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Comparison Between Fuzzy Soft Expert System and Intuitionistic Fuzzy Set in Prediction of Luge Cancer Disease

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Abstract: Millions of people worldwide suffered from lung cancer last year. In this paper, we will build a knowledge-based medicine method and obtain a related prediction system named Fuzzy Soft Expert System and implement a new approach called Intuitionistic Fuzzy Set Expert System. Therefore, in identifying lung cancer disease, we'll compare these two ways that breakthrough has resulted in a prognostic test suggesting whether or not patients suffer from lung cancer.

Keywords: Fuzzy soft sets, Intuitionistic fuzzy sets, Lung cancer disease, Lung cancer disease detection

1 Introduction

Cancer is among the most disease that leads the world's death. The lung cancer is one of the most common causes of death from cancer. World Health Organization (WHO) figures show that among 8.2 million died from cancer, death from lung cancer exceeded 1.59 million [1]. An additional 222,500 new cases (116,990 in men and 105,510 in women) were lung in 2017 and bronchial cancer will be diagnosed with 155,870 deaths for the disease (84,590 in men and 71,280 in women) [2]. Just 17.7 per cent of all lung cancer patients are alive at least five years after diagnosis [3]. Lung cancer has become one of the world's most frequently occurring cancers, has an exponentiation pattern in its predicted prevalence, and is a cause of first death [4].

To stop such a life-threatening challenge, one of the capable remedies is to make people aware of their respective risks of lung cancer beforehand and to take effective preventive steps. It's only possible when lung cancer is diagnosed early. Early detection at the stage of death can, according to medical experts, predict death from lung cancer if treatment is given properly afterwards.

With this in mind, people are trying to build professional lung cancer systems for medical experts or for diagnosing disease with the aid of mathematics. Because uncertainty often exists during diagnosis, expert lung cancer systems based on fuzzy rule are created. A Fuzzy rule-based expert system involves a collection of fuzzy rules and membership functions where the acquisition of information (considered to be the most important problem in the design of a fuzzy rule-based inference structure) could be greatly supported by experts in the field. Until now, in many sciences, the Fuzzy inference system has become a robust research area [5]. A fuzzy rule-based inference system for diagnosing lung cancer has been developed on the basis of the National Cancer Institute database [6] as well as in medical science. The machine has 5 spheres of input, and one sphere of output. Spheres of input include weight loss, shortness of breath, chest pain, persistent sputum cough and blood. Computational intelligence handset fuzzy structures, neural network, and evolutionary computation where the lung cancer disease system integrated into the neuro fuzzy were added. To show the feasibility of the suggested method, simulation for automatic diagnosis is performed using practical causes of lung cancer disease. Six tumor markers in the auxiliary diagnosis of lung

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cancer [7] were investigated using an artificial neural network model. Following this method, people with lung cancer were discerned from those with the benign lung disease and normal control subjects. An early diagnostic method to predict the risk of lung cancer using sensitive neuro fuzzy inferences and linear discriminant analysis was proposed [8]. An efficient lung infection diagnosis was provided using Fuzzy rules [9]. It has suggested a hybrid automated method for the diagnosis of lung cancer based on genetic algorithms and fuzzy extreme learning machines [10]. Principles of Part Analysis, Fuzzy Weighting Preprocessing, and Artificial Vulnerable Recognition Method based on Diagnostic Method for Lung Cancer Diagnosis [11] were proposed. An appropriate community of tumor markers proposed coupled artificial neural network for lung cancer diagnosis [12]. Several researchers have looked at the issue of automated lung cancer diagnosis [13]. Latest literature lately suggests therapy for lung cancer [14]. Fuzzy web based expert system for diagnosing lung cancer was proposed [15]. An early detection of lung cancer disease was suggested using data mining and the analysis of medical images [16]. Analyzes of lung cancer disease using a Fuzzy logic system [17] have been suggested. Prognostic system has been presented for early diagnosis of pediatric lung disease using artificial intelligence [18]. In addition, other researchers have applied various algorithms to obtain the following findings in different fields: Consolidation of energy efficient tasks for cloud data centers has been proposed [19]. An effective algorithm for replication of data was implemented for distributed systems [20]. It proposed an inexpensive cluster focused on the hybrid cloud for safe health informatics research [21]. Computer protection philosophy, explanations for device design, security methods, management, and computer security engineering problems were introduced [22]. Even above-mentioned fuzzy expert lung cancer structures there are several disadvantages. For example, they depend primarily on rules; sometimes decisions made by the above-mentioned fuzzy expert systems of lung cancer based on two set of rules (even though both have the same degree of truth) are contrary; sometimes decisions made by the above-mentioned fuzzy expert systems of lung cancer are contrary to those made by expert doctors. This part tries to overcome these drawbacks with the help of fuzzy soft set theory based prediction system of lung cancer (named fuzzy soft expert system) and introduce new way to detect the lung cancer disease by the intuitionistic fuzzy set. Firstly, the fuzzy soft expert system is composed of four main portions: the fuzzication of real valued data, the transformation from the fuzzy numbers of data set to fuzzy soft sets, parameter reduction, get the output data by computing. Experiment shows that the fuzzy soft expert system. We develop a knowledge based prediction system of lung cancer by intuitionistic fuzzy set and introduce comparison with fuzzy soft expert system.

2 Concepts of PFS

Definition 2.1 L.A.Zadeh [23]: Let A be a nonempty set. A fuzzy set A drawn from X is defined as $A = \{(x, \mu_A(x)) : x \in X\}$ where $\mu_A(x) : X \to [0,1]$ is the membership function of the fuzzy set A. Fuzzy set is a collection of objects with membership gradation having membership degrees.

Definition 2.2 K.T.Atanassov [24]: Let X is a nonempty set. An intuitionistic fuzzy set A in X is an object having the form $A = \{(x, \mu_A(x), \nu_A(x)) : x \in X\}$ where the functions $\mu_A(x), \nu_A(x) : X \to [0,1]$ define respectively, the degree of membership and degree of non-membership of the element $x \in X$ to the set A, which is a subset of X, and for every element $x \in X, 0 \le \mu_A(x) + \nu_A(x) \le 1$.

Furthermore, we have $\pi_A(x) = 1 - \mu_A(x) - \nu_A(x)$ called the intuitionistic fuzzy set index or hesitation margin of x in A. $pi_A(x)$ is the degree of indeterminacy of $x \in X$ to the IFS A and $\pi_A(x) \in [0,1]$ i.e., $\pi_A(x) : X \to$ and for every expresses the lack of knowledge of whether x belongs to IFS A or not.

For example, let A is an intuitionistic fuzzy set with $\mu_A(x) = 0.5$ and $\nu_A(x) = 0.3 \Rightarrow \pi_A(x) = 1 - (0.5 + 0.3) = 0.2$. It can be interpreted as "The degree that the object x belongs to IFS A is 0.5, the degree that the object does not belong to IFS A is 0.3 and the degree of hesitancy is 0.2".

Definition 2.3 E.Szmidt [25]:

1) The normalized Hamming distance $d_{n-H}(A,B)$ between two IFS A and B is defined as:

$$\begin{aligned} d_{n-H}(A,B) &= \frac{1}{2n}\sum_{i=1}^{n}|\mu_A(x_i) - \mu_B(x_i)| \\ &+|V_A(x_i) - \nu_B(x_i)| + |\pi_A(x_i) - \pi_B(x_i)|, \\ X &= x_1, x_2, \ldots, x_n \quad \texttt{for} \quad i = \{1,2,\ldots,n\} \end{aligned} \tag{1}$$

2) The normalized Euclidean distance $d_{n-H}(A,B)$ between two IFS A and B is defined as:

$$\begin{aligned} d_{n-H}(A,B) &= \frac{1}{2n}\sum_{i=1}^{n}((\mu_A(x_i) - \mu_B(x_i))^2 \\ &+(\nu_A(x_i) - \nu_B(x_i))^2 + (\pi_A(x_i) - \pi_B(x_i))^2)^{1/2}, \\ X &= x_1, x_2, \ldots, x_n \quad \texttt{for} \quad i = \{1,2,\ldots,n\} \end{aligned} \tag{2}$$

3 New Operations Defined over IFS

In the section we use fuzzy intersection and union to define intuitionistic fuzzy set instead of standard intersection and union. Where the standard form defined as:

$$\begin{aligned} A \cap B = \{(x, \min(\mu_A(x), \mu_A(B), \\ \max(\nu_A(x), \nu_B(x))) : x \in X\} \\ A \cup B = \{(x, \max(\mu_A(x), \mu_A(B)), \\ \max(\nu_A(x), \nu_B(x))) : x \in X\} \end{aligned} \tag{3}$$

For each element x of the universal set, this function takes as its argument the pair consisting of the element's membership and non-membership grades in set A and in set B, and yield the membership and non-membership grade of the element in the set constituting the intersection and union of A and B, Thus

$$\begin{aligned} \min(\mu_A(x), \mu_B(x)) &= i[\mu_A(x), \mu_B(x)] \\ \max(\mu_A(x), \mu_B(x)) &= u[\mu_A(x), \mu_B(x)] \end{aligned} \tag{4}$$

Similarly

$$\begin{aligned} \min(v_A(x), v_B(x)) &= i[v_A(x), v_B(x)] \\ \max(v_A(x), v_B(x)) &= u[v_A(x), v_B(x)] \end{aligned} \tag{5}$$

$$\begin{aligned} i &: [0,1]x[0,1] \Rightarrow [0,1] \\ u &: [0,1]x[0,1] \Rightarrow [0,1] \end{aligned}$$

i must satisfy the following axioms for all a, b , $d \in [0,1]$.

Axiom i 1: $i(a,1) = a$ (boundary condition).
Axiom i 2. $b < d$ implies $i(a,b) < i(a,d)$ (monotonicity).
Axiom i 3. $i(a,b) = i(b,a)$ (commutatively).
Axiom i 4. $i(a,i(b,d)) = i(i(a,b),d)$ (associativity).
Axiom i 5i is a continuous function (continuity).
Axiom i 6: $i(a,a) = a$ (subidempotency).
Axiom i 7: $a_1 < a_2$ and $b_1 < b_2$ implies $i(a_1,b_1) < i(a_2,b_2)$ (strict monotonicity)

$$\texttt{Standard intersection} : i(a,b) = \min(a,b) \tag{6}$$

$$\texttt{Algebraic product} : i(a,b) = ab \tag{7}$$

$$\texttt{Bounded difference} : i(a,b) = \max(0, a+b-1) \tag{8}$$

$$\texttt{Drastic intersection} : i(a,b) = \begin{cases} a, b = 1 \\ b, a = 1 \\ \quad 0, 0.w \end{cases} \tag{9}$$

As shown in Fig. 1, Fig. 2, Fig. 3 and Fig. 4, drawn using MatLab. u must satisfy the following axioms for all a, b, $d \in [0,1]$

Axiom u 1: $u(a,0) = a$ (boundary condition).
Axiom u 2: $b < d$ implies $u(a,b) < u(a,d)$ (monotonicity).
Axiom u 3: $u(a,b) = u(b,a)$ (commutatively).
Axiom u 4: $u(a,u(b,d)) = u(u(a,b),d)$ (associativity).
Axiom u 5:. u is a continuous function (continuity).
Axiom u 6: $u(a,a) > a$ (subidempotency).
Axiom u 7: $a_1 < a_2$ and $b_1 < b_2$ implies $u(a_1,b_1) < u(a_2,b_2)$ (strict monotonicity).

$$\texttt{Standard union} : u(a,b) = \max(a,b) \tag{10}$$

$$\texttt{Algebraic sum} : u(a,b) = a + b - ab \tag{11}$$

$$\texttt{Bounded sum} : u(a,b) = \min(1, a+b) \tag{12}$$

$$\texttt{Drastic union} : u(a,b) = \begin{cases} a, b = 0 \\ \\ \quad 1, 0.w \end{cases} \tag{13}$$

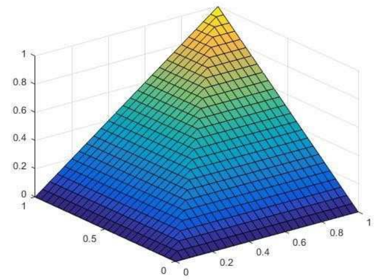

Fig. 1: Standard intersection

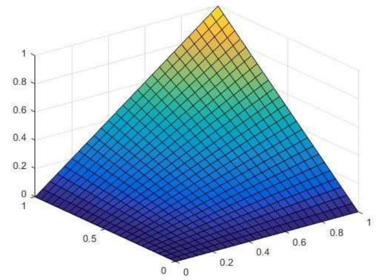

Fig. 2: Algebraic product

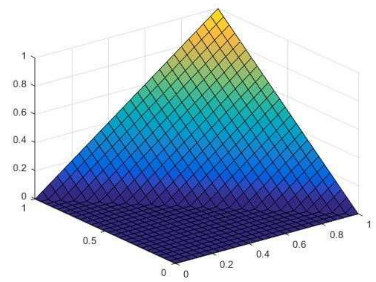

Fig. 3: Bounded difference

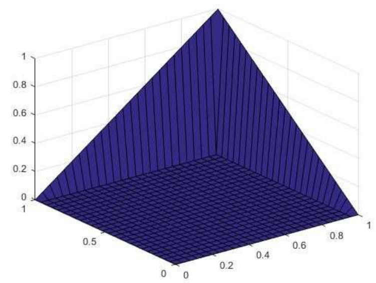

Fig. 4: Drastic intersection

As shown in Fig. 5, Fig. 6, Fig. 7 and Fig. 8 and drawn with MatLab.

For Example: If elements are Discrete, let:

$$\tilde{A} = \{(x_1, 0.3, 0.6), (x_2, 0.1, 0.9), (x_3, 0.4, 0.2), (x_4, 0.8, 0.1)\}$$
$$\tilde{B} = \{(x_1, 0.2, 0.5), (x_2, 0.3, 0.6), (x_3, 1, 0), (x_4, 0.5, 0.4)\}$$

To find $\tilde{A} \cap \tilde{B}$ with:

1.$\texttt{Standard intersection}: i(a,b) = \min(a,b)$
$\texttt{Standard union}: u(a,b) = \max(a,b)$

$$\begin{aligned} \tilde{A} \cap \tilde{B} = \{(x, \min(\mu_A(x), \mu_B(x)), \\ \max(\nu_A(x), \nu_B(x)) : x \in X\} \\ \tilde{A} \cup \tilde{B} = \{(x, \max(\mu_A(x), \mu_B(x), \\ \min(\nu_A(x), \nu_B(x)) : x \in X\} \end{aligned} \tag{14}$$

Then

$$\tilde{A} \cap \tilde{B} = \{(x_1, 0.2, 0.6), (x_2, 0, 0.9), (x_3, 0.4, 0.2), (x_4, 0.5, 0.4)\}$$
$$\tilde{B} \cap \tilde{B} = \{(x_1, 0.3, 0.5), (x_2, 0.3, 0.6), (x_3, 1, 0), (x_4, 0.8, 0.1)\}$$

2.$\texttt{Algebraic product}: i(a,b) = ab$
$\texttt{Algebraic sum}: u(a,b) = a + b - ab$

$$\begin{aligned} \tilde{A} \cap \tilde{B} = \{(x,\ (\mu_A(x).\mu_B(x)), \\ (\nu_A(x) + \nu_B(x) - \nu_A(x).\nu_B(x)) : x \in X\} \\ \tilde{A} \cup \tilde{B} = \{(x,\ (\mu_A(x) + \mu_B(x) - \mu_A(x).\mu_B(x)), \\ (\nu_A(x).\nu_B(x)) : x \in X\} \end{aligned} \tag{15}$$

Then

$$\tilde{A} \cap \tilde{B} = \{(x_1, 0.06, 0.8), (x_2, 0.03, 0), (x_3, 0.4, 0.2), (x_4, 0.4, 0.46)\}$$
$$\tilde{A} \cap \tilde{B} = \{(x_1, 0.44, 0.3), (x_2, 0.37, 0.54), (x_3, 1, 0), (x_4, 0.9, 0.04)\}$$

3.$\texttt{Bounded difference}: i(a,b) = \max(0, a + b - 1)$
$\texttt{Bounded sum}: u(a,b) = \min(1, a + b)$

$$\begin{aligned} \tilde{A} \cap \tilde{B} = \{(x, \min(0, \mu_B(x) + \mu_B(x) - 1), \\ \max(1, \nu_A(x) + \nu_B(x)) : x \in X\} \\ \tilde{A} \cup \tilde{B} = \{(x, \min(1, \mu_A(x) + \mu_B(x), \\ \max(0, \nu_A(x) + \nu_B(x) - 1) : x \in X\} \end{aligned} \tag{16}$$

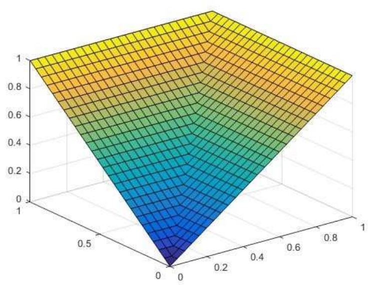

Fig. 5: Standard union

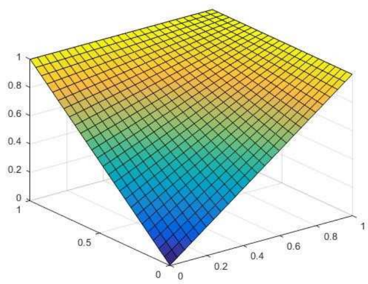

Fig. 6: Algebraic sum

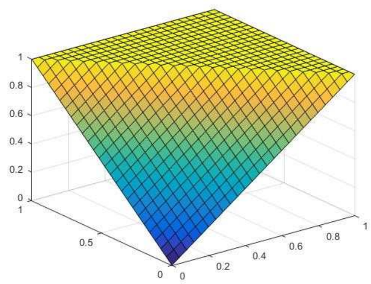

Fig. 7: Bounded sum

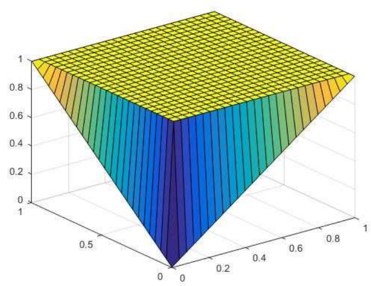

Fig. 8: Drastic union

Then

$$\tilde{A}\cap\tilde{B} = \{(x_1,0,1),(x_2,0,1),(x_3,0.4,0.2),(x_4,0.3,0.5)\}$$
$$\tilde{B}\cap\tilde{B} = \{(x_1,0.5,0.1),(x_2,0.4,0.5),(x_3,1,0),(x_4,1,0)\}$$

$$4.\texttt{Drastic intersection}: i(a,b) = \begin{cases} a, b=1 \\ b, a=1 \\ 0, 0.w \end{cases}$$

$$\texttt{Drastic union}: u(a,b) = \begin{cases} a, b=0 \\ b, a=0 \\ 1, 0.w \end{cases}$$

$$\begin{aligned} \tilde{A}\cap\tilde{B} &= \left\{ (x, \begin{bmatrix} \mu_A(x) & \mu_B(x)=1 & v_B(x)=0 \\ \mu_B(x), & \mu_A(x)=1, & v_A(x)=0 \\ 0 & 0.w & 0.w \end{bmatrix} \right\} \\ \tilde{A}\cup\tilde{B} &= \left\{ (x, \begin{bmatrix} \mu_A(x) & \mu_B(x)=0 & v_B(x)=1 \\ \mu_B(x), & \mu_A(x)=0, & v_A(x)=1) \\ 1 & 0.w & 0.w \end{bmatrix} \right\} \end{aligned} \quad (17)$$

where, $x\in X$.

Then

$$\tilde{A}\cap\tilde{B} = \{(x_1,0,1),(x_2,0,1),(x_3,0.4,0.2),(x_4,0,1)\}$$
$$\tilde{A}\cup\tilde{B} = \{(x_1,1,0),(x_2,1,0),(x_3,1,0),(x_4,1,0)\}$$

And according to the application, we use the suitable definition.

4 Comparison between Fuzzy Soft Expert System and IFS in Prediction of Lung Cancer Disease

A fuzzy soft expert system is composed of four main portions: (1) a fuzzication in which we transform real valued inputs into fuzzy sets (precisely, fuzzy numbers); (2) a transformation from the fuzzy numbers of data set to fuzzy soft sets; (3) a parameter reduction where the obtained family of fuzzy soft sets are reduced by normal parameter reduction method so as to form a new family of fuzzy soft sets; and (4) an algorithm to get the output data. The input values of these patients (P_1,P_2,P_3,P_4) are shown in 1.

As shown in Table 1, we then get the fuzzy membership functions of every patient as shown in Table 2.

1) Transform from fuzzy sets to fuzzy soft sets:

We will transform the fuzzy sets to the fuzzy soft sets which are combining results of the fuzzy sets and the soft sets. Let P={ P_1, P_2, P_3, P_4} be the set of four patients, and I the set consisting of 24 parameters: $WL(L)$, $WL(M)$, $WL(H)$, $WL(VH)$, $SHB(L)$, $SHB(M)$, $SHB(H)$, $SHB(Vh)$, $CHP(L)$, $CHP(M)$, $CHP(H)$, $CHP(VH)$, $PC(L)$, $PC(M)$, $PC(H)$, $PC(VH)$, $BS(L)$, $BS(M)$, $BS(H)$, $BS(VH)$, $Age(Y)$, $Age(M)$, $Age(O)$, $Age(VO)$.

Again, let:

$$\begin{aligned} A &= \{WL(L),WL(M),WL(H),WL(VH)\}, \\ B &= \{SHB(L),SHB(M),SHB(H),SHB(Vh)\}, \\ C &= \{CHP(L),CHP(M),CHP(H),CHP(VH)\}, \\ D &= \{PC(L),PC(M),PC(H),PC(VH)\}, \\ F &= \{BS(L),BS(M),BS(H),BS(VH)\}, \\ G &= \{Age(Y),Age(M),Age(O),Age(VO)\}. \end{aligned}$$

Then we obtain six the fuzzy soft sets (or 4-polar fuzzy sets): $(\tilde{L},A)$,$(\tilde{M},B)$, $(\tilde{N},C)$, $(\tilde{R},D)$, $(\tilde{P},F)$ and $(\tilde{T},G)$ from Table 3-8 which can be used to describes the 'WL', 'SHB', 'CHP', 'PC', 'BS', and 'Age', respectively. Where:

$WL(L)$={ P_1/0, P_2/0, P_3/0, P_4/0 },
$WL(M)$={P_1/0, P_2/0, P_3/0, P_4/0},
$WL(H)$={P_1/0.77, P_2/0.88, P_3/0, P_4/0.55},
$WL(VH)$={P_1/0.22, P_2/0.11, P_3/1, P_4/0.44},
$SHB(L)$={P_1/0, P_2/0, P_3/0, P_4/0},
$SHB(M)$={P_1/0.91, P_2/0.75, P_3/0, P_4/0.41},
$SHB(H)$={P_1/0.08, P_2/0.25, P_3/0.9, P_4/0.58},
$SHB(VH)$={P_1/0, P_2/0, P_3/0.09, P_4/0},
$CHP(L)$={P_1/0, P_2/0, P_3/0, P_4/0},
$CHP(M)$={P_1/0.92, P_2/0.76, P_3/0.84, P_4/0.38},
$CHP(H)$={P_1/0.07, P_2/0.23, P_3/0.15, P_4/0.61},
$CHP(VH)$={P_1/0, P_2/0, P_3/0, P_4/0},
$PC(L)$={P_1/0, P_2/0, P_3/0, P_4/0},
$PC(M)$={P_1/0.41, P_2/0.4, P_3/0.88, P_4/0.15},
$PC(H)$={P_1/0, P_2/0.41, P_3/0, P_4/0.7},
$PC(VH)$={P_1/0, P_2/0, P_3/0, P_4/0},
$BS(L)$={P_1/0, P_2/0, P_3/0, P_4/0},
$BS(M)$={P_1/0.91, P_2/1, P_3/0.45, P_4/0.09},
$BS(H)$={P_1/0.09, P_2/0, P_3/0.54, P_4/0.9},
$BS(VH)$={P_1/0, P_2/0, P_3/0, P_4/0},
$Age(Y)$={P_1/0, P_2/0, P_3/0, P_4/0},
$Age(M)$={P_1/0, P_2/0, P_3/0, P_4/0},

Table 1: The input values of four patients

P	P_1	P_2	P_3	P_4
WL	3.8	3.7	5	4
SHB	38	40	50	44
CHP	48	50	49	55
PC	18	40	33	45
BS	45	44	50	54
Age	55	60	49	45

Table 2: The fuzzy membership functions of every patient

P	P_1	P_2	P_3	P_4
$WL(L)$	0	0	0	0
$WL(M)$	0	0	0	0
$WL(H)$	0.77	0.88	0	0.55
$WL(VH)$	0.22	0.11	1	0.44
$SHB(L)$	0	0	0	0
$SHB(M)$	0.91	0.75	0	0.41
$SHB(H)$	0.08	0.25	0.9	0.58
$SHB(VH)$	0	0	0.09	0
$CHP(L)$	0	0	0	0
$CHP(M)$	0.92	0.76	0.84	0.38
$CHP(H)$	0.07	0.23	0.15	0.61
$CHP(VH)$	0	0	0.09	0
$PC(L)$	0	0	0	0
$PC(M)$	0.41	0.4	0.88	0.15
$PC(H)$	0	0.41	0	0.7
$PC(VH)$	0	0	0	0
$BS(L)$	0	0	0	0
$BS(M)$	0.9	1	0.45	0.09
$BS(H)$	0.09	0	0.54	0.9
$BS(VH)$	0	0	0	0
$Age(Y)$	0	0	0	0
$Age(M)$	0	0	0	0
$Age(O)$	0.3	0	0.9	0.62
$Age(VO)$	0.37	1	0	0

$Age(O)$={P_1/0.3, P_2/0, P_3/0.9, P_4/0.62},
$Age(VO)$={P_1/0.37, P_2/1, P_3/0, P_4/0}.

2) Parameter reduction of fuzzy soft sets Normal parameter reduction of fuzzy soft sets is very important in decision making problems. Using this reduce method we can minimize the number of parameters in a problem, highlighting only the key parameters, Where:

$WL(H)$={ P_1/0.77 , P_2/0.88, P_3/0, P_4/0.55},
$WL(VH)$={P_1/0.22, P_2/0.11, P_3/1, P_4/0.44},
$SHB(M)$={P_1/0.91, P_2/0.75, P_3/0, P_4/0.41},
$SHB(H)$={P_1/0.08, P_2/0.25, P_3/0.9, P_4/0.58},
$SHB(VH)$={P_1/0, P_2/0, P_3/0.09, P_4/0},
$CHP(M)$={P_1/0.92, P_2/0.76, P_3/0.84, P_4/0.38},
$CHP(H)$={P_1/0.07, P_2/0.23, P_3/0.15, P_4/0.61},
$PC(M)$={P_1/0.41, P_2/0.4, P_3/0.88, P_4/0.15},
$PC(H)$={P_1/0, P_2/0.41, P_3/0, P_4/0.7},
$BS(M)$={P_1/0.91, P_2/1, P_3/0.45, P_4/0.09},
$BS(H)$={P_1/0.09, P_2/0, P_3/0.54, P_4/0.9},
$Age(O)$={P_1/0.3, P_2/0, P_3/0.9, P_4/0.62},
$Age(VO)$={P_1/0.37, P_2/1, P_3/0, P_4/0}.

3) Computation using Kong et al.'s algorithm We are proposed the problem of decision making in an imprecise environment which has found paramount importance. They also presented a novel method of object recognition from an imprecise multi observer data. The method, slightly modified by Kong et al. (2009), involves construction of a square comparison table in which both the rows and the columns are labeled by all objects

Table 3: $(\tilde{L},A)$

P	P_1	P_2	P_3	P_4
$WL(H)$	0.77	0.88	0	0.55
$WL(VH)$	0.22	0.11	1	0.44

Table 4: $(\tilde{M},B)$

P	P_1	P_2	P_3	P_4
$SHB(M)$	0.91	0.75	0	0.41
$SHB(H)$	0.08	0.25	0.9	0.58
$SHB(VH)$	0	0	0.09	0

Table 5: $(\tilde{N},C)$

P	P_1	P_2	P_3	P_4
$CHP(M)$	0.92	0.76	0.84	0.38
$CHP(H)$	0.07	0.23	0.15	0.61

$x_1,x_2,x_3,...,x_n$ of the universe X, And the entries $c_{ij}(i,j=1,2,3,...,n)$ are defined by:

$$c_{ij}=\sum_{k=1}^{m}(f_{ik}-f_{jk})=c_i-c_j \quad (18)$$

Where f_{ik} is the membership value of object X_i for the parameter K^{th}, and m is the number of parameters.
The algorithm for the modified method used in our generic medical fuzzy soft expert system is as follows:
Step 1. Input the fuzzy soft sets $\Phi\in[0,1]^{XI}$ (standing for data from the first expert group), $\Psi\in[0,1]^{XJ}$ (standing for data from the second expert group), and $\Omega\in[0,1]^{XK}$ (standing for data from the third expert group).
Step 2. Input the parameter set L as observed by the observer.
Step 3. Compute the corresponding resultant fuzzy soft set $\Gamma\in[0,1]^{XI}$ (standing for the fusion data) from the fuzzy soft sets $\phi\in[0,1]^{XI}$, $\Psi\in[0,1]^{XJ}$ and $\Omega\in[0,1]^{XK}$ and place it in tabular form.
Step 4. Construct the comparison table of the fuzzy soft set $\Gamma\in[0,1]^{XI}$ and

$$r_i=\sum_{m=1}^{j}(c_i-c_j)(1,2,...,n).$$

Step 5. Get the decision K if

$$r_k=arg\max_j r_i.$$

We can predict which patients will suffer from lung cancer disease. Now, we will show these steps as follows: 1- Input the six new fuzzy soft sets$(\tilde{L},A)$, $(\tilde{M},B)$, $(\tilde{N},C)$, $(\tilde{R},D)$, $(\tilde{P},F)$ and $(\tilde{T},G)$ (as shown in Tables 3:8).

As an example, we show in the following table 9. how to compute the fusion fuzzy soft set $(\tilde{K},S)=(\tilde{L},A)\bigotimes(\tilde{M},B)$ from $(\tilde{L},A)$ and $(\tilde{M},B)$ (notice

Table 6: $(\tilde{R}, D)$

P	P_1	P_2	P_3	P_4
$PC(M)$	0.41	0.4	0.88	0.15
$PC(H)$	0	0.41	0	0.7

Table 7: $(\tilde{P}, F)$

P	P_1	P_2	P_3	P_4
$BS(M)$	0.9	1	0.45	0.09
$BS(H)$	0.09	0	0.54	0.9

Table 8: $(\tilde{T}, G)$

P	P_1	P_2	P_3	P_4
$Age(O)$	0.3	0	0.9	0.62
$Age(VO)$	0.37	1	0	0

Table 9: The fusion fuzzy soft set $(\tilde{K}, S)$

P	P_1	P_2	P_3	P_4
e_{11}	0.91	0.88	0	0.55
e_{12}	0.77	0.88	0.9	0.58
e_{13}	0.77	0.88	0.09	0.55
e_{21}	0.91	0.75	1	0.44
e_{22}	0.22	0.23	1	0.58
e_{23}	0.22	0.11	1	0.44

that $S = \tilde{A}x\tilde{B} = \{e_{11}, e_{12}, e_{13}e_{21}, e_{22}, e_{23}\}$, A is a 6-element set).

2- Compute the fusion fuzzy soft set $(\tilde{I}, Q) = (\tilde{L}, A) \bigotimes (\tilde{M}, B) \bigotimes (\tilde{N}, C) \bigotimes (\tilde{R}, D) \bigotimes (\tilde{P}, F) \bigotimes (\tilde{T}, G)\}$ (notice that $Q = \tilde{A}x\tilde{B}x\tilde{C}x\tilde{D}x\tilde{F}x\tilde{G} = \{\varepsilon_1, \varepsilon_2, ..., \varepsilon_{96}\}$ is a 96-element set, see table 10).

3. Compute c_{ij}, c_i, r_i and , by Kong et al.'s algorithm (Kong et al., 2009). We know:
$r_1 = (c_1 - c_2) + (c_1 - c_2) + ... + (c_1 - c_1 1) + (c_1 - c_1 2) = 0 + (-7.99) + (-6.92) + 8.02 + (-9.76) + (0.96) + 3.92 + (-11.27) + (-9.52) + 8.66 + (-6.72) + (-8.48) = -41.02.$
Similarly, $r_2 = 50.89, r_3 = 16.4, r_4 = -37.44, r_5 = 19.86, r_6 = -29.14, r_7 = -18.06, r_8 = 97.22, r_9 = 89.96, r_{10} = 90.94, r_{11} = 66.62, r_{12} = 61.94, r_{13} = -39.01, r_{14} = 80.45, r_{15} = 66.23, r_{16} = 52.44, r_{17} = 20.05, r_{18} = 22.45, r_{19} = -30.88, r_{20} = 85.67, r_{21} = 67.88, r_{22} = 90.2, r_{23} = 95.56, r_{24} = 86.78, r_{25} = 55.5, r_{26} = -19.56, r_{27} = -18.3, r_{28} = 20.66, r_{29} = 69.66, r_{30} = 73.41, r_{31} = 29.7, r_{32} = 32.43, r_{33} = 76.32, r_{34} = 79.44, r_{35} = 53.4, r_{36} = 76.65, r_{37} = 85.5, r_{38} = 18.3, r_{39} = 15.57, r_{40} = -44.25, r_{41} = 59.98, r_{42} = 16.37, r_{43} = 29.34, r_{44} = 77.45, r_{45} = 96.78.$

4. From step 3 we can see that patient P_2 have high values of r_i. Consequently, they are potentially suffering from lung cancer disease.

But in IFS, we propose a new approach for medical diagnosis by Eulalia Szmidt et al. [26] by employing intuitionistic fuzzy sets(IFS) by K. T. Atanassov [27].

Table 10: The fusion fuzzy soft set $(\tilde{I}, Q)$

P	P_1	P_2	P_3	P_4
ε_1	0.92	1	0.9	0.62
ε_2	0.92	1	0.9	0.7
ε_3	0.91	1	0.9	0.62
ε_4	0.91	1	0.9	0.7
ε_5	0.92	1	0.88	0.55
ε_6	0.92	1	0.84	0.7
ε_7	0.91	1	0.88	0.61
ε_8	0.91	1	0.45	0.7
ε_9	0.92	0.88	0.9	0.9
ε_{10}	0.92	0.88	0.9	0.9
ε_{11}	0.91	0.88	0.9	0.9
ε_{12}	0.91	0.88	0.9	0.9
ε_{13}	0.92	1	0.88	0.9
ε_{14}	0.92	1	0.84	0.9
ε_{15}	0.91	1	0.88	0.9
ε_{16}	0.91	1	0.54	0.9
ε_{17}	0.92	1	0.9	0.62
ε_{18}	0.92	1	0.9	0.7
ε_{19}	0.9	1	0.9	0.62
ε_{20}	0.9	1	0.9	0.7
ε_{21}	0.92	1	0.9	0.58
ε_{22}	0.92	1	0.9	0.7
ε_{23}	0.9	1	0.9	0.61
ε_{24}	0.9	1	0.9	0.7
ε_{25}	0.92	0.88	0.9	0.9
ε_{26}	0.92	0.88	0.9	0.9
ε_{27}	0.77	0.88	0.9	0.9
ε_{28}	0.77	0.88	0.9	0.9
ε_{29}	0.92	1	0.9	0.9
ε_{30}	0.92	1	0.9	0.7
ε_{31}	0.77	1	0.9	0.9
ε_{32}	0.77	1	0.9	0.9
ε_{33}	0.92	1	0.9	0.62
ε_{34}	0.92	1	0.9	0.7
ε_{35}	0.9	1	0.9	0.62
ε_{36}	0.9	1	0.9	0.7
ε_{37}	0.92	1	0.88	0.55
ε_{38}	0.92	1	0.84	0.7
ε_{39}	0.9	1	0.88	0.61
ε_{40}	0.9	1	0.45	0.7
ε_{41}	0.92	0.88	0.9	0.9
ε_{42}	0.92	0.88	0.9	0.9
ε_{43}	0.77	0.88	0.9	0.9
ε_{44}	0.77	0.88	0.9	0.9
ε_{45}	0.92	1	0.88	0.9
ε_{46}	0.92	1	0.84	0.9
ε_{47}	0.77	1	0.88	0.9
ε_{48}	0.77	1	0.54	0.9
ε_{49}	0.92	1	1	0.62
ε_{50}	0.92	1	1	0.7
ε_{51}	0.91	1	1	0.62
ε_{52}	0.91	1	1	0.7
ε_{53}	0.92	1	1	0.44
ε_{54}	0.92	1	1	0.7

Table 11: Continued: The fusion fuzzy soft set $(\tilde{I}, Q)$

P	P_1	P_2	P_3	P_4
ε_{55}	0.91	1	1	0.61
ε_{56}	0.91	1	1	0.7
ε_{57}	0.92	0.76	1	0.9
ε_{58}	0.92	0.76	1	0.9
ε_{59}	0.91	0.76	1	0.9
ε_{60}	0.91	0.75	1	0.9
ε_{61}	0.92	1	1	0.9
ε_{62}	0.92	1	1	0.9
ε_{63}	0.91	1	1	0.9
ε_{64}	0.91	1	1	0.9
ε_{65}	0.92	1	1	0.62
ε_{66}	0.92	1	1	0.7
ε_{67}	0.9	1	1	0.62
ε_{68}	0.9	1	1	0.7
ε_{69}	0.92	1	1	0.58
ε_{70}	0.92	1	1	0.7
ε_{71}	0.9	1	1	0.61
ε_{72}	0.9	1	1	0.7
ε_{73}	0.92	0.76	1	0.9
ε_{74}	0.92	0.76	1	0.9
ε_{75}	0.41	0.4	1	0.9
ε_{76}	0.3	0.41	1	0.9
ε_{77}	0.92	1	1	0.9
ε_{78}	0.92	1	1	0.9
ε_{79}	0.41	1	1	0.9
ε_{80}	0.37	1	1	0.9
ε_{81}	0.92	1	1	0.62
ε_{82}	0.92	1	1	0.7
ε_{83}	0.9	1	1	0.62
ε_{84}	0.9	1	1	0.7
ε_{85}	0.92	1	1	0.44
ε_{86}	0.92	1	1	0.7
ε_{87}	0.9	1	1	0.61
ε_{88}	0.9	1	1	0.7
ε_{89}	0.92	0.76	1	0.9
ε_{90}	0.92	0.76	1	0.9
ε_{91}	0.41	0.4	1	0.9
ε_{92}	0.3	0.41	1	0.9
ε_{93}	0.92	1	1	0.9
ε_{94}	0.92	1	1	0.9
ε_{95}	0.41	1	1	0.9
ε_{96}	0.3	1	1	0.9

Solution is obtained by looking for the smallest distance eq. 1, 2 between symptoms. The Decision Making Problems, particularly in the case of medical diagnosis. There is a fair chance of the existence of a non-null hesitation part at each moment of evaluation of an unknown object. To be more precise IFS let us express e.g., the fact that the temperature of a patient changes, and other symptoms are not quite clear. In this article we will present IFS as a tool for reasoning in the presence of imperfect facts and imprecise knowledge. An example of Lung Cancer will be presented assuming there is a database, i.e. description of a set of symptoms S, and a set of diagnoses D. We will describe a state of a patient knowing results of his/her medical tests. Description of the problem uses the notion of an IFS. The proposed method of diagnosis involves IFS distances as introduced by eq. 1, 2. It involves the following three steps:

1) Determination of symptoms as shown in Table 12.

Table 12: Determination of symptoms

Al	Weight Loss (WL)	(0.77, 0.22, 0.01)
	Shortest of breath (SHB)	(0.91,0.08,0.01)
	Chest Pain (CHP)	(0.92, 0.07, 0.01)
	Persistence Cough (PC)	(0.41, 0, 0.59)
	Blood in Sputum (BS)	(0.9, 0.09, 0.01)
	Age	(0.3, 0.37, 0.33)
Bob	Weight Loss (WL)	(0.88, 0.11, 0.01)
	Shortest of breath (SHB)	(0.75, 0.25, 0)
	Chest Pain (CHP)	(0.76, 0.23, 0.01)
	Persistence Cough (PC)	(0.4, 0.41, 0.19)
	Blood in Sputum (BS)	(1, 0, 0)
	Age	(0, 1, 0)
Joe	Weight Loss (WL)	(0, 1, 0)
	Shortest of breath (SHB)	(0.9, 0.09, 0.01)
	Chest Pain (CHP)	(0.84, 0.15, 0.01)
	Persistence Cough (PC)	(0.88, 0, 0.12)
	Blood in Sputum (BS)	(0.45, 0.54, 0.01)
	Age	(0.9, 0, 0.1)
Ted	Weight Loss (WL)	(0.55, 0.44, 0.01)
	Shortest of breath (SHB)	(0.41, 0.58, 0.01)
	Chest Pain (CHP)	(0.38, 0.61, 0.01)
	Persistence Cough (PC)	(0.15, 0.7, 0.15)
	Blood in Sputum (BS)	(0.09 ,0.9, 0.01)
	Age	(0.62, 0, 0.38)

2) Formulation of medical knowledge based on IFS relations as shown in table 13.

Let the set of diagnoses be $D=$ {Lung Cancer}, The considered set of symptoms is $S=$\{ Weight loss (WL), Shortest of breath (SHB), Chest Pain (CHP), Persistence Cough (PC), Blood in Sputum (BS), Age\}. The data are given in table 13: each symptom is described by three numbers: membership (μ), non-membership (ν), hesitation margin (π). For example, the weight loss is high $(\mu = 0.7, \nu = 0.0, \pi = 0.3)$. In fact data is exactly the same but by involving in an explicit way the hesitation

Table 13: Formulation of medical

R	Standard
Weight Loss (WL)	(0.9, 0, 0.1)
Shortest of breath (SHB)	(0.7, 0, 0.3)
Chest Pain (CHP)	(0.7, 0.1, 0.2)
Persistence Cough (PC)	(0.8, 0, 0.2)
Blood in Sputum (BS)	(0, 0.7, 0.3)
Age	(0.9, 0, 0.1)

margin too, we want to stress that the values of all three parameters are necessary in our approach. The considered set of patients is $P = Al, Bob, Joe, Ted$. The symptoms characteristic for the patients are given in Table 12 as before, we need all three parameters (μ, v, π) describing each symptom but the data are the same as in table 13. Our task is to make a proper diagnosis for each patient P_i , $i = 1,...,4$. To fulfill the task we propose to calculate for each patient pi a distance of his symptoms in Table 12 from a set of symptoms $S_j, j = 1,...,6$ characteristic for each diagnosis $d_k, k = 1,...,6$ in table 13.The lowest obtained distance points out a proper diagnosis. In E. Szmidt eq.1, 2 we proved that the only proper way of calculating the most widely used distances for intuitionistic fuzzy sets is to take into account all three parameters: the membership function, the non-membership function, and the hesitation margin. To be more precise, the normalized Hamming distances for all the symptoms of the i^{th} patient from the k^{th} diagnosis this is defined in eq. 1.

The distances in eq. 1 for each patient from the considered set of possible diagnoses are given in table 14. The distance is highest 0.5: Bob suffers from lung cancer.

3) Determination of diagnosis as shown in table 14.

Table 14: Diagnosis knowledge

	Lung Cancer
Al	0.445
Bob	0.5017
Joe	0.34167
Ted	0.2958

We obtained the same results, i.e. the same quality diagnosis for each patient when looking for the solution while applying soft set system.

5 Conclusion

The case study presented in this paper can be applied to a lot of applications in real life. For instance: Political or social event. So, we deduce that intuitionistic fuzzy sets possess an uncertainty about examined objects in databases that we can communicate about. The method used, which performs diagnosis based on the calculation of distances from a considered case to all considered diseases, takes into consideration values of all symptoms. As a result, our method requires the use of weights for all symptoms (some symptoms may be more relevant for some illnesses).

Data availability statement

No data were used to support this study.

Competing interests

The authors declare that they have no competing interests.

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