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Design and Implementation of a Fuzzy Expert System for Detecting and Estimating the Level of Asthma and Chronic Obstructive Pulmonary Disease

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Abstract: Soft Computing techniques have been used in a wide variety of applications and medical field is no exception. Although its usage is predominant in areas like cardiac and diabetes, sufficient amount of research has not been conducted in exploring its usage in the functioning of lungs. Keeping in view this aspect, the work carried out places a great deal of importance in the way the lung functions and also in detecting problems associated with lungs primarily Asthma and Chronic Obstructive Pulmonary Disease (COPD). A fuzzy expert system has been designed that takes into account details of various patients and identifies the problem the patient is likely to encounter. Besides, the extent of severity of the problem can also be assessed. In order to reduce the complexity of the overall system, several subsystems with independent intelligent controllers have been designed. Besides, sensitivity analysis has also been carried out to test the extent of relevance of specific inputs.

Key words: Fuzzy Logic · Expert Systems · Intelligent Controller · Asthma · COPD

INTRODUCTION

Asthma is a chronic lung disease that blocks the airways, that carries air to and from the lungs. This blockage in the airways causes inflammation which makes the patient susceptible to irritations and allergies. Due to the people's negligence of their common symptoms like cold, cough, fever and related symptoms and their failure to give due importance to their health, there is not much awareness of various lung diseases that are prevalent. Asthma being an inveterate lung disorder, if diagnosed in critical stages, may turn fatal. Thus, it is absolutely essential to detect asthma at initial stage [1]. The various factors that determine the level of asthma include age, gender, respiratory rate, chest tightness, cough and wheeze.

Another pulmonary disease, Chronic Obstructive Pulmonary Disease (COPD) also known as chronic obstructive lung disease (COLD), chronic obstructive airway disease (COAD), chronic airflow limitation (CAL) and chronic obstructive respiratory disease (CORD) which is very similar to asthma, also causes inflammation in the air passages. It is caused primarily due to tobacco smoking. The prime factor that distinguishes COPD from Asthma is that air passages in asthma are reversible whereas that in COPD are irreversible.

In this paper, severity of asthma and COPD is assessed based on the information obtained from a camp conducted on 25 patients. A spirometry test was conducted on these patients who reported with various symptoms [2-4]. Spirometry test results assisted in identifying the pulmonary disease.

Literature Survey: Fuzzy logic was introduced first in the year 1965 by Zadeh. His paper on fuzzy sets gave an insight into a kind of logic which is finding an increasing usage in day to day lives. It is a form of multi-valued logic and deals with reasoning.

The imprecision of human reasoning needed to be more efficiently handled. In 1971, Zadeh published the concept of quantitative fuzzy semantics which in turn led to the methodology of fuzzy logic and its applications. Fuzzy logic has been applied to many fields ranging from control applications to artificial intelligence. A wide variety of medical applications where its usage is significantly felt include cardiac, neural, lung and diabetes.

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Several papers that deal with Fuzzy logic have been published. A team comprising of Shaun Holt, Matthew Masoli and Richard Beasley developed a mechanism to handle problems associated with presence of asthma in adults in the year 2004. Alain Lurie, Christophe Marsala, Sarah Hartley, Bernadette Boucho-Meunier and Daniel Dusser discussed how the perception of asthma severity varies from patient to patient in July 2007. Computer-aided intelligent diagnostic system for bronchial asthma was designed by Chandan Chakraborty, Tamoghna Mitra, Amaradri Mukherjee and Ajoy K.Ray in the year 2009. M.H. Fazel Zarandi, M. Zolnoori, M. Moin and H. Heidarnejad designed a Fuzzy rule based expert system for diagnosing asthma in November 2010 and improvised it for evaluating the possibility of fatal asthma in December 2010. A computerized clinical decision support system, designed by paediatric pulmonologists for asthma was evaluated by Edwin A.Lomotan, Laura J.Hoeksema, Diana E.Edmonds, Gabriela Ramirez-Garnica, Richard N.Shiffman and Leora I.Horwitz in November 2011. An asthma management system was built for paediatric emergency department by Judith W.Dexheimer, Thomas J.Abramo, Donald H. Arnold, Kevin B.Johnson, Yu Shyr, Fei Ye, Kang-Hsien Fan, Neal Patel and Dominik Aronsky in November 2012.

Identification of Parameters: It is absolutely essential to take into consideration all symptoms that play a significant role in the cause of any pulmonary disease [5, 6]. Besides, the effect of severity also needs to be assessed. Taking these aspects into consideration, a set of input and output parameters have been taken into account. A list of factors based on which the parameters are chosen have been listed in Table 1.

Choice of Membership Functions: The proper choice of Membership Functions (MF) for each and every parameter plays a pivotal role in determining the efficiency of the system. The various symptoms of asthma that do not have definite values are considered as parameters. Membership functions are chosen for each of these parameters. It has been observed that the number of choices available is significantly large. Apart from the number of membership functions, a number of other factors need to be taken into account. These factors include the type, parameters, the conjunction, the implication or inference operator (Mamdani, Larsen), the aggregation operator and the type of fuzzification and defuzzification. On observation of behavioural characteristics each fuzzy variable encountered in the problem is represented using triangular (Asthma, Dyspnea, Tuberculosis, Nocturnal Symptoms, Oral Steroids, Alertness), trapezoidal (cough, wheeze, difficulty in speaking, respiratory rate, age, smoking, BMI, time of the day) or both (Fever). The only restriction that any membership function has to satisfy is that its values must be in the [0, 1] range. A fuzzy set can either be a crisp set or it could be represented using a number of membership functions.

Table 1: Parameters and its corresponding functions

TYPE(INPUT/OUTPUT)	PARAMETER	FACTOR ON WHICH IT DEPENDS
	Age	Age of the patient
	Alertness	Number of active hours per day
	BMI	Weight and Height of the patient
	Cough	Number of days it prolongs
	Difficulty in speaking	Ability to Speak (Number of words)
INPUT	Fever	Temperature of the patient
	Nocturnal Symptoms	Number of night time awakenings in a week
	Oral Steroids	Amount of steroids consumed per day
	Respiratory Rate	Number of breaths per minute
	Smoking	Number of Cigarettes per day
	Time of the day	Time of the day in 24-Hour format
	Wheeze	Number of days it prolongs
OUTPUT	Asthma	Severity of the disease is represented on a scale of 1-10
	COPD	
	Tuberculosis	

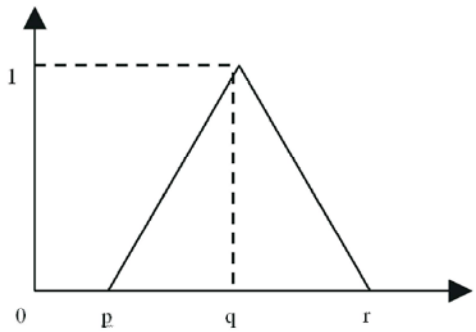


Fig. 1: Triangular Membership Function

As of today, no theory is available which accurately describes the best choice of a membership function. The choice of membership functions has been based on the behavioural aspects of each parameter after taking into consideration the sensitivity analysis. The linear nature of Nocturnal Symptoms makes it ideal for a choice of a triangular membership function. A sample choice of MF and its values has been shown below:

Name= 'NocturnalSymptoms'
Range= [0 100]
NumMFs =5
MF1= 'NoNocturnalSymptoms':'trimf', [-25 0 25]
MF2='Intermittent':'trimf', [15 30 45]
MF3='Mild':'trimf', [35 50 65]
MF4='Moderate':'trimf', [55 70 85]
MF5='Severe':'trimf', [75 100 125]

Triangular Membership Function: It is represented using three variables p, q and r in the x-axis where p and r are the lower boundary and the upper boundary respectively whose membership degree is zero and q is the centre where the membership degree is one. A sample triangular membership plot has been shown in Fig. 1.

$$Membership\ \ Degree\ (x) = \begin{cases} 0 & if\ \ x <= p \\ \dfrac{x-p}{q-p} & if\ \ p <= x <= q \\ \dfrac{r-x}{r-q} & if\ \ q <= x <= r \\ 0 & if\ \ x >= r \end{cases}$$

For example, the fuzzy variable Oral Steroids can be categorized into fuzzy modifiers Less, Moderate, High and Extreme as shown in Fig. 2. If the amount of oral steroids consumed per day is between 0 and 20mg, it is considered to be “less”. If it is between 18 and 30mg, it is “Moderate”. Values ranging from 27 to 40mg are termed as “High” and those between 38 and 60mg are “Extreme”. The mean value of each modifier’s range has a membership degree of 1.

Trapezoidal Membership Function: It is represented using four variables p, q, r and s in the x-axis where p and s are the lower and upper boundary whose membership degree is zero, q and r are the intermediate boundaries where the membership degree is 1. A plot of the same is shown in Fig.3.

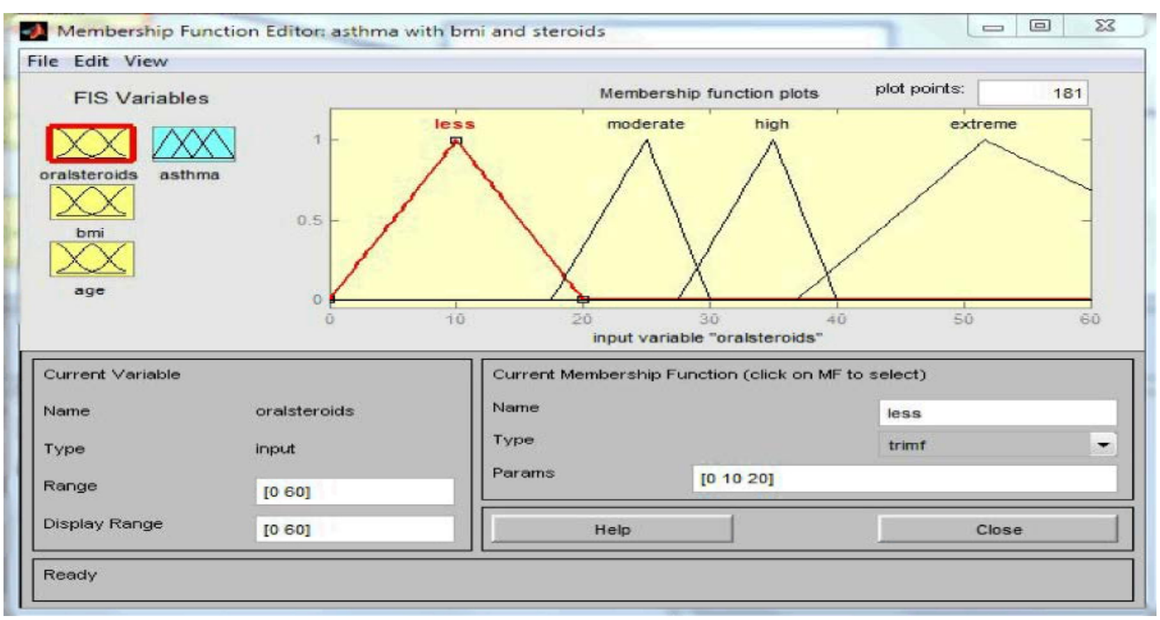


Fig. 2: Membership function for Oral Steroids

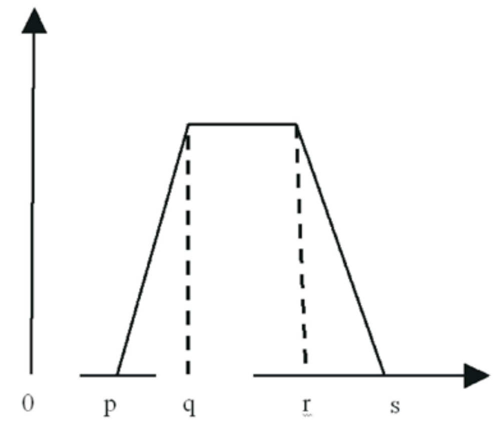


Fig. 3: Trapezoidal Membership Function

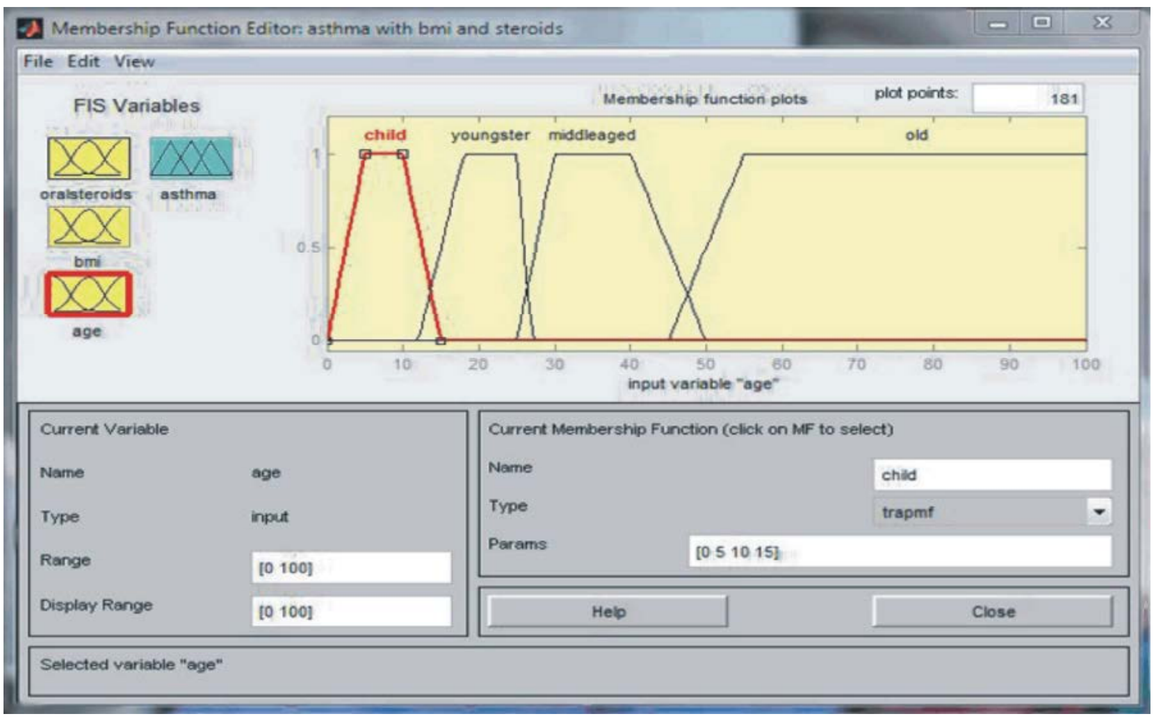


Fig. 4: Membership Function for Age

$$Membership\ \ Degree\ (x) = \begin{cases} 0 & if\ \ x <= p \\ \dfrac{x-p}{q-p} & if\ \ p <= x <= q \\ 1 & if\ \ q <= x <= r \\ \dfrac{s-x}{s-r} & if\ \ r <= x <= s \\ 0 & if\ \ r <= x \end{cases}$$

For example, the fuzzy variable Age can be categorized into fuzzy modifiers Child, Youngster, Middle-aged and Old. If the age is between 0 and 15, it is grouped under "Child" category. If it is between 11 and 27, it is grouped under "Youngster" category. The "Middle-aged" category ranges from 25 to 50 and the "Old" category is above 45. Each fuzzy modifier has a membership degree of 1 for a range of values. Hence, trapezoidal membership function is chosen. These characteristics have been depicted in Fig. 4.

The fuzzy variable "Fever" has a combination of both trapezoidal and triangular membership functions. This is shown in Fig. 5. The fuzzy modifiers "Low Temperature" and "Severe" are represented as trapezoidal membership function since a range of values has truth value of 1. The fuzzy modifiers "Normal", "Moderate" and "High" are depicted as a triangle since each of it has a definite truth value of 1.

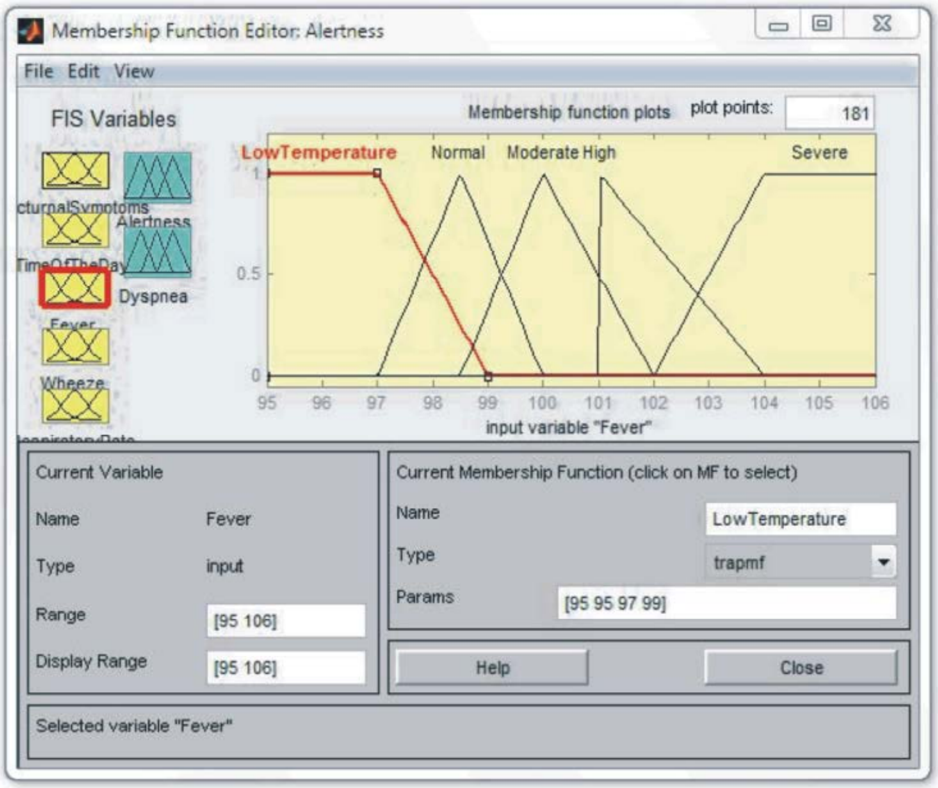


Fig. 5: Membership Function for Fever

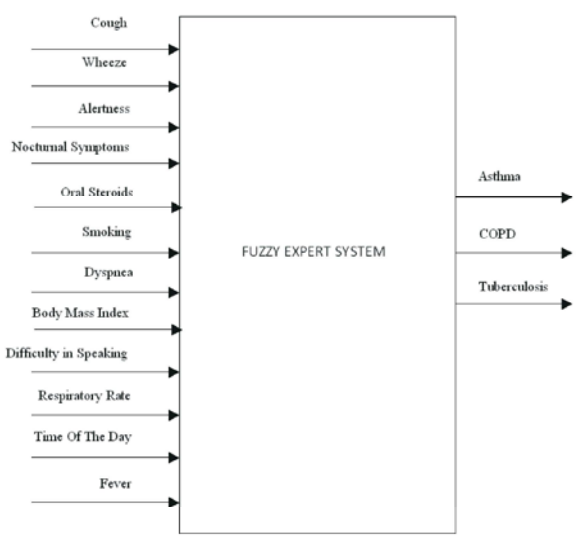


Fig. 6: Design of a Fuzzy Expert System

Most real-world entities are vague and cannot be assigned specific range of values. Hence, overlapping membership functions can be used in ontological scenarios. The value of 99^0F in the fuzzy variable "Fever" belongs to both "Normal" and "moderate" fuzzy modifier.

Design of Fuzzy Expert System: Fuzzy Expert System: An expert system deals with collection and encoding of rules. An inference engine suitably evaluates the set of rules based on the given set of inputs. In a fuzzy set, the elements might partially belong to the set. As majority of the real world characteristics deal with the fuzzy values, it is proposed to design a fuzzy expert system to assess the extent of asthma present in a patient who is tested. The parameters to be considered in the design of the expert system has been shown in Fig. 6

Fuzzy logic is an integral part in the design of fuzzy expert system in reasoning the possibilities of asthma without any misconceptions. For such a system to be competent with the existing counterparts, a number of intelligent expert systems are considered [7].

Design of Intelligent controller 1: An intelligent controller takes into consideration the values of 'nocturnal symptoms', 'Time of the day', 'Fever', 'Wheeze', 'Respiratory Rate' as inputs. Depending on these values, the degree of 'Alertness' and 'Dyspnea' can be assessed. It has been observed that variations in

Fig. 7: Intelligent Controller 1

Fig. 8: Intelligent Controller 2

Fig. 9: Intelligent Controller 3

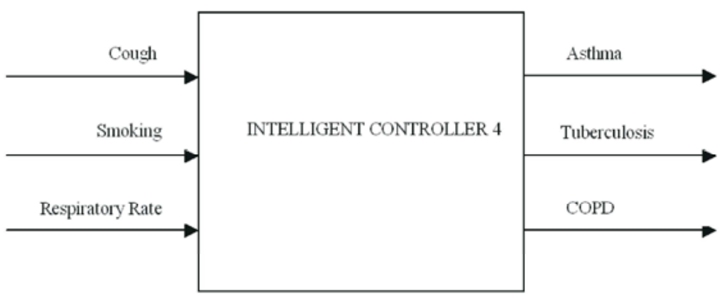


Fig. 10: Intelligent Controller 4

'Wheeze' and 'Nocturnal Symptoms' show huge spikes in 'Alertness' and 'Dyspnea' primarily depends on the extent of 'Respiratory Rate'. The design of this controller is depicted in Fig 7.

Design of Intelligent Controller 2: An intelligent controller takes into consideration the values of 'Oral Steroids' and 'Body Mass Index' as inputs. Depending on these values, the severity of 'Asthma', 'Tuberculosis' and 'COPD' can be assessed. It has been observed that variations in 'Oral Steroids' have a tremendous impact in determination of 'Asthma' and 'COPD'. The various inputs and outputs of this controller are depicted in Fig. 8.

Design of Intelligent Controller 3: An intelligent controller takes into consideration the values of 'Cough', 'Wheeze' and 'Difficulty in Speaking' as inputs. Depending on these values, the severity of 'Asthma', 'Tuberculosis' and 'COPD' can be assessed. The intelligent controller which considers the specified inputs and outputs is depicted in Fig 9. It has been observed that variations in 'Wheeze' show abrupt

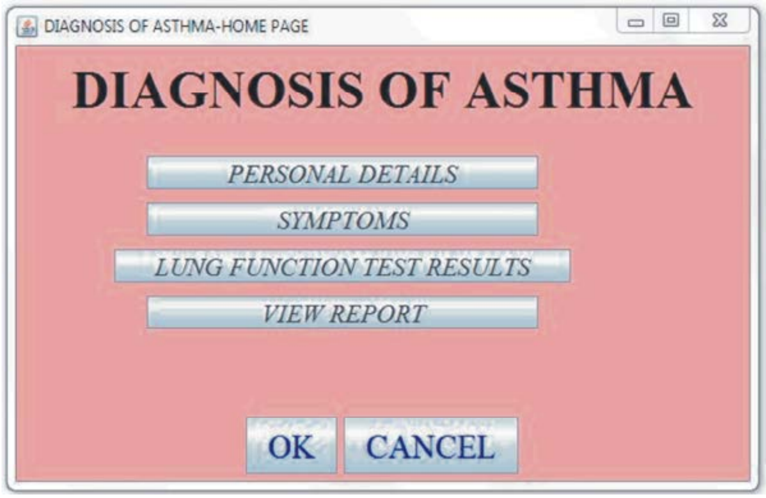


Fig. 11: (A) Graphical User Interface for Diagnosis of Asthma

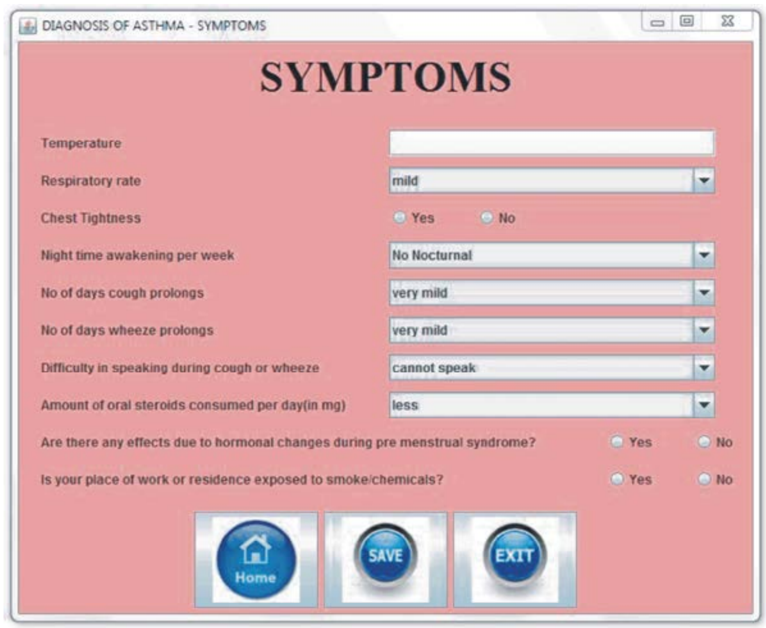


Fig. 11: (B). Integration of Fuzzy and Non-Fuzzy Parameters

changes in ‘Asthma’ and ‘COPD’. ‘Tuberculosis’ is found to primarily depend on ‘Cough’.

Design of Intelligent Controller 4: Fig.10. shows an intelligent controller that takes into consideration the values of ‘Cough’, ‘Respiratory Rate’ and ‘Smoking’ as inputs. Depending on these values, the severity of ‘Asthma’, ‘Tuberculosis’ and ‘COPD’ can be assessed. It has been observed that variations in ‘Respiratory rate’ affect the presence of Asthma to a considerable extent. The rate at which ‘COPD’ changes with levels of ‘Smoking’ could be clearly inferred [8].

Integral Design: Apart from these symptoms, there are certain parameters that have definite values and for which fuzzy representation is not possible. These parameters should also be considered for accurate diagnosis. Consequently, a graphical user interface is designed for the integration of fuzzy and non fuzzy parameters which is shown in Figures 11(a) and 11(b) [9, 10].

Once integrated, the fuzzy expert system is built in which all the parameters are considered. This system generates a report that suggests the patients with appropriate solutions for speedy recovery.

Sensitivity Analysis: Sensitivity Analysis is a detailed analysis that is done to identify the various inputs that affect the outputs. In any system, all the inputs do not produce a significant change on the output. Hence, there is a necessity to identify the degree to which the output parameter is dependent on each of its inputs.

An intelligent system where the inputs are cough, smoking and respiratory rate and the outputs are Asthma and Tuberculosis has been taken into consideration. Out of the large number of approaches that are prevalent for carrying out sensitivity analysis, One Factor At A Time (OFAT) method is followed. Here, the value of one input parameter is altered and the corresponding change in the output is observed.

It has been observed that a linear variation in the input parameter "Cough" produces a proportional variation in the output parameter "Tuberculosis". i.e., Tuberculosis is directly proportional to cough. Variations made in "Cough" keeping other inputs constant do not produce discernible changes in "Asthma". The effect of cough on Asthma is well pronounced only in the presence of other input parameters. Hence, Asthma is not solely dependent on cough. Smoking has a linear effect on both Asthma and Tuberculosis. A small variation in smoking shows a drastic change in the severity of COPD [11, 12]. Low respiratory rate results in severe asthma and COPD and the effect of both asthma and COPD reduces with increase in respiratory rate. Fig. 12 highlights these aspects.

In this system, the parameter 'cough' is found to be highly sensitive on 'tuberculosis', 'respiratory rate' is highly sensitive on 'asthma' and 'smoking' is found to be highly sensitive on 'COPD'.

Having performed a detailed analysis on all subsystems, it is observed that every input parameter has a prominent effect on the output. However, some inputs are less sensitive and do not bring about major variations in the output. Yet, it cannot be neglected. Therefore, it is not possible to prune out any input parameter.

Diagnosis of Fuzzy Expert System: The real data values of 25 patients who reported with various symptoms are tested by the designed fuzzy expert system which diagnoses the appropriate pulmonary disease (Asthma, Tuberculosis and COPD) precisely. The system does not produce the result considering one symptom alone. Rather it takes into account the severity of all symptoms as a whole.

The severity of asthma is determined based on the extent to which the symptoms affect the patients. In the camp conducted, a 64 year old patient (male, 54Kg weight, 165cm height) reported with-"59% predicted FVC",

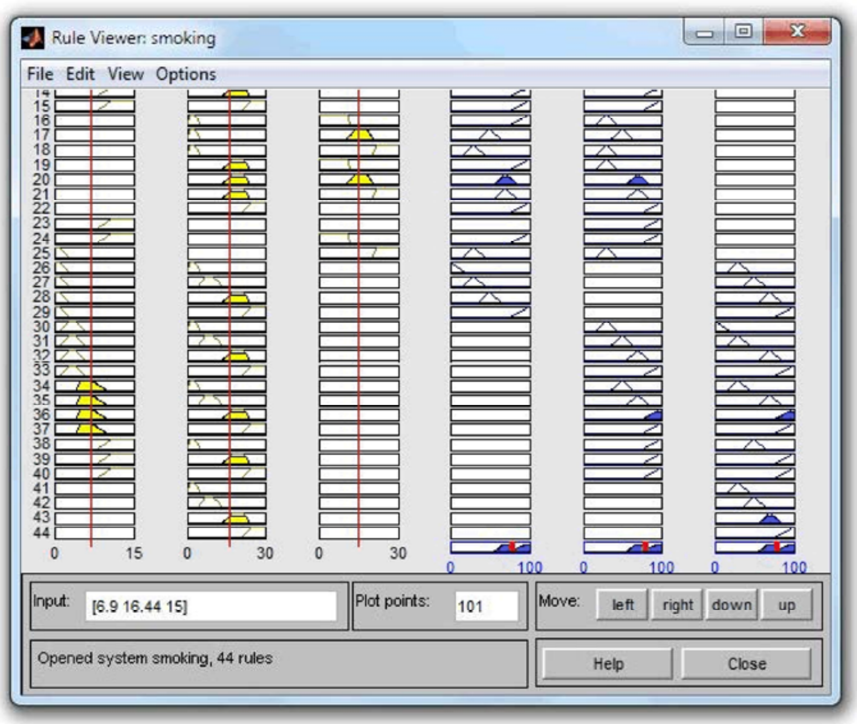
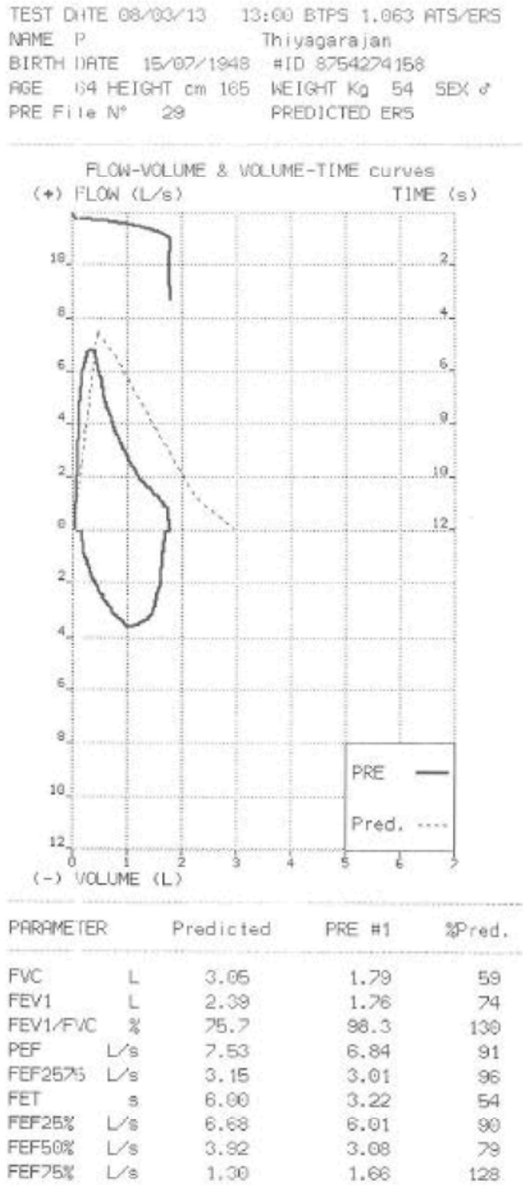


Fig. 12: Sensitivity Analysis


TEST DATE 08/03/13 13:00 BTPS 1.063 ATS/ERS
NAME P Thiyagarajan
BIRTH DATE 15/07/1948 #ID 8754274158
AGE 64 HEIGHT cm 165 WEIGHT Kg 54 SEX ♂
PRE File N° 29 PREDICTED ERS

PARAMETER		Predicted	PRE #1	%Pred.
FVC	L	3.05	1.79	59
FEV1	L	2.39	1.76	74
FEV1/FVC	%	75.7	98.3	130
PEF	L/s	7.53	6.84	91
FEF2575	L/s	3.15	3.01	96
FET	s	6.00	3.22	54
FEF25%	L/s	6.68	6.01	90
FEF50%	L/s	3.92	3.08	79
FEF75%	L/s	1.30	1.66	128

Fig. 13: Sample Patient Report

"74% predicted FEV1", "130% predicted FEV1/FVC ratio", "severe cough", "moderate wheezing", "normal temperature", "moderate respiratory rate", "smoking-less frequent", "no difficulty in speaking". The spirometry test results of this patient are shown in Fig 13.

The observed symptoms are fed as inputs to our expert system. The system processed these inputs and diagnosed that the patient had "moderate asthma" and "Intermittent COPD". The same result was diagnosed by a medical expert. This expert system diagnoses the presence of tuberculosis in a similar manner and is found to be nearly efficient as an expert [13].

The relationship between an output and two different inputs can be depicted in a three dimensional view as illustrated in Fig. 14. Here, variations in level of asthma can be evaluated by adjusting the level of cough and amount of smoking by a patient.

CONCLUSIONS AND RECOMMENDATIONS

The rules provided in the design of fuzzy expert system are not exhaustive, yet the system gives a good insight about the various pulmonary diseases by predicting its severity nearly equivalent to that of a

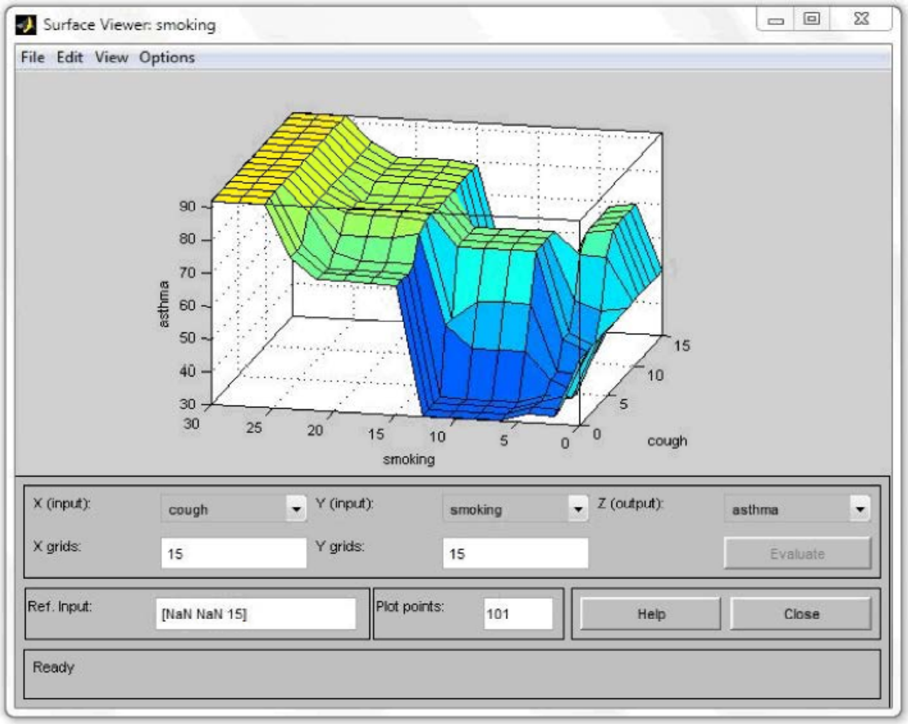


Fig. 14: Relationship of cough and smoking to asthma

medical expert. This system provides a comprehensive insight into the functioning of a lung management system. The effect of each input parameter on the various outputs has been thoroughly analysed. Suggestions are provided to the patient from time to time on ways and means of reducing the severity of asthma and COPD and in some cases eliminating the same altogether. Apart from asthma and COPD, the presence or absence of tuberculosis has also been detected.

Although the designed controllers are able to provide an excellent level of estimation and assessment of the severity of pulmonary disease, there can be situations where the result may slightly deviate from the one that is expected. In such cases, cent percent accuracy cannot be guaranteed. But the level of accuracies could be significantly enhanced by the design of a Type-2 Fuzzy Expert System. Although technology has improved in fits and bounds, there also seems to be a considerable amount of human related errors. Errors in measurement can make or break a system. Besides, uncertainties in values of some parameters can play a detrimental role in determining the efficiency of the system. Design of a Type 2 Fuzzy System can act as a panacea for handling these problems.

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