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Detection of Tumor using wavelets and Neural Network

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Abstract

Brain tumor is a great problem prevailing in the human society. A Brain tumor is the growth of cell in the brain that multiples in an abnormal, uncontrollable way. Brain tumor can either be Cancerous (malignant) or non-cancerous (bening).Cerebral Edema gives sturdily to symptoms related with brain tumors .Although the introduction of ''corticosteroids''has greatly basic treatment of patients with recently diagnosed tumors, these drugs are related with marked side effects during the long term treatment that is often necessary in the recurrences .Another technique used for the detection of the brain tumor is the MRI which stands for Magnetic resonance Imaging .This technique also faces some of the drawbacks .MRI scanners can be affected by the movement, making them unsutaible for the investigation of problems. Another drawback is the arrangement of being put in an covered space and the loud noise that are made by the magnets can make some people feel Claustrophobic while they are undergoing this method. Therefore a better understanding of mechanism related to the evolution and clearance of tumor along with edema is done with the aid of wavelets and Neural Networks in this paper.

I. INTRODUCTION

Brian is an organ which serve as the hub of the nervous system in all the vertebrates and most of the invertebrates .Brain tumor detection is an application of the MRI .Brain tumor detection is an area characterised by the need for the extensive experimental work to establish the viability of proposed solutions to a given problem

.Edema associated with the brain tumor plays an important role in finding symptoms caused by cerebral tumours. Edema not only cause additional mass effect, but also results in the increased intracranial pressure, it also leads to neurological disturbances by disturbing tissue

Fig. 1: Homeostatis And Reducing Blood Flow.

Segmentation of the anatomical regions of the brain is the fundamental problem in medical image analysis. The goal of this work is to design an automated tool for quantification of brain tumor by utilizing the MDI data sets. A brain tumor segmentation method has to be developed and validation segementation on 2D and 3D MRI Data has to be performed. This method does not require any initialisation while the others involve an initialization within the tumor .After the manual segementation, the investigation has to be carried out in order to find out the potential use of MRI data for improving the brain tumor shape approximation and 2D and 3D visualisation for surgical planning and assessing tumor. Surgical planning now makes use of both 2D and 3D models which incorporate data from many imaging modalities .

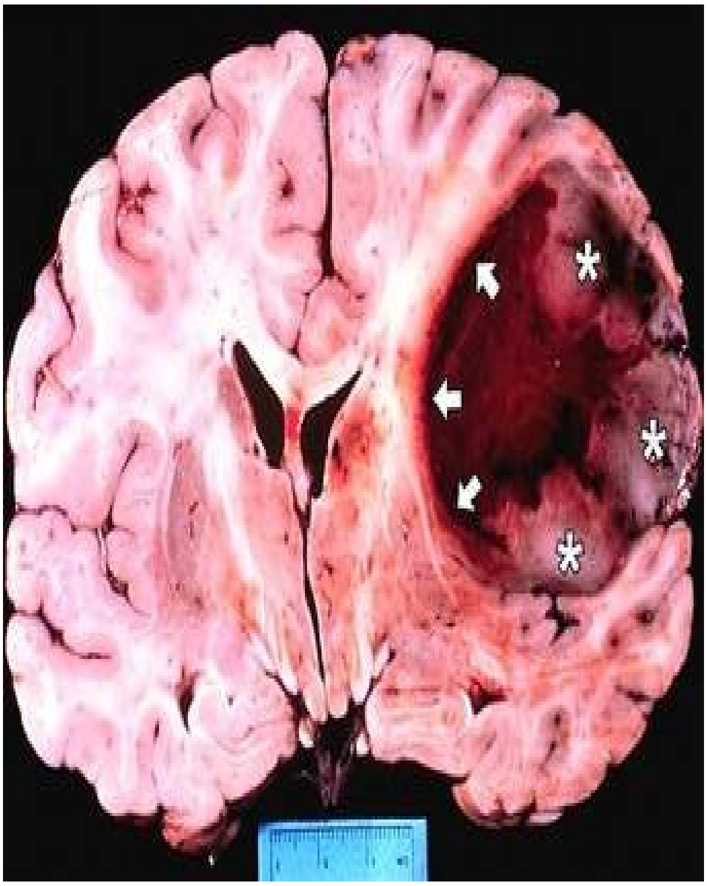


Fig. 2:

In process of Segmentation, an image is subdivided into its constituent regions or objects. The level of details to which the subdivision is done depends upon the problem being solved. Segmentation should stop when the region of interest is attained. Segmentation procedure takes can be achieved by following three methods:-

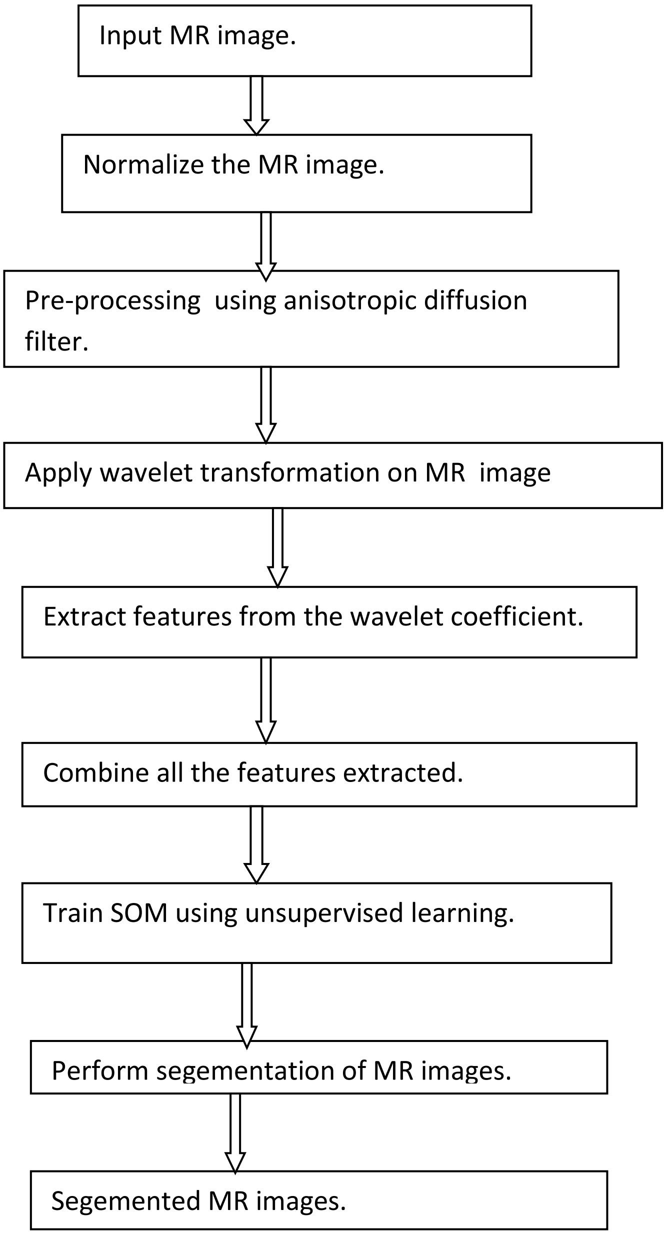
1. Snakes (Gradient Vector Flow)

2. Level Set Segmentation.

3. Watershed Segmentation.

Out of these methods, watershed segmentation can be used as a prevailing tool which implicitly extracts the tumor surface. Watershed segmentation based algorithm has been used for recognition of tumor in 2D and 3D. For tumor detection in 2dimensional, MATLAB software is used. But for the detection of tumor in 3D , the software is MATLAB and 3D Slicer .3D slicer is utilized to produce the 3D image using axial, saggital and coronal images .The 3D image is then fed to MATLAB to detect the tumor in 3D.

II. MATERIALS AND METHODS.



1:-Brain MR Images:- We will work on the dataset of the patients suffering from glial tumor. A new segementation algorithm will be presented that will segment brain MR images into Tumor, Edema,

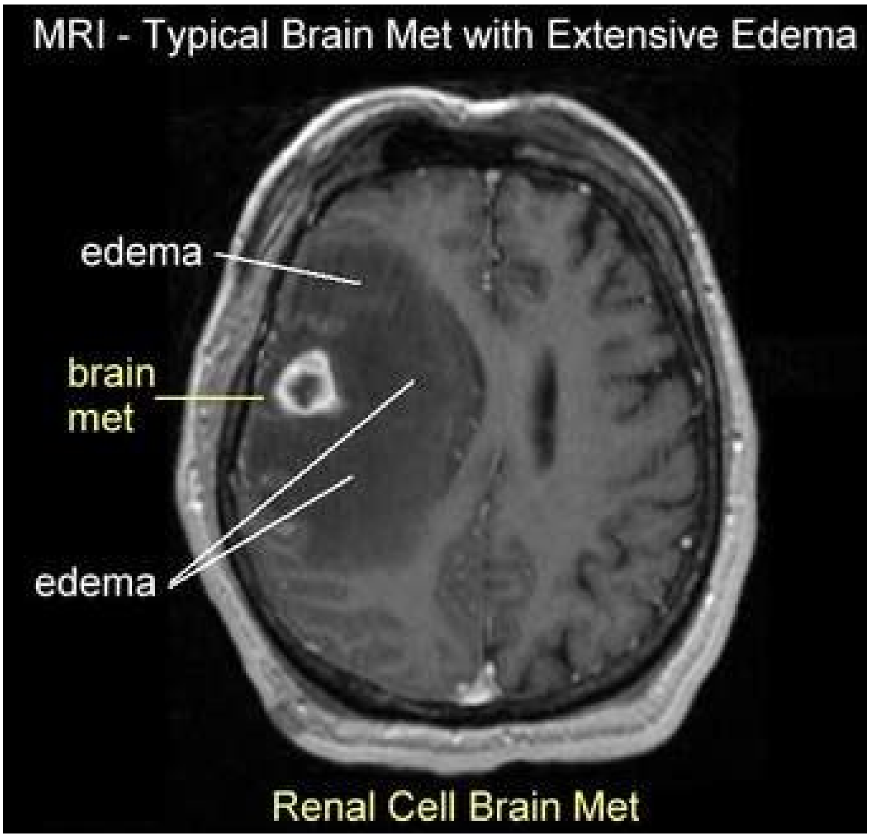


Fig. 3:

White matter, Gray matter and Cerebrospinal fluid. The detection of healthy tissues is done with the healthy tissues of brain. This is done to know about the changes caused by the infected tissue on the healthy tissue of the brain .The detection of healthy tissues is performed simultaneously along with the diseased tissue. This detection helps to know about the rate at which the tumor spreads.

2:-Pre-processing:- The intensity range of the images are normalised by dividing all the intensity values to the maximum intensity value. This filter is known as diffusion process. Inner edges of the regions are smoothed and edges are preserved by eliminating local image structure and using edge strength and the noise degradation statistics .Images of all patients are registered to the same coordinate system.T1 weighted MR image is chosen as the reference image, and we registered the other channels on it within subjects using a robust affine registration.

3:-Skull stripping:-Skull stripping also known as whole brain segmentation is an important step to remove non-cerebral tissue such as skin, skull, fats, muscles, and connective tissues. Here, an algorithm has been developed that combines thresholding and morphological operations using T1 weighted MR images.

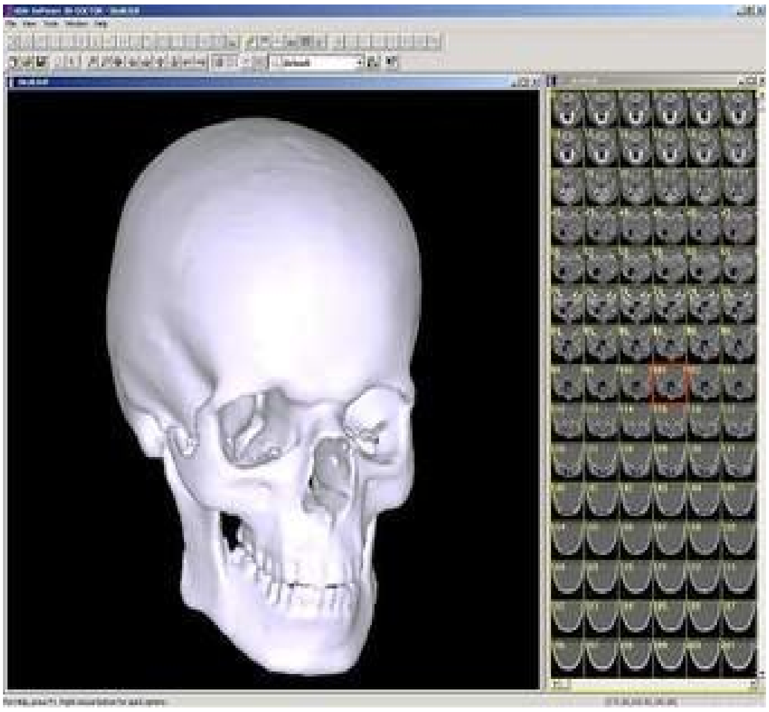


Fig.4:

4:-Feature selection:-In this case, stationary wavelet transform (SWT) is utilized in order to extract features from MR images that will be used as an input to the neural network.SWT is invariant to translations .SWT coefficient will not change even if the signal is shifted .In traditional wavelet transform, down-sampling and convolution with a filter is applied to the signal for decomposition.

5:-Self Organising Maps:-Use of SOM as the segmentation tool was made in this study. The trained SOM is used 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 group similar regions together that help to understand high dimensional image data.SOM has two layers .There are input nodes in the first layer and output nodes in the in the second layer .Output nodes are in the form of two-dimensional grid .There are adjustable weights between each and every output.

6:-Evaluation Method:-Quality of imaging, difficulty of brain structure and the necessary of accurate segmentation makes it difficult to calculate the performance of the segmentation algorithms of brain. We use Dice similarity index, which is a region –based coefficient that measures spatial overlap of ground truth (manual segmentation) and segmentation results ,sensitivity ,and specificity to evaluate the results. Let TP be the true positive, FN be the false negative and TN be the true negative

Dice coefficient is calculated as:-

(2*TP)\ ((2*TP)+FP+FN).

Sensitivity= TP\TP+FN.

Specificity=TN\FN+TN.

Working of Artificial Neural Network.

Neural networks in general are the simple clustering of the primitive artificial neuron. This clustering occurs only with the help of layers (synaptic connections) which are then connected to each other .All the neural networks possess the same topology. Even though there are helpful networks that carries only single layer or more elements, most of the application requires networks that contain atleast three types of layers: - input, hidden, output.

The layers of the neurons receive data from the sensory input and data from the outside is directly supplied to the outside world .These internal layers contain many of the neurons in various interconnected structures. The input and the output of each of these hidden layers go to the other neurons to produce the desired output.

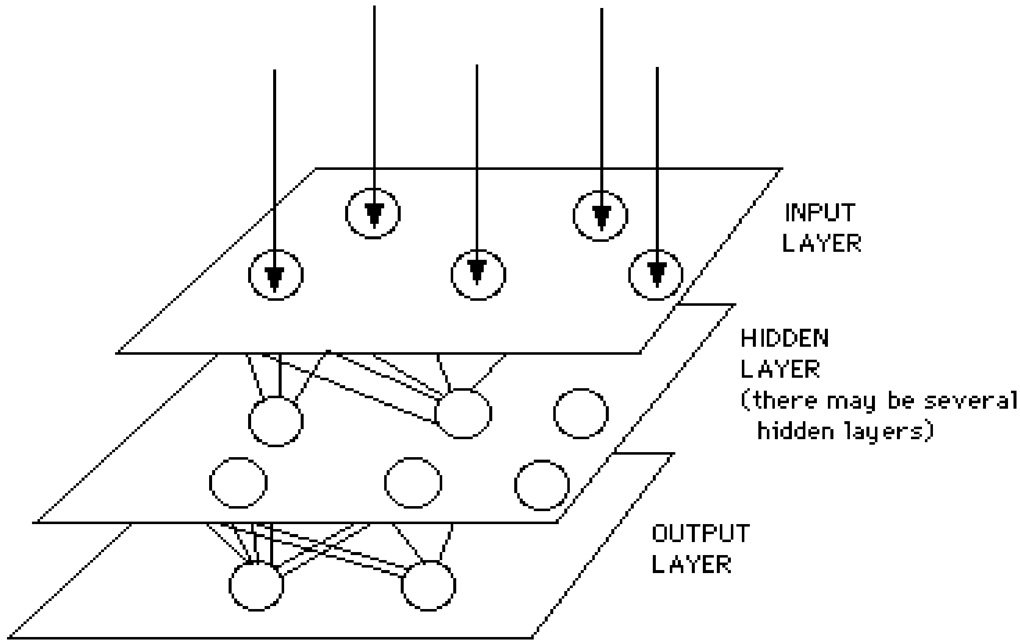


Fig. 5: A simple neural network diagram.

III. RESULTS AND CONCLUSIONS.

The limitation of the existing techniques is that algorithms produce a region for each local minimum. This will normally lead to under segmentation .So, there remains a scope of improvement in the segmentation method .So, there exists a need for pre-processing these numerous regions using a novel technique so as to improve the existing results .One way to face this problem is to remove the skull region of the image so as to enhance the affected region .This will help identify the tumour region along with edema as the processed image will contain enhanced tumour region.

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