International Journal of Engineering Technology Science and Research
IJETSR
www.ijetsr.com
ISSN 2394 – 3386
Volume 4, Issue 9
September 2017

MRI Brain Image Segmentation using Fuzzy C Means Cluster Algorithm for Tumor Area Measurement

Rajesh Kumar T[1] , Geetha K[2], Satheesh R[3] , Barkath Nisha S[4]
[1,5]Assistant Professor, Sri Krishna College of Technology, Coimbatore, India
[2]Professor, Karpagam College of Engineering, Coimbatore, India
[3]Under Graduate Scholar, Sri Krishna College of Technology, Coimbatore, India

Abstract: *The structure segmentation and analysis of MRI brain images is the primary objective. The proposed method is to segment normal tissues and abnormal tissues from MR images automatically. These MR brain images are found to be corrupted with Intensity in homogeneity artefacts that cause unwanted intensity variation and noise that affects the performance of analysing the brain image. Due to this type of artefacts and noises, one type of normal tissues in MRI is misclassified as a different normal tissue and it leads to error during diagnosis. The proposed method consists of pre-processing using wrapping based curvelet transform to remove noise and modified spatial fuzzy C means considers the spatial information and segments the normal tissues because the nearby pixels are highly correlated and also construct initial membership matrix randomly. The system also segments the tumor cells. It is used to improve the search effectiveness of identifying the tumor cells and increases the quality of segmentedMRI brain images.The proposed method is found to be 85% accurate in finding the tumor celland reducing the time complexity.*

Keywords: Fuzzy C Means Clustering, Wrapping based curvelet Transform, Membership Matrix, Image Segmentation, Dual Tree Complex Wavelet Transform

I. INTRODUCTION

The imaging technology has advanced, it has turn out to be a vital device for image diagnosing in medicine today. In medical imaging field, image is captured, digitized and processed for doing segmentation and for extracting important information (MasroorAhmed,*et al.*, 2011). Many imaging modalities like XRA are implemented vastly in clinical practice. The complementary information can be got from those images. The volume and size of images in medical has increased and it required the diagnosis automation, the developments in computer technology and reduced costs have provided a method to develop Brain tumor detection (Natarajan,*et al.*, 2012) on medical snapshots forms an essential step in solving several practical applications such as diagnosis of the tumors and registration at different time for patient images are obtained. The medical snapshots applications have formed the essence of division algorithms.

For the radiological diagnostic systems, Tumor division algorithms are the key elements. Based on the imaging modality, application domain, method being automatic or semi-automatic, and other specific factors, the division algorithm may vary. There is no single division method that can extract vasculature the systems.It can be applied for an evidence-based medical verdict provision system. The focal precise knack of cognitive system isdiagnosing and classifying images (Rajesh kumar, et al., 2016)

Unlike thresholding followed by connected element analysis that engage unmixed intensity-based sequence recognition techniques, some methods extracts the tumor contours by applying explicit tumor models (MasroorAhmed,*et al.*, 2011) Based on the image quality and the general image artefacts, prior image processing might be required by some segmentation methods.

International Journal of Engineering Technology Science and Research
IJETSR
www.ijetsr.com
ISSN 2394 – 3386
Volume 4, Issue 9
September 2017

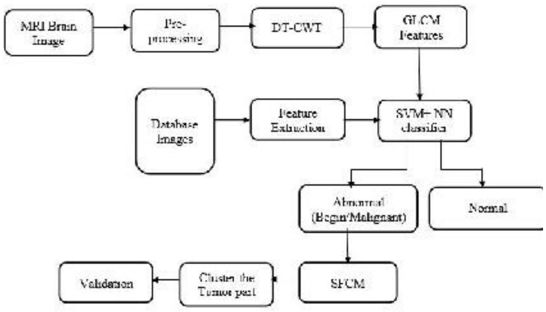

Fig. 1 Project Flow Diagram

Contrarily, some ways apply post-processing to overwhelm the problems arising from over division (Nassir Salman,*et al.*, 2006).

II.PROPOSED METHODOLOGY

The following diagram depicts the methods used in the proposed method of tumor area measurement.

A) Preprocessing

The operation of taking a manipulated/turbulent image and calculating the actual image is called as image restoration. Manipulation may come in many genres like noise; motion blur and camera miss focus (NursuriatiJamil,*et al.*, 2008). Restoration of image is designed to highlight features of the image that the observer feels more pleasing the view the image. Image improvement methods provided by "Imaging packages" does not use a-priory model to create the image. By enhancing the image, noise can be detached by foregoing some resolution, but this is not acceptable in many implementations. In a Fluorescence Microscope the resolution in z-direction is bad as it is. Few advanced image processing methods has to be applied object recovery. An example method for restoration of image can be De-Convolution that can increase resolution, removing noise in the axial direction from every medical image modality.

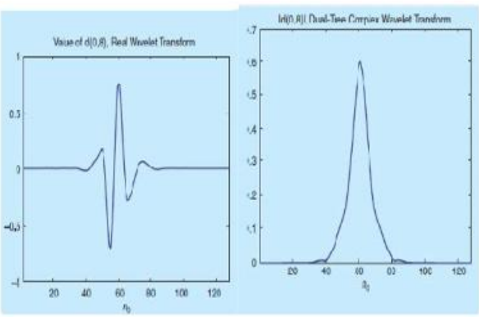

Fig. 2 The value of the wavelet coefficient

B) Dual-tree complex wavelet transform(DT-CWT)

The enhancement to the Discrete Wavelet Transform (DWT) is the Dual Tree Complex Wavelet Transform (CWT) containing additional properties. In more than two dimensions, the CWT is almost invariant of shift and is directionally selective. It gets achieved by a sacking factor of only 2*d* for *d*-dimensional signals and is lower when equated with the un decimated DWT. The multidimensional dual-tree M-D CWT(PriyankaKamboj,*et al.*, 2013) is non-separable but is based on a separable filter bank (FB) which is computationally efficient. The designing of good property complex wavelets can be got from the dual-tree transforms and it illustrates many applications in signal and image processing.

The real DWT produces vast and little wavelet coefficients in the part of an edge. In variation, the (approximately) analytic CWT produces coefficients whose magnitudes are directly related to their edge proximity(Nassir Salman,*et al.*, 2006). There is a step corner test signal at $n = no, x(n) = u(n - no)$. The figure shows the value of the wavelet coefficient *d* (0, 8) is computed using the conventional real DWT. In minor panel, the complex coefficient (0, 8) is computed using the dual-tree CWT.

C) Fuzzy clustering model

Fuzzy clustering plays a vital role in image segmentation(MasroorAhmed,*et al.*, 2011). It uses correlative distance to compute fuzzy weights. By adding process of eliminating, clustering and merging, using large initial prototypes and Gaussian weights, thespatial information and altering of every cluster's membership weights gets incorporated by the Spatial Fuzzy C Means methods after considering the cluster distribution in the neighbourhood. In standard FCM, the calculation of the associate ship function in the spectral domain is the identical in first pass. In next pass, the associate ship information of each pixel is delineated to the spatial domain and the spatial function is enumerated.

International Journal of Engineering Technology Science and Research
IJETSR
www.ijetsr.com
ISSN 2394 – 3386
Volume 4, Issue 9
September 2017

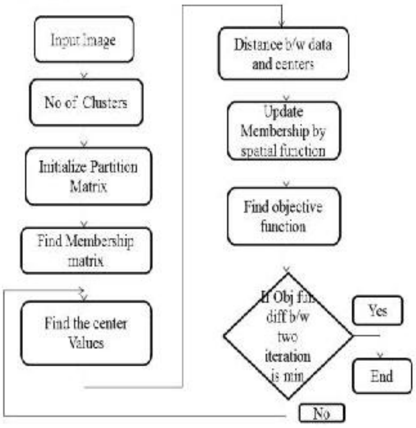

Fig. 3 Flow chart of Fuzzy C-Means Implementation

By incorporating with the spatial function, the new associate ship moved with the FCM iteration. The paramount distinction between cluster centres or associate ship functions is less than a least threshold value at two consequent repetitions, the repetition ends.

J.C. Bezdek introduced the fuzzy c-means (FCM) algorithm. The FCM uses the weights that diminish the whole weighted mean-square error:

$J(Wqk,\ \mathbf{z}^{(k)}) = \Sigma(k=1,K)\ (Wqk)\|\ \mathbf{x}^{(q)} - \mathbf{z}^{(k)}\|^2$ (1)

$\Sigma(k=1,K)\ (Wqk) = 1$ (2)

$Wqk = (1/(Dqk)^2)^{1/(p-1)}/\Sigma\ (k=1,K)(1/(Dqk)^2)^{1/(p-1)}, p>1$ (3)

By equation (3), the feature vector belonging to the fuzzy cluster truth value ranging between 0 and 1 gets computed. According to the maximal weight of the feature vector over all clusters, the algorithm sets the vector.

Initialize the Fuzzy Weights

To compare the FCM and FCFM, our execution allows the user to choose initializing the weights using feature vectors randomly(MasroorAhmed,*et al.*, 2011). By assigning the first Kinit (user-given) feature vectors to prototypes, the weights initializing using feature vectors takes place and then by Equation(4), it gets computed.

Standardize the weights over Q

The computed cluster centres gets closer during the FCM iteration. By using the following equation, the rapid convergence and grouping into a single cluster can be avoided.

$w[q,k] = (w[q,k] – wmin)/(\ wmax – wmin)$ (4)

Before standardizing the weights over Q. Wmax is the maximum weight and wmin is the minimum weight over the weights of all feature vectors for the particular class prototype.

Eliminating Empty Clusters

After the fuzzy clustering loop, it adds a step (Step 8) to eliminate the empty clusters. This step is performed before calculating the modified XB validity and is put outside the fuzzy clustering loop. Without the elimination, the minimum distance of prototype pair used in Equation (8) may be the distance of empty cluster pair. By passing 0 to the process, we can call the method of eliminating the small clusters that will only eliminate the empty clusters(Rajesh Kumar,*et al.*, 2017).

After the fuzzy c-means iteration, it calculates the cluster centres and modified Xie-Beni clustering validity k by adding step 9 for comparing and picking the optimal result.

The Xie-Beni validity is a product of compactness and separation measures. The compactness-to-separation ratio □□is defined by Equation (5).Dmin is the minimum distance between the cluster centres.

$\nu=(1/K)\sum(k=1,K)\sigma k^2\}/Dmin^2\sigma$ (5)

$k^2 = \sum(q=1,Q)\ wqk\ \|\ \mathbf{x}^{(q)} – \mathbf{c}^{(k)}\ \|^2$ (6)

The Modified Xie-Beni validity κ is defined as

$\kappa = Dmin^2/\ \{\sum(k=1,K)\sigma k^2\ \}$ (7)

With contrast to the original Xie-Beni validity measure that sums over all Q, the variance of the clusters is calculated by summing over only the members of each cluster.

$\sigma k^2 = \sum\{q: q \text{ is in cluster } k\}\ Wqk\ \|x(q) – c(k)\|2$ (8)

The spatial function is included into membership function as given in Equation (9)

$$u_i' = \frac{u_i^p h_i^q}{\sum_{k=1}^{c} u_k^p h_k^q}. \quad (9)$$

D)Morphological Process

Morphological image processing is a collection of non-linear operations related to the shape or morphology of image features. Instead of relying on numerical values, the morphological operations(NursuriatiJamil,*et al.*, 2008) rely only on the relative ordering of pixel values and are suited for processing the binary images.

International Journal of Engineering Technology Science and Research
IJETSR
www.ijetsr.com
ISSN 2394 – 3386
Volume 4, Issue 9
September 2017

The structuring element is a small shape or template through which morphological techniques probes an image. Before positioning the structuring element at all possible locations in the image, it is compared with the pixels of corresponding neighbourhood. Some operations test whether the element "fits" within the neighbourhood, while others test whether it "hits" or intersects the neighbourhood.

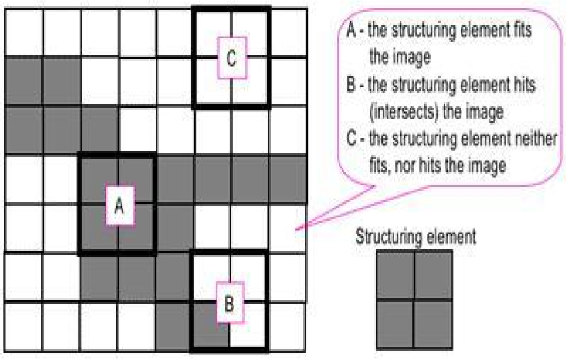

Fig. 4 probing of an image with a structuring

After a successful test, the new binary image with a non-zero value gets created at that location in the input image by the morphological operation.

The structuring element(Rajeev Ratan,*et al.*, 2009) is a small matrix of pixels, each with a value of zero or one:

1. The size of the structuring element is specified by the matrix dimensions.
2. The shape of the structuring element is specified by the ones and zeros pattern.
3. Although the origin of the pixel of structuring element is generally outside, it is usually one of its pixels.

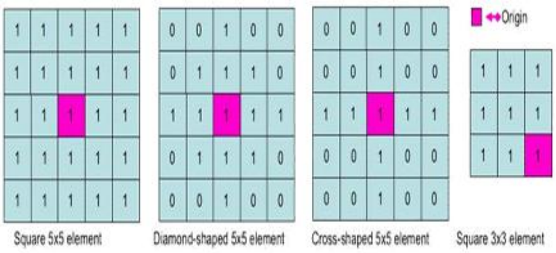

Fig. 5 Examples of Simple Structuring Element

By placing a structuring element is a binary image, every pixel is associated with the corresponding pixel of the neighbourhood under the structuring element. If the corresponding image pixel for every pixel of value 1 is 1, then the structuring element can fit the image. If the corresponding image pixel for at least one of the pixels of structuring element of value 1 is 1, then the element is said to intersect or hit.

E) Erosion and Dilation

The inner and outer boundary pixel layers can be stripped to shrink the small square structuring elements with erosion. Thus there will be an increase in the holes and gaps between different layers and can eliminate the small detail.

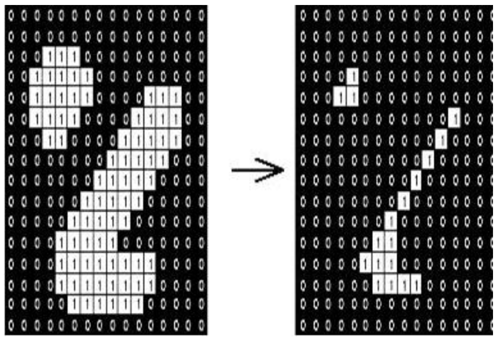

Fig.6 Erosion of a 3x3 square structuring element

Like the smaller structuring element, the obtained result by the iterated erosion (KailashSinha,*et al.*, 2014) of the larger structuring elements has a pronounced effect. Let s1 and s2 be a structuring elements pair which is identical in shape and s2 being twice the size of s1, then

$$f \ominus s2 \approx (f \ominus s1) \ominus s1. \quad (10)$$

The regions of interest have a simultaneous reduction in size when erosion removes the binary image's small scale. Every region boundaries can be calculated when the eroded image is subtracted from the actual image: $b = f - (f \ominus s)$where f denotes the image regions, s is a structuring element of matrix 3x3, and b is the image boundary regions.

The gaps between the different regions and the holes enclosed by the single region gets reduced in size and the region boundaries small intrusions gets filled in.

i. Let ***C*** be the ***nxn*** matrix that is produced by dividing ***A*** with the total number of point pairs satisfying ***P***. The measure of joint probability is denoted by **C[i][j],** which shows the pair of points satisfying **P** will have values **g[i],g[j]**.***C*** is called a co-occurrence matrix defined by ***P***.

F) Feature extraction and neural network co-occurrence matrix

First, it constructs a co-occurrence matrix that is based on the distance between the image pixels and the orientation. Then, extract the statistics from the matrix as texture representation. Haralick proposed the following texture features:

1. Energy
2. Contrast
3. Correlation
4. Homogeneity

A co-occurrence matrix (Rajesh Kumar,*et al.*, 2017) is obtained for each Haralick texture feature. The spatial distribution is represented by this co-occurrence matrix and the dependence of the grey levels within a local area. The probability of going from one pixel to another with grey levels of **'i'** and **'j'** respectively under a predefined angle and distance is represented by each ***(i,j)*** thentry in the matrices . The feature vectors which are sets of statistical measures are computed from these matrices.

	0	1	2	3	4	5	6	7
0	0	0	0	0	0	0	0	0
1	0	1	2	0	0	0	0	0
2	0	1	0	2	0	0	0	0
3	0	0	1	1	0	0	0	0
4	0	1	0	0	1	0	0	0
5	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	0

Fig.7 Classical Co-Occurrence Matrix

Energy

Energy comprises of the gray-scale image texture measure of the reflecting weight, texture informing of image gray scale and homogeneity changing.

$$E=\sum_x \sum_y p(x,y)^2 \quad (11)$$

where, p(x, y) is the GLCM.

Contrast

Contrast is the main diagonal near the moment of inertia, which measure the value of the matrix is distributed and images of local changes in number, reflecting the image clarity and texture of shadow depth.

$$\text{Contrast, } I = \sum\sum p(x,y)\,(x-y)^2 \quad (12)$$

Correlation

The specified pixel pairs joint probability occurrence gets measured.

Correlation = sum (sum ((x-µx) (y-µy)) p(x, y)/$\sigma_x\sigma_y$)) (13)

Homogeneity

Measure the closeness of the distribution of element in the GLCM to the GLCM diagonal.

Homogeneity = sum (sum (p(x, y)/ (1+[x-y]))) (14)

Drawbacks

1. Poor discriminatory power
2. High computational load
3. Loss of edge details due to shift variant property

III. RESULTS

a) Normal

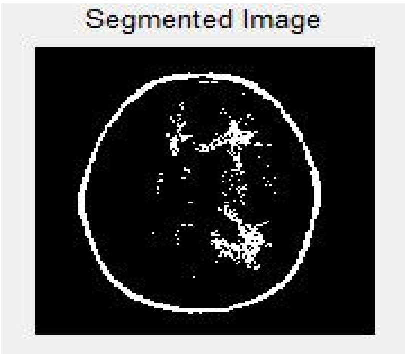

Fig.8 Normal Image

The normal category is the brain image without any possible detection of tumor area. That means, there is no tumor cells in the brain and the brain is in a healthy state.

b) Benign

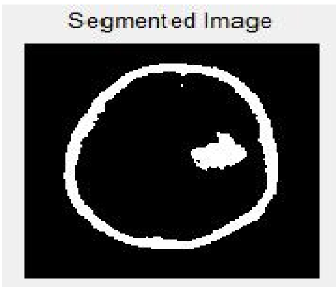

Fig.9 Benign Stage

International Journal of Engineering Technology Science and Research
IJETSR
www.ijetsr.com
ISSN 2394 – 3386
Volume 4, Issue 9
September 2017

A benign tumor is not a malignant tumor, which is cancer. It does not affect the nearby tissue or spread to other parts of the body as cancer does. The benign tumors can also become serious if they press on vital structures such as blood vessels or nerves.

c) Malignant

Classifiers have been developed through this work. Many of these methods, including Support Vector Machines (SVMs), have been applied with success to information retrieval problems, particularly text classification.At last the classifiers were tested with the data not seen during the training to evaluate their classification accuracy (Rajesh kumar, et.al.,2017). An SVM is a large-margin classifier: It is a vector space based machine learning method that finds a decision boundary between two classes that is maximally far from any point in the training data.

SVMs for two-class data sets that are separated by a linear classifier and the model is extended to a non-separable data, nonlinear models and multi-class problems. The chapter moves to consider the practical deployment of text classifiers in finding the appropriate classifier.

It will consider applying the machine learning technology back on to the problem on ranking the documents in ad hoc retrieval.

SVMs are not necessarily better than other machine learning methods, but they perform at the state-of-the-art level and have much current theoretical and empirical appeal.

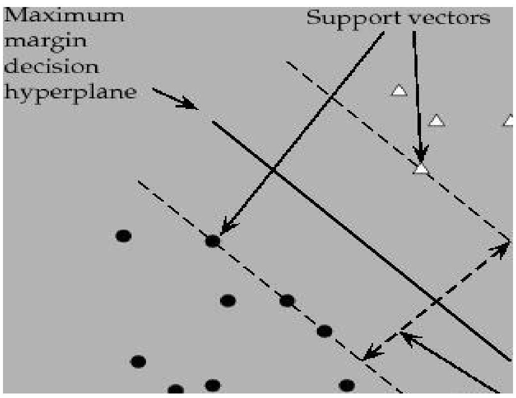

Fig.10 Support Vectors Architecture

Benign tumors andmalignant tumors are cancerous and are not a self-limited tumor cell. It is capable of affecting the adjacent tissues and can be capable of spreading to distant tissues. In short, the malignant tumors are serious stage of the cancer and treating a malignant tumor is almost a difficult task.

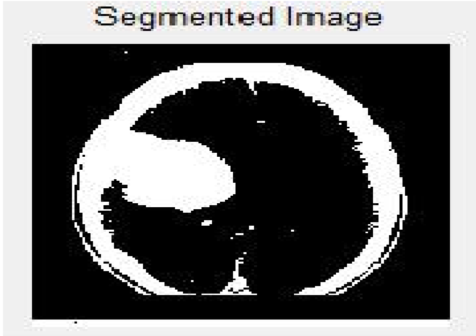

Fig.11 Malignant Tumor

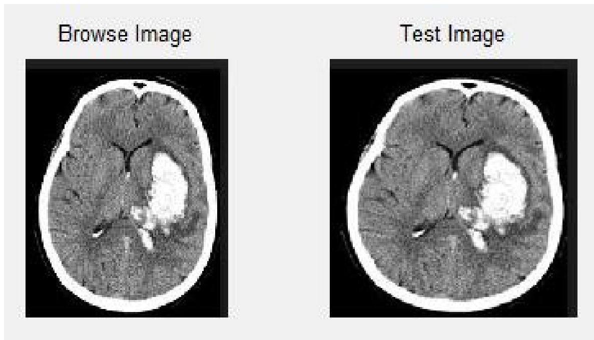

Fig.12 Noisy image and Pre-processed Image

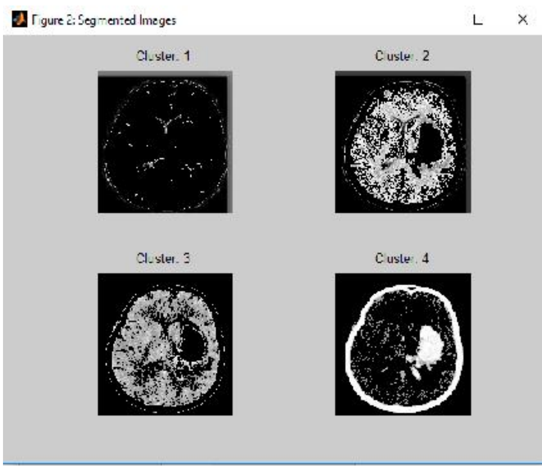

Fig.13 Clustering the MRI image

The above steps, the nature of the tumor cells can be measured. After eliminating noise from the image, Clustering has to be performed to segment and measure the tumor area.

International Journal of Engineering Technology Science and Research
IJETSR
www.ijetsr.com
ISSN 2394 – 3386
Volume 4, Issue 9
September 2017

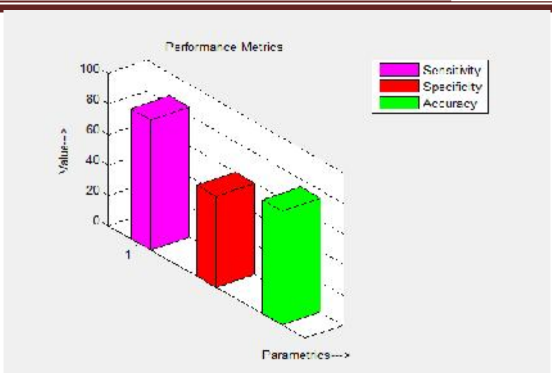

Fig.14 Validation Graph of the System

IV. CONCLUSION

The proposed method uses lossless compression technique which results in a better quality of image and thus increasing the accuracy of finding the tumor area. The proposed method is found to be 85% accurate in finding the tumor cell, which is better than the previously proposed systems. This accuracy is achieved by using the Fuzzy C Means Clustering and Back Propagation Neural Networks.

References

[1] D.Selvaraj, R.Dhanasekaran," Novel approach for segmentation of brain magnetic resonance imaging using intensity based thresholding", IEEE nternational Conference on Communication Control and Computing

[2] Natarajan, Krishnan, Natasha SandeepKenkre," Tumor Detection using threshold operation in MRI Brain Images"International Conference on Computer intelligence and Computing Research, pp 1-4, 2012

[3] Kaiqiong Sun, Shaofeng Jiang," Segmentation of Coronary Artery on Angiogram by Combined Morphological Operations and Watershed", IEEE International Conference on Biomedical Engineering and Informatics,pp1-4,2009

[4] Nassir Salman," Image Segmentation Based on Watershed and Edge Detection Techniques",The International Arab Journal of Information Technology, vol 3,pp 104-110,2006

[5] M. Masroor Ahmed. Dzulkifli Bin Mohammad, " Segmentation of Brain MR Images for Tumor Extraction by Combining Kmeans Clustering and Perona-Malik Anisotropic Diffusion Model", IEEE International Journal of Image Processing,pp27-34,2011

[6] NursuriatiJamil, TengkuMohdTengku, ZainabBakar," Noise Removal and Enhancement of Binary Images Using Morphological Operations" IEEE International Symposium on Information Technology,pp1-6,2008

[7] PriyankaKamboj, Versha Rani," A Brief Study of Various Noise Model and Filtering Techniques "Journal of Global Research in Computer Science,Vol.4,pp.166-171,2013

[8] Rajeev Ratan, Sanjay Sharma,S. K. Sharma," Brain Tumor Detection based on Multi-parameter MRI Image Analysis"International Conference of Graphics and Statistical Technology,Vol.9,pp 9-17,2009

[9] T.Rajesh kumar and K.Geetha, “An Artificial Technique Based Approach for Channel Selection and Classification of Electroencephalogram Signals”, International Journal of Printing, Packaging & Allied Sciences, Vol. 5, No. 1, February 2017, ISSN 2320-4387

[10]T.Rajesh kumar and K.Geetha, “A Perspective Approach on Artificial Cognitive Computing and its Future Development”, International Journal of Innovative Research in Computer and Communication Engineering, Vol. 4, Issue 11, November 2016, ISSN(Online): 2320-9801, ISSN (Print): 2320-9798

[11] KailashSinha, G.R.Sinha," Efficient Segmentation Methods for Tumor Detection in MRI Images", IEEE Student’s Conference on Electrical, Electronics and Computer Science, pp 1-6,2014