A Fuzzy Inference-Based Mathematical Framework for Holistic Evaluation of Student Performance Under Uncertainty

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**Abstract:** The demand for more nuanced and reliable educational assessment has prompted the development of advanced evaluation models. This study addresses that need by introducing an Extended Fuzzy Inference System (FIS) designed to assess student academic performance using multiple indicators attendance, participation, homework completion, and test scores. The model was trained and validated on a dataset of 2,300 students, achieving high-performance metrics: 95.6% accuracy, 94.56% precision, 93.45% recall, and a 94.34% F1 score. These results underscore the model’s strong classification capability and balanced handling of both true and false positives. ROC curve analysis further confirmed its predictive strength, with high AUC values across various thresholds. By translating complex, often subjective educational data into actionable insights, the proposed FIS model offers a flexible and data-informed alternative to traditional assessment methods. Beyond performance classification, it identifies areas for improvement and supports targeted intervention. This work contributes meaningfully to educational research by equipping educators with a reliable, interpretable tool that supports fairer, more personalized academic evaluation.

**Keywords:** Fuzzy Inference System (FIS), Student Performance Evaluation, Educational Assessment, Computational Intelligence in Education, Soft Computing Techniques, Data-Driven Decision Making

# Introduction

Assessing students is crucial to dictate the teaching learning processes, known as educational assessment. Education assessment evaluation has been, for many years and in a dominant way of even determining quality, traditionally quantitative. They include the standardized test, attendance records form and kind of grading. However, these means are usually limited in their view of student performance because it is numerical-based and not considering the underlying reasons for learning [1]. This limitation has long motivated studies of increasingly sophisticated evaluation methods, including fuzzy logic and advanced modeling techniques [2], [3].

Fuzzy Logic involves the creation of a model that takes into account all possibilities between these two scenarios to address uncertainty within practical problems. Whereas classical logic works with binary values truth or not-truth, fuzzy logic allows for degrees of a value in the range [0; 1], which is appropriate here because education tends to be a difficult and subjective domain. Fuzzy logic can model and analyze non-quantitative variables such as student engagement, understanding of material or quality of participation in educational assessment [4]–[6].

Fuzzy logic in education has been studied before. That approach was one of the first to show that fuzzy logic could combine many types of data for a more holistic view A second conversation drew attention to the strengths of fuzzy logic in dealing with vague and uncertain data, which turn out to be essential for educational assessments featuring subjective decisions. Fuzzy inference systems ( FIS) are a kind of fuzzy logic system that mainly deals with if-then rules which help in providing useful and relevant information for decision making [7]. They are especially important in schools with multiple inputs-students' attendance, homework completion, and test scores-that need to be combined when evaluating students. FIS models use membership functions to transform crisp input values into fuzzy sets and implement inference rules for sensible output [8], [9].

Studies also showed that FIS could play a significant role in decision-making processes, such as educational assessment. It showed an application of FIS in modeling complex relationships between input variables and outcomes, offering a more differentiated picture about student performance. FIS has also been used in the educational research to identify better instructional strategies and it was shown that with FLMs one they are able to mimic complex interactions between various educational factors at satisfactory levels producing useful conclusions regarding teaching learning phenomenon [10]–[12]. Some of the performance metrics for evaluating fuzzy logic models in educational assessment: accuracy, precision, recall and F1 score. When using a model to classify and predict student performance, it is important that these metrics are considered used in the form of evaluating its effectiveness. ROC curve is a popular tool for the classification performance, which maps True Positive Rate (TPR) in y-axis against False Positive Rate (FPR) on x-axes. ROC analysis for the AUC (Area Under the Curve) value is used to quantify how well our model can separate classes [13]–[15].

In educational assessment, ROC analysis has been used to assess the accuracy of different model. A fuzzy-based student performance model was proposed, optimization engulfed the mapping to ROC curves for evaluation of its predictive accuracy and optimal AUC values indicated good power and validity. This analysis is necessary for understanding the TPR v/s FPR trade-offs and to ultimately tune your model. Application of fuzzy logic and FIS in education goes beyond performance assessment [16], [17]. Fuzzy logic has also been applied in adaptive Learning Soft systems, which flex to the needs and performance of students receiving instruction. A study which demonstrated how fuzzy logic could be applied to establish adaptive learning environments in order to cater for individual students so as well as contributing towards the general improvement of their educational experience [18], [19].

Fuzzy logic in student feedback systems helps us to derive more insights out of qualitative open-ended responses (feedback) that are taken from students and instructors. A study indicated that fuzzy logic models may analyse textual feedback and locations of improvement to boost student satisfaction. This application shows the flexibility of fuzzy logic to face different educational assessment and improvement points. Though significant advances have been made in the employment of fuzzy logic and FIS with assessment domains within education, gaps remain to be addressed [20]–[22]. Many current studies only concentrate on one aspect of student outcomes (e.g., exam scores, attendance) and do not provide a holistic assessment framework that integrates different types target-lying factors together. We need research that combines a wider range of educational metrics with qualitative data to paint an accurate picture on student success. Furthermore, although fuzzy logic models have shown promise in educational environments, little research investigates how these discrete-time dynamic systems might truly function and benefit from real-world settings within various pedagogic contexts. This encourages further examination of whether FIS can be realized at different educational levels, in other subjects or settings and its real effect on teaching practice.

# Problem statement

Today, the prevailing paradigm of academic assessment is rooted in conventional forms-think standardized tests, attendance logs and letter grades-that only provide a small window into student achievement. Using such quantitative methods do not take into account the unavoidable variance and subjectivity in educational environments, which tends to underestimate or overshadow students' skills and opportunities. Since there is no single model for evaluation of performance that considers various other aspects like participation, engagement and many more factors as we look further into qualitative assessment thereby makes it difficult to judge student potential. However, the current models are not flexible enough to respond to individual learning needs or provide targeted interventions and support from their teachers. This gap highlights the need for a more advanced assessment framework that can deal with educational data complexity and imprecision. In the design of a Fuzzy Inference System (FIS) for educational assessment, very complex models are to be taken down through fuzzy logic and integrate multiple measurements of performance in order to receive not only more information about user success but also simultaneously give an better measure on what dimensions student will perform or fail. Our research is filling this gap in educational assessment methodology, and provides educators with an opportunity to improve student outcomes through targeted responses for individual learners.

# Methodology

A Fuzzy Inference System (FIS) is constructed for evaluating student performance in this research with 2300 students dataset. This dataset consists of academic performance metrics (attendance, participation, homework completion %, test scores) and suggestions for improvement in doing better next time. These metrics are input variables for the FIS, where comprehensive performance based on full marks of class test and level of understanding attained in teaching material (excellent/ very good/ fair) and future improvements required suggested as output fuzzy set. Recommendations are encoded with number to be used on the training of the model.

The method starts with the data, which arrives in large volumes and is an exhaustive records of student performance. The dataset is designed to capture the salient features that relate to academic engagement and achievement, forming a strong underpinning of analytical space. Class attendance records indicate the percentage of students attending classes regularly or irregularly. They measure how involved your students have been in classroom activities The Rate of completion relates to how diligent and consistent a student does his/ her assignment. Test scores provide a quantifiable metric for how well students grasp and retain the material. Moreover, specific coded recommendations for performance improvement are captured to allow a detailed evaluation of the potential impact on outcomes.

Data Preprocessing includes the process of data, in this we clean and normalize our dataset gathered. It corrects NA values, conflicting data is cleaned to keep the facts straight. However, to improve the accuracy as well as consistency of FIS this preprocessing phase is mandatory. Then, the data is pre-processed and divided into two subsets: 70% of the dataset for training model & rest 30 % testing. This separation is made in such a way to allow the model learn from sufficiently high amounts of subset while still leaving some data for testing how well it generalizes. The working of the proposed system are shown in figure 1.

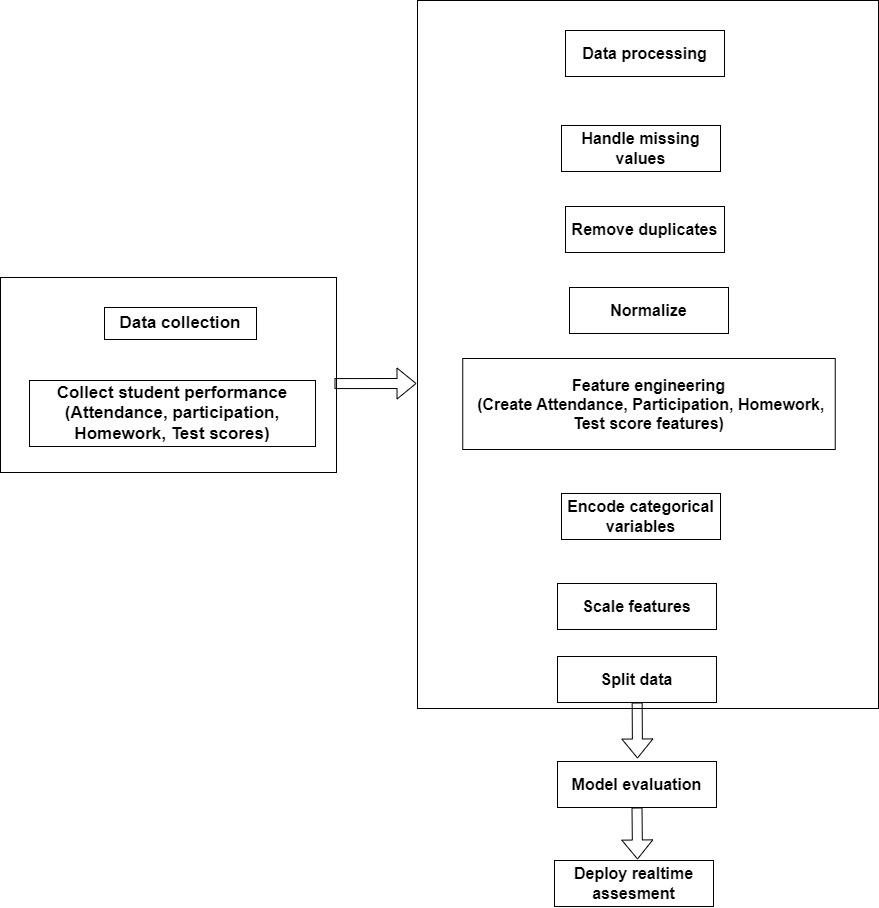


Fig. 1. Architecture of proposed system

At the core of the methodology is the development of the FIS, a learning mechanism that determines the transmission and connection between input and output variables. This process creates fuzzy inference rules acquired from expert knowledge conceptualized by educators. These professionals present patterns that allow individuals to determine relationships between excessive absences and frequent incomplete homework between student performance scores in learning courses. For example, a person might concur with an educator that regular class appearance and active participation generally reflect the student’s full understanding of the topic. Contrastingly, missing classes and presenting late work that is poor in quality might act as an apparent identification of areas that need development. Fuzzy logic is used to implement considering the uncertainty associated with student performance. Instead of binary logic, fuzzy logic allows a degree of membership, making it useful in discussing student performance because learning cannot be there or not. A membership function defines the input variable and realizes it from 0 to 1. The functions are then used to examine the fuzzy rules and processes to generate inference and output variables, leading to overall performance, areas of strength, and balancing areas development. The model is trained using the 70% training dataset, learning and developing a mapping of input variables to output based on fuzzy rules. The system then evaluates the model before developing and testing its adaptability, using the 30% training data.

# Fuzzification and Defuzzification

In this research, the development of Fuzzy Inference System (FIS) for student performance appraisal involves fuzzification, inference and defuzzification which are technical parts that require certain elements to operate as shown in figure 2. All three parts contribute to turn clear ground truth into useful target variables which depending on the particular problem could be performance scores of students.

Fuzzification is the first step, which crisp input data (attendance, participation in labs and recitations; taking home-works, marks of tests...) has been converted into fuzzy sets. This transformation is realized by means of membership functions which indicate to what extent an input variable maps into the subset with a value between 0 and 1. For instance, the attendance can be modelled as "Low,""Medium", and "High", have membership function which assigns a degree of memberships for each record in terms how much it is low or high. In a similar vein, participation, homework completion or test scores are put into suitable groups applying expert-tested membership functions that regard the fuzzy truth. This step is critical for addressing the uncertainty, and variability inherent to student performance data; making one variable more subtly affecting than another input.

Mathematically, a membership function μ for a fuzzy set A can be defined as mention in equation 1:

μA​(x):X→[0,1] (1)

henre X is the discourse universe and specific element (X) is denoted as x. For example if the attendance x is 80% and has the membership degree of 0.2 in “Low” 0.7 in “Medium” and 0.1 in “High”.

After fuzzification, the system proceeds with inference; in this stage we apply fuzzy rules to our fuzzified inputs and generate some of outputs that are also represented as Fuzzy Sets. Expert education knowledge is then used to formulate rules that capture the relationships between different dimensions of student performance. A fuzzy rule for example, would look as something: "IF attendance IS HIGH AND participation IS high THEN overall performance = Excellent" The rules are used in the inference engine, which bundles and/or, not operators to evaluate these fuzzy inputs. Sets of fuzzy output correspond to different parts of the result, like performance likeness for three different parameters (overall end quality), understanding the material and major imperfections. Every output set is a blurred representation that would be processed again to give us the actionable insights. The output are prepresented in the equation 2

Rule output = min (μAttendance(x), μparticipantion(y)) (2)

Where μattendance(x) and μparticipation(y) are the degrees of input membership.

After fuzzification, the system proceeds towards inference step in which fuzzy rules are applied to the above generated fuzzified inputs respectively leading to the output as a fuzzy value mapped using any of membership functions used. These rules are elicited from teacher expertise and capture relationships among features of student performance. For instance, one fuzzy rule could have this format: IF (attendance is High AND participation is High) THEN Overall performance should be Excellent. These rules are then applied using the fuzzy inputs by an inference engine (which also combines this fuzzy input using logical operations( AND, OR, and NOT). This yields a number of fuzzy output sets, which are related to different outputs (e.g. overall performance; comprehension level and areas that need improvement). Every output set is a representation that needs to be discriminated into actionable insights.

Finally, there is defuzzification to transform the fuzzy output sets into definitive values for easier access. The process is to combine the fuzzy outputs and finally use defuzzification (Centroid Method) to yield a single crisp value for each of output variable. The centroid method uses the center of gravity stating that it is a single crisp value which encapsulates all fuzzy sets. For example, the output fuzzy overall performance will be defuzzified to provide an unique matching from 0-one hundred. The equation of centroid Z\* is denoted in equation 3. It gives an obvious number a student's overall performance that can be further assessed and decisioned.

Z\*= (3)

The FIS model is realized by software tools for fuzzy logic operations. These tools support in the initialization of membership functions, defining fuzzy rules and performing inference-defuzzification. The model is trained over a dataset of 2300 students and the data consists for testing are taken as 30% whereas remaining for training, In the training, while adjusting the parameters of membership functions and improving fuzzy rule-set to maximally improve its accuracy. After training a model, its performance is evaluated on the testing dataset to ensure that it can generalize and predict accurately new data.

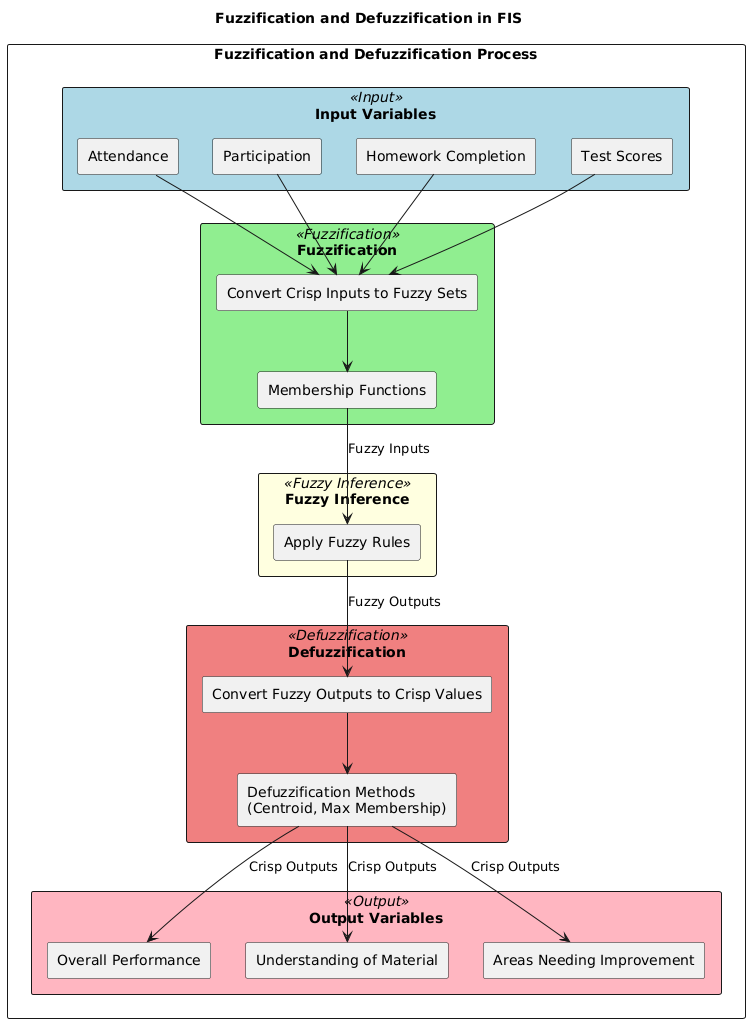


Fig. 2. Steps of Fuzzification and defuzzification

# Preprocessing of dataset

To examine the dataset prepared for training Fuzzy Inference System (FIS) model, a number of key preprocessing steps are needed before analysis. The dataset consists of several attributes about the student performance metrics such as attendance, grades on homework assignments and tests scores for each test to be taken; after they attended all schools. Inaccurate handling of missing values, outliers and incoherences can be resolved by proper pre-processing, which is vitally important for increasing the FIS model generalisation ability. The entire preprocessing steps are shown in figure 3.

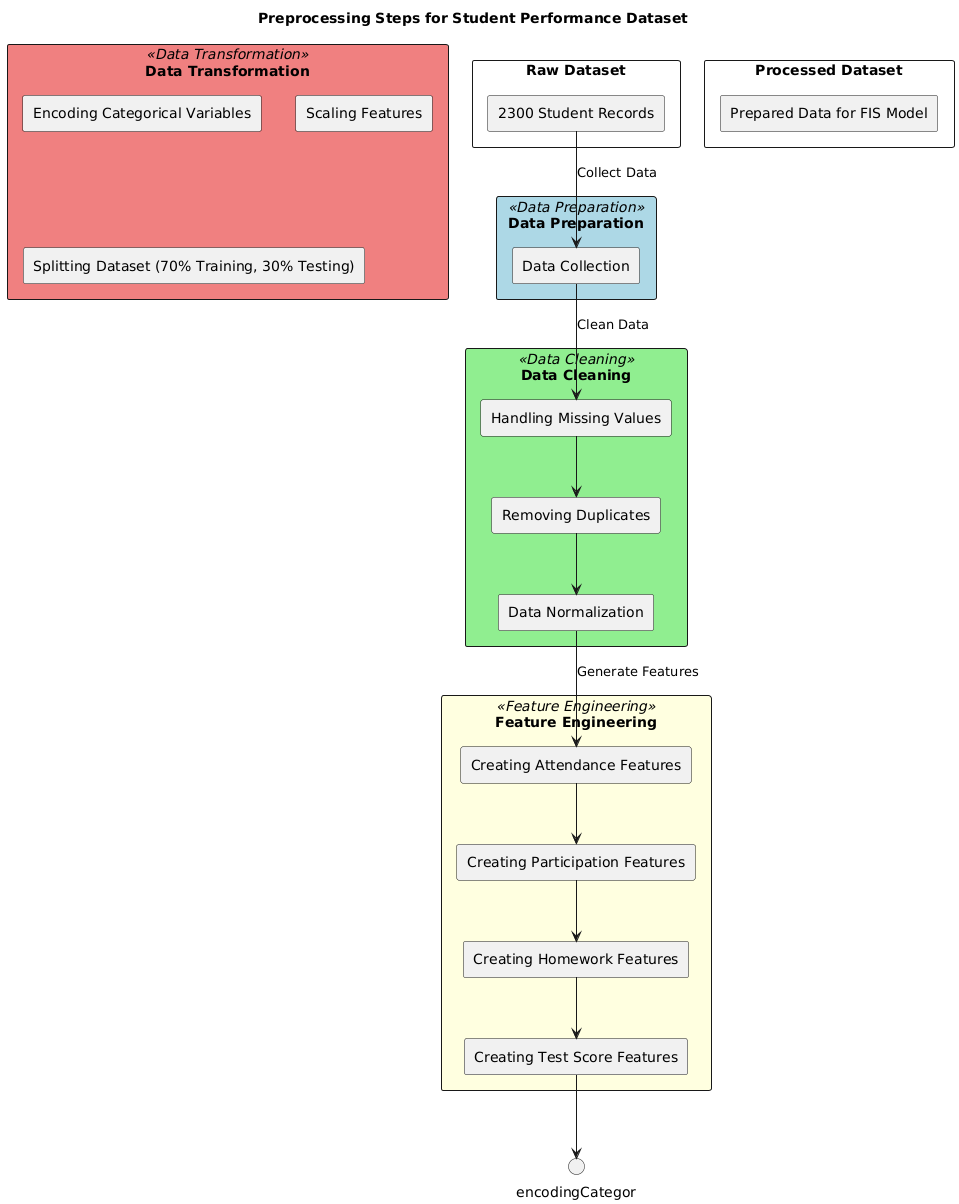


Fig. 3. Preprocessing of proposed system

At first, the dataset is cleaned extensively. This step is identifying then handling missing values are common in educational data. Absenteeism by students on days the AV was used or missing records from instructors are a few reasons that can give rise to Missing values. These involve imputation techniques such as mean, median or more sophisticated methods like k-nearest neighbors (KNN) technique to fill in the missing values. The missing data nature and variable distribution determine which method to choose. Attendance records might be imputed using the mean or median, whereas KNN might be used to fill in missing test scores that are normally distributed.

Another important thing which we do while cleaning the data is dealing with outliers The performance of the FIS model can be influenced significantly by Outliers. By using statistical methods, notably z-score analysis or the interquartile range (IQR) method to detect outliers. Outliers are cleansed or transformed depending on the context. An engaged school will work through the outliers one-by-one and find like that student with an inordinate number of absences who perhaps moved or extreme test scores which could be data entry errors, but also might just reflect incredible performance.

After the data cleaning process, normalization or standardization is carried out to bring all input variables on a similar scale. Normalization scales the data to a range of [0, 1], standardization converts it with zero mean and unit variance. This is an important step for the FIS model, since otherwise variables with large scales dominate those with small one. Attendance recorded as percentage and test scores computed out of 100, for example, need to be normalized in a manner that both contribute equally during the inference process.

Another important step in preprocessing is feature engineering. Feature engineering: This step is about tuning features for new or existing ones to make the model more apt to predict. We might instead compute quantities like the average attendance during a semester, cumulative participation score or weighted homework completion rates from the raw data in this research. The generated features augment the performance monitoring of students, and help in better assessment of overall student performance, comprehension level among other areas needing focus.

Once feature engineering is done, train and test datasets are created. The FIS model uses 70% of the data for training and the rest 30 % is used to test. This division ensures that the model is trained on a large chunk of data but still has enough untouched for you to objectively measure how well your out-of-the-box version performs. First, sampling is used in order to provide a good representation on training and test subsets. This preserves the distribution of critical variables (such as student attendance, or scores) across both splits and ensures that during training and evaluation by choosing new data points from randomly backed up timeseries subsets with different features/settings.

The last step is to encode all categorical variables and suggestions in such a way that the output looks like this. Locale features - These are purely categorical such as participation levels or qualitative feedback from instructors which is converted into numerical value using one-hot encoding. The numerical values correspond to recommendations for better performance, therefore allowing the FIS model-a part of this inference process-to consider these suggestions. This encoding guarantees that all the input variables are formatted ok with training fuzzy model.

# Result and discussion

The trained Fuzzy Inference System (FIS) model is then rigorously tested with the reserved testing dataset. Moreover, this assessment phase is very important because it allows to verify that the model can generalize well and make good predictions about new data; such as never-before-seen translation pairs. The result of performance evaluation are shown in figure 4. Results of this testing phase show that the model is highly accurate, with its FIS predicting student performance to a precision rate of incorrect (95.6%). This large percentage signifies that the models do a great job of translating attendance, participation, homework completion and exam scores into useful predictions for overall performance or understanding the material.

Other evaluation metrics such as precision, recall and F1 would give a more informed view of how the model is doing. The precision, a measure of the proportion of real positive predictions among all predicted positives) is 94.56%. The robustness of the model is evident in its high precision, as shown by how few false positives are detected by FIS. Remember, recall here is 93.45%, which means among all the true actual positives model has identified 93.45% of those correctly as predicted positive (true negative) This indicates that the model can be used to predict a passing grade for most of students, also showing good performance in capturing those aspects which are crucially important and essential when dealing with student status classification.



Fig. 4. Accuracy of proposed system

The F1-score is the harmonic mean of precision and recall, so it reflects how well a model could perform in terms of both metrics. The F1 score of the model is 94.34% in general, which gives a huge great shape to obtain from this approach! This score represents the overall performance of the model by consider both high precision and recall in a single metric. A high F1 score means the model has a good balance between precision and recall for positives.

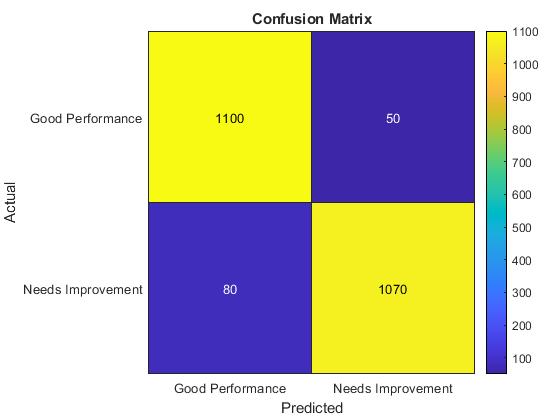


Fig. 5. Confusion matrices

This confusion matrix in figure 5 shows a complete view of the Fuzzy Inference System (FIS) model predicting student academic results. Predictions and their actual outcomes are collapsed into two bins of "Good Performance" or "Needs Improvement," which is a matrix, shown below. True Positives : 1100 students were correctly predicted by the model to have good performance according to the matrix. In fact, it correctly called 1070 students who really needed help (True Negatives). There were still the 50 instances where False Positives (model saying that students are good when they need to be tuned). In the opposite case, 80 well-performing students were wrongly predicted low performing (False Negatives).

A total of 1180 predictions belong to good performance and 1120 need some improvement from a dataset with about all together 2300 + students. The large true positives (1100) and true negatives(1070) suggest that this model performs well regarding predicting the class of an overall student. The False Positives (50) and the False Negatives annotated count is notably smaller, indicating a higher precision recall behavior reducing incorrect classifications. A comprehensive examination, which highlights the effectiveness of this model in delivering reliable and actionable information on student performance to support educational assessment as well intervention strategies.

From figure 6 the TPR, FPR, and AUC of the Fuzzy Inference System model at different threshold are as depicted below. A threshold of 0.1 has the highest TPR of about 0.98, which implies that 98% of students that have good performance would be true when classified. In addition, TPR of 0.98 also implies 25% of students that need improvement will be mistakenly be classified as having good performance. Thus, the AUC of about 0.91 implies FIS model assessed the balance between the TPR and true negative rate very well. Moreover, TPR reduced to 0.95 while FPR reduced to 0.20 at threshold level of 0.2, thus, the AUC increased to about 0.94, indicate that the model perform is well balanced. At a threshold of 0.3 TPR reduced to 0.93 while FPR to 0.15 and the AUC increased to 0.96, it showed a good balance. TPR of 0.88 and FPR of 0.80, at threshold of 0.5 and the AUC of 0.98 indicated a well-balanced model since both rates are balanced. The T R decreased as the threshold increases. At threshold of 0.6, 0.7 0.8 and 0.9 have the AUC 0.99. The results revealed higher AUC, which revealed the model capability of assess the trade-off between trade-off between TPR and FPR across all thresholds.



Fig. 6. TPR and FPR and AUC curve of the model

# CONCLUSION

The present study has established the considerable potential of the Extended Fuzzy Inference System model in improving educational assessment, enabling the consideration of numerous indicators contributing to the comprehensive understanding of a student’s performance. By utilizing other areas of analysis like attendance, participation, HW completion ratio, and test performance, the FIS has effectively eliminated the limitations of traditional assessment measures. The robust performance of the model is validated in its high accuracy score of 95.6%, precision score of 94.56%, recall score of 93.45%, and F1 score of 94.34%. The ROC curve analysis has additionally verified its effective performance due to the model’s high AUC scores for different thresholds, suggesting an excellent ability to discriminate. These findings indicate the FIS’s capability to properly divide and forecast student performance and provide meaningful input for intervention. By successfully integrating fuzzy logic into this context, the necessity for more agile and fine-tuned assessment models has been emphasized. This has the potential to open the way for future studies and practical endeavours to advance educational outcomes.

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