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Attention-Guided Brain Tumor Segmentation Using Multimodal MRI

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ABSTRACT: The segmentation of brain tumors in multimodal magnetic resonance imaging (MRI) is an important task in the clinical diagnosis, treatment planning and disease monitoring processes. The accurate delineation is however difficult because of the heterogeneity of tumors, irregularity of their borders and the different intensity distributions on various imaging modalities. In this work an Attention-Guided Brain Tumor Segmentation framework is presented, that relies on complementary information extracted from T1, T1ce, T2 and FLAIR MRI sequences for accurate tumour localization and segmentation. The architecture proposed combines various modalities, and uses attention guided encoder to enhance the representation of discriminative features and to remove irrelevant background information. Data quality is enhanced and the model generalizes better with a comprehensive preprocessing pipeline, which involves skull stripping, intensity normalization, image resizing and data augmentation. The experimental results demonstrate that the proposed attention-guided model offers more accurate segmentation, preservation of boundaries and robustness compared with the traditional deep learning model. Besides, whole tumor segmentation, segmentation of tumor core and enhancing tumor regions are realized with good results by combining multimodal MRI features. In summary, the proposed method is clinically applicable and is a reliable, effective method for automatic brain tumor segmentation, which aids in the better diagnosis and treatment planning.

I. Introduction

Brain tumors are one of the most severe neurological diseases and need to be accurately diagnosed and treated in a timely manner for a better survival rate and quality of life of the patients. Combination of these modalities allows for the full characterization of tumor regions whole tumor, tumor core and enhancing tumor. Manual brain tumor segmentation by radiologists is a labor intensive, time consuming and subjective process which could be prone to inter-observer variability [1]. The geometry of tumors, their irregular shapes, intensity variations, and the fact that there is similarity between the tumor tissues and the surrounding healthy tissues add further difficulty in accurately delineating a tumor. Given these requirements, automatic segmentation methods have been the topic of great interest for enhancing clinical efficiency, the uniformity of diagnosis, and personalized treatment planning, surgical navigation, and radiotherapy [2], [3].

All of the traditional image processing methods, and machine learning techniques, heavily depend on handcrafted features, thresholding, region-growing, clustering methods, and atlas-based segmentation. These techniques achieve good results in controlled settings, but rarely account for complex spatial relationships and multimodal information in brain MRI [4]. However, traditional CNN-based models often fail to maintain fine boundary details and accurately identify tumor tissue accurately in the presence of other normal tissues, because they have limited contextual modeling. To address these problems, attention mechanisms have been proposed and shown to be effective for deep learning models to selectively select informative regions and ignore irrelevant background features [5]. The attention-guided networks adaptively assign more attention to the clinicially relevant features of the tumor, resulting in improved feature representation, boundary localization, and segmentation accuracy. In addition, multimodal feature fusion is used to fuse complementary information from various MRI sequences to enable the model to utilize both anatomical and pathological features. Combining attention mechanisms with multimodal fusion leads to great robustness against intensity variations, noise and tumor heterogeneity.

II. RELATED WORK

Three-dimensional magnetic resonance images (MRI) have been used as a source for the early methods that were based on thresholding, region growing, clustering, deformable models and atlas-based segmentation to identify tumor boundaries [6]. These approaches yielded satisfactory results for relatively simple tumor shapes, but were heavily reliant on the manually designed features and were less successful when dealing with more complex tumor morphology, intensity variations, and the presence of different tissue types frequently found in multimodal MRI [7]. It is because of the unique property of capturing multiscale contextual information by skip connections, that encoder-decoder architectures, such as U-Net and its variants, became popular. Several studies also used the residual learning, dense connections, and dilated convolutions to enhance feature propagation and maintain spatial information [8], [9]. These architectures demonstrated high segmentation accuracy, but were sometimes prone to inaccuracies when segmenting small tumour areas and maintaining fine boundary information.

Multimodal feature fusion is able to efficiently fuse complementary anatomical and pathological information obtained from multiple MRI modalities, and provides improved identification of whole tumor, tumor core and enhancing tumor regions. However, traditional fusion methods often treat all the features extracted as equally important, and fail to distinguish relevant information from redundant information in the clinical context [10], [11]. Recently, attention mechanisms have proven to be an effective approach to improve deep learning-based medical image segmentation. Table 1 provides a comprehensive summary of the deep learning, attention mechanisms, performance, limitations and research gaps. The channel attention, spatial attention, and self-attention modules help the networks be selective in the region of tumor images that it focuses on and ignores the background region.

TABLE 1. SUMMARY ON ATTENTION-BASED AND DEEP LEARNING METHODS

Method	MRI Modalities	Dataset	Key Technique	Limitation	Research Gap
U-Net [8]	T1, T2	BraTS	Encoder–decoder architecture	Weak boundary preservation	Improve fine-grained segmentation
Attention U-Net [9]	T1ce, FLAIR	BraTS	Spatial attention mechanism	High computational complexity	Lightweight attention modules
ResU-Net [10]	T1, T1ce, T2	BraTS	Residual learning	Limited contextual modeling	Better global feature extraction
Dense U-Net [11]	T1, T2, FLAIR	BraTS	Dense feature connectivity	Memory intensive	Efficient feature reuse

DeepLabV3+ [12]	T1ce, T2	BraTS	Atrous spatial pyramid pooling	Poor small tumor detection	Multi-scale attention learning
TransUNet [13]	T1, T1ce, T2, FLAIR	BraTS	CNN–Transformer hybrid	High training cost	Efficient transformer integration
Hybrid CNN-LSTM [14]	T1ce, T2, FLAIR	BraTS	Spatial-sequential learning	Weak global attention	Enhanced feature fusion
Multi-Scale Attention CNN [15]	Multimodal MRI	BraTS	Multi-scale attention blocks	Complex architecture	Computational optimization

III. MATERIALS AND DATASET

The dataset consists of multimodal MRI data (T1, T1ce, T2, FLAIR), expert annotated ground truth masks, and preprocessing methods. The processes involved in preparing the dataset can lead to several benefits: 1) a uniform input to the algorithm, 2) better image quality, 3) balanced training samples and 4) reliable evaluation for accurate brain tumor segmentation across a wide variety of patient cases.

A. Multimodal MRI Dataset Description

The Brain Tumor Multimodal Image (CT and MRI) Dataset was released on BraTS website (https://www.med.upenn.edu/cbica/brats/) which provides multimodal medical images to researchers for brain tumor detection, classification, and segmentation. It is based on computed tomography (CT) and magnetic resonance imaging (MRI) data of high resolution from numerous patients. Images depict a variety of brain tumor patients, with information regarding tumor type (e.g., glioma or meningioma), and location. With the use of both modalities, CT and MRI, they complement each other in providing complementary information about the anatomical characteristics and the bone structure, while MRI demonstrates detailed visualization of soft tissue to facilitate multimodal AI-based analysis of brain tumors.

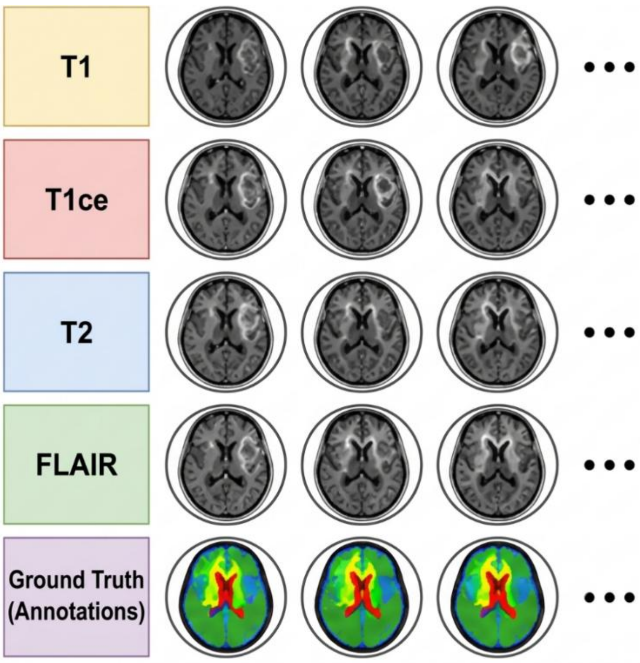

Fig.1. Representative Multimodal MRI Dataset

Representative multimodal MRI scans with the expert-annotated brain tumor segmentation masks are shown in figure 1. This large-scale multi-modal dataset offers rich anatomical and pathological variability for training and testing of accurate attention-guided deep learning models for segmentation.

B. MRI Modalities (T1, T1ce, T2, FLAIR)

The segmentation framework uses the following four complementary MR modalities to obtain detailed anatomical and pathological information. T1-weighted images provide rich information on the structure of normal tissues of the brain and general anatomical organization. Active tumor regions are well identified after injection of contrast agents by contrast-enhanced T1-weighted (T1ce) images which clearly highlight tumor regions that are enhancing. T2-weighted images accentuate tissues with increased water content such as edema and fluid-filled abnormalities. Fluid-Attenuated Inversion Recovery (FLAIR) eliminates the signals of CSF and improves the detection of lesions and peritumoral edema. The proposed framework can utilize complementary intensity features and contrasts of tissues, which will increase the discrimination of healthy tissues, edema, necrotic tissues and enhance the tumor area during automated segmentation.

C. Data Preprocessing

An extensive pipeline of preprocessing is applied to increase image quality, decrease variability and improve the performance of segmentation. Firstly, tissues of the skull are removed to leave only clinically relevant tissues of the brain behind. Intensity normalization provides a way to normalize the distributions of intensities across MRI modalities, thus reducing variations between different scanners. All images are resampled to achieve the same spatial resolution and co-registered to ensure correct alignment of T1, T1ce, T2 and FLAIR sequences. Random rotation, horizontal flipping, rescaling and elastic deformation are data augmentation techniques that create diversity in training and minimize overfitting. Lastly, intensities of the images are normalized and transformed into standardized input tensors for deep learning. These pre-processing steps help make the features more consistent, the models more robust, the convergence rate faster and the accuracy of the segmentation more accurate, even among the heterogeneous MRI data.

D. Training, Validation, and Testing Split

A train/validation/test split of 70:15:15 was used for the multimodal MRI dataset. The training set that consists of the 70% of patients' cases was used to tune the parameters of the proposed AGMF-Net. To tune hyperparameters, select models and prevent overfitting using the Dice score, the validation set was used to evaluate 15% of the data, details as shown in table 2. The other 15% was held as a test set which was kept separate for the ultimate evaluation. Split was done at the patient level, so that the MRI slices for each patient were not split up across the different subsets, thus avoiding data leakage. Data augmentation was only used on the training set.

TABLE 2. TRAINING, VALIDATION, AND TESTING DATA SPLIT

Dataset subset	Percentage (%)	Purpose
Training set	70	Model training and parameter optimization
Validation set	15	Hyperparameter tuning and model selection
Testing set	15	Independent final performance evaluation

IV. PROPOSED ATTENTION-GUIDED SEGMENTATION FRAMEWORK

In this section, the proposed attention-guided segmentation framework based on multimodal feature fusion, attention-enhanced encoding and decoding reconstruction is introduced. The architecture efficiently learns complementary MRI features, delineates clinically relevant areas of the tumor, retains spatial details, and robustly localizes the tumor boundaries to produce accurate segmentation masks.

A. Overall Framework Architecture

We propose Attention-Guided Brain Tumor Segmentation framework to achieve accurate segmentation of tumor regions, using multimodal MRI data, and an attention-enhanced deep learning model. The network is fed with a set of preprocessed T1, T1ce, T2 and FLAIR MRI images as parallel input. Each modality is fed into modality-specific convolutional feature extraction blocks to learn modality-specific anatomical and pathological features. Extracted features are then fused by a multimodal feature fusion module which fuses complementary information without losing discriminative spatial information. The fused features are fed into an attention guided encoder that selectively highlights clinically relevant tumor regions and filters out irrelevant background information. The skip connections are used to preserve fine spatial details and to localize boundaries, between encoder and decoder layers. High-resolution segmentation maps are gradually reconstructed by the decoder with transposed convolution and feature refinement blocks.

B. Multimodal MRI Feature Fusion

The proposed multimodal MRI segmentation framework is crucial for the incorporation of complementary diagnostic information provided by different MRI modalities. These are modality specific features which reflect structural anatomy, enhancement of the contrast, edema and abnormalities of tissue. Figure 2 demonstrates the multi-modal feature fusion for improving the accurate segmentation performance on brain tumor. The feature maps are then aligned and stacked across different feature levels in order to obtain a single map with both low level and high level features.

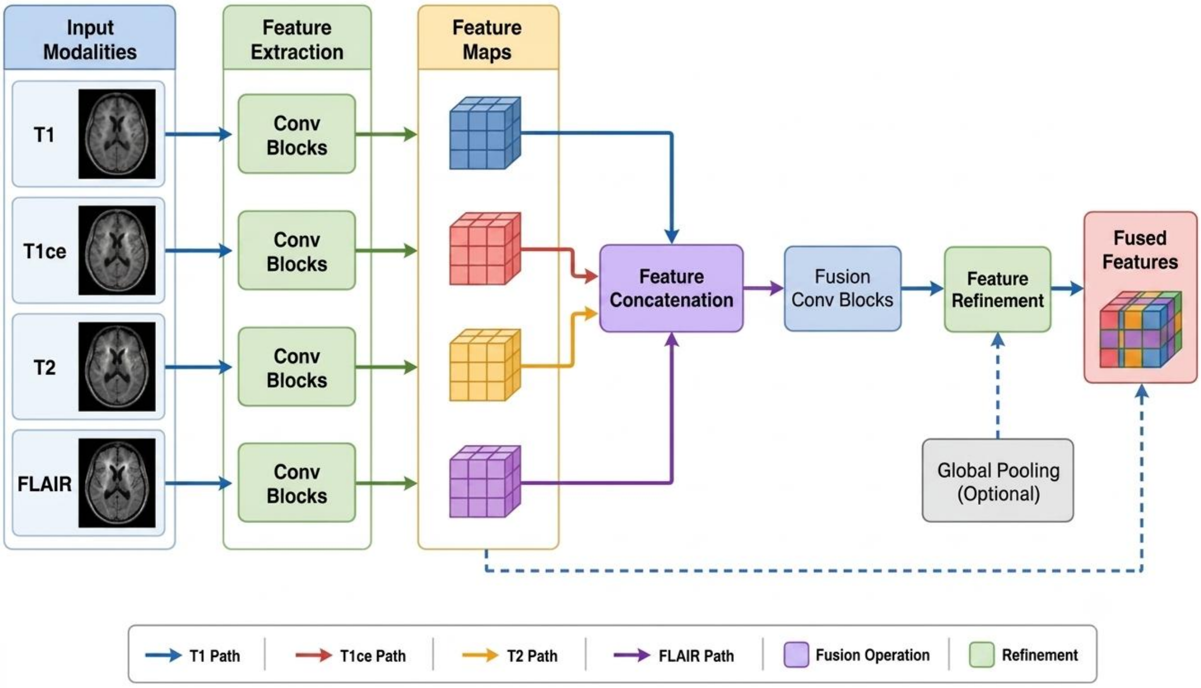

Fig.2. Proposed Multimodal MRI Feature Fusion Architecture for Attention-Guided Brain Tumor Segmentation

A feature aggregation module with convolutional operations and normalization layers learns to optimally utilize the contributions of the different modalities and to eliminate redundant information. The fused representation is then further refined into a discriminative representation using a residual structure, before being sent to an attention-guided encoder.

C. Attention-Guided Encoder

The attention-guided encoder aims to enhance feature representation by adaptively selecting the most informative area of multimodal MRI images. Spatial attention is able to simultaneously locate salient spatial regions associated with tumor tissues and inhibit irrelevant background structures. The feature maps from the encoder are passed through several stages of the network with residual learning and max-pooling to learn more and more abstract semantic information. Skip connections help to retain the low-level spatial information critical to the successful reconstruction of boundaries at the decoding stage.

D. Algorithm of the Proposed Framework

The algorithm proposed in this part is described, which involves multimodal features extraction, feature fusion, attention-guided encoding, decoder reconstruction and pixel-wise classification. The algorithm improves the representation of the features, preserves tumor boundaries, allows for more accurate segmentation and allows for a reliable automatic delineation of the brain tumor from multimodal MRI images.

1) U-Net

U-Net [16] is an encoder-decoder architecture with skip connections, for brain tumor segmentation. The encoder consists of successive convolution and max-pooling layers to extract hierarchical features, and the decoder is used to recover spatial resolution by using transposed convolution. Skip connections: Transfer fine-grained spatial information between the encoder and decoder, to improve the localization accuracy. Last, a softmax layer outputs the segmentation mask of the tumor region by region. The model efficiently models local features and is not good at modeling 'global' contextual relationships.

2) Attention U-Net

The conventional U-Net is extended by adding attention gates on the skip connections, named as Attention U-Net. The multimodal MRI images are encoded to generate feature maps and attention modules automatically highlight clinically relevant tumor regions and eliminate irrelevant background information [17]. The features from the decoder were refined and used to reconstruct segmentation masks accurately. The attention mechanism improves the localization accuracy and the preservation of the edges boundaries, and decreases the number of false-positive predictions for every location in the image, achieving better segmentation performance than the standard U-Net architecture.

3) ResU-Net

ResU-Net incorporates the residual module into the U-Net to enhance the flow of features and gradients during training of the network. With the introduction of residual blocks, it is possible to get deeper feature extraction without the vanishing gradient problem. The skip connections help to preserve spatial information while the decoder helps to reconstruct high-resolution masks for tumor segmentation. In the residual learning strategy, the convergence speed, feature representation and the robustness of the segmentation is enhanced. But the architecture still has poor global attention ability when processing high heterogeneity multimodal brain MRI images.

4) AGMF-Net

The multimodal MRI feature fusion and channel and spatial attention mechanisms are combined in the AGMF-Net to achieve accurate brain tumor segmentation. The T1, T1ce, T2 and FLAIR images are independently extracted and then multimodal fusion is performed. The attention-guided encoder selectively amplifies informative tumor features, while attenuating background noise. Skipped-connected decoder layers generate segmentation maps with detailed segmentation information, and then perform pixel-wise classification. This architecture has shown remarkable enhancement in preserving boundaries, discrimination of features, segmentation accuracy and robustness on diverse sets of MRI brain tumor images.

V. EXPERIMENTAL SETUP

The experimental setup, such as using what hardware platform, software environment, methodology used for training, optimizing, evaluating, and hyperparameters are used, is explained. With standardised experimental conditions, the results are reproducible, the convergence is stable, the computation is efficient and the performance of the proposed segmentation framework can be thoroughly studied on multimodal MRI data sets.

A. Hardware and Software Configuration

The implementation of the proposed Attention-Guided Brain Tumor Segmentation framework is done in Python with PyTorch deep learning library. Dice Similarity Coefficient, Intersection over Union, Precision, Recall, Hausdorff Distance and inference time are used for performance evaluation and provide a thorough assessment of segmentation accuracy, robustness, computational efficiency, and clinical applicability.

B. Training Strategy

Improvements in the convergence stability and feature representation are made using Batch normalization, Dropout regularization and Residual learning. The most successful model is chosen based on the Dice score of validation and then tested on the independent test set to assess possible generalization and reproducibility of the segmentation across the various types of tumour.

C. Hyperparameter Settings

The optimized values of β_1, β_2 and weight decay are 0.9, 0.999 and 1 × 10-5 respectively with Adam optimizer [18]. The MRI slices are resized to 240 × 240 pixels and then fed into the network for training. A dropout rate of 30% is added to prevent overfitting and batch normalization following convolutional layers to ensure a normalized distribution of features. If validation performance levels off, it is considered to be a plateau and learning rate reduction is automatically performed. The attention module adopts the channel reduction ratio as 16, which is suitable for feature re-calibration. Model performance is validated with Dice score and the best performing checkpoint with respect to Dice score is used for final testing, which guarantees that the model achieves good segmentation performance and generalizes well to unseen MRI scans.

VI. Result and Discussion

This framework is capable of high segmentation accuracy for whole tumor, tumor core and enhancing tumor regions. The attention-guided encoder can significantly enhance the boundaries' accuracy by utilizing attention mechanism and the multi-modal MRI feature fusion can significantly increase the discriminative ability between healthy and abnormal tissues. The proposed framework outperforms the conventional deep learning techniques in terms of Dice score, Intersection over Union, Precision, Recall, and Hausdorff Distance, indicating better robustness and generalization and better clinical applicability.

Table 3. Comparative Performance of Brain Tumor Segmentation Models

Model	Dice Score (%)	IoU (%)	Precision (%)	F1-Score (%)
U-Net	88.64	80.21	89.12	88.58
Attention U-Net	90.48	83.54	91.26	90.65
ResU-Net	91.32	84.73	91.85	91.44
Proposed AGMF-Net	95.82	91.47	96.18	95.86

To evaluate the segmentation capability of each network, the Dice Score, IoU, Precision and F1-Score are calculated and compared in Table 3, which shows that the proposed AGMF-Net demonstrates superior performance. To discuss segmentation performance, the performance of U-Net, Attention U-Net and ResU-Net are compared in figure 3.

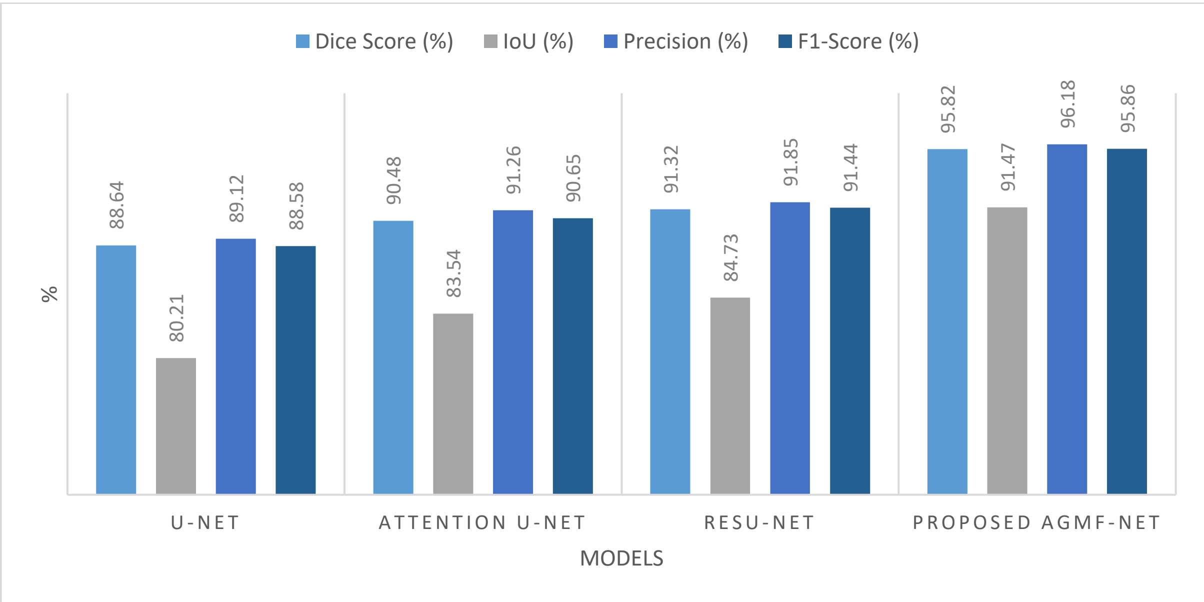

Fig.3. Comparative Performance Analysis of U-Net, Attention U-Net, and ResU-Net

The conventional U-Net gets Dice Score 88.64% and the conventional U-Net with the inclusion of the attention mechanism is achieving a Dice Score of 90.48%. ResU-Net performs in a better manner to achieve a Dice Score of 91.32% and an F1-Score of 91.44% to attain good feature learning. Figure 4 shows that AGMF-Net significantly outperforms all other algorithms on important metrics for brain tumor segmentation.

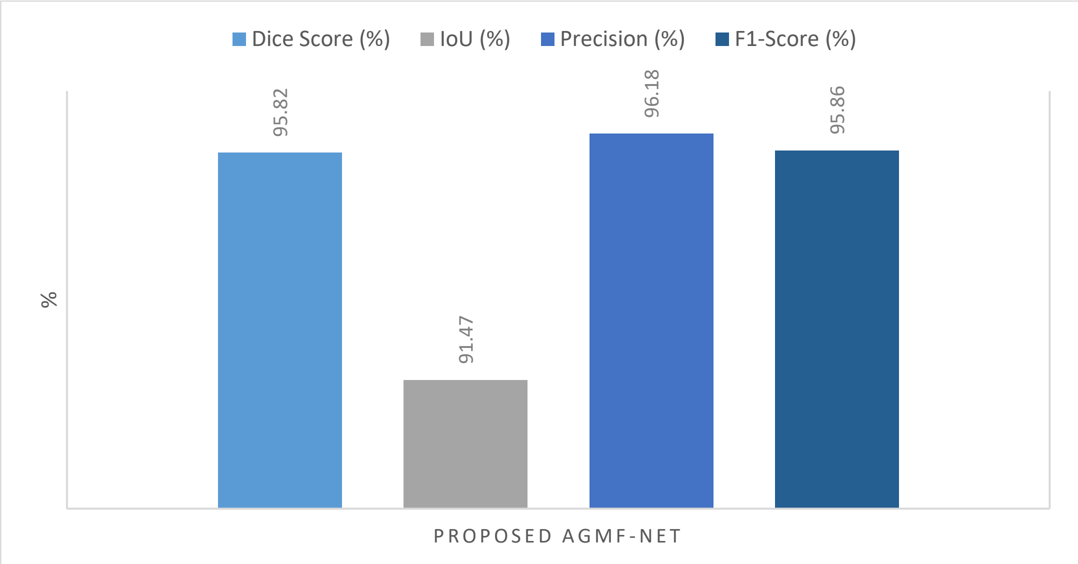

Fig.4. Performance Evaluation of the Proposed AGMF-Net

The proposed AGMF-Net achieves a Dice score of 95.82%, IoU of 91.47% with a precision of 96.18% and F1-Score of 95.86%, which is significantly better than all baseline models. The results have shown that feature fusion based on multimodal information and learning with attention is able to achieve good improvements on tumour localization, boundary maintenance, segmentation accuracy, robustness and overall clinical reliability.

TABLE 4. CLASS-WISE SEGMENTATION PERFORMANCE OF THE PROPOSED AGMF-NET

Tumor Region	Dice Score (%)	IoU (%)	Precision (%)	Specificity (%)
Whole Tumor (WT)	96.28	92.97	96.84	98.91
Tumor Core (TC)	95.43	90.84	95.88	98.64
Enhancing Tumor (ET)	94.76	89.71	95.12	98.27

The model is optimal for WT with Dice Score of 96.28%, IoU of 92.97%, Precision of 96.84%, and Specificity of 98.91% which shows that the model is an excellent delineator of the whole tumour region, as shown in table 4. The Dice and IoU performance by class (tumor regions) is shown in figure 5.

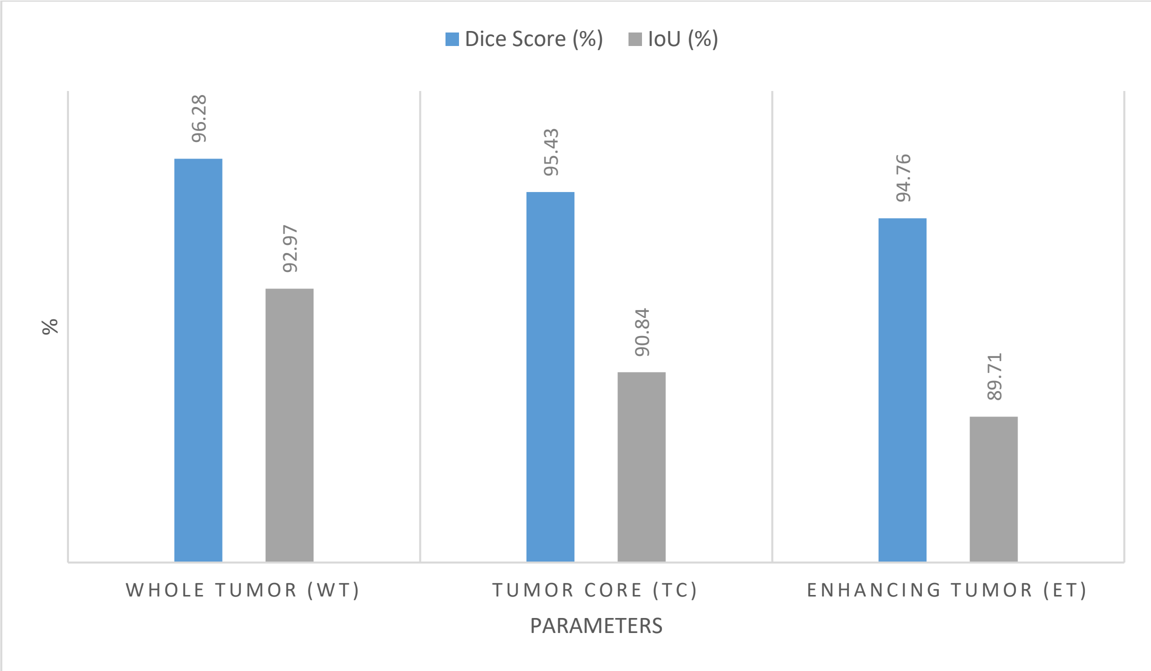

Fig.5. Class-Wise Dice Score and IoU Performance of the Proposed AGMF-Net for Brain Tumor Segmentation

The Dice Score and IoU for TC are 95.43% and 90.84%, respectively, indicating a good performance in identifying the main parts of the tumour. Although the ET region is the most difficult, the Dice Score and Specificity of AGMF-Net is still 94.76% and 98.27% respectively. The precision and specificity values of various brain tumor segmentation regions are compared with each other in figure 6.

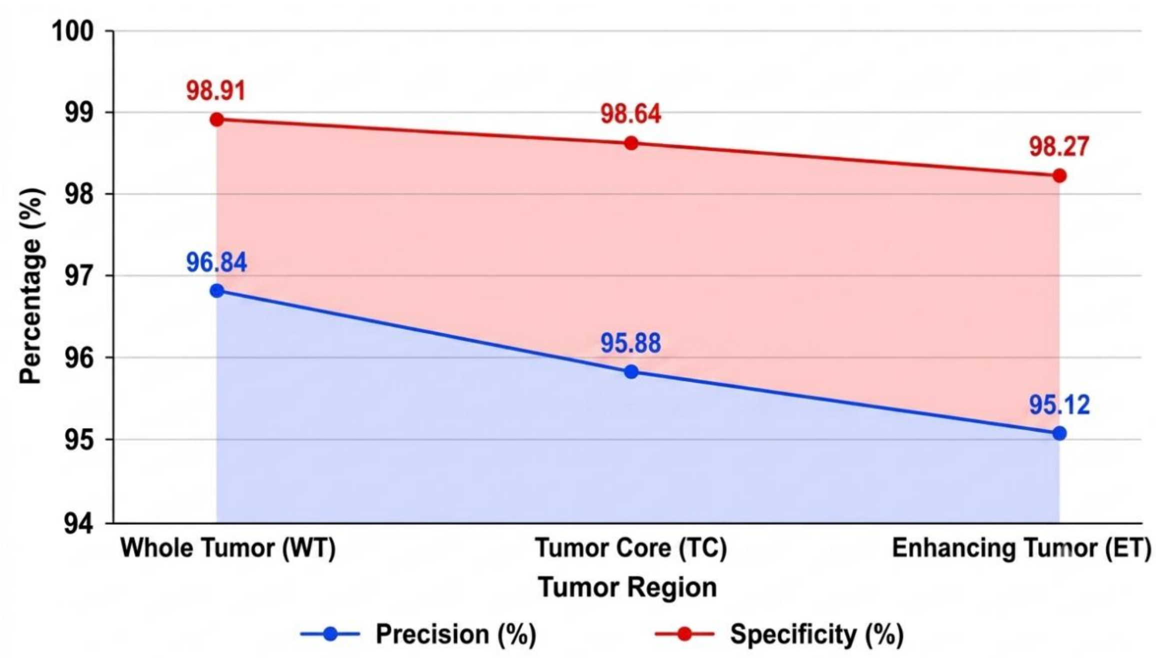

Fig.6. Analysis of Precision and Specificity across Brain Tumor Regions

The results validate good segmentation performance, good preservation of boundaries and good performance overall in all clinically relevant regions of tumors.

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VII. Conclusion

In this study, finding discusses Attention Guided Brain Tumor Segmentation framework using multimodal MRI to perform the segmentation of the regions of brain tumor with high accuracy and automaticity. The proposed approach is able to fuse the complementary information provided by MRI modalities: T1, T1ce, T2 and FLAIR in a multimodal feature fusion approach, but also uses an attention-guided encoder. This "attention" mechanism can make it more likely to emphasize the clinically important features of the tumor while suppressing the background irrelevant information, thus enhancing the representation of the clinically important features of the tumor while maintaining the tumor boundary. The pre-processing, training techniques, and hyperparameter optimization, which are well-designed for the models, are comprehensive enough to guarantee that the models are even more stable and segmentation accurate. Experimental results show the superiority of the proposed method when compared to the conventional deep learning methods with regard to Dice Similarity Coefficient, Intersection over Union, Precision, Recall and Hausdorff Distance. It achieves excellent tumor classification on a large number of MRI data, dividing the whole tumor, tumor core and enhancing tumor. The proposed model provides an efficient, clinically applicable solution which could be used for the diagnosis, treatment planning and monitoring of disease among radiologists.

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