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RESEARCH ARTICLE

An Approach of Segmenting Brain Tumor using Self Organising Map.

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Abstract

In all vertebrate and most of invertebrate animal's brain serves as the area of sensation. The growth of abnormal cells in the brain may leads to the tumor. This tumor can be either cancerous or non-cancerous. The earlier stage of detection and the necessary treatment of tumor may prevent from the human death. The process of segmenting the brain tumor is an important task in the area of medical field. The process of collecting or extracting the pixel values from the MRI brain image based on their intensity values is defined as the brain tumor segmentation. There are many ways available in which the segmentation is achieved. This includes contours, region growing method and the water shed method. The drawbacks of previous segmentation process are overcome by the thresholding method. In order to extract the features of the tissues first the non-specific parts are removed that are not constitutes to the region. Then the filtering process is applied to eliminate the noise from the MRI images. For the process of segmentation Self Organising Map is used along with the class labeling method. We developed an algorithm for clustering instead of using an additional network. Input feature vector is constructed with the features obtained from stationary wavelet transform coefficients. The experimental results show us the higher precision value and dependability of the proposed tumor segmentation algorithm. This method is highly helpful to estimate the location of the tumor.

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Introduction:-

An important phenomenon in the medical field research is considered to be the brain tumor segmentation process. The growth of abnormal cells in the brain may leads to the tumor. This tumor can be either cancerous or non-cancerous. Based on the growth of the abnormal cells the tumor can be classified into Malignant Tumor or else Benign Tumor. In order to prevent from the various complications earlier stage of identification and diagnosis is recommended. So that it may prevent the human from the death and various complexities of disorders. The traditional way of segmenting the brain tumor process takes the multimodal MRI images and they process it simultaneously. The analysts and clinical research utilizes the multimodal MRI images because it may provide the various complexities of information regarding the tumor area. Though they provide complex and various knowledge of the tumor area, the process of segmenting the tumor is still defined to be the tedious task. The reason for this is due to their heterogeneity of tumor area. This all problems were overcome by the proposed method in which it provides the better segmentation results.

Tumor Types:-

Brain tumor is mainly divided into two types, namely:

- Primary tumor
- Secondary tumor

Primary tumors are further classified into:-

- Benign Tumor
- Malignant Tumor

Background:-

An important process in the tumor diagnosis and the radiotherapy planning is defined as the brain tumor segmentation. Since there are finite tumor segmentations have been in presented, the process of elevating the tumor segmentation method is still demanding because they are having diverse characteristics, which includes high miscellany in the tumor appearance and they exhibit equivocal boundaries. In order to resolve this problem, an automatic tumor segmentation method for the MRI images has been defined. In this, the solution is addressed by the classification problem. In addition to this, to differentiate among the voxels Local Independent Projection-based Classification (LIPC) method has been utilized. The main technique behind the local independent projection-based classification (LIPC) method is to identify the locality. Locality is also considered in determining whether local anchor embedding is more applicable in solving linear projection weights compared with other coding methods. In LIPC, the distribution of the data among different classes (i.e., tumor, edema, and brain tissue) may widely vary. Therefore, the data distribution of each class should be considered when segmenting brain tumors. This is addressed by the softmax regression model.³

Toward brain tumor segmentation:-

In this research, machine learning and computer vision techniques are used to develop some approaches to automatically segment brain tumors and lesions in MR images. A method of dividing or segmenting image in to homogeneous regions is termed as Image segmentation. This phenomenon's needs a measure in order to define the homogeneity. The image segmentation task defined in this workutilizes an anatomic objective measure in order to assess segmentation quality, in contrast to methods that use an image-based objective measure.This mainly focuses on the goal to segment the image in order to classify the regions of the image based on the homogeneous (and known) anatomic properties, and the regions that have similar intensities or textures. The importance of this study is obvious, since brain tumors are among first five leading causes of deaths. It is said that the Tumor management is considered to be a critical phase because the exact detection and segmentation of brain tumor and lesions in medical images have a great influence on clinical diagnosis, predicting prognosis, and treatment of these ailments. In addition to this, it's an advantage of designing the brain atlases. The vast knowledge regarding the location and volume of brain lesions is essential to number of researches in this field, which includes the functionalities and defects of the brain. Typical medical imaging techniques are ultrasonography, computed tomography (CT), positron emission tomography (PET), and magnetic resonance images (MRI). Apart, from this MRI has been widely employed. One reason is being highly sensitive to local changes in tissue water since changes in tissue water reflect physiologic alterations that can be visualized by MRI.

A. MRI Imaging

One of the benefited imaging techniques among the technological innovation is termed to be MRI. The advancement in imaging has led to the accuracies in quality and improvements in speed. The main purpose of MRI in medical imaging technique is mainly to study about the detailed internal structures. MRI utilizes the mechanism of nuclear magnetic resonance (NMR) in order to image nuclei of atoms inside the body. As one among the visualization technique, Magnetic Resonance Imaging (MRI) allows images of internal anatomy to be acquired in a safe and non-invasive way. It is mainly based on the principles of Nuclear Magnetic Resonance (NMR). The main idea behind this principle of NMR is to allow the different type of visualizations to perform. The main usage of this medium is to deliver the images of the brain because of the ability of MRI to record signals, where it helps us to differentiate among the different 'soft' tissues (such as gray matter and white matter).In imaging the brain, two of the most commonly used MRI visualizations are T1-weighted and T2-weighted images. Here the weightings defined as the dominant signal (whether it be the T1 time or the T2 time) measured to produce the contrast observed in the image. The areas with thehigh fat content have a short T1 time due to the water;T1-weighted images can be thought of as visualizinglocations of fat. In contrast, since areas with high water content have a short T2 time relative to areas of high fat content, T2-weighted images can be thought of as visualizing locations of water.

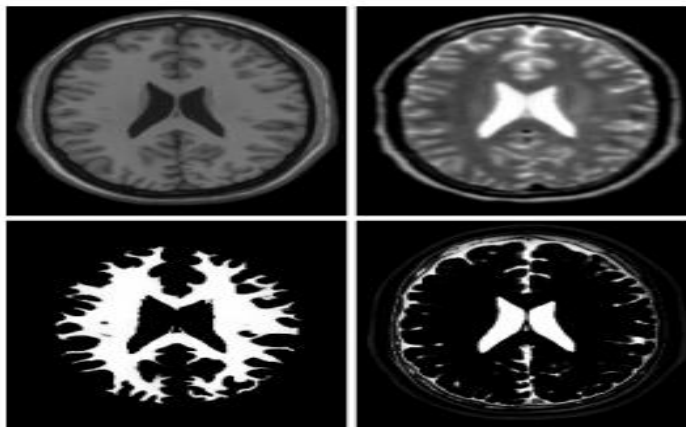


Figure 3.1. T1-weighted and T2-weighted signal properties. Top left: T1-weighted image (light regions evoke the locations of fat). Top right: T2-weighted image (light regions evokes the locations of water). Bottom left: White matter (high fat) locations. Bottom right: Cerebrospinal fluid (high water) locations.

Figure 1.1 demonstrates an example T1- and T2-weighted image, and the locations of two normal tissue types in these modalities. In visualizing brain tumors, a second T1-weighted image is often acquired after the injection of a 'contrast agent'. These 'contrast agent' compounds generally consists of the element whose composition causes a decrease in the T1 time of nearby tissue (gadolinium is one example). From the results, the brighter regions in the image tell us the image contains the leaky blood cells (where blood moves through the brain-blood barrier). Hence the 'enhancing' area can visualizes the presence of a tumor.

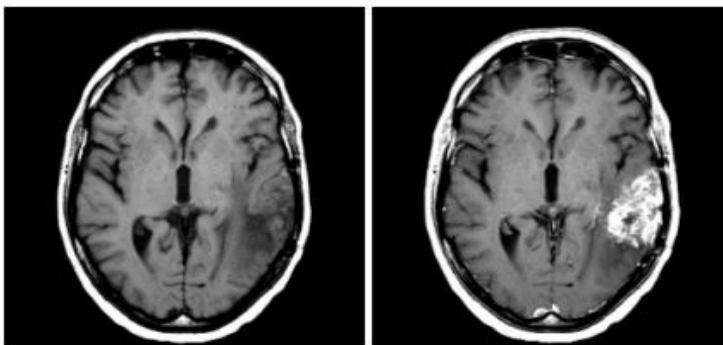


Figure 3.2 Effects of contrast enhancement on T1-weighted image data. Left: T1-weighted image prior to the injection of a contrast enhancement. Right: T1-weighted image after the injection of a contrast agent

Figure 1.2 illustrates a T1-weighted image before and after the injection of a contrast agent. Here the enhancement present in the image depicts the presence of tumor, hence there are different types of tumor available in which they appearance may vary. It is said that some of them are fully 'enhancing' (ie. appear hyper-intense after the injection of a contrast agent) or some of it may have an 'enhancing' boundary, since only some of the tumors shows partial enhancement or no enhancement. Edema (swelling) can also be observed in many types of primary tumors, and appears as hyper-intense in T2 images. Treatment to the tumor mainly includes a combination of surgical resection, radiation therapy, and chemotherapy. MRI is used in tumor diagnosis, monitoring tumor progression, planning treatments, and monitoring responses to treatment.

B. Multi-spectral MR images

It is one of varieties of MRI Imaging for lesion identification. There are four main difficulties when we are moving to multi spectral MR images. As first, the knowledge of gaining the information is not always feasible because of patient condition severity and time shortage. Next, the process of gathering multi-spectral MR images is considered to be quiet expensive. Thirdly, they can bring a lot of redundant information which is considered to the time consuming process and in some cases it gives the segmentation errors. And finally, multi-spectral MRI data is mainly affected by the criteria's of inconsistency and misalignment, which requires image registration and bias

correction prior to applying the segmentation algorithm [3]. Note that, any 5 inaccuracy in registration or bias correction stages will directly affect the precision of the lesion segmentation. Owing to these limitations, detection and segmentation of the brain lesion based on single contrast mechanism MR images is desirable.

C. Benefits of MRI

It is a non-Invasive Procedure which enables the differentiation of soft tissues with high resolution

MRI is that it produces multiple images of the same tissue with different contrast visualization via the application of different image acquisition protocols and parameters.

These multiple MR images provide additional useful anatomical information for the same tissue. Complementary information from multiple contrast mechanisms helps researchers study the brain pathology more precisely. Brain lesion detection and segmentation can be carried out either manually or automatically. In manual segmentation, the lesion areas are manually located on all contiguous slices in which the lesion is considered to exist. It provides various data on the tumor region as it reveals different parts in tumor area.

Materials and methods:-

A. Dataset Description:

Brain tumor MRI images are taken testing data for tumor segmentation with division like tumor core and edema part. These data is taken for evaluation with fivefold cross validation.

B. Overview of the Proposed Method

In order to extract the features of the tissues first the non-specific parts are removed that are not constitutes to the region. Then the filtering process is applied to eliminate the noise from the MRI images. For the process of classifying voxels, a classifier called Self Organising Map (SOM) is used. Self-Organizing Map (SOM) includes the unsupervised learning algorithm and class labeling method with high diversity data like tumor appearance and its contour deformation. On comparing with other techniques, Instead of using Multimodal MRI images for clustering of voxels Self Organising Map has been used. A feature vector has been constructed in which the features for constructing vector have been gained from the Wavelet Transform coefficients. This has been constructed mainly for identifying tissue types which includes White Matter (WM), Grey Matter (GM), Cerebrospinal Fluid (CSF) and sometimes pathological tissues. The accuracies and the performance are provided in terms of training performance and the classification accuracies.

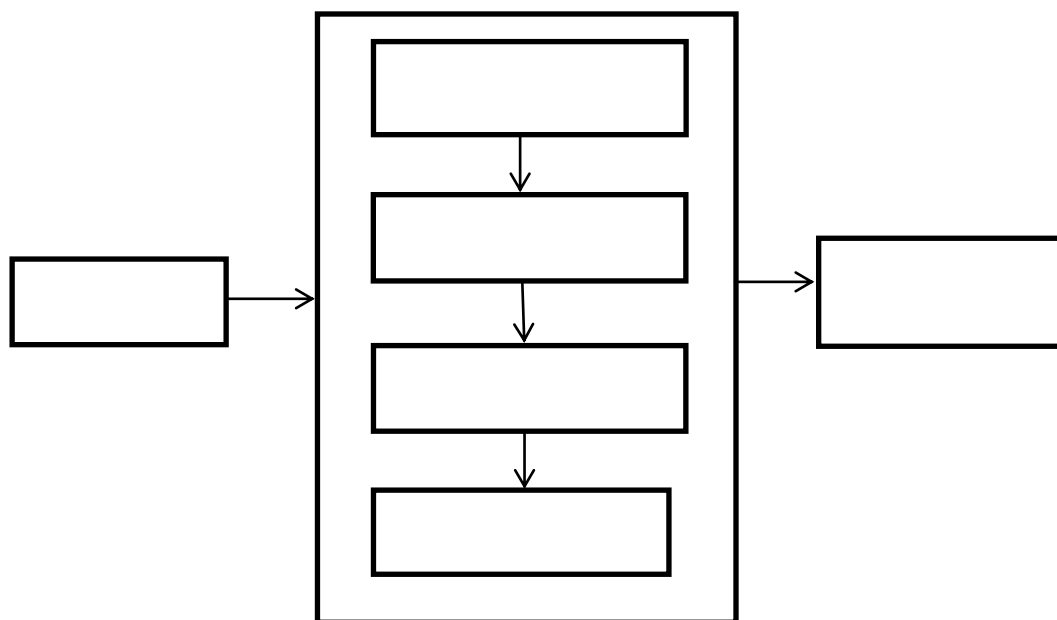


Figure 4.1 Architecture diagram

Results and discussions:-

A. Removal of Noise

Noise is an important criterion in all images i.e., here we have considered the MRI image of the brain which makes the brain image to blur. This is because of presence of noise in the MRI image. It is important that to eliminate the noise in the brain because the noise in the image increases the probability of complexity when we are moving to the segmentation process. There are many ways are advised to handle the noises in the MRI image. In earlier days noise can be removed through the simple process acquired by morphological operations. Here the noise removal process is handled by the filtering process. There are many filters currently available to filter the noises in the affected pixels. In this work we are going for anisotropic filtering technique to eliminate the noise and the blur contained in the image. Hence this noise removal approach is regarded as the important approach in image processing techniques.

B. Segmentation of White and Grey Matters

Segmentation in the image processing is defined as the segmenting the image into homogeneous regions. Therefore it needs a measure to elaborate the homogeneity of regions. The main principle of using image segmentation in this work is that it takes an anatomic objective which assesses the segmentation quality of the brain MRI. Depending upon the anatomic properties of the brain image, the image is divided into similar homogeneous regions. There are various algorithms used in the segmentation process. In this work Thresholding algorithms are used to segment the grey matters and the white matters of the brain. It is a technique which converts the grey-scale image into the monochrome image in which the two levels of 0 and 1 are defined to the pixels. Therefore all the pixels are assigned either 0 or 1 based on the thresholding condition. If the pixel value is higher than the threshold value, it holds the value of 0 else it holds the value of 1. It is said that the brain MRI image has contradictory lighting conditions. For these contradictory types of lighting conditions, it uses the algorithm of adaptive thresholding where that algorithm evaluates the value of the threshold for the regions. From these processes, we obtained the best results for the brain image with the different lighting conditions.

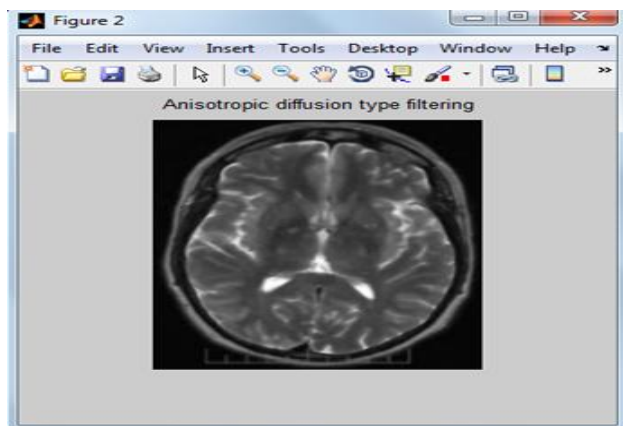


Figure 5.1. Pre-processing of the MRI image

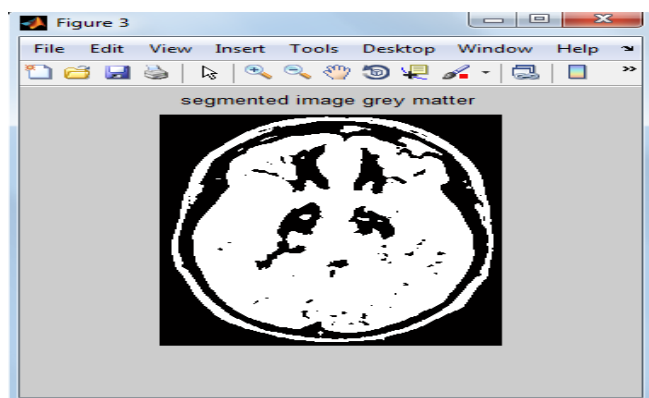


Figure 5.2. Image Segmentation based on grey matters

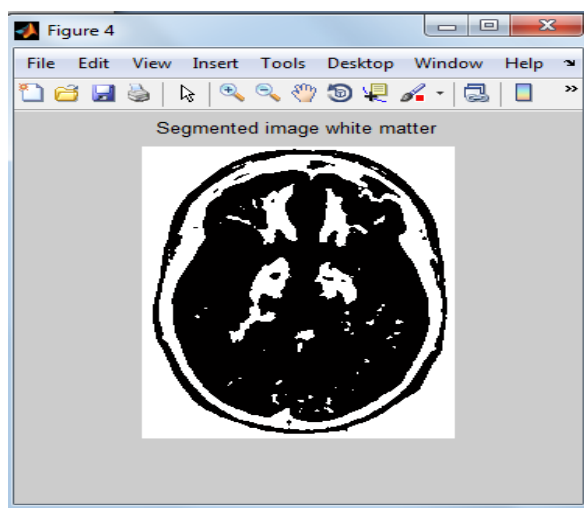


Figure 5.3. Image Segmentation of White Matters

C. Bounding box method

The fast bounding box technique is mainly based on the phenomenon of symmetrical areas defined in the brain, which means the lobes of the brain. It is said that the two lobes of the brain are almost similar. In simple words, the right and the left lobe have almost the similar pixel values. This statement is true until and unless any abnormalities that happen to be occur either in right lobe or left lobe of the brain. As a first step, the skull is identified in order to define the bounding box. A straight line is drawn on the brain image in order to discriminate between the right lobe and the left lobe of the brain. One lobe act as the testing image while the other lobe act as the training image. Both regions were scanned horizontally and vertically in order to find the abnormalities in the lobes. From the abnormality regions a graph can be constructed. Based on the abnormality values a plot function has been obtained which we mark it as 'E'. From the graph the points of minimum and maximum points are obtained. Among all the pairs, the pair (a, b) is found for which difference $(E(a) - E(b))$ is maximum. This provides the boundary of the bounding box. This bounding box method utilizes the probability mass function. The bounding box of a brain image is defined by using the effective approaches of binary test and a decision tree. From the fig 5.4 we provided this technique reduces the miss detections when the scanning grid spacing is increased.

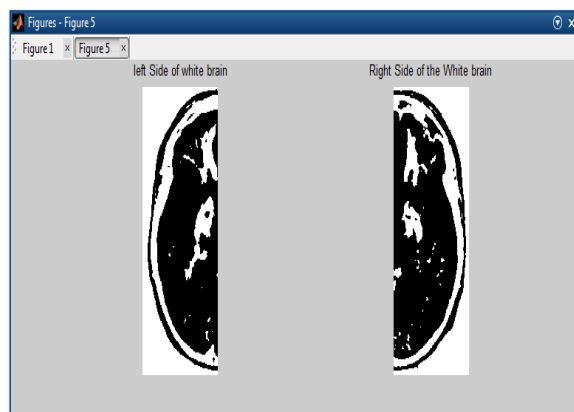


Figure 5.4. Classification of the Brain in to left lesions and right lesions

D. Classification Technique

The distribution of data among different classes of tumor regions, edema may vary accordingly. While segmenting the brain tumor, this distribution of data among different classes has been taken in to account. To extract the features

of the image a patch based method is employed. The intensities of pixels 'v' have been constructed and it has been allowed to rearrange in order to obtain the feature vector.

In this work, a classification optimization technique is employed by the method of Softmax regression. This optimization technique does not need the explicit regularization. This is because the proposed method provides the natural smoothness to the results of segmentation without using the explicit regularization. This patch feature is found to be insufficient to differentiate the task of brain tumor Segmentation. This is because of the various complex characteristics which includes the accuracy and efficiency.

E. Skull Segmentation

It is an essential step to eliminate the tissues of non-cerebral part such as connective tissues, skull, muscle, fat and skin, which are not the elements of segmentation part. For this skull segmentation an algorithm is used which combines the functionalities of erosion, dilation and the thresholding functions. At first filtering process is applied in order to smoothen the image. Here we are using the Gaussian filter for the softening process. After that intensity histogram is evaluated in order to find the global value of threshold, in which the pixels with the higher threshold value assigns with the value of 0. By using the Otsu's method we have obtained the threshold value, in which further converted to monochrome image. To remove the brain from the tissues we are using the morphological operations of dilation and erosion along with the octagon structuring element.

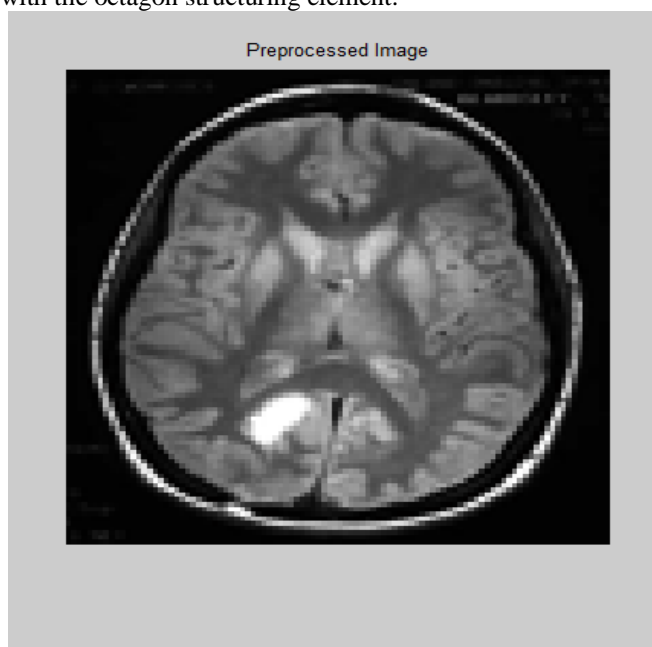


Figure 5.5 preprocessed image

F. Feature Extraction

To extract the features from the MRI images we have utilized the Discrete Wavelet Transform in which in turn given as the input to the neural networks. The coefficients of Wavelet Transform will not change its value even though there is a shift in the signal. In the traditional Wavelet Transform for the decomposition down sampling along with the convolution with the filter are applied to the signal. It is an iterative algorithm and it utilizes the over complete decomposition that provides a tight frame. Decomposition filter is up sampled and convolved with the signal to obtain the coefficients of the subsequent level, unlike the traditional wavelet transform that down samples the signal for decomposition of each level.

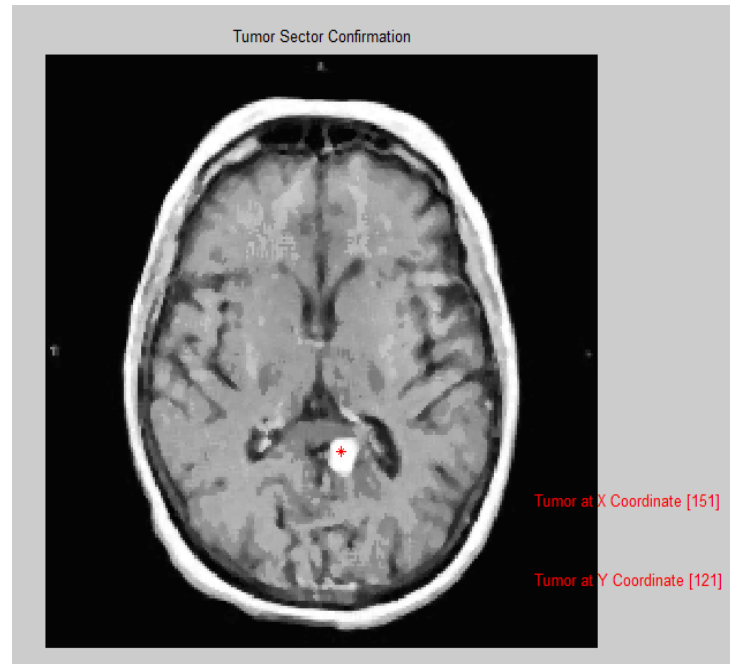


Figure 5.6 Tumor sector Confirmation

G. Tumor Segmentation process

We trained Self Organising Map to map the input image to the corresponding tissue regions according to their characteristic features by considering their natural grouping in the input space. This mapping reduces the dimension and groups similar regions together that help to understand high dimensional image data. Self Organising Map has two layers. There are input nodes in the first layer and output nodes in the second layer. Output nodes are in a form of two-dimensional grid. There are adjustable weights between each and every output. A multidimensional observation, i.e., a feature vector, is associated with each unit. The map attempts to represent features with optimal accuracy using a restricted set of clusters. At the end of training process, the clusters become ordered on the grid so that similar clusters are close to and dissimilar clusters are far from each other. SOM clusters the data by having output units compete for the current input feature vector during training. The unit closest to the input becomes the winning unit or best matching unit (BMU) and weight vectors of this unit and its neighbors are updated.

We used hexagonal lattice with random initialization and unsupervised sequential training algorithm with Gaussian neighborhood function for training. We clustered the images into five regions corresponding to White Matter, Grey Matter, Cerebra Spinal Fluid, tumor, and edema. These clusters are then labeled using the manually selected image regions.

H. Linear vector quantization – Class Labeling method

The supervised Linear Vector Quantization algorithm that utilizes labeled data for the process of fine-tuning the weight vectors of the trained and labeled Self Organising Map. The main function of this part is to provide the best placement of the neurons. The purpose of Linear Vector Quantization is to define class regions in the input space by placing similarly labeled codebook vectors into classes even if there is an overlap of class distributions of the input samples at the class borders. It is recommended to start learning with the Linear Vector Quantization1 algorithm, which converges very fast, and continue with the Linear Vector Quantization3 algorithm using a low initial value of learning to improve recognition accuracy.

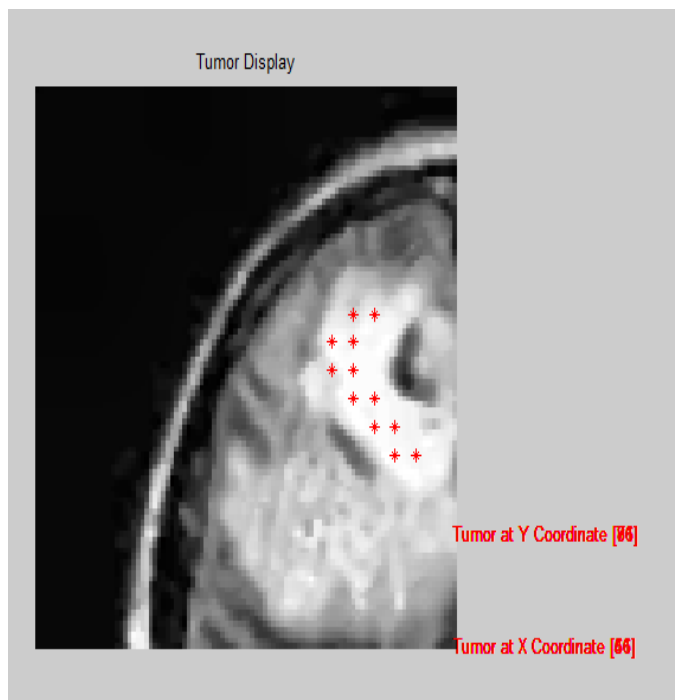


Figure 5.7 Tumor Display

Conclusion:-

We designed and implemented a new classifier for brain tumor diagnosis using self-organizing map (SOM) that is trained with unsupervised learning algorithm and fine-tuned with learning vector quantization (LVQ) with high diversity data like tumor appearance and its contour deformation. An Algorithm has been presented for clustering the SOM of voxel instead of using an additional process for Multimodal MRI images. Input feature vector is constructed with the features obtained from discrete wavelet transform (DWT) coefficients for identifying tissue types which includes White Matter (WM), Grey Matter (GM), Cerebrospinal Fluid (CSF) and sometimes pathological tissues. The performance of this classifier was evaluated in terms of training performance and classification accuracies. The simulated results shown that classifier and segmentation algorithm provides better accuracy than previous method.

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