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Least Centre Distance Based MAXNET Architecture to Obtain Threshold for Brain Tumor Edema Segmentation From FLAIR MRI

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***Abstract*— In recent years, Brain Tumor has become one of the most common deadly diseases and MRI is commonly used to diagnose it. Automated recognition of brain tumors from MRI is a difficult task because of the variability of size, shape, and contrast of the tumor. On the other hand, it has a huge impact in helping the physicians by assessing the type, size, exact topological location and other related parameters of the tumor. Image segmentation techniques are often applied in identifying the tumor from the MRI images in addition to other techniques. There are numerous segmentation techniques available for this purpose such as: (i) Region based (ii) Edge based (iii) Threshold based. Here a threshold based approach has been designed and proposed to do the segmentation of edema, where the threshold is determined by MAXNET, a Self Organization Map (SOM) based artificial neural network.**

Keywords*— Artificial Neural Network (ANN); Brain Tumor; Least centre distance method; Magnetic resonance imaging; MAXNET; segmentation; Self Organizing Map (SOM).

I. INTRODUCTION

Tumor is a group of cells growing abnormally in many organs of many animal bodies and brain tumor is especially located in the brain region. Our concentration here is human brain tumors only. Basically tumor can be categorized into two groups: (i) Benign and (ii) Malignant. *Benign tumor* does not invade in other parts, but *malignant tumors* are cancerous and may invade its surrounding tissues [1]. Both of these types of tumors may be associated with cerebral edema, which is caused from leakage of plasma across the vessel wall into the parenchyma secondary to disruption of the blood-brain barrier [2].

MRI scan is the most common and effective tool for brain tumor diagnosis, though in some cases Computed Tomography (CT) is also used. The most commonly used standard modalities are:

a) Spin-echo T1-Weighted Image (T1WI),
b) Proton Density-Weighted Image (PDWI),
c) T2-Weighted Image (T2WI), and
d) T1WI after the administration of paramagnetic agent

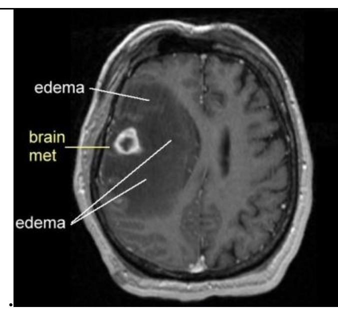


Figure 1: MRI- Typical Brain Met with Extensive Edema [5]

To improve the diagnostic efficacy for tumor imaging before and after treatment, an additional number of MR techniques have been applied *viz.*:

a) Fast Spin Echo (FSE)
b) Inversion Recovery (IR)
c) Short Tau Inversion Recovery (STIR)
d) Fluid Attenuated Inversion Recovery (FLAIR)
e) Gradient Echo Pulse Sequences
f) Echo-Planar Imaging (EPI)

In FLAIR imaging the high CSF signal is suppressed so that adjacent CSF area can be seen more clearly. FLAIR MRI gives better classification between edema and tumor [3]. FLAIR MRI has been used to achieve a particularly high contrast between tumor and surrounding tissue [4].

Image segmentation techniques are often applied in identifying the tumor from the MRI images in addition to other techniques. Image segmentation is the process of dividing a digital image into various parts. Various techniques have been used by researchers for brain tumor and edema image segmentation. Artificial Neural Network (ANN) has also been introduced by several researchers using the supervised learning mechanism to accomplish automatic segmentation. On the other hand, in case of unsupervised learning mechanism, limited work has been carried out. The self organizing neural network is mainly used to describe the topological structure among the cluster units. But in case of segmentation, it has a very limited use. In some work et al. [6] proposed a method to segment out brain tumor and edema from MRI where the segmentation problem stated as the optimization problem of several cost functions of the same form, each containing two terms: (i) a distribution function to finds a global similarity between distributions, and (ii) a smoothness function to avoid the occurrence of small isolated objects. A fully automatic technique has been proposed by S. Reza and K. M. Iftekharuddin [7]. They extract two primary sets of features such as non-local and spatial/texture for segmentation purpose. On the contrary, Marcel Prastawa, Elizabeth Bullitt, Sean Ho and Guido Gerig [8] proposed a geometric and spatial constraint based segmentation method to segment out the brain tumor along with edema. While a region based threshold have been applied by Bassam Al-Naami, Adnan Bashir, Hani Amasha, Jamal Al-Nabulsi, Abdul-Majeed Almalty et al. [9], a novel technique proposed by Wei Wu Albert, Y. C. Chen, Liang Zhao, Jason J. Corso et al. [10] adequately segments the various elements of the Glioblastoma (GBM), such as local contrast enhancement, necrosis, and edema. Some researchers use the concept of symmetry of brain structure to segment the brain and edema et.al. [11]. But, if the tumor grows in both of the segments uniformly, then these methods will not be able to perform the detection. Considering the work by K. Sarkar, A. Mandal and R. K. Mandal [12], threshold point is determined form histogram peaks by finding the peak pair which has the maximum difference. But in this method, if two pairs have the same difference then the minimum intensity pair is chosen as threshold which always may not give the correct threshold. In the other works by K. Sarkar, A. Mandal and R. K. Mandal [13], the threshold point is determined by choosing the peak (NP) which satisfies the equation:

$$10 * \mathbf{NP} <= \mathbf{P}.$$

This method provides approximate threshold of the actual one and may also, sometimes, fail to provide proper segmentation. In this paper, a technique is proposed based on histogram thresholding which overcomes the problems i.e. the symmetric growth, conflict in peak difference, and approximated threshold.

II. Architectute of MAXNET

Here a fixed weight competition based Artificial Neural Network (ANN) has been designed to find the deterministic threshold. A competition among a group of neurons is called *Winner Take All* – i.e. After the competition only one neuron among the group will have a nonzero output signal. MAXNET is one such competitive net which performs *Winner Take All*. It picks the node among all competing nodes whose input is largest and it does not have any training algorithm [14].

The proposed architecture consists of 256 neurons representing the gray level from 0 to 255 and every neuron is connected to all other neurons. There are, in total,

(256*255)/2 + 256 = 32896 connections.

Activation function for the MAXNET is as follows:

$$f(x) = \begin{cases} x & if\ x \geq 0 \\ 0 & otherwise \end{cases}$$

where, x is a real number.

The weights are initialized as follows

$$w(i,j) = \begin{cases} 1, & i = j \\ -\epsilon, & otherwise \end{cases}$$

The activation is modified until only one node has non-zero activation. The activation is modified as follows:

$$a_j(\text{new}) = f[a_j(\text{old}) - \epsilon \sum_{k \neq i} a_k(\text{old})].$$

Here we need some precautions to ensure that no two or more nodes have the same maximal value, else it will go for an infinite loop of epoch which itself is the drawback of MAXNET.

III. Methodology

A. Pre-processing Applied

Image preprocessing is highly required because medical images commonly have very poor contrast, unknown irregular noise, weak boundaries and non homogeneity [1] like properties.

About the experimental data set: Here the BRATS 2012 [16] Data set has been used. This consists of 20 HG and 10 LG skull Striped MRI images.

In this phase, the three main functions such as skull stripping, background removal and noise removal are performed.

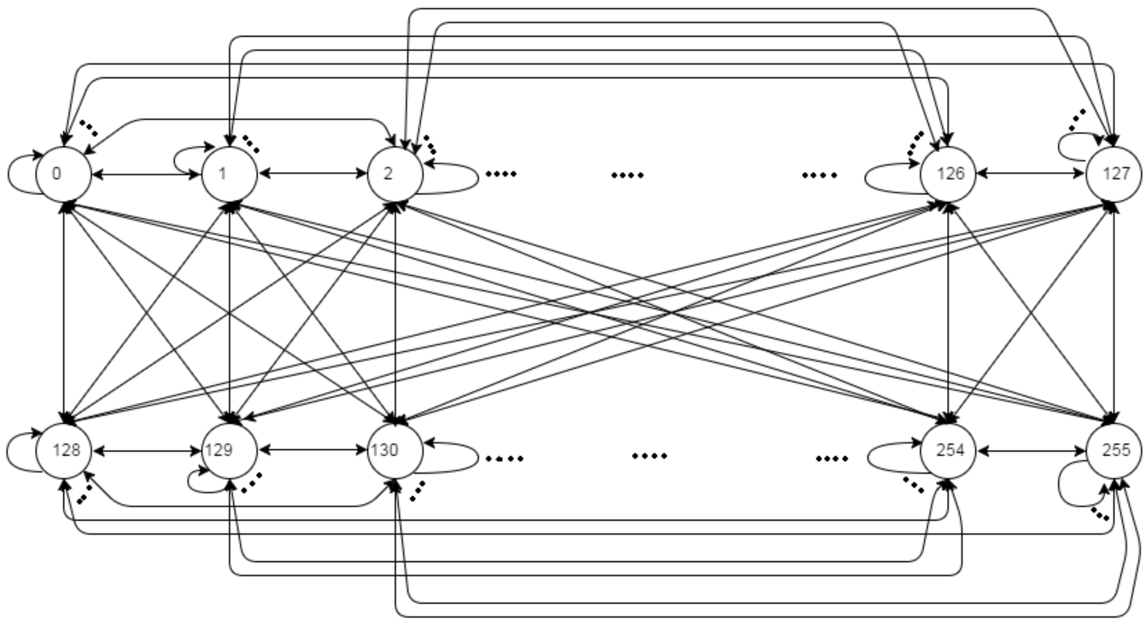


Figure 2: Proposed MAXNET architecture.

1) Skull Stripping: As BRATS 2012 dataset is used for experimental data and all the sample data are already skull stripped, so this step has been skipped here. For other datasets, BET (Brain Extraction Tool) can be used.

2) Background Removing: Here the non-brain portion is termed as "*Background*" and this portion have to be discarded to reduce the computation. Initially, the nonbrain portion has to be masked using a masking image and then the brain image is croped using the crop window [13].

3) Noise Removing: Median filter is widely used in digital image processing because it preserves edges while removing noise [15]. Median filter has been used here to removed thermal noise generated while capturing the image.

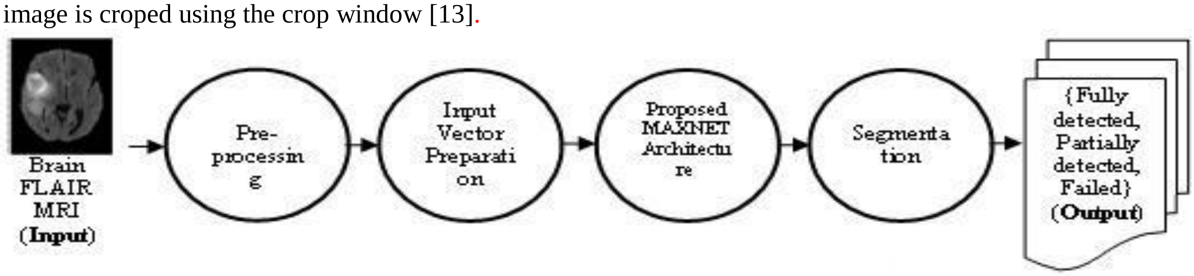


Figure 3: Proposed brain tumor extraction technique from Brain FLAIR MRI

B. Input Vector Preparation

In this phase the input vector is prepared for the MAXNET.

1) Histogram Normalization

From the image histogram, obtain the intensity *i* which have the maximum count *(max)*. For all intensity $j < i$ set the corresponding count to *max*. On the other hand, if the count of some intensity is zero then set the count of the corresponding intensity with the count of the previous intensity. To reduce the computational complexity the count is normalized to value ranging from 1 to 256. This is done by first obtaining the normalization point as follows:

$$NP = max(Count)\ /max(i) \quad (8)$$

Then the Y axis is normalized is as follows:

$$Count_i = Count_i/NP \quad (9)$$

2) Distance Array Formation

A *Distance Array* is formed from the normalized histogram by using the following equation:

$$D_i = \sqrt{(i-1)^2 + (Count_i - Count_{255})^2}$$

The *Distance Array* is also normalized by setting all the elements of the distance vector to 255 whose value is higher than 255.

3) Complement of Distance

The intensity with the minimum distance is best candidate to be choosen as the threshold. To convert it to a maximization problem the distance array is complemented using the following equation.

$$D_i' \; D_i'=255-D_i$$

C. Algorithm for MAXNET

INPUT: Initialized activation function (A_i)
OUTPUT: Winner intensity (*Thres*)
Step1 : Start
Step2 : Repeat step 3 to 4for *i= 1 to 255*
Step3 : Repeat step 4 for *j=1 to 255*
Step4 : if *i* is equal to *j* then *w(i,j)= 1* otherwise *w(i,j)= -0.01*
Step5 : Initialize *x=1*and $Temp_i= A_i$
Step6 : Repeat step 7 to 18 while *x* is equal to *1*
Step7 : Initialize *c=0*
Step8 : Repeat step 9 to14 for *i=1 to 255*
Step9 : Initialize *sum=0*
Step10 : Repeat step 11 for *j=1:255*
Step11 : if *i* is not equal to *j* then *sum =sum+A(j)*
Step12 : Set *sum=sum*0.01*
Step13 : Set $x=A_i-sum$
Step14 : if *x* is greater than 0 then $Temp_{i=}x$ otherwise *Temp(i)=0*
Step15 : Set $A_i=Temp_i$
Step16 : Repeat step 17 to 18 for i=1to 255
Step17 : if Ai>0 then c=c+1 and initialize *Thres* = i
Step 18 : if c is less than 2 the set x=0 otherwise x= 1
Step 19 : End

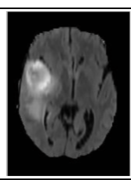
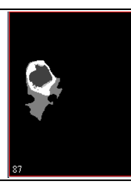
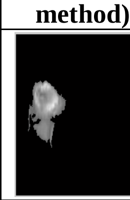
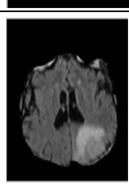
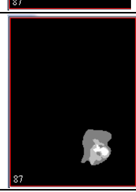
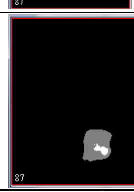
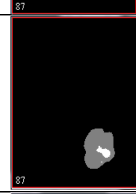
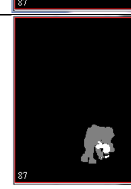
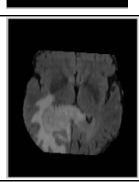
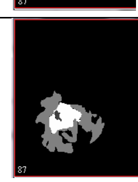
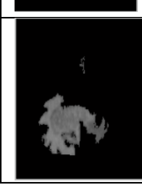
D. Segmentation

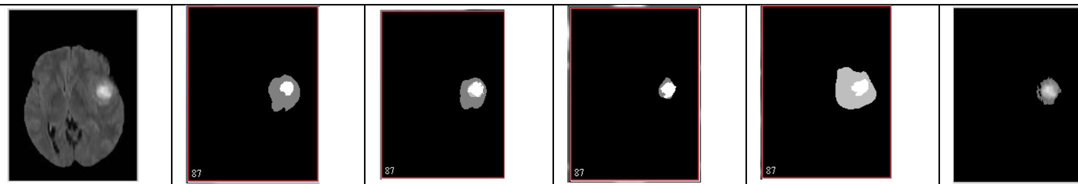
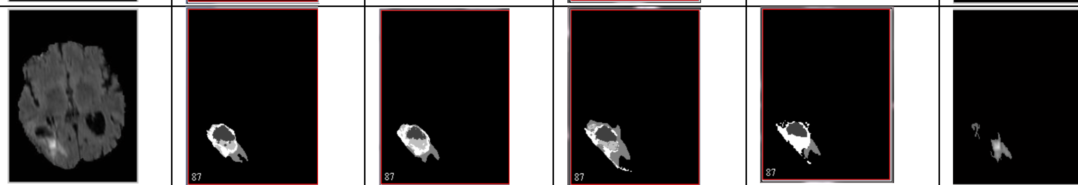
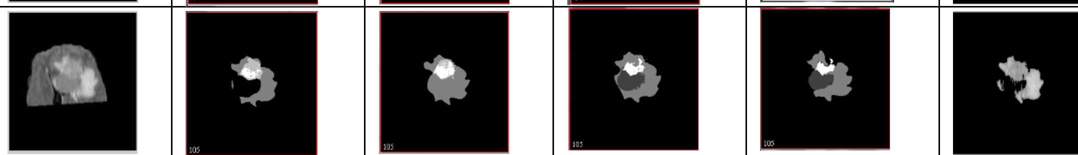
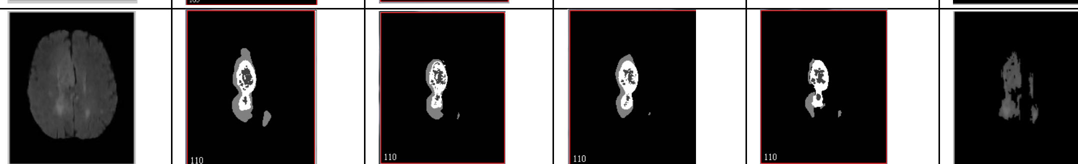
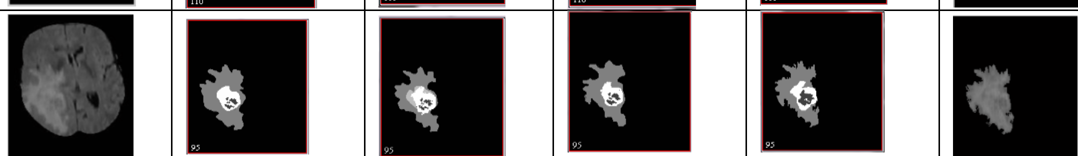
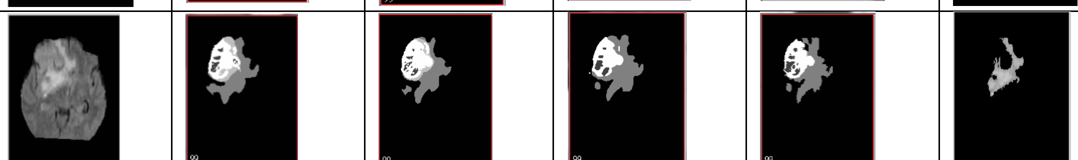
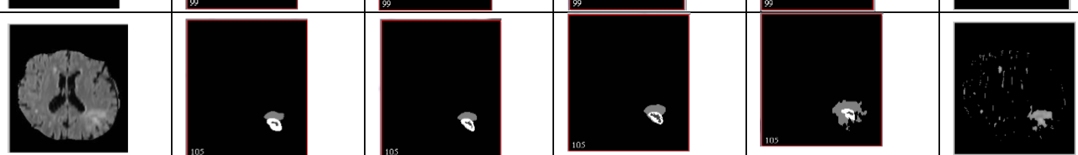
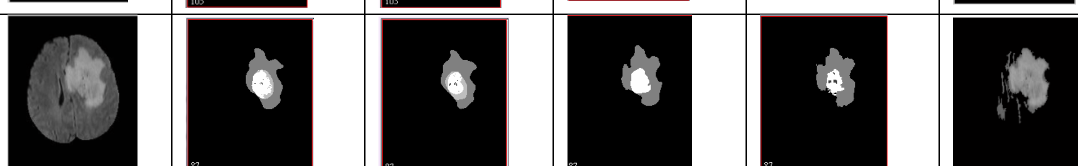
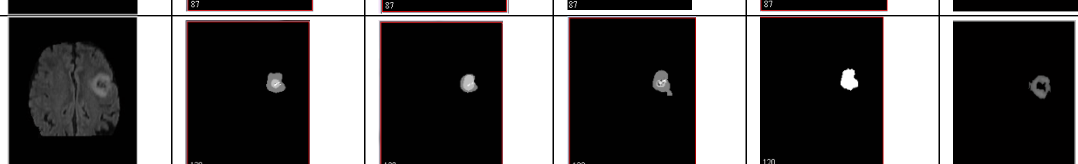
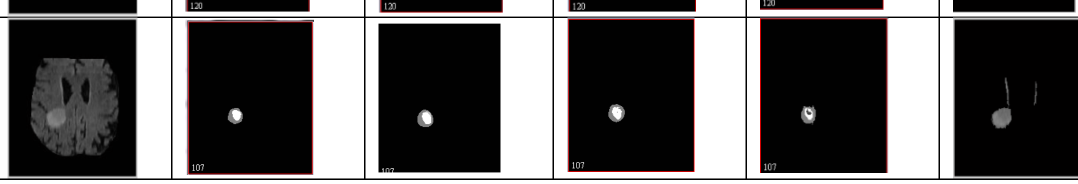
In this final phase, all the intensities obtained in the previous step are set to zero which are smaller than the threshold (*Thres*) else the intensity value is set to 255. Thus a binary image is constructed from the original image that depicts only the lesion affected area in the brain. The proposed technique is shown abstractly in Figure 3.

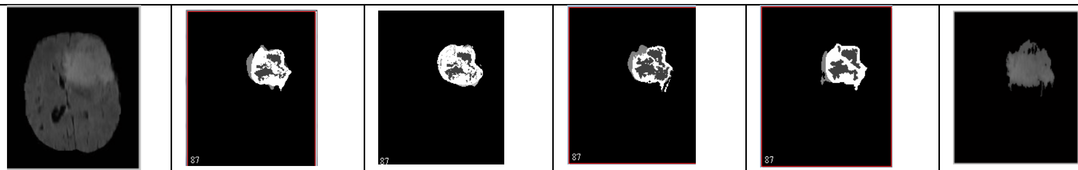
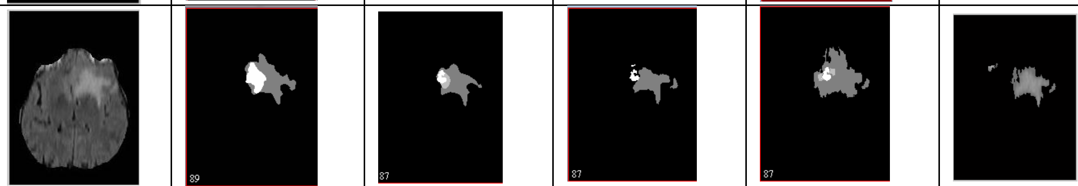
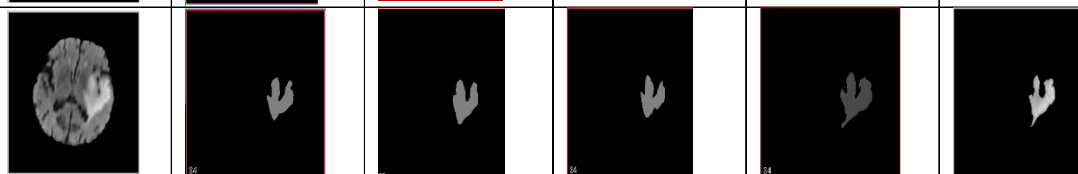
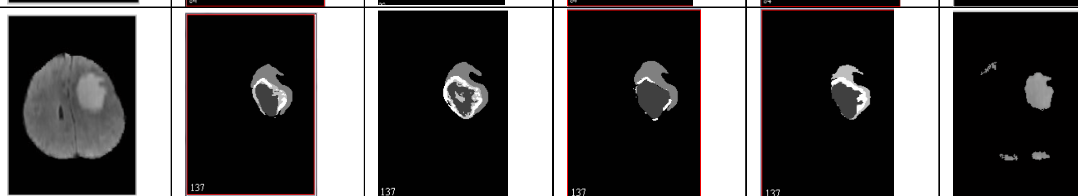
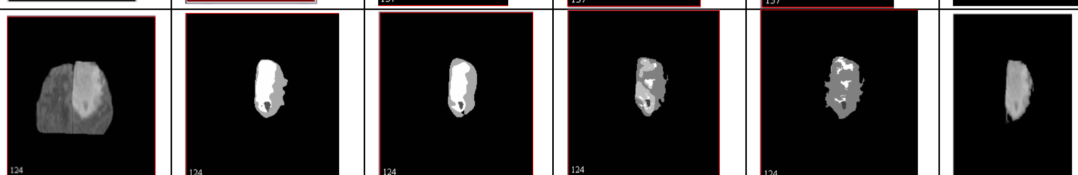
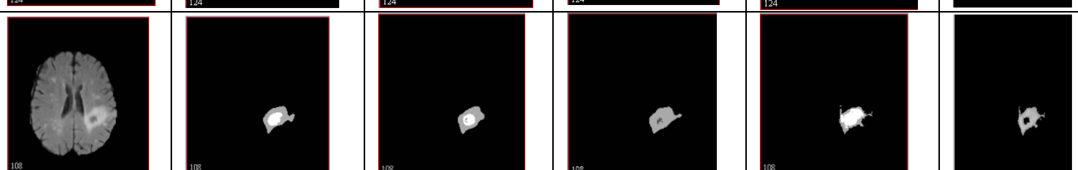
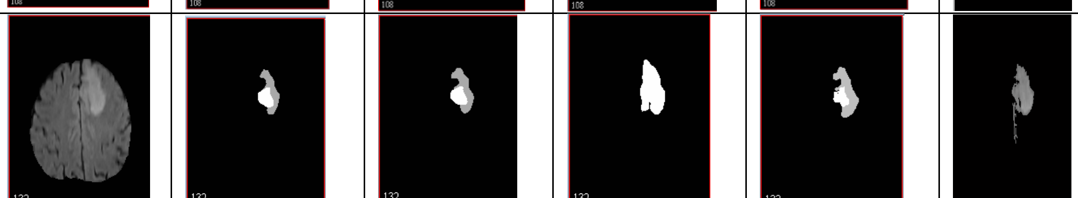
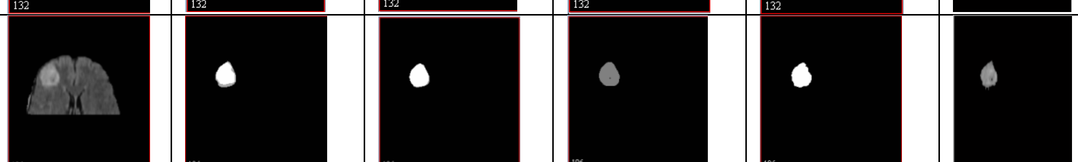
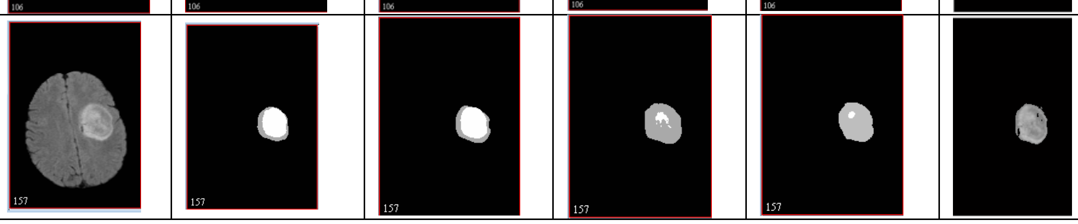
IV. EXPERIMENTAL RESULTS

A. Data Set

Here the BRAST database [16] is used in order to evaluate the performance of the proposed algorithm. The data set have brain MRI of 30 different patients in .mha format. For each case, there are four types of MRI such as T1, T2, FLAR and T1 with contrast enhancement. The proposed algorithm is only concerned with the FLAIR images. The images are opened with MIPAV and converted into .jpg format. The slice which has the better view of tumor is taken as an input to the proposed method.

Case No.	BRATS-12 dataset	Observer ground truth data				Segmented Data (proposed method)	Grade	Result	Matched with
		Observer 1	Observer 2	Observer 3	Observer 4				
1							HG	Fully detected	All 4 observers
2							HG	Fully detected	All 4 observers
3							HG	Fully detected	All 4 observers

4							HG	Fully detected	. Observers 2 and 3.
5							HG	Fully detected	All 4 observers
6							HG	Fully detected	All 4 observers
7							HG	Fully detected	All 4 observers
8							HG	Fully detected	All 4 observers
9							HG	Fully detected	All 4 observers
10							HG	Fully detected	All 4 observers
11							HG	Fully detected	All 4 observers
12							HG	Fully detected	All 4 observers
13							HG	Fully detected	All 4 observers

14		HG	Fully detected	All 4 observers
15		HG	Fully detected	Observers 2 and 3.
16		HG	Fully detected	All 4 observers
17		HG	Fully detected	All 4 observers
18		LG	Fully detected	All 4 observers
19		LG	Fully detected	All 4 observers
20		LG	Fully detected	Observer 3
21		LG	Fully detected	All 4 observers
22		LG	Fully detected	All 4 observers

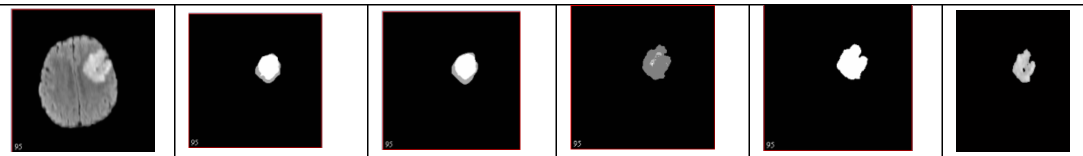
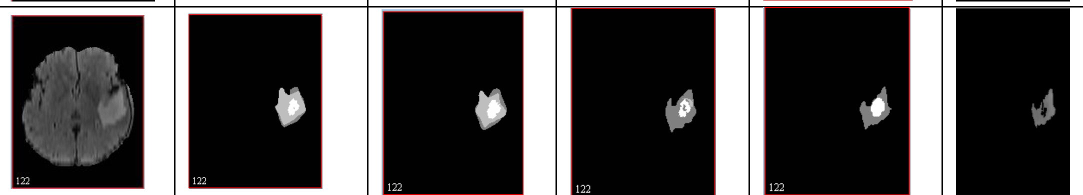
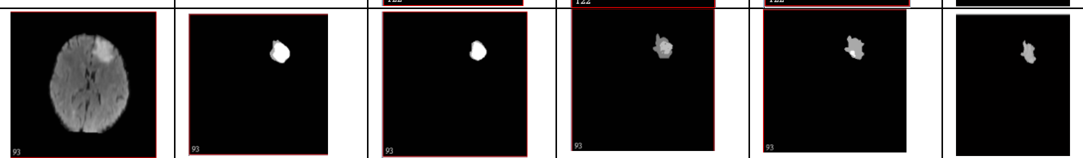
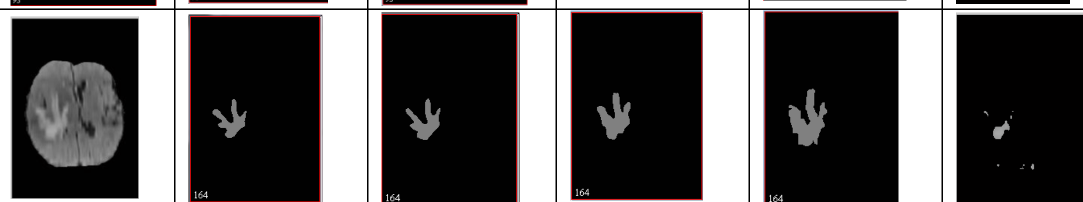
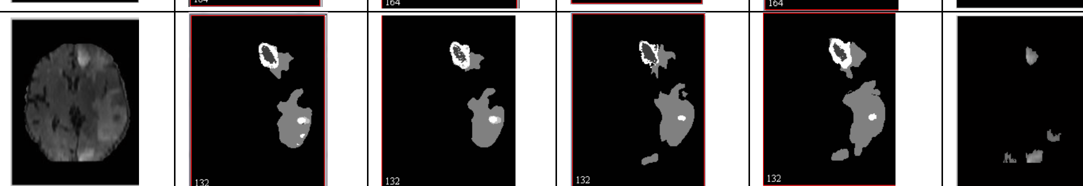
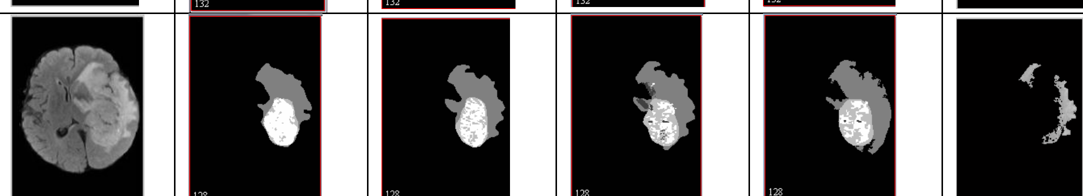
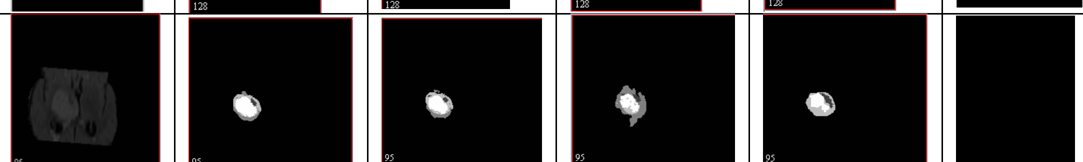
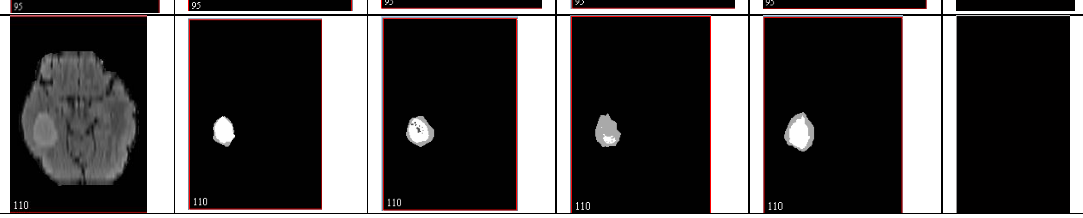
23		LG	Fully detected	All 4 observers
24		LG	Fully detected	All 4 observers
25		LG	Fully detected	All 4 observers
26		HG	Partially detected	No observers
27		HG	Partially detected	No observers
28		HG	Partially detected	No observers
29		LG	Failed	No observers
30		LG	Failed	No observers

Figure 4: Descriptive Test Case Analysis

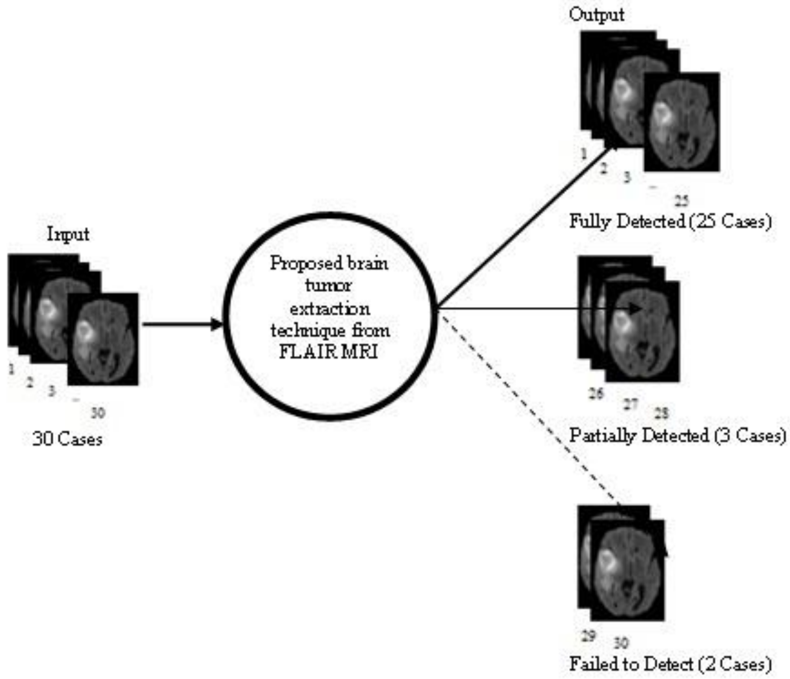


Figure 5: Analytical Results

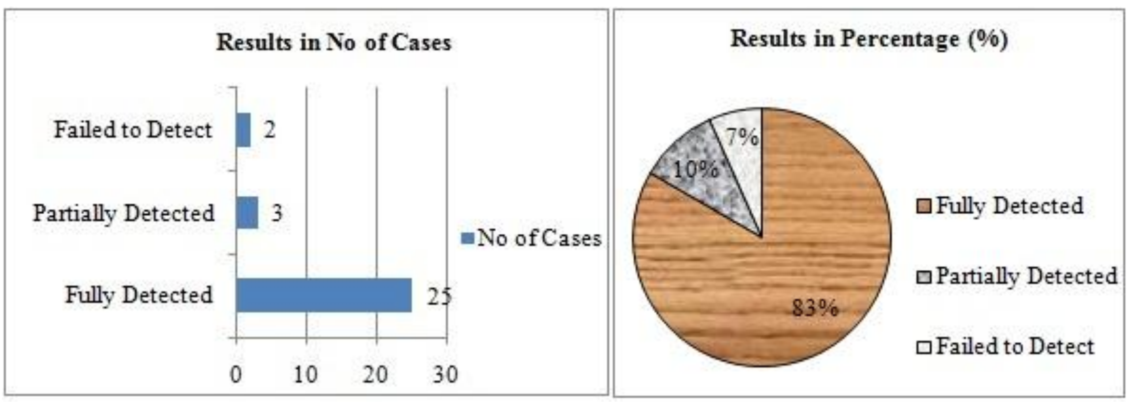


Figure 6: Statistical Results

V. CONCLUSION

An automatic brain tumor edema extraction technique from FLAIR axial slices has been proposed in this work. This technique has overcome the problem of symmetry analysis and thresholding methods as stated earlier. But in some cases the proposed algorithm failed to detect the tumor, such as case 29 and case 30, while for case no 26, 27 and 28 the tumor was partially detected. With full detection and considering the partial detection, the proposed algorithm attained 93% significance success rate. The future work is to try to enhance the algorithm in order to overcome the limitations. On the other hand, the MAXNET architecture has some limitation as it may invoke in an infinite epoch. Some work needs to be done in this field to overcome this difficulty too.

ACKNOWLEDGMENT

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