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ORIGINAL PAPER

Development of a Fuzzy Decision Support System to Determine the Severity of Obstructive Pulmonary in Chemical Injured Victims

Taha Samad-Soltani[1], Mostafa Ghanei[2], Mostafa Langarizadeh[3*]

[1]Health Information Management Department, School of Health Management & Information Sciences, Tabriz University of Medical Sciences, Tabriz, Iran
[3]Chemical Injuries Research Center, Baqiyatallah University of Medical Sciences, Tehran, Iran
[3]Health Information Management Department, School of Health Management & Information Sciences, Iran University of Medical Sciences, Tehran, Iran

Corresponding author: Mostafa Langarizadeh. Health Information Management Department, School of Health Management & Information Sciences, Iran University of Medical Sciences, Tehran, Iran. Telephone: +989148657072, Fax no : +984135540192. E-mail: Langarizadeh.m@iums.ac.ir

ABSTRACT

Background: Chronic Obstructive Pulmonary Disease (COPD) is the most common known complication of exposure to mustard gas. Thus, all clinical guidelines have provided some recommendation for diagnosis, clinical management and treatment of this disease. Decision support systems are used to increase the acceptance of clinical guidelines. The purpose of this research is to develop a CDSS to determine the severity of COPD in chemical injured victims. **Objectives**: Development of a decision support system to determine the severity of COPD. **Patients and Methods**: First, the variables influencing to determining the severity of the disease was classified through studying the clinical guidelines. Then, the fuzzy model was implemented. To testing the system, the data from 50 patients were used. **Results**: the overall accuracy in determining the severity of the injury is equal to 92%, these indicators reflect the proper functioning of the system to assist the physician regarding the diagnosis of chronic obstructive pulmonary disease and determining its severity. **Conclusions**: The CDSS has efficient results and satisfactory performance. Although, the medical expert systems cannot be expected to provide 100 percent correct responses, however, they can be useful in the areas of patient management, diagnosis and treatment planning.
Key words: Chronic Obstructive Pulmonary Disease, Clinical Decision Support Systems, Fuzzy Logic, Military Trauma, Fuzzy system.

1. BACKGROUND

Nuclear, chemical and biological wars are the cause of health disruption. Today, the effects of mustard gas and its adverse effects on humans and other things is not hidden (1). The most extensive chemical attacks occurred in the eight-year war between Iraq and Iran. These attacks exposed thousands soldiers and civilians with mustard gas (2). Iranian foundation of martyrs and veterans affairs reported that, currently, there are 34,000 chemical injured (3).

In Khateri et al. study on 34,000 Iranian chemical victims, 13 to 20 years after exposure, the most common late complication in injured has been reported in the lung (42.5%) (4). Chronic obstructive pulmonary disease (COPD) is known as the most common injury caused by mustard exposure (5).

The disease has significant negative effects on different aspects of quality of life (6). Mustard gas causes early and late complications, but what chemical injured victims actually suffer from as the reason for their referring to medical health care centers are the late and chronic respiratory complications (7, 8).

Continuous monitoring and proactive care of the health status of them is one of the main priorities of Health & Treatment Deputy to make decisions on health status and disease development of chemical casualties. To this end, determining the intensity of injuries and symptoms should be performed periodically (9).

On the other hand, making decisions in clinical practice and public health policies is considered as a central core, since the outputs and outcomes are probable in the medical field; most decisions are made under uncertain conditions and the professionals interpret the clinical data based on their experience that such perceptions are not also entirely reliable (10). From the early days of the advent of computers, the health experts expected the machines to assist them in the diagnosis process, and by integrating them in clinical practice, it seems logical that the health care professionals will benefit from them to support the treatment procedures (11).

Clinical Decision Support Systems (CDSS) are precise instruments and approaches to implement clinical solutions for diagnosing, treating and managing the diseases, which are capable of improving the adherence to guidelines and solutions by providing consultation and advice (12, 13). Studies conducted by research institutes and centers have tried to explain the developed and used CDSSs in such centers, and numerous other studies done indicate the positive impact of these systems (14). In a systematic study about the impact of CDSSs on the performance of physicians and patient related outcomes, it was found that the performance of physicians has been improved in 64% of studies (15). The usefulness of these systems includes minimizing of errors and providing diagnostic programs to assist in the diagnosis process of patients' problems (16).

2. OBJECTIVES

Thus, in this study, through designing a fuzzy decision support module to determine the severity of obstructive lung disease, the researchers tried to effectively and efficiently detect the rate of obstruction in chemical injured victims.

3. MATERIALS AND METHODS

First, through studying the clinical references and solutions of determining the injury severity of chemical victims and veterans, the system knowledge were extracted. Given that the dominant approach in the design of decision support systems relies on knowledge-based systems, and nowadays, decision making is done based on knowledge and data methods, thus, this research focused on this aspect of the system and the discussions were done in this area. The expert systems are composed of four main components, namely: Knowledge base, Inference engine, Database and Interface (17).

Many intelligent systems have been developed to improve the health of individuals,reduce the treatment costs and improve the quality of life. These systems use various aspects such as image processing, neural networks,expert systems and fuzzy systems (18). In this study, the fuzzy systems were used that are a popular computational framework. Fuzzy inference systems, also known as fuzzy decision support systems (19).

Basic structure of fuzzy inference systems consists of three conceptual parts, namely fuzzy rules, database and the inference process (Figure 1). The rules are extracted from clinical resources and guidelines with respect to the specialists' opinions. These rules are stored in database, and the inference process includes conventional methods such as Sugeno and Mamdani. The input of fuzzy inference systems can be in the form of traditional or fuzzy sets, but their output is always as fuzzy sets. In case of need to conventional output, a procedure known as defuzzification should be used to extract the best non-fuzzy values from a fuzzy set (20).

The most common fuzzy approach is Mamdani Fuzzy Inference Model. This method control a combined steam engine with a set of linguistic rules obtained from individuals' experiences. Fuzzy rules are a set of linguistic phrases that describe how to make decisions by fuzzy inference system based on the classification of an input or controlling an output. Fuzzy rules are often written in the form of: *if (input 1 is membership function 1) and/or (input 2 is membership function 2) and/or. . . then (output$_n$ is output membership function$_n$).*

Classical numerical output is obtained through defuzzification process. The usual method for defuzzification is the center of mass method that finds the center of mass of output distribution, which is calculated as follows Where in the formula, z is the center of mass and u_c is the membership in class c in the z_j value (21)

$$z = \frac{\sum_{j=1}^{q} z_j u_c(z_j)}{\sum_{j=1}^{q} u_c(z_j)} \quad (1)$$

For software implementation the benefits of open source software were used as far as possible.

4. RESULTS

Based on domestic agreement, the extent of lung disability and malfunctioning based on Spirometric measures is expressed as percentage, which is presented in Table 1. This measure is used in medical commission (relating to chemical injured victims). The severity of chronic obstructive pulmonary disease is calculated based on the Table results and clinical findings as well.

Severity (percentage)	Spirometry	Classification
0	FVC>80/FEV1>80 65<FVC<80	Passive lung disease
5-20	65<FEV1<80 50<FVC<65	Mild
25-45	50<FEV1<65 40<FVC<50	Moderate
50-70	40<FEV1<50	Severe

Table 1. *Classification of pulmonary disease severity in patients with respiratory problems based on Spirometry*

NO		Variable	Rules	Linguistic Label	Fuzzy interval
1	inputs	FEV_1	FEV_1>80	VH	75-85-95-100
			65<FEV_1<80	H	60-70-80- 85
			50<FEV_1<65	L	45-55-60-70
			40<FEV_1<50	VL	0-10-45-55
2		FVC	FVC>80	VH	75-85-95-100
			65<FVC<80	H	60-70-80- 85
			50<FVC<65	L	45-55-60-70
			40<FVC<50	VL	0-10-45-55
3		FEV_1/FVC	FEV_1/FVC>80	VH	75-85-95-100
			65<FEV_1/FVC<80	H	60-70-80- 85
			50<FEV_1/FVC<65	L	45-55-60-70
			40<FEV_1/FVC<50	VL	0-10-45-55
4	output	Severity	At risk	At risk	0 –1-2- 3
			Mild	Mild	2-3-4-5
			Moderate	Moderate	4-5-7-8
			Severe	Severe	7-8-10-11

Table 2. *Inputs and outputs related to calculation of severity of lung obstruction*

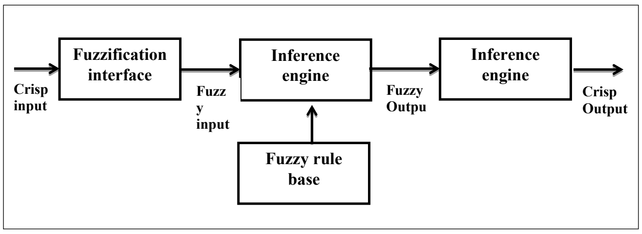

Figure 1. *The structure of a fuzzy expert system*

The first step in fuzzy systems is the fuzzification of input variables. These variables are the same criteria for determining the severity in the decision-making table. The fuzzy variables of this module used to determine the obstructive pulmonary include three variables of "Forced Vital Capacity", "Forced Expiratory Volume in 1 second" and "FEV1 / FVC Ratio".

These variables were assessed and approved by specialists of chemical injuries center in the guidelines of diagnosis and treatment of chemical victims, and were implemented in Visual Studio environment. The Open Source Fuzzy Library of Dot Fuzzy was used for fuzzy calculation (22). The characteristics of fuzzy inputs and outputs of this module are shown in Table 2.

Membership functions of input and output fuzzy variables are shown in Figures 2 and 3. The Dot Fuzzy supports triangular and spline-based (Soft trapezoidal) membership functions. Thus, spline-based curve membership functions and

Figure 2. *Overview of membership functions of fuzzy variables of FEV1, FVC, FEV1_FVC*

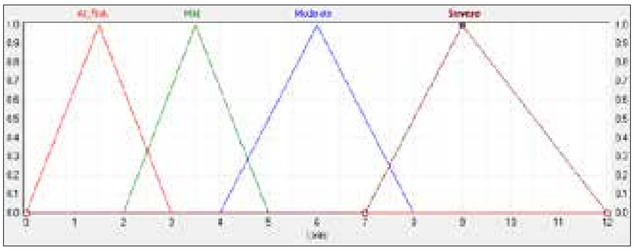

Figure 3. *Output membership functions for severity variable in outline*

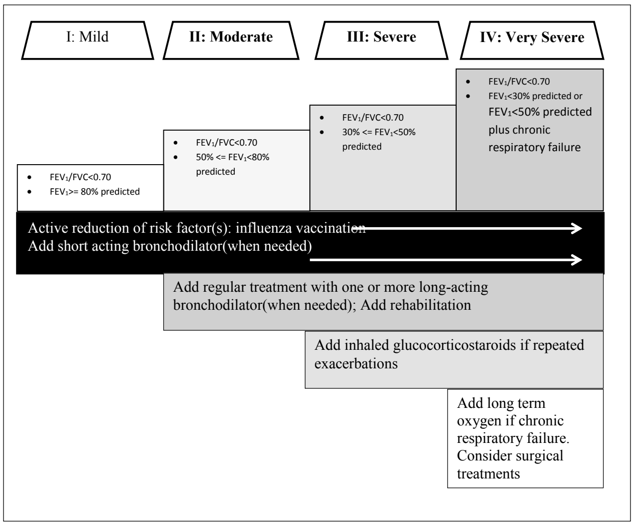

Figure 4. *Therapeutic recommendations consistent with GOLD clinical guidelines*

Accuracy (system detection)		At risk	Mild	Moderate	Severe	Total
100%	At risk	18	0	0	0	18
33.33%	Mild	1	1	1	0	3
100%	Moderate	0	0	3	0	3
100%	Severe	0	0	0	1	1

Table 3. *Confusion matrix of severity determination module outputs*

Mamdani fuzzy inference system were used.

Knowledge base in the determining severity module and health status contains fuzzy rules. These rules were obtained through extraction of professionals experiences and expressed as linguistic rules

The system provides treatment recommendations consistent with GOLD clinical guidelines for each level of disease severity. Figure 4 shows these recommendations (23).

The system inference engine was designed using the Open Source Library of Dot Fuzzy. The library provides functions to work with linguistic, fuzzy and non-fuzzy variables. The library is developed in C # language and is supported by Net Framework languages. This library is used due to its object oriented approach,easy implementation, flexibility and powerfulness.

The decision support system for diagnosis of chronic obstructive pulmonary disease and determining the severity of lung injuries were assessed with a data set of 50 cases that half of them were related to patients with asthma and the other half to the patients with chronic obstructive pulmonary disease. The data were collected from data files of patients monitored by the chemical injuries center in the last period of 2012. In the system severity determination module, of 25 cases of chronic obstructive pulmonary disease, 23 cases were correctly diagnosed.

The confusion matrix of severity determining module analysis is shown in Table 3. The matrix displays the number of correct answers on the main diagonal and the number of different solutions based on the outputs on other calls of the matrix.

The accuracy of this module was obtained as 92% and the Kappa value was also equal to 0.813, which according to the Table provided by Landis & Koch was almost completely consistent with the physician diagnosis.

5. DISCUSSION

Due to the use of various techniques in the system, two separate modules were used to simplify management, designing and implementation of codes and make them more manageable as well as to maintain the independence of the components. Furthermore, this research by utilizing high features and capabilities of open source software, despite the initial complexity of the basic design,has created high flexibility, high running speed and very low cost. The module to determine the severity of COPD has been designed based on Spirometry test variables and clinical findings. As a rule, patients classification, either at universal level (to manage the disease and classification of patients) or in the center for chemical injuries (to determine the ratio of casualties or injured) is done based on Spirometry test results.

In diagnosing asthma fuzzy system developed by Zarandi et al., the need assessment of variables effective in asthma diagnosis was done through dialogue with professionals and completing this knowledge area using medical literature. The semantic network is then used to represent the problem knowledge. The semantic network constructed in this study showed the causal relationship between variables and symptoms. The network contained 7 main nodes representing the system fuzzy variables and their values range (23). In the present study, the production rules were used to display the rules for severity determining module and the health status. For more simplification, the experts understanding of these rules are much better than understanding of the semantic network, and the rules of this model can be easily analyzed.

In fuzzy expert system for the diagnosis of pneumonia in children, developed by Pereira and Tunneli, despite the use of fuzzy logic, the decision table was not used; since only one output was intended for the diagnosis of pneumonia. If there is a correlation, a positive number between 0 and 1will be obtained, and in the absence of relationship between inputs and outputs, a negative number would be obtained (24). But, in the present study, the decision tables were used as rules with programming language in each sector.

To determine the severity and health status, Mamdani fuzzy inference engine and calculation rules were used, respectively. In a research by Akramian et al. in 2013, a fuzzy expert system for the diagnosis of pneumonia was designed in which Mamdani fuzzy inference engine and the rules as decision making table were used for differential diagnosis between five similar conditions (23). In disease severity determining module implemented by using fuzzy rules, Mamdani fuzzy inference system was used due to ease of use and efficiency. To implement the rules, the numerical tables associated with linguistic equivalent values were applied, and the modeling was performed based on variables numerical ranges.

To use fuzzy algorithms, Dot Fuzzy open source library functions were used. Hence, system design was done as open source, which has a great flexibility and can be run in Linux and Windows OSs due to coding independent from software platform.

In Akramian et al. research, MATLAB development environment was used to implement fuzzy expert system for diagnosis of pneumonia, and the interface design was done through its interface component (25). MATLAB development environment has two major flaws. First, it is an interpretive language; therefore, its running speed is very slow and boring compared to compiled languages such as C #. As a result, it cannot be used in complex structures. The second major disadvantage is the cost. The price of MATLAB is about ten times the price of a C language compiler, and hence, is not cost-effective for a researcher or designer engineer (26). In addition, the operationalization of programs developed in MATLAB is a common and major problem. In the present study, to address these two fundamental problems, the C # compiler programming languages were used for application rapid running. The Dot Fuzzy open source library was also used for free system implementation. Also, the Visual Studio development environment provides all the necessary facilities to operate the system in a real environment.

The methodology proposed is considered an appropriate approach for modeling and analysis of data in the area of medical decision making with a satisfactory performance. However, no system can provide strictly excellent one hundred percent correct results, but in patient management area, differential diagnosis and treatment planning can be useful for clinicians and provide effective contribution. The system is independent of the platform and has integration capabilities in different environments and various operating systems.

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CONFLICT OF INTERESTS: NONE DECLARED.

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