Hacettepe University

Artificial Intelligence Engineering Department

AIN 421 Fuzzy Logic - 2024 Fall

Project 1 – Fuzzy Inference System For Sepsis Classification

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1.Introduction

Sepsis is a life-threatening medical condition that arises from the body's extreme response to infection, often leading to organ failure and, if left untreated, death. Ensuring early and accurate detection is critical, as timely intervention—through antibiotic therapy, fluid resuscitation, and supportive measures—significantly reduces morbidity and mortality. Traditional detection methods, which commonly rely on clinical experience and standard criteria (e.g., SIRS, qSOFA), may produce unacceptable false negative rates, delaying critical treatments. In this context, a Fuzzy Inference System (FIS) presents a promising alternative. By leveraging fuzzy logic to transform key physiological parameters—such as blood pressure, respiratory rate, blood urea nitrogen, heart rate, and bicarbonate levels—into linguistic variables and interpretable rules, an FIS can better handle the inherent uncertainty and complexity of clinical decision-making. The resulting framework accommodates the nuances that crisp threshold-based systems often miss, allowing medical professionals to trust the decision process and, more importantly, reducing the likelihood that a septic patient is misclassified as non-septic. By carefully designing fuzzy rules that emphasize minimizing false negatives, an FIS offers a more sensitive and responsive tool in the critical task of sepsis classification.

2.Data

The data selection was guided by a preliminary analysis of correlation coefficients and distributional differences between sepsis and non-sepsis patient data. Initially, a wide range of clinical features were considered. After evaluating correlations with the outcome (sepsis vs. no sepsis) and examining how each feature's distribution varies between septic and non-septic cases, we selected five features for our FIS model:

- Respiratory Rate **(resp)**
- Heart Rate **(heart_rate)**
- Blood Urea Nitrogen **(bun)**
- Systolic Blood Pressure **(bp_systolic)**
- Bicarbonate **(bicarbonate)**

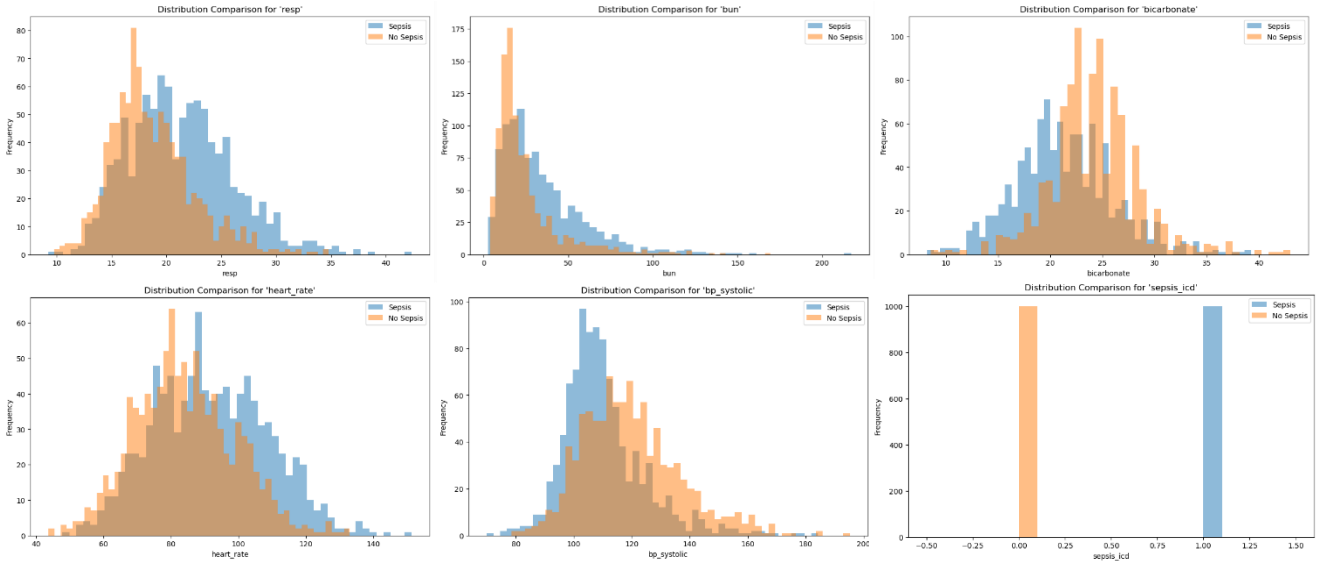

Figure 1. Distribution Comparisons

Correlations with sepsis_icd:

- resp 0.30
- heart_rate 0.24
- bun 0.22
- bp_systolic -0.28
- bicarbonate -0.30

A positive correlation indicates that as the input increases, the likelihood of sepsis also tends to increase while a negative correlation suggests the opposite relationship. Here, higher respiratory rates, heart rates, and bun levels are associated with sepsis, whereas higher systolic blood pressure and bicarbonate levels show a negative correlation.

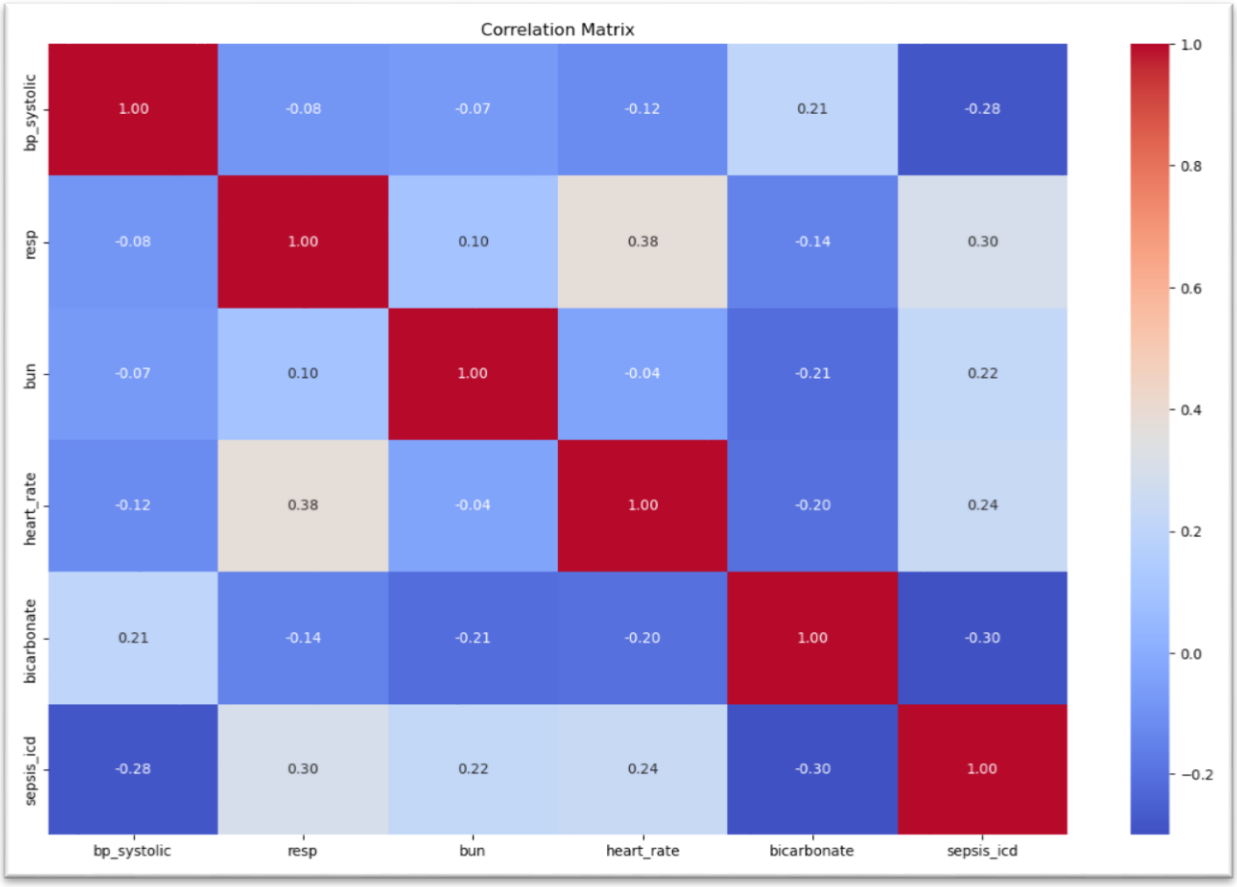

Figure 2. Correlation Matrix for selected features and output

Most of the correlations between inputs are relatively weak, indicating that these features capture somewhat distinct physiological dimensions of the patient's state. Notably, heart_rate and resp show a moderate positive correlation (0.38), suggesting patients with higher respiratory rates may also have elevated heart rates, which is plausible clinically. Other relationships are generally mild and do not indicate severe multicollinearity.

Table 1. Statistical properties of the data

Feature	Min	Max	Mean	Median	Std Dev	Min-Max Range
bp_systolic	70.00	195.20	114.92	112.15	16.32	125.20
resp	9.25	42.33	19.98	19.39	4.50	33.08
bun	2.66	217.00	29.65	22.00	23.35	214.33
heart_rate	43.73	151.25	88.02	87.04	16.41	107.51
bicarbonate	8.20	43.00	22.70	22.95	4.71	34.80

3. Methodology

3.1 Fuzzy Inference System (FIS) Framework

A Fuzzy Inference System (FIS) provides a means for mapping input features into a desired output using the principles of fuzzy logic. Unlike traditional binary or crisp thresholds, an FIS leverages linguistic variables and membership functions to accommodate uncertainty and complexity inherent in clinical data. By interpreting patient physiological parameters (e.g., blood pressure, heart rate) as fuzzy sets—such as "low," "normal," and "high"—the FIS allows for more nuanced decision-making. This approach is particularly useful in sepsis detection, where rigid cutoffs can lead to misclassification, especially false negatives that delay essential treatments. A well-designed FIS can capture subtle patterns in the data, offering improved sensitivity and an explanation-oriented framework that clinicians can more readily trust.

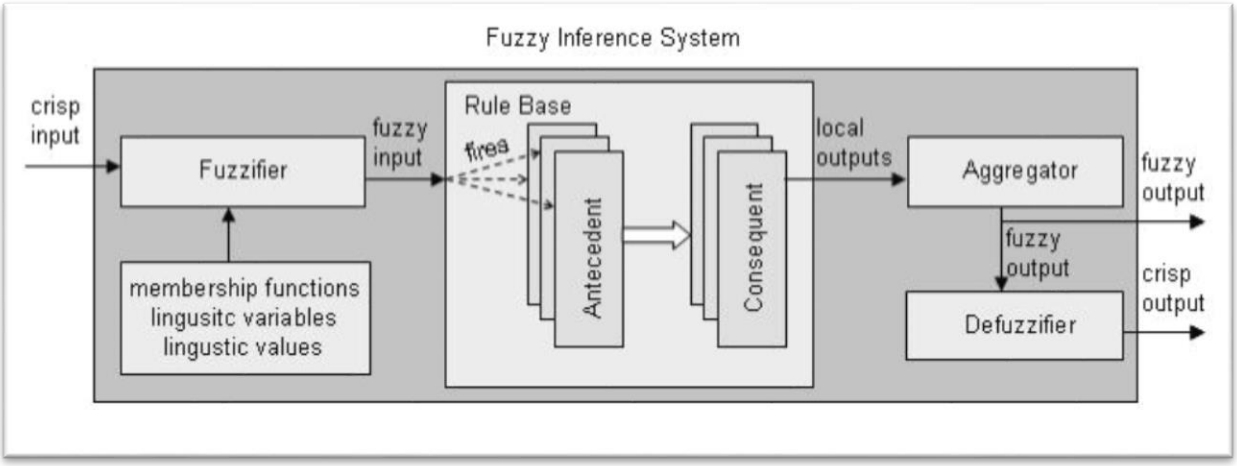

Figure 3. FIS Model

The chosen fuzzy inference approach in this project is based on the Mamdani-type inference, which is widely used for interpretability. This type of FIS computes fuzzy outputs through a set of linguistic if-then rules and subsequently defuzzifies the aggregated fuzzy result into a crisp output—here, a "sepsis risk" score that ranges from 0 to 1.

3.2 Data Preparation and Feature Selection

Before implementing the FIS, the data underwent a preprocessing stage. Missing values in the selected features were imputed using median values to maintain dataset consistency. Five physiological parameters—**Respiratory Rate**, **Heart Rate**, **Blood Urea Nitrogen (BUN)**, **Systolic Blood Pressure**, and **Bicarbonate**—were chosen based on correlation analyses and distributional differences between septic and non-septic patients. Each feature was standardized to its observed range, and summary statistics (minimum, maximum, mean, median, standard deviation, and range) were computed to guide fuzzy set definitions.

3.3 Libraries and Tools

The implementation of the FIS utilized Python's **scikit-fuzzy** library, specifically the fuzz and control submodules. These libraries offer ready-to-use methods for defining fuzzy sets, membership functions, and rules, as well as simulating the entire inference process. Additional Python libraries, including **pandas** and **NumPy**, supported data manipulation, while **matplotlib** and **seaborn** assisted in visualization (e.g., correlation matrices, confusion matrices). The **scikit-learn** library provided functions for computing performance metrics such as confusion matrices, F1 scores, and ROC AUC scores.

3.4 Definition of Fuzzy Sets and Membership Functions

For each input variable, three fuzzy sets—**low**, **normal**, and **high**—were defined. The membership functions were primarily triangular (using the fuzz.trimf method) and parameterized by the minimum, median, and maximum values observed in the dataset. This data-driven approach ensured that the fuzzy sets reflected the underlying distribution of each feature. Specifically:

- **Bicarbonate**: low, normal, high
- **BUN**: low, normal, high
- **Heart Rate**: low, normal, high
- **Respiratory Rate (resp)**: low, normal, high
- **Systolic Blood Pressure (bp_systolic)**: low, normal, high

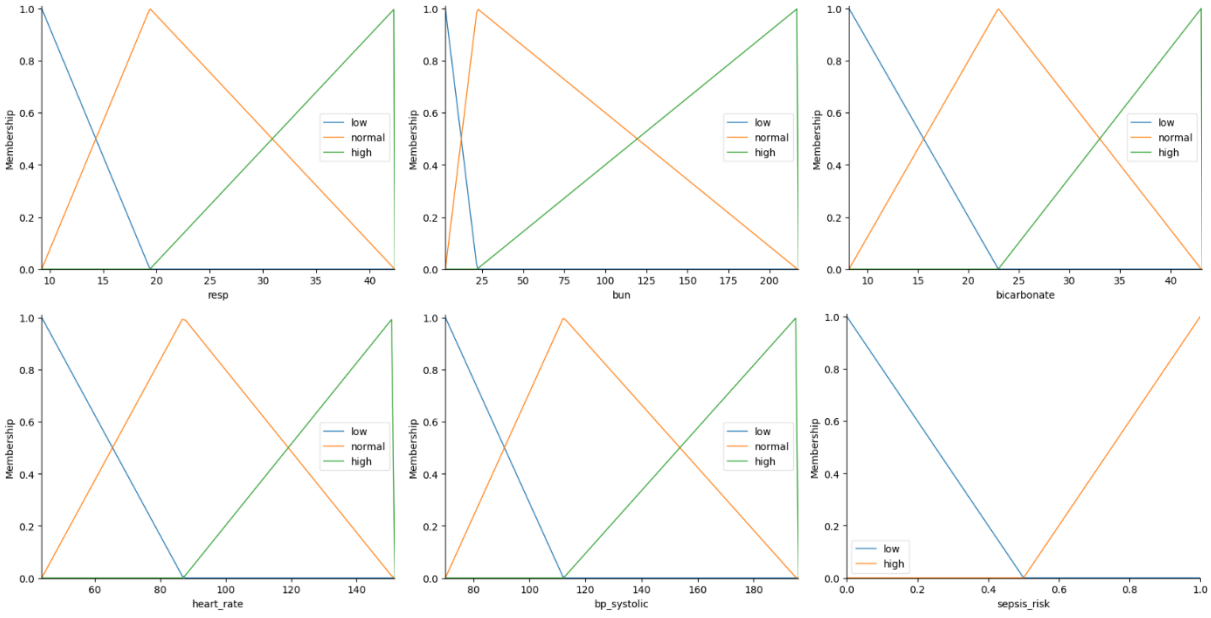

Figure 4. Membership Functions

The output (consequent) variable, **sepsis_risk**, was also defined as a fuzzy variable with two membership functions (low, high) spanning from 0 to 1. This ensured that the system could produce a continuous risk score, which was later converted into a binary classification based on a chosen threshold.

3.5 Rule Base Specification

The core of the FIS lies in its rule base. Rules were constructed in the form:

If (Input1 is [low/normal/high]) *and* (Input2 is [low/normal/high]) *and* … *then* (Sepsis Risk is [low/high]).

Seven rules were specified, 4 rule for low sepsis risk and 3 rule for high sepsis risk. Each focusing on combinations of input memberships that are clinically meaningful. For instance, certain patterns—such as low bicarbonate or low systolic blood pressure—are known risk indicators for sepsis and were assigned rules that push the sepsis risk toward "high." Conversely, more normal physiologic conditions led to "low" sepsis risk conclusions. This rule set was small and interpretable, allowing for adjustments based on domain knowledge or empirical findings.

3.6 Inference and Defuzzification

Once the input feature values were fed into the system, the FIS applied the rules using a Mamdani-type inference mechanism. Each rule's antecedent (the input conditions) was evaluated, and the rule's consequent (the output fuzzy set) was activated proportionally to the degree of match. All activated consequents were aggregated, and a defuzzification step—such as the centroid method—was applied to produce a single crisp sepsis risk score.

3.7 Thresholding and Classification

Although the FIS inherently produces a continuous output (the sepsis risk), clinical decisions often require binary classification: identifying whether a patient is septic (1) or not (0). A threshold of 0.40 was chosen (based on exploratory tuning) to label cases with risk ≥ 0.40 as septic. Adjusting this threshold allows control over the trade-off between false negatives and false positives, a crucial consideration in clinical contexts where missing a septic patient is far more dangerous than flagging a non-septic patient for further testing.

3.8 Performance Evaluation

The performance of the FIS-based classification was assessed using standard metrics:

- **Confusion Matrix**: To visualize true positives (TP), false positives (FP), false negatives (FN), and true negatives (TN).
- **True Positive Rate (TPR) / Sensitivity**: Measures how well the model detects actual sepsis cases (TP/(TP+FN)).
- **False Positive Rate (FPR)**: Indicates how often the model flags non-septic patients as septic (FP/(FP+TN)).
- **True Negative Rate (TNR)**: Measures how well the model identifies non-septic cases correctly (TN/(TN+FP)).
- **False Negative Rate (FNR)**: Shows how often the model fails to detect sepsis when it is present (FN/(TP+FN)).

- **F1 Score**: The harmonic mean of precision and recall, providing a single metric that balances the two.
- **Accuracy**: Measures the proportion of correct predictions among the total number of cases
- **Precision**: Indicates the proportion of true positive predictions among all positive predictions made by the model.
- **ROC AUC Score**: Evaluates overall performance across varying thresholds.

4. Results and Discussion

4.1 Obtained Results

After running the FIS-based model on the dataset of 250 septic and 250 non-septic patients (total 500 samples), we obtained the following results with a chosen threshold of 0.40 for sepsis classification:

Table 2. Results

Metric	Value
True Positive Rate (TPR) / Recall	0.82
False Positive Rate (FPR)	0.39
True Negative Rate (TNR)	0.61
False Negative Rate (FNR)	0.18
F1 Score	0.74
Accuracy	0.71
Precision	0.67
ROC AUC Score	0.71

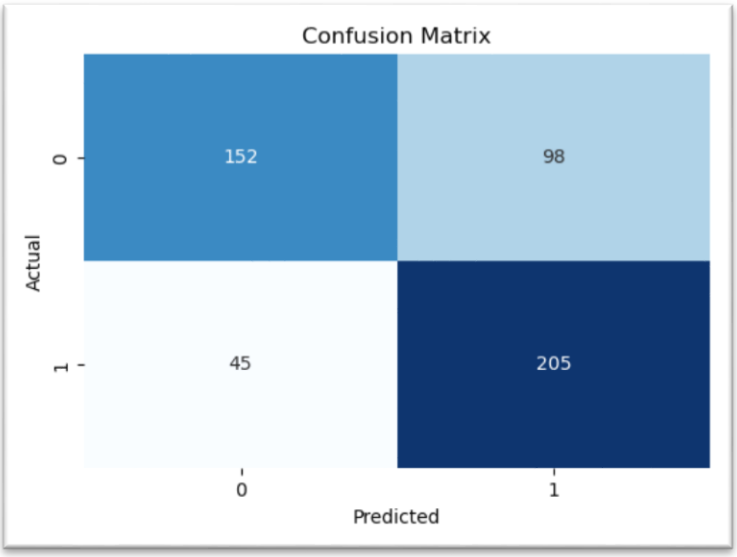

Figure 5. Confusion Matrix

The confusion matrix visually represents these results. Notably, the model achieved a TPR of 82%, indicating that it correctly identified 82% of the truly septic patients. In contrast, the FNR stands at 18%, signifying that 18% of actual sepsis cases were not flagged as such.

The distribution shows that the majority of risk scores are not tightly clustered around the 0.5 threshold, which can be seen as a positive outcome. Instead, there are clear tendencies toward lower or higher values, reducing the proportion of borderline cases that might be difficult to classify. With only about 16.6% of scores falling within a narrow band around 0.5, the system may more confidently separate likely septic from likely non-septic patients. This relative spread can provide clearer guidance for clinical decision-making, as fewer patients will hover in uncertain territory and require subtle threshold adjustments.

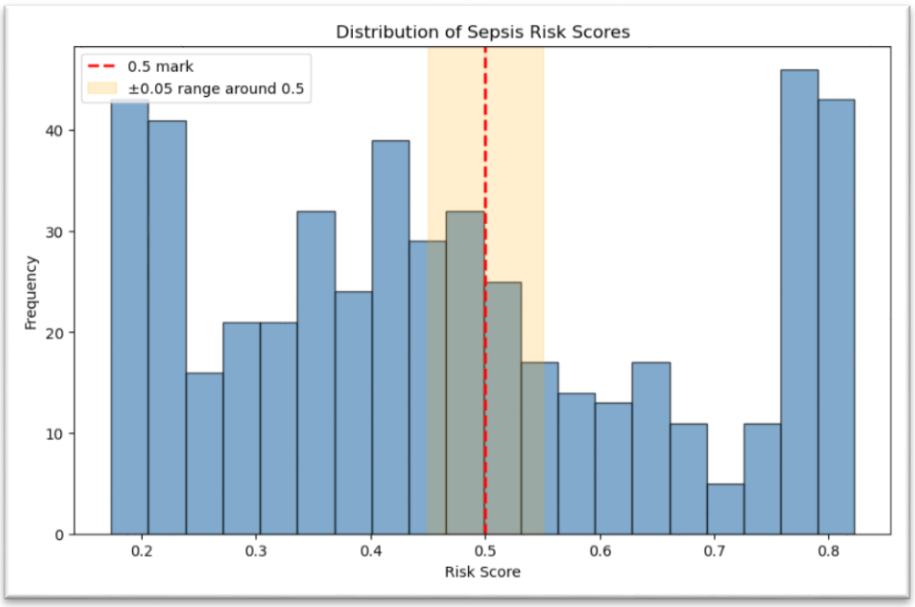

Figure 6. Distribution of predicted risk scores

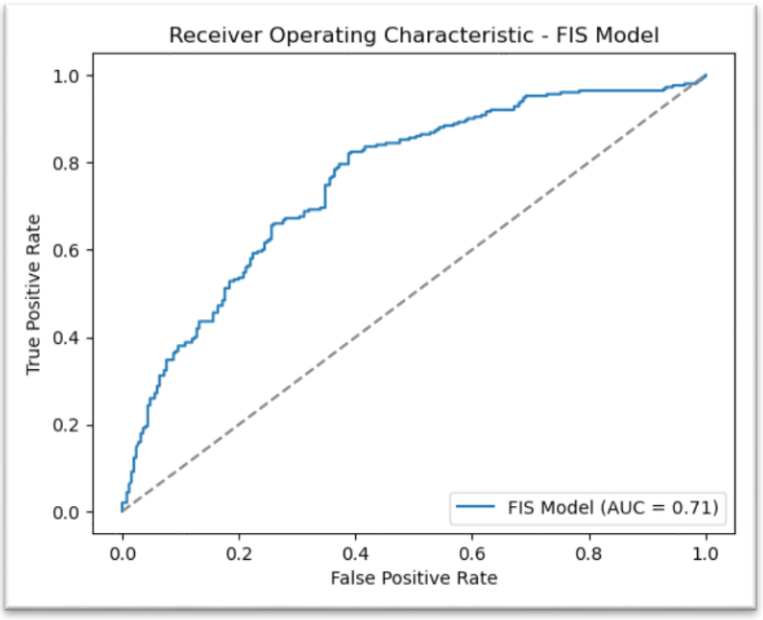

Figure 7. ROC Curve

4.2 Interpretation of False Positives and False Negatives

In a clinical setting, the distinction between false positives and false negatives is critically important:

- **False Positives (FP)**: These are non-septic patients who have been classified as septic. While such cases may lead to unnecessary additional tests or monitoring, the clinical implications are relatively less severe compared to missing a truly septic patient. False positives can still generate patient anxiety, increase costs, and potentially lead to overtreatment. However, given the high stakes of sepsis management, the healthcare system often considers this trade-off acceptable if it means fewer missed cases of sepsis.
- **False Negatives (FN)**: These represent the most concerning error type in sepsis classification. A false negative means that a patient who is actually septic was not identified by the system and might therefore miss timely treatment interventions. In the context of sepsis, delayed identification can significantly increase the risk of severe complications and mortality. As a result, minimizing FN values is paramount.

Within this study's results, the false negative rate (18%) is not trivial. Although the majority of septic patients are identified, there remains a subset who are at risk due to non-detection. Improving upon this aspect is crucial, as the cost of missing a septic patient can be catastrophic—the difference between a timely intervention and a life-threatening delay.

4.3 Emphasis on Recall in Healthcare

In healthcare-oriented classification tasks, **Recall (also referred to as Sensitivity or TPR)** is often considered the most critical metric. This emphasis stems from the need to capture as many true cases of the condition as possible. For conditions like sepsis, where a delayed or missed diagnosis can be fatal, achieving a high recall minimizes the probability that a truly septic patient goes unnoticed. Although the presented system achieves a recall of 82%, which may be acceptable in certain contexts, there is still room for improvement. A higher recall would mean fewer patients slipping through the cracks and would be an essential step toward more reliable, life-saving clinical support tools.

4.4 Areas for Further Study and Improvement

To address the observed performance gaps and refine the sepsis detection tool, several avenues can be considered:

1. **Refining Membership Functions and Rules:**
   The current FIS relies on a relatively small set of rules and straightforward membership functions derived from basic statistics (min, median, max). Future work could involve more sophisticated membership function tuning, incorporating domain expert knowledge or data-driven optimization techniques (e.g., genetic algorithms) to create more discriminative fuzzy sets.
2. **Incorporation of Additional Features:**
   Additional physiological parameters, laboratory values, or temporal trends in patient data may capture subtle signs of early sepsis onset. Integrating more comprehensive patient profiles could help reduce the false negative rate by providing richer information to the FIS.

3. **Adaptive Thresholding and Ensemble Methods:**
   The binary classification threshold (currently 0.40) could be dynamically adjusted based on patient context (e.g., comorbidities, age, or setting), or the fuzzy inference could be integrated into ensemble methods with more advanced machine learning techniques. This hybrid approach might yield a higher recall without excessively increasing false positives.
4. **Prospective Validation and Clinical Trials:**
   Ultimately, validating the system in real-world clinical settings with prospective data is crucial. Feedback from clinicians using the tool in a live environment would provide insights into its utility, highlight areas for improvement, and confirm whether the enhancements in recall translate into better patient outcomes.

The results of the implemented Mamdani Fuzzy Inference System (FIS) for sepsis detection highlight its potential as a sensitive tool in clinical decision-making. With a true positive rate of 82%, the system demonstrates a strong ability to identify septic patients, a critical factor in preventing adverse outcomes associated with delayed intervention. However, the 18% false negative rate underscores the need for further optimization, as undetected sepsis cases can lead to life-threatening consequences.

Importantly, the reliance on interpretable rules and membership functions makes it suitable for clinical environments where transparency and explainability are paramount. False positives, while less critical than false negatives, present their own challenges, such as unnecessary interventions and increased healthcare costs. These trade-offs are typical in healthcare applications, where the priority is often on minimizing the risk of missing critical conditions.

5. Conclusion

The Mamdani Fuzzy Inference System (FIS) developed in this project serves as a promising tool for early sepsis detection. By translating physiological data into interpretable fuzzy logic rules, the system effectively manages the uncertainties inherent in medical diagnosis. With an 82% true positive rate, it proves capable of supporting clinicians in identifying septic patients, thus potentially reducing mortality rates through timely interventions.

However, the false negative rate of 18% indicates room for enhancement to ensure no critical cases are missed. Future work focusing on optimizing membership functions, expanding the input feature set, and validating the model in clinical trials could further improve its robustness and utility. Moreover, adapting the system to dynamic patient contexts through machine learning integration may offer a path toward higher recall and precision.

This project underscores the importance of combining computational methods with domain expertise to tackle complex medical challenges. The developed FIS is not just a computational artifact but a step toward advancing clinical tools that prioritize patient safety and care quality. With continued refinement and validation, it has the potential to contribute significantly to the field of sepsis management.

References

1. **CodeCrucks. (2021, August 22).** Mamdani Fuzzy Inference System https://codecrucks.com/mamdani-fuzzy-inference-system-concept/
2. **Igodan, C. E., & Akwukwuma, V. V. N. (2013).** Knowledge-Based Fuzzy Inference System for Sepsis Diagnosis. *International Journal of Computational Science and Information Technology*, 1(3), 1–7. https://airccse.org/journal/ijcsity/papers/1313ijcsity01.pdf
3. **Scikit-Fuzzy Development Team. (2024**). "Scikit-Fuzzy: Fuzzy Logic Toolkit for Python." [Online Resource]. Available at: https://scikit-fuzzy.readthedocs.io/