



HACETTEPE UNIVERSITY
FACULTY OF ENGINEERING

DEPARTMENT OF ARTIFICIAL INTELLIGENCE
ENGINEERING

**Comparative Analysis of Rule-Based (FIS) and
Adaptive Neuro-Fuzzy (ANFIS) Approaches for
Academic Performance Prediction**

AIN 421 – Fuzzy Logic
TERM PROJECT REPORT

Prepared by:

Yusuf Emir Cömert - 2220765023

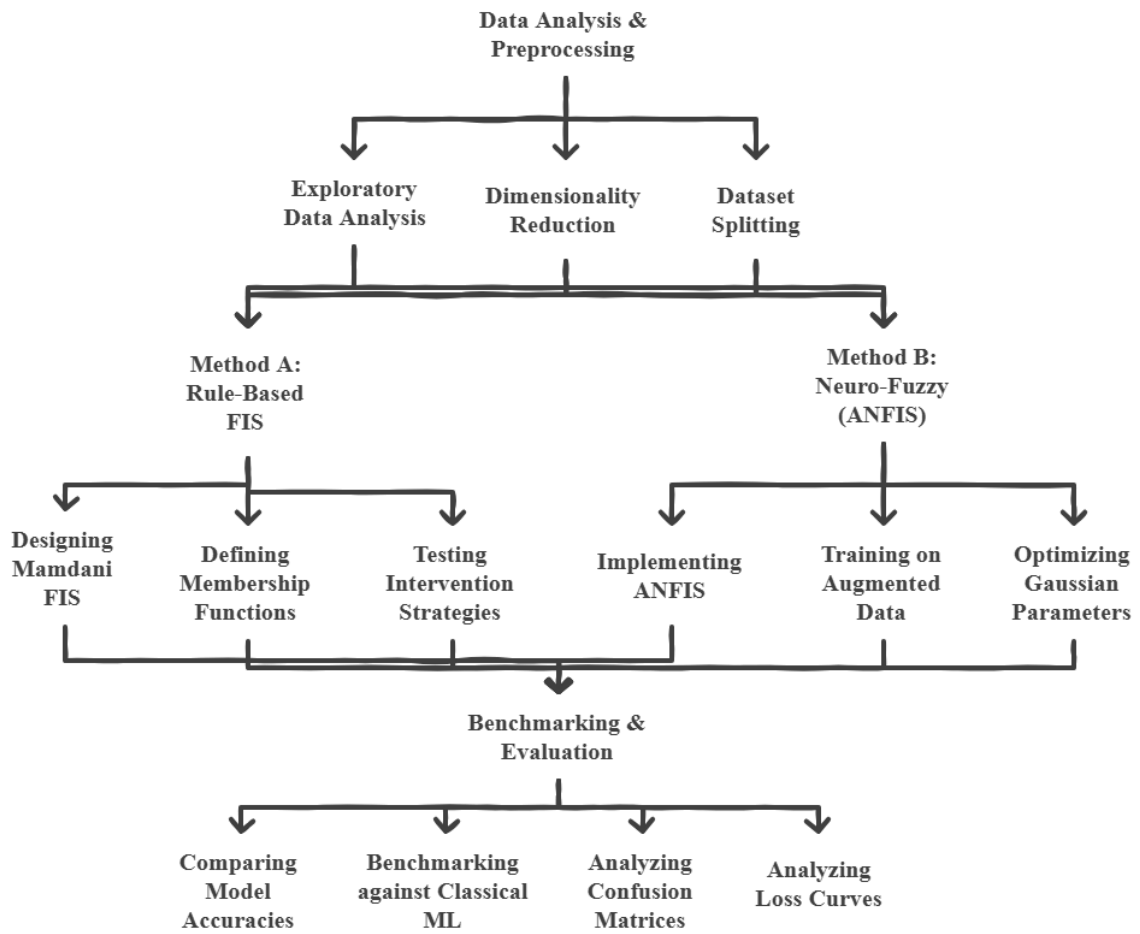
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Table of Contents

1. Abstract	4
2. Introduction.....	4
3. Data Analysis & Preprocessing	5
3.1 Data Preparation	5
3.2 Exploratory Data Analysis (EDA).....	5
4 Methodology	7
4.1 Method A: Rule-Based Fuzzy Inference System (FIS)	7
4.2 Method B: Adaptive Neuro-Fuzzy Inference System (ANFIS)	8
5 Experimental Results.....	8
5.1 FIS Results (Method A)	9
5.2 ANFIS Results (Method B)	9
6 Discussion & Benchmarking	10
6.1 Comparison with Classical Machine Learning	10
6.2 The Neuro-Fuzzy Advantage	10
7 Conclusion.....	11
8 References	12

Academic Performance Prediction Project Roadmap



1. Abstract

In this term project, the prediction of student academic performance is addressed using Fuzzy Logic methodologies. The primary objective is to conduct a comparative analysis between a human-driven **Rule-Based Fuzzy Inference System (FIS)** and a data-driven **Adaptive Neuro-Fuzzy Inference System (ANFIS)**.

Initially, the **academicPerformanceData.xlsx** dataset was analyzed, and it was observed that the Final Exam score is the most dominant factor influencing the output. Based on this insight, a Mamdani-type FIS was designed with manually defined rules. However, experimental results indicated that the Rule-Based system struggled to distinguish between intermediate grades, achieving an accuracy of approximately **58%**.

Consequently, to overcome the limitations of static rules, an ANFIS model was implemented using the PyTorch library. By optimizing Gaussian membership functions through a training process, the complex non-linear patterns in the data were successfully learned, and an accuracy of **95.46%** was achieved. This report presents the data analysis, model architectures, and comparative results, demonstrating that neuro-fuzzy systems significantly outperform static rule-based systems for this classification problem.

2. Introduction

Assessing student performance is a critical task in educational data mining. However, defining 'success' or 'failure' is often not a precise process due to the uncertainty inherent in grading systems. A student with a score of 49 might be very similar to a student with a score of 51, yet traditional logic separates them sharply. To handle this uncertainty, **Fuzzy Logic** provides a mathematical framework that mimics human reasoning.

In this study, a robust prediction model was developed using the provided academic dataset. The research was conducted following a systematic roadmap consisting of four main stages:

1. **Data Analysis:** First, the dataset was examined using correlation matrices and visualization techniques (t-SNE, Box-plots) to understand the relationship between inputs (quizzes, exams) and the output (grades). It was found that the dataset is non-linearly separable, which poses a significant challenge for simple linear models.
2. **Rule-Based Approach (Method A):** A Fuzzy Inference System (FIS) was established using the skfuzzy library. Membership functions (Low, Medium, High) were defined, and logic rules were constructed based on the initial analysis. Both 'Hard' and 'Soft' intervention strategies were tested to evaluate performance improvements.
3. **Neuro-Fuzzy Approach (Method B):** Recognizing the limitations of manually defined rules, an ANFIS model was developed. This method combines the interpretability of fuzzy logic with the learning capability of neural networks. A large synthetic dataset (50,000 samples) was generated and used to train the model parameters.

4. **Benchmarking:** Finally, the proposed fuzzy models were compared against standard Machine Learning algorithms (Decision Tree and Random Forest) to validate the results.

This report details the technical implementation, the challenges encountered during rule design, and the statistical evidence demonstrating why the ANFIS approach provides a superior solution for academic performance prediction.

3. Data Analysis & Preprocessing

3.1 Data Preparation

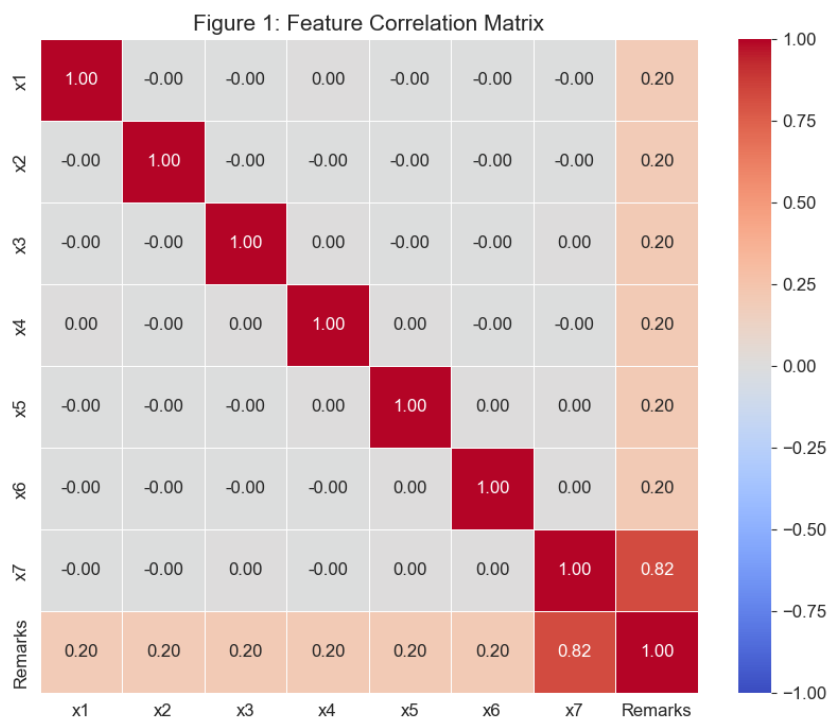
The academicPerformanceData.xlsx dataset, containing 7 input features (x1 to x7) and 1 target variable ('Remarks'), was used. Preprocessing involved cleaning non-numeric values and target labels. Two distinct subsets were generated for the models:

- **FIS Subset:** A balanced set of 100 samples (20 per class) to test manual logic.
- **ANFIS Subset:** A synthetic set of 50,000 samples, generated via stratified sampling with replacement, to ensure sufficient data for neural network training.

3.2 Exploratory Data Analysis (EDA)

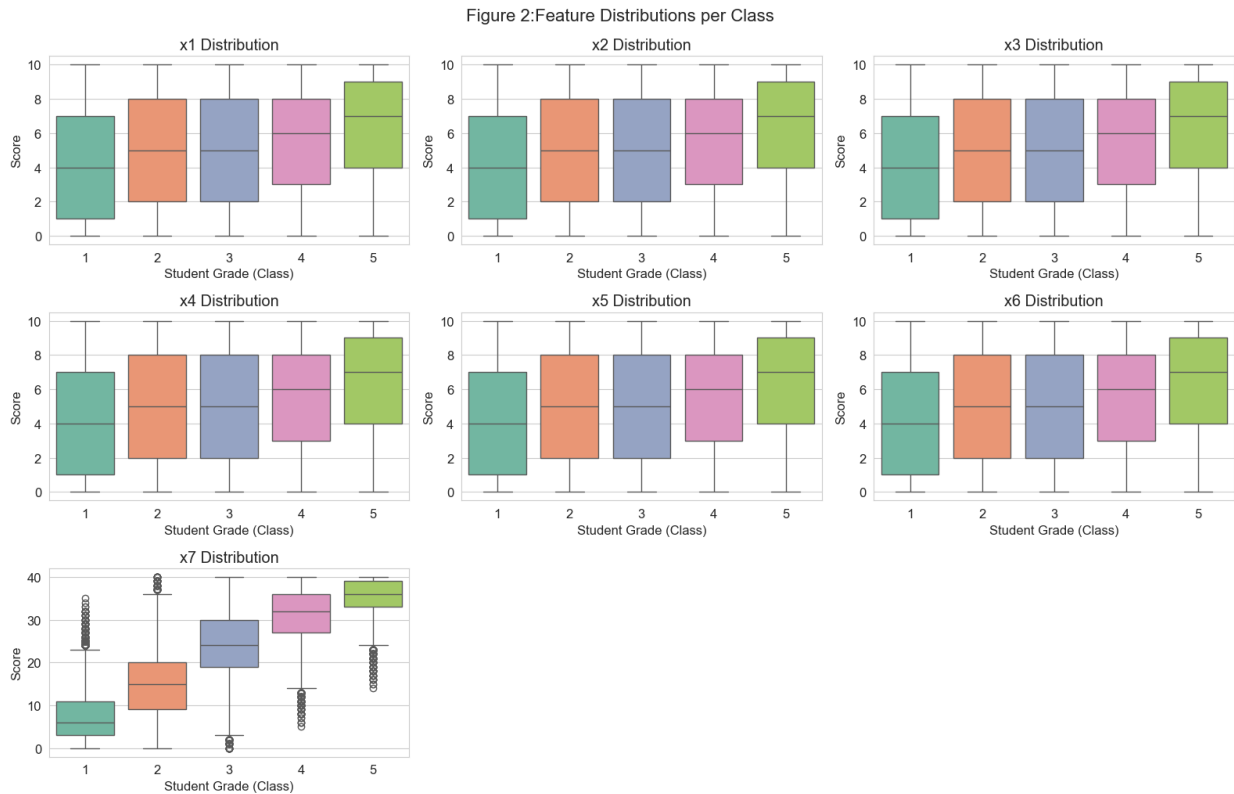
A statistical analysis was conducted to understand feature relationships and class separability.

First, the **Correlation Matrix** was examined.



As shown in **Figure 1**, the feature **x7 (Final Exam)** exhibits a strong positive correlation (**0.82**) with the grade, making it the dominant predictor. In contrast, other features (x1 to x6) show weak correlations (0.20) and are independent of each other (correlation exactly 0.00).

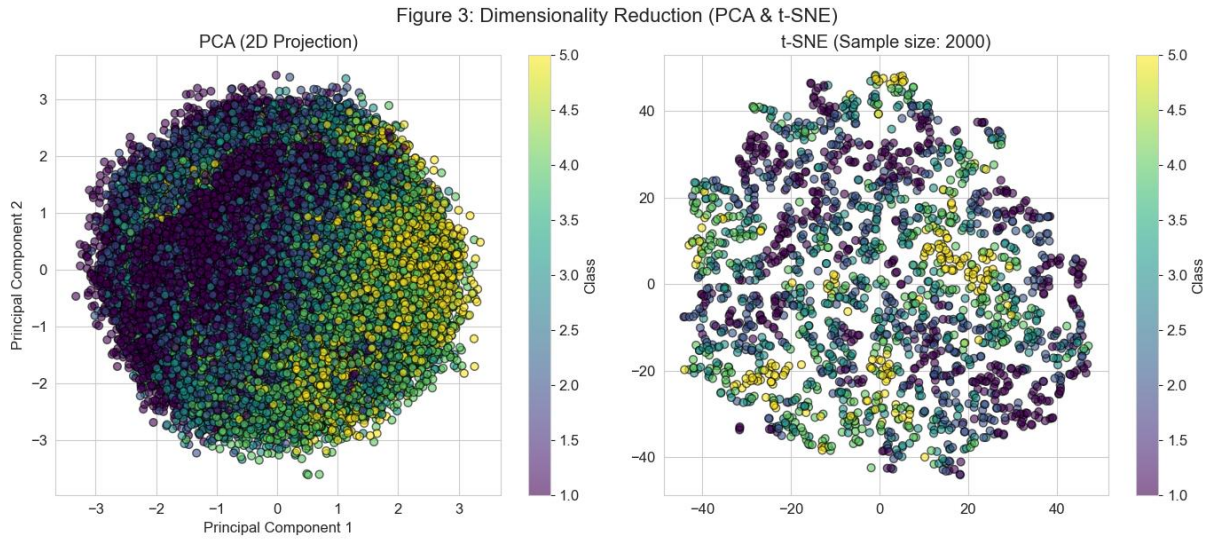
Next, **Box Plots** were analyzed to assess the boundaries between different grades.



The analysis of **Figure 2** reveals critical insights into the dataset's difficulty:

1. **Feature x7:** This feature shows a clear stepwise progression in median scores from Class 1 to Class 5. However, significant **outliers** (represented by the circles outside the whiskers) are visible. These outliers indicate that high exam scores do not always guarantee high grades (and vice versa), creating "fuzzy" boundaries that rigid rules fail to capture.
2. **Features x1-x6:** These features exhibit substantial overlap. The interquartile ranges (the colored boxes) for Classes 1 through 5 are nearly aligned, implying that quizzes and attendance alone have poor discriminative power and act as "noise" in linear classification models.

Finally, dimensionality reduction techniques (**PCA** and **t-SNE**) were applied to visualize the 7-dimensional data in 2D space.



As shown in the t-SNE plot in **Figure 3**, the classes do not form distinct, separated clusters. Instead, they appear as a highly intermixed cloud. This visual evidence confirms that the academic performance dataset is **non-linearly separable**. Simple linear decision boundaries are insufficient to resolve this complexity, justifying the need for the advanced mapping capabilities of the Neuro-Fuzzy (ANFIS) architecture.

4 Methodology

In this study, two distinct computational frameworks were developed to address the problem of student grade prediction. The first approach utilizes expert knowledge through a Rule-Based System, while the second employs a data-driven learning algorithm.

4.1 Method A: Rule-Based Fuzzy Inference System (FIS)

System was constructed using the skfuzzy library. The design process consisted of three main stages:

- **Fuzzification:** Each input variable (x_1 to x_7) was mapped to linguistic terms (*Low*, *Medium*, *High*). Based on the correlation analysis, the Final Exam (x_7) was identified as the critical feature and was assigned a higher granularity in the decision process.
- **Weighted Rule Base:** A rigorous rule set was established. To reflect the importance of the final exam, a **Weighted Scoring** mechanism was implemented. The feature x_7 was assigned a weight of 6.0, whereas other quizzes and attendance features received lower weights (ranging from 1.0 to 1.5). This ensured that the final exam score had the most significant impact on the output.
- **Intervention Strategies:** Two distinct decision strategies were tested to evaluate the system's flexibility:

Hard Intervention: A strict logic where the final grade is determined solely by rigid thresholds of the Final Exam score (e.g., if $x_7 > 34$, then Grade 5). This ignores the fuzzy contribution of other inputs.

Soft Intervention (Hybrid): A flexible approach where the Fuzzy Logic system determines the grade for the majority of students. Strict interventions are applied only for extreme cases (Fail or High Distinction) to prevent logical errors.

4.2 Method B: Adaptive Neuro-Fuzzy Inference System (ANFIS)

To overcome the limitations of static rules and manual thresholding, a custom **ANFIS** architecture was implemented using the PyTorch deep learning framework. This model integrates the interpretability of fuzzy logic with the learning capabilities of neural networks.

The proposed ANFIS model consists of a 5-layer Sugeno-type network:

1. **Layer 1 (Fuzzification):** Input values are transformed into membership degrees using **Gaussian Bell Functions**. Unlike Method A where shapes were fixed, here the parameters (mean and variance) are learnable.
2. **Layer 2 (Rule Firing):** The firing strength of each rule is calculated by multiplying the membership values of the inputs.
3. **Layer 3 (Normalization):** The firing strengths are normalized to determine the relative contribution of each rule.
4. **Layer 4 (Defuzzification):** The consequent parameters (linear equations of the Sugeno model) are computed.
5. **Layer 5 (Aggregation):** The final output is derived by summing the weighted outputs of all rules.

Training Process: The network was trained on the augmented dataset of 50,000 samples. The **Adam optimizer** was employed to minimize the Mean Squared Error (MSE) loss function over 50 epochs. This training phase allowed the model to automatically adjust the Gaussian curves to fit the complex, non-linear boundaries of the dataset.

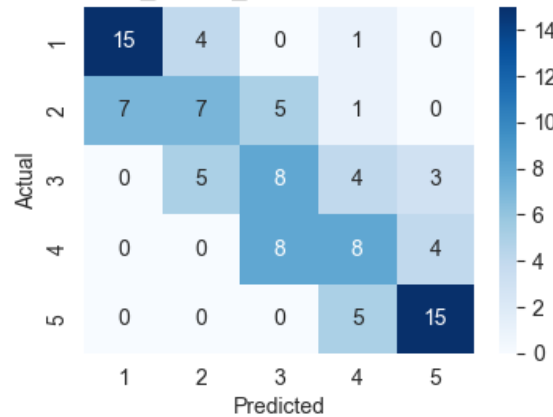
5 Experimental Results

This section presents the quantitative performance of the implemented models. The primary metric for evaluation is **Accuracy**, supplemented by **Confusion Matrices** to analyze class-specific errors and **Loss Curves** to assess learning convergence.

5.1 **FIS Results (Method A)** The Rule-Based Fuzzy Inference System was evaluated on the balanced test subsets using both Hard and Soft intervention strategies.

- The **Hard Intervention** strategy yielded an accuracy of **58.0%**.
- The **Soft Intervention** strategy yielded an accuracy of **57.0%**.

Model A (Hard) Figure 4: Confusion Matrix for FIS Model.
(fis_subset_1.csv) Acc: %53.0

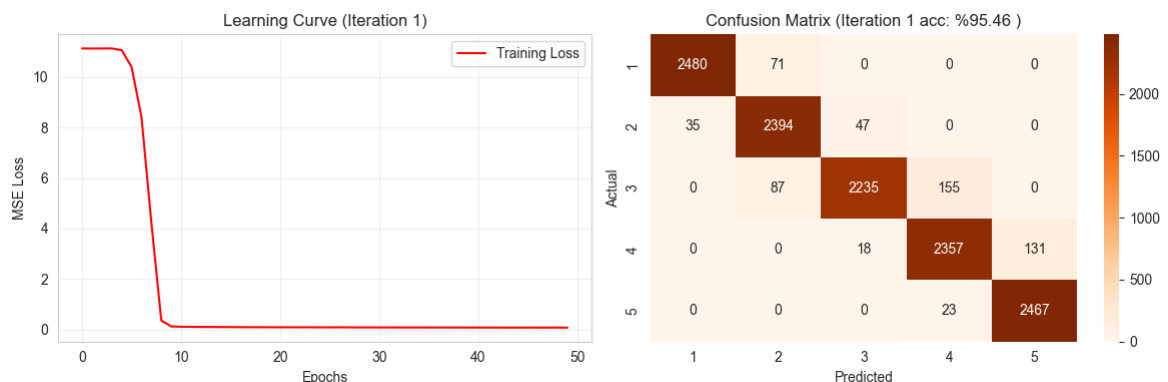


As illustrated in **Figure 4**, the FIS model demonstrates specific strengths and weaknesses. It achieves high recall for **Grade 1 (Fail)**, successfully identifying students at risk of failure. However, performance degrades significantly for intermediate classes (Grades 3 and 4). The predictions for these grades are dispersed along the diagonal, indicating that the model struggles to distinguish between adjacent classes (e.g., misclassifying a Grade 4 student as Grade 3 or Grade 5).

This "diagonal blur" suggests that the manually defined static thresholds lack the flexibility required to accommodate the outliers identified in the Exploratory Data Analysis. The marginal difference between Hard and Soft strategies implies that the limitation lies within the static rule base itself, rather than the specific intervention method.

5.2 ANFIS Results (Method B)

The Adaptive Neuro-Fuzzy Inference System was trained for 50 epochs on the augmented dataset. The results indicate a substantial improvement over the Rule-Based approach.



The training process, visualized in the Loss Curve (**Figure 5, left**), shows a dramatic reduction in Mean Squared Error (MSE) starting around the 9th epoch, stabilizing at a very low error rate (approximately 0.09). This indicates rapid convergence and effective learning of the underlying data patterns.

On the test set, the ANFIS model achieved a final accuracy of **95.46%**. The Confusion Matrix (**Figure 5, right**) reveals a distinct and clean diagonal, contrasting sharply with the FIS results. The network successfully resolved the ambiguity between adjacent classes, achieving high precision and recall across all grades, including the previously problematic intermediate ones. This demonstrates that the learnable Gaussian parameters allowed the model to adapt to the non-linear separability of the features and effectively filter out the noise present in the quiz and attendance data.

6 Discussion & Benchmarking

To rigorously evaluate the proposed fuzzy architectures, the results were compared against standard Machine Learning algorithms. Decision Tree and Random Forest classifiers were trained on the same dataset to serve as performance benchmarks.

6.1 Comparison with Classical Machine Learning

The benchmark experiments yielded the following accuracy results:

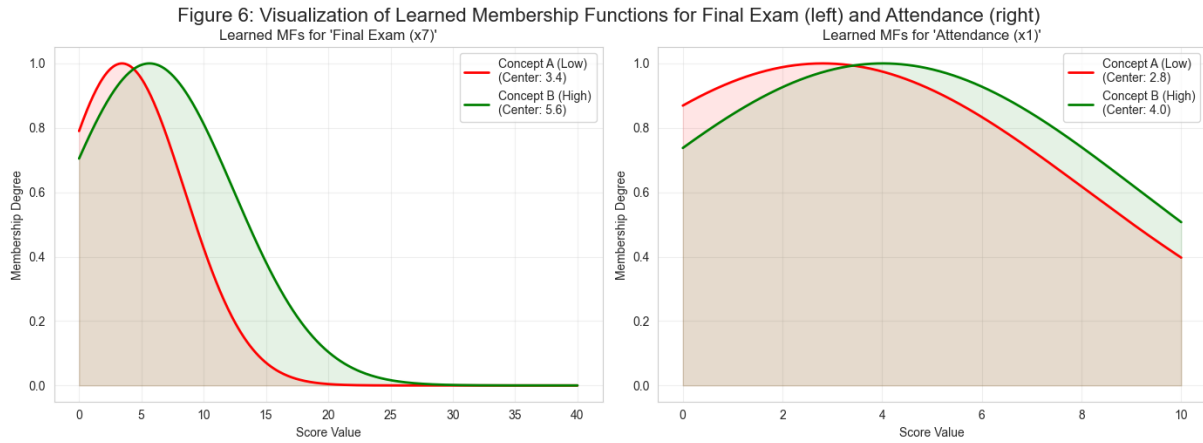
- **Decision Tree:** 58.0%
- **Random Forest:** 63.0%

A critical observation arises when comparing the Rule-Based FIS (Method A) with the Decision Tree classifier. Both models achieved an identical accuracy of approximately **58%**. In scenarios where computational performance is equivalent, the choice of model depends on qualitative factors.

It is argued that for educational applications, **explainability** is paramount. Classical ML models, particularly Deep Learning or complex ensembles, often operate as "**Black Boxes**," where the decision-making process is opaque. In contrast, the FIS model operates as a "**White Box**." Its logic is derived from linguistic rules (e.g., "*If Final Exam is Low, then Grade is Fail*"), which are transparent and intuitively understandable by educators and students. Therefore, in contexts involving small datasets or requiring justification for grades, the Rule-Based FIS is preferable to a Decision Tree, despite similar numerical accuracy.

6.2 The Neuro-Fuzzy Advantage

While FIS offers interpretability, its static nature limited its accuracy to 58%. Even the Random Forest only improved this to 63%, suggesting that the data contains complex, non-linear overlaps that neither rigid rules nor linear splits can fully resolve.



The **ANFIS (Method B)** approach overcame this limitation, achieving **95.46%** accuracy. As illustrated in **Figure 6**, ANFIS retained the fuzzy structure but utilized neural learning to optimize the shapes of the membership functions:

1. **Adaptive Boundaries:** For the critical feature *Final Exam (x7)*, the model shifted the "Low" and "High" curves to specific centers (e.g., Low center at 3.4 and High center at 5.6) that mathematically minimize error, effectively handling the outliers observed in the box plots.
2. **Noise Filtering:** For less dominant features like *Attendance (x1)*, the model learned broad, overlapping curves, effectively assigning them a lower impact on the final decision.

This demonstrates that ANFIS combines the best of both worlds: the structural logic of a fuzzy system and the high-performance learning capability of neural networks.

7 Conclusion

This comparative study addressed the challenge of predicting student academic performance using two distinct fuzzy logic methodologies: a Rule-Based Fuzzy Inference System (FIS) and an Adaptive Neuro-Fuzzy Inference System (ANFIS). Based on the comprehensive experimental analysis, the following conclusions are drawn:

1. **Limitations of Static Rules:** The Rule-Based FIS approach achieved a baseline accuracy of **58.0%**. The analysis revealed that this performance ceiling stems from the significant overlap in feature distributions for intermediate grades (Grades 2, 3, and 4) and the presence of outliers in the Final Exam scores. Static, manually defined thresholds were insufficient to capture these non-linear complexities.
2. **Superiority of Neuro-Fuzzy Learning:** The ANFIS model demonstrated exceptional performance, achieving a final accuracy of **95.46%**. By employing neural network learning algorithms, the system successfully optimized the Gaussian membership functions. This allowed the model to adaptively shift decision boundaries to handle

outliers and resolve the ambiguities between adjacent classes that were invisible to standard linear models.

3. **The Accuracy vs. Explainability Trade-off:** While ANFIS offers superior predictive power, the Rule-Based FIS retains value due to its "**White Box**" nature. In educational contexts where transparent feedback is prioritized over raw accuracy, the linguistic logic of FIS provides an explainable alternative to the opaque decision processes of data-driven models.

In conclusion, this project proves that while expert knowledge provides a foundational logic, **data-driven optimization via Neuro-Fuzzy architecture** is essential for achieving high-precision classification in complex, real-world educational datasets.

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