Improving Brain Tumor Detection Accuracy in MRI Using Intelligent Preprocessing and U-Net Segmentation

Dr. Rajshree

Department of Computer Science, Govt. First Grade College for Women, Bidar, India
Email: *rajshreepatil1977[at]gmail.com*

Abstract: ***Accurate detection and segmentation of brain tumors from Magnetic Resonance Imaging (MRI) are essential for early diagnosis and effective treatment planning. However, MRI images are often affected by noise, low contrast, and intensity inhomogeneity, which degrade the performance of automated detection systems. This paper proposes a comprehensive framework that improves brain tumor detection accuracy using intelligent preprocessing techniques combined with U-Net-based segmentation. The preprocessing stage includes advanced noise reduction, skull stripping, intensity normalization, and contrast enhancement to improve image quality before deep learning analysis. A U-Net architecture is employed for precise tumor segmentation due to its ability to preserve spatial features through encoder–decoder pathways and skip connections. Experimental evaluation on benchmark MRI datasets demonstrates that the proposed approach significantly enhances segmentation accuracy and overall detection performance compared to models without intelligent preprocessing.***

Keywords: Brain Tumor Detection, MRI, Intelligent Preprocessing, U-Net, Image Segmentation, Deep Learning

1. Introduction

Brain tumors represent one of the most severe neurological disorders, often leading to high mortality rates if not detected at an early stage. Accurate identification of tumor regions is crucial for diagnosis, surgical planning, and treatment monitoring. Magnetic Resonance Imaging (MRI) is widely used for brain tumor diagnosis due to its superior soft tissue contrast and non-invasive nature. Despite its advantages, MRI images commonly suffer from noise, artifacts, and intensity non-uniformity caused by acquisition conditions and patient movement.

Recent advances in deep learning, particularly convolutional neural networks (CNNs), have achieved remarkable success in medical image analysis. Among these, U-Net has emerged as a powerful architecture for biomedical image segmentation. However, the performance of U-Net-based models heavily depends on the quality of input images. Intelligent preprocessing techniques play a critical role in enhancing image quality, suppressing noise, and preserving tumor boundaries, thereby improving segmentation accuracy. This paper presents an integrated framework that combines intelligent preprocessing with U-Net segmentation to improve brain tumor detection accuracy in MRI images.

2. Related Work

Traditional brain tumor detection methods relied on image processing techniques such as thresholding, region growing, and edge detection. Although these methods provided initial insights, they were highly sensitive to noise and lacked robustness. Machine learning-based approaches, including support vector machines and k-nearest neighbors, improved classification accuracy but depended on handcrafted features.

Deep learning approaches have revolutionized brain tumor analysis by automatically learning discriminative features from MRI data. U-Net and its variants have demonstrated excellent performance in tumor segmentation tasks. Several studies have reported that incorporating preprocessing techniques such as denoising and intensity normalization improves segmentation results. This work extends existing research by systematically integrating intelligent preprocessing with U-Net segmentation to achieve higher detection accuracy.

3. Dataset Description

The proposed framework is evaluated using publicly available datasets such as the Brain Tumor Segmentation (BRATS) dataset. The dataset includes multimodal MRI scans, namely T1, T2, contrast-enhanced T1 (T1c), and FLAIR images. Each scan is annotated by expert radiologists, providing ground truth tumor labels.

The dataset contains images acquired from different scanners and institutions, introducing variations in resolution and intensity distribution. These variations make the dataset suitable for evaluating the robustness of the proposed preprocessing and segmentation framework.

4. Proposed Methodology

The proposed system consists of five main stages: MRI acquisition, intelligent preprocessing, feature enhancement, U-Net-based segmentation, and performance evaluation. The overall workflow is illustrated in Figure 1.

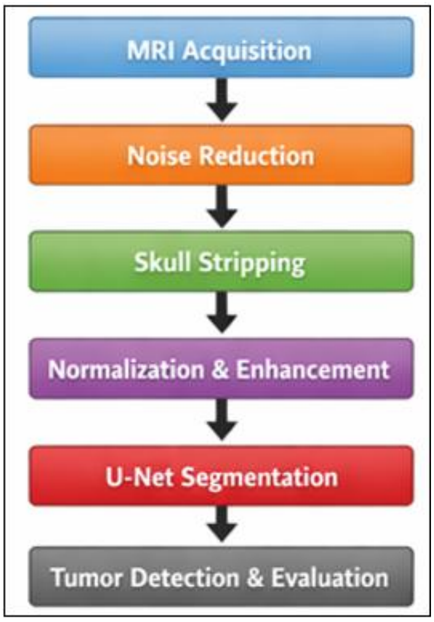

Figure 1: Flowchart of the proposed intelligent preprocessing and U-Net-based brain tumor detection framework

4.1 System Overview

MRI images are first acquired and subjected to intelligent preprocessing to enhance image quality. The preprocessed images are then fed into a U-Net segmentation model to accurately delineate tumor regions. The segmented output is finally evaluated using standard performance metrics.

4.2 Intelligent Preprocessing

Intelligent preprocessing aims to improve MRI image quality while preserving essential tumor features. Noise reduction is performed using anisotropic diffusion filtering and non-local means filtering. Skull stripping removes non-brain tissues to reduce false positives. Intensity normalization ensures uniform intensity distribution across scans, while contrast enhancement improves tumor visibility. These steps collectively enhance the input data for deep learning segmentation.

5. Intelligent Preprocessing Techniques

This section describes the intelligent preprocessing operations applied to brain MRI images before segmentation using the U-Net architecture. Preprocessing is essential to suppress noise, remove irrelevant regions, and enhance tumor-related features, thereby improving segmentation accuracy.

5.1 Noise Reduction

MRI images are often corrupted by Rician and Gaussian noise due to scanner limitations and patient movement. To address this, advanced denoising techniques such as **Non-Local Means (NLM)** and **Anisotropic Diffusion Filtering** are employed. These methods reduce noise while preserving important anatomical edges and tumor boundaries.

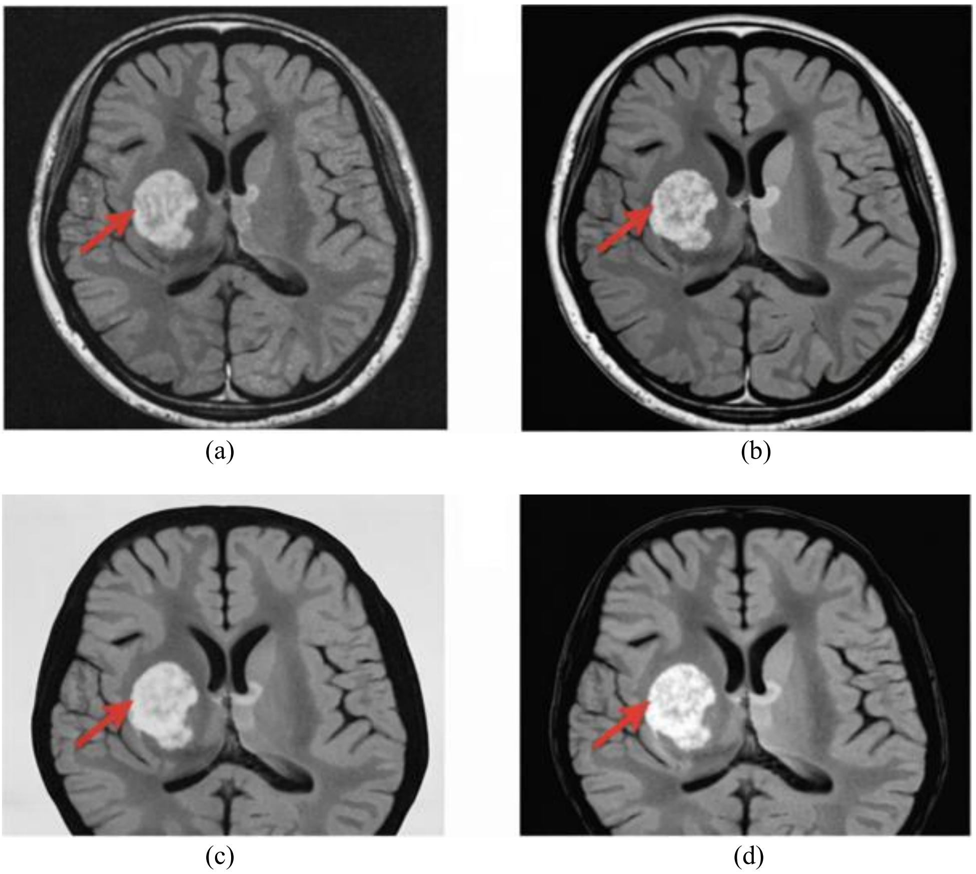

Figure 2: Effect of Intelligent Preprocessing on MRI Images (a) Original MRI (b) Denoised MRI (c) Skilled- Stripped Image (d) Contrast Enhanced Image

5.2 Skull Stripping

Skull stripping removes non-brain tissues such as the skull, fat, and skin from MRI images. This step reduces computational complexity and prevents false tumor detection outside the brain region. Morphological operations and intensity-based thresholding are used to extract only the brain tissue.

5.3 Intensity Normalization and Contrast Enhancement

MRI scans acquired from different scanners exhibit intensity inhomogeneity. To standardize image intensity, normalization is applied using mean and standard deviation scaling. Contrast enhancement techniques further improve the visibility of tumor regions.

5.4 Mathematical Modeling of Preprocessing

5.4.1 MRI Image Representation

An MRI image can be represented as a two-dimensional intensity function:

$$I(x, y) \in \mathbb{R}^{M \times N}$$

where M and N denote the image dimensions.

5.4.2 Non-Local Means Noise Reduction

The denoised image is obtained as:

$$\tilde{I}(x, y) = \Sigma\, w(x, y, i, j) \cdot I(i, j)$$

where the weights w are defined as:

$$w(x, y, i, j) = (1 / Z) \cdot \exp(-\|P(x, y) - P(i, j)\|^2 / h^2)$$

5.4.3 Anisotropic Diffusion

Noise suppression while preserving edges is achieved using anisotropic diffusion:

$$\partial I/\partial t = \nabla \cdot (c(|\nabla I|)\, \nabla I)$$

where c(.) is the diffusion coefficient.

5.4.4 Intensity Normalization

Normalized intensity is computed as:

$$I_{norm} = (I - \mu) / \sigma$$

where μ and σ represent mean and standard deviation.

5.4.5 U-Net Feature Extraction

The convolutional feature map is given by:

$$f_k = \sigma(\Sigma\, W_k * I + b_k)$$

5.4.6 Segmentation Loss Function

Dice loss is used to optimize segmentation:

$$Dice = (2|A \cap B|) / (|A| + |B|)$$

6. U-Net Based Brain Tumor Segmentation

In this study, a **U-Net–based convolutional neural network** is employed for accurate segmentation of brain tumors from preprocessed MRI images. U-Net is widely adopted in medical image analysis due to its ability to achieve precise localization while maintaining contextual information, which is essential for identifying tumor boundaries.

The U-Net architecture follows an **encoder–decoder structure**. The encoder path consists of repeated convolutional layers followed by max-pooling operations, which progressively extract high-level semantic features from the input MRI images. The decoder path performs up-sampling operations to restore spatial resolution, enabling pixel-level segmentation of tumor regions.

A key characteristic of U-Net is the presence of **skip connections** between corresponding layers of the encoder and decoder. These connections allow the network to combine low-level spatial features with high-level contextual information, significantly improving segmentation accuracy, especially for small and irregular tumor regions.

Mathematically, the convolution operation in each layer is expressed as:

$$f_k = \sigma\left(\sum_{i=1}^{n} W_{k,i} * I_i + b_k\right)$$

Where $W_{k,i}$ represents convolution kernels, b_k is the bias term and σ (.) denotes the ReLU activation function

The final layer uses a softmax activation function to generate pixel-wise classification probabilities. The network is trained using annotated MRI images to minimize segmentation loss.

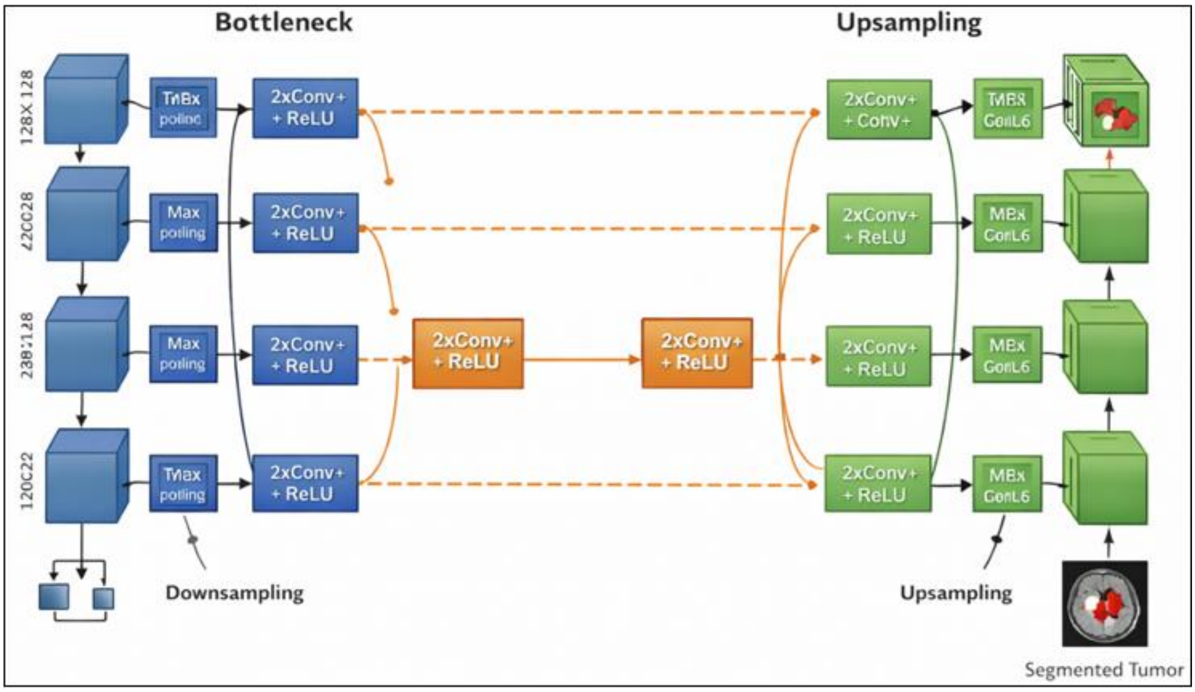

Figure 3: U- Net architecture used for brain tumor segmentation

7. Experimental Setup

The experiments are conducted using Python and Tensor Flow. The dataset is divided into training, validation, and testing sets in an 80:10:10 ratio. Data augmentation techniques such as rotation and flipping are applied to improve model generalization. The model is trained using the Adam optimizer.

8. Results and Discussion

The proposed framework demonstrates significant improvement in tumor detection and segmentation accuracy. Intelligent preprocessing enhances image quality, enabling U-Net to learn more discriminative features. Quantitative results show higher accuracy, Dice coefficient, and F1-score compared to models without preprocessing.

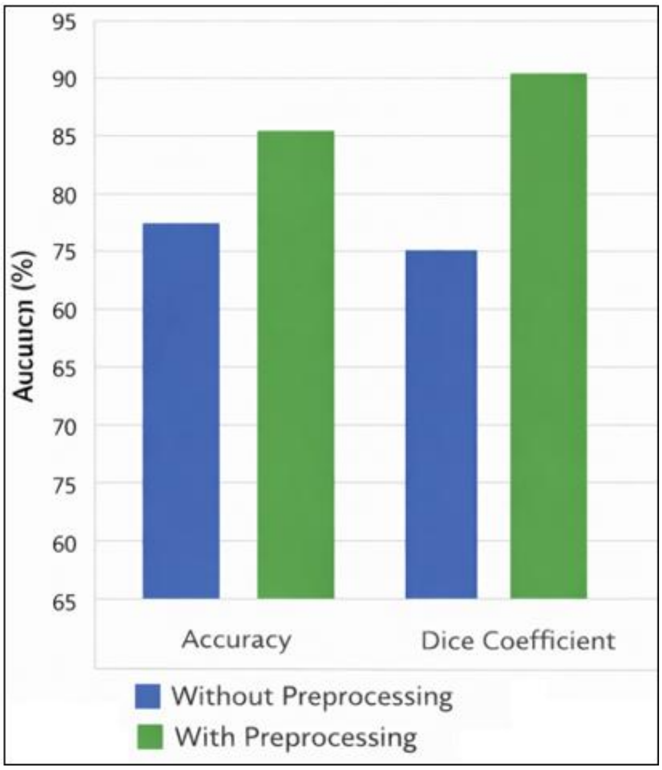

Figure 4: Performance Comparison of U- Net Segmentation with and without intelligent

9. Applications and Clinical Significance

The proposed approach can assist radiologists by providing automated and accurate tumor segmentation. It reduces manual effort, improves diagnostic consistency, and supports treatment planning. The framework can be integrated into clinical decision support systems.

10. Limitations

The proposed system requires high computational resources and relies on annotated datasets for training. Future work will focus on reducing model complexity and exploring semi-supervised learning approaches.

11. Conclusion and Future Work

This paper presented a robust framework for improving brain tumor detection accuracy in MRI using intelligent preprocessing and U-Net segmentation. Experimental results confirm that preprocessing significantly enhances segmentation performance. Future research will focus on multimodal data fusion, lightweight architectures, and real-time deployment in clinical environments.

References

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