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METHODOLOGIES AND APPLICATION

A new expert system in prediction of lung cancer disease based on fuzzy soft sets

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Abstract

Every year, millions of people worldwide (including a major portion in China) are suffering from lung cancer disease (Chinese report of Smoking and Health 2017). The aim of this paper is to develop a new fuzzy soft expert system which can be used to predict lung cancer disease. A prediction process using this fuzzy soft expert system is composed of four main steps: (1) Transform real-valued inputs into fuzzy numbers. (2) Transform fuzzy numbers of data into fuzzy soft sets. (3) Reduce, using normal parameter reduction method, the obtained family of fuzzy soft sets into a new family of fuzzy soft sets. (4) Use the proposed algorithm to get the output data. An experiment is conducted on forty five patients (thirty males, fifteen females, all are cigarette smokers) who endure treatment in the Respiratory Department of Nanjing Chest Hospital, China. The number of training data taken was 55 records, and the remaining 45 records were used for the testing process in our system by using weight loss, shortness of breath, chest pain, persistence a cough, blood in sputum, and age of patients. The quantized accuracies of the proposed system were found to be 100%. In this work, we developed a fuzzy soft expert system based on fuzzy soft sets; we used a fuzzy membership functions and an algorithm to predict those patients who may suffer lung cancer. In this way, it is possible to conclude that the use of fuzzy soft expert system can produce valuable results for lung cancer detection. It is found that the fuzzy soft expert system developed is useful to the expert doctor to decide if a patient has lung cancer or not. Finally, we introduce comparison diagnosed between our proposed system and the fuzzy inference system.

Keywords Fuzzy inference system · Fuzzy soft expert system · Comparison diagnosed · Prevention and control of cancer-like diseases

Mathematics Subject Classification 92C50 · 93A30 · 92B05 · 92B10

1 Introduction

Among the most illness leading the death in all the world is cancer. One of the most common causes of cancer death is lung cancer. The statistic data from World Health Organiza-

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tion (WHO) reveal that the death from lung cancer reached 1.59 million; among 8.2 million died due to cancer (American cancer society 2017). It was estimated that about 222,500 new cases (116,990 in men and 105,510 in women) in 2017 of lung and bronchial cancer would be diagnosed and that 155,870 deaths (84,590 in men and 71,280 in women) for the disease (Siegel et al. 2017). Only 17.7% of all patients with lung cancer are alive at least 5 years after diagnosis (Howlader et al. 2017). Lung cancer has become one of the majority occurring diseases in the world, it has exponentiating trend in its incidence in future, and it is a cause of the first death.

In order to avoid such a life-threatening difficulty, one of the able solutions is to make people aware of their respective lung cancer risks previously and ought to take preventive measures suitably. It is only possible when an early detection of lung cancer occurs. Conforming to medical experts, an early detection at the stage of dead may anticipate the death caused by lung cancer if proper medication is given thereafter.

In light of this, people try to develop medical expert systems or disease diagnosis expert systems of lung cancer with the help of mathematics. As uncertainty always appears in the course of diagnosis, fuzzy rule-based expert systems of lung cancer are developed. A fuzzy rule-based expert system includes a set of fuzzy rules and membership functions, where knowledge acquisition (regarded to be the most important query in the design of fuzzy rule-based inference structure) could be aided greatly by experts in the particular area. So far, the fuzzy inference system has become a vigorous area of research in many sciences (Farahani et al. 2015; Avci 2012; Jagadeesh et al. 2016; Hiremath and Tegnoor 2014; Ulutagay et al. 2015). In addition to in medical science, a fuzzy rule-based inference system for lung cancer illness diagnosis was designed based on the National Cancer Institute database (Lavanya et al. 2011). The system has 5 input spheres and one output sphere. Input spheres are weight loss, shortness of breath, chest pain, persistent cough, and blood in sputum. There were computational intelligence handset fuzzy systems, neural network, and evolutionary computing where the neuro-fuzzy incorporated system for lung cancer illness was introduced. In order to show the efficiency of the suggested system, simulation for automated diagnosis is performed by using realistic causes of lung cancer illness. An artificial neural network model was used to examine six tumor markers in the auxiliary diagnosis of lung cancer (Feng et al. 2012). This template was used to discern the people with the lung cancer from those with the benign lung disease and the normal control subjects. An early diagnosis system for anticipating lung cancer risk using susceptible neuro-fuzzy inference system and linear discriminant analysis was proposed (Billah and Islam 2016). An effective analysis of lung infection using fuzzy rules was presented (Tiwari et al. 2015). A hybrid automatic system for the diagnosis of lung cancer based on genetic algorithm and fuzzy extreme learning machines was proposed (Daliri 2012). Principle component analysis, fuzzy weighting preprocessing, and artificial vulnerable recognition system founded on diagnostic system for diagnosis of lung cancer were proposed (Polat and Günes 2008). An optimal tumor marker group-coupled artificial neural network for diagnosis of lung cancer was proposed (Wu et al. 2011). Several researchers have examined the problem of automatic diagnosis of the lung cancer (Flores-Fernández et al. 2012; Boeria et al. 2011; Sasaki et al. 2010; Shen et al. 2011; Bagherieh et al. 2013; Wooda et al. 2015; Yang and Chen 2015; Langevin et al. 2015; Manikandan et al. 2017). Later, current research indicates treatment for lung cancer (Karen 2016). Web-based fuzzy expert system for lung cancer diagnosis was proposed (Rodiah et al. 2016). An early diagnosis of lung cancer disease using data mining and medical image processing processes was proposed (Muthazhagan and Ravi 2016). Lung cancer disease analyses using based fuzzy logic system were proposed (Bhaktavastalam and Reddy 2016). Prognostic system for early diagnosis of pediatric lung disease using artificial intelligence was presented (Rajan and Chelvan 2017). Moreover, other scholars have applied various algorithms to obtain the following results in different fields: Energy-efficient task consolidation for cloud data center was proposed (Patra 2018). An efficient data replication algorithm for distributed systems was introduced (Panda and Naik 2018). An affordable hybrid cloud-based cluster for secure health informatics research was presented (Qureshi 2018). The theory of computer security, reasons for the design of applications, security techniques, management, and engineering issues of computer security were introduced (Gupta 2018).

There are some drawbacks in above fuzzy expert systems of lung cancer. For example, they depend chiefly on rules; sometimes decisions made by above fuzzy expert systems of lung cancer based on two group of rules (even if both have the same degree of truth) are contrary; sometimes the decisions made by above fuzzy expert systems of lung cancer are contrary to that of expert doctors. The present paper tries to overcome these drawbacks with the help of fuzzy soft set theory. We develop a knowledge-based prediction system of lung cancer (named fuzzy soft expert system). The system is composed of four main portions: the fuzzification 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 developed improves that of the fuzzy inference system (Lavanya et al. 2011).

The rest of the paper consists of four sections: Sect. 2 introduces the notions of fuzzy set, soft set, fuzzy soft set, and fuzzy inference system and describes the database used. In Sect. 3, methodology and implementation of the proposed system are expounded. Details of the experimental results are explored in Sect. 4. Finally, conclusions and discussion are given in Sect. 5.

2 Background

2.1 Fuzzy sets, soft sets and fuzzy soft sets

Fuzzy sets were introduced by Zadeh in 1965 to represent/manipulate data and information possessing nonstatistical uncertainties.

Definition 1 (Zadeh 1965) Let $[0,1]^X$ be the set of all mappings from the set X to the ordinary closed interval $[0,1]$ (with the ordinary order $\leq$). Then, $[0,1]^X$, with the point-wise order (still written as $\leq$), is a fuzzy lattice or a Hutton algebra (i.e., a completely distributive complete lattice equipped with an order-reversing involution $'$). Each $A \in [0,1]^X$ is called a fuzzy set on X, and the value $A(x)$ is called the membership of $x \in X$. The supremum $\bigvee_{k\in K} A_k$ (write as also $\bigcup_{k\in K} A_k$) and the infimum $\bigwedge_{k\in K} A_k$ (write as also $\bigcap_{k\in K} A_k$) of a family $\{A_k\}_{k\in K} \subseteq [0,1]^X$,[1] Defined by

$$\left(\bigvee_{k\in K} A_k\right)(x) = \bigvee_{k\in K} A_k(x) \ (\forall x \in X),$$

$$\left(\bigwedge_{k\in K} A_k\right)(x) = \bigwedge_{k\in K} A_k(x) \ (\forall x \in X),$$

are also called union and intersection of $\{A_k\}_{k\in K}$, respectively. When $X = \{x_1, x_2, \ldots, x_n\}$ is a finite set, a fuzzy set A on X can also be written as

$$A = \left\{\frac{A(x_1)}{x_1}, \frac{A(x_2)}{x_2}, \ldots, \frac{A(x_n)}{x_n}\right\}.$$

The fuzzy sets $[a,a,b\rangle, \langle a,b,b] \in [0,1]^{\mathrm{R}}$ (called trapezoidal fuzzy numbers, where $a \leq b$ and R is the set of all real numbers) and $\langle a,b,c\rangle \in [0,1]^{\mathrm{R}}$ (called triangular fuzzy number, where $a \leq b \leq c$), are used frequently in this paper, and they are defined as follows:

$$[a,a,b\rangle(x) = \begin{cases} 1, & x \leq a, \\ \frac{b-x}{b-a}, & a < x < b, \\ 0, & x \geq b; \end{cases}$$

$$\langle a,b,b](x) = \begin{cases} 0, & x \leq a, \\ \frac{x-a}{b-a}, & a < x < b, \\ 1, & x \geq b; \end{cases}$$

$$\langle a,b,c\rangle(x) = \begin{cases} \frac{x-a}{b-a}, & a \leq x < b, \\ \frac{c-x}{c-b}, & b \leq x < c, \\ 0, & \text{otherwise.} \end{cases}$$

[1] In practical problems $A_k \in [0,1]^{Y_k}$ $(Y_k \subseteq X, k \in K)$ hold since data are usually incomplete. In this paper, we identify a fuzzy set $A \in [0,1]^Y$ $(Y \subseteq X)$ with its extension $A^* \in [0,1]^X$ which is defined by $A^*(x) = A(x)$ (if $x \in Y$) or $A^*(x) = 0$ (if $x \in X - Y$).

Example 2 Let $X = \{\text{white, red, black, orange, brown}\}$ be a set of colors. If the memberships of white, red, black, orange, and brown are defined as 0, 0.3, 0.5, 0.8, and 0.9, respectively, then the fuzzy set A on X can be written as

$$A = \left\{\frac{0}{\text{white}}, \frac{0.3}{\text{red}}, \frac{0.5}{\text{black}}, \frac{0.8}{\text{orange}}, \frac{0.9}{\text{brown}}\right\}$$

or

$$A = \left\{\frac{0.3}{\text{red}}, \frac{0.5}{\text{black}}, \frac{0.8}{\text{orange}}, \frac{0.9}{\text{brown}}\right\}.$$

In the course of rapidly progressing of the theory of fuzzy sets, people also find it is difficult to set the membership values in particular case. Thinking the possible reason for these difficulties to be the inadequacy of the parametrization tool of the theory, Molodtsov (1999) proposed the notion of soft set, which was generalized by Maji et al. (2003) to the notion of fuzzy soft set later on. Recently, research works on soft sets and fuzzy soft sets are very active and progressing rapidly (Guan et al. 2013; Feng et al. 2010; Malik and Shabir 2017; Khalil et al. 2019; Khalil and Hassan 2019).

Next, we present the notions of soft set, fuzzy soft set, and some examples.

Definition 3 (Molodtsov 1999; Maji et al. 2001; Chen et al. 2014; Li et al. 2017) Elements of 2^{XI} (the set of all mappings from I, called parameter set, to 2^X, the set of all subsets of X) are called soft sets on X indexed by I, and elements of $[0,1]^{XI}$ (the set of all mappings from I to $[0,1]^X$) are called fuzzy soft sets on X indexed by I. $\Phi \in [0,1]^{XI}$ can also be written as (Φ, I) and looked to be an m-polar fuzzy set on I (i.e., a mapping from I to $[0,1]^m$), where m is the cardinality of X.

Example 4 A fund manager in a wealth management firm is assessing five potential investment opportunities from $X = \{x_1, x_2, x_3, x_4, x_5\}$. The firm mandates that the fund manager has to evaluate the following four parameters: i, j, k, and l, where i stands for the parameter "risk," j stands for the parameter "growth," k stands for the parameter "social–political issues," and l stands for the parameter "environmental impacts."

(1) Suppose that $\Phi(i) = \{x_1, x_3\}$ (meaning x_1 and x_3 are risk potential investments, but x_1 and x_5 are unknown or roughly think neither to be risk potential investment), $\Phi(j) = \{x_2, x_3, x_4\}$, $\Phi(k) = \{x_1, x_4, x_5\}$, and $\Phi(l) = \{x_2, x_5\}$. Then, we obtain a soft set

$$\Phi = \left\{\frac{\{x_1, x_3\}}{i}, \frac{\{x_2, x_3, x_4\}}{j}, \frac{\{x_1, x_4, x_5\}}{k}, \frac{\{x_2, x_5\}}{l}\right\},$$

which describes the "opportunities of the potential investment."

(2) Assume that

$$\Psi(i)=\left\{\frac{0.9}{x_1},\frac{0.1}{x_2},\frac{0.8}{x_3},\frac{0.1}{x_4},\frac{0.2}{x_5}\right\},$$
$$\Psi(j)=\left\{\frac{0.1}{x_1},\frac{0.9}{x_2},\frac{0.9}{x_3},\frac{1}{x_4},\frac{0.2}{x_5}\right\},$$
$$\Psi(k)=\left\{\frac{0.9}{x_1},\frac{0.1}{x_2},\frac{0}{x_3},\frac{1}{x_4},\frac{0.8}{x_5}\right\},$$
$$\Psi(l)=\left\{\frac{0}{x_1},\frac{1}{x_2},\frac{0.4}{x_3},\frac{0.4}{x_4},\frac{0.9}{x_5}\right\}.$$

Then, we obtain a fuzzy soft set

$$\Psi=\left\{\frac{\left\{\frac{0.9}{x_1},\frac{0.1}{x_2},\frac{0.8}{x_3},\frac{0.1}{x_4},\frac{0.2}{x_5}\right\}}{i},\frac{\left\{\frac{0.1}{x_1},\frac{0.9}{x_2},\frac{0.9}{x_3},\frac{1}{x_4},\frac{0.2}{x_5}\right\}}{j},\frac{\left\{\frac{0.9}{x_1},\frac{0.1}{x_2},\frac{1}{x_4},\frac{0.8}{x_5}\right\}}{k},\frac{\left\{\frac{1}{x_2},\frac{0.4}{x_3},\frac{0.4}{x_4},\frac{0.9}{x_5}\right\}}{l}\right\},$$

which also describes the "opportunities of the potential investment" in a more precise or more complete way.

Definition 5 (Maji et al. 2001) Let $\Phi \in [0,1]^{XI}$ and $\Psi \in [0,1]^{XJ}$. Then, $\Phi\check{\otimes}\Psi \in [0,1]^{X(I\times J)}$, defined by $\left(\Phi\check{\otimes}\Psi\right)(i,j)=\Phi(i)\vee\Psi(j)$ $(\forall(i,j)\in I\times J)$, is called sup product (or fusion) of Φ and Ψ.

Example 6 Let $X=\{x_1,x_2,x_3,x_4\}$ be a set of air-condition systems and $E=\{i,j,k,l\}$ be a set of parameter, where i stands for the parameter economical, j stands for the parameter energy efficient, k stands for the parameter low maintenance, l stands for the parameter quality. Now consider the incomplete data: $I=\{i,k\}$, $J=\{j,l\}$, and $\Phi\in[0,1]^{XI}$ and $\Psi\in[0,1]^{XJ}$ which are defined by

$$\Phi(i)=\left\{\frac{0.7}{x_1},\frac{0.8}{x_2},\frac{0.5}{x_3},\frac{0.3}{x_4}\right\},$$
$$\Phi(k)=\left\{\frac{0.4}{x_1},\frac{0.2}{x_2},\frac{0.1}{x_3},\frac{0.5}{x_4}\right\},$$
$$\Psi(j)=\left\{\frac{0.6}{x_1},\frac{0.9}{x_2},\frac{1}{x_3},\frac{0.4}{x_4}\right\},$$
$$\Psi(l)=\left\{\frac{0}{x_1},\frac{0.7}{x_2},\frac{0.8}{x_3},\frac{0.1}{x_4}\right\}.$$

Then, the fusion datum $\Phi\check{\otimes}\Psi\in[0,1]^{X(I\times J)}$ is given by

$$\left(\Phi\check{\otimes}\Psi\right)(i,j)=\left\{\frac{0.7}{x_1},\frac{0.9}{x_2},\frac{1}{x_3},\frac{0.4}{x_4}\right\},$$
$$\left(\Phi\check{\otimes}\Psi\right)(i,l)=\left\{\frac{0.7}{x_1},\frac{0.8}{x_2},\frac{0.8}{x_3},\frac{0.3}{x_4}\right\},$$
$$\left(\Phi\check{\otimes}\Psi\right)(k,j)=\left\{\frac{0.6}{x_1},\frac{0.9}{x_2},\frac{1}{x_3},\frac{0.5}{x_4}\right\},$$
$$\left(\Phi\check{\otimes}\Psi\right)(k,l)=\left\{\frac{0.4}{x_1},\frac{0.7}{x_2},\frac{0.8}{x_3},\frac{0.5}{x_4}\right\}.$$

Definition 7 (Kong et al. 2008) Let $\tilde{F}\in[0,1]^{XI}$ be a fuzzy soft set with I a finite set. $J\subseteq I$ is called a normal parameter reduction in I if $I-J$ is a maximal subset of I such that $\sum_{i\in I-J}\tilde{F}(i)(x)$ is a constant for each $x\in X$.

2.2 Algorithms

Roy and Maji (2007) 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 $x_1,x_2,x_3,\ldots,x_n$ of the universe X, and the entries c_{ij} $(i,j=1,2,\ldots,n)$ are defined by

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

where f_{ik} is the membership value of object x_i for the kth parameter, $c_i=\sum_{k=1}^{m}f_{ik}$, 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 $\Gamma\in[0,1]^{XL}$ (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 $\Gamma\in[0,1]^{XL}$ and compute $r_i=\sum_{j=1}^{m}(c_i-c_j)$ $(i=1,2,\ldots,n)$.
Step 5 Get the decision k if $r_k=\arg\max_i r_i$.

2.3 Fuzzy inference system

A Mamdani-type fuzzy inference system is a mapping $f: U\longrightarrow R$ defined, relying on a number of fuzzy IF-THEN

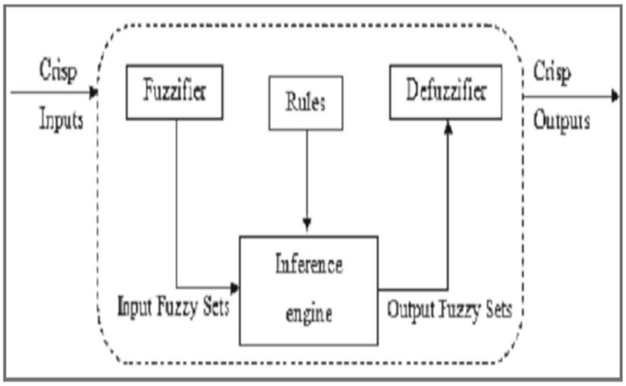

Fig. 1 Architecture of a fuzzy inference system

rules from experts' experience, by

$$f(\mathbf{x}) = \frac{y^{(1)}A^{(1)}(\mathbf{x}) + y^{(2)}A^{(2)}(\mathbf{x}) + \cdots + y^{(m)}A^{(m)}(\mathbf{x})}{A^{(1)}(\mathbf{x}) + A^{(2)}(\mathbf{x}) + \cdots + A^{(m)}(\mathbf{x})}$$
$$= \sum_{i=1}^{m} \left(\frac{\prod_{s=1}^{n} A_s^{(i)}(x_s)}{\sum_{t=1}^{m} \prod_{s=1}^{n} A_s^{(t)}(x_s)} \times y^{(i)} \right) \quad (2)$$

where $\mathbf{x} = (x_1, x_2, \ldots, x_n) \in U$ is the input, $f(\mathbf{x})$ is the output, $U \subseteq R^n$ is a compact set, $y^{(i)}$ (the result of defuzzification which is normally sent back to the process as control feedback) satisfies $B^{(i)}(y^{(i)}) = 1$, $A^{(i)}(\mathbf{x}) = A_1^{(i)}(x_1)A_2^{(i)}(x_2)\cdots A_n^{(i)}(x_n)$, and $A_1^{(i)}, A_2^{(i)}, \ldots A_n^{(i)}$ and $B^{(i)}$ is fuzzy sets on R $(i = 1, 2, \ldots, m)$ which are used in the relied on fuzzy rules:

R$^{(i)}$: IF x_1 is $A_1^{(i)}$ and $\cdots$ and x_n is $A_n^{(i)}$, THEN y is $B^{(i)}$ $(i = 1, 2, \ldots, m)$.

The structure of the Mamdani-type fuzzy inference system is illustrated in Fig. 1.

2.4 Database description

As shown in Fig. 1, after the preprocessing step, lung cancer disease data in our approach are entered into the fuzzy inference system and then are classified. The classification and inference are based on knowledge-based information. Data for our present work are obtained from the Respiratory Department of Nanjing Chest Hospital, China. This database collected from 190 patients contains 66 attributes, but we used only 6 of them which are relevant to lung cancer disease. The attributes we considered in this work are (the number of parameters is 24 because we will consider, for each attribute, four cases):

(1) Weight loss (WL)
(2) Shortness of breath (SHB)
(3) Chest pain (CHP)
(4) Blood in sputum (BS)
(5) Persistence cough (PC)
(6) Age

In our proposed fuzzy soft expert system, we use the most crucial six symptoms of lung cancer, based on the fact that they will occur much more frequently than any other symptoms, and also, we have not considered the irrelevant and possible bronchitis and pneumonia symptoms, which was the case in most other previous works, into our system. There is a relation between the occurrence of some of the symptoms and the growth in stage of the lung cancer into stage 2 and stage 3, as "shortness of breath" mostly occurs in stage 2 so it also one of the symptoms in stage 3. Some symptoms like "unintentional weight loss" are much more likely to happen in stage 3 than in stage 2 of the cancer. However, "blood of sputum" most often occurs in stage 3 which is the most advanced stage. Despite the presence of small levels of these symptoms along with the other symptoms like "chest pain," "persistent cough" and considering that the person is aged, there is a strong possibility of the existence of stage 1 lung cancer for that patient. Consequently, we have considered all of these situations in designing our proposed system.

3 The proposed methodology and implementation

In this section, we illustrate a methodology of decision-making by presenting a generic medical fuzzy soft expert system in an imprecise environment. This system provides a diagnostic assistance concerned with lung cancer diseases where the output is compared to an independent diagnosis given by physicians. It is found that the fuzzy soft expert system can diagnose the disease risk with accuracy. The basic structure includes four main portions (as depicted in Fig. 2):

(1) The fuzzication part which translates inputs (real-valued) into fuzzy values.
(2) The part to obtain fuzzy soft sets from fuzzication part of data set.
(3) The part to obtain a new fuzzy soft sets by normal parameter reduction in fuzzy soft sets.
(4) An algorithm to get the output data.

Figure 2 represents the basic structure of a fuzzy soft expert system. There are many uncertain risk factors in the lung cancer risk: weight loss, shortness of breath, chest pain, blood in sputum, persistence cough, and age are the main risk factors. Having all these six main risk factors included in the diagnostic tool offers great help for an expert to obtain certain results in uncertain terms.

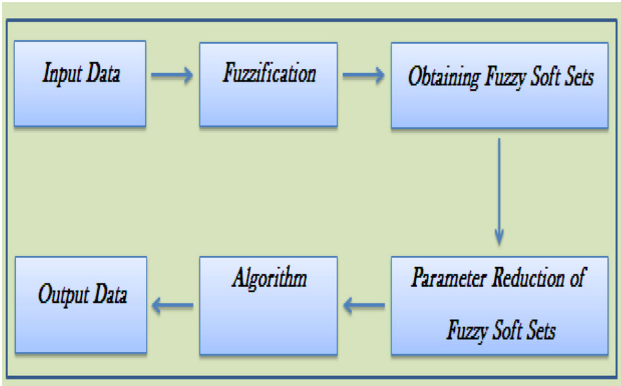

Fig. 2 Basic structure of a fuzzy soft expert system

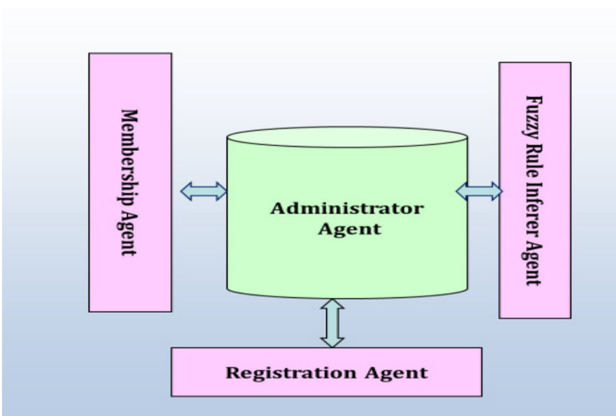

Fig. 3 Basic structure of Lavanya's fuzzy inference system

Our basic structure differs from that of Lavanya et al. (2011) because their basic structure (as shown in Fig. 3) uses fuzzy sets to create a fuzzy inference system for the diagnosis of lung cancer.

Figure 3 represents the basic flow of information of Lavanya's fuzzy inference system in which the knowledge-based fuzzy inference system contains both static and dynamic information. There are registration agent, fuzzy rule inference agent, and membership agent variables, which are analyzed to arrive at a diagnostic conclusion. The fuzzy logic methodology involves fuzzification, inference engine, and defuzzification as the significant steps. A disease is usually characterized by directly observable symptoms that prompt the patient to visit a physician. A series of clinical observations are undertaken to detect the presence of a disease. The symptoms of the disease are usually expressed by the deviation of the observations from their normal state or value. The correct classification of the symptoms leads to diagnosis of the disease that enables the doctor to plan further treatment. Thus, our proposed fuzzy soft expert system provides a simpler implementation to diagnose lung cancer disease risk, using the six main attributes.

Table 1 Classification of weight loss

Weight loss	
Low	< 2
Medium	2–3.6
High	2.8–4.5
Very high	$3.6 >$

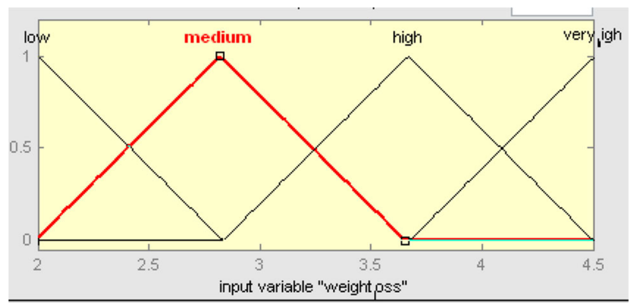

Fig. 4 Membership functions of weight loss

3.1 Fuzzification of data set

In this subsection, we will introduce the relationship between all fuzzy membership functions and associate with each component of the membership parameter. For each input parameter, the fuzzy membership function is shown as follows:

(1) *Weight loss* Different values of weight loss may easily contribute a change to the results. If there is more than 10% of weight loss in six months, then it corresponds to the symptoms of lung cancer. This input variable is divided into four fuzzy sets: low (i.e., $L = [2, 2, 2.8\rangle$), medium (i.e., $M = \langle 2, 2.8, 3.6\rangle$), high (i.e., $H = \langle 2.8, 3.6, 4.5\rangle$), and very high (i.e., $\mathrm{VH} = \langle 3.6, 4.5, 4.5]$) as classified in Table 1. Membership functions of "low" and "very high" are trapezoidal, while membership functions of "medium" and "high" are triangular as shown in Eq. 3 and mentioned as well in Fig. 4.

$$
\begin{aligned}
A_L(x) &= \begin{cases} 1, & x < 2, \\ \frac{2.8-x}{0.8}, & 2 \le x < 2.8; \end{cases} \\
A_M(x) &= \begin{cases} \frac{x-2}{0.8}, & 2 \le x < 2.8, \\ \frac{3.6-x}{0.8}, & 2.8 \le x < 3.6; \end{cases} \\
A_H(x) &= \begin{cases} \frac{x-2.8}{0.8}, & 2.8 \le x < 3.6, \\ \frac{4.5-x}{0.9}, & 3.6 \le x < 4.5; \end{cases} \\
A_{\mathrm{VH}}(x) &= \begin{cases} \frac{x-3.6}{0.9}, & 3.6 \le x < 4.5, \\ 1, & x \ge 4.5. \end{cases}
\end{aligned} \tag{3}
$$

Thus, for a patient having weight loss $x = 3.4$, the fuzzy membership function is $A_{WL} = \left\{\frac{0}{L}, \frac{0.25}{M}, \frac{0.75}{H}, \frac{0}{\mathrm{VH}}\right\}$.

Table 2 Classification of shortness of breath

Shortness of breath	
Low	< 25
Medium	25–49
High	37–60
Very high	49 >

Table 3 Classification of chest pain

Chest pain	
Low	< 35
Medium	35–60
High	47–72
Very high	60 >

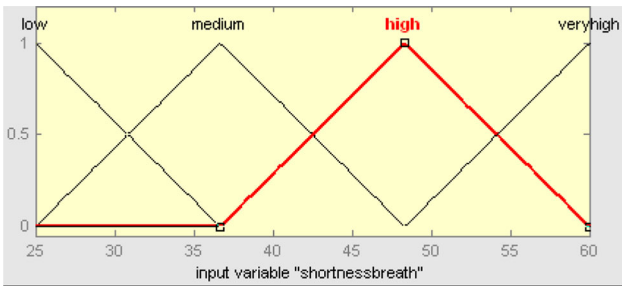

Fig. 5 Membership functions of shortness of breath

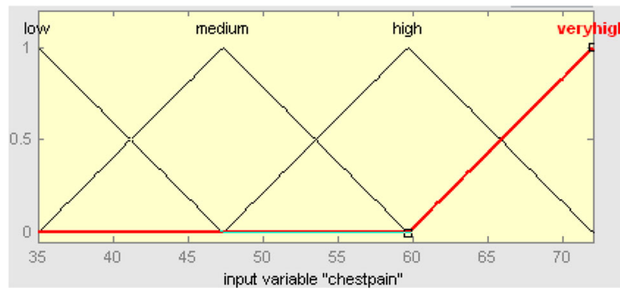

Fig. 6 Membership functions of chest pain

(2) *Shortness of breath* Range of shortness of breath has salient effect on the result and can change it easily. The range 14–16 is normal for this; if it is more than this range, then we need to check for the occurrence of lung disease. The shortness of breath field is categorized into four fuzzy sets: low (i.e., $L = [25, 25, 37\rangle)$, medium (i.e., $M = \langle 25, 37, 49\rangle)$, high (i.e., $H = \langle 37, 49, 60\rangle)$, and very high (i.e., $\mathrm{VH} = \langle 49, 60, 60])$ as classified in Table 2. Membership functions of "low" and "very high" are trapezoidal, while membership functions of "medium" and "high" are triangular as shown in Eq. 4 and mentioned as well in Fig. 5.

$$A_L(x) = \begin{cases} 1, & x < 25, \\ \frac{37-x}{12}, & 25 \le x < 37; \end{cases}$$
$$A_M(x) = \begin{cases} \frac{x-25}{12} & 25 \le x < 37, \\ \frac{49-x}{12}, & 37 \le x < 49; \end{cases}$$
$$A_H(x) = \begin{cases} \frac{x-37}{12}, & 37 \le x < 49, \\ \frac{60-x}{11}, & 49 \le x < 60; \end{cases}$$
$$A_{\mathrm{VH}}(x) = \begin{cases} \frac{x-49}{11}, & 49 \le x < 60, \\ 1, & x \ge 60. \end{cases} \tag{4}$$

Thus, for a patient having shortness of breath $x = 35$, the fuzzy membership function is $A_{\mathrm{SHB}} = \{\frac{0.16}{L}, \frac{0.83}{M}, \frac{0}{H}, \frac{0}{\mathrm{VH}}\}$.

(3) *Chest pain* The input field divides the chest pain group into four fuzzy sets: low (i.e., $L = [35, 35, 47\rangle)$, medium (i.e., $M = \langle 35, 47, 60\rangle)$, high (i.e., $H = \langle 47, 60, 72\rangle)$, and very high (i.e., $\mathrm{VH} = \langle 60, 72, 72])$ as classified in Table 3. Membership functions of "low" and "very high" are trapezoidal, while membership functions of "medium" and "high" are triangular as shown in Fig. 6 and mentioned as well in Eq. 5.

$$A_L(x) = \begin{cases} 1, & x < 35, \\ \frac{47-x}{12}, & 35 \le x < 47, \end{cases}$$
$$A_M(x) = \begin{cases} \frac{x-35}{12}, & 35 \le x < 47, \\ \frac{60-x}{13}, & 47 \le x < 60; \end{cases}$$
$$A_H(x) = \begin{cases} \frac{x-47}{13}, & 47 \le x < 60, \\ \frac{72-x}{12}, & 60 \le x < 72; \end{cases}$$
$$A_{\mathrm{VH}}(x) = \begin{cases} \frac{x-60}{12}, & 60 \le x < 72, \\ 1, & x \ge 72. \end{cases} \tag{5}$$

Thus, for a patient having chest pain $x = 65$, the fuzzy membership function is $A_{\mathrm{CHP}} = \left\{\frac{0}{L}, \frac{0}{M}, \frac{0.58}{H}, \frac{0.41}{\mathrm{VH}}\right\}$.

(4) *Persistence cough* If there exists persistence cough for more than eight weeks, then there exists symptoms of lung cancer. This input field divides the persistence cough group into four fuzzy sets: low (i.e., $L = [5, 5, 14\rangle)$, medium (i.e., $M = \langle 11, 28, 48\rangle)$, high (i.e., $H = \langle 3, 50, 65\rangle)$, and very high (i.e., $\mathrm{VH} = \langle 59, 65, 65])$ as classified in Table 4. Membership functions of "low" and "very high" are trapezoidal, while membership functions of "medium" and "high" are triangular mentioned as well in Fig. 7 and shown in Eq. 6.

$$A_L(x) = \begin{cases} 1, & x < 5, \\ \frac{14-x}{9}, & 5 \le x < 14; \end{cases}$$
$$A_M(x) = \begin{cases} \frac{x-11}{17}, & 11 \le x < 28, \\ \frac{48-x}{20}, & 28 \le x < 48; \end{cases}$$

Table 4 Classification of persistence cough

Persistence cough	
Low	< 14
Medium	11–48
High	33–65
Very high	59 >

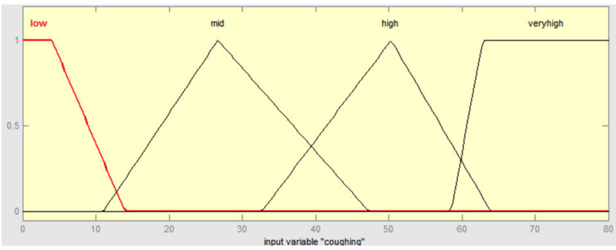

Fig. 7 Membership functions of persistence cough

Table 5 Classification of blood in sputum

Blood in sputum	
Low	< 30
Medium	30–55.1
High	44–67
Very high	67 >

$$A_H(x) = \begin{cases} \frac{x-33}{17}, & 33 \le x < 50, \\ \frac{65-x}{15}, & 50 \le x < 65; \end{cases}$$
$$A_{\mathrm{VH}}(x) = \begin{cases} \frac{x-59}{6}, & 59 \le x < 65, \\ 1, & x \ge 65. \end{cases} \tag{6}$$

Thus, for a patient having persistence cough $x = 2.2$, the fuzzy membership function is $A_{\mathrm{PC}} = \{\frac{0}{L}, \frac{0.55}{M}, \frac{0.23}{H}, \frac{0}{\mathrm{VH}}\}$.

(5) *Blood in sputum* This field is one of the most important factors considered in this system. If the blood in sputum is brownish in color, then it is one of the symptoms of lung cancer. This input field divides the blood in sputum group into four fuzzy sets: low (i.e., $L = [30, 30, 44\rangle$), medium (i.e., $M = \langle 30, 44, 55.1\rangle$), high (i.e., $H = \langle 44, 55.1, 67\rangle$), and very high (i.e., $\mathrm{VH} = \langle 55.1, 67, 67]$) as classified in Table 5. Membership functions of "low" and "very high" are trapezoidal, while membership functions of "medium" and "high" are triangular as shown in Fig. 8 and mentioned as well in Eq. 7.

$$A_L(x) = \begin{cases} 1, & x < 30, \\ \frac{44-x}{14}, & 30 \le x < 44; \end{cases}$$
$$A_M(x) = \begin{cases} \frac{x-30}{14}, & 30 \le x < 44, \\ \frac{55.1-x}{11.1}, & 44 \le x < 55.1; \end{cases}$$
$$A_H(x) = \begin{cases} \frac{x-44}{11.1}, & 44 \le x < 55.1, \\ \frac{67-x}{11.9}, & 55.1 \le x < 67; \end{cases}$$

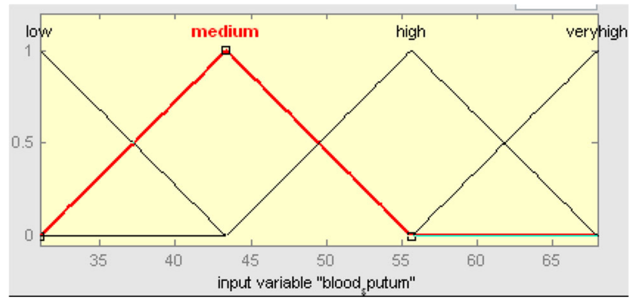

Fig. 8 Membership functions of blood in sputum

Table 6 Classification of age

Age	
Young	< 38
Mild	33–45
Old	40–58
Very old	52 >

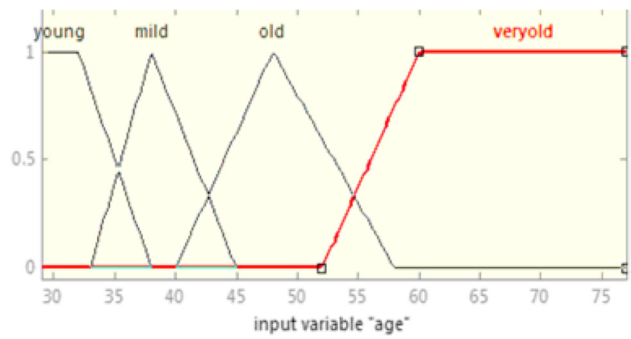

Fig. 9 Membership functions of age

$$A_{\mathrm{VH}}(x) = \begin{cases} \frac{x-55.1}{11.9}, & 55.1 \le x < 67, \\ 1, & x \ge 67. \end{cases} \tag{7}$$

Thus, for a patient having blood in sputum $x = 56$, the fuzzy membership function is $A_{\mathrm{BS}} = \{\frac{0}{L}, \frac{0}{M}, \frac{0.92}{H}, \frac{0.07}{\mathrm{VH}}\}$.

(6) *Age* This input field divides the age group into four fuzzy sets: young (i.e., $Y = [29, 29, 38\rangle$), mild (i.e., $M = \langle 33, 38, 45\rangle$), old (i.e., $O = \langle 40, 48, 58\rangle$), and very old (i.e., $\mathrm{VO} = \langle 52, 60, 60]$) as classified in Table 6. Membership functions of "young" and "very old" are trapezoidal, while membership functions of "mild" and "old" are triangular as shown in Fig. 9 and mentioned as well in Eq. 8.

$$A_Y(x) = \begin{cases} 1, & x < 29, \\ \frac{38-x}{9}, & 29 \le x < 38; \end{cases}$$
$$A_M(x) = \begin{cases} \frac{x-33}{5}, & 33 \le x < 38, \\ \frac{45-x}{7}, & 38 \le x < 45; \end{cases}$$

Table 7 Input values of forty five patients

P	p_1	p_2	p_3	p_4	p_5	p_6	p_7	p_8	p_9	p_{10}	p_{11}	p_{12}	p_{13}	p_{14}	p_{15}
WL	3.8	3.7	5	4	4.1	4.5	3.7	3.6	3.9	4.4	4.8	4.6	3.7	3.6	4.1
SHB	38	40	50	44	38	54	59	62	63	55	40	60	37	39	42
CHP	48	50	49	55	60	51	56	60	47	53	59	57	47	50	51
PC	18	40	33	45	48	35	39	29	44	57	50	59	16	19	30
BS	45	44	50	54	49	52	53	45	54	47	46	50	44	50	47
Age	55	60	49	45	48	50	54	66	70	55	62	72	45	61	59

P	p_{16}	p_{17}	p_{18}	p_{19}	p_{20}	p_{21}	p_{22}	p_{23}	p_{24}	p_{25}	p_{26}	p_{27}	p_{28}	p_{29}	p_{30}
WL	4.7	5	3.7	3.9	4	4.1	4.7	4.5	4.2	4.9	5.1	5.4	5.7	6	3.6
SHB	44	45	50	55	52	53	38	40	60	61	44	43	39	38	43
CHP	47	49	54	52	53	60	54	48	49	55	56	51	57	49	48
PC	32	40	42	16	20	22	24	27	29	37	49	43	44	53	50
BS	53	54	45	47	51	53	52	50	49	48	44	49	45	44	54
Age	70	48	49	50	72	73	55	60	66	64	49	46	54	56	74

P	p_{31}	p_{32}	p_{33}	p_{34}	p_{35}	p_{36}	p_{37}	p_{38}	p_{39}	p_{40}	p_{41}	p_{42}	p_{43}	p_{44}	p_{45}
WL	3.8	3.9	3.8	3.9	4.7	4.8	4.9	5.1	5.3	5.2	5.5	3.7	3.9	4.1	4.3
SHB	41	42	55	53	54	63	62	46	47	49	44	43	40	57	63
CHP	47	60	54	47	49	55	52	54	56	57	60	49	49	55	56
PC	28	59	48	55	56	18	21	25	16	26	25	39	52	54	15
BS	49	50	51	49	53	47	54	49	50	51	52	54	48	50	54
Age	71	46	51	56	55	62	61	63	45	49	75	56	65	55	59

$$A_O(x) = \begin{cases} \frac{x-40}{8}, & 40 \le x < 48, \\ \frac{58-x}{10}, & 48 \le x < 58; \end{cases}$$
$$A_{\mathrm{VO}}(x) = \begin{cases} \frac{x-52}{8}, & 52 \le x \le 60, \\ 1, & x \ge 60. \end{cases} \tag{8}$$

Thus, for a patient having age $x = 44$, the fuzzy membership function is $A_{\mathrm{Age}} = \{\frac{0}{Y}, \frac{0.14}{M}, \frac{0.5}{O}, \frac{0}{VO}\}$.

4 Experimental results and discussion

In this section, we discuss the experimental results by presenting a preparatory study conducted on forty five patients divided over thirty males ($p_1, p_3, p_6 - p_9, p_{11}, p_{16}, p_{18} - p_{20}, p_{22}, p_{25} - p_{30}, p_{32}, p_{33}, p_{36} - p_{45}$) and fifteen females ($p_2, p_4, p_5, p_{10}, p_{12} - p_{15}, p_{17}, p_{21}, p_{23}, p_{24}, p_{31}, p_{34}, p_{35}$) in the Respiratory Department of Nanjing Chest Hospital, China. The input values of these patients are shown in Table 7.

As shown in Table 7, we then get the fuzzy membership functions of every patient as shown in Tables 8, 9 and 10.

4.1 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 $P = \{p_1, p_2, p_3, \ldots, p_{45}\}$ be the set of forty five patients (thirty males and fifteen females) 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

$$A = \{\mathrm{WL}(L), \mathrm{WL}(M), \mathrm{WL}(H), \mathrm{WL}(\mathrm{VH})\},$$
$$B = \{\mathrm{SHB}(L),\ \mathrm{SHB}(M),\ \mathrm{SHB}(H), \mathrm{SHB}(\mathrm{VH})\},$$
$$C = \{\mathrm{CHP}(L), \mathrm{CHP}(M), \mathrm{CHP}(H), \mathrm{CHP}(\mathrm{VH})\},$$
$$D = \{\mathrm{PC}(L), \mathrm{PC}(M), \mathrm{PC}(H), \mathrm{PC}(\mathrm{VH})\},$$
$$F = \{\mathrm{BS}(L), \mathrm{BS}(M), \mathrm{BS}(H), \mathrm{BS}(\mathrm{VH})\},$$

and

$$G = \{\mathrm{Age}(Y), \mathrm{Age}(M), \mathrm{Age}(O), \mathrm{Age}(\mathrm{VO})\}.$$

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 $(\tilde{T}, G)$ (as shown in Figures 10, 11, 12, 13, 14 and 15) from Tables 8,

Table 8 The fuzzy membership functions of forty five patients

P	p_1	p_2	p_3	p_4	p_5	p_6	p_7	p_8	p_9	p_{10}	p_{11}	p_{12}	p_{13}	p_{14}	p_{15}
WL(L)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
WL(M)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
WL(H)	0.77	0.88	0	0.55	0.44	0	0.88	1	0.66	0.11	0	0	0.88	1	0.44
WL(VH)	0.22	0.11	1	0.44	0.55	1	0.11	0	0.33	0.88	1	1	0.11	0	0.55
SHB(L)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SHB(M)	0.91	0.75	0	0.41	0.91	0	0	0	0	0	0.75	0	1	0.83	0.58
SHB(H)	0.08	0.25	0.90	0.58	0.08	0.54	0.09	0	0	0.45	0.25	0	0	0.16	0.41
SHB(VH)	0	0	0.09	0	0	0.45	0.90	1	1	0.54	0	1	0	0	0
CHP(L)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
CHP(M)	0.92	0.76	0.84	0.38	0	0.69	0.30	0	1	0.53	0.07	0.23	1	0.76	0.69
CHP(H)	0.07	0.23	0.15	0.61	1	0.30	0.69	1	0	0.46	0.92	0.76	0	0.23	0.30
CHP(VH)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
PC(L)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
PC(M)	0.41	0.4	0.88	0.15	0	0.65	0.45	0.95	0.2	0	0	0	0.29	0.47	0.9
PC(H)	0	0.41	0	0.70	0.88	0.11	0.35	0	0.64	0.53	1	0.4	0	0	0
PC(VH)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
BS(L)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
BS(M)	0.90	1	0.45	0.09	0.54	0.27	0.18	0.90	0.09	0.72	0.81	0.45	1	0.45	0.72
BS(H)	0.09	0	0.54	0.90	0.45	0.72	0.81	0.09	0.90	0.27	0.18	0.54	0	0.54	0.27
BS(VH)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Age(Y)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Age(M)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Age(O)	0.3	0	0.9	0.62	1	0.8	0.4	0	0	0.3	0	0	0.62	0	0
Age(VO)	0.37	1	0	0	0	0	0.25	1	1	0.37	1	1	0	1	0.87

9 and 10 which can be used to describes the "WL," "SHB," "CHP," "PC," "BS," and "Age," respectively.

Figures 10, 11, 12, 13, 14, and 15 represent the following 6 fuzzy soft sets:

$$
\begin{aligned}
(\tilde{L}, A) &= \{\mathrm{WL}(L), \mathrm{WL}(M), \mathrm{WL}(H), \mathrm{WL}(\mathrm{VH})\},\\
(\tilde{M}, B) &= \{\mathrm{SHB}(L), \mathrm{SHB}(M), \mathrm{SHB}(H), \mathrm{SHB}(\mathrm{VH})\},\\
(\tilde{N}, C) &= \{\mathrm{CHP}(L), \mathrm{CHP}(M), \mathrm{CHP}(H), \mathrm{CHP}(\mathrm{VH})\},\\
(\tilde{R}, D) &= \{\mathrm{PC}(L), \mathrm{PC}(M), \mathrm{PC}(H), \mathrm{PC}(\mathrm{VH})\},\\
(\tilde{P}, F) &= \{\mathrm{BS}(L), \mathrm{BS}(M), \mathrm{BS}(H), \mathrm{BS}(\mathrm{VH})\},\\
(\tilde{T}, G) &= \{\mathrm{Age}(Y), \mathrm{Age}(M), \mathrm{Age}(O), \mathrm{Age}(\mathrm{VO})\},
\end{aligned}
$$

where

$$
\mathrm{WL}(L) = \left\{\frac{p_1}{0}, \frac{p_2}{0}, \frac{p_3}{0}, \ldots, \frac{p_{45}}{0}\right\},
$$

$$
\mathrm{WL}(M) = \left\{\frac{p_1}{0}, \frac{p_2}{0}, \frac{p_3}{0}, \ldots, \frac{p_{45}}{0}\right\},
$$

$$
\begin{aligned}
\mathrm{WL}(H) = \Big\{&\frac{p_1}{0.77}, \frac{p_2}{0.88}, \frac{p_3}{0}, \frac{p_4}{0.55}, \frac{p_5}{0.44}, \frac{p_6}{0}, \frac{p_7}{0.88},\\
&\frac{p_8}{1}, \frac{p_9}{0.66}, \frac{p_{10}}{0.11}, \frac{p_{11}}{0}, \frac{p_{12}}{0}, \frac{p_{13}}{0.88}, \frac{p_{14}}{1},\\
&\frac{p_{15}}{0.45}, \frac{p_{16}}{0}, \frac{p_{17}}{0}, \frac{p_{18}}{0.88}, \frac{p_{19}}{0.66}, \frac{p_{20}}{0.55},\\
&\frac{p_{21}}{0.44}, \frac{p_{22}}{0}, \frac{p_{23}}{0}, \frac{p_{24}}{0.33}, \frac{p_{25}}{0}, \frac{p_{26}}{0}, \frac{p_{27}}{0},\\
&\frac{p_{28}}{0}, \frac{p_{29}}{0}, \frac{p_{30}}{1}, \frac{p_{31}}{0.77}, \frac{p_{32}}{0.66}, \frac{p_{33}}{0.77},\\
&\frac{p_{34}}{0.66}, \frac{p_{35}}{0}, \frac{p_{36}}{0}, \frac{p_{37}}{0}, \frac{p_{38}}{0}, \frac{p_{39}}{0},\\
&\frac{p_{40}}{0}, \frac{p_{41}}{0}, \frac{p_{42}}{0.88}, \frac{p_{43}}{0.66}, \frac{p_{44}}{0.44}, \frac{p_{45}}{0.22}\Big\},
\end{aligned}
$$

$$
\begin{aligned}
\mathrm{WL}(\mathrm{VH}) = \Big\{&\frac{p_1}{0.22}, \frac{p_2}{0.11}, \frac{p_3}{1}, \frac{p_4}{0.44}, \frac{p_5}{0.55}, \frac{p_6}{1}, \frac{p_7}{0.11},\\
&\frac{p_8}{0}, \frac{p_9}{0.33}, \frac{p_{10}}{0.88}, \frac{p_{11}}{1}, \frac{p_{12}}{1}, \frac{p_{13}}{0.11}, \frac{p_{14}}{0},\\
&\frac{p_{15}}{0.55}, \frac{p_{16}}{1}, \frac{p_{17}}{1}, \frac{p_{18}}{0.11}, \frac{p_{19}}{0.33}, \frac{p_{20}}{0.44},\\
&\frac{p_{21}}{0.55}, \frac{p_{22}}{1}, \frac{p_{23}}{1}, \frac{p_{24}}{0.66}, \frac{p_{25}}{1}, \frac{p_{26}}{1}, \frac{p_{27}}{1},\\
&\frac{p_{28}}{1}, \frac{p_{29}}{1}, \frac{p_{30}}{0}, \frac{p_{31}}{0.22}, \frac{p_{32}}{0.33}, \frac{p_{33}}{0.22},\\
&\frac{p_{34}}{0.33}, \frac{p_{35}}{1}, \frac{p_{36}}{1}, \frac{p_{37}}{1}, \frac{p_{38}}{1}, \frac{p_{39}}{1}, \frac{p_{40}}{1},\\
&\frac{p_{41}}{1}, \frac{p_{42}}{0.11}, \frac{p_{43}}{0.33}, \frac{p_{44}}{0.55}, \frac{p_{45}}{0.77}\Big\},
\end{aligned}
$$

Table 9 The fuzzy membership functions of forty five patients

P	p_{16}	p_{17}	p_{18}	p_{19}	p_{20}	p_{21}	p_{22}	p_{23}	p_{24}	p_{25}	p_{26}	p_{27}	p_{28}	p_{29}	p_{30}
WL(L)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
WL(M)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
WL(H)	0	0	0.88	0.66	0.55	0.44	0	0	0.33	0	0	0	0	0	1
WL(VH)	1	1	0.11	0.33	0.44	0.55	1	1	0.66	1	1	1	1	1	0
SHB(L)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SHB(M)	0.41	0.33	0	0	0	0	0.91	0.75	0	0	0.41	0.5	0.83	0.91	0.5
SHB(H)	0.58	0.66	0.90	0.45	0.72	0.63	0.08	0.25	0	0	0.58	0.5	0.16	0.08	0.5
SHB(VH)	0	0	0.09	0.54	0.27	0.36	0	0	1	1	0	0	0	0	0
CHP(L)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
CHP(M)	1	0.84	0.46	0.61	0.53	0	0.46	0.92	0.84	0.38	0.30	0.69	0.23	0.84	0.92
CHP(H)	0	0.15	0.53	0.38	0.46	1	0.53	0.07	0.15	0.61	0.69	0.30	0.67	0.15	0.07
CHP(VH)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
PC(L)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
PC(M)	0.8	0.4	0.3	0.29	0.52	0.64	0.76	0.94	0.95	0.55	0	0.25	0.2	0	0
PC(H)	0	0.41	0.52	0	0	0	0	0	0	0	0.23	0.94	0.58	0.8	1
PC(VH)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
BS(L)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
BS(M)	0.18	0.09	1	0.72	0.36	0.18	0.27	0.45	0.54	0.63	1	0.54	0.90	1	0.09
BS(H)	0.81	0.90	0	0.27	0.63	0.81	0.72	0.54	0.45	0.36	0	0.45	0.09	0	0.90
BS(VH)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Age(Y)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Age(M)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Age(O)	0	1	0.9	0.8	0	0	0	0	0	0	0.9	0.75	0.4	0.2	0
Age(VO)	1	0	0	0	1	1	0.37	1	1	1	0	0	0.52	0.5	1

$$\mathrm{SHB}(L)=\left\{\frac{p_1}{0},\frac{p_2}{0},\frac{p_3}{0},\ldots,\frac{p_{45}}{0}\right\},$$

$$\mathrm{SHB}(M)=\left\{\frac{p_1}{0.91},\frac{p_2}{0.75},\frac{p_3}{0},\frac{p_4}{0.41},\frac{p_5}{0.91},\frac{p_6}{0},\frac{p_7}{0},\right.$$
$$\frac{p_8}{0},\frac{p_9}{0},\frac{p_{10}}{0},\frac{p_{11}}{0.75},\frac{p_{12}}{0},\frac{p_{13}}{1},\frac{p_{14}}{0.83},$$
$$\frac{p_{15}}{0.58},\frac{p_{16}}{0.41},\frac{p_{17}}{0.33},\frac{p_{18}}{0},\frac{p_{19}}{0},\frac{p_{20}}{0},$$
$$\frac{p_{21}}{0},\frac{p_{22}}{0.91},\frac{p_{23}}{0.75},\frac{p_{24}}{0},\frac{p_{25}}{0},\frac{p_{26}}{0.41},\frac{p_{27}}{0.5},$$
$$\frac{p_{28}}{0.83},\frac{p_{29}}{0.91},\frac{p_{30}}{0.5},\frac{p_{31}}{0.66},\frac{p_{32}}{0.58},\frac{p_{33}}{0},$$
$$\frac{p_{34}}{0},\frac{p_{35}}{0},\frac{p_{36}}{0},\frac{p_{37}}{0},\frac{p_{38}}{0.25},\frac{p_{39}}{0.16},$$
$$\left.\frac{p_{40}}{0},\frac{p_{41}}{0.41},\frac{p_{42}}{0.5},\frac{p_{43}}{0.75},\frac{p_{44}}{0},\frac{p_{45}}{0}\right\},$$

$$\mathrm{SHB}(H)=\left\{\frac{p_1}{0.08},\frac{p_2}{0.25},\frac{p_3}{0.90},\frac{p_4}{0.58},\frac{p_5}{0.08},\frac{p_6}{0.54},\frac{p_7}{0.09},\right.$$
$$\frac{p_8}{0},\frac{p_9}{0},\frac{p_{10}}{0.45},\frac{p_{11}}{0.25},\frac{p_{12}}{0},\frac{p_{13}}{0},\frac{p_{14}}{0.16},$$
$$\frac{p_{15}}{0.41},\frac{p_{16}}{0.58},\frac{p_{17}}{0.66},\frac{p_{18}}{0.90},\frac{p_{19}}{0.45},\frac{p_{20}}{0.72},$$
$$\frac{p_{21}}{0.63},\frac{p_{22}}{0.08},\frac{p_{23}}{0.25},\frac{p_{24}}{0},\frac{p_{25}}{0},\frac{p_{26}}{0.58},\frac{p_{27}}{0.5},$$
$$\frac{p_{28}}{0.16},\frac{p_{29}}{0.08},\frac{p_{30}}{0.5},\frac{p_{31}}{0.33},\frac{p_{32}}{0.41},\frac{p_{33}}{0.45},$$
$$\frac{p_{34}}{0.63},\frac{p_{35}}{0.54},\frac{p_{36}}{0},\frac{p_{37}}{0},\frac{p_{38}}{0.75},\frac{p_{39}}{0.83},$$
$$\left.\frac{p_{40}}{1},\frac{p_{41}}{0.58},\frac{p_{42}}{0.5},\frac{p_{43}}{0.25},\frac{p_{44}}{0.27},\frac{p_{45}}{0}\right\},$$

$$\mathrm{SHB}(\mathrm{VH})=\left\{\frac{p_1}{0},\frac{p_2}{0},\frac{p_3}{0.09},\frac{p_4}{0},\frac{p_5}{0},\frac{p_6}{0.45},\frac{p_7}{0.90},\frac{p_8}{1},\right.$$
$$\frac{p_9}{1},\frac{p_{10}}{0.54},\frac{p_{11}}{0},\frac{p_{12}}{1},\frac{p_{13}}{0},\frac{p_{14}}{0},\frac{p_{15}}{0},$$
$$\frac{p_{16}}{0},\frac{p_{17}}{0},\frac{p_{18}}{0.09},\frac{p_{19}}{0.54},\frac{p_{20}}{0.27},\frac{p_{21}}{0.36},$$
$$\frac{p_{22}}{0},\frac{p_{23}}{0},\frac{p_{24}}{1},\frac{p_{25}}{1},\frac{p_{26}}{0},\frac{p_{27}}{0},\frac{p_{28}}{0},$$
$$\frac{p_{29}}{0},\frac{p_{30}}{0},\frac{p_{31}}{0},\frac{p_{32}}{0},\frac{p_{33}}{0.54},\frac{p_{34}}{0.36},$$
$$\frac{p_{35}}{0.45},\frac{p_{36}}{1},\frac{p_{37}}{1},\frac{p_{38}}{0},\frac{p_{39}}{0},\frac{p_{40}}{0},$$
$$\left.\frac{p_{41}}{0},\frac{p_{42}}{0},\frac{p_{43}}{0},\frac{p_{44}}{0.72},\frac{p_{45}}{1}\right\},$$

$$\mathrm{CHP}(L)=\left\{\frac{p_1}{0},\frac{p_2}{0},\frac{p_3}{0},\ldots,\frac{p_{45}}{0}\right\},$$

$$\mathrm{CHP}(M)=\left\{\frac{p_1}{0.92},\frac{p_2}{0.76},\frac{p_3}{0.84},\frac{p_4}{0.38},\frac{p_5}{0},\frac{p_6}{0.69},\frac{p_7}{0.30},\right.$$

Table 10 The fuzzy membership functions of forty five patients

P	p_{31}	p_{32}	p_{33}	p_{34}	p_{35}	p_{36}	p_{37}	p_{38}	p_{39}	p_{40}	p_{41}	p_{42}	p_{43}	p_{44}	p_{45}
WL(L)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
WL(M)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
WL(H)	0.77	0.66	0.77	0.66	0	0	0	0	0	0	0	0.88	0.66	0.44	0.22
WL(VH)	0.22	0.33	0.22	0.33	1	1	1	1	1	1	1	0.11	0.33	0.55	0.77
SHB(L)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SHB(M)	0.66	0.58	0	0	0	0	0	0.25	0.16	0	0.41	0.5	0.75	0	0
SHB(H)	0.33	0.41	0.45	0.63	0.54	0	0	0.75	0.83	1	0.58	0.5	0.25	0.27	0
SHB(VH)	0	0	0.54	0.36	0.45	1	1	0	0	0	0	0	0	0.72	1
CHP(L)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
CHP(M)	1	0	0.46	1	0.84	0.38	0.61	0.46	0.30	0.23	0	0.84	0.84	0.38	0.30
CHP(H)	0	1	0.53	0	0.15	0.61	0.38	0.53	0.69	0.76	1	0.15	0.15	0.61	0.69
CHP(VH)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
PC(L)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
PC(M)	1	0	0	0	0	0.41	0.58	0.82	0.29	0.88	0.82	0.45	0	0	0.23
PC(H)	0	0.4	0.88	0.66	0.6	0	0	0	0	0	0	0.35	0.86	0.73	0
PC(VH)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
BS(L)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
BS(M)	0.45	0.45	0.36	0.54	0.18	0.72	0.09	0.54	0.45	0.36	0.27	0.09	0.63	0.45	0.09
BS(H)	0.54	0.54	0.63	0.45	0.81	0.27	0.90	0.45	0.54	0.63	0.72	0.90	0.36	0.54	0.90
BS(VH)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Age(Y)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Age(M)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Age(O)	0	0.75	0.7	0.2	0.3	0	0	0	0.62	0.9	0	0.2	0	0.3	0
Age(VO)	1	0	0	0.5	0.37	1	1	1	0	0	1	0.5	1	0.37	0.87

$$\frac{p_8}{0}, \frac{p_9}{1}, \frac{p_{10}}{0.53}, \frac{p_{11}}{0.07}, \frac{p_{12}}{0.23}, \frac{p_{13}}{1}, \frac{p_{14}}{0.76}, \frac{p_{15}}{0.69}, \frac{p_{16}}{0.1}, \frac{p_{17}}{0.84}, \frac{p_{18}}{0.46}, \frac{p_{19}}{0.61}, \frac{p_{20}}{0.53}, \frac{p_{21}}{0}, \frac{p_{22}}{0.46}, \frac{p_{23}}{0.92}, \frac{p_{24}}{0.84}, \frac{p_{25}}{0.38}, \frac{p_{26}}{0.30}, \frac{p_{27}}{0.69}, \frac{p_{28}}{0.23}, \frac{p_{29}}{0.84}, \frac{p_{30}}{0.92}, \frac{p_{31}}{1}, \frac{p_{32}}{0}, \frac{p_{33}}{0.46}, \frac{p_{34}}{1}, \frac{p_{35}}{0.84}, \frac{p_{36}}{0.38}, \frac{p_{37}}{0.61}, \frac{p_{38}}{0.46}, \frac{p_{39}}{0.30}, \frac{p_{40}}{0.23}, \frac{p_{41}}{0}, \frac{p_{42}}{0.84}, \frac{p_{43}}{0.84}, \frac{p_{44}}{0.38}, \frac{p_{45}}{0.30}\Big\},$$

$$\mathrm{CHP}(H) = \Big\{\frac{p_1}{0.07}, \frac{p_2}{0.23}, \frac{p_3}{0.15}, \frac{p_4}{0.61}, \frac{p_5}{1}, \frac{p_6}{0.30}, \frac{p_7}{0.69}, \frac{p_8}{1}, \frac{p_9}{0}, \frac{p_{10}}{0.46}, \frac{p_{11}}{0.92}, \frac{p_{12}}{0.76}, \frac{p_{13}}{0}, \frac{p_{14}}{0.23}, \frac{p_{15}}{0.30}, \frac{p_{16}}{0}, \frac{p_{17}}{0.15}, \frac{p_{18}}{0.53}, \frac{p_{19}}{0.38}, \frac{p_{20}}{0.46}, \frac{p_{21}}{1}, \frac{p_{22}}{0.53}, \frac{p_{23}}{0.07}, \frac{p_{24}}{0.15}, \frac{p_{25}}{0.61}, \frac{p_{26}}{0.69}, \frac{p_{27}}{0.30}, \frac{p_{28}}{0.67}, \frac{p_{29}}{0.15}, \frac{p_{30}}{0.07}, \frac{p_{31}}{0}, \frac{p_{32}}{1}, \frac{p_{33}}{0.53}, \frac{p_{34}}{0}, \frac{p_{35}}{0.15}, \frac{p_{36}}{0.61}, \frac{p_{37}}{0.38}, \frac{p_{38}}{0.53}, \frac{p_{39}}{0.69}, \frac{p_{40}}{0.76}, \frac{p_{41}}{1}, \frac{p_{42}}{0.15}, \frac{p_{43}}{0.15}, \frac{p_{44}}{0.61}, \frac{p_{45}}{0.69}\Big\},$$

$$\mathrm{CHP}(\mathrm{VH}) = \Big\{\frac{p_1}{0}, \frac{p_2}{0}, \frac{p_3}{0}, \dots, \frac{p_{45}}{0}\Big\},$$

$$\mathrm{PC}(L) = \Big\{\frac{p_1}{0}, \frac{p_2}{0}, \frac{p_3}{0}, \dots, \frac{p_{45}}{0}\Big\},$$

$$\mathrm{PC}(M) = \Big\{\frac{p_1}{0.41}, \frac{p_2}{0.4}, \frac{p_3}{0.88}, \frac{p_4}{0.15}, \frac{p_5}{0}, \frac{p_6}{0.65}, \frac{p_7}{0.45}, \frac{p_8}{0.95}, \frac{p_9}{0.2}, \frac{p_{10}}{0}, \frac{p_{11}}{0}, \frac{p_{12}}{0}, \frac{p_{13}}{0.29}, \frac{p_{14}}{0.47}, \frac{p_{15}}{0.9}, \frac{p_{16}}{0.8}, \frac{p_{17}}{0.4}, \frac{p_{18}}{0.3}, \frac{p_{19}}{0.29}, \frac{p_{20}}{0.52}, \frac{p_{21}}{0.64}, \frac{p_{22}}{0.76}, \frac{p_{23}}{0.94}, \frac{p_{24}}{0.95}, \frac{p_{25}}{0.55}, \frac{p_{26}}{0}, \frac{p_{27}}{0.25}, \frac{p_{28}}{0.2}, \frac{p_{29}}{0}, \frac{p_{30}}{0}, \frac{p_{31}}{1}, \frac{p_{32}}{0}, \frac{p_{33}}{0}, \frac{p_{34}}{0}, \frac{p_{35}}{0}, \frac{p_{36}}{0.41}, \frac{p_{37}}{0.58}, \frac{p_{38}}{0.82}, \frac{p_{39}}{0.29}, \frac{p_{40}}{0.88}, \frac{p_{41}}{0.82}, \frac{p_{42}}{0.45}, \frac{p_{43}}{0}, \frac{p_{44}}{0}, \frac{p_{45}}{0.23}\Big\},$$

$$\mathrm{PC}(H) = \Big\{\frac{p_1}{0}, \frac{p_2}{0.41}, \frac{p_3}{0}, \frac{p_4}{0.70}, \frac{p_5}{0.88}, \frac{p_6}{0.11}, \frac{p_7}{0.35},$$

$$\frac{p_8}{0}, \frac{p_9}{0.64}, \frac{p_{10}}{0.53}, \frac{p_{11}}{1}, \frac{p_{12}}{0.4}, \frac{p_{13}}{0}, \frac{p_{14}}{0},$$
$$\frac{p_{15}}{0}, \frac{p_{16}}{0}, \frac{p_{17}}{0.41}, \frac{p_{18}}{0.52}, \frac{p_{19}}{0}, \frac{p_{20}}{0}, \frac{p_{21}}{0},$$
$$\frac{p_{22}}{0}, \frac{p_{23}}{0}, \frac{p_{24}}{0}, \frac{p_{25}}{0}, \frac{p_{26}}{0.23}, \frac{p_{27}}{0.94}, \frac{p_{28}}{0.58},$$
$$\frac{p_{29}}{0.8}, \frac{p_{30}}{1}, \frac{p_{31}}{0}, \frac{p_{32}}{0.4}, \frac{p_{33}}{0.88}, \frac{p_{34}}{0.66}, \frac{p_{35}}{0.6},$$
$$\frac{p_{36}}{0}, \frac{p_{37}}{0}, \frac{p_{38}}{0}, \frac{p_{39}}{0}, \frac{p_{40}}{0}, \frac{p_{41}}{0},$$
$$\left.\frac{p_{42}}{0.35}, \frac{p_{43}}{0.86}, \frac{p_{44}}{0.73}, \frac{p_{45}}{0}\right\},$$

$$\mathrm{PC(VH)} = \left\{\frac{p_1}{0}, \frac{p_2}{0}, \frac{p_3}{0}, \ldots, \frac{p_{45}}{0}\right\},$$

$$\mathrm{BS}(L) = \left\{\frac{p_1}{0}, \frac{p_2}{0}, \frac{p_3}{0}, \ldots, \frac{p_{45}}{0}\right\},$$

$$\mathrm{BS}(M) = \left\{\frac{p_1}{0.90}, \frac{p_2}{1}, \frac{p_3}{0.45}, \frac{p_4}{0.09}, \frac{p_5}{0.54}, \frac{p_6}{0.27}, \frac{p_7}{0.18},\right.$$
$$\frac{p_8}{0.90}, \frac{p_9}{0.09}, \frac{p_{10}}{0.72}, \frac{p_{11}}{0.81}, \frac{p_{12}}{0.45}, \frac{p_{13}}{1}, \frac{p_{14}}{0.45},$$
$$\frac{p_{15}}{0.72}, \frac{p_{16}}{0.18}, \frac{p_{17}}{0.09}, \frac{p_{18}}{1}, \frac{p_{19}}{0.72}, \frac{p_{20}}{0.36}, \frac{p_{21}}{0.18},$$
$$\frac{p_{22}}{0.27}, \frac{p_{23}}{0.45}, \frac{p_{24}}{0.54}, \frac{p_{25}}{0.63}, \frac{p_{26}}{1}, \frac{p_{27}}{0.54}, \frac{p_{28}}{0.90},$$
$$\frac{p_{29}}{1}, \frac{p_{30}}{0.09}, \frac{p_{31}}{0.45}, \frac{p_{32}}{0.45}, \frac{p_{33}}{0.36}, \frac{p_{34}}{0.54}, \frac{p_{35}}{0.18},$$
$$\frac{p_{36}}{0.72}, \frac{p_{37}}{0.09}, \frac{p_{38}}{0.54}, \frac{p_{39}}{0.45}, \frac{p_{40}}{0.36}, \frac{p_{41}}{0.27},$$
$$\left.\frac{p_{42}}{0.09}, \frac{p_{43}}{0.63}, \frac{p_{44}}{0.45}, \frac{p_{45}}{0.09}\right\},$$

$$\mathrm{BS}(H) = \left\{\frac{p_1}{0.09}, \frac{p_2}{0}, \frac{p_3}{0.54}, \frac{p_4}{0.90}, \frac{p_5}{0.45}, \frac{p_6}{0.72}, \frac{p_7}{0.81},\right.$$
$$\frac{p_8}{0.09}, \frac{p_9}{0.90}, \frac{p_{10}}{0.27}, \frac{p_{11}}{0.18}, \frac{p_{12}}{0.54}, \frac{p_{13}}{0}, \frac{p_{14}}{0.54},$$
$$\frac{p_{15}}{0.27}, \frac{p_{16}}{0.81}, \frac{p_{17}}{0.90}, \frac{p_{18}}{0}, \frac{p_{19}}{0.27}, \frac{p_{20}}{0.63}, \frac{p_{21}}{0.81},$$
$$\frac{p_{22}}{0.72}, \frac{p_{23}}{0.54}, \frac{p_{24}}{0.45}, \frac{p_{25}}{0.36}, \frac{p_{26}}{0}, \frac{p_{27}}{0.45}, \frac{p_{28}}{0.09},$$
$$\frac{p_{29}}{0}, \frac{p_{30}}{0.90}, \frac{p_{31}}{0.54}, \frac{p_{32}}{0.54}, \frac{p_{33}}{0.63}, \frac{p_{34}}{0.45}, \frac{p_{35}}{0.81},$$
$$\frac{p_{36}}{0.27}, \frac{p_{37}}{0.90}, \frac{p_{38}}{0.45}, \frac{p_{39}}{0.54}, \frac{p_{40}}{0.63}, \frac{p_{41}}{0.72},$$
$$\left.\frac{p_{42}}{0.90}, \frac{p_{43}}{0.36}, \frac{p_{44}}{0.54}, \frac{p_{45}}{0.90}\right\},$$

$$\mathrm{BS(VH)} = \left\{\frac{p_1}{0}, \frac{p_2}{0}, \frac{p_3}{0}, \ldots, \frac{p_{45}}{0}\right\},$$

$$\mathrm{Age}(Y) = \left\{\frac{p_1}{0}, \frac{p_2}{0}, \frac{p_3}{0}, \ldots, \frac{p_{45}}{0}\right\},$$

$$\mathrm{Age}(M) = \left\{\frac{p_1}{0}, \frac{p_2}{0}, \frac{p_3}{0}, \ldots, \frac{p_{45}}{0}\right\},$$

$$\mathrm{Age}(O) = \left\{\frac{p_1}{0.3}, \frac{p_2}{0}, \frac{p_3}{0.9}, \frac{p_4}{0.62}, \frac{p_5}{1}, \frac{p_6}{0.8}, \frac{p_7}{0.4}, \frac{p_8}{0},\right.$$
$$\frac{p_9}{0}, \frac{p_{10}}{0.3}, \frac{p_{11}}{0}, \frac{p_{12}}{0}, \frac{p_{13}}{0.62}, \frac{p_{14}}{0}, \frac{p_{15}}{0}, \frac{p_{16}}{0},$$
$$\frac{p_{17}}{1}, \frac{p_{18}}{0.9}, \frac{p_{19}}{0.8}, \frac{p_{20}}{0}, \frac{p_{21}}{0}, \frac{p_{22}}{0}, \frac{p_{23}}{0}, \frac{p_{24}}{0},$$

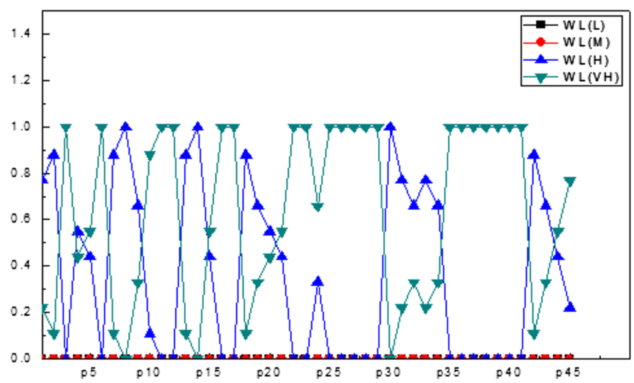

Fig. 10 Fuzzy soft set $(\tilde{L}, A)$

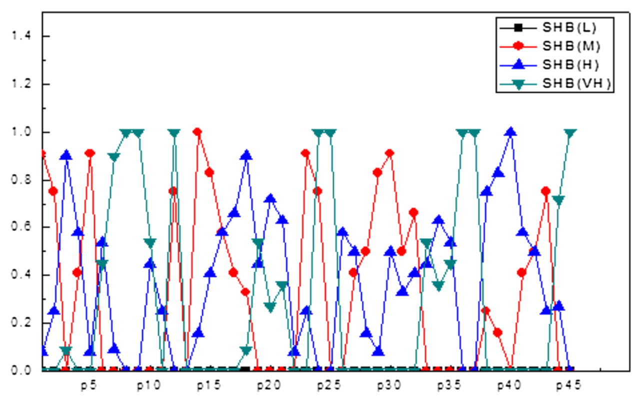

Fig. 11 Fuzzy soft set $(\tilde{M}, B)$

$$\frac{p_{25}}{0}, \frac{p_{26}}{0.9}, \frac{p_{27}}{0.75}, \frac{p_{28}}{0.4}, \frac{p_{29}}{0.2}, \frac{p_{30}}{0}, \frac{p_{31}}{0},$$
$$\frac{p_{32}}{0.75}, \frac{p_{33}}{0.7}, \frac{p_{34}}{0.2}, \frac{p_{35}}{0.3}, \frac{p_{36}}{0}, \frac{p_{37}}{0}, \frac{p_{38}}{0},$$
$$\left.\frac{p_{39}}{0.62}, \frac{p_{40}}{0.9}, \frac{p_{41}}{0}, \frac{p_{42}}{0.2}, \frac{p_{43}}{0}, \frac{p_{44}}{0.3}, \frac{p_{45}}{0}\right\},$$

$$\mathrm{Age(VO)} = \left\{\frac{p_1}{0.37}, \frac{p_2}{1}, \frac{p_3}{0}, \frac{p_4}{0}, \frac{p_5}{0}, \frac{p_6}{0}, \frac{p_7}{0.25}, \frac{p_8}{1},\right.$$
$$\frac{p_9}{1}, \frac{p_{10}}{0.37}, \frac{p_{11}}{1}, \frac{p_{12}}{1}, \frac{p_{13}}{0}, \frac{p_{14}}{1}, \frac{p_{15}}{0.87},$$
$$\frac{p_{16}}{1}, \frac{p_{17}}{0}, \frac{p_{18}}{0}, \frac{p_{19}}{0}, \frac{p_{20}}{1}, \frac{p_{21}}{1}, \frac{p_{22}}{0.37},$$
$$\frac{p_{23}}{1}, \frac{p_{24}}{1}, \frac{p_{25}}{1}, \frac{p_{26}}{0}, \frac{p_{27}}{0}, \frac{p_{28}}{0.52}, \frac{p_{29}}{0.5},$$
$$\frac{p_{30}}{1}, \frac{p_{31}}{1}, \frac{p_{32}}{0}, \frac{p_{33}}{0}, \frac{p_{34}}{0.5}, \frac{p_{35}}{0.37}, \frac{p_{36}}{1},$$
$$\frac{p_{37}}{1}, \frac{p_{38}}{1}, \frac{p_{39}}{0}, \frac{p_{40}}{0}, \frac{p_{41}}{1}, \frac{p_{42}}{0.5},$$
$$\left.\frac{p_{43}}{1}, \frac{p_{44}}{0.37}, \frac{p_{45}}{0.87}\right\}.$$

4.2 Parameter reduction in fuzzy soft sets

Normal parameter reduction in fuzzy soft sets (see Definition 7) is very important in decision-making problems.

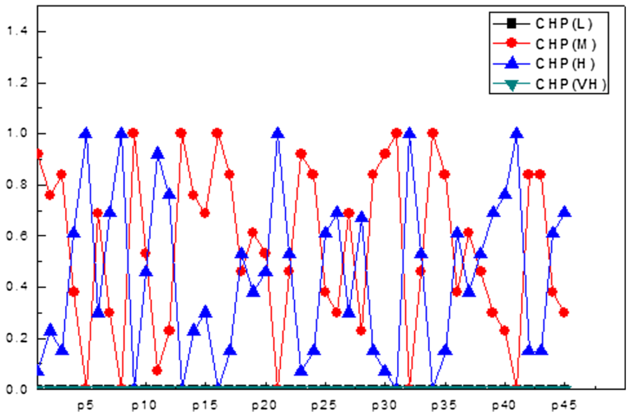

Fig. 12 Fuzzy soft set $(\tilde{N}, C)$

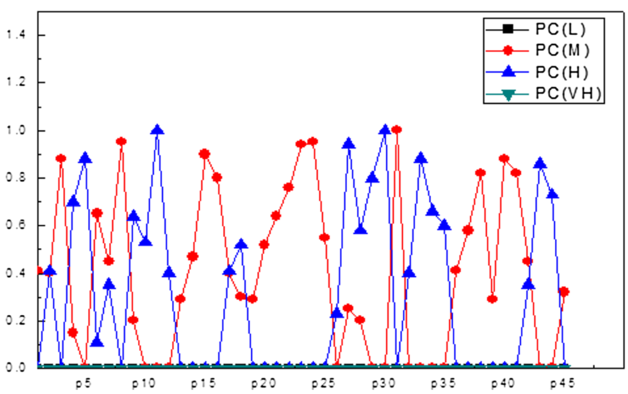

Fig. 13 Fuzzy soft set $(\tilde{R}, D)$

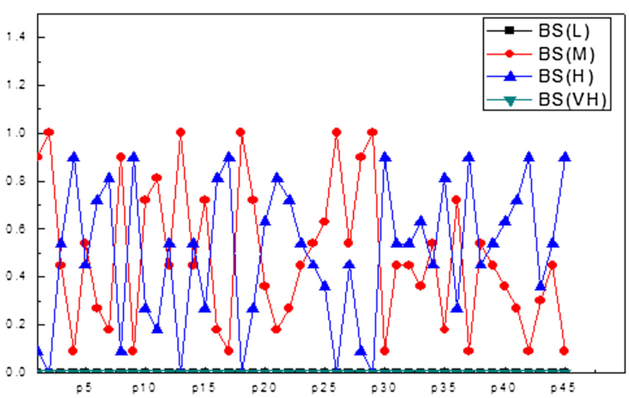

Fig. 14 Fuzzy soft set $(\tilde{P}, F)$

Using this reduce method, we can minimize the number of parameters in a problem, highlighting only the key parameters. In our problem, the new fuzzy soft sets obtained are shown in Figs. 16, 17, 18, 19, 20 and 21, where $\hat{A} = \{\mathrm{WL}(H), \mathrm{WL}(\mathrm{VH})\}$, $\hat{B} = \{\mathrm{SHB}(M), \mathrm{SHB}(H), \mathrm{SHB}(\mathrm{VH})\}$, $\hat{C} = \{\mathrm{CHP}(M), \mathrm{CHP}(H)\}$, $\hat{D} = \{\mathrm{PC}(M), \mathrm{PC}(H)\}$, $\hat{F} = \{\mathrm{BS}(M), \mathrm{BS}(H)\}$, $\hat{G} = \{\mathrm{Age}(O), \mathrm{Age}(\mathrm{VO})\}$.

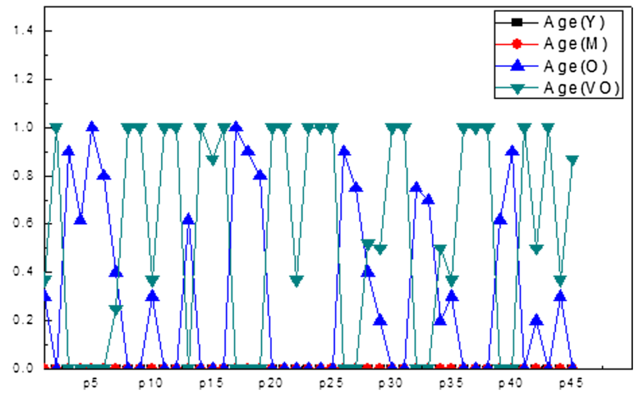

Fig. 15 Fuzzy soft set $(\tilde{T}, G)$

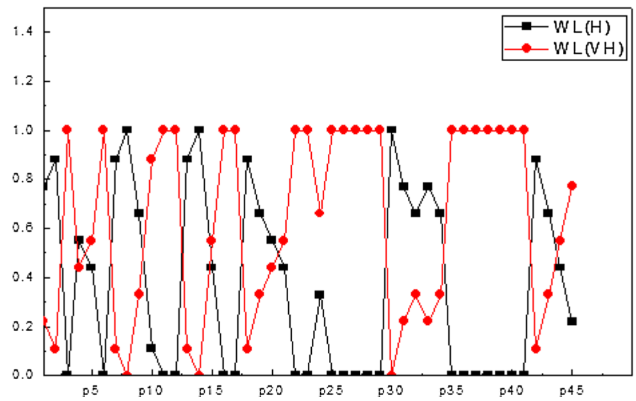

Fig. 16 New fuzzy soft set $(\hat{L}, \hat{A})$

Figures 16, 17, 18, 19, 20, and 21 represent the following 6 new fuzzy soft sets:

$$\begin{aligned}
(\hat{L}, \hat{A}) &= \{\mathrm{WL}(H), \mathrm{WL}(\mathrm{VH})\},\\
(\hat{M}, \hat{B}) &= \{\mathrm{SHB}(M), \mathrm{SHB}(H), \mathrm{SHB}(\mathrm{VH})\},\\
(\hat{N}, \hat{C}) &= \{\mathrm{CHP}(M), \mathrm{CHP}(H)\},\\
(\hat{R}, \hat{D}) &= \{\mathrm{PC}(M), \mathrm{PC}(H)\},\\
(\hat{P}, \hat{F}) &= \{\mathrm{BS}(M), \mathrm{BS}(H)\},\\
(\hat{T}, \hat{G}) &= \{\mathrm{Age}(O), \mathrm{Age}(\mathrm{VO})\},
\end{aligned}$$

where

$$\begin{aligned}
\mathrm{WL}(H) = \Big\{ &\frac{p_1}{0.77}, \frac{p_2}{0.88}, \frac{p_3}{0}, \frac{p_4}{0.55}, \frac{p_5}{0.44}, \frac{p_6}{0}, \frac{p_7}{0.88},\\
&\frac{p_8}{1}, \frac{p_9}{0.66}, \frac{p_{10}}{0.11}, \frac{p_{11}}{0}, \frac{p_{12}}{0}, \frac{p_{13}}{0.88}, \frac{p_{14}}{1},\\
&\frac{p_{15}}{0.45}, \frac{p_{16}}{0}, \frac{p_{17}}{0}, \frac{p_{18}}{0.88}, \frac{p_{19}}{0.66}, \frac{p_{20}}{0.55},\\
&\frac{p_{21}}{0.44}, \frac{p_{22}}{0}, \frac{p_{23}}{0}, \frac{p_{24}}{0.33}, \frac{p_{25}}{0}, \frac{p_{26}}{0}, \frac{p_{27}}{0},\\
&\frac{p_{28}}{0}, \frac{p_{29}}{0}, \frac{p_{30}}{1}, \frac{p_{31}}{0.77}, \frac{p_{32}}{0.66}, \frac{p_{33}}{0.77},
\end{aligned}$$

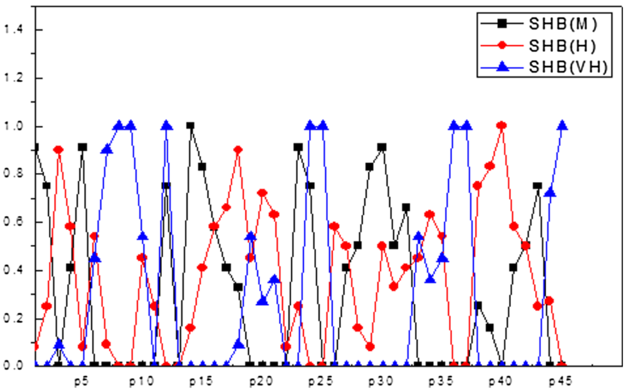

Fig. 17 New fuzzy soft set $(\hat{M}, \hat{B})$

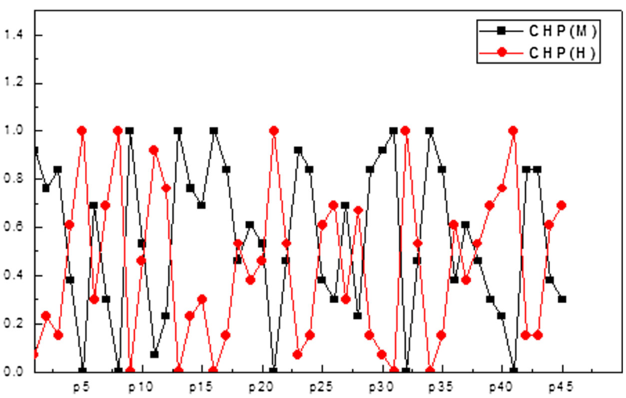

Fig. 18 New fuzzy soft set $(\hat{N}, \hat{C})$

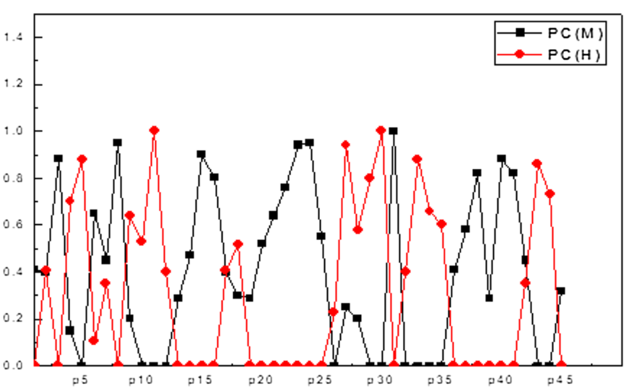

Fig. 19 New fuzzy soft set $(\hat{R}, \hat{D})$

$$\frac{p_{34}}{0.66}, \frac{p_{35}}{0}, \frac{p_{36}}{0}, \frac{p_{37}}{0}, \frac{p_{38}}{0}, \frac{p_{39}}{0},$$
$$\frac{p_{40}}{0}, \frac{p_{41}}{0}, \frac{p_{42}}{0.88}, \frac{p_{43}}{0.66}, \frac{p_{44}}{0.44}, \frac{p_{45}}{0.22} \Big\},$$
$$\mathrm{WL(VH)} = \Big\{ \frac{p_1}{0.22}, \frac{p_2}{0.11}, \frac{p_3}{1}, \frac{p_4}{0.44}, \frac{p_5}{0.55}, \frac{p_6}{1}, \frac{p_7}{0.11},$$
$$\frac{p_8}{0}, \frac{p_9}{0.33}, \frac{p_{10}}{0.88}, \frac{p_{11}}{1}, \frac{p_{12}}{1}, \frac{p_{13}}{0.11}, \frac{p_{14}}{0},$$
$$\frac{p_{15}}{0.55}, \frac{p_{16}}{1}, \frac{p_{17}}{1}, \frac{p_{18}}{0.11}, \frac{p_{19}}{0.33}, \frac{p_{20}}{0.44},$$

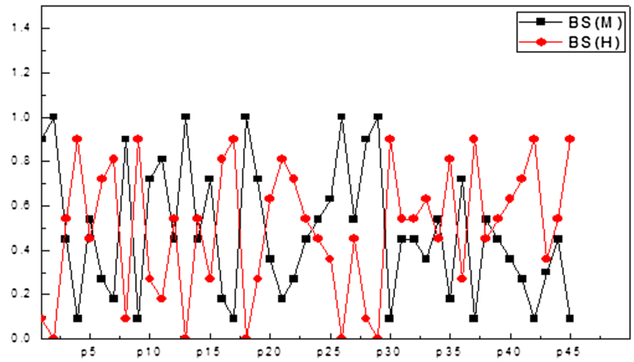

Fig. 20 New fuzzy soft set $(\hat{P}, \hat{F})$

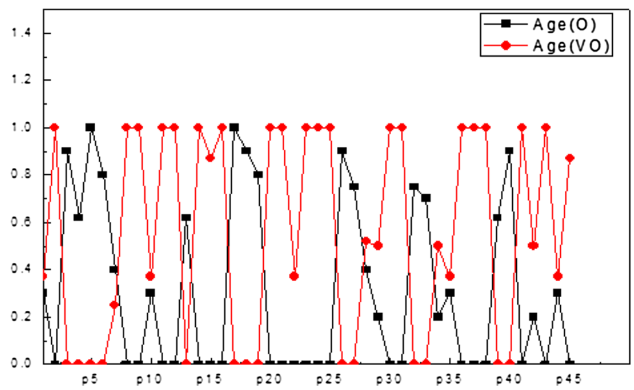

Fig. 21 New fuzzy soft set $(\hat{T}, \hat{G})$

$$\frac{p_{21}}{0.55}, \frac{p_{22}}{1}, \frac{p_{23}}{1}, \frac{p_{24}}{0.66}, \frac{p_{25}}{1}, \frac{p_{26}}{1}, \frac{p_{27}}{1},$$
$$\frac{p_{28}}{1}, \frac{p_{29}}{1}, \frac{p_{30}}{0}, \frac{p_{31}}{0.22}, \frac{p_{32}}{0.33}, \frac{p_{33}}{0.22},$$
$$\frac{p_{34}}{0.33}, \frac{p_{35}}{1}, \frac{p_{36}}{1}, \frac{p_{37}}{1}, \frac{p_{38}}{1}, \frac{p_{39}}{1},$$
$$\frac{p_{40}}{1}, \frac{p_{41}}{1}, \frac{p_{42}}{0.11}, \frac{p_{43}}{0.33}, \frac{p_{44}}{0.55}, \frac{p_{45}}{0.77} \Big\},$$

$$\mathrm{SHB}(M) = \Big\{ \frac{p_1}{0.91}, \frac{p_2}{0.75}, \frac{p_3}{0}, \frac{p_4}{0.41}, \frac{p_5}{0.91}, \frac{p_6}{0}, \frac{p_7}{0},$$
$$\frac{p_8}{0}, \frac{p_9}{0}, \frac{p_{10}}{0}, \frac{p_{11}}{0.75}, \frac{p_{12}}{0}, \frac{p_{13}}{1}, \frac{p_{14}}{0.83},$$
$$\frac{p_{15}}{0.58}, \frac{p_{16}}{0.41}, \frac{p_{17}}{0.33}, \frac{p_{18}}{0}, \frac{p_{19}}{0}, \frac{p_{20}}{0},$$
$$\frac{p_{21}}{0}, \frac{p_{22}}{0.91}, \frac{p_{23}}{0.75}, \frac{p_{24}}{0}, \frac{p_{25}}{0}, \frac{p_{26}}{0.41}, \frac{p_{27}}{0.5},$$
$$\frac{p_{28}}{0.83}, \frac{p_{29}}{0.91}, \frac{p_{30}}{0.5}, \frac{p_{31}}{0.66}, \frac{p_{32}}{0.58}, \frac{p_{33}}{0},$$
$$\frac{p_{34}}{0}, \frac{p_{35}}{0}, \frac{p_{36}}{0}, \frac{p_{37}}{0}, \frac{p_{38}}{0.25}, \frac{p_{39}}{0.16},$$
$$\frac{p_{40}}{0}, \frac{p_{41}}{0.41}, \frac{p_{42}}{0.5}, \frac{p_{43}}{0.75}, \frac{p_{44}}{0}, \frac{p_{45}}{0} \Big\},$$
$$\mathrm{SHB}(H) = \Big\{ \frac{p_1}{0.08}, \frac{p_2}{0.25}, \frac{p_3}{0.90}, \frac{p_4}{0.58}, \frac{p_5}{0.08}, \frac{p_6}{0.54}, \frac{p_7}{0.09},$$
$$\frac{p_8}{0}, \frac{p_9}{0}, \frac{p_{10}}{0.45}, \frac{p_{11}}{0.25}, \frac{p_{12}}{0}, \frac{p_{13}}{0}, \frac{p_{14}}{0.16},$$

$$
\begin{aligned}
&\frac{p_{15}}{0.41},\frac{p_{16}}{0.58},\frac{p_{17}}{0.66},\frac{p_{18}}{0.90},\frac{p_{19}}{0.45},\frac{p_{20}}{0.72},\\
&\frac{p_{21}}{0.63},\frac{p_{22}}{0.08},\frac{p_{23}}{0.25},\frac{p_{24}}{0},\frac{p_{25}}{0},\frac{p_{26}}{0.58},\frac{p_{27}}{0.5},\\
&\frac{p_{28}}{0.16},\frac{p_{29}}{0.08},\frac{p_{30}}{0.5},\frac{p_{31}}{0.33},\frac{p_{32}}{0.41},\frac{p_{33}}{0.45},\\
&\frac{p_{34}}{0.63},\frac{p_{35}}{0.54},\frac{p_{36}}{0},\frac{p_{37}}{0},\frac{p_{38}}{0.75},\frac{p_{39}}{0.83},\\
&\left.\frac{p_{40}}{1},\frac{p_{41}}{0.58},\frac{p_{42}}{0.5},\frac{p_{43}}{0.25},\frac{p_{44}}{0.27},\frac{p_{45}}{0}\right\},
\end{aligned}
$$

$$
\begin{aligned}
\mathrm{SHB}(\mathrm{VH}) = \Big\{&\frac{p_{1}}{0},\frac{p_{2}}{0},\frac{p_{3}}{0.09},\frac{p_{4}}{0},\frac{p_{5}}{0},\frac{p_{6}}{0.45},\frac{p_{7}}{0.90},\frac{p_{8}}{1},\\
&\frac{p_{9}}{1},\frac{p_{10}}{0.54},\frac{p_{11}}{0},\frac{p_{12}}{1},\frac{p_{13}}{0},\frac{p_{14}}{0},\frac{p_{15}}{0},\\
&\frac{p_{16}}{0},\frac{p_{17}}{0},\frac{p_{18}}{0.09},\frac{p_{19}}{0.54},\frac{p_{20}}{0.27},\frac{p_{21}}{0.36},\\
&\frac{p_{22}}{0},\frac{p_{23}}{0},\frac{p_{24}}{1},\frac{p_{25}}{1},\frac{p_{26}}{0},\frac{p_{27}}{0},\frac{p_{28}}{0},\\
&\frac{p_{29}}{0},\frac{p_{30}}{0},\frac{p_{31}}{0},\frac{p_{32}}{0},\frac{p_{33}}{0.54},\frac{p_{34}}{0.36},\\
&\frac{p_{35}}{0.45},\frac{p_{36}}{1},\frac{p_{37}}{1},\frac{p_{38}}{0},\frac{p_{39}}{0},\frac{p_{40}}{0},\\
&\frac{p_{41}}{0},\frac{p_{42}}{0},\frac{p_{43}}{0},\frac{p_{44}}{0.72},\frac{p_{45}}{1}\Big\},
\end{aligned}
$$

$$
\begin{aligned}
\mathrm{CHP}(M) = \Big\{&\frac{p_{1}}{0.92},\frac{p_{2}}{0.76},\frac{p_{3}}{0.84},\frac{p_{4}}{0.38},\frac{p_{5}}{0},\frac{p_{6}}{0.69},\frac{p_{7}}{0.30},\\
&\frac{p_{8}}{0},\frac{p_{9}}{1},\frac{p_{10}}{0.53},\frac{p_{11}}{0.07},\frac{p_{12}}{0.23},\frac{p_{13}}{1},\frac{p_{14}}{0.76},\\
&\frac{p_{15}}{0.69},\frac{p_{16}}{0.1},\frac{p_{17}}{0.84},\frac{p_{18}}{0.46},\frac{p_{19}}{0.61},\frac{p_{20}}{0.53},\\
&\frac{p_{21}}{0},\frac{p_{22}}{0.46},\frac{p_{23}}{0.92},\frac{p_{24}}{0.84},\frac{p_{25}}{0.38},\frac{p_{26}}{0.30},\\
&\frac{p_{27}}{0.69},\frac{p_{28}}{0.23},\frac{p_{29}}{0.84},\frac{p_{30}}{0.92},\frac{p_{31}}{1},\frac{p_{32}}{0},\frac{p_{33}}{0.46},\\
&\frac{p_{34}}{1},\frac{p_{35}}{0.84},\frac{p_{36}}{0.38},\frac{p_{37}}{0.61},\frac{p_{38}}{0.46},\frac{p_{39}}{0.30},\\
&\frac{p_{40}}{0.23},\frac{p_{41}}{0},\frac{p_{42}}{0.84},\frac{p_{43}}{0.84},\frac{p_{44}}{0.38},\frac{p_{45}}{0.30}\Big\},
\end{aligned}
$$

$$
\begin{aligned}
\mathrm{CHP}(H) = \Big\{&\frac{p_{1}}{0.07},\frac{p_{2}}{0.23},\frac{p_{3}}{0.15},\frac{p_{4}}{0.61},\frac{p_{5}}{1},\frac{p_{6}}{0.30},\frac{p_{7}}{0.69},\\
&\frac{p_{8}}{1},\frac{p_{9}}{0},\frac{p_{10}}{0.46},\frac{p_{11}}{0.92},\frac{p_{12}}{0.76},\frac{p_{13}}{0},\frac{p_{14}}{0.23},\\
&\frac{p_{15}}{0.30},\frac{p_{16}}{0},\frac{p_{17}}{0.15},\frac{p_{18}}{0.53},\frac{p_{19}}{0.38},\frac{p_{20}}{0.46},\\
&\frac{p_{21}}{1},\frac{p_{22}}{0.53},\frac{p_{23}}{0.07},\frac{p_{24}}{0.15},\frac{p_{25}}{0.61},\frac{p_{26}}{0.69},\\
&\frac{p_{27}}{0.30},\frac{p_{28}}{0.67},\frac{p_{29}}{0.15},\frac{p_{30}}{0.07},\frac{p_{31}}{0},\frac{p_{32}}{1},\frac{p_{33}}{0.53},\\
&\frac{p_{34}}{0},\frac{p_{35}}{0.15},\frac{p_{36}}{0.61},\frac{p_{37}}{0.38},\frac{p_{38}}{0.53},\frac{p_{39}}{0.69},\\
&\frac{p_{40}}{0.76},\frac{p_{41}}{1},\frac{p_{42}}{0.15},\frac{p_{43}}{0.15},\frac{p_{44}}{0.61},\frac{p_{45}}{0.69}\Big\},
\end{aligned}
$$

$$
\begin{aligned}
\mathrm{PC}(M) = \Big\{&\frac{p_{1}}{0.41},\frac{p_{2}}{0.4},\frac{p_{3}}{0.88},\frac{p_{4}}{0.15},\frac{p_{5}}{0},\frac{p_{6}}{0.65},\frac{p_{7}}{0.45},\\
&\frac{p_{8}}{0.95},\frac{p_{9}}{0.2},\frac{p_{10}}{0},\frac{p_{11}}{0},\frac{p_{12}}{0},\frac{p_{13}}{0.29},\frac{p_{14}}{0.47},\\
&\frac{p_{15}}{0.9},\frac{p_{16}}{0.8},\frac{p_{17}}{0.4},\frac{p_{18}}{0.3},\frac{p_{19}}{0.29},\frac{p_{20}}{0.52},\frac{p_{21}}{0.64},\\
&\frac{p_{22}}{0.76},\frac{p_{23}}{0.94},\frac{p_{24}}{0.95},\frac{p_{25}}{0.55},\frac{p_{26}}{0},\frac{p_{27}}{0.25},\\
&\frac{p_{28}}{0.2},\frac{p_{29}}{0},\frac{p_{30}}{0},\frac{p_{31}}{1},\frac{p_{32}}{0},\frac{p_{33}}{0},\frac{p_{34}}{0},\\
&\frac{p_{35}}{0},\frac{p_{36}}{0.41},\frac{p_{37}}{0.58},\frac{p_{38}}{0.82},\frac{p_{39}}{0.29},\frac{p_{40}}{0.88},\\
&\frac{p_{41}}{0.82},\frac{p_{42}}{0.45},\frac{p_{43}}{0},\frac{p_{44}}{0},\frac{p_{45}}{0.23}\Big\},
\end{aligned}
$$

$$
\begin{aligned}
\mathrm{PC}(H) = \Big\{&\frac{p_{1}}{0},\frac{p_{2}}{0.41},\frac{p_{3}}{0},\frac{p_{4}}{0.70},\frac{p_{5}}{0.88},\frac{p_{6}}{0.11},\frac{p_{7}}{0.35},\\
&\frac{p_{8}}{0},\frac{p_{9}}{0.64},\frac{p_{10}}{0.53},\frac{p_{11}}{1},\frac{p_{12}}{0.4},\frac{p_{13}}{0},\frac{p_{14}}{0},\\
&\frac{p_{15}}{0},\frac{p_{16}}{0},\frac{p_{17}}{0.41},\frac{p_{18}}{0.52},\frac{p_{19}}{0},\frac{p_{20}}{0},\frac{p_{21}}{0},\\
&\frac{p_{22}}{0},\frac{p_{23}}{0},\frac{p_{24}}{0},\frac{p_{25}}{0},\frac{p_{26}}{0.23},\frac{p_{27}}{0.94},\frac{p_{28}}{0.58},\\
&\frac{p_{29}}{0.8},\frac{p_{30}}{1},\frac{p_{31}}{0},\frac{p_{32}}{0.4},\frac{p_{33}}{0.88},\frac{p_{34}}{0.66},\frac{p_{35}}{0.6},\\
&\frac{p_{36}}{0},\frac{p_{37}}{0},\frac{p_{38}}{0},\frac{p_{39}}{0},\frac{p_{40}}{0},\frac{p_{41}}{0},\\
&\frac{p_{42}}{0.35},\frac{p_{43}}{0.86},\frac{p_{44}}{0.73},\frac{p_{45}}{0}\Big\},
\end{aligned}
$$

$$
\begin{aligned}
\mathrm{BS}(M) = \Big\{&\frac{p_{1}}{0.90},\frac{p_{2}}{1},\frac{p_{3}}{0.45},\frac{p_{4}}{0.09},\frac{p_{5}}{0.54},\frac{p_{6}}{0.27},\frac{p_{7}}{0.18},\\
&\frac{p_{8}}{0.90},\frac{p_{9}}{0.09},\frac{p_{10}}{0.72},\frac{p_{11}}{0.81},\frac{p_{12}}{0.45},\frac{p_{13}}{1},\frac{p_{14}}{0.45},\\
&\frac{p_{15}}{0.72},\frac{p_{16}}{0.18},\frac{p_{17}}{0.09},\frac{p_{18}}{1},\frac{p_{19}}{0.72},\frac{p_{20}}{0.36},\frac{p_{21}}{0.18},\\
&\frac{p_{22}}{0.27},\frac{p_{23}}{0.45},\frac{p_{24}}{0.54},\frac{p_{25}}{0.63},\frac{p_{26}}{1},\frac{p_{27}}{0.54},\frac{p_{28}}{0.90},\\
&\frac{p_{29}}{1},\frac{p_{30}}{0.09},\frac{p_{31}}{0.45},\frac{p_{32}}{0.45},\frac{p_{33}}{0.36},\frac{p_{34}}{0.54},\frac{p_{35}}{0.18},\\
&\frac{p_{36}}{0.72},\frac{p_{37}}{0.09},\frac{p_{38}}{0.54},\frac{p_{39}}{0.45},\frac{p_{40}}{0.36},\frac{p_{41}}{0.27},\\
&\frac{p_{42}}{0.09},\frac{p_{43}}{0.63},\frac{p_{44}}{0.45},\frac{p_{45}}{0.09}\Big\},
\end{aligned}
$$

$$
\begin{aligned}
\mathrm{BS}(H) = \Big\{&\frac{p_{1}}{0.09},\frac{p_{2}}{0},\frac{p_{3}}{0.54},\frac{p_{4}}{0.90},\frac{p_{5}}{0.45},\frac{p_{6}}{0.72},\frac{p_{7}}{0.81},\\
&\frac{p_{8}}{0.09},\frac{p_{9}}{0.90},\frac{p_{10}}{0.27},\frac{p_{11}}{0.18},\frac{p_{12}}{0.54},\frac{p_{13}}{0},\frac{p_{14}}{0.54},\\
&\frac{p_{15}}{0.27},\frac{p_{16}}{0.81},\frac{p_{17}}{0.90},\frac{p_{18}}{0},\frac{p_{19}}{0.27},\frac{p_{20}}{0.63},\frac{p_{21}}{0.81},\\
&\frac{p_{22}}{0.72},\frac{p_{23}}{0.54},\frac{p_{24}}{0.45},\frac{p_{25}}{0.36},\frac{p_{26}}{0},\frac{p_{27}}{0.45},\frac{p_{28}}{0.09},\\
&\frac{p_{29}}{0},\frac{p_{30}}{0.90},\frac{p_{31}}{0.54},\frac{p_{32}}{0.54},\frac{p_{33}}{0.63},\frac{p_{34}}{0.45},\frac{p_{35}}{0.81},\\
&\frac{p_{36}}{0.27},\frac{p_{37}}{0.90},\frac{p_{38}}{0.45},\frac{p_{39}}{0.54},\frac{p_{40}}{0.63},\frac{p_{41}}{0.72},
\end{aligned}
$$

Table 11 $(\hat{L}, \hat{A})$

P	p_1	p_2	p_3	p_4	p_5	p_6	p_7	p_8	p_9	p_{10}	p_{11}	p_{12}	p_{13}	p_{14}	p_{15}
WL(H)	0.77	0.88	0	0.55	0.44	0	0.88	1	0.66	0.11	0	0	0.88	1	0.44
WL(VH)	0.22	0.11	1	0.44	0.55	1	0.11	0	0.33	0.88	1	1	0.11	0	0.55
P	p_{16}	p_{17}	p_{18}	p_{19}	p_{20}	p_{21}	p_{22}	p_{23}	p_{24}	p_{25}	p_{26}	p_{27}	p_{28}	p_{29}	p_{30}
WL(H)	0	0	0.88	0.66	0.55	0.44	0	0	0.33	0	0	0	0	0	1
WL(VH)	1	1	0.11	0.33	0.44	0.55	1	1	0.66	1	1	1	1	1	0
P	p_{31}	p_{32}	p_{33}	p_{34}	p_{35}	p_{36}	p_{37}	p_{38}	p_{39}	p_{40}	p_{41}	p_{42}	p_{43}	p_{44}	p_{45}
WL(H)	0.77	0.66	0.77	0.66	0	0	0	0	0	0	0	0.88	0.66	0.44	0.22
WL(VH)	0.22	0.33	0.22	0.33	1	1	1	1	1	1	1	0.11	0.33	0.55	0.77

Table 12 $(\hat{M}, \hat{B})$

P	p_1	p_2	p_3	p_4	p_5	p_6	p_7	p_8	p_9	p_{10}	p_{11}	p_{12}	p_{13}	p_{14}	p_{15}
SHB(M)	0.91	0.75	0	0.41	0.91	0	0	0	0	0	0.75	0	1	0.83	0.58
SHB(H)	0.08	0.25	0.90	0.58	0.08	0.54	0.09	0	0	0.45	0.25	0	0	0.16	0.41
SHB(VH)	0	0	0.09	0	0	0.45	0.90	1	1	0.54	0	1	0	0	0
P	p_{16}	p_{17}	p_{18}	p_{19}	p_{20}	p_{21}	p_{22}	p_{23}	p_{24}	p_{25}	p_{26}	p_{27}	p_{28}	p_{29}	p_{30}
SHB(M)	0.41	0.33	0	0	0	0	0.91	0.75	0	0	0.41	0.5	0.83	0.91	0.5
SHB(H)	0.58	0.66	0.90	0.45	0.72	0.63	0.08	0.25	0	0	0.58	0.5	0.16	0.08	0.5
SHB(VH)	0	0	0.09	0.54	0.27	0.36	0	0	1	1	0	0	0	0	0
P	p_{31}	p_{32}	p_{33}	p_{34}	p_{35}	p_{36}	p_{37}	p_{38}	p_{39}	p_{40}	p_{41}	p_{42}	p_{43}	p_{44}	p_{45}
SHB(M)	0.66	0.58	0	0	0	0	0	0.25	0.16	0	0.41	0.5	0.75	0	0
SHB(H)	0.33	0.41	0.45	0.63	0.54	0	0	0.75	0.83	1	0.58	0.5	0.25	0.27	0
SHB(VH)	0	0	0.54	0.36	0.45	1	1	0	0	0	0	0	0	0.72	1

Table 13 $(\hat{N}, \hat{C})$

P	p_1	p_2	p_3	p_4	p_5	p_6	p_7	p_8	p_9	p_{10}	p_{11}	p_{12}	p_{13}	p_{14}	p_{15}
CHP(M)	0.92	0.76	0.84	0.38	0	0.69	0.30	0	1	0.53	0.07	0.23	1	0.76	0.69
CHP(H)	0.07	0.23	0.15	0.61	1	0.30	0.69	1	0	0.46	0.92	0.76	0	0.23	0.30
P	p_{16}	p_{17}	p_{18}	p_{19}	p_{20}	p_{21}	p_{22}	p_{23}	p_{24}	p_{25}	p_{26}	p_{27}	p_{28}	p_{29}	p_{30}
CHP(M)	1	0.84	0.46	0.61	0.53	0	0.46	0.92	0.84	0.38	0.30	0.69	0.23	0.84	0.92
CHP(H)	0	0.15	0.53	0.38	0.46	1	0.53	0.07	0.15	0.61	0.69	0.30	0.67	0.15	0.07
P	p_{31}	p_{32}	p_{33}	p_{34}	p_{35}	p_{36}	p_{37}	p_{38}	p_{39}	p_{40}	p_{41}	p_{42}	p_{43}	p_{44}	p_{45}
CHP(M)	1	0	0.46	1	0.84	0.38	0.61	0.46	0.30	0.23	0	0.84	0.84	0.38	0.30
CHP(H)	0	1	0.53	0	0.15	0.61	0.38	0.53	0.69	0.76	1	0.15	0.15	0.61	0.69

Table 14 $(\hat{R}, \hat{D})$

P	p_1	p_2	p_3	p_4	p_5	p_6	p_7	p_8	p_9	p_{10}	p_{11}	p_{12}	p_{13}	p_{14}	p_{15}
PC(M)	0.41	0.4	0.88	0.15	0	0.65	0.45	0.95	0.2	0	0	0	0.29	0.47	0.9
PC(H)	0	0.41	0	0.70	0.88	0.11	0.35	0	0.64	0.53	1	0.4	0	0	0
P	p_{16}	p_{17}	p_{18}	p_{19}	p_{20}	p_{21}	p_{22}	p_{23}	p_{24}	p_{25}	p_{26}	p_{27}	p_{28}	p_{29}	p_{30}
PC(M)	0.8	0.4	0.3	0.29	0.52	0.64	0.76	0.94	0.95	0.55	0	0.25	0.2	0	0
PC(H)	0	0.41	0.52	0	0	0	0	0	0	0	0.23	0.94	0.58	0.8	1
P	p_{31}	p_{32}	p_{33}	p_{34}	p_{35}	p_{36}	p_{37}	p_{38}	p_{39}	p_{40}	p_{41}	p_{42}	p_{43}	p_{44}	p_{45}
PC(M)	1	0	0	0	0	0.41	0.58	0.82	0.29	0.88	0.82	0.45	0	0	0.23
PC(H)	0	0.4	0.88	0.66	0.6	0	0	0	0	0	0	0.35	0.86	0.73	0

Table 15 $(\hat{P}, \hat{F})$

P	p_1	p_2	p_3	p_4	p_5	p_6	p_7	p_8	p_9	p_{10}	p_{11}	p_{12}	p_{13}	p_{14}	p_{15}
BS(M)	0.90	1	0.45	0.09	0.54	0.27	0.18	0.90	0.09	0.72	0.81	0.45	1	0.45	0.72
BS(H)	0.09	0	0.54	0.90	0.45	0.72	0.81	0.09	0.90	0.27	0.18	0.54	0	0.54	0.27
P	p_{16}	p_{17}	p_{18}	p_{19}	p_{20}	p_{21}	p_{22}	p_{23}	p_{24}	p_{25}	p_{26}	p_{27}	p_{28}	p_{29}	p_{30}
BS(M)	0.18	0.09	1	0.72	0.36	0.18	0.27	0.45	0.54	0.63	1	0.54	0.90	1	0.09
BS(H)	0.81	0.90	0	0.27	0.63	0.81	0.72	0.54	0.45	0.36	0	0.45	0.09	0	0.90
P	p_{31}	p_{32}	p_{33}	p_{34}	p_{35}	p_{36}	p_{37}	p_{38}	p_{39}	p_{40}	p_{41}	p_{42}	p_{43}	p_{44}	p_{45}
BS(M)	0.45	0.45	0.36	0.54	0.18	0.72	0.09	0.54	0.45	0.36	0.27	0.09	0.63	0.45	0.09
BS(H)	0.54	0.54	0.63	0.45	0.81	0.27	0.90	0.45	0.54	0.63	0.72	0.90	0.36	0.54	0.90

Table 16 $(\hat{T}, \hat{G})$

P	p_1	p_2	p_3	p_4	p_5	p_6	p_7	p_8	p_9	p_{10}	p_{11}	p_{12}	p_{13}	p_{14}	p_{15}
Age(O)	0.3	0	0.9	0.62	1	0.8	0.4	0	0	0.3	0	0	0.62	0	0
Age(VO)	0.37	1	0	0	0	0	0.25	1	1	0.37	1	1	0	1	0.87
P	p_{16}	p_{17}	p_{18}	p_{19}	p_{20}	p_{21}	p_{22}	p_{23}	p_{24}	p_{25}	p_{26}	p_{27}	p_{28}	p_{29}	p_{30}
Age(O)	0	1	0.9	0.8	0	0	0	0	0	0	0.9	0.75	0.4	0.2	0
Age(VO)	1	0	0	0	1	1	0.37	1	1	1	0	0	0.52	0.5	1
P	p_{31}	p_{32}	p_{33}	p_{34}	p_{35}	p_{36}	p_{37}	p_{38}	p_{39}	p_{40}	p_{41}	p_{42}	p_{43}	p_{44}	p_{45}
Age(O)	0	0.75	0.7	0.2	0.3	0	0	0	0.62	0.9	0	0.2	0	0.3	0
Age(VO)	1	0	0	0.5	0.37	1	1	1	0	0	1	0.5	1	0.37	0.87

$$\frac{p_{42}}{0.90}, \frac{p_{43}}{0.36}, \frac{p_{44}}{0.54}, \frac{p_{45}}{0.90}\Big\},$$

$$\begin{aligned}\mathrm{Age}(O) = \Big\{&\frac{p_1}{0.3}, \frac{p_2}{0}, \frac{p_3}{0.9}, \frac{p_4}{0.62}, \frac{p_5}{1}, \frac{p_6}{0.8}, \frac{p_7}{0.4}, \frac{p_8}{0}, \\ &\frac{p_9}{0}, \frac{p_{10}}{0.3}, \frac{p_{11}}{0}, \frac{p_{12}}{0}, \frac{p_{13}}{0.62}, \frac{p_{14}}{0}, \frac{p_{15}}{0}, \frac{p_{16}}{0}, \\ &\frac{p_{17}}{1}, \frac{p_{18}}{0.9}, \frac{p_{19}}{0.8}, \frac{p_{20}}{0}, \frac{p_{21}}{0}, \frac{p_{22}}{0}, \frac{p_{23}}{0}, \frac{p_{24}}{0}, \\ &\frac{p_{25}}{0}, \frac{p_{26}}{0.9}, \frac{p_{27}}{0.75}, \frac{p_{28}}{0.4}, \frac{p_{29}}{0.2}, \frac{p_{30}}{0}, \frac{p_{31}}{0}, \\ &\frac{p_{32}}{0.75}, \frac{p_{33}}{0.7}, \frac{p_{34}}{0.2}, \frac{p_{35}}{0.3}, \frac{p_{36}}{0}, \frac{p_{37}}{0}, \frac{p_{38}}{0}, \\ &\frac{p_{39}}{0.62}, \frac{p_{40}}{0.9}, \frac{p_{41}}{0}, \frac{p_{42}}{0.2}, \frac{p_{43}}{0}, \frac{p_{44}}{0.3}, \frac{p_{45}}{0}\Big\},\end{aligned}$$

$$\begin{aligned}\mathrm{Age}(\mathrm{VO}) = \Big\{&\frac{p_1}{0.37}, \frac{p_2}{1}, \frac{p_3}{0}, \frac{p_4}{0}, \frac{p_5}{0}, \frac{p_6}{0}, \frac{p_7}{0.25}, \frac{p_8}{1}, \\ &\frac{p_9}{1}, \frac{p_{10}}{0.37}, \frac{p_{11}}{1}, \frac{p_{12}}{1}, \frac{p_{13}}{0}, \frac{p_{14}}{1}, \frac{p_{15}}{0.87},\end{aligned}$$

Table 17 Fusion fuzzy soft set $(\tilde{K}, S)$

P	p_1	p_2	p_3	p_4	p_5	p_6	p_7	p_8	p_9	p_{10}	p_{11}	p_{12}	p_{13}	p_{14}	p_{15}
e_{11}	0.91	0.88	0	0.55	0.91	0	0.88	1	0.66	0.11	0	0.75	1	1	0.58
e_{12}	0.77	0.88	0.9	0.58	0.44	0.54	0.88	1	0.66	0.45	0.25	0	0.88	1	0.44
e_{13}	0.77	0.88	0.09	0.55	0.44	0.45	0.9	1	1	0.54	0	1	0.88	1	0.44
e_{21}	0.91	0.75	1	0.44	0.91	1	0.11	0	1	0.33	0.88	1	1	0.83	0.58
e_{22}	0.22	0.23	1	0.58	0.55	1	0.11	0	0.33	0.88	1	1	0.11	0.16	0.55
e_{23}	0.22	0.11	1	0.44	0.55	1	0.9	1	1	0.88	1	1	0.11	0	0.55

P	p_{16}	p_{17}	p_{18}	p_{19}	p_{20}	p_{21}	p_{22}	p_{23}	p_{24}	p_{25}	p_{26}	p_{27}	p_{28}	p_{29}	p_{30}
e_{11}	0.41	0.33	0.88	0.66	0.55	0.44	0.91	0.75	0.33	0	0.41	0.5	0.83	0.91	1
e_{12}	0.58	0.66	0.90	0.66	0.72	0.63	0.08	0.25	0.33	0	0.58	0.5	0.16	0.08	1
e_{13}	0	0	0.88	0.66	0.55	0.44	0	0	1	1	0	0	0	0	1
e_{21}	1	1	0.11	0.33	0.44	0.55	1	1	0.66	1	1	1	1	1	0.5
e_{22}	1	1	0.90	0.45	0.72	0.63	1	1	0.66	1	1	1	1	1	0.5
e_{23}	1	1	0.11	0.54	0.54	0.55	1	1	1	1	1	1	1	1	0

P	p_{31}	p_{32}	p_{33}	p_{34}	p_{35}	p_{36}	p_{37}	p_{38}	p_{39}	p_{40}	p_{41}	p_{42}	p_{43}	p_{44}	p_{45}
e_{11}	0.77	0.66	0.77	0.66	0	0	0	0.25	0.16	0	0.41	0.88	0.75	0.44	0.22
e_{12}	0.77	0.66	0.77	0.66	0.54	0	0	0.75	0.83	1	0.58	0.88	0.66	0.44	0.22
e_{13}	0.77	0.66	0.77	0.66	0.45	1	1	0	0	0	0	0.88	0.66	0.72	1
e_{21}	0.66	0.58	0.22	0.33	1	1	1	1	1	1	1	0.5	0.75	0.55	0.77
e_{22}	0.33	0.41	0.45	0.63	1	1	1	1	1	1	1	0.5	0.33	0.55	0.77
e_{23}	0.22	0.33	0.54	0.36	1	1	1	1	1	1	1	0.11	0.33	0.72	1

$$\frac{p_{16}}{1}, \frac{p_{17}}{0}, \frac{p_{18}}{0}, \frac{p_{19}}{0}, \frac{p_{20}}{1}, \frac{p_{21}}{1}, \frac{p_{22}}{0.37}, \frac{p_{23}}{1}, \frac{p_{24}}{1}, \frac{p_{25}}{1}, \frac{p_{26}}{0}, \frac{p_{27}}{0}, \frac{p_{28}}{0.52}, \frac{p_{29}}{0.5}, \frac{p_{30}}{1}, \frac{p_{31}}{1}, \frac{p_{32}}{0}, \frac{p_{33}}{0}, \frac{p_{34}}{0.5}, \frac{p_{35}}{0.37}, \frac{p_{36}}{1}, \frac{p_{37}}{1}, \frac{p_{38}}{1}, \frac{p_{39}}{0}, \frac{p_{40}}{0}, \frac{p_{41}}{1}, \frac{p_{42}}{0.5}, \frac{p_{43}}{1}, \frac{p_{44}}{0.37}, \frac{p_{45}}{0.87}\Big\}.$$

4.3 Computation using Kong et al.'s algorithm

Using Kong et al.'s algorithm (Kong et al. 2009), we can predict which patient will suffer from lung cancer disease. Now, we will show these steps as follows:

Step 1 Input the six new fuzzy soft sets $(\hat{L}, \hat{A})$, $(\hat{M}, \hat{B})$, $(\hat{N}, \hat{C})$, $(\hat{R}, \hat{D})$, $(\hat{P}, \hat{F})$, and $(\hat{T}, \hat{G})$ (as shown in Tables 11, 12, 13, 14, 15 and 16).

As an example, we show in Table 17 how to compute the fusion fuzzy soft set $(\tilde{K}, S) = (\hat{L}, \hat{A})\check{\otimes}(\hat{M}, \hat{B})$ from $(\hat{L}, \hat{A})$ and $(\hat{M}, \hat{B})$ (notice that $S = \hat{A} \times \hat{B} = \{e_{11}, e_{12}, e_{13}, e_{21}, e_{22}, e_{23}\}$ is a 6-element set).

Step 2 Compute the fusion fuzzy soft set $(\tilde{I}, Q) = (\hat{L}, \hat{A})\check{\otimes}(\hat{M}, \hat{B})\check{\otimes}(\hat{N}, \hat{C})\check{\otimes}(\hat{R}, \hat{D})\check{\otimes}(\hat{L}, \hat{A})\check{\otimes}(\hat{T}, \hat{G})$ (notice that $Q = \hat{A} \times \hat{B} \times \hat{C} \times \hat{D} \times \hat{F} \times \hat{G} = \{\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_{96}\}$ is a 96-element set, see Tables 18, 19, 20, 21, 22 and 23).

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

Step 4 From step 3 we can see that patients $p_2, p_8 - p_{12}, p_{14} - p_{16}, p_{20} - p_{25}, p_{29}, p_{30}, p_{33} - p_{37}, p_{41}, p_{44}$

Table 18 Fusion fuzzy soft set $(\tilde{I}, Q)$

P	ε_1	ε_2	ε_3	ε_4	ε_5	ε_6	ε_7	ε_8	ε_9	ε_{10}	ε_{11}	ε_{12}	ε_{13}	ε_{14}	ε_{15}	ε_{16}
p_1	0.92	0.92	0.91	0.91	0.92	0.92	0.91	0.91	0.92	0.92	0.91	0.91	0.92	0.92	0.91	0.91
p_2	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.88	0.88	0.88	0.88	1.0	1.0	1.0	1.0
p_3	0.9	0.9	0.9	0.9	0.88	0.84	0.88	0.45	0.9	0.9	0.9	0.9	0.88	0.84	0.88	0.54
p_4	0.62	0.7	0.62	0.7	0.55	0.7	0.61	0.7	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9
p_5	1.0	1.0	1.0	1.0	0.91	0.91	1.0	1.0	1.0	1.0	1.0	1.0	0.91	0.91	1.0	1.0
p_6	0.8	0.8	0.8	0.8	0.69	0.69	0.65	0.3	0.8	0.8	0.8	0.8	0.72	0.72	0.72	0.72
p_7	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88
p_8	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
p_9	1.0	1.0	0.66	0.66	1.0	1.0	1.0	1.0	1.0	1.0	0.9	0.9	1.0	1.0	1.0	1.0
p_{10}	0.72	0.72	0.72	0.72	0.72	0.72	0.72	0.72	0.53	0.53	0.64	0.64	0.53	0.53	0.64	0.64
p_{11}	0.81	1.0	0.92	1.0	0.81	1.0	0.92	1.0	0.18	1.0	0.92	1.0	0.18	1.0	0.92	1.0
p_{12}	0.75	0.75	0.76	0.75	1.0	1.0	1.0	1.0	0.75	0.75	0.76	0.76	1.0	1.0	1.0	1.0
p_{13}	0.91	0.9	1	0.88	0.92	0.92	0.91	0.88	0.92	0.92	0.54	0.91	0.92	0.92	0.91	1.0
p_{14}	0.4	0.3	1.0	1.0	1.0	0.92	0.88	1.0	0.88	0.88	0.92	0.88	0.92	0.92	0.91	1.0
p_{15}	0.9	0.9	0.9	0.9	0.88	0.84	0.88	0.7	0.7	0.9	0.9	0.9	0.9	0.9	0.9	0.9
p_{16}	0.62	0.7	0.62	0.7	0.55	0.7	0.61	0.7	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9
p_{17}	1.0	1.0	1.0	1.0	0.91	0.91	1.0	1.0	1.0	1.0	1.0	1.0	0.91	0.91	1.0	1.0
p_{18}	0.8	0.8	0.8	0.8	0.69	0.69	0.65	1.0	1.0	1.0	0.8	0.8	0.72	0.72	0.72	0.72
p_{19}	0.45	0.9	0.88	0.9	0.84	0.88	0.84	0.88	0.54	0.88	0.88	0.9	0.53	0.88	0.88	0.88
p_{20}	1.0	1.0	1.0	0.9	1.0	1.0	0.88	1.0	1.0	1.0	1.0	1.0	0.99	1.0	1.0	0.72
p_{21}	1.0	1.0	0.66	0.66	1.0	1.0	1.0	1.0	1.0	1.0	0.9	0.9	1.0	1.0	1.0	1.0
p_{22}	0.72	0.72	0.72	0.72	0.72	0.54	0.88	0.88	0.9	0.53	0.88	0.88	0.88	0.53	0.64	0.64
p_{23}	0.81	1.0	0.92	1.0	0.81	1.0	0.92	1.0	0.18	1.0	0.92	1.0	0.18	1.0	0.92	1.0
p_{24}	0.75	0.75	0.76	0.75	1.0	1.0	1.0	1.0	0.75	0.75	0.76	0.76	1.0	1.0	1.0	1.0
p_{25}	0.92	0.92	0.91	0.91	0.92	0.92	0.91	0.91	0.92	0.92	0.91	0.91	0.92	0.92	0.91	0.91
p_{26}	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.88	0.88	0.88	0.88	1.0	1.0	1.0	1.0
p_{27}	0.9	0.9	0.9	0.9	0.88	0.84	0.88	0.45	0.9	0.9	0.9	0.9	0.88	0.84	0.88	0.54
p_{28}	0.62	0.7	0.62	0.7	0.55	0.7	0.61	0.7	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9
p_{29}	1.0	1.0	1.0	1.0	0.91	0.91	1.0	1.0	1.0	1.0	1.0	1.0	0.91	0.91	1.0	1.0
p_{30}	0.8	0.8	0.8	0.8	0.69	0.69	0.65	0.3	0.8	0.8	0.8	0.8	0.72	0.72	0.72	0.72
p_{31}	0.88	0.88	1.0	1.0	1.0	0.8	0.8	0.72	0.72	0.72	0.72	0.88	0.88	0.88	0.88	0.88
p_{32}	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.8	0.8	0.72	0.72	0.72	0.72
p_{33}	1.0	1.0	0.66	0.66	1.0	1.0	1.0	1.0	1.0	1.0	0.8	0.8	0.72	0.72	0.72	0.72
p_{34}	0.72	0.72	0.72	0.72	0.72	0.72	0.72	0.72	0.53	0.53	0.64	0.64	0.53	0.53	0.64	0.64
p_{35}	0.81	1.0	0.92	1.0	0.81	1.0	0.92	1.0	0.18	1.0	0.92	1.0	0.18	1.0	0.92	1.0
p_{36}	1.0	1.0	1.0	0.8	0.8	0.72	0.72	0.72	0.72	0.75	0.76	0.76	1.0	1.0	1.0	1.0
p_{37}	0.92	0.92	0.91	0.91	0.92	0.92	0.91	0.91	0.92	0.92	0.91	0.91	0.92	0.92	0.91	0.91
p_{38}	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.88	0.88	0.88	0.88	1.0	1.0	1.0	1.0
p_{39}	0.9	0.9	0.9	0.9	0.88	0.84	0.88	0.45	0.9	0.9	0.9	0.9	0.88	0.84	0.88	0.54
p_{40}	0.62	0.7	0.62	0.7	0.55	0.7	0.61	0.7	0.54	0.88	0.88	0.9	0.53	0.88	0.88	0.88
p_{41}	1.0	1.0	1.0	1.0	0.91	0.91	1.0	1.0	1.0	1.0	1.0	1.0	0.91	0.91	1.0	1.0
p_{42}	0.8	0.8	0.8	0.8	0.69	0.69	0.65	0.3	0.8	0.8	0.8	0.8	0.72	0.72	0.72	0.72
p_{43}	0.54	0.88	0.88	0.9	0.53	0.88	0.88	0.88	0.88	0.53	0.64	0.64	0.53	0.53	0.64	0.64
p_{44}	1.0	1.0	1.0	1.0	0.53	0.64	0.64	0.53	0.53	0.64	0.64	1.0	1.0	1.0	1.0	1.0
p_{45}	1.0	1.0	0.66	0.66	1.0	0.92	0.92	0.91	0.91	1.0	0.9	0.9	1.0	1.0	1.0	1.0

Table 19 Fusion fuzzy soft set $(\tilde{I}, Q)$

P	ε_{17}	ε_{18}	ε_{19}	ε_{20}	ε_{21}	ε_{22}	ε_{23}	ε_{24}	ε_{25}	ε_{26}	ε_{27}	ε_{28}	ε_{29}	ε_{30}	ε_{31}	ε_{32}
p_1	0.92	0.92	0.9	0.9	0.92	0.92	0.9	0.9	0.92	0.92	0.77	0.77	0.92	0.92	0.77	0.77
p_2	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.88	0.88	0.88	0.88	1.0	1.0	1.0	1.0
p_3	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9
p_4	0.62	0.7	0.62	0.7	0.58	0.7	0.61	0.7	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9
p_5	1.0	1.0	1.0	1.0	0.54	0.88	1.0	1.0	1.0	1.0	1.0	1.0	0.88	0.88	1.0	1.0
p_6	0.8	0.8	0.8	0.8	0.69	0.69	0.65	0.54	0.8	0.8	0.8	0.8	0.72	0.72	0.72	0.72
p_7	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88
p_8	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
p_9	1.0	1.0	0.66	0.66	1.0	1.0	1.0	1.0	1.0	1.0	0.9	0.9	1.0	1.0	1.0	1.0
p_{10}	0.72	0.72	0.72	0.72	0.72	0.72	0.72	0.72	0.53	0.53	0.64	0.64	0.53	0.53	0.64	0.64
p_{11}	0.81	1.0	0.92	1.0	0.81	1.0	0.92	1.0	0.18	1.0	0.92	1.0	0.18	1.0	0.92	1.0
p_{12}	0.45	0.45	0.76	0.45	1.0	1.0	1.0	1.0	0.54	0.54	0.76	0.76	1.0	1.0	1.0	1.0
p_{13}	0.9	0.9	0.9	0.9	0.9	0.88	0.84	0.88	0.54	0.92	0.92	0.91	0.91	0.92	0.92	0.91
p_{14}	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.88	0.88	0.88	0.88	1.0	1.0	1.0	1.0
p_{15}	0.9	0.9	0.9	0.9	0.88	0.84	0.88	0.45	0.9	0.9	0.9	0.9	0.88	0.84	0.88	0.54
p_{16}	0.62	0.7	0.62	0.7	0.55	0.7	0.61	0.7	0.9	0.9	0.9	0.9	1.0	1.0	1.0	1.0
p_{17}	1.0	1.0	1.0	1.0	0.91	0.91	1.0	1.0	1.0	1.0	1.0	1.0	0.91	0.91	1.0	1.0
p_{18}	0.8	0.8	0.8	0.8	0.69	0.69	0.65	0.3	0.8	0.8	0.8	0.8	0.72	0.72	0.72	0.72
p_{19}	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.64	0.64	0.53	0.53	0.64	0.64	0.88	0.88
p_{20}	1.0	1.0	1.0	1.0	1.0	0.8	0.8	0.72	0.72	0.72	0.72	1.0	1.0	1.0	1.0	1.0
p_{21}	1.0	1.0	0.66	0.64	0.64	0.53	0.53	0.64	0.64	1.0	0.9	0.9	1.0	1.0	1.0	1.0
p_{22}	0.72	0.72	0.72	0.72	0.72	0.72	0.72	0.72	0.53	0.53	0.64	0.64	0.53	0.53	0.64	0.64
p_{23}	0.81	1.0	0.92	1.0	0.81	1.0	0.92	1.0	0.18	1.0	0.92	1.0	0.18	1.0	0.92	1.0
p_{24}	0.75	0.75	0.76	0.75	1.0	1.0	1.0	1.0	0.75	0.75	0.76	0.76	1.0	1.0	1.0	1.0
p_{25}	0.92	0.92	0.91	0.91	0.92	0.92	0.91	0.91	0.92	0.92	0.91	0.91	0.92	0.92	0.91	0.91
p_{26}	1.0	1.0	1.0	1.0	0.88	0.88	0.88	0.88	0.88	0.88	1.0	0.92	1.0	0.18	1.0	0.92
p_{27}	0.9	0.9	0.9	0.9	0.88	0.84	0.88	0.45	0.9	0.9	0.9	0.9	0.88	0.84	0.88	0.54
p_{28}	0.62	0.7	0.62	0.7	0.55	0.7	0.61	0.7	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9
p_{29}	1.0	1.0	0.92	1.0	0.81	1.0	0.92	1.0	1.0	1.0	1.0	1.0	1.0	0.91	0.91	1.0
p_{30}	0.8	0.8	0.8	0.8	0.69	0.69	0.65	0.3	0.8	0.8	0.8	0.8	0.72	0.72	0.72	0.72
p_{31}	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88
p_{32}	0.72	0.72	0.72	0.72	1.0	1.0	1.0	1.0	1.0	1.0	0.72	0.72	0.72	0.72	1.0	1.0
p_{33}	1.0	1.0	0.92	1.0	0.81	1.0	0.92	1.0	1.0	1.0	1.0	0.92	1.0	0.18	1.0	0.92
p_{34}	0.72	0.72	0.72	0.72	0.72	0.72	0.72	0.72	1.0	1.0	1.0	0.81	1.0	0.92	1.0	0.64
p_{35}	0.81	1.0	0.92	1.0	0.81	1.0	0.92	1.0	0.18	1.0	0.92	1.0	0.18	1.0	0.92	1.0
p_{36}	0.75	0.75	0.76	0.75	1.0	1.0	1.0	1.0	0.75	0.75	0.76	0.76	1.0	1.0	1.0	1.0
p_{37}	0.92	0.92	0.72	0.72	0.72	0.72	0.72	0.53	0.92	0.92	0.91	0.91	0.92	0.92	0.91	0.91
p_{38}	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.88	0.88	0.88	0.88	1.0	1.0	1.0	1.0
p_{39}	0.9	0.9	0.9	0.9	0.88	0.84	0.88	0.45	0.9	0.9	0.9	0.9	0.88	0.84	0.88	0.54
p_{40}	0.62	0.7	0.62	0.7	0.55	0.7	0.61	0.7	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9
p_{41}	1.0	1.0	1.0	1.0	0.91	0.91	1.0	1.0	1.0	1.0	1.0	1.0	0.91	0.91	1.0	1.0
p_{42}	0.8	0.8	0.8	0.8	0.69	0.69	0.65	0.3	0.8	0.8	0.72	0.72	0.72	0.72	1.0	1.0
p_{43}	0.88	0.88	1.0	0.92	1.0	0.18	1.0	0.92	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88
p_{44}	1.0	1.0	1.0	1.0	0.72	0.72	0.72	0.72	0.72	0.53	1.0	1.0	1.0	1.0	1.0	1.0
p_{45}	1.0	1.0	0.66	0.66	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.92	1.0	0.18	1.0	0.92

Table 20 Fusion fuzzy soft set $(\tilde{I}, Q)$

P	ε_{33}	ε_{34}	ε_{35}	ε_{36}	ε_{37}	ε_{38}	ε_{39}	ε_{40}	ε_{41}	ε_{42}	ε_{43}	ε_{44}	ε_{45}	ε_{46}	ε_{47}	ε_{48}
p_1	0.92	0.92	0.9	0.9	0.92	0.92	0.9	0.9	0.92	0.92	0.77	0.77	0.92	0.92	0.77	0.77
p_2	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.88	0.88	0.88	0.88	1.0	1.0	1.0	1.0
p_3	0.9	0.9	0.9	0.9	0.88	0.84	0.88	0.45	0.9	0.9	0.9	0.9	0.88	0.84	0.88	0.54
p_4	0.62	0.7	0.62	0.7	0.55	0.7	0.61	0.7	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9
p_5	1.0	1.0	1.0	1.0	0.54	0.88	1.0	1.0	1.0	1.0	1.0	1.0	0.88	0.88	1.0	1.0
p_6	0.8	0.8	0.8	0.8	0.69	0.69	0.65	0.45	0.8	0.8	0.8	0.8	0.72	0.72	0.72	0.72
p_7	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9
p_8	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
p_9	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
p_{10}	0.72	0.72	0.72	0.72	0.72	0.72	0.72	0.72	0.54	0.54	0.64	0.64	0.54	0.54	0.64	0.64
p_{11}	0.81	1.0	0.92	1.0	0.81	1.0	0.92	1.0	0.18	1.0	0.92	1.0	0.18	1.0	0.92	1.0
p_{12}	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
p_{13}	0.92	0.92	0.91	0.91	0.92	0.92	0.91	0.91	0.92	0.92	1.0	0.81	1.0	0.92	1.0	0.18
p_{14}	1.0	1.0	0.92	0.92	0.91	0.91	0.92	0.92	0.88	0.88	0.88	0.88	1.0	1.0	1.0	1.0
p_{15}	0.9	0.9	0.9	0.9	0.88	0.84	0.88	0.45	0.9	0.9	0.9	0.9	0.88	0.84	0.88	0.54
p_{16}	0.62	0.7	0.62	0.7	0.55	0.7	0.92	0.92	0.91	0.91	0.92	0.92	0.9	0.9	0.9	0.9
p_{17}	1.0	1.0	1.0	1.0	0.81	1.0	0.92	1.0	0.18	1.0	1.0	1.0	0.91	0.91	1.0	1.0
p_{18}	0.8	0.8	0.8	0.8	0.69	0.69	0.65	0.3	0.8	0.8	0.8	0.8	0.72	0.72	0.72	0.72
p_{19}	1.0	1.0	1.0	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	1.0	1.0	1.0
p_{20}	1.0	1.0	1.0	1.0	1.0	0.88	0.88	0.88	0.88	0.88	0.88	1.0	1.0	1.0	1.0	1.0
p_{21}	1.0	1.0	0.66	0.66	1.0	0.81	1.0	0.92	1.0	0.18	0.9	0.9	1.0	1.0	1.0	1.0
p_{22}	0.72	0.72	0.72	0.72	0.72	0.72	0.72	0.72	0.53	0.53	0.64	0.64	0.53	0.53	0.64	0.64
p_{23}	0.81	1.0	0.92	1.0	0.81	1.0	0.92	1.0	0.18	0.62	0.7	0.55	0.7	0.92	0.92	0.91
p_{24}	0.75	0.75	0.62	0.7	0.55	0.7	0.92	0.92	0.91	0.75	0.76	0.76	1.0	1.0	1.0	1.0
p_{25}	0.92	0.92	0.91	0.91	0.92	0.92	0.91	0.91	0.92	0.92	0.91	0.91	0.92	0.92	0.91	0.91
p_{26}	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.88	0.88	0.88	0.88	1.0	1.0	1.0	1.0
p_{27}	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88
p_{28}	0.62	0.7	0.62	0.7	0.55	0.7	0.61	0.7	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9
p_{29}	1.0	1.0	1.0	1.0	0.91	0.91	1.0	1.0	1.0	1.0	1.0	1.0	0.91	0.91	1.0	1.0
p_{30}	0.8	0.8	0.8	0.8	0.69	0.69	0.65	0.3	0.8	0.8	0.8	0.8	0.72	0.72	0.72	0.72
p_{31}	0.7	1.0	1.0	1.0	0.92	0.92	0.91	0.45	0.9	0.9	0.9	0.9	0.88	0.84	0.88	0.54
p_{32}	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.9	0.88	0.84	0.88	0.45	0.9
p_{33}	0.7	1.0	0.66	0.66	1.0	1.0	1.0	1.0	1.0	1.0	0.9	0.9	1.0	1.0	1.0	1.0
p_{34}	0.72	0.72	0.72	0.72	0.72	0.72	0.72	0.72	0.53	0.53	0.64	0.64	0.53	0.53	0.64	0.64
p_{35}	0.81	1.0	0.92	1.0	0.81	1.0	0.92	1.0	0.18	1.0	0.92	1.0	0.18	1.0	0.92	1.0
p_{36}	0.75	0.75	0.76	0.75	1.0	1.0	1.0	1.0	0.75	0.75	0.76	0.76	1.0	1.0	1.0	1.0
p_{37}	0.92	0.92	0.91	0.91	0.92	0.92	0.91	0.91	0.92	0.92	0.91	0.91	0.92	0.92	0.91	0.91
p_{38}	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.88	0.88	0.88	0.88	1.0	1.0	1.0	1.0
p_{39}	0.9	0.9	0.9	0.9	0.88	0.84	0.88	0.45	0.88	0.88	0.88	0.88	0.88	0.84	0.88	0.54
p_{40}	0.88	0.88	0.88	0.88	0.7	0.61	0.7	0.62	0.7	0.55	0.7	0.92	0.92	0.91	0.9	0.7
p_{41}	1.0	1.0	0.66	0.66	1.0	1.0	1.0	1.0	1.0	1.0	0.9	0.9	1.0	1.0	1.0	1.0
p_{42}	0.8	0.8	0.8	0.8	0.69	0.69	0.65	0.3	0.8	0.8	0.8	0.8	0.72	0.72	0.72	0.72
p_{43}	0.9	0.88	0.84	0.88	0.45	0.9	0.88	0.9	0.88	0.84	0.88	0.45	0.9	0.88	0.88	0.88
p_{44}	0.88	0.88	0.88	0.88	1.0	1.0	1.0	0.88	0.88	0.88	0.88	1.0	1.0	1.0	1.0	1.0
p_{45}	1.0	1.0	1.0	1.0	0.91	0.91	1.0	1.0	1.0	1.0	1.0	1.0	0.91	0.91	1.0	1.0

Table 21 Fusion fuzzy soft set $(\tilde{I}, Q)$

P	ε_{49}	ε_{50}	ε_{51}	ε_{52}	ε_{53}	ε_{54}	ε_{55}	ε_{56}	ε_{57}	ε_{58}	ε_{59}	ε_{60}	ε_{61}	ε_{62}	ε_{63}	ε_{64}
p_1	0.92	0.92	0.91	0.91	0.92	0.92	0.91	0.91	0.92	0.92	0.91	0.91	0.92	0.92	0.91	0.91
p_2	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.76	0.76	0.76	0.75	1.0	1.0	1.0	1.0
p_3	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
p_4	0.62	0.7	0.62	0.7	0.44	0.7	0.61	0.7	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9
p_5	1.0	1.0	1.0	1.0	0.91	0.91	1.0	1.0	1.0	1.0	1.0	1.0	0.91	0.91	1.0	1.0
p_6	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
p_7	0.4	0.4	0.69	0.69	0.3	0.35	0.69	0.69	0.81	0.81	0.81	0.81	0.81	0.81	0.81	0.81
p_8	0.95	0.9	1.0	1.0	1.0	1.0	1.0	1.0	0.95	0.09	1.0	1.0	1.0	1.0	1.0	1.0
p_9	1.0	1.0	0.33	0.64	1.0	1.0	1.0	1.0	1.0	1.0	0.9	0.9	1.0	1.0	1.0	1.0
p_{10}	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88
p_{11}	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
p_{12}	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
p_{13}	0.55	0.7	0.61	0.7	0.9	0.92	0.91	0.91	0.92	0.92	0.91	0.91	0.92	0.92	0.91	0.91
p_{14}	0.55	0.88	0.88	0.88	0.88	0.7	0.9	0.88	0.88	0.88	0.88	1.0	1.0	1.0	1.0	0.91
p_{15}	0.9	0.9	0.9	0.9	0.88	0.84	0.88	0.45	0.9	0.9	0.9	0.55	0.7	0.61	0.7	0.9
p_{16}	0.62	0.7	0.62	0.7	0.55	0.7	0.61	0.7	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9
p_{17}	1.0	1.0	1.0	1.0	0.91	0.91	1.0	1.0	1.0	1.0	1.0	1.0	0.91	0.91	1.0	1.0
p_{18}	0.8	0.8	0.8	0.8	0.69	0.69	0.65	0.3	0.8	0.8	0.8	0.8	0.72	0.72	0.72	0.72
p_{19}	0.92	1.0	0.18	1.0	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88
p_{20}	0.62	0.7	0.62	0.7	0.55	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.92	1.0	0.18	1.0
p_{21}	1.0	1.0	0.66	0.66	1.0	1.0	1.0	1.0	1.0	1.0	0.9	0.9	1.0	1.0	1.0	1.0
p_{22}	0.92	1.0	0.18	1.0	0.72	0.72	0.72	0.72	0.53	0.53	0.64	0.64	0.53	0.53	0.64	0.64
p_{23}	0.81	1.0	0.92	1.0	0.81	1.0	0.92	1.0	0.18	1.0	0.92	1.0	0.18	1.0	0.92	1.0
p_{24}	0.75	0.75	0.76	0.75	1.0	0.62	0.7	0.62	0.7	0.55	0.76	0.76	1.0	1.0	1.0	1.0
p_{25}	0.92	0.92	0.91	0.91	0.62	0.7	0.62	0.7	0.55	0.92	0.91	0.91	0.92	0.92	0.91	0.91
p_{26}	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.88	0.88	0.88	0.88	1.0	1.0	1.0	1.0
p_{27}	0.62	0.7	0.62	0.7	0.55	0.84	0.88	0.45	0.9	0.9	0.9	0.9	0.88	0.84	0.88	0.54
p_{28}	0.62	0.7	0.62	0.7	0.55	0.7	0.61	0.7	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9
p_{29}	1.0	1.0	1.0	1.0	0.91	0.91	1.0	1.0	1.0	1.0	1.0	1.0	0.91	0.91	1.0	1.0
p_{30}	0.8	0.8	0.8	0.8	0.69	0.69	0.65	0.3	0.8	0.8	0.8	0.62	0.7	0.62	0.7	0.55
p_{31}	0.88	0.88	0.88	0.88	0.62	0.7	0.62	0.7	0.55	0.88	0.88	0.88	0.88	0.88	0.88	0.88
p_{32}	0.55	0.7	0.61	0.7	0.9	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
p_{33}	0.7	0.9	0.9	0.9	0.9	1.0	1.0	1.0	1.0	0.9	0.9	1.0	1.0	1.0	1.0	0.91
p_{34}	0.72	0.72	0.72	0.72	0.72	0.72	0.72	0.72	0.53	0.53	0.64	0.64	0.53	0.53	0.64	0.64
p_{35}	0.81	1.0	0.92	1.0	0.81	1.0	0.92	1.0	0.18	1.0	0.92	1.0	0.18	1.0	0.92	1.0
p_{36}	0.75	0.75	0.76	0.75	1.0	1.0	1.0	1.0	0.75	0.75	0.76	0.76	1.0	1.0	1.0	1.0
p_{37}	0.92	0.92	0.91	0.55	0.7	0.61	0.7	0.9	0.92	0.92	0.91	0.91	0.92	0.92	0.91	0.91
p_{38}	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.88	0.88	0.88	0.88	1.0	1.0	1.0	1.0
p_{39}	0.9	0.9	0.9	0.9	0.88	0.84	0.88	0.45	0.9	0.9	0.9	0.9	0.88	0.84	0.88	0.54
p_{40}	0.62	0.7	0.62	0.7	0.55	0.7	0.61	0.7	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9
p_{41}	1.0	1.0	1.0	1.0	0.91	0.91	1.0	1.0	1.0	1.0	1.0	1.0	0.91	0.91	1.0	1.0
p_{42}	0.8	0.8	0.8	0.8	0.69	0.69	0.65	0.3	0.8	0.8	0.8	0.8	0.72	0.72	0.72	0.72
p_{43}	1.0	1.0	1.0	1.0	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88
p_{44}	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
p_{45}	0.7	0.9	0.9	0.9	0.9	1.0	1.0	1.0	1.0	1.0	0.9	0.9	1.0	1.0	1.0	1.0

Table 22 Fusion fuzzy soft set $(\tilde{I}, Q)$

P	ε_{65}	ε_{66}	ε_{67}	ε_{68}	ε_{69}	ε_{70}	ε_{71}	ε_{72}	ε_{73}	ε_{74}	ε_{75}	ε_{76}	ε_{77}	ε_{78}	ε_{79}	ε_{80}
p_1	0.92	0.92	0.9	0.9	0.92	0.92	0.9	0.9	0.92	0.92	0.41	0.3	0.92	0.92	0.41	0.37
p_2	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.76	0.76	0.4	0.41	1.0	1.0	1.0	1.0
p_3	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
p_4	0.62	0.7	0.62	0.7	0.58	0.7	0.61	0.7	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9
p_5	1.0	1.0	1.0	1.0	0.55	0.88	1.0	1.0	1.0	1.0	1.0	1.0	0.88	0.88	1.0	1.0
p_6	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
p_7	0.4	0.4	0.69	0.69	0.3	0.35	0.69	0.69	0.81	0.81	0.81	0.81	0.81	0.81	0.81	0.81
p_8	0.95	0.9	1.0	1.0	1.0	1.0	1.0	1.0	0.95	0.09	1.0	1.0	1.0	1.0	1.0	1.0
p_9	1.0	1.0	0.33	0.64	1.0	1.0	1.0	1.0	1.0	1.0	0.9	0.9	1.0	1.0	1.0	1.0
p_{10}	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88
p_{11}	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
p_{12}	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
p_{13}	0.88	0.84	0.88	0.45	0.9	0.9	0.91	0.91	0.92	0.92	1.0	1.0	1.0	1.0	0.91	0.91
p_{14}	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.88	0.88	0.88	0.88	1.0	1.0	1.0	1.0
p_{15}	0.9	0.9	0.9	0.9	0.88	0.84	0.88	0.45	0.9	0.9	0.9	0.9	0.88	0.84	0.88	0.54
p_{16}	0.62	0.7	0.62	0.7	0.55	0.7	0.61	0.7	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9
p_{17}	1.0	1.0	1.0	1.0	0.91	0.91	1.0	1.0	1.0	1.0	1.0	1.0	0.91	0.91	1.0	1.0
p_{18}	0.8	0.8	0.8	0.8	0.69	0.69	0.65	0.3	0.8	0.8	0.8	0.8	0.72	0.72	0.72	0.72
p_{19}	1.0	1.0	0.66	0.66	1.0	1.0	1.0	1.0	1.0	1.0	0.9	0.9	1.0	1.0	1.0	1.0
p_{20}	0.53	0.64	0.64	0.53	0.53	0.64	0.64	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
p_{21}	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88
p_{22}	0.72	0.72	0.72	0.72	0.72	0.72	0.72	0.72	0.53	0.53	0.64	0.64	0.53	0.53	0.64	0.64
p_{23}	0.81	1.0	0.92	1.0	0.81	1.0	0.92	1.0	0.18	1.0	0.92	1.0	0.18	1.0	0.92	1.0
p_{24}	0.75	0.75	0.76	0.75	1.0	1.0	1.0	1.0	0.75	0.75	0.76	0.76	1.0	1.0	1.0	1.0
p_{25}	0.53	0.64	0.64	0.53	0.53	0.64	0.64	0.75	0.76	0.76	0.88	0.88	1.0	1.0	1.0	1.0
p_{26}	0.92	0.92	0.91	0.91	0.92	0.92	0.91	0.91	0.92	0.92	0.91	0.91	0.92	0.92	0.91	0.91
p_{27}	0.9	0.9	0.9	0.9	0.88	0.84	0.88	0.45	0.9	0.9	0.9	0.9	0.88	0.84	0.88	0.54
p_{28}	0.62	0.7	0.62	0.7	0.55	0.7	0.61	0.7	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9
p_{29}	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88
p_{30}	0.8	0.8	0.8	0.8	0.69	0.69	0.65	0.3	0.8	0.8	0.8	0.8	0.72	0.72	0.72	0.72
p_{31}	1.0	1.0	1.0	1.0	0.91	0.91	1.0	1.0	1.0	1.0	1.0	1.0	0.91	0.91	1.0	1.0
p_{32}	1.0	1.0	1.0	0.53	0.64	0.64	0.53	0.53	0.64	0.64	1.0	1.0	1.0	1.0	1.0	1.0
p_{33}	1.0	1.0	0.66	0.66	1.0	1.0	1.0	1.0	1.0	1.0	0.9	0.9	1.0	1.0	1.0	1.0
p_{34}	0.53	0.64	0.64	0.53	0.53	0.64	0.64	0.72	0.53	0.53	0.64	0.64	0.53	0.53	0.64	0.64
p_{35}	0.81	1.0	0.92	1.0	0.81	1.0	0.92	1.0	0.18	1.0	0.92	1.0	0.18	1.0	0.92	1.0
p_{36}	0.75	0.75	0.76	0.75	1.0	1.0	1.0	1.0	0.75	0.75	0.76	0.76	1.0	1.0	1.0	1.0
p_{37}	0.9	0.9	0.9	0.9	0.88	0.84	0.88	0.45	0.9	0.9	0.9	0.9	0.88	0.84	0.88	0.54
p_{38}	0.92	0.92	0.91	0.91	0.92	0.92	0.91	0.91	0.92	0.92	0.91	0.91	0.92	0.92	0.91	0.91
p_{39}	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.88	0.69	0.69	0.65	0.3	0.8	1.0	1.0
p_{40}	0.92	0.92	0.91	0.91	0.92	0.7	0.61	0.7	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9
p_{41}	1.0	1.0	1.0	1.0	0.91	0.91	1.0	1.0	1.0	1.0	1.0	1.0	0.91	0.91	1.0	1.0
p_{42}	0.53	0.64	0.64	0.53	0.53	0.64	0.64	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
p_{43}	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88
p_{44}	0.8	0.8	0.8	0.8	0.69	0.69	0.65	0.3	0.8	0.8	0.8	0.8	0.72	0.72	0.72	0.72
p_{45}	1.0	1.0	0.66	0.66	1.0	0.69	0.69	0.65	0.3	0.8	0.9	0.69	0.69	0.65	0.3	0.8

Table 23 Fusion fuzzy soft set $(\tilde{I}, Q)$

P	ε_{81}	ε_{82}	ε_{83}	ε_{84}	ε_{85}	ε_{86}	ε_{87}	ε_{88}	ε_{89}	ε_{90}	ε_{91}	ε_{92}	ε_{93}	ε_{94}	ε_{95}	ε_{96}
p_1	0.92	0.92	0.9	0.9	0.92	0.92	0.9	0.9	0.92	0.92	0.41	0.3	0.92	0.92	0.41	0.37
p_2	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.76	0.76	0.4	0.41	1.0	1.0	1.0	1.0
p_3	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
p_4	0.62	0.7	0.62	0.7	0.44	0.7	0.61	0.7	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9
p_5	1.0	1.0	1.0	1.0	0.55	0.88	1.0	1.0	1.0	1.0	1.0	1.0	0.88	0.88	1.0	1.0
p_6	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
p_7	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9
p_8	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
p_9	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
p_{10}	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88
p_{11}	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
p_{12}	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
p_{13}	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.88	0.88	0.88	0.88	1.0	1.0	1.0	1.0
p_{14}	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.88	0.88	0.88	0.88	1.0	1.0	1.0	1.0
p_{15}	0.9	0.9	0.9	0.9	0.88	0.84	0.88	0.45	0.9	0.9	0.9	0.9	0.88	0.84	0.88	0.54
p_{16}	0.62	0.7	0.62	0.7	0.55	0.7	0.61	0.7	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9
p_{17}	1.0	1.0	1.0	1.0	0.91	0.91	1.0	1.0	1.0	1.0	1.0	1.0	0.91	0.91	1.0	1.0
p_{18}	0.8	0.8	0.8	0.8	0.69	0.69	0.65	0.3	0.8	0.8	0.8	0.8	0.72	0.72	0.72	0.72
p_{19}	0.72	0.72	0.72	0.72	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88
p_{20}	0.8	0.8	0.8	0.72	0.72	0.72	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
p_{21}	1.0	1.0	1.0	1.0	1.0	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88
p_{22}	0.72	0.72	0.72	0.72	0.72	0.72	0.72	0.72	0.53	0.53	0.64	0.64	0.53	0.53	0.64	0.64
p_{23}	0.81	1.0	0.92	1.0	0.81	1.0	0.92	1.0	0.18	1.0	0.92	1.0	0.18	1.0	0.92	1.0
p_{24}	0.75	0.75	0.76	0.75	1.0	1.0	1.0	1.0	0.75	0.75	0.76	0.76	1.0	1.0	1.0	1.0
p_{25}	0.53	0.64	0.64	0.53	0.53	0.92	0.91	0.91	0.92	0.92	0.91	0.91	0.92	0.92	0.91	0.91
p_{26}	0.92	0.92	0.91	0.91	0.92	0.92	0.91	0.91	0.92	0.92	0.91	0.91	0.92	0.92	0.91	0.91
p_{27}	0.9	0.9	0.9	0.9	0.88	0.84	0.88	0.45	0.9	0.9	0.9	0.9	0.88	0.84	0.88	0.54
p_{28}	0.62	0.7	0.62	0.7	0.55	0.7	0.61	0.7	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9
p_{29}	1.0	1.0	1.0	1.0	0.91	0.91	1.0	1.0	1.0	1.0	1.0	1.0	0.91	0.91	1.0	1.0
p_{30}	0.53	0.64	0.64	0.53	0.53	0.69	0.69	0.65	0.3	0.8	0.8	0.8	0.8	0.72	0.72	0.72
p_{31}	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88
p_{32}	0.53	0.64	0.64	0.53	0.53	0.69	0.69	1.0	1.0	1.0	0.8	0.8	0.8	0.72	0.72	0.72
p_{33}	1.0	1.0	0.66	0.66	1.0	1.0	1.0	1.0	1.0	1.0	0.9	0.9	1.0	1.0	1.0	1.0
p_{34}	0.72	0.72	0.72	0.72	0.72	0.72	0.72	0.72	0.53	0.53	0.64	0.64	0.53	0.53	0.64	0.64
p_{35}	0.81	1.0	0.92	1.0	0.81	1.0	0.92	1.0	0.18	1.0	0.92	1.0	0.18	1.0	0.92	1.0
p_{36}	0.75	0.75	0.76	0.75	1.0	1.0	1.0	1.0	0.75	0.75	0.76	0.76	1.0	1.0	1.0	1.0
p_{37}	0.92	0.92	0.91	0.91	0.92	0.92	0.91	0.91	0.92	0.92	0.91	0.91	0.92	0.92	0.91	0.91
p_{38}	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.88	0.88	0.88	0.88	1.0	1.0	1.0	1.0
p_{39}	0.9	0.9	0.9	0.9	0.88	0.84	0.88	0.45	0.9	0.9	0.9	0.9	0.88	0.84	0.88	0.54
p_{40}	1.0	1.0	0.66	0.66	1.0	1.0	1.0	1.0	1.0	1.0	0.9	0.9	1.0	1.0	1.0	1.0
p_{41}	0.62	0.7	0.62	0.7	0.55	0.7	0.61	0.7	0.9	0.9	0.9	0.9	1.0	1.0	1.0	1.0
p_{42}	0.8	0.8	0.8	0.8	0.69	0.69	0.65	0.3	0.8	0.8	0.8	0.8	0.72	0.72	0.72	0.72
p_{43}	1.0	1.0	0.66	0.66	1.0	1.0	1.0	1.0	1.0	1.0	0.9	0.9	1.0	1.0	1.0	1.0
p_{44}	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
p_{45}	0.62	0.7	0.62	0.7	0.55	0.7	0.61	0.7	0.9	0.9	0.9	0.9	1.0	1.0	1.0	1.0

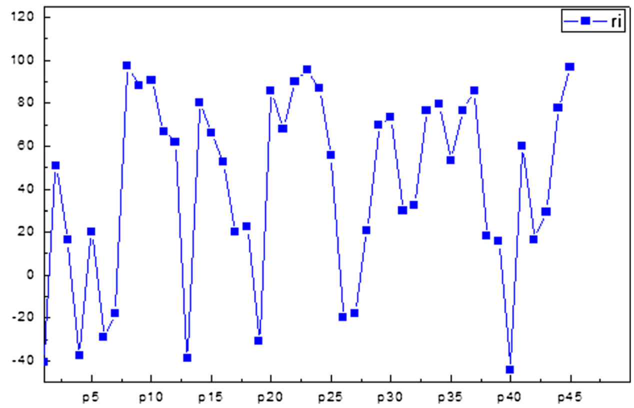

Fig. 22 Relationship between p_i and r_i

and p_{45} have high values of r_i. Consequently, they are potentially suffering from lung cancer disease. Figure 22 shows the relationship between p_i and r_i $(i = 1, 2, 3, \ldots, 45)$.

4.4 Comparison diagnosed

Table 24 shows the decision from specialist doctor for these forty five patients.

The difference between Lavanya's fuzzy inference system and our's lies in the fuzzy counterpart. Table 25 shows the rules of Lavanya's fuzzy inference system (Lavanya et al. 2011) (i.e., Stage 1: when it is located and limited only within the lung or lungs and not spread to the lymph nodes or to other organs, and this stage is considered the best cure rate of the stages; Stage 2: when the tumor is spread through the metastasis to neighboring lymph nodes; Stage 3: when the tumor spread to the lymph nodes in the center of the chest; and final Stage 4, which is the most dangerous stage, which is when the spread of the tumor through the transfer to other organs such as the brain, bone, liver); we replace the fuzzy sets in Lavanya's fuzzy inference system by the fuzzy soft sets.

The first step of Lavanya's fuzzy inference system is determination of input and output assigns. The inputs are accepted through a form designed in JADE and exported to MATLAB in which fuzzy logic toolbox computes the membership function parameters that best allow the fuzzy inference system to track the given input/output data. The system uses Mamdani-type inference system in which the output membership function and the defuzzification process use a centroid method to aggregate the inference of Lavanya's fuzzy inference system. If we use the data from Tables 7, 8, 9 and 10 and apply Lavanya's fuzzy inference system, then we get the results as shown in Table 26.

We must notice the differences of the decision parts in Tables 24 and 26 for patients $p_1, p_3, p_4 - p_7, p_{13}, p_{17} - p_{19}, p_{26} - p_{28}, p_{31}, p_{32}, p_{38} - p_{40}, p_{42}$, and p_{43}. Patients

Table 24 Decision from specialist doctor

P	WL	SHB	CHP	PC	BS	Age	Decision
p_1	3.8	38	48	18	45	55	No cancer
p_2	3.7	40	50	40	44	60	Lung cancer
p_3	5	50	49	33	50	49	No cancer
p_4	4	44	55	45	54	45	No cancer
p_5	4.1	38	60	48	49	48	No cancer
p_6	4.5	54	51	35	52	50	No cancer
p_7	3.7	59	56	39	53	54	No cancer
p_8	3.6	62	60	29	45	66	Lung cancer
p_9	3.9	63	47	44	54	70	Lung cancer
p_{10}	4.4	55	53	57	47	55	Lung cancer
p_{11}	4.8	40	59	50	46	62	Lung cancer
p_{12}	4.6	60	57	59	50	72	Lung cancer
p_{13}	3.7	37	47	16	44	45	No cancer
p_{14}	3.6	39	50	19	50	61	Lung cancer
p_{15}	4.1	42	51	30	47	59	Lung cancer
p_{16}	4.7	44	47	32	53	70	Lung cancer
p_{17}	5	45	49	40	54	48	No cancer
p_{18}	3.7	50	54	42	45	49	No cancer
p_{19}	3.9	55	52	16	47	50	No cancer
p_{20}	4	52	53	20	51	72	Lung cancer
p_{21}	4.1	53	60	22	53	73	Lung cancer
p_{22}	4.7	38	54	24	52	55	Lung cancer
p_{23}	4.5	40	48	27	50	60	Lung cancer
p_{24}	4.2	60	49	29	49	66	Lung cancer
p_{25}	4.9	61	55	37	48	64	Lung cancer
p_{26}	5.1	44	56	49	44	49	No cancer
p_{27}	5.4	43	51	43	47	46	No cancer
p_{28}	5.7	39	57	44	45	54	No cancer
p_{29}	6	38	49	53	44	56	Lung cancer
p_{30}	3.6	43	48	50	54	74	Lung cancer
p_{31}	3.8	41	47	28	49	71	No cancer
p_{32}	3.9	42	60	59	50	46	No cancer
p_{33}	3.8	55	54	48	51	51	Lung cancer
p_{34}	3.9	53	47	55	49	56	Lung cancer
p_{35}	4.7	54	49	56	53	55	Lung cancer
p_{36}	4.8	63	55	18	47	62	Lung cancer
p_{37}	4.9	62	52	21	54	61	Lung cancer
p_{38}	5.1	46	54	25	49	63	No cancer
p_{39}	5.3	47	56	16	50	45	No cancer
p_{40}	5.2	49	57	26	51	49	No cancer
p_{41}	5.5	44	60	25	52	75	Lung cancer
p_{42}	3.7	43	49	39	54	56	No cancer
p_{43}	3.9	40	49	52	48	65	No cancer
p_{44}	4.1	57	55	54	50	55	Lung cancer
p_{45}	4.3	63	56	15	54	59	Lung cancer

Table 25 Rules of Lavanya's fuzzy inference system

No.	WL	SHB	CHP	PC	BS	Stage	Disease
1	VH	VH	VH	VH	VH	4	Lung cancer
2	H	VH	H	VH	VH	4	Lung cancer
3	VH	VH	H	H	VH	4	Lung cancer
4	VH	H	H	VH	H	4	Lung cancer
5	VH	H	H	VH	VH	4	Lung cancer
6	H	H	M	VH	M	3	Lung cancer
7	H	H	M	H	H	3	Lung cancer
8	M	H	M	M	H	3	Lung cancer
9	M	H	M	M	M	2	Lung cancer
10	M	H	M	H	M	1	Lung cancer
11	L	L	M	L	L	Nil	No cancer

p_1, p_{19}, p_{31}, p_{38}, p_{42}, and p_{43} have no lung cancer since all of the patient's six assigns are less than that of patient p_{12}. Patients p_{26}, p_{27}, and p_{28} have significantly less values in the three important assigns compared to that of p_{11}. Also, patients p_4 and p_5 have significantly less value in the five main assigns compared to that of p_{12}. Patients $p_3 - p_5$, p_{13}, p_{17}, p_{18}, p_{32}, p_{39}, and p_{40} have no lung cancer due to their younger ages. All of patient's p_6 three important assigns are fewer than that of p_8. Thus, patient p_6 has no lung cancer. Patient p_7 four important assigns are less than that of patient p_9. Therefore, patient p_7 has no lung cancer.

In contrast to Lavanya's fuzzy inference system, the decision from our fuzzy soft expert system is the same as the decision from specialist doctors. Consequently, our fuzzy soft expert system is demonstrate to furnish a remarkable improvement to that of the fuzzy inference system (Lavanya et al. 2011). As the decision is made by our fuzzy soft expert system without utilization of rules and programming software, there is a space for further improvement.

5 Conclusion and future research

In this research, we developed a fuzzy soft expert system to guess those patients who may suffer lung cancer disease by using weight loss, shortness of breath, chest pain, persistence cough, blood in sputum, and age of patients. Experiment on forty five patients in the Respiratory Department of Nanjing Chest Hospital in China shows the predict result of our system is better than that of fuzzy inference system, where the number of training data taken was 55 records and the remaining 45 records were used for the testing process. The quantized accuracies of the proposed system were found to be 100%. The reason for this should be found out further since fuzzy soft sets were not applied before in the diagnosis of ailments. It would be a work of practical meaning to ver-

Table 26 Proposed Lavanya's fuzzy inference system

P	WL	SHB	CHP	PC	BS	Age	Stage	Decision
p_1	3.8	38	48	18	45	55	3	Lung cancer
p_2	3.7	40	50	40	44	60	4	Lung cancer
p_3	5	50	49	33	50	49	2	Lung cancer
p_4	4	44	55	45	54	45	2	Lung cancer
p_5	4.1	38	60	48	49	48	4	Lung cancer
p_6	4.5	54	51	35	52	50	3	Lung cancer
p_7	3.7	59	56	39	53	54	3	Lung cancer
p_8	3.6	62	60	29	45	66	4	Lung cancer
p_9	3.9	63	47	44	54	70	4	Lung cancer
p_{10}	4.4	55	53	57	47	55	4	Lung cancer
p_{11}	4.8	40	59	50	46	62	4	Lung cancer
p_{12}	4.6	60	57	59	50	72	4	Lung cancer
p_{13}	3.7	37	47	16	44	45	1	Lung cancer
p_{14}	3.6	39	50	19	50	61	4	Lung cancer
p_{15}	4.1	42	51	30	47	59	3	Lung cancer
p_{16}	4.7	44	47	32	53	70	4	Lung cancer
p_{17}	5	45	49	40	54	48	2	Lung cancer
p_{18}	3.7	50	54	42	45	49	2	Lung cancer
p_{19}	3.9	55	52	16	47	50	2	Lung cancer
p_{20}	4	52	53	20	51	72	4	Lung cancer
p_{21}	4.1	53	60	22	53	73	4	Lung cancer
p_{22}	4.7	38	54	24	52	55	3	Lung cancer
p_{23}	4.5	40	48	27	50	60	4	Lung cancer
p_{24}	4.2	60	49	29	49	66	4	Lung cancer
p_{25}	4.9	61	55	37	48	64	4	Lung cancer
p_{26}	5.1	44	56	49	44	49	2	Lung cancer
p_{27}	5.4	43	51	43	47	46	1	Lung cancer
p_{28}	5.7	39	57	44	45	54	3	Lung cancer
p_{29}	6	38	49	53	44	56	3	Lung cancer
p_{30}	3.6	43	48	50	54	74	4	Lung cancer
p_{31}	3.8	41	47	28	49	71	4	Lung cancer
p_{32}	3.9	42	60	59	50	46	1	Lung cancer
p_{33}	3.8	55	54	48	51	51	3	Lung cancer
p_{34}	3.9	53	47	55	49	56	3	Lung cancer
p_{35}	4.7	54	49	56	53	55	3	Lung cancer
p_{36}	4.8	63	55	18	47	62	4	Lung cancer
p_{37}	4.9	62	52	21	54	61	4	Lung cancer
p_{38}	5.1	46	54	25	49	63	4	Lung cancer
p_{39}	5.3	47	56	16	50	45	1	Lung cancer
p_{40}	5.2	49	57	26	51	49	2	Lung cancer
p_{41}	5.5	44	60	25	52	75	4	Lung cancer
p_{42}	3.7	43	49	39	54	56	3	Lung cancer
p_{43}	3.9	40	49	52	48	65	4	Lung cancer
p_{44}	4.1	57	55	54	50	55	3	Lung cancer
p_{45}	4.3	63	56	15	54	59	4	Lung cancer

ify our systems by more experiments (because this system can also be used to the similar case, for example, to predict cancer of the breast, colon, and liver). The proposed fuzzy soft expert system approach is better than the fuzzy inference system in the sense that the former approach does not depend on configuration rules which vary according to the number of parameters leading to different results, as does the latter. Our proposed method is easy since it does not require the utilization of programming software such as MATLAB as required by fuzzy inference system (Farahani et al. 2015; Lavanya et al. 2011; Bagherieh et al. 2013). Therefore, the fuzzy soft expert system can be performed quickly, without risk compared to traditional diagnostic systems, highly reliable, and can be easily taught to be utilized by medical students. This proposed methodology is a suitable tool to diagnose lung cancer diseases, since it provides an interpretable model that can be easily comprehended by doctors (even aged people, including senior researchers who are interested to prevention and control of cancer-like diseases). Our subsequent work is to investigate those people (in hospitals, centers for disease control, or nursing homes relaying on the Traditional Chinese Medicine) who have experiences in prevention and control of cancer-like diseases to make our study more practicable. In addition, we will extend the knowledge-based system by integrating our approach of fuzzy soft expert system into other fields. For instance, in industrial, we will apply fuzzy soft expert system for aluminum electrolysis instead of fuzzy expert system (Cao et al. 2011) and similarly in management sphere, as the fuzzy expert system for business management (Arias-Aranda et al. 2010).

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Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

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