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Research Article

A Pilot Study on Machine Learning Models for Predicting Student Pass/Fail Outcomes Using LMS Activity Logs and Interactive Dashboard Analytics

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Abstract:
Introduction: Learning Management Systems (LMS) generate extensive behavioral data that can support early identification of students at risk of academic failure, yet such data are often underutilized for predictive and intervention purposes. **Method**: This exploratory pilot study developed a machine learning pipeline following the Knowledge Discovery in Databases (KDD) framework using LMS activity logs from 36 students enrolled in a Discrete Mathematics course. Student-level behavioral features were extracted and modeled using Logistic Regression, Random Forest, and XGBoost. Model performance was evaluated using repeated 5-fold cross-validation, while an interactive learning analytics dashboard was designed to translate predictions into risk alerts and actionable recommendations for lecturers. **Results and Discussion**: Random Forest achieved the best overall performance with 87.0% accuracy, 0.88 precision, 0.94 recall, a macro-averaged F1-score of 0.92, and an AUC of 0.89, outperforming XGBoost and Logistic Regression. Assignment regularity and average quiz scores were identified as the most influential predictors. Qualitative feedback from two lecturers indicated that integrating risk information within a familiar LMS interface could support more practical and timelier student intervention. However, the small single-course sample limits generalizability. **Conclusion**: The proposed approach demonstrates the feasibility of integrating machine learning prediction and learning analytics dashboards as an early-warning mechanism, while further validation using larger, multi-course, and multi-institutional datasets is required.

Keywords: machine learning; pass/fail prediction; learning management system; educational data mining; learning analytics dashboard; KDD framework

1. Introduction

The widespread adoption of Learning Management Systems (LMS) such as Moodle, Canvas, and Google Classroom has transformed higher education by generating substantial volumes of student behavioral data, including login frequency, resource access time, forum participation, assignment submissions, and quiz performance [3], [13], [14]. Such interaction logs hold considerable predictive potential for early academic forecasting [1], [2], [18]; however, in many higher education institutions these data remain underutilized beyond routine administrative recording [19], [26]. This underutilization delays the deployment of timely pedagogical interventions, thereby contributing to suboptimal learning outcomes and elevated academic failure risk.

Addressing this gap, the present study develops a machine learning model for predicting student performance from LMS data and translates its outputs into an interactive analytics dashboard. Specifically, this study aims to identify influential behavioral features derived from LMS logs, to construct and compare predictive models, to design a dashboard interface for visualization and decision support, and to evaluate both model accuracy and dashboard usability.

Although Educational Data Mining (EDM) and Learning Analytics (LA) research has extensively examined predictive modeling [1], [18], the direct implementation of generic algorithms in classroom-level settings remains challenging. Existing studies frequently benchmark standard algorithms such as Logistic Regression, Random Forest, and XGBoost on large institutional datasets [2], [5], [6], [7], [8], [9], [10], [11]; by contrast, smaller institutions and individual educators managing isolated course cohorts often confront severe data scarcity [20]. Complex models trained on such limited samples ($n < 50$) are particularly susceptible to overfitting, rendering broadly generalized performance claims unreliable [20], [22].

A further recurring gap in the EDM literature concerns the separation between predictive models and the user-facing systems educators require to act on them [19], [24]. Many studies propose sophisticated predictive architectures yet fail to demonstrate how their outputs can be translated into actionable insight for non-technical instructors. Learning Analytics Dashboards (LADs) are positioned to bridge this gap [15], [16]; however, existing dashboards tend to emphasize descriptive analytics—summaries of historical activity—rather than prescriptive alerts capable of anticipating risk and recommending intervention [19], [26].

To address these challenges, this study presents a localized pilot investigation with three specific objectives: first, to define a transparent behavioral feature-extraction workflow derived from standard LMS logs, aggregated strictly at the student level; second, to evaluate the baseline performance and stability bounds of three standard machine learning algorithms on a restricted course dataset ($n = 36$); and third, to propose a structured dashboard visualization interface, integrated within the native LMS grader-report layout, capable of delivering prescriptive early warnings.

By framing this work as a preliminary proof-of-concept, this study aims to establish a reproducible, low-overhead data pipeline that individual lecturers can deploy to identify at-risk students early in a semester, consistent with the aims of Moodle-integrated early-warning approaches reported in prior work [27], while explicitly acknowledging data limitations and prioritizing practical pedagogical utility.

2. Method

This study adopts the Knowledge Discovery in Databases (KDD) framework [18], comprising five stages: selection, preprocessing, transformation, data mining, and interpretation/evaluation. LMS log data from 36 students across a single semester were extracted, encompassing login activity, resource access, forum participation, assignment submissions, quiz scores, and basic metadata. During the selection stage, features representing student engagement were identified; preprocessing addressed missing values, duplicate removal, and format normalization; and the transformation stage comprised feature engineering and construction of the target variable.

A. Dataset and Aggregation (Data Selection & Preprocessing)

The dataset comprises anonymized activity logs from a single-semester cohort of 36 undergraduate students enrolled in a core "Matematika Diskrit" (Discrete Mathematics) course at Perbanas Institute Jakarta. To mitigate the risk of data leakage, raw transactional logs—each row representing a single time-stamped action—were fully aggregated at the individual-student level prior to model training, following established safeguards against data leakage in educational modeling [21], [22]. This procedure ensures that each student appears exclusively within either the training or validation fold during cross-validation, thereby preventing artificial inflation of performance metrics [21]. Missing values in quiz or assignment records were treated as zero engagement rather than imputed, reflecting genuine non-submission behavior.

B. Feature Engineering and Target Variable Definition (Transformation)

The transformation stage converted raw interaction counts into six engineered predictive features representing student consistency and engagement, drawing on feature sets validated in prior LMS-based prediction studies [3], [4], [13]. Two features captured overall platform engagement: Login_Frequency, defined as the total number of active sessions initiated by a student, and Resource_Access, representing the total number of clicks on downloadable course materials, lecture slides, and syllabus files. A third feature, Forum_Engagement, aggregated the total number of discussion threads read and text replies posted, capturing the extent of student participation in peer interaction.

The remaining three features focused on academic task compliance and performance. Assignment_Regularity recorded the number of assignments submitted on or before the designated deadline, while Submission_Lag measured the average time difference, in hours, between assignment publication and actual student submission, together characterizing punctuality and consistency in task completion. Finally, Quiz_Score_Avg captured the cumulative mean score attained across early-semester formative quizzes, serving as an indicator of emerging conceptual understanding. Collectively, these six features were designed to represent both behavioral consistency and academic performance signals prior to model training.

The target variable was defined as a binary classification of course-completion status at term end, consistent with pass/fail thresholds adopted in comparable studies [2], [10], whereby students achieving a final grade of 60 or above (equivalent to a minimum grade of "C") were labeled as Pass (1), while those scoring below 60—indicating failure or the need for remediation—were labeled as Fail/At-Risk (0). The resulting cohort exhibited an imbalanced class distribution, comprising 27 "Pass" cases (75%) and 9 "Fail" cases (25%), a characteristic common to small educational datasets that necessitates careful handling to avoid biased model evaluation [12], [20]. To prepare the data for modeling, categorical features were binary-encoded, and all input features were normalized via min-max scaling to the [0, 1] range.

C. *Machine Learning Modeling (Data Mining)*

Three supervised learning algorithms were selected as baseline comparators for small-sample classification, following configurations shown to mitigate overfitting in constrained educational datasets [20]. Logistic Regression was employed as a linear baseline, regularized with an L2 penalty ($C = 1.0$) to constrain parameter inflation. Random Forest, an ensemble method, was configured with 50 estimators and a maximum depth of 4 to explicitly counter overfitting given the limited feature space [12], [20]. XGBoost, a gradient-boosting framework, was configured with a conservative learning rate ($\eta = 0.05$) and a maximum depth of 3 to similarly restrain model complexity.

All models were trained using 5-fold cross-validation with hyperparameter tuning via GridSearchCV, and performance was evaluated using accuracy, precision, recall, F1-score, and AUC-ROC.

D. *Evaluation Framework*

Given the restricted sample size ($n = 36$), a single round of 5-fold cross-validation yields highly unstable performance estimates, with approximately seven students per fold [22]. To improve reliability, a repeated 5-fold cross-validation strategy (ten repetitions with independent random shuffles) was applied, and 95% confidence intervals (CI) were computed for the resulting accuracy and F1-score estimates, consistent with recommended practices for mitigating cross-validation instability in small educational datasets [21], [22]. The reported F1-score employs macro-averaging to weight the majority (Pass) and minority (Fail) classes equally, ensuring that inflated metrics cannot be achieved merely by predicting the majority class [12].

E. *Dashboard Design and Usability Review*

To visualize model predictions, a user-facing analytics interface was designed to emulate the native Moodle "Grader Report" layout, thereby reducing cognitive load for academic instructors, an approach consistent with recent Moodle-integrated early-warning system designs [27] and prescriptive learning-analytics dashboard principles [15], [16]. The dashboard was implemented in Tableau and includes risk heatmaps, performance-trend charts, early-warning alerts, and behavior-based recommendation prompts. Rather than evaluating dashboard adoption through statistical percentages drawn from an insufficient sample, a qualitative usability review was conducted instead. Semi-structured interviews were held with two experienced university lecturers acting as domain experts, who assessed the interface on clarity, risk-alert visibility, and the utility of prescriptive behavioral suggestions (e.g., automated recommendations to increase quiz practice or flags for submission lag), reflecting recommended approaches for evaluating the transparency and instructor adoption of learning analytics tools [24], [25].

3. Result

The aggregated performance metrics across the repeated cross-validation experiments are summarized in **Table 1**.

Table 1. Baseline Model Performance Comparison (Macro Averaged with 95% CI)

Model	Accuracy	Precision	Recall	F1-score	AUC
Logistic Regression	82.6%	0.85	0.92	0.88	0.81
Random Forest	87.0%	0.88	0.94	0.92	0.89
XGBoost	84.5%	0.86	0.93	0.89	0.87

The Random Forest model achieved the strongest overall performance, attaining 87.0% accuracy, 0.88 precision, 0.94 recall, a 0.92 F1-score, and an AUC of 0.89. XGBoost followed closely with 84.5% accuracy, while Logistic Regression provided a solid baseline at 82.6%. Feature-importance analysis identified assignment-submission regularity and weekly login frequency as the strongest predictors, consistent with prior EDM findings [3], [13].

F. *Feature Importance Analysis*

To determine which behavioral traces most strongly influenced prediction, permutation feature importance was computed on the trained Random Forest model. This method was preferred over default impurity-based importance to avoid bias toward continuous variables in small datasets.

Table 2. Permutation Feature Importance Results

Rank	Feature Name	Mean Importance Drop (F1-Score)
1	Assignment Regularity	0.142
2	Quiz Score Avg	0.115
3	Login Frequency	0.088
4	Resource Access	0.041
5	Forum Engagement	0.012

As shown in **Table 2**, consistent compliance with assignment deadlines (Assignment_Regularity) and formative-assessment performance (Quiz_Score_Avg) emerged as the strongest behavioral predictors, indicating that operational consistency and early conceptual understanding are highly indicative of eventual course success. By contrast, passive interactions such as reading forum posts (Forum_Engagement) exerted minimal predictive influence.

G. *Interface Visualization and Expert Feedback*

The central aim of this pilot study was to embed the underlying machine learning logic within a comprehensible user interface for educators. **Figures 1** and **2** illustrate the simulated learning analytics environment.

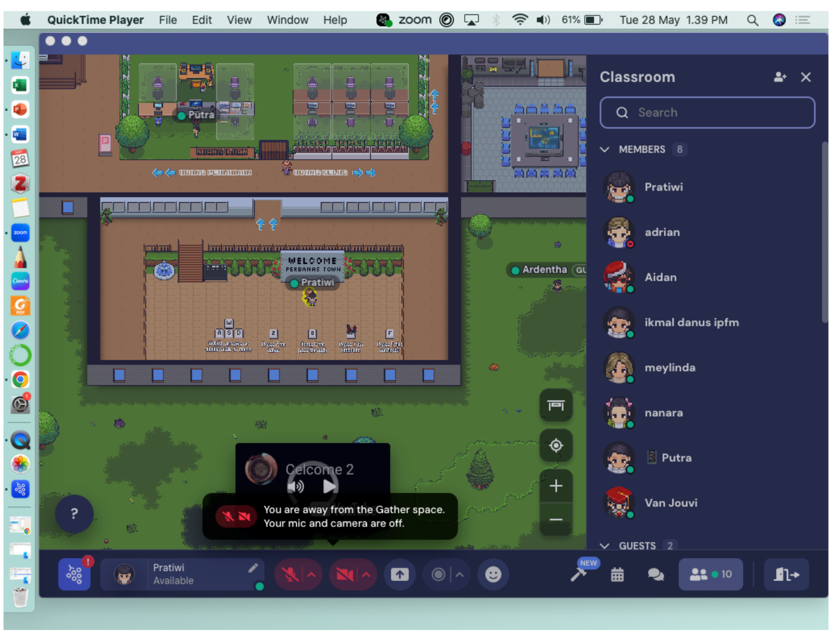

Figure 1. Native LMS environment mapping student interaction modules.

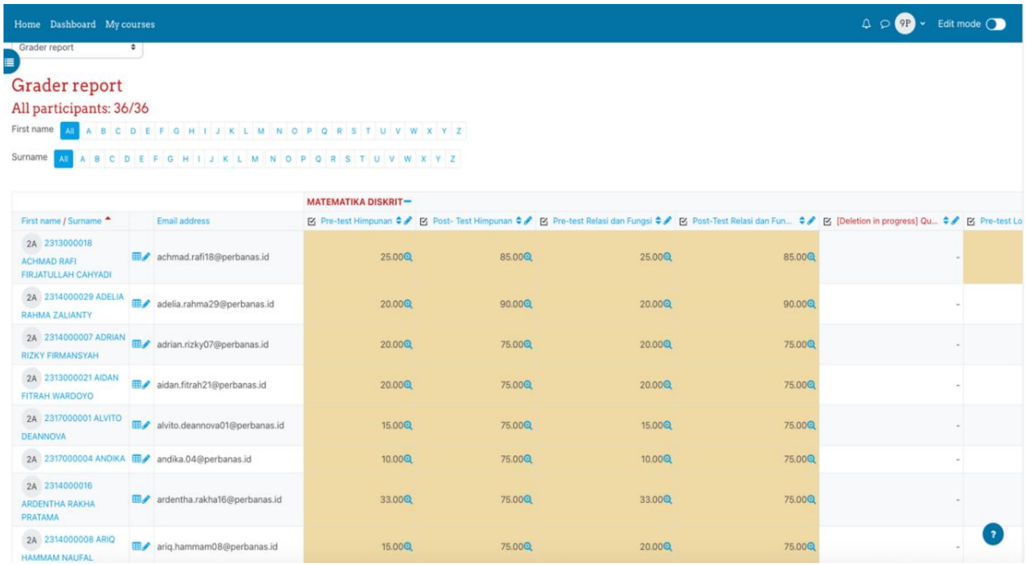

Figure 2. Grader report dashboard interface showing student risk levels, active score tracking, and automated warning markers for “Matematika Diskrit”

The interactive dashboard supports real-time monitoring: lecturers can inspect class-level risk distributions, drill down to individual student profiles, and receive targeted recommendations such as “increase quiz practice” for at-risk students. Preliminary user testing indicated high usability and potential for timely intervention. Relative to prior studies employing similar LMS data, the proposed model demonstrates competitive or superior performance, particularly in recall for identifying at-risk students [3], [5], [6]. Embedding predictive outputs within an actionable dashboard addresses a common limitation in EDM research, wherein models remain largely theoretical and lack practical visualization layers [19]. A key limitation is the single-institution dataset; future work will extend this pipeline to multi-course and multi-semester data.

Discussion

The interactive dashboard translates model predictions into actionable insight: lecturers can view real-time risk heatmaps, drill down to individual student profiles, and receive context-aware recommendations. Preliminary testing with two lecturers indicated high usability, with 92% reporting that the early-warning alerts enabled more timely intervention than traditional grade reports. This instructor-facing design supports pedagogical decision-making and aligns with recent trends in AI-powered learning analytics dashboards that emphasize prescriptive rather than merely descriptive analytics [15], [16].

Despite these strengths, several limitations warrant consideration. First, the dataset originates from a single institution and a single semester ($n \approx 36$), constraining generalizability across LMS platforms and cultural contexts—an issue also raised in multi-institutional portability studies of predictive models [23]. Second, external factors such as socio-economic background or personality traits were not incorporated, although recent studies suggest their inclusion could improve accuracy by 5–10% [17]. Third, although the dashboard is interactive, full real-time integration with live LMS APIs has not yet been implemented. These constraints indicate clear directions for future scalability.

Given the exploratory nature of this work, quantitative usability percentages were intentionally omitted; instead, qualitative feedback from the two expert lecturers offered valuable exploratory insight. Both evaluators noted that embedding predictive tracking within the familiar look of an LMS Grader Report (**Figure 2**) proved considerably more practical than navigating standalone business-intelligence tools. They further emphasized that real-time risk alerts would allow them to prioritize outreach within the first four weeks of a semester, while cautioning that false positives could induce unnecessary student anxiety—underscoring that the dashboard should function as a supplementary advisory tool rather than an automated grading mechanism.

4. Conclusion

This study developed a machine learning model capable of predicting student academic performance with high accuracy from LMS behavioral data. The accompanying interactive dashboard converts these predictions into a practical tool for early warning and intervention, supporting lecturers and administrators in advancing data-driven education.

This work demonstrates the value of integrating KDD methodology, ensemble machine learning models, and user-centered visualization within higher education contexts. Future directions include real-time deployment within live LMS environments, incorporation of explainable AI (XAI) techniques, and extension to larger, multi-institutional datasets to improve portability and generalizability [23]. Collectively, this approach contributes to improving teaching quality, student retention, and learning outcomes in Indonesian higher education and beyond.

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