An Experimental Approach for Detecting Brain Tumor from MRI Images using Digital Image Processing Techniques in MatLab

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Abstract:- The Digital Image Process plays a very important role in Medical Research and processing the MRI images. Using image processing techniques the MRI images can be used to detect and analysis the tumor growing in brain. SAR images are the high resolution images which cannot be collected manually. In this work, we identified the SAR images randomly from web with different region inclusions. The comparative results are generated against the statistical observations obtained for existing and proposed approach. The parameters considered are the mean value, standard deviation, entropy etc. The comparative results show that the method has improved the accuracy of region classification.

Keyword: *SAR, Tumor Detection, MRI Images, Digital Image Processing.*

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1. INTRODUCTION

Automated classification and detection of tumors in different medical images is motivated by the necessity of high accuracy when dealing with a human life. Also, the computer assistance is demanded in medical institutions due to the fact that it could improve the results of humans in such a domain where the false negative cases must be at a very low rate. It has been proven that double reading of medical images could lead to better tumor detection. Conventional methods of monitoring and diagnosing the diseases rely on detecting the presence of particular features by a human observer.

TYPES OF DIGITAL IMAGES

Binary image

The binary images are one bit images. In binary image the value of each pixel is either black or white. The binary image is a combination of two possible values either 0 or 1. In such type of images only one bit is used to represent each pixel. In this type of images black color is represented by'0' and white color by '1'.

Grayscale image

Gray scale image is 8 bit image. In grayscale image each pixel is represented by a gray level. There are 256 gray levels. The gray level range is from 0 to 255where '0' gray level represents black color and '255'represents white color. Each pixel is a combination of eight bits in gray scale image.

True color or RGB image

RGB image is a 24 bi image where every pixel has a particular color. This color in the image is described by the combination of three matrices that represents red, green and blue component values. The combination of these three components gives 16,777,216 different colors when each of the color has a gray scale range from 0 to 255.Every pixel in true color image is a combination of three gray scale values. Figure 1.11 shows color model of primary and secondary colors.

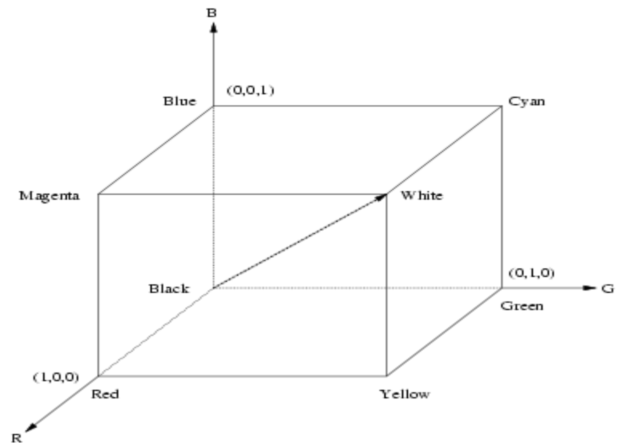


Figure Color model

Clustering

Clustering can be considered the mos importan unsupervised learning problem, so i deals with finding a structure in a collection of unlabeled data. A cluster is therefore a collection of objects which are "similar" between them and are "dissimilar" to the objects belonging to other clusters Clustering algorithms may be classified as listed below

(1) Exclusive Clustering
(2) Overlapping Clustering
(3) Hierarchical Clustering
(4) Probabilistic Clustering

In the firs case data are grouped in an exclusive way, so tha if a certain datum belongs to a definite cluster then it could not be included in another cluster.

2. LITERATURE REVIEW

Q. Li et al., [2018] proposed uses Gray Level Run Length Matrix (GLRLM) to extract features.The reduced GLRLM features are deferred to support vector machine for training and testing.The brain MRI images were classified using SVM techniques which are widely used for data analyzing and pattern recognizing[1].

H. Ohgaki and P. Kleihues [2005] proposed method used an approach to detect brain tumor using four different methods namely Otsu, K-means, Fuzzy-c-Means and thresholding. The main objective of this paper is to develop a fully automated brain tumor detection system that can detect and extract tumor from MR Image of brain. This paper also gives the comparison between the algorithms presented [2].

S. Pereira, A. Pinto, et al., [2016] proposed that deals with such a system which uses computer based procedures to detect tumor blocks and classify the type of tumor using Artificial Neural Network Algorithm for MRI images of different patients. Different image processing techniques such as histogram equalization, image segmentation, image enhancement, morphological operations and feature extraction are used for detection of the brain tumor in the MRI images of the cancer affected patients[3]

G Rajesh Chandra et al.,[2016] proposed one automatic brain tumor detection method to increase the accuracy and yield and decrease the diagnosis time. Here, it is tried to give clear description from brain tissues using Multi-Layer Perception Network, energy, entropy, contrast and some other statistic features such as mean, median, variance and correlation. It is used from a feature selection method to reduce the feature space too. This method uses from neural network to do this classification.[4]

B. H. Menze et al.,[2015] proposed a survey has been made on the applications of intelligent computing techniques for diagnostic sciences in biomedical image classification. This study gathers representative works that exhibit how AI is applied to the solution of very different problems related to different diagnostic science analysis. It also detects the methods of artificial intelligence that are used frequently together to solve the special problems of medicine. SVM neural network issued in almost all imaging modalities of medical image classification. Similarly fuzzy C means and improvements to it are important tool in segmentation of brain images. Various diagnostic studies like mammogram analysis, MRI brain analysis, bone and retinal analysis etc., using neural network approach result in use of back propagation network, probabilistic neural network, and extreme learning machine recurrently. Hybrid approach of GA and PSO are also commonly used for feature extraction and feature selection [5]

3. PROBLEM FORMULATION AND OBJECTIVE

This chapter gives an overview of the given system. It shows that what knowledge gained from the previous chapter and what this research is approaching to achieve to adding new techniques to fulfill the system objectives.

3.1 PROBLEM FORMULATION

The human body is made up of many organs and brain is the most critical and vital organ of them all. One of the common reasons for dysfunction of brain is brain tumor. A tumor is nothing but excess cells growing in an uncontrolled manner. Brain tumor cells grow in a way that they eventually take up all the nutrients meant for the healthy cells and tissues which results in brain failure. Currently, doctors locate the position and the area of brain tumor by looking at the MR Images of the brain of the patient manually. This results in inaccurate detection of the tumor and is also considered to be very time consuming. A tumor is a mass of tissue that grows out of control of the normal forces that regulates growth (Pal and Pal,1993). Brain tumor s are abnormal and uncontrolled proliferations of cells. An inferior or metastatic brain tumor takes place when cancer cells extend to the brain from a primary cancer in a different component of the body.

4. OBJECTIVE

The main objectives of the study are listed below:

I. To extract features from MRI images
II. To design classifier for tumor extraction
III. To implement K-means and Genetic algorithm for clustering and classification

5. METHODOLOGY

In the existing system four different segmentation methods have been used for extracting the brain tumor from MRI. The algorithms presented in this are fully automatic in nature so that no human intervention is required for tumor extraction. A fully automated system for brain tumor detection using K-means, Fuzzy c-means, Otsu's method and Thresholding. K-means is an effective segmentation method which aims to divide the image into a fixed number of clusters. Otsu's Thresholding divides the image into two classes of regions namely foreground and background. Fuzzy c-means uses fuzzy logic by assigning membership values to

ISSN: 2454-4248
108 - 116

each pixel. Thresholding works by defining a threshold and then testing various pixels of an image against the threshold.

- The main task of the doctors is to detect the tumor which is a time cosuming for which they feel burden.
- The only optimal solution for this problem is the use of 'image segmentation' .
- Brain tumor extraction and its analysis are challenging tasks in medical image processing because brain image is complicated .
- Segmentation plays a very important role in medical image processing.

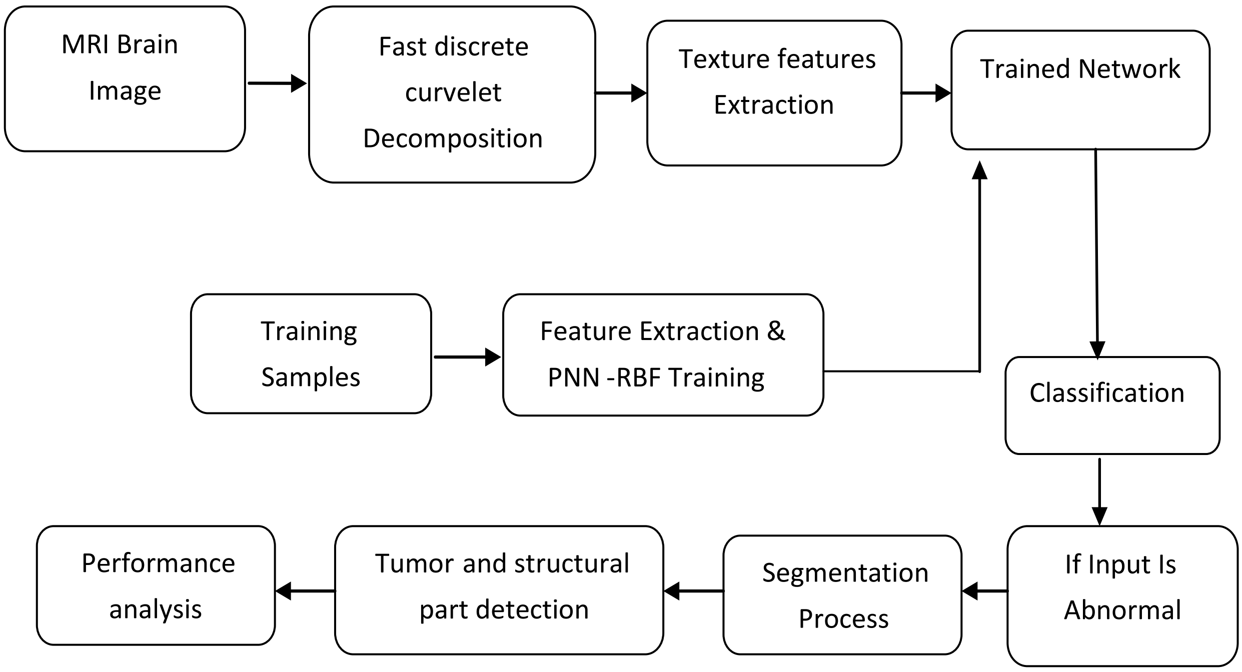


Fig 4.1: Block Diagram of Proposed System

The two new fast discrete curvelet transforms (FDCTs) which are simpler, faster, and less redundant than existing proposals:

(1) Curvelets via USFFT

(2) Curvelets via Wrapping.

The block size can be changed at each scale level. The wrapping construction is shown is taken to be a Cartesian array and ˆ *f*[*n*1, *n*2] denotes its 2-D discrete Fourier transform, then the architecture of the FDCT via wrapping is as follows.

1) Apply the 2-D FFT and obtain Fourier samples,

$\hat{f}[n_1, n_2], \quad -\frac{n}{2} \leq n_1, \quad n_2 < \frac{n}{2}$

2) For each scale *j* and angle *l*, form the product

$$\bar{U}_{j\ell}[n_1, n_2]\hat{f}[n_1, n_2]$$

3) Wrap this product around the origin and obtain

$\tilde{f}_{j,\ell}[n_1, n_2 = W(\bar{U}_{j,\ell}\hat{f})[n_1, n_2]$

4) Apply the inverse 2-D FFT to each ˜ *fj*,*l*, hence collecting the discrete coefficient .

Results

This section provides the outcome of the proposed system. Step by step outcome is presented below in screenshots.

Input Image with its curvelet Decomposition

Fig 2: Input Image

Here the input MRI image is taken for the implementation.

 ISSN: 2454-4248
108 - 116

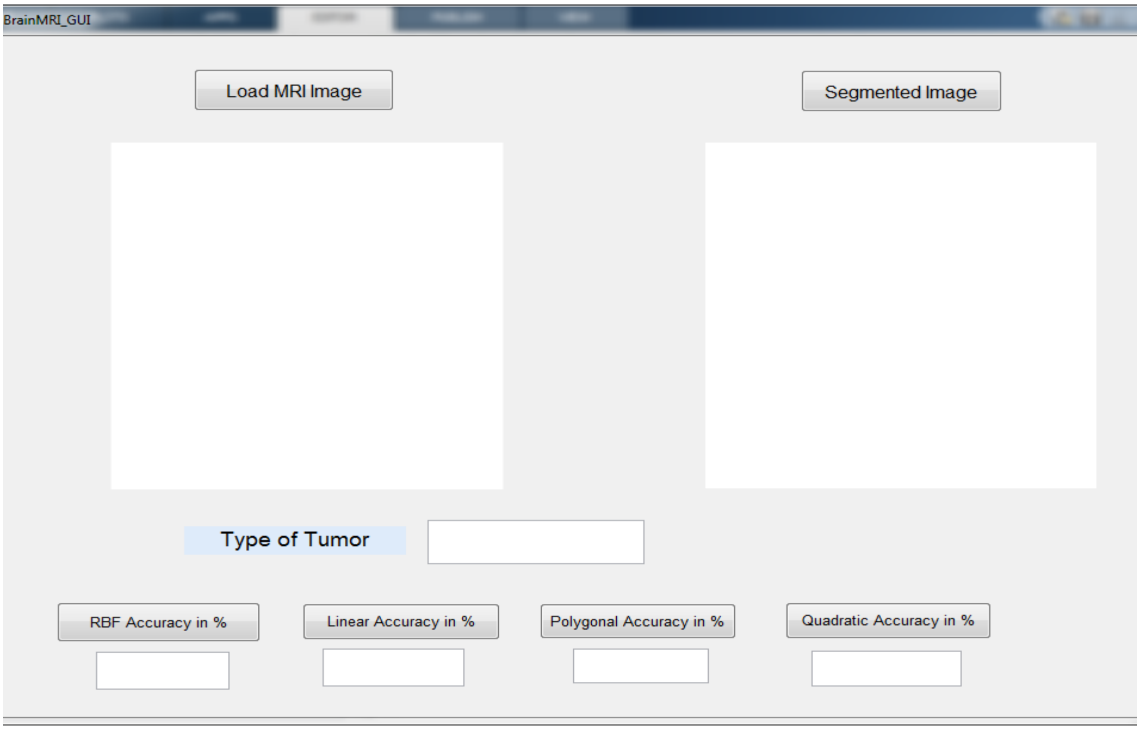


Fig 3: GUI of the System

In figure 5.6 there are two windows. One shows input image and second shows the output image.

6. IMAGE SEGMENTATION

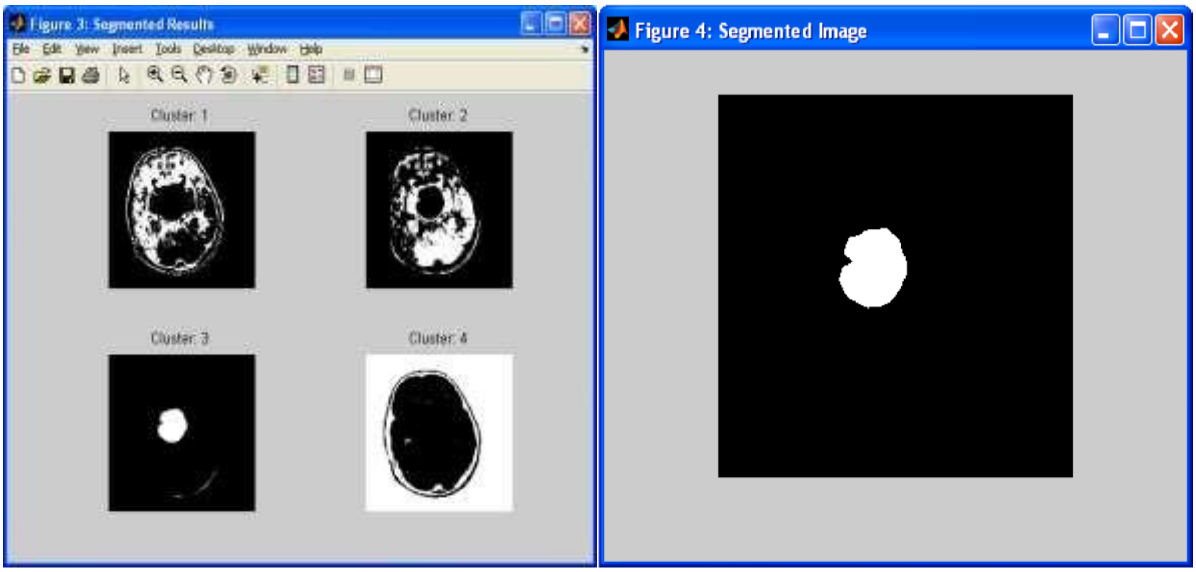


Fig 4 : MRI Brain with Benign Case

The Figure 5.7 shows the segmentation of the input image. The Bengin Tumor plot is shown in the output window.

ISSN: 2454-4248
108 - 116

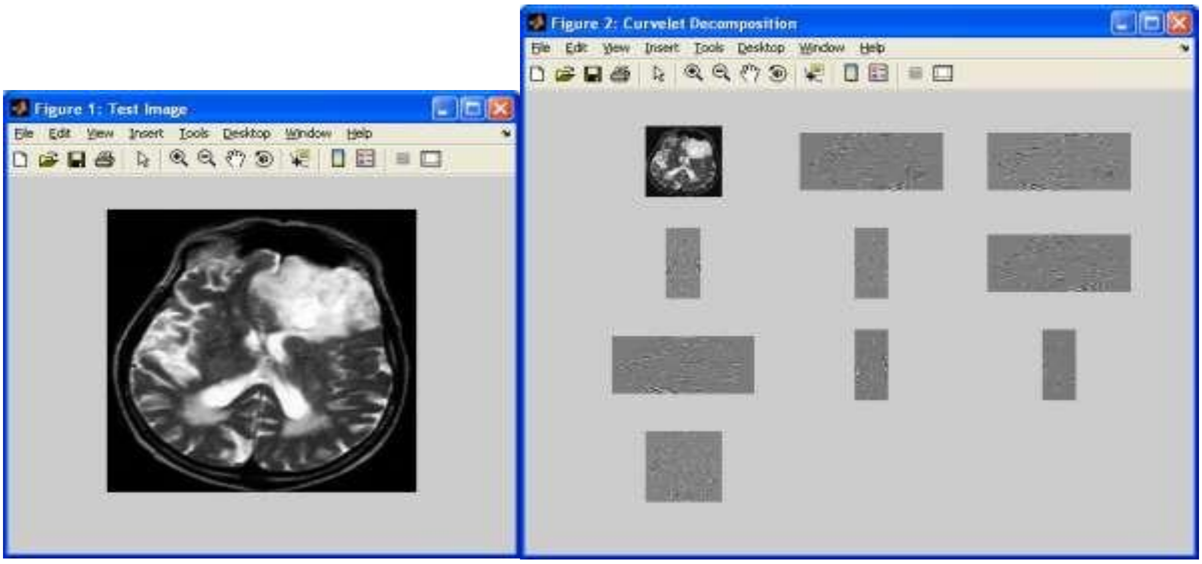


Fig. 5: MRI Brain with Malignant Case

IMAGE SEGMENTATION

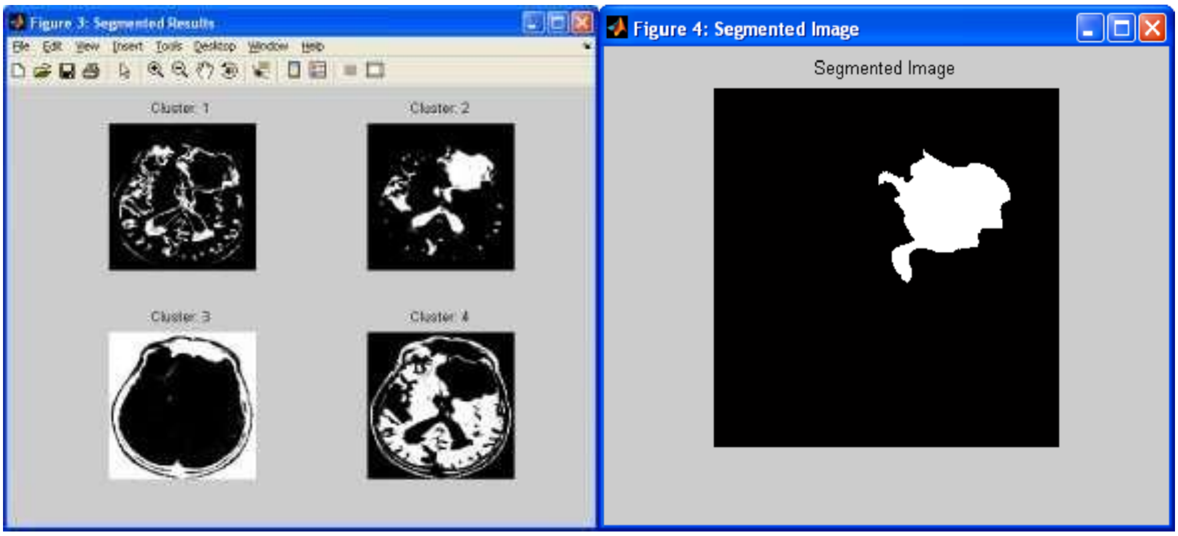


Fig 6: Malignant Tumor Image

The Figure 5.9 shows the segmentation of the input image. The Bengin Malignant plot is shown in the output window.

ISSN: 2454-4248
108 - 116

MRI Brain with Normal Case

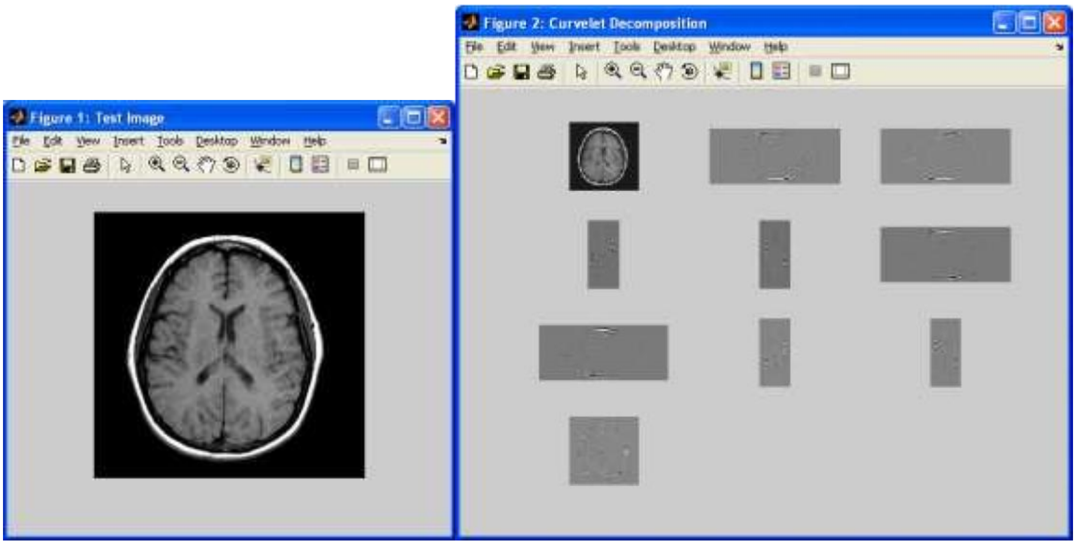
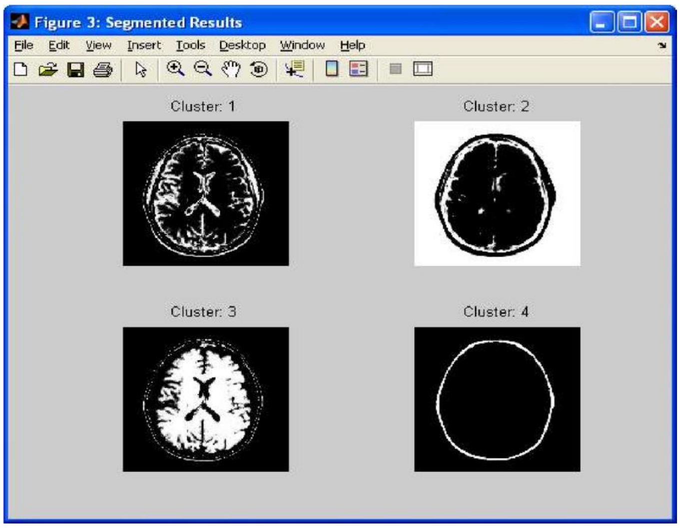


Fig. 7: MRI Brain with Normal Case

The figure 5.10 shows the normal image of brain. So in the output window there is no plots or tumor segmentation.

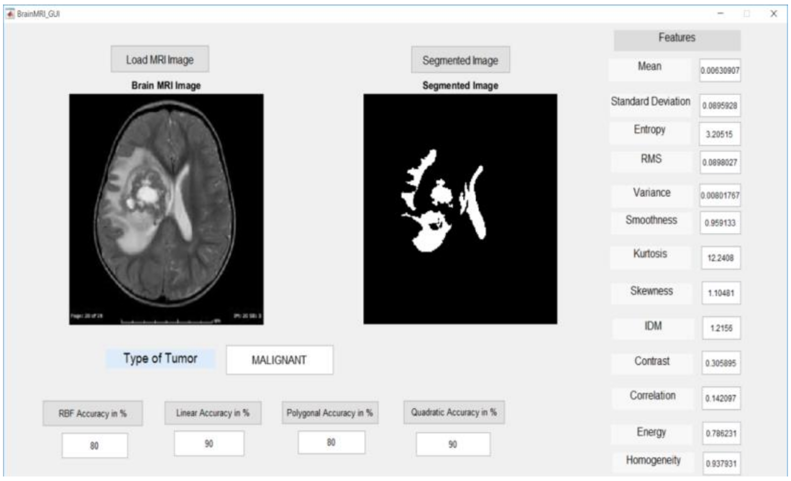
IMAGE SEGMENTATION



Screenshot 8: Segmented Image

The input image segmentation process is shown in the figure 5.11. The segmentation is shown cluster wise.

 ISSN: 2454-4248
108 - 116



Screenshot 9: Final Output of the System

Above image shows the tumor segmentation and classification. It shows type of tumor and its parameters. Above image shows four accuracy that can be calculated.

7. PERFORMANCE MEASUREMENT

The performance of the given system measured by using the following table that given various condition for outputs. They give the multiple images of brain MRI that are detected by the system. The first condition if one brain MRI image is provided from the dataset and system detected it as tumor is present then it is considered as the true positive. If another image from the dataset is provided and system detected is tumor is absent then it is considered as the false negative. For calculating a precision, it is required a relevant dataset and for the recall it take the overall dataset of the given system. For the result analysis the number of tumor present and tumor absent are provided and tumor absent and find the precision and recall by the following formula.

Precision = Relevant instance / Retrieve instance

Recall = Relevant instance that have been retrieve / Total amount of instance

8. EVALUATION RESULT

The graph shows 6.1 the result of precision and recall of the brain MRI image of the current system as well as existing system according to the accuracy from the 23 images which are taken from the dataset.

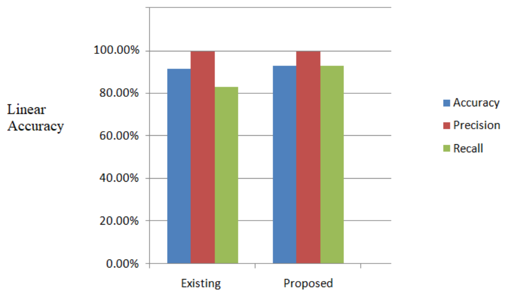


Fig 10: Graph based on Linear accuracy

The graph based on Linear accuracy in figure 5.13 shows the comparison of accuracy, precision and recall between existing work and proposed work.

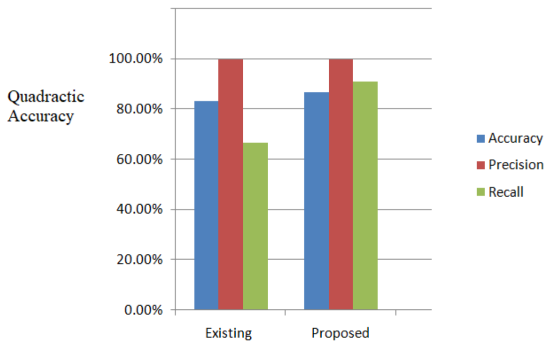


Fig 5.14: Graph based on Quadractic Accuracy

The graph based on Quadractic accuracy in figure 5.14 shows the comparison of accuracy, precision and recall between existing work and proposed work.

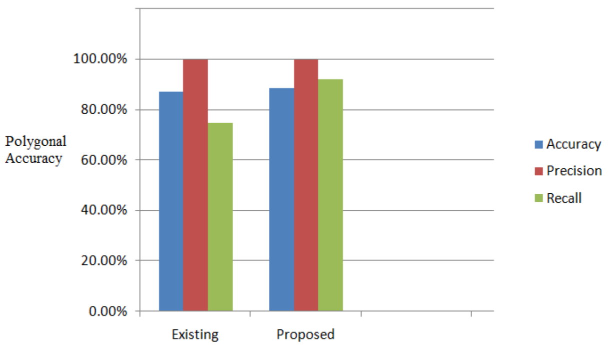


Fig 5.15: Graph based on Polygonal Accuracy

The graph based on Quadractic accuracy in figure 5.15 shows the comparison of accuracy, precision and recall between existing work and proposed work. The proposed work results are given in the table 5.2 below:

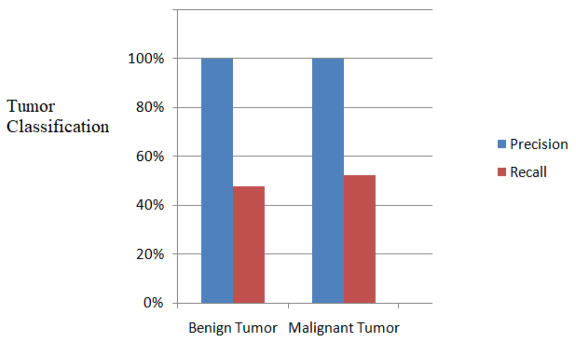


Fig 5.16 : Graph for Tumor Classifications

The figure 5.2 shows the classification of tumor for both types. First plot shows Precision and Recall for Benign Tumor and Second Plot shows Precision and Recall for Malignant Tumor.

9. CONCLUSION

The project presented that automated brain image classification for early stage abnormality detection with use of neural network classifier and spotting of tumor was done with image segmentation. Pattern recognition was performed using probabilistic neural network with radial basis function and pattern will be characterized with the help of fast discrete curvelet transform and haralick features analysis. From an experiment, system proved that it provides better classification accuracy with various stages of test samples and it consumed less time for process.

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