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A Comparative Study to Detect Tumor in Brain MRI Images using Clustering Algorithms

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***Abstract*—The identification of the tumor area in the magnetic resonance images(MRI) by radiologists or experts is a tedious and time-consuming task. This task requires high accuracy, and that comes with experience and knowledge. With the growth in the information technology, medical imaging field is also reducing the complexities and increasing the accuracy in diagnosis. To increase the efficiency and accuracy of the Fuzzy K-Mean clustering, K-Mean clustering, and Birch clustering algorithms, these algorithms are incorporated with contour-based cropping, pre-processing, and post-processing. In pre-processing, anisotropic diffusion filter, non-local means filter, and Gaussian filter are used and compared. In post-processing, erosion and median filter are used. The experimental results show the significance by comparing the quality parameters with the state-of-the-art methods. Index Terms—MRI image, Tumor, Clustering algorithm, morphological, and contour detection**

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I. INTRODUCTION

Recently, the e-health care system has advanced with the introduction of information technology and giving better clinical service to patients. This study addresses the issues in segmentation of tumour detection in the Magnetic Resonance Imaging(MRI) images using pre-processing, clustering algorithms, and post-processing [1]. The tumor is made up of cells and usually, cells have three stages namely, growth, age, and then death. After the death of old cells, new cells are formed to replace these cells. In unusual cases, formation and destructive activities begin to function differently than usual [2]. This unusual behavior starts to form undesired cells and these undesired cells do not die in time and begin to group a structure called the tumor. This tumor may be cancerous [3]. This cancerous tumor must be diagnosed at an early stage to save the life of humans. Nowadays, the detection technology is generally based on MRI imaging [4]. MRI technology is contrasting from CT as it utilizes the effective magnetic field to line up the nuclear-magnetized hydrogen atoms of water in the body, and not ionizing radiation [5]. The new imaging multimodalities, such as X-Rayy, Ultrasonography, Computed Tomography (CT), Magneto Encephalo Graphy (MEG), Electro EncephaloGraphy (EEG), Positron Emission Tomography (PET), Single-Photon Emission Computed Tomography(SPECT), and Magnetic Resonance Imaging (MRI), provide a path for correlation of anatomical and various functional metrics associated with each imaging modality [6]. The main purpose of rendering accurate representations of important anatomical features, that are used in the form of quantitative studies to correlate volumes obtained from anatomical structures using pathological process [7]. Once a brain tumor is diagnosed by a medical practitioner then radiological assessment is necessary to estimate the precise location, the stage of the tumor and effect in the surrounding structures [8]. This is vital and critical information in diagnosing the different levels of the therapy at different locations by applying therapy. Hence, the diagnosing of brain tumors from imaging modalities is a key issue among medical practitioners [9]. MRI is a very popular imaging modality that has a non-invasive process and not only uses good soft tissue contrast but also gives critical information related to the localization of the brain tumor such as shape, size without affecting the patient in high ionization radiation. MRI is getting popular day by day due to the advanced properties and non-invasive features in the clinical setting [10]. The procedure of segmentation of tumor in MRI is a very tough and time-consuming task. Generally, tumor size in the brain varies in terms of size, location, shape, and appearance and has varying intensities overlapped with normal tissues of the brain, and often a tumor in growing phase can affect badly its surrounding structures in the brain area and generate abnormal structures for healthy tissue [11].

The rest of the paper is structured as follows: Section 2 discusses the related work, the methodology is presented in Section 3, experimental results are explained in Section 4 and Section 5 concludes the work of this paper.

II. RELATED WORK

In the process of detecting the tumor from brain MR images, medical image segmentation plays a significant role. In the literature, there are many methods to classify tumors in brain MR images, such as fuzzy k-mean, artificial neural network, expectation-maximization, support vector machine, etc. These methods are used for segmenting the region and to find out the crucial data from the medical images. In this section, a summary of the current work related to this area is presented here. T. Logeswari et al. proposed two-phase segmentation method to find tumor in MR images of the brain using HSom segmentation, which classifies the image row by row using self-organizing map and obtained better values of tumor Pixels [12]. Hanafy M. Ali Modified a median filter algorithm with added noise such as Salt, Gaussian and Pepper in MR image. Further, they implemented the filters namely, median, adaptive median and adaptive wiener. To compare the performances of the filters, noise density has been added gradually in the MR image. The efficiency of filters is compared based on the parameter Peak Signal -to- Noise Ratio(PSNR) [13]. Selvaraj Damodharan et al. proposed a neural network (NN) based approach for detecting tumors and segmentation of brain tissues. They analyzed empirical results using means of quality-rate (QR) on normal and abnormal MR images. There are also several other evaluation parameters such as sensitivity, accuracy, and specificity which are used with classification methods such as Neural Network, k-mean, etc. Mustaqeem et al. applied the NNs for segmentation [14]. Anam Mustaqeem et al. used a method using segmentation and morphological operators for detecting the tumors. This algorithm improved the results of scanned images [15]. Jiang-tao Xu. et al. adopted a method to remove noise, that depends on a semi-adjustable threshold in anisotropic diffusion filter. This semi-adjustable threshold will generate better information with robustness to noise and protection. Hence, anisotropic diffusion with a semi-adjustable threshold is better to use for restoration of the image in diffusion function. The threshold value consists of gradient information from corrupt pixels, which gives more and less diffusion in smooth and boundary regions respectively. When it is compared with the anisotropic diffusion method, PSNR increased by 30% and SSIM also increased by 5% and also preserved edges information by eliminating noises [16]. Hakeem A.A. et al. proposed a pillar k-mean algorithm for segmentation of images and compared with the k-means algorithm-based image segmentation method using a Gaussian mixture model with various color spaces. This method also used a new technique for classifying the members of images with high resolution to enhance accuracy and to decrease the running time. This method was able to utilize efficiently k-means clustering algorithm in image segmentation [17]. Pritee et al. used the k-means and fuzzy c-means clustering algorithms for segmentation in place of manual segmentation to increase the efficiency [17]. After overview of the literature, there are significant scope of work in pre-processing, segmentation methods and post-processing of the medical images. Hence, in this paper, a method is proposed to detect tumor in the brain MRI, that consists of three steps namely, Pre-processing using contour based cropping and denoising filters, using different clustering algorithms and finally post-processing having morphological operations on clustered MRI images to detect the brain tumor precisely.

III. METHODOLOGY

This section presents the algorithm used to detect tumor in the brain MR images. Fig. 1 illustrates the flow of the methodology. First, pre-processing of the method is discussed and later clustering algorithms are presented. In the end, post-processing methods are described.

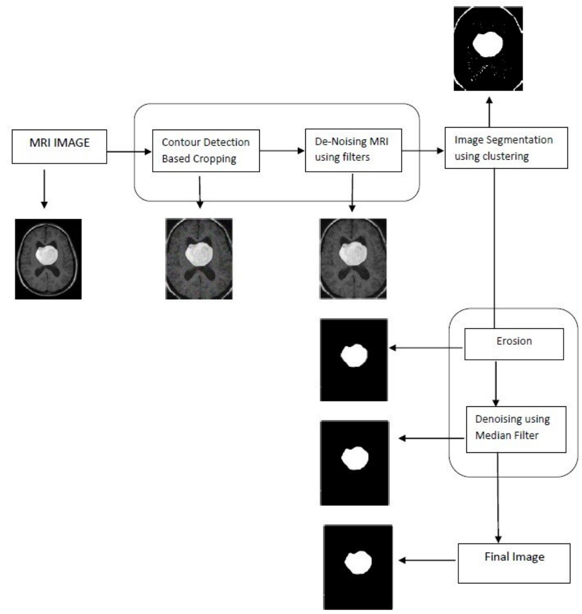


Fig. 1. Flow diagram

The proposed implementation involves four steps: Pre-Processing, Image Segmentation, Post-Processing and Analysis of extracted tumor. Pre-processing step involves 2 sub-steps: Contour detection based cropping of MRI and De-noising using filter. Contour detection based cropping of MRI which crops the unwanted portions of image, hence giving an output image in which the maximum portion is occupied by scanned brain image is discussed in the Algorithm 1. This step helps in improving the efficiency of algorithms used for image segmentation since they need to work only on useful portion and thereby reducing computational time.

Algorithm 1 Contour detection based cropping of MR images
Input: Original MR Images
Output: Cropped MR Images
1: Thresholding to segment the required region
2: Finding contours in the segmented image
3: Sorting out the largest contour which is boundary of brain itself
4: Find extreme points along the contour
5: Add these extreme points on the image
6: Crop the image along the largest contour line and extreme points

MRI's are often affected by Gaussian noise, which can affect Brain Tumor segmentation. Hence, it is needed to de-noise images so as to the improve the classification efficiency. For this purpose, Gaussian Noise is added to our cropped images and then de-noised them to accurately simulate the real life scenario. For the purpose of de-noising 3 different filters viz.

Anisotropic Diffusion Filter [18], Non-Local Means [19]and Gaussian Filters [20] have been compared based upon their Peak Signal to Noise Ratio(PSNR) values to determine the de-noising capabilities of each of them. Image Segmentation step involves simultaneous clustering and feature extraction. K-means, Fuzzy K-means and Birch clustering algorithms have been used separately with their classification compared [21] [22]. Post-processing step involves repairing the tumor area from the segmented image using erosion followed by further de-noising using a median filter [23].

Clustering of tumor area obtained after brain tumor featuree extraction contains some unwanted portions which can be removed to improve the quality. This can be done by morphological operations. The morphological operation best suited for this purpose is erosion. In the process of erosion, it takes two inputs into two parts. Initially, an image is taken as input for erosion and later, structuring elements that are a set of coordinate points. Structuring elements specify the accurate impression of the erosion of input medical images [24]. Median filter works in a nonlinear pattern and reduces the noises from the images. It is also effective in preserving the edges information. The median filter scans the whole image pixel by pixels and then substitutes the value by the median value, that is obtained from neighboring pixels. Neighboring pixels are denoted by a ”window”. This procedure continues over all the pixels of the images. The median value is estimated by sorting pixels in numerical order and then substituted by the middle pixel value [25].

IV. RESULTS AND DISCUSSION

The proposed method was implemented in MATLAB2019a and Spyder on a machine with Intel Core i5 8th Gen 3.0GHz processor with 8GB RAM. Dataset of MR images was obtained from Kaggle dataset repository [26]. This dataset contains a total of 155 images with both tumor and normal brain MR images. Efficiency of the experiment is evaluated based on the two parameters namely, Peak Signal-to-Noise Ratio (PSNR) and accuracy of the clustering. PSNR is measured in dB. PSNR is used to measure the quality of output image after the reconstruction and it is given as follows in equation 1.

$$psnr = 20\log_{10}\left(\frac{max_f}{\sqrt{mse}}\right), \qquad (1)$$

where mse is known as mean square error and max_f is representing the maximum signal value, present in original image(known as good). mse is denoted by the equation 2

$$mse = \frac{1}{mn}\sum_{0}^{m-1}\sum_{0}^{n-1}||f(i,j) - f'(i,j)||^2, \qquad (2)$$

where, f is a data in a matrix form of original image, f' represent matrix data of degraded images, m is the number of pixels in a row, and n is the number of pixels in an image.

Accuracy is one of popular metric for determining the efficiency of classification models [27]. Accuracy denotes the ratio of predicting right in our model and the formula for accuracy is given in equation 3 as:

$$Accuracy = \frac{TP + TN}{TP + TN + FN + FP}, \qquad (3)$$

where TP shows true positives cases, FN represents false negatives cases, TN denotes true negative cases and FP is false positives cases.

State-of-the-art methods have been compared experimentally on the basis of PSNR and accuracy. Gaussian filter is used with k-means algorithm then it is known as M 1, with Birch algorithm, it is represented as M 2 and with fuzzy k-mean, it is denoted by M 3. Non-local means filter is used with k-means algorithm then it is labeled as M 4, with Birch algorithm, it is represented as M 5 and with fuzzy k-mean, it is denoted by M 6. Anisotropic diffusion filter is used with k-means algorithm then it is labeled as M 7, with Birch algorithm, it is known as M8 and with fuzzy k-mean, it is denoted by M9.

Contour detection based cropping of MRI which crops the unwanted portions of image and giving an output image in which the maximum portion is of brain image as given in the fig. 2. This step helps in improving the computation and efficiency of algorithms used for image segmentation.

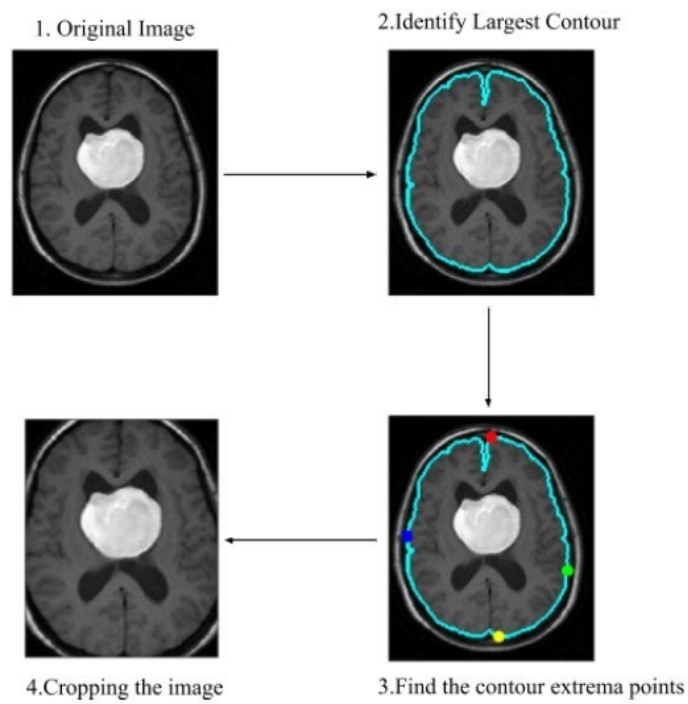


Fig. 2. Contour detection-based cropping

In the fig. 3, denoising of the MR images is conducted based on PSNR values and it is found that the maximum PSNR is achieved using the anisotropic diffusion filter for

different test images. Anisotropic Diffusion Filter works best for de-noising amongst these 3 filters. These three filtering algorithms were further tested on 2 more images and denoised images with respective PSNR values have been tabulated below:

In the fig. 4, MR images are segmented using k-means, fuzzy k-means, and Birch clustering algorithm and their output are shown in this figure. In fig 5, the result of post-processing

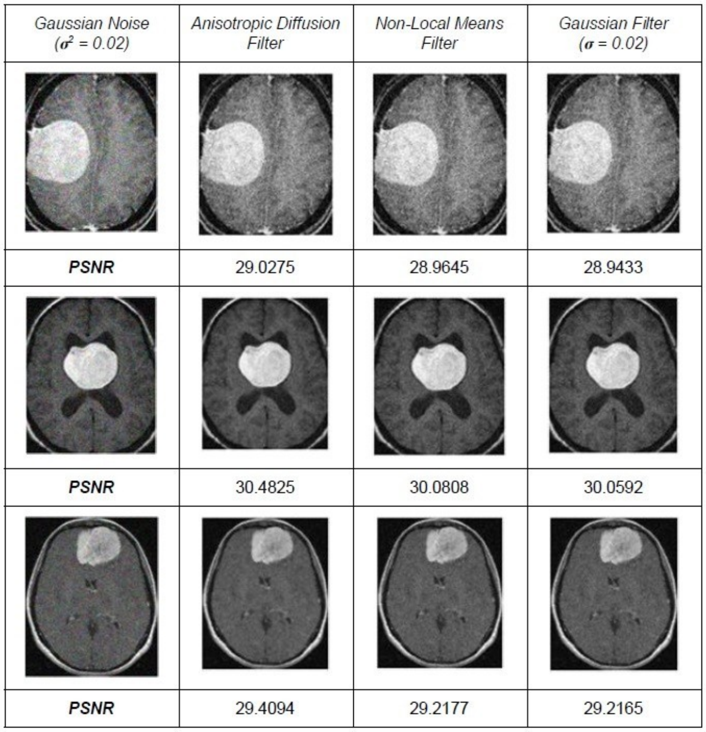


Fig. 3. Denoising using different filters

(a) K-means

(b) Fuzzy K-means

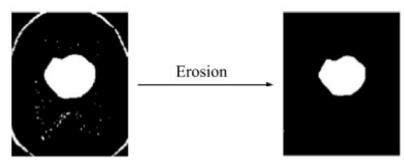
(c) Birch

Fig. 4. Image segmentation using clustering

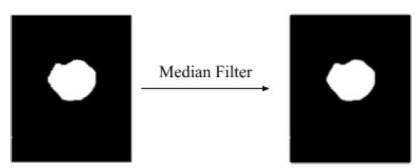
methods namely, erosion and median filter is shown. Segmentation methods are compared using the accuracy index on the dataset in Table 1 and the proposed M 9 performed better as compared to other methods.

TABLE I
COMPARISON OF METHODS ON THE BASIS OF ACCURACY

Method	Accuracy (%) without Pre-processing and Post Processing	Accuracy (%) with Pre-processing and Post Processing
M1	80.29	82.14
M2	81.54	84.06
M3	84.14	86.55
M4	82.04	84.29
M5	83.54	85.06
M6	86.55	87.14
M7	85.06	88.54
M8	88.04	90.29
M9	92.51	94.55



(a) Erosion



(b) Median filter

Fig. 5. Image Post-Processing

V. CONCLUSION

In this study, MR images are classified into the normal and images with tumor category. In this study, 155 MR images of the brain are taken. In the pre-processing, contour-based cropping of MR images is performed to improve the computational efficiency of segmentation algorithms. Various filters have been used to compare their results and anisotropic diffusion filter performed the best based on the PSNR parameter. Segmentation performance is evaluated on the basis of the *accuracy* index and later many post-processing operations are performed to improve the efficiency such as erosion and median filter. Proposed method M 9 achieved the highest accuracy and demonstrate the effectiveness of the technique in detecting normal and abnormal tissues, present in the MR images.

In our future work, the accuracy of the classification of this work will be enhanced by considering the other methods of the machine learning.

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