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ASSIGNMENT_8

NEURAL NETWORKS AND DEEP LEARNING

https://github.com/niteesh0301/Assignment_8.git

1.HIDDEN LAYER TO THE AUTOENCODER AND VISUALIZING THE DATA. ADDING

CODE :-

```
from keras.layers import Input, Dense
from keras.models import Model
import matplotlib.pyplot as plt
# Define the size of encoded representations and the additional hidden layer size
encoding_dim = 32
hidden_dim = 64
# Input placeholder
input_img = Input(shape=(784,))
# First Encoding Layer
encoded1 = Dense(hidden_dim, activation='relu')(input_img)
# Second Encoding Layer
encoded2 = Dense(encoding_dim, activation='relu')(encoded1)
# First Decoding layer
decoded1 = Dense(hidden_dim, activation='relu')(encoded2)
# Second Decoding layer
decoded = Dense(784, activation='relu')(decoded1)
# Creating the autoencoder model
autoencoder = Model(input_img, decoded)
# Compile the autoencoder model
autoencoder.compile(optimizer='adam', loss='binary_crossentropy')
# Loading and preprocessing the data
from keras.datasets import fashion_mnist
import numpy as np
```

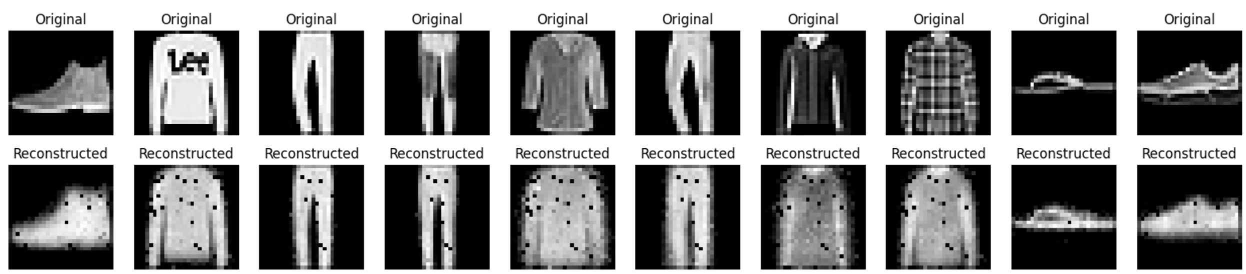
```python
(x_train, y_train), (x_test, y_test) = fashion_mnist.load_data()
x_train = x_train.astype('float32') / 255.
x_test = x_test.astype('float32') / 255.
x_train = x_train.reshape((len(x_train), np.prod(x_train.shape[1:])))
x_test = x_test.reshape((len(x_test), np.prod(x_test.shape[1:])))
# Train the autoencoder
history = autoencoder.fit(x_train, x_train, epochs=25, batch_size=256, shuffle=True, validation_data=(x_test,
# Predict and visualize one of the reconstructed test data
decoded_imgs = autoencoder.predict(x_test)
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),cmap='gray')
    plt.title("Original")
    plt.axis('off')

    # Display reconstructed images
    ax = plt.subplot(2, n, i + 1 + n)
    plt.imshow(decoded_imgs[i].reshape(28, 28),cmap='gray')
    plt.title("Reconstructed")
    plt.axis('off')
plt.show()
```

Output:-

```
Epoch 1/25
235/235 [==============================] - 4s 15ms/step - loss: 1.1138 - val_loss: 0.9577
Epoch 2/25
235/235 [==============================] - 3s 13ms/step - loss: 0.9140 - val_loss: 0.8558
Epoch 3/25
235/235 [==============================] - 3s 12ms/step - loss: 0.7981 - val_loss: 0.7760
Epoch 4/25
235/235 [==============================] - 3s 12ms/step - loss: 0.7358 - val_loss: 0.7051
Epoch 5/25
235/235 [==============================] - 3s 13ms/step - loss: 0.6788 - val_loss: 0.6419
Epoch 6/25
235/235 [==============================] - 4s 15ms/step - loss: 0.6280 - val_loss: 0.6339
Epoch 7/25
235/235 [==============================] - 3s 12ms/step - loss: 0.6185 - val_loss: 0.6119
Epoch 8/25
235/235 [==============================] - 3s 12ms/step - loss: 0.6079 - val_loss: 0.6084
Epoch 9/25
235/235 [==============================] - 3s 12ms/step - loss: 0.6039 - val_loss: 0.5889
Epoch 10/25
235/235 [==============================] - 4s 16ms/step - loss: 0.5776 - val_loss: 0.5965
Epoch 11/25
235/235 [==============================] - 3s 12ms/step - loss: 0.5721 - val_loss: 0.5602
Epoch 12/25
235/235 [==============================] - 3s 11ms/step - loss: 0.5788 - val_loss: 0.5541
Epoch 13/25
235/235 [==============================] - 3s 12ms/step - loss: 0.5513 - val_loss: 0.5559
Epoch 14/25
235/235 [==============================] - 4s 15ms/step - loss: 0.5348 - val_loss: 0.5252
Epoch 15/25
235/235 [==============================] - 3s 13ms/step - loss: 0.5205 - val_loss: 0.5125
```

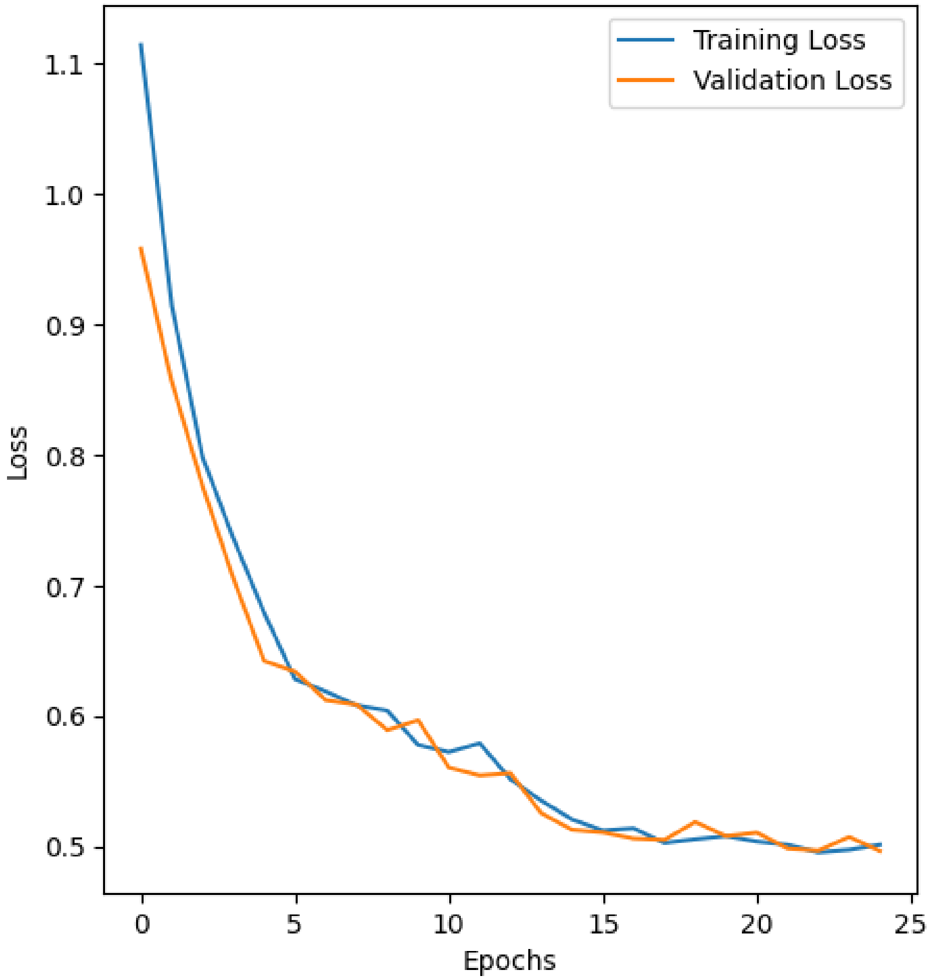
```
Epoch 15/25
235/235 [==============================] - 3s 13ms/step - loss: 0.5205 - val_loss: 0.5125
Epoch 16/25
235/235 [==============================] - 3s 11ms/step - loss: 0.5119 - val_loss: 0.5106
Epoch 17/25
235/235 [==============================] - 3s 11ms/step - loss: 0.5136 - val_loss: 0.5059
Epoch 18/25
235/235 [==============================] - 3s 12ms/step - loss: 0.5024 - val_loss: 0.5048
Epoch 19/25
235/235 [==============================] - 4s 15ms/step - loss: 0.5053 - val_loss: 0.5185
Epoch 20/25
235/235 [==============================] - 3s 12ms/step - loss: 0.5077 - val_loss: 0.5077
Epoch 21/25
235/235 [==============================] - 3s 12ms/step - loss: 0.5035 - val_loss: 0.5104
Epoch 22/25
235/235 [==============================] - 3s 12ms/step - loss: 0.5011 - val_loss: 0.4982
Epoch 23/25
235/235 [==============================] - 4s 17ms/step - loss: 0.4953 - val_loss: 0.4966
Epoch 24/25
235/235 [==============================] - 3s 12ms/step - loss: 0.4973 - val_loss: 0.5070
Epoch 25/25
235/235 [==============================] - 3s 12ms/step - loss: 0.5011 - val_loss: 0.4963
313/313 [==============================] - 1s 2ms/step
```



CODE:-

```
# Visualize the loss and accuracy
plt.figure(figsize=(12, 6))
plt.subplot(1, 2, 1)
plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
```

Output:-



2. ADDING HIDDEN LAYER TO THE DENOISING AUTOENCODER AND VISUALIZING THE DATA

CODE:-

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

# Define the size of encoded representations and the additional hidden layer size
encoding_dim = 32
hidden_dim = 64  # Increased hidden layer size for better representation

# Input placeholder for noisy data
input_img = Input(shape=(784,))

# First encoding layer
encoded1 = Dense(hidden_dim, activation='relu')(input_img)

# Second encoding layer
encoded2 = Dense(encoding_dim, activation='relu')(encoded1)

# First decoding layer
decoded1 = Dense(hidden_dim, activation='relu')(encoded2)

# Second decoding layer
decoded = Dense(784, activation='sigmoid')(decoded1)

# Create the denoising autoencoder model
autoencoder = Model(input_img, decoded)
```

```python
# Compile the denoising autoencoder model
autoencoder.compile(optimizer='adam', loss='binary_crossentropy')

# Load and preprocess the data
from keras.datasets import fashion_mnist
(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:])))

# Introduce noise
noise_factor = 0.1  # Reduced noise factor
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)

# Train the denoising autoencoder
history = autoencoder.fit(x_train_noisy, x_train, epochs=20, batch_size=256, shuffle=True, validation_data=(x_

# Predict and visualize one of the reconstructed test data
decoded_imgs = autoencoder.predict(x_test_noisy)

# Display original, noisy, and reconstructed images vertically
num_display = 10  # Number of digits to display
plt.figure(figsize=(10, 30))
```

```python
for i in range(num_display):
    # Original images
    ax = plt.subplot(num_display, 3, i*3 + 1)
    plt.imshow(x_test[i].reshape(28, 28), cmap='gray')
    plt.title('Original')
    plt.axis('off')

    # Noisy images
    ax = plt.subplot(num_display, 3, i*3 + 2)
    plt.imshow(x_test_noisy[i].reshape(28, 28), cmap='gray')
    plt.title('Noisy')
    plt.axis('off')

    # Reconstructed images
    ax = plt.subplot(num_display, 3, i*3 + 3)
    plt.imshow(decoded_imgs[i].reshape(28, 28), cmap='gray')
    plt.title('Reconstructed')
    plt.axis('off')

plt.tight_layout()
plt.show()
```

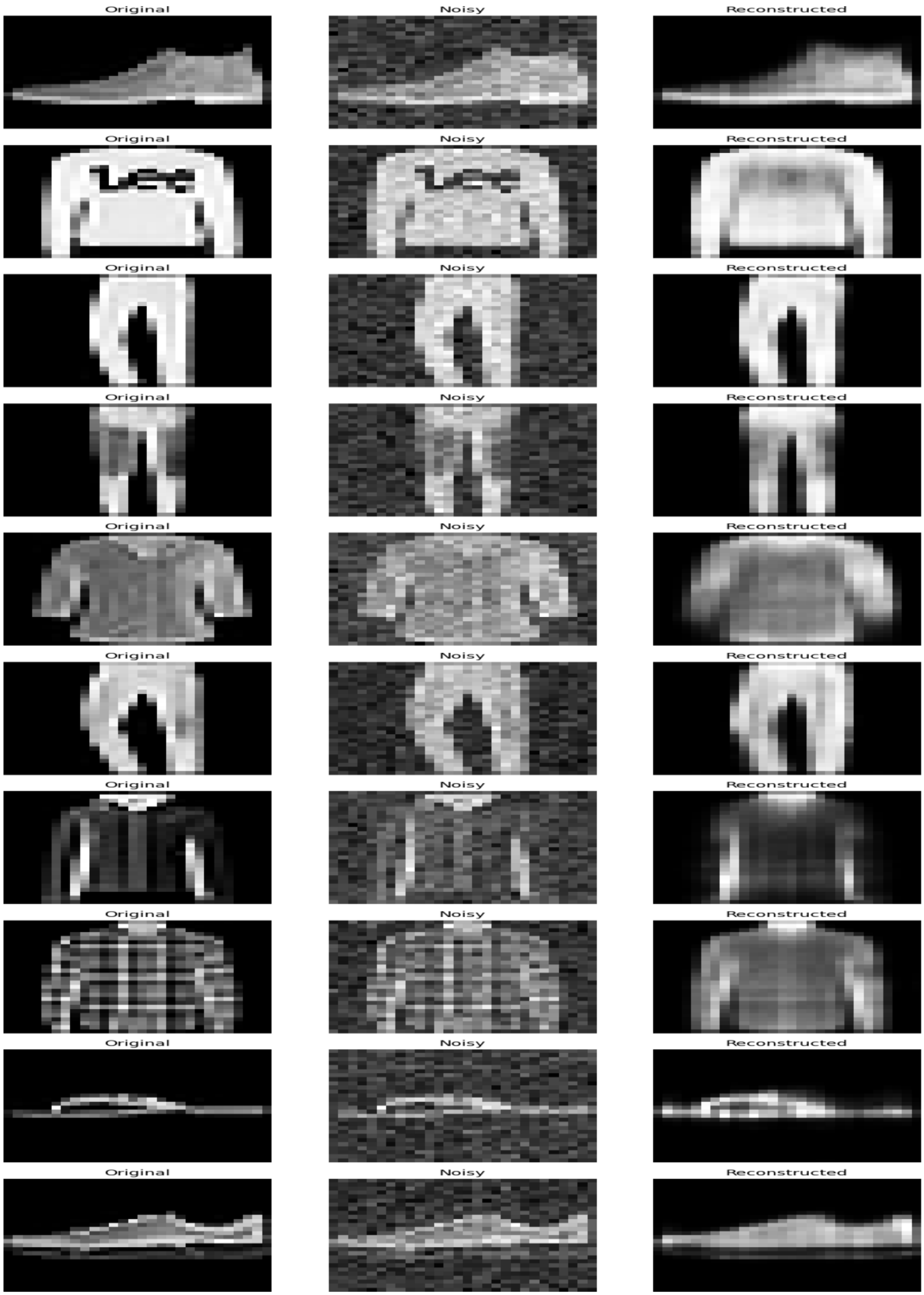
```python
# Visualize the loss and accuracy
plt.figure(figsize=(12, 6))
plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()
```

Output:-

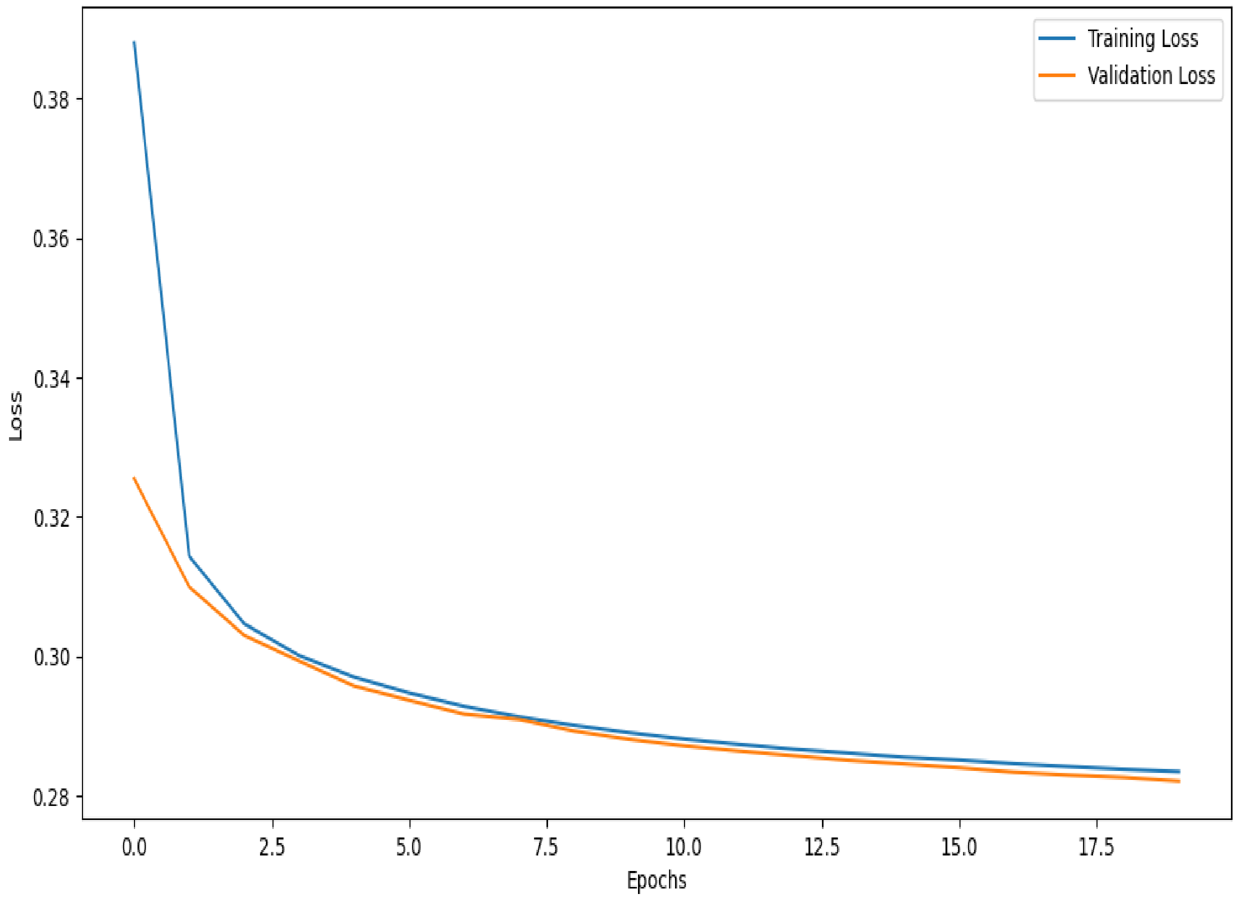
```
Epoch 1/20
235/235 [==============================] - 4s 13ms/step - loss: 0.3880 - val_loss: 0.3254
Epoch 2/20
235/235 [==============================] - 3s 12ms/step - loss: 0.3143 - val_loss: 0.3099
Epoch 3/20
235/235 [==============================] - 5s 20ms/step - loss: 0.3046 - val_loss: 0.3030
Epoch 4/20
235/235 [==============================] - 4s 15ms/step - loss: 0.3001 - val_loss: 0.2993
Epoch 5/20
235/235 [==============================] - 4s 16ms/step - loss: 0.2970 - val_loss: 0.2957
Epoch 6/20
235/235 [==============================] - 3s 12ms/step - loss: 0.2947 - val_loss: 0.2937
Epoch 7/20
235/235 [==============================] - 4s 17ms/step - loss: 0.2928 - val_loss: 0.2917
Epoch 8/20
235/235 [==============================] - 3s 12ms/step - loss: 0.2913 - val_loss: 0.2909
Epoch 9/20
235/235 [==============================] - 3s 12ms/step - loss: 0.2901 - val_loss: 0.2892
Epoch 10/20
235/235 [==============================] - 3s 12ms/step - loss: 0.2890 - val_loss: 0.2880
Epoch 11/20
235/235 [==============================] - 3s 14ms/step - loss: 0.2881 - val_loss: 0.2871
Epoch 12/20
235/235 [==============================] - 3s 13ms/step - loss: 0.2873 - val_loss: 0.2863
Epoch 13/20
235/235 [==============================] - 3s 11ms/step - loss: 0.2866 - val_loss: 0.2857
Epoch 14/20
235/235 [==============================] - 3s 12ms/step - loss: 0.2861 - val_loss: 0.2850
Epoch 15/20
235/235 [==============================] - 3s 12ms/step - loss: 0.2855 - val_loss: 0.2845
```

Epoch 15/20
235/235 [==============================] - 3s 12ms/step - loss: 0.2855 - val_loss: 0.2845

```
Epoch 16/20
235/235 [==============================] - 4s 15ms/step - loss: 0.2851 - val_loss: 0.2840
Epoch 17/20
235/235 [==============================] - 3s 11ms/step - loss: 0.2845 - val_loss: 0.2833
Epoch 18/20
235/235 [==============================] - 3s 12ms/step - loss: 0.2841 - val_loss: 0.2829
Epoch 19/20
235/235 [==============================] - 3s 12ms/step - loss: 0.2837 - val_loss: 0.2826
Epoch 20/20
235/235 [==============================] - 4s 17ms/step - loss: 0.2834 - val_loss: 0.2821
313/313 [==============================] - 1s 2ms/step
```


Original
Noisy
Reconstructed
Original
Noisy
Reconstructed
Original
Noisy
Reconstructed
Original
Noisy
Reconstructed
Original
Noisy
Reconstructed
Original
Noisy
Reconstructed
Original
Noisy
Reconstructed
Original
Noisy
Reconstructed
Original
Noisy
Reconstructed
Original
Noisy
Reconstructed

Graph :-


Training Loss
Validation Loss
0.38
0.36
0.34
0.32
0.30
0.28
Loss
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
Epochs