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Multimodal weighted network for 3D brain tumor segmentation in MRI images

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ABSTRACT

Brain tumor segmentation plays an important role in brain tumor diagnosis and treatment. In this study, we propose a multimodal weighted deep network (MW-Net) for 3D tumor segmentation which makes fully use of different types of biological information from multiple MR imaging modalities. Furthermore, since the contribution from different modalities is different, the relative weight for each modality is introduced into MW-Net, which is considered as the hyperparameter during the training. Additionally, 3D-U-Net are taken as the basic model in MW-Net. In training stage, four different imaging modalities with the weight are fed into MW-Net to train the parameters, and the whole network is trained in an end-to-end way. The final 3D segmentation results can be directly obtained when the test images are input into the trained model. By testing the model on BraTS 2018 dataset, it is demonstrated that MW-Net can obtain better performance compared with traditional 3D-U-Net.

Keywords: Brain tumor segmentation, multimodal, deep neural network

1. INTRODUCTION

Gliomas has become the most frequently primary tumors in adults [1] and Magnetic resonance imaging (MRI) has become the first choice in clinical routine work. Accurately segmenting brain tumor plays an important role in making optimal treatment plan, image-guided surgery and treatment outcome follow-up [2]. On the other hand, unreliable segmentation may lead to mislead surgery, which may cause the loss of brain functions such as speaking and reading. However, due to the complexity of brain structure, physicians have to spend too much time to segment the tumor manually, particularly in 3D MR images. Therefore, developing an automatic and reliable brain tumor segmentation model is necessary.

In recent years, deep learning has achieved great success in tumor segmentation. Particularly, U-net should be the most successful deep learning-based model for automatic medical image segmentation [3]. It has been applied to colon histology, kidney, vascular boundary, lung nodule, etc. The most advantage of U-net is learning the tumor location, which can efficiently incorporate the location in training phase. However, the traditional U-net can't utilize multimodal imaging to perform segmentation, while we can obtain a large variety of imaging modalities including T1 (T1-weighted MRI), T1Gd (Post-contrast T1-weighted MRI), T2 (T2-weighted MRI), and FLAIR(T2 Fluid Attenuated Inversion Recovery MRI) [1]as shown in figure 1. Each of these modalities can provide different types of biological information, and they are also complementary.

To overcome the above issue, a new multimodal weighted network (MW-Net) is developed for 3D brain tumor segmentation in this study. In MW-Net, four different MRI modalities are fed into the network and 3D-U-Net [4] is taken as the basic model. Meanwhile, since the contribution from different modalities are different, the relative weight

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is introduced for each modality. The experimental results demonstrated that MW-Net can obtain better performance compared with traditional 3D-U-Net.

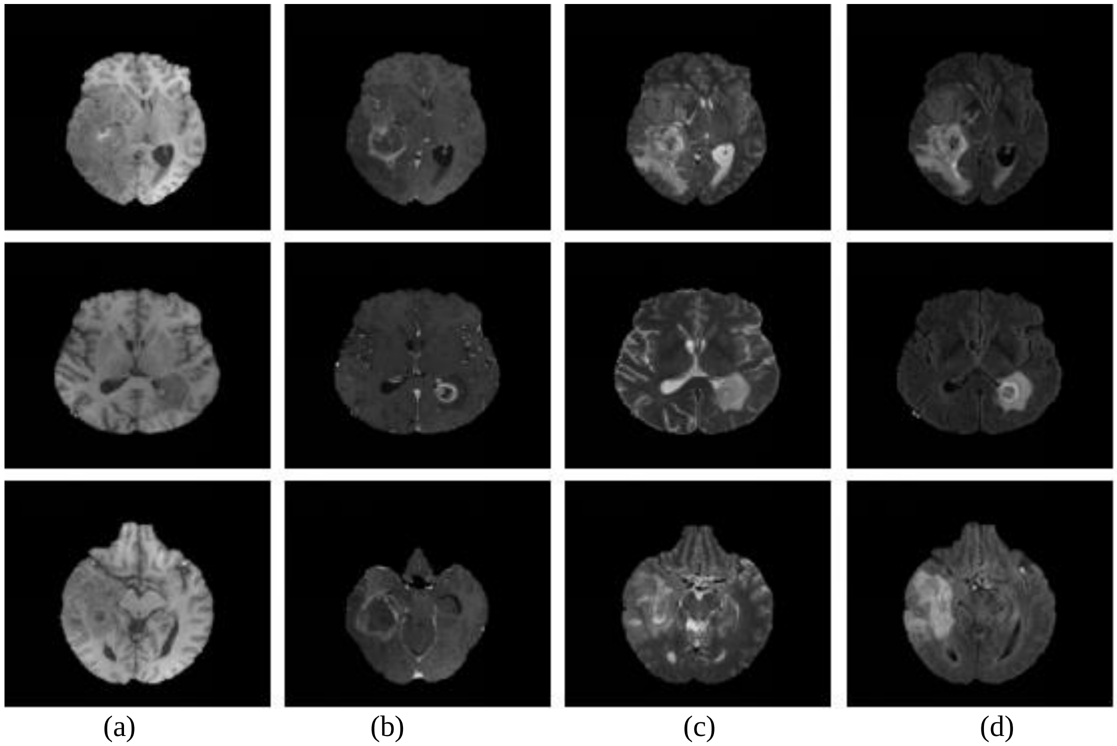


Figure 1: Four MRI modalities. (a) T1, (b) T1Gd, (c) T2, (d) FLAIR.

2. METHODS

2.1 Framework

The whole workflow is shown in figure 2. Four MRI modalities multiple with the corresponding weight are fed into the 3D-U-Net simultaneously. In other words, all these modalities share the same network. The relative weights are considered as the hyperparameter and they are trained with other parameters in the network simultaneously in an end-to-end way. The backpropagation algorithm was employed to train the model. The final 3D segmentation result can be directly obtained when input test images into the trained MW-Net.

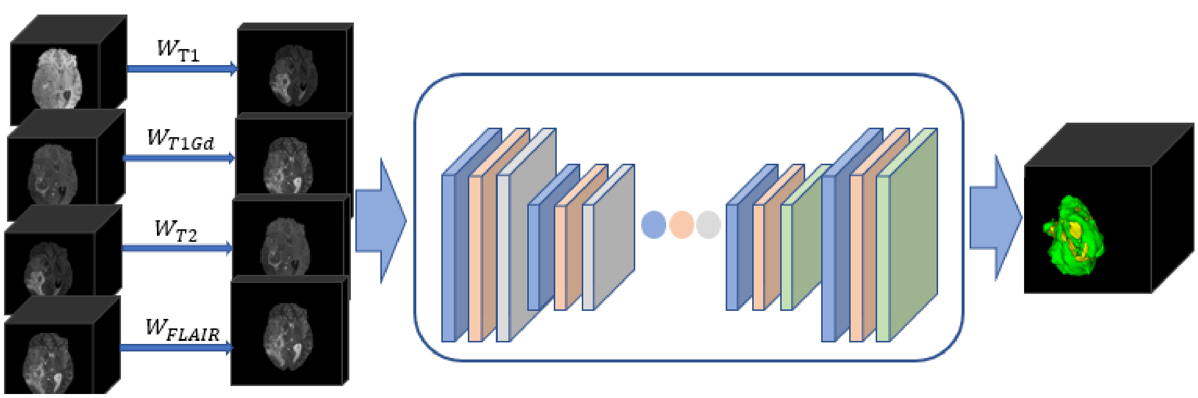


Figure 2: MW-Net workflow.

2.2 3D-U-Net

Since 3D-U-Net is the basic model in MW-Net, it is briefly described in this subsection. 3D-U-Net is developed based on U-Net, which is mainly used for segmenting 3D images, and the architecture is shown in figure 3. The mainly difference between 3D-U-Net and U-Net is the operations such as convolutional, pooling and upsampling layers are modified from 2D to 3D type. In this model, ReLU is considered as the activation function. Cross entropy is taken as the loss function, and the Adam function is used for model optimization and iteration number is set as 90.

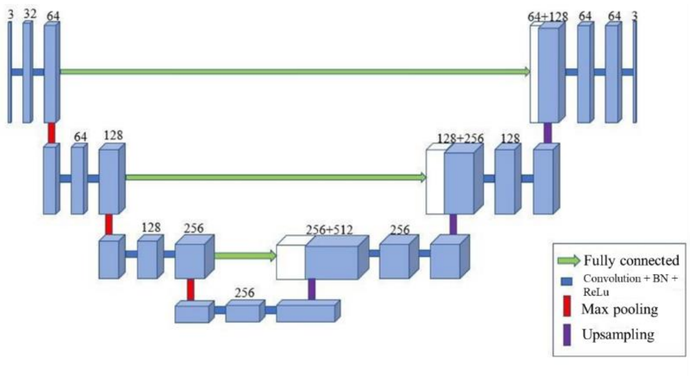


Figure 3: 3D-U-Net architecture

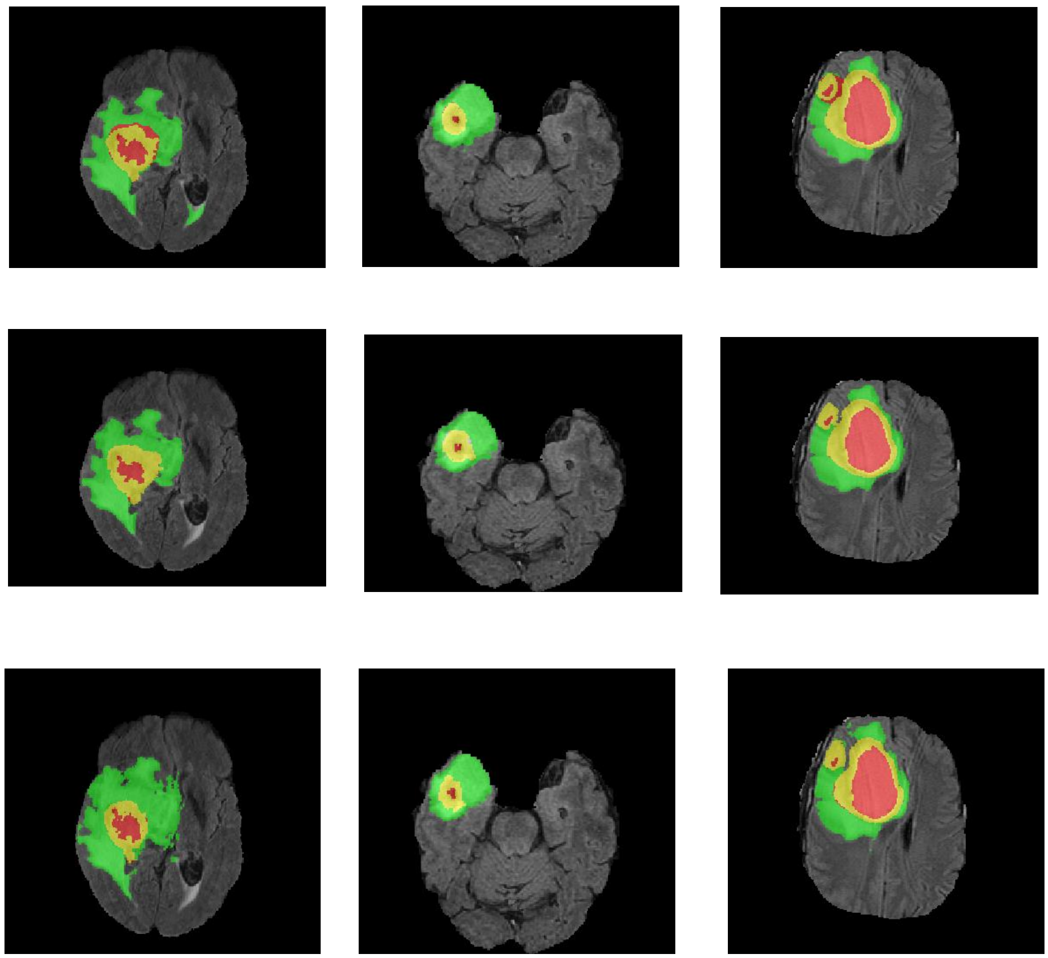
3. EXPERIMENTS

3.1 Materials and setup

In this study, Brats 2018 dataset which consists of 285 patients (including 210 high grade and 75 low grade gliomas) is used. Each case contains four MRI modalities including T1, T1Gd, T2 and FLAIR and the registration was performed among each modality. The image size is 240 x 240 x 155. All the images are manually contoured from the multiple experienced physicians. Five-folder cross validation was performed in this experiment. Five-folder cross validation was performed in this experiment. Dice coefficient, Positive Predictive Value (PPV), sensitivity is used for evaluation. 3D-U-Net is used for comparison.

3.2 Results

The segmentation examples on 2D images are shown in figure 4. Compared with the 3D-U-Net, MW-Net can obtain more accurate results in visually. The 3D segmentation results on whole, core and enhancement tumors are shown in figure 5, which also demonstrate the similar results. The quantitative evaluation on whole, core and enhancement tumors are shown in table 1. It is shown that MW-Net can obtain better performance in most results.



(a) (b) (c)

Figure 4: 2D segmentation results on 3D-U-Net and MW-Net. (a), (b) and (c) are segmentation results for three cases. The first row is the 3D-U-Net segmentation results and the second row is MW-Net results. The third row is the ground truth.

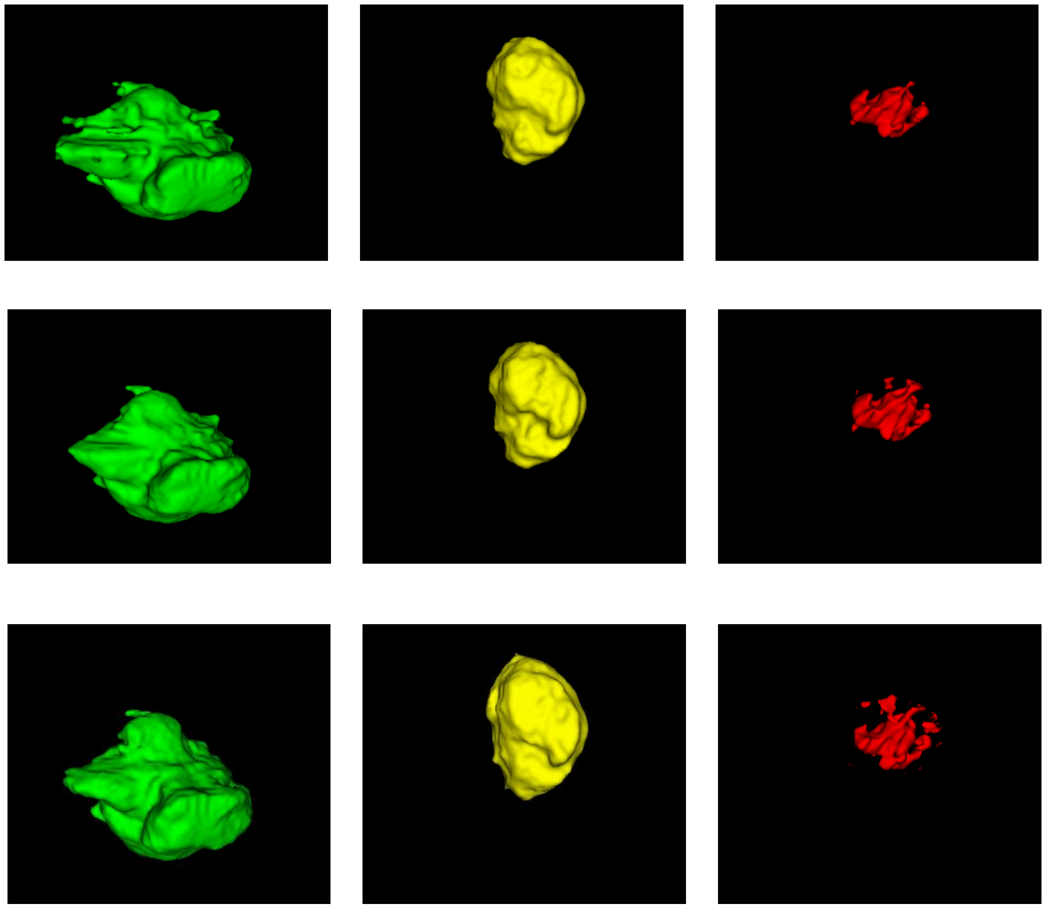


Figure 5: 3D segmentation results on 3D-U-Net and MW-Net. (a), (b) and (c) are segmentation results for three cases. The first row is the 3D-U-Net segmentation results and the second row is MW-Net results. The third row is the ground truth.

Table 1 Quantitative results on two methods

Method	Dice			PPV			Sensitivity		
	Whole	Core	Enh.	Whole	Core	Enh	Whole	Core	Enh
3D-U-Net	85.24	73.69	**70.14**	89.95	86.99	75.3	84.75	72.7	77.84
MW-Net	**88.24**	**81**	69.13	**88.23**	**84.24**	**71.45**	**89.63**	**82.36**	**80.94**

4. CONCLUSIONS

To fully utilize multi-modality MRI information, a new multimodal weighted network (MW-Net) was developed for 3D brain tumor segmentation in this study. Since the importance of different modalities are different, the relative weights are introduced and taken as the hyperparameters to be trained in network. The experimental results in quantitative and visual evaluation demonstrated that MW-Net outperformed 3D-U-Net.

ACKNOWLEDGEMENTS

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REFERENCE LINKING

[1] B. H. Menze *et al.*, "The multimodal brain tumor image segmentation benchmark (BRATS)," *IEEE transactions on medical imaging,* vol. 34, no. 10, pp. 1993-2024, 2014.

[2] H. Shen, J. Zhang, and W. Zheng, "Efficient symmetry-driven fully convolutional network for multimodal brain tumor segmentation," in *2017 IEEE International Conference on Image Processing (ICIP)*, 2017, pp. 3864-3868: IEEE.

[3] O. Ronneberger, P. Fischer, and T. Brox, "U-net: Convolutional networks for biomedical image segmentation," in *International Conference on Medical image computing and computer-assisted intervention*, 2015, pp. 234-241: Springer.

[4] H. Hwang, H. Z. U. Rehman, and S. Lee, "3D U-Net for skull stripping in brain MRI," *Applied Sciences,* vol. 9, no. 3, p. 569, 2019.