Lab Report TP-IMA4103 TP 1: MNIST Digit Recognition

Vakine KLABI

Outline: Introduction: 2 I) Application I: 2 a) Code for this part 2 b) Answer for all the exercises related to the script, and outputs of the script related to each 5 exercise Exercise 1: Modify the number of neurons on the hidden layer as specified in Table 1. What can be observed regarding the system accuracy? How about the convergence time necessary for the system to train a model? Exercise 2: Modify the batch size used to train the model as specified in Table 2. Select a value of 8 neurons for the hidden layer. What can be observed regarding the system accuracy? Exercise 3: Modify the metric used to determine the system performance from accuracy to mean square error (mse). Has this parameter any influence over the training process? 11 Exercise 4: Using the default parameters specified at Application 1 (8 neurons in hidden layer, 10 epochs and a batch size of 200 images), train the model and save the associated weights in a file (model.save weights), so it can be load anytime to perform further tests. Exercise 5: Write a novel Python script that loads the saved weights (model.load weights) at Exercise 4 and make a prediction on the first 5 images of the testing dataset 13 (mnist.test images()). I) Application II: 16 c) Code for this part 16 d) Answer for all the exercises related to the script, and outputs of the script related to each exercise 21 Exercise 6: Modify the size of the feature map within the convolutional layer as specified in Table 3. How is the system accuracy influenced by this parameter? 21 Figure 7: Table of results for exercise 6 23 Exercise 7: Modify the number of neurons in the dense hidden layer as specified in Table 4. Select a value of 3x3 neurons for the convolutional kernel. What can be observed regarding the system accuracy? How about the convergence time necessary for the system to train a 23 Exercise 8: Modify the number of epochs used to train the model as specified in Table 5. Select a value of 128 neurons in the dense hidden layer. What can be observed regarding the system accuracy? How about the convergence time? 25 Exercise 9: Modify the CNN architecture with additional convolutional, max pooling layers and fully connected layers 27

Introduction:

In this lab, we focus on the MNIST dataset, which contains images of handwritten digits. Our goal is to write Python scripts that will be able to recognize the digits from an input image. We will use two implementations, namely a CNN architecture (in the second application), and compare their performances.

I) Application I:

Please note: for your convenience, the outputs of this part have been grouped by exercise, not in one single part of the report.

The objective of this part is to write a Python script that is able to recognize the digit from an input image. The digits range from 0 to 9: as a result, there are 10 classes to predict. To train our model, we are going to use the MNIST dataset, which contains 60 000 images in the training set and 10 000 images in the validation set.

a) Code for this part

The following code (Figure 1) is the one we will analyze in this first part of our report. To improve our understanding of the code, we decided to rename a few variables (please see table below):

Name in the original code	Name in our code
X_train	train_images
Y_train	train_labels
X_test	test_images
Y_test	test_labels

We also added minor modifications to the code (namely to implement loops: for example, we added parameters in the function "trainAndPredictMLP(train_images, train_labels, test_images, test_labels, neurons, batch_size)", such as "neurons", or "batch_size". It allowed us to perform several trainings of the model by using a loop, to solve exercises 1 and 2. The code here is "frozen" in the state it has after solving exercise 4: if you want to check the solving of a particular exercise, please uncomment the corresponding parts.

```
#TODO - Application 1 - Step 6b - Define a hidden dense layer with 8 neurons
   model.add(layers.Dense(neurons, input dim=num pixels, kernel initializer='normal',
activation='relu')) # the number of neurons has to be modified here
    # for exercise 1
   #TODO - Application 1 - Step 6c - Define the output dense layer
   model.add(layers.Dense(num classes, kernel initializer='normal',
activation='softmax'))
    # TODO - Application 1 - Step 6d - Compile the model
   model.compile(loss='categorical crossentropy', optimizer='adam',
metrics=['accuracy'])
# the following line has been used to solve exercise 3:
 # model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['mse'])
   return model
def trainAndPredictMLP(train_images, train_labels, test_images, test_labels, neurons,
batch size):
   #TODO - Application 1 - Step 3 - Reshape the MNIST dataset - Transform the images to
1D vectors of floats (28x28 pixels to 784 elements)
   num_pixels = train_images.shape[1] * train_images.shape[2]
   train_images = train_images.reshape((train_images.shape[0],
num pixels)).astype('float32')
    test images = test images.reshape((test images.shape[0],
num pixels)).astype('float32')
   #TODO - Application 1 - Step 4 - Normalize the input values
   train images = train images / 255
   test images = test images / 255
   #TODO - Application 1 - Step 5 - Transform the classes labels into a binary matrix
   train labels = to categorical(train labels)
   test labels = to categorical(test labels)
   num_classes = test_labels.shape[1]
   #TODO - Application 1 - Step 6 - Build the model architecture - Call the
baseline model function
   model = baseline model(num pixels, num classes, neurons) #Modify this
   #TODO - Application 1 - Step 7 - Train the model
 start time=time.time()
   model.fit(train images, train labels, validation data=(test images, test labels),
epochs=10, batch size=batch size, verbose=2)
end time=time.time()
```

```
model.save weights('./application1.h5')
 convergence time=end time-start time
   #TODO - Application 1 - Step 8 - System evaluation - compute and display the
prediction error
   scores = model.evaluate(test images, test labels, verbose=2)
   print("Baseline Error: {:.2f}".format(100-scores[1]*100))
   #This line has also been used to solve exercise 3 instead of the line above using
the baseline error
  #print(f"mse of batch size {batch size}is: {scores[1]}")
print(f"the convergence time is : {convergence time:.2f} seconds\n")
   return
def main():
   #TODO - Application 1 - Step 1 - Load the MNIST dataset in Keras
   (train images, train labels), (test images, test labels) = mnist.load data()
#TODO - Application 1 - Step 2 - Train and predict on a MLP - Call the
trainAndPredictMLP function
# loop used to solve exercise 1
# neurons =[8,16,32,64,128]
# for neuron in neurons :
  # print("system performance with :", neuron, "neurons")
 # mlp = trainAndPredictMLP(train_images, train_labels, test_images, test_labels,
neuron, batch size=200)
   ### MLP : application 1, exercise 4
   neurons=8
   batch size=200
   mlp = trainAndPredictMLP(train images, train labels, test images, test labels,
neurons, batch size)
   # loop used to solve exercise 2
   # batch_sizes =[32,64,128,256,512]
   # for batch size in batch sizes :
       print("system performance with the following batch size :", batch size)
       mlp = trainAndPredictMLP(train images, train labels, test images, test labels,
neurons, batch size)
   #TODO - Application 2 - Step 1 - Train and predict on a CNN - Call the
trainAndPredictCNN function
   cnn = trainAndPredictCNN(train images, train labels, test images, test labels)
_name__ == '__main__':
   main()
```

b) Answer for all the exercises related to the script, and outputs of the script related to each exercise

Exercise 1: Modify the number of neurons on the hidden layer as specified in Table 1. What can be observed regarding the system accuracy? How about the convergence time necessary for the system to train a model?

In the first exercise, we are asked to train the model several times, but with a different number of neurons in the hidden layer each time. To do so, we implemented the yellow part of the code above: we added the parameter "neurons" to the trainAndPredictMLP function. In the main function, we defined an array "neurons" that contains all the different values of the number of neurons on the hidden layer that we want to use to train our model. We then used a "for" loop to perform the training. To obtain the convergence time (time necessary to perform the training), we recorded the time when the training started thanks to the function "time.time()", and the time when it ended. We then subtracted those two parameters and we obtained the following output and result (figure 2):

```
300/300 - 2s - loss: 1.1997 - accuracy: 0.6730 - val_loss: 0.52
90 - val_accuracy: 0.8612 - 2s/epoch - 6ms/step
Epoch 2/10
.
300/300 - 1s - loss: 0.4468 - accuracy: 0.8813 - val loss: 0.36
50 - val_accuracy: 0.9003 - 922ms/epoch - 3ms/step
Epoch 3/10
300/300 - 1s - loss: 0.3557 - accuracy: 0.9027 - val_loss: 0.32
42 - val_accuracy: 0.9095 - 949ms/epoch - 3ms/step
Fnoch 4/10
300/300 - 1s - loss: 0.3253 - accuracy: 0.9103 - val loss: 0.30
54 - val_accuracy: 0.9140 - 621ms/epoch - 2ms/step
Epoch 5/10
300/300 - 0s - loss: 0.3074 - accuracy: 0.9147 - val loss: 0.29
63 - val accuracy: 0.9174 - 486ms/epoch - 2ms/step
Epoch 6/10
300/300 - 1s - loss: 0.2953 - accuracy: 0.9179 - val loss: 0.28
35 - val_accuracy: 0.9207 - 613ms/epoch - 2ms/step
Epoch 7/10
300/300 - 1s - loss: 0.2864 - accuracy: 0.9205 - val loss: 0.27
71 - val_accuracy: 0.9236 - 752ms/epoch - 3ms/step
Epoch 8/10
300/300 - 1s - loss: 0.2788 - accuracy: 0.9225 - val_loss: 0.27
29 - val accuracy: 0.9236 - 628ms/epoch - 2ms/step
Fpoch 9/10
300/300 - 1s - loss: 0.2726 - accuracy: 0.9239 - val_loss: 0.27
00 - val_accuracy: 0.9252 - 550ms/epoch - 2ms/step
Epoch 10/10
300/300 - 1s - loss: 0.2674 - accuracy: 0.9256 - val loss: 0.26
40 - val_accuracy: 0.9261 - 651ms/epoch - 2ms/step
313/313 - 1s - loss: 0.2640 - accuracy: 0.9261 - 525ms/epoch -
Baseline Error: 7.39
the convergence time is: 8.15 seconds
```

```
system performance with : 16 neurons
Fnoch 1/10
300/300 - 1s - loss: 0.9446 - accuracy: 0.7575 - val_loss: 0.40
31 - val_accuracy: 0.8946 - 1s/epoch - 4ms/step
Epoch 2/10
300/300 - 1s - loss: 0.3570 - accuracy: 0.9014 - val loss: 0.30
16 - val accuracy: 0.9173 - 662ms/epoch - 2ms/step
Epoch 3/10
300/300 - 1s - loss: 0.2977 - accuracy: 0.9159 - val loss: 0.26
83 - val_accuracy: 0.9232 - 678ms/epoch - 2ms/step
Epoch 4/10
300/300 - 1s - loss: 0.2685 - accuracy: 0.9238 - val loss: 0.24
75 - val accuracy: 0.9304 - 698ms/epoch - 2ms/step
Epoch 5/10
300/300 - 1s - loss: 0.2493 - accuracy: 0.9296 - val loss: 0.23
82 - val_accuracy: 0.9318 - 594ms/epoch - 2ms/step
Epoch 6/10
63 - val_accuracy: 0.9349 - 584ms/epoch - 2ms/step
Epoch 7/10
300/300 - 1s - loss: 0.2239 - accuracy: 0.9370 - val loss: 0.21
80 - val accuracy: 0.9375 - 666ms/epoch - 2ms/step
Epoch 8/10
300/300 - 0s - loss: 0.2153 - accuracy: 0.9392 - val_loss: 0.20
90 - val_accuracy: 0.9394 - 478ms/epoch - 2ms/step
Epoch 9/10
300/300 - 1s - loss: 0.2075 - accuracy: 0.9413 - val_loss: 0.20
55 - val accuracy: 0.9408 - 652ms/epoch - 2ms/step
Epoch 10/10
.
300/300 - 1s - loss: 0.2010 - accuracy: 0.9431 - val_loss: 0.20
18 - val_accuracy: 0.9417 - 809ms/epoch - 3ms/step
313/313 - 1s - loss: 0.2018 - accuracy: 0.9417 - 640ms/epoch -
2ms/step
Baseline Error: 5.83
the convergence time is : 7.27 seconds
```

```
system performance with : 32 neurons
Epoch 1/10
200/300 - 1s - loss: 0.7385 - accuracy: 0.8179 - val_loss: 0.31
84 - val_accuracy: 0.9119 - 1s/epoch - 5ms/step
Epoch 2/10
300/300 - 1s - loss: 0.2906 - accuracy: 0.9181 - val_loss: 0.25
10 - val_accuracy: 0.9276 - 766ms/epoch - 3ms/step
Epoch 3/10
300/300 - 1s - loss: 0.2395 - accuracy: 0.9321 - val_loss: 0.21
71 - val_accuracy: 0.9369 - 864ms/epoch - 3ms/step
300/300 - 1s - loss: 0.2089 - accuracy: 0.9402 - val_loss: 0.19
70 - val_accuracy: 0.9431 - 722ms/epoch - 2ms/step
Epoch 5/10
300/300 - 1s - loss: 0.1873 - accuracy: 0.9461 - val_loss: 0.18
19 - val_accuracy: 0.9455 - 1s/epoch - 4ms/step
Epoch 6/10
300/300 - 1s - loss: 0.1698 - accuracy: 0.9514 - val_loss: 0.16
84 - val_accuracy: 0.9509 - 1s/epoch - 3ms/step
Epoch 7/10
300/300 - 1s - loss: 0.1569 - accuracy: 0.9554 - val loss: 0.15
83 - val_accuracy: 0.9532 - 557ms/epoch - 2ms/step
Epoch 8/10
300/300 - 1s - loss: 0.1465 - accuracy: 0.9575 - val_loss: 0.15
49 - val_accuracy: 0.9521 - 881ms/epoch - 3ms/step
300/300 - 1s - loss: 0.1374 - accuracy: 0.9604 - val_loss: 0.14
48 - val_accuracy: 0.9561 - 606ms/epoch - 2ms/step
300/300 - 1s - loss: 0.1294 - accuracy: 0.9622 - val_loss: 0.14
12 - val_accuracy: 0.9576 - 570ms/epoch - 2ms/step
313/313 - 1s - loss: 0.1412 - accuracy: 0.9576 - 569ms/epoch -
Baseline Error: 4.24
the convergence time is : 8.59 seconds
```

6

```
system performance with: 64 neurons
Epoch 1/10
.
300/300 - 1s - loss: 0.5940 - accuracy: 0.8554 - val_loss: 0.28
73 - val accuracy: 0.9205 - 1s/epoch - 5ms/step
Epoch 2/10
300/300 - 1s - loss: 0.2610 - accuracy: 0.9260 - val loss: 0.22
31 - val accuracy: 0.9371 - 909ms/epoch - 3ms/step
Epoch 3/10
300/300 - 1s - loss: 0.2070 - accuracy: 0.9418 - val loss: 0.18
78 - val_accuracy: 0.9450 - 1s/epoch - 4ms/step
Epoch 4/10
300/300 - 1s - loss: 0.1717 - accuracy: 0.9510 - val_loss: 0.16
22 - val accuracy: 0.9518 - 1s/epoch - 4ms/step
Epoch 5/10
300/300 - 1s - loss: 0.1474 - accuracy: 0.9576 - val loss: 0.14
43 - val_accuracy: 0.9564 - 810ms/epoch - 3ms/step
Epoch 6/10
300/300 - 1s - loss: 0.1275 - accuracy: 0.9637 - val_loss: 0.13
38 - val accuracy: 0.9626 - 1s/epoch - 3ms/step
Epoch 7/10
300/300 - 1s - loss: 0.1133 - accuracy: 0.9673 - val loss: 0.11
96 - val accuracy: 0.9634 - 985ms/epoch - 3ms/step
Epoch 8/10
31 - val_accuracy: 0.9669 - 1s/epoch - 4ms/step
Epoch 9/10
300/300 - 1s - loss: 0.0912 - accuracy: 0.9736 - val loss: 0.10
75 - val_accuracy: 0.9671 - 750ms/epoch - 2ms/step
Epoch 10/10
300/300 - 1s - loss: 0.0826 - accuracy: 0.9761 - val loss: 0.10
20 - val_accuracy: 0.9689 - 685ms/epoch - 2ms/step
313/313 - 1s - loss: 0.1020 - accuracy: 0.9689 - 543ms/epoch -
2ms/step
Baseline Error: 3.11
the convergence time is : 10.01 seconds
     system performance with : 128 neurons
     Epoch 1/10
     300/300 - 2s - loss: 0.4863 - accuracy: 0.8773 - val_loss: 0.25
     Fnoch 2/10
     300/300 - 1s - loss: 0.2193 - accuracy: 0.9381 - val_loss: 0.18
     87 - val accuracy: 0.9454 - 1s/epoch - 5ms/step
     Epoch 3/10
     300/300 - 2s - loss: 0.1646 - accuracy: 0.9531 - val loss: 0.14
     41 - val accuracy: 0.9583 - 2s/epoch - 6ms/step
     Epoch 4/\overline{10}
     300/300 - 1s - loss: 0.1312 - accuracy: 0.9628 - val_loss: 0.13
     15 - val_accuracy: 0.9614 - 1s/epoch - 4ms/step
     Epoch 5/10
     300/300 - 1s - loss: 0.1063 - accuracy: 0.9697 - val_loss: 0.10
     75 - val_accuracy: 0.9675 - 1s/epoch - 4ms/step
     Epoch 6/10
     300/300 - 1s - loss: 0.0887 - accuracy: 0.9746 - val loss: 0.09
     81 - val accuracy: 0.9707 - 1s/epoch - 4ms/step
     Epoch 7/10
     300/300 - 1s - loss: 0.0758 - accuracy: 0.9786 - val_loss: 0.09
      30 - val_accuracy: 0.9723 - 1s/epoch - 4ms/step
     Epoch 8/10
     300/300 - 1s - loss: 0.0654 - accuracy: 0.9811 - val_loss: 0.08
     85 - val_accuracy: 0.9735 - 1s/epoch - 4ms/step
     Epoch 9/10
     300/300 - 1s - loss: 0.0570 - accuracy: 0.9840 - val_loss: 0.08
49 - val_accuracy: 0.9750 - 1s/epoch - 4ms/step
     Epoch 10/10
     300/300 - 1s - loss: 0.0500 - accuracy: 0.9859 - val_loss: 0.08
12 - val_accuracy: 0.9750 - 1s/epoch - 4ms/step
     313/313 - 1s - loss: 0.0812 - accuracy: 0.9750 - 530ms/epoch -
      2ms/step
     Baseline Error: 2.50
     the convergence time is: 13.44 seconds
```

Number of	8	16	32	64	128
neurons					

System Accuracy	0.9261	0.9417	0.9576	0.9689	0.9750
Convergence time (s)	8.15	7.27	8.59	10.01	13.44

Figure 2: Table of results for exercise 1

The first thing we can notice is that the accuracy seems to increase with the number of neurons contained by the hidden layer. It seems quite logical to us: the more neurons there are, the more complex patterns the neural network can learn/the better it learns. As for the convergence time, it seems to increase with the number of neurons. However, it does not increase "linearly" mathematically speaking.

In fact, this increase seems obvious because adding more neurons to the hidden layers of the network generates more operations and more calculations, which requires more computations. This is why the convergence time increases with the number of neurons.

Exercise 2: Modify the batch size used to train the model as specified in Table 2. Select a value of 8 neurons for the hidden layer. What can be observed regarding the system accuracy?

Let's take a look at the orange part of the code above. The exercise asks us to train the model using different batch sizes. To do so, we have used the same strategy as in exercise 1, which is to create a loop (see below) that does all the training processes we need in one run of the program.

```
batch_sizes =[32,64,128,256,512]
for batch_size in batch_sizes :
    print("system performance with the following batch size :", batch_size)
    mlp = trainAndPredictMLP(train_images, train_labels, test_images, test_labels,
neurons, batch_size)
```

Extract from the code above: loop to train the model with different batch sizes

The outputs of our code are shown below. They are summarized in the following table (figure 3):

```
system performance with the following batch size: 32
Epoch 1/10
1875/1875 - 14s - loss: 0.5999 - accuracy: 0.8301 - val_loss: 0.3415 - val_accuracy: 0.9015 - 14s/epoch - 8ms/step
Epoch 2/10
1875/1875 - 11s - loss: 0.3265 - accuracy: 0.9071 - val loss: 0.3014 - val accuracy: 0.9142 - 11s/epoch - 6ms/step
Epoch 3/10
1875/1875 - 8s - loss: 0.3004 - accuracy: 0.9147 - val loss: 0.2896 - val accuracy: 0.9191 - 8s/epoch - 4ms/step
Epoch 4/10
1875/1875 - 13s - loss: 0.2869 - accuracy: 0.9195 - val_loss: 0.2847 - val_accuracy: 0.9196 - 13s/epoch - 7ms/step
Epoch 5/10
1875/1875 - 13s - loss: 0.2782 - accuracy: 0.9219 - val_loss: 0.2876 - val_accuracy: 0.9172 - 13s/epoch - 7ms/step
1875/1875 - 11s - loss: 0.2718 - accuracy: 0.9232 - val loss: 0.2799 - val accuracy: 0.9190 - 11s/epoch - 6ms/step
1875/1875 - 12s - loss: 0.2657 - accuracy: 0.9253 - val loss: 0.2730 - val accuracy: 0.9244 - 12s/epoch - 6ms/step
Epoch 8/10
1875/1875 - 12s - loss: 0.2610 - accuracy: 0.9265 - val loss: 0.2701 - val accuracy: 0.9254 - 12s/epoch - 7ms/step
Epoch 9/10
1875/1875 - 13s - loss: 0.2565 - accuracy: 0.9280 - val_loss: 0.2709 - val_accuracy: 0.9258 - 13s/epoch - 7ms/step
Epoch 10/10
1875/1875 - 13s - loss: 0.2532 - accuracy: 0.9287 - val_loss: 0.2733 - val_accuracy: 0.9225 - 13s/epoch - 7ms/step
313/313 - 2s - loss: 0.2733 - accuracy: 0.9225 - 2s/epoch - 6ms/step
Baseline Error: 7.75
the convergence time is 119.87452912330627 seconds
```

```
system performance with the following batch size: 64
Epoch 1/10
938/938 - 7s - loss: 0.7368 - accuracy: 0.8009 - val loss: 0.3736 - val accuracy: 0.8947 - 7s/epoch - 7ms/step
Epoch 2/10
938/938 - 6s - loss: 0.3502 - accuracy: 0.9003 - val loss: 0.3144 - val accuracy: 0.9112 - 6s/epoch - 7ms/step
Epoch 3/10
938/938 - 6s - loss: 0.3109 - accuracy: 0.9112 - val_loss: 0.2968 - val_accuracy: 0.9168 - 6s/epoch - 7ms/step
Epoch 4/10
938/938 - 6s - loss: 0.2936 - accuracy: 0.9164 - val_loss: 0.2866 - val_accuracy: 0.9197 - 6s/epoch - 7ms/step
Epoch 5/10
938/938 - 6s - loss: 0.2831 - accuracy: 0.9195 - val_loss: 0.2795 - val_accuracy: 0.9222 - 6s/epoch - 7ms/step
Epoch 6/10
938/938 - 7s - loss: 0.2755 - accuracy: 0.9222 - val loss: 0.2755 - val accuracy: 0.9241 - 7s/epoch - 7ms/step
Epoch 7/10
938/938 - 7s - loss: 0.2693 - accuracy: 0.9242 - val_loss: 0.2708 - val_accuracy: 0.9229 - 7s/epoch - 8ms/step
Epoch 8/10
938/938 - 7s - loss: 0.2646 - accuracy: 0.9251 - val_loss: 0.2707 - val_accuracy: 0.9251 - 7s/epoch - 8ms/step
Epoch 9/10
938/938 - 7s - loss: 0.2611 - accuracy: 0.9266 - val loss: 0.2674 - val accuracy: 0.9242 - 7s/epoch - 8ms/step
Epoch 10/10
938/938 - 7s - loss: 0.2569 - accuracy: 0.9273 - val_loss: 0.2623 - val_accuracy: 0.9262 - 7s/epoch - 7ms/step
313/313 - 1s - loss: 0.2623 - accuracy: 0.9262 - 903ms/epoch - 3ms/step
Baseline Error: 7.38
the convergence time is 67.12950158119202 seconds
system performance with the following batch size: 128
Epoch 1/10
469/469 - 3s - loss: 0.9532 - accuracy: 0.7358 - val_loss: 0.4515 - val_accuracy: 0.8720 - 3s/epoch - 7ms/step
Epoch 2/10
469/469 - 3s - loss: 0.4156 - accuracy: 0.8787 - val_loss: 0.3641 - val_accuracy: 0.8929 - 3s/epoch - 7ms/step
Epoch 3/10
469/469 - 3s - loss: 0.3622 - accuracy: 0.8944 - val loss: 0.3377 - val accuracy: 0.9009 - 3s/epoch - 7ms/step
Epoch 4/10
469/469 - 2s - loss: 0.3368 - accuracy: 0.9020 - val loss: 0.3262 - val accuracy: 0.9069 - 2s/epoch - 5ms/step
Epoch 5/10
469/469 - 2s - loss: 0.3198 - accuracy: 0.9073 - val loss: 0.3145 - val accuracy: 0.9086 - 2s/epoch - 5ms/step
Epoch 6/10
469/469 - 2s - loss: 0.3079 - accuracy: 0.9113 - val loss: 0.3055 - val accuracy: 0.9150 - 2s/epoch - 5ms/step
Epoch 7/10
469/469 - 2s - loss: 0.2973 - accuracy: 0.9149 - val_loss: 0.2972 - val_accuracy: 0.9161 - 2s/epoch - 5ms/step
469/469 - 2s - loss: 0.2891 - accuracy: 0.9176 - val_loss: 0.2918 - val_accuracy: 0.9192 - 2s/epoch - 5ms/step
Epoch 9/10
469/469 - 2s - loss: 0.2834 - accuracy: 0.9199 - val_loss: 0.2872 - val_accuracy: 0.9213 - 2s/epoch - 5ms/step
Epoch 10/10
469/469 - 2s - loss: 0.2781 - accuracy: 0.9216 - val_loss: 0.2849 - val_accuracy: 0.9212 - 2s/epoch - 4ms/step
313/313 - 1s - loss: 0.2849 - accuracy: 0.9212 - 900ms/epoch - 3ms/step
Baseline Error: 7.88
the convergence time is 25.393945455551147 seconds
```

```
system performance with the following batch size : 256
Epoch 1/10
235/235 - 2s - loss: 1.3310 - accuracy: 0.6032 - val_loss: 0.6583 - val_accuracy: 0.8206 - 2s/epoch - 8ms/step
Epoch 2/10
235/235 - 1s - loss: 0.5269 - accuracy: 0.8572 - val loss: 0.4214 - val accuracy: 0.8829 - 1s/epoch - 5ms/step
Epoch 3/10
235/235 - 2s - loss: 0.3952 - accuracy: 0.8905 - val_loss: 0.3533 - val_accuracy: 0.9023 - 2s/epoch - 8ms/step
Epoch 4/10
235/235 - 2s - loss: 0.3489 - accuracy: 0.9023 - val_loss: 0.3228 - val_accuracy: 0.9075 - 2s/epoch - 9ms/step
Epoch 5/10
235/235 - 2s - loss: 0.3241 - accuracy: 0.9076 - val_loss: 0.3101 - val_accuracy: 0.9115 - 2s/epoch - 9ms/step
Epoch 6/10
235/235 - 2s - loss: 0.3088 - accuracy: 0.9120 - val_loss: 0.2960 - val_accuracy: 0.9153 - 2s/epoch - 8ms/step
Epoch 7/10
235/235 - 2s - loss: 0.2980 - accuracy: 0.9154 - val loss: 0.2916 - val accuracy: 0.9168 - 2s/epoch - 8ms/step
Epoch 8/10
235/235 - 1s - loss: 0.2904 - accuracy: 0.9179 - val_loss: 0.2834 - val_accuracy: 0.9194 - 1s/epoch - 5ms/step
Epoch 9/10
235/235 - 2s - loss: 0.2836 - accuracy: 0.9199 - val loss: 0.2794 - val accuracy: 0.9206 - 2s/epoch - 6ms/step
Epoch 10/10
235/235 - 2s - loss: 0.2784 - accuracy: 0.9215 - val_loss: 0.2733 - val_accuracy: 0.9231 - 2s/epoch - 8ms/step
313/313 - 1s - loss: 0.2733 - accuracy: 0.9231 - 756ms/epoch - 2ms/step
Baseline Error: 7.69
the convergence time is 17.468879222869873 seconds
system performance with the following batch size : 512
Epoch 1/10
118/118 - 2s - loss: 1.7648 - accuracy: 0.4765 - val_loss: 1.0723 - val_accuracy: 0.7776 - 2s/epoch - 14ms/step
Epoch 2/10
118/118 - 1s - loss: 0.7582 - accuracy: 0.8181 - val loss: 0.5422 - val accuracy: 0.8634 - 778ms/epoch - 7ms/step
Epoch 3/10
118/118 - 1s - loss: 0.4864 - accuracy: 0.8743 - val loss: 0.4128 - val accuracy: 0.8891 - 809ms/epoch - 7ms/step
Epoch 4/10
118/118 - 1s - loss: 0.4017 - accuracy: 0.8911 - val_loss: 0.3622 - val_accuracy: 0.8996 - 758ms/epoch - 6ms/step
Epoch 5/10
118/118 - 1s - loss: 0.3623 - accuracy: 0.9000 - val_loss: 0.3368 - val_accuracy: 0.9044 - 864ms/epoch - 7ms/step
Epoch 6/10
118/118 - 1s - loss: 0.3400 - accuracy: 0.9057 - val_loss: 0.3222 - val_accuracy: 0.9067 - 1s/epoch - 11ms/step
Epoch 7/10
118/118 - 1s - loss: 0.3251 - accuracy: 0.9085 - val_loss: 0.3097 - val_accuracy: 0.9112 - 1s/epoch - 11ms/step
Epoch 8/10
118/118 - 1s - loss: 0.3139 - accuracy: 0.9112 - val loss: 0.3024 - val accuracy: 0.9138 - 1s/epoch - 10ms/step
Epoch 9/10
118/118 - 1s - loss: 0.3058 - accuracy: 0.9136 - val_loss: 0.2955 - val_accuracy: 0.9155 - 914ms/epoch - 8ms/step
Epoch 10/10
118/118 - 1s - loss: 0.2986 - accuracy: 0.9162 - val_loss: 0.2900 - val_accuracy: 0.9161 - 1s/epoch - 10ms/step
313/313 - 1s - loss: 0.2900 - accuracy: 0.9161 - 1s/epoch - 4ms/step
Baseline Error: 8.39
the convergence time is 10.958871364593506 seconds
```

Batch size	32	64	128	256	512
System Accuracy	0.9225	0.9262	0.9212	0.9231	0.9161

Figure 3: Table of results for exercise 2

In our case, we did not really notice any relationship between the batch_size and the accuracy of our model. However, we think that as the batch_size represents the number of samples from the dataset that is used to train the model in one forward/backward pass, when the batch_size is relatively important, the training time decreases. However, it has several side effects: indeed, the higher the batch size, the more memory space we might need to perform the training. Moreover, a large batch_size can cause a decrease in accuracy (the neural network does not manage to generalize very well the patterns it finds). On the other hand, having a relatively small batch_size can be useful to converge more quickly towards good results. However, the training can take more memory space with

this setting, and can cause overfitting because of a possibly noisy weight update. Thus, it is important to find a good tradeoff between accuracy, speed and memory space taken to reach the best performance possible according to the hardware's capacity.

Exercise 3: Modify the metric used to determine the system performance from accuracy to mean square error (mse). Has this parameter any influence over the training process?

The MSE is defined as follows:

$$MSE = \frac{1}{N} \sum_{i=1}^{N} (y_i - y_{i_{predicted}})^2$$

Here, the subtraction represents the difference between the ground truth score and the predicted score. To implement the mse as a metrics in the code, we have written the line in pink, where we replace "accuracy" by "mse" in the "metrics" parameter of the compile function. We have used the same process as in the previous exercise, where we have trained our model using different batch sizes every time.

The following outputs are summarized in the table below:

1875/1875 - 3s - loss: 0.5881 - mse: 0.0258 - val_loss: 0.3447 - val_mse: 0.0152 - 3s/epoch - 2ms/step

```
Epoch 2/10
1875/1875 - 2s - loss: 0.3266 - mse: 0.0143 - val loss: 0.3024 - val mse: 0.0132 - 2s/epoch - 1ms/step
Epoch 3/10
1875/1875 - 3s - loss: 0.3040 - mse: 0.0133 - val_loss: 0.3023 - val_mse: 0.0134 - 3s/epoch - 2ms/step
Epoch 4/10
1875/1875 - 3s - loss: 0.2923 - mse: 0.0127 - val_loss: 0.2897 - val_mse: 0.0125 - 3s/epoch - 2ms/step
1875/1875 - 3s - loss: 0.2841 - mse: 0.0123 - val_loss: 0.2840 - val_mse: 0.0124 - 3s/epoch - 2ms/step
Epoch 6/10
1875/1875 - 3s - loss: 0.2775 - mse: 0.0121 - val_loss: 0.2814 - val_mse: 0.0122 - 3s/epoch - 2ms/step
Epoch 7/10
1875/1875 - 3s - loss: 0.2722 - mse: 0.0119 - val loss: 0.2806 - val mse: 0.0124 - 3s/epoch - 2ms/step
Epoch 8/10
1875/1875 - 3s - loss: 0.2695 - mse: 0.0117 - val_loss: 0.2795 - val_mse: 0.0121 - 3s/epoch - 2ms/step
Epoch 9/10
1875/1875 - 3s - loss: 0.2651 - mse: 0.0116 - val_loss: 0.2773 - val_mse: 0.0120 - 3s/epoch - 2ms/step
Epoch 10/10
1875/1875 - 3s - loss: 0.2632 - mse: 0.0115 - val_loss: 0.2807 - val_mse: 0.0122 - 3s/epoch - 2ms/step
313/313 - 0s - loss: 0.2807 - mse: 0.0122 - 388ms/epoch - 1ms/step mse of batch size 32is: 0.012228482402861118
the convergence time is: 29.40 seconds
                                                                                       Activer Windows
system performance with the following batch size : 64
938/938 - 2s - loss: 0.7241 - mse: 0.0318 - val loss: 0.3736 - val mse: 0.0167 - 2s/epoch - 2ms/step
Epoch 2/10
938/938 - 2s - loss: 0.3514 - mse: 0.0155 - val_loss: 0.3162 - val_mse: 0.0138 - 2s/epoch - 2ms/step
Fnoch 3/10
938/938 - 1s - loss: 0.3150 - mse: 0.0138 - val loss: 0.2988 - val mse: 0.0129 - 1s/epoch - 1ms/step
 Epoch 4/10
 938/938 - 2s - loss: 0.2966 - mse: 0.0130 - val_loss: 0.2935 - val_mse: 0.0128 - 2s/epoch - 2ms/step
Epoch 5/10
938/938 - 2s - loss: 0.2849 - mse: 0.0124 - val loss: 0.2854 - val mse: 0.0123 - 2s/epoch - 2ms/step
Epoch 6/10
938/938 - 2s - loss: 0.2762 - mse: 0.0120 - val_loss: 0.2782 - val_mse: 0.0119 - 2s/epoch - 2ms/step
Epoch 7/10
938/938 - 2s - loss: 0.2695 - mse: 0.0117 - val_loss: 0.2734 - val_mse: 0.0116 - 2s/epoch - 2ms/step
 Epoch 8/10
938/938 - 2s - loss: 0.2641 - mse: 0.0115 - val loss: 0.2701 - val mse: 0.0116 - 2s/epoch - 2ms/step
Epoch 9/10
938/938 - 2s - loss: 0.2593 - mse: 0.0113 - val_loss: 0.2719 - val_mse: 0.0117 - 2s/epoch - 2ms/step
Epoch 10/10
938/938 - 2s - loss: 0.2551 - mse: 0.0111 - val loss: 0.2730 - val mse: 0.0118 - 2s/epoch - 2ms/step
313/313 - 0s - loss: 0.2730 - mse: 0.0118 - 389ms/epoch - 1ms/step
 mse of batch size 64is: 0.011778264306485653
the convergence time is: 15.96 seconds
```

```
system performance with the following batch size : 128
  Epoch 1/10
  469/469 - 1s - loss: 0.9530 - mse: 0.0413 - val_loss: 0.4280 - val_mse: 0.0190 - 1s/epoch - 3ms/step
  Epoch 2/10
  469/469 - 1s - loss: 0.3866 - mse: 0.0170 - val loss: 0.3438 - val mse: 0.0151 - 852ms/epoch - 2ms/step
  Epoch 3/10
  469/469 - 1s - loss: 0.3373 - mse: 0.0147 - val_loss: 0.3185 - val_mse: 0.0138 - 861ms/epoch - 2ms/step
  Epoch 4/10
  469/469 - 1s - loss: 0.3159 - mse: 0.0137 - val loss: 0.3023 - val mse: 0.0131 - 868ms/epoch - 2ms/step
  Fnoch 5/10
  469/469 - 1s - loss: 0.3038 - mse: 0.0132 - val_loss: 0.2913 - val_mse: 0.0127 - 918ms/epoch - 2ms/step
  Epoch 6/10
  469/469 - 1s - loss: 0.2941 - mse: 0.0128 - val_loss: 0.2854 - val_mse: 0.0124 - 854ms/epoch - 2ms/step
  Epoch 7/10
  469/469 - 1s - loss: 0.2862 - mse: 0.0124 - val loss: 0.2793 - val mse: 0.0120 - 884ms/epoch - 2ms/step
  Fnoch 8/10
  469/469 - 1s - loss: 0.2796 - mse: 0.0121 - val loss: 0.2759 - val mse: 0.0120 - 847ms/epoch - 2ms/step
  469/469 - 1s - loss: 0.2736 - mse: 0.0119 - val loss: 0.2754 - val mse: 0.0120 - 862ms/epoch - 2ms/step
  Epoch 10/10
  469/469 - 1s - loss: 0.2688 - mse: 0.0117 - val_loss: 0.2666 - val_mse: 0.0115 - 862ms/epoch - 2ms/step
  313/313 - 0s - loss: 0.2666 - mse: 0.0115 - 384ms/epoch - 1ms/step
  mse of batch size 128is: 0.011471958830952644
 the convergence time is : 9.13 seconds
system performance with the following batch size: 256
Epoch 1/10
235/235 - 1s - loss: 1.3177 - mse: 0.0571 - val loss: 0.6546 - val mse: 0.0293 - 865ms/epoch - 4ms/step
Epoch 2/10
235/235 - 1s - loss: 0.5453 - mse: 0.0245 - val loss: 0.4455 - val mse: 0.0197 - 505ms/epoch - 2ms/step
Epoch 3/10
235/235 - 1s - loss: 0.4139 - mse: 0.0184 - val loss: 0.3701 - val mse: 0.0162 - 516ms/epoch - 2ms/step
Epoch 4/10
235/235 - 0s - loss: 0.3548 - mse: 0.0157 - val_loss: 0.3293 - val_mse: 0.0145 - 478ms/epoch - 2ms/step
Epoch 5/10
235/235 - 1s - loss: 0.3234 - mse: 0.0143 - val loss: 0.3105 - val mse: 0.0136 - 501ms/epoch - 2ms/step
Epoch 6/10
 235/235 - 1s - loss: 0.3058 - mse: 0.0134 - val_loss: 0.2996 - val_mse: 0.0131 - 510ms/epoch - 2ms/step
Epoch 7/10
235/235 - 1s - loss: 0.2948 - mse: 0.0129 - val loss: 0.2910 - val mse: 0.0127 - 504ms/epoch - 2ms/step
Epoch 8/10
235/235 - 1s - loss: 0.2864 - mse: 0.0125 - val loss: 0.2852 - val mse: 0.0124 - 503ms/epoch - 2ms/step
Epoch 9/10
235/235 - 1s - loss: 0.2799 - mse: 0.0122 - val loss: 0.2810 - val mse: 0.0122 - 505ms/epoch - 2ms/step
Epoch 10/10
235/235 - 0s - loss: 0.2747 - mse: 0.0120 - val loss: 0.2796 - val mse: 0.0121 - 496ms/epoch - 2ms/step
313/313 - 0s - loss: 0.2796 - mse: 0.0121 - 394ms/epoch - 1ms/step
mse of batch size 256is: 0.012083479203283787
the convergence time is : 5.50 seconds
  system performance with the following batch size: 512
  Epoch 1/10
  118/118 - 1s - loss: 1.7463 - mse: 0.0737 - val_loss: 1.0546 - val_mse: 0.0484 - 854ms/epoch - 7ms/step
  Epoch 2/10
  118/118 - 1s - loss: 0.7773 - mse: 0.0354 - val loss: 0.5846 - val mse: 0.0264 - 503ms/epoch - 4ms/step
  Epoch 3/10
  118/118 - 1s - loss: 0.5309 - mse: 0.0239 - val_loss: 0.4639 - val_mse: 0.0208 - 624ms/epoch - 5ms/step
  Epoch 4/10
  118/118 - 1s - loss: 0.4472 - mse: 0.0199 - val_loss: 0.4014 - val_mse: 0.0177 - 611ms/epoch - 5ms/step
  Epoch 5/10
  118/118 - 1s - loss: 0.3864 - mse: 0.0169 - val loss: 0.3580 - val mse: 0.0156 - 632ms/epoch - 5ms/step
  Epoch 6/10
  118/118 - 1s - loss: 0.3556 - mse: 0.0155 - val_loss: 0.3359 - val_mse: 0.0146 - 637ms/epoch - 5ms/step
  Epoch 7/10
  118/118 - 0s - loss: 0.3380 - mse: 0.0147 - val loss: 0.3236 - val mse: 0.0139 - 287ms/epoch - 2ms/step
  Epoch 8/10
  118/118 - 0s - loss: 0.3249 - mse: 0.0141 - val_loss: 0.3139 - val_mse: 0.0136 - 250ms/epoch - 2ms/step
  118/118 - 0s - loss: 0.3151 - mse: 0.0137 - val loss: 0.3058 - val mse: 0.0132 - 228ms/epoch - 2ms/step
  Epoch 10/10
  118/118 - 0s - loss: 0.3070 - mse: 0.0134 - val loss: 0.3000 - val mse: 0.0130 - 218ms/epoch - 2ms/step
  313/313 - 0s - loss: 0.3000 - mse: 0.0130 - 339ms/epoch - 1ms/step
 mse of batch size 512is: 0.012964930385351181
                                                                                             Activer Windo
 the convergence time is: 4.96 seconds
                                                                                             Accédez aux naram
```

Batch size	32	64	128	256	512
Last Mean Square Error recorded in the training process	0.0114	0.0117	0.0120	0.0121	0.0127

Figure 4: Table of results for exercise 3

What we notice is that the MSE is very low, meaning that our model seems to perform well on the data. When we look at a metrics, we have to be particularly careful when it comes to its meaning: we are looking for MSEs close to zero, but to accuracies close to 1! However, we notice that the baseline error seems very high. It might be because it is computed according to an "accuracy" metric, whereas we use the MSE metric there, which quantifies the errors of our model... and not its good guesses (which correspond to the "baseline error" metrics there!).

Exercise 4: Using the default parameters specified at Application 1 (8 neurons in hidden layer, 10 epochs and a batch size of 200 images), train the model and save the associated weights in a file (model.save_weights), so it can be load anytime to perform further tests.

Let's take a look at the lines in blue in the code above. The exercise asks us to save the weights of the model using the function <code>save_weights</code>. It is what we implemented, by saving our model's weights in the file "application1.h5". We have used the HDF5 format, widely used in machine learning to store large amounts of data. In the next exercise, we will be able to reload the weights saved in this part to perform a test of our model!

Exercise 5: Write a novel Python script that loads the saved weights (model.load_weights) at Exercise 4 and make a prediction on the first 5 images of the testing dataset (mnist.test_images()).

This exercise asks us to reload the weights, computed after training our model, and to perform a prediction on the five first images of the MNIST test dataset. The code we have implemented is presented below:

```
#TODO - Application 1 - Step 6b - Define a hidden dense layer with 8 neurons
   model.add(layers.Dense(neurons, input dim=num pixels, kernel initializer='normal',
activation='relu')) # the number of neurons has to be modified here
    # for exercise 1
   #TODO - Application 1 - Step 6c - Define the output dense layer
   model.add(layers.Dense(num classes, kernel initializer='normal',
activation='softmax'))
    # TODO - Application 1 - Step 6d - Compile the model
   model.compile(loss='categorical crossentropy', optimizer='adam',
metrics=['accuracy'])
    # the following line has been used to solve exercise 3:
    # model.compile(loss='categorical crossentropy', optimizer='adam', metrics=['mse'])
    return model
def PredictMLP(train images, train labels, test images, test labels, neurons,
batch_size):
    #TODO - Application 1 - Step 3 - Reshape the MNIST dataset - Transform the images to
1D vectors of floats (28x28 pixels to 784 elements)
   num pixels = train images.shape[1] * train images.shape[2]
   train_images = train_images.reshape((train_images.shape[0],
num pixels)).astype('float32')
   test images = test images.reshape((test images.shape[0],
num pixels)).astype('float32')
   #TODO - Application 1 - Step 4 - Normalize the input values
   train images = train images / 255
   test_images = test_images / 255
   #TODO - Application 1 - Step 5 - Transform the classes labels into a binary matrix
   train labels = to categorical(train labels)
   test labels = to categorical(test labels)
   num classes = test labels.shape[1]
   print("size of the initial test dataset (images) :" + str(len(test images)))
   print("size of the initial test dataset (labels) :" + str(len(test labels)))
 test_images_cropped = test images[0:5]
test_labels_cropped = test_labels[0:5]
   print("size of the test dataset containing the 5 first images (images) :" +
str(len(test_images_cropped)))
   print("size of the test dataset containing the 5 first images :" +
str(len(test labels cropped)))
    #TODO - Application 1 - Step 6 - Build the model architecture - Call the
baseline model function
```

```
model = baseline model(num pixels, num classes, neurons) #Modify this
   model.load weights('./application1.h5')
   model.summary()
   # Prediction on the test dataset - first five images
   Y result = model.predict(test images cropped, verbose=1)
   Y_pred = np.argmax(Y_result, axis=1)
   #TODO - Application 1 - Step 8 - System evaluation - compute and display the
prediction error
   scores = model.evaluate(test images cropped, test labels cropped, verbose=2)
   print("Baseline Error: {:.2f}".format(100-scores[1]*100))
def main():
   #TODO - Application 1 - Step 1 - Load the MNIST dataset in Keras
   (train_images, train_labels), (test_images, test_labels) = mnist.load_data()
   (train images, train labels), (test images, test labels) =
tf.keras.datasets.mnist.load data()
   neurons=8
   batch size=200
   mlp = PredictMLP(train_images, train_labels, test_images, test_labels, neurons,
batch size)
   return
if __name__ == '__main__':
   main()
```

Figure 5: code for this part

The parts we have highlighted in yellow are the ones we have heavily modified to answer the exercise. We have reused the code given for the TP and adapted it in our particular case: after reshaping the images as it had to be done in Step 5 of the TP, we only used the five first images of the test dataset (instruction "test_images_cropped = test_images[0:5]") and their labels (instruction "test_labels_cropped = test_labels[0:5]"). We then create the model (instruction "model = baseline_model(num_pixels, num_classes, neurons)") and reload the weights (instruction "model.load_weights('./application1.h5')") with the help of the file created in Exercise 4.

The figure 6 shows the output we have obtained:

```
size of the initial test dataset (images) :10000
size of the initial test dataset (labels) :10000
size of the test dataset containing the 5 first images (images) :5
size of the test dataset containing the 5 first images :5
Model: "sequential"
Layer (type)
                            Output Shape
                           (None, 8)
dense (Dense)
                                                     6280
dense 1 (Dense)
                           (None, 10)
                                                     90
Total params: 6370 (24.88 KB)
Trainable params: 6370 (24.88 KB)
Non-trainable params: 0 (0.00 Byte)
1/1 [======] - 1s 628ms/step
1/1 - 1s - loss: 0.0157 - accuracy: 1.0000 - 546ms/epoch - 546ms/step
Baseline Error: 0.00
```

Figure 6: output for this part

We note that according to the accuracy and the baseline error, all the images have been classified properly. It seemed a bit strange to us to see this absence of flaws: it could be because our model has been tested on a very small amount of images (5), which, given its overall good results, did not allow us to see its potential mistakes and misclassifications.

I) Application II:

Please note: for your convenience, the outputs of this part have been grouped by exercise, not in one single part of the report.

The objective of this part is to develop a more sophisticated neural network (a Convolutional Neural Network) to classify the digits. The goal remains the same; in this part, only the neural network (that is to say, the classification "method") changes. We filled in the blanks left in the code of the first application. Please note that the names of the variables have been changed according to the table in part I (it helped us improve our understanding of the code) and that the code has been left in its "final" state (that is to say, its state when we solved the last exercise). If you want to check our solutions to the previous exercises, please uncomment the corresponding lines.

c) Code for this part

```
import keras
import tensorflow as tf
import time
from keras.datasets import mnist
#from keras.utils import np utils
from keras.utils import to categorical
from keras import layers
def baseline model (num pixels, num classes, neurons):
   #TODO - Application 1 - Step 6a - Initialize the sequential model
   model = tf.keras.models.Sequential()
                                      # Modify this
   #TODO - Application 1 - Step 6b - Define a hidden dense layer with 8 neurons
   model.add(layers.Dense(neurons, input dim=num pixels, kernel initializer='normal',
activation='relu')) # the number of neurons has to be modified here
   # for exercise 1
```

```
#TODO - Application 1 - Step 6c - Define the output dense layer
   model.add(layers.Dense(num classes, kernel initializer='normal',
activation='softmax'))
    # TODO - Application 1 - Step 6d - Compile the model
   model.compile(loss='categorical crossentropy', optimizer='adam',
metrics=['accuracy'])
    # the following line has been used to solve exercise 3:
    # model.compile(loss='categorical crossentropy', optimizer='adam', metrics=['mse'])
   return model
def trainAndPredictMLP(train_images, train_labels, test_images, test_labels, neurons,
batch size):
   #TODO - Application 1 - Step 3 - Reshape the MNIST dataset - Transform the images to
1D vectors of floats (28x28 pixels to 784 elements)
   num_pixels = train_images.shape[1] * train_images.shape[2]
   train images = train images.reshape((train_images.shape[0],
num_pixels)).astype('float32')
   test images = test images.reshape((test images.shape[0],
num pixels)).astype('float32')
   #TODO - Application 1 - Step 4 - Normalize the input values
   train images = train images / 255
   test images = test images / 255
   #TODO - Application 1 - Step 5 - Transform the classes labels into a binary matrix
   train labels = to categorical(train labels)
   test_labels = to_categorical(test_labels)
   num classes = test labels.shape[1]
   #TODO - Application 1 - Step 6 - Build the model architecture - Call the
baseline model function
   model = baseline_model(num_pixels, num_classes, neurons) #Modify this
   #TODO - Application 1 - Step 7 - Train the model
   start time=time.time()
   model.fit(train images, train labels, validation data=(test images, test labels),
epochs=10, batch size=batch size, verbose=2)
   end time=time.time()
    # the following line has been used to solve exercise 4
   model.save weights('./application1.h5')
   convergence time=end time-start time
    #TODO - Application 1 - Step 8 - System evaluation - compute and display the
```

```
prediction error
   scores = model.evaluate(test images, test labels, verbose=2)
   print("Baseline Error: {:.2f}".format(100-scores[1]*100))
   print("the convergence time is", convergence time, "seconds")
   return
def CNN model (input shape, num classes, size, neurons):
   # TODO - Application 2 - Step 5a - Initialize the sequential model
   model = tf.keras.models.Sequential() #Modify this
   #TODO - Application 2 - Step 5b - Create the first hidden layer as a convolutional
layer
   # model.add(layers.Conv2D(8, size, activation='relu', input shape=(28, 28, 1)))
   model.add(layers.Conv2D(30, size, activation='relu', input shape=(28, 28, 1)))
#the line above has been modified for exercise 9
   #TODO - Application 2 - Step 5c - Define the pooling layer
   model.add(layers.MaxPooling2D(pool_size=(2,2)))
   #the two following lines have been added in Exercise 9
   model.add(layers.Conv2D(15, (3,3), activation='relu'))
   model.add(layers.MaxPooling2D(pool size=(2,2)))
   #TODO - Application 2 - Step 5d - Define the Dropout layer
   model.add(layers.Dropout(rate=0.2))
   #TODO - Application 2 - Step 5e - Define the flatten layer
   model.add(layers.Flatten())
   #TODO - Application 2 - Step 5f - Define a dense layer of size 128
   # model.add(layers.Dense(128, activation='relu'))
   model.add(layers.Dense(neurons, activation='relu'))
  #the following line has been added in Exercise 9
   model.add(layers.Dense(50, activation='relu'))
   #TODO - Application 2 - Step 5g - Define the output layer
   model.add(layers.Dense(num classes, activation='softmax'))
   #TODO - Application 2 - Step 5h - Compile the model
   model.compile(loss='categorical crossentropy', optimizer='adam',
metrics=['accuracy'])
   return model
def trainAndPredictCNN(train images, train labels, test images, test labels, size,
neurons, epochs):
```

```
#TODO - Application 2 - Step 2 - reshape the data to be of size
[samples] [width] [height] [channels]
    train images = train images.reshape((train images.shape[0], 28, 28,
1)).astype('float32')
    test images = test images.reshape((test images.shape[0], 28, 28,
1)).astype('float32')
   \#TODO - Application 2 - Step 3 - normalize the input values from 0-255 to 0-1
   train images = train images / 255
   test images = test images / 255
   #TODO - Application 2 - Step 4 - One hot encoding - Transform the classes labels
into a binary matrix
   train labels = to categorical(train labels)
   test labels = to categorical(test labels)
   #TODO - Application 2 - Step 5 - Call the cnn model function
   model = CNN model(input shape=(28,28,1), num classes=10, size=size, neurons=neurons)
#Modify this
   #TODO - Application 2 - Step 6 - Train the model
   start time=time.time()
   model.fit(train images, train labels, validation data=(test images, test labels),
epochs=epochs, batch size=200, verbose=1)
   end time=time.time()
   convergence time=end time-start time
   #TODO - Application 2 - Step 8 - Final evaluation of the model - compute and display
the prediction error
   scores = model.evaluate(test_images, test labels, verbose=2)
   print("Baseline Error: {:.2f}".format(100-scores[1]*100))
   print("the convergence time is", convergence_time, "seconds")
   return
def main():
   #TODO - Application 1 - Step 1 - Load the MNIST dataset in Keras
    (train images, train labels), (test images, test labels) = mnist.load data()
   #TODO - Application 1 - Step 2 - Train and predict on a MLP - Call the
trainAndPredictMLP function
   # loop used to solve exercise 1
   \# neurons =[8,16,32,64,128]
   # for neuron in neurons :
       print("system performance with :", neuron, "neurons")
       mlp = trainAndPredictMLP(train images, train labels, test images, test labels,
neuron, batch size=200)
    ### MLP : application 1, exercise 4
```

```
# neurons=8
    # batch size=200
    # mlp = trainAndPredictMLP(train images, train labels, test images, test labels,
neurons, batch size)
    # loop used to solve exercise 2
    \# batch sizes =[32,64,128,256,512]
    # for batch size in batch sizes :
    # print("system performance with the following batch size :", batch size)
      mlp = trainAndPredictMLP(train_images, train_labels, test_images, test_labels,
neurons, batch size)
    #TODO - Application 2 - Step 1 - Train and predict on a CNN - Call the
trainAndPredictCNN function
   #the following lines have been used to solve exercise 6
 \# sizes = [(1,1), (3,3), (5,5), (7,7), (9,9)]
 # epochs = 10
  # neurons = 128
 # for size in sizes :
 # print("system performance for the following size of the feature map of the
convolutional layer:", size)
 # cnn = trainAndPredictCNN(train_images, train_labels, test_images, test labels,
size, neurons, epochs)
 #the following lines have been used to solve exercise 7
 #neurons = [16, 64, 128, 256, 512]
  \#size = (3,3)
   \# epochs = 10
   #for neuron in neurons :
   # print("system performance with :", neuron, "neurons")
    # cnn = trainAndPredictCNN(train images, train labels, test images, test labels,
size, neuron, epochs)
    #the following lines have been used to solve exercise
    \#size = (3,3)
    \#neurons = 128
    #epochs = [1, 2, 5, 10, 20]
#for epoch in epochs :
       print("system performance with :", epoch,"epochs")
         cnn = trainAndPredictCNN(train_images, train_labels, test_images, test_labels,
    #the following lines have been used in Exercise 9
   size = (5, 5)
   neurons = 128
   epochs = 10
   cnn = trainAndPredictCNN(train images, train labels, test images, test labels, size,
neurons, epochs)
    return
```

d) Answer for all the exercises related to the script, and outputs of the script related to each exercise

Exercise 6: Modify the size of the feature map within the convolutional layer as specified in Table 3. How is the system accuracy influenced by this parameter?

In this exercise, we are asked to modify the size of the feature map of the convolutional layer "Conv2D" and to perform the training of our model each time. We assessed the system accuracy for each size of the feature map.

To understand our implementation, let's take a look at the yellow part of the code above. It features the following loop (commented below):

```
#the following lines have been used to solve exercise 6
# sizes = [(1,1), (3,3), (5,5), (7,7), (9,9)]
# epochs = 10
# neurons = 128
# for size in sizes :
# print("system performance for the following size of the feature map of the convolutional layer:", size)
# cnn = trainAndPredictCNN(train_images, train_labels, test_images, test_labels, size, neurons, epochs)
```

This loop has been used to perform the training of the different models in one run of our script. To do so, we defined an array of sizes called "sizes", that contains all the sizes of the feature map that we are going to study. We also added the parameters "epochs" and "neurons" according to the requirements of the lab for this exercise (we could have specified them as numbers in the functions, but we preferred this implementation that allowed us to perform loops in order to train the model for different epoch sizes and numbers of neurons, something that will be required in the next exercises). Then, the loop "for" allows us to train the model for each size of the feature map by calling the "trainAndPredictCNN" function. We obtained the following outputs and table of results:

```
system performance for the following size of the feature map of the convolutional layer: (1, 1)
Epoch 1/5
              300/300 [=
Epoch 2/5
            ============== 1 - 7s 25ms/step - loss: 0.3284 - accuracv: 0.9003 - val loss: 0.2543 - val accuracv: 0.9243
300/300 [==
Enoch 3/5
300/300 [=
              ========] - 7s 24ms/step - loss: 0.2732 - accuracy: 0.9168 - val loss: 0.2074 - val accuracy: 0.9389
Epoch 4/5
300/300 [===
         Epoch 5/5
313/313 - 3s - loss: 0.1434 - accuracy: 0.9562 - 3s/epoch - 11ms/step
Baseline Error: 4.38
the convergence time is 44.777148485183716 seconds
system performance for the following size of the feature map of the convolutional layer: (3, 3)
Epoch 1/5
300/300 [=
            ==========] - 11s 31ms/step - loss: 0.3677 - accuracy: 0.8969 - val_loss: 0.1349 - val_accuracy: 0.9620
Epoch 2/5
Epoch 3/5
300/300 [=
               Epoch 4/5
300/300 [==:
           Epoch 5/5
300/300 [==:
                313/313 - 2s - loss: 0.0528 - accuracy: 0.9819 - 2s/epoch - 7ms/step
Baseline Error: 1.81
the convergence time is 55.72983407974243 seconds
system performance for the following size of the feature map of the convolutional layer: (5, 5)
Epoch 1/5
        300/300 [===
Epoch 2/5
300/300 [=
              ========] - 13s 44ms/step - loss: 0.1348 - accuracy: 0.9597 - val_loss: 0.0791 - val_accuracy: 0.9755
Epoch 3/5
300/300 [=
                ========] - 13s 43ms/step - loss: 0.0935 - accuracy: 0.9712 - val loss: 0.0573 - val accuracy: 0.9820
Epoch 4/5
300/300 [===
        Epoch 5/5
300/300 [==
           313/313 - 3s - loss: 0.0438 - accuracy: 0.9851 - 3s/epoch - 11ms/step
Baseline Error: 1.49
the convergence time is 64.82084465026855 seconds
system performance for the following size of the feature map of the convolutional layer: (7, 7)
Epoch 1/5
300/300 [==
             ========] - 13s 42ms/step - loss: 0.3367 - accuracy: 0.9059 - val loss: 0.1014 - val accuracy: 0.9702
Epoch 2/5
300/300 [=
             =========] - 15s 49ms/step - loss: 0.1029 - accuracy: 0.9687 - val_loss: 0.0632 - val_accuracy: 0.9802
Epoch 3/5
300/300 [===
            Epoch 4/5
300/300 [=:
          :========] - 14s 45ms/step - loss: 0.0620 - accuracy: 0.9815 - val_loss: 0.0421 - val_accuracy: 0.9870
Epoch 5/5
300/300 [==
                 313/313 - 3s - loss: 0.0414 - accuracy: 0.9865 - 3s/epoch - 10ms/step
Baseline Error: 1.35
the convergence time is 69.36883354187012 seconds
system performance for the following size of the feature map of the convolutional layer: (9, 9)
Epoch 1/5
300/300 [=
            ===========] - 15s 46ms/step - loss: 0.3608 - accuracy: 0.8949 - val_loss: 0.1247 - val_accuracy: 0.9625
Epoch 2/5
300/300 [=
               :========] - 16s 52ms/step - loss: 0.1190 - accuracy: 0.9652 - val_loss: 0.0669 - val_accuracy: 0.9782
Epoch 3/5
300/300 [=
              :========] - 16s 52ms/step - loss: 0.0831 - accuracy: 0.9747 - val_loss: 0.0533 - val_accuracy: 0.9829
Epoch 4/5
300/300 [===
        300/300 [=================] - 15s 50ms/step - loss: 0.0552 - accuracy: 0.9830 - val loss: 0.0399 - val accuracy: 0.9873
313/313 - 3s - loss: 0.0399 - accuracy: 0.9873 - 3s/epoch - 8ms/step
Baseline Error: 1.27
the convergence time is 76.3290011882782 seconds
```

Size of the feature map	1 x 1	3 x 3	5 x 5	7 x 7	9 x 9
System Accuracy	0.9562	0.9819	0.9851	0.9865	0.9873
Convergence time (s)	44.8	55.7	64.8	69.4	76.3

Figure 7: Table of results for exercise 6

We notice that increasing the size of the feature map also increases the accuracy of our model. However, after a certain size, the accuracy of our system does not seem to increase a lot anymore (it seems "bounded"; for example, the accuracy does not increase so much between the size 3 x 3 and 5 x 5). This increase is caused by the fact that the feature maps are the results of filters that are multiplied with the input image. If the size of the filter is increased, it can recognize patterns more globally and in a better/more relevant way. However, increasing the size of the feature map seems to increase the convergence time as well: a tradeoff between accuracy and convergence time might need to be found to choose the "best" size of the feature map in a given context.

Exercise 7: Modify the number of neurons in the dense hidden layer as specified in Table 4. Select a value of 3x3 neurons for the convolutional kernel. What can be observed regarding the system accuracy? How about the convergence time necessary for the system to train a model?

In this exercise, we are asked to modify the number of neurons in the dense hidden layer. To do so, we implemented the following loop (highlighted in pink in the code above and commented here):

```
#the following lines have been used to solve exercise 7
#neurons = [16, 64, 128, 256, 512]
#size = (3,3)
# epochs = 10
#for neuron in neurons:
# print("system performance with :", neuron, "neurons")
# cnn = trainAndPredictCNN(train_images, train_labels, test_images, test_labels, size, neuron, epochs)
```

This loop has been used to perform the training of the different models in one run of our script. To do so, we defined an array of neurons containing the number of neurons, called "neurons". The loop "for" allowed us to train the model for each number of neurons that we wanted to study by calling the "trainAndPredictCNN" function. We obtained the following outputs and table of results:

```
system performance with: 16 neurons
Enoch 1/5
         ===========] - 15s 42ms/step - loss: 0.6000 - accuracy: 0.8264 - val_loss: 0.2336 - val_accuracy: 0.9368
300/300 [=
Fnoch 2/5
          300/300 [=
Enoch 3/5
Epoch 4/5
        300/300 [=
Epoch 5/5
300/300 [===
        :========= ] - 10s 35ms/step - loss: 0.1303 - accuracy: 0.9613 - val loss: 0.0972 - val accuracy: 0.9712
313/313 - 2s - loss: 0.0972 - accuracy: 0.9712 - 2s/epoch - 7ms/step
Baseline Error: 2.88
the convergence time is 52.43540716171265 seconds
system performance with : 64 neurons
Epoch 1/5
        300/300 [==
Epoch 2/5
300/300 [=============] - 11s 37ms/step - loss: 0.1644 - accuracy: 0.9522 - val loss: 0.1078 - val accuracy: 0.9685
Epoch 3/5
300/300 [============] - 11s 35ms/step - loss: 0.1218 - accuracy: 0.9635 - val_loss: 0.0878 - val_accuracy: 0.9722
Epoch 4/5
300/300 [==
         :=========] - 11s 36ms/step - loss: 0.1028 - accuracy: 0.9693 - val_loss: 0.0732 - val_accuracy: 0.9782
Epoch 5/5
313/313 - 3s - loss: 0.0653 - accuracy: 0.9796 - 3s/epoch - 8ms/step
Baseline Error: 2.04
the convergence time is 54.035040616989136 seconds
system performance with : 128 neurons
Epoch 1/5
Epoch 2/5
300/300 [=
          Epoch 3/5
Epoch 4/5
300/300 [=
         ========= - 11s 38ms/step - loss: 0.0917 - accuracy: 0.9731 - val loss: 0.0680 - val accuracy: 0.9780
Epoch 5/5
313/313 - 3s - loss: 0.0636 - accuracy: 0.9794 - 3s/epoch - 8ms/step
Baseline Error: 2.06
the convergence time is 56.2769672870636 seconds
system performance with : 256 neurons
Enoch 1/5
      300/300 [===
Epoch 2/5
300/300 [==========] - 13s 44ms/step - loss: 0.1217 - accuracy: 0.9632 - val loss: 0.0772 - val accuracy: 0.9764
Epoch 3/5
      300/300 [===
Epoch 4/5
300/300 [=
         Epoch 5/5
       300/300 [===
313/313 - 2s - loss: 0.0565 - accuracy: 0.9814 - 2s/epoch - 6ms/step
Baseline Error: 1.86
the convergence time is 67.21643209457397 seconds
system performance with: 512 neurons
Epoch 1/5
        300/300 [=:
Fnoch 2/5
300/300 [==
          Epoch 3/5
300/300 [=
           Fnoch 4/5
300/300 [:
           Epoch 5/5
313/313 - 4s - loss: 0.0467 - accuracy: 0.9853 - 4s/epoch - 13ms/step
Baseline Error: 1.47
the convergence time is 79.67010450363159 seconds
```

Number of neurons	16	64	128	256	512
System Accuracy	0.9712	0.9796	0.9794	0.9814	0.9853
Convergence time (s)	52.4	54.0	56.3	67.2	79.7

Figure 8: Table of results for exercise 7

As we saw for the previous implementation of the classifier (in application 1), increasing the number of neurons increases the accuracy of our system, because it allows it to learn more complex patterns and to fit the training data in a better way. However, it also increases the convergence time. The previous implementation converges more quickly than the CNN, but it yielded results that were less satisfying in terms of accuracy (please see the table in exercise 1). Thus, we can see how efficient the CNN architecture is compared to the other implementation we have studied in this lab.

Exercise 8: Modify the number of epochs used to train the model as specified in Table 5. Select a value of 128 neurons in the dense hidden layer. What can be observed regarding the system accuracy? How about the convergence time?

Here, we are asked to modify the number of epochs used to train the model. We used the same strategy as in the exercises above, which is to say, we implemented the following loop (highlighted in blue in the code above and commented here):

```
#the following lines have been used to solve exercise 8
#size = (3,3)
#neurons = 128
#epochs = [1, 2, 5, 10, 20]
#for epoch in epochs:
# print("system performance with :", epoch, "epochs")
# cnn = trainAndPredictCNN(train_images, train_labels, test_images, test_labels,
size, neurons, epoch)
```

This loop has been used to perform the training of the different models in one run of our script. To do so, we defined an array of epochs containing the number of epochs, called "epoch". The loop "for" allowed us to train the model for each number of epochs that we wanted to study by calling the "trainAndPredictCNN" function. We obtained the following outputs and table of results:

```
system performance with : 1 epochs
313/313 - 4s - loss: 0.1589 - accuracy: 0.9553 - 4s/epoch - 13ms/step
Baseline Error: 4.47
the convergence time is 17.242071628570557 seconds
system performance with : 2 epochs
Epoch 1/2
300/300 [=
           Epoch 2/2
313/313 - 4s - loss: 0.0981 - accuracy: 0.9717 - 4s/epoch - 12ms/step
Baseline Error: 2.83
the convergence time is 23.2792649269104 seconds
system performance with : 5 epochs
300/300 [=
             ============= ] - 13s 37ms/step - loss: 0.4058 - accuracy: 0.8912 - val loss: 0.1577 - val accuracy: 0.9559
Epoch 2/5
300/300 [=
                Epoch 3/5
300/300 [====
         =========================== - 12s 41ms/step - loss: 0.1086 - accuracy: 0.9675 - val loss: 0.0752 - val accuracy: 0.9763
Fnoch 4/5
Epoch 5/5
300/300 [==
                    :=======] - 12s 40ms/step - loss: 0.0756 - accuracy: 0.9768 - val_loss: 0.0581 - val_accuracy: 0.9802
313/313 - 2s - loss: 0.0581 - accuracy: 0.9802 - 2s/epoch - 7ms/step
Baseline Error: 1.98
the convergence time is 61.107154846191406 seconds
system performance with: 10 epochs
Epoch 1/10
300/300 [==
                ========] - 14s 39ms/step - loss: 0.4079 - accuracy: 0.8838 - val_loss: 0.1494 - val_accuracy: 0.9580
Epoch 2/10
300/300 [==
                  ========] - 12s 39ms/step - loss: 0.1480 - accuracy: 0.9567 - val_loss: 0.0893 - val_accuracy: 0.9745
Epoch 3/10
300/300 [===
             =========] - 12s 42ms/step - loss: 0.1084 - accuracy: 0.9675 - val_loss: 0.0705 - val_accuracy: 0.9774
Epoch 4/10
300/300 [===
               :========] - 12s 40ms/step - loss: 0.0875 - accuracy: 0.9730 - val_loss: 0.0612 - val_accuracy: 0.9798
Epoch 5/10
300/300 [==
                  ========] - 12s 40ms/step - loss: 0.0735 - accuracy: 0.9771 - val_loss: 0.0550 - val_accuracy: 0.9830
Epoch 6/10
300/300 [==
                 :========] - 12s 40ms/step - loss: 0.0637 - accuracy: 0.9802 - val loss: 0.0498 - val accuracy: 0.9834
Epoch 7/10
300/300 [===========] - 12s 41ms/step - loss: 0.0575 - accuracy: 0.9818 - val loss: 0.0485 - val accuracy: 0.9828
Fnoch 8/10
             300/300 [===:
Epoch 9/10
                 :========] - 12s 40ms/step - loss: 0.0448 - accuracy: 0.9861 - val loss: 0.0415 - val accuracy: 0.9864
300/300 [===
Epoch 10/10
                 :========] - 11s 38ms/step - loss: 0.0411 - accuracy: 0.9866 - val_loss: 0.0424 - val_accuracy: 0.9861
300/300 [===
313/313 - 3s - loss: 0.0424 - accuracy: 0.9861 - 3s/epoch - 10ms/step
Baseline Error: 1.39
the convergence time is 122.27370858192444 seconds
system performance with: 20 epochs
Epoch 1/20
300/300 [==
               =========] - 12s 34ms/step - loss: 0.3982 - accuracy: 0.8889 - val_loss: 0.1610 - val_accuracy: 0.9541
Epoch 2/20
Epoch 3/20
300/300 [====
              ==========] - 11s 37ms/step - loss: 0.1099 - accuracy: 0.9665 - val_loss: 0.0805 - val_accuracy: 0.9755
Epoch 4/20
300/300 [==:
                 Epoch 5/20
300/300 [==
                 Epoch 6/20
300/300 [==
                Epoch 7/20
300/300 [==
                 :=======] - 11s 37ms/step - loss: 0.0584 - accuracy: 0.9820 - val_loss: 0.0523 - val_accuracy: 0.9814
Epoch 8/20
300/300 [==
                  =========] - 11s 37ms/step - loss: 0.0501 - accuracy: 0.9845 - val_loss: 0.0456 - val_accuracy: 0.9837
Epoch 9/20
300/300 [==
                  ========] - 12s 39ms/step - loss: 0.0466 - accuracy: 0.9854 - val_loss: 0.0443 - val_accuracy: 0.9858
Epoch 10/20
                  ========] - 11s 38ms/step - loss: 0.0409 - accuracy: 0.9871 - val loss: 0.0411 - val accuracy: 0.9863
300/300 [===
Epoch 11/20
300/300 [===
                  Epoch 12/20
300/300 [====
            ==========] - 14s 48ms/step - loss: 0.0348 - accuracy: 0.9887 - val_loss: 0.0412 - val_accuracy: 0.9869
Epoch 13/20
300/300 [===
             Epoch 14/20
300/300 [====
               =========] - 16s 52ms/step - loss: 0.0292 - accuracy: 0.9909 - val_loss: 0.0415 - val_accuracy: 0.9848
```

```
Epoch 15/20
Epoch 16/20
Epoch 17/20
           ========] - 11s 37ms/step - loss: 0.0218 - accuracy: 0.9927 - val_loss: 0.0425 - val_accuracy: 0.9862
300/300 [===
Epoch 18/20
        =========] - 11s 38ms/step - loss: 0.0188 - accuracy: 0.9941 - val loss: 0.0392 - val accuracy: 0.9876
300/300 [===
Epoch 19/20
       300/300 [===
Epoch 20/20
        300/300 [====
313/313 - 2s - loss: 0.0405 - accuracy: 0.9876 - 2s/epoch - 7ms/step
Baseline Error: 1.24
the convergence time is 246.78136801719666 seconds
```

Number of epochs	1	2	5	10	20
System Accuracy	0.9553	0.9717	0.9802	0.9861	0.9876
Convergence time (s)	17.2	23.3	61.1	122.3	246.8

Figure 9: Table of results for exercise 8

Increasing the number of epochs used to train the model increases the accuracy. An epoch is defined as one pass of the training set in the model (it is the number of times the model "sees" the training data and learns from it). If the model does this several times, it allows it to learn better, thus increasing the accuracy. However, the increase does not seem to be significant anymore after a certain number of epochs (it does not seem to increase so much between 10 and 20 epochs. However, the convergence time doubles! It is why a tradeoff has to be found between increasing the accuracy and increasing the number of epochs, which might make the model converge only after a lot of time.) This increase of the convergence time can be explained by the fact that "seeing the data several times" requires more computations, which take time.

Exercise 9: Modify the CNN architecture with additional convolutional, max pooling layers and fully connected layers

In this last exercise, we added (or modified) the lines in purple in the code above, to add layers to our CNN architecture. We then determined the accuracy of the system, given by the following output:

```
=======] - 23s 70ms/step - loss: 0.3814 - accuracy: 0.8841 - val_loss: 0.0750 - val_accuracy: 0.9767
Epoch 2/10
300/300 [==
          :=======] - 26s 87ms/step - loss: 0.0718 - accuracy: 0.9777 - val loss: 0.0397 - val accuracy: 0.9869
300/300 [===
          300/300 [==:
        ========] - 28s 92ms/step - loss: 0.0494 - accuracy: 0.9844 - val loss: 0.0321 - val accuracy: 0.9882
300/300 [===
Epoch 6/10
          Fnoch 7/10
        Epoch 8/10
         Epoch 9/10
300/300 [==:
          Epoch 10/10
Baseline Error: 0.83
the convergence time is 263.44080209732056 seconds
```

We chose to restore the parameters used in the previous exercises (namely, we performed the training for 10 epochs). The accuracy of our system has reached 99.2%: adding layers, or slightly altering the architecture has drastically improved it. Even if the convergence time is quite long, the model's performance is relatively good. Adding more convolutional layers seems to allow the model to learn more complex patterns, whereas adding fully connected "dense" layers seems to allow the model to generalize them more easily, thus leading to an increase in accuracy.