A Novel Improved Brain Tumor Segmentation Method Using Deep Learning Network

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Abstract. Aiming at the problems of uneven brain tumor data classification and insufficient feature extraction, an improved brain tumor segmentation (BTS) method using deep learning network is proposed in this study. Here, we use U-net as to be the main network architecture, combined with the advantages of the residual network Resnet, which uses skip connections in each layer of encoding and decoding to form a residual module to avoid the disappearance of the gradient. Data enhancement is applied in data processing. To further improve the processing performance, we add a learning mechanism to the network and incorporates the compression and excitation module scSE on both space and channel to extract more useful features. This article is verified on the BraTS 2018 public brain data set. On the 66 officially provided verification sets, the network after adding the scSE module has obtained better segmentation results for the entire tumor, tumor core and enhanced tumor.

1. Introduction

As we known, brain disease is the most dangerous one among many diseases. And this disease can be divided into two classes in medicine, i.e., high-grade gliomas (HGG) and low-grade gliomas (LGG). People with this disease usually have a low survival rate. At present, brain tumors are mainly observed by using the magnetic resonance imaging (MRI). We know the MRI is a non-invasive, safe and can provide detailed brain tissue information. MRI has the characteristics of multi-parameters, which can generate multi-modal images mainly including T1, T1c, FLAIR and T2. Thus, MRI is an effective way for diagnosing brain tumors. Doctors can obtain the diameter, volume, and number of tumors from the brain MRI to formulate treatment plans. Therefore, tumor segmentation is a very important step in diagnosis. Under the common needs of medical applications and scientific study, brain tumor segmentation (BTS) method has received widespread attention, and many methods have been emerging.

The methods for BTS tasks can be divided into two classes, namely methods based on traditional machine learning and methods based on deep learning. In machine learning methods, the clustering algorithms are often used for BTS. In literature [1-4], a method based on fuzzy C-means clustering algorithm is used to segment the entire brain tumor area. The deep learning technologies for BTS tasks mainly include methods based on convolutional neural networks (CNN) and fully connected network (FCN) [5]. Pereira et al. [6] used a smaller convolution kernel and designed a deeper architecture, which is an effective way for BTS in MRI images. Havaei et al. [7] constructed a dual-path two-dimensional CNN network, using convolution kernels with different sizes to extract different features. Ronneberger proposed the U-net network based on FCN [8]. U-net uses a symmetrical encoding and decoding structure, which has a very good segmentation effect compared to medical images with relatively little
data. Because the left down sampling process can obtain semantic information, while the right upsampling process can recover part of the semantic information and achieve accurate positioning by concatenating with the feature graph in the down sampling process. U-net has been proved to be very effective in the end-to-end training of a small number of images, and is widely used in the field of medical image segmentation. Gadosey et al [9] proposed SD-Unet on BTS which is smaller and faster than U-net. Mehrdad Noori et al [10] proposed a 2D u-net with multi view technology, which can better combine 3D information. Although these methods have certain advantages in various aspects, for BTS, the problem of uneven distribution of tumor and background voxels needs to be solved urgently. Therefore, this paper introduces the learning mechanism to improve U-net, and proposes an improved BTS method.

Here, we want to summarize our contribution of this study:
1) Network structure improvement: We use U-net as to be the main network architecture, combined with the advantages of the residual network Resnet to avoid the disappearance of the gradient. Combined with the skip connection in Resnet, the improved u-net can better combine the context information.
2) Targeted data preprocessing and enhancement: In this paper, 3D MRI is sliced into 2D slices, which is very effective to reduce the occupation of GPU memory and reduce the difficulty of training. And a variety of data enhancement methods can be better applied to fewer training images.
3) Attention mechanism: We incorporates the compression and excitation module scSE on both space and channel to extract more useful features. In this way, the network can learn more useful features through the attention mechanism, and the effect of image segmentation is better.
4) Improved segmentation performance: We validated our model qualitatively and quantitatively on the BraTS 2018 dataset. Experimental results show that the segmentation results are close to the expert annotation results. Compared with the original u-net segmentation method, the segmentation effect is also improved, and compared with other methods, the score is also competitive.

2. Improved Algorithm
This article combines U-net and Resnet network structures, inspired by the scSE module[11], and proposes an improved BTS method, named after scSE-Res-U-net, the structure of the adopted network is shown in Figure 1.

Figure 1. the structure of the adopted network
The structure of this network is similar to the U-net. The contracted path on the left contains three residual modules instead of the ordinary modules in the original U-net. Each module has a scSE module.
and two convolution units, each unit contains a batch normalization BN (Batch Normalization) layer and a parameter correction activation function (PReLU), instead of the original U-net architecture ReLU.

The compression and excitation module (scSE) on space and channel consists of two modules: space compression and channel excitation module (cSE), channel compression and space excitation module (sSE) [12]. The structure diagram is shown in Figure 2.

Figure 2. squeeze and excitation (SE) blocks. (a) cSE; (b) sSE; (c) scSE

The combination of these two modules can effectively introduce attention mechanism from two aspects of space and channel, extract more useful features for segmentation, and suppress features that have little effect.

3. Experimental analysis

3.1 Dataset and preprocessing
This experiment uses the BraTS2018 dataset [13]. This dataset contains totally 285 samples (210 HGG patients, 75 LGG patients), and the BraTS2018 challenge also has 66 multimodal validation sets, which are composed of a mixture of HGG and LGG. The model in this paper is trained on 285 data sets. After randomly scrambling HGG and LGG, this dataset has been divided into five (4 training set and 1 validation set).

In terms of data preprocessing, we removed the 1% highest and 1% lowest intensities. In this paper, 3D brain MRI data is sliced into 2D data, which can be used for training with lower memory. MRI images of each mode are normalized within the slice by subtracting the average value and dividing by the standard deviation of the intensity within the slice. Data enhancement is mainly through the operation and transformation on the data and the corresponding expert segmentation label to obtain a new composite image to enrich the data. Transformation operations include horizontal flip, rotation, and left-right translation.

3.2 Experimental results and analysis
This paper compares the segmentation performance before and after the improvement. There are three labels for tumor segmentation: whole tumor (WT), tumor core (TC) and enhanced tumor (ET). We validate the model on the official unlabeled dataset to verify the generalization ability of the model.

This experiment chooses some of the segmentation results to show the qualitative analysis of segmentation performance.
Figure 3. From left to right (HGG): FLAIR, Pre_FLAIR, GT_FLAIR, T1c, Pre_T1c, GT_T1c

Figure 4. From left to right (LGG): FLAIR, Pre_FLAIR, GT_FLAIR, T1c, Pre_T1c, GT_T1c

Figure 3 and Figure 4 respectively show the segmentation results of brain tumors in a HGG patient and an LGG patient. The prefix ‘Pre’ represents the network predicted value, and the prefix ‘GT’ represents the true label segmentation value. Red represents necrosis and non-enhancing tumors, green represents edema, and yellow represents tumor core. The tumor core is the tumor from which the edema is removed. It can be seen from the figure that whether it is in HGG or LGG, the network segmentation results proposed in this paper are very close to the segmentation results marked by experts.

At the same time, we also conducted quantitative experiments to compare the segmentation performance before and after the network improvement. The network integrated with Resnet is named Res-U-net, and the network added with the scSE module is named scSE-Res-U-net. The segmentation performance comparison is shown in Table 1:

| Method             | DSC  | SEN  |
|--------------------|------|------|
|                    | ET   | WT   | TC   | ET   | WT   | TC   |
| U-net              | 0.7641 | 0.8708 | 0.7959 | 0.8196 | 0.8893 | 0.7872 |
| Res-U-net          | 0.7641 | 0.8759 | 0.8019 | 0.8184 | 0.8985 | 0.8042 |
| scSE-Res-U-net     | **0.7715** | **0.8812** | **0.8171** | 0.8382 | 0.8832 | 0.8028 |

In Table 1, DSC (Dice Similarity Coefficient) is used to calculate the degree of similarity between the brain tumor and the ground truth label of the network segmentation. SEN (Sensitivity) measures the proportion of voxels in real brain tumors that are correctly segmented. The above two evaluation index formulas are as follows:

\[
D_{SC}(P, T) = \frac{2|P \cap T|}{|P| + |T|} \tag{1}
\]

\[
S_{EN}(P, T) = \frac{|P \cap T|}{|T|} \tag{2}
\]

In formula (1) and (2), P represents the network prediction segmentation result; T represents the segmentation result marked by experts.

The result shows that after the network is integrated into the Resnet and scSE modules, the segmentation performance of each tumor has been improved.

To further reflect the superiority of the improved algorithm in this paper, the segmentation effect of other algorithms on the Brats2018 verification set is compared. The result is obtained under the same validation set.
Table 2. Comparison of segmentation performance between this method and other methods on the validation set

| Method        | DSC  | SEN  |
|---------------|------|------|
|               | ET  | WT  | TC  | ET  | WT  | TC  |
| Aibio[14]     | 0.773 | 0.881 | 0.777 | 0.8196 | 0.8893 | 0.7872 |
| Chen[15]      | 0.7493 | 0.8759 | 0.8019 | 0.8184 | 0.8985 | 0.8042 |
| scSE-Res-U-net | **0.7715** | **0.8812** | **0.8171** | **0.8382** | **0.8832** | **0.8028** |

In Table 2, although our method is a 2D network, through improvement, it is very close to the results of some 3D networks, and even better in the performance of the tumor core. Successfully used a 2D network with lower complexity than a 3D convolutional neural network, and got very good performance.

4. Conclusion

This paper proposes a 2D brain tumor automatic segmentation network for factors such as imbalance of brain tumor data and the time and labor consuming manual segmentation of doctors. Using U-net as the network theme architecture, the residual module is introduced to reduce the possibility of gradient disappearance. And further introduce the learning mechanism into the network, integrate the scSE module, extract more important features in the channel and space, ignore the less important features, and improve the fine-grained segmentation effect.

Quantitative and qualitative experimental results prove that the added scSE module has improved the segmentation performance, and compared with other methods, it also has very good segmentation results. It is fully qualified for the automatic segmentation of brain tumors and assists doctors in quickly formulating treatment plans. Since only the axial slices are extracted for training in this paper, it can be combined with slice training in other directions to make better use of spatial information. In the case of sufficient video memory, 3D convolutional networks can also be introduced to use richer spatial information to improve segmentation performance.

Reference

[1] Abdel-Maksoud, E., M. Elmogy, and R. Al-Awadi 2015 Brain tumor segmentation based on a hybrid clustering technique. *Egyptian Informatics Journal* 16(1): p. 71-81.

[2] El-Melegy, M.T. and H.M. Mokhtar 2014 Tumor segmentation in brain MRI using a fuzzy approach with class center priors. *Eurasip Journal on Image & Video Processing*. 2014(1): p. 21.

[3] Menon, N. and R. Ramakrishnan. 2015 Brain Tumor Segmentation in MRI images using unsupervised Artificial Bee Colony algorithm and FCM clustering. *International Conference on Communications & Signal Processing*.

[4] Sharma, M. and S. Mukherjee 2013 Fuzzy C-Means, ANFIS and Genetic Algorithm for Segmenting Astrocytoma –A Type of Brain Tumor. *IAES International Journal of Artificial Intelligence (IJ-AI)*. 3(1).

[5] Long, J., E. Shelhamer, and T. Darrell 2015 Fully Convolutional Networks for Semantic Segmentation. *IEEE Transactions on Pattern Analysis and Machine Intelligence*. 39(4): p. 640-651.

[6] Pereira, S., et al. 2016 Brain Tumor Segmentation Using Convolutional Neural Networks in MRI Images. *IEEE Transactions on Medical Imaging*. 35(5): p. 1240-1251.

[7] Havaei, M., et al. 2017 Brain Tumor Segmentation with Deep Neural Networks. *Medical Image Analysis*. 35: p. 18-31.

[8] Ronneberger, O., P. Fischer, and T. Brox 2015 U-Net: Convolutional Networks for Biomedical Image Segmentation. *Medical Image Computing and Computer-Assisted Intervention – MICCAI 2015*. p. 234-241.

[9] Gadosey, P.K., Li, Y., Agyekum, E.A., Zhang, T., Liu, Z., Yamak, P.T. and Essaf, F., 2020. SD-
UNet: Stripping down U-Net for Segmentation of Biomedical Images on Platforms with Low Computational Budgets. *Diagnostics* **10**, 110.

[10] M. Noori, A. Bahri and K. Mohammadi 2019 Attention-Guided Version of 2D U-Net for Automatic Brain Tumor Segmentation. *2019 9th International Conference on Computer and Knowledge Engineering (ICCKE)*, Mashhad, Iran. pp. 269-275.

[11] Roya G., Navab N., and Wachinger C. Concurrent Spatial and Channel Squeeze & Excitation in Fully Convolutional Networks. *International Conference on Medical Image Computing and Computer Assisted Intervention*. 2018.

[12] Hu, J., L. Shen, and G. Sun 2018 Squeeze-and-Excitation Networks *2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition*. p. 7132-7141.

[13] Menze BH, Jakab A, Bauer S, et al. 2015 The Multimodal Brain Tumor Image Segmentation Benchmark (BRATS). *IEEE Trans Med Imaging*. **34**(10):1993-2024.

[14] Albiol, A., A. Albiol, and F. Albiol 2019. Extending 2D Deep Learning Architectures to 3D Image Segmentation Problems *Brainlesion: Glioma, Multiple Sclerosis, Stroke and Traumatic Brain Injuries*. p. 73-82.

[15] Chen, W., et al. 2019 S3D-UNet: Separable 3D U-Net for Brain Tumor Segmentation *Brainlesion: Glioma, Multiple Sclerosis, Stroke and Traumatic Brain Injuries*. p. 358-368.