```
In [1]: import numpy as np
        import tensorflow as tf
        from tensorflow.keras.models import Sequential
        from tensorflow.keras.layers import Dense, Flatten, Conv2D, MaxPooling2D, Si
        from tensorflow.keras.datasets import mnist
        from sklearn.model selection import train test split
        import matplotlib.pyplot as plt
        # Load the MNIST dataset
        (x train, y train), (x test, y test) = mnist.load data()
        # Normalize the data
        x train = x train.astype('float32') / 255.0
        x test = x test.astype('float32') / 255.0
        # Reshape data for CNN (28x28x1) and RNN (28 timesteps, 28 features)
        x train cnn = x train.reshape(-1, 28, 28, 1)
        x_{\text{test\_cnn}} = x_{\text{test.reshape}}(-1, 28, 28, 1)
        x_{train_rnn} = x_{train_reshape(-1, 28, 28)}
        x \text{ test rnn} = x \text{ test.reshape}(-1, 28, 28)
        # Split the data into train and validation sets
        x train cnn, x val cnn, y train cnn, y val cnn = train test split(x train cr
        x_train_rnn, x_val_rnn, y_train_rnn, y_val_rnn = train_test_split(x_train_rr
        # CNN model
        cnn model = Sequential([
            Conv2D(32, kernel size=(3, 3), activation='relu', input shape=(28, 28, 1
            MaxPooling2D(pool size=(2, 2)),
            Flatten(),
            Dense(128, activation='relu'),
            Dense(10, activation='softmax')
        ])
        cnn model.compile(optimizer='adam', loss='sparse categorical crossentropy',
        cnn history = cnn model.fit(x train cnn, y train cnn, validation data=(x val
        # RNN model
        rnn model = Sequential([
            SimpleRNN(128, input shape=(28, 28)),
            Dense(10, activation='softmax')
        ])
        rnn model.compile(optimizer='adam', loss='sparse categorical crossentropy',
        rnn history = rnn model.fit(x train rnn, y train rnn, validation data=(x val
        # Evaluate both models on the test set
        cnn test loss, cnn test acc = cnn model.evaluate(x test cnn, y test)
        rnn test loss, rnn test acc = rnn model.evaluate(x test rnn, y test)
        # Print the results
        print(f"CNN Test Accuracy: {cnn test acc}")
        print(f"RNN Test Accuracy: {rnn test acc}")
```

```
# Plot the training history
plt.figure(figsize=(12, 5))
plt.subplot(1, 2, 1)
plt.plot(cnn history.history['accuracy'], label='CNN Training Accuracy')
plt.plot(cnn history.history['val accuracy'], label='CNN Validation Accuracy
plt.title('CNN Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.subplot(1, 2, 2)
plt.plot(rnn history.history['accuracy'], label='RNN Training Accuracy')
plt.plot(rnn history.history['val accuracy'], label='RNN Validation Accuracy
plt.title('RNN Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.show()
```

Epoch 1/5

```
D:\anaconda\Lib\site-packages\keras\src\layers\convolutional\base conv.py:10
7: UserWarning: Do not pass an `input shape`/`input dim` argument to a laye
r. When using Sequential models, prefer using an `Input(shape)` object as th
e first layer in the model instead.
  super(). init (activity regularizer=activity regularizer, **kwargs)
                 9s 20ms/step - accuracy: 0.8701 - loss: 0.4752
375/375 -
- val accuracy: 0.9668 - val loss: 0.1112
Epoch 2/5
                        8s 22ms/step - accuracy: 0.9741 - loss: 0.0882
375/375 -
- val accuracy: 0.9778 - val loss: 0.0761
Epoch 3/5
                        7s 20ms/step - accuracy: 0.9833 - loss: 0.0550
375/375 -
- val_accuracy: 0.9806 - val_loss: 0.0629
Epoch 4/5
375/375 —
                        8s 22ms/step - accuracy: 0.9884 - loss: 0.0392
- val accuracy: 0.9852 - val loss: 0.0520
Epoch 5/5
                        7s 20ms/step - accuracy: 0.9914 - loss: 0.0291
375/375 -
- val accuracy: 0.9813 - val loss: 0.0618
Epoch 1/5
D:\anaconda\Lib\site-packages\keras\src\layers\rnn\rnn.py:204: UserWarning:
Do not pass an `input shape`/`input dim` argument to a layer. When using Seq
uential models, prefer using an `Input(shape)` object as the first layer in
the model instead.
  super(). init (**kwargs)
```

```
— 6s 11ms/step - accuracy: 0.7466 - loss: 0.8400
        - val accuracy: 0.9205 - val loss: 0.2797
       Epoch 2/5
       375/375 -
                                     — 4s 11ms/step - accuracy: 0.9309 - loss: 0.2440
        - val accuracy: 0.9312 - val loss: 0.2345
       Epoch 3/5
       375/375 -
                                     — 6s 15ms/step - accuracy: 0.9447 - loss: 0.1893
        - val accuracy: 0.9586 - val loss: 0.1546
       Epoch 4/5
                                     — 4s 11ms/step - accuracy: 0.9586 - loss: 0.1429
       375/375 -
        - val accuracy: 0.9528 - val loss: 0.1602
       375/375 -
                                     4s 10ms/step - accuracy: 0.9613 - loss: 0.1345
        - val accuracy: 0.9627 - val loss: 0.1336
                                      - 1s 2ms/step - accuracy: 0.9776 - loss: 0.0666
       313/313 -
                                      - 1s 3ms/step - accuracy: 0.9559 - loss: 0.1555
       CNN Test Accuracy: 0.9817000031471252
       RNN Test Accuracy: 0.9595999717712402
                         CNN Accuracy
                                                                     RNN Accuracy
         0.99
                                                    0.96
         0.98
                                                    0.94
         0.97
                                                    0.92
                                                  Accuracy
06:0
         0.96
         0.95
                                                    0.88
         0.94
                                                    0.86
                                 CNN Training Accuracy
                                                                            RNN Training Accuracy
         0.93
                                 CNN Validation Accuracy
                                                                            RNN Validation Accuracy
             0.0
                 0.5
                     1.0
                         1.5
                             2.0
                                  2.5
                                     3.0
                                          3.5
                                                             0.5
                                                                 1.0
                                                                     1.5
                                                                         2.0
                                                                             2.5
                                                                                 3.0
                                                                                     3.5
                                                                        Epochs
In [2]: import numpy as np
         import tensorflow as tf
         from tensorflow.keras.models import Sequential
         from tensorflow.keras.layers import Dense, Flatten, Conv2D, MaxPooling2D, Ur
         from tensorflow.keras.datasets import mnist
         import matplotlib.pyplot as plt
         # Load the MNIST dataset
         (x train, ), (x test, ) = mnist.load data()
         # Normalize the data
         x train = x train.astype('float32') / 255.0
         x test = x test.astype('float32') / 255.0
         # Reshape data for CNN (28x28x1) and RNN (28 timesteps, 28 features)
         x train cnn = x train.reshape(-1, 28, 28, 1)
         x \text{ test cnn} = x \text{ test.reshape}(-1, 28, 28, 1)
         x train rnn = x train.reshape(-1, 28, 28)
         x \text{ test rnn} = x \text{ test.reshape}(-1, 28, 28)
```

```
# CNN autoencoder model
            cnn autoencoder = Sequential([
                # Encoder
                Conv2D(32, kernel size=(3, 3), activation='relu', padding='same', input
                MaxPooling2D(pool size=(2, 2), padding='same'),
                # Decoder
                Conv2D(32, kernel size=(3, 3), activation='relu', padding='same'),
                UpSampling2D(size=(2, 2)),
                Conv2D(1, kernel size=(3, 3), activation='sigmoid', padding='same')
            ])
            cnn autoencoder.compile(optimizer='adam', loss='binary crossentropy')
            cnn autoencoder.fit(x train cnn, x train cnn, epochs=5, batch size=128, vali
            # RNN autoencoder model
            rnn autoencoder = Sequential([
                # Encoder
                SimpleRNN(128, activation='relu', input shape=(28, 28), return sequences
                RepeatVector(28),
                # Decoder
                SimpleRNN(128, activation='relu', return sequences=True),
                TimeDistributed(Dense(28, activation='sigmoid'))
            ])
            rnn autoencoder.compile(optimizer='adam', loss='binary crossentropy')
            rnn autoencoder.fit(x train rnn, x train rnn, epochs=5, batch size=128, vali
            # Reconstruct images using both models
            cnn reconstructed = cnn autoencoder.predict(x test cnn)
            rnn reconstructed = rnn autoencoder.predict(x test rnn)
            # Plot original and reconstructed images
            n = 10 # number of images to display
            plt.figure(figsize=(20, 4))
            for i in range(n):
                # Display original
                ax = plt.subplot(2, n, i + 1)
                plt.imshow(x test[i], cmap='gray')
                plt.title("Original")
                plt.axis('off')
                # Display CNN reconstructed
                ax = plt.subplot(2, n, i + 1 + n)
                plt.imshow(cnn reconstructed[i].reshape(28, 28), cmap='gray')
                plt.title("CNN Reconstructed")
                plt.axis('off')
            plt.figure(figsize=(20, 4))
            for i in range(n):
                # Display original
                ax = plt.subplot(2, n, i + 1)
                plt.imshow(x test[i], cmap='gray')
                plt.title("Original")
                plt.axis('off')
Loading [MathJax]/extensions/Safe.js play RNN reconstructed
```

```
ax = plt.subplot(2, n, i + 1 + n)
            plt.imshow(rnn reconstructed[i].reshape(28, 28), cmap='gray')
            plt.title("RNN Reconstructed")
            plt.axis('off')
        plt.show()
       Epoch 1/5
       375/375 -
                                    - 14s 33ms/step - loss: 0.2324 - val loss: 0.0673
       Epoch 2/5
                                     13s 35ms/step - loss: 0.0661 - val loss: 0.0650
       375/375 -
       Epoch 3/5
                                    14s 38ms/step - loss: 0.0645 - val loss: 0.0641
       375/375 -
       Epoch 4/5
       375/375 -
                                   - 17s 46ms/step - loss: 0.0634 - val loss: 0.0635
       Epoch 5/5
       375/375 -
                                    - 15s 40ms/step - loss: 0.0628 - val loss: 0.0631
       Epoch 1/5
                                    23s 42ms/step - loss: 0.3235 - val loss: 0.2001
       375/375 -
       Epoch 2/5
       375/375 -
                                     15s 41ms/step - loss: 0.1892 - val loss: 0.1670
       Epoch 3/5
                                    - 14s 38ms/step - loss: 0.1625 - val loss: 0.1518
       375/375 -
       Epoch 4/5
                                     15s 39ms/step - loss: 0.1476 - val loss: 0.1418
       375/375 -
       Epoch 5/5
       375/375
                                     14s 37ms/step - loss: 0.1398 - val loss: 0.1341
       313/313
                                     2s 5ms/step
       313/313 •
                                     3s 8ms/step
         Original
                 Original
                         Original
In [3]: import numpy as np
        import tensorflow as tf
        from tensorflow.keras.models import Sequential
        from tensorflow.keras.layers import Dense, Flatten, Conv2D, MaxPooling2D, Up
        from tensorflow.keras.datasets import mnist
        import matplotlib.pyplot as plt
        # Load the MNIST dataset
        (x train, ), (x test, ) = mnist.load data()
```

```
x train = x train.astype('float32') / 255.0
            x test = x test.astype('float32') / 255.0
            # Reshape data for CNN (28x28x1), RNN and LSTM (28 timesteps, 28 features)
            x train cnn = x train.reshape(-1, 28, 28, 1)
            x \text{ test cnn} = x \text{ test.reshape}(-1, 28, 28, 1)
            x train rnn = x train.reshape(-1, 28, 28)
            x \text{ test rnn} = x \text{ test.reshape}(-1, 28, 28)
            # CNN autoencoder model
            cnn autoencoder = Sequential([
                # Encoder
                Conv2D(32, kernel size=(3, 3), activation='relu', padding='same', input
                MaxPooling2D(pool size=(2, 2), padding='same'),
                # Decoder
                Conv2D(32, kernel size=(3, 3), activation='relu', padding='same'),
                UpSampling2D(size=(2, 2)),
                Conv2D(1, kernel size=(3, 3), activation='sigmoid', padding='same')
            ])
            cnn autoencoder.compile(optimizer='adam', loss='binary crossentropy')
            cnn autoencoder.fit(x train cnn, x train cnn, epochs=5, batch size=128, vali
            # RNN autoencoder model
            rnn autoencoder = Sequential([
                # Encoder
                SimpleRNN(128, activation='relu', input shape=(28, 28), return sequences
                RepeatVector(28),
                # Decoder
                SimpleRNN(128, activation='relu', return_sequences=True),
                TimeDistributed(Dense(28, activation='sigmoid'))
            ])
            rnn autoencoder.compile(optimizer='adam', loss='binary crossentropy')
            rnn_autoencoder.fit(x_train_rnn, x_train_rnn, epochs=5, batch size=128, vali
            # LSTM autoencoder model
            lstm autoencoder = Sequential([
                # Encoder
                LSTM(128, activation='relu', input shape=(28, 28), return sequences=Fals
                RepeatVector(28),
                # Decoder
                LSTM(128, activation='relu', return sequences=True),
                TimeDistributed(Dense(28, activation='sigmoid'))
            ])
            lstm autoencoder.compile(optimizer='adam', loss='binary crossentropy')
            lstm autoencoder.fit(x train rnn, x train rnn, epochs=5, batch size=128, val
            # Reconstruct images using all models
            cnn reconstructed = cnn autoencoder.predict(x test cnn)
            rnn reconstructed = rnn autoencoder.predict(x test rnn)
            lstm reconstructed = lstm autoencoder.predict(x test rnn)
            # Plot original and reconstructed images
Loading [MathJax]/extensions/Safe.js number of images to display
```

```
plt.figure(figsize=(20, 6))
for i in range(n):
   # Display original
   ax = plt.subplot(3, n, i + 1)
   plt.imshow(x test[i], cmap='gray')
   plt.title("Original")
   plt.axis('off')
   # Display CNN reconstructed
   ax = plt.subplot(3, n, i + 1 + n)
   plt.imshow(cnn reconstructed[i].reshape(28, 28), cmap='gray')
   plt.title("CNN Reconstructed")
   plt.axis('off')
   # Display RNN reconstructed
   ax = plt.subplot(3, n, i + 1 + 2 * n)
   plt.imshow(rnn reconstructed[i].reshape(28, 28), cmap='gray')
   plt.title("RNN Reconstructed")
   plt.axis('off')
plt.figure(figsize=(20, 4))
for i in range(n):
   # Display original
   ax = plt.subplot(2, n, i + 1)
   plt.imshow(x test[i], cmap='gray')
   plt.title("Original")
   plt.axis('off')
   # Display LSTM reconstructed
   ax = plt.subplot(2, n, i + 1 + n)
   plt.imshow(lstm reconstructed[i].reshape(28, 28), cmap='gray')
   plt.title("LSTM Reconstructed")
   plt.axis('off')
plt.show()
```

Epoch 1/5	- 14c 25mc/cton 10cc. 0 2272 vol 10cc. 0 0070
Epoch 2/5	- 14s 35ms/step - loss: 0.2273 - val_loss: 0.0670
	- 13s 35ms/step - loss: 0.0659 - val_loss: 0.0650
Epoch 3/5	
•	- 15s 40ms/step - loss: 0.0643 - val_loss: 0.0642
Epoch 4/5	
	- 14s 38ms/step - loss: 0.0635 - val_loss: 0.0636
Epoch 5/5	
	- 15s 39ms/step - loss: 0.0630 - val_loss: 0.0632
Epoch 1/5	- 23s 45ms/step - loss: 0.3144 - val_loss: 0.2045
Epoch 2/5	233 +31113/31cp 1033. 0.3144 Vai_1033. 0.2043
	- 19s 50ms/step - loss: 0.1922 - val loss: 0.1662
Epoch 3/5	_
	- 14s 37ms/step - loss: 0.1615 - val_loss: 0.1492
Epoch 4/5	
	- 14s 37ms/step - loss: 0.1471 - val_loss: 0.1394
Epoch 5/5	- 13s 36ms/step - loss: 0.1380 - val_loss: 0.1328
Epoch 1/5	- 133 Johns/Step - 1055. 0.1300 - Vat_1055. 0.1320
	- 46s 103ms/step - loss: 0.3271 - val loss: 0.186
3	· '
Epoch 2/5	
	- 37s 98ms/step - loss: 0.1758 - val_loss: 0.1434
Epoch 3/5	- 41s 110ms/step - loss: 0.1367 - val_loss: 0.122
4	- 415 110ms/step - toss: 0.1307 - Vat_toss: 0.122
Epoch 4/5	
	- 2060s 6s/step - loss: 0.1205 - val_loss: 0.1128
Epoch 5/5	
	- 41s 108ms/step - loss: 0.1104 - val_loss: 0.105
2	
313/313 ————————————————————————————————	•
313/313	- 6s 16ms/step
Original Original Original Original	•
~ 2 / /	11 1 4 4 6 6
/ 4 / 6	7 4 7 7 4 5 7
CNN ReconstructedCNN ReconstructedCNN ReconstructedCNN Recons	structed:NN Reconstructed:NN Reconstructed:NN Reconstructed:NN Reconstructed:NN Reconstructed:NN Reconstructed
- 2 / A	11 1 11 1 1 1 1 1 1 1 1 1
/ / / 0) 4 / 9 4 5 9
RNN ReconstructedRNN ReconstructedRNN ReconstructedRNN Recons	structedRNN ReconstructedRNN ReconstructedRNN ReconstructedRNN ReconstructedRNN ReconstructedRNN Reconstructed
- 2 / 4	1 1 11 11 11 11 11
7 4 6	9 4 4 4
, – ,	
Original Original Original Origin	nal Original Original Original Original Original
7 7 /	11/40000
/ - / -	7 7 / / ~ ~ ~ 7
LSTM ReconstructebSTM ReconstructebSTM ReconstructebSTM Recon	structebSTM ReconstructebSTM ReconstructebSTM ReconstructebSTM ReconstructebSTM ReconstructebSTM Reconstructed
7 2 /	1110000
/ - / -	7 7 7 7 7 7
,	

```
In [4]: import numpy as np
        import tensorflow as tf
        from tensorflow.keras.models import Sequential
        from tensorflow.keras.layers import Dense, Flatten, Conv2D, MaxPooling2D, Ur
        from tensorflow.keras.datasets import mnist
        import matplotlib.pyplot as plt
        # Load and preprocess the MNIST dataset
        (x train, ), (x test, ) = mnist.load data()
        x train = x train.astype('float32') / 255.0
        x test = x test.astype('float32') / 255.0
        x train cnn = x train.reshape(-1, 28, 28, 1)
        x \text{ test cnn} = x \text{ test.reshape}(-1, 28, 28, 1)
        x train rnn = x train.reshape(-1, 28, 28)
        x \text{ test rnn} = x \text{ test.reshape}(-1, 28, 28)
        # Define CNN autoencoder model
        cnn autoencoder = Sequential([
            # Encoder
            Conv2D(32, kernel size=(3, 3), activation='relu', padding='same', input
            MaxPooling2D(pool size=(2, 2), padding='same'),
            # Decoder
            Conv2D(32, kernel size=(3, 3), activation='relu', padding='same'),
            UpSampling2D(size=(2, 2)),
            Conv2D(1, kernel size=(3, 3), activation='sigmoid', padding='same')
        ])
        # Define RNN autoencoder model
        rnn autoencoder = Sequential([
            SimpleRNN(128, activation='relu', input shape=(28, 28), return sequences
            RepeatVector(28),
            # Decoder
            SimpleRNN(128, activation='relu', return sequences=True),
            TimeDistributed(Dense(28, activation='sigmoid'))
        ])
        # Define LSTM autoencoder model
        lstm autoencoder = Sequential([
            # Encoder
            LSTM(128, activation='relu', input shape=(28, 28), return sequences=Fals
            RepeatVector(28),
            # Decoder
            LSTM(128, activation='relu', return sequences=True),
            TimeDistributed(Dense(28, activation='sigmoid'))
        ])
        # Compile models (no need to fit to display summaries)
        cnn autoencoder.compile(optimizer='adam', loss='binary crossentropy')
        rnn autoencoder.compile(optimizer='adam', loss='binary crossentropy')
        lstm autoencoder.compile(optimizer='adam', loss='binary crossentropy')
        # Print summaries of the models
        print("CNN Autoencoder Summary:")
        cnn autoencoder.summary()
```

```
print("\nRNN Autoencoder Summary:")
rnn_autoencoder.summary()

print("\nLSTM Autoencoder Summary:")
lstm_autoencoder.summary()
```

CNN Autoencoder Summary:
Model: "sequential 7"

Layer (type)	Output Shape	Par
conv2d_7 (Conv2D)	(None, 28, 28, 32)	
max_pooling2d_3 (MaxPooling2D)	(None, 14, 14, 32)	
conv2d_8 (Conv2D)	(None, 14, 14, 32)	9
up_sampling2d_2 (UpSampling2D)	(None, 28, 28, 32)	
conv2d_9 (Conv2D)	(None, 28, 28, 1)	

Total params: 9,857 (38.50 KB)

Trainable params: 9,857 (38.50 KB)

Non-trainable params: 0 (0.00 B)

RNN Autoencoder Summary:
Model: "sequential_8"

Layer (type)	Output Shape	Par
simple_rnn_5 (SimpleRNN)	(None, 128)	20
repeat_vector_3 (RepeatVector)	(None, 28, 128)	
simple_rnn_6 (SimpleRNN)	(None, 28, 128)	32
time_distributed_3 (TimeDistributed)	(None, 28, 28)	3

Total params: 56,604 (221.11 KB)

Trainable params: 56,604 (221.11 KB)

Non-trainable params: 0 (0.00 B)

LSTM Autoencoder Summary: Model: "sequential_9"

Layer (type)	Output Shape	Par
lstm_2 (LSTM)	(None, 128)	80
repeat_vector_4 (RepeatVector)	(None, 28, 128)	
lstm_3 (LSTM)	(None, 28, 128)	131
time_distributed_4 (TimeDistributed)	(None, 28, 28)	3

Total params: 215,580 (842.11 KB) **Trainable params:** 215,580 (842.11 KB)

Non-trainable params: 0 (0.00 B)

In []: