Multi-modality brain tumor segmentation using a modified cascaded 3D U-Net for imbalanced classes

Wenwen Kong[1,2], Dengwang Li[1] and Youming Yang[2]
1Shandong Province Key Laboratory of Medical Physics and Image Processing Technology, School of Physics and Electronics, Shandong Normal University, Jinan, Shandong, China
2University of California, Los Angeles, CA

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INTRODUCTION

Gliomas are the most commonly encountered malignant brain tumors. The gliomas can be roughly graded into glioblastoma (GBM/HGG) and low grade glioma (LGG) and 57.3% of gliomas are HGG which is more aggressive and infiltrative than LGG. Brain tumor segmentation using multi-modality MRI scans is critical for disease diagnosis, surgical planning and treatment assessment.

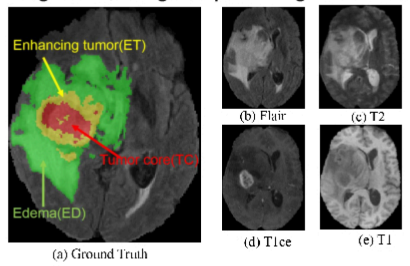

Fig1: The manual segmentation results of the different substructures are shown in (a).A brain tumor example(b–e) show four slices with the same position in different MRI scans.

AIM

- Surpassing previous methods due to improved handling of dataset imbalance
- Suppressing false-positive classifications

METHOD

The data used in experiments comes from BraTS 2019 training set. We use 80% of the dataset for training(207HGG,60LGG) and the remaining 20% for validation(52HGG,16LGG). Pre-processing include N4BiasFieldCorrection and z-score normalization for the brain region. Nonbrain regions are removed. Each pre-processed image was divided into 27 patches and the patch size is 64×64×64. We used a cascaded 3D U-Net to segment the brain tumors. The first 3D U-Net uses four modalities images as inputs, and outputs the mask of whole tumor (WT). The second 3D U-Net only uses T1ce, T2 and Flair images and the patches which comprise all three tumor classes are kept for training to segment the WT into three substructures: edema (ED), tumor core (TC) and enhancing tumor (ET). The depth of 3D U-Net is 4. P-ReLu and focal loss were used as the activation and loss function, providing the activation of negative features and the reduction of the relative loss for well-classified examples.

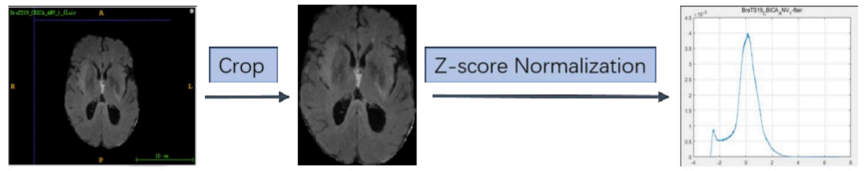

Fig2: The flow chart of image preprocessing.

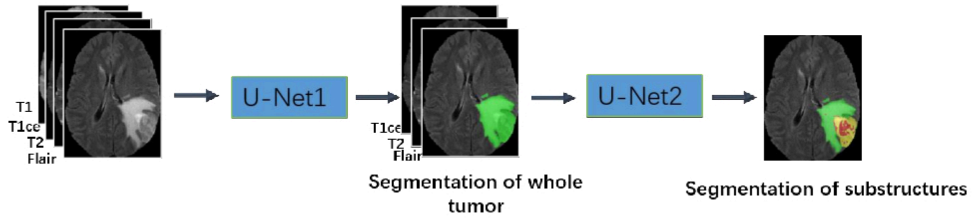

Fig3: The framework of the cascaded 3D U-Net.

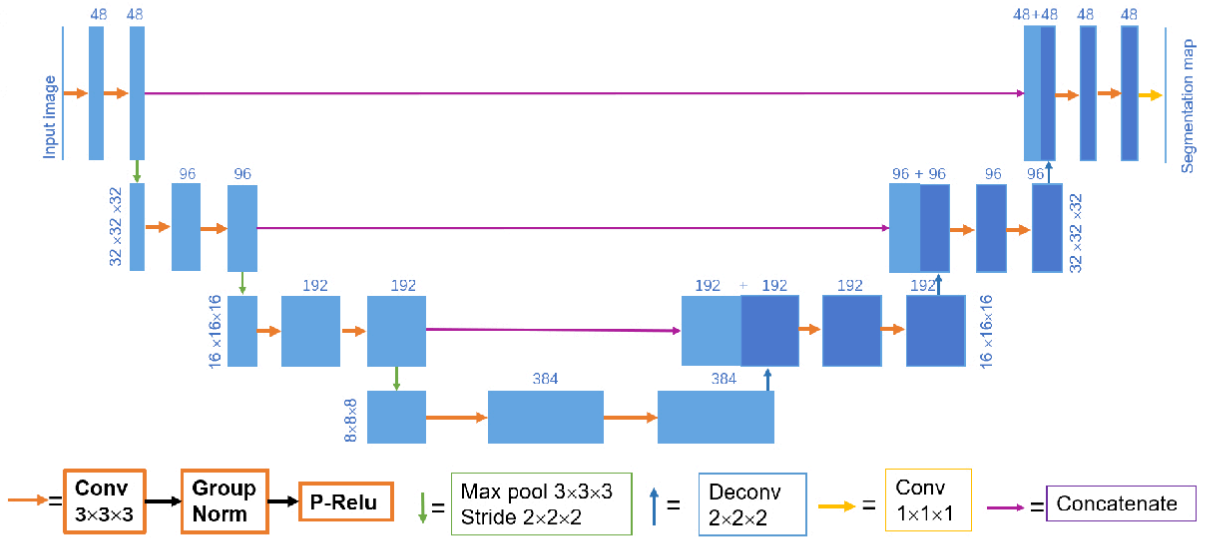

Fig4: The architecture of the 3D U-Net.

CONCLUSIONS

There are two distinct advantages of the two-step framework:

- The initial segmentation of WT helps suppress false-positive classifications in non-tumorous areas during subsequent segmentation step.
- The initial WT segmentation of the proposed method also method mitigates the effect of unbalanced data by reducing the number of normal tissue voxels in the region of interest.
- Combined with the use of focal loss, this method improves on the previous work by traditional 3D U-Net

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RESULT

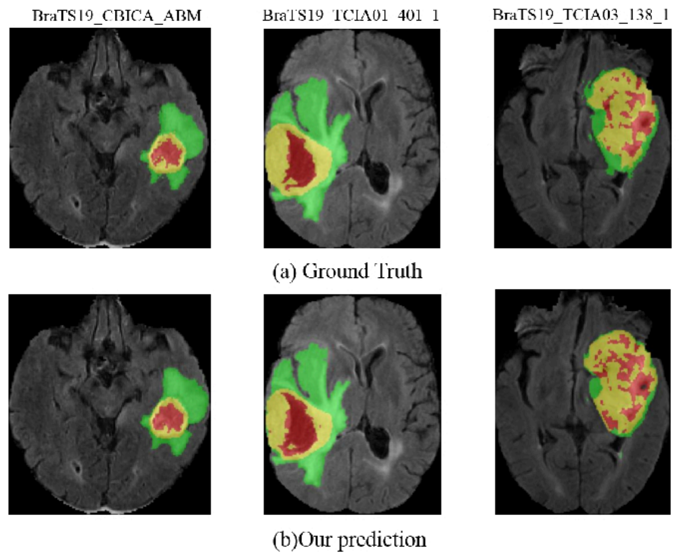

Fig 5: Comparison of our segmentation result with the ground truth labels.

Table1. Dice, Sensitivity and Specificity Hausdorff95 measurements of the proposed method on training dataset.

	Whole tumor	Tumor core	Enhancing tumor
Dice mean ± SD	0.91104 ± 0.06264	0.82313 ± 0.17412	0.72895 ± 0.26661
Sensitivity mean ± SD	0.9407 ± 0.06772	0.81506 ± 0.18246	0.77544 ± 0.21057
Specificity mean ± SD	0.99221 ± 0.00757	0.99721 ± 0.00477	0.99833 ± 0.00197
Hausdorff95 mean± SD (mm)	5.55044 ± 12.49017	5.87044 ± 6.10405	4.78968 ± 6.77919

Table2. Dice, Sensitivity and Specificity Hausdorff95 measurements of the proposed method on validation dataset.

	Whole tumor	Tumor core	Enhancing Tumor
Dice mean ± SD	0.90817 ± 0.06135	0.82215±0.17346	0.73125±0.28098
Sensitivity mean ± SD	0.91516 ± 0.09355	0.849±0.16018	0.84147±0.13609
Specificity mean ± SD	0.99369 ± 0.00594	0.99602±0.00637	0.99851±0.00155
Hausdorff95 mean ± SD (mm)	5.61991 ± 7.49201	6.33857±6.15973	4.98616±8.82816

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CONTACT INFORMATION

youmingyang@mednet.ucla.edu