Simple Neural Network for Handwritten Digit Recognition

Description

The MNIST dataset consists of 70,000 images of handwritten digits, each of size 28x28 pixels. Our goal is to train a neural network to classify these images into their corresponding digit classes. The project involves the following steps:

- **Data Preparation**: Load and preprocess the MNIST dataset.
- **Model Creation**: Build a simple feedforward neural network.
- **Model Training**: Train the model on the training set.
- **Evaluation**: Evaluate the model's performance on the test set.
- **Prediction**: Use the trained model to make predictions on new data.

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

1. **Data Preparation**:
   - We load the MNIST dataset using `mnist.load_data()`, which returns training and test sets.
   - The pixel values are normalized to the range [0, 1] for better convergence during training.
   - Labels are converted to categorical format using `to_categorical()`.

```
# Step 1: Data Preparation
# Load the MNIST dataset
(xTrain, yTrain), (xTest, yTest) = mnist.load_data()
```

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

```
xTrain, yTrain
```

```
(array([[[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.]]], dtype=float32),
 array([[0., 0., 0., ..., 0., 0., 0.],
        [1., 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., 1., 0.]]))
```

```
print(xTrain, yTrain)
```

```
[[[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]]] [5 0 4 ... 5 6 8]
```

```
xTest, yTest
```

```
(array([[[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]]], dtype=uint8),
 array([7, 2, 1, ..., 4, 5, 6], dtype=uint8))
```

```
print(xTest, yTest)
```

```
[[[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.]]] [7 2 1 ... 4 5 6]
```

```
# Normalize the pixel values to the range [0, 1]
xTrain = xTrain.astype('float32') / 255.0
xTest = xTest.astype('float32') / 255.0
```

```
xTrain
xTest
```

```
array([[[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.]]], dtype=float32)
```

```
# Convert labels to categorical format
yTrain = to_categorical(yTrain, num_classes=10)
yTest = to_categorical(yTest, num_classes=10)
```

```
yTrain, yTest
```

```
(array([[0., 0., 0., ..., 0., 0., 0.],
        [1., 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., 1., 0.]]),
 array([[0., 0., 0., ..., 1., 0., 0.],
        [0., 0., 1., ..., 0., 0., 0.],
        [0., 1., 0., ..., 0., 0., 0.],
        ...,
        [0., 0., 0., ..., 0., 0., 0.],
        [0., 0., 0., ..., 0., 0., 0.],
        [0., 0., 0., ..., 0., 0., 0.]]))
```

```
print(yTrain, yTest)
```

```
[[0. 0. 0. ... 0. 0. 0.]
 [1. 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. 1. 0.]] [[0. 0. 0. ... 1. 0. 0.]
[0. 0. 1. ... 0. 0. 0.]
[0. 1. 0. ... 0. 0. 0.]
...
[0. 0. 0. ... 0. 0. 0.]
[0. 0. 0. ... 0. 0. 0.]
[0. 0. 0. ... 0. 0. 0.]]
```

2. **Model Creation**:
   - A sequential model is initialized, and we add layers:
     - **Flatten Layer**: Converts the 28x28 images into a 784-dimensional vector.
     - **Dense Layer**: A hidden layer with 128 neurons and ReLU activation function.
     - **Output Layer**: A dense layer with 10 neurons (for digits 0-9) and softmax activation function to output probabilities.

```
# Step 2: Model Creation
# Initialize the model
model = Sequential()


# Add layers to the model
model.add(Flatten(input_shape=(28, 28))) # Flatten the input
model.add(Dense(128, activation='relu')) # Hidden layer with 128 neurons
model.add(Dense(10, activation='softmax')) # Output layer with 10 classes
```

```
/usr/local/lib/python3.10/dist-packages/keras/src/layers/reshaping/flatten.py:37: UserWarning:
  super().__init__(**kwargs)
```

3. **Model Compilation**:
   - The model is compiled using the Adam optimizer and categorical cross-entropy loss function, with accuracy as a metric.

```
# Step 3: Model Compilation
model.compile(optimizer='adam',
              loss='categorical_crossentropy',
              metrics=['accuracy'])
```

4. **Model Training**:
   - The model is trained on the training set for 10 epochs with a batch size of 32. We also use 20% of the training data for validation.

```
# Step 4: Model Training
model.fit(xTrain, yTrain, epochs=10, batch_size=32, validation_split=0.2)
```

```
Epoch 1/10
1500/1500 ━━━━━━━━━━━━━━━━━━━━ 8s 4ms/step - accuracy: 0.8701 - loss: 0.4688 - va
Epoch 2/10
1500/1500 ━━━━━━━━━━━━━━━━━━━━ 9s 3ms/step - accuracy: 0.9611 - loss: 0.1367 - va
Epoch 3/10
1500/1500 ━━━━━━━━━━━━━━━━━━━━ 7s 5ms/step - accuracy: 0.9744 - loss: 0.0901 - va
Epoch 4/10
1500/1500 ━━━━━━━━━━━━━━━━━━━━ 5s 3ms/step - accuracy: 0.9816 - loss: 0.0626 - va
Epoch 5/10
1500/1500 ━━━━━━━━━━━━━━━━━━━━ 7s 5ms/step - accuracy: 0.9848 - loss: 0.0495 - va
```

```
Epoch 6/10
1500/1500 ━━━━━━━━━━━━━━━━━━━━ 8s 3ms/step - accuracy: 0.9902 - loss: 0.0350 - va
Epoch 7/10
1500/1500 ━━━━━━━━━━━━━━━━━━━━ 7s 4ms/step - accuracy: 0.9909 - loss: 0.0303 - va
Epoch 8/10
1500/1500 ━━━━━━━━━━━━━━━━━━━━ 5s 3ms/step - accuracy: 0.9942 - loss: 0.0219 - va
Epoch 9/10
1500/1500 ━━━━━━━━━━━━━━━━━━━━ 7s 4ms/step - accuracy: 0.9945 - loss: 0.0185 - va
Epoch 10/10
1500/1500 ━━━━━━━━━━━━━━━━━━━━ 9s 3ms/step - accuracy: 0.9955 - loss: 0.0152 - va
<keras.src.callbacks.history.History at 0x7a19d43293f0>
```

5. **Model Evaluation**:
    - The model is evaluated on the test set, and the accuracy is printed.

```
# Step 5: Model Evaluation
test_loss, test_accuracy = model.evaluate(xTest, yTest)
print(f'Test accuracy: {test_accuracy:.4f}')
```

```
313/313 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9708 - loss: 0.1031
Test accuracy: 0.9745
```

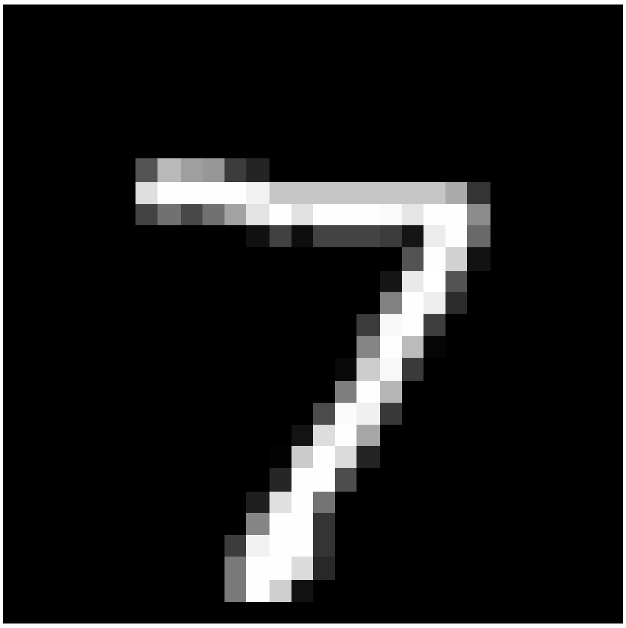
6. **Prediction**:
    - The model predicts the labels of the test set, and we visualize the first five test images along with their predicted and actual labels.

```
# Step 6: Prediction
predictions = model.predict(xTest)
```

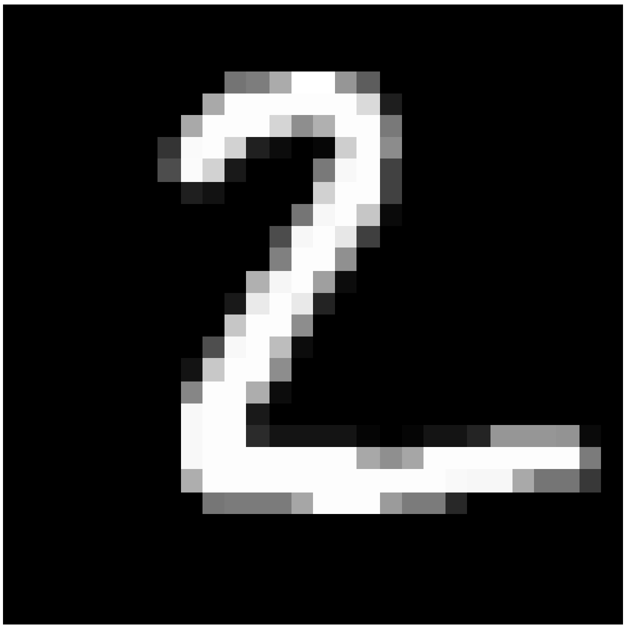
```
313/313 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step
```

```
# Display the first 5 test images and their predicted labels
for i in range(5):
    plt.imshow(xTest[i], cmap='gray')
    plt.title(f'Predicted: {np.argmax(predictions[i])}, Actual: {np.argmax(yTest[i])}')
    plt.axis('off')
    plt.show()
```

Predicted: 7, Actual: 7



Predicted: 2, Actual: 2



Predicted: 1, Actual: 1