Study of Prediction of Student Academic Outcomes Using Machine Learning and Deep Learning Model

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Abstract—**A prominent area of focus in modern research in education is using ML models to predict student outcomes for academic success. The explosive generation of educational data that might be triggered by a technological learning environment fosters improved learning experiences. This review paper examines the literature on the use of Machine Learning (ML) and Deep Learning (DL) models for the prediction of student academic performance. The study discusses many of the ML and DL algorithms such as Random Forest (RF), Decision Tree (DT), Support Vector Machine (SVM), and Deep Neural Networks (DNN) to find their comparison on the prediction of student performance. Findings have been highlighted for better accuracy by DL models such as Gated Recurrent Neural Networks and DNN, which have even reached over 99%. This paper would provide insights for teachers and policymakers on optimizing instructional strategy and improving student achievement by using predictive analytics. Then, future studies will need to concentrate on the real-time integration of data and dynamic model development to achieve more accurate predictions.**

Keywords— Student performance predictions, Deep learning, Artificial Neural Network, Machine learning, Random Forest.

I. INTRODUCTION

Higher education institutions have been profoundly affected by the exponential growth of online educational data produced by technology-enhanced learning platforms, which in turn has led to an abundance of educational repositories [1]. Opportunities to improve the learning experience through user interaction optimization with technological platforms are emerging alongside the fast growth of educational data [2]. Several academic groups, such as learning analytics, have emerged in response to the proliferation of educational data in an effort to forecast student actions and offer metrics for more effective policymaking [3-5]. Researchers from a wide range of academic fields have established educational data as a distinct area of study [6]. This data is generated naturally as a result of interactions between students and teachers. This has led to the incorporation of other words related to the investigation of educational data, including learning analytics, academic analytics, and predictive analytics. There is a relatively new phrase that has emerged: "educational data science." This field brings together experts from many academic backgrounds to work together on projects involving educational data [7].

Data collection, organisation, analysis, and interpretation from students is a crucial component of learning analytics. This helps us understand the learning environment and how to maximise the performance of both students and teachers. In addition, it encourages effective decision-making by dealing with the formulation of policies and strategies to enhance the academic-level capabilities of institutions [8].

Figure 1 depicts how the learning analytics process works.
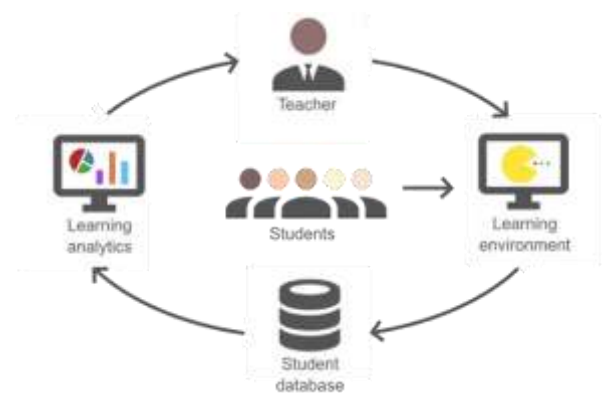
Figure 1. Learning analytics (LA) Process [9]

Learning analytics suggests learning patterns from educational data, which helps optimize students' performance and improve the overall learning environment with supplementary support in teaching processes through adjusted teaching techniques.

A. The Role of Machine Learning in Education

Machine learning (ML) is one of the new technologies that has been shown to be an essential resource for improving our comprehension of the academic results of students [9]. The creation of algorithms that allow computers to learn from data and make predictions or judgments is known as machine learning, a branch of artificial intelligence [10]. Machine learning (ML) can sift through mountains of data in the field of education, revealing previously hidden patterns and insights. These insights can inform policy, curriculum development, teaching strategies, and individualized learning plans, ultimately aiming to improve student performance and educational equity [11].

Predictive analytics is one of the main uses of ML in the field of education. In order to predict how well students will do in the future, pinpoint those who are most vulnerable, and propose solutions in a timely manner, machine learning algorithms examine past data [12]. This proactive approach can significantly enhance student retention and success rates. ML facilitates personalized learning experiences by adapting educational content and instructional strategies to meet the individual needs of students. Adaptive learning technologies use ML algorithms to assess a student's current understanding and tailor the learning path accordingly, ensuring that each student can progress at their own pace and in their preferred learning style [13].

B. Educational analytics terms

The term "learning analytics" is used interchangeably with "academic analytics" in the context of higher education. It helps institutions financially by lowering attrition rates, improves learning outcomes by taking student behaviour into account, and suggests policies for instructors to implement that lead to a stable institute and efficient use of its resources [14]. Learning analytics phenomena help schools retain students, which in turn increases graduation rates [15], which has been a typical strategic priority for schools. The 'Educational Analytics' paradigm is a product of continuous collaboration between academic and learning analytics, with the former focusing on the student's journey and the latter on the institution as a whole and its efficacy [16]. Figure 1 also shows a semantic mapping between machine learning and educational data science, which includes both the goals of educational data science and the methods and technologies used in the current literature connected to machine learning.

Learning analytics, educational analytics, and academic analytics are all part of the educational data science paradigm, which includes the many overlapping words seen in Figure 2. Machine learning allows for more precise recording of students' perceptions of their learning, which in turn allows for more effective longitudinal interventions by academic institutions and more personalized approaches to instruction [17].
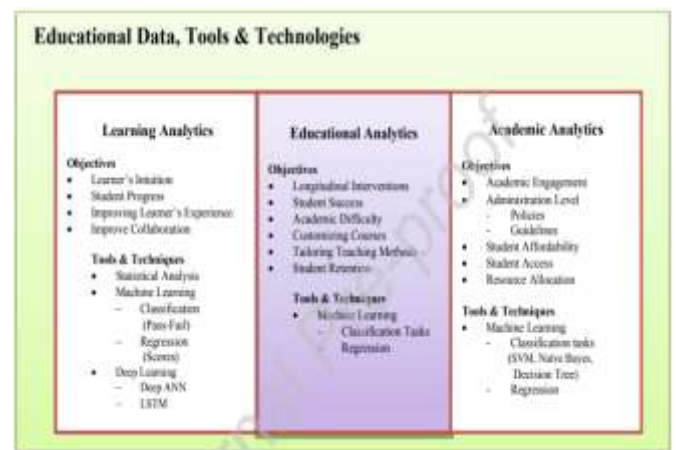
Figure 2. Relationship between Learning Analytics, Educational Analytics, and Academic Analytics [17].

Online education has emerged as a significant trend alongside the expansion of the internet, serving as a repository for a wealth of data pertaining to its students and learners. Analysis for pattern prediction in an educational context, stakeholder association definition, and learning environment optimization are all made possible by this. Various web-based educational systems, such as Intelligent Tutoring Systems (ITS), Learning Management Systems (LMS), Virtual Learning Environments (VLEs), Course Management Systems (CMS), and others, leave digital footprints that can be used to forecast students' future behaviour, determine which students are succeeding and which ones require additional support, and, in the end, assist teachers in improving their teaching methods.

This review study supports the use of machine learning to improve education. It serves as a helpful guide for researchers, educators, and policymakers aiming to use data to achieve better student results. By showcasing effective methods and pointing out areas needing more research, the study helps advance the field.

II. LITERATURE REVIEW

The literature review section summarises recent previous studies that have used ML models to forecast students' academic performance.

Farhood et al., (2024) [18] analysed ten ML and DL models using traditional algorithms and advanced techniques like RF, DT, SVM, K-nearest neighbours (KNN), Logistic Regression (LR), Linear Regression, Extreme Gradient Boosting (XGBoost), Fully Connected Feed-Forward Neural Network (FCNN), CNN, and Gradient-Boosted Neural Network. Every one of them was built and tweaked with the help of Python 3.9.5. This study compared approaches using two public student datasets, which posed a significant challenge in terms of prediction accuracy and model performance. There was a dual evaluation technique that used k-fold cross-validation and holdout approaches to evaluate the performance of the models. The primary purpose was to determine whether students passed or failed the final test.

Alnomay et al., (2024) [19] applied regression and supervised learning techniques on information from King Saud University in Riyadh, Saudi Arabia to build a model that would predict the performance of the students, which could further lead to early academic interventions. The study utilized vast course records from numerous years and courses in comparing Machine and Deep Learning methods. These models used Grade Point Averages (GPA) of courses and semesters to predict the final GPA of students. According to the results, linear and bagging regression models performed better on average along the Mean Absolute Error metric.

Bhushan et al., (2024) [20] proposed a model based on the previous academic performance, study habits, and personal behaviors of the computer science students throughout the semester to predict their SGPA. Multiple ML models had been applied with regression, classification, and deep learning techniques that had been compared using accuracy parameters. The results showed that, depending on the attributes considered for the prediction, the deep learning technique outperformed the others in terms of accuracy and effectiveness.

Baniata et al., (2024) [21] developed an innovative DL-based model to classify the students in need of academic support. The suggested model's performance was optimised using a Gated Recurrent Neural Network (GRU) design, which included a dense layer, max pooling layer, and ADAM optimisation. Further, a dataset including 15,165 assessment records from different educational institutions was used for the testing. The accuracy of 99.70% was shown to be superior to other models in a comparative analysis with Recurrent Neural Network (RNN), AdaBoost, and Artificial Immune Recognition System v2. Institutionalised students could benefit greatly from it, as it could lessen the likelihood of underachievement and dropout.

Alshamaila et al., (2024) [22] introduced a deep learning approach in convolution for resolving class imbalances in the form of oversampling and undersampling. Undergraduate students at the University of Jordan were the focus of this research, for which data was collected from the registration unit of the university. The features studied included demographic information, majors-related attributes, course history (passed, repeated, and completed), high school averages, and performance during the first four semesters. The model performance manifestly showed very strong abilities in predetermining the excellence of the students, most particularly concerning gmean.

Chen et al., (2023) [23] used three types of task-oriented educational data to evaluate ML methods across various applications. Seven optimized machine learning methods were experimented on to study both binary and multi-class performance prediction tasks. Four evaluation metrics and visualizations have been used to carry out the comparison of methods across three different tasks, with a profound discussion of the experimental results. The random forest was the most generalizing model across the entire dataset, however besides that, the decision tree and artificial neural network models suggested that they were capable enough of being a good representative of predicting students' performance.

Nayak et al., (2023) [24] examined different ML algorithms, including Decision Tree (J48), Naïve Bayes (NB), RF, and Multilayer Perceptron (MLP). To

find important qualities, filter-based feature selection approaches were used, such as Info gain, gain ratio, and correlation. The "Opt-MLP" model was created using the optimized MLP learning parameters, and it has been compared to the other models. The results show that in dataset 1, Opt-MLP achieved an accuracy of 87.14% Without Feature Selection (WOFS) and 90.74% with Feature Selection (WFS). In dataset 2, the accuracy was 79.37% WOFS and 97.08% WFS. Adding the behavioural features of the students into the model, the RF model was able to attain 100% accuracy in prediction, which again emphasizes the significance of a student's behavior in the prediction of their outcomes.

Korchi et al., (2023) [25] explored a student dataset that had personal information and grades with several regression algorithms, including J48, RF, LR, KNN, XGBoost, and Deep Neural Network (DNN). These algorithms were selected due to their respective strengths. Their performance was ascertained using the coefficients of determination, mean average error, mean squared error, and root mean squared error. The coefficient of the DNN was 99.97%, which implied excellent predictive capabilities concerning grades for students. This approach could help in developing models that predict academic performance in advance and provide support services on time to the teaching staff.

Yağcı et al., (2022) [26]created an ML model to estimate the final grades of undergraduate students based on their midterm grades. The algorithms evaluated included RF, KNN, SVM, LR, and NB. Academic records from 1,854 students enrolled in a Turkish university's Turkish Language-I course in the 2019–2020 autumn semester made up the dataset. Using midterm grades and data based on department and faculty, the model obtained classification accuracy of 70–75%.

Li et al., (2022) [27] suggested an end-to-end DL model capable of automatically extracting features from multi-source heterogeneous behavior data to predict the performances of students. The model captured the time-series feature of each behavior type by using LSTM networks and extracts correlation features between different behaviors with two-dimensional convolutional networks. In experiments with four kinds of daily behavior data from university students in Beijing, this model achieved significantly better performance than that of several other ML algorithms.

Olabanjo et al., (2022) [28]erformed a study using the data from a secondary school repository that consisted of students' academic, cognitive, and psychomotor scores. Preprocessed dataset was also placed to train the RBFNN model on which the impact of PCA was measured against the performance of the model. The developed model predicted student pass success with 93.49% sensitivity, failure success with 75% specificity, the overall accuracy of 86.59%, and AUC score of 94%. This study helped in a way to project students' academic success before they take their exams to be of benefit to the student, parents, and teachers.

Ojajuni et al., (2021) [29] developed a ML model aimed at the prediction and classification of academic success based on student results by employing supervised algorithms involving RF, SVM, Gradient Boosting, DT, LR, Regression, XGBoost, and DL. The approach highlighted the prediction of academic outcomes in light of historical data and pointed out critical factors that affect success. A comparison of several models to DL gave the results: with the XGBoost predicting the performance of academics with an accuracy of about 97.12%. Moreover, the findings highlighted social and demographic factors crucial to students' success.

Neha et al., (2021) [30] proposed the mathematical model based on internal and external predictive indicators for predicting student academic performance. The model had used several predictive variables that assess the performance of the student and evaluates it by using DNN (Deep Neural Network). The proposed model exhibited a better accuracy ratio against traditional models based on the prediction of student's performance.

Hussain et al., (2021) [31] suggested a regression model based on DL to assess student academic performance. Techniques of regression, including DL and linear regression, were applied to the set while going for resolution of overfitting problems usually prevailing in the smaller datasets through parameter tuning. The mean absolute error for the model was 1.61 and loss value at $k = 3$ was 4.7, where this deep learning model outperformed the linear regression model, which had the loss value at 6.7 and MAE of 1.97. This type of DL could be applied in other

educational programs to predict and analyze learner performance.

Aslam et al., (2021) [32] proposed a deep learning architecture for academic performance prediction, considering two courses, namely, mathematics and Portuguese. The data information was based on demographic, social, educational, and course grade data, and SMOTE (synthetic minority oversampling technique) was added to the data since it was featured with class imbalance. Precision, recall, F-score, and accuracy measurements were used in the model evaluation. However, it revealed that the model was adequate in the prediction at early stages. The accuracy values of 0.964 were obtained for the Portuguese language and 0.932 for mathematics with precision scores of 0.99 and 0.94, respectively.

Table 1 below presents a summary of some studies that predict student academic outcomes based on different machine learning techniques.

Table 1. Summary of Studies on ML Techniques for Predicting Student Academic Performance

Author	Technique Used	Main Findings	Benefit	Limitation
Farhood et al., (2024) [18]	Random Forest, Decision Tree, SVM, KNN, Logistic & Linear Regression, XGBoost, CNN, Gradient Boosted NN	Used two evaluation methods to see if students passed or failed the final exam	Tested a wide variety of models for a comprehensive comparison	Accuracy and performance of models presented significant challenges
Alnomay et al., (2024) [19]	Regression, Supervised Learning	Predicted final GPA using past grades, with Linear and Bagging Regression performing best	Helps identify students needing early academic support	Relies mostly on GPA data, which may not capture the full picture of student performance
Bhushan et al., (2024) [20]	Regression, Classification, Deep Learning	Found deep learning models to be the most accurate in predicting SGPA	Effective at predicting outcomes based on behavior and habits	Results depend heavily on the attributes used for the predictions
Baniata et al., (2024) [21]	Gated Recurrent Neural Network (GRU)	Achieved an impressive 99.70% accuracy in identifying students needing support	Very high accuracy and useful for educational support systems	Tested only on a specific dataset, which may limit generalization
Alshamaila et al., (2024) [22]	Deep Learning (Convolutional)	Addressed class imbalance and showed strong performance in predicting student excellence	Effectively handled class imbalance issues	Oversampling and undersampling techniques could introduce bias
Chen et al., (2023) [23]	Random Forest, Decision Tree, Artificial Neural Network	Random Forest was the best overall model across multiple tasks	Worked well across different educational tasks	Other models had less consistent generalization
Nayak et al., (2023) [24]	Decision Tree, Naïve Bayes, Random Forest, MLP	The optimized MLP model reached 97.08% accuracy with feature selection	Highly accurate model with behavioral insights	Behavioral data was essential for the highest accuracy

| Korchi et al., (2023) [25]	J48, RF, LR, KNN, XGBoost, DNN	DNN model performed best, with a high accuracy of 99.97%	Exceptional accuracy for predicting grades	Focused mainly on regression techniques, limiting the scope for classification tasks
Yağcı et al., (2022) [26]	Random Forest, SVM, Logistic Regression, Naïve Bayes, KNN	Midterm grades predicted final results with around 70-75% accuracy	Simple model that provides early performance insights	Lower accuracy compared to other more complex models
Li et al., (2022) [27]	LSTM, 2D Convolutional Networks	Excelled in predicting student performance using behavior data	Great at handling time-series and correlating different behaviors	Focused more on behavior data than academic grades
Olabanjo et al., (2022) [28]	RBFNN, PCA	Achieved 86.59% accuracy for predicting pass/fail rates	Balanced sensitivity and specificity	Limited to secondary school data, making it less applicable to higher education
Ojajuni et al., (2021) [29]	Random Forest, SVM, XGBoost, Gradient Boosting, DL	XGBoost achieved 97.12% accuracy in predicting academic outcomes	Highlighted key social and demographic factors affecting success	Focus on XGBoost limited comparison with other advanced models
Neha et al., (2021) [30]	Deep Neural Network	Showed better accuracy than traditional models in predicting student success	Effective in early-stage performance predictions	Focus on certain indicators may not provide a holistic view
Hussain et al., (2021) [31]	Deep Learning, Linear Regression	Deep learning outperformed linear regression in terms of prediction error	Tuned parameters helped solve overfitting issues	Challenges arise with smaller datasets
Aslam et al., (2021) [32]	Deep Learning (SMOTE)	Achieved high accuracy for Portuguese and Mathematics courses	Handled class imbalance effectively, with good precision and recall	Techniques for handling imbalance might affect real-world applications

III. COMPARATIVE STUDY

In this section, a comparative analysis is provided which is done by considering some studies from the literature review section. This comparison is performed based on accuracy parameter of the study with their respective utilized ML and DL models. Table 2 summarizes the eight accuracy-oriented studies for different machine learning techniques to forecast the grade of the student. Farhood et al. employed Logistic and Linear Regression, with an application of LASSO, thereby achieving an accuracy rate of 91.39%. Baniata et al. apply Gated Recurrent Neural Networks for achieving astonishing accuracy of 99.70%. Nayak et al. (2023) was able to deliver an accurate estimation of 97.08% based on the MLP model, while Korchi et al. got an incredible 99.97% based on the DNN. Yağcı et al. (2022) had made use of multiple algorithms, such as Random Forest, SVM and Logistic Regression, with the maximum being at 75%. Olabanjo et al. (2022) used RBFNN and attained an accuracy of 86.59%. Ojajuni et al. (2021) used XGBoost to get 97.12% accuracy. Finally, Aslam et al. (2021) applied Deep Learning techniques with SMOTE for handling imbalanced data and obtained an accuracy of 96.4%.

Table 2. Comparative Study

Author & Reference	Techniques Utilized	Accuracy
Farhood et al., (2024) [18]	Logistic and Linear Regression, and LASSO	91.39%
Baniata et al., (2024) [21]	GRU	99.70%
Nayak et al., (2023) [24]	MLP	97.08%
Korchi et al., (2023) [25]	Deep Neural Network	99.97%
Yağcı et al., (2022) [26]	Random Forest, SVM, Logistic Regression, Naïve Bayes, KNN	75%
Olabanjo et al., (2022) [28]	RBFNN	86.59%
Ojajuni et al., (2021) [29]	XGBoost	97.12%
Aslam et al., (2021) [32]	Deep Learning (SMOTE: synthetic minority oversampling technique)	96.4%

The graph illustrated in figure 3 shows accuracy differences between different machine learning techniques that were applied to predict the academic performance of students. This graph represents a comparison based on accuracy of the several literatures which are studies during this review. Deep learning models, DNN and GRU, revealed the highest accuracy rates for these analyses.
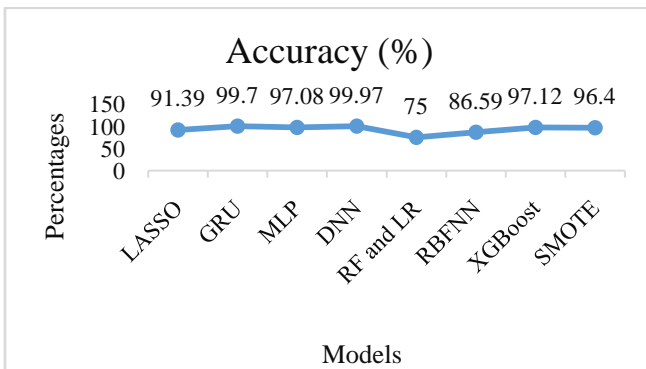
Figure 3 Performance comparison of various techniques in terms of accuracy

IV. CONCLUSION

An important topic of educational research that could greatly improve learning experiences and instructional tactics is the prediction of student academic results using ML and DL techniques. These models provide a quantitative framework for analyzing educational data, offering actionable insights that can be used to tailor teaching methods and improve student outcomes. This study explores the role of ML and DL in forecasting student academic performance, a topic of increasing relevance as educational data becomes more accessible and varied. The review thoroughly evaluates a range of ML and DL models, such as SVM, DNN, GRU, SMOTE, XGBoost, etc., highlighting their potential to reshape educational approaches through accurate predictions. It emphasizes the significance of diverse data inputs to enhance prediction accuracy and discusses the challenges faced, including model overfitting, concerns around data privacy, and ethical issues in using predictive analytics. Comparative results show that the DL models, DNN (99.97%) and GRU (99.7%), revealed the highest accuracy rates for these analyses among ML models. The paper recommends fostering ethical transparency and augmenting machine learning predictions with qualitative data, providing a valuable framework for educators and policymakers aiming to optimize educational outcomes using technology. Looking forward, the study suggests that future research should explore the integration of more real-time data sources and the development of dynamic models that can adapt to changing educational environments, potentially enhancing predictive accuracy and student engagement.

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