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Improved Tumor Detection Using Modified Hough Mertic Trasformation

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ABSTRACT:- The brain tumor detection is a very important vision application in the medical field. In this paper, an efficient brain tumor detection using the object detection and modified hough metric has been proposed. To enhance the tumor detection rate further we have integrated the proposed object based tumor detection with the Decision based alpha trimmed global mean. The proposed technique has the ability to produce effective results even in case of high density of the noise. This approach has been tested on various images thus defining an efficient and robust technique for automated detection and segmentation of brain tumors.

KEYWORDS:- IMAGE SEGMENTATION, BRAIN TUMOR, MRI

1. INTRODUCTION

Brain Tumor is a group of abnormal cells that grows out of control of the normal forces inside the brain or around the brain. Diagnosis of brain tumors is dependent on the detection of abnormal brain structure, i.e. tumor with the exact location and orientation.

Brain tumor can be of two types

(1) Beginning tumors or primary tumors

(2) Malignant tumors.

Beginning tumors are generally not need to be treated. Malignant tumor is basically termed as brain cancer. **Beginning tumors a**ren't cancerous. They could often be removed, and, generally, they don't come back. Cells in beginning tumors don't spread to the areas of the body. **Malignant tumors** are cancerous and are composed of cells that grow out of control. Cells in these tumors can invade nearby tissues and spread to the rest of the body. Sometimes cells move from the initial (primary) cancer site and spread to other organs and bones where they are able to continue to develop and form another tumor at that site. This is recognized as metastasis or secondary cancer.

MAGENTIC RESOSANCE IMAGING

It is a technique that uses a magnetic field and radio waves to create detailed images of the organs and tissues within your body. Magnetic Resonance Imaging (MRI) is widely used to visualize brain structures such as white matter, grey matter, and ventricles and to detect abnormalities. The MRI is the usually used modality for brain tumor growth imaging and location finding. Most MRI machines are large, tube-shaped magnets. When you lie inside an MRI machine, the magnetic field temporarily realigns hydrogen atoms in your body. Radio waves cause these aligned atoms to produce very faint signals, which are used to create cross-sectional MRI Images.

2. BRAIN TUMOR TECHNIQUES

There are numerous kinds of segmentation possible to segment a tumor from MRI of brain, those segmentation have several advantages and disadvantages. These advantage and disadvantage have described |meticulously with output are describe here. There no such algorithms which always produce positive results for several kind of MRI of brain images, thus a quick overview for different kind of segmentation are discussed here. Though optimal choice of features, tissues, brain and non–brain elements are thought as main difficulties for brain image segmentation. Thus accurate segmentation over full field of view is another quite definitely problem but throughout the segmentation procedure verification of results is another supply of difficulty.

Threshold Based Segmentation: Threshold is among the aged procedures for image segmentation. These threshold techniques are quite definitely helpful for image binarization that will be very essential task for any kind of segmentation. It assumes that images are made up of regions with various gray level ranges. A thresholding procedure determines an intensity value, called the threshold, which separates the specified classes

Texture-based: Texture analysis is a good task in image processing for classification, identification and segmentation of images. Textures are the reproduction, symmetries and amalgamation of large number of basic patterns with some random changes. In texture segmentation the goal is to assign an unknown sample image to one of a set of known texture classes Texture segmentation consist of two phases they are learning phase and recognition phase. In the learning phase, target is to build a model or pattern for each the texture content. The texture content of the training images is captured with the selected texture analysis techniques, which yields a set of textural description for each image. These features, which can be scalar numbers or discrete histograms or empirical distributions, or any other type of processing characterize given textural properties of the images, such as 18 spatial structure, contrast, roughness, orientation, brightness, intensity etc. In the recognition phase the texture content of the unknown sample is first described with the same texture analysis method. Then the textural features of the sample are compared to those of the training images with a classification algorithm, and the sample is assigned to the category with the best match.

A rtificial neural networks (ANNs): ANN is one of the powerful AI techniques that have the capability to learn from a set of data and construct weight matrices to represent the learning patterns. Artificial neural networks (ANNs) are massively parallel networks of processing elements or nodes that simulate biological learning. Each node in an ANNs is capable of performing elementary computations. The motivation for the development of neural network technology stemmed from the desire to develop an artificial system that could perform intelligent tasks similar to those performed by the human brain. ANN is a mathematical model which emulates the activity of biological neural networks in the human brain.

Watershed Methods: It is one of the best methods to group pixels of an image on the basis of their intensities. Watershed algorithm is based on morphological process although it can be mixed up with edge based segmentation to yield a hybrid technique. Normally, images acquired by various techniques in the electromagnetic spectrum, possesses a large no of discontinuities in the intensity and these ultimately give rise to over segmentation when morphological segmentations like watersheds are carried out. Pixels falling under similar intensities are grouped together. It is a good segmentation technique for dividing an image to separate a tumor from the image Watershed is a mathematical morphological operating tool.

Level Set Methods: Level set methods use non parametric deformable models with active contour energy minimization techniques which solve computation of geodesics or minimal distance curves. Level set methods are governed by curvature defining speeds of moving curves or fronts. There are large numbers of level set methods developed for segmentation of medical images and all most all these methods follow some common generic steps. First placement of an initial contour arbitrarily, outside or inside the region of interest, level set φ = signed Euclidean distance function of the contour and Function φ allowed to evolving according to first or second derivative partial differential equation (PDE), then it is reinitialized after a number of iterations and go to second statement until the function φ converges or = 0

Self-organizing maps (SOM) : SOM consists of two layers: first is the input layer and the number of neurons in this layer is equal to dimension of input and second is the competitive layer and each neuron in this layer corresponds to one class or pattern. The number of neurons in this layer depends on the number of clusters and is arranged in regular geometric mesh structure. Each connection from input layer to a neuron in competitive layer is assigned with a weight vector. The SOM functions in two steps, viz, firstly finding the winning neuron i.e. the most similar neuron to input by a similarity factor like Euclidean distance, and secondly, updating the weight of winning neuron and its neighbour pixels based on input.

Hybrid SOM: HSOM combines self organization and topographic mapping technique. HSOM combines the idea of regarding the image segmentation process as one of data abstraction where the segmented image is the final domain independent abstraction of the input image. The HSOM is organized in a pyramidal mannered structure consisting of multiple layers where each layer resembles the single layer SOM. Learning process has sequential corrections of the vectors representing neurons. On every step of the learning process a random vector is chosen from the initial data set and then the best-matching neuron coefficient vector is identified. The most similar to the input vector is selected as a winner.

Edge-based segmentation methods: In this method an algorithm searches for pixels with high gradient values that are usually edge pixels and then tries to connect them to produce a curve which represents a boundary of the object. The user determines an initial guess for the contour, which is then deformed by image driven forces to the boundaries of the desired objects. In these models, two types of forces are considered. The internal forces, defined within the curve, are designed to keep the model smooth during the deformation process. The external forces, which are computed from the image data, are defined to move the model toward an object boundary. The Canny edge detection algorithm is known to many as the optimal edge detector. Canny's intentions were to enhance the many edge detectors already out at the time he started his work. Canny has shown that the first derivative of the Gaussian closely approximates the operator that optimizes the product of signal-to-noise ratio and localization. The algorithm then tracks along these regions and suppresses any pixel that is not at the maximum.

3. LITERATURE SURVEY

Prastawa, Marcel et al. [1] described a structure for automatic brain tumor segmentation from MR images. The detection of edema is performed simultaneously with tumor segmentation, as the information of the extent of edema is essential for diagnosis, planning, and treatment. Whereas a great many other tumor segmentation methods depend on the intensity enhancement made by the gadolinium contrast agent in the T1-weighted image, the technique proposed here doesn't require contrast enhanced image channels. The only real required input for the segmentation procedure may be the T2 MR image channel, but it may take advantage of any extra non-enhanced image channels for improved tissue segmentation. The segmentation framework consists of three stages. First, they detected abnormal regions utilizing a registered brain atlas as a design for healthy brains. Then they made utilization of the robust estimates of the place and dispersion of the standard brain tissue intensity clusters to find out the intensity properties of the various tissue types. In the next stage, they determined from the T2 image intensities whether edema appears as well as tumor in the abnormal regions. Finally, they applied geometric and spatial constraints to the detected tumor and edema regions. The segmentation procedure has been put on three real datasets, representing different tumor shapes, locations, sizes, image intensities, and enhancement. Goyal, Soniya et al. [2] presented an automated and clinically-tested method for detection of brain abnormalities and tumor-edema segmentation utilizing the MRI sequences. It follows a Radiologist's method of the brain diagnosis using multiple MRI sequences rather than any prior models or training phases. Their procedure includes the next steps: a) Pre-processing of the MRI sequences, T2, T1 and T1 post contrast for size standardization, contrast equalization and division into active cells b) Identification of the T2 MRI sequence as normal or abnormal by exploiting the vertical symmetry of the brain c) Determination of the region of abnormality having its hyper-intense nature. d) Separation of tumor from edema utilising the T1 and its post-contrast (enhanced) sequences and e) Estimation of the quantity of tumor found and generation of an anatomical differential of the possible disorders. This method has been tested on greater than a hundred real dataset both normal and abnormal representing tumors of different shapes, locations and sizes and results being checked by radiologists thus defining an efficient and robust technique for automated detection and segmentation of brain tumors. Harati, Vida et al. [3] presented a better fuzzy connectedness (FC) algorithm centered on a range in that the seed point is selected automatically. This algorithm is independent of the tumor type when it comes to its pixels intensity. Tumor segmentation evaluation results centered on similarity criteria (similarity index (*SI*), overlap fraction (*OF*), and extra fraction (*EF*) are 92.89%, 91.75%, and 3.95%, respectively) indicate a greater performance of the proposed approach set alongside the conventional methods, especially in MR images, in tumor regions with low contrast. Thus, the suggested method is helpful for increasing the power of automatic estimation of tumor size and position in brain tissues, which supplies more accurate investigation of the necessary surgery, chemotherapy, and radiotherapy procedures . Meenakshi, S. R et al. [4] proposed to use K-means clustering algorithm under Morphological Image Processing (MIP). The input to this algorithm is an MR image of the human brain. The position of tumor objects is detected from an MR image by using a clustering algorithm. This enhances the tumor boundaries more precisely and the performance is evaluated based on execution time and accuracy of the algorithms. It produces the reliable results that are less sensitive to error. Ghanavati, Sahar et al. [5] presented a multi-modality framework for automatic tumor detection, fusing different Magnetic Resonance Imaging modalities including T1-weighted, T2-weighted, and T1 with gadolinium contrast agent. The intensity, shape deformation, symmetry, and texture features were extracted from each image. The AdaBoost classifier was used to select the most discriminative features and to segment the tumor region. Multi-modal MR images with simulated tumor have been used as the ground truth for training and validation of the detection method. Preliminary results on simulated and patient MRI show 100% successful tumor detection with average accuracy of 90.11%. Bhattacharjee, Rupsa, and Monisha Chakraborty [6] developed a novel algorithm to feature out tumor from diseased brain Magnetic Resonance (MR) images. In this work, based on a study of quality parameter comparison of two filters, adaptive median filter is selected for de-noising the images. Image slicing and identification of significant planes are done. Logical operations are applied on selected slices to obtain the processed image showing the tumor region. A novel image reconstruction algorithm is developed based on the application of Principal Components Analysis (PCA). This reconstruction algorithm is applied on original raw images as well as on the processed images. Results of this work confirm the sole efficiency of the developed image processing algorithm to detect brain tumor. For this work randomly chosen 20 normal brain MR images and 20 brain tumor MR images are considered. Also in this work, statistical significance testing is carried out to justify the uniformity of population means of the processed output. Finally normal and processed outputs are compared. Farjam, Reza et al. [7] developed an approach for computer-aided detection (CAD) of small brain metastases in post-Gd T1-weighted magnetic resonance imaging (MRI).A set of unevenly spaced 3D spherical shell templates was optimized to localize brain metastatic lesions by cross-correlation analysis with MRI. Theoretical and simulation analyses of effects of lesion size and shape heterogeneity were performed to optimize the number and size of the templates and the cross-correlation thresholds. Also, effects of image factors of noise and intensity variation on the performance of the CAD system were investigated. A nodule enhancement strategy to improve sensitivity of the system and a set of criteria based upon the size, shape and brightness of lesions were used to reduce false positives. An optimal set of parameters from the FROC curves was selected from a training dataset, and then the system was evaluated on a testing dataset including 186 lesions from 2753 MRI slices. Reading results from two radiologists are also included. Overall, a 93.5% sensitivity with 0.024 of intra-cranial false positive rate (IC-FPR) was achieved in the testing dataset. Their investigation indicated that nodule enhancement was very effective in improving both sensitivity and specificity. The size and shape criteria reduced the IC-FPR from 0.075 to 0.021, and the brightness criterion decreases the extra-cranial FPR from 0.477 to 0.083 in the training dataset. Readings from the two radiologists had sensitivities of 60% and 67% in the training dataset and 70% and 80% in the testing dataset for the metastatic lesions <5 mm in diameter. Their proposed CAD system has high sensitivity and fairly low FPR for detection of the small brain metastatic lesions in MRI compared to the previous work and readings of neuroradiologists. The potential of this method for assisting clinical decision- making warrants further evaluation and improvements. Sapra, Pankaj et al. [8] summarized and compared the methods of automatic detection of brain tumor through Magnetic Resonance Image (MRI) used in different stages of Computer Aided Detection System (CAD). Brain Image classification techniques are studied. Existing methods are classically divided into region based and contour based methods. These are usually dedicated to full enhanced tumors or specific types of tumors. The amount of resources required to describe large set of data is simplified and selected in for tissue segmentation. In this paper, modified image segmentation techniques were applied on MRI scan images in order to detect brain tumors. Also in this paper, a modified Probabilistic Neural Network (PNN) model that is based on learning vector quantization (LVQ) with image and data analysis and manipulation techniques is proposed to carry out an automated brain tumor classification using MRI-scans. The assessment of the modified PNN classifier performance is measured in terms of the training performance, classification accuracies and computational time. The simulation results showed that the modified PNN gives rapid and accurate classification compared with the image processing and published conventional PNN techniques. Simulation results also showed that the proposed system out erforms the corresponding PNN system presented and successfully handle the process of brain tumor classification in MRI image with 100% accuracy. Arshad Javed et al. [9] aimed to reduce the noise, enhance the image quality by considering the spatial information without losing any important information about the images and perform the segmentation process in noise free environment. K-Means clustering technique is used for the purpose of segmentation of brain tissue classes which is considered more efficient and effective for the segmentation of an image. They tested the proposed technique on different types of brain MR images which generates good results and proved robust against noise. Conclusion had been concluded at the end of this study. Deshmukh, G. B., and P. D. Lambhate [10] focused on the application of Modified FCM algorithm for Brain tumor detection and its classification by SVM algorithm. The Magnetic Resonance image is converted in to vector format and that is given as input to the modified fuzzy c-means algorithm. In modified fuzzy c-means the steps are: initial fuzzy partitioning and fuzzy membership generation Cluster updation based on objective function, Assigning labels to pixels of each category and display segmented image that will give more meaningful regions to analyze. This clustered images served as inputs to SVM. The basic SVM takes a set of input data and predicts, for each given input, which of two possible classes. Yang, Hongzhe et al. [11] presented an extensive survey on brain tumor methods and technology using MRI images. Generally, brain tumor segmentation methods can divided in to two main categories, spatial continuous and spatial discrete methods. Several methods, techniques, related advantage and weakness is likely to be described and discussed. The evaluation measures are mentioned and the qualities of different method concentrate on the techniques which were applied on the conventional data sets. The efficient and stably brain tumor segmentation continues to be a difficult task for the unpredictable appearance and model of the brain tumor. Roy, Sudipta et al. [12] discussed tumor segmentation from magnetic resonance imaging (MRI) data is an essential but time intensive manual task performed by medical experts. Automating this method is just a challenging task due to the high diversity in the look of tumor tissues among different patients and oftentimes similarity with the standard tissues. MRI is an enhanced medical imaging technique providing rich details about the human soft-tissue anatomy. There are different brain tumor detection and segmentation techniques to detect and segment a brain tumor from MRI images. These detection and segmentation approaches are reviewed by having a importance positioned on enlightening the advantages and drawbacks of those methods for brain tumor detection and segmentation. The usage of MRI image detection and segmentation in various procedures will also be described. Here a quick overview of different segmentation for detection of brain tumor from MRI of brain has been discussed. Kawadiwale et al. [13] presented various clustering techniques are employed to detect brain

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tumor. The classification involves classification of images into normal and malformed. The algorithm handles steps such as for instance preprocessing, segmentation, feature extraction and classification of MR brain images. Finally, the confirmatory step is specifying the tumor area by technique called region of interest. Njeh, Ines et al. [14] investigated a quick distribution-matching, data-driven algorithm for 3D multimodal MRI brain glioma tumor and edema segmentation in various modalities. They learnt non-parametric model distributions which characterize the standard regions in the present data. Then, they stated their segmentation problems because the optimization of several cost functions of exactly the same form, each containing two terms a distribution matching prior, which evaluates a worldwide similarity between distributions, and (a smoothness just before prevent the occurrence of small, isolated regions in the solution. Obtained following recent bound-relaxation results, the optima of the cost functions yield the complement of the tumor region or edema region in nearly real-time. Centered on global as opposed to pixel wise information, the proposed algorithm doesn't require an additional learning from a sizable, manually-segmented training set, as may be the case of the present methods. Therefore, the ensuing results are independent of the option of an exercise set. Quantitative evaluations within the publicly available training and testing data set from the MICCAI multimodal brain tumor segmentation challenge (BraTS 2012) demonstrated that their algorithm yields a very competitive performance for complete edema and tumor segmentation, among nine existing competing methods, with an appealing computing execution time (less than 0.5 s per image). El-Dahshan et al. [15] proposed a cross intelligent machine learning technique for computer-aided detection system for automatic detection of brain tumor through magnetic resonance images. The proposed technique is on the basis of the following computational methods; the feedback pulse-coupled neural network for image segmentation, the discrete wavelet transform for features extraction, the principal component analysis for reducing the dimensionality of the wavelet coefficients, and the feed forward back-propagation neural network to classify inputs into normal or abnormal. The experiments were carried on| 101 images consisting of 14 normal and 87 abnormal (malignant and benign tumors) from a genuine human brain MRI dataset. The classification accuracy on both training and test images is 99% that was significantly good. Moreover, the proposed technique demonstrates its effectiveness in contrast to another machine learning recently published techniques. The outcomes revealed that the proposed hybrid approach is accurate and fast and robust. Finally, possible future directions are suggested. CHARFI, SAID et al. [16] proposed a cross intelligent machine learning technique for computer-aided detection system for automatic detection of brain tumor through magnetic resonance images. The proposed technique is on the basis of the following computational methods; the histogram dependent thresholding for image segmentation, the discrete wavelet transform for features extraction, the principal component analysis for reducing the dimensionality of the wavelet coefficients, and the feed forward back-propagation neural network to classify inputs into normal or abnormal. The experiments were carried from 80 images consisting of 37 normal and 43 abnormal (malignant and benign tumors) from an actual human brain MRI dataset. The classification accuracy on both training and test images is 90% that was significantly good. The outcomes revealed that the proposed hybrid approach is accurate and fast and robust. Finally, possible future directions are suggested . Sharma, Komal et al. [17] discussed Magnetic resonance imaging is important imaging technique used in the detection of brain tumor. Brain tumor is one of the most dangerous diseases occurring among the human beings. Brain MRI plays a very important role for radiologists to diagnose and treat brain tumor patients. Study of the medical image by the radiologist is a time consuming process and also the accuracy depends upon their experience. Thus, the computer aided systems becomes very necessary as they overcome these limitations. Several automated methods are available, but automating this process is very difficult because of different appearance of the tumor among the different patients. There are various feature extraction and classification methods which are used for detection of brain tumor from MRI images. Kaur, Harneet, and Sukhwinder Kaur et al. [18] has centered on the brain tumor detection techniques. The brain tumor detection is an essential vision application in the medical field. This work has firstly presented an evaluation on various well-known approaches for automatic segmentation of heterogeneous image data that requires a step toward bridging the gap between bottom-up affinity-based segmentation methods and top-down generative model based approaches. The key objective of the job is always to explore various techniques to detect brain tumor within an efficient way. It's been unearthed that the absolute most of existing methods has ignored the indegent quality images like images with noise or poor brightness. Also the all of the existing focus on tumor detection has neglected the usage of object based segmentation. So to overcome the limitations of earlier work a new technique has been proposed in this research work.

4. PROPOSED METHODOLGY

Figure 1 shows the flowchart of the proposed methodology

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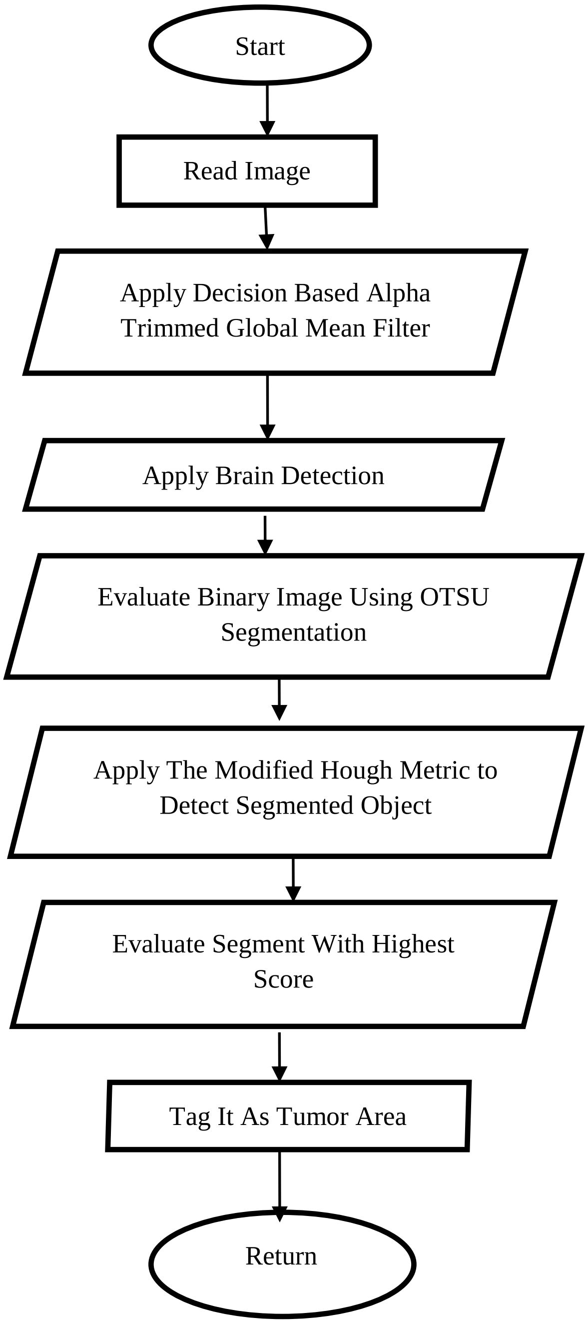

Fig 1: Flowchart of the proposed methodology

5. RESULTS AND DISCUSSIONS

In this section, we explain the results of the proposed methodology and its comparison with the existing techniques.

EXPERIMENTAL SETUP

Figure 2 is the input image

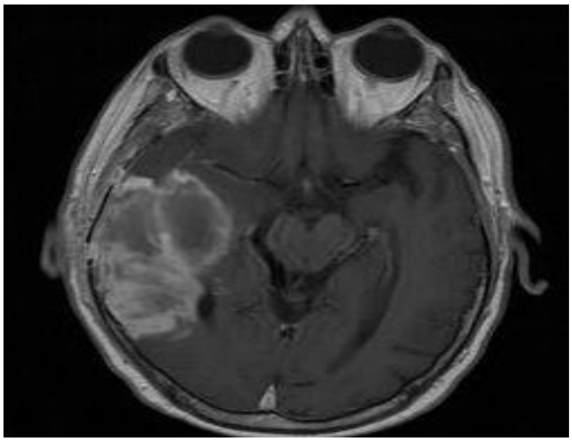

Fig 2: Input image

Figure 3 is the filtered image after applying Decision Based Alpha Trimmed Global Mean Filter

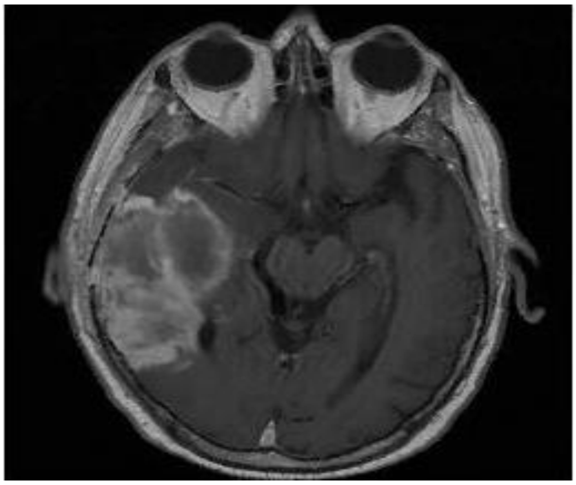

Fig 3: Filtered image

Figure 4 is the Binary Image Using OTSU Segmentation

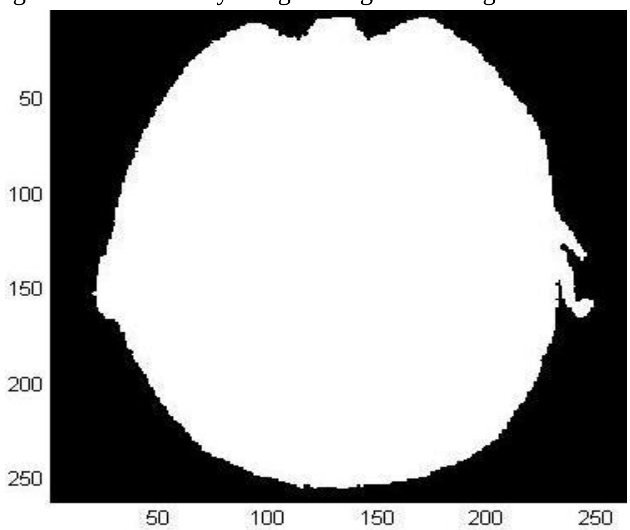

Fig 4: Binary Image Using OTSU Segmentation

Figure 5 is the output of figure 5 after applying the Modified Hough Metric to Detect Segmented Object

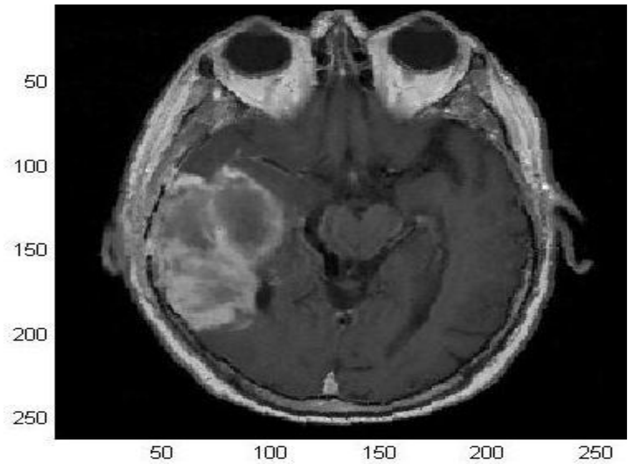

Fig 5 : After applying the Modified Hough Metric to Detect Segmented Object

Figure 6 is the image after evaluating Segment with Highest Score

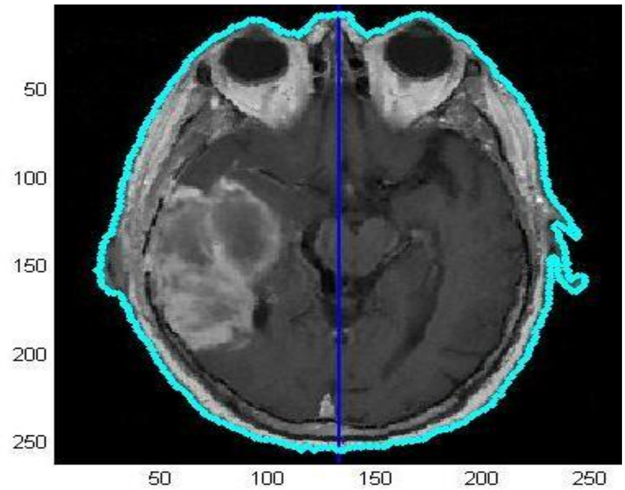

Fig 6: Image after evaluating Segment with Highest Score

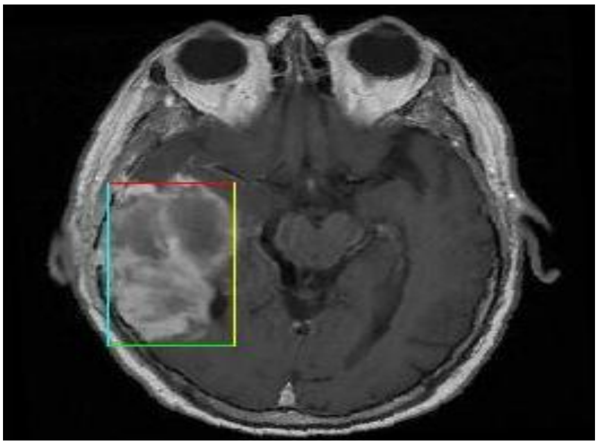

Fig 7: Image after tagging it As Tumor Area

Figure 7 is the image after tagging it As Tumor Area

PERFROMANCE EVALUATION

This segment contains the cross approval between the existing and proposed systems.

ACCURACY RATE:- Accuracy is the mean of sensitivity and specificity

$$A = \frac{\sum T_p + \sum T_n}{\sum T_p + \sum T_n + \sum F_p + \sum F_n}$$

T_p is total positives, T_n are total negatives, F_p is falsel positives, F_p are false negatives

Table 2 is showing the comparative analysis of the Accuracy. As Accuracy need to be maximized; so the main goal is to increase the F-measure as much as possible.

Table 2: Accuracy Evaluation

Noise Density	Existing	Proposed
0.1	0.5552	0.9484
0.2	0.5471	0.9004
0.3	0.5461	0.8466
0.4	0.5460	0.8022
0.5	0.5465	0.7436
0.6	0.5497	0.6999
0.7	0.5461	0.6475
0.8	0.5203	0.5988
0.9	0.5138	0.5477

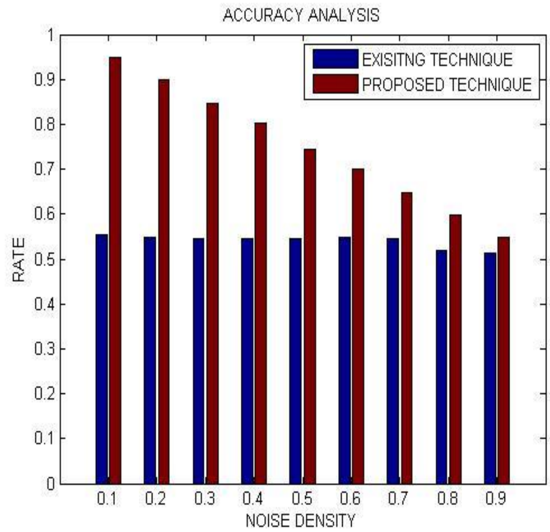

Fig 8: Accuracy Evaluation

Figure 8 has shown the quantized analysis of the accuracy of different. It is very clear from the plot that there is increase in f-measure value of images with the use of method over existing methods. This increase represents improvement in the objective quality of the image.

F-MEASURE:- The F-Measure computes average of the information retrieval precision and recall metrics. Table 2 is showing the comparative analysis of the F-measure. As F-measure need to be maximized; so the main goal is to increase the F-measure as much as possible..

Table 2: F-measure Evaluation

Noise Density	Existing	Proposed
0.1	70.6167	97.2003
0.2	70.2366	94.4624
0.3	70.1921	91.2461
0.4	70.1812	88.3221
0.5	70.1894	84.5447

0.6	70.2188	81.4879
0.7	68.8870	77.6160
0.8	60.8793	73.7881
0.9	56.0283	69.5542

Figure 9 has shown the quantized analysis of the f-measure of different. It is very clear from the plot that there is increase in f-measure value of images with the use of method over existing methods. This increase represents improvement in the objective quality of the image.

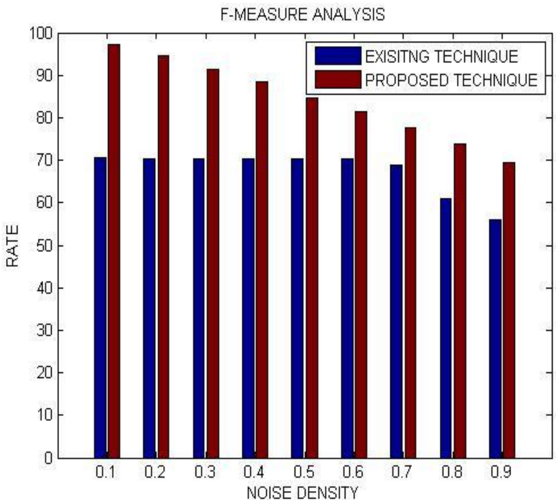

Figure 9: F-measure Evaluation

PSNR:- .**Peak Signal to Noise Ratio (PSNR):** The PSNR block computes the peak signal-to-noise ratio, between two images.

$$PSNR = 10\log_{10}\left(\frac{255^2}{MSE}\right)$$

Table 2 is showing the comparative analysis of the Peak Signal to Noise Ratio (PSNR). As PSNR need to be maximized; so the main goal is to increase the PSNR as much as possible.

Table 2: PSNR Evaluation

Noise Density	Existing	Proposed
0.1	7.0376	25.7538
0.2	6.8792	20.0313
0.3	6.8612	16.2854
0.4	6.8591	13.9882
0.5	6.8682	11.8208
0.6	6.9300	10.4544
0.7	6.8602	9.0570
0.8	6.3811	7.9321
0.9	6.2635	6.8914

Figure 10 has shown the quantized analysis of the peak signal to noise ratio of different. It is very clear from the plot that there is increase in PSNR value of images with the use of method over existing methods.

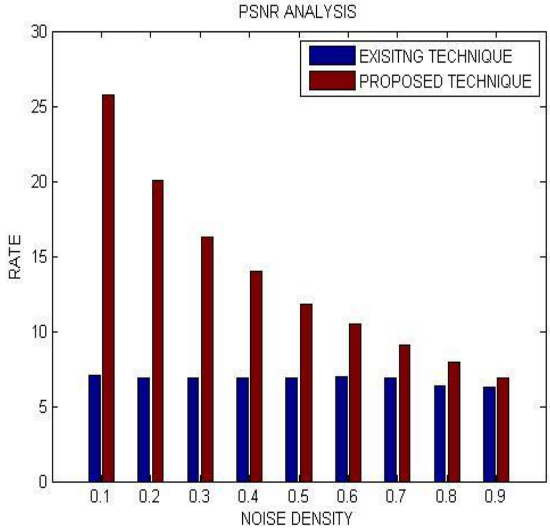

Figure 10: PSNR Evaluation

BIT ERROR RATE:- The bit error rate or bit error ratio (BER) is the number of bit errors divided by the total number of transferred bits during a studied time interval.

$$(\text{BER}) = \frac{\text{Numbers of Errors}}{\text{Total number of bits sent}}$$

Table 2 has clearly shown that the BER is minimum in the case of the algorithm; therefore algorithm is providing better results than the available methods.

Table 2: BER Evaluation

Noise Density	Existing	Proposed
0.1	22.7284	4.8723
0.2	22.9966	9.8681
0.3	23.1404	15.3809
0.4	23.7777	20.3809
0.5	25.0132	25.1351
0.6	30.8355	29.8468
0.7	43.9713	35.1346
0.8	49.1649	39.6907
0.9	49.0941	44.8962

Figure 11 has shown the quantized analysis of the bit error rate of different. It is very clear from the plot that there is decrease in BER value of images with the use of method over existing methods.

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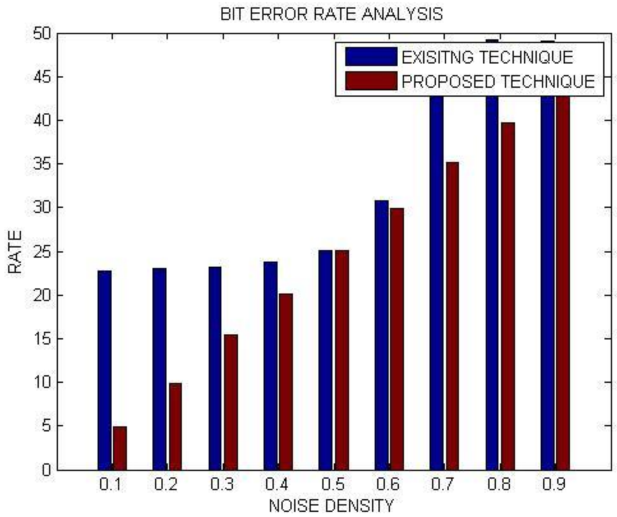

Figure 11: BER Evaluation

6.CONCLUSION AND FUTURE SCOPE

The brain tumor detection is a very important application of medical image processing. The literature survey has shown that the most of existing methods has ignored the poor quality images like images with noise or poor brightness. Also the most of the existing work on tumor detection has neglected the use of object based segmentation. The overall objective of this research work is to increase the accuracy of the brain tumor detection. Therefore new object detection based tumor detection algorithm using modified hough metric has been proposed integrating with the Decision based alpha trimmed global mean. The proposed work has been designed and implemented in MATLAB. The proposed work has been compared with existing work on the basis of various performance metrics. From the comparison, it has been proved that proposed technique performs much better as compared to existing technique.

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