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Research Article

Deep Learning-Based Segmentation of High-Grade Glioma Tumors: A Comparative Analysis of MRI-Based Models

Emre Serçe[1], Cansu Muş[2], Mustafa Sönmez[3], Berat Ağır[4], Ramazan Bayram[5], Mustafa Burak Bayram[6] and Ahmet Furkan Bayram[*6]

[1]Mechatronics Engineering, Faculty of Engineering, Istanbul Commerce University, Istanbul
[2]Biomedical Engineering, Faculty of Engineering, Fatih Sultan Mehmet Foundation University, Istanbul
[3]Department of Statistics and Data Science, Graduate School, Istanbul Gedik University, Istanbul
[4]Control Automation Engineering, Faculty of Electrical and Electronics, Istanbul Technical University, Istanbul
[5]Department of Electrical Engineering, Nişantaşı University, Istanbul
[6]Department of Computer Engineering, Faculty of Engineering, Karadeniz Technical University, Trabzon

[*](bayramahmet48@gmail.com) Email of the corresponding author

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Abstract – Brain tumors, particularly high-grade malignant gliomas, pose a significant public health challenge due to their high lethality and impact on patients' quality of life. Recent advancements in deep learning-based medical imaging techniques have revolutionized brain tumor detection and segmentation, enabling more precise and automated diagnostic processes. This study evaluates the performance of multiple deep learning architectures, including UNet, Attention UNet, ESNet, LEDNet, LinkNet, SQNet, and SegNet, for brain tumor segmentation using MRI scans from the Gazi Brains 2020 dataset. The models were assessed based on various performance metrics, including Intersection over Union (IoU), sensitivity, accuracy, and specificity. The results indicate that Attention UNet achieved the highest segmentation accuracy, demonstrating superior performance in delineating tumor regions. However, the trade-off between segmentation accuracy and computational efficiency remains a critical consideration. The findings underscore the potential of deep learning-based segmentation techniques in improving the accuracy and efficiency of brain tumor diagnosis, paving the way for more effective clinical decision-making. Future research could explore hybrid architectures and multi-modal MRI integration to further enhance segmentation precision while optimizing computational resources.

Keywords – Attention UNet, Brain Tumor Segmentation, Deep Learning, Medical Imaging, MRI.

I. INTRODUCTION

The global incidence of brain tumors has gradually increased over the past half-century. With advancements in diagnostic capabilities, there has been a steady rise in brain cancer incidence, particularly over the past 30 years. For instance, in 2019, approximately 348,000 new cases of brain and central nervous system tumors were reported worldwide. This figure represents a significant increase compared to previous decades. Although some high-income regions have shown stable or slightly declining trends in cases over the past decade, the overall global trend remains upward. Indeed, according to World Health Organization projections, the number of new brain tumor cases in the European region alone is expected to rise to approximately 85,000 by 2030, compared to 2015. These data indicate that brain tumors are becoming an increasingly significant public health concern.

Brain tumors—particularly high-grade malignant gliomas—have severe health impacts. Although primary brain and central nervous system cancers account for only about 1.9% of all cancers, they are responsible for 2.5% of global cancer-related deaths, highlighting their lethality [1,2]. While survival rates for many other cancer types have significantly improved in recent years, similar progress has not been achieved for malignant brain tumors. Due to their location, these tumors can affect neurological functions, leading to permanent physical and cognitive impairments and severely reducing patients' quality of life. Glioblastoma multiforme (GBM), the most common and aggressive type of high-malignancy gliomas, constitutes approximately 14% of all primary brain tumors and half of malignant brain tumors. GBM has an extremely poor prognosis, with a five-year relative survival rate of only ~6.9%, and despite treatment, the median survival time is limited to approximately eight months [braintumor.org]. Consequently, high-grade brain tumors pose a significant burden in terms of both mortality and morbidity.

Advancements in medical imaging techniques have also had a major impact on the diagnosis and assessment of brain tumors. With the introduction of computed tomography (CT) in the 1970s and magnetic resonance imaging (MRI) in the 1980s, earlier and more accurate detection of these tumors became possible. Today, MRI is considered the gold standard for brain tumor imaging, and various sequences (T1, T2, FLAIR, contrast-enhanced T1, etc.) that distinguish tumor tissue from surrounding structures are routinely used. Determining tumor boundaries (segmentation) through these high-resolution images is critical for multiple stages, from surgical resection planning to radiotherapy targeting. However, manually delineating tumors on radiological images is a laborious and subjective process, necessitating the development of automated segmentation techniques to expedite and standardize the diagnostic process. Indeed, computer-aided methods enable the automatic identification of tumor regions in images, allowing for more precise differentiation between tumor tissue, surrounding edema, and healthy brain tissue, thereby optimizing treatment planning [3,4].

In recent years, significant advancements have been made in the analysis of brain tumors through medical imaging, driven by the development of deep learning-based approaches. Artificial intelligence and machine learning have shown promising results in the automatic detection, classification, and segmentation of brain tumors from MRI scans. In particular, deep neural networks—especially convolutional neural networks (CNNs)—have been widely adopted for processing brain tumor MRI images, achieving superior performance in tumor segmentation compared to previous methods. Literature suggests that deep learning algorithms currently represent the most advanced methods for image-based diagnosis and differentiation of various brain tumor types. As a result, the accuracy of imaging-based diagnoses in brain tumor patients has improved, facilitating more effective management of the treatment process.

II. RELATED WORKS

Zhang et al. [5] aimed to automatically segment brain tumors from MRI scans using a novel Attention Gate Residual U-Net (AGResU-Net). The network was trained and tested on the multi-modal BraTS (Brain Tumor Segmentation) challenge dataset. The method uses a combined loss (generalized Dice + weighted cross-entropy) for class imbalance and was optimized with SGD (momentum 0.97) during training. The AGResU-Net architecture incorporates residual blocks and attention gates into a U-Net, focusing on segmentation (not just tumor detection). It achieved Dice scores of 0.876 for whole tumor, 0.772 for tumor core, and 0.720 for enhancing tumor on the BraTS dataset, outperforming baseline U-Net variants on these metrics.

Wang et al. [6] introduced TransBTS, which for the first time integrates a Transformer into a 3D CNN for brain tumor segmentation. The goal was to capture both local 3D context and global relationships in multi-modal MRI. They trained TransBTS on the BraTS 2019 and 2020 datasets using a softmax Dice loss for segmentation and the Adam optimizer (initial LR 4e-4 with polynomial decay). The TransBTS network follows an encoder–decoder design: a 3D CNN encoder extracts volumetric features which are fed into a Transformer for global attention, and a decoder outputs the segmentation map. Dice scores on the BraTS validation set reached 90.0% for whole tumor, 81.94% for tumor core, and 78.93% for enhancing tumor (with test-time augmentation), marking comparable or better performance than previous state-of-the-art 3D CNN methods.

Aziz et al. [7] aimed to improve brain tumor (glioma) segmentation by leveraging capsule networks. The authors optimized the SegCaps model (the first capsule-based segmentation network) to better handle the blurred and irregular tumor boundaries. They introduced dilated convolution blocks in the primary capsule layer to capture deeper features without losing resolution, and modified the final prediction layer with 1D convolutions to regularize capsule orientations. A curriculum learning strategy was applied to training: a novel curriculum-based training algorithm with a hybrid Dice-based loss function was used to progressively improve performance. The model was trained and evaluated on the BraTS 2020 MRI dataset. The improved SegCaps (segmentation capsule network) achieved Dice scores of 85.16% for tumor core and 81.88% for enhancing tumor, surpassing the original U-Net's accuracy on these subregions. Notably, the capsule network used 90% fewer parameters than a typical U-Net while maintaining high accuracy.

Zhang et al. [8] proposed a Dilated Multi-Scale Residual Attention U-Net (DMRA U-Net) for 3D brain tumor segmentation. The goal was to address the variability in tumor appearance by capturing multi-scale features and long-range dependencies. The BraTS 2018–2021 multi-modal MRI datasets were used for training and evaluation. The DMRA U-Net augments the standard 3D U-Net with dilated convolution residual (DCR) blocks in early layers to broaden the receptive field, and multi-scale convolution residual (MCR) blocks in the bottleneck to gather richer features. An attention mechanism (channel/spatial attention) is incorporated to focus on tumor regions. The network was trained as a pure segmentation model (distinguishing whole tumor, core, and enhancing regions), and metrics such as Dice, Hausdorff distance (HD), and sensitivity were used for evaluation. The proposed model achieved DSC scores of 0.9012 (whole tumor), 0.8867 (tumor core), and 0.8813 (enhancing tumor), with improved sensitivity and reduced HD compared to a baseline 3D U-Net. These results demonstrate state-of-the-art performance, with ~4.5% higher Dice on whole tumor than the vanilla 3D U-Net.

Ferreira et al. [9] focused on boosting segmentation performance through extensive data augmentation and ensembling. The team's goal was to overcome limited data by generating synthetic training examples. They used GAN-based augmentation and registration techniques to massively expand the training set. Three different segmentation models were trained: an nnU-Net (a robust self-configuring 3D U-Net), a Swin-UNETR (a 3D Swin-Transformer U-Net), and the BraTS 2021 winning model. These were then combined in an ensemble, leveraging both convolutional and transformer-based architectures. The pipeline largely built upon nnU-Net's framework (with its default Dice+Cross-Entropy loss and optimization), and the ensemble's predictions were post-processed for refinement. On the BraTS 2023 validation set, their approach achieved Dice scores of 0.9005 for whole tumor, 0.8673 for tumor core, and 0.8509 for enhancing tumor. This high performance underscores the benefit of synthetic data augmentation and model ensembling in brain tumor segmentation, pushing the state-of-the-art close to human-level annotations.

Table 1. Comparison with previous similar studies

Authors	Data Sets	Segmentation Networks	Results
Zhang et al. [5]	BraTS (multi-modal MRI)	AGResU-Net	Dice: 0.876 (whole), 0.772 (core), 0.720 (enhancing)
Wang et al. [6]	BraTS 2019-2020	TransBTS (Transformer + 3D CNN)	Dice: 0.900 (whole), 0.8194 (core), 0.7893 (enhancing)
Aziz et al. [7]	BraTS 2020	SegCaps (Capsule Networks)	Dice: 0.8516 (core), 0.8188 (enhancing)
Zhang et al. [8]	BraTS 2018-2021	DMRA U-Net (Dilated Residual Attention U-Net)	Dice: 0.9012 (whole), 0.8867 (core), 0.8813 (enhancing)
Ferreira et al. [9]	BraTS 2023	Ensemble (nnU-Net, Swin-UNETR, BraTS 2021 winner)	Dice: 0.9005 (whole), 0.8673 (core), 0.8509 (enhancing)

III. MATERIALS AND METHOD

The methodologies adopted in this study are systematically categorized into three main sections: dataset and preprocessing, segmentation networks, and performance evaluation metrics. These sections outline the data acquisition and preparation steps, the deep learning models utilized for segmentation, and the metrics employed to assess the model's effectiveness.

A. Data Set and Preprocessing

In this study, the Gazi Brains 2020 Dataset [10] was utilized, which comprises 100 patient MRI scans, including 50 patients diagnosed with brain tumors and 50 healthy individuals. The dataset provides T1-weighted (T1W), T2-weighted (T2W), and FLAIR sequences in .nii format, along with corresponding ground-truth segmentation masks for each scan.For model training, only MRI scans of patients with brain tumors were included in the study. The dataset was split into training and validation sets, with 90% of the images used for training and 10% allocated for validation to ensure a balanced model evaluation.

Since the original image dimensions varied across patients, all MRI scans were resized to 256×256 pixels for uniformity. To maintain the integrity of tumor boundaries, nearest-neighbor interpolation was applied during the resizing of segmentation masks. Among the available imaging modalities, only T2-weighted (T2W) scans were used for model training. This decision was based on the fact that T2W images provide superior contrast in highlighting brain tumors, making it easier to distinguish the tumor regions from normal brain tissues.The segmentation labels in the dataset initially included multiple tumor subregions, such as peritumoral edema area, contrast-enhancing tumor region, necrotic tumor core and non-enhancing tumor region.

To simplify the segmentation task, all tumor components were merged into a single tumor mask, resulting in a three-class segmentation problem where the background was assigned a pixel value of 0, brain tissue was labeled with a pixel value of 1, and the brain tumor region was represented by a pixel value of 2. Additionally, model development was conducted using axial MRI slices, and slices that contained only the background or background with brain tissue (without a visible tumor) were removed. This ensured that all remaining images contained at least some tumor region, preventing class imbalance. After filtering out non-informative slices, a total of 394 axial images remained in the dataset. To facilitate efficient preprocessing and model training, the .nii MRI images were converted into .npy files, with each axial slice stored separately. All preprocessing steps, including resizing and filtering, were performed directly on these .npy files.

B. Performance Evulation Metrics

To assess the effectiveness of the segmentation model, the evaluation was conducted using accuracy, intersection over union (IoU), precision, and sensitivity metrics. These measures provide a comprehensive understanding of the model's ability to accurately delineate tumor regions in MRI scans. The mathematical formulations of the selected evaluation metrics are as follows:

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN} \tag{1}$$

$$\text{Precision} = \frac{TP}{TP + FP} \tag{2}$$

$$\text{Sensitivity} = \frac{TP}{TP + FN} \tag{3}$$

$$\text{IoU} = \frac{TP}{TP + FP + FN} \tag{4}$$

Here, True Positive (TP) refers to the number of correctly identified pixels belonging to the brain tumor region, while True Negative (TN) represents the number of pixels correctly classified as non-tumor areas. False Positive (FP) denotes pixels that were incorrectly labeled as tumor tissue, whereas False Negative (FN) accounts for pixels that should have been classified as part of the tumor but were missed by the model.

The IoU (Intersection over Union) metric measures the overlap between the predicted tumor region and the ground truth mask, providing insight into segmentation accuracy. Precision evaluates how many of the pixels predicted as tumors are actually correct, ensuring the model minimizes false positives. Sensitivity, also known as recall, quantifies the model's ability to correctly detect tumor pixels, emphasizing its effectiveness in capturing true tumor regions. Lastly, accuracy represents the proportion of correctly classified pixels across all categories, offering an overall measure of the segmentation model's performance.

C. Segmentation Networks

In this study, multiple deep learning-based segmentation architectures were employed to automatically segment brain tumors from MRI scans. The models used include UNet [11], Attention UNet [12], ESNet [13], LEDNet [14], LinkNet [15], SQNet [16], and SegNet [17], each with distinctive architectural features tailored for medical image segmentation tasks. UNet, a widely used encoder-decoder-based model, leverages skip connections to retain spatial information and enhance segmentation precision. Attention UNet builds upon UNet by incorporating an attention mechanism that enables the model to focus on the most relevant regions, improving segmentation accuracy. ESNet, an efficient segmentation network, is designed to minimize computational complexity while maintaining high segmentation performance. LEDNet, a lightweight model, optimizes real-time segmentation while ensuring effective feature extraction. LinkNet introduces residual connections to facilitate better gradient flow, making it suitable for deeper networks. SQNet integrates a squeeze-and-excitation mechanism to improve feature representation, enhancing class differentiation. SegNet, another encoder-decoder-based architecture, utilizes max-pooling indices from the encoder during upsampling in the decoder, allowing for better spatial accuracy in segmentation results. These models were trained and evaluated to determine their effectiveness in accurately delineating brain tumor regions.

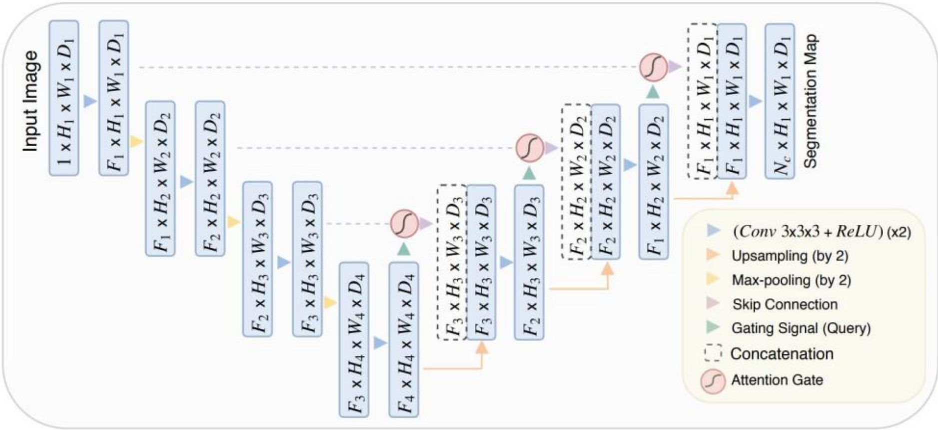

Figure 1. Attention U-Net architecture design [12]

The training process was conducted using CrossEntropyLoss combined with DiceLoss, ensuring both class-wise prediction balance and optimized segmentation performance. The RMSProp optimizer was utilized for weight updates during model training. The initial learning rate was set to 1e-4, and an adaptive learning rate adjustment mechanism was implemented, where the learning rate was reduced by a factor of 0.1 if no improvement was observed for 15 consecutive epochs. The models were trained for 50 epochs with a batch size of 4 to optimize segmentation performance. All experiments were executed in the Google Colab environment, utilizing an NVIDIA T4 GPU to accelerate model training. These segmentation networks were trained and validated using the Gazi Brains 2020 Dataset, and their performance was evaluated based on multiple metrics, as described in the next section.

IV. RESULT AND DISCUSSION

The performance of different segmentation models was evaluated using various metrics, including Intersection over Union (IoU), sensitivity, accuracy, and specificity. Table 2 presents the obtained results, highlighting the effectiveness of each model in segmenting brain tumors from MRI images.

Table 2. Results obtained by segmentation models

Model Name	**IoU**	**Specificity**	**Sensitivity**	**Accuracy**	**Time (Minutes)**
UNet	0,709	0,993	0,797	0,866	40
Attention UNet	0,721	0,994	0,842	0,832	48
ESNet	0,716	0,993	0,854	0,816	37
LEDNet	0,715	0,994	0,841	0,827	30
LinkNet	0,711	0,995	0,808	0,856	16
SQNet	0,715	0,995	0,818	0,85	30
SegNet	0,712	0,994	0,834	0,829	34

Among the evaluated architectures, Attention UNet demonstrated the highest performance across multiple metrics. This model achieved an IoU of 0.720, a sensitivity of 0.842, and an accuracy of 0.832, outperforming other architectures in capturing tumor regions effectively. The attention mechanism integrated into this model likely contributed to its superior segmentation capability by enhancing the focus on critical features within the images. However, this improvement in segmentation accuracy came at the cost of computation time, as Attention UNet required 48 minutes for processing, which was the longest among the tested models.

The ESNet model also exhibited strong segmentation ability, with an IoU score of 0.716 and the highest sensitivity of 0.854, suggesting that it was particularly effective in identifying true tumor pixels. Its accuracy was measured at 0.816, indicating a robust overall performance. The processing time for ESNet was 37 minutes, making it relatively efficient in terms of computational cost compared to Attention UNet.

LEDNet achieved an IoU of 0.715, a sensitivity of 0.841, and an accuracy of 0.827, placing it among the well-performing models. This suggests that it maintained a balance between computational efficiency and segmentation performance. The model completed processing in 30 minutes, indicating a reasonable trade-off between accuracy and inference speed.

Similarly, SQNet attained an IoU of 0.715 and a sensitivity of 0.818, with an accuracy of 0.850, making it another strong candidate for segmentation. Its processing duration was 30 minutes, which aligns with LEDNet in terms of efficiency.

SegNet, another encoder-decoder-based model, achieved an IoU of 0.712, a sensitivity of 0.834, and an accuracy of 0.829. While slightly lower than Attention UNet, its segmentation capability was still competitive. SegNet required 34 minutes for processing, making it a moderately efficient choice.

UNet, the baseline model, achieved an IoU of 0.709, a sensitivity of 0.797, and an accuracy of 0.866. While it demonstrated strong accuracy, its sensitivity was comparatively lower, suggesting that it struggled in some cases to identify all tumor regions accurately. The computational time for UNet was 40 minutes, making it slower than models like LinkNet and SQNet.

LinkNet had the lowest computational cost, completing processing in 16 minutes. It achieved an IoU of 0.711, a sensitivity of 0.808, and an accuracy of 0.856. While its performance was slightly lower in segmentation accuracy, its speed made it a viable option for time-sensitive applications.

In summary, Attention UNet demonstrated the highest segmentation accuracy, but at the expense of processing time. ESNet and LEDNet also delivered strong performance, balancing accuracy and computational efficiency. UNet, as the baseline model, performed reliably, whereas LinkNet was the fastest model with reasonable accuracy. The choice of model depends on the specific requirements of the application, whether prioritizing accuracy or computational efficiency.

Input Images **Ground Truths** **Predicted Masks**

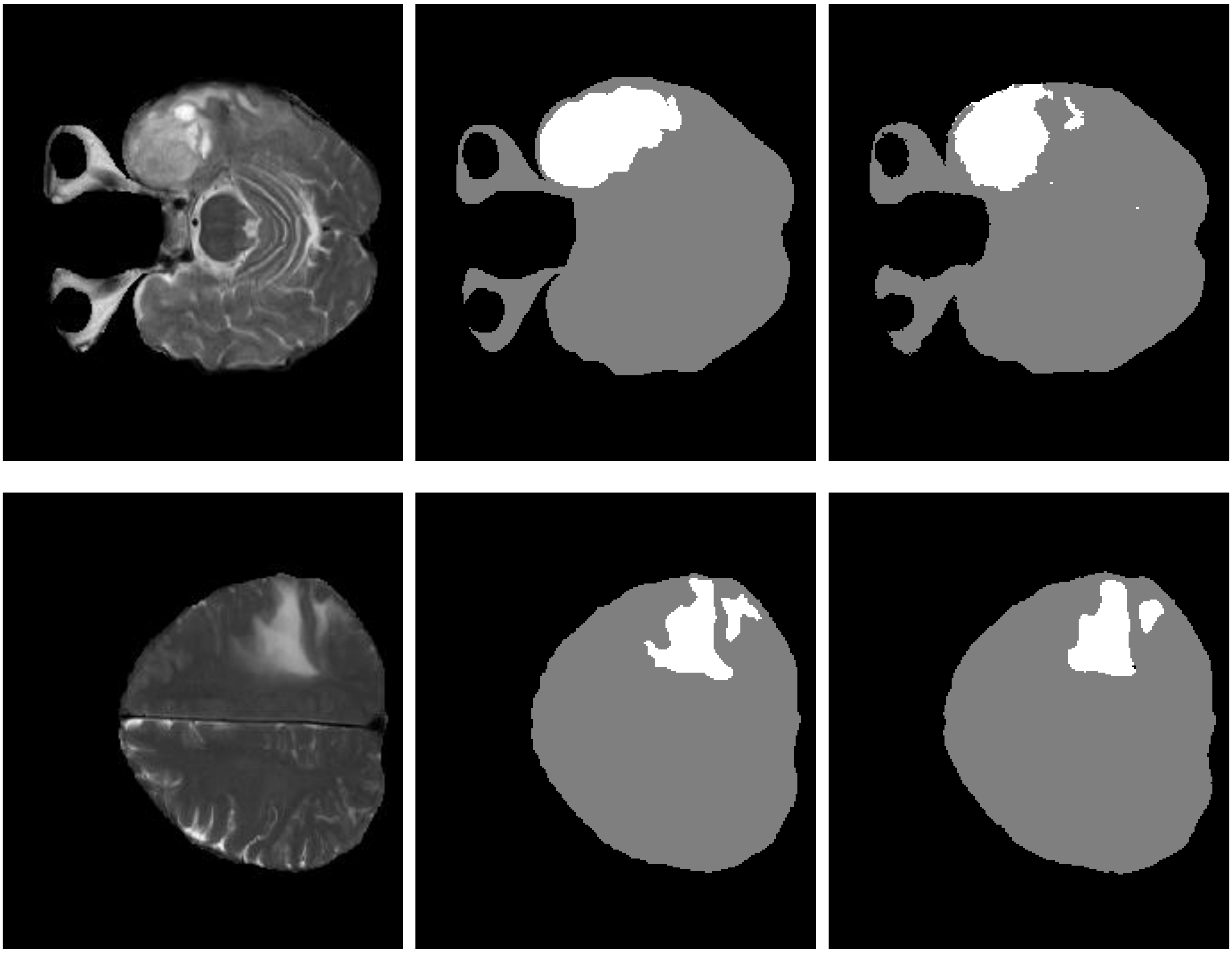

Figure 2. Results obtained by using Attention UNet

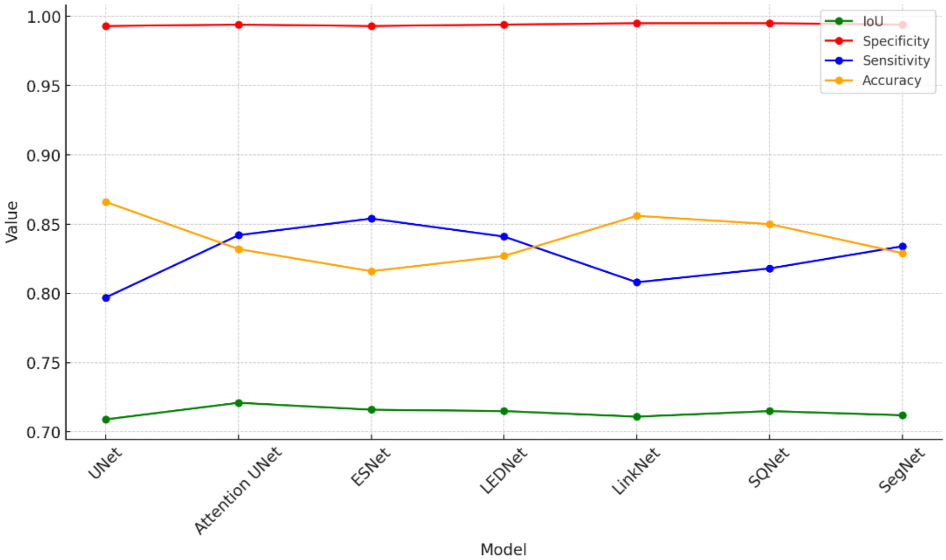

Figure 3. Performance evaluation metrics results of models

V. CONCLUSION

In this study, various deep learning-based segmentation models were evaluated for brain tumor segmentation using MRI scans. The experimental results demonstrated that Attention UNet achieved the highest segmentation accuracy, sensitivity, and IoU scores, making it the most effective model for identifying tumor regions. The integration of the attention mechanism significantly enhanced feature extraction and tumor boundary delineation. However, this improvement came with an increased computational cost, as Attention UNet required the longest processing time.

Other models, such as ESNet and LEDNet, also exhibited strong segmentation performance while maintaining a more efficient computation time. These models provided a balance between accuracy and speed, making them viable alternatives when computational efficiency is a priority. The baseline UNet model performed reliably but showed lower sensitivity compared to its advanced variants. LinkNet, on the other hand, demonstrated the fastest processing time, though with a slight reduction in segmentation performance.

The findings of this study highlight the trade-offs between segmentation accuracy and computational efficiency among different architectures. The selection of an appropriate segmentation model depends on the specific application requirements, whether prioritizing higher accuracy for precise medical diagnosis or faster inference times for real-time clinical applications. Future work could explore hybrid architectures and optimization techniques to further improve segmentation performance while reducing computational complexity. Additionally, incorporating multi-modal MRI data or transformer-based architectures could enhance segmentation accuracy by leveraging richer spatial and contextual information.

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