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Brain MRI Image Analysis and Segmentation using Machine Learning

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ABSTRACT

The brain magnetic resonance imaging (MRI), analysis and segmentation plays one of the crucial roles in medical diagnosis and facilitates in an early detection of diseases in critical medical conditions, Due to the structural complexity and type of the tumor, radiologists are facing difficulties in extracting essential features of the image which are crucial in treating the patient. Therefore, correct, and meaningful segmentation of brain MRI is a challenging task and is required for further processing. This article proposes machine learning based automatic brain MRI segmentation and classification. The pre-processing step is the vital part of the algorithm, where the discrete wavelet transforms (DWT) and median filtering help in identifying and pointing the exact location of the tumor. The preprocessed image is further segmented by an improved original Fuzzy C-means (FCM) clustering technique. The feature extraction and classification is performed by support vector machine (SVM) classifier. It is found that the simulation associated with ground truth data provides better segmentation results in terms of accuracy, sensitivity, and dice coefficient.

Keywords: Magnetic resonance image (MRI) data, Discrete wavelet transform (DWT), Median filtering, Original fuzzy c-means clustering, Support Vector Machine (SVM) classifier.

I. INTRODUCTION

The rapid development of new technologies in the field of image processing, especially artificial intelligence and machine learning has significant impact on medical field, which help in detecting human abnormalities. Recent improvements in the field of medical imaging and computer vision have helped in discovering brain pathologies at earlier stages and faster than manual methods. Computer vision and medical imaging play a vital role in diagnosing the MRI images of many diseases [1]. MRI, computer tomography (CT) and positron emission tomography (PET) imaging are the most widely used therapies for detection of tumor location. Visual examination of MRI image may take more time by experts in extracting required features from the images. Sometimes, this manual examination may cause errors or omissions. Therefore, machine learning and deep learning algorithms can support specialists in diagnosis and detection of brain tumor [2] in better way. Different methods have been developed over the last few decades to analyze medical images, however, one of the critical problems in medical image analysis is the accurate segmentation of the image. Therefore, it is necessary to have a robust segmentation technique for medical image preprocessing and the goal of segmentation is to split an image into regions, which can help in extracting the necessary features of the image. The usage of various segmentation techniques like threshold, edge, region, cluster and CNN will help in obtaining the useful features of the image, such as boundaries, shape and abnormal regions of defected organs [3][4]. Before the advancement of machine learning techniques, the most popular and efficient segmentation is FCM thresholding and region growing technique, which are frequently used for detecting the tumor region, however the method was not fully automatic. The automatic image analysis techniques like supervised and unsupervised learning are the leading techniques, which play a major part in medical image analysis. In an unsupervised technique, prior understanding of the pixels is not necessary and it provides better results particularly in case of medical images often by using FCM and K-means clustering, however the K-means algorithm only consider the gray values during the process and in case of FCM it computes the each local pixel during each iteration are major drawbacks and performance of both methods with different parameters will provide lack of consistency [5-10]. In this paper, the machine learning based unsupervised segmentation method is proposed, which provides better results with improved consistency.

A. K-means clustering

K-means algorithm is a simple and effective unsupervised technique, which can be used for various applications like abnormality detection, pattern analysis and image scene understanding etc. It classifies a sample set Y (y1, y2, y3…. yn) into k clusters with the endeavor at minimizing an objective function J is given by,

$$J = \sum_{i=1}^{k} \sum_{j=1}^{n} \left\| y_j^{(i)} - c_i \right\|^2 \tag{1}$$

where, n is the number of samples and C_i represents the clustering center, where $\left\| y_j^{(i)} - c_i \right\|^2$ is theEuclidean distance measure between a data point y_j and the cluster center C_i [11-13].

Algorithm steps

- Compare the intensity distribution of the objects.
- Initialize the centroids with K random intensities.
- Repeat the process until each cluster gets labeled.

$$C_i = \frac{1}{N_i} \sum_{x \in xi} x \,, i = 1,2 \ldots, k; \tag{2}$$

Here, N is the sample number of the i_{th} cluster.

- Cluster the points based on distance of their intensities from the centroid intensities.
- Compute the new centroid for each of the clusters.

B. Fuzzy c-means clustering

FCM algorithm for detecting compact well-separated cluster points is one of the popular techniques for analysis of cell and MRI images. It divides the data points into groups called clusters, in which data points can belong to several clusters with degree of membership varying in the range [0, 1]. It is an iterative optimization of the objective function. An image I= {z (I, j), 0<i≤M, 0<j≤N} with M*N number of

pixels or data points will be clustered into K-clusters and the fuzzy c-means optimization function is given by

$$\mathrm{J}(\mathrm{X},\mathrm{Y}) = \sum_{i,j}\sum_{c=0}^{k-1}\left(u_c(i,j)\right)^m \left(d_c(i,j)\right)^2 \qquad (3)$$

where, X= [μ_c (i, j)] is the fuzzy clustering matrix, Y= {Y0, Y1, Y2, Yc-1} denotes the set of clustering centers. μc (I, j) is the membership of the data point z (I, j) in the C_{th} cluster, m is the constant used to control the fuzziness of the resulting partitions, Dc (I, j) is the Euclidian distance of the data point z (I, j) from the C_{th} cluster.

The number of clusters K(2≤K<M*N) and original values of fuzzy clustering matrix are designated. Then the clustering centers Y_c and fuzzy clustering matrix X_c (i, j) are assigned using equations (2), and (3) respectively. The process is repeated until the coefficients varying between two iterations is not more than ε

$$Y_c = \frac{\sum_{i,j} u_c(i,j)^m \; z(i,j)}{\sum_{i,j} u_k(i,j)^m} \qquad (4)$$

$$x_c(i,j) = \frac{1}{\sum_{p=0}^{k-1} \left(\frac{d_c(i,j)}{d_p(i,j)}\right)^{\frac{2}{m-1}}} \qquad (5)$$

This paper is organized as follows: Proposed method is discussed in section 2. The results and discussions are presented in section 3 and the conclusion is given in section 4.

II. PROPOSED METHOD

An intelligent and improved segmentation technique is proposed in this article. Initially brain MRI image is processed by discrete wavelet transform (DWT) to eliminate the noise and the reconstructed image is treated with median filter which provides better denoising effect, and by fixing the appropriate image contrast level will provides better image quality. The preprocessed image is segmented by original fuzzy C-means clustering (FCM) automatic segmentation technique, which is one of the better unsupervised learning techniques. The segmented image is further subjected to support vector machine (SVM) classifier. Before the classification stage, the density-based operation is used to remove the unwanted skull region of the image. Finally, tumor and non-tumor parts of the brain MRI image are classified. The analysis results were found to be better, and correctness of the segmentation is improved significantly, compared to other popular methods. The experiment was carried out on more than 200 image samples.

III.PREPROCESSING

In pre-processing the image is subjected to DWT, where, bi-orthogonal (bior3.7) wavelet family is used and level 2 decomposition is carried out, so that more meaningful image can be reconstructed during the inverse DWT transform. The reconstructed image is denoised by median filter and image quality is improved by contrast enhancement as it helps in segmentation process [2-5][9].

A. Original Fuzzy C-means (FCM) clustering

The FCM clustering technique is the most superior unsupervised algorithm for pattern analysis, which helps to classify the similar objects during segmentation [6]. In the proposed method, the usage of original FCM clustering technique is used to recognize the abnormality in brain tissues in MRI. It is an improved unsupervised technique, which helps in avoiding the traditional morphology-based process before the segmentation. Here the clustering points are automatically assigned after the pre-processing stage and the associate function is the curve that defines how each point in the input space is mapped to degree of associated value in between 0 and 1. During this process it provides three random clusters at each cycle and an optimized cluster among them is automatically selected by feature extraction stage [8][14] [17-19].

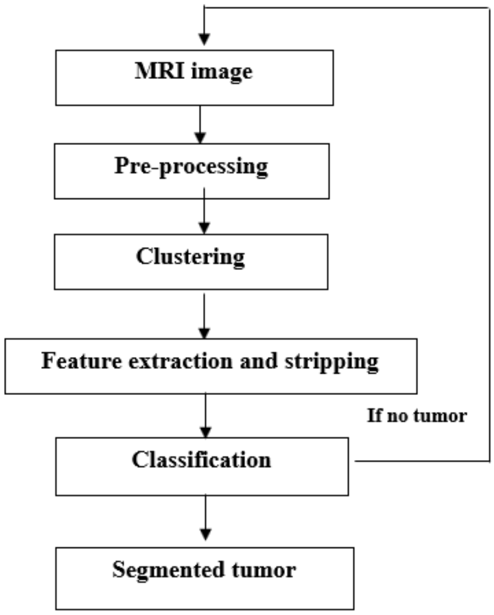
$$FCM = \sum_{k=1}^{n}\sum_{i=1}^{c}(u_a)^q \, d^2(X_k, V_i) \qquad (6)$$

where, $X_k = \{X_1, X_2 \ldots X_3\}$ are the data points,
n is the number of objects,
c represents the number of clusters,
Degree of association of X_k in the i^{th} cluster is represented as uik,
Q is the weighted exponent on each fuzzy association,
v_i represents the cluster center i,
d^2 is the distance between data point x_k and cluster centre v_i.

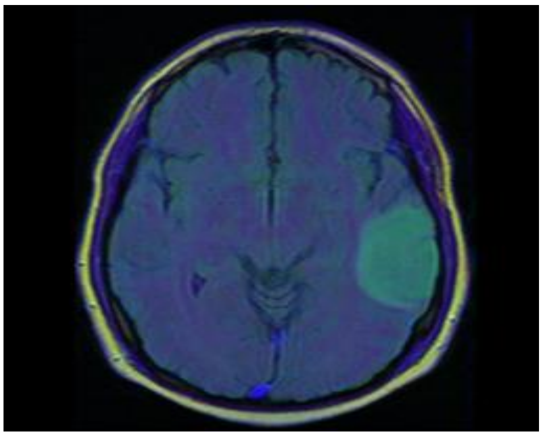
B. Support Vector Machine (SVM)

In feature extraction the segmented image features are converted into compressed form and it provides the characteristics of the input type to the classifier by considering the appropriate properties of the image into feature vectors. Subsequently, the normal and abnormal features of the brain tissues are classified based on decision tree [2-4]. A variety of techniques have been reported in the last few decades for extracting features from brain MRI images, such as gray level co-occurrence matrix (GLCM), Gabor filter, Discrete wavelet transform (DWT) etc., the GLCM approach works better in case of texture feature extraction but the texture features of MR image particularly tumor objects are unlike compared to normal image objects, therefore, the support vector machine (SVM) based approach used in this work [8-10]. SVM works based on decision trees, the main key point of the method is, the use of hyperplanes to define the decisions, which divide the various data points between the boundaries. It helps to find the better features as well as to generate lower dimensional polynomials to increase the performance of classification stage [14][15]. In many cases it avoids redundant and over-fitting issues. Before the classification stage. The skull region of the MR image is removed by density-based stripping process, which makes the tumor region distinct, and it helps in classifying the tumor and non-tumor parts [16][20][21].

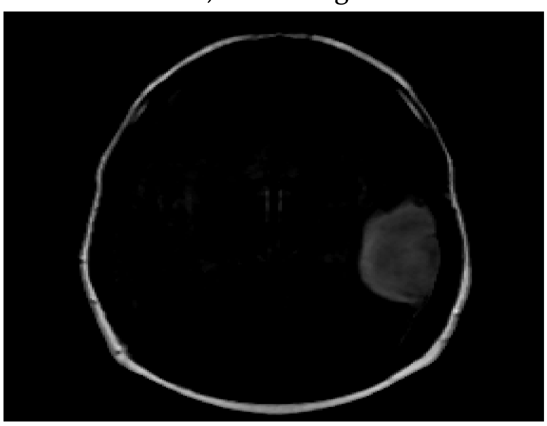
IV.FLOW CHART



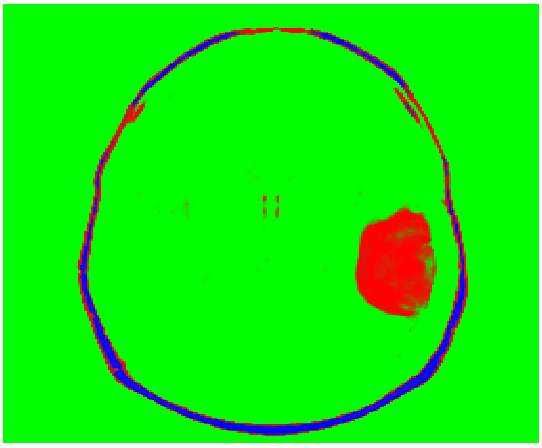
V. RESULTS AND DISCUSSION



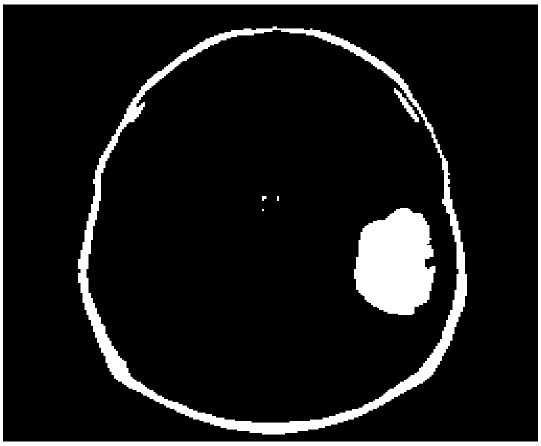
A) MRI Image



B) Pre-processing Image

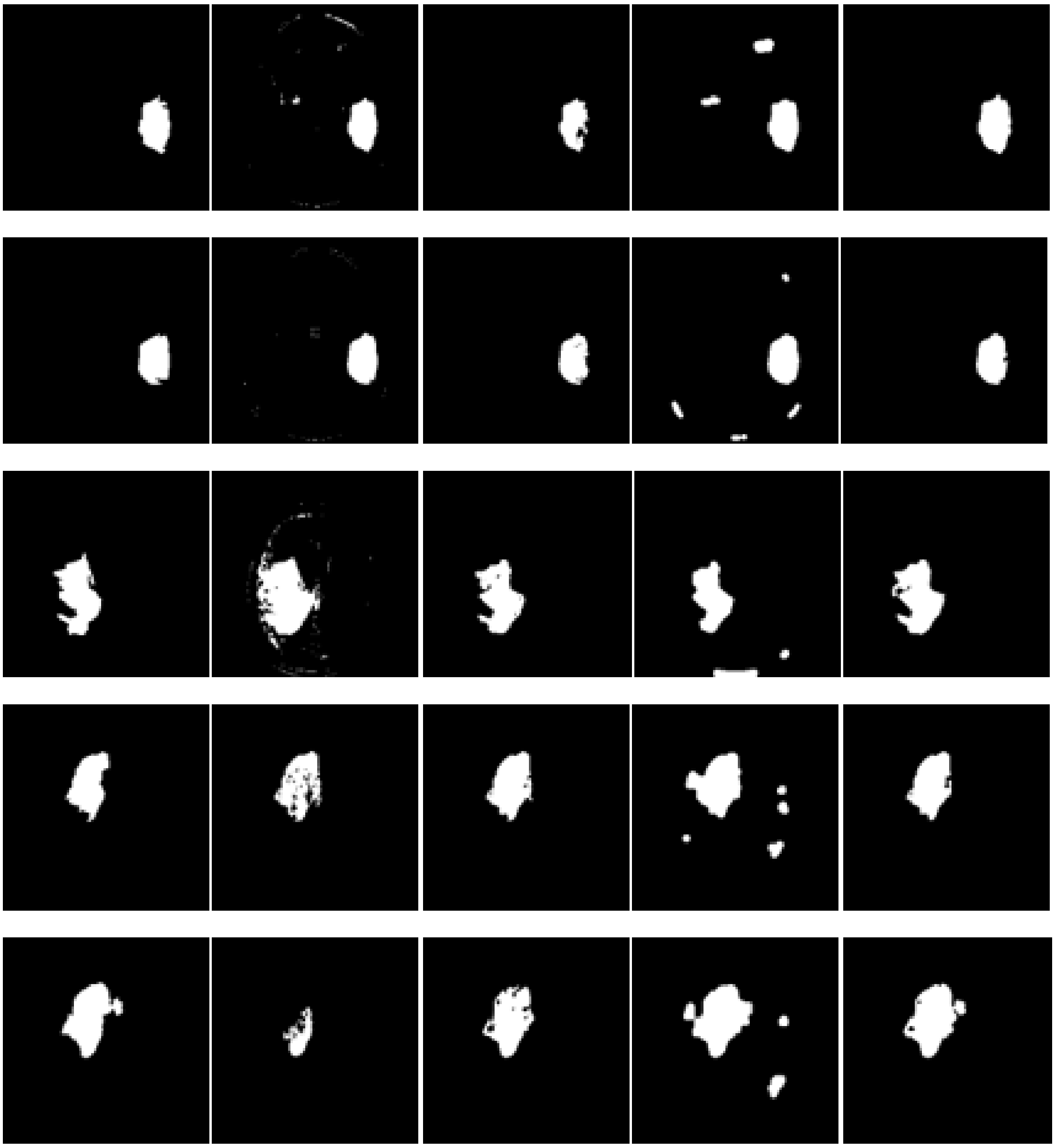


C) Segmented Image



D) Feature Extraction Image

Ground Truth K-means clustering FCM clustering FCM thresholding Proposed method



Ground Truth **K-means clustering** **FCM clustering** **FCM thresholding** **Proposed method**

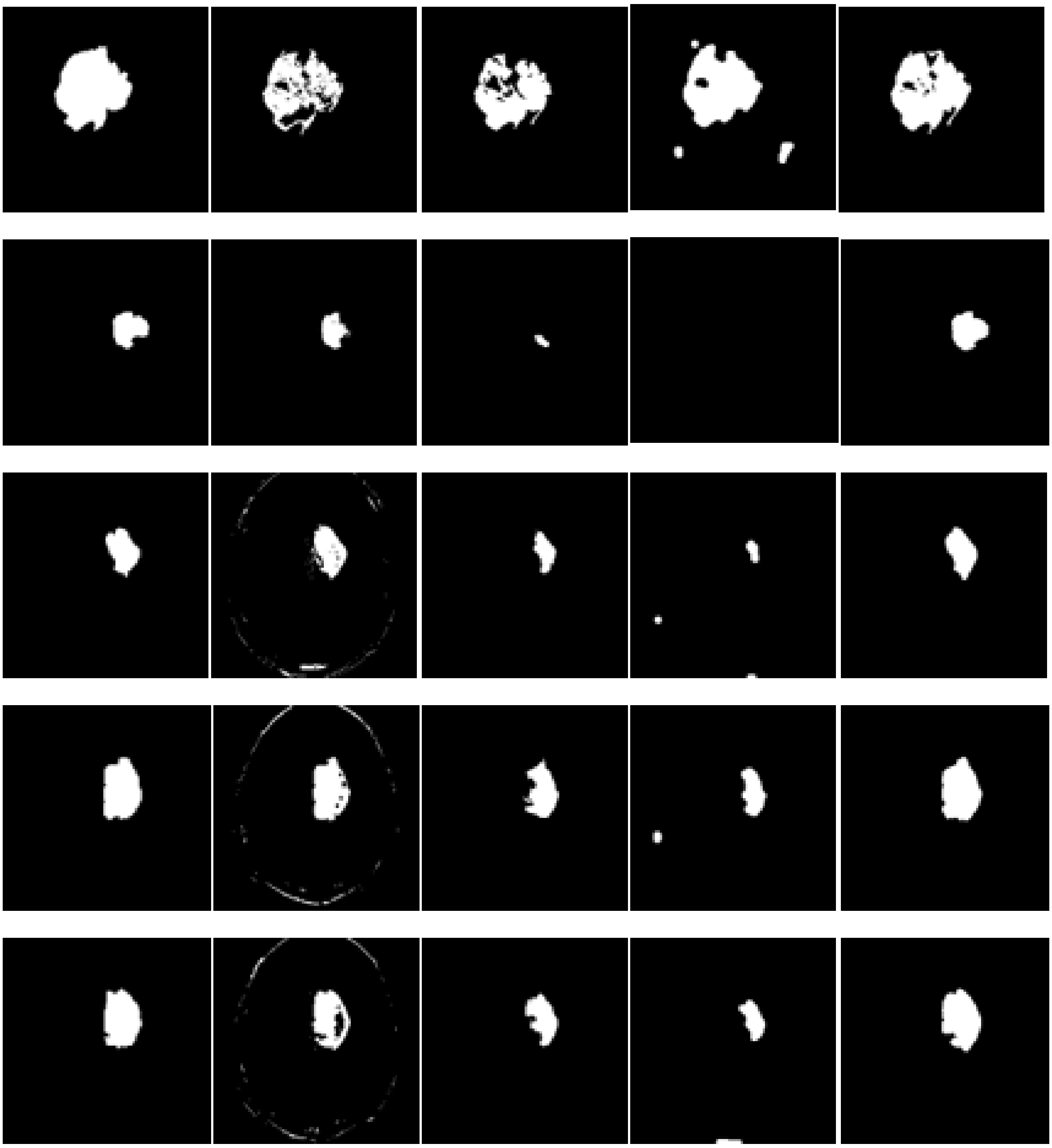


Table 1. Segmentation score

Image	Accuracy				Sensitivity				F-measure			
	K-means	FCMC	FCMT	Our method	K-means	FCMC	FCMT	Our method	K-means	FCMC	FCMT	Our method
1	0.9930	0.9935	0.9897	0.9953	0.8949	0.7862	0.9547	0.9840	0.8826	0.8773	0.8455	0.9254
2	0.9962	0.9962	0.9909	0.9972	0.9321	0.8880	0.9632	0.9955	0.9350	0.9327	0.8615	0.9515
3	0.9718	0.9920	0.9801	0.9940	0.9797	0.9008	0.7925	0.9341	0.7780	0.9193	0.8011	0.9208
4	0.9868	0.9921	0.9772	0.9933	0.8614	0.9705	0.9682	0.9514	0.8399	0.9085	0.7737	0.9072
5	0.9602	0.9867	0.9778	0.9911	0.2690	0.8240	0.9618	0.9060	0.4230	0.8705	0.8243	0.9208
6	0.9682	0.9731	0.9784	0.9859	0.7205	0.7538	0.9085	0.9525	0.8204	0.8497	0.8844	0.9282
7	0.9932	0.9812	0.9788	0.9960	0.6897	0.1145	0	0.9203	0.8119	0.2054	0	0.9105
8	0.9869	0.9887	0.9784	0.9966	0.9285	0.5345	0.1834	0.9203	0.7741	0.6960	0.2909	0.9288
9	0.9851	0.9846	0.9734	0.9958	0.8743	0.6484	0.4340	0.9270	0.8372	0.7859	0.5878	0.9517
10	0.9841	0.9834	0.9717	0.9937	0.7932	0.5852	0.3586	0.9673	0.8002	0.7383	0.5040	0.9219

Table 2. Segmentation score

Image	Matthew's correlation coefficient(MCC)				Dice-coefficient				Specificity			
	K-means	FCMC	FCMT	Our method	K means	FCMC	FCMT	Our method	K-means	FCMC	FCMT	Our method
1	0.8791	0.8820	0.8462	0.9247	0.8826	0.8773	0.8455	0.9254	0.9950	0.9898	0.9907	0.9956
2	0.9330	0.9320	0.8620	0.9502	0.9350	0.9327	0.8615	0.9515	0.9981	0.9995	0.9917	0.9992
3	0.7827	0.9153	0.7907	0.9025	0.7780	0.9193	0.8011	0.9072	0.9714	0.9860	0.9901	0.9933
4	0.8333	0.9064	0.7798	0.9185	0.8399	0.9085	0.7737	0.9208	0.9920	0.9930	0.9776	0.9943
5	0.5050	0.8650	0.8223	0.9166	0.4230	0.8705	0.8243	0.9208	0.9898	0.9960	0.9787	0.9934
6	0.8128	0.8435	0.8825	0.9207	0.8204	0.8497	0.8944	0.9282	0.9960	0.9977	0.9862	0.9948
7	0.8220	0.3351	0	0.9094	0.8119	0.2054	0	0.9105	0.9898	1	1	0.9970
8	0.7790	0.7260	0.3519	0.9271	0.7741	0.6960	0.2909	0.9288	0.9884	1	0.9981	0.9985
9	0.8302	0.7977	0.6185	0.9495	0.8372	0.7859	0.5878	0.9517	0.9921	0.9999	0.9981	0.9977
10	0.7919	0.7584	0.5408	0.9186	0.8002	0.7383	0.5040	0.9219	0.9902	1	0.9973	0.9965

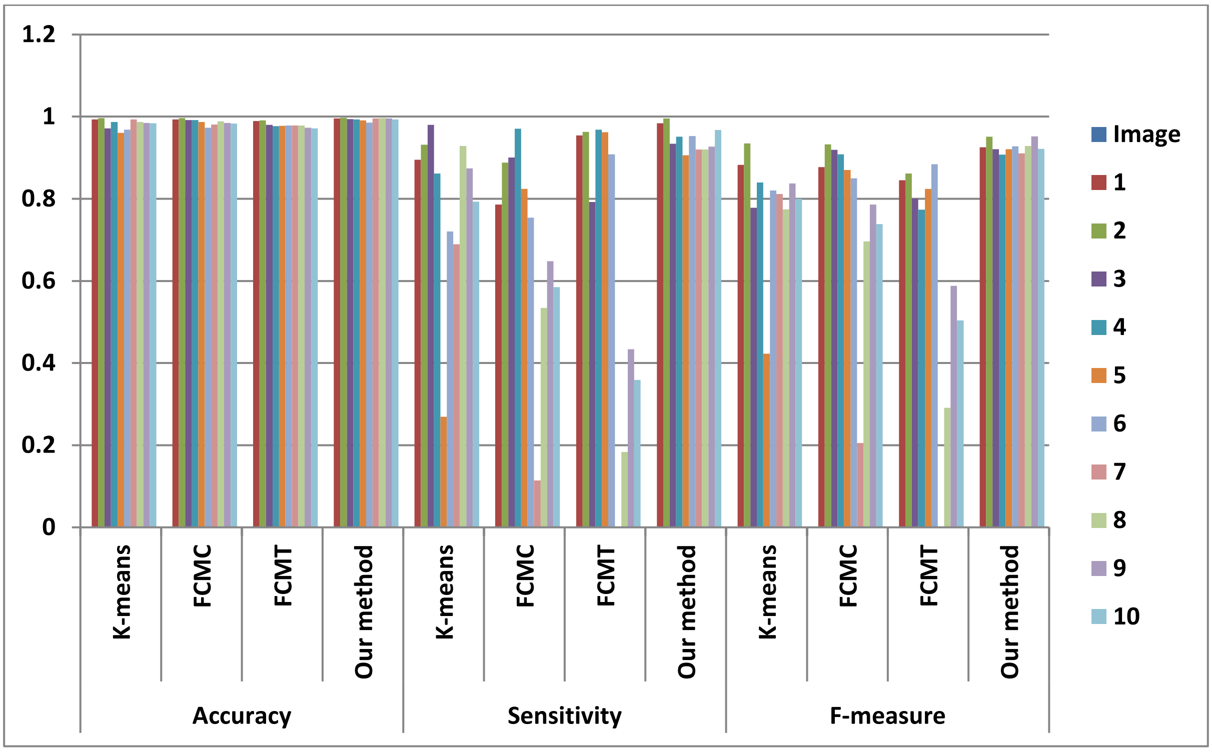


Figure shows the performance of the proposed method.

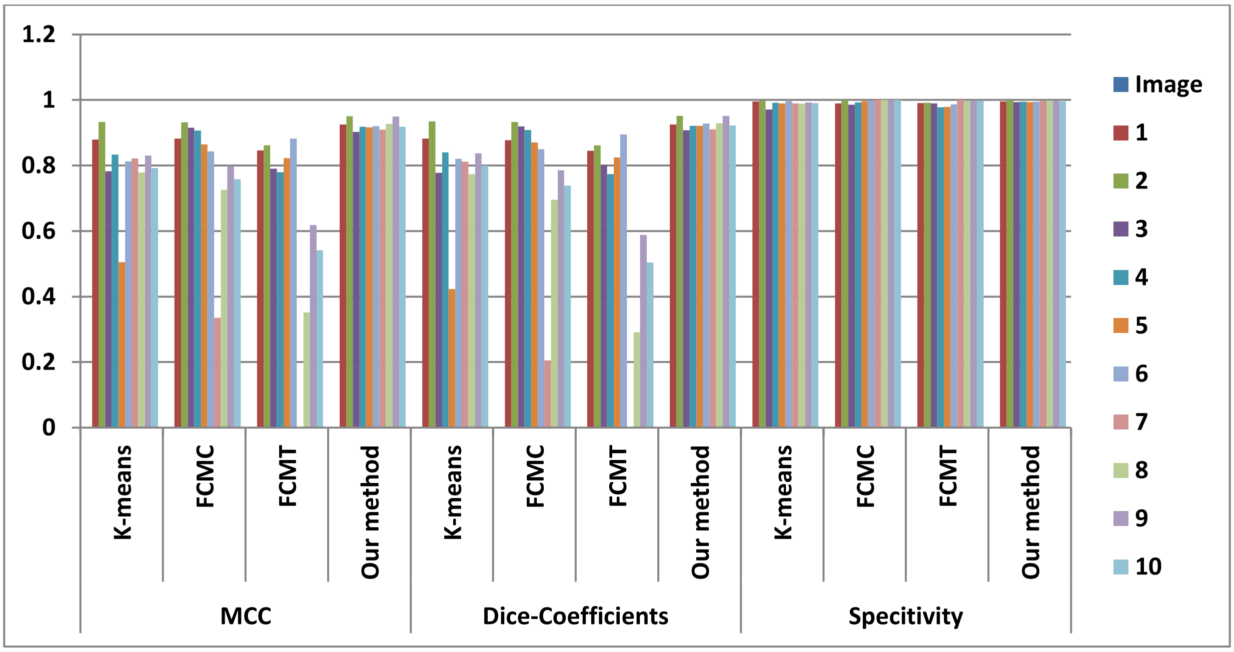


Figure shows the performance of the proposed method.

A). Performance matrices

Experimental setup

The proposed method is executed in MATLAB. The MRI images and the corresponding ground truth images are obtained from Kaggle website. The results are compared with optimized K-means clustering, FCM clustering and FCM thresholding techniques in terms of accuracy, sensitivity, F-measure, Mathew's correlation coefficient (MCC), Dice-coefficient and specificity.

- Accuracy

It specifies the pixels of the image which are perfectly classified. Perfection of the segmentation technique is given by.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \times 100 \qquad (7)$$

Pixels which are perfectly incorporated into the given class are represented by TP and TN represents the pixels which are not belonging to the given class. FN is wrongly predicted pixels, which do not belong to the given class.

- Sensitivity

Sensitivity is calculated through positive predictive values and negative predicted values, which is ratio of true outcome of all segmented results.

$$\text{Sensitivity} = \frac{\text{TP}}{(\text{TP} + \text{FN})} \qquad (8)$$

- F-measure

A measure that combines the average of precision and recall is the harmonic mean of precision and recall, the traditional F-measure or balanced F-score.

$$\text{F} = \frac{2\text{TP}}{2\text{TP} + \text{FP} + \text{FN}} \qquad (9)$$

MCC (Matthew's correlation coefficient)

The MCC can be calculated directly from the confusion matrix using the formula.

$$\text{MCC} = \frac{\text{TP} * \text{TN} - \text{FP} * \text{FN}}{\sqrt{(\text{TP} + \text{FP})(\text{TP} + \text{FN})(\text{TN} + \text{FP})(\text{TN} + \text{FN})}} \qquad (10)$$

If any of the four sums in the denominator is zero, the denominator can be randomly set to one; this results in a Matthews correlation coefficient of zero,

- Dice co-efficient.

Dice-coefficient examines the identical things in between segmented image and the ground truth image, which is retrieved from manual segmentation. Dice coefficient of segmented image is given by.

$$\text{DC} = \frac{2|M \cap N|}{|M| + |N|} \qquad (11)$$

where, $|M|$ and $|N|$ cardinalities of two sets.

- Specificity

Specificity refers to the measure of true negative rate, if higher the specificity, significantly sensitivity rate will be less, vice versa [22][23].

$$\text{Specificity} = \frac{\text{TN}}{(\text{TN} + \text{FN})} \qquad (12)$$

VI.CONCLUSION

In proposed study a robust pre-processing stage is developed, here, the combination DWT based bi-orthogonal (bior3.7) wavelet and median filtering provides better denoising effect at pre-processing stage and it helps to simplify the segmentation process, During segmentation usage of original FCM based clustering algorithm will reduce the noise level significantly, and it provides better segmentation with finer visual quality of the image, is one of the major novelty used in this work. In feature extraction stage SVM classifier will extracts the necessary and meaningful details of the segmented image, all through it classifies both tumor and non-tumor part of the image. Before the classification stage the skull stripping is performed, in most cases skull region will be removed in earlier stages, Due to this, sometimes essential features of the image will be eroded, which may affect the segmentation process. Therefore, removal of skull region after the segmentation is one of key points used in this study. Also, the performance result shows the correctness of the segmentation in terms of accuracy, sensitivity, dice coefficient, F-measure etc. are found to be better.

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