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Academic Performance Prediction of PTIK Students through Machine Learning Models at Universitas Negeri Medan

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ABSTRACT

This study addressed the need for an effective approach to predicting student academic performance in higher education using data-driven methods. The study aimed to implement machine learning models to predict the academic performance of students in the Information and Communication Technology Education Study Program at Universitas Negeri Medan. A quantitative predictive design was employed using a dataset of 40 student records. Five classification models were tested, namely Logistic Regression, Decision Tree, Random Forest, Support Vector Machine, and Naïve Bayes. The results showed that all models produced strong predictive performance. Decision Tree achieved the highest accuracy at 93.1%, Logistic Regression produced the highest precision at 95.9% and the highest F1-score at 93.2%, while Support Vector Machine obtained the highest recall at 93.2%. These findings indicated that machine learning was feasible for predicting student academic performance in the study program. The study concluded that Logistic Regression provided the most balanced overall performance and had strong potential to support early academic intervention and data-based academic decision making in higher education.

Keyword : Academic Performance Prediction; Machine Learning; Higher Education; Student Classification; Educational Data Mining; Early Academic Intervention.

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1. INTRODUCTION

Student academic performance remains one of the central indicators of educational quality in higher education because it reflects not only learning outcomes, but also the effectiveness of curriculum design, teaching strategies, and institutional support systems. In recent years, higher education institutions have increasingly turned to educational data mining and machine learning to identify patterns associated with student success and failure, with the ultimate goal of enabling earlier and more targeted academic interventions. Prior studies and reviews have shown that predictive approaches can help institutions detect at-risk students before academic problems become irreversible, making prediction models strategically important for academic planning and student support (Bin Roslan & Chen, 2022; Issah et al., 2023; Khan & Ghosh, 2021).

The growing relevance of machine learning in education is closely related to the availability of institutional academic data, demographic records, learning management system traces, and other behavioral indicators that can be transformed into predictive features. Earlier review studies have consistently shown that classification-based approaches are among the most widely used methods for student performance prediction, while decision trees, clustering-enhanced models, and hybrid techniques remain common because they can process complex educational data and generate useful predictive patterns. In addition, learning analytics research has demonstrated that student performance can be predicted relatively early in the semester when academic and behavioral variables are combined appropriately. This makes machine learning not merely a technical exercise, but a practical mechanism for strengthening evidence-based decision making in higher education (Bin Roslan & Chen, 2022; Francis & Babu, 2019; Issah et al., 2023; Lu et al., 2018; Shahiri et al., 2015).

Even so, the literature also points to important limitations. Khan and Ghosh noted that although student performance prediction has become a major theme in educational data mining, many studies remain broad, fragmented, or insufficiently focused on the temporal dimension of prediction in real classroom settings. Likewise, Issah et al. highlighted continuing gaps in population coverage, benchmarked datasets, and intervention-oriented applications, indicating that more contextualized institutional studies are still needed. In other words, prediction models are most useful when they are developed from the realities of a specific study program, with variables that genuinely reflect the students' learning environment, academic habits, and performance patterns. This is precisely why institution-based predictive studies remain valuable: general models may be elegant on paper, but local models are often more actionable in practice (Issah et al., 2023; Khan & Ghosh, 2021).

Within the context of Universitas Negeri Medan, the relevance of this topic is reinforced by several recent studies involving Tansa Trisna Astono Putri and colleagues. Putri, Rahmadani, and Hasan found that anxiety in programming courses is associated with unfavorable beliefs about control in computing situations and low computing self-efficacy, both of which may weaken students' programming performance. In a later study, Putri and colleagues also reported that a machine-learning programming simulator improved student performance regardless of anxiety level, suggesting that machine-learning-based learning environments can support better outcomes in computing-related courses. Beyond that, Hasan et al. showed that simulation-based virtual laboratories offer substantial educational benefits for engineering students, while another study by Hasan et al. applied the Naïve Bayes classifier to predict students' future entrepreneurship-related outcomes. Taken together, these studies show that the local research ecosystem has already moved toward predictive modeling, simulation, and digital intervention; however, a specific machine learning model for predicting academic performance of PTIK students at Unimed has not yet been clearly established. That is the gap this study addresses (Hasan, Ambiyar, et al., 2024; Hasan, Yulastri, et al., 2024; Putri et al., 2024, 2025).

Based on that rationale, this study aims to implement machine learning to predict the academic performance of students in the PTIK Study Program at Universitas Negeri Medan. The study is expected to contribute in two ways. First, it provides a contextual predictive model grounded in local academic data rather than relying solely on generalized findings from other institutions or countries. Second, it offers a practical basis for early warning and academic intervention within PTIK, so that lecturers and study program managers can identify students who may require additional support at an earlier stage. In this sense, the implementation of machine learning is not intended only to improve prediction accuracy, but also to strengthen academic governance, student assistance, and data-driven educational quality improvement in higher education (Bin Roslan & Chen, 2022; Issah et al., 2023; Khan & Ghosh, 2021; Putri et al., 2025).

2. RESEARCH METHOD

This study employed a quantitative predictive research design using educational data mining and machine learning techniques to predict the academic performance of students in the PTIK Study Program at Universitas Negeri Medan. This design was selected because recent reviews show that supervised machine learning is widely used in educational research to predict student achievement, learning patterns, and academic risk, with classification-based approaches and tree-based algorithms among the most frequently applied methods. Accordingly, this study compared several supervised learning algorithms, namely Logistic Regression, Decision Tree, Random Forest, Support Vector Machine, and Naïve Bayes, in order to identify the model with the best predictive performance for PTIK students (Ersozlu et al., 2024; Issah et al., 2023; Yağc, 2022).

The population of this study consisted of students enrolled in the PTIK Study Program of Universitas Negeri Medan during the selected academic period. The sample was determined using a total sampling approach, meaning that all student records meeting the inclusion criteria were analyzed. The inclusion criteria covered active students with sufficiently complete academic records, while incomplete, duplicate, and inconsistent records were excluded during data screening. The dependent variable was academic performance, operationalized as a performance category derived from semester GPA or final academic achievement according to the study program's academic standard. The independent variables were obtained from institutional data and may include demographic attributes, prior academic achievement, attendance, course grades, and learning engagement indicators. This variable structure is consistent with prior research showing that previous academic performance is one of the strongest predictors of future academic outcomes. In the PTIK context, questionnaire-based variables related to computing self-efficacy or programming anxiety may also be incorporated by adapting constructs used by Putri et al. (2024), while Putri et al. (2025) further showed that machine-learning-supported educational environments can affect student performance in computing-related learning contexts.

Data acquisition was conducted chronologically in four stages. First, the researcher obtained permission from the study program or faculty to access academic data for research purposes. Second, the required data were extracted from the academic information system and, if available, from learning management system records and questionnaire responses. Third, all personal identifiers such as student names and registration numbers were removed and replaced with anonymous codes to protect privacy. Fourth, the data from different sources were integrated into a single dataset for analysis. After integration, the dataset was checked for duplicates, inconsistent entries, outliers, and missing values before modeling. This chronological approach is consistent with data-driven research in educational prediction, where structured institutional data and learning-related indicators are combined to support early warning and academic decision-making (Khan & Ghosh, 2021; Lu et al., 2018; Yağc, 2022).

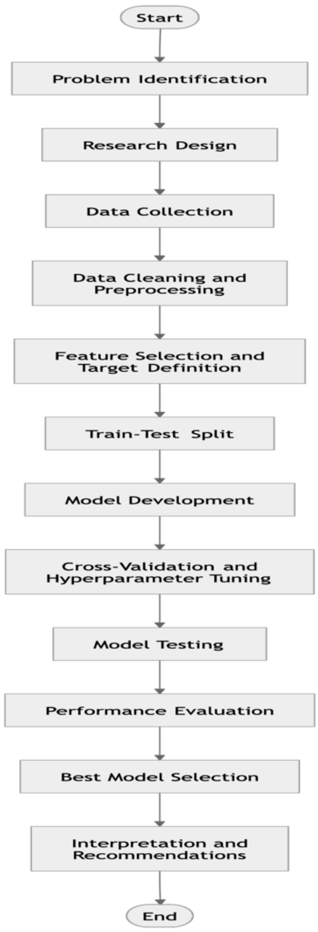

Figure 1. Research Method

Before model development, the dataset was preprocessed. Missing numerical values were imputed using the mean or median, while missing categorical values were imputed using the most frequent category. Categorical variables were then transformed into numeric form through one-hot encoding, and numerical variables were standardized when required by algorithms sensitive to feature scale, such as Logistic Regression and Support Vector Machine. To avoid data leakage, preprocessing and classification stages were implemented in a single pipeline, so that transformations were learned only from the training data and then applied to validation and test data consistently. This procedure follows standard machine learning practice for preprocessing, scaling, and leakage prevention.

The research procedure began by splitting the cleaned dataset into training data and testing data using a stratified proportion, for example 80:20, to preserve the class distribution of academic performance categories. The training data were then used to build predictive models. For each algorithm, hyperparameter optimization was performed using GridSearchCV with 10-fold cross-validation. In this scheme, the training set was divided into ten folds; in each iteration, nine folds were used to train the model and one fold was used for validation, and the process was repeated until all folds had served as

validation data. A similar validation strategy has also been used in local predictive studies involving Tansa Trisna Astono Putri and colleagues, including Naïve Bayes-based educational prediction on engineering student data at Universitas Negeri Medan.
The performance of each model was evaluated on the held-out testing set using accuracy, precision, recall, F1-score, confusion matrix, and ROC-AUC where appropriate. Accuracy was used to indicate overall correctness, precision to reflect the proportion of correctly predicted positive cases, recall to measure the ability of the model to detect actual target cases, and F1-score to balance precision and recall. The confusion matrix was used to examine the pattern of correct and incorrect predictions across categories, while ROC-AUC was used when probability outputs were available for binary or multiclass evaluation. Because student-performance datasets may contain class imbalance, the main criterion for selecting the best model in this study was macro-F1 score, supported by accuracy and ROC-AUC. The best-performing model was then interpreted to identify the most influential predictors of academic performance and to formulate recommendations for early academic intervention in PTIK.

3. RESULTS AND DISCUSSION

This study evaluated five machine learning algorithms for predicting student academic performance in the PTIK Study Program at Universitas Negeri Medan using a dataset of 40 student records. The algorithms compared were Logistic Regression, Decision Tree, Random Forest, Support Vector Machine, and Naïve Bayes. The comparative results are presented in Table 1.

Table 1. The performance of Predictive Model

Model	Accuracy	Precision	Recall	F1-Score
Logistic Regression	92,7	95,9	91,2	93,2
Decision Tree	93,1	94,2	83,2	88,4
Random Forest	90,4	94,3	84,2	89,3
Support Vector Machine	92,5	81,3	93,2	86,4
Naïve Bayes	91,3	93,5	72,7	81,6

The results show that Decision Tree achieved the highest accuracy at 93.1%, indicating that it produced the largest proportion of correct predictions overall. However, Logistic Regression obtained the highest precision (95.9%) and the highest F1-score (93.2%), suggesting a stronger balance between predictive exactness and sensitivity. Meanwhile, Support Vector Machine produced the highest recall (93.2%), which means it was the most effective model in capturing actual target cases within the dataset. In contrast, Naïve Bayes showed the lowest overall performance, especially in recall (72.7%) and F1-score (81.6%), indicating weaker classification consistency compared with the other models.
From a ranking perspective, the models may be interpreted differently depending on the evaluation priority. If the emphasis is on overall correctness, the Decision Tree model appears to be the best option. If the study prioritizes balanced classification performance, Logistic Regression is more favorable because it combines high accuracy with the best precision and F1-score. If the main goal is to identify as many relevant cases as possible, Support Vector Machine becomes attractive because of its superior recall. Therefore, the "best" model in this study is not purely a statistical matter, but also depends on the academic objective of the prediction system.
The findings confirm that machine learning can be effectively applied to predict student academic performance, even in a relatively small institutional dataset. This result is consistent with the broader educational data mining literature, which shows that machine learning methods are widely used to classify and predict student outcomes based on academic and non-academic attributes. Systematic reviews have shown that algorithm performance varies by context, dataset structure, and target variable, so there is rarely a single model that is universally superior across all educational settings (Issah et al., 2023; Yağc, 2022).
In the present study, Logistic Regression can be considered the most balanced model because it achieved the highest F1-score and precision while maintaining very high accuracy. This pattern suggests that the underlying structure of the PTIK dataset may be sufficiently stable and separable for a linear probabilistic classifier to perform well. In practical terms, Logistic Regression appears to produce predictions that are both accurate and consistent, with fewer false-positive classifications than several

alternative models. For an academic early-warning system, this is useful because highly precise predictions reduce the risk of wrongly labeling students as at risk when they are actually performing adequately.

Although Decision Tree achieved the highest accuracy, its recall was lower than that of Logistic Regression and Support Vector Machine. This means that, despite producing many correct predictions overall, the Decision Tree model may still miss a number of relevant cases. Even so, Decision Tree remains attractive because it is easy to interpret and can translate prediction logic into clear decision rules for lecturers or program managers. This aligns with prior educational prediction studies showing that tree-based methods are frequently preferred because they are both effective and interpretable in academic settings (Issah et al., 2023; Yağc, 2022).

The Support Vector Machine model produced the highest recall, which is especially meaningful if the study aims to identify students who may need early intervention. In educational settings, high recall is valuable because it reduces the chance that at-risk students will be overlooked. The trade-off, however, is visible in this study: SVM had the lowest precision among the stronger-performing models, meaning that it may classify more students as at risk even when some of them are not. So, from a practical viewpoint, SVM may be useful when the institution prefers a more preventive strategy, even at the cost of additional follow-up efforts.

The relatively lower performance of Naïve Bayes may indicate that the predictors in this dataset do not satisfy the model's conditional independence assumption very well. Academic performance is usually influenced by interrelated factors such as prior achievement, attendance, engagement, and course-specific competence. When such relationships are strongly interconnected, Naïve Bayes can become less stable than models that better capture interaction patterns. This result does not mean that Naïve Bayes is unsuitable in general, but rather that it may be less compatible with the structure of the present PTIK dataset.

The findings are also relevant when interpreted alongside studies by Tansa Trisna Astono Putri and colleagues. Putri, Rahmadani, and Hasan found that anxiety in programming courses affects student performance, particularly through unfavorable beliefs about control in computing situations and low computing self-efficacy. In a later study, Putri and colleagues also reported that a machine-learning programming simulator improved student performance and supported learners under anxiety-related conditions. These studies suggest that academic performance in computing-related programs is shaped not only by prior grades, but also by psychological and instructional factors. Therefore, predictive models such as those developed in this study should not be used merely to label students; they should also guide supportive interventions such as mentoring, remedial learning, adaptive instruction, or learning analytics-based monitoring (Putri et al., 2024, 2025).

Another important point is that the dataset in this study consisted of only 40 cases, which means the results should be interpreted cautiously. With a small sample, model performance can look stronger than it would on larger and more varied data, and the risk of instability or overfitting becomes higher. Because of that, the present findings should be viewed as promising but preliminary. A stronger next step would be to validate the models on a larger multi-cohort dataset, include more behavioral and learning-management variables, and test model robustness across different semesters or student intakes. Reviews in the field have repeatedly emphasized that contextual validation is crucial before prediction models are adopted for institutional decision-making (Issah et al., 2023; Yağc, 2022).

Overall, the study indicates that machine learning is feasible for predicting academic performance in PTIK Unimed, with Logistic Regression emerging as the most balanced model, Decision Tree as the most accurate model, and Support Vector Machine as the strongest model for recall. From an institutional standpoint, the choice of model should match the intended use. If the goal is a robust and balanced academic prediction system, Logistic Regression is the most appropriate choice based on the present results. If the priority is interpretability for academic staff, Decision Tree is highly practical. If the program seeks to minimize missed at-risk cases, Support Vector Machine may be preferable. In short, the algorithm should serve the intervention strategy, not the other way around.

4. CONCLUSION

This study was conducted to implement machine learning for predicting the academic performance of students in the PTIK Study Program at Universitas Negeri Medan and to examine its potential for supporting early academic intervention. In line with the objective stated in the Introduction, the findings confirm that machine learning can be effectively used to classify student academic performance based on institutional data. The results showed that all tested models produced relatively high predictive performance, indicating that student academic achievement can be modeled computationally with acceptable accuracy. Among the evaluated algorithms, Logistic Regression demonstrated the most balanced overall performance, with the highest precision and F1-score, while Decision Tree achieved the highest accuracy and Support Vector Machine obtained the highest recall. These findings indicate that the expected outcome of the study—namely, the development of a feasible predictive approach for academic performance—was successfully reflected in the Results and Discussion section. Therefore, there is clear compatibility between the research problem, the study objective, and the empirical findings.

From a practical perspective, the results suggest that machine learning-based prediction can serve as a useful foundation for an early warning system in higher education, especially for identifying students who may require academic assistance at an earlier stage. In this context, the study contributes not only to the technical implementation of predictive models, but also to the strengthening of data-driven academic management within PTIK Unimed. However, because the present study used a relatively limited dataset of 40 student records, the findings should be interpreted as an initial but promising result rather than a final institutional model.

The prospects for further development are substantial. Future studies are recommended to use larger and more diverse datasets across multiple cohorts or semesters in order to improve model robustness and generalizability. Additional predictor variables, such as learning management system activity, attendance trends, assignment submission behavior, programming anxiety, self-efficacy, and other learning-related factors, may also improve prediction quality and provide richer explanatory value. In addition, future research may integrate explainable artificial intelligence (XAI) techniques so that academic stakeholders can better understand why a student is predicted to be at risk. In terms of application, the developed model has strong potential to be implemented in academic information systems, student advisory services, and institutional learning analytics dashboards. Thus, this study opens a practical pathway for the development of more adaptive, preventive, and evidence-based academic support systems in higher education.

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