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Brain Tumor Segmentation and Classification using Graph Cut Segmentation and DRLBP

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Abstract:
Image segmentation is the process of splitting an image into multiple segments, so as to change the representation of an image into something that is more expressive and easier to analyze. Accurate automated segmentation of brain tumors in MR images is challenging due to overlapping tissue intensity distributions and amorphous tumor shape. However, a clinically feasible solution providing precise quantification of tumor and enema volume would enable better pre-operative planning, treatment monitoring and drug development. Image pre-processing, edges and boundaries detection, histogram thresholding and segmentation with graph cuts will be performed in applying the selected method. Diagnosis can be challenging and MR imaging may aid as a non-invasive method to increase prediction accuracy. To analyze the use of 2D local binary pattern (LBP) mined from MR images of the brain. In this experiment proposed a DRLBP for features extracted from MRI. The classification of normal and abnormal brain using ANN-Back propagation Neural Network.

Keywords: Artificial neural network, Back propagation neural network, Dominant rotated local binary pattern.

1. INTRODUCTON:

To digitally process an image, it is first specified to reduce the image to a series of numbers that can be manipulated by the computer. Each number representing the brightness value of the image at a particular location is called a picture element, or pixel. An ideal digitized image may have 512 × 512 or roughly 250,000 pixels, although much larger images are becoming common. Once the image has been digitized, there are three basic operations that can be performed on it in the computer. For a point operation, a pixel value in the output image depends on a pixel value in the input image. For local operations, several neighboring pixels in the input image impel the value of an output image pixel. In a global operation, all of the input image pixels supply to an output image pixel value. These operations, can take single or in combination, are the means by which the image is enhanced, restored, or compressed. An image is enhanced when it is improved so that the information containsmore clearly evident, but improvement can also include effecting the image more visually present. To smooth a noisy image, median filtering can be applied with a 3 × 3 pixel window. This means that the value of every pixel in the noisy image is noted, along with the values of its neighbors. These nine numbers are then ordered according to size, and the median is selected as the value for the pixel in the new image. As the 3 × 3 window is moved one pixel at a time over the noisy image, the refined image is formed.

1.1 CLASSIFICATION OF IMAGES:-

There are 3 types of images used in Digital Image Processing. They are

- Binary Image
- Gray Scale Image
- Color Image

1.1.1binary Image:-

A binary image in a digital image that has only two possible values for each pixel. Typically, the two colors used for a binary image are black and white can be used. The color used for the object(s) in the image is the foreground color whereas the rest of the image is the background color. Binary images are also called bi-level or two-level. This means that each pixel is kept as a single bit (0 or 1).This named as black and white, monochrome or monochromatic are often used for this concept, but may also designate any images that have only one sample per pixel, such as gray scale images Binary images often arise in digital image processing as masks or as the result of certain operations such as segmentation, thresholding, and dithering. Some of the input/output devices, such as laser printers, fax machines, and bi-level computer can handle the binary images.

1.1.2 GRAY SCALE IMAGE:-

A gray scale Image in digital image is an image in which the value of each pixel is a single sample, that is, it carries only intensity information. Images of this type, also known as black-and-white, which are composed of shades of gray (0-255), varying from black (0) at the weakest intensity to white (255) at the strongest. Gray scale images are distinct from black and white images, which in the context of computer images with only the two colors black and white

(also called bi-level or binary images). Gray scale images have many shades of gray in between them. Gray scale images are often the result of computing the intensity of light at each pixel in a single band of the electromagnetic spectrum

(e.g. infrared, visible light, ultraviolet, etc.) and in such cases they are monochromatic proper when only a given frequency is captured and they can be synthesized from a complete color image.

1.1.3 COLOUR IMAGE:-

A color image in a digital image that includes color information for each pixel. Each pixel has a particular value which determine it's appearing color. The value is appropriate by three numbers giving the decomposition of the color in the three primary colors Red, Green and Blue. Any color visible to human eye can be represented this way. The decomposition of a color in the three primary colors is measured by a number between 0 and 255. For example, white will be coded as R = 255, G = 255, B = 255; black will be known as (R,G,B) = (0,0,0); and say, bright pink will be : (255,0,255). In other words, an image is ahuge two-dimensional array of color values, pixels, each of them coded on 3 bytes, representing the three primary colors. This allows the image to contain a total of 256x256x256 = 16.8 million different colors. This technique is also known as RGB encoding, and is specifically adapted to human vision.

2. LITERATURE SURVEY ANALYSIS:-

Review of MRI-Based Brain Tumor Image Segmentation Using Deep

Learning Methods

Brain tumor segmentation is an important task in medical image processing. Early diagnosis of brain tumors plays an important role in improving treatment possibilities and increases the survival rate of the patients. Manual segmentation of the brain tumors for cancer analysis, from large amount of MRI images are generated in clinical routine, which is a difficult and time consuming task. There is a necessity for automatic brain tumor image segmentation. The purpose of this paper is to offer a review of MRI-based brain tumor segmentation methods. Recently, automatic segmentation using deep learning methods proved popular since these methods achieve the state-of-the-art results and can address this problem better than other methods. Deep learning methods can also efficient processing and objective evaluation of the large amounts of MRI-based image data. There are number of existing review papers, focusing on traditional methods for MRI-based brain tumor image segmentation. Different than others, in this paper, we focus on the modern trend of deep learning methods in this field. First, an introduction to brain tumors and methods for brain tumor segmentation is given. Then, the state-of-the-art algorithms with a focus on modern trend of deep learning methods are discussed. Finally, an assessment of the current state is presented and future developments to standardize MRI-based brain tumor segmentation methods into daily clinical routine are addressed.

Brain Tumor Segmentation with Deep Neural Networks

In this paper, we present a fully automatic brain tumor segmentation method based on Deep Neural Networks (DNNs). The proposed networks are tailored to glioblastomas (both low and high grade) pictured in MR images. By their very nature, these tumors can appear anywhere in the brain and have any kind of shape, size, and contrast. These reasons motivate our exploration of a machine learning solution that exploits a flexible, high capacity DNN while being extremely efficient. Here, we give a description of different model choices that we have found to be necessary for obtaining competitive performance. We explore in particular different architectures based on Convolution Neural Networks (CNN), i.e. DNNs specifically adapted to image data. We present a novel CNN architecture which varies from those traditionally used in computer vision. Our CNN exploits both local features as well as more global contextual features simultaneously. Also, unlike from most traditional uses of CNNs, our networks use a final layer that is a convolutional implementation of a fully connected layer which allows a 40 fold speedup. We also describe a 2-phase training procedure that allows us to tackle difficulties related to the imbalance of tumor labels. Finally, we discover a cascade architecture in which the output of a basic CNN is treated as an additional source of information for a subsequent CNN. Results reported on the 2013 BRATS test dataset reveal that our architecture improves over the currently published state-of-the-art while being over 30 times faster.

Tumor or abnormality identification from magnetic resonance images using statistical region fusion based segmentation

In this article, a statistical fusion based segmentation technique is proposed to identify different abnormality in magnetic resonance images (MRI). The proposed scheme follows seed selection, region growing–merging and fusion of multiple image segments. In this process initially, an image is divided into a number of blocks and for each block we compute the phase component of the Fourier transform. The phase component of each block reflects the gray level variation among the block but contains a large correlation among them. Hence singular value decomposition (SVD) technique is adhered to generate a singular value of each block. Then a thresholding procedure is applied on these singular values to identify edgy and smooth regions and some seed points are selected for segmentation. By considering each seed point we perform a binary segmentation of the complete MRI and hence with all seed points we get an equal number of binary images. A parcel based statistical fusion process is used to fuse all the binary images into multiple segments. Effectiveness of the proposed scheme is tested on identifying different abnormalities: prostatic carcinoma detection, tuberculosis granulomas identification and intracranial neoplasm or brain tumor detection. The proposed technique is established by comparing its results against seven state-of-the-art techniques with six performance evaluation measures.

Automatic Image Segmentation Using Graph Cut

Image segmentation is the practice of splitting an image into multiple segments, so as to change an image into somewhat that is more meaningful and easier to analyze. Several general purpose algorithms and techniques have been developed for image segmentation. Image segmentation refers to splitting of an image into different regions that are homogenous or similar and inhomogeneous in some characteristics as the new graph cut approach is an emerging technique for image segmentation, as it can minimize an energy function composed of data term estimated in feature space and smoothness term estimated in an image domain. Previous approaches using graph cuts have shown good performance for image segmentation, they manually obtained prior information to estimate the data term, thus automatic image segmentation is one of issues in application using the graph cuts method. As it needs low computational complexity and is therefore very feasible for real-time image segmentation processing. In the experiments, we investigated problems of previous methods such as mean shift segmentation, watershed technique and automatic graph cut based image segmentation. As a result, the graph cut method displayed better performance than previous methods.

Efficient Segmentation Methods for Tumor Detection in MRI Images

Brain tumor extraction and its analysis are challenging tasks in medical image processing because brain image and its structure is complicated that can be analyzed only by expert radiologists. Segmentation plays an important role in the processing of medical images. MRI (magnetic resonance imaging) has become a particularly useful medical diagnostic tool for diagnosis of brain and other medical images. This paper presents a comparative study of three segmentation methods implemented for tumor detection. The methods contain k-means clustering with watershed segmentation algorithm, optimized k-means clustering with genetic algorithm and optimized c- means clustering with genetic algorithm. Traditional k-means algorithm is complex to the initial cluster centers. Genetic c-means and k-means clustering techniques are used to detect tumor in MRI of brain images. At the end of process the tumor is extracted from the MR image and its exact position and the shape are determined. The experimental results indicate that genetic c-means not only eliminate the over segmentation problem, but also provide fast and efficient clustering results.

3. EXISTING METHOD :-

- Thresholding method
- K means clustering
- k-nearest neighbors algorithm(KNN)
- Edge detection
- Principal Component analysis

3.1 THRESHOLDING:-

The simplest method of image segmentation is called the thresholding. This method is based on a clip-level (or a threshold value) to turn a gray-scale image into a binary image. The fundamental of this method is to select the threshold value (or values when multiple-levels are selected). Several popular methods are used in industry including the maximum entropy method, Otsu's method (maximum variance), and k-means clustering. Now these methods have been developed for thresholding computed tomography (CT) images. The key idea is that, unlike Otsu's method, the thresholds are resultant from the radiographs instead of the (reconstructed) image.

3.1.1 DESIGN STEPS:-

- **(1)** Set the initial threshold T= (the maximum value of the image brightness + the minimum value of the image brightness)/2.
- (2) Using T segment the image to get two sets of pixels B (all the pixel values are less than T) and N (all the pixel values are greater than T);
- (3) Calculate the average value of B and N separately, mean ub and un.
- (4) Calculate the new threshold: T= (ub+un)/2
- (5) Repeat Second steps to fourth steps up to iterative conditions are met and get necessary region from the brain image.

3.2 K-MEANS CLUSTERING:-

K-means is one of the simplest unsupervised learning algorithms that solve the well-known clustering problem. The procedure follows a simple and easy way to classify a given data set over a certain number of clusters (assume k clusters) fixed a priori. The main idea is to describe k centroids, one for each cluster. After we have these k new centroids, a new binding has to be done between the similar data set points and the nearest new centroid. A loop has been generated. As a result of this loop we may notice that the k centroids change their location step by step until no more changes are done. In other words centroids do not transfer any more. Finally, this algorithm aims at minimizing an *objective function*, in this case a squared error function.

3.3 KNN:-

Cluster analysis, an important technology in data mining, which is an effective method of analyzing and discovering useful information from numerous data. Cluster algorithm groups the data into classes or clusters so that objects within a cluster have high similarity in compare to one another, but are very dissimilar to objects in other clusters..Dissimilarities are assessed based on the attribute values describing the objects

$J_c = \sum_{j=1}^{c} \sum_{k=1}^{nj} \|xkj - mj\|^2$

Where*J*, is the sum of square-error for all objects in the database, $X_k$is the point in space representing **a** given object, and $M_J$is the mean of cluster C_j. Adopting the squared-error criterion, K-means works well when the clusters are compact clouds that are rather well distinct from one another and are not suitable for discovering clusters with nonconvex shapes or clusters of very different size.

3.4 EDGE DETECTION:-

Edge detection is a well-developed field on image processing. Region boundaries and edges are closely related, since there is often a sharp adjustment in intensity at the region boundaries. Edge detection techniques have been used as the base of another segmentation technique. The edges identified by edge detection are often disconnected. To segment an object from an image however, one needs closed region boundaries.

3.5 PRINCIPALCOMPONENT ANALYSIS:-

PCA is generally regarded as a computationally expensive technique which has0particularlylimited its domain of applications. The size of each retinal image used in fovea localization by PCA was 500 by 500 pixels. The size of the spots from the foveae regions used in training the PCA was 70 by 70 pixels.

Drawbacks

- Difficult to get accurate results
- Not applicable for multiple images for Tumour detection in a short time
- Medical Resonance images contain a noise caused by operator performance which can lead to serious inaccuracies classification.
- Time consuming

- inaccurate and requires intensive trained person to avoid diagnostic errors

4. PROPOSED METHOD:-

MRI Brain image Classification and anatomical structure analysis are proposed based on below methodologies.

4.1 METHODOLOGIES:-

- Edges and boundaries detection
- Histogram thresholding
- Graph Cut Segmentation
- DRLBP features
- ANN-BPN Training and Classification

4.1.1 BOUNDARY DETECTION AND IMAGE SEGMENTATION:-

In most computer vision applications, the edge/boundary detection and image segmentation organize a primary step before performing high-level tasks such as object recognition and scene interpretation. In the image analysis literature, normally segmentation performance was demonstrated on a very small example set of images. Large scale image database annotation demands robustness with very little parameter tuning over a wide range of image data.

4.1.2 HISTOGRAM THERSHOLDNG:-

This method generally increases the global contrast of many images, especially when the usable data of the image is represented by close contrast values. Through this adjustment, the intensities can be well distributed on the histogram. This allows for areas of lower local contrast to gain a higher contrast. Histogram equalization accomplishes this by efficiently spreading out the most frequent intensity values. The method is essential for images with backgrounds and foregrounds that are both bright or both dark.

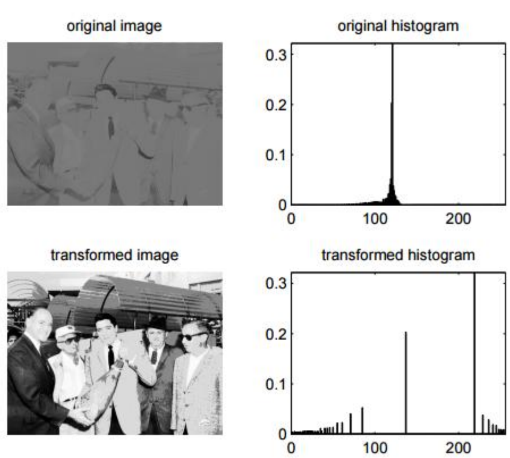
Let p denote the normalized histogram of with a container for each possible intensity. So,

$$P_n = \frac{Number\ \ of\ pixels\ \ with\ intensity\ \ n}{Total\ number\ \ of\ pixels} \qquad n=0,1,2……L\text{-}1$$

The histogram equalized image g will be defined by,

$$g_{i,j}= \text{floor}((L – 1 \textstyle\sum_{n=0}^{fi,j} pn)$$

where floor() rounds down to the nearest integer



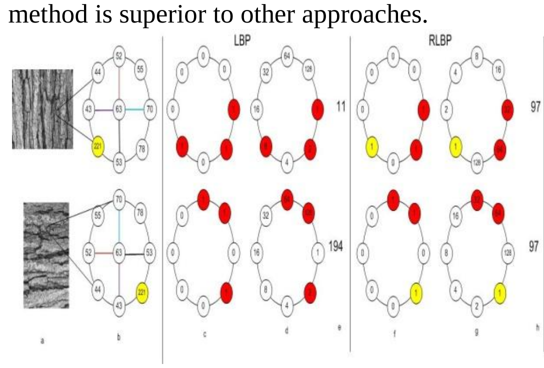
One of the major challenges in image processing, especially in case of backlit images is to improve the contrast of images. In case of a fog image, concentration of pixel grey levels is experimental that the strengthening and weakening of the lower and higher ones grey levels respectively. Hence, the cleanliness of such a fog image strains efficient image contrast enhancement.

4.1.3 GRAPH CUT SEGMENTION:-

The goal is to segment the main objects out of an image using a segmentation method based on graph cuts. We used MAXFLOW - software for computing the mincut/maxflow of a graph. This software library implements the maxflow algorithm described in"An Experimental Comparison of Min-Cut/Max-Flow Algorithms for Energy Minimization in Vision."(Yuri Boykov and Vladimir Kolmogorov). A graph-based approach makes use of efficient solutions of the max flow/mincut problem between source and sink nodes in directed graphs. To take advantage of this we generate a s-t-graph as follows: The set of nodes is equal to the set of pixels in the image. To segment the object, we set edges with very high weight from the source to the user seeds in the object and from the background user seeds to the sink. This ensures a flow via these edges in the maximal flow solution. Applying the MAXFLOW - software gives the minimal cut of this graph. Segmentation based on graph cuts works very well for most of the images, for some issues it becomes more laborious. This means if we want to base the segmentation on the gradient of an image we need more detailed user seeds if the boundaries of the object don't differ clearly enough from the edges in the background.

4.1.4 DOMINANT ROTATED LOCAL BINARY PATTERNS (DRLBP):-

A rotation invariance is attained by computing the descriptor with respect to a reference in a local neighbourhood. A reference is fast to compute maintaining the computational ease of the Local Binary Patterns (LBP). The proposed approach not only maintains the complete structural information extracted by LBP, but it also captures the complimentary information by utilizing the magnitude information, thereby succeeding more discriminative power. For feature selection, we learn a dictionary of the most frequently occurring patterns from the training images, and discard redundant and non-informative features. The performance is compared with the state-of-the-art rotation invariant texture descriptors and results show that the proposed method is superior to other approaches.



4.1.5 DRLBP OPERATOR:-

Different faces have not the same shapes and colors. The features like iris, eye brose, and lips are in different colors. The

RLPB is more powerful tool to describe color textures. But fail to identify edge or shape information with in the face image. The uneven illumination and weak contrast local patterns and similarly strong local pattern cannot be discriminated by RLBP because it uses only texture information. Consequently in this method edge and texture information integrated to retain local structure that RLBP misinterpret and named as discriminative robust local binary pattern (DRLBP).

4.1.6 BACK PROPAGATION ALGORITHM:-

Consider a network with a single real input x and network function F. The derivative F'(x) is calculated in two phases:

Feed-forward: the input x is fed into the network. The primitive functions at the nodes and their derivatives are estimated at each node. The derivatives are stored.

Back propagation: The constant 1 is fed into the output unit and the network run backwards. Incoming information to a node is added and the result is increased by the value stored in the left part of the unit. The result is transmitted to the left of the unit. The result collected at the input unit is the derivative of the network function with respect to x.

STEPS OF THE ALGORITHM

The back propagation algorithm is used to compute the necessary corrections, after choosing the weights of the network randomly.

The algorithm can be decomposed in the following four steps:

i) Feed-forward computation
ii) Back propagation to the output layer
iii) Back propagation to the hidden layer
iv) Weight updates

The algorithm is stopped when the value of the error function has become Sufficiently small. The following figure is the notation for three layered network.

ADVANTAGES:-

- It can segment the Brain regions from the image accurately.
- It is useful to classify the Brain Tumor images for accurate detection
- Brain Tumor will be detected in an early stages

5. RESULT:-

Figure.5.1. Input image

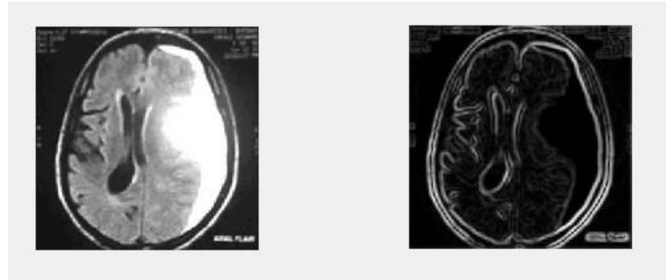


Figure.5.2. Edge feature detection

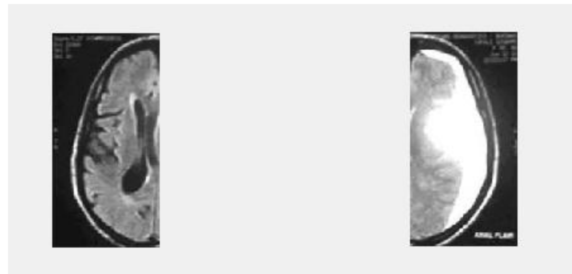


Figure.5.3. Histogram features

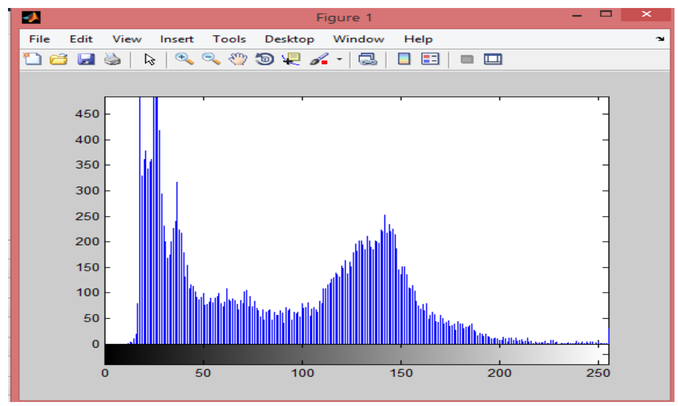


Figure.5.4. Histogram for sobel gradient

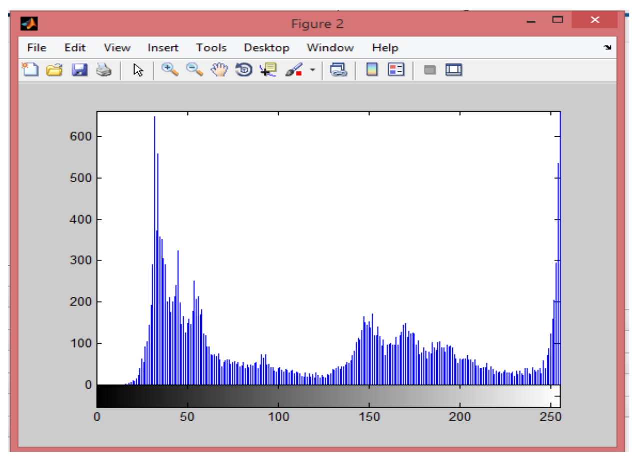


Figure.5.5.Histogram of laplacian guassion

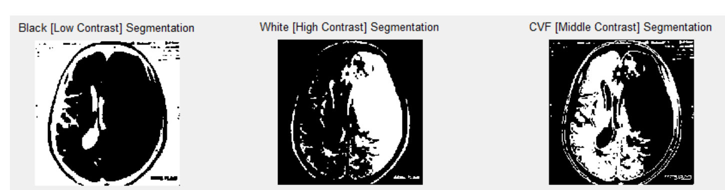


Figure.5.6. Graph cut segmentation

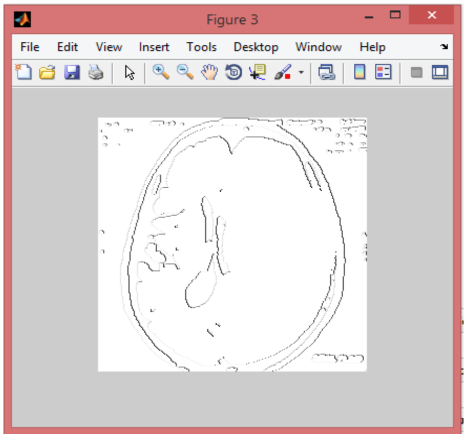


Figure.5.7. DRLBP

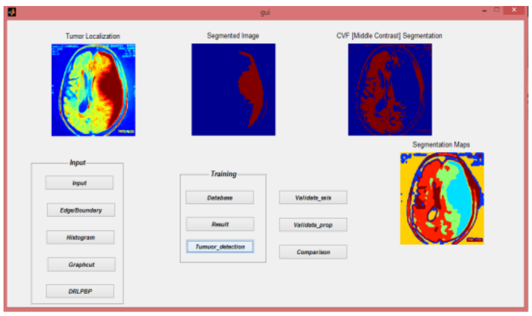


Figure.5.8. Tumor detection

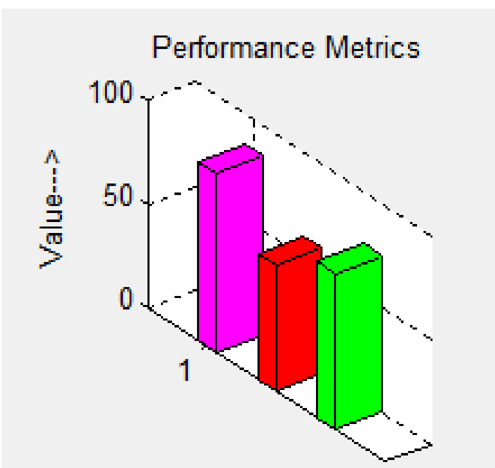


Figure.5.9. Existing performance

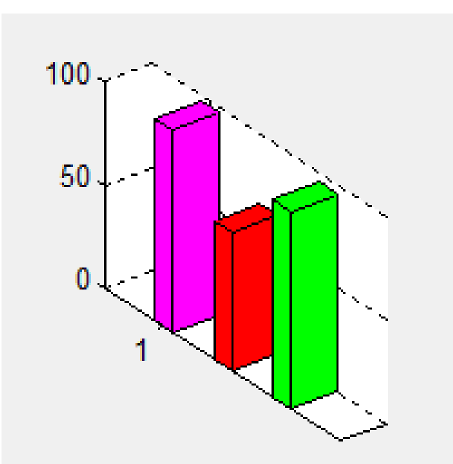


Figure.5.10. Proposed performance

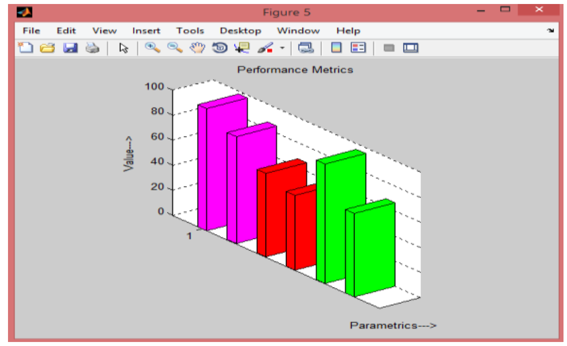


Figure.5.11. Comparison of existing and proposed

6. CONCLUSION:-

In this paper, BPN has been implemented for classification of MR brain image. The method is incorporated into a segmentation system that provides 2D interactive based on graph-cut techniques. Image pre-processing, edge and boundaries detection, histogram thresholding and segmentation with graph cuts is achieved in applying the appropriate method. The classification normal and abnormal brain is occurred using ANN-Back propagation Neural Network. More images were used to train the BPN classifier and tests were run on different set of images to examine classifier accuracy. The developed classifier was observed under different spread values as a smoothing factor. Experimental result indicates that BPN classifier is workable with an accuracy ranged from 100% to 73% according to the spread value.

7. FUTURE SCOPE:-

Automatic defects detection in images is very important in many diagnostic and therapeutic applications. This work has introduced one automatic brain tumor detection method to increase the accuracy and yield and decrease the diagnosis time. Future scope of our project using fast discrete curve let transform. And then last stage,BPN are employed to classify the Normal and abnormal. An efficient algorithm is proposed for tumor detection and deal with 3D images for depth calculation of the image.

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