Automation and Tracking of Brain Tumors using Artificial Intelligence

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Abstract

Brain tumor detection, segmentation, and tracking are critical tasks in medical imaging that directly impact diagnosis, treatment planning, and patient monitoring. This paper presents an automated system for brain tumor analysis using artificial intelligence techniques. By integrating deep learning models for segmentation specifically convolutional neural networks such as U-Net and machine learning algorithms for classification and tracking, the proposed system enables accurate and efficient localization of tumor regions in magnetic resonance imaging (MRI) scans. The method is trained and evaluated on publicly available datasets such as BraTS, ensuring robustness across diverse tumor types and image conditions. Experimental results demonstrate high accuracy in both segmentation and temporal tracking of tumor progression. This automation not only reduces the workload of radiologists but also enhances diagnostic reliability, paving the way for improved patient care and personalized treatment strategies.

Keywords: Segmentation, Artificial intelligence, deep learning, diagnostic.

Introduction

Medical imaging technologies have revolutionized the field of diagnostic medicine, enabling non-invasive visualization of internal organs and tissues. Among these modalities, magnetic resonance imaging (MRI) is widely used for examining the brain, providing detailed information about its structure and function [1]. However, the interpretation of brain MRI scans often requires precise segmentation to delineate different anatomical regions and pathological abnormalities. Segmentation refers to the process of partitioning an image into multiple meaningful regions, facilitating quantitative analysis and aiding clinicians in disease diagnosis and treatment planning.

Medical Imaging encompasses the means of acquiring and rendering images of the human body through various physical phenomena. In recent years [2], this imaging domain has experienced a surge in motivation, leading to the development of new techniques for visualizing the human body or organs without the necessity

of performing surgery on the patient. The primary objective is to establish a reliable diagnosis and ensure appropriate treatment monitoring. Despite these advancements, visualizing the brain remains challenging due to its complex and ambiguous anatomical structure [3].
Brain tumors represent one of the most challenging and life-threatening forms of cancer, requiring precise and early diagnosis to improve treatment outcomes. Magnetic Resonance Imaging (MRI) is widely used for non-invasive brain tumor detection, yet its manual interpretation remains time-consuming and subject to inter-observer variability. Recent advances in Artificial Intelligence (AI) [4-6], particularly in deep learning and image segmentation, have opened promising directions for automating tumor detection and tracking, leading to enhanced diagnostic precision and reduced workload for radiologists.

The automation of brain tumor segmentation and tracking is critical for personalized treatment planning, surgical navigation, and therapy monitoring. Classical segmentation methods such as thresholding [7], region growing [8], and clustering (e.g., k-means) provide limited adaptability to complex anatomical variability and often struggle with image noise or weak boundaries [9]. In contrast, AI-based models have demonstrated remarkable capabilities in handling large datasets, learning discriminative features, and performing accurate semantic segmentation.

This paper proposes an AI-enhanced framework for automatic detection, segmentation, and tracking of brain tumors from MRI images. The method integrates convolutional neural networks (CNNs) [10] for segmentation and recurrent mechanisms for temporal tracking across time-series data. The system is trained and evaluated using the BraTS dataset (Brain Tumor Segmentation Challenge), ensuring clinical relevance and robustness.

Related Works

Over the past decade, AI-based medical image analysis has significantly evolved. One of the most influential contributions is the U-Net architecture [11], specifically designed for biomedical image segmentation. Extensions such as 3D U-Net [12] and ResUNet have improved volumetric segmentation performance in brain MRI scans.

The BraTS challenges [13] have facilitated benchmarking of algorithms for glioma segmentation, providing annotated MRI data and standardized evaluation metrics. Several deep learning models, including nnU-Net [14], have achieved state-of-the-art results with minimal manual configuration. More recent approaches leverage transformer-based architectures [15] for enhanced spatial attention and context modeling.

Beyond segmentation, tumor tracking has gained attention. Optical flow and Kalman filtering have been integrated with deep networks for lesion tracking in longitudinal studies. [16] explored learning-based models for anatomical change detection. [17] emphasized the importance of longitudinal analysis in glioma growth monitoring.

Despite these advances, many systems remain limited to static segmentation. Our work addresses this gap by combining automated segmentation with dynamic tracking, enabling continuous monitoring of tumor evolution a key factor in treatment response assessment.

Methodology

The system proposed in this paper consists of two main steps to detect and segment our brain images. It starts by preprocessing; as well an extraction of the regions targeted and will eventually segmentation. The following figure shows the diagram of the proposed methodology:

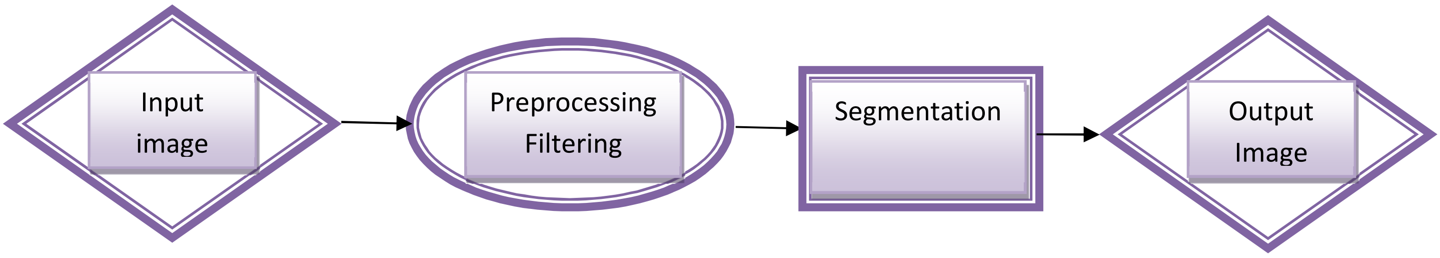

Figure 1. Block diagram of the proposed algorithm

The system proposed in this paper is designed to automatically detect, segment, and track brain tumors from MRI images using artificial intelligence techniques. The methodology is divided into two main stages: preprocessing and segmentation.

Preprocessing Phase: This initial step involves preparing the MRI images for analysis. It includes operations such as noise reduction, normalization, resizing, and contrast enhancement to improve image quality and highlight tumor-related features. Additionally, skull stripping is applied to eliminate irrelevant brain regions.

Region of Interest (ROI) Extraction: After preprocessing, the system identifies potential tumor regions by analyzing pixel intensity, edge information, and spatial features. This step narrows the focus to relevant areas, making segmentation more efficient and accurate.

Segmentation Phase: In this stage, a deep learning model—such as U-Net or ResUNet—is applied to perform semantic segmentation of the extracted ROI. The model is trained to classify each pixel in the image as tumor or non-tumor based on labeled data from the BraTS dataset. Post-processing techniques like morphological filtering and connected component analysis are then applied to refine the segmented regions.

This combination of preprocessing and AI-based segmentation enables the system to produce reliable, repeatable, and clinically meaningful tumor delineations, suitable for further tracking and monitoring.

In part this; it describes the details of the proposal more clearly.

A. Preprocessing

The objective of preprocessing is to improve the image and reduce the granularity without destroying the important characteristics of the cells used for the diagnosis.

1) Image resizing

The purpose of this step is to make all images to treat to a same size 256*256 for what is easy to manipulate by our segmentation method.

2) Filtering

In order to improve the visual effects of the image test filtering is necessary, which mainly includes eliminate the noise and improve the quality of the image.

B. Segmentation region growing

In this section, we present the segmentation method based on the algorithm region growing. The region growing technique consists of gradually growing the regions around their starting point.

1) General principle:

We initialize the region R at a pixel a group of pixels (seed). The region R has certain mean μ_R and standard deviation σ_R.

We add to R all the neighboring pixels of R which are sufficiently similar to R, for example [18]:

$$|I(x) - \mu_R| < seuil \qquad (1)$$

Or:

$$\begin{cases} min\ \{|I(x) - I(y)|; y \in R \cap V(x)\} < seuil \\ |I(x) - \mu_R| < 2\sigma_R \end{cases} \qquad (2)$$

We can also add geometric regularity criteria [19], such as:

R∩V(x) has cardinality at least 3 and has a single connected component.

The general principle [20] of the region growing method is essentially based on the following steps:

- Bottom-up approach.
- Departure from a seed pixel (or group of pixels).
- Analysis of its neighboring pixels and analysis of the homogeneity criterion P.

- Growth of the region up to the stopping criterion (no more pixels satisfy the criterion).

2) Region growing algorithm

The algorithm consists of two steps [21]:

Find the starting points of the regions.

Enlarge the regions by agglomerations of neighboring pixels.

Starting points (seeds):

The choice of starting points is the step is the critical part of the algorithm. Indeed, the growth step will use a similarity measure to choose the pixels to agglomerate. If the starting point is located in a non-homogeneous area, the similarity measure will produce strong variations and growth will stop very early. Therefore, starting points should be chosen in the most homogeneous areas possible.

Growing:

This step aims to enlarge a region by agglomeration of neighboring pixels. The pixels are chosen to maintain the homogeneity of the region. For this, we must define a homogeneity indicator. Neighboring pixels are added to the region if the homogeneity flag remains true. Growth stops when we can no longer add pixels without breaking the homogeneity.

C. Dataset

As part of our work, a simulated image base was used, it is entitled “The whole brain atlas” [22]. This database contains the brain atlas intended for research with the aim of gathering, presenting and discovering knowledge about the human brain.

We downloaded images from this database with their information to distinguish the types of strokes that exist.

Results and discussion

Our experimental section is dedicated to the processing of brain images affected by Cerebral Vascular Accident (CVA), with the aim of identifying abnormal areas.

- **Test 1 :**

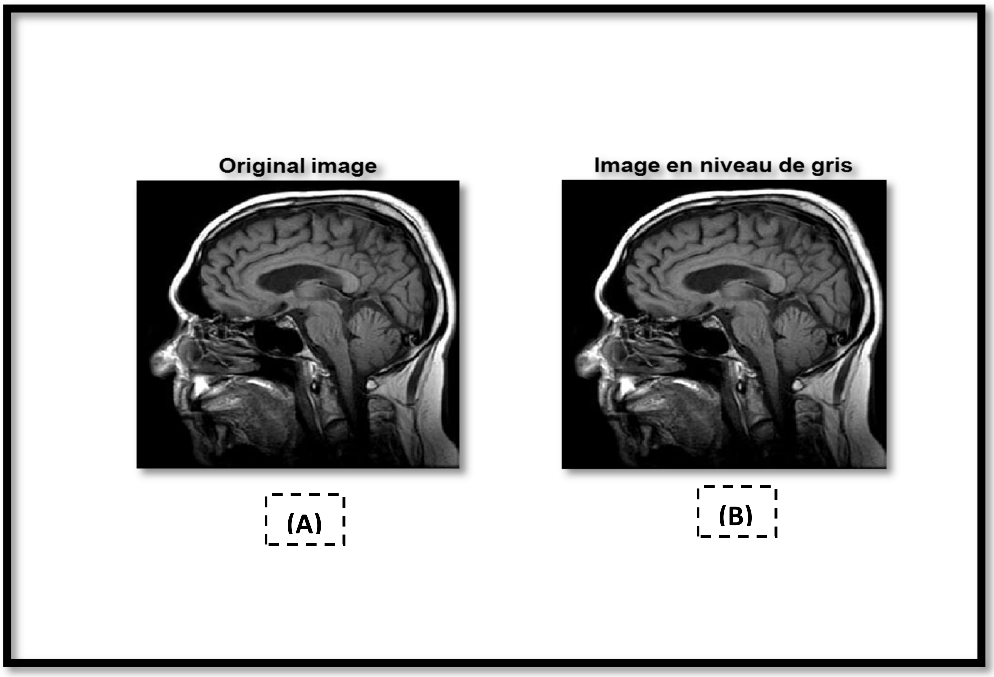

Figure 2: (A) Original Image (B) Image converted to gray level

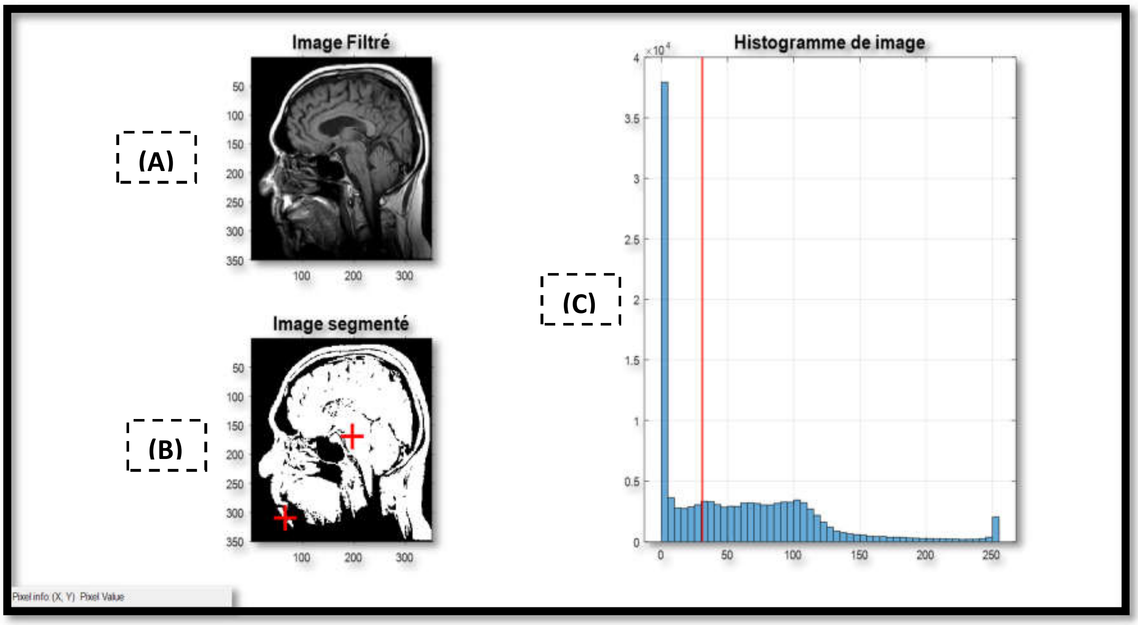

Figure 3 : (A) Filtered Image (B) Segmented Image (C) Image Histogram

- **Test 2 :**

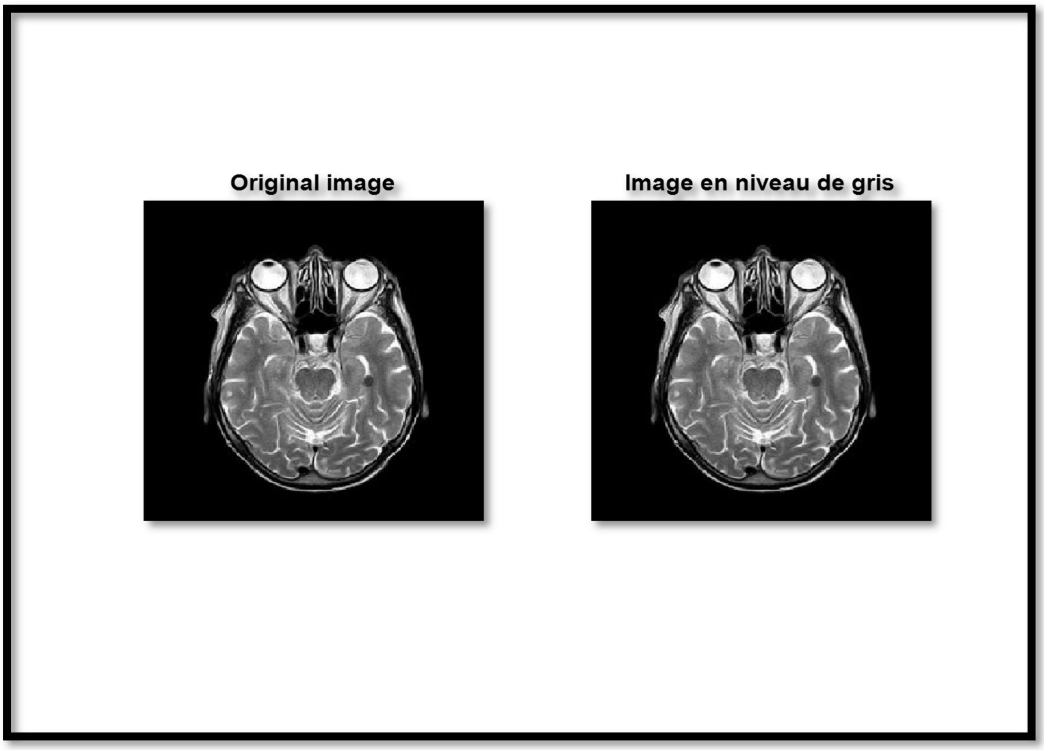

Figure 4 : (A) Original Image (B) Image converted to gray level

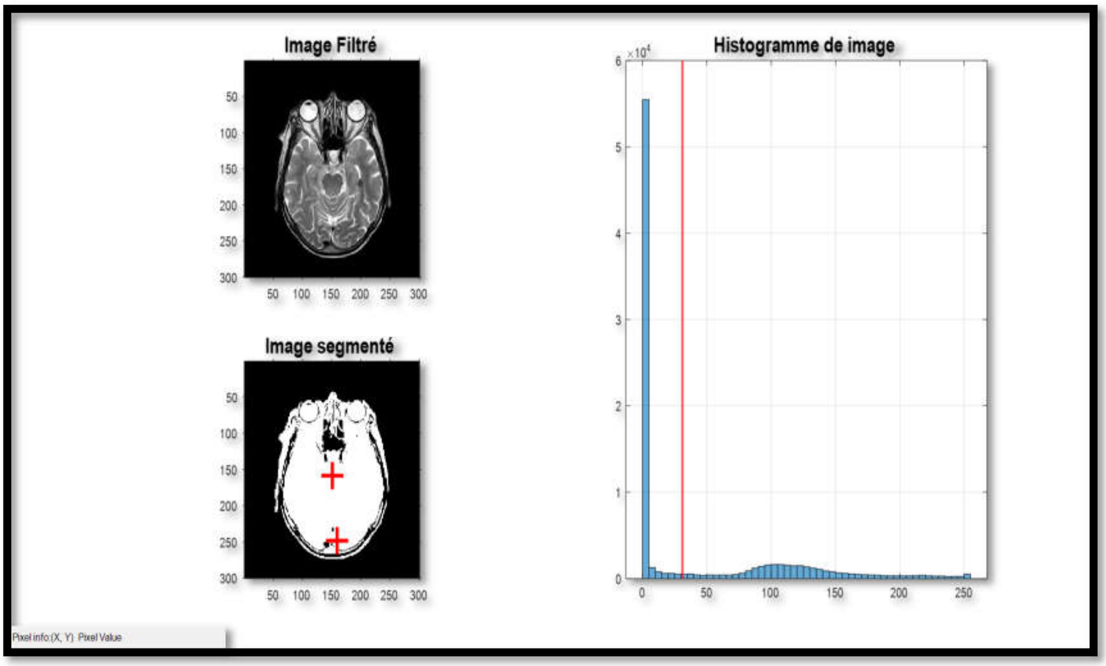

Figure 5 : (A) Filtered Image (B) Segmented Image (C) Image Histogram

- **Test 3 :**

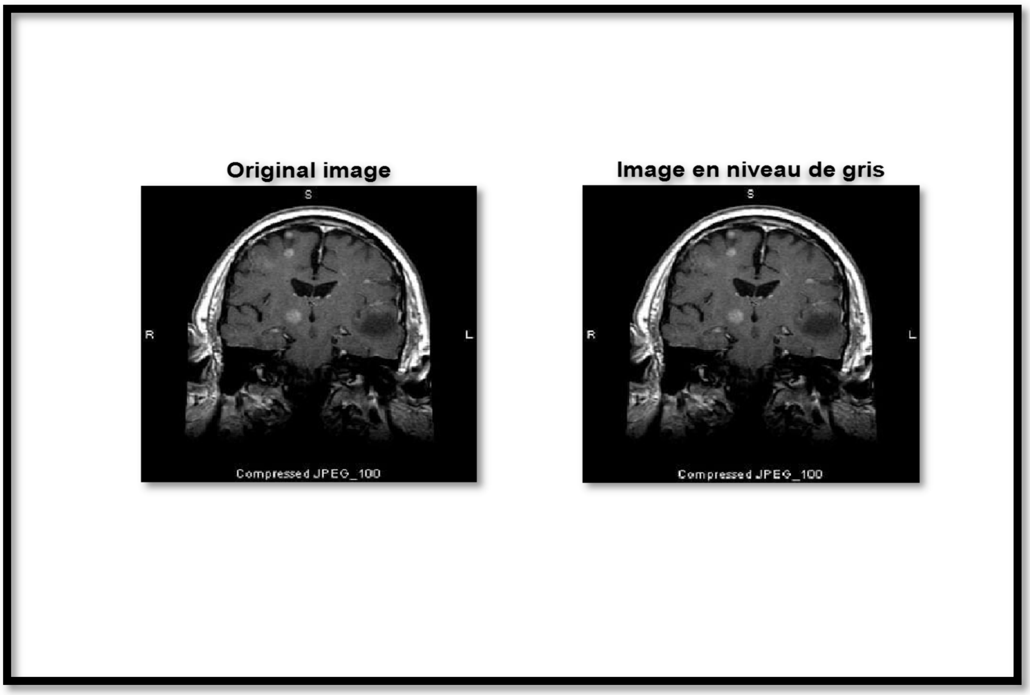

Figure 6 : (A) Original Image (B) Image converted to gray level

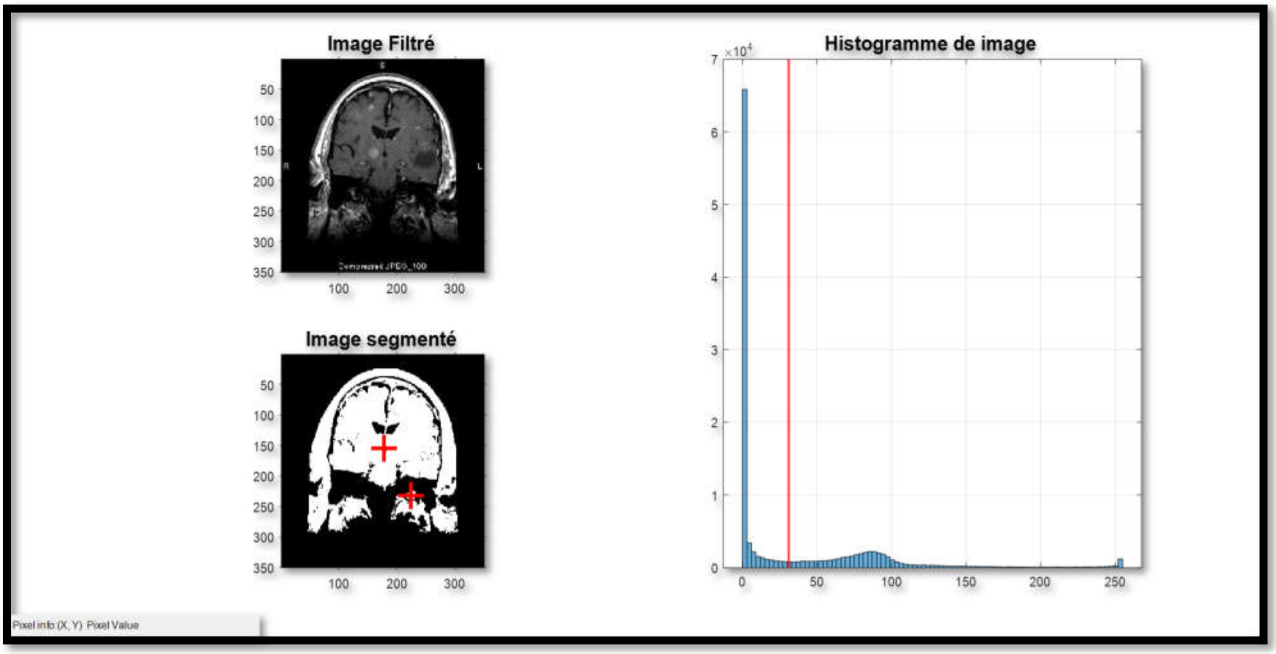

Figure 7 : (A) Filtered Image (B) Segmented Image (C) Image Histogram

- **Test 4 :**

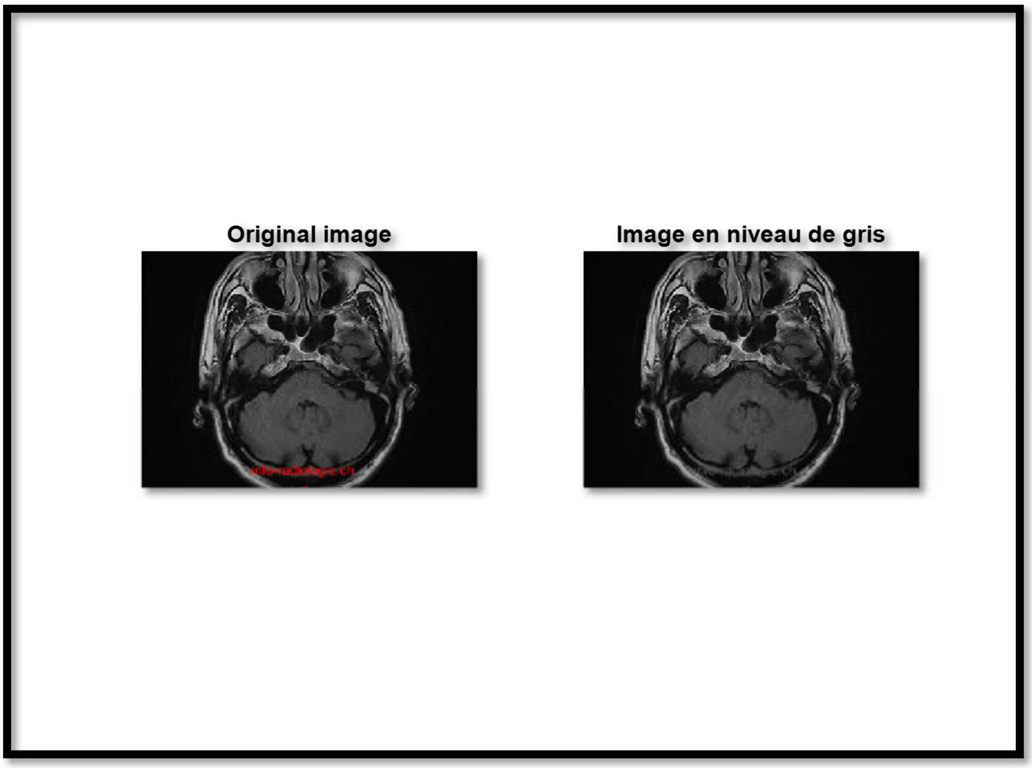

Figure 8 : (A) Original Image (B) Image converted to gray level

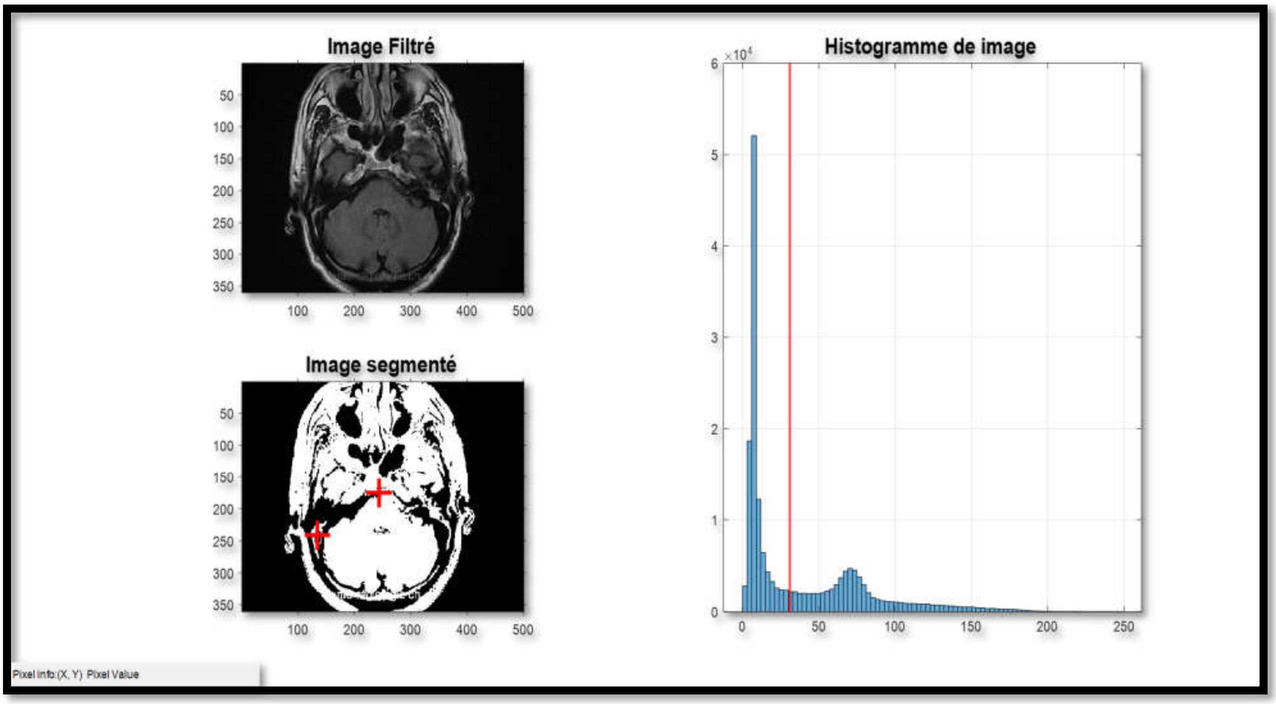

Figure 9 : (A) Filtered Image (B) Segmented Image (C) Image Histogram

The results of our work clearly demonstrate the identification of the anomaly zone (Figure 3,5,7 and 9 (B)), indicating that our method assists specialized medical professionals in monitoring tumors and diagnosing patients in an easy and straightforward manner. We were able to detect even the coordinates of existing abnormal pixels.

Conclusion

The segmentation of brain images is a crucial step in any image analysis process. It involves preparing the image to make it more accessible for an automated process such as interpretation. There are two major purely local approaches. The approach employed in our work demonstrates the effectiveness of the obtained results, providing a clear insight and effective monitoring of our treated condition (Cerebral Vascular Accident - CVA). Segmentation of brain images plays a vital role in medical diagnostic assistance, enabling accurate detection and analysis of various neurological conditions. While the region growing technique of image processing has been widely used, have shown promise in overcoming many of the limitations associated with traditional methods. However, several challenges remain to be addressed, including the availability of annotated data, robustness to imaging variations, and integration into clinical workflows. Addressing these challenges will require interdisciplinary collaborations between computer scientists, radiologists, and clinicians, ultimately leading to improved diagnostic accuracy and patient care in neuroimaging.

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