NEURO-FUZZY EXPERT SYSTEM FOR DIAGNOSIS OF THYROID DISEASES

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ABSTRACT: The computerization of medical procedures has been identified to be one of the major challenges in the medical sector. Several techniques have been used in order to automate the processes in diagnosis of diseases; such processes include incorporation of artificial neural network and fuzzy logic techniques as expert systems with the knowledge about the domain. Such expert systems help to hasten the speed of diseases diagnosis, its accuracy and efficiency. In this paper, two artificial intelligence techniques; neural network and fuzzy logic system are considered. The two techniques are used to develop a hybrid intelligent computational system for the diagnosis of thyroid diseases. The experimental results obtain depend on the inputs to the neural network and also are set using a decision making system for making decisions on the thyroid disease according to the output of the neuro-fuzzy system.
KEYWORDS: Expert System, Fuzzy Logic, Neural Network, Diagnosis, Thyroid Diseases.

1. INTRODUCTION

Thyroid disorders comprise of diseases and conditions such as graves disease, thyroid nodules, Hashimoto's thyroiditis, trauma to the thyroid, thyroid cancer and birth defects ([AC12]). These include being born with a defective thyroid gland or without a thyroid gland. Thyroid disorders can cause the thyroid gland to become overactive (hyperthyroidism) or underactive (hypothyroidism) ([RR16]). Thyroid disorders occur when the thyroid gland secretes too many or too few hormones, which result in a slowing of the body's chemical processes and metabolism with symptoms like weight gain, fatigue and depression ([ElB15]).

The range of thyroid cases over the past few years has increased drastically; since thyroid involves a complicated relation with metabolism and weight, it's extremely compulsory to diagnose thyroid disease as early as possible ([GR16]). Diagnosis of thyroid disease is one among the needed problems to develop a medical decision support system which is able to assist the doctors in making effective decisions. The technologies include the use of artificial intelligence techniques like artificial neural networks and fuzzy logic which when combined are referred to as hybrid expert systems.

Disease diagnosis is a wide-ranging and challenging area; its task is to detect the disease that a patient has based on the symptoms, laboratory reports and various other techniques ([T+15]). The process can be said to be complicated because not all disease symptoms are specific to only one disease and often the symptoms are overlapping. Errors caused by human factors are not rare in the process of diagnoses. To reduce the high occurrence of human errors in modern medicine different technologies are now in use.

Artificial neural networks as an area of artificial intelligence is a tool with the ability to learn and produce artificial systems capable of sophisticated perhaps intelligent computations ([KNC13]), similar to those that the human brain routinely performs and possibly to enhance the understanding of the human brain . The artificial neural networks have distinct advantages over statistical classification methods. The Artificial neural networks are suitable in cases, where traditional classification methods fail, because of noisy or incomplete data.

The diagnosis of diseases is a good example of such complex classification problems. Fuzzy logic has proved to be the remarkable tool for building intelligent decision making systems based on the expert's knowledge and observations. Neural network automatically adjusts their weights to optimize their behaviour as pattern recognizers, decision makers, system controllers, predictors and so on ([AL11]).

Hybridize techniques using the combination of fuzzy logic and neural networks have proven their effectiveness in a wide variety of real-world problems ([KDK14]). The neuro-fuzzy expert systems are being used to diagnose a large of variety diseases ([AP14]). In this paper, the neuro-fuzzy expert system was applied in the diagnosis of thyroid diseases by analyzing the laboratory reports and to perform diagnosis of the particular conditions of the patients.

2. RELATED WORK

Neuro-fuzzy expert system has been employed by several researchers in diagnosing different diseases. Among so many studies carried out include:
([Sid17]) performed a comparative study of existing techniques for diagnosing various thyroid ailments. The study carried out the survey of existing data mining techniques used to diagnose various thyroid ailments and to present the techniques used and its accuracy. A diagnosis system based on hybrid intelligent systems (Nero-fuzzy network) as classifier was designed by ([SJA16]). Neural Network and Fuzzy Logic were combined to get the main features of artificial neural networks with those of fuzzy logic and to overcome some of the limitations of these techniques.
The evaluation of the developed system was done using thyroid disease datasets from UCI machine learning dataset. The experimental results presented for different proportions of training and testing groups gave high classification accuracy and convergence in rates. The overall accuracy of 100% for training and range between 87 % and 95% for testing were recorded.
([MJ15]) presented a review of literature that included some types of fuzzy medical expert system (FMES) for applications in some medical domains. The work introduced structure and applications of fuzzy expert system in medical field and also discusses the advantages and limitations of expert systems. ([AC12]) developed an application of Neuro-Fuzzy Expert System for the probe and prognosis of thyroid disorder. The study demonstrated the practical application of information technology (IT) in the health sector, with presentation of hybrid neuro-fuzzy expert system to help in diagnosis of thyroid disorder using a set of symptoms. The system was designed in an interactive way that tells the patient his current condition as regards thyroid disorder.

3. METHODOLOGY

3.1 The Approach for Developed Neuro-Fuzzy System

The study collected primary data by acquisition of information from expert medical personnel. Information included how a patient can be affected, in what kind of environment a patient can be affected and to know how often the problem has been encountered and basic knowledge on how the problem faced can be tackled and treated. The developed neuro-fuzzy expert system employed expert knowledge of the disease and a comprehensive dataset of test values and a neural network to train the expert system. With the aid of the results (outputs of the network) being trained, the fuzzy logic system was used to give an efficient diagnosis report through the fuzzy stimulation of the trained neural network data and also to determine the state of the disease and would reduce the time frame for the diagnoses of the illness.
The process of the developed system entailed collection of data to make up a dataset, in which the data (laboratory test reports) were collected and further classified into a training set and testing set. Data were fed to the neural network for training, the trained output samples were passed into the fuzzy logic system in which the trained neural network outputs were normalized (crisp input) and converted into fuzzy values with the aid of a membership function. The fuzzification process was evaluated across fuzzy rules (conditions for diagnoses) and after the inference the fuzzy values were defuzzified to non-fuzzy values which were more understandable as shown in Figure 1.

3.2 Data Collection Phase

The data used in this study to build a Knowledge base of the system was obtained from a Classification of data from the University of California, Irvine (UCI) machine learning data set repository. The dataset contains 3 classes and 215 samples. These classes are assigned to the values that correspond to the hyper-, hypo-, and normal function of the thyroid gland.

3.3 Data Processing Phase

The dataset obtained from the UCI repository were processed and prepared with the aid of Microsoft Excel 2016 tool to organize and also classify the dataset values before it was used in the expert system.

3.4 Component Breakdown for the Proposed System

This section entails the basic break down of the component processes of the neuro-fuzzy system. The data used in Neuro-Fuzzy Expert System has the following attributes:-

a) Class attribute (1 = normal, 2 = hyper, 3 = hypo)
b) T3-resin uptake test. (A percentage)
c) Total Serum thyroxin as measured by the isotopic displacement method.
d) Total serum triiodothyronine as measured by radioimmunoassay.
e) Basal thyroid-stimulating hormone (TSH) as measured by radioimmunoassay.
f) Maximal absolute difference of TSH value after injection of 200 micro grams of thyrotropin-releasing hormone as compared to the basal value.

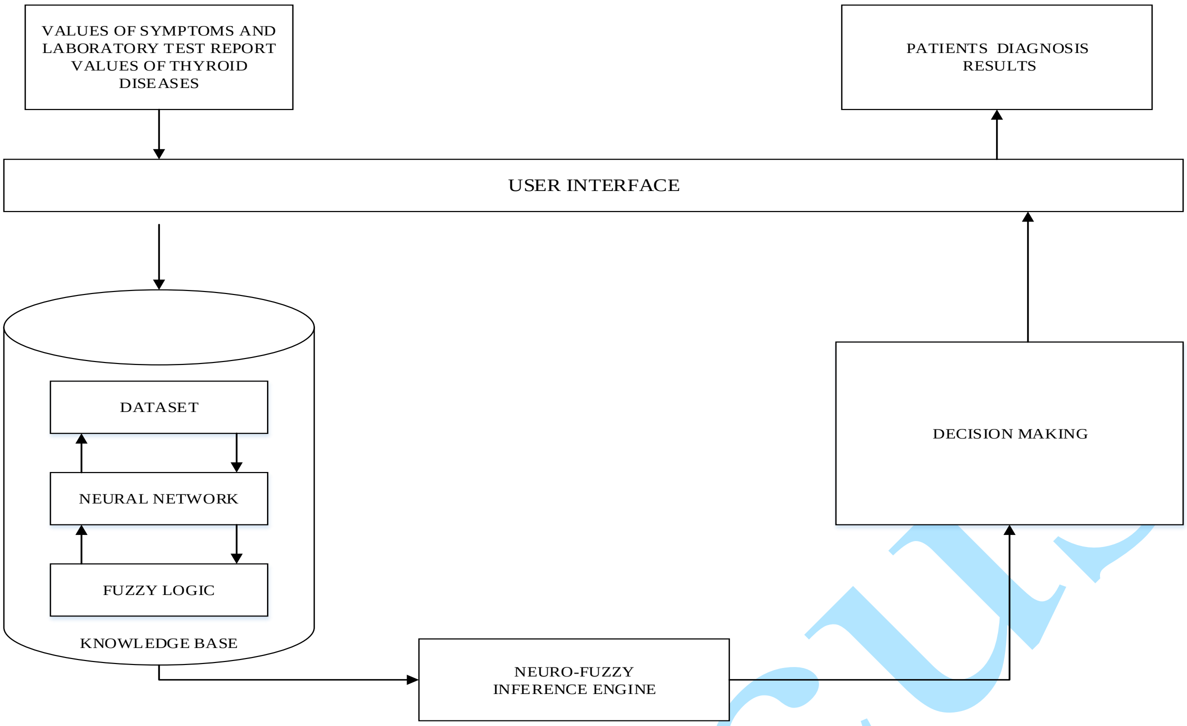

Figure 1: Framework of Thyroid Diagnosis System

150 samples of 215 belong to hyper-function class namely class-1. The 35 samples of 215 belong to hypo-function class namely class-2. 30 samples of 215 belong to normal-function class namely class-3. The representative codes for the attribute are given in Table 1.

Table 1: Representative Code Table

Attributes	Representative Code
T3-resin uptake test	T3RU
Total Serum thyroxin	T3
Total serum triiodothyronine	T4
basal thyroid-stimulating hormone (TSH)	TSH

3.5 Neural Network

Adapting the structural and training of a back propagation algorithm of a neural network which consist of two phases which are forward and backward pass, in which the training of the network referred to as the back propagation itself uses error signals propagated backwards into the network. From each output the error signal propagates from output to hidden and hidden to input layer based on the weights which are updated in the neural network. In the training of neural network for thyroid disease diagnosis the algorithm which gives a description of the neural network is stated as follows:

Step 1: Collection of dataset values from the user.
Step 2: Normalizing dataset to input data.
Step 3: Splitting of dataset into testing and testing set.
Step 4: Initialize the connection weights for all neurons to some random numbers between 0 and 1.
Step 5: Use the vector (x_i) comprising attributes of thyroid diseases as inputs to the system
Step 6: Select the first training input and output pair (x, *d)* from the training pair vectors (x_i, d_k)
Step 7: Compute the value of the hidden layer (h_j) defined by:

$$h_j = f\left(\left(\sum_{j=1}^{m}\sum_{i=1}^{n} x_i W_{ij}\right) + \theta_j\right) \tag{1}$$

Step 8: Compute the value of the Output layer (o_k) defined by:

$$o_k = f\left(\left(\sum_{j=1}^{m} w_{jk} h_j\right) + \theta_k\right) \quad (2)$$

Step 9: Compare the result and obtain the difference

$$\text{Difference} = d_k - o_k \quad (3)$$

where d_k = desired value and o_k = computed value

Step 10: Obtain output error defined by:

$$e_k = (d_k - o_k)(ok)(1 - o_k) \quad (4)$$

Step 11: Compute the error at the hidden layer using:

$$e_j = h_j\left(1 - h_j\left(\sum_{j=1}^{m} w_{jk} e_k\right)\right) \quad (5)$$

Step 12: Propagate the error back into the network if the error is greater than a certain predefined value, by means of adjustment of the weights connecting the output to the hidden layers as well as the weights connecting the hidden layers to the input layers.

Step 13: Adjust the weights between *kth* output neuron and jth hidden neuron, thus

$$w_{jk}(n+1) = w_{jk}(n) + h_j \beta e_k \quad (6)$$

Step 14: Repeat steps 'b' through 'j' as many cycles as needed until the Sum of Squared Error(SSE) is within a prescribed tolerance using the formula

$$\text{SSE} = \sum_{k=1}^{p} (e_k)^2 \quad (7)$$

Step 15: Calculate the network performance after training.

3.6 Fuzzy Logic Component

The process of fuzzy logic system is explained in the flow model shown in Figure 2. Firstly, a crisp set of input data were gathered and converted to a fuzzy set using fuzzy linguistic variables, fuzzy linguistic terms and membership functions. This step is known as Fuzzication. Afterwards, an inference was made based on a set of rules in the rule base of the fuzzy logic system. Lastly, the resulting fuzzy output was mapped to a crisp output using the membership functions, in the Defuzzication step.

3.6.1 Linguistic Terms and Variables

The linguistic variables used for this study range from low to high conditions for the diagnosis of thyroid diseases. Each diagnosis attribute of thyroid diseases was represented by the linguistic term that belongs to the fuzzy set, while each linguistic term has its associated numerical value.

$$TD(x) = \begin{cases} 1 & if\ x\ is\ absent \\ 2 & if\ x\ is\ low \\ 3 & if\ x\ is\ Normal \\ 4 & if\ x\ is\ High \end{cases} \quad (8)$$

From Equation 8, x represents the linguistic variables of the fuzzy set, while TD means Thyroid Disease.

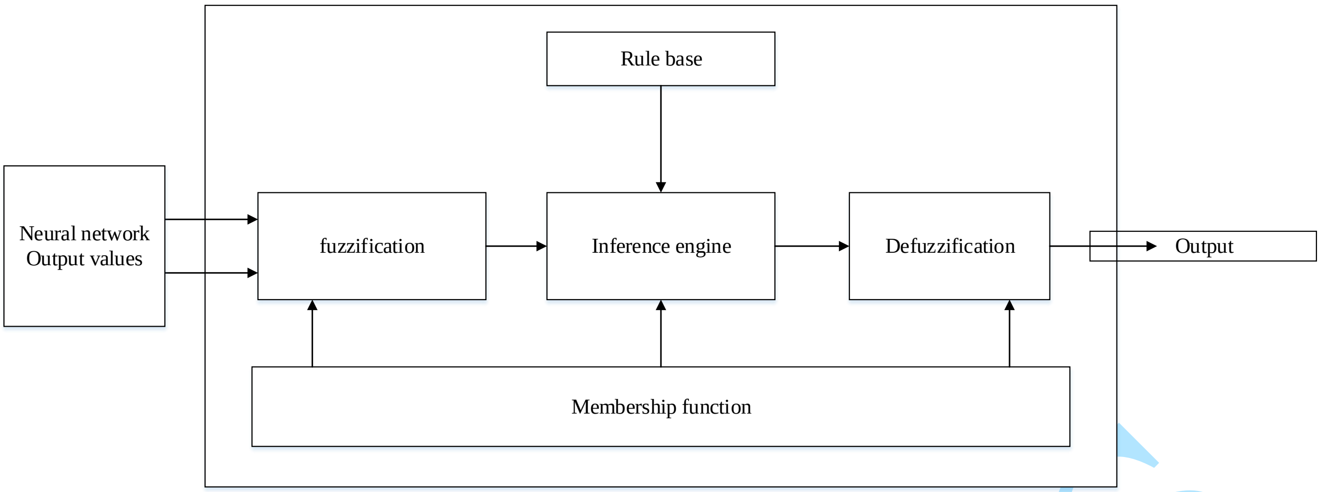

Figure 2: Fuzzy Logic Process Flow

3.6.2 Fuzzy Membership Functions

The triangular membership function was used in this study.

$$\mu_A(x)=\begin{cases}0 & \text{if } x<a\\ \dfrac{x-a}{b-a} & \text{if } a\le x<b\\ \dfrac{c-x}{c-b} & \text{if } b\le x<c\\ 0 & \text{if } c\le x\end{cases} \tag{9}$$

where a, b, c are the parameters of the Member Function (MF) governing triangular shape.
The fuzzification of T3- Resin uptake test (T3RU) denoted by *x*, measured in milli-internation units of hormone per liter of blood are expressed as follows:

$$VAR(x)=\begin{cases}low & if\ x<3.2\\ normal & if\ 3.2\le x<3.3\\ high & if\ 3.3\le x\le 4.2\end{cases} \tag{9}$$

The fuzzification of Total serum thyroxine (T3) denoted by *y*, measured in milli-internation units of hormone per liter of blood are expressed as follows:

$$VAR(y)=\begin{cases}low & if\ x<3.2\\ normal & if\ 3.2\le x<3.3\\ high & if\ 3.3\le x\le 4.2\end{cases} \tag{10}$$

The fuzzification of Total serum triiodothyronine (T4) denoted by *z*, measured in milli-internation units of hormone per liter of blood are expressed as follows:

$$VAR(z)=\begin{cases}low & if\ x<1.2\\ normal & if\ 1.2\le x<1.3\\ high & if\ 1.3\le x\le 1.8\end{cases} \tag{11}$$

The fuzzification of Basal thyroid stimulating hormone(TSH) denoted by *r*, measured in milli-internation units of hormone per liter of blood are expressed as follows:

$$VAR(r)=\begin{cases}low & if\ x<1.3\\ normal & if\ 1.3\le x<1.8\\ high & if\ 1.8\le x\le 4.5\end{cases} \tag{12}$$

The fuzzy input and output variables are used in the rule formulation and implication to guide the fuzzy inference.

3.6.3 Fuzzy Rule Base

The fuzzy rule base for the thyroid disease diagnosis is characterized by sets of IF – THEN rules in which the antecedents (IF parts) and the consequents (THEN parts) involves linguistic variable which are formulated from Table 1. The rules used for this study are:

Rule1: If (T3RU is high) and (T3 is high) and (T4 is high) and (TSH is low) Then (THD is high)
Rule2: If (T3RU is low) and (T3 is normal) and (T4 is low) and (TSH is high) then (THD is low)
Rule3: If (TSRU is low) and (T3 is low) and (T4 is low) and (TSH is high) Then (THD IS low)
Rule4: If (T3RU is high) and (T3 is high) and (T4 is high) and (TSH is low) Then (THD is high)
Rule 5: If (T3RU is high) and (T3 is high) and (T4 is normal) and (TSH is low) Then (THD is high)
Rule 6: If (T3RU is low) and (T3 is normal) and (T4 is normal) and (TSH is low) Then (THD is low)

Rule 7: If (T3RU is normal) and (T3 is normal) and (T4 is normal) and (TSH is normal) Then (THD is normal)
Rule 8: If (T3RU is normal) and (T3 is normal) and (T4 is normal) and (TSH is high) Then (THD is low)
Rule 9: If (T3RU is low) and (T3 is low) and (T4 is low) and (TSH is low) Then (THD is low)

where T3RU, T3, T4, TSH are the codes of the input parameters and THD is the output parameter as described in Table 1

3.6.4 Neuro-Fuzzy Component

In this paper, the neuro fuzzy approach was used to integrate training with Back Propagation Neural Network (BPNN) algorithm and a fuzzy logic system. The algorithm of the neuro-fuzzy approach based on the self-generating fuzzy rules inference system is outlined as follows:

Step 1: Normalize the data between 0 and 1
Step 2: Perform input contribution measures on all available input logs
Step 3: Select the significant input logs to form the training set
Step 4; Train the BPNN
Step 5: Define fuzzy membership (triangular)
Step 6: Define the space of the membership evenly
Step 7: Randomly generate input instances to cover the universe of discourse
Step 8: Present the generated input instances into trained BPNN
Step 9: Obtain output from BPNN
Step 10; The generated input instances and the output form the training data for fuzzy rule extraction
Step 11: Generate rules for each instance
Step 12: Use centroid defuzzification method to deduce the crisp output production

4. RESULTS ANALYSIS

4.1 Functionalities of System

The basic functions performed by the neuro-fuzzy system are;

- Load dataset in the right format (csv).
- Compute training of the neural network.
- Graphical User Interface (GUI) which hides the complexity of the diagnosis in the backend and also gives help when needed.
- Displaying of the membership functions and rule base.
- Displaying the fuzzy rule mapping structure of the fuzzy rules.
- Displaying a useful output which can be easily used by the user

4.2 Graphical User Interface for the Developed Thyroid Diagnosis

The first interface which the user interacts with is shown in Figure 3. This gives an option to continue or to exit the GUI.

4.3 Interface for Diagnosis

Figure 4 shows the interface phase that allows the loading of dataset into the system. Training of Data or Diagnosis can be performed using this GUI.

4.4 Loading Data Interface for Diagnosis

The process of loading data for the diagnosis of thyroid is shown in Figure 5. The necessary training and fuzzy logic operation of the system is computed by clicking on the Train Data button

4.5 Interface for Diagnosis of Thyroid

This section carries out diagnosis which leads to another interface for the output of results as shown in Figure 6 and the parameters setting is shown in Figure 7. Here the user views the membership functions (MF) variable and also a graphical representation of the membership functions is illustrated in Figure 8.

4.6 Fuzzy Rule Mapping of the Rules

The Fuzzy rule mapping is displayed for the inputs into the system. The mapping structure changes for different inputs to the system as shown in Figure 9.

4.7 Fuzzy Rule Mapping of the Rules

Results of the computation of Neuro-Fuzzy system are shown in Figure 10. The experimental results are represented in a clear and understandable manner. The Help menu interface gives a guide on understanding the results better.

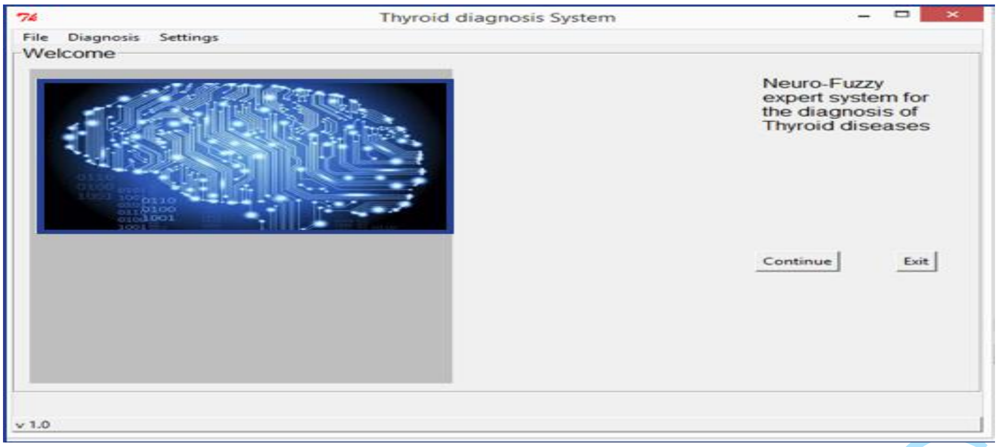

Figure 3: Homepage of System

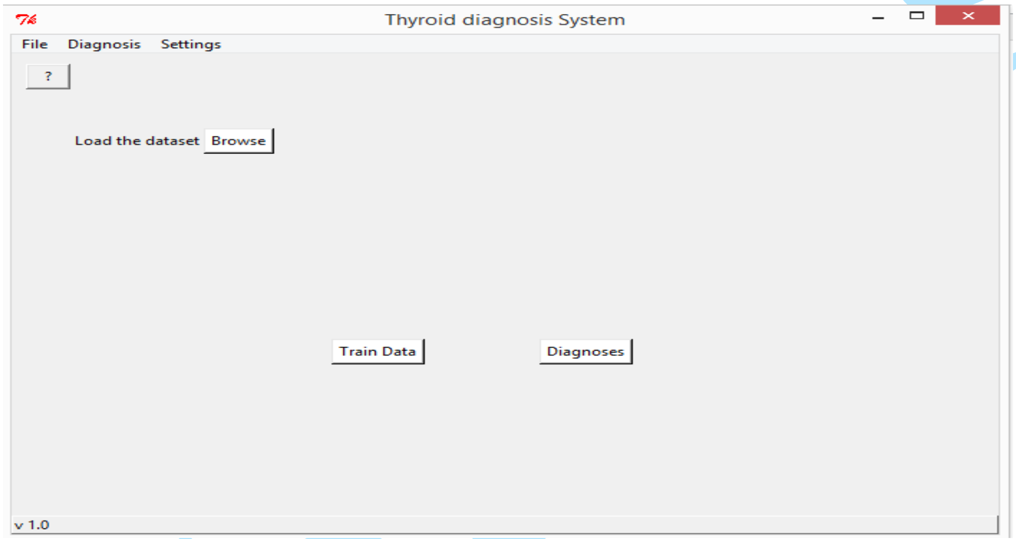

Figure 4: Diagnosis Interface

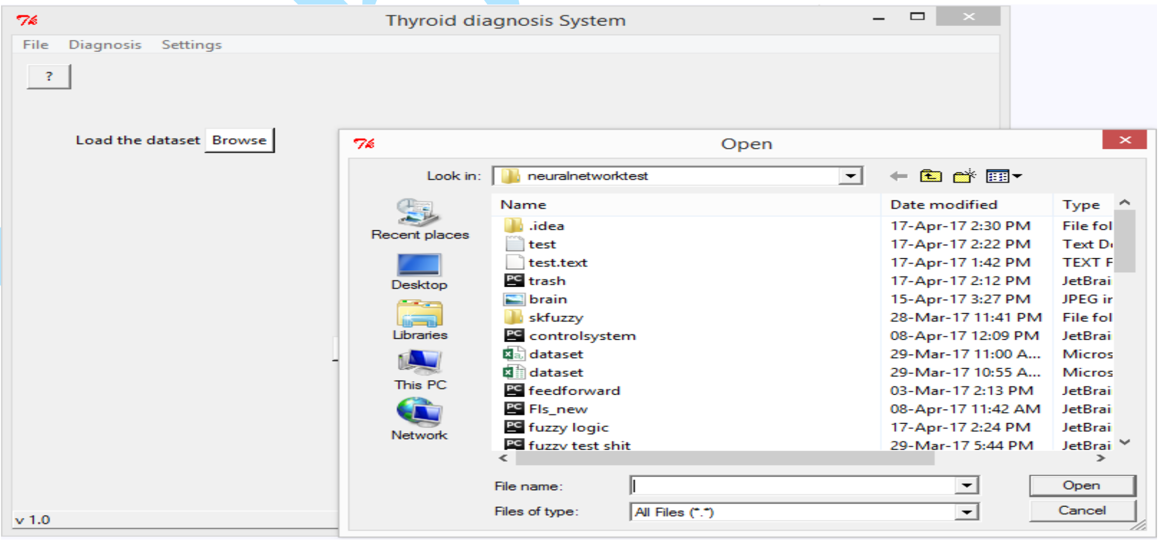

Figure 5: Loading Data Interface

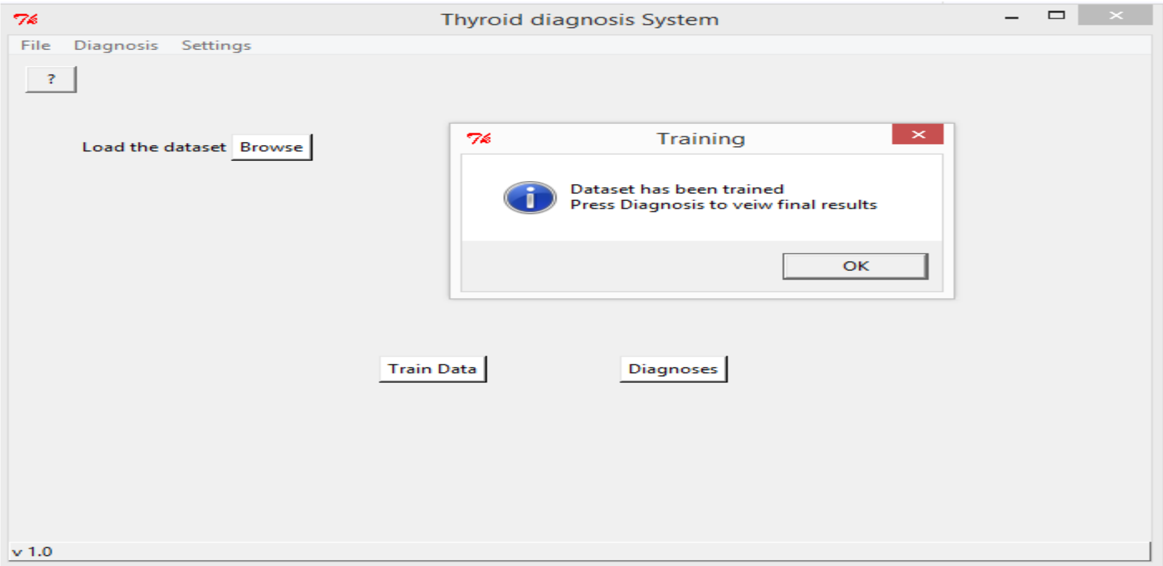

Figure 6: Diagnosis train data Interface

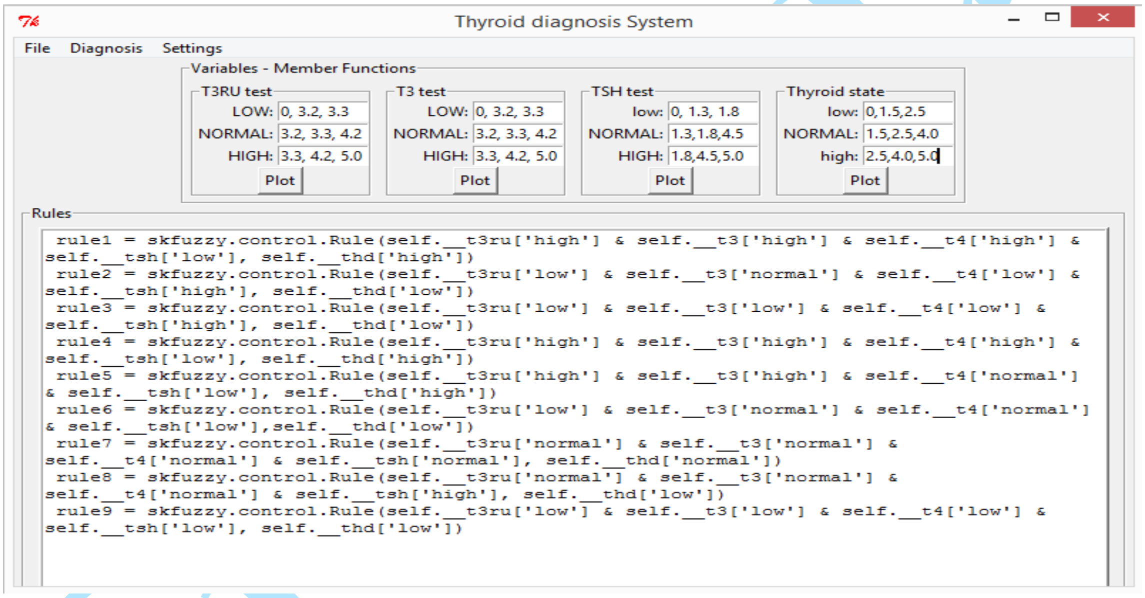

Figure 7: Settings Interface

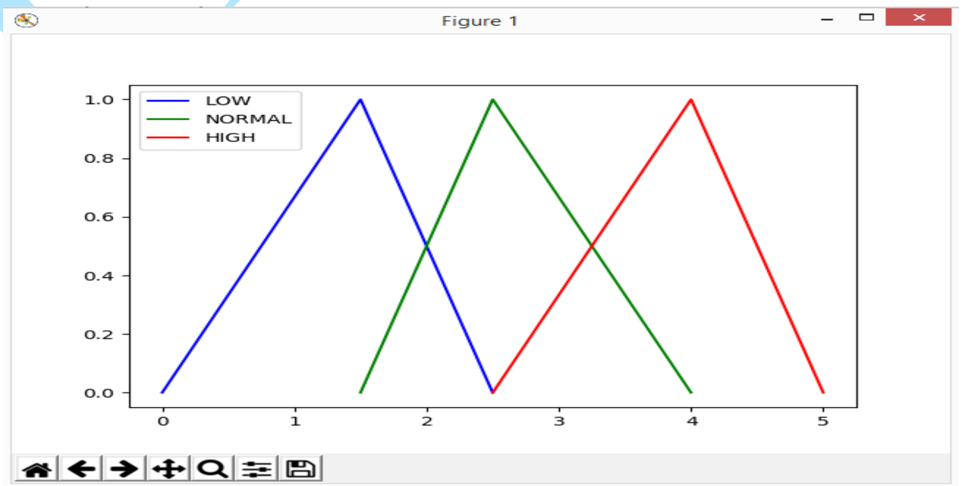

Figure 8: Graphical Representation of Membership Functions

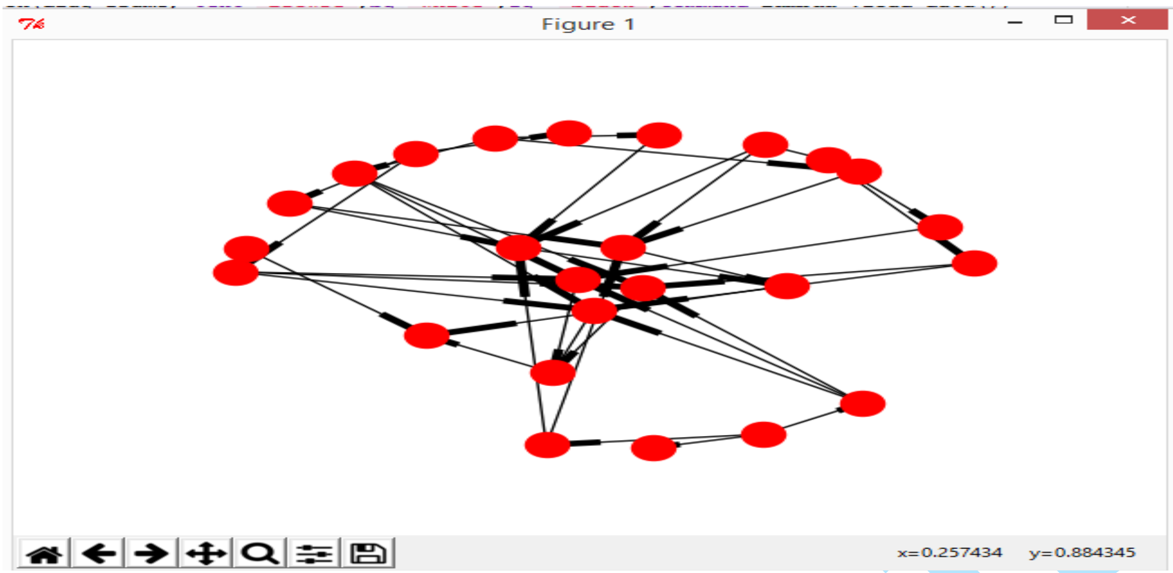

Figure 9: Graphical Representation of the fuzzy rule mapping

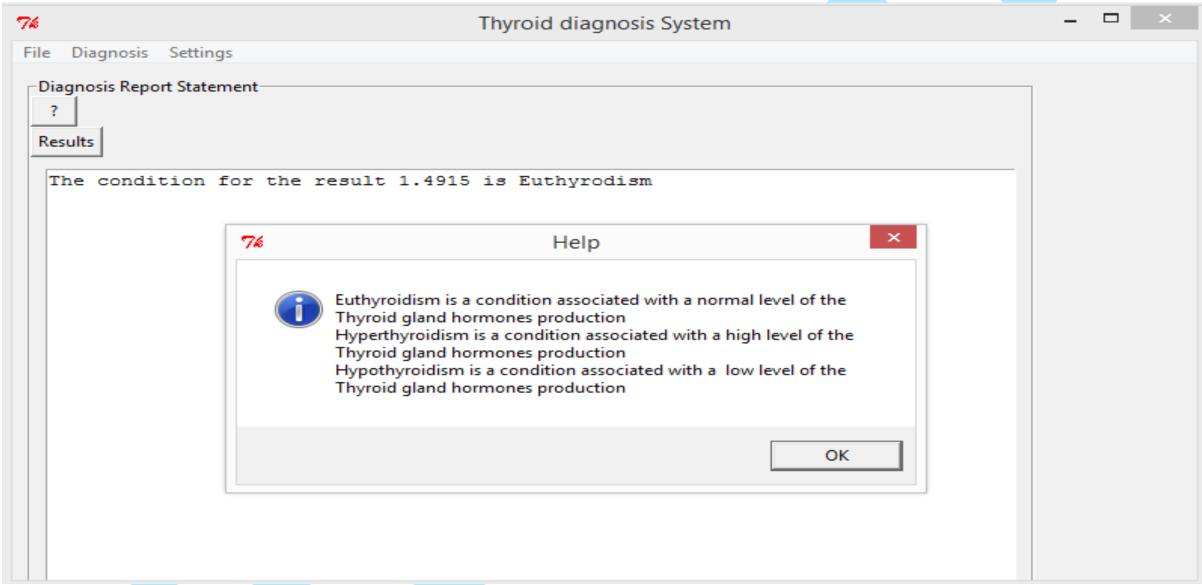

Figure 10: Result of Graphical Interface

5. SUMMARY AND DISCUSSION

The results of the system were computed using a range of default values in which each condition of a Thyroid disease falls within, the range of values for Hypothyroidism is from values less than 0.4 on a TSH test Scale and range of values for Euthyroidism is from values within 0.45 and 4.5 and for Hyperthyroidism ranges from values higher than 4.5, all measured in milli-internation units of hormone per litre of blood. The values of the output of neuro-fuzzy system was compared with the stated range of the three categories of Euthyroidism (normal), (4.0-4.5), Hyperthyroidism (High) above 4.5 and Hypothyroidism (low) below 4.5 to determine the actual state of diagnosis of patients respectively.

6. CONCLUSION

The neuro-fuzzy expert system was developed as an efficient tool to diagnose thyroid diseases by classifying them into three categories which are normal, hyper and hypo. Expert systems are not meant to replace doctors, but to aid doctors in the diagnoses of thyroid diseases. The hybridization of neural network and fuzzy logic system has enhanced the efficiency and accuracy of the diagnosis over other expert systems built using either neural network or fuzzy logic systems separately.

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