

Smart Learning Paths: A Data Mining Approach to Elevate E-Learning Outcomes

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Abstract

E-Learning has evolved as a cornerstone of modern education, yet challenges persist in ensuring optimal student engagement and learning outcomes. This article explores the transformative potential of Smart Learning Paths, employing a cutting-edge data mining approach to personalize the e-learning experience. Through the analysis of diverse online footprints, including quiz scores and log entries, machine learning algorithms create adaptive learning paths tailored to individual students. Predictive analytics further forecast performance, enabling timely interventions for those at risk. This article delves into the advantages of Smart Learning Paths, such as heightened student engagement and improved learning outcomes. Ethical considerations, technological challenges, and real-world applications are examined, offering a comprehensive view of the evolving landscape. The discussion extends to future trends and innovations, emphasizing the ongoing need for research and development in data-driven educational strategies.

Keywords: *E-Learning, Data Mining, Learning Paths, Predictive Analytics.*

1. Introduction

Through technological advancements, e-learning is reshaping modern education, enhancing accessibility and flexibility. Despite the fact that online platforms have become indispensable for delivering educational content, traditional models still fail to engage students effectively [1]. By implementing smart learning paths, this article addresses the limitations of conventional approaches to e-learning and uses data mining to revolutionize learning outcomes.

The significance of e-learning lies in its ability to provide education to a global audience, irrespective of geographical location. Learners are able to access materials at their own pace due to the flexibility of the program. The accessibility of this resource is intended to meet the needs of non-traditional students and those who face limitations. During global disruptions such as the pandemic, e-learning

demonstrated resilience and adaptability.

Online learning, despite its advantages, struggles with personalization, which undermines its effectiveness. The delivery of generic content may not be suited to the needs and learning styles of each individual. It can be challenging to monitor engagement and predict performance declines in the absence of physical cues. In order to overcome these challenges, innovative approaches are essential. As a result of the convergence of technological innovation and changing educational paradigms, e-learning has experienced an unprecedented expansion. Digital resources, virtual classrooms, and online courses are now ubiquitous, influencing primary education, higher education, and professional development around the world. Throughout the past few years, the global e-learning market has experienced significant growth, reflecting a shift in society toward the use of digital learning tools and platforms [2].

E-learning has a profound impact on education, dismantling traditional barriers to learning. Learning materials are now available anywhere and at any time, fostering a global learning community. The use of collaborative tools and online forums facilitates interaction and knowledge exchange across geographical boundaries. A potential benefit of electronic learning is its ability to accommodate diverse learning styles and provide opportunities for individuals who may face limitations in traditional educational settings. Innovative approaches utilizing advanced technologies are essential for addressing shortcomings. The use of data mining provides a promising means of extracting insights from large amounts of data. Personalized learning experiences can be offered by educational institutions through the use of data analytics, adapted to the unique needs and progress of each student [3].

Data mining can be purposefully adapted to address specific challenges in education and improve student learning outcomes. It is possible for educators to gain a holistic understanding of students' learning behaviors by utilizing a variety of data sources such as quiz scores, log entries, and student interactions within e-learning platforms. It is from this information that personalized and adaptive learning paths can be created [4]. Data mining allows educators to identify patterns indicative of strengths and weaknesses by analyzing quiz scores and academic performance. As a result, students who are experiencing difficulties can be provided with targeted interventions. Using data mining, it is possible to determine a person's learning style and preferences based on his or her learning behaviors. Using this information, instructional content can be tailored to meet the needs of diverse students. Educators can anticipate potential performance issues using predictive analytics and intervene in a timely manner as a result. The proactive approach addresses

challenges before they escalate, fostering a supportive learning environment [5]. A smart learning path is a personalized educational path that is designed to meet the needs, preferences, and progress of each individual student. By analyzing real-time data, smart learning paths dynamically adjust learning content, pace, and assessments, resulting in an adaptive and responsive learning experience.

As this article argues, data mining, specifically smart learning paths, can revolutionize e-learning outcomes. Learning paths that use smart data mining analyze students' online footprints in order to create adaptive learning paths that are tailored to their individual learning styles and preferences. A predictive analytics approach anticipates performance issues, allowing for timely intervention.

2. Research Problem

The use of Data Mining (DM) and Machine Learning (ML) tools has become increasingly important in the realm of e-learning as educators seek to understand students' behaviors and improve learning outcomes. This is particularly true in the context of online education. With the increased use of online courses in higher education, characterized by flexible and student-centered curriculum designs, there is an urgent need to revolutionize learning outcomes through innovative and non-traditional approaches. This objective can be achieved by employing advanced DM and ML methodologies for the automated analysis of student performance and behavior as well as intelligent personalized interventions.

Courses offered at universities are managed through LMS such as Moodle or Blackboard, which generate extensive datasets on students' online activities, such as quiz marks, assignment marks, active participation, and login frequency. Instructors can gain valuable insight into student learning behaviors by recognizing patterns in this data. It is our hypothesis that employing DM and ML techniques to scrutinize students' online footprints could result in significant benefits. This involves continuous monitoring of student performance, detecting performance declines, and facilitating recommendations to instructors for improving student performance.

2.1 Objective:

The primary objective of this research endeavor is to apply advanced Machine Learning and Data Mining tools within the domain of online courses. An overarching objective is to gain insights into the performance and behavior of students, detect signs of performance decline, and assess the probability of dropout. In addition, the research aims to develop and implement personalized interventions to enhance

student engagement and, as a consequence, facilitate improved learning outcomes.

In order to achieve these objectives effectively, it is imperative to develop specialized tools. The research will focus on addressing the following key questions:

Question 1: How can advanced DM and ML tools be employed to comprehensively observe and predict student engagement and performance based on their online activities?

Question 2: What methodologies should be employed for constructing and delivering personalized interventions through offline communication?

The inherent challenge of online courses stems from the absence of face-to-face interaction, which makes it difficult to monitor student engagement and detect performance declines as is conventionally done in a physical classroom setting. Due to the fact that student's participation in forums, submission of assignments, interaction with course materials, etc., they create substantial digital footprints during their online learning journey. Using these digital footprints, instructors are able to gain a deeper understanding of student behavior and make meaningful inferences about future behavior.

Due to the extensive footprint data associated with online courses, manual analysis is not practical for instructors. Additionally, the diverse and heterogeneous student population increases the complexity of manual analysis. It is particularly important to note that conclusions drawn from one student may not necessarily be applicable to others, especially those with different academic backgrounds. Therefore, the research will focus on developing automated tools that leverage DM and machine learning techniques to streamline the analysis of digital footprints, in order to provide instructors with scalable and tailored insights related to online education.

3. Literature Review

There has been a significant increase in the number of online education programs, including those that are completely online, hybrid, or web-enhanced, over the past decade [6]. The trend does not appear to be slowing down. Massive Open Online Courses (MOOCs) continue to play a pivotal role in providing various online courses from universities around the world. With their detailed logs that provide insights into learner experiences, online courses have become integral parts of the educational process [7]. However, challenges persist in MOOCs, such as high dropout rates and limited social interaction, prompting ongoing scrutiny. A collaborative effort

between San Jose State University and Udacity, for instance, revealed a failure rate of 71% [8]. As a result of these challenges, the volume of data generated from online courses continues to grow exponentially, leading researchers and developers to explore advanced techniques to gain insight into learners' online activities [9].

A number of dynamic models have been developed in Educational Data Mining (EDM) in recent years in order to monitor the dynamic nature of student behavior. There are several models of student factors modeled within a state space framework [10] and explicit transition matrixes in a Bayesian framework for latent factors [11]. A nuanced understanding of how student behavior in online learning environments evolves over time can be gained by using these dynamic models, which reflect the latest technological advancements in education.

Over the past few years, online education has undergone significant changes due to the integration of emerging technologies. The use of artificial intelligence (AI) and augmented reality (AR) is at the forefront of creating a more interactive and personalized learning environment [2]. Online courses are increasingly utilizing AI-driven components such as chatbots, virtual assistants, and adaptive learning platforms to provide real-time support and customize content according to individual learning styles [12].

Furthermore, EDM efforts are being complemented by the increasing adoption of Learning Analytics (LA). As a result of data analysis, LA offers insights into student behavior, engagement, and learning patterns [13]. LA and EDM techniques when integrated provide a holistic view of the online learning landscape, which allows educators and institutions to make more informed decisions [14].

While advances in online education and EDM are promising, challenges remain. There are a number of ethical concerns surrounding the use of student data, privacy concerns, and the potential for algorithmic bias that require ongoing attention [15]. Keeping student privacy protected while leveraging data-driven insights is crucial to maintaining trust in online learning environments.

Furthermore, online courses are diverse and evolving in nature, necessitating ongoing research into adaptive methodologies. Researchers are actively exploring the possibility of dynamically adapting interventions based on real-time data. Research has been conducted on how artificial intelligence-driven systems can predict performance and recommend interventions aligned with individual learning preferences and goals [16].

In the global context, online education has a very diverse landscape, with varying

degrees of access and adoption. Efforts are underway to address infrastructure and accessibility issues, aiming to make quality online education more accessible globally [17]. There are some regions where online education is becoming the primary mode of learning, which has a significant impact on the future of education globally.

4. Methodology

In order to address Question 1, our proposed methodology involves the application of Deep Learning (DL) and Machine Learning tools to analyze the digital footprint of an online course that has been carefully selected. The focus will be on extracting key information, including:

- The amount of time that students spend reading course materials and watching videos.
- The number of students logging into the learning management system on a regular basis.
- Participation in online forums and the length of time spent participating.
- Interactions with other students on the forum, including asking/answering questions.
- Performance metrics such as assignment scores, quiz scores, and individual question performance.

In order to answer Question 2, our approach involves identifying students who are experiencing declining performance. The delivery of customized learning materials and interventions will take the form of homework assignments and email communications. Our analysis will categorize students based on a variety of factors, including insufficient reading skills or a lack of conceptual understanding.

The intervention process is divided into three stages:

1. **Data Collection:** Digital footprints will be collected and formatted, emphasizing the variables mentioned above.
2. **Model building:** Students' general behaviors will be analyzed initially to determine their relationship with learning outcomes. We can later apply the DM and ML models, taking into account the heterogeneity of our students.
3. **Model Testing:** The model will be applied to students, and feedback will be

collected. Continuous improvement will occur based on student feedback and model predictions.

The chosen course for this study is Bachelor of Science in Management and Information Technology (BSc. In MIT) at Faculty of Management and Commerce of South Eastern University of Sri Lanka with an annual enrollment of over 150 students. The course attracts a diverse student body majoring in various disciplines. Online learning is part of the course to leverage large enrollments and address the unique challenges posed by online education, such as the lack of interaction. The online is a suitable environment for testing the proposed approach since it requires strong time management skills and self-discipline.

A Moodle learning management system is used to publish all of the study materials, instructions, and assignments during the semester in this study. There will be a variety of assignments, including projects, quizzes, reading materials, and exams.

Assignment 1	Assignment 2	Assignment 3	Assignment 4	Assignment 5	Page visits	Total Access Time(Minutes)
92	85	91	86	100	578	854
88	90	100	78	98	650	962
100	95	94	100	100	512	785
85	84	78	75	90	478	702
80	80	86	84	100	741	1254
75	76	90	92	95	665	1025
92	78	65	79	96	702	1200
94	98	75	72	98	485	769
76	97	85	78	100	502	832
84	68	85	75	100	745	1401
55	74	78	94	95	654	1054
93	96	84	90	94	625	985
69	71	76	80	92	596	996
71	72	78	84	100	547	875
66	70	90	76	97	495	725
100	98	95	80	100	742	1540

Figure 1: Students access the course web pages an average of five times per week, and the total duration of their login is shown in minutes.

Test Name	Due Date	Median	Low Marks	Highest Marks	Performance
Quiz 01: Client Site Technologies	12/5/2023	86	0	100	Good
Quiz 02: JavaScript	15/06/2023	76	0	100	Good
Assignment 01: Creating UI	30/06/2023	78	0	100	Good
Assignment 02: CRUD	22/07/2023	81	0	100	Excellent
Quiz 03	7/8/2023	17	0	20	Good
Assignment 03: Login System	10/10/2023	65	0	100	Average

Figure 2: An overview of the submission status for each assignment.

Correct Responses Count	Wrong Responses Count	Correct Response Ratio	Wrong Response Ratio
75	36	0.675675676	0.324324324
84	27	0.756756757	0.243243243
68	43	0.612612613	0.387387387
77	34	0.693693694	0.306306306
69	42	0.621621622	0.378378378
83	28	0.747747748	0.252252252
66	45	0.594594595	0.405405405
90	21	0.810810811	0.189189189
76	35	0.684684685	0.315315315
88	23	0.792792793	0.207207207
96	15	0.864864865	0.135135135
75	36	0.675675676	0.324324324

Figure 3: An analysis of the quiz results item by item.

Data extraction from Moodle will focus on critical learning patterns, including time spent on the platform, quiz scores, assignment performance, and exam results. This comprehensive dataset will be instrumental in identifying areas of weakness in concept understanding and informing personalized interventions. Figures 1, 2, and 3 illustrate snapshots of the data set, showcasing metrics such as page views, login times, grades, and assignment submission statuses. These detailed insights will contribute to the effectiveness of our proposed methodology in enhancing personalized interventions and improving overall learning outcomes.

5. Expected Outcomes

Anticipated outcomes from the implementation of data mining (DM) and machine learning (ML) in the educational setting are geared towards fostering a more enriching learning experience and ultimately improving students' final grades. The introduction of personalized interventions and communications is expected to enhance student engagement, while customized homework assignments aim to solidify mastery of course materials.

Learning Experience Enhancement:

- **Personalized Interventions:** Tailored interventions are projected to make students more actively involved in the course.
- **Customized Assignments:** Targeted assignments designed through DM and ML analysis are expected to reinforce understanding and application of course concepts.

Performance Improvement:

- **Better Grades:** The expectation is for students to achieve higher grades on assignments, reflecting improved understanding and application of the

course content.

- **Overall Final Grades Improvement:** Enhanced learning experiences and improved engagement are anticipated to result in better overall final grades.

Evaluation and Feedback Mechanisms:

- **Course Evaluation Data:** Monitoring course evaluation data before and after implementation to gauge the impact on student perceptions.
- **Student Surveys:** Conducting surveys at the beginning and end of the semester to collect feedback on the effectiveness and preference for DM and ML analysis.
- **Comparison Studies:** Identifying the differences in performance between students with DM and ML to those from previous years without these applications, ensuring fair comparisons based on similar backgrounds.
- **Periodical Surveys:** Regularly seeking feedback from students to adjust analysis strategies and models based on their experiences and suggestions.

Direct and Indirect Evidence:

- **Final Grades:** Direct evidence is expected in the form of improved final grades with the application of DM and ML analysis.
- **Performance Progression:** Tracking students' increasing performance throughout the course as a result of personalized interventions.
- **Online Forum Participation:** Indirect evidence includes active participation in online forums, measured by time spent and the number of posts.
- **Communication Patterns:** An indicator of improved engagement and understanding is the email exchanges frequency and question/answer interactions with instructors.

The success of the approach will be validated through a multifaceted evaluation process, combining quantitative measures of academic performance with qualitative insights derived from student feedback and engagement metrics.

3 Conclusion

In education, the integration of data mining and machine learning offers significant potential for transformation. Smart systems can be used to enhance personalized and adaptive learning paths in order to overcome the limitations of traditional online learning models. Based on the increasing volume of data from online courses, educational data mining (EDM) has become increasingly important, reflecting the prevalence of online learning.

The proposed approach involves the application of deep learning (DL) and machine learning (ML) to diverse aspects of student engagement. The iterative process ensures a dynamic and responsive system.

Integrating personalized interventions seeks to foster increased engagement and mastery of course materials. Anticipated positive shifts in course evaluation data will validate effectiveness.

In essence, this research pioneers the use of advanced technologies to revolutionize e-learning outcomes, offering a more personalized and effective learning experience for students in the digital age.

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