

Detection of Brain Tumor in MRI Images Using Watershed and Threshold-Based Segmentation

Ghinwa M. Tarhini and Reda Shbib

Department of Computer Science, Lebanese International University, Saida, Lebanon

Email: ghinwa.tarhini@hotmail.com, reda.shbib@liu.edu.lb

Abstract—Brain Cells control all body organs including the critical ones where any disorder of these cells will directly cause other organs to malfunction and thus threatens human's life. That is why the brain is considered the most crucial organ in the human body. Disorder of brain cells, appear as inflamed cells in the brain known as a tumor. The early detection of these tumorous cells will increase the possibility of curing disease in a short time. Magnetic Resonance Imaging (MRI) is now used for detection of brain tumor. Image processing and segmentation of the MRI images is now an emerging research field where several techniques have been developed for MRI segmentation and tumor detection like Fuzzy C-Means (FCM) and Support Vector Machine (SVM). In this paper, an efficient algorithm based on threshold segmentation technique, followed by some morphological operations is proposed. The quality of the MRI scanned image is enhanced at first, then threshold segmentation is applied to divide the pixels into different classes, then to detect the tumor part of the image with the highest intensity, morphological operators are applied.

Index Terms—brain tumor, image processing, MRI, threshold segmentation

I. INTRODUCTION

The most critical parts of the human body are controlled by the brain cells like brain, heart, and lungs. That means the brain is a very important organ inside our bodies. These days, the brain tumor has become one of the most spreading diseases among children and adults. As it is one of the fatal diseases, the location of the tumor and its rapid spreading makes it one of the basic issues in treatment. Image segmentation is a critical technique to identify and tackle medical problems of different diseases.

A tumor is a mass of tissues that are formed by the accumulation of abnormal cells. Usually, the cells in your body age die and are replaced by new cells. With cancer and other tumors, something disrupts this cycle. Tumor cells grow, even though the body does not need them, and unlike healthy old cells, they do not die. As this process goes on, the tumor continues to grow as more and more cells are added to the mass. Different types of brain tumor exist; benign brain tumor and Malignant brain tumor. Benign brain tumors are noncancerous with a uniform structure containing non-active cancer cells like gliomas and meningiomas. Malignant primary brain tumors with nonuniform or heterogeneous structure and active cancer

cells are cancers that originate in the brain, typically grow faster than benign tumors, and aggressively invade surrounding tissues like glioblastoma and astrocytoma. Although brain cancer rarely spreads to other organs, it can spread to other parts of the brain and central nervous system.

Brain tumors can be also classified as primary or secondary. A primary brain tumor is a tumor which originates from the brain whereas secondary brain tumor starts in other organs outside the brain and then spread into the human body to reach the brain.

According to the American Brain Tumor association and World Health Organization, the classification of benign or malignant tumors uses a grading system scale from grade I to grade IV. Based on that scale, tumor of grade I and II fall under benign glioma tumor or low-grade tumors with slow growth; whereas tumor of grade III and IV glioma are malignant tumors or high-grade tumors with rapid growth. If the low-grade tumors are left untreated, they may grow and develop into malignant tumor.

Brain tumor can be manually diagnosed using several imaging techniques such as CT-Scans (Computed Topography) and Magnetic Resonance Imaging (MRI) of the head. MRI is considered as the best technique since it analyzes the internal structure of the brain.

Image processing techniques can be used for brain tumor identification. Where the image is converted into digital format and relevant operations are performed on it like enhancement and extraction of some useful information. So automated detection of the brain tumor in brain MRI is essential in the context of accurate measurement and time. This automation is based on MRI image segmentation which is the process of segmenting the image into different parts or regions having similar or identical properties. Brain tumor segmentation is the process of separating the tumor part of the image from the normal brain tissues. Several techniques have been used by researchers like Fuzzy C-Means, K-Means, Support Vector Machine for image segmentation.

Watershed Segmentation and Threshold-based segmentation are essential techniques in automating the process of brain tumor detection. We will focus in this paper on identifying brain tumor by using image-processing techniques. Threshold Segmentation, Watershed Segmentation, and Morphological Operations and all steps of the proposed methods are described in the proposed work section.

Manuscript received September 11, 2019; revised February 20, 2020.

II. LITERATURE REVIEW

The tumor can be defined as the abnormal growth of tissues. Brain tumors are rapidly increasing nowadays. It was estimated in 2016 that 23,800 adults would be diagnosed with cancerous brain and spinal cord tumors in the United States (13,450 men and 10,350 women) [1]. Since the shape, size, location, and appearance of tumor differ, it is difficult to diagnose it, especially in the beginning stage because of the tumor's accurate measurement. However, the tumor can be curable or treated if it is detected at the beginning stages. For clinical analysis and medical researches, medical imaging techniques were present to visualize the interior of the body. The most useful imaging technique used is MRI for brain tumor detection. Currently, the diagnosis of a tumor is made using manual methods based on human experience, which increases the possibility of detection errors.

Since MRI image enhancement is an essential matter before proceeding with segmentation and analysis [2], T. Logeswari started by enhancing the image so he improved perceptibility by increasing the brightness of the image, then improved the contrast and converted the images into gray-scale or intensity images, then improved the image quality by stretching the middle range intensity values where gray-scale image pixels are mapped between 0 and 1.

$$X_{ij} = \frac{\text{Image}(i)}{255} \quad (1)$$

After that he converted the image into binary one by using double thresholding and then removed unwanted pixels by using a disk of radius 3 for erosion. Fuzzy C-Means (FCM) was used by T. Logswari for the image segmentation to find out the suspicious regions and then used the Gray Level Run Length Matrix (GLRLM) to isolate MRI image relevant features and to understand the brain MRI image well. Finally, he used the Support Vector Machine (SVM) for the classification and detection of brain tumor, where a decision plane is used to separate items with different class memberships. Two basic steps of training and testing are involved in the use of SVM [3] using the equation:

$$y = \sum_{i=1}^N w_i + x_i + b \quad (2)$$

where x_i is the input patterns, w is the weight vector, b the offset.

Since the classes are defined as ± 1 the equation for the line dividing the classes will be:

$$x_i w + b \geq 1 \text{ when } y = +1 \quad (3)$$

$$x_i w + b \leq -1 \text{ when } y = -1 \quad (4)$$

The distance from the hyper plane ($x_i + b = 0$) to the origin is:

$$M = \frac{-b}{w} \quad (5)$$

where w is the norm of w . The distance from the hyper plane to the origin is:

$$M = \frac{2}{w} \quad (6)$$

where M is the margin. So, the maximum margin is obtained by minimizing w . [4]

S.G. Hate and A.D. Vidhate started by cleaning up the image background and removing the noise by using a binary mask where they got a black image after multiplying the binary image by the original image, and then extracted the brain using the Brain Extraction Tool (BET). After that, they increased the classification accuracy result by improving the image contrast using histogram equalization technique for detecting the edge. Then they segmented the image to detect the tumor portion of the image by Self Organizing Map (SOM) clustering using fast volume segmentation algorithm Histogram Based Fast Segmentation (HFS-SOM) method that is based on the histogram image and the features generated from the computed histogram. After that, they used the Gray Level Co-occurrence Matrix (GLCM) for defining texture features [5], so they generated the image co-occurrence matrix using the grayscale image obtained from the segmentation phase. For brain tumor recognition, extraction of important features like Autocorrelation, contrast, correlation, cluster prominence, cluster shade, dissimilarity, energy, entropy, homogeneity and... was involved where the property of the texture of extracted features was stored and then compared by features of an unknown sample image for classification. Finally, to get the most favorable features from the entire data set, they reduced the dimensionality of data using Principle Component Analysis (PCA) which converts the input feature space to high dimensional feature space wherever they are linearly distinguishable. Then Proximal Support Vector Machine (PSVM) classification [6] is performed to identify brain tumor.

The performance measures such as the sensitivity, specificity, and accuracy were calculated using the below formulas:

- True Positive (TP): Abnormal brain correctly identified as abnormal
- True Negative (TN): Normal brain correctly identified as normal
- False Positive (FP): Normal brain incorrectly identified as abnormal
- False Negative (FN): Abnormal brain incorrectly identified as normal

Sensitivity=

$$\frac{TP}{(TP+FN)} \times 100\% \quad (7)$$

Specificity=

$$\frac{TN}{(TN+FP)} \times 100\% \quad (8)$$

Accuracy=

$$\frac{(TP+TN)}{(TP+TN+FP+FN)} \times 100\% \quad (9)$$

All the three parameters above are used to check the performance of the classifiers. [7]

Deepa V, Benson C. C, Lajish V. L used clustering methods for extracting gray matter and white matter from MRI brain images where clustering could be the process of organizing objects into groups whose members are similar in some way. To do this they implemented some famous clustering algorithm such as Kohonen-Means (k-Means) and FCM. The latter are clustering algorithms that partition a data set into clusters according to some defined distance measures. They applied the clustering algorithm using intensity-based values and statistical feature-based values. Finally, the results are compared with the manual segmentation ground truths using segmentation accuracy checking measures such as Dice and Tanimoto coefficients. Three preprocessing steps were applied; image denoising, image enhancement, and skull stripping. Therefore, speckle noise reduction is an essential preprocessing step whenever MR imaging is used for medical imaging. The Median filter is commonly used for reducing speckle noise due to their robustness against impulsive type noise and edge-preserving characteristics. There are mainly four types of clustering algorithms [8]: Exclusive Clustering, Overlapping Clustering, Hierarchical Clustering, and Probabilistic Clustering.

The main problem with the k-means algorithm is the selection of initial centroid where the clustering results will be affected if the initial centroid selection is not proper. Whereas Fuzzy C-Means may affect the data vagueness by giving an inaccurate description, and slower speed of convergence.

Clustering methods are separately applied based on intensity values and statistical feature-based values. In statistical feature extraction, the following features are investigated: mean, variance, standard deviation, kurtosis, skewness, and range. Among them clustering using mean produces excellent result. Therefore, they have only considered the mean feature and other statistical features are excluded [9].

III. PROPOSED WORK

Our proposed work focuses on brain tumor segmentation concept. It is well known that MRI and Computed Topography (CT-Scan) help in viewing the structure and anatomy of the brain. While MRI Scans uses radio waves and CT-Scan uses X-rays, MRI scans highly adapt at capturing images than CT-scan, which help in determining abnormal tissues within the body. For that, MRI images are used in our technique.

The most important task of medical image analysis is the image segmentation, which is the most critical step in clinical applications. In brain MRI analysis, it is mainly used for visualizing and measuring the anatomical structure of the brain, surgical planning, and detection of pathological regions. Due to complex structure of different brain tissues such as white matter (WM), gray matter (GM) and cerebrospinal fluid (CSF) in brain images, Segmentation becomes very challenging and essential task since it influences the outcome of the entire analysis. A better feature extraction result is fundamental to successful image segmentation. The search for robust

features is complicated due to the variability in tumor location, shape, size, and texture properties.

Different types of algorithms have been developed for the sake of brain tumor detection, extraction, and classification. The detection was never a hundred percent successful, many drawbacks existed. In this paper, we used Thresholding and Watershed Segmentation to analyze and compare their results based on different criteria such as time, accuracy. Fig. 1 shows the flow diagram of the proposed work.

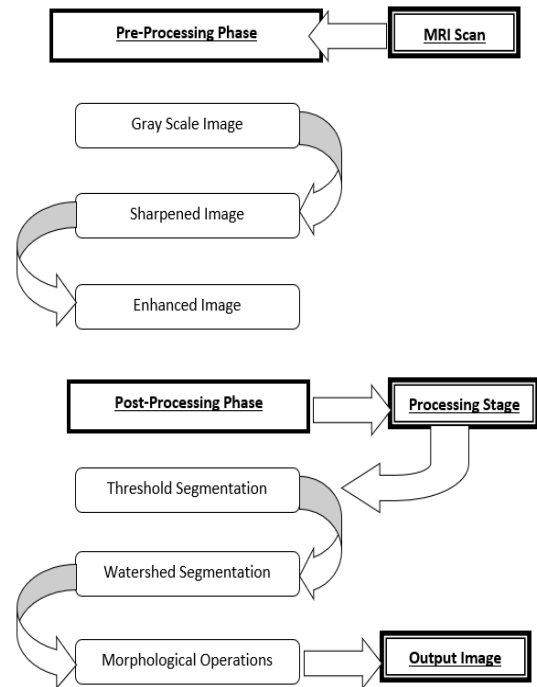


Figure 1. The block diagram of the proposed work.

A. MRI Image Acquisition

Images are acquired using MRI scan and those scanned images are displayed in a two-dimensional matrix having pixels as its elements where these matrices are dependent on matrix size and its field of view. The images are stored in a file and displayed as gray-scale images. The entries of a gray-scale image are running from 0 to 255, where 0 shows aggregate dark shading and 255 shows pure white shading. Entries between these extents differ in intensity from dark and white.

B. Image Pre-processing

In Digital Image Processing, in order to improve and enhance the qualities of an image, modification of digital data is involved with the help of a computer, so in this phase image details are improved and noise is expelled from the image where enhancement and noise reduction techniques are implemented to achieve the best possible results.

Because of enhancement, we will have edges that are more prominent, sharpened image, low noise image, and thus reducing the blurring effect from the image. In addition to this, segmentation is also applied which help in detecting the location of the tumor.

- **Gray Level Conversion:** Images stored are converted from RGB to greyscale image.
- **Noise Removal:** To expel noise from images, many filters are utilized. Linear filters like Gaussian averaging filters; these types of filters are used to remove salt and pepper noise from the image. In this filter, pixel's value is replaced with its neighborhood values. Additionally, the median filter is used to remove the noise like salt and pepper from images and the weighted average filter is the variation of this filter that can be executed and give a good result. The median filter is less sensitive than other filters and the value of the pixel is calculated based on the neighboring pixels.
- **Image Sharpening:** To detect the boundary of the tumor, sharp edges are needed. As noise has been removed, Gaussian high pass filters are used to enhance object boundaries of an image and are widely used to enhance finer details of objects.

C. Processing Phase

Segmentation is mainly utilized during this stage. It is the process of dividing the image into regions and partitioning it into multiple segments where similar attributes are isolated into groups so the image is more meaningful and easier to analyze.

In the processing stage, segmentation is done using the below methods:

- **Threshold Segmentation**

Threshold Segmentation is considered as one of the most straightforward segmentation techniques. The input gray-scale image is changed into a binary image. The fundamental idea of this method is picking a threshold value to differentiate the object from the background and partition the pixels into various classes. [10]

- **Watershed Segmentation**

Watershed Segmentation is probably the best technique to group the pixels of the image based on their intensities. Pixels with comparable intensities are assembled together, which makes it a decent segmentation technique to separate the tumor from the image. Watershed Segmentation is a morphological operation tool to segment the grayscale image. Watershed is typically utilized for checking output rather than using it as an input segmentation because it usually suffers from over-segmentation and under segmentation. [11]

- **Morphological Operations:**

Following the preprocessing of the image and applying the segmentation methods over the image in the binary format, some morphological operations are applied to it. The main purpose behind the morphological operator is to separate the tumor part of the image. Now only the tumor segment of the image, having the highest intensity, is visible with white color. This morphological operation is applied after the watershed segmentation. Here erosion is applied to detect the tumor. The erosion of A by B is given by the expression:

$$A \ominus B = \{(i, j): B(i, j)\}$$

where, A= the paired image, B= the structuring element

(i, j) = the center pixel of structuring element

Some of the morphing commands used in this paper are given below:

Strel: A flat structuring element with a binary-valued neighborhood used for making morphological structuring element in which only the true pixels are included in the morphological computation.

Imerode: Used to erode (Shrink) the grayscale, binary, or packed binary image.

$J = \text{imerode}(I, SE)$ where I is the input binary image, J is the eroded image, SE is the structuring element used to erode the image. Example of SE: [0 1 0; 1 1 1; 0 1 0]

Imdilate: Used for dilating (filling, expanding) an image. [12]

D. Evaluation

The above steps summarize the procedure of the proposed method. The proposed method shows an excellent output after applying the morphological operations where only the tumor part is visible in the image.

So far, segmentation is a very challenging task in the medical science field. Here we have used the threshold method and watershed method for segmentation purpose and some morphological operation to isolate the tumor with high intensity values from the rest of the brain image.

IV. EXPERIMENTAL RESULTS

A. Introduction

The methodology of the implemented methods as described above, and the results are shown where Fig. 2 contains the original image, while Fig. 3 contains the output image after applying the different techniques of the method used. The applied segmentation method to the brain MRI image was very effective and helpful in the extraction process and attained results regarding detecting the brain tumor.

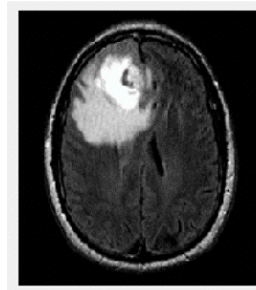


Figure 2. The input image.

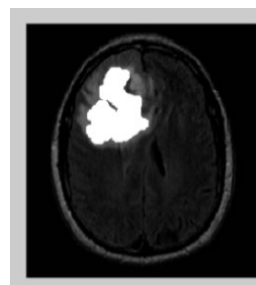


Figure 3. The output image.

B. Evaluation and Results

The goal of the implemented method is to detect the brain tumor in the MRI images by applying some pre-processing of the image, threshold segmentation, watershed segmentation, and finally some morphological operations. To engage in this task, computer tools were needed that can perform image processing and allow us rapidly to test different image algorithms. MATLAB (matrix laboratory) is well known for its high-level language and interactive environment for numerical computation, visualization, and programming.

MATLAB is used for analyzing data, developing algorithms, and creating models and applications. The language, tools, and built-in math functions enable us to explore multiple approaches and reach a solution faster than using spreadsheets or traditional programming languages such as C, C++, or JAVA.

Many mathematics functions are contained in MATLAB. Graph functions can be used to solve equations, perform statistical tests, and many more. It is considered as a high-level programming language that can communicate with cousins like FORTRAN and C. We can also do simulations and modeling (especially if we have access not just to basic MATLAB but also to its accessory Simulink). In addition, we can use MATLAB to combine mathematical computations with text and graphics in order to produce a polished, integrated, interactive document.

So, this tool was chosen since it offers a lot of experimental testing possibilities and flexible simulation. It contains many libraries that support image operations like video and image processing library.

In our paper, we start by the Preprocessing Phase where in this phase the image is enhanced where the image is converted into gray-scale image (Fig. 4), then noise is removed and the image is passed into high pass filter to detect edges (Fig. 5), then the obtained image is added to the original image where we obtain the enhanced image (Fig. 6).

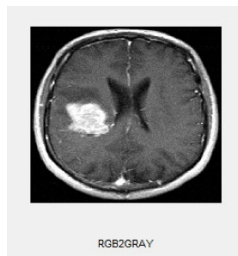


Figure 4. The image after converting it into gray-scale image.



Figure 5. The image after applying high-pass filter.

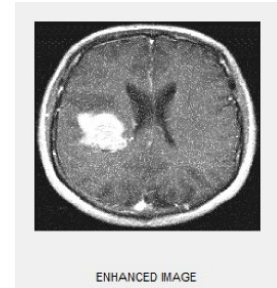


Figure 6. The enhanced image.

In the Processing Phase, Threshold-Based Segmentation algorithm is used where the whole image is converted into the binary image using the MATLAB thresholding commands (Fig. 7). The basic concept of this technique is choosing a threshold value to differentiate the object from background and divide the pixels in different classes.

Then we used Watershed segmentation to check our output (Fig. 8) where pixels having similar intensities are grouped together, which makes it a good segmentation technique to separate the tumor from the image.

Here it is used for checking output rather than using it as an input segmentation because it usually suffers from over segmentation and under segmentation.

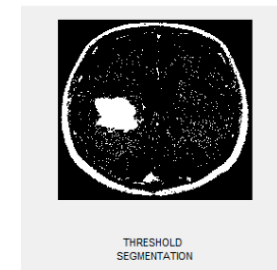


Figure 7. The result after applying threshold segmentation.

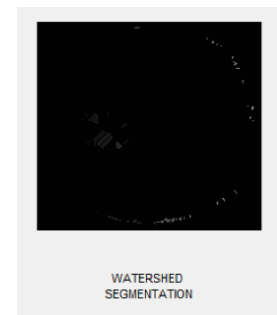


Figure 8. The result after applying watershed segmentation.

Then some Morphological operations are applied to show the tumor part of the image, which has the highest intensity. In this part, the image is eroded by the MATLAB function `imerode` and dilated by the function `imdilate` using a disk of radius 1 on the left side of Fig. 9 and a disk of radius 6 on the right side of Fig. 9.

- Using erosion, we removed the unwanted pixels from the MRI and portions of the skull are removed.
- Using dilation, the holes present in the eroded MRI images are filled.

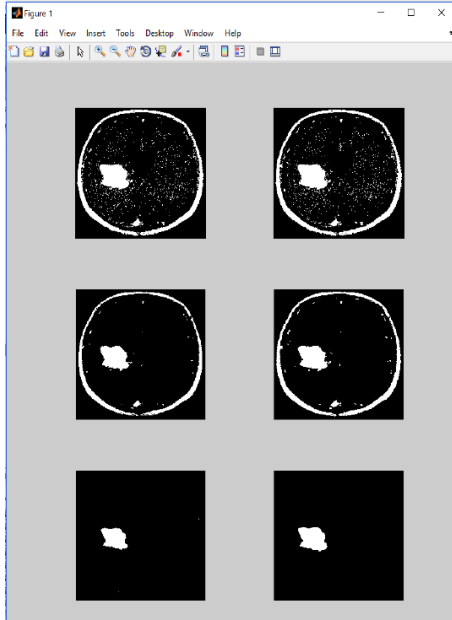


Figure 9. The result after applying morphological operations.

And finally, the tumor result (Fig. 10).

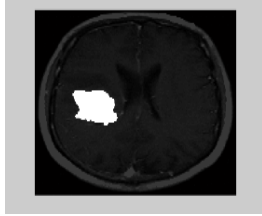


Figure 10. The detected tumor.

C. Discussion

For this system 155 images were taken for analysis. What makes this analysis easier is the fact that the intensity of the tumor in the MRI image is higher than that of its background. But the experiments show the possibility of error such that the system is not giving the correct result all the time, but most of the time.

We use the following methods to observe the comparison and observation of the quantity and quality of the proposed method.

D. Sensitivity and Accuracy

In each experiment, a comparison is generally done between the measurements taken. The results of comparing the proposed algorithm with the original data are as follows:

(TP): Tumor pixels that are correctly diagnosed as tumors.

(FP): Pixels that have not been included in the tumor and are detected by the tumor in error.

(TN): Non-tumor pixels are correctly identified as non-tumors.

(FN): Tumor pixels that are mistakenly recognized as non-tumors.

Sensitivity:

$$\text{Sensitivity} = \frac{n_{TP}}{n_{TP} + n_{FN}} \quad (10)$$

Accuracy:

$$\text{Accuracy} = \frac{n_{TP} + n_{TN}}{n_{TP} + n_{TN} + n_{FP} + n_{FN}} \quad (11)$$

Specificity:

$$\text{Specificity} = \frac{n_{TN}}{n_{TN} + n_{FP}} \quad (12)$$

TABLE I. SHOWS SOME METRICS THAT HAVE BEEN TAKEN INTO CONSIDERATION TO CHECK THE ACCURACY OF THE PROPOSED SYSTEM

Method	Sensitivity	Accuracy	Specificity
Proposed Algorithm	0.852	0.888	0.768
GLCM	0.721	0.814	0.667
SVM	0.912	0.721	0.899

The results show that the proposed algorithm has higher sensitivity and accuracy, and specificity compared to GLCM, while high accuracy compared to both SVM and GLCM. This means the proposed method is more accurate in detecting the tumor area compared to other methods.

V. RESULTS DISCUSSION

The experimental results show that the proposed technique, threshold-based segmentation followed by some morphological operations, provides a very promising and effective method for brain tumor detection in MRI images with high accuracy. The noise removal from the MRI images we performed in the pre-processing phase using low pass filters shows a very good effect when applying the segmentation whereas other algorithms didn't remove the noise from the image before using the SVM algorithm, or others used a noise removal filter which is not reliable and may not remove all the noise. Moreover, our segmentation technique used, threshold-based, which depends on pixel intensities, is better than that of SVM and GLCM. Also, the final step applying morphological operations returned a very significant result compared to other algorithms where morphological operations was not applied. The results in Table I showing the performance measures of used algorithm compared to other algorithms shows that the proposed technique is more accurate than other techniques showing 0.888 which is much higher compared to GLCM 0.814 and SVM 0.721, it also shows higher sensitivity 0.852 and Specificity 0.768 than GLCM 0.721 and 0.667 respectively. This means our proposed algorithm is better in terms of accuracy compared to both SVM and GLCM.

VI. CONCLUSION

From the experimental results performed, it is evident that the analysis and detection of brain tumor is faster and more accurate compared by the manual work performed by radiologists and experts. Our experimental results show that the proposed technique can help in the accurate and timely detection of brain tumor along with the identification of its exact location. Thus, the proposed

approach is significant for brain tumor detection from MR images.

This work can be improved by combining more than one segmentation and feature extraction techniques and work on large datasets with real clinical cases. We can also improve by specifying the severity of the tumor; benign or malignant.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

GT conducted the research, GT and RS analyzed the data, GT wrote the paper, RS revised the paper.

ACKNOWLEDGMENT

I would like to acknowledge my indebtedness and render my warmest thanks to my supervisor, Dr. Reda Shbib, who helped in making this work possible through his invaluable guidance and advice in all work stages.

I also express my thanks to my loving parents for their indirect contribution and encouragement throughout my work.

My special thanks go to my sister Zeina Tarhini who helped, assisted, and motivated me to complete this work.

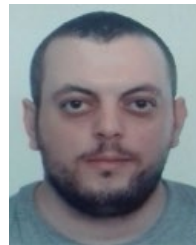
REFERENCES

- [1] V. Shinde, P. Kine, S. Gadge, and S. Khatal, "Brain tumor identification using MRI images," *International Journal on Recent and Innovation Trends in Computing and Communication*, vol. 2, no. 10, pp. 3050-3054, October 2014.
- [2] H. Kaur and J. Rani, "MRI brain image enhancement using histogram equalization techniques," in *Proc. International Conference on Wireless Communications, Signal Processing and Networking (WiSPNET)*, 2016, pp. 770-773.
- [3] D. Meyer and F. T. Wien, "Support vector machines, the interface to libsvm in package e1071," *R Project*, 2015.
- [4] T. Logeswari and M. Karnan, "Hybrid self-organizing map for improved implementation of brain MRI segmentation," in *Proc. International Conference on Signal Acquisition and Processing*, 2010.
- [5] Y. Sun, H. M. Reynolds, D. Wraith, S. Williams, M. E. Finnegan, C. Mitchell, and A. Haworth, "Automatic stratification of prostate tumour aggressiveness using multiparametric MRI: A horizontal comparison of texture features," *Acta Oncologica*, vol. 58, no. 8, pp. 1118-1126, 2019.
- [6] L. Ma, D. Song, L. Liao, and J. Wang, "PSVM: A preference-enhanced SVM model using preference data for classification," *Science China Information Sciences*, vol. 60, no. 12, 2017.
- [7] S. G. Hate and A. D. Vidhate, "Advancement of brain tumor detection using SOM-clustering and proximal support vector machine," *International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering*, vol. 6, no. 7, pp. 5552-5558, 2017.
- [8] D. Xu and Y. Tian, "A comprehensive survey of clustering algorithms," *Annals of Data Science*, vol. 2, no. 2, pp. 165-193, 2015.
- [9] V. Deepa, C. C. Benson, and V. L. Lajish, "Gray matter and white matter segmentation from MRI brain images using clustering methods," *International Research Journal of Engineering and Technology (IRJET)*, 2015.
- [10] J. Shi and H. Zhang, "Adaptive local threshold with shape information and its application to object segmentation," in *Proc. IEEE International Conference on Robotics and Biomimetics (ROBIO)*, 2009, pp. 1123-1128.
- [11] G. Li, "Improved watershed segmentation with optimal scale based on ordered dither halftone and mutual information," in *Proc. 3rd IEEE International Conference on Computer Science and Information Technology (ICCSIT)*, 2010, pp. 296-300.
- [12] T. Logeswari and M. Karnan, "An improved implementation of brain tumor detection using segmentation based on soft computing," *Journal of Cancer Research and Experimental Oncology*, vol. 2, pp. 6-14, March 2010.

Copyright © 2020 by the authors. This is an open access article distributed under the Creative Commons Attribution License ([CC BY-NC-ND 4.0](https://creativecommons.org/licenses/by-nc-nd/4.0/)), which permits use, distribution and reproduction in any medium, provided that the article is properly cited, the use is non-commercial and no modifications or adaptations are made..



Ghinwa M. Tarhini was born in Abba, Nabatieh, South Lebanon on September 3, 1992. She got the BS degree in Computer Science from the Lebanese International University (LIU) in 2013, then got her Master degree in Computer Science from the same university in 2019. She was a student partner in Microsoft, Lebanon for the years 2012 and 2013. Currently, she occupies the position of System Analyst in the Department of Information Technology at Hammoud Hospital University Medical Center, Saida, South Lebanon since December 2013.



Reda Shbib is an assistant professor at the Lebanese International University, Computer Science Department. He holds a PhD, Image Processing and Computer Vision from University of Portsmouth UK and MSc in Computer Administration Network and Management from the same university. His research interests include image processing, Cloud Computing, IoT, and Medical Image Processing. Reda has published more than 12 articles in academic journals including Facial Recognition, Brain Tumor Detection.