IJIRCCE

e-ISSN: 2320-9801 | p-ISSN: 2320-9798

INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN COMPUTER & COMMUNICATION ENGINEERING

Volume 11, Issue 11, November 2023

INTERNATIONAL STANDARD SERIAL NUMBER INDIA

Impact Factor: 8.379

International Journal of Innovative Research in Computer and Communication Engineering

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 | Monthly Peer Reviewed & Referred Journal |

|| Volume 11, Issue 11, November 2023 ||

| DOI: 10.15680/IJIRCCE.2023.1111048 |

Unleashing the Power of Machine Learning: Predicting Student Performance through LMS Activity Logs

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ABSTRACT: Educational Data Mining plays a critical part in advancing the literacy terrain by contributing state- of- the- art styles, ways, and operations. The recent development provides precious tools for understanding the pupil learning terrain by exploring and exercising educational data using machine literacy and data mining ways. ultramodern academic institutions operate in a largely competitive and complex terrain. assaying performance, furnishing high- quality education, strategies for assessing the scholars' performance, and unborn conduct are among the prevailing challenges universities face. The review results indicated that colorful Machine literacy (ML) ways are used to understand and overcome the underpinning challenges; prognosticating scholars at threat and scholars drop out vaticination. also, utmost studies use two types of datasets data from pupil sodalities university databases and online literacy platforms. ML styles were verified to play essential places in prognosticating scholars at threat and powerhouse rates, therefore perfecting the scholars' performance.

I. INTRODUCTION

Modern learning institutions operate in a largely competitive and complex terrain. Therefore, assaying performance, furnishing high- quality education, formulating strategies for assessing the scholars' performance, and relating unborn requirements are some challenges faced by utmost universities moment. Pupil intervention plans are enforced in universities to overcome scholars' problems during their studies. Student performance vaticination at entry- position and during the posterior ages helps the universities effectively develop and evolve the intervention plans, where both the operation and preceptors are the heirs of the scholars' performance vaticination plans. E-learning is a fleetly growing and advanced form of education, where scholars are enrolled in online courses. E-learning platforms similar as the Intelligent Tutoring Systems (ITS), Learning Management Systems (LMS), and Massive Open Online Courses(MOOC) take maximum advantage of EDM in developing and erecting automatic grading systems recommender systems, as well as adaptative systems. These platforms use intelligent tools that collect precious stoner information similar as; frequency of a pupil's access to thee-learning system, the delicacy of the pupil's answers to questions, and the number of hours spent reading textbooks and watching videotape tutorials.

II. RELATED WORK

An automated evaluation system has been proposed to estimate pupil performance and to dissect pupil achievement. Then the author uses three algorithms for prognosticating pupil performance directly (2- 3). In the proposed system Education Data Mining (EDM) is used for the bracket. Clustering data mining fashion is used for assaying the large set of pupil databases. This fashion will speed up the searching process and yield the bracket affect more directly. A new literacy model has been proposed using the pupil information from the council enrollment. The final dataset is handed as input to ML algorithms which can apply and prognosticate pupil's academic performance. (11) They named 13 algorithms from 5 orders of ML they're Naïve Bayes, SVM, MLP, IBK, Rules and Tree. A relative study on supervised literacy for pupil vaticination has been proposed. The author handles with 14-point set for bracket. The tools used for brackets are KNN, Decision tree, Navie Bayes. (13- 15) Psychometric analysis of the pupil gets has been proposed by using intellectual parameters of the pupil which

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affect their study. colorful mining ways are used to determine the educational data covering cerebral factors. The delicacy rate of the former study is 89 but by using the proposed system the delicacy rate has increased to 90. %.

III. LITERATURE REVIEW

Chancing new patterns in a huge mass of information is known as data mining. Lately, the operation of data mining ways on educational data has gained notable significance (6). A methodical literature review is conducted to explore prophetic analysis tools in advanced education, with a specific focus on pressing the most material cases of predictors and early warning systems employed in practical operations (22). interesting trends regarding the literacy process and its results may be set up using the data supplied by learning systems (5), known as Educational Data Mining(EDM). Data mining and machine literacy ways are used to identify and cover pupil performance, schoolteacher effectiveness, and other educational issues. By using data to guide decision- timber and point areas for enhancement, education data mining aims to increase the efficacity and effectiveness of education. Predicting pupil performance, spotting at- threat kiddies, and enhancing course design are some specific operations of educational data mining. The honored patterns aid in decision- making and serve as a foundation for soothsaying future trends . More specifically, EDM can help in four areas, 1) structure models, and defining pupil characteristics; 2) discovering the effectiveness of the support handed by thee-learning software; 3) perfecting models for the knowledge structure of the sphere; and 4) scientific discovery regarding learners and literacy. Decision tree induction is the most common system used in EDM. In a study conducted in India on 50 university scholars, features similar as the CGPA of the last semester, grades of quizzes and assignments of the current semester, class attendance frequency, grades in lab work, general proficiency, and final test marks to establish pupil gets and prognosticate pupil performance(30). It indicates that grades or marks earned by course conditioning have a direct impact on pupil's overall performance in any course. Some unconventional conditioning like the participation of scholars in conversations, similar as posting questions and answering corresponding dispatches, may have a significant impact on pupil performance. An analysis conducted on an online business course with 17,934 garçon logs of 98 undergraduate scholars concluded that low situations of participation lead to a advanced threat of poor performance (20).

The relationship between online presence and pupil performance in a amalgamated course by assaying pupil log data. The study revealed that both the frequency and duration of online presence had a statistically significant impact on pupil's final grades. A analogous conducted study revealed a strong correlation between pupil attendance and academic performance. scholars with further than 60 attendances tended to achieve Good, veritably Good, and Excellent (18.9) academic grades compared to other orders of academic achievement. Also, the study indicated that assignments and exercises had a significant impact on undergraduates' final grades, as determined by the logistic retrogression model(16). One of the most comprehensive studies used data from seven courses and 438 scholars. colorful data mining and statistical ways were applied using Weka and Keel data mining tools. The outgrowth of this trouble was to integrate a stoner-friendly data mining capability with Moodle. Weka has been used in other EDM sweets as well. Pupil gets. modeling using machine literacy is the process of using machine literacy algorithms to dissect and prognosticate pupils who get grounded on data about their once conduct and characteristics. This can involve using machine literacy ways to identify patterns and trends in pupil gets data, and to make prognostications about how a pupil is likely to bear in the future. Machine literacy algorithms can be used to dissect pupil gets data in order to identify scholars who may be at threat of academic literacy difficulties or dropping out.

This can allow preceptors to intermediate beforehand and give targeted support to help these scholars succeed. Machine literacy algorithms can be used to dissect pupil gets data in order to identify patterns and trends that can inform the design of substantiated literacy guests. This can ensure that scholars admit learning guests that are acclimatized to their requirements and preferences. Machine literacy algorithms can be used to dissect pupil gets data in order to identify patterns and trends that can inform the design of courses and course accoutrements. This can help ensure that courses are designed in a way that's most likely to engage and motivate scholars. Radial Base Function (RBF), a neural network fashion was used to prognosticate pupil performance. The dataset was taken from a Chinese University, that included the information on marks attained during 2010- 11 and 2011- 12 sessions and former year marks to prognosticate the current semester's subject marks. Based on vaticination, the scholars were divided into different orders with respect to their performance. Machine literacy algorithms can be used to dissect pupil gets data to make prognostications about how a pupil is likely to bear in the future. This can help preceptors anticipate and respond to implicit issues before they

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arise. The dataset of 300 undergraduate scholars from 2003 to 2012 is taken from the University of Illinois, USA, for this study. Scholars' attributes of age, coitus, race, citizenship status, and pupil grades were used to make the Bayesian Network model to prognosticate scholars' academic performance. Model the pupil's grades in the three major courses of the alternate semester and work as an alarm system for scholars at threat. Random timber is a kind of supervised ML classifier and is considerably used in retrogression and bracket problems. It works inversely on categorical and numeric variables. One of the essential aspects of arbitrary timber classifiers is to induce several individual decision trees grounded on the given data and display the final target affair grounded on the maturity voting. The creation of decision trees does 'not examine all attributes.

It aimlessly selects the root knot in the decision tree structure. Logistic Retrogression Logistic Retrogression is a supervised machine- learning fashion extensively used to break Retrogression- grounded problems. This fashion uses a collection of independent variables to prognosticate the order dependent variable. Logistic Retrogression can get from direct retrogression expression. RESULT OF enforced CASSIFIERS STRUCTURE OF DATASET CONCLUSTION The pupil's academic progress is a critical quality dimension index in- learning. The vaticination of academic achievement offers a foundation for preceptors to acclimatize their tutoring approach for scholars who may have study difficulties. This study used machine literacy algorithms and statistical ways to assay the pupil data. The dataset used in the study is uprooted from the Kaggle website, which is intimately available. After collecting data, we converted it into a suitable form before passing it into the machine literacy model. We elect the point grounded on the information gain sludge system from the dataset. Also, we applied machine literacy classifiers to the data set support vector, Logistic Retrogression, arbitrary timber, and decision tree. We estimated them by peaking the data into 80 for training and 20 for testing. The trial result demonstrates arbitrary timber achieves 89 advanced delicacies among other tested classifiers. In Table 3 and figure 4, confusion criteria indicate that arbitrary timber is most applicable for classifying pupil performance into high, medium, and low orders.

A predictor grounded on the Naïve Bayes algorithm modeled on a dataset of 300 records was attained from the Bachelor of Computer Application for the 2009- 2010 session. The study established that pupil grades depend upon attributes like former academic performance, living position, and medium of instruction. Other contributing attributes include gender, family size, periodic income status, food habits, council type, parents' qualifications, and occupation.

The K- Means clustering algorithm was used to group scholars into high, medium, and low achievers using attributes like former grades, GPA, number of scholars, and chance. Result summaries show that8.33 percent of scholars needed special attention. The study also conducted an analysis of the goods of the two variables on scholars' academic performance by employing K- Means clustering ways. The University of Tuzla collected 257 records from the faculty (Economics) to compare the performance of Naive Bayes, decision tree and Multilayer Perceptron algorithm over attributes similar as gender, family size, distance from academy, GPA, literacy, entrance test marks, accoutrements (books, notes), time(study hours), internet operation and earnings. The performance of each algorithm was assessed grounded on three criteria i.e., vaticination delicacy, error rate and literacy time. Naive Bayes prognosticated further cases rightly and also performed more in vaticination delicacy as compared to others. Decision Tree and Naïve Bayes performed inversely wellw.r.t literacy time.

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Paper No.	Name of Author	Methodology	Dataset	Advantages	Limitations	Results
1	J. Abbas, J. Aman, M. Narun Nabi, S. Bano.	The impact of social media on learning behaviour for sustainable education.	The Positive Effects of social media.	This research presents new empirical findings regarding social media usage.	Adolescents and youths.	This research focused to investigate the positive and adverse effects of social media on students' learning environment.
2	M. Adnan, K. Anwar.	Online learning amid the covid-19 pandemic Student's perspectives.	Online Submission	The option to cater individually to the students.	Biggest challenges we face is technology adjustment, Internet issues, software problems.	This research helps us students to focus on online studies.
3	H. A. Mangesh	Using data mining techniques to predict student performance.	Data mining techniques	This study was conducted with the records of students.	The results show that a high-performance model to predict students performance.	The results of this study showed that students' first-year CGPAs could be predicted based on admission criteria
4	H. Aldowah, H. Al-Samarraie, W. M. Fauzy.	Educational data mining and learning analytics for 21st century higher education.	Telematics and Informatics.	Data mining techniques are increasingly gaining significance in the education sector.	There are chances of data loss.	This review is an attempt to shed light on more specific learning problems.

IV. DESIGN AND IMPLEMENTATION

In this section, we present the details of our proposed approach. We used a variety of data mining approaches to read pupil progress in online literacy terrain. The primary step of our proposed system is shown in figure 1, and details are given below.

Machine learning techniques :

Several types of data mining approaches have been used to develop vaticination models. Four kinds of DM classifiers are tested, as this study's vaticination model is illustrated below.

Support Vector Machine

A Support Vector Machine(SVM) is a kind of supervised ML classifier and is considerably used in retrogression and bracket problems. The SVM can be used for both numeric and Categorical data. It's a direct classifier that can be used to prognosticate the class of an observation using a training set. It gives largely accurate results and a lower quantum of overfitting. The ideal hyperplane improves the border between the two classes where the support vector is located. It converts the original input data into high-dimension point space. It also discovers the hyperplane in a new dimension by separating the two classes. The hyperplane finds by an algorithm using a support vector.

Decision tree

A decision tree(DT) classifier is considerably used in bracket problems. It works in resemblant and periodical form according to massive data. In DT, construction doesn't need any factor or sphere knowledge. The DT is extensively useful in the decision- making process. It has a tree- suchlike structure in which spheres represent leaves and a cube represents internal bumps. Each internal knot consists of two children. Each knot produces child bumps until the group is not divided further and generates meaningful information. The internal knot and splint represent the dataset features and the values of attributes. The terminal knot is the down most bumps representing the target affair value.

Random forest Classifier r Association rule mining can be used to identify patterns in pupil performance data that may indicate why certain scholars are more successful than others (32). For case, an association rule might reveal that scholars who spend a certain quantum of time studying each week tend to get advanced grades (36). Association rule mining can be used to identify factors that are associated with pupil retention and powerhouse rates (38). An association rule might reveal that scholars who live on lot are more likely to remain enrolled in academy than those who swap. Association rule mining can be used to identify patterns in pupil gets that can inform the design of substantiated literacy gets

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(29). similar as an association rule might reveal that scholars who prefer hands on learning guests tend to perform better in certain subjects. Association rule mining can be used to identify patterns in pupil performance data that can inform the design of courses and course accoutrements. Therefore, an association rule might reveal that scholars who engage with certain types of educational accoutrements tend to perform better on examinations. Association rule mining has also been used to discover patterns in the LMS logs (13). A dataset of 29 scholars was used to prognosticate final test marks grounded on assignments and quizzes, as well as runner views on the discussion forum. University of Windsor, Canada study identify that pupil performance had a direct relationship with assignments. An association rule mining algorithm was used on a dataset from CLEW (Collaboration and Learning Environment Windsor) to show the association.

between assignments and the final marks of scholars. The results indicate that the weight of assignments had a positive impact on final marks, and assignments should be given the right precedence. (15). The relationship between online presence and pupil performance in a amalgamated course by assaying pupil log data. The study revealed that both the frequency and duration of online presence had a statistically significant impact on pupil's final grades. (35). An analogous conducted study revealed a strong correlation between pupil attendance and academic performance. scholars with further than 60 attendances tended to achieve Good (37.7), veritably Good (32.1), and Excellent (18.9) academic grades compared to other orders of academic achievement. also, the study indicated that assignments and exercises had a significant impact on undergraduates' final grades, as determined by the logistic retrogression model (16). One of the most comprehensive studies used data from seven courses and 438 scholars. colorful data mining and statistical ways were applied using Weka and Keel data mining tools. The outgrowth of this trouble was to integrate a stoner-friendly data mining capability with Moodle.

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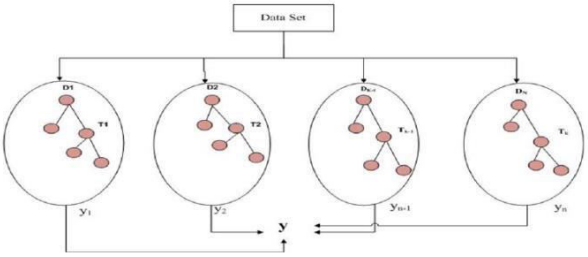

Figure 2: Random forest model

Logistic Regression

Logistic Retrogression is a supervised machine- learning fashion extensively used to break Retrogression grounded problems. This fashion uses a collection of independent variables to prognosticate the order dependent variable. Logistic Retrogression can get from direct retrogression expression.

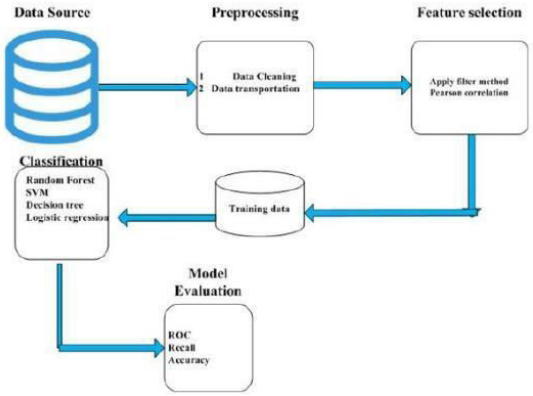

Figure 3: Student performance Prediction Model

RESULT OF IMPLEMENTED CASSIFIERS

Classification Techniques	Accuracy	Recall	F Measure
Random Forest	0.89	0.89	0.88
Support vector	0.83	0.82	0.82
Logistic Regression	0.81	0.81	0.81
Decision tree	0.82	0.80	0.80

STRUCTURE OF DATASET

Name of attributes	Description	Data types
Gender	Student gender detail	object
Nationality	Student belong to which country	object
Birthplace	Birth place of the student	object
Grade_id	The detail of student obtaining grade	object
Section	The detail of student belong to which section	object
Topic	Student learning course detail	object
Semester	The detail of student enroll semester	object

V. CONCLUSION

The pupil's academic progress is a critical quality dimension index in-learning. The vaticination of academic achievement offers a foundation for preceptors to acclimatize their tutoring approach for scholars who may have study difficulties. This study used machine literacy algorithms and statistical ways to assay the pupil data. The dataset used in the study is uprooted from the Kaggle website, which is intimately available. After collecting data, we converted it into a suitable form before passing it into the machine literacy model. We elect

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