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SEGMENTATION AND CLASSIFICATION OF MRI BRAIN TUMOR IMAGES USING CELLULAR AUTOMATA AND PNN

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ABSTRACT

The conventional method for classification and tumor detection of medical resonance brain tumor images is by human inspection, where in a lot of time and effort is put in by the specialists to analyze the problem area and to come up with a conclusion regarding the spread of the tumor region and its current stage.

This paper proposes a fast and robust practical tool for segmentation of solid tumors with minimal user interaction to assist clinicians and researchers in radio surgery planning and assessment of the response to the therapy and classification of tumors using probabilistic neural network. Particularly, cellular automata (CA) based seeded tumor segmentation method on magnetic resonance (MR) images, and a standardized process called seed selection, is proposed. ANN with image and data processing techniques were employed to implement an automated brain tumor classification. Decision making was performed in two stages: feature extraction using the principal component analysis and the classification using Probabilistic Neural Network (PNN). The performance of the PNN classifier was evaluated in terms of training performance and classification accuracies.

Keywords: *Cellular Automata, Magnetic Resonance, Probabilistic Neural Network (PNN)*

1. INTRODUCTION

The brain is a soft, delicate, non-replaceable and spongy mass of tissue. It is a stable place for patterns to enter and stabilize among each other. A tumor is a mass of tissue that grows out of control of the normal forces that regulates growth. Brain tumor is a group of abnormal cells that grows inside of the brain or around the brain. Tumors can directly destroy all healthy brain cells. It can also indirectly damage healthy cells by

crowding other parts of the brain and causing inflammation, brain swelling and pressure within the skull. Tumor is not synonymous with cancer. A tumor can be benign, pre-malignant or malignant, whereas cancer is by definition malignant. Over the last 20 years, the overall incidence of cancer, including brain cancer, has increased by more than10%, as reported in the National Cancer Institute statistics (NCIS). The National Brain Tumor Foundation (NBTF) for research estimates that 29,000 people are diagnosed with primary brain tumors each year, and nearly 13,000 people die. In children, brain tumors are the cause of one quarter of all cancer deaths. The overall annual incidence of primary brain tumors is 11 to 12 per 100,000 people for primary malignant brain tumors, that rate is 6 to 7 per 1,00,000.

Figure 1: Brain Tumor Image

2. LITERATURE SURVEY

The survey on Segmentation and classification of brain tumors is extensive. The main aim of this project is to provide a clear understanding of selecting certain type of image and the respective process required to perform on the image. Experimental observations of various other phenomena are reviewed and discussed in this section.

Many theories have been proposed in the segmentation and classification process of brain tumor images and therefore this project work consists of various important elements of which the input image selected for this process to take place is the key. The input image selected needs to be clear and should comprise of even the minute details. Hence the chosen image should help to simplify the process of segmentation and classification. In order to satisfy this purpose the image selected is a magnetic resonance image.

MAGNETIC RESONANSE IMAGING:

Magnetic Resonance Imaging (MRI), ***nuclear magnetic resonance imaging (NMRI)***, or ***magnetic resonance tomography (MRT)*** is a medical imaging technique used in radiology to visualize internal structures of the body in detail. MRI makes use of the property of nuclear magnetic resonance (NMR) to image nuclei of atoms inside the body.

In clinical practice, MRI is used to distinguish pathologic tissue (such as a brain tumor) from normal tissue. One main advantage of an MRI scan is that it is harmless to the patient. It uses strong magnetic fields

and non-ionizing electromagnetic fields in the radio frequency range, unlike CT scans and traditional X-rays, which both use ionizing radiation.

Primary malignant brain tumors, such as gliomas, appear as hypo intense, dark areas on gadolinium enhanced T1-weighted MRI images, and as hyper intense, bright areas on T2-weighted images.While interpretation of gadolinium-enhanced T1-weighted images and T2-weighted images remains the mainstay of brain tumor diagnosis, this approach has limitations. Techniques other than T1- and T2-weighted MRI can help overcome these limitations. Hence, MR Images can be undoubtedly used for analysis of brain tumors.

Generally segmentation of the brain tumoris carried out using the following methods

GRADIENT-BASED METHOD:

Gradient descent is a first-order optimization algorithm. To find a local minimum of a function using gradient descent, one takes steps proportional to the *negative* of the gradient (or of the approximate gradient) of the function at the current point. If instead one takes steps proportional to the *positive* of the gradient, one approaches a local maximum of that function; the procedure is then known as gradient ascent.

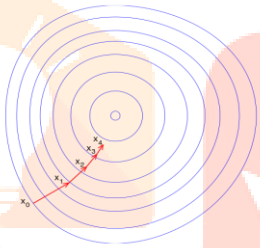

Figure: 2 Gradient based method

THRESHOLDING:

The simplest method of image segmentation is called the thresholding method. This method is based on a clip-level (or a threshold value) to turn a gray-scale image into a binary image.The key of this method is to select the threshold value (or values when multiple-levels are selected). Several popular methods are used in industry including the maximum entropy method, Otsu's method (maximum variance), and k-means clustering.

Recently, methods have been developed for thresholding computed tomography (CT) images. The key idea is that, unlike Otsu's method, the thresholds are derived from the radiographs instead of the (reconstructed) image.

CLUSTERING METHODS

Fig. 3: Source image.

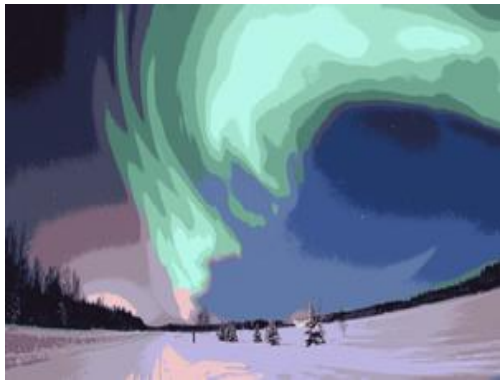

Fig.4: Image after running *k*-means with *k = 16*.

Note that a common technique to improve performance for large images is to down sample the image, compute the clusters, and then reassign the values to the larger image if necessary.

The K-means algorithm is an iterative technique that is used to partition an image into *K* clusters. The basic algorithm is:

1. Pick *K* cluster centres, either randomly or based on some heuristic
2. Assign each pixel in the image to the cluster that minimizes the distance between the pixel and the cluster centre
3. Re-compute the cluster centres by averaging all of the pixels in the cluster
4. Repeat steps 2 and 3 until convergence is attained (e.g. no pixels change clusters)

The main drawbacks of these existing methods are

- These methods are less effective and it has greater robustness to noise.
- Tumor boundaries aren't defined accurately.

Finally to overcome the drawbacks of the existing process, it is necessary to develop a process which provides accurate output. Therefore we have chosen to do segmentation process based on cellular automata and the classification process based on neural networks.

TECHNICAL OVERVIEW

The method employed for segmentation of the tumor region is by using a gradient based method or thresholding and clustering method. But, these methods do not give the exact tumor region of the brain. Hence, there might be a chance of either selecting a part of non-tumor region as tumor region or neglecting a part of tumor region by considering it unaffected. Therefore an advanced technique using Cellular Automata has been proposed in this project, which determines the boundaries of the tumor regions accurately. Proposed technique for classification of brain tumor images into various stages is by using Artificial Neural Networks. They are mainly classified into feed forward and feedback networks. A probabilistic neural network which is a feed forward network is used mainly for pattern recognition and classification. Hence Probabilistic Neural Network is applied for classifying brain tumor into stages.

BLOCK DIAGRAM

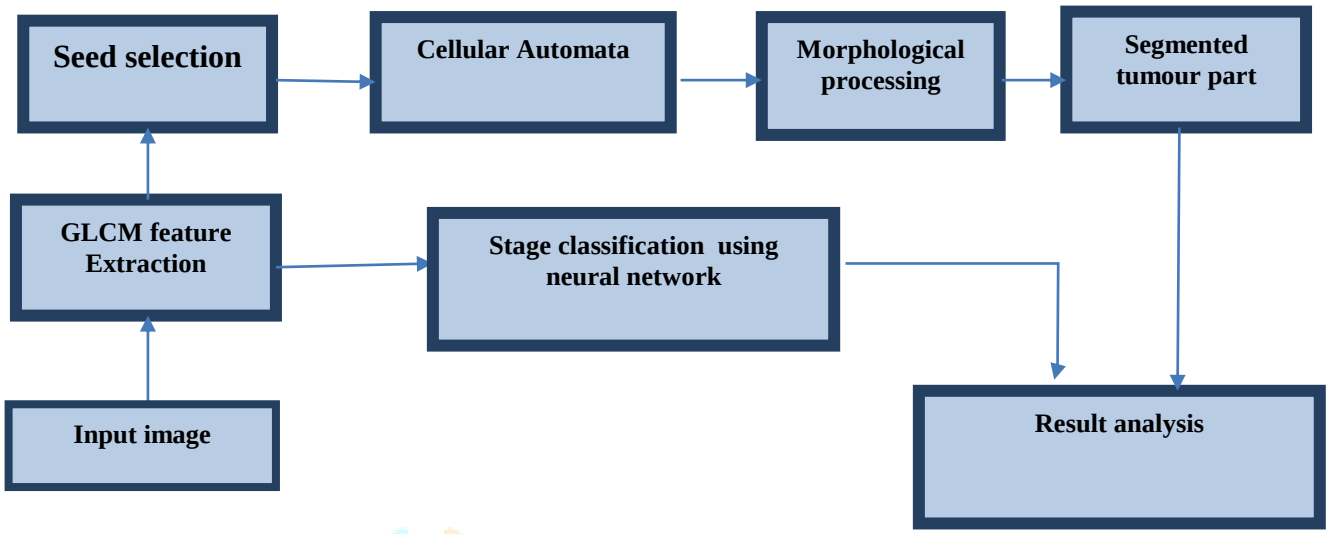

Fig. 5: Block diagram

FLOWCHART FOR THE ENTIRE PROCESS:

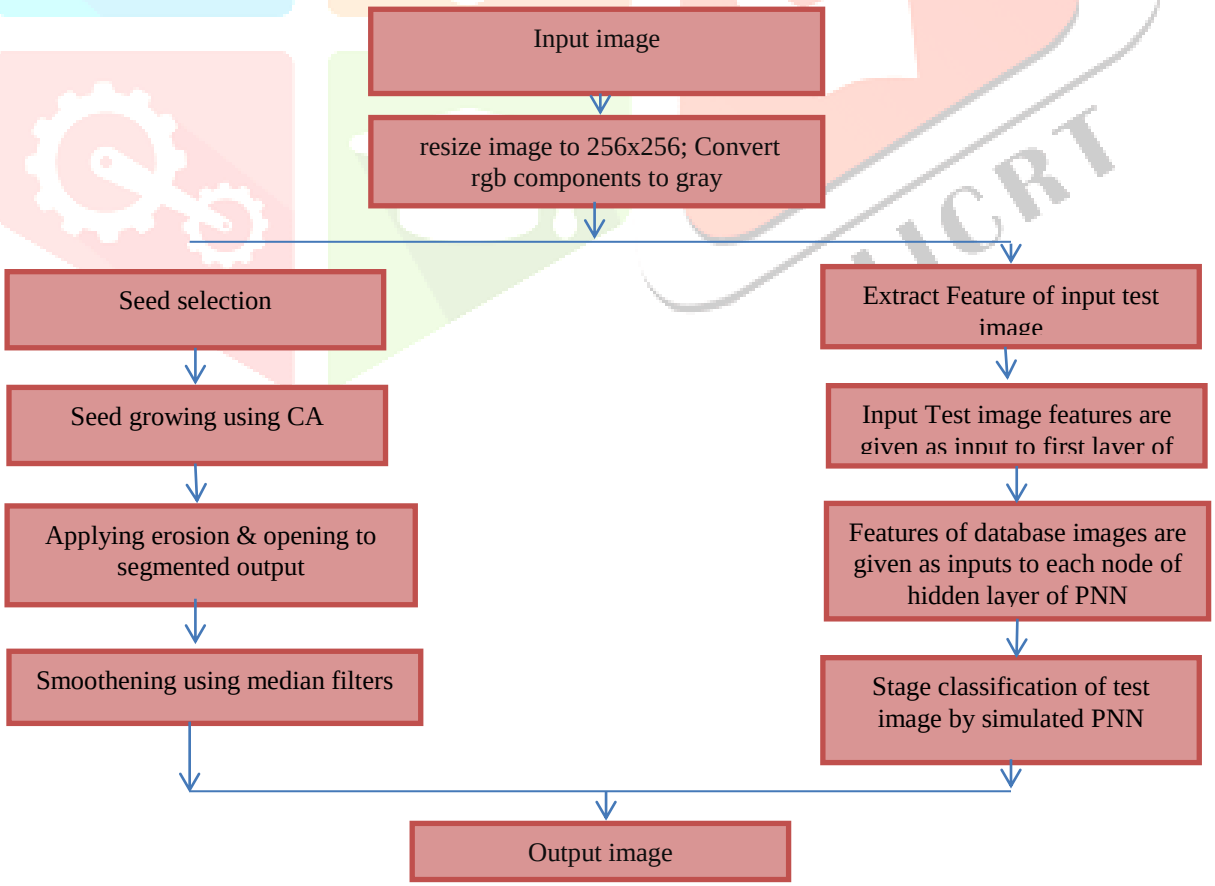

Fig.6: Entire flow diagram

IMAGE SEGMENTATION:

The main objective in image processing applications is extraction of important image features from image data which will eventually lead to automatic computerized description, interpretation and analysis of the scene.

SEED SELECTION:

An appropriate cell is chosen in such a way that the probability of this cell being at the centre of the tumor is maximum. This cell is taken as the seed. At this stage, we are interested in the entropy and energy values of the input image. Hence, the energy and entropy values are calculated and thereby a seed is chosen in such a way that it has minimum energy and maximum entropy values.

GENERATION OF GLCM MATRIX:

At this stage of the project we calculate the Gray Level Co occurrence Matrix of an image in order to extract the set of features required for further calculations.

The figure below represents the formation of the GLCM of the grey-level (4 levels) image at the distance d = 1 and the direction of 0°.

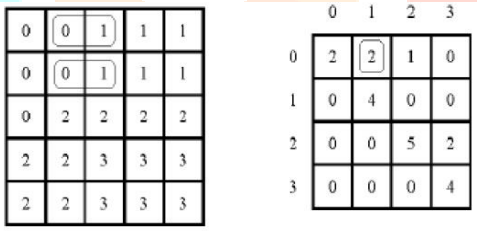

Fig.7(a) Reference Matrix Fig.7(b) GLCM matrix

Figure 7(a). is an example matrix of pixels intensity representing image with 4 (four) levels of grey. Note the intensity level intensity level 0 and 1 are marked with a thin box. The thin box representing pixel-intensity 0 with pixel intensity 1 as its neighbour (in the horizontal direction or the direction of 0 o). There are two occurrences of such pixels.

Initially, a seed is selected in the image. This seed selection is done in such a way that the position of the seed is at coordinates where the value of energy isminimumand the value of entropyis maximum. The coordinates of this seed are determined by taking the mean value of the medians having minimum energy and maximum entropy coordinates. Finally, the pixel value at these coordinates is considered as the seed value. The main purpose of selecting such a point as the seed is because the probability of this point lying in the tumor region is high.

Table 1: Features extracted from the input image:

Features	Stage 1		Stage 2		Stage 3	
	Tumor region	Unaffected area	Tumor region	Unaffected area	Tumor region	Unaffected area
Energy	0.0212	0.643781	0.009421	0.543306	0.009013	0.390413
Entropy	6.4431	2.0345	6.07832	2.11074	6.7741	2.64912

SEED GROWING USING CELLULAR AUTOMATA:

CELLULA AUTOMATA

A cellular automaton consists of a regular grid of *cells*, each in one of a finite number of*states*, such as *on* and *off* (in contrast to a coupled map lattice). The grid can be in any finite number of dimensions. For each cell, a set of cells called its *neighbourhood*(usually including the cell itself) is defined relative to the specified cell. An initial state (time *t*=0) is selected by assigning a state for each cell. A new *generation* is created (advancing *t* by 1), according to some fixed *rule* (generally, a mathematical function) that determines the new state of each cell in terms of the current state of the cell and the states of the cells in its neighbourhood. Typically, the rule for updating the state of cells is the same for each cell and does not change over time, and is applied to the whole grid simultaneously, though exceptions are known, such as the probabilistic cellular automaton and asynchronous cellular automaton.

STAGE CLASSIFICATION BASED ON NEURAL NETWORKS

At this level, the tumor stage is classified by adopting certain neural network techniques.

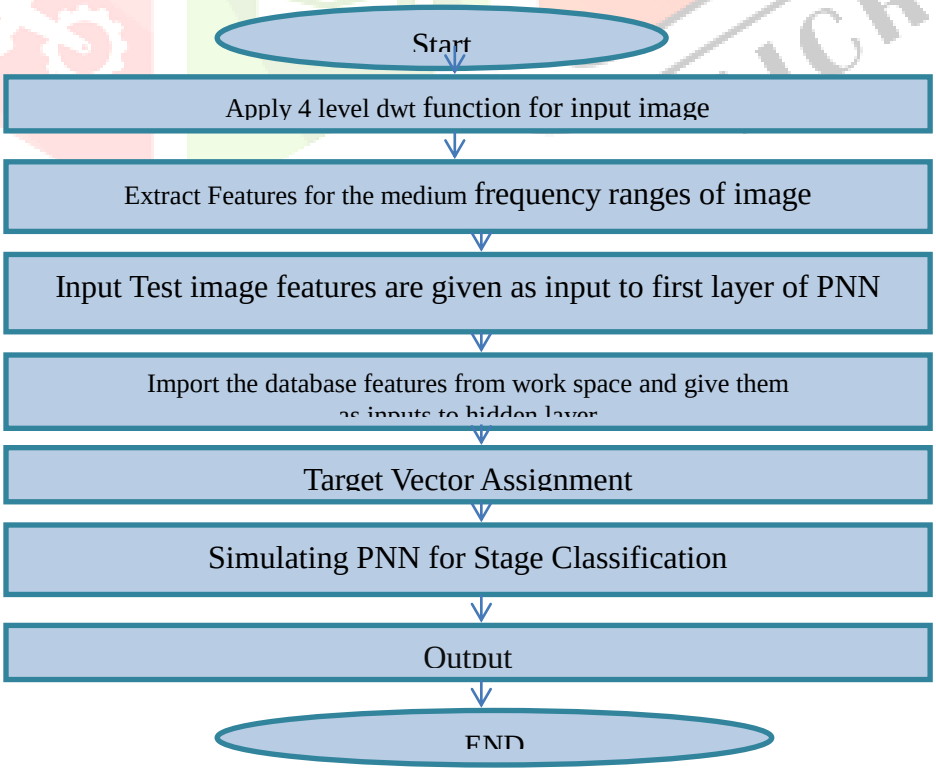

Fig.: Stage Classification Flow Diagram

2.4.2 DISCRETE WAVELET TRANSFORM

This project deals with using discrete wavelet transform derived features used fordigital image texture analysis. Wavelets appear to be a suitable tool for this task, because they allow analysis of images at various levels of resolution.

In this work only two sets of DWT derived features is considered. It is a vector, which contains energies of wavelet coefficients calculated in subbands at successive scales. A special module for program was developed which allows evaluating of those features.

To compute the wavelet features in the first step dwt is calculated for whole image. As a result of this transform there are 4 sub band images at each scale (Fig.).Sub band imageLH^3 and$HL^3$are used processing at the next level.

FEATURE EXTRACTION

Feature extraction involves simplifying the amount of resources required to describe a large set of data accurately. When performing analysis of complex data one of the major problems stems from the number of variables involved. Feature extraction is a general term for methods of constructing combinations of the variables to get around these problems while still describing the data with sufficient accuracy.

Correlation:

Returns a measure of how correlated a pixel is to its neighbourover the whole image. Range = [-1 1] Correlations 1 or -1 for a perfectly positively or negatively correlated image.

$$\sum_{i,j} \frac{(i-\mu i)(j-\mu j)P(i,j)}{\sigma_i \sigma_j}$$

Homogeneity:

Returns a value that measures the closeness of the distributionof elements in the GLCM to the GLCM diagonal. Range = [0 1].Homogeneityis 1 for a diagonal GLCM.

$$\sum_{i,j} \frac{P(i,j)}{1+|i-j|}$$

Energy:

Returns the sum of squared elements in the GLCM. Range = [0 1]Energyis 1 for a constant image.

$$\sum_{i,j} P(i,j)^2$$

Contrast:

It returns a measure of the intensity contrast between a pixel and its neighbour over the whole image. Range = [0 (size (GLCM, 1)-1) ^2] .Contrast is 0 for a constant image.

$$\sum_{i,j} |i-j|^2 P(i,j)$$

Entropy:

Entropy is a mathematically-defined thermodynamic quantity that helps to account for the flow of energy through a thermodynamic process.

$$-\sum_{i=0}^{G-1}\sum_{j=0}^{G-1} P(i,j) \times \log\left(P(i,j)\right)$$

The following table shows the values of above mentioned features extracted from database images.

Table 2.2: Features of database images

FEATURES	DB1	DB2	DB3	DB4	DB5	DB6	DB7	DB8	DB9
Energy LH Image	0.126	0.104	0.173	0.118	0.209	0.120	0.098	0.114	0.135
Contrast of LH Image	6397	4765	7193	8237	4767	8876	7292	12086	8363
Correlation of LH Image	0.506	0.534	0.391	0.264	0.279	0.412	0.396	0.310	0.411
Homogeneity of LH Image	0.429	0.380	0.536	0.409	0.492	0.413	0.385	0.400	0.429
Entropy of LH Image	5.513	5.786	4.729	5.508	4.653	5.378	5.628	5.453	5.388
Energy HL Image	0.065	0.043	0.120	0.089	0.156	0.079	0.088	0.096	0.066
Contrast of HL Image	9375	10655	11264	10484	9299	13639	18471	17127	16342
Correlation of HL Image	0.049	-0.059	-0.019	-0.0789	0.002	0.038	0.033	0.003	0.095
Homogeneity of HL Image	0.301	0.235	0.377	0.348	0.437	0.313	0.318	0.335	0.292
Entropy of HL Image	6.232	6.485	5.069	5.598	4.985	5.884	5.513	5.439	5.883

DB-Database images

The above shown tabular column gives the various values of the selected features taken into reference in order to use neural networks. Out of which the values from the first 3 columns represent the values of the respective first 3 database images, the next 3 columns represent the values of the respective next 3 database images and finally the last 3 columns give the respective values of the final database images.

PROBABILISTIC NEURAL NETWORKS:

PNN is often used in classification problems.[4] When an input is present, the first layer computes the distance from the input vector to the training input vectors. This produces a vector where its elements indicate how close the input is to the training input. The second layer sums the contribution for each class of inputs and produces its net output as a vector of probabilities. Finally, a complete transfer function on the output of the second layer picks the maximum of these probabilities, and produces a 1 (positive identification) for that class and a 0 (negative identification) for non-targeted classes.

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NETWORK ARCHITECTURE

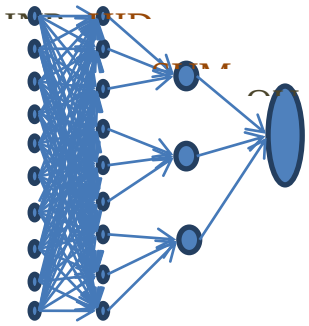


Fig.: network architecture

The architecture consists of a *four layered feed forward network* designed with 10 input neurons, 9 hidden neurons,3summation neurons and 1 output neuron for the classification.

- 10 input neurons describe 5 features of input image
- 9 hidden neurons describe features of database images
- 3 summation neurons differentiate between the 3 classes

Output neuron gives us the final classified output

RESULTS & DISCUSSIONS

STAGE 1 Tumor detection

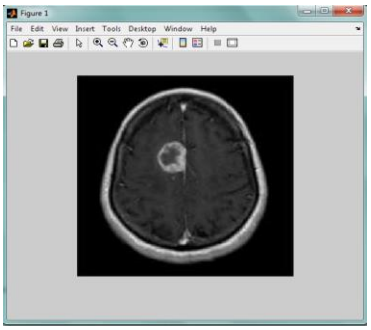


Fig.4.1: Input MRI Image

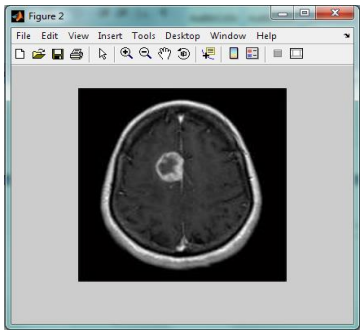


Fig. 4.2: Resizing of image

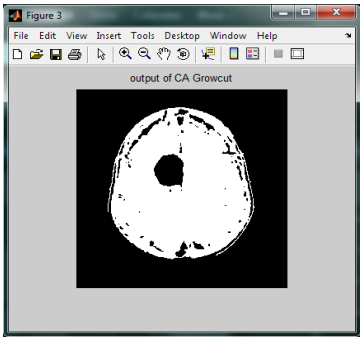
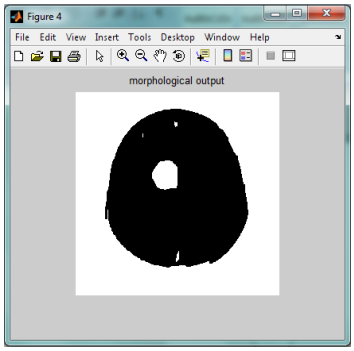
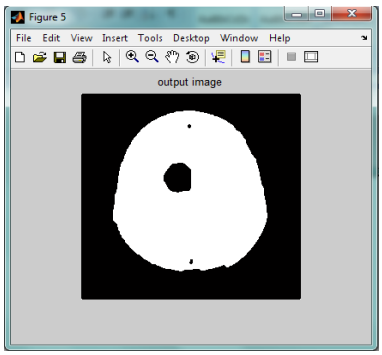


Figure 4.3: The tumor region





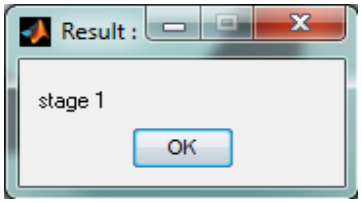
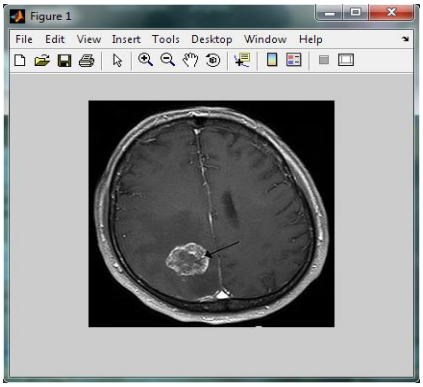


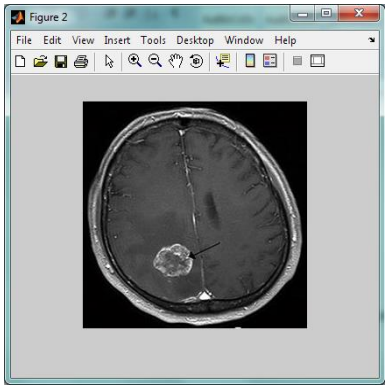
Fig. 4.4: morphological operations **Fig. 4.5:** Contrast Output after filtering **Fig.4.6:** The input brain image has a benign tumor in its initial stage.

4.2 STAGE 2 Tumor detection

Description:

This figure shows an input Magnetic Resonance image of a human brain.





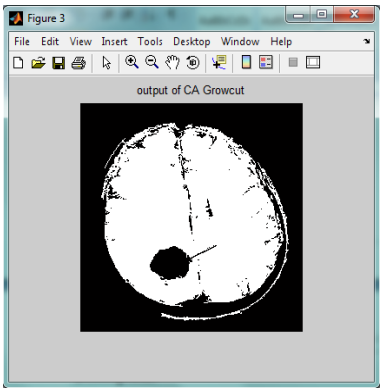
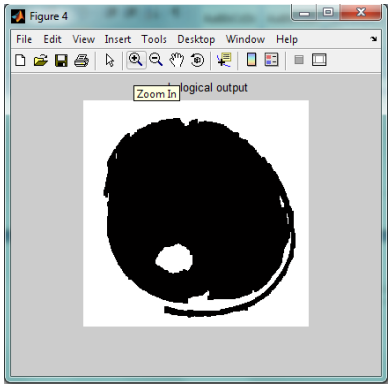
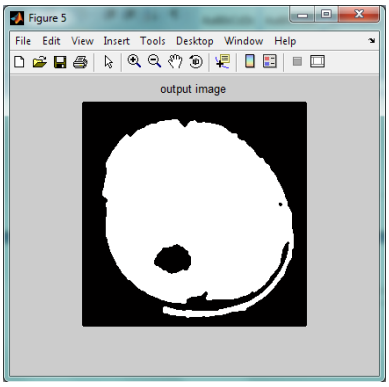


Fig. 4.7: Input MRI Image **Fig. 4.8: Resizing of image** **Fig. 4.9: The tumor region is obtained**





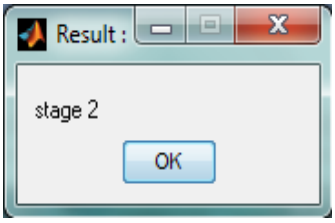
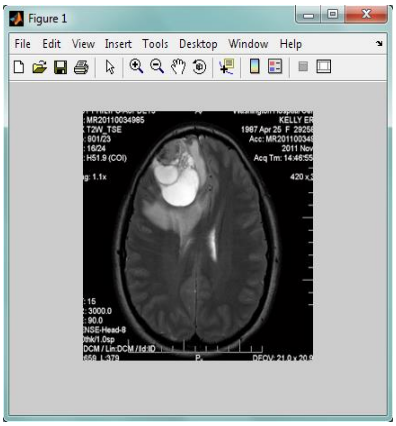


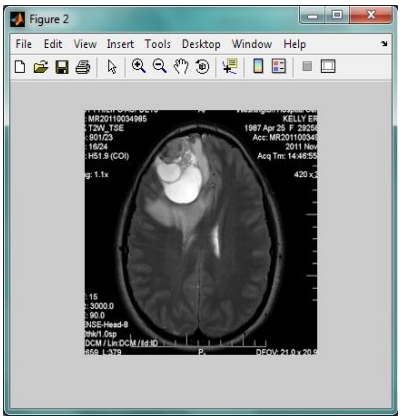
Figure 4.10: Output after morphological operations **Figure 4.11:** Contrast Output after filtering operations **4.12.** The input brain image has a malignant-1 tumor in its medieval stage.

4.3 STAGE 3 Tumor detection

Description:

This figure shows an input Magnetic Resonance image of a human brain.





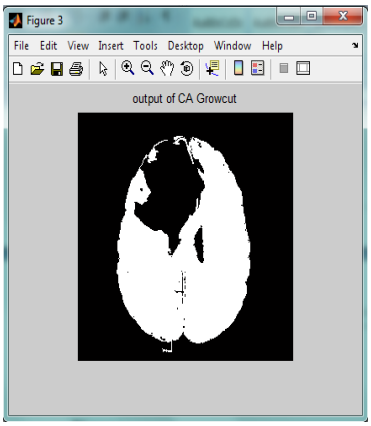
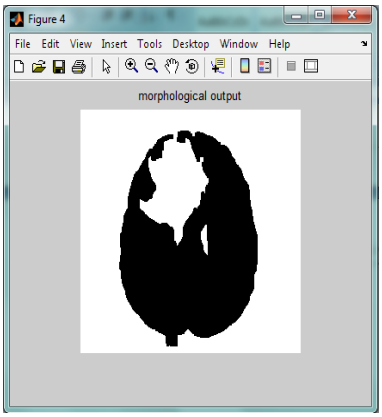
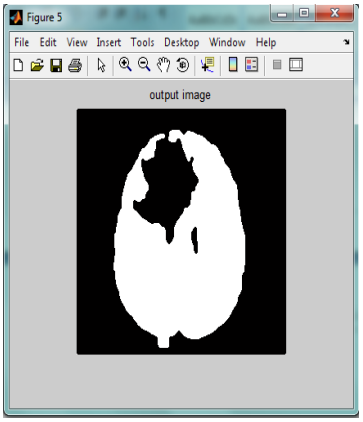


Figure 4.13: Input MRI Image **Fig.4.14 Resizing of image** **Fig.4.15 t**he tumor region is obtained





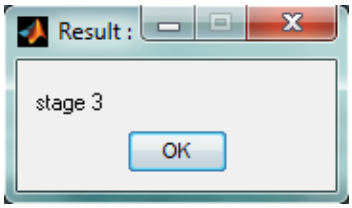


Fig.4.16 Output after morphological operations **Fig.4.17** Contrast Output after filtering operations

Fig.4.18 The input brain image has a malignant-2 tumor in its final stage

CONCLUSION

In this paper, presented a segmentation algorithm for the problem of tumor delineation which exhibit varying tissue characteristics. As the change in necrotic and enhancing part of the tumor after radiation therapy becomes important,I also applied the Tumor-cut segmentation to partition the tumor tissue further into its necrotic and enhancing parts.

REFERENCES

[1] "Image Segmentation and Classification of MRI Brain Tumor Based on Cellular Automata and Neural Networks"-R.S.RajKumar and G.Niranjana, IJREAT International Journal of Research in Engineering & Advanced Technology, Volume 1, Issue 1, March, 2013, ISSN: 2320 – 8791

[2] "Brain Tumor Classification and Segmentation in MRI Images using PNN"- R. Lavanyadevi, M.Machakowsalya, J.Nivethitha, A.Niranjil Kumar, International Conference of Electrical, Instrumentation and Communication Engineering (ICEICE2017)

[3] "MRI Brain image Segmentation and Classification: A Review", Bhavana B. Ghotekar, K. J. Mahajan, International Research Journal of Engineering and Technology (IRJET) Volume: 03 Issue: 03 | Mar-2016.

[4] E. D. Angelini, O. Clatz, E. Mandonnet, E. Konukoglu, L. Capelle,and H. Duffau, "Glioma dynamics and computational models: A reviewof segmentation, registration, and in silico growth algorithms andtheir clinical applications,"*Curr. Med. Imag. Rev.*, vol. 3, no. 4, pp.262–276, 2007.

[5] M. Prastawa, E. Bullitt, S. Ho, and G. Gerig, "A brain tumor segmentationframework based on outlier detection," *Med. Image Anal.*, vol.8, no. 3, pp. 275–283, 2004.

[6] RafaelC.Gonzalez, Richard E.Woods, Steven I.Eddins " Digital Image Prosessing using MATLAB" by Rafael

[7] N. K .Bose and P. Liang, "Neural Network Fundamenttals with Graphs, Algorithms, and Applicationns"