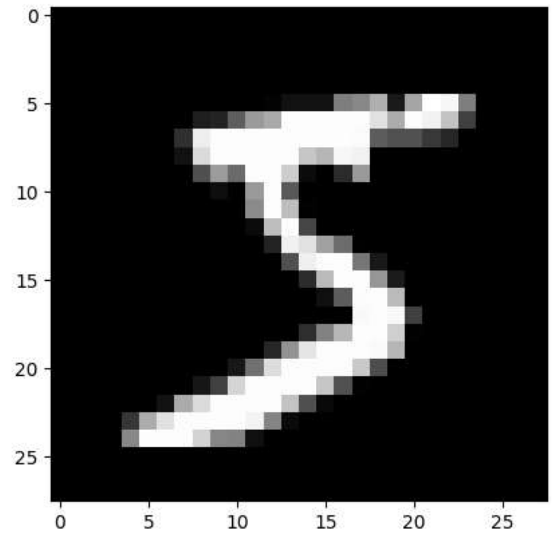
```
import numpy as np
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout
from tensorflow.keras.optimizers import RMSprop
from tensorflow.keras.datasets import mnist
import matplotlib.pyplot as plt
from sklearn import metrics

# 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()

# 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.

# 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 g
# 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]
```

```
# 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 (28x
# 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 valu
# (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,)
  250 182   0   0   0   0   0   0   0   0]
```

```
# 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 tc
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%2C00


# 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 row
```

```
# 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
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'))


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


# 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
                                                      # validation_split means you only provide a training set and keras splits it into a
```

```
Epoch 1/20
469/469 [==============================] - 12s 24ms/step - loss: 0.2539 - accuracy: 0.9216 - val_loss: 0.1443 - val_accuracy: 0.954
Epoch 2/20
469/469 [==============================] - 9s 20ms/step - loss: 0.1039 - accuracy: 0.9665 - val_loss: 0.0730 - val_accuracy: 0.9789
Epoch 3/20
469/469 [==============================] - 10s 22ms/step - loss: 0.0742 - accuracy: 0.9767 - val_loss: 0.0693 - val_accuracy: 0.979
Epoch 4/20
469/469 [==============================] - 11s 22ms/step - loss: 0.0565 - accuracy: 0.9827 - val_loss: 0.0669 - val_accuracy: 0.981
Epoch 5/20
469/469 [==============================] - 10s 22ms/step - loss: 0.0480 - accuracy: 0.9850 - val_loss: 0.0747 - val_accuracy: 0.979
Epoch 6/20
469/469 [==============================] - 10s 22ms/step - loss: 0.0396 - accuracy: 0.9872 - val_loss: 0.0699 - val_accuracy: 0.981
Epoch 7/20
469/469 [==============================] - 10s 20ms/step - loss: 0.0342 - accuracy: 0.9889 - val_loss: 0.0687 - val_accuracy: 0.983
Epoch 8/20
469/469 [==============================] - 11s 22ms/step - loss: 0.0294 - accuracy: 0.9903 - val_loss: 0.0661 - val_accuracy: 0.983
Epoch 9/20
469/469 [==============================] - 10s 22ms/step - loss: 0.0255 - accuracy: 0.9923 - val_loss: 0.0745 - val_accuracy: 0.982
Epoch 10/20
469/469 [==============================] - 10s 22ms/step - loss: 0.0220 - accuracy: 0.9930 - val_loss: 0.0734 - val_accuracy: 0.983
Epoch 11/20
469/469 [==============================] - 9s 19ms/step - loss: 0.0202 - accuracy: 0.9934 - val_loss: 0.0679 - val_accuracy: 0.9843
Epoch 12/20
469/469 [==============================] - 10s 22ms/step - loss: 0.0179 - accuracy: 0.9944 - val_loss: 0.0721 - val_accuracy: 0.985
Epoch 13/20
469/469 [==============================] - 10s 22ms/step - loss: 0.0170 - accuracy: 0.9946 - val_loss: 0.0684 - val_accuracy: 0.985
Epoch 14/20
469/469 [==============================] - 11s 23ms/step - loss: 0.0147 - accuracy: 0.9949 - val_loss: 0.0841 - val_accuracy: 0.982
Epoch 15/20
469/469 [==============================] - 10s 22ms/step - loss: 0.0138 - accuracy: 0.9956 - val_loss: 0.0802 - val_accuracy: 0.983
Epoch 16/20
469/469 [==============================] - 10s 21ms/step - loss: 0.0139 - accuracy: 0.9956 - val_loss: 0.0712 - val_accuracy: 0.984
Epoch 17/20
469/469 [==============================] - 10s 22ms/step - loss: 0.0124 - accuracy: 0.9959 - val_loss: 0.0695 - val_accuracy: 0.985
Epoch 18/20
469/469 [==============================] - 10s 22ms/step - loss: 0.0120 - accuracy: 0.9960 - val_loss: 0.0772 - val_accuracy: 0.986
Epoch 19/20
469/469 [==============================] - 11s 23ms/step - loss: 0.0094 - accuracy: 0.9968 - val_loss: 0.0829 - val_accuracy: 0.985
Epoch 20/20
469/469 [==============================] - 9s 20ms/step - loss: 0.0095 - accuracy: 0.9969 - val_loss: 0.0791 - val_accuracy: 0.9843
```

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

```
Test loss: 0.07907029986381531
Test accuracy: 0.9843000173568726
```