



Development of a Machine Learning Model for Predicting Graduate Learning Outcome Achievement in Outcome-Based Vocational Education

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Abstract. Outcome-Based Education (OBE) requires continuous monitoring of Graduate Learning Outcome (GLO) achievement, yet in most Indonesian vocational institutions this monitoring remains a retrospective, end-of-program exercise rather than a tool for early intervention. This study develops and evaluates a machine learning approach for predicting GLO achievement using institutional academic assessment records of 137 first-year students (2024 cohort) enrolled in the D3 Accounting program at Politeknik Negeri Bali. After excluding 29 students whose GLO indicators had not yet been assessed, 108 records covering 24 measurable indicators were analyzed. Knowledge- and Attitude-domain scores were used as predictors for a composite Skills-domain achievement outcome, modeled both as a continuous score (regression) and as OBE-defined achievement categories (classification); the two framings were combined because a continuous score supports fine-grained risk ranking while a categorical output maps directly onto the discrete achievement bands academic advisors already use. Five regression algorithms and six classification algorithms were compared using 10-fold and leave-one-out cross-validation, respectively. Ridge Regression achieved the best regression performance ($R^2 = 0.97$, MAE = 0.32), while Gaussian Naive Bayes achieved the best macro-F1 (0.80) for the imbalanced three-class categorization. Correlation analysis further revealed that several indicators, despite representing conceptually distinct competencies, carried identical scores for nearly all students — a data-integrity artifact traced to the institution's indicator-to-course mapping rather than genuine pedagogical association. The findings demonstrate the technical feasibility of GLO prediction from partial assessment data while underscoring the need for cleaner, more granular, and longitudinal data before such models can be reliably deployed for early-warning decision-making.

Keywords: Outcome-Based Education; Graduate Learning Outcomes; Machine Learning; Prediction Model; Vocational Education

1 Introduction

Outcome-Based Education (OBE) has become the dominant curriculum paradigm in Indonesian higher and vocational education, shifting curriculum design and evaluation from content coverage toward demonstrable achievement of Graduate Learning

Outcomes (GLO), known locally as *Capaian Pembelajaran Lulusan*. Institutions translate GLO into course-level outcomes, assess them throughout the curriculum, and are expected to use the resulting data for continuous improvement (Anindya et al., 2024; Rahate et al., 2020). In practice, however, GLO measurement in most Indonesian institutions remains a descriptive, end-of-semester or end-of-program reporting exercise. Several studies have proposed information systems and dashboards to compute and visualize GLO achievement (Aminuddin et al., 2024; Herlambang et al., 2023; Wijaya et al., 2023; Zakyradi & Saptadi, 2023), but these are fundamentally summative: they report what has already happened rather than anticipating what is likely to happen. A genuine continuous-improvement loop needs an early-warning capability that flags likely under-achievement while pedagogical intervention is still possible.

Problem Statement. The practical problem this study addresses is therefore twofold. First, academic advisors have no data-driven way to anticipate a student's likely GLO achievement before it is formally measured, since existing institutional systems only report indicators once complete. Second, advisors need such anticipation in two complementary forms: a continuous risk score that ranks students by urgency, and a discrete achievement category that maps onto the OBE bands (e.g., "Developing") already used in advising and accreditation. A regression-only model gives a ranking but no actionable category; a classification-only model gives a category but discards prioritization detail. This is why the study develops and compares both a regression and a classification approach to the same prediction problem, rather than treating either as sufficient alone.

Machine learning (ML) has been used for exactly this kind of anticipatory task elsewhere: predicting dropout risk so intervention protocols can be triggered in time (Setiawan & Wibowo, 2024), predicting graduation outcomes from academic records with decision-tree and Naive Bayes classifiers (Fansyuri & Yunita, 2025; Prahastiwi et al., 2022), predicting graduates' employment status (Syahputra Ritonga et al., 2025), and, beyond education, deploying regression models via CRISP-DM (Fattah et al., 2022), recommender systems (Sibuea & Widodo, 2024), sequence forecasting (Sudiatmika et al., 2024), health-risk prediction (Kaur et al., 2022), and text classification such as plagiarism detection (Triputra et al., 2019) and sentiment analysis (Meliyawati & Hasan, 2024). Within OBE specifically, Tjandra et al. (2024) showed that course-level OBE outcomes can be predicted with ML, and Li and Li (2023) argued that ML should itself be integrated within OBE-oriented curricula. What remains unexplored is whether GLO achievement — the program-level outcome OBE ultimately exists to guarantee — can be predicted directly from an institution's own routinely collected assessment records, and what practical and data-quality obstacles arise when doing so with real, unaltered institutional data.

This study addresses that gap using actual GLO assessment records from the D3 Accounting program at Politeknik Negeri Bali (2024 cohort). Rather than assuming the dataset is analysis-ready, the study interrogates its structure — missingness patterns, the mapping between indicators and the courses that produce them, and inter-indicator redundancy — before committing to a modeling strategy, and reports the resulting constraints transparently alongside the model results. The two research questions are: (1) how should a machine learning model be designed to predict GLO achievement in

OBE-based vocational education, given the structure of routinely collected institutional data; and (2) how does such a model perform when implemented and evaluated on real student records? The intended contributions are a documented pipeline for constructing an analysis-ready GLO dataset from institutional PDF reports; an empirical account of the data-quality characteristics any GLO-based ML effort at this institution must confront; and a comparative evaluation of regression and classification algorithms for predicting GLO achievement, to inform future development of an OBE monitoring and early-warning capability.

The remainder of this paper is organized as follows. Section 2 describes the data source, preprocessing, feature and target construction, and the modeling and validation procedure. Section 3 presents descriptive statistics, model performance, and a critical discussion of what the results do and do not support. Section 4 concludes with the study's contributions, limitations, and directions for future work.

2 Methodology

This study followed a CRISP-DM-inspired workflow business understanding, data understanding, data preparation, modeling, and evaluation consistent with prior applied machine learning work in similarly structured prediction problems (Fattah et al. 2022). Each stage is described below.

2.1 Data Source

The dataset was derived from the official CPL Achievement Report (*Laporan Capaian Pembelajaran Lulusan*) issued by the D3 Accounting program, Politeknik Negeri Bali, for the 2024 admission cohort. The institutional report is a per-student, multi-page administrative PDF document (548 pages, one 4-page block per student) listing scores (*Nilai*, 0–100) and achievement categories for 28 CPL indicators: 9 Specific Skills (*Keterampilan Khusus*, KK1–KK9), 8 General Skills (*Keterampilan Umum*, KU1–KU8), 9 Knowledge (*Pengetahuan*, P1–P9), and 2 Attitude (*Sikap*, S1–S2) indicators. The report covered 137 registered students.

2.2 Data Extraction and Screening

Structured records were programmatically extracted from the PDF using text-layout extraction and pattern matching, yielding one row per student with 28 score/category fields. Screening revealed that 29 of 137 students (21.2%), all belonging to a single class section, had no CPL scored at all (recorded as “Belum Diukur” / not yet measured for every indicator); these were excluded as non-informative for modeling, leaving 108 usable student records. Four indicators — KK8, KU1, KU2, and S2 — were unmeasured for the entire cohort (all 137 students) and were excluded from further analysis, leaving 24 usable indicators. Two students had 2–3 missing values among the remaining 24 indicators; the single missing predictor value occurring in the modeling subset (P7, one student) was imputed with the column median.

2.3 Redundancy Screening

Before treating the 24 indicators as independent features, a Pearson correlation analysis was performed across all indicator pairs on the 106 students with fully complete records. This step is reported in detail in Section 3 because it surfaced a data-quality finding — several indicator pairs from conceptually unrelated competency domains carried identical scores for nearly all students — that materially affects how the modeling results should be interpreted.

2.4 Feature and Target Construction

The available dataset is a single cross-sectional snapshot rather than a longitudinal, per-semester record, so “early prediction” in this study is operationalized as predicting the composite achievement of the applied-skill domain from currently available knowledge-and-attitude scores, rather than forecasting across calendar time. The 9 Knowledge (P1–P9) and 1 measured Attitude (S1) indicators were used as the 10-feature predictor set. The composite target was constructed from the 14 measured Skills-domain indicators (KK1–KK7, KK9, KU3–KU8) in two forms: (a) a continuous score, the arithmetic mean of the 14 indicator values, used for regression; and (b) a categorical label, obtained by applying the institution's own achievement bands to the continuous composite — *Berkembang/Developing* (<75), *Kompeten/Competent* (75–84), and *Sangat Kompeten/Exemplary* (≥ 85) — together with a simplified binary At-Risk (<75) versus Achieving (≥ 75) grouping intended for early-warning use.

2.5 Modeling and Validation

Regression was evaluated with 10-fold cross-validation using Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R^2 , compared against a naive mean-prediction baseline, across five algorithms: Linear Regression, Ridge Regression, Random Forest Regressor, Support Vector Regression (RBF kernel), and k-Nearest Neighbor Regression ($k=5$). Classification was evaluated with Leave-One-Out Cross-Validation (LOOCV) rather than stratified k-fold, because the minority class in the three-class target (*Berkembang*, $n=5$) is too small to populate stratified folds reliably. Six algorithms with class-balanced weighting were compared: Gaussian Naive Bayes, Decision Tree, Random Forest, Logistic Regression, Support Vector Machine (RBF kernel), and k-Nearest Neighbor ($k=5$), reported with Accuracy, macro-averaged Precision/Recall/F1, and confusion matrices; the binary At-Risk framing additionally reports At-Risk-class recall as the metric most relevant to an early-warning use case. All feature-scaling-sensitive algorithms (SVR/SVM, KNN, Logistic Regression) used standardized (zero-mean, unit-variance) inputs. All analyses were implemented in Python 3.12 using scikit-learn 1.8.

3 Result and Discussion

3.1 Result

Table 1 summarizes the dataset after screening: its composition (top) and domain-level descriptive statistics for the 108 usable students (bottom).

Table 1. Dataset Composition and Domain-Level Descriptive Statistics (n = 108)

Description / Domain	Value	Mean	SD	Min–Max
Total registered students (2024 cohort)	137			
Excluded — no CPL measured (21.2%)	29			
Usable students	108			
Indicators analyzed of 28 total (4 unmeasured cohort-wide: KK8, KU1, KU2, S2)	24			
<i>Pengetahuan</i> — P1–P9 (predictors)		80.78	4.67	65–99
<i>Sikap</i> — S1 (predictor)		79.73	4.13	67–92
<i>Keterampilan Khusus</i> — 8 measured (target)		80.44	4.83	66–99
<i>Keterampilan Umum</i> — 6 measured (target)		80.35	4.10	66–95

Figure 1 shows the Pearson correlation matrix across all 24 usable indicators. Correlations within and between domains were generally moderate-to-strong ($r = 0.6\text{--}0.95$), consistent with a general academic-ability factor underlying student performance. However, the analysis also revealed three indicator pairs with $r = 1.00$, i.e., identical scores for 106–107 of 108 students, all crossing the predictor–target boundary defined in Section 2: one Specific-Skills indicator was identical to a Knowledge indicator concerning scientific writing and communication; a second Specific-Skills indicator was identical to a General-Skills indicator concerning self-evaluation of teamwork; and a third Specific-Skills indicator (an audit-procedure competency) was identical to the same Knowledge indicator on scientific writing. This is notable because the paired indicators describe conceptually unrelated competencies — for instance, the audit-procedure indicator has no substantive connection to scientific-writing competency. Manual inspection of the source report confirmed the duplication was present in the original document rather than introduced during data extraction. This finding is treated as a probable data-quality artifact arising from the institution's indicator-to-course mapping configuration and is discussed further in Section 3.2, since it directly affects how the regression performance below should be interpreted.

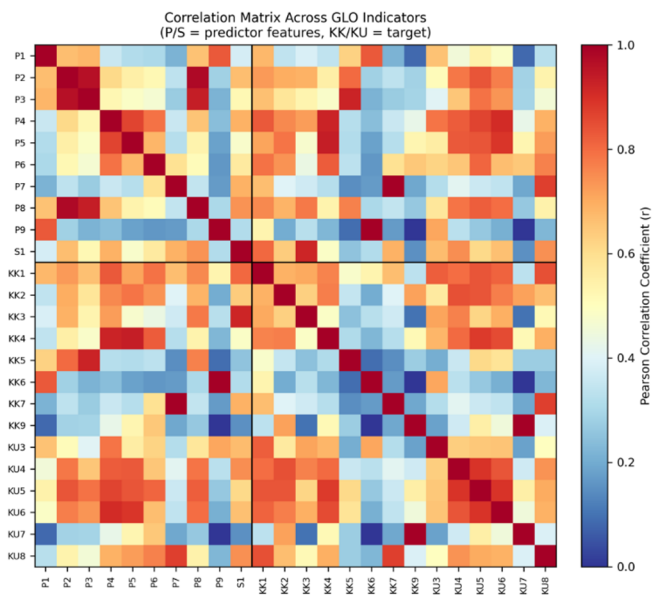


Figure 1. Pearson correlation matrix across 24 CPL indicators (P1–P9, S1 = predictors; KK/KU = target components).

Table 2 compares regression algorithms for predicting the continuous composite Skills-domain score from the 10 Knowledge/Attitude features, against the mean-prediction baseline (MAE = 2.29, RMSE = 3.08).

Table 2. Dataset Composition and Domain-Level Descriptive Statistics (n = 108)

Model	MAE	RMSE	R ²
Linear Regression	0.323	0.537	0.970
Ridge Regression	0.320	0.522	0.971
Random Forest Regressor	0.801	1.157	0.859
SVR (RBF kernel)	0.662	1.445	0.781
KNN Regressor (k=5)	0.702	1.111	0.870
Baseline (predict mean)	2.293	3.085	0.000

Ridge Regression achieved the best overall regression performance ($R^2 = 0.971$, MAE = 0.320), narrowly ahead of ordinary Linear Regression, with both linear models clearly outperforming the nonlinear alternatives (Random Forest, SVR, KNN). Figure 2 shows predicted versus actual composite scores for the Ridge model. A supplementary Random Forest feature-importance analysis (computed for interpretability, though Random Forest was not the top-performing model) found that two Knowledge indicators — P6 (business/economics/quantitative-methods

knowledge) and P4 (taxation operational knowledge) — jointly accounted for over 60% of importance, while the remaining seven Knowledge/Attitude indicators contributed comparatively little.

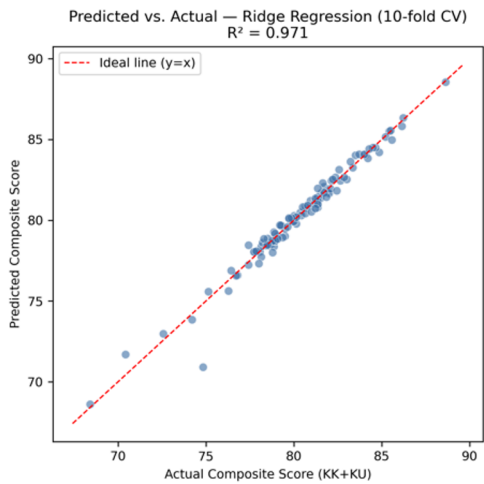


Figure 2. Predicted vs. actual composite Skills-domain score, Ridge Regression, 10-fold cross-validated predictions.

For the categorical framing, the composite target was highly imbalanced: of 108 students, 96 (88.9%) fell in the “Kompeten” band, 7 (6.5%) in “Sangat Kompeten”, and only 5 (4.6%) in “Berkembang”. Table 3 reports three-class classification performance under LOOCV.

Table 3. Three-Class Classification Performance (LOOCV, class-balanced weighting)

Model	Accuracy	Macro-P	Macro-R	Macro-F1
Gaussian Naive Bayes	0.926	0.748	0.865	0.797
Decision Tree	0.907	0.691	0.687	0.686
Random Forest	0.944	0.900	0.720	0.788
Logistic Regression	0.907	0.715	0.858	0.768
SVM (RBF kernel)	0.880	0.681	0.848	0.734
KNN (k=5)	0.917	0.807	0.577	0.642

Gaussian Naive Bayes achieved the best macro-F1 (0.797), ahead of the ensemble and kernel-based alternatives. Figure 3 shows its LOOCV confusion matrix: of 5 *Berkembang* students, 4 were correctly identified; of 7 *Sangat Kompeten* students, 6 were correctly identified; and 90 of 96 *Kompeten* students were correctly identified.

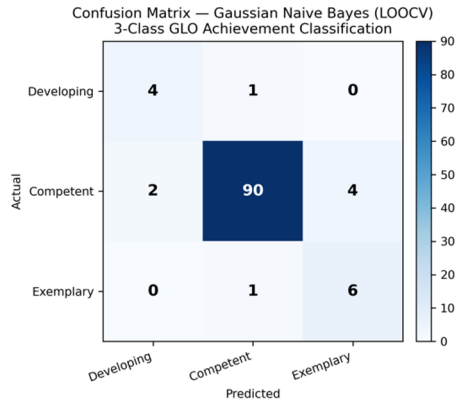


Figure 3. Predicted vs. actual composite Skills-domain score, Ridge Regression, 10-fold cross-validated predictions.

Under the simplified binary At-Risk/Achieving framing (LOOCV), Gaussian Naive Bayes, Logistic Regression, and SVM tied for both the best overall metrics (Accuracy = 0.972, macro-F1 = 0.856) and the best At-Risk-class recall (0.800, i.e., 4 of 5 at-risk students correctly flagged), while Decision Tree and Random Forest reached similar accuracy (0.954–0.963) but a substantially lower At-Risk recall (0.400), and KNN achieved the highest raw accuracy (0.981) with an intermediate At-Risk recall (0.600). This pattern — high overall accuracy but variable minority-class recall — illustrates why accuracy alone is a misleading metric for this imbalanced, early-warning-oriented task, and why At-Risk recall was reported as the decision-relevant metric.

3.2 Discussion

The regression results (R^2 up to 0.971) should not be read at face value as evidence of a strong, generalizable early-warning signal. Part of the apparent predictability is a genuine general-ability effect, consistent with prior OBE findings that overall academic engagement correlates across competency domains (Rahate et al., 2020). Part of it, however, is mechanical: one Specific-Skills target indicator was found to be an exact duplicate of a Knowledge predictor indicator (Section 3.1), so the composite target is partly a linear function of one of its own predictors — a leakage-like artifact, not a true predictive relationship, that inflates R^2 by an unknown degree. The dominant role of the taxation- and business-related Knowledge indicators in the importance ranking is more plausibly substantive, since this knowledge plausibly underpins several practical accounting skills in the target set, but this too cannot be fully disentangled from the duplication artifact without the institution's indicator-to-course mapping table. Before this or any model built on this indicator set informs advising decisions, the mapping should be verified with the academic information system administrator to confirm whether the three $r = 1.00$ pairs reflect an intentional shared-assessment design or a configuration error.

The classification results must likewise be read cautiously given class imbalance. With only 5 Developing and 7 Exemplary students among 108, LOOCV metrics for these minority classes are statistically fragile: one additional student classified differently shifts recall by 20 percentage points for the Developing class. The 0.800 At-Risk recall achieved by three algorithms is an encouraging feasibility signal, consistent with prior early-warning work (Setiawan & Wibowo, 2024), but with an effective minority sample of five this should be treated as preliminary feasibility evidence, not a validated performance guarantee. It is also consistent with related graduation- and outcome-prediction studies (Fansyuri & Yunita, 2025; Prahastiwi et al., 2022; Syahputra Ritonga et al., 2025) in which simple, well-regularized classifiers (Naive Bayes, Logistic Regression) matched or outperformed more complex ensemble and kernel methods on small, largely linear datasets — algorithm complexity was not a substitute for more or cleaner data.

Against existing OBE monitoring tools, most current systems in the Indonesian literature are descriptive dashboards or reporting applications (Aminuddin et al., 2024; Herlambang et al., 2023; Wijaya et al., 2023; Zakyrafi & Saptadi, 2023). This study shows a predictive layer is technically achievable on top of such systems' underlying data, extending the course-level prediction work of Tjandra et al., (2024) to the program-level GLO construct and responding to calls to integrate machine learning more deeply into OBE curricula (Li & Li, 2023). At the same time, the greatest obstacle is not algorithm selection but data structure: a single-cohort, cross-sectional, potentially mis-mapped indicator export is a fundamentally weaker basis for prediction than genuine longitudinal, course-level data collected across multiple semesters and cohorts.

Limitations. This study has five main limitations. First, the data represent a single cohort at a single institution, so generalizability is untested. Second, the dataset is a cross-sectional snapshot; “early prediction” here means predicting less-observed indicators from currently observed ones at the same time point, not forecasting a student's future trajectory. Third, the usable sample ($n = 108$) is small, and classification suffers severe class imbalance (5 and 7 students in the minority classes). Fourth, the duplicate-indicator artifact is a genuine, unresolved data-quality concern limiting confidence in the regression results specifically. Fifth, predictors and target derive from the same institutional scoring pipeline, so any unknown upstream error propagates into both.

Future Work. Future research should prioritize (a) verifying and, if necessary, correcting the indicator-to-course mapping with the institution's academic system; (b) collecting genuine longitudinal, course-level data across multiple semesters and cohorts, enabling true early-to-later-time prediction rather than same-time-point prediction; (c) extending the analysis to other study programs to test generalizability; and (d) applying explainable-AI methods (e.g., SHAP) to make predictions interpretable for academic advisors.

4 Conclusion

This study developed and evaluated a machine learning pipeline for predicting Graduate Learning Outcome (GLO) achievement using real institutional assessment records from the D3 Accounting program at Politeknik Negeri Bali. Regression and classification were pursued jointly because they serve complementary advising needs — continuous risk ranking versus discrete, actionable categories — rather than because either was assumed sufficient alone. Using Knowledge and Attitude domain scores as predictors, Ridge Regression predicted the composite Skills-domain score with $R^2 = 0.971$, and Gaussian Naive Bayes achieved the best macro-F1 (0.797) for a three-class categorization, with an 0.800 recall for at-risk students under a simplified binary framing. These results demonstrate the technical feasibility of building GLO prediction models directly from an institution's own routinely collected data. However, the study also surfaced important, disclosed caveats: a probable indicator-to-course mapping artifact producing exact-duplicate indicator pairs across the predictor–target boundary, a small and severely imbalanced sample for classification, and a cross-sectional rather than longitudinal data structure that constrains what “early prediction” can honestly mean with the current dataset. The contribution of this work is therefore twofold: a working, comparatively-evaluated GLO prediction pipeline, and a transparent account of the data-quality conditions that must be resolved before such a model can be responsibly deployed as an OBE early-warning tool. Future work extending this study to multi-cohort, course-level longitudinal data is needed to build a genuinely predictive, rather than same-time-point descriptive, GLO monitoring capability

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