```
In [1]: 

#Import necessary libraries
import tensorflow as tf
from tensorflow.keras import layers, models
import matplotlib.pyplot as plt
from tensorflow.keras.datasets import mnist
```

```
In [2]: #Load the MNIST dataset
   (x_train, y_train), (x_test, y_test) = mnist.load_data()
   print("Training data shape:", x_train.shape)
   print("Test data shape:", x_test.shape)
```

Training data shape: (60000, 28, 28) Test data shape: (10000, 28, 28)

```
In [3]:  #Normalize the pixel values between 0 and 1
x_train = x_train.astype('float32') / 255.0
x_test = x_test.astype('float32') / 255.0
```

```
In [4]:
         Out[4]: array([[[0., 0., 0., ..., 0., 0., 0.],
                     [0., 0., 0., \ldots, 0., 0., 0.]
                     [0., 0., 0., \ldots, 0., 0., 0.]
                     [0., 0., 0., \ldots, 0., 0., 0.]
                     [0., 0., 0., ..., 0., 0., 0.]
                     [0., 0., 0., ..., 0., 0., 0.]
                    [[0., 0., 0., ..., 0., 0., 0.],
                    [0., 0., 0., ..., 0., 0., 0.]
                     [0., 0., 0., \ldots, 0., 0., 0.]
                     . . . ,
                     [0., 0., 0., ..., 0., 0., 0.]
                     [0., 0., 0., ..., 0., 0., 0.]
                     [0., 0., 0., \ldots, 0., 0., 0.]
                    [[0., 0., 0., ..., 0., 0., 0.],
                    [0., 0., 0., \ldots, 0., 0., 0.]
                    [0., 0., 0., ..., 0., 0., 0.]
                     [0., 0., 0., \ldots, 0., 0., 0.]
                     [0., 0., 0., \ldots, 0., 0., 0.]
                     [0., 0., 0., \ldots, 0., 0., 0.]
                    . . . ,
                    [[0., 0., 0., ..., 0., 0., 0.],
                    [0., 0., 0., \ldots, 0., 0., 0.]
                    [0., 0., 0., \ldots, 0., 0., 0.]
                     . . . ,
                     [0., 0., 0., \ldots, 0., 0., 0.]
                     [0., 0., 0., ..., 0., 0., 0.]
                     [0., 0., 0., \ldots, 0., 0., 0.]
                    [[0., 0., 0., ..., 0., 0., 0.],
                    [0., 0., 0., \ldots, 0., 0., 0.]
                     [0., 0., 0., \ldots, 0., 0., 0.]
                     [0., 0., 0., ..., 0., 0., 0.]
                     [0., 0., 0., \ldots, 0., 0., 0.]
                     [0., 0., 0., \ldots, 0., 0., 0.]
                    [[0., 0., 0., ..., 0., 0., 0.],
                    [0., 0., 0., ..., 0., 0., 0.],
                    [0., 0., 0., ..., 0., 0., 0.]
                     [0., 0., 0., ..., 0., 0., 0.]
                     [0., 0., 0., \ldots, 0., 0., 0.]
```

[0., 0., 0., ..., 0., 0., 0.]]], dtype=float32)

```
In [5]:
         N x_test
   Out[5]: array([[[0., 0., 0., ..., 0., 0., 0.],
                     [0., 0., 0., \ldots, 0., 0., 0.]
                     [0., 0., 0., ..., 0., 0., 0.]
                     [0., 0., 0., \ldots, 0., 0., 0.]
                     [0., 0., 0., ..., 0., 0., 0.]
                     [0., 0., 0., ..., 0., 0., 0.]
                    [[0., 0., 0., ..., 0., 0., 0.],
                     [0., 0., 0., ..., 0., 0., 0.]
                     [0., 0., 0., \ldots, 0., 0., 0.]
                     . . . ,
                     [0., 0., 0., ..., 0., 0., 0.]
                     [0., 0., 0., ..., 0., 0., 0.]
                     [0., 0., 0., \ldots, 0., 0., 0.]
                    [[0., 0., 0., ..., 0., 0., 0.],
                     [0., 0., 0., \ldots, 0., 0., 0.]
                     [0., 0., 0., ..., 0., 0., 0.]
                     [0., 0., 0., \ldots, 0., 0., 0.]
                     [0., 0., 0., \ldots, 0., 0., 0.]
                     [0., 0., 0., \ldots, 0., 0., 0.]
                    . . . ,
                    [[0., 0., 0., ..., 0., 0., 0.],
                    [0., 0., 0., \ldots, 0., 0., 0.]
                     [0., 0., 0., \ldots, 0., 0., 0.]
                     . . . ,
                     [0., 0., 0., \ldots, 0., 0., 0.]
                     [0., 0., 0., ..., 0., 0., 0.]
                     [0., 0., 0., \ldots, 0., 0., 0.]
                    [[0., 0., 0., ..., 0., 0., 0.],
                     [0., 0., 0., \ldots, 0., 0., 0.]
                     [0., 0., 0., ..., 0., 0., 0.]
                     [0., 0., 0., ..., 0., 0., 0.]
                     [0., 0., 0., \ldots, 0., 0., 0.]
                     [0., 0., 0., \ldots, 0., 0., 0.]
                    [[0., 0., 0., ..., 0., 0., 0.],
                     [0., 0., 0., ..., 0., 0., 0.],
                     [0., 0., 0., ..., 0., 0., 0.]
                     [0., 0., 0., ..., 0., 0., 0.]
```

 $[0., 0., 0., \ldots, 0., 0., 0.]$

[0., 0., 0., ..., 0., 0., 0.]]], dtype=float32)

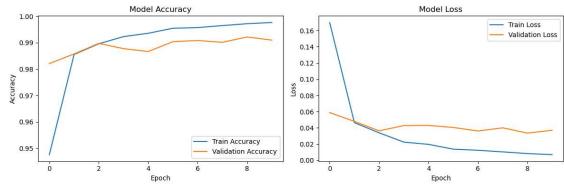
```
▶ #Reshape data to fit the model (28x28x1)
In [6]:
              x_train = x_train.reshape((x_train.shape[0], 28, 28, 1))
             x_{\text{test}} = x_{\text{test.reshape}}((x_{\text{test.shape}}[0], 28, 28, 1))
          N x_train
In [7]:
                        [0.]]],
                      [[[0.],
                        [0.],
                        [0.],
                        . . . ,
                        [0.],
                        [0.],
                        [0.]],
                       [[0.],
                        [0.],
                        [0.],
                        . . . ,
                        [0.],
                        [0.],
                        [0.]],
                       [[0.],
In [8]:
          ⋈ x_test
                       [[0.],
                        [0.],
                        [0.],
                        . . . ,
                        [0.],
                        [0.],
                        [0.]]],
                      [[[0.],
                        [0.],
                        [0.],
                        . . . ,
                        [0.],
                        [0.],
                        [0.]],
                       [[0.],
                        [0.],
```

```
In [9]:
         y train = tf.keras.utils.to_categorical(y_train, 10)
            y_test = tf.keras.utils.to_categorical(y_test, 10)
In [10]:
          N y_train
   Out[10]: array([[0., 0., 0., ..., 0., 0., 0.],
                   [1., 0., 0., ..., 0., 0., 0.]
                   [0., 0., 0., ..., 0., 0., 0.]
                   [0., 0., 0., ..., 0., 0., 0.]
                   [0., 0., 0., ..., 0., 0., 0.]
                   [0., 0., 0., ..., 0., 1., 0.]
          y test
In [11]:
   Out[11]: array([[0., 0., 0., ..., 1., 0., 0.],
                   [0., 0., 1., \ldots, 0., 0., 0.]
                   [0., 1., 0., \ldots, 0., 0., 0.]
                   [0., 0., 0., \ldots, 0., 0., 0.]
                   [0., 0., 0., ..., 0., 0., 0.]
                   [0., 0., 0., \ldots, 0., 0., 0.]
In [13]:
          ▶ #Build a CNN model using Input layer
            #Include MaxPooling layers
            model = models.Sequential()
            model.add(layers.Input(shape=(28, 28, 1))) # Specify the input shape here
            model.add(layers.Conv2D(32, (3, 3), activation='relu'))
            model.add(layers.Conv2D(64, (3, 3), activation='relu'))
            model.add(layers.MaxPooling2D((2, 2)))
            model.add(layers.Conv2D(64, (3, 3), activation='relu'))
            model.add(layers.MaxPooling2D((2, 2)))
In [14]:
         #Add Dense Layers and output Layer
            model.add(layers.Flatten())
            model.add(layers.Dense(64, activation='relu'))
            model.add(layers.Dense(10, activation='softmax'))
        #Compile the model
In [15]:
            #Use the 'adam' optimizer.
            #Set the loss function to 'categorical crossentropy'.
            #Track accuracy as the metric
            model.compile(optimizer='adam',
                          loss='categorical_crossentropy',
                          metrics=['accuracy'])
```

```
In [16]:
         #Train the model
            history = model.fit(x_train, y_train, epochs=10, batch_size=64, validation
            Epoch 1/10
            750/750 ---
                             168s 193ms/step - accuracy: 0.8734 - loss:
            0.4090 - val_accuracy: 0.9821 - val_loss: 0.0588
            Epoch 2/10
                             164s 142ms/step - accuracy: 0.9836 - loss:
            750/750 —
            0.0523 - val accuracy: 0.9858 - val loss: 0.0480
            Epoch 3/10
                         144s 145ms/step - accuracy: 0.9903 - loss:
            750/750 ----
            0.0328 - val_accuracy: 0.9898 - val_loss: 0.0363
            Epoch 4/10
            750/750 ---
                             127s 124ms/step - accuracy: 0.9922 - loss:
            0.0224 - val_accuracy: 0.9877 - val_loss: 0.0428
            Epoch 5/10
            750/750 -
                                 103s 137ms/step - accuracy: 0.9942 - loss:
            0.0177 - val accuracy: 0.9867 - val loss: 0.0430
            Epoch 6/10
                                102s 137ms/step - accuracy: 0.9957 - loss:
            750/750 -
            0.0131 - val accuracy: 0.9904 - val loss: 0.0405
            Epoch 7/10
            750/750 -
                          99s 132ms/step - accuracy: 0.9957 - loss:
            0.0128 - val_accuracy: 0.9908 - val_loss: 0.0361
            Epoch 8/10
                           145s 136ms/step - accuracy: 0.9975 - loss:
            750/750 ---
            0.0084 - val_accuracy: 0.9902 - val_loss: 0.0400
            Epoch 9/10
                                154s 152ms/step - accuracy: 0.9972 - loss:
            750/750 ——
            0.0075 - val_accuracy: 0.9922 - val_loss: 0.0335
            Epoch 10/10
            750/750 -
                                 62s 83ms/step - accuracy: 0.9980 - loss: 0.
            0058 - val_accuracy: 0.9910 - val_loss: 0.0371
test_loss, test_acc = model.evaluate(x_test, y_test)
            print("Test accuracy:", test_acc)
            313/313 -
                                     - 3s 10ms/step - accuracy: 0.9888 - loss: 0.0
            424
```

Test accuracy: 0.9908999800682068

```
In [19]:
            plt.figure(figsize=(12, 4))
            # Plot training & validation accuracy values
            plt.subplot(1, 2, 1)
            plt.plot(history.history['accuracy'], label='Train Accuracy')
            plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
            plt.title('Model Accuracy')
            plt.xlabel('Epoch')
            plt.ylabel('Accuracy')
            plt.legend()
            # Plot training & validation loss values
            plt.subplot(1, 2, 2)
            plt.plot(history.history['loss'], label='Train Loss')
            plt.plot(history.history['val_loss'], label='Validation Loss')
            plt.title('Model Loss')
            plt.xlabel('Epoch')
            plt.ylabel('Loss')
            plt.legend()
            plt.tight_layout()
            plt.show()
```



In []: ▶