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A COMPARATIVE REVIEW OF MACHINE LEARNING AND DEEP LEARNING TECHNIQUES FOR EARLY STUDENT DROPOUT DETECTION AND PREVENTION

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ABSTRACT

The review examined the use of Machine Learning (ML) and Deep Learning (DL) techniques for early student dropout detection and prevention. Employing systematic search of academic database (google Scholar) for peer-reviewed studies published between 2021 and 2026, following inclusion and exclution criteria, 16 relevant rearrch papers were selected and analyzed, the scope focus on higher education context, Studies show that ML algorithms such as Logistic Regression, Decision Trees, Random Forests, Support Vector Machines, and Gradient Boosting provide reliable and interpretable predictions, while DL models, including Artificial Neural Networks, Recurrent Neural Networks, and Long Short-Term Memory networks, are more effective at capturing complex patterns in student academic and behavioral data. Although ML models require less computational power and perform well on smaller datasets, DL models often achieve higher predictive accuracy with larger datasets. Key challenges include data quality, class imbalance, privacy concerns, model interpretability, and generalization across institutions. The review highlights the potential of hybrid ML-DL approaches and recommends future research on explainable AI, real-time intervention systems, and standardized evaluation methods to improve student retention and academic success. These findings support the design and implementation of a predictive analytics system for early student dropout detection and prevention at the Federal College of Education, Gidan Madi.

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INTRODUCTION

Tertiary education serves as a cornerstone for human capital development, socio-economic growth, and national transformation. It equips individuals with the knowledge, skills, and competencies required for innovation, productivity, and leadership in various sectors of the economy. In developing countries like Nigeria, Colleges of Education play a vital role in training future teachers and shaping the quality of the foundational education system. However, this critical sector faces persistent challenges that compromise its performance and long-term impact, one of the most pressing being the increasing rate of student dropout. Reducing student attrition remains a key objective of higher education institutions in Nigeria and globally. Between 2020 and 2026 student dropout has continued to pose significant challenges to universities and colleges of education due to its negative impact on both students and institutions. According to (Ahmadu et al., 2024), approximately 25% of students leave higher instituations during their first year of study, and this figure may increase to about 50% by the end of the second academic year. Improving student retention offers numerous benefits, including enhanced career opportunities, improved quality of life for graduates, and greater academic success (Ahmadu et al., 2024). From an institutional perspective, higher retention rates contribute to improved institutional reputation, stronger performance in university rankings, increased access to government funding, higher student enrollment, and smoother accreditation processes. Consequently, university administrators and policymakers are under growing pressure to develop and implement effective strategies aimed at identifying at-risk students and reducing dropout rates (Ahmadu et al., 2024).

In recent years, the growing use of technology in classrooms has significantly reshaped the education sector. Globally, data-driven strategies have emerged as effective tools for addressing such challenges in the education sector (Poonam et al., 2026). Predictive analytics, a subset of data science and artificial intelligence, offers the capability to analyse historical and real-time data to forecast future outcomes (Poonam et al., 2026). When applied in education, it can predict student behaviour, assess academic risk, and support early intervention strategies (Poonam et al., 2026). Institutions that have adopted predictive analytics systems have reported improved student retention, better allocation of resources, and data-informed decision-making by staff members and administrators (Poonam et al., 2026). With more institutions relying on digital platforms, Data Mining (DM) in education has gained momentum by enabling large-scale collection of student data and analysis (Poonam et al., 2026). Digital tools, e-learning environments, and Learning Management Systems (LMS) now provide practitioners and educators with detailed information about students' academic progress, learning behaviour, and overall engagement (Poonam et al., 2026). In today's system of education, data-driven decision-making relies on advanced predictive models that can effectively enhance, analyse and forecast student performance (Namoun, 2021). These models provide actionable insights that support informed decision-making, enhance learning experiences, and enable personalized education strategies (Namoun, 2021). By predicting student performance, educators can identify struggling students early and implement targeted interventions to improve their learning outcomes (Namoun, 2021). Over the years, student performance prediction has been based on teacher evaluations and statistical methods, which often fail to capture the evolving and interconnected nature of student learning outcomes (Yağcı, 2022). However, with advancements in intelligence system (IS), machine learning (ML) and deep learning (DL) techniques have emerged as powerful tools for analysing sequential educational data and making accurate predictions (E. Ahmed, 2024).

A student's academic performance is influenced by multiple factors, including socio-economic background, learning behaviours, cognitive abilities, and institutional policies (Kuş, 2025).

Understanding how these factors cooperate over time is critical for designing effective interventions that enhance student performance (Kuş, 2025). Traditional models, such as random forest, linear regression and decision trees, may struggle to capture these temporal relationships, making other ML and DL models a more promising alternative (Kuş, 2025). This research aims to develop at least two ML-based predictive models that can enhance the accuracy of student performance forecasting using small sample records, providing practitioners, educators and policymakers with the tools to implement proactive and data-driven intervention strategies. Student dropout is a versatile problem that not only affects the individuals involved but also weakens institutional efficiency, wastes limited educational resources, and undermines national education goals (Kuş, 2025). At the Federal College of Education, Gidan Madi, several factors have been linked to student attrition, including poor academic performance, financial hardship, low levels of motivation, socio-economic barriers, and personal issues such as health and family crises. Unfortunately, the institution currently lacks a proactive, structured mechanism for detecting students who are at risk of dropping out. The existing approach is largely reactive, responding only after students have exited the system, when it is often too late for meaningful intervention.

METHODOLOGY

The study adopted a systematic literature review and comparative analysis design to examine the application of Machine Learning (ML) and Deep Learning (DL) techniques for early student dropout detection and prevention. Relevant literature was identified through a systematic search of Google Scholar using keywords such as student dropout prediction, machine learning, deep learning, educational data mining, predictive analytics, and early warning systems. The review focused on peer-reviewed journal articles published between 2021 and 2026. Studies were included if they investigated ML or DL techniques for predicting student dropout or academic performance in higher education settings and reported measurable evaluation outcomes. Studies that were not peer-reviewed, lacked sufficient methodological details, were unrelated to educational prediction, or did not report performance metrics were excluded. Following the application of the inclusion and exclusion criteria, 16 relevant studies were selected for detailed review. Data relating to research objectives, datasets, features, algorithms, tools, evaluation metrics, findings, and limitations were extracted and synthesized through comparative analysis to identify prevailing trends, strengths, limitations, and future research directions in student dropout prediction and prevention.

REVIEW OF RELATED STUDIES

This section presents a summary of the selected research studies as shown in Table 1. It synthesizes the authors' approaches after conducting the review, highlighting the objectives, datasets, techniques, findings, and model architectures used in the comparative analysis. Overall, this section provides an overview of the data extracted from the reviewed papers, including the methodologies employed and the key results obtained across the selected studies. This research by (Sandeepa, 2025) investigated the use of ML and DL models for predicting student academic performance using academic, behavioural, and demographic data. The multi-layer perceptron classifier (MLPC) achieved a maximum accuracy of 86.46% on the test set and an average accuracy of 79.58% under 10-fold cross-validation, highlighting the effectiveness of neural network models compared to traditional ML approaches.

The study, (Diekuu et al., 2025) proposed a temporal intelligent model using semester-wise student data to predict academic performance. The study emphasized the importance of time-series data, showing that incorporating temporal dynamics compared to static approaches leads to more accurate predictions. The model was tested on a large dataset of over 3,000 students and demonstrated improved forecasting performance. Similarly, (Augustine et al., 2025) developed a predict student Grade Point Average (GPA) using Bidirectional LSTM (Bi-LSTM) model. The model incorporated SHAP (Shapley Additive Explanations) techniques for interpretability, allowing better understanding of feature contributions. The proposed approach achieved an accuracy of 88.23%, outperforming several machine learning models such as XGBoost, CatBoost, and LightGBM. The study demonstrated that DL models are more effective in capturing temporal dependencies in student data.

This study in (Adefemi & Mutanga, 2025b) proposed a hybrid deep learning model combining CNN and Bidirectional Gated Recurrent Units (BiGRU) to predict student academic performance. The model was evaluated using multiple datasets and key performance metrics like accuracy, precision, recall and F-score. The experimental results showed that the proposed model achieved improved prediction accuracy of 97.48%, 90.90%, and 95.97% across three datasets, demonstrating strong performance compared to baseline approaches. In another study, (Hajoui et al., 2025) applied RNNs with optimization techniques for student performance prediction. The research focused on improving model efficiency using training optimizations techniques and sequential data processing. The results from the research indicated that optimized RNN models significantly improved predictive performance compared to baseline deep learning models, highlighting the importance of sequence modelling in educational data analysis.

A study by (Adefemi & Mutanga, 2025a) proposed a hybrid plain CNN and LSTM model for predicting student performance. The model combined plain CNN for feature extraction and LSTM networks for sequential learning. The authors applied advance preprocessing methods such as handling missing data and class imbalance and evaluated the model on benchmark datasets. The results from this research showed that the hybrid model achieved 98.93% and 98.82% accuracy, outperforming traditional machine learning models and standalone deep learning approaches in terms of accuracy, precision, recall, and F1-score. The study in (Alsumaidaie et al., 2024) implemented a student performance prediction system using RF, L R, and ANN. The evaluation was conducted using accuracy, precision, recall, and F1-score. The results showed that the RF model achieved the highest accuracy of 95.6% and an F1-score of 94.8%, making it the most reliable model among those tested models. The research conducted in (Bello et al., 2025) applied regression-based ML models such as LR, RF Regressor, and XGBoost. The models were evaluated using regression metrics such as MAE and RMSE. The results shows that XGBoost achieved the lowest MAE of 0.12 and RMSE of 0.18, indicating better predictive accuracy compared to other models. The authors in study (Id & Yu, 2025) used LR, DT, and ensemble learning methods to predict student academic performance in an online learning environment setting. The models were evaluated using classification metrics. The results showed that ensemble learning achieved an accuracy of 94.3%, precision of 93.8%, and recall of 94.1%, outperforming individual models and demonstrating better generalization ability.

The research in (W. Ahmed et al., 2025) proposed an ensemble-based machine learning approach using RF, SVM, and Gradient Boosting for prediction of student performance. The study applied hyper parameter tuning and feature engineering to optimize model performance. The evaluation results showed that the RF model achieved an accuracy of 97.8%, precision of 96.5%, recall of 95.9%, and an F1-score of 96.2%, outperforming the other models in classification performance. The study in (Muresan et al., 2026.) integrated heterogeneous graph DL models with traditional ML techniques to predict student success. On the Open University Learning Analytics (OULA) dataset, the model achieved a validation F1 score of 68.6% early in the semester and up to 89.5% near the semester's end, outperforming top ML models by 4.7% in early prediction performance.

Table 1: Overview of Selected Studies

Ref.	Objective	Methodology	Dataset Used	Features Used	Algorithms Used	Tools	Evaluation Metrics	Result	Limitations
(Sandeepa, 2025)	Predict student academic performance using ML	Supervised learning using neural networks and ML	Behavioura, academic, demographc data	Student behaviour, grades, demographics	MLP Classifier	Python (Scikit-learn, TensorFlow /Keras)	Accuracy, Cross-validation accuracy	86.46% (test), 79.58% (CV)	Performance drops with small or imbalanced datasets
(Diekuu et al., 2025)	Improve prediction using temporal patterns in student data	Temporal AI-based time-series modelling	Dataset of 3,000+ students	Sequential academic records	Temporal AI / Sequential models	Python (TensorFlow/PyTorch)	Accuracy	Improved accuracy via temporal modelling	Depends on availability of sequential data
(Augustine et al., 2025)	Enhance prediction with explainable deep learning	Deep learning with explainability (SHAP)	GPA prediction dataset	GPA trends, historical performance	Bi-LSTM	Python (TensorFlow, SHAP library)	Accuracy	88.23% accuracy	Limited scalability on small datasets
(Adefemi & Mutanga, 2025b)	Improve accuracy using hybrid feature extraction	Hybrid deep learning (dual extraction)	Multiple student datasets	Multi-source student features	CNN, BiGRU	Python (TensorFlow/Keras)	Accuracy	97.48%, 90.90%, 95.97%	Complex architecture, high computation
(Hajoui et al., 2025)	Optimize sequential learning for student prediction	Optimized deep learning with sequential modeling	Educational datasets	Sequential academic data	RNN	Python (TensorFlow/PyTorch)	Accuracy	Improved performance over baseline DL	Sensitive to hyperparameters
(Adefemi & Mutanga, 2025a)	Improve robustness using preprocessing techniques	Deep learning + preprocessing	Benchmark educational datasets	Cleaned and balanced student data	CNN, LSTM	Python (TensorFlow/Keras)	Accuracy, Precision, Recall, F1-score	98.93%, 98.82%	Requires large datasets and high computation
(Alsumai	Compare ML	Supervised	Student	Academic	Random	Python	Accuracy,	RF:	LR may

daie et al., 2024)	models for classification performance	classification	academic dataset	performance indicators	Forest, Logistic Regression, ANN	(Scikit-learn)	F1-score	95.6% accuracy, 94.8% F1	underfit complex patterns
(Bello et al., 2025)	Predict performance using regression models	Regression-based prediction	Academic dataset	Continuous performance variables	Linear Regression, RF Regressor, XGBoost	Python (Scikit-learn, XGBoost)	MAE, RMSE	XGBoost: MAE=0.12, RMSE=0.18	Less suitable for classification
(Id & Yu, 2025)	Improve prediction via ensemble learning	Ensemble and classification modeling	Online learning dataset	LMS interaction data	Logistic Regression, Decision Trees, Ensemble	Python (Scikit-learn)	Accuracy, Precision, Recall	94.3%, 93.8%, 94.1%	High computational cost
(W. Ahmed et al., 2025)	Enhance accuracy using feature engineering + ensembles	Ensemble learning with tuning	Educational dataset	Engineered academic features	RF, SVM, Gradient Boosting	Python (Scikit-learn)	Accuracy, Precision, Recall, F1-score	Accuracy 97.8%, F1 96.2%	Poor at sequential dependencies
(Muresan et al., 2026)	Model complex relationships in student data	Heterogeneous graph deep learning	OULA dataset	Relational and interaction data	Graph-based DL + ML	Python (PyTorch Geometric, DGL)	F1-score	68.6% – 89.5%	Requires structured relational data

CONCLUSION

From the table shown above, based on the reviewed literature, significant progress has been made in student academic performance prediction from using traditional ML and modern DL techniques and hybrid architectures. Studies such as (Adefemi & Mutanga, 2025a), (Adefemi & Mutanga, 2025b) demonstrate that hybrid deep learning models (CNN-BiGRU, CNN-LSTM) achieve very high predictive accuracy above 97%, indicating the strength of combining temporal learning with spatial feature extraction. However, these predictive techniques are heavily reliant on large datasets and computationally expensive, which limits their applicability in real-world scenarios where data availability is often restricted. Furthermore, studies like (Augustine et al., 2025), (Hajoui et al., 2025) and (Diekuu et al., 2025) highlight the effectiveness of sequence-based models (RNN, Bi-LSTM, and temporal models) in capturing temporal dependencies in student performance dataset. Despite their strong performance, these approaches are often data-hungry and sensitive to dataset size and quality, and there is limited research evaluating how these models perform under small or constrained datasets. Most existing works focus on large datasets, leaving a gap in understanding their generalization capability in data-scarce environments.

In addition, several studies such as (W. Ahmed et al., 2025), (Alsumaidaie et al., 2024) and (Id & Yu, 2025) focus on traditional ML and ensemble methods like RF, SVM, LR, and DT. While these techniques show competitive results (with accuracies above 94%), they are primarily evaluated in isolation, and there is a lack of direct comparative analysis between classical ML and DL models under the same small dataset conditions. This makes it difficult to determine which class of algorithms is more suitable when data is limited. Another important gap identified from (Bello et al., 2025) is that most studies focus on classification metrics (accuracy, precision, recall, F1-score), while regression-based evaluation metrics (such as MAE and RMSE, R2) are less explored in academic performance prediction tasks. This limits the understanding of model performance from a broader predictive perspective. Moreover, studies such as (Sandeepa, 2025) and (Muresan et al., 2026) emphasize the use of neural networks and graph-based DL techniques, achieving reasonable performance (e.g., up to 89.5% F1-score in [25]). However, these approaches often rely on complex data structures (e.g., behavioral or relational data) and require significant computational resources. There is a gap in evaluating simpler yet effective models that can perform well on small, structured datasets with lower computational cost.

Finally, although several studies highlight high accuracy in student performance prediction, there is still a lack of research focusing on model efficiency, robustness, and performance under limited data scenarios, particularly using small datasets (such as 250 records). Additionally, there is limited work that evaluates models based on both predictive performance and computational efficiency in a unified framework.

RECOMMENDATIONS

1. Higher education institutions should implement machine learning-based early warning systems to identify students at risk of dropping out.

2. Traditional machine learning models should be used where datasets and computational resources are limited, while deep learning models should be adopted for larger datasets.

3. Researchers should develop hybrid ML–DL models and incorporate explainable AI techniques to improve prediction accuracy and model interpretability.

4. Institutions should strengthen student data management and evaluate predictive models using multiple performance metrics.

5. Future research should focus on small datasets, real-time intervention systems, and ethical data management to enhance student retention and academic success.

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