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Examining Student Psychology Profile Modeling Methods Based on Machine Learning Programme

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Abstract

Propose: This study aims to analyzed global perspective of the student profile has a global perspective model may be created.

Theoretical Framework: Computer-aided education (CAE) techniques used for various purposes, such as predicting failure, dropout, and academic achievement, have to be researched, and the prominent features employed. The Decision Tree is the most commonly used method in research studies. Personal and online behavioral aspects are taken into account when students are rated.

Methodology: An experiment was conducted to reinforce the survey results using the most recent machine learning techniques applied to the same datasets.

Findings: According to the survey results, the best outcomes were achieved using a decision tree.

Implications: ICT developments have led to an increase in online learning and the development of e-recommendation services, online recruiting, and other educational tools.

Value: Advances in Machine Learning make it possible to tailor services for students based on their specific requirements and preferences. Student profile modeling has come a long way in the previous four years thanks to advances in machine learning approaches, which we detail in this work.

Keywords: Machine Learning, Student Profile, Artificial Intelligence, Decision Tree

1. Introduction

Their profiles must capture their most important traits logically, completely, and practically to model students effectively. It's critical to understand the student's educational history and learning style. Student data, social media, e-learning platforms, and web forms can all be utilized to build student profiles. To recommend a course of study or advise the student on a future career route. Machine learning (ML) is one technology utilized for student profile modeling. Classification, forecasting, and decision-making are all areas in which they are frequently employed (Hamim et al., 2021). However, as artificial intelligence has progressed, other classifications have emerged, such as "deep," "transfer," and "reinforcement" learning, in addition to the more traditional "supervised," "unsupervised," and "semi-supervised." Predicting failure and dropping out of school

and providing guidance and making academic decisions were all made possible through the use of these strategies, which were implemented at multiple levels (Van den Besselaar & Leydesdorff, 2018).
We review recent research on student profile modeling using machine learning methodologies. Our research focuses on the student's features classification, machine learning approaches, and our study setting (Yang et al., 2021).
An outline for this article is as follows: Using machine learning to model student profiles is discussed in Section II. In Section III, we compare and statistically analyze the many studies that we looked at. Finally, we offer a case study in which we used various machine learning approaches to analyze two online datasets, and we conclude and speculate on the future.

2. Literature Review

There have been several research done on e-learning platforms aimed at adapting the training and personalizing the information to the needs of the learners. It was proposed by A. (Hessen et al., 2022) to use the Decision Tree (DT) technique to maximize the development of e-learning systems. Clustering and NN-based classification algorithms, as proposed by (Soleymanifard & Hamghalam, 2022), can be used to identify how pupils learn to adapt to the delivery of the resource. To classify their relationship, teachers' and students' learning styles can be categorized using J48, NBTree (NB in conjunction with DT), and NBTree and SMO (respectively) to classify their relationship (Harihar & Bhalke, 2020). It is possible to use student behavior to predict academic progress, according to (Bernacki et al., 2020); There were other EM and K-means models for student performance (Qiao et al., 2019) that were proposed (as well as SVM and Association Rules).

Much research has been done on academic failure and student dropouts. Researchers proposed using data-driven early-warning systems like Random Forest, Logistic Regression, and Artificial Neural Networks (Nafouanti et al., 2021). (ANN). The Random Forest TH algorithm was by far the best (threshold). (Han et al., 2020) used Bayesian networks and DT to prevent student failure. NB's prognosis was crucial. RTV-SVM and ANN are two more classifier models developed for failure prediction. Among the reasons students drop out, researchers cite finances, social standing, drug use, and motivation. Yuan & Yang (2019) used K-means clustering to characterize MOOC students. (Mduma et al., 2019) used an LR system to predict student dropouts. Researchers exploited big data to reduce dropout rates (Munshi & Alhindi, 2021). SVM won out over NB and K-NN. Participants in an online college program can be anticipated using J-Rip and J-48 decision trees (Yilmaz et al., 2019). Using random forests, high-risk high school pupils were discovered [19]. The research suggested looking for patterns in student dropout prediction and offering recommendations to reduce it using massive datasets (Yaacob et al., 2020). Several studies used ID3 DT to forecast student dropout rates. Early in the experiment, intelligible grammar-based genetic programming student dropout prediction models were produced (GBGP).

Recommendation systems use students' attributes to offer the best pedagogical materials or learning paths. The study's recommendations helped students, teachers, and administrators alike. With the C4.5 algorithm, teachers may better fit information to their students' learning styles. To improve e-learning platforms, LDA, LR, and Linear SVM (LSVM) were used (Mohammadi et al., 2021). Based on their academic experience, the RF algorithm helped pupils choose a subject to read.

Other studies investigated student achievement. According to Zhao & Zhou, K-means detect student-related characteristics (Zhao & Zhou, 2021). The three classifiers ANN, NB, and J48 predict student success in an online learning environment. They constructed an educational prediction model for the most effective classifiers, Multiple Layer Perceptron, DT (C4.5), and NB, and used CART to examine social networking's impact on academic performance. To uncover information based on association rules, categorization (J48), and EM clustering (to improve higher education quality). To increase module outcomes and student satisfaction, RF and SMO were proposed. Some strategies to help pupils improve their grades and future performance evaluations include Student qualities that directly affect student achievements are found using regression trees in traditional schooling. The following strategies can identify student concerns and difficulties to reduce educational issues. The best results came from NB. An analysis of student comments using DT(C4.5) and RF

comment data mining. The best method was RF. NN was used to measure students' first-year academic performance and the cognitive entrance criteria.
Students' performance in higher education was predicted using four DT algorithms, NB, and the variables "neighborhood" (household) and "school" (educational establishment). According to a new model, BFTree outperforms existing classifiers in predicting student success. Students can forecast their future performance and enhance it. SVM and Clustering (Enhanced K-Means) were combined in the CESVM-SPPS project, encouraging results. For example, the authors used K-means clustering to identify students who needed extra help early in the course. So that educators could build instructional programs to increase students' academic achievement, teachers needed to understand students' learning and psychological states. Based on student performance and the director's program, the NB was the most reliable technique for forecasting four-year university graduation rates.

Improvements to learning platforms were the topic of some studies. Students' input will be analyzed by utilizing BN to assist the administration in creating a better learning environment. To better understand how students feel about using digital technologies in their learning, the authors used association rules to examine how students' levels of comfort and involvement with technology varied. It was shown that SVM outperformed the other two machine learning algorithms (NB and K-NN) in comparing online learning evolution using extensive data to detect student learning patterns and guide course improvement.

3. Material and Methodology

Analytical Study

Criteria

To find practical solutions, the state-of-the-art requires a model of a typical student profile. Techniques are helpful in many situations. Clustering algorithms are widely used to find trends among students to forecast their profiles accurately. Here are some areas where we compare Table 1's criteria: what the paper hopes to achieve in a given year. It includes all variables that affect distance learning or e-learning.

Following the categorization (Makridakis et al., 2018), each paper's feature is assigned to a category of parts, and their performance is evaluated. Only the best results were chosen for performance, and the techniques are given in the bold text for easy reading.

Table 1. Criteria (Prepared by the authors, 2023)

Attribute	**Explanation**
Year	The year of publication
Context	Learner-centered (CL), traditional (TL), E-learning and conventional education
Objective	In addition to boosting academic accomplishment, adaptive learning can improve the learning environment and forecast failure and dropout..
Dataset	(Q or D) and the data's total size
Student features' categories	a person's personal, social, intellectual, online, and learning identities (LS)
Technique	MA, RF, K-means, FCM, EM, LR, AR, etc..
Performance metrics	Accuracy, Precision, Recall, and F-Score (together with AUC, average silhouette, and the area under the curve, respectively) are some of the more commonly used performance metrics.

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Table 2 compares four years of research on student profile modeling using machine learning to summarize the last part. Most papers are created to help students improve their grades, understand their study challenges, and learn new abilities. Another study's failure or cessation was challenging to determine in other studies. It is possible to predict a student's future outcomes and solve educational challenges using a variety of traits and attributes. Adaptive learning has many purposes, including improved student learning outcomes and a better learning environment. Questionnaires, databases (from the institution or acquired online), or both. Their sample sizes range from hundreds to thousands of individuals, rare.

We need to investigate the research objectives that have been addressed most frequently to understand academic problems better. As shown in Figure 1, numerous machine learning strategies have been investigated to improve student academic performance and explain why students fail and drop out. The second most prevalent setting is e-learning, with 25% of works mentioning both.

Machine learning relies heavily on high-quality data and a large enough quantity. Although LMS databases can be hundreds of gigabytes in size, university databases can be thousands of gigabytes. Our study found that the vast majority of researchers relied on academic databases or online e-learning systems, with only 27% using surveys and 13% using data from both.

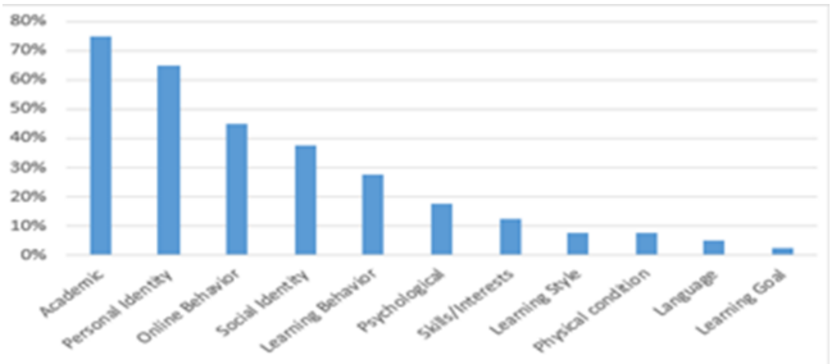

Fig. 1. Student features' categories distribution (Prepared by the authors, 2023)

Student features were re-searched, and their distribution is shown in Figure 2. With 75% of the total, academic data (grades, degree, etc.) is the most widely used, followed by personal identity characteristics (gender, age, nationality, etc.), online behavior (45%), and social identity (37.5%) (marriage status, educational and professional background of parents, address, etc.). Regardless of the study's goal, academic and personal data must be collected.
In Figure 3, for example, there is a correlation between student traits and context, with online behavior being necessary in e-learning while academic performance and social identity being important in traditional settings.

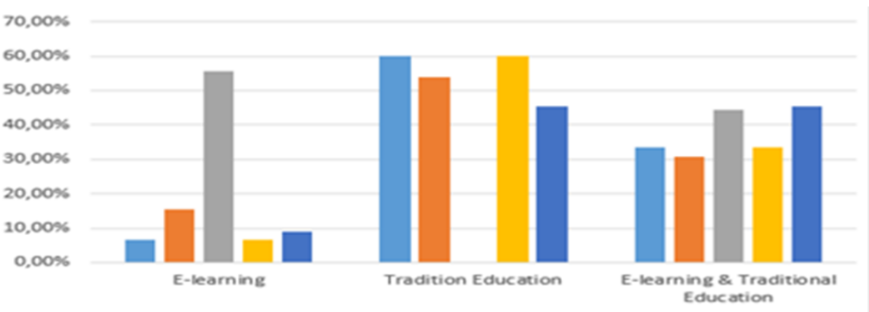

Fig. 2. Study-based student attribute categorization (Prepared by the authors, 2023)

Figure 4 shows that Decision Trees and their variants (63%) outnumber other techniques (a). (NB: 35%, NN: 35%, SVM: 23%). Based on the number of studies, decision trees (40%) surpass NB (13%), SVM (12%), and neural networks (10).

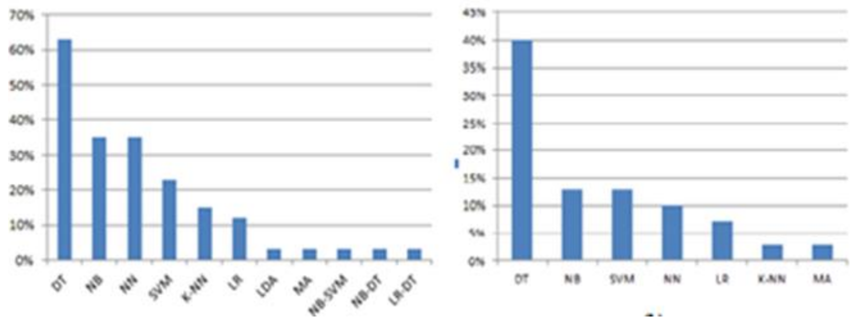

Fig.3. (a) Popular and (b) efficient classification algorithms (Prepared by the authors, 2023)

Experiments

However, this cannot be proved because the techniques were employed on different datasets. To test our findings, we used two datasets: TE and EL&TE.

History of applied machine learning

Making complex judgments is easier to examine and understand with a Decision Tree (DT) (Wen & Wu, 2021). The most frequent implementations are ID3, C4.5, C50, and CART. This is achieved through ID3 (Iterative Dichotomiser 3), which uses Shanon's entropy to build a decision tree (Feutrill & Roughan, 2021). It is one of C4.5's extensions to ID3 that addresses its flaws. Classification and Regression Trees are CART. Untagged instances are classified using K-NN, an old and straightforward pattern classification method. Support It seeks to reduce learning errors while enhancing class separation in high-dimensional data. In many disciplines, neural networks have proven helpful generalizations of mathematical models of organic nervous systems. It assesses the possibility of a new observation fitting into a specified grouping. A set of explanatory variables predicts/explains an explanatory variable (typically a binary) (usually quantitative).

Dataset

Both cases used traditional and e-learning. Formal Education (TE) contains 395 student records and 33 features for predicting student mathematics achievement. This dataset was chosen because it mimics traditional education and has many of the same feature categories we found throughout our analysis. This dataset (EL & TE) offers data about students' online behavior, such as visiting online resources, forums, etc. Personal identification, social identity, online conduct, learning behavior, and other essential traits from our study are included in this dataset.

4. Results and Discussion

To preserve the relevant qualities, we use a feature selection by information gain strategy, and we split our data (30% for testing, 70% for training) (figure 5). The chosen ML techniques were evaluated on two datasets (with the highest accuracy). It includes C4.5, J48, ID3, CART, NB, SVM, NN, LR, and K-NN.

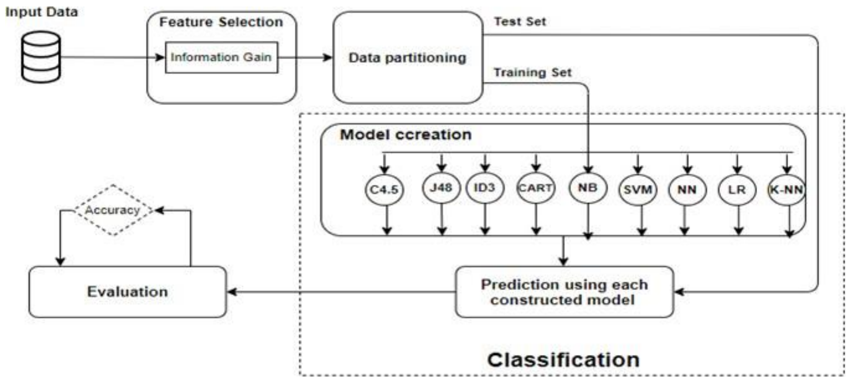

Fig. 4. Methods of comparison (Prepared by the authors, 2023)

Table 3 compares each approach's accuracy on each dataset. Table 3 reveals that Decision Tree algorithms (C4.5, J48, and CART) outperform SVM on the TE dataset (79.83 percent). On the EL&TE dataset, neural networks outperformed other approaches by 70% or more.

Technique		**C4.5**	**J48**	**ID3**	**CART**	**NB**	**SVM**	**NN**	**LR**	**K-NN**
Data										
A (%)	TE	95.08	94.23	89.99	94.23	84.91	80.84	87.45	88.26	82.37
	EL & TE	71.15	52.41	57.95	64.21	66.98	53.79	77.78	73.94	56.57

Table 3: Result 1. (Prepared by the authors, 2023)

However, our other dataset, which includes online data, showed that the neural network was the most efficient, coming in third place for the most commonly used algorithms and fourth place for the highest performing algorithms.

5. Conclusions

As well as describing possible career paths for students, this study also provides an introduction to machine learning-based approaches to creating a student profile. Decision Tree algorithms were the most widely used and influential research breakthroughs in this cross-sectional comparison. More than 70 percent of profile models incorporated academic information, followed by personal identity and online conduct, suggesting that merging academic and online behavior is essential. When used in traditional classroom settings, it's very effective with both datasets. We will offer a student profile model for prediction, categorization, adaptive learning, and e-recommendation.

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