HandWritten Digit Recognition

First DeepLearning project

In this project, we are using mnist dataset and try to train a neural network to do the digit classification

In [33]:
```
import numpy as np
import pandas as pd
import matplotlib as plt
import tensorflow as tf
from tensorflow import keras
import matplotlib.pyplot as plt

print(tf.__version__)
```

```
2.13.0
```

load the mnist data

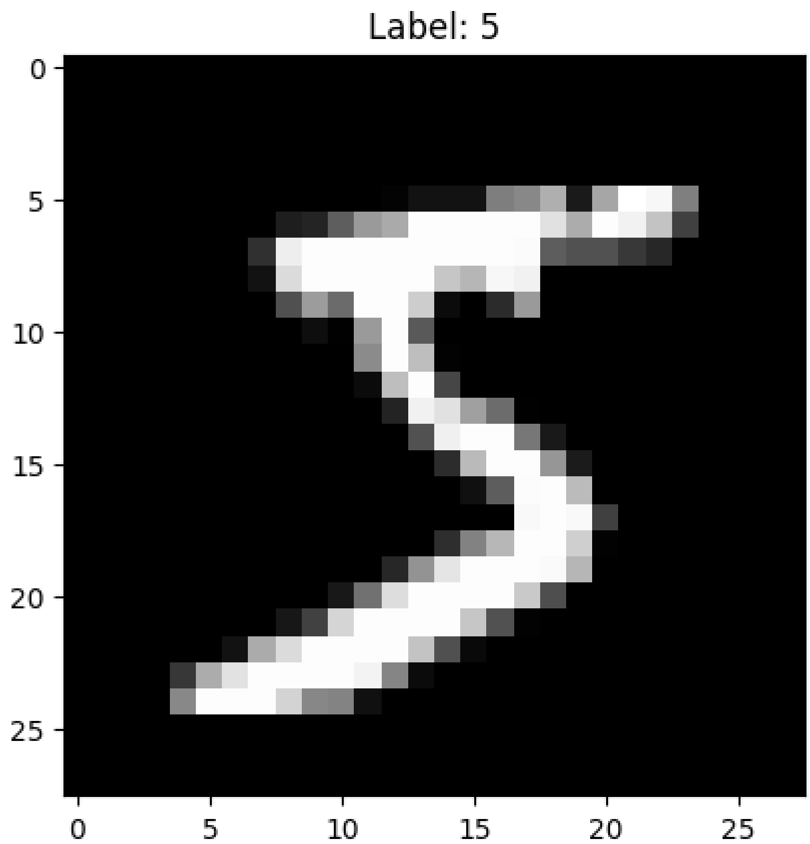
In [2]:
```
from tensorflow.keras.datasets import mnist
```

load the mnist dataset

In [3]:
```
(train_images, train_labels), (test_images, test_labels) = mnist.load_data(
```

Inspect the data

In [4]:
```
plt.imshow(train_images[0], cmap='gray')
plt.title(f"Label: {train_labels[0]}")
plt.show()
```



before we do anything, we have to remember to normalize the data

Normalize the images to be values between 0 and 1

In [5]:
```
train_images = train_images.astype('float32') / 255
test_images = test_images.astype('float32') / 255
```

then,

One-hot encode the labels

In [6]:
```
train_labels = tf.keras.utils.to_categorical(train_labels)
test_labels = tf.keras.utils.to_categorical(test_labels)
```

to understand how the data is structured, we print it

In [7]:
```
print(train_images)
```

```
[[[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.]
  [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.]
  [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.]
  ...
  [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.]
  [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.]
  [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.]]

 [[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.]
  [0. 0. 0. ... 0. 0. 0.]]]
```

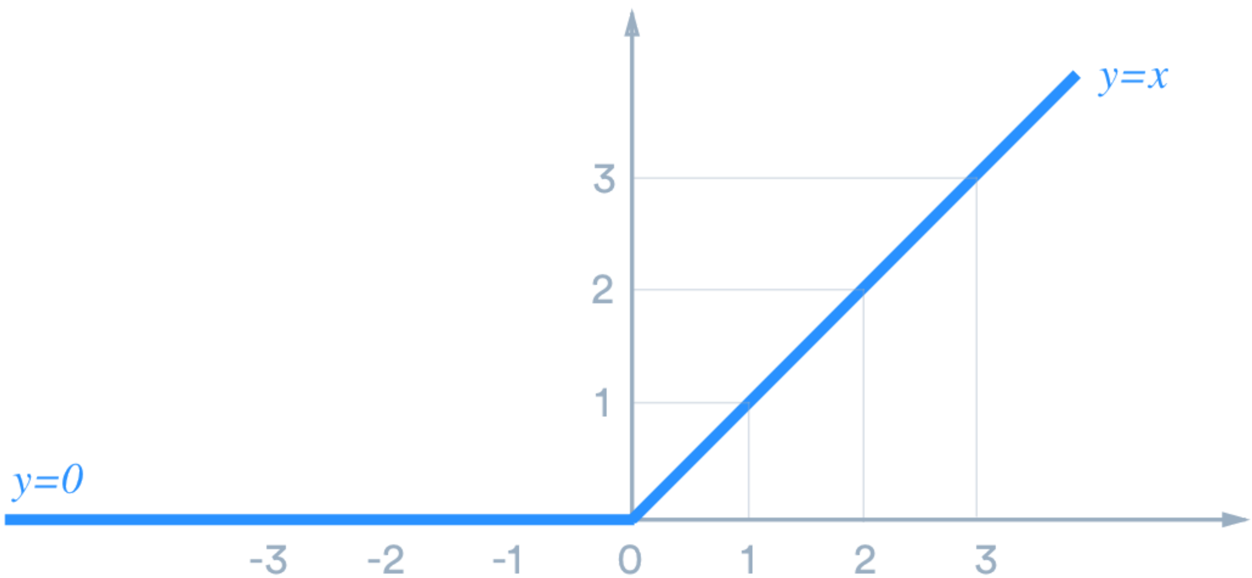
In [8]:
```
print(train_labels.shape)
print(train_images.shape)
```

```
(60000, 10)
(60000, 28, 28)
```

so each number is 28 pixels x 28 pixels

1. Now, we start to set up layers for it

we use relu functions as the activation function since is good and its simple, easy for training and processing data



In [9]:
```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Flatten, Dense


model = Sequential([
    Flatten(input_shape=(28, 28)),  # Flatten the 28x28 images
    Dense(128, activation='relu'),  # Fully connected layer with 128 units
    Dense(10, activation='softmax')  # Output layer with 10 units (for 10 c
])
```

2. Complie the Model

In [10]:
```
model.compile(optimizer='adam',
              loss='categorical_crossentropy',
              metrics=['accuracy'])

model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 flatten (Flatten)           (None, 784)               0

 dense (Dense)               (None, 128)               100480

 dense_1 (Dense)             (None, 10)                1290

=================================================================
Total params: 101770 (397.54 KB)
Trainable params: 101770 (397.54 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

3. Train the Model

In [11]:
```
history = model.fit(
    train_images,
    train_labels,
    epochs=5,
    batch_size=32,
    validation_data=(test_images, test_labels)
)
```

```
Epoch 1/5
1875/1875 [==============================] - 2s 817us/step - loss: 0.2555
- accuracy: 0.9281 - val_loss: 0.1287 - val_accuracy: 0.9625
Epoch 2/5
1875/1875 [==============================] - 1s 761us/step - loss: 0.1095
- accuracy: 0.9682 - val_loss: 0.0963 - val_accuracy: 0.9700
Epoch 3/5
1875/1875 [==============================] - 1s 714us/step - loss: 0.0759
- accuracy: 0.9769 - val_loss: 0.0829 - val_accuracy: 0.9726
Epoch 4/5
1875/1875 [==============================] - 1s 694us/step - loss: 0.0575
- accuracy: 0.9820 - val_loss: 0.0816 - val_accuracy: 0.9748
Epoch 5/5
1875/1875 [==============================] - 1s 726us/step - loss: 0.0447
- accuracy: 0.9858 - val_loss: 0.0749 - val_accuracy: 0.9777
```

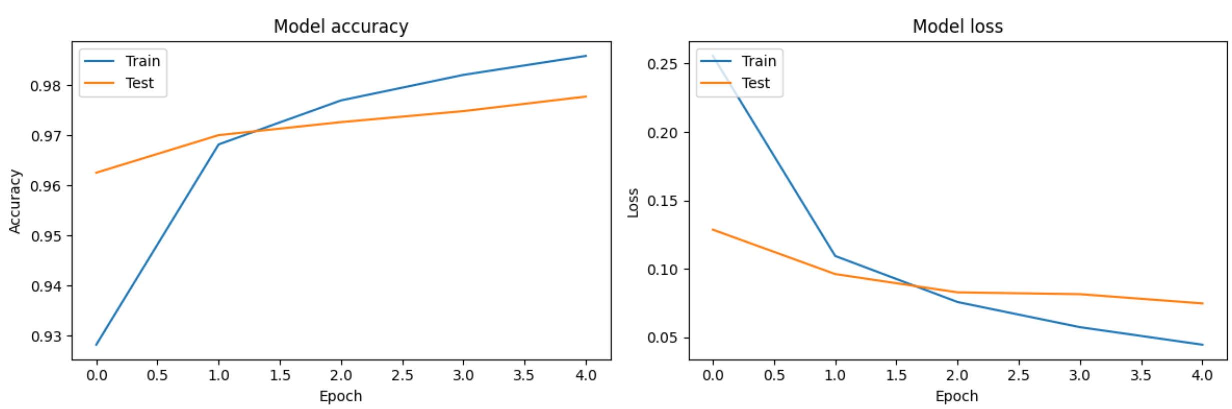
4. Evaluate the Model

In [12]:
```
test_loss, test_acc = model.evaluate(test_images, test_labels)
print(f"Test Accuracy: {test_acc * 100:.2f}%")
```

```
313/313 [==============================] - 0s 418us/step - loss: 0.0749 -
accuracy: 0.9777
Test Accuracy: 97.77%
```

lets vitualize it

In [13]:
```
# Plot training & validation accuracy values
plt.figure(figsize=(12, 4))

plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('Model accuracy')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend(['Train', 'Test'], loc='upper left')

# Plot training & validation loss values
plt.subplot(1, 2, 2)
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('Model loss')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(['Train', 'Test'], loc='upper left')

plt.tight_layout()
plt.show()
```



Great! we got 97% accuracy!

we can still do some improvments

In [14]:
```
model = Sequential([
    Flatten(input_shape=(28, 28)),  # Flatten the 28x28 images
    Dense(256, activation='relu'),  # Fully connected layer with 128 units
    Dense(10, activation='softmax')  # Output layer with 10 units (for 10 c
])

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

model.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 flatten_1 (Flatten)         (None, 784)               0

 dense_2 (Dense)             (None, 256)               200960

 dense_3 (Dense)             (None, 10)                2570

=================================================================
Total params: 203530 (795.04 KB)
Trainable params: 203530 (795.04 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

now we change the epochs count to 10, but just in case we add early_stopping to avoid overfitting

In [15]:
```
from tensorflow.keras.callbacks import EarlyStopping
early_stopping = EarlyStopping(
    min_delta=0.001, # minimium amount of change to count as an improvement
    patience=20, # how many epochs to wait before stopping
    restore_best_weights=True,
)

history = model.fit(
    train_images,
    train_labels,
    epochs=10,
    batch_size=32,
    callbacks=[early_stopping], # put your callbacks in a list
    validation_data=(test_images, test_labels)
)
```

```
Epoch 1/10
1875/1875 [==============================] - 2s 837us/step - loss: 0.2265
- accuracy: 0.9342 - val_loss: 0.1143 - val_accuracy: 0.9652
Epoch 2/10
1875/1875 [==============================] - 1s 790us/step - loss: 0.0937
- accuracy: 0.9721 - val_loss: 0.0896 - val_accuracy: 0.9692
Epoch 3/10
1875/1875 [==============================] - 1s 782us/step - loss: 0.0622
- accuracy: 0.9815 - val_loss: 0.0675 - val_accuracy: 0.9786
Epoch 4/10
1875/1875 [==============================] - 1s 795us/step - loss: 0.0438
- accuracy: 0.9866 - val_loss: 0.0682 - val_accuracy: 0.9785
Epoch 5/10
1875/1875 [==============================] - 2s 822us/step - loss: 0.0347
- accuracy: 0.9889 - val_loss: 0.0706 - val_accuracy: 0.9780
Epoch 6/10
1875/1875 [==============================] - 2s 829us/step - loss: 0.0247
- accuracy: 0.9922 - val_loss: 0.0760 - val_accuracy: 0.9775
Epoch 7/10
1875/1875 [==============================] - 2s 801us/step - loss: 0.0196
- accuracy: 0.9936 - val_loss: 0.0744 - val_accuracy: 0.9793
Epoch 8/10
1875/1875 [==============================] - 2s 982us/step - loss: 0.0164
- accuracy: 0.9946 - val_loss: 0.0748 - val_accuracy: 0.9802
Epoch 9/10
1875/1875 [==============================] - 1s 783us/step - loss: 0.0130
- accuracy: 0.9956 - val_loss: 0.0791 - val_accuracy: 0.9796
Epoch 10/10
1875/1875 [==============================] - 1s 779us/step - loss: 0.0109
- accuracy: 0.9965 - val_loss: 0.0784 - val_accuracy: 0.9815
```

Great! almost 100% accuracy, lets try further with higher epoches

In [16]:
```
history = model.fit(
    train_images,
    train_labels,
    epochs=15,
    batch_size=32,
    callbacks=[early_stopping], # put your callbacks in a list
    validation_data=(test_images, test_labels)
)
```

```
Epoch 1/15
1875/1875 [==============================] - 2s 838us/step - loss: 0.0098
- accuracy: 0.9968 - val_loss: 0.0725 - val_accuracy: 0.9830
Epoch 2/15
1875/1875 [==============================] - 2s 823us/step - loss: 0.0094
- accuracy: 0.9967 - val_loss: 0.0832 - val_accuracy: 0.9801
Epoch 3/15
1875/1875 [==============================] - 2s 840us/step - loss: 0.0080
- accuracy: 0.9973 - val_loss: 0.0831 - val_accuracy: 0.9815
Epoch 4/15
1875/1875 [==============================] - 2s 836us/step - loss: 0.0070
- accuracy: 0.9976 - val_loss: 0.0913 - val_accuracy: 0.9792
Epoch 5/15
1875/1875 [==============================] - 1s 788us/step - loss: 0.0061
- accuracy: 0.9981 - val_loss: 0.0992 - val_accuracy: 0.9785
Epoch 6/15
1875/1875 [==============================] - 1s 791us/step - loss: 0.0050
- accuracy: 0.9985 - val_loss: 0.0985 - val_accuracy: 0.9808
Epoch 7/15
1875/1875 [==============================] - 1s 785us/step - loss: 0.0072
- accuracy: 0.9976 - val_loss: 0.1078 - val_accuracy: 0.9798
Epoch 8/15
1875/1875 [==============================] - 2s 816us/step - loss: 0.0049
- accuracy: 0.9983 - val_loss: 0.1113 - val_accuracy: 0.9797
Epoch 9/15
1875/1875 [==============================] - 2s 802us/step - loss: 0.0055
- accuracy: 0.9979 - val_loss: 0.1200 - val_accuracy: 0.9784
Epoch 10/15
1875/1875 [==============================] - 1s 787us/step - loss: 0.0059
- accuracy: 0.9979 - val_loss: 0.1132 - val_accuracy: 0.9809
Epoch 11/15
1875/1875 [==============================] - 2s 810us/step - loss: 0.0045
- accuracy: 0.9986 - val_loss: 0.1189 - val_accuracy: 0.9804
Epoch 12/15
1875/1875 [==============================] - 2s 847us/step - loss: 0.0060
- accuracy: 0.9980 - val_loss: 0.1043 - val_accuracy: 0.9813
Epoch 13/15
1875/1875 [==============================] - 2s 819us/step - loss: 0.0022
- accuracy: 0.9993 - val_loss: 0.1362 - val_accuracy: 0.9780
Epoch 14/15
1875/1875 [==============================] - 2s 811us/step - loss: 0.0060
- accuracy: 0.9979 - val_loss: 0.1164 - val_accuracy: 0.9798
Epoch 15/15
1875/1875 [==============================] - 1s 799us/step - loss: 0.0034
- accuracy: 0.9988 - val_loss: 0.1139 - val_accuracy: 0.9815
```

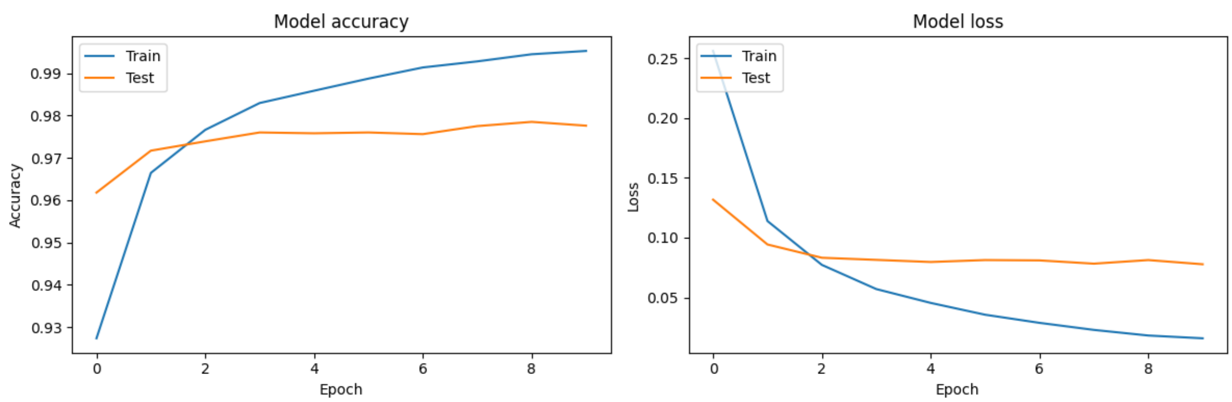
it seems if I directly use another fit functions, the loss start as where I ended last time, which might suggest that it trains again on the model I have just trained

If we want to avoid it, I guess we should start it over

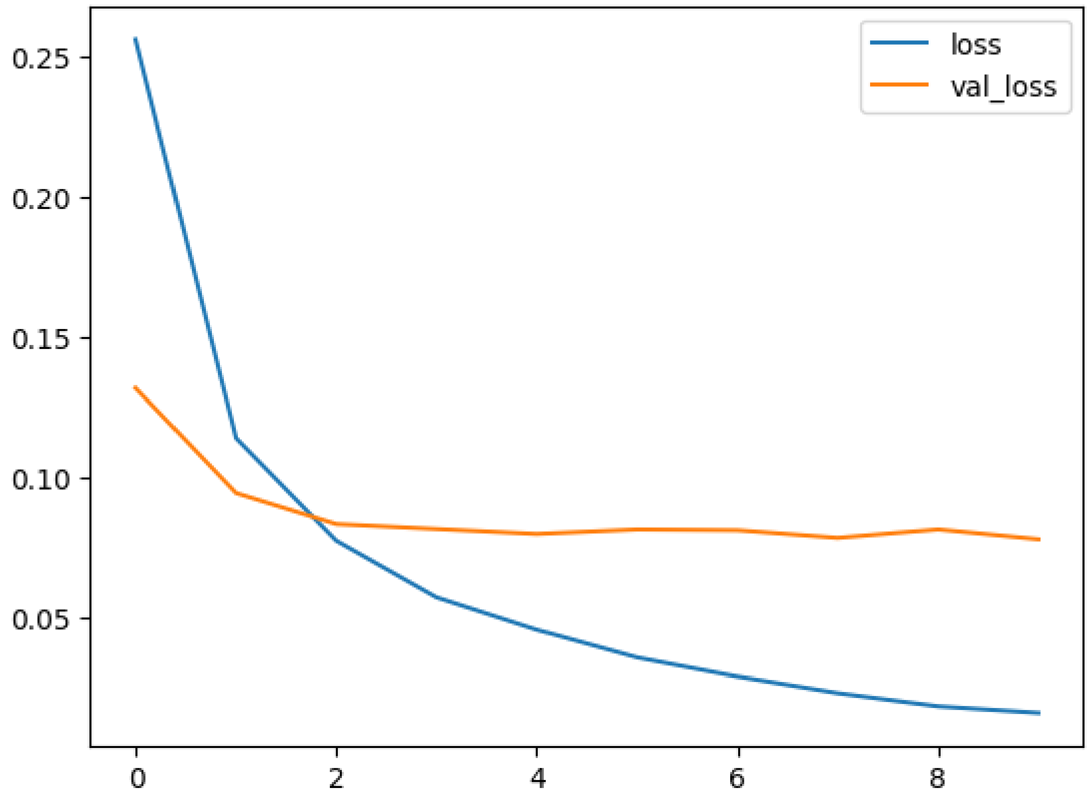
In [28]:
```
model = Sequential([
    Flatten(input_shape=(28, 28)),  # Flatten the 28x28 images
    Dense(128, activation='relu'),  # Fully connected layer with 128 units
    Dense(10, activation='softmax')  # Output layer with 10 units (for 10 c
])

model.compile(optimizer='adam',
              loss='categorical_crossentropy',
              metrics=['accuracy'])
early_stopping = EarlyStopping(
    min_delta=0.001, # minimium amount of change to count as an improvement
    patience=20, # how many epochs to wait before stopping
    restore_best_weights=True,
)
history = model.fit(
    train_images,
    train_labels,
    epochs=10,
    batch_size=32,
    callbacks=[early_stopping], # put your callbacks in a list
    validation_data=(test_images, test_labels)
)
```

```
Epoch 1/10
1875/1875 [==============================] - 1s 696us/step - loss: 0.2561
- accuracy: 0.9274 - val_loss: 0.1318 - val_accuracy: 0.9618
Epoch 2/10
1875/1875 [==============================] - 1s 673us/step - loss: 0.1139
- accuracy: 0.9664 - val_loss: 0.0943 - val_accuracy: 0.9717
Epoch 3/10
1875/1875 [==============================] - 1s 713us/step - loss: 0.0772
- accuracy: 0.9766 - val_loss: 0.0832 - val_accuracy: 0.9739
Epoch 4/10
1875/1875 [==============================] - 1s 660us/step - loss: 0.0570
- accuracy: 0.9829 - val_loss: 0.0814 - val_accuracy: 0.9760
Epoch 5/10
1875/1875 [==============================] - 1s 659us/step - loss: 0.0454
- accuracy: 0.9858 - val_loss: 0.0796 - val_accuracy: 0.9758
Epoch 6/10
1875/1875 [==============================] - 1s 659us/step - loss: 0.0356
- accuracy: 0.9887 - val_loss: 0.0813 - val_accuracy: 0.9760
Epoch 7/10
1875/1875 [==============================] - 1s 657us/step - loss: 0.0287
- accuracy: 0.9913 - val_loss: 0.0810 - val_accuracy: 0.9756
Epoch 8/10
1875/1875 [==============================] - 1s 725us/step - loss: 0.0229
- accuracy: 0.9928 - val_loss: 0.0782 - val_accuracy: 0.9775
Epoch 9/10
1875/1875 [==============================] - 1s 673us/step - loss: 0.0182
- accuracy: 0.9945 - val_loss: 0.0813 - val_accuracy: 0.9785
Epoch 10/10
1875/1875 [==============================] - 1s 657us/step - loss: 0.0158
- accuracy: 0.9952 - val_loss: 0.0777 - val_accuracy: 0.9776
```

In [29]:
```
# Plot training & validation accuracy values
plt.figure(figsize=(12, 4))

plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('Model accuracy')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend(['Train', 'Test'], loc='upper left')

# Plot training & validation loss values
plt.subplot(1, 2, 2)
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('Model loss')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(['Train', 'Test'], loc='upper left')

plt.tight_layout()
plt.show()
```



In [34]:
```
history_df = pd.DataFrame(history.history)
history_df.loc[:, ['loss', 'val_loss']].plot();
```



In [19]:
```
history.history
```

Out[19]:
```
{'loss': [0.22070597112178802,
  0.09154766798019409,
  0.06130516901612282,
  0.04478169232606888,
  0.03293851763010025,
  0.025184987112879753,
  0.019530057907104492,
  0.01601477712392807,
  0.01281061489135027,
  0.010680190287530422,
  0.009442095644772053,
  0.008974487893283367,
  0.007534516975283623,
  0.007101559080183506,
  0.006281865295022726],
 'accuracy': [0.9360666871070862,
  0.9730833172798157,
  0.9814833402633667,
  0.9863499999046326,
  0.989983320236206,
  0.9916666746139526,
  0.9935666918754578,
  0.9950666427612305,
  0.9958999752998352,
  0.996483325958252,
  0.9971833229064941,
  0.9970333576202393,
  0.9974666833877563,
  0.9975166916847229,
  0.9977666735649109],
 'val_loss': [0.11028121411800385,
  0.08852854371070862,
  0.07909859716892242,
  0.0747181624174118,
  0.07619019597768784,
  0.06984405219554901,
  0.06666118651628494,
  0.07518196105957031,
  0.08322479575872421,
  0.0868171975016594,
  0.08774709701538086,
  0.08541646599769592,
  0.11101407557725906,
  0.09484095126390457,
  0.09372469782829285],
 'val_accuracy': [0.9681000113487244,
  0.9710999727249146,
  0.9753999710083008,
  0.975600004196167,
  0.9771999716758728,
  0.9801999926567078,
  0.9805999994277954,
  0.9793999791145325,
  0.9779999852180481,
  0.9785000085830688,
  0.9782999753952026,
  0.9807000160217285,
```

```
  0.9757999777793884,
  0.9789000153541565,
  0.9801999926567078]}
```

well, it seems that loss and the accuracy still have some space to impove since they are not following to the trend of train.

OK, now its time to see if this model acctually works,

Lets Predict

Make Predictions:

Use the predict method of your trained model to get predictions. This method will return the predicted probabilities for each class

predictions will be an array with shape (number_of_samples, number_of_classes). Each row will contain the predicted probabilities for each class.

In [35]:
```
predictions = model.predict(test_images)
```

```
313/313 [==============================] - 0s 323us/step
```

Get Predicted Classes:

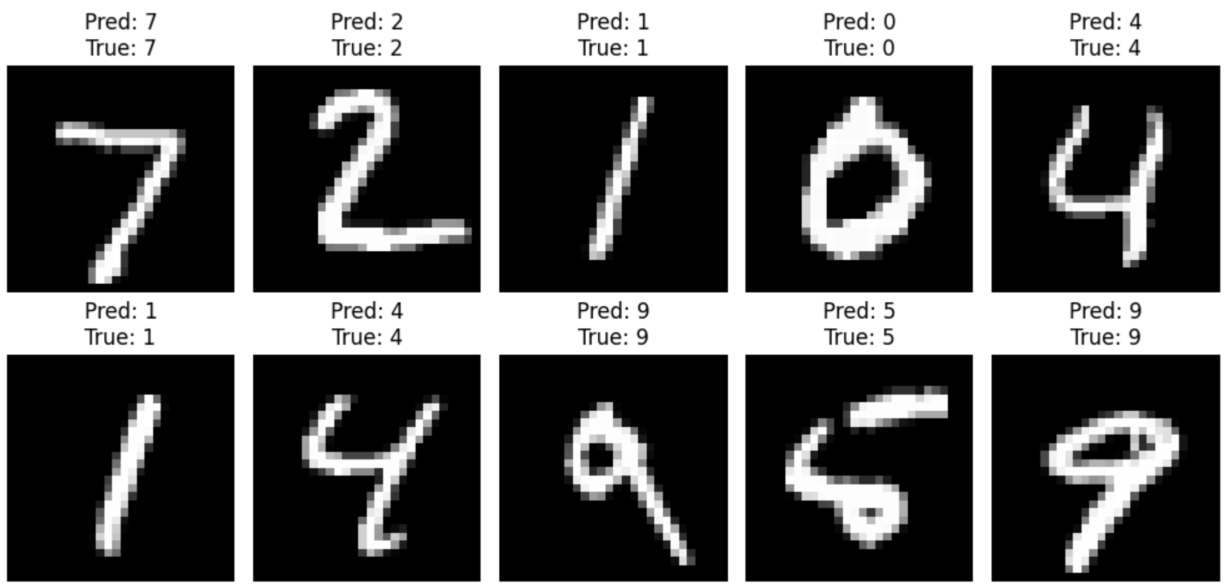
If we want to get the class with the highest probability for each sample (i.e., the predicted class label), we can use np.argmax:

In [36]:
```
predicted_labels = np.argmax(predictions, axis=1)
```

Visualize Predictions

In [37]:

```python
# Visualize the first 10 predictions
plt.figure(figsize=(10, 5))
for i in range(10):
    plt.subplot(2, 5, i+1)
    plt.imshow(test_images[i], cmap='gray')
    plt.title(f"Pred: {predicted_labels[i]}\nTrue: {np.argmax(test_labels[i
    plt.axis('off')
plt.tight_layout()
plt.show()
```



Evaluate Prediction Accuracy

In [38]:

```python
accuracy = np.mean(predicted_labels == np.argmax(test_labels, axis=1))
print(f"Prediction accuracy: {accuracy * 100:.2f}%")
```

```
Prediction accuracy: 97.76%
```

In [ ]: