Service Mechanism for Diagnosis of Respiratory Disorder Severity Using Fuzzy Logic for Clinical Decision Support System

Faiyaz Ahamad, Manuj Darbari and Rishi Asthana

Abstract One of the most chronic lung diseases known worldwide is respiratory disorder. Respiratory disorder is based on the functional consequences of airway inflammation, calamitous nature, and improper diagnosis. In this paper our aim is to develop a service discovery mechanism for diagnosis of respiratory disorder severity using fuzzy logic for a clinical decision-support system. A mechanism system has been created for a fuzzy rule-based system. Five symptoms have been taken for the decision of the respiratory disorder conditions.

Keywords Respiratory disorder · Information system · Fuzzy logic

1 Introduction

Respiratory disorder is a major issue of discussion worldwide [1, 2]. According to a recent survey the United States alone has 7.2 million teenagers and 14.8 million stricken adults in total affecting an estimated 350 million families [WHO], with casualties of approximately 1 out of every 250 deaths [3, 4]. The major causes for such a boost are still not apparent and identified although it may imitate augmented exposure to environmental risk factors [5]. Some sources claim respiratory disorder is underdiagnosed in teenagers, with events of coughing and sneezing or diagnosis of respiratory disorder earlier can show a basic feature of analysis [6]. Because doctors have different opinions there is a strong possibility of variability of information [7–9]. In order to quantify this information we have used fuzzy set theory developed by Zadeh [10] in order to derive a crisp solution. We use a fuzzy rule base that will refine the output diagnostic process [11].

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2 Designing of Fuzzy Inference System for Diagnosis of Respiratory System

The goal of this paper is to establish a method that could possibly use the concept of a fuzzy inference system (FIS) for respiratory disorder severity. Our work is divided into two sections, the first phase deals with creation of data for the analysis. The second phase deals with generation of a FIS that can predict the exact result.

The process flow diagram shown in Fig. 1 represents comprehensive software architecture in order to diagnose respiratory disorder. In order to the judge the complexity of severity we have combined the modules, for example, compliance and decision-support systems that maintain a high degree of cohesion and low coupling [12]. The above system gives the entire blueprint of the information flow

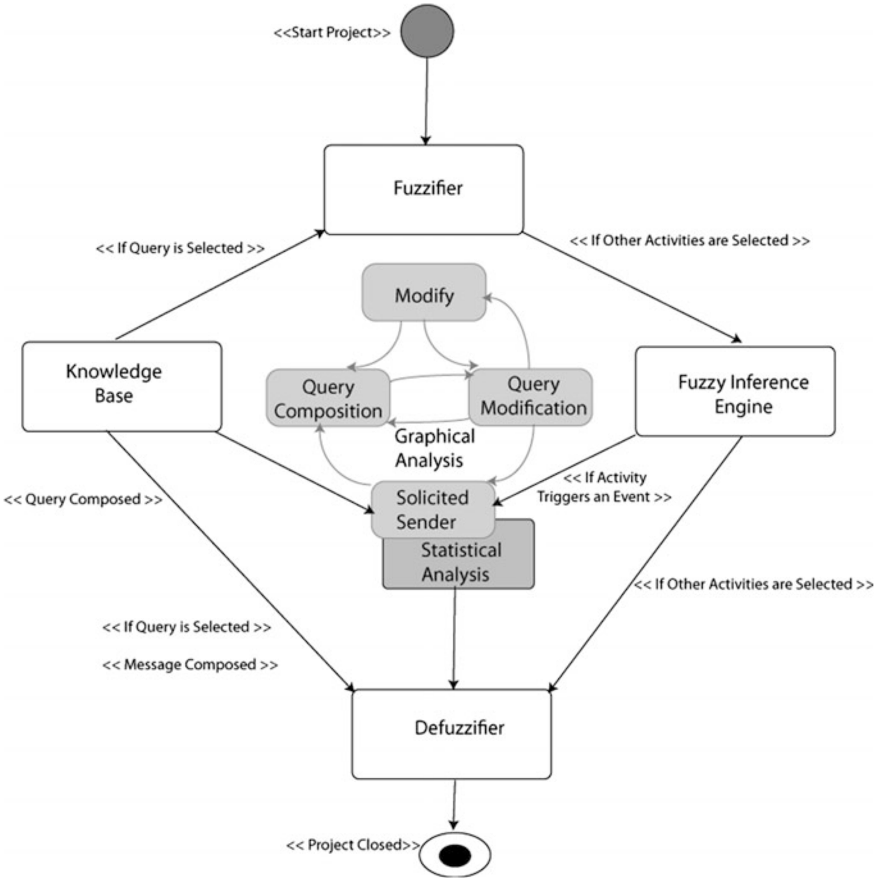

Fig. 1 Comprehensive software architecture of fuzzy inference system for diagnosis of respiratory system information system

and the activities being performed. The architecture's step-by-step refinement of the diagnosis process is related to respiratory disorder severity.

2.1 Model Development

FIS can be divided into various classifications; in this paper we have introduced a number of different variables to judge the relationship of respiratory disorders. A decision-support system plays a major part in the formation of the fuzzy inference system in order to diagnose respiratory disorder severity. To date much research has been done in developing an efficient decision-support system (DSS). There are a number of events under each classification of the fuzzy inference system, where they can work input variable to output variable find out. We can introduce a number of different types of variables to find the accurate severity of respiratory disorder in the patient. Due to this inference system, we give worldwide standards for the management, integration, as well as exchange of the data that aid the medical patient (Fig. 2). Particularly, in order to develop bendable, budget-supportive approaches, guidelines, standards, as well as methodologies that permit the healthcare information system interoperability for distribution of the health records.

We can classify various respiratory disorder symptoms as

I. Peak expiratory flow rate (PEFR)
II. Daytime symptom frequency (DSF)
III. Nighttime symptom frequency (NSF)
IV. Peak expiratory flow rate variability (PEFR variability)
V. Oxygen saturation (SaO_2)

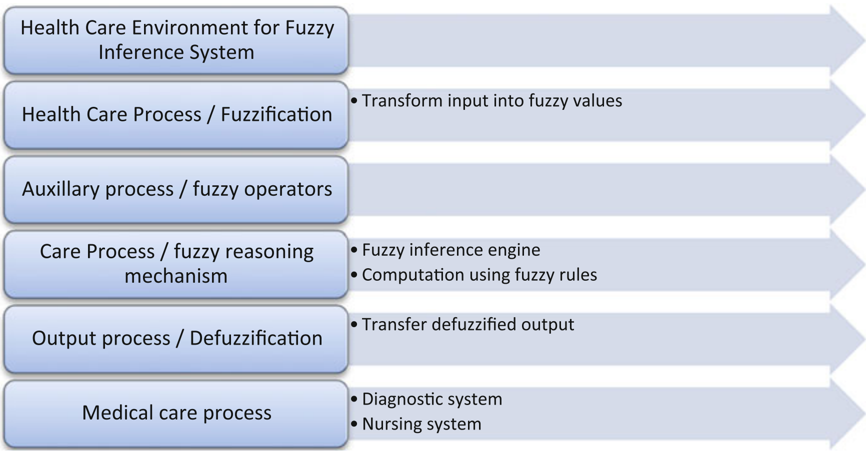

Fig. 2 The number of events under each classification of fuzzy inference system

2.2 Algorithm for Repository Disorder

In the present work all input variables (PEFR, FVC, FEV1, and FEF25–75 %) have been divided into four categories such as low, medium, high, and very high (Figs. 3, 4, 5, 6, 7 and Tables 1, 2, 3, 4, 5, 6). Each one is defined by the individual membership functions. Low, very high is shown by a trapezoidal membership function and medium, high is shown by triangular membership functions. But in the case of output variables, it is also divided into four categories as severe, moderate, mild, and normal. Normal and severe are shown by a trapezoidal membership function and moderate, mild is shown by triangular membership functions [13, 14] (Figs. 8 and 9).

Table 6 shows the rule base for the respiratory disorder inference system (Table 7).

Fig. 3 Input variable PEFR

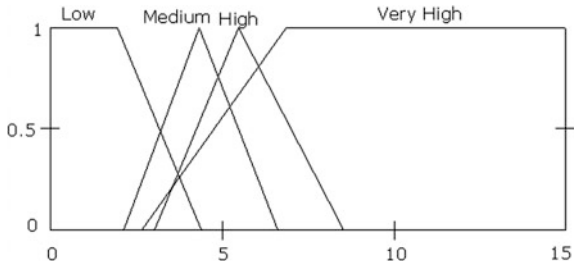

Fig. 4 Plot for input variable FEV1

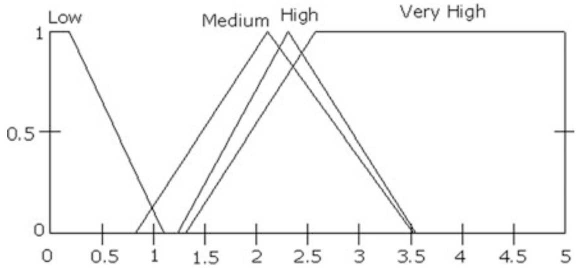

Fig. 5 Plot for input variable FVC

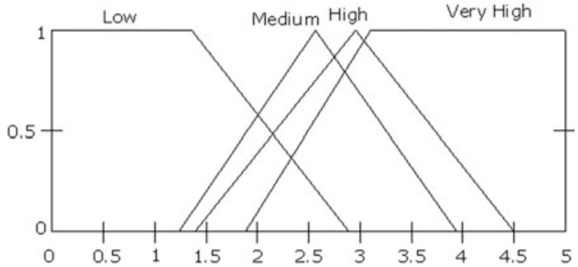

Fig. 6 Plot for input variable FEF2575

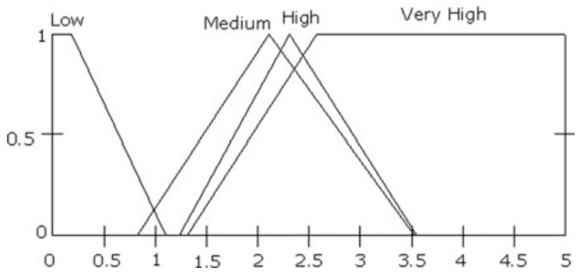

Fig. 7 Plot for output variable respiratory disorder severity

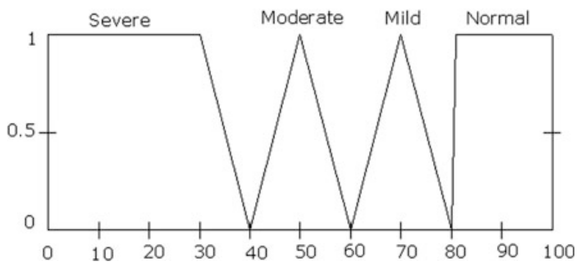

Table 1 Parameters for PEFR

Membership levels	Type	Parameter
Low	Trapmf	[0.0 1.92 4.61]
Medium	Trimf	[2 4.27 6.55]
High	Trimf	[3.04 5.87 8.7]
Very High	Trapmf	[2.54 6.28 15.15]

Table 2 Parameters for input variable FEV1

Membership levels	Type	Parameter
Low	Trapmf	[0 0 0.34 1.14]
Medium	Trimf	[0.8 2.15 3.51]
High	Trimf	[1.24 2.39 3.54]
Very high	Trapmf	[1.33 2.56 5 5]

Table 3 Parameters for input variable FVC

Membership levels	Type	Parameter
Low	Trapmf	[0 0 0.61 1.47]
Medium	Trimf	[0.94 1.83 2.72]
High	Trimf	[1.19 2.18 3.17]
Very high	Trapmf	[1.53 2.6 5 5]

Table 4 Parameters for input variable FEF2575

Membership levels	Type	Parameter
Low	Trapmf	[0 0 1.35 2.77]
Medium	Trimf	[1.24 2.57 3.9]
High	Trimf	[1.44 2.96 4.48]
Very high	Trapmf	[1.86 3.14 5 5]

Table 5 Parameters for output variable respiratory disorder severity

Membership levels	Type	Parameter
Severe	Trapmf	[0 0 30 35]
Moderate	Trimf	[35 45 55]
Mild	Trimf	[55 65 75]
Normal	Trapmf	[75 80 100 100]

Table 6 Respiratory disorder inference system rule base

S. no.	Force vital capacity (FVC)	Force expiratory volume in one second (FEV1)	Peak expiratory flow rate (PEFR)	Forced expiratory flow 25–75 % (FEF25–5 %)	Respiratory disorder severity
1.	Low	Low	Low	Low	Severe
2.	Medium	Medium	Medium	Medium	Moderate
3.	High	High	high	High	Mild
4.	Very high	Very high	Very high	Very high	Normal
5.	None	Very high	High	High	Mild
6.	None	Very high	High	Very high	Mild
7.	None	Very high	High	Medium	Moderate
8.	None	Very high	High	Low	Severe
9.	None	Very high	Medium	Low	Severe
10.	None	Very high	Medium	Medium	Severe
11.	None	Very high	Medium	High	Moderate
12.	None	Very high	Medium	Very high	Mild
13.	None	High	Low	High	Mild
14.	None	High	Low	Medium	Moderate
15.	None	Medium	Low	Medium	Moderate
16.	Medium	Medium	Low	Medium	Moderate
17.	Low	Medium	Low	Medium	Moderate
18.	Low	Low	Low	Medium	Severe
19.	Medium	Low	Low	Medium	Moderate

There are various input and output variables, on the basis of which we design a rule base consisting of 19 rules set with input and output. These variables are selected as the basis of rules defined in the FIS. The rules are spreads on the left row. The graph with blue plots shows the membership function, with a set of defined rules. The end plot in the fifth column represents the cumulative weighted for the given FIS system that provides the input values defined for the plot. The output is represented as a vertical line of the plot. The current values are displayed at the top of the columns of the plot.

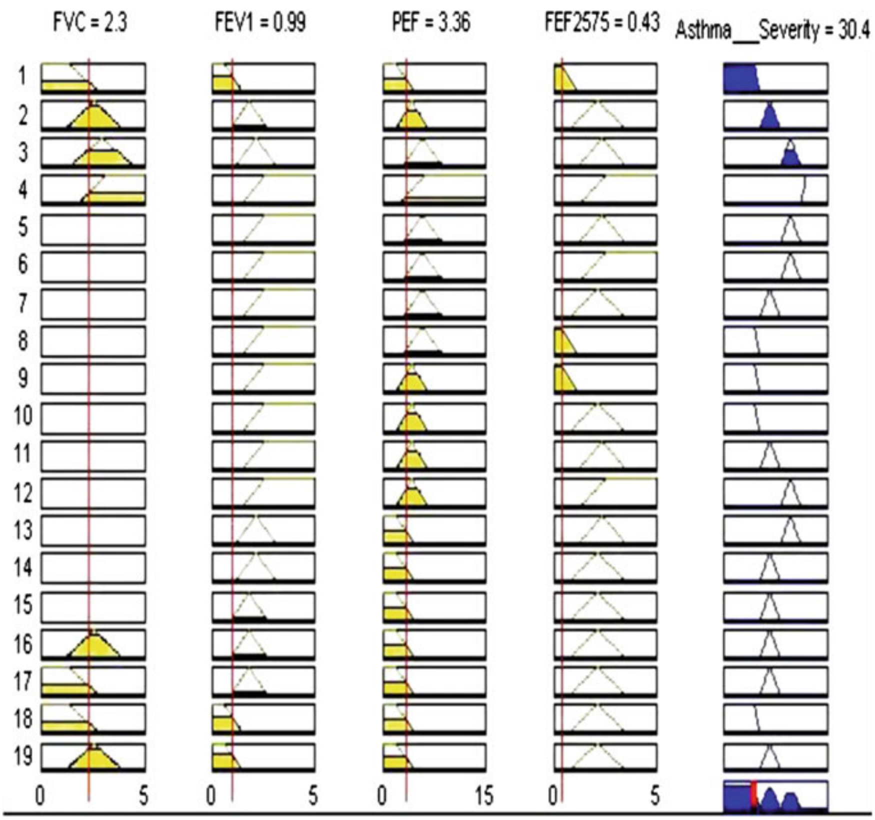

Fig. 8 Rule viewer for repository disorder inference system

Fig. 9 AND operation over truth values A and B

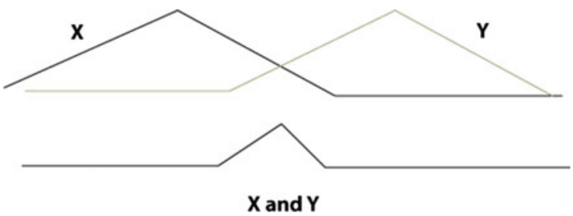

Table 7 Fuzzy logic AND operation

X	*Y*	Min (*X*, *Y*)
0	0	0
0	1	0
1	0	0
1	1	1

Table 8 Results of fuzzy inference system output and field data output

S. no.	FVC	FEV1	PEFR	FEF25–75 %	Field data output	System output
1.	3.78	4.15	7.13	3.32	Normal	81.7(N)
2.	4.28	3.34	8.13	3.29	Normal	83.2(N)
3.	2.68	2.29	5.74	3.21	Mild	60.5(Mi)
4.	3.49	4.14	6.80	3.31	Normal	78.9(Mi)
5.	1.99	1.96	3.58	2.49	Moderate	41.2(Mo)
6.	2.74	1.42	5.50	1.41	Moderate	58.7(Mo)
7.	0.86	0.72	1.79	1.29	Severe	21.5(Se)
8.	2.08	1.98	2.57	2.29	Moderate	38.6(Se)

3 Results

Based on the analysis rules defined in the FIS system we computed on the basis of information severity of respiratory disorder by implement AND connection and after that we defuzzified the output [15, 16].

The output of this system presents the possibility of respiratory disorder severity gradation from very high to very low in terms of measured values (0–100). These outputs are classified in four classes presenting the status of patients at risk of respiratory disorder. These classes include Severe (0–40), Moderate (40–60), Mild (60–80), and Normal (80–100) (Table 8).

4 Conclusion

Table 8 shows the output generated by the inference system providing necessary aid to the doctors showing a co-relation between field data output and system output. The fuzzy logic system used for respiratory system severity shows that these results are better than other conventional systems. These systems are well supported in medical science by doctors and practitioners. Who faced a problem due to result of respiratory in conventional systems? The result obtained by the use of the FIS system is accurate and very helpful in the field of medical science. The Table 8 results of the fuzzy inference system output and field data output equality of the developed system is to be approved by the health experts.

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