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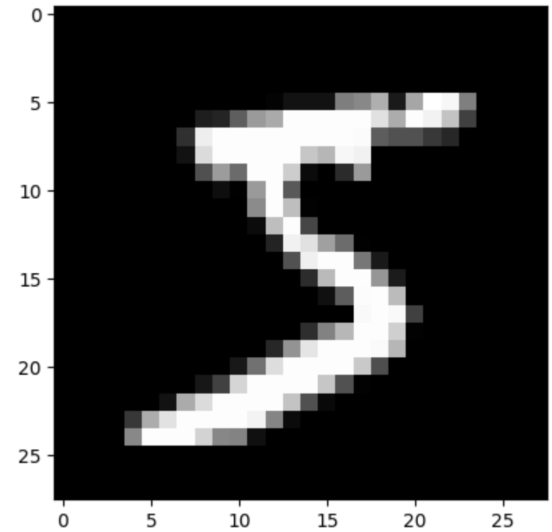
```
import numpy as np
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout
from tensorflow.keras.optimizers import RMSprop
from tensorflow.keras.datasets import mnist
import matplotlib.pyplot as plt
from sklearn import metrics


# 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
```

```
# 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.
# 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 (2
print(x_train[0])
```



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

```
# 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
# Therefore, each value in the [28][28] array tells the computer which color to put in that position when.
# reformat our X_train array and our X_test array because they do not have the correct shape. # Reshape the data to fit the model
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)
# Here you can see that for the training sets we have 60,000 elements and the testing sets have 10,000 elements.
# y_train and y_test only have 1 dimensional shapes because they are just the labels of each element.
# x_train and x_test have 3 dimensional shapes because they have a width and height (28x28 pixels) for each element.
# (60000, 28, 28) 1st parameter in the tuple shows us how much image we have 2nd and 3rd parameters are the pixel values from x to y (28
# The pixel value varies between 0 to 255.
# (60000,) Training labels with integers from 0-9 with dtype of uint8. It has the shape (60000,).
# (10000, 28, 28) Testing data that consists of grayscale images. It has the shape (10000, 28, 28) and the dtype of uint8. The pixel val
# (10000,) Testing labels that consist of integers from 0-9 with dtype uint8. It has the shape (10000,).
```

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

```
import numpy as np
import tensorflow as tf
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

# Load the MNIST dataset
(x_train, y_train), (x_test, y_test) = mnist.load_data()

# Reshape: flatten 28x28 images into vectors of size 784
x_train = x_train.reshape(60000, 784)
x_test = x_test.reshape(10000, 784)

# Convert pixel values from integers 0–255 to floats 0.0–1.0
x_train = x_train.astype('float32') / 255
x_test = x_test.astype('float32') / 255

# One-hot encode the labels (convert to binary class matrices)
num_classes = 10
y_train = np.eye(num_classes)[y_train.astype(int)]
y_test = np.eye(num_classes)[y_test.astype(int)]

# Define the model architecture
model = Sequential()
model.add(Dense(512, activation='relu', input_shape=(784,)))
model.add(Dropout(0.2))
model.add(Dense(512, activation='relu'))
model.add(Dropout(0.2))
model.add(Dense(num_classes, activation='softmax'))

# Compile the model
model.compile(
    loss='categorical_crossentropy',
    optimizer=RMSprop(),
    metrics=['accuracy']
)

# Train the model
batch_size = 128
epochs = 20

history = model.fit(
    x_train, y_train,
    batch_size=batch_size,
    epochs=epochs,
    verbose=1,
    validation_data=(x_test, y_test)
)

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

```
Epoch 1/20
469/469 ━━━━━━━━━━━━━━━━━━━━ 9s 18ms/step - accuracy: 0.8590 - loss: 0.4444 - val_accuracy: 0.9583 - val_loss: 0.1314
Epoch 2/20
469/469 ━━━━━━━━━━━━━━━━━━━━ 11s 19ms/step - accuracy: 0.9673 - loss: 0.1073 - val_accuracy: 0.9725 - val_loss: 0.0945
Epoch 3/20
469/469 ━━━━━━━━━━━━━━━━━━━━ 10s 21ms/step - accuracy: 0.9778 - loss: 0.0707 - val_accuracy: 0.9798 - val_loss: 0.0713
Epoch 4/20
469/469 ━━━━━━━━━━━━━━━━━━━━ 10s 20ms/step - accuracy: 0.9832 - loss: 0.0536 - val_accuracy: 0.9792 - val_loss: 0.0753
Epoch 5/20
469/469 ━━━━━━━━━━━━━━━━━━━━ 9s 18ms/step - accuracy: 0.9859 - loss: 0.0445 - val_accuracy: 0.9811 - val_loss: 0.0648
Epoch 6/20
```

```
469/469 ━━━━━━━━━━━━━━━━━━━━ 9s 20ms/step - accuracy: 0.9875 - loss: 0.0387 - val_accuracy: 0.9846 - val_loss: 0.0562
Epoch 7/20
469/469 ━━━━━━━━━━━━━━━━━━━━ 9s 20ms/step - accuracy: 0.9894 - loss: 0.0327 - val_accuracy: 0.9827 - val_loss: 0.0643
Epoch 8/20
```