DEVELOPMENT OF BRAIN TUMOR DETECTION AND CLASSIFICATION USING SEGMENTATION TECHNIQUES

[1]**Krunal V. Patel**, [2]**Dr. Anil C. Suthar**
[1]Research Scholar,[2]Director, LJIET
[1]Information Technology Department,
[1]L.J. Institute of Engineering and Technology, Ahmedabad,India

Abstract : Biomedical Image Processing consists many different types of imaging methods likes CT scans, X-Ray and MRI. These techniques allow humans to identify even the smallest abnormalities in the human body. The primary goal of medical imaging is to extract meaningful and accurate information from the images with the least error possible. MRI (Magnetic Resonance Imaging) is a medical technique, mainly used by the radiologist for visualization of internal structure of the human body. MRI provides useful information about the human soft tissue, which helps in the diagnosis of brain tumor. Image segmentation refers to partitioning of image into multiple regions or segments such that it can meaningfully represent the image through which information can be extracted. In this paper we are using Canny and SIFT techniques for segmentation of brain image considering shape and texture features. After that Support Vector Machine (SVM) is used to classify tumor and non-tumor regions.The performance of the proposed method is evaluated in terms of Sensitivity(Se), specificity (Sp), precision (Pr) and accuracy(Acc)and PSNR.

Keywords: MRI Images, Brain tumor detection, Segmentation, Brain tumor extraction, Classification

I. INTRODUCTION

Cancer in a body occurs when the cell in the body grows and divides in an uncontrollable manner. If this happens in brain then it is called as brain tumor[1]. A brain tumor is a mass of unnecessary and abnormal cell growing in the brain or it can be defined as an intracranial lesion which occupies space within the skull and tends to cause a rise in intracranial pressure[1]. Brain tumors are mainly classified in to two i.e. Benign and Malignant. Benign tumors are noncancerous and they seldom grows back where as malignant tumors are cancerous and they rapidly grows and invade to the surrounding healthy brain tissue[1]. The location of tumor in brain helps the individual to determine how the brain tumor effects an individual normal functioning.

Whole brain segmentation, or brain extraction, is one of the first fundamental steps in the analysis of magnetic resonance images (MRI) in advanced neuroimaging. applications such as brain tissue segmentation and volumetric analysis [3], longitudinal and group analysis [4], cortical and sub-cortical surface analysis and thickness measurement [5],[6], and surgical planning. Manual brain extraction is time consuming especially in large-scale studies. Automated brain extraction is necessary but its performance and accuracy are critical as the output of this step can directly affect the performance.

Processing a medical image involves two main steps. The first is the pre-processing of the image. This involves performing operations like noise reduction and filtering so that the image is suitable for the next step. The second step is to perform segmentation and morphological operations[2]. These determine the size and the location of the tumor
Paper orientation consists Related work in section II, Proposed method in section III, Result and analysis in section IV and at last Conclusion in section V and References.

II. Related Work

Many algorithms have been developed and continuously improved over the past decade for whole brain segmentation, which has been a necessary component of large-scale neuroscience and neuroimage analysis studies. As the usage of these algorithms dramatically grew, the demand for higher accuracy and reliability also increased. Consequently, while fully-automated, accurate brain extraction[10].

In [7] S. Réjichi and F. Chaabane, uses graph based multi temporal classification in the context of MRI time series classification in order to extract tumor region in a human brain. Here the proposed approach is mainly based on two steps. First, a Radial basis function (RBF) kernel for SVM classification is applied in order to identify regions in each MRI time series image. Then, a graph, called Spatial-Object Temporal Adjacency Graph (SOTAG), is constructed for regions of the MRI time series images. Second, a graph based kernel for SVM classification is applied on produced SOTAG in order to extract tumor region.

In [8] Asit Subudhi,Jitendra Jena, Sukanta Sabut presents a technique for segmenting the brain from skull in a synthetic T1-weighted magnetic resonance images (MRIs) of the human head collected from Brain web database. The skull-stripping method consists of a series of sequential steps including image enhancement with particle swarm optimization (PSO) to improve the performance, background removal, histogram based thresholding with maximum divergence for extraction of brain region and morphological operation for removal of non-brain tissues.

In [9] Prakash Tunga P, Vipula Singh, focuses on extraction of brain tumor and its region description through segmentation from the brain MRI image. At first, pre-processing step for noise removal is carried out. Brain tumor extraction is done by considering the methods based on k-means clustering, morphological operations and region growing. K-means clustering has the advantage of being automatic, faster in execution and lesser computational complexity. Morphological operators based segmentation is more accurate than k-means clustering, effectively eliminates the noise and in-homogeneities due to irregularities in MR scanner, but is semi-automatic and not so accurate as region growing method. Region growing method, though semi-automatic, gives most accurate results among three methods, but the user has to select the initial seed which should be accurate and also this results in more execution time than the other methods.

In [10] Seyed Sadegh Mohseni, Salehi Deniz Erdogmus and Ali Gholipour Proposed and evaluated a new technique based on an auto-context convolutional neural network (CNN), in which intrinsic local and global image features are learned through 2D patches of different window sizes. They consider two different architectures: 1) a voxelwise approach based on three parallel 2D convolutional pathways for three different directions (axial, coronal, and sagittal) that implicitly learn 3D image information without the need for computationally expensive 3D convolutions, and 2) a fully convolutional network based on the U-net architecture. Posterior probability maps generated by the networks are used iteratively as context information along with the original image patches to learn the local shape and connectedness of the brain to extract it from non-brain tissue.

In [11] Asra Aslama,Ekram Khanb,M.M. Sufyan Bega, proposes an Improved Edge Detection algorithm for brain-tumor segmentation. It is based on Sobel edge detection. It combines the Sobel method with image dependent thresholding method and finds different regions using closed contour algorithm. Finally tumors are extracted from the image using intensity information within the closed contours. the edge detection method is modified so that it can be extended for object segmentation, which can be efficiently used for separation of tumor in the images. This method considers three parameters: gray level uniformity measure (GU), Q-parameter and relative ultimate measurement accuracy (RUMA).

In this paper we suggests a novel method in which for image pre-processing we used median filter. For segmentation of image we used Canny edge detection method and SIFT method. After that we classified the images using SVM.

III. Methodology

In this section the proposed method is described which is based on Segmentation technique. The work is divided into to three steps: (1) MRI image Pre-Processing by median filter (2) MRI image Segmentation by Canny edge detection technique and SIFT technique and (3) Brain tumor classification using SVM technique. Fig. 1 shows the flow chart of the proposed method.

First step of proposed system is taking a brain MRI image as an input. Then pre-processing of the image takes place. Pre-processing is required to reduce the various kind of noise from the image. For this process various kinds of filters are used. Among that here median filter is used which is best suited for removing noise from bio-medical gray images. After that segmentation of image is takes place. The process of splitting an image into multiple parts is known as segmentation. It creates various sets of pixels within the same image. Segmenting an image makes it easier for us to further analyze and extract meaningful information from it. Here we segment the MRI image based on its shape and texture. For shape based segmentation canny algorithm is used and for texture based segmentation SIFT algorithm is used. Both algorithms are superior in their category results in providing accuracy of segmentation. After segmentation we got optimized image from that tumor region is easily extracted.

At last for classify the tumor region tested and trained MRI images are given to SVM algorithm which compares the images and effectively classifies it into malignant and benign tumor.

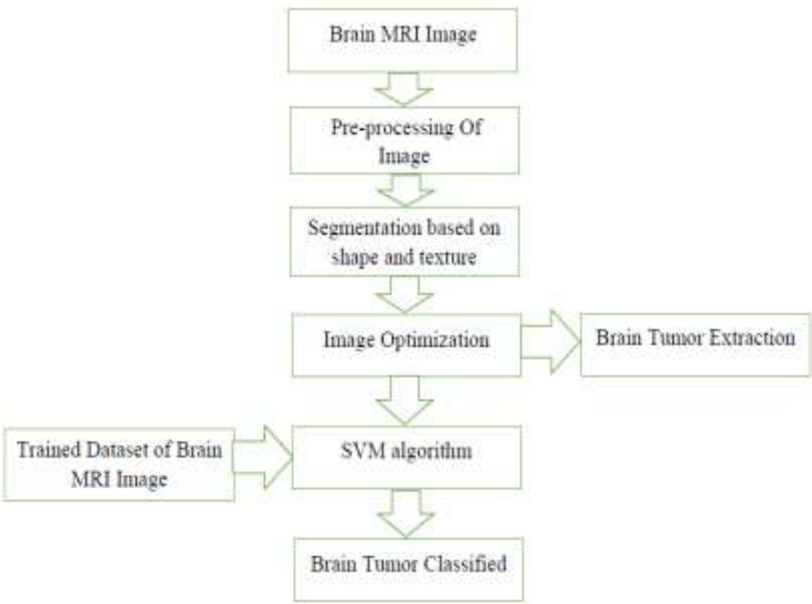


Fig 1: Proposed Method

1) **MRI image Pre-Processing by median filter**

The median filter works by moving through the image pixel by pixel, replacing each value with the median value of neighbouring pixels. The pattern of neighbours is called the "window", which slides, pixel by pixel over the entire image pixel, image The median is calculated by first sorting all the pixel values from the window into numerical order, and then replacing the pixel being considered with the middle (median) pixel value.

2) MRI image Segmentation by Canny edge detection technique and SIFT technique

It is based on the canny operator. Canny operator is based on three criteria. The basic idea uses a Gaussian function to smooth image firstly. Then the maximum value of first derivative also corresponds to the minimum of the first derivative. In other words, both points with dramatic change of gray-scale (strong edge) and points with slight change of grayscale (weak edges) correspond to the second derivative zero-crossing point. Thus these two thresholds are used to detect strong edges and weak edges[12]. The fact that Canny algorithm is not susceptible to noise interference enables its ability to detect true weak edges.

Canny defined optimal edge finding as a set of criteria that maximize the probability of detecting true edges while minimizing the probability of false edges. To smooth the image, the Canny edge detector uses Gaussian convolution, is the spread of the Gaussian and controls the degree of smoothing.

The Canny edge detection algorithm runs in 5 separate steps:

1. **Smoothing:** Blurring of the image to remove noise.

In smoothing the image is first smoothed by applying a Gaussian filter. The kernel of a Gaussian filter with a standard deviation of 1.4 is shown in Equation.

$$B = \frac{1}{159} \cdot \begin{bmatrix} 2 & 4 & 5 & 4 & 2 \\ 4 & 9 & 12 & 9 & 4 \\ 5 & 12 & 15 & 12 & 5 \\ 4 & 9 & 12 & 9 & 4 \\ 2 & 4 & 5 & 4 & 2 \end{bmatrix} \quad (1)$$

2. **Finding gradients:** The edges should be marked where the gradients of the image has large magnitudes.

The Canny algorithm basically finds edges where the grayscale intensity of the image changesthe most. These areas are found by determining gradients of the image. Gradients at each pixelin the smoothed image are determined by applying what is known as the Sobel-operator. Firststep is to approximate the gradient in the x- and y-direction respectively by applying the kernelsshown in Equation (2).

$$K_{GX} = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}$$
$$K_{GY} = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix} \quad (2)$$

The gradient magnitudes (also known as the edge strengths) can then be determined as an Euclidean distance measure by applying the law of Pythagoras as shown in Equation (3). It is sometimes simplified by applying Manhattan distance measure as shown in Equation (4) to reduce the computational complexity.

$$|G| = \sqrt{G_x^2 + G_y^2} \quad (3)$$
$$|G| = |G_x| + |G_y| \quad (4)$$

3. **Non-maximum suppression:** Only local maxima should be marked as edges.

The purpose of this step is to convert the “blurred” edges in the image of the gradient magnitudesto “sharp” edges. Basically this is done by preserving all local maxima in the gradient image,and deleting everything else.

The algorithm is for each pixel in the gradient image:

1) Round the gradient direction theta to nearest 45°, corresponding to the use of an 8-connected neighborhood.
2) Compare the edge strength of the current pixel with the edge strength of the pixel in the positive and negative gradient direction. I.e. if the gradient direction is north (theta = 90°), compare with the pixels to the north and south.
3) If the edge strength of the current pixel is largest; preserve the value of the edge strength. If not, suppress (i.e. remove) the value.

4. **Double thresholding:** Potential edges are determined by thresholding.

The edge-pixels remaining after the non-maximum suppression step are (still) marked with theirstrength pixel-by-pixel. Many of these will probably be true edges in the image, but some maybe caused by noise or color variations for instance due to rough surfaces. The simplest way todiscern between these would be to use a threshold, so that only edges stronger that a certainvalue would be preserved. The Canny edge detection algorithm uses double thresholding. Edgepixels stronger than the high threshold are marked as strong. Edge pixels weaker than the lowthreshold are suppressed and edge pixels between the two thresholds are marked as weak.

5. **Edge tracking by hysteresis:** Final edges are determined by suppressing all edges that are not connected to a very certain (strong) edge.

Edge tracking can be implemented by BLOB-analysis (Binary Large Object). The edge pixels are divided into connected BLOB’s using 8-connected neighborhood. BLOB’s containing at least one strong edge pixel are then preserved, while other BLOB’s are suppressed.

- **Steps of SIFT algorithm**

1. Determine approximate location and scale of salient feature points (also called keypoints)

The keypoints are maxima or minima in the “scale-space-pyramid”, i.e. the stack of DoG images. Hereby, we get both the location as well as the scale of the keypoint.

2. Refine their location and scale.
The keypoint location and scale is discrete – we can interpolate for greater accuracy.
For this, we express the DoG function in a small 3D neighborhood around a keypoint (xi,yi,σi) by a second-order Taylor-series:

$$D(x,y,\sigma) = D(x_i,y_i,\sigma_i) + \underbrace{\boxed{\left(\frac{\partial D(x,y,\sigma)}{\partial(x,y,\sigma)}\right)^T_{\substack{x=x_i,\\ y=y_i,\\ \sigma=\sigma_i}}}}_{\substack{\text{Gradient vector}\\ \text{evaluated digitally at}\\ \text{the keypoint}}} \Delta + \frac{1}{2}\Delta^T \underbrace{\boxed{\left(\frac{\partial^2 D(x,y,\sigma)}{\partial(x,y,\sigma)^2}\right)_{\substack{x=x_i,\\ y=y_i,\\ \sigma=\sigma_i}}}}_{\substack{\text{3 x 3 Hessian matrix}\\ \text{evaluated digitally at the}\\ \text{keypoint}}} \Delta;$$

$$\Delta = \begin{pmatrix} x - x_i \\ y - y_i \\ \sigma - \sigma_i \end{pmatrix}$$

(5)

3. Determine orientation(s) for each keypoint.
Compute the gradient magnitudes and orientations in a small window around the key point – at the appropriate scale.

4. Determine descriptors for each keypoint.
Consider a small region around the keypoint. Divide it into *n*x *n*cells (usually *n*= 2). Each cell is of size 4 x 4.
Build a gradient orientation histogram in each cell. Each histogram entry is weighted by the gradient magnitude and a Gaussian weighting function with σ= 0.5 times window width.
Sorteach gradient orientation histogram bearing in mind the dominant orientation of the keypoint
We now have a descriptor of size *rn*2if there are *r* bins in the orientation histogram. Typical case used in the SIFT paper: *r* = 8, *n*= 4, so length of each descriptor is 128. The descriptor is invariant to rotations due to the sorting.

(3) Brain tumor classification using SVM technique
In this step trained data set having information about brain tumor is giving as an input to SVM technique and comparison is made between newly inserted image and trained image. Thus tumor is classified in benign and malignant category.

IV. Experiments and Results

The proposed segmentation methods are implemented on the images of various patients received from civil hospital Ahmedabad which are T1-weighted. We are using Matlab 2017a as an implementation environment. We did the experiment of 60 various images of tumor and non-tumor and calculated various parameters such as Accuracy, Sensitivity, Specificity, Precision, PSNR. The results of the experiment are tested on windows 7 OS with core 2 due processor, 3 GB RAM.

Accuracy, sensitivity and specificity are used as evaluation metrices. Sensitivity is the measure of the fraction of the correctly classified brain in the segmentation. It is determined as

$$sensitivity = \frac{|TP|}{(|TP| + |FN|)} \quad (6)$$

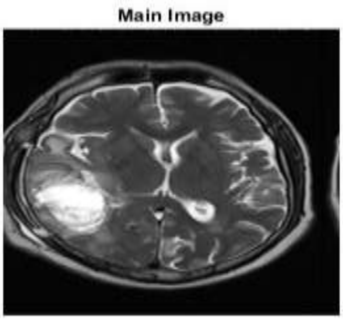
where is TP indicates true positive and is FN indicates false negative.
Specificity is the measure of the fraction of the correctly classified non-brain voxels in the segmentation. It is determined as

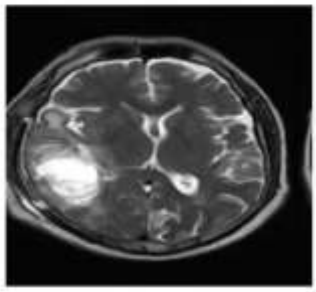
$$specificity = \frac{|TN|}{(|TN| + |FP|)} \quad (7)$$

where
TN is true negative and FP is false positive.
Accuracy is the statistical measure of how well a binary classification test correctly identifies or excludes a condition.

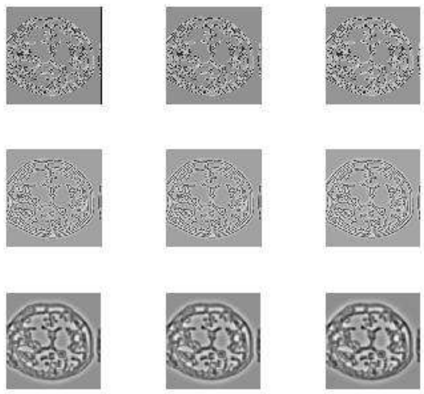
$$accuracy = \frac{|TP| + |TN|}{|TP| + |FP| + |FN| + |TN|} \quad (8)$$

The performance of the proposed method is compared to histogram partitioning with maximum entropy divergence method. The evaluated results (Graph 1) shows a good detection performance with a global Precisionof 100%, specificity of 100%, with an accuracy of 96.26% compared to normal image which has specificity of 97.65%, precision of 97.55% with a accuracy of 93.63%. Thus the proposed method could be used for Precisely classification of tumor and non-tumor portion in T1-weighted MRI images of brain. Though sensitivity we got is 87.23%. Diagrammatic representation is shown below.

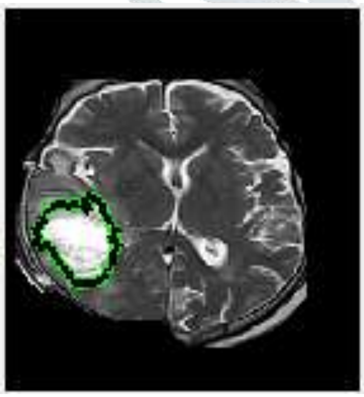




(a) (b)



(c) (d)

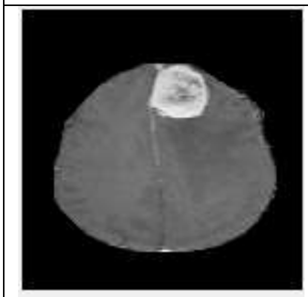
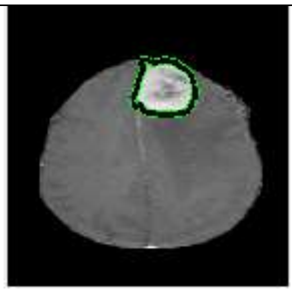
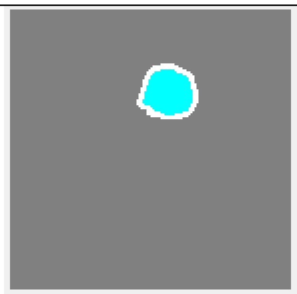
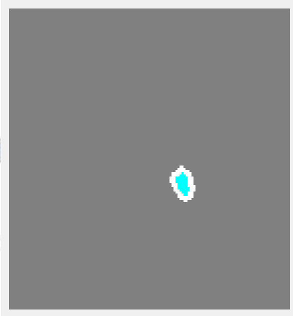
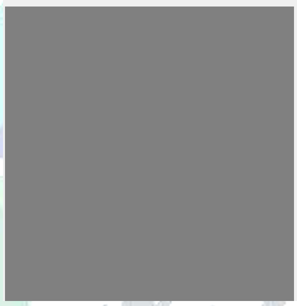


(e) (f)

Fig.1 Tumor Detection and Classification Process (a)Input Image (b) Filtered image using median filter (c) Edge detection (d) Texture based detection (e) Detected Tumor Portion (f) Classified tumor portion

Some other image comparison with performance measure is shown in below table.

Table 1 Comparison table with Result analysis

Input Image	Detected Tumor Portion	Classified Tumor Portion	Performance Measure
 Image 1			Accuracy= 96.57% Sensitivity= 98.13% Specificity= 100% Precision= 100% PSNR= 40.91 db
 Image 2			Accuracy= 91.79% Sensitivity= 78.60% Specificity= 100% Precision= 100% PSNR= 39.22 db
 Image 3	 No Portion Detected	 Non-tumor	Accuracy= 97.95% Sensitivity= 39.75% Specificity= 100% Precision= 100% PSNR= 37.31 db

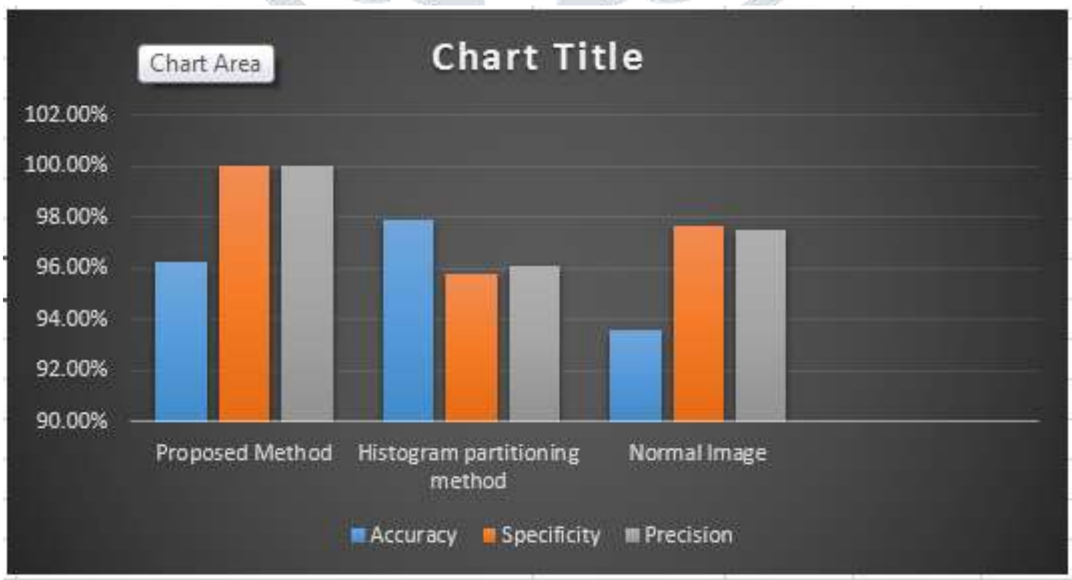


Fig 2: Comparison of performance measures

V. **Conclusion**

In this paper, Segmentation and classification based method for T1-weightd MRI based on Shape and texture factors is proposed to detect tumor and non-tumor regions Precisely. Before applying the method, the image was filtered by median filter. Detecting the tumor and non-tumor portion from the structural images of the head is a critical component for a variety of post-processing tasks. Besides, there are growing amount of clinical data acquired daily in hospitals. Because of several factors, current techniques require manual intervention but manual delineation of MR images is very tedious and time consuming. So developing automated and semi-automated method for brain tumor detectionis of great importance. Though this is the method that provides support to the expert doctors in better diagnostic. The evaluated performance of the proposed method is found to be effective for extracting tumor and non-tumor region from T1weighted MRI images.in some scenario sensitivity we got in this method is lower a bit that can be improved using other techniques.

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