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A Study on Brain Mri Image Segmentation Techniques

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Abstract: *Image Segmentation is an important and challenging factor in the field of medical image processing. In the present days, for the human body anatomical study and for the treatment planning medical science very much depend on the medical imaging technology and medical images. Specifically for the human brain, MRI (Magnetic Resonance Imaging) widely prefers and using for the imaging. But by nature medical images are complex and noisy. This leads to the necessity of processes that reduces difficulties in analysis and improves quality of output. Brain tumor detection and segmentation is one of the most challenging and time consuming task in medical image processing. MRI is a medical technique, mainly used by the radiologist for visualization of internal structure of the human body without any surgery. MRI provides plentiful information about the human soft tissue, which helps in the diagnosis of brain tumour. Accurate segmentation of MRI image is important for the diagnosis of brain tumor by computer aided clinical tool. After appropriate segmentation of brain MR images, tumor is classified to malignant and benign, which is a difficult task due to complexity and variation in tumor tissue characteristics like its shape, size, gray level intensities and location. Taking in to account the aforesaid challenges, this study is focussed towards highlighting the MRI brain image segmentation techniques. However, this paper presents a comprehensive review of the methods and techniques used to detect brain tumor through MRI image segmentation.*

Keywords: *Image segmentation, Tumors, MRI, FCM, K-Means, MKFC, RFLICM, KWFLICM, NN, KBBTS.*

1. INTRODUCTION

Image segmentation is a process of subdividing or splitting an image into the constituent part or object in the image. The main purpose of subdividing an image into its constituent parts or objects present in the image is that, we can further analyze each of the constituents or each of the objects present in the image once they are identified. So, each of the constituents can be analyzed to extract some information in order to make those information useful for high level machine vision application.

If an image has been pre-processed appropriately to remove noise and artifacts, segmentation is often the key step in interpreting the image. Image segmentation is a process in which regions or features sharing similar characteristics are identified and grouped together. Image segmentation may use statistical classification, thresholding, edge detection, region detection, or any combination of these techniques. The output of the segmentation step is usually a set of classified elements, Most segmentation techniques are either region-based or edge based [1].

1.1 Region Based Approach

A group of connected pixels with similar properties is called a region. Region is an important concept in interpreting an image because region may corresponds to object in a scene. Basically Region-based techniques are relying on common patterns in intensity values within a cluster of neighbouring pixels. The cluster is referred to as the region, and the major goal of the segmentation algorithm is to group regions according to their anatomical or functional roles.

1.1.1 Region Growing Based Segmentation

Region growing starts with a small region. The small region grows into a bigger region by merging its neighbouring regions if the neighbouring regions have the same properties as the small region. The growing procedure is iterated until no region needs merge. [2]Region growing is a technique for extracting a region of the image that is connected based on some predefined criteria. This criterion is based on intensity information. Region growing is an approach to image segmentation in which neighbouring pixels are examined and added to a region class of no edges are detected. This process is iterated for each boundary pixel in the region. If the adjacent regions are found, then a region-merging algorithm is used in which weak edges are dissolved and strong edges are left intact [3].
Homogeneity of regions is used as the main segmentation criterion in region growing. The criteria for homogeneity [1]:

Gray level (ii) Colour Texture (iii) Shape model

The basic purpose of region growing is to segment an entire image R into smaller sub-images, Ri, where i=1, 2… N. which satisfy the following conditions:

R= $\bigcup_{i=1}^{N}$Ri ; Ri $\cap$ Rj = $\emptyset$, i≠ j

H(Ri) = True; i=12......N;

H(Ri ∪ Rj) = False, i ≠ j;

1.1.1. Region Splitting and Merging

The image is subdivided into a set of arbitrary unconnected regions and merge/split the region according to the condition of the segmentation. The basic idea of region splitting is to break the image into a set of disjoint regions, which are coherent within themselves [4]. Particularly splitting technique is usually implemented with theory based on quad tree data. Quad tree is a tree in which each node has exactly four branches [5]. This includes different steps such as Start splitting the region into four branches, Merge any region when no further splitting is possible, Stop when no further merging is possible.

1.2. Edge Based Approach

Edge-based techniques rely on discontinuities in image values between distinct regions, and the goal of the segmentation algorithm is to accurately demarcate the boundary separating these regions.

1.2.1. Edge Detection

An edge consists of a connected sequence of edge pixels. Edge detectors are designed to identify and locate the edge pixels. Edge detectors can be simple or complicated depending on how well they localize the edge and how well they handle the noise content and false responses. Edges are places in the image with strong intensity contrast. Since edges often occur at image locations representing object boundaries, edge detection is extensively used in image segmentation when we want to divide the image into areas corresponding to different objects. Edge detection techniques are generally used for finding discontinuities in gray level images. Edge detection is the most common approach for detecting meaningful discontinuities in the gray level. Image segmentation methods for detecting discontinuities are boundary based methods. Edge detection can be done using either of the following methods. Edges are local changes in the image intensity. Edges typically occur on the boundary between two regions [6].

A sharp image has stronger edges whereas a blurred image has weak edges. Hence boundaries of objects are more clearly visible in sharp images. A strong edge represents a sharp change in intensity. Such discontinuities in the intensity profile can be detected using the derivative operator.

- First order derivative
- Second order derivative.

The first order derivative for edge detection is mathematically denoted by:

$$\nabla f \equiv grad(f) \equiv \begin{bmatrix} gx \\ gy \end{bmatrix} = \begin{bmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \end{bmatrix}$$

$$\text{Magnitude of } \nabla f \quad M(x,y) = mag(\nabla f) = \sqrt{gx^2 + gy^2}$$

$$\text{Direction of } \nabla f \quad \alpha(x,y) = tan^{-1}\left[\begin{array}{c} gx \\ gy \end{array}\right]$$

Here direction of the edge is perpendicular to the direction of the gradient.

Spatial filters are used to compute the derivatives.

$$R = w1z1 + w2z2 + \cdots + w9z9$$
$$= \sum_{k=1}^{9} WkZk$$

Spatial filter provides digital approximation of the partial derivatives over a neighbourhood about a point.

Gradient operator can be mathematically expressed approximation to the first order derivatives at point x as $\frac{\partial f}{\partial x} = f^{'}(x) = f(x+1) - f(x)$

Approximation to the first order derivative at point x in an image $f(x,y)$

$$\frac{\partial f(x,y)}{\partial x} = gx = f(x+1,y) - f(x,y)$$

$$\frac{\partial f(x,y)}{\partial y} = gy = f(x,y+1) - f(x,y)$$

$$\text{Magnitude of } \nabla f \quad M(x,y) = mag(\nabla f) = \sqrt{gx^2 + gy^2} \quad \approx |gx| + |gy|$$

Edges can be identified using the first order derivative; however, to localize the edge we need to identify the peaks in the derivative magnitude. The magnitude of second order derivative of the intensity profile crosses zero at the location of the peak of the first order derivative. Zero crossing is flanked by positive and negative peaks which indicate, respectively, the dark and the bright side of the edge. In the presence of noise we may be required to use sophisticated procedures to detect zero crossings e.g. fitting the local data to a plane using least squares fit and then computing where this plane crosses zero. A zero crossing detector can mark edge points even if it does not have a strong edge response due to lack of contrast.

The second order derivative or the Laplacian can be implemented using second order differencing.

$$\frac{\partial^2 f}{\partial x^2} = \frac{\partial f^{'}(x)}{\partial x} = f^{'}(x+1) - f^{'}(x)$$
$$= f(x+2) - f(x+1) - f(x+1) + f(x)$$
$$= f(x+2) - 2f(x+1) + f(x)$$

To obtain the expansion around point x

$$\frac{\partial^2 f}{\partial x^2} = f^{''}(x) = f(x+1) + f(x-1) - 2f(x)$$

The second order derivative can be expressed as the sum of the horizontal and vertical components of second order difference. However we need a single Laplacian mask and not two as was the case of first order derivative. A Laplacian operator is isotropic, i.e. its response remains the same in all directions. Its response does not change irrespective of the rotation of the image. This property is due to the symmetry of the Laplacian operator. A major disadvantage of the Laplacian operator is its sensitivity to noise. It is essential to apply Gaussian smoothing to the image prior to applying the Laplacian template. The two operations can be combined together to form a composite operation the Laplacian of Gaussian (LoG) operator. Since Gaussian smoothing is isotropic, the LoG operator is also isotropic.

1.2.2. Line and Point Detection

Isolated points can be detected using a Laplacian mask. A point leads to a discontinuity in the intensity function along all directions around that point. The best operator to detect such an Omni-directional discontinuity is the Laplacian operator.

The Laplacian filter mask can be formulated in two ways:

- Considering the horizontal and vertical directions
- Considering the horizontal, vertical and diagonal directions

Considering the horizontal and vertical directions the filter mask to implement the Laplacian can be formulated as:

$$\nabla^2 f(x,y) = f(x+1,y) + f(x-1,y) + f(x,y+1) + f(x,y-1) - 4f(x,y)$$

0	1	0
1	-4	1
0	1	0

0	-1	0
-1	4	-1
0	-1	0

We can also include the partial derivatives along the diagonal directions.

$$\nabla^2 f(x,y) = f(x+1,y) + f(x-1,y) + f(x,y+1) + f(x,y-1) + f(x+1,y+1) + f(x-1,y-1) + f(x-1,y+1) + f(x+1,y-1) - 8f(x,y)$$

1	1	1
1	-8	1
1	1	1

-1	-1	-1
-1	8	-1
-1	-1	-1

We evaluate the response $R(x, y)$ of the Laplacian operator against a suitably chosen threshold T.

$$g(x,y) = \begin{cases} 1 & if\ |R(x,y)| > T \\ 0 & otherwise \end{cases}$$

Isolated points are identified at location at which the function$g(x, y)$ is one.

A Line is a special case of an edge segment in which the intensity on either side of the edge pixels is different. Laplacian can be used for line detection.

-1	-1	-1		2	-1	-1		-1	2	-1		-1	-1	2
2	2	2		-1	2	-1		-1	2	-1		-1	2	-1
-1	-1	-1		-1	-1	2		-1	2	-1		2	-1	-1

(Horizontal) (Diagonal-45^o) (Vertical) (Diagonal-45^0)

Lines in **specified directions** can also be detected using appropriate masks as shown above. These masks can detect lines of thickness one pixel only.

1.3. Applications of Segmentation

Image segmentation is mostly applied in the following fields [7]:

- Medical Imaging :Locate tumors, Measure tissue volumes, Computer-guided surgery, Diagnostic Treatment planning, Study of anatomical structure
- Objects location of satellite images
- Face recognition
- Automatic traffic controlling systems
- Machine vision.

2. LITERATURE REVIEW

Brain image segmentation is the process, which consists of separating the brain disease or abnormality from the brain images. It is very difficult for doctors to separate the brain abnormality from the MRI brain images and to diagnose brain anomalies like tumor or study of anatomical structure. Therefore, the brain image classification becomes a very important as well as a challenging task for the treatment of different brain diseases. MRI brain images classification can be manually performed, but it does not provide accurate results and has higher error rate. So, different methods are used for segmentation and classification of MRI brain images which have been discussed in this review paper.

Alen Jose et al, 2014 implemented k-means and fuzzy c-means algorithm for brain tumor detection and its area calculation from Magnetic Resonance images (MRI). The main advantages of this process is to determine the patient's stage whether it can be cured with medicine or not. The proposed system includes mainly four modules namely Pre-processing, segmentation using k-means and fuzzy c-means, Feature extraction, and approximate reasoning. If the tumor area is a mass then K- means algorithm is enough to extract tumor from the brain cells. If there is any noise present in the MR image then first it is removed before the K-means process. The noise free image is given as input to the k-means and tumors are extracted from the MRI image [8]. The limitations of this technique is fuzzy membership determination is not a minor job and also calculation occupied in fuzzy approaches could be intensive.

M. Ganesh et al, 2012 used a multiple kernel fuzzy C-means clustering (MKFCM) algorithm for fuzzy segmentation of magnetic resonance (MR) images. The new multiple kernel fuzzy clustering algorithm is capable of utilizing local contextual information to impose local spatial continuity, thus improving the classification accuracy and reduces the number of iterations. The used method not only overcome the effect of the noise effectively, but also prevents the edge from blurring. The model may need less iteration and can obtain results in less time while initialization is good [9].

FCM algorithm is noise sensitive and complex. To overcome the such limitation, A.J.Patil et al, 2014 proposed K-means and improved fuzzy C-means (RFLICM) algorithm introducing weighted fuzzy factor local similarity measure to make a trade-off between image detail and noise. This technique also provides highly efficient noise reduction and maintains its accuracy while segmentation of tumor tissue. In addition, it also reduces the time for analysis. At the end of the process the tumor is extracted automatically from the MR image and its position and the shape is determined. The major advantage of this technique is RFLICM is able to extract the local information more exact and accurate. It is also insensitive to noise [10].

R. Shalini et al, 2014 implemented a technique KWFLICM. In this approach a method trade-off weighted fuzzy factor is used to segment the brain tumor from the MRI images and kernel metric is used to increase the performance of segmentation results. Finally experimental results of the proposed framework gives better efficiency and provides higher accuracy than other compared existing approaches. Performance metrics are handled by some parameters such as area, solidity, Equivalent Diameter, Perimeter, Entropy, Segmentation accuracy and Elapsed Time. These parameters are calculated by using region props. Here the author observed that the proposed method KWFLICM gives better segmentation accuracy [11]. We can extend it further to find out the types of brain disease from CT-Scan.

Shan Shen et al, 2005 proposed MRI Fuzzy segmentation using neighbourhood attraction with neural network optimization which is one of the most thoroughly observed approaches for brain tumor detection. Neighbourhood attraction is dependent on the relative location and features of neighbouring pixels to improve the segmentation performance dramatically. The degree of attraction is optimized by a neural-network model. In this technique, during clustering, each pixel attempts to attract its neighbouring pixels toward its own cluster. If a pixel has a very similar intensity to one of its neighbours, the attraction between them should be stronger than the attraction between the pixel and another neighbour with rather different intensities. The components of the neighbourhood can also influence the attraction. Including neighbourhood attraction, segmentation using IFCM is not only decided by the pixel itself but also by its neighbouring pixels. Future work will focus on developing the automatic image based classification system for brain tumor using data mining. Pre-processing techniques could be enhanced that brain model fitting may be considered to do the non brain region removal. More comprehensive comparison of IFCM and the generalization of the ANN model will be addressed [12].

Selvaraj Damodharan et al, 2015 used one of the most effective brain tumor detection techniques is based on Neural Network (NN) and is also designed for brain tissue segmentation. This technique confirms the target with the help of the following important steps that includes: Pre-processing of the brain images, segmentation of pathological tissues (Tumor), normal tissues (White Matter (WM) and Gray Matter (GM)) and fluid (Cerebrospinal Fluid (CSF)), extraction of the relevant features from each segmented tissues and classification of the tumor images with NN. Here both the experimental results and analysis are determined by means of Quality Rate (QR) with normal and the abnormal Magnetic Resonance Imaging (MRI) images. The performance of the proposed technique undergoes validation process and then compared with the standard evaluation metrics such as sensitivity, specificity and accuracy values for NN, K-NN classification and bayesian classification techniques. The obtained results reveal that the classification results provide better results in NNs when compared with the other techniques. The desired efficiency is found satisfactory with brain tissue and tumor segmentation, feature extraction of the segmented regions and the classification based on NNs [13].The proposed NN based tumor classification technique has been found to be more efficient. But we can extend it further to detect tumor automatically.

Kotikalapudi Raviteja et al, 2013 proposed a knowledge based brain tumor segmentation system (KBBTS) using histogram interpretations for predicting of brain tumor area from trans-axial Magnetic Resonance Imaging (MRI). This system gives significant improvements over traditional threshold-based tumor segmentation methods. This technique is composed of a series of steps involved in segmenting brain tumor using KBBTS. Data acquisition, pre-processing, tumor segmentation, morphological operations and location-window filtering form the basic logical components of the GUI. The tumor slices of interest have been hand-labeled by two radiologists and the performance parameters have been drawn by comparing these manually labeled slices with the ones generated by KBBTS. This technique can successfully segment 2-D tumors from all the slices. But this particular methodology could be implemented for 3-D tumor segmentation [14].

Vinay Parameshwarappa et al, 2014 proposed a segmented Morphological approach to detect brain tumor images. It has successfully achieved the target to detect and segment tumours in the brain using some of the classical image processing tools. Here, image enhancement techniques are applied to enhance the contrast and normalize the pixel values in the image. Then the Fast Fourier Transform is carried out and then some morphological operations to get the desired results. The major advantages by using this algorithm is able to clearly distinct the shape and outline of the tumor. It is a vital requirement of doctors to analyse but fails to identify the area and thickness of the tumor [15].

3. Methodology Studied And Result Analysis

Several general-purpose algorithms and techniques have been developed for image segmentation, like region growing and merging algorithm, K-Means algorithm, Fuzzy C-means algorithm, MKFCM algorithm, RFLICM algorithm, FLICM algorithm, KFLICM algorithm, WFLICM algorithm, KWFLICM algorithm, K-NN algorithm etc.. In this study we are focusing all these techniques to obtain a comparison of segmentation techniques for brain tumor detection. The general flow chart for these entire algorithm to detect brain tumor from MRI images is shown in the below figure 1.

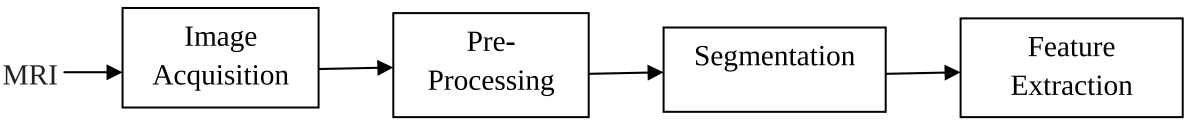

Fig1. *To Detect Brain Tumor From MRI*

Consider an example which shows the comparison result and the tumor area by using KWFLICM approach and obtains better result as compared to FLICM, KFLICM and WFLICM. Here two images are taken for performance evaluation and the images are collected from the open source and it is evaluated by MATLAB [11].

Table1. *Comparison of Existing and Author's Proposed Framework for Image 1*

Parameters	FLICM	KFLICM	WFLICM	KWFLICM
Area	432	440	719	440
Solidity	0.95	0.87	0.51	0.87
Equivalent Diameter	23.45	23.66	30.25	23.66
Perimeter	83.01	95.74	269.66	95.74
Entropy	0.56	0.55	0.47	0.55
Segmentation Accuracy	89.26	89.41	82.75	90
Elapsed Time	4.22	9.9	9.52	9.49

Table2. *Comparison of Existing and Author's proposed Framework for Image 2*

Parameters	FLICM	KFLICM	WFLICM	KWFLICM
Area	226	503	2849	503
Solidity	0.25	0.03	0.76	0.02
Equivalent Diameter	16.96	25.30	60.22	25.30
Perimeter	250.02	636.15	339.26	636.15
Entropy	0.97	0.73	0.68	0.73
Segmentation Accuracy	30.15	82.75	87.92	92.85
Elapsed Time	7.43	9.7	9.20	9.00

Table I and II gives the value for seven parameters they are area, solidity, equivalent diameter, perimeter, entropy, segmentation accuracy and elapsed time for image 1 and image 2.The seven parameters are evaluated by techniques such as FLICM, KFLICM, WFLICM and KWFLICM.

The below figure 2 illustrates the segmentation result of brain tumor segmentation. Original image is shown in figure 2.a. The original image is segmented by using existing approaches like FLICM, KFLICM, WFLICM and proposed approach KWFLICM. From the figure it is clearly observed that the proposed method of KWFLICM gives better segmentation than other approaches.

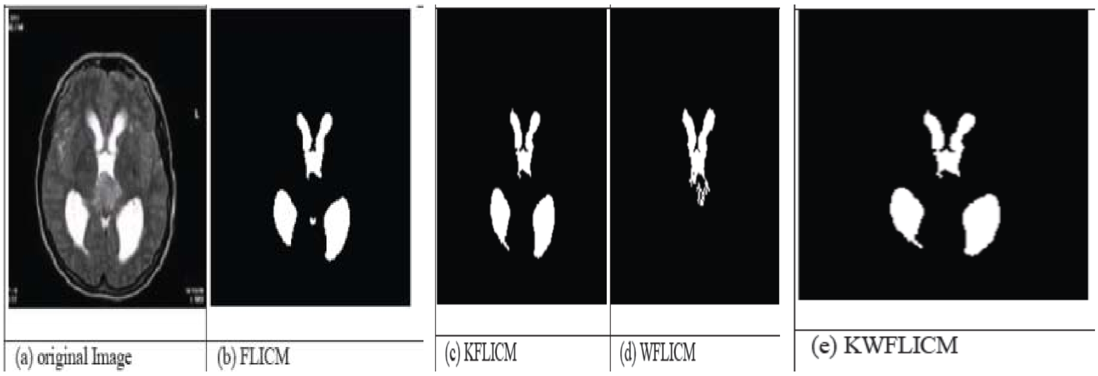

Fig2. *Brain Tumor Segmentation results for Image 1*

2.(a) Original Image (b) FLICM Segmentation Result (c) KFLICM Segmentation Result (d) WFLICM Segmentation Result and (e)) KWFLICM Segmentation Result

The below figure 3 illustrates the segmentation result of brain tumor segmentation. Original image is shown in figure 3.a. The original image is segmented by using existing FLICM, KFLICM, WFLICM and proposed KWFLICM. From the figure clearly observed that the proposed method of KWFLICM gives better segmentation than other approaches.

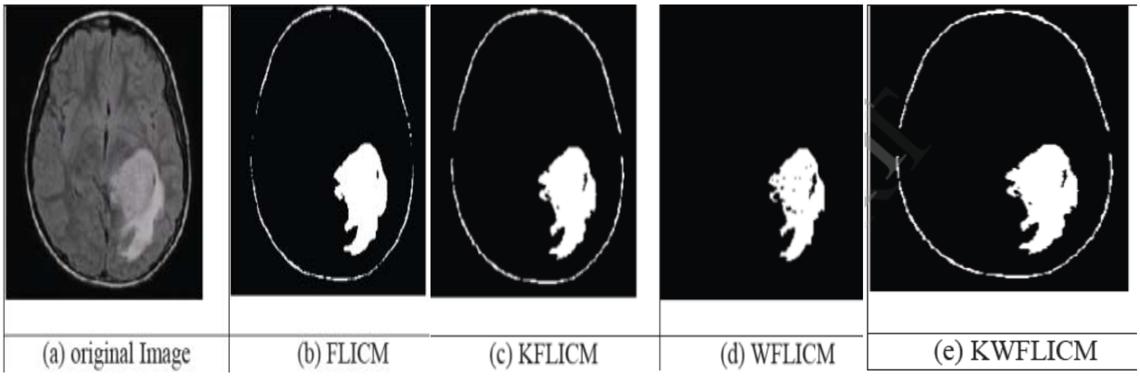

Fig3. *Brain Tumor Segmentation for Image 2*

3 (a) Original Image (b) FLICM Segmentation Result (c) KFLICM Segmentation Result (d)WFLICM Segmentation Result and (e) KWFLICM Segmentation Result

Table3. Comparison of Segmentation Accuracy

Techniques	**Segmentation Accuracy**	
	Image 1	**Image 2**
FLICM	89.26	30.15
KFLICM	89.41	82.75
WFLICM	82.75	87.92
KWFLICM	90	92.85

4. COMPARISON

The given table shows summary among all the literatures we have studied.

Table4. *Summary Chart*

Motivation	Reference	Highlights		
		Existing Method	Proposed Method	Future Scope

Brain Tumor Segmentation Using K-Means Clustering and Fuzzy C-Means Algorithms and Its Area Calculation	Alen Jose et al [8]	Threshold and Region growing.	Preprocessing, segmentation using k-means and fuzzy c-means, Feature extraction, and approximate reasoning.	The limitations of this technique is fuzzy membership determination is not a minor job and also calculation occupied in fuzzy approaches could be intensive.
A multiple kernel fuzzy c-means clustering algorithm for brain MR image segmentation	M. Ganesh et al [9]	FCM and KFCM algorithm.	MKFCM algorithm.	We can extend it to find out the types of disease in brain from MRI and automatic image based classification system for brain tumor detection.
Automatic Brain Tumor Detection Using K-Means and RFLICM	A.J.Patil et al [10]	Automated segmentation method using FCM and multispectral tool,(BCFCM) (FPCM)	Reformulated fuzzy local information C-means clustering algorithm (RFLICM) segmentation technique	Our future work will concentrate on to increase the accuracy rate of obtained result. We can also further extend to detect tumor at any location from the brain MRI image.
MRI Brain Tumor Segmentation using Kernel Weighted Fuzzy Clustering	R. Shalini et al [11]	FLICM, KFLICM and WFLICM	KWFLICM	We can extend it to find out the types of disease in brain from CT-Scan.
MRI Fuzzy Segmentation of Brain Tissue Using Neighborhood Attraction With Neural Network Optimization.	Shan Shen et al [12]	traditional FCM and RFCM algorithm.	IFCM which offers better continuity compared to the traditional FCM algorithm.	Future work will focus on developing the automatic image based classification system for brain tumor using data mining.
Combining Tissue Segmentation and Neural Network for Brain Tumor Detection.	Selvaraj Damodharan et al [13]	NN, K-NN classification and the Bayesian classification	Skull Stripping., CSF Segmentation, GM and WM Segmentation	The proposed NN based tumor classification technique performs better than the existing ones. But we can extend to detect tumor automatically.
Knowledge Based Brain Tumor Segmentation Graphical User Interface.	Kotikalapudi Raviteja et al [14]	NN, Fuzzy Logic, Region Growing, thresholding and knowledge based algorithms	KBBTS	The proposed method was implemented in detection of 2-D tumor images. This can further extended to detect 3-D tumor images. We can also use this method for segmentation of tumors occurring outside of the brain.

A Segmented Morphological Approach to Detect Tumor in Brain Images.	Vinay Parameshwarappa et al [15]	Thresholding and Region Growing	The proposed algorithm applied a series of operation i.e. image enhancement techniques and then morphological techniques to detect the tumor in the brain.	Further we can extend the feature to calculate the area and the thinness of the tumor by using simple algorithm. We can also calculate the location of the tumor by addressing simple algorithms.

CONCLUSION

Image segmentation is used in many biomedical-applications. Diagnosis of tumor is a sensitive and difficult task. Further, accuracy and reliability play a very important role in case of brain diseases. The techniques involved in Brain MRI have not been found to be significantly satisfactory. Hence, there is need to develop a robust technique which should be high in precision and help for the proper diagnosis in field of medical sciences.

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