IAES International Journal of Artificial Intelligence (IJ-AI)
Vol. 5, No. 2, June 2016, pp. 55~63
ISSN: 2252-8938

Effective Analysis of Lung Infection using Fuzzy Rules

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Article Info

Article history:

Received Mar 3, 2016
Revised May 7, 2016
Accepted May 24, 2016

Keyword:

Decision support system
Fuzzy logic
Medical support system
Rulebase diagnosis

ABSTRACT

Soft Computing is conglomerate of methodologies which works together and provides an ability to make a decision from reliable data or expert's experience. Nowadays different types of soft computing techniques such as neural network, fuzzy logic, genetic algorithm and hybrid system are largely used in medical areas. In this paper, an algorithm for analysis of lung infection is presented. The main focus is to develop system architecture to find probable disease stage patient may have. Severity level of disease is determined by using rule base method. The algorithm uses an output of Rulebase entered by the user to determine a level of infection.

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1. INTRODUCTION

Medical diagnosis is one of the most important issues in healthcare. The medical industry requires new engineering technologies, to assess information objectively. The medical industry is one of the fields, which requires new engineering technologies to access uncertain information objectively. With recent developments in medical engineering and other control areas have been achieved by state-of-art intelligent computing techniques ranging from computer-aided diagnosis, computer aided radiography, intensive care units. Making the use of artificial intelligence, information processing and data mining holds new method for approximate inference [1]. In effect, the role of soft computing is the human mind. The guiding principle of soft computing is to exploit the tolerance of imprecision, uncertainty, and partial truth to achieve tractability, robustness and low solution cost, as described by Prof. Lofti Zahed in 1965 [2]. The accuracy of the diagnosis contributes into the right treatment and subsequently the cure of the disease. In recent years, computational intelligence has been widely used to solve many complex problems because of its capability to handle the complexity of human mind, partial truth, approximate inference, and uncertainty. Soft computing is a combination of fuzzy logics (FL), neural network (NN) and genetic algorithms (GA) methodologies. All these techniques work synergistically together and provide a solution from one form to another. Due to its flexible information processing capability for decision-making systems, such as expert systems and pattern classification system [3] it is widely employed in medical science applications. In real world computing environment, information is not complete, full of uncertainty and imprecise which makes difficult to derive actual decision. Various decision support systems have been constructed with the help of the artificial intelligence. These systems have widely proved very useful for medical experts in making a prompt decision about diagnosis [4]. In the advent of technology, computerization in the health care unit allows a various clinical decision-making unit to be constructed; that can perform computation as a human expert in narrow domain problem. These Clinical decision support systems are broadly classified into two main categories as shown in "Figure 1" (i) Knowledge-based Clinical Decision Support System (ii) NonKnowledge based Clinical Decision Support System.

1.1. Knowledge based Clinical Decision Support System

The knowledge-based clinical system contains a set of Ifthen rules that are used to describe certain patterns. Rules are evaluated based on observed data collected. When the given sets of rules are logically satisfied, the pattern is identified and the problem associated with that pattern is evaluated. For example, if pain intensity exceeded up to a certain level then warning pattern is generated. Each particular problem employs a specific treatment. The knowledge based clinical decision support system consists of three main parts: Knowledge base component, Inference engine, Fuzzification component. Knowledge base unit contains rule base and database that defines the membership functions of fuzzy sets used in fuzzy rules. Inference unit performs the operation on the rules to convert crisp quantity into fuzzy quantities. Fuzzification unit use to translate input values into fuzzified values [5].

1.2. Non-Knowledge based Clinical Decision Support System

Clinical decision support systems without knowledge base unit are called non knowledge based clinical decision support system. These systems make use of artificial intelligence called machine learning to produce decision output. This system is divided into two types as mentioned below:

1.2.1. Artificial Neural Network (ANN)

A neural network is a data processing system consisting of a large number of simple, highly interconnected processing elements (artificial neurons) inspired by neuroscience or neurobiology. It resembles human brain in two respects, (i) knowledge is acquired by network from its environment through a learning process, (ii) interneuron connection strengths, known as synaptic weights, are used to store the acquired knowledge. It is a system with input and outputs composed of many simple and similar processing elements. The procedure used to perform the learning process is called learning algorithm, the function of which is to modify synaptic weights of the network in an orderly fashion to attain desired design objective. The neural network is robust systems having the capability of fault tolerance and exhibit learning ability to map input patterns to associate output patterns based on a limited set of data [6, 7]. Neural network use nodes and weighted connections to derive a relationship between symptoms and diagnosis.

1.2.2. Genetic Algorithm (GA)

Genetic algorithm are subclass of evolutionary algorithm (EA's) that use biology inspired mechanism, where elements of search space are binary strings (chromosomes) which correspond to a particular solution. GA is computer based global search technique effective in acquiring optimal solution for solving optimization problems by simulating the mechanisms of genetics and natural selection. The major weakness of GA is that it usually tends to be (i) computationally expensive in real systems, (ii) premature convergence and (iii) slow search speed. This method is appropriate when we don't need to find the best solution, only appropriate is required [8]. Selection algorithm evaluates components of a solution to a complex problem. The generic system goes through a number of iterative methods to evaluate the best solution of required problem. The parameter optimization approach has been widely adopted in a number of genetic fuzzy systems [9]. Fuzzy set theory offers a number of properties that makes it prominent for formalizing the uncertain information upon which medical diagnosis and treatment are usually based. Firstly, it makes to define in exact medical entities as fuzzy sets based on membership rather than classical binary logic. Secondly, it makes a linguistic approach with an excellent approximation to medical texts. It is a powerful tool to tackle imprecision and uncertainty. Finally, fuzzy logic offers reasoning methods which are capable of making approximate inferences. Fuzzy set theory is an aid in providing symbolic knowledge information in more human comprehensible or natural form, and can handle suspicions at various levels. These facts make it possible to employ fuzzy set theory for the development of a computerized diagnosis system [10, 11]. Since fuzzy logic resembles human decision making with its ability to work from approximate reasoning and ultimately to find a precise solution, it can be applied in the diagnosing and monitoring of diseases including lung infections. The goal is to mimic the actions of a domain expert who can solve complex problems. Fuzzy logic has proved wonderful tool for decision-making systems and it is appropriate if sufficient expert knowledge about the process is available [9]. In the present paper, fuzzy rule base system is designed to serve a decision support for predicting lung infection. A lung disease occurs mainly through contagious bacterial infections and involves lungs, but may spread to other organs. The person gets infected by breathing in air droplets from a cough or sneeze of an infected person. Common symptoms involve breathing difficulty, cough, haemoptysis are the common indications of lung infections. The scope of this work is to develop prototype warning system for clinical activity, based on assumption that clinical problems can be analyzed using simple rules and decision process of physician can be modelled by using sets of fuzzy rules. Rule based systems are mainly used in medical diagnosis. In this, the knowledge base stores all information about the symptoms and disease in the form of rules in the Rule base [12]. Fuzzy logic provides inference morphology to build a system based on a set of user supplied human language rules. However, fuzzy logic is highly abstract and converts these rules to their mathematical equivalents equivalents. This simplifies the job of the system designer and the computer, and results in a much more accurate representation of the way systems behave in the real world [13, 3].

2. REVIEW OF RELATED WORK

In this section, we will introduce some related works in the field of fuzzy logic. A detailed survey of fuzzy logic techniques is found in this section. There are many works in literature that explains design and implementation of a medical experts system. A computational system based on neuro-fuzzy logic for identification of Alzheimer was presented by J.C. Obi et al. (2011) [15]. This system uses a set of fuzzified dataset symptoms into a neural system to produce more precise output than the traditional method. The implementation results reveal that hybrid system is introduced in healthcare delivery centers to help ease the work of physicians. To handle uncertainty and imprecision in measurements related to shape, size of abnormality of ulcers, fuzzy inference system was designed for assessment of peptic ulcers by K. Rezai et al. (2014) [16]. The results of proposed approach models reveal that vagueness and uncertainty associated to the measurements of small objects in low-resolution images can be enhanced using soft computing techniques. The encouraging results of intelligent fuzzy inference system can help medical experts as second reader for detection of peptic ulcer in a decisionmaking process and consequently, improves the treatment process. Experimental simulation studies show that intelligent system provides maximum accuracy of 98.1%, which shows a superiority of the inference approach. Fuzzy logic can be applied to determine and identify lung cancer by designing fuzzy rule-based inference system was discussed by K. Lvanaya et al. (2011) [17]. The proposed system accepts the required symptoms for the lung infection and calculates the confirmed disease stage as output. Based on the inputs provided, the system calculates the membership function for both inputs and outputs variables. This approach requires expert knowledge gathered to generate rules and rules are fired accordingly to generate symptoms. The implementation results were carried out in JADE accordingly to generate appropriate symptoms. The implementation results were carried out in JADE and MATLAB using features of the fuzzy logic toolbox. An attempt has also been implemented for providing treatment to patients. Further, it was generated that this system is compatible with other techniques and can be easily implemented using other methods such as case-based reasoning, decision tree, and data mining methods. System efficiency can be increased by making use of a neurofuzzy system and rough sets. O.Opeyemi et al. (2012) suggested a novel approach for early prediction of heart attack using a neuro-fuzzy system. The neuro-fuzzy system was designed using eight input variables and one output variable [18]. Initially, the dataset used was extracted from a database, and then the initial fuzzy logic system was generated. The network was trained with a set of trained data and validation is performed. An output of the system was designed in such a way that patient can use it personally. Based on the values (symptoms provided by patient) supplied, the system will able to predict the risk level of a patient. The result of proposed designed system achieves accuracy 90% and it is inferred from results that neuro-fuzzy model is suitable and feasible to be used as a supportive tool for disease diagnosis. Usefulness of fuzzy-neural algorithm techniques for prediction of various diseases as well as to determine critical stage of patients in medical diagnosis, can be used to provide timely remedial actions and it can prevent a major damage to health of patients, was demonstrated by K.Ketal et al. (2014) [20]. The purpose of this study is to evaluate increasing usage of fuzzyneural network and FPGA-based implementation can be used as an expert system for predicting various physiological diseases. The design of various fuzzy neural algorithms was presented such as back propagation, inverse delayed function and time averaging types are frequent to predict a level of various diseases. An attempt was made to explain why smart type prediction systems such as FPGA, mostly used by doctors to provide a complete smart solution for the prediction of any disease. An integrated approach for detection of glaucoma was carried using an adaptive neuro-fuzzy inference system by M. Huang et al. (2007) [19]. The main objective of this work was to develop an automated classifier based on adaptive neurofuzzy inference system, to differentiate between normal and glaucomatous eyes from the results obtained by quantitative evaluation of summary data reports of the Stratus optical coherence tomography (OCT) in Taiwan Chinese population. In this study decision making was performed in two stages; features are selected using an orthogonal array and then training is performed using backpropagation gradient method in combination with a least square method. It is investigated that with stratus OCT parameter as input, ANFIS generates better results for discriminating between glaucomatous and normal eyes. Therefore, use of adaptive neuro-fuzzy inference system is preferable since output concludes the if-then rules and membership functions, which enhances the readability of the output. A survey on the application of fuzzy logic in medical diagnosis was performed by V. Prasath et al. (2013) [4]. The author surveyed that various clinical decision support system have been constructed via the aid of artificial intelligence and are widely accepted in hospitals, clinics for making decisions. This system seems to be designed in such a way that they have the ability to think logically and to deal with approximate reasoning. This paper presents application of fuzzy logic in medical field such as tuberculosis, cancer, image and signal processing, aphasia, pharmacy, heart diseases, asthma, diabetes, malaria, hypothyroidism, HIV, arthritis, anesthesia and menigioma. The author concludes that fuzzy logic system provides a means for encapsulating the subjective decision-making process suitable for computer implementation. Soft computing is a combination of methodologies which works synergistically and provides flexible information processing potential for handling uncertain situations. A. Yardimci (2009) surveyed on various soft computing techniques in the medicinal field and aims to explain briefly about various soft computing methodologies between years 2000 and 2008 [1]. In this paper research work research work on MEDLINE was explained. The basic study involves the current elements of soft computing, different mechanisms implemented in soft computing techniques and to establish a guide which help to forecast the future developments of soft computing in medicine. Further, use of soft computing methods in a wide range of fields such as imaging, classification, diagnosis, prediction and control in medicine was suggested. Data mining solution for the diagnosis of tuberculosis by T. Ucar et al. (2013) was developed for providing decision support to tuberculosis researchers [14]. The purposed technique used adaptive neurofuzzy inference system and rough sets that makes a diagnosis of tuberculosis as accurate as possible. This approach helps in deciding whether it is reasonable to start treatment on suspected patients without waiting for exact medical test results. Experimental results show that use of Sugeno-type ANFIS classifies the instances with an accuracy of 97%, whereas rough sets do same classification with an accuracy of 92%. It is inferred from above literature survey on fuzzy logic that they are successfully applied in many medical fields for diagnosing and monitoring of various diseases. In this work, fuzzy rules are applied to determine the probability of lung infection.

3. FUZZY DIAGNOSTIC DECISION SUPPORT SYSTEM

3.1. Proposed Fuzzy Medical Diagnosis System

This section describes the approach adopted in developing the overall framework for a medical diagnosis system of a lung infection. The framework comprises of three main components: knowledge-based, fuzzy inference system and fuzzified value as shown in “Figure. 2”. This system will offer potential assistance to medical practitioners and health care sector in making a prompt decision of lung infection.

3.2. Identification Parameter

It is essential to take into consideration of all symptoms that plays a significant role in causing lung infection [23]. Take these aspects into consideration for the purpose of this study, a set of input and output parameters taken into account have been listed in table 1.

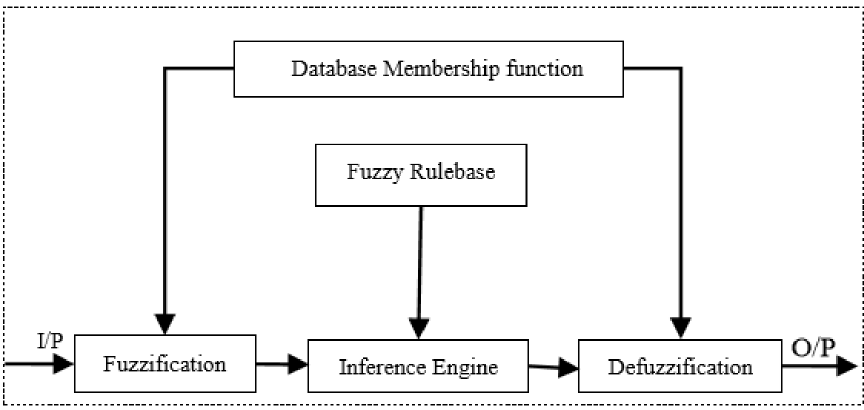

Figure 2. Framework of fuzzy system

3.3. Identification Parameter

It is essential to take into consideration of all symptoms that plays a significant role in causing lung infection [23]. Take these aspects into consideration for the purpose of this study, a set of input and output parameters taken into account have been listed in table 1.

Table 1. Parameters and its corresponding functions

Type (input/ output)	Parameter	Membership values
Input	Cough	Low using trapmf, Medium using trimf High using trapmf
	Haemoptysis	Low using trimf Medium using trapmf High using trimf
Output	Probability of lung infection	Severity of disease represented on scale 1-10

3.4. Choice of Membership Function

Membership functions are chosen for each values of the input parameter. A selection of appropriate membership value for every value of input and output plays a vital role in mapping efficiency of a system. The degree an input belongs to a fuzzy set is denoted by membership function between 0 and 1. Apart from these the number of membership functions, a number of other correspondence factor need to be taken into account. These factors include the type, parameter, aggregation operator, inference operator, type of fuzzification and defuzzification used. On observation of behavioral characteristics of each fuzzy variable encountered in a problem is represented by using triangular and trapezoidal membership function as shown in "Figure 3" and "Figure 4".

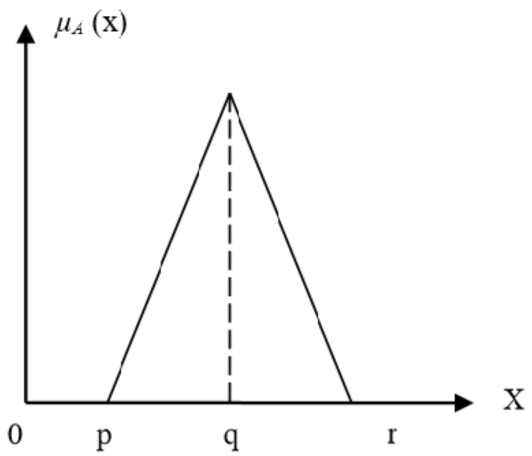

Figure 3. Triangular Membership Function

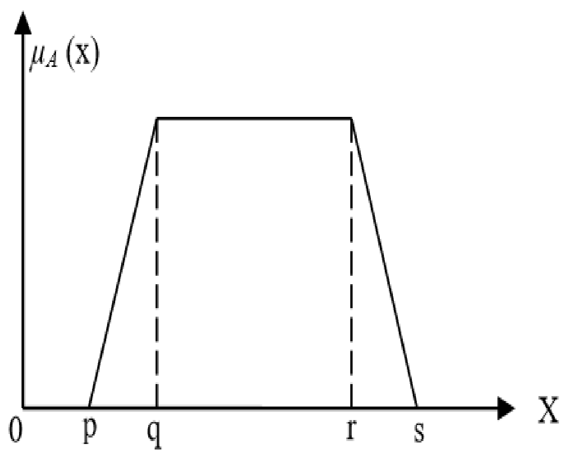

Figure 4. Trapezoidal Membership Function

A membership function related with particular fuzzy set maps an input value to its appropriate membership value and its value must be in [0, 1]. Fuzzy set A in X is defined as set of ordered pairs:

A= {x, μA (x), x € X}

µA (x), is called membership function of x in A. fuzzy set is a set without a crisp value, clearly defined a boundary. It contains elements with the only partial degree of membership. The triangular membership function curve is function of three variables p, q, r in x-axis where p, r are "feet values" respectively, having membership degree zero and q is the "peak value" whose membership degree is one. Trapezoidal membership function is represented by using four variables p, q, r and s in x-axis where p and s locate "feet" of trapezoid Gaussian, Sigmoid and other types of linear functions can also be useful to distinguish the fuzzy sets. Non-linear functions can also be used, but they will further cause computational complexity to the algorithm.

4. SYSTEM MODELLING AND WORKING

Fuzzy logic was the tool used to develop the algorithm of the system for determining the actual output.By using fuzzy, researcher will able to classify the intensity of each symptom according to description prescribed by pulmonary physicians. This paper is a simulation based paper and the medical diagnosis system is performed on the fuzzy logic model by using MATLAB 2013b software package developed by Mathworks Inc. "Figure. 5" shows the command window of MATLAB software where we use write commands to operate given set of rules while programming [24].

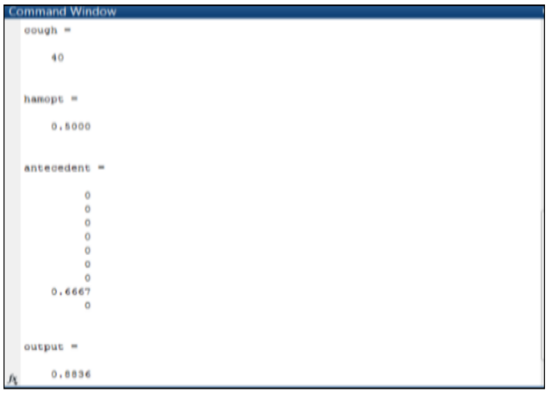

Figure 5. Command window view

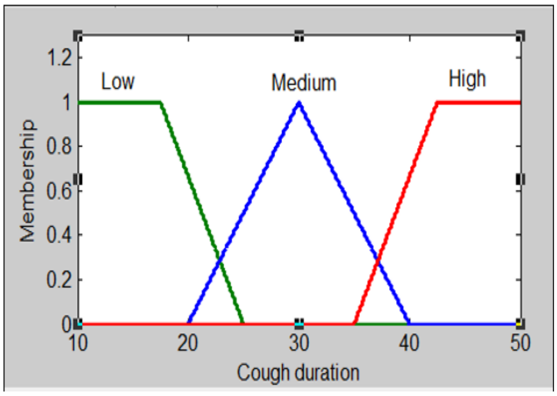

Figure 6. Fine tuned membership plot for Cough

Rulebase method is designed and implemented to determine the probability of lung infection populated by rules made for above inputs. Fuzzy logic employs the output of the rule-based method and calculates the range of scores in order to determine final output [22]. Defuzzification process is used to formulate the rules that correspond to different conditions determined by the matrix. Symptoms used to determine the probability of lung infection like a cough, haemoptysis were classified as low risk, medium risk, and high risk. In the formulation of fuzzy sets, the ranges of input and output variable symptoms are identified and a corresponding range of meaningful linguistic states are selected by expressing with appropriate fuzzy logic for each symptom. "Figure 6" shows fine tuned membership function plot for a cough showing a number of day's patient suffering from a cough.

The proposed system requires the physician to input all necessary scores of symptoms needed in order to meet the required output. System input symptom scores with corresponding level of intensity as follows:
Cough duration [10 50],
Haemoptysis [0 1]
A sample choice of membership function and its values has been shown below:

Name = 'Cough'
Range = [10 50]
NumMFs = 3 MF1 = 'Low': 'trapmf', [10 10 17.5 25]
MF2 = 'Med': 'trimf', [20 30 40]
MF3 = 'High': 'trapmf', [35 42.5 50 50]

"Figure 7" shows fined tuned fuzzy relations of haemoptysis showing membership to different categories (low, med, high). A sample choice of membership function and its values for haemoptysis has been shown below:

Name = 'Haemoptysis'
Range = [0 1]
NumMFs = 3
MF1 = 'Low': 'trimf', [0 0.15 3]
MF2 = 'Med': 'trimf', [0.2 0.5 0.8]
MF3 = 'High': 'trimf', [0.7 0.85 1]

After the graph, fuzzy sets were then intersected and it is determined the matrix. Two symptoms used are intersected and it describes one output condition. The matrix illustrates the intersection between two symptoms. For evaluation of rules, the input scores had undergone defuzzification process. After defuzzification, the scores were subjected to determine a value of crisp output. Below is a sample illustration of input and output scores:

Antecedent rules:
antecedent1=min(coughlow_mf(find(x==cough)),hamlow_mf (find(y==hamopt)));
antecedent2=min(coughlow_mf(find(x==cough)),hammed_mf (find(y==hamopt)));
antecedent3=min(coughlow_mf(find(x==cough)),hamhigh_mf (find(y==hamopt)));
antecedent4=mincoughmed_mf(find(x==cough)), hamlow_mf (find(y==hamopt)));
antecedent5=min(coughmed_mf(find(x==cough)),hammed_m f (find(y==hamopt)));
antecedent6=min(coughmed_mf(find(x==cough)),hamhigh_m f (find(y==hamopt)));
antecedent7=min(coughhigh_mf(find(x==cough)),hamlow_mf (find(y==hamopt)));
antecedent8=min(coughhigh_mf(find(x==cough)),hammed_m f (find(y==hamopt)));
antecedent9=min(coughhigh_mf(find(x==cough)),hamhigh_m f (find(y==hamopt)));

Consequent rules:
consequent1 = infelow_mf.* antecedent1;
consequent2 = infelow_mf.* antecedent2;
consequent3 = infemedlow_mf.* antecedent3;
consequent4 = infemedlow_mf.* antecedent4;
consequent5 = infemed_mf.* antecedent5;
consequent6 = infemedhigh_mf. * antecedent6;
consequent7 = infemedhigh_mf. * antecedent7;
consequent8 = infehigh_mf.*antecedent8;
consequent9 = infehigh_mf.*antecedent9;

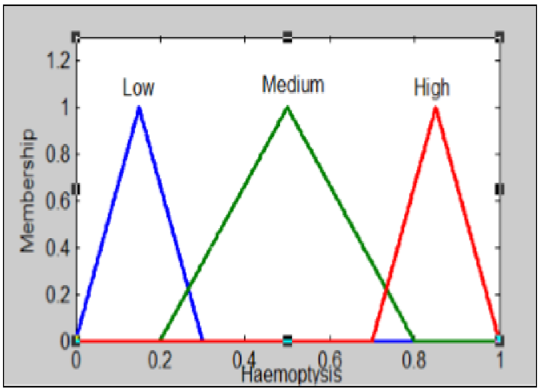

Figure 7. Fine tuned membership plot for Haemoptysis

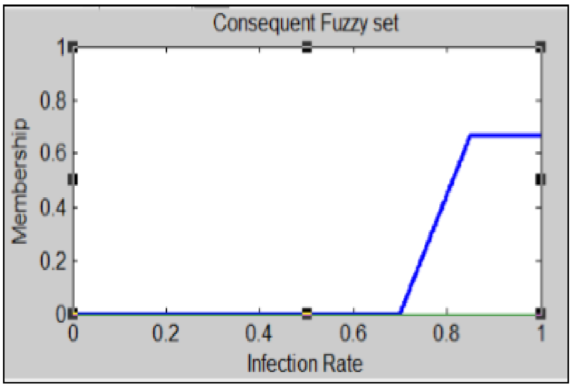

Figure 8. Consequent ruleview

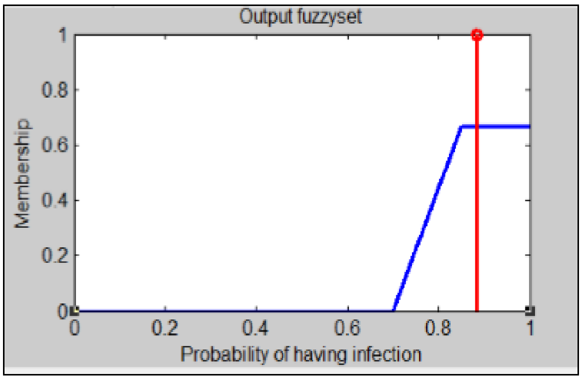

Figure 9. Defuzzified value

"Figure 8" illustrates consequent fuzzy set for a value of haemoptysis 0.5 and cough 40. Upon entering values of a cough as 40 and haemoptysis as 0.5, the system generates output 0.8836 which corresponds that there is a probability of lung infection. When we type values in editor window then system corresponds to defuzzify a value which is shown in "Figure 9".

5. CONCLUSION

In this paper, we have investigated the probability of occurrence of lung infection using a random number of inputs for the lung management system. The design of fuzzy logic in the design of such automated system gives an innovative and professional means of lung infection diagnosis especially in areas where the infection is in the wide spread. In this paper, we formalize medical entities as fuzzy sets and formalize reasoning using rule-based systems. The use of fuzzy logic in the design of diagnostic system proposed in this paper is believed to serve as a dependable and cheap means of treating lung diseases. Furthermore, implementation of fuzzy logic provides a set of techniques generating a reliable solution.

ACKNOWLEDGMENT

Navneet Walia author wishes to express her sincere gratitude to Mr. Harsukhpreet Singh, CT Institute of Technology and Research, Jalandhar for guiding throughout the current research work.

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