A Hybrid Approach to the Classification of Brain Tumours from MRI Images using Fast Bounding Box Algorithm

E.Murali [1], K. Meena [2]

[1] SIST Puttur, Andhra Pradesh, India
[1, 2] *Department of Computer Science & Engineering*
Veltech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology
Chennai, India.
[1] sai4murali@gmail.com, [2] meen.nandhu@gmail.com

Abstract **- Recently, image processing in medical applications has been one of the most inspiring emerging fields. In medical image processing MRI techniques are widely used to detect brain tumours. There is a different strategy to detect and extract the brain tumour signal. The process of detecting and extracting the brain tumour signals is based on the MRI scanned images for the cerebrum. This method includes segmentation, morphological operations and some noise removal functions. This hybrid approach includes Bhattacharyya Coefficient for extraction of features and bounding box methodology for brain tumour classification. The work is implemented in MATLAB 2016a.**

Keywords - Medical Images, Magnetic Resonance Images, Hybrid Approach, Machine Learning, Segmentation, Morphological Operator.

I. INTRODUCTION

At present, brain tumour has become one of the prominent causes of demise among children as well as in adults [1]. To identification of tumour are using segmentation, patient observing, remedy scheduling, neurosurgery and radiotherapy making plans. The aim of segmentation is to discover the tumour and consult with distinct sub-regions of the tumour, specifically edema, non-enhanced and enhanced regions (Fig. 1) [2]. Different modalities can used to diagnose a brain tumour using MRI images.

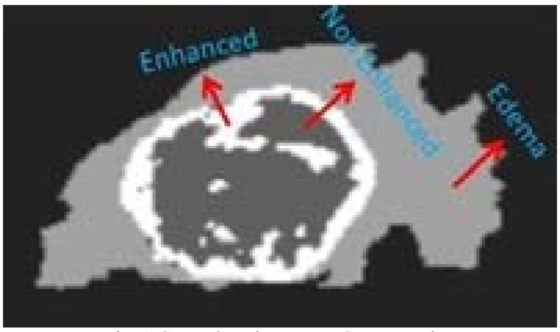

Fig. 1 Ground truth Tumour Segmentation

Properly, tumour (especially glioblastomas, metastases) can show up successfully several positions in the brain. They don't have earlier shape, and every now and again have un-all around categorized edges. Additionally, they at first sighting initiate themselves in dark scales that are existing in solid tissues also. As prominence, still we are doing brain tumour segmentation [10] manually. This practice is consuming lot of time and tedious [3]. The growing of abnormal group of cell inside the skull is called a tumour. It may occur in any person at any stage and display at any district and has huge assortment of sizes and styles. It may be divided through radiotherapy or by means of chemotherapy [4].

II. OUTLINE OF PROPOSED APPROACH

The first stage in specifying a course of treatment is identifying the presence of brain tumour. By and large the detail of a mind tumour includes neurological tests, cerebrum sweeps and investigation of the mind tissue. The tumour classification is from least to most aggressive by using diagnostic statistics. Tumour can occur in various parts of the brain i.e. benign and malignant, and it may or may not be primary.

The objective of the proposed system is:

- Design and implement the GUI for segmentation of Tumour region
- The input image is divided into two slices, once containing tumour region (original image) and other containing without tumour (reference image)
- Identify the tumour region from an MR image.
- Segmentation of tumour region using FBB and Mean shift clustering.

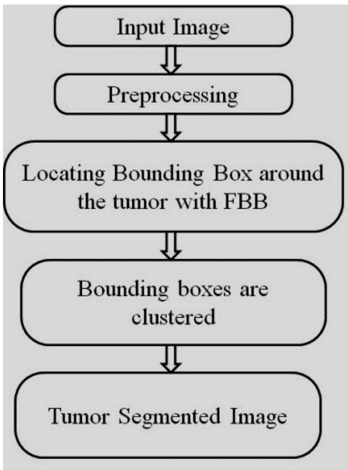

Fig. 2 Flow Diagram

The proposed system consists of five steps:

1. Input image
2. Image pre-processing
3. Fast bounding box
4. Mean shift clustering
5. Segmented Tumour

In the proposed system, the input image is pre-processed to remove the noise. Here image is altered into binary image and it normalizes the intensity values. After pre-processing, the tumour region is identified and segmented using fast bounding box and mean clustering algorithm. The segmented region is displayed as output.

III. METHODOLOGY

Various methods for tumour segmentation [10] determined in the works are does not completely automated as like they want person communication to region a kernel privileged the tumour/ edema region [5]. Based on Region growing [6] tumour detection [12] techniques suffers extreme time density. Geometric pattern recognition primary methods [7] decrease short; partially due to the fact massive distortions occur within the intracranial muscle because of the expansion of the tumour/edema. These strategies identify peculiar regions are using a register brain diagrams as a sample for normal brains. On the other hand, those methods need to consider ably adapt the brain diagrams to containing tumours, which is normally direct to negative grades. The greater part of the fluffy models function admirably just for hyper power tumours and show bad execution on recognizing non-upgraded tumours. This is due to those fluffy models often making use of thresholding [8] [11] techniques or morphological tasks as pre or post-handling.

We introduce an automatic [15], speedy and inexact partition approach that maintains intentional distance from those problems with the aid of finding a bounding box. We would then have the ability to make use of this bounding box find solution consequent questions that acquire several data position of tumour size.

A set of MR slice is input to Fast Bounding Box (FBB) to a single affected person. The yield might be a set of cuts which consists of tumour/edema, which can be each one marked with associated axis parallel bounding box which limits the tumour and edema scene. The indication of results numerous imaging modalities are perfect to distinguish those regions: T1C for tumour and T2 for edema. Input of every magnetic resonance piece, fast bounding box initially determine the both the axis of regularity of human brain. The tumour, those are chosen into concern associated irregularity within the brain, usually intrudes this symmetry. This algorithm looks for parallelogram in the left aspect, it is very distinctive as of its appearance concerning in the right aspect of symmetry, concentration histograms of 2 rectangles are unit mainly divergent; however, the skin histograms are comparatively parallel. We tend to calculate on it one in every of the rectangles can include the growth of the tumour showing up in a single hemisphere of the brain. Formerly those rectangle boxes are an initiate on input pieces, an unsupervised MSC practises the positions of those bounding boxes to discover major bunch of successive magnetic resonance pieces; fast bounding box then result is extent, mounted as collection of pieces by way of their regions.

A. Fast Bounding Box Algorithm

Fast bounding box works in two consecutive steps:

- A set of magnetic resonance image slices are treated separately, to detection potential bound boxes.
- These bound boxes are grouped to classify that actually edge the tumour or edema.

A1. Detecting bounding boxes on MR slices

Simple standard behind FBB is modification detection techniques, anywhere a region of modification (D) is spotted in a testing image (I), just the once equated with reference image (R). In fast bounding box algorithm, an MR slice the axis of symmetry finding after, the left aspect half image serve as the assessment image I, and the right aspect half of the image serve a suggestion image R. The area of modification D at this point is categorized to be a rectangle, which basically intentions to restrict the anomaly.

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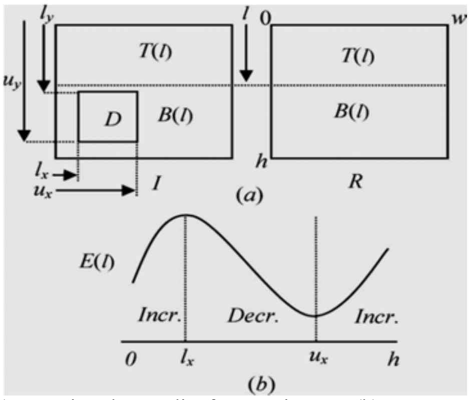

Fig.3: (a) Detection abnormality from I using R, (b) Energy score plot.

Fig.3 shows the representations, I and R in Figure 3(a) shows that testing and referencing images, correspondingly, they having height ‘h’ and width ‘w’. The significance of rectangular region D = [lx, ux] × [ly, uy] is to change the region interest tumour or edema containing among images I and R. This method discovers the rectangle D. It finds the best ly and uy data in a vertical arc and then finding lx and ux in a horizontal arc above the couple of images. Let be a sub rectangle of images is $T(l)\ and\ B(l)$ be the “top” and “bottom”, divided from top of the image at a distance from : T(l) = [0, w] × [0, l] and B(l) = [0, w] × [l, h]. We define a vertical source function:

$$E(l) = BC\left(Pl^{T(l)}, PR^{T(l)}\right) - BC\left(Pl^{B(l)}, PR^{B(l)}\right) \qquad (1)$$

Where$Pl^{T(l)}$representsimage I with histograms of region T(l).

$$\mathrm{BC}(\mathrm{a}, \mathrm{b}) = \sum_{i=i}^{n} \sqrt{p(i)q(i)} \in [0,\ 1] \qquad (2)$$

Equation (2) signifies BC among the two standardized histograms $p(i), q(i)$, by I representing histogram box. The BC processes the match among two standardized intensity [14] histograms. When same between two histograms, the Bhattacharya coefficient among them is 1 and when dissimilar of 2 normalized histograms, the BC amid them is 0.

We now show specific property of $E(l)$, that change to rapid localization of the parallelogram D. Here, something surveys exactly is visible with the aid of figure 3(b), wherein we see that rating score in the beginning high, then low, and next high yet again as l will increase from zero to h. The mounting and reducing segments hazards at l = ly and l = uy, the bottom and top certain of D, correspondingly. Now the minor and major boundaries of D should be notified from the score plot very rapidly and purely [16]. Likewise, the left-right certain of D, correspondingly, lx and ux, could be reported from the horizontal score function plot.

A2. Mean Shift Clustering

The MSC set of rules is a nonparametric method, which don’t need preceding facts of the huge kind of bunch, and do not restrain the form of the clusters.

Specified n input elements xi, i=1 ton on a d-dimensional Rd, the statistics of the kernel solidity assessment attained through kernel K(x) and space radius h is:

$$f(\mathrm{x}) = \frac{1}{nhd} \sum_{i=1}^{n} K\left(\frac{x-xi}{h}\right) \qquad (3)$$

For fundamentally symmetry kernels, it surfaces to describe the shape of the kernel k(x) fulfilling:

$$K(x) = ck, d^{k}(\ \|x^{2}\|) \qquad (4)$$

Here ‘ck’ and constant d which promises K(x) integrates to 1. After finding the bounding boxes on each of the MR slices, MSC synchronizes the bounding box is applied.

B. Skull Detection

The consecutive responsibilities related with machine controlled localisation of a bounding box magnetic resonance segment images is defined in Figure 4. Figure4 (a) indicates a tumour on the left aspect of the brain on a T1C magnetic resonance image slice. Figure 4 (b) represents the skull boundary detect with the aid of automatic universal thresholding [9] and next post-processing. After that the skull was bounded with an oval. The perspective of direction of the skull is originated with the aid of computing the position between the major axis of the oval demonstrating the vertical axis of the skull boundary. The major axis are become a vertical when the cranium is alternated by a position.

An ALOS draws a vertical line through Centroid of skull image shows in figure 4(b), which divides the given entire image into two slices: the left aspect of ALOS is treating as assessment image I and the right aspect treat as a suggestion image R [17]. The score plots vertical and horizontal are adjacent the distance from the top of the image shows in figure 4(c) and 4(d). The both vertical and horizontal plots display the raising, falling and then raising the score plots. The bounds are represented by bounding box are max and minimal points are related to left, top, right and bottom are imposed in figure 3(a), those are represent by black dots in figure 4(c) and 4(d). To verify the left and right half aspect image whether it holds tumour, we determine the normal solidity beside the bounding boxes located on together. The bounding box is suggested to which side contains the high mean T1C image intensity is supposed to surround the tumour.

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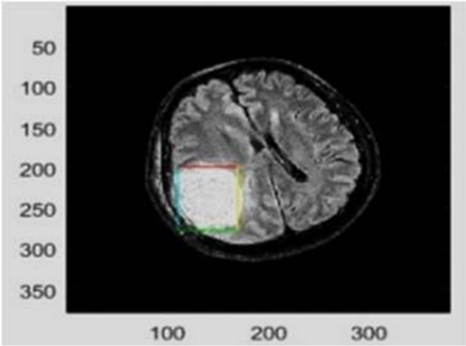
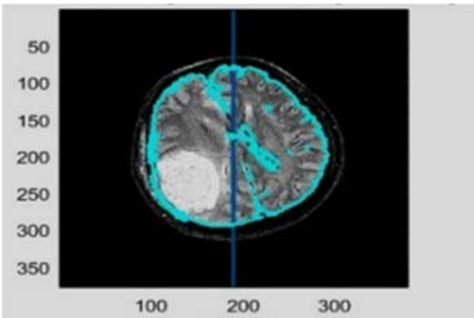
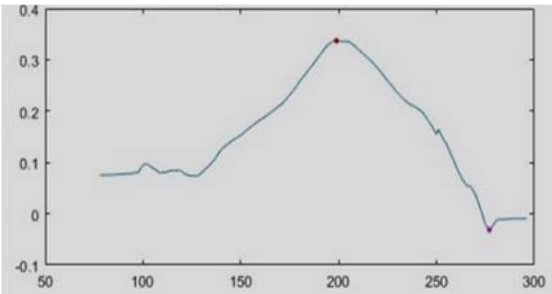


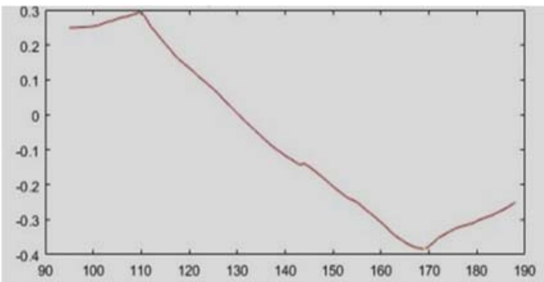
(a) MR Image



(b) Skull Boundary and Line of Symmetry



(c) Score Plot for Vertical Direction

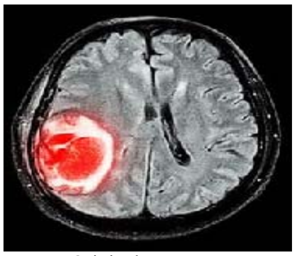


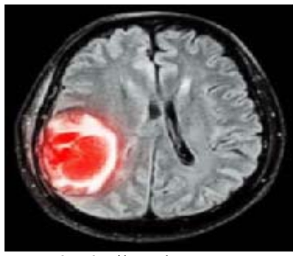
(d) Score Plot for Horizontal Direction

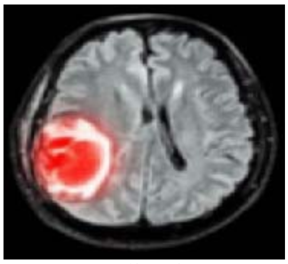
Fig.4. Brain Tumour Locating by FBB

C. Mask Creation

The new variables are created for mask has been declared as STATS and Midx. By using "region pnp" command, that describe the property of image region under the STATS variable. Consider as non-zero matrix for all pixels. The filter is need for an image is rotated in 900in clock or anti clockwise. The masking range is fixed from -1 to 1 and variable "Midx" have been selected. After rotating the image left aspect is masked, then right aspect is masked and then selects the Midx variable again. At last, brain tumour has been masked to cross go with the comparison between two parts.


Original Image


3 x 3 Filtered Image


5 x 5 Filtered Image

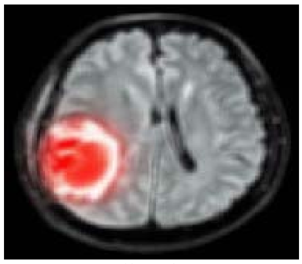

7 x 7 Filtered Image

Fig.5. Mask Creation

D. Computing the BC score function for Vertical and Horizontal Scanning

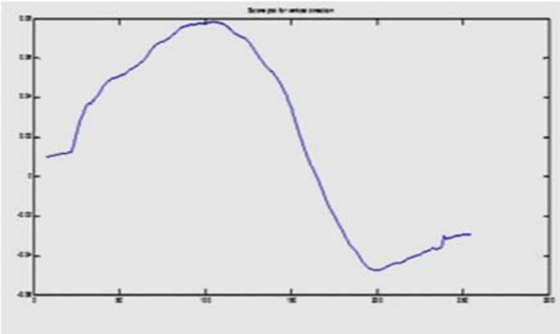
Between two samples, an estimate size of the amount of overlay in Bhattacharyya coefficient (BC). To establish the comparative ness of these two models existence considered, this constant can be used.

Computing the BC encompasses a simple basic form of combination of the overlay of these 2models. The rest of the values of those 2models are divided into elect amount of division and the amount of members of each replica in each divider is use in the successive method,

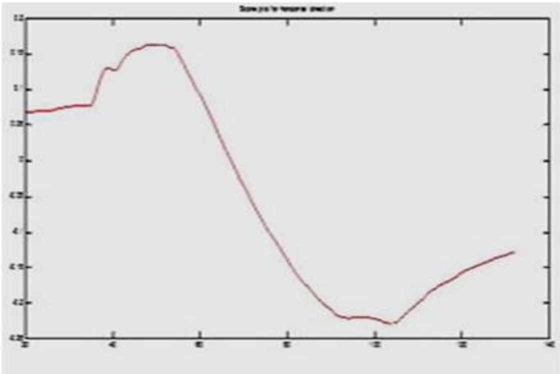
$$\mathrm{BC(p,q)} = \sum_{i=i}^{n} \sqrt{p(i).q(i)} \qquad (5)$$

Where, samples are p and q, n is number of partitions. $\mathrm{BC(a,b)} = \sum_{i=i}^{n} \sqrt{\{a(i).b(i)\}}\varepsilon[0,1]$ signifies the BC among two standardized histograms $a(i)\ and\ b(i)$ by specify a histogram bin.

The BC calculates the similarity in the centre of two standardised strength histograms. Bhattacharyya coefficient has previously used effectively in various computer perception application, such as edge-detection [9], object tracking, registration, etc.



(a)



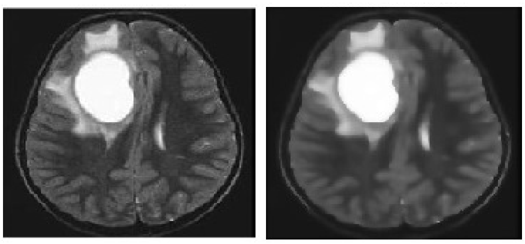
(b)

Fig. 6 (a) Score plot for vertical direction (b) Score plot for Horizontal direction

E. Tumour Cell Detection by Bounding Box Plotting Graphical Interpretation

The procedure related with computerized localisation of a cube box on a magnetic resonance image slice which is showing, and left side boundaries [13] of the bounding box are overlaid and are also displayed by burnet spots. To calculate approximately whether the right/ left half image comprises the tumour, the reason able strictness inside the bounding boxes have been placed on left and right sides. Lastly the tumour is unveiled where the bounding box is displayed. Fig .8 shows the representation of tumour detected image through a box and a pictorial clarification is plotted in the figure.

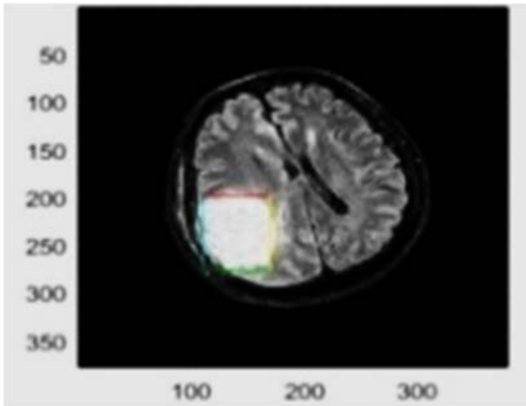
IV. RESULTS AND DISCUSSION



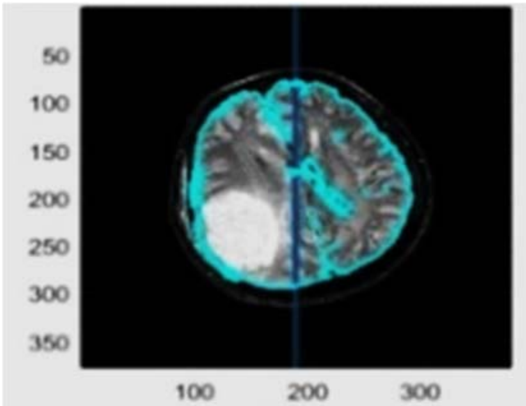
–a. Input Image -b. Filtered Image

Fig. 7 Filtering Image

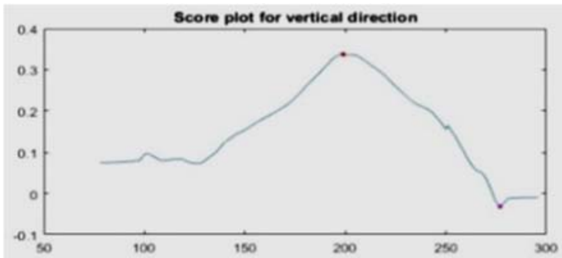
Figures 7, 8, 9, 10 and 11 show the results in the form of images obtained from the experiments.



(a). MR Image



(b). Skull Bounday and Liner of syummatry



(c)

(d)

Fig.8. (a) MR Image (b) Skull Boundary and Line of Symmetry (c) Score plot for vertical direction(d) Score plot for Horizontal direction.

Figure 7 shows to perform filtering operation on the image to improve the image quality by reducing the salt and pepper noise and locate tumour using fast bounding box technique. Figure 9 shows the original input image, filtered image and image having location of tumour using bounding box with threshold value 60 and density 0.8660. Figure 10 shows the original input image, filtered image and image having location of tumour using bounding box with threshold value 40 and density 0.8687. Figure 11 shows the original input image, filtered image and image having location of tumour using bounding box with threshold value 10 and density 1. To compare the above results figure 11 shows the exact tumour location based on low threshold value and high density of image pixel. The SVM technique used for the efficient segmentation of brain tumour which provides the result as extracted tumour.

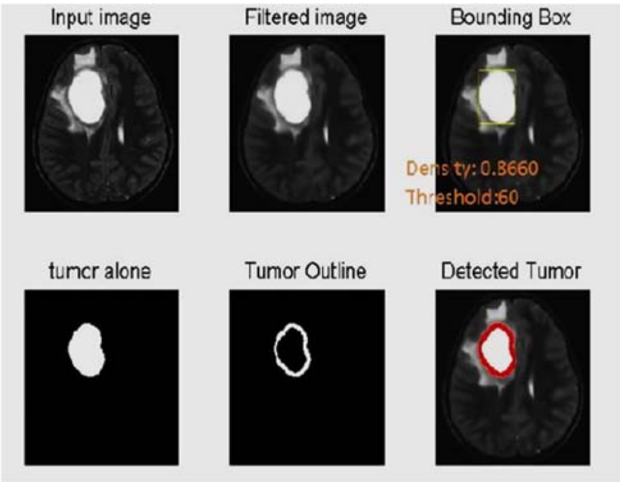


Fig. 9. Detection of Brain Tumour using FBB for Threshold =60 and Density 0.8660

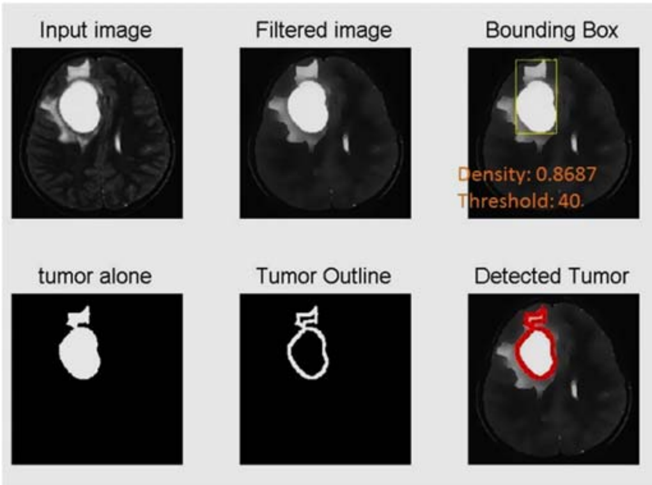


Fig.10. Detection of Brain Tumour using FBB for Threshold =40 and Density 0.8687

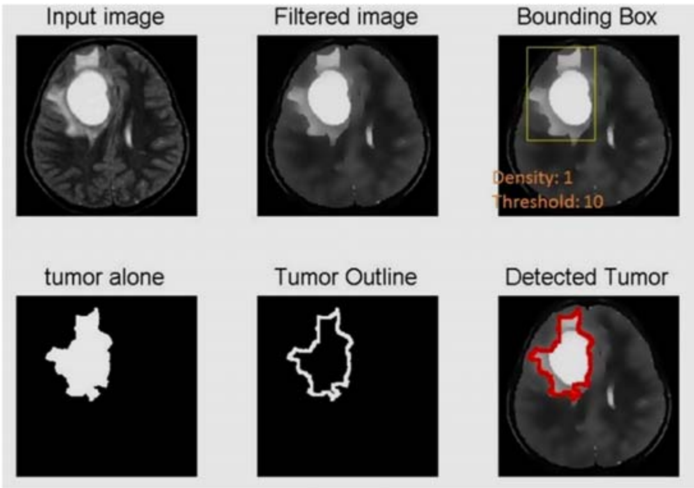


Fig. 11. Detection of Brain Tumour using FBB for Threshold=10and Density=1

In existing system location of brain tumour is not accurate because they used fixed threshold value. In fixed threshold value it find the tumour tissues with low density of image pixels. If the density of pixels are high then the existing algorithm cannot find the surrounding tissues. So that in proposed algorithm, the threshold values are randomly changing with the density of image pixel. If its value is higher than threshold, the pixel is considered to be 'foreground' and is set to white. All the white pixels within the bounding box are shown as tumour output. When threshold value is decrease, then automatically bounding box position also increased with density value.

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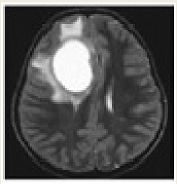
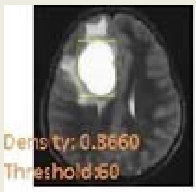
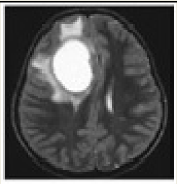
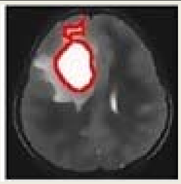
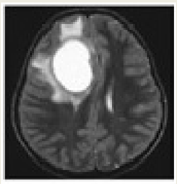
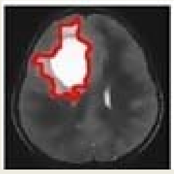
S. No.	Threshold value	Density	Original Image	Bounding Tumour Location	Detected Tumour	Accuracy
1	60	0.8660				93%
2	40	0.8676				95%
3	10	1				98%

Fig:11. Detection of Brain Tumour using FBB for Threshold=10 and Density=1.

V. CONCLUSION

The fast bounding box is a unique firm segmentation approach, which uses symmetry to enclose an abnormality with the aid of the bounding box inside an axial-parallel magnetic resonance image. In a particular area score plot is utilized, which uses BC to calculate neighbourhood histogram comparison among test and reference images. As this technique usually generate a bounding box on a magnetic resonance piece, even though within the non-appearance of the tumour/edema, an experimental scheme designed to separate relevant slices from the normal ones of a patient use of the mean shift clustering algorithm is presented. This region based estimated segmentation approach can explore new possibilities of the effective MR database indexing system.

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Mr. E Murali is a Research Scholar in Veltech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology. He has completed his M.Tech in Computer Science and Engineering from JNT University Anantapur and B.Tech in Computer Science and Engineering from JNT University Hyderabad. He is presently working as an Associate Professor in SIST Puttur, Andhra Pradesh, India. His research interests include image processing, image segmentation and tumour detection.

Dr K.Meena received her Ph.D in Computer Science from the Department of Computer Science and Engineering, Manonmaniam Sundaranar University, India in 2014. She received the degrees of B.E. (Electronics and Communication Engineering) and M.E. (Computer Science and Engineering) from the same University in 2002 and 2009. She is currently Associate Professor in Computer Science & Engineering Department, Veltech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology, Chennai. Her research interests include Machine Learning, Pattern Recognition, Image Processing, Biometrics and Cyber security. She has published 30 international journal papers, 7 international conference papers and 11 national conference papers.