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Tversky Loss Mechanisms: A ResUNet Approach to Improving Brain Tumor Segmentation

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Abstract & Introduction

Biomedical imaging plays a critical role in healthcare, particularly for the detection and diagnosis of brain tumors. These tumors—whether benign or malignant—can significantly disrupt brain function, much like damage to a computer's central processing unit [1]. Early detection is essential, especially for malignant tumors that grow quickly. Although MRI is widely used for brain imaging, manually segmenting tumors from MRI scans is labor-intensive, time-consuming, and often inconsistent due to inter-observer variability. To overcome these challenges, this study presents a deep learning-based solution using the **ResUNET** architecture. ResUNET builds upon the traditional UNET model by integrating **residual blocks** and **skip connections**, which enhance feature extraction and segmentation performance. Additionally, the study employs the **Tversky loss function** to effectively manage class imbalance between tumor and non-tumor pixels—especially crucial for accurately detecting small, critical tumor regions. The proposed model achieves high performance, with an IoU of 0.95 and a Dice coefficient of 0.98, showing it accurately matches ground-truth annotations. These results highlight its potential for automating brain tumor segmentation, enabling faster, consistent, and accurate diagnosis, and improving treatment planning and outcomes.

Objectives

- ✓ To effectively improve brain tumor segmentation accuracy by developing a ResUNET model incorporating the Tversky loss function to address class imbalance.
- ✓ **To specifically address the class imbalance challenge** in brain tumor datasets, ensuring accurate segmentation of smaller and diagnostically critical tumor regions.
- ✓ **To improve segmentation performance for small tumor areas** by leveraging the adaptive nature of the Tversky loss in the ResUNET framework.
- ✓ **To assess the effectiveness of the proposed ResUNET model** in comparison to traditional Convolutional Neural Network (CNN) and U-Net models for brain tumor detection and segmentation

Methodology

A dual-model approach was adopted. Initially, a ResNet-50 classifier—pre-trained on ImageNet—was employed to detect the presence of a tumor. Upon detection, the image was passed to a ResUNET model for segmentation. The ResUNET architecture integrates residual connections from ResNet within the UNET framework, consisting of an encoder with convolutional layers, max pooling , and ReLU activation, and a decoder that reconstructs spatial features to generate a binary segmentation mask. The Tversky loss function was used during training to address the class imbalance problem, especially for small tumour regions. This helps improve the model's sensitivity to pixels belonging to the minority class. Model training was conducted using a generator-based approach with a batch size 16, and early stopping was applied based on validation loss to avoid overfitting. Performance evaluation was carried out using standard metrics.

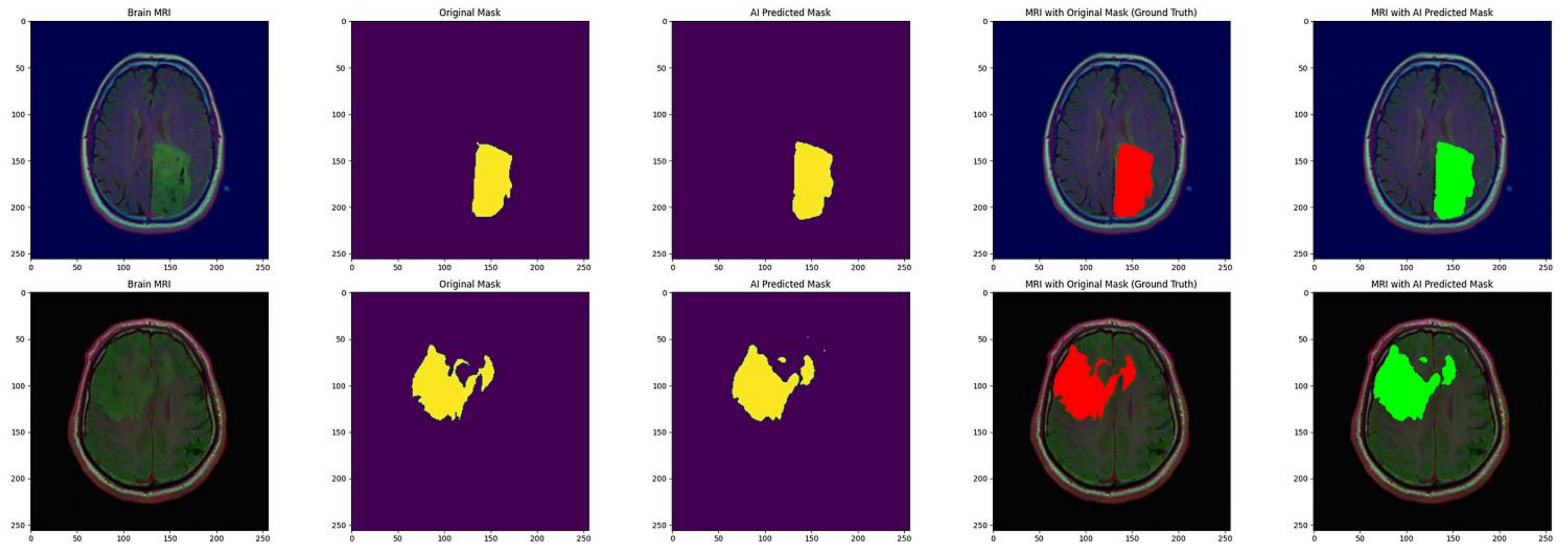

Fig.1: Segmentation Outcomes (Original Image, Ground Truth Mask, AI Predicted Mask)

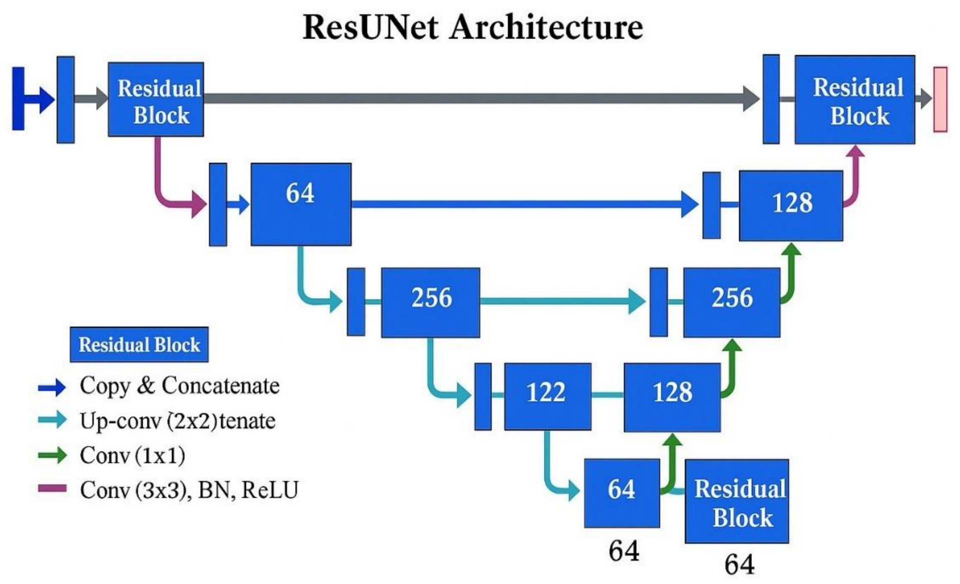

Fig. 2. A dual model system designed for detecting brain tumors using MRI

Result

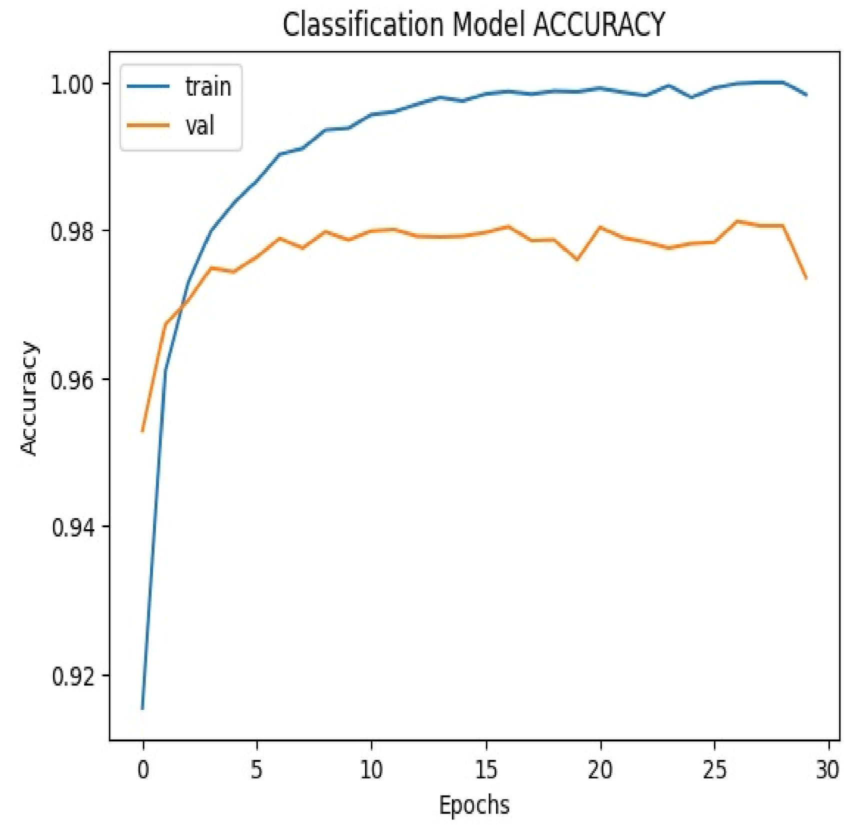

Fig. 3: Train and Validation Accuracy

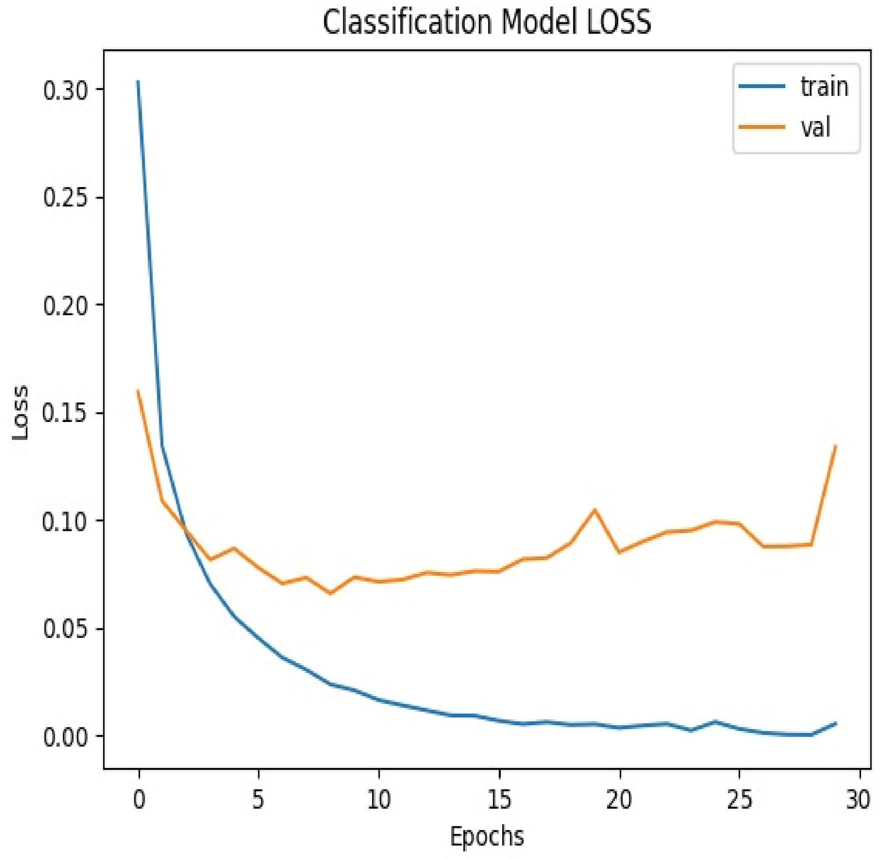

Fig. 4: Train and Validation Loss

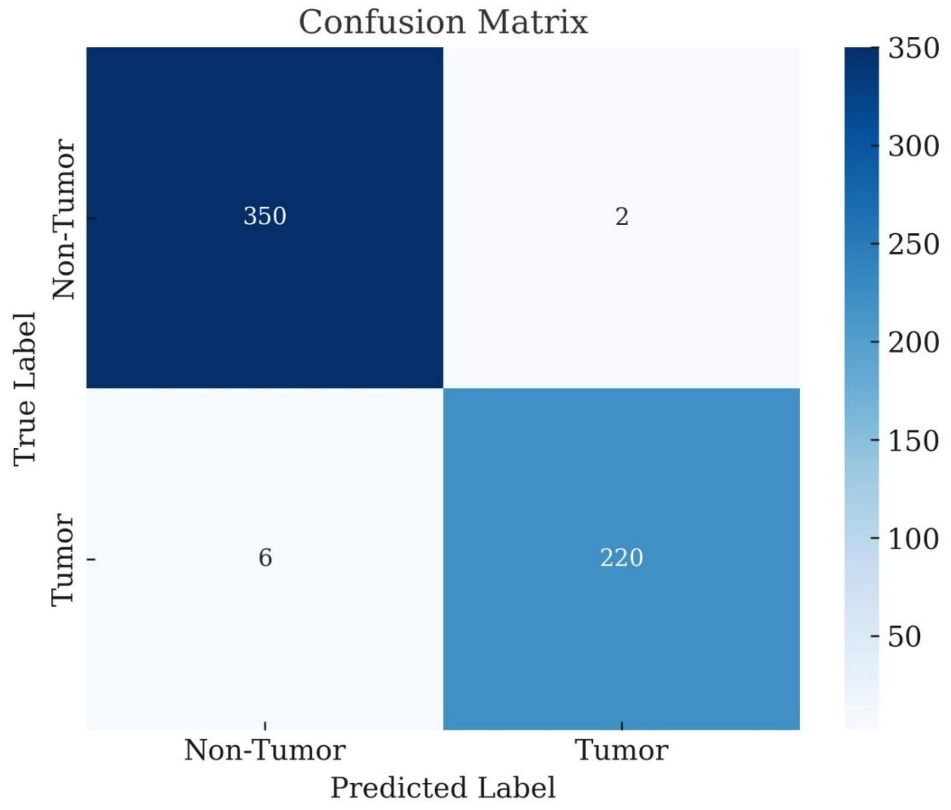

Fig. 5: Confusion Matrix

Table I: Classification Report

Label	Precision (%)	Recall (%)	F1-score (%)	Support
0	97	99	98	361
1	99	99	94	215
Accuracy	**98% (576)**			
Micro Avg	98	98	98	576
Weighted Avg	98	97	98	576

Table II: Performance comparison with recent studies

Study's	Model	Dice	IoU
Our	ResUNET	0.98	0.95
Yan et al. [15]	SEResU-Ne	0.93	N/A
Metlek and etıner. [5]	ResUNet+	0.92	N/A
Micallef et al. [2]	U-Net++	0.87	N/A
Ali et al. [9]	CNN + U-Net Ensemble	0.90	N/A

Conclusion & Future Work

The proposed ResUNET model with Tversky loss offers a robust and efficient solution for brain tumor segmentation. It achieves high accuracy (Dice: 0.98, IoU: 0.95) and addresses class imbalance and small tumor detection challenges. Its dual-stage architecture—classification followed by segmentation—optimizes computation and precision. Residual blocks and skip connections enhance gradient flow and feature retention, improving segmentation quality. Future work will include cross-validation, external dataset testing for generalization, and extending the model to 3D MRI scans and other cancer types for broader clinical applicability.

References

[1] A. Tiwari, S. Srivastava, and M. Pant, "Brain tumor segmentation and classification from magnetic resonance images: Review of selected methods from 2014 to 2025," Pattern recognition letters, vol. 131, pp. 244–260, 2025.