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REVIEW ON EVALUATION TECHNIQUES FOR BETTER STUDENT LEARNING OUTCOMES USING MACHINE LEARNING

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Abstract: *This paper reviews student learning outcomes based on various evaluation parameters critical to the education system. It considers student learning outcomes alongside factors such as learner engagement, use of learning strategies, teacher experience, motivational beliefs, and technology in learning. Examination and evaluation are essential for measuring student learning outcomes. Classification algorithms like Decision Trees, Naïve Bayes, and Support Vector Machines aid in categorizing student performance, facilitating ongoing monitoring of their progress. Machine learning techniques are employed to determine whether learning outcomes have been achieved. Regular assessment of student learning is crucial to accurately measure true learning outcomes. Once assessed regularly, aggregation of learning outcomes should be conducted to summarize the overall course learning outcomes.*

I. Introduction

The meaning of education varies with time and context. Education equips us to navigate social life more effectively. It is one of the most important assets a person can have, offering numerous benefits on personal, social, and monetary levels. Education provides access to the best opportunities, serving as a foundation for better job prospects. It instills self-confidence, enabling individuals to work and live confidently in society. Education is often viewed as a golden ticket to a better life, contributing to the growth of a country as a whole. Educated individuals tend to lead more managed and meaningful lives, actively embracing events and challenges.

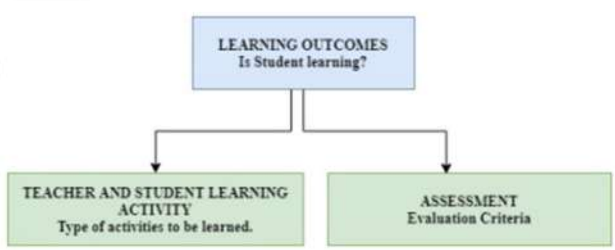


Fig. 1. Assessment and teaching learning activities.

Higher education plays a crucial role in shaping the future of young people, aiming to prepare them to handle future problems in their lives. In the past, education was closely tied to teachers, but the current scenario has evolved to encompass learning, ethics, fairness, community association, and the role of research at institutions . This transformation in education calls for a reevaluation of education policies, which can be achieved through the active participation of both academics and teachers in transforming learning .Education can be broadly categorized into three types: formal, informal, and non-formal .Learning outcomes are directly linked to education. Learning outcomes refer to the skills and knowledge that students must acquire upon completing a course. They focus on the application and integration of knowledge rather than the amount of material covered .

Learning outcomes are crucial, whether for long-term or short-term courses. They provide a clear picture of what students will gain from a course, benefiting both students and teachers. Students can choose appropriate courses without wasting

time, and teachers can develop effective teaching strategies .

II. Literature Survey

1) Review on evaluation techniques for better student learning outcomes using machine learning

Authors: Pooja Rana

The DT, NB, and SVM are widely used in evaluation techniques to assess students' learning outcomes. These algorithms can estimate or predict the student's expected performance (based on their continuous internal assessment) in advance and are used for validity purposes while doing answer script evaluation (Rana et al., 2021). ML has a significant role in adapting to be integrated with other systems to design innovative assessment models.

2) Review on evaluation techniques for better student learning outcomes using machine learning

Authors:Lovi Raj Gupta, M. K. Dubey, G. Kumar

The paper represents review on student learning outcomes on the basis of various evaluation parameters which plays an important role in an education system. Student learning outcomes along with other attributes are taken into consideration like learner factor, learner engagement, learning strategies use, teacher experience, motivational beliefs and technology in learning etc. With the help of examination and evaluation we can measure student learning outcome. Classification Algorithms like Decision Tree, Naïve Bayes and Support Vector Machine can help us to classify student’s performance. This classifier helps in tracking student performance. With the use of machine learning techniques we are trying to identify whether learning outcome is achieved or not. Students learning evaluation should be done on regular basis so that true learning outcomes can be measure. Once learning outcome is evaluated on regular basis, its aggregation should be done to sum up the learning outcome of course.

3) Evaluating Student Knowledge Assessment Using Machine Learning Techniques

Authors :Nuha Alruwais

The process of learning about a student’s knowledge and comprehension of a particular subject is referred to as student knowledge assessment. It helps to identify areas where students need additional support or challenge and can be used to evaluate the effectiveness of instruction, make important decisions such as on student placement and curriculum development, and monitor the quality of education. Evaluating student knowledge assessment is essential to measuring student progress, informing instruction, and providing feedback to improve student performance and enhance the overall teaching and learning experience. This research paper is designed to create a machine learning (ML)-based system that assesses student performance and knowledge throughout the course of their studies and pinpoints the key variables that have the most significant effects on that performance and expertise. Additionally, it describes the impact of running models with data that only contains key features on their performance. To classify the students, the paper employs seven different classifiers, including support vector machines (SVM), logistic regression (LR), random forest (RF), decision tree (DT), gradient boosting machine (GBM), Gaussian Naive Bayes (GNB), and multi-layer perceptron (MLP). This paper carries out two experiments to see how best to replicate the automatic classification of student knowledge. In the first experiment, the dataset (Dataset 1) was used in its original state, including all five properties listed in the dataset, to evaluate the performance indicators.

In the second experiment, the least correlated variable was removed from the dataset to create a smaller dataset (Dataset 2), and the same set of performance indicators was evaluated. Then, the performance indicators using Dataset 1 and Dataset 2 were compared. The GBM exhibited the highest prediction accuracy of 98%, according to Dataset 1. In terms of prediction error, the GBM also performed well.

The accuracy of optimistic forecasts on student performance, denoted as the performance indicator ‘precision’, was highest in GBM at 99%, while DT, RF, and SVM were 98% accurate in their optimistic forecasts for Dataset 1. The second experiment’s findings demonstrated that practically no classifiers showed appreciable improvements in prediction accuracy with a reduced feature set in Dataset 2. It showed that the time required for related learning objects and the knowledge level corresponding to a goal learning object have less impact.

III .SYSTEM ANALYSIS

Existing system: A novel method has been developed for predicting students’ future performance in degree programs based on their current and past performance. This method employs a latent factor model-based course clustering approach to identify relevant courses for constructing base predictors. Additionally, an ensemble-based progressive prediction architecture has been created to integrate students’ evolving performance into the prediction process. These data-driven methods can complement other pedagogical approaches for evaluating student performance, providing academic advisors with valuable information to recommend subsequent courses and implement necessary pedagogical interventions. This approach also influences curriculum design in degree programs and the formulation of education policies in general. Disadvantages Of Existing System:

1. Some predictions yield incorrect results.
2. The evolving progress of students needs to be better incorporated into the predictions.
3.Algorithm:KNN,LSTM

Proposed system:

To address the problems identified above, a new methodology is proposed. This approach captures real-time learning outcomes of students on a lecture-by-lecture basis. After collecting this data, it is aggregated to determine the overall course learning outcomes. Machine learning techniques are then applied to this data to draw inferences. Classification algorithms such as Decision Tree, Naïve Bayes, and SVM can be used to categorize students' learning outcomes as either achieved or not achieved. Graphical representations will be provided to offer a clear and accurate assessment of learning outcomes. Advantages of proposed system:

- These parameters are used to regularly assess student learning, and the data is stored in a database.
- Machine learning algorithms are applied to this data to improve learning outcomes.

IV.SYSTEM STUDY

Feasibility Study: The feasibility of the project is analyzed in this phase and business proposal is put forth with a very general plan for the project and some cost estimates. During system analysis the feasibility study of the proposed system is to be carried out. This is to ensure that the proposed system is not a burden to the company. For feasibility analysis, some understanding of the major requirements for the system is essential.Three key considerations involved in the feasibility analysis are,

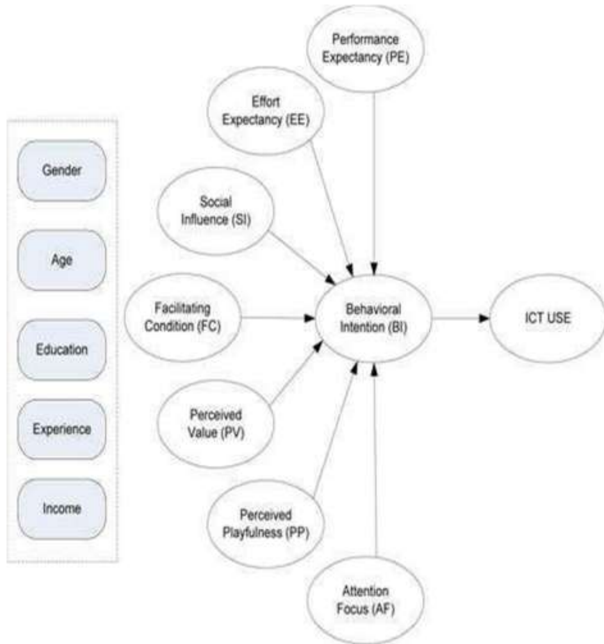
- Economical feasibility
- Technical feasibility
- Social feasibility

Economical feasibility: this study is carried out to check the economic impact that the system will have on the organization. The amount of fund that the company can pour into the research and development of the system is limited. The expenditures must be justified. Thus the developed system as well within the budget and this was achieved because most of the technologies used are freely available. Only the customized products had to be purchased.

Technical feasibility: This study is carried out to check the technical feasibility, that is, the technical requirements of the system. Any system developed must not have a high demand on the available technical resources. This will lead to high demands on the available technical resources. This will lead to high demands being placed on the client. The developed system must have a modest requirement, as only minimal or null changes are required for implementing this system.

Social feasibility: The aspect of study is to check the level of acceptance of the system by the user. This includes the process of training the user to use the system efficiently. The user must not feel threatened by the system, instead must accept it as a necessity. The level of acceptance by the users solely depends on the methods that are employed to educate the user about the system and to make him familiar with it. His level of confidence must be raised so that he is also able to make some constructive criticism, which is welcomed, as he is the final user of the system.

V. SYSTEM DESIGN



Data flow diagram:

The DFD is also called as bubble chart. It is a simple graphical formalism that can be used to represent a system in terms of input data to the system, various processing carried out on this data, and the output data is generated by this system.

The data flow diagram (DFD) is one of the most important modelling tools. It is used to model the system components. These components are the system process, the data used by the process, an external entity that interacts with the system and the information flows in the system.

DFD shows how the information moves through the system and how it is modified by a series of transformations. It is a graphical technique that depicts information flow and the transformations that are applied as data moves from input to output.

DFD is also known as bubble chart. A DFD may be used to represent a system at any level of abstraction. DFD may be partitioned into levels that represent increasing information flow and functional detail.

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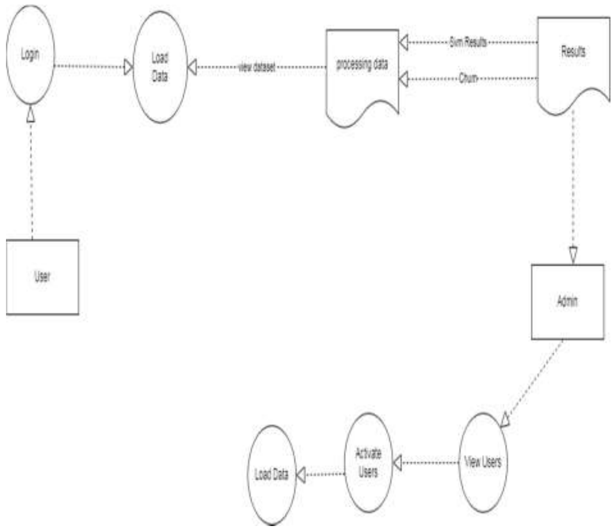

UML stands for Unified Modelling Language. UML is a standardized general-purpose modelling language in the field of object-oriented software engineering. The standard is managed, and was created by, the Object Management Group.

The goal is for UML to become a common language for creating models of object oriented computer software. In its current form UML is comprised of two major components: a Meta-model and a notation. In the future, some form of method or process may also be added to; or associated with, UML.

The Unified Modelling Language is a standard language for specifying, Visualization, Constructing and documenting the artefacts of software system, as well as for business modelling and other non-software systems.

The UML represents a collection of best engineering practices that have proven successful in the modelling of large and complex systems.

The UML is a very important part of developing objects oriented software and the software development process. The UML uses mostly graphical notations to express the design of software projects.

Goals:

The Primary goals in the design of the UML are as follows:

Provide users a ready-to-use, expressive visual modelling Language so that they can develop and exchange meaningful models.

Provide extendibility and specialization mechanisms to extend the core concepts.

Be independent of particular programming languages and development process.

Provide a formal basis for understanding the modelling language.

Encourage the growth of OO tools market.

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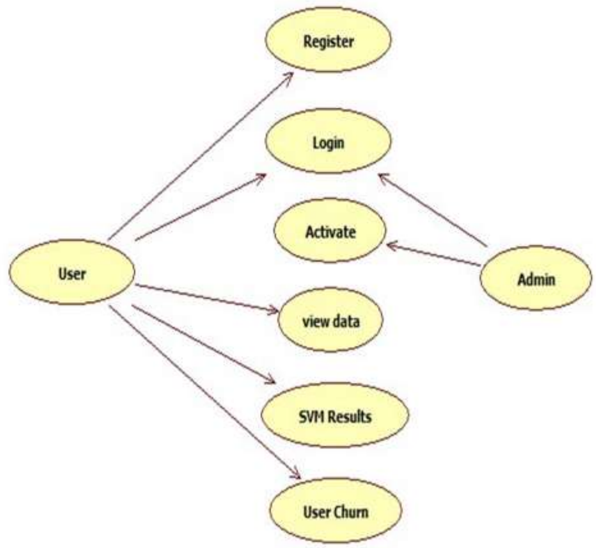
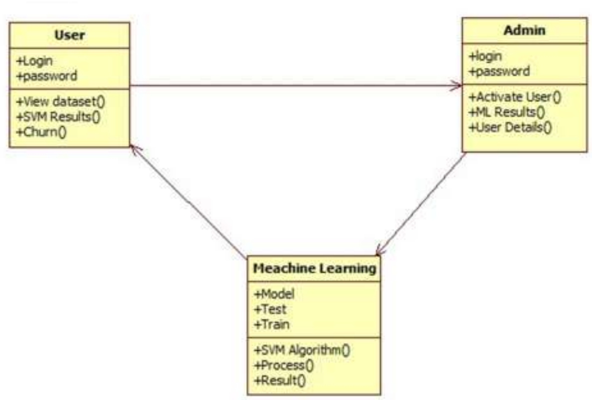
Support higher level development concepts such as collaborations, frameworks, patterns and components. Integrate best practices.



A use case diagram in the Unified Modelling Language (UML) is a type of behavioural diagram defined by and created from a Use-case analysis. Its purpose is to present a graphical overview of the functionality provided by a system in terms of actors, their goals (represented as use cases), and any dependencies between those use cases. The main purpose of a use case diagram is to show what system functions are performed for which actor. Roles of the actors in the system can be depicted.

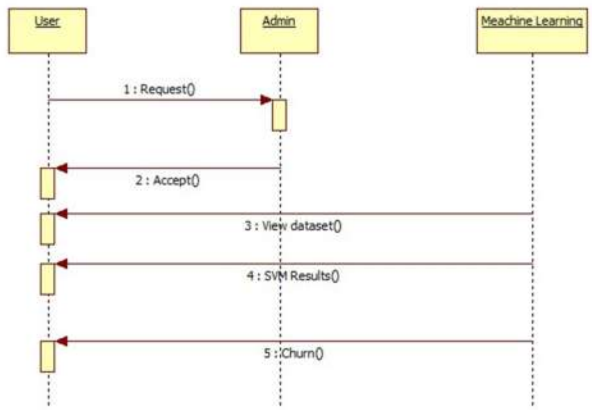
Class diagram:

In software engineering, a class diagram in the Unified Modeling Language (UML) is a type of static structure diagram that describes the structure of a system by showing the system's classes, their attributes, operations (or methods), and the relationships among the classes. It explains which class contains information.



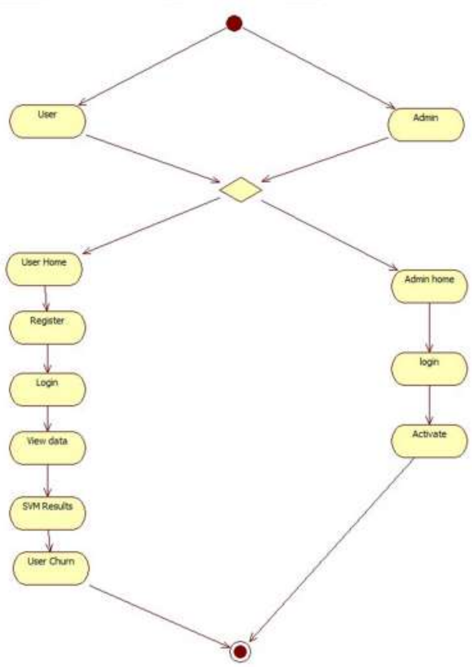
Sequence diagram:

A sequence diagram in Unified Modelling Language (UML) is a kind of interaction diagram that shows how processes operate with one another and in what order. It is a construct of a Message Sequence Chart. Sequence diagrams are sometimes called event diagrams, event scenarios, and timing diagrams



Activity diagram:

Activity diagrams are graphical representations of workflows of stepwise activities and actions with support for choice, iteration and concurrency. In the Unified Modeling Language, activity diagrams can be used to describe the business and operational step-by-step workflowsof components in a system. An activity diagram shows the overall flow of control.



VI.MODULES DESCRIPTION

User:

The User can register the first. While registering he required a valid user email and mobile for further communications. Once the user register then admin can activate the user. Once admin activated the user then user can login into our system. User can upload the dataset based on our dataset column matched. For algorithm execution data must be in float format. Here we took Three Customer Behaviour dataset for testing purpose. User can also add the new data for existing dataset based on our Django application. User can click the Classification in the web page so that the data calculated Accuracy and F1-Score, Recall, Precision based on the algorithms. User can click Prediction in the web page so that user can write the review after predict the review that will display results depends upon review like positive, negative or neutral.

Admin:

Admin can login with his login details. Admin can activate the registered users. Once he activate then only the user can login into our system. Admin can view the overall data in the browser. Admin can click the Results in the web page so calculated Accuracy and F1-Score, Precision, Recall based on the algorithms is displayed. All algorithms execution complete then admin can see the overall accuracy in web page.

Data Preprocessing:

A dataset can be viewed as a collection of data objects, which are often also called as a records, points, vectors, patterns, events, cases, samples, observations, or entities. Data objects are described by a number of features that capture the basic characteristics of an object, such as the mass of a physical object or the time at which an event occurred, etc. Features are often called as variables, characteristics, fields, attributes, or dimensions. The data preprocessing in this forecast uses techniques like removal of noise in the data, the expulsion of missing information, modifying default values if relevant and grouping of attributes for prediction at various levels.

Machine learning:

Based on the split criterion, the cleansed data is split into 60% training and 40% test, then the dataset is subjected to four machine learning classifiers such as Support Vector Machine (SVM). The accuracy, Precision, Recall, F1-Score of the classifiers was calculated and displayed in my results. The classifier which bags up the highest accuracy could be determined as the best classifier.

VII. CONCLUSION

In most educational institutions, students' learning outcomes are typically measured based on the marks they receive in exams and assignments, which are conducted weeks or months apart. However, it can be easily deduced that factors such as motivation, cognitive skills, teaching context, assessment methods, and learning engagement significantly influence student learning outcomes. This review highlights how classification models can aid in student assessment and help identify the impact of these proposed features.

The feature space includes characteristics of the semester curriculum, learning activities, continuous assessment, and students' knowledge. Regular measurement of student learning outcomes is essential for better results. Implementing artificial intelligence and machine learning algorithms can further improve current outcomes by employing classification techniques. These techniques can display results on a dashboard and issue warnings to students whose learning outcomes are not achieved. Continuous assessment of student learning allows for regular tracking and enhances learning outcomes. Providing timely reports on students' learning status, especially when done at a micro level, such as lecture-wise, can be considered a true measure of learning outcomes in the future.

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