

A Professional Estimate on the Segmentation of Brain Cancer in MR Images using M-FCM



Tessy George, T. Ramakrishnan

Abstract: Brain imaging innovations have been forever made for a significant part in analyzing and focusing the unused sees of the brain life systems and functions. A computer software code is designed for the detection of cancer in brain magnetic resonance images. Image segmentation, morphological operations and feature extraction are some of the image processing methods developed for the brain cancer detection in MR images concerning the cancer influenced sufferers. In the proposed research, a Modified morphological-based Fuzzy-C-Means (M-FCM) algorithm is proposed to segment the cancer region in the brain MR images. M-FCM algorithm is used to perform the segmentation process significantly through the idealize choice of a cluster, based on the updated membership function. Quantitative analysis between ground truth and segmented cancer is presented in terms of segmentation accuracy and segmentation sensitivity.

Keywords: Brain cancer, M-FCM, Segmentation Accuracy and Segmentation Sensitivity.

I. INTRODUCTION

The brain and the spinal cord come under central nervous system (CNS). The cancer can commence or advance in the CNS. Tumors that contour from the cells within the brain are generally known as the Primary brain tumors [1]. All primary brain tumors are not similar. Benign and Malignant tumors are classified under primary brain tumor. Malignant brain tumors are more threatening in nature and also tend to invade the neighbor cells [2]. Brain metastasis occurs when cancer spreads somewhere in the body like breast, lungs, kidney, colon, etc., and moves quickly to the brain [3]. Benign brain tumors always start in the brain cells.

II. PROBLEM IDENTIFICATION

The detection of brain cancer is somewhat difficult rather than finding of brain tumor. Even though some research articles are evidenced, they are commonly acknowledged within certain range of performance measures (eg. segmentation accuracy is 91.36%). The point of this extend is to segment the cancerous region in the brain. The accuracy and sensitivity of the segmentation process can be enhanced with this appropriate proposed methodology.

III. PROPOSED METHODOLOGY

In the proposed line of research, a novel semi-automatic segmentation method is recommended based on population and individual statistical information present in the given magnetic resonance (MR) images.

The block diagram of the suggested technique is given hereunder in Fig. 1. The probability of each pixel belonging to the foreground (cancer) and the back ground is estimated by the morphological based FCM is utilized. It can easily be realized that the full or semi-automatic segmentation and classification methods are in fact, region segmentation methods.

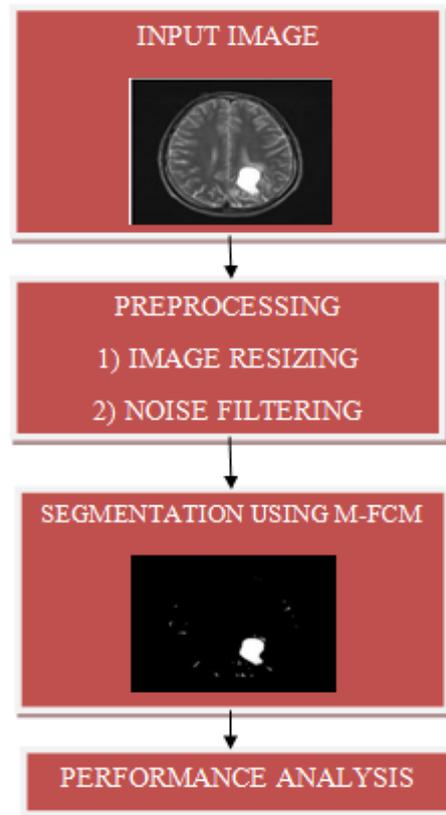


Fig.1 Proposed methodology

A. Preprocessing

The given input MR brain image is converted from the color image to grey scale image. This is the introductory step taken before the major image processing task [4]. In general, a few fundamental steps are performed in order to render the resulting image more appropriate for the work to follow [5]. Also, it may necessitate like removing noise, enhancing the contrast, or identifying regions likely to contain the postcode [6].

Manuscript received on April 30, 2020.

Revised Manuscript received on May 06, 2020.

Manuscript published on May 30, 2020.

* Correspondence Author

Tessy George*, PG Scholar, Department of Electronics and Instrumentation Engineering, National Engineering College, Kovilpatti, Tamilnadu, India. Email: tessygeorge21@gmail.com

Dr. T. Ramakrishnan, Assistant Professor (Senior Grade), Department of Electronics and Instrumentation Engineering, National Engineering College, Kovilpatti, Tamilnadu, India. Email: ramakrishnan@nec.edu.in

© The Authors. Published by Blue Eyes Intelligence Engineering and Sciences Publication (BEIESP). This is an open access article under the CC BY-NC-ND license (<http://creativecommons.org/licenses/by-nc-nd/4.0/>)

In the proposed research, the preprocessing of the given input image is fulfilled through image resizing and noise filtering.

B. Image Resizing

Image resizing is done when the pixel size in the images increases or decreases. The given input image can be of any dimensions. There is no loss in the quality of the pixels when the image is resized. Image resizing is done according to the Nyquist Sampling Theorem [7].

C. Noise Filtering

Noise filtering removes the unwanted noise in the input image. The output results can be improved by this step in the preprocessing. In this method, Gaussian filter is used for filtering. It is a non-uniform low pass filter [8]. This filter is isotropic in nature and faster than the median filter.

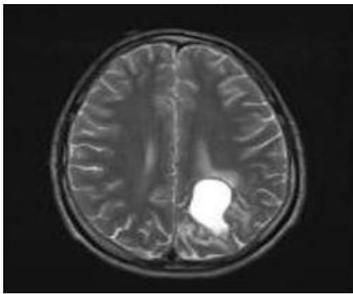


Fig.2 Input image

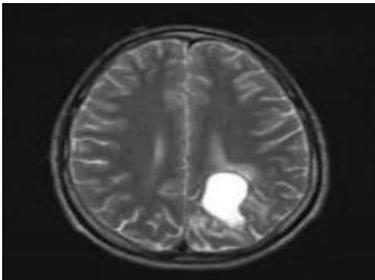


Fig.3 Resized image

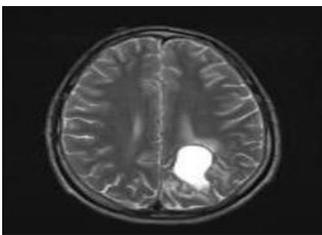


Fig.4 Filtered image

The Gaussian filter is highly successful in smoothing the images [9]. In that case, the halftone image has been smoothed with a Gaussian filter with lofty level of noise removal. The preprocessing of the given input image is shown in the figures 2, 3 and 4.

D. Segmentation Process

Image segmentation specifies the technique of segregating the given input image into numerous divisions [10]. Segmenting an image helps to understand the minute details more correctly. The brain image here gets segmented

into 4 clusters i.e, brain region, skull region, background and the cancer region [11]. These regions get segmented based on their texture. Several algorithms have been proposed to segment the images. In this work, a morphological based segmentation is done based on the shapes. Two inputs namely the input image and the number of clusters are given. This method avoids the overlapping of clusters [12].

E. M-FCM

The proposed framework introduces a model that incorporates the Modified morphological-based Fuzzy-C-Means (M-FCM) technique in the location of human brain cancers in magnetic resonance images. To boot-up the segmentation process by the culminate selection of clusters, the M-FCM algorithm is employed using the intensity of grey-levels present in the image. To detect cancer, the M-FCM is implemented by revising the membership function for clustering the data points.

F. Performance Measures

The significant output results are analyzed by obtaining the performance measures like segmentation accuracy and sensitivity in the segmented cancer MR images. The segmented cancer image and the ground truth(target) are compared [13]. The radiologist determines the ground truth from the boundary drawings.

Accuracy is the percentage of accurately anticipated perception to the overall number of observations [14]. This parameter is the checking parameter for ensuring the preciseness of the test. The accuracy can be determined by the following equation.

$$\text{Accuracy} = (TP+TN) / (TP+FP+FN+TN)$$

Sensitivity is the capability of the test to faithfully determine and exclude the healthy patients (without the disease) more accurately. This test indicates the true number of patients who have illness among the whole set.

$$\text{Sensitivity} = (TP) / (TP+FN)$$

Specificity determines the probability of the test in the determination of the patients who is not having the disease [15]. The therapeutic test for specificity is the rate of healthy patients noted, who don't have the illness.

$$\text{Specificity} = (TN) / (TP+FN)$$

Precision is the fraction of truly envisaged positive values to the entire anticipated optimistic interpretations.

$$\text{Precision} = (TP) / (TP+FP)$$

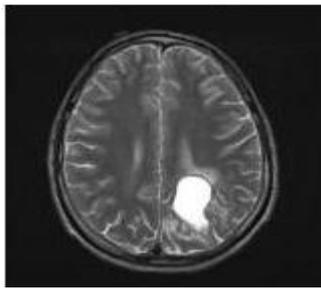
Jacard Index is a statistic used for gauging similarity between limited sample sets.

IV. OUTCOMES AND DISCUSSIONS

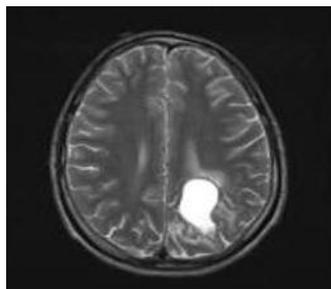
The proposed algorithm is carried out in the working platform of MATLAB R2015a with the image measure of 256 x 256.

The obtained experimental results are given hereunder with validations (For example, three different input images are segmented and analyzed).

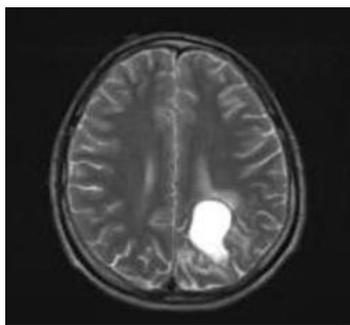
Segmentation analysis of the input image 1:



(a)



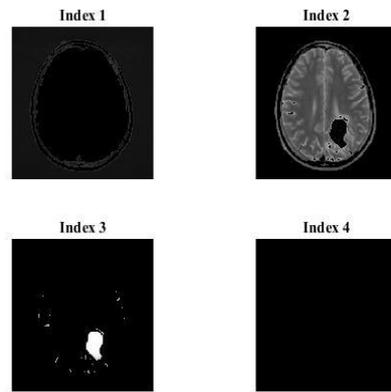
(b)



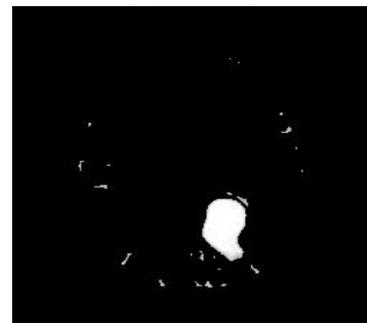
(c)



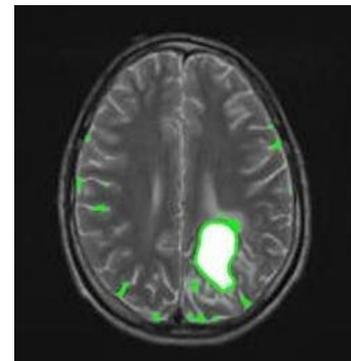
(d)



(e)



(f)



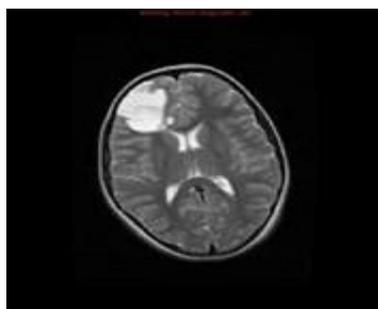
(g)

Fig. 5 Segmentation of input image 1: (a) Input image (b) Resized image (c) Filtered image (d) M-FCM (e) Clustered images (f) Segmented Image (g) Contour tracking

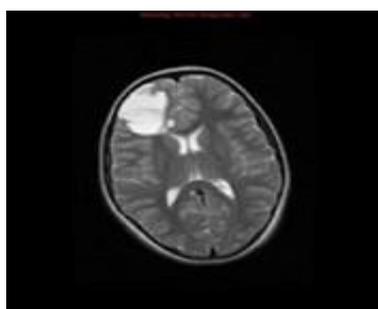
Segmentation analysis of the input image 2:



(a)



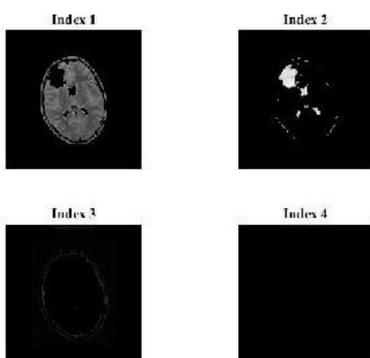
(b)



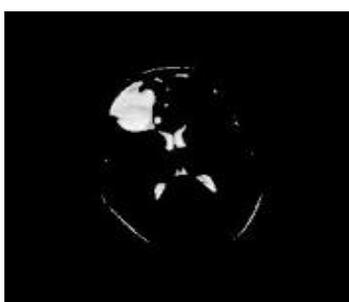
(c)



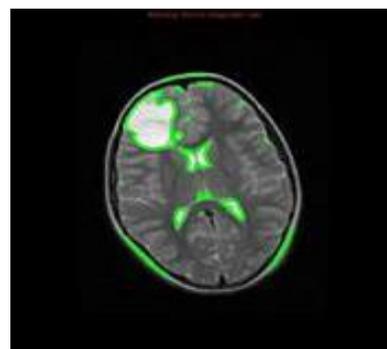
(d)



(e)



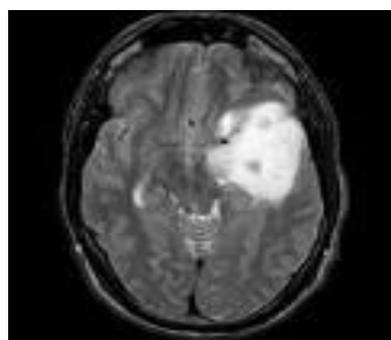
(f)



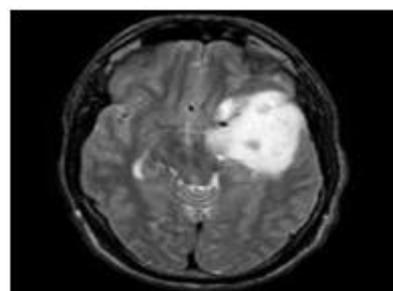
(g)

Fig. 6 Segmentation of Input image 2: (a) Input image (b) Resized image (c) Filtered image (d) M-FCM (e) Clustered images (f) Segmented Image (g) Contour tracking

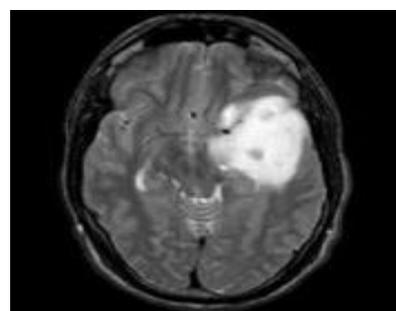
Segmentation analysis of the input image 3:



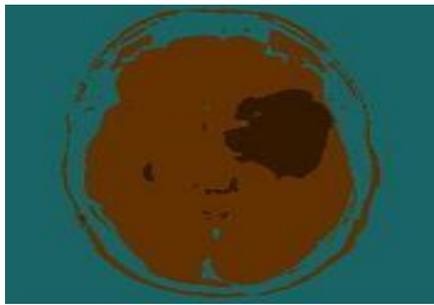
(a)



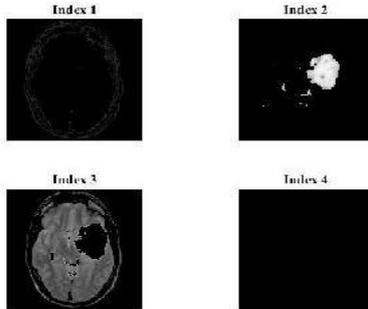
(b)



(c)



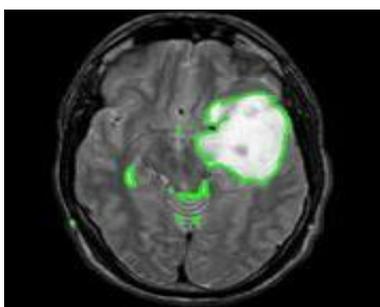
(d)



(e)



(f)



(g)

Fig. 7 Segmentation of Input image 3: (a) Input image (b) Resized image (c) Filtered image (d) M-FCM (e) Clustered images (f) Segmented Image (g) Contour tracking

Table - I: Performance Analysis using M-FCM

Input Image No.	Accuracy	Sensitivity	Specificity	Precision	Jacard Index
1	98.4375	98.4402	100	100	99.218
2	98.4924	98.4228	100	100	99.117
3	96.7501	96.4015	100	100	96.875

Table - II: Performance Analysis using Improved Fuzzy C-Means (I-FCM)

Input Image No.	Accuracy	Sensitivity	Specificity	Precision	Jacard Index
1	91.3641	91.3612	92.5011	91.5322	93.802
2	91.2404	91.7389	90.6453	90.2041	94.356
3	90.3684	90.5925	91.5774	90.9578	91.985

Table - III: Performance Analysis using k-means algorithm

Input Image No.	Accuracy	Sensitivity	Specificity	Precision	Jacard Index
1	87.3675	87.7924	86.4721	84.3217	89.238
2	88.7464	88.5109	88.3264	87.3001	90.197
3	83.8572	83.2304	85.6102	82.3566	89.075

Comparative Analysis (through average values):

S. No.	Method	Accuracy	Sensitivity
1	I-FCM	90.9909	91.2308
2	k-means algorithm	86.6570	86.5112
3	M-FCM	97.8933	97.7548

The first three tables show the performance measures of 3 input dataset using different segmentation methods. The comparative analysis indicates that the average values of accuracy and sensitivity obtained using M-FCM are 97.8933% and 97.7548% at its maximum respectively, in comparison to the other segmentation methods like k-means algorithm and I-FCM methods for the same input images. The distinction in values depends on the esteem of TP, TN, FP and FN in each sample.

V. CONCLUSION AND FUTURE SCOPE

In the recommended approach, the severity of the brain cancer in MR images can be detected with high accuracy and sensitivity. The input data set is preprocessed by resizing and filtering the input MR image. The filtered image is taken as the input to perform the segmentation process utilizing the M-FCM algorithm. The maximum accuracy and maximum sensitivity obtained in the segmented brain images using M-FCM are almost same (about 98%). The experimental results proved the hallmark of the viability of the proposed strategy (M-FCM) when it comes to be in comparison with I-FCM and k-means algorithm methods in identifying the normal and cancerous regions in the brain MR images. As a future scope, this investigate may moreover be implemented in other imaging modalities viz., CT, PET etc., with high segmentation accuracy. It can also be extended to determine the lesions in lungs, liver etc.

REFERENCES

1. B. H. Menze, K. Van Leemput, D. Lashkari, M. A. Weber, N. Ayache, and P. Golland, "A generative model for brain tumor segmentation in multimodal images," in Proc. Int. Conf. Med. Image Comput.-Assisted Intervent., pp. 151–159, 2010.
2. A. Gooya et al., "GLISTR: Glioma image segmentation and registration," IEEE Trans. Med. Imaging., vol. 31, no. 10, pp. 1941–1954, Oct. 2012.
3. J. Sachdeva, V. Kumar, I. Gupta, N. Khandelwal, and C. K. Ahuja, "Segmentation, feature extraction, and multiclass brain tumor classification," J. Digit. Imaging., vol. 26, no. 6, pp. 1141–1150, 2013.
4. M. Huang, W. Yang, Y. Wu, J. Jiang, W. Chen, and Q. Feng, "Brain tumor segmentation based on local independent projection-based classification," IEEE Trans. Biomed. Eng., vol. 61, no. 10, pp. 2633–2645, Oct. 2014.
5. B. H. Menze et al., "The multimodal brain tumor image segmentation benchmark (BRATS)," IEEE Trans. Med. Imaging., vol. 34, no. 10, pp. 1993–2024, Oct. 2015.
6. S. Pereira, A. Pinto, V. Alves, and C. A. Silva, "Brain tumor segmentation using convolutional neural networks in MRI images," IEEE Trans. Med. Imag., vol. 35, no. 5, pp. 1240–1251, May 2016.
7. X. Zhao, Y. Wu, G. Song, Z. Li, Y. Zhang, and Y. Fan, "A deep learning model integrating FCNNs and CRFs for brain tumor segmentation," Med. Image Anal., vol. 43, pp. 98–111, Jan. 2017.
8. G. Wang, W. Li, S. Ourselin, and T. Vercauteren, "Automatic brain tumor segmentation using cascaded anisotropic convolutional neural networks," in Proc. Int. MICCAI Brainlesion Workshop. Quebec City, QC, Canada: Springer, pp. 178–190, 2017.
9. M. Havaei, A. Davy, D. Warde-Farley, A. Biard, A. Courville, Y. Bengio, C. Pal, P.-M. Jodoin, and H. Larochelle, "Brain tumor segmentation with deep neural networks," Med. Image Anal., vol. 35, pp. 18–31, Jan. 2017.
10. Pham TX, Siarry P, Oulhadj H, "Integrating fuzzy entropy clustering with an improved PSO for MRI brain image Segmentation", Applied Soft Computing, vol. 65, pp. 230-242, 2018.
11. Tong J, Zhao Y, Zheng P, Chen L, Jiang L, "MRI brain tumor segmentation based on texture features and kernel sparse coding.", Biomedical Signal Processing and Control, vol. 47, pp. 387-392, 2018.
12. M. Marcinkiewicz, J. Nalepa, P. R. Lorenzo, W. Dudzik, and G. Mrukwa, "Automatic brain tumor segmentation using a two-stage multi-modal FCNN," in Proc. Int. MICCAI Brain lesion Workshop. Granada, Spain: Springer, pp. 314–321, 2018.
13. G. Wang, W. Li, S. Ourselin, and T. Vercauteren, "Automatic brain tumor segmentation using convolutional neural networks with test-time augmentation," in Proc. Int. MICCAI Brain lesion Workshop. Granada, Spain: Springer, pp. 61–72, 2018.
14. S. Chandra, M. Vakalopoulou, L. Fidon, E. Battistella, T. Estienne, R. Sun, C. Robert, E. Deutsch, and N. Paragios, "Context aware 3D CNNs for brain tumor segmentation" in Proc. Int. MICCAI Brain lesion Workshop. Granada, Spain: Springer, pp. 299–310, 2018.
15. G. Wang, M. A. Zuluaga, W. Li, R. Pratt, P. A. Patel, M. Aertsen, T. Doel, A. L. David, J. Deprest, S. Ourselin, and T. Vercauteren, "Deep IGeoS: A deep interactive geodesic framework for medical image segmentation," IEEE Trans. Pattern Anal. Mach. Intell., vol. 41, no. 7, pp. 1559–1572, Jul. 2019.



Ramakrishnan obtained his bachelor's degree (B.E) in Electronics and Instrumentation Engineering from Manonmaniam Sundaranar University (*National Engineering College, Kovilpatti*), State of Tamilnadu, India, in 1999. Then he obtained his Master's degree (M.Tech.) in Biomedical Engineering from Indian Institute of Technology Madras (IITM), Chennai, India, in 2008. He has completed his Ph.D degree in Medical Image Processing at Anna University, Chennai, India in 2018. He has 18 years of teaching professional competencies since 2002. Currently, he is working as Assistant Professor (Senior Grade) in the Department of Electronics and Instrumentation Engineering at National Engineering College, Kovilpatti, Tamilnadu, India. His research interests include Biomedical Engineering, Biomedical Instrumentation, Pattern Recognition, Video Frame Processing, Video Data Analytics and Medical Image Processing. Also, he is a Life Member of ISTE (LM 40871) and Life Member of Biomedical Engineering Society of India (LM 1262).

AUTHORS PROFILE



Ms. Tessy George obtained her bachelor's degree (B.E) in Electronics and Instrumentation Engineering from Anna University (*K.L.N College of Engineering, Sivagangai*), State of Tamilnadu, India, in 2018. She was a member of Instrument Society of India during the year 2015–2018. Then she is pursuing (final yr PG) her Master's degree (M.E.) in Control and Instrumentation Engineering from National Engineering College, Kovilpatti, India, in 2020. Her research interests include Bio medical Engineering, Bio medical Instrumentation, Medical Image Processing, Transducer Engineering, Analysis of Computational Mathematics and Health Informatics.