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RESEARCH ARTICLE

CLASSIFICATION OF TB DISEASE DIAGNOSIS USING ANFIS

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ABSTRACT

Symptoms based diagnosis of a disease is one of the challenging tasks in the medical field. Several techniques are available for classification. In this paper,used ANFIS for classification of TB disease on the available data. Hybrid system is a learning algorithms that utilizes the training and learning networks to find parameters of a fuzzy system based on the symptoms created by the mathematical model. In this paper, an expert system is proposed to detect the Tuberculosis disease, which are very common and important disease using an adaptive neuro-fuzzy inference system (ANFIS). The main objective of this study is classification of Tuberculosis disease based on the symptoms. The dataset for the training of an ANFIS is collected from the various physicians for the classification of TB disease. Finally obtained the accuracy of classification result is 89%.

INTRODUCTION

Artificial neural networks are nonlinear information (signal) processing devices, which are built from interconnected elementary processing devices called neurons. An Artificial Neural Network (ANN) is an information-processing paradigm that is inspired by the way biological nervous systems, such as the brain, process information processing system. It is composed of a large number of highly interconnected processing elements (neurons) working in union to solve specific problems. ANN's, like people, learn by example. An ANN is configured for a specific application, such as pattern recognition or data classification, through a learning process. Learning in biological systems involves adjustments to the synaptic connections that exist between the neurons. This is true of ANN"s as well. ANN's are a type of artificial intelligence that attempts to imitate the way a human brain works. Rather than using a digital model, in which all computations manipulate zeros and ones, a neural network works by creating connections between processing elements, the computer equivalent of neurons. The organization and weights of the connections determine the output. Tuberculosis (TB) is an infectious disease caused by a Bacterium, Mycobacterium tuberculosis. It is spread through the air by a person suffering from TB. A single patient can infect 10 or more people in a year. Tuberculosis was declared a global health emergency in 1993, but it has been growing unchecked. Today, TB is causing millions of deaths every year globally.

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Like any infectious disease, TB is prevalent even in developed countries. But it is a more serious problem in the developing and populous countries. India and China together account for nearly 40 per cent of the global burden. Tuberculosis is one of India's major health problems, According to WHO estimates, (Kochi, 1991; World Health Organisation-1993).India has the world's largest tuberculosis epidemic. India accounts for one-fifth of the global TB incident cases. Each year nearly 2 million people in India develop TB, of which around 0.87 million are infectious cases. It is estimated that annually around 330,000 Indians die due to TB. In India, the prevalence is 3.1 million at best and 4.3 million at high. In China, the figures are 1.4 million and 1.6 million respectively.

II. ADAPTIVE NEURO FUZZY INFERENCE SYSTEMS (ANFIS)

The acronym ANFIS derives its name from adaptive neuro fuzzy inference system. ANFIS is a hybrid neuro fuzzy technique that brings learning capabilities of neural networks to fuzzy inference systems. Jang was one of the first to introduce ANFIS. He reported that the ANFIS architecture can be employed to model nonlinear functions (JyhShing and Roger Jang, 1993). This technique provides a method for fuzzy modeling procedure to learn information about a data set, in order to compute membership function parameters that best allow the associated FIS to track the given input/output data. Using a given input/output data set ANFIS constructs a FIS whose membership function parameters are tuned. The modeling approach used by ANFIS is: first to hypothesize a parameterized model structure. Next, collect input/output data in a form that will be usable by ANFIS for training (MATLAB (R2008b). In ANFIS two optimization methods are available one is back propagation and other is hybrid in which back propagation is combined with least squares method.

A. ANFIS Architecture

In ANFIS, Takagi-Sugeno type fuzzy inference system is used. The output of each rule can be a linear combination of input variables plus a constant term or can be only a constant term. The final output is the weighted average of each rule's output. Basic architecture with two inputs x and y and one output z is shown in Fig. 1.

Suppose that the rule base contains two fuzzy if-then rules of Takagi and Sugeno's type.

Rule 1: If x is A1 and y is B1, then f1 = p1x + q1y + r1,
Rule 2: If x is A2 and y is B2, then f2 = p2x + q2y + r2.

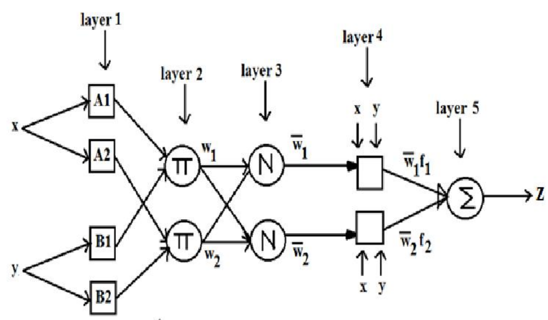

FIG.1.Architecture of ANFIS

B. DESCRIPTION OF THE METHOD

Layer 1: Every node *i* in this layer is an adaptive node with a node function

$$O_i^{\,1} = \mu_{Ai}(x) \qquad (1)$$

Where x is the input to node *i*, and *Ai* is the linguistic label (small, large, etc.) associated with this node function. In other words, Eqn (1) is the membership function of *Ai* and it specifies the degree to which the given x satisfies the quantifier *Ai*. Usually we equal to 1 and minimum equal to 0, such as choose $\mu_{Ai}(x)$ to be bell shaped with maximum

$$\mu_{Ai}(x) = \frac{1}{1+\left[\left(\frac{x-c_i}{a_i}\right)^2\right]b_i} \qquad (2)$$

$$\mu_{Ai}(x) = e^{\left\{-\left(\frac{x-c_i}{a_i}\right)^2\right\}} \qquad (3)$$

Where $\{a_i, b_i, c_i\}$ is the parameter set. As the values of these parameters change, the bell shaped functions vary accordingly, thus exhibiting various forms of membership functions on linguistic label A_i. In fact, any continuous and piecewise differential functions, such as trapezoidal or triangular shaped membership functions, can also be used for node functions in this layer. Parameters in this layer are referred to as premise parameters.

Layer 2: Every node in this layer is a fixed node labeled Π which multiplies the incoming signals and sends the product out. For instance,

$$w_i = \mu_{Ai}(x) * \mu_{\mathbf{B}i}(y), \qquad i \le 2 \qquad (4)$$

Each node output represents the firing strength of a rule.

Layer 3: Every node in this layer is a circle node labeled N. The i^{th} node calculates the ratio of the i^{th} rule's firing strength to the sum of all rules firing strengths:

For convenience, outputs of this layer will be called as normalized firing strengths

$$\overline{w_i} = \frac{w_i}{w_1 + w_2} \qquad (5)$$

Layer 4: Every node *i* in this layer is a square node with a node function .

$$O_1^{\,4} = \overline{w_1} f_i = \overline{w_i}\,(p_i x + q_i y + r_i) \qquad (6)$$

Where w_i is the output of layer 3, and $\{p_i, q_i, r_i\}$ is the parameter set. Parameters in this layer will be referred to are consequent parameters.

Layer 5: The single node in this layer is a circle node labeled as $\sum$ that computes the overall output as the summation of all incoming signals ,i.e.,

$$o_1^{\,5} = \text{overalloutput}(z) = \sum_i \overline{w_1} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \qquad (7)$$

III. HYBRID METHOD

From the proposed type-3 ANFIS architecture it is observed that given the values of premise parameters, the overall output can be expressed as a linear combinations of the consequent parameters. More precisely, the output f in above fig can be rewritten as

$$f = \frac{w_1}{w_1 + w_2} f_1 + \frac{w_2}{w_1 + w_2} f_2$$
$$= \overline{w}_1 f_1 + \overline{w}_2 f_2$$
$$= (\overline{w}_1 x) p_1 + (\overline{w}_1 y) q_1 + (\overline{w}_1) r_1 + (\overline{w}_2 x) p_2 + (\overline{w}_2 y) q_2 + (\overline{w}_2) r_2$$

which is linear in the consequent parameters (p_1, q_1,r_1,p_2, $q_2$and r_2) . we have,

$$S = S_1 \oplus S_2$$

Where S= set of total parameters, S_1= set of premise(nonlinear) parameters, S_2= set of consequent(linear) parameters. Fuzzy systems are more favorable in that their behavior can be explained based onfuzzy rules and thus their performance can be adjusted by tuning the rules. But since, in general, knowledge acquisition is difficult and also the universe of discourse of each input variable needs to be divided into several intervals, applications of fuzzy systems are restricted to the fields where expert knowledge is available and the number of input variables is small. To overcome the problem of knowledge acquisition, neural networks are extended to automatically extract fuzzy rules from numerical data.

Consider a fuzzy rule-based system of the form

R_1: if x is A_1 and y is B_1 then z is C_1
R_2: if x is A_2 and y is B_2 then z is C_2
. . . .
R_n: if x is $A_n$and y is $B_n$then z is C_n
fact :$x = x_0$ and $y = y_0$

consequence : z is C
where$A_i$and $B_i$are fuzzy sets, $i = 1, \dots, m$.
The procedure for obtaining the fuzzy output of such a knowledge base consists from the following three steps:
• Find the firing level of each of the rules.
• Find the output of each of the rules.
• Aggregate the individual rule outputs to obtain the overall system output.

IV. BACKPROPAGATION LEARNING

Based on approach of error correction learning, Back propagation is a systematic method for training, provides a computationally efficient method for changing the synaptic weights in the neural network, with differentiable activation function units. The error back propagation algorithm uses method of supervised learning. We provide the algorithm with the recorded set of observations or training set. i.e. examples of the inputs and the desired outputs that we want the network to compute, and then the error (difference between actual and expected results) is computed. These differences in output are back propagated in the layers of the neural networks and the algorithm adjusts the synaptic weights in between the neurons of successive layers such that overall error energy of the network, E is minimized. The idea of the back propagation algorithm is to reduce this error, until the ANN learns the training data. Training of network i.e. error correction is stopped when the value of the error energy function has become sufficiently small and as desired in the required limits(Parveensehgal et al., 2011).Total error for p^{th} observation of data set and j^{th} neuron in the output layer can be computed as: $E_i = t_i - y_i$(8)

where, t_i represents the desired target output and represents the predicted from the system.

V. DESCRIPTION OF DATABASE

The data has been collected from the National Institute for Research in Tuberculosis (ICMR) at Chennai from a clinical trial on Pulmonary TB patients who were undergone diagnosis and allocated to different treatments. The data consists of 220 cases with 6 condition attributes of various types. The condition attributes taken for the study are the symptoms associated with Tuberculosis, namely Cough, Fever, Haempothesis, Breathe restlessness, Chestpain, Weight loss. Each record also has a binary decision attribute that reveals the severity of Tuberculosis disease in the respondent. The input attributes six symptoms are taken as numerical or nominal attributes. The data set is converted into a decision table in which the rows are represented by cases and columns are represented by attributes. The above six symptoms are collected from each patient and duration of the symptoms is also collected. In Matlabsoftware , ANFIS is used to find the training and testing error using Hybrid which gives the less error rate and better classification result.

VI. ANFIS MODEL

This ANFIS model has been used for Tuberculosis disease classification that needs input values of symptoms of TB. For ANFIS designing, model should be passed four steps: 1) Load data, 2) Generate FIS, 3) Train FIS, 4) Test FIS. There are three different data types for loading to model. These dataset includes Training data, checking data and testing data. At first, usage dataset contains seven columns and 220 rows. After that, this set was further broken down into three sets: training set, checking set and testing set. The Checking and testing sets known as validation set .The validation set monitors the fuzzy system's ability to generalize during training (the same principle as cross validation training in neural networks terminology). Fig.2 shows the loaded dataset into ANFIS.

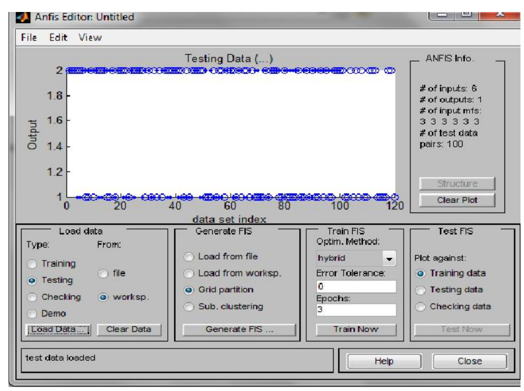

Fig.2. Load Data

A. GENERATE FIS

For FIS generation, model has three selections, which are designed FIS, Grid Partition and Subtractive Clustering. Grid partition divides the data space into rectangular subspaces using axis-paralleled partition based on pre-defined number of membership functions and their types in each dimension (Minghzen Wei*et al.,* 2007). The wider application of grid partition in FL and FIS is blocked by the curse of dimensions, which means that the number of fuzzy rules increases exponentially when the number of input variables increases .For example, if there are averagely m MF for every input variable and a total of n input variables for the problem, the total number of fuzzy rules is m^n .It is obvious that the wide application of grid partition is threatened by the large number of rules. According to (Minghzen Wei*et al.,* 2007), grid partition is only suitable for cases with small number of input variables. The subtractive clustering method clusters data points in an unsupervised way by measuring the potential of data points in the feature space. When there is not a clear idea how many clusters there should be used for a given data set, it can be used for estimating the number of clusters and the cluster centers (Minghzen Wei *et al.,* 2007). Subtractive clustering assumes that each data point is a potential cluster center and calculates the potential for each data point based on the density of surrounding data points.Then data point with highest potential is selected as the first cluster center, and the potential of data points near the first cluster center) within the influential radius (is destroyed .Then data points with the highest remaining potential as the next cluster center and the potential of data points near the new cluster (Minghzen Wei *et al.,* 2007). This ANFIS model (model 1) uses Grid Partition method for FIS generation. Generated FIS includes six inputs and one output. Input variables are: Cough, Fever, Haempothesis, Chestpain, Breathe restlessness, Weight loss. The number and type of membership functions for each input variable is two and triangular. Output field is the severity of TB disease. Membership function type of output variable is constant. The structure (rules) of tuned FIS has been shown in FIG.3 and contains 64 rules with AND logical connector for all rules.

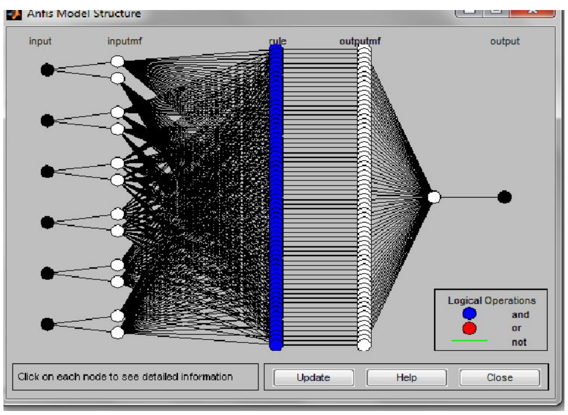

Fig.3 Anfis structure

B. Train FIS

The optimization methods train membership function parameters to emulate the training data. In this step, there are two optimization methods: Hybrid method and Back propagation. The hybrid optimization method is a combination of least-squares and back propagation gradient descent method. In hybrid method, model tunes with to pass: forward pass and backward pass. In the forward pass, with fixed premise parameters, the least squared error estimate approach is employed to update the consequent parameters and to pass the errors to the backward pass. In the backward pass, the consequent parameters are fixed and the gradient descent method is applied to update the premise parameters .Premise and consequent parameters will be identified for MF and FIS by repeating the forward and backward passes. The ANFIS model 1 uses hybrid optimization method. For this ANFIS model, the number of training epochs is 50 and training error tolerance sets to zero. The training process stops whenever the maximum epoch number is reached or the training error goal is achieved.

C. Test FIS

After FIS training, validate the model using a testing or checking data that differs from the one you used to train the FIS. Average testing error of training and testing data in the ANFIS model are 0.26 and 0.3 respectively that have been shown in FIG.4 and FIG.5 respectively.

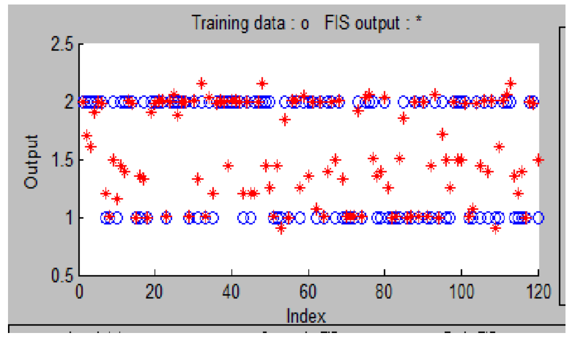

FIG.4 Training data

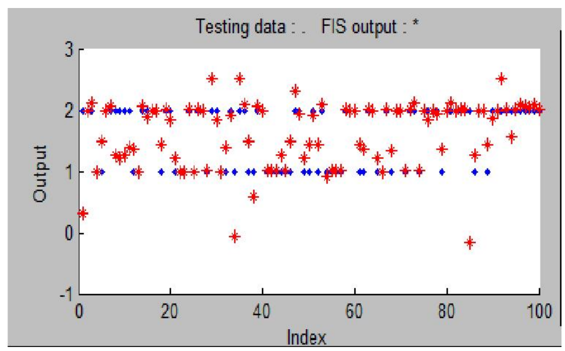

FIG.5 Testing data

VII. RESULTS

A.Training error: The experiment was carried out with 220 sample data for comparing the neural network learning Algorithms. MATLAB is used in our experiment to evaluate the results. ANFIS is relatively fast to convergence due to its hybrid learning strategy and its easy interpretation. It is a more transparent model and its behavior can be explained in human understandable terms, such as linguistic terms and linguistic rules. This provides for a better understanding of the data and gives the researchers a clear explanation for how the diagnostic results are arrived (Jang and Sun 1997). The average training error of Hybrid learning algorithms for training data in the ANFIS architecture is 0.26.

B.Classification accuracy

The classification accuracy for the considered dataset was measured according to the following equation

$$\text{Accuracy(S)}= \frac{\sum_{i=1}^{|S|} asseess(s_i)}{|s|} \quad s_i \in \text{S} \qquad (9)$$

$$\text{assess(s)}= \begin{cases} 1, & if \;\; classify(s) = s.c \\ 0, & otherwise \end{cases} \qquad (10)$$

where, S is the set of data items to be classified (the test set), sεS, s.c is the class of the item s and classify(s) returns the classification done by ANFIS. The total cases are 220, using ANFIS Hybrid method correctly classified 196 cases. Finally, the classification result is 89%, this gives better accuracy level.

VIII. CONCLUSION

This study has employed the usage of adaptive network-based fuzzy inference system (ANFIS), to construct a diagnostic system for Tuberculosis disease. ANFIS is a mighty fuzzy logic neural network, which renders a process for fuzzy modeling to memorize selective information from the data set that permit the related fuzzy inference system to map out the known input/output data. In this paper symptoms based on Tuberculosis disease diagnosis was predicted by using ANFIS Method. The model is constructed with 2 membership function using Triangular function and the results apparently demonstrated in upper section which shows that ANFIS has the potency for modeling in diagnosis of Tuberculosis disease by applying appropriate membership function and the total number of membership function that is very helpful to proceed out the correct result.

In this study, the data is transformed into the knowledge that the symptoms are the significant ones in diagnosing Tuberculosis. The presented results provide a reasonable estimate about the quality of approximation. The Hybrid model is able to gives the better prediction level is 89%. Further studies are to improve the accuracy level.

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