ICP-5

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Github link: [GitHub - Nagi-131/ICP-5]()

Google drive link: https://docs.google.com/document/d/1Yg9keeUyHtwQWEZVy47O2arb2btPsLAvyM_A2SoA5x8/edit?usp=drive_link

```
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=105,
                batch_size=256,
                shuffle=True,
                validation_data=(x_test, x_test))
```

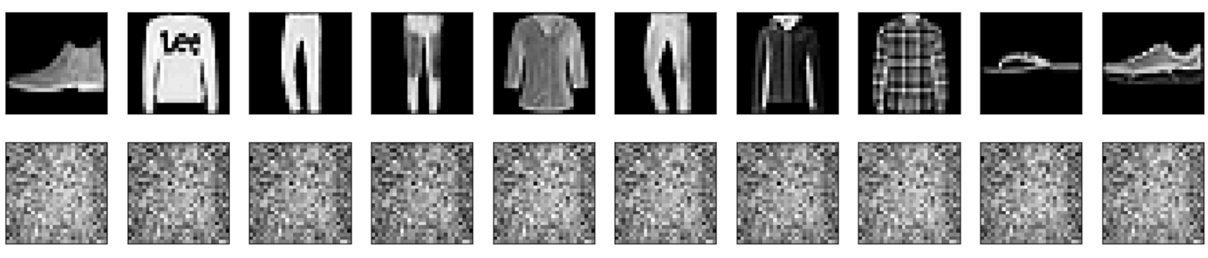
```python
from keras.layers import Input, Dense
from keras.models import Model
from keras.datasets import mnist, fashion_mnist
import numpy as np
import matplotlib.pyplot as plt

# Define the encoder dimension
encoding_dim = 32

# Define the input placeholder
input_img = Input(shape=(784,))

# Define the first hidden layer
hidden_1 = Dense(256, activation='relu')(input_img)

# Define the second hidden layer
encoded = Dense(encoding_dim, activation='relu')(hidden_1)

# Define the first hidden layer of the decoder
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()

# 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:])))

# Train the autoencoder
```

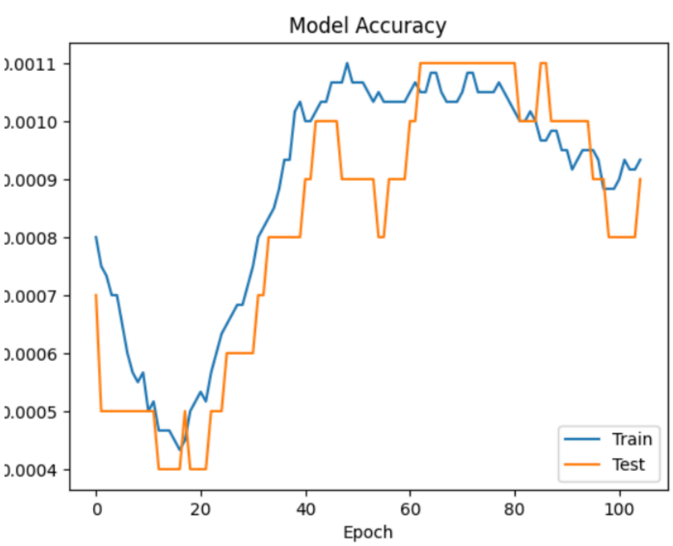
```python
history = autoencoder.fit(x_train, x_train,
                epochs=105,
                batch_size=256,
                shuffle=True,
                validation_data=(x_test, x_test))

# Make predictions on the test data
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()

# Plot the loss and accuracy over time
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')
```

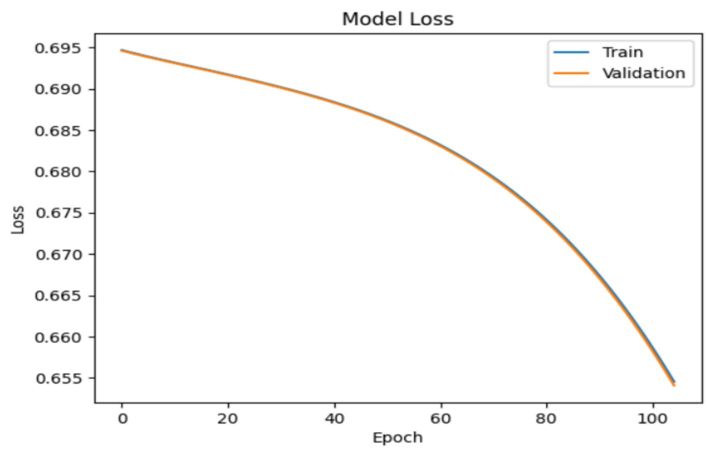
```
plt.show()
```

When we add more layers and increase the epoch the image will be more clear. The autoencoder learns to compress the input images into a lower-dimensional representation and then reconstruct the original images from this representation. The plots of loss and accuracy provide insights into the training process, and the visualizations show how well the autoencoder can reconstruct the original images.

Output:







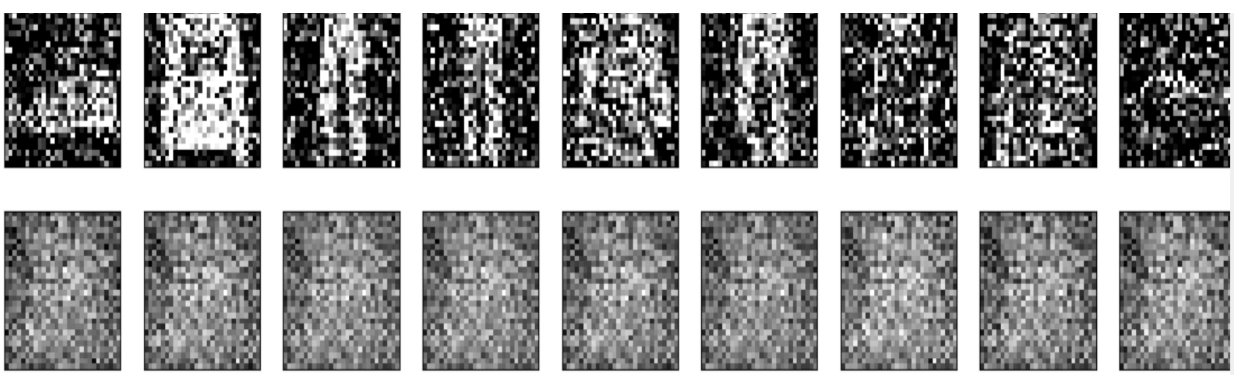
When we add noise autoencoder can reconstruct the original images from noisy inputs, and the plots of loss and accuracy provide in the training process.

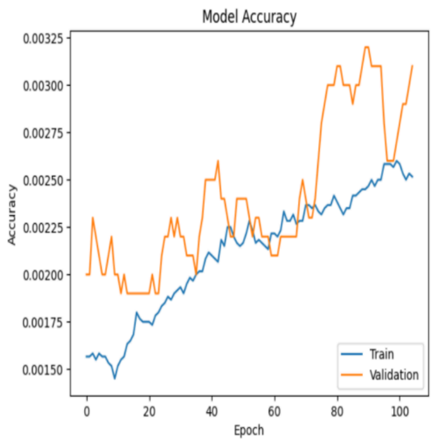
```
from keras.layers import Input, Dense
from keras.models import Model
from keras.datasets import fashion_mnist
import numpy as np
import matplotlib.pyplot as plt

# Define the encoder dimension
encoding_dim = 32

# Define the input placeholder
input_img = Input(shape=(784,))

# Define the encoder layer
encoded = Dense(encoding_dim, activation='relu')(input_img)

# Define the decoder layer
decoded = Dense(784, activation='sigmoid')(encoded)

# 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()
```

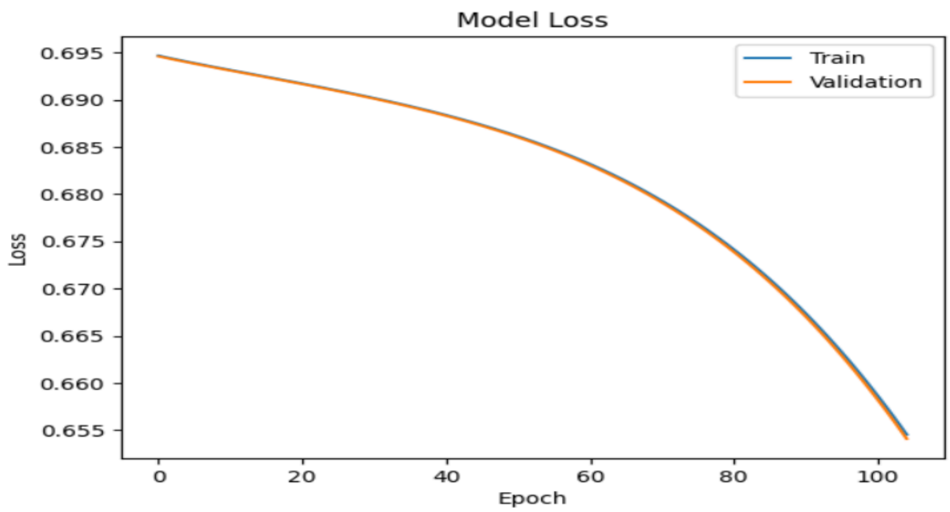
```python
# Normalize the data and flatten the images
x_train = x_train.astype('float32') / 255.
x_test = x_test.astype('float32') / 255.
x_train = x_train.reshape((len(x_train), np.prod(x_train.shape[1:])))
x_test = x_test.reshape((len(x_test), np.prod(x_test.shape[1:])))

# Add noise to the training and test data
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)

# Ensure the noisy data is still within the valid range
x_train_noisy = np.clip(x_train_noisy, 0., 1.)
x_test_noisy = np.clip(x_test_noisy, 0., 1.)

# Train the autoencoder
history = autoencoder.fit(x_train_noisy, x_train,
                epochs=105,
                batch_size=256,
                shuffle=True,
                validation_data=(x_test_noisy, x_test))

# Generate reconstructed images from the noisy test data
decoded_imgs = autoencoder.predict(x_test_noisy)

# Visualize noisy and reconstructed test images
plt.figure(figsize=(20, 4))
n = 10
for i in range(n):
    # Display original + noise
    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()

# Plot the loss over time
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('Model Loss')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(['Train', 'Validation'], loc='upper right')
plt.show()

# Plot the accuracy over time
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('Model Accuracy')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend(['Train', 'Validation'], loc='lower right')
plt.show()
```

Output:




Model Accuracy
0.00325
0.00300
0.00275
0.00250
0.00225
0.00200
0.00175
0.00150
Accuracy
0
20
40
60
80
100
Epoch
Train
Validation


Model Loss
0.695
0.690
0.685
0.680
0.675
0.670
0.665
0.660
0.655
Loss
0
20
40
60
80
100
Epoch
Train
Validation