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COMPARATIVE ANALYSIS OF BAGGING AND BOOSTING MODELS IN ENSEMBLE LEARNING FOR GRADUATION PREDICTION

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Abstract— *Student graduation prediction is an important aspect in supporting academic decision-making in higher education. However, conventional evaluation approaches have not been able to identify the risk of early graduation delays. This study aims to compare the performance of two ensemble learning approaches, namely Bagging using Random Forest and Boosting using XGBoost, in predicting student graduation. The study used the Predict Students' Dropout and Academic Success dataset consisting of 4,424 student data. Both models were trained on the same data and evaluated using the Accuracy, Precision, Recall, F1-Score, and ROC-AUC metrics. The results of the experiment showed that both models had almost equal accuracy, i.e. 82.6% for Random Forest and 82.5% for XGBoost. However, XGBoost showed better performance on Recall (0.878) and F1-Score (0.834), which indicated a higher ability to detect students who actually graduated. Based on these results, this study concludes that XGBoost is more effective than Random Forest in the context of predicting student graduation and is more suitable to be applied to the Academic Early Warning System in universities.*

Keywords: *Bagging, Boosting, Ensemble Learning, Machine Learning, Student Graduation Prediction.*

Intisari— Prediksi kelulusan mahasiswa merupakan aspek penting dalam mendukung pengambilan keputusan akademik di perguruan tinggi. Namun, pendekatan evaluasi konvensional belum mampu mengidentifikasi risiko keterlambatan kelulusan secara dini. Penelitian ini bertujuan untuk membandingkan kinerja dua pendekatan ensemble learning, yaitu Bagging menggunakan Random Forest dan Boosting menggunakan XGBoost, dalam memprediksi kelulusan mahasiswa. Penelitian menggunakan dataset Predict Students' Dropout and Academic Success yang terdiri dari 4.424 data mahasiswa. Kedua model dilatih pada data yang sama dan dievaluasi menggunakan metrik Accuracy, Precision, Recall, F1-Score, dan ROC-AUC. Hasil eksperimen menunjukkan bahwa kedua model memiliki akurasi yang hampir setara, yaitu 82,6% untuk Random Forest dan 82,5% untuk XGBoost. Namun, XGBoost menunjukkan kinerja lebih baik pada Recall (0,878) dan F1-Score (0,834), yang mengindikasikan kemampuan lebih tinggi dalam mendeteksi mahasiswa yang benar-benar lulus. Berdasarkan hasil tersebut, penelitian ini menyimpulkan bahwa XGBoost lebih efektif dibandingkan Random Forest dalam konteks prediksi kelulusan mahasiswa dan lebih sesuai untuk diterapkan pada Academic Early Warning System di perguruan tinggi.

Kata Kunci: *Bagging, Boosting, Pembelajaran Ansambel, Pembelajaran Mesin, Prediksi Kelulusan Mahasiswa.*

INTRODUCTION

Student graduation on time is one of the indicators of the quality of higher education institutions and has a great influence on the university's reputation and the effectiveness of academic management. In many colleges, the problem of late graduation or students who do not complete their studies is a serious challenge [1]. To prevent this, institutions need to identify at-risk students as early as possible so that interventions can be provided. Therefore, a reliable approach to predicting student graduation is needed [2]. The advancement of artificial intelligence and machine learning technologies has substantially transformed the educational sector, particularly in the domain of Educational Data Mining (EDM)[3][4]. The application of data-driven analytics allows universities to gain deeper insights into students' academic behavior and performance [5]. One of the important problems that is still a major concern is the low graduation rate of students on time, which reflects the effectiveness of the learning process and academic policies. According to [6], The use of machine learning can help educational institutions in identifying students at risk of not graduating early and provide more targeted academic interventions.

A growing body of research in Educational Data Mining and Learning Analytics has explored the use of ensemble learning techniques as a means of increasing the accuracy of models for predicting students' academic performance and educational status. Research by [7] shows that the combination of bagging and boosting methods can produce higher prediction performance than a single model in the context of STEM students. Furthermore, research by [8] through the EASE Predict approach integrates an ensemble model with explainable artificial intelligence (SHAP) to predict student dropouts and obtain better accuracy than a single Random Forest. In addition, the research conducted by [9] combines ensemble learning with unbalanced data handling techniques (SMOTE) and parameter optimization to improve the accuracy of timely graduation predictions. However, most of the research still focuses on improving the performance of one particular ensemble approach or integrating additional techniques, without conducting a direct and systematic comparison between Bagging and Boosting methods on the same dataset. Therefore, this study is specifically focused on comparing the performance of Random Forest and XGBoost in predicting student graduation, in order to provide empirical evidence regarding the most effective ensemble method to support academic early warning systems [10][5].

In line with that, recent research highlights the importance of using ensemble methods in predicting academic performance and student graduation [12]. The Improving Student Graduation Timeliness Prediction study combines ensemble learning techniques with *SMOTE* and parameter optimization, resulting in improved accuracy of on-time graduation predictions[13]. These studies show that ensemble-based approaches are able to provide more stable and accurate results than single models such as Decision Tree or Logistic Regression [14]. However, there have not been many studies that specifically compare Bagging and Boosting performance systematically in the context of predicting student graduation, especially considering more comprehensive metrics such as F1-score and ROC-AUC. Table 1 below is the results of research from the last five years related to the application of machine learning and ensemble learning in predicting student graduation or dropout related to the research conducted:

Table 1. The Comparison with Previous Studies

Reference	Algorithm	Accuracy
[15]	Ensemble (Bagging + Boosting)	92,3%
[16]	Ensemble + SHAP	90,8%
[17]	Ensemble + SMOTE + tuning	89,5%
[18]	XGBOOST and SHAP	91,6%
[19]	Ensemble deep learning (RG-DMML)	93,0%

Source: (Research Results, 2025)

Based on the literature review in Table 1, it was found that the use of ensemble learning has become the dominant approach in research on predicting student academic performance. However, there are several research gaps that are still open [20]. Where most studies only discuss one particular ensemble approach without making a direct comparison between Bagging and Boosting on the same dataset and some studies only focus on accuracy metrics, whereas in education data that tends to be unbalanced, metrics such as precision, recall, F1-score, and ROC-AUC are more representative to evaluate model performance [21].

Then the application of the ensemble learning method in the context of higher education in Indonesia is still very limited, even though the characteristics of local data have significant differences compared to international datasets. Based on this, this study aims to analyze and compare the performance of two main approaches in ensemble learning, namely Bagging (Random Forest) and Boosting (XGBoost), to predict student graduation using the Predict Students' Dropout and Academic Success dataset from Kaggle [22]. The evaluation was carried out with five main metrics, namely Accuracy, Precision, Recall, F1-Score, and ROC-AUC. In addition, this study also identifies dominant features that affect student graduation based on feature importance analysis [23]. Accordingly, this research seeks to examine and compare the effectiveness of Bagging and Boosting approaches in forecasting student graduation using academic and socio-economic variables. The study further assesses both models through Accuracy,

Accredited Rank 2 (Sinta 2) based on the Decree of the Dirjen Penguatan RisBang Kemenristekdikti No.225/E/KPT/2022, December 07, 2022. Published by LPPM Universitas Nusa Mandiri

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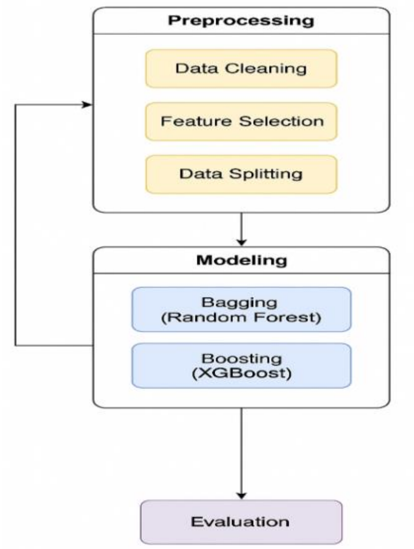
Precision, Recall, F1-Score, and ROC-AUC metrics, and determines the academic factors that most significantly contribute to graduation outcomes. The results of this study are expected to be an empirical basis in the development of an accurate and adaptive machine learning based graduation prediction system to support the Academic Early Warning System in Indonesian universities.

MATERIALS AND METHODS

The figure below is the process flow in the research which consists of three main phases, namely Preprocessing, Modeling, and Evaluation. Where each stage has an important role in ensuring the quality of the prediction results and the validity of the research being carried out.



Source : (Research Result, 2025)
Figure 1. Research Methodology

Prepocessing

This stage marks the beginning of the machine learning process and is dedicated to preparing data to enable efficient processing by learning algorithms. The dataset analyzed in this research was sourced from Kaggle, namely the Predict Students Dropout and Academic Success dataset. This dataset contains 4,424 student entries that represent academic historical data over several semesters from various study programs. Each entry (record) represents one student with demographic, socio-economic, and academic attributes that are used to predict their graduation status. The stages of this prepocessing are as follows [24][25]:

a. Data Cleaning
To ensure reliable modeling, a data preprocessing step is performed to refine the dataset. Missing entries in numerical features are replaced with median values, while categorical features are imputed with the most frequent category to limit distortion caused by extreme values. Duplicate data is identified and removed using full line similarity checks to prevent bias due to data repetition. In addition, feature selection is performed using a Random Forest–based importance technique, in which variables with minimal contribution to the target outcome are removed. This procedure is intended to preserve the most informative features, simplify model structure, and enhance both predictive performance and interpretability of student graduation outcomes.

b. Feature Selection
This stage focuses on selecting the features (variables) that are most relevant to the research target, namely student graduation. Features such as Curricular Units (Approved/Grade) and Admission Grade usually make a major contribution to the model's results. The selection of features is carried out using feature importance *or* correlation analysis [26].

c. Data Splitting
Following preprocessing and feature selection, the data are divided into 80% training and 20% testing sets. This split is widely used in machine learning research as it balances the need for robust model training with reliable assessment of model performance. This division is also considered effective for medium-sized datasets such as in this study, so that the risk of overfitting can be minimized without reducing the reliability of the test. A stratified sampling technique was applied during data splitting to ensure that the class proportions of Pass and Non Pass were maintained across the training and test datasets, helping to prevent biased evaluation results [27].

Table 2. Details of the amount of data

Information	Sum	Percentage
Total Data	4424	100 %
Training Data	3539	80 %
Test Data	885	20 %

Source : (Research Result, 2025)

Modeling

The modeling stage is the core stage of this research. Where by applying two ensemble learning approaches namely Bagging and Boosting with the following explanation:

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1. Bagging (Random Forest)
   This method works by creating several decision trees that are trained on different subsets of data (through bootstrap sampling). The predicted results of each tree were then combined using majority voting. The goal is to reduce model variance and improve prediction stability.

2. Boosting (XGBoost)
   While Bagging builds multiple models independently, Boosting adopts a sequential strategy in which each model iteratively refines the errors made by earlier models through gradient-based learning. XGBoost is recognized for its high computational efficiency and superior predictive performance, particularly in terms of accuracy and ROC-AUC, when dealing with complex and class imbalanced datasets.

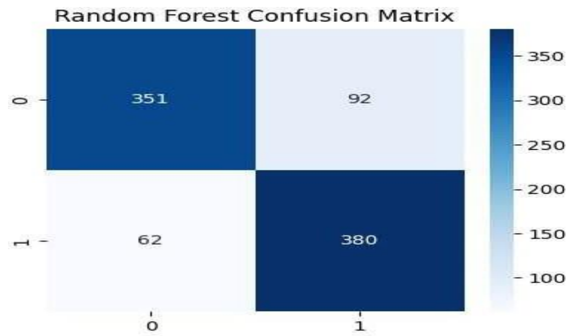
Evaluation

This stage aims to measure how well the model makes predictions on test data. Evaluations were conducted using five key metrics [28]:

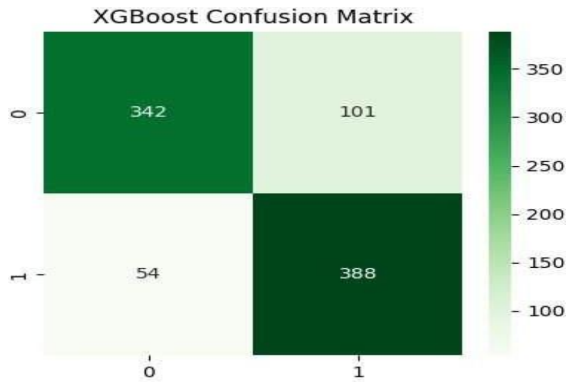
1. Accuracy: Measures the overall accuracy of a prediction.
2. Precision: Shows how many "pass" predictions are actually accurate.
3. Recall (Sensitivity): Measures the model's ability to detect students who actually graduated.
4. F1-Score: A harmonic average between Precision and Recall, suitable for unbalanced data.
5. ROC-AUC: Assesses the model's ability to distinguish between passing and non-passing classes based on probability.

RESULTS AND DISCUSSION

At the modeling stage, two ensemble learning algorithms were chosen, namely Random Forest and XGBoost, because both are known to be effective in handling complex and non linear data patterns, such as student academic data that are influenced by many heterogeneous factors (grades, study load, and socio-economic conditions). Random Forest was chosen because of its ability to reduce model variance and maintain prediction stability through a bagging mechanism, making it suitable for data with noise and interfeature correlation. Meanwhile, XGBoost was chosen for its ability to model non linear relationships more adaptively through a boosting approach that iteratively corrects previous model errors, often resulting in higher performance on complex classification tasks. The results obtained are as follows:



Source : (Research Result, 2025)
Figure 2. Confusion Matrix Random Forest



Source : (Research Result, 2025)
Figure 3. Confusion Matrix XGBoost

Figure 2 and Figure 3 show the comparison of the confusion matrix between the Random Forest (Bagging) and XGBoost (Boosting) models in predicting student graduation using the Predict Students' Dropout and Academic Success dataset. Each matrix consists of four main components, namely True Negative (TN), False Positive (FP), False Negative (FN), and True Positive (TP). In the Random Forest model, 351 TN and 380 TP were obtained, with 92 FP and 62 FN. Meanwhile, the XGBoost model produces 342 TN and 388 TP, with 101 FP and 54 FN. The main difference between the two models lies in the number of false negatives, where XGBoost produces a lower FN than Random Forest. In the context of the Academic Early Warning System, false negatives have more serious consequences than false positives, because FN represents students who are actually at risk of not graduating but not detected by the system, so they do not get academic interventions such as guidance, counseling, or learning support. On the other hand, false positives only cause students who are not actually at risk to still get additional attention, which is relatively not negatively impacted academically. Therefore, minimizing FN is a top priority in the academic early warning system, as it directly contributes to the prevention of late graduation and dropouts. Based on these

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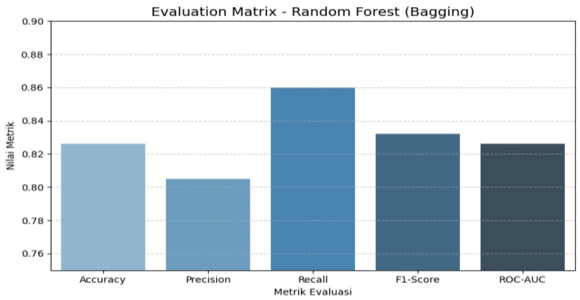
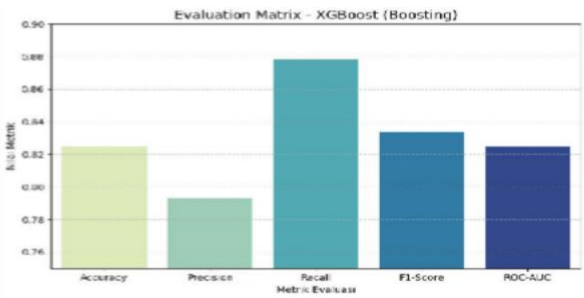
considerations, XGBoost is considered more suitable for the implementation of early warning systems, although it results in a slight increase in FP.



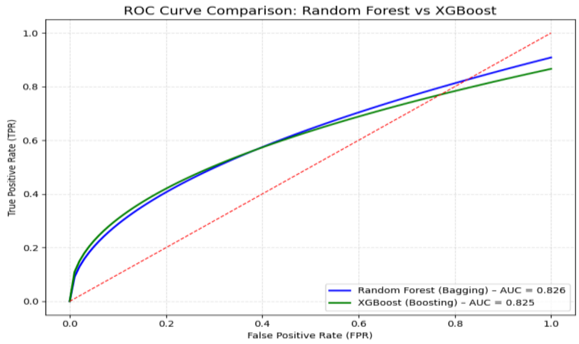
Source : (Research Result, 2025)
Figure 4. Evaluation Matrix Random Forest (Bagging)

Figure 4 shows the Evaluation Matrix for the Random Forest (Bagging) model used in the student graduation prediction research. The bar graph displays five main metrics, namely Accuracy, Precision, Recall, F1-Score, and ROC-AUC. An accuracy value of 0.826 indicates that the model is able to correctly predict about 82.6% of the total test data. Precision (0.805) indicates that of all the pass predictions, about 80.5% actually pass, while Recall (0.860) indicates that the model managed to recognize 86% of college students who actually graduated. The F1-Score value (0.832) illustrates a good balance between prediction accuracy and sensitivity. Meanwhile, the ROC-AUC (0.826) shows the model's ability to distinguish between students who graduate and do not graduate quite highly.



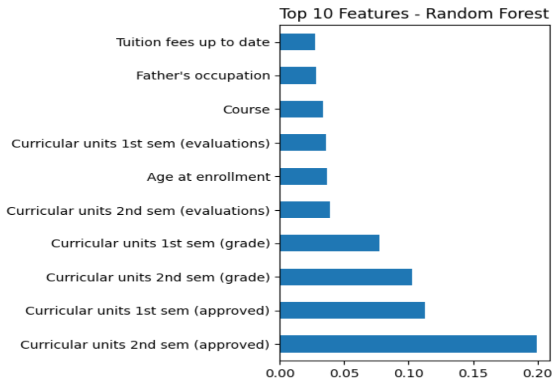
Source : (Research Result, 2025)
Figure 5. Evaluation Matrix XGBoost (Boosting)

Figure 5 shows the Evaluation Matrix for the XGBoost (Boosting) model on the student graduation prediction task. The five bars represent key metrics with Accuracy of 0.825 (approximately 82.5% of the correct predictions of all test data), Precision of 0.793 (of all predicted passes, 79.3% actually passed), Recall of 0.878 (the model captured 87.8% of students who actually passed, indicating high sensitivity), F1-Score of 0.834 (a balance between precision and recall), and ROC-AUC of 0.825 (the ability to distinguish between passing vs not passing classes probabilically is at a good level). Substantively, this metric profile shows that XGBoost is very effective for detecting students who actually pass (high recall) with a trade-off of slightly lower precision.

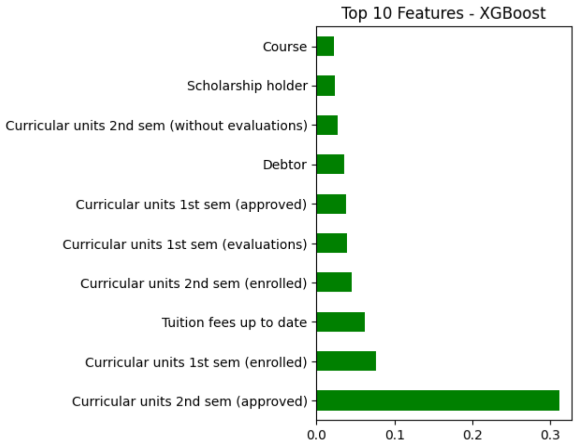


Source : (Research Result, 2025)
Figure 6. ROC Curve random Forest vs XGBoost

Figure 6 illustrates the Receiver Operating Characteristic (ROC) curve employed to evaluate and compare the predictive performance of the Random Forest and XGBoost ensemble models. Based on the graph, both models produce curves that climb well above the diagonal line with an AUC (Area Under Curve) of 0.826 for Random Forest and 0.825 for XGBoost, which indicates that both are in the very good category. Although the AUC difference is very small, Random Forest is slightly superior in prediction stability and consistency, while XGBoost shows a better tendency to detect students who actually pass because they have higher recall on previous evaluation results. Thus, for the context of this study, XGBoost is considered more optimal to be applied to the Academic Early Warning System due to its better ability to identify students who have the potential to graduate or fail on time, while Random Forest remains a strong model as a basic comparator due to its stability and interpretability.



Source : (Research Result, 2025)
Figure 7. Top 10 Feature Random Forest



Source : (Research Result, 2025)
Figure 8. Top 10 Feature XGBoost

Figure 7 and figure 8 shows the visualization of the feature importance of two ensemble learning models, namely Random Forest (Bagging) and XGBoost (Boosting), which were used in the Bagging and Boosting Model Comparative Analysis study for Student Graduation Prediction. This graph shows the ten most influential variables on the results of student graduation predictions. These findings indicate that students' first-semester academic achievement, particularly the number of courses successfully completed and overall grade averages, represents the primary determinant of graduation likelihood. Additional variables, including age at enrollment and the status of tuition fee payments, also contribute to graduation outcomes, albeit to a lesser extent, suggesting that demographic and economic factors still influence academic success. In contrast, the XGBoost model identifies the number of curricular units approved in the second semester as the most influential feature, with an importance weight of approximately 0.30, substantially higher than that of other variables. Followed by Curricular Units 1st Semester Enrolled and Tuition Fees Up to Date. Where these results strengthen the finding that XGBoost is able to emphasize the importance of academic performance in the second semester as an indicator of graduation, while still taking into account financial variables such as the regularity of tuition fee payments and scholarship status (Scholarship Holder).

CONCLUSION

The evaluation results derived from the confusion matrix, performance metrics, and ROC curve indicate that Random Forest and XGBoost achieve similarly strong performance in predicting student graduation, with accuracy values of approximately 82.5%–82.6%. However, XGBoost outperforms Random Forest in terms of recall, reaching 0.878 and yielding fewer false negatives (54 versus 62). This suggests that XGBoost is more effective in identifying students who may fail to graduate on time. From the perspective of an Academic Early Warning System, this advantage is particularly important, as early identification allows universities to apply focused academic interventions, including mentoring, counseling, and course load management. Thus, XGBoost is recommended as the main model to support the implementation of data-driven academic early warning systems in universities. For further research, it is recommended to test other ensemble models or deep learning approaches, expand the use of datasets from the context of universities in Indonesia, and explore additional academic and non academic factors to improve the accuracy and generalization of student graduation prediction models.

REFERENCE

[1] L. R. Pelima, Y. Sukmana, and Y. Rosmansyah, "Predicting University Student Graduation Using Academic Performance and Machine Learning: A Systematic Literature Review," *IEEE Access*, vol. 12, pp. 23451–23465, 2024, doi: 10.1109/ACCESS.2024.3361479.

[2] O. Saidani, L. J. Menzli, A. Ksibi, N. Alturki, and A. S. Alluhaidan, "Predicting Student Employability Through the Internship Context Using Gradient Boosting Models," *IEEE Access*, vol. 10, pp. 46472–46489, 2022, doi: 10.1109/ACCESS.2022.3170421.

[3] S. D. A. Bujang *et al.*, "Multiclass Prediction Model for Student Grade Prediction Using Machine Learning," *IEEE Access*, vol. 9, pp. 95608–95621, 2021, doi: 10.1109/ACCESS.2021.3093563.

[4] A. Rabelo, M. W. Rodrigues, C. Nobre, S. Isotani, and L. Zárate, "Educational data mining and learning analytics: a review of educational management in e-learning," *Inf. Discov. Deliv.*, vol. 52, no. 2, pp. 149–163, 2023, doi: 10.1108/IDD-10-2022-0099.

[5] G. ElSharkawy, Y. Helmy, and E. Yehia, "Employability Prediction of Information Technology Graduates using Machine Learning Algorithms," *Int. J. Adv. Comput. Sci. Appl.*, vol. 13, no. 10, pp. 359–367, 2022, doi: 10.14569/IJACSA.2022.0131043.

[6] V. Christou *et al.*, "Performance and early

VOL. 11. NO. 3 FEBRUARI 2026
P-ISSN: 2685-8223 | E-ISSN: 2527-4864
DOI: 10.33480/jitk.v11i3.7579

drop prediction for higher education students using machine learning," *Expert Syst. Appl.*, vol. 225, p. 120079, 2023, doi: https://doi.org/10.1016/j.eswa.2023.120079.

[7] A. J. Fernández-García, J. C. Preciado, F. Melchor, R. Rodriguez-Echeverria, J. M. Conejero, and F. Sánchez-Figueroa, "A Real-Life Machine Learning Experience for Predicting University Dropout at Different Stages Using Academic Data," *IEEE Access*, vol. 9, pp. 133076–133090, 2021, doi: 10.1109/ACCESS.2021.3115851.

[8] Z. Liu, "Student Dropout Prediction Using Ensemble Learning with SHAP-Based Explainable AI Analysis," vol. 2, pp. 111–131, 2025.

[9] K. Okoye, J. T. Nganji, J. Escamilla, and S. Hosseini, "Machine learning model (RG-DMML) and ensemble algorithm for prediction of students' retention and graduation in education," *Comput. Educ. Artif. Intell.*, vol. 6, no. January, p. 100205, 2024, doi: 10.1016/j.caeai.2024.100205.

[10] L. G. R. Putra, D. D. Prasetya, and M. Mayadi, "Student Dropout Prediction Using Random Forest and XGBoost Method," *INTENSIF J. Ilm. Penelit. dan Penerapan Teknol. Sist. Inf.*, vol. 9, no. 1, pp. 147–157, 2025, doi: 10.29407/intensif.v9i1.21191.

[11] Y. Rimal and N. Sharma, "Ensemble machine learning prediction accuracy: local vs. global precision and recall for multiclass grade performance of engineering students," *Front. Educ.*, vol. 10, no. April, pp. 1–16, 2025, doi: 10.3389/feduc.2025.1571133.

[12] A. Anggrawan, H. Hairani, and C. Satria, "Improving SVM Classification Performance on Unbalanced Student Graduation Time Data Using SMOTE," *Int. J. Inf. Educ. Technol.*, vol. 13, no. 2, pp. 289–295, 2023, doi: 10.18178/ijiet.2023.13.2.1806.

[13] G. H. Yakin, I. M. Satriya Wibawa, and I. K. Putra, "Design of Soil pH Measuring Instruments Using pH Meter Sensor Module V1.1 SEN0161 Based on Arduino Uno," *Bul. Fis.*, vol. 22, no. 2, 2021, doi: 10.24843/bf.2021.v22.i02.p08.

[14] I. Riadi, R. Umar, and R. Anggara, "Comparative Analysis of Naive Bayes and K-NN Approaches to Predict Timely Graduation using Academic History," *Int. J. Comput. Digit. Syst.*, vol. 16, no. 1, pp. 1163–1174, 2024, doi: 10.12785/ijcds/160185.

[15] A. M. Messele, "Ensemble machine learning for predicting academic performance in STEM education," *Discov. Educ.*, vol. 4, no. 1, 2025, doi: 10.1007/s44217-025-00710-4.

[16] Y. Zhang, J. Liu, and W. Shen, "A Review of Ensemble Learning Algorithms Used in Remote Sensing Applications," *Appl. Sci.*, vol. 12, no. 17, 2022, doi: 10.3390/app12178654.

[17] A. Jain, A. K. Dubey, S. Khan, A. Panwar, M. Alkhatib, and A. M. Alshahrani, "A PSO weighted ensemble framework with SMOTE balancing for student dropout prediction in smart education systems," *Sci. Rep.*, vol. 15, no. 1, p. 17463, 2025, doi: 10.1038/s41598-025-97506-1.

[18] H. Sun, Y. Jiang, and X. Tang, "Artificial Intelligence-Driven Academic Performance Early Warning System for Engineering Universities: Application of XGBoost-SHAP Algorithm," *Int. J. High Speed Electron. Syst.*, vol. 0, no. 0, p. 2540536, doi: 10.1142/S0129156425405364.

[19] R. Muniappan *et al.*, "An optimized deep learning framework based on LEE for real time student performance prediction in educational data," *Bull. Electr. Eng. Informatics*, vol. 14, no. 5, pp. 3671–3682, 2025, doi: 10.11591/eei.v14i5.9773.

[20] F. E. Arévalo-Cordovilla and M. Peña, "Evaluating ensemble models for fair and interpretable prediction in higher education using multimodal data," *Sci. Rep.*, vol. 15, no. 1, p. 29420, 2025, doi: 10.1038/s41598-025-15388-9.

[21] A. A. Khan, O. Chaudhari, and R. Chandra, "A review of ensemble learning and data augmentation models for class imbalanced problems: Combination, implementation and evaluation," *Expert Syst. Appl.*, vol. 244, p. 122778, 2024, doi: https://doi.org/10.1016/j.eswa.2023.122778.

[22] M. Imani, A. Beikmohammadi, and H. R. Arabnia, "Comprehensive Analysis of Random Forest and XGBoost Performance with SMOTE, ADASYN, and GNUS Under Varying Imbalance Levels," *Technologies*, vol. 13, no. 3, 2025, doi: 10.3390/technologies13030088.

[23] S. Zhao, D. Zhou, H. Wang, D. Chen, and L. Yu, "Enhancing Student Academic Success Prediction Through Ensemble Learning and Image-Based Behavioral Data Transformation," *Appl. Sci.*, vol. 15, no. 3, 2025, doi: 10.3390/app15031231.

[24] R. Natras, B. Soja, and M. Schmidt, "Ensemble Machine Learning of Random Forest,

AdaBoost and XGBoost for Vertical Total Electron Content Forecasting," *Remote Sens.*, vol. 14, no. 15, 2022, doi: 10.3390/rs14153547.

[25] S. Kim, E. Choi, Y.-K. Jun, and S. Lee, "Student Dropout Prediction for University with High Precision and Recall," *Appl. Sci.*, vol. 13, no. 10, 2023, doi: 10.3390/app13106275.

[26] T. Kavzoglu and A. Teke, "Predictive Performances of Ensemble Machine Learning Algorithms in Landslide Susceptibility Mapping Using Random Forest, Extreme Gradient Boosting (XGBoost) and Natural Gradient Boosting (NGBoost)," *Arab. J. Sci. Eng.*, vol. 47, no. 6, pp. 7367–7385, 2022, doi: 10.1007/s13369-022-06560-8.

[27] M. Sivakumar, S. Parthasarathy, and T. Padmapriya, "Trade-off between training and testing ratio in machine learning for medical image processing.," *PeerJ. Comput. Sci.*, vol. 10, p. e2245, 2024, doi: 10.7717/peerj-cs.2245.

[28] L. Huang *et al.*, "Combining Random Forest and XGBoost Methods in Detecting Early and Mid-Term Winter Wheat Stripe Rust Using Canopy Level Hyperspectral Measurements," *Agriculture*, vol. 12, no. 1, 2022, doi: 10.3390/agriculture12010074.