

Diagnosis of heart disease using Advanced Fuzzy resolution Mechanism

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ABSTRACT

Heart disease is a disorder that affects the heart, the number one killer of human community. To diagnosis the heart patients the study was conducted. The components of this study are Fuzzification, Advanced Fuzzy Resolution Mechanism and defuzzification. Crisp values are transferred into fuzzy values through the fuzzification. Advanced fuzzy resolution mechanism uses predicted value to diagnosis the heart disease with five layers, each layer has its own nodes. The proposed mechanism is tested with Cleveland heart disease dataset. Advanced Fuzzy Resolution Mechanism was developed using MATLAB. Defuzzification converts the fuzzy set into crisp values. The proposed method with predicted value technique can work more efficiently for diagnosis of heart disease and also compared with earlier method using accuracy as metrics.

Keywords: ANFIS, Advanced Fuzzy Resolution Mechanism, fuzzy predicted value, Heart disease

INTRODUCTION

In adaptive neuro fuzzy inference there are number of nodes connected through links. To handle the vagueness the fuzzy logic is used. The Advanced Fuzzy Resolution Mechanism designed with predictive value and if then rules to diagnosis the heart disease.

Roan, Chiang et al.[1] to represent the models in the real world the concept of fuzzy set is used. J-S.R Jang[2] used adaptive neuro-fuzzy inference system and NN approach is used to design fuzzy inference system. B. Kosko [3] neural network uses learning and adaptation that makes the fuzzy system less dependent on the knowledge of experts and can be used as universal approximator. Serpen et al.[4] neural network algorithm was developed with probabilistic potential function. Haykin [5], for non linear physiological system neural network and fuzzy logic approached are used. The most common classifier technique is artificial neural networks, the reason for being common is that it uses learning from examples and exhibits some generalized capability beyond the training dataset. Mukhopadhyay et al.[6]. Granular support vector machines is new learning model. accuracy rates given as 83.04% and 84.04% for SVM and GSVM, respectively with Cleveland heart disease database. Tang et al. [7], Humar Kahramanli et al.[9] used artificial neural network and fuzzy neural network to develop a hybrid system for diabetes and heart diseases. Min Liu et al. [10] to predict the parameter of numeric and categorical inputs new ANFIS was designed. Mohamad forouzanfar et al.[12] developed adaptive neuro fuzzy inference system to estimate blood pressure. Tarig Faisal et al.[21] to diagnosis dengue patients an Adaptive Neuro-Fuzzy Inference System was developed using subtractive clustering technique.

The Adaptive Neuro-Fuzzy Inference developed helps to solve many challenging task related to heart disease. The configuration of this paper is as follows: Section 2 deals with the Adaptive Neuro-Fuzzy Inference System for Heart Disease. The experimental rebuttals, implemented in MATLAB fuzzy logic toolbox are presented in Section 3 and experimental rebuttals indicates that the proposed Advanced Fuzzy Resolution Mechanism can work more effectively than other methods can [7], [9],[15],[23][24]in section 4.

ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM FOR HEART DISEASE

This section describes a Fuzzification, Advanced Fuzzy Resolution Mechanism and Defuzzification.

Cleveland heart disease dataset

Data are retrieved from Cleveland dataset. The experimental 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

Table 1: Attributes of Cleveland dataset

Abbreviation	Fullname
age	age in years
sex	sex (1 = male; 0 = female)
cp	chest pain type
trestbps	resting blood pressure (in mm Hg)
chol	serum cholestorol in mg/dl
lbs	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)

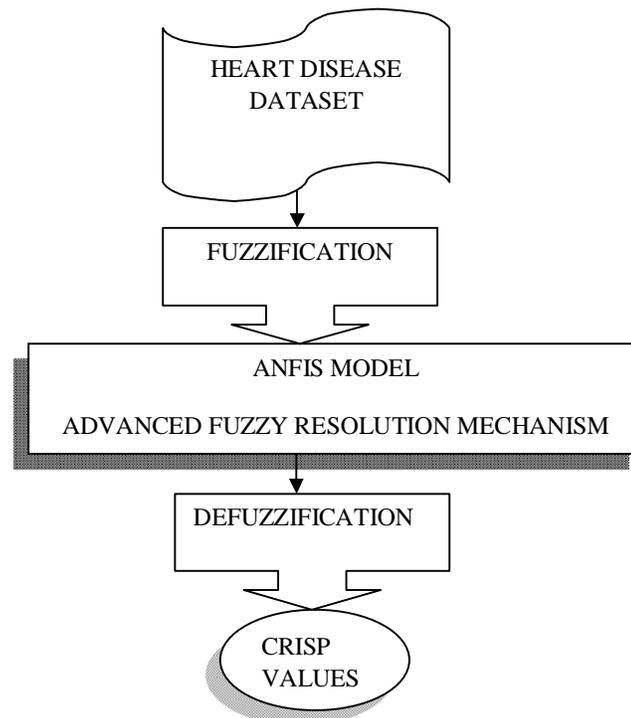


Figure 2: Architecture of Adaptive Neuro-Fuzzy Inference System for Heart Disease

Fuzzification

Crisp input values are transferred into fuzzy values is referred as fuzzification[13]. Uncertainty happens because of imprecision and vagueness, the variable may be fuzzy and represented by membership function.

Architecture of the Advanced Fuzzy Resolution Mechanism for Heart Disease

Input variable for Advanced Fuzzy Resolution Mechanism are taken from Cleveland dataset. Fourteen variable such as age, sex, cp, trestbps, chol, lbs, restecg, thalach, exang, oldpeak, slope, ca, thal are selected as the input variables and num as output variable. Advanced Fuzzy Resolution Mechanism uses fuzzy if then rules, with five layers. The first layer uses Sugeno fuzzy model, the output in this model is predicted by fuzzy predicted values.

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Learning technique used is hybrid method which learns about the heart disease from Cleveland dataset. The membership function, fuzzy predicted values; fuzzy if then rules are computed from the Cleveland dataset. The Architecture of the Advanced Fuzzy Resolution Mechanism using ANFIS is shown in figure 2. The parameter which are fixed are represented by circular nodes whereas parameter which are to be learnt are represented by square nodes. The fuzzy variables are represented in Table 2.

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

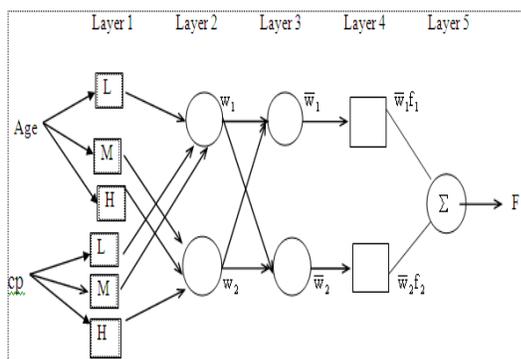


Figure 2: Architecture of the Advanced Fuzzy Resolution Mechanism using ANFIS

Layer 1

In Layer 1 the node function is the membership of fuzzy set with its related input. Rule based structure are given by first order sugeno fuzzy model[14]. The fuzzy if then rules has input variables, membership function and output variable. The parameter are determined by Gaussian membership function[11].

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

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

The output variable for the sugeno fuzzy model is determined by predicted fuzzy values. To determine the predicted fuzzy values determine the 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

$$y = a_1x_1 + a_2x_2 + a_3x_3 + a_4x_4 + a_5x_5 + a_6x_6 + a_7x_7 + a_8x_8 + a_9x_9 + a_{10}x_{10} + a_{11}x_{11} + a_{12}x_{12} + a_{13}x_{13} + c$$

Parameter is predicted for linear equation using the formula

$$a_i = \frac{\{(\text{mean}(y) / \text{Max}(x_i)) + (\text{mean}(y) / \text{mean}(x_i))\}}{\text{mean}(y) * \text{no. of attributes}} \quad i=1 \text{ to } 13$$

The predicted fuzzy values are used in ANFIS method to diagnosis heart disease. The rules obtained from the ANFIS method to diagnosis heart disease is shown in Figure 3

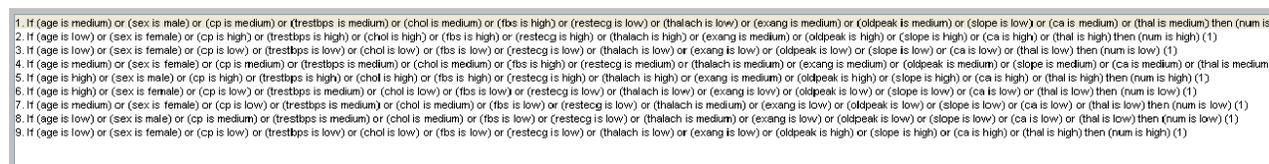


Figure 3: Rule to derive the ANFIS method

Layer 2

Nodes are fixed to calculate the firing strength of rule. T-norm operator is used to perform AND operator[10]. 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 are generated. The output of the Layer 2 is given by

$$w_i = \mu_{Age_i}(x) \mu_{Sex_i}(y) \mu_{cp_i}(z) \mu_{trestbps_i}(d) \mu_{chol_i}(b) \mu_{fbs_i}(c) \mu_{restecg_i}(d) \mu_{thalach_i}(e) \mu_{exang_i}(f) \mu_{oldpeak_i}(g) \mu_{slope_i}(h) \mu_{ca_i}(j) \quad i=1,2$$

where w_i is the firing strength of rule i .

Layer 3

In this layer nodes calculates the weight, they are normalized. The i^{th} node calculates the portion of the i^{th} rules firing strength to the sum of all rules firing strengths.

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

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

Layer 4

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

$$\bar{w}_i f_i = \bar{w}_i (a_i x + b_i y + c_i z + d_i trestbps + e_i chol + f_i fbs + g_i restecg + h_i thalach + i_j exang + j_k oldpeak + l_m slope + n_p ca + o_q thal + t_i)$$

where \bar{w}_i is a normalized firing strength from layer 3 and

{ $A_{ge}_i, sex_i, cp_i, trestbps_i, chol_i, fbs_i, restecg_i, thalach_i, exang_i, oldpeak_i, slope_i, ca_i, thal_i, t_i$ } are the parameter set of this node.

Layer 5

This layer is the simple summation of overall output.

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

The input is fed through layer by layer.

Algorithm for Advanced Fuzzy Resolution Mechanism

INPUT

Input the fuzzy set are $x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8, x_9, x_{10}, x_{11}, x_{12}, x_{13}$.

OUTPUT

Output the fuzzy set be y

METHOD

Begin

Step1: Input the crisp values for $x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8, x_9, x_{10}, x_{11}, x_{12}, x_{13}$.

Step 2: Set Sugeno fuzzy model, with fuzzy if-then rules.

Step 3: Assign fuzzy numbers for the input each variables.

Step 4: Output variable is predicted using the linear equation

$$y = a_1x_1 + a_2x_2 + a_3x_3 + a_4x_4 + a_5x_5 + a_6x_6 + a_7x_7 + a_8x_8 + a_9x_9 + a_{10}x_{10} + a_{11}x_{11} + a_{12}x_{12} + a_{13}x_{13} + c$$

Parameter is predicted for linear equation using the formula

$$a_i = \frac{\{(\text{mean}(y) / \text{Max}(x_i)) + (\text{mean}(y) / \text{mean}(x_i))\}}{\text{mean}(y) * \text{no. of attributes}} \quad i=1 \text{ to } 13$$

Step 5: Generate the rule as

If Input 1 = x_1 or Input 2 = x_2 or Input 3 = x_3 or Input 4 = x_4 or Input 5 = x_5 or Input 6 = x_6 or Input 7 = x_7 or Input 8 = x_8 or Input 9 = x_9 or Input 10 = x_{10} or Input 11 = x_{11} or Input 12 = x_{12} or Input 13 = x_{13} or, then Output is $y = a_1x_1 + a_2x_2 + a_3x_3 + a_4x_4 + a_5x_5 + a_6x_6 + a_7x_7 + a_8x_8 + a_9x_9 + a_{10}x_{10} + a_{11}x_{11} + a_{12}x_{12} + a_{13}x_{13} + c$

Step 6: Layer 1 Calculate the membership values using triangular membership function.

$$O_i^{1,1} = \mu_{age}(x), \text{ for } i = 1, 2, 3$$

$$O_i^{1,2} = \mu_{sex}(x), \text{ for } i = 1, 2$$

$$O_i^{1,3} = \mu_{cp}(x), \text{ for } i = 1, 2, 3$$

$$O_i^{1,4} = \mu_{trestbps}(x), \text{ for } i = 1, 2, 3$$

$$O_i^{1,5} = \mu_{chol}(x), \text{ for } i = 1, 2, 3$$

$$O_i^{1,6} = \mu_{fbs}(x), \text{ for } i = 1, 2$$

$$O_i^{1,7} = \mu_{restecg}(x), \text{ for } i = 1, 2, 3$$

$$O_i^{1,8} = \mu_{thalach}(x), \text{ for } i = 1, 2, 3$$

$$O_i^{1,9} = \mu_{exang}(x), \text{ for } i = 1, 2$$

$$O_i^{1,10} = \mu_{oldpeak}(x), \text{ for } i = 1, 2, 3$$

$$O_i^{1,11} = \mu_{slope}(x), \text{ for } i = 1, 2, 3$$

$$O_i^{1,12} = \mu_{ca}(x), \text{ for } i = 1, 2, 3$$

$$O_i^{1,13} = \mu_{thal}(x), \text{ for } i = 1, 2, 3$$

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 7: 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 8: 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.

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

Step 9: In Layer 4, the consequent of the rules are performed by the nodes in this layer.

Step 10: In layer 5 single node computes the overall output:

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

Step 10: Present the knowledge in the form of human natural language.

End

Defuzzification process is to convert fuzzy values into crisp values by using weighted average method[11]. This process is to convert aggregation result into crisp values for the output variable num.

EXPERIMENTAL RESULTS

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 in Figure 5 and output variable num in Figure 6. The result of the proposed method is shown in Figure 7.

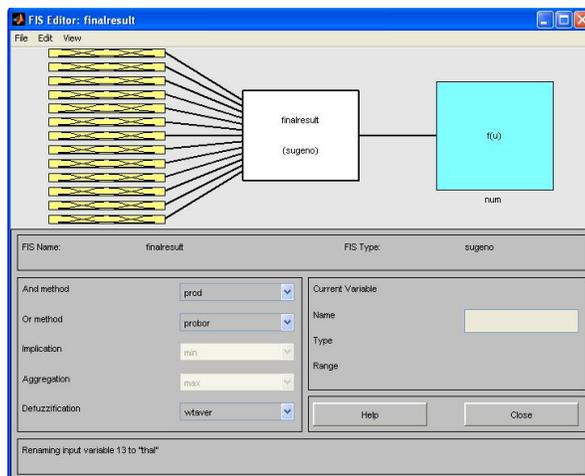


Figure 4: ANFIS modeling framework

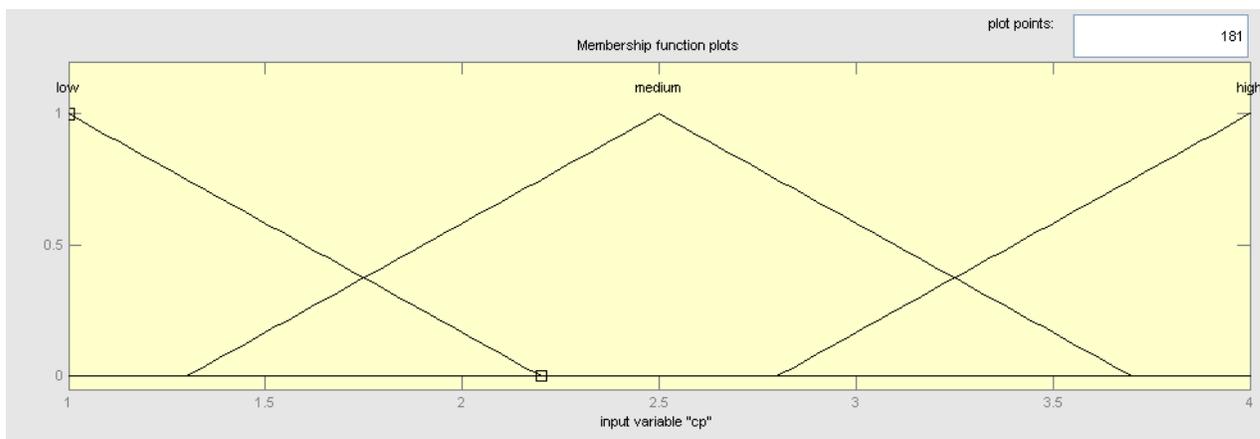


Figure 5: Membership function for input variable cp

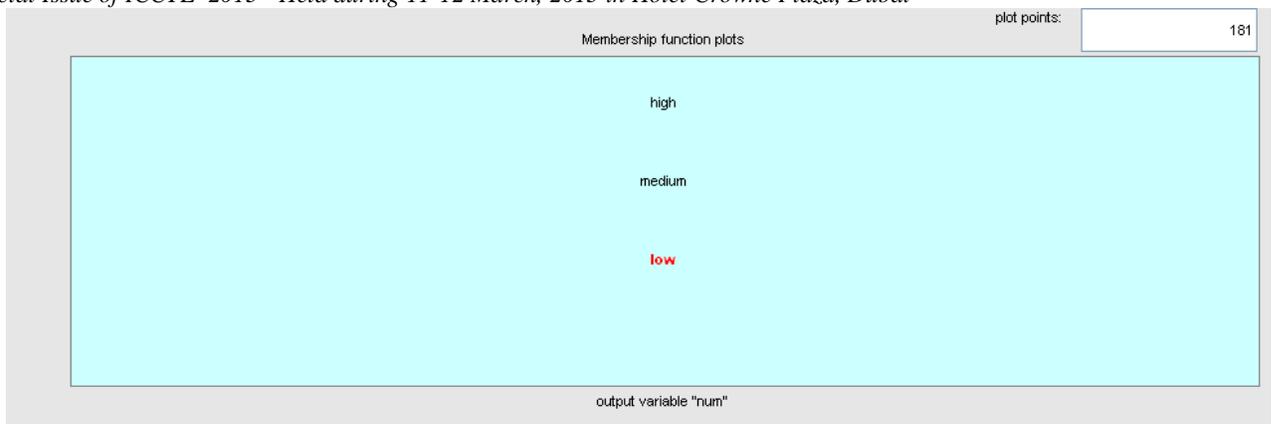


Figure 6: Membership function for output variable num

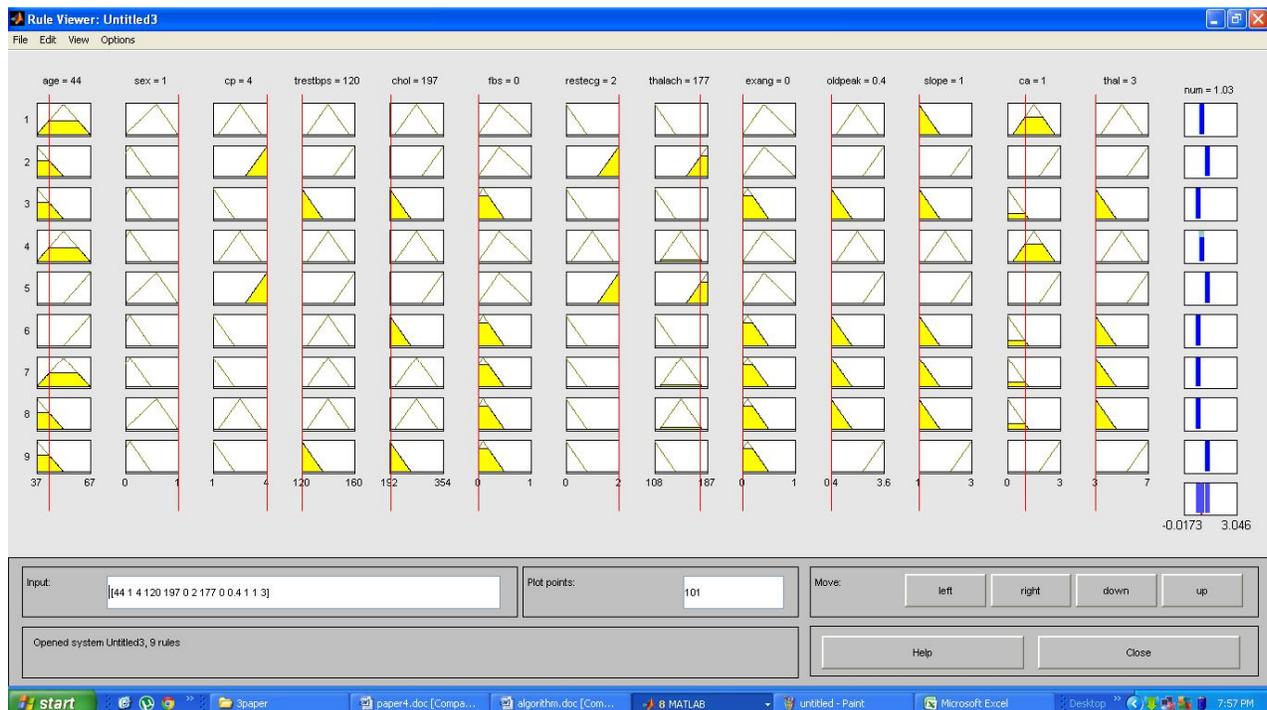


Figure 7: Result obtained from MATLAB

In proposed mechanism fuzzy predicted value technique is used to diagnosis the heart disease. The decision 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 using the second experiment. Accuracy is metrics used in medical diagnosis. The measure of ability to produce accurate diagnosis is determined by accuracy.

So that accuracy [8] is given by eqn. (4)

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

Table 3: Comparison of Proposed method Accuracy with earlier methods

Method	Accuracy (%)	Author
Current study	93.88	Dr. A.V.Senthil Kumar
Adaptive Neuro-Fuzzy Inference System based on subtractive clustering to diagnosis the heart disease[24]	92.00	Dr. A.V.Senthil Kumar
Diagnosis Of Heart Disease Using Fuzzy Resolution[23] Mechanism	91.83	Dr. A.V.Senthil Kumar
Adaptive Neuro-Fuzzy Inference System for Heart Disease diagnosis [15]	91.18	Dr. A.V.Senthil Kumar
IncNet[17]	90	Norbert Jankowski
Hybrid system[9]	86.8	Humar Kahramanli and Novruz Allahverdi
26-NN, Manhattan, 1 feature removed[19]	86.8	WD/KG
24-NN, Manhattan[19]	84.8	WD/KG
LDA [16]	84.5	Ster and Dobnikar
Fisher discriminant analysis [16]	84.2	Ster and Dobnika
FSM, 82.4–84% on test only[18]	84.0	Rafał Adamczak
Naive Bayes[16]	83.4	Ster, Dobnikar
7-NN[20]	83.2	Duch W, Grudzinski K and Diercksen G.H.F
k-NN, k=27, Manhattan[18]	82.8	Rafał Adamczak

The experimental results are compared with earlier methods involving Cleveland heart disease dataset[9][15][23][24]. Comparing these methods, as listed in Table III, reveals that the proposed method achieves the first highest accuracy values based on the proposed 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

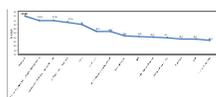


Figure 8: Graphical represent of accuracy

CONCLUSIONS AND FUTURE RESEARCH

To diagnosis the heart disease Advanced Fuzzy Resolution Mechanism was developed. The Cleveland heart disease dataset is taken; crisp values are converted into fuzzy values in the stage of fuzzification. Advanced Fuzzy Resolution Mechanism has five layers, membership function, fuzzy if then rules and output variables for the fuzzy model are predicted using fuzzy predicted value to improve the accuracy of the result. The outputs from the Advanced Fuzzy Resolution Mechanism are fuzzy values. By defuzzification process the fuzzy values are converted into crisp values angiographic disease status. The proposed study has better performance compared with the previous study to diagnosis heart disease. Future Research should test for other similar tasks or other related data sets to evaluate its ability to produce a similar accuracy.

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