Convolutional neural networks for multiple sclerosis lesion detection

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Abstract

Acknowledgements

To my father,

for all the things that can only be learnt by example.

Contents

Chapter 1

Introduction

In the last years, with the increase of the available biomedical data and the computation power in GPUs together with the appearance of new Artificial Intelligence (AI) models and techniques, it has existed and exists a growing interest and research effort on applying Artificial Intelligence to several biomedical tasks. In many of these tasks, most of them currently performed manually by doctors or medicine professionals, there have appeared automatic tools based on Artificial Intelligence models which show a performance close to the accuracy of a doctor. In other words, the application of Artificial Intelligence to medicine has proved to be useful and is definitely part of the future of the discipline. It will help by saving doctor's time, increasing the efficiency and the scope of the medicine professionals, helping them to provide more accurate diagnoses or even creating diagnoses by themselves and ultimately contributing to save lives.

Aware of this, the European Comission starts in 2019 the DeepHealth project. This aims to offer a unified framework completely adapted to exploit underlying heterogeneous High-Performance Computing (HPC) and Big Data architectures, framework to be assembled with state-of-the-art techniques in Deep Learning (DL) and Computer Vision. In particular,the project combines High-Performance Computing infrastructures with Deep Learning (DL) and Artificial Intelligence techniques to support biomedical applications that require the analysis of large and complex biomedical datasets and thus, new and more efficient ways of diagnosis, monitoring and treatment of diseases. The framework consist on two general purpopse libraries which are currently being developed, EDDL for Deep Learning computing infrastructure and ECVL for computer vision tools.

The goal of this project is to create state-of-the art Deep Learning models to detect of Multiple Sclerosis (MS) lesions in Magnetic Resonance Images (MRI) using EDDL library, analyzing its performance and comparing it with other commonly used libraries.

1.1 Multiple Sclerosis

Multiple sclerosis is the most common immune-mediated disorder affecting the central nervous system.

1.2 Multiple Sclerosis lesion segmentation

Multiple Sclerosis lesion segmentation consists on identifying in an MRI the damaged parts of the brain. This task plays a role in every stage of the disease, it has a huge importance in the patients for an early diagnose, for following the evolution of the disease and for measuring the effects of the treatment. However, this task has to be done manually by experts and involves analyzing a huge amount of data so it's highly time-consuming and prone to errors. Considering also the how relatively common this disease is, it's clear the importance of trying to optimize it. In fact, MS lesion segmentation was established as one of the main use cases for the development of the DeepHealth project.

MS lesion segmentation is a difficult task *per se*, but even more given the difficulty and cost of obtaining and labeling the data. This makes almost impossible for anybody without the needed resources to access to a dataset and, in the best case, to have only a few samples, what makes almost any Machine Learning approach to be unfeasible. However, in recent years, within MICCAI2008 and MICCAI2016 challenges, there have been a big research effort which has led to the emergence of various different approaches and solutions. These include the usage of classical image segmentation networks[1], Random Forests [1], Hybrid Artificial Neural Networks [1], Automated Multimodal Graph Cut [1], unsupervised approaches using Rules and Level Sets [1]...

In this project we'll focus our attention on the state-of-the-art approaches using 2-D and 3-D Convolutional Neural Networks (CNN).

We first analyze the application of 2-D CNN, starting with the U-Net as the standard for biomedical image segmentation, building, training, evaluating and profiling the model. Then we try a newer approach, the Double U-Net, which has proved to improve U-Net in some datasets, comparing both the performance of EDDL library with respect to a keras-tensorflow implementation and the models between themselves.

By last, we analyze the application of a cascade 3-D CNN. Evaluating and profiling the model and comparing it to an equivalent implementation with keras-tensorflow.

Chapter 2

Data

The two main datasets for MS lesion segmentation are those for MICCAI 2008 and MICCAI 2016 challenges. In this project we'll work over MICCAI 2016 dataset.

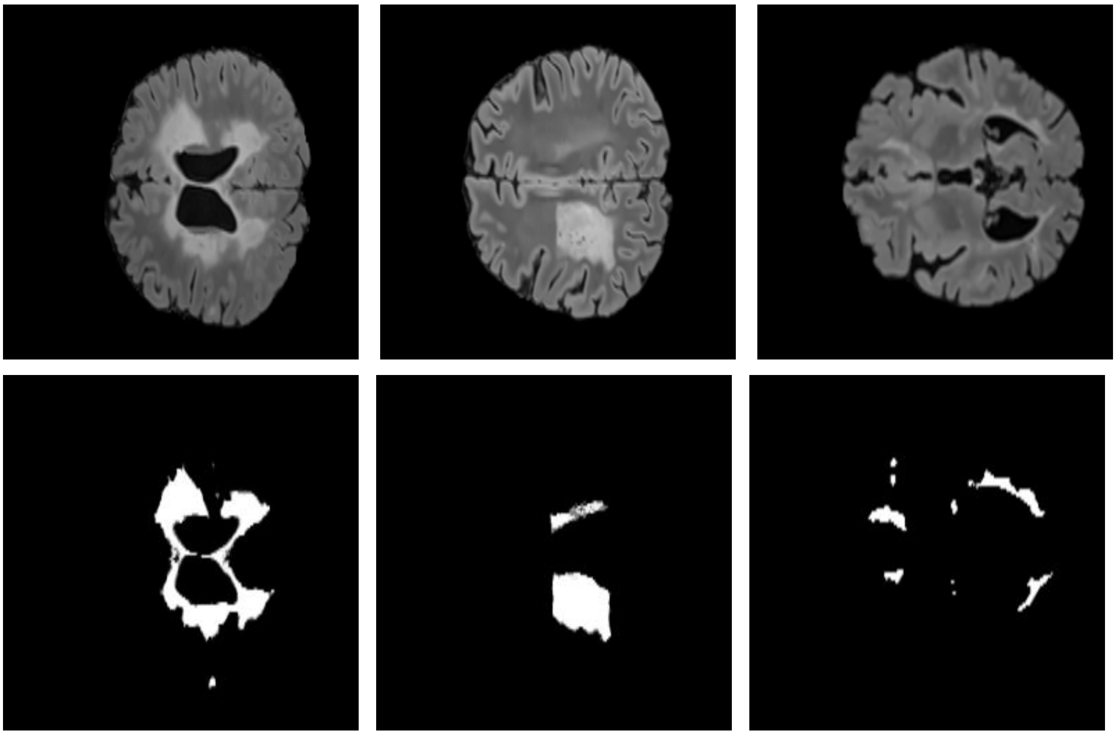
2.1 MICCAI 2016 dataset

MICCAI 2016 dataset consists on 15 MRIs together with a lession mask generated by consensus among various doctors. These are generated with three different scanners, each one with a certain data shape. We verified that all the MRIs are present with the same orientation, what will be meaningfull when slicing the 3-D MRIs for the 2-D models. The dataset contains also preprocessed data in which the skull has been removed from the MRIs, for simplicity, we'll be using these for all the models.

We split randomly the data in a train and a validation set with size 12 and 3 MRIs respectively. We don't keep a test set because given the fact that the size of this would be reduced to only one or two MRIs at most and the inhomogeneity in the different lesions shape, size, quantity and distribution, the evaluation over the test set would lead to a unreliable measurement. This is something certain after seeing the big differences in the metrics over different validation MRIs. Therefore we encourage to everyone who wants to use this models in practice to previously evaluate them over his own data.

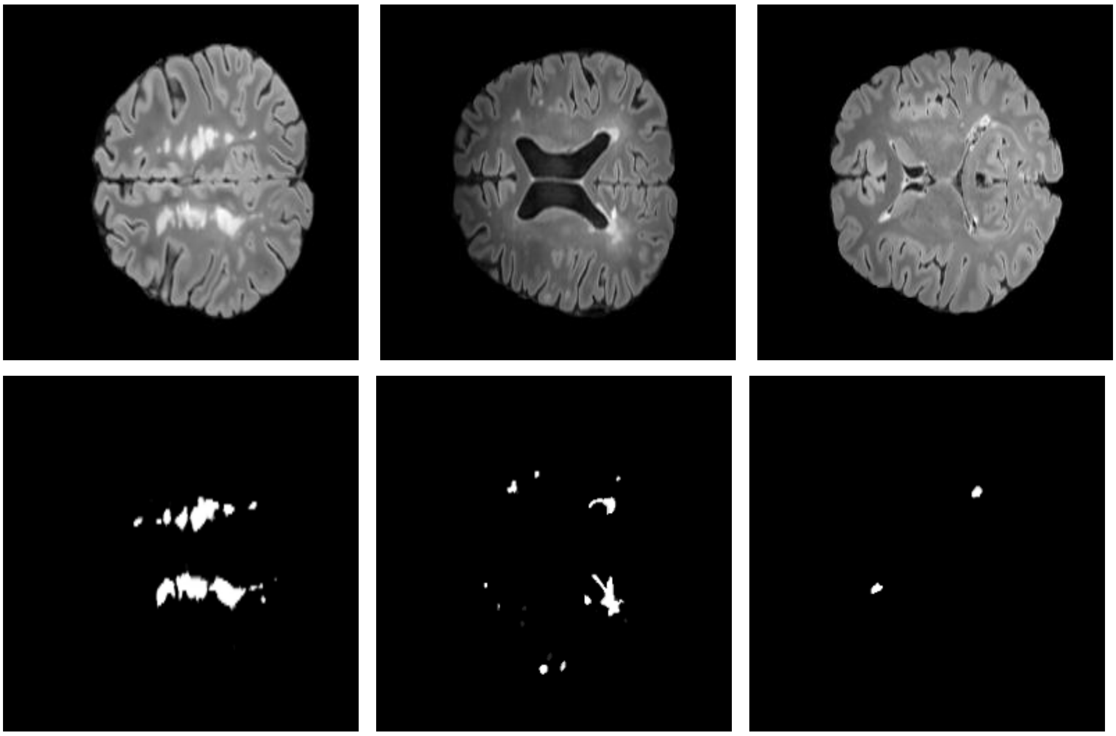
We present in the next page some slices of MRIs used as benchmarks for fast evaluation and visual confirmation from both the train and validation datasets.

Sample of images from the training set:



(a) tr175 (b) tr943 (c) tr1426

Sample of images from the validation set:



(d) ts175 (e) ts431 (f) ts687

2.2 Evaluation metrics

The metrics used for evaluation are ...

Chapter 3

2-D Convolutional Nerual Networks

During the development of the project, we have worked with four different PyEDDL versions (0.12, 0.13, 0.14 and 1.0.0) since this is a library currently in development. 3-D Convolutional Neural Networks were finally supported in PyEDDL version 1.0.0, which was released on May 27th 2021. Therefore the first CNN had to be 2-dimensionals.

This has two main drawbacks. The first one is the loss of some context information since our CNN can not analize at once a whole region of the MRI but it has to slice it, an issue inherent of working in a lower dimension. The second one is the need of having to consider also the different axles and orientations, which can be solved with data preprocessing.

3.1 Data preprocessing

For the 2-D CNN we have only used *FLAIR* modality of the MRI. We first resize the *FLAIR* image to $(256 \times 256 \times 256)$ so that, independently of the scanner used, the input has the same shape. After this we slice the data by the last axis. We decided this shape even when the first axis is being upsampled in all the MRI because it allows us to change the orientation or slicing axis and still having the same input shape so transfer learning techniques are possible. As a final preprocessing step we normalize each image.

No data augmentation techniques have been used since the final purpose of this project is not achieving the best accuracy (we remit to MICCAI 2016 challenge and later research works for that) but having a fair analysis and comparison of EDDL library.

3.2 U-Net

U-Net [2] first appeared in 2015 and it quickly became the standard for biomedical image segmentation. We chose it as the model for our first approach. The network structure can be seen in the image below, the only change in the network structure in our implementation with respect to the one originally presented is that we have added batch normalization after each convolution for a better convergence and stability.

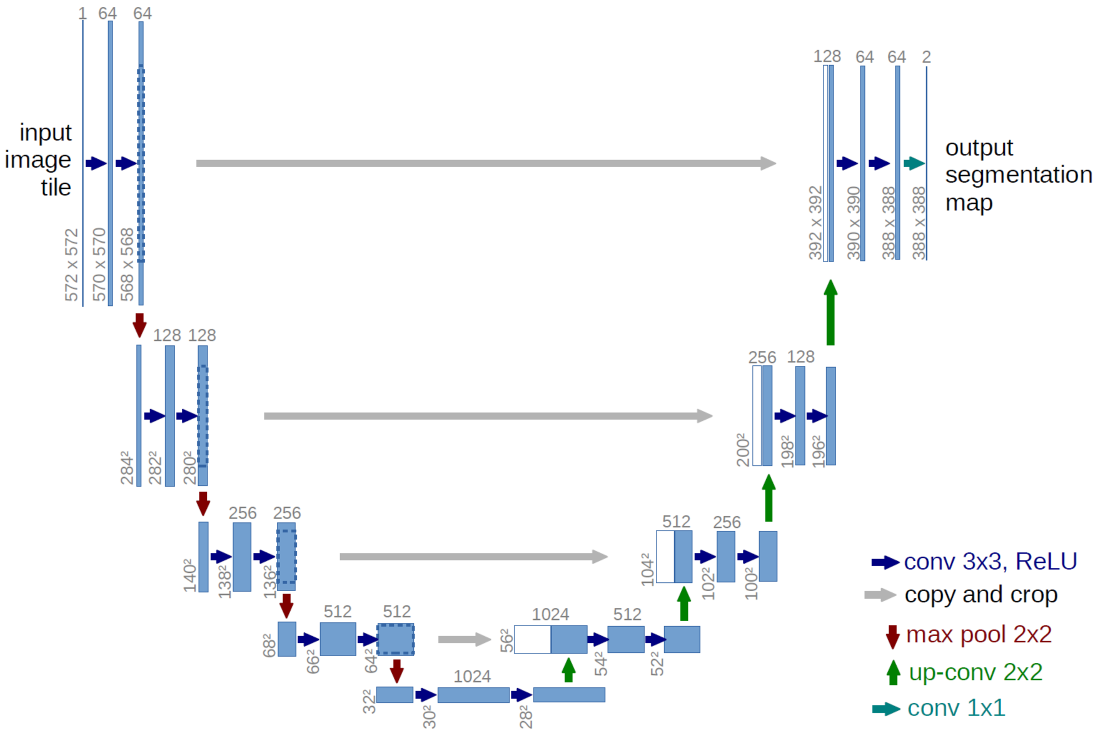
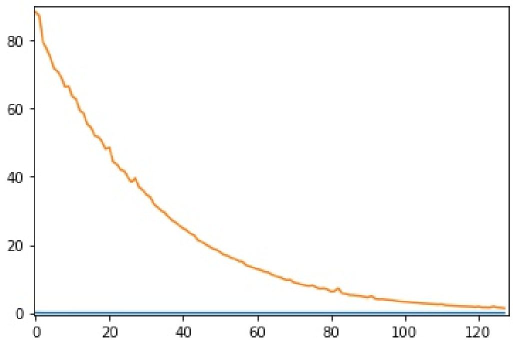


FIGURE 3.1: U-Net model [2]

The training configuration was the following:

- **Loss function:** Binary cross entropy.
- **Optimizer:** Adam, learning rate 0.0001
- **Batch size:** 8

3.2.1 U-Net evaluation



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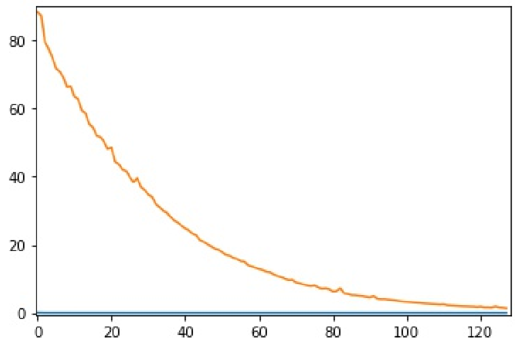
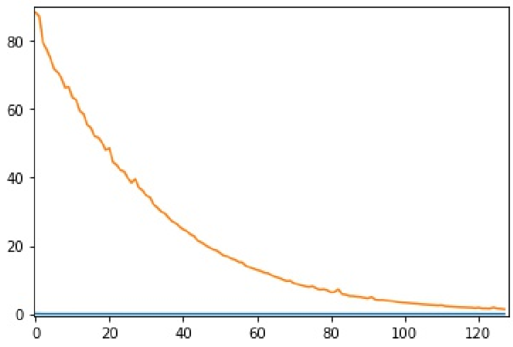


(b) tr1426



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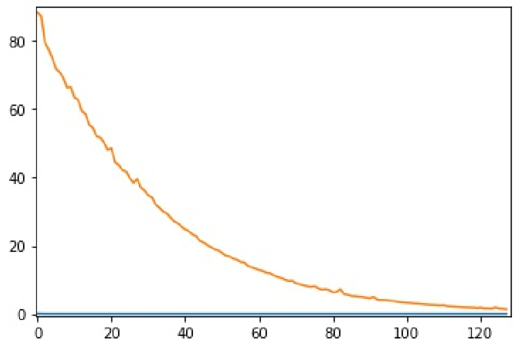

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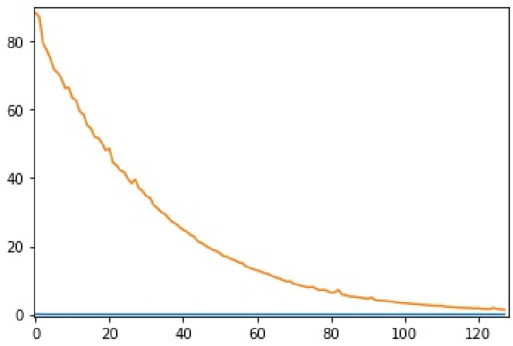

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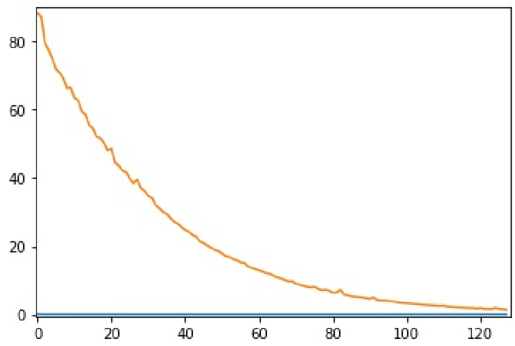

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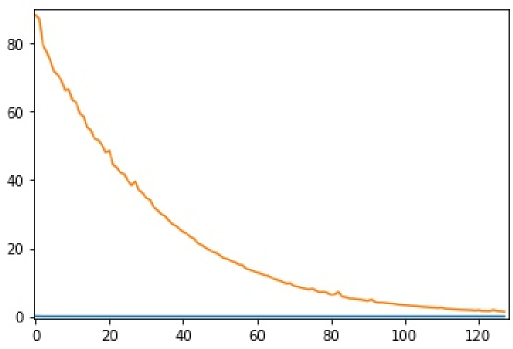
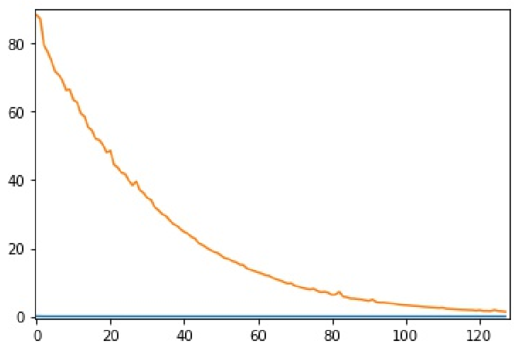
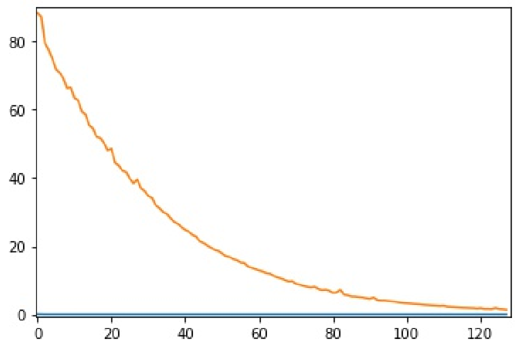


(g) tr943

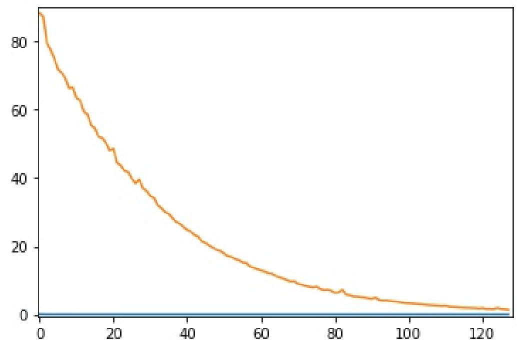


(h) tr1426

3.2.2 U-Net profiling



(i) tr943



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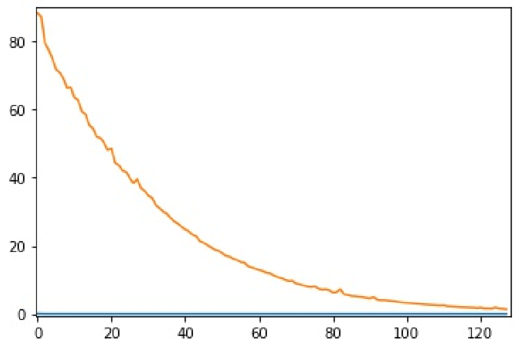

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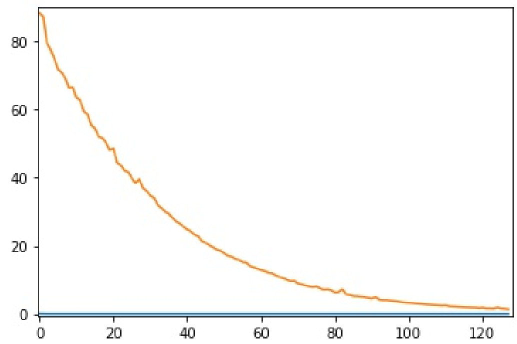
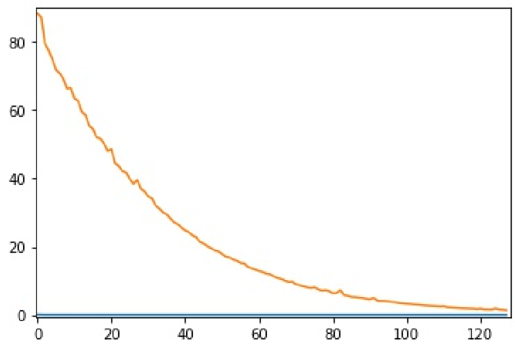


(l) tr1426



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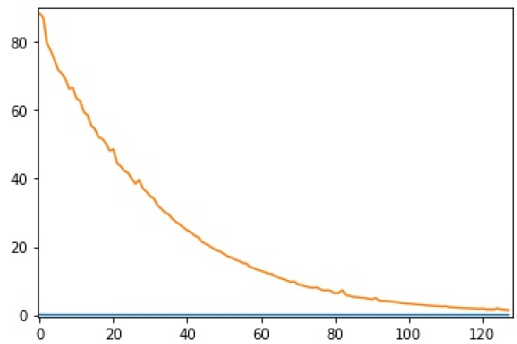

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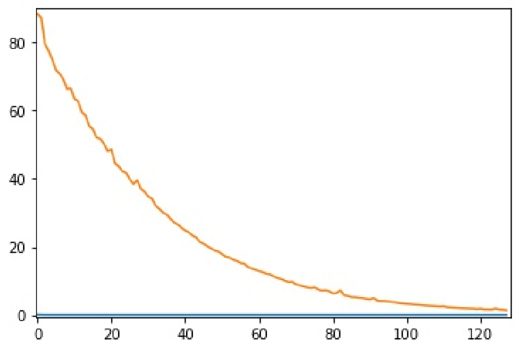

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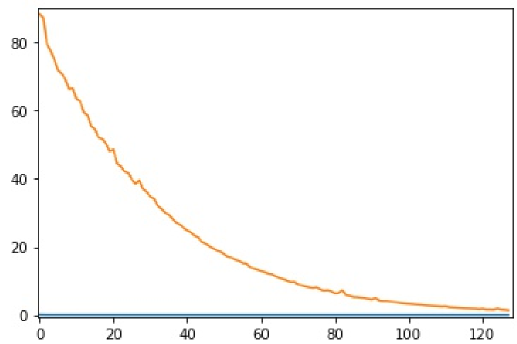


(p) tr1426

3.3 Double U-Net

Start writing about Double U-Net.

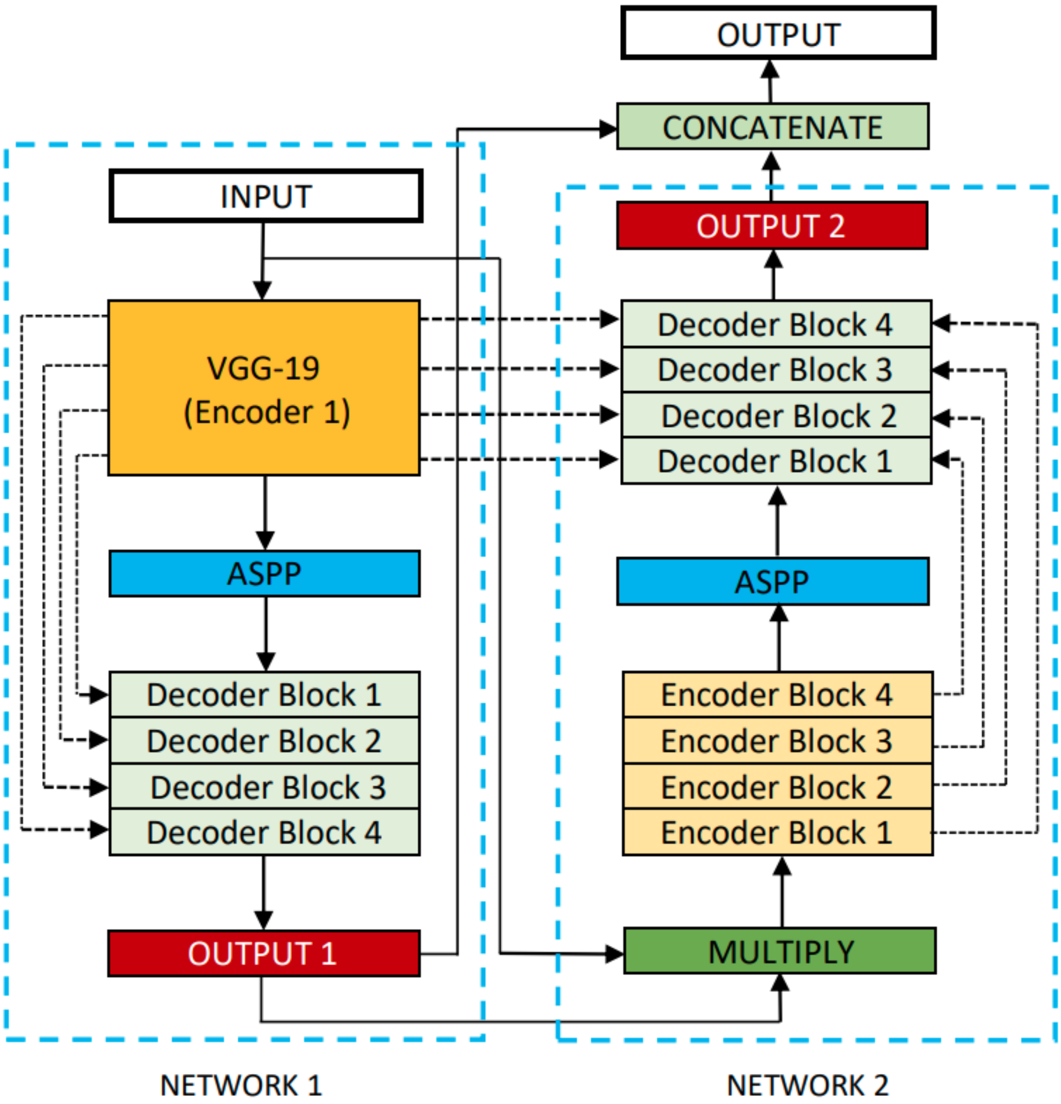
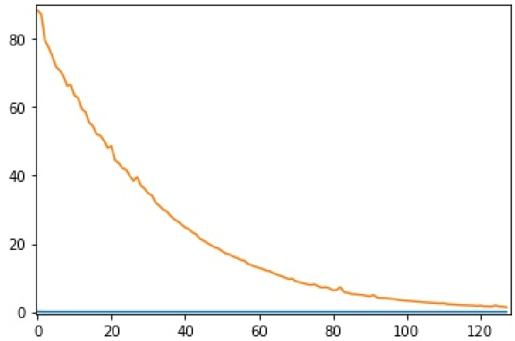


FIGURE 3.2: Double U-Net model [3]

3.3.1 Double U-Net evaluation



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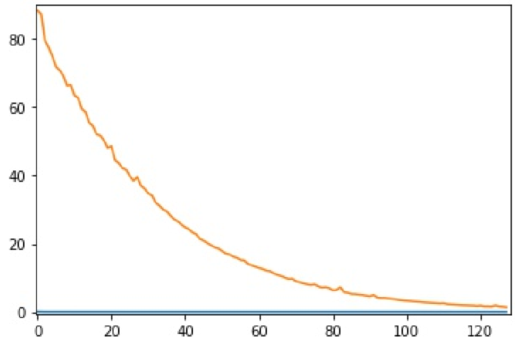

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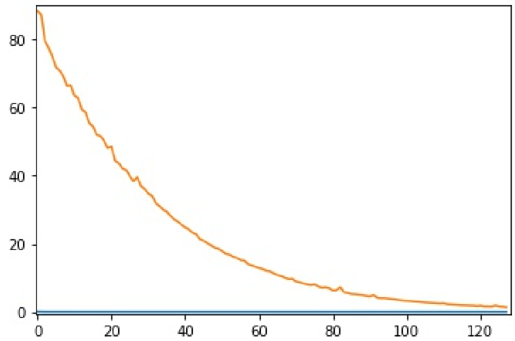

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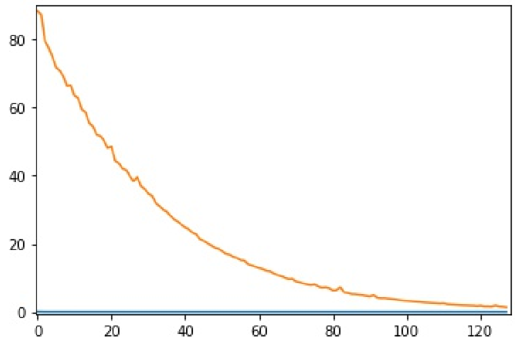

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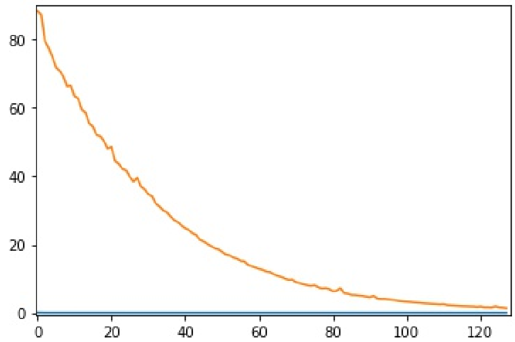

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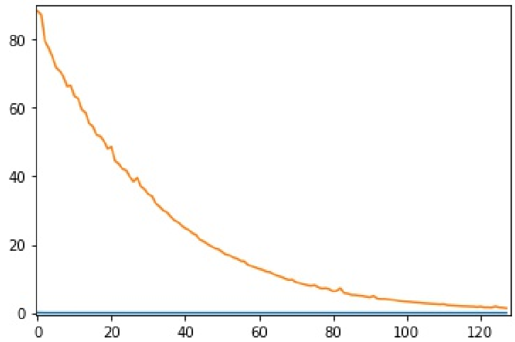

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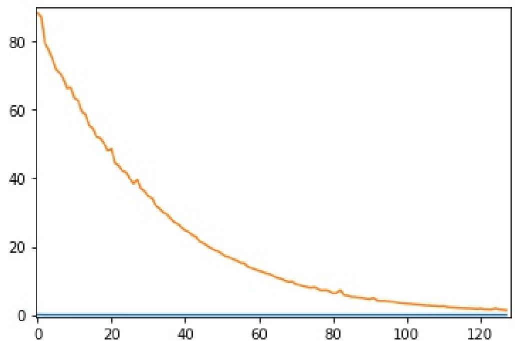

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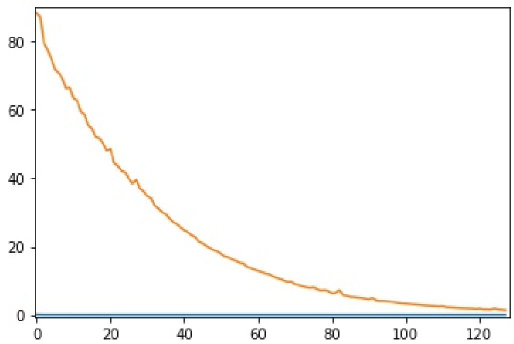

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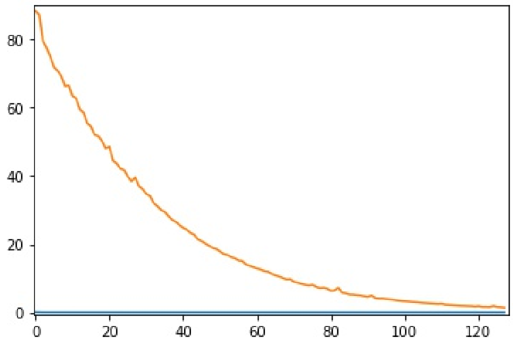
3.3.2 Double U-Net profiling



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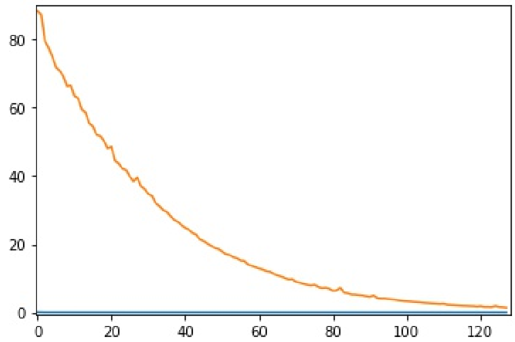

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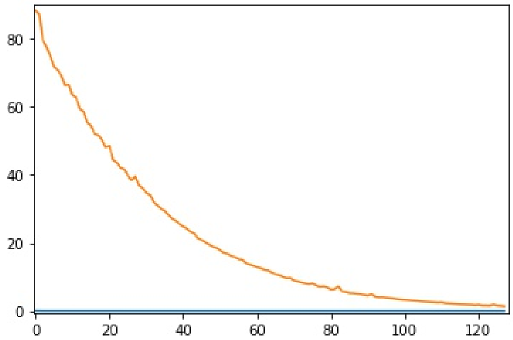

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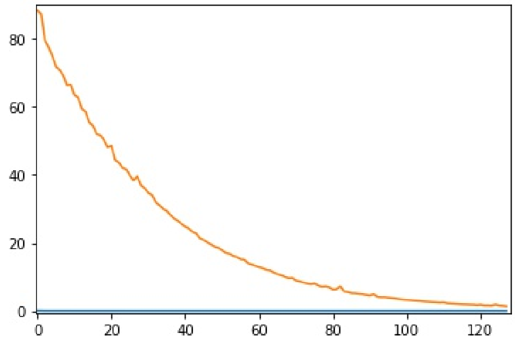

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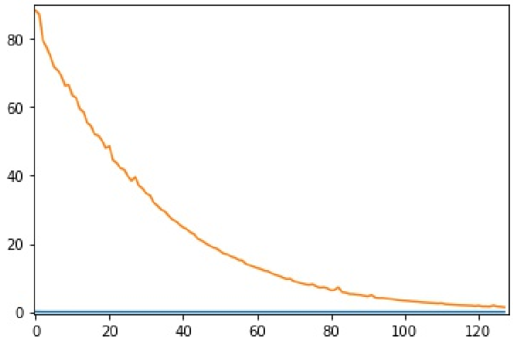

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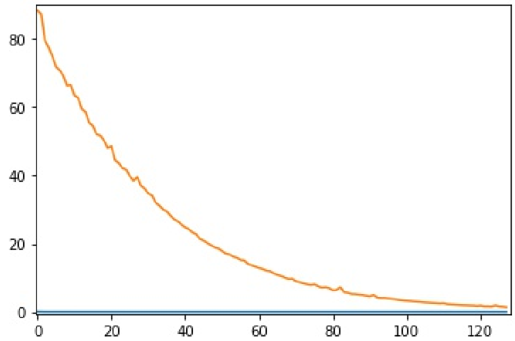

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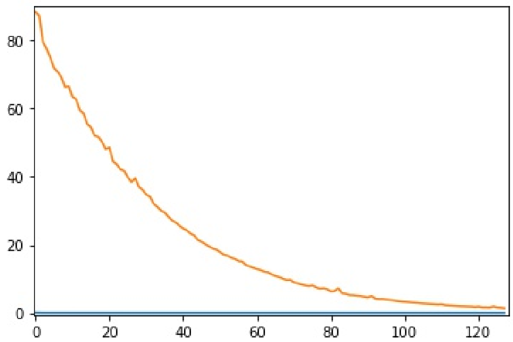

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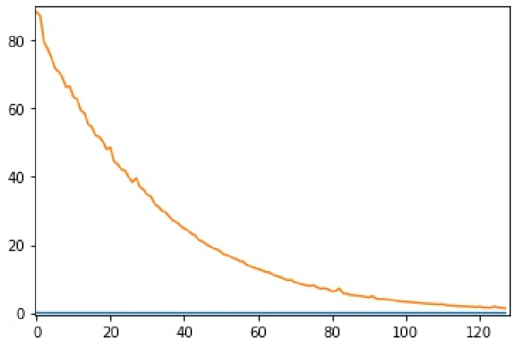

(p) tr1426

3.4 Comparison

Chapter 4

3-D Convolutional Nerual Networks

La idea no es mía, viene de Valverde [4]...

4.1 Data preprocessing

Este modelo lo que se come son los voxels, esto es, segmentos de 11x11x11...

4.2 Cascade model

El modelo tiene esto y esto y lo otro...

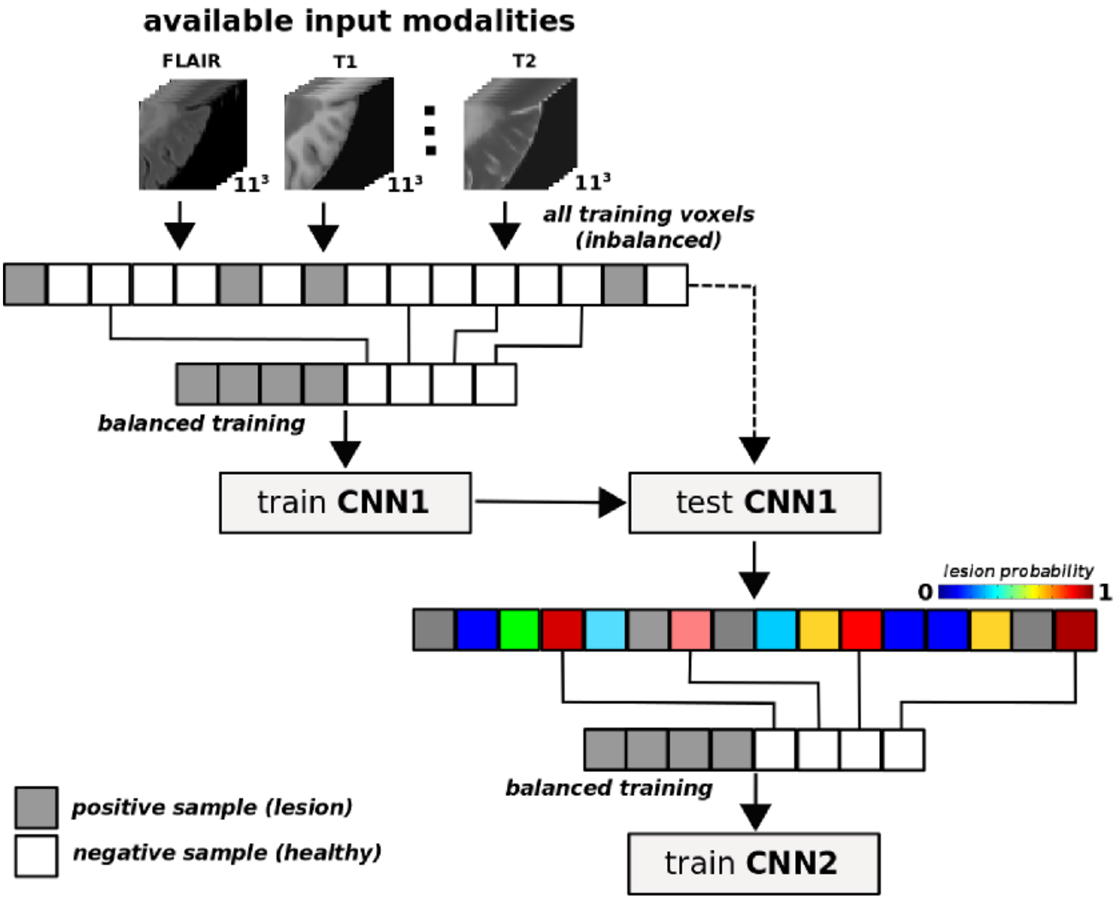

FIGURE 4.1: 3-D Convolutional Neural Network cascade model [4]

Appendix A

Apendix title

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