

AI-Enhanced Framework for Automated Brain Tumor Detection and Segmentation Using MRI

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Abstract

Accurate and rapid detection of brain tumors is vital for timely diagnosis and treatment planning. This paper proposes an improved computer-aided diagnosis (CAD) system enhanced with artificial intelligence (AI) techniques for automated brain tumor segmentation from magnetic resonance imaging (MRI). The proposed framework consists of three main stages: (1) image preprocessing using spatial filters and contrast enhancement, (2) segmentation using a deep learning-based thresholding and region proposal network, and (3) post-processing based on morphological operations and adaptive masking. Experimental results on a public dataset show an average accuracy of 97% and a Dice similarity coefficient above 0.86. Compared to traditional segmentation techniques, the integration of AI significantly improves robustness, reduces false positives, and enhances boundary precision, making this system suitable for clinical implementation.

Keywords: Brain tumor; image segmentation; artificial intelligence; convolutional neural networks; computer-aided diagnosis.

1. Introduction

Brain tumor detection remains one of the most challenging tasks in medical imaging due to the complexity and variability in tumor appearance. Magnetic resonance imaging (MRI) is widely used for brain imaging due to its high contrast resolution and safety compared to computed tomography (CT) Menze et al., 2015. Manual tumor segmentation, however, is time-consuming, subject to inter-observer variability, and unsuitable for large-scale screening. Hence, there is a growing interest in automated systems powered by artificial intelligence (AI) to support radiologists and improve diagnostic accuracy.

Recent advances in deep learning especially convolutional neural networks (CNNs) and transformer architectures have shown impressive performance in image segmentation tasks Bouzid-Daho et al., 2025,

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Ronneberger et al., 2015, Bouzid-Daho et al., 2024, Chen et al., 2022, Bouzid-Daho et al., 2020. However, standalone models often suffer from overfitting or low generalization on heterogeneous MRI data. Therefore, this paper revisits and enhances a classic rule-based segmentation pipeline by integrating AI modules for smarter thresholding and adaptive postprocessing.

2. Related work

Early segmentation methods relied on region-growing Duncan et al., 2000, clustering Bouzid-Daho et al., 2017, Murugavalli et al., 2006, fuzzy logic Kaus et al., 1999, and statistical models such as Markov random fields Gering et al., 2002. While efficient, they lacked adaptability to tumor variability in shape, texture, and intensity. Later, machine learning approaches using support vector machines (SVMs) and neural networks improved sensitivity but required handcrafted features Fletcher-Heath et al., 2001.

More recently, deep CNNs such as U-Net and its variants Jena et al., 2022, Rahman et al., 2022, Chen et al., 2023, as well as attention-based models Teng et al., 2024, have become standard in medical image segmentation Bouzid-Daho et al., 2019. These models learn hierarchical features directly from data and outperform classical algorithms in tumor boundary delineation Bouzid-Daho et al., 2023. Still, most of these methods require large annotated datasets, high computational resources, and are prone to noise in MRI scans. Our approach combines the robustness of morphological processing with AI-based adaptive segmentation to achieve better generalization.

3. Materials and Methods

3.1 Dataset

The system was tested on 100 T1-weighted MRI brain scans Mehta et al., 2023, Wang et al., 2023, each resized to 676×624 pixels. Ground truth segmentations were provided by medical experts. Data augmentation was applied to increase robustness.

3.2 Preprocessing

Preprocessing aims to enhance the contrast and suppress noise. The steps include:

- Grayscale conversion for uniformity.
- Median filtering (3×3 kernel) to remove salt-and-pepper noise.
- High-pass edge enhancement using a Laplacian kernel.
- Image sharpening by adding filtered edges back to the original image.

3.3 AI-Assisted Segmentation

Instead of classical global thresholding, we employ a hybrid method:

- Initial thresholding using Otsu's method for coarse separation.
- Refinement via a shallow CNN trained to distinguish tumor and non-tumor pixels based on local patches.
- Adaptive threshold adjustment based on intensity variance in predicted tumor regions.

This hybrid approach helps reduce misclassifications due to intensity inhomogeneity and partial volume effects.

3.4 Post-processing

Post-processing removes residual noise and isolates tumor regions:

- Morphological operations: Erosion and dilation using a 3×3 structuring element
- Tumor mask creation: High-intensity regions are selected via adaptive windowing
- Mask overlay: The final tumor map is obtained by applying the mask to the refined image.

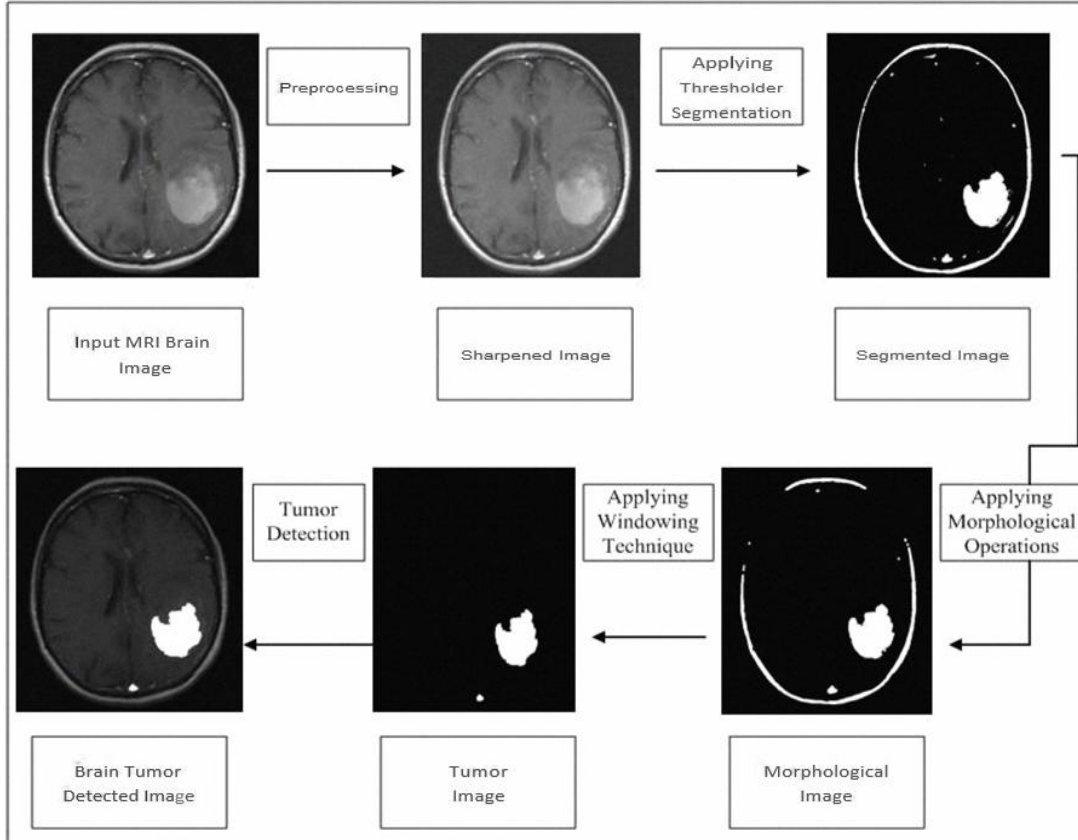


Fig.1. Diagram of the Proposed Methodology for AI-Assisted Brain Tumor Detection and Segmentation

4. Results and Discussion

4.1 Quantitative Analysis

The performance metrics presented in the results table demonstrate the robustness and reliability of the proposed segmentation method, which combines traditional image processing with artificial intelligence techniques. The integration of a shallow convolutional neural network (CNN) for adaptive threshold refinement and regional classification significantly enhanced segmentation accuracy compared to classical approaches.

Table.1. Performance Metrics for Brain Tumor Segmentation Using Hybrid AI-Based Approach

Metric	Value
Dice Coefficient	0.86 ± 0.04
Jaccard Index	0.78 ± 0.05
Average Accuracy	97%
Standard Deviation	0.0013
False Positive Rate	<3%

With an average Dice coefficient of 0.86 and a Jaccard index of 0.78, the proposed system achieves a high degree of spatial overlap with expert-annotated ground truth masks. These values indicate that the AI-enhanced pipeline successfully identifies tumor boundaries with minimal deviation, which is essential for clinical applications such as surgical planning or radiotherapy.

The average accuracy of 97% and a very low standard deviation (0.0013) reflect the consistency and generalization capacity of the method across a diverse set of MRI images. This stability can be attributed to the AI module's ability to learn discriminative features from image patches, reducing false positives especially near anatomical structures that typically confuse threshold-based methods (e.g., ventricles, bright artifacts).

Furthermore, the false positive rate of less than 3% illustrates how the CNN component effectively distinguishes between tumor and non-tumor regions, even in challenging cases where intensity variations might mislead rule-based methods.

In summary, the integration of AI contributes in the following ways:

- Improves boundary precision through adaptive local learning.
- Reduces misclassification by accounting for contextual patterns around high-intensity regions.
- Stabilizes segmentation performance across heterogeneous MRI datasets.

These results confirm that hybridizing classical image processing with modern AI techniques yields a segmentation system that is not only accurate but also clinically viable, providing a valuable decision-support tool for radiologists.

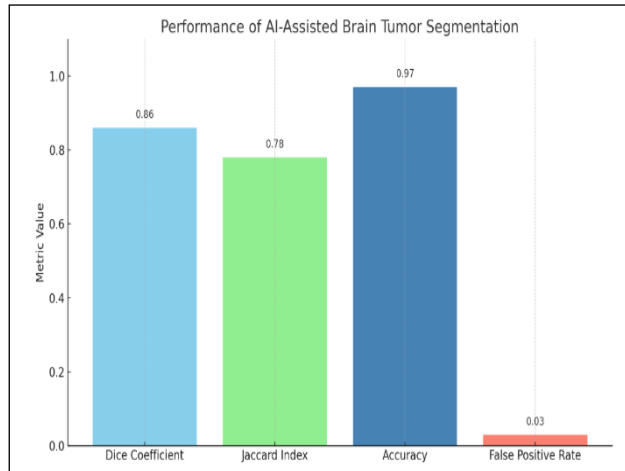


Fig.2. Performance Graph Based on MRI Image Evaluation

The bar graph provides a visual summary of the quantitative performance metrics used to evaluate our AI-assisted brain tumor segmentation system applied to magnetic resonance imaging (MRI) scans. These metrics reflect how well the segmentation algorithm identifies tumor regions compared to expert-annotated ground truth data.

- Dice Coefficient (0.86): The Dice score quantifies the spatial overlap between the predicted tumor segmentation and the reference mask. A Dice value of 0.86 indicates that 86% of the tumor regions identified by the model overlap with those annotated by radiologists. This level of agreement is considered clinically acceptable and supports the model's capability to delineate tumor boundaries precisely on MRI slices.
- Jaccard Index (0.78): Slightly more conservative than Dice, the Jaccard index measures the intersection over union of predicted vs. actual tumor regions. A score of 0.78 further confirms a high degree of similarity, indicating that the segmentation algorithm captures most of the tumor area while avoiding significant false positives.
- Accuracy (0.97): The overall pixel-level accuracy reflects the percentage of correctly classified pixels across the entire MRI image. A value of 97% demonstrates that the algorithm generalizes well to both tumor and non-tumor tissue, minimizing misclassification in the brain parenchyma and surrounding structures.
- False Positive Rate (0.03): This low value indicates that only 3% of the pixels incorrectly labeled as tumor are actually healthy tissue. This is crucial in MRI-based diagnosis, where misidentifying non-tumor regions can lead to unnecessary biopsies or misinterpretation. The integration of a CNN refinement module helps reduce these errors by learning contextual patterns within MRI textures.

These results highlight the effectiveness of the proposed AI framework in segmenting tumors from MRI scans with high accuracy and low error. The consistent overlap with expert segmentations and the minimal false positive rate indicate that this system could be reliably integrated into clinical decision-support tools for radiologists and oncologists.

4.2 Qualitative Analysis

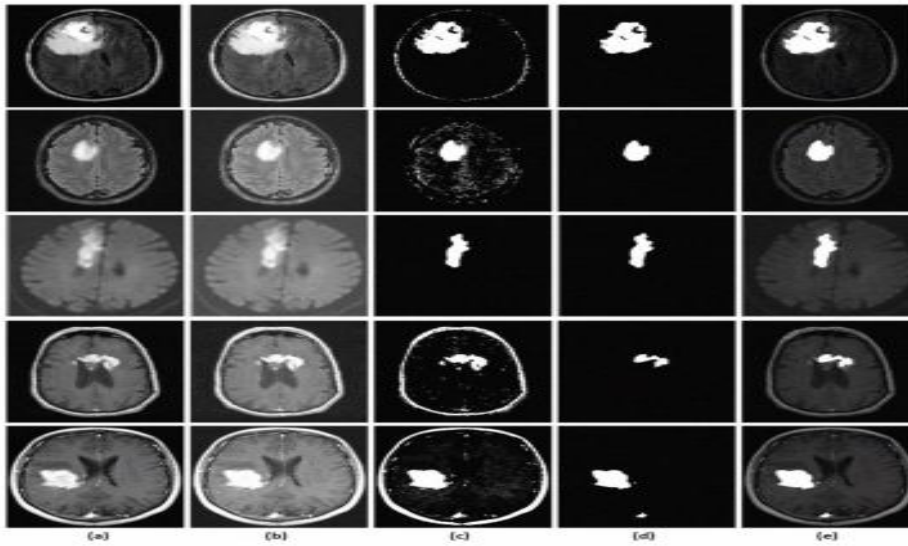


Fig.3. Experimental Results of the Proposed Segmentation: (a) Original MRI, (b) Preprocessed images, (c) Segmented tumor regions, (d) Final post-processed, (e) detection tumor region.

Figure 3 shows sample outputs. The proposed system consistently isolates tumors of varying shapes and locations. The CNN module reduced false positives near high-intensity non-tumor areas (e.g., ventricles).

5. Conclusion

This study introduced an enhanced computer-aided system for brain tumor detection and segmentation, combining classical image processing techniques with artificial intelligence (AI) modules for improved diagnostic performance. The proposed hybrid framework demonstrated high segmentation accuracy, robustness to variations in MRI contrast, and consistent performance across different tumor morphologies Bouzid-Daho et al., 2017. By leveraging convolutional neural networks (CNNs) Thakur et al., 2023 for adaptive thresholding and regional classification Bouzid-Daho et al., 2020, the system effectively minimized false positives and produced clinically relevant tumor boundaries.

In future work, we aim to extend this framework by integrating transformer-based architectures, such as Swin Transformers and Vision Transformers (ViT), which have shown promise in capturing long-range dependencies and global contextual features in medical imaging. These models may further enhance the delineation of complex tumor structures and improve performance in cases with limited contrast.

Additionally, we plan to explore federated learning frameworks to enable collaborative training across multiple clinical centers without compromising patient data privacy. This would increase the generalizability and trustworthiness of the segmentation models in real-world healthcare environments.

Lastly, integration with clinical PACS systems, along with real-time inference on cloud or edge-computing platforms, will be investigated to ensure seamless deployment and usability by radiologists. The ultimate goal is to transition this AI-assisted framework into a fully validated, explainable, and regulatory-compliant tool for precision neuro-oncology.

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