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Analysis of Parameter Relationships Influencing Prostate Cancer using the Soft Set Model

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Abstract **–** The diagnosis of prostate cancer relies on various commonly used criteria, including PSA, fPSA, PV and AGE. This study explores the application of the soft set model to analyze these parameters and determine their relationships, aiming to identify the most influential parameter for the diagnosis of prostate cancer. Through the analysis of these parameters, the dominant parameter is determined, enabling healthcare professionals to prioritize and focus on the most significant factor when assessing the likelihood of prostate cancer in patients. The findings of this research provide valuable insights for medical practitioners to make informed decisions in the management of prostate cancer.

Keywords – Soft Set, Prostat Cancer, PSA, fPSA, PV, AGE, Algorithm

I. INTRODUCTION

Uncertainty is an inherent characteristic of many real-world problems, and effectively handling it is crucial for making informed decisions. In recent years, the soft set model has emerged as a powerful mathematical framework for dealing with uncertainty and capturing the complex relationships among parameters in various domains [1]. This model offers a flexible and intuitive approach to analyze and represent uncertain information, making it particularly relevant in problem domains where data is incomplete, imprecise, or vague. The soft set model, introduced by Molodtsov in 1999, extends the traditional set theory [1]. Unlike crisp sets, which categorize elements as either fully belonging or not belonging to a set, soft sets allow for gradual memberships, accommodating varying degrees of uncertainty or ambiguity. This flexibility makes the soft set model suitable for tackling uncertainty-related problems, enabling decision-makers to effectively handle imprecise information and capture the intricate relationships among parameters [2-7].

Prostate cancer diagnosis is one area where uncertainty plays a significant role. Traditional diagnostic criteria, such as Prostate-Specific Antigen (PSA) levels, Prostate Volume (PV) and patient Age (AGE), often exhibit inherent uncertainties due to various factors, including biological variations and measurement errors [8-14]. In this context, the application of the soft set model can be particularly valuable in capturing the imprecision and interdependencies present in prostate cancer diagnosis.

This study aims to utilize the soft set model to analyze the relationships among PSA, PV, AGE, and other relevant parameters in the context of prostate cancer diagnosis. By incorporating uncertainty into the modeling process, the soft set model provides a robust framework for evaluating the impact of these parameters and determining their relative importance in the diagnostic process. The primary objective of this research is to enhance the accuracy and effectiveness of prostate cancer diagnosis by addressing the inherent

uncertainties associated with the diagnostic criteria. By applying the soft set model, healthcare professionals can gain a deeper understanding of the interrelationships among parameters and make more informed decisions based on the varying degrees of membership. The significance of this study lies in its potential to provide healthcare professionals with a comprehensive and systematic approach to prostate cancer diagnosis, considering the uncertainties inherent in the diagnostic criteria. By capturing the complex relationships among parameters, the soft set model offers a more nuanced understanding of prostate cancer diagnosis, enabling improved decision-making processes and potentially leading to more personalized and effective treatment strategies.

In conclusion, the soft set model offers a powerful mathematical framework for addressing uncertainty-related problems and capturing parameter relationships in various domains. In the context of prostate cancer diagnosis, the application of the soft set model holds promise for improving diagnostic accuracy by considering the inherent uncertainties associated with diagnostic criteria. This research aims to contribute to the existing body of knowledge by leveraging the soft set model to enhance our understanding of the relationships among PSA, PV, AGE and other parameters, ultimately facilitating more informed decisions in prostate cancer diagnosis and management.

II. PRELIMINARIES

In this section, we aim to provide a recap of the fundamental concepts of soft set theory that are central to the focus of this article. Additionally, we have undertaken a partial revision and restructuring of the algorithms presented in [14] to ensure their applicability and alignment with the objectives of this research.

Throughout this paper, let U be an initial universe and S^X denotes the power set of $X \subseteq U$. Also, let E be a set of parameters and $A \subseteq E$.

Definition 1. [15] A soft set F_A over $X \subseteq U$, denoted by F_A^X, is a set defined by $f_A^X : E \to S^X$ such that $f_A^X(e) = \emptyset$ if $e \notin A$. Thus a soft set over X can be represented by

$$F_A^X = \{(e, f_A^X(e)) : e \in E, f_A^X(e) \in S^X\}$$

Note that the set of all soft sets over $X \subseteq U$ will be denoted by $S(X)$.

Definition 2. [14] Let $F_A^X \in S(X)$. The following mapping is used to get information about what parameters each object in F_A^X provides or does not:

$$\gamma_{F_A}^X(e_i)(u_j) = \begin{cases} 1, & u \in f_A^X(e_i) \\ 0, & u \notin f_A^X(e_i) \end{cases}$$

The mapping given here is in the form of $\gamma_{F_A}^X : E \times U \to \{0,1\}$.

Definition 3. [14] Let $F_A^X \in S(X)$. The relationship between the parameters provided by the objects belonging to F_A^X expressed by using the following mapping:

$$\Upsilon_{F_A}^X(e_i, e_j) = 1 - [M_X]$$

such that

$$M_X = \frac{1}{|X|} \sum_{k=1}^{|X|} \left| \gamma_{F_A}^X(e_i)(u_k) - \gamma_{F_A}^X(e_j)(u_k) \right|$$

This mapping is called the "Interaction Function" and is in the form of $\Upsilon_{F_A}^X : A \times A \to [0,1]$ for $e_i \neq e_j$. Also $|X|$ is the cardinality of X.

Proposition 1. [14] Let $|A| = p$. Then, the total different interaction number of all parameters in A is $\frac{p(p-1)}{2}$.

Definition 4. [14] Let $F_A^X \in S(X)$. As a result of interactions between all parameters in F_A^X, the sum of the interactions of one parameter with all other parameters indicates the total effect of that parameter on all objects belonging to X for F_A^X. This total effect expressed by using the following mapping:

$$\Gamma_{F_A}^X(e_i) = \sum_{j=1}^{s(A)} \Upsilon_{F_A}^X(e_i, e_j)$$

This mapping is called the "Parametric Effect Function" and is in the form of $\Gamma_{F_A}^X : E \to [0, |A| - 1]$ for $e_i \neq e_j$. Here, $|A|$ is the cardinality of A.

The depiction of the Algorithm 1 provided for $X \subseteq U$ in [14] is presented as follows:

Algorithm 1: (Identify the most robust relationship among parameters within a soft set)

Step 1: Input the soft set F_A^X.

Step 2: Calculate all interactions for F_A^X using the "Interaction Function".

Step 3: Find $max_{1\leq i,j\leq|A|}\Upsilon_{F_A}^X(e_i,e_j)$ for $e_i \neq e_j$.

The depiction of the Algorithm 2 provided for $X \subseteq U$ in [14] is presented as follows:

Algorithm 2: (Determination of the parameter with the strongest interaction for a soft set)

Step 1: Input the soft set F_A^X.

Step 2: Calculate the total effect of all parameters in F_A^X on objects belonging to X by using "Parametric Effect Function".

Step 3: Find $max_{1\leq i,j\leq|A|}\Gamma_{F_A}^X(e_i)$ for $e_i \neq e_j$.

III. STUDY CASE

This section focuses on a dataset consisting of 78 patients who presented to Necmettin Erbakan University Meram Medical Faculty with suspected prostate cancer. It is known that several parameters are taken into consideration for the diagnosis of prostate cancer including PSA, fPSA, PV and AGE [8-14].

The threshold value for the PSA parameter is commonly based on the recommendations of the American Urological Association (AUA). The AUA suggests that prostate cancer should be considered in patients with a PSA value of 4.0 ng/mL or higher [9].

The fPSA value is considered an important marker for the diagnosis of prostate cancer. For example, in patients with a PSA level between 2.5-10 ng/mL, an fPSA/PSA ratio below %25 is considered as a criterion that may reduce the risk of cancer [1,9]. Since fPSA is a test that evaluates a combination of PSA, a specific threshold value for fPSA is generally not used.

The prostate volume (PV) parameter plays a significant role in the diagnosis of prostate cancer. Normal prostate volume generally ranges from 20 to 30 mL, although individual variations exist [10,14].

Age (AGE) factor is associated with the risk of prostate cancer. Screening for prostate cancer is generally recommended for men aged 50 and above [11-14].

This analysis emphasizes the importance of threshold values for PSA, fPSA, PV, and AGE in the evaluation of patients with suspected prostate cancer at Necmettin Erbakan University Meram Medical Faculty. In line with the analysis conducted, a case study was conducted involving patients exhibiting specific values for the aforementioned parameters. Patients who meet the following criteria mean that they have a high risk of cancer with the recommendation of a doctor [16]:

PSA: Patients with a PSA level of 50 or higher

fPSA: Patients with an fPSA value of 12 or higher

PV: Patients with a prostate volume of 20 mL or more

AGE: Patients aged 54 and older

This study case aimed to examine the correlation between these selected patients and their potential risk of prostate cancer. By focusing on individuals exceeding the established threshold values, the study sought to shed light on the significance of these parameters in identifying patients at risk and the subsequent need for further diagnostic procedures.

A part of the dataset focused on in this study is provided in Table 1 as follows:

Table 1. Parameter measurements of each patient with biopsy result

Patient ID	PSA(ng/ml)	fPSA(%)	PV(ml)	AGE	Biopsy Result
1	76	17	30	65	+
4	76	19	33	76	+
13	88	19	37	77	+
19	95	23	37	69	-
25	76	16	36	72	+
31	79	19	39	69	+
50	40	9	45	65	-
54	39	9	52	68	-
64	60	13	29	71	+
68	51	12	78	67	+
69	26	6	37	60	-

Step 1 for Algorithm 1 and Algorithm 2: The set of patients is denoted as $X = \{u_1, u_2, \ldots, u_{78}\} \subseteq U$, and the set of considered parameters is denoted as $A = \{PSA, fPSA, PV, AGE\} \subseteq E$. Based on the established threshold values, the soft set F_A^X is constructed and expressed as follows:

$$F_A^X = \begin{Bmatrix} (PSA, f_A^X(PSA)), (fPSA, f_A^X(fPSA)) \\ (PV, f_A^X(PV)), (AGE, f_A^X(AGE)) \end{Bmatrix}$$

such that

$$f_A^X(PSA)) = X - \begin{Bmatrix} u_2, u_3, u_5, u_8, u_{10}, u_{12}, \\ u_{14}, u_{17}, u_{21}, u_{24}, u_{27}, \\ u_{30}, u_{32}, u_{35}, u_{38}, u_{41}, \\ u_{44}, u_{50}, u_{51}, u_{54}, u_{57}, \\ u_{59}, u_{61}, u_{65}, u_{67}, u_{69}, \\ u_{76}, u_{78} \end{Bmatrix}$$

$$f_A^X(fPSA)) = X - \begin{Bmatrix} u_2, u_3, u_5, u_6, u_{12}, u_{14}, \\ u_{21}, u_{27}, u_{30}, u_{38}, u_{41}, \\ u_{44}, u_{47}, u_{50}, u_{54}, u_{57}, \\ u_{59}, u_{61}, u_{65}, u_{67}, \\ u_{69} \end{Bmatrix}$$

$$f_A^X(PV)) = X - \{u_{30}, u_{57}, u_{59}\}$$

$$f_A^X(AGE)) = X$$

Step 2 for Algorithm 1: We will utilize the interaction function to provide insights into the interactions among parameters in F_A^X. For example, $\Upsilon_{F_A}^X(PSA, PV) = A$, $\Upsilon_{F_A}^X(PSA, AGE) = B$ and $\Upsilon_{F_A}^X(PV, AGE) = C$ for F_A^X are calculated as follows:

$$A = 1 - \left[\frac{1}{78}\sum_{k=1}^{78}\left|\gamma_{F_A}^X(PSA)(u_k) - \gamma_{F_A}^X(fPSA)(u_k)\right|\right]$$

$$= 1 - \frac{25}{78} = 0.68$$

$$B = 1 - \left[\frac{1}{78}\sum_{k=1}^{78}\left|\gamma_{F_A}^X(PSA)(u_k) - \gamma_{F_A}^X(AGE)(u_k)\right|\right]$$

$$= 1 - \frac{28}{78} = 0.64$$

$$C = 1 - \left[\frac{1}{78}\sum_{k=1}^{78}\left|\gamma_{F_A}^X(PV)(u_k) - \gamma_{F_A}^X(AGE)(u_k)\right|\right]$$

$$= 1 - \frac{3}{78} = 0.96$$

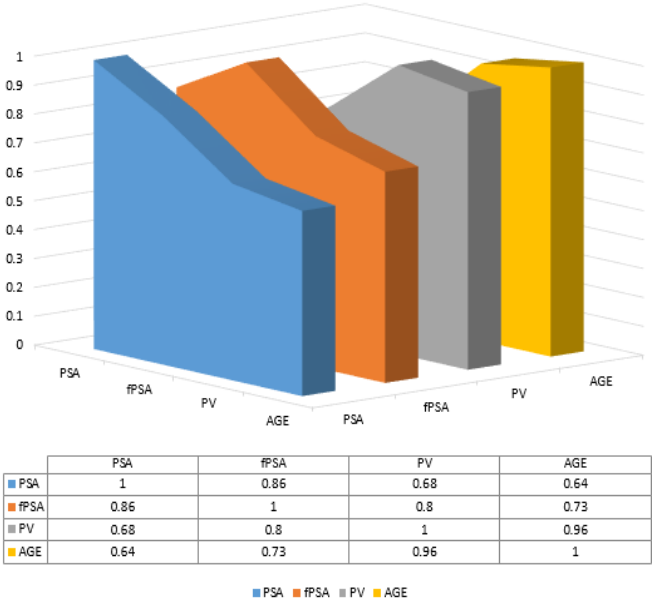
Similarly,

$$\Upsilon_{F_A}^X(PSA, fPSA) = 0.86,$$

$$\Upsilon_{F_A}^X(fPSA, PV) = 0.8,$$

$$\Upsilon_{F_A}^X(fPSA, AGE) = 0.73$$

A graphical representation of the obtained values over the parameters is given in Figure 1 as follows:



	PSA	fPSA	PV	AGE
PSA	1	0.86	0.68	0.64
fPSA	0.86	1	0.8	0.73
PV	0.68	0.8	1	0.96
AGE	0.64	0.73	0.96	1

PSA fPSA PV AGE

Fig. 1 A representation of the relationships between parameters affecting prostate cancer

Step 3 for Algorithm 1: It can be concluded that the interaction between PV-AGE is stronger because of

$$max\begin{Bmatrix} \Upsilon_{F_A}^X(PSA, fPSA), \Upsilon_{F_A}^X(PSA, PV), \\ \Upsilon_{F_A}^X(PSA, AGE), \Upsilon_{F_A}^X(fPSA, PV), \\ \Upsilon_{F_A}^X(fPSA, AGE), \Upsilon_{F_A}^X(PV, AGE) \end{Bmatrix} = 0.96$$

Step 2 for Algorithm 2: The parametric effect function is employed to determine the strongest

parameter. The obtained results are provided as follows:

$$\Gamma_{F_A}^X(PSA) = \begin{bmatrix} \Upsilon_{F_A}^X(PSA, fPSA) + \\ \Upsilon_{F_A}^X(PSA, PV) + \\ \Upsilon_{F_A}^X(PSA, AGE) \end{bmatrix} = 2.18$$

$$\Gamma_{F_A}^X(fPSA) = \begin{bmatrix} \Upsilon_{F_A}^X(fPSA, PSA) + \\ \Upsilon_{F_A}^X(fPSA, PV) + \\ \Upsilon_{F_A}^X(fPSA, AGE) \end{bmatrix} = 2.36$$

$$\Gamma_{F_A}^X(PV) = \begin{bmatrix} \Upsilon_{F_A}^X(PV, PSA) + \\ \Upsilon_{F_A}^X(PV, fPSA) + \\ \Upsilon_{F_A}^X(PV, AGE) \end{bmatrix} = 2.41$$

$$\Gamma_{F_A}^X(AGE) = \begin{bmatrix} \Upsilon_{F_A}^X(AGE, PSA) + \\ \Upsilon_{F_A}^X(AGE, fPSA) + \\ \Upsilon_{F_A}^X(AGE, PV) \end{bmatrix} = 2.33$$

Step 3 for Algorithm 2: It has been determined that due to the presence of

$$max \begin{Bmatrix} \Gamma_{F_A}^X(PSA), \Gamma_{F_A}^X(fPSA), \\ \Gamma_{F_A}^X(PV), \Gamma_{F_A}^X(AGE) \end{Bmatrix} = 2.41$$

the most important parameter to be considered in the diagnosis of prostate cancer is PV.

IV. CONCLUSION

In this study, the application of the soft set model was utilized to analyze the widely recognized criteria, namely PSA, fPSA, PV and AGE, for the diagnosis of prostate cancer. The relationships between these parameters were examined, and the identification of the dominant parameter was determined. By evaluating the relationships among PSA, fPSA, PV and AGE, it was observed that the parameter PV emerged as the most influential factor in the diagnosis of prostate cancer. This suggests that PV plays a crucial role in distinguishing between cancerous and non-cancerous conditions. Therefore, healthcare professionals should pay particular attention to PV when assessing the likelihood of prostate cancer in patients.

The utilization of the soft set model and the analysis of these parameters offer a comprehensive understanding of the interdependencies within the diagnostic process for prostate cancer. The results obtained from this study can guide physicians in making more accurate and informed decisions regarding potential treatment options for patients suspected of having prostate cancer.

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