Techniques for Examining Student Data for Indicators of Future Success - A Survey and Analysis

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Abstract:- Education is a broad and essential subject that cannot be effectively discussed in a little amount of space. The amount of data maintained in educational databases has grown considerably in recent years. The database contains confidential information regarding the academic and behavioral progression of students. In educational settings, the potential to identify student performance in learning is much important. Educational Data Mining (EDM) is considered as the developed research area along with the computational and psychological methods for predicting the students' achievements. EDM entails in evaluating the student data in order to identify hidden student knowledge. Unbalanced datasets are one of the most critical issues influencing the performance of classifiers. It is a significant challenge in the EDM domain that contributes to inaccurate outcomes. Recently, machine learning (ML) and deep learning (DL) approaches are generally developed for tracking and predicting student achievements by considering different aspects like student's academic achievement data, personal data , behavior data etc., Predicting student outcomes with ML and DL methods emphasizes on inferring information from student achievements data which helps to comprehend the students' affinity on learning, adjusting to new challenges or subjects, and accomplishing the challenges or activities appropriately. This paper provides a comprehensive review on various ML and DL frameworks designed to track and predict student achievements using an online educational dataset with various student observation variables. Initially, various frameworks for predicting student performance based on ML and DL algorithms that have been developed by numerous researchers are examined in detail. Then, a comparative analysis is performed to comprehend the shortcomings of these frameworks and to provide a new solution to effectively predict the students' achievements.

Keywords: *Educational Data Mining, Student Achievements Machine Learning, Deep Learning, Online Courses.*

I. INTRODUCTION

Predicting student performance is becoming increasingly important in the contemporary environment due to the essential role it plays in the growth of nations throughout the worldwide and how dependent it is on the educational system to produce a population capable of leading the own nation and its progress towards expansion of all sectors of life (scientific, economic, social, and military, etc.) [1]. In addition, the determination of students' accomplishments indicates the efficacy of educational institutions, which are responsible for influencing successive generations in line with the diverse phases of people's lives in each nation. As a result, focusing on the growth of the educational process is one of the most compelling needs that drives governments constituted through educational institutions to make enormous and tedious efforts to propel towards continuous and increasing improvement in educational systems [2].

Achievement, dropout rate, and student's performances are just some of the academic outcomes which are wisely observed using DM methods [3]. In education, DM methods are particularly helpful for analyzing and predicting students' learning efficiency. "EDM" is the subset of "data mining" (DM) [4, 5]. The main goal of educational data mining (EDM) is to improve the learning process by studying how students learn and making predictions about their subsequent outcomes. EDM uses a variety of DM methods, including as categorization, regression, time-interval, and association rule mining, to analyze and evaluate different aspects of educational statistics gathered from diverse e-learning contexts or higher education organizations. EDM is often used as a method for creating predictive algorithms that can help in education and learning [6]. However, one of the most significant aspects deciding a model's efficacy is the problem of imbalanced data. It's a major issue since it causes incorrect assumptions and lowers productivity in EDM. The figure 1 provides the EDM process utilized for student achievements prediction.

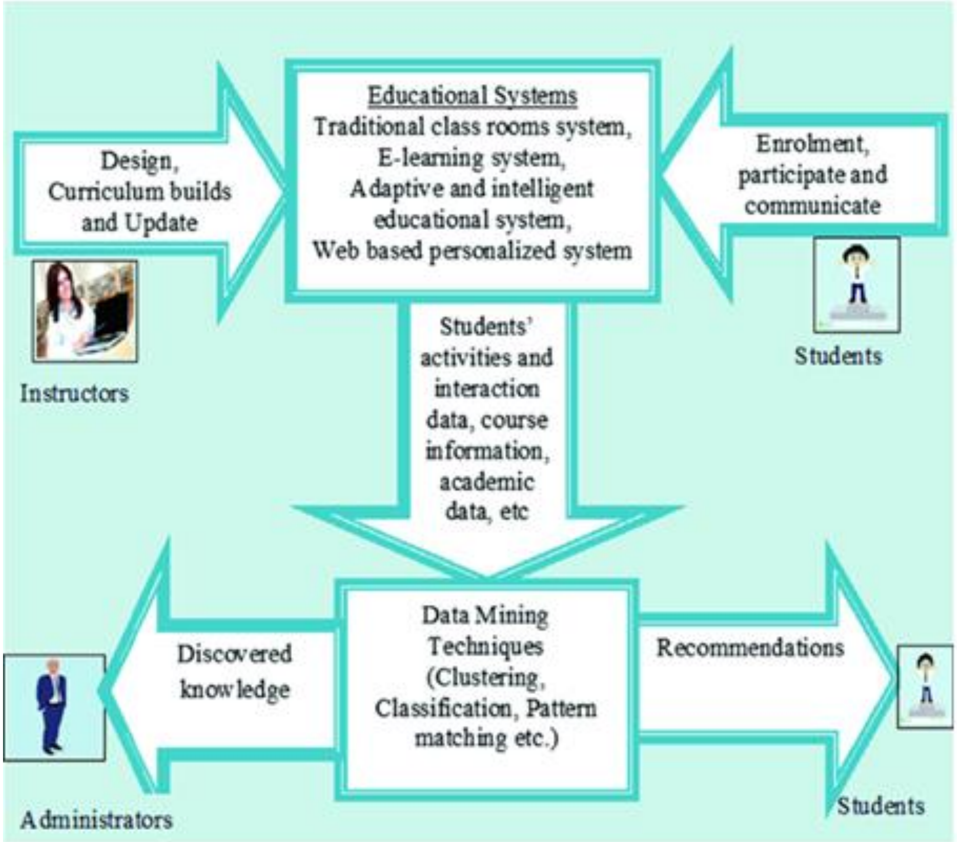

Fig 1 Working Process of EDM for Student Achievements Prediction

In order to improve the achievements of student's prediction, the ML methods have been widely used in recent days [7]. Some of the ML algorithms like clustering based approaches (K-means, NMF, SOM based clustering) and classification based approaches (Artificial neural networks (ANN), linear regression, logistic regression, random forest (RF), k-Nearest Neighbors (kNN), Support vector machines (SVM)). These ML systems can assist to forecast the student achievement and inform teachers about students at risk so that they can provide the necessary support. As a result, the investigation of predicting student achievements have to engage with the construction of the learning classifier utilizing students' observed records as the training set and correlating student historical information as features with their label as the real achievements [8]. This improves student achievement and increases persistence and graduation rates [9]. Furthermore, ML in conjunction with EDM provides periodic monitoring systems and improves the prediction of student achievement. However, there is a constraint to such algorithms, when an input is presented to ML algorithms in a continuous range, the accuracy of the models decreases. Such prediction algorithms are more effective with discrete data.

DL based models have considerably improved prediction performance in a variety of sectors, including health, business, agriculture, and educational data. DL model are categorized into different categories like Deep Neural Network (DNN), Recurrent Neural Network (RNN), Convolutional Neural Network (CNN), Q-learning etc. DL intends to model complicated representations in data by employing a multi-level architecture, most frequently neural networks, and non-linear transformations in its own algorithm [9]. For example, DL models focus on inferring knowledge from student achievement information in order to determine how students learn, how fast or slowly they adapt to new issues or subjects, and whether students effectively perform the challenges or activities. The outcomes of student prediction utilizing DL may enhance course effectiveness, grades, and future curriculum [10, 11]. When the expected failure rate is high, it may be due to an inadequate syllabus, which can be examined and improved.

A wide range of articles in the literature using ML and DL methods for student's prediction achievements have yielded promising solutions to improve their academic conduct and grade. So, the primary intention of this paper is to provide a comprehensive review of various ML and DL methods for improving the achievements of student's predictions. A comparative analysis is also presented to address the benefits and drawbacks of various models in order to suggest the future scope. The following sections have been constructed as follows: Section II discusses alternative models for monitoring and forecasting the student's achievements. Section III gives a comparison of the models. Section IV highlights the entire work and offers future research directions.

II. SURVEY ON MACHINE AND DEEP LEARNING-BASED STUDENT'S ACHIEVEMENTS PREDICTION

Chaplot et al. (2015) [12] used sentiment analysis to develop an ANN-based method for predicting the student achievement in MOOCs. Initially, information like students' names, classes, student sentiment, and study schedule were extracted from the provided dataset. Then, the lexicon-based technique was employed as the sentiment analysis which allows the course educator and his team to take the required steps to prevent student attrition during the course time. Finally, the ANN model was utilized to categorize the students based on their sentimental score preventing them from dropping out.

Xu et al. (2017) [13] developed a ML strategy for forecasting students' future achievements in their graduation programs by analyzing their recent and previous achievements. To determine which classes should be used to generate the structural predictors, a residual element model-based course clustering approach was implemented. An ensemble-based continuous forecasting structure was developed to include learners' increasing capabilities into the predictive operation. These data-driven strategies were utilized in conjunction with other educational techniques to evaluate students' achievements, providing important data for academic advisers to suggest further courses to students and implement pedagogical assistance measures.

Liao et al. (2019) [14] suggested an early-term detection algorithm based on SVM binary categorization to detect at-risk students. This algorithm evaluates student final exam results using clicker statistics acquired autonomously for instructors by utilizing the Peer Instruction pedagogy. A SVM binary classifier was used in this modeling technique to trace and determine results in the subsequent term. Finally, this model effectively identifies at-risk students at a earlier phase in the semester to allow for corrective actions.

Martin and Dominic (2019) [15] used an ML system to categorize students according to their preferred learning methods, designate each student in an appropriate learning style group, and provide the most effective supplementary resources. There were three distinct components to this model like the Learner, Domain and the Learner Recommender System. These three components would cooperate with one another to identify the learners and decide the learning route for providing the appropriate learning materials to the students.

Alabri et al. (2019) [16] introduced a rule-based methodology for mining students' chats in a customized e-Learning environment. This model is made up of four main actions. Initially, chat messages from a single collaboration tool or many tools were gathered. Following that, text mining was used as a pre-processing technique to filter the acquired data. The retrieved concepts and semantic relations from the pre-processed chat messages were then used to generate domain ontology. Finally, a collaborative filtering activity was executed to estimate the detection accuracy by identifying different learners' characteristics such as students' learning style and understanding level.

Qu et al. (2019) [17] employed a multi-task learning long short-term memory (LSTM) to identify student achievement and mastery of knowledge scores in Massive open online courses (MOOCs). This multi-task approach extracts temporal aspects such as solo temporal features, aggregating temporal features, and substantial features. Cross-entropy was used as the loss operation to predict students' overall performance and competence of every knowledge point. An LSTM-based attention mechanism (Att-Mec) includes a shared parameters layer, which eliminates over fitting concerns. This model integrates multi-task and thorough prediction with Att-Mec to obtain the multi-dimension knowledge for improving the prediction accuracy.

Qiu et al. (2019) [18] developed an dropout forecasting method using the CNN (DP-CNN) in order to decrease the student dropout issue in MOOCs. This methodology combines feature extraction and categorization into a single method by employing a data modification approach based on time window (DTTW) that adjusts actual apparent-time information based on various temporal frames and directly retrieves attributes to produce enhanced feature depiction. This approach first extracts temporal aspects from the given data and then analyses those features using sequence models such as the hidden Markov model (HMM) and the non-linear state space model. Finally, the CNN was used to directly analyze and forecast the clickstream data.

Liu et al. (2019) [19] proposed a DL model to enhance the prediction of student accomplishments using exercise-aware knowledge tracing. Initially, the Exercise-Enhanced RNN (EERNN) architecture investigated the practicing reports with the material of the associated activities for each student. In EERNN, an RNN model was applied to track every student's activities into an integrative vector, and a bidirectional LSTM (Bi-LSTM) was constructed to train the encoding of every activity based on its content. In addition, two implementations like EERNN with the Markov features and EERNN with the Att-Mec were designed to produce the final prediction. By merging the EERNN with the EKT framework, the integrated student's state vector was constructed to directly quantify the knowledge development on different knowledge concepts.

Suzan et al. (2021) [20] presented a ML approach for predicting the adaptability grade of students in online education. According to their degree of education, online and offline information were gathered. Students' adaptability grades have been predicted using ML models such as KNN, SVM, and RF. Then, the confusion matrix was constructed by the employed models using the test data in order to get reliable predicted results.

Guerrero-Roldán (2021) [21] designed a flexible model called Learning Intelligent System (LIS) to enhance the online learners achievements. This model incorporates an Early Warning System and tested in an online institution in order to boost student’s' achievements, decrease abandoned rates, and provide appropriate feedback to assist the student’s performances. Initially, instructors and educational institutions projected and communicated the learner's success rate. Then, the LIS system was developed to enhance the achievements of students. Finally, it was developed and evaluated in various real-world learning settings using an iterative cycle of plan-act-reflect, which improves prediction level.

Burhan et al. (2021) [22] proposed an Intelligent Teaching System (ITS) concept employing Bayesian Network (BN) for high schools in order to analyze the range of students' abilities, educate skills and information based on every student's potential level. This quantitative approach was utilized to create a quasi-experimental paradigm with a pre-test and post-test for a particular group, which intended to improve students' expertise. The specified topics were initially administered as a pre-test to ascertain the level of the students' proficiency. The subject's degree of comprehension was then determined by administering a learning treatment based on the ITS model. After the completion of the learning process, the students were given a post-test to determine the degree of comprehension of their knowledge after being treated by the ITS model. Finally, the BN with ITS provides the material suggestions and categorize students' ability levels using variables obtained from the test outcomes of student's ability level.

Khan et al. (2021) [23] developed an AI method for evaluating student performance and developing preventative actions. Initially, the academic record of students was used to compile the information. Then, data pre-processing and feature selection were performed to observe students achievements and inform instructors of those students whose forecasted performance was poor. The generated findings were then categorized using ML models to detect difficult students earlier in the semester. This result to obtain the sufficient time to instructor for remodeling with students and achieve a suitable outcome.

Aslam et al. (2021) [24] provided an enhanced DL model for predicting early student academic progress. This approach attempts to forecast students' grades in advance and identify the most influential elements that influence their performance. It also addresses the relationship and ranking of data set features utilizing the boruta feature selection algorithm. Boruta feature selection method utilizes RF classifier to determine the relationship between features and the target. By upgrading the DL model, the assessment matrix was designed to improve academic outcomes and increase overall performances.

Zhang et al. (2022) [25] presented ceramic art learning methodologies for modern students utilizing the DL framework. Using several DL models, an automated queries-answers (QA) system was developed, novel teaching strategies were examined, and the Internet was integrated with the automated QA platform to assist students in resolving difficulties presented throughout the learning process. The gathered queries were chosen and processed, and empirical parameters were assigned to several models for comparison testing. The concept facilitates not only the observation of novel educating activities by educators, but also the modification of learning plans by students in order to enhance their learning outcomes.

Qiu et al. (2022) [26] constructed a behavior categorization based E-learning achievements prediction (BCEP) frameworks. This predictive framework was developed using an E-learning Process-Behavior Classification (EPBC) paradigm. This model consists of four modules. Initially, data pre-processing comprises cleansing and normalizing an initial e-learning platform-obtained activity data. Then, feature selection was conducted on pre-processed e-learning activity records to acquire essential e-learning activities; (iii) feature integration categories core training behaviors based on specified criteria and generates a collection of behavior types and (iv) the method was trained using the various ML algorithms to develop an e-learning achievement classifier.

Baashar et al. (2022) [27] constructed a ML system to determine the postgraduate cumulative grade point average (CGPA) of students. Initially, the academic results of post-graduate students were gathered using a private university's official dataset. Then, a novel set of characteristics, such as promotion, curriculum and course structure, was utilized to determine the greatest significant determinants of student accomplishment. Next, the obtained student achievement data were analyzed using regression model to categories the students' CGPA points. Least Square Regression (LSR), Gaussian Process Regression (GPR), and Ensemble models were used to select the most accurate prediction model.

Gao et al. (2022) [28] designed CNN algorithm with obstructive series prospecting (OSP) to enhance MOOC educating platform customized recommendation performance. Based on learner’s course enrolment, completion status, and overall result, this technique shows the course-learning series as an OSP, where the unconstructive word suggests that students should not accept and perform the course-learning concept improperly. The structure of CNN was then used to detect the inherent characteristics of negative series structures for the purpose of description learning. A subject schedule was then offered to every learner using the convolutional series encoding model, which contained the learners utmost need in present time parameters and the modules were often mis- selected by students.

Gaftandzhieva et al. (2022) [29] designed a ML model to determine students' final scores based on their Moodle Learning Management System (LMS) activity and attendance at online lectures. Utilizing the single-point crossover approach, the data set was gathered and balanced. Several quantitative methods, including the chi-square test and regression analysis, were used to evaluate the relationship among academic accomplishments (grade) and event context. Lastly, ML approaches were used to forecast low-performing and high-performing students in order to increase academic performance.

Li et al. (2022) [30] introduced a DNN model to autonomously extract features from multi-source heterogeneous behavior data of students in order to identify their academic performance. This model employs LSTM networks to simulate the temporal properties of behavior data and a two-dimensional CNN (2DCNN) structure to capture the correlational features between distinct behaviors. Finally, fully connected layers were leveraged to produce the academic achievements result by concatenating the time-series features, correlative features, and biographical data of the students.

III. COMPARATIVE ANALYSIS

In this part, a comparative study is presented according to the benefits and drawbacks for student's achievements prediction using different ML and DL methods which are briefly studied in above section are illustrated below.

In [12], the developed approach achieves prediction accuracy of 77.4% and Analyzing the data collected from the Coursera MOOC, which consists of 3,000,000 student activity logs and over 5000 forum entries, yielded a false negative rate of 0.132. It strikes a reasonable balance between accuracy and false-negative rates. But, it was resulted in over fitting issues which was the major drawback.

For the experimental analysis in [13], an undergraduate learner's data information gathered over three years at UCLA was considered. This dataset includes 1169 anonymized ndergraduate students from two separate areas. This model takes into account variable course matrix rates (K); when K=5, the accuracy rate is 72%, and when K=20, the accuracy rate is 79%. It has a stronger impact on degree program curriculum design and education policy design. On the other hand, more parameters should be included to improve the accuracy rate.

According to [14], this model uses the dataset gathered from the Institutional Review Board to produce AUC ranges from 0.63 to 0.76 with a 95% confidence interval. Additionally, it was a lightweight model that could be accessed was free to access at anyplace and anytime. However, this model focuses only on smaller group of at-risk student's data.

The model of [15] applies 9 characteristics to the test data of one thousand students and achieves an accuracy rate and Mean absolute error of 0.99% and 0.095, respectively. Information on Registration Number, Name, Gender, Visual, Auditory, Read Comment, Kinesthetic, aggregate, and type will be considered. Additionally, it takes less time to train the data and produces accurate predictions. Less impressive student learning outcomes over a broader data sample, however, led to lower marks.

The data in [16] was collected from social media platforms with 278 annotations, and an overall knowledge level estimation result of 85% was used for the experimental evaluation. The technique's overall performance was satisfactory. This model was also adaptable in terms of determining learning style and estimating knowledge level. Nonetheless, this model was only tested on a smaller number of students.

By evaluating data from 1528 participants who want to take the C-Programming course; our model obtains an accuracy of 92.52% and a recall of 94.68% in [17]. This strategy was specifically designed for students' learning states in order to improve prediction outcomes. On the other hand, this model required more time to train the collected data.

The obtained dataset in [18] comprised of 39 courses information on the MOOC site XuetangX throughout a specific time line. Precision, recall, F1-Score, and AUC for this model are 84.52%, 84.93%, 84.21%, and 87.85%, respectively. This methodology effectively minimizes the complexity of dealing with the dropout prediction problem. Nonetheless, lesser performance was obtained as a result of the limited data sample.

For the experiment evaluation in [19], data was collected form online learning system which consists of 84,909 students and 15,045 exercises. The method achieves 0.81% of prediction Accuracy; 0.44 of Mean Absolute Error (MAE) 0.473 of Root Mean Square Error (RMSE) = 0.473 and 0.80% of AUC for predicting student achievements. This method was scalable and accurate prediction level for massively large datasets. On the other hand, this model results in higher computational time issues.

In [20], 1205 data has been collected online and offline survey with 14 attributes for the model's experimental analysis. The performance of SVM, KNN and RF was resulted with 66.80%, 76.34% and 89.63% respectively. This model provides an accurate prediction and higher training speed. However, more features required to increase the prediction efficiency.

The dataset for the performance analysis was gathered from online learners' profile information for the experimental study in [21]. This model obtains 91.5% accuracy rate, 83.4% true positive rate (TPR), and 94.34% true negative rate (TNR) after evaluating the provided dataset. This model has a greater success rate for learners than other learning models. However, this model achieves lower performance on larger data sample.

The experimental sample in [22] comprised of 69 learners' from SMK Negeri 4 Gowa and SMK Negeri 1 Gowa in South Sulawesi Province, Indonesia. This model achieves accuracy, precision, recall, and F1-Scores of 82.6%, 79.8%, 88.8%, and 84%, respectively. This model proved successful in improving skill competencies. However, the classification error was high.

Buraimi University College (BUC) data was collected for performance analysis in [23]. The training dataset contains 151 cases with 10 detection characteristics and one prediction class. The accuracy, F-Measure, and Mathew Correlation Coefficient of this model are 86%, 91%, and

63%, respectively. This methodology improves learning skills and yields satisfactory results. However, it model took large time to predict the struggling students.

Two data sets were employed [24] including a mathematics course with 395 records and a Portuguese language course with 695 records. Using the given dataset, this model obtains 96.4% and 93.2% accuracy, 99% and 94.9% precision for the Portuguese and mathematics course data sets, respectively. The computational complexity of this model is reduced. However, it causes over fitting concerns for prediction due to data imbalance.

For the objectives of the experiment, a Q&A dataset pre-training to ceramic art on the Internet with 300 multiple choice questions was used in [25]. This model has an accuracy of 84% and a mean reciprocal rank of 83%. It works well on long sequences learning strategy. However, the data required for this system was very low to improve the learning effect.

By evaluating the OULAD dataset, this model gets 97.9% of accuracy and 97.9% of F1-Score in [26]. This model achieves a high prediction effect while requiring less training time. However, this model has high error rate was possible due to e-learning behavior.

Annual achievements of students were estimated in [27] by projecting the final CGPAbased on six variables used for performance analysis. This model has a prediction error of 0.08 and an accuracy of 89%. This model has improved decision interpretation and a simple training approach. On the other hand, this method has high computational cost.

The information was acquired via the Coursetalk site, which has 500 students and 20 courses, according to [28]. This model's overall precision rate on the dataset analysis is 0.3914%, and its overall recall is 0.210%. Additionally, this model achieves a lower computing cost and higher forecast accuracy. However, this model had greater over fitting problems as a result.

The dataset in [29] contains information on 105 students who took the "Object Oriented Programming" course. This analysis helps this model to achieve an accuracy rating of 78%. Additionally, this approach worked well with all in-depth online learning resources. But the classification error of this approach was high.

The dataset in [30] was obtained from a Beijing institution and consists of 9000 students' daily behavior activity. This model achieves 81%, 84%, 77% and 79% of accuracy, precision, recall and F1-Score respectively. This model good scalability and versatility and easily adaptable to new behaviors knowledge. On the hand, high computational time was resulted due to fixed time period of the behavior data.

From the above comparative analysis, the article [12-30] is studied and it is concluded that the article [19] yields better prediction result for student's achievements. In the paper [19], the upgraded RNN model was designed for the estimation of student exercising statistics and activity content. By utilizing the Bi-LSTM, markov property, and the Att-Mec enables the observation of student achievements on subsequent exercises based on their knowledge conditions about different explicit principle. This article's architecture facilitates tracing the information of knowledge ideas included in every exercise. Moreover, this model works well on larger datasets by tracing the student's knowledge effectively to improve the prediction achievements.

IV. CONCLUSION

In this article, a comprehensive review on student achievements prediction using based on different ML and DL models has been presented. Predicting student achievements strives to provide high-quality education by improving their grade points, leading to a better career pathway. The student's achievements should be communicated to the class teacher ahead of time to reduce student dropout and improve their academic achievements. Educators have many obstacles, including classifying students, maintaining student's database and predicting their exam success. The EDM is widely used in educational sector data by the researchers to predict the student achievements. ML and DL are current popular methods utilized for assessing a student's academic achievement and improvisation. This paper conducted a comprehensive review of different ML and DL methods for student's prediction achievements according to their strengths and weaknesses and prediction efficiencies. Thus, this review can help academics to choose the most efficient and reliable predictive methods for identifying the students achievements. So, future work will focus on tracing and predicting the student achievements with advanced computation models based on student's knowledge states on academics, behavioural learning, and extracurricular activities.

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