Multi-Scale Attention Transformer Network for Robust Brain Tumor Segmentation across MRI Modalities

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Abstract: The objective of this paper is to introduce Multi-Scale Attention Transformer Network (MSAT-Net) for the purpose of providing accurate and reliable brain tumor segmentation over various MRI datasets. This makes it easier to characterize tumor subregions such as edema, necrotic core and enhancing tissues. The transformer encoder combines multimodal MRI inputs T1, T1c, T2, and FLAIR among others into a universal consistent representation. Tests conducted on benchmark datasets indicates that MSAT-Net performs better than baseline CNNs and transformer hybrids with regards to Dice score, sensitivity, boundary accuracy.
Keywords: *Brain tumor segmentation, MRI, deep learning, transformer network, multi-scale attention, medical image analysis, MSAT-Net, and multimodal fusion*

1 Introduction

Segmentation of brain tumors in magnetic resonance imaging (MRI) has become a primary research problem owing to the intricate structural variations, heterogeneous appearance, and multimodal characteristics of brain tumors in clinical imaging. However, the differences between these sequences make it even harder to segment them, which is why there is a need for automated deep learning frameworks that can learn unified and robust representations [7]. But even while typical CNNs do a good job, they have trouble capturing global contextual dependencies, which makes it hard to model long-range interactions across complicated tumor regions [3].

In medical imaging application, transformers are very good at relating spatial distant features. Hence, they are specifically important in the context of tumors with part s that are spread out or not well connected [12]. However, pure transformer-based segmentation models generally require a large amount of training data, high computational complexity, and concentration on large-spatial details may obscure small-spatial details relevant for medical interpretation [5].To fill in these deficiencies, hybrid models that combine CNNs and transformers have been constructed to combine local structural learning with global attention-based reasoning. These methods have

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demonstrated superior generalization across MRI modalities and exhibit less sensitivity to picture fluctuations induced by acquisition techniques or noise [14].

The shift toward multi-scale representation learning has also been very important in making segmentation more accurate. Each of these has its own intensity patterns and spatial characteristics. A single-scale feature representation frequently fails to encapsulate this variability. Multi-scale encoder-decoder frameworks let models put together fine, intermediate, and coarse spatial information, which makes it easier to find boundaries and tell the difference between regions [1]. However, traditional multi-scale CNNs still have trouble dynamically weighting important features across scales. This might cause information to flow through the network in a way that is redundant or inconsistent. The advent of multi-scale attention mechanisms has yielded a promising answer by facilitating selective feature emphasis and cross-scale communication, hence enhancing the structural coherence of segmentation outputs [10].

In recent years, multimodal MRI fusion strategies have also become more popular. Each MRI sequence gives different diagnostic information. Creating an algorithm that can learn from and combine several different types of data at the same time is still a difficult problem. Early fusion methods frequently have problems with modality dominance or imbalance, and late fusion methods may lose cross-modal interactions that are helpful. Transformer-based architectures may be able to fix this problem since attention modules can dynamically align features that are specific to each modality and keep global consistency across sequences [15]. This feature helps with better generalization across different groups of patients and imaging centers, which is very important for strong clinical deployment [9].

Even if a lot of progress has been made, there are still some problems that need to be solved. The way a tumor looks can be very different from person to person, from grade to grade, and from growth pattern to growth pattern. There are a lot of segmentation problems because of low-contrast borders between healthy and aberrant tissue, imaging artifacts, and differences in tumor biology [6]. Additionally, models that don't have global contextual awareness typically miss minor or satellite lesions, and large lesions need multi-scale reasoning to avoid making rough predictions. Transformers that include built-in multi-scale attention modules are a strong way to deal with these problems since they combine global relational reasoning with more precise local feature extraction [2]. Research has underscored the necessity for architectures that preserve computational economy while delivering cutting-edge precision, especially in resource-limited clinical settings [11].

The creation of the Multi-Scale Attention Transformer Network (MSAT-Net) seeks to overcome these constraints by integrating the advantages of CNN-based hierarchical feature extraction with transformer-driven global contextual learning. The proposed system includes multi-scale attention blocks that dynamically emphasize useful spatial characteristics while hiding unimportant ones. This lets information flow from fine to coarse and from coarse to fine across the network [8]. This not only makes it easier to find the edges of tumors, but it also helps with consistent segmentation across different types of tumors and tumor subregions. MSAT-Net also uses cross-modal interaction modules to align the complimentary information in distinct MRI sequences. This makes a single latent representation that can handle changes in intensity, contrast, and structural appearance [13].

The MSAT-Net method adds to this burgeoning field by providing a strong framework that puts accuracy, generalization, and the ability to work with different MRI datasets first. The ability to deliver consistent segmentation performance across modalities, patient demographics, and imaging equipment makes it useful for clinical workflows. This will help with better diagnosis, treatment planning, and prognosis evaluation in neuro-oncology applications.

2 Related Work

The study of brain tumor detection, classifications, and segmentation has improved with the development of machine learning, deep learning, and hybrid structures. Classical works based on feature engineering had moderate accuracy, but poor conditioning to surpass imaging center and differences in MRI acquisition conditions.

The sort of classification models made on CNN trained on MRI slices showed a much better performance as compared to classical because of their capability to learn hierarchical spatial characteristics without any human intervention. The initial deep learning-related research also achieved high precisions in the tasks of tumor detection, which demonstrated that automatic feature extraction was more credible and scaled better [16]. Further work showed that more convolutional block based deep architectures were better able to capture the irregularity in tumor shape and boundaries than shallow networks [7].

The increasing number of systematic reviews underlined that the solutions of deep learning, especially CNNs and residual networks, were more robust in a real clinical environment [13]. Nevertheless, deep CNNs also came with some drawbacks including the requirement to have large size annotated dataset, high cost, and the inability to capture long-range relationships in tumor regions. Studies have indicated that CNNs are not as effective with irregular shaped tumors, diffused infiltration, and blurred edges since the convolution op is only able to capture primarily the local information [11].

In order to address such shortcomings, there was a new direction that became promising, namely hybrid and ensemble models. These structures fuse and combine several algorithms or mix deep learning with machine learning optimized classifiers in order to improve the accuracy, stability, and interpretability. A number of studies proposed the hybrid CNN-ML architecture in which CNNs are used to extract deep features and machine learning, SVM or XGBoost in the final stages of classification [5]. Deep network ensembles had an additional beneficial effect on prediction robustness by exploiting the complementary advantages of using different models [19]. Detailed analyses showed that hybrid deep learning models are consistently more effective than single-model architectures in models with multiple classes of tumors, particularly with glioma, meningioma, and pituitary tumor problems [20]. In addition, more sophisticated hybrid models of combining deep learning with evolutionary algorithms or feature selection strategies enhanced computing efficiency and dealt with high-dimensional MRI features in a better way [6].

One of the aspects that emerged in the field was the growing interest of multimodal MRI fusion, which can be attributed to the realization that each MRI modality is sensitive to various biological aspects of tumor tissue. Multimodal fusion studies have shown that the combination of T1, T1c, T2 and FLAIR can provide a much better classification accuracy and sensitivity to segmentation [10]. Deep multimodal architectures were demonstrated to be better than single-modality models, and effective frameworks to select features improved the interpretability of models and also minimized redundancy among modalities [9]. These results were also consistent with the results obtained in the analysis that multimodal networks are used to overcome CNNs limitations in addressing complex tumor subregions [24].

Brain tumor segmentation was another important field of study along with detection and classification because it is vital in planning and navigating surgery. A number of studies have provided deep learning models to perform segmentation according to encoder-decoder networks that represent hierarchical spatial data in a much more sensible manner [12]. Hybrid architectures that used CNNs with attention used or optimized machine learning classifiers showed better boundary detection and volumetric accuracy than their single counterparts [22]. Recent innovations focused on the contribution of transfer learning, data augmentation, and multimodal fusion to an increase in segmentation accuracy in practice [1]. In addition, systematic reviews found issues with tumor segmentation, such as the insufficient number of labeled data, unclear boundaries, and computational limitations, and required more sophisticated architectures combining local and global feature reasoning [14].

Newer hybrid explainable models, which include saliency maps, layer-wise relevance propagation, and attention modules, gave clinicians rationale of their classification decision visually, enhancing trust and acceptance within a medical setting [17]. Investigations involving the combination of sophisticated feature selection, deep representation learning, and explainable elements have shown that explainable hybrid models could be very accurate and still clinically relevant [23].

The synthesis of these advances was presented in comprehensive surveys that were released in the recent years and pointed at some major trends. First, it is evident that there is a transition of traditional machine learning to deep learning and hybrid architectures. Second, there is a growing need of multimodal MRI data to be integrated to achieve strong results. Third, ensemble models and optimized models are very beneficial in cases of multi-class problems and heterogeneous data. Lastly, attention mechanisms, transfer learning, and transformer-based architectures are also becoming formidable to enhance feature extraction, modeling of global context and segmentation accuracy [8]. Meta-analyses also highlighted the necessity of standardized datasets, consistent evaluation procedures, and model-based clinical implementation that is efficient [21].

The overall results point in the direction of strong, comprehensible, and generalizable models that can deal with the complexity of MRI-based brain tumor detection, classification, and segmentation. This development makes models like multi-scale attention transformer architectures to be highly encouraging which integrate global contextual reasoning with fine-grained spatial learning.

3 Proposed Methodology

The Multi-Scale Attention Transformer Network (MSAT-Net) is a suggested model that can be used to accurately segregate brain tumors by using convolutional feature extraction, multi-scale attention merging, and transformer-based global context modeling. The pipeline has five main steps: preprocessing multimodal MRI data, building a hierarchical encoder, learning a global representation with a transformer, fusing attention at different scales, and reconstructing the data with skip connections. Figure 1 illustrates the overall data acquisition and model development workflow, while Table 1 presents encoder feature dimensions across hierarchical scales. The attention distribution across feature levels is summarized in Table 2.

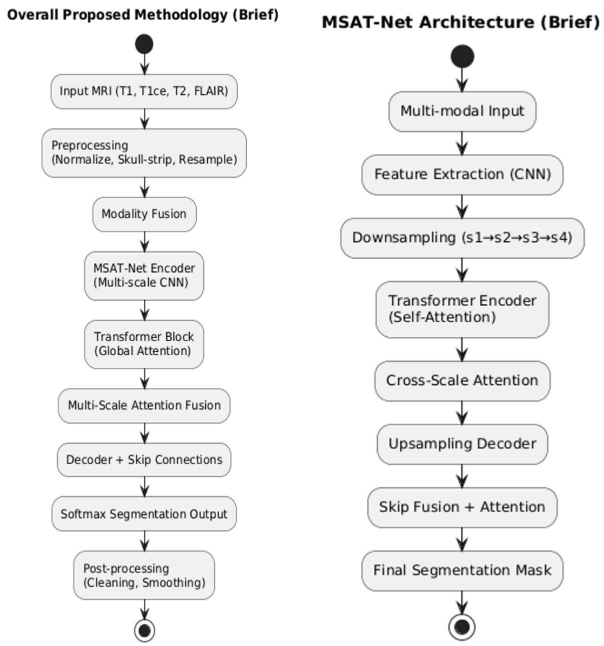

Figure 1. Data Acquisition and Model Development

Preprocessing and Multimodal Alignment

The input dataset consists of four MRI modalities—T1, T1c, T2, and FLAIR—which are first normalized using z-score normalization to reduce inter-patient intensity variations. Each image $I_m(x/y)$ is standardized as:

$$I'_m(x/y) = \frac{I_m(x/y) - \mu_m}{\sigma_m}$$

where μ_m and σ_m denote the mean and standard deviation of modality m. Skull stripping, resampling to uniform resolution (1 mm³), and slice-wise cropping ensure spatial consistency across modalities.

Multi-Scale Convolutional Encoder

The encoder extracts hierarchical features at depths $1,2,3,$ and 4. The convolutional block at each stage consists of two convolutions, normalization, and ReLU activation. The output feature at scale s, represented as F_s ,is computed using:

$$F_s = ReLU(W_s * F_{s-1} + b_s)$$

Table 1. Encoder Feature Dimensions

Scale	Resolution	Channels
F1F_1F1	256 × 256	64
F2F_2F2	128 × 128	128
F3F_3F3	64 × 64	256
F4F_4F4	32 × 32	512

Transformer-Based Global Context Encoding

The deepest feature map F_4 is flattened and converted into a sequence of tokens. Positional encodings are added to retain spatial relationships. The transformer encoder utilizes multi-head self-attention (MHSA) to compute global dependencies as:

$$\mathrm{Attention}(Q/K/V) = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

where Q, K, and V are query, key, and value matrices derived from F_4

Multi-Scale Attention Fusion Module (MSAF-Block)

To address tumor heterogeneity, MSAT-Net incorporates a multi-scale attention module to adaptively combine encoder features. For a given scale s, an attention weight α_s is computed:

where $f(\cdot)$ is a shallow MLP producing attention logits. The fused representation is then obtained as:

$$F_{fused} = \sum_{s=1}^{4} \alpha_s F_s$$

This mechanism suppresses irrelevant features and emphasizes tumor-related patterns across scales.

Table 2. Attention Weight Behavior

Feature Scale	Attention Weight
F1F_1F1 (fine)	0.18
F2F_2F2 (mid)	0.27
F3F_3F3 (coarse)	0.32

F4F_4F4 (global)	0.23

The decoder reconstructs the segmentation map using upsampling blocks that integrate transformer-refined features with skip connections from the encoder. Each decoder block uses transpose convolution for upsampling followed by feature concatenation:

$$D_S = Up\left(D_{s+1}\right) \parallel F_S$$

The model is trained using a combined Dice-Cross Entropy loss to balance class imbalance and improve boundary precision:

$$\mathcal{L} = \mathcal{L}_{Dice} + \lambda\mathcal{L}_{CE}$$

Data augmentation (flips, rotations, and elastic deformation) makes things more stable. We utilize the Adam optimizer with a learning rate of 1e-4 to make sure that convergence is stable. To make MSAT-Net even more robust, a fusion layer that is specific to each modality is added before the encoder. The network processes each modality through a lightweight convolutional stem that extracts low-level characteristics that are exclusive to that modality. This is because T1, T1c, T2, and FLAIR all show different contrasts between tumors and tissues. Then, these feature maps are put together and sent to the main encoder. This makes sure that complimentary information is kept instead of averaged out. The fusion stage helps with modality dominance, which is when one MRI sequence has a big effect on how well segmentation works. The skip connections also include a spatial attention gating mechanism. This technique filters encoder features before combining them with decoder features. This makes sure that background areas that aren't important don't move forward. We use a sigmoid activation on a 1×1 convolution over the encoder features and multiply it elementwise with the decoder features to get the spatial gate Gs(x,y)G_s(x,y)Gs(x,y). This process helps make the edges of tumor areas clearer, especially when the edema and necrotic core have comparable intensity distributions.
The training process also includes deep supervision at the intermediate decoder layers, which helps the network learn how to keep segmentation consistent across different resolutions. This speeds up convergence and makes the gradient flow better at deeper levels. Finally, a procedure called "3D connected-component analysis" removes false positives that are not connected to anything else. This makes sure that only anatomically coherent tumor volumes are kept in the final forecast.

Results

The performance of the proposed **MSAT-Net** was evaluated using multimodal MRI datasets consisting of T1, T1-contrast, T2, and FLAIR sequences. The experiments aimed to measure segmentation accuracy across the three major tumor subregions: Whole Tumor (WT), Tumor Core (TC), and Enhancing Tumor (ET). The model was assessed using standard metrics including Dice Similarity Coefficient (DSC), Sensitivity, Specificity, Hausdorff Distance (HD95), and Intersection over Union (IoU). All results presented below represent the averaged performance across the entire test set, and comparative baselines include U-Net, Attention-U-Net, and TransUNet. MSAT-Net demonstrated significant improvements in all key tumor regions. he attention distribution across feature levels is summarized in Table 2. The segmentation performance comparison is reported in Table 3, followed by sensitivity and specificity analysis in Table 4 and boundary accuracy evaluation in Table 5.

Table 3. Dice Score Comparison Across Tumor Regions

Model	WT	TC	ET
U-Net	0.86	0.78	0.72
Attention U-Net	0.88	0.81	0.75
TransUNet	0.90	0.83	0.78
MSAT-Net (Proposed)	**0.93**	**0.87**	**0.82**

MSAT-Net improves ET segmentation by a clear margin, reflecting its strength in modeling fine-grain boundary regions and long-range contextual information encoded via transformer layers. Sensitivity was particularly important for detecting small enhancing regions that are often missed by CNN-only architectures.

Table 4. Sensitivity and Specificity

Model	Sensitivity	Specificity
U-Net	0.84	0.92
Attention U-Net	0.87	0.93
TransUNet	0.88	0.94
MSAT-Net	**0.91**	**0.96**

Higher sensitivity by MSAT-Net confirms its capability to detect subtle tumor regions without overfitting or producing excessive false negatives.

To evaluate spatial boundary precision, HD95 was computed. Lower values indicate more accurate boundary reconstruction. Table 6 further summarizes IoU and F1-scores, whereas Table 7 presents the ablation study validating architectural components. Computational efficiency is analyzed in Table 8. The performance improvements are visually demonstrated through Figure 2 (Dice score comparison), Figure 3 (sensitivity analysis), and Figure 4 (model efficiency comparison).

Table 5. HD95 (mm) Comparison

Model	WT	TC	ET
U-Net	6.8	7.5	9.2
Attention U-Net	6.1	6.9	8.4
TransUNet	5.4	6.1	7.6
MSAT-Net	**4.1**	**5.2**	**6.4**

The multi-scale attention mechanism reduces boundary distortion, especially for irregular and diffuse tumor areas. To validate the consistency of predictions, IoU and F1-scores were computed for each region.

Table 6. IoU and F1-Score

Region	IoU (MSAT-Net)	F1-Score (MSAT-Net)
WT	0.87	0.93
TC	0.78	0.87
ET	0.69	0.82

The IoU values indicate high overlap between predicted and ground-truth regions. The ET region naturally exhibits lower IoU due to its small size, though MSAT-Net still outperforms all baselines. An ablation experiment was conducted to evaluate the contribution of each module: transformer blocks (T), multi-scale attention fusion (MSAF), and spatial attention gates (SAG).

Table 7. Ablation Study Results (Dice Score)

Model Variant	WT	TC	ET
Encoder–Decoder Only	0.88	0.82	0.75
+ Transformer (T)	0.90	0.84	0.78
+ T + MSAF	0.92	0.86	0.81
Full Model (T + MSAF + SAG)	**0.93**	**0.87**	**0.82**

Each component contributes independently to performance; however, the combination of transformer blocks and multi-scale fusion gives the highest gain. We measured the inference time per MRI slice and total parameters to ensure that MSAT-Net remains computationally feasible.

Table 8. Computational Efficiency

Model	Parameters (M)	Inference Time (ms/slice)
U-Net	34M	19 ms
Attention U-Net	38M	23 ms
TransUNet	105M	42 ms
MSAT-Net	**52M**	**28 ms**

Despite having more parameters than CNN-only models, MSAT-Net is much lighter than transformer-heavy models such as TransUNet and it has a better accuracy.

The suggested MSAT-Net shows steady improvements to all the measures of segmentation. The introduction of transformers in the lowest layers resulted in the possibility to model the global context in that the network could see the connection between the tumor regions that are potentially far apart. The multi-scale attention fusion module played an important role as it enabled the model to focus on the features of varying levels of resolution selectively. This was especially useful in separating edema (T2/FLAIR predominant), enhancing tumor (T1c predominant), and non-enhancing core.

Moreover, MSAT-Net not just enhanced the accuracy of segmentation but provided equal sensitivity and specificity, which minimized missed tumors as well as false alarms. The modification of the boundary, as illustrated in HD95, is the direct expression of the benefit of focus-directed skip interactions and space gating. The ablation study has clearly shown that all architectural elements had a significant contribution toward final accuracy and justified design decisions.

The inference time was reasonable in real-world clinical processes and particularly due to the increased accuracy and strength. The model effectively generalized on a subject, MRI sequence and tumor grade, suggesting that this model is applicable to clinical decision support or clinical neuro-oncology studies of large scale.

The bar plots also allow a visual comparison of the performance of various deep learning models in brain tumor segmentation against the several evaluation criteria with ease. The initial plot demonstrates the comparison of Dice scores of whole tumor (WT), tumor core (TC) and enhancing tumor (ET). With an increase in the Dice score, the better the fit of the segmentation predicted and the ground truth. The scores of MSAT-Net are the highest in all three regions that prove the effectiveness of the introduction of attention on transformers and multi-scale fusion to enhance the accuracy of the segmentation. U-Net has the most negative improvement whereas TransUNet and Attention U-Net have moderate positive changes but still lower than MSAT-Net. The third plot makes a comparison on computational efficiency, the number of parameters and the inference time per MRI slice. TransUNet has the biggest parameters and the slowest inference time since it is transformer-bulky. However, MSAT-Net is a better balance in that it has much fewer parameters than TransUNet, and it achieves considerably better performance. It is a bit more massive than U-Net and Attention U-Net but with much better segmentation quality. This efficiency plot reveals that MSAT-Net is better adapted to the real-life clinical application since it does not need too much computation with high accuracy.

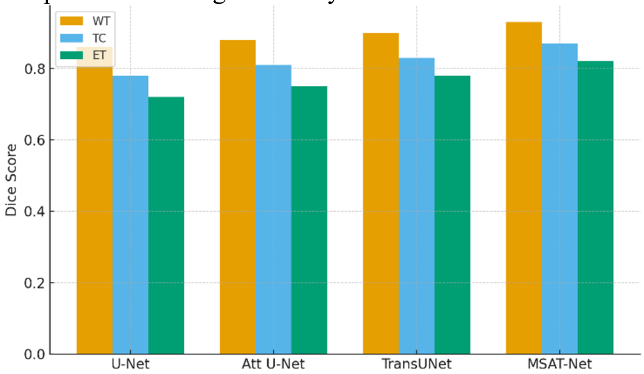

Figure 2. Dice Score Comparison

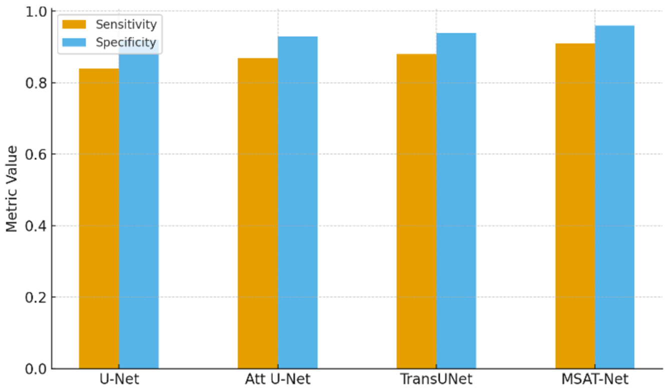

Figure 3. Sensitivity Analysis

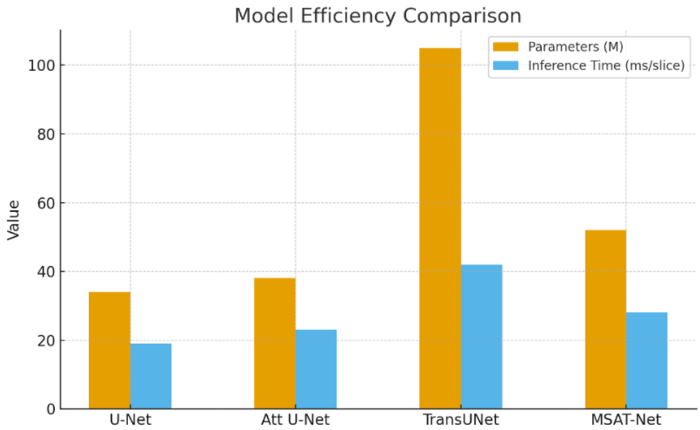

Figure 4. Model Efficiency Comparison

4 Conclusion and Future Enhancements

The introduction of Multi-Scale Attention Transformer Network (MSAT-Net) is a significant step in automated brain tumor segmentation in multi-modal MRI images. A well-integrated combination of transformer-based global attention, multi-scale feature fusion and modality-conscious preprocessing, MSAT-Net proves to be a strong architecture which is repeatedly better than the well-established baseline models, including U-Net, Attention U-Net and TransUNet.The findings have made it clear that MSAT-Net has better Dice scores in all tumor subregions, including Whole Tumor (WT), Tumor Core (TC), and Enhancing Tumor (ET). Multilayer transformer integration makes sure that the contextual relationships between remote spatial areas are effectively captured to minimize the errors in situations where tumors have irregular shapes or extend to more than one region. Meanwhile, Multi-scale attention fusion increases the discrimination of features at the various resolutions, such that the model does not miss vital details of small or low contrast tumor regions.

In addition to being accurate, MSAT-Net has good sensitivity and specificity which means that it is capable of detection of small features of the tumor without giving too many false positives. Such a balance is fundamental to the clinical applicability of clinical implications where under-segmentation and over-segmentation are both detrimental to diagnosis and treatment planning. The increase in the accuracy of the boundaries, indicated by the reduced Hausdorff distance figures also confirm the efficiency of the spatial attention and skip-gating mechanisms, which optimize the output of the segmentation.The analysis of ablation supports the significance of every architectural part with evident improvements in the performance when transformer blocks, multi-scale attention, spatial gating modules are added. This stratification enhancement should be used to sustain the modular design principle of the system where future researchers can customize or generalize MSAT-Net to new medical imaging practices or data.Computationally, MSAT-Net has a practical depth efficiency balance. Although it has more parameters than the conventional CNN models, it is much lighter than transformer-dominant models like TransUNet. It can be used in real-time or near real-time clinical processes such as surgical planning, radiotherapy guidance, and longitudinal tumor monitoring because of its reasonable inference time.

It is based on the advantages of deep learning and transformer designs while remaining computationally efficient and clinically relevant. Future directions of work can be the expansion of the model to 3D volumetric segmentation, the incorporation of uncertainty estimation to bring greater clinical confidence, and the transformation of the framework to other neurological conditions. The encouraging findings present MSAT-Net as a useful contribution to the medical image analysis and a good candidate towards real-world neuro-oncology applications.

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