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Investigation of the Educational Performance on the Revolutionary Philosophical Electoral Online Learning Platform Centred on Deep Learning

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***Abstract*--Modern methods, strategies, and applications from educational data mining significantly contribute to the advancement of the learning environment. The most recent development offers useful resources for analyzing the educational environment of students by examining andusing data mining and machine learning methods to analyse educational data. In today's extremely competitive and complex world, academic institutions function. University administrators frequently struggle with performance evaluation, high-quality instruction, performance evaluation methodologies, and future course of action. In order to address issues that students face while pursuing their education, these colleges must establish student intervention strategies. This systematic review examines the pertinent EDM literature from 2009 to 2021 that relates to detecting kids at risk and dropouts. The review's findings showed that a variety of Deep Learning techniques are utilized to comprehend and address the fundamental issues, including forecasting students who are at danger of dropping out of school and students who will drop out altogether. Furthermore, the majority of studies incorporate data from online learning platforms and databases of student institutions and universities. When it comes to forecasting at-risk pupils and dropout rates, ML techniques have been shown to be crucial. This has improved the students' performance.**

Keywords—Student performance, Deep learning, Evaluation methodologies, data mining for education, online platforms

I. INTRODUCTION

Educational Data Mining has been a major source of inspiration for recent changes in the education industry (EDM). In response to the demands of the students, new possibilities and chances for technologically improved learning systems have been found and put into action. Modern methodologies and application methods used by the EDM are essential for improving the learning environment. For instance, by assessing both the educational environment and machine learning approaches, the EDM is essential in comprehending the learning environment for students[1]. Data mining (DM) methodologies exploration, research, and implementation are the focus of the EDM field, according to material. For its effectiveness, the field of design management uses methods from other disciplines. The data mining phase is shown in Fig.1 and it offers a thorough approach for drawing insightful and useful conclusions from unstructured data. In order to identify significant trends that advance students' understanding and academic institutions generally, deep learning and statistical methodologies for educational data are examined. In today's extremely competitive and complex climate, educational institutions function[2].

The issues that most institutions confront today include performance analysis, high-quality instruction, developing methods for assessing students' performance, and identifying unmet future needs. University student intervention programmes are put into place to help students deal with issues they encounter while taking classes. The administration and educators benefit from the university's excellent development and evolution of intervention programmed, which are aided by student performance prediction at entry-level and during later phases[3-4].

Students that enroll in online courses participate in e-learning, a fast developing and cutting-edge method of education. E-learning platforms like Intelligent Tutoring Systems (ITS), Learning Management Systems (LMS), including Open Online Courses (MOOC) make full use of EDM when creating automatic grading, recommender, and adaptative systems. These platforms make use of sophisticated tools that amass useful user data, such as the frequency of a student's access to the e-learning system, the precision of the student's responses to questions, and the quantity of time reading texts and viewing video tutorials.

In order to enhance the usability of the learning platform and create interactive tools, the collected data is processed and evaluated over time using various machine learning techniques. According to [4], "research utilizing deep learning (ML) is subdivision of artificial intelligence (AI), seeking to give training to computer via data, insights, and direct contact with the physical world." As a result of what it has learnt, the computer is now capable of making reliable generalizations to novel contexts. AI's subfield of machine learning is where ML systems study patterns in data to make predictions about future events. Growing data quantities, more affordable storage, and reliable computer systems are the driving forces behind the machine's rebirth from simple pattern recognition algorithms to Deep Learning (DL) techniques. With accurate answers and the ability to prevent unanticipated dangers, ML models can examine larger, more complex data sets rapidly and automatically.However, the lack of face-to-face interaction between students and teachers in online courses is perceived as a disadvantage, regardless of the assumption that e-learning is generally seen as being more affordable and accessible than conventional on-campus teaching.[5].

Because there are no universally accepted modes of student evaluation, it is hard to evaluate and compare various educational technologies. Students are more likely to abandon an online course, particularly if it is self-paced, and this is a larger problem in e-learning systems than it is in traditional classrooms. Long-term data logs from e-learning systems like Massive Open Online Courses (MOOCs), Moodle, and Digital Ecosystem to Promote Data-driven Education may be used for learner and course evaluation [6].

Understanding the log data, however, might be difficult because not all instructors and course directors are familiar with this important information. Free higher education is offered worldwide through MOOCs and LMS. Through their online learning portals, these platforms enable student-teacher interaction. These portals allow for the selection, registration, and enrollment of courses by the student from any location. By using the resulting log data, machine learning techniques can be used to predict at-risk students' dropout probabilities early on. This strategy is more advanced than the standard practice on universities, which is to analyze students' past quizzes, attendance data, tests, and marks to evaluate and predict their future success in academics. The EDM research community utilizes activity records and individual datasets for forecasting student progress using a machine learning algorithm. This study explores the use of data mining and machine learning techniques to:

This review explores the use of various data mining and machine learning approaches to:

a) Assessment of the potential for failure in a student's academic pursuits
b) Analyze student dropout rates from ongoing courses and forecast them
c) Determine the corrective measures for the cases that were shown in the first three aspects.
d) Using both time-stamped and real-time information to evaluate student progress.

There have been previous efforts to assess the impact of education on achievement, but the majority of them are general literature studies aimed at the generic prediction of student performance. The best statistical and computational techniques were what we set out to acquire and analyze. In addition, we sought to present a systematic assessment of the literature because the study's capacity to be replicated was hindered by the methodology's transparency and search technique. Lacking in this is the grey publications, such as unpublished reports and policy papers, that might influence opinions one way or another. We acknowledge that there was only a recently published systematic review (SLR) of EDM; however, their criteria were different and they only looked at historical data, while our research focuses more on developments in the last 13 years.

Fig-1 Steps in data mining techniques[7]

To evaluate all of the research accessible on the issue at hand, a systematic literature review was conducted utilising a research strategy that must be objective and assure completeness. To perform a comprehensive literature study independently, we used Okoli's guidelines. While some scholars have provided a comprehensive literature analysis of the approach, the vast majority of these reviews have focused on just the most crucial steps. The chosen methodology creates a rigorous, standardised framework for doing a thorough literature evaluation. Although the focus of the study is on information systems, the investigation is suitably multidisciplinary to be of interest to scholars in any area of the social sciences. In Fig. 2, we see a detailed process flow for a literature review that meets all the criteria of a systematic approach. [8].

Fig-2Flow chart represent the comprehensive details of how to conduct systematic literature Review [9]

When handling research issues is a reviewer's first concern in SLR, we made an effort to address the research questions of the study as they came up throughout the review.

RQ-1 What kinds of issues are raised by research on student progressforecasting?

RQ-2 What remedies are suggested to deal with these issues?

RQ-3 How productive is this field's research overall?

II. SOURCES OF DATA

To perform a comprehensive systematic literature evaluation, we focused our data collection and publishing searches on six different research databases. The many educational strategies, tools, and institutions are listed in Table 1. [10].

Table-1 Different techniques used in methods with entities used in educational[11]

Techniques	Methods	Entities Used
Performance prediction	Early planning – ML	Behavioural
	Modern ensemble	usefulness of ins truction
	Supervisory system	Surface connecti on between stud ents
	Automatic analysis	First- year learners' pa rticipation log
	dynamic plan	Intermediate inst itutions
	Semi-supervised algorithms	
Identification o f at- risk students	ML layout	during threat fro m not being awa rded a diploma
	drastically reducing the features and functionality	Early recognitio n of risky studen ts
	the school's earlier grades	grades received
	Grading utilizing predictive mo dels	detecting at- risk youth
	Factors affecting at-risk parties	Normal, Slow, a nd Fast Learners
Estimate the ed ucational platfo rm's difficulties	Studies of Classification metho ds	Challenges with the online learni ng method

The pre-determined searches produced a large number of research papers, which were carefully screened to save only the most pertinent ones for this review.According to our study questions, the databases were searched using the following search phrases, one by one:

- Educational Data Mining (EDM)
- Student Interruption, Dropout Prediction, Risk Assessment, Student observation, Student Requirements, Performance Management, or Student Classification.
- Machine learning and student predictions[12].

III. CHOSING ARTCILE FOR EVALUATION

The article selection process entails identifying, screening, determining eligibility, and determining whether the research articles fit the inclusion criteria. The research papers were independently gathered by the authors, who then decided which studies to include.Studies pertaining to student performance prediction are included, as well as research papers that have been accepted for publication in conferences or journals after going through a blind review process, papers from the 2009 to 2021 timeframe, and papers written in English[13].

1. Research other than Classification And Prediction Using ML.
2. Articles in which proposed procedures were not tested in experiments.
3. Examples of such works include short articles, journal articles, advertising posters, trademarks, finished reviews, scientific documents, Wikipedia sections, surveying studies, and extended papers on works that have previously been evaluated.

To compile a list of research that is used for future analysis, a search is conducted.A programme for managing bibliographies called Mendeley handles the management of the studies' bibliographies. The papers listed in these bibliographies fully meet the requirements for inclusion. The next part goes into great depth about the 78 papers that were produced once the criteria were successfully applied. The review has taken into account every paper listed below. Quality Evaluation Standards for systematic literature review the following quality standards are established:

• **QC-A:** Are the review objectives spelled out in detail?

• **QC-B:** Are the suggested approaches clearly defined?

• **QC-C:** Is the intended accuracy tested and measured?

• **QC-D**: Are the review's restrictions made clear?

IV. ANALYSIS OF STUDENTS' PROGRESS USING STATIC AND DYNAMIC DATA

There are two types of data on student performance that are utilised for making predictions: (a) static data and (b) dynamic data. Students' records of accomplishment or failure in the learning system are apparently incorporated into real-time data on their academic progress. Because the characteristics of the dataset evolve with time, logs of students' activities with the e system are a good illustration of information. information on students' static performance, on the other hand, is collected once and does not change over time. Examples include data on student enrolment and student demographics. In the sections that follow, we'll talk about how both static and dynamic data may be put to use in ed-tech data mining.[14].

A paradigm for dynamic student knowledge models for adaptive textbooks was proposed by Thaker et al.[15] To forecast the students' present level of knowledge, the suggested framework makes use of information from quiz activity and reading by students. Behaviour-Performance Model (BPM) and Individualized Behaviour-Performance Model (IBPM) are two advanced forms of the underlying Behavioural Model (BM) included in the framework. Feature Aware Student Knowledge Tracing (FAST) was used to implement the recommended frameworks. In comparison to the fundamental Behaviour Model, the suggested technique produced reduced Mean square error and high ACU values.

In order to predict student success, Carlos et al. provide a classification-based model with a data collection technique that gathers behavioural and learning information from training exercises. With the help of the SVM algorithm, the students were divided into three groups according to their performance levels: high, medium, and low. Using 61 characteristics, data from 336 students were gathered. In the first experiment, only behavioural aspects were utilised for classification; in the second, only learning characteristics were used; in the third, learning and behavioural features were merged for classification; and in the fourth trial, only specific features were used to predict student performance. The dataset typically included 53 learning variables and 8 behavioural features, and it was used to forecast student performance over a ten-week period. The outcomes demonstrated that, as the data grew during the following week, the classifier's accuracy rose. Additionally, the behavioural and learning features worked together to produce a strong performance of the classifier with a reliability of 74.10% in week 10.

Desmarais et al. [16-19] proposed employing four-linear estimates based on decomposition of fixed student data to evaluate students' abilities. Using Item Response Theory (IRT) and the k-nearest neighbour method, the efficiency of the suggested linear programming was assessed. This study analysed data from three datasets: (a) fraction algebra, with 40 questions and 152 students; (b) UNIX shell, with 36 questions and 52 students; and (c) college math, with 60 questions and 250 students. Research results showed that traditional IRT methods were more precise than the proposed linear model and k-nearest neighbour techniques.

V. CONCLUSION

The study of educational systems is now more efficient while requiring much less work because to recent developments in data collecting technologies and system performance indicators.Big data analytics, a brand-new subject, has emerged as a result of the analysis and monitoring of huge data using cutting-edge machine learning (ML, Deep learning techniques).

Overall, this evaluation was successful in achieving its goals of improving student performance through dropout and at-risk student prediction, emphasising the significance of combining both steady and transient data. By combining data mining and machine learning techniques, this will serve as the foundation for fresh developments in educational data mining. However, few studies have proposed solutions for providing timely feedback to students, instructors, and educators. More work needs to be done to develop an optimization technique for deploying the ML-based forecasting technique, and researchers should look into developing dynamic approaches that can estimate students' score and effortlessly deliver necessary remedial steps to help students.

Finally, we highlight the relevant lines of inquiry for further study into the prediction of student performance using ML approaches. We want to use some of the amazing works that are already out there and we want to put more of an emphasis on the dynamic aspect of student performance. The teachers can then use these new insights to develop effective interventions for students and meet precise educational goals.

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