Segmentation of Brain Tumor using Hybrid Approach of Fast Bounding Box and Thresholding in MRI

V Ramakrishna Sajja, Sajja Radha Rani , D.S Bhupal Naik, K Pratyusha

ABSTRACT--- Brain tumor is a deadly sickness and proliferate its cells in an uncontrolled way where it cannot be confidently detected without MRI. MRI image technique provides more accurate results than CT, Ultrasound and X-ray clinical methods. As we realize that Brain tumor is the most hazardous thus its identification ought to be quick and more precise. This can be achieved by processing of automated tumor detection methods on MRI brain images. Noise and delay for detection of tumor will affect the image accuracy. Here we proposed an automatic detection method to easily separate tumor and non-tumor parts of the brain. Anisotropic Diffusion filter applied to eliminate noise information and artifacts from the input brain MRI. Fast Bounding Box (FBB) and Threshold methodologies have been employed for segmentation of the brain tumor at image level of the brain.

Keywords: Image Segmentation, Anisotropic diffusion filter, Fast bounding box, Naïve Bayes classifier

I. INTRODUCTION

Cerebrum tumor is called an unordinary development of the cells in the brain. On the off chance that tumor isn't analyzed appropriately then it generally spread in the mind which prompts lose the life[1].

Around fifteen thousand deaths in every year are happening due to the malignant tumors which are the risky types of tumor. In spite of wide exertions in explore over various decades, the center Overall Life-time (OLT) will be fifteen months just for the Glioblastoma Multiforme (GBM) , dangerous glioma [2]. Because of seriousness stage, the cerebrum tumor has been isolated into various evaluations. At stage1 minimum risky tumor is ordinarily identified with drawn out survival. When it is seen through a magnifying instrument, they develop step by step and for all intents and purposes have a standard appearance. Dignosis by means of medical procedure may be recommended for such kind of tumor review. Ganglioglioma, gangliocytoma and pilocytic astrocytoma are instances of stage1 brain tumor. The tumor which develops gradually and looks irregular under a tiny instrument is treated as stage2 brain tumor. A tumor which is hardly distributed to adjacent tissues and replicates multiple times is known as high grade tumor [3]. The tumor which is dangerous however by and large is called stage3 brain tumor; there is certifiably not a noteworthy difference between stage2 and stage3 tumors. This tumor tends to often rehash as stage4. Stage4 is the most extreme threatening tumor. It copies rapidly having an interesting look when found in the minute tool and viably develops into the adjacent tissues of the cerebrum bringing about the presence of new vessels. Such tumor cells have groups of dead cells in their middles. GBM is an example of stage4 tumor [4].

Tumors can be detected by rich techniques of image processing. Segmentation of images is one among them. The objective of image division is to divide an image into different partitions thus discovering states of the partitions [5– 6]. The brain life structure will be examined by either Computed Tomography (CT) or Magnetic Resonance Imaging (MRI). CT scan is less effective when compared with MRI scan due to the utilization of radiation [7]. Just a single sort of MRI can't give entire data identified with typical tissues because it consists of different biologic tissues. Joining distinctive correlative data can overhaul the divided locale of tumors. Highlights of MR pictures used for division involve three pictures of weighted (T1, T2 and flair) for each cut axial. The visual difference between those pictures is given in figure 2 and their differences are explained in table 1. The strategies of segmentation have been completely powerful particularly in the development phases of contaminated tissues [8– 10].

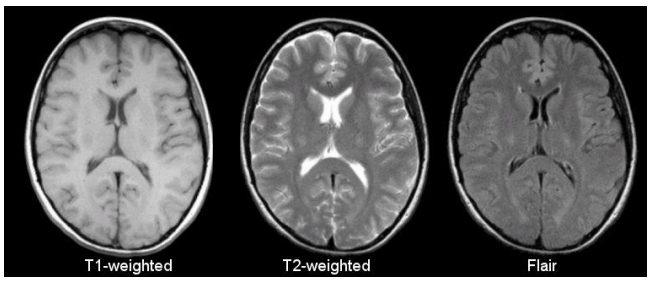

Fig. 1: Three types of brain MRI images

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Table 1: Differences between T1, T2 and Flair images

Tissue	T1-Weighted	T2-Weighted	Flair
CSF	Dark	Bright	Dark
White Matter	Light	Dark Gray	Dark Gray
Cortex	Gray	Light Gray	Light Gray
Fat (Within Bone marrow)	Bright	Light	Light
Inflammation (infection, demyelination)	Dark	Bright	Bright

In proposed method, as a first step preprocessing has to be employed on input image to remove noise. As a second step segmentation has to be employed to extract tumor portion which removes unwanted portions and increase accuracy rate. Finally to recover the pixels which are related to tumor portions, morphological operations like dilation has been employed.

The paper is organized as the following. Literature work for tumor identification is described at section II, Proposed technique steps are depicted at section III and outcomes after the performance assessment of recommended strategy are illustrated in Section IV.

II. RELATED WORK

Various research papers have been identified for medical image segmentation and several strategies were examined.

Vallabhaneni, R. B et al. [11] said a programmed tumor detection technique in clamor contained pictures. The De-noising of the photo is approved using Edge Adaptive Total Variation De-noising Technique (EATVD). The framework is used to defend the edges amid the way toward taking out the clamor from the picture. Once the commotion is far from the picture, the picture is sectioned utilizing mean move bunching. The divided cuts are given to gray level co-occurrence matrix (GLCM) to get highlights from those cuts. The highlights are utilized by multi class SVM to find the tumor in the pictures. The progression took after concentrates the tumor with increased precision in noisy images.

Chaplot, S et al. [12] developed a procedure for classification purpose of MR pictures of cerebrum that utilizations wavelets as responsibility to support vector machines as non-uniform or prototypical. The proposed system has the information of 52 MRI pictures. The accuracy 90% was refined by self-organizing out Maps (SOM) while 98% utilizing support vectors system. The classification percentage is great for support vectors while contrasting and self-arranging map-based approach.

Maitra, Met al. [13] built up another approach for computerized analysis for an arrangement of Magnetic Resonance Imaging pictures. The method is apparently a variation of orthogonal DWT, called Slantlet change for feature extraction. A 2D MRI image forms its power histogram and after that associated with Slantlet changes as its histogram signal. In this manner a component vector matrix is built by taking the sizes of Slantlet change yields contrasting with six ways which should be exceptional, picked by a specific method of reasoning. The parts are removed to set up a neural framework classifier. The principal purpose behind this classifier is to mastermind the photos either as ordinary or strange for Alzheimer's affliction. By this procedure, they achieved the 100% accuracy in precisely describing the Alzheimers ailment.

MohammadrezaSoltaninejad et al. [14] developed a strategy of 3D super voxel based learning methodology for segmentation of tumor in multimodal MRI brain images.

Super voxels are created utilizing the data over the multimodal MRI dataset. For each super voxel, an assortment of highlights including histograms of text on descriptor, ascertained utilizing an arrangement of Gabor channels with various sizes and introductions, and first request power factual highlights are separated. Those highlights are bolstered into an irregular timberlands (RF) classifier to arrange each super voxel into tumor center, edema or sound cerebrum tissue.

Zhang, Yet al. [15] presented a crossbreed system in light of forward neural system (FNN) to assemble Magnetic Resonance mind pictures. In this paper they proposed philosophy at first employed the DWT (Discrete Wavelet Transform) in order to extricate features (highlights) from Magnetic Resonance Images and associated the critical part examination strategy to diminish incorporate space beyond what many would consider possible utilizing PCA. The reduced portions were forwarded to a forward neural network(FNN), henceforth the variables are enhanced utilizing counterfeit artificial honey bee(ABC) figuring in setting of both wellbeing scaling and confused speculation.

JankiNaik et al. [16] projected technique to categorize the medical images for diagnosing. Some experiments with tomography pictures for neoplasm detection are administrated here. Preprocessing has been finished the assistance of median filter method. Hence, essential options are extracted with textual feature method. By then extricating of association rules are done from wiped highlight component utilizing Decision Tree (DT) classifier. They surmised that proposed approach improves the quality of grouping of CT filter pictures than customary techniques.

III. PROPOSED METHODOLOGY

A computerized methodology is given for identification of the tumor at image level. Prescribed method is executed on MR imaging. Brain Tumor detection in Magnetic Resonance Imaging is a ton of prudent because of its less radiation, more complexity, and spatial determination. Proposed frame work is depicted in figure 2.

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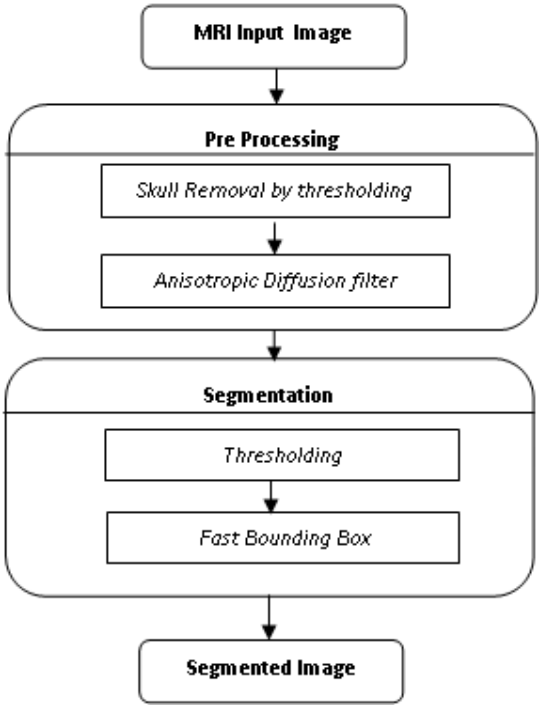

Fig. 2: Proposed System Architecture

MRI images provide data with respect to area and size. Anyway these MR images are not ready to expose the tumor type. Physicians, therefore, progress to an insidious system wherever spinal tap and diagnostic assay are painful. The processing time will be more. This insufficiency empowers developing an exact framework to strengthen the identification mechanism of MRI images. Also, the underlying stage doesn't require an indicative examine on the grounds that the motivation behind proposed framework is to partition the brain tumors utilizing MRI images. The recommended strategy incorporates of three noteworthy advances that are noise eliminating stage, tumor extraction stage and magnifying tumor stage.

3.1 Preprocessing

The images are gathered from various image sources and have noisier and artifacts in that image data. The image with non-useful information won't create better outcomes and it prompts low level accuracy. In this step, the Magnetic Resonance Images are changed over into gray images. Eventually, gray images are smoothened utilizing adjustment of contrast level.

3.1.1 Skull Removal

It is preprocessing stage which is necessary to deliver better outcomes. In skull expulsion, the external piece of the brain encompassing its non-cerebral tissues. The crucial issue in skull-stripping is that the segmentation of the non-cerebral and also the intracranial tissues as a result of their homogeneity intensities. A few perceptions are required to discover the scope of gray value estimation of the skull partition. Primarily, the illumination adjusted images are changed to binary images and discover crop areas utilizing these binary images. Therefore, the contrast balanced image is trimmed for the tumor part of the brain image. Select a low threshold incentive for converting cropped contrast adjusted image. The trimmed differentiation balanced picture is changed over to binary image. In this manner, apply the morphological activity Dilation to the binary image. At last, brain area is wiped out utilizing region based binary mask extraction.

3.1.2 Anisotropic Diffusion Filter

The anisotropic diffusion filter [17] is the spearheading work in partial derivatives equations (PDE) based denoising. Anisotropic diffusion smoothing or dissemination is done relying upon the picture edges and their regions. It will smooth homogeneous picture areas but holds picture edges. It applies the law of dispersion on pixel intensities to smooth surfaces in a picture. A threshold function is utilized to avoid dispersion to occur crosswise over edges, and along these lines it preserves edges in the picture. (Not at all like for example Gaussian blur channel.) This makes it extremely intriguing on the off chance that you need to evacuate commotion, yet would prefer not to smooth out the edges of your picture, for example in the event that you need to utilize these edges to portion the picture, without being annoyed by the noise.

$$\frac{\partial I}{\partial t} = \text{div}\,(c(x, y, t)\nabla I) = \nabla c\,.\nabla I + c(x, y, t)\Delta I \quad (1)$$

Where' Δ 'indicates the laplacian,' ∇ 'indicates the gradient, div (…) is the divergence operator and c(x, y, t) is the diffusion coefficient. C(x, y, t) controls the rate of diffusion and is usually chosen as a function of the image.

$$C\,(\|\nabla I\|) = e^{-(\|\nabla I\|/K)2} \quad (2)$$

$$C\,(\|\nabla I\|) = \frac{1}{1+\left(\frac{\|\nabla I\|}{K}\right)^2} \quad (3)$$

The constant K controls the sensitivity to edges and is usually chosen experimentally or as s function of the noise in the image. Outcomes of preprocessing stage are depicted in figure 3.

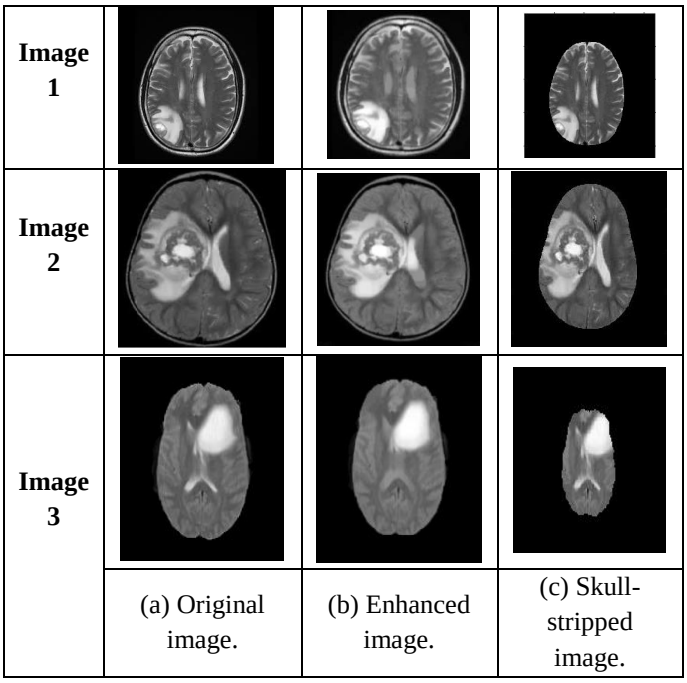

Fig. 3: Experimental results of preprocessing stage

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3.2 Segmentation

In segmentation stage, tumor part will be extracted from the normal tissue by using thresholding with bounding box approach. Such segmented part will be examined by radioligists to suggest furthur treatment.

3.2.1 Thresholding with Fast Bounding Box

The segmented tumor area from threshold method is superimposed with bounding box approach[18]. This approach puts the rectangle box around the tumor area portioned tumor of MRI. The fragmented tumor from the Thresholding strategy contains the tumor partition as well as some sound tissues will be misclassified. These cells are wiped out by applying the Thresholding procedure that is expanding the edge an incentive until the misclassified tissues are wiped out to acquire fine tumor. At that point at long last bounding box will be put around the tumor part in light of the shape characteristics of the recognized tumor.

FBB works in two consecutive advances. In the first step, the info set of 2D MR cuts are prepared to discover parallel square shapes, i.e., rectangle boxes on every one of tumor slices. Further, these boxes are bunched to distinguish the ones that encompass the tumor or edema. The FBB with Thresholding strategies will receive tumor without solid tissues of brain.

3.2.1.1 Silhouette Coefficient

Silhouette coefficient [19] is a good metric which speaks about the quality of cluster. Suppose a data set D contains n objects, and D has been divided into m clusters, $C_1,\ldots\ldots,C_m$. For every object which belongs to data set, compute p(x) and q(x). Where p(x) is the mean distance between x and all other objects which are residing in same cluster like x belongs. Likely, q(x) is the least mean distance between x and all clusters to which x does not belong. Formally, suppose $x \in Ci$ $(1 \leq i \leq m)$; then

$$\boldsymbol{p(x)} = \left\{\frac{\sum_{x' \in C_i, x \neq x'} \boldsymbol{dist(x,x')}}{|C_i|-1}\right\} \quad (4) \text{ and}$$

$$\mathbf{q(x)} = \min_{C_j:1 \leq j \leq m, j \neq i} \left\{\frac{\sum_{x' \in C_j} \boldsymbol{dist}(\mathbf{x}, \mathbf{x}')}{|C_j|}\right\} \quad (5)$$

The silhouette coefficient of x is then defined as

$$\boldsymbol{r(x)} = \frac{\boldsymbol{q(x)} - \boldsymbol{p(x)}}{\mathbf{max}\{\boldsymbol{p(x)}, \boldsymbol{q(x)}\}} \quad (6)$$

Quality of cluster can be determined as good only when Silhouette coefficient value lies between -1 and 1. Otherwise it concludes that quality of cluster is poor. Outcomes of segmentation stage are depicted in figure 4.

IV. EXPERIMENTAL RESULTS

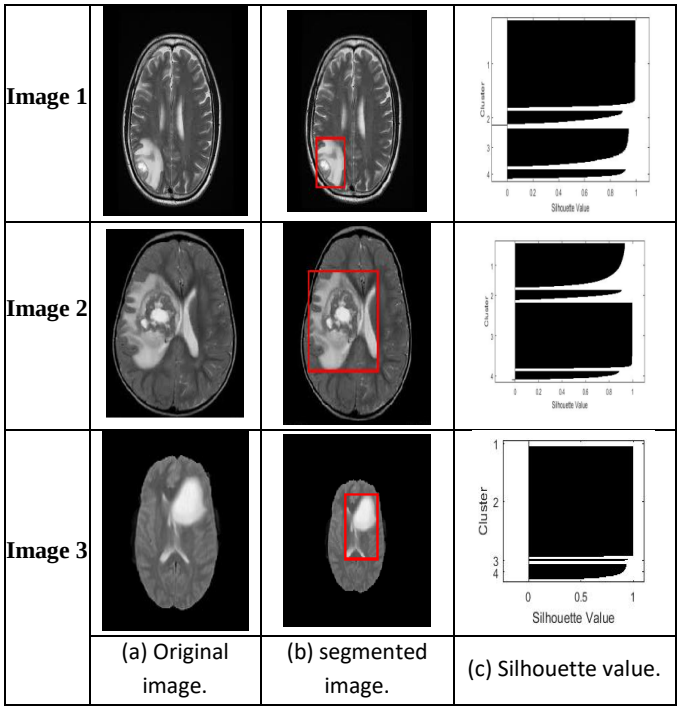

Fig. 4: Experimental results of segmentation stage

3.3 Morphological operations

Morphological tasks [20] are basic for precise recognition of tumor pixels in a given picture. If not utilized it increment non-tumor pixels demonstrating as tumor pixels because of which poor quality tumor [benign] is appeared as a high review tumor. Hence employing of morphological activities like erosion and dilation is obligatory. Despite the fact that disintegration evacuates additional pixels and lessens the tumor territory, it doesn't dispense with actual tumor pixels. In the event that a few pixels are missed then enlargement will recover them also.

The proposed frame work was experimented on 50 images. All images are correctly segmented where the tumor is located in the image. For instance, results for 3 images are depicted in figure 5.

V. CONCLUSION

Segmentation of MRI images using hybrid approach of Fast Bounding Box and Thresholding detects tumors with better segmentation results. Bounding box is a quick segmentation algorithm in which the tumor locales are distinguished by denoting a box and further segment this tumor part.In this approach thresholding algorithm will segment the tumors whereas Fast bounding box will identify the area and location of the tumor in a 2D images. Morphological operations like erosion and dilation used for showing tumor as big and as well as small tumor.

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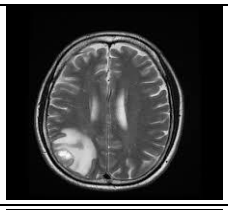
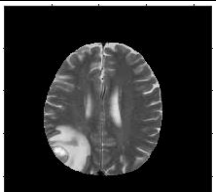
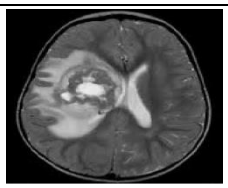
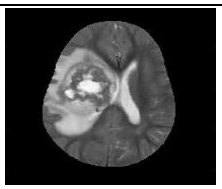
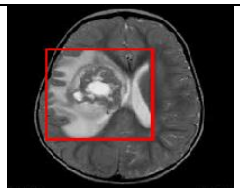
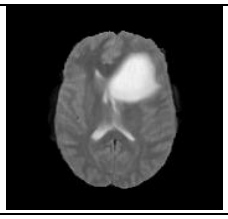
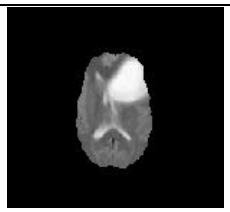
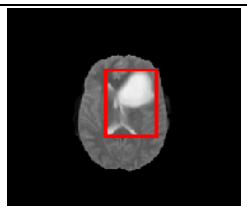
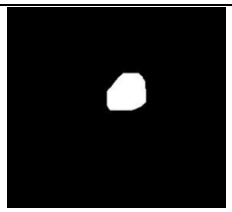
VI. FUTURE WORK

Future work may incorporate extracting features from segmented portion and tumor grade can be classified with the help of feature set. It also incorporate broadening the method into 3D application. Assist the difficult quality can be lessened along with diminished calculation time. Additionally, algorithms can be adjusted to improve better exactness.

Image 1				
Image 2				
Image 3				
	(a) Input image.	(b) After Preprocessing	(c) After Segmentation	(d) Output image

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