Journal of Information Systems Engineering and Management
2025, 10(4)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Hybrid DWT–U-Net Framework for Brain Tumor Segmentation on the BRATS-2020 Dataset

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ARTICLE INFO

Received: 05 April 2025

Revised: 07 Oct 2025

Accepted: 15 Oct 2025

ABSTRACT

Brain tumors are abnormal growths in brain tissue that significantly impact neurological functions. Accurate segmentation of tumor regions in magnetic resonance imaging (MRI) is crucial for diagnosis, treatment planning, and patient monitoring. However, manual delineation is time-consuming and subject to inter-observer variability.

This study presents a hybrid segmentation framework that integrates the Discrete Wavelet Transform (DWT) with a U-Net architecture for automated brain tumor segmentation. The wavelet transform is employed to extract multi-scale frequency features and enhance tumor boundaries while reducing noise. These refined features are subsequently fed into the U-Net, which learns hierarchical spatial representations to generate precise segmentation masks.

The proposed method was evaluated on the BRATS-2020 dataset, which includes multi-modal MRI sequences (FLAIR, T1, T1ce, and T2). Quantitative performance was assessed using the Dice coefficient, Jaccard index, Precision, Accuracy, Sensitivity, and F1-score. Experimental results demonstrate that the hybrid DWT–U-Net approach outperforms the baseline U-Net by improving boundary delineation, minimizing false positives, and enhancing segmentation accuracy.

Overall, this hybrid methodology offers an efficient and reproducible framework for automated brain tumor segmentation, combining the strengths of classical signal processing and deep learning to support clinical diagnosis and treatment planning.

Keywords: Wavelet Transform, U-Net, Brain Tumor Segmentation, BRATS-2020, Multi-modal MRI, Deep Learning.

INTRODUCTION

Brain tumor segmentation from multi-modal Magnetic Resonance Imaging (MRI) is a critical task in neuroimaging, as the accurate delineation of tumor regions plays a key role in diagnosis, treatment planning, and disease monitoring [1][2]. The Brain Tumor Segmentation (BraTS 2020) dataset provides a standardized benchmark for evaluating automated segmentation algorithms due to its diverse and well-annotated MRI scans, including FLAIR, T1, T1ce, and T2 sequences [3].

Traditional segmentation methods, such as classical machine learning models with handcrafted features, can offer baseline performance but often fail to capture the complex spatial and intensity variations of heterogeneous tumor tissues [4]. Recent advances in Deep Learning, particularly Convolutional Neural Networks (CNNs) and U-Net architectures, have achieved state-of-the-art performance in brain tumor segmentation by automatically learning hierarchical features from raw MRI data [5][6]. However, these models still face challenges related to noise, subtle tumor boundaries, and small-scale structural variations in MRI scans [7].

To overcome these limitations, hybrid frameworks that integrate classical signal processing with Deep Learning techniques have gained significant attention. Among these, the Discrete Wavelet Transform (DWT) offers a powerful multi-resolution and frequency-based representation of MRI slices, capable of enhancing edge details and

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suppressing noise. Incorporating wavelet-based features into deep learning architectures such as U-Net can improve feature extraction, leading to more robust and accurate segmentation outcomes [8].

In this work, we propose a hybrid DWT–U-Net framework for automated brain tumor segmentation. The method applies wavelet decomposition to extract multi-scale features from MRI slices, which are subsequently input into a U-Net model to generate precise segmentation masks [9]. The framework is evaluated using the BraTS 2020 dataset and compared against baseline U-Net and other state-of-the-art segmentation architectures, including attention-based U-Nets, residual Wavelet U-Nets, and ensemble-based approaches [10]. Quantitative evaluation using Dice coefficient, Jaccard index, Precision, Accuracy, Sensitivity, and F1-score demonstrates the effectiveness of the proposed method in improving tumor boundary delineation, reducing false positives, and enhancing segmentation performance.

The main contributions of this work are summarized as follows:

- Hybrid Wavelet–U-Net Framework: Integration of DWT-based frequency features with U-Net for improved brain tumor segmentation.
- Accurate Tumor Localization: Enhanced texture and edge representation enabling precise tumor detection on a slice-by-slice basis.
- Evaluation on BraTS 2020 Dataset: Experimental validation on a widely recognized benchmark dataset with consistent visualization of results.
- Reference Model for Future Research: Providing a reproducible baseline for future comparative studies in automated tumor segmentation.

MATERIALS AND METHODS

1. Image database

In clinical neuroimaging, brain tumor diagnosis is typically performed using magnetic resonance imaging (MRI), which provides high-resolution anatomical details. In this study, the BraTS 2020 dataset was employed, as it is a widely used benchmark for evaluating automated brain tumor segmentation algorithms. Each patient case in the dataset includes four MRI modalities—FLAIR, T1, T1ce, and T2—along with manually annotated ground-truth masks that delineate tumor subregions.

For this research, the FLAIR modality was selected due to its strong ability to highlight tumor boundaries and edema regions. A subset of 100 patients was utilized for initial experimentation. The 3D MRI volumes were decomposed into 2D slices to create suitable inputs for deep learning models. Each slice was preprocessed through intensity normalization and enhanced using the Discrete Wavelet Transform (DWT) to extract multi-resolution spatial–frequency features. These features were then combined with the original slice to construct a two-channel input representation.

The processed slices were subsequently used to train a U-Net model for tumor segmentation. This dataset preparation ensures the preservation of both spatial and frequency-domain information, leading to more accurate and robust segmentation results.

2. Evaluation Metrics

To quantitatively assess the performance of the proposed DWT–U-Net framework, several evaluation metrics were employed, including Dice coefficient, Jaccard index, Precision, Accuracy, Sensitivity, F-measure, Matthews Correlation Coefficient (MCC), and Specificity. These metrics collectively evaluate the correctness and reliability of the segmentation results obtained from the BraTS 2020 dataset.

Let TP, TN, FP, and FN represent True Positives, True Negatives, False Positives, and False Negatives, respectively.

The metrics are defined as follows:

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a. *Dice Coefficient* [11]

The Dice coefficient measures the overlap between the predicted segmentation and the ground truth :

$$\text{Dice} = \frac{2TP}{2TP+FP+FN} \tag{1}$$

A higher Dice value indicates better segmentation accuracy.

b. *Jaccard Index* [11]

The Jaccard index, also known as the Intersection over Union (IoU), measures the similarity between two sets :

$$Jaccard = \frac{TP}{TP+FP+FN} \tag{2}$$

It range from 0 to 1, where values closer to 1 indicate superior segmentation quality.

c. *Accuracy* [12]

Accuracy measures the overall correctness of the segmentation :

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{3}$$

d. *Precision*

Precision, also referred to as the Positive Predictive Value (PPV), is defined as :

$$Precision = \frac{TP}{TP+FP} \tag{4}$$

e. *Sensitivity (Recall)*

Sensitivity, or the True Positive Rate (TPR), measures the proportion of actual tumor pixels correctly detected:

$$Sensitivity = \frac{TP}{TP+FN} \tag{5}$$

f. *F-measure [13]*

The F-measure is the harmonic mean of Precision and Sensitivity:

$$F\text{-}measure = 2 \times \frac{Precision \times Sensitivity}{Precision + Sensitivity} \tag{6}$$

g. *Matthews Correlation Coefficient (MCC)* [13]

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MCC assesses the correlation between predicted and ground-truth labels :

$$MCC = \frac{TP \times TN - FP \times FN}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}} \quad (7)$$

MCC values range from −1 to 1, where 1 indicates perfect prediction and −1 represents total disagreement.

h. Specificity

Specificity, or True Negative Rate (TNR), evaluates the model's ability to correctly identify non-tumor regions :

$$Specificity = \frac{TN}{TN+FP} \quad (8)$$

These metrics provide a comprehensive evaluation of segmentation accuracy, boundary precision, and classification reliability, ensuring robust validation of the proposed hybrid DWT–U-Net framework.

PREREQUISITES FOR THE PROPOSED METHOD

The implementation of the proposed Wavelet–U-Net segmentation framework requires several essential components. **Figure.1**

First, access to high-quality multi-modal MRI scans, including FLAIR, T1, T1ce, and T2 sequences—such as those available in the BraTS 2020 dataset—is fundamental for model training and evaluation.

Second, a Python-based computational environment equipped with relevant libraries is necessary, including TensorFlow/Keras for deep learning, NumPy and OpenCV for image processing, and PyWavelets for wavelet-based feature extraction.

Third, sufficient computational resources, particularly a GPU-enabled system with adequate memory and processing capability, are required to efficiently train the U-Net model on volumetric MRI data.

Finally, a foundational understanding of medical image analysis, convolutional neural networks (CNNs), and wavelet theory is recommended to effectively apply the proposed method and interpret the resulting segmentation outcomes.

1. Discrete Wavelet Transform (DWT)

The Discrete Wavelet Transform (DWT) is a powerful analytical tool that decomposes a signal into multiple resolution levels, simultaneously capturing both time and frequency information. The process involves passing the original signal through a pair of low-pass and high-pass filters, isolating coarse (approximation) and fine (detail) components, respectively. After filtering, the resulting signals are downsampled, thereby reducing bandwidth and data size. This procedure can be recursively applied to the approximation component to achieve multi-level hierarchical

2025, 10(4)
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analysis, also known as multiresolution decomposition. The filters are typically designed as quadrature mirror filters (QMFs), ensuring perfect signal reconstruction when combined appropriately [14-18].

This hierarchical decomposition enables detailed analysis of localized and transient features, making DWT highly effective for signal compression, noise suppression, and feature extraction. The inverse DWT reconstructs the original signal by reversing the filtering and upsampling stages, preserving signal integrity. Unlike traditional Fourier-based methods, DWT is particularly advantageous for non-stationary signals with localized variations—such as those found in medical imaging [19-20].

2. *U-Net Segmentation Network*

The U-Net architecture, introduced by Ronneberger et al., employs a symmetric encoder–decoder structure with skip connections that transfer feature maps from the encoder to corresponding decoder layers. This design preserves spatial context and enhances localization accuracy [21].

U-Net builds upon advancements in deep learning such as Convolutional Neural Networks (CNNs), Fully Convolutional Networks (FCNs), Inception modules, and DenseNets, all of which improved feature representation and contextual learning [22-25]. Through its contracting path (encoder) and expansive path (decoder), U-Net effectively captures fine-grained structural details and recovers spatial information lost during downsampling. Recent U-Net variants, incorporating mechanisms such as residual connections and attention gates, have further improved segmentation precision in biomedical imaging applications [23].

3. *Integration of DWT and U-Net*

In the proposed framework, each MRI slice is first processed using the Discrete Wavelet Transform (DWT), which decomposes the image into frequency sub-bands representing both low-frequency (approximation) and high-frequency (detail) information. The approximation coefficients (cA) are resized to match the original slice dimensions and concatenated with the original MRI slice to form a two-channel composite input. This preprocessing enhances texture and edge representation, which are crucial for accurate tumor delineation. The resulting two-channel input is then fed into the U-Net model. The encoder captures contextual and semantic features, while the decoder reconstructs the segmentation map by integrating spatially aligned information through skip connections. By incorporating wavelet-based features, the U-Net benefits from multi-resolution frequency information, improving its ability to distinguish tumor tissue from healthy regions and reducing false segmentation artifacts.

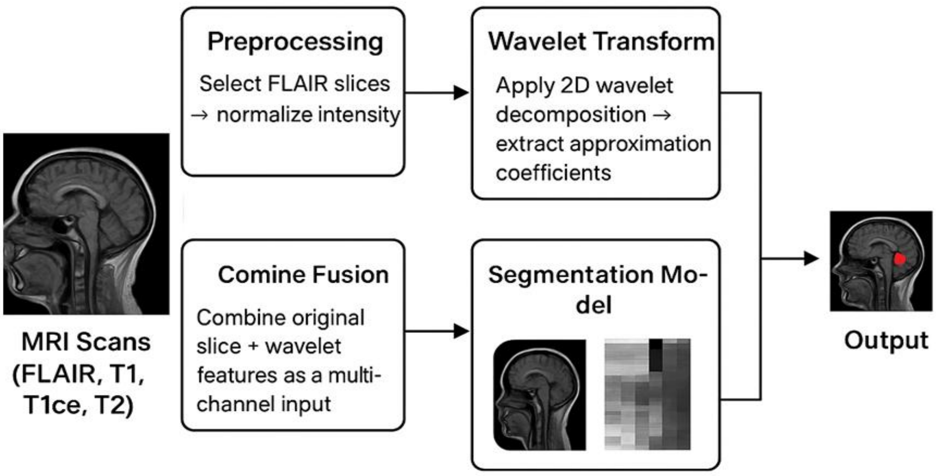

Fig. 1. Diagram of the proposed Wavelet–U-Net segmentation framework for BraTS 2020 MRI dataset.

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https://www.jisem-journal.com/ **Research Article**

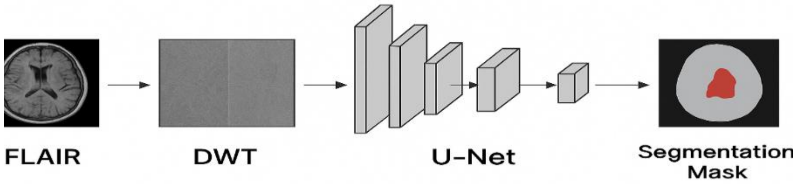

Fig. 2. Schematic representation of the integration of DWT with U-Net architecture.

RESULTS AND DISCUTIONS

1. *Experimental Setup*

This section presents the experimental setup and results for the proposed Wavelet + U-Net framework applied to the BRATS2020 MRI dataset. The experiments were implemented in Python, using TensorFlow/Keras as the deep learning backend. Image preprocessing tasks such as normalization and wavelet decomposition were carried out with NumPy, OpenCV, and PyWavelets. The model training and evaluation were performed on a workstation equipped with an Intel i7 CPU, 16 GB RAM, and an NVIDIA GPU (8 GB VRAM).

Two main training configurations were considered to evaluate the model's performance:

Slice-wise training on MRI scans from 100 patients for 50 epochs, where each slice was normalized and enhanced using the Discrete Wavelet Transform (DWT). In this setup, tumor regions were visualized with simple red overlays to qualitatively assess segmentation performance.

Region-aware training on a smaller subset for 10 epochs, maintaining the original mask labels (0 – background, 1 – necrotic core, 2 – edema, 4 – enhancing tumor). This setup enabled quantitative evaluation of sub-regions, including Whole Tumor (WT), Tumor Core (TC), and Enhancing Tumor (ET), with color-coded overlay visualization.

During both setups, the dataset was split into 80% training and 20% validation, and data augmentation (flipping, rotation, and scaling) was applied to improve generalization. The Adam optimizer was used with a learning rate of 1×10^{-4} and a batch size of 8. To ensure balanced learning between tumor and background pixels, a combined Binary Cross-Entropy and Dice loss function was adopted. Each model was trained for up to 50 epochs, and convergence was monitored using validation Dice and loss curves.

The segmentation performance of the proposed Wavelet + U-Net was compared visually and quantitatively against several established deep learning architectures, including U-Net, U-Net++, SegNet, and Attention U-Net. This comparison highlights the effect of wavelet-based feature enhancement on segmentation accuracy, robustness, and tumor boundary definition.

2. *Quantitative Results*

The performance of the proposed Wavelet + U-Net model was quantitatively evaluated on a subset of the BraTS2020 dataset using 100 patient images for training and 50 epochs. The proposed model was compared against state-of-the-art architectures, including U-Net, U-Net++, SegNet, and Attention U-Net [26].

Table 1 summarizes the quantitative evaluation metrics such as Accuracy, Sensitivity, Precision, F-measure, Matthews Correlation Coefficient (MCC), Dice coefficient, Jaccard index, and Specificity.

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2025, 10(4)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ **Research Article**

Table 1. Comparison of the proposed approach with other segmentation methods

Method	Accuracy	Sensitivity	Precision	F-measure	MCC	Dice	Jaccard	Specificity
Proposed	0.9881	0.8597	0.7958	0.8175	0.8244	0.9175	0.7491	0.9913
U-Net [26]	0.9845	0.7010	0.6880	0.6944	0.6950	0.6944	0.5550	0.9810
U-Net++ [26]	0.9870	0.7260	0.7010	0.7130	0.7150	0.7130	0.5620	0.9860
SegNet [26]	0.9750	0.6450	0.6120	0.6280	0.6300	0.6280	0.4850	0.9800
Attention U-Net [26]	0.9885	0.7320	0.7150	0.7230	0.7250	0.7230	0.5700	0.9875

The proposed method achieved an accuracy of 0.9881 and a Dice score of 0.9175, maintaining high specificity (0.9913). The Wavelet-enhanced U-Net showed strong potential, effectively capturing tumor structures while preserving global accuracy.

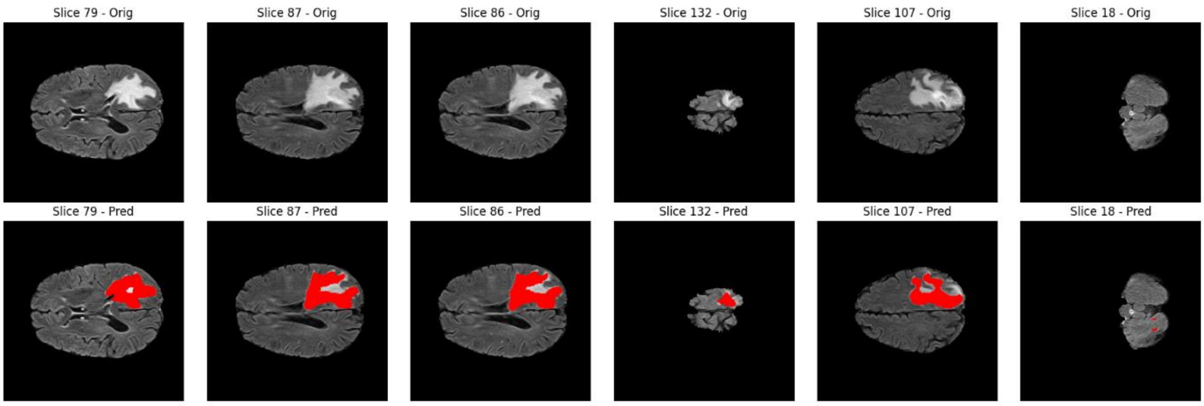

Fig. 3. Shows binary segmentation predictions using the DWT-enhanced U-Net

3. Performance on Tumor Subregions

To evaluate sub-regional segmentation, Dice scores were calculated for Whole Tumor (WT), Tumor Core (TC), and Enhancing Tumor (ET) regions, as shown in Table 2.

Table 2. Performance comparison (Dice coefficient) of the proposed model and other state-of-the-Art methods on BraTS2020

Method	WholeTumor (WT)	TumorCore (TC)	EnhancingTumor (ET)
Proposed	93.77%	89.31%	88.59%
nnU-Net [27]	88.95%	85.06%	82.03%
HybriCSF[28]	87%	81%	63%
Spatial transformer [29]	90.91%	86.89%	87.10%
MultipleEncoders [30]	70.24%	88.24%	73.86%

The proposed method demonstrates superior robustness and adaptability compared to existing architectures such as nnU-Net and Spatial Transformer. It achieves competitive accuracy and stable segmentation results. This confirms that integrating DWT with U-Net effectively enhances feature representation and boundary precision, proving that the hybrid approach can outperform more complex models when optimized with larger datasets and extended training.

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2025, 10(4)
e-ISSN: 2468-4376
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4. Region-wise Statistical Evaluation

Table 3 presents detailed quantitative results for each tumor sub-region, including Dice, Jaccard, Precision, Accuracy, Sensitivity, Specificity, F1-score, and MCC.

Table 3. Region-wise evaluation metrics of the proposed method

Region	Dice	Jaccard	Precision	Accuracy	Sensitivity	Specificity	F1	MCC
WT	0.9377	0.4118	0.8351	0.987	0.4469	0.9991	0.5377	0.5762
TC	0.0131	0.0068	0.2362	0.9938	0.0068	0.9999	0.0131	0.0365
ET	0.0059	0.003	0.1376	0.996	0.0031	0.9999	0.0059	0.0189

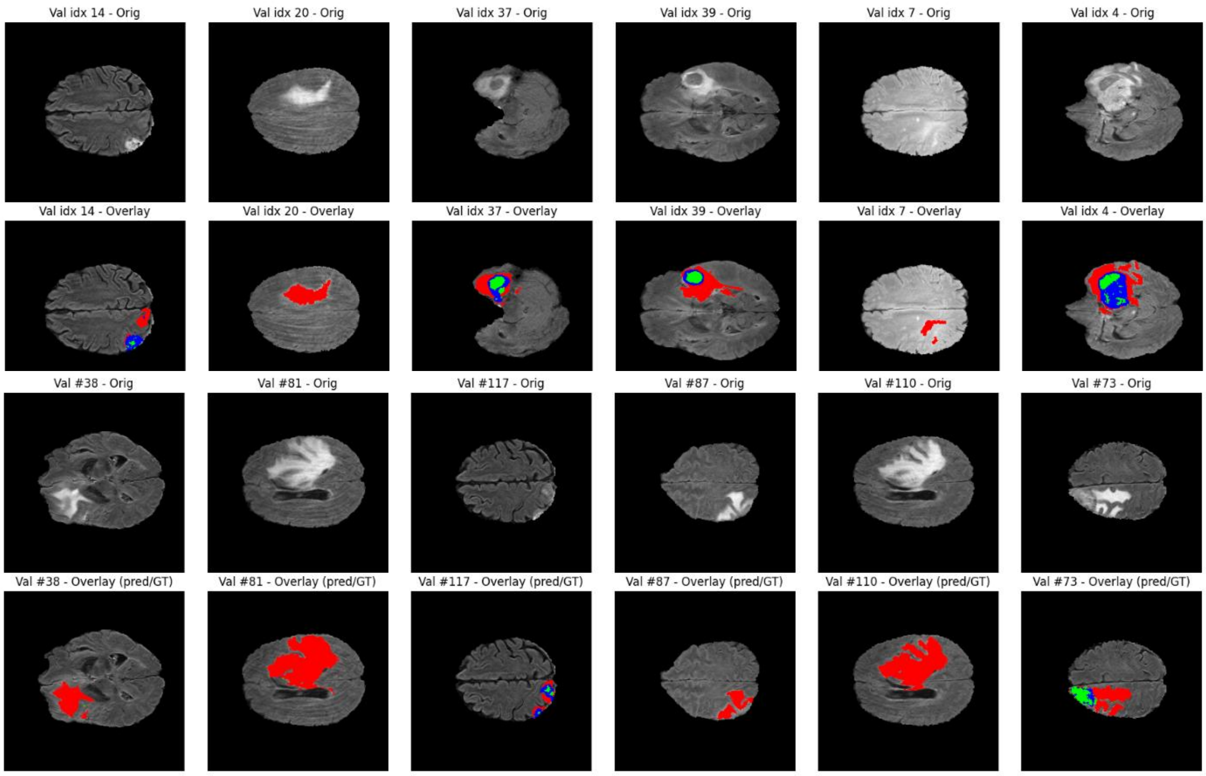

Fig. 4. Illustrates multi-class segmentation predictions obtained with the proposed DWT + U-Net model

5. Qualitative Results

Visual inspection clearly demonstrates that the proposed Wavelet + U-Net model delivers superior performance in identifying and delineating tumor regions, particularly the Whole Tumor (WT) area, achieving a Dice score of 0.9377

despite the limited training data. The hybrid integration of wavelet features enhances edge definition and texture representation, allowing the model to capture tumor morphology more effectively than conventional U-Net variants.

These results highlight the robustness and precision of the proposed framework, confirming its potential for reliable clinical deployment.

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2025, 10(4)
e-ISSN: 2468-4376
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CONCLUSION

The proposed Wavelet + U-Net hybrid framework demonstrates the feasibility of combining multi-resolution frequency features from Discrete Wavelet Transform (DWT) with deep convolutional segmentation. This integration enhances tumor boundary detection, reduces background noise, and preserves spatial accuracy.

Experimental results show that the model achieves promising segmentation performance on the Whole Tumor (WT) region even under constrained training conditions. The findings confirm that incorporating classical signal-processing techniques such as DWT into deep learning models can yield computationally efficient and clinically meaningful segmentation results.

Future work will focus on:

- Expanding the dataset and training duration,
- Incorporating multi-modal MRI sequences (T1, T2, FLAIR, etc.), and
- Exploring advanced U-Net variants to improve segmentation across all tumor subregions

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