JAIIT (*Journal of Advances in Information and Industrial Technology*)
Vol. 7, No. 1 May 2025, ISSN 2716-1935, E-ISSN 2716-1927

Prediction of Higher Education Student Academic Achievement Using Mamdani Fuzzy Logic

Afifah Nurul Izzati [*1)], Ummi Khaira Latif [2)], Endah Septa Sintiya[3)]
[1)] Department of Informatics Engineering, Kahuripan University of Kediri, Kediri, Indonesia
[2)]Center for Ubiquitous Computing, University of Oulu, Oulu, Finland
[3)] D2 Website Software Development, Malang State Polytechnic, Malang, Indonesia
[1*]afifah.n.i.@kahuripan.ac.id, [2]ummi.latif@oulu.fi, [3]e.septa@polinema.ac.id

ARTICLE INFO

Article history:
Received 30 April 2025
Revised 14 May 2025
Accepted 27 May 2025
Available online 30 May 2025

Keywords:
Artificial intelligence
Mamdani fuzzy logic
Prediction
Student academic performance

ABSTRACT

Student academic performance assessment is not only determined by exam scores, assignments, and attendance but also influenced by other factors such as attitude. However, evaluating this factor tends to be subjective. Additionally, the absence of an early prediction system to estimate students' academic performance can hinder timely study finish for at-risk students. The purpose of this study is to use the Mamdani fuzzy logic method to develop a system for predicting student academic performance. The input variables used in this system include attendance, assignments, midterm exams, final exams, and attitude. The system is modeled using fuzzy membership functions and assessed based on appropriate weightings. The inference process is conducted based on a set of fuzzy rules and is determined by the combination of input values. The next stage is defuzzification, which is the process of generating a final value used to classify academic performance into categories of "poor," "fair," or "good." This system is developed using the Python programming language with the scikit-fuzzy library and tested using the Mean Absolute Percentage Error (MAPE) method. The test results show an error rate of 1.35%. These results indicate that the Mamdani fuzzy logic approach is considered effective in assisting the assessment of student academic performance.

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1. Introduction

Student academic performance is one of the key factors in every academic institution as it affects the overall performance of the educational institution [1]. Predicting students' academic performance becomes important to identify which students require more attention so that the institution can provide the appropriate support to improve learning outcomes. However, conventional approaches are often ineffective in understanding the complexity of data that are subjective and uncertain in assessing academic performance.

University X is one of the private universities located in East Java, which is currently facing a similar challenge. Based on initial observations of students in the Informatics Engineering study program, there are noticeable differences in academic achievement that cannot be solely explained by exam results and attendance. Other factors, such as task completion and student attitude, play a significant role in determining academic success. However, assessments of these factors tend to be subjective, resulting in variations in final evaluations. Furthermore, there is currently no early prediction system developed to utilize existing data to determine the likelihood of student academic success or failure. This absence hinders academic staff from taking immediate preventive measures for students at risk, such as failing to graduate on time or dropping out.

The fuzzy logic theory was introduced by Professor Lotfali Asker Zadeh from the University of California, Berkeley, in 1965 as a methodology that offers better results than conventional control algorithms [2]. This is because fuzzy logic mimics human reasoning in decision-making, allowing it to handle imprecision and uncertainty in various domains such as industry, education, and nature, thereby enhancing the accuracy of assessments [3][4][5]. One of the methods in fuzzy logic is the Mamdani method, introduced by Ebrahim Mamdani in 1975. Mamdani fuzzy logic is a form of decision support model that provides an intuitive and more human-centric approach [6] [7]. The Mamdani method consists of four stages: fuzzy set formation, implication function application, rule formulation, and defuzzification [8]. The Mamdani method has the advantage of integrating expert knowledge directly through linguistic rules [9]. This method enables the system to manage data more flexibly by considering various aspects that affect student academic performance. Through the application of a fuzzy system, decision-making in assessing academic performance can be carried out more adaptively and in line with real-life student conditions.

Various studies have been conducted on the application of Mamdani fuzzy logic to assess student academic performance. In a study conducted by Najeeb Ullah Jan et al. [10], a fuzzy inference system was used to monitor student academic performance using three input variables: direct assessment, indirect assessment, and stress. The output variable used was consolidated assessment, which grouped the assessment into comfort zone, average zone, and highly stressed zone. The purpose of the study was to compare the Mamdani and Sugeno methods, with results showing that Mamdani performed better than Sugeno. Meanwhile, in a study by Mohamed O. Hegazi [11], a fuzzy model called FPM (Fuzzy Propositional Model) was proposed to reason and predict student academic performance using two input variables: attendance rate and final exam score. The results showed that FPM was effective in predicting and evaluating student academic performance. Another study by Mahmoud Attieh et al. [12] focused on student performance assessment using the Adaptive Neuro-Fuzzy Inference System (ANFIS) model for forecasting, with input variables such as attendance, assessment scores, exams, assignments, and projects. The results indicated that ANFIS performed better due to its use of neural network capabilities to build a large number of rules.

Based on previous studies, this research will use five input variables, namely attendance, assignments, midterm exam scores, final exam scores, and an additional variable, attitude, to predict student academic performance. Unlike prior works such as Najeeb Ullah Jan et al. [10], which focused primarily on educational and stress-related metrics, and Hegazi [11], which used only attendance and final exams, this study incorporates a broader and more holistic set of academic indicators. Furthermore, in contrast to Mahmoud Attieh et al. [12], who used ANFIS and required extensive training data for rule learning, this research employs the Mamdani fuzzy inference system for its interpretability and suitability in integrating expert knowledge via linguistic rules. The inclusion of attitude variable is added since University X considers student attitude as part of the final evaluation. The implementation of this academic performance prediction system is expected to support higher education institutions, especially lecturers, in conducting more objective and comprehensive student assessments, as well as enabling early intervention for at-risk students.

2. Methods

The stages in conducting this research are illustrated in Figure 1, which include the following:

2.1 Problem Identification

University X faces a gap in evaluating students' academic performance, particularly in the Informatics Engineering study program, which cannot be explained solely by exam scores and attendance. The assessment of other factors, such as assignments and student attitude, remains subjective, potentially leading to unfair final evaluations. Moreover, the absence of an early prediction system makes it difficult for academic staff to identify and address students at risk of academic failure.

 DOI: https://doi.org/10.52435/jaiit.v7i1.682

2.2 Data Collection

The research sample consisted of 30 students from the Informatics Engineering Study Program, selected using purposive sampling, which involves the intentional selection of samples based on specific criteria. These criteria included students who were actively enrolled in the current semester and had complete academic data, including assignments, midterm exams, final exams, attendance, and attitude. This selection was made to ensure that the data obtained were complete and valid for analysis in the fuzzy logic-based prediction system.

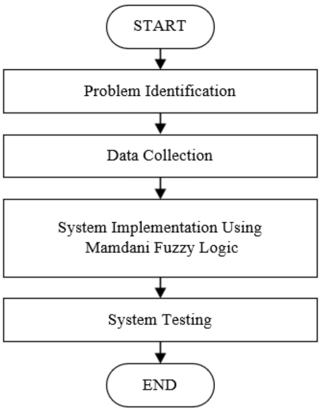

Figure 1. Research Stages

The academic data gathered include variables that influence the evaluation of academic performance, namely assignment scores, midterm exam scores, final exam scores, attendance levels, and students' attitudes. The assessment of students' attitudes was conducted through direct observation during the learning process over the course of one academic semester. A structured rubric was employed as the assessment instrument, encompassing indicators such as responsibility in completing assignments, discipline, and classroom ethics. Each indicator was evaluated by the course instructor using a 5-point Likert scale, and the scores were subsequently averaged to derive the final attitude score for each student.

2.3 System Implementation Using Mamdani Fuzzy Logic

A fuzzy Inference System (FIS) is a comprehensive process that transforms crisp inputs into crisp outputs through four main stages: fuzzification, fuzzy rule base, fuzzy inference, and defuzzification [13]. The first is fuzzification, which transforms numeric input values into linguistic terms (such as low, medium, and high). The second process involves the formulation of fuzzy rules using if-then statements. The third is the Mamdani fuzzy inference process, which processes the fuzzy rules to generate fuzzy outputs. The fourth is defuzzification, which converts the fuzzy output into a final value (i.e., a prediction of student academic performance). The system will be developed using the Python programming language.

A total of five input variables are used in the system: attendance, assignments, midterm exam scores, final exam scores, and student attitude. Each input is classified into three linguistic terms (low, medium, high), resulting in 243 fuzzy rules (3^5 combinations). These rules were designed with the guidance of academic staff to reflect practical evaluation logic commonly used by lecturers.

The Mamdani fuzzy logic model was chosen over machine learning techniques for two key reasons. First, this model allows the integration of expert-defined rules, which is particularly beneficial when the number of samples is limited, as is often the case in educational settings. Fuzzy logic has proven to be effective in making accurate predictions even with a small number of samples, whereas machine learning typically requires large datasets to build accurate predictive models [14]. Second, the Mamdani approach offers high interpretability, allowing academic staff to understand and trust the reasoning behind the predictions.

2.4 System Testing

The system will be tested using the Mean Absolute Percentage Error (MAPE). MAPE measures the level of accuracy by comparing the system's predictions with the lecturer's manual assessments. MAPE has four interpretation criteria, namely less than 10%: very good model, 10% – 20%: good model, 20% – 50%: fair model, and more than 50%: Poor model [15].

The final assessment score determined by the lecturer as the ground truth is obtained from a weighted composite score of several evaluation components, namely assignments (20%), midterm exams (20%), final exams (30%), attendance (15%), and attitude (15%). These assessment weights are based on the grading policy applied in the Informatics Engineering Study Program at Universitas X and have been approved by the course instructor. This final score is systematically calculated to reflect the academic performance of students, making it a valid reference for evaluating the accuracy of predictions generated by the Mamdani fuzzy logic-based system.

3. Results and Discussions

The dataset used in this research consists of academic performance data of students from the Informatics Engineering study program at University X. There are five input variables used in this study: assignment scores, midterm exam scores, final exam scores, attendance, and attitude. The testing phase was conducted on data from 30 students of the Informatics Engineering program at University X. Each data entry was processed using the Mamdani fuzzy system, and the results were compared with the final grades assigned by the lecturer as a reference. Table 1 presents the dataset used in this study.

Table 1. Dataset

Attendance Rate	Assignment Scores	Midterm Exam Scores	Final Exam Scores	Attitude	Final Scores
92	99	81	100	90	93
100	97	77	94	90	92
85	98	86	92	90	91
78	98	85	93	90	90
100	99	72	94	90	91
71	73	75	50	80	67
100	93	80	86	90	89
100	96	72	93	90	90
92	99	75	95	90	91
85	95	75	92	90	88
50	70	70	70	70	67
71	90	85	87	90	85
78	76	60	55	90	69
50	44	70	82	85	68

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Attendance Rate	Assignment Scores	Midterm Exam Scores	Final Exam Scores	Attitude	Final Scores
71	88	75	82	90	81
78	89	70	50	90	72
64	85	84	82	90	82
92	90	70	82	80	82
85	91	70	82	80	82
64	74	70	82	90	77
71	90	90	88	90	87
92	71	80	85	90	83
100	24	80	70	85	70
50	80	89	80	90	79
92	98	89	85	90	90
57	37	89	79	85	70
100	96	86	78	90	88
100	98	95	86	90	93
75	31	89	86	80	73
64	97	81	86	90	85

3.1. Fuzzification

The fuzzification process aims to convert crisp input values into fuzzy inputs that have a certain degree of membership [16]. This is done by dividing the universe of discourse into fuzzy sets. Table 2 describes the universe of discourse, intervals, and fuzzy sets for each input and output variable used in this study.

Table 2. Fuzzy Sets

Function	Variable Name	Universe of Discourse	Interval	Fuzzy Sets
Input	Assignment Scores	0-100	0-60	Low
			50-80	Medium
			70-100	High
	Midterm Exam Scores	0-100	0-60	Low
			50-80	Medium
			70-100	High
	Final Exam Scores	0-100	0-60	Low
			50-80	Medium

Function	Variable Name	Universe of Discourse	Interval	Fuzzy Sets
			70-100	High
	Attendance Rate	0-100 (%)	0-60	Low
			50-85	Medium
			80-100	High
	Attitude	0-100	0-50	Low
			40-75	Medium
			70-100	High
Output	Academic Performance	0-100	0-60	Poor
			50-80	Fair
			75-100	Good

Figure 2 illustrates the use of the matplotlib.pyplot and scikit-fuzzy libraries in Python to visualize the membership function graph. In the universe of discourse section, a universe set x is created ranging from 0 to 100 with an interval of 1. This represents the domain of values possessed by the input variables. Trimf is used to define how the numerical values of input variables are mapped into linguistic values (low, medium, high) using triangular-shaped fuzzy membership functions. This is a crucial part of the fuzzy logic system before the inference rules are applied. Figures 3 and 4 show the graphical visualizations of the membership functions for each variable.

```
import numpy as np
import matplotlib.pyplot as plt
import skfuzzy as fuzz

# Universe of Discourse
x = np.arange(0, 101, 1)

# Assignment Variables
assignment_low = fuzz.trimf(x, [0, 0, 60])
assignment_medium = fuzz.trimf(x, [50, 65, 80])
assignment_high = fuzz.trimf(x, [70, 100, 100])

# Midterm Exam Variables
midterm_low = fuzz.trimf(x, [0, 0, 60])
midterm_medium = fuzz.trimf(x, [50, 65, 80])
midterm_high = fuzz.trimf(x, [70, 100, 100])

# Final Exam Variables
final_low = fuzz.trimf(x, [0, 0, 60])
final_medium = fuzz.trimf(x, [50, 65, 80])
final_high = fuzz.trimf(x, [70, 100, 100])
```

```
# Attendance Variables
attendance_low = fuzz.trimf(x, [0, 0, 60])
attendance_medium= fuzz.trimf(x, [50, 70, 85])
attendance_high = fuzz.trimf(x, [80, 100, 100])

# Attitude Variables
attitude_low = fuzz.trimf(x, [0, 0, 50])
attitude_medium = fuzz.trimf(x, [40, 60, 75])
attitude_high = fuzz.trimf(x, [70, 100, 100])

# Academic Performance
performance_poor = fuzz.trimf(x, [0, 0, 60])
performance_fair = fuzz.trimf(x, [50, 65, 80])
performance_good = fuzz.trimf(x, [70, 100, 100])
```

Figure 2. Implementation of The Scikit-Fuzzy Libraries in Python

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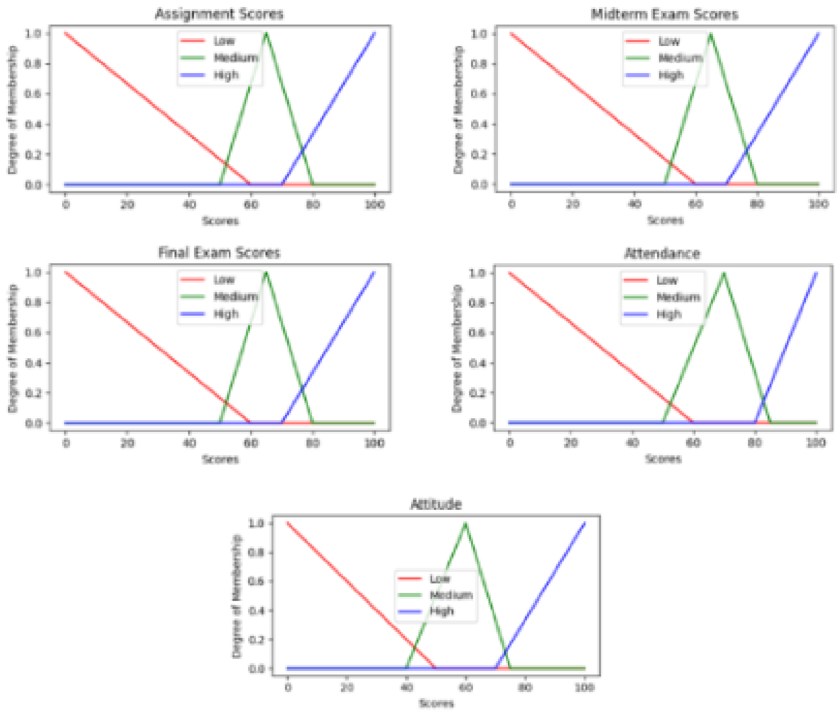

Figure 3. Graph of Input Variable Membership Functions

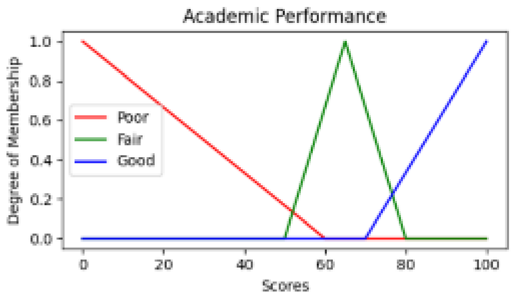

Figure 4. Graph of Output Variable Membership Functions

3.2. Inference

Inference is a reasoning mechanism used to determine fuzzy outputs based on a combination of input information and established rules. The development of the fuzzy rule base involves creating a set of IF-THEN rules that connect input variables to the output. These rules serve as the foundation for the inference process [17]. These rules serve as the foundation for the inference process [14]. The rules are constructed using the ctrl.Rule() function from the scikit-fuzzy library. In this case, the input variables include assignments, midterm exams, final exams, attendance, and attitude, each with linguistic membership levels such as low, medium, and high. Meanwhile, the output variable performance has linguistic labels such as poor, fair, and good. Each line of code represents a single rule. For example, in Table 3, the first row states that if all input variables have high values, then the predicted academic performance is good. This rule construction enables the system to automatically perform the inference process to determine the output in the form of academic performance based on the given combination of input values. Figure 5 presents a snippet of Python code utilizing the scikit-fuzzy library to define five sample fuzzy rules within the Mamdani fuzzy inference system.

Table 3. Fuzzy Rule Base

Number	Assignments	Midterm Exams	Final Exams	Attendance	Attitude	Academic Performance
1	High	High	High	High	High	Good
2	Medium	High	High	High	High	Good
3	High	Medium	High	Medium	High	Good
4	High	High	Medium	Medium	Medium	Fair
5	Medium	Medium	Medium	Medium	Medium	Fair

```
rules = [
    ctrl.Rule(assignment['high'] & midterm['high'] & final['high'] & attendance['high'] & attitude['high'], performance['good']),
    ctrl.Rule(assignment['medium'] & midterm['high'] & final['high'] & attendance['high'] & attitude['high'], performance['good']),
    ctrl.Rule(assignment['high'] & midterm['medium'] & final['high'] & attendance['medium'] & attitude['high'], performance['good']),
    ctrl.Rule(assignment['high'] & midterm['high'] & final['medium'] & attendance['medium'] & attitude['medium'], performance['fair']),
    ctrl.Rule(assignment['medium'] & midterm['medium'] & final['medium'] & attendance['medium'] & attitude['medium'], performance['fair'])
]
```

Figure 5. Python Code Snippet for Defining Fuzzy Rules

3.3. Defuzzification

After the fuzzification and inference processes, the system produces fuzzy membership values according to the predefined rules, which are then aggregated to generate a fuzzy output value. The purpose of the defuzzification process is to convert the fuzzy output into a final crisp numerical value that can be easily understood [18]. The result of this process is the numerical prediction of academic performance. The centroid method (center of gravity) is commonly used to perform the defuzzification process [19].

The implementation of Mamdani fuzzy logic in Python uses the scikit-fuzzy library, which produces a numerical output from the fuzzy inference findings. The scikit-fuzzy library is a Python library for performing fuzzy logic computations. The inference and defuzzification processes are executed automatically using the command performance_simulation.compute(), while the syntax performance_simulation.output['performance'] provides the defuzzification result in the form of a numerical score that reflects the predicted academic performance of the student. Figure 6 shows the result of the defuzzification process.

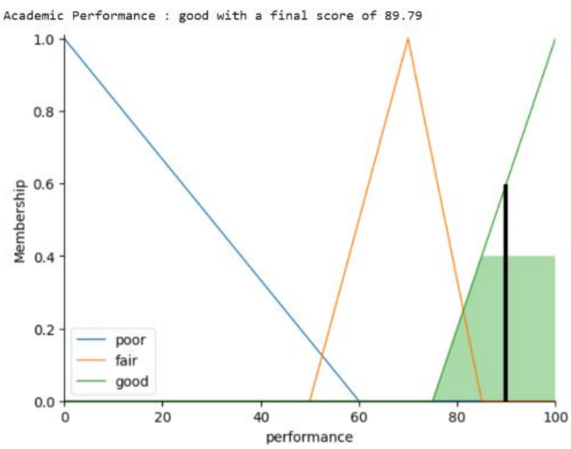

Figure 6. The Predicted Academic Performance Result

3.4 System Testing

The implementation of Mean Absolute Percentage Error (MAPE) is carried out using the mean_absolute_percentage_error function from the scikit-learn library, which is imported from the sklearn.metrics module to calculate the prediction error rate in percentage form. The system was tested using Mean Absolute Percentage Error (MAPE) by comparing the predicted values (which contain the

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results generated by the fuzzy system) with the actual values (obtained from the lecturer's manual assessment). The calculation process involves multiplying the result of the MAPE function by 100 to present the value as a percentage. The result obtained was 1.35%, indicating that the model is very good or highly accurate, as the value is less than 10%.

3.5 Discussion

The results of testing the student academic performance prediction system using the Mean Absolute Percentage Error (MAPE) yielded a value of 1.35%. This indicates that the prediction system produces fairly accurate results with a low error rate below 10%. The low error value suggests that the difference between the system's predictions and the actual final grades is minimal, making the system a reliable tool for assessing student academic performance. This high level of accuracy can provide confidence that the system can be used in academic decision-making, particularly in objectively assessing students' academic performance.

The findings also reveal that attendance and attitude variables significantly influence academic performance, in addition to task completion, midterm exams, and final exams. This highlights the importance of non-cognitive aspects in determining student success at Universitas X. Therefore, strategies to improve academic performance should not only focus on cognitive factors but also emphasize student discipline and attitude development. With the implementation of this system, lecturers and university management at Universitas X can utilize it as a tool to monitor and evaluate student academic performance. Furthermore, the system can assist in taking early intervention measures for at-risk students, such as those who may not complete their studies on time or who are at risk of dropping out due to poor academic performance. Hence, this predictive system serves as a fundamental reference in determining appropriate learning strategies and providing additional academic support to enhance student outcomes. Appropriate learning strategies have an impact on determining better academic performance [20].

Strategies for improving academic performance can be categorized into two main approaches: cognitive and non-cognitive. The cognitive strategies can be applied by enhancing the learning process qualities through methods such as problem-based learning, offering interactive learning modules, providing additional academic guidance for poor-performing students, and regularly assigning structured exercises to strengthen material comprehension. On the other hand, a non-cognitive approach can be implemented by giving recognition to students who actively participate in learning activities and providing periodic soft skills training to improve attitudes and discipline. With these strategies in place supported by a fuzzy logic Mamdani-based prediction system, it is expected that decision-making processes in educational management will become more informative, adaptive, and targeted, especially in efforts to improve student academic performance at Universitas X.

4. Conclusion

The Mamdani fuzzy logic method can be used to handle the complexity and uncertainty of assessments while predicting students' academic performance by considering five variables, namely attendance, assignments, midterm exams, final exams, and attitude. The Python programming language is used to develop procedures for fuzzification, inference, and defuzzification, which are then evaluated for accuracy by comparing the system's predicted results with the actual values (manual evaluations by the lecturers). The accuracy testing process utilizes the Mean Absolute Percentage Error (MAPE), with a result of 1.35%. This value indicates that the predicted academic performance system is highly accurate, as it has a small error rate (less than 10%). However, the limitation of this study is the dataset used is limited to 30 students from one specific program of study, which may not represent the wider student population. For future research, it would be valuable to expand the dataset to include a larger and more diverse group of students from different disciplines. Further, exploring additional variables that may influence academic performance.

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