IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 7, October 2026
Impact Factor: 8.2

An Intelligent Academic Performance Prediction Model Using Hybrid Machine Learning Techniques

Dr Chintal Kumar Patel
Associate Professor, CSE
Geetanjali Institute of Technical Studies, Dabok, Rajasthan
chintal.patel@gits.ac.in

Abstract: *Predicting student academic performance accurately is vital to inform academic interventions and institutional decisions. However, existing educational prediction approaches may rely on individual machine learning (ML) models with limited predictive capabilities. In view of these limitations, this study introduces a hybrid model for Student Academic Outcome Prediction (SAOP) based on Random Forest and Extreme Gradient Boosting (RF-XGBoost). The proposed framework combines the merits of both algorithms by aggregating their probabilities with weights for better classification results. Experimental results demonstrate that the hybrid model achieves 96.5% accuracy (ACC), 96.3% precision (PRE), 96.2% recall (REC), and a 96.7% F1-score (F1). Compared with Support Vector Machine (SVM), Convolutional Neural Network (CNN), and Stacking Ensemble models, the proposed approach achieves the highest reported ACC, outperforming them at 87.08%, 90.49%, and 91%, respectively. The results suggest the proposed framework can be a viable solution to predict students' academic outcomes and inform data-driven educational planning.*

Keywords: Student Performance Prediction, Educational Data Mining, Machine Learning, Academic Performance Prediction, Educational Data Mining, Machine Learning, Classification Algorithms, Academic Achievement

I. INTRODUCTION

The academic success of college students is a key measure of the quality of their education and the results they achieve in the real world [1]. It reflects students' knowledge, learning abilities, and overall academic progress. Students' achievements are influenced by attendance, study habits, previous grades, time management, classroom participation, and extracurricular activities. Differences in learning styles, life experiences, and access to resources in the classroom could cause their progress to fluctuate over time [2][3][4]. Therefore, predicting academic performance is essential for identifying learning difficulties, improving teaching strategies, and supporting effective educational decision-making [5].

Institutions are using data-driven methods to assess student conduct and academic results as educational data becomes more readily available [6]. Educational Data Mining (EDM) applies computational techniques to extract meaningful patterns from educational datasets. EDM assists in identifying elements linked to student success by examining academic records, attendance, assessment outcomes, demographic variables, and behavioral traits [7] [8]. Exploratory Data Analysis (EDA) supports the examination of feature distributions, detection of missing values, and identification of relationships among variables. However, imbalanced datasets and complex relationships among student attributes can affect prediction reliability [9][10][11].

Traditional student performance prediction approaches may produce inconsistent results depending on dataset characteristics, data quality, and feature distributions. Some models struggle to identify complex relationships among

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429 Volume 6, Issue 7, October 2026 Impact Factor: 8.2

academic and behavioral attributes, while others are affected by class imbalance and overlapping performance categories [12][13][14]. These limitations can increase prediction errors and reduce model reliability. Therefore, an effective prediction framework is required to improve classification performance and identify students who need additional academic support [15][16].

Machine Learning (ML) and Deep Learning (DL) enable the automated analysis of educational datasets and the identification of complex patterns associated with student achievement [17]. ML techniques analyse structured academic information, while DL techniques learn complex data representations. Integrating complementary algorithms through a hybrid approach can improve prediction reliability and classification performance [18][19]. Consequently, this investigation suggests the development of an intelligent academic performance prediction model that employs hybrid ML techniques, including EDA, relevant feature identification, and a hybrid prediction strategy, to classify student academic outcomes. The proposed framework aims to improve predictive ACC, identify academically at-risk students early, and support personalized interventions and data-driven decision-making in higher education institutions.

A. Motivation and Contribution

The goal of this research is to find ways to use hybrid ML approaches to predict students' academic achievement more accurately and reliably. The proposed RF–XGBoost model aims to overcome the limitations of individual classifiers by combining their predictive strengths. It also seeks to identify academically at-risk students at an early stage. This approach supports timely academic interventions and effective data-driven decision-making in educational institutions. The following are a few of the most important contributions made by this study:

- Utilizes the Student Performance Prediction dataset to analyze academic and behavioral attributes associated with student outcomes.
- Applies data cleaning, missing-value removal, duplicate elimination, label encoding, and Min-Max normalization to improve data quality.
- Examines feature distributions, class balance, and correlations to understand the characteristics of student academic performance.
- Employs Recursive Feature Elimination (RFE) to identify relevant features and reduce unnecessary information.
- Proposes a hybrid Random Forest–Extreme Gradient Boosting (RF–XGBoost) model that combines the predictive capabilities of both algorithms through weighted probability aggregation.
- This section evaluates the suggested model in comparison to three other models: SVM, CNN, and Stacking Ensemble.
- A data-driven framework developed via a comparative study of ML might help schools spot pupils who might need more help in the classroom and devise strategies to help them succeed.

This study is justified by the need for a dependable and efficient framework to forecast students' academic performance. Simple ML models might not be able to capture complex relationships between academic and behavioral attributes. The novelty is that this work combines the two algorithms in the form of weighted probability aggregation using RF and Extreme Gradient Boosting. The suggested architecture incorporates many steps to enhance prediction reliability, including data pretreatment, feature selection, and class balance. It is intended to identify pupils who may struggle academically and to offer early support. This approach facilitates data-driven decision-making and contributes to improving academic performance assessment in higher education institutions.

B. Paper Structure and Overview

The paper is organized as follows: Section II reviews existing studies on Student Academic Outcome Prediction, while Section III describes the dataset, preprocessing techniques, and proposed hybrid ML methodology. Section IV presents the experimental results and comparative performance analysis, whereas Section V concludes the study by summarizing the key findings, limitations, and future research directions.

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 7, October 2026
Impact Factor: 8.2

II. LITERATURE REVIEW

A comprehensive review of recent studies on Intelligent Student Performance Forecasting was conducted to identify existing approaches, research gaps, and opportunities for improvement. Table I summarizes the proposed models, datasets, major findings, and key limitations of previous studies. This analysis provides a foundation for developing an optimized framework for accurate and reliable academic performance prediction.

Harshitha, Preethi and Jyothi (2026) approach integrates traditional ML, ensemble models, and DL to analyses academic and behavioral attributes using 2,000 student records, including attendance, study habits, sleep duration, stress, physical activity, and extracurricular participation. Five models—DTs, RFs, Grid Search-optimized RF, XGBoost, and LSTM—are evaluated using regression metrics. The optimized RF achieves the best performance, with an R^2 of 0.80, MAE of 0.09, and RMSE of 0.10. Feature importance analysis identifies attendance, study hours, and sleep duration as the most influential factors affecting GPA [20].

Goyal et al. (2026) presents a contrasting assessment of ML models used for predictive analytics, with an emphasis on how well they execute categorization tasks. We compare a proposed hybrid model to more traditional models such as XGBoost, LR, RF, and SVM. PRE, ACC, REC, F1, and AUC are some of the performance measures used for assessment. The results show that the Proposed Hybrid Model achieves a 95.3% ACC rate, which is far better than the baseline models [21].

Yarram et al. (2025) Java-based web framework introduces a Hybrid Neuro-Decision Intelligence Architecture (HNDIA) using neuro-feature encoding and decision-fusion methods. Student Academic Data Set (SADS) and Student Performance Dataset benchmarks are used for training and validation. Preprocessing, feature normalization, and correlation-based dimensionality reduction ensure data consistency. HNDIA outperforms ANN (91.18%), Gradient Boosting (90.24%), Random Forest (89.62%), and SVM (88.11%), achieving an MAE of 0.057 and RMSE of 0.123 [22].

X. Gao (2024) The traditional single prediction model is planned into a feature set. Through integrating a plurality of teaching indexes, a plurality of feature sets is innovatively input into the model for feature processing. After determining the weight, the optimized regression algorithm makes adjustments to guarantee a precise forecast. Lastly, the experimental setting is prepared for the simulation. The suggested model outperforms the single data prediction algorithm in terms of prediction ACC, according to the comparison test results. Compared with the traditional prediction algorithm, the prediction ACC is 92. 4% and 89. 1%, respectively [23].

Y. N. Al Husaini and N. S. Ahmad Shukor, (2024) The goal of this research is to find out how well ML and DL can forecast how well pupils will do in school. DL LSTM and DTs, RFs, and LR were among the ML and DL methods used in the research. And it found that the LSTM model was best for sequential classification of time series and used the OULAD to develop predictive models. The LSTM achieved the highest ACC, with an impressive 94.4% [24].

E. Jimenez Delgado, A. Linnette Roldan Morales, and Y. Calvo Araya (2022) reviews ML algorithms for classifying student performance in the Software Engineering program at the National Technical University. It analyses academic and student variables to predict course outcomes before enrollment, helping institutions improve retention and reduce failure risks. Performance measures are used to assess several algorithms; the top algorithms achieve an ACC of 80%-82% and may be reproduced at other universities [25].

Research Gaps: Previous research on predicting student academic achievement has mostly concentrated on individual ML models, DL methods, or traditional ensemble approaches. However, several methods are difficult to deal with the misbalance of classes, to select relevant features, and to capture complex relationships between academic and behavioral attributes. The existing literature on classifying student outcomes using a mix of RF, XGBoost, and weighted probability aggregation is scant. There has to be further research on how well preprocessing, feature selection, and class balance work together. To fill these gaps and improve classification ACC and early detection of children at risk of academic failure, a hybrid prediction model is needed.

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 7, October 2026
Impact Factor: 8.2

Table 1: Recent Studies on Optimized Frameworks for Student Academic Performance Prediction

Author	Proposed Work	Dataset	Key Findings	Limitations & Future Work
Harshitha, Preethi and Jyothi (2026)	Evaluated Decision Tree, Random Forest, Grid Search-optimized Random Forest, XGBoost, and Long Short-Term Memory (LSTM) for student GPA prediction.	2,000 student records containing attendance, study habits, sleep duration, stress, physical activity, and extracurricular participation.	Optimized Random Forest achieved (R^2=0.80), MAE = 0.09, and RMSE = 0.10. Attendance, study hours, and sleep duration were influential features.	The dataset is relatively small. Future work could validate hybrid models on larger, more diverse datasets and incorporate additional academic and behavioral factors.
Goyal *et al.*, (2026)	Compared a proposed hybrid model with Random Forest, Support Vector Machine (SVM), Logistic Regression, and XGBoost.	Not specified in the provided summary.	The hybrid model achieved 95.3% accuracy and 97.1% AUC, outperforming the reported baseline models.	The dataset details and student-specific applicability require verification. Future work could evaluate the approach using educational datasets and more diverse student populations.
Yarram *et al.*, (2025)	Proposed a Hybrid Neuro-Decision Intelligence Architecture (HNDIA) for web-based student performance prediction.	Student Academic Data Set (SADS) and Student Performance Dataset.	HNDIA outperformed the reported ANN (91.18%), Gradient Boosting (90.24%), Random Forest (89.62%), and SVM (88.11%) results, with MAE = 0.057 and RMSE = 0.123.	Generalization across institutions and datasets requires further validation. Future work could assess scalability and robustness across different academic environments.
X. Gao, (2024)	Developed an enhanced student online-learning performance prediction model by integrating multiple teaching indicators and feature sets with an optimized regression algorithm.	Online learning data incorporating students' network behavior and interaction information. The exact dataset name is not confirmed from the provided description.	The proposed model achieved 92.4% accuracy, compared with 89.1% for a traditional prediction algorithm. The study demonstrated the value of combining multiple learning-related indicators.	The generalizability of the model across different educational platforms requires further evaluation. Future work could explore hybrid machine learning models, additional student attributes, and broader datasets.
Y. N. Al Husaini and N. S. Ahmad Shukor, (2024)	Investigated machine learning and deep learning techniques, including Decision Tree, Random Forest, Logistic Regression, and Long Short-Term Memory (LSTM), for predicting academic performance.	Open University Learning Analytics Dataset (OULAD).	The LSTM model achieved 94.4% accuracy, outperforming the evaluated Decision Tree, Random Forest, and Logistic Regression models for sequential classification.	The study could be extended by combining complementary machine learning and deep learning models, evaluating additional datasets, and examining the generalizability of predictions across different student populations.
E. Jimenez Delgado, A. Linnette Roldan Morales, and Y. Calvo Araya, (2022)	Reviewed machine learning algorithms for classifying student performance and identifying academic failure risk.	Student records from the National Technical University, focusing on Software Engineering.	The selected classification approach achieved approximately 80–82% accuracy and could support early identification of students at risk of failure.	The study focuses on a particular university and academic program. Future work could evaluate additional institutions, broader features, and ensemble or hybrid models.

III. RESEARCH METHODOLOGY

The proposed methodology involves data gathering, exploratory data analysis, preprocessing, label encoding, Min-Max normalization, SMOTE-based class balancing, Recursive Feature Elimination (RFE), and an 80:20 training–testing split. A hybrid RF–XGBoost model is developed using weighted probability aggregation to predict student academic outcomes. PRE, ACC, REC, F1, and the ROC curve are used to measure the model's prediction performance and dependability. Figure 1 shows the suggested process flow for intelligently predicting students' academic achievement using ML methods.

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 7, October 2026
Impact Factor: 8.2

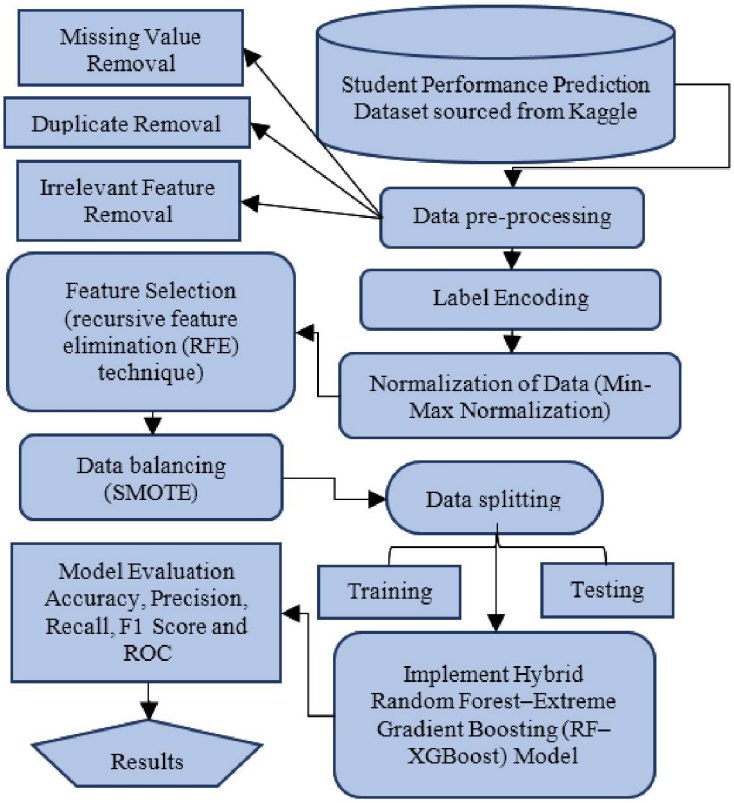


Figure 1: Proposed Workflow of the Intelligent Academic Performance Prediction Framework Using Machine Learning Techniques

The following section presents a detailed explanation of each step involved in the proposed methodology:

A. Data Gathering and Analysis

This study uses the Student Performance Prediction dataset, containing 40,000 instances and 7 features, including study hours, attendance, previous grades, extracurricular participation, and pass status. Histograms, bar plots, and correlation heatmaps analyze feature distributions and relationships to support ML-based academic performance prediction:

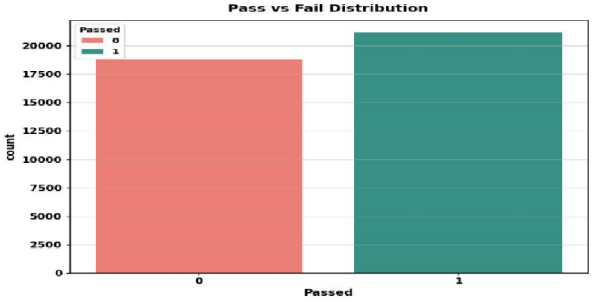


Figure 2: Bar Graph of Class Distribution

The goal variable Passed has a binary distribution, as seen in Figure 2, where the counts of students who did not pass (0) and those who did pass (1) are compared. The visualization displays a relatively even set of data, with about 19,000 students failing and just over 20,000 students passing.

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 7, October 2026
Impact Factor: 8.2

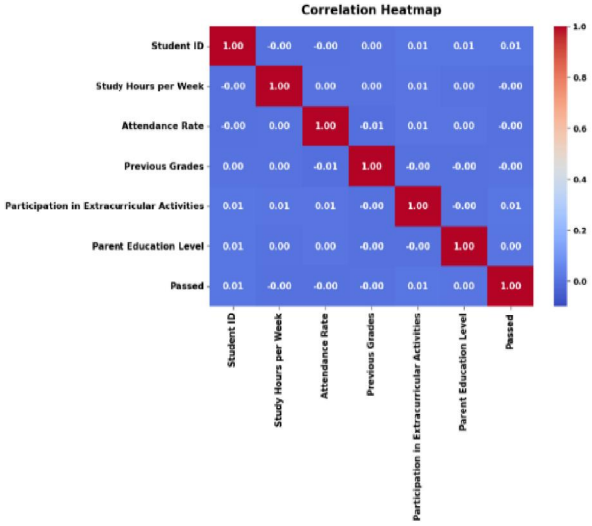


Figure 3: Correlation Matrix Heatmap

The pair-wise linear relationships among the seven numerical and categorical features in the student performance dataset are presented in Figure 3. Diagonal cells show self-correlation values of 1.0, while off-diagonal cells range from approximately −0.0093 to 0.0089. The predominantly blue off-diagonal cells indicate no strong linear multicollinearity among the features.

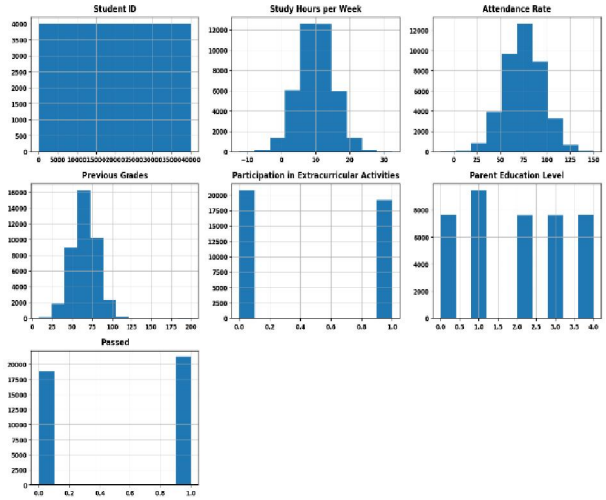


Figure 4: Feature Distribution Grid using Histograms

Histograms of numerical and categorical attributes in the student performance dataset are presented in Figure 4 for exploratory data analysis. Continuous variables, including study hours, attendance rate, and previous grades, exhibit approximately symmetrical distributions, while binary features show relatively balanced class frequencies. Parent education levels display discrete categorical distributions, and Student ID represents a sequential identifier rather than a predictive feature.

B. Data Pre-Processing

The Student Performance Prediction dataset underwent preprocessing, including data cleaning, label encoding, Min-Max normalization, SMOTE, and feature selection. Missing values, duplicate records, and irrelevant attributes were

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 7, October 2026
Impact Factor: 8.2

removed to improve data quality. The main preprocessing procedures for accurate academic performance prediction are summarized as follows:

- Missing Value Removal: The dataset is examined to identify missing values in student records. Incomplete records are removed to maintain data quality and consistency.
- Duplicate Removal: Duplicate records are identified and eliminated from the dataset. This prevents repeated observations from affecting model training and prediction.
- Irrelevant Feature Removal: Unnecessary attributes that do not contribute to academic performance prediction are removed. This reduces redundant information and improves computational efficiency.
- Label Encoding: Categorical attributes are converted into numerical representations using label encoding. This transformation enables ML algorithms to process categorical data effectively.

C. Normalization of Data (Min-Max Normalization)

Normalization standardizes or scales data to a common range or format. Data normalization to prevent numerical instability and remove bias towards variables with higher values. In this study, Min-Max normalization techniques are employed to scale the features to a range between 0 and 1. Normalization can be expressed mathematically as Equation (1):

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)} \qquad (1)$$

where x is the original value, x^' is the normalized value, min (x) is the minimum value in the dataset, and max (x) is the maximum value of the feature.

D. Data balancing Synthetic Minority Over-sampling Technique (SMOTE)

Data imbalance is an important phase in data preprocessing as it can have a major impact on the model's performance. In this study, the SMOTE approach was employed to address the issue of data imbalance. It works by picking samples from the minority class, finding their nearest neighbors, and creating new similar samples.

E. Feature Selection using Recursive Feature Elimination (RFE) technique

Feature selection is an essential step that identifies the most relevant attributes while eliminating redundant or less informative features. In this study, RFE is employed to iteratively remove features that contribute least to model performance. This process reduces computational complexity and minimizes the risk of overfitting. Figure 5 illustrates the correlation between student attributes and the target variable, Passed, using a horizontal bar chart. The chart highlights positive and negative relationships among features, including study hours, parent education level, and extracurricular participation. This approach is useful for predicting students' academic achievement since it identifies significant features.

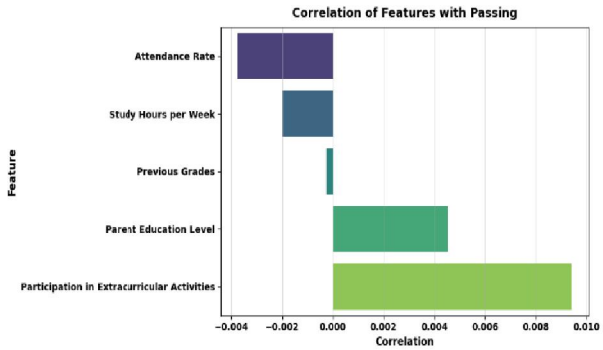


Figure 5: Feature Correlation Bar Chart

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 7, October 2026
Impact Factor: 8.2

F. Data Splitting

A training set is utilized to train the classifier, and a testing set is utilized to assess its prediction ability. The dataset is split into these sets in an 80:20 ratio.

G. Proposed Hybrid Random Forest–Extreme Gradient Boosting (RF–Xgboost) Model

The proposed Hybrid RF–XGBoost model combines the ensemble learning capabilities of RF and XGBoost to predict student academic performance. RF generates predictions by aggregating multiple DTs, while XGBoost sequentially builds trees to minimize prediction errors. The hybrid model integrates the outputs of both algorithms to improve classification performance, robustness, and generalization.

Random Forest (RF) Model

Random Forest constructs multiple decision trees using randomly selected training samples and features. The final class is determined through majority voting across the individual trees, as expressed in Equation (2).

$$\hat{y}RF = mode\{T_1(x), T_2(x), \dots\dots, T_N(x)\} (2)$$

where y^RF represents the predicted class, T_i (x) denotes the prediction of the ith decision tree, and N is the total number of trees.

Extreme Gradient Boosting (XGBoost) Model

XGBoost builds an additive ensemble of decision trees, with each new tree improving the predictions of the existing ensemble by minimizing a regularized objective function. The prediction function is represented in Equation (3).

$$\hat{y}XGB(x) = \sum_{k=1}^{K} f_k(x) \quad (3)$$

Where, f_k (x) represents the output of the kth tree and K denotes the total number of boosting trees. The model optimizes the objective function given in Equation (4).

$$\mathcal{L} = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k) \quad (4)$$

where L denotes the classification loss, y_i is the actual class, y^_i is the predicted output, and Ω(f_k)penalizes model complexity to reduce overfitting.

Hybrid RF–XGBoost Classification

The hybrid model combines the prediction outputs of RF and XGBoost using a weighted aggregation strategy. The final prediction is calculated using Equation (5).

$$\hat{y}Hybrid = argmax_{c\in\{0,1\}}[\alpha P_{RF}(c|x) + (1-\alpha)P_{XGB}(c|x)] \quad (5)$$

Here, $P_{RF}(c|x)$ and $P_{XGB}(c|x)$denote class probabilities from RF and XGBoost, respectively, while α controls their relative weights. The hybrid model predicts pass (1) or fail (0) based on the highest combined probability, with α optimized using validation data. Its effectiveness must be experimentally evaluated against individual models.The proposed RF–XGBoost model uses Random Forest with 100 trees, maximum depth of 10, minimum split samples of 2, and Gini criterion, while XGBoost uses 100 boosting rounds, learning rate of 0.1, maximum depth of 6, and subsample ratio of 0.8. The hybrid model applies weighted probability aggregation with (alpha=0.5) and random seed 42 to combine both classifiers for student academic outcome prediction.

H. Evaluation Metrics

The ACC, PRE, REC, and F1 are some of the conventional performance metrics used to evaluate student grade prediction systems, which are what the suggested prediction model is tested against. True Positive (TP): number of positive instances correctly identified as positive; False Positive (FP): negative instances wrongly classified as positive. True Negative (TN) is the negative instances that are classified correctly as negative, and False Negative (FN) is the positive instances that are classified incorrectly as negative. These values are used to compute essential performance metrics, such as ACC, PRE, REC, and F1, which are explained in detail below Equation(6)-(9):

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 7, October 2026
Impact Factor: 8.2

$$Accuracy = \frac{TP+TN}{TP+Fp+TN+FN} \quad (6)$$

$$Precision = \frac{TP}{TP+FP} \quad (7)$$

$$Recall = \frac{TP}{TP+FN} \quad (8)$$

$$F1-score = 2 \times \frac{Precision \times Recall}{Precision+Recall} \quad (9)$$

The ACC, PRE, REC, F1, and ROC curve are used to assess the performance of the suggested prediction model. ACC measures the proportion of correctly predicted instances among all instances in the dataset, while PRE indicates the proportion of correctly predicted positive instances among all instances classified as positive. The F1 provides a balanced evaluation of both metrics within the range of 0 to 1, whereas REC indicates the proportion of real positive examples accurately recognized by the model. The ROC curve illustrates the model's classification performance at different decision thresholds by plotting the TPR, also known as sensitivity or REC, against the FPR, which is calculated as one minus specificity.

IV. RESULTS AND DISCUSSION

The experimental setup and performance evaluation of the proposed hybrid model for student academic outcome prediction are detailed in this section. The model is implemented on a 64-bit Windows operating system with an Intel Core i5-3630QM processor running at 2.40 GHz and 4 GB of RAM. The development environment used Anaconda with Python 3.11, Scikit-learn, TensorFlow, NumPy, Pandas, and Matplotlib for model implementation, data processing, and visualization. Using the Student Performance Prediction dataset, the RF-XGBoost model is trained and assessed. It is a mix of the two popular methods. Results from the model's ACC (96.5%), PRE (96.3%), REC (96.2%), and F1 (96.7%), as shown in Table II, show that it is successful in predicting students' academic performance.

Table 2: Classification Performance of the Proposed Hybrid Model for Intelligent Academic Performance Assessment

Matrix	Hybrid Random Forest–Extreme Gradient Boosting (RF–XGBoost) Model
Accuracy	96.5
Precision	96.3
Recall	96.2
F1-score	96.7

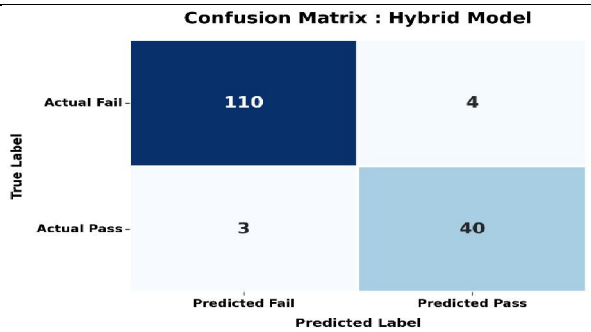


Figure 6: Confusion Matrix for the Proposed Model

Figure 6 confusion matrix evaluates the Hybrid RF–XGBoost model across 157 instances, correctly classifying 110 failure cases and 40 pass cases. The model produces only 7 misclassifications, including 4 false passes and 3 false failures, indicating a low error rate. The dominant diagonal values demonstrate effective class discrimination and promising classification performance for the given task.

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 7, October 2026
Impact Factor: 8.2

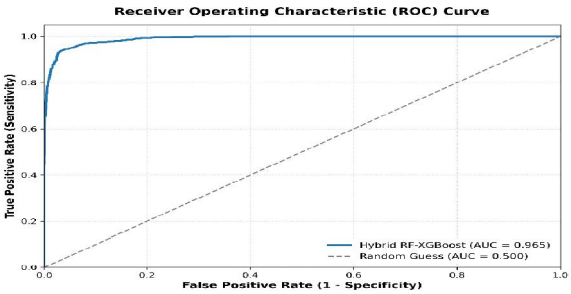


Figure 7: ROC Curve for Proposed Model

Figure 7 shows the ROC curve, which compares the Hybrid RF-XGBoost model's performance at various thresholds for FPR and TPR-based class distinctions. When compared to the random classifier baseline of 0.500, the model's AUC of 0.965 shows exceptional classification performance. This strong performance demonstrates effective class discrimination by combining Random Forest and XGBoost, although further validation is required to confirm generalization.

A. Comparative Analysis

Table III displays the results of a comparative performance evaluation of several DL and ML models, which was used to evaluate the efficacy of the suggested hybrid RF-XGBoost model. Achieving accuracies of 87.08%, 90.49%, and 91%, respectively, are the results of the SVM, CNN, and Stacking Ensemble. The proposed hybrid RF–XGBoost model achieves the highest ACC of 96.5%, outperforming all the compared models. The efficacy of integrating RF with Extreme Gradient Boosting for predicting students' academic achievement is demonstrated by this improvement. This study proves that the proposed model is more accurate and dependable than competing models.

Table 3: Comparative Performance Analysis of Machine Learning and Deep Learning Models for Student Academic Performance Prediction

Model	Accuracy	Precision	Recall	F1-score
SVM[26]	87.08	87.21	87.08	86.36
CNN[27]	90.49	90.77	90.70	90.73
Stacking Ensemble[28]	91	77	80	79
Proposed Hybrid RF–XGBoost Model	96.5	96.3	96.2	96.7

Predicting students' academic outcomes is a strong suit for the suggested hybrid RF-XGBoost model, which attains an ACC of 96.5%. By combining the strengths of both algorithms, the model improves classification effectiveness and captures complex patterns in student data. This hybrid approach supports reliable identification of students' academic outcomes. Therefore, it offers an effective solution for data-driven academic performance assessment and decision-making

V. CONCLUSION AND FUTURE STUDY

Academic institutions are increasingly interested in predicting student academic outcomes to identify performance patterns and support effective educational decision-making. Student performance prediction involves analyzing various academic and behavioral attributes, making accurate classification a challenging task. This study proposes a hybrid RF–XGBoost model for intelligent student academic outcome prediction. As compared to SVM at 87.08%, CNN at 90.49%, and Stacking Ensemble at 91%, the suggested model achieves an ACC of 96.5%. These results demonstrate the potential of the proposed hybrid approach to improve predictive performance and support the early identification of students at academic risk. Future research will focus on evaluating the framework using diverse educational datasets and optimizing its generalization, scalability, and practical applicability in intelligent educational systems.

Copyright to IJARSCT
www.ijarsct.co.in
DOI: 10.48175/IJARSCT-40489

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 7, October 2026
Impact Factor: 8.2

The suggested hybrid RF-XGBoost model may not be applicable to other schools because this study only used one dataset on student performance. Future work will involve testing the framework with larger multi-institutional datasets, extending the academic and behavioral attributes, and tuning the model parameters for increased ACC and usefulness in prediction.

REFERENCES

[1] N. Sapar, S. Narayankeri, A. Buchade, and P. Desai, "Algorithmic Fairness in Higher Education: Predicting Debt, Graduation, and Earnings with Tree-Based ML Models," in 2025 IEEE Pune Section International Conference (PuneCon), Pune, India: IEEE, Dec. 2025, pp. 1–6. doi: 10.1109/PuneCon67554.2025.11378299.

[2] F. Marbouti, H. A. Diefes-Dux, and K. Madhavan, "Models for early prediction of at-risk students in a course using standards-based grading," Comput. Educ., vol. 103, pp. 1–15, Dec. 2016, doi: 10.1016/j.compedu.2016.09.005.

[3] T.-T. Huynh-Cam, L.-S. Chen, and H. Le, "Using Decision Trees and Random Forest Algorithms to Predict and Determine Factors Contributing to First-Year University Students' Learning Performance," Algorithms, vol. 14, no. 11, p. 318, Oct. 2021, doi: 10.3390/a14110318.

[4] M. A. Mahmoud, L. Subramainan, I. L, and M. H., "An Agent-Based Evaluation Model of Students' Emotional Engagement in Classroom," Int. J. Adv. Comput. Sci. Appl., vol. 12, no. 4, pp. 495–505, 2021, doi: 10.14569/IJACSA.2021.0120463.

[5] A. M. Abd El-Haleem, M. M. Eid, M. M. Elmesalawy, and H. A. H. Hosny, "A Generic AI-Based Technique for Assessing Student Performance in Conducting Online Virtual and Remote Controlled Laboratories," IEEE Access, vol. 10, pp. 128046–128065, 2022, doi: 10.1109/ACCESS.2022.3227505.

[6] J. M. Aiken, R. De Bin, H. J. Lewandowski, and M. D. Caballero, "Framework for evaluating statistical models in physics education research," Phys. Rev. Phys. Educ. Res., vol. 17, no. 2, p. 020104, Jul. 2021, doi: 10.1103/PhysRevPhysEducRes.17.020104.

[7] S. Deupala, S. Shakya, S. Dahal, and R. Khadka, "The Reinforcing Cycle of AI Disadvantages: A Systematic Review of Job Displacement, Algorithmic Bias, Privacy Erosion, and Global Inequality," in 2026 4th Cognitive Models and Artificial Intelligence Conference (AICCONF), Prague, Czech Republic: IEEE, Apr. 2026, pp. 1–6. doi: 10.1109/AICCONF69182.2026.11600674.

[8] S. Iqbal, "Modified Teacher Learning Algorithm Based Pri- vacy Preserving of Student Data for Grade Prediction," Internatinal J. Comput. Resurch Sci. Technol., vol. 2, no. 3, pp. 01–09, May-Jun, 2026, doi: 10.5281/zenodo.21279545.

[9] S. Ayouni, F. Hajjej, M. Maddeh, and S. Al-Otaibi, "A new ML-based approach to enhance student engagement in online environment," PLoS One, vol. 16, no. 11, p. e0258788, Nov. 2021, doi: 10.1371/journal.pone.0258788.

[10] K. Borhani and R. T. K. Wong, "An artificial neural network for exploring the relationship between learning activities and students' performance," Decis. Anal. J., vol. 9, p. 100332, Dec. 2023, doi: 10.1016/j.dajour.2023.100332.

[11] Y. Chen, L. Lin, and X. Wang, "Online Teacher-Student Interpersonal Management under Crisis Conditions: A Sentiment Analysis through Machine Learning," in 2022 International Conference on Cloud Computing, Big Data and Internet of Things (3CBIT), IEEE, Oct. 2022, pp. 48–52. doi: 10.1109/3CBIT57391.2022.00019.

[12] G. Du, Y. Sun, and Y. Zhao, "The Innovation of Ideological and Political Education Integrating Artificial Intelligence Big Data with the Support of Wireless Network," Appl. Artif. Intell., vol. 37, no. 1, Dec. 2023, doi: 10.1080/08839514.2023.2219943.

[13] K. Fahd, S. J. Miah, and K. Ahmed, "Predicting student performance in a blended learning environment using learning management system interaction data," Appl. Comput. Informatics, vol. 21, no. 3–4, pp. 220–231, Oct. 2025, doi: 10.1108/ACI-06-2021-0150.

[14] I. Issah, O. Appiah, P. Appiahene, and F. Inusah, "A systematic review of the literature on machine learning application of determining the attributes influencing academic performance," Decis. Anal. J., vol. 7, p. 100204, Jun. 2023, doi: 10.1016/j.dajour.2023.100204.

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429 Volume 6, Issue 7, October 2026 Impact Factor: 8.2

[15] G. Il Kim, S. Kim, and B. Jang, "Classification of mathematical test questions using machine learning on datasets of learning management system questions," PLoS One, vol. 18, no. 10, p. e0286989, Oct. 2023, doi: 10.1371/journal.pone.0286989.
[16] B. Albreiki, N. Zaki, and H. Alashwal, "A Systematic Literature Review of Student' Performance Prediction Using Machine Learning Techniques," Educ. Sci., vol. 11, no. 9, p. 552, Sep. 2021, doi: 10.3390/educsci11090552.
[17] A. Khan and S. K. Ghosh, "Student performance analysis and prediction in classroom learning: A review of educational data mining studies," Educ. Inf. Technol., vol. 26, no. 1, pp. 205–240, Jan. 2021, doi: 10.1007/s10639-020-10230-3.
[18] E. Tanuar, Y. Heryadi, Lukas, B. S. Abbas, and F. L. Gaol, "Using Machine Learning Techniques to Earlier Predict Student's Performance," in 2018 Indonesian Association for Pattern Recognition International Conference (INAPR), IEEE, Sep. 2018, pp. 85–89. doi: 10.1109/INAPR.2018.8626856.
[19] M. Yağcı, "Educational data mining: prediction of students' academic performance using machine learning algorithms," Smart Learn. Environ., vol. 9, no. 1, p. 11, Dec. 2022, doi: 10.1186/s40561-022-00192-z.
[20] M. Harshitha, M. A. Preethi, and K. Jyothi, "A Hybrid Machine Learning and Explainable Analytics Framework for Predicting and Monitoring Student Academic Performance," in 2026 8th International Conference on Intelligent Sustainable Systems (ICISS), IEEE, Mar. 2026, pp. 1574–1579. doi: 10.1109/ICISS67859.2026.11453811.
[21] G. P. Goyal, V. S. Kolte, M. K. B, L. Elizarova, and D. J. R, "Hybrid Predictive Analytics Framework for Student Stress Monitoring and Dropout Prevention in Higher Education," in 2026 2nd International Conference on Innovations in Mechanical, Robotics, Computing and Biomedical Engineering (ICIMRBE), IEEE, Aug. 2026, pp. 1–6. doi: 10.1109/ICIMRBE70745.2026.11709978.
[22] V. K. Yarram, S. K. Parimi, R. Cherukuri, and B. Jegajothi, "Intelligent Web based Student Performance Prediction using Machine Learning in Java," in 2025 4th International Conference on Applied Artificial Intelligence and Computing (ICAAIC), IEEE, Dec. 2025, pp. 591–598. doi: 10.1109/ICAAIC64647.2025.11331046.
[23] X. Gao, "Online Education Intelligent Performance Prediction Model Based on Logistics Regression Algorithm," in 2024 International Conference on Artificial Intelligence, Deep Learning and Neural Networks (AIDLNN), IEEE, Sep. 2024, pp. 187–193. doi: 10.1109/AIDLNN65358.2024.00038.
[24] Y. N. Al Husaini and N. S. Ahmad Shukor, "Virtual Learning Environment to Predict Students' Academic Performance Using Deep Learning Technique," in 2024 Sixth International Conference on Intelligent Computing in Data Sciences (ICDS), IEEE, Oct. 2024, pp. 1–7. doi: 10.1109/ICDS62089.2024.10756329.
[25] E. Jimenez Delgado, A. Linnette Roldan Morales, and Y. Calvo Araya, "Implementation of Machine Learning algorithms to classify university academic success," in 2022 17th Iberian Conference on Information Systems and Technologies (CISTI), IEEE, Jun. 2022, pp. 1–4. doi: 10.23919/CISTI54924.2022.9820593.
[26] H. E. F. Sayed and M. M. Fouad, "Hybrid Machine Learning Models for Enhanced Student Performance Prediction," SciNexuses, vol. 2, pp. 167–183, Nov. 2025, doi: 10.61356/j.scin.2025.2616.
[27] K. O. Adefemi, M. B. Mutanga, and V. Jugoo, "Hybrid Deep Learning Models for Predicting Student Academic Performance," Math. Comput. Appl., vol. 30, no. 3, pp. 10–20, 2025, doi: 10.3390/mca30030059.
[28] N. T. H. Thuy, N. T. V. Ha, N. N. Trung, V. T. T. Binh, N. T. Hang, and V. T. Binh, "Comparing the Effectiveness of Machine Learning and Deep Learning Models in Student Credit Scoring: A Case Study in Vietnam," Risks, vol. 13, no. 5, p. 99, May 2025, doi: 10.3390/risks13050099.