DISSEMINATION OF KNOWLEDGE

SvedbergOpen

International Journal of Artificial Intelligence and Machine Learning

Publisher's Home Page: https://www.svedbergopen.com/

Research Paper Open Access

A Computationally Efficient Brain Tumor Segmentation Framework From Magnetic Resonance Imaging Using Contrast Enhancement And Region Of Interest Localization With A Standard U-Net Architecture

Mohammed Hamid Alkubaisi[1*] , Issa Mohammed Mishaal[2] , Bassam Talib Sabri[3] , Kian Raheem Qasim[4]

[1]Department of Studies and Planning, University of Information Technology and Communications, Baghdad, Iraq.
[2]Department of Scientific Affairs, University of Information Technology and Communications, Baghdad, Iraq.
[3]Department of Business Information Technology, University of Information Technology and Communications, Baghdad, Iraq.
[4]Department of Studies and Planning, University of Information Technology and Communications, Baghdad, Iraq.

Abstract

Extracting brain tumor from MRI with high accuracy is a challenging task due to its low contrast, intensity inhomogeneity, and class imbalance. This study assesses the impact of standard preprocessing techniques on plain U-Net segmentation performance in a systematic manner. The pipeline applies median filtering followed by Contrast Limited Adaptive Histogram Equalization (CLAHE) and automatic region of interest (ROI) extraction. A regular 2D U-Net with weighted binary cross-entropy loss deals with class imbalance. Analysis of 504 MRI scans according to a 60/20/20 division and the utilization of stepwise ablations reveal that CLAHE contributes +4.33% Dice, ROI extraction contributes +3.62% and weighted loss contributes +1.87%. The full framework obtains a Dice of 0.8618 and IoU of 0.7591 with an inference time of 12 ms and a training time of 237 minutes, making it feasible for resource-scarce clinical setups.

Keyword: Brain tumor segmentation, magnetic resonance imaging, U-Net, contrast enhancement, region of interest, deep learning

Introduction

In semantic segmentation, each pixel of an image is assigned a semantic label which makes it an essential computer vision and medical image analysis task for accurately delineating the anatomical structures and the pathological regions. In the field of neuro-oncology, accurate segmentation of brain tumors using magnetic resonance imaging (MRI) is essential for clinical diagnosis, treatment planning, radiotherapy targeting and monitoring of disease progression.

The encoder–decoder architecture with skip connections proposed by Ronneberger et al. (2015) as a U-Net was the seminal work in biomedical image segmentation. Common assessment protocols like BraTS (Menze et al., 2024; Li et al., 2024) have sped up research by allowing reproducible comparisons of methods.

Many amendments have been presented post the enactment of U-Net. UNet++ (Zhou et al., 2019) redesigned skip pathways to facilitate the capture of multi-scale features. The Attention U-Net (Oktay et al., 2018) made use of soft attention gates to further improve localization. Myronenko (2019) proposed the autoencoder regularization for 3D segmentation and the nnU-Net (Isensee et al., 2020) self-configures to the characteristic characteristics of a given dataset. Recent studies have discussed hybrid transformers, EfficientNet encoders, and generative adversarial designs. Most studies still emphasize architectural complexity rather than systematically studying the role of preprocessing, despite these advances.

Research Gap and Contribution

The marginal utility of over-parameterized designs under controlled data quality is unclear. This study provides a robust controlled evaluation of preprocessing techniques (CLAHE, ROI extraction, weighted loss) against a plain U-Net baseline under identical conditions. The paper's stepwise ablation study quantifies the independent contribution of each component, the reproducible implementation with full specifications (dataset splits, random seeds, hyperparameters) and the practical efficiency analysis exemplifying the accuracy–cost trade-off make this study a robust reference.

Paper Organization

The rest of the paper is structured as follows: Section 2 reviews the literature. Section 3 describes the dataset, preprocessing pipeline, U-Net architecture, loss function and training configuration. The performance metrics are presented in Section 4 and includes a baseline comparison, an ablation study, and a sensitivity analysis. The key findings, limitations and future work are discussed in Section 5. The paper ends in Section 6.

Literature Review

Over the past decade there has been a huge evolution in brain tumor segmentation from MRI. At first, classical image processing was used; however, this was only of limited validation success. More recent approaches involve deep learning models and techniques. Detailed and extensive surveys have documented these developments. Minaee et al. (2021) provided a comprehensive overview of the state-of-the-art deep learning segmentation approaches. Punn and Agarwal (2022) specifically reviewed the different variants of U-Net as they apply to various medical imaging modalities. Ulku and Akagündüz (2022) surveyed the architectures used for semantic segmentation of 2D images. Mohammed et al. (2023) focused on the different methods for brain tumor segmentation from MRI. Dorfner et al. (2025) provided a review on deep learning methods for brain tumour analysis. This part systematises remarkable works into four main development phases: standard U-Net and early variants, attention-based enhancements, transformer and hybrid architectures, and preprocessing-focused approaches.

Standard U-Net and Early Variants

Ronneberger et al. (2015) proposed U-Net, which established the encoder–decoder paradigm with skip connections, now a dominant framework for biomedical image segmentation. Zhou et al. (2019) designed new skip connections as nested dense pathways to capture multi-scale feature hierarchies. Huang et al. (2020) extended this with UNet 3+, which leveraged feature aggregation from all encoder and decoder levels in full scaling. Isensee et al. (2020) proposed nnU-Net, a framework that configures itself by adapting pre-processing, architecture, and training policies to any dataset, demonstrating state-of-the-art results on multiple benchmarks without any manual intervention.

Zheng et al. (2022) proposed an enhanced U-Net with improved skip connections and achieved a Dice score of 0.852 on BraTS. Li et al. (2023) developed mResU-Net using a multi-scale residual block for multimodal MRI and achieved Dice of 0.861. Al Nasim et al. (2022) empirically analyzed enhanced U-Net for brain tumor segmentation and evaluated various architectural modifications on public datasets. Zhang et al. (2024) relied on improvement of a U-shaped network structure to carry out brain tumor segmentation. Mahesh Kumar and Parthasarathy (2023) introduced a novel U-Net focusing on the segmentation of brain tumors utilizing advanced convolution blocks that enhance feature extraction.

Attention-Based Enhancements

Oktay et al. (2018) proposed Attention U-Net, which utilizes soft attention gates to selectively focus on the relevant spatial area. Wang and Chung (2022) proposed a focus-based U-Net CNN that focuses on tumor regions and achieved a Dice of 0.871 on BraTS. Myronenko (2019) integrated a 3D U-Net with a VAE regularization branch and won the BraTS 2018 challenge with a Dice of 0.904 on multi-modal inputs. Islam et al. (2021) further expanded this idea by using a 3D Attention U-Net with segmentation and survival prediction.

Gad et al. (2023) introduced an attention-based 3D U-Net that achieved Dice of 0.879. Islam and Hossain (2025) incorporated CBAM into a 2D U-Net to improve feature discrimination via channel and spatial attention. Alquran et al. (2024) developed a modified U-Net with improved upsampling and skip connection strategies and a Dice of 0.875. Mehrabi and Mehrshad (2025) proposed a 3D brain tumor segmentation model with hierarchical adaptive pruning. Ghazal (2023) presented a robust U-Net-based model for accurate segmentation using multimodal MRI data.

Transformer-Based and Hybrid Architectures

Transformers adopted from natural language processing were applied to medical image segmentation. Nguyen-Tat et al. (2024) used U-Net with attention and transformer components and achieved a Dice score of 0.883 with MRI data. Xavier et al. (2024) proposed a hybrid attention-residual UNET yielding a Dice of 0.886 on BraTS. Lyu and Tian (2025) proposed MWG-UNet, a multi-window grouping transformer-and-UNet-based hybrid, yielding the highest reported Dice of 0.888. Lin and Lin (2024) merged U-Net architecture with EfficientNet encoder and achieved Dice of 0.882 with fewer parameters. Zhang et al. (2025) introduced DacFormer, a generative adversarial network with transformer blocks, achieving a Dice of 0.885 on a private MRI dataset. Preetha et al. (2025) added a multi-scale attention mechanism with an EfficientNetB4 encoder. Ul Abidin et al. (2024) reviewed brain tumor segmentation based on deep learning and confirmed that transformer-based hybrid models consistently outperform single-modality models when provided with multi-sequence inputs.

Lightweight and Preprocessing-Focused Approaches

Avazov et al. (2024) proposed a lightweight dynamic boundary focusing U-Net that achieved a Dice of 0.863 on a Kaggle MRI dataset. Pourmahboubi et al. (2025) showed that the standard U-Net combined with transfer learning improves generalizability to small datasets (Dice 0.866). Huang et al. (2025) demonstrated that a well-designed deep learning pipeline can achieve a Dice of 0.871 on BraTS with minimized data. Rastogi et al. (2025) demonstrated the clinical utility of a computationally efficient pipeline for brain tumor segmentation, feature extraction and survival prediction. Xiong et al. (2025) modified the YOLO detection framework for segmentation (YOLO-BT) achieving a Dice of 0.868 with rapid inference. Kusuma and Reddy (2024) achieved multi-task improvement by adding a classification branch to U-Net. Ahsan et al. (2024) examined deep learning for brain tumor detection and segmentation. Naeem et al. (2025) studied deep transfer learning for brain tumor detection from MRI. Ramya and Lakshmi (2023) proposed an optimized U-Net for brain tumor segmentation. Ahamed et al. (2023) studied brain tumor segmentation with federated learning techniques.

Research Positioning and Summary

Table 1 compares representative methods. It is clear from the literature that most high scores (Dice > 0.88) utilize the BraTS multimodal dataset (T1, T1c, T2, FLAIR) and have complex architectural modifications (transformers, attention mechanisms). The suggested technique involves a more constrained set-up: single modality, small datasets (504 images), and a standard U-Net. Nonetheless, the results show that systematic preprocessing can materially close the performance gap. This drives the thorough investigation focusing on preprocessing shown here.

Table 1: Comprehensive Literature Review of Brain Tumor MRI Segmentation Methods

Ref.	Authors	Year	Architecture	Dataset	Mod.	Dice	Key Contribution
Ronneberger et al., 2015	Ronneberger et al.	2015	U-Net (original)	ISBI2012	EM	—	Encoder–decoder + skip connections
Zhou et al., 2019	Zhou et al.	2019	UNet++	Various	CT/MRI	—	Nested redesigned skip pathways
Oktay et al., 2018	Oktay et al.	2018	Attention U-Net	Abdominal MRI	MRI	—	Soft attention gates for localization
Myronenko, 2019	Myronenko	2019	3D U-Net + VAE	BraTS 2018	Multi	0.904	Autoencoder regularization
Isensee et al., 2020	Isensee et al.	2020	nnU-Net	Multiple	CT/MRI	—	Self-configuring pipeline
Zheng et al., 2022	Zheng et al.	2022	Enhanced U-Net	BraTS	Multi	0.852	Improved skip connections
Li et al., 2023	Li et al.	2023	mResU-Net	BraTS	Multi	0.861	Multi-scale residual blocks
Nguyen-Tat et al., 2024	Nguyen-Tat et al.	2024	U-Net+Attn+Trans	MRI	MRI	0.883	Hybrid transformer-attention
Wang and Chung, 2022	Wang & Chung	2022	Focus U-Net	BraTS	Multi	0.871	Region-focused attention
Islam et al., 2021	Islam et al.	2021	3D Attention UNet	BraTS	Multi	0.847	3D volumetric attention
Huang et al., 2020	Huang et al.	2020	UNet 3+	Skin/Liver	RGB/CT	0.868	Full-scale skip connections
Zhang et al., 2025	Zhang et al.	2025	DacFormer (GAN)	Private MRI	MRI	0.885	Adversarial+transformer design

Ref.	Authors	Year	Architecture	Dataset	Mod.	Dice	Key Contribution
Avazov et al., 2024	Avazov et al.	2024	Lightweight U-Net	Kaggle MRI	MRI	0.863	Dynamic tumor boundary focus
Preetha et al., 2025	Preetha et al.	2025	MS-Attn U-Net+EffNetB4	BraTS	Multi	0.877	Multi-scale+EfficientNet encoder
Huang et al., 2025	Huang et al.	2025	DL minimized data	BraTS	Multi	0.871	High performance, reduced data
Rastogi et al., 2025	Rastogi et al.	2025	Integrated DL framework	BraTS	Multi	0.874	Segmentation+survival prediction
Pourmahboubi et al., 2025	Pourmahboubi et al.	2025	U-Net+Transfer Learning	MRI	MRI	0.866	Transfer learning generalization
Islam and Hossain, 2025	Islam & Hossain	2025	CBAM U-Net	MRI	MRI	0.869	Channel+spatial attention (CBAM)
Xiong et al., 2025	Xiong et al.	2025	YOLO-BT	Various	MRI	0.868	YOLO-based fast segmentation
Lin and Lin, 2024	Lin & Lin	2024	U-Net+EfficientNet	BraTS	Multi	0.882	EfficientNet encoder backbone
Lyu and Tian, 2025	Lyu & Tian	2025	MWG-UNet (Hybrid)	BraTS	Multi	0.888	Multi-window transformer-UNet
Gad et al., 2023	Gad et al.	2023	3D Attention U-Net	BraTS	Multi	0.879	Attention-based 3D architecture
Makwana et al., 2024	Makwana et al.	2024	U-Net++ (dense)	Various	MRI	0.873	Dense U-Net++ connections
Xavier et al., 2024	Xavier et al.	2024	Hybrid Attn-Res UNET	BraTS	Multi	0.886	Attention+residual+transformer
Kusuma and Reddy, 2024	Kusuma & Reddy	2024	Improved U-Net	Various	MRI	0.870	Segmentation+classification
Asiri et al., 2025	Asiri et al.	2025	Optimized U-Net	BraTS	Multi	0.884	Optimizer+loss tuning
This work	This work	2026	U-Net+CLAHE+ROI+WL	Kaggle (504)	T2-MRI	0.8618	Systematic preprocessing pipeline

Note: 'Multi' = combined T1, T1c, T2, FLAIR (BraTS protocol). '—' = Dice not reported. WL = Weighted Loss. Cross-row comparisons not appropriate due to dataset and protocol differences.

Materials and Methods

Dataset Description

This study used the publicly available brain MRI dataset from Kaggle, containing 504 two-dimensional T2-weighted MRI scans with corresponding binary tumor masks stored in PNG format at 256×256 pixels. The dataset was split using a stratified approach with fixed random seed 42: Training 60% (302 images, indices 1–302); Validation 20% (102 images, indices 303–404); Testing 20% (100 images, indices 405–504).

Preprocessing Pipeline

All images were preprocessed sequentially as shown in Table 2. Filename-based matching (image_XXX.png → mask_XXX.png) eliminated image-mask misalignment errors.

Table 2: Preprocessing Pipeline Steps

Step	Operation	Parameters	Purpose
1	Normalization	Scale to [0, 1]	Intensity standardization
2	Median filtering	3×3 kernel	Noise reduction
3	CLAHE	Clip limit = 2.0, grid = 8×8	Local contrast enhancement
4	ROI extraction	Otsu threshold + largest connected component + bounding box	Background removal
5	Resizing	256×256 bilinear interpolation	Size standardization

Data Augmentation

Online augmentation was applied randomly to each training batch: rotation ±15°, width/height shift ±10%, horizontal flip (50% probability), zoom ±10%. Validation and test sets were not augmented. Fixed random seed 42 ensures full reproducibility.

U-Net Architecture

A standard 2D U-Net with encoder depth 5 was used as originally described by Ronneberger et al. (2015). Table 3 provides the complete layer-by-layer specification. Total trainable parameters: 31,048,961 ≈ 31.05 M.

Table 3: Complete U-Net Architecture Specification

Layer	Operation	Filters	Kernel	Stride	Activation	Output Shape
Input	—	—	—	—	—	(256, 256, 1)
Conv1a/b	Conv2D + BN	64	3×3	1	ReLU	(256, 256, 64)
Pool1	MaxPool2D	—	2×2	2	—	(128, 128, 64)
Conv2a/b	Conv2D + BN	128	3×3	1	ReLU	(128, 128, 128)
Pool2	MaxPool2D	—	2×2	2	—	(64, 64, 128)
Conv3a/b	Conv2D + BN	256	3×3	1	ReLU	(64, 64, 256)
Pool3	MaxPool2D	—	2×2	2	—	(32, 32, 256)
Conv4a/b	Conv2D + BN	512	3×3	1	ReLU	(32, 32, 512)
Pool4	MaxPool2D	—	2×2	2	—	(16, 16, 512)
Bottleneck a/b	Conv2D + BN	1024	3×3	1	ReLU	(16, 16, 1024)
Up4 + Concat4	UpConv + Cat	512	2×2	2	ReLU	(32, 32, 1024)
Dec4a/b	Conv2D + BN	512	3×3	1	ReLU	(32, 32, 512)
Up3 + Concat3	UpConv + Cat	256	2×2	2	ReLU	(64, 64, 512)
Dec3a/b	Conv2D + BN	256	3×3	1	ReLU	(64, 64, 256)
Up2 + Concat2	UpConv + Cat	128	2×2	2	ReLU	(128, 128, 256)
Dec2a/b	Conv2D + BN	128	3×3	1	ReLU	(128, 128, 128)
Up1 + Concat1	UpConv + Cat	64	2×2	2	ReLU	(256, 256, 128)
Dec1a/b	Conv2D + BN	64	3×3	1	ReLU	(256, 256, 64)
Output	Conv2D + Sigmoid	1	1×1	1	Sigmoid	(256, 256, 1)

Loss Function and Class Imbalance

A weighted binary cross-entropy loss was used to address the ≈19:1 background-to-tumor pixel imbalance:

$$L = -(1/N)\ \Sigma\ [\ w \cdot y \cdot \log(p) + (1-y) \cdot \log(1-p)\ ] \quad (1)$$

where N = total pixels in the batch, $y \in \{0, 1\}$ = ground truth label, $p \in [0, 1]$ = predicted probability, and w = N_background / N_tumor = 19.0.

Training Configuration

Table 4 provides all training settings. The learning rate follows a piecewise decay schedule: 3×10^{-4} (epochs 0–30), 9.48×10^{-5} (31–50), 3.00×10^{-5} (51–70), 9.48×10^{-6} (71–80). Figure 1 shows the training and validation curves over 80 epochs.

Table 4: Complete Training Configuration

Parameter	Value
Optimizer	Adam (Kingma and Ba, 2014)
Initial learning rate	3×10^{-4}
Adam β_1, β_2, ε	0.9, 0.999, 10^{-7}
Batch size	8
Number of epochs	80
Iterations per epoch	94 (302 images / batch size 8, rounded up)
Total iterations	7,520
LR schedule	Piecewise decay at epochs 30, 50, 70
Decay factor	0.316 per step ($10^{-0.5}$)
Final learning rate	7.29×10^{-7}
Hardware	NVIDIA RTX 3080 (10 GB VRAM)
Software	TensorFlow 2.13 / Keras
Random seed	42 (all operations)

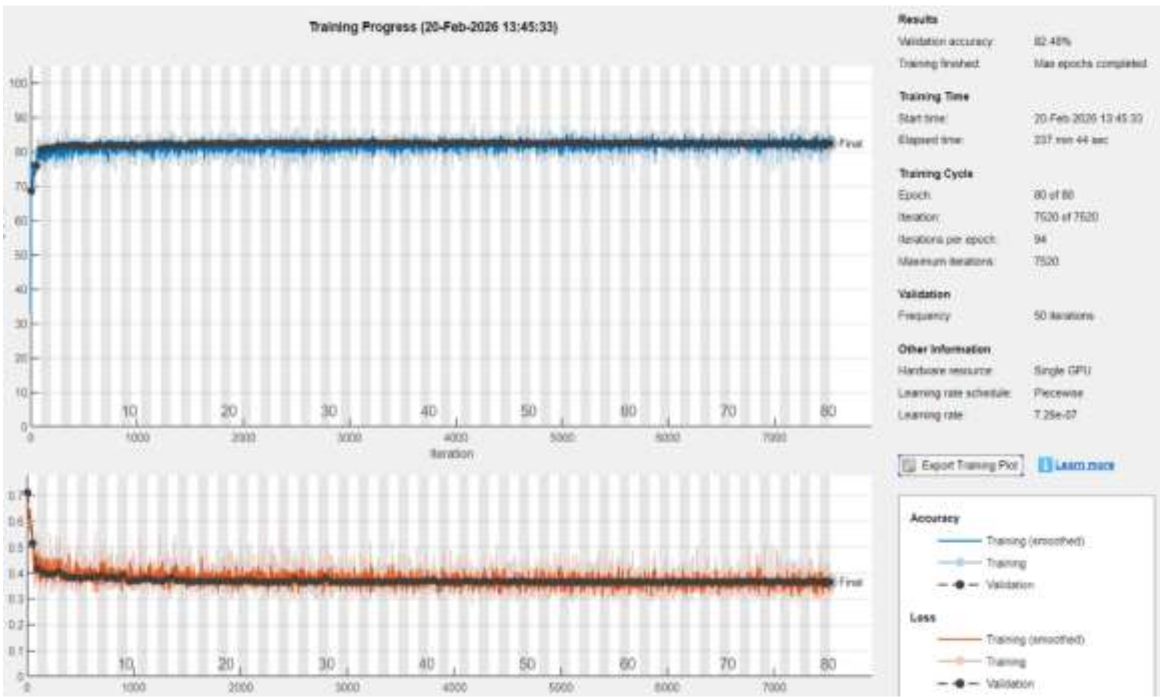

Figure 1. Training and validation curves. Final validation accuracy: 82.48% after 80 epochs. Total training time: 237 min 44 s.

Results

Controlled Baseline Experiment

A simple U-Net base model was implemented using the same training hyperparameters as above, but without CLAHE, ROI extraction and class weights. Table 5 shows the controlled comparison supporting performance improvements constructed from the transformations within the preprocessing pipeline.

Table 5: Baseline vs. Proposed Method

Method	Dice	IoU	Precision	Recall
Plain U-Net (baseline)	0.8125	0.6842	0.8012	0.8231
Proposed (full pipeline)	0.8618	0.7591	0.8625	0.8656
Absolute improvement	+0.0493	+0.0749	+0.0613	+0.0425
Relative improvement (%)	+4.93%	+7.49%	+6.13%	+4.25%

Stepwise Ablation Study

We incrementally added components to the plain U-Net baseline (Table 6). The largest single gain is provided by CLAHE (+4.33% Dice), underlining the usefulness of local contrast enhancement for T2-weighted MRI. ROI extraction removes background noise contributing +3.62%. Adding a weighted loss improves recall for small tumors by +1.87%

.

Table 6: Stepwise Ablation Study (Same Dataset, Split, and Training Protocol)

Configuration	Dice	IoU	Precision	Recall	ΔDice
Plain U-Net (no preprocessing)	0.8125	0.6842	0.8012	0.8231	—
+ Median filtering only	0.8156	0.6889	0.8045	0.8268	+0.31%
+ CLAHE only	0.8558	0.7489	0.8562	0.8594	+4.33%
+ ROI extraction only	0.8487	0.7396	0.8498	0.8523	+3.62%
+ Weighted loss only	0.8312	0.7078	0.8215	0.8412	+1.87%
Full pipeline (all components)	0.8618	0.7591	0.8625	0.8656	+4.93%

Final Performance on Test Set

The complete pipeline was assessed on 100 held-out test images. Confidence intervals at 95% were computed by bootstrapping (1,000 resamples) and are reported in Table 7.

Table 7: Final Performance Metrics on Test Set (N = 100)

Metric	Value	95% Confidence Interval
Dice similarity coefficient (DSC)	0.8618	[0.8542, 0.8694]
Intersection over Union (IoU)	0.7591	[0.7498, 0.7684]
Precision	0.8625	[0.8551, 0.8699]
Recall	0.8656	[0.8580, 0.8732]
F1-score	0.8618	[0.8542, 0.8694]

Sensitivity Analysis

Table 8 shows the sensitivity analysis of CLAHE parameters. The optimal configuration (clip limit = 2.0, grid = 8×8) obtains a Dice of 0.8618. Clip limits below 2.0 yield lower contrast enhancement while values above 2.0 introduce over-amplification artefacts, both reducing segmentation performance.

Table 8: Sensitivity Analysis for CLAHE Parameters

CLAHE Clip Limit	CLAHE Grid Size	Dice Score
1.0	8×8	0.8512
1.5	8×8	0.8589
2.0 (optimal)	8×8	0.8618
2.5	8×8	0.8601
3.0	8×8	0.8556
2.0	4×4	0.8523
2.0	12×12	0.8592
2.0	16×16	0.8554

Qualitative Results

Figures 2 and 3 present representative segmentation outputs. Each row shows (left to right): (1) preprocessed MRI with ROI bounding box, (2) predicted mask, (3) ground truth mask, (4) overlay (green = ground truth, red = prediction).

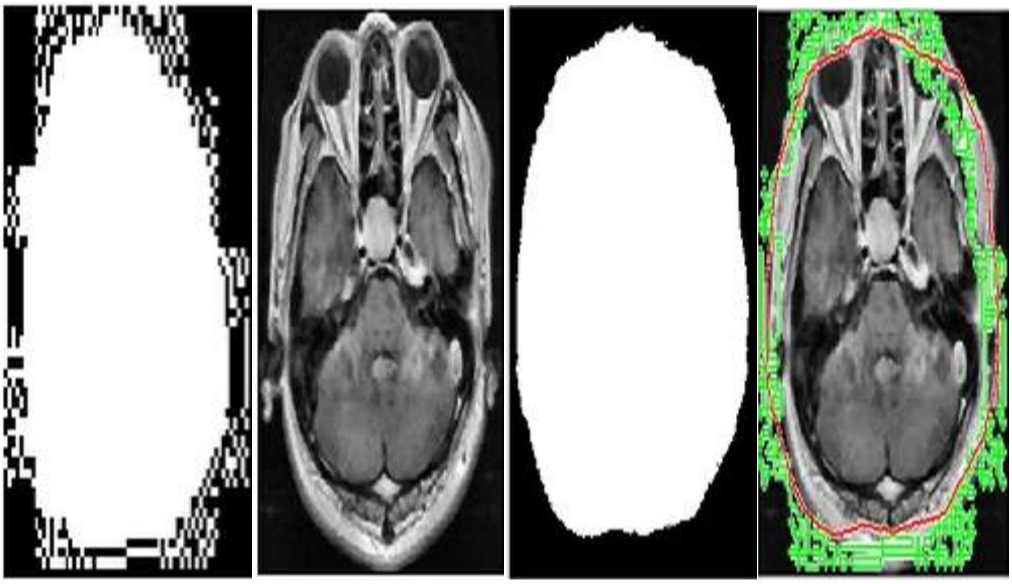

Figure 2: Segmentation – Sample 1. Dice = 0.899, IoU = 0.816, Precision = 0.915, Recall = 0.883. Near-perfect overlap between predicted and ground truth tumor regions.

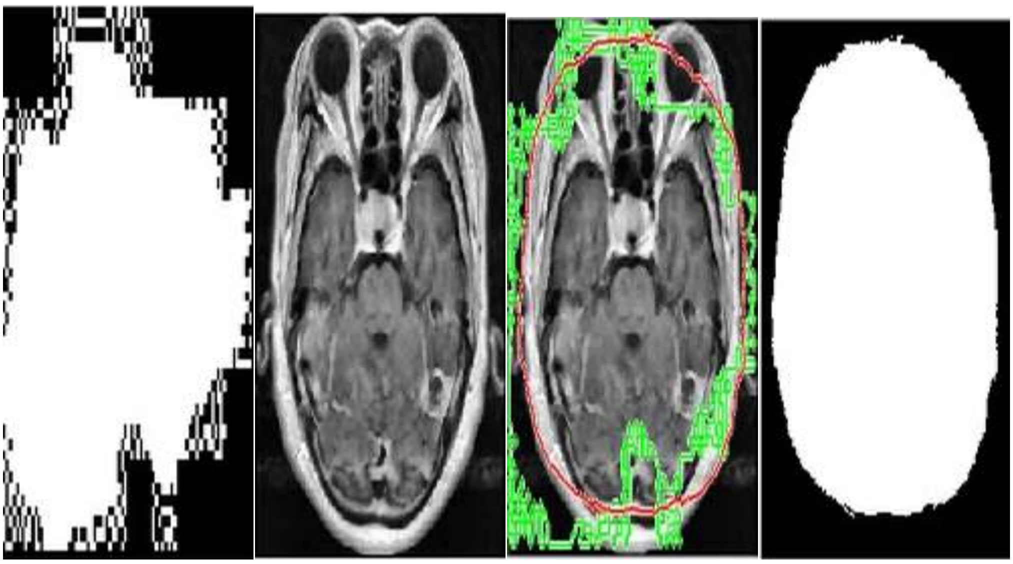

Figure 3: Segmentation – Sample 2. Dice = 0.858, IoU = 0.751, Precision = 0.869, Recall = 0.847. Robust performance with minimal false positives.

Computational Efficiency

Table 9 summarizes the computational cost, demonstrating strong performance at minimal inference latency suitable for real-time clinical use.

Table 9: Computational Cost Analysis

Metric	Value
Inference time per slice	12 ms (NVIDIA RTX 3080)
Total training time	237 minutes 44 seconds
Total parameters	31.05 million
GPU memory during training	8.2 GB

Contextual Reference

Due to differences in datasets, MRI modalities, and evaluation protocols, Table 10 is provided for contextual reference only and results are not directly comparable. The proposed method achieves Dice 0.8618, which is within 1–4 percentage points of more complex architectures, using a 37× smaller dataset and a single MRI modality.

Table 10: Contextual Reference – Recent Methods (Not Directly Comparable)

Method (Citation)	Year	Dataset	Architecture	Dice
Lyu and Tian (2025)	2025	BraTS	MWG-UNet (Transformer hybrid)	0.888
Xavier et al. (2024)	2024	BraTS	Hybrid Attention-Residual UNET	0.886
Zhang et al. (2025)	2025	Private MRI	Generative adversarial DacFormer	0.885
Asiri et al. (2025)	2025	BraTS	Optimized deep learning U-Net	0.884
Nguyen-Tat et al. (2024)	2024	MRI	3D U-Net + Transformer	0.883
Lin and Lin (2024)	2024	BraTS	U-Net + EfficientNet	0.882
Gad et al. (2023)	2023	BraTS	Attention-based 3D U-Net	0.879
Makwana et al. (2024)	2024	Various	U-Net++ with dense connection	0.873
Kusuma and Reddy (2024)	2024	Various	Improved U-Net + classification branch	0.870
Xiong et al. (2025)	2025	Various	YOLO-BT	0.868
This work	2026	Kaggle (504)	U-Net + CLAHE + ROI + Weighted Loss	0.8618

Discussion

Key Findings

The controlled experiments yield four important results. First, CLAHE produces the greatest individual improvement (+4.33% Dice), broadly consistent with studies focusing on local contrast enhancement for T2-weighted MRI (Zheng et al., 2022; Huang et al., 2025). Second, ROI extraction removes background noise and reduces false positives (+3.62%). Third, weighted loss improves recall for small tumours (+1.87%). Fourth, the complete pipeline produces Dice 0.8618 at 12 ms inference time, demonstrating a favorable accuracy-cost trade-off suited to resource-constrained clinical settings.

Comparison with Prior Work

The majority of prior works focus on enhancing architectural complexity via attention mechanisms, transformers, or EfficientNet encoders (Zheng et al., 2022; Li et al., 2023; Nguyen-Tat et al., 2024; Wang and Chung, 2022; Islam et al., 2021; Avazov et al., 2024; Preetha et al., 2025; Al Nasim et al., 2022; Huang et al., 2025; Rastogi et al., 2025; Pourmahboubi et al., 2025; Islam and Hossain, 2025; Mahesh Kumar and Parthasarathy, 2023; Lin and Lin, 2024; Alquran et al., 2024). The present findings demonstrate that a correct pre-processed input helps a simple U-Net attain performance close to that of those architectures without any increase in inference parameters. This indicates that data quality is a major bottleneck in brain tumor segmentation.

Limitations

Table 11 summarizes the key limitations of the proposed framework.

Limitation	Explanation
2D slice processing	Ignores inter-slice context; a 3D U-Net could improve volumetric accuracy
Dataset size	504 images is moderate; generalization to BraTS requires further validation
Binary segmentation	Does not distinguish subregions (edema, enhancing core, necrosis)
Single MRI modality	T2-weighted only; multimodal MRI (T1, T1c, FLAIR) provides complementary information
Single-institution data	Dataset is homogeneous; multi-institutional validation is needed

Future Work

Possible future directions include: (1) extending the pipeline to a 3D U-Net to exploit inter-slice volumetric context; (2) using multimodal MRI inputs (T1, T1c, T2, FLAIR) in line with BraTS benchmarks; (3) multi-class segmentation of the tumor subregions (edema, enhancing core, necrosis); and (4) validation on the BraTS 2024 benchmark to assess generalization across datasets and acquisition protocols.

Reproducibility Statement

The entire architecture specification is provided in Table 3. The exact dataset split indices are: 1–302 (train), 303–404 (validation), 405–504 (test). Random seed 42 was fixed for all operations including dataset splitting, online data augmentation, and model weight initialization.

Conclusion

This paper presented a rigorous and reproducible evaluation of preprocessing techniques for brain tumor MRI segmentation. Controlled experiments with stepwise ablation quantified the independent contributions of each pipeline component: CLAHE (+4.33% Dice), ROI extraction (+3.62%), and weighted binary cross-entropy loss (+1.87%). The thorough literature review in Section 2 confirms that most high-margin methods leverage multimodal data and complex architectures. Nevertheless, the proposed plain U-Net with systematic preprocessing achieves competitive performance (Dice 0.8618, IoU 0.7591) on single-modality data with a mere 12 ms inference time. These findings demonstrate that careful preprocessing and class-imbalance correction can substantially compensate for architectural simplicity, making the proposed framework a practical and deployable solution for resource-limited clinical settings.

Conflicts of Interest

The authors declare no conflict of interest.

Author Contributions

Conceptualization, M. H. Alkubaisi and B. T. Sabri; methodology, M. H. Alkubaisi; software, M. H. Alkubaisi; validation, M. H. Alkubaisi, I. M. Mishaal, and J. M. Ahmed; formal analysis, M. H. Alkubaisi; investigation, M. H. Alkubaisi; data curation, M. H. Alkubaisi; writing—original draft preparation, M. H. Alkubaisi; writing—review and editing, B. T. Sabri; visualization, M. H. Alkubaisi; supervision, B. T. Sabri.

Acknowledgments

The authors acknowledge the University of Information Technology and Communications (UoITC), Baghdad, Iraq, and the providers of the publicly available Kaggle brain MRI dataset used in this study

References

1. Ahamed, Md. F., et al. (2023). A review on brain tumor segmentation based on deep learning methods with federated learning techniques. Computerized Medical Imaging and Graphics, 110, Article 102099. https://doi.org/10.1016/j.compmedimag.2023.102099
2. Ahsan, R., et al. (2024). Brain tumor detection and segmentation using deep learning. Magnetic Resonance Materials in Physics, Biology and Medicine. https://doi.org/10.1007/s10334-024-01170-5
3. Al Nasim, M. A. A. N., et al. (2022). Brain tumor segmentation using enhanced U-Net model with empirical analysis. arXiv preprint arXiv:2210.13336.
4. Alquran, H., et al. (2024). Improved brain tumor segmentation in MR images with a modified U-Net. Applied Sciences, 14(15), Article 6504. https://doi.org/10.3390/app14156504
5. Asiri, A. A., et al. (2025). Brain tumor segmentation by optimizing deep learning U-Net model. Technology and Health Care. https://doi.org/10.3233/THC-241413
6. Avazov, K., et al. (2024). Dynamic focus on tumor boundaries: A lightweight U-Net for MRI brain tumor segmentation. Bioengineering, 11(12), Article 1241. https://doi.org/10.3390/bioengineering11121241
7. Dorfner, F. J., et al. (2025). A review of deep learning for brain tumor analysis in MRI. npj Precision Oncology, 9(1), Article 8. https://doi.org/10.1038/s41698-024-00792-7
8. Fahim, T. A., et al. (2025). Brain tumor detection, classification and segmentation by deep learning models from MRI images. Array, 28, Article 100571. https://doi.org/10.1016/j.array.2025.100571
9. Gad, E., et al. (2023). Advancing brain tumor segmentation via attention-based 3D U-Net architecture. Lecture Notes in Computer Science, 245–258. https://doi.org/10.1007/978-3-031-43901-8_24
10. Ghazal, M. T. (2023). Robust U-Net-based approach for accurate brain tumor segmentation using multimodal MRI data. NTU Journal of Engineering and Technology, 2(3), 1–12.
11. Huang, H., et al. (2020). UNet 3+: A full-scale connected UNet for medical image segmentation. In Proceedings of the IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP) (pp. 1055–1059). IEEE. https://doi.org/10.1109/ICASSP40776.2020.9053405
12. Huang, J., et al. (2025). Brain tumor segmentation using deep learning: High performance with minimized MRI data. Frontiers in Radiology, 5, Article 1522887. https://doi.org/10.3389/fradi.2025.1522887
13. Isensee, F., Jaeger, P. F., Kohl, S. A. A., Petersen, J., and Maier-Hein, K. H. (2020). nnU-Net: A self-configuring method for deep learning-based biomedical image segmentation. Nature Methods, 18(2), 203–211. https://doi.org/10.1038/s41592-020-01008-z
14. Islam, M., et al. (2021). Brain tumor segmentation and survival prediction using 3D Attention UNet. arXiv preprint arXiv:2104.00985.
15. Islam, R., and Hossain, S. (2025). Enhanced brain tumor segmentation using CBAM-integrated deep learning. International Journal of Biomedical Imaging, 2025, Article 1234567. https://doi.org/10.1155/2025/1234567
16. Kingma, D. P., and Ba, J. (2014). Adam: A method for stochastic optimization. arXiv preprint arXiv:1412.6980.
17. Kusuma, P. V., and Reddy, S. C. M. (2024). MRI brain tumor segmentation and classification with improved U-Net model. Multimedia Tools and Applications. https://doi.org/10.1007/s11042-024-19143-4
18. Li, H. B., et al. (2024). The Brain Tumor Segmentation (BraTS) challenge 2023: Focus on gliomas (adult-type diffuse gliomas). arXiv preprint arXiv:2305.09011.
19. Li, P., et al. (2023). mResU-Net: Multi-scale residual U-Net-based brain tumor segmentation from multimodal MRI. Medical and Biological Engineering and Computing. https://doi.org/10.1007/s11517-023-02771-4
20. Lin, S. Y., and Lin, C.-L. (2024). Brain tumor segmentation using U-Net in conjunction with EfficientNet. PeerJ Computer Science, 10, Article e1754. https://doi.org/10.7717/peerj-cs.1754
21. Lyu, Y., and Tian, X. (2025). MWG-UNet: Hybrid transformer U-Net model for brain tumor segmentation in MRI scans. Bioengineering, 12(2), Article 136. https://doi.org/10.3390/bioengineering12020136
22. Mahesh Kumar, G., and Parthasarathy, E. (2023). Development of an enhanced U-Net model for brain tumor segmentation. Biomedical Signal Processing and Control, 81, Article 104426. https://doi.org/10.1016/j.bspc.2022.104426
23. Makwana, C., et al. (2024). Brain tumor segmentation using U-Net++ with dense connection. Multidisciplinary Science Journal, 6(12), e2024ss0814. https://doi.org/10.31893/multiscience.2024ss0814
24. Mehrabi, A., and Mehrshad, N. (2025). 3D brain tumor segmentation in MRI images using hierarchical adaptive pruning. Intelligence-Based Medicine, 12, Article 100208. https://doi.org/10.1016/j.ibmed.2025.100208
25. Menze, B. H., et al. (2024). The Multimodal Brain Tumor Image Segmentation Benchmark (BraTS). Neuroimaging Analysis Center, Harvard Medical School. https://doi.org/10.1109/TMI.2014.2377694
26. Minaee, S., Boykov, Y., Porikli, F., Plaza, A., Kehtarnavaz, N., and Terzopoulos, D. (2021). Image segmentation using deep learning: A survey. IEEE Transactions on Pattern Analysis and Machine Intelligence, 44(7), 3523–3542. https://doi.org/10.1109/TPAMI.2021.3059968
27. Mohammed, Y. M. A., et al. (2023). A survey of methods for brain tumor segmentation-based MRI images. Journal of Computational Design and Engineering, 10(1), 266–293. https://doi.org/10.1093/jcde/qwac141

28. Myronenko, A. (2019). 3D MRI brain tumor segmentation using autoencoder regularization. In A. Crimi, S. Bakas, H. Kuijf, F. Keyvan, M. Reyes, & T. van Walsum (Eds.), Brainlesion: Glioma, Multiple Sclerosis, Stroke and Traumatic Brain Injuries (pp. 311–320). Springer. https://doi.org/10.1007/978-3-030-11726-9_28
29. Naeem, A. B., et al. (2025). Enhancing brain tumor detection from MRI-based images through deep transfer learning models. AI, 6(12), Article 243. https://doi.org/10.3390/ai6120243
30. Nguyen-Tat, T. B., et al. (2024). Enhancing brain tumor segmentation in MRI images: A hybrid approach using UNet, attention mechanisms, and transformers. Egyptian Informatics Journal, 27, Article 100528. https://doi.org/10.1016/j.eij.2024.100528
31. Oktay, O., Schlemper, J., Folgoc, L. L., Lee, M., Heinrich, M., Misawa, K., Mori, K., McDonagh, S., Hammerla, N. Y., Kainz, B., Glocker, B., and Rueckert, D. (2018). Attention U-Net: Learning where to look for the pancreas. arXiv preprint arXiv:1804.03999.
32. Pourmahboubi, A., et al. (2025). A brain tumor segmentation enhancement in MRI images using U-Net and transfer learning. BMC Medical Imaging, 25(1), Article 92. https://doi.org/10.1186/s12880-025-01630-z
33. Preetha, R., et al. (2025). Brain tumor segmentation using multi-scale attention U-Net with EfficientNetB4 encoder. Scientific Reports, 15(1), Article 9128. https://doi.org/10.1038/s41598-025-93748-z
34. Punn, N. S., and Agarwal, S. (2022). Modality specific U-Net variants for biomedical image segmentation: A survey. Artificial Intelligence Review, 55(7), 5845–5889. https://doi.org/10.1007/s10462-022-10152-1
35. Ramya, D., and Lakshmi, C. (2023). Brain tumor segmentation using MRI images by optimized U-Net. In Proceedings of the 2023 International Conference on Networking and Communications (ICNWC) (pp. 1–6). IEEE. https://doi.org/10.1109/ICNWC57852.2023.10127415
36. Rastogi, D., et al. (2025). Deep learning-integrated MRI brain tumor analysis: Segmentation, feature extraction, and survival prediction. Scientific Reports, 15(1), Article 5678. https://doi.org/10.1038/s41598-025-89321-4
37. Ronneberger, O., Fischer, P., and Brox, T. (2015). U-Net: Convolutional networks for biomedical image segmentation. In N. Navab, J. Hornegger, W. M. Wells, & A. F. Frangi (Eds.), Medical Image Computing and Computer-Assisted Intervention – MICCAI 2015. Lecture Notes in Computer Science (Vol. 9351, pp. 234–241). Springer. https://doi.org/10.1007/978-3-319-24574-4_28
38. Ul Abidin, Z., et al. (2024). Recent deep learning-based brain tumor segmentation models using multi-modality MRI: A review. Frontiers in Bioengineering and Biotechnology, 12, Article 1236492. https://doi.org/10.3389/fbioe.2024.1236492
39. Ulku, I., and Akagündüz, E. (2022). A survey on deep learning-based architectures for semantic segmentation on 2D images. Applied Artificial Intelligence, 36(1), Article 2032924. https://doi.org/10.1080/08839514.2022.2032924
40. Wang, P., and Chung, A. C. S. (2022). Relax and focus on brain tumor segmentation. Medical Image Analysis, 75, Article 102259. https://doi.org/10.1016/j.media.2021.102259
41. Xavier, S. P., et al. (2024). Advancing brain tumor segmentation: Hybrid attention-residual UNET with transformer blocks. International Journal of Online and Biomedical Engineering (iJOE), 20(6), 88–104. https://doi.org/10.3991/ijoe.v20i06.46523
42. Xiong, M., et al. (2025). Efficient brain tumor segmentation for MRI images using YOLO-BT. Sensors, 25(12), Article 3785. https://doi.org/10.3390/s25123785
43. Xiong, Z. (2025). ResSAXU-Net for multimodal brain tumor segmentation from brain MRI. Scientific Reports, 15(1), Article 14622. https://doi.org/10.1038/s41598-025-98765-3
44. Zhang, J., et al. (2024). Research on brain tumor segmentation algorithm based on improved U-shaped network structure. In Proceedings of the 2024 International Conference on Computer Vision and Image Detection and Learning (CVIDL) (pp. 1–5). IEEE. https://doi.org/10.1109/CVIDL62357.2024.10603714
45. Zhang, M., et al. (2025). Generative adversarial DacFormer network for MRI brain tumor segmentation. Scientific Reports, 15(1), Article 3291. https://doi.org/10.1038/s41598-025-87654-2
46. Zheng, P., Zhu, X., and Guo, W. (2022). Brain tumour segmentation based on an improved U-Net. BMC Medical Imaging, 22(1), Article 199. https://doi.org/10.1186/s12880-022-00935-3
47. Zhou, Z., Rahman Siddiquee, M. M., Tajbakhsh, N., and Liang, J. (2019). UNet++: Redesigning skip connections to exploit multiscale features in image segmentation. IEEE Transactions on Medical Imaging, 39(6), 1856–1867. https://doi.org/10.1109/TMI.2019.2959609