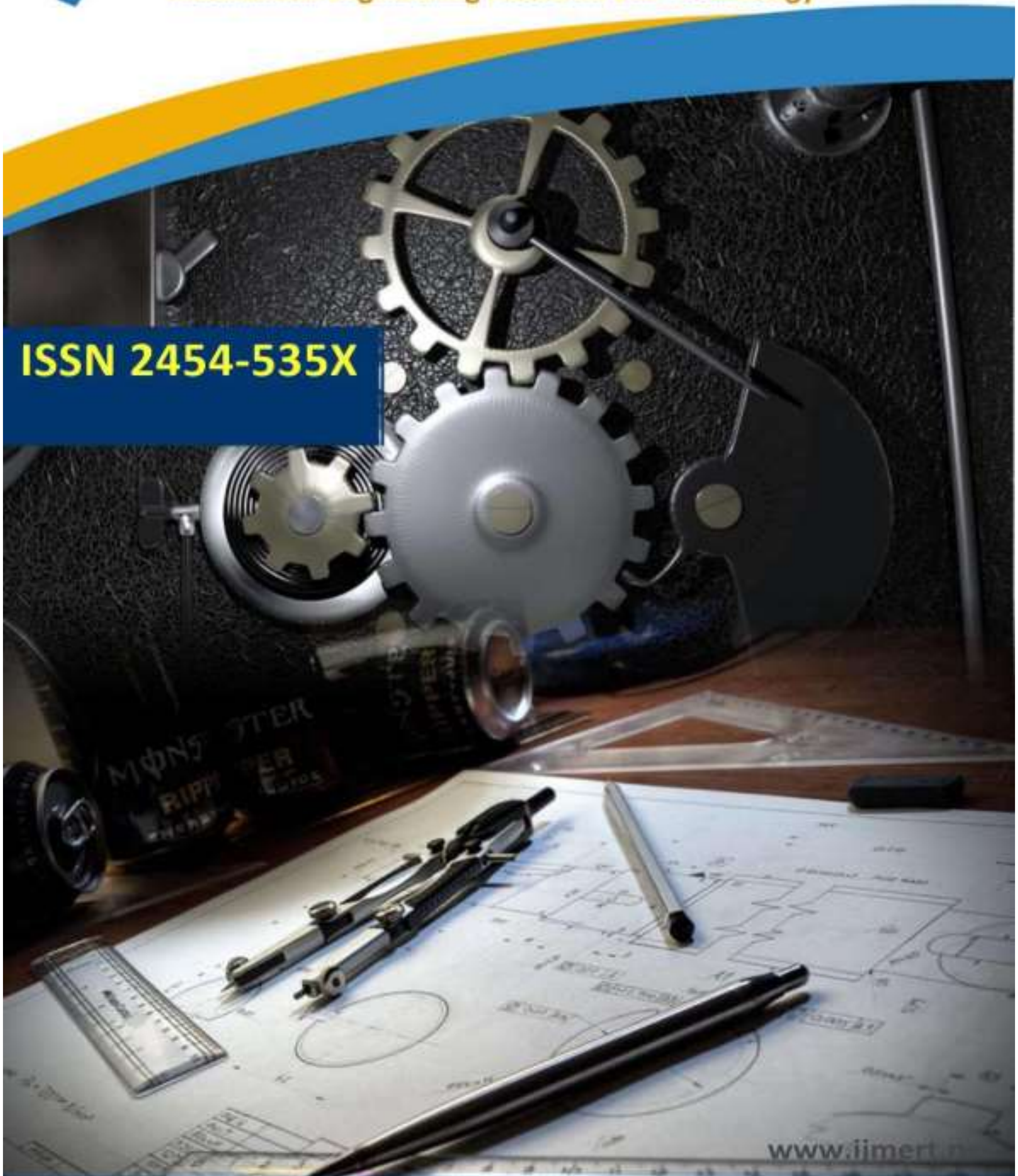
International Journal of
Mechanical Engineering Research and Technology

ISSN 2454-535X



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Int. J. Mech. Eng. Res. & Tech 2023

ISSN 2454 – 535X www.ijmert.com
Vol. 11, Issue.3, July 2023

Using Machine Learning To Predict Student Performance In Online Learning Environments

By

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Abstract

Prediction of academic performance of students is one of the major topics for universities and schools as it can be helpful to design the right mechanisms to avoid dropouts and improve academic results, among others. A lot of processes have been automated in usual activities of students to benefit them and manage big data gathered from software products for tech-based learning. Hence, processing and analyzing the same data properly can give a lot of vital insights to their knowledge and relation between students and their homework. This information can feed promising methods and algorithms for prediction of student performance.

This study is conducted to analyze various machine learning models used for predicting student's performance. This study presents an in-depth review of studies examining data of online learning environments to predict students' outcomes with machine learning techniques. This study will help identify the online course features used for prediction of learners' outcome, determine the outputs of prediction, strategies, and methodologies of feature extraction for prediction of performance, evaluation metrics, and challenges and limitations for analyzing the outcomes.

Keywords: *academic performance, student performance, online learning, machine learning algorithms, machine learning models, online learning environments*

Introduction

The way people used to learn has been revolutionized by online learning and education has never been so convenient and affordable to billions of people worldwide. Irrespective of rising interest and benefits of distance and online learning, universities and schools are highly concerned about students' retention and academic performance, along with low degree/certification completion rates and high dropout rates.

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Dropping out or failing an online program or course is usually an important parameter to assess course/program quality and allocate resources by institutional authorities.

Low certification and dropout rates are also a major risk factor to profitability, funding, and reputation of an institution (Arce et al, 2015). These outcomes have vast impact on well-being, self-esteem, odds of graduating, and employment of students (Arce et al., 2015; Larusson & White, 2014). Hence, it is important to find more efficient methods to forecast performance of students as early as possible for students, educators, and institutions to take necessary measures for improving online learning experiences of students and building intervention strategies to meet the needs of students. With rising interest of online learning and big data produced by students by interacting with online learning environments, several machine learning methods are proposed by researchers to predict students' performance and improve their learning outcomes.

1.1 Background

Machine learning is applied in different areas. For example, machine learning is used in search engines to create relations between webpages and search terms. Search engines scan the website's content and define the most important terms and words to define a specific webpage and use the same information to return the most relevant information to a given search term (Witten et al., 2016). Machine learning is also used in image recognition to identify specific objects like faces (Alpaydin, 2020). Initially, machine learning model analyzes images with a specific object. If enough images are given for processing, the algorithm can determine whether an image has object(Watt et al, 2020).

Additionally, machine learning can understand the products a customer might like. After analyzing the previous products, the system suggests new product that might be interesting to the customer (Witten et al, 2016). All such examples have similar principle. The data is processed by the system and this data can be identified, and then this knowledge is used to make future decisions. The rise in data has been effective to make such applications more effective. Machine learning is categorized into supervised and unsupervised learning as per the type of input. Input data belongs to a common class structure in supervised learning (Mitchell, 2007; Kumar et al, 2012). This input data is called training data. The algorithm is basically aimed to create a prediction model for predicting a property with other properties. After creating the model, it processes data with similar class structure to input data. There is no known class structure in input data and algorithm is aimed to reveal the data structure in unsupervised learning (Mitchell, 1997; Sugiyama, 2015).

Literature Reviews

Student retention is said to be a major concern in education. Though intervention strategies can improve retention rates, prior knowledge of students' performance for those programs (Yadav et al., 2012). This is where it is important to predict student performance. Using machine learning for performance prediction or dropout is a common pattern in academic studies. In online learning, dropout prediction is a very common concern in those studies because of both easy availability of data and high dropout rates (Kalles and Pierrakeas, 2006). Areas out of online learning are major contexts where performance or dropout predictions are widely used for research purposes. Purpose of these studies varies. Finding the best prediction approach is important in some studies. Some studies are aimed to determine the viability of machine learning to predict student performance ordropout.

A study was conducted at the "Eindhoven University of Technology" to determine the effectiveness of machine learning to predict students' dropout rate (Dekker et al., 2009). Building various prediction models with various machine learning approaches like Logit, BayesNet and CART are the basic methodology here. Then, they compared prediction outcomes of various models in terms of effectiveness. J48 classifier has successfully built the most efficient model. A group of researchers from three Indian universities have conducted a similar study. They analyzed the dataset of university students using various algorithms. They compared the recall value and precision later. They got most accurate results with the ADT decision tree algorithm (Yadav et al.,2012).

However, prediction of performance of students rather than dropouts is more relevant with this study. There are also some studies which have predicted students' performance. In "Hellenic Open University", a study was done to analyze the use of ML in distance education by Kalles & Pierrakeas (2006). They used decision trees and genetic algorithms to come up with a predictive model and compared the results for accuracy. The "Genetically Evolved Decision Trees (GATREE)" model has provided most accurate results.

Amrieh et al (2016) conducted a study on predicting performance at the "University of Jordan". They used a dataset of students from various nations. Along with separate machine learning models, they also used ensembled techniques and compared the results. They found best result with decision trees. Behavioral features were the other area focused by the researchers. They created a model by taking these features or without them. The prediction results were improved by including these behavioral features.

Cortez & Silva (2008) conducted a study on performance prediction at the "University of Minho, Portugal". The dataset had information on whether exam has been passed by the students in Portuguese language and Mathematics. They used ML models like random forest, decision trees, support vector machines, and neural networks and compared them for accuracy. They also compared a dataset with previous exam results and the one which didn't have past grades. Performance was improved by adding previous results.

2.1 Research Gap

E-learning has become a common form of education and a vital part of development of online education (Giannakos & Vlamos, 2013). E-learning has become a common phenomenon because of the impact of COVID-19 across the world because of its spatial flexibility, high temporal, rich education materials, and low learning curve. However, teachers cannot perceive learning status of the students easily in this mode (Qu et al., 2019). Hence, it raises concerns over the quality of online learning. Hence, this study is based on education, i.e., by predicting student performance. It also evaluates effectiveness of various machine learning approaches. Recall, precision, F-measure, etc. are some of the most common indicators to determine the effectiveness of machine learning models (Powers, 2020).

2.2 Research Question

- What are the effective machine learning models to predict students' performance in e-learning?

2.3 Research Objectives

- To predict student's performance in online learning with machine learning
- To evaluate various machine learning models for performance prediction

Research Methodology

The study of performance prediction provides a foundation to teachers for adjusting their approaches of teaching for students who may have trouble by predicting their performance on upcoming exams. It can help reduce the risk of failure during the course and improve the quality of online education. With a lot of empirical studies investigating the relation between learning performance and e-learning behavior, the e-learning behavior plays a vital role on learning outcome. Research community has focused a lot on prediction of learning performance on the basis of data on learning process in recent years. Teachers can modify their teaching strategies over time with the help of collection, analysis, and measurement of data on learning process to predict learning performance and start using early warning and supervision during the learning processes.

This study is qualitative in nature as around 70 recent studies have been selected related to various machine learning techniques to predict student performance (out of which 90% of the studies were published over the past two decades). The studies selected for this paper are published in various journals, conferences, and book chapters. The corresponding literature has been extracted from various online databases like IEEE, Springer, Science Direct, ACM Digital Library, iJET, Sage Journals, Wiley Online Library, Google Scholar, etc.

Exclusion criteria for this study includes papers without proper contribution or having lack of quality or clarity. Research papers without impact factor or not peer-reviewed have been excluded. The papers published in conferences not supported or published by Springer, IEEE, ACM or other reputed editorials or organizations were excluded as well.

Analysis of Study

There are various reasons researchers have learned students' learning behavior and characteristics, such as understanding learning styles of students, building students' profiles to provide personalized learning, and boosting educational outcomes. They have investigated different outcomes which can be grouped into completion and retention predictions as well as performance predictions as retention and success rate are important variables to assess and measure constantly in institutions. The performance prediction is done to predict the efficiency of students on completing the given course like grade value, grade category, failure/success, certificate, and risk prediction. A lot of researchers have studied "student dropout prediction" in this field.

4.1. Predicting Student's Performance in Online Learning

There are three performance measures examined in recent studies for prediction of student performance – certificate acquisition, grade prediction, and student at-risk prediction.

4.1.1. Certificate Acquisition

Certificate acquisition of student is one of the best measures to predict performance of students in professional courses. In this category, all the studies have predicted achievement of certificate of completion. Hence, achieving course completion and certificate prediction are the same. A "certificate prediction model" has been developed by Kórösi et al. (2018) on the basis of features associated with mouse behavior, learning behavior, text inputs, and video-watching attributes. Various classification models are used to implement the "gain-ratio feature selection" method and bagging and random forest are used to obtain the best performance.

In the same way, "Al-Shabandar et al. (2017)" have proposed hill climbing and random forest model to choose statistical features automatically from behavioral and demographical attributes of students. The "HarvardX (2014)" dataset was used to under-sample majority class to solve the problem related to class imbalance. A "deep neural network" model has been proposed by Imran et al (2019) for the prediction of certificate acquisition and student dropout on the basis of learner behavioral data.

An approach has been proposed by Liang et al. (2017) to provide personalized profile to boost e- learning to manage student behavior. They explored various classification models for prediction of whether a students will get a certificate on the basis of "Jaccard coefficient similarity" of learning behavior and student profiles. They tested the model over 5 to 7 weeks and obtained best results at 7 weeks with the SVM model. An approach has been proposed by Ruipérez-Valiente et al. (2017) which uses "statistical learning behavior" and progress features with various approaches of machine learning to predict whether a certificate will be given to a student or not.

4.1.2. Grades

It is yet another perspective on success for any student. A lot of publications have proposed prediction models for grades of students in different assessments like final-exam grades, course grades, assignments, or quizzes in the course. Researchers have tested regression and classification models to predict grades. Binary classification has been used in various studies for prediction of success and failure of students (Huang et al, 2020; Liu et al., 2017; Wan et al., 2019; Lemay & Doleck, 2020; Kokoç et al., 2021). Various machine learning models have been examined in mainstream studies with manually selected features of statistical learning behavior to predict grades of students. Xiao et al. (2018) used “classification and regression tree (CART)” model on learning behavior data and statistical demographic for the classification of final grades of students into multiple classes. Additionally, a machine learning model has been proposed by Villagrá- Arnedo et al. (2016) which used normalized behavior data for classification of students in 5 categories of grades. Here, “support vector machine (SVM)” model performed better than other baseline models.

4.1.3. Predicting Students-at-risk

Along with predicting performance, it is also important to identify students who might be failed in a course. Kondo et al (2017) identified at-risk and off-task students using “attendance attributes” and “learning interaction” of “SPOCs dataset”. Cano & Leonard (2019) proposed a “genetic programming (GP)” based “early warning system to address socioeconomic disadvantages of students. It extracts classification rules automatically on the basis of learning interaction, student demographic, registration, academic background, and socioeconomic and family data.

A transfer-based model has been proposed by Wan et al. (2019) to identify “at-risk students” on a class test which is held every week. They extracted behavioral and statistical features like % of total accurate answers and total time invested on video resources from data and combined the same with weights which were previously learned from former courses for prediction of “students-at- risk” and protecting them from failing in existing course. A model has been proposed by “El Aouifi et al (2021)” for prediction of final grade on the basis of interactions of students with pedagogical sequences of behaviors related to educational video like jump forward, play, pause, jump back, and end. They fathered sequences as features as per educational sequences. They used MLP and K-NN to achieve best results.

4.2. Machine Learning Models for Performance Prediction

A huge range of deep learning and machine learning techniques have been used by researchers for prediction of outcomes of e-learning from the data of students’ online interaction. In this field, the machine learning models are categorized into linear models like “logistic regression”, probabilistic (Naïve Bayes), tree-based models like “decision tree (DT)”, ensemble model like AdaBoost, linear model like “logistic regression (LR)”, instance-based model like “K-nearest neighbor (kNN)”, and rule-based models like “fuzzy logic” approaches. Additionally, some studies have used heuristic or optimization methods like K-star model for prediction of outcomes.

Recent studies have investigated deep learning-based models like “long short-term memory (LSTM)” and “convolutional neural networks (CNNs)” to predict e-learning outcomes. Table 1 lists all the models based on deep learning and machine learning used in earlier studies. Figure 1 illustrates the categories of predictive models in relevant literature. Deep learning models are used most commonly in recent studies. It is also worth considering that "deep learning" is the term which refers to models implementing neural network with over 3 layers. Hence, studies developing the "feed-forward neural network" with over 3 hidden layers are considered as deep learning.

Category	Machine Learning Models
Linear Models	"Logistic regression (LR), support vector machine (SVM), linear discriminant analysis (LDA), generalized linear model (GLM), lasso linear regression (LLG), boosted logistic regression"
"Probabilistic"	"Naive Bayes, Bayes network, Bayesian generalized linear (BGL), Bayesian belief networks"
"Tree-based models"	"Decision tree (DT), random forest (RF), Bayesian additive regression trees (BART)"
Instance-based	"k-nearest neighbors (kNN)"
Rule-Based	"Rule-based classifier (JRip), fuzzy set rules"
Neural network	"Multilayer perceptron(MLP) or artificial neural network (ANN)"
Deep neural network	"Recurrent neural network (RNN), gated recurrent unit (GRU), long short-term memory (LSTM), convolutional neural network (CNN), squeeze-and-excitation networks (SE-net)"

Table 1 – Machine learning models and their categories used in previous studies

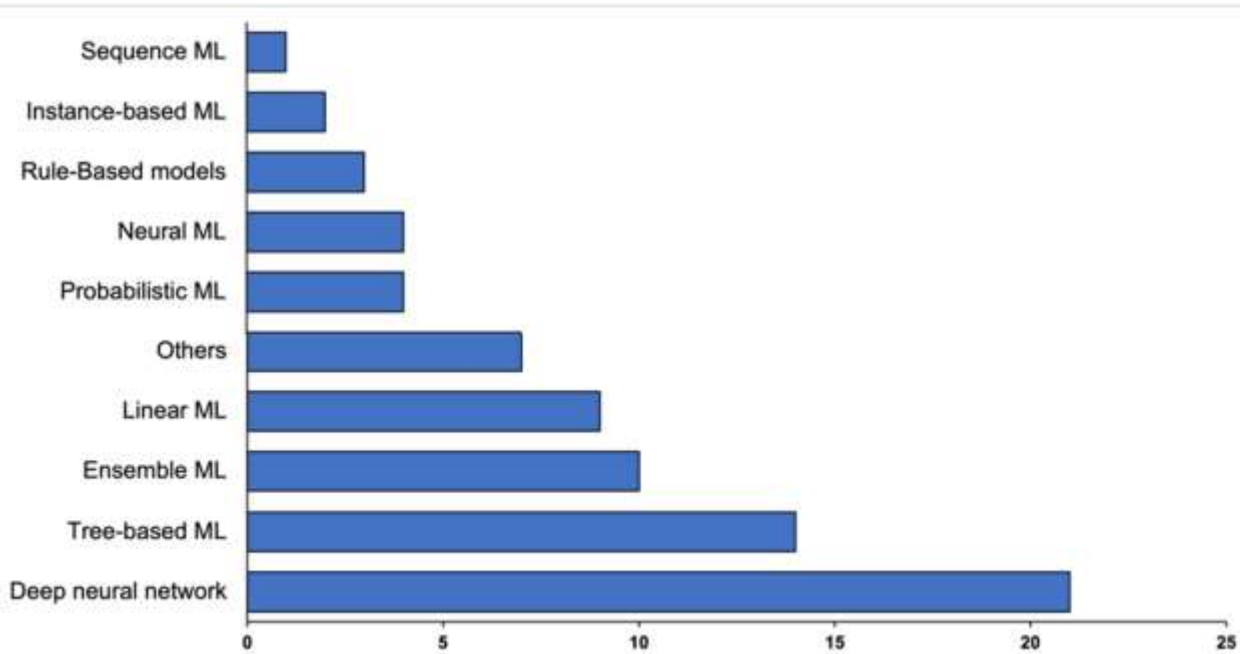

Figure 1 – Machine learning models used in previous studies
Source – Alhothali et al. (2022)

Recommendation systems gather data on user choices for a range of elements like websites, books, applications, travel destinations, e-learning, etc. In context of performance of students, it is possible to acquire explicit information or implicit information by gathering scores and monitoring their behavior like materials downloaded and visiting study materials (Bobadilla et al, 2013). Recommender systems consider various data sources for predictions. They manage factors like novelty, precision, stability, and dispersion.

4.2.1. Collaborative Filtering

It plays a vital role in prediction, even though it is used with other filtering methods like knowledge-based, content-based, or social approaches (Bobadilla et al, 2013). Just like decisions are based as per previous knowledge and experiences, collaborative filtering is used to perform prediction. Some studies have predicted various issues regarding performance of students with collaborative filtering. Hence, Bydžovská (2015) found similarities between students where their knowledge was represented as a range of grades from earlier courses.

4.2.2. "Artificial Neural Networks (ANN)"

ANN includes a range of entities which are highly connected internally like "Processing Elements". The function and structure of the network is inspired by human brain. Each element of processing is designed to work like its neuron, which accepts weighted inputs and responds by giving output (Adewale et al., 2018). ANN is applied in various prediction models, usually by taking in evaluation outcomes of students. The scores of tests were predicted with a feedforward ANN by taking in partial scores (Gedeon & Turner, 1993). The academic performance is predicted by the ANN which uses "Cumulative Grade Point Average" in 8th semester (Arsad & Buniyamin, 2013). Researchers compared two ANN models, i.e., "Generalized Regression Neural Network" and "Multilayer Perceptron" to identify the best prediction model for academic performance (Iyanda et al., 2018). Finally, ANN's potential for prediction of learning outcomes is compared to "multivariate LR model" in medical education (Dharmasaroja & Kingkaew, 2016).

Results

Application of techniques like collaborative filtering, machine learning, artificial neural network and recommender systems can consider different types of information for students' behavioral prediction, for example, tasks' grades and demographic characteristics. A study by the "Hellenic Open University" is a good point to start, where researchers applied various supervised and machine learning models to a specific dataset. In this study, it is observed that "Naïve Bayes" model was the best algorithm to predict both probability and performance of dropout of students (Kotsiantis et al., 2004).

Machine learning consists of techniques which enables computers to learn without human intervention (Navamani & Kannammal, 2015). Machine learning has helped in different applications like stock market analysis, medical diagnostics, classification of DNA sequence, robotics, games, and predictive analysis. Rastrollo-Guerrero et al. (2020) focused on predictive analysis where they implemented complex models for prediction. These approaches can be helpful to promote decision-making with relevant data. Supervised learning promotes models to reason from cases which are supplied externally to generate hypothesis which can make predictions on future events (Kotsiantis, 2007).

All in all, supervised learning is mainly aimed to come up with a clear distribution model of class labels in predictor features. Rule indication is an excellent supervised learning approach to make predictions which can reach 94% accuracy level when it comes to predict new student dropouts in nursing (Moseley & Mead, 2008). It is important to maintain caution with classification techniques and look for any unbalanced datasets as they can mislead when it comes to prediction. This way, Nandeshwar et al. (2011) proposed various improvements for prediction of student dropout like exploring a huge range of methods, attributes, and evaluating theory effectiveness and studying factors among non-dropout and dropout students.

Collaborative filtering approaches play a vital role in recommendation, even though they usually go hand in hand with other techniques like social, content-based and knowledge based (Bobadilla et al., 2013). Just like decisions made by humans are based on their knowledge and past experience, collaborative filtering acts just like the same for predictions. Some studies predicted various issues regarding the performance of students with collaborative filtering. Majority of studies discussed in this article use large data metrices for performance prediction of students. Hence, collaborative filtering was not that accurate in prediction when used in small sample sizes for the same purpose (Pero & Horváth, 2015).

Conclusion

On the basis of data collected here, supervised learning is the most common technique for student behavioral prediction as it provides reliable and accurate results. The SVM model was used most widely by the authors and has given most accurate results. Along with SVM, decision tree, naïve bayes, and random forests are widely used for good results. Collaborative filtering algorithms and recommender systems are widely used in this arena. It is worth noting that recommending activities and resources are more successful than prediction of student behavior. Neural networks are not used widely but they achieved great accuracy when it comes to predict performance of students. This study can help researchers and give them a lot of possibilities to apply machine learning for prediction of performance in e-learning and other platforms.

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