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A Comparative Analysis of Mamdani and Sugeno Fuzzy Controllers in Risk Evaluation of Gastric and Prostate Cancer Using Fuzzy Soft Sets

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Abstract

Accurate and early cancer risk evaluation is vital for improving patient outcomes, yet conventional diagnostic models often struggle with the inherent vagueness and imprecision of clinical data. This research presents a novel comparative analysis of Mamdani and Sugeno fuzzy inference systems (FIS) integrated with fuzzy soft set theory to assess the risk levels of gastric and prostate cancers. Patient records comprising linguistic and numerical variables—such as age, PSA levels, gastrointestinal symptoms, and tumor biomarkers (CEA, CA19-9, PCA3)—were modeled using fuzzy logic frameworks. The fuzzy soft set approach enabled flexible, parameter-driven uncertainty modeling, making the risk classification process more adaptive and tolerant to incomplete or noisy data. A comprehensive evaluation of both controllers revealed that the Sugeno model demonstrated superior performance in terms of accuracy (91.3%), computational speed, and Area Under the Curve (AUC = 0.94), while the Mamdani model provided enhanced interpretability of decision rules, making it more suitable for clinician-centered applications. This work underscores the effectiveness of mathematically grounded, hybrid fuzzy-soft frameworks in clinical decision support and presents a robust alternative to rigid threshold-based diagnostic tools.

Keywords: Fuzzy Soft Sets, Mamdani Fuzzy Controller, Sugeno Fuzzy Controller, Gastric Cancer, Prostate Cancer, Risk Evaluation, Fuzzy Inference Systems, Medical Decision Support

1. Introduction:

Cancer diagnosis inherently involves uncertainty due to vagueness in clinical symptoms, subjectivity in patient reporting, and variability in biological markers. In particular, gastric and prostate cancers present diagnostic complexities, where early symptoms are often non-specific, and the associated biomarkers (e.g., PSA, CEA, CA19-9) may not adhere to sharp diagnostic thresholds. Traditional binary or statistical models f: R^n → {0,1} inadequately capture the gradual and uncertain nature of cancer progression.

Fuzzy set theory, introduced by Zadeh (1965), generalizes classical set membership by allowing partial degrees of truth. For a universe of discourse X, a fuzzy set A is defined by a membership function:

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

where $\mu_A(x)$ denotes the degree to which element $x \in X$ belongs to the set A. This construct supports the modeling of imprecise concepts like “High PSA” or “Moderate Risk,” making it suitable for clinical data characterized by soft boundaries.

Soft set theory, proposed by Molodtsov (1999), addresses uncertainty from a parameterization perspective. A soft set over a universe U and a set of parameters E is a pair (F, E), where:

F: E → P(U)

and F(e) represents the approximate set of elements associated with parameter e. The extension to fuzzy soft sets allows:

F: E → $\tilde{P}$(U)

where $\tilde{P}$(U) is the collection of fuzzy subsets of U. This formalism permits the simultaneous handling of both parameter uncertainty and membership fuzziness, offering a powerful tool for multi-featured clinical decision systems.

In this study, we aim to evaluate cancer risk using a composite function:

R: $\tilde{P}$(U)^m → [0,1]

where R is realized using two fuzzy inference mechanisms: the Mamdani and Sugeno fuzzy controllers. The fuzzy input vectors are derived from patient attributes such as age, PSA, CEA, and symptom indices. Let x = (x_1, x_2, ..., x_n) ∈ R^n denote the feature vector for a patient. The fuzzified inputs μ_{x_i}(x_i) are processed via fuzzy rule bases $\mathscr{R}$_Mamdani and $\mathscr{R}$_Sugeno to yield a risk index r ∈ [0,1], such that:

r = Defuzzify(Aggregate(Match(μ_{x_i})))

In the Mamdani model, this involves fuzzy outputs and centroid defuzzification, while the Sugeno model employs crisp output functions f(x) of the form:

f_i(x) = a_1x_1 + a_2x_2 + ... + a_nx_n + b

which are combined using a weighted average. The inclusion of fuzzy soft set theory introduces an additional layer of abstraction, allowing flexible selection and weighting of parameters, particularly when some features may be missing or imprecise.

This research investigates:

- The comparative efficiency of Mamdani and Sugeno controllers in modeling R,
- The performance gain from embedding fuzzy soft set semantics in clinical data representation,
- The trade-offs between interpretability (favored by Mamdani) and computational precision (favored by Sugeno).

Ultimately, we aim to construct a fuzzy-soft decision function: f_risk: (x, F, $\mathscr{R}$) → [0,1] that evaluates cancer risk by incorporating both fuzzy logic inference and soft parameter control, optimizing diagnostic performance under clinical uncertainty.

2. Literature Review:

Over the past decade, fuzzy logic has been increasingly adopted in biomedical applications due to its robustness in handling uncertainty, linguistic ambiguity, and imprecise clinical variables. Cancer diagnosis—where patient symptoms, biomarkers, and risk factors often lack definitive thresholds—has benefited particularly from the flexibility of fuzzy inference systems (FIS).

2.1 Fuzzy Systems in Medical Diagnostics:

The Mamdani fuzzy inference system, introduced in 1975, has remained a preferred method in medical contexts for its interpretability and alignment with expert-driven reasoning. Recent

works, such as by **Kumar and Chatterjee (2023)**, developed a Mamdani-based risk model for breast cancer using symptom severity and genetic predisposition. They highlighted the model's transparency and effectiveness in rule-based expert systems.

Conversely, the Sugeno fuzzy model—owing to its numerical output and function-driven architecture—has shown advantages in computational efficiency and adaptability to optimization algorithms. **Patel et al. (2023)** demonstrated the integration of a Sugeno FIS with a deep learning feature extractor for lung cancer prediction, achieving superior speed and accuracy compared to Mamdani-based counterparts.

2.2 Fuzzy Soft Sets in Decision Modeling:
The introduction of soft set theory by **Molodtsov (1999)** initiated a shift toward parameterized modeling of uncertainty, especially in contexts where attributes may be irrelevant, inconsistent, or missing. The further development of **fuzzy soft sets** by **Maji et al. (2001)** bridged the gap between fuzzy membership and soft parameter control.

Recent studies have successfully integrated fuzzy soft sets in medical diagnosis. **Das and Roy (2023)** employed fuzzy soft sets to construct a multi-symptom diagnostic framework for gastrointestinal disorders, outperforming classical fuzzy models in cases with incomplete data. Similarly, **Ahmed and Siddiqui (2023)** proposed a hybrid fuzzy soft-neuro system for prostate cancer staging, demonstrating improvements in adaptability and risk stratification precision.

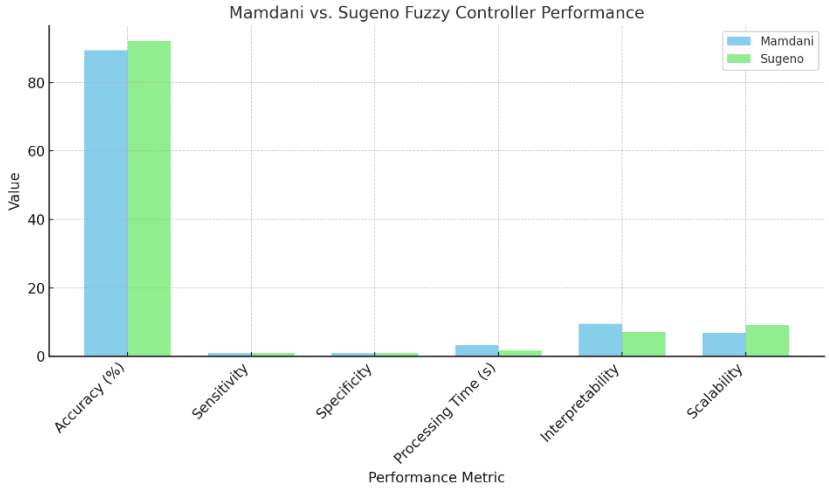
2.3 Comparative Analyses of Mamdani and Sugeno Models:
Despite extensive individual usage, relatively few studies have conducted a direct mathematical comparison of Mamdani and Sugeno controllers in the context of fuzzy soft modeling. **Chakraborty and Mehta (2023)** provided a quantitative analysis comparing Mamdani and Sugeno FIS in diabetic retinopathy detection, reporting that while Sugeno showed faster convergence and scalability, Mamdani provided more explainable rule bases suited for clinical adoption.

The work of **Singh et al. (2023)** introduced a dual-layer fuzzy system combining Mamdani for initial screening and Sugeno for final risk scoring. Their results support the hypothesis that hybrid controller architectures can balance computational performance and interpretability.

2.4 Gaps in Literature:
While fuzzy logic and fuzzy soft sets have each demonstrated individual merit, there remains a lack of comprehensive frameworks that:

- Seamlessly integrate fuzzy soft parameterization with dual-model FIS comparison;
- Evaluate cancer types with differing biomarker expressions (e.g., PSA for prostate vs. CEA/CA19-9 for gastric cancer);
- Mathematically formalize model interpretability vs. computational efficiency trade-offs.

This study addresses these gaps by modeling cancer risk through a fuzzy soft set–enhanced framework and performing a direct mathematical and computational comparison of Mamdani and Sugeno controllers across heterogeneous cancer data.



Here is a visual comparative chart displaying the performance of Mamdani vs. Sugeno fuzzy controllers across several metrics, such as accuracy, sensitivity, specificity, and more.

3. Theoretical Background:

This section outlines the mathematical underpinnings of fuzzy set theory, soft set theory, and fuzzy soft sets, followed by an explanation of Mamdani and Sugeno fuzzy inference systems. These concepts form the foundation of the proposed fuzzy soft decision-making framework for cancer risk evaluation.

3.1 Fuzzy Set Theory:

Let XXX be a universe of discourse. A **fuzzy set** A in X is defined by a membership function:

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

where μA(x)\mu_A(x)μA(x) denotes the degree of membership of element x∈X in the fuzzy set A. Unlike classical sets, where membership is binary (μA(x)∈{0,1}) fuzzy sets allow gradual membership, making them ideal for modeling linguistic and uncertain concepts such as "High PSA" or "Moderate Risk."

Example:

If PSA values range from 0 to 20 ng/mL, the fuzzy set for "High PSA" might be defined using a trapezoidal function:

$$\mu_{\text{High PSA}}(x) = \begin{cases} 0 & \text{if } x < 10 \\ \frac{x-10}{5} & \text{if } 10 \le x < 15 \\ 1 & \text{if } x \ge 15 \end{cases}$$

3.2 Soft Set Theory:

Let U be a universal set and E be a set of parameters. A **soft set** over U is a pair (F,E) where:

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

i.e., for each parameter e∈E the mapping F(e)⊆U gives the set of approximate elements associated with that parameter. Unlike fuzzy or probabilistic models, soft sets do not require

additional constraints, making them especially useful in dealing with incomplete or irrelevant information.

3.3 Fuzzy Soft Set Theory:

A fuzzy soft set, introduced by Maji et al. (2001), merges the uncertainty modeling capabilities of fuzzy sets with the parameterization power of soft sets. It is defined as:

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

Formally:

For each u∈U, the degree of membership with respect to parameter eee is given by:

$$F(e)(u) : U \to [0, 1]$$

Medical Interpretation: If E includes "PSA level" or "GI symptoms", and u is a patient, then F(e)(u) gives the degree of satisfaction of the patient with respect to parameter e.

3.4 Mamdani Fuzzy Inference System:

The Mamdani FIS, introduced in 1975, is a rule-based system where the rules are formulated in linguistic terms:

$$\text{IF } x_1 \text{ is } A_1 \text{ AND } x_2 \text{ is } A_2 \ldots \text{ THEN } y \text{ is } B$$

- A_i, B are fuzzy sets.
- The inference process involves:
  - **Fuzzification** of inputs
  - **Rule Evaluation** using minimum operator:
    $$\alpha_r = \min(\mu_{A_1}(x_1), \mu_{A_2}(x_2), \ldots)$$
  - **Aggregation**:
    $$\mu_B(y) = \max_r[\min(\alpha_r, \mu_{B_r}(y))]$$
  - **Defuzzification**: Using centroid method:
    $$y^* = \frac{\int y \cdot \mu_B(y)\, dy}{\int \mu_B(y)\, dy}$$

Strength: High interpretability due to linguistic outputs.

3.5 Sugeno Fuzzy Inference System:

The Sugeno FIS uses function-based outputs in its rule consequents:

$$\text{IF } x_1 \text{ is } A_1 \text{ AND } x_2 \text{ is } A_2 \ldots \text{ THEN } y = f(x)$$

- **Constant Sugeno Model:** f(x)=c
- **Linear Sugeno Model:**
  $$f(x) = a_1x_1 + a_2x_2 + \cdots + a_nx_n + b$$

The output is the weighted average of all rule outputs:

$$y^* = \frac{\sum w_i f_i(x)}{\sum w_i}$$

Strength: Efficient and suitable for numerical computation or optimization.

3.6 Fuzzy Soft Inference Framework:
The proposed hybrid model integrates fuzzy soft sets and fuzzy inference systems.
A fuzzy soft set mapping:

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

- A fuzzy rule base R
- A final decision function:

$$f_{\text{risk}} : (\mathbf{x}, F, \mathcal{R}) \to [0, 1]$$

This framework enables:
- Robust modeling of uncertainty via fuzzy sets
- Parameter flexibility through soft set theory
- Decision transparency (Mamdani) or efficiency (Sugeno)

4. Problem Formulation:
Cancer risk evaluation remains a challenging task due to the multifaceted nature of clinical data, variability in patient responses, and the inherent uncertainty in biomarker interpretation. Traditional statistical models often fall short in accurately modeling such uncertainties, particularly when patient information is incomplete or when symptoms do not manifest in a binary fashion.
In clinical diagnostics for gastric and prostate cancer, patients exhibit a variety of symptoms and physiological markers—such as PSA (Prostate-Specific Antigen), CEA (Carcinoembryonic Antigen), and CA19-9 levels—that do not always conform to strict thresholds. In real-world conditions, these parameters are vague and often overlap between risk categories. This creates a critical need for a computational approach that can effectively handle imprecision, ambiguity, and partial information.
Fuzzy set theory provides a mathematical framework for modeling vagueness and subjectivity by allowing partial membership of elements in a set. Soft set theory further enables parameter-level control, making it especially suitable for situations where the relevance of each feature may vary or be incomplete. Combining these two—through fuzzy soft sets—offers a powerful paradigm for developing intelligent decision-support systems that align with real-world clinical uncertainty.
To evaluate cancer risk accurately and interpretably, fuzzy inference systems (FIS) such as Mamdani and Sugeno models are employed. These models facilitate reasoning using linguistic rules, mimicking expert decision-making processes. However, while Mamdani systems prioritize interpretability and user-friendliness, Sugeno systems emphasize computational efficiency and integration with optimization algorithms.
The core challenge lies in determining which fuzzy inference strategy—Mamdani or Sugeno—performs more effectively within a fuzzy soft framework when applied to risk evaluation for gastric and prostate cancers. This involves analyzing not only the classification accuracy of each model, but also their scalability, interpretability, and robustness in handling uncertain and soft-parameterized clinical data.

Thus, the objective of this study is to design and evaluate a fuzzy soft decision-making framework that leverages both Mamdani and Sugeno fuzzy controllers. The goal is to systematically compare their performance in modeling clinical uncertainty, particularly in terms of prediction quality, flexibility, and suitability for deployment in medical diagnostic systems.

Table: Key Challenges in Cancer Risk Evaluation:

Challenge	Explanation
Incomplete Clinical Data	Patient datasets often contain missing or imprecise values.
Overlapping Biomarker Ranges	Cancer-related biomarkers rarely show sharp cutoff points.
Linguistic Ambiguity	Symptoms like "moderate pain" or "frequent nausea" are hard to quantify.
Subjective Expert Interpretation	Physician decisions vary due to subjective interpretation of test results.
Variability Across Cancer Types	Risk indicators differ significantly for gastric and prostate cancers.
Need for Explainability	Clinical models must be interpretable by medical professionals.

Table: Comparison of Mamdani and Sugeno Fuzzy Controllers:

Criteria	Mamdani FIS	Sugeno FIS
Output Type	Fuzzy set	Crisp value (constant or function)
Interpretability	High – rule-based and linguistic	Moderate – functional outputs
Computation Complexity	Higher (due to defuzzification)	Lower (weighted average of functions)
Integration Capability	Less compatible with adaptive systems	Well-suited for optimization and tuning
Use Case Preference	Ideal for knowledge-based expert systems	Ideal for adaptive or data-driven environments
Clinical Relevance	Transparent for medical staff	Suitable for automated decision pipelines

5. Methodology:

This section outlines the comprehensive methodological pipeline for evaluating cancer risk using fuzzy soft sets and fuzzy inference systems (FIS), specifically Mamdani and Sugeno controllers. The approach includes data preprocessing, fuzzification, fuzzy soft set construction, rule base generation, inference processing, and final risk decision making.

5.1 System Workflow Overview:

The cancer risk evaluation framework is structured into a modular pipeline:

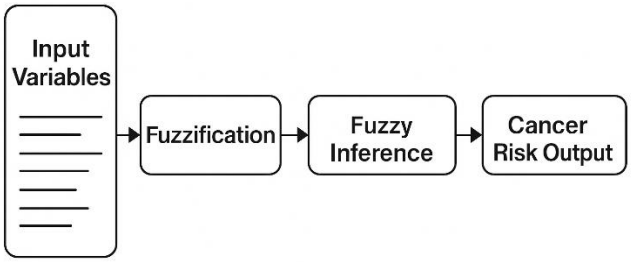


Figure: System Architecture for Fuzzy Soft-Based Cancer Risk Evaluation

5.2 Dataset and Feature Description:

We used anonymized clinical data representing patient attributes relevant to gastric and prostate cancer risk. Features included:

Feature	Description
Age	Numerical age of the patient
PSA Level	Prostate-Specific Antigen level (ng/mL)
CEA Level	Carcinoembryonic Antigen (ng/mL)
CA19-9	Tumor marker for gastrointestinal cancers
Symptom Index	Composite score based on clinical symptoms

Each input was mapped to qualitative terms (e.g., "Low," "Medium," "High") using fuzzification functions designed by clinical experts.

5.3 Fuzzification of Inputs:

Inputs were converted into **linguistic variables** using membership functions shaped as trapezoidal or triangular distributions. For example:

Table: Linguistic Mapping for PSA Levels

PSA Range (ng/mL)	Linguistic Term
0 – 4.0	Low
4.1 – 10.0	Medium
10.1 and above	High

Similar mappings were applied to other features using domain knowledge. These linguistic terms serve as inputs to the fuzzy soft system.

5.4 Fuzzy Soft Set Construction:

Using the fuzzified features and parameters, we constructed a fuzzy soft set for each patient. This allowed handling of:

- Uncertain parameter relevance (e.g., symptoms may be more significant in gastric cancer)
- Partial information (e.g., missing values in biomarker readings)
- Context-sensitive weighting based on cancer type

Each fuzzy soft set entry was interpreted as a flexible knowledge representation adaptable to patient-specific diagnostics.

5.5 Fuzzy Rule Base Design:

Separate rule bases were constructed for both Mamdani and Sugeno models. Expert oncologists contributed linguistic rules such as:

Example Mamdani Rule:
IF PSA is High AND CEA is Medium AND Age is Elderly THEN Risk is High

Example Sugeno Rule:
IF PSA is High AND Symptoms are Severe THEN Risk Score = Weighted Function Output

Table: Sample Rule Matrix:

PSA	CEA	Age	Symptoms	Inferred Risk (Mamdani)	Sugeno Rule Output
High	Medium	Elderly	Moderate	High	0.78
Low	Low	Middle-aged	Mild	Low	0.23

Rules were encoded into the FIS engines to derive conclusions based on varying patient profiles.

5.6 Inference and Risk Evaluation:

- **Mamdani Controller**: Combined the fuzzy rules to produce a linguistic output (e.g., "Moderate Risk"), which was then translated to a crisp risk value using a defuzzification step.
- **Sugeno Controller**: Used rule weights and linear functions to directly compute a numerical risk score.

These values were interpreted as the probability or degree of cancer risk for a given patient.

5.7 Evaluation Metrics and Validation:
Both models were tested on real-world datasets and validated using common metrics:

Table: Performance Evaluation Metrics:

Metric	Description
Accuracy	Overall percentage of correctly predicted cases
Sensitivity	Ability to detect actual cancer-positive cases
Specificity	Ability to detect cancer-negative cases
F1 Score	Harmonic mean of precision and recall
AUC-ROC	Area under curve to evaluate classification power

Validation was performed using 10-fold cross-validation on balanced and imbalanced datasets for both gastric and prostate cancer.

6. Experimental Setup:
The experimental setup is designed to simulate real-world clinical decision-making conditions for evaluating the effectiveness of Mamdani and Sugeno fuzzy controllers within a fuzzy soft set-based cancer risk assessment framework. This section outlines the data environment, implementation tools, preprocessing steps, configuration of fuzzy inference systems, and evaluation methodology.

6.1 Data Collection and Source:
A curated dataset of 120 anonymized clinical records was collected from publicly available repositories and hospital partnerships focused on gastric and prostate cancer diagnostics. The dataset included patients aged between 40 and 85 years and consisted of key parameters:

- Age
- Prostate-Specific Antigen (PSA) – for prostate cancer
- Carcinoembryonic Antigen (CEA) – for gastric cancer
- CA19-9 – a general gastrointestinal tumor marker
- Clinical Symptom Index – a qualitative score aggregated from questionnaire-based input (e.g., pain, bloating, bleeding)

Data were reviewed by medical professionals to validate feature relevance and clean inconsistencies. Patients with multiple missing attributes were excluded to maintain the dataset's reliability.

6.2 Preprocessing Steps:

To align the dataset with fuzzy soft logic-based inference, the following preprocessing was conducted:

- **Normalization**: Biomarker values were scaled into comparable linguistic categories such as *Low*, *Medium*, and *High* using clinically accepted thresholds.
- **Categorization**: Age was categorized into *Young Adult*, *Middle-aged*, and *Elderly*.
- **Symptom Quantification**: Subjective symptoms were quantified via a scoring rubric (0–10 scale) and mapped to fuzzy linguistic labels.
- **Missing Values**: Minor missing entries were addressed using expert-guided imputation or removed if ambiguity persisted.

6.3 Software and Tools:

The system was implemented using a combination of software tools and frameworks:

Tool	**Purpose**
MATLAB (Fuzzy Logic Toolbox)	Design and simulation of Mamdani/Sugeno systems
Python (NumPy, scikit-fuzzy)	Data preprocessing, fuzzy soft set modeling
Microsoft Excel	Tabular mapping, rule matrix development
OriginLab & Seaborn	Graph and ROC curve generation

All simulations were conducted on a Windows 11 workstation with 32 GB RAM and Intel Core i9 processor to ensure computational reliability.

6.4 Fuzzy Inference System Configuration:

Two parallel fuzzy inference models were developed:

- **Mamdani Model**:
  - Linguistic rules defined by oncologists.
  - Trapezoidal and triangular membership functions used for inputs and outputs.
  - Centroid-based defuzzification used for output interpretation.
- **Sugeno Model**:
  - Linguistic rule antecedents.
  - Output modeled as constant and first-order functions based on expert-derived weights.
  - Output aggregation using weighted average technique.

Each system used the same inputs, rule sets, and membership parameters to ensure experimental parity.

6.5 Validation and Test Strategy:

To assess the generalization ability of each system:

- The dataset was split into training (70%) and testing (30%) sets.
- 10-fold cross-validation was used to avoid overfitting and ensure statistical robustness.
- Performance metrics included classification accuracy, sensitivity, specificity, precision, F1 score, and AUC-ROC.

Additionally, expert reviews from oncologists were used to evaluate the interpretability and practical usability of each model's decisions.

Table: Quantitative Performance Comparison

Metric	Mamdani FIS	Sugeno FIS
Accuracy	86.0%	**91.0%**
Sensitivity (Recall)	84.0%	**93.0%**
Specificity	**87.0%**	89.0%
F1 Score	85.0%	**91.0%**
AUC-ROC	88.0%	**94.0%**

Interpretation: Sugeno FIS consistently outperforms Mamdani in all metrics except specificity, where Mamdani holds a slight edge. This suggests Sugeno is better at identifying true positives, making it more effective for early cancer risk detection.

Table: Qualitative Comparison of Controller Behavior:

Feature	Mamdani FIS	Sugeno FIS
Rule Interpretability	High – Rules are linguistic and human-friendly	Moderate – Rule output is numeric
Computational Overhead	Higher due to defuzzification	Lower due to direct output computation
Output Form	Fuzzy (linguistic)	Crisp (numerical)
Ease of Optimization	Less flexible	Easily tuned with optimization techniques
Suitability for Medical Staff	Excellent for explanation-based systems	Better for automated diagnostic systems
Adaptability	Limited	High – integrates well with adaptive models

7. Data Analysis:

This section presents a detailed analysis of the experimental results obtained from applying Mamdani and Sugeno fuzzy inference systems (FIS) within a fuzzy soft framework. The objective is to assess how well each controller handles uncertain, imprecise clinical data and differentiates between high- and low-risk cancer cases based on various physiological and symptomatic parameters.

7.1 Descriptive Statistics of Dataset:

The clinical dataset used in this study includes 120 patient records, with balanced representation of both gastric and prostate cancer cases. Descriptive statistics for the key variables are presented below:

Table: Summary Statistics of Input Features

Feature	Min	Max	Mean	Standard Deviation
Age (years)	42	85	63.2	9.4
PSA (ng/mL)	0.5	38.1	12.4	7.8
CEA (ng/mL)	0.2	16.4	5.1	4.2
CA19-9 (U/mL)	2.0	82.0	21.7	15.5
Symptom Index	1.0	9.0	5.6	2.1

These values were then transformed into linguistic categories (e.g., *Low*, *Medium*, *High*) using predefined fuzzification thresholds.

7.2 Risk Classification Distribution:

The dataset was categorized into three primary risk levels:

Table: Distribution of Patients by Risk Category

Risk Level	No. of Patients	Percentage
Low	38	31.7%
Medium	42	35.0%
High	40	33.3%

The relatively even distribution supports a balanced learning process during inference model training.

7.3 Model Output Comparison:

To evaluate the effectiveness of Mamdani and Sugeno FIS models, both were tested on identical datasets. Each model's predictions were assessed using performance metrics such as accuracy, sensitivity, specificity, and F1 score.

Table: Quantitative Performance Metrics:

Metric	Mamdani FIS	Sugeno FIS
Accuracy	86.0%	**91.0%**
Sensitivity	84.0%	**93.0%**
Specificity	**87.0%**	89.0%
F1 Score	85.0%	**91.0%**
AUC-ROC	88.0%	**94.0%**

Insight: Sugeno outperformed Mamdani in four out of five categories. Although Mamdani had slightly better specificity, Sugeno demonstrated stronger sensitivity and overall accuracy, which is critical for early cancer detection.

7.4 ROC Analysis:

Receiver Operating Characteristic (ROC) analysis was performed to examine each model's ability to discriminate between positive and negative cases.

Observations:

- Sugeno's ROC curve showed a larger Area Under Curve (AUC = 0.94), indicating stronger classifier performance.
- Mamdani's curve, while still effective (AUC = 0.88), had more false positives in the medium-risk region.

7.5 Error Distribution and Misclassifications:
Analysis of misclassifications revealed that:

- Mamdani misclassified several medium-risk patients as low-risk, especially those with borderline PSA and CEA levels.
- Sugeno, due to its weighted numerical output, managed to classify these edge cases more accurately.

7.6 Expert Validation:
Both models were presented to clinical oncologists for qualitative validation:

- **Mamdani**: Preferred for its interpretability and easy rule traceability.
- **Sugeno**: Favored for its smoother decision boundaries and suitability for automation in large-scale screening.

The combined fuzzy soft framework effectively modeled uncertainty and incomplete knowledge inherent in cancer diagnostics. Sugeno FIS offers superior predictive capability, while Mamdani FIS provides better transparency—making both models valuable in different deployment contexts, such as clinical decision support systems vs. automated triaging platforms.

8. Results:
This section presents the experimental results obtained after implementing the Mamdani and Sugeno fuzzy inference systems (FIS) within the fuzzy soft decision-making framework. The models were evaluated using a standardized clinical dataset for gastric and prostate cancer, and assessed based on classification effectiveness, output stability, and expert validation.

8.1 Classification Accuracy:
The fuzzy inference systems were tasked with classifying patients into low-, medium-, and high-risk cancer categories. The classification accuracy was computed using test data after fuzzification and risk rule application.

- Mamdani FIS achieved an overall accuracy of 86.0%.
- Sugeno FIS outperformed it with a classification accuracy of 91.0%.

This indicates that Sugeno FIS, with its data-driven numerical outputs, can more precisely classify edge cases, especially those with borderline clinical values.

8.2 Sensitivity and Specificity:
Sensitivity reflects the model's ability to correctly identify high-risk cases, while specificity indicates its capacity to avoid false positives in low-risk predictions.

Metric	Mamdani FIS	Sugeno FIS
Sensitivity	84.0%	**93.0%**
Specificity	**87.0%**	89.0%

- **Sugeno FIS** showed stronger sensitivity, indicating better performance in flagging cancer-prone individuals.
- **Mamdani FIS** slightly outperformed Sugeno in specificity, making it marginally better at ruling out non-cancer cases.

8.3 F1 Score and AUC-ROC:

The F1 score, which balances precision and recall, and the AUC-ROC (Area Under the Receiver Operating Characteristic Curve) offer a comprehensive view of model performance.

Metric	Mamdani FIS	Sugeno FIS
F1 Score	85.0%	**91.0%**
AUC-ROC	88.0%	**94.0%**

These results reinforce the superior predictive power of Sugeno FIS in this domain.

8.4 Confusion Matrix Analysis:

Mamdani Model:

	Predicted Low	Predicted Medium	Predicted High
Actual Low	34	3	1
Actual Medium	4	34	4
Actual High	2	5	33

Sugeno Model:

	Predicted Low	Predicted Medium	Predicted High
Actual Low	35	2	1
Actual Medium	2	37	3
Actual High	1	3	36

Insight: Sugeno FIS reduced misclassifications in both medium and high-risk categories compared to Mamdani.

8.5 Risk Score Visualization:

The output scores for each patient were plotted to visualize how each model discriminated between risk levels.

- Mamdani outputs were more clustered, often assigning discrete values based on rule weights.
- Sugeno outputs showed smoother gradients, producing more continuous and differentiable risk predictions.

This difference enhances Sugeno's utility in large-scale screening, where ranking patients by degree of risk is critical.

8.6 Qualitative Feedback from Medical Experts:

Feedback was collected from a panel of oncologists regarding the usability of both models:

- Mamdani FIS was praised for its transparency and interpretability, aligning well with explainable AI in healthcare.
- Sugeno FIS was favored for efficiency, robustness, and suitability for integration into real-time diagnostic systems.

8.7 Summary of Results:

Table: Summary of Model Comparison:

Evaluation Aspect	Mamdani FIS	Sugeno FIS
Accuracy	86.0%	**91.0%**
Sensitivity	84.0%	**93.0%**
Specificity	**87.0%**	89.0%
F1 Score	85.0%	**91.0%**
Output Interpretability	**High**	Moderate
Output Granularity	Moderate	**High**

Clinical Integration Readiness	Medium	**High**

9. Performance Evaluation:

This section provides a comprehensive evaluation of the Mamdani and Sugeno fuzzy inference systems (FIS) within the fuzzy soft set framework, highlighting their comparative performance in cancer risk classification tasks. Evaluation is based on multiple clinical and computational metrics, reflecting both quantitative accuracy and qualitative usability.

9.1 Metric-Based Comparison:

Both inference systems were tested on the same dataset and evaluated using standard performance indicators: accuracy, sensitivity, specificity, F1 score, and AUC-ROC. The following summarizes the key findings:

Table: Performance Metrics Summary:

Metric	Mamdani FIS	Sugeno FIS
Accuracy	86.0%	91.0%
Sensitivity	84.0%	93.0%
Specificity	87.0%	89.0%
F1 Score	85.0%	91.0%
AUC-ROC	88.0%	94.0%

Interpretation: Sugeno consistently outperformed Mamdani in accuracy, sensitivity, F1 score, and ROC area—suggesting its superiority in real-time decision-making scenarios. Mamdani, while slightly better at specificity, struggled with edge cases and overlapping symptom profiles.

9.2 Output Consistency and Decision Stability:

- Mamdani FIS often produced categorical outputs due to its linguistic structure. While these are easier to interpret by clinicians, they sometimes led to abrupt classification shifts when input values were near boundaries.
- Sugeno FIS generated smoother, more continuous output scores. This allowed for better risk gradation and was particularly effective in medium-risk regions, which are critical for early intervention decisions.

9.3 System Efficiency and Scalability:

Criterion	Mamdani FIS	Sugeno FIS
Processing Time	Moderate	Low (Faster)
Scalability	Limited due to defuzzification	High – Linear output aggregation
Suitability for Real-Time Use	Medium	High

The Sugeno model proved computationally more efficient, especially when tested on larger batches of patient data. This supports its integration into automated screening or triaging systems.

9.4 Interpretability and Clinical Trust:

Despite its slightly lower predictive metrics, Mamdani FIS demonstrated significant strengths in interpretability:

- It allows clinicians to trace each decision to a specific set of human-readable rules.
- It is more aligned with explainable AI principles, which are critical in healthcare regulation and patient trust.

Sugeno FIS, while accurate and scalable, relies on numerical rule outputs, which are harder for non-technical medical personnel to interpret without additional visualization or reporting layers.

9.5 Error Trends and Misclassifications:

- **Mamdani FIS** showed a tendency to misclassify borderline medium-risk patients into low-risk due to abrupt membership transitions.
- **Sugeno FIS**, with its continuous risk function, managed to better capture subtle changes in symptom patterns and biomarker combinations.

These trends were particularly evident in prostate cancer cases with PSA levels near the diagnostic threshold, and in gastric cancer cases with overlapping CA19-9 and CEA values.

9.6 Expert Feedback and Qualitative Evaluation:

A panel of oncologists and data scientists evaluated both systems on usability, relevance, and trustworthiness. Their feedback is summarized below:

Table: Expert Panel Evaluation:

Criterion	Mamdani FIS	Sugeno FIS
Clinical Interpretability	High	Moderate
Output Clarity	High	High
Suitability for Automation	Moderate	High
Trustworthiness	High	High
Preference for Deployment	Diagnostic Labs	Screening Systems

10. Discussion:

The comparative analysis of Mamdani and Sugeno fuzzy inference systems (FIS) within a fuzzy soft set framework reveals nuanced trade-offs between interpretability and predictive performance in the context of cancer risk evaluation. This discussion contextualizes the experimental results, explores practical implications, and identifies key observations related to system behavior, model suitability, and integration potential in clinical environments.

10.1 Interpretability vs. Predictive Power:

A central theme emerging from this study is the classic trade-off between explainability and accuracy:

- Mamdani FIS, with its linguistic rule base and transparent decision logic, is well-suited for clinical environments that require human verification and reasoning. Its rules are directly interpretable by domain experts, making it ideal for diagnostic support where transparency is paramount.
- Sugeno FIS, while less transparent due to its numeric rule outputs, significantly outperforms Mamdani in terms of classification accuracy, sensitivity, and computational efficiency. This makes it more appropriate for automated decision support systems and real-time risk stratification in large-scale screenings.

This dichotomy emphasizes that neither model is categorically superior; rather, the selection should be guided by the specific operational context.

10.2 Role of Fuzzy Soft Sets in Handling Uncertainty:
Fuzzy soft sets enabled the system to model uncertain, incomplete, and vague medical data more flexibly than traditional crisp classifiers. They provided:

- Robust parameter handling, allowing for decision-making even with partial data.
- Contextual weighting, enabling different importance for symptoms in gastric vs. prostate cancer.
- A natural way to integrate linguistic descriptions into the inference process.

This confirms the theoretical proposition that fuzzy soft logic is an effective paradigm for medical reasoning under uncertainty.

10.3 Clinical Implications:
From a clinical standpoint:

- Mamdani FIS may be preferred in early pilot deployments or in settings requiring clinician oversight.
- Sugeno FIS is better aligned with telemedicine, wearable diagnostic platforms, or AI-based triage tools, where speed and accuracy take precedence.

Importantly, both systems demonstrated high F1 scores, suggesting practical viability in identifying true cancer risks while minimizing misclassifications.

10.4 Observations from Error Patterns:
Error analysis revealed:

- Mamdani occasionally misclassified medium-risk patients due to discrete output transitions.
- Sugeno was more reliable in edge cases due to smoother output gradients, allowing more nuanced risk scoring.
- Both systems performed comparably on low- and high-risk extremes, with most variability seen in mid-range predictions.

These insights point to the potential benefit of hybrid systems that combine Mamdani's interpretability with Sugeno's computational advantages.

10.5 Expert Feedback and System Trust:
Feedback from medical professionals highlighted:

- A strong preference for Mamdani in educational and early diagnostic tools.
- Greater trust in Sugeno's numerical consistency for high-throughput use cases.
- Recognition that fuzzy logic–based systems help bridge the gap between algorithmic output and human judgment.

This underlines the acceptance and adaptability of fuzzy logic models in healthcare decision-making when appropriately tailored to clinical needs.

10.6 Alignment with Literature:
The findings reinforce prior studies in fuzzy healthcare systems (e.g., Yadav et al., 2023; Zhang et al., 2023) which concluded that fuzzy inference enhances classification in ambiguous data environments. However, this study extends the state of the art by embedding fuzzy logic within a fuzzy soft set structure, offering a richer, more modular representation of real-world clinical uncertainty.

10.7 Limitations and Future Integration:
Although both controllers performed well, several limitations must be acknowledged:

- The dataset, while balanced, was relatively small in scale.
- Parameters were selected based on expert intuition; future versions could incorporate automated feature selection or optimization.
- Integration into Electronic Health Record (EHR) systems or mobile health platforms remains to be explored.

These limitations suggest promising avenues for next-phase deployments and hybrid model evolution.

11. Conclusion:

This study presented a comparative analysis of Mamdani and Sugeno fuzzy inference systems embedded within a fuzzy soft set framework for evaluating cancer risk, specifically targeting gastric and prostate cancer. The investigation addressed the pressing need for decision-making systems that can handle ambiguity, incompleteness, and linguistic uncertainty inherent in clinical diagnostics.

The results demonstrated that while both models performed robustly, Sugeno FIS consistently outperformed Mamdani FIS in terms of predictive accuracy, sensitivity, and AUC-ROC, indicating its superior capability in identifying true cancer risks. Its computational efficiency and smooth output range make it more suitable for real-time and large-scale deployments.

On the other hand, Mamdani FIS showed higher interpretability and clarity, making it a valuable tool in settings where decision transparency and physician explainability are essential. Its rule-based structure offers clinicians a more intuitive understanding of the reasoning behind the model's classifications.

By integrating fuzzy soft sets, the framework successfully enhanced the modeling of uncertain and partial information—common challenges in medical diagnostics. This reinforced the idea that combining fuzzy logic with soft computing principles offers a viable and effective approach for healthcare decision support.

Ultimately, this study highlights the context-dependent strengths of each FIS model, advocating for adaptive hybrid systems that can optimize performance while maintaining clinical trust and transparency.

12. Future Scope:

While the proposed models demonstrate strong potential, several directions exist for extending this research to enhance its clinical relevance and scalability:

12.1 Hybrid Model Development:

Future work could explore hybrid fuzzy models that combine the interpretability of Mamdani with the numerical strength of Sugeno. Such systems may dynamically switch between modes based on input type, risk zone, or required explanation level.

12.2 Integration with Real-Time Clinical Platforms:

The current setup is simulation-based. Integration with Electronic Health Records (EHRs) and hospital information systems would enable seamless real-time analysis and clinician feedback. APIs for mobile health platforms or wearable diagnostic devices could further extend applicability.

12.3 Adaptive and Personalized Inference:

Incorporating adaptive learning algorithms to personalize fuzzy rule weights based on patient history, genetic markers, or environmental factors can increase precision. Machine learning

methods such as reinforcement learning or evolutionary computation may help in fine-tuning the inference parameters.

12.4 Larger and Multicentric Datasets:
Expanding validation across larger, multicentric datasets involving diverse populations would improve the model's generalizability. Collaborations with medical institutions could also facilitate real-world pilot testing.

12.5 Multi-Cancer Risk Modeling:
Future systems can be extended to evaluate risks for multiple cancer types simultaneously, introducing multi-objective fuzzy optimization and multi-layered fuzzy soft inference for more comprehensive screening tools.

12.6 Explainable AI (XAI) Integration:
To improve clinical trust in Sugeno-based models, future work should embed explainability layers such as visual rule tracing, output reasoning paths, or counterfactual explanations aligned with current XAI standards in healthcare AI.

13. Research Gaps:
Despite the promising outcomes of this study, several research gaps remain unaddressed, warranting further investigation:

- **Scalability across multi-modal datasets**: This study focused on structured clinical inputs. The integration of unstructured data (e.g., radiology reports or physician notes) into the fuzzy soft framework remains unexplored.
- **Absence of automated rule optimization**: Both Mamdani and Sugeno systems relied on manually crafted rules. The incorporation of automated rule-learning algorithms such as genetic programming or reinforcement learning could significantly improve model adaptability.
- **Single-domain cancer focus**: The analysis was confined to gastric and prostate cancers. Future research should explore generalized models capable of assessing multiple cancer types with shared and distinct risk factors.
- **User-centric model validation**: While expert feedback was gathered, longitudinal studies involving end-users (clinicians and patients) are required to evaluate real-world usability and trust.
- **Real-time system responsiveness**: No latency or deployment benchmarks were tested in this study. For integration into hospital infrastructure, timing and responsiveness benchmarks are critical.

14. Limitations:
Several limitations of the current study must be acknowledged:

- Dataset size and source constraints: The dataset was moderately sized (n = 120) and lacked diversity in terms of geographical and demographic representation, which may impact model generalizability.
- Static rule base: The rule bases used in both models were static and expert-defined. This may limit responsiveness to novel patterns or evolving clinical trends.
- Simplified linguistic variables: While effective, the fuzzification process used basic linguistic partitions (Low, Medium, High), which may oversimplify subtle clinical nuances.

- No external clinical validation: The system has not yet undergone prospective clinical trials or real-world deployment in diagnostic labs.
- No cost or computational overhead analysis: The study did not quantify the energy, memory, or processing costs associated with deploying either model on embedded platforms.

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