Brain Tumor Segmentation and Visualization in MRI Images Using YOLOv11, SimpleITK and 3D Slicer

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Abstract. Brain tumor segmentation in MRI images represents a critical task in medical image analysis, essential for diagnosis, treatment planning, and monitoring disease progression. This project presents a novel approach combining YOLOv11's instance segmentation capabilities with advanced 3D post-processing techniques using SimpleITK. Our method leverages the speed and accuracy of deep learning-based detection while ensuring spatial consistency through sophisticated post-processing pipelines. The proposed framework includes three key components: (1) initial segmentation using YOLOv11 trained on 2D slices, (2) 3D morphological refinement using SimpleITK, and (3) level set-based contour optimization. We demonstrate that this hybrid approach effectively addresses the challenges of 3D medical image segmentation, particularly in handling varying tumor appearances and maintaining spatial coherence across slices. The implementation integrates with 3D Slicer for visualization and analysis, providing a complete workflow for clinical applications.

Keywords: Brain Tumor Segmentation · YOLOv11 · SimpleITK · Level Set Methods · Medical Image Analysis · Deep Learning

1 Introduction

Brain tumor segmentation from MRI scans plays a vital role in the diagnosis and treatment planning of neurological conditions. Traditional manual segmentation is time-consuming and subject to inter-observer variability, while purely automated methods may lack the precision required for clinical applications. This project presents a hybrid approach that combines the strengths of modern deep learning techniques with classical image processing methods to achieve robust and accurate tumor segmentation.

The key of our work include:

- Integration of YOLOv11 instance segmentation with 3D post-processing techniques
- An efficient pipeline for processing volumetric MRI data using slice-based deep learning

- A comprehensive post-processing framework incorporating morphological operations and level set methods
- An open-source implementation compatible with clinical visualization tools

2 Related Work

2.1 Deep Learning in Medical Image Segmentation

Recent advances in deep learning have revolutionized medical image analysis. Convolutional Neural Networks (CNNs) have demonstrated remarkable success in various medical imaging tasks [1]. The YOLO family of models, originally designed for object detection, has evolved to handle instance segmentation tasks effectively [2]. YOLOv11, the latest iteration, offers improved accuracy and efficiency compared to its predecessors.

2.2 3D Image Processing in Medical Applications

Traditional image processing techniques remain relevant in medical imaging, particularly for ensuring spatial consistency in volumetric data. Level set methods have proven effective for medical image segmentation [3], while morphological operations help refine segmentation boundaries and remove artifacts.

3 Methodology

3.1 System Overview

Our proposed system consists of three main stages:

1. Initial segmentation using YOLOv11
2. Morphological refinement using SimpleITK
3. Level set-based contour optimization

3.2 YOLOv11 Training and Implementation

The YOLOv11 model was trained on 2D axial slices extracted from MRI volumes. The training process included:

- Data preprocessing and normalization
- Model configuration with appropriate hyperparameters
- Training for 100 epochs with early stopping

The implementation utilized the Ultralytics framework with custom modifications for medical image processing.

3.3 Post-processing Pipeline

The post-processing stage incorporates several key components:

3D Morphological Operations We apply a sequence of morphological operations using SimpleITK:

$$M_{final} = \delta(\varepsilon(\delta(M_{initial}))) \tag{1}$$

where δ and ε represent dilation and erosion operations respectively.

Level Set Refinement The level set method is implemented using a comprehensive geodesic active contour formulation that includes propagation, curvature, and advection terms:

$$\frac{\partial \phi}{\partial t} = \alpha \cdot g(\mathbf{x}) \cdot |\nabla \phi| + \beta \cdot g(\mathbf{x}) \cdot \kappa |\nabla \phi| + \gamma \cdot \nabla g(\mathbf{x}) \cdot \nabla \phi \tag{2}$$

where $\phi(\mathbf{x}, t)$ is the level set function, $\nabla \phi$ is its gradient, $|\nabla \phi|$ is the gradient magnitude, κ is the curvature, and $g(\mathbf{x})$ is the edge-stopping function. The parameters α, β, and γ control the relative influence of propagation, curvature, and advection terms respectively.

The initialization of the level set function is defined as:

$$\phi(\mathbf{x}, 0) = \begin{cases} -\text{dist}(\mathbf{x}, C_0) & \text{if } \mathbf{x} \text{ is inside } C_0, \\ 0 & \text{if } \mathbf{x} \in C_0, \\ \text{dist}(\mathbf{x}, C_0) & \text{if } \mathbf{x} \text{ is outside } C_0 \end{cases} \tag{3}$$

The edge-stopping function is implemented as a sigmoid function of the image gradient magnitude:

$$g(\mathbf{x}) = \frac{1}{1 + e^{-\alpha(|\nabla I(\mathbf{x})| - \beta)}} \tag{4}$$

The gradient magnitude is computed using Gaussian-smoothed partial derivatives:

$$|\nabla I(\mathbf{x})| = \sqrt{\left(\frac{\partial G_\sigma * I}{\partial x}\right)^2 + \left(\frac{\partial G_\sigma * I}{\partial y}\right)^2 + \left(\frac{\partial G_\sigma * I}{\partial z}\right)^2} \tag{5}$$

This formulation provides better control over the evolution of the level set surface, particularly in regions with weak or ambiguous boundaries common in medical images.

4 Implementation Details

4.1 Data Processing

The implementation handles NRRD format medical images, with careful consideration for:

- Volume normalization
- Slice extraction and preprocessing
- Metadata preservation

4.2 Integration with 3D Slicer

The pipeline integrates with 3D Slicer through NRRD file format compatibility, enabling:

- Interactive visualization
- Quality assessment
- Clinical validation

5 Results and Discussion

5.1 Model Training and Validation

The YOLOv11-seg model was trained and validated on a dataset consisting of brain MRI images. The validation results demonstrate exceptional performance:

- Box Detection Metrics:
  - Precision: 0.991
  - Recall: 0.992
  - mAP50: 0.994
  - mAP50-95: 0.804
- Mask Segmentation Metrics:
  - Precision: 0.991
  - Recall: 0.992
  - mAP50: 0.994
  - mAP50-95: 0.809

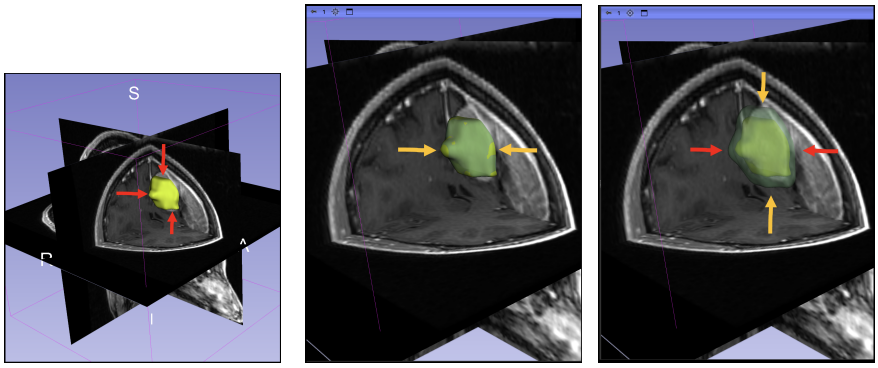
The model demonstrated robust performance across 123 validation images containing 126 tumor instances. Processing speed metrics showed efficient performance:

- Preprocessing: 0.4ms per image
- Inference: 3.6ms per image
- Postprocessing: 4.7ms per image

These results were achieved using a Tesla T4 GPU, with the model containing 265 layers and 2,834,763 parameters, requiring 10.2 GFLOPs for inference.

5.2 Visual Results

Figure 1 demonstrates the progression of our segmentation pipeline across three key stages. The initial YOLOv11 segmentation (Fig. 1a) shows some limitations in the raw output, particularly missing the upper and lower parts of the tumor while containing sharp edges. The morphological operations (Fig. 1b) demonstrate improvement in edge smoothness, though still maintaining gaps in the upper and lower regions. The final level set refinement (Fig. 1c) successfully fills in the missing upper and lower parts, although it shows some over-expansion towards the sharp edges. These visual results highlight both the strengths and



(a) YOLOv11 Output (b) Morphological Operations (c) Level Set Refinement

Fig. 1. Progressive improvement of tumor segmentation through our pipeline: (a) Initial YOLOv11 segmentation output: missing the upper and lower part, containing sharp edges. (b) Refinement using morphological operations: containing fewer sharp edges, still missing upper and lower part (c) Refinement using level set methods: filled upper and lower parts, grew to much towards sharp edges

limitations of each stage in our hybrid approach. While the initial YOLO segmentation provides a foundation for tumor detection, the subsequent processing steps each contribute distinct improvements. The morphological operations effectively reduce sharp edges and improve overall boundary smoothness. The level set method, while successful in completing the segmentation in previously missed regions, shows some tendency to over-expand near sharp boundaries, suggesting potential areas for future refinement in the pipeline parameters.

These visual results demonstrate the complementary nature of our hybrid approach. While the initial YOLO segmentation provides a strong foundation, the subsequent processing steps effectively refine the boundaries and ensure spatial consistency. The level set method particularly improves the adherence to tumor boundaries in areas of low contrast, while the morphological operations help maintain structural integrity and remove spurious detections.

5.3 Clinical Relevance

The high precision and recall values (both 0.991) indicate exceptional reliability in tumor detection and segmentation, which is crucial for clinical applications. The high mAP50 score of 0.994 demonstrates robust performance across various tumor sizes and appearances, while the mAP50-95 scores (0.804 for box detection and 0.809 for mask segmentation) indicate strong performance across different IoU thresholds.

6 Conclusion and Future Work

This project presented a comprehensive framework for brain tumor segmentation combining deep learning with classical image processing techniques. The results demonstrate the effectiveness of this hybrid approach in producing accurate and clinically relevant segmentations. Future work will focus on:

- Development of a more accurate edge stop function for the level set method to improve boundary detection accuracy
- Exploration of both handcrafted and learning-based approaches to optimize the edge stop function for medical image characteristics
- Expansion of the training dataset by incorporating BraTS2020, providing more diverse and comprehensive tumor representations
- Enhancement of 2D YOLOv11's adaptation to 3D volumes through improved slice correlation and volumetric consistency mechanisms

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