# 3D MRI Brain Tumor Segmentation based on U-Net

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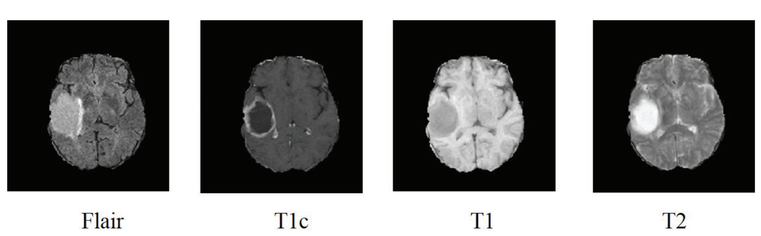
## Introduction

Automatic segmentation of brain tumor in magnetic resonance images (MRI) is necessary for diagnosis, monitoring and treatment. Manual segmentation is time-consuming, expensive and subjective. We present a robust automatic segmentation algorithm based on U-Net, which incorporates residual block, dilated convolution and deep supervision to improve the segmentation results.

## Dataset

- BraTS 2017 dataset
- Training set: 285 data patients.
- Validation set: 46 data patients.
- Input Modalities:
  - post-contrast T1-weighted
  - native T1
  - native T2-weighted
  - T2 Fluid Attenuated Inversion Recovery
- Volume Size: $240 \times 240 \times 155$
- Resolution: $1mm \times 1mm \times 1mm$

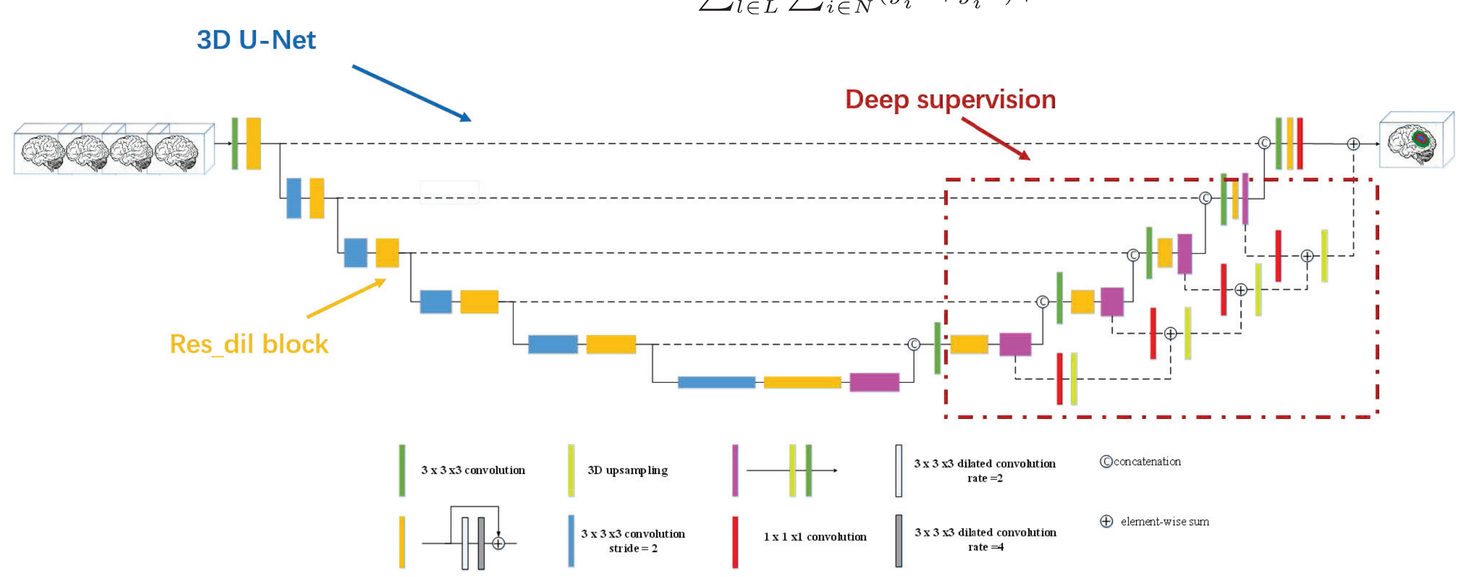



Input Modalities

## Method

- Pre-processing
  - Crop: $240 \times 240 \times 155$ to $128 \times 128 \times 128$
  - Bias Field Correction and Intensity Normalization
- Architecture:
  - Residual block: use dilated convolutions to aggregate features at multiple scales.
  - Deep supervision: integrate segmentation layers at different levels of the network and combine them using element-wise summation.
- Training implementation: Keras with Nvidia GPU Quadro P5000, adam optimizer, initial learning rate is 5e-4 with a decreasing learning rate factor 0.5 with patience of 10 epochs.

$$Loss_{dice} = 1 - 2\frac{\sum_{l\in L}\sum_{i\in N} y_i^{(l)}\hat{y}_i^{(l)} + \epsilon}{\sum_{l\in L}\sum_{i\in N}(y_i^{(l)} + \hat{y}_i^{(l)}) + \epsilon}$$

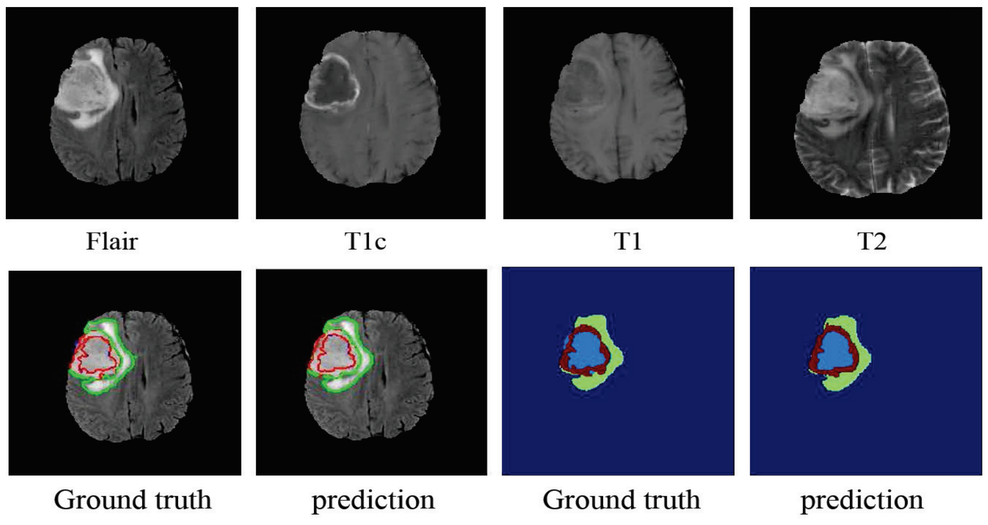



## Results

| Method | Dice | | | Sensitivity | | | Specificity | | | Hausdorff95 | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | whole | core | enh | whole | core | enh | whole | core | enh | whole | core | enh |
| Baseline | 0.8660 | 0.7679 | 0.6406 | 0.8544 | 0.7513 | 0.6737 | 0.9947 | 0.9972 | 0.9980 | 8.3942 | 8.8408 | 8.1346 |
| Baseline + Deep supervision | 0.8786 | 0.8122 | 0.6666 | 0.8740 | 0.8040 | 0.7249 | 0.9936 | 0.9967 | 0.9975 | 7.5355 | 7.5855 | 7.6735 |
| Baseline + Res_dil | 0.8824 | 0.8193 | 0.6954 | 0.8781 | 0.8180 | 0.7397 | 0.9936 | 0.9963 | 0.9974 | 7.5180 | 6.8994 | 6.2579 |
| Baseline + Res_dil + Deep supervision | 0.8851 | 0.8455 | 0.7342 | 0.9172 | 0.8303 | 0.7425 | 0.9910 | 0.9966 | 0.9974 | 5.8088 | 6.4748 | 6.8110 |

Quantitative segmentation results on BraTS 2017 dataset

Qualitative segmentation results from a randomly chosen patient, edema is shown in green, enhancing tumor is shown in red and necrotic and non-enhancing tumor are shown in blue.




## Conclusion

A semantic segmentation network is proposed for multimodal 3D MRI brain tumor segmentation, a novel residual block with dilated convolution and deep supervision are employed to improve the segmentation performance. Experiments show the effectiveness of the proposed method.

## References

[1] Olaf Ronneberger, Philipp Fischer, and Thomas Brox. U-net: Convolutional networks for biomedical image segmentation. In *International Conference on Medical image computing and computer-assisted intervention*, pages 234–241. Springer, 2015.

[2] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 770–778, 2016.