0.6921 - val_accurac
y: 0.0018
313/313 [==============================] - 1s 3ms/step
```











3. Repeat the question 2 on the denoisening autoencoder

In [7]:
```
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,))
```

```
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 13ms/step - loss: 0.6966 - val_loss: 0.6965
Epoch 2/10
235/235 [==============================] - 4s 17ms/step - loss: 0.6963 - val_loss: 0.6962
Epoch 3/10
235/235 [==============================] - 3s 13ms/step - loss: 0.6960 - val_loss: 0.6959
Epoch 4/10
235/235 [==============================] - 3s 12ms/step - loss: 0.6957 - val_loss: 0.6956
Epoch 5/10
235/235 [==============================] - 3s 12ms/step - loss: 0.6954 - val_loss: 0.6953
```

```
Epoch 5/10
235/235 [==============================] - 3s 12ms/step - loss: 0.6954 - val_loss: 0.6953
Epoch 6/10
235/235 [==============================] - 4s 17ms/step - loss: 0.6951 - val_loss: 0.6950
Epoch 7/10
235/235 [==============================] - 3s 12ms/step - loss: 0.6949 - val_loss: 0.6948
Epoch 8/10
235/235 [==============================] - 3s 12ms/step - loss: 0.6946 - val_loss: 0.6945
Epoch 9/10
235/235 [==============================] - 3s 13ms/step - loss: 0.6943 - val_loss: 0.6942
Epoch 10/10
235/235 [==============================] - 4s 17ms/step - loss: 0.6941 - val_loss: 0.6940
```

Out[7]: <keras.src.callbacks.History at 0x7b60d1610940>

4. plot loss and accuracy using the history object

In [8]:

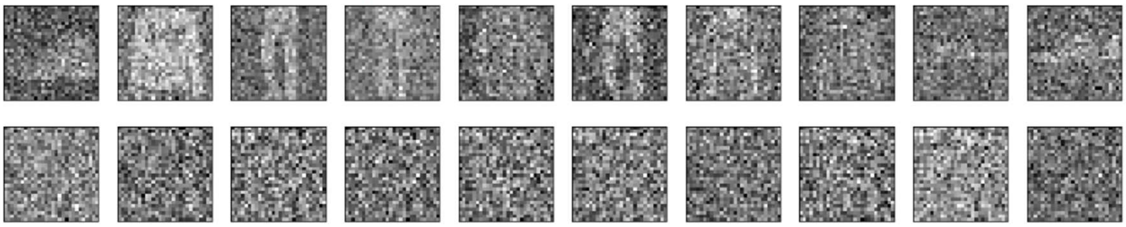
```
from keras.layers import Input, Dense
from keras.models import Model
from keras.datasets import fashion_mnist
import numpy as np
import matplotlib.pyplot as plt

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
```

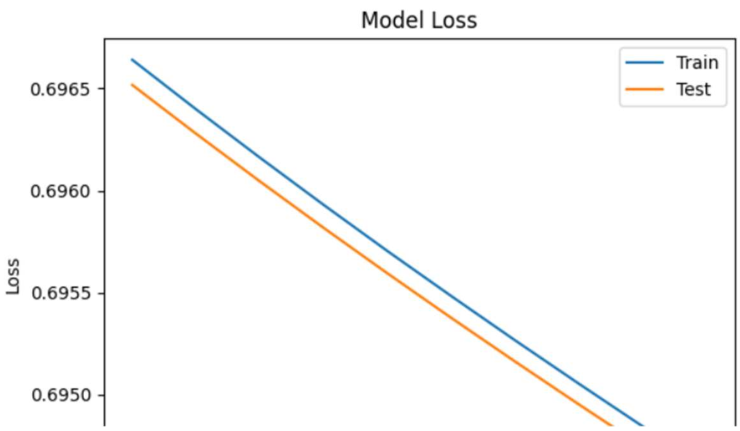
```
(x_train, _), (x_test, _) = fashion_mnist.load_data()

# 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)

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()
```

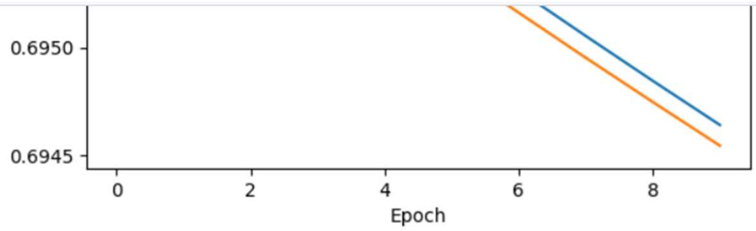
```
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('Model Loss')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(['Train', 'Test'], loc='upper right')
plt.show()

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()
```

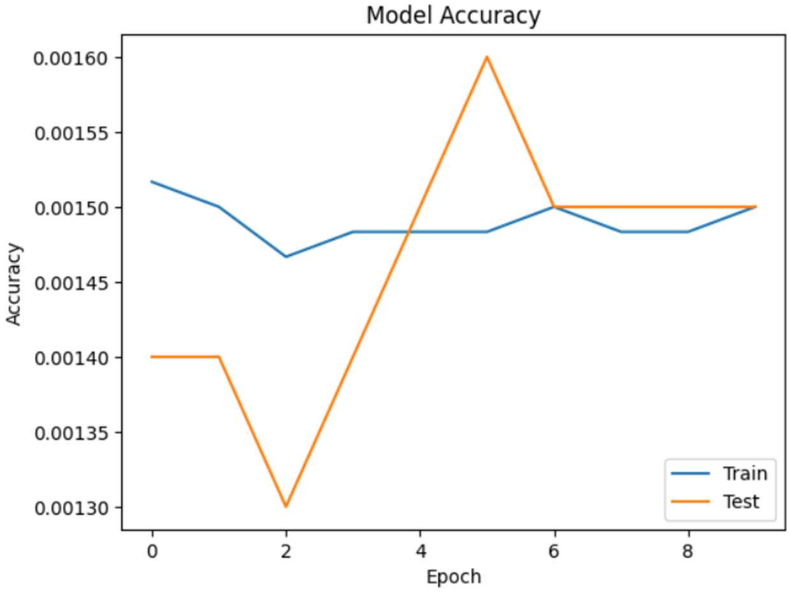
```
Epoch 1/10
235/235 [==============================] - 5s 16ms/step - loss: 0.6966 - accuracy: 0.0015 - val_loss: 0.6965 - val_accurac
y: 0.0014
Epoch 2/10
235/235 [==============================] - 3s 13ms/step - loss: 0.6964 - accuracy: 0.0015 - val_loss: 0.6963 - val_accurac
y: 0.0014
Epoch 3/10
235/235 [==============================] - 3s 12ms/step - loss: 0.6962 - accuracy: 0.0015 - val_loss: 0.6960 - val_accurac
y: 0.0013
Epoch 4/10
235/235 [==============================] - 3s 15ms/step - loss: 0.6959 - accuracy: 0.0015 - val_loss: 0.6958 - val_accurac
y: 0.0014
Epoch 5/10
235/235 [==============================] - 4s 15ms/step - loss: 0.6957 - accuracy: 0.0015 - val_loss: 0.6956 - val_accurac
y: 0.0015
Epoch 6/10
235/235 [==============================] - 3s 14ms/step - loss: 0.6955 - accuracy: 0.0015 - val_loss: 0.6954 - val_accurac
y: 0.0016
Epoch 7/10
235/235 [==============================] - 3s 12ms/step - loss: 0.6953 - accuracy: 0.0015 - val_loss: 0.6952 - val_accurac
y: 0.0015
```

```
Epoch 9/10
235/235 [==============================] - 4s 16ms/step - loss: 0.6948 - accuracy: 0.0015 - val_loss: 0.6947 - val_accurac
y: 0.0015
Epoch 10/10
235/235 [==============================] - 3s 12ms/step - loss: 0.6946 - accuracy: 0.0015 - val_loss: 0.6945 - val_accurac
y: 0.0015
313/313 [==============================] - 1s 2ms/step
```






0.6950
0.6945
0
2
4
6
8
Epoch


Model Accuracy
0.00160
0.00155
0.00150
0.00145
0.00140
0.00135
0.00130
Accuracy
Train
Test
0
2
4
6
8
Epoch