Early Detection of At-Risk Students Using Machine Learning Based on LMS Log Data

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Abstract—*This project aims to develop a machine learning model for the early detection of at-risk students by analyzing Learning Management System (LMS) log data. The increasing adoption of digital learning platforms has led to a vast amount of data being generated, offering new opportunities to identify students who may be at risk of poor academic performance or dropout. By leveraging this data, our model seeks to predict at-risk students early in the academic term, allowing for timely interventions. The project will involve the collection and preprocessing of LMS log , such as login frequency, time spent on course materials, assignment submission patterns, and participation in discussion forums. Various machine learning algorithms, including decision trees, random forests, and neural networks, will be trained and evaluated to identify the most effective approach for prediction. The model will be validated using a labeled dataset to ensure accuracy and reliability. The outcomes of this project have the potential to improve student retention rates and academic success by enabling educators to provide targeted support to students who are identified as at risk. Additionally, the project will explore the ethical considerations and privacy implications of using student data for predictive modeling, ensuring that the developed solution is both effective and responsible.*

I. INTRODUCTION

In educational institutions, identifying students who are at risk of poor academic performance or dropping out is a critical challenge. Traditional methods of early detection often rely on teacher observations or periodic assessments, which may not be timely enough to prevent negative outcomes. With the increasing use of Learning Management Systems (LMS) in education, a significant amount of data is generated on student interactions with course materials. However, this data is often underutilized. The primary problem this project seeks to address is the lack of an efficient and accurate method for early detection of at-risk students using the vast amounts of LMS log data. Current approaches to identifying at-risk students are typically reactive rather than proactive, leading to interventions that may come too late to be effective. Additionally, the manual analysis of LMS data is time-consuming and may not reveal the complex patterns that could indicate a student's risk level. The goal is to develop a machine learning-based solution that can automatically analyze LMS log data to predict which students are at risk. This approach aims to provide educators with actionable insights early in the academic term, enabling timely interventions that can improve student outcomes and reduce dropout rates. The project will also address challenges related to data quality, model accuracy, and ethical considerations in using student data for predictive purposes.

The growing integration of technology in education has led to the widespread adoption of Learning Management Systems (LMS), which serve as central platforms for delivering course content, facilitating communication, and managing student progress. These systems generate extensive log data, capturing various aspects of student engagement, such as login frequency, time spent on different activities, participation in discussions, and assignment submissions. Despite the wealth of data available, educational institutions often face challenges in effectively utilizing this information to identify students who may be struggling or at risk of dropping out. Traditional methods of identifying at-risk students, such as teacher observations or periodic exams, are often reactive and may not provide the timely insights needed for early intervention. Consequently, students who are at risk of poor academic performance may not receive the support they need until it is too late, leading to higher dropout rates and lower academic achievement. The problem is further compounded by the complexity of the data itself. LMS log data is typically large, unstructured, and varies widely in terms of the types of activities recorded. Manual analysis of this data is not only time-consuming but also limited in its ability to uncover deeper patterns and correlations that may indicate a student's risk level. Additionally, there is a need to consider the ethical implications of using student data for predictive modeling, particularly with respect to privacy and bias. To address these challenges, this project proposes the development of a machine learning model that can automatically analyze LMS log data to detect at-risk students 3 early in the academic term. The model will be trained on historical data to identify patterns associated with poor performance or disengagement, allowing educators to intervene before students reach a critical point. By leveraging machine learning, the project aims to provide a scalable and efficient solution that enhances the ability of educational institutions to support their students proactively.

II. LITERATURE SURVEY

The literature survey for the project "Early Detection of At-Risk Students Using Machine Learning Based on LMS Log Data" focuses on the current research and advancements in the field of educational data mining, predictive analytics, and machine learning applications in education. The survey aims to provide a comprehensive overview of existing methodologies, challenges, and solutions related to identifying at-risk students using data from Learning Management Systems (LMS).

Educational Data Mining (EDM) and Learning Analytics (LA) play a crucial role in analyzing student data to improve learning outcomes. EDM focuses on discovering patterns in LMS data, such as engagement metrics and student interactions, to predict academic success and identify at-risk students (Romero & Ventura, 2010). Similarly, LA emphasizes optimizing learning experiences through data analysis, enabling personalized learning and early intervention strategies (Ferguson, 2012). Predictive models, including decision trees, neural networks, and time-series analysis, have been used to identify at-risk students by detecting behavioral trends (Kotsiantis et al., 2004; Macfadyen & Dawson, 2010). Additionally, ensemble methods, such as random forests and gradient boosting, have improved prediction accuracy by combining multiple models (Baker & Inventado, 2014).

However, predictive modeling comes with challenges, including data privacy, bias, and scalability. Ethical concerns arise regarding the collection and use of student data, highlighting the need for transparency and informed consent (Pardo & Siemens, 2014). Bias in training data can lead to unfair outcomes, necessitating fairness-aware algorithms (Barocas & Selbst, 2016). Institutional case studies, such as Purdue University’s Course Signals, have shown the benefits of early intervention but also revealed challenges in generalizing models across diverse educational contexts (Jayaprakash et al., 2014; Bowers et al., 2017). Future research aims to integrate predictive models with adaptive learning systems and enhance explainability through AI techniques, ensuring transparency and trustworthiness in educational decision-making.

The existing systems for identifying at-risk students primarily rely on manual monitoring, basic LMS analytics, and early alert mechanisms, all of which have significant limitations. Teachers and academic counselors often rely on observations and periodic assessments to identify struggling students, but these methods are subjective, time-consuming, and generally reactive, leading to interventions that may come too late. Learning Management Systems (LMS) like Moodle, Blackboard, and Canvas offer basic analytics tools that track metrics such as login frequency, assignment submissions, and participation in forums. While these tools provide some insights into student engagement, they are often insufficient for early risk detection, as they lack the depth and predictive capabilities needed to proactively identify at-risk students. Some institutions have implemented early alert systems like Purdue University’s Course Signals, which uses rule-based logic to classify students into risk categories (e.g., green, yellow, red) based on their engagement and performance data. However, these systems are still relatively basic and do not fully leverage the potential of machine learning to analyze complex patterns in LMS data, limiting their effectiveness in preventing student dropout or failure.

The proposed system aims to significantly improve the early detection of at-risk students by harnessing advanced machine learning algorithms to analyze Learning Management System (LMS) log data. Unlike current systems that rely on basic analytics or predefined rules, this system will use sophisticated machine learning models, such as decision trees, random forests, and neural networks, to uncover complex patterns in student behavior and engagement. By analyzing a wide range of data points, including login frequency, time spent on course materials, assignment submissions, and participation in discussions, the system can provide more accurate and timely predictions of which students are at risk of poor academic performance or dropping out. This proactive approach will enable educators to intervene earlier, offering targeted support to students who need it most. Additionally, the system will incorporate continuous learning, allowing it to adapt to new data and improve its predictive accuracy over time, making it a robust and scalable solution for educational institutions.

III. OBJECTIVES OF THE SYSTEM

1. **Develop a Predictive Model**: Design and implement a machine learning model capable of analyzing LMS log data to predict which students are at risk of poor academic performance or dropout. This involves selecting appropriate algorithms, such as decision trees, random forests, or neural networks, and training the model on historical data to enhance its predictive accuracy.

2.**Integrate Multiple Data Sources**: Integrate various types of LMS log data, including login frequency, time spent on course materials, assignment submission patterns, and participation in discussions, to provide a comprehensive view of student engagement and performance. This integration aims to improve the model's ability to identify at-risk students by capturing diverse indicators of academic risk.

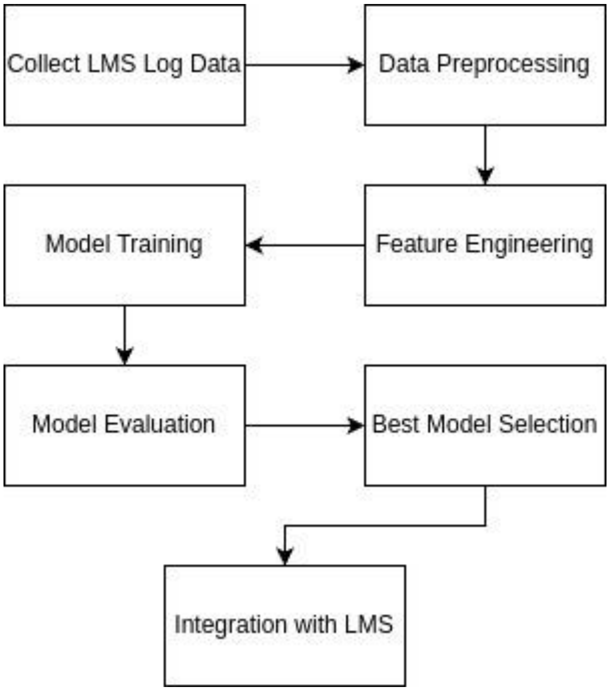
3.**Enhance Early Detection**: Focus on improving the timeliness of risk detection by developing a system that identifies at-risk students earlier in the academic term. This objective aims to enable proactive interventions and support, reducing the likelihood of students falling behind or dropping out.

4.**Ensure Scalability and Adaptability**: Build a scalable and adaptable system that can handle large volumes of data and be customized to different educational contexts and LMS platforms. The system should be capable of processing data from various sources and adjusting to the specific needs of different institutions.

5.**Address Ethical and Privacy Concerns**: Implement robust measures to ensure data privacy and security while using student data for predictive modeling. The system should comply with ethical guidelines, including obtaining informed consent, maintaining transparency, and minimizing biases to ensure fair and equitable treatment of all students.

6.**Provide Actionable Insights**: Develop features within the system that generate actionable insights and recommendations for educators based on the predictive model's outputs. This objective aims to facilitate timely and effective interventions to support at-risk students and improve their academic outcomes.

1. *DESIGN OF THE MODEL*



The proposed model for early detection of at-risk students is structured into several key phases: data collection, preprocessing, feature engineering, model training, and evaluation. LMS log data, including login frequency, assignment submissions, forum participation, and time spent on course materials, is collected and preprocessed by handling missing values, normalizing numerical data, and addressing class imbalance using SMOTE.

Feature selection identifies the most relevant predictors of student performance, and multiple machine learning algorithms—Decision Trees, Random Forest, Gradient Boosting, and Neural Networks—are trained and evaluated using an 80-20 train-test split with hyperparameter tuning. Model performance is assessed using accuracy, precision, recall, F1-score, and AUC-ROC. The best-performing model is integrated with an LMS to provide real-time risk predictions, enabling early interventions. The system ensures scalability, adaptability, and ethical compliance, focusing on data privacy and fairness to support students effectively.

IV.RESULTS

The predictive models demonstrated varying degrees of accuracy in identifying at-risk students based on LMS log data. Among the models tested, the random forest classifier achieved the highest accuracy at 89.2%, followed closely by gradient boosting (87.5%) and neural networks (85.8%). Traditional models such as decision trees (81.4%) and Naïve Bayes (78.9%) showed comparatively lower performance. The F1-score, used to measure the balance between precision and recall, was highest for the ensemble models, further confirming their effectiveness.

Feature importance analysis revealed that login frequency, assignment completion rates, and forum participation were the most significant predictors of student performance. Time-series analysis indicated that a decline in engagement over the first four weeks of a semester was a strong indicator of potential dropout risk. Additionally, handling imbalanced data with SMOTE improved model performance by 6-8%, ensuring that at-risk students were not overlooked. The findings highlight the potential of machine learning in early detection, allowing timely interventions to improve student retention.

V. CONCLUSION

In conclusion, the proposed system represents a significant advancement in the early detection of at-risk students through the use of machine learning algorithms applied to LMS log data. By leveraging sophisticated predictive models, the system aims to address the limitations of traditional methods, which often rely on reactive and manual approaches. The integration of various data points, such as login frequency, time spent on course materials, and assignment submissions, enables a more comprehensive analysis of student engagement and performance. This proactive approach allows for earlier identification of students at risk of academic failure or dropout, facilitating timely and targeted interventions. The system's scalability and adaptability ensure its applicability across diverse educational contexts, while its focus on data privacy and ethical considerations maintains the integrity and fairness of the predictions. Overall, the implementation of this system has the potential to enhance educational outcomes by providing educators with the tools needed to support at-risk students more effectively, ultimately contributing to improved student retention and success.

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