A Systematic Review and Performance Evaluation of Algorithms for Tumor Detection from MR Brain Images

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ABSTRACT-Biomedical Image Processing is a growing and demanding field. The primary goal of medical imaging is to extract meaningful and accurate information from these images with the least error. MRI is the most reliable, safe, radiation-safe and non-invasive imaging modality used for imaging soft tissues. There are many algorithms for detecting tumor from MR Brain images but problems like non-uniform illumination, obscure contours, poor contrast and complexity of images are still faced. This paper presents a review on state-of-the-art methods and algorithms available for segmentation of medical images. Performance evaluation of Tumor detection algorithms is performed both subjectively and objectively using parameters like Precision, Recall, and F-measure. From experimental results, Otsu method outperforms other algorithms for tumor detection.

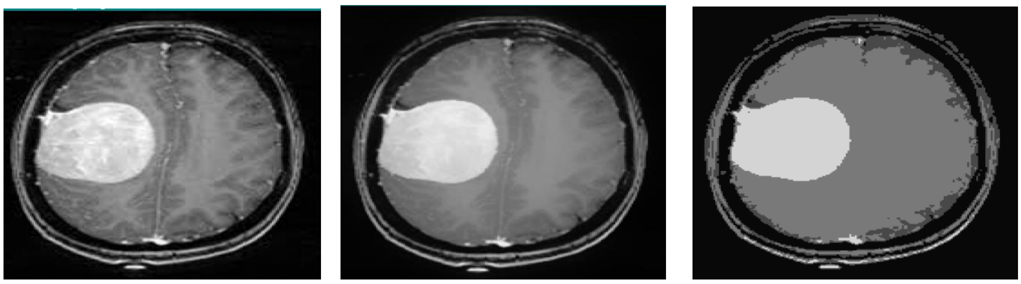
KEYWORDS-*Image Segmentation, Tumor Detection, MR Images, Brain Tumor.*

1 INTRODUCTION

The image segmentation process is one of the fundamental steps of digital image processing based applications. Its importance can be realized as it has vast and extensive use in multidisciplinary areas of medical imaging, computer vision, remote sensing, agricultural imaging, object recognition to name a few. Digital image processing refers to the use of various computer algorithms in order to perform image processing on digital images. It is mainly concerned with:

- Improvement of the pictorial information for better human interpretation
- Processing of image data for storage, representation and transmission.

DIP focuses on developing a computer system that is able to perform processing on an image. The input of that system is a digital image and the system process that image using efficient algorithms and gives an image as an output. Brain tumor [12] can be considered as the abnormal growth of the cell inside the skull. Normally tumor grows from the blood vessels, from the cell of the brain or nerves that emerge from the brain. Basically There are two types of tumor which are benign (non-cancerous) and malignant (cancerous). Tumor can cause damage to the normal brain cells by producing inflammation, exerting pressure on parts of brain and increase pressure within the skull. Brain tumor [11] at early stage is very difficult task for doctors to identify, so it becomes difficult for doctors to identify tumor and their causes.



(a) Original Image (b) Image after noise removal (c) Region of Tumor detected

1.1 MOTIVATION FOR WORK

Although a huge amount of review work exists regarding image segmentation methods but after assaying the work the following pinpoints emerged:

- Paper addresses the problem of lack of comprehensive review of segmentation techniques for extracting region of interest from medical images
- Paper contributes towards the performance evaluation of few state-of-the-art techniques using some performance metrics for detecting tumor region from MR brain image

This paper is organized as follows: Section 2 describes the various state-of-the art segmentation techniques and need of segmentation for medical images. Section 3 presents the relevant research questions to be addressed, key research areas and various existing algorithms for medical image segmentation giving their methodology, contributions and research gaps. Section 4 presents evaluation methods used for evaluation, performance metrics for quantitative evaluation and experimental results of algorithms for detection of Tumor from MR Brain Images, both quantitative and qualitative. Section 5 presents a discussion on the findings and Section 6 gives the conclusions and future work for further research.

2 BACKGROUND

For interpreting an image automatically , first of all segmentation process partitions the image into different regions. This partition process is guided by some common parameters such as texture , color, gray-level,depth,motion etc.[4] In medical images segementation is mainly performed on gray-level values of pixcels because most of the medical images are represented using gray-level values of pixcels.After partitioning the image it extracts the homogeneous region of interest for further analysis. Homogeneity of the region depends upon the application. Here brain tumor is the region of interest in medical images so segmentation process is consummated to detect the tumor[13].

2.1 STATE-OF-THE-ART SEGMENTATION:

Studying the various segmentation techniques, it is seen that each of the technique has given the best results. Each has its own advantage and disadvantage which has been tried to overcome using its advanced version. Let's have a look at the result of each basic technique:

2.1.1 WATERSHED AND EDGE DETECTION METHOD

It is being applied on the colored MR images of the brain [1]. The advanced watershed technique, which is Marker Based Watershed Technique, has been used. This algorithm has proved that brain tumor is better detected from colored MR image than the gray scale image. Watershed techniques [1] are presented to perform image segmentation and edge detection tasks. We first used the K-means technique to obtain a primary segmented image. We then employed a watershed technique that works on that image; this process includes gradient of the segmented input image, divides the image into markers, completes the watershed line by using the markers, and stores the image in the format of region adjacency graph (RAG). The initial segmentation result was obtained by the watershed algorithm. We then used merging techniques based on mean gray values and two edge strengths to obtain edge maps.

2.1.2 K-MEANS CLUSTERING

This segmentation method has combined the segmentation of MR image with the k-means clustering [8]. The basic emphasis is given on removing the outer scull before the morphological processes. The algorithm is proved to take lesser execution time. K-means is one of the simplest unsupervised learning algorithms that solves the well known clustering problem. The procedure follows a simple and easy way to classify a given data set through a certain number of clusters (assume k clusters) fixed apriori. The main idea is to define k centers, one for each cluster. These centers should be placed in a cunning way because of different location causes different result. So, the better choice is to place them as much as possible far away from each other. The next step is to take each point belonging to a given data set and associate it to the nearest center. When no point is pending, the first step is completed and an early group age is done. At this point we need to re-calculate k new centroids as BabyCenter of the clusters resulting from the previous step. K-means clustering is a type of unsupervised learning, which is used when you have unlabeled data (i.e., data without defined categories or groups). The goal of this algorithm is to find groups in the data, with the number of groups represented by the variable K [8].

$$J = \sum_{j=1}^{K} \sum_{n \in S_j} |x_n - \mu_j|^2,$$

2.1.3 FUZZY C-MEANS

The Fuzzy c-Means algorithm is a clustering algorithm[4] where each item may belong to more than one group (hence the word 'fuzzy'), where the degree of membership for each item is given by a probability distribution over the clusters. It is useful when the required number of clusters is pre-determined thus the algorithm tries to put each of the data points to one of the clusters. What makes FCM different is that it does not decide the absolute membership of a data point to a given cluster instead it calculates the likelihood (the degree of membership) that a data point will belong to that cluster. Hence, depending upon the accuracy of the clustering that is required in practice, appropriate tolerance measures can be put in place. Since the absolute membership is not calculated, FCM can be extremely fast because the number of iterations required to achieve a specific clustering exercise corresponds to the required accuracy [4].

$$\mu_{ij} = 1 / \sum_{k=1}^{c} (d_{ij} / d_{ik})^{(2/m-1)}$$

$$v_j = (\sum_{i=1}^{n} (\mu_{ij})^m x_i) / (\sum_{i=1}^{n} (\mu_{ij})^m), \forall j = 1, 2, ...c$$

2.1.4 THRESHOLDING METHOD

Thresholding[11] is an important technique for image segmentation that tries to identify and extract a target from its background on the basis of the distribution of gray levels or texture in image objects. Most thresholding techniques are based on the statistics of the one-dimensional histogram of gray levels and on the two-dimensional co-occurrence matrix of an image Thresholding is a process of converting a grayscale input image to a bi-level image by using an optimal threshold. Segmentation involves separating an image into regions (or their contours) corresponding to objects. We usually try to segment regions by identifying common properties. Or, similarly, we identify contours by identifying differences between regions (edges). The simplest property that pixels in a region can share is intensity. So, a natural way to segment such regions is through thresholding, the separation of light and dark regions[11].

2.1.5 SKULL STRIPPING METHOD

Skull stripping is an important process in biomedical image analysis, and it is required for the effective examination of brain tumor from the MR images. Skull stripping is the process of eliminating all non-brain tissues in the brain images. By skull stripping, it is possible to remove additional cerebral tissues such as fat, skin, and skull in the brain images. There are several techniques available for skull stripping; some of the popular techniques are automatic skull stripping using image contour, skull stripping based on segmentation and morphological operation, and skull stripping based on histogram analysis or a threshold value. This study uses the skull stripping technique that is based on a threshold operation to remove skull tissues [10].

2.1.6 EDGE DETECTION METHOD

The edge representation of an image significantly reduces the quantity of data to be processed, yet it retains essential information regarding the shapes of objects in the scene. The major property of the edge detection technique is its ability to extract the exact edge line with good orientation as well as more literature about edge detection has been available in the past three decades. On the other hand, there is not yet any common performance directory to judge the performance of the edge detection techniques. The performance of an edge detection techniques are always judged personally and separately dependent to its application. Edge detection is a fundamental tool for image segmentation. In image processing especially in computer vision, the edge detection treats the localization of important variations of a gray level image and the detection of the physical and geometrical properties of objects of the scene. It is a fundamental process that detects and outlines an object and its boundaries among other objects and from the background of the image. Edge detection is the most familiar approach for detecting significant discontinuities in intensity values. Edges are local changes in the image intensity. Edges typically occur on the boundary between two regions. The main features can be extracted from the edges of an image. Edge detection has major feature for image analysis. These features are used by advanced computer vision algorithms. Edge detection is used for object detection which serves various applications like medical image processing, biometrics etc. Edge detection is an active area of research as it facilitates higher level image analysis. There are three different types of discontinuities in the grey level like point, line and edges. Spatial masks can be used to detect all the three types of discontinuities in an image. There are many edge detection techniques in the literature for image segmentation. The most commonly used discontinuity based edge detection techniques are Roberts edge detection, Sobel Edge Detection, Prewitt edge detection, Kirsh edge detection, Robinson edge detection, Marr-Hildreth edge detection, LoG edge detection and Canny Edge Detection. Some of these techniques are reviewed in this section.

(a) ROBERTS EDGE DETECTION: The Roberts edge detection is introduced by Lawrence Roberts (1965). It performs a simple, quick to compute, 2-D spatial gradient measurement on an image. This method emphasizes regions of high spatial frequency which often correspond to edges. The input to the operator is a grayscale image the same as to the output is the most common usage for this technique. Pixel values in every point in the output represent the estimated complete magnitude of the spatial gradient of the input image at that point[14].

(b) SOBEL EDGE DETECTION: The Sobel edge detection method is introduced by Sobel in 1970 (Rafael C.Gonzalez (2004)). The Sobel method of edge detection for image segmentation finds edges using the Sobel approximation to the derivative. It precedes the edges at those points where the gradient is highest. The Sobel technique performs a 2-D spatial gradient quantity on an image and so highlights regions of high spatial frequency that correspond to edges. In general it is used to find the estimated absolute gradient magnitude at each point in input grayscale image. In conjecture at least the operator consists of a pair of 3x3 complication kernels as given away in under table. One kernel is simply the other rotated by 90o . This is very alike to the Roberts Cross operator[14].

(c) PREWITT EDGE DETECTION: The Prewitt edge detection is proposed by Prewitt in 1970 (Rafael C.Gonzalez [1]. To estimate the magnitude and orientation of an edge Prewitt is a correct way. Even though different gradient edge detection wants a quite time consuming calculation to estimate the direction from the magnitudes in the x and y-directions, the compass edge detection obtains the direction directly from the kernel with the highest response. It is limited to 8 possible directions; however knowledge shows that most direct direction estimates are not much more perfect. This gradient based edge detector is estimated in the 3x3 neighborhood for eight directions. All the eight convolution masks are calculated. One complication mask is then selected, namely with the purpose of the largest module [14].

2.1.7 REGION BASED SEGMENTATION METHOD

Segmentation of images is crucial to our understanding of them. Consequently many efforts have been devoted to devise algorithms for this purpose. Since the sixties a variety of techniques have been proposed and tried for segmenting images by identifying regions of some common property [15]. These can be classified into two main classes:

(a) MERGING ALGORITHMS: In which neighboring regions are compared and merged if they are close enough in some property.

(b) SPLITTING ALGORITHMS: In which large non-uniform regions are broken up into smaller areas which may be uniform.

There are algorithms which are a combination of splitting and merging. In all cases some uniformity criteria must be applied to decide if a region should be splitted or two regions should be merged. This criteria is based on some region property which will be defined by the application, and could be one of many measurable image attributes such as mean intensity, color etc. Uniformity criteria can be defined by setting limits on the measured property, or by using statistical measures, such as standard deviation or variance.

➢ **REGION MERGING**: Merging must start from a uniform seed region. Some work has been done in discovering a suitable seed region. One method is to divide the image into 2x2 or 4x4 blocks and check each one. Another is to divide the image into strips, and then subdivide the strips further. In the worst case the seed will be a single pixel. Once a seed has been found, its neighbors' are merged until no more neighboring regions confirm to the uniformity criteria. At this point the region is extracted from the image, and a further seed is used to merge another region. There are some drawbacks which must be noted with this approach:

- The process is inherently sequential, and if fine detail is required in the segmentation then the computation time will be long.
- Moreover, since in most cases the merging of two regions will change the value of the property being measured, the resulting area will depend on the search strategy employed among the neighbors, and the seed chosen.

➢ **REGION SPLITTING**: These algorithms begin from the whole image, and divide it up until each sub region is uniform. The usual criteria for stopping the splitting process is when the properties of a newly split pair do not differ from those of the original region by more than a threshold.

- The chief problem with this type of algorithm is the difficulty of deciding where to make the partition. Early algorithms used some regular decomposition methods, and for some classes these are satisfactory, however, in most cases splitting are used as a first stage of a split/merge algorithm.

2.2 NEED OF SEGMENTATION FOR MEDICAL IMAGES

As the segmentation process [6] divides the digital image into separate parts based on some specific parameters, so it becomes easy to extract the useful and meaningful information from the segmented image. Following are the reasons why segmentation is needed for medical images:

- MR images are more prone to noise and other environmental degradation.
- Early detection of tumor is difficult.
- Radiologist's/ doctor's cost and time efforts are huge.
- Poor contrast of images.
- To extract useful and meaningful information.
- Further analysis of diseased region becomes possible.

3 REVIEW METHOD

3.1 RESEARCH QUESTIONS

Research questions are the fundamental building blocks for scientists in order to plan and conduct any research; therefore it is compulsory to formulate such questions. Key questions encountered during my study are as follows:

- What are the existing techniques and algorithms for extracting the region of interest from medical images along with the research gaps in the existing literature?
- Which are the key areas of research in the field of Tumor detection?

KEY RESEARCH AREAS

Medical image segmentation is a challenging process but it is of great importance for medical images as it involves analysis, interpretation and understanding of images for subsequent computer aided diagnosis and treatment planning. Medical imaging can be performed using various modalities, such as magnetic resonance imaging (MRI), computed tomography (CT), ultrasound etc.

Segmentation is typically performed manually by expert physicians as a part of treatment planning and diagnosis [12]. Due to the increasing amount of medical data and the complexity of features of interest, it is becoming essential to develop automated segmentation methods to reduce time for detection and speed up the process. Before giving the treatment, radiologist examines the patient physically with the help of Computed Tomography (CT Scan) and Magnetic Resonance Imaging (MRI). MRI shows the brain structure, tumor size and location. From the MRI it becomes easy to diagnose the tumor [2].

Multi-modal medical imaging processes are available to us and MRI is the most reliable and safe among all these processes as it does not involve exposing the body to any sorts of harmful radiation. The brain tumor segmentation studies which are based on MRI are attracting more and more attention in recent years due to noninvasive imaging. The unusual growth of tissues and block of blood in nervous system can be seen in an MRI image. This paper contributes in tumor detection which plays vital role in medical research.

Table 1 presents existing algorithms for segmentation of medical images for extracting region of interest giving their methodology and research gaps.

Table 1 Existing Algorithms for Segmentation of Medical Images

Study	Methodology	Research Gaps
F.W. Prior (2014)	In this paper, noise is removed from MRI image by high pass and median filtering and then segmentation of MRI image is done by threshold segmentation, watershed segmentation	The median filter does not find accuracy in image
Li Wang, Feng Shi and Gang Li (2013)	Proposed a novel and an efficient detection of the brain tumor region from cerebral image was done using Fuzzy C means clustering and histogram. The histogram equalization was used to calculate the intensity values of the grey level image. The decomposition of image was done using principle component analysis which was used to reduce dimensionality of the wavelet co -efficient. The results of the proposed Fuzzy C-means (FCM) clustering algorithm successfully and accurately extracted the tumor region from MRI brain image.	They do not classify the un-relevant pixels from the image properly.
S. Cao, S.Iftikhar and A. A. Bharath (2013)	Proposed a novel and an efficient detection of the brain tumor region from cerebral image was done using Fuzzy C means clustering and histogram. The histogram equalization was used to calculate the intensity values of the grey level images. The decomposition of images was done using principle component analysis which was used to reduce dimensionality of the wavelet co -efficient. The results of the proposed Fuzzy C-means (FCM) clustering algorithm successfully and accurately extracted the tumor region from MRI brain images.	They have not removed noise from image properly
Wenjia Bai , Wenzhe Shi and D. P. O'Regan (2013)	Described clustering algorithms for image segmentation and did a review on different types of image segmentation techniques. They also proposed a methodology to classify and quantify different clustering algorithms based on their consistency in different applications. They described the various performance parameters on which consistency will be measured.	Their image segmentation approach takes more time to find area of brain tumor from image.
Rueckert (2013)	Calculated the tumor affected area for symmetrical analysis. They showed its application with several data sets with different tumor size, intensity and location. They proved that their algorithm can automatically detect and segment the brain tumor. MR images give better result as compared to other techniques like CT images and X-rays.	Label map is not regularized in image
A. Bianchi and J. V. Miller (2013)	This method has low computational time, less complexity and the algorithm is effective and efficient	They do not use clustering approach to cluster area of tumor
Q. Sun and H. Tian (2012)	They have used power water shed algorithm to segment image and find contour of brain tumor using active contour model	They only worked on image segmentation still noise problem is there
Maiti and M. Chakraborty (2012)	They converted color brain image into HSV color space which divides the image into three sections later on they combined three images using canny edge detection algorithm to find tumor	They do not work on clustering based on that we can classify the region of brain tumor in image easily
Kai Hu and Guang-Yu Tang (2012)	Proposed a novel fast and robust fuzzy c-means clustering framework for image segmentation based on local spatial and gray information	They only cover boundary of images not the edges
Y. Liu and Q. Zhao (2010)	They have used top bottom transformation to enhance image .A combined transformation and multi scale gradient is proposed	Time consuming algorithm to detect tumor from the image
K. J. Gorgolewski (2010)	The proposed algorithm uses the local statistical data to separate dependable neighbor pixels thereby improving the segmentation performance and the result of segmentation is adaptive to the original image	The image segmentation approach is not efficient

4 PERFORMANCE EVALUATION OF SEGMENTATION ALGORITHMS FOR TUMOR DETECTION FROM MR BRAIN IMAGES

4.1 EVALUATION METHODOLOGY

QUANTITATIVE EVALUATION: It is the systematic computation and investigation of statistical metrics for Tumor detection techniques [16]. Selected application specific metrics are precision, recall, and F-measure.

QUALITATIVE EVALUATION: It is the realization of Tumor detection techniques' outcomes based on human observations.

4.2 EVALUATION METRICS

This section monitors the performance evaluation of existing techniques which have been used to detect the tumor region from brain MR image. For pattern recognition and for finding the final results some parameters such as Precision, Recall, F-measure are used. These parameters are fundamental for tumor detection applications and provide satisfactory factors for computing the results.

Possible Outcomes of Confusion Matrix are True Positive (TP), False Positive (FP), True Negative (TN), False Negative (FN); TN and TP are correctly segmented tumor and brain pixels, FP pixels are incorrectly detected as tumor and FN are falsely detected as brain element [4]. Precision, Recall, and F-measure are derived from confusion matrix.

PRECISION measures the exactitude of quality, i.e., fragments of fetched pixel elements that are admissible. It is Type 2 Error. Mathematically Precision can be represented as

$$Pr = (TP)/(TP + FP)$$

RECALL measures the completeness of quantity which means fragment of admissible pixel elements that are fetched. It is also known as sensitivity or Type 1 Error. Mathematically Recall can be represented as

$$Rc = (TP)/(TP+FN)$$

F-MEASURE is measurement of accuracy which is computed in terms of precision and recall. It provides trade-off between precision and recall. Mathematically F- Measure can be represented as

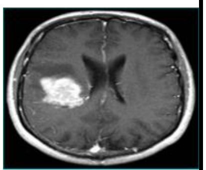
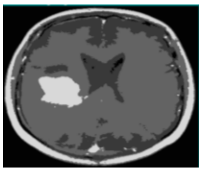
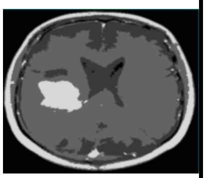
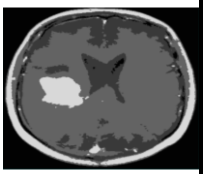
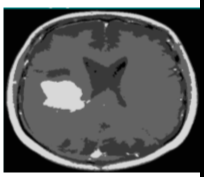
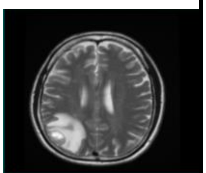
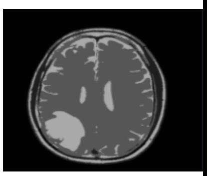
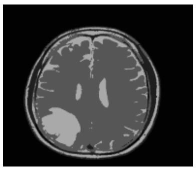
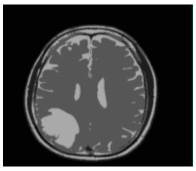
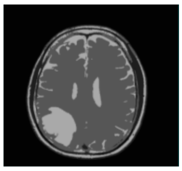
$$\text{F-measure} = (2.\text{recall}.\text{precision}) / (\text{precision} + \text{recall})$$

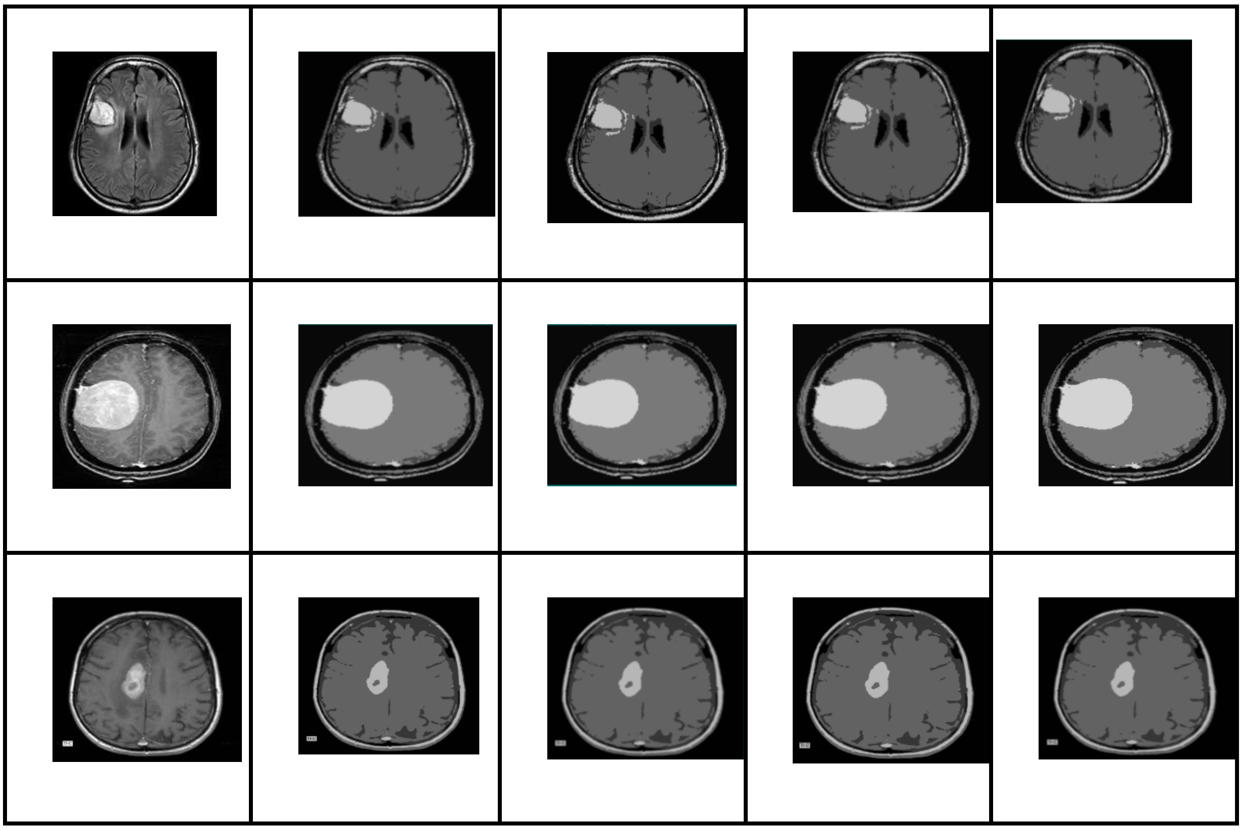
4.3 EXPERIMENTAL RESULTS

For evaluating and comparing the performance of above mentioned methods experiments are set up in Java Jdk 1.8 version, Net beans 8.1 on i5 processor. Segmentation results of few images from the tested image set are presented for both subjective and objective evaluation.

SUBJECTIVE EVALUATION: Human observations and visualizations play a vital role for evaluating the medical images. Table 2 presents the graphical results of the experiments.

Table 2 Experimental Results of Algorithms for detection of Tumor from MR Brain Images

Input Image/ Method	Otsu	K-means	Fuzzy c-mean	Watershed
				
				



OBJECTIVE EVALUATION: Objective analysis provides the actual judgment and justification .Also it helps in eliminating the inaccuracy of the results based on human observations. Objective evaluation of algorithms is done using performance parameters presented in Sect. 4.2. Table 3 presents the numerical results.

Table 3 Quantitative Results for Various Algorithms

	Otsu	**Fuzzy c-mean**	**K-means**	**Watershed**
Precision	0.72	0.68	0.60	0.65
Recall	0.75	0.60	0.72	0.52
F-measure	0.81	0.72	0.69	0.61

5 DISCUSSION

Algorithms may perform well for one parameter but may not be much suitable for other parameters which are stated in Section 4.2. So studied algorithms are tested for the stated parameters using a dataset out of which results of few images are presented in Table 2 and Table 3. Quantitative results in Table 3 depicts that Otsu delivers best results for all the three parameters. K-means also provides good results for Recall but it gives comparatively less suitable values for Precision and F-measure as compared to Otsu. FCM is a tradeoff between K-means and Watershed. It behaves well for all Precision, Recall as well as for F-measure. Among all the studied algorithms Watershed gives the lowest results when tested for all three parameters. Quantitative results as well as graphical outputs suggest that Otsu attains the highest performance.

6 CONCLUSIONS AND FUTURE SCOPE

This paper presents a comprehensive review of state-of –the-art techniques for extracting region of interest from medical images. Next, performance evaluation of various algorithms for segmenting an MR Brain image for Tumor

Detection is performed using performance metrics like Precision, Recall and F-measure. In future work, the techniques will be compared on the basis of other parameters along with the execution time parameter. In-depth study of medical image segmentation techniques and algorithms establishes that the segmentation process of medical images is a challenging task due to some issues like non-uniform illumination, obscure contours, poor contrast. Apart from these issues medical images are complex in nature and segmentation methods are also dependent upon imaging modalities that result into missing or diffuse boundaries of the tissues. There is no single algorithm which can deliver good results for all images so universal method applicable to all types of images is required. This study will be extended to propose an algorithm for tumor detection from MR brain images, which addresses the gaps identified by this study.

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