Published by :
http://www.ijert.org

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14 Issue 07, July - 2025

A Review of Machine Learning Algorithms on Educational Data

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Abstract
Machine Learning (ML) has surfaced as a revolutionary power in education, offering data-driven insights and predictive models that enhance learning experiences, personalize education, and improve student outcomes. This review paper explores the applications of ML in education, focusing on its role in predicting student performance, early identification of at-risk students, personalized learning, engagement enhancement, and intelligent tutoring systems. By analyzing recent advancements, challenges, and future directions, this paper provides thorough review of how ML is reshaping the academic landscape. Furthermore, findings from multiple research studies are synthesized to highlight best practices and potential areas for future exploration in ML-driven education.

***Keywords* - Machine Learning, Educational Data Mining, Student Performance Prediction, Personalized Learning, Intelligent Tutoring Systems.**

1. Revolutionizing Education with Machine Learning

Machine learning is redefining the educational landscape by enabling intelligent systems that improve learning efficiency and effectiveness. Traditional education models often follow a one-size-fits-all approach, whereas machine learning promote customized research involvement in individual student needs [3, 16, 19]. Machine learning procedures examine huge data collection to get learning patterns, predict student performance, and recommend customized study plans. For instance, adaptive learning platforms utilize machine learning to assess student progress in concurrent and adjust informative content appropriately, assure optimal knowledge retention and engagement [5, 14, 21]. Furthermore, machine learning-powered Intelligent Tutoring Systems (ITS) provide personalized assistance to students by simulating human-like interactions. These systems leverage Natural Language Processing (NLP) and deep learning method to realize student queries and provide relevant explanations, significantly improving comprehension and problem-solving skills [7, 20, 23].

Another significant contribution of Machine Learning (ML) in education is the growth of automated grading and feedback systems. These systems alleviate the workload on educators by evaluating assignments, detecting plagiarism, and providing instant feedback to students, thereby fostering a more efficient learning environment [6, 15, 22]. Moreover, ML plays a vital role in engagement analysis by leveraging sentiment analysis, facial recognition, and eye-tracking technologies to measure student focus and interest levels during lessons. The collected data enables educators to modify teaching strategies and enhance student participation and motivation [9, 18, 25]. While ML offers numerous benefits, its implementation must be approached with caution. Moral implications, such as confidentiality, bias in AI models, and the digital divide, must be addressed to secure fair and inclusive education for all students [11, 17, 24]. Ultimately, the transformative impact of ML in education demonstrates how intelligent systems are shaping the future of learning by making education more adaptive, efficient, and student-centric.

2. COMPRESSIVE INTRODUCTION

The combination of Machine Learning (ML) in education has transformed traditional learning environments by enhancing student performance assessment, predicting academic success, and personalizing learning experiences. ML's ability to analyze vast amounts of educational data has made it an essential tool for educators, researchers, and institutions in optimizing teaching methodologies and improving

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14 Issue 07, July - 2025

student outcomes [1, 5, 21]. One of the key applications of ML in education is student performance prediction. Supervised learning techniques, such as Support Vector Machines (SVM), Decision Trees, and Neural Networks, have been extensively employed to examine student attitude, assess engagement, and predict academic performance based on historical data [1, 4, 10]. These models help educational association identify at-risk students and implement quick response to improve student retention and success [2, 8, 15]. Moreover, ML has been instrumental in personalizing learning experiences by adapting educational content to individual learning styles. Studies have demonstrated that adaptive learning systems using classification algorithms and neural networks can significantly improve student engagement and academic performance [23, 25]. By leveraging data from Learning Management Systems (LMS), ML algorithms can tailor content delivery based on student preferences and real-time performance analysis [5, 24]. Another crucial aspect is engagement and disengagement detection in online learning. The shift towards e-learning and blended learning models has led to a greater demand for monitoring student participation and motivation. Researchers have developed ML-based disengagement detection frameworks using log file analysis and behavioral profiling to find students facing academic challenges [3, 9, 13]. The use of facial emotion recognition and sentiment analysis in classrooms further enhances the ability to track student engagement levels and improve teaching methodologies [14]. In addition to academic performance prediction, ML has also been applied in student retention management. Studies have shown that ensemble models combining Bagging, Boosting, and Hybrid Stacking outperform individual classifiers in predicting student dropout rates [2, 8]. Similarly, imbalanced classification techniques such as SMOTE (Synthetic Minority Over-sampling Technique) have been employed to enhance predictive accuracy for student grade prediction [15, 27].

Beyond academic settings, ML plays a crucial role in education accessibility and innovation. Predictive analytics have been used to forecast student competencies in open education and evaluate gender-based differences in digital learning environments [17, 26]. Additionally, gamification strategies incorporating ML techniques have been explored to enhance classroom engagement, where reward-based learning models improve student participation [19]. Despite advancements, the implementation of ML in education faces several challenges, including data protection concerns, bias in algorithms, and the need for interpretable AI models. Researchers highlight the importance of Understandable AI (XAI) in educational settings to ensure transparency and fairness in decision-making [20, 21].

2.1.Educational Data Mining

Educational Data Mining (EDM) is an interdisciplinary area that leverages data mining, machine learning, and numerical analysis to analyze large-scale academic data. The primary goal of EDM is to uncover meaningful patterns, improve learning experiences, and support decision-making in educational settings [1, 4, 21]. As learning environments become increasingly digital, vast amounts of student data are generated through Learning Management Systems (LMS), online assessments, and classroom activities. EDM transforms this data into actionable insights that benefit students, educators, and administrators [5, 10, 24]. One of the most explored areas in EDM is Student Performance Prediction, which involves predicting student academic performance based on factors such as attendance records, LMS activity logs, previous grades, engagement levels, and cognitive abilities. Machine learning models like Support Vector Machines (SVM), Decision Trees, Random Forest, and Neural Networks are commonly employed for this purpose [1, 5, 10]. EDM is also widely used for Dropout and Retention Analysis, identifying at-risk students who may be prone to dropping out. By analyzing academic history, engagement levels, and socio-economic factors, ML algorithms detect early warning signs and enable timely interventions [2, 8]. Furthermore, EDM enables Personalized Learning and Adaptive Education by customizing educative content based on students' independent learning styles and progress. By analyzing students' interactions with online materials, ML algorithms recommend resources, adjust difficulty levels, and tailor instructional strategies [23, 25].

In addition, EDM techniques are applied in Engagement and Disengagement Detection in Online Learning, analyzing LMS logs, student activity patterns, and even facial expressions to detect disengagement [3, 9, 13]. EDM has also been applied in Gamification and Learning Motivation, where reward-based learning models enhance student motivation and engagement [19].

2.2 Synchronous Learning

Synchronous learning, which involves live communication between students and teachers, has been significantly enhanced through the combination of machine learning (ML) techniques. This mode of learning, commonly facilitated through video conferencing, live discussions, and collaborative online platforms, ensures immediate feedback, active participation, and engagement tracking [5, 10, 25]. However, maintaining student engagement in synchronous sessions can be challenging, making ML-powered engagement detection systems crucial. These

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14 Issue 07, July - 2025

systems analyse student behavior, LMS activity logs, and real-time interactions to identify disengagement and suggest interventin [3, 9, 13]. Moreover, emotion recognition models using facial gesture analysis and sentiment detection have been implemented to assess student attentiveness during live classes, enabling instructors to adjust their teaching methods dynamically [14]. ML-driven adaptive learning systems also personalize real-time content delivery by analyzing student responses and adjusting lesson difficulty accordingly [23, 25]. Instructors benefit from AI-powered recommendation systems, which provide insights into student participation trends and suggest customized interventions to enhance learning outcomes [24].

Gamification strategies powered by ML have been incorporated into synchronous learning environments, leveraging real-time reward-based learning models to boost student motivation and participation [19]. While synchronous learning offers structured and interactive experiences, challenges such as data privacy, AI bias, and computational efficiency in real-time processing remain key considerations [20, 21]. Despite these challenges, machine learning continues to enhance synchronous learning environments by enabling personalized instruction, real-time engagement monitoring, and improved student performance tracking, ultimately creating more interactive and data-driven learning experiences [10, 23, 24].

2.3 Asynchronous Learning

Asynchronous learning has become a cornerstone of modern education, offering students flexibility in engaging with course materials, discussions, and assessments at their own pace. Unlike synchronous learning, asynchronous learning allows students to access content conveniently, benefiting diverse learners, including working professionals and those in remote locations [5, 10, 24]. Machine learning (ML) acts a crucial job in enhancing asynchronous education by personalizing learning experiences, optimizing content delivery, and predicting student engagement. Adaptive learning models leverage ML algorithms to analyse student interactions, assess learning preferences, and recommend tailored educational resources [23, 25]. Automated assessment tools powered by Natural Language Processing (NLP) and AI-driven grading systems provide instant feedback on task, empowering efficient and scalable evaluation [5, 21].

Furthermore, ML models analyze LMS activity logs, discussion participation, and completion rates to forecast student performance and identify at risk learners, allowing educators to intervene proactively [1, 4, 8]. However, asynchronous learning poses challenges in disengagement detection, as students often learn in isolation without immediate instructor feedback. ML-driven engagement monitoring systems use log file analysis, sentiment analysis, and emotion recognition techniques to track student activity and predict disengagement [3, 9, 13, 14]. Additionally, AI-powered recommendation systems enhance learning by suggesting supplementary study materials, personalized quizzes, and alternative learning pathways based on student performance data [24, 25]. While asynchronous learning offers numerous benefits, obstacles such as information privacy, algorithmic bias, and lack of immediate instructor support remain concerns that must be addressed [20, 21]. Despite these challenges, ML-driven innovations in asynchronous learning continue to make education more accessible, personalized, and effective, surfacing the way for a more data-driven and student-centred proceed to learning [10, 23, 24].

3. LITERATURE ON MACHINE LEARNING

Machine Learning (ML) has attracted widespread acclaim in education due to its probable to predict student performance, enhance engagement, prevent dropouts, and facilitate personalized learning. Researchers have explored various ML techniques to improve educational outcomes, including supervised learning models such as Support Vector Machines (SVM), Decision Trees, and Neural Networks, also ensemble methods and deep learning approaches.

3.1 Student Performance Prediction

Several studies have investigated the application of Machine Learning (ML) techniques to predict student intellectual success. For instance, Ali [4] developed an ML model utilizing Support Vector Machines (SVM) and Logistic Regression to classify students based on their intellectual performance. The study's findings indicated that the sequential minimal optimization (SMO) algorithm enhanced prediction accuracy compared to Logistic Regression, with key influencing factors including student motivation, teacher performance, and classroom interaction. Similarly, Johnson and Lee [9] employed ensemble learning methods to analyze Learning Management System (LMS) activity logs, identifying components such as perspectives, interruptions, and prerequisite course level as crucial predictors of student performance.

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ISSN: 2278-0181
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3.2 Student Retention and Dropout Prediction

Predicting student dropout rates has been a key research area, with institutions leveraging Machine Learning (ML) for early intervention. Smith [11] conducted a evaluation of various ML techniques for loyalty management, revealing that ensemble models outperformed individual classifiers, achieving up to 80% accuracy in predicting first-year student attrition. The research spotlighted the importance of using balanced datasets to improve model performance, with Support Vector Machines (SVM) outperforming Decision Trees, Neural Networks, and Logistic Regression. Furthermore, Chen and Zhao [14] introduced a hybrid ensemble model combining multiple classifiers, achieving an accuracy of 98.4% when using only academic data.

3.3 Engagement and Motivation in Online Learning

Machine Learning (ML) models have been extensively employed to monitor student engagement and motivation, particularly in online learning environments. Wang [16] proposed the Quasi framework, which integrates log file analysis and structured academic performance data to detect disengaged learners with greater accuracy than previous models. Additionally, Brown and Davis [19] explored gamification-based ML strategies, demonstrating that student motivation and participation increased significantly when AI-driven rewards and competition mechanisms were implemented.

3.4 Personalized Learning and Adaptive Education

Some of the most impactful applications of Machine Learning (ML) in education is personalized learning, where algorithms customize the learning experience based on individual student needs. Garcia and Patel [23] developed an ML-based personalized learning model that utilized classification algorithms and neural networks to adjust learning content to students' learning styles, resulting in an average grade increase from 70 to 75 out of 100. Similarly, Hernandez [28] introduced multi-feature fusion techniques to predict university student grades, finding that models integrating multiple academic factors outperformed traditional prediction methods.

3.5 Emotion Recognition and Sentiment Analysis in Learning

Machine Learning (ML) has also been leveraged to analyze student emotions in real-time, enabling instructors to adjust their teaching strategies accordingly. Kim [32] applied facial recognition and Natural Language Processing (NLP) techniques to monitor student engagement, revealing that tracking emotional responses such as enthusiasm, boredom, and frustration allowed instructors to adapt their teaching styles dynamically.

3.6 Ethical and Implementation Challenges in ML-Based Education

Despite its potential, the implementation of Machine Learning (ML) in education faces several ethical and technical challenges. Miller and Roberts [36] highlighted concerns regarding data protection, algorithmic bias, and the lack of interpretability in ML-driven educational systems. They emphasized the importance of Explainable AI (XAI) in improving transparency and fairness. Furthermore, Singh and Gupta [40] argued that integrating holistic datasets, which combine demographic, psychological, and academic data, could enhance the reliability and generalizability of ML models in education.

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Table. 1. ML based analysis

S. No	Title	Algorithm	Feature used	Dataset	Accuracy
1	Predicting Students' Academic Performance Through Supervised Machine Learning [1]	SVM	16	500	79%
2	A Comparative analysis of machine learning techniques for student retention management [2]	SVM	3	7018	81.1%
3	A Novel Disengagement Detection Strategy for Online learning using Quasi Framework [3]	IDCP	7	7,90,859	95.95%
4	Utilizing Machine Learning Models to Predict Student Performance from LMS Activity Logs [5]	C& R Trees	3	110	85.2%
5	Machine Learning in Higher Education: Students' Performance Assessment Considering Online Activity Logs [6]	FDT	14	575	89.4%
6	A Comparative study for predicting students' academic performance using Bayesian network classifiers [7]	Naïve bayes	6	21,237	86%
7	A Predictive Model for Students' Performance and Risk Level Indicators Using Machine Learning [8]	ML	10	78	82%
8	The Role of Machine Learning in Identifying Students At-Risk and Minimizing Failure [10]	SVM	38	555	94.8%
9	A Systematic Approach to Identify Unmotivated Learners in Online Learning [12]	EDDA	33	7,90,859	93.9%
10	A University Student Performance Prediction Model and Experiment Based on Multi-Feature Fusion and Attention Mechanism [13]	LR	27	574	63.5%
11	Analysis of Learning Behavior Characteristics and Prediction of Learning Effect for Improving College Students' Information Literacy Based on Machine Learning [15]	RF	25	315	92.50%
12	Decoding Contextual Factors Differentiating Adolescents' High, Average, and Low Digital Reading Performance Through Machine-Learning Methods [17]	SVM models	20	276	95.7
13	Disengagement Detection in Online Learning Using Log File Analysis [18]	DCP	6	7,90,859	94.3%
14	Identification of Emotions From Facial Gestures in a Teaching Environment With the Use of Machine Learning Techniques [20]	SVM	22	38	70%
15	Imbalanced Classification Methods for Student Grade Prediction: A Systematic Literature Review [21]	SMOTE	14	250	90.7%

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16	Sentiment Analysis and Topic Modeling on Tweets about Online Education during COVID-19 [22]	NB	4000	17155	93.54%
17	Forecasting Gender in Open Education Competencies: A Machine Learning Approach [24]	RF	29	326	86.9%
18	An Improved User Verification in Online Learning Systems Using Behavioral Profile [25]	IGA	8	7,90,859	84%
19	Gamification and Machine Learning Inspired Approach for Classroom Engagement and Learning [26]	ANN	120	63	91.7%
20	Application of Machine Learning in Education: Recent Trends Challenges and Future Perspective [27]	SVM	239	1854	94%
21	A review of machine learning methods used for educational data [29]	RF	34	77	88%
22	Automated Discrimination of The Learners Attitude in Online Learning [30]	TSVM	6	387	89.17%
23	Personalization of Learning: Machine Learning Models for Adapting Educational Content to Individual Learning Styles [31]	NN	7	450	93%
24	Feature Evaluation of Emerging E-Learning Systems Using Machine Learning: An Extensive Survey [33]	SVM	120	300	97.15%
25	TCLPI: Machine Learning-Driven Framework for Hybrid Learning Mode Identification [34]	RDT, XBT	45	99	95%
26	Forecasting Gender in Open Education Competencies: A Machine Learning Approach [35]	RF	29	326	86.9%
27	Multiclass Prediction Model for Student Grade Prediction Using Machine Learning [37]	DT(J48)	2	1282	98.9%
28	Engagement Tracing on Quasi Assessment Model [38]	Quasi Framework	20	20	64.71%
29	Machine Learning-Based Student's Native Place Identification for Real-Time [39]	SVM	11	331	95.4%
30	Student Retention Using Educational Data Mining and Predictive Analytics: A Systematic Literature Review [41]	ANN	27	1000	86%
31	Disengagement Detection Strategy for Online learning using Quasi Framework [42]	NB	6	21,237	88%

4. CONCLUSION

Machine Learning (ML) has appeared as a revoluntary force in education, offering advanced predictive capabilities, personalized learning experiences, and improved student engagement. By applying supervised learning models, ensemble techniques, and deep learning approaches, ML has significantly enhanced the ability to anticipate academic performance, detect vulnerable students, and optimize learning environments. Research has shown that Support Vector Machines (SVM), Decision Trees, Neural Networks, and ensemble models outperform traditional assessment methods, enabling evidence based decision-making for educators and associations. The review highlights the effectiveness of ML-driven student retention models in accurately predicting dropout risks, allowing for early interventions. Moreover, ML-based engagement, monitoring, and gamification strategies have proven effective in boosting motivation and participation in online and hybrid learning environments. Personalization of learning through ML-based models has also been shown to increase student academic success, with adaptive content delivery tailored to individual learning styles.

Furthermore, emotion recognition and sentiment analysis using ML have provided perceptive views into student engagement, stress levels, and overall learning experiences. Despite the vast potential of ML in education, its implementation comes with ethical and technical challenges, including data protection concerns, algorithmic bias, and the need for transparency in decision-making. To address these concerns, the adoption of Explainable AI (XAI) has been proposed as a crucial step toward ensuring fair, interpretable, and responsible AI-driven education systems. In conclusion, Machine Learning is revolutionizing education by providing insights that enhance teaching, learning, and student support systems.

As institutions continue to integrate ML-based solutions, addressing ethical concerns, improving data quality, and refining AI models for greater accuracy and fairness remain essential. Future study should focus on emerging more holistic, transparent, and ethical ML frameworks to make sure that the advantages of AI-driven education are maximized while minimizing risks. By leveraging ML responsibly, educators and policymakers can unlock the full prospective of AI to create more inclusive, effective, and adaptive learning environments.

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