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AUTOMATED 3D SEGMENTATION ON POST-TREATMENT GLIOMA

Introduction

Gliomas are the most prevalent and fatal primary brain tumors, with high genetic and phenotypic diversity. Automated segmentation of post-treatment glioma MRI scans is essential for monitoring tumor progression, distinguishing recurrence from treatment effects, and developing personalized treatment strategies. The 2024 BraTS (Brain Tumor Segmentation) challenge provided post-treatment glioma multiparametric MRI scans to advance automated MRI segmentation and integrate these models into clinical practice [1].

Dataset Overview

- **Multiple Timepoints per Patient**: The varying number of MRI scans per patient complicates data consistency and analysis.
- **Class Imbalance:** The background often dominates the image, complicating accurate identification of smaller target areas.

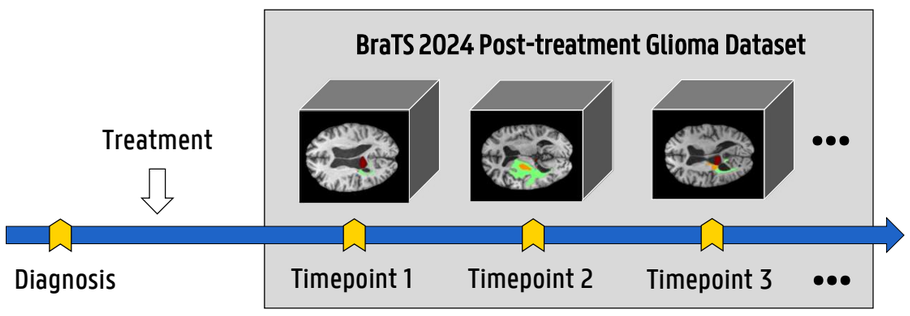

Figure 1: A timeline diagram illustrating the progression of a patient's MRI scans across multiple timepoints in the BraTS 2024 Adult Glioma Post-Treatment Dataset [1].

3D Segmentation on Brain MRI

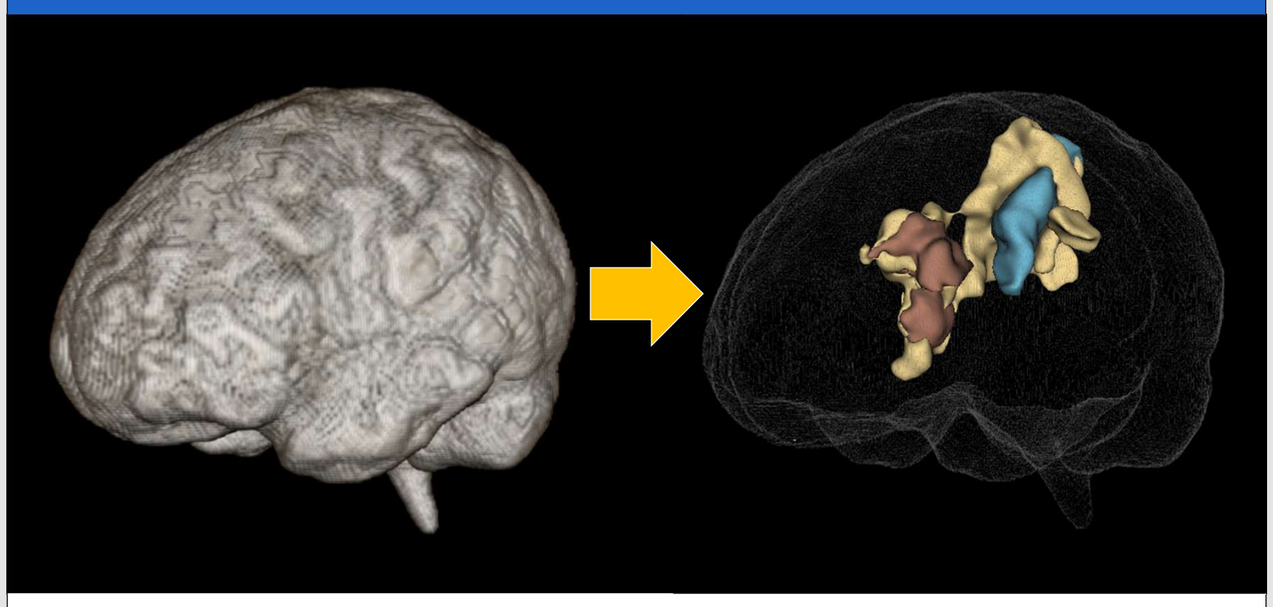

Figure 2: Visualization of a 3D brain MRI volume and its corresponding segmentation labels

Methodology

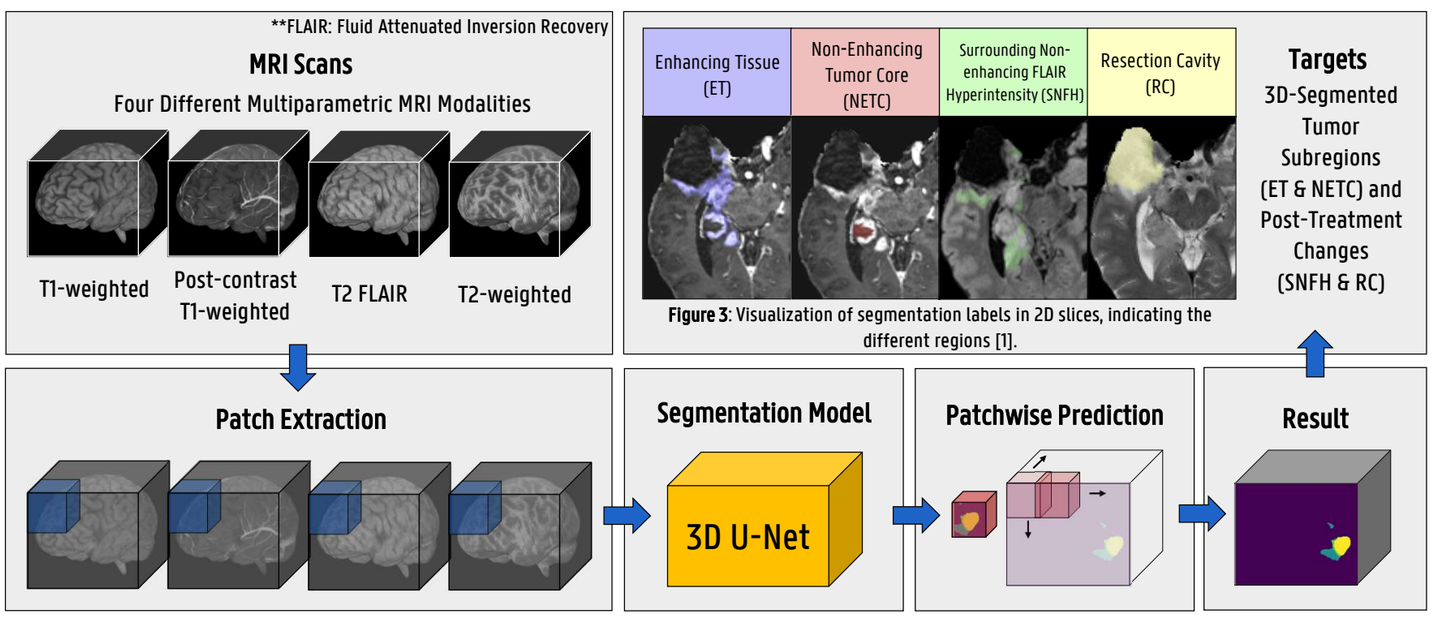

Figure 3: Visualization of segmentation labels in 2D slices, indicating the different regions [1].

Figure 4: The segmentation workflow starts with combining four MRI modalities into a multichannel 3D object, followed by extracting 96^3 patches for training the 3D U-Net model, and validation using a sliding window approach.

Results

Dice Score ↑	ET	NETC	SNFH	RC
3D U-Net	0.9248	0.0112	0.9474	0.8495
Winner	**0.9738**	**0.0905**	**0.9831**	**0.9378**
Hausdorff Distance 95% ↓	**ET**	**NETC**	**SNFH**	**RC**
3D U-Net	1.4142	**31.064**	1.4142	5.0990
Winner	**1.0000**	39.810	**1.0000**	**1.0000**

Table 1: Tables comparing dice scores and Hausdorff distance at 95th percentile between the challenge winner's model and 3D U-Net model for each lesion type.

- **Dice Score**: Higher for the winner's model.
- **Hausdorff Distance 95% (HD95)**: Lower for 3D U-Net.
- **Small NETC Volume**: Affected segmentation accuracy.
- **Trade-off**: 3D U-Net had better boundary precision; winner's model captured lesion volumes better.

Lesion-wise Overlay of Segmentation Results: Ground Truth, Challenge Winner, and 3D U-Net

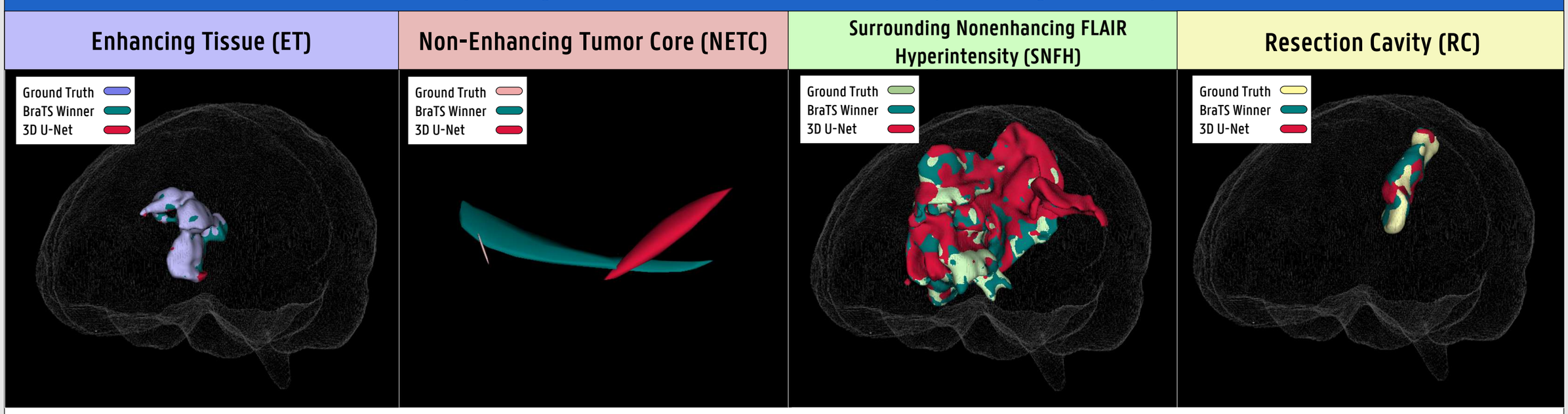

Figure 5: Overlayed segmentations from Ground Truth, the Challenge Winner's Model, and the MONAI-based 3D U-Net Model for four classes (ET, NETC, SNFH, RC), with color coding for each model. NETC segmentation is zoomed in due to the lesion's small area.

Conclusion

The results highlight a trade-off between boundary precision (HD95) and volume overlap (Dice score) in glioma segmentation. While the 3D U-Net model showed better spatial localization for Non-Enhancing Tumor Core (NETC), the BraTS 2024 Challenge winner's model—based on Hybrid Deep Learning models with synthetic data augmentation (GAN) [2] —achieved higher Dice scores, indicating superior volumetric segmentation. Future work will focus on 5-fold cross-validation training to improve model robustness and developing a real-time interactive segmentation tool for better visualization and analysis. Additionally, I am joining a team for the BraTS 2025 Challenge as part of a team.

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References:

1. Verdier, M.C., Saluja, R., Gagnon, L., Labella, D., Baid, U., et al. (2024). The 2024 Brain Tumor Segmentation (BraTS) Challenge: Glioma Segmentation on Post-treatment MRI. ArXiv, abs/2405.18368.
2. Ferreira, A., Jesus, T., Puladi, B., Kleesiek, J., Alves, V., & Egger, J. (2024). Improved Multi-Task Brain Tumour Segmentation with Synthetic Data Augmentation. *ArXiv*, 2411.04632.

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Code and PPT