

## Assignment 3

Advanced Machine Learning  
University of Milano-Bicocca  
M.Sc. Data Science

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## Design of a CNN Architecture for a Digits Recognition Problem

The task of this assignment is to design a CNN architecture and its training for recognizing handwritten digits. The input dataset used is *MNIST digits*, and it was divided into a training set, with 60000 images 28x28 and a test set, with 10000 images 28x28. The number of classes is 10.



Figure 1: MNIST digits

In this report are presented the following concepts:

- Data Preprocessing;
- Description of the designed architecture;
- Plots of the training and validation loss/accuracy;
- Classification performance on training and test sets.

## Data Preprocessing

Before starting to develop a CNN architecture for this problem, it was necessary to make a couple of changes. The images of the dataset have been normalized and reshaped to obtain images define with three values: height, width, and channel. In this situation, there is only one channel because the pictures are in gray scale.

Finally, the class variable has been converted to be suitable for the neural network through a process called *one-hot encoding*.

## Description of the designed architecture

In this section there is an overview of the Convolutional Neural Network that was implemented to solve the proposed task:

- an **input layer** with *shape* = (28,28,1);
- a **convolutional layer** with 16 filters of *kernel\_size* = 3x3 and activation function *ReLU*;
- a **pooling layer** with Average function and *pool\_size* = 2x2;
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- a **pooling layer** with Average function and *pool\_size* = 2x2;
- a **flatten layer** that convert the output shape of the previous layer to a *mono-dimensional array*;
- a **fully-connected output layer** with one neuron for each class (10) and activation function *softmax*.

Model: "sequential\_1"

Layer (type)	Output Shape	Param #
conv2d_1 (Conv2D)	(None, 26, 26, 16)	160
average_pooling2d_1 (Average)	(None, 13, 13, 16)	0
conv2d_2 (Conv2D)	(None, 11, 11, 16)	2320
average_pooling2d_2 (Average)	(None, 5, 5, 16)	0
flatten_1 (Flatten)	(None, 400)	0
dense_1 (Dense)	(None, 10)	4010
Total params: 6,490		
Trainable params: 6,490		
Non-trainable params: 0		

Figure 2: Model summary

As can be seen from the summary of the network above, the number of parameters is 6490 and it is lower than the maximum limit of 7500 imposed in the assignment. In particular, the number of parameters of the first convolutional layer is equal to the kernel\_size plus 1 (bias), multiplied by the number of filters:  $((3 \times 3) + 1) \times 16 = 160$ .

The number of parameters of the second Conv2D layer is  $((3 \times 3 \times 16) + 1) \times 16 = 2,320$  while, the final Dense layer has  $(400 + 1) \times 10 = 4010$  parameters, where 400 is the dimension of the previous flatten layer, 1 is bias and 10 is the number of classes.

The result of using a pooling layer and creating down sampled or pooled feature maps is a summarized version of the features detected in the input.

The excellent results obtained confirm that the relevant information present in the input data is not lost during the pooling phase.

In addition, *Figure 2* shows that the output shape of the first convolutional layer is (26,26,26) because a *no-padding* has been applied. This technique is preferred to *zero-padding* because, being the digits centered, there is no risk of losing information.

The model is compiled using *Adam* optimizer (with *learning\_rate* = 0.001) and *categorical cross-entropy* such as loss function. After several tests, the number of epochs have been set to 15 and the batch size equal to 128.

Finally, it was used 10% of the training set as a validation set to control the possible overfitting of the Convolutional Neural Network.

## Plots of the training and validation loss/accuracy

In the following figures are presented the accuracy and the loss function on the training set (green) and on the validation set (blue).

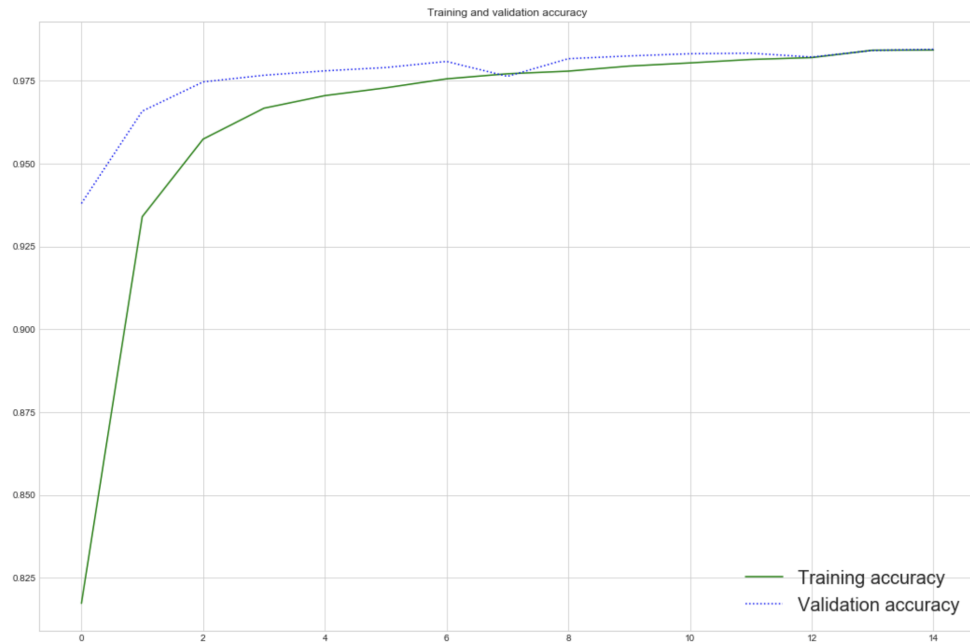


Figure 3: Accuracy on training set and validation set

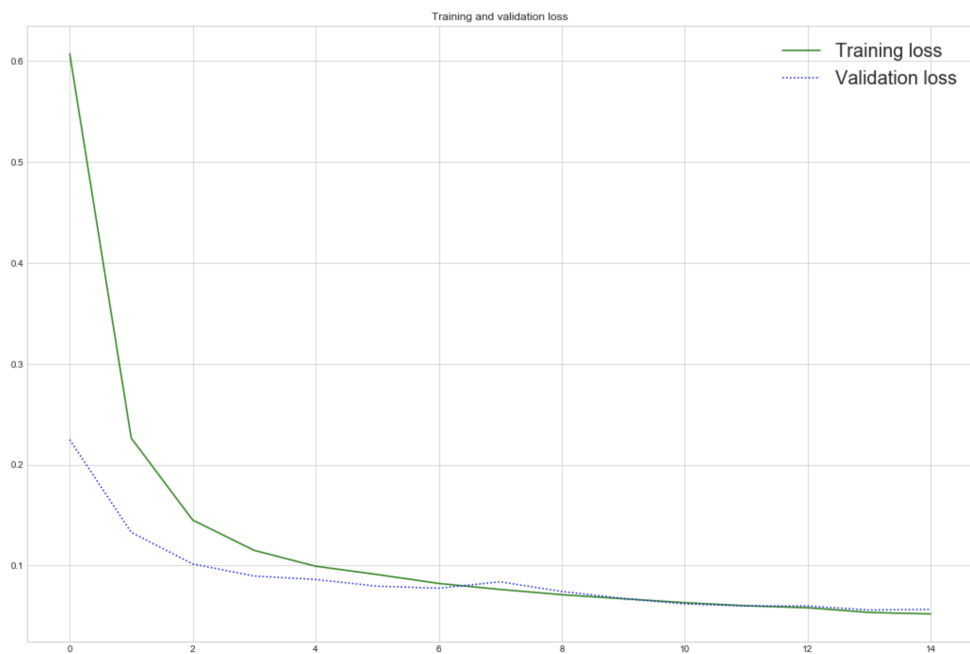


Figure 4: Loss function on training set and validation set

## Classification performance on training and test sets

After training the network and avoiding overfitting, the model was evaluated on the data present in the test set. As it can be seen from the following figures, the model continues to obtain excellent results even on data not considered during the training phase. The generalisation error is minimal and the overall accuracy is 99% both on the training and on the test set.

Classification report on training set:					Classification report on test set:				
	precision	recall	f1-score	support		precision	recall	f1-score	support
0	1.00	0.99	0.99	5923	0	0.98	0.99	0.99	980
1	0.99	0.99	0.99	6742	1	0.99	1.00	0.99	1135
2	0.98	0.99	0.98	5958	2	0.98	0.98	0.98	1032
3	0.99	0.98	0.99	6131	3	0.99	0.99	0.99	1010
4	0.99	0.98	0.99	5842	4	0.99	0.98	0.99	982
5	0.99	0.98	0.99	5421	5	0.99	0.98	0.98	892
6	0.99	0.99	0.99	5918	6	0.99	0.99	0.99	958
7	0.98	0.99	0.99	6265	7	0.98	0.98	0.98	1028
8	0.98	0.98	0.98	5851	8	0.97	0.98	0.98	974
9	0.98	0.98	0.98	5949	9	0.99	0.98	0.98	1009
accuracy			0.99	60000	accuracy			0.99	10000
macro avg	0.99	0.99	0.99	60000	macro avg	0.99	0.99	0.99	10000
weighted avg	0.99	0.99	0.99	60000	weighted avg	0.99	0.99	0.99	10000

Figure 5: Classification report on training set and test set.