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 MICCAI2008 and MICCAI2016 challenges. In this project we'll work over MICCAI2016 dataset.

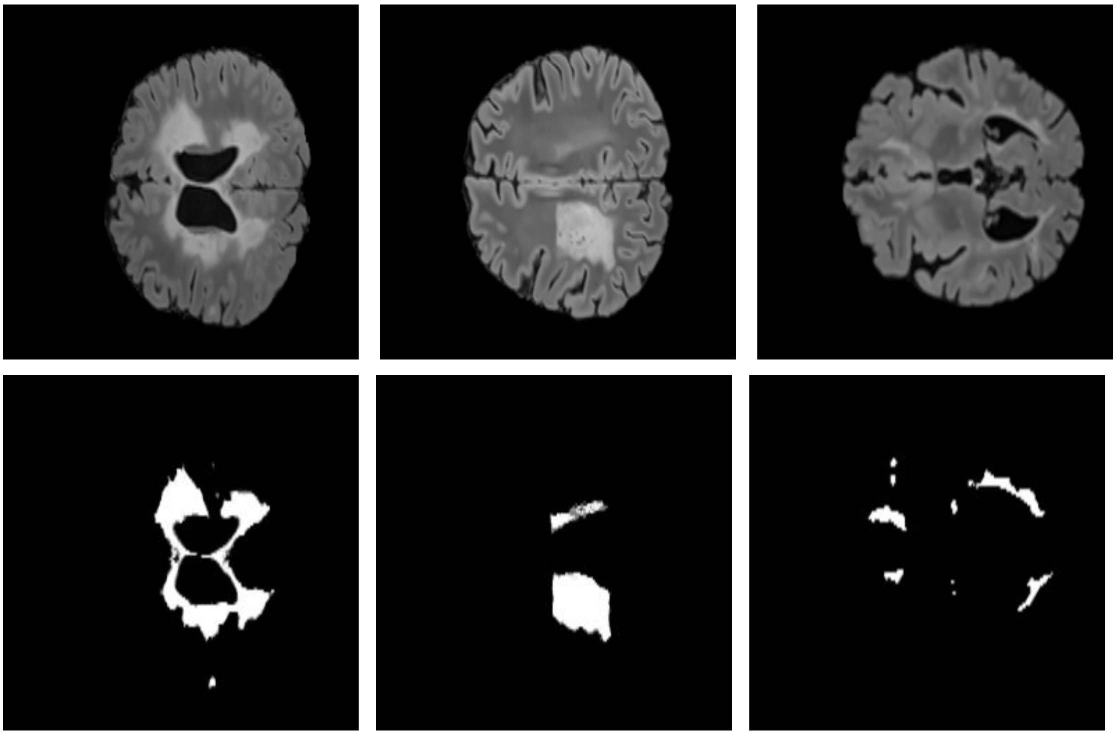
2.1 MICCAI 2016 dataset

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.

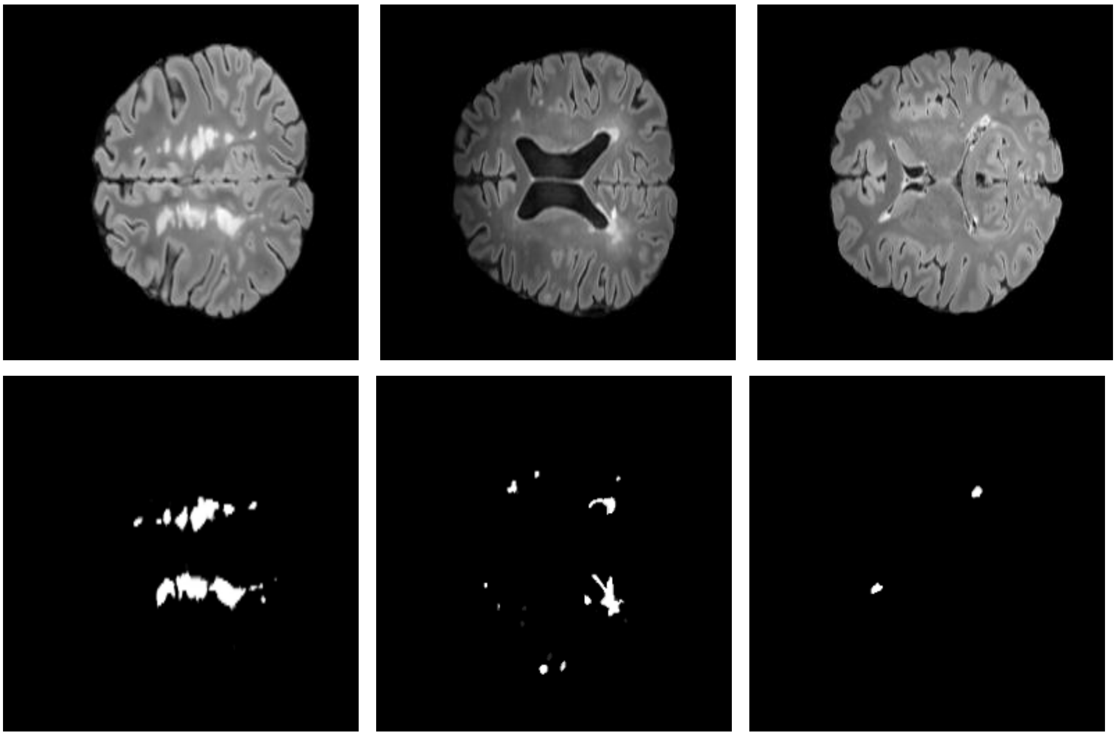
We present in the next page some slices of MRIs used as benchmarks for fast evaluation and visual confirmation from both the train and validation datasets.

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

Escribir algo de cabecera.

3.1 Data preprocessing

3.2 U-Net

Start writing about U-Net.

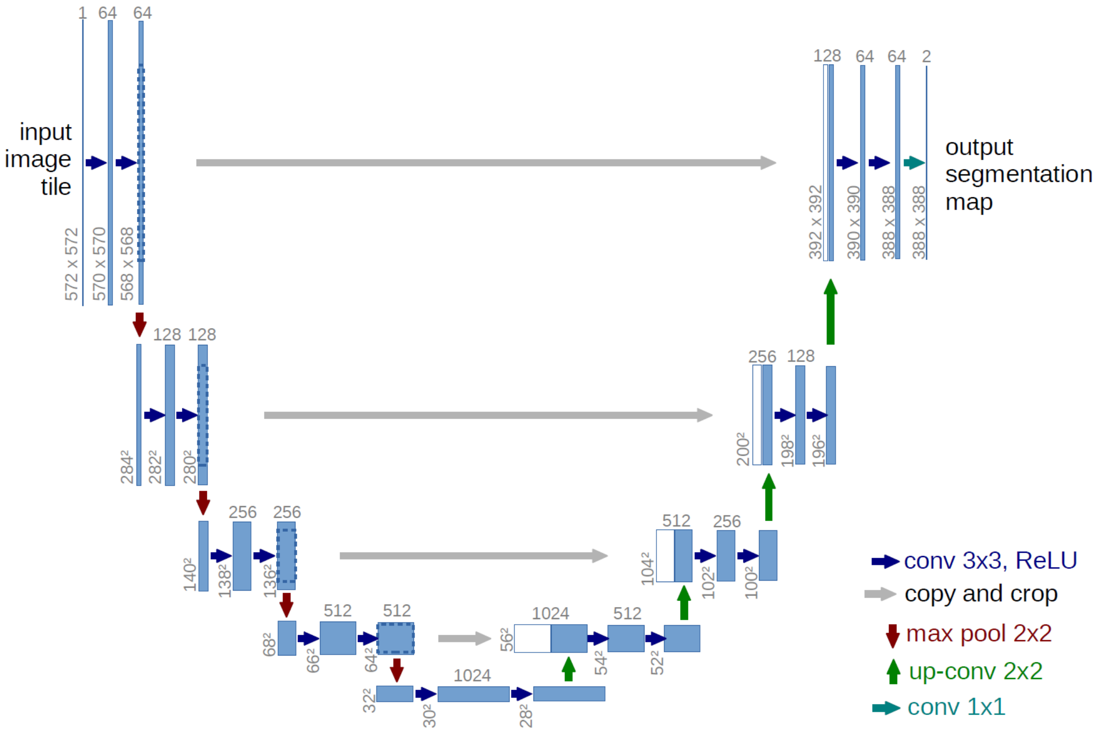


FIGURE 3.1: U-Net model

3.3 Double U-Net

Start writing about Double U-Net.

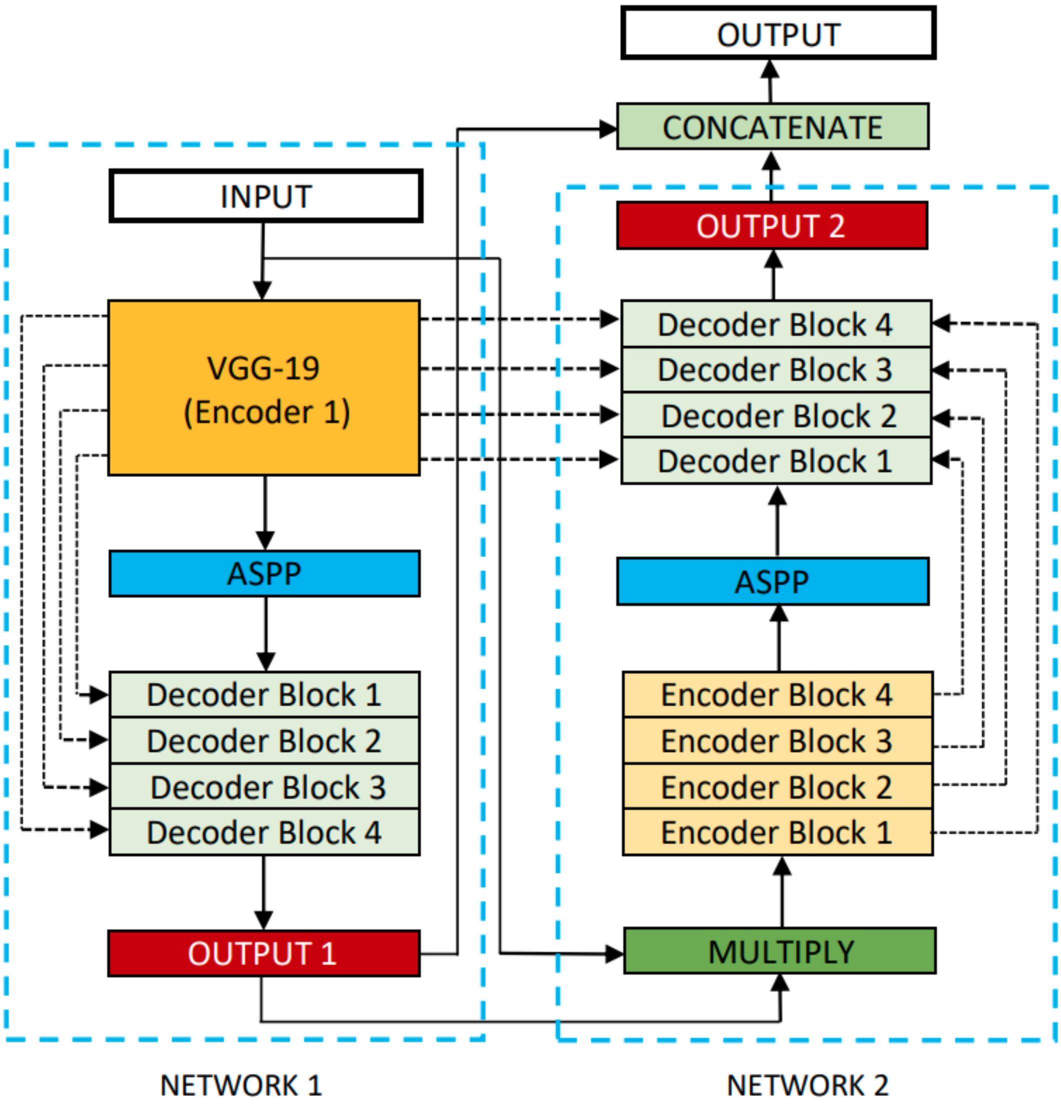


FIGURE 3.2: Double U-Net model

Chapter 4

3-D Convolutional Nerual Networks

4.1 Data preprocessing

4.2 Cascade model

Appendix A

Apendix title

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