```
import tensorflow as tf
from tensorflow.keras import layers, models
from tensorflow.keras.utils import to_categorical
import matplotlib.pyplot as plt

# Load the MNIST dataset
mnist = tf.keras.datasets.mnist

# Split into train and test sets
(X_train, y_train), (X_test, y_test) = mnist.load_data()

# Reshape data to add a single channel (since the images are grayscale)
X_train = X_train.reshape((X_train.shape[0], 28, 28, 1))
X_test = X_test.reshape((X_test.shape[0], 28, 28, 1))

# Normalize the pixel values (from 0-255 to 0-1)
X_train, X_test = X_train / 255.0, X_test / 255.0

# One-hot encode the labels
y_train = to_categorical(y_train)
y_test = to_categorical(y_test)
```

```
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/mnist.npz
11490434/11490434 ━━━━━━━━━━━━━━━━━━━━ 1s 0us/step
```

```
# Build the CNN model
model = models.Sequential()

# First convolutional layer (32 filters, 3x3 kernel)
model.add(layers.Conv2D(32, (3, 3), activation='relu', input_shape=(28, 28, 1)))
model.add(layers.MaxPooling2D((2, 2)))

# Second convolutional layer (64 filters, 3x3 kernel)
model.add(layers.Conv2D(64, (3, 3), activation='relu'))
model.add(layers.MaxPooling2D((2, 2)))

# Flatten the output before feeding it into fully connected layers
model.add(layers.Flatten())

# Fully connected layer
model.add(layers.Dense(64, activation='relu'))

# Output layer with 10 neurons (one for each class)
model.add(layers.Dense(10, activation='softmax'))

# Print the model summary
model.summary()
```

```
/usr/local/lib/python3.10/dist-packages/keras/src/layers/convolutional/base_conv.py:107: UserWarning: Do not pass an `input_shape`/`inpu
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 26, 26, 32)	320
max_pooling2d (MaxPooling2D)	(None, 13, 13, 32)	0
conv2d_1 (Conv2D)	(None, 11, 11, 64)	18,496
max_pooling2d_1 (MaxPooling2D)	(None, 5, 5, 64)	0
flatten (Flatten)	(None, 1600)	0
dense (Dense)	(None, 64)	102,464
dense_1 (Dense)	(None, 10)	650

Total params: 121,930 (476.29 KB)
Trainable params: 121,930 (476.29 KB)

```
# Compile the model
model.compile(optimizer='adam',
              loss='categorical_crossentropy',
```

```
              metrics=['accuracy'])


# Train the model
history = model.fit(X_train, y_train, epochs=10, batch_size=64, validation_split=0.2)
```

```
Epoch 1/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 49s 63ms/step - accuracy: 0.8620 - loss: 0.4523 - val_accuracy: 0.9804 - val_loss: 0.0703
Epoch 2/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 72s 50ms/step - accuracy: 0.9805 - loss: 0.0637 - val_accuracy: 0.9838 - val_loss: 0.0494
Epoch 3/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 43s 53ms/step - accuracy: 0.9873 - loss: 0.0397 - val_accuracy: 0.9873 - val_loss: 0.0413
Epoch 4/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 40s 52ms/step - accuracy: 0.9915 - loss: 0.0268 - val_accuracy: 0.9862 - val_loss: 0.0449
Epoch 5/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 41s 52ms/step - accuracy: 0.9926 - loss: 0.0225 - val_accuracy: 0.9887 - val_loss: 0.0409
Epoch 6/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 41s 52ms/step - accuracy: 0.9945 - loss: 0.0164 - val_accuracy: 0.9902 - val_loss: 0.0381
Epoch 7/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 41s 52ms/step - accuracy: 0.9962 - loss: 0.0125 - val_accuracy: 0.9890 - val_loss: 0.0390
Epoch 8/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 40s 53ms/step - accuracy: 0.9975 - loss: 0.0089 - val_accuracy: 0.9889 - val_loss: 0.0394
Epoch 9/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 46s 59ms/step - accuracy: 0.9971 - loss: 0.0086 - val_accuracy: 0.9903 - val_loss: 0.0405
Epoch 10/10
750/750 ━━━━━━━━━━━━━━━━━━━━ 80s 57ms/step - accuracy: 0.9967 - loss: 0.0092 - val_accuracy: 0.9905 - val_loss: 0.0417
```

```
# Evaluate the model on the test set
test_loss, test_acc = model.evaluate(X_test, y_test)

print(f"Test accuracy: {test_acc}")
```

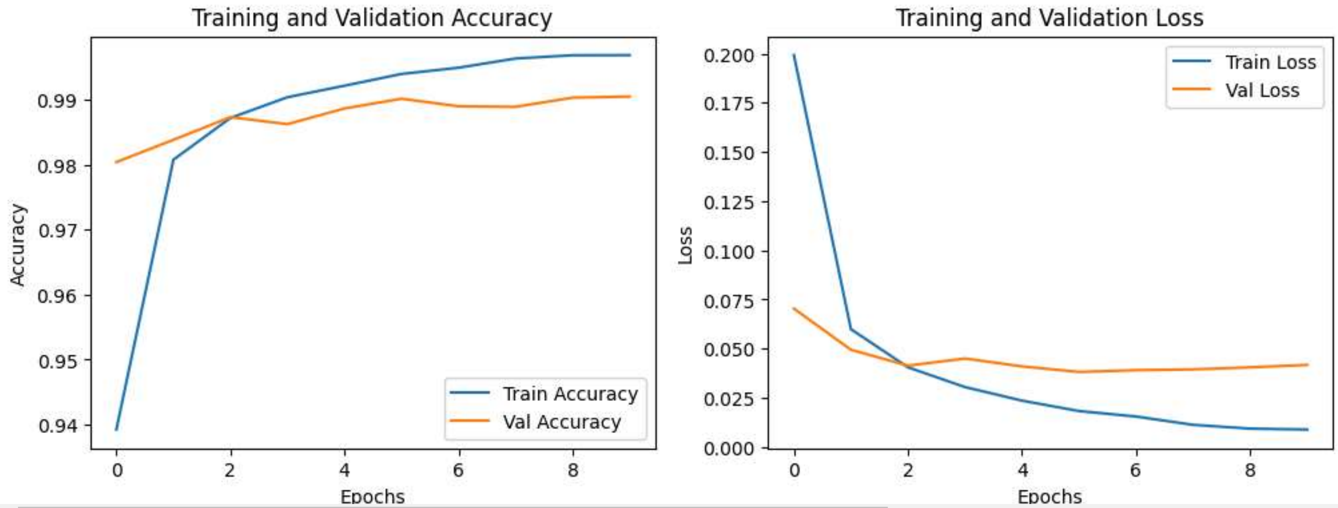
```
313/313 ━━━━━━━━━━━━━━━━━━━━ 2s 7ms/step - accuracy: 0.9879 - loss: 0.0418
Test accuracy: 0.9904000163078308
```

```
# Plot training & validation accuracy and loss
plt.figure(figsize=(12, 4))

plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'], label='Train Accuracy')
plt.plot(history.history['val_accuracy'], label='Val Accuracy')
plt.title('Training and Validation Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()

plt.subplot(1, 2, 2)
plt.plot(history.history['loss'], label='Train Loss')
plt.plot(history.history['val_loss'], label='Val Loss')
plt.title('Training and Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()

plt.show()
```


Training and Validation Accuracy
Accuracy
Epochs
Train Accuracy
Val Accuracy
Training and Validation Loss
Loss
Epochs
Train Loss
Val Loss