A Multilayer Feedforward Network trained with BPN for diagnosis of Brain Tumor

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Abstract— **Studies states that in India, about 40000-50000 persons are diagnosed with Brain tumor and 20% of them are children. This paper deals with the detection of brain tumor in brain MRI. Brain tumor is an excessive growth of anomalous cells in our brain. The tumors can destroy all fit brain cells. It can also indirectly damage the stronger cells by bringing more parts of the brain together causing inflammation, swelling and pressure inside the skull. Deep learning has found its way through medical field in the form of neural network. Neural networks, when instigated with Magnetic Resonance Imaging (MRI) helps find tumors and has its way to calculate the shape and size of the tumor. Neural networks trained with back propagation learning algorithm helps to diagnose brain disease.**

Keywords — *Neural Networks, Deep neural networks, Feed forward neural networks, Back propagation Learning algorithm, Brain Tumor, Multilayer Perceptron.*

I. INTRODUCTION

This paper proposes the concept of automatic brain tumor detection. Most of the research shows that imprecise detection has led to the death of number of people with brain tumor. The detection of brain tumor at an initial state is a key problem for providing advanced treatment. Once a brain tumor is medically inferred, a radiological analysis is needed to figure out its location, size and impact on the surrounding areas. Based on this information, the most suitable treatment decision is made. It is clear that the chances of survival of the patient with the tumor increased significantly, if the tumor is accurately detected at an early stage. Consequently, the study of brain tumors using imaging modalities has gained prominence in the field of radiology. CT scans and MRI scans are 2 distinct medical imaging system which helps us to produce detailed images of internal parts of the body. Even though both of the scan methods are used for same purpose they create images in distinct ways. CT scans are more common and less expensive which uses X-Rays whereas MRI scan uses strong magnetic fields and radio waves which is better than CT scans. Unlike CT scans MRI doesn't use potentially harmful ionizing radiation. MRI can be used to measure the size of the tumor and is a preferred way to detect a brain tumor. The field of medical image analysis includes denoising, restoration and segmentation.

In this proposed work, the input image is preprocessed to remove the noise and make the image fit for further process. the Region growing method. Later on the extracted features such as Mean, area, correlation and Co-variance are given to the Neural network for training. At the end, the image classification can be done with the help of trained neural network.

II. METHODOLOGY

Region Growing Technique for detection of Tumor:

This section discusses about how region-growing technique is used for detecting brain tumor effectively from MRI. The proposed work consists of 4 stages such as pre-processing, segmentation, feature extraction and classification of tumor. In the pre-processing stage, the RGB image is converted into Grayscale after the Weiner filter is done. The second phase is segmentation where the image is partitioned into regions. The purpose of segmentation is to find the boundaries from regions based on intervals in grayscale or color properties. Next to segmentation, feature extraction will take place. It is used to eliminate inappropriate and inordinate features. In addition, it is used to enhance the classification precise. At last, Neural network classifier is used to detect the brain tumor.

A. *Pre-processing:*

In the proposed technique, MRI brain images cannot be directly provided as input. Making the image more suitable for processing, the input image is subjected to a set of 2 pre-processing steps.

• In order to reduce the noise and also to enhance the image quality the input image is traversed through Weiner Filter.
• Convert RGB image into Grayscale image so that the image is ready for region-growing process.

1. *Weiner Filter:*
   Image noise is a random difference of brightness or color information. It is a dissemination caused by external sources during transmission, acquisition and storage / retrieval process. Image denoising is a crucial image processing task. The fundamental technique used for image denoising is filtering. Weiner filter is a linear filter in which one of the biggest advantage is speed. The main aim of Weiner filter is to reduce the amount of noise present in a signal by comparing it to

the value of the desired noiseless signal.

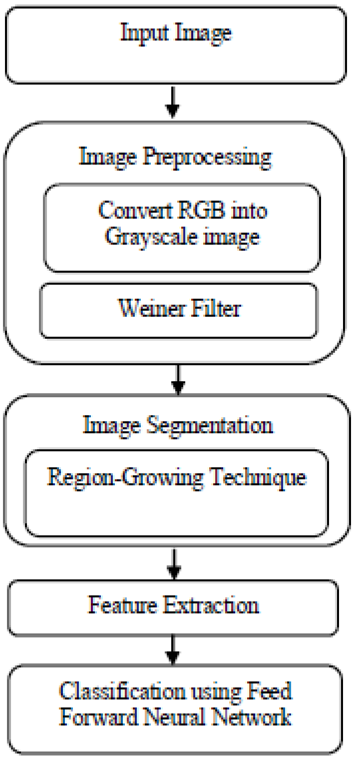

Fig. 1. Block diagram of the Proposed work

2. *RGB into Grayscale image conversion:*
A Grayscale image is the one in which the levels of red, green and blue are equal in RGB space. Grayscale image has only 256 colors of Gray tones like RGB(R,R,R), RGB(G,G,G), RGB(B,B,B) where each of them has a number between 0 and 255. Weighted / Luminosity method is often used for the conversion of Grayscale image. Applying the following equation, the image has been properly converted to Grayscale.

$$Grayscale\ image = (0.3 * R) + (0.59 * G) + (0.11 * B) \quad (1)$$

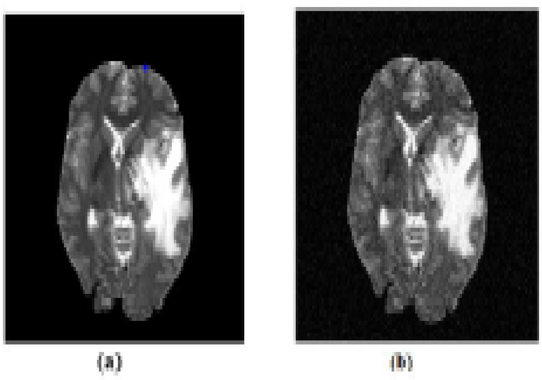

Fig. 2. Fig. a) Original image Fig. b) After Pre-Processing

B. Region-Growing Technique:

Region growing is a simple region-based image segmentation method. Segmentation is the process of dividing an image into partitions which is called segments. It is often effective for applications like image compression or object recognition which restraint to process the whole image. Region-growing methods often give very good segmentations that are well adapted to the observed edges.

Region-growing is a technique in which pixels or subregions are grouped together to form a largest regions. The basic approach is to initiate with a set of "seed" points and check whether the neighbouring pixels that are similar in intensity or color should be appended.

This process is a bottom-up method which begins by selecting a random seed pixel and comparing it to neighbouring pixels. From the seed pixel the region is grown by adding in the neighbouring pixels, which increases the size of the region. When one region's growth stops, we select another seed pixel that does not belong to any region and restart. This whole process will continue until all the pixels belong to a particular region.

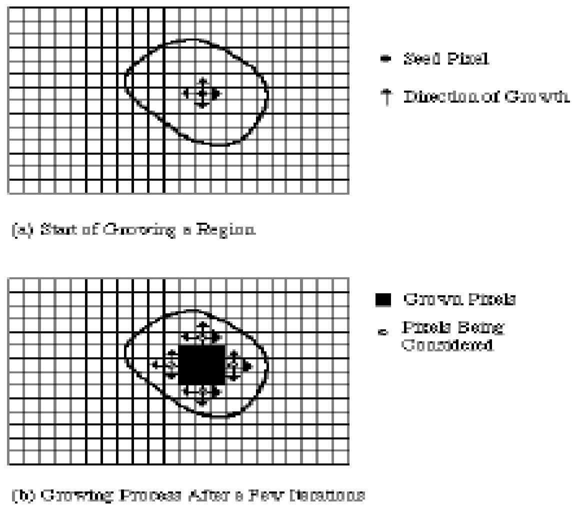

Fig. 3. Region-Growing Method

Selecting the seed pixel often can be based on the nature of the problem. When a priori knowledge is not available, the process is to calculate the same characteristics for each pixel, which can eventually be used to assign pixels to regions during the growing process. If the result of the calculations shows cluster of values, the pixels placed near the centroid of these clusters can be used as seed pixel.

The selection of similarity criteria / predicates can be based on any features of the regions in the image such as average intensity, Variance, Color, Shape, Texture and size. If the images are monochrome, region analysis must be carried out with a set of descriptors based on intensity levels and spatial properties. Region growth must be stopped when pixels don't satisfy the inclusion rule in that region. A total segmentation of an image R is a finite set of regions R1, R2, …., Rn such that

$$R = \bigcup_{i=1}^{S} R_i \text{ and } Ri \,\Omega\, Rj = \Phi, \text{ if } i \neq j \qquad (2)$$

Connectivity in digital images are based on the number of neighbours connected to pixel.

- 8-connectivity: all 8 neighbours
- 4-connectivity: only 4 neighbours

A basic region-growing algorithm stated as follows:

Let us consider an input array as f(x,y) and seed array be s(x,y) which contains 1 at the locations of seed points and 0 elsewhere. A predicate Q has to be applied at each location-(x,y) f and s are considered as the same in size.

- All the connected component has to found in s(x,y) and makeeach connected component to one pixel. Label all such pixels found as 1, All other pixels in s are labelled as 0.
- Form an image fQ such that, fQ(x,y) = 1 at a pair of coordinates (x,y), if the input image satisfies the given predicate Q at (x,y), else fQ(x.y) = 0.
- Let g be a new image formed where all the 1-valued points that are 8 – connected to that seed point in fQ are appending to each seed point in S.
- Label each connected component in g with different region label (like 1,2,3…)

Thus the segmented image using region-growing is obtained.

C. Feature Extraction:

Feature extraction is the process that represents interesting parts of an image to make decision making such as pattern detection, classification/recognition easier. Finding and extracting reliable and biased features is always an important step to accomplish the task of image recognition and computer vision.

In this proposed work, the features of the segmented regions are extracted after finding the regions for every grid. In this paper Histogram of Oriented Gradients commonly known as HOG is discussed among the various feature descriptors which can be used to extract features from image. The HOG counts the occurrences of gradient orientation in localized parts of an image.

The HOG feature descriptor mainly focused on the structure of the shape of an object. HOG works as follows:

- Resize the image.
- Gradient vector for every pixel and its magnitude and direction has been calculated.
- Divide the image into many 8 x 8 pixel cells. Then the magnitude values of these 64 cells are binned in each cell and cumulatively added into 9 buckets of unsigned direction.
- Then 4 histograms of 4 cells are inter-connected into one dimensional vector of 36 values in each block region and normalized to get a unit weight.
- Finally, concatenate all the block vectors to get the final result of HOG feature vector and it can be fed into Feed Forward Neural Network (FFNN) for learning object recognition tasks.

D. Final classification:

In this Proposed work, Feed Forward Neural Network classifier is used in-order to detect the presence of tumor in the MRI input Image. In machine learning, Classification is a Supervised Learning approach in which a conclusion will be drawn from the observed values learned from the input data. The features extracted from the image is fed into the neural network which has to be trained with the features after the Pre-processing and Region-Growing has been completed. The classifier compares the training data. A classification model will try to either predict categorical class labels or classifies data based on the training set. Among the various classification model, Multi-layer Perceptron also known as Feed Forward Neural Networks to be used. Training is the process of learning the decision function from a set of labelled samples (also called Training data).

A FFNN is a directed acyclic graph which consists of 3 layers such as input layer, hidden layer and output layer. There can be any number of hidden layers in the network. Each node in the neural network is called Neuron which is considered as a basic processing unit.

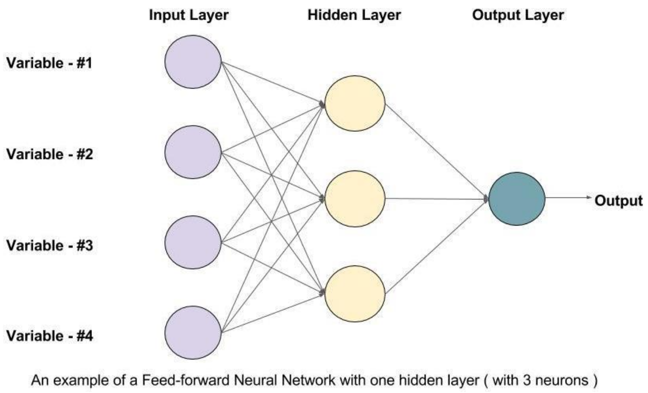

Fig. 4. Example of FFNN with 1-hidden layer

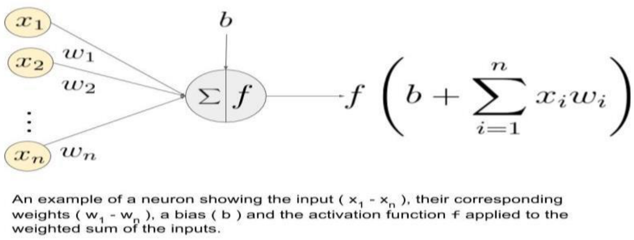

Fig. 5. Symbolic representation of Neuron

A neuron works as follows:

- Compute the weighted sum of inputs.
- Then Normalize the sum by applying an activation function which can be linear or non-linear.

The input layer which is connected to the hidden layer provides the features as input data to the network. The hidden layer is connected to the output layer which gives out the predictions calculated by the activation function. The weights in each input neuron are the parameters which has to be learned by the network in the training phase. The activation function is used as a decision making at the output of a neuron. The training samples are passed through the network and the output resulted from the network is compared with the actual output. It is the error used to change the neuron's weight so that the error decreases gradually. This method of decreasing the error is called Stochastic Gradient Descent(SGD). To achieve this, Back Propagation Network (BPN) algorithm is used. The training algorithm of BPN involves 4 stages:

- Initialization of weights
- Feed forward
- Back propagation of error
- Updation of the Weights

During the initialization stage, some random values are assigned. In the second stage of feed forward, each input unit receives an input signal and transmit it to each of the hidden units. The activation function will be calculated and its signal sent to each output unit. Now the activation function will be computed by the output unit to produce the correct response for the given input pattern. In the third stage of the training algorithm is Back propagation of errors. In this step, the output unit determines the associated error for that pattern by comparing the activation value and the target value. Then the error factor of output and hidden unit will be calculated for each corresponding unit and distribute the error back to all the previous layer. At the final step, the weight and biases are updated using the error factor and the activation.

III. CONCLUSION

This paper proposes an automatic segmentation of Brain tumor using Feed Forward Neural Networks trained with Back Propagation learning algorithm. The proposed work uses MRI images for the tumor detection. The input image first completes the pre-processing step to remove the noise and make it fit for further process such as Region-Growing, Feature extraction and for further classification. This work can probably be implemented using a large data set and enhanced by including the feature such as the analysis of the tumor volume which is an important predictive factor in the treatment of Malignant tumors.

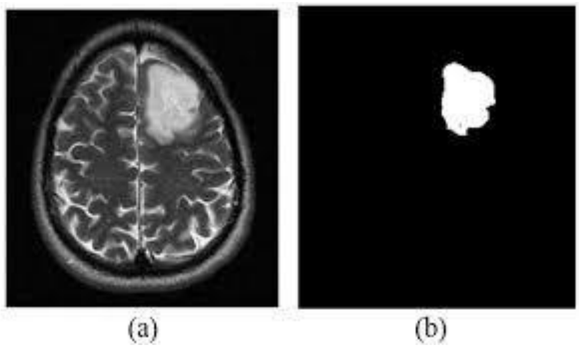

Fig. 6. Detection of tumor in Brain MRI

References

[1] Bhandarkar, S.M. and p, Nammalwar, "Segmentation of Multispectral MR images Using a Hierarchical Self-Organizing Map", Proceedings of the 14th IEEE Symposium on Computer-Based medical system CBMS,Vol: 26,No: 27,pp: 294-299,2001.

[2] Rafael C. Gonzalez, Richard E. Woods, "Digital Image Processing", Third Edition, published by Pearson Education, Inc.,

[3] S N Sivanandam, s Sumathi, S N Deepa, "Introduction to Neural Networks using MATLAB 6.0", Tata McGraw-Hill Publishing Company Limited, New Delhi

[4] E, Wan, "Neural network classification: A Bayesian interpretation," IEEE Trans, Neural Networks, vol. I,no. 4,pp. 303-305,1990.

[5] Arvind R. Yadav, R.S. Anand, M.L. Dewal, "Comparison of feature extraction techniques for classification of hardwood species" Int. J. Computational Systems Engineering, Vol. 4, Nos. 2/3, 2018.

[6] Komal Sharma, Akwinder Kaur, Shruti Gujral, "Brain Tumor Detection based on Machine Learning algorithms", International Journal of Computer Applications (0975 – 8887) Volume 103 – No.1, October 2014.

[7] Sanjib Das, Jonti Saikia, Soumita Das, Nural Goni, "A Comparative Study of Different Noise Filtering Techniques in Digital Images", International Journal of Engineering Research and General Science Volume 3, Issue 5, September-October, 2015. ISSN 2091-2730.

[8] Rajesh C. Patil, Dr. A.S. Bhalchandra, "Brain Tumor Extraction from MRI Images Using MATLAB", International Journal of Electronics, Communication & Soft Computing Science and Engineering. ISSN: 2277-9477, Volume 2, Issue 1.