
An Enhanced 3D U-NET CNN for Brain Segmentation and Grading

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Abstract.

Magnetic Resonance Imaging (MRI) is widely used for brain tumor diagnosis, but manually analyzing large volumes of MRI data is time-consuming. This paper proposes an automated machine learning pipeline for brain tumor segmentation, grading, and volume measurement using T1, T1ce, T2, and FLAIR MRI images from the BraTS 2020 dataset. A MONAI-implemented U-Net segments Whole Tumor (WT), Tumor Core (TC), and Enhancing Tumor (ET), while a rule-based module performs tumor grading and voxel-based volume estimation. The system achieved a Dice score of 0.77 for WT, while TC and ET achieved 0.10 due to class imbalance and complex tumor structures. Despite these challenges, the unified pipeline can reduce analysis time and support radiologists in diagnosis, treatment planning, and disease monitoring.

Keywords: Brain Tumor Segmentation, MRI, 3D U-Net, Tumor Grading, Volumetric Analysis.

1. INTRODUCTION

Brain tumors require rapid and accurate diagnosis for effective treatment and disease monitoring. MRI provides detailed soft-tissue information through T1, T1ce, T2, and FLAIR sequences, but manual interpretation is time-consuming and challenging due to tumor variability and differences in imaging protocols. Deep learning, particularly 3D U-Net, improves tumor segmentation by capturing complete 3D spatial information. While segmentation identifies tumor regions, grading assesses tumor aggressiveness, and volumetric analysis measures tumor size. Therefore, this work proposes an integrated system using 3D U-Net for segmentation, rule-based grading, and volume estimation from multimodal MRI data.

2. RELATED WORK

Brain tumor detection and segmentation have evolved from traditional image-processing methods to machine learning and deep learning [3]. Early approaches used MRI segmentation and texture analysis [5], while diffusion imaging and self-organizing maps were applied for tumor grading. Multimodal MRI methods improved tumor boundary detection by combining spatial and intensity features [2], with studies showing better performance than single-modality scans [1] and reduced computational cost [8]. Hybrid and machine learning approaches further improved automatic tumor detection and segmentation. Recent deep learning methods include CNNs with transfer

learning [6], 2D V-Net, SegNet, and modified U-Net architectures. Attention and transformer-based models such as TransUNet and pyramid convolution with attention gates, along with multitask learning [7], have further advanced glioma segmentation. Reviews have summarized these developments and highlighted the widespread use of U-Net-based approaches [4], while integrated diagnostic systems combine segmentation with classification.

Table 1: Comparative Analysis of Existing Methods and Proposed System

Category	Method / Model	Strengths	Limitations
Traditional Methods	Thresholding, Region Growing, Edge Detection	Low computational cost, simple implementation	Highly sensitive to noise, poor accuracy for complex tumors
Classical Machine Learning	SVM, KNN, Random Forest	Better than rule-based methods, interpretable	Feature engineering required, limited generalization
Proposed Approach	3D U-Net (MONAI + PyTorch)	Accurate tumor delineation, clinical relevance	Training time, hardware dependency

2.1. Key Contribution

The main contribution of this work is that it builds an integrated framework that performs outlining, grading, and size measurement of brain tumors in one automated system. A 3D U-Net built on the MONAI platform is used to outline tumors from multimodal MRI scans.

3. METHODOLOGY

This methodology provides an automatic process for multimodal MRI brain tumor analysis. The system. Measures tumors by combining outlining, grading and size measurement into one flow. A 3D convolutional neural network trained with learning looks at the whole MRI volume and gives useful clinical data. The BraTS 2020 dataset supplies multimodal MRI scans, including T1, T1 contrast-enhanced (T1ce) T2 and FLAIR. Because MRI images vary in resolution and angle, a preprocessing stage is needed.

Table 3: Network Architecture Configuration

Parameter	Value
Optimizer	Adam
Learning Rate	1e-4
Loss Function	Dice Loss
Batch Size	1
Number of Epochs	5

Device	CUDA / CPU
Patch Size	$128 \times 128 \times 128$
Data Augmentation	Random Crop, Flip, Rotation
Label Mapping	Class 4 $\rightarrow$ 3

Table 4: Network Architecture Configuration

Parameter	Value
Model Type	3D U-Net (MONAI)
Input Channels	4 (T1, T1c, T2, FLAIR)
Output Channels	4 (Background + 3 Tumor Classes)
Spatial Dimensions	3D
Encoder Channels	(16, 32, 64, 128, 256)
Number of Levels	5
Strides	(2, 2, 2, 2)
Number of Residual Units	2 per level
Kernel Size	$3 \times 3 \times 3$
Activation Function	PReLU
Normalization	Instance Normalization
Final Activation	Softmax

4. RESULT ANALYSIS

The proposed brain tumor analysis system was evaluated on the BraTS 2020 dataset for segmentation, grading, and volumetric analysis. The 3D U-Net effectively extracted spatial features from multimodal MRI images, particularly FLAIR and T1ce. The model achieved a Dice score of 0.77 for Whole Tumor (WT), while Tumor Core (TC) and Enhancing Tumor (ET) showed lower performance due to class imbalance and smaller tumor regions. High specificity across classes indicates effective reduction of false-positive predictions.



Figure 3. 2 Tumor Segmentation of 3D MRI

Table 4 : Performance Metrics

	Dice	Sensitivity	Specificity
WT	0.77	0.70	0.998
TC	0.20	0.39	0.989

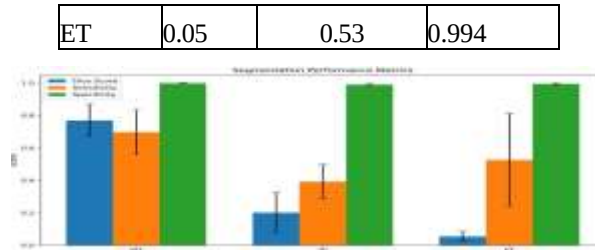


Figure 3.3: Segmentation Performance metrics

5. DISCUSSION

The proposed system integrates deep learning for brain tumor segmentation, grading, and volumetric analysis, providing pixel-level interpretation through a decoupled pipeline. It performs well in Whole Tumor segmentation but struggles with smaller regions such as Tumor Core and Enhancing Tumor due to class imbalance. Future improvements could include attention and transformer-based architectures. Despite computational costs and lower accuracy for small tumor regions, the framework demonstrates useful clinical potential.

6. CONCLUSION

The proposed system integrates MRI preprocessing, 3D U-Net-based tumor segmentation, rule-based grading, and volume estimation into a single automated pipeline. Using multimodal MRI data, the model achieved a Dice score of 0.77 for Whole Tumor segmentation. Its modular and interpretable design provides clinically useful information for diagnosis, treatment planning, and efficient clinical decision-making.

7. REFERENCES

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Biographies



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