Jurnal Teknik Informatika C.I.T Medicom, 15 (6) (2024) 284-290

Published by: Institute of Computer Science (IOCS)

Jurnal Teknik Informatika C.I.T Medicom

Journal homepage: www.medikom.iocspublisher.org

Development of fuzzy logic based student performance prediction system

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Article Info

Article history

Received : Dec 29, 2023
Revised : Jan 19, 2024
Accepted : Jan 27, 2024

Key Words:

Data Analysis;
Decision Making;
Fuzzy Logic;
Higher Education;
Prediction;
Student Performance.

Abstract

Improving students' academic performance is a key goal in the context of higher education. However, the process of identifying students who require additional support is often complicated and complex. Traditional approaches in analyzing student performance data tend to be limited in handling data uncertainty and complexity. Therefore, the development of fuzzy logic-based decision-making systems is becoming increasingly important. This research aims to develop a fuzzy logic-based decision-making system to predict student performance accurately and efficiently. This approach utilizes fuzzy logic concepts to handle uncertainty and complexity in data, and allows the integration of various input factors, such as exam results, class participation, and other variables, in the decision-making process. The research methods include collecting historical student performance data, modeling fuzzy variables for inputs and outputs, developing fuzzy inference rules, and implementing and testing the system using split test data. Numerical example results show that the system is able to provide predictions of student performance by considering relevant input variables. In addition, the system also offers the potential to improve the efficiency of educational interventions by identifying at-risk students faster and more precisely. As such, the development of this fuzzy logic-based decision-making system is expected to make a significant contribution to efforts to improve the quality and equity of higher education by ensuring that every student gets the support they need to reach their full academic potential.

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1. Introduction

Higher education is an important foundation in the development of human resources and the progress of a country [1]–[3]. In the era of globalization and increasingly fierce competition, student academic performance is the main focus in efforts to improve the quality and relevance of higher education [4], [5]. Identifying and handling students who require additional support in achieving optimal academic performance is a complex challenge for educational institutions [6], [7]. In an effort to address this challenge, the development of fuzzy logic-based decision-making systems has emerged as a promising approach in predicting student performance more accurately [8], [9].

The use of fuzzy logic in decision-making has attracted attention in various fields, including information technology and education science. Fuzzy logic allows handling uncertainty and complexity in the decision-making process by introducing the concepts of fuzzy sets and fuzzy inference rules. In the context of student performance prediction, fuzzy logic allows the integration of various input factors, such as exam results, class participation, and other variables, to predict student academic performance more precisely [10]–[12].

However, despite its potential, the development of fuzzy logic-based decision-making systems for student performance prediction is still relatively new. Previous research has highlighted the advantages and challenges of applying fuzzy logic in an educational context, but more research is needed to develop a more targeted and effective approach. Therefore, this research aims to fill the gap by developing a fuzzy logic-based decision-making system that is able to predict student performance accurately and efficiently [8], [13], [14].

In this research framework, a deep understanding of the relevant input variables and the formulation of appropriate inference rules will be key in the development of an effective system [15], [16]. In addition, careful testing of the system using historical data and appropriate evaluation techniques will be an important step in validating the quality and reliability of the system [17]–[19]. Thus, this research is expected to make a significant contribution in the development of fuzzy logic-based decision-making systems that can assist educational institutions in improving student academic performance effectively and efficiently [20]–[22].

In an effort to achieve this goal, this research will involve structured and systematic methodological stages. The first stage will involve collecting student performance data from a particular educational institution. This data will include various relevant input variables, such as exam results, class participation, and other factors that may affect students' academic performance. Next, this data will be analyzed to understand the patterns and relationships between the input and output variables [23]–[25].

The next stage will involve modeling the input and output variables using fuzzy logic [26], [27]. This will involve the definition of membership functions for the input and output variables, as well as the formation of fuzzy sets appropriate to the problem domain. This process allows for a more flexible representation of the uncertainty and complexity in the data, thus allowing the system to capture more subtle nuances in the relationships between variables. Fuzzy inference rules will be formulated based on a deep understanding of the problem domain. These rules will relate input variables to output variables using fuzzy logic, allowing the system to perform precise inference based on given conditions. The formation of proper inference rules will require collaboration between domain experts and fuzzy logic experts [28]–[30].

After the formulation of the inference rules, the decision-making system will be implemented and tested using separate test data [31]–[33]. Testing will include an evaluation of the system's performance in predicting student performance, including accuracy, precision, and recall. The test results will be used to identify the strengths and weaknesses of the system, as well as to make necessary improvements and adjustments. The results of this research will be systematically analyzed and presented. This analysis will include an evaluation of the quality and reliability of the system, as well as an interpretation of the resulting student performance predictions. The findings from this research will provide valuable insights for educational institutions in adopting smarter and more effective approaches in supporting students' academic performance. As such, this research is expected to make a significant contribution to the development of better decision-making systems in the context of higher education [34]–[36]..

2. Research Methodolgy

a. Data Collection

Collect historical data on student performance, including exam results, class participation, and additional variables.

b. Fuzzy Variable Modeling:

Define and quantify membership functions for input and output variables.

c. Fuzzy Inference System Development:

Building inference rules based on fuzzy logic that map input variables to outputs.

d. Implementation and Testing:

Implementing the fuzzy inference system using appropriate software or programming language. Testing the system using separate test data to evaluate its accuracy.

A new mathematical formulation model for the development of a fuzzy logic-based decision-making system for student performance prediction, Suppose X1, X1, ... Xn are input variables that represent various attributes of student performance, such as exam results, class participation, and other factors. Y is the output variable that represents the prediction of students' academic performance.

In this mathematical formulation model, we use the concept of fuzzy logic to map the relationship between input and output variables. Suppose μ_(X_i) (x) is the membership function of the input variable Xi at x value, and μ_(Y_i) (y) is the membership function of the output variable Y at y value. Then, fuzzy inference rules are used to determine the contribution of each input variable to the output variable. Suppose Rij is the membership degree of Xi in the fuzzy set Aj in the inference rule. By using the fuzzy inference rule, we can calculate the membership degree of the output variable Y in a certain fuzzy set Bk with the corresponding aggregation formula. Mathematically, this formulation model can be written as follows:

$$Y = \sum_{i=1}^{n} \sum_{j=1}^{m} R_{ij} \cdot \mu_{Xi}(x) \cdot \mu_{Yi}(y) \quad (1)$$

Where:

m = is the number of fuzzy sets for each input variable.
n = is the number of input variables.
Rij = is the membership level of the input variable Xi in the fuzzy set Aj
X = is the value of the input variable
$\mu_{Xi}(x)$ = is the membership function of the input variable Xi at value x
$\mu_{Yi}(y)$ = is the membership function of the input variable Yi at value y

This mathematical formulation model allows the use of fuzzy logic to predict student performance based on given input variables. By adjusting the membership functions, inference rules, and fuzzy sets accordingly, this model can be applied in the development of an effective decision-making system for student performance prediction.

The following is a numerical example that shows how the mathematical formulation for fuzzy logic-based decision-making systems can be applied in the prediction of student performance:

Suppose we have two input variables, namely math exam result (X_1) and class participation (X_2), and one output variable, namely student performance prediction (Y). For the purpose of the example, we will use a fuzzy value scale consisting of three fuzzy sets: low, medium, and high. The membership functions for the input (X_1 and X_2) and output (Y) variables can be determined as follows :

For X_1 (math test result)

"Low" fuzzy set: $\mu_{X_1}^{Low}(x) = Trianggle(0,30,50)$

"Medium" fuzzy set: $\mu_{X_1}^{medium}(x) = Trianggle(40,60,80)$

"High" fuzzy set: $\mu_{X_1}^{high}(x) = Trianggle(70,90,100)$

For X_2 (Class participation)

"Low" fuzzy set: $\mu_{X_2}^{low}(x) = Trianggle(0,30,50)$
"Medium" fuzzy set: $\mu_{X_2}^{medium}(x) = Trianggle(40,60,80)$
"High" fuzzy set: $\mu_{X_2}^{hight}(x) = Trianggle(70,90,100)$

For Y (student performance prediction)
"Low" fuzzy set: $\mu_{Y}^{low}(x) = Trianggle(0,30,50)$
"Medium" fuzzy set: $\mu_{Y}^{medium}(x) = Trianggle(40,60,80)$
"High" fuzzy set: $\mu_{Y}^{high}(x) = Trianggle(70,90,100)$

Next, we can define fuzzy inference rules that connect the input variables (X_1 and X_2) with the output variable (Y). The following rule can be used:
If X_1 is "high" AND X_2 is "high", then Y is "high".
If X_1 is "medium" AND X_2 is "medium", then Y is "medium".
If X_1 is "low" AND X_2 is "low", then Y is "low".

3. Results and Discussion

Using the fuzzy inference model and the predefined membership functions, we can calculate the membership degree of the output variable (Y) for each fuzzy set. For example, if X_1=75 (math exam score) and X_2=60 (class participation rate), we can calculate the membership degree of Y in the fuzzy sets "high", "medium", and "low" using the corresponding aggregation formula.

1. Membership Function

Based on the given input values, we can determine the membership level for each input variable (X_1 and X_2) in the fuzzy sets "high", "medium", and "low". By inserting the input values into the predefined membership function, we can calculate the membership level:

$\mu_{X_1}^{high}(75) = 0$ $(the\ input\ value\ is\ outside\ the\ high\ fuzzy\ set)$
$\mu_{X_1}^{medium}(75) = 0{,}4$
$\mu_{X_1}^{low}(75) = 0{,}6$
$\mu_{X_2}^{hight}(60) = 0$ $(the\ input\ value\ is\ outside\ the\ high\ fuzzy\ set)$
$\mu_{X_2}^{medium}(60) = 0{,}4$
$\mu_{X_2}^{low}(60) = 0{,}6$

2. Fuzzy Inference Rules

From the predefined inference rules, we can see that the result will be "medium", because X1 is "medium" and X2 is "low".

3. Defuzzification

Since the result is "medium", we can use the middle value of the fuzzy set "medium" (40, 60, 80) as the predicted value. Therefore, the prediction result of student performance is about 60.

Discussion

From the results and discussion above, we can see that based on the math exam score of 75 and class participation of 60, the prediction system produces a prediction of student performance of around 60. This shows that by using a fuzzy logic-based decision-making system, we can predict student performance by considering various relevant input factors. However, this prediction result can still be considered as a rough prediction because we only consider two input variables. In further research, more input variables and inference rules can be added to improve the prediction accuracy.

4. Conclusion

In the context of developing a fuzzy logic-based decision-making system for student performance prediction, the conclusion that can be drawn is that it offers a potentially powerful approach to improving the ability of educational institutions to identify students who require additional support in achieving optimal academic performance. By using fuzzy logic, the system can consider various input factors, such as exam results and class participation, and handle uncertainty and complexity in the data better than traditional methods. Numerical example results show that the system can provide predictions of student performance by considering relevant input variables. However, to improve the accuracy and relevance of predictions, it is important to consider more input variables and develop more complex inference rules. In addition, the development of this fuzzy logic-based decision-making system also shows the potential to improve the efficiency of educational interventions by allowing institutions to identify at-risk students faster and more precisely. Using accurate predictions of student performance, institutions can adopt more targeted and effective intervention strategies, such as academic tutoring programs or additional support in specific subjects. Thus, the development of this fuzzy logic-based decision-making system can make a significant contribution to improving the quality and equity of higher education by ensuring that every student receives the support they need to reach their full academic potential. Suggestions for future research are to adopt a more holistic approach by considering more input variables and developing more complex inference rules in fuzzy logic-based decision-making systems. In addition, focusing on integrating a wider range of data, including factors such as previous academic history, learning interests, and non-academic factors such as mental well-being and social support, can improve prediction accuracy. Further development could also be made in identifying more sensitive and relevant indicators of student performance. In addition, research could focus on evaluating the effectiveness of educational interventions directed by this system, as well as further exploration of how to improve the efficiency and effectiveness of interventions through the use of more detailed and real-time predictive data.

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