

# Predicting Student Performance Using Subtractive Clustering Fuzzy C-Means and Multiple Linear Regression

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## ABSTRACT

A common method for measuring student performance is to average all assessment component results. However, the average score does not accurately reflect students' true performance, since each component assesses different learning outcomes related to knowledge, skills, and attitudes. To overcome this limitation, this study suggests a systematic approach for evaluating students' academic achievement and behavioral attributes using a hybrid model that combines soft computing and statistical techniques. Several methods were developed and compared, including Fuzzy Inference System (FIS), Adaptive Neuro-Fuzzy Inference System (ANFIS), Fuzzy C-Means (FCM), Subtractive Clustering (SC), entropy-weighted FCM, and Linear Regression (LR). A hybrid model combining Subtractive Clustering Fuzzy C-means with LR using two independent variables (ScFCMLR2) was proposed. Experimental results on 415 student records showed that ScFCMLR2 achieved the highest accuracy (85%) and F-score (82.7%) among the models. The results demonstrate the reliability of the proposed model in evaluating overall student performance across both academic and behavioral attributes.

*Keywords-student performance; fuzzy logic; clustering; linear regression; expert system*

## I. INTRODUCTION

The current method for assessing student performance is through examinations that primarily focus on academic skills [1-3]. However, this method has several drawbacks. For instance, in essay assessments, students aware of the marking scheme can score highly without genuinely understanding the subject [4]. Additionally, the growth of third-party services and the use of Generative AI tools like ChatGPT have raised concerns about academic integrity, cheating, and plagiarism [5-6]. Students' focus on grades rather than true learning can lead to poor mastery of knowledge and skills essential for real-world use. Assessment should be a systematic process that collects and analyzes information about students' knowledge, skills, attitudes, and values to reflect meaningful learning outcomes [7]. However, current methods of measuring performance often depend on marks, percentages, and Grade Point Average (GPA), which may not fully reflect a student's

abilities [8, 9]. These conventional methods also fail to differentiate between various types of learning outcomes, especially those associated with behavioral attributes.

Observations indicate that student performance should be evaluated across the cognitive, psychomotor, affective, and social domains [10-13], which are aligned with the Malaysian Qualifications Framework (MQF) [14]. Inaccuracies may occur when average scores are used, as they may not reflect a student's strengths or progression over time. For instance, two students with different assessment trends may attain the same average score, despite possessing different learning patterns. Such ambiguities in performance measurement can cause the misinterpretation of students' capabilities [9]. To address this issue, soft computing techniques such as Fuzzy Logic (FL) and Machine Learning (ML) are proposed. FL can handle uncertainties and imprecision in data by representing human knowledge through linguistic variables such as weak, moderate, and strong [8, 15-17]. However, FL systems rely

heavily on expert knowledge and need frequent updates to membership functions and rules. Therefore, combining FL with other ML techniques, such as clustering and regression, is a promising approach for automatically generating membership functions and rules. For instance, authors in [18] applied logistic and polynomial regression with regularization to forecast student dropout, demonstrating the potential of regression-based methods in educational data mining.

In this study, a hybrid model is proposed that combines SC and Fuzzy C-Means (ScFCM) with LR using two independent variables (LR2), referred to as the ScFCMLR2 model. This model is developed to evaluate student performance based on both academic achievement and behavioral attributes. A dataset of 415 student records is used to assess the model's effectiveness, including attributes from the cognitive, psychomotor, affective, and social domains. The proposed method is then compared with other techniques, such as FIS, ANFIS, and FCM, to determine the most suitable for educational performance measurement.

II. METHODOLOGY

This study applied soft computing and statistical methods to assess student performance based on their academic achievement and behavioral attributes. The model development included data preprocessing, clustering, rule creation, and performance assessment with suitable evaluation metrics.

A. Dataset Overview

The dataset used in this study includes 415 anonymized student records from a Malaysian public university. It is not publicly accessible and was obtained with official permission through a 'Letter of Approval to Use Undergraduate Student Performance Data Samples'. Each record contains assessment scores from various learning outcomes across four domains: cognitive, psychomotor, affective, and social [10-13]. The selected attributes encompass both academic and behavioral skills, such as knowledge, problem-solving ability, laboratory work, design and experimentation, attitude, appreciation, communication skills, and teamwork.

These attributes align with the learning outcomes defined by the Malaysian Qualifications Framework (MQF) [14]. Table I displays the input-output mappings for the attributes, where academic performance is derived from cognitive and psychomotor scores, while affective and social factors determine behavioral attributes. The final score reflects the overall student performance, ranging from 0.00 to 4.00. The choice of these attributes is based on their importance in educational assessment methods and learning outcome benchmarks. Including both technical and non-technical skills gives a more complete view of student performance. Although the dataset size (n = 415) is modest, it is sufficient to conduct performance analysis across three academic programs: Engineering, Mechanical, and Computer Science. Further statistical power analysis was not performed; however, the dataset includes multiple semesters and diverse student profiles. All personal identifiers in the dataset were removed to ensure anonymity, and no sensitive information, such as student names or IDs, was included. The use of student records in this study adhered to institutional guidelines for ethical

research and complied with data protection protocols. The dataset was stored securely and used only for research purposes.

TABLE I. VARIABLE FOR INPUT AND OUTPUT

| Input               | Output 1          | Output 2              | Final Output        |
|---------------------|-------------------|-----------------------|---------------------|
| Knowledge           | Cognitive Score   | Academic Performance  | Overall Performance |
| Problem Solving     |                   |                       |                     |
| Laboratory Work     | Psychomotor Score | Behavioral attributes |                     |
| Design & Experiment |                   |                       |                     |
| Attitude            | Affective Score   | Behavioral attributes |                     |
| Appreciation        | Social Score      |                       |                     |
| Communication       |                   |                       |                     |
| Teamwork            |                   |                       |                     |

B. Role of Expert System and Clustering in Educational Assessment

An expert system consists of programs created to simulate the decision-making ability of a human expert in a particular field [19]. Expert knowledge is encoded using information gathered from experienced lecturers, academic resources, and institutional guidelines. In fuzzy expert systems, knowledge is represented using fuzzy logic rules expressed in linguistic terms. For example, if the knowledge score is high and the attitude score is good, then the overall performance is excellent. These rules are flexible and enable the system to model human reasoning more realistically. In educational data mining, clustering methods assist in identifying groups of students with similar characteristics or learning outcomes. This process facilitates performance analysis by grouping students based on achievement levels or patterns. By using clustering, the system can organize students' performance according to observed similarities. It also helps determine which attributes have a greater impact on academic and behavioural scores [20-22].

C. Fuzzy Expert Systems

Several fuzzy expert systems were developed and evaluated, including FIS, ANFIS, FCM, ScFCM, and SC with Entropy-Weighted FCM (ScEwFCM). These systems were also tested with LR, either with one independent variable (SLR) or two (LR2), to compare prediction accuracy and model effectiveness. The main objective is to determine which method is most suitable for predicting overall student performance. Each model was tested on the same dataset to ensure consistent comparison. The proposed model, ScFCMLR2, integrates SC and FCM with LR2 to improve rule generation and prediction performance. The overall model framework is illustrated in Figure 1.

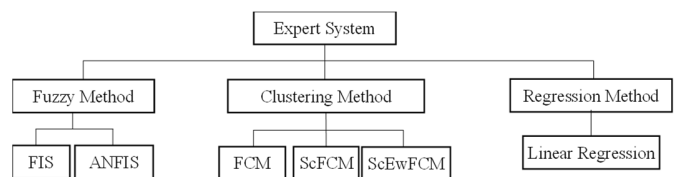


Fig. 1. The proposed method to evaluate students' overall achievement.

#### D. Fuzzy Clustering Techniques

The following three fuzzy clustering methods were employed to create membership functions during the fuzzification process:

Fuzzy C-Means (FCM): assigns each data point a degree of membership to each cluster. The algorithm aims to minimize the following objective function:

$$J_m = \sum_{i=1}^N \sum_{j=1}^c u_{ij}^m \|x_i - c_j\|^2 \quad (1)$$

where  $u_{ij}$  is the membership degree of data point  $x_i$  to cluster  $j$ ,  $c_j$  is the cluster center of cluster  $j$ ,  $m$  is the fuzzifier, and  $\|\cdot\|$  denotes the Euclidean distance. The membership values are updated iteratively until convergence.

Subtractive Clustering with FCM (ScFCM): The Subtractive Clustering (SC) algorithm serves as an initial step to replace random number generation. SC identifies potential cluster centers by analyzing data density, which are then passed to FCM for improved clustering. This hybrid method lowers sensitivity to the initial choice of cluster locations.

Subtractive Clustering with Entropy Weighting and FCM (ScEwFCM): Authors in [22] modified the objective function by adding a Shannon Entropy component to adjust the cluster center locations and reduce the influence of noise. ScEwFCM combines all three algorithms to analyze student performance. The entropy weighting function is applied before the FCM membership function generation process begins. This algorithm enhances feature importance in clustering, improving robustness when the dataset contains irrelevant or noisy variables. The cluster results are used to define membership functions for each attribute in the fuzzy system.

#### E. Linear Regression Models

Two types of linear regression models were used:

Simple Linear Regression (SLR): LR models estimate the fuzzy expert system's output based on rules derived from regression analysis of predicted output values. SLR analyzes the relationship between a single independent variable and a single dependent variable. For example, the lab score is used to predict the final score. The model is expressed as:

$$y = \beta_0 + \beta_1 x + \epsilon \quad (2)$$

where  $y$  is the dependent variable,  $x$  is the independent variable,  $\beta_0$  and  $\beta_1$  are the regression coefficients, and  $\epsilon$  is the error term.

Multiple Linear Regression (LR2) uses two independent variables to enhance prediction accuracy. For example, combining test scores in knowledge and project scores related to problem-solving is used to forecast academic results. The model is defined as:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \epsilon \quad (3)$$

where  $x_1$  and  $x_2$  are the independent variables, while the other terms retain their previous definitions.

The regression models generate output values that are then used in evaluating the fuzzy rules. These rules help the system

estimate student performance more effectively using observed data.

#### F. Architecture of the ScFCMLR2 Expert System

The ScFCMLR2 system combines clustering and regression into a fuzzy inference system. Its architecture comprises four main components: 1) Fuzzification: Clustering is performed using ScFCM to generate membership functions for input attributes, 2) Rule Generation: LR2 is used to form the fuzzy rules, 3) Inference Process: The fuzzy rules are applied to infer the output values for student performance and 4) Defuzzification: The fuzzy output values are converted into final scores using the Takagi-Sugeno-Kang (TSK) method. The process starts by clustering students' data using ScFCM, then proceeds with fuzzification, LR2 rule evaluation, and final defuzzification with the TSK model. The entire step-by-step process is shown in Figure 2, while the overall system setup is displayed in Figure 3.

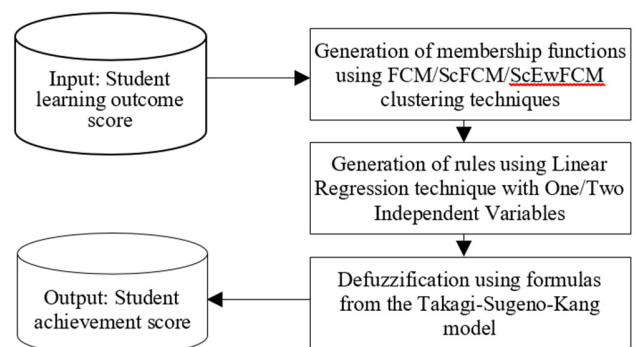


Fig. 2. Process flow of the ScFCMLR2 expert system for student performance evaluation.

In this system, the fuzzification process determines membership functions and classifies students based on their performance levels. After forming the clusters, LR2 is used to predict student outcomes based on the patterns observed within each group. The resulting regression outputs are then employed to create fuzzy inference rules that direct the reasoning process. The defuzzification step translates the fuzzy output into a crisp performance score for each student. This process is repeated for every learning outcome attribute to provide a comprehensive evaluation of student achievement. Figure 4 illustrates the mapping of input attributes to output categories, which determines how academic performance and behavioral attributes are calculated.

As illustrated in Figure 4, scores for learning outcome attributes related to knowledge and problem-solving are used as inputs to the cognitive score calculation. Likewise, laboratory work and design or experiment scores contribute to the psychomotor domain. This process continues until all four learning domains, cognitive, psychomotor, affective, and social, are obtained. The cognitive and psychomotor scores are then combined to form the academic achievement score, while the affective and social scores are used to determine the student's behavioral score. Finally, both the academic and behavioral scores are inputs to compute the overall student achievement score, which ranges from 0.00 to 4.00 and is

compared with the student’s actual Cumulative Grade Point Average (CGPA) for validation. If a particular domain (cognitive, psychomotor, affective, or social) does not have learning outcome attributes, its score is excluded from the calculation of academic or behavioral attributes. To calculate the final score, each category must include at least one domain: either cognitive or psychomotor for academic performance, and

either affective or social for behavioral attributes. For instance, if the affective domain cannot be assessed due to missing learning attributes such as values and appreciation, but the social domain is available through communication and teamwork, the social score alone will represent the student’s behavioral attributes.

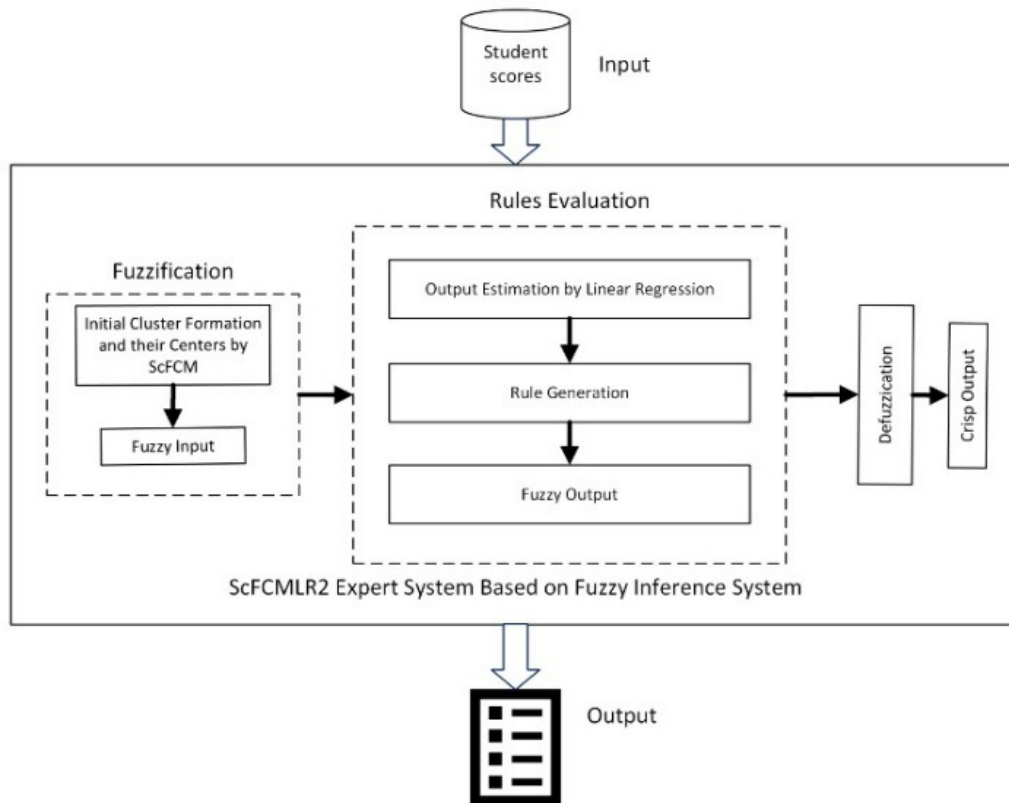


Fig. 3. Architecture of the ScFCMLR2 Expert System.

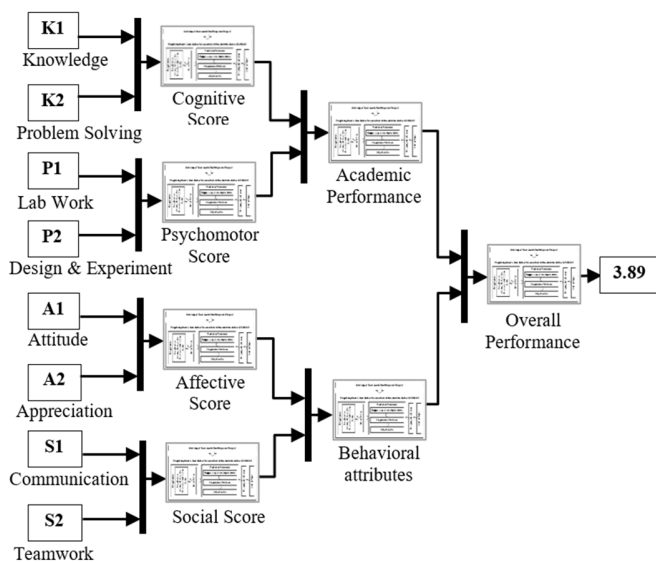


Fig. 4. Input-Output Mapping Structure.

These attributes and mappings can be customized for specific learning programs, provided they still reflect the learning outcomes intended to be measured. This flexibility allows the system to adapt to different academic structures and curriculum designs while maintaining a consistent evaluation framework.

### III. EXPERIMENTAL RESULTS

Results from each technique are compared with the original dataset to determine the most suitable method for measuring student performance. Clustering results are validated against students’ original CGPA values, using RMSE, accuracy, precision, recall, and F-score as evaluation metrics. Table II presents the Root Mean Square Error (RMSE) values for each evaluated method. The results of this investigation are assessed based on the minimum RMSE value. Since RMSE measures the difference between the original and the tested data, the smaller this difference, the higher the method’s accuracy. The ANFIS technique attained the lowest RMSE value of 0.152. Furthermore, all the proposed hybrid FCM with linear

regression techniques also demonstrated low RMSE values, with the most favorable at 0.177. at 0.177.

TABLE II. RMSE EVALUATION RESULTS

| Program  | Current Method |       | Proposed Method |           |             |               |
|----------|----------------|-------|-----------------|-----------|-------------|---------------|
|          | FIS            | ANFIS | FCM + LR1       | FCM + LR2 | ScFCM + LR2 | ScEwFCM + LR2 |
| Eng. Y1  | 0.592          | 0.138 | 0.264           | 0.108     | 0.108       | 0.108         |
| Eng. Y2  | 0.302          | 0.156 | 0.257           | 0.162     | 0.162       | 0.160         |
| Eng. Y3  | 0.416          | 0.103 | 0.671           | 0.133     | 0.137       | 0.137         |
| Eng. Y4  | 0.469          | 0.107 | 0.694           | 0.181     | 0.182       | 0.181         |
| Mech. Y2 | 1.104          | 0.219 | 0.861           | 0.287     | 0.283       | 0.285         |
| CS Y2    | 1.012          | 0.191 | 0.387           | 0.197     | 0.190       | 0.189         |
| Average  | 0.649          | 0.152 | 0.522           | 0.178     | 0.177       | 0.177         |

Eng. Y1–Y4: Engineering Year 1 to Year 4, Mech. Y2: Mechanical Year 2, CS Y2: Computer Science Year 2

Although ANFIS recorded the lowest RMSE, it was not chosen as the most suitable method due to its limitations in performance classification and generalizability. ANFIS requires retraining for each new case, which makes it less practical in dynamic academic environments. It also tends to overfit noisy or imbalanced datasets, reducing its ability to generalize across different student performance profiles. In contrast, the proposed hybrid ScFCMLR2 model combines clustering and regression, and consistently performs well across all metrics while also offering better interpretability. Additionally, to evaluate accuracy and F-score, the students' original CGPA and the results from each technique were converted to a scale: 1 for less than 2.0, 2 for 2.0 or above, 3 for 3.0 or above, and 4 for 3.67 or above (based on the GPA scale). The classification test results are shown in Tables III and IV. Table III shows that ScFCMLR2 achieved the highest accuracy of 0.85, followed closely by ScEwFCMLR2 at 0.848. Both models outperformed ANFIS (0.828), especially in the Mechanical and Computer Science datasets. Table IV presents the F-score results, with ScFCMLR2 again recording the highest average of 0.827. This suggests better and more consistent classification performance in identifying student categories. These results indicate that the hybrid approach ScFCMLR2 is the most effective model for predicting student performance. The model not only strikes a good balance between prediction accuracy and classification reliability but also offers flexibility in interpreting input-output relationships through fuzzy rules derived from regression patterns.

TABLE III. RESULTS OF THE ACCURACY TEST

| Program  | Current Method |       | Proposed Method |           |             |               |
|----------|----------------|-------|-----------------|-----------|-------------|---------------|
|          | FIS            | ANFIS | FCM + LR1       | FCM + LR2 | ScFCM + LR2 | ScEwFCM + LR2 |
| Eng. Y1  | 0.260          | 0.900 | 0.600           | 0.900     | 0.900       | 0.860         |
| Eng. Y2  | 0.600          | 0.760 | 0.660           | 0.860     | 0.860       | 0.860         |
| Eng. Y3  | 0.520          | 0.920 | 0.220           | 0.920     | 0.920       | 0.920         |
| Eng. Y4  | 0.460          | 0.880 | 0.180           | 0.840     | 0.800       | 0.820         |
| Mech. Y2 | 0.085          | 0.763 | 0.246           | 0.788     | 0.797       | 0.805         |
| CS Y2    | 0.041          | 0.742 | 0.526           | 0.773     | 0.825       | 0.825         |
| Average  | 0.328          | 0.828 | 0.405           | 0.847     | 0.850       | 0.848         |

TABLE IV. RESULTS OF THE F-SCORE TEST

| Program  | Current Method |       |           | Proposed Method |             |               |
|----------|----------------|-------|-----------|-----------------|-------------|---------------|
|          | FIS            | ANFIS | FCM + LR1 | FCM + LR2       | ScFCM + LR2 | ScEwFCM + LR2 |
| Eng. Y1  | 0.403          | 0.839 | 0.631     | 0.904           | 0.904       | 0.851         |
| Eng. Y2  | 0.586          | 0.823 | 0.643     | 0.859           | 0.859       | 0.859         |
| Eng. Y3  | 0.569          | 0.896 | 0.351     | 0.870           | 0.870       | 0.866         |
| Eng. Y4  | 0.549          | 0.858 | 0.513     | 0.759           | 0.811       | 0.839         |
| Mech. Y2 | 0.177          | 0.744 | 0.378     | 0.715           | 0.727       | 0.732         |
| CS Y2    | 0.073          | 0.757 | 0.559     | 0.738           | 0.790       | 0.790         |
| Average  | 0.393          | 0.820 | 0.513     | 0.807           | 0.827       | 0.823         |

#### IV. CONCLUSION AND DISCUSSION

The main objective of educational institutions is to ensure that student assessment reports are accurate, relevant, and aligned with the intended learning outcomes of the program. Grouping students by cognitive, psychomotor, affective, and social domains provides a more comprehensive view of their overall performance, consistent with previous studies that emphasize multi-domain assessment beyond academic scores [7, 10-12, 14]. While traditional methods such as Grade Point Average (GPA) and average-based scoring remain widely used, they may not be enough when dealing with uncertain or overlapping learning characteristics. Similar issues were noted in [4] and [9], where performance scores alone did not accurately reflect actual mastery or meaningful learning outcomes. Therefore, this study introduces an additional technique that supports existing assessment approaches by incorporating soft computing methods.

The proposed expert system, ScFCMLR2, combines Subtractive Clustering with Fuzzy C-Means and linear regression with two independent variables. Linear Regression (LR) was chosen for this study because it is already widely used in educational settings and well understood by educators. Its simplicity and interpretability make it a practical option for integrating into fuzzy inference systems, especially when transparency and explainability are crucial. This builds on previous applications of regression in educational data mining, such as authors in [18], who showed its effectiveness in predicting student dropout. Instead of replacing traditional assessment methods, using regression in this fuzzy expert system aims to extend its functionality and generate decision rules based on observable academic patterns. Other techniques, such as Adaptive Neuro-Fuzzy Inference System (ANFIS), decision trees, or deep learning models, were not selected for several reasons. ANFIS, although adaptive, needs retraining for each new dataset and becomes more complicated to manage as the number of datasets increases. Deep learning and complex classifiers can achieve high predictive accuracy but often operate as black-box models, limiting their interpretability in educational environments where explaining the reasoning behind scores is important. Moreover, many of these models need larger datasets and more computational power, which may not be practical or necessary for this study's goals.

The results of this study demonstrate that the proposed hybrid method achieves reliable performance across Root

Mean Square Error (RMSE), accuracy, and F-score. The clustering approach helps to organize student data based on performance patterns, while regression provides a clear rule-based output aligned with real assessment results. Importantly, this system is not meant to replace the traditional assessment method, but rather to enhance it by offering additional perspectives that may help identify student strengths and weaknesses more clearly. This aligns with the arguments in [8], [16], and [17] that soft computing methods can better capture uncertainty and imprecision than conventional methods. However, challenges still exist in optimizing fuzzy inference systems, especially when dealing with high-dimensional or highly correlated educational data. Future research could focus on improving the model's scalability and accuracy through feature selection, entropy-based weighting, or combining it with other learning models. It is also advisable to validate the model using larger datasets from different programs or institutions and to incorporate additional variables, such as demographic profiles or real-time academic performance, to improve broader applicability and insights.

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