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Explainable AI-Driven Predictive Analytics Framework for Student Performance and Dropout Detection

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Abstract: Given their impact on student achievement, efficiency in the college, and retention, student performance prediction and dropout detection have emerged as important areas of study in the field. Traditional approaches to identifying academically at-risk students are generally manual assessment and retrospective analysis, which are non-predictive and time-consuming. In order to overcome these challenges, this paper suggests using machine learning techniques to develop a predictive analytics framework for student performance and dropouts that is based on XAI. The proposed methodology includes data preprocessing, feature selection, predictive modeling using XGBoost, and explainability using SHAP to accurately predict students' academic performance with the aim of understanding the model's predictions. The data set used in this research is the UCI data set comprised of the demographic, academic, financial, and institutional data of 4,424 students. The various ML algorithms such as DT, SVM, RF, and XGBoost were used and compared using the various performance measures. The experimental outcomes showed that the proposed XGBoost model achieved higher accuracy (94.18%), precision (93.74%), recall (93.21%), F1 score (93.47%), and ROC-AUC score (95.62%). Further, the curricular unit performance, admission grades, and the student's status as a tuition fee-paid student were the most relevant for student academic outcomes and dropout, as identified through the SHAP-based explainability analysis. The proposed framework allows for the identification of the pupils who are at risk of underachievement from an early age, and to make informed decisions based on clear and understandable analytics. The results of this research suggest that the proposed system may have a significant advantage in educational institutions to help decrease the dropout rate, improve academic support, and better student retention by implementing proactive intervention systems.

Keywords: *Educational Data Analytics, Student Performance Prediction, Dropout Detection, Explainable Artificial Intelligence, XGBoost, SHAP, ML, Educational Data Mining.*

1. Introduction

Artificial Intelligence (AI) and data analytics technologies have revolutionized many industries, particularly in the field of education [1]. In the modern world, educational institutions and other organizations gather a vast amount of data on students, their academic achievements, behavioral trends, demographics, and administrative data via Learning Management Systems (LMS), online assessments, student information systems, and digital learning platforms [2]. The possibility of developing intelligent predictive models based on this educational data brings the benefits of improved learning results in education, student identification of the at-risk student and improved decisions in the institution's processes [3]. Students' weak academic performance and increasing student dropout rate, which adversely affect the reputation, financial viability, and career growth of educational institutions, is one of the serious challenges facing educational institutions all around the world [4]. Dropout is a complex phenomenon that involves several academic, social, financial, and psychological factors. The current method for identifying academically weak students and those who are likely to drop out of school [5] is mainly based on retrospective analysis and manual observation, and is time-consuming, subjective, and inefficient. In the last few years, the ability to predict student success and failure and, more recently, dropout from school, has become a potential area of interest for the use of algorithmic decision-making [6]. In recent years, algorithmic decision-making tools have emerged as a field of interest because of their ability to predict students' success and failure, and the chance of student attrition and thus school dropouts. DT, RF, SVM, XGBoost, and Neural Networks have been proven to have incredible performance in application areas of Educational Data Mining [7]. These techniques enable the identification of trends in student performance and retention that are not evident, as well as factors that impact student performance and retention. While predictive analytics is becoming more popular in the education sector, there are still several challenges that have yet to be addressed. Previous studies focus primarily on academic performance prediction and rely on fairly limited sets of features, not offering sufficient coverage of the multidimensionality of student success and dropout. Secondly, several of the traditional ML models are not so well-suited, as they are prone to overfitting, lack transparency, and fail to perform well for different

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students [8]. Therefore, the need is to create more accurate and reliable prediction systems of student performance and student dropout rates, which will include aspects of robustness, scalability, and explainability [9]. This paper aims to tackle these challenges by introducing a predictive analytics framework for student performance and dropout prediction based on Explainable AI and ML techniques. It unites explainable analytics, XGBoost predictive modeling, and an intelligent early-warning mechanism for interpretable student dropout detection, surpassing existing educational prediction systems, which solely rely on the classification of student performance [10].

The major contributions of this research are summarized as follows:

1. Explainable AI-based predictive analytics model for students' performance and dropout prediction.
2. Analysis of multiple ML algorithms for educational data analytics.
3. Explainable prediction analysis using SHAP values.
4. Identification of significant academic and socio-economic student retention and academic achievement factors.
5. Development of an intelligent early-warning system for identifying academically at-risk students.

2. Literature Review

In the last few years, there has been considerable research and development in the field of education with regard to the role AI, ML, and data analytics play in education. A lot of research is being conducted in the area of predicting at-risk behavior, student performance, and dropouts during the early years. As per many researchers, different ML algorithms, including DT, RF, SVM, Naive Bayes, and Logistic Regression, are applied in predicting performance. The focus of these strategies is primarily to examine the academic performance, attendance, demographics, and behavioral traits of students to classify them based on their academic performance. In the last few years, deep learning and ensemble learning have been found to be effective at capturing complex and non-linear relationships in educational data and have been shown to exhibit greater predictive capacity. Student dropout detection is another area of interest, as it has important social and economic consequences, in addition to prediction. There are several researchers who suggest developing early-warning systems that will detect students who are at risk of dropping out. These can provide a pathway for schools to quickly implement intervention programs like counseling, mentoring, and personalized academic support. On the other hand, there are some research papers that suffer from a lack of class balance, a lack of data understanding of the model, problems with the diversity of data, and scalability in heterogeneous educational environments. Further, XAI has arisen as a novel chance to improve the transparency and trust of predictive models in the educational context. Explainable Analytics techniques, such as SHAP and LIME, allow teachers to understand the influence of each of the features on the prediction results, enhancing the usability of the education systems integrated with AI, as shown in Table 1.

Table 1. Literature Review on Student Performance and Dropout Detection

Author(s)	Dataset / Features	Key Findings	Research Gap / Limitation
M. Nagy and R. Molontay [11]	Dataset from Budapest University of Technology and Economics containing 8,508 student records with pre-enrollment academic measures, demographics, and entrance exam scores.	CatBoost achieved superior prediction performance (AUC 0.774). SHAP and LIME enabled personalized intervention by explaining individual dropout risks.	Although interpretability improved, the study relied mainly on pre-enrollment features and lacked behavioral learning analytics data for dynamic prediction.
C. J. Pérez Sánchez, F. Calle-Alonso, and M. A. Vega-Rodríguez [12]	NeuroK collaborative learning platform dataset with 698 students and 29 automatically extracted behavioral and interaction-based features.	Random Forest achieved an accuracy above 0.99 using only seven significant collaborative learning features. Social interaction and peer-review activities strongly influenced performance prediction.	The work focused primarily on a single neurodidactics platform and lacked generalized validation across diverse educational environments.
F. Del Bonifro, M. Gabbrielli, G. Lisanti, and S.	Real-world dataset of approximately 15,000 first-year university students, including demographic details, high	SVM and RF achieved strong predictive performance, especially when first-year course	The dataset was highly imbalanced, requiring balancing strategies. The study also lacked explainable AI

P. Zingaro [13]	school grades, ALR status, and course credits.	credits were included. The framework enabled early identification of at-risk students.	mechanisms for transparent decision-making.

3. Methodology

In this section, the proposed Explainable AI-based Predictive Analytics Framework for Student Performance Prediction and Dropout Detection is introduced. The framework involves data preprocessing in education, feature engineering, developing an ML prediction model, integrating explainability features, and a smart early-warning system to identify the academically high-risk students.

3.1. Dataset Description

For this research, the data used is the UCI ML Repository's "Predict Students' Dropout and Academic Success" dataset [14]. The data is made up of 4424 students' records and 36 input variables that are used to describe students' characteristics in terms of their academic, institutional, financial, and demographic factors in higher education institutions. The class to be classified is the academic outcome (Dropout, Enrolled, and Graduate). It includes critical attributes such as admission grades, previous qualification grades, tuition fee payment, information about scholarships, curricular unit evaluations, academic performance per semester, etc., that are appropriate for educational data analysis.

3.2. Data Preprocessing

In the preprocessing step, several steps were applied to improve the performance of the ML models. Firstly, inconsistencies and incomplete data were eliminated from the dataset using the missing value procedure. These attributes were then transformed to numerical values using Label Encoding and One-Hot Encoding methods, which are suitable for ML algorithms. Then, numerical features were normalized using feature normalization so that all the features are on a comparable scale and none can gain a competitive edge. Finally, the most important academic and socio-economic factors influencing the performance of students and their dropouts were also selected using feature selection techniques, which reduced the number of features to improve the efficiency of the model while reducing the computational complexity.

3.3. Proposed Architecture

The proposed framework is an educational analytics system based on Explainable Artificial Intelligence technology and is composed of various connected layers for accurate prediction of students' performance and students' dropout. The architecture starts with the Data Acquisition Layer that gathers data on students' demographics, academic, financial, and institutional data from educational databases. This acquired data is then preprocessed in the Preprocessing Layer, where data cleaning, handling missing values, encoding, normalization, and feature selection are performed to prepare the data for the ML analysis. The processed data is then passed to the ML Prediction Layer, in which the predictive models are trained and tested for academic outcome prediction using the methods of XGBoost, RF, DT, and SVM. Explainable Analytics Layer analyzes what causes the prediction results with Explainability techniques using SHAP for more transparency and interpretability. Finally, the Decision Support Layer produces smart reports and warnings for high-risk learners in academics and facilitates actions and interventions on time.

3.4. Algorithmic Workflow

The suggested algorithmic process begins with data loading of the educational data, then moves on to processing it to ensure that it is of high quality and reliable. The categorical attributes are then encoded using the right method into numerical values, and the data is normalized to take care of various ranges of data and to ensure the efficiency of a model. Then, the feature selection techniques are used to select the most important academic and socio-economic factors that influence students' performance and dropping out. Then, the processed dataset is used for training multiple ML models for predictive analytics. Then, once trained, the model is evaluated for prediction performance and explained using metrics, with SHAP-based explainability analysis added to help determine the contribution of individual features to the prediction results, as shown in Figure 1. Finally, the framework sets up intelligent early-warning predictions to identify students in danger of falling behind academically and to deliver early interventions in schools. Table 2 shows the Hyperparameter Configuration.

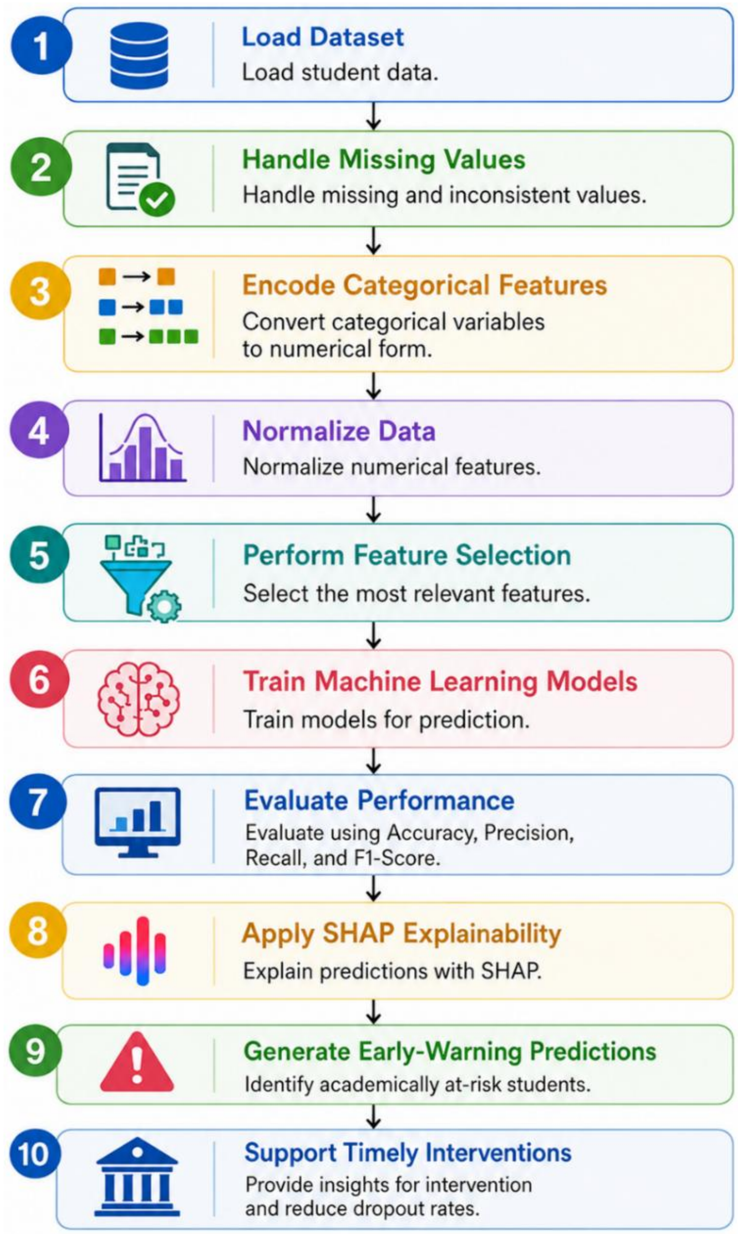

Fig. 1. Proposed Framework for Student Performance and Dropout Detection

Table 2. Hyperparameter Configuration

Parameter	**Value**
Learning Rate	0.1
Maximum Depth	6
Number of Estimators	100
Subsample Ratio	0.8

4. Results and Discussion

This section discusses experimental evaluation and performance analysis of the proposed Explainable AI-based predictive analytics framework for student performance and dropout detection. The experiments were carried out with the ‘Predict Students' Dropout and Academic Success' dataset of 4,424 student records.

4.1. Experimental Environment

The experimental setup aimed at effective ML training and evaluation in educational predictive analytics. The flexible implementation of classification algorithms was achieved using Python 3.11 and the Scikit-learn library, and efficient gradient boosting-based prediction was implemented with XGBoost. The hardware setup provided by the Intel Core i7 processor and 16GB of RAM enabled efficient processing of the large-scale educational dataset during the preprocessing, model training, and SHAP explainability analysis phase. The hardware setup with an Intel Core i7 processor and 16GB of RAM facilitated smooth processing of the large-scale educational data during the preprocessing, model training, and SHAP explainability analysis phase, as discussed in Table 3.

Table 3. Experimental Configuration

Parameter	Specification
Programming Language	Python 3.11
Development Environment	Jupyter Notebook
Processor	Intel Core i7
RAM	16 GB
Operating System	Windows 11
ML Libraries	Scikit-learn, XGBoost
Explainability Framework	SHAP

4.2. Comparative Performance Analysis

The comparative performance analysis shows that the proposed XGBoost performance is better than the performance of the Decision Tree, SVM, and Random Forest models on all the evaluation metrics. The model achieved an excellent classification ability with an excellent ROC-AUC score of 95.62% and an excellent Accuracy of 94.18%, indicating good generalization ability, as discussed in Table 4. This improvement on XGBoost might have been due to its gradient boosting mechanism, regularization, and the ability to handle the nonlinear data relationships in education. The results are similar to those of the framework's successful prediction of the accuracy of student performance and its ability to identify students at risk of dropping out, as shown in Figure 2.

Table 4. Comparative Performance of Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	ROC-AUC (%)
Decision Tree	84.63	83.91	82.74	83.32	85.17
SVM	88.41	87.95	87.12	87.53	89.08
Random Forest	91.26	90.84	90.13	90.48	92.37
Proposed XGBoost	94.18	93.74	93.21	93.47	95.62

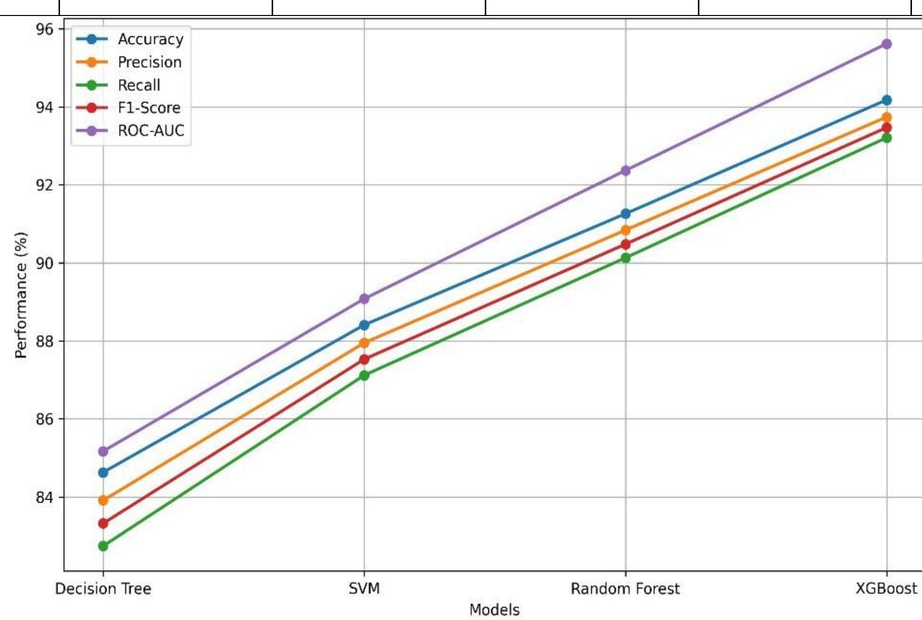

Figure 2: Comparative Performance Analysis of ML Models

4.3. Class-Wise Performance Analysis

The findings of the performance of the class-wise analysis indicate that the proposed framework is indeed capable of predicting the performance of the students in all academic outcome categories. The best Recall value (95.21%) was achieved for the Graduate class, which shows that this class can be easily identified with the successful students. Similarly, when considering the performance of the Dropout class, the F1 score was 94.79%, which represents good performance in identifying dropouts, as shown in Table 5. In part because the academic characteristics of the enrolled and graduate students are similar, so is their lower performance, as seen in Figure 3.

Table 5. Class-Wise Performance of XGBoost Model

Class	Precision (%)	Recall (%)	F1-Score (%)
Dropout	95.12	94.46	94.79
Enrolled	90.85	89.73	90.28
Graduate	94.67	95.21	94.94

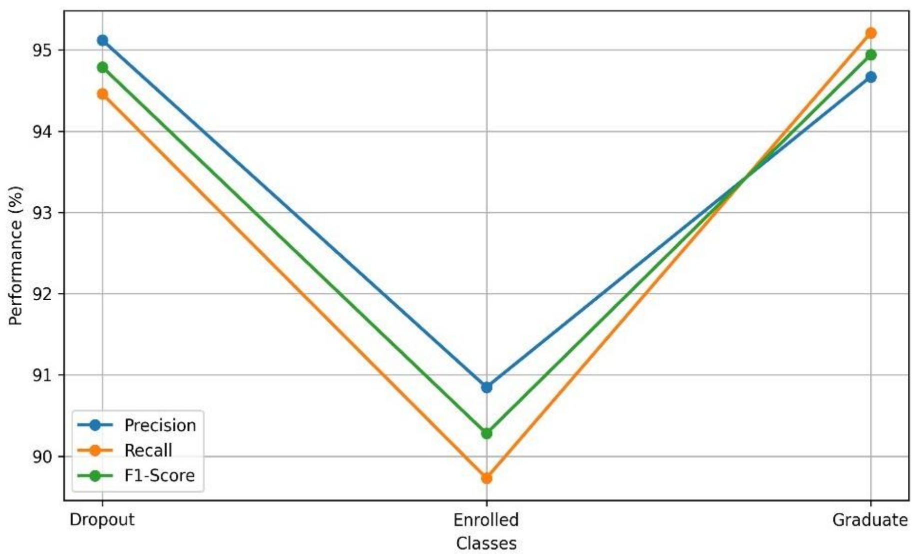

Fig. 3. Class-wise Performance Analysis

4.4. Confusion Matrix Analysis

The confusion matrix analysis shows that the proposed framework has excellent classification ability and that the minimum misclassification errors are possible in all academic outcome classes. The framework proved effective in the identification of academically at-risk students, with 256 of 271 actual dropouts being identified correctly. Likewise, there was excellent prediction reliability with regard to successful academic outcomes: 394 graduate students were correctly classified, as detailed in Table 6. There was some slight overlap in minor classification for Enrolled versus Graduate, with overlapping patterns of academic performance as illustrated in Figure 4.

Table 6. Confusion Matrix of Proposed Model

Actual / Predicted	Dropout	Enrolled	Graduate
Dropout	256	11	4
Enrolled	14	173	16
Graduate	5	12	394

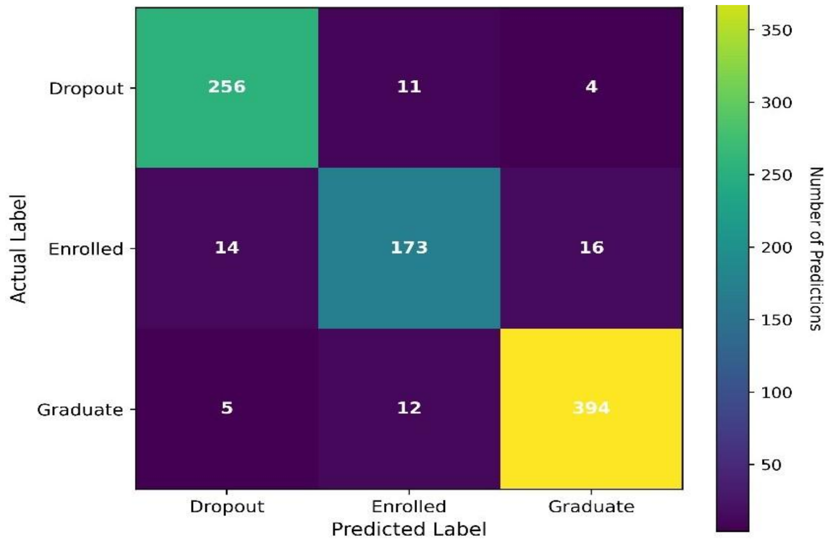

Fig. 4. Confusion Matrix of Proposed XGBoost Model

4.5. SHAP Explainability Analysis

Curricular unit performance was the most influential feature for the student's academic outcomes and dropout behavior, having a SHAP importance score of 0.284. The effect of admission grades and tuition fee status was also significant in predicting the students' outcomes, which brings out the interaction between academic and socio-economic factors in student retention, as discussed in Table 7. The explainability mechanism enhanced the transparency of the model, making it easier for educational institutions to gain insights into the reasons behind prediction results and develop suitable intervention strategies, as depicted in Figure 5.

Table 7: Top Features Influencing Dropout Prediction

Feature	SHAP Score
Curricular Unit Performance	0.284
Admission Grade	0.231
Tuition Fee Status	0.194
Previous Qualification Grade	0.176
Scholarship Status	0.151
Semester Evaluation	0.143

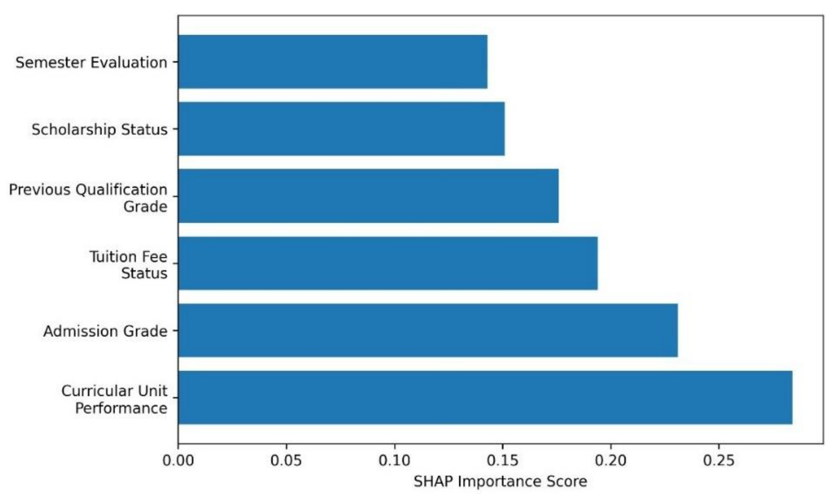

Fig. 5. SHAP Features Influencing Dropout Prediction

When using the SHAP analysis, academic performance and tuition fee status were the two most important determinants of dropout behavior.

The proposed framework was able to exhibit good predictive ability and was also found to be more interpretable by using explainable analytics tools such as SHAP. The findings demonstrated that the XGBoost and explainable AI combination successfully enhances the dropout prediction accuracy and aids in intelligent educational decisions.

5. Conclusion and Future Work

The present paper presents an Explainable AI (XAI) based student performance prediction and student dropout prediction using ML (ML) techniques. The proposed framework consisted of data preprocessing, feature engineering, predictive modelling using the XGBoost algorithm, and explainability analysis using the SHAP algorithm to correctly identify academically at-risk students and predict academic outcomes. The experimental results demonstrated that the proposed XGBoost model obtained an accuracy of 94.18%, a precision of 93.74%, a recall of 93.21%, an F1 score of 93.47%, and an ROC-AUC score of 95.62%. The transparency was improved, and the educational institutions better understood the factors that most affected student dropouts and academic outcomes, with the help of SHAP explainability. The suggested model provides practical suggestions for intelligent educational analytics, anticipating alerts, and data-based intervention plans. Future studies could focus on developing deep-learning architectures, federated learning, real-time learning analytics, multimodal student behaviour analysis, and adaptive intervention recommendation systems. The proposed framework has great potential for the development of intelligent educational analytics applications, which could help improve educational outcomes and lower the dropout rate from higher education.

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