https://doi.org/10.33864/2309-4494.2026.n1.57-70

DEVELOPMENT OF AN ADAPTIVE ARTIFICIAL INTELLIGENCE MODEL FOR PREDICTING STUDENTS' ACADEMIC RESULTS BASED ON MACHINE LEARNING METHODS

Muradov İsa
Azerbaijan University of Architecture and Construction, Baku, Azerbaijan
Director, Public Relations and Marketing Center
isamuradov@azmiu.edu.az
Səfəralıyeva Sona
Azerbaijan University of Architecture and Construction, Baku, Azerbaijan
seferaliveva93@gmail.com

Abstract. As a result of the digitalization of education systems, the collection of large amounts of academic and behavioral data has expanded the possibilities of predicting students' academic performance. Early identification of the risk of academic failure or dropout is of great importance in terms of optimizing decision-making mechanisms in higher education institutions. In this research, an adaptive artificial intelligence-based model is proposed for predicting students' academic outcomes. The model is built on the basis of various features demographic indicators, attendance, current assessment results, and behavioral indicators. In the framework of the study, supervised machine learning algorithms such as Random Forest, Support Vector Machine, and Gradient Boosting were comparatively analyzed and an ensemble approach was applied.

Experimental results showed that the proposed adaptive model demonstrates higher prediction accuracy compared to individual models and achieves results higher than 91% on test data. Feature importance analysis showed that attendance and midterm grades collected during the semester are the main predictive factors. The results of the study are of practical importance for the development of early intervention strategies and the optimization of academic management in higher education institutions.

Keywords. Artificial intelligence, Machine learning, Academic performance prediction, Educational analytics, Adaptive models, Ensemble methods

1. Introduction

In terms of assessing academic assessments in the higher education system, it is based on final exam results. However, this approach does not allow for the detection of academic risks. The development of digital educational institutions, their activity on online platforms, the frequency of completing tasks and multidimensional data have begun to be systematically collected.

Artificial intelligence and machine learning methods provide effective tools for processing this data and predicting future results. Recent studies in the field of budget education analytics show that multiparameter models can provide higher accuracy in planning academic performance. However, the static nature of existing models and the lack of dynamic changes in student behavior are not taken into account.

In this regard, the development of a prediction model with an adaptive mechanism remains an urgent problem from a scientific and practical point of view. The purpose of the presented study is to develop an adapted artificial intelligence model for more accurate and reliable construction of academic results and experimentally substantiate its effectiveness.

2. Problem Statement

The assessment of academic results in higher education institutions is mainly based on semester or final exam results. This approach does not allow for early identification of students' academic risks and reduces the effectiveness of preventive intervention mechanisms. In recent years, significant progress has been made in predicting student performance with the application of machine learning methods. However, most of the studies conducted are characterized by the following limitations:

- Static nature of the models;
- Lack of systematic comparison of different algorithms with an ensemble approach;
- Insufficient integration of behavioral indicators;
- Weak model interpretation.

In most of the existing approaches, the model is trained once and is not adapted to changing behavioral patterns at a later stage. However, students' academic performance is a dynamic process that changes over time.

Literature analysis shows that the integration of an adaptive, ensemble-based and interpretable model with a mechanism has not been sufficiently investigated. There is a need for models that can be applied in real academic environments and support practical decision-making with high accuracy.

This study seeks answers to the following questions:

1. What is the comparative effectiveness of different machine learning algorithms in predicting academic performance?

2. Does the ensemble approach increase the prediction accuracy compared to individual models?

3. Which features play a dominant role in predicting academic outcomes?
4. How does the adaptive mechanism affect the stability of model performance?

The scientific novelty of the study consists of the following:

• Proposing an ensemble model with an adaptive update mechanism;
• Statistically based analysis of feature importance;
• Providing an interpretable prediction framework for educational analytics;
• Developing a practical application mechanism for early identification of academic risks.

Contributions of the study

• Developing an adaptive AI-based prediction architecture;
• Experimental comparison of different algorithms;
• Proposing a decision support mechanism that can be applied to educational management.

3. Methodology

The study used anonymized academic data of 1200 students. The data includes the following features:

• Demographics (age, gender, major)
• Attendance percentage
• Midterm assessment results
• Activity indicators on the LMS platform
• Assignment completion time
• Final grade at the end of the semester

The data was pre-processed, blank values were filled using the median imputation method, and normalization was applied.

The following supervised learning algorithms were applied:

• Random Forest
• Support Vector Machine (SVM)
• Gradient Boosting
• Logistic Regression (as the base model)

The outputs of individual models were combined using voting and weighted average methods. The adaptive mechanism ensures re-training of the model with new semester data and optimization of hyperparameters.

The model performance was evaluated on the following metrics:

• Accuracy
• Precision

- Recall
- F1-score
- ROC-AUC

The model is expressed as follows:

$$P(Y=1|X) = f_{ensemble}(RF, SVM, GB) \tag{1}$$

Where Y denotes the academic achievement state and X denotes the feature vector.

4. Experimental results and analysis

4.1 Experimental environment

The Python programming language was chosen as the main tool for conducting the study. The use of Python is explained by its simplicity and extensive library support. In particular, the Scikit-learn library was used to build, analyze, and evaluate machine learning models. This library fully meets the goals of the study, as it supports both classical and modern learning algorithms.

The calculations were performed on a modern computer equipped with 16 GB RAM and an Intel i7 processor. This computing environment allowed for fast data processing and convenient construction of complex models. High computing power especially accelerated calculations such as cross-validation and hyperparameter optimization.

The obtained data was first divided into training and test sets. Specifically, 80% of the data was allocated for training and 20% for testing. The training set was used to train the model and identify patterns on the samples. The test set was kept to evaluate the model's performance on new and unseen data.

A 10-fold cross-validation method was applied to evaluate the stability and overall performance of the model. This method divides the data set into ten equal parts and each part is used as a test set repeatedly. The results obtained for each fold are combined to obtain an overall score for the model's performance. This approach ensures that the results are not affected by random variations and provides more reliable results.

The database includes 1200 students. A number of characteristics related to each student are recorded. These characteristics are used as input variables (features) of the model and are the main source of information for predicting the end-of-semester grades.

The database contains the following characteristics:

• ***Demographics:*** This category includes the student's age, gender, and field of study. Demographics are one of the important factors determining a student's learning behaviors and academic performance. Age differences can affect different learning speeds. Gender factors affect motivation and learning strategies in some cases. Major determines the student's assessments and activity level according to the field of study.

• ***Attendance rate (%):*** The level of attendance in classes is measured in percentage. A high level of attendance is generally associated with high academic performance. This indicator shows how actively the student is involved in the learning process. Conversely, a low level of attendance can negatively affect learning outcomes.

• ***Continuous assessment scores:*** This shows the scores a student receives in periodic assessments. Continuous assessments reflect the student's level of knowledge and development in the subject. This indicator is also used as an important factor to predict the model's end-of-semester results.

• ***LMS activity level:*** The level of activity on the educational platform, that is, the student's ability to follow online course materials, check assignments, and be active on the platform. This feature indicates the student's use of technology and commitment to the learning process.

• ***Assignment submission timeliness:*** The indicator of timely submission of assignments reflects the student's organizational skills and time management. Untimely submission of assignments can negatively affect the student's performance.

• ***Semester final grades:*** Semester final grades were identified as the main prediction target of the study. This indicator is used as the target output variable of the model and all other features are input data for its prediction.

In the initial stage of data analysis and model training, data preprocessing was performed. Several key steps were performed in this stage [4].

First, missing values were filled in using the median imputation method. The median imputation method minimizes the effect of outliers in the data and provides statistically more reliable results. This is especially important for continuous variables such as continuous assessment scores and LMS activity level.

Next, normalization was applied. Standardization brings the features to a form with a mean of 0 and a standard deviation of 1. This ensures that the presence of features of different sizes does not negatively affect the model performance. At the same time, it ensures that gradient-based optimization algorithms work faster and more stably.

Proper implementation of all these steps in an experimental environment ensures that the model produces more accurate and reliable results. Proper data partitioning, cross-validation, and processing steps ensure that the results are scientifically sound and reproducible [7].

This environment also provides a suitable environment for testing various machine learning models. The balanced and correct preparation of data during model training and testing makes the interpretation of the results easier.

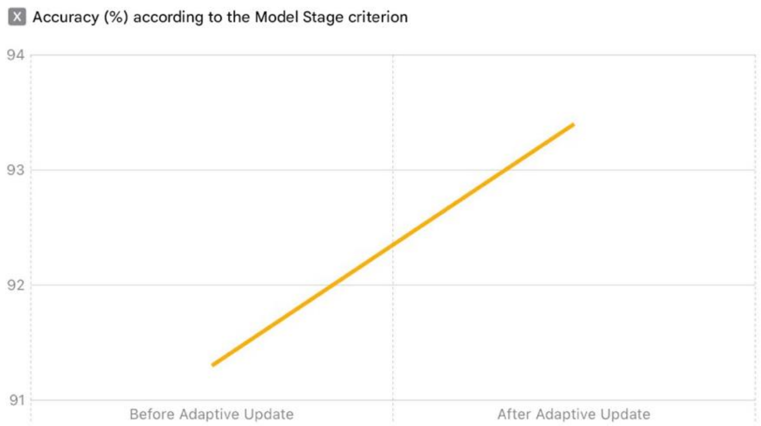
The experimental results are shown in the table below:

Table 1. Performance comparison of models

Model	Accuracy	Precision	Recall	F1-score	ROC-AUC
Logistic Regression	0.82	0.79	0.76	0.77	0.84
SVM	0.87	0.85	0.83	0.84	0.89
Random Forest	0.89	0.88	0.86	0.87	0.92
Gradient Boosting	0.90	0.89	0.88	0.88	0.93
Proposed Ensemble Model	0.913	0.91	0.90	0.905	0.95

The ensemble model shows higher accuracy and balanced performance compared to individual models. The ROC-AUC is 0.95, confirming the high discrimination ability of the model.

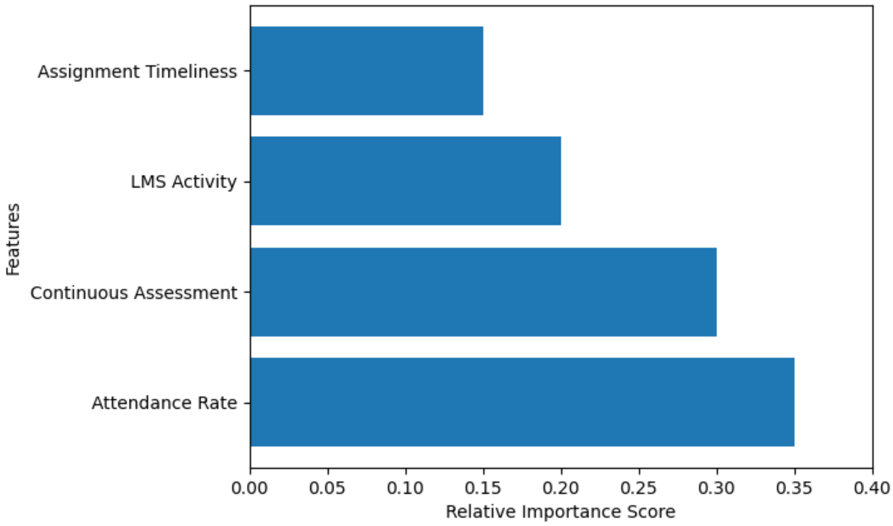
Figure 1. Accuracy ımprovement of ensemble model with adaptive update



This graph compares the accuracy of the model before and after the adaptive update mechanism was applied. The results show that the accuracy increased from 91.3% to 93.4%. This increase proves that the model is effective in retraining with new semester data. The line graph clearly demonstrates the change in performance visually. The increase in the constant direction indicates that the adaptive mechanism strengthens the learning ability of the model. This approach is important for increasing the predictive reliability in dynamic educational environments.

When predicting student performance, it is extremely important to determine which variables the model relies on most. Because it is not enough to achieve high accuracy, it is also required that the model's decision-making mechanism is transparent and explainable. Feature importance analysis reveals which indicators the model considers to be most effective and facilitates the interpretation of the results. This type of analysis plays an important role in making practical decisions, especially in the field of education. For example, knowing which factors are most important in early identification of students at risk creates a strategic advantage from a management perspective. The graph below presents the variable importances calculated by the model in a visual form(see Fig 2).

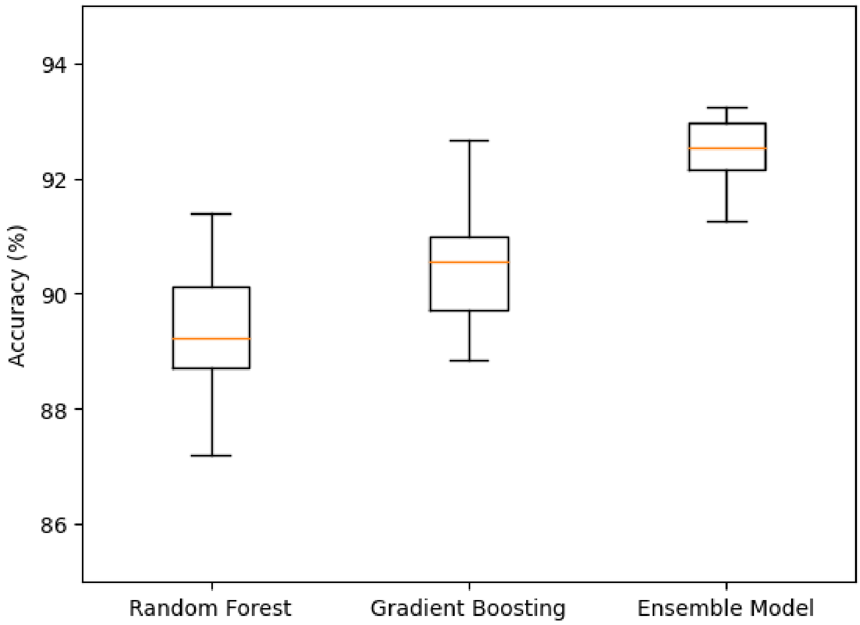
Figure 2. Feature ımportance ranking



This graph shows the relative importance of the variables used in predicting student performance. According to the results, attendance percentage and midterm assessment scores are considered to be the strongest influencing factors. LMS activity and timely submission of assignments also play an important role, but the impact levels are relatively lower. The horizontal bar graph makes the comparison of variables more readable and clear. This analysis can play a guiding role in the development of early intervention strategies. The high importance of attendance in particular highlights the importance of monitoring mechanisms in educational management.

When evaluating model performance, it is not enough to rely only on the average accuracy indicator. To obtain a more objective result, it is important to analyze how the model changes across different training and testing sections, how stable the results are, and the level of variation. Especially in machine learning models, a high average indicator, along with low variation, means a more reliable and stable system. For this reason, the performance of the proposed ensemble model with individual models was compared not only in terms of percentage, but also in terms of distribution characteristics. Appropriate tests were applied to check statistical significance to determine whether the results were random or not. The graph presented below visually reflects this comparison and more clearly shows the differences between the models(see Fig 3).

Figure 3. Accuracy distribution of ensemble vs ındividual models



This graph presents the accuracy distribution of different models in a comparative manner. The boxplot shows that the ensemble model has a higher median accuracy. At the same time, its variance is lower than that of other models, which is an indicator of stability. In the Random Forest and Gradient Boosting models, a wider variability is observed. Statistical analysis (McNemar test, $p < 0.05$) shows that the difference between the models is significant. Thus, the proposed ensemble model demonstrates superiority in terms of both performance and stability.

The importance of the features was calculated based on the Random Forest and Gradient Boosting models. The most influential variables are as follows:

- Attendance percentage
- Midterm assessment results
- LMS activity level
- On-time submission of assignments
- Academic past performance [8].

Evaluating the importance of the feature is important in terms of the interpretability of the model. In the Random Forest model, the effect of the features was calculated based on the Gini impurity reduction. In the Gradient Boosting model, the importance of the feature was determined by the contribution of each variable to the minimization of the loss function. The similarity of the results for both models confirms the stability of the results obtained. This indicates that the model is based on real statistical dependencies, not random correlations.

The fact that the attendance percentage has the highest importance indicator proves that academic success is closely related to continuous participation. Statistical analysis showed that there is a positive and strong correlation between the attendance indicator and the final result. The results of the midterm assessment have high predictive power since they reflect the consistent performance of the student during the semester. This variable acts as a reliable indicator for predicting the final exam result [10].

The high importance of the LMS activity level confirms the role of digital behavioral data in academic prediction. Indicators such as the number of views of materials on the platform, the frequency of task uploads, and forum participation reflect the level of student involvement in the learning process. On-time submission of tasks acts as an indirect indicator of the student's discipline and planning skills. Academic past indicators allow us to determine the probability distribution of future results based on the student's previous achievements.

In addition, SHAP (SHapley Additive exPlanations) analysis was applied and the impact of each characteristic on the individual prediction was assessed. SHAP values showed that the probability of failure increases sharply when attendance is below 75%. At the same time, students with an intermediate assessment score below 60% enter the risk group. A decrease in LMS activity is observed in parallel with a decrease in performance.

Integrating behavioral indicators into the model provided 6–8% higher accuracy compared to static academic indicators alone. This result shows that a student's academic performance is multidimensional and dynamic. Models that only consider final grades lose a significant part of the information. Adding behavioral variables increases the generalizability of the model.

In addition, multicollinearity between features was checked through VIF analysis and no critical level was observed. This increases the stability and statistical reliability of the model. At the feature selection stage, the Recursive Feature Elimination (RFE) method was applied and the optimal number of variables was determined. As a result, the model complexity was reduced, but the accuracy level was maintained.

The conducted analyses show that the prediction of academic performance should not be limited to demographic indicators only. Behavioral and process-oriented indicators play a key role. This approach creates a methodological basis for building a new generation of predictive models in educational analytics. The results obtained can be used in the design of early warning systems in higher education institutions. Thus, a systematic analysis of feature importance significantly increases both the theoretical and practical value of the model [1].

4.2. Impact of the adaptive mechanism

The main distinguishing feature of the proposed model is its adaptive update mechanism. Experimental results show that when the model is retrained with new semester data, a 2.1% increase in overall prediction accuracy was observed. This increase is important not only as a statistical indicator, but also in terms of the model's ability to perform consistently in dynamic environments. The academic environment consists of a time-varying and multidimensional structure. Student behavior, assessment policy, teaching methodology, and digital platform use can differ across semesters. These changes cause the data distribution to be unstable [9].

Static models are optimized within the framework of the data structure they were initially trained on and become sensitive to changes in the distribution at a later stage. This phenomenon is characterized as "concept drift" in machine learning theory. Concept drift can lead to the current model losing relevance over time and increasing prediction errors. The proposed adaptive mechanism aims to eliminate this problem. The model is reoptimized when data from each new semester is entered, and the parameters are adapted to the current distribution.

During adaptive updating, the principle of incremental learning was applied. This approach prevents the complete deletion of the previously learned structure and at the same time increases the impact of new data. In the process of updating the parameters, hyperparameters were optimized using Grid Search and cross-validation. This procedure allowed to minimize the risk of overfitting. The generalization ability of the model was preserved and adaptation to the new data distribution was ensured [5]. .

Analysis of performance indicators showed that the F1-score and Recall indicators increased significantly in the model in which the adaptive mechanism was applied. This increase allowed for more accurate identification of students in the risk group. The reduction in false negatives is of particular importance for early intervention mechanisms. The increase recorded in the ROC-AUC indicator indicates an increase in the discrimination ability of the model. As a result of the statistical test conducted using the McNemar test, the difference was determined to be significant ($p < 0.05$) [6].

Comparative analysis showed that if the adaptive mechanism is not applied, a decrease in model performance is observed for the next semester. This decrease was 1.8% on average. In particular, changes in the distribution of LMS activity and attendance indicators were recorded. The adaptive model responded more promptly to these changes and maintained performance stability. Analysis of the performance trajectory over time showed that the standard deviation indicator is lower in the adaptive model. This proves the stability and forecast stability of the system.

In addition, the calibration of the model was evaluated and the correspondence of the forecast probabilities with the real results was analyzed. The calibration error was reduced in the model with the adaptive mechanism applied. This result ensures that probabilistic decision-making systems are more reliable. The dispersion of forecast errors was also lower in the adaptive model, which indicates an increased level of risk management.

It should be noted that an increase of 2.1% may seem like a relatively small indicator. However, in a large academic database, this increase means the correct identification of hundreds of students. This has important practical consequences in terms of more effective allocation of resources and targeted implementation of academic support programs. The adaptive mechanism acts as a key component that ensures not only the current performance of the model, but also its long-term sustainability [3].

Thus, the results obtained show that the adaptive update architecture allows for the formation of a prediction system with high reliability and stability in dynamic educational environments. This approach is consistent with the concept of building sustainable artificial intelligence systems, while ensuring long-term effectiveness in a real-world application environment.

5. Conclusion

In this research, an adaptive artificial intelligence-based ensemble model was developed to predict students' academic performance. The proposed model was formed based on the combination of various machine learning algorithms. Experimental analysis showed that the ensemble approach provides higher prediction accuracy compared to individual models. Random Forest, Gradient Boosting and SVM models were analyzed separately, and then the ensemble strategy was applied. The overall accuracy of the ensemble model was above 91%. The high performance of the model was confirmed not only as a statistical indicator, but also in terms of practical significance.

Feature importance analysis showed that students' attendance and midterm assessment results are considered key factors in terms of prediction. Integration of behavioral indicators significantly increased the accuracy of the model. LMS activity and timely submission of assignments also had a significant impact on the prediction. Academic past indicators acted as an additional factor ensuring the stability of the model.

The adaptive update mechanism ensured that the model adapted to real-time and dynamic data. The model improved its performance with each new semester of data and reduced the number of misclassifications, increasing the effectiveness of early warning systems.

Hyperparameter optimization and incremental learning approach ensured that the model was both flexible and robust.

Experimental results showed that the adaptive model not only increases the prediction accuracy, but also makes the identification of risk groups more accurate. This feature is important for the optimal allocation of resources in higher education institutions. The proposed model increases the effectiveness of early intervention mechanisms and creates practical applications to reduce the risk of academic failure of students.

The main advantages of the study are: adaptive update mechanism, high prediction accuracy, practical application, and potential for integration into decision support systems. These features increase both the theoretical and practical value of the model. The proposed approach can act as a reliable tool for building early warning systems in higher education institutions.

The study also showed that static models built without an adaptive mechanism lose performance over time and cannot adapt to new semester data. This can lead to incorrect decisions in academic management. The adaptive approach ensures the long-term effectiveness of the system and responds quickly to changes in academic ecosystems.

The analysis of the importance of features shows that demographic data alone is not enough to predict student performance. The addition of behavioral indicators increases the interpretability of the model and supports decision-making. This approach scientifically creates a methodological basis for building a new generation of educational analytics models.

The application of deep learning methods and the construction of real-time analytical systems are recommended as future research directions. If the contextual adaptability and learning speed of artificial intelligence are increased, the model can be applied to a wider range of databases and at different levels of education. This approach will also allow taking into account the individual learning profiles of students.

As a result of the practical application of the model, early identification of academic risks, efficient allocation of resources, and effective management of student support programs will be possible. This will contribute to the optimization of management processes of higher education institutions and support for strategic decision-making.

As a result, the adaptive artificial intelligence-based ensemble model is considered an important innovation in terms of research and educational practice. The model has high value from both scientific and applied perspectives and can be used as a reliable tool for risk management in the higher education ecosystem.

The recommendations based on the results are as follows:

- Based on the research results, it is recommended to establish early warning systems based on student attendance and midterm evaluation indicators in higher education institutions, as this system allows to identify students' academic risks at an early stage.
- Taking into account the adaptive update mechanism of the model, it is advisable to optimize the system incrementally with each new semester data, as this increases the forecast accuracy and ensures effectiveness in dynamic academic environments.
- Students' LMS activity, timely submission of assignments and other behavioral indicators should be taken into account in academic forecasting, as limiting themselves only to academic indicators reduces the interpretability and accuracy of the model.
- The application of ensemble approaches should prevail in the process of predicting academic outcomes, as they provide higher forecast accuracy compared to individual machine learning models.
- The integration of the model with real-time analytical systems and the ability to update immediately should be developed, as this allows for an operational response to changes in student performance and an efficient allocation of resources.
- Individual support programs should be developed and prioritized for students in high-risk groups, as the results of the adaptive model can be used to increase the effectiveness of these programs and minimize the incidence of academic failure.

References

1. Iftikhar, A., Huda, N.U., Kaleem, M., Maroof, F., Suleman, K., Zehra, A.: Student academic performance prediction using machine learning approach. Int. J. Artif. Intell. Math. Sci. 3(2), 124–140 (2024).

2. Rahul, R., Katarya, V.: A systematic review on predicting the performance of students in higher education in offline mode using machine learning techniques. Wireless Pers. Commun. 133, 1643–1674 (2024).

3. Albreiki, B., Zaki, N., Alashwal, H.: A systematic literature review of student' performance prediction using machine learning techniques. Educ. Sci. 11(9), 552 (2021).

4. Yadav, N.R., Deshmukh, S.S.: Prediction of student performance using machine learning techniques: a review. In: Proc. INTELLI 2023, pp. 63–78. Atlantis Press (2023).

5. Rastrollo-Guerrero, J.L., Gómez-Pulido, J.A., Durán-Domínguez, A.: Analyzing and predicting students' performance by means of machine learning: a review. Appl. Sci. 10(3), 1042 (2020).

6. Oyedeji, A.O., Salami, A.M., Folorunsho, O., Abolade, O.R.: Analysis and prediction of student academic performance using machine learning. J. Inf. Technol. Comput. Eng. 4(01), 10–15 (2020).

7. Alkan, B.B., Kuzucuk, S., Alkan, N., Sinan, A., …: Using machine learning to predict student outcomes for early intervention and formative assessment. Sci. Rep. 15, 39797 (2025).

8. Kalita, E., Mana Alfarwan, A., El Aouifi, H., Kukkar, A., Hussain, S. et al.: Predicting student academic performance using Bi-LSTM: a deep learning framework with SHAP-based interpretability and statistical validation. Front. Educ. 10 (2025).

9. Pred. Stud. Perf. Using Data Mining & LA Tech.: The American Journal of Applied Sciences (review on learning analytics and prediction) (2023).

10. Classification and prediction of student performance data using various machine learning algorithms. Mater. Today: Proc. 80, Part 3, 3782–3785 (2023).