Brain MRI Segmentation Using U-Net and SegNet: A Comparative Study Across Modalities with Robust Loss Functions

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Keywords: Brain MRI, Segmentation, U-Net, SegNet, Robust Loss Functions, Robust Dice Loss, Brain Tumor Segmentation, Medical Image Analysis.

Abstract: This paper presents a comprehensive comparative study of brain tumor segmentation using two well-known Convolutional Neural Network (CNN) architectures, U-Net and SegNet, across multiple MRI modalities, specifically T2-weighted and Fluid Attenuated Inversion Recovery (FLAIR) images from the BraTS 2020 dataset. We evaluated the performance of these models using four different loss functions: Dice Loss, Focal Loss, Adaptive Robust Loss, and the novel Robust Dice Loss. Our contributions are twofold: first, we provide a detailed comparison of the performance of U-Net and SegNet for brain tumor segmentation across distinct MRI modalities, offering insights into the role of modality-specific features in segmentation outcomes. Second, we introduce the novel Robust Dice Loss, which significantly improved SegNet's training efficiency, allowing it to handle challenging segmentation scenarios involving data imbalance and intricate tumor boundaries with much greater ease. Our results indicate that U-Net generally outperforms SegNet in terms of segmentation accuracy, particularly when trained with Adaptive Robust Loss. However, the introduction of Robust Dice Loss enabled SegNet to achieve competitive performance, particularly with the FLAIR modality, demonstrating its potential as an effective alternative. This study emphasizes the importance of selecting appropriate loss functions to handle imbalanced data and enhance model performance, thereby contributing valuable insights for the advancement of automated medical image analysis and its clinical utility in neuro-oncology.

1 INTRODUCTION

Brain tumors remain one of the most challenging diseases in neuro-oncology, necessitating precise diagnosis and treatment planning. Magnetic Resonance Imaging (MRI) plays a crucial role in the diagnosis of brain tumors, offering multiple modalities, including T1-weighted (T1), T2-weighted (T2), contrast-enhanced T1 (T1CE) and fluid-attenuated inversion recovery (FLAIR). These modalities provide complementary information about the anatomy and pathology of brain tissues, enhancing diagnostic accuracy and segmentation efficacy. However, manual segmentation of brain tumors in MRI images is labor-intensive, subject to significant inter- and intra-observer variability, and requires substantial expertise, making automated segmentation methods highly desirable.

Deep learning methods, particularly Convolutional Neural Networks (CNNs), have revolutionized automated medical image segmentation. CNNs can learn complex hierarchical features directly from data, outperforming traditional methods. Among these, U-Net and SegNet have emerged as prominent architectures in medical image segmentation due to their efficiency and adaptability to complex datasets. U-Net is well-known for its encoder-decoder architecture with skip connections that preserve spatial information, facilitating precise segmentation of intricate boundaries (Ronneberger et al., 2015). SegNet, on the other hand, employs a similar encoder-decoder structure but emphasizes computational efficiency by omitting explicit skip connections (Badrinarayanan et al., 2017).

Despite their success, the performance of CNN models in medical segmentation tasks is heavily influenced by the choice of loss function. Brain tumor segmentation often suffers from class imbalance, as tumor regions typically constitute only a small fraction of the overall image. Standard loss functions may struggle to focus adequately on these small, clinically significant regions. To address this challenge,

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advanced loss functions such as Dice Loss (Milletari et al., 2016), Focal Loss (Lin and et al., 2017), Robust Dice Loss, and Adaptive Robust Loss (Barron, 2017) have been developed to prioritize regions of interest and mitigate class imbalance issues.

This study aims to provide a comparative evaluation of U-Net and SegNet models for brain tumor segmentation across MRI modalities. By analyzing these models under the influence of robust loss functions, particularly the novel Robust Dice Loss, this work highlights how different loss functions address class imbalance and improve segmentation accuracy. The insights gained can help advance automated medical image analysis and contribute to enhancing clinical workflows and patient outcomes.

2 RELATED WORKS

Brain tumor segmentation is a critical task in medical imaging, fundamental for diagnosis, treatment planning, and monitoring of therapeutic outcomes. However, accurately segmenting brain tumors is challenging due to their variability in size, shape, and appearance across patients. This section provides an overview of the evolution of brain tumor segmentation techniques, from traditional machine learning to modern deep learning-based approaches, and discusses the key advancements in robust loss functions and hybrid models that address current challenges.

2.1 Traditional Approaches

Early approaches to brain tumor segmentation relied heavily on generative and discriminative models. **Generative models**, such as atlas-based techniques, leveraged predefined anatomical knowledge to identify abnormalities. For instance, Prastawa et al. (Prastawa and et al., 2004) utilized the ICBM brain atlas to compare patient images, isolating tumor regions using posterior probabilities and thresholding. Similarly, Khotanlou et al. (Khotanlou and et al., 2008) and Popuri et al. (Popuri and et al., 2012) employed brain symmetry and iterative refinement to detect tumor regions. Despite their utility, these methods often struggled with significant tumor-induced deformations, resulting in segmentation inaccuracies.

On the other hand, *discriminative models* focused on local image features using pixel-based measures, texture analysis, and neighborhood histograms. Machine learning algorithms such as Support Vector Machines (SVMs), Fuzzy C-means (FCM), and Decision Forests (DFs) were commonly applied to classify pixels based on local characteristics. While effective in simple segmentation tasks, these methods did not incorporate the contextual information necessary to delineate complex tumor boundaries, especially for multi-class segmentation.

2.2 Deep Learning-Based Approaches

The introduction of **deep learning**, particularly Convolutional Neural Networks (CNNs), marked a paradigm shift in medical image segmentation by eliminating the need for manual feature engineering. CNNs learn hierarchical features directly from the data, capturing both local and global structures effectively. **U-Net**, introduced by Ronneberger et al. (Ronneberger et al., 2015), has been especially influential in medical imaging due to its encoder-decoder structure and skip connections, which help retain spatial information and enhance segmentation precision, particularly for small or intricate regions.

SegNet, proposed by Badrinarayanan et al. (Badrinarayanan et al., 2017), features a similar encoder-decoder architecture but omits explicit skip connections, focusing instead on computational efficiency. Although U-Net generally provides superior accuracy for brain tumor segmentation, SegNet is a competitive choice for settings with limited computational resources. CNNs have been extensively evaluated on datasets like BraTS (Menze and et al., 2015), consistently achieving state-of-the-art results in brain tumor segmentation.

2.3 Advanced Loss Functions

Despite the success of CNNs, brain tumor segmentation presents unique challenges, such as *class imbalance*, where tumor regions often occupy only a small portion of the overall image. To address these challenges, several *robust loss functions* have been developed: *Dice Loss* (Milletari et al., 2016) focuses on maximizing the overlap between predicted and ground truth regions, making it particularly suitable for medical segmentation tasks with imbalanced classes. *Focal Loss* (Lin and et al., 2017) emphasizes difficult-to-classify samples, ensuring improved attention to smaller and complex tumor regions. The novel *Robust Dice Loss* introduced in this study introduces tunable parameters that adaptively prioritize regions with higher errors, further enhancing segmentation accuracy, particularly in challenging scenarios involving intricate boundaries.

These advanced loss functions help CNNs focus on small but clinically significant tumor regions, ultimately improving segmentation performance.

2.4 Hybrid Approaches

Recent advancements in the field has seen approaches which combines deep learning models with traditional machine learning techniques to address the limitations of standalone models. Rao et al. (Rao and et al., 2020) incorporated CNN-derived features into ensemble learning frameworks, while Saouli et al. (Saouli and et al., 2020) utilized ensemble-based methods to enhance the robustness and generalizability of CNN-based segmentations. These approaches leverage the strengths of CNNs for feature extraction alongside the robustness of ensemble methods, thus addressing limitations such as overfitting and variability in performance.

2.5 Summary and Motivation for the Present Study

The evolution from traditional models to deep learning-based segmentation has greatly improved the accuracy and reliability of brain tumor segmentation. However, the challenges of class imbalance, complex tumor boundaries, and the variability in MRI modalities remain significant obstacles. This study builds on previous research by providing a detailed comparative analysis of U-Net and SegNet architectures for brain tumor segmentation across separate MRI modalities (T2 and FLAIR). By introducing the novel *Robust Dice Loss* and exploring its impact on the segmentation performance of these models, our work aims to contribute new insights into how the choice of loss functions can enhance model performance, addressing key challenges in brain tumor segmentation.

- We provide a comprehensive comparison of U-Net and SegNet for brain tumor segmentation across distinct MRI modalities.
- We introduce and evaluate the novel *Robust Dice Loss*, demonstrating its potential to enhance the training dynamics of SegNet, particularly in scenarios involving class imbalance and challenging tumor boundaries.

These contributions are expected to advance automated brain tumor segmentation, with the potential to significantly impact clinical workflows in neuro-oncology by enhancing accuracy and reducing the variability in segmentation outcomes.

3 METHODOLOGY

The methodology adopted in this study involves the application of U-Net and SegNet models to segment brain tumors across MRI modalities. To address challenges related to class imbalance and intricate tumor boundaries, we employ multiple robust loss functions. The following subsections detail the various components of our methodology.

3.1 Data Preparation

Dataset: The Brain Tumor Segmentation (BraTS) 2020 dataset was used in this study. It contains preoperative magnetic resonance imaging scans in four imaging modalities: T1-weighted (T1), T2-weighted (T2), T1-weighted contrast-enhanced (T1CE), and fluid-attenuated inversion recovery (FLAIR). Each modality highlights different aspects of tumor structure, such as the enhancing tumor, the nonenhancing tumor core, and the surrounding edema. These complementary views make the dataset ideal for tumor segmentation tasks.

Preprocessing: To prepare the data for training, we applied the following steps:

- *Normalization:* The intensity values of each MRI modality were scaled to a common range to reduce variability caused by different scanner settings.
- *Resizing and Slice Extraction:* The 3D volumes were split into 2D slices along the transverse plane for training, simplifying the segmentation task and focusing on one slice at a time. All MRI scans were resized to 240×240 pixels to reduce computational cost while maintaining sufficient detail.

Data Augmentation: To improve the diversity of training data and reduce overfitting, several augmentation techniques were used:

- *Rotation and Flipping:* Random rotations within a range of -15° to 15° and horizontal/vertical flips were applied to simulate variations in patient orientation.
- *Elastic Deformation:* Deformations were introduced to mimic the variability of natural tissue, enhancing the model's ability to handle irregular shapes.
- *Intensity Adjustments:* Random noise and contrast changes were added to simulate differences in imaging conditions and scanners, making the model more robust to real-world variations.

These preprocessing and enhancement steps ensured that the data set was consistent and diverse, helping the models learn effectively while improving their ability to generalize to unseen data.

3.2 Model Implementation

3.2.1 Architectures

We employed the **U-Net** and **SegNet** architectures for brain tumor segmentation. Both are encoder-decoder networks, but differ in how they retain and reconstruct spatial information.

Figure 1a illustrates the U-Net architecture, which uses *skip connections* to directly transfer high-resolution feature maps from the encoder to the decoder, allowing precise recovery of spatial details (Ronneberger et al., 2015). The encoder consists of repeated 3×3 convolutions with ReLU activation, followed by 2×2 max-pooling. The decoder performs 2×2 transposed convolutions (up-convolutions) concatenated with the corresponding encoder output. It has 23 convolutional layers and uses ReLU as the activation function.

In contrast, SegNet, depicted in Figure 1b, prioritizes computational efficiency by using *max-pooling indices* to guide upsampling in the decoder (Badrinarayanan et al., 2017). Its encoder mirrors VGG16, with multiple convolutional layers and 2×2 max-pooling. The decoder reconstructs dense feature maps using pooling indices, reducing memory requirements. SegNet has 13 convolutional layers at its encoder and decoder with ReLU as the activation function.

3.3 Loss Functions

The segmentation models were trained using four different loss functions to handle challenges such as class imbalance and to refine the focus on difficult regions. The loss functions used are as follows:

- **Dice Loss:** This is a commonly used metric for medical image segmentation, particularly effective for handling class imbalance by focusing on maximizing the overlap between the predicted and ground truth regions. The Dice loss is defined as:

$$Dice\ Loss = 1 - \frac{2\sum_i p_i g_i}{\sum_i p_i^2 + \sum_i g_i^2} \tag{1}$$

  where p_i and g_i represent the predicted and ground truth values for voxel i.

- **Focal Loss:** Focal Loss is used to emphasize difficult-to-classify examples by reducing the influence of easy-to-classify regions, thereby helping to address the issue of class imbalance effectively. Focal Loss is formulated as:

$$Focal\ Loss(p_t) = -(1-p_t)^{\gamma} \cdot \log(p_t) \tag{2}$$

  where p_t represents the model's estimated probability for the target class, and γ is a tunable parameter that controls the rate at which easy examples are down-weighted.

- **Robust Dice Loss:** The segmentation To improve segmentation accuracy, particularly for error-prone regions, we introduced a novel *Robust Dice Loss* that adapts the emphasis on higher-error regions through a tunable parameter λ. This loss is defined as:

$$Robust\ Dice\ Loss = 1 - \frac{2\sum_i p_i^{\lambda} g_i}{\sum_i p_i^{2\lambda} + \sum_i g_i^2} \tag{3}$$

  The parameter λ allows adaptive prioritization of regions with high errors, which is particularly useful for ensuring focus on the most challenging parts of the segmentation task. In our work we have kept the value of λ as 2.

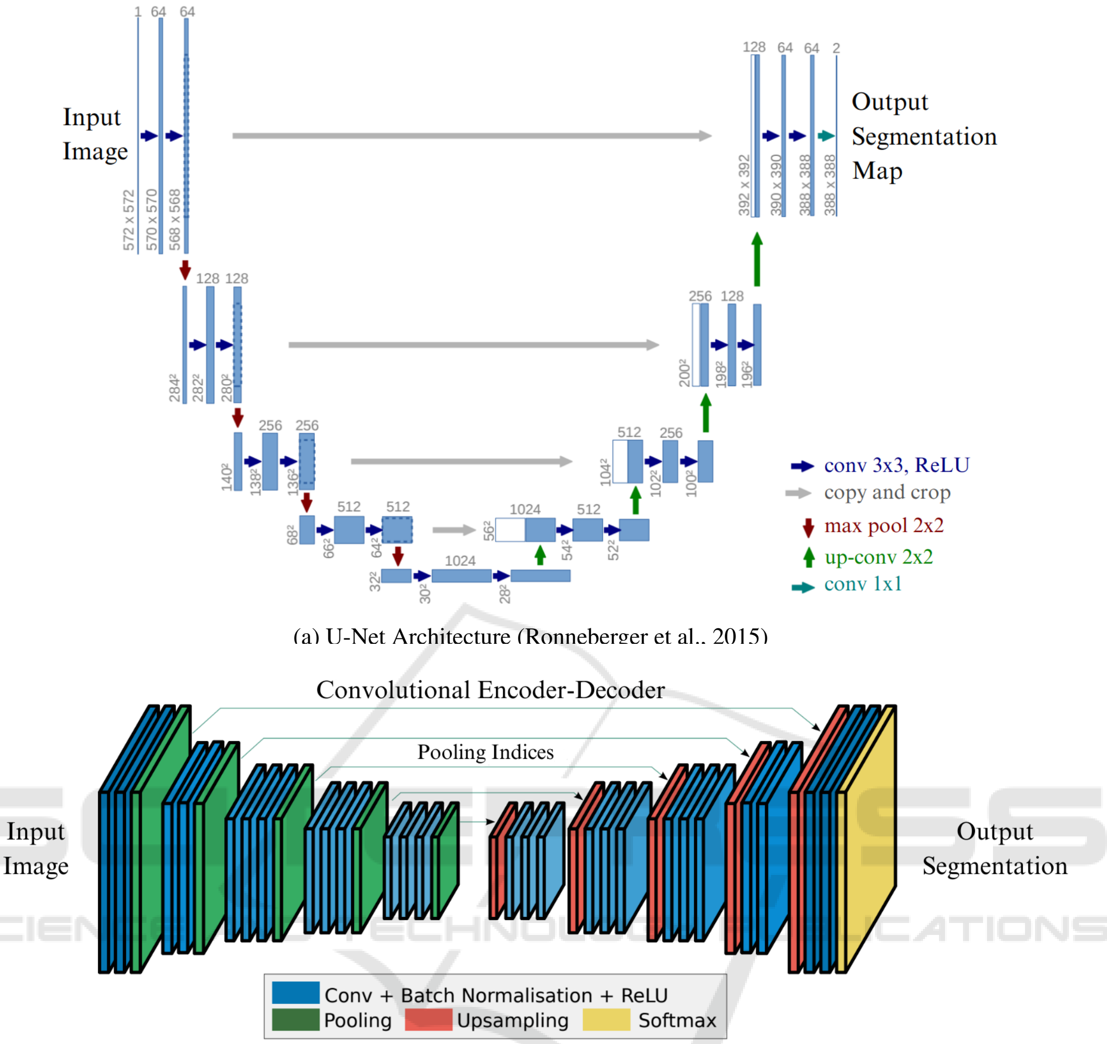
- **Adaptive Robust Loss:** Adaptive Robust Loss combines properties of several existing robust loss functions and adjusts the degree of robustness dynamically during training to enhance segmentation performance in complex scenarios. The loss function is defined as:

$$AR\ Loss(x,\alpha,c) = |\alpha-2|\left(\left(\frac{\left(\frac{x}{c}\right)^2}{|\alpha-2|+1}\right)^{\frac{\alpha}{2}} - 1\right) \tag{4}$$

  Here, x represents the input, α is a parameter controlling the robustness level, and c is a scaling constant. This formulation allows the loss to adapt based on the characteristics of the data during training, effectively managing the model's robustness.

3.4 Training and Evaluation

The dataset was split into training, validation, and testing sets using an 70:15:15 ratio. Training was conducted using the Adam optimizer with an initial learning rate of 0.001, which was reduced by a factor of 0.5 if validation loss plateaued. Early stopping was employed to prevent overfitting, with a patience of 15 epochs. The models were trained for up to 100 epochs. we have used *Dice Coefficient* as evaluation metrics To assess the segmentation performance, which measures the overlap between the predicted segmentation and ground truth. We have done qualitative analysis of the performance by visual inspection of segmentation results to interpret the impact of different loss functions, particularly in capturing fine boundaries and complex tumor regions.



(a) U-Net Architecture (Ronneberger et al., 2015)

(b) SegNet Architecture (Badrinarayanan et al., 2017)

Figure 1: Visual comparison of U-Net and SegNet architectures. Figures are adapted with permission from the cited sources.

4 RESULTS

The results of our experiments demonstrate the effectiveness of U-Net and SegNet for brain tumor segmentation using different MRI modalities and robust loss functions. Below, we present the findings for each model, modality, and loss function.

Table 1 presents the segmentation accuracy achieved by the U-Net and SegNet models for T2-weighted (T2) and Fluid Attenuated Inversion Recovery (FLAIR) MRI modalities using four different loss functions: Dice Loss, Focal Loss, Robust Dice Loss, and Adaptive Robust Loss. The results indicate that both U-Net and SegNet achieve optimal performance when trained with advanced loss functions, particularly Adaptive Robust Loss for U-Net and Robust Dice Loss for SegNet.

The choice of loss function significantly influences the segmentation performance of both U-Net and SegNet models. Specifically, Robust Dice Loss demonstrated substantial improvements for SegNet, achieving the highest accuracy with the FLAIR modality, yielding a Dice coefficient of 0.801. This result suggests that the adaptive nature of the Robust Dice Loss enables SegNet to effectively overcome some of its architectural limitations, such as the absence of skip connections, by focusing more efficiently on challenging regions.

Adaptive Robust Loss outperformed the other loss functions when used with U-Net, yielding Dice scores of 0.775 and 0.847 for the T2 and FLAIR modalities,

Table 1: Performance comparison of models across different modalities and loss functions. Bold values indicate the best performance for each row.

Model	Modality	Dice Loss	Focal Loss	Robust Dice Loss	Adaptive Robust Loss
U-Net	T2	0.705	0.725	0.443	**0.775**
U-Net	FLAIR	0.448	0.453	0.475	**0.847**
SegNet	T2	0.563	0.581	**0.619**	0.562
SegNet	FLAIR	0.598	0.537	**0.801**	0.547

respectively. This result suggests that the flexibility of Adaptive Robust Loss aligns well with U-Net's architecture, which relies heavily on its skip connections to retain spatial information throughout the segmentation process. The dynamic adjustment of the loss function's robustness during training may help U-Net more accurately segment complex tumor regions while reducing the impact of noise.

In comparison, Dice Loss and Focal Loss showed mixed outcomes. Although they produced reasonably competitive results with U-Net, especially with the T2 modality, they struggled with generalizing effectively in the case of SegNet, particularly with the T2 modality. This suggests that SegNet's reliance on pooled feature indices may hinder its capacity to effectively leverage global context, especially without the adaptive emphasis provided by the advanced loss functions. The advanced loss functions, such as Adaptive Robust Loss and Robust Dice Loss, therefore prove to be more suitable for addressing the challenges of brain tumor segmentation, such as class imbalance and intricate tumor boundaries.

A visual analysis of segmentation performance is provided in Figures 2, 3, and 4, showing the predicted segmentation masks generated by U-Net and SegNet for T2 and FLAIR modalities using various loss functions. Figure 2 demonstrates the segmentation outputs from the U-Net model for the T2 modality. Notably, the use of Adaptive Robust Loss yields the most well-defined tumor boundaries, demonstrating the highest segmentation quality among the evaluated loss functions, with fewer errors around the boundaries. This observation aligns with the quantitative results where Adaptive Robust Loss resulted in the highest Dice scores for U-Net across both modalities.

Figure 4 illustrates the impact of Robust Dice Loss on SegNet's performance with the FLAIR modality. Compared to Dice Loss, Robust Dice Loss facilitated more precise delineation of tumor regions, particularly along the boundary of the tumor. The adaptive feature of the Robust Dice Loss appears to be crucial for improving SegNet's segmentation performance, allowing it to handle the fine-grained details that Dice Loss struggles to capture.

The results also indicate that segmentation performance was consistently higher for the FLAIR modality compared to T2 for both models. This outcome can be attributed to the improved contrast provided by FLAIR images, which enhances the visibility of the tumor and surrounding tissues, allowing the models to achieve better segmentation results. The advanced nature of the loss functions (specifically Adaptive Robust Loss for U-Net and Robust Dice Loss for SegNet) further amplified these gains by focusing effectively on regions of high variability and complexity.

In summary, the results from both quantitative and qualitative analyses highlight the critical role of loss function selection in enhancing the performance of segmentation models for brain tumor imaging. Adaptive Robust Loss significantly boosts U-Net's performance by dynamically adjusting to segmentation complexities, while Robust Dice Loss provides SegNet with an adaptive focus that compensates for its inherent architectural limitations. These advanced loss functions prove especially effective in addressing the class imbalance issues inherent in medical image segmentation and in achieving superior delineation of complex tumor boundaries.

Furthermore, the differences in performance between the T2 and FLAIR modalities emphasize the importance of selecting the appropriate imaging modality to facilitate tumor visibility. The FLAIR modality, in particular, allows for better segmentation accuracy due to enhanced contrast, which becomes even more beneficial when combined with adaptive and robust loss functions.

The experimental outcomes suggest that the integration of sophisticated loss functions, tailored to both the network architecture and the characteristics of the imaging modality, is essential for advancing the performance of automatic segmentation in neuro-oncology. Future research could extend these experiments to larger datasets that include a wider variety of MRI modalities and employ hybrid approaches that leverage multiple architectures and loss functions. Additionally, the integration of attention mechanisms or multi-modal inputs could potentially enhance segmentation capabilities by allowing the model to exploit complementary features across different MRI modalities.

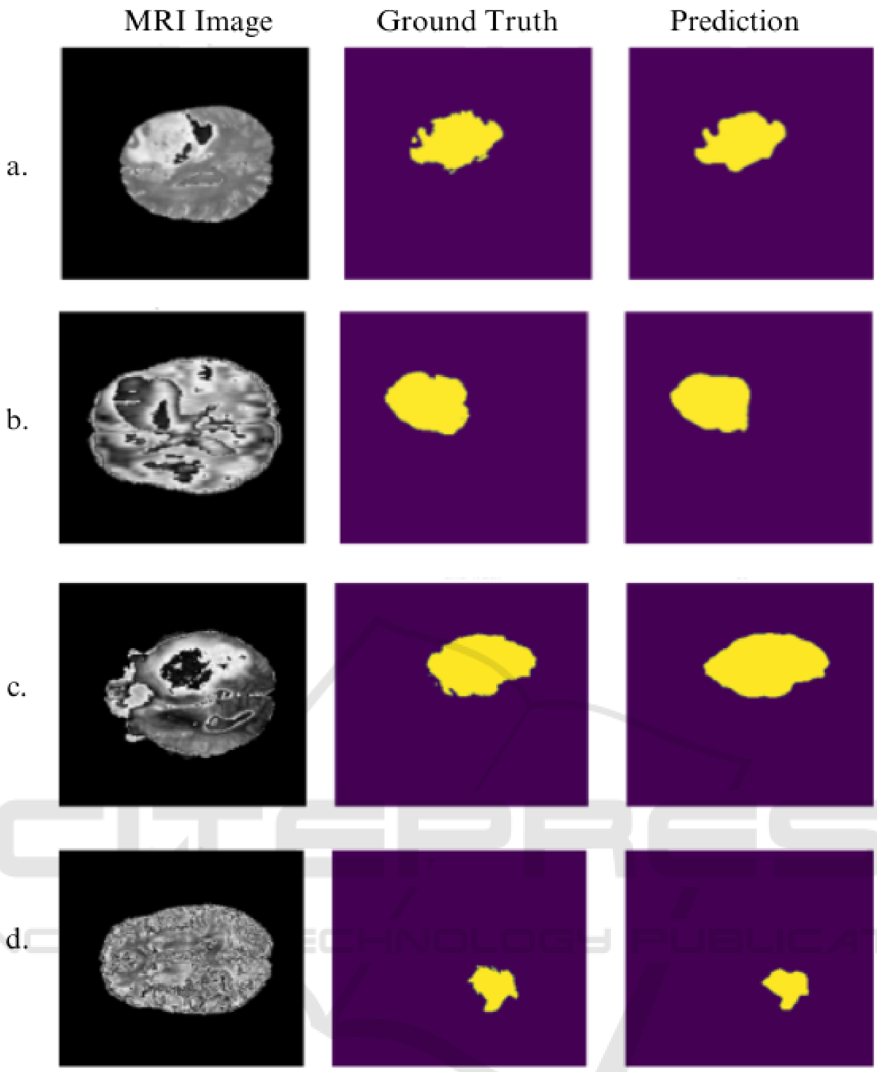


Figure 2: U-Net predictions for the T2 modality using different loss functions (a. Focal, b. Dice, c. Robust Dice, d. Adaptive Robust Loss). The Adaptive Robust Loss results in superior boundary delineation and segmentation completeness.

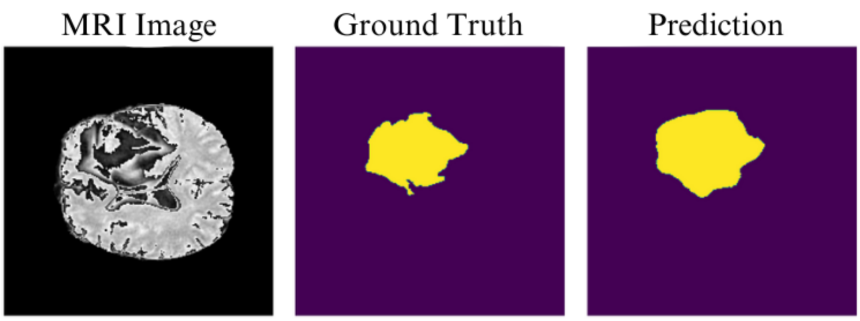


Figure 3: SegNet predictions for the T2 modality using Dice Loss. The segmentation output exhibits incomplete boundary delineation, indicating challenges in handling subtle boundaries with this loss function.

4.1 Discussion

The experiments demonstrate that U-Net generally outperformed SegNet, particularly when using Adaptive Robust Loss. This superior performance is attributed to the synergy between U-Net's skip connections and the adaptive capabilities of the loss func-

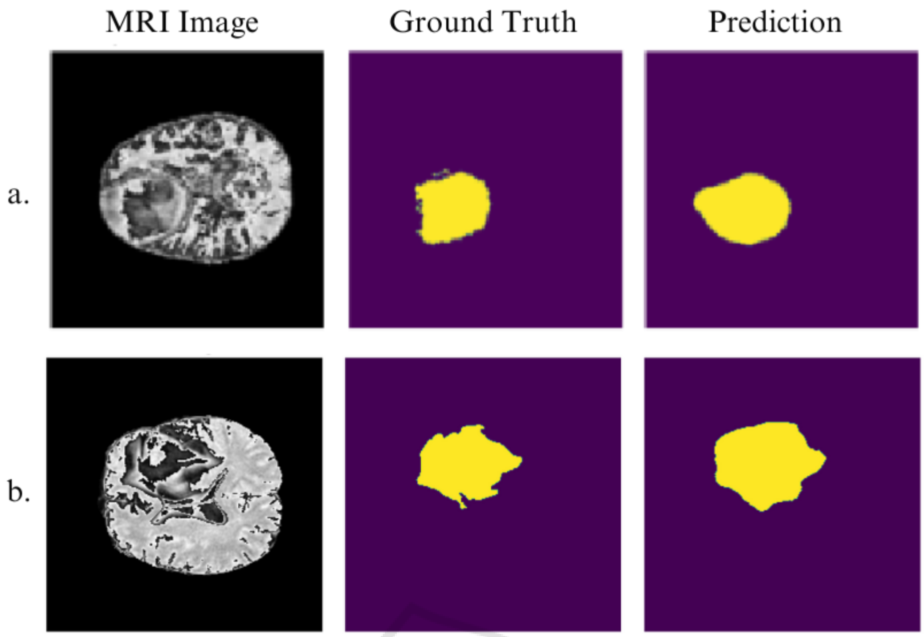


Figure 4: SegNet predictions for the FLAIR modality using a. Dice Loss and b. Robust Dice Loss. The use of Robust Dice Loss produces more precise and contiguous segmentation, particularly around tumor boundaries, compared to Dice Loss.

tion, which together enhance spatial accuracy and effectively handle complex tumor boundaries. The results also emphasize the significance of the FLAIR modality, which consistently yielded better segmentation outcomes due to enhanced contrast, allowing more precise differentiation of tumor regions.

SegNet's performance improved significantly with the novel Robust Dice Loss, particularly for the FLAIR modality. This suggests that Robust Dice Loss is well-suited to SegNet, compensating for its architectural limitations by focusing more adaptively on challenging tumor regions. The advanced loss functions—Adaptive Robust for U-Net and Robust Dice for SegNet—demonstrated effectiveness in addressing class imbalance, ensuring that both models focus appropriately on underrepresented regions during training.

The findings highlight that a tailored combination of architecture, modality, and loss function is essential for optimal brain tumor segmentation. The choice of loss function plays a crucial role in handling the inherent challenges of medical image segmentation, such as class imbalance and intricate boundary delineation.

5 CONCLUSIONS

This study presented a comparative analysis of U-Net and SegNet for brain tumor segmentation using the BraTS 2020 dataset. We evaluated their performance on T2 and FLAIR MRI modalities using four loss functions: Dice, Focal, Robust Dice, and Adaptive Robust Loss. U-Net, particularly with Adaptive Robust Loss, demonstrated superior accuracy, benefiting from the adaptability of this loss function. Conversely, the newly introduced Robust Dice Loss significantly enhanced SegNet's performance, especially on the FLAIR modality, by adaptively prioritizing challenging areas.

The findings indicate that advanced loss functions are key to enhancing segmentation performance, particularly for models like SegNet that lack mechanisms to preserve spatial detail. The results also emphasize the role of modality-specific characteristics, with FLAIR providing improved segmentation outcomes over T2 due to better contrast.

Future work could focus on evaluating additional CNN architectures, incorporating attention mechanisms, and exploring multi-modal training to leverage the complementary features of MRI scans. Further validation of these models in a clinical setting would provide critical insights into their real-world applicability, enhancing their potential impact in neuro-oncology.

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