



Hacettepe University
Artificial Intelligence Engineering Department

AIN 421 Fuzzy Logic - 2024 Fall

**Project 1 – Adaptive Neuro Fuzzy Inference System for Sepsis
Classification**

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Table of Contents

1. [Introduction](#)
 - Overview of Sepsis and Diagnostic Challenges
 - Objectives of the Study
2. [Data](#)
 - Data Selection and Standardization
 - Feature Selection and Correlation Analysis
 - Statistical Properties of Selected Features
3. [Methodology](#)
 - Overview of Adaptive Neuro-Fuzzy Inference System (ANFIS)
 - Overview of Random Forest (RF)
 - Preprocessing and Feature Engineering
 - Implementation Details of ANFIS and RF
 - Performance Metrics
4. [Results and Discussion](#)
 - Performance of ANFIS Model
 - Performance of Random Forest Model
 - Comparative Analysis
 - Discussion on False Positives and False Negatives
 - Emphasis on Sensitivity and Recall in Healthcare
5. [Conclusion](#)
 - Summary of Findings
 - Recommendations for Future Work
6. [References](#)

1. Introduction

Sepsis, a severe and life-threatening response to infection, remains one of the most challenging medical conditions due to its complex presentation and rapid progression. Early detection and timely treatment are essential to reducing the high morbidity and mortality rates associated with sepsis. While traditional diagnostic tools such as SIRS and qSOFA have served as the primary clinical standards, their limitations in sensitivity and adaptability to individual patient variability have spurred the exploration of advanced computational models. These models aim to improve diagnostic accuracy by leveraging diverse clinical data.

This report extends the exploration of sepsis classification by integrating an Adaptive Neuro-Fuzzy Inference System (ANFIS) and Random Forest (RF) for comparative evaluation. While a previous study highlighted the potential of Fuzzy Inference Systems (FIS) to address the uncertainties and imprecision in sepsis diagnosis, this phase investigates whether the adaptability of ANFIS offers further advantages. ANFIS combines the interpretability of fuzzy logic with the learning capabilities of neural networks, making it a promising candidate for tackling the nonlinear and dynamic patterns inherent in sepsis data.

The suitability of ANFIS for this problem lies in its unique ability to learn and refine fuzzy rules from data. Unlike static rule-based systems, ANFIS dynamically adjusts its parameters to optimize classification performance, bridging the gap between domain knowledge and data-driven insights. This adaptability is particularly important in sepsis detection, where physiological responses vary widely among individuals and across different stages of infection. By contrast, Random Forest, a well-established machine learning technique, offers a robust baseline for comparison due to its capability to handle high-dimensional data and complex feature interactions.

This investigation into ANFIS and RF aims to address the critical need for reliable, interpretable, and scalable solutions for sepsis classification. By comparing these models, the study seeks to identify optimal approaches to harness clinical data effectively, ultimately contributing to improved patient outcomes and advancing computational tools for critical healthcare challenges.

2. Data

The data selection process for this study was carried out with meticulous attention to ensure the reliability and relevance of the features used in sepsis classification. To standardize the dataset, the mean values of the patients' 24-hour records were calculated for each physiological parameter. Feature selection was guided by two key criteria: the correlation coefficients of the features with the target outcome (sepsis vs. non-sepsis) and their distributional differences between the two groups. Features with strong correlations to the target value were prioritized, as they likely carried significant predictive information. Additionally, features with distinct distributions between septic and non-septic patients were considered to enhance the model's ability to discriminate effectively between the two classes.

An effort was made to align the selected features with those used in the earlier Fuzzy Inference System (FIS) study. This consistency in feature selection served a dual purpose: maintaining comparability across studies and enabling an in-depth analysis of performance differences between FIS and ANFIS. By holding the features constant, the study isolates the effects of the modeling approach on classification outcomes, providing a more meaningful evaluation of the relative strengths and weaknesses of these systems. Through this carefully designed data selection process, the study ensures that the models are trained on a high-quality, representative dataset, paving the way for a robust comparison between ANFIS and alternative classification methods such as Random Forest and FIS.

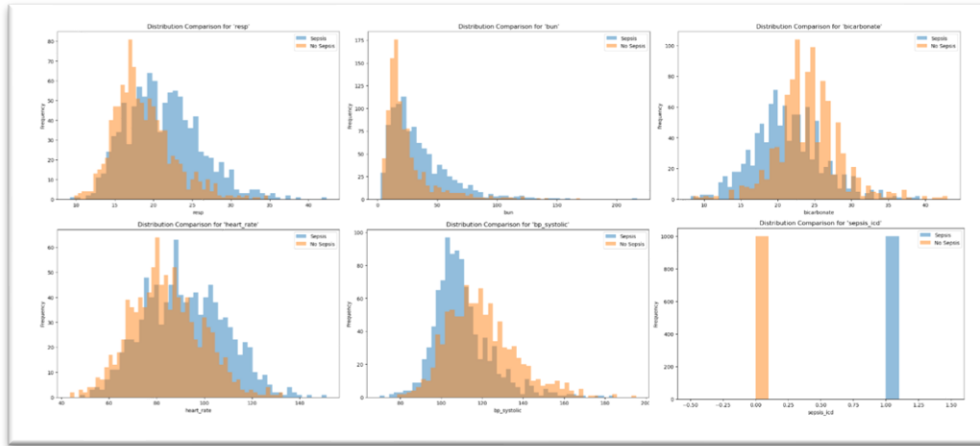


Figure 1. Distribution Comparisons

Selected features and correlation coefficients according to target (**sepsis_icd**) were Respiratory Rate (**resp**) 0.30, Heart Rate (**heart_rate**) 0.24, Blood Urea Nitrogen (**bun**) 0.22, Systolic Blood Pressure (**bp_systolic**) -0.28, Bicarbonate (**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.

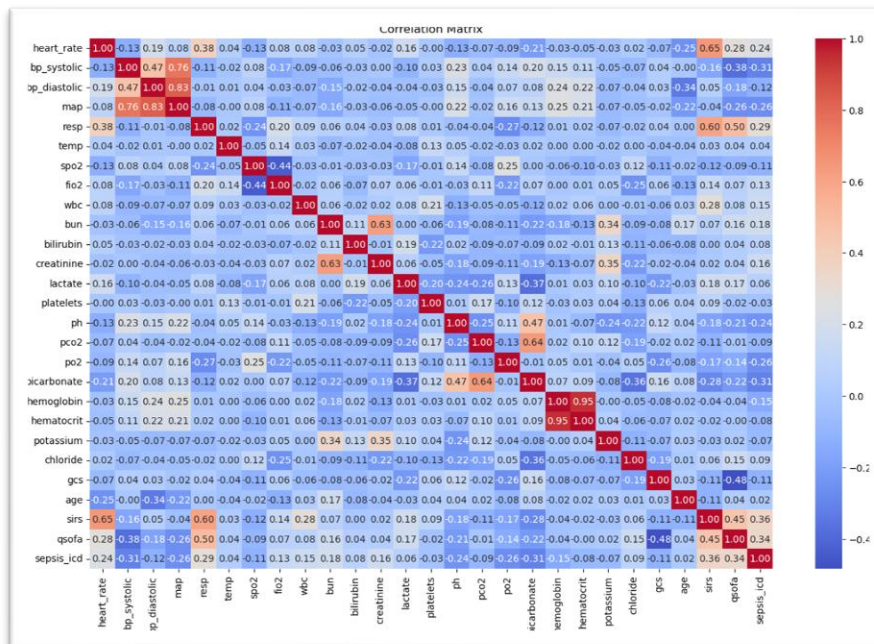


Figure 2. Correlation Matrix



Figure 3. Correlation Matrix for Selected Features and Target

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	183.91	114.74	111.80	16.23	113.91
resp	9.25	37.62	19.98	19.29	4.24	28.37
bun	2.66	217.00	29.24	21.78	22.74	214.33
heart_rate	45.50	151.25	87.90	86.84	16.27	105.75
bicarbonate	8.54	42.70	22.51	22.41	4.75	34.16

3. Methodology

This study applies two computational frameworks, Adaptive Neuro-Fuzzy Inference System (ANFIS) and Random Forest (RF), to classify sepsis. Each method is chosen for its unique capabilities in modeling complex relationships in clinical data, allowing for a comprehensive evaluation of their performance in sepsis detection.

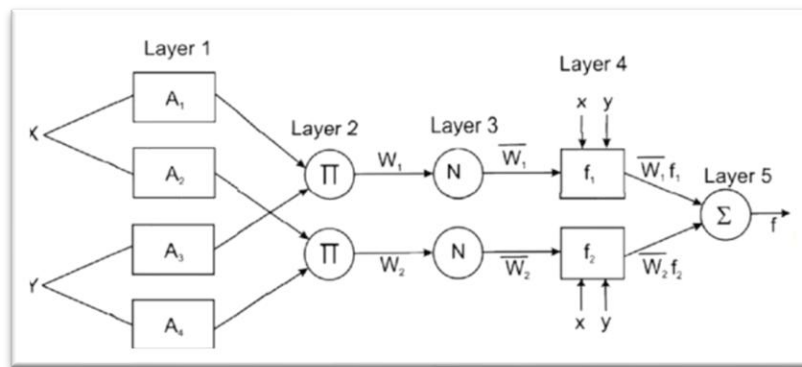


Figure 4. ANFIS Framework

The Adaptive Neuro-Fuzzy Inference System (ANFIS) is a hybrid model that combines fuzzy logic with the adaptive learning capabilities of neural networks. ANFIS begins with a fuzzy inference system, where input variables are converted into linguistic fuzzy sets and classified using if-then rules. However, unlike traditional fuzzy systems, ANFIS dynamically optimizes the parameters of its membership functions and rules through a learning algorithm inspired by neural networks. This process enables the model to adapt to nonlinear and intricate patterns in the data. The system operates in a layered architecture where inputs are fuzzified, rules are applied, and outputs are defuzzified to produce a final prediction.

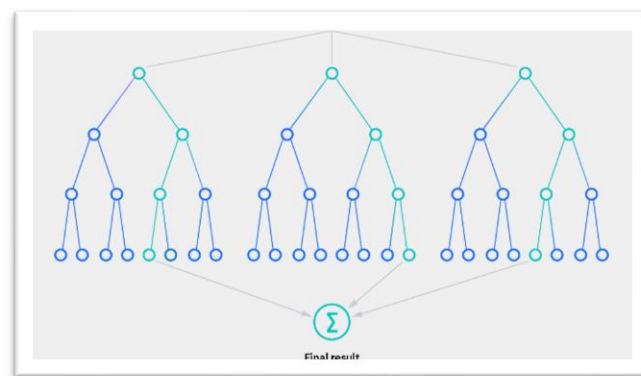


Figure 5. Random Forest Framework

Random Forest (RF), on the other hand, is a powerful ensemble learning technique that constructs multiple decision trees and aggregates their predictions to deliver a final classification. By training each tree on a random subset of the data and considering a random subset of features at each split, Random Forest reduces the risk of overfitting while maintaining robust predictive performance. RF provides an inherent measure of feature importance, which can aid in interpreting the model's decision-making process and identifying key clinical indicators of sepsis.

Before implementing the ANFIS, 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**, **Systolic Blood Pressure**, and **Bicarbonate**—were chosen based on correlation analyses and distributional differences between septic and non-septic patients. Summary statistics (minimum, maximum, mean, median, standard deviation, and range) were computed to guide fuzzy set definitions. The implementation of the ANFIS utilized a custom ANFIS library adapted from GitHub ([twmeegs/anfis](https://github.com/twmeegs/anfis)). This library was modified to ensure Python 3 compatibility. 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. Membership functions were defined for each of the five selected features. Gaussian membership functions were chosen because they provide smooth transitions and are commonly used in ANFIS frameworks. For each variable, three membership functions were employed: low, normal, and high. The key parameters used in defining the Gaussian MFs were mean (center of the gaussian curve) and sigma (spread of the gaussian curve). These parameters were derived from the descriptive statistics (minimum, median, maximum) of each feature, with sigma approximated as one-sixth of the range (max - min). This approach allowed the system to capture low, median, and high ranges of each physiological feature in a data-driven manner.

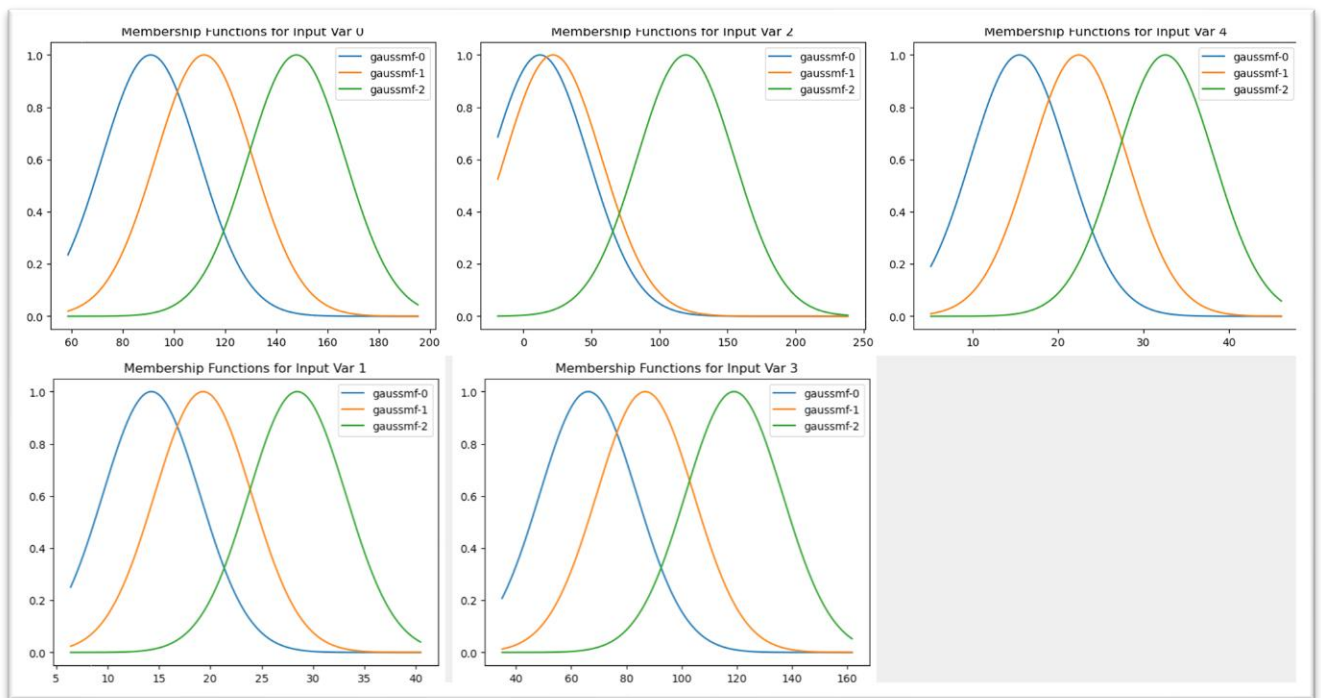


Figure 6. Membership Function

Using three membership functions for each of the five features generated $3 \times 3 \times 3 \times 3 \times 3 = 243$ rules. Each rule has the following form:

IF x_0 is MF1 **AND** x_1 is MF2 **AND** ... **AND** x_4 is MF3
THEN $y = \alpha_0 + \alpha_1 x_0 + \alpha_2 x_1 + \dots + \alpha_5 x_4$

where α_i are parameters learned during the training phase. This rule structure enables the model to capture interactions among all input features, providing a rich representation of the underlying relationships critical for sepsis detection. Once the membership degrees for each rule are computed, the system aggregates the contributions of all 243 rules using fuzzy operations such as conjunction (AND) and implication. The final output of the ANFIS model is a defuzzified crisp value, representing the likelihood of sepsis. The Hybrid Jang Off-Line method was employed to train the network, iteratively adjusting both the premise (membership function parameters) and consequent (linear regression coefficients) parameters to minimize the error between predicted and actual values. After the model outputs a continuous score, a threshold of 0.5 was used to determine the final classification. This binary cutoff was chosen for simplicity and interpretability. The same threshold was applied when calculating performance metrics for both ANFIS and the Random Forest classifier, ensuring a fair comparison.

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 means 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

The ANFIS model effectively classifies sepsis, achieving an 87% recall by correctly identifying 87% of septic cases and maintaining a low false positive rate of 8%. It accurately classifies 92% of non-septic cases, with a false negative rate of 13%, which needs improvement due to the critical nature of missed sepsis diagnoses. The model has an F1 score and overall accuracy of 0.89, a precision of 0.91, and a ROC AUC of 0.89, indicating strong performance across metrics. The confusion matrix shows 458 correct non-septic and 434 correct septic classifications, with 42 false positives and 66 false negatives. Overall, the ANFIS model demonstrates robust performance, though reducing false negatives is crucial for enhancing its clinical utility.

Table 2. Results

Metric	Value
True Positive Rate (TPR) / Recall	0.87
False Positive Rate (FPR)	0.08
True Negative Rate (TNR)	0.92
False Negative Rate (FNR)	0.13
F1 Score	0.89
Accuracy	0.89
Precision	0.91
ROC AUC Score	0.89

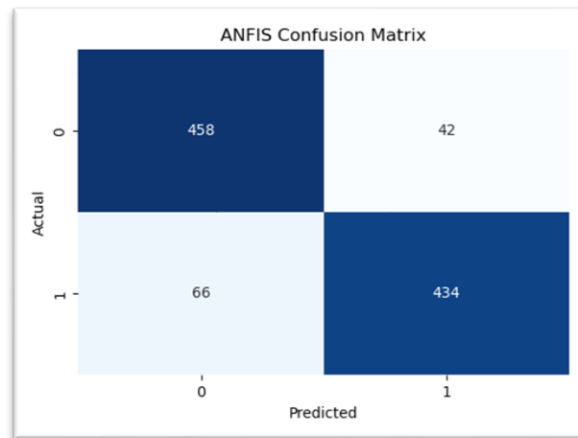


Figure 5. Confusion Matrix of ANFIS Model

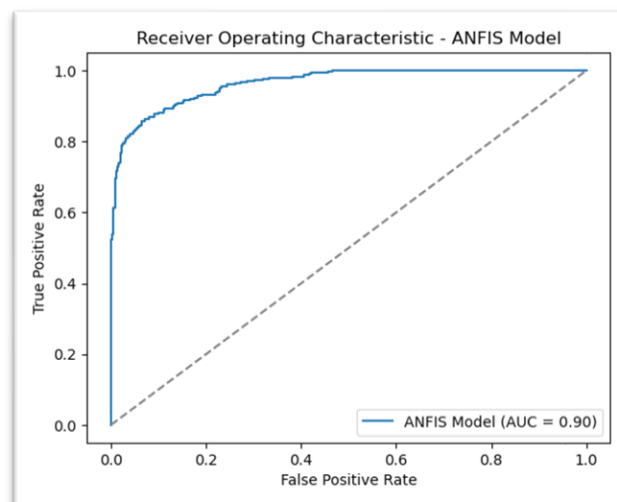


Figure 7. ROC Curve of ANFIS Model

The Random Forest model for sepsis classification shows moderate effectiveness with a recall of 0.71, correctly identifying 71% of septic cases. However, it has a high false positive rate of 0.30, incorrectly flagging 30% of non-septic cases, which may lead to unnecessary interventions. The true negative rate is also 0.71, accurately classifying 71% of non-septic cases, while the false negative rate is 0.29, missing 29% of septic cases—a critical issue due to the serious implications of missed diagnoses. The model has an F1 score and overall accuracy of 0.70, indicating balanced but moderate performance. Precision is 0.70, meaning 70% of predicted septic cases are correct. The ROC AUC score of 0.70 reflects a fair discriminative ability. The confusion matrix shows 457 correct non-septic and 433 correct septic classifications, with 43 false positives and 67 false negatives.

Table 3. Results

Metric	Value
True Positive Rate (TPR) / Recall	0.71
False Positive Rate (FPR)	0.30
True Negative Rate (TNR)	0.71
False Negative Rate (FNR)	0.29
F1 Score	0.70
Accuracy	0.70
Precision	0.70
ROC AUC Score	0.70

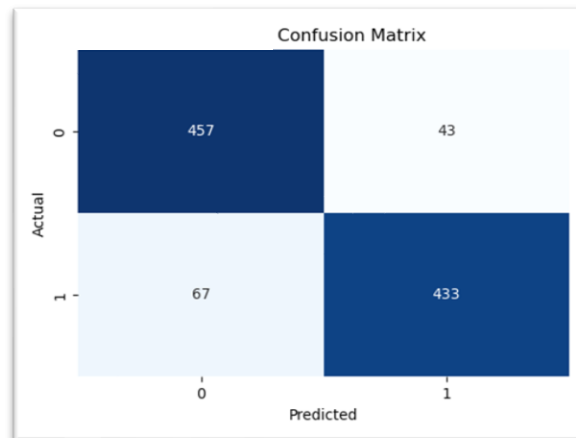


Figure 6. Confusion Matrix of Random Forest Model

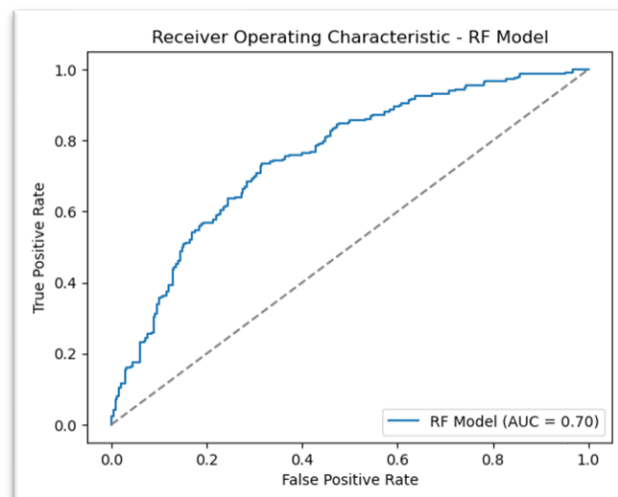


Figure 8. ROC Curve of Random Forest Model

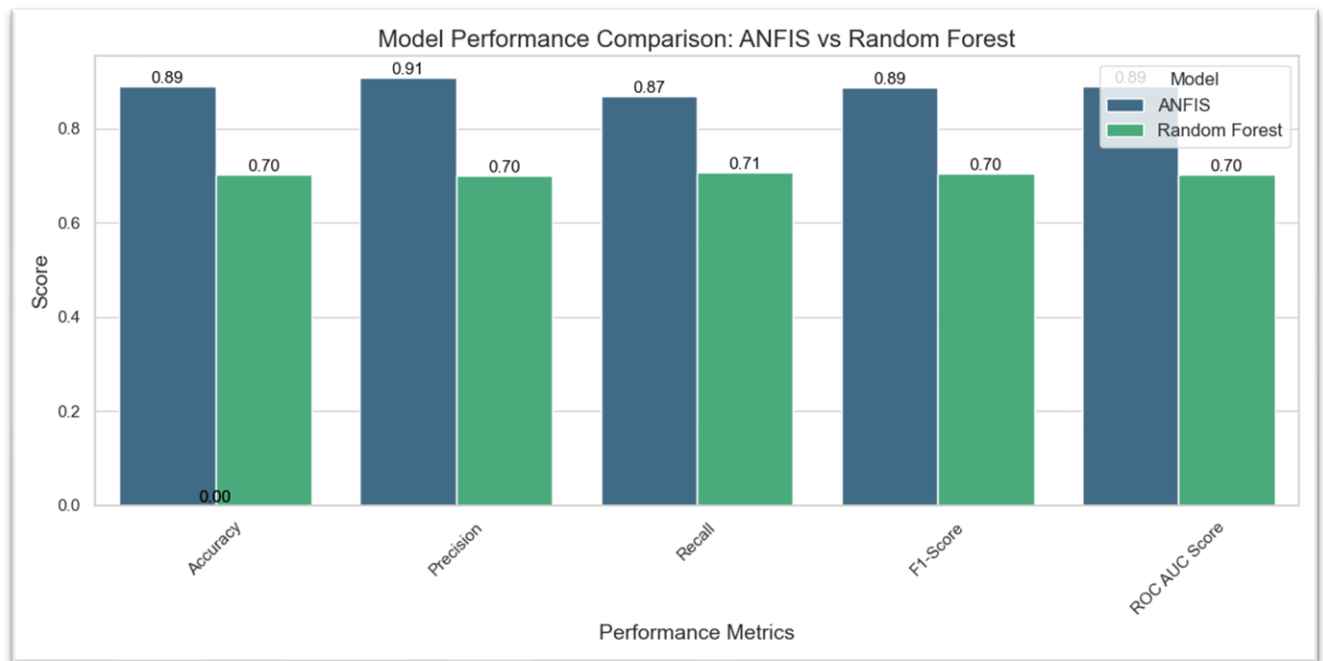


Figure 7. Model Performance Comparison

The false positives (FP) and false negatives (FN) observed in both the ANFIS and Random Forest models highlight critical trade-offs in their application to sepsis detection. False positives, though less severe in their consequences, can lead to unnecessary diagnostic tests, treatments, and increased healthcare costs, emphasizing the need to refine both models to enhance specificity. False negatives, on the other hand, pose a significant clinical risk, as missed septic cases can delay life-saving interventions and worsen patient outcomes. Reducing these errors requires improving model sensitivity, ensuring that fewer septic cases go undetected.

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 87%, 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.

To address these challenges, future studies should explore the inclusion of more discriminative and dynamic features, such as temporal trends in patient data, to enhance model performance. Integrating complementary techniques, such as combining ANFIS's adaptability with Random Forest's robustness, could yield a more balanced and effective system. Additionally, optimizing thresholds and validating the models in real-world clinical settings would provide valuable insights into their practical applicability. These efforts can pave the way for developing more reliable and actionable tools for sepsis classification, improving both patient outcomes and clinical efficiency.

5. Conclusion

This study explored the performance of two computational models, Adaptive Neuro-Fuzzy Inference System (ANFIS) and Random Forest, for the classification of sepsis, a life-threatening medical condition that demands timely and accurate diagnosis. Both models were evaluated using standardized clinical data, focusing on their ability to minimize false positives and false negatives while maintaining high overall accuracy and reliability. The ANFIS model demonstrated strong adaptability by leveraging its neuro-fuzzy structure to capture complex, nonlinear patterns in the data. With high sensitivity and precision, it provided a robust classification framework while maintaining interpretability. However, the occurrence of false negatives, though relatively low, underscores the critical need for further optimization to ensure that no septic cases are missed. The Random Forest model, while providing a solid baseline, exhibited a slightly higher rate of false negatives and false positives, highlighting its limitations in handling the intricate dynamics of sepsis-related clinical data. Despite this, its inherent robustness and ability to handle high-dimensional datasets make it a valuable component for ensemble approaches or as a benchmarking tool. Overall, the study underscores the strengths and limitations of both models in sepsis detection, highlighting the trade-offs between interpretability, sensitivity, and computational efficiency. Future work should focus on refining these models through advanced feature engineering, integrating complementary techniques, and validating their performance in real-world clinical settings. By addressing these challenges, it is possible to develop more reliable and actionable tools that support early sepsis detection and improve patient outcomes, ultimately advancing the role of AI in critical healthcare applications.

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