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Artificial Intelligence in Education: A Systematic Review of Machine Learning for Predicting Student Performance

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ABSTRACT

Artificial Intelligence is increasingly being employed in education, specifically through machine learning techniques, to improve the quality of education and refine teaching and learning methods. Despite its positive impacts on education quality and social life, machine learning technology poses ethical and practical concerns, especially in predicting student performance. To address these concerns, this study conducts a systematic literature review on machine learning technology for predicting student performance, analysing 51 relevant articles from Scopus and Science Direct databases between 2019 and 2023 using the PRISMA method. The findings reveal that the primary motivation for employing machine learning in educational institutions is to improve predictive accuracy, identify early interventions, and optimise decision-making processes. Supervised machine learning approaches such as Decision Trees, Linear Models, and Neural Networks are commonly used. However, machine learning techniques encounter challenges such as overfitting, scalability, and generalizability, which may impact education practices' fairness, accountability, and transparency. The study provides valuable insights into the benefits of machine learning, ethical considerations, and practical recommendations to guide stakeholders, including educators, researchers, policymakers, and administrators, in navigating the convergence of artificial intelligence and education. These insights emphasise the critical need for equitable model implementation, data collection, and decision-making to mitigate bias in real-world educational settings.

1. Introduction

The age of digital transformation, the advent of Artificial Intelligence (AI), a rapidly expanding technology with numerous applications, has ushered in a wide variety of disciplines such as medicine,

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finance, transportation, engineering, and education[1]. This technology has a well-known capacity to automate jobs, improve decision-making, optimise processes, increase efficiency, reduce cost and time consumption, and have the potential to influence every aspect of social life [2]–[6]. As a result of the COVID-19 outbreak in 2020, there has been a significant impact on the education sector, leading to challenges in online learning for both students and teachers who are using digital technology [7]. Jaafar *et al.,* [8], for instance, analyzed how technology and applications affect students' understanding and visualization when learning mathematics. The study, in addition to many others, aimed to benefit educators and institutions seeking innovative and future-oriented education.

Recently, education is one of the fields that has keenly embraced AI's technological potential, seeing the revolutionary influence it may have on the future of learning, such as virtual learning [9],[10]. AI in education is a research area that employs AI technologies, such as machine learning and deep learning, to transform and improve teaching and learning strategies and experiences in a variety of educational contexts and environments [11],[12]. Furthermore, AI has had significant impacts, particularly on the administration, teaching, and learning areas in the education sector or within the context of specific learning institutions [13].

According to Munir *et al.,* [14], student performance prediction is an evolving study area in the field of AI applications in education. Machine learning (ML), a subset of AI, has emerged as one of the most often employed approaches in educational institutions. In recent years, there has been an increase in the number of articles on using ML to analyze and predict student performance using educational data in a variety of educational platforms. For instance, Aydoğdu [15] intended to predict students' final performance in online learning using artificial neural networks, emphasising students' use of the learning management system (LMS). In a related study by Qiu *et al.* [16], an ML-based learning performance predictor has been proposed to predict students' success in e-learning using learning process and behaviour data.

The predictive potential of ML has opened the way for data-driven education, in which massive amounts of educational data are analysed to identify relationships, patterns, and trends that may be used to forecast students' progress [17],[18]. By utilising AI's ability to analyse and understand massive amounts of information, educators may get actionable insight to optimise teaching strategies, identify students with issues early, and execute personalised strategies to improve overall learning outcomes.

Numerous studies have relied on developing intelligent systems, predictive models, and enhanced ML algorithms that can adapt to the needs of individual students and provide personalised feedback and support to improve educational quality. Development prediction models based on ML methodologies also support educators in predicting and managing student performance, as well as improving educational quality in rural schools [19]. As an example, Yan and Yanshen [20] discovered that their proposed prediction model offers practical reference values for instructors in conducting and motivating potential students to engage in academic competitions.

Although ML technology has a significant impact on educational institutions, improving the quality of education and satisfying the dynamic needs of society, it still raises concerns about ethical and practical implications regarding the use of ML in predicting students' performance. Therefore, further investigation is required to fully understand and overcome issues related to the implementation and effectiveness of ML in educational institutions. A beneficial resource on the benefits of ML and practical recommendations or guidelines are essential to assist educators, researchers, policymakers, administrators, and others interested in the convergence of AI and education. This study aims to provide a comprehensive review of the literature on ML technology in the context of predicting students' performance, exploring the research motivations, strengths, and weaknesses associated with its application, and providing insights into the implications for educational institutions.

1.1 Related Work

This section briefly overviews relevant ML approaches in the literature on students' performance prediction. Several systematic review studies were discovered that are relevant to the application of ML in students' performance prediction. Still, they differ regarding the highlighted issues, educational contexts, and methodologies used.

For example, Alamri and Basma [21] presented a review on explainable ML models in students' performance prediction. According to the findings, explainable students' performance models mainly predict a student's outcomes per course, frequently presented as multi-class issues. Socioeconomic features and pre-course performance are the top predictors, with Decision Trees and rule-based learning algorithms being common ML methods.

Another review study by Fahd *et al.,* [22] particularly focused on the application of ML in higher education. They performed a thorough review and meta-analysis of the literature emphasising students' academic performance, at-risk students, and student attrition. The evidence-based framework PRISMA: Preferred Reporting Items for Systematic Reviews and Meta-Analyses is used to analyse literature on ML models, algorithms, evaluation metrics, and demographics. A small-scale dataset of 89 studies published between 2010 and 2020 is used for in-depth analysis. Their findings provide insights into publication patterns and future trends in predicting and monitoring students' academic progress in higher education.

Several review studies conducted by Shah *et al.,* [23]*,* and Oppong [24]*,* investigated ML methodologies for predicting students' performance, including the most effective prediction algorithms, tools, features, and datasets employed. Khasanah [25] conducted a thorough study on classification techniques and attributes used in educational data mining to predict student performance. According to the survey, the most used methods are Decision Trees and Bayesian Networks, and the most widely used attributes are students' personal information, family information, pre-university characteristics, and university features. Another survey conducted by Sandra *et al.,* [26] concentrated on classification ML algorithms and classification data to predict students' learning success. Other researchers, such as Enughwure and Mercy [27], observed existing prediction methods, tools, and variables commonly used to forecast students' performance.

Based on the literature, it can be observed that ML approaches significantly impact students' performance prediction across various methodologies. There's much research on this topic, but reviews differ in focus. Some emphasise the explainability of models, while others target specific educational contexts like higher education. Many studies predict performance within a single course, often framed as a multi-class classification problem (e.g., excellent, good, average, fail). Socioeconomic background and prior performance in related courses are frequently identified as strong predictors of future results. Decision Trees and rule-based learning algorithms are popular choices due to their interpretability. However, other methods, like Bayesian Networks, are also used. The type of features used for prediction varies but often includes demographics, pre-university characteristics, and university features.

However, there is a lack of research on the motivation for employing ML and its practical implications for educational institutions. For instance, potential biases in data or algorithms and how they might affect student outcomes or create unfair labeling (e.g., "at-risk") might require further exploration. Therefore, this study conducted a systematic review to explore the ML literature on students' performance prediction from multiple perspectives, such as motivation studies, methodologies, strengths, and weaknesses of the ML approach used. The following section explains the methodology implemented for this systematic review process.

2. Methodology

This study follows the guidelines for performing a systematic review established by Moher *et al.,* [28]. The systematic review procedure comprises three primary processes in choosing diverse qualifying literature from databases. This study's methodology has been organized into three main phases: Identification, Screening, and Eligibility. The flow diagram of the proposed study is shown in Figure 1. This section discussed the four primary subsections employed in the current study: Identification, Screening, Eligibility, and Data abstraction and analysis.

2.1 Identification

The first phase in the systematic review process is to identify keywords and search for similar, comparable terms using the thesaurus, dictionaries, encyclopedias, and past studies. As shown in Table 1, the search string keywords were formulated to search the literature from two online citation databases: Scopus and ScienceDirect. Initially, the current study efficiently collected a total of 1,179 papers from two selected databases during this first phase of the systematic review procedure.

Table 1
The Search Strings

Database	Search string keyword
Scopus	*TITLE-ABS-KEY* ("artificial intelligence" OR "machine learning" OR "deep learning" AND "student* performance*" OR "student performance prediction" AND "performance prediction")
ScienceDirect	("artificial intelligence" OR "machine learning" OR "deep learning" AND student OR "student performance" OR "academic performance" AND prediction OR predicting)

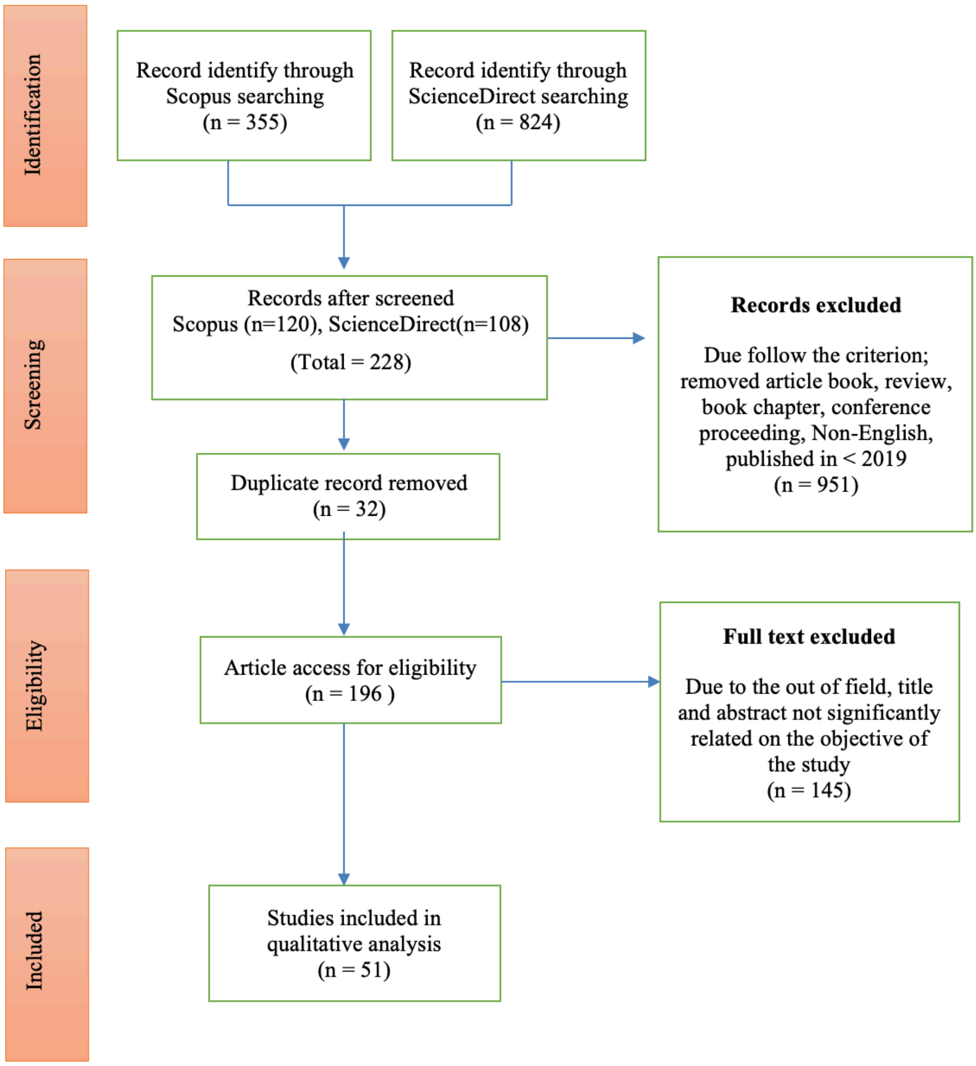

Fig. 1. Flow Diagram of The Proposed Searching Study

2.2 Screening

The second phase, screening, was comprised of two processes. The first process was to remove duplicate articles obtained from selected databases during the previous identification phase. In the first stage, 951 publications were removed. In the second process, 228 articles were examined to identify the most applicable studies based on the inclusion and exclusion criteria defined in Table 2. The first criterion was the timeline, which was limited to ensure the scope of the search procedure only included publications published between 2019 and 2023. The authors consequently decided to focus only on journal sources as the primary source of literature (research publications). Other document types were not included, such as book chapters, reviews, article books, conferences, and notes. Furthermore, this review's analysis was restricted to English-language literature. Based on these criteria, a total of 32 items were eventually removed.

Table 2
The Inclusion and Exclusion Criteria

Criteria	Inclusion	Exclusion
Timeline	Between 2019-2023	< 2019

Sources Type	Journal (only research article)	Conference proceeding
Document Type	Article	Article book, Book Chapter, Letter, Review, Conference, Note
Language	English	Non-English

2.3 Eligibility

In the eligibility step, the title and abstract of publications were thoroughly examined to ensure that the inclusion and exclusion criteria were adequately satisfied. Furthermore, the whole text of the publications was extensively evaluated to determine if the selected research was compatible with the major aims of this study. Consequently, 145 publications were excluded since their titles and abstracts were not significantly related to the study's purpose. Finally, 51 publications were selected and available for the quality assessment.

2.4 Quality Assessment

This study conducted a quality assessment on selected studies to ensure they meet research objectives based on specific quality measurements [29]. Two reviewers independently assessed the quality of the remaining articles based on abstract, method, and main results. The articles were classified based on quality assessment criteria (QAC) to avoid bias in the selection of primary studies. Each article was evaluated using six criteria ranked into three categories: Yes (satisfied), Partial (partially satisfied), and No (not satisfied). The quality assessment results of 51 selected articles are shown in Table 3.

Table 3
Quality Assessment of Selected Studies

Assessment Criteria	Yes (%)	Partial (%)	No (%)
QAC1 : Are the aims and objectives of research clearly defined?	51 (100 %)	0.0 %	0.0 %
QAC2 : Does the research use ML approaches for predicting student performance?	51 (100 %)	0.0 %	0.0 %
QAC3 : Is the research methodology explained clearly?	51 (100 %)	0.0 %	0.0 %
QAC4 : Did the researchers explain and define the performance measurements used?	35 (68.6%)	16(31.4%)	0.0%
QAC5 : Are the results and findings clearly stated?	41 (80.4%)	10(19.6%)	0.0%
QAC6 : Are the strengths and limitations of research explicitly stated?	28 (54.9%)	23(45.1%)	0.0%

Based on the result of the quality assessment in Table 3, the reviewers decided that if the articles fulfill five or four criteria, then the articles are of a high level of quality. If the articles fulfill at least three criteria, then they are categorized as moderate in quality. If the articles fulfill merely one or two criteria, then the articles are of low quality. The reviewers of this study mutually agreed that 51 articles met the minimum requirement (high or moderate). Thus, all of the 51 remaining articles were eligible for the review.

2.5 Data Abstraction and Analysis

The integrated review is one of the review procedures that examines and synthesizes numerous study designs (qualitative, quantitative, and mixed methods). This step is crucial for synthesizing information and drawing meaningful conclusions. It also seeks to add to the understanding of the research issue or topic under consideration by employing a systematic and transparent method. As shown in Figure 1, the authors extensively analyzed and extracted information from a collection of 51 articles using meta-analysis to guarantee that primary studies had adequate information to address the study's objective. The analysis was carried out by two experts, one specializing in ML and the other in educational technology, to determine the reliability of the selected articles. The expert review process ensures each sub-theme's clarity, relevance, and applicability by ensuring domain validity. The author improves his or her judgment based on feedback and expert judgments.

3. Results

This section presents the review findings into three subsections: (1) motivations for using ML for student performance prediction, (2) ML approaches for performance prediction, and (3) strengths and weaknesses of ML techniques.

3.1 Motivations For Using ML For Student Performance Prediction

The first review finding of this study aims to identify the primary motivations for using ML technology in predicting student performance. We categorize primary studies into three purposes: (1) designing and developing ML prediction models, (2) developing ML prediction methods, and (3) comparative analysis of ML techniques.

3.1.1 Design and Development ML Prediction Model

A total of 28 primary studies (54.9%) focused on designing and developing a ML prediction model for student performance, with three main motivations: predictive accuracy, early intervention, and personalized learning. Table 4 provides a summary of these studies and their implications for educational institutions.

Table 4
Summary of studies on the design and development of ML prediction model

Key Motivation	Study Motivation	Implications For Education Institutions	Studies
Predictive Accuracy	• analysis of student achievement with educational or academic data • identify the key factors affecting performance	• optimization and improvement decision-making in admission strategic planning • enhanced personalized student learning and support • enhancement of data-driven and decision-making institutional strategies and policies	[30]–[44]
Early Intervention	• early identification of at-risk students in learning using educational or academic data • estimate early student dropout prediction	• enhancing academic achievement with the provision of educational interventions • tailored interventions, including student counseling, intelligent tutoring systems, ongoing progress monitoring, and policy development	[45]–[52]

Personalized Learning	• analyze and categorize student achievement using academic performance and student data • predict and simulate student performance in higher education	• enhancement decision-making Institutional focusing on personalized learning plans based on predicted achievement • enable to monitor progress for personalized feedback and recommendation systems	[53]–[57]

Table 4 shows that the pursuit of higher predictive accuracy drives 15 primary studies (53.6%). These studies aimed to create prediction models that could accurately predict student performance. The studies by Pal and Vimal [30] and Saluja *et al.,* [43] have developed student performance prediction models with 90% or higher accuracy rates. These models help institutions identify at-risk students early and support improvement. The enhanced predictive model has 83.16% accuracy, as proposed by Yacoub *et al.,* [40], while Aljohani *et al.*, [44] proposed a model for predicting academic performance in a virtual learning environment with high precision (93.46%) and recall (75.79%). These findings highlight the potential of ML algorithms in higher education decision-making, leading to the formulation of effective policies and strategies for supporting students and promoting their success.

Other studies have developed predictive models for predicting student performance in courses [42] and online interactive sessions [37], with a high classification accuracy of 97.4%. These models are useful for educators in estimating student performance and planning strategies to reduce failures. Khan *et al.,* [31] proposed a framework that offers an opportunity to set precautionary measures for low-performing students early in the semester, improving data-driven institutional strategies and policies. The model proposed by Dixit *et al.,* [41] achieved 99.77% accuracy in predicting and evaluating student characteristics, meeting university-industry selection parameters. These models are expected to provide robust performance and employment opportunities models for optimization and improvement in admission strategic planning.

Early identification of at-risk students is crucial for educational institutions to provide timely interventions and support. For example, Albreiki [45] aimed to identify students at risk of low performance during the early stages of learning. Their proposed explainable ML and rule-based models provide valuable information for educators and instructors to provide early interventions. The effectiveness model by Tamada *et al.,* [46] predicts student success or failure, understanding student behavior, and supporting corrective and preventive actions. Brdesee *et al.,* [47] developed a predictive model to enhance retention rates of at-risk students, aiding academic decision-making and forming instructional pedagogical interventions.

Numerous studies have developed prediction models for personalized learning paths, highlighting the potential of ML in enhancing education standards. A study by Nuankaew and Wongpanya [53] developed success models for personalized learning plans based on predicted academic achievement. Hussain and Muhammad [54] achieved remarkable results, highlighting the potential of ML in enhancing education standards and providing valuable information for planning and future development. Meanwhile, Kukkar *et al.,* [56] used the proposed SAPP system on e-learning platforms to monitor and support students, identify at-risk students, and develop interventions for improved academic performance. Apart from that, Atalla *et al.,* [57] developed an intelligent recommendation system for automating academic advising based on curriculum analysis and course recommendations.

3.1.2 Development of ML Prediction Method

In this category, the study analyzed 18 publications (35.3%) focusing on developing prediction methods or approaches to improve prediction performance. The primary motivations for developing ML prediction methods were divided into method optimization and feature engineering. Table 5 provides a summary of these motivations and their implications for educational institutions.

Table 5
Summary of studies on the design and development of ML prediction method

Key Motivation	Study Motivation	Implications For Education Institutions	Studies
Method optimization	• improved performance prediction using academic, behavioral, and demographic data from educational systems. • predicting future grades and study duration based on their past course data. • considering significance features and impact on learning outcomes.	• enhancing decision-making and effective learning outcomes • enhanced support and reliability, personalized teaching, and learning • early at-risk identification and interventions • early recognition of low-performance students	[58]–[69]
Feature engineering	• identifying potential factors in learning behavior • finds essential features for performance prediction • predicting at-risk students using data on learning behavior	• approach for selecting valuable features for performance prediction • supporting at-risk students with designing more effective future courses and teaching interventions • enhancing teaching quality and strategy	[70]–[75]

Table 5 indicates that most studies concentrate on optimizing and developing efficient ML prediction methods for handling large datasets and complex student information or data features. Numerous studies have developed robust prediction models using educational data across various learning systems or environments. For example, Huang *et al.,* [60] demonstrated the effectiveness of a hybridized method for predicting student performance using student datasets from Portuguese secondary schools. The proposed method by Liu *et al.,* [69] uses a hybrid deep learning model to accurately identify high-risk students and provide timely assistance to improve learning performance and online teaching quality. Meanwhile, Al-Azazi and Mossa [64] proposed a multi-class model that predicts student performance in MOOC environments using demographic and activity clickstream data, assisting instructors in making in-time interventions. Unlike the study by Sood and Munish [66], their hybrid approach focuses on student performance prediction and comments evaluation, aiming to improve teaching and learning capabilities by offering motivational comments and video recommendations to prospective students.

This review identified and highlights the primary studies focusing on improving prediction accuracy through feature selection and engineering techniques. Arif *et al.,* [70] used a feature selection algorithm to identify valuable features for predicting student performance, finding factors such as demographic state, socioeconomic status, parental educational status, extra-curricular activities, teaching quality, and learning behavior. Sengupta [71] introduced an algorithm for identifying essential features from a new dataset, reducing failure rates. Other studies developed ML prediction methods to reduce failure rates and enhance performance. For instance, Christou *et al.,*

[73] used a grammatical evolution-based feature selection and construction method to select relevant features for students' future grades and study duration. Liu *et al.,* [72] demonstrated a deep learning method to identify critical learning sites in clickstream data, influencing student performance.

3.1.3 Comparative Analysis of ML techniques

In this section, the remaining five primary studies (9.8%) conducted a comparative analysis of ML techniques to determine the most suitable model for predicting student performance. Table 6 provides a summary of these studies and their impact on educational institutions.

Table 6
Comparison studies of ML techniques

Key Motivation	Study Motivation	Implications For Education Institutions	Studies
Model Selection	• comparing and evaluating ML techniques	• enhancing data-driven decisions for improving student outcomes, encouraging self-preparation, and decreasing dropout rates through data-driven decisions • enhanced decision-making and intervention student support	[76]–[80]

Table 6 presents five primary studies aiming to identify the most suitable ML techniques for student performance prediction. Mohiddin *et al.,* [76] compared four ML techniques to analyze student performance on a student dataset, while Chen and Linbo [77] and Alruwais and Mohammed [79] compared the effectiveness of seven ML methods for predicting student performance using various scenarios and educational data. A study by Ismanto *et al.,* [78] highlighted the importance of investigating student participation and performance in virtual learning environments (VLEs) to enhance academic achievement. The best ML algorithms can effectively predict academic success in VLEs, offering potential methods to improve student achievement. This is the same as with a study by Kaensar and Worayoot [80], who contributed to educational research by analyzing student behavior data using predictive analytics with various ML techniques.

3.2 ML Approaches for Performance Prediction

This section presents the results of the second review by summarizing the commonly used ML approaches in primary studies. We categorize these approaches into three subcategories: (1) type of ML approach, (2) ML techniques used for student performance prediction, and (3) comparison performance of ML techniques.

3.2.1 Types of ML Approach For Predicting Student Performance

The classical definition categorizes ML approaches into supervised, unsupervised, and reinforcement learning. Figure 2 illustrates the types and frequency of these approaches in primary studies.

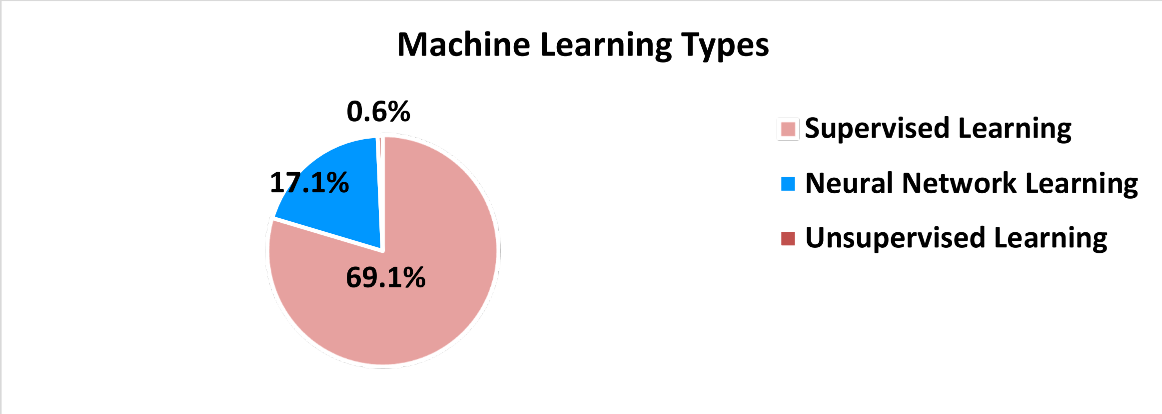

Fig. 2. Type of ML Approach Used In The Primary Studies

As shown in Figure 2, the results reveal that more than 60% of primary studies used the established learning type, supervised ML, which classifies the pattern in data for predicting student performance. The neural network learning is the second most popular type used in primary studies, accounting for 17.1% of all studies. In supervised learning, ML algorithms are trained to predict and classify data in labeled datasets. Neural network learning is also used for prediction, as it automatically learns and represents data in complex ways. However, unsupervised learning is less used in primary studies, with one study exploring hidden patterns in educational data.

3.2.2 ML Techniques For Student Performance Prediction

Based on the review, several ML approaches were identified. The study classified ML approaches into five categories: Decision Tree, Linear Models, Deep and Shallow Neural Networks, Ensemble Learning and others. Table 7 displays the number of studies on these ML techniques.

Table 7
ML techniques used in predicting student performance

Category	ML Technique	Total	References
Decision Tree	Decision Tree	20	[32], [33], [35], [41], [46], [47], [48], [49], [52], [53], [56], [64], [65], [69], [71], [74], [77], [78], [79], [80]
	Random Forest (RF)	26	[34], [36], [37], [40], [45], [46], [47], [48], [49], [51], [53], [55], [56], [58], [61], [62], [65], [70], [71], [72], [74], [75], [77], [78], [79], [80]
	j48	2	[31], [68]
	ID3	1	[31]
	C4.5	1	[31]
Linear Models	Linear Regression	5	[45], [48], [62], [76], [80]
	Logistic Regression	19	[36], [37], [38], [40],[41], [44], [46], [47], [49], [52], [55], [58],[68], [71], [72], [77], [78], [79], [80]
	Support Vector Machine (SVM)	21	[36], [37], [38], [41], [43], [45], [46], [48], [49], [55], [56], [58], [59], [67], [71], [73], [76], [77], [78], [79], [80]
	Generalized Linear Model (GLM)	1	[35]
	Support Vector Regression (SVR)	1	[62]

Deep and Shallow Neural Networks	Neural Network (NN)	18	[30], [34], [35], [36], [41], [44], [52],[56], [59], [62], [64], [65], [66], [68],[69], [71], [77], [80]
	Multilayer Perceptron (MLP)	6	[42], [32], [45], [69], [74], [79]
	Long Short-Term Memory (LSTM)	7	[33],[38], [44], [47], [56], [64], [72]
	Convolutional Neural Network (CNN)	3	[38], [56], [65]
	Back Propagation (BP-NN)	1	[39]
	Recurrent Neural Network (RNN)	2	[52], [64]
Ensemble Learning	AdaBoost	5	[36], [49], [50], [61], [71]
	XGBoost	4	[50], [53], [55], [61]
	Stacking	3	[45], [49], [65]
	Gradient Boosting	2	[56], [79]
Others	Extreme Learning Machine (ELM)	1	[75]
	Denoising Auto-encoder	1	[75]
	Genetic Algorithm	1	[42]
	K-Means Algorithm Classifier	1	[37]
	Bayesian Network	1	[48]
	Naïve Bayes	14	[36], [37], [40], [41], [43], [46], [48], [49], [56], [63], [68], [71], [77], [79]
	k-Nearest Neighbor (kNN)	10	[33], [35], [52], [55], [65], [69], [60], [71], [72], [77]

Table 7 lists the most frequently used ML techniques categorized as Decision Tree, and Linear models. Random Forest (RF) in Decision Tree was the most commonly used for student performance prediction, while Support Vector Machine (SVM) and Logistic Regression were commonly used in Linear Model studies. In Deep and Shallow Neural Networks, Neural Networks(NN) were the most frequently used, followed by Naïve Bayes and k-Nearest Neighbor (kNN).

RF is an ensemble learning method that combines multiple decision trees to reduce overfitting and improve model generalization [36],[37]. It produces high-accuracy predictions, reduces individual tree biases [78], and handle missing data without significant loss of accuracy [46]. RF effectively captures complex relationships within data, making it suitable for classification and regression tasks as well as can handle complex datasets and provide accurate predictions in study [51].

RF is a powerful tool for predicting student performance, helping educators and researchers identify influential factors contributing to student success. It can handle large datasets with high features and automatically select the most influential ones, reducing the dimensionality of the dataset [37]. RF is known for its ability to handle large datasets and high-dimensional feature spaces in the studies [36], [78] making it suitable for analyzing academic data and records from Learning Management Systems [46]. It is also known for its ability to handle high-dimensional data and effectively handle missing values in study [77]. RF's capabilities make it an effective tool for predicting student success.

The second most commonly used ML technique is SVM. Based on linear models, SVM have become a popular choice for predicting student performance due to their higher accuracy in terms of performance, indicating their effectiveness for binary classification tasks that have proven to classify student performance levels [76] and have shown good performance in classification tasks in study[55]. SVMs effectively recognize student performance patterns and handle non-linear relationships in educational datasets. They can transform data into higher-dimensional spaces using kernel functions, enabling them to find decision boundaries that linear models may struggle to capture. This ability has been proven in the study by Smadi *et al.,* [67] which successfully handles both linear and non-linear classification problems by mapping data into a higher-dimensional space.

NNs are the other ML approach that is also commonly used in the selected primary studies. NNs, particularly shallow neural networks, are a popular ML approach for predicting student performance because they can handle complex, multidimensional data and provide accurate predictions in educational contexts. Deep learning techniques and Artificial Neural Networks (ANN) are used to improve prediction accuracy in educational data in the study conducted by Pal and Vimal [30]. ANN can handle large amounts of data and make predictions based on learned patterns, making it suitable for handling diverse and extensive data as found in the study [66]. NNs can learn complex patterns and relationships in data, accurately predicting student performance by capturing intricate factors influencing performance [41]. They can handle large amounts of data and process both numerical and categorical variables, making them suitable for analyzing diverse student characteristics and capturing non-linear relationships between input variables [41].

3.2.3 Comparison performance of ML techniques

Notably, combining multiple ML methods can markedly enhance the performance of prediction. Table 8 presents five primary studies that compared the different ML approaches to find the best-performing model that efficiently addresses the prediction performance problem.

Table 8
Comparison studies of ML approaches

References	Total ML techniques	Best performance technique
Mohiddin *et al.,* [76]	4	Support Vector Machine (SVM)
Chen & Linbo [77]	7	Random Forest (RF)
Ismanto *et al.,* [78]	5	Random Forest (RF)
Alruwais & Muhammed [79]	7	Gradient Boosting Machine (GBM)
Kaensar & Worayoot [80]	6	Decision Tree (DT)

The results in Table 8, a list of a number of ML techniques, were used and evaluated to find the optimal technique to achieve high accuracy before constructing the prediction model or method. The selection is based on the most commonly used classifiers in the subject matter of the experiments. RF is found to be the best-performing method compared to other ML approaches. Research by Chen and Linbo [77] has shown that RF is the most effective model for predicting student performance using various application scenarios and educational data. It also has been found by Ismanto *et al.,* [78] to be highly accurate, handle large datasets, and reduce overfitting. Overall, RF is a promising tool for predicting student performance.

Other performance techniques, including SVM, Gradient Boosting Machine (GBM), and Decision Tree, were also the best performance techniques in the other respective studies. Linear SVM has been found to be more effective in classifying performance levels in study [76], while Decision Tree has shown the highest accuracy at 81.10% upon course completion in study [80]. In the study conducted by Alruwais and Muhammed [79], GBM has also shown the highest prediction accuracy of 98%, with a low prediction error for evaluating student performance and knowledge.

3.3 Strengths and Weaknesses of ML Techniques

In this section, we outline the strengths and weaknesses exhibited by ML techniques as reported by researchers in their primary studies. These are based on the author's opinions and may not be reliable or accurate. Hence, the strengths and weaknesses of the ML techniques supported by more than one study are only presented in this section. Table 9 summarizes the strengths and weaknesses of ML techniques for predicting student performance with the supporting primary studies.

Table 9
Strengths and Weaknesses of ML techniques

ML Technique	Strengths	Weaknesses	Supporting Studies
Neural Network (NN)	• effectively capturing non-linear relationships among input variables • ability to identify intricate factors from learning complex patterns of data • handling diverse educational data, including both numerical and categorical variables • ability to learn from large amounts of data and make predictions based on learned patterns	• the impact of training data can lead to overfitting and reduced interpretability • computational demands with larger datasets can limit the model's ability to scale • interpretability challenge due to the complexity of neural networks • black-box nature and hard to interpret due to their lack of transparency • costly computational resources when training the model • data quality sensitivity of training data, and biases and imbalances data • overfitting risk when using limited training data and performing poorly on new data • optimal performance complexity when working with tuning hyperparameters, the number of hidden layers, and neurons	[30], [33], [59], [68], [69], [74]
Long Short-Term Memory (LSTM)	• analyzing and handling sequential data • ability to capture long-term dependencies and complex patterns • handling time-series data and making predictions based on past observations • ability to learn from performance history and analyze sequential data	• performance varies based on data and context dependency • limitations and biases dealing with missing and imbalanced data • training data duration impact on model performance • hyperparameter tuning affects algorithm performance	[33], [44], [47], [51], [52], [72]

Random Forest (RF)	• accuracy and robustness dealing with complex datasets • versatility with data types • robustness with noise and outliers in the dataset • handling large datasets with many features effectively • handle numerous features and automatically selecting the most influential features and ability to reduce dataset dimensionality • high-dimensional data and handles missing values well • versatile classification for both binary and multi-classification tasks • handling categorical data and numerical data without requiring extensive data preprocessing • handle imbalanced data effectively and less prone to overfitting	• computational expensive and highly time-consuming with large datasets • interpretability challenge in understanding the underlying decision-making process • imbalanced data issue leading to biased predictions • algorithm's performance may vary depending on the specific dataset and context • ensemble complexity dealing with a large number of decision trees • imbalanced classes in the dataset impact on performance • overfitting risk occurred if improperly tuned and validated	[36], [37], [46], [51], [70], [77], [78]
XGBoost	• handling large datasets with many features and variables • optimizing complex models and dealing with non-linear relationships in the data • effectice in reducing error and prediction uncertainty • offer scalability for analyzing student performance in educational systems	• high computational cost with large datasets • overfitting risk without proper tuning and validation • model interpretability challenge	[50],[53], [61]
Ensemble Learning	• balancing bias and variance on reliable predictions compared to individual algorithms • minimizing overfitting and enhancing generalization • efficiency with high-dimensional data • improved binary classification • combination of multiple algorithms for enhances prediction accuracy	• generalizability limited in the diverse educational settings • computational complexity and model interpretability challenge • model performance dependency on the accuracy and quality of individual base learners and their predictions	[40], [43],[48], [49]

Table 9 demonstrates that ML techniques like RF, LSTM, XGBoost, and NN are effective for predictive modeling and handling non-linearity relationships in data. RF is a powerful algorithm for handling complex datasets, both numerical and categorical [51], and is robust against overfitting and missing data without significant loss of accuracy [74]. Meanwhile, XGBoost optimizes complex models and handles non-linear relationships, making it suitable for analyzing diverse student characteristics [41], [53].

In study by Martins *et al.,* [51], ML techniques have shown remarkable effectiveness in handling imbalanced student datasets, which are common in educational contexts. They are known effectively for handling high-dimensional data, including demographic information and academic records. Primary studies have demonstrated their ability to handle large datasets with high features and variables [53], making them suitable for analyzing the performance of a large number of students [36]. Furthermore, ML models offer interpretability and feature importance, enabling researchers in study [51] identify the factors for academic performance and dropout risk. They can handle large datasets and automatically select influential ones, which can reduce dimensionality [37] and make them suitable for analyzing large academic data from learning systems and environments [46].

While ML's predictive capabilities are robust, several models may struggle with small datasets or complex models, which can lead to overfitting. Overfitting is a prevalent issue, particularly when using complex models, limited training data [74], improper parameter tuning, and validation [51], leading to poor generalization to new data [53]. Complex ML models, especially NNs, can be computationally intensive, requiring significant resources and time for training and inference [46].

This can be impractical in resource-limited settings, especially with larger datasets. For example, LSTM models may have higher computational complexity compared to other algorithms, impacting scalability and efficiency [59]. The specific architecture and number of neurons in the proposed MLP model make it difficult to assess scalability and generalizability [74]. According to Nuankaew and Wongpanya [53], these computational requirements and scalability could be crucial for real-world implementation. In addition, the interpretability and explainability of ML models are also crucial for gaining trust and understanding from educators and administrators, as their black-box nature can limit transparency and understandability in decision-making processes [53], [78].

4. Challenges and Ethical Considerations

This section discusses the ethical and privacy concerns surrounding the use of AI and ML in predicting student performance. It highlights potential bias and privacy issues, particularly in the context of predicting performance. Ethical considerations in educational settings involve considering moral principles, potential risks, and fairness issues when using ML and predictive modeling techniques to predict student performance. The study highlights the discussion on ethical and privacy concerns in primary studies, highlighting challenges encountered, research impact, and ethical considerations for educational institutions.

4.1 Data quality and bias

Data quality and bias challenges are crucial for maintaining research integrity and ensuring accurate, fair, and unbiased findings. These challenges impact the ethical responsibility of safeguarding privacy, data quality, and the validity and reliability of results from the previous studies [70], [73]. Ethical considerations should prioritize implementing methods to minimize biases and enhance data quality, upholding ethical standards, and ensuring privacy protection, especially in educational research involving sensitive student data. Furthermore, addressing data collection and analysis challenges is essential to enhance research quality while respecting privacy and data protection in educational contexts.

ML models' credibility and reliability can be impacted by limitations or biases in the data used for training and testing. These issues raise ethical and privacy concerns, requiring responsible data handling and transparency in study [62]. Bias in resource selection and decisions to handle missing data also raise these concerns by Tamada *et al.,* [46]. Addressing these limitations, considering alternative data sources, and adopting robust data handling methods can enhance the quality of the dataset and model, align with ethical standards, and safeguard privacy in handling sensitive data.

4.2 Methodological Limitations

The study's methodology in study [52], lacking a comprehensive comparison of ML techniques, raises concerns about reliability, ethical considerations, and fairness in model selection. Researchers should consider incorporating diverse algorithms for comparison, addressing ethical concerns, and fairness in model selection processes to ensure responsible and unbiased ML utilization in educational settings.

The computational complexity and efficiency of algorithms can hinder their practical implementation and scalability, raising ethical and privacy concerns. Christou *et al.,* [73] suggest researchers should conduct computational analyses and optimizations to promote efficient implementation and enhance interpretability. This will contribute to the responsible and ethical use of algorithms in educational contexts, ensuring their practical feasibility in real-world settings.

The study by Martins *et al.,* [51] emphasizes the importance of addressing potential biases in ML algorithms to ensure the fairness and equity of prediction models, which could impact the credibility and reliability of findings. It suggests that by addressing these issues, researchers can contribute to the development of more accurate, ethical, and fair prediction models.

4.3 Practical Implementation

In several studies [35], [40], [48], [64], it has been acknowledged that implementing the proposed model in real-world educational settings may face ethical and privacy challenges due to issues like data integration, resource availability, technical expertise, and system compatibility, which could hinder the understanding of the practical feasibility and limitations of the system. Ethical considerations are crucial in the real-world implementation of predictive models, including data availability, handling, and stakeholder engagement [35]. Therefore, respecting privacy regulations, informed consent and data protection is essential for practically adopting predictive models while safeguarding individual and institutional rights. As suggested by Saluja *et al.,* [35], future research should assess these implications in real employment contexts to ensure responsible and secure utilisation of predictive outcomes. This approach will contribute to the responsible and secure utilisation of predictive models in real-world educational settings, ensuring the protection of student data.

4.4 Generalizability and Applicability

Several authors in their studies [32], [48], [70], [75] highlight that the model's applicability to diverse educational settings or student populations may be limited due to its generalizability and potentially raising ethical and privacy concerns about the fairness and inclusiveness of the model. Consequently, future research should evaluate the model's generalizability with diverse datasets in diverse educational settings while also considering ethical and privacy concerns related to data usage and model performance. This approach is crucial to ensure equitable and privacy-conscious predictive models.

Yacoub *et al.,* [40] encountered that using ML predictive models in education can lead to significant ethical implications, impacting fairness, accountability, and transparency. In the future, research should address ethical concerns in model implementation, data collection, and decision-making and explore methods to mitigate bias and ensure equity in educational applications [43], [64].

5. Practical Recommendations

This section presents the following practical recommendations for educational institutions utilising ML to predict student performance, leading to improved educational outcomes and student support.

5.1 Data collection and preparation

According to the studies [58], [63], [73], [78], the initial step of developing the ML prediction model involves conducting data collection protocols and preparing high-quality datasets to gather a reliable dataset that includes various potential factors affecting student performance. Furthermore, the implementation of effective data quality and preprocessing techniques are considered to ensure the efficient training and testing of ML models by handling missing values [49], [54], [57], [74].

5.2 Feature Engineering and Preprocessing

Feature selection and feature engineering are crucial techniques in ML preprocessing. Feature selection involves identifying and eliminating relevant features, resulting in improved model performance [55], [72]. This reduces noise and focuses on influential attributes, making the model more accurate. Moreover, fewer features reduce training time, making ML models more efficient, especially for large datasets with numerous attributes. Meanwhile, feature engineering creates new or transforms existing features to enhance their informativeness, potentially capturing complex relationships in the data [59].

Selecting the right ML algorithm is crucial for improving model performance and reducing the risk of overfitting [80]. Different algorithms have different strengths and weaknesses, so choosing one that aligns with the data's characteristics can lead to better predictions. This saves computational resources and reduces the risk of overfitting, especially for high-dimensional datasets [65], [73]. In addition, some algorithms are more efficient, reducing training and inference times and making the model more practical for real-time applications or large-scale datasets [65].

5.3 Model Training and Validation

According to the studies [51], [55], [64], the practical guide is divided into two parts, namely (1) Train and validate models and (2) Evaluate and compare prediction models. Firstly, the data will be split into training and validation sets to train and evaluate the ML models. The appropriate evaluation metrics, such as accuracy, precision, recall, and f-score, are used to assess and validate the performance of the models [50], [55], [56], [80] and ensure they are accurate and reliable in predicting student outcomes. In addition, it is important to ensure that adequate training data is available to optimise the parameters of the ML models and avoid overfitting [77]. Secondly, comparative studies are conducted to determine the most accurate and efficient model for predicting student performance, with institutions urged to compare developed models against existing approaches to determine the most accurate model [76]–[80].

5.4 Model Maintenance and Improvement

The proposed prediction models are required to be monitored consistently and refine their prediction performance based on new data and feedback to improve the accuracy and effectiveness of the ML models [43], [55], [61], [63]. Furthermore, the studies [48], [67], [73] also recommended monitoring the performance of the models over time and making necessary adjustments to ensure their effectiveness in predicting student performance.

5.5 Practical Implementation

In this guideline, the studies [48], [50], [55], [64] recommend using ML models' predictions for targeted interventions and support programs to enhance students' success chances. It encourages collaboration with administrative and teaching staff on this insight to improve educational planning and resource allocation [54], [74]. The study by authors [48], [49], [63] also highlights the importance of providing appropriate training to educators and administrators to interpret and utilise these predictions in their decision-making process effectively.

5.6 Ethical and Privacy Considerations

Several studies recommended that educational institutions emphasise the importance of ethical considerations and privacy concerns when collecting student data for performance prediction, requiring appropriate safeguards and protocols, transparency, and informed consent from students and parents [43], [48], [49], [51], [55]. Therefore, further research is needed to investigate potential biases in the data and address any limitations encountered while implementing ML techniques.

6. Conclusions

This study reviewed and summarised existing literature using ML approaches to predict student performance. We mainly examined the literature using ML in student performance prediction from multiple perspectives, such as motivation studies, methodologies, strengths, and weaknesses of the ML approach used for student performance prediction. Our review revealed that most researchers employ ML to enhance the model's predictive accuracy, identify early intervention, and optimise the prediction method. Furthermore, supervised learning ML approaches such as Decision Trees, Linear Models, and Neural Networks were mostly used for the proposed predictive models or methods, which educational institutions can make better academic decisions, enhance educational practices, and ultimately provide intervention and support for student success as well could enhance the quality of education provided.

This study also revealed that ML techniques used in primary studies are remarkably effective in handling large, imbalanced student datasets with high features and variables. While ML's predictive capabilities are robust, several models may struggle with small datasets or complex models, leading to overfitting, scalability, and generalizability issues. However, using ML predictive models in education can lead to significant ethical implications, impacting fairness, accountability, and transparency. Thus, the study proposed several practical recommendations and ethical consideration concerns in model implementation, data collection, and decision-making and explored methods to mitigate bias and ensure equity in real-world educational institution applications.

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References

[1] Malik, Hasmat, Gopal Chaudhary, and Smriti Srivastava. "Digital transformation through advances in artificial intelligence and machine learning." *Journal of Intelligent & Fuzzy Systems* 42, no. 2 (2022): 615-622. https://doi.org/10.3233/JIFS-189787

[2] Aly, Heidi. "Digital transformation, development and productivity in developing countries: is artificial intelligence a curse or a blessing?." *Review of Economics and Political Science* 7, no. 4 (2020): 238-256. https://doi.org/10.1108/REPS-11-2019-0145

[3] Osborne, Stephen P., Maria Cucciniello, Greta Nasi, and Edwina Zhu. "Digital transformation, artificial intelligence and effective public services: challenges and opportunities." *Global Public Policy and Governance* 2, no. 4 (2022): 377-380. https://doi.org/10.1007/s43508-022-00058-7

[4] Ng, Win Son, Siew Chin Neoh, Kyaw Kyaw Htike, and Shir Li Wang. "Particle Swarm Feature selection for microarray Leukemia classification." Progress in Energy and Environment (2017): 1-8.

[5] Yagoub, Sami Abdelrahman Musa, Gregorius Eldwin Pradipta, and Ebrahim Mohammed Yahya. "Prediction of bubble point pressure for Sudan crude oil using Artificial Neural Network (ANN) technique." Progress in Energy and Environment (2021): 31-39.

[6] Saharuddin, Kasma Diana, Mohd Hatta Mohammed Ariff, Irfan Bahiuddin, Nurhazimah Nazmi, Mohd Azizi Abdul Rahman, Mohd Ibrahim Shapiai, Fauzan Ahmad, and Sarah'Atifah Saruchi. "A Comparative Study on Various ANN Optimization Algorithms for Magnetorheological Elastomer Carbonyl Iron Particle Concentration Estimation." Journal of Advanced Research in Micro and Nano Engineering 16, no. 1 (2024): 124-133.

[7] Abd Rahman, Haliza, Zarina Mohd Khalid, Noraslinda Mohamed Ismail, Nur Arina Bazilah Kamisan, Siti Mariam Norrulashikin, Siti Rohani Mohd Nor, Ani Shabri, and Muhammad Fauzee Hamdan. "Statistical Analysis on Students' Evaluation and Students' Final Exam Marks in Undergraduate Mathematical Courses at Universiti Teknologi Malaysia." International Journal of Advanced Research in Future Ready Learning and Education 27, no. 1 (2022): 1-8.

[8] Jaafar, Nurulaini, Siti Rohani Mohd Nor, Siti Mariam Norrulashikin, Nur Arina Bazilah Kamisan, and Ahmad Qushairi Mohamad. "Increase students' understanding of mathematics learning using the technology-based learning." *International Journal of Advanced Research in Future Ready Learning and Education* 28, no. 1 (2022): 24-29.

[9] Roslan, Nur Widad, Normaliza Abd Rahim, Nur Maisarah Roslan, and Siti Nur Aliaa Roslan. "Students' presupposition towards incooperating AI (Artifical Intelligence) technology in virtual and face-to-face classes." International Journal of Advanced Research in Future Ready Learning and Education 27, no. 1 (2022): 16-19.

[10] Edwards, Bosede I. "Emerging Trends in Education: Envisioning Future Learning Spaces and Classroom Interaction." *Emerging Technologies for Next Generation Learning Spaces* (2021): 7-18. https://doi.org/10.1007/978-981-16-3521-2_2

[11] Ouyang, Fan, and Pengcheng Jiao. "Artificial intelligence in education: The three paradigms." *Computers and Education: Artificial Intelligence* 2 (2021): 100020. https://doi.org/10.1016/j.caeai.2021.100020

[12] Chen, Lijia, Pingping Chen, and Zhijian Lin. "Artificial intelligence in education: A review." *Ieee Access* 8 (2020): 75264-75278. https://doi.org/10.1109/ACCESS.2020.2988510

[13] Huang, Jiahui, Salmiza Saleh, and Yufei Liu. "A review on artificial intelligence in education." *Academic Journal of Interdisciplinary Studies* 10, no. 206 (2021). https://doi.org/10.36941/ajis-2021-0077

[14] Munir, Hussan, Bahtijar Vogel, and Andreas Jacobsson. "Artificial intelligence and machine learning approaches in digital education: a systematic revision." *Information* 13, no. 4 (2022): 203. https://doi.org/10.3390/info13040203

[15] Aydoğdu, Şeyhmus. "Predicting student final performance using artificial neural networks in online learning environments." *Education and Information Technologies* 25, no. 3 (2020): 1913-1927. https://doi.org/10.1007/s10639-019-10053-x

[16] Qiu, Feiyue, Guodao Zhang, Xin Sheng, Lei Jiang, Lijia Zhu, Qifeng Xiang, Bo Jiang, and Ping-kuo Chen. "Predicting students' performance in e-learning using learning process and behaviour data." *Scientific Reports* 12, no. 1 (2022): 453. https://doi.org/10.1038/s41598-021-03867-8

[17] Zheng, Lu, Cong Wang, Xue Chen, Yihang Song, Zihan Meng, and Ru Zhang. "Evolutionary machine learning builds smart education big data platform: Data-driven higher education." *Applied Soft Computing* 136 (2023): 110114. https://doi.org/10.1016/j.asoc.2023.110114

[18] Duong, Hanh Thi-Hong, Linh Thi-My Tran, Huy Quoc To, and Kiet Van Nguyen. "Academic performance warning system based on data driven for higher education." *Neural Computing and Applications* 35, no. 8 (2023): 5819-5837. https://doi.org/10.1007/s00521-022-07997-6

[19] Nuankaew, Pratya, and Wongpanya Sararat Nuankaew. "Student Performance Prediction Model for Predicting

Academic Achievement of High School Students." *European Journal of Educational Research* 11, no. 2 (2022): 949-963. https://doi.org/10.12973/eu-jer.11.2.949
[20] Yan, Lijuan, and Yanshen Liu. "An ensemble prediction model for potential student recommendation using machine learning." *Symmetry* 12, no. 5 (2020): 728. https://doi.org/10.3390/sym12050728
[21] Alamri, Rahaf, and Basma Alharbi. "Explainable student performance prediction models: a systematic review." *IEEE Access* 9 (2021): 33132-33143. https://doi.org/10.1109/ACCESS.2021.3061368
[22] Fahd, Kiran, Sitalakshmi Venkatraman, Shah J. Miah, and Khandakar Ahmed. "Application of machine learning in higher education to assess student academic performance, at-risk, and attrition: A meta-analysis of literature." *Education and Information Technologies* (2022): 1-33. https://doi.org/10.1007/s10639-021-10741-7
[23] Shah, Bhavesh, Tushar Nimse, Vikas Choudhary, and Vijendra Jadhav. 'A Review on Students Performance Prediction Using Machine Learning Algorithms'. International Journal of Advanced Research in Science, Communication and Technology, 07 2021, 123-26. https://doi.org/10.48175/IJARSCT-1715
[24] Oppong, Stephen. 'Predicting Students' Performance Using Machine Learning Algorithms: A Review' 16 (07 2023): 128-48. https://doi.org/10.9734/ajrcos/2023/v16i3351
[25] Khasanah, Annisa Uswatun. "A review of student's performance prediction using educational data mining techniques." *Journal of Engineering and applied sciences* 13, no. 6 (2018): 5302-5307. DOI: 10.36478/jeasci.2018.5302.5307
[26] Sandra, Lidia, Ford Lumbangaol, and Tokuro Matsuo. "Machine Learning Algorithm to Predict Student's Performance: A Systematic Literature Review." *TEM Journal* 10, no. 4 (2021). https://doi.org/10.18421/TEM104-56
[27] Enughwure, Akpofure Avwerosuoghene, and Mercy Ebitiminipre Ogbise. "Application of machine learning methods to predict student performance: a systematic literature review." *Int. Res. J. Eng. Technol* 7, no. 05 (2020): 3405-3415.
[28] Moher, David, Alessandro Liberati, Jennifer Tetzlaff, Douglas G. Altman, Doug Altman, Gerd Antes, David Atkins et al. "Preferred reporting items for systematic reviews and meta-analyses: the PRISMA statement (Chinese edition)." *Journal of Chinese Integrative Medicine* 7, no. 9 (2009): 889-896. https://doi.org/10.3736/jcim20090918
[29] Page, Matthew J., David Moher, Patrick M. Bossuyt, Isabelle Boutron, Tammy C. Hoffmann, Cynthia D. Mulrow, Larissa Shamseer et al. "PRISMA 2020 explanation and elaboration: updated guidance and exemplars for reporting systematic reviews." *bmj* 372 (2021).
[30] Pal, Vinod Kumar, and Vimal Kamlesh Kumar Bhatt. "Performance prediction for post graduate students using artificial neural network." *Int. J. Innov. Technol. Explor. Eng* 8, no. 7 (2019): 446-454.
[31] Khan, Ijaz, Abdul Rahim Ahmad, Nafaa Jabeur, and Mohammed Najah Mahdi. "Machine Learning Prediction and Recommendation Framework to Support Introductory Programming Course." *International Journal of Emerging Technologies in Learning* 16, no. 17 (2021). https://doi.org/10.3991/ijet.v16i17.18995
[32] Kuo, Jong-Yih, Hao-Ting Chung, Ping-Feng Wang, and BAIYING LE. "Building Student Course Performance Prediction Model Based on Deep Learning." *Journal of Information Science & Engineering* 37, no. 1 (2021). https://doi.org/10.32604/iasc.2021.014437
[33] Raza, Salman Hussain, Bibhya Nand Sharma, and Kaylash Chaudhary. "A new pair of watchful eyes for students in online courses." *Frontiers in Applied Mathematics and Statistics* 7 (2021): 620080. https://doi.org/10.3389/fams.2021.620080
[34] Aslam, Nida, Irfan Khan, Leena Alamri, and Ranim Almuslim. "An improved early student's academic performance prediction using deep learning." *International Journal of Emerging Technologies in Learning (iJET)* 16, no. 12 (2021): 108-122. https://doi.org/10.3991/ijet.v16i12.20699
[35] Yanta, Sorawee, Sotarat Thammaboosadee, Pornchai Chanyagorn, and Rojjalak Chuckpaiwong. "Course performance prediction and evolutionary optimization for undergraduate engineering program towards admission strategic planning." (2021). https://doi.org/10.1109/KST51265.2021.9415762
[36] Manjushree, D. Laddha, T. Lokare Varsha, W. Kiwelekar Arvind, and D. Netak Laxman. "Performance analysis of the impact of technical skills on employability." *International Journal of Performability Engineering* 17, no. 4 (2021): 371. https://doi.org/10.23940/ijpe.21.04.p5.371378
[37] Brahim, Ghassen Ben. "Predicting student performance from online engagement activities using novel statistical features." *Arabian Journal for Science and Engineering* 47, no. 8 (2022): 10225-10243. https://doi.org/10.1007/s13369-021-06548-w
[38] Chen, Hsing-Chung, Eko Prasetyo, Shian-Shyong Tseng, Karisma Trinanda Putra, Sri Suning Kusumawardani, and Chien-Erh Weng. "Week-Wise Student Performance Early Prediction in Virtual Learning Environment Using a Deep Explainable Artificial Intelligence." *Applied Sciences* 12, no. 4 (2022): 1885. https://doi.org/10.3390/app12041885

[39] Su, Yingying, Shengxu Wang, and Yi Li. "Research on the improvement effect of machine learning and neural network algorithms on the prediction of learning achievement." *Neural Computing and Applications* (2022): 1-15. https://doi.org/10.1007/s00521-021-06333-8
[40] Yacoub, Mohamed Farouk, Huda Amin Maghawry, Nivin A. Helal, Sebastian Ventura, and Tarek F. Gharib. "An enhanced predictive approach for students' performance." *International Journal of Advanced Computer Science and Applications* 13, no. 4 (2022). https://doi.org/10.14569/IJACSA.2022.01304101
[41] Dixit, Prashant, Harish Nagar, and Sarvottam Dixit. "Student performance prediction using case based reasoning knowledge base system (CBR-KBS) based data mining." *International Journal of Information and Education Technology* 12, no. 1 (2022): 30-35. https://doi.org/10.18178/ijiet.2022.12.1.1583
[42] Begum, Safira, and Sunita S. Padmannavar. "Genetically Optimized Ensemble Classifiers for Multiclass Student Performance Prediction." *International Journal of Intelligent Engineering & Systems* 15, no. 2 (2022). https://doi.org/10.22266/ijies2022.0430.29
[43] Saluja, Rajan, Munishwar Rai, and Rashmi Saluja. "Original Research Article Designing new student performance prediction model using ensemble machine learning." *Journal of Autonomous Intelligence* 6, no. 1 (2023). https://doi.org/10.32629/jai.v6i1.583
[44] Aljohani, Naif Radi, Ayman Fayoumi, and Saeed-Ul Hassan. "Predicting at-risk students using clickstream data in the virtual learning environment." *Sustainability* 11, no. 24 (2019): 7238. https://doi.org/10.3390/su11247238
[45] Albreiki, Balqis, Tetiana Habuza, and Nazar Zaki. "Framework for automatically suggesting remedial actions to help students at risk based on explainable ML and rule-based models." *International Journal of Educational Technology in Higher Education* 19, no. 1 (2022): 1-26. https://doi.org/10.1186/s41239-022-00354-6
[46] Tamada, Mariela Mizota, Rafael Giusti, and José Francisco de Magalhães Netto. "Predicting students at risk of dropout in technical course using LMS logs." *Electronics* 11, no. 3 (2022): 468. https://doi.org/10.3390/electronics11030468
[47] Brdesee, Hani Sami, Wafaa Alsaggaf, Naif Aljohani, and Saeed-Ul Hassan. "Predictive model using a machine learning approach for enhancing the retention rate of students at-risk." *International Journal on Semantic Web and Information Systems (IJSWIS)* 18, no. 1 (2022): 1-21. https://doi.org/10.4018/IJSWIS.299859
[48] Latif, Ghazanfar, Sherif E. Abdelhamid, Khaled S. Fawagreh, Ghassen Ben Brahim, and Runna Alghazo. "Machine Learning in Higher Education: Students' Performance Assessment considering Online Activity Logs." *IEEE Access* (2023). https://doi.org/10.1109/ACCESS.2023.3287972
[49] Pek, Reyhan Zeynep, Sibel Tariyan Özyer, Tarek Elhage, Tansel Özyer, and Reda Alhajj. "The role of machine learning in identifying students at-risk and minimizing failure." *IEEE Access* 11 (2022): 1224-1243. https://doi.org/10.1109/ACCESS.2022.3232984
[50] Xue, Han, and Yanmin Niu. "Multi-Output Based Hybrid Integrated Models for Student Performance Prediction." *Applied Sciences* 13, no. 9 (2023): 5384. https://doi.org/10.3390/app13095384
[51] Martins, Mónica V., Luís Baptista, Jorge Machado, and Valentim Realinho. "Multi-Class Phased Prediction of Academic Performance and Dropout in Higher Education." *Applied Sciences* 13, no. 8 (2023): 4702. https://doi.org/10.3390/app13084702
[52] Waheed, Hajra, Saeed-Ul Hassan, Raheel Nawaz, Naif R. Aljohani, Guanliang Chen, and Dragan Gasevic. "Early prediction of learners at risk in self-paced education: A neural network approach." *Expert Systems with Applications* 213 (2023): 118868. https://doi.org/10.1016/j.eswa.2022.118868
[53] Nuankaew Pratya, and Wongpanya Sararat Nuankaew. "Student Performance Prediction Model for Predicting Academic Achievement of High School Students," *European Journal of Educational Research* 11, no. 2 (2022): 949-963. https://doi.org/10.12973/eu-jer.11.2.949
[54] Hussain, Shah, and Muhammad Qasim Khan. "Student-performulator: Predicting students' academic performance at secondary and intermediate level using machine learning." *Annals of data science* 10, no. 3 (2023): 637-655. https://doi.org/10.1007/s40745-021-00341-0
[55] Alhazmi, Essa, and Abdullah Sheneamer. 'Early Predicting of Students Performance in Higher Education'. IEEE Access 11 (2023): 27579-89. https://doi.org/10.1109/ACCESS.2023.3250702
[56] Kukkar, Ashima, Rajni Mohana, Aman Sharma, and Anand Nayyar. "Prediction of student academic performance based on their emotional wellbeing and interaction on various e-learning platforms." *Education and Information Technologies* (2023): 1-30. https://doi.org/10.1007/s10639-022-11573-9
[57] Atalla, Shadi, Mohammad Daradkeh, Amjad Gawanmeh, Hatim Khalil, Wathiq Mansoor, Sami Miniaoui, and Yassine Himeur. "An Intelligent Recommendation System for Automating Academic Advising Based on Curriculum Analysis and Performance Modeling." *Mathematics* 11, no. 5 (2023): 1098. https://doi.org/10.3390/math11051098
[58] Munshi, M., Tarun Shrimali, and Sanjay Gaur. "An intelligent graph mining algorithm to analyze student performance in online learning." *Education and Information Technologies* 28, no. 6 (2023): 6667-6693.

https://doi.org/10.1007/s10639-022-11447-0

[59] Sahlaoui, Hayat, Anand Nayyar, Said Agoujil, and Mustafa Musa Jaber. "Predicting and interpreting student performance using ensemble models and shapley additive explanations." *IEEE Access* 9 (2021): 152688-152703. https://doi.org/10.1109/ACCESS.2021.3124270

[60] Huang, Chenxi, Junsheng Zhou, Jinling Chen, Jane Yang, Kathy Clawson, and Yonghong Peng. "A feature weighted support vector machine and artificial neural network algorithm for academic course performance prediction." *Neural Computing and Applications* 35, no. 16 (2023): 11517-11529. https://doi.org/10.1007/s00521-021-05962-3

[61] Asselman, Amal, Mohamed Khaldi, and Souhaib Aammou. "Enhancing the prediction of student performance based on the machine learning XGBoost algorithm." *Interactive Learning Environments* 31, no. 6 (2023): 3360-3379. https://doi.org/10.1080/10494820.2021.1928235

[62] Asthana, Pallavi, Sumita Mishra, Nishu Gupta, Mohammad Derawi, and Anil Kumar. "Prediction of Student's Performance With Learning Coefficients Using Regression Based Machine Learning Models." *IEEE Access* (2023). https://doi.org/10.1109/ACCESS.2023.3294700

[63] Rahul, and Rahul Katarya. "Deep auto encoder based on a transient search capsule network for student performance prediction." *Multimedia Tools and Applications* 82, no. 15 (2023): 23427-23451. https://doi.org/10.1007/s11042-022-14083-5

[64] Al-Azazi, Fatima Ahmed, and Mossa Ghurab. "ANN-LSTM: A deep learning model for early student performance prediction in MOOC." *Heliyon* 9, no. 4 (2023). https://doi.org/10.1016/j.heliyon.2023.e15382

[65] Zhang, Yupei, Rui An, Shuhui Liu, Jiaqi Cui, and Xuequn Shang. "Predicting and understanding student learning performance using multi-source sparse attention convolutional neural networks." *IEEE Transactions on Big Data* (2021).

[66] Sood, Sakshi, and Munish Saini. "Hybridization of cluster-based LDA and ANN for student performance prediction and comments evaluation." *Education and Information Technologies* 26 (2021): 2863-2878. https://doi.org/10.1007/s10639-020-10381-3

[67] Smadi, Ala, Ahmad Al-Qerem, Ahmad Nabot, Issam Jebreen, Amjad Aldweesh, Mohammad Alauthman, Awad M. Abaker, Omer Radhi Al Zuobi, and Musab B. Alzghoul. "Unlocking the Potential of Competency Exam Data with Machine Learning: Improving Higher Education Evaluation." *Sustainability* 15, no. 6 (2023): 5267. https://doi.org/10.3390/su15065267

[68] De Leon Evangelista, Edmund, and Benedict Descargar Sy. "An approach for improved students' performance prediction using homogeneous and heterogeneous ensemble methods." *International Journal of Electrical and Computer Engineering* 12, no. 5 (2022): 5226. https://doi.org/10.11591/ijece.v12i5.pp5226-5235

[69] Liu, Tieyuan, Chang Wang, Liang Chang, and Tianlong Gu. "Predicting High-Risk Students Using Learning Behavior." *Mathematics* 10, no. 14 (2022): 2483. https://doi.org/10.3390/math10142483

[70] Arif, Md, Asma Jahan, Mausumi Islam Mau, and Razia Tummarzia. "An Improved Prediction System of Students' Performance Using Classification model and Feature Selection Algorithm." *International Journal of Advances in Soft Computing & Its Applications* 13, no. 1 (2021). https://doi.org/10.1155/2021/5581806

[71] Sengupta, Souvik. "Towards Finding a Minimal Set of Features for Predicting Students' Performance Using Educational Data Mining." IJ Modern Education and Computer Science 3, no. 1 (2023): 44-54. https://doi.org/10.5815/ijmecs.2023.03.04

[72] Liu, Yutong, Si Fan, Shuxiang Xu, Atul Sajjanhar, Soonja Yeom, and Yuchen Wei. "Predicting Student performance using clickstream data and machine learning." *Education Sciences* 13, no. 1 (2022): 17. https://doi.org/10.3390/educsci13010017

[73] Christou, Vasileios, Ioannis Tsoulos, Vasileios Loupas, Alexandros T. Tzallas, Christos Gogos, Petros S. Karvelis, Nikolaos Antoniadis, Evripidis Glavas, and Nikolaos Giannakeas. "Performance and early drop prediction for higher education students using machine learning." *Expert Systems with Applications* 225 (2023): 120079. https://doi.org/10.1016/j.eswa.2023.120079

[74] Beckham, Nicholas Robert, Limas Jaya Akeh, Giodio Nathanael Pratama Mitaart, and Jurike V. Moniaga. "Determining factors that affect student performance using various machine learning methods." *Procedia Computer Science* 216 (2023): 597-603. https://doi.org/10.1016/j.procs.2022.12.174

[75] Deo, Ravinesh C., Zaher Mundher Yaseen, Nadhir Al-Ansari, Thong Nguyen-Huy, Trevor Ashley Mcpherson Langlands, and Linda Galligan. "Modern artificial intelligence model development for undergraduate student performance prediction: An investigation on engineering mathematics courses." *IEEE Access* 8 (2020): 136697-136724. https://doi.org/10.1109/ACCESS.2020.3010938

[76] Mohiddin, S. K., P. S. Kumar, S. A. M. Sai, and M. V. B. T. Santhi. "Machine learning techniques to improve the results of student performance." *International Journal of Innovative Technology and Exploring Engineering* 8, no. 5 (2019): 590-594.

[77] Chen, Yawen, and Linbo Zhai. "A comparative study on student performance prediction using machine learning." *Education and Information Technologies* (2023): 1-19. https://doi.org/10.1007/s10639-023-11672-1
[78] Ismanto, Edi, Hadhrami Ab Ghani, and Nurul Izrin Binti Md Saleh. "A comparative study of machine learning algorithms for virtual learning environment performance prediction." *IAES International Journal of Artificial Intelligence* (2023). https://doi.org/10.11591/ijai.v12.i4.pp1677-1686
[79] Alruwais, Nuha, and Mohammed Zakariah. "Evaluating Student Knowledge Assessment Using Machine Learning Techniques." *Sustainability* 15, no. 7 (2023): 6229. https://doi.org/10.3390/su15076229
[80] Kaensar, Chayaporn, and Worayoot Wongnin. "Analysis and Prediction of Student Performance Based on Moodle Log Data using Machine Learning Techniques." *International Journal of Emerging Technologies in Learning (Online)* 18, no. 10 (2023): 184. https://doi.org/10.3991/ijet.v18i10.35841