Detection of Brain Tumor From MRI Images By Classification

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Abstract*- In this paper we propose brain tumor detection, Image processing is used in the medical tools for detection of tumor, MRI images are used as they can identify the tumorous region when using Fully Connected Neural Networks. We take our dataset from Kaggle.com which contains de-noised MRI images. Now we convert our image into a n*n matrix in order to process it as an input to the Fully Connected Neural Network. We are using supervised learning where the dataset that we use has an output associated with it. A Neural Network is used where each node in the network represents a neuron that works similar to the neurons in the brain. We use a Fully Connected Neural Network in which every input node is connected to every output node. A fully connected layer learns features from all the combinations of the features of the previous layer, where a convolutional layer relies on local spatial coherence with a small receptive field. We use Fminunc in order to minimize the output that we get.*

Keywords- Imread function, Fully Connected Neural Network, Forward propagation, Backward propagation, Fminunc function.

I. INTRODUCTION

It is important to find out tumor from MRI images but it is somewhat time-consuming and a difficult task sometimes performed manually by medical experts. Large amount of time was spent by radiologists and doctors for identification of tumor and segmenting it from other brain tissues. However, exactly labeling brain tumors is a time-consuming task, and considerable variations are observed between doctors [2]. Subsequently, over the last decade, from various research results it is being observed that it is a very time consuming method but it will get faster if we use image processing techniques [3]. Primary brain tumors do not spread to other body parts and can be malignant or benign and secondary brain tumors are always malignant. Malignant tumor is more dangerous and life threatening than benign tumor.

The benign tumor is easier to identify than the malignant tumor. Also the first stage tumor may be malignant or benign but after the first stage it will change to a dangerous malignant tumor which is life threatening [12].

Different brain tumor detection algorithms have been developed in the past few years. Normally, the automatic segmentation problem is very challenging and it is yet to be fully and satisfactorily solved. The main aim of this system is to make an automated system for detecting and identifying the tumor from normal MRI. It takes into account the statistical features of the brain structure to represent it by significant feature points. Most of the early methods obtained for tumor detection and segmentation may be largely divided into three groupings: region-based, edge-based and a fusion of region and edge-based methods. Well known and broadly used classification techniques are Fully Connected Neural Networks where very input node is connected to every output node. Also, the time spent to detect the tumor is getting condensed due to the detailed demonstration of the medical image by withdrawal of feature points.

II. IDENTIFY, RESEARCH AND COLLECT DATA

R.Muthukrishnan, et.al [4] proposed brain tumor detection in which Segmentation separates an image into its component regions or objects. Image segmentation needs to segment the object from the background to read the image properly and classify the content of the image carefully. In this framework, edge detection was an important tool for image segmentation. In this paper their effort was made to study the performance of most commonly used edge detection techniques for image segmentation and also the comparison of these techniques was carried out with an experiment.

In [3], Othman and Ariffanan proposed a new system for brain tumor automatic diagnosis (shown in Figure 1). The Proba- bilistic Neural Network (PNN) provides a solution to pattern classification problems. The paper uses a dataset from University Teknologi Malaysia (UTK) and the dataset goes through a preprocessing phase as follows. The MRI images are first converted to matrices by using MATLAB. Then, the classification algorithm PNN is used to classify the MRI images. The results show that the proposed system achieves a diagnosis accuracy of more than 73%. The accuracy level can even be higher than that depending on what the authors call “a smoothing factor” [3].

A. Laxami et.al, [9] proposed the work on information (region of interest) in the medical image and thereby vastly improved upon the computational speed for tumor segmentation results. Significant feature points based approach for primary brain tumor segmentation was proposed. Axial slices of T1- weighted Brain MR Images with contrast enhancement have been analyzed. In order to extract significant feature points in the image, a feature point extraction algorithm based on a fusion of edge maps using morphological and wavelet methods was applied. Evaluation of feature points thus obtained had been done for geometric transformations and image scaling. A region growing algorithm was then employed to isolate the tumor region. Preliminary results show that our approach has achieved good segmentation results. Also this approach had reduced a large amount of calculation. Future work will involve an investigation of the method in automatic 3D tumor segmentation, segmentation of ROI’s in other medical images, as well as the importance of implemented technique in medical image retrieval applications.

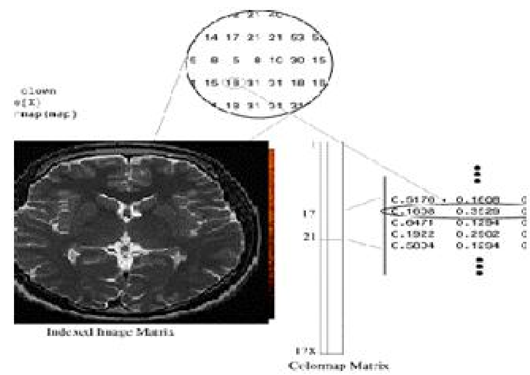
III. STUDIES AND FINDINGS

The main purpose of this paper is to identify the region of tumor and to do the detailed diagnosis of that tumor which will be used in treating the cancer patient. The detailed diagnosis about the proposed system is given below.

At first, we take the de-noised dataset from kaggle.com in which every image has an output associated with it. Now, we convert each image into a matrix where each value of the matrix represents a pixel value of the image. Since we are using supervised learning, we need to train the program from the dataset. To do this, we use a Fully Connected Neural Network where the input layer consists of matrix we formed from the dataset images and the output is a 2*1 matrix in which one vale corresponds to the presence of the tumor and the other corresponds to the absence of a tumor. This technique consists of a number of intermediate layers which maps the input layer to the output layer. Once we complete the forward propagation, we use backward propagation to compute the error values (Cost Function). We use Gradient descent to compute the values of the parameters of the cost function. Using the computed parameter values, we can map the new datasets into two classes: Tumor and Non-tumor.

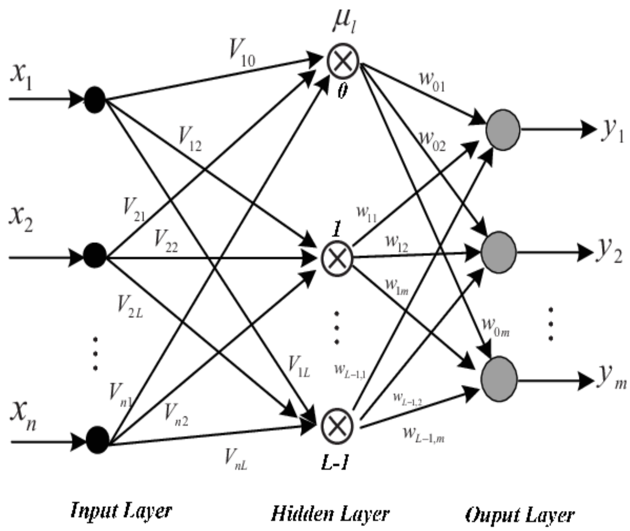
A. Image to Matrix conversion

After preprocessing the image, we take the gray scale image and convert it into a matrix, since it is more simpler to process a matrix using Fully Connected Neural Network than to input the actual image itself. At first, we take the image and convert it into an image with a fixed pixel resolution. Now map each pixel value into the matrix. For example: If our image is of 100*100 resolution then we will have a 100*100 matrix which consists of 10,000 values. To do this, we use the Imread function of the OCtave programming language which maps the pixel values into a matrix. Since the input to the Fully connected Neural Network needs to be a vector, we convert the 100*100 matrix into a 10,000*1 vector.



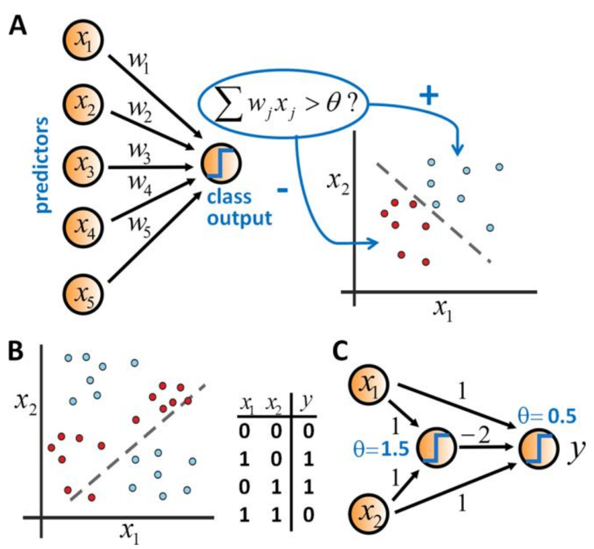
B. Fully connected Neural Network

A Fully Connected Neural Network is a neural network in which every input layer is connected to every output layer. This is more commonly known as Densely Connected Neural Network. Here our input layer is a 10,000*1 vector which had been obtained from the brain MRI image and the output layer is a 2*1 matrix in which one value corresponds to tumor and the other corresponds to a non-tumor. This neural network consists of a number of intermediate layers which maps the input layer to the output layer. In this particular project, we have used 1200 intermediate layers.



C. Forward propagation

As the name suggests, in forward propagation we move from the input layer to the output layer, i.e. we move from left to right. Firstly it maps the 10,000*1 matrix to the 1200 hidden layers and then it maps the 1200 hidden layers to the 2*1 output layer. The forward propagation is used to train the dataset and map the given dataset images into two classes: Tumor and Non-tumor.



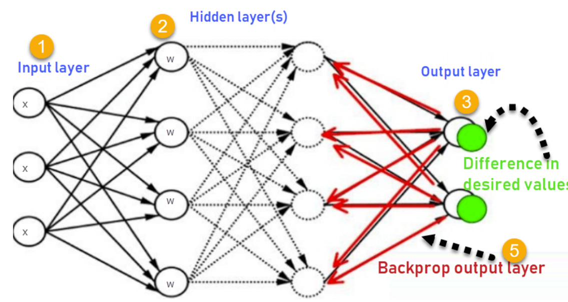
The octave code to implement forward propagation is as follows:

```
theta1=reshape(theta(1:(hnodes*(inodes+1))),hnodes,inodes+1);
theta2=reshape(theta((hnodes*(inodes+1))+1:end),onodes,hnodes+1);

z2=X*theta1';
a2=sigmoid(z2);
a2=[ones(size(a2,1),1) a2];
z3=a2*theta2';
hx=sigmoid(z3);
```

D. Backward Propagation

After completing forward propagation, we implement backward propagation to compute the error values i.e. the cost function which will help us map the testset data into the two classes: Tumor and Non-tumor. The cost function is nothing but the difference between the computed output and the actual output.



The octave code to implement Backward propagation is as follows:

```
grad1=0;
grad2=0;

del3=hx-y;
del2=(del3*theta2).*a2.*(1-a2);
del2=del2(:,2:end); %removing bias unit
grad1=(1/m)*(del2'*X);
grad2=(1/m)*(del3'*a2);
```

The cost function formula:

$$MSE = \frac{1}{2m}\sum_{i=1}^{m}(\hat{y}^{(i)} - y^{(i)})^2$$

i - index of sample, ŷ - predicted value, y - expected value, m - number of samples in dataset.

E. Fminunc Function

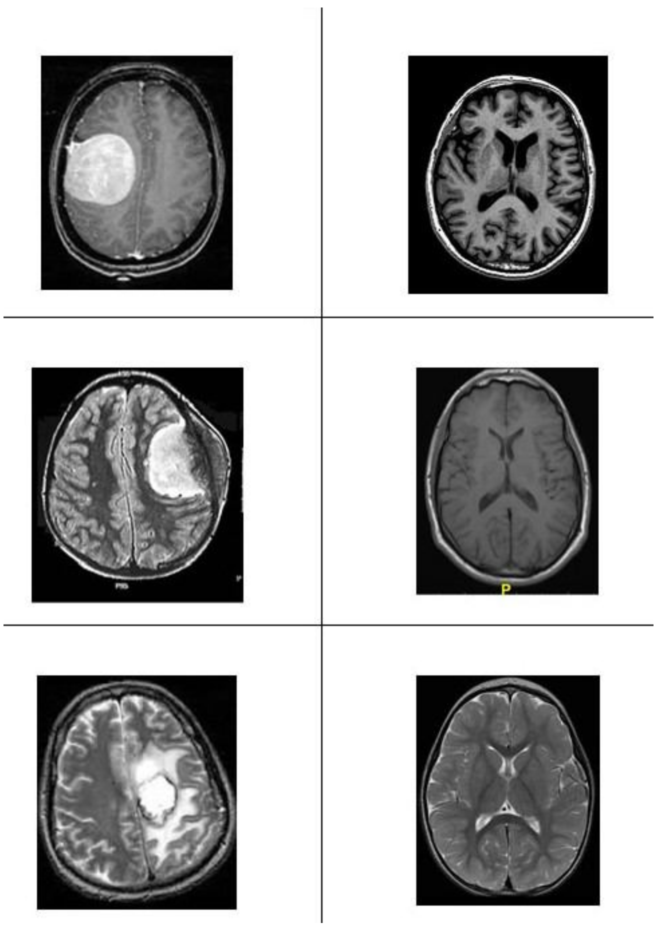
Fminunc is used to minimize the values of the parameters of the cost function. By doing this we can minimize the difference between computed output and the actual output associated with each of the dataset images

The syntax for Fminunc is as follows:

Fminunc(@(t)(lrCostFunction(t, X, (y==c),lambda))).

IV. EXPERIMENTAL RESULTS

The test of projected technique to discover and segment brain tumor is performed using MR images of diverse long- suffering. Each test image has brain tumor of diverse size, shape and intensity. Manual examination is used to check the correctness of automated segmented tumor area. The experimental result for different MR images containing tumor of different shapes, sizes and intensities. As the size of our training set increases, we would be able to obtain more accurate results. It is also essential to choose the number of intermediate nodes precisely as this would greatly affect the outcome of our project. The method used in this project is very efficient as we would not be needing much processing power and the use of Octave programming language makes the project run with ease. Here are few example of images with tumor and without tumor .



V. CONCLUSION

Brain tumor detection in this paper is done by first converting the image into a pixel matrix and then feeding this as an input to the Fully Connected Neural Network. The Neural Network maps the input layer to the output layer which detects the presence of a brain tumor. In our project we have achieved an accuracy of 96.3% through a simple yet efficient method.

Image processing has become a very important task in today's world. Today applications of image processing can be implemented in number of areas like medical, remote sensing, electronics and so on. If we focus on medical applications, image segmentation is widely used for diagnosis purpose.

In this paper, we have proposed a system that can be used for segmentation of brain MR Images for detection and identification of brain tumor. Future scope for detection and segmentation of brain tumor is that, if we obtain the three dimensional image of brain with tumor then we can also find out its tumor size and also can evaluate its tumor type and also its stage of tumor.

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