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A COMPARATIVE STUDY OF SEGMENTATION TECHNIQUES FOR IDENTIFICATION OF BRAIN TUMOR FROM MAGNETIC RESONANCE IMAGES

Sugandha Singh
Department of Computer Science, Babasaheb Bhimrao Ambedkar University, Vidya Vihar, Rae Bareli Road, Lucknow (U.P.) 226025, India.
Email: singhsugandha3@gmail.com, Orchid Id: 0000-0002-9202-8507

Vipin Saxena
Department of Computer Science, Babasaheb Bhimrao Ambedkar University, Vidya Vihar, Rae Bareli Road, Lucknow (U.P.) 226025, India.
Email: vsax1@rediffmail.com, Orchid Id: 0000-0003-1035-1704

Abstract
From the literature, it is revealed that identification of accurate position of the brain tumor in Magnetic Resonance Images (MRI)is a very challenging task. The tumor orientation, shape and size are having different position in the brain so that it identification of it by the use of various segmentation techniques became more difficult. For handling and analysing of the above-mentioned issue, the present work is an attempt to propose various segmentation methods using edge-based, threshold and region growing on pre-processed MRI brain images. During the pre-processing stage, filter images use themedian filter function and thereafter skull stripping technique is applied to remove unnecessary border region from the brain. After removing the unnecessary region of the border, the segmentation methods are applied over the pre-processed images. For performance evaluation and analysis, quality metrics are measured to compute the difference between original image and pre-processed image. The quality metricsare computed on the collected MRI brain imagesand results are presented in the form of tables and graphs.

Keywords: MRI, Brain Tumor, Pre-processed Images, Segmentation, Quality Metrics

I. Introduction

Due to availability of high computing technical machines, medical image processing is gaining the popularity in the recent years and collaborative research with medical practitioners; Mathematicians; Computer Scientists produce excellent methods and accurate data for finding the brain tumor in the MRI. In the literature, several studies are available in the field of medicalimaging. It is observed that the brain tumor is most common disease inthe human being that arises due to several reasons. In this regard, the patient's history is very helpful for diagnosing the accurate position of the brain tumor region of interest. Brain tumor isdefined as unnecessary and extraneous growth of cells in the human being and the skull of the brain is extremely inflexible whileany abnormal growth inside the brain, may arises some issues of the brain tumor. The pressure inside skull may produce the type of cancerous brain tumor cell which may grow in different shape and size. The abnormal growth of the brain may reduce the life of human being and sometimes it may be life threatening and also can harm the human brain.
There are the two important categories of the brain tumor, one is primary and other is secondary. The category of the primary brain tumor is of benign type which may in due course of the time because of

growth of non-cancerous cells in the brain inside the skull while the cancer cells from another organ such as lungs spreads to the brain is called as a secondary or metastatic brain tumor which may harm extremely to the human being.There are the various reasons of development of the above-mentioned two types of brain tumor. It is observed that thehuman beings which frequently exposedby ionising radiation or specific chemicals are having high chances of risk for the abnormal growth of brain tumor. It can be diagnosed by the physical examination and through the MRI scan of the brain for which special dye is used to aid in the diagnosis to enhance the accurate position of the region of tumor. The MRI scan is the most popular testing technique which produces the precise detailingof the structures if the tumor images. Some cells are extracted from the infected region of the brain for the biopsyand after the critical examination, these cells may be identified either as non-cancerous or cancerous cells. By the use of critical examination, one can say that the tumor brain is type of benign or metastatic brain tumor.

Generally, the machine which is doing Computing-Tomography Scan (CT-Scan) produce huge number of images after placing the patient inside the CT-Scan machine and generating a magnetic field. Some images may be blur although, the patient must remain motionless position throughout the imaging process with strong magnetic field. For increasing the speed and rate for getting the accurate images, Intravenous Therapy (IV) is administered and therefore, MRI images get brighter more quickly.Further, image segmentation is most widely used technique in which large image is segmented in sub images to predicting the exact pixel which is affected by the tumor. The concept of the digital image processing is used and is analysed after to dividing an image into multiple regionsknown as sub regions. By doing this activity, the foreground and background areas are categorized by the use of any segmentation technique. The image segmentation technique is classified into two dimensional or three dimensional (2D or 3D) segmenting the images and it is observed that the 3D segmentation technique produces more accurate results in the comparison of 2D analysis of the segmentation technique. To identify and label pixels in an image or voxels in 3D volume that represents a tumor in a patient's brain or other organs, for instance, is a typical application of image segmentation in medical imaging.

In the present work, various segmentation techniques are applied to identify the region of interest from the collection of real images of the patient in which the haematoxylin and eosin staining of body tissues help to the pathologists to identify different tissue types for diagnosing brain cancer. The different tissue types are collected in the form of images called as Magnetic Resonance Images and thereafter of breaking up of imagesstart and produces into similar or non-similar pixels that are represented by a mask or labelled images. The process only the key portions of an image by segmenting,is applied and determined the accurate position of brain tumor image and computed results are given and thereafter compared with each segmentation technique to produce the effective and accurate results.

II. Related Work

Medical imaging is the technique for observation of body tissues to provide the accurate diagnosis of disease without surgery. The several medical imaging techniques are available for diagnosis of diseases. As soon as the disease has been diagnosed it may increase the chances for patient to cure very fast and effectively. The computer aided diagnosis of brain tumor also gives satisfactory results in the field of medical image processing. For this purpose, several research articles have been studied. Some of the important research papers are described here. Gopalachari et. al.[1] proposed a method for brain tumor detection. The image enhancement has been done using Woelfel filter and the combined approach of threshold and morphological technique had been used for brain tumor segmentation. Mamatha et. al. [2] gives graph theory-based segmentation method. Before segmentation, pre-processing of MR images is performed using region of interest, inverse method and boundary detection method. After that graph base image segmentation is performed by constructing weighted directed graph correspond to every pixel of image in the graph and edge weight is determined as cost of group of pixels in the image.Islam et. al. [3] proposed optimized convolution neural network process used with enhanced dataset of MRI and CT images. Using publicly available datasets, authors determined that the method gives better results than existing method.Habib et. al. [4] proposed hybrid approach for image segmentation using threshold and watershed algorithm for brain tumor segmentation, after that the feature extraction is performed using GLCM, MSER, HOG, FAST, LBP, and gabor wavelet techniques. The classification is done using Support Vector Machine (SVM), K-nearest Neighbor (KNN), Tree and ensemble classifiers. The analysed results found that threshold segmentation with SVM classifiers gives better results as compared to other techniques. Mandle et. al. [5] proposed K-means clustering and kernel-based support vector machine for segmentation and classification, respectively. The method applied on dataset consists of 160 MRI images. The approach achieved 98.75% accuracy, 95.43% precision and 97.65% recall.Bal et. al. [6] proposed rough fuzzy C-means and shape based topological properties for automated brain tumor segmentation and it is found that Rough Fuzzy C-means (RFCM) achieve better accuracy results as compared to Hard C-means and fuzzy c-means algorithms.Ottomet. al [7] proposed deep neural network-based technique which is used for 2D MRI brain tumor images. Znet is the approach based on skip connection, encoder-decoder architecture, and data amplification and evaluated experimental results of dice is 96% for model training and 92% for testing dataset, pixel accuracy determined is 99.6%, F1 score 81% and MCC 81%.Ugale et. al. [8] have proposed watershed algorithm to detect brain tumor using MRI data.Divya et. al. [9] proposed OTSU threshold-based segmentation technique to segment brain tumor. Before segmentation process, pre-processing has been done for better results and also compared the algorithm with OTSU threshold. Anand [10] combined watershed and Self Organizing Map (SOM) for tumor segmentation and classification. Before segmentation and classification, pre-processing of image has been done for noise removal using gabor filter and then skull stripping is done to remove unnecessary borders from MRI images. It is analyzed that by combining these two techniques gives improved accuracy of 95.93 %.

Further, Bangare [11] proposed modified approach of region growing method with texture feature phase and combine tumor area with region merging method after that classification has been done using fuzzy min max neural network.Shankara and Hariprasad [13] proposed a salt, pepper, and speckle noise which are added to the input lung CT images and used different filtering techniques, including the Median filter, Wiener filter, Gaussian filter, and Guided filterfor noisy images. The effectiveness of various filters is calculated using metrics such as Peak Signal to Noise Ratio (PSNR), Structural similarity index method (SSIM), Mean Square Error (MSE), and Signal to Noise Ratio (SNR). The best filter is chosen to remove noise from the lung CT images based on performance metrics and observed 4.065604 as the Mean Square Error (MSE), with high SNR values of 36.5931, 0.983545 as the SSIM, and 42.0395 as the PSNR.

III. Methodology

For analysis of brain tumor in human being, various DICOM images have been collected and a system model is designed for performing the following steps. A system model is shown below in the figure 1.

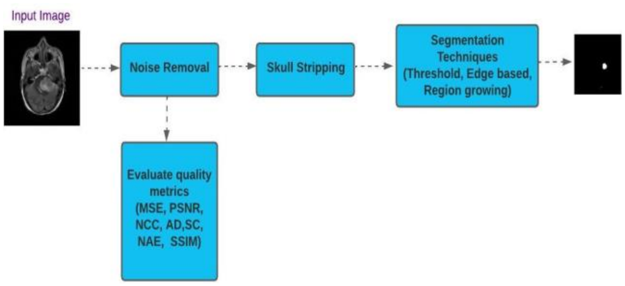

Fig. 1.A system model

Step 1. Using median filter function, during the pre-processing, the noise from the original input images is first removed;

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Step 2. Once the filtered image is done, then perform the skull stripping;
Step 3. Apply the various segmentation methods on the brain tissues to identify the tumor region;
Step 4. Analyze the quality metrics for the original and pre-processed images;

Each step as mentioned above is described below in brief:

A. Pre-processing

Brain tumor diagnosis will result in bias and significant physiological parameter differences that may affect the segmentation's images for which further processing and analysis are necessary steps for efficiently performing the segmentation operations, hence the pre-processing phase is used.

- Median Filter is the most popular technique to improve image quality used in medical image processing is the median filter algorithm, which is used in the proposed work to reduce the noise. The median value of a designated nearby N-by-N neighborhood is substituted for each input pixel by the median filter block. Relative to the mean, the median becomes less dependent on extreme occurrences. The block can be used to eliminate salt-and-pepper noise from an image while maintaining the image's clarity. For the edges of the input image, one can provide the neighborhood size and padding values.
- Anisotropic Filter spatial information is used as the basis for the filter, which lowers the noise level. In this process, an image generates a parametrized family of blurrier images based on the diffusion process, creating a scale space. The image with a 2D isotropic Gaussian filter, whose width grows as the parameter are output images in this family which are produced through by convolution method. The parameters for anisotropic filter image can be enhanced as:

num_iter = 10; delta_t = 1/7; kappa = 15; option = 2;
inp = anisodiff (s, num_iter, delta_t, kappa, option);

B. Skull Stripping

After filtering the image during pre-processing phase, the skull stripping process is carried out, this removes non-cerebral regions of the brain. For skull stripping, the image is cropped to get rid of the light box that surrounds it. The following figure 2 represents the computed results from the five MRI images:

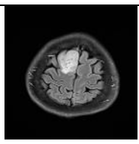
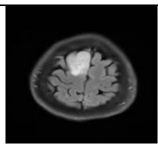
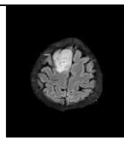
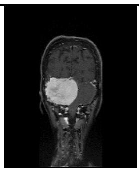
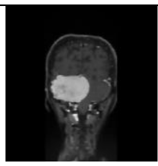
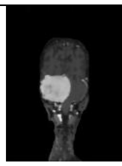
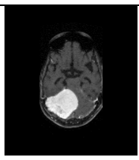
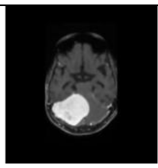
	Input Image	**Anisotropic Filter**	**Skull striping**
Image1			
Image2			
Image3			

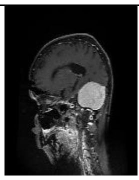
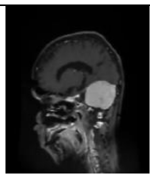
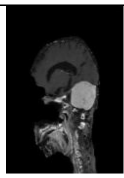
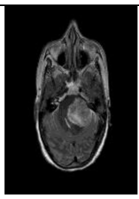
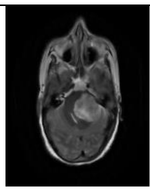
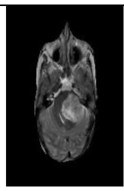
Image4			
Image5			

Fig. 2. Pre-processed images afterfiltering and skull stripping

C. Segmentation Techniques

The segmentation task for image processing is most difficult task due to the inhomogeneous properties of MRI images. Accurate segmentation will determine whether computerised analysis procedures are ultimately successful or unsuccessful. The two techniques are used in segmentation procedures which are detecting similarity between pixels based on intensity values and identifying discontinuity in images and connecting edges to form the region. In the present work different segmentation techniques are compared over the DICOM images, therefore, different segmentation techniques are described below in brief:

a) Edge Based Segmentation

The edge-based segmentation uses a variety of edge detection operators to locate edges in an image. These edges identify the areas in an image where the texture, colour, or grey levels are different. The degree of grey may vary as we move from one area to another. Therefore, we can locate the edge if we can identify that discontinuity. In order to segment the image, we have to perform additional processing on image and to reduce the number of segments rather than chunks of small borders that might impede the process of region filling, additional steps include combining the edges segments that were obtained into one segment. The process is done to give the object's border a seamless appearance. To obtain the final segmented image, threshold-based or any other type of segmentation can be applied to the intermediate segmentation result obtained through edge segmentation. The various edge detectors, including Sobel, Canny, Prewitt, and Robert's edge operators are summarized as:

- *Sobel Operator*

The Sobel operator is an edge-based detection algorithm that calculates the first derivative of an image by convolutioning it with two unique vertical and horizontal kernels. The two 3 x 3 kernels or masks used to approximate the vertical and horizontal derivatives of the input image are displayed as:

-1	0	1
-2	0	2
1	0	1

1	-2	-1
0	0	0
1	2	1

- *Prewitt Operator*

The Prewitt edge detection method and the Sobel operator are almost identical. Additionally, it can identify an image as horizontal and vertical edges. It is effective method for determining an image orientation and size. The kernels or masks that are used are as follows:

-1	-1	-1
0	0	0
1	1	1

-1	0	1
-1	0	1
-1	0	1

- *Robert Operator*

It uses discrete differentiation to calculate the sum of squares of the differences between pixels that are diagonally adjacent in an image. It is then made to approximate the gradient. It employs the subsequent masks or 2 x 2 kernels are represented as:

1	0
0	-1

0	1
-1	0

- *Canny Operator*

It uses a Gaussian-based operator for edge detection. The operator is not affected by the noise. It extracts image features without affecting or changing the feature. The following are the three factors which are used to identify edges are as follows:

1. Minimal error rate;
2. Edge points need to be localized precisely;
3. There needs to be a single edge response;

In the present work, the implementation on the selected images uses the canny edge-based operator for segmentation and represented in the figure 3.

Fig.3. Canny edge operator for edge segmentation

b) Threshold Segmentation

The goal of the threshold segmentation technique is to create a binary image from a given grayscale image by splitting the image into two regions and applying a threshold value to each region. Due to the fact that there are only two possible values for each pixel as 0 or 1, the pixel intensity can only store one bit in a binary image. As a result, pixels in the output image will be addressed as either white/1 or black/0, depending on whether the intensity values are lower than the specified threshold.

In other words, the segmented image g (x, y) can be represented by threshold T which is determined as follows:

$$g(x,y) = \begin{cases} 1 \ if \ f(x,y) > T \\ 0 \ if \ f(x,y) \le T \end{cases} \qquad (1)$$

As a result, the output segmented image only contains two categories of pixels i.e., 1 or 0. Threshold based segmentation implementation is shown below in figure 4.

(a) (b)

Fig.4. Threshold based tumor segment. (a) MR image, (b) Tumor tissues segment

c) Region Growing Segmentation

The process of combining nearby pixels with similar characteristics into larger regions is known as region-growing. The straightforward segmentation method is also referred to as pixel-based segmentation. By recursively including the adjacent, connected, and similar pixels to the seed pixel, the region expands in this manner. As soon as the growth of one pixel stops, we pick a new seed pixel that does not yet belong to any region and restart. It will compare the seed pixel to its eight nearby pixels. The first region would receive a homogeneity function and have its pixel value changed to the seed pixel value if any of the surrounding pixels met the criteria.If a new pixel is added that does not meet the homogeneity function assigned to the first region, this neighbour comparison will be carried out again until the region is entirely bounded by the image's edge. By selecting the first unassigned pixel and navigating the image from right to left and bottom to top, the next seed pixel for the second region would be determined.Every pixel in the image would then be assigned to a region after repeating the process.In region growing method, firstly input pre-processed image, resize the image, and then eight seed points are selected in input image for tumor tissues segmentation. The results over the DICOM image are shown in figure 5.

(a) (b)

Fig.5. Region growing segmentation (a) Pre-processed image (b) Tumor segment

IV. Experimental Results

The results are evaluated on MRI brain images which consist of tumor tissues. The images are collected from three different hospitals and three different cases of brain tumors are considered for the evaluation and segmentation. The brain tumor occurs in the MRI images are atypical meningioma, glioma and schwannoma brain tumor. The collected MRI images was in DICOM format it was then converted in the jpg and png format for further analysis. After converting DICOM images into jpg and png format, pre-processing of images iscompleted. The pre-processing step consists of noise removal using anisotropic filtering and skull stripping to locate the region of interest more accurately and efficiently. The skull stripping is executed to remove the non-cerebral region.

On the collected images, the brain tumor is localized using three different segmentation techniques following the pre-processing step.The input image consists of 2D MRI mages which is in RGB image form. The results of the segmentation are shown below in the figure 6.

Input Image	Edge-Based	Threshold	Region-Growing

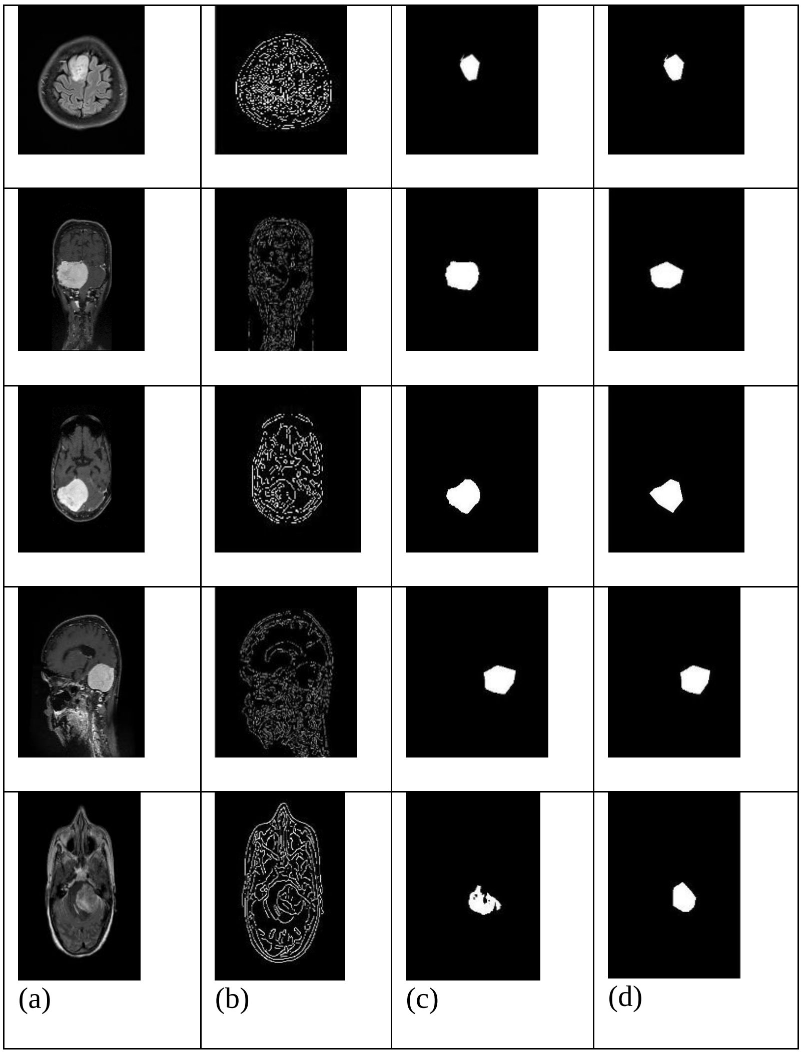


Fig.6. Performance oftumor segmentation(a) Original image (b) Edge-based (c) Threshold(d) Region-growing

Further, quality metrics has been computed to analyze the difference between original image and pre-processed image. Image Quality Measurement (IQM) is a crucial activity for the development of image processing methods such assharpening, enhancement, and noise removal because it can be used to evaluate how well the quality of the processed images as a whole will perform. The quality metrics for the proposed work are represented as:

a) Mean Square Error (MSE)

It calculates the squared cumulative error between the original and earlier-processed images by using following formula [13]:

$$MSE=\frac{\sum_{R,C}[I_1(r,c)-I_2(r,c)]^2}{R*C} \qquad (2)$$

where, R and C are the number of rows and columns in the input images, $I_1(r, c)$ is the original image and $I_2(r, c)$ is the decompressed image.

b) Peak Signal to Noise Ratio (PSNR)

It is a measurement of the peak errorand computed by following formula [12, 13]:

$$\text{PSNR} = 10log_{10}(\frac{R^2}{MSE}) \quad (3)$$

c) Normalized Cross Co-relation (NCC)

Depending on the size of the images, the cross correlation in the spatial or frequency domain is calculated by following formula [13]:

$$\text{NCC} = \frac{\sum_{x,y}[f(x,y)-\bar{f}_{u,v}][t(x-u),y-v)-\bar{t}]}{\{\sum_{x,y}[f(x,y)-\bar{f}_{u,v}]^2 \sum_{x,y}[t(x-u),y-v)-\bar{t}]^2\}^{0.5}\}} \quad (4)$$

$\bar{t}$ is the mean of the template.

$\bar{f}_{u,v}$ is the mean of f (x, y) in the region under the template.

d) Average Difference (AD)

The average difference between the values of the pixels is expressed by the number and should ideally be 0 [14]. The representation of average difference is given by

$$\text{AD} = \frac{\sum_{i=1}^{R}\sum_{j=1}^{C}|X(i,j)- X^{(i,j)}|^2}{R*C} \quad (5)$$

e) Structural Content (SC)

A crucial component of SC is the evaluation of the restored image quality standard. The poor quality of the image is indicated by the high value of SC. SC is formulated as [14]:

$$\text{SC} = \frac{\sum_{i=1}^{R}\sum_{j=1}^{C}|X(i,j)|^2}{\sum_{i=1}^{R}\sum_{j=1}^{C}|X^{(i,j)}|^2} \quad (6)$$

Where, X(i, j) is original image, R and C are the number of rows and columns in image.

f) Normalized Absolute Error (NAE)

The important characteristics of NAE are used to evaluate the quality in the reconstruction of images. The image of poor quality will highlight with the high value of NAE [14]. NAE is defined as:

$$\text{NAE} = \frac{\sum_{i=1}^{R}\sum_{j=1}^{C}|X(i,j)-X^{(i,j)}|}{\sum_{i=1}^{R}\sum_{j=1}^{C}|X(i,j)|} \quad (7)$$

where, R and C are number of rows and columns in the image and X (i, j) is the original image

g) Structural Similarity Index Method (SSIM)

SSIM index method isdepended on the computation of three necessary factors these are contrast, luminance, and correlation terms. These three factors are computed by multiplying together to create SSIM index and computed by following formula [12, 14].

$$\text{SSIM (x, y)} = [l(x,y)]^p \cdot [c(x,y)]^q \cdot [s(x,y)]^r)] \quad (8)$$

where, l denotes luminance which is used to compare brightness between two images, c denotes contrast to compare the ranges between the bright and darkarea of two images, s denotes structure to compare the local luminance pattern between two imagesand p, q and r are the positive constants.

The quality metrics are also calculated to evaluate the difference between original and filtered images that are shown in the table 1 and table 2. The comparative analysis of anisotropic and median filter is proposed for image enhancement for MRI images is evaluated. For experimental purpose, five MRI brain tumor images are used.

TABLE1. EVALUATION OF PRE-PROCESSED RESULTS BY EMPLOYINGQUALITY METRICS (MSE, PSNR, NCC, AD, SC, NAE andSSIM)FUNCTIONSFOR ANISOTROPIC FILTER

Input Image	**MSE**	**PSNR**	**NAE**	**SSIM**	**AD**	**SC**	**NCC**
Image1	68.17	29.79	0.1254	0.8863	-0.3636	1.030	0.9748
Image2	70.76	29.63	0.1325	0.8869	-0.3886	1.0065	0.9784
Image3	252.90	24.10	0.2785	0.7959	-0.7277	0.9493	0.9752
Image4	100.13	28.12	0.1527	0.8323	-0.5940	1.0116	0.9731
Image5	286.09	23.56	0.2591	0.7604	-1.115	1.003	0.9396

TABLE2. EVALUATION OF PRE-PROCESSED RESULTS BY EMPLOYINGQUALITY METRICS (MSE, PSNR, NCC, AD, SC, NAE ANDSSIM)FUNCTIONSFOR MEDIAN FILTER

Input Image	**MSE**	**PSNR**	**NAE**	**SSIM**	**AD**	**SC**	**NCC**
Image1	435.55	21.74	0.2815	0.7259	-1.413	0.9572	0.9573
Image2	141.62	26.61	0.1953	0.8169	-1.083	0.9531	0.9879
Image3	45.38	31.56	0.0924	0.9428	-0.431	0.9822	0.9999
Image4	131.42	26.94	0.1747	0.7883	-0.990	0.9704	0.9875
Image5	106.05	27.87	0.1594	0.8677	-0.389	0.9960	0.9802

Table 3 shows the average results in terms of PSNR, MSE, NAE, SSIM, AD, SC, and NCC respectively for MRI images of anisotropic and median filter. The comparative analysis of anisotropic and median filter is proposed for enhancement of image quality to accurately segment brain tumor is measured. Figures 7, 8, 9, 10, 11, 12 and 13 represent the comparison results of anisotropic and median filter in terms of PSNR, MSE, NAE, SSIM, AD, SC, and NCC respectively of MRI input images.

TABLE3. EVALUATION OF ANISOTROPIC AND MEDIAN FILTER IN TERMS OF PSNR,MSE, SSIM, AD,NCC, SC, NAE OF FIVE INPUT MRI IMAGES

Filter Method	**PSNR (Higher bette**	**MSE (Lower better)**	**SSIM (Higher bette**	**AD (Zero better)**	**NCC (One bett**	**SC (Lower better)**	**NAE (Lower better)**

	r)		r)		er)		
Anisotropic	29.79	68.17	0.8869	-0.3636	0.9784	0.9493	0.1254
Median	31.56	29.79	0.9428	-0.389	0.9999	0.9531	0.0924

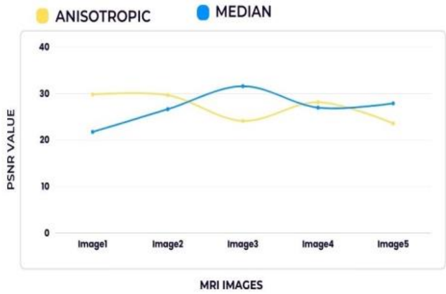


Fig.7.Comparison of PSNR values of anisotropic and median filter methods for fiveinput MRI images

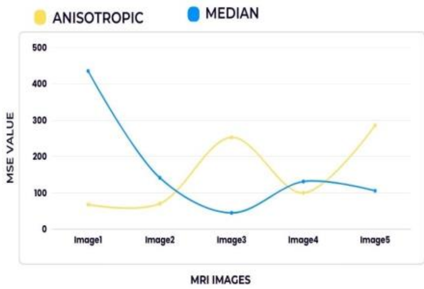


Fig. 8. Comparison of MSE values of anisotropic and median filter methods for fiveinput MRI images

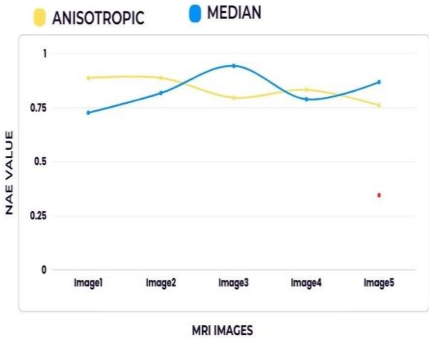


Fig. 9. Comparison of NAE values of anisotropic and median filter methods for five input MRI images

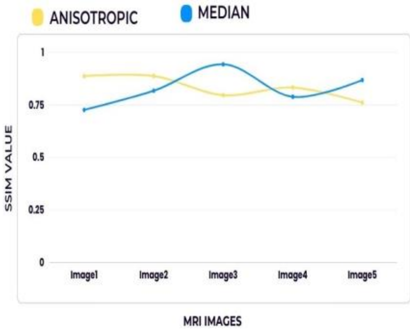
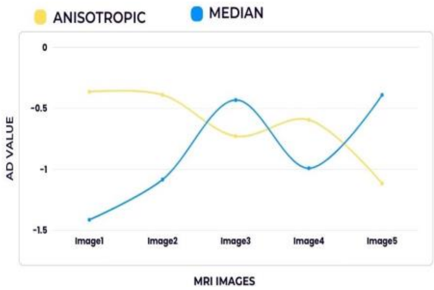


Fig. 10. Comparison of SSIM values of anisotropic and median filter methods for five input MRI images



Fi
g. 11. Comparison of AD values of anisotropic and median filter methods for fiveInput MRIimages

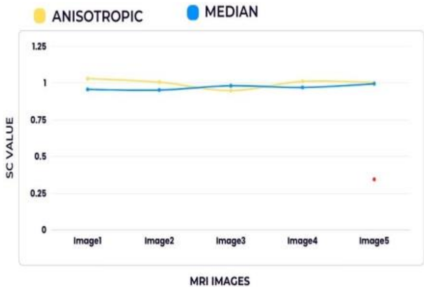


Fig. 12.Comparison of SC values of anisotropic and median filter methods for fiveinput MRI images

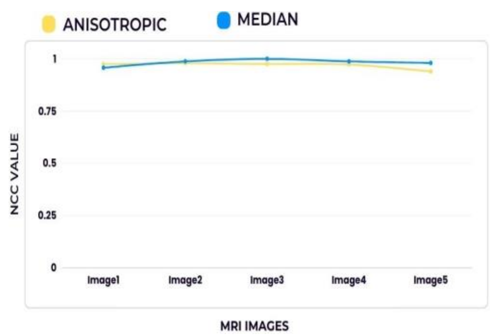


Fig. 13. Comparison of NCC values of anisotropic and median filter

From the above tables and figures, it is observed that the median filter for MRI brain image enhancement method is showing excellent results in comparison to anisotropic filter method.

V. CONLUSION

From the proposed work, it is concluded that various segmentation methods are very helpful for finding the accurate position of the brain tumor in Magnetic Resonance Images (MRI) as the tumor varies in shape, size and location of tumor in the brain. The edge-based, threshold and region growing segmentation techniques are compared by pre-processing, filtering of images with the anisotropic filter function and thereafter skull stripping technique is applied to remove unnecessary border region from the brain. After applying the various segmentation techniques, it is observed that the median filter for MRI brain images enhancement method is producing the excellent results in comparison to anisotropic filter method. The present work
can be extended to compare the segmentation techniques for the various wheat, rice and other grain varieties in the agricultural field or it can detect the tumor in other parts of the human body.

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