

HOMEWORK 2 – DEEP LEARNING

I. Using Convolutional Neural Network for Image Recognition

I build a CNN network in order to classify the images from the MNIST dataset. I used the API Keras to implement it, to earn some time and to have optimized computation. Since my computer doesn't have any Graphic card, it would've been too long to implement it manually and to make it run on this kind of large dataset. Even using Keras, one epoch takes up to 30 seconds depending on the architecture of my CNN.

Here are the results of my CNN using the following architecture :

- 2 convolutional layers : filters number = 32, kernel size = 3, stride = (2,2), activation = relu
- 1 pooling layer : pooling size = (2,2)
- 2 dropout layers
- 1 flatten layer
- 2 dense layers : one dense has 392 units with relu activation, and the other one has 10 units with softmax activation.

Model: "sequential_8"		
Layer (type)	Output Shape	Param #
conv2d_14 (Conv2D)	(None, 13, 13, 32)	320
conv2d_15 (Conv2D)	(None, 6, 6, 32)	9248
max_pooling2d_6 (MaxPooling2D)	(None, 3, 3, 32)	0
dropout_11 (Dropout)	(None, 3, 3, 32)	0
flatten_7 (Flatten)	(None, 288)	0
dense_12 (Dense)	(None, 392)	113288
dropout_12 (Dropout)	(None, 392)	0
dense_13 (Dense)	(None, 10)	3930
Total params: 126,786		
Trainable params: 126,786		
Non-trainable params: 0		

Figure 0. Architecture summary

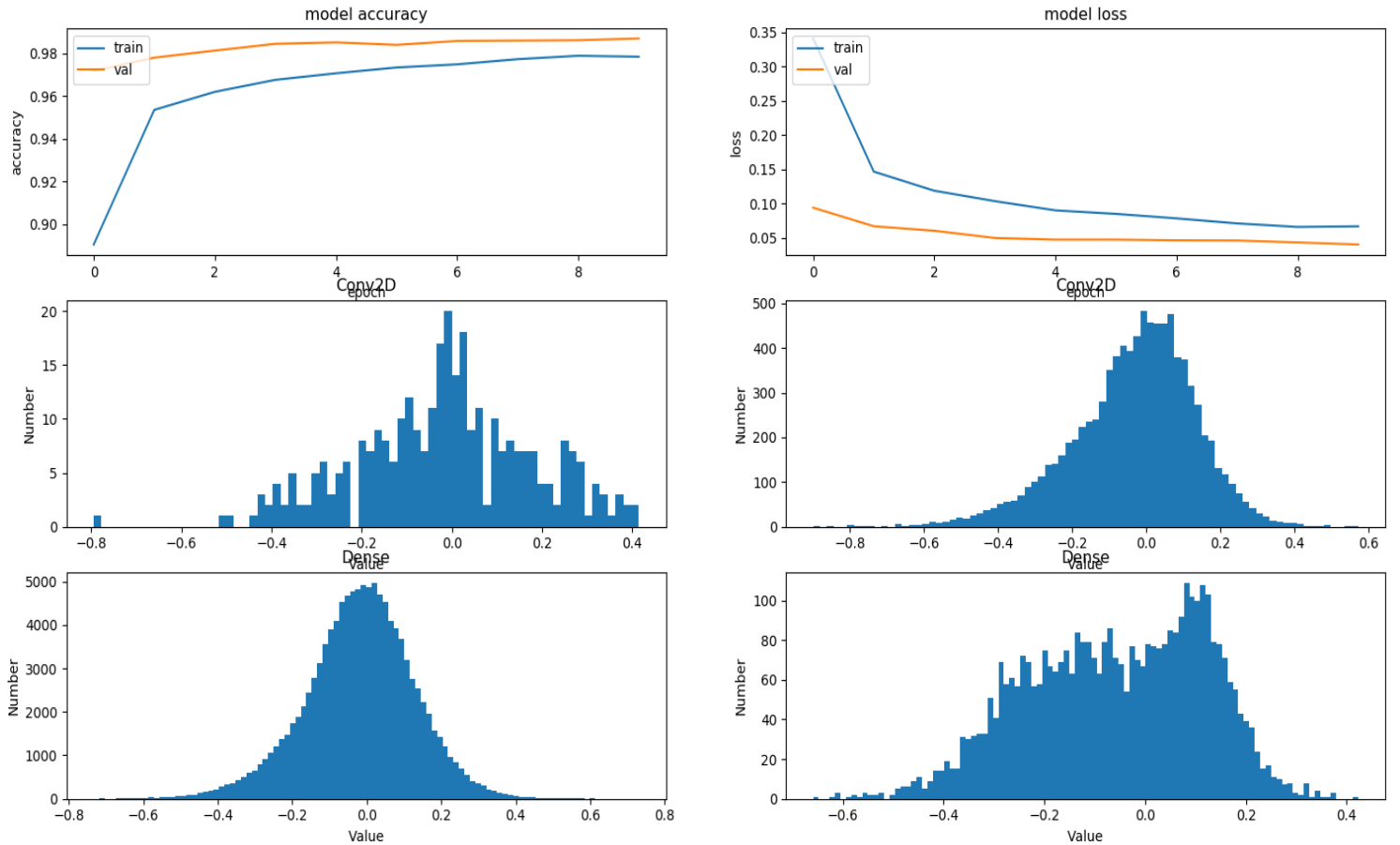


Figure 1. Results of the CNN, with weight details

Reducing the number of filters increase the error rate, and therefore decrease the accuracy. But it makes the computation faster. I tried to implement the same architecture with 8 filters instead of 32, the results are still very good, and the computation are a little faster. The following figure shows the weight with 8 filters for the convolutionnal layers, other parameters are the same.

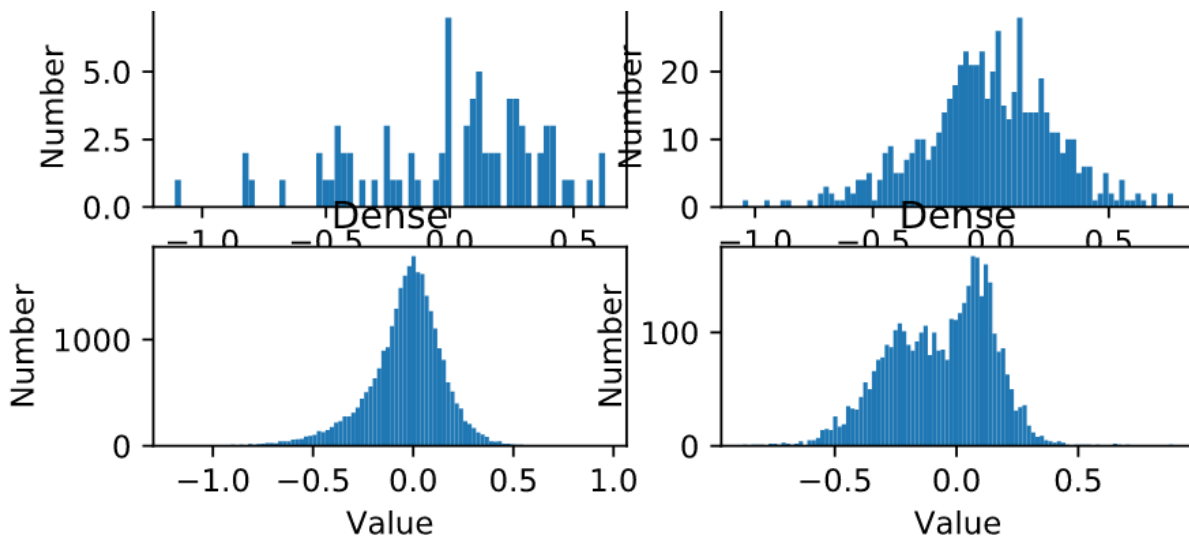


Figure 2. Weight repartition using less filters

On the following figure, you can see histograms of the weights, with stride increased to (4,4) instead of (2,2). The error is increasing as well, and the accuracy a bit lower. But as for the filters, it makes the computation slightly faster.

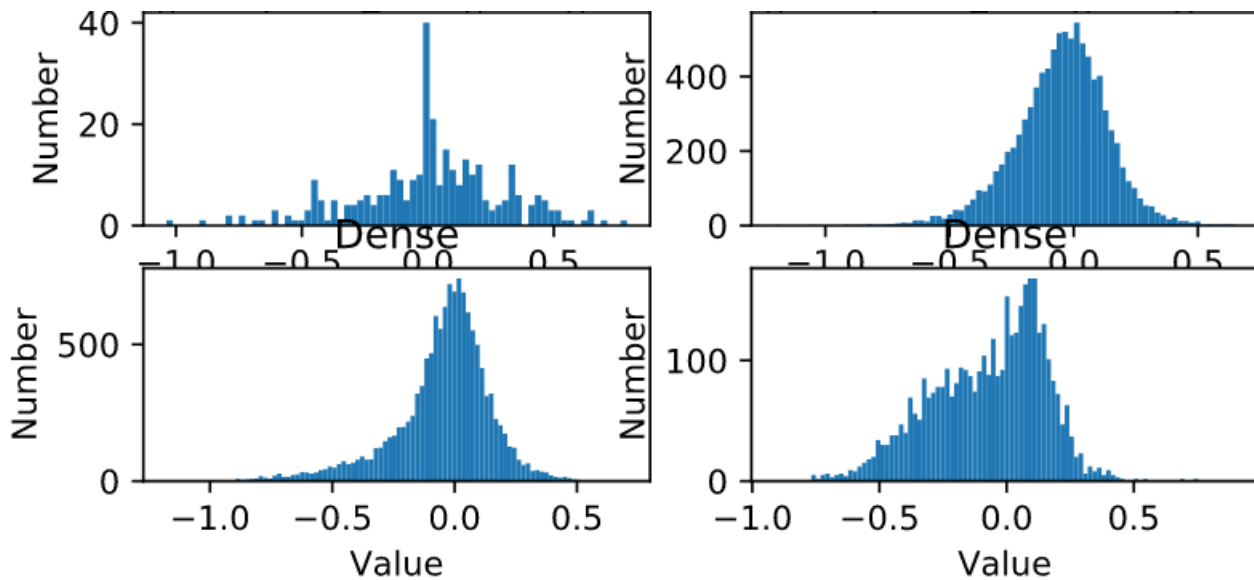


Figure 3. Weight repartition using a larger stride (4,4)

Example of misclassified images :

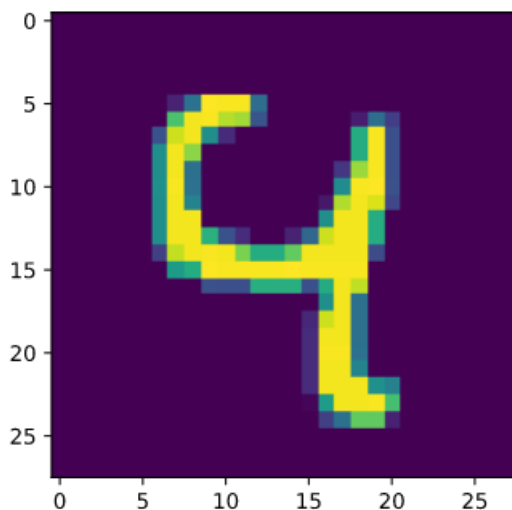


Figure 4. Predicted 4 but is actually 9

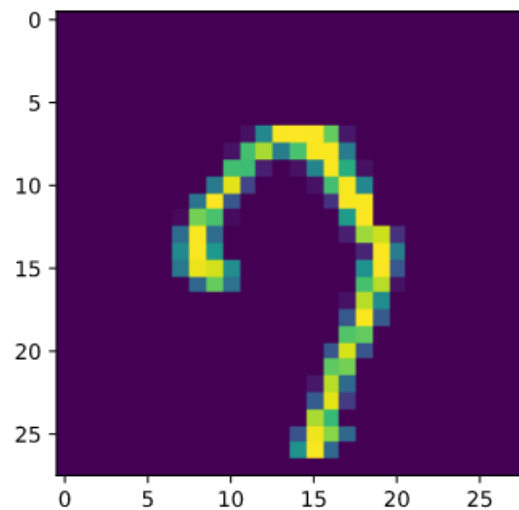


Figure 5. Predicted 7 but is actually 9

We see that for these misclassified numbers, there are legitimate doubt. Prediction of 4 can be explained by the fact that the top part of the digit is not closed. But the curve suggest that it will be a 9. So we see that the quality of the handwritten digits explain that our prediction is not perfect.

Aside from that, looking the prediction of our CNN for these images, the prediction (probability between 0 and 1) is very close between two numbers. For example, the left figure has around 0.9 for both 4 and 9, a tiny difference makes it predict 4 instead of 9, which suggest our CNN is hesitating between 4 and 9. It is the same for the right figure.

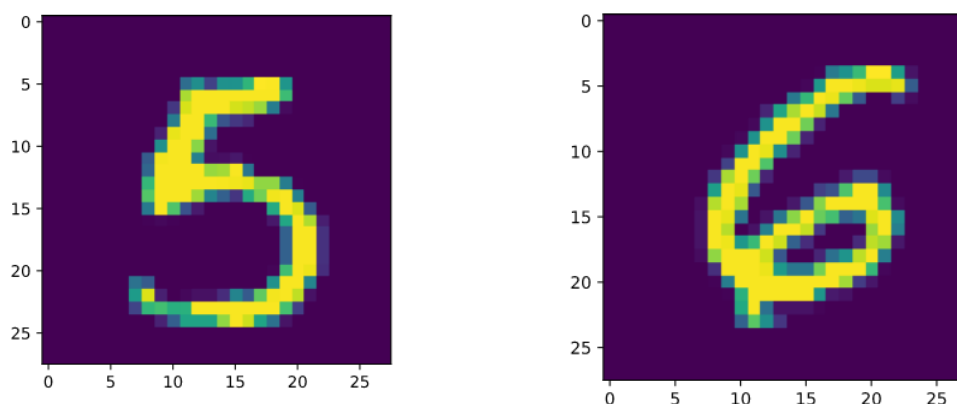
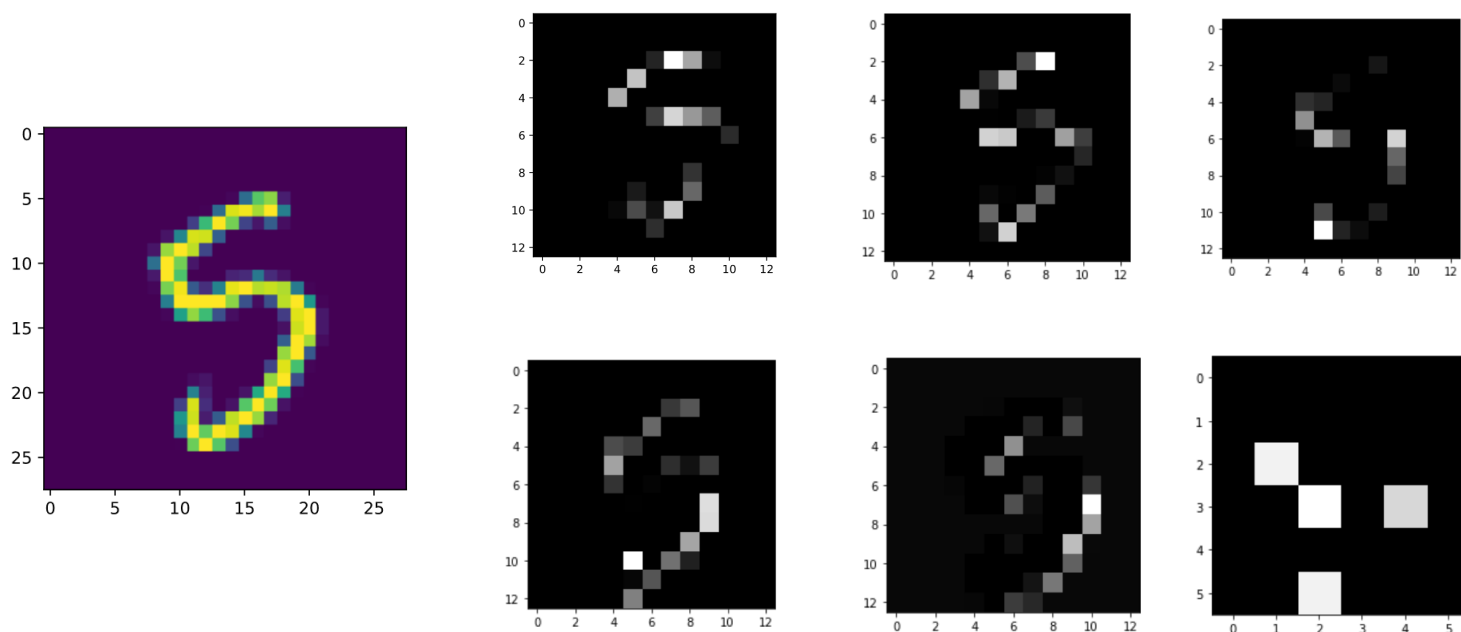


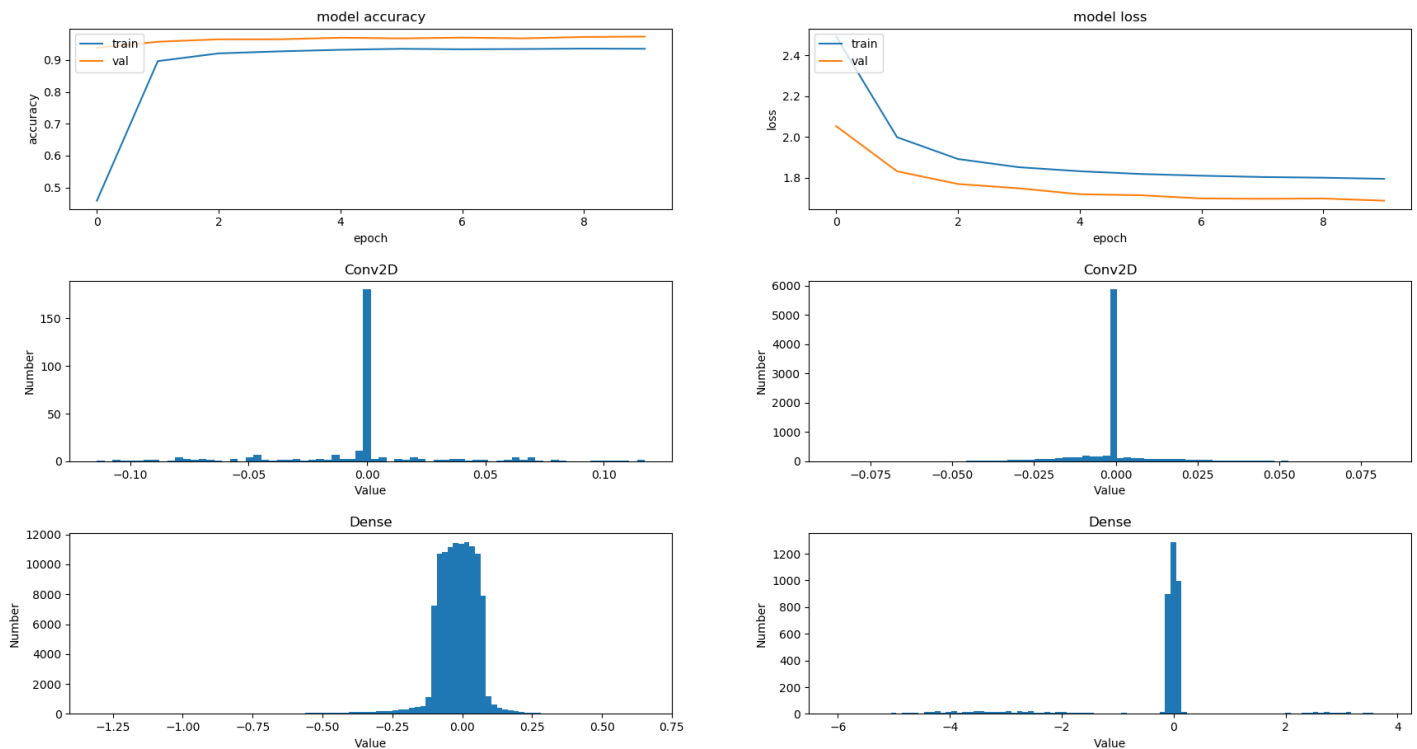
Figure 6. Right classified digits

Feature maps of a right classified number :



We can see that the first layer keeps a lot of information from the initial picture. We are still able to recognize the digits it refers to. But as we go to a deeper layer, we are getting more abstract images, until we can't recognize what is the digit. The figure carry no more informations about the aspect of the number, but more abstract information such as the curve, borders, corners and so on. It contains informations important in order to determine the class of the digit.

Adding the regularization :



We observe that the weights are all closer to 0, which is the aim of regularization. Therefore, it worked well. The accuracy is still as high ! But the loss is higher, which is because the weight have been reduced and fit not as much as without regularization. Note that it avoid overfitting to regularize.

I could improve my CNN by adding more layers, but it would largely increase the time to compute everything. The results are already really fine so I kept my architecture as it is.

Part 2 – CIFAR-10

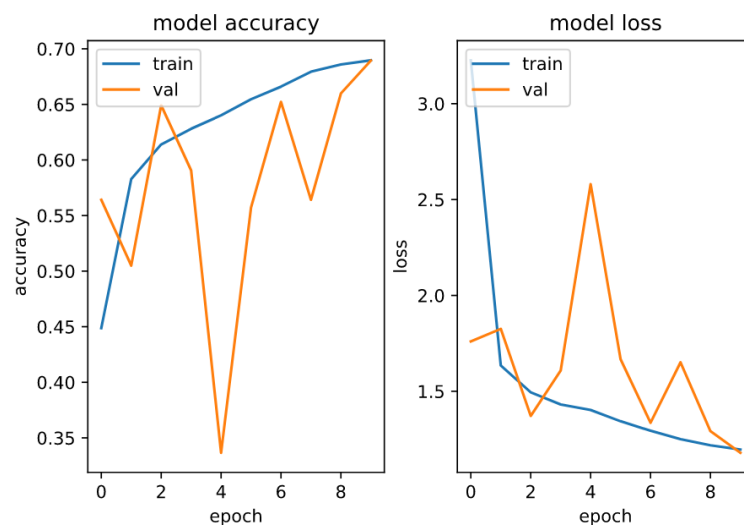
I first tried to use a similar architecture as for the MNIST dataset, but I hadn't any really good result. I managed to have around 0.5 accuracy but I felt like I could do better with another architecture. Based on research on internet and reading of several forums, I tried the following architecture :

Model: "sequential_3"			batch_normalization_3 (Batch Normalization)	(None, 16, 16, 64)	256
Layer (type)	Output Shape	Param #	conv2d_7 (Conv2D)	(None, 16, 16, 64)	36928
conv2d_4 (Conv2D)	(None, 32, 32, 32)	896	activation_6 (Activation)	(None, 16, 16, 64)	0
activation_3 (Activation)	(None, 32, 32, 32)	0	batch_normalization_4 (Batch Normalization)	(None, 16, 16, 64)	256
batch_normalization_1 (Batch Normalization)	(None, 32, 32, 32)	128	max_pooling2d_3 (MaxPooling2D)	(None, 8, 8, 64)	0
conv2d_5 (Conv2D)	(None, 32, 32, 32)	9248	dropout_6 (Dropout)	(None, 8, 8, 64)	0
activation_4 (Activation)	(None, 32, 32, 32)	0	conv2d_8 (Conv2D)	(None, 8, 8, 128)	73856
batch_normalization_2 (Batch Normalization)	(None, 32, 32, 32)	128	activation_7 (Activation)	(None, 8, 8, 128)	0
max_pooling2d_2 (MaxPooling2D)	(None, 16, 16, 32)	0	batch_normalization_5 (Batch Normalization)	(None, 8, 8, 128)	512
dropout_5 (Dropout)	(None, 16, 16, 32)	0	conv2d_9 (Conv2D)	(None, 8, 8, 128)	147584
conv2d_6 (Conv2D)	(None, 16, 16, 64)	18496	activation_8 (Activation)	(None, 8, 8, 128)	0
activation_5 (Activation)	(None, 16, 16, 64)	0	batch_normalization_6 (Batch Normalization)	(None, 8, 8, 128)	512

max_pooling2d_4 (MaxPooling2D)	(None, 4, 4, 128)	0
dropout_7 (Dropout)	(None, 4, 4, 128)	0
flatten_2 (Flatten)	(None, 2048)	0
dense_5 (Dense)	(None, 10)	20490
Total params: 309,290		
Trainable params: 308,394		
Non-trainable params: 896		

The computation was really long, around 30 minutes for ten epoch. So I stopped at ten epoch.

I had the following results :

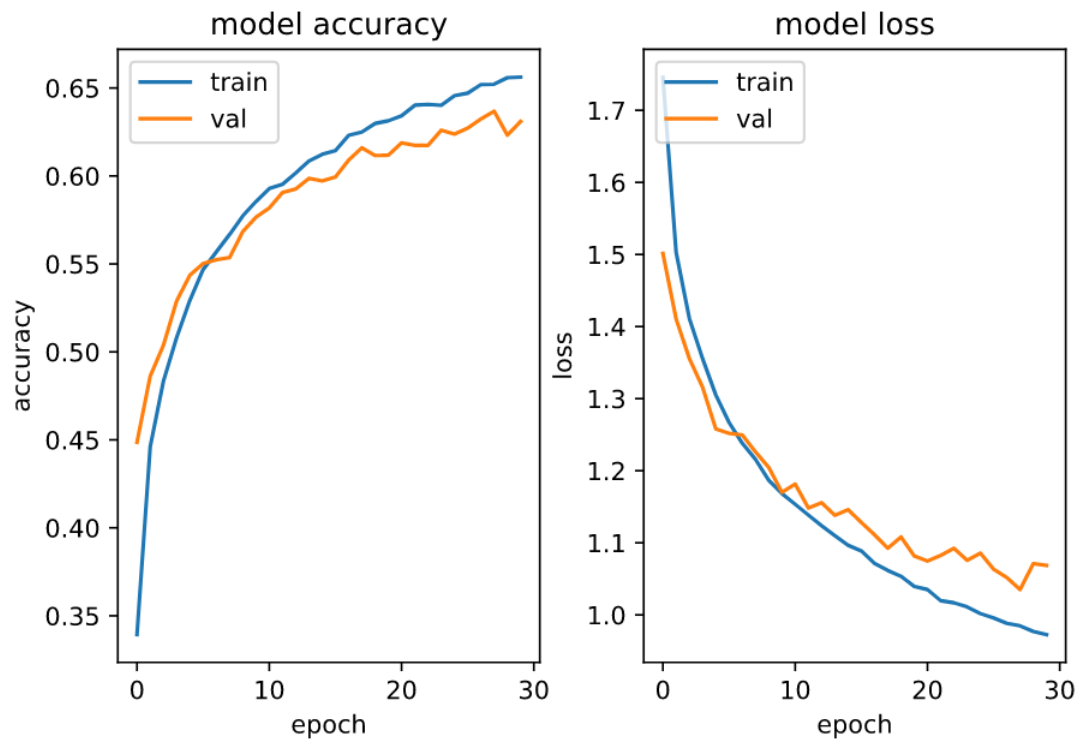


I was really not satisfied with these, because the validation set was really not stable, probably because the model is overfitting the training set. So I went back to my first architecture and tried to triple the number of epoch. Here is my architecture, much simpler than the previous one :

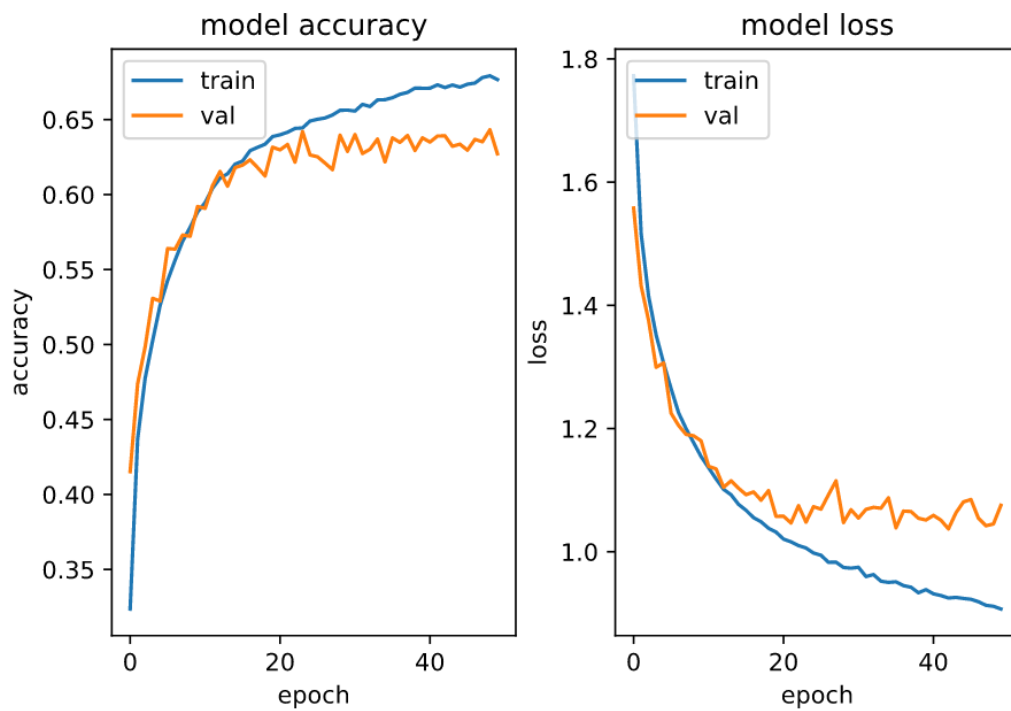
Model: "sequential_5"		
Layer (type)	Output Shape	Param #
conv2d_13 (Conv2D)	(None, 15, 15, 32)	896
activation_11 (Activation)	(None, 15, 15, 32)	0
conv2d_14 (Conv2D)	(None, 7, 7, 32)	9248
activation_12 (Activation)	(None, 7, 7, 32)	0
max_pooling2d_6 (MaxPooling2D)	(None, 3, 3, 32)	0
dropout_12 (Dropout)	(None, 3, 3, 32)	0
conv2d_15 (Conv2D)	(None, 1, 1, 16)	4624
flatten_4 (Flatten)	(None, 16)	0
dense_10 (Dense)	(None, 128)	2176
dropout_13 (Dropout)	(None, 128)	0

dense_11 (Dense)	(None, 256)	33024
dropout_14 (Dropout)	(None, 256)	0
dense_12 (Dense)	(None, 512)	131584
dropout_15 (Dropout)	(None, 512)	0
dense_13 (Dense)	(None, 10)	5130
Total params: 186,682		
Trainable params: 186,682		
Non-trainable params: 0		

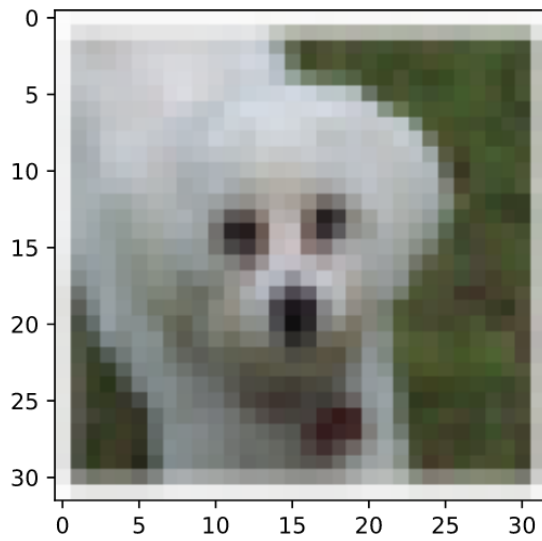
I had the following accuracy and loss with 30 epoch, for 10 minutes of computation



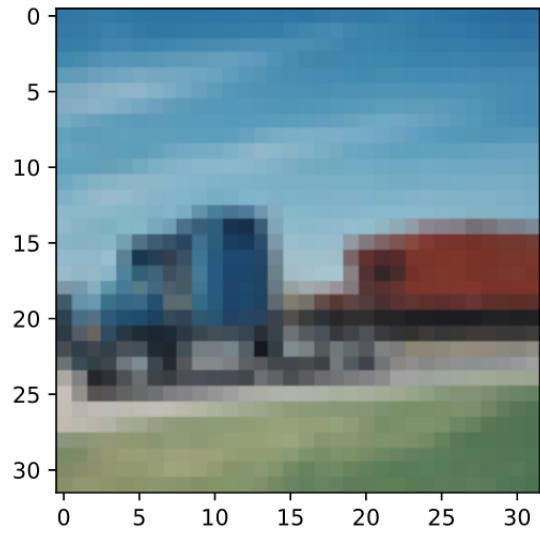
Since my results were still increasing decently, I tried to increase another time the number of epoch to 50. Following figure shows my results :



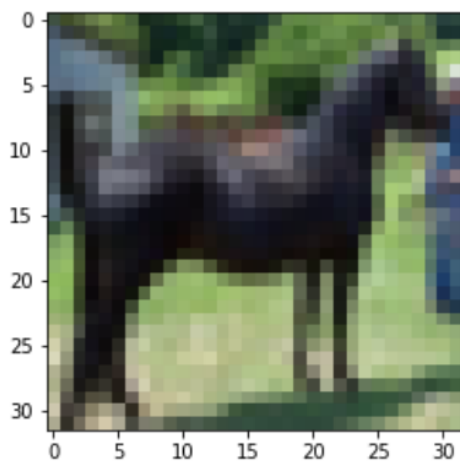
Missclassified image



This image was classified as being a cat, whereas it is a dog.

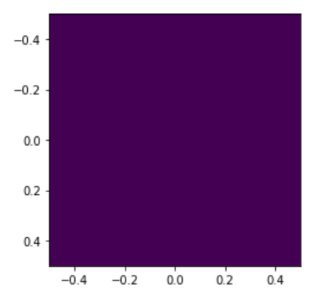
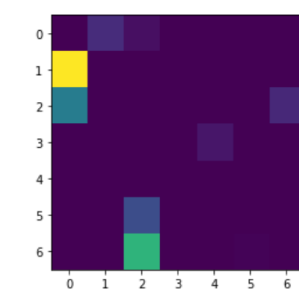
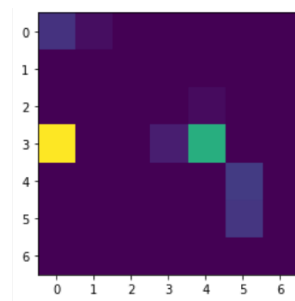
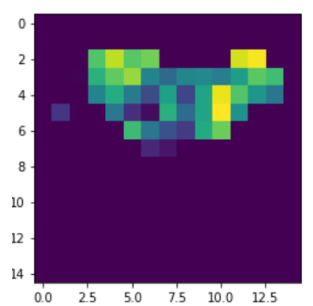
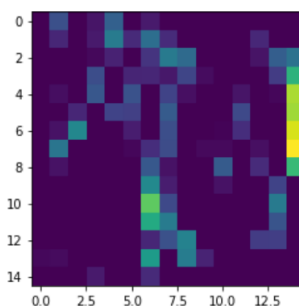
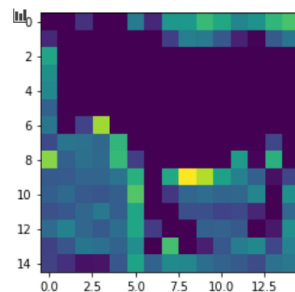
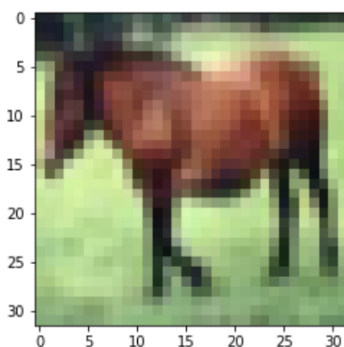


This image was classified as being an airplane, whereas it is a truck.



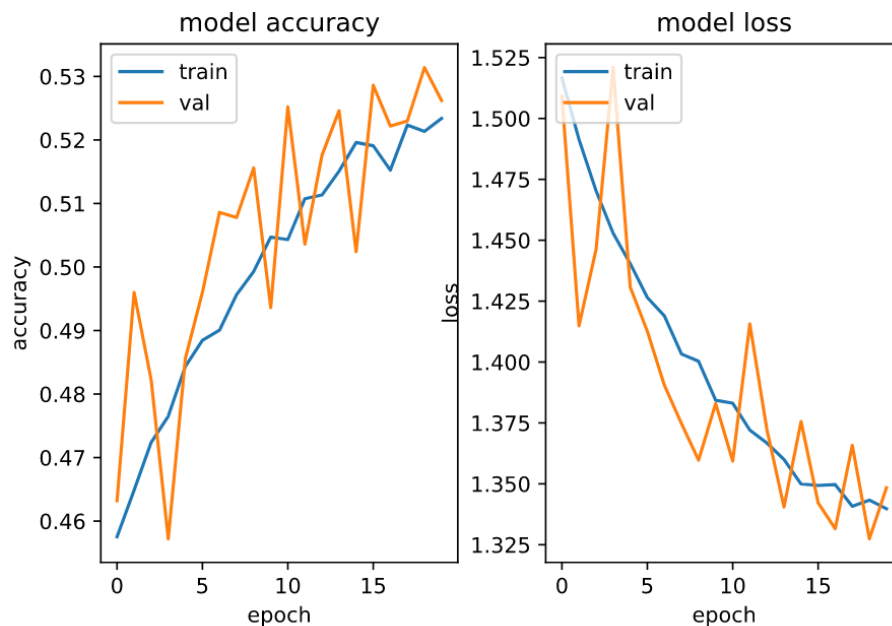
And this image was correctly guessed by our CNN as being a horse.

Feature maps



Adding regularization

I tried to add a regularization term on every convolutional layer and fully connected layer but I had a bad result. So I think it was underfitting the data way too much, so I just added a regularization term on a few layer and had the following results :



Bias is getting lower but the variance is increasing, which is a known phenomenon.

Preprocessing

The data were not really ready to use directly from the downloaded file. I first had to use pickle to load the data. There were 5 separated files to use, so I decided to concatenate their content into two large numpy array for the images (one training set and one validation set) and another one for the labels (as for the images, one training set and validation set). I used keras to one-hot vectorize the labels, and I normalized the array containing the pictures data. Once everything was done I was ready to use my CNN to fit my classifier using keras again.

I wrote my preprocessing in a separate file, which needs the initial files in the same directory to output new files corresponding to my processed data. I wrote my new file using pickle as well.