A Brain Abnormality Detection and Tissue Segmentation Technique by Using Dual Mode Classifier

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Abstract: *In the analysis of brain Magnetic Resonance Images (MRI), tissue classification is an important issue. Many works have been done to classify the brain tissues from the brain MRI. This paper presents a new technique to classify the brain MRI images and to perform tissue classification by using Dual Mode Classifier (DMC). Initially, the brain MRI images are obtained from the brain databases and features such as covariance and correlation are calculated from the input brain MRI images. These calculated features are given to Feed Forward Back Propagation Neural Network (FFBNN) to detect whether the given MRI brain image is normal or abnormal. After detection, the resultant image is subjected to the segmentation process with the use of Optimized Region Growing (ORGW) technique to accomplish efficient segmentation. Following that, by utilizing Local Binary Pattern (LBP), texture feature is computed from the segmented brain MRI images. Then this texture feature is given as the input to the DMC which has two branches. One branch classifies the normal tissues such as Grey Matter (GM), White Matter (WM) and Cerebrospinal Fluid (CF) and the other branch classifies the abnormal tissues such as Tumor and Edema. The performance of our proposed technique is compared with other techniques such as Conventional Region Growing (RGW), and MRGW.*

Keywords: *ORGW, LBP, dual mode classifier, FFBNN, correlation, covariance.*

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1. Introduction

Medical images are significant among the other available data sources, because these images are usually used by physicians to detect different diseases [5, 9]. A huge number of medical images collected over years, along with related medical diagnosis, present a valuable data set that helps in building a model to classify future cases [10, 12]. Today, medical data captured from brain diagnosis are usually acquired in the form of massive spatial and temporal data, known as Multidimensional Time-Series (MDTS) data [4]. Classification and segmentation techniques are widely performed in brain images to segment and classify the brain tissues. A classification approach has been presented to examine the brain abnormalities, i.e., due to prenatal cocaine exposure, using both structural and functional brain image [14, 20]. Magnetic Resonance Imaging (MRI) is an important diagnostic imaging technique for the early detection of abnormal changes in tissues and organs [6, 16] and it allows a radiologist to generate an image of the interior aspects of living tissue as it is a non-invasive imaging technique [15]. MRI is well suited for monitoring and evaluating brain images. In MRI, they appear either as hypo-intense (darker than brain tissues) or as iso-intense (same intensity as brain tissue) in T1-weighted scans and as hyper-intense (brighter than brain tissues) in T2- weighted scans [17]. Brain images based on metabolic function may prove to be even more sensitive than MRI [2]. The main obstacles to segmentation of MR images are the presence of noise and errors in the scanners and structural variations of the imaging objects, which can be categorized into four types: Thermal/electronic noise, magnetic field in homogeneities, biological tissue variations, and partial volume effects [13]. However, manual detection and analysis of these lesions from MR brain images are usually time consuming, expensive and can produce unacceptably high intra observer and inter-observer variability [19].

Identifying 3-D brain structures in medical imagery, particularly in MRI scans, is important for early detection of tumors, lesions, and abnormalities, with applications in diagnosis, follow-up, and image-guided surgery [7, 21]. The ultimate goal is to automatically identify structural brain abnormalities by estimating the differences between normal subjects and patients affected by a certain disease [3]. MR-image segmentation techniques are often evaluated in terms of their ability to differentiate between

1. Cerebro-Spinal Fluid (CSF), White Matter (WM), and Gray Matter (GM).
2. Normal tissues and abnormalities [8, 11].

Several methods that have been proposed in recent years for the segmentation of brain tissues from MR image include classical pattern recognition methods, rule-based systems, image analysis methods, crisp and fuzzy clustering procedures, feed-forward neural networks, fuzzy reasoning, geometric models to determine lesion boundaries, connected component analysis, deterministic annealing, atlas based methods and contouring approaches [1, 18]. In this work, brain abnormality detection and tissue classification system is proposed. Initially the brain MRI images are collected from the brain database and classified using Feed Forward Back Propagation Neural Network (FFBNN) which uses covariance and correlation features that are calculated from the input image. The resultant image is segmented using Optimized Region Growing (ORGW). Subsequently, texture feature is computed from the segmented image using Local Binary Pattern (LBP) pattern and this feature is given to Dual Mode Classifier (DMC) to perform the tissue classification. The rest of the paper is organized as follows: Section 2 discusses about the proposed technique. Section 3 shows the experimental result of the proposed technique and section 4 concludes the paper.

2. Proposed Brain Magnetic Resonance Imaging Image Classification and Tissue Classification

Here a new technique is proposed to classify the brain MRI images and performs the tissue classification using DMC. Initially, the features such as covariance and correlation are extracted from the input MRI brain images, which are obtained from the database. Soon after, the extracted features are fed as the input to the FFBNN to classify the brain MRI images. Subsequently, the resultant image is given to segmentation process which utilizes ORGW technique in which intensity, orientation thresholds are used and that are optimized using genetic algorithm to improve the segmentation accuracy. Followed by, texture features are extracted using local binary pattern from the segmented image. Then these calculated features are given to the well known classifier such as DMC. This DMC has two branches where one branch classifies the normal tissues such as WM, GM and Cerebrospinal Fluid (CF) and another one branch classifies the abnormal tissues such as Tumor, Edema. Architecture of the proposed brain MRI image classification and tissue classification Technique by using DMC is given in Figure 1. The proposed technique consists of the following stages including feature extraction, classification using FFBNN, segmentation using ORGW, exploitation of lbp and tissue classification using DMC.

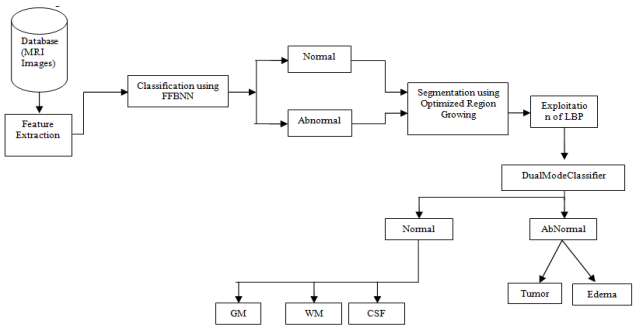


Figure 1. Architecture of the proposed brain MRI Image classification and tissue classification technique by using dual mode classifier.

2.1. Feature Extraction

Let the database (D) which consists of MRI brain images and $x_{i,j}$ be one of the MRI brain images has the size of (mXn) taken from the database as the input where i € 1, 2,…., n and j € 1, 2,…., n. The calculation of covariance (c_o) and correlation (c_r) are given below in the Equations 1 and 2.

$$co = \frac{1}{mn}\sum\left(x(i,j) - \left(\frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{n} x(i,j)\right)\right) \quad (1)$$

$$cr = \frac{co}{\sqrt{\left(\frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{n}\left(x(i,j) - \left(\frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{n} x(i,j)\right)\right)\right)}} \quad (2)$$

Where, m-number of rows of given input image and n-number of columns of the given input image. These calculated correlation and covariance features are given to the FFBNN to classify the MRI brain images.

2.2. Classification using Feed Forward Back Propagation Neural Network

In order to detect whether the given input image is abnormal or normal, FFBNN is utilized and it is trained using the covariance and correlation values extracted from each and every image in the database. The extracted features are given to neural network for training and well trained using these extracted features. The neural network consists of 2 input units, h hidden units and one output unit. The structure of the FFBNN is given as below in Figure 2. If the learning error is greater than the threshold value it is classified as normal MRI brain image otherwise it is denoted as abnormal brain image.

$$result = \begin{cases} normal, Y^{3}\tau 1, \\ abnormal, Y < \tau 1 \end{cases} \quad (3)$$

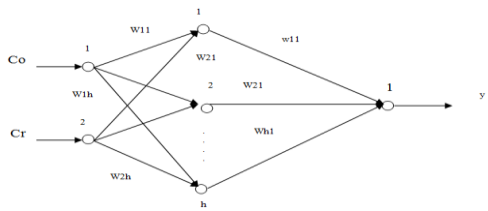


Figure 2. Diagram of the FFBNN.

Then the resultant MRI brain image (x') is subjected to segmentation process.

2.3. Segmentation using Optimized Region Growing

2.3.1. Skull Stripping

The resultant image (x') obtained from the FFBNN is then subjected to segmentation process. Before doing segmentation, the image need to be preprocessed using skull stripping technique to remove the distinct dark ring surrounding the brain tissues ie brain cortex in the MRI images. In skull stripping, the given MRI brain image is converted into gray scale image at first and then a morphological operation is carried out in the gray scale image. Then by using region based binary mask extraction, the brain cortex in the gray scale image is stripped. The preprocessing process is performed in the classified normal images, not abnormal images. Because preprocessing process helps to improve the normal tissue CSF is lightly placed in the cortex surrounding area. The threshold value used in the skull stripping process is optimized to attain efficient segmentation.

2.3.2. Tumor Segmentation

For segmentation process, intensity, orientation features are calculated from the resultant image. These calculated intensity, orientation features are utilized in the seed point selection of the ORGW technique. ORGW technique is a popular technique for image segmentation which involves seed point selection. In the segmentation process, the neighboring pixels are compared with the initial seed points to check whether the neighboring pixels can added to the region, based on the similarity. Seed point selection is important in the segmentation process. But the region growing Technique is poor in the seed point selection so that result obtained in the segmentation process also poor. To overcome these problems, in our proposed technology intensity, orientation features are utilized in the ORGW. The process of ORGW is given in steps which are shown below:

- *Step 1*. Calculate the gradient of the image for both $x'x_1$ axis and $x'y_1$axis.
- *Step 2*. Form the gradient vector GV by combine the gradient values using the Equation:

$$GV = 1/(1+(X'X1^2 + X'Y1^2)) \quad (4)$$

- *Step 3*. Change the gradient vector values into degrees to get the values of orientation.
- *Step 4*. Segregate the image into grids G_i.
- *Step 5*. Set intensity threshold (T_1) and orientation threshold (T_2).
- *Step 6*. Until the number of grids reached maximum, go to step 7, else go to step 15.
- *Step 7*. Find the histogram of each pixel in G_i.
- *Step 8*. Determine the most frequent histogram of the G_i^{th} grid and denote it as R_h.
- *Step 9*. Prefer any pixel according to R_h and assign that pixel as seed point which has the intensity In_x and Or_x.
- *Step 10*. Consider the neighboring pixel having the intensity I_n and orientation O_n.
- *Step 11*. Find $d_1 = \| In_x - In_n \|$ and $d_2 = \| Or_x - Or_n \|$.
- *Step 12*. If $d_1 <= T1 \&\& d_2 <= T2$, then add the corresponding pixel to the region and grow the region, else go to step 14.
- *Step 13*. Check whether all pixels are added to the region. If true go to step 6 otherwise go to step 14.
- *Step 14*. Re estimate the region and find the new seed points and go to step 7.
- *Step 15*. Stop.

Using the ORGW, tumor tissues are segmented from the abnormal images. After that, to segment the edema, GM, WM and CSF tissues abnormal and normal images are subjected to histogram equalization process.

2.3.3. Edema Segmentation

To carry out the edema segmentation, histogram equalization process is performed over the abnormal image. First, the quality of image is enhanced by the histogram equalization and it is converted into indexed image using multilevel thresholding function which utilizes grayslice function. After that, the image is converted into HSV (hue, saturation and value) color model and the threshold process is performed on the image. We define separate threshold value for hue, saturation, and value. Each pixel in the image is compared with these threshold values to chose the pixels. H→th_1, S→th_2 and V→th_3

$$X' = \begin{cases} Pu; Pu \le th1, th2 \& \ge th4 \\ 0; otherwise \end{cases} \quad (5)$$

In the above Equation 5, X' is the pixel values which satisfy the above conditions. Morphological closing operation is applied on the mask X' and the resultant image is denoted as $X'^{(c)}$. Now the image $X'^{(c)}$ contains z number of regions and then we calculate the centroid value for each region that is denoted as $X_h^{(c)}(x, y)$, h= 1, 2, … z. Consequently, the distance is determined between the coordinates of center pixels of the regions in $X_h^{(c)}(x, y)$ and the tumor centroid coordinate value $t(x, y)$.

$$O(x,y) = X_h^{(c)}(x,y) - t(x,y) \quad (6)$$

The resultant O(x,y) is then verified with threshold value th_4 and an edema region coordinate values are obtained,

$$I = \begin{cases} O(x,y)\ ^3\ th4 \\ 0; otherwise \end{cases} \quad (7)$$

Then the morphological dilation and closing operations are performed in the image I.

2.3.4. GM, WM and CSF Segmentation

Here, the resultant image obtained after preprocessing which is explained in section 3.3.1 is utilized for GM, WM and CSF tissues segmentation. The same process carried out for edema segmentation is repeated for segmenting the GM, WM and CSF from the normal images by varying threshold values except finding the distance between the coordinates of center pixels of the regions in $X_h^{(c)}(x, y)$ and the tumor centroid coordinate value $t(x, y)$.

2.3.5. Optimization using Genetic Algorithm

Genetic algorithm is a metaheuristic algorithm that minimizes the natural evolution process. Generally it used to produce useful solutions to optimization and search problems. It generates solutions to optimization problems using techniques stirred by natural evolution, such as inheritance, mutation, selection, and crossover.

- *Initial Phase*: Initially the populations of the chromosomes d (d=1, 2, 3, ..., N) are generated randomly. N denotes the size of the population.
- *Fitness function*: Fitness value of each parameter is calculated and the chromosome which has the highest fitness value is selected as the best chromosome.
  - *Mutation*: In the mutation process chromosome values are changed according to the probability. To do the mutation process, probability should be set low.
  - *Crossover*: After mutation, one or more parent chromosomes are selected using roulette wheel and new solution is created.
  - *Evaluation*: Then the fitness of the new solution is calculated.

$$F = best(GT_i); i = 1, 2, ..., N \quad (8)$$

GT_i - grey threshold. If the new fitness value is better than the current fitness value, it replaces the current value. This process is continued until the termination criterion is reached. Thus the GM, WM and CF are segmented from the normal brain MRI image and tumor and edema are segmented from the abnormal brain MRI image from the above process finally and result is given to feature extraction process.

2.4. Texture Feature Extraction by employing Local Binary Pattern

The segmented regions obtained using ARGW is subjected for texture feature extraction. Texture feature is computed by employing the local binary pattern. The LBP pattern is obtained using the following Equation 9:

$$lbp_{p,r} = \sum_{p=0}^{p-1} s(g_p - g_c)2^p, s(v) = \begin{cases} 1, v\ ^3 0 \\ 0, v < 0 \end{cases} \quad (9)$$

In Equation 9, g_c, g_p-gray level of the center pixel and its neighbor of segmented image respectively, P-total number of neighbors, r-radius. If the coordinate values of the g_c is (0, 0), then g_p is predicted using ((rcos (2Πp /P)), (r sin(2Πp/P))). The texture feature gained using LBP is then fed as the input to the DMC.

2.5. Tissue Classification using Dual Mode Classifier

To classify the tissues, DMC is utilized, that is constructed by make use of two FFBNN. Texture feature obtained from the LBP pattern is given as the input to DMC and the output is the corresponding tissue i.e., normal tissue (GM, WM, CF) or abnormal tissue (Tumor, Edema). One phase determines the GM, WM and CF from the normal segmented MRI brain image. Another phase determines the tumor and edema from the abnormal MRI brain image. The DMC is well trained using the extracted features. The working process of DMC same as FFBNN is detailed in section 3.2. DMC consists of one input unit, one output unit and N_{hd} number of hidden units. The architecture of DMC is shown in Figure 3 shows the normal tissue classifier and abnormal tissue classifier. In training, the normal tissue classifier is trained using texture feature of normal tissues such as GM, WM and CF whereas the abnormal classifier is trained using the texture feature of abnormal tissues such as tumor and edema. During the testing, more number of texture features is given to well trained both normal and abnormal tissue classifier to validate whether it classify the tissues perfectly or not.

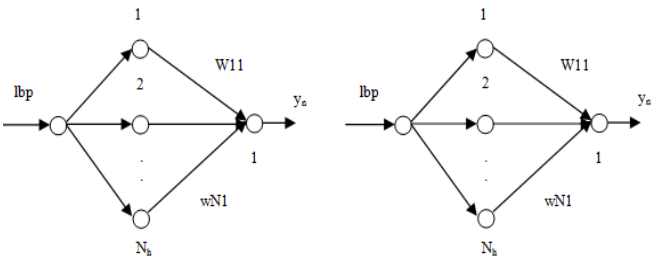


Figure 3. Dual Mode Classifier (one for normal and other for abnormal tissue classification).

3. Experimental Results and Discussions

The proposed MRI abnormality detection and tissue segmentation technique is implemented in the working platform of MATLAB (version 7.12). In our work, the given brain MRI image database has both normal and abnormal Images. To accomplish the abnormal tissue segmentation, there is a need to classify the images as normal and abnormal. To perform the classification,

the correlation and covariance features are extracted and given to the FFBNN for the image classification. The database sample and classified result images are given in Figures 4 and 5. Thus, the classified abnormal images are given to the modified region growing algorithm for abnormal tissues segmentation process. After segmentation, the segmented tissues texture features are extracted and given to the DMC for accomplishing the tissues classification. The normal and abnormal tissues segmented result images are given in Figure 6.

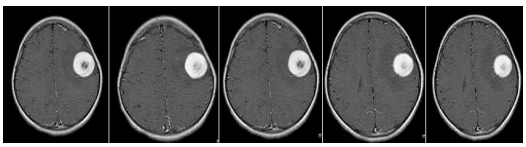
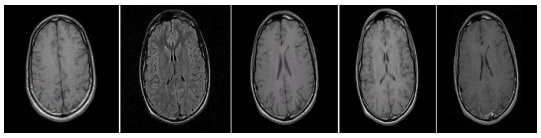
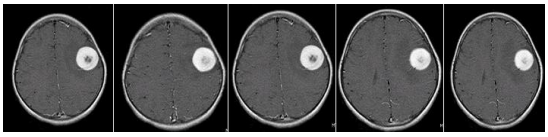


Figure 4. Sample brain MRI abnormal images.

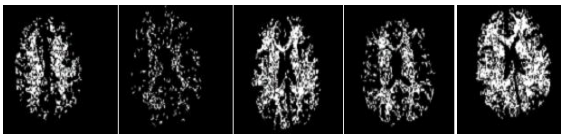


a) Normal.

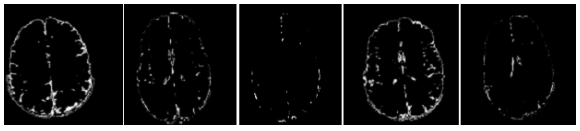


b) Abnormal.

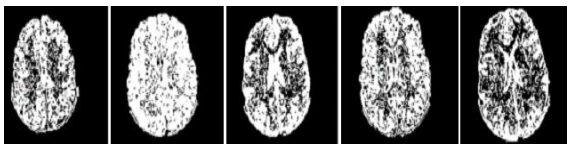
Figure 5. Classified Image results.



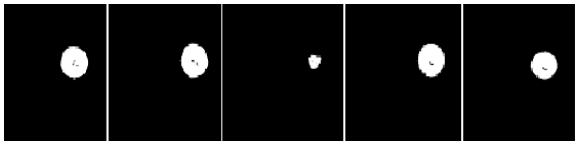
a)WM.



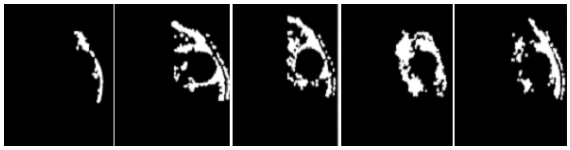
b) CSF.



c) GM.



d) Tumor.



e) Edema.

Figure 6. Segmentation result.

The extracted texture features from the segmented abnormal tissues are given to the DMC for performing tissue classification process. Our proposed technique obtained 100% normal and abnormal brain MRI image classification result. For the normal and abnormal brain MRI image classification FFBNN utilizes correlation and covariance features. The performance of the proposed MRI image abnormal tissue segmentation is evaluated by the quantitative evaluation performance metrics tanimoto coefficient (T), accuracy and dice coefficient. The quantitative evaluation matrices are computed by exploiting the following Equations:

$$DC = \frac{2\left|A_i \text{ Ç } B_i\right|}{\left|A_i\right| + \left|B_i\right|} = \frac{2XTP}{(2XTP) + FP + FN} \tag{10}$$

$$T = \frac{\left|A_i \text{ Ç } B_i\right|}{\left|A_i \text{ È } B_i\right| - \left|A_i \text{ Ç } B_i\right|} = \frac{TP}{TP + FP + FN} \tag{11}$$

Where Ai and Bi are the reference and the resulting segmented pixels' set respectively.

$$Accuracy = \left(\frac{TP + TN}{TP + TN + FP + FN}\right) X100 \tag{12}$$

The graphical representation of the mean quantitative evaluation results of proposed and existing techniques are shown in Figure 7. In figure 7-c, the average of accuracy of the proposed technique is compared with the other techniques. By seeing the graph, the accuracy of the proposed technique is significantly higher than other techniques. Average Accuracies of the proposed technique are 98.6, 94.4, 99.4, 93.2 and 97.8 for GM, WM, CSF, Tumor and Edema Tissues classification respectively. When compared to the other techniques the proposed technique is 2.2-13.2%, 1.2-4.6%, 5.4-11.2%, 2.4%, 2.8-10.2% greater for GM, WM, CSF, Tumor and Edema Tissues classification respectively. It indicates the performance and the exactness of the proposed technique is higher than the other techniques. Also, the performance of our proposed, conventional Region Growing (RGW) and MRGW segmentation techniques is evaluated in terms of their quantitative evaluation measures. The evaluation results show that our proposed segmentation technique has given high performance results than the other segmentation techniques. From the graph we can see that the DC and T values of the proposed technique is drastically greater than the conventional RGW and MRGW which in turn denotes that our proposed segmentation technique accurately segments the WM, GM, CSF, Tumor and Edema tissues from the MRI images. As can be seen from Table 5, our proposed technique has attained 90% accuracy for abnormal and 93.33% accuracy for normal image classification. Existing FCM technique has achieved 70% and 73.33% for abnormal and normal image classification. Thus the performance of our proposed technique is 20% higher than the existing technique which in turn indicates that

our proposed technique is classifying the tissues successfully and it can be utilized in the real time applications.

Table 1. Performance of proposed, conventional region growing and existing MRGW MRI image segmentation technique results in terms of their accuracy values.

Images	Proposed					RGW					MRGW				
	WM	GM	CSF	T	E	WM	GM	CSF	T	E	WM	GM	CSF	T	E
1	97	96	100	95	99	86	95	95	95	88	96	95	98	98	96
2	99	83	97	93	97	97	89	90	89	90	97	91	97	97	97
3	100	99	100	94	100	83	90	87	86	87	97	94	100	100	90
4	97	96	100	92	97	82	96	92	96	92	96	92	98	77	96
5	100	98	100	92	96	79	96	77	88	81	96	77	77	82	96

Table 2. Quantitative evaluation results of proposed system.

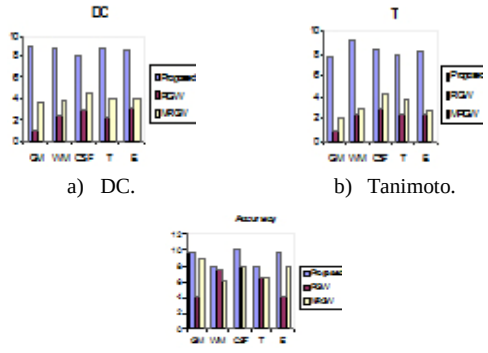
Images	DC					T				
	WM	GM	CSF	Tumor	Edeme	WM	GM	CSF	Tumor	Edema
1	0.6732	0.9012	0.9711	0.5000	0.8189	0.9383	0.6731	0.9012	0.9711	0.5000
2	0.9401	0.4148	0.0042	0.8870	0.1818	0.0021	0.9401	0.4148	0.0042	0.8870
3	0.9984	0.9924	0.9998	0.9968	0.9623	0.9665	0.9984	0.9924	0.9998	0.9968
4	0.7090	0.8721	0.8862	0.5492	0.7732	0.7957	0.7090	0.8721	0.8862	0.5492
5	0.9999	0.9474	0.9167	0.9996	0.9002	0.8463	0.9999	0.9474	0.9167	0.9996

Table 3. Quantitative evaluation results of MRGW system.

Images	DC					T				
	WM	GM	CSF	Tumor	Edeme	WM	GM	CSF	Tumor	Edema
1	0.4062	0.6388	0.6243	0.6343	0.4062	0.2549	0.4693	0.4538	0.4538	0.2549
2	0.2280	0.3610	0.0041	0.0037	0.2280	0.1287	0.2203	0.0021	0.0018	0.1287
3	0.2672	0.4681	0.9470	0.9470	0.2672	0.1542	0.3055	0.8993	0.8993	0.1542
4	0.4462	0.0747	0.6022	0.1690	0.4462	0.2872	0.0388	0.4309	0.0923	0.2872
5	0.1230	0.1610	0.0373	0.0379	0.1230	0.0655	0.0875	0.0190	0.0193	0.0655

Table 4. Quantitative evaluation results of existing RGW system.

Images	DC					T				
	WM	GM	CSF	Tumor	Edeme	WM	GM	CSF	Tumor	Edema
1	0.2217	0.3578	0.6388	0.3578	0.4000	0.1246	0.2178	0.4693	0.2178	0.2500
2	0.0037	0.0789	0.3590	0.0789	0.3590	0.0018	0.0411	0.2188	0.0411	0.2188
3	0.0738	0.2672	0.2760	0.2108	0.2760	0.0383	0.1542	0.1601	0.1178	0.1601
4	0.1690	0.4462	0.0747	0.4462	0.0747	0.0923	0.2872	0.0388	0.2872	0.0388
5	0.0379	0.1230	0.1610	0.0484	0.1610	0.0193	0.0655	0.0875	0.0248	0.0875



a) DC. b) Tanimoto.

c) Accuracy.

Figure 7. Graphical representation of the proposed, RGW and MRGW techniques quantitative evaluation results.

Table 5. Overall performance of our proposed system and existing system.

Techniques	Abnormal	Normal
Dual Mode Classifier	90	93.33
FCM	70	73

4. Conclusions

This paper proposes a new technique for brain abnormality detection and tissue classification using DMC. The proposed systemwas implemented and a more number of images were utilized to analyze the outcomes. The performance of our proposed technique is compared with other techniques such as conventional Region Growing (RGW) and MRGW and the experimental results show that the proposed technique attains 90% accuracy for abnormal and 93.33% for abnormal classification which indicates the proposed technique yields high performance than the existing FCM technique.

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