Morphological and Marker-based Watershed Method for Detection and Segmentation of Brain Tumor Regions

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Abstract

Brain tumor detection is a complex problem in medical image analysis. Brain tumor is an abnormal growth of brain cells that is usually detected by Magnetic Resonance Imaging (MRI) brain images. In this paper, we propose an efficient algorithm for detecting brain tumors using MRI images without skull removal. After applying basic image preprocessing techniques, morphological operations are used to detect the boundaries and sharpen the regions. Subsequently, segmentation is performed using Otsu thresholding and then a marker watershed technique is used for final brain tumor segmentation. The proposed approach is evaluated on 3000 images from Brain Tumor Detection 2020 dataset (Br35H). Experiments showed that with appropriate preprocessing and appropriate thresholding, good segmentation results can be achieved to segment brain tumor.

Keywords: Brain Tumor Detection, Marker-Based Watershed Method, Morphological Operation, Image Segmentation, Medical Image Analysis, BRATS dataset, Otsu Threshold

Introduction

A brain lump is a group of abnormal cells in the brain. Brain tumors are thought to develop when specific genes within the mobile chromosomes are broken and malfunctioning. A primary task involves coordinating treatments for tumors within the brain and determining the level of determination in reducing the tumor as well as minimizing the negative impact of treatment on patient's health. MRI, non-invasive imaging technique, has already been used as a device to diagnose brain tissue without ionizing radiation.

Brain Tumor is considered to be one of the most deadly and unpredictable disease all around the world. In the US, for example, each year about 3,000 children are diagnosed with brain tumors. About half of them die within five years, showing a low survival rate from brain tumor in children [1]. Cancer is a huge burden on the country's economy and a source of family and community suffering [3]. Advances in medical facilities altered the process of detection and classification of brain tissue using MRI Images [4]. Previous research indicates that the features observed in MRI images can be useful for both diagnostic and therapeutic strategies when incorporated with machine learning approaches to detect and classify brain tumor [3], [4], [5], [6], [7].

Literature Review

Manual brain tumor detection involves identifying specific characteristics. Using MRI (or any other imaging modality) is a time- concerning task and diagnosis of the tumor by clinical experts can be variable. An inaccurate diagnosis can lead to inappropriate treatment.

Common existing techniques for brain tumor segmentation are color-based segmentation, region-growing segmentation, texture segmentation, amplitude thresholding, and template matching. These methods extract the required image features from the image using pixel-based, structural-based, or texture-based techniques. [8], [9], [10]

Wu, et al [8] purposed a method where they used K-means clustering for brain tumor detection using color-based k-means clustering segmentation that uses a color-based segmentation method. They applied K-means clustering to isolate the tumor from the image after converting the gray-scale image to a color space image. In another work [9], common image segmentation techniques with morphological operators were used for the detection of the brain tumor region. In [10], watershed and image thresholding techniques were used for the detection of tumor regions. They first improved the quality of the image by using different filters that enhanced the image quality. Afterwards, using the morphological operators and edge detection technique, they isolated the tumor region.

Xuan and Liao [11] proposed another segmentation machine learning technique using intensity-based, symmetry-based, and texture-based feature extraction techniques. In the proposed technique, they classified the image elements into normal and abnormal tissue.

Another method proposed by Sharma et al. [12] used the Gray Level Co-occurrence Matrix (GLCM) for extracting the features of the image and then segmented the image into normal and abnormal tissue.

A number of studies have been conducted during the past few years for the identification of tumors using image processing techniques. Each approach has its own set of benefits and drawbacks. These techniques are evolving day by day with the aim to achieve more accuracy in brain tumor detection. Some of the methods use machine learning technique[8] and some use segmentation [9], [10] techniques, but the purpose of all of these methods is to detect and isolate the tumor. In this paper, we proposed a method for segmentation of brain tumors using image preprocessing (image enhancement), thresholding, and morphological operations. The effect of image enhancement is also studied with respect to accurate tumor segmentation. Initial results showed that image enhancement has a considerable effect on brain tumor segmentation.

Dataset

In this paper, we are using a publicly available dataset, Br35H

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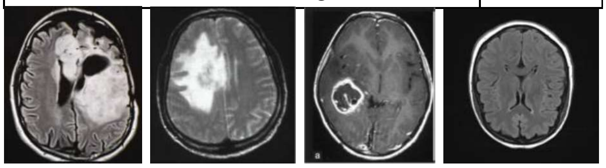
2020 for Brain Tumor Detection and Segmentation [13]. The dataset is freely available to be used by researchers. Br35H 2020 dataset contains MRI brain images that are tumorous as well as non-tumorous. For current work, we categorized the images from the dataset as tumorous class (including both high grade and low grade tumors) and normal class (non-tumorous images). Sample images from the dataset are shown in Figure 1, whereas an overall distribution of images from the dataset is shown in Table I.

Table I: Tumor and Normal Class Images for Brain Tumor Detection [13]

Total dataset images	3000
High and low grade tumor image	1500
Non-tumorous images	1500

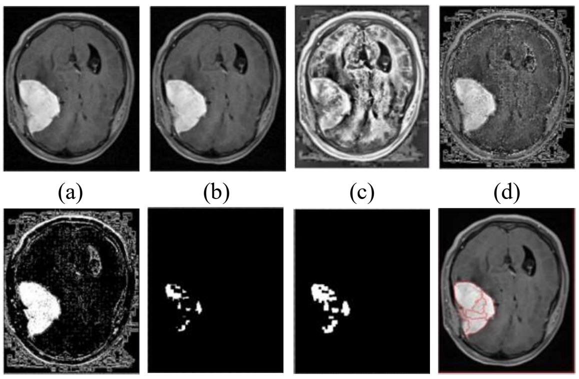


(a) (b) (c) (d)

Figure 1: Sample Images from Dataset; (a) and (b) are showing High Grade Tumors, (c) is showing Low Grade Tumor, (d) is showing an Image with No Tumor.

Methodology

We proposed a method for segmentation of brain tumours, where image processing techniques have been used for morphological operation. We investigated the effect of image enhancement (as a preprocessing step) on the overall segmentation accuracy. In addition, simple methods for thresholding and segmentation are used to identify the tumor region without removing the brain skull. Details of the proposed method can be found in subsequent subsections.



(e) (f) (g) (h)

Figure 2: Stepwise Execution of Proposed Method (a) Original Image (b) Noise Removal (c) Enhanced Image (d) Laplacian Filter (e) Threshold Image (f) Morphological Erosion (g) Morphological Dilation (h) Final Result After Watershed Segmentation

A) Pre-Processing

Image preprocessing is an initial step in many medical image analysis techniques. The purpose of preprocessing is either to remove unwanted signals from the image or to enhance certain features. In medical image analysis, noise removal and enhancing image features both are important as it helps to improve the overall image processing results. We applied the following steps as image preprocessing step.

1 Noise Removal

Noise removal is an important step for medical image processing as all imaging modalities (ultrasound, MRI and CT) tend to contain noise factors obtained during image acquisition. There are various kinds of noise removal filters available where each filter is used to remove a certain type of noise. In this work, we performed experiments using both linear filters (e.g. Geometric Mean, Harmonic Mean, and Arithmetic Mean) and nonlinear filters (e.g. Median Filter, Mean Filter, and Gaussian Filter). In this work, we selected Geometric Mean as linear and median as nonlinear filter. Because Geometric mean and median are showing better results than others.

The geometric mean filter is derived from the mathematical geometric mean i.e. $\prod_{i,j\in S} S(i,j)\frac{1}{mn}$ whereas the median filter is computed by taking the median value of the values lying under the filter kernel. For both of these filters, the kernel value is set to 3 times 3. Both of these filters gave good results when applied for noise removal. The result is shown in Figure 2b.

2 Histogram Equalization

As the next step of our algorithm, we applied histogram equalization to improve the contrast of the image. Histogram equalization is used to distribute the intensity values equally to improve the overall contrast of the image. Through experimental evaluation, we found that histogram equalization is a good way to improve the segmentation results. Generalized histogram equalization im- proves the background contrast of the image, but also loses much information from interested image regions. To solve this issue, we applied Contrast Limited Adaptive Histogram Equalization (CLAHE) [16]. In this method, if any histogram bin is above the specified Contrast Limit(by default it is set to 40), those bins are clipped and distributed uniformly to each other before applying Histogram Equalization. Overall better contrast is achieved by applying CLAHE for histogram equalization. The results are shown in Figure 2c.

B) Image Enhancement

To enhance image features (i.e. edges), we applied image enhancement to the sharpened image and to get the most prominent edges. For this, we used a Laplacian filter and then subtract es the results of the Laplacian filter from the original image (after applying preprocessing and image enhancement). The results afterapplying this step are clearly showing the visible edges within the image. The results are shown in Figure 2d.

C) Thresholding

Thresholding can be a crucial step in segmenting the region of Interest (RoI), and the final segmentation output strongly depends on the threshold value. We used Otsu's method [14] for tumor identification. Otsu method is a nonparametric and unsupervised method for selecting the optimum threshold value. Experiments showed that Otsu's method works well for brain tumor segmentation compared to other automatic thresholding techniques (adaptive thresholding, etc.). For some images, where the tumor region is very small, Otsu thresholding did not provide satisfactory results. For those images, we applied global thresholding by looking at the appropriate threshold values from the image histogram. The basic idea is to evaluate the image histogram that to indicate what to use Otsu method or for global thresholding and apply the thresholding technique accordingly. The binary results are shown in Figure 2e.

D) Morphological and Watershed Operation

To refine the outcome of image binarization, we used the morphological version and operators.

At first, we applied erosion to the output of the image of Thresholding Section. Erosion basically “shrinks” or “thin” pixels in the image (so remove the unnecessary details from the selected tumor region). Dilation is the opposite to erosion, i.e., it expands the pixels in the image. Therefore, after erosion operation, we apply dilation. Detailed results are shown in Results and Discussionsection.

The amount of shrinking and growing pixels depends on the structuring element. We used a size 3x3 structuring element. The results of applying erosion and dilation operations are shown in figure 2gand 2h. Subsequently, we apply a standard watershed to generate the final segmentation [15]

Results and Discussion

A) Stepwise analysis of algorithm steps on overall segmentation accuracy

In this section, we will discuss in detail the effect of various steps in achieving good segmentation results.

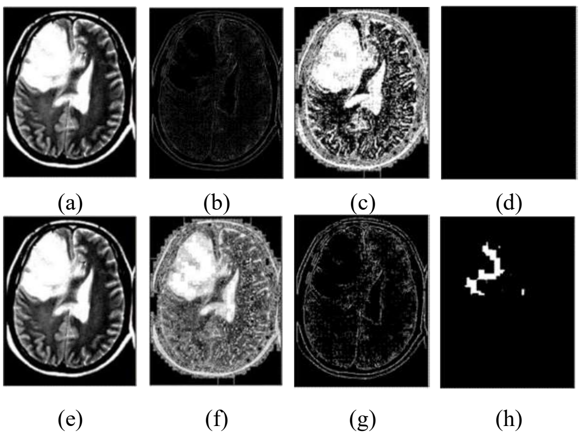


Figure 3: (a-d) Results Without Image Sharpening (a) Original Image (b) No-Sharp Image (c) Threshold Image (d) Morphological Erosion Image; (e-h) Result with Image Sharpening (e) Original Image (f) Sharp Image (g) Threshold Image (h) Morphological Erosion Image.

1. Effect of Image Sharpening on Laplacian

As stated in the Image enhancement section, we subtracted the results of the image after applying a Laplacian filter to the original image. This step is crucial in obtaining an appropriate threshold for image segmentation. The results of obtaining the threshold (without image sharpening) and the result of subsequent steps are shown in Figure 3a to 3d and Figure 4a to 4d, where it can be seen that the results of final segmentation are not appropriate. Whereas results on the same image after subtracting the Laplacian image from the original image before applying thresholding step are seen in Figure 3e to 3h and Figure 4e to 4h.

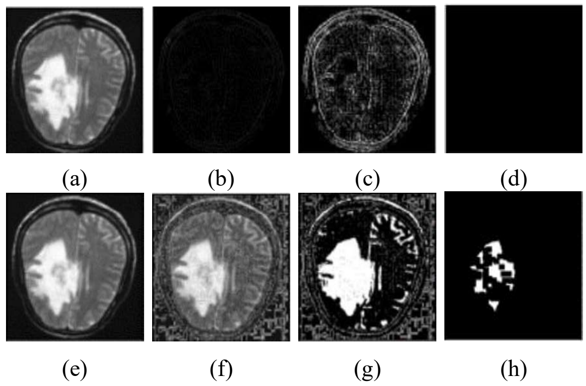


Figure 4: (a-d) Results Without Image Sharpening (a) Original Image (b) No-Sharp Image (c) Thresholding Image (d) Morphological Erosion Image; (e-h) Results with Image Sharpening (e) Original Image (f) Sharp Image (g) Thresholding Image (h) Morphological Erosion Image an accurate result is obtained after applying the step of image sharpening.

2. Effect of Image Enhancement

Image enhancement is also an important step to obtain accurate segmentation results. During the algorithm implementation, 50% of images were not showing good results without applying his- to gram equalization for image enhancement. Without enhancing images, most of the image area was selected as tumor region, i.e. an inaccurate segmentation Figure (5a to 5d) and Figure 10a to 13a.

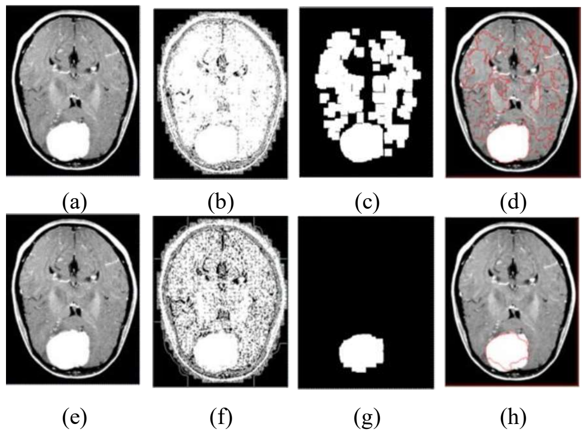


Figure 5: (a-d) Results Without Applying Contrast Enhancement (a) Original Image (b) Threshold Image (c) Morphological Dilation (d) Final Result After Watershed Segmentation; (e-h) Results with Applying Contrast Enhancement (e) Original Image (f) Threshold Image (g) Morphological Dilation (h) Final Result After Watershed Segmentation.

The result on the same image after the applying Histogram and Contrast Limiting Adaptive Histogram Equalization technique is shown in Figure 5e to 5h and Figure 6e to 6h.

3. Effect of Morphological Operators

After applying thresholding, the next step is to apply morphological operators (erosion and dilation) to improve the selected region.

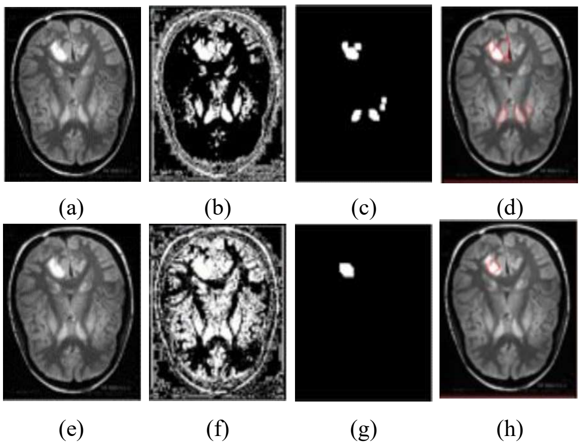


Figure 6: (a-d) Results Without Applying Contrast Enhancement (a) Original Image (b) Threshold Image (c) Morphological Dilation (d) Final Result After Watershed Segmentation; (e-h) Resultswith Applying Contrast Enhancement Using Histogram Equalization (e) Original Image (f) Threshold Image (g) Morphological Dilation (h)Final Result After Watershed Segmentation

The parameters used to define these morphological operators are also essential for achieving good tumor segmentation results. In the morphological operation step, we use the kernel window size of 3x3, 5x5, and 7x7. Experiment showed that using 7x7 window size we achieved good results. Results on the image using different kernel window size for erosion and dilation are shown in figure 7a to 7h of kernal 3x3, figure 8a to 8h of kernal 5x5, figure 9a to 9h of kernal 3x3.

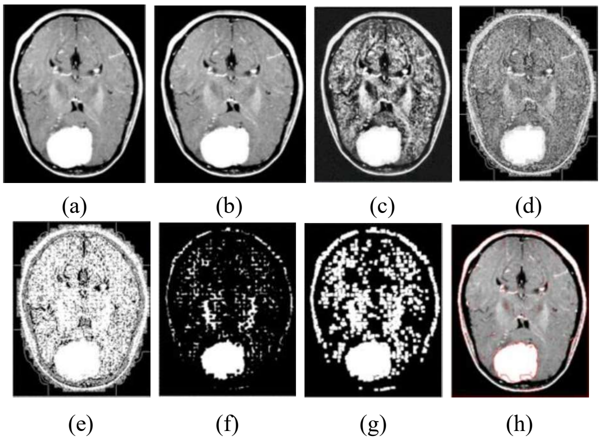


Figure 7: Results With Kernel Size 3x3 Morphological Operations(a) Original Image (b) Noise Removal (c) Enhanced Image (d) Laplacian Filter (e) Threshold Image(f) Morphological Erosion (g) Morphological Dilation (h) Final Result After Watershed Segmentation

It can be seen that the kernel size affects the final segmentation results. From the images, it can be seen that the results for kernel size 5x5 and 7x7 are better than kernel size 3x3.

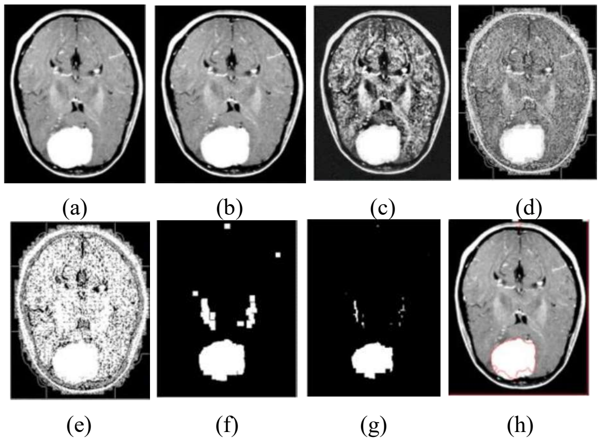


Figure 8: Results With Kernel Size 5x5 For Morphological Operations (a) Original Image (b) Noise Removal (c) Enhanced Image (d) Laplacian Filter (e) Threshold Image(f) Morphological Erosion (g) Morphological Dilation (h) Final Result After Watershed Segmentation

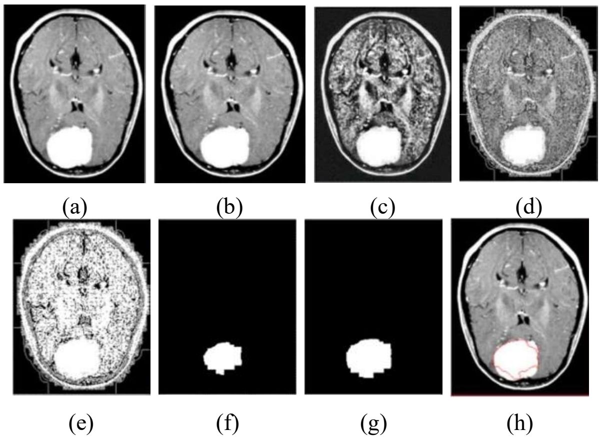


Figure 9: Results With Kernel Size 7x7 For Morphological Operations (a) Original Image (b) Noise Removal (c) Enhanced Image (d) Laplacian Filter (e) Threshold Image(f) Morphological Erosion (g) Morphological Dilation (h) Final Result After Watershed Segmentation

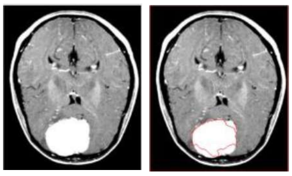
B) Results on the Dataset

We achieved an overall accuracy of about 77.60% on the overall dataset. As we have in total 3000 images (1500 with tumor and 1500 non-tumorous) in the dataset [13]. From 1500 tumorous images, 1100 were identified correctly. with an accuracy of 72.9% , whereas from 1500 non-tumorous images 1250 were identified correctly and have an accuracy of 82.26%. For correctly identified instances we only considered those results where only the tumor region is segmented without any unwanted segmentation from normal region. The confusion matrix for the results achieved on the overall dataset is shown in Table II.

Table II: Confusion Matrix

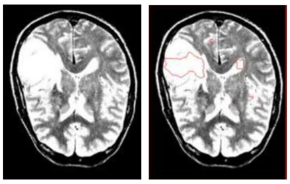
	Tumor Image	Non-Tumor Image
Tumor Image	1094	406
Non-Tumor Image	266	1234

Figure 10 is showing a result for an image from the dataset, where the tumorous image is detected accurately. Such results are indicated by True Positive (TP) identification, where only the tumorous region is showing as final detection. In some cases (Figure 11), tumor part is detected accurately (from tumorous image) but area other than tumorous region is also detected as tumor. These results are marked as False Positive (FP), indicating instances where the algorithm incorrectly identifies the normal area of a tumorous image as tumor. Similarly, instances where the proposed algorithm detected no tumor in non-tumorous images are marked as True Negative (TN) results (Figure 12). This is attributed to the ability of the proposed method to not establish a threshold value for images without tumor, leading to a non-detection for non-Tumorous images. Consequently, when the algorithm is applied, the final result indicates no findings. More-ever, instances where the proposed algorithm detected images with tumor as no-tumorous images, are marked as False Negative (FN) (Figure 13).



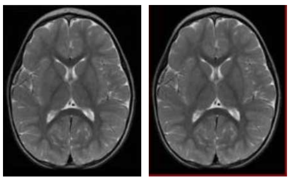
(a) (b)

Figure 10: True Positive Detection (Tumorous Image as Tumorous) (a) Original Image (b) Final Watershed Image



(a) (b)

Figure 11: False Positive Detection (Non-tumorous Region as Tumor) (a) Original Image (b) Final Watershed Image

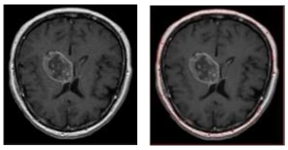


(a) (b)

Figure 12: True Negative Detection (Non-Tumorous Image as Non-Tumorous) (a) Original Image (b) Final Watershed Image.

Conclusion

We proposed an algorithm composed of a series of steps to achieve brain tumor segmentation using brain MRI. Initial result showed satisfactory results for tumor segmentation. In the future, we will investigate the use of different post-processing techniques to reduce the False Positive results. In addition, we will try to implement the proposed approach on different imaging modalities and different medical imaging problems to make this algorithm generalized for other medical imaging problems.



(a) (b)

Figure 13: False Negative Detection (Tumorous Image As Non-Tumorous) (a) Original Image (b) Final Watershed Image

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