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Brain Tumor Detection and Segmentation in MRI Images Using Neural Network

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Abstract- Automatic faults detection in MR images is very significant in many symptomatic and cure applications. Because of high quantity data in MR images and blurred boundaries, tumor segmentation and classification is very hard. This work has introduced in one automatic brain tumor detection method to increase the precision and yield however it decreases the diagnosis time. The goal is to classifying the tissues to two classes of normal and abnormal. The proposed method can be used successfully and applied to detect the contour of the tumor and its geometrical dimensions. Furthermore based on discovering vector quantization with that image and data analysis although a manipulation technique is aimed to carry out an automated brain tumor classification using MRI-scans. The assessment of the changed ANN classifier execution is measured in price of the training execution, classification accuracies and computational time. MRI brain tumor images detection is a difficult task due to the variance and complexity of tumors. This research presents two techniques for the detection purpose; first one is Edge detection and segmentation instant is Artificial Neural Network proficiency. The aimed Neural Network technique comprises of some stages, namely, feature extraction, dimensionality reduction, detection, segmentation and classification. In this research, the proposed method is more accurate and effective for the brain tumor detection and segmentation. For the implementation of this proposed work we use the Image Processing Toolbox below Matlab.

Keywords- Artificial Neural Network (ANN), Edge detection, image segmentation and brain tumor detection and recognition.

I. INTRODUCTION

Brain tumor is nothing but any mass that results from an abnormal and an uncontrolled growth of cells in the brain. Its threat levels depend upon the combination of factors like the type of tumor, its position, its size and its state of growth. Brain tumors can be malignant (malignant) or non- malignant (benign). Benign brain tumors are a low grade and it's said to be non-cancerous brain tumors, which grows slowly and push aside normal tissue but do not invade the surrounding normal tissue. They are homogeneous, well defined and are known as non- metastatic tumors, as they do not form any secondary tumor. The malignant brain tumors are cancerous brain tumors, which grows rapidly and invade the surrounding normal tissue. Malignant brain tumors or cancerous brain tumors can be counted among the at most deadly diseases.

An artificial neural network (ANN), generally called neural network (NN), is a mathematical model or computational example that is inspired by the structure and/or functional expressions of biological neural networks. A neural network comprises of an interconnected group of artificial neurons (processing element), working in unison to solve specific problems. ANNs the is like in peoples, we'll learn by an example. The neuron has two modes of operations they are: The training/learning mode even though the using/testing mode. In mainly some cases an ANN is an adaptive system that converts its structure based on an external or the internal information that flows through the network in the learning phase. Recent epoch neural networks are the non-linear statistical data modeling tools. They are in general used to model complex relationships between inputs and outputs or it is used to find the practices in data. Multi-layer percept learning algorithm is a supervised learning algorithm. It is one of the most important developments in neural networks. This learning of algorithm is applied to multilayer feed-forward networks consisting of processing elements (neurons) with continuous differentiable activating functions (Tan-sigmoid and log- sigmoid). For a given set of aiming input-output correspond, this algorithm allows for a procedure for changing the weights in a BPN to classify an input correctly. The concept for this weight update algorithm is basically to the gradient descent method as used in case of simple percept networks with differentiable units. This is a way where the error is propagated back to concealed unit. The aim of the neural network is to train the net to accomplish a balance among the net's ability to respond (memorization) and its ability to give reasonable responses to the input that is similar but not identical the one of that which is used in training [2].

II. REVIEW OF RELATED WORKS

The literature survey carried out related to the technology which impacts in the study of brain related diseases revealed that a fair amount of research has gone into this area. Analysis and diagnosis of various brain associated illnesses like brain shot applying neural network [1], atherosclerotic disease in human carotid arteries [2], basal ganglia for accurate detection of human spongiform brain disease [3], brain tumours [4], Alzheimer‘s illness (AD) [5], brain infarct, infection, hamartoma, and tumor [6], neurosarcoidosis(NS) [7], cystic or necrotic brain tumours [8], unlike pathologic positions [9], nodular enhancement of the oculomotor nerve [10], Hemangioblastoma (Tumors) of the conus medullaris [11], MS lesions [12], [13], Parkinson‘s disease [14], pathological/normal brain [15], [16] are being cited in literature on processing of Brain MRI images. Brain MRI segmentation (for different applications) by applying unlike techniques such as nonparametric compactness estimation [17], Topology- continuing, v-driven segmentation (TOADS) [18], atlas-based whole brain segmentation method with an intensity renormalization procedure [19], a cognition -driven algorithm [20], tractography proficiencies [21], fuzzy logic [22-24], self-organizing map (SOM) neural network [25], k-means objective data combined genetic algorithm [26], Hidden Markov Model (HMM) [27], analytic thinking of brain MRI information applying registration based on deformation tensor morphometry [28], learning-based method [29], active markers [30] are being cited in the literature.

We have come across many works like detection of brain activation using conditional random field (CRF) [31], age-related changes brain white matter (WM) [32], analyzing areas of neuronal energizing [33], brain growth and foetal brain pathology [34],the effect of caffeine on verbal working memory task [35], neural correlates of retrieval success for music memory [36] and early functional brain development with the data collected from the children during natural sleep [37]. Extraction of texture places of the brain‘s white matter (WM) [38], orbicular rippling translation to extract shape characteristics of cortical surfaces [39],single cell detection [40], Bayesian decision theory employed to the brain weave assortment [41], calculation and visualization of volumetric white affair property in diffusion tensor (DT) MRI [42], topological visualization of human brain diffusion MRI [43], labeling of structures in 3D brain MRI data adjusts using expert anatomical cognition that is coded in fuzzy sets and fuzzy rules [44] are detected in literature.

III. METHODOLOGY

A. Image Acquisition

In our suggested approach we first believed that the MRI scan images of a given patient are either color, Gray-scale or intensity images herein are displayed with a default size of 220×220. If it is color image, a Gray-scale converted image is determined by using a big matrix whose entrances are numerical values between 0 and 255, where 0 represents to black and 255 to white for illustrate. Then the brain tumor detection of a given patient constitute of two main stages namely, image segmentation and edge detection.

B. Image Segmentation

The accusative of image segmentation is to cluster pixels into high image region. In this research, segmentation of Gray level images is used to furnish data such as anatomical structure and naming the Region of Interest i.e. settle tumor, lesion and other abnormalities. The aimed approach is based on the data of anatomical structure of the healthy parts and compares it with the infected parts. It starts by apportioning the anatomical structure of the healthy parts in a reference image of a normal candidate brain scan image as shown in Fig. 1 then it allocates the abnormal parts in the unhealthy patient brain. Scan MRI image by comparison it with the reference image information as shown in Fig. 2.

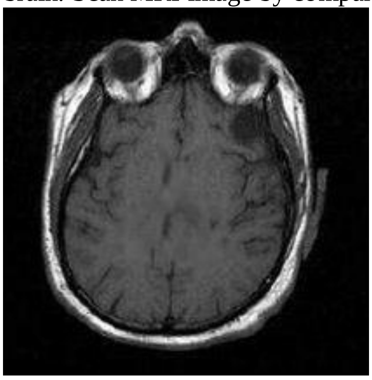


Figure 1: Normal Brain

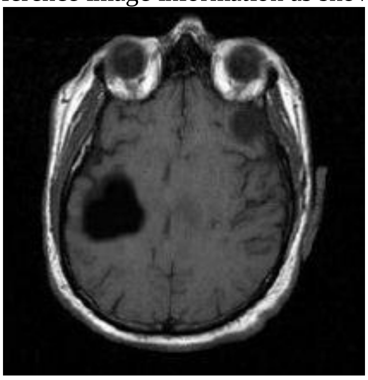


Figure 2: Abnormal Brain

1) Enhancement and Segmentation:

There are different types of noise found by different techniques, depending on the noise nature and features, namely Gaussian noise and momentum noise. In this research we assumed that the main image noise is additive and random; that is spurious and random signal, n(i, j), added to the true pixel value I(i, j): $II(i, j) = I(i, j) + n(i, j)$. in this algorithm the enhancement in spatial field is based on direct manipulation of pixels in a small neighborhood of pixels, in generally accepts the form; $g(x, y) = T[f(x, y)]$ in which f(x, y) is the remark image, g(x, y) is the marched image, and T is an operator on f, determined over some neighborhood of (x, y). Then we employed the next enhancement in frequency field which is based on the concept of the convolution theorem and spatial filters. In this research, the proposed edge algorithm is based on using spatial filters and includes the following:

- Segmentation filters that are used to reduce or remove Gaussian noise from the MRI image.
- Sharpening filters that are used for highlighting edges in an image, and are based on the use of beginning and instant order derivatives.

2) Polishing by Linear filter:

Linear operations compute the resulting value in the output Image Pixel IA (i,j) as a linear combination of light in a local neighborhood of the pixel I(i,j) in the input image. In this algorithm we accepted I as an N×M image, m is an odd number smaller than both N and M, and A is the convolution kernel or the filter mask of the linear filter that is an m×m mask. The filtered interpretation of I is afforded by the discrete convolution as follows:

$$I_A\,(i,j) = I\,*\,A = \sum_{h=-n/2}^{n/2} \sum_{k=-m/2}^{m/2} \mathrm{A(h,k)}I\,(i-h, j-k)$$

Where i=1 to N and j=1 to M. This filter substitutes the value I(i, j) with a weighted sum of I values in a neighborhood of (i, j). If all entrances of an in Eq. (3) are non-negative, the filter does average smoothing. Then the matrix of the abnormal brain scan image is deducted from that of the pattern brain image resulting in a matrix of the region of interest came with some noise as illustrated in Fig.3.

3) Smoothing using Gaussian filter

In this research, the suggested Gaussian polishing filter, Gf, is a nonnegative, real-valued column matrix defined by,

$$G_f\,(x,y) = \frac{1}{c} exp + \frac{-[x^2+y^2]^{\cdot}}{2\sigma^2}$$

In which c is expressed as $c = \sqrt{2\pi\sigma^2}$

However this type of filters enhanced the noise reduction level equated with the linear filters, it was celebrated that these polishing and noise filters did not altogether satisfy the noise removal level from the original image as shown in Fig. 4. Thus, for these applications a set of cascaded filters are recommended. We hence proposed another stage of noise filtering by using an mean filter.

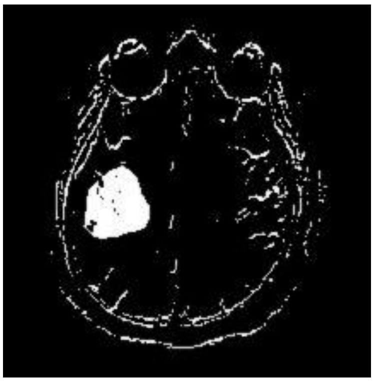


Fig 3: Applying Gaussian filter

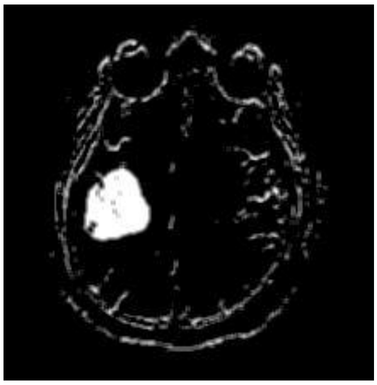


Fig 4: applying Average Filter

Applying the average filter resulted in an acceptable noise reduction level for such applications. The decision from this part is cascaded filter lay out is recommended to reach an satisfactory noise reduction levels brain tumor detection.

C. Edge Detection

An edge is a place attached to a person pixel and is computed from the image occasion behavior in a neighborhood of the pixel. It is also believed as a vector variable (magnitude of the gradient, focus of an edge). The aim of edge detection in universal is to significantly reduce the amount of data in an image, while preserving the structural properties to be used for further image processing. In this research, other than filtering the region of interest (ROI) is proposed to identify different tumor types and/or different infected areas. It also universal to enhance the marching time by accomplishing the boasts processing algorithm in the named areas or else of the whole image figure. In this explore, we first employed a vector subtraction algorithm then the ROI is decided by finding the associated adjacent allots in the outcome image from the vector subtraction. The area of each associated adjacent allot is calculated and the irrelevant portions removed resulting in the desired tumor region as shown in Fig. 6. To enhance the results of the proposed edge detection algorithm we base that the most crucial criteria that impress the edge detection performance are by reducing the rate error of missing edges in an image and that edge degrees must be well localized. Hence, we successfully modeled and carried out Canny's mathematical patterns [17] to gain the performance of the aimed edge detection algorithm. Even though it is quite old, it has become one of the standard edge detection methods and it is still used in explore [18].

D. Canny Edge detection

The Canny algorithm can be used an optimum edge detector based on a set of criteria which include detecting the almost edges by minimizing the error rate, marking edges as closely as potential to the actual edges to maximize localization, and marking edges only once when a single edge exists for minimum reaction. Allowing to Canny [29], the optimum filter that meets all three criteria above can be efficiently estimated using the first estimated of a Gaussian occasion in Eq. (4). These derivatives are used to calculate gradient magnitude (edge strength) and gradient focus of most rapid alter in intensity.

E. The altered Canny Edge Detection Algorithm

The algorithm runs in some break steps as shown in Fig. and depicted as follows:

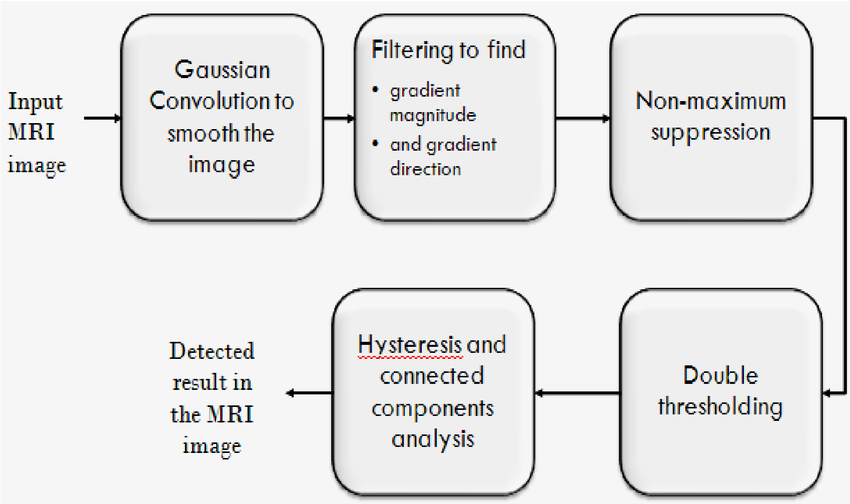


Fig 5: Block diagram for brain tumor extraction [11].

1. Polishing: Blurring of the image to remove noise. Therefore the image is first polished by employing a Gaussian filter. Our aimed method uses 5×5 Gaussian template and the original image to weight locality. Denote any point (x, y) of the image as the center when marching and extracting 5×5 neighborhood, the weighting neighborhood can be pointed as follows:

$$I_A\,(x,y) = \frac{1}{5\times 5}\sum_{i=-2}^{2}\ \sum_{j=-2}^{2} I(\mathrm{x+i,y+j}) \times M(2+i,2+j-h,j)$$

where x=1,2,…,m; y=1,2,…,n , I(x,y) is the pixel value of the original sub-image, M is the Gaussian template, and IA(x,y) is the pixel assess of the polished image.

2. Detecting gradients: The edges should be noted where the gradients of the image has big magnitudes (edge strength). In this step we calculate gradient focus and amplitude of polished image IA(x,y) adopting first order partial finite difference of 2×2 neighborhood.

$$M\,(x,y)=\sqrt{\mathrm{x} = \sigma^2(x,y) + y = \sigma^2(x,y)}$$

$$\theta = \arctan\,(g_y\ (\mathrm{x,\ y})/\ g_x\ (\mathrm{x,\ y}\,))$$

$$f_x \begin{pmatrix} \frac{-1}{2} & \frac{1}{2} \end{pmatrix} \qquad f_y \begin{pmatrix} \frac{-1}{2} & \frac{1}{2} \end{pmatrix}$$

Where gx and gy are the gradients in the x- and y-directions respectively and constitutes the effects of the original image filtered on rows and lines. θ is the gradient focus.

3. Non-maximum suppression: Only local maxima should be marked as edges. If the gradient amplitude of the pixel is no less than the gradient amplitude among two adjacent pixels in the gradient focus, the point can be judged as the edge point maybe. The aim of this step is to convince the "blurred" edges in the image of the gradient magnitudes to "sharp" edges. Essentially this is done by continuing all local maxima in the gradient image, and deleting everything else.

The algorithm is for each pixel in the gradient image.

A. Round the gradient focus θ to nearest 45 , matching to the use of an 8-connected neighborhood.

B. Compare the edge force of the current pixel with the edge force of the pixel in the convinced and negative gradient focus. I.e. if the gradient direction is north (θ =90◦), equate with the pixels to the north and south.

C. If the edge strength of the current pixel is largest; continue the value of the edge strength. If not, inhibit (i.e. remove) the value.

4. Double thresholding: possible edges are decided by thresholding. Edge pixels firmer than the high threshold are noted as strong; edge pixels weaker than the low threshold are inhibited and edge pixels among the two thresholds are marked as weak.

5. Edge tracking by hysteresis: Final edges are decided by inhibiting all edges that are not associated to a very certain (strong) edge. Firm edges are understood as "certain edges", and can directly be included in the final edge image. Weak edges are included if and only if they are associated to firm edges. The logic is of naturally that noise and other small versions are unlikely to result in a strong edge (with proper adjustment of the threshold degrees). Thus strong edges will (nearly) alone be due to true edges in the original image. The weak edges can either be due to true edges or noise/color versions. The latter type will likely be disseminated independently of edges on the entire image, and thus only a small number will be settled next to strong edges. Weak edges due to true edges are a lot more possible to be associated immediately to strong edges. In this research edge tracking is carried out by iterative BLOB-analysis (Binary Large Object). The edge pixels are classified into associated BLOB's using 8-connected neighborhood. BLOB's associating at least one strong edge pixel is then continued, while other BLOB's are inhibited.

F. Neural Network features

The word network in Neural Network concerns to the interconnection among neurons present in several layers of a system. Every system is essentially a 3 layered system, which are Input layer, concealed Layer and Output Layer. The input layer has input neurons which transfer data via synapses to the concealed layer, and likewise the hidden layer transfers this data to the output layer via more synapses.

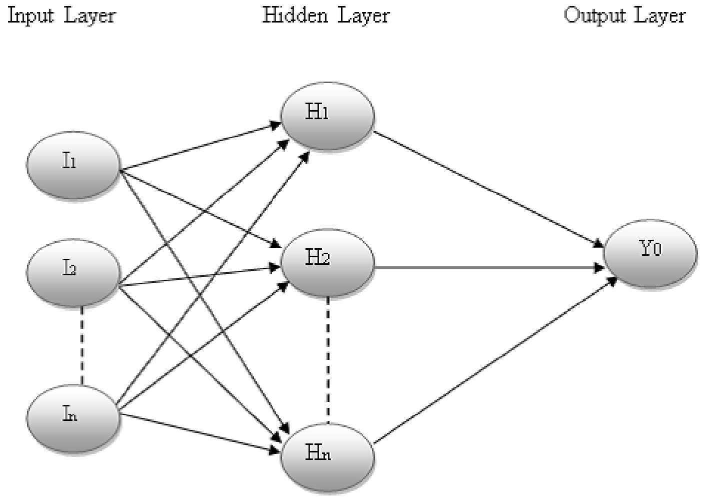


Fig1.6 Architecture of Neural Network

Neural Network (NN) can be constituted employing a directed graph G, an ordered 2-tuple (V, E) comprising of a set V of vertices and E of edges with vertices V={1, 2, n} and arcs A= {<i,j>|i>=1,j <=n } ,having the following restrictions:

- V is partitioned into a set of input nodes VI , hidden nodes, VH, and output Nodes VO.
- The vertices are also partitioned into layers.
- Any arc <i, j> must have node i in layer h-1 and node j in layer h.
- Arc <i, j> is labeled with a numeric value wij.
- Node i an labeled with a occasion fi.

When each edge is allotted an orientation, the graph is aimed and is called a aimed graph or a diagraph. A feed forward network has directed acyclic graph. Diagraphs are crucial in neural network theory since signals in NN systems are limited to flow in detail guidance. The vertices of the graph constitute neurons (input\output) and the edges, the synaptic links. The edges are marked by the weights attached to the synaptic links.

G. Simulation solutions

Aimed algorithm is enforced using MATLAB where the source image and the thresholds can be chosen arbitrarily and the implementation uses the adjust Euclidean amount for the edge forces. Simulation answers after applying Canny-based edge detection algorithm on MRI scan images showed the power of the aimed algorithm to accurately detect and five the contour of the tumor as shown in Fig. 7.

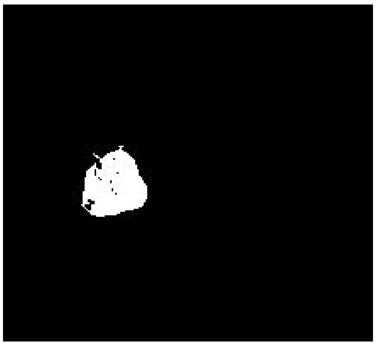


Fig 6: Region of Interest

Fig 7: Canny Edge Detection

IV. DISCUSSION AND RATING

4.1 Experimental Results

Various simulated experiments are carried out to establish the validity and feasibility of the segmentation method for segmenting areas from brain images. amounts muse the effectiveness of a image segmentation method. The system has been implemented applying Matlab since of powerful inherent mathematical and image marching purposes.[8] In the first step, the color image is translated from RGB to gray scale. Although, traditionally, the most normally used model for MRI images. All of our data are developed scanning lab and 1.5T scanners for brain image segmentation.

A. Inference and Forecasting

The brain tumor image is given as input to the subsystem. The input brain tumor image is pre- marched and then feature extracted and the ROIs are segmented by using the ANN method. Then the suggested back propagation edge detection algorithm neural network method is enforced to predict the brain tumor as either benign or malignant. Some of the being methodology is very hard to find the exact results in brain tumor images since it loss of edge details due to the shift version place. On the other hand, through the suggested methodology exact detection of the classification of the images can be done. The high characteristic texture characterization method is fast and flexible aiming and classification can also be done through suggested methodology.

B. Calculation procedure

All classification results could have an error rate and on occasion will either fail to name the normal and abnormal images. It is common to depict this error rate by the terms true and false convinced and true and false negative.

$$\text{Classification Accuracy (CA)} = \frac{TP + TN}{(TP + TN + FP + FN)}$$

Sensitivity = TP / TP + FN

Specificity = TN /TN + FP

Finally Classification result computed based on the accuracy formula.

Usually the Accuracy evaluate is used

$$\text{Accuracy} = \frac{\text{No of Correctly Classified record}}{\text{Total Records in the test set}}$$

True Positive (TP): The test result is positive in the presence of the objective abnormality.

True Negative (TN): The test result is negative in the absence of the clinical abnormality.

False Positive (FP): The test result is positive in the absence of the clinical abnormality.

False Negative (FN): The test result is undesirable in the presence of the clinical abnormality

FP= False Positive value pixel count /tumor size

FN= False Negative value pixel count /tumor size

Correct rate= FP+FN

The suggested model is tried over a large no. of database of MRI brain images. In this suggested work many boasts have been extracted from these images. In below table.1, shows the some significant extracted characteristics and their values of these images data's.

First the input image is shown here, Fig 2 shows input images which has brain tumor. Threshold segmentation is applied on this image which contains brain tumor. The result is shown in the Fig 3.

Table 1: Number of Detected Edges

Patient ID	**Grade**	**Number of Detected Edges**		
		Robert	**Prewitt**	**Canny**
397384	High	5259	4382	1997
1941040	High	5120	4323	1836
1953042	High	6807	5757	2302
197906	Low	1491	649	317
1956041	Low	2509	1080	433
1943061	Low	2567	1072	417

Table 2: Areas of Tumor

Patient ID	**Lesion**	**Volume of tumor areas (Pixels)**	**% of Damage areas**
397384	Left Frontal Parietal	4315	17.26
19410407	Left High Parietal	1068	4.27
19530428	Left Temporal Lobe	435	1.74
19790628	Left Frontal Parietal	1776	7.10
19560416	Left Thalamus	1060	4.24
19430618	Left High Parietal	3824	15.30

After extracting the boasts by GLCM feature extraction method, we get the unlike feature measures for the abnormal and normal MRI brain images. Below some graph shows the Entropy and Contrast values for the MRI brain normal and abnormal images.

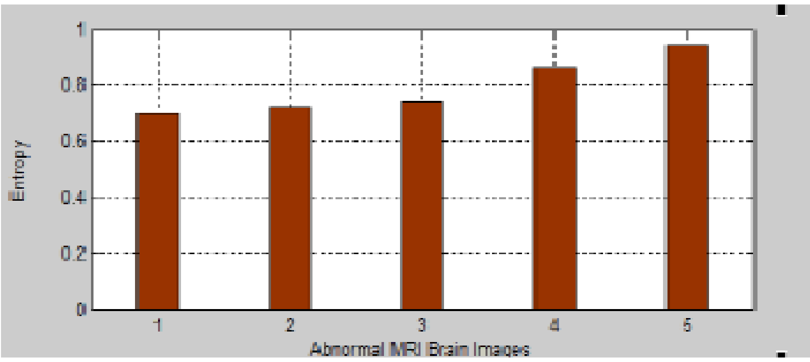


Fig4.1: Entropy graph for abnormal MRI brain images.

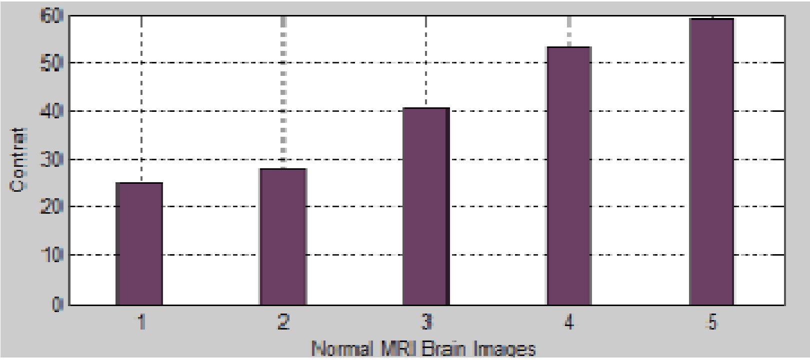


Fig 4.2: Entropy graph for normal MRI brain images.

Here in this practical work, we have used information of100 images in which 50 images are Abnormal MRI brain images and 50 images are Normal MRI brain images. He real the parameters are computed and they are as follows: Accuracy = 98%, Specificity = 97.50% and Sensitivity = 98.80%.All those values are achieved through suggested method. The graph of performance measurement is shown in the below figure 3.8:-

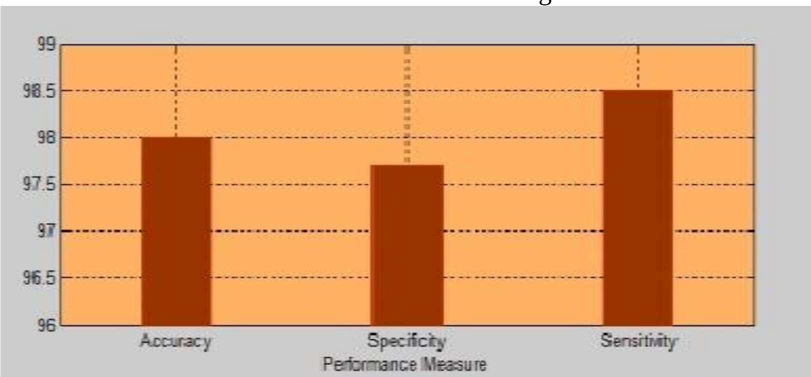


Figure 4.3: Performance Measure of suggested Classifier

V. RESULT AND DISCUSSION

There are lots techniques for brain tumor detection. I have used edge detection technique for brain tumor detection. Edge-based method is by far the most common method of detecting boundaries and discontinuities in an image. The parts on which immediate exchanges in grey tones occur in the images are called edges. Edge detection techniques translate images to edge images gaining from the changes of grey tones in the images.

Then there is a technique called segmentation which is employed on the ensued image found after segmentation. After employing edge detection algorithm we discovering tumor from the image and showing in below, but outcome image give small size of tumor as compared to the input image and the edge detection algorithm give an effective result of tumor detection, so we are conceiving result which is acquiring from edge detection algorithm for further part of explore.

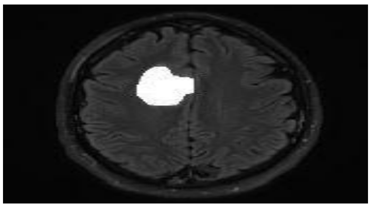
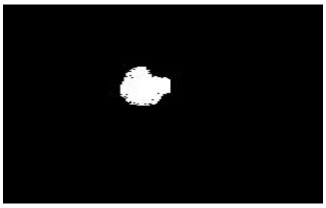
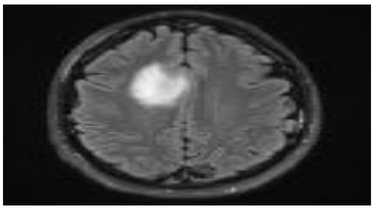
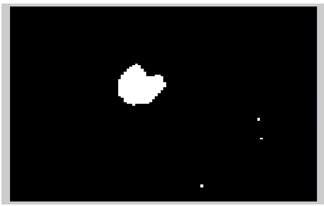
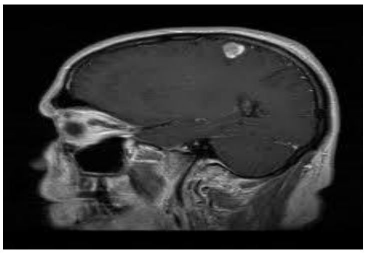
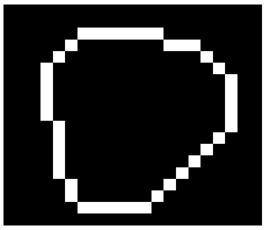
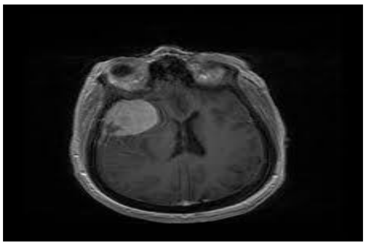
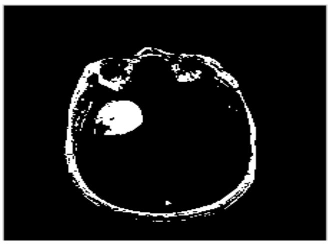
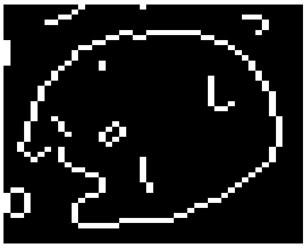
One’s we are acquiring tumor from the algorithm then we are going to limit extraction of brain tumor. Essentially we are employing edge detection operator such as pewit, canny and sober operator are used and result from this three operator are shown in below. As seen these three results, canny edge detection operator gives an effective of limit extraction or tumor. The size of brain tumor we are accepting the result of boundary extraction which is given from canny edge operator, from this boundary we can decide the determine of tumor. After finding shape we are detecting size of brain tumor in the matrix form (m*n), the consequence is showing in below along with size of the tumor.

The result of segmented brain tumor images using segmentation techniques and its area is as shown in table 3.

Table 3. The Result is Showing in Beneath on With Size of the Tumor.

	Max. Width of Tumor (w)	Max. length of Tumor (l)	Tumor Area (a)	Max. Width of Brain (W)	Max. length of Brain (L)	Brain Area (A)	Ratio of widths (w/W)	Ratio of lengths (l / L)	Ratio of Areas (a /A)
	pixels	Pixels		pixels	Pixels				
GT	54	59	2497	172	225	31543	0.314	0.262	0.079
Algorithm	55	60	2639	182	229	32298	0.302	0.262	0.082

Table 4. Segmented Brain Tumor Images and Edge Detection Identity.

Input Image	Tumor Detection	Boundary Extraction	Size (m*n)
			Name aa Size 64x56 Class uint8 Bytes 3584 N
			Name bb Size 116x87 Class uint8 Bytes 10092
			Name cc Size 21x22 Class uint8 Bytes 462
			Name dd Size 47x44 Class uint8 Bytes 2068

VI. CONCLUSION

In this research from the effects found are much exact and clear. Accuracy found in final result depends on marching of each step. For each step, there are numerous methods available and the methods allowing for best effects were preferred. The last step is detection of edges of the tumor. The Cellular Automata rule number 252 provides firm edge detection. The algorithm was employed on numerous images and the effects found were very good and effective. Also the suggested algorithm can be applied with some change for detection of lung cancer. The algorithm can be employed to the CT scan of the lungs and region bearing from cancerous cells can be named. A new system that can be used as a second conclusion for aimed. It influences whether an input MRI brain image constitutes a healthy brain or tumor brain. High grade tumors have more true edges than low grade. MRI of healthy brain has an obviously quality almost bilateral symmetric However, if there is macroscopic tumor, the symmetry feature will be weakened. Allowing to the determine on the symmetry by the tumor, we develop a section algorithm to detect the tumor region automatically. The suggested novel approach of improved de-noising method was equated with the being de-noising method. And the effects were employed the algorithm to find out the dissimilarity between original and de-noise images. The experimental results establish the effectiveness of the suggested work. In future, the tumor part is taken for classification of tumor types such as benign and malignant.

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