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AN EXPLAINABLE EARLY WARNING SYSTEM FOR ACADEMIC DROPOUT PREDICTION AND INTERVENTION

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Student dropout is a major concern in higher education. Early identification of at-risk students enables institutions to implement timely and effective interventions. While many existing early warning systems achieve high predictive accuracy using complex black-box models, they often lack interpretability and practical support for intervention planning. This paper proposes an explainable early warning system for academic dropout prediction that emphasizes intervention readiness rather than prediction alone. The framework integrates interpretable machine learning techniques with explainable artificial intelligence to identify key behavioral risk factors. Experiments conducted on a simulated behavioral dataset demonstrate that the proposed system provides reliable predictions along with clear and actionable explanations to support informed educational decision-making.

of 800 student records, of which approximately 30% represent dropout cases. The selected indicators reflect realistic behavioral patterns commonly observed in higher education settings.

Table 1. Simulated Dataset Description

Feature	Description
Attendance (%)	Percentage of classes attended
Assignment Delay	Average delay in submissions (days)
Learning Activity	LMS interaction frequency
Participation	Classroom participation score
Consistency	Engagement trend over time
Dropout (Target)	Binary (Dropout / Non-dropout)

The proposed system aims to identify students at risk of dropout at an early stage and provide meaningful explanations to support timely intervention. It is designed for data-constrained educational environments and leverages student behavioral and academic indicators to enable interpretable and preventive decision-making. The framework consists of five stages: data input, feature extraction, risk prediction, interpretability, and intervention control. Behavioral indicators such as attendance, assignment submission delay, learning engagement, and classroom participation are considered. A simulated dataset is used to model realistic student behavior while preserving privacy. Data preprocessing involves handling missing values using basic statistical methods and applying feature normalization. Temporal behavioral trends are incorporated to improve early dropout risk detection. Dropout prediction is performed using interpretable and semi-interpretable models, including Decision Tree and Random Forest classifiers. Although XGBoost is included for performance comparison, interpretability and intervention reasoning rely primarily on the Decision Tree and Random Forest models. Students are categorized into low-, moderate-, and high-risk groups, and feature importance analysis is used to identify key behavioral risk factors. An intervention preparedness score is then derived to assist educators in prioritizing timely support actions.

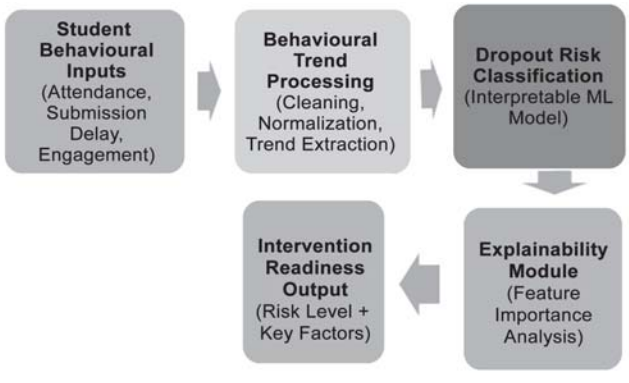

Fig 1. Overview of the proposed explainable and actionable early warning framework.

Results and Discussion

An 80:20 train–test split was used to evaluate the proposed framework, along with five-fold cross-validation to ensure robustness. Precision, recall, and F1-score were employed as evaluation metrics, with dropout treated as the positive class.

Table 2. Dropout risk prediction performance

Model	Precision	Recall	F1-score
Decision Tree	0.80	0.78	0.79
Random Forest	0.84	0.82	0.83
XGBoost	0.86	0.84	0.85

Although XGBoost achieves slightly higher predictive performance, it is not used for intervention reasoning due to its limited interpretability. In contrast, interpretable models enable the identification of key behavioral risk factors, thereby supporting timely and informed intervention.

Conclusion and Future Work

This paper presented an explainable and actionable early warning system for student dropout prediction using interpretable machine learning models and simulated behavioral data. The proposed framework emphasizes intervention readiness by providing clear explanations of dropout risk factors. The results demonstrate that the system achieves reliable predictive performance while maintaining interpretability, making it suitable for data-constrained educational environments. Future work will focus on validating the framework using real institutional data and extending it with automated intervention recommendation mechanisms. ❐

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