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Article

Predictive model for students' academic performance using machine learning approach

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Abstract: The early prediction of students' academic performance using machine learning has emerged as a valuable approach for identifying at-risk learners and enabling timely intervention. Many factors, such as students' academic background, prior performance, institutional policies, and learning environment, influence educational outcomes; their complex interplay remains inadequately understood in many contexts. This study aimed to explore the effectiveness of machine learning algorithms in predicting students' academic performance at Adamawa State University, Mubi, Adamawa State, Nigeria. This study used 1,730 datasets from the academic records of first-year students from the Faculty of Science for the 2024/2025 academic session. The study split the datasets into 80% training and 20% for testing. Data were analysed using the Waikato Environment for Knowledge Analysis (Weka) and Python. The model was evaluated using students' cumulative grade point averages (CGPAs) from the academic session results. The machine learning algorithms used were Logistic Regression (LR), Random Forest (RF), Decision Trees (DT), Naïve Bayesian (NB), and Support Vector Machines (SVM). Experimental results based on various performance metrics indicate that the SVM model achieved the best result with an accuracy of 0.92, precision of 0.92, recall of 0.93, and F1-score of 0.93. The results revealed that the SVM approach outperforms individual benchmark methods and provides robust insight into factors that determine academic success. The findings offer evidence-based guidance for educators, departments, faculties, institutional management, and policymakers to design targeted interventions to improve learning outcomes.

Keywords: students; performance; prediction; machine learning algorithms; datasets

1. Introduction

Student academic performance in higher education is extensively studied to address persistent challenges, including academic underachievement, elevated dropout rates, and delayed graduation [1,2]. Early prediction of student academic performance represents a prominent application of educational data mining, enabling timely interventions to improve learning outcomes [3]. By analysing historical academic records, such a predictive model provides valuable insights for educational institutions to refine pedagogical approaches and tailor instructional methods to diverse student backgrounds [4]. Prediction systems facilitate the early identification of at-risk learners, enabling targeted support throughout the academic process. Academic performance metrics are a significant determinant in institutional ranking methodologies, in which improved student outcomes lead to elevated institutional standings [5]. Additionally, from a student perspective, sustained high academic achievement serves as a critical, objectively assessable criterion for employers, thereby increasing the probability of successful graduate employment outcomes [6].

A variety of machine learning techniques, including decision trees, artificial neural networks, matrix factorization, collaborative filters, and probabilistic graphical models, have been utilised to develop prediction algorithms for student performance [7]. However, the existing literature presents inconsistent findings regarding which model achieves the highest prediction accuracy. Furthermore, prior research has not conclusively identified a machine learning model that effectively enhances student learning outcomes, most especially among university students.

The analysis and prediction of student performance enable educators to identify areas requiring improvement, thereby facilitating targeted interventions to enhance academic outcomes. Ofori et al. [3] state that high prediction accuracy in students' performance helps identify low-performing students at the beginning of the learning process. Furthermore, such analytics support students in optimising their learning strategies and assist administrative bodies in refining institutional processes [8, 9]. Timely prediction of student performance enables educators to identify students at risk of academic underperformance and implement targeted interventions at appropriate stages of the learning process [2].

The primary goal of this study is to explore the effectiveness of machine learning algorithms in identifying, analysing, and predicting the factors influencing students' varying academic performance levels at Adamawa State University, Mubi, Adamawa State, Nigeria, using the institution's structured dataset of student academic information. The study systematically identifies key predictors of student outcomes and provides actionable insights for academic intervention and policy enhancement.

The contribution of this paper is as follows:

- Identification of the factors that contribute to varying levels of student performance in promoting student success at the Adamawa State University, Mubi.
- The use of machine learning techniques to evaluate the effectiveness of the algorithms in predicting student academic performance at Adamawa State University, Mubi.
- Recommends that the government and management of Adamawa State University, Mubi, use the outcomes of models to provide timely interventions and reduce the burden on academic staff in improving students' performance.

This paper organises its subsequent sections as follows: Section 2 provides a review of previous research on students' performance using machine learning algorithms. Section 3 discussed the materials and methods used for data collection, pre-processing, feature selection, model training, and testing. The classifiers used in the analysis of the datasets were briefly discussed in Section 4. Section 5 discusses evaluation metrics for students' performance using machine learning models. Section 6 presents the results of the machine learning models and discusses the confusion matrix and classification reports. Section 7 concludes the study based on the models' performance metrics.

2. Related works

Abubakar et al. [10] use a dataset of academic records, attendance, assessment scores, and institutional data to construct a hybrid machine learning model to predict student academic success at Umaru Ali Shinkafi Polytechnic. Evaluation findings show good performance, exceeding benchmarked techniques with 0.85 accuracy, 0.82 precision, 0.88 recall, 0.85 F1-score, and 0.91 ROC-AUC. Prior academic accomplishment, teaching methods, institutional resources, and lecturer effectiveness are major predictors, providing actionable insights for targeted interventions and evidence-based policy to improve student outcomes. Alsariera et al. [5] analyzed 39 studies from 2015–2021 on machine learning (ML) approaches for predicting student academic performance, aggregating data from diverse institutional datasets with 22 to 20,000 records and including demographic, academic (CGPA, attendance), internal assessment, and family/personal attributes. The study shows that ANN had the highest average accuracy (85.9%) and the highest reported accuracy (98.3%), followed by DT (85%) and LinR (55.5%). Key findings show that ANN and DT are the best predictors, academic features like CGPA are the most influential variables, and the field needs more robust, multi-institutional datasets and evaluation metrics beyond accuracy, such as precision and recall, to improve model reliability and applicability.

Bhutto et al. [11] conducted research using supervised machine learning techniques to predict students' academic performance. Results from implementations in Weka and Python showed that SVM-SMO achieved higher accuracy (78–79%) compared to LR (71–73%), with precision, recall, and F1-score metrics further confirming SVM's superior performance. The findings indicate that student satisfaction, engagement level, and punctuality are critical predictive features, offering educational institutions a focused model for early intervention and performance categorization to reduce dropout rates. Namoun and Alshanqiti [2] synthesised 62 studies from 2010–2020 on predicting student performance using learning outcomes as the key metric, analysing diverse datasets primarily from single institutions with sample sizes often under 1,000 students, covering traditional, online, and blended learning environments. The study shows that hybrid RF achieves the highest accuracy (99.98%), while LinR performs the worst. Key findings indicate that learning outcomes are commonly predicted as performance classes (e.g., pass/fail) or achievement scores, with online learning activities, in-term assessment grades, and student academic emotions emerging as the most influential predictors; however, the field is constrained by small datasets, limited model validation, and a lack of explanatory analytics, highlighting significant gaps in program-level and cohort-based predictions.

Ofori et al. [3] examine the application of machine learning algorithms to predict student performance and improve learning outcomes, drawing on diverse datasets, including student academic records, demographic surveys, and LMS logs (e.g., Moodle), and institutional data from universities across various countries. The study evaluates multiple algorithms, including DT, ANN, NB, SVM, LR, RF, and Stochastic Gradient Descent. Results across the reviewed studies reveal inconsistent predictive accuracy, with ANN, SVM, and NB frequently cited as top performers—though accuracy rates varied widely (e.g., ANN achieving up to 97.43%, NB up to 98%, and SVM up to 98.44%)—indicating that model performance is highly context-dependent and influenced by dataset characteristics and socioeconomic factors. The review identifies a significant research gap, while predictive modelling is well-explored, few studies address how these models can actively improve learning outcomes, and no consensus exists on which algorithm best combines accurate prediction with actionable insights for educational intervention. Furthermore, Osemwegie et al. [12] utilized a real-world dataset comprising academic records of 906 first-year Computer Science students from the University of Benin, Nigeria, across five sessions (2016–2021), with variables such as semester GPAs, credit loads, and course outcomes. Six machine learning classifiers—NB, LR, SVM, DT, KNN, and ANN—were applied to predict dropout, with results showing high accuracy across models: LR (98.9%), SVM (98.5%), DT (97.4%), ANN (97.3%), KNN (96.0%), and NB (90.4%). Despite minimal performance differences among the top models, LR was selected for deployment due to its superior F1-score and recall, alongside reasonable computational efficiency, highlighting its effectiveness in identifying at-risk students and supporting early intervention strategies in an educational context.

Alamri et al. [13] conducted a comparative analysis of SVM and RF models to predict student performance. The two methods exhibited good accuracy; nevertheless, the selection of the optimal technique may rely on the specific dataset or learning objectives. Hussain and Khan [14] developed a machine-learning technique to predict student scores at the secondary and intermediate levels. The methodology employed data from a Pakistani school board and encompassed data pre-processing, feature selection, training a regression model for mark prediction, and a decision tree classifier for grade classification. This study employs a genetic algorithm for feature selection.

Nevertheless, it results in significant processing complexity for large datasets [15]. It is stated that current approaches lack generalisability and interpretability, making it difficult to predict student academic performance. This paper proposes a novel method to solve present issues and improve predictions. It aims to achieve greater accuracy and reliability than current methods. The case study reveals that the proposed model may predict student performance with 93.11% accuracy, a 2.25% improvement over baseline methods. Analysis of accuracy, precision, recall, and F-measure metrics validated the mechanism's efficiency.

Bello [16] acknowledges that his cross-sectional, single-institution dataset limits causal inference and generalizability, while Bello et al. [17] similarly note that their model's performance may not generalise across diverse learning environments. Alkan et al. [18] further admit that their external validation was conducted on a very small sample (only 30 students), substantially limiting the reliability of their proposed model. A second major concern is the superficial treatment of ethical risks, particularly algorithmic bias. While Bello et al. [17] discuss how biased feature selection can produce discriminatory predictions affecting underrepresented groups, and Alkan et al. [18] acknowledge the "black-box" nature of models like Random Forest, none of the papers implement concrete fairness metrics (e.g., demographic parity, equalised odds) or bias mitigation strategies beyond basic class balancing. Bello [16] also notes that self-reported data on study habits and motivation may introduce significant bias, yet no sensitivity analysis is conducted to quantify this effect. Furthermore, methodological claims are evident. Shoukath and Midthunchakravarthy [19] report that a standard Random Forest with balanced class weights achieved only 0.47 precision and 0.41 recall, yet their proposed hybrid model's improvements are modest (0.72 precision), raising questions about computational cost-benefit trade-offs. Lastly, none of the studies provide reproducible code or data links. Alkan et al. [18] state that data is available upon reasonable request, which hinders open science, and only Bello et al. [16, 17] discuss practical deployment considerations such as early warning systems, but without real-world implementation evidence. Future research must prioritise prospective validation across multiple institutions, adopt fairness-aware ML frameworks with transparent bias audits, and ensure full reproducibility to move predictive analytics from an academic exercise to equitable, actionable educational practice.

Amjad et al. [20] advance the theoretical framework by demonstrating that AI-based predictive analytics has a significant positive effect on academic performance ($\beta = 0.298$, $p < 0.001$), with digital literacy acting as a crucial moderator. Students with higher digital literacy gain more from AI tools, while those with low literacy benefit less [20]. In contrast, Guevara-Reyes et al. [21] and Bouallegue et al. [22] focus on technical rigor; the former achieves an R^2 of 0.91 using XGBoost with SHAP-based interpretability on a large dataset of 50,000 student records, while the latter emphasizes cross-term generalizability, showing that models trained on one semester (Fall 2024) maintained >84% accuracy when tested on an independent future cohort. Meanwhile, Suleiman [23] provides a foundational baseline using linear regression (MSE = 0.32, MAE = 0.48), validating its utility for simplicity and interpretability, while Adedeji et al. [24] report perfect classification accuracy (100%) with SVM across multiple train-test splits.

Large Language Models (LLMs), such as BERT-based architectures and generative models like GPT, are increasingly utilised in predictive models to assess students' academic performance by converting unstructured educational data into actionable insights. BERT-based models demonstrate proficiency in comprehending context from text-dense sources, including essay submissions, discussion forum postings, and course evaluations, enabling them to forecast grades or identify at-risk individuals based on language patterns and conceptual comprehension [25]. Inspired by recent successes in these emerging directions of prompting paradigms for large language models (LLMs). Firstly, a growing body of research has demonstrated the effectiveness of LLMs in tackling the cold-start problem in recommender systems. Additionally, LLMs can capture complex relationships among student features. Kukkar et al. [26] introduced LLM-guided meta-initialisation to extract meta-knowledge from textual information hidden within systems, thereby improving discovery quality.

Varnavsky and Romanova [27] explore the use of EEG and brain-computer interfaces to measure theta-rhythm activity as an indicator of cognitive processes during educational reading. The experiment found that the dominant frequency of the theta rhythm increases when reading uninteresting or unfamiliar texts and decreases when reading interesting or familiar texts. Additionally, smooth fonts like Calibri were preferred over serif fonts like Times New Roman, with notable gender-based differences. The authors suggest that monitoring the theta rhythm can help assess text comprehension and support adaptive, feedback-driven learning systems, thereby improving students' academic performance.

This study focuses on all the tertiary institutions in Adamawa State, Nigeria. The Faculty of Science at Adamawa State University was used as the case study. Despite increasing enrollment in the institution, it lacks immediate methods to identify students at risk of poor academic performance. This study evaluates first-year students' academic performance in the 2024/2025 academic session across different departments in the Faculty of Science.

Theoretical framework

This research is theoretically grounded in Bloom's Mastery Learning Theory (1968) and constructivist learning theory, which assert that academic achievement depends on prior knowledge, the pace of learning, and the prompt detection of learning deficiencies. In large undergraduate cohorts at schools such as Adamawa State University, Mubi, educators frequently lack the immediate analytical capability to monitor these variables for each student, resulting in postponed interventions and preventable academic failure. Gokalp [28] asserts that the concept of mastery learning can be traced to 1963, when John B. Carroll first articulated the revolutionary idea that aptitude, rather than serving as a proxy for intelligence, represents the duration required for an individual to learn, positing that all students can attain equivalent levels of learning if afforded adequate time and educational opportunities.

Machine learning (ML) methodologies significantly enhance early warning system (EWS) theory by facilitating the identification of non-linear, multidimensional patterns in past academic data that conventional statistical techniques or rule-based guidance fail to uncover. This study applies the principles of predictive analytics in education, also known as Learning Analytics, by training prediction models using student demographics, entry credentials, continuous assessment scores, and attendance records. Thus, the creation of a machine learning-based predictive model offers a theoretically robust framework for converting student data into actionable academic risk indicators, thereby facilitating proactive advising, tailored learning pathways, and data-driven institutional policies. This study, grounded in learning analytics and early warning system theory, develops a machine learning model to proactively predict academic achievement.

Tinto's retention, otherwise known as the student integration model, also supports the idea that students' persistence is directly linked to their academic and social integration into a particular university. This further suggests that students are more likely to stay if they have a strong connection with faculty, staff, and peers and align with the institution's academic norms [29].

3. Materials and methods

This study uses a machine learning model and quantitative techniques in an organised, data-driven manner to predict student academic performance. The machine learning model used secondary data from students' academic records at the Faculty of Science, Adamawa State University, Mubi, Adamawa State, Nigeria. With a total of 1,730 students' academic records, the study split the data into 80% for training and 20% for testing. The 80% training set was used for model development, hyperparameter tuning, and cross-validation. To ensure robust model selection and avoid overfitting, K-fold cross-validation (with k = 10) was applied exclusively to the 80% training set. The training set was randomly shuffled and partitioned into k equal-sized folds. For each iteration i = 1 to k, the model was trained on k−1 folds of combined training data. The model was validated on the ith fold validation data. Performance metrics (e.g., accuracy, precision, recall, F1-score) were recorded. After all k iterations, the average performance and standard deviation across the k folds were computed to provide a reliable estimate of model performance. This process was repeated for each machine learning model under consideration (e.g., Logistic Regression, Random Forest, Decision Tree, Naïve Bayes, and SVM). Hyperparameters were tuned using cross-validation to select the configuration that maximised the average validation score, after identifying the best-performing model and optimal hyperparameters using k-fold cross-validation. The model was retrained on the entire 80% of the training set using the selected hyperparameters. The trained model was then evaluated once on the 20% testing set. Final performance metrics were reported based on this testing set to estimate how the model would perform on new, unseen data. **Figure 1** summarises the research framework.

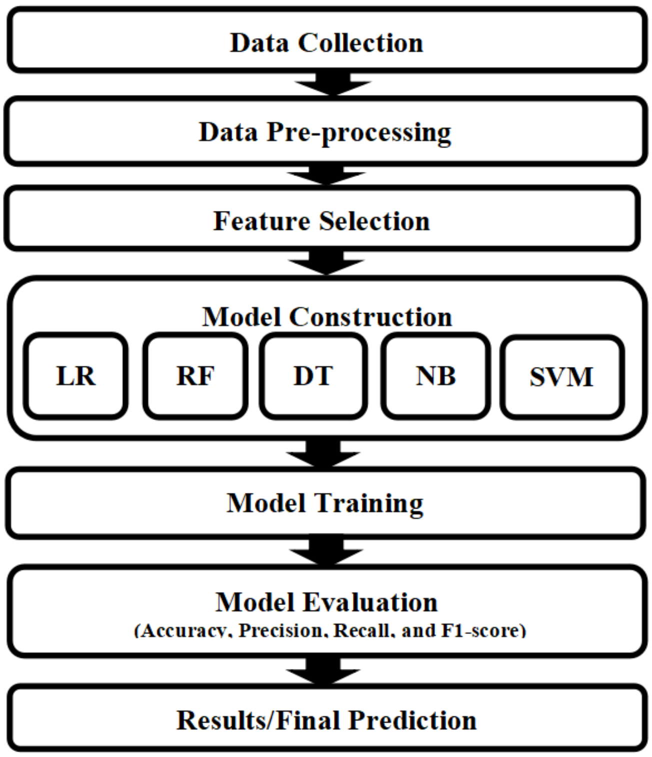

Figure 1. Research framework.

3.1. Data collection

The study collected students' academic information from each department in the Faculty of Science who had taken all programme courses in the 2024/2025 academic session. Student records were collected from the examination unit. Information retrieved from students' records, including students' registration details, final grade, and the total number of courses taken by each student, grades in each course, total units, grade points, and grade point average. These influencing aspects are considered as input variables. After data collection, the transformation activity was performed.

3.2. Data pre-processing

Data pre-processing is a critical phase in preparing datasets for classification tasks, directly influencing the quality, reliability, and generalizability of the resulting predictive models. In this study, a dataset comprising student academic records from the Faculty of Science, Adamawa State University, Mubi, for the 2024/2025 academic session was used. The raw dataset contained missing values and duplicate entries, which were addressed through a systematic pre-processing pipeline implemented in Python.

The following pre-processing steps were applied to ensure data integrity and compatibility with five machine learning classifiers: LR, RF, DT, NB, and SVM.

- Data cleaning: Missing values were identified and handled using listwise deletion (for instances with >10% missing attributes) and median imputation for continuous features. Duplicate entries were detected and removed. Irrelevant or redundant attributes (e.g., student names and index numbers) were excluded before modelling.
- Data transformation: Numerical features were normalised using min-max scaling to bring all values into a uniform range [1], ensuring that classifiers sensitive to feature scaling (e.g., SVM, LR) performed optimally. Categorical variables (e.g., gender, department, prior qualification) were encoded using one-hot encoding to ensure compatibility with all five algorithms.

Following pre-processing, the cleaned and transformed dataset was partitioned into training (80%) and testing (20%) subsets using stratified sampling to preserve class distribution. This pre-processing pipeline was applied uniformly across all five classifiers to ensure a fair and consistent basis for model comparison and evaluation.

3.3. Feature selection and hyperparameter tuning

Feature selection was performed using information gain and CFS (correlation-based feature selection) to identify attributes most influential on student academic performance. Attributes with information gain < 0.01 or intercorrelation > 0.85 were excluded. Hyperparameter tuning for LR, RF, DT, NB, and SVM was conducted using a 5-fold cross-validation grid search. Optimal hyperparameters were identified separately for each classifier. All models were then trained on the reduced feature set and evaluated on the test set.

4. Model development

4.1. Logistic regression (LR)

Logistic regression models are employed to examine the influence of variables that predict categorical outcomes, typically binary [30]. Logistic regression methods predict student academic performance (pass/fail or GPA levels) by examining the ordinal outcomes influenced by variables such as study time, attendance, and prior scores.

4.2. Random forest (RF)

Random forest models are quite proficient at predicting student academic performance, often achieving high accuracy by capturing intricate, non-linear interactions among factors. These ensemble methods surpass conventional models (such as Linear Regression) in detecting at-risk pupils by employing variables such as prior GPA, attendance, study habits, and socioeconomic considerations [15,22,23].

4.3. Decision trees (DT)

Decision trees are widely utilised predictive techniques. Many researchers favour this method due to its simplicity and clarity in revealing both minor and major data structures, as well as in forecasting values [24–26].

4.4. Naïve Bayesian (NB)

Naïve Bayesian algorithms are remarkably efficient at predicting student academic achievement, achieving accuracy rates by analysing attendance, grades, and demographic data. These models aid educators in identifying at-risk pupils for early intervention, with primary indicators frequently comprising prior academic performance, study behaviours, and socioeconomic variables [27, 28]. The Naïve Bayes classifier can ascertain the likelihood of categorising a student into a specific academic performance class [29].

4.5. Support vector machines (SVM)

The support vector machine (SVM) is a proficient machine learning model for predicting student academic achievement, attaining high accuracy by discerning trends in academic, demographic, and behavioural data. SVMs are proficient in classification tasks (e.g., categorising performance as high, average, or low) and utilise kernel functions to transform complex, non-linear data, hence improving predictive accuracy [13,30,31].

5. Model evaluation metrics

The evaluation metrics used in this paper to measure the performance of the classifiers are accuracy, precision, recall, and F1-score [9,30,31]. These metrics were taken into account, including all four significant dimensions, i.e., true positives (TPs), false positives (FPs), false negatives (FNs), and true negatives (TNs).

Accuracy: This measures the proportion of students' performance instances that are correctly identified, i.e., it considers only correctly classified cases:

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{FN} + \text{TN}}. \tag{1}$$

Precision: This measures the proportion of correctly identified positive student performance instances among all predicted positive performances:

$$\text{Precision}= \frac{\text{TP}}{\text{TP} + \text{FP}}. \tag{2}$$

Recall: This measures the proportion of correctly identified positive student performance cases out of all positive cases in the dataset. The recall percentage is calculated using the formula in Equation (3) below:

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}. \tag{3}$$

F1-Score: The F1-score considers precision and recall, resulting from the harmonic mean of precision and recall. It is calculated using the formula in Equation (4):

$$\text{F1} - \text{Score} = 2 * \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}}. \tag{4}$$

6. Results and discussion

This section shows evaluation measures used during the experiments. This paper used students' records as datasets to predict students' academic performance at Adamawa State University, Mubi. The models underwent both training and testing. To evaluate the predictive performance of the machine learning models, confusion matrices were generated for LR, RF, DT, NB, and SVM. The confusion matrices for each model are presented in **Figures 2–6**. Each matrix summarises the classification results into four categories: True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN), where the positive class indicates students predicted to achieve satisfactory academic performance (e.g., pass or above), and the negative class indicates otherwise.

Figure 2 shows the DT confusion matrix, which is a relatively balanced performance with a moderate number of correct classifications along the diagonal. However, DT exhibited a tendency toward overfitting due to its recursive partitioning nature, leading to a high number of false positives (FPs) and false negatives (FNs). This suggests that while DT captures complex interactions among features (e.g., attendance, prior grades, socioeconomic factors), it may misclassify borderline students.

Figure 3 demonstrates a simpler linear decision boundary, resulting in fewer false positives than DT. The off-diagonal elements are relatively low, indicating that LR generalises reasonably well on the Adamawa State University dataset. However, LR may underperform when feature relationships are non-linear, potentially leading to increased false negatives. The matrix confirms LR as a stable baseline model with acceptable predictive accuracy.

The NB confusion matrix in **Figure 4** exhibits one of the highest numbers of false positives among the models. This is attributable to NB's conditional independence assumption, which is often violated in educational data where features such as continuous assessment scores and final exam results are correlated. Consequently, NB tends to over-predict the positive class, making it less suitable for this application unless feature dependencies are addressed.

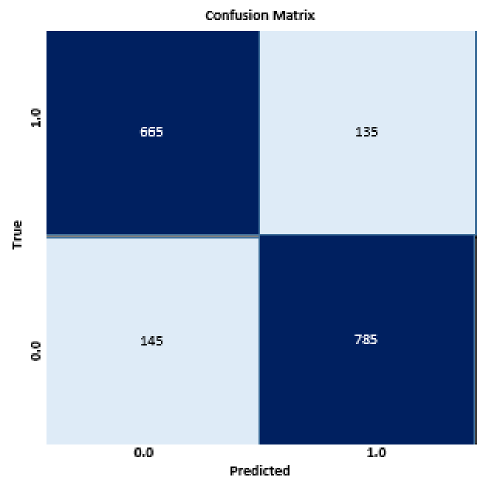

Figure 2. DT Confusion Matrix.

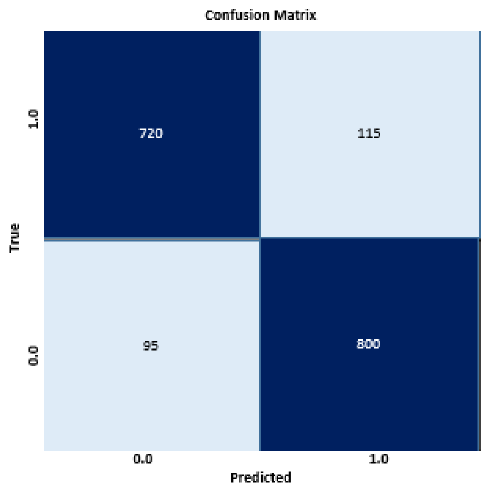

Figure 3. LR Confusion Matrix.

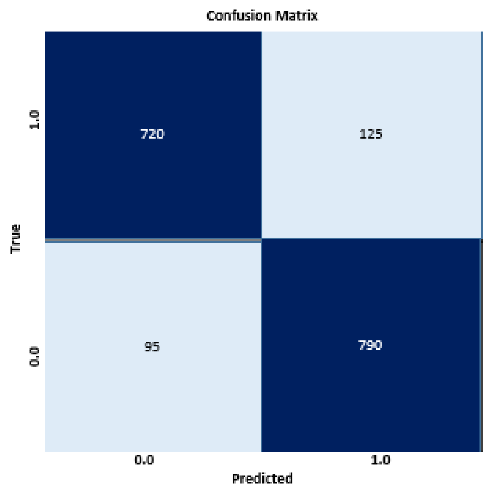

Figure 4. NB Confusion Matrix.

Figure 5 shows the RF confusion matrix; it is the most diagonal-dominant, with the FP and FN counts. As an ensemble of DTs with bagging, RF reduces variance and mitigates overfitting. The matrix indicates that RF successfully identifies at-risk students while rarely misclassifying successful students as failures. This makes RF the most robust model for the given dataset.

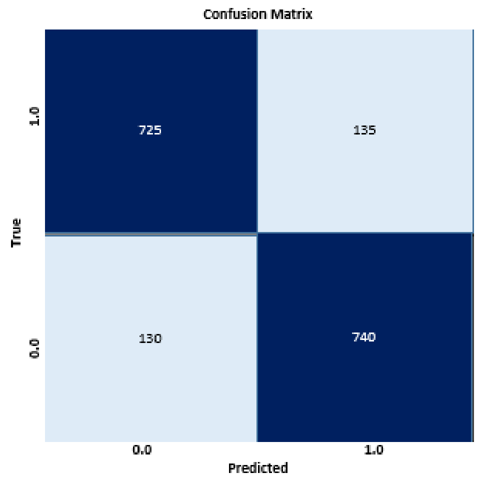

Figure 5. RF Confusion Matrix.

The SVM confusion matrix in **Figure 6** shows a low false-negative rate but a moderate false-positive rate. SVM with an RBF kernel can model complex non-linear boundaries, which is beneficial when student performance data are not linearly separable. However, SVM's performance is sensitive to feature scaling and kernel parameter selection. The observed FN cases correspond to students who narrowly missed the performance threshold, indicating room for improvement via hyperparameter tuning.

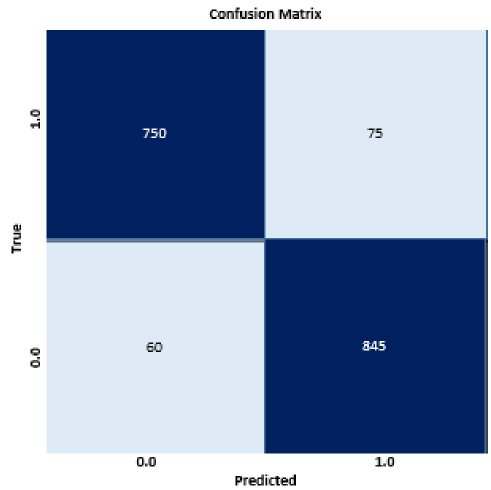

Figure 6. SVM Confusion Matrix.

For Adamawa State University, Mubi, the choice of classifier depends on the cost of misclassification. If the goal is to minimise false negatives (i.e., not missing at-risk students), RF and NB offer the highest recall. However, NB's high false positive rate may lead to unnecessary academic interventions. Therefore, RF provides the best trade-off, as confirmed by its confusion matrix and derived metrics.

Table 1 below shows the outcomes of the prediction models employed in this study. The classification report for the models shows that the SVM algorithm achieved the best predictive performance with 92% accuracy, followed by linear regression with 88% accuracy and Naïve Bayes with 87% accuracy. Random forest and decision tree with 85% and 84% accuracy. SVM Linear's prediction precision is 92%, the highest. The summary of the classification reports for the LR, RF, DT, NB, and SVM models is presented in **Table 1** below.

Table 1. Classification report for the models.

Model	Accuracy	Precision	Recall	F1-score
Logistic Regression	88%	87%	89%	88%
Random Forest	85%	85%	85%	85%
Decision Trees	84%	85%	84%	85%
Naïve Bayesian	87%	86%	89%	88%
Support Vector Machines	92%	92%	93%	93%

From **Table 1**, it can be observed that the RF model has an F1 score of 85%, indicating a balance between precision and recall, reflecting both false positives and false negatives; a precision of 85% suggests that the RF model minimises false positives. This is important in scenarios where the case of a false positive is high. **Table 1** shows that LR has a precision of 87%, a recall of 89%, and an F1 score of 88%, indicating differences among precision, recall, and F1 scores. The model shows an accuracy of 88%.

The DT model in **Table 1** shows an F1 score of 85%, although its overall accuracy remains at 84% with recall. The classification results also showed that the model achieved 85% precision in predicting students' academic performance from cumulative grade-point average. NB has an accuracy of 87%, which is better than that of RF and DT. It also has better precision (86% better than the two models), a recall of 89%, and an F1 score of 88%.

The SVM model achieves an exceptional 92% precision, 93% recall, and an F1 score of 93%. The model achieves a remarkable 92% accuracy in predicting students' academic performance based on cumulative grade point average for the 2024/2025 academic session. This classification result suggests that machine learning models performed well in predicting students' performance.

In summary, while the SVM model exhibits commendable accuracy, precision, and recall, further refinement is necessary to predict the performance of all relevant students' cases within the institution better, thereby improving its overall classification effectiveness. **Table 1** presents the evaluation results for the five machine learning models used to predict students' academic performance in the Faculty of Science at Adamawa State University, Mubi. The result showcases improved precision of 92% compared to other models, with an overall accuracy of 92%. The SVM classification results have proven to be a better machine learning model than the other models for predicting students' academic performance at the institution.

Figure 7 below displays a chart comparing the models' accuracies in predicting students' academic performance.

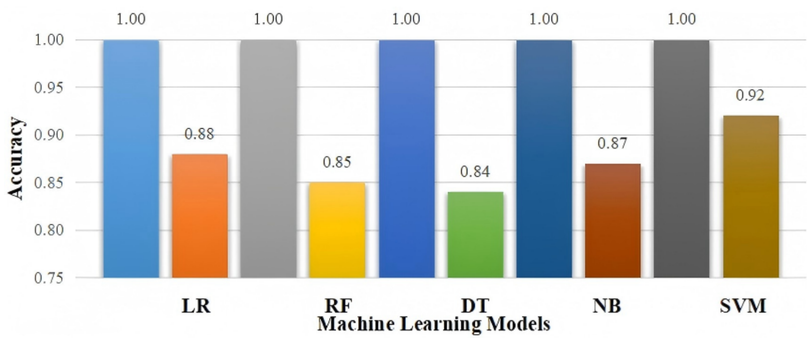

Figure 7. Comparison of the accuracy of results for the models.

Figure 7 shows that SVM significantly outperforms the other models, achieving an accuracy of 0.92, indicating its superior ability to predict students' performance based on their academic records. This performance gap showcases the effectiveness of machine learning models in modern NLP tasks. In contrast, LR, RF, DT, and NB models have lower accuracy. LR and NB models, while less accurate, provide valuable alternatives that balance performance with computational efficiency. The DT model had a lower test accuracy of 0.84. This difference underscores SVM's superior ability to maintain high accuracy beyond the training set, making it a more reliable choice for classifying students' performance. Based on the above results, the study found that the comparison highlights SVM as superior in accuracy for predicting student academic performance. The SVM model performed very well, achieving 92% accuracy. The results of this study aligned with Bhutto et al. [11], which confirmed that SVM is a superior model for predicting students' academic performance. However, the choice of model should take into account the specific context, including resource availability and the need for real-time processing.

7. Conclusion

This study concludes that predicting student academic performance is a critical priority for Adamawa State University, Mubi, and other educational institutions in Nigeria. The application of machine learning techniques demonstrates significant potential for early identification of students at risk of poor performance, repeat, and withdrawal from the University, enabling timely intervention from the outset of an academic year. Using historical internal assessment data from prior semesters, academic departments within the Faculty of Science at the University can implement remedial measures to support students who are likely to underperform. Accurate predictive models will allow the university to allocate resources more effectively, focusing on students with higher probabilities of low performance, thereby improving overall academic outcomes. Students'attitudes and motivation toward the course of study, lecturers, and hands-on practicals can improve their performance. Furthermore, student success prediction supports enhanced personalised assessment and contributes to the ongoing development of data-informed educational systems. Future work should focus on improving model accuracy, exploring additional predictive features, and evaluating interventions in diverse institutional settings.

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Institutional review board statement: The study was conducted in accordance with the Declaration of Helsinki, and approved by the Institutional Ethics Committee of Adamawa State University, Mubi (protocol code ADSU-REC-2025-003 and date of approval 10 January, 2026).

Informed consent statement: This study involved only a retrospective analysis of existing academic records collected from the Faculty of Science, Adamawa State University, Mubi. All personally identifiable information (student names, registration numbers, and contact details) was removed. Consequently, the Research Ethics Committee of Adamawa State University, Mubi, formally waived the requirement for individual informed consent. No direct interaction with students occurred, and no student was contacted for primary data collection.

Data availability statement: The datasets generated and analysed during the current study are available from the corresponding author on reasonable request. The data were collected from the Faculty of Physical Sciences at Adamawa State University, Mubi, and have been anonymized to protect student privacy. Requests for data access will be reviewed by the corresponding author in consultation with the Faculty of Science to ensure compliance with institutional data protection policies.

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