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Semantic Classification And Region Growing Of Brain MRI Using CANFIS Model For Tumor Identification

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ABSTRACT

Background: Semantic Classification and region growing of brain MRI using CANFIS model for Tumor Identification. **Objective:** Tumor identification in brain MRI by incorporating semantics in feature extraction and region growing phase. Statistical features using wavelet and semantic features using novel method are extracted from the input MRI image. These features are fed into the neuro fuzzy classifier for normal and abnormal image identification. **Results:** The result of implementation shows the efficiency of semantic segmentation technique in identifying the pathological tissues accurately from the MRI images. The effectiveness of the system is measured with the parameters such as accuracy, specificity and sensitivity. **Conclusion:** The concept of semantics and feature extraction enables extraction of region of interest based on relationship between the components of objects in the image. Semantic region growing solves the problem of over segmentation and false edge deduction.

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INTRODUCTION

The front most part of the central nervous system is the brain. The maladies caused in the brain are Brain Tumors. The tumors that nurture in the brain are Brain tumors. A strange development caused by cells reproducing themselves in an unrestrained way is known as Tumor. A gentle brain tumor contains benign (harmless) cells and has separate boundaries. By means of Magnetic Resonance Imaging (MRI), the configuration and function of the brain can be learned noninvasively by doctors and researchers. The MRI image is really a lean horizontal piece of the brain. The white region at lower left is the cancer. It appears white since MRI scans increase tissue differences. The cancer is really on the right side of the brain. Lately, to examine the relation between white matter growth and neural maladies, several people exploit the MRI data the precision of fragmenting white matter is the main problem. To fragment white matter, Attention deficit hyperactivity disorder (ADHD) is moreover required. Despite many algorithms for fragmenting MRI of data, the watershed algorithm, eSneke algorithm and generic algorithm are widely used. Besides, those algorithms are based on the homogeneity of image. Based on the expectation-maximization (EM) algorithm (Arnaldo Mayer and Hayit Greenspan, 2009), Wells progressed a novel statistical strategy but the results are too reliant on the early values. Concerning one or more features, the fundamental objective in fragmentation process is to divide an image into areas that are uniform.

Fragmentation is essential in medical image processing and it has been constructive in several applications, such as: detection of tumors, surgical planning, measuring tumor volume and its response to therapy etc (S.Javeed Hussain et.al, 2012). It may be helpful to categorize image pixels into anatomical areas in various applications, such as bones, muscles, and blood vessels, though in others into pathological areas, such as cancer, tissue deformities, and multiple sclerosis lesions. The goal is to separate the White Matter (WM), gray matter (GM) and cerebrospinal fluid (CSF) from the MRI image. For instance, in a number of neurological turmoil such as multiple sclerosis (MS) and Alzheimer's disease (Dalila Cherifi et.al. 2011), the capacity varies in total brain, WM, and GM can give main data about neuronal and axonal loss. A lot of algorithms have been suggested for brain MRI segmentation in latest years.

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II. Proposed Methodology:

In the proposed methodology, both the normal tissues such as WM (White Matter), GM (Gray Matter) and CSF (Cerebrospinal Fluid) and the pathological tissues for identification of Tumor in the MRI Brain images are segmented effectively. Initially, the Wavelet Transform features and the Semantic features from the MRI Brain Images are extracted. These extracted features are the input to the next process. Then the proposed segmentation technique performs classification process by utilizing Neuro Fuzzy classifier. The Classifier is helpful for classifying whether the image is normal or abnormal. Based on the results the segmentation is carried out. In Segmentation, the normal tissues such as WM, GM and CSF are segmented from the normal MRI images and the pathological tissue (Tumor) is segmented from the abnormal images. The diagram for proposed methodology is given in fig 1.

The proposed technique is classified into three stages for the efficient segmentation of the MRI Brain Images into normal as well as pathological tissues. The three stages of the proposed technique are given below and

1. Feature Extraction
2. Classification
3. Tumor Segmentation

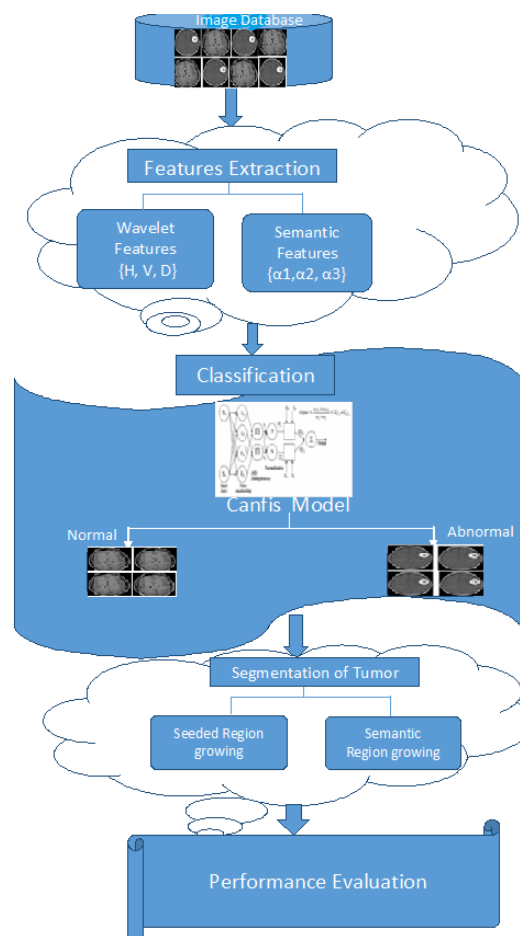


Fig. 1: Diagram for Proposed Methodology.

1.Feature extraction:

1.1. Wavelet Transform Features Extraction:

In order to extract the Wavelet Transform features, the Haar Wavelet is applied to the input MRI. Later a two level Wavelet Transform is performed to the $n \times n$ dimension image. The features such as Horizontal, Vertical and Diagonal bands of Wavelet Transform are obtained as the result of two level Wavelet Transform that is applied on the input images. Wavelet Transform features such as Horizontal, Vertical and Diagonal bands are calculated for the pixel co-efficients using the following equations(Y. A. Alsultanny,2008)

$$\text{Horizontal Band, } H = \frac{1}{r} \sum_{r=1}^m h_r \quad (1)$$

$$\text{Vertical Band, } V = \frac{1}{r} \sum_{r=1}^m v_r \quad (2)$$

$$\text{Diagonal Band, } D = \frac{1}{r} \sum_{r=1}^m d_r \quad (3)$$

In equations (1), (2), (3), the value m indicates the pixel co-efficients and the parameters h_r, v_r and d_r represents the coefficients of the horizontal, vertical, and diagonal bands. Each feature has four pixel co-efficients.

1.2. Semantic Features Extraction:

For extracting the semantic features the following steps are proceeded to map the low-level features with the high-level semantic features.

- (i) Shape as Low-level feature
- (ii) Keyword as High-level feature
- (iii) Interpretation of low-level and high-level features
- (i) Shape as Low-level Feature

In this paper, one of the low-level features named as, shape feature is used, to map with the semantic information of the image. The edge detection is performed using Slope Magnitude method. The edges of the shape feature that are extracted by the extraction process of input image should be connected. This makes the image to reflect the object boundaries. For extracting shape features in the form of connected boundaries, from the given MRI Brain Image, Sobel Gradient Operator is utilized.

Sobel Gradient Operator

It is a discrete differentiation operator that is used to perform an approximation of the gradient of the image intensity function. Convolution of the image with a small, separable and integer valued filter in horizontal and vertical direction, is the operation performed by the Sobel Operator. Based on computations, Sobel Operator is inexpensive.

Steps to apply Slope Magnitude method

Step 1: Convolve the original image with the Sobel mask S_x and S_y . S_x mask is used to obtain the x gradient and S_y mask is used to obtain the y gradient.

$$S_x = \begin{bmatrix} +1 & 0 & -1 \\ +2 & 0 & -2 \\ +1 & 0 & -1 \end{bmatrix} \quad (4)$$

$$S_y = \begin{bmatrix} +1 & +2 & +1 \\ 0 & 0 & 0 \\ -1 & -1 & -1 \end{bmatrix} \quad (5)$$

Step 2 : Get the individual squares of both values as S_x^2 and S_y^2 in equation (4) and (5).

Step 3 : Add the two squared terms as $S_x^2 + S_y^2$.

Step 4 : Take square root of the sum and then we get the equation as,

$$S = \sqrt{S_x^2 + S_y^2} \quad (6)$$

Thus low-level shape feature is obtained using the slope magnitude method.

(ii) Keyword as High-level Feature

Keywords are the features that are helpful for describing the high-level domain concepts. The attributes of semantics includes some subjectivity, uncertainty etc. The shape edge property is directly extracted using edge detection. High level semantic property can be extracted as the keyword, on the basis of low-level visual feature, shape. In the MRI Brain Image, the shape edge is initially extracted and according to the clearance of shape edge.

The semantic terms that are related with the clearance of the shape edge are:

$ST = \{ "low, medium, high" \}$.

(iii) Interpretation of low-level and high-level features. Initially find out the bounds of the semantic class, clearance.

(i.e.) $\{ "low = \alpha_1, medium = \alpha_2, high = \alpha_3" \}$ (7)

For mapping the shape feature edge S into semantic term ST , the following inference rules or the degree of clearance are used.

$$I \rightarrow \begin{cases} low, & \text{if } S < \inf \\ medium, & \text{if } \inf < S < \sup \\ high, & \text{otherwise} \end{cases} \quad (8)$$

The upper \sup and lower \inf bounds are representation of shape feature edge and both are related to α_1 and α_2 , respectively.

Thus the high level semantic features α_1 , α_2 and α_3 are extracted. Hence the Wavelet Transform features as well as the Semantic Features are extracted effectively, from the MRI Brain Images.

2. Classification Using Canfis:

From the input MRI Brain Image I , both Wavelet Transform as well as Semantic features are extracted, directly. Using the equations (1), (2), (3), (7) and (8), the features are extracted for the entire image, The features that are extracted using direct extraction are represented as,

$$F = \{ H, V, D, \alpha_1, \alpha_2, \alpha_3 \} \quad (9)$$

2.1 Classification using CANFIS:

The six features such as H,V,D of wavelet that representing the statistical co-ordinates and $\alpha_1, \alpha_2, \alpha_3$, of semantic co-ordinates are used for classification. The extracted features namely $F = \{ H, V, D, \alpha_1, \alpha_2, \alpha_3 \}$ are fed as input to the Co Active Neuro-Fuzzy Inference System (CANFIS) model. The architecture of the CANFIS is shown below. The central component of CANFIS is a fuzzy axon, it applies the membership functions to the input responses. The following formula illustrates the output of the fuzzy axon:

$$f_j(x, w) = \min_i \forall i = (MF(x_i, w_{ij})) \quad (10)$$

where i = input index, j = output index, x_i =input, w_{ij} =weights(MF parameters) corresponding to the j th MF of input i and MF=membership function of the particular subclass of the fuzzy axon. This system is a special three-layer feed forward neural network. In the first layer input variables are represented and in the middle (hidden) layer the fuzzy rules are represented. The third layer signifies the output variables. Consider a CANFIS structure with n inputs and one output.

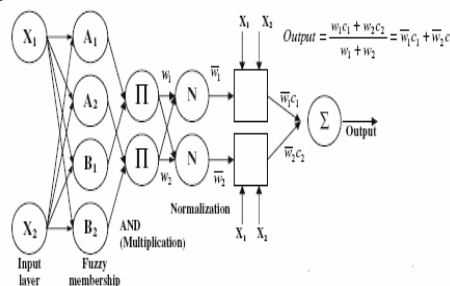


Fig. 2: Two-input one-output CANFIS network and output calculation.

2.2.Layers of CANFIS:

Layers in CANFIS structure can be adaptive or fixed and their functions are:

Layer 1 (Premise Parameters):

Each node of this layer is a complex-valued membership function μ_{ij} with a node function.

$$O_{1,ij} = |\mu_{A_{ij}}(z_i)| \mid \mu_{A_{ij}}(z_i) \quad \text{for } (1 \leq i \leq n, 1 \leq j \leq m) \quad (11)$$

Each node in layer 1 is the membership grade of a fuzzy set (A_{ij}) and specifies the degree to which the given input belongs to one of the fuzzy sets.

Layer 2 (Firing Strength):

Every node in this layer is product of all the incoming signals. The product of all the output pairs from the first layer is given as input to this layer:

$$O_{2,j} = w_j = \mu A_{i1}(z_1) \mu A_{i2}(z_2) \dots \mu A_{in}(z_n) \quad \text{for } (1 \leq i \leq n, 1 \leq j \leq m) \quad (12)$$

Layer 3 (Normalized Firing Strength):

All the nodes in this layer are used to calculate rational firing strength:

$$O_{3,j} = \overline{W_j} = \frac{w_j}{\sum_{j=1}^m w_j} \quad \text{for } (1 \leq j \leq m) \quad (13)$$

Layer 4 (Consequence Parameters):

Each node in this layer is obtained from the multiplication of Normalized Firing Strength from the third layer and output of neural network:

$$O_{4,j} = \overline{W_j} u_j = \overline{W_j} (P_{j1}Z_1 + P_{j2}Z_2 + \dots + P_{jn}Z_n + q_j) \quad \text{for } (1 \leq i \leq n, 1 \leq j \leq m) \quad (14)$$

Layer 5 (Overall Output):

The node here computes the output of CANFIS network:

$$O_{5,1} = \sum \overline{W_j} u_j$$

2.3. If-then Rules:

For model initialize, a common rule set with n inputs and m IF-THEN rules as follows

Rule 1: If Z_1 is A_{11} and Z_2 is $A_{12} \dots$ and Z_n is A_{1n} then $u_1 = p_{11z1} + p_{12z2} + \dots + p_{1n}Z_n + q_1$

Rule 2: If Z_1 is A_{21} and Z_2 is $A_{22} \dots$ and Z_n is A_{2n} then $u_2 = p_{21z1} + p_{22z2} + \dots + p_{2n}Z_n + q_2$

⋮

and upto rule m as follows.

Rule m: If Z_1 is A_{m1} and Z_2 is $A_{m2} \dots$ and Z_n is A_{mn} then $u_m = p_{m1z1} + p_{m2z2} + \dots + p_{mnzn} + q_m$

The data are fed as input to the CANFIS model.

2.4. Experimental Study:

In this study the CANFIS architecture is used, and the problem is proposed to network models by means of five inputs and one output parameter. The system produces the output either 1 or 0 that represents normal or abnormal. All experimental data were randomly placed in these sets. Before applying the CANFIS to the data, the training, cross-validation, testing and production subsets were scaled (normalized) to the range of 0–1 using the following equation:

$$X_{norm} = 0.5 + 0.5 \left(\frac{X - \bar{X}}{X_{max} - X_{min}} \right) \quad (15)$$

where X is the input value, X_{norm} is the scaled input value of the input value X , and X_{max} and X_{min} are the respective maximum and minimum values of the unscaled measured data. In this paper, the Bell membership functions and TSK fuzzy models were used. For small to medium-sized data sets, the number of membership functions assigned to each network input, will usually be between 1 and 10. The various algorithms (i.e., Levenberg-Marquardt, Delta-Bar-Delta, Step, Momentum, Conjugate Gradient and Quick prop) were applied in order to identify the one which trains a given network more efficiently. Besides, different transfer functions (i.e., Sigmoid, Linear sigmoid, Tanh, Linear Tanh, Linear and Bias) were used in order to identify the best results in depicting the non-linearity of the modelled natural system. The best architecture of the network was determined by trial and error. In fact, the optimal network architecture for each model was selected from the one which resulted in minimum errors and best correlation in the data set. The process of designing the networks is managed by NeuroSolution for Excel Release 6 software produced by NeuroDimension, Inc.

2.5. Criteria of Evaluation:

To evaluate the success of CANFIS in learning, several statistical measures could be used. The comparison of the actual and desired values will be obtained. The statistical criteria considered here were minimum mean square error (MSE), mean absolute error, minimum absolute error, maximum absolute error and percentage error of estimate (PE). Also, the MSE and PE are used to determine how much the network has reached to desired output values. The performance evaluation criteria used in this study can be calculated utilizing the following equations:

$$MSE = \frac{\sum_{i=1}^n (P_i - O_i)^2}{n} \quad (16)$$

$$PE = \left| \frac{\bar{P} - \bar{O}}{\bar{O}} \right| \times 100\% \quad (17)$$

where P_i and O_i are the predicted and observed values respectively; \bar{P} and \bar{O} are the average of P_i and O_i , and n is the total number of data. The data used for developing this model was obtained from the experimental study and the prediction capability of the model was done by statistical and semantic features of input MRI as parameters

3. Segmentation:

Segmentation is the important part of this proposed methodology since this work involves semantics. Medical image segmentation is a complex and challenging task due to the indefinite nature of input images for further processing. This work involves the partitioning of the input image space into non-overlapping meaningful homogeneous regions

After the classification of the images, normal and abnormal images are obtained. Segmentation is done on both these normal and abnormal images. In the normal images, the normal tissues such as WM (White Matter), GM (Gray Matter) and CSF (Cerebrospinal Fluid) are segmented. And in abnormal images, the pathological tissues such as Tumor, Edema and Atrophy are segmented. In Segmentation, the following two stages are performed,

- 1) Pre-Processing Stage
- 2) Tissue Segmentation Stage
 - a) Normal tissue's Segmentation
 - b) Abnormal tissue's Segmentation

3.1. Pre-Processing Stage:

In this paper, Skull Stripping method is used for pre-processing the normal brain tissues. In the MRI images, the brain cortex is normally a separate dark ring surrounding the brain tissues. This separate dark ring surrounding the brain tissues are removed with the usage of Skull stripping method. Initially, in Skull stripping method, the Normal brain tissue images are converted into gray scale image and then in the gray scale image, a Morphological Operation is performed. Then, with the help of Region Based Binary Mask Extraction, the brain cortex is stripped in the gray scale image. The preprocessing process is performed only in the classified normal images and not in the abnormal images. Because, the Pre-Processing task help the normal tissue CSF (Cerebrospinal Fluid) to be lightly placed in the cortex surrounding area. The representation of the obtained normal Image, after Skull Stripping method is I_S .

3.2. Tissue Segmentation Stage:

After the Pre-Processing stage using Skull Stripping method, the Tissue Segmentation is performed in the MRI Brain Images. Different methods are helpful to segment both normal as well as the pathological brain tissues (S.Javeed Hussain et.al, 2012)

From the normal brain tissue images, the segmentation of the normal tissues such as WM (White Matter), GM (Gray Matter) and CSF (Cerebrospinal Fluid) are obtained in two ways.

1. White Matter and Gray Matter Segmentation using Gradient Method.
2. Cerebrospinal Fluid Segmentation using OPT method

3.2.1. White Matter and Gray Matter Segmentation using Gradient Method:

The input for this White Matter and Gray Matter Segmentation is the Skull Stripped image I_S . Using Gradient Method, the WM and GM normal brain tissues are segmented from the image I_S . By utilizing Gaussian Convolution filter, the smoothing process is performed in the input image I_S . The resulting image,

I_G , is the smoothed image that is obtained from the Gaussian Convolution filter. Then, the Gradient Operation is applied to the smoothed image, I_G . The representation of the gradient of two variables x and y is as follows,

$$\nabla I_G(x, y) = \frac{\partial I_G}{\partial x} \hat{e} + \frac{\partial I_G}{\partial y} \hat{f} \quad (18)$$

The current edges in the image are marked as the following equations, by applying the values of gradient.

$$G = x_{(e)}^2 + y_{(f)}^2 \quad (19)$$

$$EM = \frac{1}{1 + G} \quad (20)$$

After that, the process of binarization is performed in the edge marked image EM . During the binarization process, by using a global threshold T_G , the gray level value of each pixel in the image is observed EM and the final binarized image is I_K . Then, Morphological Opening and Closing operations are applied to the binarized image I_K . These Opening and Closing operations are used to remove small holes and small objects from the image I_K . Based on the intensity values, the WM and GM normal brain tissues are segmented.

$$I_{wg} = \begin{cases} WM, & \text{if } I_{K_i} = 1 \\ GM, & \text{if } I_{K_i} = 0 \end{cases} \quad (21)$$

3.2.2. Cerebrospinal Fluid Segmentation using OPT method:

Skull Stripped image I_S is subjected to Orthogonal Polynomial Transform (OPT) for segmenting the normal brain tissue Cerebrospinal Fluid. The computation of the image in OPT is as follows,

$$I_{CFS} = \sin \left(\frac{I_{S(i)}^3}{100} \right)^2 + (0.05 * \text{rand}(|I_S|)) \quad (22)$$

After the Polynomial Transform, the corresponding Cerebrospinal Fluid region is segmented in the resultant image, I_{CSF} .

From the classified abnormal MRI Brain Images, the abnormal tissues of Tumor is segmented. The segmentation of pathological tissues is performed by region growing method. This region growing involves the semantic approach for the effective segmentation.

3.2.3. Tumor Segmentation using RGM:

From the pathological MRI Brain Image I_A , the tumor tissues are segmented. For segmenting the abnormal tumor tissue image I_A , Seeded Region Growing Method (RGM) is used here.

Region growing method is a region based image segmentation method; it selects the initial seed points from the input image I_A . The RGM observes the neighbor pixel values with the initial seed points, that is it checks whether the neighbor pixels are included in this region or not.

Semantic Region Merging:

The segmented image has clusters of data that are heterogeneous, the clustered information has to be grouped to make them enable for classification, here we propose a semantic approach for grouping the neighbours. The non-semantic and semantic portion for clustering is given below.

a) Non-Semantic Criteria- Seeded Region Growing:

T1 and T2 are preset thresholds

1. Merge region i, j as long as they have one weak separating edge until no two regions pass this test.

2. Merge regions i, j where $s(i, j) \leq T$ Where $s(i, j) = (c1 + a_{ij}) / (c2 + a_{ij})$

Where $c1$ and $c2$ are pre set constants, T is threshold

$$a_{ij} = ((\text{area}_i)^{1/2} + (\text{area}_j)^{1/2}) / (\text{perimeter}_i + \text{perimeter}_j)$$

Until no two regions pass this test.

b) Semantic Criteria:

3. Let B_{ij} be the boundary between R_i and R_j . Evaluate each B_{ij} with a Bayesian decision function that measures the (conditional) probability that B_{ij} separates two region R_i and R_j of the same interpretation. Merge R_i and R_j this conditional probability is less than some threshold. Repeat steps 3 until no regions pass the threshold test.

4. Evaluate the interpretation of each region R_i with a Bayesian decision function that measures the (conditional) probability that an interpretation is the correct one for that region. Assign the interpretation to the region with the highest confidence of correct interpretation. Update the conditional probabilities for different interpretations of neighbors. Repeat the p until all regions have interpretation assignments.

The semantic portion of the above algorithm maximizes the evaluation function by measuring the probability of a correct interpretation (labeled partition), given the measurements on the boundaries and region of the partition. The resultant segmented pathological tumor tissue image is represented as I_T .

RESULTS AND DISCUSSION

The proposed Segmentation method is implemented in MATLAB platform. MRI Brain images are gathered from various database and given as the input to this implementation. Initially normal and abnormal images are present in the whole MRI Brain Images. After the Classification, the group of images is classified into normal and abnormal. The following fig 3 shows the sample MRI Brain Images that are used as input for the Classification purpose.

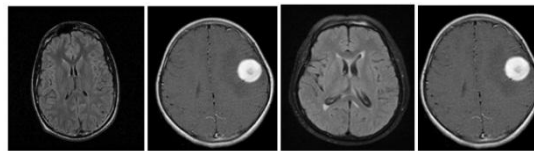


Fig. 3: Sample MRI Brain images in the database.

The given MRI Brain Images are classified using CANFIS classifiers. Six features such as 3 Wavelet Transform Features, and 3 Semantic features are the inputs of the neuro fuzzy classifier. The testing images are the classified images that are shown in the fig 4.

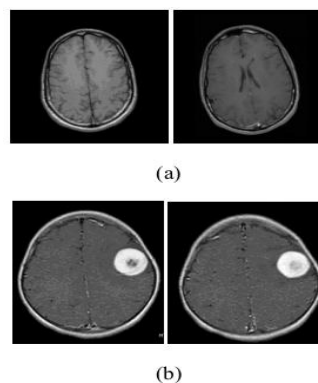


Fig. 4: Classified images a) normal b) abnormal.

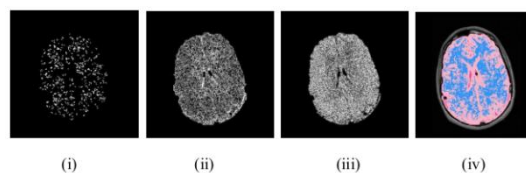


Fig. 5: Segmentation outputs of normal tissues (i) WM Segmentation (ii) GM Segmentation (iii) CSF Segmentation.

Then the abnormal images are segmented into Tumor and Edema pathological tissues using RGM and Multi-level Thresholding function. The Segmentation process for the pathological tissues is explained in Section 4.3.2.2. The results of Tumor and Edema tissue Segmentation is given in fig 6.

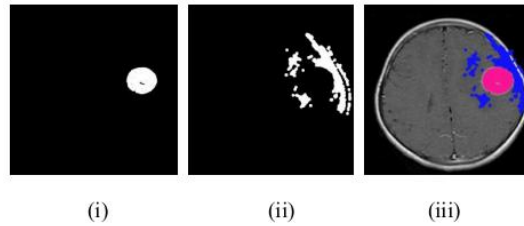


Fig. 6: Segmentation of abnormal tissues output:(i)Segmented Tumor region image (ii) Segmented Edema region image (iii) Original image for the abnormal tissues Tumor and Edema.

Performance Analysis:

The performance of the brain tissue segmentation method is analyzed by various statistical measures. The statistical performance measures that are obtained for the normal and abnormal MRI brain images are shown in below table 1.

Table I: Statistical Performance Measures of normal and abnormal tissues of MRI Brain Images.

Tissues	Measures		
	Sensitivity	Specificity	Accuracy
WM	80	100	98.41
GM	74.2	99.1	94.45
CSF	72.2	99.125	99.5
Tumor	48	95.6	94.1

Comparative Analysis:

To analyze the performance of tissue segmentation, the proposed method is compared with K-means clustering and existing fuzzy ANN based segmentation method. K-means clustering and Fuzzy ANN method is applied to five MRI brain images in order to segment the normal and abnormal tissues. The clustering method segmentation performance is shown in the below table 2.

Table II: Performance comparison of Existing K-Means and Fuzzy-ANN with the proposed method, in segmenting (i) WM, (ii) GM, (iii) CSF and (iv) Tumor.

Tissues	Methods		
	Proposed method	K-means	Fuzzy ANN
GM	98.41	92.6	52.998
WM	94.45	84.6	43.164
CSF	99.5	90.8	93.296
Tumor	94.1	80.6	0

The fig 7 shows the result of a graph, while comparing the accuracy for segmenting the normal tissues such as WF, GF, and CSF and also the abnormal tissues such as Atrophy, Edema, Tumor. From the fig 8, it is observed that the accuracy of the proposed method is higher than the existing methods such as K-Means and Fuzzy ANN.

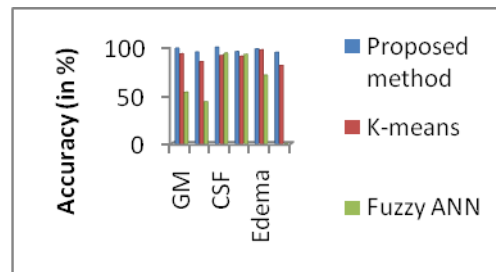


Fig. 7: Graph result for comparing accuracy of segmenting the tissues GM, WM, CSF and Tumor of Proposed method with K-Means and Fuzzy ANN.

IV. Conclusion:

The normal tissues such as WF, GF and CSF and abnormal tissues of Tumor were effectively segmented from the given MRI Brain Images, with the help of our proposed Segmentation method. The features were extracted in using wavelet and semantic approach. With those extracted features, the normal and abnormal

images were classified using neuro fuzzy classifier. After Classification, the normal images were given under pre-processing operation and then Segmentation was performed to segment WF, GF and CSF tissues. Then the Segmentation process was done on abnormal tissues for segmenting the Tumor tissues, here the segmentation based on normal region growing and semantic region growing is done. In this proposed method, the normal and abnormal images were utilized for analyzing the performance of our proposed Segmentation method. The results of the proposed methodology for Segmentation showed that the Segmentation is more accurate and very sensitive since it involves semantics in two levels(i.e) for feature extraction and region growing.

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