Adaptive Neuro-fuzzy Inference System for Hypertension Analysis

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***Abstract*—*Adaptive Neuro-fuzzy inference system (ANFIS) is multi-layer system proposed by Jang, enables to increase the performance by integrates the best features of Artificial Neural Networks and Fuzzy inference system into a single framework. It is a popular framework for solving complex problems. In this present work, an ANFIS is proposed for detection the risk factor of hypertension. In this work, for training the ANFIS system hypertension patient's data set is collected under the supervision of physician in clinical trials on hypertension patients in civil hospital. Additionally, the performance analysis has been performed using the parameters Specificity and Precision. This paper gives a comprehensive performance analysis of the proposed approach and compares its results with existing Fuzzy Expert System technique. Simulation results have demonstrated that the proposed technique shows a better outcome then existing system in terms of Specificity and Precision. We obtained that the specificity and precision of proposed model results is 93.33% and 98.11% resp.*

***Keywords*—Adaptive Neuro-fuzzy Inference System (ANFIS), fuzzy expert system, expert system, hypertension, medical diagnosis.**

I. INTRODUCTION

On analyzing modern development, it becomes noticeable that the tendency is to develop new techniques for computer decision-making in tablets and to estimate critically these techniques in clinical practice. It becomes more demanding issue to build up reliable medical expert system, for reduce diagnosis time and improving the diagnosis accuracy. Recent advances in the pasture of artificial intelligence have lead to the appearance of expert systems for medical applications designed to diagnose the disease. There are many medical expert systems in recent technologies such as rule-based, fuzzy expert system, Adaptive neuro-fuzzy inference system (ANFIS). ANFIS has been establishing to be more helpful than other systems in the judgment of disease because it supports when patients may not have related signs and symptoms while having similar disease.

ANFIS is multi-layer system proposed by Jang, enables to increase the performance by integrates the best features of Artificial Neural Networks and Fuzzy inference system into a single framework. It is a popular framework for solving complex problems. ANFIS system is very competent system for solving the distracted equations involving the automatic knowledge expressed only by the if-then rules. ANFIS has advantages over the fuzzy expert system are: automatic adapts the non-linear connections between inputs and outputs also it has more accurate performance shown by testing the results.

Hypertension is an unrelieved situation in which the continuing force of the blood adjacent to your artery walls is high an adequate amount that it might eventually cause many health problems. Hypertension affects approximately 75 million grown persons in the United States and is a major risk factor for heart attack, stroke, vascular disease, myocardial infarction and chronic kidney disease. Hypertension is defined as having a blood pressure reading, occurs when too high pressure inside the blood vessels. When your heart pumps it sends blood towards the arteries. Your blood pushing adjacent to the walls of your arteries by force cause pressure. The additional blood pump by your heart and the narrower your arteries, the elevated your blood pressure.

In this paper, we have proposed an adaptive neuro-fuzzy inference system used for diagnosis of hypertension. Hypertension patient's data has been collect from physician are age, blood pressure, body mass index, heart rate, diabetes, physical activities and genetics of the patients are used to determine the risk factor of hypertension developed. Then a proposed model result has been compared with existing Fuzzy expert system [13] techniques with the help of performance parameters: Specificity and Precision. We obtained 93.33% specificity and 98.11% precision values from the experiments made on the hypertension patient's dataset for diagnosis.

II. RELATED WORK

The authors in [13] proposed a Fuzzy Expert System to diagnose hypertension for different patients. Hypertension also called as high blood pressure and input parameters used in this system are age, body mass index, blood pressure, heart rate, diabetes, physical activity and genetics. Fuzzy expert system input parameters divided into three crisp values like low, medium and high. Fuzzy expert system based on symptoms and rules. The authors in [12] propose a Fuzzy EuroSCORE and also study EuroSCORE after Cardiac surgery that is method for predicting the risk of mortality. There are eight parameters from EuroSCORE data chosen by using expert's knowledge and fuzzy inference system is applied. The risk of mortality for determining after cardiac surgery also the patients are categorized into three different groups' i.e. low risk, medium risk and high risk. From the medical data in Fuzzy EuroSCORE system the range of mortality risk is calculated. The authors in [1] developed a self- efficacy scale and evaluated in hypertensive african-american patients. In the item-generation phase, interview taken from patients were used to extract their experiences with attractive antihypertensive medications. Response is recorded into nine categories by using qualitative techniques and these categories have their own functions. Clinicians and researchers can recognize situations in which patients have small self-efficacy in adhere to agreed medications. The fuzzy expert system [2] is proposed in simulation of clinic foundation cardio pulmonary bypass rotary blood pump controller. By using this model flow of blood is determine and this model has steps for implementation fuzzification, fuzzy inference engine, and defuzzification. Input parameters to fuzzy model are pump speed and delta pressure are for measuring the pump speed. In which rules are obtained from possibilities occur from combination of blood flow and delta pressure. Non-linear model used for measuring pump dynamometer for blood. Fuzzy controller has capability of maintaining a pressure when its range cross the baseline limits. The multiplayer perceptron- based decision support system in [4] proposed for diagnosis of heart diseases. In this system input variables categorized into groups then encoded using proposed schemes and system is trained using the back propagation algorithm. Medical records collected from the patients also these data used to train and test the system. The result of proposed system can has high diagnosis accuracy then clinic decision process of heart disease. The author in [9] proposed a Fuzzy expert system for diagnosis of the risk of hypertension patients. Data set are acquires from 10 people and input parameters used for this system are age, body mass index, blood pressure and heart rate. In diagnosis process, linguistic variables and their membership functions are based on medical expert's knowledge. The author in [10] diagnosis of acid-base disorders by using fuzzy inference system and has main three parts: measured blood parameters (MBP), extracted features (EF) and fuzzy classifier (FC). The proper treatment of acid base disorder by the sufficient way diagnosis. The author used four parameters hydrogen-ion concentration (pH), arterial blood carbon dioxide partial pressure, sodium ions concentration and chloride ions concentration that are directly measured in blood and features extracted from these parameters. Fuzzy rules that are used to map the input mfs to the output mfs are collected from medical experts.

III. MEDICAL DATA COLLECTION

The predictable approach to create medical expert system needs the information to analyze the input data. Hypertension patient's record has been collected under the supervision of experienced physician in clinical trials on patients in Civil Hospital, Jagraon from March to June, 2015. Interview and consultation used to collect information about patients and disease. The input/output data are collected in a form that will be compatible for training and testing purpose to ANFIS in (MATLAB). In this study, 550 patient's cases are considered with 7 patient's health parameters(symptoms related with hypertension) i.e. Age, Blood pressure, Body mass index, Heart rate, Diabetes, Physical activities and Genetics. Each record contains the patients symptoms used as system inputs parameter as well as the risk factor of hypertension diagnoses by physician used as system output parameter. In this research, the risk factor of hypertension has three classes classifiers are considered i.e. Low risk (L) factor, Medium risk (M) factor and High risk (H) factor hypertension patients. The low risk factor of hypertension patient's are considered as normal patients or we can say that slightly suffer from disease and both medium and high risk factor of hypertension patients are considered as abnormal patients or we can say that patients suffer from disease. The patient's data collected in form of table that contains the numerical values in which rows are represented by cases and columns are represented by symptoms.

IV. ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM (ANFIS)

The acronym ANFIS stands for Adaptive Neuro-Fuzzy Inference System is multi-layer system proposed by Jang, enables to produce a powerful processing tool named neuro-fuzzy systems by integrates the best features of Artificial Neural Networks and Fuzzy Inference System.

ANFIS is a hybrid in such a way that neural networks algorithms are used to determine parameters of fuzzy inference system. ANFIS architecture engaged to model non-linear functions and provides a method for fuzzy modeling formula to learn information regarding dataset. For compute the membership function parameters that allow the correlated FIS to follow the given input/output data. ANFIS constructs a FIS from given input/output dataset whose MF is tuned. In this research, system is optimized by hybrid algorithm that combines the back-propagation and least square method.

4.1 ANFIS Architecture

The ANFIS is basically has five layered arch used in this research as shown in Fig 1. In architecture circle represents a fixed node and a square represents an adaptive node. ANFIS analyzed the first-order Takagi Sugeno type fuzzy inference system. In this research, the analysis has seven inputs: Age(I_1), BP(I_2), BMI(I_3), HR(I_4), DBT(I_5), PA(I_6), Genetics(I_7) and output is ROH(z).

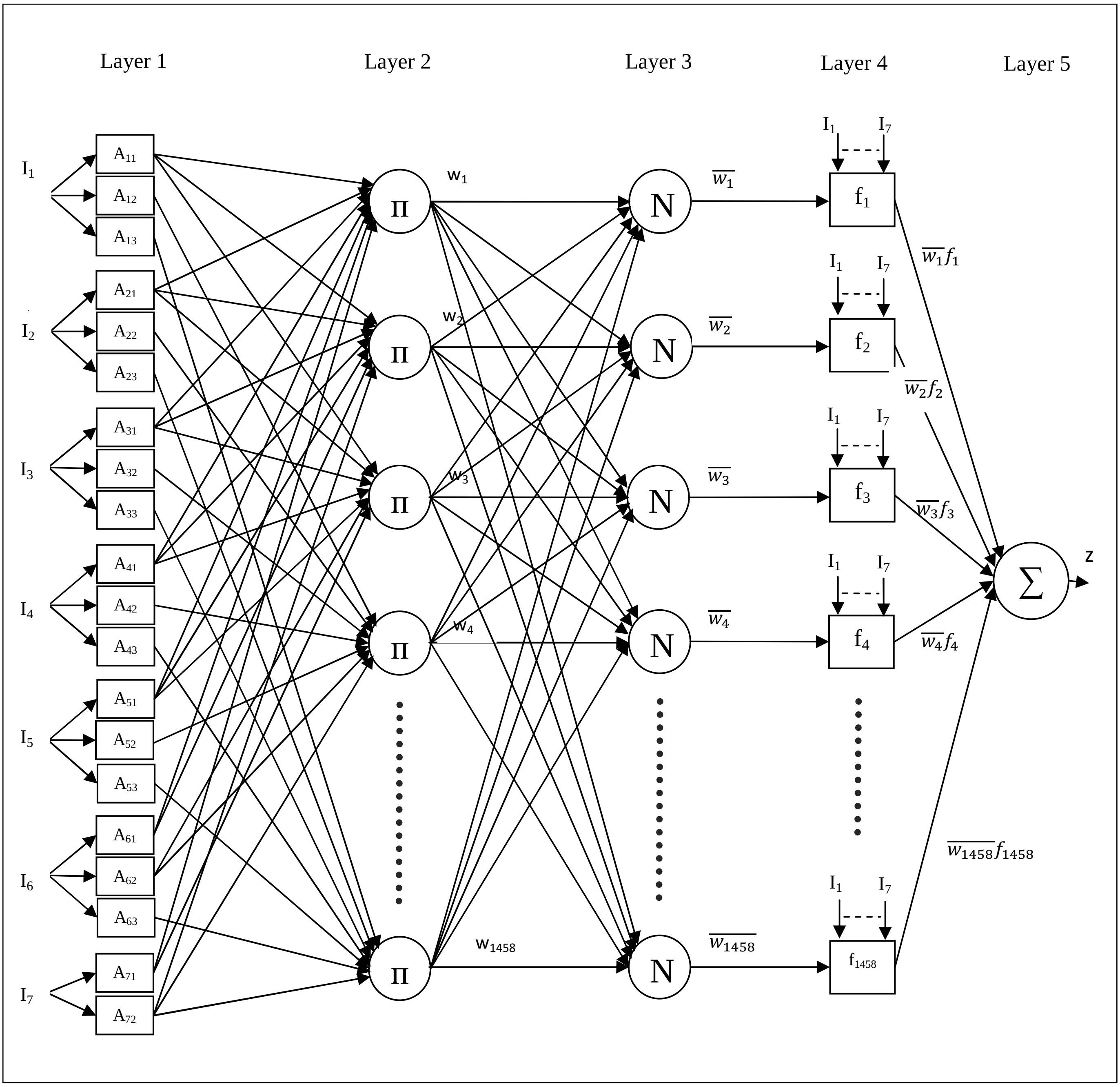

Fig. 1: Proposed ANFIS Architecture

4.1.1 Layer 1 (Fuzzification Layer)

In this layer of architecture, input fuzzification performed and all nodes are adaptive nodes. It means the each crisp input values is assigned a membership function to each fuzzy subset. The every node output is the fuzzy MF of each input node is given by equations:

$$O_{ij}^{(1)} = \mu_{A_{ij}}(I_i)$$

$$j = \begin{cases} 1,2,3 & for\ i = 1,2,\ldots.6 \\ 1,2 & for\ i = 7 \end{cases}$$

Where, $O_{ij}^{(1)}$ is layer 1 node's output which associated to the j^{th} linguistic value of the i^{th} input variable I_i. A_{ij} is the linguistic label (low, medium & high) of the i^{th} input node.

In this research, triangular-shaped of MF $\mu_{A_{ij}}$ for every inputs are used:

$$\mu_{A_{ij}}(I_i) = max\left(min\left(\frac{I_i - a_{ij}}{b_{ij} - a_{ij}}, \frac{c_{ij} - I_i}{c_{ij} - b_{ij}}\right), 0\right)$$

Where, $i = 1,2 \ldots.7$ Input variable

$j = 1, \ldots.$. Num Input Linguistic values

(a_{ij}, b_{ij}, c_{ij}) are referred to as premise parameters.

The parameter a_{ij} & c_{ij} represents the 'feet' of triangle and parameter b_{ij} represents the peak of triangle.

4.1.2 Layer 2 (Rule Layer)

This layer of ANFIS represents fixed nodes labeled with algebraic product"Π". Each node in this layer deals with $\mathrm{T} - norm\ operator$ that performs fuzzy-AND operation to obtain the firing strength(w_k). Node's output give results of being product of all its incoming inputs and every input node value is connected to that rule node. $O_k^{(2)}$ is the output given as:

$$O_k^{(2)} = w_k = \prod_{i=1}^{7inputs} \mu_{A_{ij}}(I_i)$$

for all j connected to k^{th} rule node.

Where, j= Input Linguistic term

$k = 1,2, \ldots \ldots \ldots 1458(Num\ Rules)$

A_{ij} = Linguistic label of the i^{th} input node

The output of every node represents the firing strength of corresponding fuzzy rule.

n^{th} Rule of firing strength is evaluated as:

$$w_n = A_{1j}(I_1) \times A_{2j}(I_2) \times \ldots \ldots \ldots \ldots . A_{7j}(I_7)$$

4.1.3 Layer 3 (Normalization Layer)

This layer of ANFIS contains the fixed nodes labeled with"N", that specify a normalization function to the firing strength of rules from previous layer. The k^{th} node output calculates the ratio of corresponding rule's firing strength to the sum of activation values of all rule's firing strength. This layer result in normalization of activation value obtained by equation:

$$O_k^{(3)} = \overline{w_k} = \frac{w_k}{\sum_{k=1}^{NumRules} w_k}$$

Where, $k = 1,2, \ldots \ldots..1458\ Num\ Rules$

w_k = Firing strength from layer 2

4.1.4 Layer 4 (Defuzzification Layer)

This layer of ANFIS contains all nodes are adaptive nodes. The output of each node k in this layer is accompanied by product of normalized firing strength and a first order polynomial. The output of this layer obtained by equation:

$$O_k^{(4)} = \overline{w_k} f_k = \overline{w_k}\left(\sum_{i=1}^{7} p_{ik} I_i + q_k\right)$$

Where, $k = 1,2, \ldots \ldots 1458\ Num\ Rules$

$\overline{w_k}$ = Normalized activation value from layer 3.

p_{ik} & q_k = consequent parameters of system and adjusted by hybrid algorithm.

4.1.5 Layer 5(Summation Layer)

This layer contains single fixed node labeled with $\sum$ that summation of all incoming signal to computes the overall output of system is expressed as:

$$O^{(5)} = \sum_{k=1}^{NumRules} \overline{w_k} f_k = \frac{\sum_{k=1}^{NumRules} w_k f_k}{\sum_{k=1}^{NumRules} w_k}$$

4.2 ANFIS Hybrid Learning Algorithm

In this paper, ANFIS parameters are adjusted by using a hybrid learning algorithm. The hybrid algorithm is combination of least-square method and the back-propagation gradient descent method for training the MF to follow a specified training dataset. In ANFIS the adaptive parameters split into premise parameters in layer 1 and consequent parameters in layer 4. The final output of network is

$$z = \sum_{k=1}^{NumRules} \overline{w_k} \left(\sum_{i=1}^{7} p_{ik} I_i + q_k \right)$$

Therefore, their computation in forward pass of hybrid the node output values go forward to layer 4 and consequent parameters identifies by least-square method. Also, in backward pass, the error propagates back and the premise parameters are adjusted by gradient descent.

V. PROPOSED METHODOLOGY

ANFIS is intelligent system that combines knowledge, techniques and methodologies from various sources also solution of function approximation problems. For development of ANFIS model, the criterion is chosen shown in Table 1

Table 1: ANFIS-based modeling standard

S.No.	Custom ANFIS	Variables
1	Number of Training data	412 records
2	Number of Testing data	138 records
3	Generate FIS	Grid Partition
4	Inputs	Age, BP, BMI, HR, PA, DBT and GEN
5	Membership function type	Triangular shaped membership function
6	Number of Membership function	Three(1st six inputs) and two for 7th input
7	Learning algorithm	Hybrid learning algorithm
8	Number of Epochs	10 then increased to 40 and 100
9	Sugeno type-system	First order
10	Hybrid learning algorithm	Least-square method and Back- propagation gradient descent method

In Table 1 criterion adapted to system give minimize the error measure and enhanced performance. Training and Testing dataset used for development the system. The testing data set known as validation set used to test the output of trained FIS to ensure the accuracy and to check the total number of cases provided true results and having false results.

The 4 steps required for designing of ANFIS model can be shown as follows:

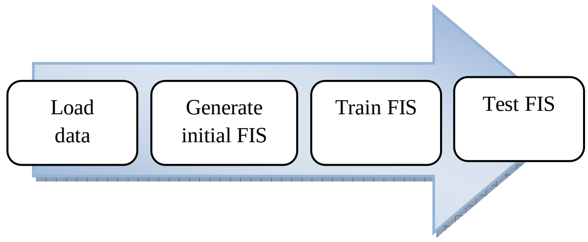

Fig. 2: ANFIS modeling Steps

5.1 Load Input/output Data

ANFIS modeling process starts by obtaining a data set and two different data types for loading to system that includes training and testing data sets. In this study, dataset contains the 550 records out of which 75% data set were used for the design of ANFIS structure's training and remaining 25% data set used for testing accuracy of the trained system.

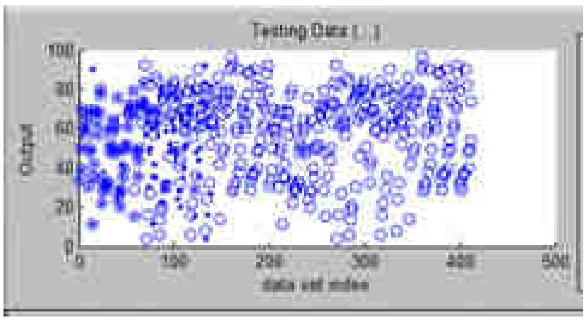

Fig. 3: Loaded training and testing data set into ANFIS

5.2 Generate an Initial FIS Structure

In this paper system uses Grid Partition method for generation of FIS. The main advantage of using the grid partition in FIS is block by dimensions curse, means when we increase the number of input variables then number of rules also increases. Assume an example, if there are n input variables having m MF of each input variable, then total number of rules is m^n also presents the connection among inputs with output. Generate FIS presents a black box diagram contains three different interfaces: inputs (patient’s symptoms), fuzzy inference engine and output (diagnosis the risk of hypertension).

ISSN: 2349-6495

Each input having their different number of membership function (MF), two sets of MF defined having Linguistic values in this system. The first set, having three number of MF for inputs (Age, BP, BMI, HR, DBT and PA) also its Linguistic values defined as Low, Middle & High and the second set has two number of MF for last input (Genetics) also its Linguistic values defined as Yes or No.

5.3 Train FIS

In this paper, we use a hybrid learning algorithm that combines the Least-square method and Back- propagation gradient descent method for training the generated FIS. Training is done to adjust the MF parameters of generated FIS and achieved Root Mean Square Error. Through the hybrid learning algorithm, training process is done by selecting the number of iterations. Different number of epochs in system performed in order to achieve the lower training error. Training error records the RMSE of the training data set at each epoch. This system, training is started with 10 epochs also error tolerance sets to zero.

Training error occur during the training of ANFIS is 0.0010369 at 10 number of epochs.

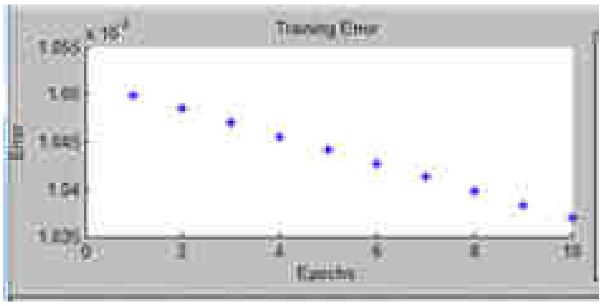

Fig. 4: ANFIS at 10 epochs

System is then trained by increases epochs to 40 and then increased to 100. Training error occur during the training of ANFIS is 0.00099495 and 0.00090773 at 40 and 100 epochs. System training process is a stop when the error goal is achieved with maximum epoch number is reached.

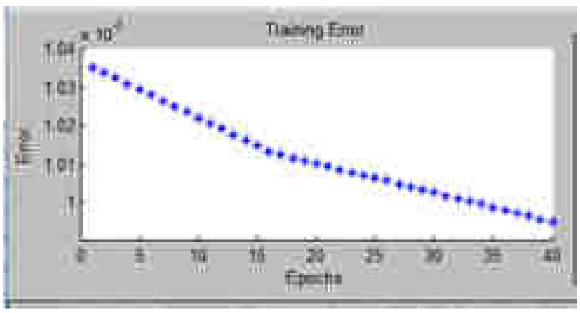

Fig. 5: ANFIS at 40 epochs

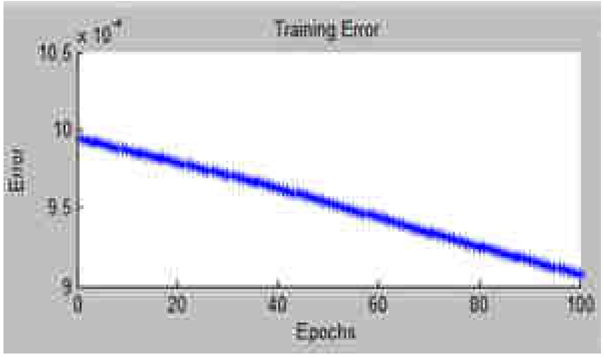

Fig. 6: ANFIS at 100 epochs

It can be seen that while increasing the total number of epochs, training error is reduced because ANFIS adapts itself. Table 2 shows the error rate while increasing the total number of epochs.

Table 2: Error Rate at Different Epochs

Total number of epochs	Training error rate
10	0.0010369
40	0.00099495
100	0.00090773

5.4 Test FIS

After the training process of FIS, validate the model means test the FIS output to ensure the accuracy using a testing data set that is not the part of training data set. In proposed ANFIS model, the average testing error of trained ANFIS is 0.913 and represents in following Fig 7.

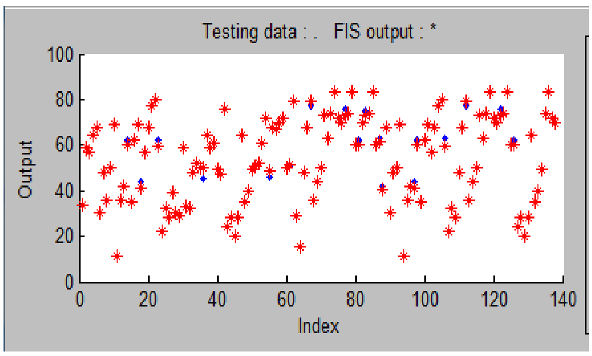

Fig. 7: ANFIS model Testing with Testing data

The rule viewer after ANFIS Training for evaluating the output risk of hypertension.

ISSN: 2349-6495

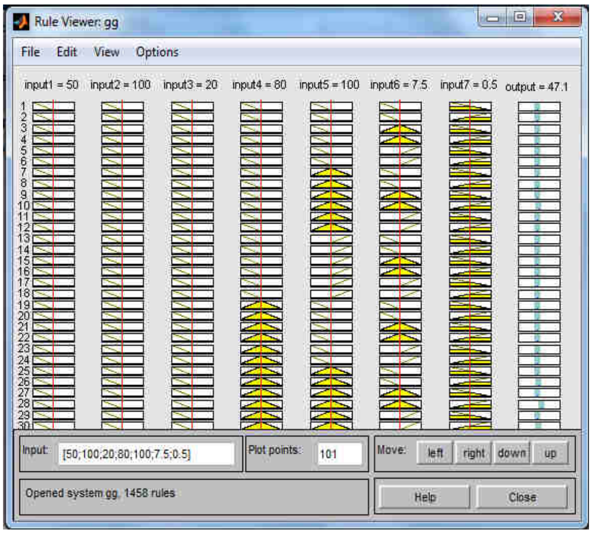

Fig. 8: Result viewer after ANFIS Training

The 3-D surface generated by the designed ANFIS model shown in Fig 9 represents the relationship between inputs and output acquired by the system. Fig 9 illustrates the relationship between the two inputs and output is risk of hypertension.

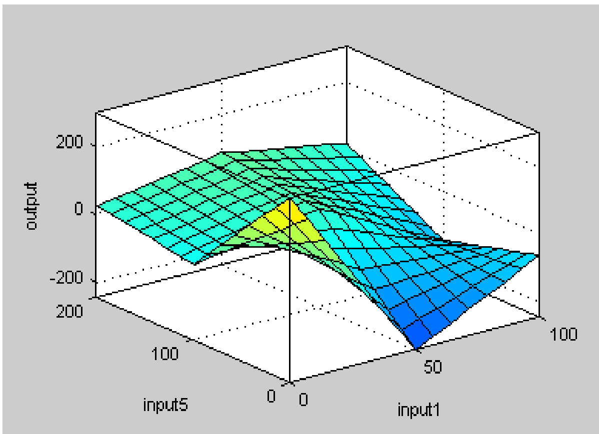

Fig. 9: Surface view after ANFIS Training

VI. RESULTS AND DISCUSSION

6.1 Performance Evaluation

The valuation consists of comparing the predicted risk output by the system with collected physician's judgment. The evaluation metrics used to compare the performance of proposed system.

Specificity: It denotes the percentage of normal patients correctly classified by the system. Specificity is defined as:

$$Specificity = \frac{TN}{TN + FP}\%$$

Precision: It denotes the proportion of true positives against all the positive results (diagnostic tests i.e. true positives and false positives). It is also known as Positive Predictive value (PPV). It is defined as:

$$Precision = \frac{TP}{TP + FP}\%$$

True positive (TP): It represents the number of abnormal (hypertensive) patients classified correctly by the system.

True negative (TN): It represents the number of normal (non- hypertensive) patients classified correctly by the system.

False Positive (FP): It represents the number of normal patients wrongly classified as abnormal patients by the system.

6.2 Comparative Analysis and Simulation Results

The proposed ANFIS system compared with existing Fuzzy expert system for diagnosis of hypertension with the help of performance parameters: Specificity and Precision.

For testing the performance of the model, we have to test some hypertension patient's cases by comparing the predicted risk output by the system with collected physician's judgment on the same test case.

For estimate the performance of the model we have to use confusion matrix. Confusion matrix will summarize the classification results for testing the system and was attained to determine the specificity and precision. In this study, hypertension risk has three class classifier i.e. Low risk (considered as normal patients); medium and high risk (both considered as abnormal patients) which classification given by physician during survey.

Table 3: Confusion matrix using ANFIS

ANFIS based prediction		Predicted Class		
		Low (Normal)	**Medium**	**High**
Actual Class	**Low (Normal)**	42	3	0
	Medium	3	65	2
	High	1	2	87

ISSN: 2349-6495

Table 3 shows the confusion matrix using proposed Adaptive Neuro-fuzzy inference system. The entries in the matrix has the meaning: total 205 diagnosed patient's cases tested on the system, row first has 45 patient's cases are categorized as hypertension risk factor is low out of which 42 cases truly categorized and 3 cases wrongly categorized as medium risk by the system which is closer to the physician judgments. The second row, total 70 diagnosed cases, 65 patient's cases are truly categorized as medium risk factor of hypertension and 3 & 2 cases wrongly categorized as low & high risk resp. Similarly, third row, total 90 diagnosed cases, 87 cases are categorized as high risk and 1 & 2 cases wrongly categorized as low & medium risk resp.

Table 4: Comparison results for proposed method and existing method

Comparison Results		Performance Parameters	
		Specificity	Precision
Models	Proposed ANFIS	93.33%	98.11%
	FES	91.11%	97.40%

Table 4 shows the comparison table of performance parameters for proposed Adaptive Neuro-Fuzzy Inference System (ANFIS) model and existing Fuzzy expert system (FIS) for diagnosis of hypertension.

There are two performance parameters used to compare these models i.e. Specificity and Precision. In this research, proposed model shows the value of specificity and precision is higher from existing model for diagnose of hypertension. The Specificity and Precision of proposed model is 93.33% and 98.11%. So, it is proved that the proposed Adaptive Neuro-Fuzzy Inference System method has better performance than the existing Fuzzy Expert System.

The following figure shows the comparison graph of performance parameter Specificity between proposed and existing model. Along x-axis the models are represented and along y-axis the performance are represented.

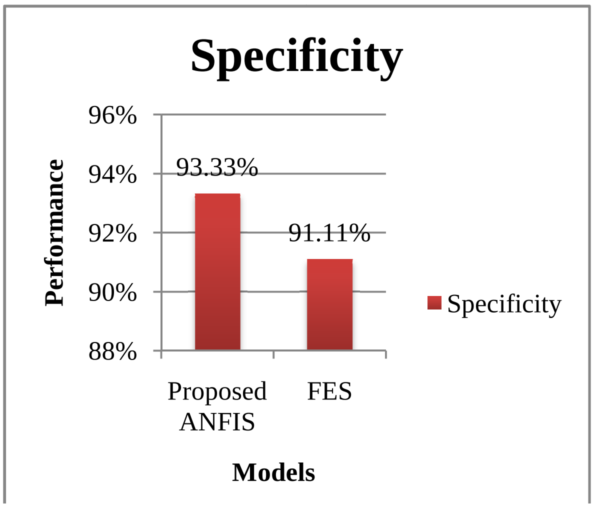

Fig. 10: Comparison graph of performance parameter Specificity

The following figure shows the comparison graph of performance parameter Precision between proposed and existing model.

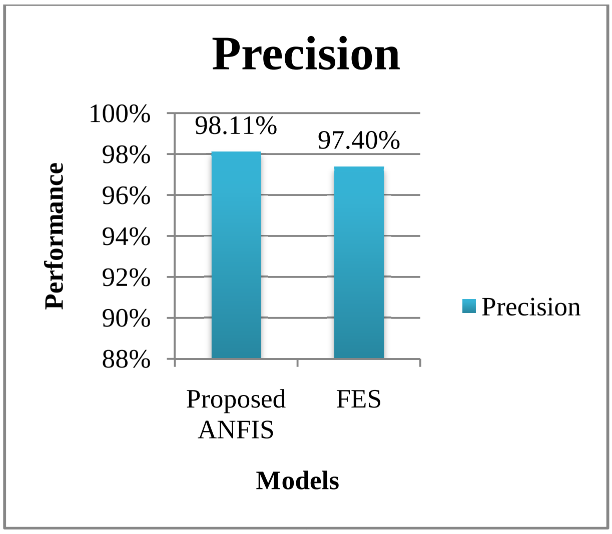

Fig. 11: Comparison graph of performance parameter Precision

VII. CONCLUSION

It may be concluded from this research for diagnosis of hypertension; the outcome achieved from proposed ANFIS model has more efficient as compared to fuzzy expert system. Nowadays the advancements in computer science giving new technologies in the fields of medical area though there are various existing problems like diagnosis of many diseases deals with real time information which have not been fully solved till now. The proposed ANFIS technique deals with diagnosis of hypertension with collecting patient's data from physician. ANFIS model is designed for successfully diagnosis estimation is depending upon the patients data collected under the supervision of physician. The proposed ANFIS has been simulated using the performance parameters. Simulation results shows that the proposed technique shows a better outcome then existing fuzzy expert system. Our proposed technique has a significant improvement over the existing system in terms of Specificity and Precision due to deal with real and large number of knowledge base. Hence, it is proved that proposed method give highest value of Specificity and Precision as compared to Fuzzy expert system.

ACKNOWLEDGEMENTS

The authors are deeply thankful to the Department of Computer Science and Engineering, D.A.V Institute of Engineering and Technology, Jalandhar for providing excellent lab facilities that make this work possible

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