A Framework To Detect Brain Tumor Cells Using MRI Images

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***Abstract*—Tumor indicates unfettered presence of a cluster of cells in a specific area of the body part. Brain tumor is considered one of the most common tumors for both men and women and can lead to high death risk if patients fail to obtain appropriate medical treatment. In order to diagnose brain tumors, electronic modalities are integrated and among them MRI is a popular one. For MRI brain tumor region analysis segmentation, detection and classification are considered as important steps in digital imaging pathology laboratory. Existing state-of-the-art approaches demand widespread amount of supervised training data from pathologists and may still accomplish poor results in images from unseen tissue types. A suitable framework has been presented in this study to identify brain tumor cells for MRI images. In this study for the first time in compare to all other existing accessible approaches morphological operations has been incorporated to eliminate undesirable regions and to assist segmentation and identification of region of interests. Compared with existing state-of the-art supervised models, our method generalizes considerably improved identified results on brain tumor cells deprived of training data. Even with training data, our approach attains the identical performance without supervision cost. This study results indicates an accuracy rate above 96.23% accuracy associated to existing works.**

Keywords—Brain tumor, MRI, morphology, OTSU.

I. INTRODUCTION

Current state-of-the-art supervised image analysis approaches [1, 2, 3] fundamentally depend on the accessibility of large annotated training datasets which entails the contribution of domain experts. This analysis approaches are time-consuming and expensive. Besides, for techniques that simplify on several input types, supervised data needs to be composed for each input category. It has been observed that analysis of cells in the pathological image analysis detection, segmentation, and classification are common steps [1, 2, 3].

According to medical science information there are different types of cancer which are deadly including breast cancer, lung cancer, brain tumor, cervical cancer, ovarian cancer etc. According to the American Brain Tumor Association, about 80,000 men, women and children were analyzed with a primary brain tumor in 2018 [4]. The estimation includes both benign (noncancerous) and malignant (cancerous) brain tumors. The American Cancer Society predicts that in 2021, about 23,880 people will be analyzed through a malicious brain or spinal cord tumor and about 70 percent of those with a malevolent tumor will not persist as an outcome of their analysis [5].

Principal brain tumors devise from cells inside the brain and subordinate (metastatic) brain tumors initiate in supplementary part of the body and then extent to the brain [5]. According to WHO it has been revealed that there are over 120 different types of brain tumor based on the tumor cell type and location [5]. Brain tumor can be categorized based on the tumor cells where they ascend, and a quantity fluctuating from I-IV [5]. Among grade I-IV, Grades I and II are measured as minor grade, while III and IV are measured as advanced grade tumors [5]. Brain tumors can be lethal if not treated with proper care and hence accurate analysis and essential treatment is vital [5]. To analyze brain tumors options include-

Microscopic biopsy analysis and

Electronic scanners such as MRI, Ultrasound, PET etc.

An electronic scanner is used to produce computerized images of the brain and spinal cord while inspecting from diverse positions. Sometimes histopathology experts suggest patients to undergo more than one type of scanning to analyze a tumor, which depends on tumor type, stage and location.

Among all existing available electronic scanners Magnetic Resonance Imaging (MRI) is considered as one of the supreme used and common for brain tumor analysis. In this study, an automated framework has been suggested where MRI gray-scale brain tumor images were incorporated for recognition.

II. RELATED WORKS

In image processing and computer vision brain tumor recognition is one of the most tedious and weighty research. Researchers incorporate diverse type of procedures to distinguish brain tumor. There are two major different ways for brain tumor segmentation which include generative approach and discriminative approach. Generative approach profoundly depend on domain detailed information about healthy and tumorous brain tissue.

Existing research work by [6] suggested an approach to distinguish brain tumor cells from MRI images where 3 stages incorporated which include: pre-processing, detection of edges edge and threshold based segmentation. Lastly, a supervised clustering approach named k-means clustering was implemented to identify the tumor region. Although they claim to have satisfactory results but it has been observed that there are several regions found after identification which can create confusion for the pathology experts. Another related study by [7] revealed the greater precision of brain

978-1-7281-9352-6/20/$31.00 ©2020 IEEE

tumor recognition while using watershed segmentation and morphological operation for analysis achieving a precision rate of 97.34%. However; this method is not suitable for low-contrast images as a fact that for low-contrast image the precision rate falls below 80%. Study by [5] mentioned that morphological operations technique can be used to detect the tumor from MRI images but not mentioned it can be used for filter instead of a single filter itself for an appropriate segmentation. For segmentation purpose, threshold based segmentation can be used.

Study by [8] incorporated k-means clustering for miss clustered tumor. Another research work by [9] incorporated watershed and threshold based approach for MRI brain tumor analysis. Edge detection approach was used to extract the boundary. Lastly, mathematical procedures were incorporated to identify the outline of the tumor cell. Efficacy of segmentation using brain tumor MRI images were investigated by [10]. From all the above studies indicate that segmentation step is considered as one of the most fundamental part for MRI brain tumor examination. Some of the works mentioned the use of morphological operations as well however; none have used for filter and reshaping the regions while shrinking and enlarging tumor regions for better identification when necessary features are used for identification purpose.

III. PROPOSED METHOD

The design of the proposed framework is demonstrated in Figure 1. MRI grayscale images were incorporated as test input images. First step include enhancement operation followed by morphological filter operation to reshape the region boundaries. Median filter was incorporated to preserve region boundary edges followed by segmentation. Necessary features that are used in the pathology laboratory were used for identification based on the shape and size parameters and finally classification approach was incorporated to increase the precision rate.

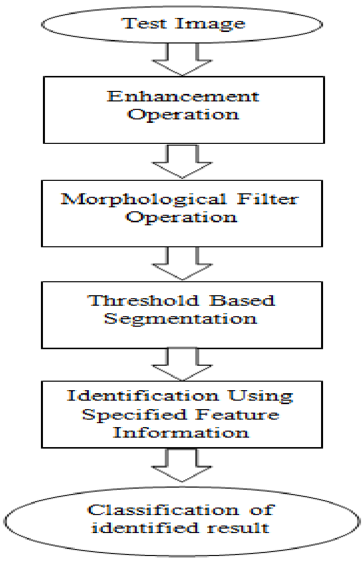


Fig. 1. Framework for MRI brain tumor analysis

A. Image Acquisition

MRI brain tumor dataset incorporated from [11] was used in this proposed framework. The dataset has various contrast images including glioma, meningioma and pituitary tumor. In this proposed framework 3 different batches were incorporated where each batch contains around 120 images and the size of each image was set as 350x350 and are in .JPEG image format.

B. Pre-processing

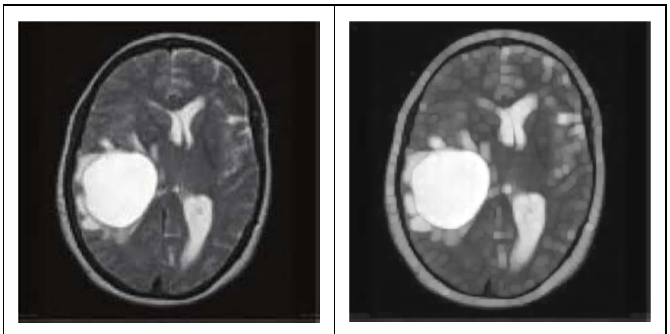
For this study framework a number of steps were assimilated which include: a. Image Enhancement b. Morphological Filter operation and c. Segmentation.

a. Enhancement

As mentioned earlier that 3 different batches were used in this study; each batch of images contains different types of contrast. To minimize the issues associated with contrast this step was incorporated. At first grayscale images were converted in RGB images and then converted to HSV as this color model assists to acquire better contrast [12, 14]. This is due to the fact that RGB images are not suitable for image processing rather they are suitable for hardware based processing. It is to mention that for converted HSV images S (saturation) and V (value) can be modified. S was not considered here and thus local histogram equalization approach was used only on V channel for enhancement. This is done due to the fact that this equalization approach does not produce a synthetic looking image which can be found after histogram equalization processing [5]. After enhancement on V channel median filter [3x3] was applied to preserve the image edges. Finally the images were converted back to RGB images. A sample test image result is shown in Figure 2

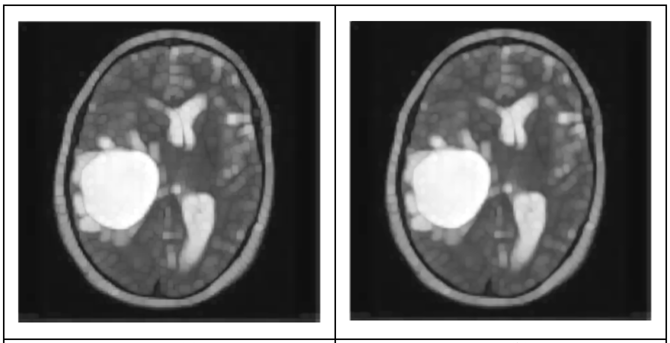
b. Morphological Filter Operation

In image processing, computer vision and pattern recognition filter operation is used to reduce or eliminate unnecessary regions, to escalate the smoothness and or sharpness and sometimes little enhancement of region edges. Existing related research studies indicate that median filter was incorporated as filter operation as it can preserve region edges better than mean and Gaussian filter [13]. None have implemented morphological operation as filter operation but rather used for identification purpose. In this study instead of using a filter operation directly Mathematical Morphological Operation was incorporated using Erosion and opening. This is due to the fact that, when median filter operation is carried out in real time it is cumbersome to get good results and the computational cost is high when the filter mask size is bigger. A sample test image result is shown in Figure 3.



(a)	(b)

Fig. 2. (a) Original test images, (b) Applied enhancement operation



(a) (b)

Fig. 3. (a) Enhancement image, b) Filtered image

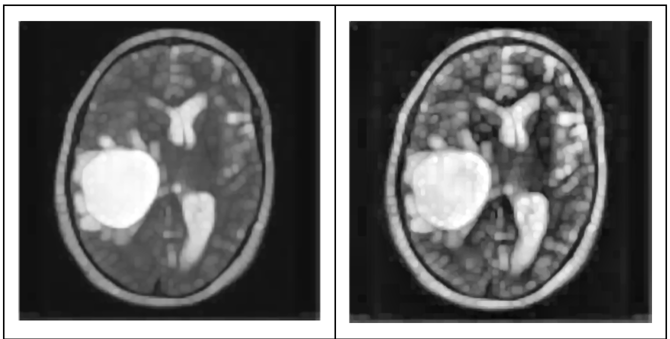
c. Segmentation

The main and the basic purpose of segmentation is to split the image into regions based on the related characteristics. This is the final step of pre-processing for this proposed framework and as mentioned earlier this is one of the common and essential step for MRI brain tumor image analysis. Most of the existing related studies performed threshold based binary segmentation and mostly Otsu's method was incorporated. This is a fast processing approach as it takes less time to computer the threshold value and it has simple mathematical expression and calculation [15]. While working with filtered images for segmentation it has been observed that among RGB (R, G and B channel) only G and B are suitable for segmentation and it has also been mentioned in [5]. A sample result is shown in Figure 4 as only G and B channels were considered for segmentation.

Finally, the threshold based Otsu's segmentation was implemented on the filtered image consisting of only green and blue channels while eliminating the red channel. A sample result of segmentation is shown in Figure 5.

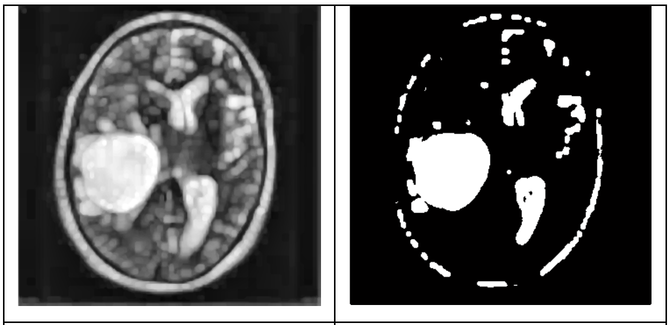
A. Post-processing

This is second stage of this proposed framework where mainly 2 steps were used which include (a) feature extraction and (b) Identification of ROI. Lastly, classification was incorporated to see if there is a chance of increasing the precision value.



(a) (b)

Fig. 4. (a) Filtered RGB image, b) Filtered image with only G and B channels



(a) (b)

Fig. 5. (a) Filtered image with only G and B channels (b) Segmented image

a. *Feature Extraction*

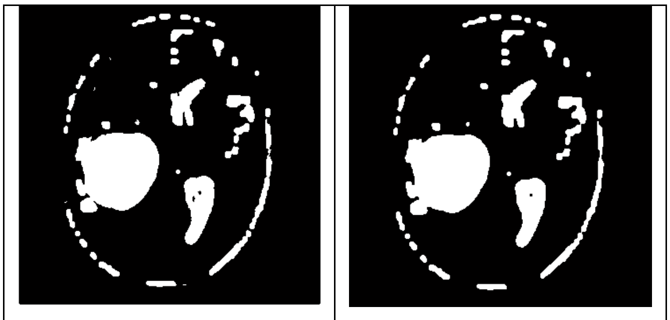
The basic purpose of feature extraction approach/approaches is to use the important features while ignoring the redundant features which may lead to inaccurate identification. To identify the region of interests (ROIs) features can be categorized in 3 different categories which include shape, size and color features. For this study after segmentation the images became binary and thus color features were not usable. Ignoring color features, this study incorporated pathology laboratory experts' used shape and size features which include regions area, circularity, solidity, roundness, radius, and diameter [5].

b. Identification of Region of Interest (ROI)

Only for a very rare occasion it can be observed that only a specific regions are processed for identification while leaving other regions untouched and thus it is called region of interest (ROI) processing. Before identifying the ROIs using the useful and necessary features once again morphological operation was implemented as a fact that it assists binary segmented regions to have some shape and size reconstruction. A sample results is shown in Figure 6.

It is possible to achieve more than one ROI from an image based on the feature information [16]. Considering the difference between foreground and background the radiologist needs to determine a region of interest (ROI) in a semi-automated manner where shape and size features are incorporated. In this study same shape and size features were incorporated to obtain the required ROIs. A sample result is shown in Figure 7.

Finally images of identified ROIs were placed over the original test image to check the results. A sample result is shown in Figure 8.



(a) (b)

Fig. 6. (a) Segmented image, (b) applied morphological operation to fill image holes, reshape and resize

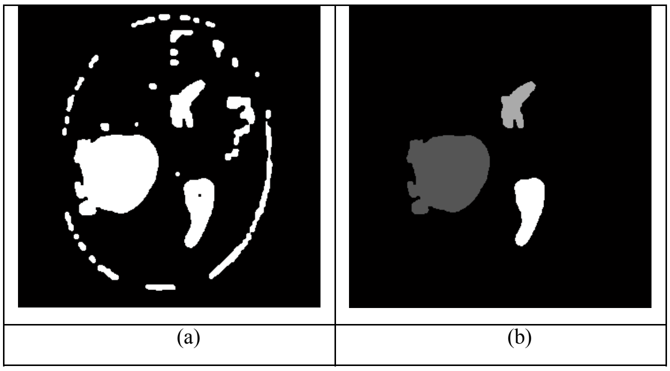


Fig. 7. (a) Applied morphological operation on segmented image, (b) Identified ROIs

c. *Classification*

Classification is used to check whether it is possible to increase the precision rate or not. After identification it was found that in most cases the identified regions are accurate. However; still there are a very images where some anomaly found and this in this study SVM classifier was implemented. It was observed that the accuracy rate did not change.

IV. Experimental Results

In this experimental results section we have presented the outcome of this study experiment which indicates that our proposed framework grasps the possible unsurpassed result.

A. *Result Analysis of the Proposed Method*

It was mentioned earlier that 3 different image batches were incorporated in this study. The detailed result information is shown in Table 1.

Table 1 point to the accuracy rate for each batch used in this research study where for batch 1 the accuracy rate was found highest which is 99.13%, for batch 2 the accuracy rate found lowest which is 94.34% and for batch 3 the accuracy rate found 95.16%. According to pathology expert's identification criteria, ±17% accuracy rate is considered as an acceptable accuracy rate. This proposed framework is capable of obtaining an average accuracy rate of 96.23% which is acceptable in the pathology laboratory by pathology experts.

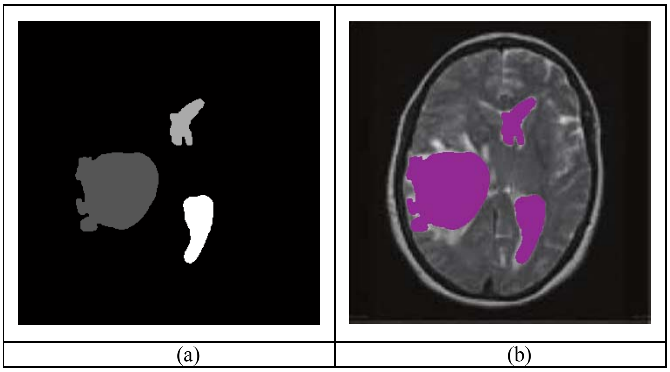


Fig. 8. (a) Identified ROIs, (b) Identified ROIs placed over original test image to check the result

TABLE I. RESULT ANALYSIS OF THE PROPOSED METHOD

Dataset(No.of Images)	True Positive (TP)	True Negative (TN)	False Positive (FP)	False Negative (FN)	Accuracy
Batch1 (115)	**114**	**0**	**1**	**0**	**99.13%**
Batch2 (106)	**100**	**1**	**3**	**2**	**94.34%**
Batch3 (124)	**118**	**1**	**3**	**1**	**95.16%**
Total = 345	**332**	**2**	**7**	**3**	**Average = 96.23%**

B. *Experimental Outcomes*

The possible experimental outcomes of this study proposed method are shown in Figure 9.

The first column shows the input images followed by filtered image in the second column. Segmented images are shown in third column and finally identified regions placed over the original images in column four.

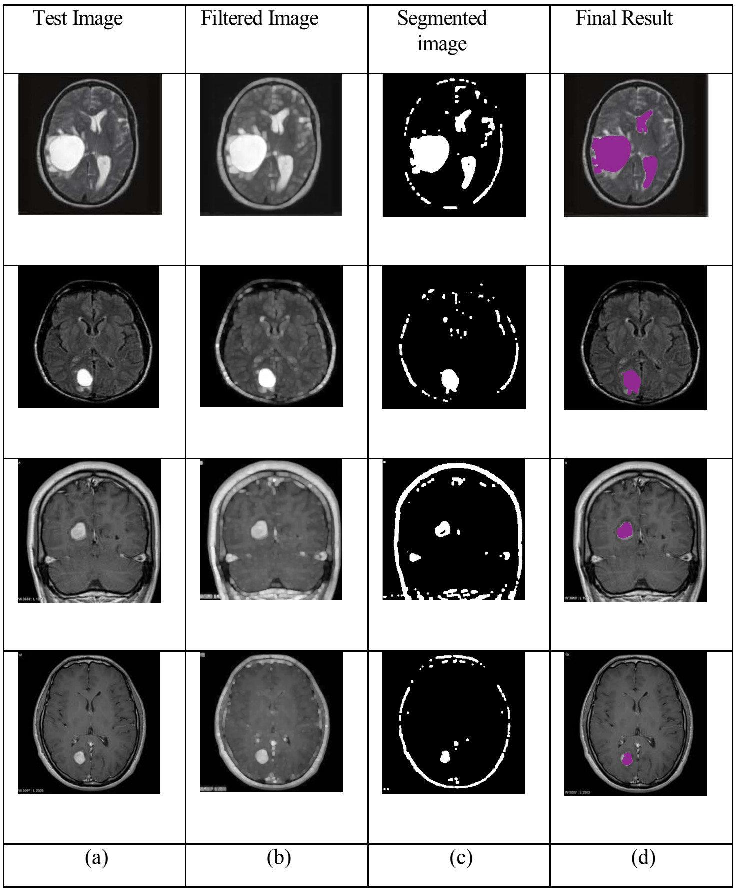


Fig. 9. (a) Test image, (b) Filtered image, (c) Segmented image, (d) Identified

TABLE II. RESULT ANALYSIS OF DIFFERENT APPROACHES

Serial Number	Proposed approach	Number of test images	Accuracy
1	**Proposed by [5]**	**345**	**93.45%**
2	**Proposed by [6]**	**345**	**92.67%**
3	**Proposed by [7]**	**345**	**92.16%**
4	**Proposed by [17]**	**345**	**93.11%**
5	**This study proposed approach**	**345**	**96.23%**

C. *Comparative Results Analysis*

Comparative results of existing related approaches are shown in Table 2.

From Table II it is clear that this study proposed approach achieved highest accuracy rate compared to other related existing approaches followed by work [5] with second highest accuracy. Work of [17] implemented neural network but still their accuracy under 95%.

The comparative results in Figure 10 indicates that this study approach has a better accuracy rate in compare to [6].

Existing research work carried out by [6] claimed that their approach performs better than other existing available approaches and thus we have compared our tested result with [6] for comparison purpose. Result obtained from [6] indicates that there is a circular shape available in the result which may create confusion for laboratory experts but for our case the accurate and only the region is identified. To escalate the accuracy rate SVM (support vector machine) was integrated in this study but it did not help to increase the accuracy rate. For this reason, for this framework classification approach is not included. Yet; the accuracy rate is for this study is under 98% and thus there is still a possibility to escalate the accuracy rate.

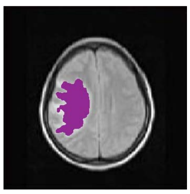
Test Image	Result obtained by [6]	Result obtained by this study
		
(a)	(b)	(c)

Figure 10. (a) Test Image, (b) Proposed by [6] (c) This study approach

V. Conclusion

We would like to thank Dr. Md. Sadequel Islam Talukder for supporting our work while providing all the necessary MRI brain tumor test images along with feature information to identify the ROIs. This study also thanks Military Institute of Science and Technology for their support to carry out this study successfully.

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