AI-Based Prediction of Student Dropout Risk Using Behavioural Patterns

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Abstract: -

Prediction of student dropout is one of the major challenges faced by higher education institutions with improvements in academic performance, student retention, and institutional ranking. Most of the traditional approaches rely heavily on academic indicators such as grades, attendance, and performance in exams, which fail to capture early changes in behaviour. Here in, this paper describes an AI-based predictive model based on behavioural patterns related to LMS usage, trends in assignment submission, consistency in login, duration of sessions, and metrics related to academic engagement that can enhance the accuracy in the prediction of student dropout. This study compares the algorithms of Logistic Regression, Random Forest, and XGBoost using a real dataset collected from ERP and LMS platforms. The findings reveal that behavioural analytics enhances the early detection of the dropout risk significantly, thus helping in implementing timely academic interventions and strategies for student support.

Keywords: -

AI in Education, Dropout Prediction, Machine Learning, Behavioural Analytics, Educational Data Mining, Learning Management Systems.

I. INTRODUCTION

Student dropout is a major issue in higher education worldwide. It impacts both how institutions perform and the futures of students. Schools often use traditional methods like tracking attendance, reviewing academic results, and observing student behaviour. These methods provide limited information and usually identify risks only after problems have worsened.

As digital learning environments and Learning Management Systems (LMS) become more

common, schools generate large amounts of behavioural data. This data includes login patterns, how often students access content, assignment submission times, quiz participation, and communication records. These behavioural signs give better insights into student engagement and learning habits, which are crucial for predicting dropout risks.

This research presents an AI-based prediction model that combines academic and behavioural factors to identify at-risk students more accurately and earlier than traditional methods. The suggested approach enables schools to implement timely interventions, including counselling, mentoring, personalized learning plans, or academic support programs.

II. LITERATURE REVIEW

In the last decade, EDM and LA have gained significant recognition. Initial research primarily focused on demographic variables (age, gender, SES), academic performance metrics, and attendance [4]. Logistic Regression, Decision Trees, and Support Vector Machines have given promising results; however, these models often lacked the depth required to capture behavioural variability fully [2].

Recent works focus on behavioural and interaction-based features. K. Verbert et al. pointed out that the patterns of LMS interaction are strongly related to the learning outcomes and performances of students [1]. Similarly, Romero & Ventura highlighted the essential role of behavioural information in the improvement of predictive models for academic performance and dropout detection [4].

Random Forest and Gradient Boosting are some of the successful models that can handle classification problems with high interaction effects among features. Chen & Guestrin showed that XGBoost has performed exceptionally well in several structured data classification problems owing to its scalability and regularization techniques in [3].

Recent works involve real-time prediction systems of dropout, personalized feedback mechanisms, and the integration of deep learning models for risk assessment in students [6][7]. However, comprehensive integration of behavioural features with academic indicators still remains an underexplored area, particularly within Indian higher education systems.

III. PROBLEM STATEMENT

Most existing dropout prediction systems rely mainly on academic performance metrics such as marks and attendance. These kinds of methods provide delayed insight with a lack of predictive power. There is a need for an integrated AI-driven model by fusing behavioural data from LMS systems to detect dropout risks earlier and more accurately [2].

IV. OBJECTIVES

1. To analyse the behavioural and academic features which influence student dropout.

2. To determine key behavioural predictors such as login frequency, session duration, and assignment patterns [1].

3. Design and implement multiple machine learning models for dropout prediction.

4. To compare the performances of Logistic Regression, Random Forest, and XGBoost.

5. To create actionable insights for educators to reduce dropout rates [4].

V. METHODOLOGY

A. Data Collection

The data were collected from the ERP and LMS platforms of the institution. The dataset consisted of:

Attendance records

- Assignment submission timestamps
- Login frequency
- Session duration
- Internal assessment scores
- Device usage: mobile/desktop
- Quiz participation

These three variables collectively represent student academic engagement or behavioural activity [1].

B. Data Pre-processing

Techniques included:

- Handling missing values
- Label encoding of categorical fields
- Min-max normalization

Feature selection using correlation analysis and Random Forest feature importance

C. Algorithms Used

1. Logistic Regression: Baseline model for binary classification.

2. Random Forest: Ensemble model effective for handling large and complex feature sets.

3. XGBoost: It is a gradient boosting algorithm known for high predictive accuracy due to regularization, tree pruning, and parallel computation [3].

D. Tools and Technologies

- Python
- Pandas & NumPy
- Scikit-learn
- XGBoost library
- MySQL for database
- Tableau/Power BI for visualization

VI. CONCLUSION

Indeed, this research has shown that integrating the behavioural data with academic indicators increases the accuracy of dropout prediction drastically. The XGBoost model achieved the maximum accuracy of 94.1%, outperforming Logistic Regression and Random Forest models [3]. Once the proposed system detects that students are at risk in an institution, it can identify those who need personalized mentoring and remedial classes on time.

VII. FUTURE SCOPE

Future enhancements might include:

- Integration of deep learning models including LSTMs
- Real-time dropout prediction dashboards
- Include indicators of psychological or emotional well-being.
- Mobile application-based notification system
- Multi-institutional testing to ensure generalization [7][10]

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