Generating Rules for Advanced Fuzzy Resolution Mechanism to Diagnosis Heart Disease

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ABSTRACT
Fuzzy logic plays an important role in the field of medicine. Many diseases are diagnosed using fuzzy logic. Heart disease is the number one killer to the human community throughout the world. This study was conducted to diagnosis the heart disease among the patients. The components of this study are Fuzzification, Generating rules for Advanced Fuzzy Resolution Mechanism and defuzzification. Crisp values are transformed into fuzzy values through the fuzzification. Generating rules for Advanced Fuzzy Resolution Mechanism has five layers, each layer has its own nodes. In layer 1 rule are generated with the data to frame the new rules and output parameter are predicted. The proposed algorithm is tested with Cleveland heart disease dataset. Generating rules for Advanced Fuzzy Resolution Mechanism was developed using MATLAB Fuzzy Logic Tool Box. Transformation of fuzzy set into crisp values is called Defuzzification. The proposed algorithm can work more efficiently to diagnosis heart disease and also compared with earlier method using accuracy as metrics.

Keywords
Generating rules for Advanced Fuzzy Resolution Mechanism, Rules, fuzzy predicted value, Heart disease

1. INTRODUCTION
In Generating rules for Advanced Fuzzy Resolution Mechanism there are number layers with nodes which are connected through links. The Generating rules for Advanced Fuzzy Resolution Mechanism designed with predictive values and if then rules are generated to diagnosis the heart disease.

Detlef Nauck et al.[6] discussed a neuro-fuzzy approach, were learning strategies are used to derive rules from data and results are achieved. Harsh Bhasin and Supreet Singh[10] used genetic algorithms to generate rules in expert system. The rules are generated using correlation coefficient, results are analyzed and it is encouraging. Humar Kahramanli et al.[11] A hybrid model was developed using artificial neural network and fuzzy neural network for diagnosis of diabetes and heart diseases. Li-Xin Wang [14] developed a new method to generate fuzzy rules from the numerical data for time series prediction problem. J-S.R Jang[12] designed fuzzy inference system using adaptive neuro-fuzzy inference system and NN. Mohamad forouzanfar et al.[16] to estimate blood pressure adaptive neuro fuzzy inference system was developed. Min Liu et al. [19] a new ANFIS was designed to predict the parameter of numeric and categorical inputs. Min-You Chen and D.A. Linkens[20] designed a fuzzy rule based model from the numerical data. In this model the fuzzy rules are extracted from the data. The method derived helps to remove the redundant fuzzy rules from the model. Mukhopadhyay et al.[21] accuracy rates are given as 83.04% and 84.04% for SVM and GSVM, respectively with Cleveland heart disease database using a new learning model called Granular support vector machines. Robert J. Hammell II[22] developed a fuzzy model, fuzzy rule are derived through training data set. The research presents the architecture of fuzzy model and inference that learns the rule from training dataset. Tarig Faisal et al.[23] designed an Adaptive Neuro-Fuzzy Inference System using subtractive clustering technique to diagnosis dengue patients.

The configuration of this paper is as follows: Section 2 deals with the Adaptive Neuro-Fuzzy Inference System for Heart Disease. The experimental results, implemented in MATLAB fuzzy logic toolbox are presented in Section 3 and experimental result indicates that the proposed Generating rules for Advanced Fuzzy Resolution Mechanism can work more effectively than other methods can [1],[2][3] [7], [9] and [11]in section 4.

2. DESIGN OF ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM (ANFIS) FOR HEART DISEASE
This section describes a Fuzzification, Generating rules for Advanced Fuzzy Resolution Mechanism and Defuzzification as shown in figure 1.

2.1. Cleveland heart disease dataset
To test the ANFIS Cleveland dataset is taken. The Cleveland dataset is retrieved from http://archive.ics.uci.edu/ml and it contains the collected personal data. Table 1 lists the attributes of Cleveland dataset

2.2. Fuzzification
Crisp input values are transferred into fuzzy values in the stage of fuzzification [18]. The Fuzzy values are taken into the Generating rules for Advanced Fuzzy Resolution Mechanism.

Table 1. Attributes of Cleveland dataset

Abbreviation	Full name
age	age in years
sex	sex (1 = male; 0 = female)
cp	chest pain type
trestbps	resting blood pressure (in mm Hg)
chol	serum cholestoral in mg/dl
fbs	fasting blood sugar > 120 mg/dl
restecg	resting electrocardiographic results
thalach	maximum heart rate achieved
exang	exercise induced angina
oldpeak	ST depression induced by exercise
slope	the slope of the peak exercise ST segment
ca	number of major vessels
thal	3 = normal; 6 = fixed defect; 7 = reversable defect
num the predicted attribute	diagnosis of heart disease (angiographic disease status)

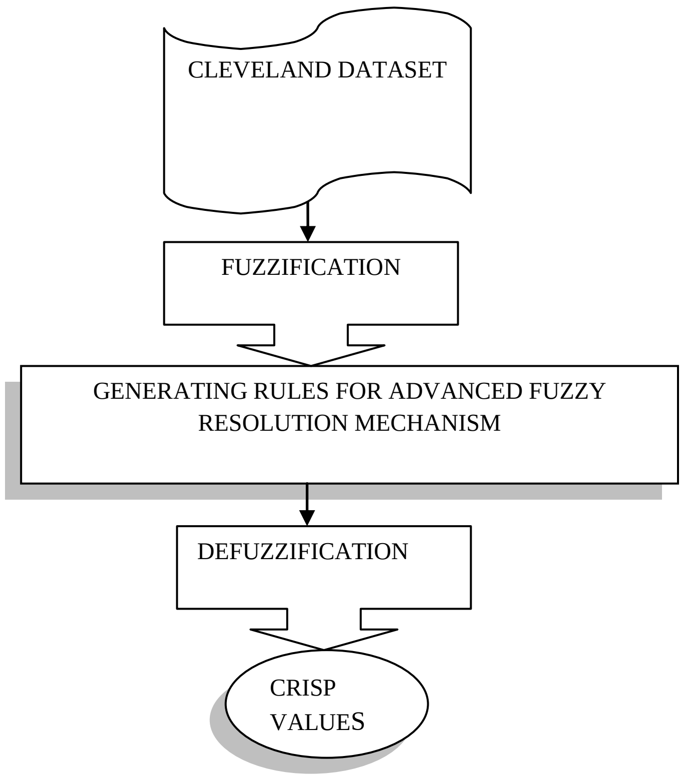

Fig 1: Architecture of Adaptive Neuro-Fuzzy Inference System for Heart Disease

2.3. An Overview of Generating rules for Advanced Fuzzy Resolution Mechanism for Heart Disease

Input variables for Generating rules for Advanced Fuzzy Resolution Mechanism are taken from Cleveland dataset. Fourteen variables such as age, sex, cp, trestbps, chol, fbs, restecg, thalach, exang, oldpeak, slope, ca, thal are selected as the input variables and num as output variable.

The first layer uses Sugeno fuzzy model, the output in this model is predicted by fuzzy predicted values. The membership function, fuzzy predicted values; generating if then rules are computed from the Cleveland dataset. The Architecture of the Generating rules for Advanced Fuzzy Resolution Mechanism using ANFIS is shown in figure 2. The parameters are fixed by represented the circular nodes whereas parameters which are to be learnt are represented by square nodes. The fuzzy variables are represented in Table 2.

Layer 1

In Layer 1 the node function is the membership of fuzzy set with its related input. Rule based structure is given by first order sugeno fuzzy model [4]. The fuzzy if then rules have input variables, membership function and output variable which are generated from the numerical data. The parameters are determined by Gaussian membership function[17].

$$O_i^{1,3} = \mu_{cp}(x) = e^{-\frac{1}{2}\left(\frac{x-c_i^1}{\sigma_i^1}\right)^2} \qquad (3)$$

where c and σ represent the membership function center and width respectively in order to determine coordinates of Gaussian membership function.

Table 2. Representation of Fuzzy variables

Fuzzy variables	Representation of Fuzzy Variables
age	x1
sex	x2
cp	x3
trestbps	x4
chol	x5
fbs	x6
restecg	x7
thalach	x8
exang	x9
oldpeak	x10
slope	x11
ca	x12
thal	x13
num the predicted attribute	y

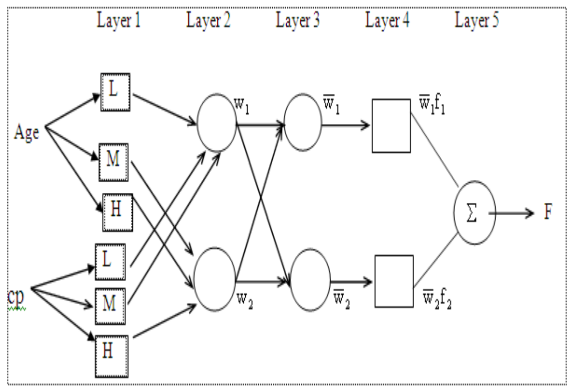

Fig 2: Architecture of the Generating rules for Advanced Fuzzy Resolution Mechanism

Generating rules using numerical data

Step 1: The number of data in the database = 191

Step 2: Calculate the number of attributes = 14

Step 3: Total number of rules

= Calculate the number of data in the database

Calculate the number of attributes.

= 191

-------- = 14 (approximately)

14

Step 4: Data are sorted according to age and given in Table 3.

Step 5: The maximum value are calculated for each variable.

Step 6: The fuzzy numbers in Table 3 forms the antecedents and consequent part of the rule.

Step 7: Rule 1 is framed as

If (x1 is young) or (x2 is male) or (x3 is high) or (x4 is high) or (x5 is medium) or (x6 is low) or (x7 is high) or (x8 is high) or (x9 is high) or (x10 is high) or (x11 is low) or (x12 is high) or (x13 is high) then (y is high)

Step 8: To frame the next rule, the next 14 data are taken, the step 4, 5 are repeated and generated rules are shown in figure 3

Output variable are determined by predicted fuzzy values for sugeno fuzzy model.Predicted fuzzy values are determined with mean and maximum values for the input and the output variables. The number of attributes for used in predicted fuzzy values is thirteen.

Output variable is predicted using the linear equation
y=a1x1+ a2x2+ a3x3+ a4x4+ a5x5+ a6x6+ a7x7+ a8x8+ a9x9+ a10x10+ a11x11+ a12x12+ a13x13+c
Parameter is predicted for linear equation using the formula

{(mean(y) / Max(xi))+(mean (y) / mean (xi))}
ai= --- i=1 to 13
mean (y)*no. of attributes

The predicted fuzzy values and generated rules are used in ANFIS method to diagnosis heart disease.

Layer 2

To calculate the firing strength of the rule, nodes are fixed.to T-norm operator with AND operator [19]. The output is derived by the product of all incoming values. Inputs from the nodes in the Layer 1 are multiplied with Layer 2 and the firing strength of the rules is generated. The output of the Layer 2 is given by

$$w_i = \mu_{Age}(x)\mu_{sex}(y)\mu_{cp}(z)\mu_{trestbps}(a)\mu_{chol}(b)\mu_{fbs}(c)\mu_{restecg}(d)\mu_{thalach}(e)\mu_{exang}(f)\mu_{oldpeak}(g)\mu_{slope}(h)\mu_{thal}(j) \quad i=1,2$$

Where w_i is the firing strength of rule i.

Layer 3

In this layer nodes calculates the weight, which are normalized. The ith node calculates the portion of the ith rules firing strength to the sum of all rules firing strengths.

$$= \overline{w}_i = \frac{w_i}{\sum_{i=1}^{m} w_i}$$

where the output are called normalized firing strengths is of this layer.

Layer 4

The output of this layer is given with the linear combination of input multiplied by the normalized firing strength. The consequent of the rules are performed in this layer.

$$\overline{w}_i f_i = \overline{w}_i(age_i x + sex_i y + cp_i z + trestbps_i a + chol_i b + fbs_i c + restecg_i d + thalach_i e + exang_i f + oldpeak_i g + slope_i h + ca_i i + thal_i j + t_i)$$

where $\overline{w}_i$ is a normalized firing strength from layer 3 and $\{Age_i, sex_i, cp_i, trestbps_i, chol_i, fbs_i, restecg_i, thalach_i, exang_i, oldpeak_i, slope_i, ca_i, thal_i, t_i\}$ are the parameter set of this node.

Layer 5

This layer is the simple summation of overall output.

$$\sum_i \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}$$

The input is fed through layer by layer.

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Table 3. Numerical data to generate Rule 1

x1	x2	x3	x4	x5	x6	x7	x8	x9	x10	x11	x12	x13	y
34	0	2	118	210	0	0	192	0	0.7	1	0	3	0
35	1	2	122	192	0	0	174	0	0	1	0	3	0
37	1	3	130	250	0	0	187	0	3.5	3	0	3	0
37	0	3	120	215	0	0	170	0	0	1	0	3	0
38	1	1	120	231	0	0	182	1	3.8	2	0	7	4
39	0	3	94	199	0	0	179	0	0	1	0	3	0
39	0	3	138	220	0	0	152	0	0	2	0	3	0
40	1	4	110	167	0	2	114	1	2	2	0	7	3
40	1	1	140	199	0	0	178	1	1.4	1	0	7	0
40	1	4	152	223	0	0	181	0	0	1	0	7	1
41	0	2	130	204	0	2	172	0	1.4	1	0	3	0
41	0	2	105	198	0	0	168	0	0	1	1	3	0
41	1	4	110	172	0	2	158	0	0	1	0	7	1
41	1	3	112	250	0	0	179	0	0	1	0	3	0
Maximum values for the fuzzy variables													
41	**1**	**4**	**152**	**250**	**0**	**2**	**192**	**1**	**3.8**	**3**	**1**	**7**	**4**
young	**male**	**high**	**high**	**medium**	**low**	**high**	**high**	**high**	**high**	**high**	**low**	**high**	**high**

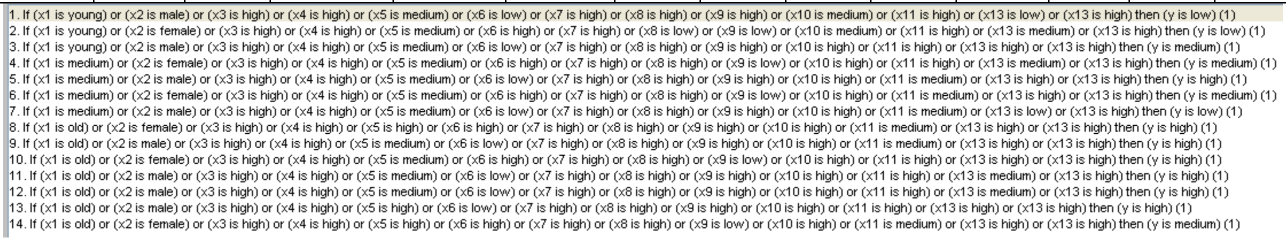
1. If (x1 is young) or (x2 is male) or (x3 is high) or (x4 is high) or (x5 is medium) or (x6 is low) or (x7 is high) or (x8 is high) or (x9 is high) or (x10 is medium) or (x11 is high) or (x13 is low) or (x13 is high) then (y is low) (1)
2. If (x1 is young) or (x2 is female) or (x3 is high) or (x4 is high) or (x5 is medium) or (x6 is high) or (x7 is high) or (x8 is low) or (x9 is low) or (x10 is medium) or (x11 is high) or (x13 is medium) or (x13 is high) then (y is low) (1)
3. If (x1 is young) or (x2 is male) or (x3 is high) or (x4 is high) or (x5 is medium) or (x6 is low) or (x7 is high) or (x8 is high) or (x9 is high) or (x10 is high) or (x11 is high) or (x13 is high) or (x13 is high) then (y is medium) (1)
4. If (x1 is medium) or (x2 is female) or (x3 is high) or (x4 is high) or (x5 is medium) or (x6 is high) or (x7 is high) or (x8 is high) or (x9 is low) or (x10 is high) or (x11 is high) or (x13 is medium) or (x13 is high) then (y is medium) (1)
5. If (x1 is medium) or (x2 is male) or (x3 is high) or (x4 is high) or (x5 is medium) or (x6 is low) or (x7 is high) or (x8 is high) or (x9 is high) or (x10 is high) or (x11 is medium) or (x13 is high) or (x13 is high) then (y is high) (1)
6. If (x1 is medium) or (x2 is female) or (x3 is high) or (x4 is high) or (x5 is medium) or (x6 is high) or (x7 is high) or (x8 is high) or (x9 is low) or (x10 is high) or (x11 is medium) or (x13 is high) or (x13 is high) then (y is medium) (1)
7. If (x1 is medium) or (x2 is male) or (x3 is high) or (x4 is high) or (x5 is medium) or (x6 is low) or (x7 is high) or (x8 is high) or (x9 is high) or (x10 is high) or (x11 is medium) or (x13 is low) or (x13 is high) then (y is low) (1)
8. If (x1 is old) or (x2 is female) or (x3 is high) or (x4 is high) or (x5 is high) or (x6 is high) or (x7 is high) or (x8 is high) or (x9 is high) or (x10 is high) or (x11 is medium) or (x13 is high) or (x13 is high) then (y is high) (1)
9. If (x1 is old) or (x2 is male) or (x3 is high) or (x4 is high) or (x5 is medium) or (x6 is low) or (x7 is high) or (x8 is high) or (x9 is high) or (x10 is high) or (x11 is medium) or (x13 is high) or (x13 is high) then (y is high) (1)
10. If (x1 is old) or (x2 is female) or (x3 is high) or (x4 is high) or (x5 is medium) or (x6 is high) or (x7 is high) or (x8 is high) or (x9 is low) or (x10 is high) or (x11 is high) or (x13 is high) or (x13 is high) then (y is high) (1)
11. If (x1 is old) or (x2 is male) or (x3 is high) or (x4 is high) or (x5 is medium) or (x6 is low) or (x7 is high) or (x8 is high) or (x9 is high) or (x10 is high) or (x11 is high) or (x13 is medium) or (x13 is high) then (y is high) (1)
12. If (x1 is old) or (x2 is male) or (x3 is high) or (x4 is high) or (x5 is medium) or (x6 is low) or (x7 is high) or (x8 is high) or (x9 is high) or (x10 is high) or (x11 is high) or (x13 is medium) or (x13 is high) then (y is high) (1)
13. If (x1 is old) or (x2 is male) or (x3 is high) or (x4 is high) or (x5 is high) or (x6 is low) or (x7 is high) or (x8 is high) or (x9 is high) or (x10 is high) or (x11 is high) or (x13 is high) or (x13 is high) then (y is high) (1)
14. If (x1 is old) or (x2 is female) or (x3 is high) or (x4 is high) or (x5 is high) or (x6 is high) or (x7 is high) or (x8 is high) or (x9 is low) or (x10 is high) or (x11 is medium) or (x13 is high) or (x13 is high) then (y is medium) (1)

Fig 3: Rule generated from numerical data

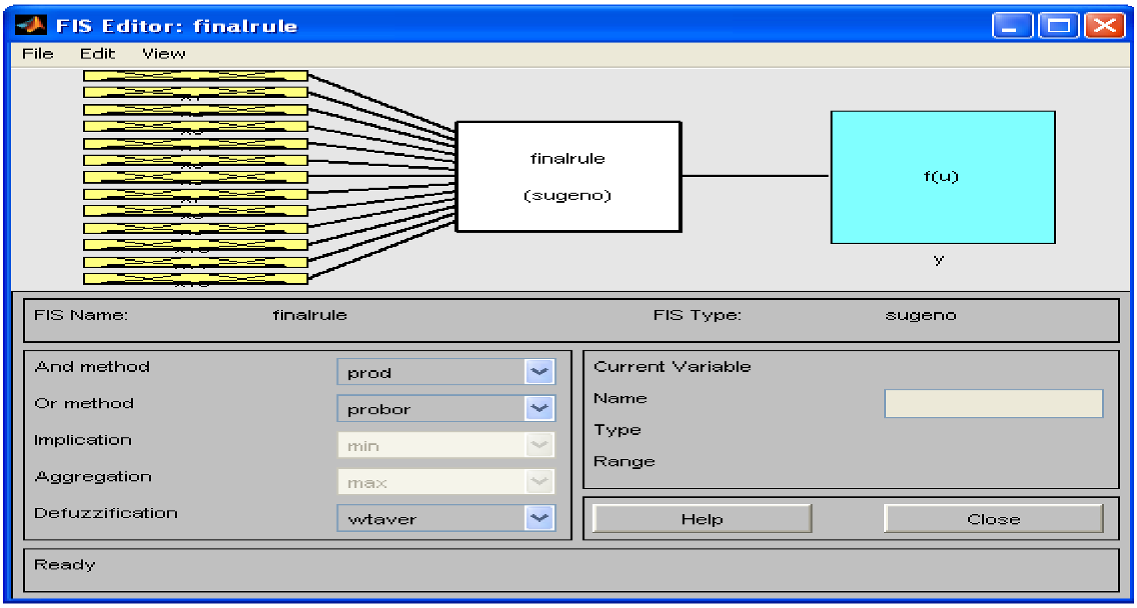

Fig 4: ANFIS modeling framework

Algorithm for Advanced Fuzzy Resolution Mechanism

Input

Input the fuzzy set are x1,x2,x3,x4,x5,x6,x7,x8,x9,x10,x11,x12,x13.

OUTPUT

Output the fuzzy set be y

Method

Begin

Step1:Input the crisp values for x1,x2,x3,x4,x5,x6,x7,x8,x9,x10,x11,x12,x13.

Step 2: Assign fuzzy numbers for the input each variables.

Step 3: Set Sugeno fuzzy model,

Step 4: Layer 1 Call (Generating Rules from numerical data)

Output variable is predicted using the linear equation

y=a1x1+ a2x2+ a3x3+ a4x4+ a5x5+ a6x6+ a7x7+ a8x8+ a9x9+ a10x10+ a11x11+ a12x12+ a13x13+c

Parameter is predicted for linear equation using the formula

{(mean(y) / Max(xi))+(mean (y) / mean (xi))}

ai= -- i=1 to 13

mean (y)*no. of attributes

Calculate the membership values using triangular membership function.

$$O_i^{1,1} = \mu_{age}(x),\ for i - 1,2,3$$
$$O_i^{1,2} = \mu_{sex}(x),\ for i - 1,2$$
$$O_i^{1,3} = \mu_{cp}(x),\ for i - 1,2,3$$
$$O_i^{1,4} = \mu_{trestbps}(x),\ for i - 1,2,3$$
$$O_i^{1,5} = \mu_{chol}(x),\ for i - 1,2,3$$
$$O_i^{1,6} = \mu_{fbs}(x),\ for i - 1,2$$
$$O_i^{1,7} = \mu_{restecg}(x),\ for i - 1,2,3$$
$$O_i^{1,8} = \mu_{thalach}(x),\ for i - 1,2,3$$
$$O_i^{1,9} = \mu_{exang}(x),\ for i - 1,2$$
$$O_i^{1,10} = \mu_{oldpeak}(x),\ for i - 1,2,3$$
$$O_i^{1,11} = \mu_{slope}(x),\ for i - 1,2,3$$
$$O_i^{1,12} = \mu_{ca}(x),\ for i - 1,2,3$$
$$O_i^{1,13} = \mu_{thal}(x),\ for i - 1,2,3$$

Where x is input to node and Age,sex.cp,trestbps,chol,fbs,restecg,thalach,exang,oldpeak,slope,ca and thal are label in this node.

Step 5: Layer 2 involves fuzzy operators, it uses AND operator to fuzzify the inputs. Layer 2, multiplies the inputs from the nodes in layer 1 and generates the firing strength of the rules.

Step 6: In Layer 3 the i[th] node calculates the portion of the i[th] rules firing strength to the sum of all rules firing strengths.

$$= \overline{w}_i = \frac{w_i}{\sum_{i=1}^{m} w_i}$$

Step 7: In Layer 4, the consequent of the rules are performed by the nodes in this layer.

Step 8: In layer 5 single node computes the overall output:

$$\sum_i \overline{w_i} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}$$

Step 9: Present the knowledge in the form of human natural language.

End

Generating Rules from numerical data

Step 1: Calculate the number of data in the database

Step 2: Calculate the number of attributes.

Step 3: Total number of rules to be framed

= Calculate the number of data in the database

Calculate the number of attributes.

Step 4: Sort the data with respect to age

Step 5: Take first 14 data to frame rule 1, next 14 for rule2 …. Last fourteen for rule 14

Step 6: In first fourteen data take maximum value of the input and output parameters.

Step 7: Set the value for each parameter with the fuzzy numbers.

Step 8: With the fuzzy numbers the rules are framed.

Step 9: Repeat the step 6, 7 and 8 to frame the rest of the rules

2.4. Defuzzification

To convert fuzzy values into crisp values defuzzification weighted average method is used. This process is to convert aggregation result into crisp values for the output variable num(y).

3. EXPERIMENTAL RESULTS

Generating rules for Advanced Fuzzy Resolution Mechanism was implemented with MATLAB Fuzzy Logic Toolbox. Cleveland dataset was taken to evaluate the performance of the proposed approach. ANFIS modeling framework to diagnosis heart disease is shown in figure 4. The first experiment shows the membership function for input variable cp(x3) in figure 5 and output variable num(y) in figure 6. The result of the proposed method is shown in Figure 7.

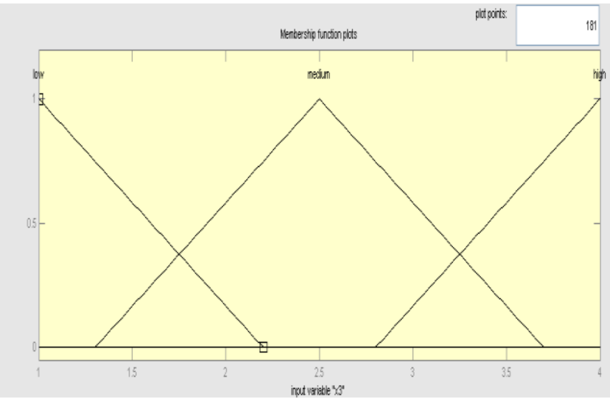

Fig 5: Membership function for input variable cp(x3)

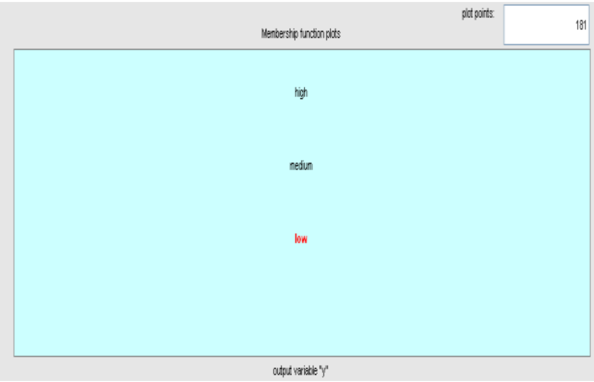

Fig 6: Membership function for output variable num(y)

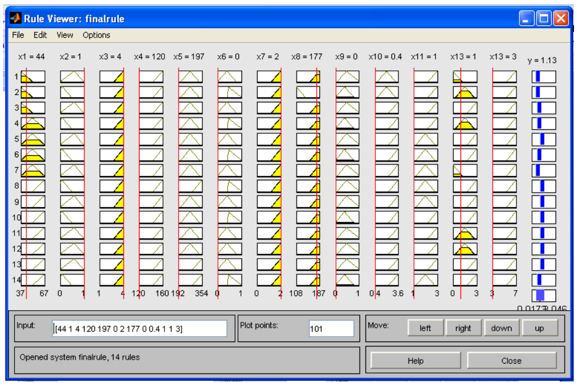

Fig 7: Result obtained from MATLAB

In proposed mechanism fuzzy predicted value technique and rules are used to diagnosis the heart disease. The decision regarding the presence of heart disease can be taken from the figure 7 about the status of angiographic disease.

4. EVALUATION OF SYSTEM PERFORMANCE

The performance of the system is evaluated in this stage. Accuracy is metrics used in medical diagnosis. The measure of ability to produce accurate heart diagnosis is determined by accuracy.

So that accuracy [15] is given by eqn. (4)

$$\text{Accuracy} = \frac{\text{Total number of correctly diagnosed cases}}{\text{Total number of cases}} \quad (4)$$

The experimental results are compared with earlier methods involving Cleveland heart disease dataset[1],[2][3] [7], [9] and [11]. Comparing these methods, as listed in Table 4, reveals that the proposed method achieves the first highest accuracy values based on the proposed Generating rules for Advanced Fuzzy Resolution Mechanism. The accuracy values of the proposed method are compared with the earlier methods and represented graphically figure 8, which shows better accuracy

Table 4. Comparison of Proposed method Accuracy with earlier methods

Method	Accuracy (%)	Author
Current study	94.11	Dr. A.V.Senthil Kumar
Diagnosis of heart disease using Advanced Fuzzy resolution Mechanism	93.88	Dr. A.V.Senthil Kumar
Adaptive Neuro-Fuzzy Inference System based on subtractive clustering to diagnosis the heart disease[3]	92.00	Dr. A.V.Senthil Kumar
Diagnosis Of Heart Disease Using Fuzzy Resolution[2] Mechanism	91.83	Dr. A.V.Senthil Kumar
Adaptive Neuro-Fuzzy Inference System for Heart Disease diagnosis [1]	91.18	Dr. A.V.Senthil Kumar
IncNet[13]	90	Norbert Jankowski
Hybrid system[11]	86.8	Humar Kahramanli and Novruz Allahverdi
26-NN, Manhattan, 1 feature removed[9]	86.8	WD/KG
24-NN, Manhattan[9]	84 .8	WD/KG
LDA [5]	84.5	Ster and Dobnikar
Fisher discriminant analysis [5]	84.2	Ster and Dobnika
FSM, 82.4–84% on test only[7]	84.0	Rafał Adamczak
Naive Bayes[5]	83.4	Ster, Dobnikar
7-NN[8]	83.2	Duch W, Grudzinski K and Diercksen G.H.F
k-NN, k=27, Manhattan[7]	82.8	Rafał Adamczak

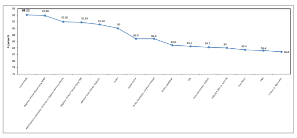

Fig 8: Graphical represent of accuracy

5. CONCLUSIONS AND FUTURE RESEARCH

Rules are generated for Advanced Fuzzy Resolution Mechanism to diagnosis the heart disease. In Cleveland heart disease dataset the values are crisp, converted into fuzzy values by fuzzification process. Generating rules for Advanced Fuzzy Resolution Mechanism has five layers. The rules are generated using numerical data and output variables for the fuzzy model are predicted using fuzzy predicted values to improve the accuracy of the result. The outputs from the Generating rules for Advanced Fuzzy Resolution Mechanism are fuzzy values. Defuzzification process converts fuzzy values into crisp values to known the angiographic disease status. The proposed method has better performance compared with the previous study to diagnosis heart disease. Future Research should test the other related data sets to evaluate its ability to produce a similar accuracy.

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