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# Adaptive Neuro-Fuzzy Inference System for Health Monitoring at Home

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***Abstract***

*Healthcare is approaching a critical situation. The ageing of population is increasing the prevalence of chronic diseases. Cardiovascular and respiratory diseases not only kill hundreds of thousands of people each year around the globe but also cost billions of dollars. Patients have to make frequent visits to their doctor to get their vital signs measured. People in remote places are deprived of proper healthcare. Hence, there is a need to develop a system which will help in reducing the frequent visits to the clinic and also help in early diagnosis of dangerous diseases. A system must be targeted both for monitoring elderly and for monitoring rehabilitation after hospitalization period and at the same time economically efficient. This paper presents our initial attempts to develop such a system with the help of Adaptive Neuro-Fuzzy Inference System (ANFIS) by adaptive learning mechanism. The MATLAB simulation results indicate that the performance of the ANFIS approach is much important and at the same time easy to implement. The study results are based on the ranges of diagnostic health parameters and the corresponding opinion of the expert. The developed healthcare system can be useful for the elderly and terminally ill patients confined within their homes and at the same time helpful to the pregnant women for their regular checkups without personally visiting to the clinic.*

***Keywords:*** *Adaptive Neuro-Fuzzy Inference System, adaptive learning mechanism, healthcare, health monitoring, rehabilitation*

## 1. Introduction

Ageing of population, growing mobility in society and growing shortage of staff resources in the health care sector require new models for information handling and communication in order to guarantee quality-oriented health care of the elderly. However, to assure high quality health services for the elderly at a reasonable cost, standardized co-ordination of information handling and communication between different care providers is a prerequisite. As the population grows older, people becomes increasingly dependent as their sensory, motor and cognitive physiological health capacities deteriorate; these age related changes, are amplified if they are accompanied by pathological conditions that are common in the elderly population. Most European countries are now facing an urgent requirement to provide appropriate retired home environments solutions for these citizens and allow them to play a role in our society. Patients have to make frequent visits to their doctor to get their vital signs measured. Regular monitoring of vital signs is essential as they are primary indicators of an Individual’s physical well-being. These vital signs include:

1. Pulse rate
2. Blood pressure
3. Body temperature

4. Breathing rate
5. Oxygen saturation level

Traditionally, it was a custom to get these vital signs measured during a visit to the doctor. With advances in medicine and technology, this concept has adapted. There are many devices available in the market today that allow patients to monitor their own health on a regular basis from the comfort of their home. These devices are having a huge impact on health care costs as they are reducing the time and resources of medical physicians and facilities required by patients. This is advantageous for both patients and physicians. Patients can monitor their health regularly and adjust their diet and physical exercise as needed to keep their vitals in balance. Health care professionals can access this information from their computers via wireless network and can check their patients' vitals at their own time. If they notice abnormalities, they can always schedule an appointment with their patients. This paper presents our initial attempts to develop a low cost, reliable, non-intrusive, and non-invasive vital signs monitor that processes and analyses the data acquired from measuring instruments to determine if an individual is within a "normal" range. Most of the population of India is located in the rural areas which are deprived of the proper health care facilities. Hence, whenever they want the health care services they have to make the regular and most frequent visits to the city hospitals. This proves to be cost ineffective with a lot of inconvenience to the patient as well as his family members. The proposed system will prove to be cost effective in such case. One of the diversified applications of this work is to monitor the regular health status of a pregnant woman at home.

Neural Fuzzy Systems can create fuzzy rules and membership functions for complex systems for which the fuzzy approach may fail, limiting themselves to lesser number of rules. This limits the performance and accuracy of the system. Whereas, the neural networks have the ability to adapt itself to the changes in input until the output matches the desired value increasing the reliability of the system. Hence a combination of fuzzy logic and adaptive nature of neural network is made use for detecting the health status of an individual. The neuro-fuzzy systems can handle any type of information (numerical, linguistic, logical, *etc.*), manage imprecise data and are self-learning. Hence it minimizes the human decision making process [1].

The patient is checked for five vital health parameters with the help of portable digital instruments such as pulse oxymeter, spirometer, thermometer and blood pressure monitor. These measured parameters are then given as input to the proposed system. If the outcome represents that the patient is abnormal then the appropriate medications are provided as shown in figure1. Family-based healthcare services allow patients full mobility at their homes, where health-care providers can monitor their health data remotely. Such family-based connected healthcare systems besides reducing the waiting time for face-to-face contact with physicians are capable of generating alerts being sent to the patients or to the informal care-taker by the physician [2].

The paper is structured as follows. In Section 2, a survey on related work is discussed. Section 3, explains the proposed work where the processes involved in neuro-fuzzy based classification are discussed. Results are discussed in section 4 followed by conclusions and future work to be carried out in section 5.

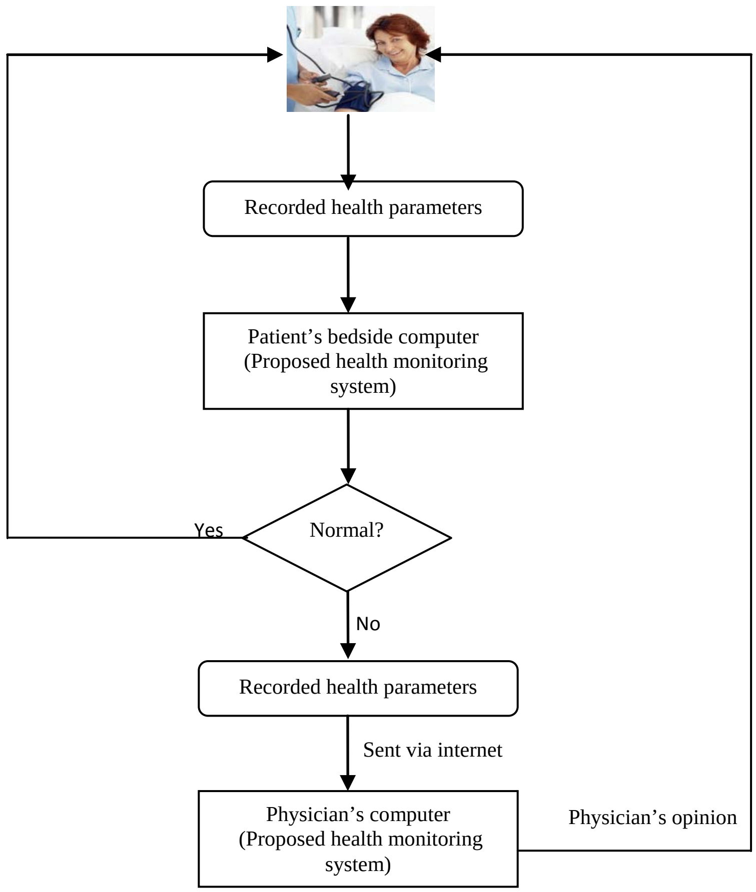


**Figure 1. Health Monitoring Workflow**

## 2. Literature Review

Ibrahim Khalil *et al.*, [3] developed an advanced prediction model to estimate the heart rates of selected patients in a mobile care system. But only heart patients can be taken care of with this system. Koji Mukai *et al.*, [4] developed a remote system for monitoring heart rate, respiration rate and movement behaviour of at-home elderly people who are living alone. Hiroshi Nakajima *et al.*, [5] described a human health monitoring system by an air pressure sensor and an ultrasonic sensor system. K. Kuwana *et al.*, [6] have developed an implantable telemetry capsule for monitoring heartbeat with FM transmitter and power supply. The capsule was capable of monitoring vital signs over the long term. However the whole system was a bit complex and economically inefficient. Mari Zakrzewski *et al.*, [7] developed the system which was targeted both for monitoring elderly and for monitoring rehabilitation after hospitalization period.

Shoko Nukaya *et al.*, [8] described a novel bed sensing method for non-invasive, constraint-free, subliminal detection of bio signals. Kyung-Ah Kim *et al.*, [9] implemented a home self healthcare monitoring system which can monitor respiration, blood glucose, urinary flow, and temperature. Dr. V. Vaidehi *et al.*, [10] proposed health care monitoring system enables significant responsiveness and process optimization by integrating complex event processing that leverages context awareness in Service Oriented Architecture. A method using the combination of ZigBee and GPRS is presented by Hongzhou Yu *et al.*, [11] which is a remote health monitoring system used to collect and transfer bio signal data from the patient to healthcare centre. This system transfers the data effectively but is not capable of decision making.

Namrata Nawka *et al.*, [2] presented "SESGARH", a scalable and extensible smart-phone based healthcare system, to provide real-time continuous monitoring of health conditions of individuals seeking professional healthcare. A real-time system for detecting the fall of elderly people in smart home is presented by V. Dhivya Poorani *et al.*, [1]. Decision-making based on neuro-fuzzy logic, makes the fall detection system more accurate and reliable. All the above approaches for health monitoring are beneficial but at the same time they have some limitations ranging from complexity to cost. Hence, there is a need to develop the proposed ANFIS based health monitoring system.

## 3. Adaptive Neuro Fuzzy Inferece System

### A. ANFIS Architecture

The Adaptive Neuro-Fuzzy Inference System technique was originally presented by Jang in 1993 [12]. ANFIS is a simple data learning technique that uses Fuzzy Logic to transform given inputs into a desired output through highly interconnected Neural Network processing elements and information connections, which are weighted to map the numerical inputs into an output. ANFIS combines the benefits of the two machine learning techniques (Fuzzy Logic and Neural Network) into a single technique [12]. An ANFIS works by applying Neural Network learning methods to tune the parameters of a Fuzzy Inference System (FIS).

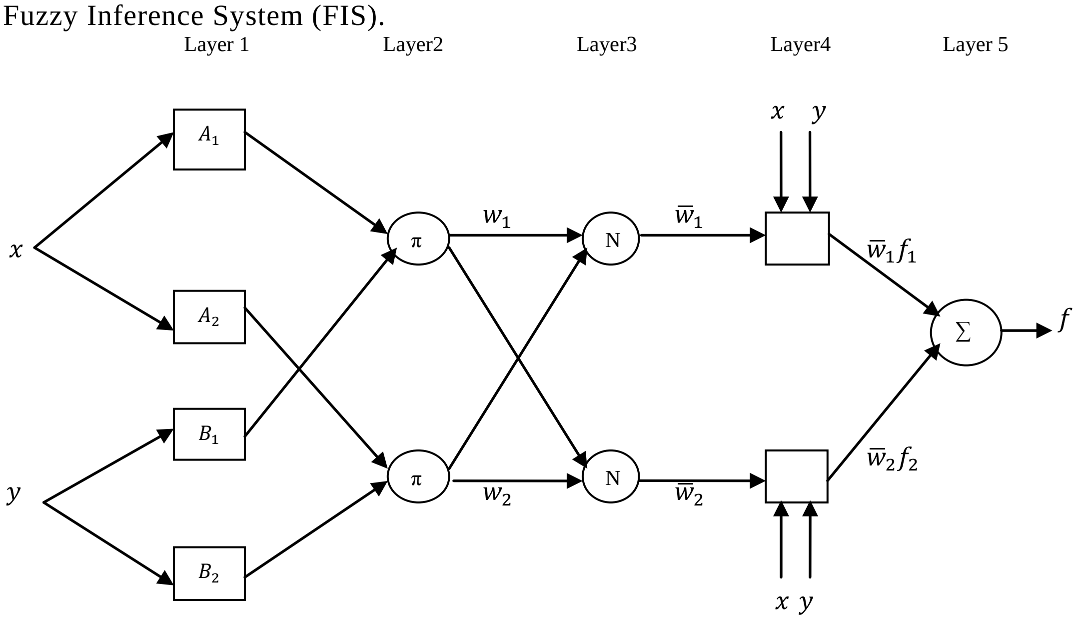


**Figure 2. ANFIS Architecture**

Different rules cannot share the same output membership function. The number of membership functions must be equal to the number of rules. To present the ANFIS architecture, two fuzzy IF-THEN rules based on a first order Sugeno model are considered:

$Rule_{(1)}$: IF $x$ $is$ $A_1$ AND $y$ $is$ $B_1$ , THEN $f_1 = p_1x + q_1y + r_1$.
$Rule_{(2)}$: IF $x$ $is$ $A_2$ AND $y$ $is$ $B_2$ , THEN $f_2 = p_2x + q_2y + r_2$.
Where:

x and y are the inputs,

Ai and Bi are the fuzzy sets,

fi are the outputs within the fuzzy region specified by the fuzzy rule, and

pi, qi, and ri are the design parameters that are determined during the training process.

The ANFIS architecture used to implement these two rules is shown in Figure 2. In this figure, a circle indicates a fixed node, whereas a square indicates an adaptive node. ANFIS has five-layer architecture. Each layer is explained in detail below. In Layer (1), all the nodes are adaptive nodes. The outputs of Layer (1) are the fuzzy membership grade of the inputs, which are given by the following equations:

$$O_{1,i} = \mu_{Ai}(x), i = 1,2, \qquad (1)$$

$$O_{1,i} = \mu_{Bi-2}(y), i = 3,4, \qquad (2)$$

Where x and y are the inputs to node i, and $Ai$ and $Bi$ are the linguistic labels (high, low, *etc*.) associated with this node function. $\mu_{Ai}(x)$ and $\mu_{Bi-2}(y)$ can adopt any fuzzy membership function. For example, if the bell-shaped membership function is employed, $\mu_{Ai}(x)$ is given by

$$\mu_{Ai}(x) = \frac{1}{1 + \left[\left(\frac{x - c_i}{a_i}\right)^2\right]^{b_i}}, i = 1,2, \quad (3)$$

Or the Gaussian membership function by

$$\mu_{Ai}(x) = exp\left[-\left(\frac{x - c_i}{a_i}\right)^2\right], \qquad (4)$$

Where$a_i$,$b_i$ and $c_i$ are the parameters of the membership function. In Layer (2), the nodes are fixed nodes. This layer involves fuzzy operators; it uses the AND operator to fuzzify the inputs. They are labeled with $\pi$, indicating that they perform as a simple multiplier. The output of this layer can be represented as

$$O_{2,i} = w_i = \mu_{Ai}(x) * \mu_{Bi}(y), i = 1,2. \quad (5)$$

These are the so-called firing strengths of the rules. In Layer (3), the nodes are also fixed nodes labeled by N, to indicate that they play a normalization role to the firing strengths from the previous layer. The output of this layer can be represented as

$$O_{3,i} = \bar{w}_i = \frac{w_i}{w_1 + w_2}, i = 1,2. \qquad (6)$$

Outputs of this layer are called normalized firing strengths. In Layer (4), the nodes are adaptive. The output of each node in this layer is simply the product of the normalized firing strength and a first order polynomial (for a first order Sugeno model). The output of this layer is given by

$$O_{4,i} = \bar{w}_i f_i = \bar{w}_i(p_i x + q_i y + r_i), i = 1,2, \quad (7)$$

Where $\overline{\omega}$ is the output of Layer (3), and pi, qi, and ri are the consequent parameters. In Layer (5), there is only one single fixed node labelled with $\sum$ his node performs the summation of all incoming signals. The overall output of the model is given by

$$O_{5,i} = \sum_i \overline{w} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}. \qquad (8)$$

### B. Hybrid Learning Algorithm

The learning algorithm for ANFIS is a hybrid algorithm that is a combination of gradient descent and least squares methods. In the forward pass of the hybrid learning algorithm, node outputs go forward until Layer (4) and the consequent parameters are determined by the least squares. In the backward pass, the error signals propagate backward and the premise parameters are updated using gradient descent. The hybrid learning approach converges much faster by reducing search space dimensions of the original back propagation method [12]. The overall output can be given by

$$f = \frac{w_1}{w_1 + w_2} f_1 + \frac{w_2}{w_1 + w_2} f_2, \quad (9)$$

$$f = \overline{w}(p_1 x + q_1 y + r_1) + \overline{w}(p_2 x + q_2 y + r_2), \quad (10)$$

$$f = (\overline{w}_1 x)p_1 + (\overline{w}_1 y)q_1 + (\overline{w}_1)r_1 + (\overline{w}_2 x)p_2 + (\overline{w}_2 y)q_2 + (\overline{w}_2)r_2, \quad (11)$$

where $p_1$, $q_1$, $r_1$, $p_2$, $q_2$, and $r_2$ are the linear consequent parameters. The least squares method is used to identify the optimal values of these parameters. When the premise parameters are not fixed, the search space becomes larger and the convergence of the training becomes slower. It should be noted that the ANFIS hybrid algorithm combines two methods, the least squares method and the gradient descent method, to solve the problem of search space. The hybrid algorithm is composed of a forward pass and a backward pass. The least squares method (forward pass) is used to optimize the consequent parameters. The gradient descent method (backward pass) is used to optimize the premise parameters. The output of the ANFIS is calculated by employing the consequent parameters found in the forward pass. The output error is used to adapt the premise parameters by means of a standard back propagation algorithm. It has been proven that this hybrid algorithm is highly efficient in training the ANFIS systems [13].

### C. ANFIS System Training Process

The ANFIS system training methodology is summarized in Figure 3. The process begins by obtaining a training data set (input/output data pairs) and testing data sets. The training data is a set of input and output vectors. Two vectors are used to train the ANFIS system: the input vector and the output vector. The training data set is used to find the premise parameters for the membership functions. A threshold value for the error between the actual and desired output is determined. The consequent parameters are found using the least squares method. If this error is larger than the threshold value, then the premise parameters are updated using the gradient decent method. The process is terminated when the error becomes less than the threshold value [12]. ANFIS training learning rules use hybrid learning, combining the gradient descent and the least squares method. The aim of using ANFIS for health monitoring is to achieve the best performance possible. ANFIS training begins by creating a set of suitable training data in order to be able to train the Neuro-Fuzzy system. The data set used as the input to the anfis function must be in a matrix form, where the last column in the matrix is the output, and the matrix contains as many columns as needed to represent the inputs to the system. The rows represent all the existing data situations. Creation of the membership functions is dependent on the system designer. The designer may create the parameters of the membership functions if they have knowledge of the expected shapes, or they can use the command genfis1 from MATLAB to help in the creation of the initial set of membership functions. This work uses the genfis1 command to create the membership functions. Once the initial membership functions are created, system training begins. When the training process is finished the final membership functions and training error from the training data set are produced. After the system training is complete, ANFIS provides a method to study and evaluate the system performance by using the evalfis function. Once the ANFIS is trained, we can test the system against different sets of data values to check the functionality of the proposed system [14].

### D. ANFIS for Health Monitoring

ANFIS is selected to solve the problem of remote health monitoring, facilitating the quality healthcare service to population of India. The proposed ANFIS model can be used for modeling the human health parameters. The steps required to apply ANFIS to modeling are: define input and output values; define fuzzy sets for input values; define fuzzy rules; and create and train the Neural Network. To implement and test the proposed architecture, a development tool is required. MATLAB Fuzzy Logic Toolbox (FLT) from MathWorks was selected as the development tool. This tool provides an environment to build and evaluate fuzzy systems using a graphical user interface. It consists of a FIS editor, the rule editor, a membership function editor, the fuzzy inference viewer, and the output surface viewer. The FIS editor displays general information about a fuzzy inference system. The membership function editor is the tool that displays and edits the membership functions associated with all input and output variables. The rule editor allows the user to construct the rule statements automatically, by clicking on and selecting one item in each input variable box, one item in each output box, and one connection item. The rule viewer allows users to interpret the entire fuzzy inference process at once. The ANFIS editor GUI menu bar can be used to load a FIS training initialization, save the trained FIS, and open a new Sugeno system to interpret the trained FIS model.

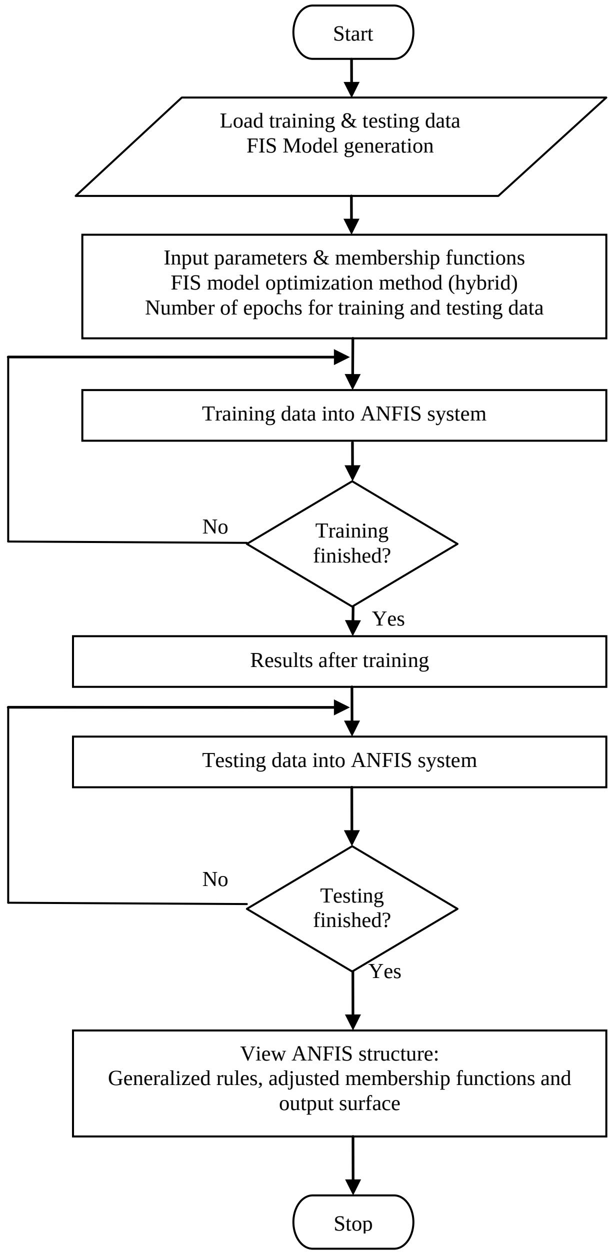


**Figure 3. ANFIS Training System**

## 4. Results and Discussion

The data were divided into two separate sets: the training data set and the testing data set. The training data set was used to train the ANFIS, whereas the testing data set was used to verify the accuracy and the effectiveness of the trained ANFIS model. The optimal ANFIS model setting will be selected based a comparison of training and testing error values for different epoch numbers. Three types of membership functions are taken into consideration in relation to ANFIS system training. The ANFIS system was structured by selecting six inputs namely: Systolic BP, Diastolic BP, Pulse Rate, Oxygen Saturation, Temperature and Breath Rate having 3,3,3,2,2,3 membership functions respectively and one output as Health Status.

We tested our model with different membership function types “Trapezoidal, Generalized bell shaped and Gaussian2” on each of the six inputs. The generated fuzzy inference system structure contains 324 fuzzy rules. Table 1.1 shows that the generalised bell shaped (gbellmf) membership function performs most effectively with minimum training and testing error during validation with the epoch numbers 10, 25, and 50, and the trapezoidal (trapmf) membership function produced the worst results with epoch numbers 10, 25, and 50. Also the other important ANFIS structures are listed below. The final membership functions for input1 *i.e.* Systolic BP obtained after training the ANFIS system for 50 epochs are shown in the Figure 4.1, 4.2, 4.3 for Trapezoidal, Generalised bell shaped and Gaussian2 membership functions respectively.

ANFIS structure parameters:

1. Number of nodes: 689
2. Number of linear parameters: 2268
3. Number of nonlinear parameters: 64
4. Total number of parameters: 2332
5. Number of training data pairs: 972
6. Number of testing data pairs: 300
7. Number of inputs: 6
8. Number of membership functions: 3*3*3*2*2*3
9. Number of fuzzy rules: 324
10. Error tolerance: 0.01

**Table 1.1. The ANFIS Structure Information**

| Membership function types | Number of epochs | Average training error | Average testing error |
|---|---|---|---|
| Trapezoidal | 10 | 0.20997 | 0.20914 |
| | 25 | 0.20964 | |
| | 50 | 0.20914 | |
| Generalized bell shaped | 10 | 0.015706 | 0.014027 |
| | 25 | 0.015089 | |
| | 50 | 0.01407 | |
| Gaussian2 | 10 | 0.048619 | 0.048619 |
| | 25 | 0.048619 | |
| | 50 | 0.048619 | |

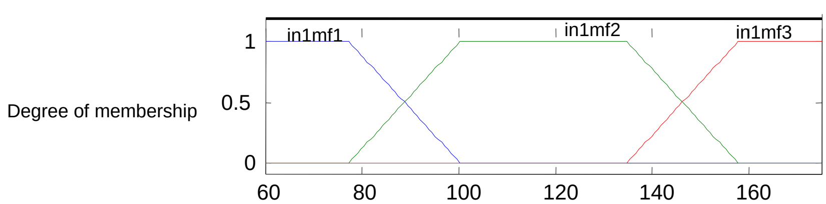


**Figure 4.1. Trapezoidal Membership Function**

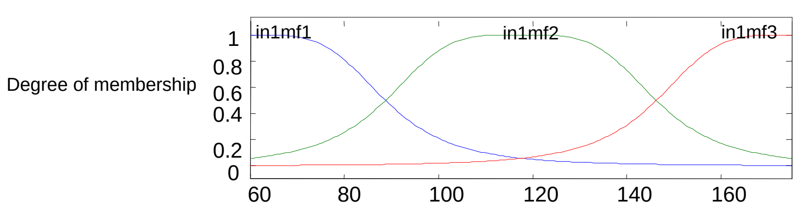


**Figure 4.2. Generalized Bell Shaped Membership Function**

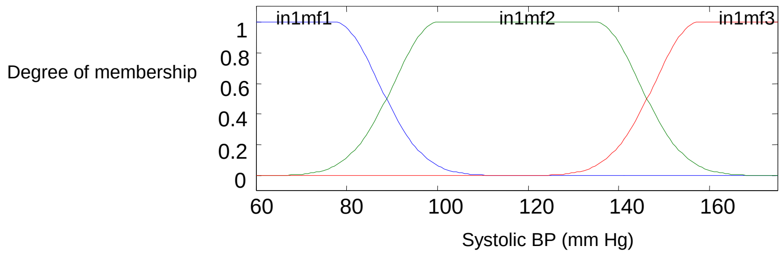


**Figure 4.3. Gaussian2 Membership Function**

## 5. Conclusion

This paper introduced the initial attempts for remote health monitoring using Adaptive Neuro-Fuzzy Inference System adaptive learning mechanism. The performance of ANFIS was evaluated by diagnosing number of patients under the supervision of a medical practitioner in a private healthcare centre. After comparing the results obtained from the developed system and the opinion of the physician it was found that the ANFIS system proved to be satisfactory with the minimum error of 1.402%. The ANFIS approach has successfully solved the problem of incompleteness in the fuzzy rule base made by the human expert. Hence, the system can be used effectively for home health monitoring. Future research could be to monitor the health of patients on a continuous, regular and real time basis. The developed healthcare system will thus be useful for the elderly and terminally ill patients confined within their homes and at the same time helpful to the pregnant women for their regular checkups without personally visiting to the clinic.

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