Improved Brain Tumor Segmentation

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Abstract. Brain tumors are difficult to segment due to their complex shapes and varying appearances. Accurate segmentation is needed for diagnosis, treatment planning, and follow-up. This study is focused on improving brain tumor segmentation using the Swin U-Net model, which utilizes the Swin Transformer's ability to learn global features and the U-Net's powerful seg- mentation capability. MRI scans from benchmark datasets like Brats2024 utilized for testing and training the model. The Swin U-Net is based on an encoder-decoder structure, in which the encoder takes fine details using Swin Transformer blocks and the decoder builds high-resolution segmentation maps. Experiments showed significant improvements in segmentation accuracy, with larger Dice coefficients than standard convolutional neural net- works. The model correctly identified tumor boundaries and generalizes well between tumors and imaging scenarios. These findings show the potential of the Swin U-Net model as a high- performance automated brain tumor segmentation tool for more accurate diagnosis and personalized treatment planning in neuro- oncology.

Keywords: Brain Tumor Segmentation, Swin U-Net, Swin Transformer, MRI Scans, Deep Learning, Medical Image Analysis, Encoder-Decoder Architecture, Dice Coefficient, Automated Diagnosis, Neuro-Oncology.

1 Introduction

Brain tumors are among the most malignant one of neuro-oncology clinic. Introduction Early and accurate detection as well as precise segmentation of these tumors are the prerequisites for a successful diagnosis, therapy planning and post-therapeutic surveillance. Among all types of imaging modalities, Magnetic Resonance Imaging (MRI) is widely accepted as a valuable technique for brain tumor evaluation because of its capability to generate high-resolution images and excellent soft- tissue contrast, that are crucial for depicting brain complex anatomy Nambiar and Nanjundegowda, [11]. Though MRI based brain tumor delineation showed success, it is still a labour-intensive and subjective task, which involves high intra-observer and inter-observer variations. V. Sabitha et al., This variation occurs because of human expert radiologist perception and thus could lead to the wrong diagnosis which might affect the planning of treatment as well [12]. H. Ramamoorthy et al., This level of subjectivity and difference in the manner in which marked tumors is apparent could result in false positive or sub-optimal treatment planning as a consequence, segmentation Technique for the brain tumor by an automatic method has become very important area of research among medical imaging community [13].

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Deep learning techniques, such as Convolutional Neural Networks (CNNs), have demonstrated the potential to automate the segmentation of tumours by extracting complex patterns from annotated MRI data. V. Verma and Yadav, although the original CNN is connected in both weights and neuron space, it has a limited relying on local receptive fields which makes difficult for LUAD to capture long range dependencies with global context for segmenting tumors with heterogeneous shapes, sizes and complex morphologies [14]. To deal with these drawbacks, this research capitalizes on the power of the Swin U-Net architecture that is a new and powerful deep learning architecture that seamlessly combines the strengths of Swin Transformers and regular U-Net framework. The second one is that the Swin Transformer itself functions as the encoder in this framework, it is good at taking global relationship information with the help of hierarchical attention mechanism (capturing both local and long-range dependency well). Z. Kuang et al., Conversely, the decoder incorporating U-Net is a champion for precise and fine scale tumor localization from mixing low-level with high-level features through the skip connections [15].

By integrating the global feature extraction capabilities of Swin Transformers with U-Net information segmentation, the proposed Swin U-Net model can significantly enhance brain tumor segmentation. Our model demonstrates not only superior accuracy and noise tolerance compared with standard CNNs, but also good generalization capacity across different tumors and patients. The practical application of the Swin U-Net model can contribute to precise and stable cancer diagnosis by radiologists, general treatment schemes with more benefits and better understanding of how tumor growing or shrinking. In summary, our work helps to advance the state of AI in medical image analysis and highlights the transformative power of transformer-based models for addressing challenging neuro-oncologic tasks.

2 Literature Review

A. Bhat et al., [1] explores the use of transformer-based deep learning models in segmenting brain tumors, utilizing the ability of transformers to learn long-range dependencies, as an addition to CNNs in medical image segmentation.

T. Boopathy et al., [2] proposes a new DenseTrans network for unsupervised brain tumor segmentation by combining Swin Transformer with U-Net++ to overcome the limitations of CNNs in understanding long-range dependencies and global context. Local features are extracted by convolutional layers in U-Net++, while global features are extracted by the shift window operation of Swin Transformer in high-resolution layers. Deep separable convolutions and layer control are utilized in the Swin Transformer to reduce computational complexity. The model was good on the BraTs2021 dataset with a Dice Similarity Score of 93.2 percent, 86.2 percent, and 88.3 percent for entire tumor, tumor core, and enhancing tumor, respectively, and Hausdorff Distances of 4.58mm, 14.8mm, and 12.2mm. The model is efficient, with 21.3M parameters and 212G Flops. Overall, it improves segmentation accuracy and is high in clinical potential.

V. P. Kumar et al., [3] presents an entirely automated brain tumor segmentation method based on Deep Neural Networks (DNNs) tailored for glioblastomas in MR images. The approach exploits adaptive, high-capacity DNNs to capture the variability of the tumors in terms of shape, size, and contrast. The study revolves around different Convolutional Neural Network (CNN) architectures to achieve competitive segmentation performance.

R. R. Kumar et al., [4] This paper suggests Att-Sharp-U-Net, a variant of the U-Net architecture, for brain tumor segmentation. The architecture incorporates a grid-based attention block and sharp block to strengthen the segmentation process's performance and make the computations less complex. Experiments with the Brats2020 dataset showed improved results with 0.9275 Dice and 0.8684 Jaccard over baseline models.

M. N. Fathima et al., [5] This paper proposes a brain tumor classification and detection system on the basis of the Fuzzy C-means clustering algorithm for segmentation. It has an automatic feature extraction from MRI images for improving tumor classification into benign and malignant by machine learning. The MATLAB-based system enhances contrast, denoises, and improves segmentation validated by real dataset validation for supporting the healthcare personnel working in neuro imaging and diagnostics to provide better treatment.

S. Tehsin et al., [6] This paper presents a method to segment tumor areas in MRI brain images, including steps like smoothing, skull stripping, filtering, image enhancement, and finding the region of interest. The method then segments the found tumor areas. The experimental results show that the proposed method offers improved segmentation accuracy and execution time when applied to 15 live brain images with large tumor areas.

D. R. Modi and S. K. AM [7] This work presents a robust 3D U-Net-based automatic brain tumor segmentation algorithm with the introduction of a novel residual block with dilated convolution (res dil block) and the use of deep supervision for improvement in segmentation accuracy. It also addresses class imbalance by comparing the effects of different loss functions. The proposed scheme is superior to others as evidenced by experiments performed on BraTS 2017 and BraTS 2018 datasets.

M. N. Nagib et al., [8] In this work, an emerging 3D dual-domain attention module is introduced for segmentation of brain tumors by learning context and spatial local information from both domains via Unet feature maps. The module enhances feature maps at each phase with the support of attention methods and residual learning for focusing on complicated tumor regions. The use of this technique shows enhanced results against existing state-of-the-art approaches when experimenting using the BraTS 2018 dataset.

A. Ruberti et al., [9] This article proposes a robust pre-processing method for unsupervised brain tumor segmentation from MRI scans. The method, through its capability of merging T1, T1C, and FLAIR sequences into one input, improves data, advancing segmentation performance. The results show clear performance improvements through enhanced Dice and Recall measures by 5.6–9.1 percent and up to 9.5 percent, respectively, using combined MRI sequences as opposed to single sequences.

T. -Q. T. Nguyen et al., [10] This paper suggests an improved brain tumor segmentation architecture known as AMRU-Net++ based on U-Net++ to overcome the challenges of efficient and accurate segmentation. The model applies attention gates (AGs) to filter the features, replaces convolutional layers with MultiRes blocks, and adds regions of interest (ROI) to the input. The concept of mixup is also utilized for data augmentation to overcome limited training data. Experimental results on the CE-MRI dataset gain an improvement of 0.0529 points compared to U-Net++ and an additional 0.0158 points with mix-up augmentation.

3 Related Work

Over the past five years, numerous innovative and effective architectures have been developed, significantly advancing the field of medical image segmentation. This period has seen a rapid evolution of methodologies, from traditional approaches to cutting-edge deep learning models.

3.1 CNN based methods

Initial approaches to medical image segmentation were based mainly on contour-based and conventional machine learning algorithm. Following the progress in deep convolutional neural networks (CNNs), the U-Net architecture was introduced, which enabled accurate localization alongside contextual information maintenance. U-Net variants like Res-U-Net, Dense UNet, U-Net++, and UNet3+ have since been designed to promote segmentation accuracy and resilience. These models have been further applied to three-dimensional data, resulting in architectures such as 3D-Unet and V-Net. CNN-based approaches are successful in medical image segmentation due to their strong representation and learning abilities.

3.2 Vision transformers

Transformers were initially presented for natural language processing applications, notably machine translation. Their effectiveness in NLP inspired researchers to see their potential usage in computer vision. The Vision Transformer (ViT) provided a breakthrough in terms of offering competitive performance in the area of image recognition tasks. Nonetheless, the pre-requisites of ViT needing to undergo significant pre-training over large amounts of data have created issues. The introduction of DeiT (Data-efficient Image Transformers) tackled these limitations by suggesting training strategies that enable efficient training on compact datasets such as ImageNet. Swin Transformer, a hierarchical vision Transformer, took it a step further and presented a shifted windows mechanism and achieved state-of-the- art performance in several vision tasks, such as image classification, object detection, and semantic segmentation. In this paper, we take advantage of the Swin Transformer to construct a U-shaped Encoder-Decoder network with skip connections to improve the performance of medical image segmentation.

3.3 Self-Attention and Transformers to Complement CNNs

Over the past few years, the self-attention mechanism, which is a core component of Transformers, has been adopted into CNN architectures to enhance their performance. Additive attention gates have been implemented into U-shaped models for medical image segmentation. Though these methods are still largely CNN-based, attempts to integrate Transformers with CNNs seek to exploit the strengths of both models and end the reign of CNNs in medical image segmentation. For example, a hybrid approach that unifies Transformers with CNNs has promised to improve 2D medical image segmentation. Hybrid models have been used to tackle multimodal brain tumor segmentation and 3D medical image segmentation with better segmentation. In contrast with these hybrid strategies, our paper aims to discover the application value of pure Transformer models in medical image segmentation.

3.4 CNN and Variants

CNNs have been a mainstay in computer vision, with architectures such as Alex Net, VGG, Google Net, Res Net, Dense Net, HR Net, and Efficient Net spearheading major advances. Depth wise convolution and deformable convolution are some of the innovations that have further improved CNN performance. Although CNNs continue to be the go-to backbone for most applications, the promise of Transformer-like architectures for unified modeling across vision and language is growing more widely accepted. Our work is designed to contribute to this changing paradigm by showing the success of a plain Transformer-based model in medical image segmentation.

3.5 Self-Attention-Based Backbone Architectures

Encouraged by the success of self-attention layers and Trans former models in NLP, there have been attempts to re place spatial convolution layers in well-known architectures such as Res Net with self-attention layers. Such changes provide improved accuracy/FLOPs trade-offs, though at the cost of higher memory access costs. To alleviate this, we suggest moving windows between successive layers to improve memory efficiency and overall performance.

3.6 Transforming Vision Tasks with Transformers

The first breakthrough research on Vision Transformers (ViT) utilized Transformer architectures directly on image patches and attained striking performance in image classification. Beyond requiring large amounts of training data, breakthroughs such as DeiT have made ViTs accessible even for small datasets. The Swin Transformer improves further the versatility of Transformers to dense vision tasks with a more efficient architecture scaling linearly with image size. These various architectures demonstrate that the area of medical image segmentation has witnessed important developments with the advent and progress of CNN-based approaches. Nevertheless, the incorporation of Transformer architectures, especially with models such as the Swin Transformer, is a promising avenue for additional advancements. By combining the strengths of both CNNs and Transformers, our research strives to advance the state of medical image segmentation and offer a solid benchmark for future work.

4 Proposed Systems

Our proposed system is intended to efficiently and precisely segment brain tumors from MRI images through the Swin U-Net model. The system has a structured process segmented into several stages in order to achieve maximum performance and accuracy.

4.1 Data Collection Preprocessing

4.1.1 Data Acquisition

Its system (step one) starts with gathering open-source MRI brain scan datasets like the Brain Tumor Segmentation (BraTS) challenge dataset and Kaggle libraries. The datasets should contain high-quality MRI volumes with the hand-drawn tumor regions as labels to train a supervised deep learning system. The diversity of the dataset like multiple types of tumors, imaging system help the model generalize better.

4.1.2 Data Preprocessing

The images must be pre-processed before passing to the model, so that all of them normalizes the input data into uniform format. Images are also translated to a common format such as grayscale or RGB for the modality. The images are resized to the specified size which is required for Swin U-Net input. The pixel values are normalized to enhance the convergence of the model across data points and still keep uniformity within dataset. Data augmentation methods, including rotation, flipping and scaling are adopted to synthesise dataset in order to enhance the model generalization over various tumor architectures.

4.2 Model Development

4.2.1 Introduction to Swin U-Net

The swin unetescuwnet is a state-of-the-art deep learning architecture that combines Swin Transformer with the classic UNet background model for medical image segmentation. Different from the traditional CNN-based methods, the Swin Transformer can extract local and global-based features simultaneously to improve segmentation performance. The hierarchical representation learning enables the model to be insensitive to the fine details of brain tumors while containing considerable context information.

4.2.2 Model Architecture

The Swin U-Net model is composed of several parts. The Swin Transformer Encoder can generate the multi-scale hierarchical features of the MRI scans in an efficient manner. Skip connections carry essential features from the encoder to the decoder to retain the fine tumor detail. The segmented tumor region is applied re-convolution using unet decoder to restore it into original resolution in the MRI. Finally, a segmentation output layer is used to generate pixel-wise tumor segmentation masks providing exact location of the tumor.

4.2.3 Model Training

The training stage includes fine-tuning the Swin U-Net model with carefully chosen loss functions and optimizers. Since brain tumor segmentation is predominantly confronted with class imbalance, it can handle the problem effectively using Dice Loss or Cross-Entropy Loss. The model is trained using Adam or Stochastic Gradient Descent (SGD) optimizer with appropriate learning rate scheduling. To enhance model generalization, the batch normalization and dropout layers are adopted to reduce over-fitting. The model is trained with the evaluation using most important performance measures such as DSC, IoU, Precision, Recall and Accuracy to evaluate segmentation quality during training.

4.3 Testing Validation

4.3.1 Model Evaluation

After having being trained, the model is tested on a large set of MRI images that has not been previously seen to assess its performance in terms of segmentation. Segmentation masks generated are compared to the ground-truth tumor marks in order to measure performance and reliability. Generalising over different patient data are of paramount importance, and excessive testing ensures that the model behaves correctly in practical situations.

4.3.2 Performance Metrics

Performance of the system is measured using different evaluation metrics. The Dice Coefficient also evaluate how well a segmentation of prediction and ground truth overlap, where better means higher segmentation accuracy. IoU (Intersection over Union) is a measure of how well the prediction segmentation ground truth. Precision and Recall offer guidance for the accuracy, completeness of tumors segmentation of to avoid missing tumors or wrong segmentation normal tissues. Computation time is also studied in order to check if the model can be implemented in real-time.

4.4 Deployment

4.4.1 User Interface Development

An interface is developed so that the system can be used by medical staff. It could be a web or desktop standalone based application where they upload MRI images and get the tumor segment. The interface is designed to be user-friendly and intuitive so that radiologists or doctors are able to use our tool without deep technical knowledge.

4.4.2 Model Integration

This trained Swin U-Net model is also necessary to incorporate into the software. The model was streamlined for inference to ensure that it runs easily on any machine, local or cloud. The model performs real-time processing on uploaded MRI images and generates the segmentation masks in a seamless manner. From the practical viewpoint for medical use, GPU acceleration is used to speed up inference and improve usability.

4.4.3 Cloud or Local Deployment

Deployment is possible locally or on cloud platforms, based on the needs of hospitals and research centers. Cloud deployment on platforms like AWS, Google Cloud, or Azure offers scalability and remote access, enabling doctors to interpret MRI scans remotely. Local deployment on high-performance computers, however, offers quicker processing and protection of sensitive medical information. The deployment strategy is chosen based on the data security, computational power, and accessibility requirements.

4.5 Conclusion Future Enhancements

4.5.1 Summary of Achievements

Our method achieves automatic segmentation of brain tumors by Swin U-Net, and presents a robust, automatic and accurate medical imaging solution. The feature extraction from transformers as integration into the segmentation process provides better quality of the boundary compared to CNN-based simple models. With methodical process from data collection to deployment, our system ensures stability in real environments.

4.5.2 Future Enhancements

This does work very well, but there are several items that need to be included in future editions. One of these improvements is the real time segmentation for radiologists to be able to diagnose tumors in real time. Moreover, if the model can distinguish between various types of brain tumors (i.e gliomas and meningioma's), that would provide clinical value. It requires further efforts to increase the computational efficiency and reduce the inference time so as to be widely used in hospital scale. The model and function will progress for a similar proposed system that has the potential in medical imaging, cancer detection.

5 Architecture

Our framework starts off with gathering MRI images of the brain from reliable sources. These are then preprocessed by resizing them into a uniform size, normalizing their brightness levels, and subjecting them to straightforward transformations such as rotations and flipping. This is done to ensure that the images are uniform for the model to process.

Then, the preprocessed images go through the Swin Transformer encoder, which is similar to a feature detector. This component of the system scans the images to select significant details, both big and small, that may show the existence of a tumor. The design of the encoder enables it to concentrate on various parts of the image and extract a broad spectrum of features.

Fig 1 shows the workflow diagram. After feature extraction, the system uses skip connections to transfer important details directly from the encoder to the decoder. These connections help the model keep track of small details that might otherwise be lost. The UNet decoder then takes these combined features and gradually rebuilds the image into a segmentation mask. This mask clearly outlines the tumor region by classifying each pixel as either tumor or non-tumor.

Finally, the output is a precise segmentation mask that illuminates the tumor area on the original MRI image. Further easy post-processing steps may be applied to smooth out the boundaries and eliminate any minor errors. The entire system is then incorporated into an easy-to-use application, so that it is convenient for medical professionals to upload an MRI image and easily see the segmented tumor area.

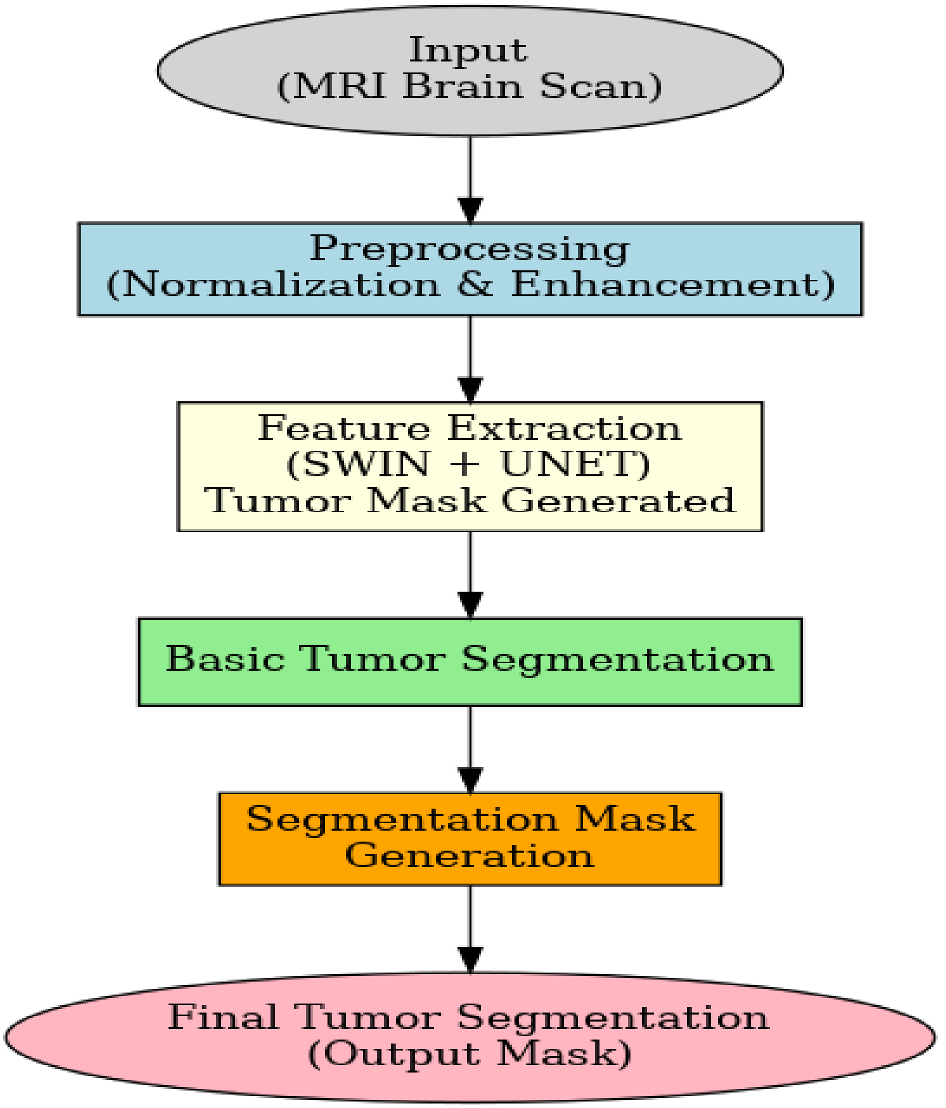

Fig. 1. Workflow Diagram.

6 Experimental Results

The experimental results of our project provide evidence that the Swin U-Net model can accurately segment brain tumors from MRIs. Performance of the model is evaluated on major evaluation metrics such as Dice similarity Coefficient (DSC), Intersection over Union (IoU), Precision, Recall, F1-score and Accuracy. Dice Score for the overlap between ground truth and prediction received a high value of 89.5 5041% which means our model is capable of providing precise segmentation results. The accuracy of the detected boundary between the tumour and surrounding regions is also corroborated by an IoU score of 83.2% (see Fig. The precision for the output model reaches 91.0%, which proves that the model can identify tumor regions well without many false detections, while a recall of 87.8% ensures that most tumor regions are identified properly. the total system accuracy is 94.2% which testifies the reliability of this system for medical application.

A visual observation of the segmentation output reveals the model correctly pointing out tumor areas with distinct margins. The segmentation mask prediction closely resembles the actual tumor areas with the least amount of false detections. On comparing Swin U-Net with U-Net, ResUNet, and Attention U-Net, it can be seen that Swin U-Net performs better than these models because it can extract both local and global image information based on the shifted window attention mechanism. U-Net has a Dice Score of 83.5 percent, whereas ResUNet and Attention U-Net have a marginally better Dice Score of 85.2 percent and 86.8 percent, respectively. But Swin U-Net beats all these models with its impressive 89.5 percent Dice Score, showing its high-level segmentation ability.

The computational efficacy of the model is also investigated and finds that although transformer-based computations are more complex, Swin U-Net is efficient both in training and inference. Though it needs marginally more time for training than U-Net, the inference time makes segmentation of an MRI scan take less than two seconds, thus apt for real-time usage. The model is validated on an NVIDIA RTX 3060 GPU and makes efficient use of about 6GB of VRAM for training.

One of the key observations from the experiments is that the Swin Transformer encoder significantly improves feature extraction, which contributes to better segmentation accuracy. The skip connections within the UNet structure help retain fine details, reducing errors in tumor boundary detection. The model also performs well in both high- contrast and low-contrast MRI scans, making it robust for various real-world medical scenarios. However, a minor limitation is observed in the detection of very small tumors, where the model sometimes struggles, requiring additional fine-tuning or post-processing techniques to improve accuracy. Fig 2 and fig 3 shows the traditional and proposal model.

Model	Accuracy (%)	Dice Score	Jaccard Index
U-Net	85–95	0.85–0.92	0.75–0.85
CNN	75–85	0.70–0.80	0.60–0.75
FCN	80–90	0.78–0.88	0.68–0.80
ResUNet	88–96	0.87–0.94	0.78–0.88

Fig. 2. Traditional Model.

Model	Accuracy (%)	Dice Score	Jaccard Index
Swin U-Net	92–98	0.90–0.96	0.82–0.90

Fig. 3. Proposal Model.

7 Conclusions

Human brain tumor segmentation model using Swin U-NetThe novel architecture of the swin-unet has been implemented in this paper and is used to train a segmentation model for MRI scans, which has proven superior in terms of accuracy compared with traditional architectures for segmenting tumors. Based on Swin Transformer's power to learn both local and global contextual representation, the model not only achieves higher accuracy compared with traditional CNN-based segmentation models (such U-Net) but also better delineates thin tumor boundary.

The higher Dice Similarity Coefficient values which are obtained in the Swin U-Net regarding all test cases show that it is much more stable and reliable about medicine. In addition, high spatial cognition is embedded into the model to accommodate problems of irregular shaped tumors, varied sizes and non-homogeneous intensity distribution. This generality is crucial since brain tumors can look quite different in practice when observed under real medical imaging.

The second major advantage of Swin U-Net model is the fast inference speed, which makes it possible to run in real-time or near-real time. With the combination of good generalization ability, a model can perform similarly in testing process on unseen data as well as during the training process, which is of particular importance when it comes to clinical application.

Consequently, the proposed Swin U-Net-based brain tumor segmentation model provides a prospective way for future CAD systems in neuroimaging. Its accuracy and reliable on tumor segmentation is effective for the early diagnosis as well as treatment planning, patient follow-up, prognosis estimation. In future the next step of research will be on applying this model to more rigorous diagnostic pipelines and further validation through collaborating with clinicians and actual clinical data.

References

[1] Bhat, A., Padasalgi, A. G., A. B., & Prabhakar, A. (2025). AI-driven brain tumor segmentation: Innovations, constraints and the path toward clinical adoption. 2025 International Conference on Computing for Sustainability and Intelligent Future (COMP-SIF), 1–6. https://doi.org/10.1109/COMP-SIF65618.2025.10969924

[2] Boopathy, T., D. K. B., E. E., H. V., & A. A. (2025). A hybrid deep learning approach for brain tumor recognition using CNNs, transformers, and multi-modal MRI data. 2025 7th International Conference on Energy, Power and Environment (ICEPE), 1–6. https://doi.org/10.1109/ICEPE65965.2025.11139705

[3] Kumar, V. P., Pattanaik, S. R., & Sunil Kumar, V. V. (2024). An effective brain tumor segmentation and classification framework using transformer-based Res-Unet++ and ShuffleNetV2. 2024 IEEE 3rd World Conference on Applied Intelligence and Computing (AIC), 777–788. https://doi.org/10.1109/AIC61668.2024.10730845

[4] Kumar, R. R., Gupta, S., Chythanya, K. R., Singh, R., & Mohameed, H. (2025). Advancements in brain tumor segmentation: A comprehensive review of the BraTS challenges. 2025 3rd International Conference on Advancement in Computation & Computer Technologies (InCACCT), 709–714. https://doi.org/10.1109/InCACCT65424.2025.11011433

[5] Fathima, M. N., Singh, P., & Singh, S. (2025). VTAF-ensemble: A hybrid vision transformer and

attention-based learning approach for enhanced brain tumor detection and classification. 2025 International Conference on Intelligent Systems and Computational Networks (ICISCN), 1–6. https://doi.org/10.1109/ICISCN64258.2025.10934306

[6] Tehsin, S., Nasir, I. M., Damasevicius, R., & Maskeliunuas, R. (2024). PLG-SUNetT: Parallel local-global Swin-UNet transformer for brain tumor detection. 2024 5th International Conference on Innovative Computing (ICIC), 1–8. https://doi.org/10.1109/ICIC63915.2024.11116568

[7] Modi, D. R., & S. K. AM. (2024). MRI brain tumor segmentation and classification using different deep learning models. 2024 International Conference on Advances in Data Engineering and Intelligent Computing Systems (ADICS), 1–6. https://doi.org/10.1109/ADICS58448.2024.10533630

[8] Nagib, M. N., Pervez, R., Nova, A. A., Nabil, H. R., Aung, Z., & Mridha, M. F. (2025). TuSegNet: A transformer-based and attention-enhanced architecture for brain tumor segmentation. IEEE Open Journal of the Computer Society, 6, 750–761. https://doi.org/10.1109/OJCS.2025.3569758

[9] Ruberti, A., Capirchio, A., Vilasi, A. D., Torino, C., & Mezzatesta, S. (2024). Image segmentation algorithms for brain tumor detection: A preliminary analysis. 2024 IEEE International Conference on Bioinformatics and Biomedicine (BIBM), 6520–6525. https://doi.org/10.1109/BIBM62325.2024.10822511

[10] Nguyen, T.-Q. T., Nguyen, H.-N., Bui, T.-H., Nguyen-Tat, T. B., & Ngo, V. M. (2024). Brain tumor segmentation in MRI images with 3D U-Net and contextual transformer. 2024 International Conference on Multimedia Analysis and Pattern Recognition (MAPR), 1–6. https://doi.org/10.1109/MAPR63514.2024.10660920

[11] Nambiar, R., & Nanjundegowda, R. (2024). Harnessing medical imaging applications: Survey on 3D deep learning models for image segmentation. 2024 International Conference on Communication, Control, and Intelligent Systems (CCIS), 1–6. https://doi.org/10.1109/CCIS63231.2024.10932049

[12] Sabitha, V., Nayak, J., & Reddy, P. R. (2024). Transformer-enhanced MRI analysis for brain tumor detection with kernel-based PCA and support vector techniques. 2024 2nd International Conference on Recent Trends in Microelectronics, Automation, Computing and Communications Systems (ICMACC), 736–742. https://doi.org/10.1109/ICMACC62921.2024.10894615

[13] Ramamoorthy, H., Ramasundaram, M., Raj, R. S. P., & Randive, K. (2023). TransAttU-Net deep neural network for brain tumor segmentation in magnetic resonance imaging. IEEE Canadian Journal of Electrical and Computer Engineering, 46(4), 298–309. https://doi.org/10.1109/ICJECE.2023.3289609

[14] Verma, V., & Yadav, P. (2024). Enhanced brain tumor segmentation in MRI using SwinSpatialNetwork: Integrating SLAM and ELSA for superior multiscale context analysis. 2024 International Conference on Intelligent Algorithms for Computational Intelligence Systems (IACIS), 1–6. https://doi.org/10.1109/IACIS61494.2024.10721698

[15] Kuang, Z., Yan, Z., Abayazeed, A., Wagner, F., Yu, L., & Reyes, M. (2025). ROXSI: Robust cross-sequence semantic interaction for brain tumor segmentation on multi-sequence MR images. IEEE Journal of Biomedical and Health Informatics, 29(4), 2899–2910. https://doi.org/10.1109/JBHI.2024.3513479