

# U-Net Based Brain Segmentation

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## Abstract

MRI can provide important information for surgeon before the surgery and provide researchers more immediate information to study the organ structure. However, manually extracting is always costly. This experiment utilized a deep learning model to segment the brain automatically and achieved a great performance.

## 1 Introduction

In this experiment, we replicated a deep learning model with the U-Net architecture [1] to segment the brain MRI. After simply amended the input and output, we can easily utilize this model to segment brain MRI in different size with a high accuracy. The codes are available at the following link: [https://github.com/yanlong-sun/brain\\_segmentation.git](https://github.com/yanlong-sun/brain_segmentation.git)

## 2 Method

### 2.1 Preprocessing

The image data we used in this experiment for training is Calgary-Campinas-359 [2](CC-359) dataset. In order to improve the contrast for some low contrast slices and keep all slices have similar contrast, we used histogram equalization to process MRI slices. Besides, all of the slices are supposed to have the same and specific size to be input into the neural network. So we cut the edges or padded zeros to slices. In a nutshell, the preprocessing of the MRI subjects includes the following steps:

- Use histogram equalization to increase the global contrast of the images
- Pad zeros to the slices and masks at the same time according to their aspect ratio.
- Center crop the slices and masks into size of 256\*256.

### 2.2 Segmentation

We kept the structure of the original model but retrained the model. After training on preprocessed CC0001-CC0030 of CC-359, about 7000 slices, we got the Average Dice

coefficient of 92.13% on 18 test subjects. Figure 1 shows our segmentation results of 3 subjects.

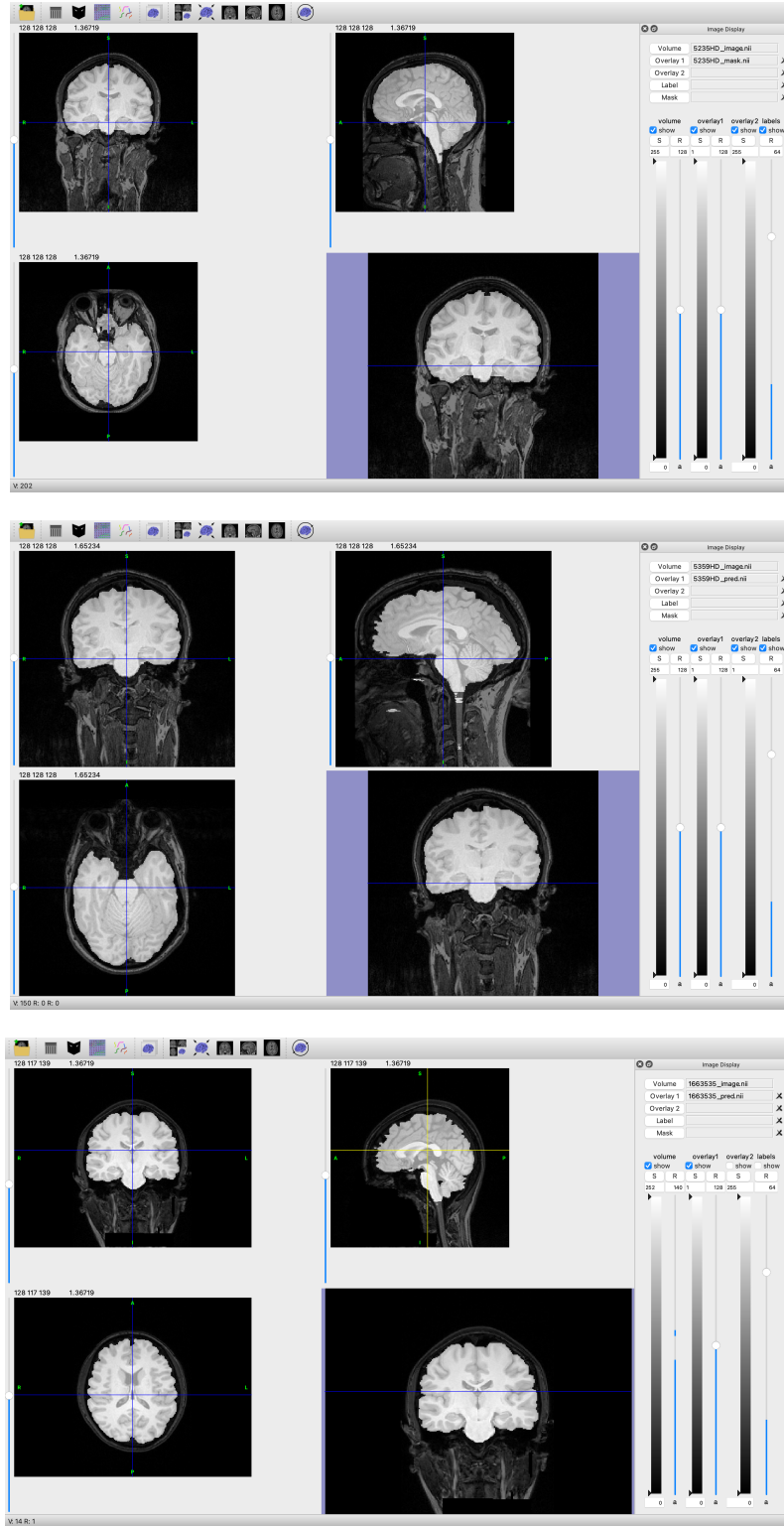


Figure 1: Examples of segmentation

## 2.3 Postprocessing

After predicting by the trained model, we got the prediction information in the 'mat' format. Then, we added these slices and predicted masks up respectively and convert them back to '.nii.gz' file.

## 3 Results

To quantify the performance, we utilized Dice metrics to evaluate the accuracy of the segmentation. Figure 2 shows the quantitative comparison of the deep learning model with the algorithm used in the Brainsuite on 18 subjects. The algorithm of the Brainsuite performs better in Dice(0.955) than the deep learning model(0.921).

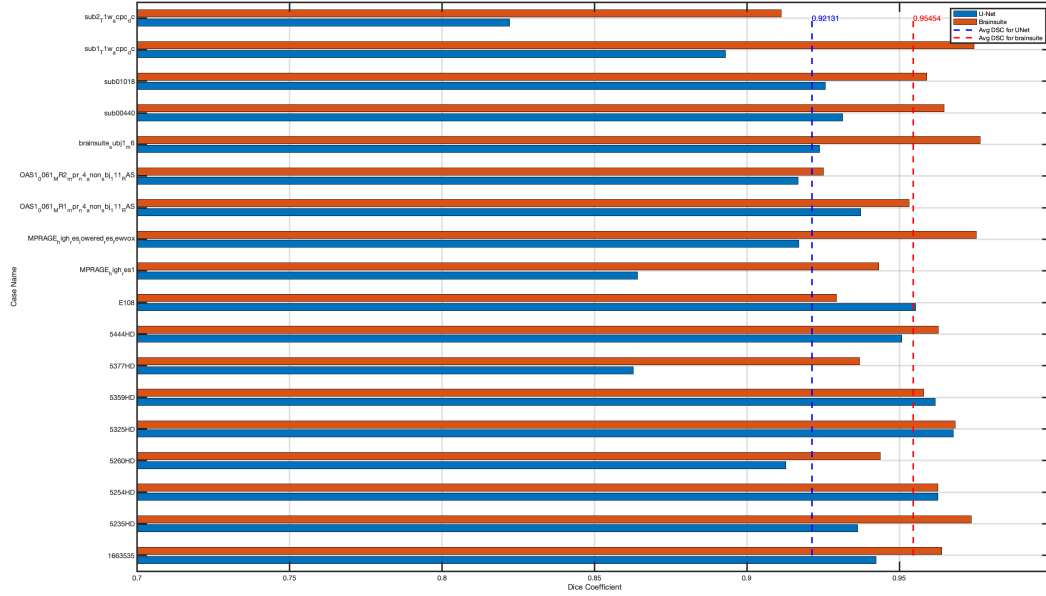


Figure 2: Quantitative analysis of 2 methods

## 4 Conclusion

In conclusion, we replicated this deep learning model and make it easier to execute even the image data are in significantly various sizes, apart from that, we also converted the prediction results into the common format, which is convenient for researchers to analyse.

## References

- [1] Mateusz Buda, Ashirbani Saha, and Maciej A Mazurowski. Association of genomic subtypes of lower-grade gliomas with shape features automatically extracted by a deep learning algorithm. *Computers in Biology and Medicine*, 109, 2019.
- [2] Zou K.H. Warfield, S.K. and W.M. Wells. Simultaneous truth and performance level estimation (staple): an algorithm for the validation of image segmentation. In *IEEE transactions on medical imaging*, pages 903–921. IEEE, 2004.