2012 International Conference on Advanced Computer Science Applications and Technologies

An Improved Image Denoising and Segmentation Approach for Detecting Tumor from 2-D MRI Brain Images

Ahmed Faisal[1], Sharmin Parveen[2]
Dept. of Computer System & Technology
Faculty of Computer Science & Information Technology, University of Malaya
Kuala Lumpur, Malaysia
[1]ahmadprof05@siswa.um.edu.my,
[2]Sharmin@um.edu.my

Shahriar Badsha[3], Hasan Sarwar[4]
[3]Dept. of Electrical Engineering, University of Malaya
Kuala Lumpur, Malaysia
[4] Department of Computer Science and Engineering
United International University
Dhaka, Bangladesh
[3]seul_cse@yahoo.com, [4]mdhasan70@yahoo.com

Abstract— **Image denoising and segmentation are the two most challenging fields in medical image processing particularly when it is application specific. The presence of noise not only degrades the visual quality but also immensely affects the accuracies of segmentation which is essential for medical diagnosis process. In this paper, we present an improved approach for denoising and segmentation of 2-D magnetic resonance brain images for detecting the tumor. We use fourth order partial differential equation based technique for removing MRI noises and thereby applied segmentation using automatic seeded region growing algorithm for detecting brain tumor automatically. The contribution of this work is the use of compass operator to preserve the anatomically significant information at the edges and a new morphological technique for skull removal from the brain MRI image which leads to the process of detecting tumor accurately. The method is tested on several real brain MRI images and it shows 100% success in detecting tumor automatically.**

Keywords- Denoising; segmentation; Magnetic Resonance Imaging; brain tumor.

I. Introduction

Over the last decades the rapid development of medical imaging technology and the introduction of various imaging modalities have transformed the medical image processing domain enormously. The purpose of medical imaging is to capture abnormality in human body such as tumor, cancer, fibroid, cyst, etc. Images are taken by different devices using different modalities, such as Magnetic Resonance Imaging (MRI), X-ray, Computed Tomography (CT) scan, Ultrasound, Positron Emission Tomography (PET), and Electrocardiogram (ECG). Among all the modalities MRI is believed to be very powerful and potential tool to visualize detailed internal structures for accurate measurement of organ anatomy [1]. MRI medical imaging provides good contrast between the different soft tissues. For that reason it is widely used for the diagnosis and treatment of brain tumors. However, MRI images are corrupted by noises during image acquisition. The sources of MRI noise include thermal noise, sample resolution etc. The incorporated noise degrades the image quality and makes obstacle for effective feature extraction, recognition, analysis and quantitative measurements. In medical image processing, it is a fundamental need to facilitate accurate observations to the physicians for proper diagnosis of the given application. Therefore, it is very important to remove the noise from the MRI medical images.

To identify a tumor from brain MRI images includes several steps of image processing. Among them denoising and segmentation plays the important role to detect the tumor from an enhanced image [2]. But there is a contradiction between image denoising and enhancement. Denoising is the process of removing noise from a signal. However doing enhancement followed by removing noise will make the noise amplified making the denoising effect poor. Moreover most existing segmentation algorithms tend to be very sensitive to noise [3]. For this reason it is necessary to first preprocess the MRI data by denoising. There are several algorithms proposed in literature for denoising MRI data namely median filter, winner filter, Gaussian filter, anisotropic-diffusion filter [4]. Although experimental result in shows [5] that fourth order Partial Differential Equations (PDEs) is good choice for denoising MR Images, still more research is needed to modify the PDEs for specific applications.

Another important step in tumor detection is segmentation. Segmentation is the main way of distinguishing the objects from background. For MRI brain image segmentation various methods have been developed namely, fuzzy set theory, mathematical morphology, clustering method, boundary based technique, thresholding, region based method, hybrid technique and so on. Choice of the specified method depends on the particular problem. Even though lots of methods for brain tumor segmentation have already been proposed [6-7], Region based segmentation is a technique for determining the region directly whereas other techniques achieve this goal by looking for the boundaries between regions based on discontinuities in gray levels or color properties [8].

In this paper an improved image denoising and segmentation approach is proposed for detecting brain tumor automatically from MRI datasets. We have modified

978-0-7695-4959-0/13 $25.00 © 2013 IEEE
DOI 10.1109/ACSAT.2012.35

the PDEs by introducing compass operator to have the benefit of preserving the edges from eight different angels. A new approach for skull removal is also applied as part of tumor detection process. An automatic seeded region growing method is applied for detecting the brain tumor automatically. The rest of the paper is organized as follows : In section two detail methodology of the model has been described step by step. Section three presents the experimetal results and discussion. Section four concludes the paper.

II. Methodology

In our study we proposed an robust technique for automatic detection of Brain Tumor form Brain MRI images. The proposed method includes noise removal, skull removal, seed selection, region growing technique, object labeling and image adjustment. In this study we have modified the fourth order PDE in terms of edge preservation and also we have proposed a new skull removal technique using morphological operation. Fig. 1 shows the flow graph of our study.

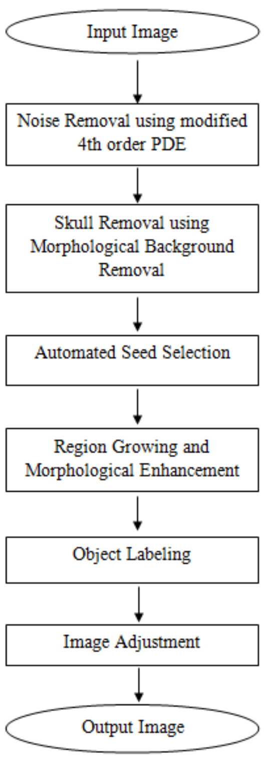


Figure 1: Flow Graph

A. Noise removal using Fourth Order PDE:

Fourth order PDE is already proven to be the best approach for MRI noise removal [9]. In case of edge preservation, the Laplacian operator is used in the fourth order PDE. Here we have used the compass operator replacing the Laplacian operator for edge preservation. As the main focus of this research is to detect the tumor so it is a challenging task to preserve the anatomically significant edges. So in our proposed technique we have implemented and tested the fourth order PDE proposed in [9] with the gradient compass operator. For the proposed approach we have used the compass gradient flow method in terms of the fourth order PDE as follows:

$$\partial I / \partial t = -O_k [C(O_k I) O_k I] \tag{1}$$

where the compass gradient is defined as

$$I(x,y) = \max_K I_K(x,y) \tag{2}$$

In equation 1, O is the operator and k is the direction of the compass of the image *I.* The proposed PDE model attempts to remove noise and preserve edges by approximating an observed image with a piecewise planar image using the compass operator. Using compass operator the image is convolved with various kernels (eight directions, i.e. 0^0, 45^0, 90^0, 135^0, 180^0, 225^0, 270^0, 315^0, 360^0) Fig. 2 shows some example of compass operator.

$$\begin{matrix} -1 & +1 & +1 \\ -1 & -2 & +1 \\ -1 & +1 & +1 \end{matrix} \qquad\qquad \begin{matrix} +1 & +1 & +1 \\ -1 & -2 & +1 \\ -1 & -1 & +1 \end{matrix}$$

(a) (b)

Figure 2: Compass operator- (a) 0^0 (b) 45^0

The compass operator divides an image window in half and compares the two sides to see if they are different. Whereas most edge detectors compute an average value for each side and then compute the Euclidean distance. The compass operator allows multiple values to exist on each side.

Equation (1) is associated with the following functional:

$$E(I) = \int_{\Omega} f(|O_k I|) \partial x \partial y \tag{3}$$

Here Ω is the image support. The global minimum of *E(I)* occurs when

$$|O_k I| = 0 \text{ for all } (x,y) \in \Omega \tag{4}$$

A planar image obviously satisfies 2, hence is a global minimum of E (I) [9]. Planar images are the only global minimum of E (I) if

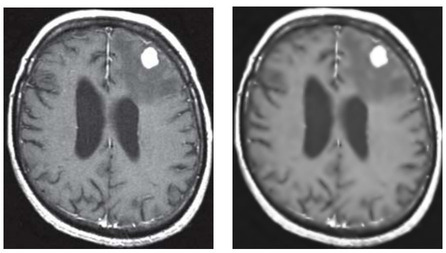
$$E_1(I) = \int_{\Omega} |I_{xx}| + |I_{yy}| dxdy \tag{5}$$

The cost function E (u) is convex under this condition. Until it becomes a planar image the image is increasingly smoothed. The image processed by fourth order PDE will look less blocky than that processed by others anisotropic diffusion or noise removal techniques.

To measure the oscillation of the noisy data we have used the equations (5) and (6):

$$E_1(I) = \int_{\Omega} |I_{xx}| + |I_{yy}| dxdy \tag{6}$$

The main difference between the two functions is that E_2 (I) is a rotational invariant while E_1(I) is not. However the implementation with E_1(I) is more simple for higher dimensional problems. So by applying these processes we can achieve a noise free image shown in Fig. 3.



(a) (b)

Figure 3: (a) Input image (b) denoised smoothed image

B. Skull removal:

Skull removal is necessary because the intensity of the skull and the tumor is almost same. Thats why if we do not remove skull first then it will be difficult to differentiate the tumor and skull. For the skull removal we have implemented the background removal technique using morphological operation. For the first step we have implemented the opening i.e erosion followed by dilation.

Considering an image *f(x)* and the structuring function *b(x)*, the grayscale dilation is as follows.

$$(f \oplus b)(x) = \sup_{y \in E} [f(y) + b(x - y)] \tag{7}$$

Hence equation (8) shows the opening operation

$$X(i, j) = f \circ b = (f \Theta b) \oplus b \tag{8}$$

Fig. 4 shows the structuring element that we have exhaustively used for this operation for all images.

0	**0**	**1**	**1**	**1**	**1**	**1**	**1**	**0**	**0**
0	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**0**
1	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**
1	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**
1	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**
1	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**
1	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**
0	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**0**
0	**0**	**1**	**1**	**1**	**1**	**1**	**1**	**0**	**0**

Figure 4: 9x9 Structuring Element

Now from equation (9) we can get the skull of the brain image

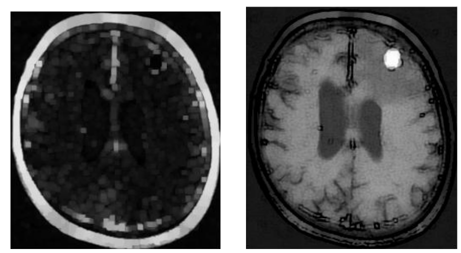
$$Y(i, j) = f(i, j) - X(i, j) \tag{9}$$

Using 5x5 small structuring element the skull is dilated lighter which is expressed in equation (10). It helps to remove the skull totally from the input image.

$$Z(i, j) = y(i, j) \oplus c = \{z \mid (c^{\wedge})_z \cap f \neq \phi\} \tag{10}$$

Finally the image at Fig. 5(b) is obtained from equation (11).

$$I(i, j) = f(i, j) - Z(i, j) \tag{11}$$



(a) (b)

Figure 5: (a) Image with skull (b) Skull removed image

C. Automatic Seed point Selection

The image obtained after skull removal is taken as input in this part of our study. In our proposed approach the seed point is selected automatically rather than the manual selection. The tumor region will grow accordingly to the shape of the tumor once the seed point is automatically selected. The algorithm flow of seed point selection process is as follows:

1. Declare an integer variable pixelcount
   Declare an integer variable pixelcount1
2. Count the number of pixel which intensities are less than 100 and greater than 100 (by exhaustive search optimal value is chosen).
   IF Pixelcount<100 THEN
   pixelcount=Pixelcount+ 1;//counting pixel
   ELSE
   pixelcount1=pixelcount1+ 1
   ENDIF
3. Declare an integer variable A
   A:= Pixelcount-pixelcount1;// the differences
   IF A=0 THEN
   then Continue
   ELSE
   A=-A;
   ENDIF

4. Set the intensity of the external part of Brain to 0;
5. T:=The threshold of current gray image I
6. I1:= Convert binary(I, T);
7. M<-Maximum Length of Brain Part containing Intensity 1 from image I1;
8. B<- Maximum Breadth of brain Part contains

Intensity 1 from image I1;

9. Rows:=Total number of image row;
10. Columns:=Total number of image columns;
11. Seed point= $Rows \cap Columns$.

D. Region Growing and Morphological Operation:

This technique is a region-based image segmentation method. As it involves the selection of initial seed points so this is also classified as a pixel-based image segmentation method.

An initial set of small areas are iteratively merged according to similarity constraints. Start by choosing an arbitrary *seed pixel* and compare it with neighbouring pixels. Region is *grown* from the seed pixel by adding in neighbouring pixels that are similar, increasing the size of the region. When the growth of one region stops we simply choose another seed pixel which does not yet belong to any region and start again. This whole process is continued until all pixels belong to some region.

The main goal of this process is to partition an image into regions. Some segmentation methods achieve it by searching the boundaries between regions based on discontinuities in gray levels or color properties. The basic formulation for Region-Based Segmentation is:

- $\bigcup_{i=1}^{n} R_i = R$
- R_i is a connected region, $i = 1,2,3...,n$
- $R_i \bigcap R_j = \phi$ for all $i = 1,2,3,..., n$
- $P(R_i) = \text{True}$ for $i = 1,2,3...,n$
- $P(R_i \cup R_j) = \text{False}$ for any adjucent region R_i and R_j. $P(R_i)$ is a logical predicate defined overthe points set $P(R_k)$ and ϕ is the null set.

After region growing we need to apply morphological operation to dilate the image so that the tumor can be visible clearly and shraply. The dilation operation is one of the mathematical morphology used to make good shape on geometrical structures. This is also almost same like grayscale dilation stated in equation (10) though it is on binary image. Equation (12) shows the dilation operation on binary image. In binary morphological operation the structuring element is also used. Here we used a small 1x1 DISK shape structuring element [10].

$$I(i,j) \oplus B = \{z \in E \,||\, (B^s)_z \cap I \neq \phi\} \quad (12)$$

Where B is the structuring element. E is an Euclidean space or an integer grid. B^s denotes the symmetric of B. We get the binarized image after applying region growing as shown in Fig. 6.

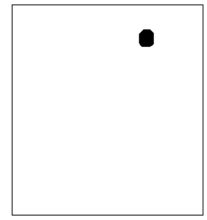


Figure 6: Binarized image

E. Object Labeling:

For labeling the objects in image the essential factor is neighborhood that may affects the number of objects found in an image. There are two types of neighborhood to label the binary image shown in Fig. 7. The main steps of this process are stated below.

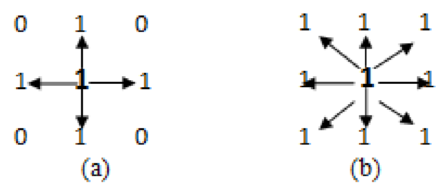


Figure 7: (a) 4-connectivity (b) 8-connectivity

1. If p denotes the pixel to be labeled then the 8-connectivity operator scans the image along row wise, column wise and diagonally until it gets the point p for which the intensity $v=\{1\}$.

   Assign a new label to p if all neighbors are 0

   Assign its label to p if $v=\{1\}$

   Assign one of the labels to p if more than one of the labels have $v=\{1\}$.

2. The equivalent pairs of labels are combined into equivalence class and new label is assigned.

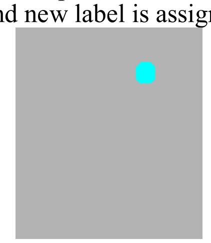


Figure 8: Labeled image

F. Image Adjustment and Final output:

After labeling the image we can detect the position of the tumor which also reflects the position of the tumor from the original image. But the contrast of the images is still low to observe by the physician. That's why in our method we have added a simple contrast adjustment technique for better output. This image adjustment method increases the global contrast, especially when the usable data of the image is represented by close contrast values. In the histogram the intensities can be better distributed. From this technique we can get higher contrast data from the low contrast [11].

As our final output is on grayscale image so considering a grayscale image g

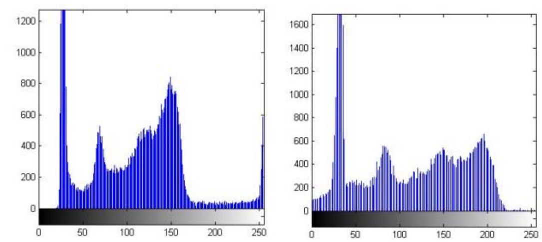
$$y' = y.(\max\{g\} - \min\{g\}) + \min\{g\} \tag{13}$$

Where

$$y = T(g) = cdf(g) \tag{14}$$

Cdf is the Cumulative Distribution Function

Fig. 9 shows the original image histogram and equalized histogram



(a) (b)

Figure 9: (a)Histogram of original image (b) Histogram equalized

Finally we get the enhanced brain image with tumor detected shown in Fig. 10

Figure 10: Final enhanced image with tumor

G. Result and Performance Analysis:

The proposed model is tested on ten brain tumor images which is available in online medical database [12]. The images contain 8 bit per channel. The performance evaluation and comparison are carried out based on the two measures. One is PSNR at the step of noise removal and another is accuracy in terms of detection of tumors from brain MRI images which is verified by physician. In literatures PSNR calculation is carried out by adding noise into image but we have used ten brain MRI images of different resolutions ranges from 252x289-383x500 with noise to do our experiment. The PSNR we achieved shows as good as standard result. For noise removal the standard range of PSNR is 20-50 dB [13] and higher the PSNR, higher the efficiency of noise removal. So we have calculated the PSNR between the original image and noise free image using equation (19).

$$\mathrm{PSNR} = 10\log_{10}\left(\frac{\mathrm{MAX}_I^2}{\mathrm{MSE}}\right) \tag{15}$$

$$= 20\log_{10}\left(\frac{\mathrm{MAX}_I}{\sqrt{\mathrm{MSE}}}\right)$$

$$= 20\log_{10}(\mathrm{MAX}_I) - 10\log_{10}(\mathrm{MSE}) \tag{16}$$

Where,

$$\mathrm{MSE} = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[I(i,j) - k(i,j)]^2$$

Table 1 shows the PSNR of the images and the average PSNR of 36.49 shows that the noise removing technique is quite powerful and good in our study.

Table 1 : PSNR calculation

Image	PSNR
1	36.51
2	36.44
3	37.49
4	35.89
5	36.77
6	39.26
7	36.45
8.	35.63
9.	34.78
10.	35.74
Average	**36.49**

In case of confirming the accuracy of tumor detection we have taken expert opinion of the output image by doctors. The accuracy is computed by the ratio of the total number of correctly detected tumor to the number of total tumors from the images. Hence our technique shows 100% accuracy in terms of tumor detection. Fig. 11 shows some samples of original images and tumor detected images obtained by using the proposed method.

III. Conclusion

In this paper a robust automatic method for brain tumor detection is presented with modified fourth order PDE for denoising the brain MRI images. A new skull removal technique is also proposed which removes the skull successfully. We have tested our method on several Brain MRI images and it gives good PSNR result in terms of noise removal and 100% accuracy in terms of detecting tumor automatically.

Our future work of this study is to carry out a novel automatic multiple seed selection technique and classify the brain tumors using SVM (Support Vector Machine) or Neural Network classifier.

References:

[1] Shen, S., Sandham, W., Granat, M., Sterr, A., "MRI fuzzy segmentation of brain tissue using neighborhood attraction with neural network optimization" *IEEE transaction on Information Technology in Biomedicine*, vol. 9, 2005, pp. 459-467.

[2] Idanis Diaz, Pierre Boulanger, Russell Griener and Albert Murtha, "A Critical Review of the Effects of Denoising Algorithms on MRI Brain Tumor Segmentation" *33rd Annual International Conference of the IEEE EMBS*, Boston, Massachusetts USA, August 30-September 3, 2011.

[3] H. S. Prashanta, Dr. Shahidhara. H.L. Dr. K.N.B. Murthy Madhavi Lata. G. "Medical Image Segmentation" (IJCSE) international *Journal on Computer Science and Engineering*, Vol. 02, 2010, No. 04, 1209-1218.

[4] K Krajsek, R Mester,"The edge preserving winer filter for scalar and tensor valued image*", DAGIM*, pp. 91-100, 2006.

[5] Yu-Li You and M. Kaveh, "Fourth order partial differential equations for noise removal*," IEEE Trans. Image Processing*, vol. 9, no. 10, 2000, pp 1723-1730.

[6] Kaus, M.R., Warfield, S.K., Nabavi, A., Black, P.M., Jolsez, F.A., Kikinis, R., "Automated segmentation of MR images of brain tumors", *Radiology*, vol. 218, , 2001, pp, 586-591.

[7] Clark, M.C., Hall, L.O., Goldgof, D.B., Velthuizen, R., Reed Murtagh, F., Silbiger, M.S., "Automatic tumor segmentation using knowledge-based techniques", *IEEE Transaction on Medical Imaging*, vol. 17, pp. 187-201.

[8] Yu-Li You, Wenguan Xu, Allen Tannenbaum and Mostafa Kaveh, "Behavioral analysis of anisotropic diffusion in image processing," *IEEE Trans. Image Processing*, vol. 5, no. 11, 1996, pp 1539-1553.

[9] Marius Lysaker, Arvid Lundervold and Xue-Cheng Tai, "Noise removal using fourth order partial differential equation with applications to medical magnetic resonance images in space and time", *IEEE Transactions on Image Processing*, VOL. 12, NO. 12, December, 2003.

[10] Rafael C. Gonzalez, Richard E. Woods, "Digital Image Processing", ISBN-10: 013168728X.

[11] A. Beghdadi, A. Le Negrate, "Contrast enhancement Technique Based on the Local Detection of Edges", *Computer Vision Graphics and Image Processing*, 46, 1989, 162-174.

[12] http://www.imageprocessingplace.com/root_files_V3/image_databases.htm. Online, Access date: 15 Oct. 2012.

[13] Bo Chen, Jin-Lin Cai, Wen-Sheng Chen, and Yan Li, "A Multiplicative Noise Removal Approach Based on, Partial Differential Equation Model", *Mathematical Problems in Engineering*, Volume 2012, March 2012(accepted).

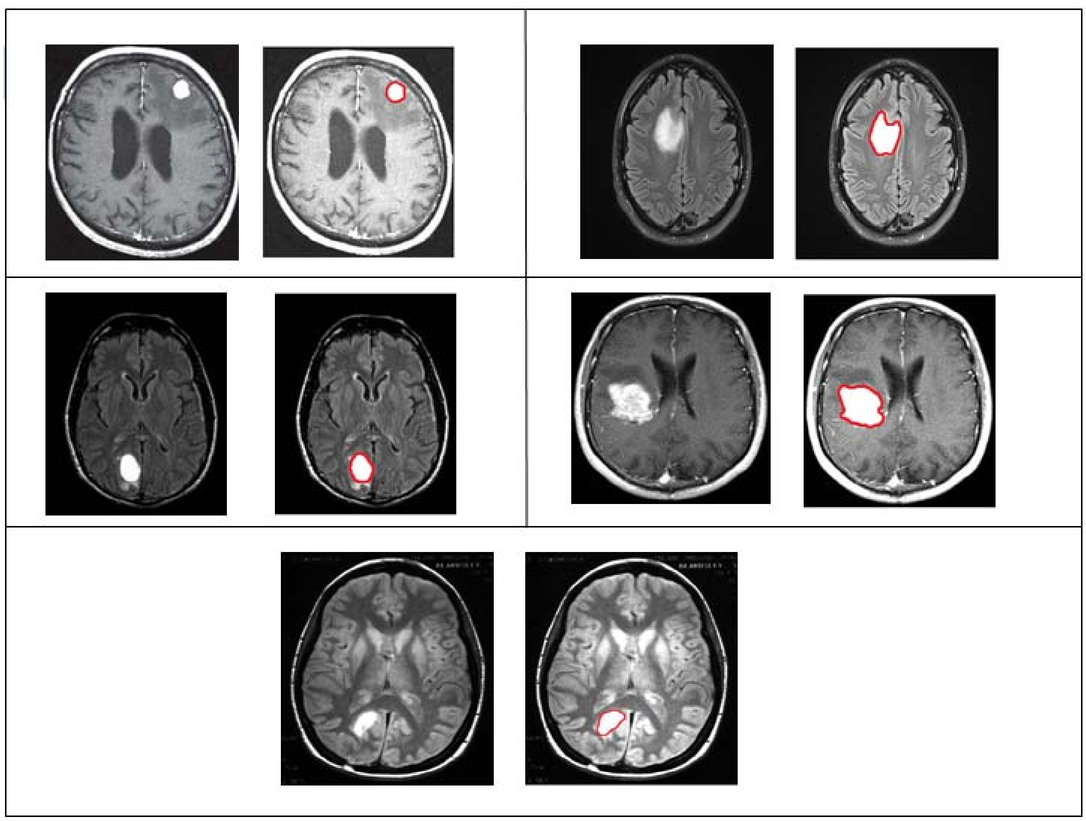


Figure 11: Original MRI Image and Brain tumor detected enhanced image.