Society for Science and Education
United Kingdom

JBEMi JOURNAL OF BIOMEDICAL ENGINEERING AND MEDICAL IMAGING

ISSN: 2055-1266
Volume 4 Issue 3

Improved Fuzzy C-Means Algorithm for Brain Tumor Identification Analysis Using Magnetic Resonance Brain Images

[1]Abd El Kader Isselmou, [2]Zhang Shuai, [3]Guizhi Xu
[123]Department of Biomedical Engineering, Hebei University of Technology, Tianjin, China;
Isselmou_kader@yahoo.com

ABSTRACT

Image processing plays a very important role in the analysis images of different standards; it supports the doctor's decision and helps to easily diagnose the patient. In this paper we processed the magnetic resonance brain images, which is the most advanced medical images using the improved fuzzy c-means algorithm, this process consists of two stages, the first stage of tumor identification in the resonance brain images and the second stage analysis of the algorithm performance using accuracy detection, TC, DOI, sensitivity and specificity, the improved fuzzy c-means algorithm has given excellent results in the terms of efficiency and performance values.

Keywords: MRI, Segmentation, Tumor Identification, FCM algorithm, Accuracy, DOI, TC.

1 Introduction

The word tumor also referred to as neoplasm, means the abnormal expansion of the tissues that results when cells divide more than they need to or do not die after they should[1].

Include tissue in the brain is most complex aspects of the body, and examine and consider the clear and therefore it is necessary to a scanner capable of images with the production of the brain tissue is bounded, where unique and gender segregation required views with tissues. The point of view is featured on the images manually impossible and can be positioned by the operator errors.

Magnetic resonance imaging techniques have an excellent importance in the domain of diagnosis the organs of the body is simulated using resonant radio frequency signals. The excited hydrogen atom can do emitting the absorbed radio frequency signals, where the several signal processing operations are carried out to acquire a clear anatomy of human organs and tissues. Brain tissues are bounded together and so are complex to analysis. Moreover, edema and tumor-infiltrated region from the tissues take time and effort both to recognize and also, to analyses.

Tumor-cut the division of the brain tumors contrast enhancing MR image applications radio surgical process proposed by Andac et al [2] can perform segmenting the only real contrast-enhancing T1-weighted images. The application of the cut tumor algorithm is limited towards enhancing images T1-weighted contrast and never on the other instrument strategies to brain images. The tumor is detected

DOI: 10.14738/jbemi.43.3110
Publication Date: 4th June 2017
URL: http://dx.doi.org/10.14738/jbemi. 43.3110

with the entire concept with the region of curiosity (ROI) and requires to the manual for help segmentation procedures.

Improved MR brain image segmentation for detected cerebrospinal fluid level using anisotropic wide speared and Fuzzy C-means proposed by Ouadfel Salima ET all [3], sliced magnetic resonance images using artificial bee colony (ABC) algorithm along with FCM technique groups, in terms consumption needs to be reduced. Using segmentation algorithm has been confined to the treatment of T1-weighted images.

Using soft computing technique and is a unique mechanism to identify the area of the tumor effectively and help the radiologist widely. In this paper, we proposed soft computing technique based on improved FCM algorithm. The technique proposed based on improved FCM algorithm segments the tissues and tumor affected the region in the MR brain images and assists radio surgeon in computer aided surgeries Algorithm and convergence rate.

T1-T2-weighted and FLAIR brain images obtained by using magnetic resonance imaging scanner. T1-weighted images help monitor and analyze the anatomy of the brain and T2-weighted images help in identification of the brain diseases. FLAIR images support in type showing brain tissue by suppressing the liquid contents.

2 Materials

In this paper we used 10 Magnetic Resonance brain Images (5 FLAIR brain images and 5 T2-weighted brain images) obtained using Siemens Areas 1,5T from Florida University brain repository have been used to validate the proficiency of the proposed improved algorithm, the main property in inhibited by improved Fuzzy C -means algorithm.

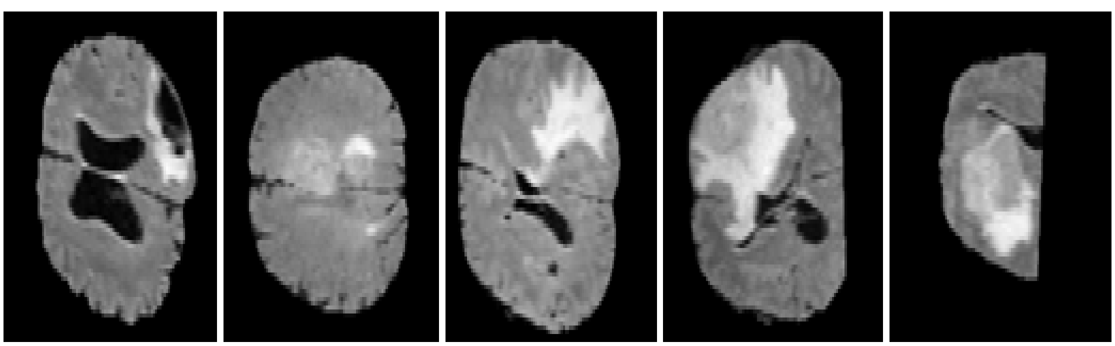

Figure.1 MR FLAIR brain images with a tumor

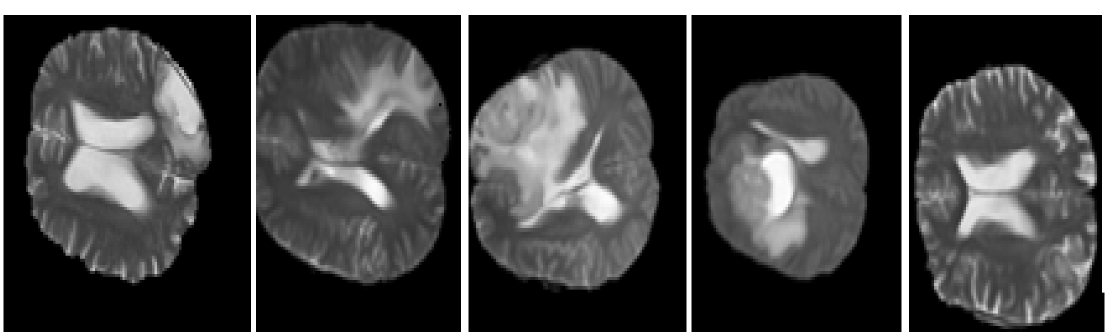

Figure.2 MR T2-weighted Brain images with a tumor

3 Methodology

This architecture explains the sequential procedure involved in the proposed improved FCM algorithm.

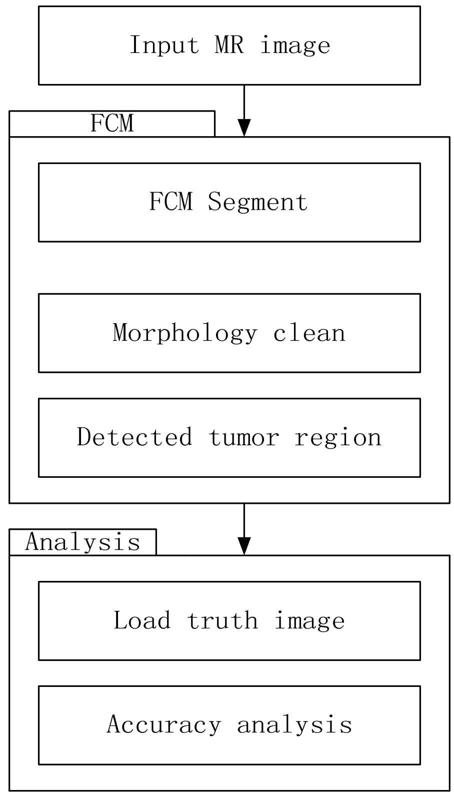

Figure.3 Architecture explaining the steps of the proposed based on improved FCM algorithm

This proposed based on improved FCM algorithm consists of the following phases:

Phase1: input MR brain image with the difference of pixel size in the images

Phase2: pre-processing involving image resizing to grayscale conversion, skull stripping, patient detail Removal is done.

Phase3: segmentation based on fuzzy c-means algorithm

Phase4: morphology cleaning to clean and remove the noise from the image.

Phase5: detected tumor region

Phase6: analysis and performance of the improved fuzzy c-means algorithm

3.1 Fuzzy C-Means algorithm (FCM)

Fuzzy C-means (FCM) algorithm is systematic collection created by Dunn, Bezdek that has been enhanced by additional titivated by Mathieu Matteucci voxels group (data) trough the magnetic resonance image (MR) brain images like a percentage variety of groups. Neighboring pixels means a smaller amount of the center pixel point you have will be the distance with a range of low value organic and grown throughout the price of the centroid, hierarchically. It is determined membership row centers and cluster repetition to limit the proposed and function of the grouping voxels.

$$J_k = \sum_{i=j}^{N} \sum_{j=1}^{C} \delta_{it} ||X_i - C_j||^2 \quad (1)$$

N Describes the number of incoming data points as input to the algorithm (the total number of voxels or voxels in the image). K It shows the number of iterations to be performed. $C = x_i\,(t+1)$ The number of blocks within which voxels to be collage, C_j Shows tankers collections center (mind point the value of voxels), x_i Known atheist ten data points (voxels), δ_{ij}Is degree from the membership of a point in x_i data from atheist ten in my cluster$J$ eleventh? $||x_i - c_j||$ measuring the similarity suggests or implies a distance voxels present in the data point x_i to the neighboring center tankers (the value of the centroid) of the cluster. And given the degree of membership as,

$$\delta_{ij} = \frac{1}{\sum_{C}^{k=1}(\left\|x_i - c_j\right\| \backslash ||x_i - c_k||^{(2\backslash(m-1))}} \quad (2)$$

m= fuzziness participated in the efficiency obtained from the overlapping defined as $1{,}5 \le m \le 2{,}5$ in order to achieve optimal results segmentation. $c_k$is the value of the centroid of the recurrence of $'k'$ iteration. Cluster is defined as,

$$c_j = \frac{\sum_{N}^{i=1} \delta_{ij} * x_i}{\sum_{N}^{i=1} \delta_{ij}} \quad (3)$$

For initial processing of the algorithm, δ_{ij}=θ_{ij}. Where θ_{ij} is a randomly create value as, $0 \le \theta_{ij} \le 1$ (expressed usually 0, 0.1, 0.2, 0.4….0.1), so that, $\sum_{j}^{c} \delta_{ij=1}$

FCM algorithm has a high capacity for data and information processing, especially the diverse data and affected the rate of convergence then if increased redundancy and decreasing the number of repetitions and groups to get him faster convergence rate has an adverse effect upon the segmentation accuracy.

3.2 Morphology Operations

After segmentation, the image to binary image, the binaries image needs some operations to improve the area of the tumor, since the segmentation of brain tumors in magnetic resonance images (MRI). Could be the quite challenging because of the various their possible shapes, locations and image intensities [4], In the work, the morphological operations are applied. The main procedure for the morphological operators opening, closing, erosion, and dilation that remove the hurdle and small holes from the image the morphological operations used within this research are erosion and dilation these operations are fundamental of morphological processing [5]. Dilation adds pixels towards the boundaries of subjects within an image, while erosion removes pixels on objects boundaries. The quantity of pixels added or taken out of the objects of an image depends on the size and model of the structuring element used to process the image, size, and model of the structuring element used to process the image, respectively show by this expressions:

$$f_e(x,y) = \text{imerode}(f(x,y), E) \quad (4)$$

$$f_e(x,y) = \text{imdilate}(f(x,y), E) \quad (5)$$

Where: $f(x,y)$ binary image, $f_e(x,y)$, returning the eroded or dilated image the argument E is a structuring element.

3.3 Parameters

3.3.1 Accuracy Detection

Accuracy, reliability also called segmentation accuracy; it is Accuracy, reliability also called segmentation accuracy; it is used to determine the effectiveness of the segmentation algorithm evaluation variables. The accuracy is denoted in Equation (6).

$$\text{Accuracy} = \left(\frac{k}{m \times n}\right) \times 100 \tag{6}$$

Here, k is the total number of pixels present in the segmented output image, and m and n are the rows and columns present in the input image.

3.3.2 Jaccard (Tanimoto Coefficient) Index

Jaccard index is denoted as exactly the common voxels present from the input image (A) along with the segmented output image (B) to the union function or perhaps the collection of voxels within the input image (A) along with the segmented output image (B) [6, 7]. Quite simply, is the ratio between the intersection and the union functions with the voxel values within the input image (A) along with the segmented resulting image (B). Explanation of TC value is saved Equation (7).

$$J(A,B) = \frac{S(A \cap B)}{S(A \cup B)} \tag{7}$$

3.3.3 Dice Overlap Index (DOI)

It is expressed with the help of the value of the Jaccard index $J(A,B)$. DOI identify the purpose of overlap of the input image (A), as well the resulting segmented image (B) [6, 7]. DOI mentions calculate in the equation (8):

$$D(A,B) = 2 \times \frac{J(A,B)}{1+J(A,B)} \tag{8}$$

3.3.4 Similarity Index (SI))

Similarity Index describes the same or identical values between your input image (A) as well as the segmented output image(B), [6, 7]. It relates to the similarity found between the input images along with the final segmented image which comprises detected tumor region combined with the identification of tissue regions which is shown in Equation (9). The employed to calculate SI are:

$$SI = \frac{2 \times TP}{2 \times TP + FP + FN} \tag{9}$$

- True Positive (TP): Exact classification of tissue region and detection of Tumor region.
- False Positive (FP): Misidentification or misclassification of normal tissue region as tumor region.
- False Negative (FN): Tumor region undetected

3.3.5 Overlap Fraction (OF) or Sensitivity

Overlap Fraction (OF) or sensitivity value refers back to the proper segmentation or classification in the input image [6, 7]. Moreover, of defines the effectiveness in exact identification of tumor region as well as other tissue regions, It is stated in Equation (10).

$$OF = \frac{TP}{TP+FN} \tag{10}$$

3.3.6 Extra Fraction (EF)

Extra Fraction (EF) mentions a number of voxels detected falsely and the region of the tumor. In addition, the misclassification of areas of tissue is also rate taken into account [9]. The algorithm which is capable of producing lower EF value offers better segmentation results. EF is described in Equation (3.9).

$$EF = \frac{FP}{TP+FN} \tag{11}$$

3.3.7 Specificity

Specificity defines specific word or algorithms to classify segments of normal tissue are present in a region in the input image capability, specificity is shown in the Equation (12).

$$\text{Specificity}\,(\sigma) = \frac{TN}{TN+FP} \tag{12}$$

Here, TN is the true negative value. It briefs the effective segmentation of non-tumor region or normal brain tissues by the algorithm.

4 Results and Discussion

4.1 MR brain Images Processing Results (Tumor Identification)

In this paper, we processed 10 magnetic resonance brain images include (5 FLAIR MR brain images and 5 T2-weighted MR brain images) using improved FCM algorithm segmentation and had given excellent results about locating the region of the tumor in the MR brain images processed as described in Figure.4 and Figure.5.

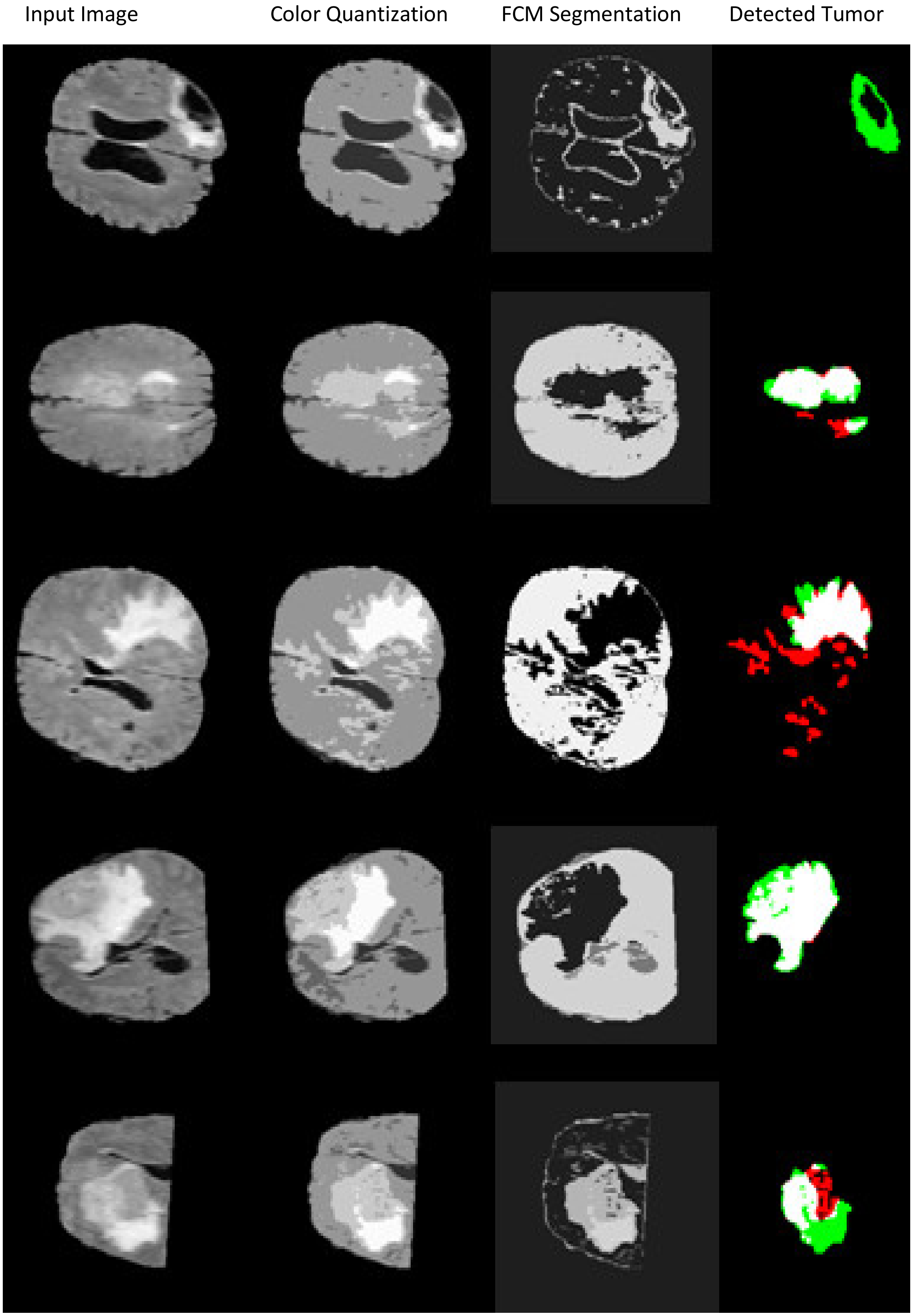

Figure.4 Segmented Results of the 5 MR brain FLAIR images using improved FCM algorithm

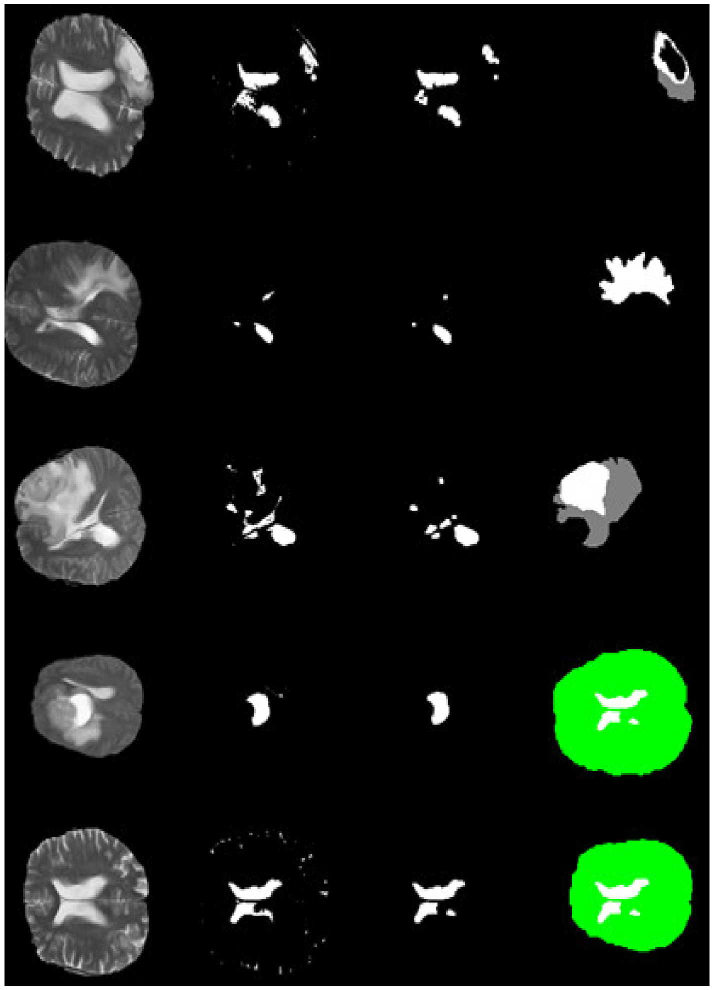

Figure.5 Segmented results of the 5 MR brain T2-weighted images using improved FCM algorithm

4.2 Performance evaluation results (Analysis)

"Table.1" Performance Evaluation of the 10 MR brain images using improved FCM algorithm in the 6 values

Images	TC	DOI	Sensitivity	Specificity	Precision	Accuracy%
FLAIR1	0,33123	0,31102	0,9846	0,9846	0,5861	98,677
FLAIR2	0,34123	0,30012	0,9823	0,9823	0,5324	98,677
FLAIR3	0,31131	0,30013	0,9817	0,9817	0,5365	98,671
FLAIR4	0,30012	0,30123	0,9811	0,9811	0,5611	98,112
FLAIR5	0,31232	0,31000	0,9832	0,9832	0,5311	98,323
T2-W1	0,29783	0,29934	0,9711	0,9711	0,5232	97,118
T2-W2	0,31023	0,29781	0,9811	0,9811	0,5511	98,113
T2-W3	0,29991	0,30001	0,9821	0,9821	0,5632	98,219
T2-W4	0,33212	0,29100	0,9734	0,9734	0,4991	97,348
T2-W5	0,31132	0,30001	0,9732	0,9732	0,5232	97,328

An algorithm producing Tanimoto Coefficient TC value above 0,3 are considered to be efficient. As the "Table.1" the proposed based improved FCM algorithm outruns the rival technique producing as TC value of the **0, 34123**.

Sensitivity or Overlap Fraction with an algorithm must be near to 1 and further fraction should bond [7] and the proposed improved FCM algorithm produce sensitivity or OF value **around 0,9846.**

Lower DOI value is derived together with the aid of proposed methodology, improved FCM algorithm produce an average DOI around 0,31102, and specificity around 0,9846, Precision around 0,5861 and accuracy detection value around **98,677%.**

5 Conclusion

In this paper we have improved Fuzzy C-Means algorithm (IFCM) given excellent results about tumor identification in MR brain images (Figure4 and Figure5) also, from the values (TC, DOI, Sensitivity, Specificity, Precision, Accuracy detection)" Table.1", the proposed improved FCM algorithm is capable to segment all T1.T2-weighted and FLAIR types brain images with low frequency signals and given excellent accuracy, the objective of this proposed to help the doctors diagnosis a patient in the period of the time with a high accuracy and what is achieved with Improved Fuzzy C-Means algorithm (IFCM).

ACKNOWLEDGEMENTS

This work was supported by the natural foundation of Hebei province under grant No: E2015202292 and No: E2015202050, high-level talent support project in Hebei province under grant No: C2015005012, key research, and development program under grant No: 15272002 and No: 15275704.

REFERENCES

[1]. Nandha Gopal, "Automatic detection of brain tumor trough MR image", Int, J.Adv.Res. Comput. Commun. Eng, 2 (April) ((4)) (2013).

[2]. Andac Hamamci, Nadir Kucuk, Kutlay Karaman, Kayihan Engin and Gozde Unal, "Tumor-Cut: Segmentation of Brain Tumors on Contrast-Enhanced MR Images for Radiosurgery Applications", IEEE transactions on medical imaging, vol. 31 (2011), 790 – 804

[3]. Karan Sikka, Nitesh Sinha, Pankaj K. Singh and Amit K. Mishra, A fully automated Algorithm under Modified FCM framework for improved brain MR image segmentation, Magnetic resonance Imaging, 27 (2009), 994–1004

[4]. R. S. PankajSapra, ShivaniKhurana, "Brain Tumor Detection Using Neural Network," International journal of Science and Modern Engineering (IJISME), vol. 1, August 2013.

[5]. Rafael C. Gonzalez, Digital Image Processing, Second Edition Ed, The United States of America: University of Tennessee, 2001

[6]. Sun. W, Segmentation method of MRI using fuzzy Gaussian basis neural network, Neural Information Processing, 8 (2) (2005), 19–24.

[7]. Nan Zhang, Su Rua, St 駱 hane Lebonvallet, Qingmin Liao and Yuemin Zhu, Kernel Feature selection To fuse multi-spectral MRI images for brain tumor segmentation, Computer Vision and image Understanding, 115 (2011) 256–269.

[8]. Rasoul Khayati, Mansur V afadusta, Farzad Towhidkhaha, and S.Massood Nabavi, Fully Automatic Segmentation of multiple sclerosis lesions in brain MR FLAIR images using Adaptive mixtures method and Markov random field model, Computers in Biology and Medicine, 38 (2008), 379 – 390.

