AN INNOVATIVE METHOD FOR MR BRAIN IMAGE CLASSIFICATION CORROBORATED ON ANFIS SYSTEM

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Abstract— In medical image analysis, classification plays an imperative role and the accessible corporeal classification plunge to congregate the requisites. Automatic image classification is emergent thriving research area and contribution diagnostician for malady to ascertain the echelon of malignant cells of brain tumor using artifical intellect Since manual classification is time devastating and bestow ambiguous classification.In the proposed methodology, features are extort from these raw images which are then fed to these classifiers as an sophisticated framework for multi-object classification of deep brain structures in MR images by consummation of Neural network and fuzzy logic as Artrifical Neural Network Fuzzy Inference System(ANFIS) functioning through explicit knowledge representation of an Fuzzy with the learning capacity of artificial feed forward neural network. This method first employs four types of tumor images including metastases, meningioma, glioma and astrocytoma Tentative outcome exemplify capable results in terms of classification accuracy and improve execution. A proportional analysis is demonstrated with the representatives of ANN and fuzzy systems to exhibit the enhanced temperament of ANFIS systems.
***Keywords*—:** ANFIS, image classification, brain tumor, MRI, Fuzzy logic

I. INTRODUCTION

In our human body, the nervous system acts as a single unit for advancement and development and it comprises of central nervous system (CNS) and the peripheral nervous system (PNS). The CNS encompasses spinal cord and brain called sensory neurons and transmit information to the PNS and the PNS comprises nerve processes that connect the CNS with receptor cells and glands called motor neurons. There are more than 1 trillion neurons in our human nervous system depends on sizes and shapes collectively called as axon which consists of specialized complex of proteins that conduct electrical impulses for communicating information. The supporting cells or Neuroglia is the classification of neuron cells which includes Schwann cells, oligodendrocytes, astrocytes, microglia, ependymals [1]. A brain tumor or intracranial solid neoplasm is uncharacteristic cells that instigate from the brain itself or spread to this location from other parts of body like liver, breast, cervical, testicular etc., It is the second major cause of cancer related death based on CBTRUS more than half millions of people affected with the disease. The main causes of brain tumor are still unknown but some major risks including ionizing radiation through mobile phone, head injuries during an accident or hereditary reasons. Some of the common symptoms are headache, nausea, memory lapses and personality changes. There are more than 120 brain tumor types are identified and it divided into four grades ranges on least, mild and most aggressive based on the World Health Organization (WHO) classification [2]. The Medical image helps to determine and diagnosis of brain tumor type and range but brain is a very complex organ in the human body. The vertebrate human brain is by far the most complex organ in the human body and it consists of a band of 2 billion nerve fibers and it consists of 6 lobes of the brain which involves in conscious thoughts by the frontal lobe,sensory information by parietal lobe,sight sensing by occipital lobe, the senses of smell and sound by temporal lobe, emotion and memory by limbic lobe, pain nerves by insular cortex [3].The diagnosis of brain tumor involves various techniques like analyze small amount of excised brain tissue specimen with the Haematoxylin and eosin (H&E) stain under microscopic range in a histology lab or standard ionized radiation of computed Tomography (CT) scan and the non-ionizing safe state Magnetic Resonance Imaging (MRI) for detail information about position and size based on magnetization along with Positron emission tomography (PET), the latest combination model of functional (fMRI) for advance measurement of brain flow activities and spatial resolution analysis of voxel for three-dimensional texture analysis [2].In medical field, the treatment planning, diagnosis abnormality and the analogous systematic procedure involves classification of MR images for compute tissue region, volume and analysis the anatomical structure. But, the existing physical classification of MR images especially brain tumor images chomp the time and prone to error which leads to momentous error [4]. Sharma and Mukharjee. [19] proposed Artrifical Neural Network Fuzzy Inference System (ANFIS) for brain tumor detection which incorporates the feature set and fuzzy rules to classify an abnormal image to enable for the corresponding tumor type which results approximate performance improvements for classifying tumor and non-tumor types of data. Hemanath et al. [20] added the application of Neuro-Fuzzy Model for MR Brain tumor image classification achieves better accuracy with large training sets and thus developed hybrid adaptive Neuro-fuzzy logic technique and yield accurate convergence rate. Ibrahim et al. [21] used a comparable scheme of seed based region growing (SBRG), adaptive Network-Based Fuzzy Inference System (ANFIS) and Fuzzy c-Means (FCM) in brain abnormalities segmentation based on abnormalities by the number of pixels and then compared with segmentation results of three techniques which concedes ANFIS corroborating best performance metrics. M.Bhattacharya and A.Das [8] proposed an approach with the aim of achieving significant feature subset of input training as well as a test pattern and machine learning simultaneously through Genetic Algorithm and Fuzzy Clustering techniques for classification of patterns of tumor lesions in human brain identified by CT and MR images. Various ANFIS classification techniques have been used to improve the performance of classification approaches and I˙nan et al. [14] replaced to electroencephalogram (EEG) signals for classification and espoused significant results. A major drawback classifying the EEG signals shows higher declassification rates and uncertainty of data into consideration. To remedy this drawback, Hosseini et al. [15] and Mohd Basri et al. [16] developed an assimilated approach to brain tumor MR Image Detection and Classification using ANFIS of the explicit knowledge representation of neural networks and learning algorithm with training data for a set of parameter of membership function.However, to our knowledge, so far those Neuro-fuzzy algorithm have not been able to overcome the difficulties caused by the error in the training data and cause considerable miscalculation rate.Thus, we propose the ANFIS with feed forward neural network to determine neoplams boundaries in the brain region.The proposed algorithm has been employed in clinical brain MR images and MATLAB simulated images regarding the segmentation of brain tumor images are reviewed in the following section.

II. LITERATURE SURVEY

A plentiful of researches has been proposed by researchers for the MRI brain image segmentation techniques. A brief review of some of the recent researches is presented here.
H. B. Kekre etal have a presented a vector quantization segmentation method to detect a cancerous mass from MRI images [5]. In order to increase radiologists' diagnostic performance, computer-aided diagnosis (CAD) scheme has been developed to improve the detection of primary signatures of this disease: masses and micro calcifications. Morphological segmentation extracts other regions with tumor region. Thresholding was used to convert the input image into a binary image. Global threshold methods suffer from the drawback as threshold value was given manually. The algorithms were tested on twenty one MRI images.

Jue Wu and Albert C.S. Chang [6] developed a framework for multi-object segmentation of deep brain structures (caudate nucleus, putamen and thalamus) in medical brain images. Deep brain segmentation is difficult and challenging because the structures of interest are of relatively small size and have significant shape variant. The structure boundaries may be blurry or even missing, and the surrounding background is full of irrelevant edges. To tackle these problems, a template-based framework was presented to fuse the information on edge features, region statistics and inter-structure constraints for detecting and locating all target brain structures. The multiple object template was organized in the form of a hierarchical Markov dependence tree (MDT), and multiple objects are efficiently matched to a target image by a top-to-down optimization strategy. The final segmentation was obtained through refinement by a B-spline based non-rigid registration between the exemplar image and the target image. This method was validated on a publicly available T1- weighted magnetic resonance image database with expert-segmented brain structures.

Caruso et al. [7] have presented a method for automatic segmentation of heterogeneous image data that takes a step toward bridging the gap between bottom-up affinity-based segmentation methods and top-down generative model based approaches. Bayesian formulation was included for incorporating soft model assignments into the calculation of affinities, which are conventionally model free. The resulting model-aware affinities were integrated into the multilevel segmentation by using a weighted aggregation algorithm, and applied the technique to the task of detecting and segmenting brain tumor and edema in multi channel MR volumes. The computationally efficient method insiders of magnitude faster than current state-of the-art techniques giving comparable or improved results. The quantitative results indicated the benefit when model aware affinities incorporated into the segmentation process in the difficult case of brain tumor.

Liang Liaoetal. [12] have proposed a fast spatially constrained kernel clustering algorithm for segmenting MRI brain images and correcting intensity inhomogeneities known as a bias field in MRI data. The algorithm uses kernel technique implicitly map image data to a higher dimensional kernel space in order to improve the separable of data and provide more potential for effectively segmenting MRI data. Based on the technique, a speedup scheme for kernel clustering and an approach for correcting spurious intensity variation of MRI images have been implemented. The fast kernel clustering and bias field correcting benefit each other in an iterative manner and have dramatically reduced the time complexity of kernel clustering. The experiments on simulated brain phantoms and real clinical MRI data have shown that the algorithm generally outperforms the corresponding traditional algorithms when segmenting MRI data corrupted by high noise and gray bias field.

III. PROPOSED METHOD

Assay of texture statistics for the extraction of assorted forms of gray level pixels is the objective function of ANFIS by extracting the region of interest (ROI) from the MRI brain images to enumerate the idiosyncrasy that extant in the brain tissue.

A. MRI Image Slices

The MRI image slices the input brain image into axial, coronal and sagittal for better enhancements are given in figure 1.2 (Courtesy to Aarthi Scans, Tirunelveli, India). Also, we assessed the above-mentioned classification algorithms in T1-weighted simulated brain MR images designated from the brain web simulated brain database (BrainWeb) [17].

Fig 1.1 : MRI Scan image in sagittal View

B. Tissue Pattern Analysis

The Data analysis of brain tissues to discriminate of normal and abnormal necrosis tissue pattern through Region of Interest (ROI) extracted from the MRI brain images that distinguish brain tissue into four major parts named a) Ventricle, b) Membrane c) Dark Abnormality d) Light Abnormality [11].

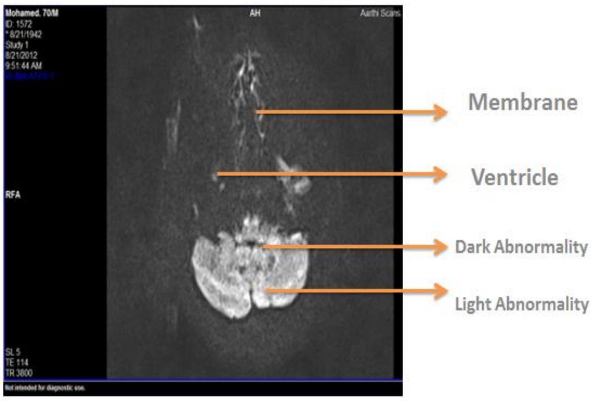

Fig 1.2 : MRI Scan in sagittal View

The characteristics are determined by the value of MinGL,MaxGL and MeanGL and the result summary shown in Table I

TABLE I

PARAMETER FOR BRAIN TISSUE ANALYSIS

Parameter	**Description**
MinGL	Minimum Gray level pixel value occurred
MaxGL	Maximum Gray level pixel value occurred
MeanGL	Mean of Gray level pixel value occurred

C. PROTOTYPE DESIGN

The MRI brain image which consists of both normal tissue and abnormalities tissue and the corresponding process to perform for ANFIS is given in the following stages

1) Preprocessing Stage:

The Image acquisition to select the brain slices of both normal and abnormalities

2) Detecting Stage:

The brain cortical region is detected using a region growing technique

3) Removing Stage:

The cortical areas are completely removed and the remaining areas are labeled as membrane area.

4) Implementation Stage:

Finally, Implementing the labeled region of the MRI respectively.

IV. FEED FORWARD NEURAL NETWORK

For detecting the existence of the tumor in the input MRI image, we accomplish the final categorization step. Here we use the Feed Forward neural network classifier to organize the image into tumors or not. A three layer Neural network was created with 500 nodes in the first (input) layer, 1 to 50 nodes in the hidden layer, and 1 node as the output layer. We mottled the number of nodes in the hidden layer in a replication so that concludes the most favorable number of hidden nodes. This was to evade over appropriate or under relevant the data. Because of hardware precincts, ten nodes in the hidden layer were selected to run the final simulation. Figure 2.1 demonstrates the strategy of the Feed Forward Neural networks manipulated in this exploration. The 500 data points extricated from every specialty were afterwards depleted as inputs of the neural networks. The output node ensued in either a 0 or 1, intended for control or patient data harmoniously. Meanwhile the nodes in the input layer might take on values from an enormous range; a relocation function was consumed to renovate data first, prior to dispatching it to the hidden layer, and then was renovated with another transfer function afore conveying it to the output layer. In this paradigm, a tan sigmoid transfer function was exploited among the input and hidden layer, and a log sigmoid function was manipulated flanked by the hidden layer and the output layer.

The weights in the hidden node necessitated to be set consuming "training" data. Consequently, subjects were alienated into training and testing data sets. Out of the 69 subjects, 2 random patients and 2 random controls were plump for as "test data", however the rest of the data set was cast off for training. Training data were utilized to feed into the neural networks as inputs and then comprehending the output, the weights of the hidden nodes were premeditated using back propagation algorithm. 120 trials were maneuvered on the same Neural Network, selecting 65 subjects erratically every time for retraining and 4 persisting subjects for testing to find the meticulousness of Neural network prediction.

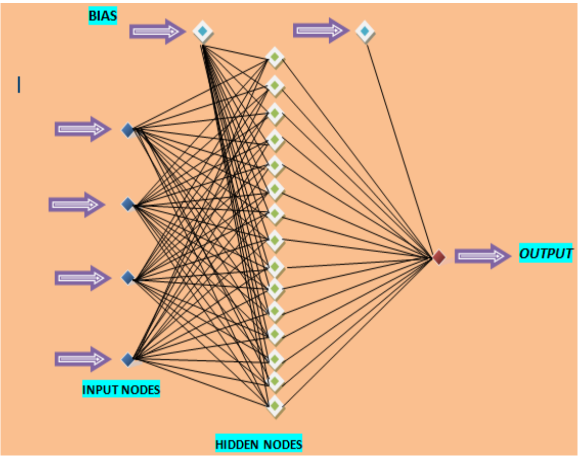

Figure 4.1 Feed Forward Neural networks

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In Back propagation algorithms restraining the weights and preferences of the network in order to abate a cost function. The cost function always includes a miscalculation term a appraise of in what manner closes the network's prognostications are with the class labels for the paradigms in the training set. Additionally, it may include a complexity term that reacts a prior distribution over the values that the parameters can take. The activation function anticipated for each node in the network is the binary sigmoidal function defined (with s = 1) as output = 1/(1+e-x), where x is the sum of the weighted inputs to that scrupulous node. This is a common function used in many BPN. This function limits the output of all nodes in the network to be between 0 and 1. Note all neural networks are basically trained until the error for each training iteration stopped decreasing. The inputs m and outputs of the j hidden layer neurons can be calculated as follows

STEP-1

$$(\mathbf{m})^h = \sum_{Y-1}^{N+1} (\mathbf{W}) j^{\mathbf{i}} x^{\mathbf{i}}$$

STEP-2

$$y^i = f(m^h_j)$$

STEP-3 **Calculate the M Inputs and Outputs of the K Output Layer Neurons are**

$$Z_k = f(m^o_k)$$

STEP-4 **Updates the contrastness** EMBED Unknown

STEP-5**Updates the Weights in the output layer (∀K, J Pairs)**

$$v_{kj} \to v_{kj} + c\lambda(\mathrm{d}_k - Z_k)Z_k(1 - Z_k)\,\mathrm{y}_j$$

STEP-6 **Updates the Weights in the hidden layer (∀I , J Pairs)**

$$w_{ji} \to w_{ji} + c\lambda^2 y_i(1 - y_i)\,\mathrm{x}_i(\mathrm{d}_k - Z_k)Z_k(1 - Z_k)\,\mathrm{v}_{kj}$$

STEP-7 **Update the Error Term**

$$E \to E + \sum_{k=1}^{k} (\mathrm{d}_k - Z_k)^2$$

and repeat from Step 1 until all input patterns have been presented . If E is under some predefined tolerance level, then stop. Otherwise, reset $E = 0$, and repeat from Step 1 for another epoch

V. ANFIS SYSTEM

A neural-fuzzy system is a hybrid of neural networks and fuzzy systems in such a way that neural networks or neural networks algorithms are used to determine parameters of fuzzy systems. The main intention of neural & fuzzy approach is to improve a fuzzy system automatically by means of neural network methods. In [21, 11], the first layer, all the nodes are adaptive nodes. The outputs of layer 1 are the fuzzy membership grade of the inputs, which are calculated using the following equation

$$O_i^1 = \pi Ai(x)$$

Where x is the input to node i and Ai is a linguistic label such as minimum, maximum and mean gray level value associated with the node. O_i^1 is the membership function of Ai and it specifies the degree to which the given x satisfies the quantifier Ai.πAi(x)
is triangle-shaped Membership Function (MF) value ranging from 0 to 1 and it is given below

$$\pi Ai(x) = \frac{1}{1 + \left(x - \frac{ci}{ai}\right) 2bi}$$

In the second layer, the nodes are fixed nodes. Each node in this layer represents the firing strength of the rules. They are labeled with π, indicating that perform as a simple multiplier. The outputs of this layer can be represented as

$$O_i^2 = \pi Ai(x1) \times \pi Bi(x2) \times \pi Ci(x3) \ldots$$

Where
$i = 1, 2, 3 \ldots n$
$x1, x2, x3 \ldots n$ = input
$o21$= output of neuron i

In the third layer, the nodes are also fixed nodes labeled by N, to indicate that they play a normalization role to the firing strength from the previous layer. The output of this layer can be represented as:

$$O_i^3 = \frac{wi}{w1 + w2 + w3 + w4}$$

In the fourth layer, the nodes are adaptive. The output of each node in this layer is simply the product of the normalized firing strength and a first order polynomial. Thus, the output of this layer is given by:

$$O_i^4 = w_i(p_i x_1 + q_i x_2 + r_i x_3 + s_i)$$

Where *wi* is the output of layer 3 and *pi*, *qi* and *ri* are the parameter set. Parameter in this layer will be referred to as consequent parameters.

In fifth layer, the single layer node is a circle node labeled that computes the overall output as the summation of all incoming signals as:

$$O_i^5 = \sum wi.fi$$

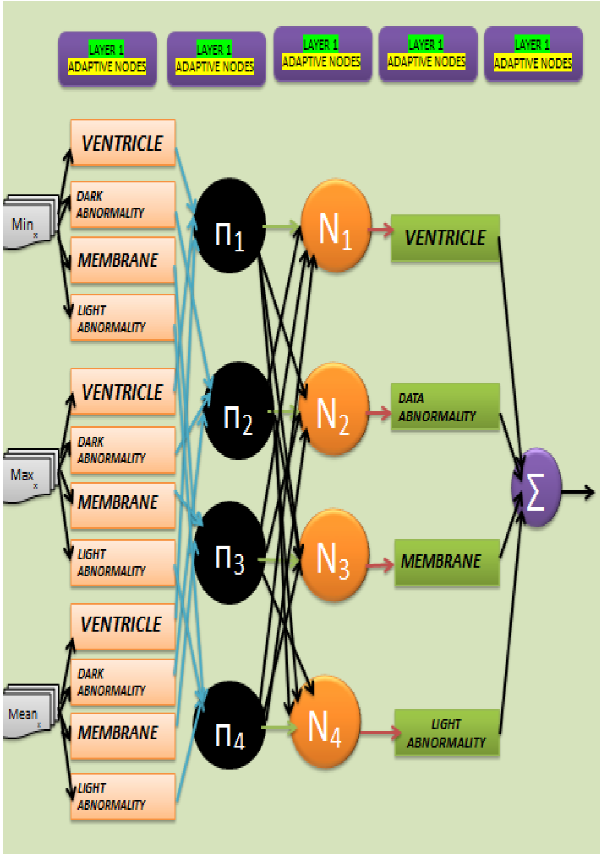

Fig 5.1: The Neural fuzzy system

VI. ANFIS CLASSIFIER

It appears like copious contemplations can trepidation the enactment of the classification part. Customarily, the enactment of classifier dangles on several aspects such as size and quality of training set, the scrupulousness of the training adapted and also constraints chosen to epitomize the input [23]. Conversely, the main advantages and drawbacks of the ANFIS classifier are discussed in this section. In most experiments, the criterion that is used to show the performance of classifiers is classification accuracy.

Moreover, in some works, convergence time and total error are pondered. Neuro-fuzzy systems harness the power of two methods: fuzzy logic and artificial neural network (ANN). Palpably, a different type of this hybrid system ensures that combines fuzzy logic and ANN. This network is known as fuzzy neural network (FNN) and, in some experiments, they apply to the classification part. For instance, in [24] for Severe Acute Respiratory Syndrome

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(SARS) thermal analysis and in [25, 26] for breast cancer, FNN is used as a classifier. The difference between Neuro-fuzzy system and FNN is that the former is a fuzzy system that makes use of the ANN learning algorithm for updating its fuzzy parameters while the latter is basically a neural network that is benefiting fuzzy rule in the network.

However, according to [27], some advantages of ANFIS are:

a) Sanitizing fuzzy if–then rules to designate the behavior of a complex system
b) Not entailing prior human expertise that is often needed in fuzzy systems and it may not perpetually be accessible
c) Presenting greater choice of membership function to use
d) Fetching very fast convergence time

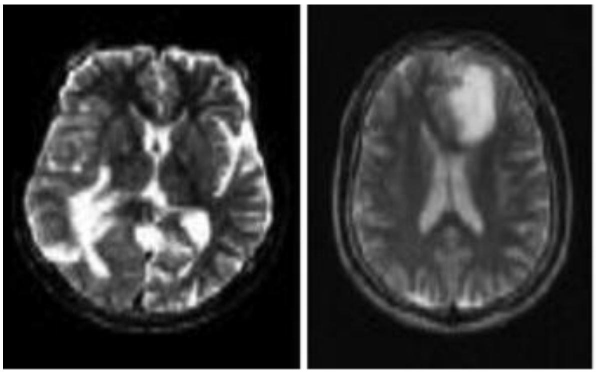
VII. NEOPLASM CLASSIFICATION

The comparison between probabilistic neural network (PNN) and ANFIS is examined for brain neoplasm. Table 2 shows a comparison between three methods that are presented in [15] for detection of four types of brain tumor. Figure 5 shows these classes. Also, the mean square curve for classifiers that are used in [43] is illustrated in Figure 6.

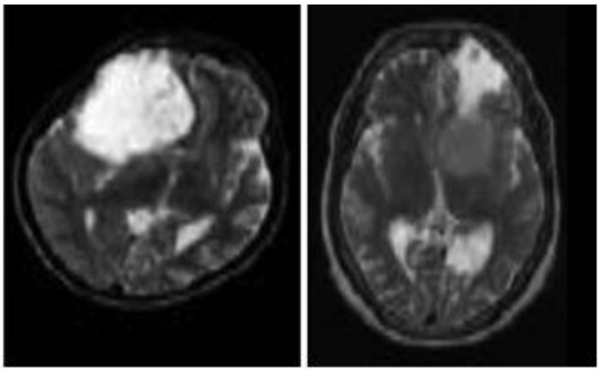
Table 2: Classifier comparison based on [15] results

Average Convergence time period	Average Mean square error	Average Classification Accuracy (%)	Classifier
1540	0.151	93.3	ANFIS
15380	0.25	88.6	FUZZY
16,245	0.37	85.65	BPN

This figure shows the superior nature of ANFIS over the other classifiers in terms of training and testing error. The three classifiers are subjected to 200 iterations and the overall training and testing error curves are simulated. The error rate of fuzzy classifier and the neural classifier are high as they suffer from the drawbacks of random initial cluster center selection and requirement of large training data set, respectively.



A B



C D

Fig 6 : Various tumor types of (A) Metastase, (B) glioma, (C) astrocytoma and (D) meningioma

VII. CONCLUSION

Our experiments with automatic classification of MR images of brain tumor is a tedious task and this paper presents a hybrid approach of Fuzzy logic parameters and Neural network machine learning representation for various tumor tissue types can be effectively applied while classifying them and exhibits higher performance in classification accuracy. Hence, it would be desirable to automatically classification for quantity approach for large sets of images. Customarily, the ANFIS classifier dangles on various aspects of size and position for exposing the quality of brain images with the reduction in the time convergence rate and the declassification of images while compared with other existing methods. Demonstrated results for the novel refinements of the ANFIS algorithm interpreted here epitomize a momentous step forward in the study of large numbers of structural MR data for classification, improving reckoning power in psychiatric or neurologic studies over exact reliability of brain tissue classification and tractability of hefty associates.

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