DETECTING CEREBELLAR FISSURES WITH CONVOLUTIONAL NEURAL NETWORKS

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ABSTRACT

The human cerebellum plays an important role in coordination tasks. Diseases such as spinocerebellar ataxias, tend to cause severe damage to the cerebellum, conducting patients to a progressive loss in motor coordination. Detecting such damages may help specialists to approximate the state of the disease, and perform statistical analysis in order to propose treatment therapies for the patients. Manual segmentation of such patterns from magnetic resonance imaging is a very difficult and time-consuming task, and is not a viable solution if the number or images to process is relatively large. In the last years, deep learning techniques like convolutional neural networks (CNNs or convnets) have experimented an increased development, and many researchers have used them to perform medical image segmentation in an automatic manner. In this research, we propose the use of convolutional neural networks for automatically segmenting the cerebellar fissures from brain magnetic resonance images.

1. INTRODUCTION

The cerebellum plays an essential role in critical tasks, like motor coordination and cognition, and it is related to another functions, e.g., language and emotions (Han, Carass, He, & Prince, 2020). Diseases like spinocerebellar ataxias (SCAs) are known to cause an important damage in the cerebellum, conducting patients to progressive loss in such functions, and, in some cases, to premature death (Klockgether, Mariotti, & Paulson, 2019). The damage caused by SCAs can be observed as big fissures, growing with the disease progression. Knowing such fissures, allows specialists to obtain some important characteristics from the patients, like volume loss related to the SCA.

Segmentation of magnetic resonance imaging (MRI) is often performed, and clinicians make researches with several patients, with the aim of obtaining more information about the disease, and how to treat it better. Nevertheless, manual segmentation of MRIs is a complex task, and can be a very long process. That makes manual segmentation impossible if the number of images is important. For that reason, computational tools are required for perform those processes in an automatic manner.

In the last decade, convolutional neural networks (convnets or CNNs) have experimented a rapid development, as the number of researchers using them for medical image processing grows. In this research we aim to propose the use convolutional neural networks for segmenting cerebellar fissures from brain MRIs.

2. MATERIALS AND METHODS

The proposed method is based on U-Net (Ronneberger, Fischer, & Brox, 2015). It consists of four down- and up-sample steps, composed of inception modules and instance normalization layers, and two chained inception modules as a bottleneck. Figure 1 shows the main architecture.

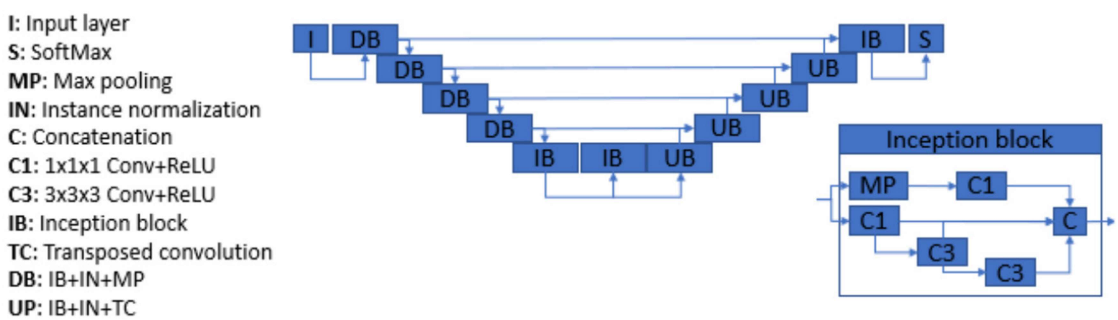

Figure 1. General architecture.
Source: self-made.

The used cohort consists of 24 T1-weighted brain MRIs, obtained from the Cuban Neurosciences Centre. The images correspond to 15 people (five controls, five presymptomatic carriers, and five patients with diagnosed SCA2).

As preprocessing, all images were passed through a bias field correction step (BFC), using Nd method (Tustison *et al*., 2010). After BFC, a registration was made to MNI 152 space. Finally, the images were binarized with the aim of relacing the dark voxels in the volume. This binarization step was achieved by combining intensity normalization, histogram equalizations, and intensity rescaling to range [0; 255]. All images were cropped to dimensions of (128×80×80). The selected crop area is the average cerebellum position of the 24 images in the dataset.

As a postprocessing step, a convex hull was created from the segmentations produced by our CNN, and was then combined with the binary map from the preprocessing stage, by applying another bitwise xor operation.

The model was trained with 16 MRIs, leaving three for validation and five for validation. The used metrics for the evaluations were sensitivity (formula 1), specificity (formula 2), and overlap coefficient (formula 3), which allow to evaluate the voxels classified as positive, the voxels classified as negative, and the overlapping between original and segmented masks, respectively. In the formulas, TP and TN refer to the voxels correctly classified as front and background, respectively, FP and FN the voxels incorrectly mapped to front and background, respectively.

Formula 1. Sensitivity.

$$\mathrm{SN} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}}$$

Source: (Fawcett, 2006)

Formula 2. Specificity.

$$\mathrm{SP} = \frac{\mathrm{TN}}{\mathrm{FP} + \mathrm{TN}}$$

Source: (Fawcett, 2006)

Formula 3. Overlap coefficient.

$$\mathrm{OC} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP\text{-}FN}}$$

Source: (Ibragimov, Likar, & Pernus, 2012)

3. RESULTS AND DISCUSSION

Results can be observed in table 1. Specificity scores are over 0.97 in all cases, which demonstrates that our method has a good performance discerning the background voxels. Sensitivity and overlap scores are between 0.84 and 0.9. this is not a very high score, but we consider it as adequate for such a difficult task as segmenting cerebellar fissures.

Table 1. Evaluation results.

SUBJECT NO.	1	2	3	4	5
Sensitivity	0.841	0.858	0.907	0.887	0.905
Specificity	0.994	0.990	0.980	0.991	0.973
Overlap	0.841	0.858	0.807	0.887	0.905

Source: self-made.

Figure 2 shows a slice of a segmentation produced by our network compared against an original segmentation. It can be appreciated that both masks, original and generated by our CNN are very alike. There are some errors that will be treated in future researches.

Figure 1. Example of segmentation. From left to right: cropped MRI, binary map, ground truth label, and segmentation obtained with our method.
Source: self-made.

The sample image and the segmentation evaluations allow to state that convnets are capable of segmenting cerebellar fissures from T1-weighted MRIs. Such results can be used for increase the quality of the outcomes produced by cerebellar segmentation/parcellation techniques, as the estimated volumes will be closer to the reality.

4. CONCLUSION

We have proposed a Deep learning method for segmenting cerebellar fissures from brain T1-weighted MRIs. The method is based in the well- known U-Net architecture, and has been provided with the inception technique, for a better use of produced feature maps. Results show that convnets are a suitable tool for this task, allowing to provide specialists with new techniques for characterizing neurodegenerative diseases such as SCAs.

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