

POLITECNICO DI TORINO

**Corso di Laurea Magistrale
in Data Science and Engineering**

Machine Learning and Deep Learning Report

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Image recognition on Caltech-101 using
different CNN models and techniques



Emanuele Fasce

1. INTRODUCTION

In this report several Convolutional Neural Networks (CNN) are implemented and used for classification on the Caltech-101 dataset using Pytorch.

The starting point of this work is the AlexNet network.

After a first step in which AlexNet is trained from scratch, some useful techniques are exploited, like pretraining the network on the ImageNet dataset, and the data augmentation technique.

In the last stage of this report, other CNN models are used.

Hyperparameters are modified manually at each run. This choice is preferred due to hardware constraints and due to the need of readjusting the hyper-parameters by analyzing the results of preceding trainings.

While all the results are reported in tables, the training graphs are available at the following link:

2. DATASET AND PREPROCESSING

The dataset Caltech-101 is composed of 5784 labeled and 2893 unlabeled pictures of 101 different categories of objects selected from the ImageNet dataset. Original images (300x200 pixels) are resized, cropped in the center, and transformed into RGB tensors with dimensions 3x224x224. Two different normalizations are used with the pretrained and non-pretrained network since the mean and the standard variation of the pictures in the Imagenet dataset are different from the mean and standard variation of pictures in Caltech-101 dataset. Half of the labeled set is split into the training set and half into the validation set, in such a way that half samples of each class belongs to the training set and the other half to the validation set. This is obtained by the parameter *stratify* in the *train_test_split* function or also by exploiting the fact that in the file that contains the labeled dataset classes are already well divided, so it is enough to put the picture described in a row in the training set and the picture described in the following row in the validation set. The unlabeled set is used as test set.

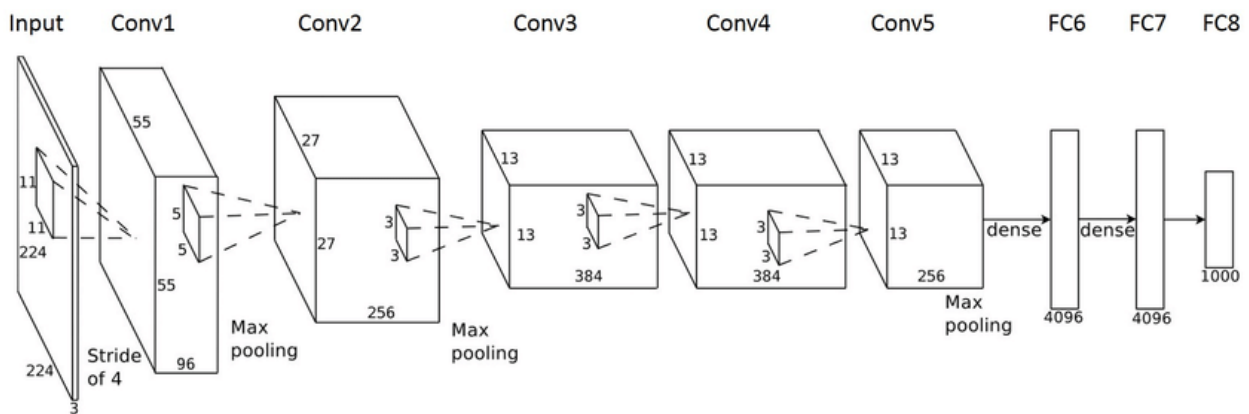
3. ALEXNET

A CNN is a neural network in which there is at least a convolutional layer.

There are several reasons why this type of network is much more effective than traditional neural networks when dealing with image recognition.

AlexNet is an extremely popular CNN used in computer vision. It was proposed by Hinton et Al. in one of the most influential papers published in the field of computer vision. It became the first Deep CNN based large database image recognition winner in 2012.

As shown below, it contains eight layers; the first five are convolutional layers, some of them followed by max-pooling layers, and the last three are fully connected layers.



4. EXPERIMENTS WITH ALEXNET

It can be noticed that importing the Alexnet network is very easy on Pytorch but this model has to be modified. Since the Caltech-101 dataset contains only 101 classes while Imagenet contains 1000 classes, the last fully connected layer of Alexnet is modified with `out_features=101`.

The Alexnet network is trained with different combinations of hyperparameters and evaluated to see which combination gives the best accuracy on the validation set. The winner combination is used to fit the model on the test set.

It can be noticed that each optimizer works better with different learning rates. For example, using SGD with a LR=1e-2 leads to suboptimal results, so the learning rate is kept lower in the other trials, and the best accuracy on the validation set is found with LR=1e-3.

The Adam and AdamW optimizers in this case do not work well with LR=1e-3, so training is performed with LR=1e-4. The Adadelata optimizer instead allows LR=1e-1.

Number	Optimizer	LR	Epochs	Momentum	Weight decay	Stepsize	Gamma	TypeNet	Pretrained	Acc.Test	Acc.Val	Acc.Train	Loss Val	Loss Train
1	SGD	1,00E-04	30	0.9	5,00E-05	20	0.1	AlexNet	No	-	56.34	99.82	4.06	0.004
2	SGD	1,00E-02	30	0.9	5,00E-05	30	0.1	AlexNet	No	-	14.97	15.31	4.00	3.95
3	SGD	1,00E-03	70	0.9	5,00E-05	40	0.1	AlexNet	No	57.76	57.98	99.79	3.48	0.005
4	Adam	1,00E-04	30	-	default (0)	20	0.1	AlexNet	No	-	58.09	99.61	3.81	0.008
5	Adadelata	1,00E-02	30	-	default(0)	20	0.1	AlexNet	No	-	44.39	64.21	2.60	1.39
6	Adadelata	1,00E-01	50	-	default(0)	30	0.1	AlexNet	No	-	58.47	99.75	5.85	0.006
7	AdamW	1,00E-04	25	-	default(0.01)	25	0.1	AlexNet	No	-	53.63	97.30	3.47	0.15

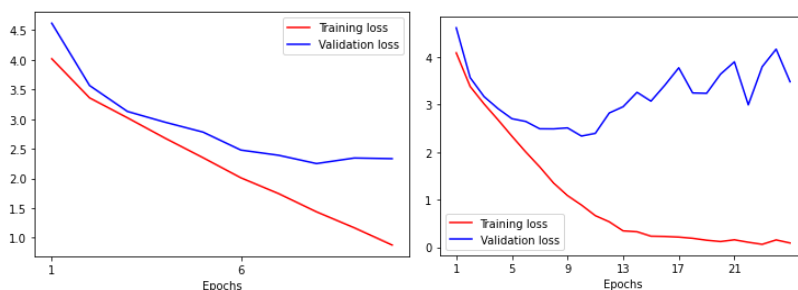
Table 1: Results with different hyper-parameters

In Table 1 the number of epochs often chosen is over 30, however by inspecting the losses it can be noticed that in some models the validation loss begins to increase while the accuracy often gets a boost. These models are trained again in order to reduce overfitting.

Number	Optimizer	LR	Epochs	Momentum	Weight deca	Stepsize	Gamma	TypeNet	Pretrained	Acc.Test	Acc.Val	Acc.Train	Loss Val	Loss Train
3bis	SGD	1,00E-03	25	0.9	5,00E-05	15	0.1	AlexNet	No	55.72	53.69	83.85	2.50	0.66
4bis	Adam	1,00E-04	10	-	default (0)	10	0.1	AlexNet	No	53.19	50.41	70.41	2.31	1.23
6bis	Adadelata	1,00E-01	50	-	default(0)	30	0.1	AlexNet	No	55.68	52.00	78.97	2.40	0.96
7bis	AdamW	1,00E-04	10	-	default(0.01)	25	0.1	AlexNet	No	51.12	51.27	67.63	2.33	1.16

Table 2 bis: Results with different hyper-parameters, reduced overfitting

In order to see the difference in the losses, as an example the losses of model 7 and model 7bis are shown.



Loss model 7bis

Loss model 7

5. TRANSFER LEARNING

Since the Caltech-101 dataset is not very big, the transfer learning technique is exploited.

It is a research problem that focuses on storing knowledge gained while solving one problem and applying it to a different but related problem.

In this case, the network that has been trained on the Imagenet dataset, which is very rich and contains more than 14 million images, could be useful on the Caltech-101 dataset, which contains only 5784 images and its classes are present in the Imagenet dataset. Loading the pretrained model is very easy in Pytorch with *pretrained=True*, but the last fully connected layer needs to be changed due the different number of classes of these two datasets.

In the first stage of this experiment, the pretrained AlexNet network gets trained also on the Caltech-101 training set and is evaluated on the Caltech-101 validation set.

On a second stage, only the fully connected layers or the convolutional layers are trained with the best hyperparameters found before.

Three different optimizers are used: SGD, Adam and AdamW.

For each group (concerning the type of layers trained), the model that behaves better on the validation set is tested on the test set. For example, in Table 2, where all the layers are trained, the model 3 has both a higher accuracy and a lower loss on the validation set, so is tested on the test set.

Number	Optimizer	LR	Epochs	Momentum	Weight deca	Stepsize	Gamma	TypeNet	Trained layers	Pretrained	Acc.Test	Acc.Val	Acc.Train	Loss Val	Loss Train
1	SGD	1,00E-04	30	0.9	5,00E-05	20	0.1	AlexNet	All	Yes	-	83.19	99.89	0.83	0.006
2	Adam	1,00E-04	30	-	default(0)	20	0.1	AlexNet	All	Yes	-	83.26	99.93	0.92	0.0004
3	AdamW	1,00E-04	40	-	default(0)	20	0.1	AlexNet	All	Yes	84.41	84.47	99.93	0.82	8.18e-5

Table 2: results with all the layers trained.

Training only the fully connected layers or both the fully connected and the convolutional layers lead to very similar results, while training only the convolutional layers leads to worse results, as seen in the following tables.

Number	Optimizer	LR	Epochs	Momentum	Weight deca	Stepsize	Gamma	TypeNet	Trained layers	Pretrained	Acc.Test	Acc.Val	Acc.Train	Loss Val	Loss Train
4	SGD	1,00E-04	30	0.9	5,00E-05	20	0.1	AlexNet	Conv	Yes	48.66	-	53.66	2.42	2.05
5	Adam	1,00E-04	30	-	default(0)	20	0.1	AlexNet	Conv	Yes	66.67	65.11	98.78	1.90	0.07
6	AdamW	1,00E-04	40	-	default(0)	20	0.1	AlexNet	Conv	Yes	66.64	-	98.72	1.96	0.08

Table 3: results with convolutional layers trained.

Number	Optimizer	LR	Epochs	Momentum	Weight deca	Stepsize	Gamma	TypeNet	Trained layers	Pretrained	Acc.Test	Acc.Val	Acc.Train	Loss Val	Loss Train
7	SGD	1,00E-04	30	0.9	5,00E-05	20	0.1	AlexNet	FC	Yes	-	83.02	99.34	0.64	0.04
8	Adam	1,00E-04	30	-	default(0)	20	0.1	AlexNet	FC	Yes	-	83.67	99.93	0.88	0.0004
9	AdamW	1,00E-04	40	-	default(0)	20	0.1	AlexNet	FC	Yes	84.96	84.37	99.93	0.79	0.0008

Table 4: results with fully connected layers trained.

A reasonable hypothesis could be that since the ImageNet dataset is already very rich, comprehends all the classes present in the Caltech dataset and the pictures in Imagenet dataset are not that different from the pictures in Caltech-101 dataset, training only the fully connected layers is enough to obtain satisfying results since the pretrained convolutional layers are already useful.

Avoiding to train fully connected layers leads to suboptimal results, but this is not unexpected, since the last fully connected layer of Alexnet was modified as discussed before (due to the different number of classes) and should be trained again.

6. DATA AUGMENTATION

Data augmentation in data analysis are techniques used to increase the amount of data by adding slightly modified copies of already existing data or newly created synthetic data from existing data. It acts as a regularizer and helps reduce overfitting when training a machine learning model.

This technique is implemented by applying on the pictures belonging to the Caltech-101 training set some transformations. The used Pytorch transforms, applied on each training picture with a given probability, have parameters that randomly change in a given interval.

When training Alexnet from scratch using data augmentation, the accuracies are very similar to the ones obtained with the standard training. The model that performs better on the validation set scores a 56.51% in accuracy on the test set.

Number	Optimizer	LR	Epochs	Momentum	Weight deca	Stepsize	Gamma	TypeNet	Trained layers	Transforms	Pretrained	Acc.Test	Acc.Val	Acc.Train	Loss Val	Loss Train
1	SGD	1,00E-03	50	0.9	5,00E-05	25	0.1	AlexNet	All	ColorJitter	No	-	57.12	98.44	3.31	0.06
2	SGD	1,00E-03	50	0.9	5,00E-05	25	0.1	AlexNet	All	RandomAffine	No	56.61	57.50	95.81	3.39	0.14
3	SGD	1,00E-03	50	0.9	5,00E-05	25	0.1	AlexNet	All	RandomHorizontalSplit	No	-	55.56	91.07	3.06	0.29

Table 5: results with all the layers trained and without transfer learning.

As seen in Table 6, when using the pretrained Alexnet and training all the layers, accuracies often worsen with respect to the standard training, and the validation losses do not decrease. However, freezing convolutional layers and training only the fully connected layers lead to accuracies which are very similar to those obtained without data augmentation. One could argue that when using these transforms on the training set, images become too different from the ones in the test set and therefore this procedure leads to worse results. This effect is obviously minimized when training only the fully connected layers.

Number	Optimizer	LR	Epochs	Momentum	Weight decay	Stepsize	Gamma	TypeNet	Trained layer:	Transforms	Pretrained	Acc.Test	Acc.Val	Acc.Train	Loss Val	Loss Train
4	SGD	1,00E-04	40	0.9	5,00E-05	25	0.1	AlexNet	All	RandAffine + RandHorSplit	Yes	-	80.77	95.53	1.01	0.13
5	SGD	1,00E-04	40	0.9	5,00E-05	25	0.1	AlexNet	All	RandHorSplit	Yes	-	78.76	98.58	1.18	0.04
6	SGD	1,00E-04	40	0.9	5,00E-05	25	0.1	AlexNet	All	ColorJitter	Yes	-	80.42	97.33	1.08	0.09
7	SGD	1,00E-03	80	0.9	5,00E-05	25	0.1	AlexNet	All	Randomcrop	Yes	-	77.42	98.16	1.08	0.05
8	SGD	1,00E-03	40	0.9	5,00E-05	25	0.1	AlexNet	FC	RandHorSplit + ColorJitter	Yes	84.82	83.22	99.10	0.93	0.03
9	SGD	1,00E-03	40	0.9	5,00E-05	25	0.1	AlexNet	FC	Split + ColorJit + RandAff + Crop	Yes	-	74.10	90.38	1.24	0.31
10	SGD	1,00E-03	40	0.9	5,00E-05	25	0.1	AlexNet	FC	Random Perspective	Yes	-	82.46	98.61	0.96	0.04
11	SGD	1,00E-03	60	0.9	5,00E-05	25	0.1	AlexNet	FC	RandomPersp + Gaussianblur	Yes	-	82.12	98.78	1.07	0.04
12	SGD	1,00E-04	60	0.9	5,00E-05	25	0.1	AlexNet	FC	RandHorSplit	Yes	-	80.77	98.75	0.84	0.06

Table 6: results with all the layers and only the FC trained with transfer learning.

The model that performs better on the validation set scores a 84.82% in accuracy on the test set. The best models without data augmentation obtained 57.76% and 84.96% respectively without and with transfer learning. Therefore, one can say that significant improvements using the data augmentation technique are not observed.

7. BEYOND ALEXNET

Several other architectures are used to see how they behave on this dataset.

Sometimes also the *in_features* parameter of the last fully connected layer has to be changed due to different architectures (as well as the *out_features* parameter for the different number of classes).

Among these networks, the one that if pretrained gives the best accuracy on the validation dataset is the ResNext50, which reaches an accuracy of 95.54% on the test set. if not pretrained, the best accuracy on the test set is given by the Densenet121.

An interesting detail to notice is that not necessarily deeper networks obtain higher accuracies: Resnet18 works better on the validation set than its deeper variants both when pretrained and when trained from scratch.

Number	Optimizer	LR	Epochs	Momentum	Weight decay	Stepsize	Gamma	TypeNet	Trained layers	Pretrained	Acc.Test	Acc.Val	Acc.Train	Loss Val	Loss Train
1	SGD	1,00E-03	30	0.9	5,00E-05	10	0.1	Vgg16	All	Yes	90.32	90.38	99.93	0.42	0.0008
2	SGD	1,00E-03	30	0.9	5,00E-05	10	0.1	Resnet18	All	Yes	93.25	93.18	99.86	0.26	0.03
3	SGD	1,00E-03	30	0.9	5,00E-05	10	0.1	Densenet121	All	Yes	90.49	91.32	99.89	0.36	0.009
4	SGD	1,00E-03	30	0.9	5,00E-05	10	0.1	Googlenet	All	Yes	93.67	93.04	99.06	0.26	0.14
5	SGD	1,00E-03	30	0.9	5,00E-05	10	0.1	Resnet50	All	Yes	91.11	90.83	99.86	0.39	0.01
6	SGD	1,00E-03	30	0.9	5,00E-05	10	0.1	Resnext50	All	Yes	95.54	95.05	99.93	0.19	0.01
7	SGD	1,00E-02	60	0.9	5,00E-05	20	0.1	Resnext50	All	No	63.46	60.85	99.75	2.57	0.01
8	SGD	1,00E-02	60	0.9	5,00E-05	20	0.1	Vgg16	All	No	49.46	50.00	99.79	4.88	0.007
9	SGD	1,00E-02	30	0.9	5,00E-05	15	0.01	Vgg16	All	No	48.15	47.82	95.05	3.20	0.17
10	SGD	1,00E-02	60	0.9	5,00E-05	25	0.1	Resnet50	All	No	57.86	56.15	99.68	3.37	0.005
11	SGD	1,00E-02	60	0.9	5,00E-05	25	0.1	Densenet121	All	No	70.16	69.81	99.93	1.44	0.01
12	SGD	1,00E-02	60	0.9	5,00E-05	25	0.1	Resnet152	All	No	56.51	54.87	99.75	8.32	0.01
13	SGD	1,00E-02	40	0.9	5,00E-05	20	0.1	Resnet18	All	No	63.84	62.10	99.93	1.80	0.003
14	SGD	1,00E-02	40	0.9	5,00E-05	20	0.1	Resnet18	All	Yes	93.70	93.36	99.93	0.24	0.01

Table 7: experiments with different networks.