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Enhancing Prostate Cancer Risk Prediction Using a Hybrid Near Sets and Soft Sets Model: A Novel Approach for Improved Patient Care

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Abstract Prostate cancer is a major health concern, and accurate risk prediction is essential for effective treatment. This paper presents a novel hybrid model combining near sets and soft sets to enhance prostate cancer risk assessment. By integrating artificial intelligence with medical data, our model captures uncertainties and provides more precise, personalized risk evaluations. Experiments focusing on key clinical factors, such as age and PSA levels, demonstrate significant improvements in early detection and treatment decisions. This research highlights the potential of hybrid AI models to improve patient care and outcomes in oncology.

Keywords Soft set; information system; near sets; near set approximations; prostate cancer

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1. Introduction

There is a rising interest among researchers in capturing the fuzziness of data to uncover valuable insights hidden within ambiguous datasets. This involves developing methods and theories to represent and analyze the uncertainties within datasets, ultimately unlocking hidden knowledge. These theories include fuzzy set theory [1], vague set theory [2], interval mathematics theory [3], and intuitionistic fuzzy set theory [4], which, along with many others, provide tools and frameworks for tackling the complexities of uncertain data.

Moreover, near sets build upon the idea of descriptions, with each object being represented by a list of its key features. To measure these features, we use special functions called probe functions. These functions assign a real number to each object, reflecting the specific characteristic being measured. Interestingly, these probe functions play a double role. They not only define near sets but also act as a special type of parameter in soft set theory, creating a bridge between the two approaches. This connection discovers intriguing relationships between models built using soft sets and those built using near sets. Numerous papers have been published, presenting variations of the traditional near set models (e.g., [5, 6, 7, 8, 9, 10]).

This study sets out to achieve two key goals. Firstly, to introduce a new concept called soft near sets. This innovative idea builds upon traditional near sets but adds the power of soft sets, which are known as soft near concepts. Secondly, to use the core principles of near sets and redefine them in the context of soft near sets. The main focus will be to establish the fundamental properties of soft near approximations, which are a crucial aspect of this new model. This hybrid model was tested as a Prostate Cancer (PCa) risk prediction system. The soft near set approach is used to identify patients who can undergo low-risk treatment for prostate cancer. PCa is the most common cancer affecting men [11]. Early detection is crucial for reducing deaths from this disease. Because

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of this, we will assess two important factors: the patient's age and prostate-specific antigen (PSA) levels. The aggressiveness of the cancer (determined by Gleason biopsy and genetic information), cancer stage and location, duration of the cancer, and whether it is contained within the prostate gland are the key clinical factors that guide the selection of the most effective and least harmful treatment for prostate cancer [12]. The following step after a complete diagnosis is established involves the doctor and patient working together to identify the most suitable choices for treating PCa. This is particularly relevant for cases where PCa is still detected within the gland. Once a complete diagnosis has been made, the doctor and patient must collaborate to identify the most suitable treatment plans for PCa. The treatment options for localized PCa (when the disease is confined to the prostate gland) are determined based on whether the tumor has infiltrated the prostate capsule.

Our approach involves utilizing a novel method that combines soft set and near set theories to assess the risks associated with treatment. We measure the extent of tumor penetration and analyze the obtained data, which is then visually represented in a diagram for statistical purposes. Our application is further supported by an algorithm and a set of decision rules.

The key contributions of this research paper include:

1. Introduction of a novel hybrid model: The paper introduces a unique approach that combines near sets and soft sets to predict prostate cancer risk, providing a more comprehensive and accurate assessment for personalized treatment planning.

2. Integration of artificial intelligence: By incorporating artificial intelligence techniques, the model enhances the accuracy of risk assessments and decision-making processes, leading to more effective patient care.

3. Improved early detection: The model facilitates early detection of prostate cancer by analyzing patient data and risk factors, enabling timely interventions and improved outcomes.

4. Personalized treatment planning: The hybrid model allows for personalized treatment planning based on individual patient profiles, considering factors such as cancer aggressiveness, stage, and location.

5. Potential for clinical impact: The integration of this innovative model into clinical practice has the potential to revolutionize prostate cancer management, leading to better patient outcomes and quality of care.

Overall, the key contributions of this paper lie in its innovative approach, integration of advanced technologies, focus on personalized care, and potential for significant impact on prostate cancer diagnosis and treatment.

The remaining sections of this paper are organized as follows: Related Work: The study discusses previous research on soft sets, near sets, and their applications in addressing uncertainties and decision-making challenges. It highlights the contributions of various researchers in advancing soft set theory and its extensions, as well as the use of AI in computer-aided detection methods for prostate cancer diagnosis. Methodology: The research methodology involves data collection, analysis techniques, and model validation for developing and implementing the hybrid near sets and soft sets model. The approach focuses on assessing patient data, risk factors, and clinical parameters to predict prostate cancer risk and recommend personalized treatment plans. Results: The results section presents the findings of the study, including the accuracy of risk assessments, personalized treatment recommendations, and the potential impact of the hybrid model on clinical practice. It discusses the effectiveness of the model in early detection, risk prediction, and personalized treatment planning for prostate cancer patients. Conclusion: The conclusion summarizes the main points of the research, emphasizing the innovative approach, integration of advanced technologies, focus on personalized care, and potential impact on prostate cancer diagnosis and treatment.

2. RELATED WORK

Molodtsov, D., introduced the innovative concept of soft sets [13], a mathematical tool aimed at addressing uncertainties. Which are associated with a set of parameters, have been applied across various fields. In addition,

Maji et al. explored the use of soft set theory in addressing decision-making challenges[14], also extending it to fuzzy soft sets [15]. Yang et al. introduced the concept of interval-valued fuzzy soft sets [16]. Chen et al. proposed an alternative method to simplify soft sets through parametrization[17]. Recent publications by several researchers have further developed the classical soft set theory, contributing to its ongoing advancement [18, 19, 20, 21]. Pawlak introduced the idea of rough set theory [22]. This theory defines a set as "rough" if the boundary region is non-empty between its lower and upper approximations. Near set theory, on the other hand, was proposed by Peters as a more generalized version of rough set theory [23]. It focuses on the process of grouping elements together without relying on the concept of set approximation boundaries. Peters and his team further explored this theory in several papers, including [24, 25, 26, 27, 28]. AI-based computer-aided detection methods may be therapeutically useful in the diagnosis of clinically significant prostate cancer (csPCa), according to a number of studies [29, 30, 31, 32]. One of the most important factors in PCa diagnosis is histopathology [33, 34]. Right now, specimens are examined under a microscope by a qualified pathologist; this technique invariably results in discrepancies in diagnosis and subjective interpretation among experts [33]. Several Machine learning (ML) and deep learning (DL) approaches have been presented in several research to be used on whole slide images (WSIs) for PCa grading, classification, and detection automatically [33, 35]. One of the main distinctions between DL and ML is the way in which they extract features. DL automatically collects features from the training data and learns to identify and represent them, whereas ML does a lot of manual feature engineering to extract meaningful correlations in a dataset [36]. In addition, John T. Wei [37] presented and covered the most important recommendations on the early detection of PCa and provided a framework to facilitate clinical decision-making in the implementation of prostate cancer screening, biopsy, and follow-up. In five phase III randomized studies, Daniel E. Spratt et al. [38] used digital pathology images and clinical data from pre-treatment prostate tissue samples of 5,727 patients. In addition to or instead of androgen deprivation therapy (ADT), radiation was used to treat these patients. Additionally, as the main outcome measure, they create and validate a predictive model based on artificial intelligence (AI) that may evaluate the advantages of ADT in terms of preventing distant metastases.

3. PRELIMINARIES

This section provides an explanation of, soft sets, An information system and near set approximations.

Definition 3.1 [39]

An information system (IS) is methodically represented by (U, E, V, f). In this system, a universe U accommodates a finite set of objects, attributes E define specific characteristics, and value sets V for each attribute are designated as $\{V_e \mid e \in E\}$.

The function $f : U \times E \to V$ is universally acknowledged as the information (knowledge) function or knowledge representation system. If the set of values for every attribute $e \in E$ is $\{0, 1\}$, then the information system is known as a Boolean-valued information system (BVIS).

Definition 3.2 [13]

An initial universe set U and a set of parameters E are given. Let $A \subseteq E$ be a subset of the parameter set E. The power set of U, denoted as $P(U)$, represents all possible subsets of U. Consider a pair $S = (F, A)$, where F is a mapping from A to $P(U)$. In simpler terms, S is a soft set over U. It consists of a collection of subsets of U, where each subset is associated with a parameter from the set A. Stated differently, for each parameter $e \in A$, the mapping $F(e)$ represents the set of elements in S that are *approximately equivalent* to e.

Definition 3.3 [22]

An **equivalence class** is a set of elements in a set U that are related to each other by an equivalence relation E. It can be represented as $[x]_E$ and is defined as the set of elements $x' \in U$ such that $E(x) = E(x')$:

$$[x]_E = \{x' \in U \mid E(x) = E(x')\} \tag{1}$$

The **partition of** U **with respect to** E, denoted as U/E, is the collection of all equivalence classes $[x]_E$ where $x \in U$. In other words, U/E is the set of all $[x]_E$ for every $x \in U$.

Let A be a family of equivalence relations on U, represented as $A = \{E_1, E_2, \ldots, E_n\}$. The equivalence class $[x]_A$ is the set of elements $x' \in U$ such that $E_i(x) = E_i(x')$ for all $E_i \in A$. The **partition of** U **with respect to** A, denoted as U/A, is the collection of all equivalence classes $[x]_A$ where $x \in U$.

Definition 3.4

Consider a collection of objects in a set X, where F represents a collection of their features. For each feature $a \in F$, we establish a function $f_a \in B$ that connects X to a specific set V_{f_a} (which represents the range of f_a). The measurement associated with a feature a of an object $x \in X$ is represented by the value of $f_a(x)$. This function f_a is commonly referred to as a *probe function*.

The exploration of near set theory demonstrates a fascination with categorizing specimens through the utilization of probe functions that have associations with entities. For instance, in the case of digital images, the defined probe functions encompass attributes such as *color*, *shape*, *contour*, *spatial orientation*, and *line length segments within a limited area*.

Definition 3.5

A **generalized approximation space**, denoted by GAS $= (U, F, Nr, VB)$, consists of the following components:

- U: A collection of objects in the universe.
- F: A set of functions that describe the features of the objects.
- Nr: A family of neighborhoods defined as follows:

$$Nr(F) = \bigcup_{A \subseteq Pr(F)} [x]_A, \tag{2}$$

  where

$$Pr(F) = \{A \subseteq F \mid |A| = r, 1 \leq r \leq |F|\}. \tag{3}$$

- VB: (Description not provided in the original text).

Definition 3.6

The lower and upper approximations for set X, regarding probe functions B (selected r at a time), are accurately represented by:

$$N_r(B)_* X = \bigcup_{x:[x]_{B_r} \subseteq X} [x]_{B_r}, \tag{4}$$

$$N_r(B)^* X = \bigcup_{x:[x]_{B_r} \cap X \neq \emptyset} [x]_{B_r}. \tag{5}$$

After defining soft sets and near sets separately, it is important to explore the interesting connections between these two concepts. The philosophy behind near sets is closely tied to the information available about each object of interest. To illustrate this, let's consider a scenario where patients with a specific illness are the objects of interest. In this case, the symptoms of the disorder can be seen as the features of these patients. Each symptom can be measured using a probe function to obtain a value. By combining all the information about the symptoms and their corresponding values, we can create an information system.

This information system resembles a table that represents a soft set, where the patients constitute the universe of this set, and the disease symptoms serve as the parameters. This implies that any soft set can be used to induce an information system, representing the relationship between objects and their associated features in a specific context. Near set approximations can be redefined using this table by leveraging the structure of the soft set's parameterized subsets.

Remark 3.1

A soft set $S = (F, A)$ over U implies that each $a \in A$ generates

$$F(a) = \{x \in U \mid a(x) = 1\}.$$

Thus, each $a \in A$ becomes a function $a : U \to \{0, 1\}$, where

$$a(x) = \begin{cases} 1 & \text{if } x \in F(a), \\ 0 & \text{otherwise.} \end{cases}$$

Consequently, every soft set $S = (F, A)$ over U is an information system (U, A).

Moreover, near set approximations can be redefined as *soft near set approximations*, aligning with the concept of soft sets.

4. SOFT NEAR SET APPROXIMATIONS (SN-SET APPROXIMATIONS

In this section, we establish lower SN-approximations and upper SN-approximations. Additionally, we derive and demonstrate their characteristics.

Definition 4.1

Let $S = (F, A)$ be a soft collection over a non-empty set U. For a parameter $a \in A$, the **basic collection** $F(a)$ is defined as

$$F(a) = \{x \in U \mid a(x) = 1\},$$

representing the set of elements in U that possess the property a. Additionally, for parameters $a, b \in A$, the collection $F(a, b)$ is defined as

$$F(a, b) = \{x \in U \mid a(x) = 1 \text{ and } b(x) = 1\},$$

representing the set of elements in U that possess both properties a and b.

Definitions and Remarks

Remark 4.1

By using Definition 4.1, we deduce:

$$F(a_1, a_2) = F(a_1) \cap F(a_2). \tag{6}$$

Consequently, as follows:

$$F(a_1, a_2, \ldots, a_r) = F(a_1) \cap F(a_2) \cap \cdots \cap F(a_r) = \bigcap_{i=1}^{r} F(a_i). \tag{7}$$

This signifies objects possessing properties $a_1, a_2, \ldots, a_r \in A$.

Definition 4.2

Let $S = (F, A)$ be a soft set defined over a nonempty set U. The collection of all elementary sets of U, with respect to each individual parameter from A (considering a single parameter at a time), is:

$$\xi_1 = \{F(a) \mid a \in A\}. \tag{8}$$

Remark 4.2

The representation of the set of elementary sets of U, considering all parameters A taken r at a time, is:

$$\xi_r = \left\{ \bigcap_{i=1}^{r} F(a_i) \;\middle|\; a_i \in A,\ 1 \leq r \leq |A| \right\}. \tag{9}$$

Definition 4.3

Let $S = (F, A)$ be a soft set defined over a set U (where U contains elements), and let ξ_r be the collection of all elementary sets of U. We denote (U, S, ξ_r) as a **Soft Near Approximation Space (SNAS)**. In this SNAS, for any subset $X \subseteq U$, the lower and upper SN-approximations are defined as:

$$\underline{\text{SN}}_r X = \bigcup \{Y \in \xi_r \mid Y \subseteq X\}, \tag{10}$$

$$\overline{\text{SN}}_r X = \bigcup \{Y \in \xi_r \mid Y \cap X \neq \emptyset\}. \tag{11}$$

Definition 4.4

Let $S = (F, A)$ represent a soft set over U. Then (U, S, ξ_r) is an **(SNAS)** corresponding to S. In the context of (U, S, ξ_r), for a set $X \subseteq U$, the **SN-positive region** is defined as:

$$\text{Pos}_r X = \underline{\text{SN}}_r X. \tag{12}$$

The SN-positive region signifies the collection of all elements that definitely belong to X and have r parameters.

Definition 4.5

Consider a soft set (F, A) defined over a nonempty set of patients U. Here, A represents a set of parameters that measure various symptoms associated with a specific disease. Let ξ_r denote the collection of all elementary sets of U. Additionally, assume that each parameter in A carries equal significance when assessing this disease.

Based on these assumptions, we can evaluate the prevalence of the disease within any subset $X \subseteq U$ using the following concept:

$$D_r(X) = D(\xi_r) \cdot d_r(X), \tag{13}$$

where

$$d_r(X) = \frac{|\text{Pos}_r(X)|}{|X|} \quad \text{and} \quad D(\xi_r) = \frac{r}{|A|}, \quad 1 \leq r \leq |A|. \tag{14}$$

It is apparent that this concept seeks to determine the occurrence of a particular illness within a defined specific area (surrounding region) in order to make an appropriate decision, with clear understanding. The variable r represents the disease category (in this case, r denotes the number of symptoms that a person must exhibit in order to be considered a patient).

5. SOFT NEAR SET CONCEPTS (SN-SET CONCEPTS)

Redefining Near-Set Principles: Understanding Definitions and Properties

Consider the soft set (U, S, ξ_r), where U represents the universal set, S represents a soft set, and ξ_r represents some relation. Let x and y be elements belonging to U. We can say that x is considered soft near y if there exists an element $a \in A$ such that both x and y are part of $F(a)$. This relationship, denoted as $x[Sn]_a y$, signifies the soft nearness between x and y.

Soft nearness is a concept used to compare object descriptions and determine the proximity between two elements. However, it's important to note that an element is not considered soft near to itself. To determine if two elements are soft near each other, we look at the parameters of Element A. If the two elements satisfy at least one parameter of A, they are considered soft near each other. By using the idea of soft nearness, we can effectively evaluate the similarities and relationships between different objects based on their shared characteristics.

Proposition 5.1

Soft Near Approximation Space (SNAS), denoted as (U, S, ξ_r), a depiction of (SNAS) itself entails a soft set $S = (F, A)$. Let's explore the concept of $[Sn]_a$, a soft nearness relation denoted by a parameter $a \in A$ as outlined in Definition 5.1, we can assert that $[Sn]_a$ stands as an equivalence relation.

proof Obvious.

Definition 5.2

Let (U, A) represent an information system that builds upon a soft set $S = (F, A)$. A subset R_i of A is referred to as a **reduct** of A if R_i is the smallest possible subset of A that satisfies the property:

$$U/R_i = U/A.$$

Definition 5.3

Let's consider an information system (U, A) that is based on a soft set (F, A). In this system, if $U/[A - a]$ is not a subset of U/A, then the parameter a in the set A cannot be removed. To further clarify this concept, we can define the **core** of parameters A in the following way:

$$\text{cor}(A) = \{a \in A \mid U/[A - a] \neq U/A\}. \tag{15}$$

Thus,

$$\text{cor}(A) = \bigcap \{R_i \mid R_i \text{ is a reduct of } A\}. \tag{16}$$

Definition 5.4

Consider an information system (U, A) built on a soft set $S = (F, A)$. Let R be the family of all reducts of A, denoted as:

$$R = \{R_i \subseteq A \mid U/R_i = U/A\}.$$

To calculate the weight of the parameter $a \in A$, we use the relation:

$$w(a) = \frac{|\{R_i \in R \mid a \in R_i\}|}{|R|}. \tag{17}$$

Proposition 5.2

Suppose we have a soft set (SNAS) represented by (U, S, ξ_r), where S is a soft set consisting of elements from F and A. For any element $a \in A$, the following conditions hold:

1. If the weight of a, $w(a) = 0$, then a can be removed from the soft set.
2. If the weight of a, $w(a) = 1$, then a is a member of the core set $\text{cor}(A)$.

Proof
Define $w(a) = 0$. Then $|\{R_i \in R \mid a \in R_i\}| = 0$. For every reduct $R_i \in R$, we have $a \notin R_i$. Therefore, $U/A = U/[A - \{a\}]$, implying parameter a can be removed.

Conversely, let $w(a) = 1$. Then $|\{R_i \in R \mid a \in R_i\}| = |R|$. For all reducts R_i, $a \in R_i$. Hence, $U/A \neq U/[A - \{a\}]$, implying a cannot be removed. Therefore, $a \in \text{cor}(A)$.

Finally, if $a \in \text{cor}(A)$, then $a \in R_i$ for all $R_i \in R$. Thus, $|\{R_i \in R \mid a \in R_i\}| = |R|$, leading to $w(a) = 1$. □

Definition 5.5

Let (U, S, ξ_r) represent a Soft Near Approximation Space (SNAS), corresponding to a soft set $S = (F, A)$. For elements $x, y \in U$ with $x \neq y$, the **soft nearness degree** between x and y is defined as:

$$r(x, y) = \frac{\sum\{w(a) \mid x[Sn]_a y,\ a \in A\}}{\sum\{w(a) \mid a(x) = 1 \text{ or } a(y) = 1\}}. \tag{18}$$

Definition 5.6

Consider the soft set representation (U, S, ξ_r) corresponding to the soft set $S = (F, A)$. For subsets $X, Y \subseteq U$, we say X is **soft near** to Y if and only if there exists $x \in X$, $y \in Y$, and $a \in A$ such that x is related to y by ξ_r. This relationship is denoted as $X[SN]_a Y$.

Remark 5.1

In the context of Definition 5.6, substituting set Y with set X leads to the inference that $X[SN]_a X$ holds true if and only if there exist elements $x, y \in X$ such that $x[Sn]_a y$. Consequently, a set X is termed **soft near** if, and only if, it is a nonempty set comprising distinct elements that exhibit a certain degree of soft nearness to one another.

Definition 5.7

Consider a soft set $S = (F, A)$ corresponding to (U, S, ξ_r), where U represents the universe and ξ_r is associated with soft nearness. For subsets $X, Y \subseteq U$, the **soft nearness degree** between X and Y is defined as:

$$R(X, Y) = \frac{\sum(\max\{r(x, y) \mid x \in X,\ y \in Y\})}{|X|}, \quad X \neq \emptyset. \tag{19}$$

Remark 5.2

In the present research, we explore the concept of **"soft nearness"**, which refers to the idea of being close in a positive sense based on certain criteria. To better understand this concept, consider a soft set that includes a group of patients and their corresponding symptoms for a specific disease. In this context, two patients are considered to be **softly near** each other if there is at least one symptom (or parameter) that they both share, indicating that they are experiencing a similar illness.

Example 5.1

Let us consider the following soft set $S = (F; A)$ which describes the conditions of patients suspected of rheumatic fever,all patients are between 9 and 12 years of age, with a history of arthralgia beginning at 3 to 5 years of age. This disease has many symptoms, usually starts at a young age, and persists throughout the patient's life. Suppose that the universe $U = \{p_1, p_2, p_3, p_4, p_5, p_6, p_7\}$, consists of seven patients and $A = \{a_1, a_2, a_3, a_4, a_5, a_6, a_7, a_8\}$ is the set of condition parameters.
The a_i $(i = 1, 2, 3, 4, 5, 6, 7, 8)$ stand for:

- a_1: Sex,
- a_2: Pharyngitis,
- a_3: Arthritis,
- a_4: Carditis,
- a_5: Chorea,
- a_6: ESR,
- a_7: Abdominal pain,
- a_8: Headache.

The soft set $S = (F; A)$ over U is defined by the following collection of approximations.
The soft set $S = (F, A)$ over U is defined as:

$$\begin{aligned}(F, A) = \{ &(\text{sex (male)}, \{p_2, p_4, p_5, p_7\}), (\text{pharyngitis}, \{p_1, p_2, p_3, p_4, p_6, p_7\}),\\ &(\text{arthritis}, \{p_1, p_2, p_3, p_4, p_6, p_7\}), (\text{carditis}, \{p_1, p_2, p_3, p_5, p_6, p_7\}),\\ &(\text{chorea}, \{p_1, p_2\}), (\text{ESR}, \{p_2, p_6\}), (\text{abdominal pain}, \{p_5\}), (\text{headache}, \{p_2, p_7\})\}.\end{aligned}$$

It is easy to see that, this soft set can be viewed as a boolean-valued information system corresponding to it, which is given by Table 1, as follows

Table 1. Boolean tabular representation of the soft set, given in Example 5.1

	a_1	a_2	a_3	a_4	a_5	a_6	a_7	a_8
p_1	0	1	1	1	1	0	0	0
p_2	1	1	1	1	1	1	0	1
p_3	0	1	1	1	0	0	0	0
p_4	1	1	1	0	0	0	0	0
p_5	1	0	0	1	0	0	1	0
p_6	0	1	1	1	0	1	0	0
p_7	1	1	1	1	0	0	0	1

From Table 1, we can deduce that,

$$\begin{aligned}U/[A] = U/[A - a_1] = U/[A - a_2] = U/[A - a_3] = U/[A - a_4] = U/[A - a_7] = U/[A - a_8] =\\ \{\{p_1\}, \{p_2\}, \{p_3\}, \{p_4\}, \{p_5\}, \{p_6\}, \{p_7\}\}, U/[A - a_5] = \{\{p_1, p_3\}, \{p_2\}, \{p_4\}, \{p_5\}, \{p_6\}, \{p_7\}\},\\ U/[A - a_6] = \{\{p_1\}, \{p_2\}, \{p_3, p_6\}, \{p_4\}, \{p_5\}, \{p_7\}\}.\end{aligned}$$

It follows that, a_5 and a_6 cannot be canceled, then $\text{cor}(A) = \{a_5, a_6\}$, and then $U/\text{cor}(A) = \{\{p_1\}, \{p_2\}, \{p_6\}, \{p_3, p_4, p_5, p_7\}\}$.
Hence, $X = \{p_3, p_4, p_5, p_7\}$ must be classified again by using the rest of parameters $[A - \text{cor}(A)] = \{a_1, a_2, a_3, a_4, a_7, a_8\}$.
For this end, Table 2 is given as follows:

Table 2. Boolean tabular representation of $(X, [A - \text{cor}(A)])$.

	a_1	a_2	a_3	a_4	a_7	a_8
p_3	0	1	1	1	0	0
p_4	1	1	1	0	0	0
p_5	1	0	0	1	1	0
p_7	1	1	1	1	0	1

From Table 2, we have the following classifications
$X/a_i = \{\{p_3\}, \{p_4, p_5, p_7\}\}$, $X/a_4 = \{\{p_4\}, \{p_3, p_5, p_7\}\}$, $X/a_8 = \{\{p_7\}, \{p_3, p_4, p_5\}\}$, $X/a_2 = X/a_3 = X/a_7 = \{\{p_5\}, \{p_3, p_4, p_7\}\}$. It is easy to see that, parameters a_2, a_3 and a_7 are equivalent in the classification of

X. In fact, there is a problem in the soft nearness with this equivalent (of classification), as the values of a_2 and a_3 are equivalent but the values of a_2 and a_7 are not equivalent. So we can drop one of a_2 and a_3, say a_2, but a_7 can not be dropped, as a result we get Table 3

Table 3. Boolean tabular representation of $(X, \{a_1, a_2, a_4, a_7, a_8\})$.

	a_1	a_2	a_4	a_7	a_8
p_3	0	1	1	0	0
p_4	1	1	0	0	0
p_5	1	0	1	1	0
p_7	1	1	1	0	1

Consequently, we can deduce the following classifications:

$$
\begin{aligned}
X/\{a_1, a_2\} &= X/\{a_1, a_7\} = \big\{\{p_3\}, \{p_5\}, \{p_4, p_7\}\big\},\\
X/\{a_1, a_4\} &= \big\{\{p_3\}, \{p_4\}, \{p_5, p_7\}\big\},\\
X/\{a_1, a_8\} &= \big\{\{p_3\}, \{p_7\}, \{p_4, p_5\}\big\},\\
X/\{a_2, a_4\} &= X/\{a_4, a_7\} = X/\{a_2, a_4, a_7\} = \big\{\{p_4\}, \{p_5\}, \{p_3, p_7\}\big\},\\
X/\{a_2, a_7\} &= \big\{\{p_5\}, \{p_3, p_4, p_7\}\big\},\\
X/\{a_2, a_8\} &= X/\{a_2\} = X/\{a_2, a_7\} = \big\{\{p_4\}, \{p_3, p_7\}\big\},\\
X/\{a_3, a_4\} &= \big\{\{p_3\}, \{p_4\}, \{p_5, p_7\}\big\},\\
X/\{a_3, a_5\} &= \big\{\{p_4\}, \{p_5\}, \{p_3, p_7\}\big\},\\
X/\{a_1, a_2, a_7\} &= \big\{\{p_3\}, \{p_5\}\big\},\\
X/\{a_1, a_2, a_4\} &= X/\{a_1, a_4, a_7\} = X/\{a_1, a_7, a_8\} = X/\{a_1, a_2, a_8\} = X/\{a_2, a_4, a_8\}\\
&= X/\{a_4, a_7, a_8\} = X/A = \big\{\{p_3\}, \{p_4\}, \{p_5\}, \{p_7\}\big\}.
\end{aligned}
$$

It follows that, $X/A_i = X/A$, where

$$A_i \in \big\{\{a_1, a_2, a_4\},\ \{a_1, a_2, a_8\},\ \{a_1, a_4, a_7\},\ \{a_1, a_4, a_8\},\ \{a_1, a_7, a_8\},\ \{a_2, a_4, a_8\},\ \{a_4, a_7, a_8\}\big\}.$$

Then, all reducts of the parameters A ($R_i = A_i \cup \mathrm{cor}(A)$) can be arranged in Table 4.

Table 4. Reducts of the parameters A, given in Example 4.1.

Reduct	**Set**
R_1	$\{a_5, a_6, a_1, a_2, a_4\}$
R_2	$\{a_5, a_6, a_1, a_2, a_8\}$
R_3	$\{a_5, a_6, a_1, a_4, a_8\}$
R_4	$\{a_5, a_6, a_2, a_4, a_8\}$
R_5	$\{a_5, a_6, a_1, a_4, a_7\}$
R_6	$\{a_5, a_6, a_1, a_7, a_8\}$
R_7	$\{a_5, a_6, a_4, a_7, a_8\}$

By using Definition 5.4, the weight of every condition parameter $a_i \in A$ can be calculated as follows:

$$w(a_5) = w(a_6) = 1, \quad w(a_1) = w(a_4) = w(a_8) = \frac{5}{7}, \quad w(a_2) = w(a_7) = \frac{3}{7}, \quad \text{and} \quad w(a_3) = 0.$$

It follows that a_3 can be canceled without losing any data.

Note that parameters a_2 and a_3 are equivalent. Hence, we can replace a_3 by a_2 in all results. In our case study, a_2 is considered and a_3 is dropped.

The set of parameters A will be:

$$A' = \{a_1, a_2, a_4, a_5, a_6, a_7, a_8\},$$

and the boolean-valued information system corresponding to the soft set $S' = (F, A')$ can be presented in Table 5, as follows.

Table 5. Boolean tabular representation of the soft set $S' = (F, A')$ over U

	a_1	a_2	a_4	a_5	a_6	a_7	a_8
p_1	0	1	1	1	0	0	0
p_2	1	1	1	1	1	0	1
p_3	0	1	1	0	0	0	0
p_4	1	1	0	0	0	0	0
p_5	1	0	1	0	0	1	0
p_6	0	1	1	0	1	0	0
p_7	1	1	1	0	0	0	1

Let $P = \{s_1, s_2, s_3, s_4, s_5, s_6, s_7\}$ be the set of standard patients, in which every patient satisfies all parameters in one reduct of A. The soft set (F, A') on P, is given in a tabular form , in Table 6

Table 6. Boolean representation of the soft set (F, A') over P

	a_1	a_2	a_4	a_5	a_6	a_7	a_8
s_1	1	1	1	1	1	0	0
s_2	1	1	0	1	1	0	1
s_3	1	0	1	1	1	0	1
s_4	0	1	1	1	1	0	1
s_5	1	0	1	1	1	1	0
s_6	1	0	0	1	1	1	1
s_7	0	0	1	1	1	1	1

By using Definitions 5.1 and 5.7, the soft nearness degree between p_1 and s_1 in the soft set $S' = (F, A')$ over $U \cup P$ is calculated as:

$$r(p_1, s_1) = \frac{w(a_2) + w(a_4) + w(a_5)}{w(a_1) + w(a_2) + w(a_4) + w(a_5) + w(a_6)} = \frac{\frac{3}{7} + \frac{5}{7} + 1}{\frac{5}{7} + \frac{3}{7} + \frac{5}{7} + 1 + 1} = \frac{15}{27}.$$

Table 7 introduces the soft nearness degrees between every element in U and every element in P:

From Table 7, we can deduce Table 8, where $s_i \in P$, as follows:

By using Definition 5.7 and Table 8, the nearness degree between singleton set $\{p_i\}$, for all $p_i \in U$, and the set P, can be calculated and arranged in Table 9:

$\{p_i\}$	$\{p_1\}$	$\{p_2\}$	$\{p_3\}$	$\{p_4\}$	$\{p_5\}$	$\{p_6\}$	$\{p_7\}$
$R(\{p_i\}, P)$	0.56	0.91	0.30	0.30	0.48	0.56	0.47

Table 9. Soft nearness degree of every singleton set in U and the set P .

Clearly, it is very important for every patient to know the degree of his/her disease because a doctor may decide that a person, at this moment, has no disease, although he/she might have the disease in a partial degree such as 30%. In classical terms, this person would not be classified as a patient, but after a few days, he/she may transition

Table 7. Soft nearness degrees between U and P

	s_1	s_2	s_3	s_4	s_5	s_6	s_7
p_1	$\frac{15}{27}$	$\frac{12}{27}$	$\frac{13}{27}$	$\frac{14}{27}$	$\frac{10}{27}$	$\frac{11}{27}$	$\frac{9}{27}$
p_2	$\frac{18}{27}$	$\frac{20}{27}$	$\frac{16}{27}$	$\frac{15}{27}$	$\frac{17}{27}$	$\frac{19}{27}$	$\frac{14}{27}$
p_3	$\frac{10}{27}$	$\frac{8}{27}$	$\frac{9}{27}$	$\frac{7}{27}$	$\frac{6}{27}$	$\frac{5}{27}$	$\frac{4}{27}$
p_4	$\frac{12}{27}$	$\frac{11}{27}$	$\frac{10}{27}$	$\frac{13}{27}$	$\frac{8}{27}$	$\frac{7}{27}$	$\frac{6}{27}$
p_5	$\frac{14}{27}$	$\frac{13}{27}$	$\frac{15}{27}$	$\frac{12}{27}$	$\frac{16}{27}$	$\frac{17}{27}$	$\frac{11}{27}$
p_6	$\frac{9}{27}$	$\frac{10}{27}$	$\frac{8}{27}$	$\frac{6}{27}$	$\frac{7}{27}$	$\frac{5}{27}$	$\frac{3}{27}$
p_7	$\frac{16}{27}$	$\frac{18}{27}$	$\frac{17}{27}$	$\frac{15}{27}$	$\frac{14}{27}$	$\frac{13}{27}$	$\frac{12}{27}$

Table 8. The maximum soft nearness degree of every element of U and every element of P

p	p_1	p_2	p_3	p_4	p_5	p_6	p_7
$\max\{r(p, s_i)\}$	$\frac{15}{27}$	$\frac{29}{32}$	$\frac{8}{27}$	$\frac{8}{27}$	$\frac{13}{27}$	$\frac{15}{27}$	$\frac{15}{32}$

into being a patient in a complete form. If the degree of his/her disease can be determined initially, this individual could then receive preventive treatment to mitigate progression.
From Table 9, we can deduce that, p_2 has the rheumatic fever with 91%, p_1, p_6 with 56%, p_5 with 48%, p_7 with 47% and p_3, p_4 with 30%.

Table 10. PROSTATE DATASET DESCRIPTION

Column	**Description Name**	**Description**	**NAME**
1	Identification code	1- 380	ID
2	Extent of Tumor Penetration into Prostatic Capsule	0 = no penetration, 1= penetration	CAPSULE
3	Patient's Age (in years)	years	AGE
4	Patient's Ethnic Background	0=white , 1 = black	RACE
5	Outcome of Digital Rectal Examination	1 =NO Nodule 2 =Unilobar Nodule (left) 3 =Unilobar Nodule (right) 4 =Bilobar Nodule	DPROS
6	Assessment of Capsular Involvement in Rectal Exam	0 = no, 1= yes	DCAPS
7	Prostate-Specific Antigen (PSA) level	(mg/ml)	PSA
8	Tumor Volume as Determined by Ultrasound	(cm^3)	VOL
9	Gleason Score (indicating the grade of the disease)	0 - 10	GLEASON

6. AN APPLICATION TO DETERMINE THE PROSTATE CANCER TREATMENT RISK BY NEW SOFT NEAR SET APPROACHES

A. Dataset

The dataset on prostate cancer comprises baseline examination outcomes obtained from prostate cancer patients under the supervision of Dr. Donn Y. at the OSUCCC [40] (refer to Table 10). In the design phase, the input parameters for AGE, RACE, DPROS, DCAPS, PSA, VOL, and GLEASON were utilized, while the output focused on determining prostate cancer risk.

B. Data Preprocessing

The steps for prostate dataset preprocessing process are as shown in Figure 1

Figure 1. Steps of Data Preprocessing.

B.1 Step 1 Discretization

To implement the soft near set methodology introduced, it is imperative to convert the continuous variable into a categorical form. To achieve this, we employed the k-means discretization technique as outlined in [41]. The prostate dataset encompasses three continuous variables (AGE, PSA, VOL). The linguistic variables assigned are as follows: for AGE - young, middle, old; for PSA - very high (VH), high (H), middle (M), low (L); and for VOL - small (S), middle (M), big (B). The delineation of each variable is represented by the red line, as depicted in Figure 2

B.2 Step 2 Checks Inconsistent

The analysis evaluates the coherence or incoherence of patients (samples) based on the presence or absence of consistency. A patient (sample) is considered consistent when there are no other patients exhibiting identical symptoms but receiving a disparate diagnosis [42]. Following this verification process, the dataset undergoes reduction, diminishing from 380 samples to 246 samples.

B.3 Step 3 Convert All Attributes to Binary Values

In order to convert a singular variable containing n observations and d unique values into d binary variables, each with n observations, the One Hot Coding scheme was employed [43]. This method involves contrasting each level of the categorical variable against a predetermined reference level. Consequently, every observation signifies the existence (1) or non-existence (0) of the dichotomous binary variable, as illustrated in Table 11.
This section describes the Algorithm for determining the risk treatment for prostate cancer.

C. Algorithm: Application for risk treatment

This section describes the Algorithm for determine the risk treatment for prostate cancer

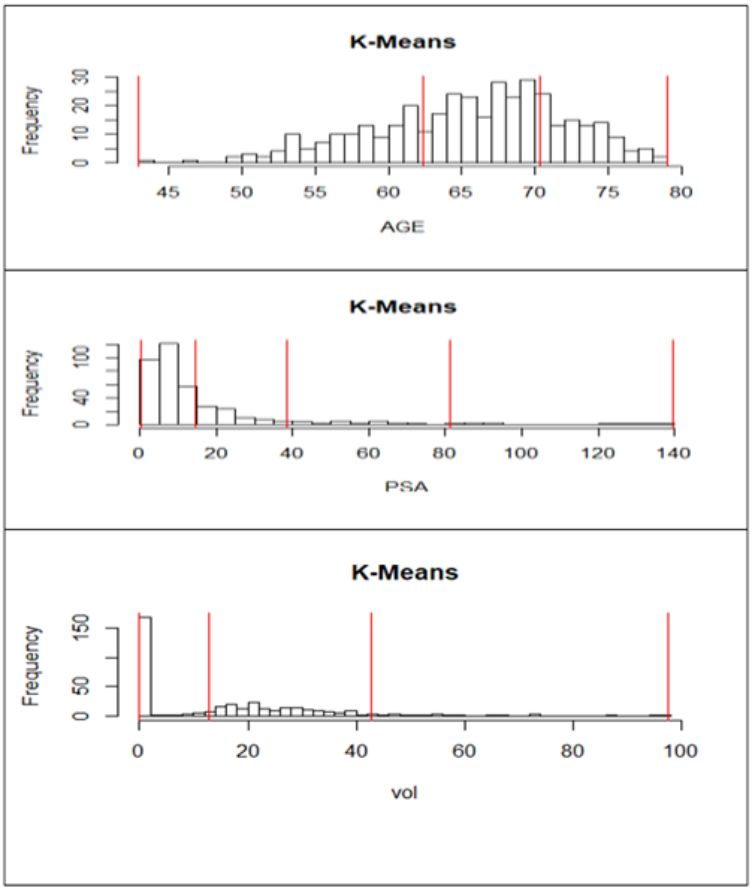

Figure 2. K-Means Discretization Technique.

1. Enter the Boolean-valued information system (BVIS) that corresponds to a given soft set $S = (F, A)$ on U.
2. Calculate the core of set A: cor(A).
3. Define $X = \bigcup\{X \in [U/\text{cor}(A) - U/A]\}$.
4. Calculate $X/A_i = X/A$ for every set of parameters $A_i \subseteq A$.
5. Calculate all reducts for A: $R = \text{cor}(A) \cup A$.
6. Enter $A' = \bigcup\{R_i \in R\}$.
7. For every a in A, calculate $w(a)$.
8. Enter the set $p = \{s_i\}$, where $a(s_i) = 1$ for every $a \in R_i$.
9. Enter the BVIS that corresponds to (F, A') on P.
10. For every p_i in U and s_j in P, calculate $r(p_i, s_j)$.
11. Calculate $R(\{p_i\}, p)$ for every p_i in U (representing the patient's level of illness).
12. Present $(p_i, R(\{p_i\}, p))$ for every p_i in U in a statistical model.
13. If $0.22588 < \lambda \leq 0.305365$, conclude that patient p exhibits no tumor penetration of the prostatic capsule.
14. If $0.320492 < \lambda \leq 0.445359$, infer that patient p has tumor penetration of the prostatic capsule.

Table 11. Patient Data with Risk Assessment

Patients	AGE_1	AGE_2	AGE_3	RACE	DPROS_1	DPROS_2	DPROS_3	DPROS_4	DCAPS	PSA_1	PSA_2	PSA_3	PSA_4	VOL_1	VOL_2	VOL_3	GLEASON_0	GLEASON_1	GLEASON_2	GLEASON_3	....	GLEASON_10
1	1	0	0	1	0	0	0	1	1	1	0	0	0	1	0	0	0	0	0	1	....	0
2	0	1	0	1	0	0	1	0	1	1	0	0	0	0	1	0	0	0	1	0	....	0
3	0	1	0	0	0	0	0	1	1	0	1	0	0	1	0	0	0	0	1	0	....	0
4	0	0	1	0	1	0	0	0	1	0	1	0	0	1	0	0	0	0	0	1	....	0
5	0	1	0	0	0	0	0	1	1	0	1	0	0	1	0	0	0	0	0	1	....	0
6	0	1	0	0	0	0	0	1	1	0	0	1	0	1	0	0	0	0	1	0	....	0

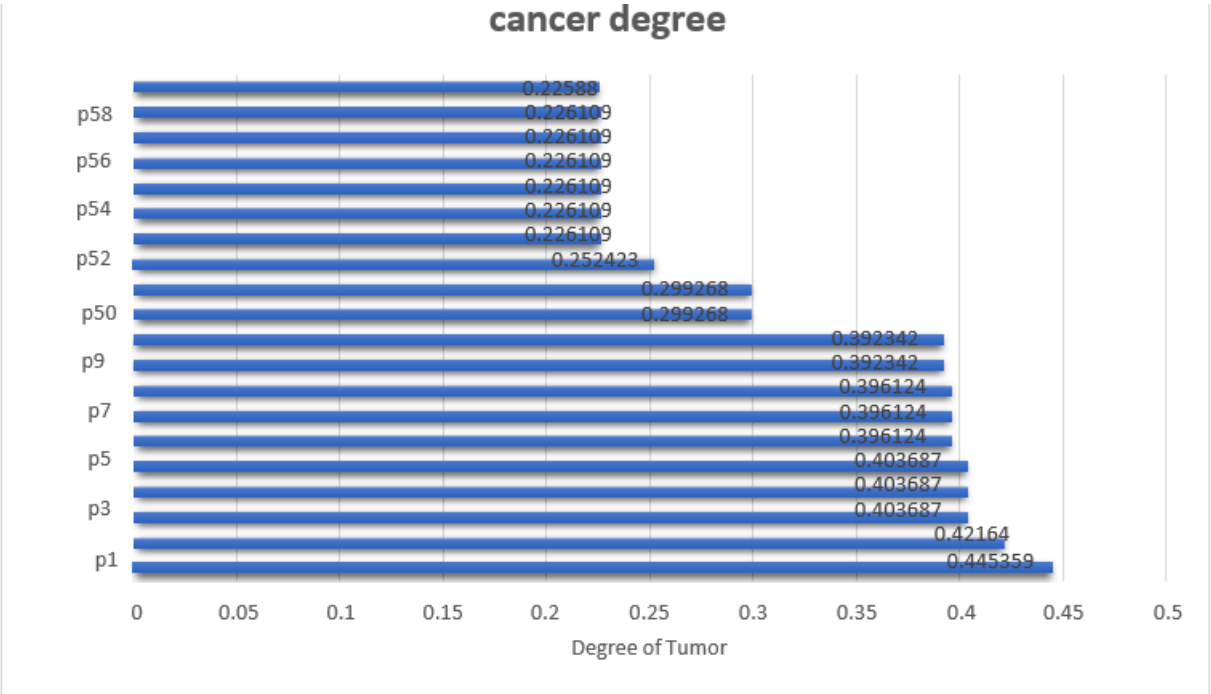

Figure 3. The Degree of Tumor Penetration of The Prostatic Capsule for a Patient p as λ

7. Result and Discussion

After applying the steps from step 1 to step 11 to compute the degree of disease by measuring the tumor penetration of the prostatic capsule, the results in Table 12 show that the patients that have localized disease have a degree between [0.22588 - 0.305365], and patients that have advanced prostate cancer have a degree between [0.320492 - 0.445359].

Let's define the degree of tumor penetration of the prostatic capsule for a patient p as λ. The following decision rules for interpretation can be obtained from Fig. 3:

1. If $0.22588 < \lambda \leq 0.305365$, then patient p has no tumor penetration of the prostatic capsule.
2. If $0.320492 < \lambda \leq 0.445359$, then patient p has tumor penetration of the prostatic capsule.

Table 12. Patient Data with Risk Assessment

Patients	AGE_1	AGE_2	AGE_3	RACE	DPROS_1	DPROS_2	DPROS_3	DPROS_4	DCAPS	PSA_1	PSA_2	PSA_3	PSA_4	VOL_1	VOL_2	VOL_3	GLEASON_0		CAPSULE_10	$R(\{p_i\}, p)$
1	1	0	0	1	0	0	0	1	1	1	0	0	0	1	0	0	0	...	1	0.445359
2	0	1	0	1	0	0	1	0	1	1	0	0	0	0	1	0	0	...	1	0.42164
3	0	1	0	0	0	0	0	1	1	0	1	0	0	1	0	0	0	...	1	0.403687
4	0	0	1	0	1	0	0	0	1	0	1	0	0	1	0	0	0	...	1	0.403687
5	0	1	0	0	0	0	0	1	1	0	1	0	0	1	0	0	0	...	1	0.403687
6	0	1	0	0	0	0	0	1	1	0	0	1	0	1	0	0	0	...	1	0.396124
7	0	1	0	0	0	0	0	1	1	0	0	1	0	1	0	0	0	...	1	0.396124
8	1	0	0	1	1	0	0	0	0	0	0	1	0	0	0	1	0	...	1	0.396124
9	0	0	1	0	0	0	0	1	1	0	0	0	1	0	1	0	0	...	1	0.392342
10	1	0	0	1	0	0	0	1	0	0	0	0	1	0	1	0	0	...	1	0.392342
11	0	1	0	0	0	0	0	1	1	0	0	0	1	1	0	0	0	...	1	0.392342
12	0	0	1	0	0	0	1	0	1	0	1	0	0	0	1	0	0	...	1	0.380761
13	0	1	0	0	0	0	1	0	1	0	1	0	0	0	1	0	0	...	1	0.380761
14	0	1	0	0	0	0	0	1	1	0	1	0	0	0	1	0	0	...	1	0.377216
15	0	0	1	0	0	0	0	1	1	1	0	0	0	1	0	0	0	...	1	0.372199
16	1	0	0	0	0	0	1	0	1	0	0	1	0	1	0	0	0	...	1	0.371792
17	1	0	0	0	0	0	1	0	1	1	0	0	0	0	1	0	0	...	0	0.348975
18	0	1	0	0	0	0	1	0	1	1	0	0	0	0	1	0	0	...	1	0.348975
19	1	0	0	0	0	0	1	0	1	1	0	0	0	1	0	0	0	...	1	0.348975
20	0	0	1	0	0	0	0	0	1	1	1	0	0	0	1	0	0	...	1	0.346594
21	0	1	0	0	0	0	0	1	1	1	0	0	0	0	1	0	0	...	1	0.346594
22	0	1	0	0	0	0	1	0	1	0	1	0	0	0	1	0	0	...	1	0.337765
23	0	1	0	1	0	0	1	0	0	0	0	1	0	0	1	0	0	...	1	0.329367
24	0	1	0	0	0	0	0	1	0	0	1	0	0	1	0	0	0	...	1	0.328291
25	1	0	0	0	0	0	0	1	0	0	1	0	0	1	0	0	0	...	1	0.328055
26	1	0	0	1	0	1	0	0	0	0	1	0	0	1	0	0	0	...	1	0.328055
27	0	1	0	1	0	1	0	0	0	0	1	0	0	0	1	0	0	...	1	0.328055
28	0	1	0	0	0	0	0	1	0	0	1	0	0	0	1	0	0	...	1	0.328055
29	0	1	0	0	1	0	0	0	0	0	1	0	0	0	1	0	0	...	1	0.328055
30	0	1	0	0	0	0	0	1	0	0	1	0	0	1	0	0	0	...	1	0.328055
31	1	0	0	0	0	1	0	0	1	0	0	1	0	1	0	0	0	...	1	0.320728
32	0	1	0	0	0	0	0	1	0	0	0	1	0	1	0	0	0	...	1	0.320492
33	0	0	1	0	1	0	0	0	0	0	0	1	0	0	0	1	0	...	1	0.320492
34	0	0	1	0	0	1	0	0	1	0	0	1	0	0	1	0	0	...	1	0.320492
35	0	1	0	0	0	0	0	1	0	0	0	1	0	1	0	0	0	...	1	0.320492
36	0	1	0	0	1	0	0	0	0	0	0	1	0	1	0	0	0	...	1	0.320492
37	0	0	1	0	0	0	1	0	0	0	1	0	0	0	0	1	1	...	0	0.305365
38	0	1	0	0	1	0	0	0	0	1	0	0	0	0	0	1	0	...	0	0.299268
39	0	1	0	1	0	1	0	0	0	1	0	0	0	0	0	1	0	...	0	0.299268
40	0	1	0	0	1	0	0	0	0	1	0	0	0	0	0	1	1	...	0	0.299268

To evaluate our Hybrid Near Set and Soft Set Model for predicting prostate cancer risk, specifically the degree of tumor penetration of the prostatic capsule, we compared it against Linear Regression, Ridge Regression, ElasticNet Regression, and Support Vector Regression (SVR). Using Receiver Operating Characteristic (ROC) curves and Area Under the Curve (AUC) metrics, as shown in Figure 4, the Hybrid Model achieved an AUC of **0.965**, significantly outperforming SVR (AUC = 0.780), ElasticNet (AUC = 0.770), and Linear and Ridge Regression (both AUC = 0.760). This indicates the Hybrid Model's superior ability to accurately classify tumor penetration, making it a valuable tool for clinical decision-making.

The Hybrid Model's clear decision rules (e.g., λ thresholds) and focus on key clinical features (e.g., **PSA**,

GLEASON) enhance its practical utility, enabling clinicians to make informed decisions about prostate cancer treatment. Its ability to quantify uncertainty through soft near set approximations aligns with the inherent vagueness in medical data, providing a robust framework for risk assessment. For instance, the λ thresholds stratify patients into localized ($0.22588 < \lambda \leq 0.305365$) and advanced ($0.320492 < \lambda \leq 0.445359$) categories, directly linking computational outputs to actionable clinical protocols.

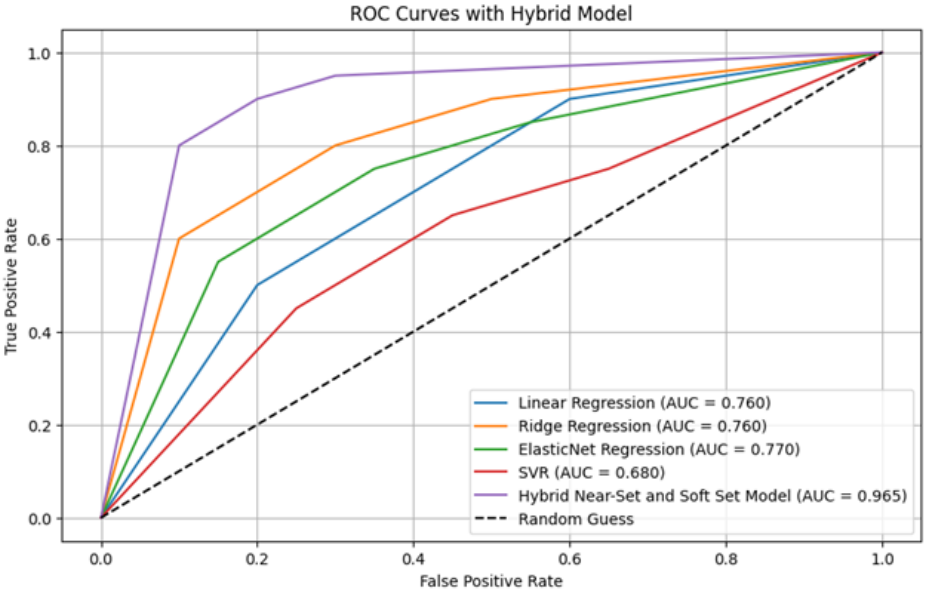

Figure 4. ROC curves comparing classification performance between the Hybrid Model and regression methods.

8. Conclusion and Future Work

In this paper, we have presented a novel approach to prostate cancer risk prediction by integrating the concepts of near sets and soft sets into a hybrid model. Our research demonstrates the effectiveness of combining artificial intelligence with medical knowledge to enhance the accuracy and personalization of prostate cancer risk assessments. By leveraging the strengths of both near sets and soft sets, our model provides a more nuanced understanding of patient data, enabling the identification of those who may benefit from low-risk treatment options. The experimental results underscore the potential of our hybrid model in improving early detection and management of prostate cancer. Specifically, our approach offers a comprehensive assessment framework that considers key clinical factors such as patient age, PSA levels, cancer aggressiveness, and other relevant medical data. This holistic evaluation facilitates more informed and precise treatment decisions, ultimately contributing to better patient outcomes.

Our study contributes to the growing body of research on the application of artificial intelligence in healthcare, highlighting the significant benefits of integrating advanced computational techniques with traditional medical practices. Future work could integrate multi-modal data, such as genomic profiles, proteomic data, or imaging results (e.g., MRI or PET scans), to provide a more comprehensive risk assessment. Exploring emerging technologies, such as natural language processing for extracting risk factors from clinical notes or virtual reality for patient education, could enhance the model's utility. The model could be tested on datasets for cancers like breast, lung, or colorectal cancer, which have distinct risk factors and diagnostic criteria.

In conclusion, the proposed hybrid near sets and soft sets model represents a promising advancement in the field of prostate cancer risk prediction, offering a robust tool for healthcare professionals to improve patient care and treatment strategies.

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