```
In [4]: #importing necessary libraries
        import numpy as np
        import matplotlib.pyplot as plt
        import tensorflow as tf
        from tensorflow.keras.datasets import mnist
        from tensorflow.keras.models import Sequential
        from tensorflow.keras.layers import Dense,Input
        from tensorflow.keras.optimizers import SGD
        from tensorflow.keras.utils import to categorical
        from tensorflow.keras.utils import plot_model
In [5]: # Load MNIST data
        (x_train, y_train), (x_test, y_test) = mnist.load_data()
        x_{train} = x_{train.reshape((x_{train.shape[0], 28 * 28)).astype('float32') / 255)}
        x_{test} = x_{test.reshape((x_{test.shape[0], 28 * 28)).astype('float32') / 255)}
        # One-hot encode labels
        y_train = to_categorical(y_train, 10)
        y_test = to_categorical(y_test, 10)
In [6]: # Define the network architecture
        model = Sequential([
            Input(shape=(28 * 28,)), # Define the input shape here
             Dense(512, activation='relu'),
            Dense(256, activation='relu'),
            Dense(10, activation='softmax')
        ])
In [7]: # Compile the model
        model.compile(optimizer=SGD(),
                       loss='categorical_crossentropy',
                      metrics=['accuracy'])
        # Train the model
        history = model.fit(x_train, y_train,
                             epochs=20,
                             batch_size=32,
                             validation_split=0.2)
        Epoch 1/20
        1500/1500
                                       · 4s 2ms/step - accuracy: 0.7351 - loss: 1.0444 - val_accuracy: 0.9071 - val_loss: 0.3205
        Epoch 2/20
        1500/1500
                                      - 4s 2ms/step - accuracy: 0.9116 - loss: 0.3111 - val_accuracy: 0.9312 - val_loss: 0.2441
        Epoch 3/20
        1500/1500
                                      - 4s 2ms/step - accuracy: 0.9353 - loss: 0.2365 - val_accuracy: 0.9403 - val_loss: 0.2134
        Epoch 4/20
        1500/1500
                                       6s 3ms/step - accuracy: 0.9411 - loss: 0.2068 - val_accuracy: 0.9463 - val_loss: 0.1875
        Epoch 5/20
        1500/1500
                                       · 4s 3ms/step - accuracy: 0.9488 - loss: 0.1812 - val_accuracy: 0.9505 - val_loss: 0.1756
        Epoch 6/20
        1500/1500
                                      - 4s 3ms/step - accuracy: 0.9544 - loss: 0.1655 - val_accuracy: 0.9557 - val_loss: 0.1572
        Epoch 7/20
                                      - 4s 2ms/step - accuracy: 0.9584 - loss: 0.1473 - val_accuracy: 0.9588 - val_loss: 0.1453
        1500/1500
        Epoch 8/20
                                       4s 2ms/step - accuracy: 0.9626 - loss: 0.1277 - val_accuracy: 0.9613 - val_loss: 0.1353
        1500/1500
        Epoch 9/20
                                       · 4s 2ms/step - accuracy: 0.9658 - loss: 0.1213 - val_accuracy: 0.9650 - val_loss: 0.1304
        1500/1500
        Epoch 10/20
        1500/1500
                                        4s 3ms/step - accuracy: 0.9694 - loss: 0.1086 - val accuracy: 0.9655 - val loss: 0.1228
        Epoch 11/20
        1500/1500
                                      - 4s 2ms/step - accuracy: 0.9722 - loss: 0.0987 - val accuracy: 0.9671 - val loss: 0.1174
        Epoch 12/20
                                       4s 3ms/step - accuracy: 0.9749 - loss: 0.0924 - val_accuracy: 0.9691 - val_loss: 0.1123
        1500/1500
        Epoch 13/20
                                       4s 3ms/step - accuracy: 0.9754 - loss: 0.0864 - val_accuracy: 0.9684 - val_loss: 0.1074
        1500/1500
        Epoch 14/20
                                       5s 3ms/step - accuracy: 0.9788 - loss: 0.0780 - val_accuracy: 0.9698 - val_loss: 0.1059
        1500/1500
        Epoch 15/20
                                       3s 2ms/step - accuracy: 0.9803 - loss: 0.0745 - val_accuracy: 0.9706 - val_loss: 0.1001
        1500/1500
        Epoch 16/20
                                       3s 2ms/step - accuracy: 0.9813 - loss: 0.0682 - val accuracy: 0.9712 - val loss: 0.0999
        1500/1500
        Epoch 17/20
                                       4s 2ms/step - accuracy: 0.9842 - loss: 0.0616 - val_accuracy: 0.9718 - val_loss: 0.0952
        1500/1500
        Epoch 18/20
        1500/1500
                                       4s 3ms/step - accuracy: 0.9839 - loss: 0.0594 - val_accuracy: 0.9707 - val_loss: 0.0965
        Epoch 19/20
        1500/1500
                                       4s 3ms/step - accuracy: 0.9856 - loss: 0.0560 - val_accuracy: 0.9718 - val_loss: 0.0934
        Epoch 20/20
        1500/1500
                                      - 4s 2ms/step - accuracy: 0.9862 - loss: 0.0517 - val_accuracy: 0.9732 - val_loss: 0.0892
In [8]: model.summary()
```

## Model: "sequential\_1"

Layer (type)	Output Shape	Param #
dense_3 (Dense)	(None, 512)	401,920
dense_4 (Dense)	(None, 256)	131,328
dense_5 (Dense)	(None, 10)	2,570

Total params: 535,820 (2.04 MB)

Trainable params: 535,818 (2.04 MB)

Non-trainable params: 0 (0.00 B)

Optimizer params: 2 (12.00 B)

**313/313** — **1s** 1ms/step - accuracy: 0.9727 - loss: 0.0970

Test Loss: 0.0831 Test Accuracy: 0.9764

In [29]: #plotting the model

 $\verb|plot_model(model, to_file='C:/Users/tmbha/Downloads/DLprac2_model.png', show\_shapes=True, show\_layer\_names=True, show\_layer\_names=Tru$ 

Out[29]:

## dense\_6 (Dense)

Activation: relu

Input shape: (None, 784)

Output shape: (None, 512)

## dense\_7 (Dense)

Activation: relu

Input shape: (None, 512)

Output shape: (None, 256)

## dense\_8 (Dense)

Activation: softmax

Input shape: (None, 256)

Output shape: (None, 10)

```
# Plot training & validation loss
plt.subplot(1, 2, 1)
plt.plot(history.history['loss'], label='Train Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.title('Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()
# Plot training & validation accuracy
plt.subplot(1, 2, 2)
plt.plot(history.history['accuracy'], label='Train Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.title('Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()
plt.show()
```

