A COMPOUND NEURAL NETWORK FOR BRAIN TUMOR SEGMENTATION

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Introduction

Brain tumor image segmentation has been a time-consuming and laborious task for decades. Since deep learning has been applied to the image field, there have been many efforts to find automatic segmentation methods. This paper proposes an end-to-end image segmentation system based on neural network. First we develop a novel Convolutional Neural Network architecture named Hybrid Two-path Convolution that combines coarse and fine features obtained by different paths. Besides, traditional method for up-sampling often leads to insufficient utilization of network parameters. By endues geometric meaning to different channels, our Region-based Upsampling Convolution can effectively improve the detailed feature capture capabilities of the network without wasting any parameters. Due to the imbalance between labels, we design category based loss function as a solution. Experiments on public datasets demonstrate that the proposed system is competitive with the state-of-the-art methods.

Main Contributions

- In this paper, we propose an end-to-end image segmentation deep learning model Mixed-Unet (M-Unet) based on the U-Net architecture, which involves our proposed substructures and loss function.
- We develop Hybrid Two-path convolution (HTC) to improve the efficiency and accuracy of neural network.
- Traditional up-sampling structures fill the feature layer with zeros, which causes the parameters be diluted. In order to avoid this problem, we proposed Region-based Unpooling convolution (RUC).

Network Architecture

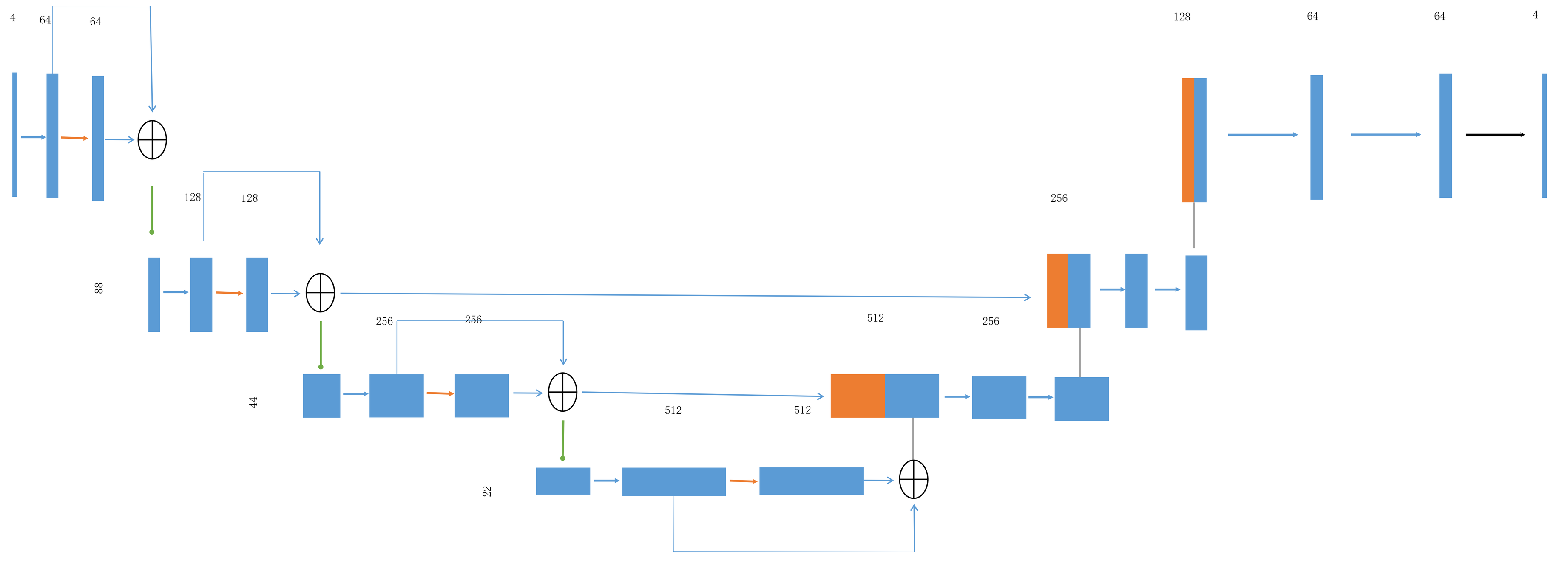

Fig. 1 Network Architecture

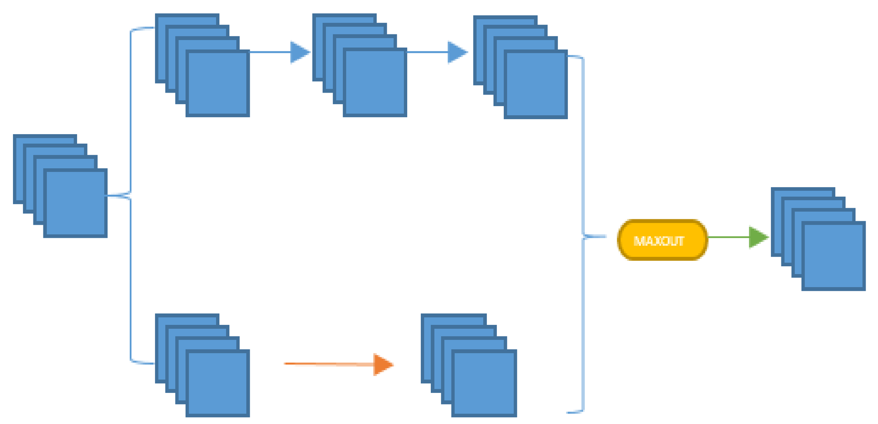

Fig. 2: Hybrid Two-path architecture.

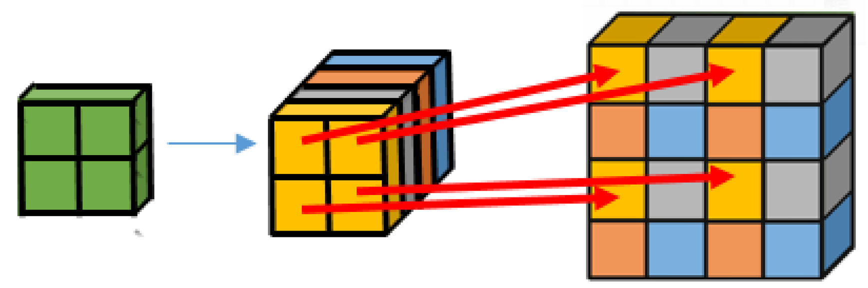

Fig. 3 RBU structure

Loss Function

$$\text{Loss} = -\sum_{i=1}^{4} w_i * L_i,$$

$$L_i = \frac{\sum_j^{N_i} u_j v_j}{\sum_j^{N_i} u_j^2 + \sum_j^{N_i} v_j^2}$$

$$w_i = \left(1 - \alpha * \frac{N_i}{N}\right), \text{i} = 1,2,3,4, \alpha \forall \in [0,1]$$

Experimental Results

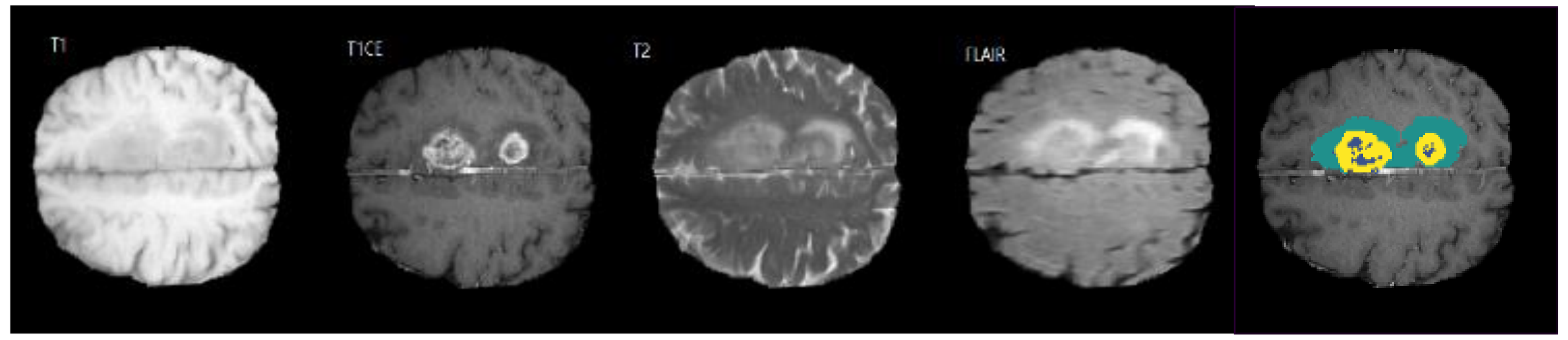

Fig. 1 The images from left to right are four MRI modalities for the same brain. And the last image is the ground true image.

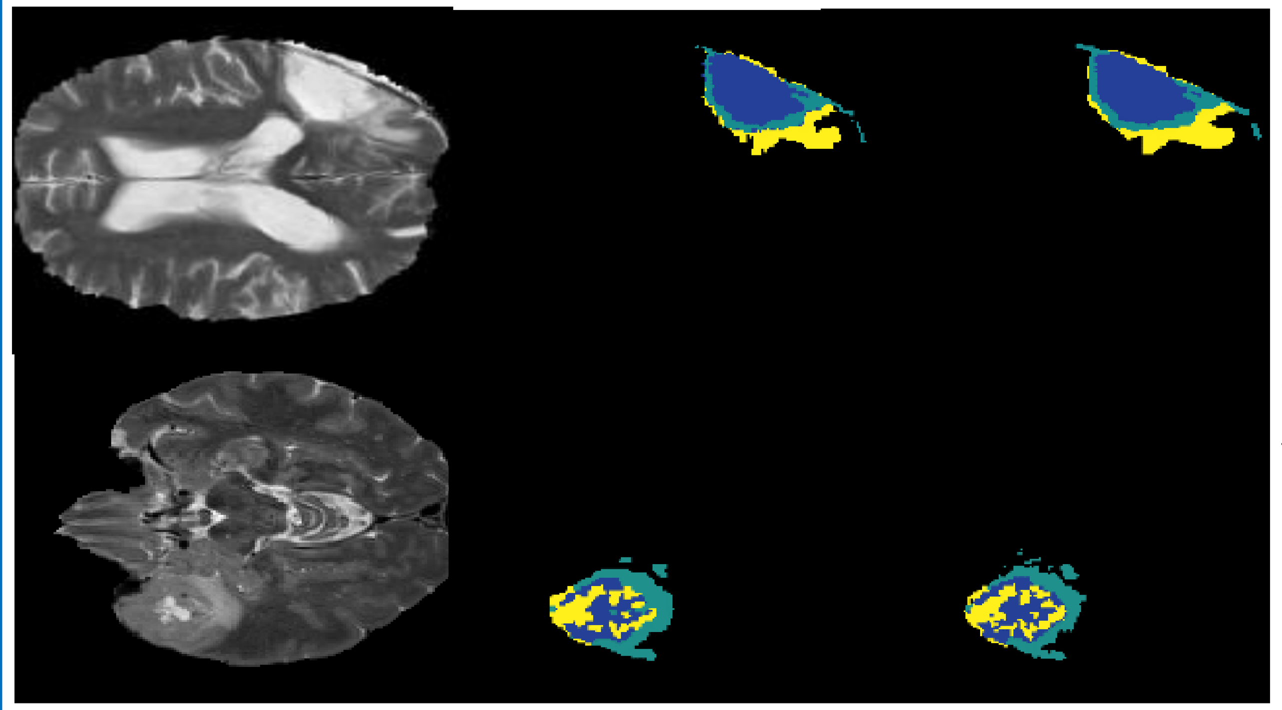

Fig.2 Our experiment results. The first image is T1 MRI, the second image is the ground truth, the third is our segmentation.

Table 1: Evaluation for substructures

Method	complete		Core		active	
	Dice	Sens	Dice	Sens	Dice	Sens
M-Unet	**0.90**	**0.89**	**0.80**	0.83	**0.74**	**0.78**
Unet	0.82	0.78	0.74	0.82	0.67	0.71
H-Unet	0.85	0.88	**0.80**	**0.88**	0.70	0.74
R-Unet	0.83	0.83	0.79	0.70	0.69	0.68

Table 1:Experiments to evaluate our substructure's effectiveness

Table 2: Baselines.

$$\text{Dice}(P, T) = \frac{|P_1 \wedge T_1|}{(|P_1| + |T_1|)/2}$$

$$\text{Sens}(P, T) = \frac{|P_1 \wedge T_1|}{|T_1|}$$

	DICE		
Method	Complete	Core	Active
M-Unet	**0.90**	0.80	**0.74**
K.Kamnitsas[12]	**0.90**	0.78	0.73
Vinoth R [3]	0.87	**0.82**	0.70