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TOPICAL REVIEW

Role of Artificial Intelligence in Online Education: A Systematic Mapping Study

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ABSTRACT Artificial intelligence (AI) comprises various sub-fields, including machine learning (ML) and deep learning (DL) perform a key role in the transformation of many industries, including education. It changes traditional learning methods by using its Innovative techniques and applications. Using its applications, the teachers may keep track of each student's development, paying close attention to the areas in which they struggle. Many researchers are working with ML and DL to exploit its discoveries and insights. In education, traditional education methods (TEM) are the same for each student, which means each student is taught in the same way as ML and DL, making this process flexible and creative for solving complex problems and enhancing productivity. Nowadays, each institution adopts E-learning methods as the primary way of learning, especially during the pandemic. Despite this evolution of creativity, delivering quality education, making strategies for analyzing performance and future goals, and career counseling for students still pose challenges. The current study aims to offer a complete overview of the significance of ML approaches in online education. To accomplish this purpose, the study synthesizes information from multiple scientific papers that investigate (a) the methodology used to construct learning analysis tools, (b) the key data resources used, and (c) the scopeÂ of data sources now available. This systematic literature review (SLR) examines the research conducted between 1961 and 2022, focusing on various machine learning (ML) and deep learning (DL) techniques. Its aim is to provide insights into the applications of these techniques and offer optimal solutions to the research questions at hand. We are convinced that our complete assessment will be a dependable resource for the research group in ascertainment the best approach and information source for their unique needs. Moreover, our findings provide valuable insights on the subject matter that could aid the research community in their future endeavors in the related field.

INDEX TERMS Machine learning, systematic literature review, distance learning, covid-19 education policy, online educational methods, artificial intelligence.

I. INTRODUCTION

Nowadays, eLearning is considered the best choice for students and organizations due to its ease in routine life [1]. Modern open education models have made education more accessible to everyone interested in learning about any topic of popular interest [2]. These methods have also enhanced user trust and aided the spread of open education [3]. As a result, there is an increasing tendency toward the dissemination of open educational materials (OER), which enable academic transparency [4]. The benefits of artificial intelligence in education are being recognized by more

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and more schools, universities, and business entities [5]. In particular, machine learning may improve the effectiveness and fun of the educational process for both students and teachers. ML and DL algorithms make it easier to understand how students acquire knowledge and use it. The education level, interests, present development, and learning style of a student are all taken into consideration. As a result, each student may move forward at their own rate. The probability of leaving someone behind is substantially lower. The teachers may keep track of each student's development, paying close attention to the areas in which they struggle. Such a strategy increases retention and student engagement rates because learners connect with refined curricula and customized material that is more than standardized ones.

A. EXISTING REVIEWS ON ONLINE EDUCATION

Numerous studies have been undergone on online education for SLR and surveys. For example, in this study [6], the field of educational data mining (EDM) and the growth of DL applications to EDM were the main topics. With appropriate data anonymization, it has also addressed privacy concerns regarding datasets. Similarly, the study [7] has undergone a comprehensive review of different fields of machine learning. This assessment concentrated on a few of the fields and applications, including social media, network security, banking and finance, and the fields of education and healthcare. Cruz-Jesus et al. [8] represented an innovative strategy for predicting academic success using AI approaches. This study used RF, ANN, SVM, and LR classifiers on various groups of datasets and concluded that AI models perform best when compared to conventional methods. A comprehensive analysis of the literature on current teaching methods and e-learning strategies was presented in the study [9]. This study compares methods that employ machine learning, crowdsourcing, or even both applications to locate the relevant research that has already been done. According to this study [10], it is possible to measure emotions using the PLS-DA as an emotion classifier, and HRV as a biomarker that discovered that pleasure and melancholy are positively correlated with LF,pNN50, HF, SDNN, RMSSD, LF/HF ratio and pNN50.

B. SCOPE OF STUDY

As far as we know, earlier research has indicated the use of ML technologies to address online education difficulties, but no complete review has been undertaken to synthesize and reveal the role of machine learning and deep learning in online education. This work employs a systematic mapping methodology to investigate the evolution of ML and DL techniques used to analyze and investigate online education. This review's findings can help with the application of different machine learning and deep learning approaches for the following purposes:

- To predict pupil's performance may be at risk in academic institutions.
- To predict and determine students' dropout from ongoing classes.
- To evaluate static/dynamic based data for students' performance.

We propose the following research questions (RQs) to further our understanding of how ML and DL approaches are applied to online education and to further our research goal:

RQ1: *Which approaches are used for education analysis and development using AI?*
RQ2: *Which machine learning or deep learning classifier is frequently used?*
RQ3: *What is the primary feature engineering technique used in analyzing education?*
RQ4: *What are the major sources of data for educational analysis?*

C. CONTRIBUTIONS

The contribution of the study is as follows:

- This systematic study intends to provide academics with insights into the influence of ML and DL in the domain of online education over a 61-year period.
- 35 peer-reviewed articles about online education are thoroughly examined. The study contains an analysis of how our study findings might improve future studies on this subject, as well as a discussion of the key factors to consider when choosing a technique to monitor online education.
- Based on the selected pool of publications, our research also provides an overview of the principal data sources and their current availability status.

This study is organized into five sections. Section II provides a detailed account of the systematic methodology used for gathering, sorting, and eliminating irrelevant data. In Section III, the results are analyzed and interpreted in relation to each research question formulated in the study. Section IV presents the findings, followed by a discussion and recommendations. Lastly, the study concludes with Section VIII.

II. BACKGROUND

The literature on education utilizing ML and DL approaches is thoroughly reviewed as part of our research employing a systematic mapping methodology. We adhered to the rules of a systematic mapping study (SMS), a technique for impartially compiling and summarizing educational data about our RQs that offers readers a stronger comprehension of insights into the primary issue [11], [12], [13], [14], [15]. To do this, we used a three-step process:

- Planning: Publications from digital libraries are located, filtered, and verified depending on criteria for inclusion and exclusion.
- Execution: Journals are examined to weed out pointless studies.
- Synthesis: Sorting and analyzing the retrieved data in order to respond to the intended RQs.

TABLE 1. The online repositories utilized to identify relevant articles in this study.

No.	Digital Library	URL
1	ACM Digital Library	https://dl.acm.org/
2	IEEE Xplore	https://ieeexplore.ieee.org/
3	Science Direct	https://www.sciencedirect.com/
4	Scopus	https://www.scopus.com/
5	Web of Science	https://webofknowledge.com/
6	Springer	https://link.springer.com/

TABLE 2. Inclusion and exclusion criteria followed in this study.

No.	Inclusion criteria
1	Published prior before October 2022.
2	Written in English.
3	Available in digital format.
4	Proposed or used machine learning or deep learning.
No.	**Exclusion criteria**
1	Websites, leaflets, reviews, and survey literature.
2	The complete text is not accessible electronically.
3	Paper has not undergone a peer-review process..
4	Retracted papers and thesis papers.
5	Papers only rely on survey-based experiments.
6	A paper solely focused on online education.

A. PLANNING

The literature search of this study included publications from journals that were indexed in 7 prominent digital libraries, as presented in Table 1. These digital libraries were selected based on their strong scientific foundation and their acceptance and relevance for the study.

1) CRITERIA FOR INCLUSION AND EXCLUSION

Incorporating inclusion and exclusion criteria is crucial as it helps in reducing bias, restricting the scope of the search, identifying relevant publications, and eliminating studies that do not align with the study's objectives. The peer-reviewed articles that have been manually screened to fulfill these criteria aid reviewers in determining if the implemented or suggested AI strategies for education are acceptable for the research. We also used backward and forwarded snowballing with the first pool of publications. Table 2 outlines the inclusion and exclusion criteria utilized in this research. The beginning date was not restricted, but the end date was set to October 3, 2022, to ensure that only articles published before that date were included in the study. This approach helped to minimize bias, focus the search, and identify relevant publications while excluding studies that did not align with the research objectives.

2) SEARCH STRING

To ensure the search for relevant articles was comprehensive and precise, a test search was carried out on two prominent digital libraries, namely the Institute of Electrical and Electronics Engineers (IEEE) and the Association for Computing Machinery (ACM) [16], [17], [18]. The ACM was selected to determine the appropriate search string for generalizability purposes.

The search string was formulated using phrases related to the research questions (RQs) objectives, with the aim of identifying relevant phrases or synonyms used in articles on sentiment analysis of popular perceptions of education. The pilot search was conducted multiple times, with adjustments made to the search keywords as necessary. The search was limited to the title and abstract of articles to increase accuracy and avoid false positives, and only the metadata of publications was included in the search.

```
Title:(“online education” OR “online
learning" OR “online teaching" AND
“artificial intelligence” OR “machine
intelligence” OR "predict*" OR
"classif*" OR “artificial neural
network*” OR “machine learn*” OR
“deep learn*” OR “AI” OR “ML”
OR “DL”) AND Abstract:(“online
education” OR "online learning" OR
"online teaching" AND “artificial
intelligence” OR “machine
intelligence” OR "predict*" OR
"classif*" OR “artificial neural
network*” OR “machine learn*” OR
“deep learn*” OR “AI” OR “ML” OR
“DL”)
```

B. EXECUTION

This section discusses the procedure for processing and filtering the publications retrieved from digital library searches. Initially, a pool of 4,079 records was obtained, consisting of article information such as title, abstract, publication year, and digital library name. The digital library "Springer" had the highest number of publications, with 2,262 records. To filter out publications that did not meet our inclusion criteria, a four-phase quality assessment procedure was implemented. Figure 1 illustrates the number of articles filtered at each step. The quality assessment procedure involved a manual review by three authors, and it began with the removal of 186 retracted and duplicate publications in Stage (1). In Stage (2), the remaining 3,893 publications were screened based on their title and abstract, resulting in the exclusion of 3,760 publications that did not use machine learning or deep learning techniques or were not peer-reviewed. In Stage (3), the 28 publications that passed the inclusion and exclusion criteria were subjected to full-text scanning. Here, 105 publications were excluded, resulting in 28 publications for the snowball sampling in Stage (4). This sampling process led to the identification of 7 additional relevant publications. Overall, a total of 35 relevant publications were identified, including 28 publications in the first three phases and 7 in the snowball sampling.

C. SYNTHESIS

This section examined the data we extracted in this stage to answer the study questions offered (RQs). To begin, we categorized the original collection of papers based on their usage of machine learning and deep learning in online education to answer RQ1. Based on approach analysis,

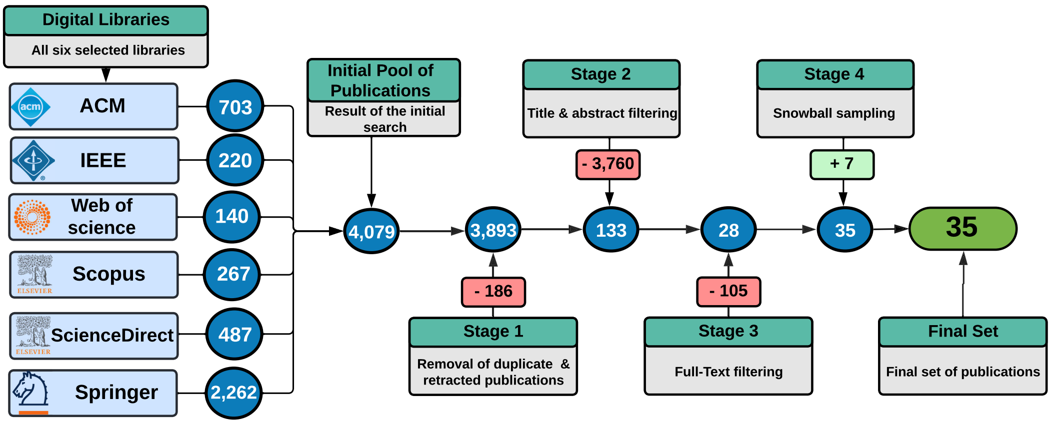

FIGURE 1. A summary of the number of articles received following the filtering procedure.

we divided our research into several areas, namely the Covid19 Pandemic, Education System, Learning Results, Student Satisfaction and Feedback, and others. We assigned the task of topic analysis research to the remaining articles that utilized topic extraction techniques such as the Latent Dirichlet Allocation (LDA) algorithm.

Moreover, we cataloged the publications by year and location of publication to provide an overview of their features. Furthermore, we examined the parameters of the dataset used in the chosen set of publications to address RQ2, which includes characteristics such as the source of data, the number of records, and the availability status.

Lastly, all data relating to the study topics gathered during the publication review process was peer-reviewed, and any disagreements were addressed through talks. To support cooperation efforts throughout the author-review process, we captured the manually extracted data in an Excel spreadsheet.

III. RESULTS

According to the analytical method described in Section II, the findings for the designed RQs are presented in this section.

A. RQ1: WHICH APPROACHES ARE USED FOR EDUCATION ANALYSIS AND DEVELOPMENT USING AI?

In order to respond to RQ1, we first present the analysis strategies used in the selected pool of research. Second, we offer details on the most popular feature extraction methods. Last but not least, we give an overview of the algorithms used in online education. We found four ways that are the most frequently used for education analysis through a review of the selected articles.

1) APPROACH (1): MACHINE LEARNING BASED APPROACH

Machine learning (ML) is quite valuable since it is a highly practical science that offers numerous answers to issues that arise in our daily lives [60]. This approach can help to access students' background, learning speed, feedback, aptitude, and cumulative performance based on various factors recommended by the teacher. Many researchers used this approach in their primary study for example [19] used an ML-based approach for mining students' opinions and TF-IDF for feature extraction.TF-IDF is a measure that determines the importance of certain keywords within specific documents by calculating the frequency of the words and comparing it to the frequency of those words in a larger corpus. [61]. Major machine learning models used in the reviewed study were described below.

- The Random Forest (RF) model is a tree-based ensemble method in which numerous decision trees collaborate to produce an accurate forecast. [62]. During training, freestanding sub-trees are produced. Training these trees involves bagging.
- SVM (Support Vector Machine) is a machine learning technique that is utilized in both classification and regression problems. [63]. The non-parametric approach for SVM regression is built on top of mathematical notation. At this stage, the kernel transformation enables the entry of needed data. The support vector machine uses linear functions to help resolve regression problems.
- Naive Bayes (NB) is a method of controlled learning [64] to solve classification problems. The Bayes theorem serves as the foundation for this strategy. An NB classifier can be trained quickly and widely since it only needs a limited amount of data points. A probabilistic classifier that forecasts the likelihood of an event occurring.
- As mentioned in [65] linear regression (LR) is a statistical approach often employed for regression analysis. This method clarifies the link between the independent factors, also known as covariates or predictors, and the dependent variables, which are the outcome variables.
- LR is used to forecast the outcome of a dependent variable it is based on prior data and the statistical technique of this approach, which is a subset of regression analysis, is frequently employed to address binary classification issues [66].

TABLE 3. List of papers.

ID	Title	Year	Ref.
PS1	Analysis of the Online Education System of Bangladesh during the COVID-19 Pandemic Based on NLP and Machine Learning: Problem and Prospect	2021	[19]
PS2	Machine Learning based model for predicting Stress Level in Online Education Due to Coronavirus Pandemic: A Case Study of Bangladeshi Students	2021	[20]
PS3	Overnight Transformation To Online Education Due to the COVID-19 Pandemic: Lessons Learned	2020	[21]
PS4	A survey assessing the health science students' perception towards online learning at a Saudi Higher Education Institution during COVID-19 pandemic	2022	[22]
PS5	A Comparative Study of Students Online Learning During Pandemic Using Machine Learning Model	2022	[23]
PS6	Deep Learning Dual Neural Networks in the Construction of Learning Models for Online Courses in Piano Education	2021	[24]
PS7	Students' Adaptability Level Prediction in Online Education using Machine Learning Approaches	2021	[25]
PS8	Data Mining Method of English Online Learning Behavior Based on Machine Learning Technology	2021	[26]
PS9	Unsupervised Learning Style Classification for Learning Path Generation in Online Education Platforms	2022	[27]
PS10	Prediction of learning outcomes with a machine learning algorithm based on online learning behavior data in blended courses	2022	[28]
PS11	A learning style classification approach based on a deep belief network for large-scale online education	2020	[29]
PS12	Sentimental Analysis on Online Education Using Machine Learning Models	2022	[30]
PS13	Impact of SARS-CoV-2 in Online Education, Predicting and Contrasting Mental Stress of Young Students: A Machine Learning Approach	2021	[31]
PS14	Predict Student's Feedback on Online Education by Applying Machine Learning Algorithms	2022	[32]
PS15	Real-time Attention Span Tracking in Online Education	2021	[33]
PS16	What predicts student satisfaction with MOOCs A gradient boosting trees supervised machine learning and sentiment analysis approach	2020	[34]
PS17	Sentiment Analysis on E-Learning Using Machine Learning Classifiers in Python	2021	[35]
PS18	Machine Learning in Education - A Survey of Current Research Trends	2018	[36]
PS19	Machine Learning Predictions for the Advancement of the Online Education in the Higher Education Institutions in Jordan	2021	[37]
PS20	Identifying At-Risk K-12 Students in Multimodal Online Environments: A Machine Learning Approach	2020	[38]
PS21	Using supervised machine learning on large-scale online forums to classify course-related Facebook messages in predicting learning achievement within the personal learning environment	2020	[39]
PS22	Understanding Student Engagement in Large-Scale Open Online Courses: A Machine Learning Facilitated Analysis of Student's Reflections in 18 Highly Rated MOOCs	2018	[40]
PS23	Using Machine Learning Algorithm to Predict Student Pass Rates In Online Education	2018	[41]
PS24	Gamification and Machine Learning Inspired Approach for Classroom Engagement and Learning	2021	[42]
PS25	A Machine Learning-Based Approach for Student Performance Evaluation in Educational Data Mining	2021	[43]
PS26	Assessing Intervention Timing in Computer-Based Education Using Machine Learning Algorithms	2014	[44]
PS27	An Online Education Data Classification Model Based on Tr MAdaBoost Algorithm	2019	[45]
PS28	Effects of the Disastrous Pandemic COVID-19 on Learning Styles, Activities and Mental Health of Young Indian Students - A Machine Learning Approach	2020	[46]
PS29	E-Learning Recommender System for Learners: A Machine Learning-based Approach	2019	[47]
PS30	English vocabulary online teaching based on machine learning recognition and target visual detection	2020	[48]
PS31	Application of wireless network and machine learning algorithm in entrepreneurship education of remote intelligent classroom	2021	[49]
PS32	Machine Learning Approach to Augment Performance of ISED Level-1 Students through their Online Learning Behaviour	2022	[50]
PS33	Design and analysis of an efficient machine learning-based hybrid recommendation system with enhanced density-based spatial clustering for digital e-learning applications	2021	[51]
PS34	Students Performance Prediction in Online Courses Using Machine Learning Algorithms	2020	[52]
PS35	Analysis of Emergency Remote Education in the COVID-19 Crisis Focused on the Perception of the Teachers	2021	[53]

- According to [67], K-Nearest Neighbor (KNN) is a fundamental machine learning (ML) model that may be used for regression and classification problems. This approach uses a distance function to classify fresh data based on its nearest neighbors.
- Decision Trees (DT) are tree-like structures that are used to develop models, as described in [68]. Because of their ease of use and short execution time, these frameworks are frequently used in the analysis of educational and medical data.
- As detailed in [69], Xtreme Gradient Boosting (XGBoost) is a fast and open-source version of the technique of the gradient-boosted tree, which is used for supervised learning. In order to create precise predictions about a target variable, this strategy integrates the predictions of numerous simpler, weaker models.
- LightGBM (LGBM) is a quick, distributed, high-performance gradient-boosting framework that may be used for many different machine learning applications, including classification and ranking. It is based on the decision tree method [70].

2) APPROACH (2): DEEP LEARNING BASED APPROACH

Deep learning (DL) is especially important in the context of sustainability education, where the ability to organize and arrange many forms of knowledge. Deep learning includes focusing on underlying significance. It also relates to the use of analytical abilities, cross-referencing, imaginative reconstruction, and free-thinking [71]. By using the DL approach the study [27] provides a rule-based system for data representation using an unsupervised learning style for classification. Data representations are learned from the inherent feature semantics when a clustering objective is used. Major Deep learning models used in the reviewed study were described below.

- Recurrent Neural Network (RNN) deals with modeling, time-dependent, and sequential data issues, such as stock market forecasting, machine translation, and text synthesis. RNN, however, is challenging to train because of the gradient issue. Vanishing gradients are a difficulty for RNNs [72].
- An Artificial Neural Network (ANN) is a computational model that is designed to mimic the structure and function of the human brain,Â comprises many processing components, accepts inputs, and produces results in accordance with predetermined activation functions [73].
- The Region-Based Convolutional Neural Network (R-CNN) is divided into two stages or phases. The first stage is aÂ subset of areas in an image that potentially contain an item are found. The item is categorized in each region in the second stage. R-CNN object detectors have the following uses: autonomous driving [74].
- Multi-Layer Perceptron classifier (MLP), or MLP classifier, is connected to a neural network by the term

TABLE 4. List of datasets used in reviewed articles.

ID	Study	Source of Info	Dataset	Dataset size	Dataset Availability
PS1	[19]	Google Form	Questionnaire	5,005	No
PS2	[20]	Google Form	Questionnaire	1,264	No
PS3	[21]	Case study	Interviewees	30	No
PS4	[22]	Google Docs	Questionnaire	2,553	No
PS5	[23]	Google Docs	Questionnaire	263	No
PS6	[24]	Audio Edited for Synchronous Tracks and Organization	Audio	1,513	Request Required
PS7	[25]	Survey	Questionnaire	1,205	No
PS8	[26]	Unknown	Feedback	25,417	No
PS9	[27]	Public opinion	MOOC	460,000	[54]
PS10	[28]	Offline Form	Questionnaire	1,627	No
PS11	[29]	StarC	Questionnaire	32,000	Request Required
PS12	[30]	Google Form	Questionnaire	1,001	No
PS13	[31]	Survey	Questionnaire	647	Request Required
PS14	[32]	Google Form	Questionnaire	170	No
PS15	[33]	Class camera	Real-Time	170	No
PS16	[34]	Class materials	Course	249	No
PS17	[35]	Twitter	Tweets	500	No
PS18	[36]	Google Scholar	Articles	67	No
PS19	[37]	Google Form	Poll	6,500	No
PS20	[38]	K-12 online learning platform	Courses	3,922	No
PS21	[39]	Facebook posts	Questionnaire	55,829	[55]
PS22	[40]	Course Talk	Posts and reviews	5,884	Open Source
PS23	[41]	Google Form	Stats	3,687	No
PS24	[42]	singular events	Multi dataset	63	Request Required
PS25	[43]	Kaggle	OULAD	7	[56]
PS26	[44]	Classroom	Questionnaire	35	No
PS27	[45]	Online LMS	LMS	150	No
PS28	[46]	Survey	Questionnaire	583	No
PS29	[47]	Google Form	Questionnaire	N/A	No
PS30	[48]	PASCAL Visual Object Classes	Images	9963	[57]
PS31	[49]	Live	Emoticon	40	No
PS32	[50]	Kaggle	Public domain dataset	N/A	[58]
PS33	[51]	GitHub	Book ratings	N/A	[59]
PS34	[52]	Kaggle	OULAD	N/A	[58]
PS35	[53]	Google Form	University of Vermont	33	Request Required

itself. MLP classifier, in contrast to other classification algorithms like Support Vectors or Naive Bayes Classifier, uses an underlying Neural Network to carry out the classification process [75].

- Gradient Boosting Machine (GBM) is one of the most often used forward learning ensemble techniques in machine learning. It is an effective method for creating predictive models for problems involving regression and classification [76].

3) APPROACH (3): STRUCTURAL EQUATION MODELING ANALYSIS BASED APPROACH

The quantitative research methodology known as structural equation modeling (SEM) can also use qualitative techniques. The causal associations between variables are displayed using SEM. The correlations shown by SEM correspond to the researchers' hypotheses. A researcher may be interested in the strength of the relationships between variables in a hypothesis, and SEM is a way to examine those variables [77]. The study [22] used the SEM analysis approach for gauging students' opinions regarding online education.

4) APPROACH (4): HYBRID APPROACH

The hybrid approach involves the combination of two or more approaches. It can either be ML and DL or it can be ML with SEM analysis-based approach. For example, the study [39] has used both approaches ML and DL, similarly [29] detect and categorized students' learning styles in a learning style categorization approach based on the deep belief network (DBN) is developed in the context of large-scale online education for recognizing distinct learning styles of students.

B. FINDINGS FOR RQ1

Out of a total of 35 publications in the pool, the machine learning-based approach is the most popular, accounting for 57% (n=20) of studies. Among these, 2 studies utilized a deep learning-based approach, while 6 studies used a combination of machine learning and deep learning, and 5 studies used SEM analysis. Hybrid studies only accounted for 2 publications. Overall, when combining the statistics, machine learning had the highest implementation rate at 65% (n=23) in the selected studies. This suggests that many researchers were interested in exploring the main topics discussed in this field.

TABLE 5. List of approaches, classification study purpose, and year in reviewed articles.

ID	Study	Year	Category	Study Purpose	Approach	Classification	Labels	Train Test Ratio
PS1	[19]	2021	COVID-19 pandemic	Mining students' opinions	ML	Multi-label	Network/internet, financial problems, device problems, lack of knowledge	80%,20%
PS2	[20]	2021	COVID-19 pandemic	Predicting students' stress levels	ML	Multi-label	Physical problems, financial problems, Mental problem, no problem	80%,20%
PS3	[21]	2020	COVID-19 pandemic	Proposed a framework for e-learning	-	-	Strategic, tactical, operational aspects,	-
PS4	[22]	2022	COVID-19 pandemic	Analysis of (OLAS) for gauging student's opinions	SEM analysis	Multi-label	BECS , BES, BI, EUT, LOS	-
PS5	[23]	2022	COVID-19 pandemic	How students will feel about online learning	ML	Multi-label	Positive, negative, neutral	70%,30%
PS6	[24]	2022	Education system	AI-based instructors for students	DNN	Multi-label	Standard score, command and interpret music memory	-
PS7	[25]	2021	Learning outcomes	Analysis for readers to understand online systems	ML&DL	Multi-label	Low adaptability, moderate adaptability, high adaptability	80%,20%
PS8	[26]	2021	Learning outcomes	E-learning for English based on ML&DM is suggested	ML	Multi-label	Method1, method2, method3	-
PS9	[27]	2022	Learning outcomes	Rule-based system provided data representations	DL	Multi-label	Behavioral object, behavior, style, occur, indicate	-
PS10	[28]	2022	Learning outcomes	A novel approach for classifying blended courses	ML	Multi-label	Cluster1, cluster2, cluster3	-
PS11	[29]	2020	Learning outcomes	Detect & categorize student's learning styles on a large scale	DBN	Multi-label	Cluster1, cluster2, cluster3	80%,20%
PS12	[30]	2022	Learning outcomes	Students satisfaction and feedback	ML	Binary	Positive, negative	-
PS13	[31]	2021	Students satisfaction and Feedback	Deals with numerous online learning environments	ML	Multi-label	Highly depressed, stressed, normal	-
PS14	[32]	2022	Students satisfaction and Feedback	Survey on predicting students' responses to online education	ML	Multi-label	Name, institution, age, feedback	-
PS15	[33]	2021	Others	Tracks student's level of concentration in real time	ML	Multi-label	Blink rate, emotions, eye gaze, background noise, body posture	-
PS16	[34]	2020	Students satisfaction and Feedback	Guided ML & sentiment analysis using gradient boosting trees	ML	Multi-label	Structure, video, instructor, content and resources, interaction	-
PS17	[35]	2021	Students satisfaction and Feedback	Sentiment analysis on e-learning has been used in this article	ML	Multi-label	Positive, negative, neutral	-
PS18	[36]	2018	Education system	Assess the potential for ML in the field of education	ML	Binary	Machine learning, education	-
PS19	[37]	2021	Education system	Identify and assess several online education principles in HEI	ML&DL	Multi-label	FM, EU, P, TS, IN, SM, EV	-
PS20	[38]	2020	Learning outcomes	Identifying at-risk students in K–12 multimodal online settings	ML	Multi-label	In-class, out-of-class, time-variant	80%,20%
PS21	[39]	2020	Others	Overcoming human coding procedure and quantitative behavior data	ML	Binary	M, SE	-
PS22	[40]	2018	Students satisfaction and Feedback	Teachers' characteristics are conducive to MOOC student engagement	ML	Binary	Positive, negative	-
PS23	[41]	2018	Learning outcomes	Feature model that forecasts student pass rates for online education	ML	Binary	Passed, failed	-
PS24	[42]	2021	Education system	New possibilities to scale up the enticement utilizing AI and ML	ML	Binary	Gamified, non-gamified	80%,20%
PS25	[43]	2021	Education system	Compares ML models using ANN and RF for student performance	DL	Binary	Pass, fail	80%,20%
PS26	[44]	2014	Learning outcomes	The effect of process-level data on ML prediction outcomes	ML	-	-	-
PS27	[45]	2019	Education system	Extracting useful data from massive online education data	ML	Multi-label	HBase, MapReduce, sqoop	26 categories, 6238 sets of data
PS28	[46]	2020	Students satisfaction and Feedback	Understand the daily lives, activities, learning styles and mental health of YIS	ML	Multi-label	ML Limited access, internet, bandwidth	-
PS29	[47]	2019	Education system	Proposed method undergone classification with ML in education	ML	Multi-label	-	70%,30%
PS30	[48]	2020	Education system	This study combines English vocabulary recognition needs of online education	DL	Binary	Detect, non-detect	-
PS31	[49]	2021	Education system	This study investigates the entrepreneurial model of distance intelligent classrooms	ML	Multi-label	S/ time, N/ time, T/ time	-
PS32	[50]	2022	Education system	Analysis of an ML technique to raise ISED	ML	Multi-label	Announcements view, discussion Level 1 students visited resources raised hands	-
PS33	[51]	2021	Others	Analysis of a new transduction SVM in education	ML	Multi-label	CF, MDHS, UPOD	-
PS34	[52]	2021	Others	Anticipate students' ultimate performance and evaluation marks	ML	Multi-label	Pass, fail, withdraw	-
PS35	[53]	2021	Others	Examine how UVM professors view the use of Microsoft Teams	ML	Multi-label	Gender, age, teaching experience, digital experience visited resources Raised hands	-

C. RQ2: WHICH MACHINE LEARNING OR DEEP LEARNING CLASSIFIER IS FREQUENTLY USED?

This section focuses on the most commonly used classifier in the underlying studies. A classifier is a type of supervised machine learning or deep learning algorithm that is typically utilized in learning-based and hybrid approaches, as described in [78]. In these approaches, a collection of labeled training data is used to infer a computational function, which is then evaluated using a collection of unlabeled testing samples and unseen test data. We provide a brief overview of the most frequently utilized algorithms in the research studies analyzed.

Table 7 shows that Decision Tree (DT) (n=12), Random Forest (RF) (n=11), and Support Vector Machine (SVM) (n=16) are the most frequently used machine learning classifiers, followed by various types of Naive Bayes (NB)

TABLE 6. Feature extraction techniques and evaluation parameters in reviewed articles.

ID	Study	Feature Extraction	Evaluation Parameters	Cross-validation	Algorithms	Results (Accuracy)
PS1	[19]	TF-IDF	Accuracy, Precision, recall, F1-Score	-	SVM, RF, MNB, LR	SVM (80%), RF(77%), MNB(77%), LR(78%)
PS2	[20]	-	Accuracy, Precision, recall, F1-Score	5 Fold	KNN, NB, DT, RF, XGB, SVM	KNN(63.24%), NB(67.05%), DT(73.91%), XGB(72.18%), SVM(68.12%)
PS3	[21]	-	-	-	-	-
PS4	[22]	Mean, Standard Deviation, Skewness, Kurtosis	-	-	BECS, BES, BI, EUT, Los	BECS(71%), BES(87%) BI(94%), EUT(86%), Los(92%)
PS5	[23]	-	Accuracy, Precision, recall, F1-Score	5 Fold	SVM, LR, RF, LGBM, DT	SVM(784%), LR(72%), RF(72%), LGBM(66.75%), DT(70.56%)
PS6	[24]	-	Frequency	-	DNN	DNN(94%)
PS7	[25]	-	Accuracy, Precision, recall, F1-Score	-	DT, RF, NB, SVM, KNN, ANN	DT(87.56%), RF(89.63%), NB(70.95%), SVM(66.80%), KNN(76.34%),ANN(82.99%) ,
PS8	[26]	-	-	-	DT	-
PS9	[27]	Heuristics1, Heuristics2, Heuristics3	BPL, NES, DBI	-	DUCK,DUCK/BPC, DUCK/LDS, DUCK/BPC/LDS	DUCK/BPC/LDS (97%)
PS10	[28]	Anova	Accuracy, Precision, recall, F1-Score	5 Fold	DT	Course I(38.2%), Course L(48.4%), Course A(42.3%), Course V(42.4%), Course H(74.4%)
PS11	[29]	-	-	-	DBNLS, BP, BN	DBNLS(84%), BP(72%), BN(72.73%)
PS12	[30]	EDA, TF-IDF	-	-	NB, SVM, LR, RF, DT	NB(84.50%), SVM(88.30%), LR(80.40%), RF(66.80%), DT(76.34%)
PS13	[31]	-	Accuracy, Sensitivity, Specificity	-	RF, KNN ,SVM, LR, NB, DT	RF(83.3%), KNN(55.18%), SVM(87.15%), LR(79.13%), NB(71%), DT(57.14%)
PS14	[32]	-	-	-	RF, LR, NB, DT	RF(80.39%), LR(78.43%), NB(82.35%), DT(74.50%)
PS15	[33]	-	-	-	SVM	SVM(84.6%)
PS16	[34]	-	F1 score	10 Fold	DT	DT(80%)
PS17	[35]	-	-	-	SVC, LR, NB	SVC(49%), LR(63%), NB(61%)
PS18	[36]	-	-	-	-	-
PS19	[37]	-	NARX	5-40 Fold	KNN, RNN, ANN	KNN(95%), RNN(92%), ANN(97.2%)
PS20	[38]	Periodic, Linguistic, Interaction, PCA	AUC, ROC, TPR, FPR	-	LR, DT, RF	LR(77%), DT(73%), RF(78%)
PS21	[39]	DF, IG, DTM	Accuracy, Sensitivity, Specificity	10 Fold	RF, SVM (Liner), SVM(Radical), ANN	RF(88%), SVM (Liner)(80%), SVM(Radical)(82%) , ANN(86%)
PS22	[40]	DF, IG, DTM	Accuracy, Precision, recall, F1-Score, Kappa	5 Fold	KNN, GBT, SVM, LR, NB	KNN(88%), GBT(90%), SVM(80%) LR(86%), NB(81%)
PS23	[41]	DF, IG, DTM	Accuracy, Precision, recall, F1-Score, Kappa	10 Fold	DT, SVM, DNN	DT(94%), SVM(93%), DNN(90%)
PS24	[42]	-	-	-	ANFIS, ANN, FS	DT(94.85%), SVM(91.77%), DNN(90.86%)
PS25 -	[43] -	IMD -	Accuracy, Precision, recall, F1-Score, ROC curve	- -	ANN, RF -	ANN(91.06%), RF(81.35%)
PS26	[44]	Prediction accuracy	- Simplicity	Linear Regression,	- LR, SVM, ANN	LR(55.14±0.56a), SVM(50.00±0.56b), ANN(Ann50.86±1.44ab)
PS27	[45]	-	-	-	Real, Gentle, Modest, Adaboost, TrMAdaBoost	Real(70%), Gentle(90%), Modest(60%), TrMAdaBoost(100%)
PS28	[46]	-	-	-	-	-
PS29	[47]	-	-	-	SVM, NB, KNN, RF	SVM(42%), NB(66%), KNN(63%), RF(98.98%)
PS30	[48]	-	-	-	R-CNN, RPN	-
PS31	[49]	-	-	-	method1, method2	method1(64.6%), method2(97.8%)
PS32	[50]	Age, Name	-	-	KNN, LR, SVM, DT	KNN(99%), LR(60%), SVM(69%), DT(80%)
PS33	[51]	-	Accuracy, Precision, recall, MAE, Ranking Score	-	EC, MTSVM	EC(82%), MTSVM(98%)
PS34	[52]	-	Root Mean Square Error (RMSE), AUC	10 Fold Nnet	MLP, RF, Rpart, GBM,	MLP(85.8%), RF(85.4%), Rpart(86.2%), GBM(86.8%), Nnet(85.4%)
PS35	[53]	Statistical Analysis	Accuracy, Precision, recall	-	UVM, ERT	UVM(80%), ERT(100%)

(n=9) such as Gaussian NB (GNB) and Multinomial NB (MNB). Logistic Regression (LR) (n=10) and K-Nearest Neighbor (KNN) (n=6) are also commonly selected by researchers, ranking third in usage. Figure 2 provides a visual representation of the distribution of machine-learning sentiment classifiers utilized in the selected pool of publications.

Table 7 shows that the most frequently used deep learning classifiers are Artificial Neural Networks (ANN) (n=6), Deep Neural Networks (DNN) (n=3), Recurrent Neural Networks (RNN) (n=1), Region-Based Convolutional Neural Network (R-CNN) (n=1), Region Proposal Network (RPN) (n=1), Back Propagation (BP) (n=1), and Batch Normalization (BN) (n=1), which are commonly selected by researchers. Figure 3 illustrates the distribution of machine learning classifiers, while Figure 2 illustrates the distribution of deep learning classifiers utilized in the selected pool of publications.

From the publications (n = 35), the best-performing machine learning algorithms are DT [20], [25], [41], [42], [50], SVM [19], [24], [33], [39], [41], [43] and LR [19], [30],

TABLE 7. Summary of approaches used in education analysis.

ID	Study	Features	Approach	ML	DL	SEM	Hybrid
PS1	[19]	TF-IDF	ML	SVM, RF, MNB, LR	-	NO	-
PS2	[20]	-	ML	KNN, NB, DT, RF, XGB, SVM	-	NO	-
PS3	[21]	-	SEM	-	-	YES	-
PS4	[22]	-	SEM	-	-	YES	-
PS5	[23]	-	ML	SVM, LR, RF,LGBM, DT	-	NO	-
PS6	[24]	-	DL	-	DNN	NO	-
PS7	[25]	-	ML & DL	DT, RF, NB, SVM,KNN	ANN	NO	-
PS8	[26]	-	ML	DT	-	NO	-
PS9	[27]	Heuristics1, Heuristics2, Heuristics3	Hybrid	K-means	-	NO	DUCK, DUCK/BPC DUCK/LDS, DUCK/BPC/LDS
PS10	[28]	Anova	ML	DT,RF	-		-
PS11	[29]	Anova	DL	-	BP, BN	NO	DBNLS
PS12	[30]	EDA, TF-IDF	ML	NB, SVM, LR, RF, DT	-	NO	-
PS13	[31]	-	ML	RF, KNN ,SVM, LR, NB, DT	-	NO	-
PS14	[32]	-	ML	RF, LR, NB, DT	-	NO	-
PS15	[33]	-	ML	SVM	-	NO	-
PS16	[34]	-	ML	DT	-	NO	-
PS17	[35]	-	ML	SVC, LR, NB	-	NO	-
PS19	[37]	-	ML & DL	KNN	RNN ANN	NO	-
PS20	[38]	Periodic, Linguistic	ML	LR, DT, RF	-	NO	-
PS21	[39]	DF, IG, DTM	ML & DL	RF, SVM (Liner), SVM(Radical)	ANN	NO	-
PS22	[40]	DF, IG, DTM	ML	KNN, GBT, SVM, LR, NB	-	NO	-
PS23	[41]	DF, IG, DTM	ML & DL	DT, SVM	DNN	NO	-
PS24	[42]	-	ML & DL	DT,SVM	DNN,ANFIS, ANN, FS	NO	-
PS25	[43]	IMD	ML & DL	RF	ANN	NO	-
PS26	[44]	-	ML & DL	Linear Regression, LR, SVM	ANN	NO	-
PS27	[45]	-	ML	Real, Gentle, Modest, Adaboost, TrMAdaBoost	-	NO	-
PS28	[46]	-	ML	-	-	NO	-
PS29	[47]	-	ML	SVM, NB, KNN, RF	-	NO	-
PS30	[48]	-	DL	-	R-CNN, RPN	NO	-
PS31	[49]	-	SEM	-	-	NO	method1, method2
PS32	[50]	Age, Name	ML	KNN, LR, SVM, DT	-	NO	-
PS33	[51]	-	Hybrid	-	-	NO	EC, MTSVM
PS34	[52]	-	Hybrid	MLP, RF, GBM	-	NO	Rpart,Nnet
PS35	[53]	Statistical Analysis	SEM	-	-	NO	UVM, ERT

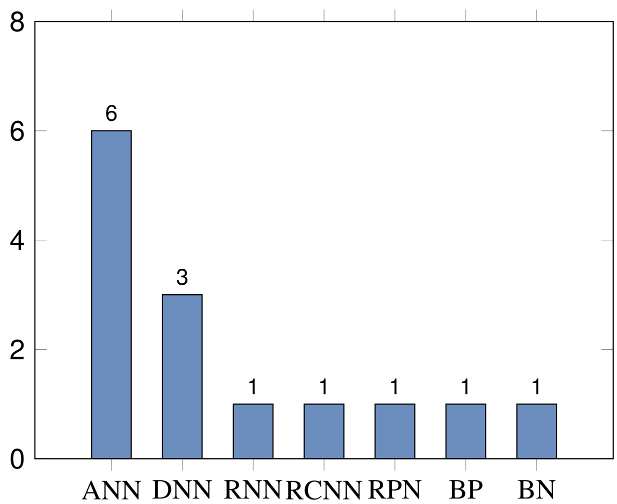

FIGURE 2. Distribution of deep learning-based classifiers used in learning-based approaches.

[32], [35] stood exceptional performances. According to [50], when comparing the performance of machine learning and deep learning models, as well as comparing machine learning and deep learning models to each other, the K-Nearest Neighbor (KNN) algorithm was found to have the highest accuracy.

D. RQ3: WHICH FEATURE ENGINEERING TECHNIQUE HAS THE DOMINANT ROLE IN EDUCATION ANALYSIS

The purpose of this section is to investigate the feature engineering strategies used in the research included in this study. This section of RQ1 was inspired by the fact that feature engineering can extract predicted data or features for successfully training learning algorithms [79]. As indicated in Table 4, we discovered six feature engineering strategies that are often employed in the chosen articles. We give a quick rundown of the six characteristics of engineering methodologies that have been used for the particular study.

- The TF-IDF is a statistical measure used in natural language processing (NLP) to assess the importance of a word in a collection of texts. It is determined by dividing the overall inverse document frequency of the word by the number of times it appears in a given document.

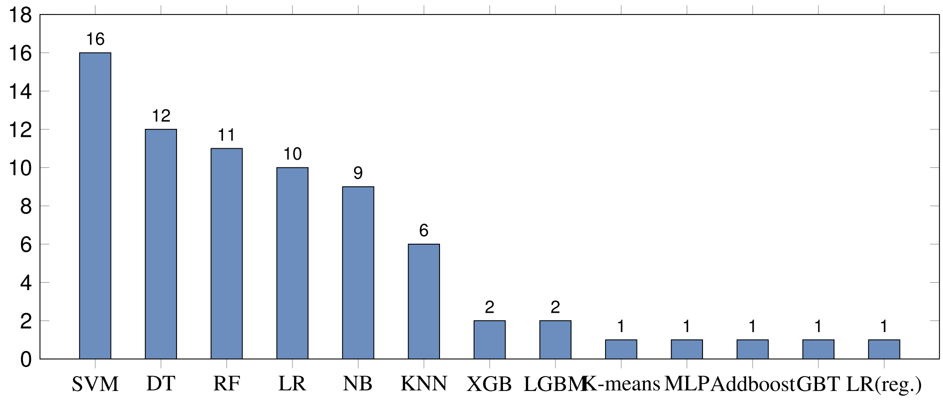

FIGURE 3. Machine learning-based classifier distribution in learning-based techniques.

TABLE 8. An overview of the techniques used for feature engineering in the studies analyzed.

No.	Feature Engineering Technique	Total	Publications
1	TF-IDF	2	[19], [30]
2	ANOVA	2	[28], [29]
3	Document frequency(DF)	3	[39]–[41]
4	Information gain (IG)	3	[39]–[41]
5	Document Term Matrix(DTM)	3	[39]–[41]

- The technique of information gain (IG) is used to determine the most useful qualities or attributes that give the most information about a specific class. IG is based on the entropy concept and operates by lowering entropy from the root node to the leaf nodes. The objective is to identify the qualities that result in the largest reduction in entropy, hence providing the most useful information for categorization.
- ANOVA is a statistical approach used to evaluate whether the means of two or more groups of data (typically three or more) are generated from the same distribution. Parametric statistics are used in this exam.
- A mathematical matrix called a document-term matrix (DTM) reveals the frequency of words used in a group of documents. In a document-term matrix, columns represent terms in the collection, and rows represent documents in the collection.
- Document frequency (DF) is the number of documents containing a particular term.

The most popular feature engineering methods across all four categories of education analysis were found to be Term Frequency-Inverse Document Frequency (TFIDF), Document Term Matrix (DTM), Document Frequency (DF), and Information Gain (IG). Machine learning models are the main users of the feature engineering method. Additionally, deep learning models automatically create features thoroughly explained in [80]. In research, [81], [82], [83] feature engineering approaches were not used in the research that used deep learning models as sentiment classifiers.

E. RQ4: WHAT ARE THE MAJOR SOURCES OF DATA FOR EDUCATIONAL ANALYSIS?

This research question seeks information on the data sources utilized in the education analysis. The majority of the datasets used were gathered through Google services, such as Google Forms and Google Documents. Surprisingly, 11 of the 35 papers examined used Twitter data. With your Google account, you may now use the free, fully functional forms application known as Google Forms. Standard question kinds may be added, questions can be dragged and dropped into the desired sequence, the form can be customized with basic images or color schemes, replies can be gathered in Forms, or they can be saved to a Google Sheets spreadsheet. The second most important source of data collecting was offline survey forms. With the help of a survey questionnaire, students' opinion is collected. It also includes teachers' options about the system and possible outcomes after going through the change in the current education system. Almost 8 publications out of 35 were utilized to collect data via survey forms. Other resources amount of contributions to the collection of data that resources involve physical activity in classroom (n=2) studies, camera monitoring for getting data of a class (n=1) study, some benchmark publicly available datasets like Kaggle(n=1) study, GitHub (n=1) study, and Twitter (n=1) study used. Table 4 presents a detailed description of the dataset sources utilized in the research under consideration, including their features, collecting techniques, and the number of records gathered. The frequency of each data source used in the selected articles is depicted in Figure 4

IV. DISCUSSION

In this part, we will describe the major findings of our literature review on the application of machine learning and deep learning in online education.

- The majority of machine learning approaches were taught utilizing limited quantities of data. It is true, however, that ML algorithms require massive volumes of data in order to work well. Studies [27], [43], [50], [52], [53] evaluated the online education performance

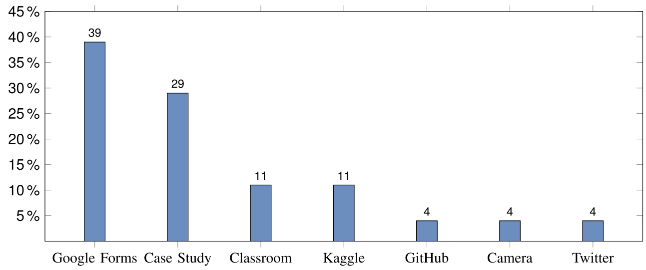

FIGURE 4. Distribution of deep learning classifiers used in machine learning-based approaches.

of students using open-source datasets. Several research collects numerical, textual, visual, and video data via Google Forms, Online Survey, Online Questioner, Public opinion, and online streaming. Ineffective classification of unstructured and disorderly datasets by ML and DL algorithms. In order to create any type of dataset to measure the influence of online education and student performance, standard parameters must be established.

- Additionally, it was observed that the dropout and prediction of students at risk studies for on-campus students only covered a relatively small percentage of the dataset. This was a point of contention among the researchers. Machine learning algorithms might not yield satisfactory results when trained on relatively small datasets. In addition, the pre-processing data method has the potential to assist considerably in providing more accurate results.
- In some instances, machine learning (ML) and deep learning (DL) algorithms provided probabilistic predictions without an actual value, which was a critical task for the evaluation of students, necessitating random test human grading to assure fair and reliable ratings.
- There hasn't been enough research on the temporal nature of the indicators used to predict at-risk and dropout pupils. Due to these properties' dynamic nature, their values fluctuate over time. The performance of the predictors can be improved by using temporal data in the classification process. For example, article [52] computes temporal features.
- The majority of research papers approached the issue as a categorization challenge. The methods used to identify the classes of students in the dataset were the topic of very few investigations. Additionally, the aforementioned issues are classified as binary issues, but numerous other classifications would be included to assist management in creating more successful intervention strategies.
- Tasks involving feature engineering, where the features used might affect how well a predictor performs, have received less attention. In the experiments, features like student demographics, TF, IDF, Heuristics 1, 2, and 3, and e-learning interaction session logs were predominantly utilized. Additionally, it was found that only a small number of researchers examined the potential of deep learning algorithms like ANN, DNN, RNN, and CNN, instead of the more common classical machine learning algorithms like SVM, DT, NB, and KNN.
- The dynamic character of student performance is not considered in the existing literature. The performance of the pupils is a dynamic process that either improves or degrades with time. Predictor performance on real-time dynamic data is still unknown.
- There have been several different kinds of studies that have focused on the class, or data balance [84], [85], [86], [87]. Maintaining a good class balance is widely regarded as the most significant component in achieving high classification success.

ML has the ability to accelerate educational development, and it is evident that instructional effectiveness has increased dramatically. By properly and effectively implementing ML approaches in the educational sphere, teaching, learning, and research will all be substantially altered. To support difficult students early and take action to increase success and retention, educators who use ML will have a better picture of how their students are developing with their learning.

V. POTENTIAL THREATS TO VALIDITY

- The study comprises online lectures that were gathered from a variety of digital databases. Thus, we may have overlooked some important ones since they weren't adequately indexed there or weren't indexed in other digital libraries.
- The Study may not have found all pertinent lectures or assignments because the search method was created to look for lectures using phrases occurring in keywords, titles, and abstracts.
- The analysis eliminates scientific studies that are not peer-reviewed, such as book chapters and novels, and instead depends on conferences and peer-reviewed publications. A few studies that carried out systematic literature reviews were also disregarded since they wouldn't have produced accurate data for our research study.
- Stage **2** on our approach, screening was done to include the pertinent research based on the articles' titles, abstracts, and keywords. In a few instances, the title, abstract, and keyword screening alone cannot determine if an article is relevant; instead, a complete paper screening is required. As a result, it is likely that we may have missed certain articles with relevant information because of this problem.

VI. SUGGESTIONS FOR FURTHER RESEARCH

Considering the challenges and restrictions mentioned earlier, we suggest the following research suggestions for predictive learning analytics of student performance.

- **Recommendation (1):** Formalize a specific definition of the variable "learning outcomes" before trying to develop prediction models that measure the achievement of learning objectives.
- **Recommendation (2):** Develop predictive models to improve teaching and learning in poor nations and for

non-technical degrees, such as humanities. In order for analytic models to be effective in multiple educational contexts and settings, they must be tailored to those contexts and settings.

- **Recommendation (3):** After any sensitive student data has been anonymized, educational datasets should be compiled and shared with other academics in order for them to utilize them.
- **Recommendation (4):** Develop intelligent algorithms that can predict a cohort's academic achievement and the results at the program level. As a result, educational leaders would have an easier time carrying out evaluation procedures and improving the overall quality of their programs.
- **Recommendation (5):** Develop machine learning models that aim to justify and explain the levels of student achievement and investigate how hybrid models might increase the precision of student outcome forecasts.
- **Recommendation (6):** Researchers in the future may look into methods for refining educational datasets to increase accessibility. Potentially, researchers may focus on making these systems more practical, modifying them to accommodate certain students' demands, and streamlining their navigation.
- **Recommendation (7):** Researchers can look into ways to lessen student mental health difficulties. It is clear that some kids are having difficulty adjusting to the epidemic, which might result in stress. Researchers can look at potential strategies for tackling the socioeconomic and educational issues that need to be addressed to provide these children peace of mind and better mental health results.
- **Recommendation (8):** It would be essential to find strategies to increase stakeholder engagement so that their efforts can be directed toward supporting students. This study has highlighted the vital significance of the efforts of numerous stakeholders in providing high-quality deaf education. Other academics may employ stakeholder engagement models and frameworks to describe how these stakeholders may collaborate to improve the learning outcomes for deaf students.

VII. STUDY IMPLICATIONS

In the following section, we delve into the major findings of our literature review, focusing on the application of machine learning and deep learning in online education. The discussion highlights key implications, including the need for larger and standardized datasets, challenges in prediction accuracy, the importance of considering temporal dynamics, and the exploration of alternative classifications and deep learning algorithms. Below are the list of implications:

A. NEED FOR LARGER AND STANDARDIZED DATASETS

The majority of machine learning approaches in online education were based on limited datasets. To improve the performance of ML and DL algorithms, it is essential to have access to massive volumes of standardized data. Establishing standard parameters for creating datasets to measure the influence of online education on student performance is necessary.

B. IMPORTANCE OF PREPROCESSING DATA AND HANDLING SMALL DATASETS

Studies focusing on dropout and risk prediction for on-campus students often covered only a small percentage of the dataset, leading to potentially unsatisfactory results. Proper preprocessing techniques and methods for handling small datasets can significantly enhance the accuracy of predictions.

C. CHALLENGES IN PROVIDING FAIR AND RELIABLE RATINGS

Machine learning and deep learning algorithms sometimes provide probabilistic predictions without an actual value. To evaluate students accurately, random human grading may be required to ensure fair and reliable ratings.

D. CONSIDERATION OF THE TEMPORAL NATURE OF INDICATORS

The temporal nature of indicators used to predict at-risk and dropout students has not been thoroughly researched. As these indicators' values fluctuate over time, incorporating temporal data in the classification process can improve the performance of predictors.

E. EXPLORING ALTERNATIVE CLASSIFICATIONS AND FEATURE ENGINEERING

Most research papers approached student classification as a binary challenge. Further investigations should explore alternative classifications to assist in creating more effective intervention strategies. Additionally, there is a need to focus on feature engineering, considering the impact of various features on predictor performance.

F. LIMITED EXPLORATION OF DEEP LEARNING ALGORITHMS

While classical machine learning algorithms like SVM, DT, NB, and KNN were commonly used, the potential of deep learning algorithms such as ANN, DNN, RNN, and CNN has been underexplored. Further research should investigate the effectiveness of deep learning approaches in the context of online education.

G. UNDERSTANDING DYNAMIC STUDENT PERFORMANCE

Existing literature often overlooks the dynamic nature of student performance. Recognizing that student performance can improve or degrade over time is crucial. Future studies should focus on evaluating predictor performance on real-time dynamic data.

H. IMPORTANCE OF CLASS BALANCE IN CLASSIFICATION

Maintaining a good class balance is considered crucial for achieving high classification success in online education.

Several studies have emphasized the significance of addressing class or data imbalances.

I. ENHANCING EDUCATIONAL DEVELOPMENT THROUGH ML

Implementing machine learning approaches effectively in the educational sphere can accelerate instructional effectiveness and lead to substantial changes in teaching, learning, and research. ML can provide educators with a better understanding of their student's development and enable early support for struggling students, ultimately increasing success and retention rates.

VIII. CONCLUSION AND FUTURE WORK

Recent developments in data-collecting techniques and system performance indicators have made studying educational systems easier and more effective. The analysis and monitoring of massive data using advanced data mining and machine learning techniques have given rise to a new field of big data analytics. Machine learning, along with data mining techniques, has been used to predict student performance and provide feedback to teachers and educators. However, limited research has been conducted on implementing corrective measures promptly. In the future, research should focus on developing effective ensemble methods to implement machine learning-based performance prediction techniques and find dynamic ways to predict student performance and offer timely remedial actions. Our goal is to apply some of the existing remarkable works and emphasize the dynamic role of machine learning in online education, providing teachers with additional insights to design effective interventions and achieve precise educational objectives.

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