dl3

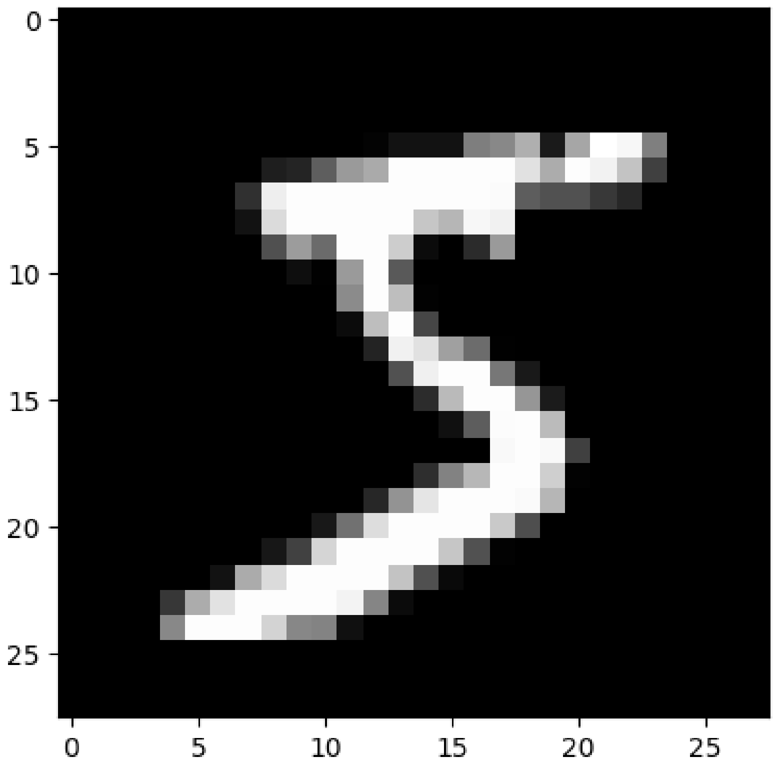
April 1, 2025

[1]:
```
import numpy as np
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout
from tensorflow.keras.optimizers import RMSprop
from tensorflow.keras.datasets import mnist
import matplotlib.pyplot as plt
from sklearn import metrics
```

[2]:
```
# Load the OCR dataset

# The MNIST dataset is a built-in dataset provided by Keras.
# It consists of 70,000 28x28 grayscale images, each of which displays a single␣
↪handwritten digit from 0 to 9.
# The training set consists of 60,000 images, while the test set has 10,000␣
↪images.

(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          0s
0us/step
```

[4]:
```
# X_train and X_test are our array of images while y_train and y_test are our␣
↪array of labels for each image.
# The first tuple contains the training set features (X_train) and the training␣
↪set labels (y_train).
# The second tuple contains the testing set features (X_test) and the testing␣
↪set labels (y_test).
# For example, if the image shows a handwritten 7, then the label will be the␣
↪intger 7.

plt.imshow(x_train[0], cmap='gray')  # imshow() function which simply displays␣
↪an image.
plt.show() # cmap is responsible for mapping a specific colormap to the values␣
↪found in the array that you passed as the first argument.
```



[5]:
```
# image appears black and white and that each axis of the plot ranges from 0 to 28.

# This is because of the format that all the images in the dataset have:

# 1. All the images are grayscale, meaning they only contain black, white and grey.
# 2. The images are 28 pixels by 25 pixels in size (28x28).

print(x_train[0])

# image data is just an array of digits. You can almost make out a 5 from the pattern of the digits in the array.
# Array of 28 values
# a grayscale pixel is stored as a digit between 0 and 255 where 0 is black, 255 is white and values in between are different shades of gray.
# Therefore, each value in the [28][28] array tells the computer which color to put in that position when we display the actual image.
```

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

```
   0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
    0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
    0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
    0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   3  18  18  18 126 136
  175  26 166 255 247 127   0   0   0   0]
 [  0   0   0   0   0   0   0   0  30  36  94 154 170 253 253 253 253 253
  225 172 253 242 195  64   0   0   0   0]
 [  0   0   0   0   0   0   0  49 238 253 253 253 253 253 253 253 253 251
   93  82  82  56  39   0   0   0   0   0]
 [  0   0   0   0   0   0   0  18 219 253 253 253 253 253 198 182 247 241
    0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0  80 156 107 253 253 205  11   0  43 154
    0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0  14   1 154 253  90   0   0   0   0
    0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0 139 253 190   2   0   0   0
    0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0  11 190 253  70   0   0   0
    0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0  35 241 225 160 108   1
    0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0  81 240 253 253 119
   25   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0  45 186 253 253
  150  27   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0  16  93 252
  253 187   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0 249
  253 249  64   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0  46 130 183 253
  253 207   2   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0  39 148 229 253 253 253
  250 182   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0  24 114 221 253 253 253 253 201
   78   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0  23  66 213 253 253 253 253 198  81   2
    0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0  18 171 219 253 253 253 253 195  80   9   0   0
    0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0  55 172 226 253 253 253 253 244 133  11   0   0   0   0
    0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0 136 253 253 253 212 135 132  16   0   0   0   0   0   0
    0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
```

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

[6]:
```
print("X_train shape", x_train.shape)
print("y_train shape", y_train.shape)
print("X_test shape", x_test.shape)
print("y_test shape", y_test.shape)
```

```
X_train shape (60000, 28, 28)
y_train shape (60000,)
X_test shape (10000, 28, 28)
y_test shape (10000,)
```

[7]:
```
# X: Training data of shape (n_samples, n_features)
# y: Training label values of shape (n_samples, n_labels)
# 2D array of height and width, 28 pixels by 28 pixels will just become 784␣
↪pixels (28 squared).
# Remember that X_train has 60,000 elemenets, each with 784 total pixels so␣
↪will become shape (60000, 784).
# Whereas X_test has 10,000 elements, each with each with 784 total pixels so␣
↪will become shape (10000, 784).

x_train = x_train.reshape(60000, 784)
x_test = x_test.reshape(10000, 784)
x_train = x_train.astype('float32') # use 32-bit precision when training a␣
↪neural network, so at one point the training data will have to be converted␣
↪to 32 bit floats. Since the dataset fits easily in RAM, we might as well␣
↪convert to float immediately.
x_test = x_test.astype('float32')
x_train /= 255  # Each image has Intensity from 0 to 255
x_test /= 255

# Regarding the division by 255, this is the maximum value of a byte (the input␣
↪feature's type before the conversion to float32),
# so this will ensure that the input features are scaled between 0.0 and 1.0.
# USING svm-https://mgta.gmu.edu/courses/ml-with-python/
↪handwrittenDigitRecognition.php#:~:
↪text=Remember%20that%20X_train%20has%2060%2C0
```

[8]:
```
# Convert class vectors to binary class matrices
num_classes = 10
y_train = np.eye(num_classes)[y_train]  # Return a 2-D array with ones on the␣
↪diagonal and zeros elsewhere.
```

```
y_test = np.eye(num_classes)[y_test] # f your particular categories is present␣
↪then it mark as 1 else 0 in remain r
```

[9]:
```
# Define the model architecture
model = Sequential()
model.add(Dense(512, activation='relu', input_shape=(784,)))  # The input_shape␣
↪argument is passed to the foremost layer. It comprises of a tuple shape,
model.add(Dropout(0.2)) # DROP OUT RATIO 20%
model.add(Dense(512, activation='relu')) #returns a sequence of vectors of␣
↪dimension 512
model.add(Dropout(0.2))
model.add(Dense(num_classes, activation='softmax'))
```

```
/usr/local/lib/python3.11/dist-packages/keras/src/layers/core/dense.py:87:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

[10]:
```
# Compile the model
model.compile(loss='categorical_crossentropy',  # for a multi-class␣
↪classification problem
              optimizer=RMSprop(),
              metrics=['accuracy'])
```

[11]:
```
# Train the model
batch_size = 128 # batch_size argument is passed to the layer to define a batch␣
↪size for the inputs.
epochs = 20
history = model.fit(x_train, y_train,
                    batch_size=batch_size,
                    epochs=epochs,
                    verbose=1, # verbose=1 will show you an animated progress␣
↪bar eg. [==========]
                    validation_data=(x_test, y_test)) # Using validation_data␣
↪means you are providing the training set and validation set yourself,
                                                      # validation_split means␣
↪you only provide a training set and keras splits it into a training set and␣
↪a validation set
```

```
Epoch 1/20
469/469              13s 25ms/step -
accuracy: 0.8615 - loss: 0.4496 - val_accuracy: 0.9598 - val_loss: 0.1299
Epoch 2/20
469/469              19s 21ms/step -
accuracy: 0.9664 - loss: 0.1092 - val_accuracy: 0.9732 - val_loss: 0.0896
Epoch 3/20
```

```
469/469              11s 23ms/step -
accuracy: 0.9767 - loss: 0.0771 - val_accuracy: 0.9775 - val_loss: 0.0757
Epoch 4/20
469/469              21s 24ms/step -
accuracy: 0.9830 - loss: 0.0571 - val_accuracy: 0.9791 - val_loss: 0.0700
Epoch 5/20
469/469              19s 22ms/step -
accuracy: 0.9849 - loss: 0.0460 - val_accuracy: 0.9838 - val_loss: 0.0617
Epoch 6/20
469/469              11s 23ms/step -
accuracy: 0.9874 - loss: 0.0388 - val_accuracy: 0.9835 - val_loss: 0.0610
Epoch 7/20
469/469              21s 24ms/step -
accuracy: 0.9892 - loss: 0.0324 - val_accuracy: 0.9812 - val_loss: 0.0658
Epoch 8/20
469/469              20s 23ms/step -
accuracy: 0.9916 - loss: 0.0272 - val_accuracy: 0.9824 - val_loss: 0.0709
Epoch 9/20
469/469              10s 21ms/step -
accuracy: 0.9913 - loss: 0.0268 - val_accuracy: 0.9823 - val_loss: 0.0661
Epoch 10/20
469/469              11s 23ms/step -
accuracy: 0.9926 - loss: 0.0230 - val_accuracy: 0.9831 - val_loss: 0.0736
Epoch 11/20
469/469              11s 23ms/step -
accuracy: 0.9939 - loss: 0.0188 - val_accuracy: 0.9840 - val_loss: 0.0754
Epoch 12/20
469/469              11s 24ms/step -
accuracy: 0.9948 - loss: 0.0161 - val_accuracy: 0.9823 - val_loss: 0.0798
Epoch 13/20
469/469              11s 23ms/step -
accuracy: 0.9944 - loss: 0.0162 - val_accuracy: 0.9841 - val_loss: 0.0730
Epoch 14/20
469/469              10s 22ms/step -
accuracy: 0.9954 - loss: 0.0135 - val_accuracy: 0.9849 - val_loss: 0.0676
Epoch 15/20
469/469              21s 23ms/step -
accuracy: 0.9957 - loss: 0.0137 - val_accuracy: 0.9819 - val_loss: 0.0801
Epoch 16/20
469/469              21s 24ms/step -
accuracy: 0.9959 - loss: 0.0125 - val_accuracy: 0.9848 - val_loss: 0.0762
Epoch 17/20
469/469              19s 21ms/step -
accuracy: 0.9967 - loss: 0.0104 - val_accuracy: 0.9850 - val_loss: 0.0759
Epoch 18/20
469/469              11s 24ms/step -
accuracy: 0.9963 - loss: 0.0111 - val_accuracy: 0.9847 - val_loss: 0.0850
Epoch 19/20
```

```
469/469                   20s 23ms/step -
accuracy: 0.9968 - loss: 0.0103 - val_accuracy: 0.9822 - val_loss: 0.0966
Epoch 20/20
469/469                   11s 23ms/step -
accuracy: 0.9968 - loss: 0.0104 - val_accuracy: 0.9842 - val_loss: 0.0831
```

[12]:

```python
# Evaluate the model
score = model.evaluate(x_test, y_test, verbose=0)
print('Test loss:', score[0])
print('Test accuracy:', score[1])
```

```
Test loss: 0.08312281966209412
Test accuracy: 0.9842000007629395
```

[ ]:

```
```