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A Recent Exploration on Student Performance Analysis using Educational Data Mining Methods

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Abstract: ***Predicting students' overall performance turns into greater difficult because of the massive quantity of records in academic databases. Currently in India, the shortage of current system to examine and display the student development and overall performance isn't always being addressed. Hence on this paper, supplied an in-depth literature assessment on predicting student overall performance through the use of data mining strategies is proposed to enhance students' achievements. The main goal of this paper is to offer an outline at the data mining strategies which have been used to predict students' overall performance. We may want to really enhance students' achievement and success greater efficaciously in an efficient manner the use of academic records mining strategies. It could convey the benefits and affects to students, educators and educational institutions.***

Keywords: ***Educational Data Mining, Comparison, Student's Performance.***

I. INTRODUCTION

There is usually a great need as a way to expect future students' behavior to be able to enhance curriculum layout and plan interventions for educational help and steering at the curriculum supplied to the students. This is where Data Mining (DM) comes into play. Knowledge discovery in databases (KDD), often known as facts mining, targets on the discovery of beneficial statistics from massive collections of facts. The fundamental capabilities of facts mining are making use of numerous strategies and algorithms to be able to find out and extract styles of stored data [1]. Data mining and understanding discovery applications have were given a wealthy cognizance because of its importance in choice making and it has emerge as an important aspect in numerous organizations. DM strategies examine datasets and extract statistics to convert it into comprehensible systems for later use. Machine Learning is the primary computational approach which method the statistics to expect students' performance, their grades or the risk of losing out of college and plenty of more. There are growing studies interests in the use of data mining in education. This new rising field, known as Educational Information Mining, concerns with growing methods that find out know-how from information, originating from instructional environments. Educational Data Mining makes use of many strategies along with Decision Trees, Neural Networks, Naïve Bayes, K- Nearest neighbor, and plenty of others. Using those strategies many types of know-how may be found along with affiliation rules, classifications and clustering.

The found know-how may be used for prediction concerning enrolment of college students in a selected course, alienation of conventional lecture room coaching model, detection of unfair way utilized in on-line examination, detection of atypical values in the end result sheets of the college students, prediction approximately college students" overall performance and so on.

Among them, pupil overall performance evaluation is one of the difficult and extensively explored famous studies subjects in instructional information mining (EDM) [2]. Educational Data Mining pursuits at coming across beneficial statistics from the big quantities of digital in-formation amassed through those instructional systems

II. TYPICAL STRUCTURE OF EDUCATIONAL DATA MINING

Lately, the growth in distribution of interactive gaining knowledge of environments, learning management systems (LMS), intelligent tutoring systems (ITS), and educational hypermedia systems in addition to the broader use of ICT in training in general has permitted the gathering of massive quantities of statistics.

The growth in instrumented enlightening software, in addition to nation databases of student take a look at scores, created big repositories of statistics reflecting how college students learn. Some examples of famous structures include: general reason LMS inclusive of Sakai1 and Moodle2, specialized ITSs just like the Cognitive Tutors3 or SQL Tutor4, expert training and training systems inclusive of simulators, structures for gaining knowledge of standard skills; for instance, analyzing and performing mathematics operations inclusive of Neure and Ekapeli5, and eHealth and affected person training inclusive of Philips Motiva6 [27]. Educational Data Mining targets at coming across beneficial records from the big quantities of digital statistics accumulated through those educational systems. EDM as a rising multidisciplinary studies place brings collectively researchers and practitioners from computer science, training, psychology, psychometrics, and statistics

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A. Educational Data mining Techniques

In this section, some of the popular education data mining techniques are discussed along with their existing experimental research. The techniques are K-Nearest Neighbour (K-NN), Support Vector Machine (SVM), Naïve Bayesian (NB), Neural networks and decision tree. K nearest neighbours is a easy set of rules that stores all to be had instances and classifies new instances primarily based totally on a similarity measure (e.g., distance functions). KNN has been utilized in statistical estimation and sample recognition. It is one of the conventional nonparametric classifiers. An unknown example signified via way of means of positive function vectors is assessed via way of means of the KNN classifier as a factor in the function area via way of means of computing the space from the factor to the factors in the training dataset. It then allocates the factor to the magnificence among its k-nearest neighbours (wherein k is an integer). Support Vector Machines is taken into consideration to be a classification method, it however may be employed in each varieties of classification and regression problems. It can effortlessly cope with more than one non-stop and specific variables. SVM con-structs a hyperplane in multidimensional area to split exceptional classes. SVM generates optimal hyperplane in an iterative manner, that's used to reduce an error. The core concept of SVM is to discover a most marginal hyperplane (MMH) that quality divides the dataset into classes. Naive Bayes is a classification technique this is appropriate for binary and multiclass class. It is easy, but powerful and commonly-used, machine learning classifier. It is a probabilistic classifier that makes classifications the use of the Maximum a Posteriori choice rule in a Bayesian setting. It also can be represented the use of a completely easy Bayesian community. An artificial Neural Network is a set of neurons which affords the preferred output with the aid of using doing positive simple processing at the set of enter. The processing task is achieved in the hidden layer. Hidden layer is the intermediate layer among enter set and the output set of the application. Thus, the actual application of the neural net-work is achieved in the Hidden layers. The maximum essential property of a Neural Network is to automatically learn / retrain coefficients in the Neural Network consistent with facts inputs and facts outputs. Decision Tree is a supervised mastering method that may be used for each class and Regression problems, however in the main it is desired for fixing Classification problems. It is a tree-based classifier, wherein inner nodes constitute the functions of a dataset, branches constitute the decision regulations and every leaf node represents the outcome. The following table 1 shows the student performance using various classification algorithms as well as different levels features to determine the students' performance. From the below table, one can infer that almost all the mentioned machine learning algorithms will make use of the all the features except one or two. The most common features are psychometric features and internal and external assessment features and finally CGPA related features. To conclude this, in our feature work will include these features are the primary features to predict the students' performance. Also when com-pared to the accuracy there is a huge difference in naïve Bayesian classifier, neural networks, and decision tree. This motivated to do the future work using K-NN and Support vector machine algorithm to predict the students' performance. Also we have analyzed behavioral as well as assessment dataset separately to identify the importance of the dataset. The table 2 shows the behavioral aspects of student's dataset analysis results. The students related features are plays a vital role in prediction the performance of the students. In order to provide better education, initially we should identify the factors which are influencing the students' performance towards their educational growth. Once the features are identified, we can reduce the drop-out from their education. In that aspect, this survey surely will help the management people to short the problems and increase the student's growth rate. Table 3 shows the analysis of student's dataset in terms of assessment perspective. From the table, one can confirm that, the internal assessment will play main role in students' performance analysis.

Table 1. Review of Performance of Student's Analysis Using Data Mining Methods

Data mining Techniques	Features	Accu (%)	Ref.
K-Nearest Neighbor (K-NN)	Psychometric factor related features.	69	[28]
	Internal assessment, CGPA, Extra-curricular activities related features.	83	[29]
	Internal assessment related features	82	[30]
Support Vector Machine (SVM)	Psychometric factor related features.	83	[31]
	Features related to external assessment, extra-curricular activities and internal assessment features.	80	[29]
	Internal assessment, CGPA related features	80	[32]
Naïve Bayesian (NB)	Features related to students interaction with social network, scholarship details, high school information, CGPA and demographic features.	76	[35]
	Student Demographic, High school background related features	50	[34]
	CGPA related features	75	[33]
	Internal assessment, CGPA, Extra-curricular activities related features	73	[29]
Neural Network	Internal assessments related features.	81	[36]
	Psychometric factors related features.	69	[28]
	External assessment related features.	97	[37]
	CGPA related features.	75	[33]
	Features related to student's interaction with social network, scholarship details, high school information, CGPA and demographic features.	71	[35]
	Student Demographic, High school background related features.	72	[34]

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	Features related to external assessment, extra-curricular activities and internal assessment features.	74	[38]
	Internal assessments, External assessment related features.	98	[39]
Decision Trees	Internal assessments related features.	76	[40]
	Psychometric factors related features.	65	[28]
	External assessment related features.	85	[41]
	CGPA related features.	91	[33]
	Features related to students interaction with social network, scholarship de-tails, high school information, CGPA and demographic features.	73	[35]
	Features related to external assessment, extra-curricular activities and internal assessment features.	66	[29]
	Student Demographic, High school background related features.	65	[34]
	Features related to external assessment, extra-curricular activities and internal assessment features.	90	[42]
	Features related to external assessment, extra-curricular activities and internal assessment features.	90	[43]
	Features related to students psychometric factors, extra-curricular activities and soft skills.	88	[44]

Table 2. Analysis of Behavioural Perspective of Student Dataset

S.no	Datasets	Behavioural Relevant Features	Techniques	Ref.
1	BIIS university dataset	Gender, residence type	Association Rule mining	[1]
2	UCI Machine Learning repository	Parent education and job	Decision tree and fuzzy multi-criteria classification.	[2]
3	bachelor students of Applied Informatics admitted to Faculty of Informatics, Masaryk University in years 2006, 2007, and 2008.	Communication skill, social behaviour	Decision trees, naïve Bayesian	[3]
4	NCEA dataset	Socio-economic status	Multi-level modelling	[4]
5	student database of the Computer Science laurea degree at the University of Florence	Order of examination taken	Clustering Techniques	[6]
6	Humboldt State & Washington University students' dataset	Programming and social measures	Predictive models	[7]
7	The data of graduate and undergraduate students from different universities of Pakistan during the period (2004 to 2011)	Family expenditure and personal information	NB, SVM, J48, CART & Bayes Network	[8]
8	course management system (CMS) data of USA university.	Study habits	Statistical methods	[9]
9	Data from 85 students enrolled in a flipped Calculus II course	Attitude, cognitive skills, and engagement	dispositional learning analytics infrastructure	[10]
10	Data from division of an Australian university about their first-year domestic undergraduate students.	Social background	SNS, DSSD, NMEEFSD, BSD, SD-Map and APRIORI-SD.	[11]
11	Data was collected by using performance reports and questionnaires which was collected and analysed by MCA department, VBS Purvanchal University, India.	Alcohol consumption	BFTree, J48, RepTree and Simple Cart.	[12]
12	Data collected on LAERS assessment environment	Temporal behaviour of answering questions	Partial least square and some more statistical techniques.	[13]
13	The historical log files of the four years (8/2009 – 7/2013) of all courses completed by all DMIT students	Learning capabilities	multilayer perceptron neural network.	[14]
14	student data logged between September 2012 and August 2013 within Assessment's, a popular intelligent tutoring system for mathematics	Assignment tool usage pattern	Random Forest.	[15][5]
15	Student records from a Bachelor's and a Master's program in Computer Science, at ETH Zurich Switzerland.	Performance in undergraduate level	linear regression models.	[16]

Table 3. Analysis of Assessment Perspective of Student Dataset

S.no	Datasets	Assessment Relevant features	Techniques	Ref
1.	Dataset taken from student information system and learning management system at SDSU university.	Internal assessment related features	Ensemble learning	[17]
2	Dataset taken from faculty of Electronics, tele-communications and in-formation technologies at Poiltehnica University.	Attendance, performance course data and credits, student activity	Decision Tree CART, Extra Trees Classifier, Random Forest Classifier, Logistic Regression, and C-Support Vector Classification	[18]

3	Student academic achievement dataset taken from electrical engineering faculty at Malaysian public university	Academic performance measured using Cumulative Grade point average (CGPA) grades.	Neuro-Fuzzy classification	[19]
4	High school student dataset taken from public schools of the federal district of Brazil.	attributes relevant to potential academic failure	Gradient Boosting Machine (GBM)	[20]
5	Dataset taken from Moodle enrolment & course Participation data, University of South Australia.	Student performance for a certain outcome (Pass or Fail).	SNS, DSSD, NMEEFSD, BSD, SD-Map and APRIORI-SD.	[21]
6	Dataset taken from academic information management system of the host institute.	Attributes related to academic performance	Association rules	[22]
7	Dataset taken from Affiliated colleges under Salem Periyar University.	Student's background and internal test attributes.	Ensemble learning	[23]
8	Dataset taken from traditional in-person lecture division, entirely online division and mixed of both.	Academic related attributes	Multiple regression	[24]
9	Graduate student's dataset taken from the college of Science and technology, Khanyounis.	Student's background and academic background related attributes.	Rule Induction and Naïve Bayesian classifier & K-Means clustering	[25]
10	Dataset taken from com-mon core standard skills and student data from Worcester Polytechnic Institute.	Prerequisite Skill Features	Not specified explicitly	[26]

To the best of our knowledge, this is the first survey which covers all the aspects of student's performance analysis, starting from the introduction, followed by structure of educational data mining, surveyed on most popular data mining techniques along with their accuracy and surveyed behavioral aspects, assessment aspects dataset for student performance analysis.

III. CONCLUSION

Predicting students' overall performance is typically beneficial to assist the educators and newcomers enhancing their mastering and coaching process. In this survey paper has reviewed preceding research on predicting students' overall performance with diverse systematic strategies. Most of the papers have used internal evaluation as data sets. While for prediction techniques, the classification approach is often utilized in academic data mining area. Under the classification techniques, naïve Bayesian, sup-port vector system, K-nearest neighbour, Neural Network and Decision Tree are used. Among them K-nearest neighbor and support vector system are the two strategies exceedingly utilized by the researchers for predicting students' overall performance. In conclusion, those strategies along with evaluation associated functions dataset will carry out nicely in prediction of student overall performance. It will assist the educational system to reveal the students' overall performance in a scientific way.

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