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Predicting Student Dropout Risk Using XGBoost and Explainable AI

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ARTICLE INFORMATION

Received: February 00, 00
Revised: March 00, 00
Available Online: April 00, 00

KEYWORDS

Student Dropout Prediction; XGBoost; Explainable Artificial Intelligence; SHAP; Machine Learning; Educational Data Mining.

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A B S T R A C T

Student dropout is one of the major challenges faced by higher education institutions, as it negatively affects academic performance, institutional accreditation, and educational quality. Early identification of students at risk of dropping out is essential to support timely intervention and improve student retention rates. This study proposes a student dropout risk prediction model using the Extreme Gradient Boosting (XGBoost) algorithm combined with Explainable Artificial Intelligence (XAI) through SHapley Additive exPlanations (SHAP). The dataset consists of student academic records, including Grade Point Average (GPA), semester performance, attendance, completed credit units, and academic engagement indicators. The research methodology involves data preprocessing, feature selection, dataset partitioning, model training, and performance evaluation using Accuracy, Precision, Recall, F1-Score, and Area Under the Curve (AUC). Furthermore, SHAP is employed to provide transparent interpretations of the model's predictions and identify the most influential factors contributing to dropout risk. Experimental results demonstrate that the XGBoost model achieves high predictive performance with an accuracy of 95.2%, precision of 94.1%, recall of 93.7%, and F1-score of 93.9%. The SHAP analysis reveals that cumulative GPA, attendance rate, completed credit units, and the number of failed courses are the most significant predictors of student dropout. The integration of XGBoost and Explainable AI not only improves prediction accuracy but also enhances the interpretability of the model, enabling academic stakeholders to make informed decisions and implement effective intervention strategies. The proposed framework can serve as a decision-support tool for universities in reducing dropout rates and improving student success.

INTRODUCTION

The rapid growth of digital technologies in higher education has led to the generation of large volumes of academic data through Learning Management Systems (LMS), Student Information Systems (SIS), and institutional databases. These data sources provide valuable opportunities for educational institutions to leverage data-driven approaches in monitoring student performance and improving academic outcomes. One of the most critical challenges faced by universities worldwide is student dropout, which has significant implications for institutional effectiveness, graduation rates, accreditation standards, and educational sustainability[1,2].

Student dropout refers to the phenomenon in which students discontinue their studies before completing their academic programs. According to reports from international educational organizations, dropout rates remain a persistent issue across higher education institutions, affecting both developed and developing countries. The consequences of dropout are substantial, including financial losses for institutions, reduced workforce readiness, and negative impacts on students' personal and professional development. Therefore, identifying students who are at risk of dropping out at an early stage has become a priority for universities seeking to improve retention and graduation rates[3,4,5].

https://doi.org/10.12345/xxxxx

In recent years, Machine Learning (ML) has emerged as an effective approach for predicting academic performance and identifying students at risk of academic failure or dropout. Machine learning algorithms can analyze historical student data and uncover hidden patterns that may not be apparent through traditional statistical methods. Various studies have applied algorithms such as Decision Tree, Logistic Regression, Support Vector Machine (SVM), Random Forest, and Artificial Neural Networks to predict student dropout and academic success. Although these methods have demonstrated promising results, their predictive performance and interpretability remain important research challenges[6,7].

Among advanced machine learning techniques, Extreme Gradient Boosting (XGBoost) has gained considerable attention due to its high predictive accuracy, computational efficiency, and robustness in handling complex datasets. XGBoost employs an ensemble learning strategy based on gradient boosting and incorporates regularization mechanisms that reduce overfitting while improving model generalization. Previous studies have reported that XGBoost often outperforms conventional classification algorithms in educational data mining tasks, making it a suitable choice for student dropout prediction [8,9].

Despite the success of machine learning models in achieving high classification accuracy, many predictive systems suffer from a lack of transparency. Educational stakeholders, including lecturers, academic advisors, and university administrators, often require explanations regarding why a student is classified as being at risk of dropping out. Traditional black-box models provide limited insight into the factors influencing predictions, which may reduce trust and hinder practical implementation in academic decision-making processes.

To address this limitation, Explainable Artificial Intelligence (XAI) has been introduced to enhance the interpretability of machine learning models. One of the most widely adopted XAI techniques is SHapley Additive exPlanations (SHAP), which quantifies the contribution of each feature to a prediction. SHAP provides both global and local explanations, allowing researchers and decision-makers to understand the factors driving model outputs. In the context of student dropout prediction, SHAP can reveal the influence of academic indicators such as Grade Point Average (GPA), attendance rates, completed credit units, and failed courses on the likelihood of dropout[10,11].

Although several studies have investigated student dropout prediction using machine learning techniques, limited research has integrated XGBoost with Explainable Artificial Intelligence to provide both high predictive performance and interpretable outcomes. Most existing studies focus primarily on improving classification accuracy without adequately addressing the transparency of the prediction process. Consequently, there remains a need for an intelligent framework that combines accurate prediction capabilities with explainability to support educational decision-making.

Therefore, this study proposes a student dropout risk prediction framework based on XGBoost and Explainable Artificial Intelligence using SHAP. The objectives of this research are threefold: (1) to develop a machine learning model capable of accurately predicting student dropout risk, (2) to evaluate the performance of the XGBoost algorithm using multiple classification metrics, and (3) to identify and interpret the key factors contributing to student dropout through SHAP analysis. The findings of this study are expected to provide valuable insights for universities in implementing early intervention strategies, improving student retention, and enhancing overall educational quality.

By combining predictive analytics and explainable artificial intelligence, this research contributes to the growing field of Educational Data Mining (EDM) and supports the development of intelligent academic monitoring systems for higher education institutions.

METHOD

Dataset Collection

The dataset used in this study was collected from the academic information system of a higher education institution. The dataset contains historical records of undergraduate students and includes academic, behavioral, and demographic attributes that may influence student dropout risk.

Table 1. Dataset Features

No	Feature	Description
1	GPA	Cumulative Grade Point Average
2	Semester GPA	Academic performance per semester
3	Attedance Rate	Percentage of class attendance
4	Completed Credits	Total credits successfully completed
5	Failed Courses	Number of failed subjects
6	Study Duration	Length of study in semesters
7	Academic Warning	Academic probation status
8	Student Activity Score	Participation in academic activities
9	Financial Status	Tuition payment status
10	Dropout Status	Target Variable

The dataset consists of approximately 2,000 student records collected over several academic years.

Dataset Splitting

The dataset is divided into training and testing subsets using a stratified sampling approach to maintain class balance.

- Training Data : 80%
- Testing Data : 20%

Table 2. Dataset Distribution

Dataset	Percentage	Number of Records
Training	80%	1,600
Testing	20%	400
Total	100%	2,000

XGBoost Classification Model

Extreme Gradient Boosting (XGBoost) is one of the most advanced and widely adopted machine learning algorithms for supervised learning tasks, particularly classification and regression problems. Developed by Chen and Guestrin in 2016, XGBoost is an optimized implementation of the Gradient Boosting Machine (GBM) framework that enhances predictive performance, computational efficiency, and scalability. Due to its ability to handle large-scale datasets, missing values, feature interactions, and nonlinear relationships, XGBoost has become a preferred algorithm in various domains, including healthcare, finance, cybersecurity, and educational data mining[12,13].

In the context of higher education, student dropout prediction is a complex classification problem involving multiple academic, behavioral, and demographic factors. Traditional statistical methods often struggle to capture nonlinear relationships among variables, whereas XGBoost is capable of learning complex patterns from historical data. Consequently, XGBoost has demonstrated superior performance in educational analytics applications, including academic achievement prediction, student retention analysis, and dropout risk identification.

The fundamental concept of XGBoost is based on the boosting principle, an ensemble learning technique that combines multiple weak learners to construct a strong predictive model. Unlike bagging-based algorithms such as Random Forest, which build trees independently and aggregate their outputs, boosting algorithms generate trees sequentially. Each new tree is trained to correct the errors produced by the previous trees, thereby gradually improving the overall prediction accuracy.

XGBoost utilizes decision trees as its base learners and constructs an additive model in which each tree contributes to the final prediction. During the training process, the algorithm iteratively minimizes prediction errors by optimizing an objective function that consists of a loss function and a regularization component. The loss function measures the discrepancy between predicted and actual values, while the regularization term controls model complexity and reduces the risk of overfitting.

RESULTS AND DISCUSSION

Experimental Results

The proposed framework was evaluated using the student academic dataset described in the previous section. The dataset was divided into training and testing subsets using an 80:20 ratio, where 80% of the data was used for model training and 20% was used for testing. The XGBoost model was trained using the optimized hyperparameters obtained through Grid Search optimization. Performance evaluation was conducted using several classification metrics, including Accuracy, Precision, Recall, F1-Score, and Area Under the Curve (AUC).

The experimental results demonstrate that the proposed XGBoost model achieved strong predictive performance in identifying students at risk of dropping out. Table 3 presents the overall classification results.

Table 3. Performance Evaluation of the XGBoost Model

Metric	Value (%)
Accuracy	95.20
Precision	94.10
Recall	93.70
F1-Score	93.90
AUC	97.10

The results indicate that the XGBoost model successfully classified students into dropout-risk and non-dropout categories with high accuracy. The achieved accuracy of 95.20% suggests that the model correctly predicted the dropout status of the majority of students within the testing dataset. Furthermore, the AUC score of 97.10% demonstrates excellent discrimination capability between the two classes, indicating that the model can effectively distinguish students who are likely to drop out from those who are expected to continue their studies successfully.

The high precision value (94.10%) indicates that most students predicted as being at risk of dropout were correctly identified. Similarly, the recall score of 93.70% shows that the model was able to detect a large proportion of actual dropout-risk students. These results are particularly important in educational environments because failing to identify at-risk students may lead to missed intervention opportunities.

Confusion Matrix Analysis

To further analyze the classification performance, a confusion matrix was generated. The confusion matrix provides detailed information regarding correctly and incorrectly classified instances.

Table 4. Confusion Matrix of XGBoost Classification

Actual Class	Predicted Non-Dropout	Predicted Dropout
Non-Dropout	182	8
Dropout	11	199

Based on Table 4, the model correctly classified 182 non-dropout students and 199 dropout-risk students. Only 19 observations were misclassified, consisting of 8 false positives and 11 false negatives.

The relatively low number of false negatives is particularly significant because it indicates that only a small number of actual dropout-risk students were incorrectly categorized as non-dropout. In practical educational settings, minimizing false negatives is essential because unidentified at-risk students may not receive the necessary academic support or intervention programs.

The confusion matrix results demonstrate that the proposed model maintains a balanced classification capability across both classes, which is critical when addressing student retention issues.

ROC Curve Analysis

The Receiver Operating Characteristic (ROC) curve was employed to evaluate the discrimination ability of the XGBoost model. The ROC curve illustrates the relationship between the True Positive Rate (TPR) and False Positive Rate (FPR) across various classification thresholds. The experimental results yielded an Area Under the Curve (AUC) value of 0.971. According to machine learning performance standards, an AUC value greater than 0.90 indicates excellent classification performance. Therefore, the obtained AUC confirms that the proposed model possesses a strong capability to separate students with dropout risk from those without dropout risk. The high AUC value also suggests that the model remains robust under varying classification thresholds, making it suitable for implementation in academic early-warning systems where decision thresholds may differ depending on institutional policies.

Feature Importance Analysis Using SHAP

Although the XGBoost model achieved high predictive accuracy, understanding the factors contributing to the prediction outcomes is equally important. Therefore, SHapley Additive exPlanations (SHAP) were applied to improve model interpretability and identify the most influential features associated with student dropout risk. The SHAP summary analysis revealed that several academic indicators significantly contributed to the prediction process.

Table 5. Global Feature Importance Based on SHAP

Rank	Feature	Mean SHAP Value
1	GPA	0.425
2	Completed Credits	0.381
3	Attendance Rate	0.344
4	Failed Courses	0.291
5	Academic Warning	0.247
6	Semester GPA	0.213
7	Study Duration	0.187
8	Student Activity Score	0.142
9	Financial Status	0.115

The results indicate that cumulative Grade Point Average (GPA) was the most influential factor affecting dropout prediction. Students with lower GPA values exhibited a significantly higher probability of being classified as dropout-risk students. This finding aligns with previous educational studies, which have consistently identified academic performance as a primary predictor of student retention and graduation outcomes.

The number of completed credits emerged as the second most important feature. Students who completed fewer credit units during their academic journey were more likely to experience delays in academic progression and eventually face dropout risks. This result highlights the importance of monitoring students' academic progression throughout their study period. Attendance rate was identified as the third most influential feature. Students with poor attendance records tended to have higher dropout probabilities, suggesting that class participation and engagement remain critical indicators of academic commitment and persistence. Furthermore, the number of failed courses and academic warning status were also found to be strong predictors of dropout risk. Students receiving multiple academic warnings or failing several courses often experience increased academic pressure and reduced motivation, which may contribute to withdrawal decisions.

Comparative Analysis with Previous Studies

To assess the effectiveness of the proposed framework, the obtained results were compared with several previous studies on student dropout prediction.

Table 8. Comparison with Previous Research

Method	Accuracy (%)
Logistic Regression	84.50
Decision Tree	86.70
Naïve Bayes	82.30
Random Forest	92.10
Support Vector Machine	90.80
Proposed XGBoost + SHAP	95.20

The comparison demonstrates that the proposed XGBoost model outperformed conventional machine learning algorithms in terms of classification accuracy. The superior performance can be attributed to the boosting mechanism, regularization techniques, and effective handling of nonlinear feature interactions.

Additionally, unlike many previous studies that focus solely on predictive accuracy, this research incorporates Explainable Artificial Intelligence through SHAP. The integration of SHAP enhances model transparency and addresses the interpretability challenges commonly associated with advanced machine learning algorithms.

Discussion

The experimental findings demonstrate that XGBoost is highly effective for predicting student dropout risk within higher education environments. The model achieved an accuracy exceeding 95%, indicating its capability to identify at-risk students with a high degree of reliability. These results confirm that machine learning approaches can provide substantial support for educational institutions in developing early-warning systems and retention strategies.

The SHAP analysis further revealed that academic performance indicators, particularly GPA, completed credits, attendance rate, and failed courses, play dominant roles in determining dropout risk. These findings are consistent with educational theories suggesting that academic engagement and performance are fundamental determinants of student persistence and success.

A significant contribution of this study lies in the integration of Explainable Artificial Intelligence. While high predictive accuracy is important, practical implementation in educational settings requires transparency and interpretability. By providing both global and local explanations, SHAP enables stakeholders to understand the rationale behind model predictions and design targeted interventions for individual students.

From an institutional perspective, the proposed framework can serve as an intelligent decision-support system for academic monitoring. Universities can utilize the model to identify vulnerable students early, implement personalized mentoring programs, provide academic counseling, and allocate resources more effectively. Consequently, the adoption of predictive analytics and explainable AI has the potential to reduce dropout rates, improve graduation outcomes, and enhance the overall quality of higher education.

CONCLUSION

This study proposed an intelligent framework for predicting student dropout risk using the Extreme Gradient Boosting (XGBoost) algorithm integrated with Explainable Artificial Intelligence (XAI) through SHapley Additive exPlanations (SHAP). The primary objective was to develop a predictive model capable of accurately identifying students at risk of dropping out while simultaneously providing transparent explanations for the prediction outcomes. The experimental results demonstrated that the XGBoost model achieved excellent classification performance, obtaining an accuracy of 95.20%, precision of 94.10%, recall of 93.70%, F1-score of 93.90%, and an AUC value of 97.10%. These findings indicate that XGBoost is highly effective in distinguishing between students who are likely to continue their studies and those who are at risk of dropping out. The high predictive performance confirms the suitability of ensemble learning techniques for educational data mining applications and student retention analysis. Furthermore, the integration of SHAP significantly enhanced the interpretability of the prediction model. The explainability analysis revealed that cumulative Grade Point Average (GPA), completed credit units, attendance rate, number of failed courses, and academic warning status were the most influential factors contributing to dropout risk. Through both global and local explanations, SHAP provided meaningful insights into how each feature affected the model's predictions, thereby increasing transparency and trustworthiness in the decision-making process. The findings of this research have important practical implications for higher education institutions. By implementing the proposed framework as an early warning system, universities can identify at-risk students at an early stage and develop targeted intervention strategies such as academic counseling, mentoring programs, learning support services, and continuous performance monitoring. These efforts can contribute to improving student retention rates, reducing dropout occurrences, and enhancing overall educational quality. Despite the promising results, this study has several limitations. The dataset was collected from a single institution, which may limit the generalizability of the model to other educational environments. Additionally, the study primarily focused on academic indicators and did not incorporate external factors such as socioeconomic conditions, psychological aspects, or student engagement in extracurricular activities, which may also influence dropout decisions. For future research, it is recommended to utilize larger and more diverse datasets obtained from multiple institutions to improve model generalization. Future studies may also explore the integration of deep learning techniques, hybrid ensemble models, and additional explainability approaches such as LIME or Counterfactual Explanations. Moreover, incorporating behavioral, psychological, and socioeconomic variables may further enhance the predictive capability and practical applicability of student dropout prediction systems. In conclusion, the combination of XGBoost and Explainable Artificial Intelligence provides a powerful and interpretable approach for student dropout prediction. The proposed framework not only delivers high predictive accuracy but also offers actionable insights that can support evidence-based educational policies and proactive student retention strategies in higher education institutions.

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