Recommender System for Low Achievers in Higher Education

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***Abstract*—Digital education platforms like learning management systems (LMS) have made the virtual teaching-learning process very much handy. The LMS must include additional features to track and review the learner's behavior in the teaching-learning process. This study aims to identify the low achievers with the assessment marks which let the course instructors understand the learner's cognitive level and enables the facilitators to recognize the student's perspective of the course based on their reviews collected from the questionnaire. In the outcome, recommender systems are incorporated with the learning analytics by using the K-Means clustering algorithm. This algorithm has helped the facilitators to segregate and identify the set of low achievers based on their assessment scores and also to predict the appropriate reason behind such slow performance. Apart from this, the results of this study have also suggested that facilitators incorporate the use of various emerging pedagogical methods in the teaching-learning process to maximize the learner's performance and accentuate the level of virtual classrooms.**

***Index Terms*—Learning management system (LMS), ICT tools, learning analytics, pedagogical models, clustering algorithms.**

I. INTRODUCTION

In the digital era, e-Learning plays a vital part to deliver knowledge and impart education to learners. From education 1.0 to education 4.0 [1] there has been a huge transformation in the education system prevalent around us. Learners are expected to move from the era of "memorization of the facts" to "the world of innovation" through advanced technology. The innovation here symbolizes the combination of digital and knowledge-based learning, to make the students ready for the requirements of industry 4.0.

The days of physical note-taking and book reading are long gone. In the current scenario, practical presentations and instructional videos have supreme importance. But, even in this newer method of learning and teaching, a standard of measuring how the student learns in a course is essential to understand and assess the learning outcomes [2] that are expected from the students.

Students mostly face difficulty in some parts of the course due to lack of motivation or focus, lack of understanding of the course material due to weakness in the specific medium of communication, which can be verbal instructions, practical usage, explanation through videos, augmented reality demonstrations, or any combination of the aforementioned. Due to this, they miss out on essential parts of the course, thereby being unable to apply their talent and skills whenever required. An LMS (Learning Management System) is a software application that provides a unified platform to share, collaborate and distribute the learning content digitally. It is one of the most widely used tools by higher education institutes to conduct classes and deliver lectures online with greater ease.

Learning Management Systems [3] go a long way in allowing instructors to interact with students in all possible interactive ways with functionalities designed to provide personalized experiences by the objective of the institutions. Learning Analytics (LA) techniques are used to collect the data, and measure & analyze the learner's performances. It helps to track the learner's behavior and analyze the results for a high-quality education system. A Learning Management System is used to deliver and manage a wide variety of content, ranging from instructional videos to books or documents, including a variety of functionality like a discussion board, forum, online collaborative workspace, and many more. Using these features, the instructor uploads the course contents in the LMS in the form of video, audio, or other formats so that the students take responsibility to learn the out-class topic and appear for the upcoming classroom sessions with basic knowledge about the topic. Combining these extensive features of an LMS, with LA would act as a boon in thriving the level of the currently prevalent pedagogical models like Flipped Classroom, Blended Learning, and active learning [4].

In this study, Moodle platform is used as the Learning Management System [5], built by the Moodle project, led and coordinated by Moodle HQ, which is financially supported by a network of over 80 Moodle Partner service companies worldwide. It has a simple interface, with drag-and-drop functionality, and well-documented resources and modules along with consistent usability improvements to make it easy to use and manage. Being an open-source software application, Moodle can be customized and tailored to individual or organizational needs [6]. Moodle's modular architecture and interoperable design allow developers to create plugins and integrate external applications to achieve specific functionalities.

In the proposed system, one such functionality is taken into consideration by designing a plugin that shows the marks distribution of the students enrolled in the course. This functionality also provides an option for selecting the parameters of the distribution. Once the grades are obtained from the Moodle LMS, learning analytics is performed on the scores to analyze the performance of the learners. The analysis of the scores and the segregation of the learners into

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various categories were done using the K-Means clustering algorithm to identify low achievers in a particular classroom.

Additionally, a questionnaire is designed and distributed to the students for collecting their reviews and feedback on the question paper used in the assessment. Their responses were considered to reflect the learner's performance through their perspectives on the teaching-learning process implemented in the classroom.

These responses were also analyzed because under many circumstances the scores obtained by the learners are driven by the teaching methodology applied and the types of questions asked in the assessments. Ultimately, the mean of the responses was computed to identify the areas of improvement and what kind of upgradation must be inculcated in the course to enhance the performance of the students.

II. Related Works

Today's education pattern comprises a wide spectrum of learning opportunities, for enabling the students to align their competency level with the requirements of the competitive world. Recent technology enhancement domains like artificial intelligence and machine learning have produced innovative ideas for technology-enhanced learning. These innovations enable the teachers to save a lot of their time by providing them digital options to create lesson plans, use media to create interesting lectures, online assessment grading, interactive classroom lectures, personalized feedback, and collaborative learning. The role of learning analytics in analyzing the feedback [7] received over a learner's work has a huge impact on the learning process. A study focussing on the backward assessment of the feedback received has highlighted various perceptions of the learner over the comments received through their peers [8]. Both positive and negative aspects of the feedback such as learners modifying and updating their submissions based on the comments, upgrading their level of work through the suggestions provided, or even getting offended sometimes by the reviews given were analyzed using learning analytics (LA). Ultimately, the use of feedback coding and analysis of huge datasets of this constructive feedback has been advantageous in terms of saving both time and manual programming. Analyzing the academic scores and contemporary fields [9] in the education industry is influenced by LA. These fields comprise areas such as caste, cultures, demographic information, and also the kind of dialects under usage. The convergence of these areas with the exploitation of learning analytics has enabled the researchers to address the gap prevalent in the current practices. Recent studies have been performed to compare and perform learning analytics on the academic scores as well as the internal state of mind of the students [10]. The results obtained showed a vast convergence of LA and educational data mining, reflecting the changing attitude of learners. A learner's behavior and attitude have been driven by various non-academic factors as well.

Despite the advancement of technology in the field of education, there is always an existence of loopholes. These shortcomings are noticed when a certain group of learners finds it difficult to adapt to these advancements and fail to attain a certain level in their academics. These learners are often categorized as "underachievers", whose performance level is comparatively lesser than the other group of learners and fail to attain the course objectives. Henceforth, to identify the areas of weakness of the learners, and to aid in the self-efficacy of the learners, a need to track the learner's behavior and analyze their performances becomes significant. The Gen Z learners of this generation are highly technology-oriented and have a higher affinity toward innovative and interactive teaching-learning processes. In this context, learning analytics can be emphasized as it has the potential to synthesize the learner's performance data, and produce an accurate report on the activity of the learner throughout the course to optimize the learning experience and the environment where the learning takes place. The process of learning analytics initially involves the extraction of students' data from educational institutes and then processing it to obtain the required outcome. Concerning this, a study has been carried out to develop an instructional framework for infusing the ADDIE model with learning analytics into an information system [11]. This system was customized to perform in 5 phases and was beneficial for recording and regulating the student's activities in a particular course. It was further helpful for the teachers to keep a track of their learner's achievements during the duration of the course. However, in terms of the authenticity of the evaluation technique, this framework is yet to be refined with various other contexts.

Learning analytics [12] has opened a wide range of opportunities for students as well as academicians to elevate their professional careers in the future. Learning analytics has reshaped the learning environment by exposing the facilitators to utilize different Information and Communication (ICT) tools and apply blended teaching-learning methodologies to deliver the course content effectively. Two different research methods namely quantitative and qualitative approaches were combined to reflect on the performance of the learners. Qualitative data samples were collected through a blend of traditional and online classes whereas quantitative data was collected via assessments, tests, exams, and discussion forums. Studies performing qualitative analysis of data have applied various LA tools [13], and collaborative learning strategies for direct interaction [14], to measure the learning outcomes achieved. The results obtained offered an insight into the student's attitude and behavior which proved to be the driving force in enhancing the learner's performance. These techniques and tools helped augment the engagement level of the learners in both traditional and digital classroom settings. Hence, LA technology has drastically reinvented the traditional classroom settings by blending numerous educational instruments [15] to augment the future of higher education. It provides the assessment for identifying the cognitive level of the students and the quality of the teaching-learning process conducted in the classrooms could be assessed using learning analytics.

The core research work of this paper is focused on learning analytics for optimizing the performance of the learners by considering their assessment scores [16] along with their perspectives on the assessment conducted for particular courses. The author [17] has reviewed 24 case studies of learning analytics in higher education. Diverse criteria such as the data considered, methodologies used and outcomes of the course were selected to perform the categorization of the cases. Although the downside of the study reflected the absence of an evaluation of the effectiveness of the technologies used, the outcomes were the inferences of the study showed tremendous improvement in the performance of the learners. It also reflected the positive impacts of the methodologies in achieving the course outcomes. The overall outline of the study presented that learning analytics do have a higher scope to be implemented for a varied number of purposes and play a vital role in the education sector. Similarly, another study focussed on the influence of learning analytics on the knowledge retention of the learners [18]. In this paper, a group of 32 facilitators was interviewed to have an insight into the challenges faced while incorporating the usage of learning analytics tools and techniques in the classroom. The findings indicated that there was a lack of proper infrastructure to support the use of LA tools and also the learner needs were misaligned with the implementation of these tools in the course. Thus, the outcomes suggested that appropriate training and practice are essential to integrate LA technology with the traditional and virtual classrooms. Another study performed on the implications of LA has exclusively focused on the privacy concerns of the learners while applying LA technology in real-life scenarios. The investigation was performed on a group of 26 learners and it reported communication with transparency as the two important factors for the adaptation of LA tools in academics.

The advantages of learning analytics could be explored on a larger scale when incorporated into an LMS like MOODLE, Canvas, and blackboard. This LMS platform serves the purpose of creating an interactive and dynamic learning environment [19] where the students can access and utilize the educational content anytime across the device. Online assessments and assignments, discussion forums, modes of self-paced learning, video tutorials, etc encourage the learners to get engrossed in the particular course. Additional pedagogical strategies such as gamification, learning style, and self-regulated learning are also helpful to anchor the attention of the students [20] for a course. It encourages the learners to be more curious about the upcoming classes and the overall course. A study performed on the deployment of LMS in various fields has stated its benefits in terms of cost-effectiveness as well as a greater medium to provide a flexible environment to the learners. Despite, having these benefits most LMS lacks the self-monitoring aspect of a learner’s day-to-day activity. Therefore, to support the modern learning environment prevailing in the present scenario a learning analytics component must be infused into the LMS itself to support the personalized learning has been suggested in this study. To address the above-mentioned downsides of an LMS, few other studies have been performed to exploit the learning analytics technology for emphasizing self-regulated learning on digital platforms [21]. The findings reported that most of the previous research has majorly focussed on the performance of the learners but has missed out on the self-reflection part of the learning process. Thereby, this paper has exclusively focussed on learning analytics to measure the performance of the learners and support self-directed learning to foster the digital learning process. The assessment scores along with the feedback and reviews provided by the learners are also of significant use [22], [23] while considering the self-directed and self-regulated learning among the students. With the implementation of learning analytics, various other learning methodologies such as heutagogy and metacognitive strategies can also be incorporated into an online course [24] to conceptualize the self-directed learning process and design innovative and interactive learning experiences for the learners.

The proposed system has mainly highlighted a data-driven investigation for determining whether the student’s learning behavior could be extracted from Moodle and visualized by the action logs. Incorporation of social learning and self-directed learning [25] in an online platform like Moodle has proved to be an effective method to enhance student participation and interaction with peers and facilitators. The analysis of the logged data from various courses was performed using a machine learning algorithm [26] to correlate the assessment instruments with the performance level of the learners. It also helped to identify the actual reasoning behind the fluctuations in the assessment scores of every student in an online environment.

Furthermore, the predictive models [27] used to identify the different types of learners also have a significant role in enhancing the learning analytics of the educational data. The results of learning analytics when combined with various pedagogical and regression models have proved to be very beneficial to the teacher’s community in terms of achieving learning outcomes and predicting the assessment goals, and performance level of the learners. Thus, it is evident that the paradigms and principles applied to develop the information systems integrated with learning analytics [28] have provided a wider avenue for the facilitators in designing interactive and dynamic pedagogical models. It supports the students in their learning process, enhancing their academic performance [29], assisting them to get accustomed to the digital environment with confidence, and utilizing the resources fruitfully. With further technological advancements, widespread research is still being carried out in LA to enrich the education sector and be highly significant to higher education [30] institutes.

III. Proposed Architecture

The plugin used in the proposed system is developed and edited using PHP, JavaScript, and Ajax. It is used to display the grade distribution in the form of bar graphs. These graphs are used to represent differently grouped grade items. The grades obtained are then analyzed to determine the different categories of the learners under which they are categorized. The categorization is based on whether the marks scored were lesser than or higher than the required pass percentage in each of these graded items.

The proposed architecture presented in Fig. 1 represents the teaching methodology adopted by the facilitators for the respective courses. Along with the regular strategy of providing the study materials and resources in a ubiquitous way to the learners, an additional approach of performing learning analytics on the grades is developed. This analytics enables the facilitators to easily identify the learners who require additional input and more attention than the other learners.

The additional features provided in the proposed system include time-based tracking [31] to see how much time students are spending on each slide, allowing them to add annotations or notes on every slide or frame inside the application itself, and mechanisms to track the completion of a particular task or course. These features would be helpful to determine which part of a course is difficult for the learners to understand and also to measure the efficiency of individual learners in a specific course respectively. Once the activities are implemented, the students can be grouped accordingly based on their scores to identify the students who require more attention than needed as well as to determine which aspect of the course can be improved further.

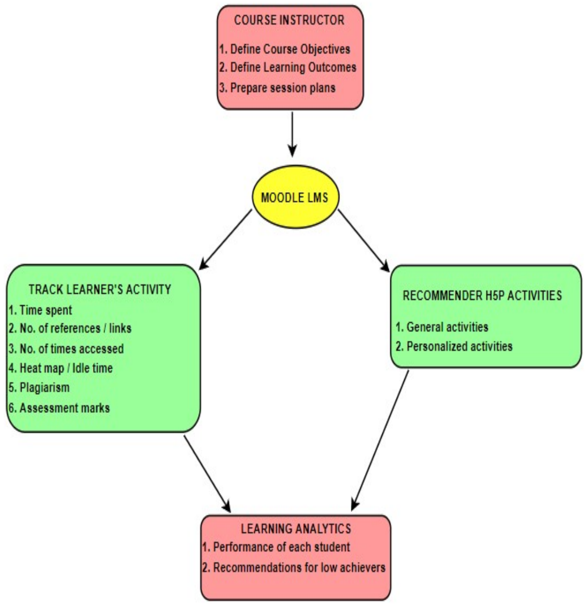


Fig. 1. Proposed system architecture.

Further analysis of these items facilitated the teachers to be more attentive toward the low achievers by incorporating different educational resources in their courses and by implementing a variety of assessment methods to help the learners grasp concepts in a better way. This plugin will help standardize the way educators determine which students need extra attention as a result of their performance in certain activities and can be a stepping stone for a more standardized system for helping low achievers.

A. Learning Analytics Module

The major significance of applying LA to the academic data is to improve and enhance the learning process carried out in higher educational institutes. The computational analysis of the student's data helps the facilitators in getting familiarized with the learning patterns of the students and achieve the learning outcomes in a better way. It also helps the course instructors in measuring and identifying the key indicators of the learner's performance and provides support to the learners whenever required. Some of the other major reasons to integrate LA with the LMS are to provide customized learning experiences to the learners and help them monitor their progress.

In the proposed system, learning analytics is applied to the data logs for the performance analysis and categorizing the learners into various groups. After the segregation, every student becomes aware of the group under which he/ she falls. By identifying their achievement level, the learners can either take responsibility for their academic accomplishments or seek the help of course instructors to complete the course successfully.

The application of LA aid in predicting varied traits available in the learning patterns of the students based on past and current data.

Among the different categories of learning analytics, the descriptive and prescriptive models are considered here to assess the performance of the learners based on their test scores and also to suggest various remedies to enhance their overall academic scores and engagement levels in particular courses.

B. K-Means Clustering algorithm:

K-Means clustering algorithm is one of the most suitable unsupervised Machine Learning algorithms used to group homogeneous samples in a single cluster. It is also a feasible algorithm to handle larger datasets. All the clusters formed under K-Means clustering are distinct from each other and have unique features of their own. However, the intra-cluster points have high similarities in contrast to the inter-cluster points who are different from each other. The lesser the differences within the cluster, the more the similarity between the points inside a cluster.

Therefore, to suit the needs of this research work the K-Means algorithm [32] is applied to the academic grades of the learner to group them appropriately under different categories. Depiction of these clusters enables the facilitators to identify how many learners are under which category. Even the individual level of each learner can be analyzed through the category to which he/ she belongs.

The algorithm is applied to 6 different classes for obtaining the marks scored by each student for every question asked in the examination. The mean of these marks helped us identify which class performed most efficiently in the assessments among the others.

In this study, one particular course handled by 3 different facilitators is considered, which is opted by 6 different classes of students. Based on the student's performance in the assessments and their ratings towards the course we have segregated the learners into various groups for providing them with better learning opportunities.

IV. Implementation

The project was started with the setup of a Web Service Stack on a virtual machine. The virtual machine was created with minimal resources dedicated to it, to imitate a restricted working environment. The Web Service Stack used was a standard LAMP (Linux, Apache, MySQL Relational Database Management System, and PHP) stack [33], since it is highly compatible with Moodle architecture. The Linux distribution Manjaro was chosen to boast a very highly compatible environment and support everything available to the general public in the Arch Linux User Repository [34]. The RDBMS chosen was MariaDB, as it is completely an open-source database system. The MOODLE LMS is created with the course instructors along with the students enrolled in a course. Two activities were created as given in Fig. 2.

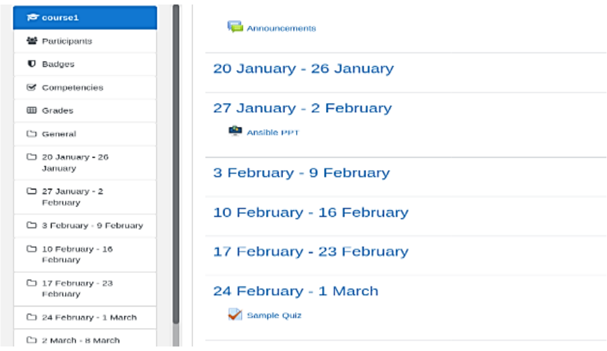


Fig. 2. Sample activities.

The Gradebook has some default viewing options in the form of tables, grouped by various participants, and activities. The Grade Report view and single view tab are available in MOODLE LMS. The grade book can also be edited to update the grading of each activity in a course. An existing plugin called 'Grade Distribution' was pulled from GitHub, installed, and validated via the menu using administrator tools in the admin account. The plugin represented in Fig. 3 was modified by adding a direct database connection to add to the analytical data. The grade boundary settings are configured for the course to configure the lower boundary with the grade letters as shown in Fig. 4.

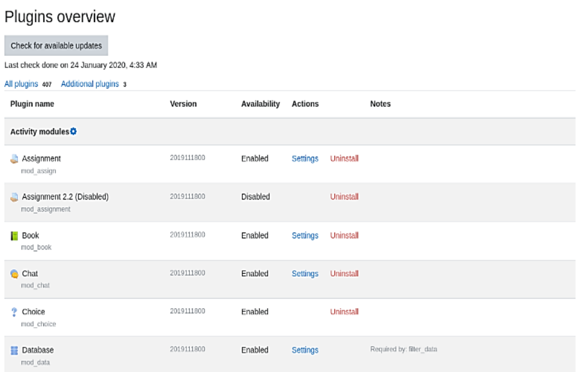


Fig. 3. Plugins overview.

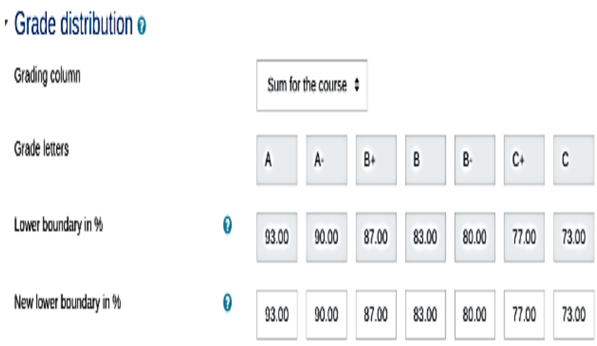


Fig. 4. Grade boundary settings.

Further, the plugin is modified to add a feature called 'Analysis' as depicted in Fig. 5 which shows the students who failed to attain the pass percentage of 41% in the course.

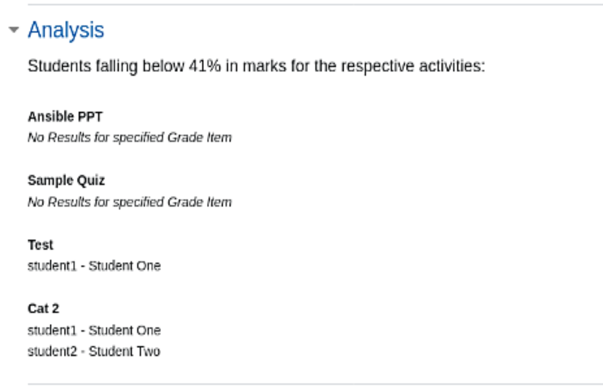


Fig. 5. Features of analysis.

Based on the student's grade update in the grade book, the "grade distribution" is updated in the interface for all the students as well as the facilitators. This development ensures that the grade report is visible to both administrators as well as teachers. The visualization of the grade analysis is given in Fig. 6.

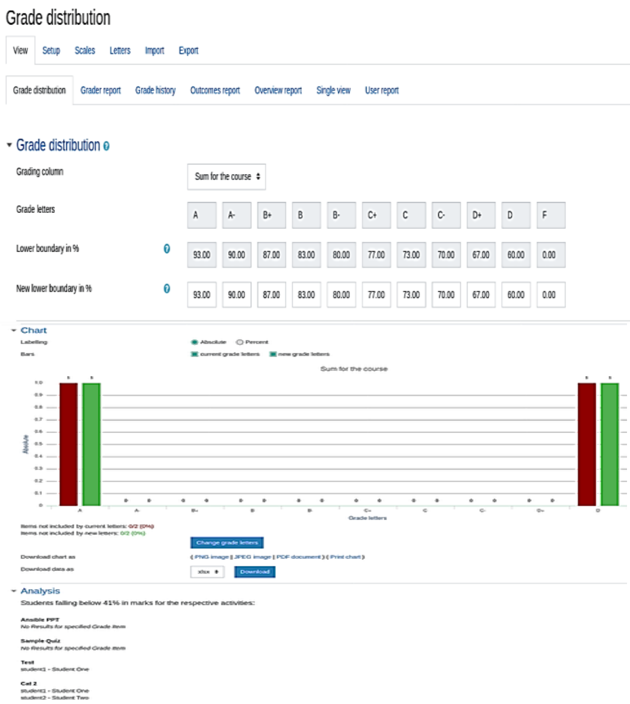


Fig. 6. Grade consolidated view.

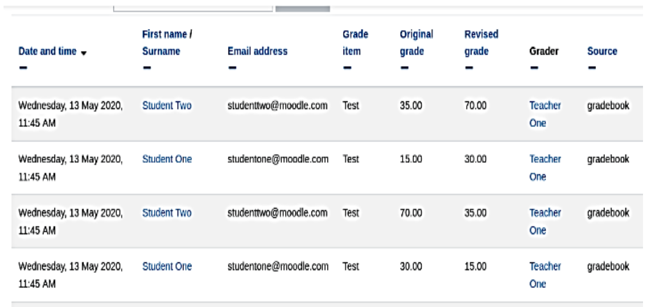
With the analytics Moodle plugin, the grades obtained by the learners and the responses observed via the questionnaires are projected to the students. The analysis of the learner's grade and the responses are performed with the learning analytics via the K-Means clustering algorithm.

V. Analysis and Results

A. Analysis of Student's Assessment

The grade sheet is imported to the MOODLE LMS which can be downloaded in various formats like XML, Spreadsheet, or CSV. The gradebook plugin shows options to map the grade sheet values to specific IDs by selecting the parameters for mapping. It gives the option to add/ignore certain columns to form new grade items, which can be reviewed and displayed in the required format.

Gradebook, by default, also has a history section, where every single activity can be viewed for all users, with an accurate timestamp, and performance results as presented in Fig. 7.



Date and time	First name / Surname	Email address	Grade item	Original grade	Revised grade	Grader	Source
Wednesday, 13 May 2020, 11:45 AM	Student Two	studenttwo@moodle.com	Test	35.00	70.00	Teacher One	gradebook
Wednesday, 13 May 2020, 11:45 AM	Student One	studentone@moodle.com	Test	15.00	30.00	Teacher One	gradebook
Wednesday, 13 May 2020, 11:45 AM	Student Two	studenttwo@moodle.com	Test	70.00	35.00	Teacher One	gradebook
Wednesday, 13 May 2020, 11:45 AM	Student One	studentone@moodle.com	Test	30.00	15.00	Teacher One	gradebook

Fig. 7. Grading activity history.

Along with the options mentioned above, a particular setting under the site administration category, accessible only to admin accounts is also available to create analytical models, which can be run on PHP, or Python as required. However, the machine learning analytics model in Moodle represented in Fig. 8 is a primitive one focusing on features like activity completion logs, read or write activities, students at risk of dropping out, at risk of not completing the assignments, and so on.

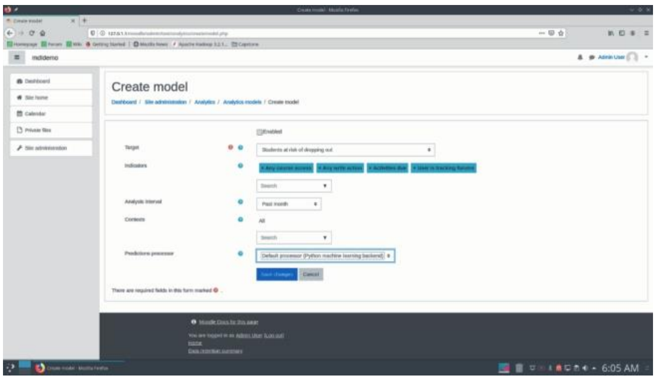


Fig. 8. Analytics model in moodle.

Therefore, to have a deeper analysis of the student's performance based on their assessment scores and also take into account their feedback/reviews about the course, a learning analytics model using an unsupervised machine learning algorithm is implemented in this study.

Student's scores on the analytical part of the assessment were similarly extracted from Moodle to obtain the overall grades of the learners on the assessment questions. These analytical scores were considered for the performance analysis of the learners. The performance of 6 different classes was compared based on the quality of teaching applied in each class by 3 different instructors. The open book examination is attended by the learners at the end of the semester.

The question paper comprised of six questions in each course which were framed based on higher-order thinking (HoTs). The HoTs questions will make the learners apply their critical thinking skills in the examination.

TABLE I: ASSESSMENT SCORES

Instructor	Class	Attendance	Difficulty Level	Q1	Q2	Q3	Q4	Q5	Q6
1	2	4	4	3	3	3	3	3	3
1	2	1	3	3	3	3	3	3	3
2	1	3	3	4	4	4	2	4	4
2	1	1	1	4	4	4	4	4	4
3	5	2	1	4	4	4	4	4	4
3	5	3	2	2	2	2	2	2	2

Based on the marks scored as shown in Table I, the learners are segregated into 3 different clusters. These clusters are formed after the analysis is performed on the above data. Using the K-Means algorithm, the row-wise clustering is being done based on the data to form different centroids. Initially, 3 different clusters i.e K=3 were pre-decided to perform the computation on the data matrix.

Once the computation is done, new centroids are created at every step until 3 different clusters are formed as shown in Fig. 9. These 3 clusters comprise learners from three different categories namely,

- Group 2 represented in green: shows the group of learners below average, otherwise termed low achievers.
- Group 1 and 3 represented in yellow and red: depicts the learner's group who are above average and top performers.

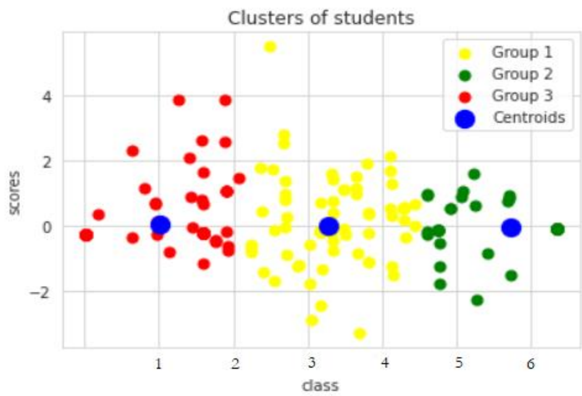


Fig. 9. Clustering.

The clusters obtained represent that every learner has been categorized into either of the groups based on his/her academic scores. This clustering provides the course instructors with insights about which student requires what kind of inputs. The outcome of this clustering method can be described as follows:

- Students belonging to Groups 1 and 3 require minimal support and guidance from the facilitators as the learners have performed comparatively well than Group 2.

These learners are the toppers and students who are self-learners. This group of learners can learn independently and can be called self-directed learners.

- Whereas, Group 2 i.e classes 5 and 6 fall under the category of low achiever and must be given additional attention and guidance to help the learners perform better in the assessments.

This group of learners requires additional efforts from the facilitators in supporting them throughout the learning process. In this context only, our proposed model is designed where it recommends the instructors in taking necessary actions to elevate the performance of the low achievers.

Methods like group-based learning, collaborative activities, and flipped classroom techniques can be incorporated in and outside the classroom to augment the performance of the low achievers and engage them for a longer duration.

B. Analysis of the Student's Feedback

Student's feedback and their perspectives about the teaching methodology followed in the class also have a significant impact on the performance of the learners. Since every individual will have a different learning style, these teaching strategies will have varied effects on the learners. How the students have perceived the lectures, the quality of teaching, and the questions asked in the assessment are considered here to incur the actual reason behind the difference in the learner's performance.

The feedback was provided by the learners on the teaching methodology used in the classroom, and whether the questions asked in the assessments aligned with the instructor's course objectives. The questionnaire for the feedback was outlined using the following criteria as given in Table II.

TABLE II: QUESTIONNAIRE CRITERIA

QUESTIONS	CRITERIA
Q1 & Q2	Course content and Teaching methodology used inside and outside of the classroom.
Q3 & Q4	The usefulness of the resources shared with learners and their contribution to the learning competence of the learner.
Q5 & Q6	The relevancy of the course with the lesson plan and its alignment with the professional competency skills of the students was the criteria.
Q7 & Q8	Efficiency and commitment of the facilitators in delivering the course content and utilizing the stipulated lecture time effectively.
Q9 & Q10	Instructor's attitude and behavior towards the learners.

The average of the responses provided by the learners from each class was calculated and the following graph in Fig. 10 was produced. The graph was further analyzed to depict that the best ratings were provided by class 6 and the least ratings were provided by class 5.

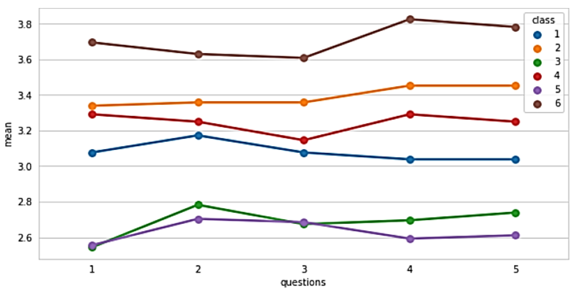


Fig. 10. Mean ratings of the questionnaire.

The K-Means Clustering algorithm has helped the facilitators to analyze each of these grades for each learner to determine which of these learners were scoring less than the minimum pass percentage and to which groups were they belonging. It provided the ease of segregating the learners into different groups based on their scores in the assessments so that it would be helpful for the teachers to understand the behavior of each learner.

Based on the analysis performed using the test scores and the responses to the questionnaire, the inferences represented not only the marks obtained by the learners but also the quality of the assessment with the teaching methodologies used in the classroom determines the overall performance of a learner. Therefore, a blend of different instructional strategies, course materials, educational resources, and independent study techniques must be provided to learners to obtain an optimum result and help the low achievers to perform better in the course.

From the clusters obtained in Fig. 9, we found that classes 5 and 6 were the group of low performers but whereas the ratings provided by the same class 6 are the best among all the other classes. This shows that even though the performance of the learners was low, the ratings provided towards the teaching-learning process applied in the classroom and the instructor were highly positive. This implies that although the methodology was suitable to the learner's needs, the students were not motivated enough to perform well in the assessments. There was a lack of self-directed and self-regulated learning which led to the low performance of the learners.

Class 5 who also belonged to the group of low achievers, has expectantly given low ratings to the instructor as well as the instructional strategies used in the classroom. In this case, the instructor has to put in extra effort to align the evaluation instruments with the course plan in such a way that the learners would explore their metacognitive skills to achieve the best. All the other responses from the remaining classes represented that the teaching-learning process was in proper alignment with the course plan implemented within the classroom and the tests conducted at the end of the semester.

Based on the inferences given above, instructor 1 who handled class 6 has used innovative strategies inside the classroom. However, the inculcation of motivational strategies and self-learning elements in the Moodle platform would be more beneficial to boost the confidence of the learners. In addition to these strategies, the learners must be encouraged to take up the responsibility for their learning and to exploit their self-reliance in the learning process.

On the contrary, instructor 3 who handled the course for class 5 needs to work more on the instructional design process as well as on the emerging pedagogical models to match the student's expectations from the course. The inclusion of materials like simulations, gamification components, immersive technologies, etc might help foster the curiosity of the learners towards the course.

VI. CONCLUSION

The outcome of this study has successfully developed and implemented a fully compatible plugin into the Moodle learning management system using PHP, JavaScript, and Ajax, to display the grade distribution for a different set of courses obtained by a different group of learners. The LMS has provided the facilitators and the learners with an interactive forum for conducting lectures and optimized the teaching-learning process to a greater extent. Alongside, the analysis of the grades using unsupervised machine learning algorithms namely K-Means clustering proved to be a better way in identifying the group of low achievers.

The Moodle plugin developed in this research will standardize the way educators determine which students need extra attention as a result of their performance in certain activities and can be a stepping stone for a more personalized system in the view of helping low achievers. The learning analytics performed in this study highlighted the aspects which were underestimated while considering the performance of the learners. The major implications stated that in addition to the assessment scores and attendance of learners the learning experiences designed by the facilitators, the strategies, and learning models applied in the course plan also have a serious effect on the learner's attitude towards learning and their academic performance. To address these issues, this study suggests that facilitators incorporate the use of self-regulated learning techniques along with innovative pedagogy and motivational models to address different learning styles and fulfill the expectations of the learners.

VII. Future Work

An ideal solution to move around the constraints of the current Learning Management System being used would be to design a web application where students can access study material and resources in a much more personified fashion. However, with additional features such as time-based tracking, allowing them to use annotations or notes on every slide or frame inside the application itself, self-assessment and progress tracking, and other options of tracking the status of a course completion would be even more impressive.

Therefore, the incorporation of the learning analytics module into an LMS itself will be an exemplary solution in determining which students need more attention and how each course can be improved more specifically. Also, if the same data is displayed to the students as well, it would help them improve their efficacy and self-regulate their learning to improve their performance.

This study has applied the use of the K-Means clustering algorithm for grouping the learners whereas in the future the implementation of other machine learning algorithms would also help apply the Learning Analytics to the student's data with much more precision and accuracy. With a variety of Machine Learning algorithms (like Logical Regression, Linear Regression, and other supervised learning algorithms), using the logged data variables like average time spent on each slide, login frequency, academic history, regularity of learning intervals, interaction with peers and instructor concerning last year's performance of students in the same course can be compared and further analyzed to improve the performance of the learners and efficiency of the teaching-learning model used.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Monica Maiti contributed to writing the paper, analyzed the data, and conducted the research; Dr. Priyaadharshini M guided the research, helped in obtaining the academic data, and reviewed the paper for corrections; all authors approved the final version.

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