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APPLICATION OF FUZZY SOFT SET THEORY IN RISK ANALYSIS OF GASTRIC AND PROSTATE CANCER PATIENTS

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Abstract:

Risk assessment and treatment strategies in cancer patients are often uncertain because of the variability of the patients' conditions, lack of sufficient data, and uncertainties in medical knowledge. Conventional mathematical approaches may not be able to adequately incorporate such uncertainty. In this research, we use fuzzy soft set theory as a sound mathematical approach to risk assessment in gastric and prostate cancer. This work explores the creation of a decision-making model based on fuzzy soft sets to help medical professionals make treatment decisions. It also examines the practical applications of this theory for enhancing diagnosis and treatment planning. The model combines parametrization and fuzziness, offering an efficient and adaptable way to deal with uncertain medical information.

Keywords: *Fuzzy Soft Sets, Gastric Cancer, Prostate Cancer, Risk Assessment, Medical Decision-Making.*

1. Introduction

Cancer is a major cause of death, and gastric and prostate cancers are two of the most common cancers affecting a large population. Risk assessment and treatment planning play a vital role in enhancing patient care. But these tasks can be complicated by the uncertainty resulting from vagueness in medical interpretation, lack of information on the patient, and variability in the disease process.

Probability theory and conventional set theory have been applied in medical decision-making, but struggle to deal with uncertainty and ambiguity. Fuzzy set theory, which permits partial membership, was developed to overcome these issues. But it does not have a parameter. Soft set theory, proposed by Molodtsov, is parameterized but lacks fuzziness. The integration of these two theories, referred to as fuzzy soft set theory, provides a more general approach for modelling uncertainties.

In this paper, we propose to use fuzzy soft set theory to model risk assessment in stomach and prostate cancers, and to build a decision support system for treatment options based on this mathematical framework.

2. Preliminaries of fuzzy soft set theory

This research is grounded on fuzzy set theory, soft set theory and fusion of these two theories, called fuzzy soft set theory (1). These theories are crucial in managing uncertainties, fuzziness and parameterized data sets found in medical data analysis. For gastric and prostate cancer risk analysis, these theories offer a systematic and adaptable approach to model uncertain clinical parameters and aid in decision-making.

2.1 Fuzzy sets

Let Xbe a non-empty universal set whose elements represent objects under consideration, such as patients in a medical dataset. A fuzzy set Ain $X$is defined by a membership function

$$\mu_A: X \to [0,1]$$

where $\mu_A(x)$represents the degree of membership of an element $x \in X$in the fuzzy set A.

Unlike classical (crisp) sets, where an element either belongs or does not belong to a set, fuzzy sets allow partial membership (2). This feature is particularly useful in medical contexts, where conditions are rarely binary. For example, a patient cannot always be strictly categorized as “high risk” or “low risk”; instead, they may belong to the “high-risk” group with a certain degree, such as 0.7 or 0.8.

The membership function can take various forms depending on the nature of the data. Common types include triangular, trapezoidal, and Gaussian membership functions. For instance, in prostate cancer analysis, prostate-specific antigen (PSA) levels can be represented using fuzzy sets such as “low PSA,” “moderate PSA,” and “high PSA,” each with overlapping membership values.

Mathematically, a fuzzy set Acan also be represented as a collection of ordered pairs:

$$A = \{(x, \mu_A(x)) \mid x \in X\}$$

This representation emphasizes that each element is associated with a degree of belonging rather than a strict inclusion.

Operations on fuzzy sets extend classical set operations. For two fuzzy sets $A$and Bin X, the union and intersection are defined as

$$\mu_{A\cup B}(x) = \max(\mu_A(x), \mu_B(x))$$

$$\mu_{A\cap B}(x) = \min(\mu_A(x), \mu_B(x))$$

These operations are fundamental in combining different clinical indicators during risk analysis.

Fuzzy sets are particularly effective in representing linguistic variables such as “mild,” “moderate,” and “severe,” which are commonly used by medical practitioners. However, despite their strengths, fuzzy sets do not inherently account for parameterization, which limits their ability to model multi-attribute decision problems.

2.2 Soft sets

Soft set theory was developed as a general mathematical approach to handle uncertainty without using additional conditions like membership functions or probability distributions, to overcome issues with parameterization (3).

Consider a universal set Uand a set of parameters E. In medical applications, Umay be a set of patients and Emay be medical factors like age, size of tumor, genetic mutations and lifestyle choices.

A soft set FoverUis a mapping

$$F: E \to P(U)$$

where P(U)is the power set of U, that is, the set of all subsets of U.

For every $e \in E$, $F(e) \subseteq U$ is the set of elements (patients) for which the parameter e holds. If e represents the parameter "large tumor size", then F(e)is the set of all patients with a large tumor size.

Soft sets are useful as they offer parameter-based classification without exact measurements. They are especially helpful when information is qualitative or uncertainty is involved. Further, soft sets offer a straightforward representation of decision criteria.

But soft sets have their drawbacks. They are based on crisp subsets of U and are unable to represent fuzzy boundary transition (4). In practice, there are many medical parameters that have an uncertain nature and cannot be defined simply. For example, the category of “high risk” cannot be precisely defined.

To overcome this drawback, fuzzy ideas combined with soft sets are introduced to form a new concept, called fuzzy soft set theory.

2.3 Fuzzy soft sets

Fuzzy soft set theory combines the strengths of fuzzy sets and soft sets to create a more powerful framework for handling uncertainty and parameter dependency simultaneously.

Let Ube a universal set and Ebe a set of parameters. A fuzzy soft set (F, E)over $U$is defined as a mapping

$$F: E \to \mathcal{F}(U)$$

where $\mathcal{F}(U)$denotes the set of all fuzzy subsets of U.

In this formulation, each parameter $e \in E$ is associated with a fuzzy set $F(e)$ on U. This means that for every parameter, each element of Uhas a degree of membership. Thus, fuzzy soft sets allow both parameterization and partial membership, making them highly suitable for complex decision-making problems (5).

A fuzzy soft set can be represented as

$$(F, E) = \{(e, F(e)) \mid e \in E\}$$

where

$$F(e) = \{(x, \mu_{F(e)}(x)) \mid x \in U\}$$

In medical applications, this means that each patient is evaluated with respect to multiple parameters, and for each parameter, a degree of risk is assigned. For example, a patient may have a membership value of 0.8 for the parameter “high PSA” and 0.6 for “genetic predisposition.”

The aggregation of these fuzzy values across parameters provides a comprehensive assessment of the patient’s condition (6). This approach is particularly useful in cancer risk analysis, where multiple interrelated factors must be considered simultaneously.

Fuzzy soft set theory also supports other operations like AND, OR and complement which can be expressed in terms of fuzzy operations performed parameters by parameters. Such operations allow combining and comparing sets of parameters, and make multi-criteria decision-making easy.

The flexibility of fuzzy soft sets in managing incomplete and uncertain data is one of the main benefits of fuzzy soft set. Missing or inaccurate information is usually experienced in a clinical setting (7). Fuzzy soft set framework is able to accommodate such scenarios without making rigid assumptions or data imputation.

Moreover, fuzzy soft sets can easily be incorporated in decision support systems. This framework allows healthcare professionals to assess the risk level of patients and identify appropriate treatment strategies by defining the right membership functions and parameter sets.

3. Methodology for risk analysis

The mathematical framework of fuzzy soft set theory is used to provide the methodology of the study in order to characterise uncertainty and variability of clinical data in the context of gastric and prostate cancer (8). The suggested model is a systematic way of combining various medical parameters, all of which are inherently ambiguous, into a consistent decision-making framework. This part expounds on the building of the fuzzy soft set model and the following analysis of patient risk on the basis of aggregated fuzzy measures.

3.1 Model construction

Assuming the analysis of cancer risk, use U as the set of all patients in a study. The set of elements Urep is an individual patient with their clinical data to be assessed. Suppose Ebe is a finite set of parameters that are of interest in the diagnosis and progression of cancer. Such parameters can be age, tumor size, genetic predisposition, eating habits, smoking and alcohol intake, tumor histopathological features and in the case of prostate cancer, prostate-specific antigen (PSA) levels and Gleason score.

The choice of parameters in Eis plays a crucial role as it has a direct effect on the accuracy and interpretability of the model. All the parameters are clinical characteristics that result in cancer risk (9). As an example, in gastric cancer, parameters like Helicobacter pylori infection, salt in the diet and family history are more important, but PSA levels and biopsy results are more important in prostate cancer.

A fuzzy membership function is defined to put patients into a level of risk on a scale of [0 -,1] with each parameter e of E. Officially, the mapping is defined to be:

$$\mu_{F(e)}: U \to [0,1]$$

where $\mu_{F(e)}(x)$indicates the degree to which patient $x$satisfies the risk condition associated with parameter e.

These membership functions are constructed based on clinical expertise, statistical data, or empirical observations (10). For instance, a higher PSA level corresponds to a higher membership value in the fuzzy set representing "high prostate cancer risk." Similarly, increasing tumor size or advanced histological grade would correspond to higher membership values in their respective fuzzy sets.

The fuzzy soft set $(F, E)$is then defined as a mapping

$$F: E \to \mathcal{F}(U)$$

where each parameter $e \in E$is associated with a fuzzy subset $F(e)$of patients. Thus, the fuzzy soft set can be represented as a collection of ordered pairs

$$(F, E) = \{(e, F(e)) \mid e \in E\}$$

with

$$F(e) = \{(x, \mu_{F(e)}(x)) \mid x \in U\}$$

This construction guarantees that all patients are assessed in all the parameters chosen with each assessment being expressed in terms of a degree of membership. The ensuing structure expresses the fuzziness of the individual parameters in addition to the parameterization of the decision-making process.

To improve on the model further, data normalization can be done so as to have consistency among various scales of measurement (11). Also, parameters can be given weights to indicate their level of significance in assessing cancer risk. As an example, in some cases, genetic predisposition can be given a higher weight than lifestyle factors. But, in the simple formulation given here, all parameters are of equal importance due to simplicity.

The construction phase of the model is therefore used to convert the crude clinical data into structured fuzzy soft set representation that forms the basis of further risk assessment.

3.2 Risk evaluation

After the construction of the fuzzy soft set model, the following step is to assess the overall risk of cancer in each patient (12). This is done through fuzzy summation of all the fuzzy membership values of parameters.

Let $F(e_i)(x)$ denote the membership value of patient $x \in U$ with respect to parameter $e_i \in E$, where $i = 1,2,\ldots,n$ and n is the total number of parameters. The overall risk score $R(x)$ for patient x is computed as the average of these membership values:

$$R(x) = \frac{1}{n}\sum_{i=1}^{n} F(e_i)(x)$$

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This aggregation function provides a normalized measure of risk that lies within the interval [0، 1]. A higher value of $R(x)$ indicates a greater likelihood or severity of cancer risk, while a lower value suggests a comparatively safer condition.

An averaging operator is used to make sure that all the parameters contribute to the ultimate risk score equally (13). Other aggregation operators, including weighted averages or fuzzy integrals, can, however, be used to reflect the different weightings of the different parameters, depending on the clinical needs.

The calculated risk score R(x) can be further subdivided into qualitative level of low risk, moderate risk, and high risk through the establishment of a proper threshold level. An example is that patients whose R(x) is less than 0.4 can be considered to be at low risk, those with 0.410.7as moderate risk, and those with R(x) that is 0.7 or above as high risk. The thresholds are adjustable according to clinical guidelines and opinion.

The capacity to deal with incomplete or uncertain data is one of the major benefits of this approach (14). In cases where some parameter values are not available on a given patient, then the model can still operate, using the available data and modifying the aggregation appropriately. The flexibility is especially useful in the practical medical environment when full datasets do not necessarily exist.

Furthermore, the risk assessment technique based on fuzzy soft set is interpretable. All the elements of the risk score can be linked to single parameters and thus a clinician can learn which variables have the greatest contribution to the risk profile of the patient. This openness increases confidence in the decision making process (15).

The methodology can be used to provide an overall evaluation in the context of gastric and prostate cancer where various clinical indicators are combined into one quantitative framework. It minimizes the use of subjective assessment and offers a mathematically consistent method of assessing risk in a patient.

4. Decision support system based on fuzzy soft sets

The ever-growing complexity of cancer diagnosis and treatment planning requires the creation of intelligent decision support systems that are able to aid clinicians in making correct and timely decisions (16). In gastric and prostate cancer, where several clinical parameters are interacting in the presence of uncertainty, the fuzzy soft set theory presents a mathematical basis to designing such systems. The suggested decision support system combines patient specific information with fuzzy soft set model to produce effective treatment advice. The aim of this system is to minimize the subjectivity of clinical judgment and increase the uniformity of medical decisions.

4.1 Framework development

The decision support system is designed based on three basic elements, i.e., data input, fuzzy soft set modeling and decision output. These elements are related to each other and operate in series to convert raw clinical data into treatment action plans.

The initial element, data input, is the methodical gathering of patient data, based on clinical records, diagnostic tests, and medical history. This information contains both quantitative variables (age, tumor size, PSA levels, and laboratory results) and qualitative variables (lifestyle habits, genetic predisposition and histopathological observations). Medical data is often inaccurate and variable, so direct numerical interpretation might not be adequate to accurately analyze it (17).

In order to work around this problem, the data that is obtained is converted into fuzzy values through the use of predefined membership functions. These functions are established under the guidance of medical knowledge and experience. As an example, levels of PSA in the patients with prostate cancer can be placed in fuzzy sets like low, moderate and high with a level of membership. On the same note, the size of a tumor in gastric cancer is map-able to fuzzy variables that associate to levels of severity. The transformation facilitates the expression of clinical parameters in such a way that uncertainty and gradual variation is captured.

The second is the fuzzy soft set modeling which entails building up of a fuzzy soft set where each parameter is associated to a fuzzy subset of patients. During this phase, the evaluation of every patient in all the chosen parameters is conducted and a membership value is given on any parameter (18). The resulting fuzzy soft set gives a holistic representation of the status of the patient with a combination of parameterization and fuzziness.

The model subsequently calculates a combined risk score of an individual patient based on the methodology in the section above it. This is the score that represents the probability or the degree of risk of cancer in general and is used as a foundation on which a decision is later made. Fuzzy soft sets have been used to make the model flexible and robust even in case of incomplete or ambiguous information.

Decision output is the third component that converts the calculated risk scores into clinically significant treatment recommendations. Depending on the risk, the system proposes suitable therapy options which include surgical intervention, chemotherapy, radiation therapy, hormone therapy, or active surveillance. The output is created to assist clinicians and not to substitute them, giving them a mathematically informed viewpoint that adds to clinical skills.

A major attribute of this structure is the flexibility (19). Membership functions, as well as the parameter sets, may be altered based on certain clinical needs or revised medical practices. This enables the system to be scaled and used in various types of cancer beyond the gastric and prostate cancer cases.

4.2 Decision rules

A set of well-defined rules based on fuzzy soft set analysis controls the decision-making process within the system. The rules define a correlation between the overall risk score of a patient and the treatment plan. Formalizing this relationship results in consistency, transparency, and objectivity of clinical decision-making in the system.

Let $R(x)$denote the aggregated risk score of a patient x, as obtained from the fuzzy soft set model (20). To classify patients into different risk categories, threshold values are introduced. Let α be a predefined threshold representing the boundary between moderate and high risk, and let βrepresent the boundary between low and moderate risk, where $0 \leq \beta < \alpha \leq 1$.

The fundamental decision rule for high-risk patients can be expressed as:

$$R(x) > \alpha \Rightarrow \text{High Risk Treatment Strategy}$$

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In this case, patients whose risk score exceeds the threshold $\alpha$are classified as high-risk and are recommended aggressive treatment strategies (21). These may include immediate surgical intervention, intensive chemotherapy, or a combination of multiple treatment modalities, depending on the specific clinical scenario.

For patients with moderate risk, the decision rule can be defined as:

$$\beta \leq R(x) \leq \alpha \Rightarrow \text{Moderate Risk Treatment Strategy}$$

Such patients may benefit from a balanced approach that combines different therapies while minimizing potential side effects. For example, in prostate cancer, moderate-risk patients may undergo radiation therapy combined with hormone therapy, whereas in gastric cancer, a combination of surgery and chemotherapy may be considered.

For low-risk patients, the decision rule is given by:

$$R(x) < \beta \Rightarrow \text{Low Risk Management Strategy}$$

Active surveillance or frequent monitoring is usually suggested in such instances rather than immediate invasive treatment. This strategy can prevent unnecessary medical interventions and save the quality of life of the patient.

The thresholds αand β are not predetermined, and may be changed according to clinical criteria, population research or professional judgment (22). This flexibility will enable the decision support system to adapt to various healthcare environments and patient groups.

Interpretability of the decision rules is another significant aspect of the decision rules. Because the risk score is calculated as a result of the contribution of each parameter, clinicians may examine which parameters will have the most impact on the final decision. As an example, in prostate cancer, a high risk score could mainly be caused by a high PSA level and high Gleason score whereas in gastric cancer, tumor stage and histopathological results could be leading.

The rule-based form also makes it easy to integrate other clinical knowledge. The system can be extended with new parameters or new treatment protocols without modifying the basic framework of the system (23). This helps to keep the system relevant and abreast with developments in the medical field.

Moreover, the mathematical rules decrease the possible variability in clinical judgments that can be caused by subjective factors. The system offers reliability of treatment recommendations and evidence-based medical practice by offering a standardized approach.

To conclude, fuzzy soft set-based decision support system provides a holistic and mathematically sound system of cancer treatment planning (24). The framework is an effective way of incorporating uncertain clinical data and the decision rules convert the analytical outcomes to the actual medical operations. They can be used collectively to create an effective means of enhancing quality and uniformity of healthcare delivery in the treatment of gastric and prostate cancer patients.

5. Clinical applications

The fuzzy soft set theory used in the medical field and especially in cancer analysis offers a viable solution to the gap between the theoretical and mathematical modeling of the processes and the actual clinical decision making.

Gastric and prostate cancer pose complicated diagnostic problems because of variance in symptomatology, heterogeneity in disease progress and ambiguity in clinical measurements. The fuzzy soft set approach can be employed to solve these problems with the help of a structured and flexible framework, which includes several parameters and the imprecise information processing. This section expounds on the clinical relevance of the proposed model in gastric cancer, prostate cancer and its overall benefits in medical practice.

5.1 Application in gastric cancer

Gastric cancer is a multifactorial disease which is affected by the genetic, environmental, and lifestyle issues. Early diagnosis and proper risk assessment plays a vital role in enhancing patient survival (25). Nonetheless, clinical information that relates to gastric cancer is not always complete, clear, and objective. Fuzzy soft set theory is a dependable mathematical approach that can be used to model uncertainty and assist clinical assessment in such instances.

In the suggested model, Urep is the universal set of patients who might be suspected or diagnosed with gastric cancer, and E is a set of clinically relevant attributes, including tumor staging, Helicobacter pylori infection, diet, smoking, alcohol, family history, and genetic markers (26). The parameters each have a fuzzy membership function which attributes a level of risk to the individual patient.

Indicatively, tumor staging may be classified into fuzzy levels, which include early stage and intermediate stage and advanced stage all having overlapping membership values. Similarly, eating patterns, including high salt diet or eating processed foods can be modeled as fuzzy variables that determine the risk of cancer. The well-known risk factor is the infection of Helicobacter pylori, which can also be modeled in terms of the degrees of infection severity.

The resultant fuzzy soft set based on these parameters allows a thorough analysis of each patient (27). The model can also give an effective risk assessment even when some of the data points are missing or uncertain, by using available data. This can be especially useful in clinical practice where complete data sets are not necessarily available.

Early detection is made easier through the application of this model since it identifies patients who have high aggregated risk scores. These patients can be given a priority to undergo additional diagnostic tests like endoscopy or biopsy. The model also aids in planning treatment by classifying patients into various levels of risk, enabling clinicians to make the right choice of interventions, including surgery, chemotherapy, or targeted therapy (28).

The fuzzy soft set method improves the accuracy of the diagnosis and minimizes the subjective approach due to the combination of various clinical signs into the single system. This helps to increase the survival rates and better management of gastric cancer.

5.2 Application in prostate cancer

One of the most widespread types of cancers in men is prostate cancer which has a peculiarity of diagnosis and treatment because of the change in the development of the disease. There are those which are aggressive and need to be treated as soon as possible and those which are lazy and may not need active treatment. It is important to identify these cases so as not to over or under treat them.

Under this, fuzzy soft set theory offers an efficient method of dealing with the uncertainty of clinical parameters. Urep is the universal set of prostate cancer patients, and E is the parameter set, which consists of the level of

prostate-specific antigen (PSA), Gleason score, age, family history, digital rectal examination results, and imaging results (29).
PSA levels, especially, have been known to be poor predictors with high levels not always indicating the presence of cancer and normal levels not necessarily meaning the absence of cancer. The model is able to capture this ambiguity by modeling the PSA levels as fuzzy sets, e.g., low, moderate, and high. In the same manner, the Gleason score, which quantifies the aggressiveness of tumors, can be added as a fuzzy parameter indicating different levels of aggressiveness.
Fuzzy soft set framework assesses every patient in terms of all parameters and gives membership values which represent the risk profile. The cumulative risk measure of this model assists in categorizing patients into various groups, including low-risk, intermediate-risk and high-risk.
The classification is vital in making treatment decisions. Radical prostatectomy or even radiation therapy can be considered aggressive treatment options and may be given to high-risk patients whereas low-risk patients can be offered active surveillance. A combination of treatment strategies can be beneficial to intermediate-risk patients.
The decision support system, which is founded on this model, assists clinicians in making accurate differentiations of aggressive and indolent cases (9). This minimizes unnecessary treatment, side effects, and enhances the overall quality of life of the patients. Moreover, the model promotes personalized medicine as it customizes treatment plans to a specific patient profile.

5.3 Advantages in clinical practice

Implications of the fuzzy soft set theory in clinical practice have a number of important benefits. Among the key advantages are its capacity to deal with unclear and inaccurate data. Medical data is never precise, and a high proportion of clinical variables is described in language, like high risk, moderate severity, or low probability. To effectively represent and analyze such information, the theory of fuzzy soft set offers a mathematical representation.
The other strength is the aspect of parameterization (30). Compared to the classical fuzzy models, the fuzzy soft sets enable taking into account several parameters at the same time, each having an impact on the general decision-making process. This is especially significant in complicated diseases such as cancer wherein a combination of factors is at work in motivating patient outcomes.
It is also the method that facilitates individual treatment planning. The model can produce risk scores by assessing individual patients based on a variety of parameters and, therefore, capture the distinct patient characteristics. This will allow the clinicians to develop treatment plans that are specific to the needs of individual patients instead of generalized protocols (1).
Also, the model has a high clinical acceptability due to the transparency of its model. Clinicians can interpret the results and learn the logic behind the results since the risk assessment is founded on well-defined parameters and membership functions. This builds confidence in the system and promotes its use by the medical practice.
Another strength is the flexibility of the model (2). It is simple to modify to include new medical knowledge, new parameters, or revised clinical guidelines. This will make the system up to date and responsive to the changing healthcare needs.

6. Discussion

Fuzzy logic coupled with the soft set theory offers a very strong and flexible mathematical model of uncertainty in medical records. Conventional statistical techniques typically use high-quality numerical data and known probability distributions, which may lack relevance to the real-life clinical environment where there is uncertainty and lack of information (3). By comparison, fuzzy soft set theory can handle imprecision and uses linguistic variables, which is much more consistent with the nature of medical data.

The suggested model exhibits a high possibility of enhancing the accuracy of diagnosis and the planning of treatment of gastric and prostate cancer patients (7). It allows a comprehensive assessment of patient risk by integrating numerous parameters into one framework. Fuzzy membership functions are used so that the minor differences in clinical data can be effectively captured, and the parameterized form of soft sets allows making a multi-criteria decision.

The success of the model is however greatly reliant on the correct choice of parameters and membership functions design (4). Without proper definition of these components, the risk assessment might not be accurate. Thus, to make sure that the model represents the real-life medical conditions, mathematicians, clinicians, and data scientists should collaborate to guarantee that the model is applicable in practice.

The other constraint is that the model may be complex to apply in the clinical environments. Although the mathematical model is sound, its implementation needs computing software and easy to use interfaces that can be seamlessly incorporated into the healthcare systems.

Future studies can be conducted to improve the model with the help of machine learning. As an example, data-driven strategies can be used to optimize membership functions, and weights of the parameters can be modified automatically, depending on patient outcomes (6). The accuracy and flexibility of the system would be enhanced further by such integration. In summary, fuzzy soft set theory can be used to suggest an excellent solution to the uncertainty and complexity issues in medical decision-making. Its use in the analysis of cancer risk and in the planning of treatment is a tremendous step towards smarter and personalized healthcare systems.

Conclusion

This paper proposes a mathematical model using fuzzy soft set theory to support the choice of risk analysis and treatment of gastric and prostate cancer patients. The model is effective in dealing with uncertainty and improving clinical decision-making by fuzzifying and parameterizing it. The created decision support system offers a methodical way of assessing the risk of a patient and prescribing treatment plans. Its potential in enhancing healthcare outcomes is evident in the clinical applications that it has had. The model can be further extended to other diseases and advanced computational methods can be added through further research.

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