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Student's Performance Evaluation Using Ensemble Machine Learning Algorithms

Oladunjoye John Abiodun[1], Andrew Ishaku Wreford[2]

[1,2]Department of Computer Science, Federal University Wukari, Nigeria

ABSTRACT: This study explores the critical domain of predicting students' academic performance in educational institutions. By harnessing the potential of machine learning algorithms, specifically Random Forest, KNN, and XGBoost, and leveraging data collected through technology-enhanced learning applications, the research aims to provide valuable insights into the factors influencing academic outcomes based on the dataset obtained from Kaggle. It is important to note that these models were also hybridized using the stacking ensemble approach. The performances of the algorithm were evaluated using the Root Mean Squared Error (RMSE), Mean Squared Error (MSE), Mean Absolute Error (MAE), and R-squared (R2) score. Resultively, the stacked ensemble model displayed remarkable results, with an impressively low RMSE of 0.1768, MSE of 0.0312, MAE of 0.1247, and a high R2-score of 0.9705. This finding showed that the Ensemble model, which combines the strengths of the Random Forest, KNN, and XGBoost algorithms, provides the best overall prediction accuracy, with a high degree of correlation between predicted and actual student performance.

KEYWORDS: Random Forest (RF), K-nearest neighbours (K-NN), Support Vector Machine (SVM), Logistic Regression (LR), Artificial Neural Network (ANN), and Naïve Bayes (NB).

1.0 INTRODUCTION

In the continuously evolving landscape of education, the assessment and evaluation of student performance assume paramount significance in shaping the future of learning (Chen & Zhai, 2023). These evaluations not only serve as metrics of academic accomplishment but also function as guiding beacons for educators, institutions, and policymakers in the development of effective pedagogical strategies and interventions. Beyond mere grading, student performance evaluations possess the potential to unearth profound insights into the dynamics of learning and the multifarious factors influencing educational outcomes (Roslan & Chen, 2023). In essence, they allow for the anticipation of students' performance based on their prior academic achievements, shedding light on how individual interests and skills may influence their academic success. Such analyses empower educators to focus their attention more effectively on those students in need of additional support (Pallathadka *et al.,* 2023).

When considering student performance, it is important to take into account the impact that teachers have on their students (Canales & Maldonado, 2018). Teacher effectiveness, including their ability to engage students, provide clear instruction, and create a positive learning environment, can directly influence academic achievement (Stronge, 2018). According to Wood (2018), effective teaching encompasses diverse pedagogies, fostering positive teacher-student relationships, providing constructive feedback, practicing differentiated instruction, and maintaining strong classroom management. In essence, understanding instructional strategies, interpersonal skills, and a supportive educational environment collectively enhance teacher effectiveness and positively influence student success. It's pivotal to acknowledge that the impact of a teacher on student performance cannot be solely attributed to academic expertise, but also to their ability to foster a positive and inclusive learning environment (Dewsbury & Brame, 2019). Research has shown that students taught by effective teachers demonstrate higher levels of academic growth and achievement. Effective teachers can motivate and inspire students, tailor their instruction to individual student needs, and provide support and resources for student success (Stronge, 2018). On the other hand, ineffective teaching may lead to disengagement, lower motivation, and decreased academic performance. The quality of the relationship between teachers and students plays a significant role in student performance (Fauth *et al.,* 2019). Positive teacher-student relationships foster a supportive learning environment, enhance student motivation, and contribute to a sense of belonging (Dewsbury & Brame, 2019). Moreover, the performance of a teacher's students is frequently utilized as a gauge of the teacher's effectiveness, thereby necessitating rigorous evaluation of student performance for institutional quality assessment.

Within the realm of education, data mining techniques have been harnessed to extract and analyze educational data, giving rise to the field of educational data mining (Okewu *et al.,* 2021). Educational institutions maintain extensive repositories of data encompassing personal and academic information of students and faculty, syllabi, examination papers, circulars, and assorted materials (Romero & Ventura, 2020). Numerous universities and independent organizations have now incorporated educational data mining methodologies into their systems to enhance the educational experiences and outcomes of both students and faculty (Wang *et al.,* 2023). These methodologies have been seamlessly integrated into their application systems to facilitate efficient data handling.

The domain of educational data mining constitutes a burgeoning area of research, facilitating the analysis and processing of educational data derived from diverse sources (Cardona *et al.,* 2023). However, the performance of students in assessments is influenced by an array of factors, encompassing levels of engagement, demographic variables, and results from ongoing evaluations. While prior studies have examined individual factors in isolation, a comprehensive modeling approach becomes imperative for the precise prediction of academic performance, thereby enabling timely interventions to enhance learning experiences and retention rates (Alghamdi & Rahman, 2023). In this context, various statistical methods, data mining techniques, visualization tools, and machine learning algorithms are deployed for the analysis of educational data. Recent advancements in the field of artificial intelligence have further pioneered the development of machine learning models that assimilate insights from mined data. Consequently, the confluence of data mining techniques and the availability of data from learning management systems (LMS) has become instrumental in predicting individual learning performance in advance and facilitating the provision of essential support. Notably, machine learning techniques such as SVM and ANN (Arashpour *et al.,* 2023), as well as Nave Bayes, ID3, C4.5, and SVM (Pallathadka *et al.,* 2023), and ANN and Random Forest (Batool *et al.,* 2023) have been applied in this pursuit.

The significance of student performance evaluations transcends the confines of the classroom, resonating with broader objectives aimed at enhancing the quality of teaching and learning experiences, improving student outcomes, and fostering educational equity (Kukkar *et al.,* 2023). At its essence, this study acknowledges that the pursuit of educational excellence is intrinsically linked to the capacity to assess, comprehend, and nurture the diverse talents and potential of every student. As such, this study proposes the application of the Random Forest, KNN, and XGBoost algorithms to a student performance dataset sourced from the Kaggle machine learning repository.

2.0 RELATED WORK

Yagci (2022) suggested a model that can estimate students' likely final exam scores from their midterm performance. An accuracy of 75% is reached using a total of six algorithms: RF, NN, SVM, LR, NB, and K-NN. Yagci's research (2022) helps pinpoint those students most in danger of failing their courses.

The use of machine learning for academic guidance in high school was investigated by (Ababneh *et al.,* 2021). The research suggests a deep learning model for predicting grades, with layers of distributed attention, convolutional neural networks, and a fully connected layer. Information such as grades, student statistics, and course descriptions were collected. Prediction accuracy for the suggested model was 81%, with 85% for failure predictions, and an explanation for the projected event was supplied.

Ashoka *et al.,* (2021) recommended employing machine learning to foretell students' performance. Google Forms were used to collect information from students at the KS School of Engineering and Management. This research chooses the most effective model for prediction from linear regression, logistic regression, SVM, Decision Tree (DT), RF, xgboost, and Gradient-Boosting Regressor. R-squared, Adjusted R-squared, Root Mean Squared Error and Mean Squared Error were employed to assess the performance of the obtained models. According to the data collected throughout the experiments, the SVM achieves an accuracy of 72.39 percent.

Hamoud *et al.,* (2017) made use of Bayesian algorithms (particularly Naive Bayes and Bayes Network) to predict student performance. A total of 62 questions were used to gather information about participants' health, social life, relationships, and academic accomplishments. Using the Weka software, they found that NB yielded 70.6% accuracy, while Bayes Network managed only 64.3%.

Data on the academic performance of 50 graduate students was mined (Abu, 2019). The authors utilized five data-mining algorithms to train their datasets, and the accuracy results were as follows: multilayer perceptron (MLP) (60.5%), neural networks (NB) (71.1%), SVMs 76.3%, K-NN (65.8%), and linear discriminant analysis (LDA) (71.1%).

3.0 RESEARCH METHODOLOGY

The research design employs a quantitative approach to predict undergraduate students' academic performance through a comprehensive three-phase methodology (Wreford & Abiodun, 2023). The first phase includes dataset acquisition, meticulous cleaning, and standardization for quality and uniformity. In the second phase, the dataset is split into training and test subsets, used for training and assessing some regression models including XGBoost, KNN, and RF. The final phase evaluates XGBoost, KNN, and RF models using metrics like MSE, RMSE, MAE, and R-squared, providing insights into their predictive accuracy. The methodological framework progresses systematically from data preprocessing through model training to final evaluation as shown in Figure 3.1.

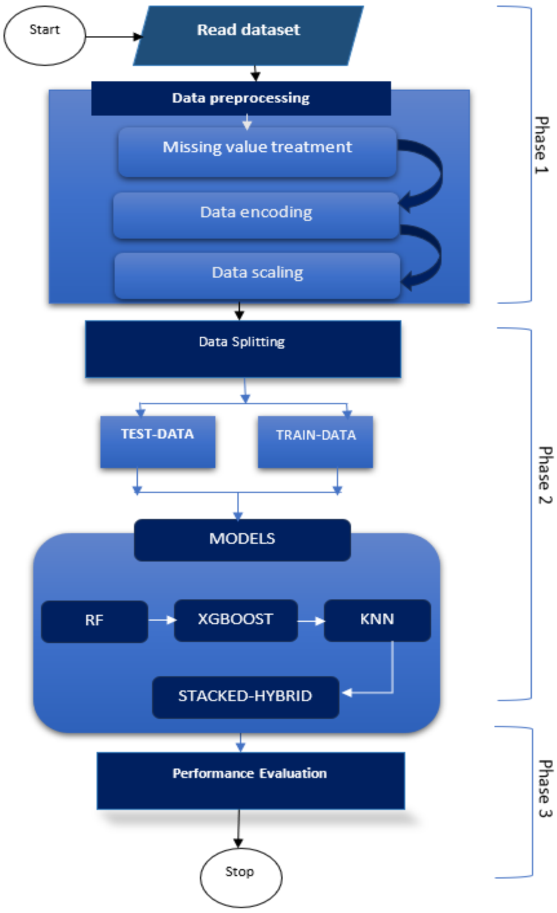

Figure 3.1: Research Methodology Framework

3.1 Dataset Description

The dataset utilized in this study is sourced from Kaggle machine learning and pertains to the evaluation of students' performance. The dataset was uploaded by Seshapampu in 2018. The dataset is structured as comma-separated values (CSV) with a file size of 9 kilobytes, and it comprises records of 1000 pupils. The dataset contains features like explain the Dataset Contains Features like school ID, gender, age, size of family, Father education, Mother education, Occupation of Father and Mother, Family Relation, Health, and Grades. The school ID is a unique identifier for the school that the individuals attend. It helps distinguish between different educational institutions. Gender indicates the gender of the individual, whether they are male or female. Age represents the age of the individual, providing information about the stage of life or educational level. Size of Family denotes the number of members in the individual's family. It can give insights into the family structure and dynamics. The Father education feature indicates the educational level attained by the individual's father. Education levels might include categories such as high school, college, or postgraduate education is similar to father education, this feature represents the educational level of the individual's mother. Occupation of Father and Mother describe the professions or jobs held by the individual's father and mother, respectively. This information can provide insights into the socio-economic status of the family. Family relation describes the quality of relationships within the family. It is a measure of family cohesion, communication, or overall harmony. Health provides information about the health status of the individual. It includes indicators such as overall health, chronic conditions, or other relevant health-related information. Lastly, the Grade feature represents the academic performance of the individual, often in terms of grades or scores. It gives an idea of the individual's achievements in their educational pursuits. These features provide a comprehensive view of the individuals and their families, allowing for the exploration of various relationships and patterns within the dataset.

3.2 Data Normalization

To improve the effectiveness of a specific machine-learning model, the idea of normalisation was proposed. When applied to numerical columns in a dataset, normalisation seeks to standardize their values while retaining the differences in their ranges. Each feature variable, let's call it V_{ij}, must be constrained to the interval [0, 1].

$$\frac{V^{ij} - min^{j}(V^{ij})}{max^{j}(V^{ij}) - min^{j}(V^{ij})} \dots \dots \dots \dots \dots \dots 3.1$$

3.3 Regression Algorithm

The dataset revealed that the student performance problem is a regression task. Regression models analyze the relationship between input features and a continuous target variable. This study suggests using three regression models including XGBoost, RF, and KNN.

3.4.1 Random Forest

Random Forest Regression is a supervised learning algorithm used for both regression and classification tasks. It leverages ensemble learning to enhance accuracy by combining predictions from multiple models (Fernández-Delgado *et al.,* 2019). This method falls under the category of bagging techniques, distinct from boosting. Bagging entails the creation of independent decision trees on subsets of training data, allowing trees to run concurrently without interaction (Fernández-Delgado *et al.,* 2019). The Random Forest algorithm constructs numerous trees, each on a unique subset achieved through bootstrapping, which involves random sampling with replacement. This variation in training subsets assists trees in capturing diverse data patterns effectively. During the prediction phase, each tree independently generates its prediction. In the context of regression, the output of each tree is a predicted value. Ultimately, the final prediction of the Random Forest model aggregates individual tree predictions, often using methods like mode or mean.

3.4.2 XGBoost

To train machine learning models quickly and in large numbers, XGBoost is an optimized distributed gradient boosting library. It is a type of ensemble learning in which the predictions of several rather unreliable models are combined into a single, more reliable one. Because of its scalability to large datasets and its ability to achieve state-of-the-art performance in many machine learning tasks like classification and regression, XGBoost (an acronym for "Extreme Gradient Boosting") has become one of the most popular and widely used machine learning algorithms (Avanijaa, 2021). XGBoost's effective handling of missing values is a critical feature that enables it to analyze real-world data with missing values without requiring extensive pre-processing. To further facilitate training models on huge datasets in a reasonable time, XGBoost incorporates native support for parallel processing. The performance of XGBoost can be fine-tuned by adjusting some model parameters.

3.4.3 KNN algorithm

Among the many classification and regression techniques available in Machine Learning, K-Nearest Neighbours (Keramat-Jahromi *et al.,* 2021) stands out as one of the simplest yet most important. KNN determines the most appropriate class by calculating the average distance between the test data and the training points. Select the K points that are most similar to the data under test. Using the training data, the KNN algorithm selects the 'K' class that is most similar to the test data. Regression uses a weighted average of 'K' randomly selected points from the training set to determine a final value.

3.5 Performance Evaluation Metric

To evaluate the performance of the regression algorithms on the student performance dataset the following metrics were utilized:

Root Mean Squared Error (MSE): It is the average of the squared difference between the predicted and actual value.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_i^f - y_i^{ob})^2}{n}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 3.2$$

Where; y_i^f is the i^{th} forecasted data,

y_i^{ob} is the i^{th} observed data, n is the amount of data.

Mean Absolute Error (MAE): describe the size of the discrepancy between the predicted value and the actual value of an observation. The mean absolute error (MAE) is a statistical measure that takes into account the size of errors over multiple predictions and observations. MAE can also be referred to as L1 loss function.

$$MAE = \frac{\sum_{i=1}^{n} abs(y_i - \lambda(x_i))}{n} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.3)$$

Where; y_i is the true target value for the test instance.

$\lambda(x_i)$ is the predicted target value for the test instance.

x_i, and n is the number of test instances.

Mean Square Error (MSE): evaluates the fit of a regression line to a data collection. The expected value of the squared error loss is a risk function. The average squared error in a set of data for a certain function is known as the mean square error. When the MSE is big, the data points are spread out widely around the mean, while when it is small, the opposite is true. When the data points cluster closely around the central moment mean, the MSE is minimal.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(Y_i - \hat{Y}_i)^2 \ldots\ldots\ldots\ldots\ldots\ldots (3.4)$$

Where; n is the number of data points

Y_i is the actual (observed) value for the i^{th} data point.

$\hat{Y}_i$ is the predicted value for the i^{th} data point.

R2-Score: when assessing the efficacy of a machine learning model, the R2 score, also known as the coefficient of determination, is crucial. A dataset's usefulness is determined by how much of its variability can be accounted for by the model's predictions. It is the discrepancy between the dataset samples and the model's predictions.

$$R^2 = \frac{\sum(\hat{y}_i - \bar{y}_i)^2}{\sum(y_i - \bar{y}_i)^2} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 3.5$$

Where; Y_i is the actual (observed) value for the i^{th} data point.

$\hat{y}_i$ is the predicted value for the i^{th} data point.

4.0 RESULTS AND DISCUSSION

4.1 Experimental setup

This investigation analyzed student performance on a 64-bit Windows OS machine, powered by an Intel(R) Corel Trade Mark (TM) i5-2560QM CPU @2.40GHZ, with 8.00 GB of RAM. The Anaconda environment with the Python 3.11 software development kit was used to put the program code into action. Sklearn, Pandas, Matplotlib, Seaborn, and NumPy were used as their respective application programming interfaces.

4.2 Result Presentation

Table 1 presents the results of the machine learning algorithms used for evaluating student performance. These algorithms include KNN, RF, and XGBoost. These algorithms were hybridized via a stacking approach forming a stacked ensemble model. The performances of the algorithm were evaluated using the RMSE, MSE, MAE, and R2 scores.

Starting with the KNN model, it achieved an RMSE of 0.4824, MSE of 0.2327, MAE of 0.3750, and an R2-score of 0.7804. The RMSE measures the average magnitude of the prediction errors, and a lower value indicates a better fit to the data. The MSE signifies the average squared difference between actual and predicted values. The KNN model performed reasonably well, with a respectable R2-score of 0.7804, indicating that it explains a significant proportion of the variance in the student performance data.

The RF model showed an improved performance compared to KNN, with an RMSE of 0.3989, MSE of 0.1591, MAE of 0.3122, and an R2-score of 0.8498. The RF model's lower RMSE and MSE values signify its ability to reduce prediction errors, resulting in a more accurate model. Additionally, the higher R2 score suggests a strong correlation between the predicted and actual student performance.

XGBoost performed even better with an RMSE of 0.3734, MSE of 0.1394, MAE of 0.2870, and an R2-score of 0.8684. These metrics demonstrate that XGBoost excels in explaining variance and minimizing prediction errors. It outperforms both KNN and RF in terms of predictive accuracy.

The Ensemble model displayed remarkable results, with an impressively low RMSE of 0.1768, MSE of 0.0312, MAE of 0.1247, and a high R2-score of 0.9705. This suggests that the Ensemble model, which combines the strengths of the KNN, RF, and XGBoost algorithms, provides the best overall prediction accuracy, with a high degree of correlation between predicted and actual student performance.

Table 1: Result Presentation

Algorithm	RMSE	MSE	MAE	R2-SCORE
KNN	0.4824	0.2327	0.3750	0.7804
RF	0.3989	0.1591	0.3122	0.8498
XGBOOST	0.3734	0.1394	0.2870	0.8684
ENSEMBLE	0.1768	0.0312	0.1247	0.9705

In summary, the Ensemble model outperforms the individual algorithms (KNN, RF, and XGBoost) for student performance evaluation. It achieves a significantly lower RMSE and MSE, indicating reduced prediction errors, and a higher R2-score, indicating a strong correlation with actual student performance. Also, the logic of comparison was based on the accuracy score and metrics like RMSE, MSE, MAE, and R2-score obtained by each author. The results of each model's performance are shown in Figure 2

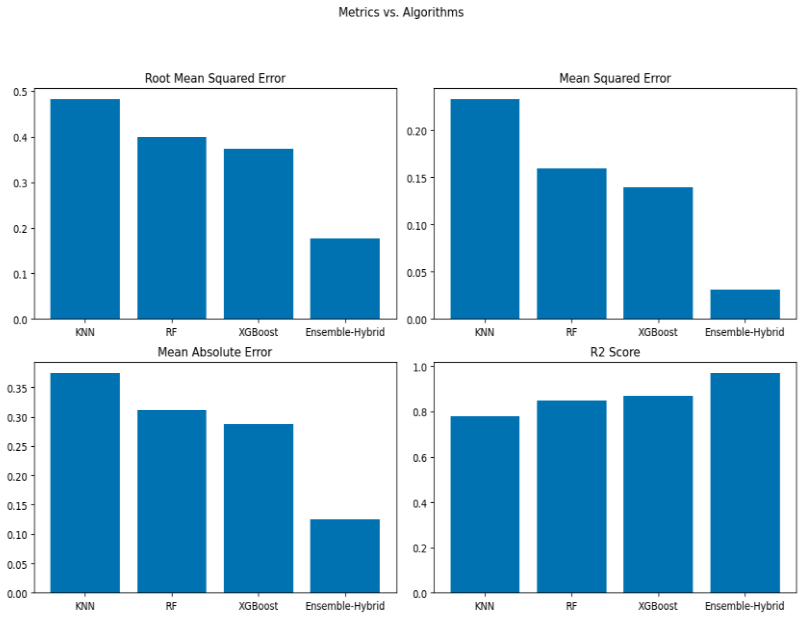

Figure 2: Model Result

The above figure displays the graphical representation of result models of KNN, RF, XGBoost, and Ensemble-Hybrid based on the evaluation metric of RMSE, MSE, MAE, and R2-Score. From the results, it is clear that the Ensemble algorithm outperforms the other algorithms in terms of RMSE, MSE, MAE, and R2-score. It has the lowest values for all the metrics, indicating that it has the best predictive performance.

Comparing the other algorithms, XGBoost performs better than Random Forest and KNN in all the metrics. It has the lowest RMSE, MSE, MAE, and the highest R2-score among the three algorithms. Random Forest performs better than KNN in all the metrics except for R2-score, where it is slightly lower than KNN.

The results show that Ensembling methods like XGBoost and Random Forest perform better than traditional methods like KNN for this particular dataset. The use of multiple models combined into an ensemble is proven to be effective in improving predictive performance.

4.3 Contribution to Knowledge

In recent times, different machine learning algorithms like Random Forest (RF), Neural Network (NN), Support Vector Machine (SVM), Linear Regression (LR), Naive Bayes (NB), Decision Tree (DT), Xgboost, multilayer perceptron (MLP), Gradient-Boosting Regressor and K-Nearest Neighbour were adopted for student performance evaluation.

Six models including RF, NN, SVM, LR, NB, and K-N N in the work of Yagci (2022) have been used to evaluate student's final exam scores which obtained an accuracy of 75%. Ababneh *et al.,*(2021) applied a deep learning model for predicting grades which achieved an accuracy of 81%. Ashoka *et al.,* (2021) employed a support vector machine and achieved an accuracy of 72.39%. Furthermore, Hamoud *et al.,* (2017) applied Bayesian algorithms (particularly Naive Bayes and Bayes Network) to predict student performance and the accuracy obtained is 70.6% and 64.3% respectively. It has been observed from the above-reviewed works that the results obtained were inefficient.

Thus, this research explored the need to adopt the Ensemble model in checking and comparing the efficiency of models that will have the ability to evaluate student performance. It was observed that the hybridization of the (KNN, RF, and XGBoost) to ensemble models has yielded a higher accuracy of 97% when compared with individual models used for the evaluation of student performance. By utilizing ensemble methods, such as bagging, boosting, and stacking, the study demonstrates improved accuracy, sensitivity, and specificity in predicting student performance compared to traditional machine learning approaches. Moreover, the research provides valuable insights into the potential of ensemble machine learning algorithms in the field of education and student performance evaluation. The findings shed light on the effectiveness and robustness of ensemble methods in handling complex and multidimensional datasets, as well as their capability to uncover hidden patterns and relationships within the data. Finally, the contribution of the study lies in its advancement of the existing knowledge base by offering a more effective and accurate approach to student performance evaluation through the use of ensemble machine learning algorithms. This has the potential to improve decision-making processes in education, leading to better support and interventions for students at risk of academic challenges.

5.0 CONCLUSION

This study harnesses the strength of some ensemble machine-learning algorithms to assess and forecast the academic performance of students. These algorithms include KNN, RF, and XGBoost. Additionally, these algorithms were hybridized via a stacking approach forming a stacked ensemble model. The analysis was conducted using the student performance evaluation dataset sourced from the Kaggle machine learning repository. To assess the effectiveness of ensemble machine learning algorithms several evaluation techniques are employed. These include the computation of the RMSE, MSE, MAE, and R2 scores.

These evaluation methods are utilized to determine the suitability of some ensemble algorithms in addressing the problem of student performance. In general, the findings of the Ensemble model were notable with a remarkably low RMSE of 0.1768, MSE of 0.0312, MAE of 0.1247, and high R2 score of 0.9705. The findings indicate that the Ensemble model, which integrates the advantageous features of the KNN, RF, and XGBoost algorithms, yields the highest level of prediction accuracy across several metrics. Thus, the result of the analysis affirms that the integration of the developed hybrid ensemble machine analytics model in future education has the potential to significantly augment students' abilities to attain exceptional academic achievements within academic institutions.

Further research should focus on developing a system that uses ensemble machine learning algorithms to predict student performance in real time based on various input data such as attendance, class participation, exam scores, and other factors. Also, testing the generalizability of ensemble machine learning algorithms for student performance evaluation across diverse educational contexts, such as different schools, districts, or countries.

AVAILABILITY OF DATASET

https://www.kaggle.com/datasets/devansodariya/student-performance-data

COMPETING INTEREST

The authors declare that they have no competing interests.

AUTHORS’ CONTRIBUTIONS

The manuscript was written by Oladunjoye John Abiodun, while the code was written by Andrew Ishaku Wreford. It should be noted that both authors contributed substantial contributions to the study.

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