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A comparative study for medical diagnosis of prostate cancer

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Abstract: In recent years great attention has been paid to studies on artificial intelligence since it can be applied easily to several areas like medical diagnosis, engineering and economics, among others. In this paper we present an example in medicine which aims to find the patients with high prostate cancer risk using a multi-criteria decision making method. Also we compare this method with another method which we studied before. We discuss which method is more convenient. Our datas are prostate specific antigen (PSA), free prostate specific antigen (fPSA), prostate volume (PV) and age factors of 78 patients from Selcuk University Meram Medicine Faculty.

Keywords: Uncertainty modelling, multi-criteria decision making, prostate cancer, Fuzzy TOPSIS, soft covering approximations.

1 Introduction

We can not solve the problems by using mathematical tools generally in the social life since in mathematics the concepts are precise and not subjective. Some theories were developed to eliminate this lack of vagueness such as fuzzy set theory [28] and rough set theory [17]. But all of these theories have their own difficulties. Soft set theory [15] is introduced by Molodtsov as a new approach to the vagueness and based on parametrization operation. It is shown that this new theory is free from some difficultness seen most useful theories of fuzzy set and rough set. In a short time the theory gave rise to many researchers and applications. Since soft set is more general concept than fuzzy set, the researchers lean to solve the problems by soft sets.

Chen [5] extended the concept of TOPSIS (Technique for order performance by similarity to ideal solution) [10] to develop a methodology for solving multi-person multi-criteria decision making problems in fuzzy environment. De et al. [6] studied Sanchez's [20,21] method of medical diagnosis using an intuitionistic fuzzy set. Feng [9] discussed soft set based group decision making in 2011. This study can be seen as a first attempt toward the possible application of soft rough approximations in multi-criteria group decision making under vagueness. Çelik and Yamak [4] applied fuzzy soft set theory through well-known Sanchez's approach for medical diagnosis using fuzzy arithmetic operations. In [27], soft set theory was introduced into grey system theory to solve multi-attribute decision making problems in which evaluation attribute sets are different and evaluation decision making values are interval grey numbers.

Yüksel et al. [25] used soft covering approximations at Feng's method and they presented an example in medicine which aims to obtain the optimal choice for applying biopsy to the patients with prostate cancer risk.

Prostate cancer is the second most common cause of cancer death among men in most industrialized countries. It depends on various factors as family's cancer history, age, ethnic background, and the level of prostate specific antigen (PSA) in the blood. Since PSA is a substance produced by the prostate, it is very important factor to an initial diagnosis

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for patients [3,23,24]. As known, when the prostate cancer can be diagnosed earlier, the patient can be completely treated. The definitive diagnosis of the prostate cancer is possible with prostate biopsy. The results of PSA test, rectal examination, and transrectal findings help the doctor to decide whether biopsy is necessary or not [14,16,22]. However the datas of the level of PSA, fPSA, the age of patient and the prostate volume can give an idea to the doctor about the cancer risk. If the risk is low then the biopsy operation which has high cost and possible complications, is unnecessary.

There are several researches in the area of the prostate cancer prognosis or diagnosis. One of them is FES which is a rule-based fuzzy expert system using the laboratory datas PSA, PV and age of the patient and aim to help to an expert-doctor to determine the necesssity of biopsy and the risk factor [18]. Benecchi [1] developed a neuro-fuzzy system by using both serum data (total prostate specific antigen and free prostate specific antigen) and clinical data (age of patients) to enhance the performance of tPSA (total prostate specific antigen) to distinguish prostate cancer. Keles et al. [12] built a neuro-fuzzy classifier to be used in the diagnosis of prostate cancer and BPH diseases. Since the symptoms of these two illness are very close to each other the differentiation between them is an important problem. Saritas et al. [19] have devised an artifical neural network that provides a prognostic result indicating whether patients have cancer or not by using their free prostate specific antigen, total prostate specific antigen and age data. Yuksel et al. [26] devised a prediction system named soft expert system (SES) by using the prostate specific antigen (PSA), prostate volume (PV) and age factors of patients based on fuzzy sets and soft sets.

In this study, we apply Chen's method to a medicine problem calculating the risk of prostate cancer and we compare the obtained results with an other method's results given by us [25]. For this process, it is used as laboratory data, prostate specific antigen (PSA), free prostate specific antigen (fPSA), prostate volume (PV) and age of the patient.

2 Preliminaries

In this section, we briefly give some basic definitions of fuzzy sets, soft sets, fuzzy soft sets and soft covering based rough sets.

Definition 1. [28] *A fuzzy set $\widetilde{A}$ in a universe of discourse U is characterized by a membership function $\mu_{\widetilde{A}}(x)$ which associates with each element x in U a real number in the interval $[0,1]$. The function value $\mu_{\widetilde{A}}(x)$ is termed the grade of membership of x in $\widetilde{A}$. The family of all fuzzy subsets of U is denoted by $P(U)$.*

Definition 2. [11].

(1) A fuzzy set $\widetilde{A}$ on the universe of discourse U is convex if and only if for $a,b \in U$, $\mu_{\widetilde{A}}(\alpha a+\beta b) \geq \mu_{\widetilde{A}}(a) \wedge \mu_{\widetilde{A}}(b)$, where $\alpha+\beta=1$.
(2) A fuzzy set $\widetilde{A}$ on the universe of discourse U is called a normal fuzzy set if there exist $a_i \in U$ such that $\mu_{\widetilde{A}}(a_i)=1$.
(3) A fuzzy number is a fuzzy subset in the universe of discourse U which is both convex and normal.

A triangular fuzzy number $\widetilde{n}$ can be defined by a triplet (a,b,c). The membership function $\mu_{\widetilde{n}}(x)$ is defined as [11]:

$$\mu_{\widetilde{n}}(x)=\begin{cases} 0, & x<a, \\ \frac{x-a}{b-a}, & a\leq x\leq b, \\ \frac{x-c}{b-c}, & b\leq x\leq c, \\ 0, & x>c. \end{cases}$$

Let $\widetilde{m}=(m_1,m_2,m_3)$ and $\widetilde{n}=(n_1,n_2,n_3)$ be two triangular fuzzy numbers. Then addition and multiplication of $\widetilde{m}$ and $\widetilde{n}$ as given in [11] are

$$\widetilde{m}\oplus\widetilde{n}=(m_1,m_2,m_3)\oplus(n_1,n_2,n_3)=(m_1+n_1,m_2+n_2,m_3+n_3)$$

and

$$\widetilde{m} \otimes \widetilde{n} = (m_1, m_2, m_3) \otimes (n_1, n_2, n_3) = (m_1 \times n_1, m_2 \times n_2, m_3 \times n_3).$$

Definition 3. [2] *$\widetilde{D}$ is called a fuzzy matrix, if at least an entry in $\widetilde{D}$ is a fuzzy number.*

Definition 4. [29] *A linguistic variable is a variable whose values are linguistic terms.*

The concept of linguistic variable is very useful in dealing with situations which are too complex or too ill-defined to be reasonably described in conventional quantitative expressions [29].

Definition 5. [5] *Let $\widetilde{m} = (m_1, m_2, m_3)$ and $\widetilde{n} = (n_1, n_2, n_3)$ be two triangular fuzzy numbers, then the vertex method is defined to calculate the distance between them as*

$$d(\widetilde{m}, \widetilde{n}) = \sqrt{\frac{1}{3}[(m_1 - n_1)^2 + (m_2 - n_2)^2 + (m_3 - n_3)^2]}.$$

Let U be an initial universe set and E be the set of all possible parameters with respect to U. Usually, parameters are attributes, characteristics or properties of the objects in U. The notion of a soft set is defined as follows:

Definition 6. [15] *A pair $G = (F, A)$ is called a soft set over U, where $A \subseteq E$ and $F : A \longrightarrow P(U)$ is a set-valued mapping.*

Definition 7. [13] *Let U be a common universe, E be a set of parameters and $A \subseteq E$. Then a pair (F, A) is called a fuzzy soft set over U, where F is a mapping given by $F : A \longrightarrow P(U)$.*

Definition 8. [8] *A soft set $G = (F, A)$ over U is called a full soft set if $\underset{a \in A}{\cup} F(a) = U$.*

Definition 9. [7] *A full soft set $G = (F, A)$ over U is called a covering soft set if $F(a) \neq \emptyset$, $\forall a \in A$.*

Definition 10. [25] *Let $G = (F, A)$ be a covering soft set over U. We call the ordered pair $S = (U, C_G)$ a soft covering approximation space.*

Definition 11. [25] *Let $S = (U, C_G)$ be a soft covering approximation space, $x \in U$, the soft minimal description of x is defined as*

$$Md_S(x) = \{F(e) : e \in A \wedge x \in F(e) \wedge (\forall a \in A \wedge x \in F(a) \subseteq F(e) \Longrightarrow F(a) = F(e))\}.$$

Definition 12. [25] *Let $S = (U, C_G)$ be a soft covering approximation space. For a set $X \subseteq U$, the soft covering lower and upper approximations are respectively defined as*

$$S_-(X) = \cup \{F(e) : e \in A \wedge F(e) \subseteq X\}$$
$$S^-(X) = \cup \{Md_S(x) : x \in X\}.$$

In addition, $POS_S(X) = S_-(X), NEG_S(X) = U - S^-(X), BND_S(X) = S^-(X) - S_-(X)$ are called the soft covering positive, negative and boundary regions of X, respectively.

Definition 13. *Let $S = (U, C_G)$ be a soft covering approximation space. A subset $X \subseteq U$ is called soft covering based definable if $S_-(X) = S^-(X)$; in the opposite case, i.e., if $S_-(X) \neq S^-(X)$, X is said to be a soft covering based rough set.*

3 Methods

Method 1. In [25], we give a multi-criteria group decision making method using soft covering approximations at Feng's method [9]. This method can be summarized as follows:

Step 1: Input the original description soft set $G = (F, A)$.

Step 2: Construct the evaluation soft set $G_1 = (V,T)$ using the primary evaluation results of the expert group T.

Step 3: Compute soft covering approximations and then obtain the soft sets $G_{1\_} = (V_-,T)$ and $G_1^- = (V^-,T)$.

Step 4: Compute the corresponding fuzzy sets μ_{G_1}, $\mu_{G_{1\_}}$ and $\mu_{G_1^-}$ of the soft sets $G_1 = (V,T)$, $G_{1\_} = (V_-,T)$ and $G_1^- = (V^-,T)$.

Step 5: Construct the fuzzy soft set $G_F = (\alpha,C)$ using the fuzzy soft sets $\mu_{G_{1\_}}$, μ_{G_1} and $\mu_{G_1^-}$.

Step 6: Input the weighting vector R and compute the weighted evaluation values $v(u_k)$ of each alternative $u_k \in U$. Then rank all the alternatives according to their weighted evaluation values; one can select any of the objects with the largest weighted evaluation value as the most preferred alternative.

We use this method to help to doctors for diagnosing the prostate cancer risk.

Method 2. Chen [5] give a systematic approach to extend the TOPSIS to the fuzzy environment. We apply this method to a medicine problem to obtain the optimal choice for applying biopsy to the patients with prostate cancer risk.

Assume that there is a set of m patients $U = \{u_1,u_2,...,u_m\}$ with a set of n symptoms $S = \{s_1,s_2,...,s_n\}$ for prostate cancer.

Step 1: Form a committee of doctors, then identify the evaluation symptoms.

Step 2: Choose the appropriate linguistic variables for the importance weight of the symptom and the linguistic ratings for patients with respect to symptom.

Step 3: Aggregate the weight of symptom to get the aggregated fuzzy weight $\widetilde{w}_j$ of symptom s_j and pool the doctors' opinions to get the aggregated fuzzy rating $\widetilde{p}_{i\ j}$ of patient u_i under symptom s_j.

Assume that a decision group has K doctors, then the importance of the symptom and the rating of patients with respect to each criterion can be calculated as

$$\widetilde{p}_{i\ j} = \frac{1}{K}[(\widetilde{p}_{i\ j}^{\,1}) + (\widetilde{p}_{i\ j}^{\,2}) + ... + (\widetilde{p}_{i\ j}^{\,K})]$$
$$\widetilde{w}_j = \frac{1}{K}[(\widetilde{w}_j^{\,1}) + (\widetilde{w}_j^{\,2}) + ... + (\widetilde{w}_j^{\,K})]$$

where $\widetilde{x}_{i\ j}^{\,K}$ and $\widetilde{w}_j^{\,K}$ are the rating and the importance weight of the Kth decision maker.

Step 4: Construct the fuzzy decision matrix P, called patient-symptom matrix, where the entries are triangular fuzzy numbers $\widetilde{p} = (a_{i\ j}, b_{i\ j}, c_{i\ j})$. Thus the general form of P is

$$P = \begin{array}{c} \\ u_1 \\ u_2 \\ u_3 \\ \vdots \\ u_m \end{array} \begin{array}{c} \begin{array}{cccc} s_1 & s_2 & s_3 & s_n \end{array} \\ \begin{bmatrix} \widetilde{p}_{11} & \widetilde{p}_{12} & \widetilde{p}_{13} & \cdots & \widetilde{p}_{1n} \\ \widetilde{p}_{21} & \widetilde{p}_{22} & \widetilde{p}_{23} & \cdots & \widetilde{p}_{2n} \\ \widetilde{p}_{31} & \widetilde{p}_{32} & \widetilde{p}_{33} & \cdots & \widetilde{p}_{3n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \widetilde{p}_{m1} & \widetilde{p}_{m2} & \widetilde{p}_{m3} & \cdots & \widetilde{p}_{mn} \end{bmatrix} \end{array}$$

Then obtain the normalized patient-symptom matrix R. Thus the general form of R is

$$R = [\widetilde{r}_{i\ j}]_{m\times n}$$

where $\widetilde{r}_{i\,j} = (\frac{a_{i\,j}}{c_j^*}, \frac{b_{i\,j}}{c_j^*}, \frac{c_{i\,j}}{c_j^*})$, $j \in S$; $c_j^* = \max_i c_{ij}$.

The normalization method mentioned above is to preserve the property that the ranges of normalized triangular fuzzy numbers belong to $[0,1]$.

Step 5: Construct the weighted normalized fuzzy decision matrix Q, called symptom-weight matrix, where the entries are triangular fuzzy numbers $\widetilde{w}$. W is the set of importance weights of symptoms.

$$Q = \begin{array}{c} \\ s_1 \\ s_2 \\ s_3 \\ \vdots \\ n \end{array} \begin{array}{c} W \\ \begin{bmatrix} \widetilde{w}_1 \\ \widetilde{w}_2 \\ \widetilde{w}_3 \\ \vdots \\ \widetilde{w}_n \end{bmatrix} \end{array}$$

Step 6: Perform the transformation operation $R \otimes Q$ to get the weighted normalized patient-symptom matrix as

$$\widetilde{V} = [\widetilde{v}_{i\,j}]_{m\times n},\ i = 1,2,...,m;\ j = 1,2,...,n$$

where $\widetilde{v}_{i\,j} = \widetilde{r}_{i\,j}.\widetilde{w}_j$.

Step 7: Determine $(FPIS, A^*)$ (fuzzy positive-ideal solution) and $(FNIS, A^-)$ (fuzzy negative-ideal solution).

$$A^* = (\widetilde{v}_1^*, \widetilde{v}_2^*, ..., \widetilde{v}_n^*),$$
$$A^- = (\widetilde{v}_1^-, \widetilde{v}_2^-, ..., \widetilde{v}_n^-)$$

where $\widetilde{v}_j^* = (1,1,1)$ and $\widetilde{v}_j^- = (0,0,0),\ j = 1,2,...,n$.

Step 8: Calculate the distance of each alternative from $FPIS$ and $FNIS$, respectively.

The distance of each alternative from A^* and A^- can be currently calculated as

$$d_i^* = \sum_{j=1}^{n} d(\widetilde{v}_{i\,j}, \widetilde{v}_j^*),\ i = 1,2,...,m;$$
$$d_i^- = \sum_{j=1}^{n} d(\widetilde{v}_{i\,j}, \widetilde{v}_j^-),\ i = 1,2,...,m$$

where $d(\cdot,\cdot)$ the distance measurement between two fuzzy numbers.

Step 9: Calculate the closeness coefficient of each alternative.

A closeness coefficient is defined to determine the ranking order of all alternatives once the d_i^* and d_i^- of each alternative A_i $(i = 1,2,...,m)$ has been calculated. The closeness coefficient of each alternative is calculated as

$$CC_i = \frac{d_i^-}{d_i^* + d_i^-},\ i = 1,2,...,m.$$

Obviously, an alternative A_i is closer to the $FPIS$ (A^*) and farther from $FNIS$ (A^-) as CC_i approaches to 1. According to the closeness coefficient, the doctors can evaluate patients who are under high degree prostate cancer risk. So the doctors decide that the biopsy is necessary for which patients.

4 Numerical Example

In this work, we aim to obtain the optimal choice for applying biopsy to the patients with prostate cancer risk by using the PSA, fPSA, Volume (PV) and Age data of patients. We choose 78 patients from Selcuk University Medicine Faculty with prostate complaint as the data (see Table 1).

Table 1: The input PSA, fPSA, PV and age values of severel patients.

	PSA	fPSA	PV	Age
u_{15}	81	21	43	68
u_{30}	27	7	28	51
u_{45}	82	22	24	75
u_{60}	96	23	32	65
u_{75}	83	20	47	75

Method 1. $U = \{u_k : k = 1,...,78\}$ be the universe, $A = \{PSA, fPSA, Volume, Age\}$ be the set of parameters and $T = \{T_{d_1}, T_{d_2}, T_{d_3}\}$ be the specialist doctors group who evaluate the patients with respect to the parameters. For simplicity, we assume that the evaluations of these specialists in T are of the same importance.

In this study, we have the results as follow:

$$\begin{aligned}
u_1 =& u_4 = u_6 = u_7 = u_9 = u_{11} = u_{13} = u_{15} = u_{16} = u_{18} = u_{20} = u_{22} = u_{23} = u_{25} = u_{26} = \\
u_{28} =& u_{29} = u_{31} = u_{33} = u_{34} = u_{36} = u_{37} = u_{39} = u_{40} = u_{42} = u_{43} = u_{45} = u_{46} = u_{47} = u_{48} = \\
u_{49} =& u_{52} = u_{53} = u_{55} = u_{56} = u_{58} = u_{60} = u_{62} = u_{64} = u_{66} = u_{68} = u_{70} = u_{72} = u_{73} = u_{75} = \\
u_{77} =& 0.83 > u_{41} = u_{51} = 0.75 > u_{19} = u_{74} = 0.67 > u_2 = u_{78} = 0.58 > u_{63} = u_{71} = 0.5 > \\
u_3 =& u_8 = u_{17} = u_{24} = u_{54} = u_{67} = u_{76} = 0.42 > u_5 = u_{10} = u_{12} = u_{14} = u_{21} = u_{27} = u_{32} = \\
u_{35} =& u_{38} = u_{44} = u_{50} = u_{61} = u_{65} = u_{69} = 0.25 > u_{30} = u_{57} = u_{59} = 0
\end{aligned}$$

By using these values and in the light of expert doctor's suggestions we get rules as follow.

Rule-1: If a patient has 0.83 as a weighted evaluation value, then this patient is under high degree cancer risk. Hence they need biopsy exactly.

Rule-2: If a patient has 0.75 as a weighted evaluation value, then this patient should be followed up by the doctor.

Rule-3: The other patients are under low risk and they do not need biopsy.

Now we can give the rule sets:

$$\begin{aligned}
R_1 =& \{u_1, u_4, u_6, u_7, u_9, u_{11}, u_{13}, u_{15}, u_{16}, u_{18}, u_{20}, u_{22}, u_{23}, u_{25}, u_{26}, u_{28}, u_{29}, u_{31}, u_{33}, u_{34}, u_{36}, u_{37}, u_{39}, u_{40}, u_{42}, u_{43}, u_{45}, u_{46}, \\
& u_{47}, u_{48}, u_{49}, u_{52}, u_{53}, u_{55}, u_{56}, u_{58}, u_{60}, u_{62}, u_{64}, u_{66}, u_{68}, u_{70}, u_{72}, u_{73}, u_{75}, u_{77}\} \\
R_2 =& \{u_{41}, u_{51}\} \\
R_3 =& \{u_{19}, u_{74}, u_2, u_{78}, u_{63}, u_{71}, u_3, u_8, u_{17}, u_{24}, u_{54}, u_{67}, u_{76}, u_5, u_{10}, u_{12}, u_{14}, u_{21}, u_{27}, u_{32}, u_{35}, u_{38}, u_{44}, u_{50}, u_{61}, u_{65}, \\
& u_{69}, u_{30}, u_{57}, u_{59}\}
\end{aligned}$$

Method 2. $U = \{u_k : k = 1,...,78\}$ be the set of patients.

Step 1: Consider the set $D = \{D1, D2, D3, D4\}$ as a committee of doctors and the set of symptoms $S = \{$PSA, fPSA,

Volume, Age}.

Step 2: The doctors use the linguistic weighting variables (see Table 2) to assess the importance of the symptoms.

Table 2: Linguistic variables for the importance weight of each symptom.

Very low (VL)	$(0,0,0.2)$
Low (L)	$(0,0.2,0.4)$
Medium (M)	$(0.3,0.5,0.7)$
High (H)	$(0.8,0.8,1)$
Very high (VH)	$(0.8,1,1)$

The doctors use the linguistic rating variables (see Table 3) to evaluate the rating of patients with respect to each symptom.

Table 3: Linguistic variables for the ratings.

Very low (VL)	$(0,0,2)$
Low (L)	$(0,2,4)$
Medium (M)	$(3,5,7)$
High (H)	$(6,8,10)$
Very high (VH)	$(8,10,10)$

Step 3: Calculate the importance of the symptoms and the rating of patients with respect to each symptom (see Table 4 and Table 5).

Table 4: The importance weight of the symptoms.

	$D1$	$D2$	$D3$	$D4$
PSA	(0.9,1,1)	(0.5,0.7,0.9)	(0.5,0.7,0.9)	(0.3,0.5,0.7)
fPSA	(0.5,0.7,0.9)	(0.9,1,1)	(0.3,0.5,0.7)	(0.5,0.7,0.9)
Volume	(0.3,0.5,0.7)	(0.5,0.7,0.9)	(0.9,1,1)	(0.3,0.5,0.7)
Age	(0.5,0.7,0.9)	(0.3,0.5,0.7)	(0.3,0.5,0.7)	(0.9,1,1)

Step 4: Construct the fuzzy decision matrix P which is called patient-symptom matrix.

$$P = \begin{array}{c} \\ \vdots \\ u_{15} \\ \vdots \\ u_{30} \\ \vdots \\ u_{45} \\ \vdots \\ u_{60} \\ \vdots \\ u_{75} \\ \vdots \end{array} \begin{array}{c} \begin{array}{cccc} \textit{PSA} & \textit{fPSA} & \textit{Volume} & \textit{Age} \end{array} \\ \begin{bmatrix} \vdots & \vdots & \vdots & \vdots \\ (5.75,7.75,9.25) & (7.75,9.5,10) & (5,7,8.5) & (7.25,9,10) \\ \vdots & \vdots & \vdots & \vdots \\ (0,0.5,2.5) & (0,0.5,2.5) & (2.25,4.25,6.25) & (0.75,1.75,3.75) \\ \vdots & \vdots & \vdots & \vdots \\ (5.75,7.75,9.25) & (7.75,9.5,10) & (2.25,4.25,6.25) & (8.5,10,10) \\ \vdots & \vdots & \vdots & \vdots \\ (8.25,10,10) & (8.25,10,10) & (2.25,4.25,6.25) & (7.25,9,10) \\ \vdots & \vdots & \vdots & \vdots \\ (5.75,7.75,9.25) & (0.55,0.725,0.875) & (0.5,0.675,0.825) & (0.5,0.675,0.825) \\ \vdots & \vdots & \vdots & \vdots \end{bmatrix} \end{array}$$

Table 5: The ratings of several patients by doctors under all symptoms.

Symptoms	Patients	Doctors			
		D1	D2	D3	D4
PSA	u_{15}	(8,10,10)	(6,8,10)	(6,8,10)	(3,5,7)
	u_{30}	(0,2,4)	(0,0,2)	(0,0,2)	(0,0,2)
	u_{45}	(8,10,10)	(6,8,10)	(6,8,10)	(3,5,7)
	u_{60}	(9,10,10)	(8,10,10)	(8,10,10)	(8,10,10)
	u_{75}	(8,10,10)	(6,8,10)	(6,8,10)	(3,5,7)
fPSA	u_{15}	(8,10,10)	(9,10,10)	(6,8,10)	(8,10,10)
	u_{30}	(0,0,2)	(0,2,4)	(0,0,2)	(0,0,2)
	u_{45}	(8,10,10)	(9,10,10)	(6,8,10)	(8,10,10)
	u_{60}	(8,10,10)	(9,10,10)	(8,10,10)	(8,10,10)
	u_{75}	(8,10,10)	(9,10,10)	(6,8,10)	(8,10,10)
Volume	u_{15}	(3,5,7)	(6,8,10)	(8,10,10)	(3,5,7)
	u_{30}	(0,2,4)	(3,5,7)	(6,8,10)	(0,2,4)
	u_{45}	(0,2,4)	(3,5,7)	(6,8,10)	(0,2,4)
	u_{60}	(0,2,4)	(3,5,7)	(6,8,10)	(0,2,4)
	u_{75}	(3,5,7)	(6,8,10)	(8,10,10)	(3,5,7)
Age	u_{15}	(8,10,10)	(6,8,10)	(6,8,10)	(9,10,10)
	u_{30}	(0,2,4)	(0,0,2)	(0,0,2)	(3,5,7)
	u_{45}	(9,10,10)	(8,10,10)	(8,10,10)	(9,10,10)
	u_{60}	(8,10,10)	(6,8,10)	(6,8,10)	(9,10,10)
	u_{75}	(9,10,10)	(8,10,10)	(8,10,10)	(9,10,10)

Then obtain the normalized patient-symptom matrix R.

$$R = \begin{array}{c} \\ \vdots \\ u_{15} \\ \vdots \\ u_{30} \\ \vdots \\ u_{45} \\ \vdots \\ u_{60} \\ \vdots \\ u_{75} \\ \vdots \end{array} \begin{array}{c} \begin{array}{cccc} PSA & fPSA & Volume & Age \end{array} \\ \begin{bmatrix} \vdots & \vdots & \vdots & \vdots \\ (0.575,0.775,0.925) & (0.775,0.95,1) & (0.5,0.7,0.85) & (0.725,0.9,1) \\ \vdots & \vdots & \vdots & \vdots \\ (0,0.05,0.25) & (0,0.05,0.25) & (0.225,0.425,0.625) & (0.075,0.175,0.375) \\ \vdots & \vdots & \vdots & \vdots \\ (0.575,0.775,0.925) & (0.775,0.95,1) & (0.225,0.425,0.625) & (0.85,1,1) \\ \vdots & \vdots & \vdots & \vdots \\ (0.825,1,1) & (0.825,1,1) & (0.225,0.425,0.625) & (0.725,0.9,1) \\ \vdots & \vdots & \vdots & \vdots \\ (0.575,0.775,0.925) & (0.775,0.95,1) & (0.5,0.7,0.85) & (0.85,1,1) \\ \vdots & \vdots & \vdots & \vdots \end{bmatrix} \end{array}$$

Step 5: Construct the weighted normalized fuzzy decision matrix Q which is called symptom-weight matrix

$$Q = \begin{array}{c} \\ PSA \\ fPSA \\ Vol \\ Age \end{array} \begin{array}{c} W \\ \begin{bmatrix} (0.55,0.725,0.875) \\ (0.55,0.725,0.875) \\ (0.5,0.675,0.825) \\ (0.5,0.675,0.825) \end{bmatrix} \end{array}$$

Step 6: Perform the transformation operation $R \otimes Q$ to get the weighted normalized patient-symptom matrix $\tilde{V}$.

$$\widetilde{V} = \begin{array}{c} \\ \vdots \\ u_{15} \\ \vdots \\ u_{30} \\ \vdots \\ u_{45} \\ \vdots \\ u_{60} \\ \vdots \\ u_{75} \\ \vdots \end{array} \begin{array}{c} \begin{array}{cccc} PSA & fPSA & Volume & Age \end{array} \\ \begin{bmatrix} \vdots & \vdots & \vdots & \vdots \\ (0.32,0.56,0.81) & (0.43,0.69,0.88) & (0.25,0.47,0.70) & (0.36,0.61,0.83) \\ \vdots & \vdots & \vdots & \vdots \\ (0,0.04,0.22) & (0,0.04,0.22) & (0.11,0.29,0.52) & (0.04,0.12,0.31) \\ \vdots & \vdots & \vdots & \vdots \\ (0.32,0.56,0.81) & (0.43,0.69,0.88) & (0.11,0.29,0.52) & (0.43,0.68,0.83) \\ \vdots & \vdots & \vdots & \vdots \\ (0.45,0.73,0.88) & (0.45,0.73,0.88) & (0.11,0.29,0.52) & (0.36,0.61,0.83) \\ \vdots & \vdots & \vdots & \vdots \\ (0.32,0.56,0.81) & (0.43,0.69,0.88) & (0.25,0.47,0.70) & (0.43,0.68,0.83) \\ \vdots & \vdots & \vdots & \vdots \end{bmatrix} \end{array}$$

Step 7: Determine $FPIS$ and $FNIS$ as

$$A^* = [(1,1,1),(1,1,1),(1,1,1),(1,1,1)],$$
$$A^- = [(0,0,0),(0,0,0),(0,0,0),(0,0,0)].$$

Step 8: Calculate the distance of each patient from $FPIS$ and $FNIS$, respectively (see Table 6).

Step 9: Calculate the closeness coefficient of each patient (see Table 6).

Table 6: The distance measurement and closeness coefficient of several patients.

	d^*	d^-	CC_i
u_{15}	1.862766	2.427228	0.565788
u_{30}	3.400914	0.801075	0.190642
u_{45}	1.964582	2.306468	0.540024
u_{60}	1.877971	2.398371	0.560846
u_{75}	1.809027	2.464637	0.576704

According to the closeness coefficient, the ranking order of the 78 patients is

$$u_{43} > u_{52} > u_{72} > u_{29} > u_{55} > u_{13} > u_{70} > u_{40} > u_{36} > u_{42} > u_{16} > u_{11} > u_{28} = u_{75} > u_{33} = u_{64} > u_{25} > u_{26} > u_{48} > u_{23} > u_{15} > u_{58} = u_{60} > u_{68} > u_{53} > u_7 > u_{45} > u_{66} > u_{20} > u_{73} > u_{46} > u_{37} > u_{39} > u_{34} > u_{18} > u_{74} > u_{31} > u_9 > u_{22} > u_{56} > u_{78} > u_1 = u_4 = u_{49} = u_{62} = u_{77} > u_6 > u_{35} > u_{63} > u_{47} > u_{32} = u_{51} = u_{76} > u_{19} > u_2 > u_{41} > u_{24} > u_8 = u_{17} > u_{71} > u_{54} > u_{10} > u_{61} > u_3 = u_{21} = u_{65} = u_{67} > u_5 > u_{14} > u_{27} = u_{44} > u_{12} = u_{50} = u_{69} > u_{57} > u_{38} > u_{30} > u_{59}$$

By using these values and in the light of expert doctor's suggestions we get rules as follow.

Rule-1: If a patient has 0.475 and up as a closeness coefficient value, then this patient is under high degree cancer risk. Hence they need biopsy exactly.

Rule-2: If a patient has a closeness coefficient value between 0.460 and 0.475, then this patient should be followed up by the doctor.

Rule-3: The other patients are under low risk and they do not need biopsy.

Now we can give the rule sets:

$$R_1 = \{u_{43}, u_{52}, u_{72}, u_{29}, u_{55}, u_{13}, u_{70}, u_{40}, u_{36}, u_{42}, u_{16}, u_{11}, u_{28}, u_{75}, u_{33}, u_{64}, u_{25}, u_{26}, u_{48}, u_{23}, u_{15}, u_{58}, u_{60}, u_{68}, u_{53}, u_7, u_{45}, u_{66}, u_{20}, u_{73}, u_{46}, u_{37}, u_{39}, u_{34}, u_{18}, u_{74}, u_{31}, u_9, u_{22}, u_{56}, u_{78}, u_1, u_4, u_{49}, u_{62}, u_{77}\}$$

$$R_2 = \{u_6, u_{35}, u_{63}, u_{47}\}$$

$$R_3 = \{u_{32}, u_{51}, u_{76}, u_{19}, u_2, u_{41}, u_{24}, u_8, u_{17}, u_{71}, u_{54}, u_{10}, u_{61}, u_3, u_{21}, u_{65}, u_{67}, u_5, u_{14}, u_{27}, u_{44}, u_{12}, u_{50}, u_{69}, u_{57}, u_{38}, u_{30}, u_{59}\}$$

5 Conclusion

After the biopsy operation in Medicine Faculty, it is seen that only 44 patients are diagnosed with cancer. According to two methods in our study, we obtained that the biopsy is necessary only to a group of 46 patients who are under high cancer risk. These groups also contain 44 patients who were diagnosed with cancer. But there are some differences in the results obtained in these two methods. For example, patients which should be followed up by the doctor are different. In this situation, the question which is thought of firstly is ”Which method is more convenient?”. The following comparisons reply this question.

In the second method (Fuzzy TOPSIS), there is a ranking among patients. Hence we can predict patients who should be applied biopsy primarily. We do not have such an advantage in the first method. Also, there are four doctors who give linguistic variables for each symptoms in the second method. Nevertheless, in the first method there are three doctors who have only their own important symptom (parameter).

Competing interests

The authors declare that they have no competing interests.

Authors’ contributions

All authors contributed equally to the manuscript and read and approved the final manuscript.

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