# Robustness of Adaptive Neuro- Fuzzy Inference System for Optimal Prediction using Roulette Wheel Method

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***Abstract*: An information system that supports automatic decision making with help of intelligent system by computerized manner. The proposed work has been developed and deployed a robust method is contributed to decision making in medical system and the diagnosis the major risk of the patients in earlier. The main goal of the proposed research is to develop data mining techniques to support decision making and to control the controllable risk factors and also overcome the other parts of organs highly affected by diabetes, kidney disease, heart condition and which in turn reduces the risk of the patients. Robustness of Adaptive Neuro-Fuzzy Inference System (RANFIS) designed a fuzzy inference system (FIS) to enrich the knowledge about the data set whose membership function parameters can be altered randomly by the process of mutation.***

***Keywords*: Adaptive Neuro-Fuzzy genetic hybridization Inference System, Fuzzy inference System, Diabetes, kidney test, heart pump test, decision making***

## I. INTRODUCTION

The research focuses, to design intelligent system is to provide automatic decision making of medical data. In recent technological era, intelligent decision support has become a need for every type of application.

Knowledge engineering, learning, searching, classification, etc. are the Smart techniques which can be used in Computational intelligence efficiently.

The major advantage of these techniques is low cost solution and ease of implementation. The success of searching and optimization in fuzzy logic, [1] [2] [3] [4] it handle the imprecision and uncertainty of data in real life applications based on soft computing and genetic algorithm.

## II. ABOUT THE RESEARCH PROBLEM

According to the National Diabetes Statistics Report of the Centers for Disease Control and Prevention (2017), around 30.3 millions of people has affected by diabetes in US. Also 87.5 % of the diabetic population is affected in obese. Such high incidence rate of diabetic population can be observed in U.S. region [5].

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To observe growth in the global kidney function test market owing to increasing change to an unhealthy lifestyle, prevalence of diabetes, high blood pressure and rising geriatric population is expected from Asia Pacific region. It damages the blood vessels of kidney which eventually leads to improper functioning of the kidney by the causes of high blood pressure.

Proper decision involves right time for giving treatment to the patients. The main aim of the proposed research is to develop data mining techniques to make a well decision making and control the controllable risk factors and also overcome with other parts of organs.

In genetic algorithm, each chromosome is evaluated by its fitness value which can be computed by the objective function of the problem; it works with a population of individuals represented by chromosomes. Selection, Crossover and Mutation are the three genetic operators which form new generation of population.

By combining Fuzzy controller and mutation process to achieve the desirable prediction of health condition which can be implemented in artificial intelligence techniques in the medical field and healthcare diagnostics.

## III. FORMULATION OF THE PROBLEM AND OBJECTIVES

A main objective of the research can be analysed for diagnosis Diabetes, kidney test, and heart condition test of the patients by learning the level of fluctuation of parameter by giving the rule base of decision making for analysing the risk factor by crisp output.

In this research, Robustness of Adaptive Neuro-Fuzzy Inference System (RANFIS) implemented for getting desirable prediction of patient’s health level by the process altered the membership range and membership functions, randomly chosen an input or the output. The rate of this mutation can be adjusted in random manner with specifying a larger upper range of the input/output set to mutate. Hence the accurate method of deep learning can be diagnosis the risk factor of the patient condition efficiently.

The result and experimental performances can be analysed by evaluate an accurate method of deep learning technique by applying medical diagnosis data.

## IV. DATA FOR RESEARCH

To determine the kidney function test, the rate by looking at factors, such as specifically creatinine levels, age, gender, race, height, weight can be collected as shown in table 3.1.

The Serum test also involving for the finding the fluctuation level of blood urea, creatinine, uric acid and other minerals in the body the creatinine result is used with the age, race, and gender to find out the glomerular filtration rate of the patients.

The Serum test of kidney function can analysis with respect to the collection of Gender, Creatine, Albumin, Uric acid in gender wise, Phosphate, CAL represents Calcium, Potassium, Sodium for analysing the fluctuation of ranges.

Heart condition can be exhibits normal, slightly below, Medium, Moderate low, High, High risk below normal, Excellent normal. Kidney test can be exhibits normal, mild damage, moderate low, severe low, kidney failure.

## V. RESEARCH MEHODOLOGY

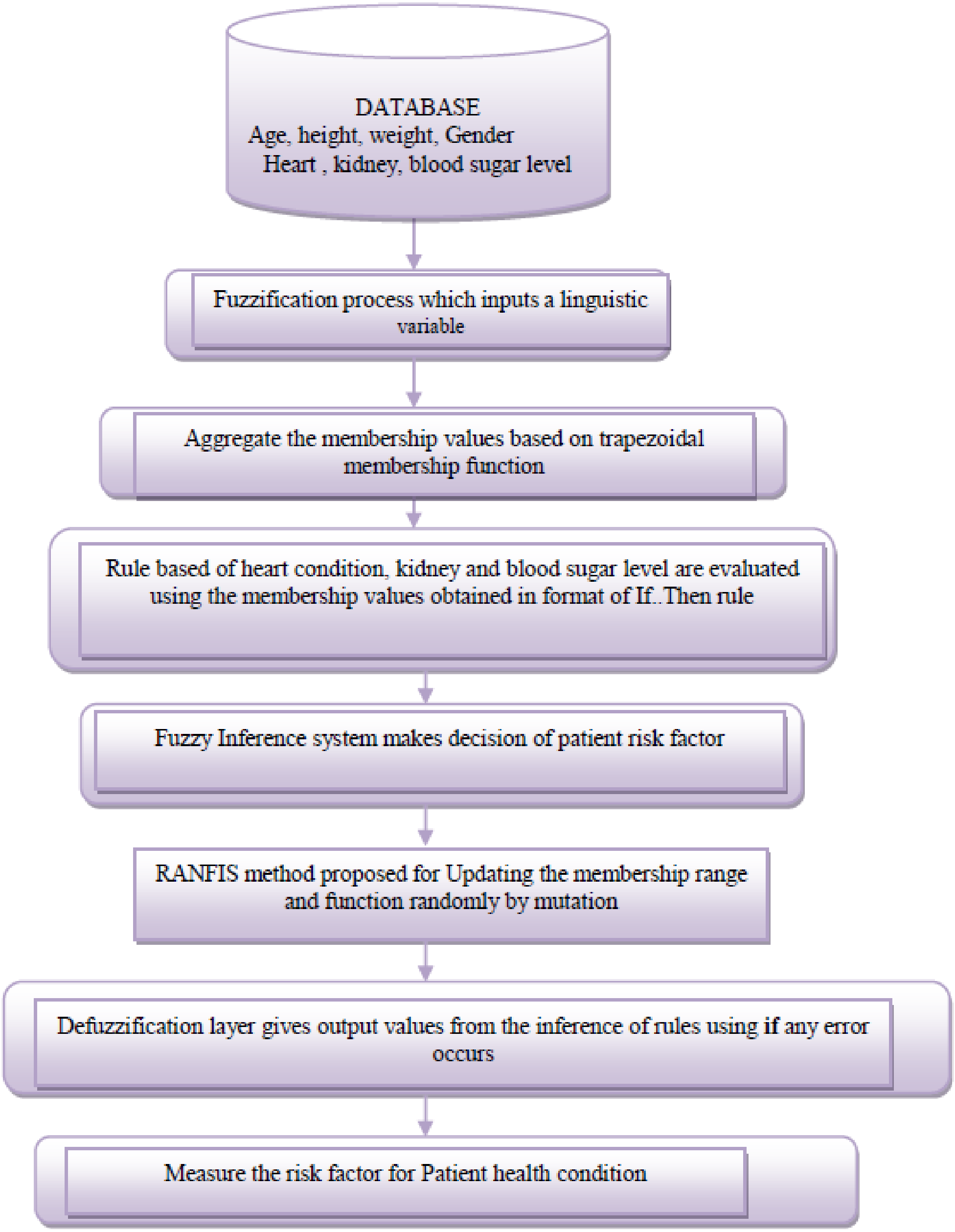


**Fig.1 Architecture of the Research Framework**

The framework of proposed RANFIS-based system is shown in fig.1. An input vector can pass through the network layer up to four layers in forward pass. An error can be sent back through the network to back propagation in the backward pass. Here it can be proposed by robustness of mutation process can be evolved for updating the membership range randomly to alter the parameter for reducing the error rate and get optimal solution.

Sugeno-type systems [6] can be used inference system by which the output membership functions is in linear.

**Fuzzification** is the process of which forms Fuzzy Linguistic variables by mapping a crisp value of an input to membership degrees [7] [8] [9] [10].

A membership function can defined a point of input space is mapped to a degree of trapezoidal membership between 0 and 1 and is denoted by $\mu_t(x)$ as represent in equation 1. Here the process of membership function can be follow in level 1 of the methodology for analyzing the risk factor of patients by level by level.

$$\mu_t(x)=\begin{cases}0,(x<a)or(x>d)\\ \dfrac{x-a}{b-a},a\le x\le b\\ 1,b\le x\le c\\ \dfrac{d-x}{d-c},c\le x\le d\end{cases} \quad (1)$$

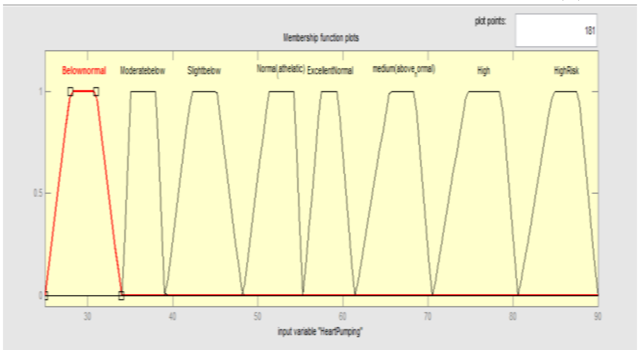


**Fig. 2 Input variables of Heart pump of membership function in Fuzzy Inference system**

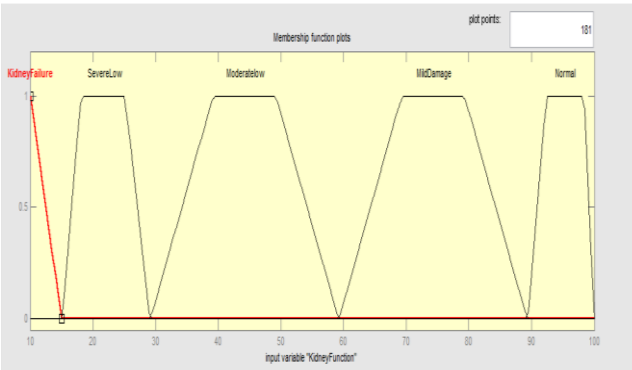


**Fig. 3 Input variables of Kidney function of membership function in Fuzzy Inference system**

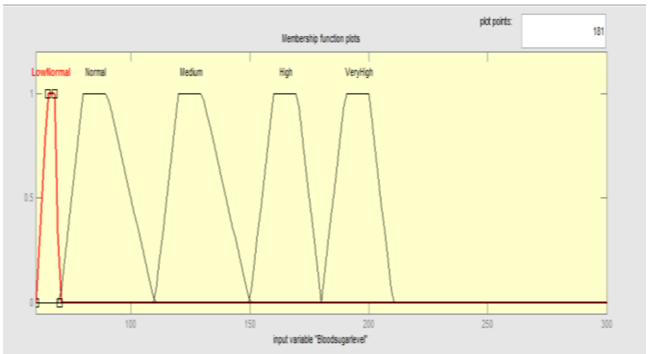


**Fig. 4 Input variables of Blood sugar level of membership function in Fuzzy Inference system**

The membership function can calculated by eight linguistic variables for analyzing an rule base for heart condition which can be allotted in trapezoidal rule membership function as shown in fig. 2.

From fig. 3 represents, the membership function can calculate by five linguistic variables for analyzing an rule base for kidney function.

From fig. 4 represents, the membership function can calculate by five linguistic variables for analyzing an rule base for blood sugar level.

If – Then rules are evaluated by using the triangular membership function and the output of fired rule can be evolved by Rule Aggregation process. The controller collects the fuzzy rules form the rule base for the fuzzy logic system for determine the outcome [11] [13]. Finally, the fuzzy inference system can generates a truth value that determines the outcome of the rules by using an equation (2 and 3) [12].

If $x$ is $R_1$ and $y$ is $S_1$ *and* $z$ *is* $T_1$ then $f_1 = a_{11}x+a_{12}y+ a_{13}z+a_{10}$

:

If $x$ is $R_n$ and $y$ is $S_n$ *and* $z$ *is* $T_n$ *then* $f_n = a_{n1}x+a_{n2}y+ a_{n3}z+a_2$

Evaluating the rule premises results in

$$w_i = \mu_{R_i}(x)\mu_{S_i}(y)\mu_{T_i}, i=1,2,3 \quad (2)$$

Where $w_i f_i$ represents the defuzzification of fuzzy output risk factor value of human being.

$$O_{3,i} = \overline{w}_i = \frac{w_i}{w_1+w_2+w_3} \quad (3)$$

Then, nodes are adaptive and perform the consequent of the rules of Equation (4),

$$O_{4,i} = \overline{w_i} f = \overline{w_i}(R_i x + S_i y + T_i z + u_i) \quad (4)$$

Aggregation can be processed which can be used to deciding an action control taken during the firing of several rules, the decision rules are constructed for input parameter and control output values. Finally the aggregation of minimum control outputs is taken into consideration to maximize the grade of output to resolve the uncertain linguistic input to produce crisp output.

Defuzzification is inverse process of fuzzification, the linguistic variable from input can put into the measurement for performing to the Sugeno member function method and assigned the rule base classifier [12] [13]. A system model has several inputs and outputs, each variable having its own minimum and maximum values.

The output parameter of patients health condition can be examined by five fuzzy sets very low, low, medium, high and very high. The parameters of $\left(R_i, S_i, T_i\right)$ are determined and referred as a consequent parameters. Where Ri represents the Heart condition value and $S_i$ represents the Kidney function value and $T_i$ represents the Blood Sugar level value. Finally the crisp value of patients health condition level can be determined by given the input variables by using the Equation (5) [14].

$$O_{5,i} = \sum_i \overline{w_i} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{5}$$

$$o_{5,i} = f(x,y,z) = \frac{w_1(x,y,z) f_1(x,y,z) + w_2(x,y,z) f_2(x,y,z) + w_3(x,y,z) f_3(x,y,z)}{w_1(x,y,z) + w_2(x,y,z) + w_3(x,y,z)}$$

In this research work, 252 different rules can be derived for analyzing a risk factor of patient's level.

## VI. ROBUSTNESS IN SUGENO FUZZY CONTROLLER

Sugeno method can be implemented to fuzzy controller involved in training data, an evolutionary algorithm being designed which can be used to desires the membership functions, and take decision from the controller based on the rule base. It can be capable of balancing the membership range and give correct parameter.

A fitness function is used to evaluate a desirable solution based on evolutionary algorithm. To evaluate fitness value of each input in the population to determines the output of the function evaluated by fuzzy controller.

Selection and Crossover process involves choosing best chance to create fitter generation from the population, which based on selective reproduction.

The linguistic variables are produces by the fitness function of first averages the data of each input. These variables are all made positive as what often happened, the decision of health condition, which resulted in three inputs having one negative value and two having positive, which when summed would produce a low number for produce a single fitness value.

To overcome this problem, in first approach were raised the minimum range and membership function constraints which had no effect. The second approach, an offset value can use which has the fitness value was exactly 0, borrowed from reinforcement learning.

The crossover procedure based on Roulette Wheel approach which can be used to takes the two selected parameter and to create two new parameters, uniformly crosses a single random input/output membership set in order with a difference of one input/output membership set.

When $P(ch=i)$ of probability that individual 'i' is selected for computing the possible segment of different size randomly based on each individual relative fitness by the equation of 6.

$$P(ch=i) = \text{def} \frac{\text{fitness}(i)}{\sum_{j=1}^{n} \text{fitness}(j)} \tag{6}$$

A uniform crossover was used to enforce the constrained values, which are chosen for each of the four inputs and the output.

Mutation involved within a constrained range, to alter the membership range and membership functions of a randomly chosen input or the output. The rate of this mutation could be adjusted randomly by specifying a larger upper range of the input/output set to mutate. The required pseudo code as given below,

```
r:=randomnumber,Where    0≤r<1;
sum:=0;
for    each    individual    i
{
sum:=sum+P(ch=i);
if      r<sum
{
return    i;
}
}
```

## VII. EXPERIMENTATION AND RESULT ANALYSIS

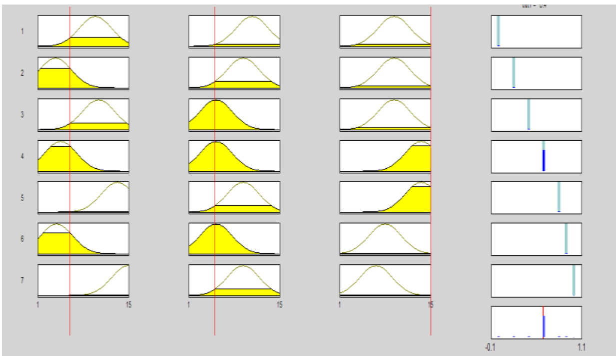

**Fig.5 Generation of Rule viewer in Fuzzy Inference System**

From fig. 5 represents, the generation of rule viewer can be appeared when the three input can be entered, here the third input of the membership can be seen as 0, so the crisp output does not come with proper way.

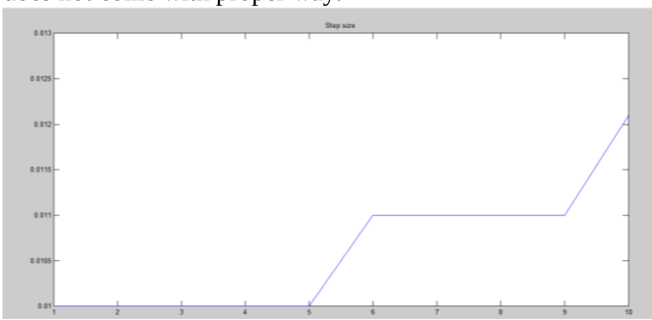


**Fig. 7 Updating the membership range during mutation process**

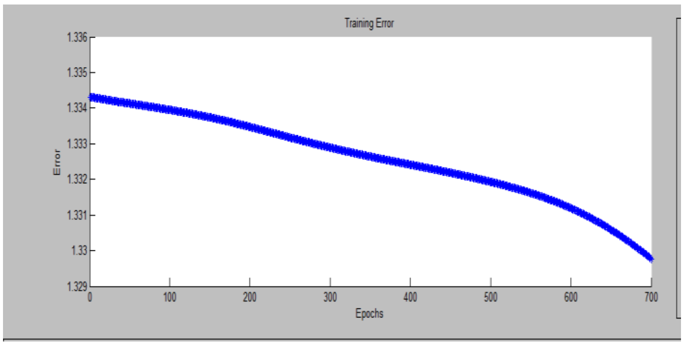


**Fig.7 Training Error to be reduced**

So the mutation process can be followed for updating the range of parameter can be altered automatically shown in fig 6. Hence the traing error can be reduced automatically from 1.34 to 1.329 for 700 training dataset as shown in fig 7.

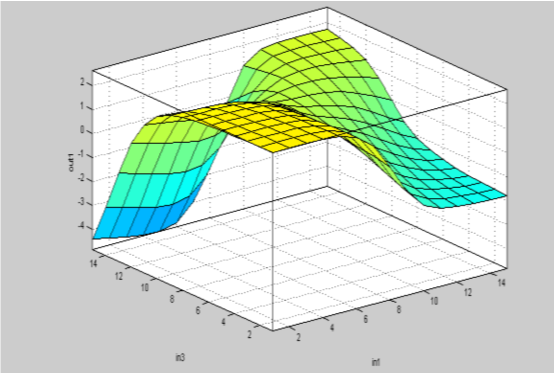

**Fig. 8 Surface view of Error occur in input 3**

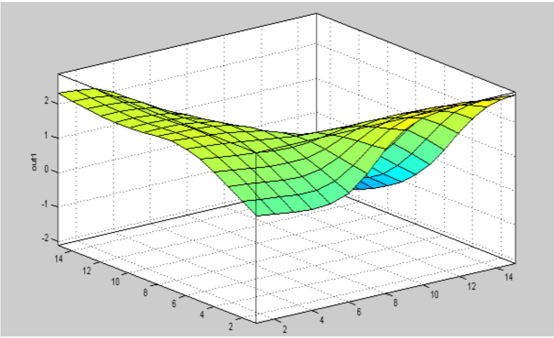

**Fig. 9 Surface view of updating the parameter fitness**

From fig 8 represents the surface view of input 1 and input 3, here an error of input 3 can be viewed as negative value. After applying the mutation cross over approach, the data will be updated automatically and reduced the error and viewed the positive range of the output respectively as shown in fig 9.

## VIII. CONCLUSION

Robustness of Adaptive Neuro-fuzzy Inference System gives efficient result while giving multiple inputs apart from searching capabilities.

In this research, artificial evolution in generating new and optimal solutions, the hybridization with other constituents of fuzzy controller with Roulette Wheel method can be implemented for updating the parameter randomly during the mutation process.

The major benefit of Roulette Wheel method is that it can be used to find optimized values from large search data as well as makes system able to learn which can be mutated the fitness of the membership range in random.

## REFERENCES


1. J.S.R. Jang, Adaptive Network Based Fuzzy Inference System", IEEE Trans. On Systems Man. and Cybemetics, Vol.23, No.3, (1993), PP 665- 685.
2. Adlassing, K.P. "Fuzzy set theory in medical diagnostics", IEEE Trans. On Systems, Man, and Cybernetics, Vol. SMC-16(1986) 260-264.
3. Constantinos Koutsojannis and Ioannis Hatzilygeroudis, ―FESMI: "A Fuzzy Expert System for Diagnosis and Treatment of Male Importance", Knowledge-Based Intelligent Systems for Health Care, pp 1106–1113, 2004.
4. Jang, J., -S. (1993). ANFIS:Adaptive-Network-Based Fuzzy Inference. IEEE Trans. on Systems, Man and Cybernetics 23: 665-685, ISSN 0018-9472.
5. https://www.globenewswire.com/news-release/2019/05/28/1853581/0/en/Kidney-Function-Test-Market-To-Reach-USD-1061-0-Million-By-2026-Reports-And-Data.html
6. Takagi T. and M. Sugeno, "Fuzzy identification of system and its applications to modeling And control", Proc. IEEE Trans. on System Man and Cybernetics, Vol. SMC-15, No. 1, pp. 116-132, 1985.
7. Shu-Hsien Liao, Pei-Hui Chu, Pei-Yuan Hsiao. "Data mining techniques and applications – A decade review from 2000 to 2011", Expert Systems with Applications, Elsevier (39):11303–11311, 2012.
8. Abraham A, 2005, "Rule-based Expert Systems". Handbook of Measuring System Design, John Wiley & Sons, 909-919.
9. Ashok Kusagur, S. F. Kodad and B V. Sankar Ram, 2010, "Modeling, Design & Simulation of an Adaptive Neuro-Fuzzy Inference System (ANFIS) for Speed Control of Induction Motor", International Journal of Computer Applications (0975 – 8887) Volume 6– No.12.
10. Chen J.Y. and C.C. Wong, 2000, "Implementation of the Takagi-Sugeno model-based
11. Fuzzy control using an adaptive gain controller", IEE Proc. - Control Theory Appl., Vol. 147, No. 5, pp.509 –514.
12. Jinjie Huang, Shiyong Li and Chuntao Man, "A TS type of fuzzy controller based on process of input output data", Proc. of 42nd IEEE Conf. on Decision & Control (CDC'03), Hawai, USA, pp.4729- 4734. Dec. 2003.
13. T. A. Runkler: Selection of Appropriate Defuzzification Methods Using Application Specific Properties, IEEE Trans. on Fuzzy Systems, 5 (1), February 1997., pp. 72-79 .
14. D.Z.Saletic: Defuzzification: criteria and classification, Fuzzy Sets and Systems, 108, (1999.) pp. 159-178


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