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STUDENT PERFORMANCE PREDICTION IN ONLINE COURSES USING MACHINE LEARNING

[1]MR.CH SURESH, [2]KOWRU YAMINI

[1](Assistant Professor), MCA, Swarnandhra College

[2]MCA, scholar, Swarnandhra College

ABSTRACT

The expansion of MOOCs, or massive open online courses, has been facilitated by developments in ICT and is particularly noticeable in online learning settings.Learners may be motivated to gain new cognitive abilities via the use of interactive information, which includes graphics, figures, and videos. Various methods have been employed to offer this content. Using massive open online courses (MOOCs) as a dashboard platform, top institutions have made it easy for students all over the globe to enroll. Using predetermined, computer-marked tests, teachers may gauge their pupils' development as learners. The computer provides instantaneous feedback to the learner once they finish the online tests. According to the study's authors, students' involvement and performance from the prior session may predict how well they do in an online course. Literature reviews have not adequately considered the possibility that students' involvement and performance on earlier tests may influence their results on subsequent exams. Two prediction models, one for students' assessment scores and one for their ultimate performance, are developed in this article. Students' success in massive open online courses (MOOCs) may be better understood with the help of these models. The outcome demonstrates that both models provide realistic and precise outcomes. With an average RSME gain of 0.086, GBM produced the most accurate results for students' final performance, while RF had the lowest RSME gain of 8.131 for their assessment grades mode

1.INTRODUCTION

Among the many kinds of online education, Massive Open Online Courses (MOOCs) have become quite popular. Massive open online courses use a variety of digital resources, including audio, video, graphics, and plain text, to provide the course content. Instead of reading lengthy text papers, most students find video lectures to be a more effective way to comprehend course material. Massive open online courses (MOOCs) include interactive videos that may help students relax, learn more efficiently, and alleviate stress [1] [2].

Two basic kinds of massive open online courses (MOOCs) exist: cMOOCs, which are connectivist, and xMOOCs, which are extended.The xMOOCs are a new way of teaching and learning that draws on cognitivist and behaviorist ideas [4]. The courses are structured similarly to conventional classroom instruction, with a final exam, multiple-choice quizzes, and video lectures making up the course outline. Once a week, students may see video lectures in which the course teacher goes over what was covered in the last online session. All participants are free to go through the movie at their own speed. In addition, students have the opportunity to engage in social interactions with both their fellow participants and the teacher via the use of discussion boards. Consequently, the discussion boards are crucial in elevating the course quality and making online sessions collaborative and engaging [3] since instructors often use them to submit questions, provide assignment solutions, and respond to student concerns. [5].

Connectivist learning theory is the foundation of the new cMOOC form of education [3][4]. Under a connectivist model, students acquire the course outline via active participation in class discussion and question-and-answer sessions rather than from the teacher. Citations [3][4][5] The learning method of collaborative massive open online courses (cMOOCs) is centered on students working together to complete assignments and share what they've learned.

In xMOOCs, university professors may evaluate their students' knowledge using computer-marked evaluation feedback, whereas in cMOOCs, experts cannot be involved in this process. Specifically, once the student finishes the online test, the computer immediately provides feedback. Upon finishing the course, the student will get a certificate in xMOOCs.There is no official evaluation in the cMOOCs. Therefore, colleges and universities are not recognized as offering cMOOCs.I have read [5][6].

In recent years, thanks to technological breakthroughs, AI has emerged as a reliable method for assessing how well students do in online classes. There has been a dearth of work examining the trajectory performance, in contrast to the abundance of studies using machine learning to predict student achievement in [7]. Consequently, teachers were unable to track their pupils' progress in real time. This study presents the results of two independent experimental sets. To estimate students' test results, the first series of experiments uses regression analysis. Predicting student outcomes makes use of both the student's past and present actions, as well as their performance in the past. The second series of trials included making predictions about students' long-term performance using supervised machine learning. There are three categories of potential predictors: behavioral, chronological, and demographic. The suggested models let teachers monitor students' progress in real time and provide fresh perspectives on how to prioritize learning activities. We are unaware of any other way that students' progress in an online class has been assessed beyond the binary "success" or "fail" options. There are three possible outcomes that our model may foretell: "success," "fail," and "withdrew."
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2.LITERATURE SURVEY

User trustworthiness in online social networks:

A comprehensive analysis The overlay panel opens when clicking the author's links. There is a risk that anonymous individuals may be able to do harmful things on social media due to the platforms' increasing popularity and their willingness to accommodate new members. These systems have a lot of motivation to stop this from happening, but they can't handle the amount of data that needs processing. Another difficulty is that attackers often alter their tactics quickly in reaction to defensive measures. As a result, there have been a lot of fascinating studies done in recent years concerning user trustworthiness on social networks. The purpose of this study is to summarize the current situation of research in this area and to evaluate the studies that have attempted to solve this issue using different approaches and published between 2012 and 2020. There are a variety of proposed remedies in the literature; some concentrate on anti-spam measures, others on bot identification methods, and still others on identifying false news or grading the veracity of user-generated information. While several of these solutions do a good job in certain areas, none of them can guarantee complete safety from every conceivable kind of assault. Keeping an eye on this area of research is crucial, and by showcasing new studies that address the topic of online user trustworthiness, this review aims to help shed light on the notion.

Acquiring Knowledge about Social Internet of Things Trustworthiness Management: In an effort to create a social network of linked items, the next iteration of the Internet of Things (IoT) makes it easier to incorporate the idea of social networking into things, or smart objects. As a result of these developments, a new paradigm known as the Social Internet of Things (SIoT) has emerged, which has great promise. In this model, smart items serve as social objects and mimic human social behavior with intelligence. In order to find new services, these social objects may form connections with other nodes in the network and leverage those interactions. To establish the credibility and dependability of systems and to accomplish the shared objective of trustworthy cooperation and collaboration among objects, trust is crucial. In the context of the SIoT, an unreliable object has the potential to compromise the service's quality and dependability while also interfering with its core operation via the delivery of harmful messages. We provide a comprehensive analysis of SIoT trustworthiness management in this survey. Prior to delving into a comprehensive analysis of the trust management components in SIoT, we covered the fundamentals of trust across several fields. Moreover, we compare and analyze the trust management schemes by mainly classifying them into four groups according to their strengths, weaknesses, the trust management components used by each scheme, and the performance of these studies on various trust evaluation dimensions. We wrap off by talking about where the new paradigm of SIoT is taking research, specifically in the area of SIoT trustworthiness management.

3. EXISTING SYSTEM

- The Factor Analysis Model (FAM) was proposed to predict the student's performance in Intelligent Tutoring System (ITS) taking into consideration the difficulty level of assessments based on Item Response Theory concept [9] [10]. The difficulty level of tasks can infer measurement of the correlation between the student's performances and assessment questions. To compute the probability of a student solving a task correctly, a set of predictor variables are defined in the FAM including the number of opportunities presented to the student at each task, the duration spent on each step and the difficulty level of each question or latent variable. The results reveal that incorporating the latent variables into the estimates of student performance can significantly enhance the model [10].
- To measure how the activities of learners could impact their learning achievement in MOOCs, the researchers found that Learning Analytics (LAs) in conjunction with machine learning, are effective tools that offer the potential to trace student knowledge. The researchers demonstrated that machine learning could help the educator in providing cohort information about the learning process, furnishing researchers with the ability to both visualise and analyse the information obtained from each tier of the learner. Thus, an accurate predictive model can be acquired in such courses[11] [12][13]. Students' marks in the first assessment and quiz scores in conjunction with social factors are used to predict students' final performance in online course [14].
- Two predictive models were introduced. In the first model, logistic regression was used to predict whether students gained a normal or distinction certificate. In the second predictive model, logistic regression was also used to predict if students achieved certification or not. The results indicated that the number of peer assessment is the most effective feature for acquiring a distinction. The average quiz scores were considered the most reliable predictor for earning a certificate. The accuracy of distinction and normal models were reported with the percentage of 92.6% for the first model and 79.6 % for the second model, respectively[14].

- The association between the Virtual Learning Environment (VLE) data and student performance has been investigated

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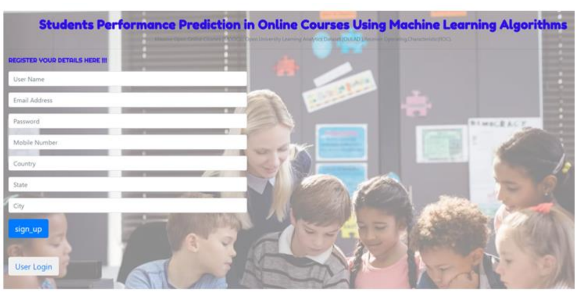
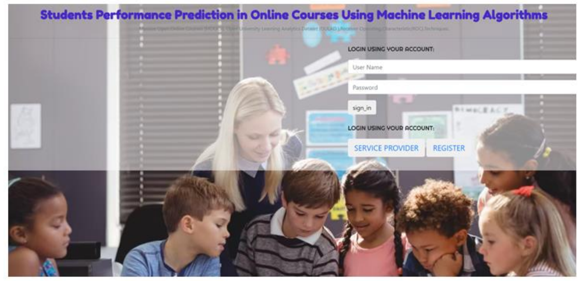
at the University of Maryland, Baltimore County (UMBC) [12]. LA used through the implementation of the Check My Activity (CMA) tool. CMA can be defined as an LA tool, which compares students VLE activities with other activities and provides lecturers frequent feedback of students' emotional states. The results showed the students who engage with the course frequently are more likely to earn mark C or higher than those who did not regularly engage [12].

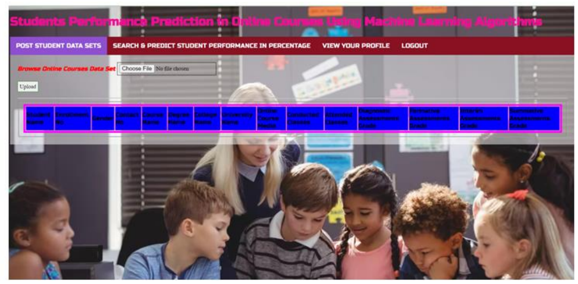
4. OUTPUT SCREENS

Register

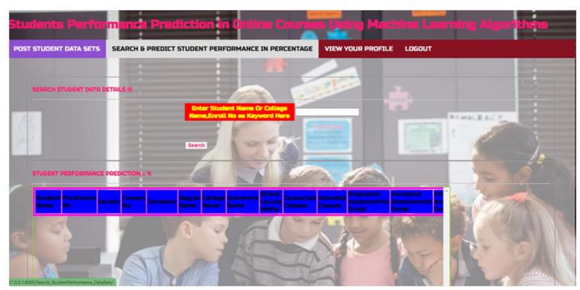


User login:

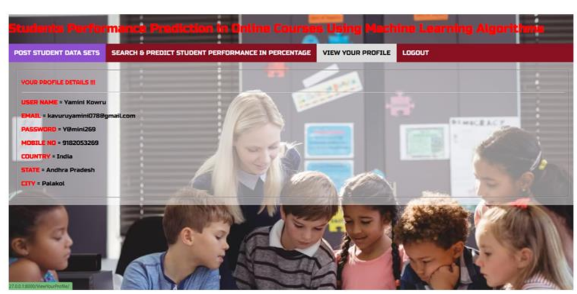




Search and predict Student Performance in Percentage:



User Profile:



Admin Login:

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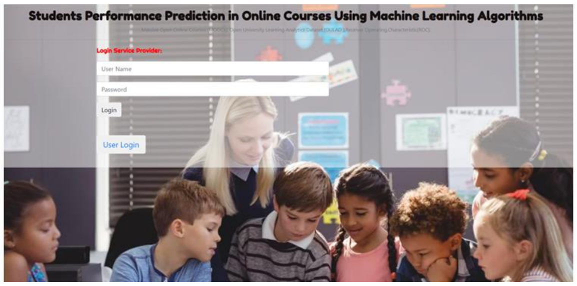
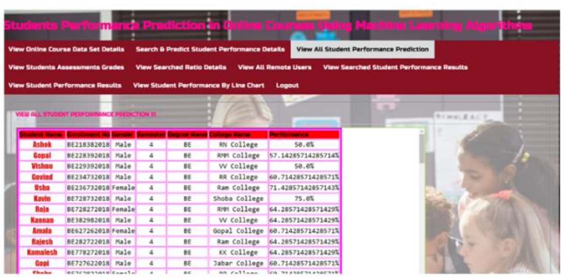


View Online Course Data Set Details:

View All Student Performance Prediction:



View Student Performance By Pie Chart:

5. CONCLUSION

This research used regression and classification analysis to do two sets of exterminates. The outcomes of the model for forecasting students' assessment marks reveal that, within a single course, students' performance in one assignment is dependent on their mark in the prior assignment. The study's authors draw the conclusion that, in a traditional classroom setting, students are more likely to drop out of subsequent classes if their prior grade point average (GPA) is low. This finding holds true in both traditional and online learning environments, according to the researchers.

Student involvement with digital content significantly affects their success throughout the whole course, according to the final student performance predicting model. Due to the omission of temporal characteristics in regression analysis, the results also show that the prediction model for students' grades is more accurate than their long-term performance. A useful predictor that is strongly associated with student performance is the date of student deregistration from the course. The data used for regression analysis does not reveal when students' last action was in relation to the tests that were administered. It has been suggested that the results of the study should be used to account for the effects of time on the prediction of future test scores.

Exploring the use of temporal cues in predicting students' evaluation marks is an area that needs more investigation. More sophisticated machine learning techniques may be used in place of time series analysis when dealing with temporal features.

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