Designing a Fuzzy Expert System of Diagnosing the Hepatitis B Intensity Rate and Comparing it with Adaptive Neural Network Fuzzy System

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***Abstract*— in this paper an adaptive neural fuzzy system has been designed for diagnosing the hepatitis B intensity rate. The main problem in determining the disease intensity is not having information about the data variation rate and its resulting effect on the system. Designing a fuzzy expert system and using a neural network for training then testing the system adaptively has resulted in a very good optimization. A Hepatitis B data bank has been collected in accordance with the recent medical findings about this disease and the endorsement of a liver specialist. This bank has 300 records and each record has 7 fields. This bank has been assembled from patients presenting at the liver biopsy department of Imam Reza hospital Mashad, Iran. Using specialist research and experience strong inference rules have been attained. Thus, the accuracy oft the system in diagnosing the hepatitis B intensity is 96.4± 0.2%.**

***Index Terms*— expert system, fuzzy, neural network, adaptive neural fuzzy system, hepatitis B.**

I. Introduction

With improvements in medical knowledge systems in medical institutes and hospitals, determining useful knowledge is becoming more difficult. Especially, because the Conventional manual data analysis techniques are not effective in diagnosis, using computer based analyses are becoming inevitable in disease diagnosis. So, it is the time to develop modern, effective and efficient computer based systems for decision support. There are a number of data analysis techniques: statistical, machine learning, expert system and data abstraction [7]. Medical analysis using expert system techniques has begun to be conducted for last twenty years. The advantages of using expert system schemes in medical analysis have caused human support and costs to decrease and caused diagnosis accuracy to increase.

Hepatitis B has a virus factor. Its size is 42 nanometers and its active part is in its central part. The Australian antigen or the HB surface antigen (HbsAg) itself is on virus surface. This virus with going through liver cells makes them produce similar viruses. It is considered an infected person when there are (HbsAg) in one's blood. The most sensitive patient's blood tests which imply viruses' propagation in Bodies are PCR and HBNDNA. If the test resulting is positive, It can PCR and HBNDNA. If the test resulting is positive, it can be concluded that the person has been infected with HB virus but determining the person pathology status and the rate of disease improvement involve modern and complicated tests.

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According to the recent world health organization (who) reports, there are nearly 400 million HB infected in the world and 50 million persons are added to them annually. This number is 2 million people in Iran [1]. This disease ranked as the third infectious one. The importance of surveying and designing an intelligence system has been sensed in this field. Some of the works that have been done in this field -using a data bank included 19 fields taken from the site UCI- have gotten different resulting [2].

The rest of the paper is organized as follows. Section 2 gives the background information including hepatitis disease classification problem, previous research in corresponding area and brief introduction to natural. We explained the method in Section 3 with subtitles of proposed a new medical diagnosis method and measures for performance evaluation. In each subsection of that section, the detailed information is given. The results obtained in applications are given in Section 4. This section also includes the discussion of these results in specific and general manner. Consequently in Section 5, we conclude the paper with summarization of results by emphasizing the importance of this study and mentioning about some future work.

II. Background

A. Hepatitis disease dataset

Hepatitis B is caused by a virus that attacks the liver. The virus, which is called hepatitis B virus (HBV), can cause lifelong infection, cirrhosis (scarring) of the liver, liver cancer, liver failure, and death. In 2003, an estimated 73,000 people were infected with HBV. People of all ages get hepatitis B and about 5000 die per year of sickness caused by HBV. HBV is spread when blood from an infected person enters the body of a person who is not infected. Healthcare personnel who have received hepatitis B vaccine and developed immunity to the virus are at virtually no risk for infection. For a susceptible person, the risks from a single needle stick or cut exposure to HBVinfected blood ranges from 6% to 30%. The annual number of occupational infections has decreased 95% since hepatitis B vaccine became available in 1982, from >10,000 in 1983 to <400 in 2001 (http://www.cdc.gov/ncidod/dhqp/bp_hepatitisb.html).

B. Previous research

As for other clinical diagnosis problems, classification systems have been used for hepatitis disease diagnosis problem. When the studies in the literature related with this classification application are examined, it can be seen that a great variety of methods were used which reached high classification accuracies using the dataset taken from UCI machine learning repository. Among these, while Karol Grudzin´ ski has obtained 92.9%, 90.2% and 89.0% [3], respectively, using weighted 9-NN, 18-NN, and stand. Manhattan and 15-NN stand. Euclidean algorithms, Rafał Adamczak has obtained 89.7%, 88.5%, 79.0% and 77.4%, respectively, using FSM with rotations, FSM without rotations, RBF and MLP + BP algorithms. While, Stern & Dobnikar have obtained 86.4%, 86.3%, 85.8%, 85.3%, 85.0%, 84.5%, 83.2%, 82.7%, 82.1%, 82.0% and 81.9%, respectively, using LDA (linear discriminate analysis), Naive Bayes and Semi- NB, QDA (quadratic discriminate analysis), 1-NN, ASR, Fisher discriminate analysis, LVQ, CART (decision tree) MLP with BP, ASI and LFC algorithms, Norbert Jankowski has obtained 86% using IncNet algorithm[4]. Ozyılmaz L. and Tu¨lay Y. have obtained 74, 37%, 83, 75% and 80, 0% using MLP, RBF and GRNN algorithms [5],Kemal polat has obtained 76%,92.59% using AIRS (Artificial immune recognition system)[10] , FS-AIRS with fuzzy algorithm[11] .

The best reported resulting in this field has been Kemal Polat [6]. This test using an artificial immune recognition immune system (AIRS) fuzzy weighted pre-processing and feature selection the accuracy of % 94.12. No report has been seen in the field of appointing the rate HB intensity and the research is a new work in this field.

C. Data

Applied data in this research for diagnosing the rate of HB intensity have been chosen- with the help of Liver specialists- from the patients that have come to Imam Reza hospital in Mashad and the HB Virus has been diagnosed in their blood. There are 300 records and each record has 8 fields. The fields are described as below:

1) Bili-T (Bilirubin: abile pigment cleared from the blood by the liver)

2) Bili-D

3) AST (Aspartate aminotransferase (SGOT): enzymes that catalyze protein transformations within hepatocytes)

4) ALT (alanine aminotransferase)

5) ALP (Alkaline phosphatase: protein found in bile duct cell membranes.)

6) Ser.ALB (Albumin: a protein in the serum that transports substances such as drugs and prevents leakage of fluid into the surrounding tissues.)

7) PT (the pro-thrombin time in serum)

8) H_B (Intension Diagnosis hepatic B)

8th field is the specialist diagnosis that divides HB intensity levels to 4 parts: Normal situation (virus has not hurt vital organs yet).Light situation (virus has just started its destroying activity).Severe situation (some parts of vital organs have been destroyed).Hyper-severe situation (necessarily, patient needs intensive cares and even patient's life is in danger).

In appointed data bank- according to specialist diagnosis – one of the table 1 amounts has been put instead of above situations in order to compare the resulting together after designing the expert system and ANFIS.

TABLE 1 DIFFERENT OUTPUT SITUATION

#	state	range
1	normal	0-3
2	light	3-5
3	high	5-7
4	Very high	7-10

III. METHOD

A. Fuzzy expert systems designing

This system is compound of an expert and a fuzzy system. It is known as Hybrid system (fuzzy expert). This system consists of expert individual, knowledge engineer, fuzzy rule base, fuzzy inference engine, fuzzification and defuzzification.

Applying the fuzzy expert system is increasing in medical diagnosis gradually. There is no doubt that attained data from patients in addition to specialists decisions are the most important recognition factors. Besides them, fuzzy expert systems and various intelligent techniques help specialists for classification. Classification systems can help specialists avoid from possible mistakes that may happen because of their tiredness or their inexperience. Also, they prepare medical data, in shorter time but more details for testing. In the works that have been done, the HB has always been diagnosed and people have been divided into two parts: healthy people and unhealthy people but no report has a grade of health and a grade of illness.

In this research, for calibration of disease risk intensity amount, the tool (FIS) in software (MATLAB) has been used and in FIG. 1 the outline of system model is shown:

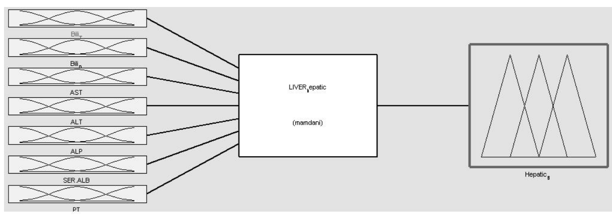

FIG 1: outline model of HB fuzzy expert system

1) Fuzzification

Designing and using of triangular and trapezoidal fuzzifier simplifies inference engine loading. According to the nature of data (Liver disease), probably this fuzzifier is used [9]. There are the normal amounts of all the disease fields in table1:

TABLE 2: SYSTEM' INPUT FIELDS WITH NORMAL AMOUNTS

field name	Normal
Bili-T	Total bilirubin: 0.3 to 1.9 mg/dL
Bili-D	Direct bilirubin: 0 to 0.3 mg/dL
AST	10 to 40 U/L^3
ALT	10 to 40 U/L^3
ALP	20to 130 U/L^3
SER.ALB	3.4 to 5.5 mg/dL
PT	9.5 to 13s

The membership functions of all the HB fields have been defined below:

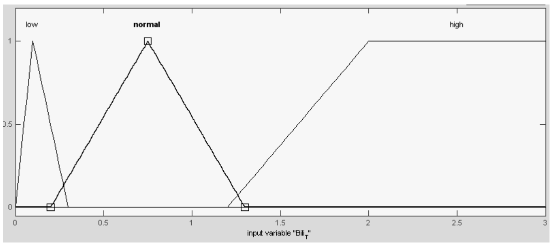

FIG 2: membership function Bili-T

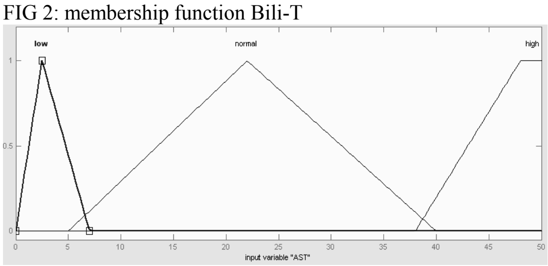

FIG 3: membership function AST

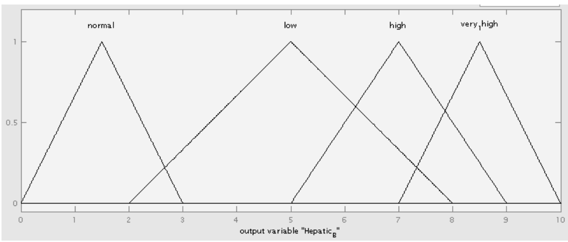

FIG 4: output fuzzy membership function (HB intensity)

The fuzzification of applied fields has been done by below functions. These formulas have been attained by specialist cooperation.

$$B\_T(\alpha) = \begin{cases} 1 & \alpha \geq 2 \\ \alpha & 0 < \alpha < 2 \\ 0 & \alpha \leq 0 \end{cases} \quad (1)$$

$$AST(\beta) = \begin{cases} 1 & \beta \geq 48 \\ 0 & \beta \leq 0 \\ \beta & 0 < \beta < 48 \end{cases} \quad (2)$$

$$ALP(\chi) = \begin{cases} 1 & \chi \geq 350 \\ 0 & \chi < 0 \\ \chi & 0 < \chi < 350 \end{cases} \quad (3)$$

$$ALB(\delta) = \begin{cases} 0 & \delta \leq 1 \\ \delta & 1 < \delta < 508 \\ 1 & \delta \geq 508 \end{cases} \quad (4)$$

$$H\_B(\mu) = \begin{cases} \mu & 0 < \mu < 100 \\ 0 & \mu < 0 \\ 0 & \mu > 0 \end{cases} \quad (5)$$

Phrases of the fields, according to the formula of triangular membership functions, are defined below. Variants of HB intensity (H-B) are low, middle and high.

$$\mu_{low}(B\_T) = \begin{cases} 0 & \alpha \leq 0 \\ \dfrac{\alpha}{0.15} & 0 < \alpha \leq 0.15 \\ \dfrac{0.3-\alpha}{0.15} & 0.15 < \alpha < 0.3 \\ 0 & \alpha \geq 0.3 \end{cases} \quad (6)$$

Variants Bili-D and Bili-t are included small, big, and medium and variants ALT, AST & ALP are included low, high and middle. The above formulas can be used for expressing these membership functions, for example $\mu_{high(B\_T)}$ is defined below based on formula 7:

$$\mu_{High}(B\_T) = \{\frac{0}{1.2} + \frac{.125}{1.3} + \frac{.25}{1.4} + \frac{.375}{1.5} + \frac{.5}{1.6} + \frac{.625}{1.7} + \frac{.75}{1.8} + \frac{.875}{1.9} + \frac{1}{2}\} \quad (7)$$

2) Rules Bank and Defuzzification

Taking into account different conditions of HB and even situations that have not yet occurred but may occur in the future, the rules have been edited.

In total, there are 58 dependent rules, where each rule is a collection of variants that have occurred "AND" together and show a special situation of HB. These rules cover all the situations that the fuzzy system may face. Also, there may occasionally be an opposition be between the base rules. This problem is solved by the inference engine and defuzzification parts of the system. The Inference engine and defuzzification parts give us an optimized result by taking an average of the attained rules.

TABLE 3: COLLECTION RULES OF FUZZY EXPERT SYSTEM

#	B_T	B_D	AST	ALT	ALP	ALB	PT	H_B
Rule1	B	B	H	H	L	L	L	H
Rule2	L	L	H	H	L	L	L	H
......								
Rule58	L	L	L	L	N	N	N	L

For example, rules 1, 2 and 34 have been defined as below:

1) $if(B\_T = B \,\&\, B\_D = B \,\&\, AST = H \,\&\, ALT = H \,\&\, ALP = L \,\&\, ALB = L \,\&\, PT = L) then (H\_B = H)$

2) $if(B\_T = L \,\&\, B\_D = L \,\&\, AST = H \,\&\, ALT = H \,\&\, ALP = L \,\&\, ALB = L \,\&\, PT = L) then (H\_B = H)$

34) $if(B\_T = N \,\&\, B\_D = N \,\&\, AST = L \,\&\, ALT = L \,\&\, ALP = N \,\&\, ALB = N \,\&\, PT = N) then (H\_B = N)$

The accuracy of α rules should be clarified at this stage. Firstly, the minimum amount of each rule is recognized and then the maximum amount between them is chosen. For instance (B_T=0.3, B_D=0.15, AST=36, ALP=85, ALB=3.5.PT=14) make rules 11 and 26 active.

$$\alpha_{11} = \min(L, L, N, N, N, L, N)$$

$$\alpha_{11} = \min(0, 0.5, 0.22, 0.72, 1, 0, 0) = 0.22$$

$$\alpha_{26} = \min(N, N, N, N, N, N, H)$$

$$\alpha_{26} = \min(0.181, 0.25, 0.22, 0.72, 1, 0.033, 0.5) = 0.033$$

Using the mamdani inference (max, min), the system's membership function is:

$$\max(\alpha_{11}, \alpha_{26}) = 0.033$$

That this rate of HB risk is Low. Defuzzification's centre

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of gravity formula is used for calculating the certain output amount (H-B).

$$D^* = \frac{\int D.\mu_{middle}(D)dD}{\int \mu_{middle}(D)dD} \tag{8}$$

As it is shown in FIG.5, the amount 0.56 indicates the HB intensity. The hepatologist's diagnosis for this field is a normal situation while the system reports a small disease risk.

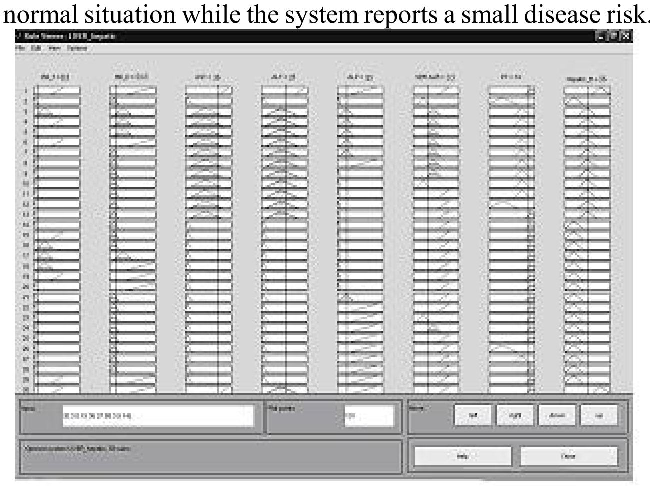

FIG.5: HB intensity with attention to the data

B. ANFIS

The basic idea behind these neuro-adaptive learning techniques is very simple. These techniques provide a method for the fuzzy modeling procedure to learn information about a data set, in order to compute the membership function parameters that best allow the associated fuzzy inference system to track the given input/output data. This learning method works in a manner similarly to that of neural networks. The Fuzzy Logic Toolbox function that accomplishes this membership function parameter adjustment is called ANFIS. Neuro-fuzzy computing enables one to build more intelligent decision-making systems [8].

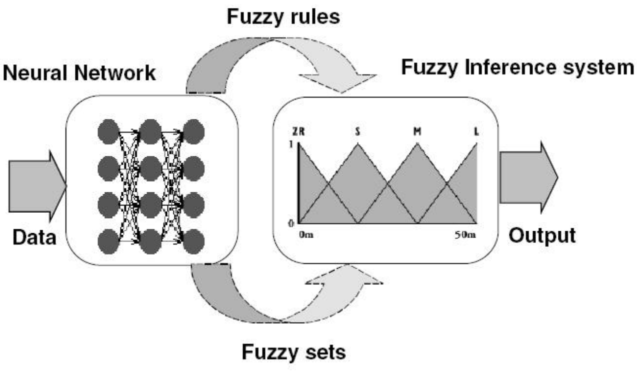

FIG 6. Shows the outline function of a neural fuzzy system.

The acronym ANFIS derives its name from Adaptive Neuro-Fuzzy Inference System. Using a given input/output data set, the function ANFIS constructs a fuzzy inference system (FIS) whose membership function parameters are tuned (adjusted) using either a back propagation algorithm alone, or in combination with a least squares type of method. This allows your fuzzy systems to learn from the data they are modeling.

A network-type structure similar to that of a neural network, which maps inputs through input membership functions and associated parameters, and then through output membership functions and associated parameters to outputs, can be used to interpret the input/output map.

The parameters associated with the membership functions will change through the learning process. The computation of these parameters (or their adjustment) is facilitated by a gradient vector, which provides a measure of how well the fuzzy inference system is modeling the input/output data for a given set of parameters. Once the gradient vector is obtained, any of several optimization routines could be applied in order to adjust the parameters so as to reduce some error measure (usually defined by the sum of the squared difference between actual and desired outputs). ANFIS uses either back propagation or a combination of least squares estimation and back propagation for membership function parameter estimation.

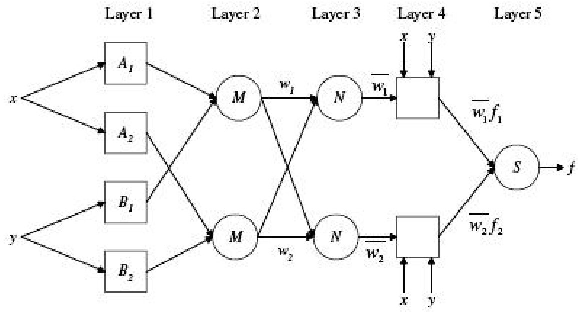

FIG.7: ANFIS architecture.

Some of the neural fuzzy systems that have been designed and have been used various fields are GARIC, FALCON , ANFIS ,NEFCON ,NEFCLASS ,NEFPROX ,FUN , SONFIN, FINEST, etc.

Generally, adaptive systems for making fuzzy models use the Segno method for reason of optimum in calculation and unity in output space. These adaptive techniques can be used for customizing the membership functions. In this situation, fuzzy system can model data better. In FIG.7 ANFIS's model is shown [9].

Layer 1: Every node i in this layer is a square node with a node function

$$\begin{aligned} O_i^1 &= \mu_{A_i}(x), \qquad i = 1,2 \\ O_i^1 &= \mu_{B_{i-2}}(y), \qquad i = 3,4 \end{aligned} \tag{9}$$

Where x is the input to node i, A_i is the linguistic label (small, large, etc.) associated with this node function, and where μ_{Ai} (x) and $\mu_{Bi=2}$ (y) can adopt any fuzzy membership function. Usually we choose μ_{Ai} (x) to be bell-shaped with maximum equal to 1 and a minimum equal to 0, such as

$$\mu_{A_i}(x) = \frac{1}{1 + \left\{\left(\frac{x - c_i}{a_i}\right)\right\}^{b_i}} \tag{10}$$

Where (a_i, b_i and c_i) is the parameter set. Parameters in this layer are referred to as premise parameters.

Layer 2: The nodes in this layer are fixed and are labeled

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M. to indicate that they play the role of a simple multiplier. The outputs of these nodes are given by:

$$O_i^2 = w_i = \mu_{A_i}(x)\mu_{B_i}(y) \qquad i = 1,2$$

(11)

Which are the so-called firing strengths of the rules?

Layer 3: Every node in this layer is a circle node that is 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:

$$O_i^3 = \overline{w}_i = \frac{w_i}{w_1 + w_2} \qquad i = 1,2 \qquad (12)$$

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

Layer 4: In this layer, the nodes are adaptive nodes. The output of each node in this layer is simply the product of the normalized firing strength and a first order polynomial (for a first order Sugeno model). Thus, the outputs of this layer are given by:

$$O_i^4 = \overline{w}_i f_i = w_i(p_i x + q_i y + r_i) \qquad i = 1,2$$

(13)

Parameters in this layer will be referred to as consequent parameters.

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

$$O_i^5 = \sum_{i=1}^{2} \overline{w}_i f_i = \frac{\sum_{i=1}^{2} w_i f_i}{w_1 + w_2} \qquad i = 1,2$$

(14)

It can be observed that there are two adaptive layers in this ANFIS architecture, namely the first layer and the fourth layer. In the first layer, there are three modifiable parameters $\{a_i, b_i, c_i\}$, which are related to the input membership functions. These parameters are the so-called premise parameters. In the fourth layer, there are also three modifiable parameters $\{p_i, q_i, r_i\}$, pertaining to the first order polynomial. These parameters are so-called consequent parameters.

1) Design description

In this research, MATLAB software with an ANFIS box has been used for creating an ANFIS. The below stages have been passed to attain this tool:

1. Loading the training and testing data
2. Appointing basic FIS model
3. Appointing optimization of the method of FIS model parameters
4. Clarifying the number of training courses and the training mistake's zone.
5. Training the system
6. Calculating the average of mistake & testing the system

Choosing training data and testing them in different classifications and situations has been performed to get the least number of mistakes on average. In fact, training data models that target the system and test the data use the extension ability of the fuzzy inference system. Every data collection that is loaded in the graphic connector ANFIS should be like a matrix such that inputs are as organized in it as vectors, expect the last column. Outputs are put in the last column in this vector.

In the second stage, a primary FIS should be designed and should be calculated. The number and the kind of input/ output membership functions are chosen. Of course, there are just two choices- constant and linear- for output membership functions and the reason for this limitation is that ANFIS works with Segno inference. In the FIS shown in FIG.3, there are 7 inputs and 1 output. Three triangular membership functions have been chosen for each input and the output is in linear. to make sure nothing was lost in the process.

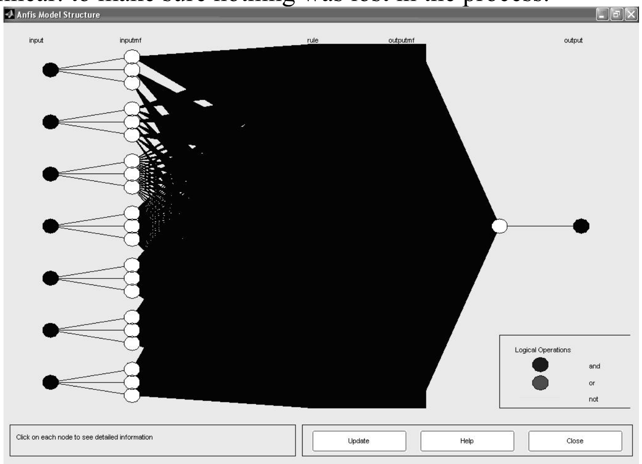

FIG.8: primary structure of FIS.

The tow method used for optimizing ANFIS parameters for learning FIS are back propagation and hybrid, which that is a combination of back propagation and least means square. Both methods have been used for system training and each one has a special quality. The hybrid method has a great calculation volume and performs training more carefully but also more slowly. Another method, back propagation, is faster but less careful.

Error tolerance is used with the purpose of finding evidence for stopping the training. Stopping is directly related to error size. When the error of the training data falls in this zone, training is stopped. It is better to put zero when there is no information about how the errors behave. The number of training stages has been considered 100 and the error tolerance had been considered zero when the system train is done.

IV. Results and Discussion

The fuzzy expert system design was modeled based on 300 HB records. Some new records that were supported by a specialist were used for testing the system. Accuracy of the HB intensity diagnosis is 94.24%, which is a large improvement. This system has taken great steps towards more complete and more accurate diagnosis for determining the rate of HB intensity. This system can be applied by a Liver specialist assistant or it can be applied in training medical students.

The training has been done using the above system's data training. This study used both methods for optimizing the parameters, hybrid and back propagation. The rate of the test's error was noted in each stage of the training process (table 2).

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TABLE 4: AMOUNT OF ERROR RATE WHILE TESTING AND TRAINING AND AVERAGE TRAIN

#	E1	E2	E3	E4	E5	E6	E7	E8	E9	E10	....	E100
Error train	1.746	1.428	1.147	0.922	0.761	0.636	0.534	0.457	0.402	0.362	....	0.271
Error test	4.541	3.117	2.984	2.239	1.976	1.824	1.710	1.607	1.543	1.495	....	0.348
Avr_e_trian		0.285		Avr_e_test		0.588			Avr_e_all		0.436	

TABLE 5: COMPARISON BETWEEN 3 METHODS OF DIAGNOSING THE RATE OF HB INTENSITY: CLASSIC, FIS AND ANFIS

Bili_T	Bili_D	AST	ALT	ALP	ALB	PT	Classic	FIS	ANFIS
0.33	0.4	37	45	241	2.4	13	3-5	3.67	4.15
0.1	0.2	18	20	22	1.5	12.8	0-3	1.34	1.51
1.3	0.3	284	306	252	4.5	13	7-10	8.2	8.41

As shown in table 3, the adaptive neural fuzzy system's accuracy is higher in comparison with two below methods below.

Function of an independent FIS that works with a mamdani inference and 54 rules. Specialist's diagnosis of appointing the HB intensity rate.

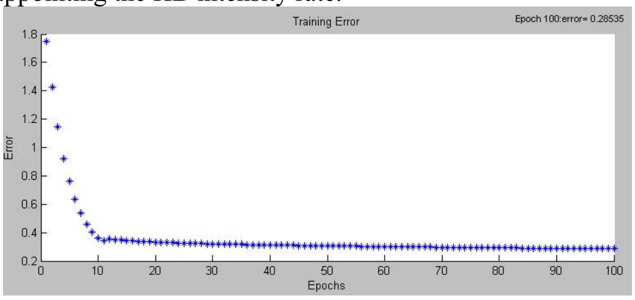

FIG.9 is the diagram of error rate in different training stages:

For appointing the rate of training error and testing randomly, with some variants among 300 records, different branches had been chosen. After the training and test stages were done, the rate of training error was .282±0.02 and .421±0.02was the rate of test error. The average of this rate of error may be near the real error rate.

V. CONCLUSION

In this research, an expert system and an adaptive neural fuzzy expert system were designed using ANFIS and FIS tools. In the fuzzy expert system, accuracy of diagnosing the HB intensity was 94.24%, however, in the adaptive neural fuzzy expert system because of the use of back propagation and least means square training methods with the purpose of estimating membership function parameters in the fuzzy expert system, we can estimate the HB intensity rate with a higher accuracy. Function accuracy of this latter system is 96.4± 0.2%. No reports regarding determining the HB intensity have been previously published. The current research is completely new in this field and the accuracy of the system function also has great importance in comparison with similar studies.

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