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Performance Analysis of brain tumor detection and its classification techniques

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***Abstract*-Brain tumor segmentation is the most significant method to characterise the early tumor. Magnifying the tumor is being a huge challenge due to the complex characteristics of the MRI Images which gives high intensive, divergent and uncertain boundaries. To address this problem, tumor segmentation method for MRI images which separates tumorous cells from healthy tissues has been carried out by the use of two types of clustering methods. In the proposed method input Image is pre-processed, followed by which the segmentation is done using K Means clustering method and Fuzzy C Means clustering method. While comparing these two techniques, it is seen that Fuzzy C Means clustering produces better segmentation. Further the features like magnitude, direction and the area are extracted from the tumorous part of Fuzzy C Means segmented Image. Based on the features extracted, the MRI image is classified as tumorous or non- tumorous. Classification is done by using the supervised neural network called the Radial Basis Function. Results of the classification gives, whether the MRI image is a normal Image or cancerous.**

Keywords- Fuzzy C Means, K Means Clustering, Radial Basis Function.

I.INTRODUCTION

Brain tumors are unusual growth of tissues in the brain. There are two categories brain tumors. Malignant and Benign tumor. Benign tumors are harmless ,non-cancerous tissues and they do not spread to other parts of the body .They can be removed by surgery but there will be a fewer chances that this will occur again. Benign tumors commonly have clearly defined boundaries and are not typically deeply ingrained in brain tissue. Hence, this feature makes them to be easily removed by surgeries. But, malignant tumors are cancers that initiate in the brain. They grow faster than benign tumors and are very harmful. These tumors spread to the other parts of the body called as the secondary tumor. Brain tumors damage the cells around them by causing swelling and putting increased pressure on the tissue underneath and nearby it as well as inside the skull. Benign tumors can sometimes turn into malignant tumors but the chances are fairly less. Common symptoms of brain tumor include nausea or vomiting, seizures, vision, hearing Impairments. But the detection of the tumors at a very early stage is very essential for the treatment and complete cure of the disease. This disease, if not detected and treated at an early stage, might lead to death. Almost 40% of all cancers spread to the brain in due course. Around 0.6 percent men and women were diagnosed with brain cancer during 2010-2012.In the year 2012, brain cancer occurrence is rising 23% greater for men and 25% greater for women when compared during 1970. The

during the year 2012, about 148,818 people were affected by this deadly disease. In 2015, about 22,850 adults (12,900 men and 9,950 women) were diagnosed with benign tumors in brain and spinal cord. It is predicted that about 15,320 adults (8,940 men and 6,380 women) may die by this disease during this year. Children diagnosed of brain tumor are mostly less than age of 15.

Detection of brain tumors manually is very difficult and time consuming. This mainly depends on the efficiency of the Individual operator. Presently, multimodal MRI images are used by the radiologists simultaneously in segmenting brain tumor images from the normal Images, because multimodal MRI images can provide innumerable data on tumors.[1]. .brain tumors may be of different size and shape and can be located in any part of the brain. In addition to tumor diversity, tumor edges will be difficult to diagnose and visually unclear. Likewise some tumors may distort adjacent structures in the brain because of the edema or bulk effect .Further, the MRI Images are affected from noise and artifacts.Noise in the MRI Images is due to the fluctuations of magnetic field in the coil. Additionally, artifacts and noise in brain tumor images increase the difficulty when segmenting tumors. Thus, designing of a semiautomatic or automatic brain tumor segmentation approach is necessary to provide an acceptable performance.[1]. Several algorithms have been used to achieve brain tumor detection and segmentation. These methods comprise morphological and thresholding techniques [2]–[4], watershed segmentation [5], region growing approach. This method is able to segment the Images according to the defined properties and this method provides good segmentation for noisy Images But this process is very time consuming and this occasionally leads to over segmentation. This also fails to distinguish the shading of the real images. [4], [6], asymmetry study In [7], atlas-based segmentation method[11]–[14], contour/surface evolution method [15]–[17], interactive algorithm [18]–[20], and supervised learning neural network [21]–[23] and unsupervised [6]. Christo Ananth et al. [10] proposed a system, this system has concentrated on finding a fast and interactive segmentation method for liver and tumor segmentation. In the pre-processing stage, Mean shift filter is applied to CT image process and statistical thresholding method is applied for reducing processing area with improving detections rate. In the Second stage, the liver region has been segmented using the algorithm of the proposed method. Next, the tumor region has been segmented using Geodesic Graph cut method. Results show that the proposed method is less prone to shortcutting than typical graph cut methods while being less sensitive to seed placement and better at edge localization than geodesic methods. This leads to increased segmentation accurac

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proposed a system, in which a predicate is defined for measuring the evidence for a boundary between two regions using Geodesic Graph-based representation of the image. The algorithm is applied to image segmentation using two different kinds of local neighborhoods in constructing the graph. Liver and hepatic tumor segmentation can be automatically processed by the Geodesic graph-cut based method. This system has concentrated on finding a fast and interactive segmentation method for liver and tumor segmentation. In the preprocessing stage, the CT image process is carried over with mean shift filter and statistical thresholding method for reducing processing area with improving detections rate. Second stage is liver segmentation; the liver region has been segmented using the algorithm of the proposed method. The next stage tumor segmentation also followed the same steps. Finally the liver and tumor regions are separately segmented from the computer tomography image. Here in section II the proposed work is explained in four stages. Initially the Image acquisition is done followed by which the pre-processing is done. In this, in order to separate the tumor from non-tumor cells in the whole head. Followed by which the MRI Image is segmented using K Means and Fuzzy C Means algorithm and classification is done using radial basis function.

II.SYSTEM MODEL

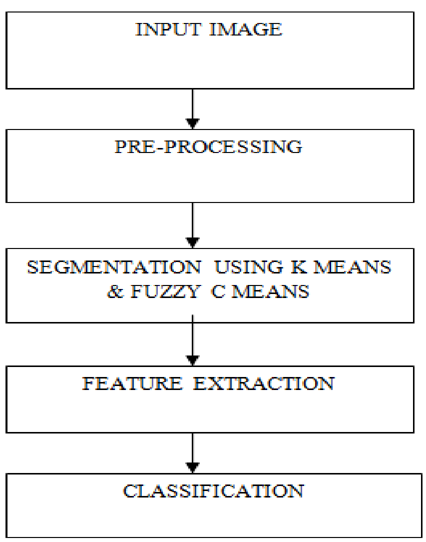

Figure1. System Model

In this section, the original Images are converted to gray scale Image and pre-processing of Images are done in which the skull stripped Images are obtained. Followed by which the Image is segmented using K Means algorithm and Fuzzy C Means algorithm and the classification of Images are done using Radial basis function.

A. *Image acquisition*

Images are obtained using MRI images and these scanned images are either colour, gray-scale image. If it is color image, then that image is converted into gray-scale image, the gray scale image is characterised by a matrix whose values between 0 and 255, where 0 represents black and 255 white.

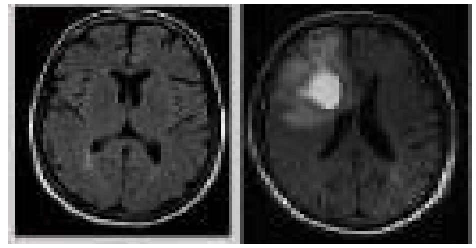

Figure2. Normal Image (left) and tumor affected image(right)

B. *Preprocessing(skull stripping)*

Before detecting the tumor in brain image a pre-processing is done for increasing the reliability of optical vision. Skull stripping is one of the pre-processing phases in imaging brain for tumor detection. It is the process of segmenting brain from non-brain tissue in whole-head Magnetic Resonance Image. Here Morphological operation is preferred in order to extract the brain portion from the skull before the application proceeds. Morphological Operation is a two stage process, the first procedure uses morphological reconstruction to produce a primary segmentation i.e. this obtains the mask of the input image, while the second technique applies thresholding to the primary segmentation to obtain the final skull stripped image, by setting the threshold condition with binarized image and input brain image. wherever the binarized image consists intensity level 1 of input image and wherever the binarized image consist 0 places 0.The output image consists only the brain tissues.

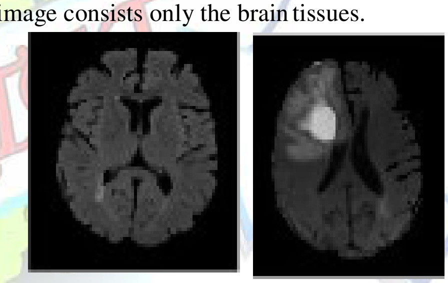

Figure3. Preprocessed Image

C. *K means segmentation*

Here, we are using k-means clustering to segment the brain tumor. In this method, the number of clusters to be formed is denoted by k.After choosing k, the Initial cluster centre for each cluster is assigned. The cost measure between data point and each of the cluster centres are calculated, and the data point is assigned to the cluster that has minimum cost measure. Then, the cluster centre is updated based on the mean value. This process is continued until the mean convergence takes place or specified number of iterations is over.

K-means algorithm:
1. Initialise the no of cluster value as k.

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3. Calculate the cost measure between data point and each of the cluster centres.

5. The data point belongs to the cluster that has minimum cost measure.

6. Calculate the mean and update the new cluster centre.

7. Repeat the process from step 3 until the centre converges

For the given image, compute the cluster means m

$$m_i = \frac{\sum_{j=(i)=i} x_j}{n_i}, \; i = 1,2..$$

Calculate the distance between the cluster center to each pixel

$$c(i) = \arg\min \|x_i - m_i\|^2$$

$$i = 1,2,..n$$

Repeat the above two steps until mean value convergence

D. Fuzzy C means algorithm

The fuzzy method considers that MRI images are essentially fuzzy, so this is the most frequently used tool for medical image processing. Furthermore, the fuzzy method can capture pixel closeness in the same region of purpose without a training step conditions. These are due to the fact that these fuzzy methods typically use intensity-based method, such as morphological operations and thresholding, as pre/post processing. Fuzzy logic represents the data by the means of a membership function. The membership function ranges from 0 to 1. In this method the data does not fully belong to an Individual cluster. The degree of belongingness of a data point to a particular cluster is given by the degree of membership function ranging from 0 to 1. this method is also called as the soft clustering .This method represents the accurate clustering and this is most suitable for overlapping clusters

$$Y = \sum_{i=1}^{N} \sum_{j=1}^{c} u_{ij}^{m} \|x_i - R_j\|^2$$

Where

m-real number above 1,

u_{ij}- Degree of membership of x_i in the cluster j,

x_i- D-dimensional data measure,

R_j- D-dimensional cluster centre,

The update of membership u_{ij} and the cluster centers R_j are given by:

$$u_{ij} = \frac{1}{\sum_{k=1}^{c} \left(\frac{\|x_i - R_j\|}{\|x_i - R_k\|} \right)^{\frac{2}{m-1}}}$$

$$R_j = \frac{\sum_{i=1}^{N} x_i \cdot u_{ij}^{m}}{\sum_{i=1}^{N} u_{ij}^{m}}$$

The above process ends when

The algorithm contain following steps:

1. Initialize $U = [u_{ij}]$ matrix $U^{(0)}$

2. At k-step: calculate the centres vectors $R^{(k)} = [R_j]$ with $U^{(k)}$

$$R_j = \frac{\sum_{i=1}^{N} x_i \cdot u_{ij}^{m}}{\sum_{i=1}^{N} u_{ij}^{m}}$$

3. Update $U^{(k)}$ and $U^{(k+1)}$

$$u_{ij} = \frac{1}{\sum_{k=1}^{c} \left(\frac{\|x_i - R_j\|}{\|x_i - R_k\|} \right)^{\frac{2}{m-1}}}$$

4. If $|u_{ij}^{(k+1)} - u_{ij}^{(k)}| < \delta$ then STOP; otherwise return to Step 2.

E. Radial basis function

Radial Basis Function (RBF) is a feed forward neural network. This belongs to the class of supervised learning algorithm where the network is provided with the Inputs and outputs in prior and trained accordingly. This network has got three layers. Input layer, hidden layer and the output layer. The number of input layer neurons depends upon the number of Inputs. The Input layer presents the Input output pair to the hidden layer and the hidden layer trains the network and passes the output to the output layer. Hidden layer consists of nonlinear units that are connected to all the layers of Input layer. The interconnections between the layers are given in terms of weights. The outputs provided by the output layer are compared with the expected output. Weight updating is until the actual output becomes equal to the expected output. This network is more often used because it can train the network much faster compared to the other methods. This is also very useful technique when non-stationary Inputs are used.

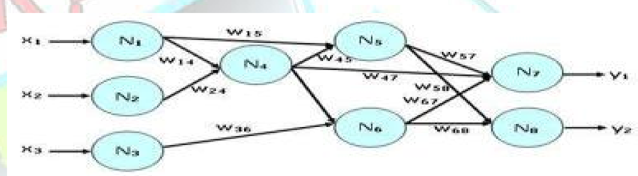

Figure 4. Radial Basis Function

The hidden layer consists of basis function with two parameters centre and width. The basis function centre for the node *i* at the hidden layer is the vector c_i.The size of c_i is same as the input vector u .Each unit in the network has different cluster centre. Initially, the radial distance d_i, between basis function centre c_i and the input vector u is calculated for as shown below,

$$d_i = \|u - c_i\|$$

Output of the *i th* hidden layer unit is calculated using the basis function G as given below,

$$h_i = G(d_i, \sigma_i)$$

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$$y_k = f_k(x) = w_{ok} + \sum_{j=1}^{n} w_{jk} h_j , k = 1,2, . . m$$

RBF network mathematical model can be represented by,

$$y = f(x), f: R^n \rightarrow R^m$$

$$y_k = f_k (x) = w_{ok} + \sum_{j=1}^{n} w_{jk} (\|x - c_j\|) k = 1,2, . . m$$

Where r_j is the Euclidean distance between x and c_j

The input output training patterns are given by (x^i, y^i) $i = 1,2. . n$.The aim of data interpolation is to estimate the function **y** from which the data is extracted. Since the function **y** is unfamiliar, this scenario can be considered as a minimization problem .This method takes only the sample points into consideration. Choose w_{jk}, c_j, $k = 1,2.. m$, $j = 1,2 ... n$ so as to minimize

$$E(w, c) = \sum_{i=1}^{n} \|y^i - f(x^i)\|^2$$

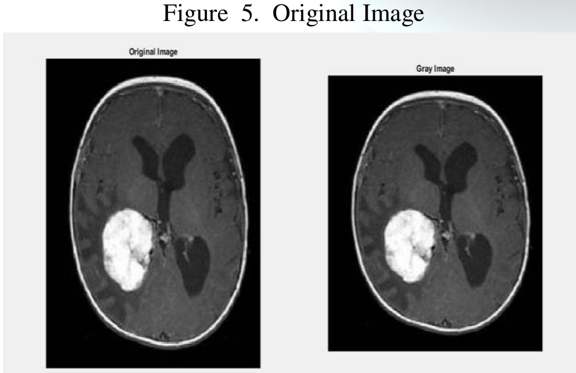
The RBF network learning can be evaluated as a nonlinear unconstrained optimization problem. The input output training patterns is given by,(x^i, y^i) $i = 1,2. . n$. w_{jk}, c_j, $k = 1,2. . m$, $j = 1,2 ... n$ are selected so as to minimize

$$E(w, c) = \sum_{i=1}^{n} \|y^i - f(x^i)\|^2$$

III. SIMULATION RESULTS

In this section, the original Image is converted to gray scale Image. Then the pre-processing operation is done and followed by which the K Means segmentation is done and Fuzzy C Means segmented Image is shown. Next the classification of the Fuzzy segmented Image is shown. The specificity and the sensitivity plot of the classifier is given which indicates the accuracy to be about 91.57%.Table 2 shows the comparison between K Means and Fuzzy C Means technique for ten Images. This shows that even though the computation time is high for fuzzy C Means,MSE is less for Fuzzy C Means than K Means Method.

Figure 5. Original Image



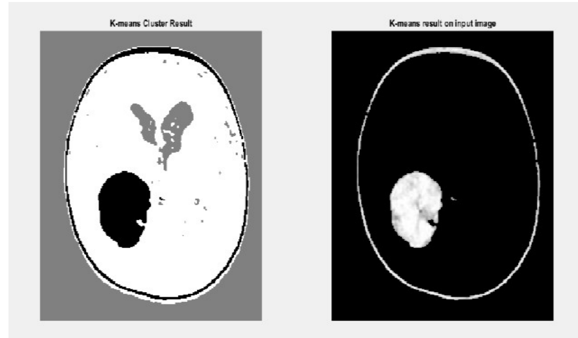


Figure 6. K Means Clustering

Features	Tumor Image	Normal Image
Area	4926	1783
Magnitude	41.9978	33.46
Direction	-1.6541	-1.0046

TABLE 1 FEATURE EXTRACTION

Figure 7. Fuzzy C Means Clustering

Figure 8. Tumor detected Image

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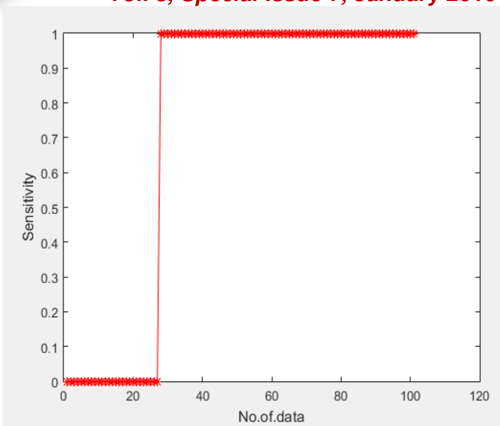

Figure 9. Sensitivity plot of RBF

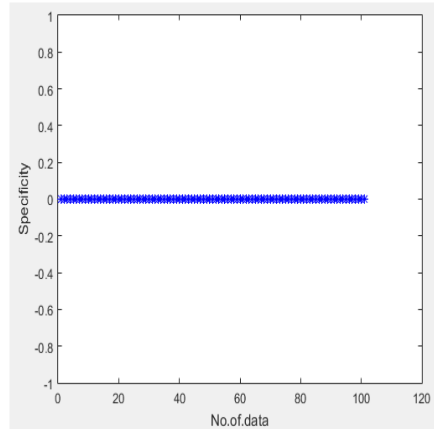

Figure10. Specificity plot of RBF

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IMAGE NO	PSNR		MSE		ENTROPY		TIME ELAPSED	
	K Means	*FCM*	*K Means*	*FCM*	*K Means*	*FCM*	*K Means*	*FCM*
1	29.95	35.03	103.56	4.06	0.6706	0	0.2655	3.0010
2	28.85	34.13	181.62	6.14	0.7233	0	0.2674	3.1117
3	31.21	34.65	44.47	4.85	0.4154	0	0.3412	2.8960
4	30.85	34.99	64.93	4.13	0.3752	0	0.2700	2.9640
5	29.60	35.29	75.17	3.68	0.2580	0	0.2780	3.0300
6	27.48	34.10	199.23	6.21	0.5575	0	0.2603	3.4496
7	31.21	34.65	44.47	4.85	0.4154	0	0.2680	2.7319
8	29.46	34.34	71.56	5.61	0.2169	0	0.2591	2.9591
9	28.32	33.62	91.37	7.80	0.2911	0	0.2647	3.0135
10	30.36	34.53	35.78	5.12	0.3159	0	0.2571	2.7302

TABLE 2 PERFORMANCE COMPARISONS OF K MEANS AND FUZZY C MEANS TECHNIQUE

In the results, initially the original Image is converted into gray scale Image and the Image is enhanced in terms of Intensity and contrast. Followed by which the K Means segmented and Fuzzy C Means segmented Image is shown in Figure 6 and Figure 7. Radial Basis Function neural network produces an accuracy of about 91.57%.The sensitivity and specificity plot is also indicated in the Figure 9 and Figure 10.

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IV. CONCLUSION

First, the proposed method pre-processes the input images. The pre-processing removes the unwanted artifacts from the images. These artifacts do not contribute anything in the analysis of the brain tumor analysis. Then the method of segmentation is used to segment the tumor part of the MRI Image and it has been shown that the fuzzy C means algorithm provides a better segmentation result compared to the K means algorithm. Then the features are extracted from the suspicions of the segmented Images. Features like mean, magnitude and direction of the tumor part are extracted and this can be used for classification of the tumor Image. For Classification, Radial basis function is used and the Image is classified as normal Image or the tumor Image and this provides an accuracy of about 91.57%.Future work can be extended by carrying out better segmentation technique that will yield a better result compared to the two techniques used here.

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