A Hybrid Approach for Brain Tumor Segmentation and Classification in MRI Scans

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ABSTRACT

Advancements in medical image processing have led to innovative tools for tumor detection, particularly through segmentation techniques. This study presents a MATLAB-based graphical user interface (GUI) for detecting brain tumors from MRI images. The system integrates various image processing methods, including a Prewitt horizontal edge-enhancing filter for preprocessing and watershed pixel-based segmentation for tumor detection. A key feature is the use of MATLAB's GUIDE tool, enabling flexible combinations of techniques to enhance accuracy and usability. This approach provides a reliable solution for early-stage brain tumor detection, contributing to improved diagnostic capabilities in medical imaging.

KEYWORDS: MATLAB, brain tumor detection, medical image segmentation, image processing.

INTRODUCTION

The growing interest in digital biomedical image processing methods has become a cornerstone in two key areas: enhancing pictorial information for human analysis and efficiently storing and processing biomedical image data. A biomedical image is often described as a two-dimensional function, F(x,y)F(x, y)F(x,y), where xxx and yyy represent spatial coordinates, and FFF indicates the intensity or gray level at a given point. These values are finite, discrete quantities. A digital image is defined as such when it consists of a finite number of elements, each with a specific location and intensity value.

For example, Figure 1 illustrates MRI imaging data with gray levels, as reported by researchers from the University at Buffalo School of Medicine and Biomedical Sciences. They studied MRI results from patients diagnosed with multiple sclerosis during childhood, using periodic MRI scans to monitor disease progression over the years [2].

Biomedical images vary significantly depending on the region of the human body being studied. For instance, soft tissues such as the brain and liver are best analyzed using MRI scans, which are well-suited for capturing detailed soft tissue images. Conversely, hard tissues like bones and cartilage are better studied using X-rays, which are optimized for imaging dense structures.

This variation in biomedical imaging extends beyond the type of tissue to the methods used for processing. MRI images, for example, require distinct processing techniques compared to X-ray images due to differences in image properties and diagnostic objectives. Understanding these distinctions is crucial for developing accurate and efficient image processing techniques tailored to specific medical needs.

Literature review

In recent years, significant advancements have been made in the field of brain tumor detection and classification using MRI images, employing various image processing and machine learning techniques. Anirban Sen Swkshar, Md. Foisal Hossain, and Md. Abdur Rafiq proposed a method encompassing stages such as image pre-processing, segmentation, feature extraction, Support Vector Machine (SVM) classification, and tumor stage classification using Artificial Neural Networks (ANN). Their approach highlights the integration of key image processing techniques, notably SVM and Fuzzy C-Means (FCM) clustering, for effective brain MRI image segmentation. Swapnil R. Telrandhe focused on tumor detection through segmentation, emphasizing the separation of an image into distinct regions or objects. This process involves segmenting the object from the background to accurately interpret and classify the image content. Edge detection plays a crucial role in this framework, serving as a vital tool for image segmentation. The study evaluated the performance of commonly used edge detection techniques for image segmentation and conducted experimental comparisons, demonstrating that their approach achieved favorable segmentation results. Recent studies have further explored the application of deep learning models in brain tumor detection. For instance, a study utilizing a fine-tuned YOLOv7 model through transfer learning demonstrated promising results in accurately identifying the presence and precise location of brain tumors in MRI images. Another research effort introduced an AI-based approach for automatic brain tumor detection and segmentation using MRI images, employing a hybrid attention mechanism to enhance segmentation accuracy. Additionally, the integration of SVM with other techniques has been explored to enhance multiclass brain tumor diagnosis, aiming to improve classification precision. These studies underscore the evolving landscape of brain tumor detection methodologies, highlighting the significance of combining traditional image processing techniques with advanced machine learning and deep learning models to improve diagnostic accuracy and efficiency.

DESCRIPTION

Detecting brain tumors and performing automatic brain tissue classification from magnetic resonance images (MRI) is critical for both research and clinical studies of the human brain, in both healthy and diseased states. A central technique for processing MRI images is image segmentation, which involves dividing objects in the image and processing each region separately. The three primary segmentation methods used in MRI imaging are:

1. Classification-based methods
2. Region-based methods
3. Contour-based methods

The detailed anatomical information provided by MRI has made it a valuable tool for medical diagnosis. However, researchers continually seek better methods to enhance the clarity and diagnostic value of MRI images. Among these methods, image segmentation has emerged as a powerful tool.

Different segmentation techniques yield different outcomes. For example, region-growing segmentation operates differently compared to watershed segmentation, and the results also vary significantly. Despite its potential, segmentation often presents challenges:

- Processing MRI images can be time-intensive.
- The same segmentation program may not work effectively for all types of images.
- Manual segmentation can be prone to errors, inconsistencies, and a lack of reproducibility, which can compromise the quality of the segmentation.

These limitations highlight the pressing need for automated MRI segmentation tools. Automated tools offer advantages such as time efficiency, reproducibility, and improved accuracy, making them indispensable for modern medical image processing and diagnosis.

FLOWCHART

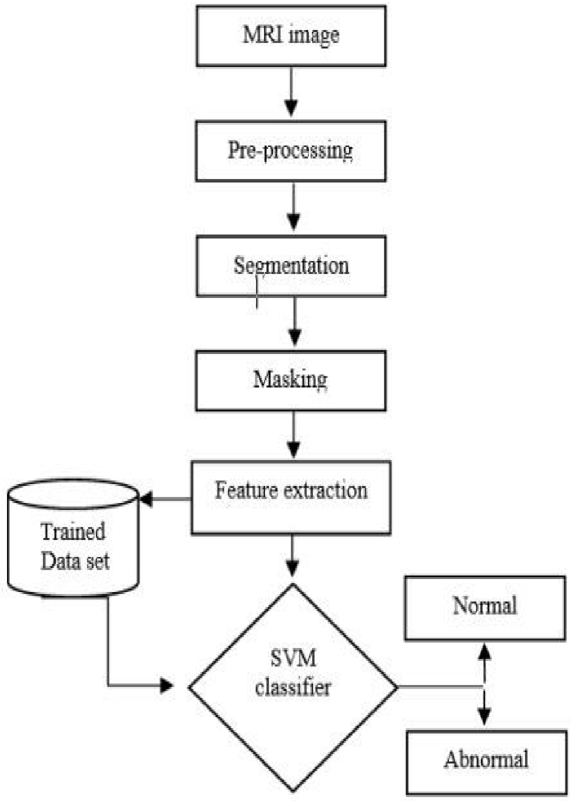
This project is divided into two main components:

1. Detection of Brain Tumor: Identifying the presence of a tumor in the provided MRI image.
2. Classification of Tumor: Categorizing the tumor based on its characteristics.

The overall process follows a structured pipeline where the input MRI images pass through several key stages to achieve these objectives. These stages are summarized as follows and illustrated in the flowchart (refer to Figure above):

- Input MRI Image: The process begins with the acquisition of MRI images.
- Preprocessing: Images are cleaned and prepared for analysis, removing noise and enhancing quality.
- Segmentation: The image is divided into meaningful regions to isolate the area of interest.
- Feature Extraction: Relevant features are identified and extracted for analysis.
- Tumor Detection: The presence of a tumor is determined.
- Tumor Classification: The detected tumor is classified into categories based on its properties.

This stepwise flow ensures systematic and efficient processing of MRI images for brain tumor detection and classification.



6.1 MRI IMAGES OF THE BRAIN

The first step in the proposed system involves the acquisition of MRI images of the brain. These images serve as the input for the system. However, MRI images may often be noisy, blurry, or have low contrast, making analysis and feature extraction challenging [14]. The grayscale MRI images provided as input are prepared for further processing to facilitate effective analysis.

6.2 PRE-PROCESSING

Pre-processing is the initial phase of data preparation, aimed at enhancing the quality of the input images for subsequent analysis. This stage includes operations that are essential before performing the primary analysis or extracting critical data. Key tasks in this phase include:

- Geometric Corrections: Addressing distortions to ensure spatial accuracy.
- Noise Reduction: Removing unwanted noise or artifacts from the images.
- Non-Brain Element Removal: Eliminating extraneous components not relevant to the analysis.
- Data Transformation: Adapting the image to a format suitable for further processing while retaining the integrity of the original data.

These enhancements improve the clarity and usability of the MRI images, ensuring accurate segmentation and analysis.

6.3 FEATURE EXTRACTION

Feature extraction is a crucial step in the imaging pipeline where specific attributes of interest within the image are identified and prepared for further analysis. This process is fundamental to computer vision and imaging solutions. Key features such as size, shape, composition, and location of the tumor are extracted from the input MRI image.

These features serve as the basis for tumor classification and analysis. By isolating these attributes, the system can accurately determine the region and characteristics of the tumor, providing essential information for diagnosis and treatment planning.

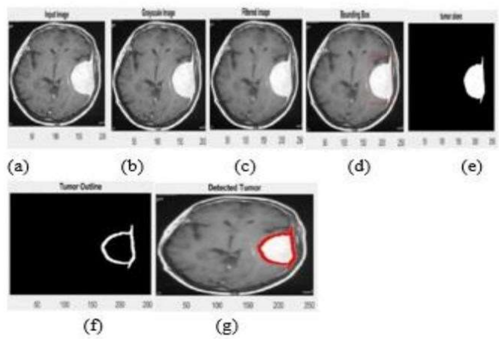


Fig. 2: (a) Input image, (b) Grayscale image, (c) Filtered image, (d) Bounding box, (e) Tumor alone image, (f) Tumor outline, (g) Detected tumor.

SEGMENTATION

Segmentation is the process of dividing an image into smaller, meaningful segments to facilitate analysis. In this project, segmentation is applied to divide MRI images into multiple segments to identify and isolate regions of interest. However, challenges in segmentation often arise due to varying image quality, differences in continuity across regions, and the distinct nature of image types, such as X-rays and MRIs.

In 2D images, each action's placement is referred to as a pixel, while in 3D images, it is termed a voxel. When the requirement for regions to connect is removed, the resulting groups are defined as pixel classifications, and these groups themselves are referred to as classes.

To overcome segmentation challenges, we employed reliable techniques such as Support Vector Machines (SVM) and Self-Organizing Maps (SOM) to detect the presence of a tumor in the MRI image.

- Support Vector Machines (SVM): Known for its high generalization performance, SVM is particularly effective in handling large feature spaces. SVM operates by taking processed images as input and applying classification algorithms to identify tumor regions accurately. This method has demonstrated performance comparable to neural networks, particularly in tasks like handwriting recognition, making it a strong candidate for image segmentation in this project.

IMAGE ANALYSIS

Once the type of tumor is determined through segmentation and classification, detailed image analysis is conducted to precisely identify and localize the tumor. This step integrates segmentation results and additional processing to extract critical insights about the tumor's characteristics, providing a comprehensive understanding of its size, shape, and location.

Fig. 3: Showing the result of the taken MRI image and providing the classification of the type of tumor.

IMPLEMENTATION

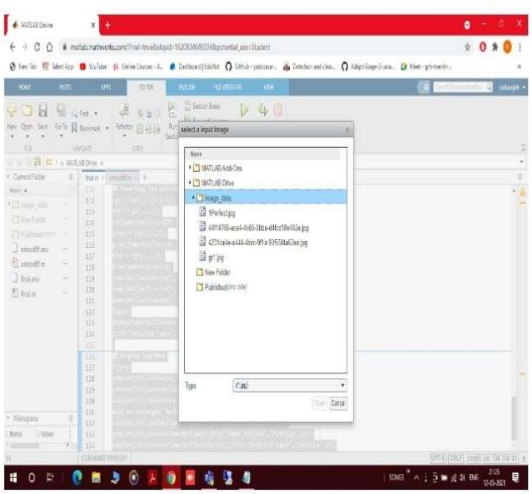


Fig. 4: Selecting the MRI for detection of tumor.

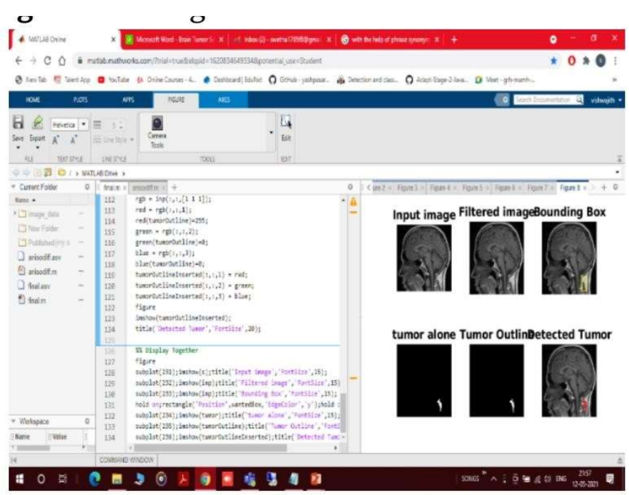


Fig. 5: Showing the output of detected tumor.

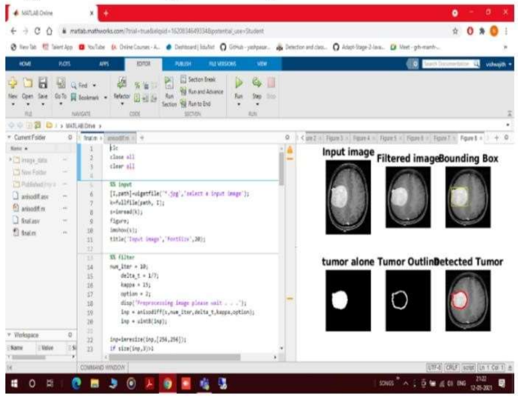
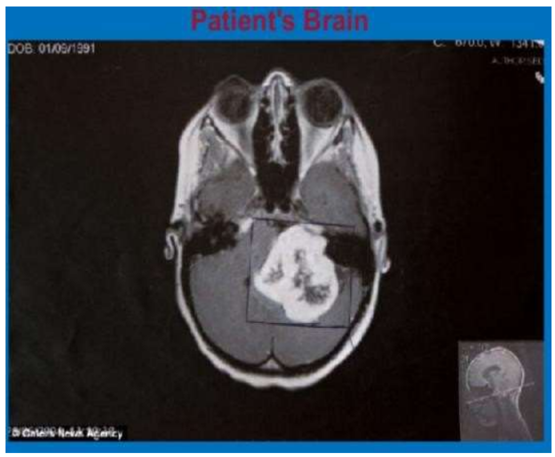
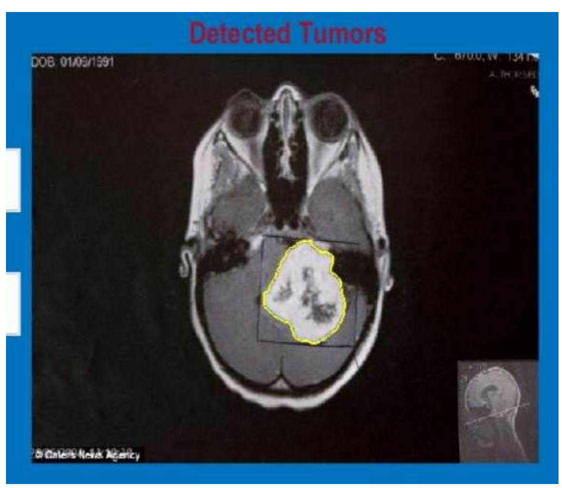


Fig. 6: Result of detected tumor which is highlighted with red colour around tumor.

RESULTS BEFORE:



AFTER:



PRE-PROCESSING OF MR IMAGES

Grayscale Conversion

The first step in pre-processing involves converting the MRI image to grayscale using MATLAB algorithms, as described by Kekre, Sarode et al. (2010). This conversion simplifies the image by reducing it to a single intensity channel, making subsequent processing more efficient. Before this step, the image is resized to standard dimensions to ensure compatibility with later morphological operations.

Morphological Operations

Morphological operations are applied to enhance the image and isolate areas of interest. One key operation used in this project is the Top Hat Filter Kernel Transformation, which is effective in highlighting sharp gradients at peaks. This transformation enhances the visibility of tumor regions by accentuating areas with high intensity contrast.

Tumor Detection and Size Estimation

The tumor is detected by leveraging the significant intensity difference between the tumor and the background in the MRI image, as noted by Mancas, Gosselin et al. (2005). MATLAB algorithms are employed to precisely locate the tumor and measure its size. These algorithms capitalize on the intensity contrast to distinguish the tumor from surrounding tissues effectively.

Through these pre-processing steps, the tumor's location can be accurately identified, enabling detailed analysis in subsequent stages of the project.

COMPARISON

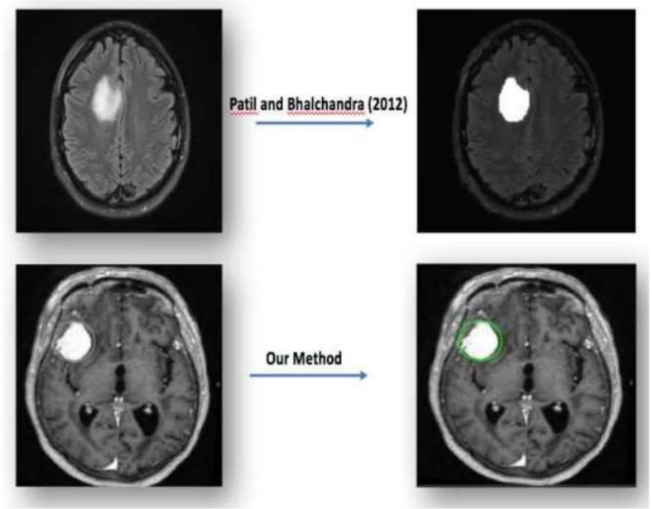
Results of the Proposed Method Compared to Existing Methods

Previously, segmentation of brain tumor MRI images was performed manually, as noted by Bezdek, Hall et al. (1993). While this method was precise in some cases, it was time-consuming and labor-intensive. To address these limitations, automated approaches were developed. However, the results of early automation methods were often unsatisfactory, particularly when dealing with complex MRI images.

For example, Patil and Bhalchandra (2012) proposed a hybrid approach for image segmentation that combined the Top Hat Filter and the Watershed Algorithm. While their method performed well on simple MRI scans, it struggled to produce accurate results on more complex cases, limiting its utility in practical scenarios.

In contrast, our proposed method demonstrates superior performance, particularly on complicated MRI images. By integrating robust segmentation techniques such as Support Vector Machines (SVM) and Self-Organizing Maps (SOM), along with advanced pre-processing and feature extraction, our method achieves greater accuracy and reliability in detecting and classifying brain tumors.

This comparison highlights the significant improvements offered by our methodology, making it a promising tool for advanced medical imaging applications.



ADVANTAGES

- Tumor Classification: In our proposed system, the classification of the image is based on the area of the tumor, allowing for more detailed and accurate analysis.
- Tumor Staging: The system includes tumor staging, which is essential for assessing the severity and progression of the tumor.
- Higher Accuracy: Our method provides more accurate results compared to previous approaches, particularly for complex MRI images.
- Tumor Area Computation: The system calculates the exact area of the tumor, which is crucial for both diagnosis and treatment planning.

DISADVANTAGES

- Limited to Segmentation: Many existing systems are confined to segmentation only, without further analysis or classification.
- Technological Limitations: Some systems suffer from technology-related issues, such as poor image quality handling or limited scalability.
- Focus on Cancerous Images: Some systems are designed specifically for detecting cancerous images and may not be applicable for other types of medical imaging.
- Lack of Tumor Staging: Several existing systems do not include tumor staging, limiting their ability to assess tumor progression.
- Lower Accuracy: Some methods offer lower accuracy, especially when applied to more complicated or noisy MRI images.
- No Tumor Area Computation: Certain systems do not compute the tumor's area, which is an important parameter for treatment evaluation.

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