

Improved Brain Tumor Detection Using Object Based Segmentation

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ABSTRACT - This paper has focused on the brain tumor detection techniques. The brain tumor detection is a very important vision application in the medical field. This work has firstly presented a review on various well known techniques for automatic segmentation of heterogeneous image data that takes a step toward bridging the gap between bottom-up affinity-based segmentation methods and top-down generative model based approaches. The main objective of the work is to explore various techniques to detect brain tumor in an efficient way. It has been found that the most of existing methods has ignored the poor quality images like images with noise or poor brightness. Also the most of the existing work on tumor detection has neglected the use of object based segmentation. So to overcome the limitations of earlier work a new technique has been proposed in this research work. The technique has shown quite effective results than neural based tumor detection technique. The design and implementation of the proposed algorithm is done in MATLAB using image processing toolbox. The comparison has shown that the proposed technique has achieved up to 94 % accuracy which was 78 % in neural based technique. Also for high corrupted noisy images the proposed technique has shown quite effective results than the neural based tumor detection.

KEY WORDS: Brain Tumor, Segmentation, Object Detection, Neural Network.

1. INTRODUCTION

Image segmentation is the process of partitioning a digital image into multiple segments (sets of pixels, also known as superpixels). The aim of segmentation is to make simpler and/or modify the representation of an image into something that is more meaningful and easier to analyze. Image segmentation is normally used to place objects and boundaries (lines, curves, etc.) in images. More precisely, image segmentation is the method of conveying a label to each pixel in an image such that pixels with the similar label divide certain visual characteristics.

MRI Images of brain tumor cannot exactly denote the position of brain tumor, so to find the exact position of tumor in the

MRI image preprocessing, segmentation, morphological operation and subtraction are used. This gives the exact shape of the tumor in that MRI image and finally detection of brain tumor in MRI images is achieved.

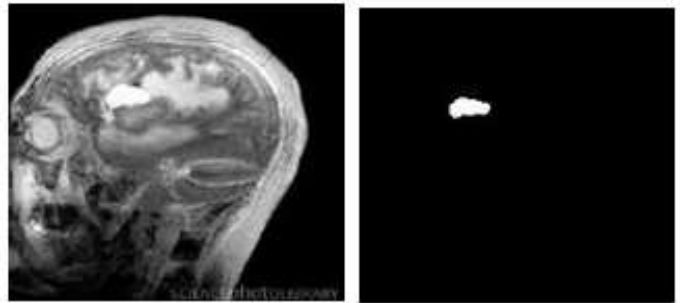


Fig. 1 left: original image, right: Segmented image

The outcome of image segmentation is a set of segments that jointly wrap the whole image, or a set of contours extracted from the image (see edge detection). All of the pixels in a area are comparable with respect to a few characteristic or computed property, such as color, intensity, or texture. Neighbouring areas are considerably dissimilar with respect to the similar characteristic(s). While useful to a heap of images, typical in medical imaging, the resultant contours following image segmentation can be used to generate 3D reconstructions with the help of exclamation algorithms like Marching cubes.

1.2 BRAIN TUMOR

A brain tumor or brain tumour, is an intracranial solid neoplasm, a tumor (defined as an abnormal growth of cells) within the brain or the central spinal canal. Some tumors are brain cancers. Brain tumors include all tumors inside the human skull (cranium) or in the central spinal canal. They are produced by an irregular and unrestrained cell division, typically in the brain itself, but also in lymphatic tissue, in blood vessels, in the cranial nerves, in the brain envelopes (meninges), skull, pituitary gland, or pineal gland. Within the brain itself, the involved cells may be neurons or glial cells (which include astrocytes, oligodendrocytes, and ependymal cells). Brain tumors may also spread from cancers primarily

located in other organs (metastatic tumors). Any brain tumor is inherently serious and life-threatening because of its invasive and infiltrative character in the limited space of the intracranial cavity. Though, brain tumors are not consistently incurable, particularly lipomas which are intrinsically kind. Brain tumors or intracranial neoplasms can be cancerous (wicked) or non-cancerous (incurable); though, the definitions of malignant or benign neoplasms differs from those generally used in other types of cancerous or non-cancerous neoplasms in the body. Its danger level depends on the grouping of factors like the form of tumor, its place, its dimension and its condition of growth. Since the brain is fine confined by the head, the early on discovery of a brain tumor occurs just while diagnostic equipment is focussed at the intracranial cavity. Main brain tumors are usually situated in the posterior cranial fossa in children and in the frontal two-thirds of the cerebral hemispheres in adults, though they can influence any fraction of the brain. Visibility of cipher and symptoms of brain tumors mostly depends on two factors: the tumor dimension (quantity) and tumor place.

1.3 BRAIN TUMOUR TECHNIQUES: There are five main techniques for brain tumour detection as given follows:

1.3.1 Tumor detection using Active Contour: The technique is based on active contours evolving in time according to intrinsic geometric measures of the image. The developing contours naturally crack and combine, allowing the concurrent discovery of some objects and both interior and exterior limits. This approach is based on the relation between active contours and the computation of geodesics or minimal distance curves. This geodesic approach for object segmentation allows connecting classical “snakes” based on energy minimization and geometric active contours based on the theory of curve evolution. Experimental results of applying the method to actual images together with objects with holes and medical data imagery reveal its influence. The results may be extended to 3D object segmentation as well.

1.3.2 Based on Region Growing: Region growing is a simple region-based image segmentation method. It is too classified as a pixel-based image segmentation method as it involves the collection of original seed points. This approach to segmentation examines closest pixels of initial “seed points” and determines whether the pixel neighbours should be supplementary to the area. The method is iterated on, in the similar way as common data clustering algorithms.

$$\text{Initialseed} = (x_i, y_i) = \arg \min_{(x,y)} (|w(x,y) - \text{mean}_w|)$$

The pixel value within the window having a minimum deviation from the mean is selected as the single initial seed for growing the car. The region is grown using the conventional region growing with the initial seed (x_i, y_i) computed.



Fig 2. left: Original image, right: segmented image

Read the input image and convert it to gray. Consider a centre window w of size 20×20 which contains some parts of the object, in this case, the car. The difference between the median of the pixel values in the window and the mean pixel value is selected as the threshold. The pixel value within the window having a minimum deviation from the mean is selected as the single initial seed for growing the car. The region is grown using the conventional region growing algorithm with the initial seed (x_i, y_i) computed and threshold T determined. Find the nearest edge to each pixel in the grown region with the Canny edge detector being the popular choice for a robust, strong edge detector giving strong connected edges. The Euclidean distance norm is used to compute the nearest edge pixel for every pixel in the grown region. The set of nearest edge pixels for the region grown.

1.3.3 Using Watershed Segmentation: A watershed is a basin-like landform defined by highpoints and ridgelines that descend into lower elevations and stream valleys. A grey-level image may be seen as a topographic relief, where the grey level of a pixel is interpreted as its altitude in the relief. A drop of water falling on a topographic relief flows along a path to finally reach a local minimum. Intuitively, the watershed of assistance corresponds to the confines of the adjacent catchment basins of the drops of stream. In image processing, different watershed lines may be computed. In graphs, some may be defined on the nodes, on the edges, or hybrid lines on both nodes and edges. There are also a lot of dissimilar algorithms to calculate watersheds. Used for a segmentation purpose, the gradient magnitude (i.e., the length of the gradient vectors) is interpreted as altitude information.

If $f(x, y)$ is an image, then the gradient vector magnitude and the angle at which maximum rate of change of intensity level occurs for the image can be computed using the following two equations.

$$g(x, y) = \sqrt{g_1^2(x, y) + g_2^2(x, y)}$$

$$\alpha(x, y) = \tan^{-1} \left(\frac{g_2(x, y)}{g_1(x, y)} \right)$$

Where $g_1(x, y)$ and $g_2(x, y)$ are the gradients in the x, y direction of the image. The magnitude of the gradient can be achieved by using sobel mask

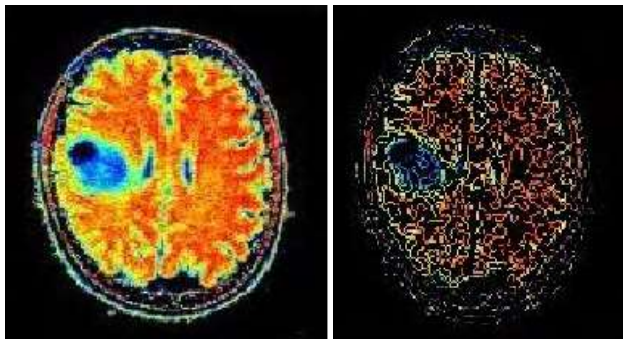


Fig.3 left: original image, right: watershed segmented image
From the above fig. it can be seen that the algorithm has performed well to detect the brain tumor. Tumor region can be detected effectively with the help of watershed algorithm, but after applying the canny operator the tumor portion is detected more accurately

1.3.4 Using neural network: Artificial neural networks (ANNs) are non-linear data driven self adaptive approach as opposed to the traditional model based methods. They are influential equipment for modeling, particularly while the fundamental data relationship is unknown. An extremely important characteristic of these networks is their adaptive character, where “learning by example” replaces “programming” in solving problems. This feature makes such computational models very appealing in application domains where one has little or incomplete understanding of the problem to be solved but where training data is readily available. The intensity, shape deformation, symmetry, and texture characters were extracted from every image. The AdaBoost classifier was used to choose the mainly discriminative character and to segment the tumor region. Multi-modal MR images with simulated tumor have been used as the ground truth for training and validation of the detection method.

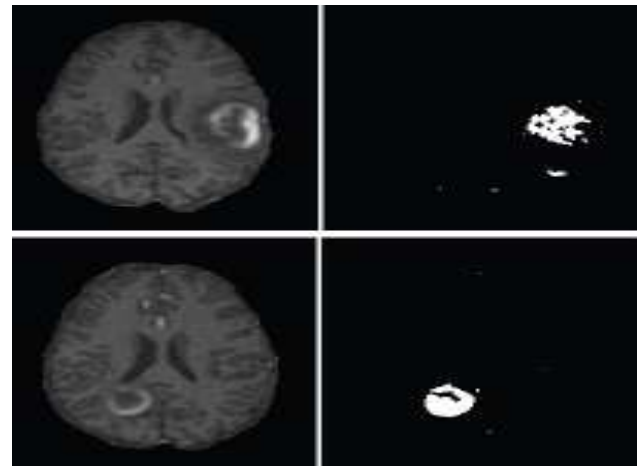


Fig.4 left: original image, right: segmented image

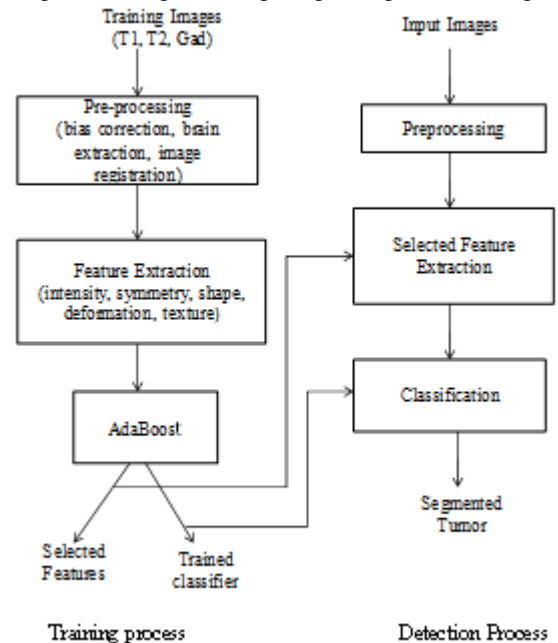


Figure 5: Block diagram of Automatic detection using neural network

The images were pre-processed as aforementioned and the four types of features were extracted from the images to be used as the training data set for the classification. A leave-one-out validation was performed on the images. The result of the tumor detection and the ground truth are shown in the above Figure.

Equation used by this technique is given as:

$$e(x, y, z) = \frac{1}{M^2} \sum_{(x!, y!, z!) \in W} |\Psi(f(x!, y!, z!))|$$

Where $(f(x, y, z))$ is the Gabor-filtered image, $\Psi(t) = \tanh(\alpha t)$ is the nonlinear transformation. The value of nonlinearity parameter, α , is set to 0.25 which causes the transformation to

behave as a blob detector. The size of the window, M , is calculated based on the Gabor filter frequency.

The workflow of this method is shown in the figure 5. Each MRI in the training set is first pre-processed to minimize the intensity bias and to remove the non-brain tissue. The preprocessing also includes multi-modality within-subject registration and co-registration to a standard template for cross subject comparison.

Next, four types of features (i.e., intensity, symmetry, shape deformation, and texture features) are extracted from the pre-processed images. Feature selection and fusion are performed using AdaBoost. For new subjects, only the selected features computed in the training process will be extracted and tumor will be detected using the trained classifier.

1.3.5 Brain Tumor Detection and Segmentation Using Histogram Thresholding:

The concept is based mainly on three points: (i) the symmetrical structure of the brain, (ii) pixel intensity of image and (ii) binary image conversion. It is a well known detail that human brain is regular about its central axis and all through it has been supposed that the tumor is moreover on the left or on the right side of the brain. MR image of the human brain can be divided into sub region such that white matter, gray matter, blood cells and cerebrospinal fluid can be easily detected. Tumor is nothing but the collection of blood cells at some specific point/s. The image of a brain in MRI is represented through pixel intensity. In gray color images the intensity lies between 0-255 with 0 indicating for black and 255 is assigned for the white color. The blood cells (RED color in RGB) are represented by white color and 255 pixel intensity. All the gray matter is having pixel intensity less than 255.

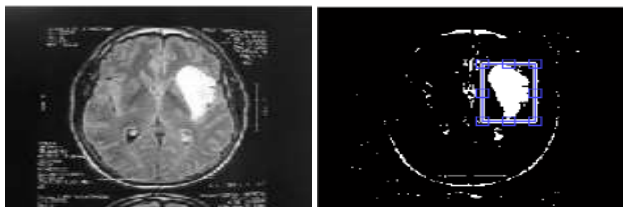


Figure 6: (a) Original Image (b) Cropped Image

Area of an image is the total number of the pixels present in the area which can be calculated by multiplying the number of pixels with the length of one pixel. To calculate the number of pixels in the cropped image the function **Bwarea()** is used. This function calculates the number pixels present in the image. A right click on the image and exploring the detail property will provide the following detail of the image:

- Size of image, e.g., 600X400
- Horizontal resolution, e.g., 96 dpi.
- Vertical resolution, e.g., 96 dpi

From the horizontal and vertical resolution one can find the dimension of a single pixel. The algorithm used is follows: There are 96 pixels in one inch. Hence vertical dimension of a pixel is 1/96 inch. Similarly horizontal dimension of a single pixel is 1/96 inch. Area of single pixel is equal to $(1/96)*(1/96)$ square inch.

$$A = (1/96)*(1/96)$$

$$\text{Area of the tumor} = A * \text{total}$$

The flowchart below depicts the stages of the work using Histogram Thresholding brain tumor detection.

2. LITERATURE SURVEY

Kharrat et al. (2009) [1] introduces an proficient detection of brain tumor from analytical MRI images. It consists of three steps: enhancement, segmentation and classification. To recover the superiority of images and bound the threat of different regions fusion in the segmentation phase an enhancement process is applied. Then Wavelet Transform is applied in the segmentation method to decompose MRI images. At very last, the k-means algorithm is implemented to take out the suspicious regions or tumors. Somasundaram and Kalaiselvi (2010) [2] described a method to sense the tumor from magnetic resonance imaging brain scans. Generally tumors reside in the normal tissues and their intensity characteristics vary from the neighboring normal tissues. At first it extracts the brain by removing the useless non-brain regions like skull, scalp, fat and muscles. After that the brain is segmented into well-known regions. In T2 scans the tumor intensity characteristics are parallel to CSF. Then this CSF class is analyzed for symmetric property along the middle vertical line. Bourouis and Hamrouni (2011) [3] described that specific demarcation of brain Tumor in MRI is a challenging problem due to the inconsistency of tumor geometry, appearance properties and the resemblance between tumor and normal tissue. Automating the method of segmentation is another challenge because manual segmentation is a mostly time-consuming task. Popuri et al. (2011) [4] described that automatic tumor segmentation from MRI data is a mainly demanding job. In adding, an increasing tumor can too turn aside and distort close to tissue. It uses the existing MRI modalities (T1, T1c, T2) and their quality characteristics to build a multidimensional facet set. After that, it extracts clusters which offer a compressed demonstration of the important information in these features. Gao and Yang (2012) [5] discussed that a new saliency-seeded active contour based

automatic natural object segmentation technique. The salient object points are in use as the seeds of curved hull to produce the original contour for our automatic object Segmentation system.. Joung et al. (2012) [6] described that object recognition and segmentation method utilize an inpainting method. Inpainting is a concept of improving absent picture regions based on their environment, which were initially used for re-establishment of spoiled painting. By means of measuring the resemblance between the inpainted area and the original image area, this approach filters out fake detections whereas maintaining right object detections. Susan et al. (2012) [7] explained that Region growing is a fine recognized technique for image segmentation. Though it suffers as of definite restrictions such as uncertainty about initial seed collection and threshold determination for region growing. The possibility of using region growing technique for segmenting out the foreground object and recommend to solve the damaged consequences by incorporate the adjacent edge information. Parisot et al. (2012) [8] explained that new technique for detection, segmentation and characterization of brain tumor. Towards most favourable use of prior information, a two layer organized graph is measured with one layer equivalent to the low-grade glioma type (description) and the next layer to voxel-based decisions of tumor occurrence. Han et al. (2012) [9] discussed that an object segmentation method to take out the identical object as of images that are captured from unlike views. By means of matting method, the target object easily segmented with effortless strokes given by a user to the preferred object and backdrop in the reference figure. After that, homography is predictable after keypoint matching between the segmented object image and the target image, which is acquired from a dissimilar point of view, containing the identical object. Bhattacharjee and Chakraborty (2012) [10] explained that algorithm is developed to trait out tumor from unhealthy brain Magnetic Resonance (MR) imagery. This is based on quality factor contrast of two filters, adaptive median filter is chosen for de-noising the imagery. Picture slicing and recognition of important planes are completed. It verifies the individual efficiency of the developed picture processing algorithm to identify brain tumor. Kenkre et al. (2012) [11] described that medicinal Image Processing is a difficult and demanding field these days. Processing of MRI imagery is one of the parts of this meadow. It proposes a policy for well-organized detection of a brain tumor in MRI brain imagery. The method consists of the following steps: preprocessing by means of sharpening and mean filters, improvement of picture is performed by histogram equalization, segmentation of the picture is performed by thresholding. Then it is followed by the additional application of morphological operations. At last the

tumor section can be obtained with the method of image subtraction. Kowar and Yadav (2012) [12] explained that the information of size of a tumor plays an vital role in the treatment of spiteful tumors. Manual segmentation of brain tumors as of Magnetic Resonance images is a demanding and time consuming job. This Li et al. (2012) [13] discussed that Automatic detection of brain tumor is a complex job due to variations in type, size, location and shape of tumors. In this, a multi-modality structure for automatic tumor detection is offered, fusing dissimilar Magnetic Resonance Imaging modalities including T1-weighted, T2-weighted, and T1 with gadolinium contrast agent. The amount, outline deformation, regularity, and consistency features were extracted from every picture. Dahab et al. (2012) [14] discussed that customized image segmentation techniques were applied on MRI scan images to sense brain tumors. A modified Probabilistic Neural Network (PNN) model based on learning vector quantization (LVQ) with picture and data examination and manipulation techniques is carried out an automated brain tumor categorization using MRI-scans. Kanimozhi and Dhanalakshmi (2013) [15] described that a simple algorithm for detecting the variety and outline of tumor in brain MR imagery is described. Normally, CT scan or MRI that is going to into intracranial cavity produces a entire image of brain. To keep away from that, it uses computer aided technique for segmentation (detection) of brain tumor based on the grouping of two algorithms. At the ending of the procedure the tumor is extracted from the MR image and its accurate location and the outline too determined. The period of the tumor is displayed based on the quantity of region calculated from the cluster.

3. Proposed algorithm

The most of existing methods has ignored the poor quality images like images with noise or poor brightness. Most of the existing researchers have neglected the use of object based segmentation; to detect tumors in brain. Neural network based brain tumor detection may provide better results; but due to training and testing phase it will comes up with some potential overheads i.e. poor in case of time complexity. The brain tumor detection is a very important application of medical image processing. The literature survey has shown that the most of existing methods has ignored the poor quality images like images with noise or poor brightness. Also the most of the existing work on tumor detection has neglected the use of object based segmentation. The overall goal of this research work is to propose an efficient brain tumor detection using the object detection and roundness metric. To enhance the tumor detection rate further we have integrated the proposed object based tumor detection with the decision based median filter.

ALGORITHM-1

```

Step 1: Read the input Brain image.
Step 2: Apply Decision based median filter. Using the
        algorithm 2
Step 3: Locate Brain
        for i = 1 : N,
            a = sum ( sum( L==i) );
            if a>maxa,
maxa=a;
maxi=i;
end
end

Step 4: Locate Centroid of brain using region properties

        if STATS.orientation <0,
            M = imrotate(L, -90
                - STATS.Orientation );
            I =
            Imrotate(I,-90 - STATS.Orientation );
        else
            M = imrotate(I, 90 - STATS.Orientation);
            I = imrotate(I, 90 - STATS.Orientation);
        end

Step 5: Divide image into various segments.
Step 6: Find largest segment using the following
        equations
        if m left > m right
            left x1 = 2* mid x-right x
            rightx1 = 2* mid x- left x
            left x = left x1
            right x = right x1
            isleft =1
        end

Step 7: Apply bounding box on detected segment.
Step 8: End.
    
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ALGORITHM-2

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Step 1: Select image from computer memory into existing
        program and Read Noisy Image.

Step 2: Set initial window of size 3x3. Take centre pixel
        P(m,n,k) of window as kernal. Where m=row, n=column,
        k=channel (k=1 for R, 2 for G, 3 for B) and P is the pixel.
Step 3: If P(m,n,k) is an uncorrupted pixel (that is,
        0<P(m,n,k)<255), then its value is not changed.
    
```

Step 4: If $P(m, n, k) = 0$ or 255 , then $P(m, n, k)$ is a corrupted pixel.

Step 5: If all pixels in the selected window are 0's and 255's, then replace $P(m, n, k)$ with the median of the pixels in the window else go to step 6.

Step 6: Replace $P(m, n, k)$ with the mean.

Step 7: Repeat steps 2-6 until all the pixels of whole image are processed.

Step 8: Apply gradient based smoothing to preserves edges in more efficient manner.

4. Experimental results

By taking different brain tumor images for experimental purpose we have seen the outcome of the existing and proposed approaches. It is revealed in the following figures why proposed algorithm is more beneficial over existing approach in case of noisy images. Figure 7 is showing the noisy input image. It is clearly shown that the visibility of the image is quite poor.

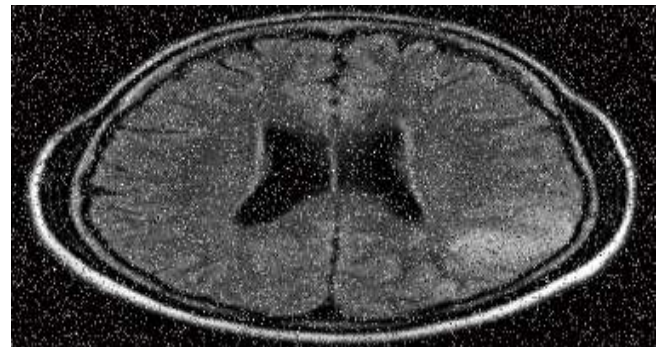


Figure 7: Input noisy Image

Figure 7 is showing the noisy input image. It is clearly shown that the visibility of the image is quite poor.

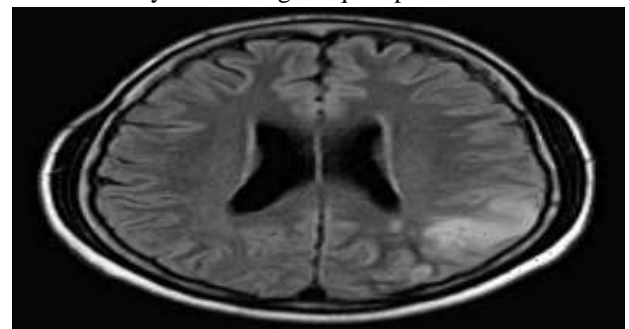


Figure 8: Filtered image using Decision based Median filter

Figure 8 shows the filtered image. It is clearly shown that the visibility of the Figure 8 is better than the image shown in figure 7.



Figure 9: output image by Ghanavati

Figure 9 shows the output results given by Ghanavati.

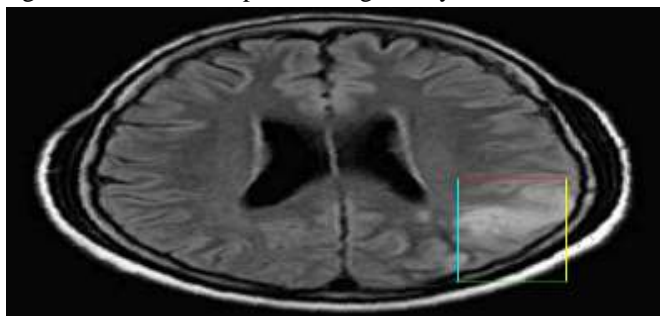


Figure 10: Output image using proposed method

Figure 10 demonstrates the output image using proposed method. It has better results than the existing approaches as shown in figure 9. Figure 10 shows the tumor using bounding box.

Table 1 is demonstrating the comparative study of the Peak Signal to Noise Ratio (PSNR). As PSNR require being maximized; thus the main goal is to increase the PSNR as much as possible. Table 1 has revealed that the PSNR is highest in the case of the proposed algorithm so proposed algorithm is providing better results than the existing methods

Table 1: PSNR

IMAGE	NEURAL	PROPOSED
1	7.1611	12.2577
2	7.4237	12.1246
3	7.5054	12.4245
4	8.7467	13.5689
5	9.3136	14.0239
6	3.0661	14.9459
7	0.7053	24.4572
8	2.6656	16.8081
9	3.2220	14.8582
10	0.8839	24.1741

Table 2 is showing the comparative study of Accuracy between the proposed and the existing technique. In the areas of science, engineering, industry, and statistics, the **accuracy** of a measurement system is the degree of nearness of measurements of a quantity to that quantity's real (true) value. Accuracy is arithmetical measures of the performance of a binary classification test. Accuracy require to enlarge. Table 2 has shown that the new technique is better than the existing as the value is more in the proposed algorithm; so proposed algorithm has shown efficient result.

Table 2: ACCURACY

IMAGE	NEURAL	PROPOSED
1	0.5615	0.7562
2	0.5746	0.7524
3	0.5786	0.7608
4	0.6347	0.7903
5	0.6578	0.8010
6	0.2971	0.8211
7	0.780	0.9401
8	0.2643	0.8556
9	0.3099	0.8192
10	0.0968	0.9382

Table 4 is showing the comparative study between the proposed and the available technique. It is necessary to decrease it. Table 4 has shown that the proposed technique has minimum BER than the available as the value is less in the proposed algorithm; so proposed algorithm has shown ad better results.

6. CONCLUSION AND FUTURE WORK

The brain tumor detection is a very important application of medical image processing. This work has presented a review on various methods for automatic segmentation of heterogeneous image data that takes a step toward bridging the gap between bottom-up affinity-based segmentation methods and top-down generative model based approaches. The main contribution of the work is to explore various techniques to detect brain tumor in an efficient way. The literature survey has shown that the most of existing methods has ignored the poor quality images like images with noise or poor brightness. Also the most of the existing work on tumor detection has neglected the use of object based segmentation. This work has proposed a new object based brain tumor detection using along with the decision based median filtering. The technique has shown quite effective results than neural based tumordetection technique. The design and implementation of

the proposed algorithm is done in MATLAB using image processing toolbox. The comparison has shown that the proposed technique has achieved up to 94 % accuracy which was 78 % in neural based technique. Also for high corrupted noisy images the proposed technique has shown quite effective results than the neural based tumor detection. Even in certain cases neural based tumor detection fails for highly corrupted noisy images. In near future we will propose a new improved brain tumor detection approach which will improve the accuracy of tumor detection techniques further using fuzzy-neurone techniques.

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