```
#1. Project Setup and Imports

#First, we import the necessary libraries. TensorFlow/Keras is the core deep learning framework, and Matplotlib is used for visualization.

import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense
from tensorflow.keras.utils import to_categorical
import numpy as np
import matplotlib.pyplot as plt
import os

# Set hyperparameters
NUM_CLASSES = 10
EPOCHS = 8  # Increased epochs for better accuracy (feel free to experiment)
BATCH_SIZE = 128
IMG_SHAPE = (28, 28, 1)

print(f"TensorFlow Version: {tf.__version__}")
# Disable TensorFlow warnings for cleaner output
os.environ['TF_CPP_MIN_LOG_LEVEL'] = '3'
```

```
TensorFlow Version: 2.19.0
```

```
#2. Load and Preprocess Data

#The MNIST dataset is built into Keras, making it easy to load. We must normalize the pixel values and reshape the images for the CNN.

# Load the dataset
print("Loading and preparing MNIST data...")
(x_train, y_train), (x_test, y_test) = tf.keras.datasets.mnist.load_data()

# 1. Normalize Images (Scale pixel values from [0-255] to [0.0-1.0])
x_train = x_train.astype('float32') / 255.0
x_test = x_test.astype('float32') / 255.0

# 2. Reshape for CNN Input (Add the channel dimension: 28x28 -> 28x28x1)
x_train = np.expand_dims(x_train, -1)
x_test = np.expand_dims(x_test, -1)

# 3. One-Hot Encode Labels (Convert integer labels to vectors)
y_train = to_categorical(y_train, NUM_CLASSES)
y_test = to_categorical(y_test, NUM_CLASSES)

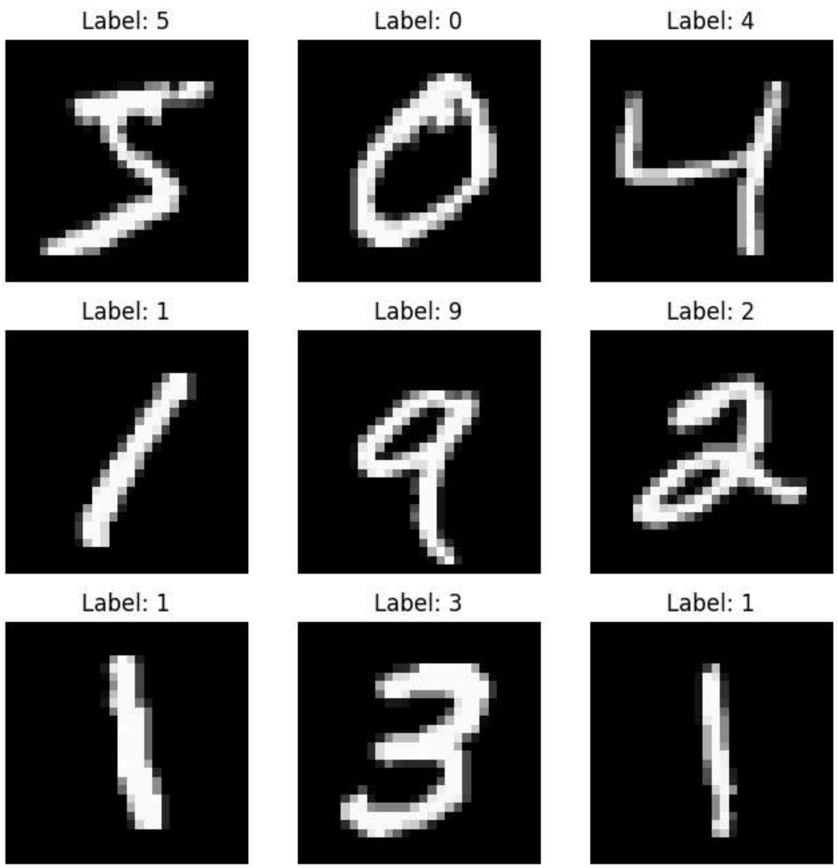
print(f"x_train shape after preprocessing: {x_train.shape}")
print(f"y_train shape after preprocessing: {y_train.shape}")
```

```
Loading and preparing MNIST data...
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/mnist.npz
11490434/11490434 ━━━━━━━━━━━━━━━━━━━━ 0s 0us/step
x_train shape after preprocessing: (60000, 28, 28, 1)
y_train shape after preprocessing: (60000, 10)
```

```
#3. Visualize Sample Data

#A good practice in any ML project is to visually inspect the data. Let's plot the first 9 images from the training set.

# Visualize the first 9 images
plt.figure(figsize=(8, 8))
for i in range(9):
    plt.subplot(3, 3, i + 1)
    # The image is 28x28x1, so we drop the channel dimension for plotting
    plt.imshow(x_train[i].reshape(28, 28), cmap='gray')
    # Get the true label by reversing the one-hot encoding
    plt.title(f"Label: {np.argmax(y_train[i])}")
    plt.axis('off')
plt.show()
```

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#4. Define the CNN Architecture

#We use a standard, yet effective, architecture for image classification: two sets of Convolutional and Pooling layers, followed by a Flatten layer and Dense layers for class

# Define the CNN model
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```
def create_cnn_model(input_shape, num_classes):
    model = Sequential([
        # Layer 1: Convolution + ReLU Activation
        Conv2D(32, kernel_size=(3, 3), activation='relu', input_shape=input_shape),
        # Layer 2: Max Pooling (downsamples feature maps)
        MaxPooling2D(pool_size=(2, 2)),

        # Layer 3: Second Convolution + ReLU
        Conv2D(64, (3, 3), activation='relu'),
        # Layer 4: Second Max Pooling
        MaxPooling2D(pool_size=(2, 2)),

        # Layer 5: Flatten for Dense layers
        Flatten(),

        # Layer 6: Fully Connected (Dense) hidden layer
        Dense(128, activation='relu'),

        # Layer 7: Output layer (10 classes) with Softmax for probability scores
        Dense(num_classes, activation='softmax')
    ])
    return model

model = create_cnn_model(IMG_SHAPE, NUM_CLASSES)

# Compile the model
model.compile(
    optimizer='adam',
    loss='categorical_crossentropy',
    metrics=['accuracy']
)

model.summary()
```

Model: "sequential_1"

Layer (type)	Output Shape	Param #
conv2d_2 (Conv2D)	(None, 26, 26, 32)	320
max_pooling2d_2 (MaxPooling2D)	(None, 13, 13, 32)	0
conv2d_3 (Conv2D)	(None, 11, 11, 64)	18,496
max_pooling2d_3 (MaxPooling2D)	(None, 5, 5, 64)	0
flatten_1 (Flatten)	(None, 1600)	0
dense_2 (Dense)	(None, 128)	204,928
dense_3 (Dense)	(None, 10)	1,290

Total params: 225,034 (879.04 KB)
Trainable params: 225,034 (879.04 KB)
Non-trainable params: 0 (0.00 B)

```
#5. Train the Model

#We fit the model to the training data and use the test data for validation during training. The results are stored in the history object.
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```python
print("\nStarting model training...")
# Train the model
history = model.fit(
    x_train, y_train,
    batch_size=BATCH_SIZE,
    epochs=EPOCHS,
    verbose=1,
    validation_data=(x_test, y_test)
)
print("Model training complete.")
```

```
Starting model training...
Epoch 1/8
469/469 ━━━━━━━━━━━━━━━━━━━━ 52s 106ms/step - accuracy: 0.8703 - loss: 0.4632 - val_accuracy: 0.9804 - val_loss: 0.0630
Epoch 2/8
469/469 ━━━━━━━━━━━━━━━━━━━━ 48s 103ms/step - accuracy: 0.9811 - loss: 0.0633 - val_accuracy: 0.9861 - val_loss: 0.0406
Epoch 3/8
469/469 ━━━━━━━━━━━━━━━━━━━━ 48s 102ms/step - accuracy: 0.9863 - loss: 0.0441 - val_accuracy: 0.9870 - val_loss: 0.0375
Epoch 4/8
469/469 ━━━━━━━━━━━━━━━━━━━━ 48s 103ms/step - accuracy: 0.9901 - loss: 0.0314 - val_accuracy: 0.9875 - val_loss: 0.0395
Epoch 5/8
469/469 ━━━━━━━━━━━━━━━━━━━━ 82s 102ms/step - accuracy: 0.9928 - loss: 0.0233 - val_accuracy: 0.9894 - val_loss: 0.0309
Epoch 6/8
469/469 ━━━━━━━━━━━━━━━━━━━━ 81s 100ms/step - accuracy: 0.9941 - loss: 0.0195 - val_accuracy: 0.9890 - val_loss: 0.0311
Epoch 7/8
 59/469 ━━━━━━━━━━━━━━━━━━━━ 44s 109ms/step - accuracy: 0.9980 - loss: 0.0097
```

```python
#6. Evaluate and Visualize Training History

#This step is critical to check for overfitting and monitor learning progress.

# --- A. Final Evaluation ---
print("\nFinal Evaluation on Test Set:")
score = model.evaluate(x_test, y_test, verbose=0)
print(f"Test Loss: {score[0]:.4f}")
print(f"Test Accuracy: {score[1]*100:.2f}%")

# --- B. Plotting Loss and Accuracy ---
plt.figure(figsize=(12, 4))

# Plot Training & Validation Accuracy
plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'], label='Training Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.title('Training and Validation Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()
plt.grid(True)

# Plot Training & Validation Loss
plt.subplot(1, 2, 2)
plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.title('Training and Validation Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()
```

```
plt.grid(True)

plt.tight_layout()
plt.show()
#
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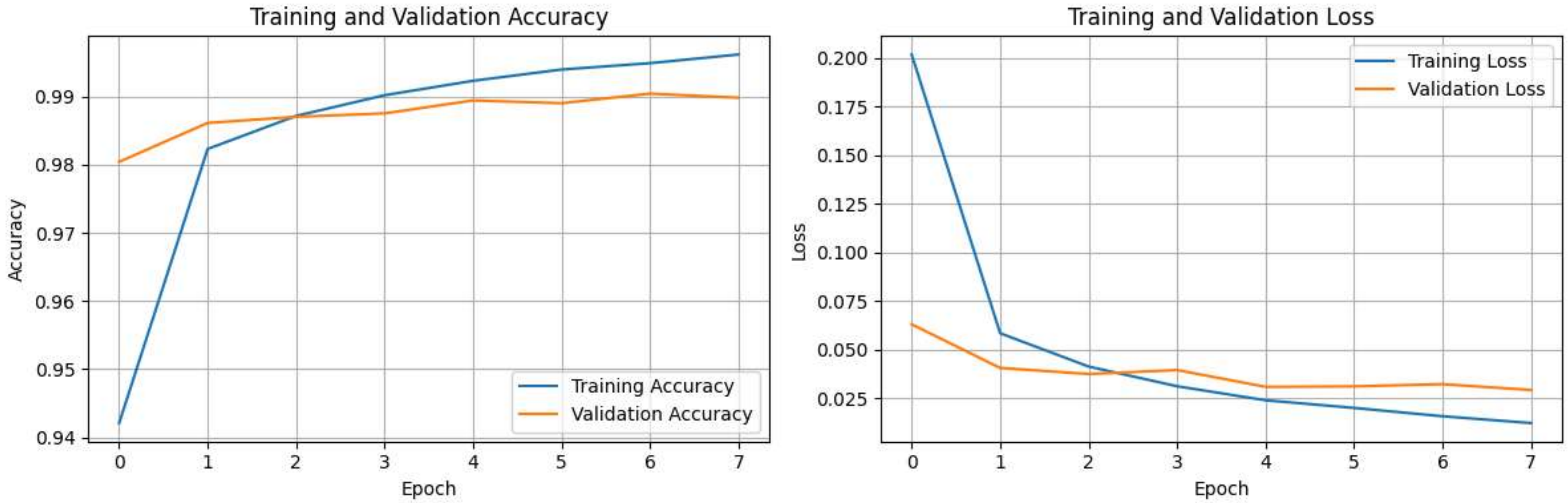
Final Evaluation on Test Set:
Test Loss: 2.3050
Test Accuracy: 9.78%
```




```
#7. Make Predictions (Inference)

#Let's use the trained model to predict a few examples from the test set.

# Predict the first 5 images in the test set
predictions = model.predict(x_test[:5])

print("\nSample Predictions:")
for i in range(5):
    predicted_class = np.argmax(predictions[i])
    true_class = np.argmax(y_test[i])

    # Display the image and results
    plt.figure(figsize=(2, 2))
    plt.imshow(x_test[i].reshape(28, 28), cmap='gray')
    plt.title(f"True: {true_class}\nPred: {predicted_class}",
              color='green' if predicted_class == true_class else 'red')
    plt.axis('off')
    plt.show()

    print(f"Image {i+1}: True Label = {true_class}, Predicted Label = {predicted_class}")
    print("-" * 30)
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 95ms/step

Sample Predictions:
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True: 7
Pred: 4

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Image 1: True Label = 7, Predicted Label = 4
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True: 2
Pred: 4

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Image 2: True Label = 2, Predicted Label = 4
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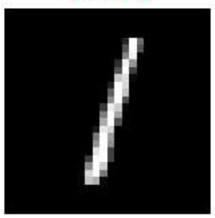
True: 1
Pred: 4



```
Image 3: True Label = 1, Predicted Label = 4
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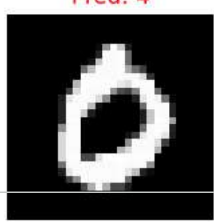
```

True: 0
Pred: 4



```
Image 4: True Label = 0, Predicted Label = 4
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```

True: 4
Pred: 4

Image 5: True Label = 4, Predicted Label = 4
