International Journal of Innovative Research and Scientific Studies, 8(3) 2025, pages: 4900-4914

IJIRSS
International Journal of Innovative Research & Scientific Studies

ISSN: 2617-6548

URL: www.ijirss.com

Integration of neuro-fuzzy modeling in learning management systems to predict academic achievement of graduates

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Abstract

This study explores the application of intelligent modeling to support academic decision-making by integrating a predictive system into a university's learning management environment. Utilizing 25,706 records from 16,158 students over an eight-year period (2015–2022), the dataset includes exam results and final grades across 353 subjects within bachelor's, master's, and PhD programs. After transforming categorical variables - such as education level, course year, and subject name - into numerical format and applying normalization, an Adaptive Neuro-Fuzzy Inference System (ANFIS) was developed to model student performance. This system was chosen for its capacity to capture complex, nonlinear relationships while providing interpretable outputs through fuzzy rules. Comparative evaluation using RMSE, MAE, MSE, and R^2 metrics demonstrated that ANFIS consistently outperformed alternative models, achieving the lowest RMSE value of 12.80. These findings highlight the model's reliability and its effectiveness in analyzing academic outcomes across diverse student cohorts. By enabling the early identification of academic risk and delivering interpretable predictions, the system offers practical value to educational institutions aiming to personalize learning pathways and implement data-informed strategies to enhance student success in digital learning environments.

Keywords: Computing programs, fuzzy systems, neuro-fuzzy models, prediction, student performance.

DOI: 10.53894/ijirss.v8i3.7637
Funding: This research was funded by the Scientific Committee of the Ministry of Science and Higher Education of the Republic of Kazakhstan (Grant Number: AP19679847).
History: Received: 21 April 2025 / **Revised:** 23 May 2025 / **Accepted:** 27 May 2025 / **Published:** 5 June 2025

Competing Interests: The authors declare that they have no competing interests.
Authors' Contributions: All authors contributed equally to the conception and design of the study. All authors have read and agreed to the published version of the manuscript.
Transparency: The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.
Institutional Review Board Statement: We confirm that the study used anonymized secondary data, with no direct interaction with human participants. Ethical approval was granted by the Ethics Committee of L.N. Gumilyov Eurasian National University (Protocol No. 3, dated April 18, 2025). This information has been added to Section 7.
Publisher: Innovative Research Publishing

1. Introduction

Higher education institutions today must balance two essential roles: delivering quality academic instruction and preparing students for their future careers. In response to rapid globalization and technological advancements, universities are upgrading their learning management systems by integrating intelligent services that enhance student learning and academic analytics. These services aim to personalize the learning experience, improve the quality of assessments, generate insightful analytical reports, detect incidents (i.e., deviations from the norm), and predict academic performance based on a student's historical academic data.

This paper is part of a comprehensive research and development initiative focused on creating a multifaceted system, which can be divided into the following key modules:

- Educational Program Constructor: As detailed in works [1-3], this module links each discipline within an educational program to the program's outcomes, facilitating the personalization of a student's educational path.
- Module for Assessing Knowledge and Forming Professional Competencies: Utilizing a fuzzy model of knowledge assessment described in [4], this module evaluates student knowledge. Current efforts are focused on assessing student responses in natural language through Natural Language Processing (NLP) techniques. A more recent study by Barlybayev et al. [5] further investigates the use of fuzzy logic to enhance grading fairness and consistency, providing valuable insights that align with the current system's objectives.
- Module for Analytics of Students' Academic Performance: This module provides comprehensive analysis and reporting on student performance, identifying trends and areas for improvement.
- Module for Predicting Students' Academic Performance: This predictive module uses advanced modeling techniques to forecast student outcomes and identify potential areas of academic risk.

These modules improve academic preparation by offering tools for better understanding and accurate student performance prediction. Over the past two decades, research has increasingly concentrated on identifying key factors influencing educational outcomes. This focus underscores the critical importance of developing and implementing innovative analytical methods in education [6-8].

Predicting academic performance is crucial for personalized learning and curriculum adaptation [9, 10]. Predictive modeling in education is not merely about assessing competencies but also about forecasting them, which is crucial for planning new specializations and ensuring their relevance in a rapidly changing world [11, 12]. Such predictive capabilities are vital for educational institutions to respond effectively to real-world challenges, thereby enhancing the overall educational structure [12, 13].

The novelty of this study lies in the application of the ANFIS model, which uniquely integrates neural networks and fuzzy logic to handle uncertainty and nonlinear relationships in educational data. Unlike traditional predictive methods, our approach not only demonstrates superior accuracy but also enhances interpretability, allowing universities to clearly understand which factors significantly influence student performance. Practically, the results of this study can be directly integrated into university Learning Management Systems (LMS), enabling educators to identify at-risk students early and implement targeted interventions for improving student outcomes.

One of the key components of an intelligent educational framework is the Module for Predicting Students' Academic Performance, which utilizes machine learning techniques to analyze historical data and forecast academic outcomes [10, 14]. This predictive system is instrumental in identifying at-risk students early, allowing for timely intervention and support strategies aimed at improving their academic achievements [10]. The integration of artificial intelligence into educational planning facilitates dynamic adjustments to curriculum, aligning with the global shift toward intelligent educational ecosystems where AI-driven recommendations play a pivotal role in decision-making and curriculum development [9, 11].

ANFIS is effective in handling uncertainties in educational data and outperforms traditional regression models. This comprehensive analysis underscores the effectiveness of various predictive approaches and highlights the potential of machine learning in enhancing educational analytics.

The results of this study contribute significantly to the advancement of educational analytics and intelligent decision-making within academic institutions. By integrating AI-based forecasting into learning management systems, universities can optimize educational processes, improve student performance, and adapt to the needs of rapidly evolving industries. This research emphasizes the transformational potential of predictive analytics in shaping the future of education, advocating for intelligent modeling as a cornerstone for data-driven decision-making and adaptive curriculum planning.

The remainder of the paper is organized as follows: Section 2 provides a comprehensive literature review on neuro-fuzzy models and their applications in educational analytics. Section 3 presents the research questions guiding this study. Section 4 describes the materials and methods, including data collection and the ANFIS modeling process. Section 5 details the data analysis and key correlation findings. Section 6 discusses the structure and training of the proposed ANFIS model. Ethical considerations are addressed in Section 7. Finally, Sections 7 and 8 provide a discussion of the results, practical implications, and conclusions, highlighting the contributions and potential future directions for research.

2. Literature Review

Research on predicting student performance using neuro-fuzzy models has demonstrated significant success. These models effectively integrate fuzzy logic with neural networks, enhancing predictive capabilities in educational contexts. For instance, studies have shown that a neuro-fuzzy approach can effectively classify student performance based on Cumulative Grade Point Average (CGPA), outperforming traditional methods [14, 15]. Further advancements, such as the Multi-Adaptive Neuro-Fuzzy Inference System (MANFIS-S), have confirmed the effectiveness of these models in educational contexts [16].

The integration of ANFIS with other technologies, including machine learning and gamification, has opened new possibilities for creating personalized and engaging learning environments [17, 18]. Applications of ANFIS extend beyond academic performance prediction; for example, it has been successfully used to forecast school enrollment rates [19] and classify core subjects in electronic libraries [20].

Behavioral data also play a critical role in improving the accuracy of academic performance predictions. Key factors such as study habits, participation in discussions, engagement with online learning platforms, and attendance rates significantly influence student outcomes. For instance, students who actively participate in virtual forums and regularly complete assignments tend to perform better academically. Studies indicate that combining behavior categorization models with neuro-fuzzy systems enhances predictive accuracy [21, 22]. Additionally, student engagement in virtual learning environments, analyzed through neuro-fuzzy systems, has been shown to significantly influence academic outcomes [23].

The ability of ANFIS to adapt to educational data complexity makes it a preferred choice over traditional regression models. Various studies have explored its role in educational data mining, uncovering patterns that predict academic outcomes [24, 25]. Moreover, explainable machine learning models facilitate the development of structured frameworks for predicting academic trajectories, incorporating regression approaches and data generation techniques to refine prediction accuracy [26, 27].

Barlybayev et al. [5] conducted a comparative analysis of grading models using fuzzy logic and demonstrated how this approach enhances the fairness and consistency of student evaluations, further validating the usefulness of fuzzy systems in education.

Empirical evidence supports the effectiveness of ANFIS in predicting student success in STEM disciplines, particularly in IT-related courses, engineering mathematics, and physics. Studies indicate that ANFIS performs well in modeling student outcomes based on coursework difficulty, laboratory performance, and exam scores, surpassing traditional regression models in predictive accuracy. For instance, CGPA has been identified as a key predictor of success in IT-related courses, where ANFIS outperforms traditional multilinear regression models [28, 29]. Studies also reveal that ANFIS-Grid configurations yield better predictive results than ANFIS-Cluster models [30]. Key influencing factors include GPA, course category, and attendance, with attendance proving to be the most significant predictor. Additionally, hybrid learning models have been found to positively impact academic performance compared to fully online or in-person formats [31].

Recent advances in educational data mining have explored hybrid intelligent systems to evaluate and predict student performance and perceptions. In Mojsilović et al. [32] proposed a novel approach that combines the Random Forest algorithm with the Adaptive Neuro-Fuzzy Inference System (ANFIS) to statistically evaluate the academic achievements of professional students. Their model demonstrated improved prediction accuracy and interpretability by integrating ensemble learning with neuro-fuzzy logic. Similarly, Göktepe Yıldız and Göktepe Körpeoğlu [33] applied ANFIS in conjunction with hierarchical regression analysis to predict students' perceptions of their problem-solving skills. Their findings highlight the strength of ANFIS in modeling complex psychological traits and emphasize the influence of behavioral and cognitive factors. Together, these studies underscore the effectiveness of ANFIS-based hybrid models in educational contexts, offering powerful tools for both predictive analysis and deeper insight into student dynamics.

Despite these advancements, several areas warrant further exploration. Longitudinal studies are needed to assess the long-term impact of ANFIS-based predictions. Additionally, scalability and generalizability remain challenges, particularly when integrating ANFIS with real-time data. Future research should also address interdisciplinary applications, ethical considerations, and user experience improvements to optimize the effectiveness of neuro-fuzzy models in education.

3. Research Questions

The considerations presented in the Introduction, along with the results of the literature and related works review, have led to the formulation of the following research questions.

Q1. How can the ANFIS be used to predict students' academic performance effectively?

Q2. What advantages does ANFIS offer over traditional predictive models in the context of educational data?

Q3. How can the insights derived from ANFIS be used to develop intervention strategies to improve educational outcomes and support students?

4. Materials and Methods

The student academic performance prediction system, based on the ANFIS, is designed to accurately forecast outcomes using historical data and additional characteristics such as socioeconomic factors, attendance, and study habits. The system includes several stages: data processing (cleaning and transformation), model configuration (membership function selection and rule definition), training and testing, outcome prediction, and accuracy assessment. It predicts the level of academic performance, representing it as a CGPA or categorical value. The use of ANFIS allows for the incorporation of data uncertainty and the identification of key factors influencing results, contributing to more accurate predictions and optimization of the educational process. The structure and workflow of the system are presented in Figure 1.

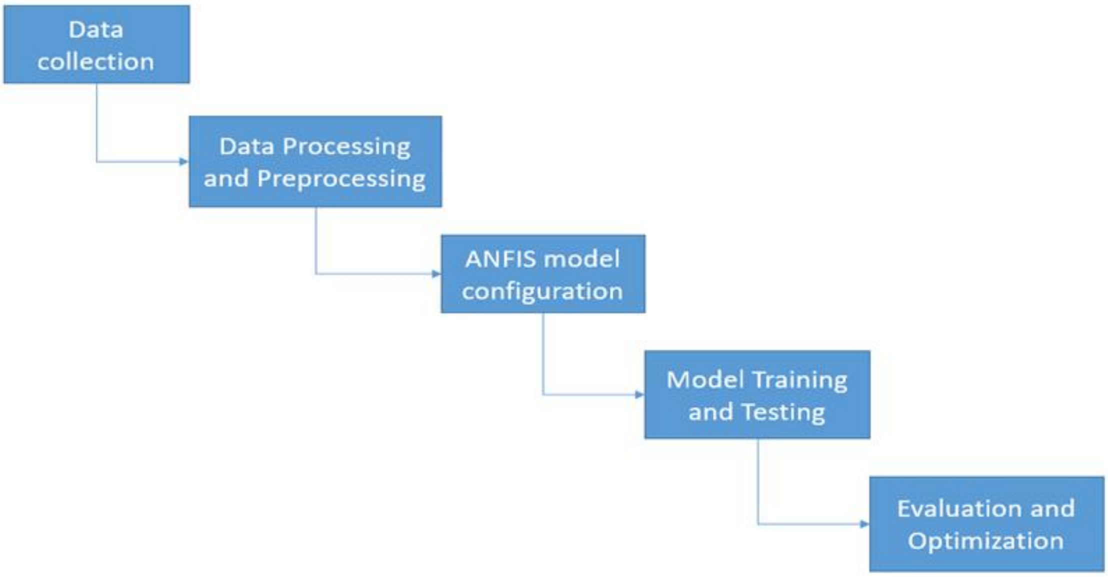

Figure 1.
The proposed method.

The proposed method provides a robust framework for analyzing and predicting academic outcomes, enabling educational institutions to proactively support students and refine academic strategies. By leveraging the adaptability of ANFIS, this approach creates a flexible tool that can be customized to diverse educational contexts and datasets, making it a valuable resource for understanding and improving academic performance.

While traditional mathematical formulas are effective for calculating final grades based on exam scores and coursework, they are limited in capturing the non-linear re-lationships and contextual factors that influence academic outcomes. The ANFIS model offers a more sophisticated solution by combining the learning capabilities of neural networks with the interpretability of fuzzy logic. This hybrid approach enables the model to address uncertainties and model complex, non-linear dependencies within educational data.

By including variables such as academic year, course content, and semester performance, ANFIS provides a more nuanced understanding of the multifactorial effects on final grades. Additionally, the model supports early predictions based on intermediate assessments, empowering educators to implement proactive intervention strategies. These insights allow for timely, personalized support tailored to each student's needs, addressing academic challenges before the course concludes and ultimately contributing to improved educational outcomes.

4.1. Adaptive Neuro-Fuzzy Inference System

ANFIS is a multilayer feedforward Sugeno-type network that establishes relationships between input and output data through a learning algorithm that dynamically adjusts the parameters of the fuzzy inference system [34]. Essentially, the ANFIS technique is a Fuzzy Logic (FL) system whose parameters are optimized through neural network training. The primary goal is to create a network capable of performing the desired nonlinear mapping, defined using a dataset consisting of multiple input-output pairs of the target system; this dataset is referred to as training data. To verify the model's generalization ability, a test dataset that was not involved in the training process was introduced. The ANFIS structure consists of five layers, as shown in the model architecture in Figure 2. The system accepts two inputs (X_1, X_2) (ANFIS supports multiple inputs but a single output system). In Figure 2, square nodes (adaptive nodes) represent adjustable parameters that the system needs to learn, while circle nodes (fixed nodes) indicate fixed parameters. A set of two fuzzy if-then rules is presented in Equations 1 and 2:

Rule 1: If Exam Score (X1) is A1 and Year (X2) is B1, then the predicted final grade (Y1) is: $Y1=p1\cdot X1+q1\cdot X2+r1$;

Rule 2: If Exam Score (X1) is A2 and Year (X2) is B2, then the predicted final grade (Y2) is: $Y2=p2\cdot X1+q2\cdot X2+r2$;

where:

In the proposed ANFIS model, the input variables are X1 (Exam Score) and X2 (Year of Graduation), which are processed by the system to predict the final grade. Each of these variables has membership functions: A1 and A2 for Exam Score, as well as B1 and B2 for Year of Graduation, which define the degree to which each rule is met. The output values Y1 and Y2 are computed as linear combinations of the input variables, where p1, p2 are coefficients for Exam Score, q1, q2 are coefficients for Year of Graduation, and r1, r2 are constants adjusting the result of each rule. At the final stage, ANFIS aggregates the outputs of all rules, forming the predicted value Y (Final Grade) using a weighted sum of the individual contributions of each rule.

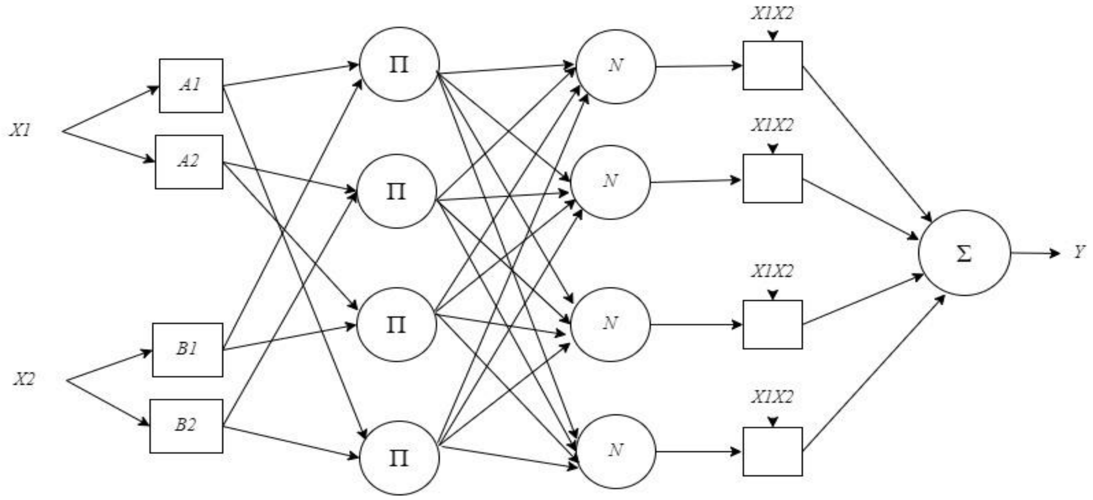

Figure 2.
Architecture of the Adaptive Neuro-Fuzzy Inference System using the Sugeno method [34].

4.2. Data Collection and Preparation

Data was collected from various academic sources, including university databases, Learning Management Systems (LMS), and student performance records [33]. The study utilized a comprehensive dataset consisting of data from 16,158 students collected over a period of eight years (2015-2022), covering bachelor's (4 years), master's (2 years), and PhD (3 years) degree programs. The average number of records per student is 25, resulting in a total of 25,706 records. This data includes exam results and final module grades across different educational levels: undergraduate, master's, and PhD. Data from students transferred from other educational institutions were included only if they aligned with the formats and standards of the current sample. Grade normalization procedures were applied to ensure consistency. The data are not publicly available; they have been anonymized and obtained from the LMS for research purposes, as the development of a dedicated analytics module based on intelligent data analysis is planned. Predicting student performance is a priority task for the university. These sources provided information on student results across various subjects over several years, enabling a comprehensive analysis of their academic performance. Key features were selected for analysis and model building. These included the unique student identifier (PersonID), level of education (Degree), year of course completion (Year), subject name (Subject), exam grade (Exam), and final subject grade (Total). The unique student identifier allowed tracking of individual student performance across all subjects and years of study. The level of education was represented as a categorical variable, including bachelor's, master's (research and teaching), PhD, and master's (professional). The year of course completion allowed for accounting for changes in the curriculum and grading system over time. The subject name facilitated the analysis of student performance across different disciplines, while exam and final grades reflected the students' knowledge and skills [26, 28].

To ensure the correct operation of the model and improve prediction accuracy, data transformation and preparation were conducted. Categorical variables, such as Degree and Subject, were converted to numerical formats through coding. Each level of education and each subject was assigned a unique numerical code. To improve model performance and accelerate the learning process, numerical features such as exam grades and final grades were normalized. Data normalization helped avoid issues related to varying scales of features. The data was split into training and testing sets for subsequent model performance evaluation. A typical ratio used was 70:30 or 80:20, with the larger portion of the data used for training the model and the smaller portion for testing and validation.

Initial visual data analysis showed that most students exhibited high academic performance, with a prevalence of grades "A+" and "A-". At the bachelor's level, lower grades such as "C+" and "C" were also observed. Exam results strongly correlated with final grades, confirming their importance in the grading system. The ANFIS model was trained, validated, and tested using data exclusively from students who had successfully completed their academic programs, thereby ensuring that the model focused on predicting final grades upon completion. Data from students who were still enrolled or had dropped out was excluded to maintain the integrity and relevance of outcome prediction [26].

The process of transforming variables and preparing data involved several key steps aimed at ensuring the correct operation of the model and improving prediction accuracy. Each step was carefully planned and implemented according to standard data processing methods.

The first step involved transforming categorical variables. The variable "Degree," reflecting the student's level of education, included several categories: bachelor's, master's (research and teaching), PhD, and master's (professional). Since machine learning models cannot directly work with categorical data, these categories were converted to numerical formats through coding. Each level of education was assigned a unique numerical code: bachelor's: 1, master's (research and teaching): 2, PhD: 3, and master's (Professional): 4.

A similar transformation was performed for the variable "Subject," representing the subject name. Each discipline was assigned a unique numerical code. For example, mathematics was assigned code 1, physics – code 2, and so on for all subjects present in the data.

The next step involved normalizing numerical features. To improve model performance and accelerate the learning process, numerical features such as exam grades and final grades were normalized. Data normalization helps avoid issues related to varying scales of features, which is especially important when using machine learning algorithms. The normalization method involved scaling values to a range from 0 to 1. The normalized value was calculated using the formula, where the original feature value was subtracted by the minimum feature value in the dataset, and then divided by the difference between the maximum and minimum feature values.

The data was then split into training and testing sets. This was necessary to evaluate how well the model would perform on new, unseen data. A typical ratio of 70:30 or 80:20 was used, with the larger portion of the data applied for training the model and the smaller portion for testing and validation. In this study, a 70:30 ratio was used.

Table 1 provides an example of a data record after variable transformation, demonstrating how student information is organized in the dataset. Each entry corresponds to key academic data points for an individual student, identified by a unique Person ID to ensure anonymity. The Degree field represents the student's education level, with "1" indicating a bachelor's degree. The Year column shows the year of course completion, which is "2021" for all entries in this example. Each Subject is encoded with a unique number, allowing for subject-specific performance tracking. The Exam column contains the student's grade for the final exam in each subject, while the Total column shows the cumulative final grade, which may include additional assessments. In this example, the student completed five subjects in 2021, with detailed records of exam scores and final grades, facilitating a comprehensive view of the student's academic performance across different subjects.

Table 1.
Example of data entry after variable transformation.

Person ID	Degree	Year	Subject	Exam	Total
857	1	2021	1	62	69.2
857	1	2021	2	90	78.6
857	1	2021	3	73	86.0
857	1	2021	4	70	70.6
857	1	2021	5	78	79.2

Data from students who successfully completed the program [26] was used for training, validating, and testing the ANFIS model. The exclusion of data on students who are currently studying or have dropped out was due to the model's goal of predicting final grades upon program completion. This approach allowed the analysis and prediction to focus on those students for whom complete performance data is available.

4.3. Structure of the ANFIS Model

In neuro-fuzzy models such as ANFIS, membership functions are fundamental in defining the degree of input data association with fuzzy sets, thereby shaping the system's interpretability and predictive capabilities. Triangular membership functions are often selected for their simplicity and efficiency, with input variables such as education level, subject, exam score, and course completion year encoded accordingly [21]. These models use fuzzy "if-then" rules to establish relationships between inputs and the predicted output. For instance, a rule might state: if a student has a bachelor's degree, the subject is mathematics, and the exam score is 62, then the predicted final grade is computed using a linear output function. This mechanism enhances the system's transparency while capturing complex, nonlinear academic patterns. Furthermore, recent studies highlight the integration of such models with big data analytics in Learning Management Systems (LMS), enabling more accurate and scalable predictions of learners' academic success [35].

The process of training the ANFIS model involved several sequential stages:

- Initialization of parameters. At this stage, the initial parameters of the membership functions and fuzzy rules were defined. Parameters were chosen to cover all possible values of the input variables.
- Forward pass. During this stage, the outputs for the current parameters of the membership functions and rules were calculated. For each set of input data, the degree of membership of each input value to the corresponding fuzzy sets was computed, and then the model output was calculated. Additionally, the prediction error was calculated by comparing the model output with the actual value.
- Backward pass. At this stage, the parameters of the membership functions and rules were updated using the gradient descent algorithm and the least squares method. Parameters have been adjusted to minimize the prediction error. This process was repeated until the error reached an acceptable level.
- Adaptation and tuning. During this stage, additional adjustments to the parameters were made to improve prediction accuracy. The model was adapted to the characteristics of the training data, enhancing overall performance.

5. Data Analysis

5.1. Correlation Analysis of Factors Affecting Student Performance

A correlation matrix is an important tool for analyzing the relationships between different features in a data set. In this study, students' grades, educational level, graduation year, subject name, and final grades were analyzed to determine the influence of different factors on student performance.

A correlation matrix was calculated for the following features: educational level (degree), graduation year (year), subject name (subject), exam grade (exam), and final grade (overall). The heat map in Figure 3 illustrates the correlation matrix for the data under study.

The correlation matrix is an important tool for analyzing the relationships between various features in a dataset. In this study, students' grades, their level of education, year of course completion, subject name, and final grades were analyzed to determine the impact of different factors on academic performance.

The correlation matrix was calculated for the following features: degree of education (Degree), year of course completion (Year), subject name (Subject), exam grade (Exam), and final subject grade (Total). The heatmap in Figure 3 illustrates the correlation matrix for the data under investigation.

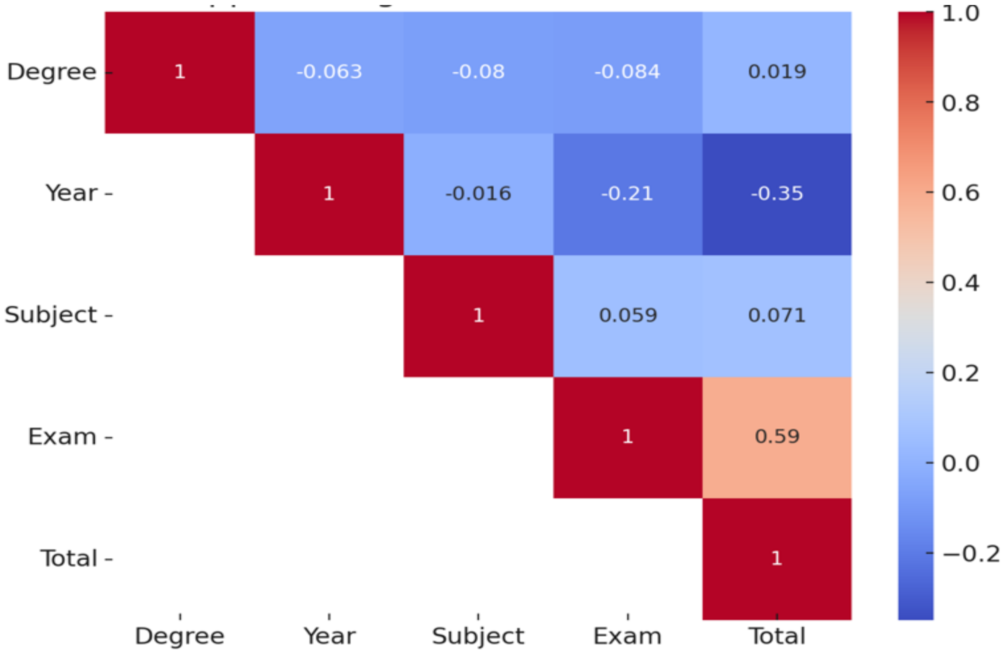

Figure 3.
Correlation matrix for academic data.

The correlation matrix provides valuable insights into the relationships between various educational features, particularly in terms of how different factors might influence students' final grades. The colors in the matrix represent the strength and direction of these correlations: red shades indicate positive correlations, while blue shades indicate negative correlations. The intensity of the color reflects the magnitude of the correlation coefficient, with darker colors indicating stronger relationships. This matrix utilizes Pearson correlation coefficients to quantify the strength and direction of linear relationships between variables, with values ranging from –1, indicating a perfect negative correlation, to +1, indicating a perfect positive correlation [36].

Examining the correlations in detail, we find that the relationship between the degree of education and final grades is very weak, with a correlation of 0.02. This suggests that the level of education - whether bachelor's, master's, or PhD - does not significantly affect students' final grades. Instead, it's likely that other factors, such as individual abilities or specific learning conditions, play a more crucial role in determining final grades.

A more notable correlation appears between the year of course completion and final grades, with a coefficient of -0.35. This moderately negative relationship suggests a trend of declining final grades over time, which could be attributed to changes in grading standards, course difficulty, or evolving learning conditions. Further investment is necessary to pinpoint the specific factors contributing to this decline.

Similarly, the correlation between the subject name and final grades is weak, with a coefficient of 0.07. This minor positive relationship implies that success in specific subjects has a limited impact on overall final grades, hinting that other variables such as individual capabilities and teaching methods may exert a stronger influence on student performance.

In contrast, the relationship between exam grades and final grades is quite strong, with a correlation of 0.59. This positive correlation underscores the significant role exams play in overall academic performance, as higher exam scores are closely linked to higher final grades. This finding aligns with expectations, as exams are typically a primary assessment tool in educational settings.

At the PhD level, students undergo specialized assessments, including exams during the first year, similar to those at the undergraduate or master's levels. PhD candidates also submit and defend research reports, which are included in this analysis. Consequently, the data structure reflects both standard exams and specialized assessments across different education levels.

The correlation between the year of course completion and exam grades is -0.21, indicating a weak negative relationship. This suggests potential shifts in grading standards or the difficulty of exams over time, again pointing to the need for a deeper analysis to account for these changes in curriculum and standards.

In summary, the correlation matrix highlights that exam grades have the most substantial impact on final grades, while factors like the level of education, subject name, and year of course completion play a lesser role. Given the strong correlation between exams and final grades, focusing on exam performance may be an effective strategy for improving overall student outcomes. Additionally, the moderate negative correlation between the year of course completion and final grades signals a potential area for further research to understand the reasons behind the decline in performance over time.

5.2. Impact of Identified Patterns on Model Formation

To develop an effective model for predicting students' academic grades, it was essential to analyze key correlation patterns in student performance. Observed across various factors influencing academic success, these patterns defined the model structure and highlighted predictors with the greatest impact on academic outcomes. Table 2 presents correlation values between student performance indicators (such as exam grades, course engagement, and study time) and final academic outcomes from multiple studies. This analysis provides an explanation for the correlation results and supports their justified use across different educational systems.

Table 2.
Correlation values between student performance indicators and final academic results in different studies.

Study title/source	Correlation type	Correlation value (r)	Significance (p-value)	Interpretation
Evaluating the Impact of Gamification on Learning Effectiveness [37]	Placement Test Scores vs. Final Grades	0.12	0.3	No significant correlation
	Course Material Usage vs. Final Grades	-0.02	0.08	No significant correlation
Correlation Analysis in Classroom Data, [38]	Attendance Grade vs. Final Grade	0.289	0.000	Low correlation
	Interaction Grade vs. Final Grade	0.451	0.000	Moderate correlation
	Test Grade vs. Final Grade	0.632	0.000	Strong correlation
A Study on Extra Study Time and Grades Earned by Students, [39]	Study Time vs. Final Grade	-0.157	> 0.05 (not specified)	No significant correlation
Pass or Fail? Prediction of Students' Exam Outcomes, [40]	Midterm Scores vs. Final Exam Scores	0.54	< 0.001	Moderate to strong correlation
Cognitive Ability and Self-Control Influence, [41]	Cognitive Ability vs. Academic Performance	0.38-0.81	< 0.05	Moderate to high correlation
Prediction of Exam Performance in PBL Students, [42]	Facilitator Grades vs. Written Exam Scores	0.342–0.622	< 0.05	Moderate to strong correlation

To develop an effective model for predicting students' academic grades, it was essential to analyze key correlation patterns from various studies. Observed across factors influencing academic success, these patterns provided critical insights for structuring the model and identifying the most impactful predictors. High correlations between exam scores and final grades, as demonstrated across multiple studies, high-lighted exam results as the primary predictors within the ANFIS model. Temporal trends, indicated by the negative correlation between course completion year and grades, pointed to a need for including time-based parameters to enhance adaptability. While factors such as education level and subject exhibited weaker correlations with final grades, they were included in the model with lower weights to maintain a comprehensive analysis. Weaker correlations between subjects and final grades suggested that individual abilities and teaching methods also play a role, leading to the inclusion of parameters that account for personalized academic achievements. The correlation data thus informed a targeted model focus on significant predictors, aiding the development of a comprehensive, adaptable system that may also explain the reduced variability in distribution grades.

6. Neuro-Fuzzy Model for Predicting Academic Performance of Graduates

The ANFIS model is well-suited for predicting academic grades because it effectively manages the ambiguity and uncertainty found in real educational contexts, particularly in assessment activities. In this study, data ambiguity refers to the challenges associated with predicting the trajectories of individual student development. These trajectories can be unpredictable due to various factors, such as changes in academic interests or external circumstances affecting learning. Uncertainty in educational assessment arises from the fact that exam results do not always accurately reflect students' knowledge and skills. Additionally, the subjectivity in grading and differences in teaching methods also contribute to this uncertainty. The ANFIS model's built-in learning and adaptation capabilities ensure high efficiency in a dynamic educational environment marked by changes in pedagogical methods and student behavior. Despite the complexity of AN-FIS models, the integration of fuzzy logic rules enhances the interpretability of results. This interpretability is often lacking in models based solely on neural networks. As a result, teachers and administrative staff can better understand the prediction mechanisms, leading to valuable insights about student performance and strategies for targeted intervention.

The ANFIS models were trained using the training data subset (Figure 4) while the test data subset (Figure 6) was used to evaluate the prediction accuracy of the trained ANFIS models.

Before starting the training of the model, an analysis was conducted to identify common patterns in the accumulated data. The data cover five characteristics: Total (final grade for a specific subject), Degree (level of education), represented by four levels: Bachelor's, Master's (research and teaching direction), Doctoral PhD, and Master's (professional direction), Year (year of graduation from 2015 to 2022), Subject (name of the discipline), and Exam (exam grade for a specific discipline). The variables Degree and Subject were transformed into categorical variables, with unique numerical codes assigned to each level of education and each discipline (for example, Mathematics – 1, Physics – 2, etc., up to 353 disciplines).

Figure 4: Illustrative Graphical Correlation Matrix of Educational Data. This figure presents a visual overview of the pairwise distributions and relationships between various educational variables. Each plot represents the correlation between two specific variables, providing insights into their distribution patterns and potential dependencies.

Figure 4.
Graphical correlation matrix of educational data.

A visual analysis of the data presented in Figure 4 shows that most students demonstrate high academic results. These results are classified as "A+, A-" and "B+, B, B-". Approximately one-third of the students, however, graduate with grades of "C+, C, C-."In higher education, particularly at the doctoral level, there is a tendency to receive higher grades, primarily "A+, A-". Conversely, lower grades have been recorded at the bachelor's level. The distribution of students with high and low grades remains stable throughout their years of study. The visual analysis did not reveal a significant dependency between the final grade and a specific academic discipline. Nevertheless, exam scores show a strong positive correlation with final grades, indicating their significance in assessing student success. As expected, the user identifier does not affect the final grade, confirming the objectivity of the grading system.

Figure 5: Illustrative Architecture of the Neuro-Fuzzy System. This figure shows the structure of the neuro-fuzzy model used for prediction. During training, we chose not to include the Person ID characteristic, as it does not significantly affect the final grade. Each layer and node in the diagram represents a stage in the neuro-fuzzy processing pipeline, providing insights into the input-output relationships and the logical operations applied.

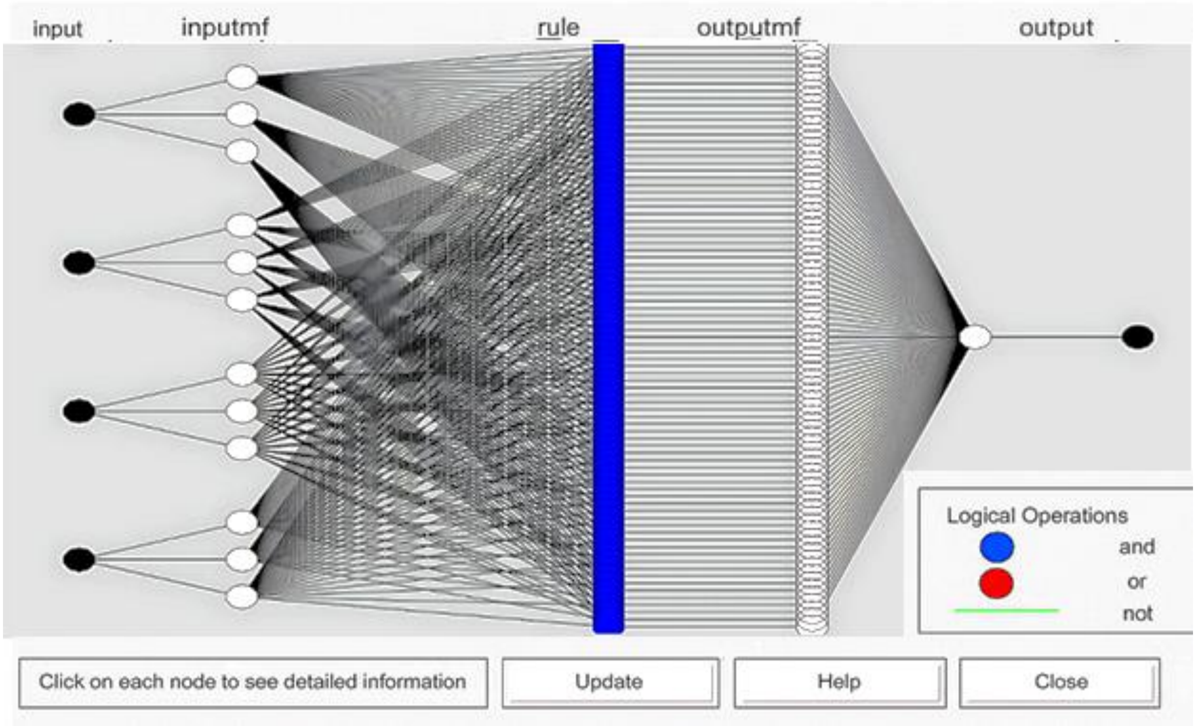

Figure 5.
Architecture of a neuro-fuzzy model for predicting graduate grades.

During the ANFIS model training over 1000 epochs, a stabilization of the prediction error (RMSE) was observed. Already in the early stages of training, the model demonstrated a rapid decrease in error, achieving a minimum RMSE value of 12.80, indicating an effective selection of initial parameters and training stability. Subsequent epochs did not show significant error improvement, confirming that the model had reached an optimal accuracy level without signs of overfitting.

Despite this limitation, the trained ANFIS model still provides valuable predictions, as demonstrated by the expert system shown in Figure 6. After completing the neural network training process, a Minimum Root Mean Square Error (RMSE) value of 12.80 was achieved. This value corresponds to our preliminary expectations and is evaluated as satisfactory in the context of the efficiency and accuracy of the training process. The minimum RMSE value serves as an indicator of successful neural network training, confirming that the obtained results meet the preestablished expectations and standards. The slight variation in RMSE during training suggests a good initial approximation of the model. This indicates that the initial parameters were appropriately selected, allowing the model to reach optimal performance without significant adjustments.

Figure 6 shows the expert system created based on fuzzy inference rules using ANFIS training.

Figure 6.
Fuzzy expert system for predicting students' final grades.

Figure 6 illustrates the operation of an expert system based on fuzzy inference rules, developed using ANFIS training. On the left side, four input variables (input1, input2, input3, input4) are displayed, each representing specific characteristics or parameters used for prediction (e.g., exam scores, course completion year, education level, etc.). The central section shows the fuzzy rules applied in the inference process; these rules were created using ANFIS, which combines neural networks and fuzzy logic to develop the rules. Yellow lines indicate activated rules that contribute to the calculation for the given input values. On the right, the output value (output = 72.4) is displayed, representing the predicted final grade of the student based on the input data and activated rules.

7. Ethical Considerations

The year of course completion was included to track changes in student performance over time. This accounts for curriculum shifts, adjustments in grading standards, and external factors such as the COVID-19 pandemic. Incorporating this variable allows the model to adapt to temporal trends and improve prediction accuracy.

To minimize ethical risks, potentially sensitive variables such as gender or ethnicity were intentionally excluded to prevent bias or discrimination. The model is designed to evaluate students solely based on academic performance, thereby promoting equity and fairness across all groups.

Future research could explore the inclusion of additional variables while maintaining ethical safeguards. Emphasis will be placed on transparency and fairness in both data use and predictive outputs to support responsible AI deployment in educational contexts.

This study used anonymized secondary data on students' academic performance collected from the university's learning management system between 2015 and 2022. No direct interaction with students occurred, and no personally identifiable information was included. The study was approved by the Ethics Committee of L.N. Gumilyov Eurasian National University (Protocol No. 3, dated April 18, 2025). Informed consent from participants was not required according to institutional guidelines.

8. Discussion

The initial phase of this study involved a detailed analysis of educational data, capturing diverse attributes such as final grades, degree levels, year of graduation, and exam scores. Transforming the degree and subject into categorical variables streamlined the data preparation process for ANFIS training, ensuring efficient handling of the data. The graphical correlation matrix indicated a prevalent trend of high academic achievement, with a significant correlation observed between exam scores and final grades. This insight underscores the importance of assessments in educational success and validates the exclusion of the PersonID characteristic from the model training, confirming the objectivity of the grading system.

The architecture of the ANFIS model is tailored to optimize both the interpretability and predictive accuracy. The training of the ANFIS model was executed over 1000 epochs, but an analysis of RMSE values revealed that the error only decreased margin-ally (by 0.02 points). This suggests that the model's learning progress may have been limited. While the achieved minimum RMSE of 12.80 aligns with expectations, future studies should investigate the impact of alternative training strategies, such as different learning rates, early stopping mechanisms, or refined fuzzy rule definitions. This would help ensure that the model is fully leveraging its learning capacity and improving predictive performance.

The application of ANFIS to predicting graduate performance has proven to be a robust method that effectively manages the inherent ambiguity and uncertainty in educational assessment. Using ANFIS allows for more effective management of both the ambiguity of individual student trajectories and the uncertainty of grades, providing more accurate predictions and recommendations for improving academic performance. The fusion of neural networks with fuzzy logic through ANFIS not only facilitates data-driven learning but also enables the model to adapt to reflect changes in pedagogical approaches and student behavior. One significant advantage of the ANFIS model over traditional neural networks is its improved interpretability, made possible by the integration of fuzzy logic rules. This feature is critical for educational administrators and educators as it provides a deeper understanding of the predictive mechanics, thereby aiding in the strategic planning of educational interventions and supports. This study not only highlights the feasibility of using advanced computational models such as ANFIS in educational settings but also lays the foundation for further innovations in academic performance analytics. Table 3 presents a comparative analysis of the proposed method with other models.

Table 3.
Comparative performance indicators of various regression models and machine learning algorithms.

Model	RMSE	MSE	R^2	MAE
Linear Regression	14.478	209.61	0.44813	7.5669
Interactions Linear Regression	14.432	208.27	0.45166	7.5384
Robust Linear Regression	15.347	235.55	0.37985	6.8642
Stepwise Linear Regression	14.433	208.3	0.45158	7.5379
Fine Tree	13.214	174.61	0.54028	6.8609
Medium Tree	13.099	171.6	0.54822	6.9571
Coarse Tree	13.169	173.43	0.5434	7.1378
Linear SVM	14.93	222.9	0.41314	6.818
Efficient Linear Least Squares	14.657	214.82	0.43441	7.9399
Rational Quadratic Gaussian Process Regression	13.24	175.3	0.53847	7.3017
Ensemble Boosted Trees	13.615	185.38	0.51193	9.1505
Ensemble Bagged Trees	13.758	162.76	0.57147	6.7244
Narrow Neural Network	13.39	179.29	0.52797	7.5167
Medium Neural Network	13.359	178.46	0.53014	7.499
Wide Neural Network	13.289	176.6	0.53504	7.4029
Proposed method ANFIS	12.80	160.57	0.58905	6.6567

Table 3 presents a comparative analysis of various regression models and machine learning algorithms based on four key performance metrics: RMSE, MSE, R^2, and MAE. The models include evaluated conventional approaches like Linear Regression, Interactions Linear Regression, and Robust Linear Regression, as well as more complex models such as Stepwise Linear Regression and several tree-based models (Fine Tree, Medium Tree, Coarse Tree). The analysis also covers advanced machine learning techniques, including SVM, Efficient Linear Least Squares, and different configurations of neural networks: Narrow, Medium, and Wide. Additionally, the table includes evaluations of ensemble methods like Boosted Trees and Bagged Trees, and a specialized method known as Rational Quadratic Gaussian Process Regression. Notably, the proposed method, ANFIS, demonstrates the best overall performance across all metrics, indicating its effectiveness in modeling the data. This systematic assessment enables the identification of models that balance accuracy and complexity, allowing for the optimal selection based on specific analytical needs.

9. Conclusions

The application of the ANFIS model to predict the academic performance of graduates produced several notable findings, demonstrating the model's effectiveness and the valuable insights derived from the analyzed data.

ANFIS achieved the lowest RMSE (12.80) and outperformed other models in MSE, R^2, and MAE, confirming its accuracy and robustness. The correlation analysis identified several important patterns that influenced the development and performance of the ANFIS model. The first key finding is the weak correlation between the degree of education and final grades (Figure 3). The correlation between the level of education (bachelor's, master's, PhD) and final grades was 0.02, indicating a very weak positive relationship. This suggests that the level of education does not significantly impact students' final grades, emphasizing the importance of considering other factors such as individual abilities and specific learning conditions. The second finding is the negative correlation between the year of course completion and final grades. A correlation of -0.35 was observed between the year of course completion and final grades, indicating a moderately strong negative relationship (Figure 3). This trend suggests a decline in final grades over time, possibly due to changes in grading standards or course difficulty. It underscores the need to incorporate temporal parameters into the predictive model.

The third finding is the weak correlation between subject and final grades. The correlation between the subject name and final grades was 0.07, indicating a weak positive relationship (Figure 3). This implies that the specific subject has a minor impact on overall final grades, suggesting that factors such as teaching methods and individual student abilities play a more significant role. The fourth finding is the strong correlation between exam grades and final grades. Exam grades strongly correlate with final grades (r = 0.59), making them a key predictor in ANFIS. The fifth finding is the negative correlation between the year of course completion and exam grades. A correlation of -0.21 between the year of course completion and exam grades indicates a weak negative relationship (see Figure 3). This may reflect changes in exam difficulty or grading standards over time, necessitating further detailed analysis to account for these trends.

The ANFIS model was trained using a comprehensive dataset consisting of 25,706 input-output data pairs. The training process was executed over 1000 epochs, during which the model parameters were continuously optimized to minimize prediction error (Figure 5). The achieved minimum RMSE value of 12.80 indicates successful training, aligning with preliminary expectations for accuracy and efficiency.

Table 3 presents a detailed comparative analysis of various regression models and machine learning algorithms. The ANFIS model outperformed traditional approaches such as Linear Regression, Robust Linear Regression, and several tree-based models. Advanced machine learning techniques, including SVM and various neural network configurations, also did not match the overall performance metrics achieved by the ANFIS model. While ensemble methods were effective, they did not surpass the ANFIS model in performance.

Implementing the ANFIS model in educational settings offers several practical benefits. Its high accuracy in predicting academic performance enables educational institutions to make more informed decisions regarding student support and intervention strategies. The integration of fuzzy logic rules within the ANFIS model enhances interpretability, allowing educators and administrators to understand the predictive mechanisms. This adaptability enables the model to reflect changes in educational methods and student behavior. Insights derived from the model can be used to develop targeted intervention strategies, ultimately improving educational outcomes and supporting students at risk of underperforming.

The practical significance of this research lies in its potential integration into university analytics modules and LMS platforms. Institutions can use the developed ANFIS model to predict student performance reliably, implement timely intervention strategies, and adapt curriculum dynamically to meet evolving labor market demands.

The research conducted made it possible to answer the research questions posed.

Q1. How can the ANFIS be used to predict students' academic performance effectively?

ANFIS leverages the combined capabilities of neural networks and fuzzy logic to manage the uncertainties present in educational data, such as fluctuations in student performance and varying assessment practices. Its ability to model complex and nonlinear relationships makes it highly effective for predicting outcomes across different student cohorts. In our experiments, the model was validated using a separate test set, achieving an RMSE of 12.80, which demonstrates a high level of accuracy in predictions. This value indicates the model's ability to minimize the average deviation between predicted and actual outcomes. Furthermore, the stability of the RMSE across multiple epochs, with minimal improvement observed between the 1st and 1,000th epochs, suggests that the model quickly converged to an optimal solution while effectively avoiding overfitting. ANFIS was also compared with traditional predictive models, such as linear regression and decision trees, which produced higher RMSE values and lower R^2 scores. These findings underscore the superior performance of ANFIS, particularly in addressing the complexity and uncertainty inherent in educational data. This reinforces its suitability for use in dynamic educational environments

Q2. What advantages does ANFIS offer over traditional predictive models in the context of educational data?

ANFIS surpasses traditional models, such as linear regression, decision trees, and ensemble methods, by effectively capturing non-linear relationships and managing uncertainties in educational data. In our experiments, ANFIS achieved lower RMSE and higher R^2 values, demonstrating superior predictive accuracy. Unlike ensemble models, ANFIS offers better interpretability through its fuzzy rules, which provide actionable insights into student performance. This combination of precision and interpretability makes ANFIS particularly valuable for developing targeted interventions to support students.

Q3. How can the insights derived from ANFIS be used to develop intervention strategies to improve educational outcomes and support students?

Insights from ANFIS enable the development of targeted intervention strategies by identifying students at risk and providing tailored support, thereby improving educational outcomes and personalizing learning experiences.

Future work will focus on enhancing the capabilities of the university's LMS. This will involve the creation and implementation of new intelligent services aimed at promoting personalized learning, improving assessment quality, and generating new analytical reports

These directions will not only enhance academic efficiency and maintain a high level of quality in educational services but also adapt to the rapidly changing conditions of modern education. In the future, it is recommended to conduct a more in-depth analysis of the impact of various pedagogical methodologies on student performance. This will enable a more precise adaptation of education to individual student needs and provide more effective support at all stages of their educational journey.

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