number-recognition

October 2, 2023

1 Number Recognition

[1]:
```
# Import necessary libraries
import numpy as np
import matplotlib.pyplot as plt
from keras.datasets import mnist
from keras.models import Sequential
from keras.layers import Dense, Flatten
from keras.utils import to_categorical
```

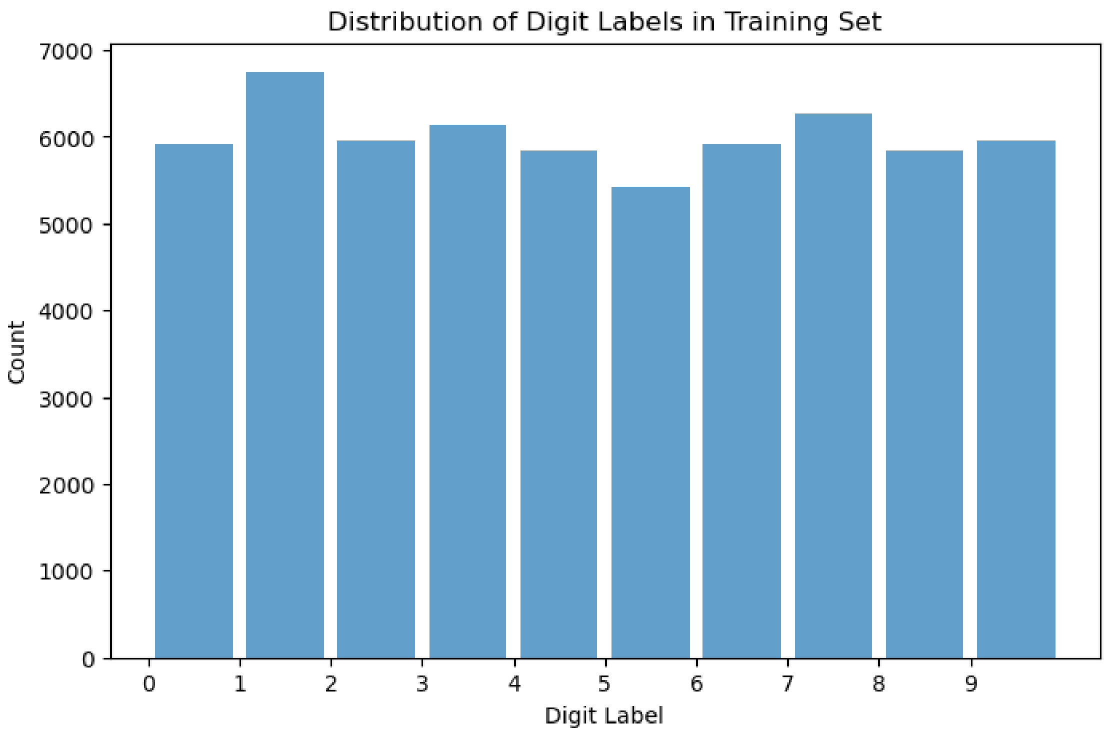
[2]:
```
# Load the MNIST dataset
(X_train, y_train), (X_test, y_test) = mnist.load_data()
```

```
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-
datasets/mnist.npz
11490434/11490434 [==============================] - 4s 0us/step
```

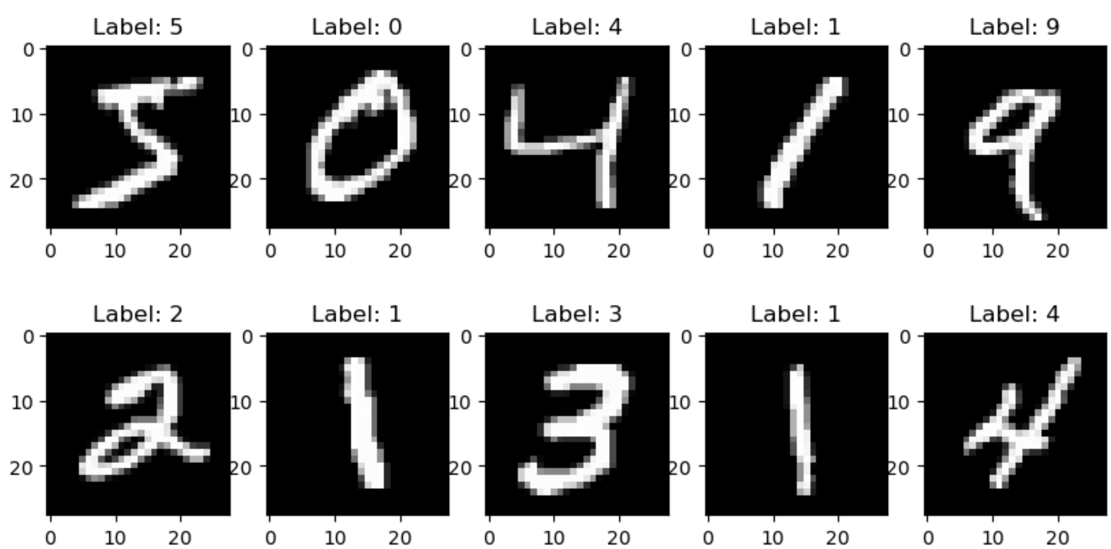
[3]:
```
# Data Cleaning & Preprocessing
# Reshape the data and normalize pixel values to the range [0, 1]
X_train = X_train.reshape(X_train.shape[0], 28, 28, 1).astype('float32') / 255
X_test = X_test.reshape(X_test.shape[0], 28, 28, 1).astype('float32') / 255
```

[4]:
```
# One-hot encode the target labels
y_train = to_categorical(y_train, 10)
y_test = to_categorical(y_test, 10)
```

[5]:
```
# Exploratory Data Analysis (EDA)
# Plot the distribution of digit labels in the training set
plt.figure(figsize=(8, 5))
plt.hist(np.argmax(y_train, axis=1), bins=range(11), alpha=0.7, rwidth=0.85)
plt.xticks(range(10))
plt.title('Distribution of Digit Labels in Training Set')
plt.xlabel('Digit Label')
plt.ylabel('Count')
plt.show()
```



[6]:
```
# Plot a few sample images
plt.figure(figsize=(10, 5))
for i in range(10):
    plt.subplot(2, 5, i + 1)
    plt.imshow(X_train[i].reshape(28, 28), cmap='gray')
    plt.title(f"Label: {np.argmax(y_train[i])}")
plt.show()
```



[7]:
```python
# Build a neural network model
model = Sequential()
model.add(Flatten(input_shape=(28, 28, 1)))
model.add(Dense(128, activation='relu'))
model.add(Dense(64, activation='relu'))
model.add(Dense(10, activation='softmax'))
```

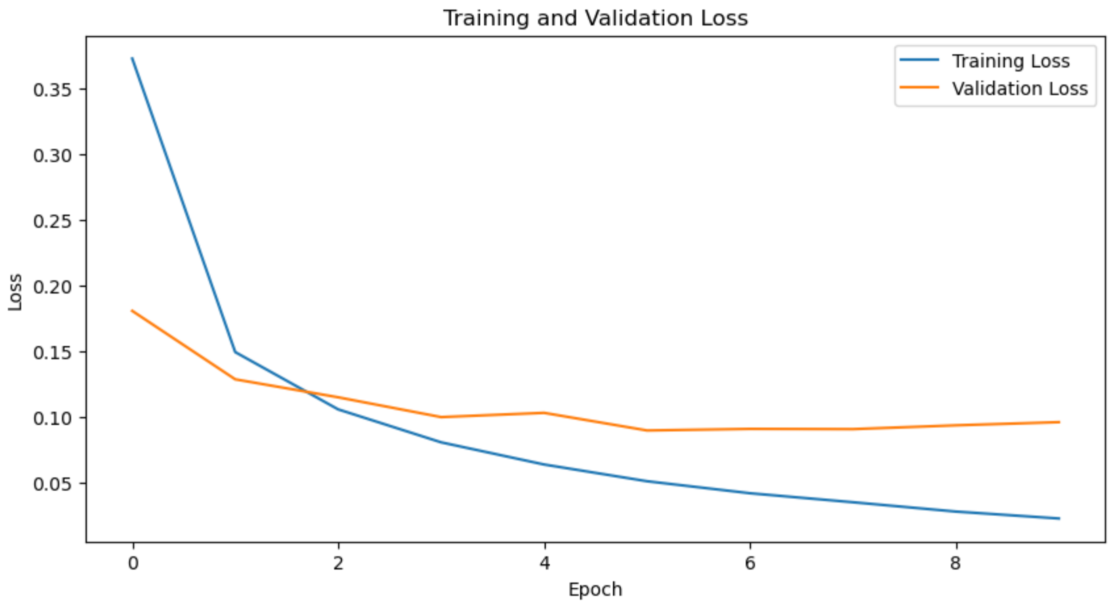
[8]:
```python
# Compile the model
model.compile(optimizer='adam', loss='categorical_crossentropy',␣
↪metrics=['accuracy'])
```

[9]:
```python
# Train the model
history = model.fit(X_train, y_train, epochs=10, batch_size=128,␣
↪validation_split=0.2)
```

```
Epoch 1/10
375/375 [==============================] - 4s 8ms/step - loss: 0.3732 -
accuracy: 0.8938 - val_loss: 0.1807 - val_accuracy: 0.9522
Epoch 2/10
375/375 [==============================] - 1s 4ms/step - loss: 0.1493 -
accuracy: 0.9565 - val_loss: 0.1285 - val_accuracy: 0.9626
Epoch 3/10
375/375 [==============================] - 3s 8ms/step - loss: 0.1056 -
accuracy: 0.9691 - val_loss: 0.1148 - val_accuracy: 0.9661
Epoch 4/10
375/375 [==============================] - 3s 7ms/step - loss: 0.0805 -
accuracy: 0.9769 - val_loss: 0.0997 - val_accuracy: 0.9707
Epoch 5/10
375/375 [==============================] - 3s 9ms/step - loss: 0.0636 -
accuracy: 0.9810 - val_loss: 0.1030 - val_accuracy: 0.9701
Epoch 6/10
375/375 [==============================] - 3s 8ms/step - loss: 0.0508 -
accuracy: 0.9853 - val_loss: 0.0895 - val_accuracy: 0.9737
Epoch 7/10
375/375 [==============================] - 3s 8ms/step - loss: 0.0416 -
accuracy: 0.9871 - val_loss: 0.0907 - val_accuracy: 0.9731
Epoch 8/10
375/375 [==============================] - 3s 9ms/step - loss: 0.0348 -
accuracy: 0.9892 - val_loss: 0.0905 - val_accuracy: 0.9726
Epoch 9/10
375/375 [==============================] - 3s 9ms/step - loss: 0.0277 -
accuracy: 0.9918 - val_loss: 0.0934 - val_accuracy: 0.9747
Epoch 10/10
375/375 [==============================] - 3s 8ms/step - loss: 0.0224 -
accuracy: 0.9934 - val_loss: 0.0959 - val_accuracy: 0.9728
```

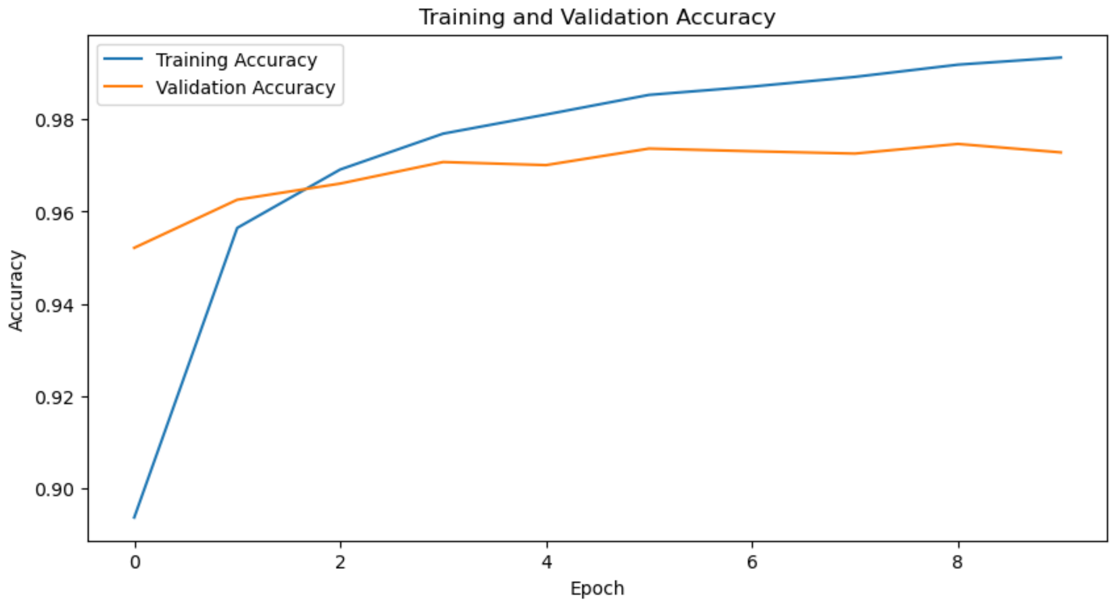
[10]:

```
# Plot training and validation loss
plt.figure(figsize=(10, 5))
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.show()
```



[11]:

```
# Plot training and validation accuracy
plt.figure(figsize=(10, 5))
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.show()
```



[12]:

```
# Evaluate the model on the test data
test_loss, test_acc = model.evaluate(X_test, y_test)
print(f"Test accuracy: {test_acc * 100:.2f}%")
```

```
313/313 [==============================] - 1s 2ms/step - loss: 0.0866 -
accuracy: 0.9747
Test accuracy: 97.47%
```

[13]:

```
# Make predictions on test data
predictions = model.predict(X_test)
```

```
313/313 [==============================] - 1s 2ms/step
```

[14]:

```
# Recognition example
def recognize_digit(image):
    # Predict the digit
    prediction = model.predict(image.reshape(1, 28, 28, 1))
    # Get the predicted label
    predicted_label = np.argmax(prediction)
    return predicted_label
```

[15]:

```
# Test recognition on a sample image
sample_index = 0  # Change this to any index in the test set
predicted_digit = recognize_digit(X_test[sample_index])
actual_digit = np.argmax(y_test[sample_index])
```

```
1/1 [==============================] - 0s 48ms/step
```

[16]:
```
print(f"Predicted Digit: {predicted_digit}")
print(f"Actual Digit: {actual_digit}")
```

```
Predicted Digit: 7
Actual Digit: 7
```

Here's a summary of the provided code and the key inferences drawn from it:

1. **Data Loading and Preprocessing:**
   - The code starts by importing necessary libraries, including NumPy, Matplotlib, and Keras.
   - It loads the MNIST dataset, which contains handwritten digit images and their corresponding labels.
   - The images are reshaped to a format suitable for training a neural network and are normalized to the range [0, 1].
   - The labels are one-hot encoded to represent the digit classes.
2. **Exploratory Data Analysis (EDA):**
   - The code performs EDA by visualizing the distribution of digit labels in the training set using a histogram.
   - It also displays sample images from the training set along with their corresponding labels, allowing you to visually inspect the data.
3. **Neural Network Model:**
   - A neural network model is defined using Keras. It consists of a flattening layer, followed by two dense (fully connected) hidden layers with ReLU activation functions, and an output layer with softmax activation for classification.
4. **Model Compilation and Training:**
   - The model is compiled with the Adam optimizer and categorical cross-entropy loss.
   - It is trained on the training data for 10 epochs with a batch size of 128, using 20% of the data as a validation set.
5. **Training and Validation Plots:**
   - The code generates two sets of plots:
     - Training and validation loss over epochs.
     - Training and validation accuracy over epochs.
   - These plots provide insights into the model's training performance.
6. **Model Evaluation:**
   - The trained model is evaluated on the test data, and the test accuracy is displayed.
7. **Digit Recognition Example:**
   - The code includes a `recognize_digit` function that takes an image and predicts the digit it represents.
   - An example digit recognition is performed on a sample image from the test set, showing the predicted and actual digits.

Inferences: - The model achieves a test accuracy of around 97% after training for 10 epochs. - The EDA plots provide an overview of the dataset's label distribution and sample images. - The training and validation loss curves indicate that the model converges during training without significant overfitting. - The training and validation accuracy curves show that the model's accuracy increases with training epochs.

Overall, this code demonstrates how to build, train, and evaluate a neural network model for handwritten digit recognition using the MNIST dataset. It also includes EDA and visualization techniques to understand the data and training progress.

[ ]:
```

```