Vol. 8, No. 1, February 2026

Journal of Information Systems and Informatics

Published By Asosiasi Doktor Sistem Informasi Indonesia

Student Performance Classification Using Academic, Socioeconomic, and Digital Behavior Features: A Comparative Study

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Received:
November 21, 2025
Revised:
January 20, 2025
Accepted:
January 30, 2026
Published:
February 13, 2026

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DOI:
10.63158/journalisi.v8i1.1460

Abstract. Accurate prediction of student academic performance is essential for universities seeking to improve learning outcomes and deliver timely, data-driven support. Prior work commonly uses regression to estimate Grade Point Average (GPA), yet numeric predictions can be difficult for administrators to translate into actionable risk levels. This study reframes the task as binary classification, categorizing students as good (GPA ≥ 3.00) or poor (GPA < 3.00) performers. Using 2,423 records from multiple programs at an Indonesian university, we combine academic indicators from the learning management system (login frequency, assignment submission, and forum activity) with socio-economic and digital behavioral variables (parental income, extracurricular participation, study-group involvement, and social media use). Seven machine learning models—Naïve Bayes, Generalized Linear Model, Logistic Regression, Deep Learning, Decision Tree, Random Forest, and Gradient Boosted Trees (GBT)—are benchmarked under a consistent evaluation design. Results indicate that integrating academic, socio-economic, and digital behavioral features improves classification performance, and ensemble methods outperform single, traditional models. GBT yields the best accuracy of 0.75, offering a practical basis for early-warning dashboards and targeted interventions. The study provides comparative evidence from Indonesian higher education and highlights the value of incorporating digital engagement signals alongside conventional academic data for more effective student support services.

Keywords: Performance prediction; Machine learning; LMS analytics; Digital behavior; Indonesian higher education

1. INTRODUCTION

Student academic performance prediction has emerged as a central topic in educational data mining (EDM) and learning analytics over the past decade [1]–[4]. Higher education institutions increasingly rely on data-driven insights to identify students who may be at risk of underachievement and to design targeted academic interventions [5]–[8]. Understanding the complex relationships between academic, socio-economic, and behavioral factors is therefore essential for enhancing learning outcomes, improving retention rates, and supporting institutional decision-making [9]–[11].

Earlier approaches to student performance prediction primarily employed regression-based models, focusing on estimating continuous academic outcomes such as Grade Point Average (GPA) [1], [12], [13]. Although regression offers numerical precision, its outputs are often less interpretable and less actionable for academic administrators, who typically require clear indicators of student risk levels rather than exact GPA values [14], [15]. As a result, classification-based approaches that group students into discrete performance categories have gained increasing attention.

A growing body of research has applied machine learning classification algorithms, including Decision Tree, Random Forest, Support Vector Machine, and Logistic Regression, to identify patterns that distinguish high-performing from low-performing students. However, most existing works focus mainly on academic records and basic demographic variables, while behavioral and digital engagement factors, including online learning activities and social media usage, remain underexplored, particularly in rapidly digitalizing learning environments Furthermore, many classification studies employ a limited number of algorithms or single-model approaches, restricting the evaluation of model robustness. Systematic comparisons across multiple machine learning techniques using the same dataset remain relatively scarce, despite their importance for ensuring reliable and methodologically sound predictive results [16]–[18]. Another significant gap concerns contextual diversity. The majority of prior studies are conducted in Western or large-scale educational settings, with limited empirical evidence from Indonesian higher education [19]–[21]. Indonesia's socio-economic diversity and distinctive digital engagement patterns may influence student performance differently, highlighting the need for context-specific investigations [22], [23]. Exploring these factors can therefore

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offer new perspectives on how academic and non-academic variables jointly shape student success [24]–[26].

Accordingly, this study aims to develop and evaluate a comprehensive machine learning based classification framework for predicting student academic performance. The proposed framework integrates academic variables derived from Learning Management System (LMS) activity, socio-economic and demographic indicators, and digital behavioral features that reflect broader patterns of student engagement.

The study addresses the following research questions (RQs): RQ1: How effectively can machine learning classification models predict student academic performance when integrating academic, socio-economic, and digital behavioral features?, RQ2: Which machine learning algorithm provides the most accurate and reliable classification of students into good (GPA ≥ 3.00) and poor (GPA < 3.00) performance categories?. Seven machine learning algorithms Naïve Bayes, Generalized Linear Model, Logistic Regression, Deep Learning, Decision Tree, Random Forest, and Gradient Boosted Trees are evaluated using a dataset of 2,423 students from multiple study programs within a single university. This comparative design enables a consistent and robust assessment of model performance.

The scope of this study is limited to one Indonesian university; therefore, the findings may not fully generalize to other institutional contexts. Nevertheless, the results provide valuable empirical insights into student performance prediction in Indonesian higher education and contribute to the broader learning analytics literature.

2. METHODS

This study employed a quantitative research approach to predict student academic performance by integrating academic, socio-economic, and digital behavioral data within a machine learning–based classification framework. The methodological design emphasizes transparency and replicability through clearly defined stages, including data collection, preprocessing, model development, and performance evaluation.

Vol. 8, No. 1, February 2026

ISI Journal of Information Systems and Informatics

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2.1. Research Design

This research adopts a supervised classification approach to predict student academic performance. It extends prior regression-based analysis by transforming continuous GPA prediction into categorical classification, thereby improving interpretability and institutional relevance. The classification framework is intended to support academic decision-making by clearly distinguishing students at risk of underperformance. As illustrated in Figure 1, the research workflow consists of data collection, data preprocessing, feature analysis, model training, and comparative evaluation.

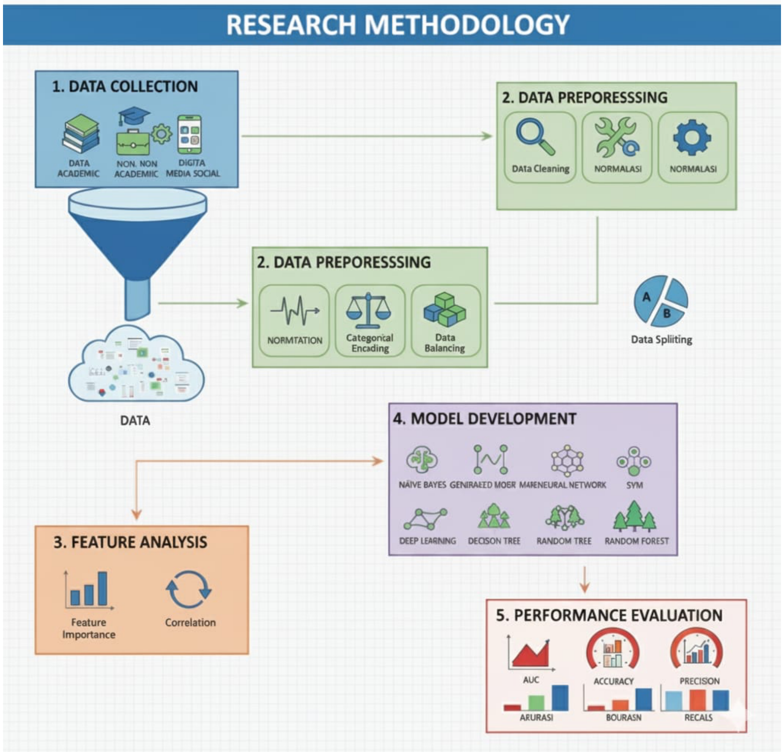

Figure 1. Research Methodology

2.2. Dataset Description

The dataset was collected from a single Indonesian higher education institution and consists of 2,423 student records drawn from multiple study programs and academic years. Each record integrates academic activity data obtained from the Learning Management System (LMS) with survey-based non-academic and digital behavioral attributes. Student academic performance was defined as the target variable and categorized according to institutional academic regulations: good performance (GPA ≥ 3.00) and poor performance (GPA < 3.00). The dataset exhibits a moderately imbalanced

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class distribution, with the good-performance category slightly more prevalent than the poor-performance category.

The dataset consists of 2,423 student records categorized into two performance classes based on GPA. A total of 1,512 students (62.4%) were classified as good performers (GPA ≥ 3.00), while 911 students (37.6%) were categorized as poor performers (GPA < 3.00). This distribution indicates a moderate class imbalance, which was addressed during model training using SMOTE applied exclusively to the training data. A summary of feature descriptions, and data types is provided in Table 2.

Table 2. Feature descriptions, and data types

Feature Category	Feature Name	Description	Data Type
Academic Variables	LMS Logins	Total number of LMS login activities	Numerical
	Assignments Submitted	Number of assignments submitted via LMS	Numerical
	Forum Participation	Number of discussion posts or replies in LMS forums	Numerical
Non-Academic Variables	Parental Income	Average monthly family income (categorized ranges)	Categorical
	Organizational Involvement	Participation in student organizations or extracurriculars	Binary
	Gender	Student gender (male/female)	Binary
	Distance from Campus	Distance between residence and campus (in kilometers)	Numerical
Digital Behavioral Vars	Social Media Usage	Average daily hours spent on social media	Numerical
	Study Group Participation	Regular participation in collaborative study groups	Binary

2.3. Feature Definition

Predictor variables were grouped into three categories to capture complementary dimensions of student learning behavior. Academic variables represent formal learning engagement, including LMS login frequency, assignment submissions, and discussion forum participation. Non-academic variables describe students' socio-economic and demographic backgrounds, such as parental income, organizational involvement, gender, and distance from campus. Digital behavioral variables capture broader engagement patterns beyond formal coursework, including daily social media usage and participation in collaborative study groups. This integrated feature structure reflects the multifaceted nature of student learning in digitally mediated higher education environments.

2.4. Data Preprocessing

Several preprocessing steps were applied to ensure data consistency and reliability prior to model training. Records containing incomplete or inconsistent information were removed during data cleaning. Continuous variables were normalized using Min–Max scaling, while categorical variables were transformed using one-hot encoding. To address class imbalance, the Synthetic Minority Over-sampling Technique (SMOTE) was applied exclusively to the training data. Specifically, SMOTE was implemented only within the training folds during cross-validation to avoid information leakage into the test data, with the number of nearest neighbors set to $k = 5$. After preprocessing, the dataset was divided into 80% training data and 20% testing data for final evaluation.

2.5. Machine Learning Algorithms

Seven machine learning classifiers were evaluated in this study: Naïve Bayes, Generalized Linear Model, Logistic Regression, Deep Learning, Decision Tree, Random Forest, and Gradient Boosted Trees. These algorithms represent probabilistic, linear, tree-based, and ensemble learning paradigms commonly used in educational data mining. All models were implemented using standard configurations provided by the Scikit-learn and H2O.ai libraries. No hyperparameter optimization or tuning procedures were applied, allowing a fair and consistent comparison of baseline model performance across classifiers.

2.6. Deep Learning Configuration

The Deep Learning model was implemented using a multilayer perceptron (MLP) architecture. The network consisted of an input layer matching the number of features,

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two hidden layers with 64 and 32 neurons, and a single-node output layer for binary classification. ReLU activation functions were used in the hidden layers, while a sigmoid activation function was applied in the output layer. The model was trained using the Adam optimizer for a maximum of 100 epochs, with early stopping based on validation loss to reduce the risk of overfitting.

2.7. Evaluation Metrics and Experimental Setup

Model performance was evaluated using accuracy, precision, recall, F1-score, and area under the ROC curve (AUC). These metrics provide a balanced evaluation of classification effectiveness, particularly in the presence of class imbalance. All experiments were conducted in a Python 3.10 environment using an Intel Core i7 workstation with 16 GB RAM. Ten-fold cross-validation was applied during model training to ensure stable and reliable performance estimates, while final results were reported on the held-out test set.

3. RESULTS AND DISCUSSION

This section presents the results of the classification models developed in this study and discusses their effectiveness in predicting student academic performance. The models were evaluated using multiple performance metrics to identify the most suitable approach for early academic risk identification. In line with the study objective, the classification framework focuses on identifying students at risk of poor academic performance rather than predicting exact GPA values.

3.1. Model Performance Comparison

Seven machine learning algorithms were employed to classify student academic performance into two categories: good (GPA ≥ 3.00) and poor (GPA < 3.00). In this study, the "poor performance" category was treated as the positive class, as correctly identifying academically at-risk students is critical for early warning and intervention systems. Accordingly, recall values reported in Table 3 reflect the models' ability to correctly detect poor-performing students. Table 3 summarizes the comparative performance of all models in terms of AUC, accuracy, precision, and recall. All reported metrics represent the mean values obtained from 10-fold cross-validation, with standard deviations ranging

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between ±0.01 and ±0.03 across models, indicating relatively stable performance across folds.

The results show that Gradient Boosted Trees (GBT) achieved the highest overall accuracy (0.75), followed closely by Random Forest and Logistic Regression (0.74). Although Naïve Bayes produced a slightly lower accuracy (0.73), its high recall value (0.89) indicates strong sensitivity in identifying students at risk of poor academic performance, which is particularly desirable in early warning contexts.

Table 3. Performance comparison of classification models

Model	AUC	Accuracy	Precision	Recall
Naïve Bayes	0.65	0.73	0.76	0.89
Generalized Linear Model	0.63	0.74	0.76	0.92
Logistic Regression	0.63	0.74	0.76	0.92
Deep Learning	0.61	0.73	0.76	0.90
Decision Tree	0.62	0.74	0.74	1.00
Random Forest	0.62	0.74	0.75	0.95
Gradient Boosted Trees	0.63	**0.75**	0.75	0.95

The Decision Tree model achieved a perfect recall score (1.00), indicating that it successfully identified all poor-performing students. However, this result was accompanied by lower AUC and precision values, suggesting a tendency toward overfitting and reduced generalization capability. In contrast, ensemble-based methods such as Random Forest and GBT exhibited more balanced performance across metrics, highlighting their robustness in handling heterogeneous academic, socio-economic, and behavioral features. Although AUC values across models are modest (0.61–0.65), this outcome is expected in educational datasets characterized by overlapping feature distributions and moderate class imbalance. In early warning applications, recall is often prioritized over AUC, as failing to identify at-risk students (false negatives) carries greater institutional consequences than issuing additional alerts. To further examine error characteristics, a confusion matrix was generated for the best-performing model (GBT). The results indicate that false negatives were relatively limited compared to false positives, supporting the suitability of the classification framework for early intervention scenarios where sensitivity to academic risk is essential.

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3.2. Feature Importance Analysis

Feature importance analysis was conducted using the Gradient Boosted Trees model to identify variables that contributed most strongly to classification outcomes. The ranking of features is presented in Table 4. Social media usage emerged as the most influential feature (weight = 0.2931), followed by total LMS logins (0.1629) and gender (0.1218). This finding suggests that digital behavioral indicators are strongly associated with academic performance categories; however, the results reflect predictive association rather than causal relationships.

Among academic indicators, LMS login frequency and assignment submissions contributed notably, reinforcing the importance of sustained engagement in digital learning environments. Non-academic factors such as domicile distance and organizational involvement showed moderate influence, while parental income and study group participation exhibited relatively low importance within this dataset.

Table 4. Feature importance ranking

Attribute	Weight
Social Media Usage (N_medsos_acces)	0.2931
Total LMS Logins (Total_login)	0.1629
Gender	0.1218
Assignments Submitted (N_assignments_submitted)	0.0857
Domicile Distance	0.0511
Organizational Involvement	0.0214
LMS Forum Answers (N_answered_questions)	0.0073
Study Group Participation	0.0047
Parental Income (Economy)	0.0027

3.2. Correlation Analysis

Pearson correlation analysis was conducted to examine relationships among predictors and assess potential multicollinearity. As illustrated in Figure 2, correlations among variables were generally weak to moderate. Social media usage showed a weak negative correlation with academic performance classification ($r = -0.293$), while LMS login frequency exhibited a weak positive correlation ($r = 0.163$). The low inter-variable correlations indicate minimal multicollinearity, supporting the suitability of the selected predictors for machine learning–based classification.

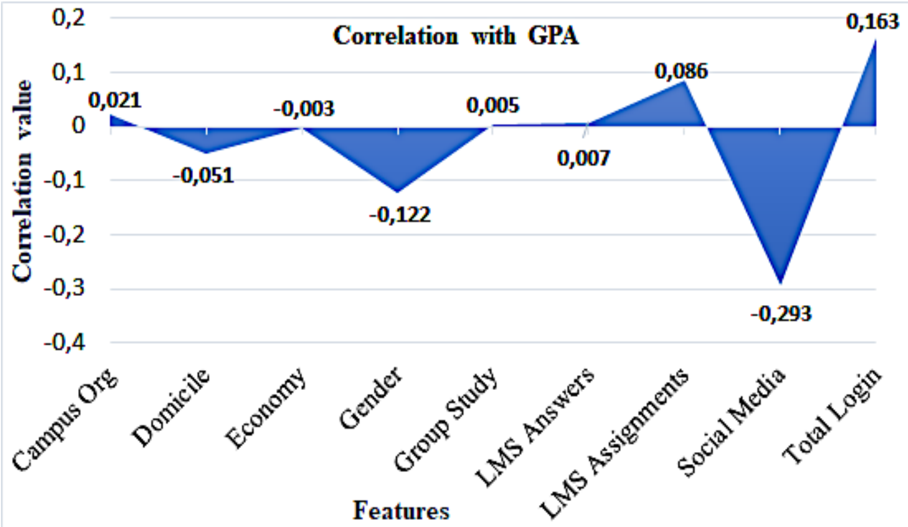

Figure 2. Correlation Features

3.3. Discussion

The findings indicate that reframing student performance prediction from regression-based GPA estimation to a binary classification task produces outputs that are more interpretable and operationally useful for academic decision-making. Instead of reporting an exact GPA value—which may be difficult to translate into policy actions—the classification framework directly identifies whether a student is likely to fall into the poor (GPA < 3.00) or good (GPA ≥ 3.00) performance category. Importantly, defining poor performance as the positive class aligns model evaluation with the practical goal of early risk detection. In this context, recall becomes a priority metric because false negatives (at-risk students incorrectly classified as not at risk) can delay intervention and potentially worsen academic outcomes.

Across the seven evaluated algorithms, ensemble-based approaches demonstrated the most consistent and balanced performance, with Gradient Boosted Trees (GBT) achieving the highest accuracy (0.75) and strong recall (0.95), followed closely by Random Forest (accuracy = 0.74; recall = 0.95). These results support prior evidence that ensemble methods are well suited for heterogeneous educational datasets that combine academic, socio-economic, and behavioral indicators [27]–[31]. While Logistic Regression and the Generalized Linear Model also performed competitively (accuracy = 0.74; recall = 0.92),

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the ensemble models provided a better balance between sensitivity and overall predictive stability under the same experimental design (10-fold cross-validation with low variability across folds). By contrast, the single Decision Tree achieved perfect recall (1.00), meaning it identified all poor-performing students; however, this came with lower precision (0.74) and modest AUC (0.62), suggesting reduced generalization and potential overfitting. For early warning systems, such a model may generate more false alarms, which can burden academic support units and reduce stakeholder trust in the system.

Although the AUC values across models are relatively modest (0.61–0.65), this pattern is common in educational prediction tasks where feature distributions overlap and outcomes are influenced by many unobserved factors. In such settings, AUC alone may understate practical utility, especially when the institutional objective is to maximize detection of at-risk students. The high recall achieved by most models—including Naïve Bayes (0.89), Deep Learning (0.90), and particularly the ensemble methods (0.95)—demonstrates strong sensitivity to academic risk. This supports the suitability of the proposed framework for early intervention scenarios, where a manageable increase in false positives is often preferable to missing students who genuinely require support. Moreover, the use of SMOTE exclusively within training folds helps mitigate the moderate class imbalance (62.4% good vs 37.6% poor) while reducing the risk of information leakage, strengthening confidence that the reported performance reflects genuine predictive signal rather than inflated results.

The feature importance analysis using GBT provides additional insight into which variables most strongly differentiate performance categories in this dataset. Social media usage emerged as the most influential predictor (weight = 0.2931), followed by total LMS logins (0.1629) and gender (0.1218). Together with the correlation results (social media usage showing a weak negative association with performance, r = −0.293; LMS logins showing a weak positive association, r = 0.163), these findings suggest that digital engagement signals can meaningfully complement traditional academic indicators. A plausible interpretation is that high social media exposure may reflect time displacement, reduced concentration, or fragmented study routines, whereas sustained LMS activity may signal consistent academic engagement. However, these patterns should be interpreted as predictive associations rather than causal relationships. Social media use, for example, may also be a proxy for other unmeasured factors (stress, motivation, or learning habits). Likewise, gender's relatively high importance warrants careful handling: it may capture structural or behavioral differences in learning engagement, but it should not be used to justify biased decision-making. Institutional implementation should prioritize supportive interventions and avoid stigmatization or differential treatment based on demographic attributes.

Among the academic variables, assignment submissions (0.0857) and forum participation (0.0073) contributed less than login frequency, suggesting that broad engagement intensity (regular access and presence in LMS) may be more informative than specific activity counts within this dataset. Non-academic factors showed mixed influence: domicile distance (0.0511) had moderate importance—possibly reflecting commuting constraints or time availability—while organizational involvement (0.0214) contributed modestly. Parental income (0.0027) and study group participation (0.0047) appeared least influential, which may reflect limited measurement granularity (e.g., income recorded in broad ranges), context-specific characteristics of the sampled institution, or the possibility that academic behaviors captured through LMS overshadow these variables in predictive power. Notably, the Pearson correlation matrix indicates generally weak inter-variable correlations, suggesting minimal multicollinearity and supporting the appropriateness of combining these predictors within machine learning models without severe redundancy.

From an institutional perspective, the results reinforce the value of integrating behavioral and digital engagement features with conventional academic variables to enhance early warning systems. Rather than treating social media usage or other digital behaviors as standalone risk markers, institutions should interpret them as complementary signals that help refine risk screening when combined with learning engagement indicators (e.g., LMS logins and submissions). Operationally, models such as GBT and Random Forest are attractive because they offer strong recall with comparatively balanced precision, which can reduce the likelihood of overwhelming academic advisors with excessive alerts while still prioritizing at-risk detection.

Ethical and privacy considerations are critical when incorporating digital behavior data into educational analytics. Institutions should ensure transparency about what data are collected and why, minimize the use of personally sensitive attributes, and rely on consent-based and appropriately aggregated indicators. Predictive outputs should be used strictly for supportive academic interventions (e.g., outreach, tutoring, counseling referrals) rather than punitive actions. In addition, governance mechanisms should be established to monitor potential bias—especially when demographic variables contribute meaningfully to predictions—and to ensure fair access to support services for all students.

With respect to the research questions, RQ1 is addressed by the observed improvement in predictive capability when combining academic (LMS), socio-economic, and digital behavioral features, as reflected in consistently high recall values across models and competitive accuracy levels, particularly for ensemble methods. RQ2 is answered by the comparative evaluation showing that Gradient Boosted Trees provides the most accurate and reliable performance overall (accuracy = 0.75; recall = 0.95), closely followed by Random Forest (accuracy = 0.74; recall = 0.95). Finally, the study's single-institution scope remains a limitation for generalizability; future work should validate these findings across multiple Indonesian universities, consider hyperparameter tuning, and incorporate interpretability analyses (e.g., local explanations) to better support responsible deployment in real academic settings.

4. CONCLUSION

This study compared seven machine learning algorithms to classify student academic performance into good and poor categories, adopting a classification framework to enhance interpretability beyond regression-based GPA prediction. The results indicate that ensemble-based models, particularly Gradient Boosted Trees and Random Forest, achieve the most reliable performance, with the highest accuracy reaching 0.75. RQ1 is addressed by showing that integrating academic, socio-economic, and digital behavioral features enables effective prediction of student academic performance, while RQ2 is answered by identifying Gradient Boosted Trees as the best-performing classifier.

Feature importance analysis highlights digital engagement indicators especially social media usage and LMS activity as influential predictors, complementing traditional academic variables, though these relationships reflect predictive associations rather than causal effects. From an institutional perspective, the proposed classification models can support early warning systems by enabling timely identification of students at academic risk and facilitating targeted academic interventions.

This study is limited by the use of data from a single institution and by moderate AUC values, which reflect overlapping student performance characteristics. Future research should explore multi-institutional or longitudinal datasets and richer behavioral indicators to improve generalizability and predictive robustness. Overall, the findings demonstrate that classification-oriented modeling provides actionable insights that effectively support data-driven decision-making in higher education.

ACKNOWLEDGMENT

The authors would like to thank Universitas Muria Kudus for funding this research through the Internal Research Scheme (PFR). We also extend our gratitude to all parties who have contributed to the completion of this study.

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