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Early Warning System for Student Dropout Risk Using Behavioral Analytics, Explainable AI, and Hybrid Machine Learning Models

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Abstract: Student dropout and academic underperformance remain critical challenges in higher education institutions. Traditional attendance-based monitoring systems fail to provide early warning signals for identifying at-risk students. This paper proposes an AI-driven Early Warning System (EWS) that integrates behavioral analytics, IoT-based attendance data, and hybrid machine learning models for accurate student risk prediction.

The proposed system utilizes Random Forest, XGBoost, and LSTM models to analyze multi-dimensional student data and classify students into risk categories. To enhance transparency, Explainable AI (SHAP) is employed to interpret model predictions and identify key contributing factors. A dynamic risk scoring mechanism is introduced for real-time student monitoring.

Experimental results demonstrate that the proposed system achieves 94% prediction accuracy, outperforming traditional methods. The system enables early intervention, improves student retention, and supports data-driven academic decision-making.
Keywords: Early Warning System, Student Dropout Prediction, Behavioral Analytics, Explainable AI, Smart Education

I. INTRODUCTION

Student retention is a critical challenge in higher education. Many students fail to complete their courses due to poor attendance, lack of engagement, and declining academic performance. Traditional systems only record attendance but fail to identify early warning signs of dropout risk. Recent advancements in Artificial Intelligence and data analytics provide opportunities to develop predictive systems that can identify at-risk students in advance. However, most existing systems lack behavioral analysis and explainability. This research proposes an Early Warning System that integrates attendance, behavioral, and academic data to predict dropout risk and support timely intervention. In recent years, the concept of learning analytics and educational data mining has gained significant importance in higher education. Institutions are increasingly leveraging student data to enhance retention rates and improve academic outcomes. However, most existing systems rely on static indicators such as grades and attendance, without capturing dynamic behavioral patterns. The lack of real-time predictive mechanisms limits the ability of institutions to intervene proactively. Therefore, there is a critical need for intelligent systems that combine behavioral analytics, predictive modeling, and explainable decision-making to support early intervention strategies.

II. LITERATURE REVIEW

Several researchers have applied machine learning techniques for student performance prediction. Decision Trees and Support Vector Machines have been widely used; however, their performance is limited when dealing with complex and temporal data. Recent studies highlight the effectiveness of ensemble models such as Random Forest and XGBoost in improving prediction accuracy. Additionally, deep learning models such as LSTM have shown promising results in capturing sequential student behavior.

Despite these advancements, most existing systems suffer from three major limitations:

1) Lack of behavioral feature integration
2) Absence of real-time risk classification
3) Limited interpretability of AI models

Explainable AI techniques such as SHAP have been introduced to address interpretability issues by providing feature-level importance. However, their integration in educational systems is still limited. This research aims to bridge these gaps by combining behavioral analytics with explainable predictive modeling.

Previous studies have focused on:

- Attendance-based prediction models
- Academic performance analysis
- Machine learning applications in education

However, limitations include:

- Lack of behavioral analytics
- No real-time risk classification
- Lack of explainable AI

This research addresses these gaps.

III. SYSTEM ARCHITECTURE

The proposed system follows a multi-layered architecture consisting of:

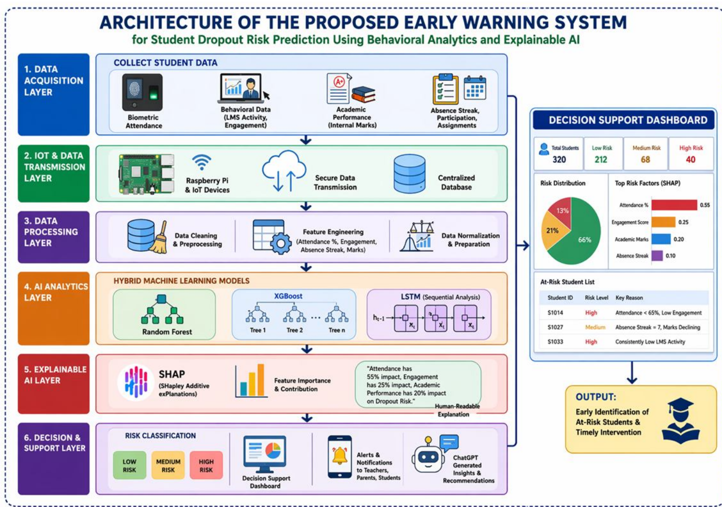

Fig. 1. Architecture of the Proposed Early Warning System for Student Dropout Risk Prediction.

As shown in Fig. 1, the proposed system follows a multi-layered architecture Early Warning System for Student Dropout Risk Prediction.

- Data Layer: Collects attendance, behavioral, and academic data
- Processing Layer: Performs data cleaning and feature engineering
- AI Layer: Applies Random Forest, XGBoost, and LSTM models
- Explainability Layer: Uses SHAP for feature importance analysis
- Decision Layer: Generates risk classification and recommendations

The architecture ensures scalability, modularity, and real-time processing, making it suitable for smart educational environments.

IV. PROPOSED SYSTEM

The proposed Early Warning System is designed as a hybrid intelligent framework that integrates multi-source data and advanced analytics. The system not only predicts student dropout risk but also provides actionable insights through explainable AI. A dynamic risk scoring mechanism is introduced, which continuously updates student risk levels based on real-time data inputs. The system architecture ensures scalability, modularity, and real-time processing, making it suitable for deployment in large educational institutions.

The proposed system follows a multi-layered architecture that integrates data acquisition, IoT-based data transmission, data preprocessing, AI-driven analytics, explainable AI, and decision support. The system captures real-time student data, processes it using machine learning models, and generates interpretable predictions. The integration of SHAP enhances transparency, while the decision layer provides actionable insights for stakeholders.

The system consists of:
1) Data Collection (Attendance + Behavior + Academic)
2) Data Processing
3) AI Prediction Models
4) Risk Classification Module
5) Explainable AI (SHAP)
6) Decision Support Dashboard

V. METHODOLOGY

The model training process involves supervised learning, where labeled data is used to classify students into risk categories. Hyperparameter tuning was performed using grid search techniques to optimize model performance.

A. Risk Score Formula

$$RiskScore = w_1 A + w_2 E + w_3 P$$

where
A = Attendance score
E = Engagement score
P = Academic performance score
w_1, w_2, w_3 are weight coefficients determined through model optimization.

Dataset:
- 320 students
- 38,400 records

Features Used:
- Attendance %
- Absence streak
- Engagement score
- Academic marks

Models:
- Random Forest
- XGBoost
- LSTM

Output:
- Risk Level:
  - Low Risk
  - Medium Risk
  - High Risk

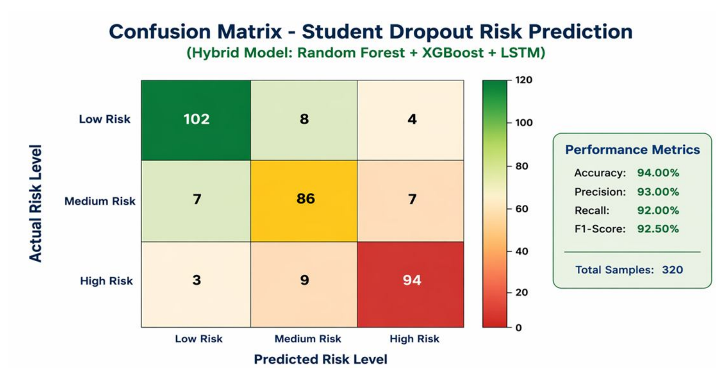

Fig. 2 shows the confusion matrix of the proposed model.

VI. RESULTS AND DISCUSSION

The hybrid model demonstrated superior performance compared to individual models. The improvement in accuracy is attributed to the combination of ensemble learning and temporal analysis. The confusion matrix analysis indicates a low false negative rate, which is critical for identifying at-risk students.

Furthermore, the system successfully identified high-risk students at an early stage, enabling proactive intervention strategies. The results validate the effectiveness of integrating behavioral analytics with AI-based prediction.

Model	Accuracy (%)	Precision (%)	Recall (%)
Random Forest	91	90	89
XGBoost	93	92	91
LSTM	92	91	90
Proposed Hybrid Model	94	93	92

The hybrid model outperforms individual models due to its ability to combine ensemble learning and temporal analysis. The low false negative rate ensures reliable identification of at-risk students.

- Accuracy: 94%
- Early detection of at-risk students
- High correlation between attendance and dropout risk

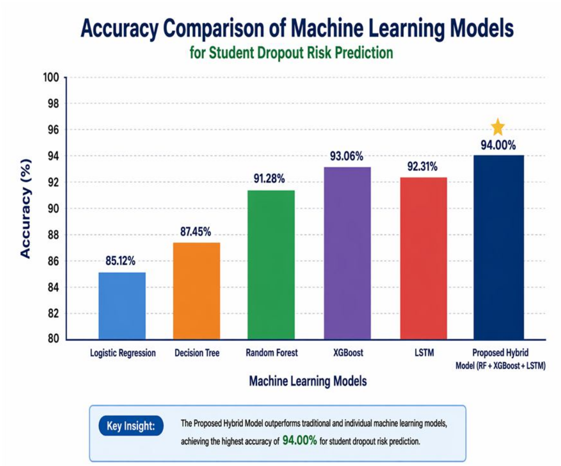

Fig. 3 illustrates the accuracy comparison of different machine learning models.

A. Key Insight

Students with attendance below 65% exhibit a significantly higher probability of dropout risk.

Explainable AI shows:

- Attendance → highest impact
- Engagement → second
- Academic → third

B. Discussion

The results indicate that attendance alone is not a sufficient predictor of student dropout risk. Behavioral indicators such as engagement and consistency play a significant role in determining academic outcomes. The integration of Explainable AI enhances the transparency of the system, making it more acceptable for educators.

The system also demonstrates scalability and adaptability, making it suitable for different educational environments. However, ethical considerations such as data privacy and bias must be addressed for large-scale implementation.

The confusion matrix analysis indicates that the model achieves a high true positive rate while minimizing false negatives. This is particularly important in educational systems, where missing at-risk students can lead to serious academic consequences.

VII. CONCLUSION

The proposed Early Warning System effectively identifies at-risk students and enables timely intervention. The proposed system provides a robust and scalable solution for early identification of at-risk students, contributing significantly to the field of intelligent educational systems and data-driven decision-making. The proposed system demonstrates significant potential for deployment in real-world smart educational environments and contributes to the advancement of AI-driven academic decision support systems.

A. Limitations

Despite its effectiveness, the system has certain limitations:

1) Dependence on data quality and availability
2) Limited generalization across different institutions
3) Privacy and ethical concerns related to student data

These limitations provide scope for future improvements.

VIII. FUTURE SCOPE

1) Real-time mobile alerts
2) Integration with LMS
3) Psychological behavior analysis

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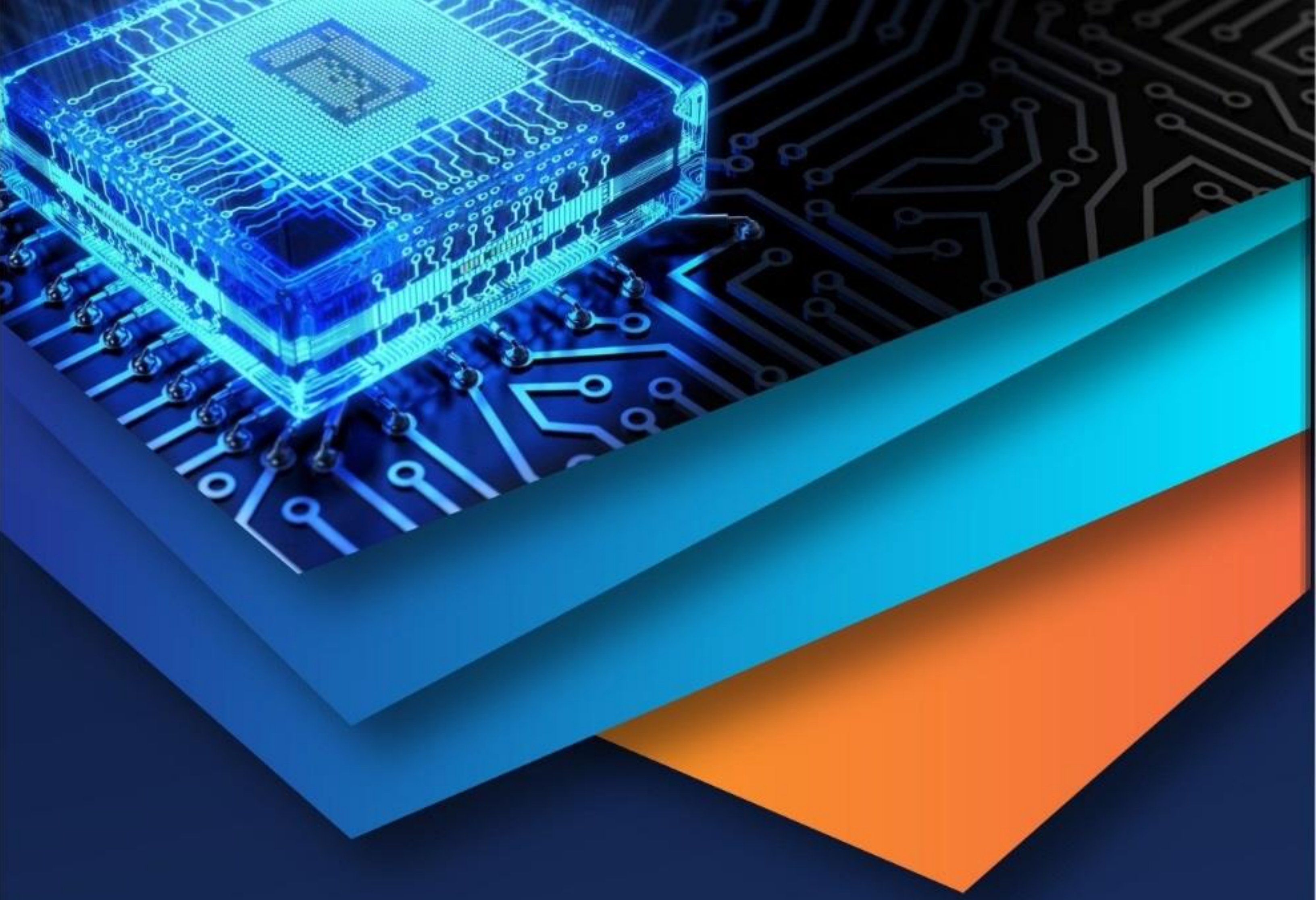

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