Corpus Callosum Segmentation using UNET and Transfer Learning

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Introduction

The Corpus Callosum (CC) is a brain structure composed of white matter, and abnormalities in it's size and shape can be a predictor of neurological diseases. Thus an automatic and precise segmentation of CC, like the one that is proposed in this poster, can be advantageous for the diagnosis of the mentioned diseases. For the segmentation task it was used an UNET network, that is composed by a contracting path, responsible for image down-sampling, and an expanding path, responsible for image up-sampling. This network is usually used for segmentation purposes due to the network capability of combining localized and contextual information, and its accuracy. Also the UNET doesn't need a large amount of data for the training phase, making use of data augmentation.

Transfer Learning was also used in this work, with the objective of ease the learning process for the CC's segmentation, obtaining fastest results and more accurate.

Methodology

The UNET model was trained according to the following workflow:

Download images from ABIDE dataset		
Training images for model updating: **32**	Validation images for model supervision during training: **6**	Testing images for evaluation of trained model: **5 autism + 5 control**

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Volbrain image processing

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Manual CC segmentation (extraction of the ground truth)

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Network training with cerebellum segmentations

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Lock the encoder weights

⇩

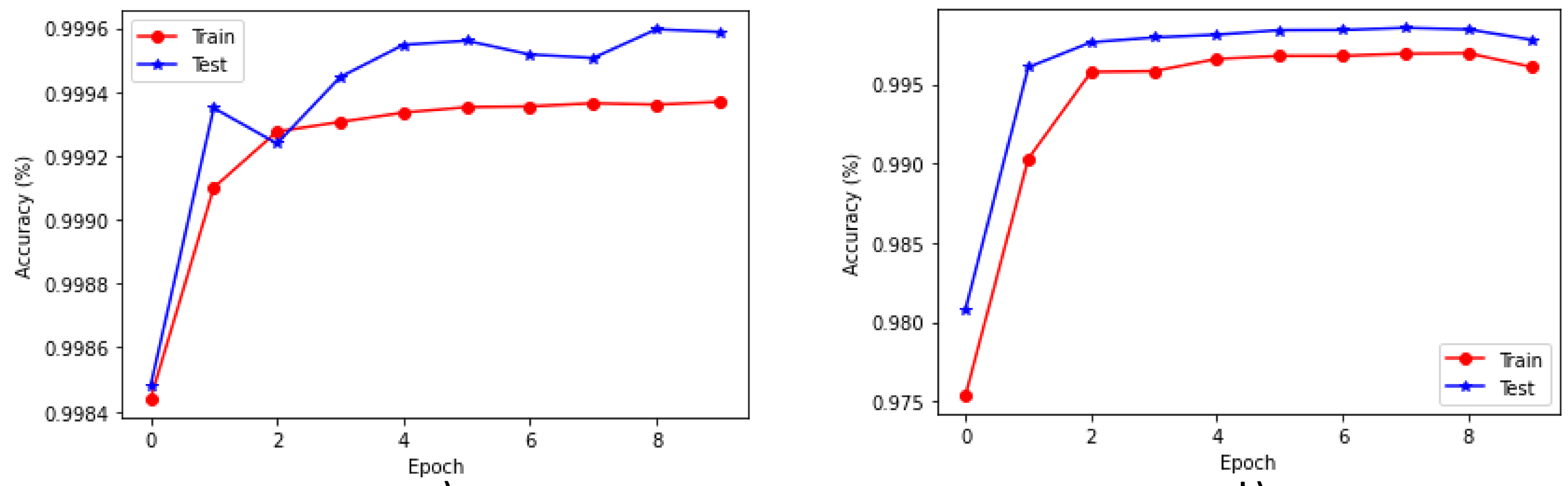
Network training with CC segmentations

⇩

Model evaluation

Results

The training of the network was carried out on a CPU, which took 21h53 for the cerebellum phase and 22h35 for the CC phase. Both phases were trained during 10 epochs. The results can be seen below in Figure 1 a) and b), respectively.

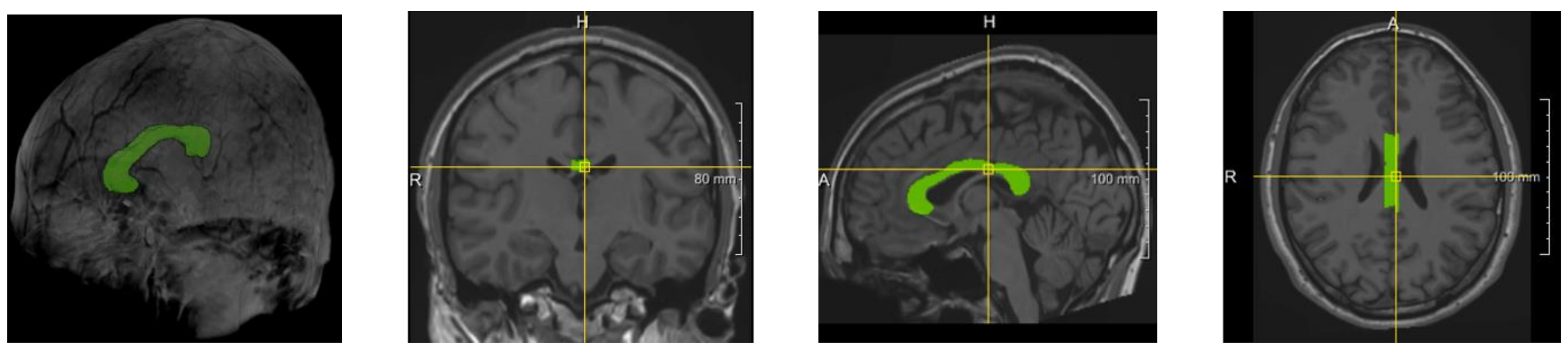


a) b)

Figure 1: Voxelwise accuracy evolution in the training task through epochs: (a) cerebellum segmentation; (b) CC segmentation;

The training in the CC segmentation phase achieved a very high accuracy in very few epochs. This is due to the fact that most of the training of the encoder was performed during the cerebellum phase. The algorithm only had to adapt to a similar task by slightly changing the weights. The test dataset had higher accuracy that the training one probably because it didn't have enough data, causing the supervision of the model to be biased towards a small group of images.

To evaluate the network performance, 5 MRIs of autistic patients and 5 MRIs of normal patients were processed by the trained model. Dice score was used to evaluate the quality of the segmentation performed when compared to the ground truth. For the autistic patients the score was of 81,62% and for the normal ones it was 62,51%. This disparity is probably due to lower image quality of some MRI scans in the control group. An example of a segmentation performed by the UNET can be found in Figure 2.



a) b) c) d)

Figure 2: CC segmentation in the anatomical planes: (a) axial; (b) coronal; (c) sagittal; (d) 3D representation;

Conclusion

- This work proved that this methodology is capable of generating a model that can perform segmentations of the CC, given an MRI of the brain. Such an algorithm opens the way for mass gathering of data that can advance the knowledge of pathologies associated with this structure.
- Transfer learning demonstrated to be effective in this situation because it was able to overcome the random errors in the ground truth and it was still able to generate a sufficiently accurate model. Also this model is able to generate good segmentations of the desired structure, within few epochs of training, with a good accuracy. This accuracy seems dependent of the first phase of training of the model. If the cerebellum phase is optimized, the training of the second phase should produce even more accurate results.
- Some limitations prevented further research that is necessary for optimizing this procedure. These include: manual segmentation errors due to execution by an untrained individual; lack of a GPU for training, which would allow more epochs to be run, facilitating the study of the algorithm and finally, the validation dataset should be bigger to ensure that the model can be properly supervised during training.
- With further research, it may be possible to use this algorithm for the segmentation of various structures with minimal training, since the model already understands the anatomical context of the structure being analysed. This workflow may be used by other researchers which aim to obtain a segmentation algorithm by using small datasets and training during short times with limited hardware.

References

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