



## NEURO-FUZZY BASED HEART DISEASES DIAGNOSIS

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**Abstract-** Major challenges being faced by healthcare organizations (hospitals, medical centers) are correct, affordable cost diagnosis services that lead to effective treatments. Computer-based patient records Integration with clinical decision system can reduce medical errors, decrease in unwanted practice variations, and decrease in overall cost and increase in patient safety.

In recent years, number of soft computing based techniques including neural and fuzzy have been developed. Current work aims to develop and analyze performance of such methods.

In this work, multilayer feed forward neural network, Fuzzy Inference System and Adaptive Neuro Fuzzy System (ANFIS) are used to classify heart diseases in a person. Total 13 different attributes are given to the system to generate single output classify person into normal or person with possibility of number of heart attack already occurred. After training the network with sufficient number of training pair derived from standard data set, testing is done on the various cases that show the effectiveness of proposed approach.

### I. INTRODUCTION

Heart disease, which is usually called coronary artery disease (CAD), is a broad term that can refer to any condition that affects the heart. Statistics have consistently shown that heart disease is one of the most prevailing diseases, Faced by the population all over the world. And to come over the situational cause of diseases various studies had been carried out in past which came up with several diagnosis systems to analyze heart diseases.

Following somehow no method of diagnosis had been proved to be most accurate. Accuracy of each methods developed lacked something which fails than to arrive at a particular diagnosis decisions.

For instance, the clinic symptoms, the functional and the pathologic manifestations of heart diseases are associated with many organs other than the heart, and very often heart diseases may exhibit various syndromes. And other heart disease may have similar symptoms. So there is a need for development in such relative diagnosis methods which can lead to an accurate diagnosis system for better results.

To reduce the diagnosis time and improve the diagnosis accuracy, it has become more demanding issue to develop reliable and powerful medical decisions support systems (MDDS) to support the yet and still increasingly complicated diagnosis decision process.

Somehow with different types of soft computing methods being applied deals with all the different types of heart disease, In fact all the known heart diseases.

Soft computing systems such as Neural Network (NN), Fuzzy Inference System (FIS) and Adaptive Neuro Fuzzy inference System (ANFIS) deals with all such heart diseases with intense accuracy to give diagnosis decision for various heart causes.

Soft computing methods algorithm works into different phases:

1. Patient is tested for 13 attributes for health assessment data.
2. The data are feeded into system.
3. The diagnosis process arrives to a diagnosis decision for further assistance.

## II. SOFT COMPUTING BASED METHODS

In this paper there are mainly three techniques defined.

### A. Neural Network

A neural network is a representation of the human brain, artificially developed which tries to stimulate the process of learning. Traditionally the neural network is referred to as the nervous system which has biological neurons in it which transmit necessary information. Generally NN consists of large/huge processors which are parallelly operated, each having its own minor/smaller sphere of knowledge and data which are accessible in its local memory. It is basically defined as, "Free parameters of NN in the process of learning are adapted through the stimulation process by the environment in which the network is embedded. The types of learning can be determined such that the way in which the parameters change takes place."

This is carried out through a number of sequential events:

- ✓ The neural network is stimulated by an environment.
- ✓ The neural network undergoes changes in its free parameters as a result of this stimulation.
- ✓ The neural network responds in a new way to the environment because of the changes that have occurred in its internal structure.

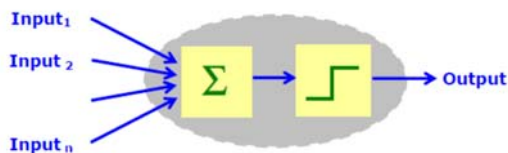


Figure 1 Basic Neural-network Model [2]

An artificial neuron is a mathematical function conceived as a simple model of a real (biological) neuron as shown in Figure 1.

The McCulloch-Pitts Neuron:-

This is a simplified model of neurons, known as a Threshold

- ✓ A set of input connections brings in activation from other neurons.
- ✓ A processing unit sums the input, and then applies a non-linear activation function (i.e. squashing/transfer/threshold function).
- ✓ An output line transfers the results to other neurons.

### B. Fuzzy Inference System (FIS)

Fuzzy if-then rules form a core part of the fuzzy inference system to be introduced below.

Fuzzy Systems include Fuzzy Logic and Fuzzy Set Theory.

Knowledge exists in two distinct forms:

- ✓ The Objective knowledge that exists in mathematical form is used in engineering problems.
- ✓ The Subjective knowledge that exists in linguistic form, usually impossible to quantify.

Fuzzy Logic can coordinate these two forms of knowledge in a logical way. Fuzzy Systems can handle simultaneously the numerical data and linguistic knowledge. Fuzzy Systems provide opportunities for modeling of conditions which are inherently imprecisely defined. Many real world problems have been modeled, simulated, and replicated with the help of fuzzy systems.

The applications of Fuzzy Systems are many like:

- ✓ Information retrieval systems,
- ✓ Navigation system

Robot vision

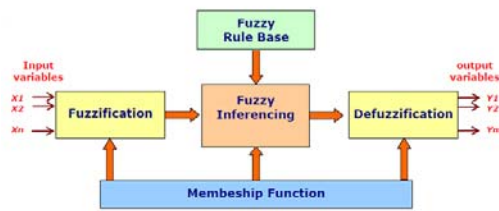


Fig. Elements of Fuzzy System

Figure 2 Fuzzy inference system<sup>[2]</sup>

**Input Vector:**  $X = [x_1, x_2, \dots, x_n]^T$  are crisp values, which are transformed into fuzzy sets in the fuzzification block.

**Output Vector:**  $Y = [y_1, y_2, \dots, y_m]^T$  comes out from the defuzzification block, which transforms an output fuzzy set back to a crisp value.

**Fuzzification:** a process of transforming crisp values into grades of membership for linguistic terms, "far", "near", "small" of fuzzy sets.

**Fuzzy Rule base:** a collection of propositions containing linguistic variables; the rules are expressed in the form:

**If (x is A) AND (y is B) THEN (z is C)**

Where x, y and z represent variables (e.g. distance, size) and A, B and C are linguistic variables (e.g. 'far', 'near', 'small'). **Fuzzy If-Then Rules**

**Fuzzy if-then rules** or **fuzzy conditional statements** are expressions of the form **IF A THEN B**, where A and B are labels of **fuzzy sets** [66] characterized by appropriate membership functions. Due to their concise form, fuzzy if-then rules are often employed to capture the imprecise modes of reasoning that play an essential role in the human ability to make decisions in an environment of uncertainty and imprecision.

An example that describes a simple fact is **If pressure is high, then volume is small** where **pressure** and **volume** are **linguistic variables**, **high**

and **small** are **linguistic values** or **labels** that are characterized by membership functions. Another form of fuzzy if-then rule, proposed by Takagi and Sugeno has fuzzy sets involved only in the premise part. By using Takagi and Sugeno’s fuzzy if-then rule, we can describe the resistant force on a moving object as follows:

**If velocity is high, then force = IC \*velocity**

where, again, **high** in the premise part is a linguistic label

characterized by an appropriate membership function. However, the consequent part is described by a nonfuzzy equation of the input variable, velocity. Both types of fuzzy if-then rules have been used extensively in both modelling and control. Through the use of linguistic labels and membership functions, a fuzzy if-then rule can easily capture the spirit of a “rule of thumb” used by humans. From another angle, due to the qualifiers on the premise parts, each fuzzy if-then rule can be viewed as a local description of the system under consideration.

**Membership function:** provides a measure of the degree of similarity of elements in the universe of discourse U to fuzzy set.

**Fuzzy Inference:** combines the facts obtained from the Fuzzification with the rule base and conducts the Fuzzy reasoning process.

**Defuzzification:** Translate results back to the real world values.

**C. Adaptive Neuro fuzzy inference system (ANFIS)**

The architecture combines the properties of neural networks and fuzzy logic, creating a dynamic fuzzy inference system similar to the Sugeno fuzzy model built as a network based on the same manner as in neural networks.

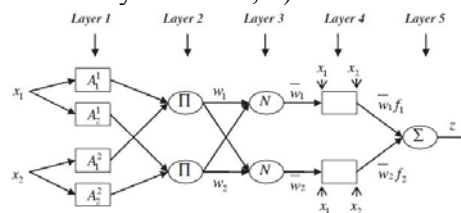
Adaptive-Network-based Fuzzy Inference System (ANFIS) were firstly presented by Jang. It is made made out of five layers as

demonstrated in figure 2-5. Layer 1 is known as the “Fuzzification layer”. Crisp inputs are changed into the membership degree of the fuzzy sets in the predecessor part. Layer 2 is recognized as “rule Layer”. In this method bell-shaped membership function is prefer. It figures the rule terminating quality from the result of every input signal. These rule terminating qualities are standardized in layer 3. So, this layer is called the “normalization layer”. Layer 4 is define as the “defuzzification layer”. In this layer, output of layer 3 and a first-order polynomial function of its inputs is calculated. Final layer of the system is called “output layer”.

It delivers the crisp output as the summation of every single approaching sign.[3] The ANFIS is a fuzzy Sugeno model put in the framework of adaptive systems to facilitate learning and adaptation (Jang, 1993; Jang, 1992). For a first-order Sugeno fuzzy model Sugeno and Kang, 1988; Takagi and Sugeno, 1985, a typical rule set with two fuzzy if-then rules can be expressed as Rule 1: if (x is A<sub>1</sub>) and (y is B<sub>1</sub>) then (f<sub>1</sub> =p<sub>1</sub>x +q<sub>1</sub>y+ r<sub>1</sub>).

Rule 2: if (x is A<sub>2</sub>) and (y is B<sub>2</sub>) then (f<sub>2</sub> =p<sub>2</sub>x +q<sub>2</sub>y+ r<sub>2</sub>).

Where x and yare the inputs, A<sub>i</sub> and B<sub>i</sub> are the fuzzy sets, f<sub>i</sub> are the outputs within the fuzzy region specified by the fuzzy rule, p<sub>i</sub>, q<sub>i</sub> and r<sub>1</sub>are the design parameters that are determined during the training process. Figure 3-3 illustrates the reasoning mechanism for this Sugeno model. The corresponding equivalent ANFIS architecture is as shown in Figure 3-3, where nodes of the same layer have similar functions, as described below. (Here we denote the output node i in layer 1 as O<sub>1</sub>, i.)



**Figure 3 ANFIS architecture [3]**

**Layer 1:**

Every node i in this layer is an adaptive node with a node output define by

$$O_i^1 = \mu_{A_i}(x), i = 1,2 \tag{1}$$

$$O_i^1 = \mu_{B_{i-2}}(y), i = 3,4 \tag{2}$$

μ<sub>A<sub>i</sub></sub>(x) and μ<sub>B<sub>i-2</sub></sub>(x) can adopt any fuzzy membership function.X (or y) is the input node i and A<sub>i</sub> (or B<sub>i-2</sub>) is a linguistic label (small, large,

etc.) Associated with this node. If the bell shaped membership function is employed  $\mu_{A_i}(x)$  is given by:

$$\mu_{A_i}(x) = \frac{1}{1 + \left| \frac{x - c_i}{a_i} \right|^{2b_i}} \quad 3$$

$A_i, b_i, c_i$  are the parameter set. Parameters are referred to as premise parameters.

**Layer 2:**

Every node in this layer is a fixed node. The output is the product of all the incoming signals.

$$O_i^2 = w_i = \mu_{A_i}(x) \mu_{B_i}(y), i = 1, 2 \quad 4$$

Each node represents the fire strength of the rule.

**Layer 3:**

Every node in this layer is affixed node 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:

$$O_i^3 = \overline{w_i} = \frac{w_i}{w_1 + w_2}, i = 1, 2 \quad 5$$

Output of this layer will be called Normalized firing strengths.

**Layer 4:**

Every node  $i$  in this layer is an adaptive node with a node function:

$$O_i^4 = \overline{w_i} f_i = \overline{w_i} (p_i x + q_i y + r_i) \quad 5$$

$\overline{w_i}$  is the normalized firing strength from layer 3.  $\{P_i, q_i, r_i\}$  is the parameter set of this node. These are referred to as consequent parameters.

**Layer 5:**

The single node in this layer is a fixed node labeled sum, which computes the overall output as the summation of all incoming signals:

$$O_i^5 = \sum_{i=1}^2 \overline{w_i} f_i = \frac{\sum_{i=1}^2 w_i f_i}{w_1 + w_2} \quad 6$$

Constructed an adaptive network that has exactly the same function as a Sugeno fuzzy model.

**III. PARAMETER OF HEART DISEASES DIAGNOSIS**

The heart disease database was taken from UCI machine learning repository. The Cleveland heart disease database contains 297 Samples. The datasets chosen for project are taken Heart diseases database. It concern classification of person into normal and abnormal person. All attributes and the values are given. attributes. However, all the published experiments only refer to 13 of them, and are listed as follows:

- (1) age,
- (2) sex,
- (3) chest pain type (four values),
- (4) resting blood pressure,
- (5) serum cholestoral in mg/dl,
- (6) fasting blood sugar >120 mg/dl,
- (7) resting electrocardiographic results (values 0, 1 and 2),
- (8) maximum heart rate achieved,
- (9) exercise induced angina,
- (10) old peak = ST depression induced by exercise relative to rest,
- (11) the slope of the peak exercise ST segment,
- (12) number of major vessels (0–3) colored by flourosopy,
- (13) thal: 3 = normal; 6 = fixed defect and 7 = reversable defect

Class attributes

Class0: Normal person

Class1: First stroke

Class2: Second stroke

Class3: End of life<sup>[4]</sup>

**Comparison Table**

The summary of all methods listed in below table. In the table shows that there are mainly two data sets define. First is Cleveland data and another is heart data. In Cleveland dataset there are 297 data pairs and in heart dataset there are 270 data pairs. The result of all methods shown in last column.

**Table 1 Comparison table**

Trained data	Test Data	Method	Percentage
Cleveland data*	24 Sample	Neural network	100
Heart data**	24 Sample	Neural Network	100
Cleveland data*	Heart data**	Neural Network	100
Heart data	32 rule	Fuzzy Inference System	72
Heart data	24 sample	ANFIS	99.99
Cleveland data	24 sample	ANFIS	99.90
Cleveland data	Heart data	ANFIS	99.05

#### IV. Conclusion

In conclusion, there were three methods used NN, ANFIS, FIS for the diagnosis of different heart diseases. In these methods different variables are been tested at there full potentials, for getting most favorable outcomes of diagnosis decision making process. The outcomes had been shown in the above comparison table.

#### References

[1]	Simon Haykin, "Neural Network – a comprehensive foundation", Pearson Education Asia, 2nd Edition, 1999
[2]	RC Chakraborty, "Soft Computing-Fundamental of neural network", Dec 2009
[3]	Orrawan Kumdee, Thongchai Bhongmakapat and Panrasee Ritthipravat "Prediction of nasopharyngeal carcinoma recurrence by Neuro-fuzzy techniques", <i>Elsevier journal on fuzzy sets and systems</i> , vol 203 ,pp.95-111 , 2012.
[4]	Resul Das, Ibrahim Turkoglu, Abdulkadir Senger "Effective diagnosis of heart disease through

	neural networks ensembles", <i>Elsevier journal on Expert System with Application</i> , vol36, no (4), pp.7675-7680, 2009.
[5]	Mahmut Tokmakci, Demet Unalan, Ferhan Soyuer and Ahmet Ozturk "The Reevaluate Statistical results of quality of life in patients with cerebrovascular disease using Adaptive network based fuzzy inference system", <i>Elsevier journal on Expert System with Application</i> , vol34, no (2), pp.958-963 , 2008.
[6]	Hongmei Yan, Yingtao Jiang, Junzheng, Chenglin Peng and Qinghuili, "A multilayer Perceptron-based medical decision support System for heart disease diagnosis", <i>Elsevier Journal on Expert System with Application</i> , pp 272-281, 2006.
[7]	Jyh-shing Roger Jang, "Anfis-adaptive-network-based fuzzy inference system", <i>IEEE transactions on systems, man, and cybernetics</i> , vo-l. 23, no. 3, pp. 665-685 ,May-.June 1993