Journal of Soft Computing and Computer Applications

Volume 2 | Issue 1 Article 1019

2025

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Recommended Citation
Rashid, Shatha Talib and Abdullah, Hasanen S. (2025) "Cutting-Edge Methods for Analyzing Student Behavior in Educational Settings: A Review," *Journal of Soft Computing and Computer Applications*: Vol. 2: Iss. 1, Article 1019.
DOI: https://doi.org/10.70403/3008-1084.1019

JOURNAL OF SOFT COMPUTING AND COMPUTER APPLICATIONS 2025;2:1019

REVIEW

Cutting-Edge Methods for Analyzing Student Behavior in Educational Settings: A Review

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ABSTRACT

The ability to predict students' performance in educational settings like schools and universities is crucial. A key objective of this effort is to increase academic outcomes and prevent dropout rates, among other benefits. Automating student activities, encouraged by information collected from any technology-based learning tool, has an important role in the process here. Those big quantities of information ought to be completely studied theoretically and processed for gaining worthy insights concerning a student's background as well as interacting with scientific missions, facilitating the development of advanced ways and algorithms to predict students' performance. The current study reviews several contemporary mechanisms to analyze how a student behaves, along with a specific concentration on mechanisms of video analysis. Twenty-six research papers published between 2018 and 2023 were under review. The review focused on the significance of video analysis in comprehending how a student behaves and presents insight into future tendencies in this regard. The outcomes propose that the incorporation of those mechanisms could improve educational results by providing data-driven backup for every process of decision-making.

Keywords: Prediction, Dropout, Students' performance, Artificial neural networks, Machine-learning, Deep-learning

1. Introduction

Videos generally contain many images, each representing a frame. The digital image is represented as matrices of values in those frames. In those matrices, each element represented an image element or pixel [1]. In this sense, a perception of motion may occur, especially when displaying sequences of still images quickly in videos [2]. A clip

Received 11 May 2024; revised 26 August 2024; accepted 28 April 2025.
Available online 14 June 2025

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https://doi.org/10.70403/3008-1084.1019

making includes the condensation of one or more scenes. Subsequently, scenes comprise a frame series captured through one movement of a camera [3].

The analysis of scenes achieves an identification of individuals as well as objects in live video sequences utilizing dynamic processes [4]. While artificial intelligence (AI) and computer vision have developed over recent years, there have been vibrant research domains that have significantly contributed to the development of every automated application. An analysis of videos comprises many fields [5]. The significance of using modern technology for enhancing visual data, comprehended and interpreted in a real-time scenario, is highlighted by the outstanding progress here [6].

Many study fields testing people's movement in a photo and footage can nearly be of relevance to the detection of people's activities. There have been many methods for identifying motion, and actions have repeatedly been related to a specific activity, shaping a powerful relationship between them. Furthermore, seeing a video does not just need the identification of an action, but also the interpretation of the situation. Except for the action and activity identification, providing videos with captions and explanations for the situation in a video is significant [7].

Student educational behavior could include engagement, attitude, discipline, behavioral issues, interactions, as well as the impact on performance and learning. Several changes have occurred in educational settings like schools and universities, with one noticeable shift being in student behavior. Student behavior in the classroom can significantly influence their performance on assessments. Educators use various strategies to manage their classrooms, and numerous studies have been conducted to identify the strengths and weaknesses of these methods. Analyzing student behavior through video analysis offers a unique opportunity to gather insights that are difficult to obtain through traditional methods. Video analysis, combined with other data-driven approaches, can play a pivotal role in enhancing educational practices. Current trends in this area suggest a growing interest in utilizing video analysis for these purposes [8].

The contribution of this study is to explore the most effective methods for analyzing student behavior, particularly through video analysis, and how these methods can be applied in various educational contexts. The analysis includes a full review of their benefits, limits, and potential future research directions. Also, it provides a comprehensive review of modern techniques, evaluating their advantages and limitations while highlighting their impact on learning environments. Additionally, the study identifies research gaps and offers insights for future advancements in student behavior analysis.

This study has the following structure: Deep Learning (DL) approaches and popular feature representation strategies for video scene analysis are covered in Section 2. Recent developments in scene comprehension, video captioning, and deep learning-based activity recognition are examined in Section 3. The main problems with Deep Scene Analysis (DSA) systems are discussed in Section 4, along with potential fixes. The review results are finally summed up in Section 5, which also outlines anticipated future research opportunities in the area of video-based student behavior analysis.

2. Methodology

This section is dedicated to discussing the utilization of a systematic approach that focuses on discovering, assessing, and integrating relevant research studies to ensure a complete and comprehensive literature review. The methodology here ensures superior source incorporation which backs up a strong understanding of the analysis of video-based behaviors of students.

Table 1. Search strategy.

No.	Search Term
1	Video analysis using machine learning
2	Video analysis using deep learning
3	Student behavior analysis
4	Video analysis
5	Educational data mining
6	predictive modeling
7	Educational video analysis
8	Students' Performance analysis
9	Student Behavior Analysis using ANN

2.1. Strategy of search

A comprehensive literature review was conducted by searching all databases. The primary emphasis was on the most contemporary articles, although some early research papers were also selected. To be specific, more than one particular keyword was utilized, with terms like “video analysis using ML”, “video analysis using deep learning”, “student behavior analysis”, “video analysis”, “educational data mining”, “predictive modeling” and “Student Behavior Analysis using ANN”, “Students' Performance analysis”, “educational video analysis”. These keywords were carefully selected to cover a broad range of research topics in educational predictive modeling and video-based behavior analysis. Their selection supported an in-depth examination of current methodologies, prevailing trends, and significant challenges in the field by enabling a thorough and accurate search for pertinent studies as shown in Table 1. This search strategy yielded relevant research papers.

2.2. Criteria of inclusion and exclusion

The research encompassing the evaluation of DL model performance in analyzing class scene videos, as well as comprehensive reviews or survey articles addressing the application of DL in scene analysis videos, were considered. The inclusion timeframe was set for studies published between 2018 and 2023.

The criteria of exclusion comprised every paper that reports outcomes exclusively over image data, these which explore Machine Learning (ML) without delving into DL or solely investigating every common approach, every paper of conference that is not being under index in Scopus as well as every abstract, grey literature, preprint, case report, non-English study, book chapter and each study irrelevant to the topic.

2.3. Search result and selection of studies

Initially, papers were selected based on the relevance of the titles to the topic under study. Therefore, every identified article's abstract and title have been estimated for relevance by every writer. The inclusion's determining as well as the exclusions were created and built upon the particular criteria. Committing to the method hereinbefore, there were comprehensive text reviews for each relevant study. Any differences related to the research's relationship were dealt with via consensus after comprehensive text revision and screening. This study aims to identify the best methods for analyzing student behavior and making recommendations for future research in this field.

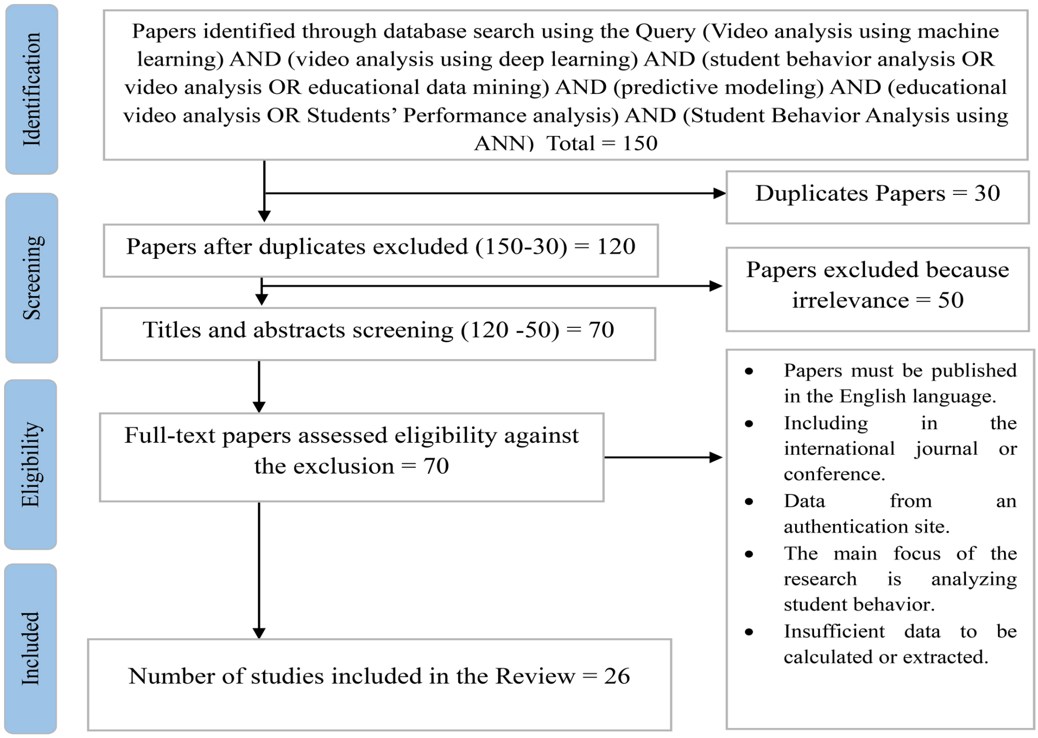

Fig. 1. Flow diagram of the search for eligible studies on analyzing student behavior.

Fig. 1 illustrates the flow diagram of the search process for identifying eligible studies on student behavior analysis.

3. Insights from reviewed studies: A detailed analysis

The application of ML strategies in academic contexts has attracted a lot of attention due to its ability to enhance several aspects of engagement analysis, intervention strategies, and scholar performance prediction [9]. This section provides the results of reviewing exclusive papers, with an emphasis on both supervised and unsupervised learning approaches. Furthermore, the use of Artificial Neural Networks (ANN) and characteristic representations in predictive analytics and engagement evaluation is investigated. Investigations can also be conducted on research that uses DL methodologies or, in other words, video data analysis to estimate any expected dropout expense or scholar engagement. A thorough theoretical study is presented here, concentrating on:

Any learning approach, supervised or unsupervised, is utilized to model student engagement as well as predict scientific performance.

- ANN's role as well as the mechanisms of representing features in predicting analysis.
- Each DL methodology, especially video-based analysis, is used to estimate all levels of students' engagement and identify any risk of dropout.
- The outcomes focus on the way DL-driven video analysis becomes a more significant tool to understand how students behave as well as improve every outcome of learning.

3.1. Machine learning studies in educational video analysis

Machine learning can be referred to as techniques which permit a PC or laptop to gain independent learning with no need for human programming [10]. It locates any application in more than one field, from medical diagnostics, doing an analysis for the stock market, classifying a sequence resembling DNA, games, robotics and mechanisms of predicting. The research here focuses on the mechanisms of predicting. ML helps build a more complex model that can be utilized to predict. Such a model is based on exhaustive records and provides valuable help to individuals by offering necessary information to finalize judgments [11]. In this sense, there are two main types of ML algorithms: supervised and unsupervised [12].

3.1.1. Supervised learning applications in educational performance prediction

Supervised Learning (SL) is a branch of ML that aims to provide algorithms that employ external instances to build general hypotheses, which can then be utilized to predict future events. Based on predictor characteristics, SL aims to construct a model of how class labels are distributed. SL's rule induction method demonstrated 94% accuracy in predicting the dropout of new nursing students based on 3978 records from 528 students [13]. Unbalanced datasets must be handled carefully when using classification methods since they can lead to predictions that are not correct. [14] Presented a thorough methodology for dropout prediction that looked at various learning strategies, and specific attributes, assessed theoretical efficacy, and analyzed variations between dropouts and non-dropouts. In the study, a variety of classifier algorithms were investigated, including One Rule, C4.5 Decision Tree Algorithm (C4.5), Adaptive Decision Trees (ADTrees), Naive Bayes (NB), Bayesian Networks (BN), and Radial Basis Networks (RBN) [15]. The use of multiple algorithms and comparison of their results is beneficial in this context, as demonstrated in [16]. Four LR, DT, ANN and SVM algorithms of classification were under comparison with three mechanisms of data balance: Under-Sampling, Over-Sampling, and SMOTE. The outcomes illustrated that SVM with SMOTE had the most proper accuracy (90.24%) in predicting retention.

In [17], multiple ML algorithms were evaluated for predicting how a fresh student acts, with NB emerging as the top performer in a web tool. In [18], the SVM was identified as the most effective among the four techniques examined to predict scientific performance. BNN was also utilized for predicting a student's grade averages previously on [19], alongside LR and SVM [20]. However, the accuracy of these prediction systems can be enhanced by carefully analyzing and implementing various algorithmic features [21]. To achieve this goal, preprocessing techniques and classification algorithms DT, NB and SVM were employed to enhance the prediction outcomes [22].

Another approach for predicting student performance is detailed in [23], where key performance indicators are derived from students' daily interactions with specific Moodle modules. In this context, Random Forests (RF) and SVM were employed to develop prediction models, with RF yielding the best results. Equally, another number of algorithms of SL studied every dataset theoretically in a direct way online for assessing student performance [24]. Additionally, e-learning software platforms have enabled the analysis and application of Data Mining (DM) and ML algorithms to inform decision-making and validate educational strategies [25].

Furthermore, various SL techniques were effectively used to predict student performance. For example, Bayesian Additive Regressive Trees (BART) were applied to forecast students' final grades by the sixth week [26]. Another model using SVM predicted the weekly likelihood of students falling into a performance category out of three: low, medium

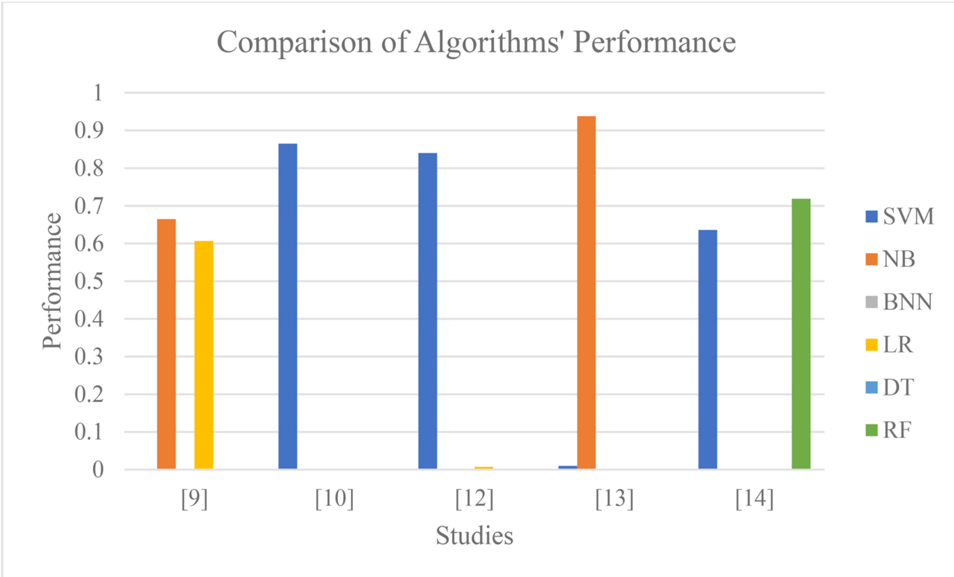

Fig. 2. Comparison of supervised learning algorithms' performance in term of accuracy.

or high [27]. LDA was also employed to predict student grades based on their descriptions of learning situations after each lesson [28]. Fig. 2 provides a comparison of the accuracy of different supervised learning algorithms.

The SL techniques used to forecast students' performance are described in Table 2. In terms of retention prediction, the accuracy of determining the optimal performance level to be SVM using Synthetic Minority Over-Sampling Technique (SMOTE) was as high as 90.24%. Other potential methods for assessing educational data assessment in relation to early performance prediction on e-learning platforms include RF, DT, and NB. These demonstrate how preprocessing methods and algorithm selection are sensitive to developments.

3.1.2. Unsupervised learning techniques in student performance assessment

Unsupervised Learning (UL), also referred to as class discovery, differs from SL in that it does not rely on a training dataset [29], thus eliminating the need for cross-validation [30]. Unlike most clustering algorithms that aim for an optimal criterion, UL does not guarantee the attainment of an optimal solution. A technique employing UL, particularly Sparse Auto-Encoder, was devised to construct a classification model for forecasting students' academic achievement by autonomously comprehending diverse representing tiers [31]. Additionally, clustering and classifying methods are used to assess the performance of every student [32]. Similarly, clustering in a recursive way was employed in [33] to categorize every student in a course of programming built upon their performance.

As shown in Table 3, these techniques demonstrate the importance of data segmentation and the success of education prediction. While clustering approaches can examine trends in student performance, auto encoders and other methods can develop more complicated models to better predict educational attainment in machine learning.

Table 2. SL techniques in educational performance prediction.

Ref. No.	Method Used	Results	Advantage	Dataset	Limitation
[13]	Rule Induction	Achieved 94% accuracy in predicting nursing student dropouts.	Thorough examination of ML techniques for predicting student achievement in higher education.	No systematic review dataset	No experimental results to support conclusions
[14]	C4.5, ADTrees, NB, RBN	Comprehensive analysis of dropout prediction with different learning strategies and attributes.	Finding trends in student retention.	Student retention data.	Insufficient facts to make generalizations.
[16]	SVM with SMOTE	Most superior accuracy (90.24%) to predict retention.	Enhanced evaluation of the performance of first-year students.	Data on large-scale institutional students from 2005 to 2011.	High processing costs and problems with data imbalance.
[17]	NB	Top performer for predicting student performance.	Forecasting distant learning students' performance	Information from the Hellenic Open University (354 and 28 occurrences).	Small datasets have lower accuracy; better results require at least 70 instances.
[18]	SVM	Found to be the most reliable indicator of academic achievement.	Comparing several prediction models.	2907 data points from 323 students over four semesters.	Computationally demanding; additional data is needed for the best training.
[19]	BBN	Used to forecast Grade Point Averages (GPAs) in advance.	Predicting student success based on past performance	Data from 22 semesters (3 per year), tracking student grades and progress.	Limited initial modeling variables; more elements are required.
[22]	SVM, DT, NB	Enhanced prediction outcomes using preprocessing methods.	Enhancing the ability of the prediction system for student outcomes.	A student dataset of 648 instances and 32 attributes.	Performance in minority classes may be impacted by an unbalanced dataset.
[23]	RF and SVM	For prediction models based on Moodle interactions, RF produced the best outcomes.	Predicting student performance in blended learning	Anonymized actual data from two academic years' worth of Moodle Learning Management System (LMS) site logs.	Less interpretable than SVM; maybe slower for huge datasets.

Table 2. Continued.

Ref. No.	Method Used	Results	Advantage	Dataset	Limitation
[25]	DM with ML	Made it possible for e-learning platforms to validate instructional methodologies.	Learning analytics for student performance prediction.	Performance of students in corporate education programs.	Depending on the quality of the data, it could oversimplify complex relationships.
[26]	BART	Predicted students' final grades by the sixth week.	Comparison of methods for undergraduate early warning systems.	Performance of students in corporate education programs.	In certain situations, certain techniques might not be accurate.
[27]	SVM	Weekly probability of high, medium, and low student performance categories.	Predicting academic performance using behavioral data.	Statistics data from a first-year university course (continuous evaluation, Learning Management System (LMS) Blackboard).	May necessitate considerable tweaking and processing power.
[28]	LDA	Predicted student grades based on their descriptions of learning situations.	Using past teachings to estimate student performance.	Information from successive classes.	Restricted to particular educational settings.

3.2. Utilizing artificial neural networks for student behavior analysis

ANN comprises interconnected processing elements, which are analogous to neurons in the nervous system [34]. These elements mimic neurons by processing weighted outcomes and producing consistent results [35].

ANN was utilized in numerous prediction endeavors, with a notable application being the assessment of student performance, as exemplified by the subsequent instances. In one instance, partial test scores from throughout a course were incorporated into a feedforward ANN to forecast test scores [36]. ANNs were also used to predict academic performance in the eighth semester using Cumulative Grade Point Averages (CGPA) [37]. An evaluation of two ANN models, multilayer perceptron and generalized regression neural network, was conducted in order to find out which model is the most effective at predicting students' academic performance. In the domain of medical education, ANNs and multivariate LR models were contrasted in terms of their predictive capabilities [38]. Additional information beyond simple evaluation results can enhance the predictive capabilities of ANNs. For instance, predictive models of student performance were developed using basic student information, as well as cognitive and non-cognitive measures, employing three different ANN models [39]. Another study employed an ANN to investigate the relevance between psychological factors and cognitive factors influencing scientific achievement. This method effectively classified students based on their expected performance levels [40]. Additionally, an Extreme Learning Machine (ELM), a variant of ANN, forecasted student performance by emphasizing the significance of subjects focusing on the final

Table 3. UL techniques in educational performance assessment.

Ref. No.	Method Used	Results	Advantage	Dataset	Limitation
[29]	Sparse Auto-Encoder.	Developed a classification model that learns several layers of representation to forecast academic success.	A thorough analysis of techniques for unsupervised learning.	General review in a number of fields.	No particular dataset because it's a review.
[32]	Hierarchical clustering and k-means.	Used clustering techniques for estimating student performance.	Educational data mining for student performance prediction.	Gathered from 100 Chinese junior high schools in the Hubei Province.	Computationally costly; for optimal performance, Graphics Processing Units (GPU)-based training is required.
[33]	Recursive clustering (k-Means, hierarchical clustering, classification Via clustering, and classification Via regression).	Simplicity, increased precision, and readability, but also drawbacks, such as the requirement for appropriate preprocessing, and computational complexity.	Utilizing hybrid approaches to forecast student performance	Information from the third semester of the Bachelor of Engineering (BE) (information technology) program at Punjab University's University Institute of Engineering and Technology (UIET).	This could make comparing forecasts over time more computationally challenging.

national examination [41]. Table 4 provides a summarization of studies utilizing ANNs for student behavior analysis.

The above table demonstrates the potential usefulness of ANNs in analyzing and forecasting academic performance. Yet, there are also a number of severe problems: a lack of data on the most specific factors, processing costs, and generalization of model results. If a full return on this technology is ever to be achieved, the models must be refined and fitted to a selection of scenarios using sufficient and different data.

3.3. Representation techniques for video analysis

Various methods for extracting features from videos are introduced. Some existing approaches consider temporal variations during the extraction of features, while others extract features separately for each frame. In such methodologies [42], temporal fluctuations can be addressed during the classification stage. Image representations are broadly classified into two main categories: global representations and local representations. Global representations are obtained in a top-down manner, involving the

Table 4. Summarization of studies utilizing ANN for student behavior analysis.

Ref. No.	Method	Dataset	Result	Advantage	Limitation
[37]	Feedforward ANN.	Raw data: lab exercises, assignments, mid-term quiz results.	Feedforward ANN reproduces the correct output in 94% of cases.	Efficient at classifying students into performance groups and forecasting academic achievement.	Reduces interpretability by failing to explicitly state the mathematical link between input and output variables.
[38]	ANN	Matriculation and Diploma student data compiled in Excel: ID, gender, CGPA, subject GP.	The ANN demonstrated effectiveness with Mean Square Error (MSE) of 0.0409 for Matriculation students in semester three and MSE of 0.0488 for Diploma students.	Demonstrates how early semester performance has a significant impact on overall academic success.	Exclusive to University Teknologi MARA (UiTM) students studying electrical engineering; has to be modified for other departments.
[39]	ANN	The dataset includes 864 university students, diverse in gender, age, and discipline, from three private universities in Argentina.	ANN models achieved 100% identification for top/lowest 33%; and 87%-100% precision for low/mid/high performance levels.	Manages intricate, nonlinear interactions; it is more accurate than conventional techniques (e.g., Discriminant Analysis (DA), SVM).	Careful parameter tweaking is necessary and it requires a lot of resources.
[40]	ANN with Extreme Learning Machine forecast-ing.	Data sourced from Sekolah Menengah Atas Negeri (SMAN) 1 Batuan Sumenep.	The model achieves a Root MSE (RMSE) value of 0.314.	Training is quicker than with traditional ANN techniques.	Data size affects RMSE; instability results from fewer data points. Data is limited to a single school year.

initial localization of the person in the frame through background subtraction, followed by the segmentation of the region of interest for feature representations. While these approaches are effective, they heavily depend on precise object localization and background subtraction, making them sensitive to changes in viewpoint, noise, and occlusions [43]. However, if these challenges are addressed, global representations generally demonstrate good performance [44]. An alternative method for local representation includes the combining of distinct local segments into a conclusive representation, which is termed as Bag-of-Features. However, Bag-of-Feature algorithms exhibit lower sensitivity to noise and partial occlusion, and they do not mandate background subtraction [45].

3.4. Deep learning in student engagement analysis using video data

DL is categorized under ML and AI [46], and it replicates the human learning process for acquiring specific types of knowledge. DL models are capable of learning to classify data and identify patterns across different forms of information, including photos, text, and audio [47]. Moreover, they are employed to automate tasks typically requiring human intelligence, such as image description and audio file transcription [48]. In the exploration of student engagement in their learning, [49] employed a comprehensive approach. The study involved live monitoring of students using a live stream, which combined videos related to faces, overlaying stares of students on-screen videos, and capturing their voices. To facilitate this, a deep learning-based dialogue classifier was developed, leveraging those three sources of information. The experimental outcomes indicated that every model of DL integrating the logs of game trace and every unit of actions related to face demonstrated the biggest level of predicting accuracy [50].

The research conducted by [51] focused on assessing the intensity of engagement by analyzing gaze and pose movements while participants viewed web-based course videos. Every writer developed a framework of DL which could integrate diverse every input feature. The evaluation centered on comparing the efficacy of various modalities within this framework. The empirical findings compellingly validated the efficiency of the proposed approach. Another significant contribution to the study of student engagement comes from the work of [52]. This research aimed to identify disengaged or distressed students, providing valuable insights for teachers to discern whether students are focusing on appropriate content or if there are specific concerns. The researchers developed a prototype system based on DL for automated eye gaze tracking, accurately estimating the focal point of each individual in the classroom [53]. The proposed method demonstrated a remarkable ability to predict gaze target locations with a precision significantly surpassing chance and outperforming other traditional baseline methods [54].

Furthermore, detecting undesirable student behaviors involves three distinct subtasks: predicting dropout rates, addressing issues related to student involvement in assessing, and learning social interactions. In the context of predicting every rate of dropout, [55] approached this task as a sequence labeling problem, employing temporal models. By leveraging DL techniques, they achieved notably superior performance compared to traditional ML approaches across every dropout definition: taking part in the last week, engagement's final week and taking part in the following one. While [56] stated dropout to be a challenge of binary classification.

Various DL architectures have been integrated in [57] as a step-by-step approach, choosing a number of attributes out of the dataset to be input. The findings indicated that the suggested model could accomplish similar performance for methods which depend on the engineering of features conducted by scholars. The research inducted in [58] tried to optimized a joint embedding function to represent both students and course elements in a unified space. The outcomes suggested that co-embeddings effectively captured the underlying factors contributing to dropout, surpassing other representations that were disjointed and not embedded. The authors in [59] raised a question regarding the predominant focus in predicting dropout on the exploration of various architectures of classification and representation. They compared clickstream features with the standard dropout prediction architecture accuracy under different training settings. This comparison aimed to provide insights into the balance between the classifier's practical deployment ability and accuracy.

Eventually, focuses on identifying dropout risks and personalizing student intervention based on individual student dropout probabilities. They constructed more than one model and generated more than dropout probability using a DL model. Using this data, instructors could customize and prioritize interventions for students at academic risk. Based on the findings, DL can be used to predict and design personalized interventions for Massive Open Online Courses (MOOC) datasets [60]. Table 5 provides an overview of state-of-the-art methods for behavior analysis.

Table 5 provides an overview of advanced ML and DL techniques for behavior analysis. Most of the research incorporates multiple data types, including text, video, motions, and facial expressions, to enhance the results based on their accuracy and reliability. The more diverse your data is, the better the prediction. DL possesses huge potential to improve instructional predictions and understanding of the behavior of the students. There are still drawbacks, such as the unavailability of ready-to-use data, the demand for high computing power, and accurate evaluation. These challenges may be critical to smart education; however, each technology could become significant for smart education, especially after overcoming hurdles.

4. Discussion

Predicting student dropout can be a decisive factor, especially when it comes to identifying and addressing unwanted behaviors in education. A lot of attention has been paid to the area here for the past few years, with research articles initially concentrating on the prediction of a dropout at specific times. Along with the assistance of the mechanisms of analyzing videos, scholars have achieved the identification of more than subtle disagreeing signs, gaining characteristics like patterns of stares from the videos of students. The predicting abilities made by a model of DL could be improved via the incorporation of features with many models, such as behavioral characteristics like seeking assistance or scientific dishonesty.

The algorithms of DL have the ability to be enhanced in more than one way for improving how effective they are in order to predict the behavior of students. First, it is essential to comprehend the early researches' DL algorithms' framework. Furthermore, every method of DL ought to be under configuration as well as training suitably for refining their representing and classifying abilities. As important progress was achieved, there is still space for development, especially in the optimization of those algorithms to analyze the data of time series. In addition, each DL model is robust via incorporating long-term and short-term dependencies into its internal structure.

To enable quicker exercising as well as developed learning of features, every algorithm of DL has to extend every application concerning real-time video processing. Moreover, any bigger dataset is necessary for analyzing every real-time scene, especially in the interpretation of scenes as well as the classifying of activities. For improving more generalizable predictive and accurate models, the efforts of researchers ought to be concentrated on gaining data sets reflecting real-world scenarios accurately. HCI and human surveillance can be instances of applications related to activity classifying as well as scene interpreting. Every algorithm of DL has to be highly enhanced for meeting every diverse requirement of the analyzing of real-time video scenes.

A review of the literature indicates that every algorithm of SL, especially SVM, has been excessively used in every educational setting to predict how students behave. SVM's usage, usually in combination with other mechanisms, illustrated high accuracy in the prediction of retention. More than the ensemble method proved to be effective in the prediction of

Table 5. Advanced ML and DL techniques for behavior analysis.

Ref. No.	Method	Dataset	Result	Advantage	Limitation
[53]	Long Short-Term Memory Networks (LSTMs) and Conditional Random Fields (CRFs).	Multimodal data streams of student interactions with a game-based learning environment.	LSTMs achieve 34.1% accuracy using game logs and facial expressions.	Deeper understanding of cognitive-affective states is provided, and intelligent tutoring systems' adaptability is improved.	Requires fine-grained data gathering (such as electrodermal activity and facial action units) and a great deal of preprocessing.
[57]	LSTM + OpenPose	Dataset for predicting EmotiW2018 engagement.	LSTM + OpenPose demonstrated effectiveness with MSE 0.0626.	Strong LSTM prediction accuracy that outperformed baseline results thanks to ensemble learning and data splitting.	Excellent LSTM performance that surpasses baseline findings thanks to ensemble learning and data splitting.
[58]	Convolutional Neural Network (CNN).	Video dataset of classroom observations.	ANN analyzes 2-D images, estimates gaze target with higher accuracy (0.62 %).	Increases the accuracy of dropout prediction by efficiently capturing temporal trends in student activity data.	Needs ongoing, time-series data for training, which is not always available or comprehensive.
[60]	Deep Neural Network (DNN) combines CNNs and Recurrent Neural Network (RNN).	Dataset from Knowledge Discovery and Data Mining (KDD) Cup 2015.	RNN achieves 87.42% accuracy, comparable to feature-based methods.	Characteristics from raw MOOC data automatically, saving human labor and enabling adaptation to new datasets.	It can take a lot of computer power to train the DL model.
[61]	DNN and LR	HarvardX MOOCs dataset.	The model achieved higher accuracy of 90.20%	DNN considerably improve prediction accuracy over LR, while proxy-label training demonstrates competitive accuracy.	Overestimation of model performance may result from too optimistic accuracy estimations when training and testing are done on the same track.

Table 5. Continued

Ref. No.	Method	Dataset	Result	Advantage	Limitation
[62]	DL, K-Nearest Neighbours (KNN), SVM, DT	Click-stream data from Canvas.	DL prediction accuracy: 0.954 - 0.984.	Uses DL to increase the accuracy of dropout prediction.	For model training, a lot of data and processing power could be needed.

how students perform. In comparison with SL, UL received little attention due to the lack of accuracy.

However, testing each probability for each UL method, such as clustering algorithms, could facilitate further research in this field. In connection with the accuracy, ANNs proved to have high effectiveness, more than every standard regression model in predicting how students perform. Further studies concerning ANNs, like generalized regression neural network models and multilayer perceptron, could improve predictive analytics for any educational setting.

Eventually, the review here emphasizes ML's important role, especially SL, in the prediction of how students behave as well as improving educational results. Future research ought to concentrate on enhancing each existing algorithm, as well as exploring every ensemble method and benefiting from the mechanisms of DL for developing models that are more efficient and accurate in predicting. Through these efforts, the academic well-being and success of any student, as well as educational success, can be supported.

5. Conclusion

The current study reviews more than one research paper that studies predicting how students behave educationally. By studying those papers theoretically, many conclusions were drawn. In accordance with the outcomes, SL grew as the prevalent way for the prediction of how students behave because of its capability to give accurate results. The algorithm of SVM appeared to be the most common by scholars and yielded precise predictions. With SVM, several other algorithms, such as DT, NBLR, ANN like generalized regression neural network and multilayer perceptron, along with each model of DL, had a resemblant purpose.

UL cannot be a favored mechanism among researchers due to its small accuracy in predicting how students behave. However, this serves to be a motivation for more study, giving a chance for enhancing those mechanisms to achieve impeccable outcomes. A comprehensive overview of each potential application of ML in predicting student performance and related considerations is provided by the review here. However, given the current high level of interest in this field, this problem is likely to be addressed by many researchers using various innovative ML tools in the future.

Acknowledgement

None.

Conflicts of interest

Regarding this manuscript publication, the authors declare no conflicts of interest.

Authors' contributions

The authors' contributions are as follows: Shatha Talib Rashid: conceptualization, methodology, analysis, and writing. Hasanen S. Abdullah: review and editing.

Data availability

There is no dataset has been used here.

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