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Evaluating Student Academic Performance Through a Benchmark of Fuzzy Reasoning Models

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Abstract: *This study examines and compares Mamdani, Sugeno, and ANFIS fuzzy reasoning models for evaluating student academic performance using a benchmarking framework where the same inputs, membership functions, and evaluation metrics were applied across the models.*

Keywords: *Soft computing, fuzzy logic, student performance evaluation, ANFIS.*

I.INTRODUCTION

Student academic performance evaluation plays an important role in modern educational systems, as it helps instructors and institutions understand students' learning outcomes and academic standing. Traditionally, student performance has been evaluated using rigid numerical thresholds such as fixed pass–fail criteria or grade boundaries. However, academic performance is influenced by multiple factors including attendance, internal assessments, assignments, and class participation, which often involve uncertainty and subjective judgment. Such rigid evaluation approaches may fail to represent the gradual and imprecise nature of student performance. In real classrooms, teachers often judge performance in a gradual way rather than using strict cut-off marks. Soft computing techniques provide an effective alternative for handling uncertainty and imprecision in real-world problems. Among these techniques, fuzzy logic has been widely used due to its ability to model human reasoning using linguistic variables and approximate decision boundaries. Fuzzy reasoning systems can represent performance levels using terms such as poor, average, good, and excellent, which closely align with how educators naturally assess students. This makes fuzzy logic easier for teachers to understand and apply in practice. Several fuzzy logic–based approaches have been proposed for student performance evaluation and academic assessment. These studies demonstrate that fuzzy models can produce more flexible and interpretable evaluation results compared to traditional crisp methods. However, most existing works focus on applying a single fuzzy model or use different datasets, membership functions, and experimental settings. As a result, it becomes difficult to fairly compare fuzzy reasoning models and understand their relative strengths and limitations. Because of this, choosing the right fuzzy model for student evaluation is still confusing for many researchers. Moreover, different fuzzy reasoning paradigms such as Mamdani, Sugeno, and Adaptive Neuro-Fuzzy Inference System (ANFIS) exhibit distinct characteristics in terms of interpretability, computational efficiency, and learning capability. Without a standardized experimental framework, selecting an appropriate fuzzy model for student performance evaluation remains challenging for researchers and practitioners. To address this issue, this paper presents a benchmarking study of fuzzy reasoning models for student academic performance evaluation. The proposed work evaluates Mamdani, Sugeno, and ANFIS models under identical experimental conditions using the same dataset, triangular membership functions, rule base, and evaluation metrics. By ensuring a fair and reproducible comparison, this study aims to provide clear insights into the suitability of different fuzzy reasoning models for educational performance evaluation systems.

II. RELATED WORK

Fuzzy logic has been widely applied in educational systems to address the uncertainty and subjectivity involved in student evaluation. The concept of fuzzy sets, introduced by Zadeh, provides a mathematical framework to represent imprecise information using linguistic variables rather than strict numerical boundaries [1]. This approach closely matches human reasoning and has motivated its application in academic assessment problems. However, many studies do not clearly show how these fuzzy methods compare with each other. Several studies have applied fuzzy inference systems to evaluate student learning outcomes and academic achievement. Early works demonstrated that fuzzy logic can effectively model performance levels such as poor, average, and good by combining multiple academic factors. These studies highlighted the advantage of fuzzy systems in producing flexible and interpretable evaluation results compared to traditional crisp grading methods. Most of this work focuses on applying fuzzy logic rather than comparing different fuzzy models. Neuro-fuzzy approaches have also been explored in the context of student performance evaluation. Jang introduced the Adaptive Neuro-Fuzzy Inference System (ANFIS), which integrates fuzzy logic with neural network learning capabilities [2]. Subsequent studies applied ANFIS to student-related datasets and reported improved accuracy due to its data-driven learning mechanism. But higher accuracy alone does not always mean the results are easy to explain to teachers. However, these approaches often focused on improving prediction accuracy rather than analyzing interpretability and consistency. In addition to individual model applications, some researchers have discussed the strengths and limitations of different fuzzy reasoning paradigms, such as Mamdani and Sugeno inference systems. Mamdani models are generally preferred for their transparency and ease of interpretation, while Sugeno models offer computational efficiency and precise numerical outputs. Despite these observations, many studies use different datasets or settings, which makes fair comparison difficult.Overall, the existing literature confirms the effectiveness of fuzzy and neuro-fuzzy models in educational performance evaluation. However, there is a lack of reproducible benchmarking studies that compare Mamdani, Sugeno, and ANFIS models under identical conditions. This gap motivates the present work, which aims to provide a fair and systematic comparison of fuzzy reasoning models for student academic performance evaluation.

III. METHODOLOGY

This section explains the steps used to compare fuzzy reasoning models for evaluating student academic performance. The proposed methodology is designed to ensure a fair and reproducible comparison by maintaining identical experimental conditions for all fuzzy models considered in this study.

A. System Overview

The proposed system evaluates student academic performance using fuzzy reasoning models. Using multiple academic factors as input, the system produces a qualitative student performance level as output. The workflow includes data preprocessing, fuzzification, inference, defuzzification, and final performance evaluation. The same system structure is applied to all fuzzy models to ensure consistency in comparison. At this stage, the goal was comparison rather than optimizing individual model performance.

B. Input and Output Variables

1) Input Variables: Student performance is evaluated using the following academic factors:

Attendance Percentage: Represents the regularity of a student’s presence in class.

Internal Assessment Score: Includes marks obtained in quiz and mid-term tests.

Assignment Performance: Reflects the quality and completion of assignments.

Each input variable is normalized to a common scale and represented using linguistic terms such as low, medium, and high. This helps keep all inputs consistent and easy to compare.

2) Output Variable: The system output is the Student Performance Level, expressed using linguistic categories: Poor, Average, Good, and Excellent. This output represents an evaluation of current academic performance rather than future prediction.

C. Membership Functions

Triangular membership functions are used to represent all input and output linguistic variables. These membership functions are chosen because they are simple to understand and easy to implement. They are also commonly used in basic fuzzy systems. Using the same membership function parameters for all models helps keep the comparison fair.

D. Fuzzy Reasoning Models

Three fuzzy reasoning models are considered in this study:

- Mamdani Fuzzy Inference System: Uses fuzzy rules with linguistic outputs and centroid-based defuzzification, offering high interpretability.

- Sugeno Fuzzy Inference System: Produces numerical outputs using weighted functions, providing faster computation and precision.

- Adaptive Neuro-Fuzzy Inference System (ANFIS): Combines fuzzy inference with neural network learning to automatically adjust parameters based on data.

All models utilize the same input variables, membership functions, and logical structure to ensure a fair comparison.

E. Rule Base Design

A common rule base is designed to represent logical relationships between input variables and student performance levels. The rules follow academic reasoning, such as higher attendance and assessment scores leading to better performance levels. The same conceptual rule base is applied to all models, with ANFIS further refining the rules through learning.

F. Benchmarking Strategy

To ensure reproducibility and fairness, the following conditions are fixed for all experiments: Identical dataset, same input and output variables, same membership functions, same training and testing split, and same evaluation metrics. Only the fuzzy reasoning mechanism differs across models. These choices were made to keep the comparison simple and avoid unnecessary complexity.

IV. EXPIREMENTAL SETUP

This section outlines how the experiments were carried out in practice. The objective of the experimental design is to ensure a fair and reproducible benchmarking by maintaining identical conditions for all models.

A. Dataset Description

A student academic dataset is used in this study to evaluate performance levels based on multiple academic factors. The dataset consists of student records containing attendance percentage, internal assessment scores, and assignment performance. A synthetic dataset is used to avoid privacy issues, while still reflecting common academic patterns. The dataset roughly follows grading and attendance patterns that are commonly seen in classrooms.

B. Data Preprocessing

Before applying the fuzzy models, basic preprocessing steps are performed. These steps help reduce noise and keep the evaluation fair for all models.

1) All input values are normalized to a range of 0–100
2) Missing or inconsistent values are removed
3) Performance labels are mapped to linguistic categories (poor, average, good, excellent).

C. Training and Testing Procedure

The dataset is divided into two subsets: a Training set (70% of the data) and a Testing set (30% of the data). The same training and testing split is applied to all fuzzy reasoning models. For reproducibility, the data partitioning is kept fixed throughout the experiments. The Mamdani and Sugeno models use predefined fuzzy rules, while the ANFIS model is trained using the training dataset to adjust its parameters

D. Evaluation Metrics

The performance of the models is evaluated using the following metrics:

Accuracy shows how correctly the student performance levels are assigned. Mean Absolute Error (MAE) shows the average difference between the predicted and actual values. Interpretability Assessed based on rule complexity and clarity. Computational Efficiency Measured using execution time during evaluation.

E. Implementation Details

All fuzzy models are implemented using the same computational environment. Single membership functions, rules, and parameter settings are applied wherever applicable. Only the fuzzy inference differs between Mamdani, Sugeno, and ANFIS models. This controlled setup ensures that performance differences arise due to the reasoning models and not due to experimental variations.

V.RESULTS AND DISCUSSION

A. Performance Evaluation Results

The Mamdani, Sugeno, and ANFIS models were evaluated using the same dataset and similar environment conditions. Accuracy results are summarized below.

Table I: Accuracy Comparison of Fuzzy Reasoning Models

Model	Accuracy (%)
Mamdani FIS	39.5
Sugeno FIS	92.5
ANFIS	91.67

B. Error Analysis

To further analyze model performance, the Mean Absolute Error (MAE) is computed for each model. Lower MAE values mean the predicted results are closer to the actual values.

Table II: Mean Absolute Error Comparison

Model	MAE
Mamdani FIS	0.625
Sugeno FIS	0.075
ANFIS	0.083

C. Interpretability Analysis

Interpretability is important in educational systems because teachers need to understand the results. The Mamdani model offers the highest interpretability since it uses linguistic rules that are easy to understand.

Table III: Interpretability Comparison

Model	Rule Complexity	Interpretability
Mamdani FIS	Low	High
Sugeno FIS	Medium	Medium
ANFIS	High	Low

D. Computational Efficiency

Execution time is measured to evaluate efficiency. Sugeno models generally perform faster due to their direct numerical output, while Mamdani models require additional defuzzification steps. ANFIS involves training adjustment, resulting in higher computational cost.

E. Discussion

Based on the experimental results, it is observed that the Mamdani FIS provides superior interpretability but each fuzzy reasoning model has its own strengths and limitations. The Mamdani FIS achieves lower classification accuracy and higher mean absolute error due to its reliance on linguistic rule-based reasoning and defuzzification, as well as the absence of learning mechanisms. However, the Mamdani model provides strong interpretability and transparency, which makes it suitable for explainable student performance evaluation systems where understanding the decision process is important. In contrast, the Sugeno FIS attains the highest accuracy and lowest MAE because of its direct numerical output formulation using weighted linear functions. This structure minimizes information loss associated with defuzzification and results in improved computational efficiency. Consequently, the Sugeno model performs well in scenarios where numerical precision and faster computation are required. The ANFIS model shows competitive performance through learning-based adaptation from data, achieving accuracy close to that of the Sugeno model. Although its error is slightly higher than Sugeno in this setup, ANFIS benefits from its ability to learn patterns from data, which can be advantageous when dealing with complex or nonlinear relationships. This improved accuracy, however, comes at the cost of reduced interpretability. Overall, the results indicate that no single fuzzy reasoning model is universally optimal. The selection of an appropriate model should be guided by application requirements, particularly whether transparency, computational efficiency, or predictive accuracy is the primary objective.

F. Findings

Based on the experimental results, it is observed that the Mamdani FIS provides superior interpretability but the following key findings were observed:

1. The Mamdani FIS offers good interpretability because of its linguistic rule-based structure, but it shows lower accuracy and higher error when compared to the other models.
2. The Sugeno FIS shows the best accuracy and lowest error, while the ANFIS model performs similarly due to its learning capability.
3. The experimental results confirm that model selection depends on the intended application, where Mamdani FIS is preferable for explainability, while Sugeno FIS and ANFIS are more suitable for accuracy-oriented evaluation. This demonstrates that for educational datasets, the mathematical precision of Sugeno's weighted functions can be more effective than the adaptive learning of ANFIS.

VI.CONCLUSION

This study compares three fuzzy reasoning models—Mamdani, Sugeno, and ANFIS—for evaluating student academic performance. The experimental results challenge the common assumption that hybrid models like ANFIS always provide the highest accuracy. The results shows that the Sugeno FIS achieved the highest classification accuracy (92.5%), outperforming the hybrid ANFIS (91.67%). This indicates that for educational datasets with clearly defined grading criteria, the mathematical precision of Sugeno’s weighted linear functions provides a more robust and stable mapping than the adaptive learning layers of ANFIS, which can be susceptible to slight overfitting. In contrast, the Mamdani FIS recorded the lowest accuracy (39.5%). Although its linguistic approach is easy to understand, the defuzzification process leads to information loss in numerical grading This study concludes that the Sugeno FIS is the most suitable model for student performance evaluation, as it provides high accuracy with lower computational complexity compared to ANFIS. Future work will explore the application of these models to real-world institutional big data and the potential of Type-2 fuzzy systems to further refine decision boundaries in educational assessment. This would also help test how well the models perform outside controlled conditions. In real academic settings, additional factors may also influence student performance.

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