

# TP Deep learning - Segmentation of Brain MR Images

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The goal is to run and get familiarized with a very popular deep learning architecture for 2D segmentation of medical data.

## 1 Background

### 1.1 Architecture

Image Segmentation is one of the most important problems for medical imaging but also other communities such as computer vision, robotics, surveillance etc. Image segmentation aims to generate maps or volumes on which every pixel correspond to a specific class. Generating automatically volumes with accurate segmentations of different organs and/or anomalies can potentially provide tools to help doctors on their everyday life. This topic was quite popular for a lot of years, however with the entrance of deep learning the performance of the algorithms have been boosted significantly.

In this exercise, we will explore a state of the art architecture based on 2D fully convolutional architecture, namely U-Net. U-Net is currently one of the most popular architectures for the segmentation of different organs and medical diseases. The architecture is based on an encoder-decoder scheme contracting path that follow the typical architecture of a convolutional network. In particular, it consists of the repeated application of two  $3 \times 3$  convolutions (unpadded convolutions), each followed by a rectified linear unit (ReLU) and a  $2 \times 2$  max pooling operation with stride 2 for downsampling. At each downsampling step the number of feature channels are doubled. Every step in the expansive path consists of an upsampling of the feature map followed by a  $2 \times 2$  convolution ("up-convolution") that halves the number of feature channels, a concatenation with the correspondingly cropped feature map from the contracting path, and two  $3 \times 3$  convolutions, each followed by a ReLU. Figure 1 depicts the different components of the U-Net architecture, for more details check the paper <https://arxiv.org/pdf/1505.04597.pdf>.

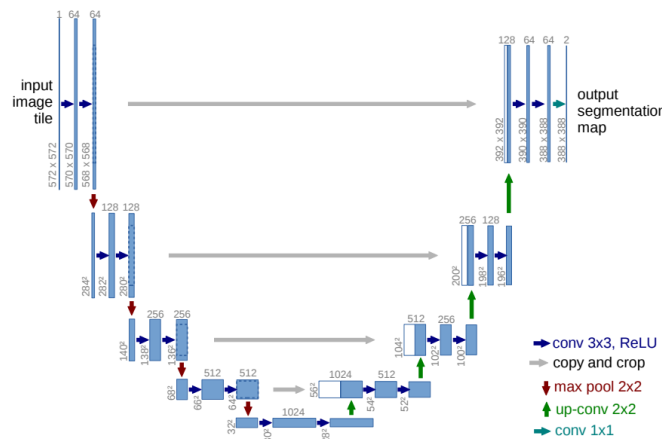


Figure 1: An illustration of the different layers of U-Net architecture.

To obtain and optimize the parameters of the network variety of loss functions can be used. For this exercise we will use one of the most commonly used losses for classification and segmentation problems namely categorical cross entropy.

$$Loss = - \sum_{i=1}^C t_i \log(s_i) \quad (1)$$

where  $t_i$  and  $s_i$  are the ground truth and the CNN score for each class  $i$  and  $C$  is the set of the different classes.

## 1.2 Dataset

For this exercise we will train our model using the publicly available BraTS19 dataset (<https://www.med.upenn.edu/cbica/brats2019/data.html>). In particular, the dataset consists of a multi-institutional routine clinically-acquired pre-operative multimodal MRI scans of glioblastoma (GBM/HGG) and lower grade glioma (LGG), with pathologically confirmed diagnosis. Annotations comprise the GD-enhancing tumor (ET — label 4), the peritumoral edema (ED — label 2), and the necrotic and non-enhancing tumor core (NCR/NET — label 1). An illustration of the dataset is presented in Figure 2

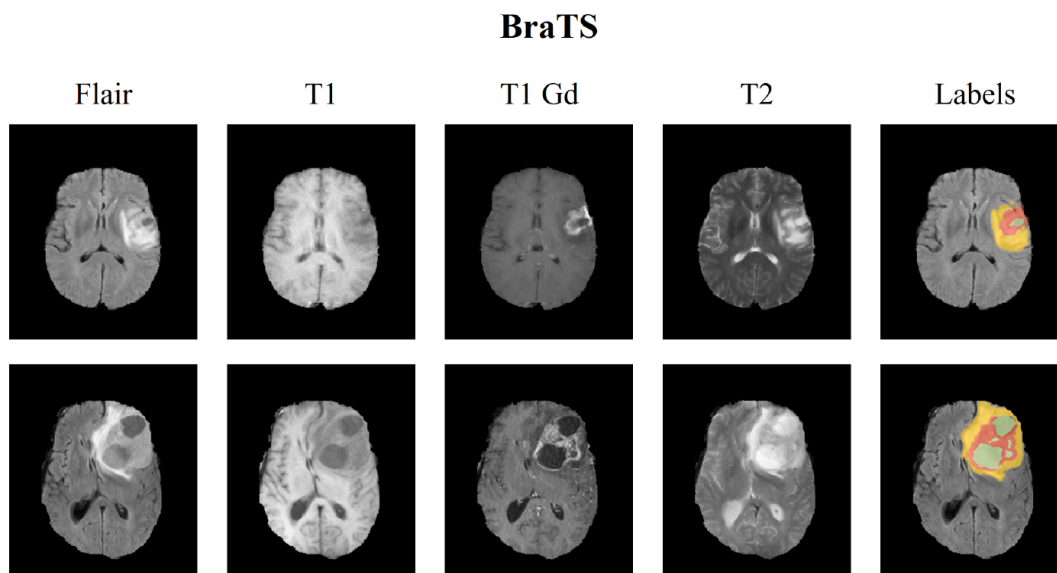


Figure 2: An illustration of two different subjects from the BraTS dataset.

## 2 Practical Exercise

Download the file TP\_sujet.ipynb : on your browser, Open the file TP\_sujet.ipynb on google colab <https://colab.research.google.com/notebooks/intro.ipynb>, "Fichier - Importer le notebook", and follow the instructions directly on it. You will have to understand and fill the code in order to run U-Net architecture for segmentation.