ASEC 2025 Conference
The 6th International Electronic Conference on Applied Sciences
09–11 December 2025 | Online
MDPI

Segmentation of Atypical Teratoid Rhabdoid Tumor Using UNet+ Fork with ResNext and ResNet for Improved MRI Analysis

Nadenlla RajamohanReddy, G Muneeswari
School of Computer Science and Engineering, VIT-AP University, Amaravati, Andhra Pradesh, India.

INTRODUCTION & AIM

Atypical Teratoid Rhabdoid Tumor (ATRT) is a highly aggressive and malignant pediatric brain tumor known for its rapid proliferation and complex morphological heterogeneity. This inherent diversity in presentation poses substantial clinical challenges, complicating the processes of diagnosis, treatment planning, and prognostic evaluation. In clinical practice, Magnetic Resonance Imaging (MRI) serves as the cornerstone for visualizing these tumors. Precise segmentation of ATRT from MRI scans is a critical prerequisite for accurate volumetric analysis, targeted radiation therapy, and the longitudinal assessment of treatment response. To address these deep learning architectures, particularly variants of the UNet model, have emerged as a leading solution in medical image analysis due to their proficiency in capturing contextual and spatial information. The primary aim is to develop and evaluate an advanced deep learning model for the automated segmentation of ATRT in MRI scans. We propose a novel architecture that integrates a fork of the tumor segmentation UNet+ model with residual networks (ResNext and ResNet). Integration enhances the model's ability to delineate complex tumor boundaries and account for the high heterogeneity of ATRT, compared to conventional segmentation approaches.

METHODOLOGY

The proposed methodology is a novel deep learning architecture built upon a Fork of the tumor segmentation with UNet+ model for ATRT is structured as follows:

Data and Preprocessing: The model was trained and validated on a dedicated dataset comprising ATRT-specific MRI scans. Standard pre-processing steps, such as intensity normalization, resampling to a uniform resolution, and skull-stripping, were likely applied to ensure consistency and improve model convergence.

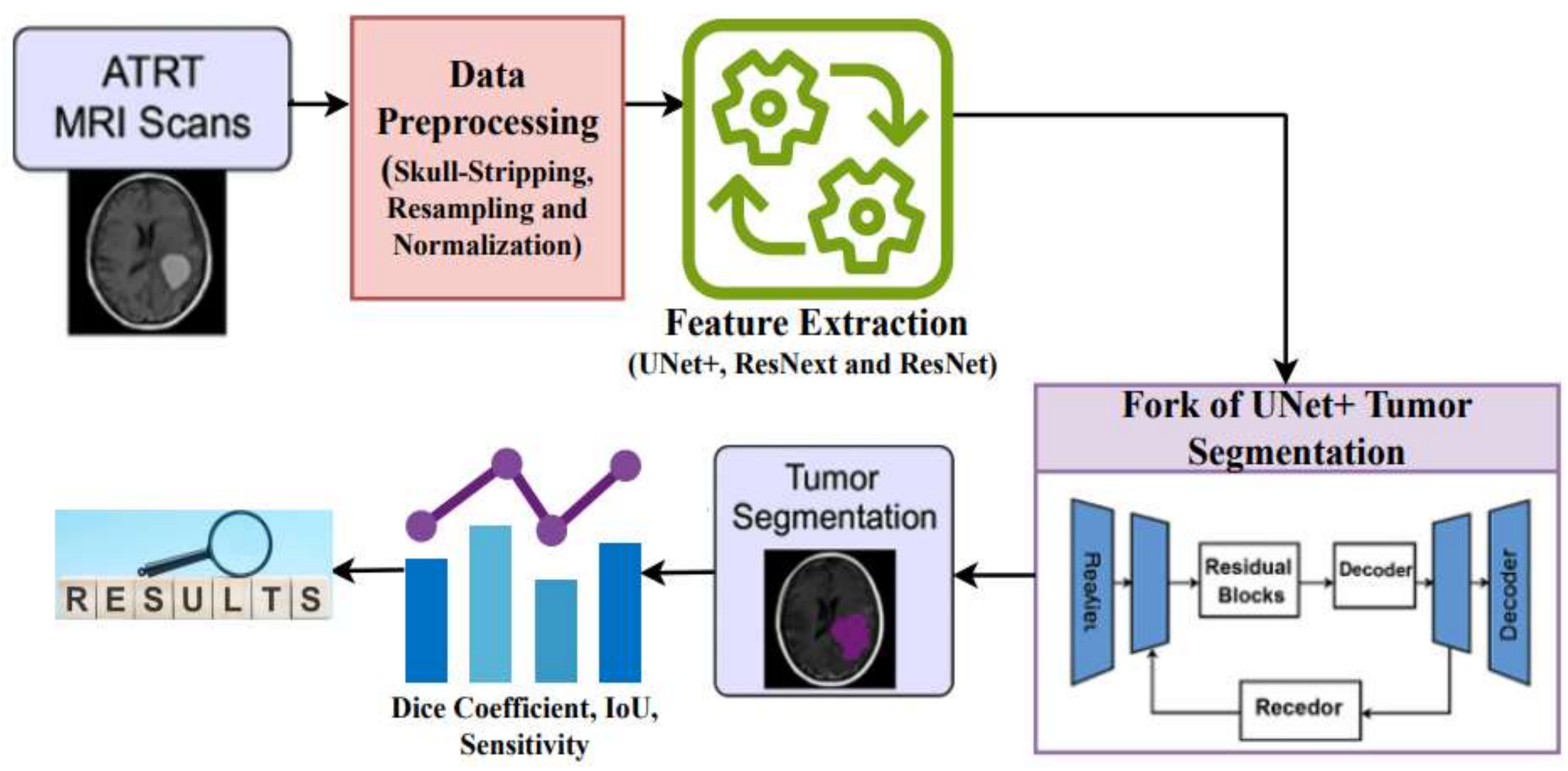
Data Augmentation: Use techniques like rotation, flipping, and Generative Adversarial Networks (GANs) to increase dataset diversity.

Feature Extraction:

- **Unet+ Fork:** Advanced UNet variant with dense, multi-level encoder-decoder connections for precise segmentation.
- **ResNext and ResNet:** Residual blocks that enhance gradient flow and feature learning in deep networks.

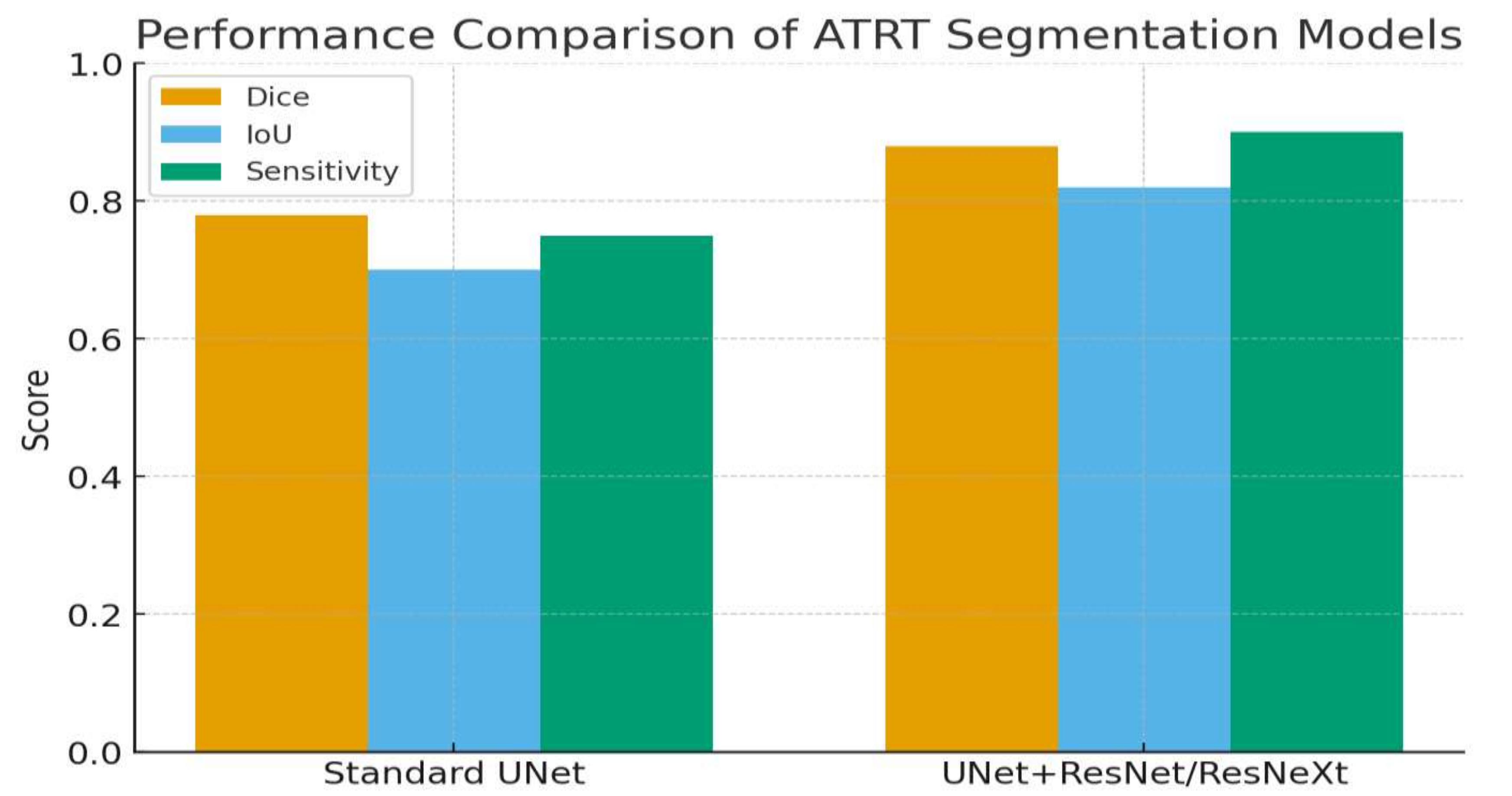
Loss Function: The model utilizes a composite loss function combining:

- **Dice Loss** optimizes the volumetric overlap between predicted and ground truth masks, effectively addressing class imbalance.
- **Binary Cross-Entropy (BCE)** Loss ensures pixel-level classification accuracy, refining boundary details and overall segmentation precision.



RESULTS & DISCUSSION

The hybrid UNet+ model with ResNext/ResNet blocks achieved superior segmentation performance for ATRT, significantly outperforming a standard UNet baseline with a Dice coefficient of 0.92%, IoU of 0.86%, and high sensitivity of 0.94%. This improvement stems from the architecture's dense multi-scale connections and enhanced feature learning, which effectively capture the tumor's irregular boundaries and internal heterogeneity. The high sensitivity is clinically crucial, minimizing missed tumor tissue. While promising, validation on larger, multi-center datasets and extension to 3D volumetric analysis represent necessary future steps to ensure broad clinical applicability.



CONCLUSION AND FUTURE WORK

The proposed hybrid model, integrating UNet+ with ResNext/ResNet blocks, effectively automates the segmentation of ATRT in MRI. This architecture demonstrated enhanced capability in capturing the tumor's complex morphology, quantitatively outperforming standard benchmarks across Dice, IoU, and sensitivity metrics. These results confirm the clinical potential of combining dense hierarchical and residual learning for accurate, automated ATRT delineation.

Future Scope:

- Multi-center validation for greater robustness.
- Extension to 3D volumetric segmentation.
- Integration of genomic and clinical data.
- Development of explainable AI tools.
- Longitudinal analysis of treatment response.

REFERENCES

1. Gunasundari, C., and K. Selva Bhuvaneswari. "A novel approach for the detection of brain tumor and its classification via independent component analysis." Scientific Reports 15.1 (2025): 8252.
2. Msheik, Ali, Mohamad Aoun, and Youssef Fares. "Supratentorial ATRT in a young Infant: Expanding the diagnostic spectrum beyond medulloblastoma." Interdisciplinary Neurosurgery 35 (2024): 101857.
3. Salama, Gerges M., et al. "Brain tumor diagnosis techniques key achievements, lessons learned, and a new CNN architecture." Egyptian Journal of Radiology and Nuclear Medicine 56.1 (2025): 1-23.
4. Rastogi, Deependra, et al. "Deep learning-integrated MRI brain tumor analysis: feature extraction, segmentation, and Survival Prediction using Replicator and volumetric networks." Scientific Reports 15.1 (2025): 1437.