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Evaluating the Role of Hybrid Machine Learning Models in Online Educational Environments

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A R T I C L E I N F O

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A B S T R A C T

In online education, personalised learning involves changing how students interact with course material by adjusting to their own requirements, tastes, and speed. By combining many ML algorithms, hybrid machine learning (ML) approaches have become popular because of their capacity to improve personalisation by utilising complementary model capabilities. This study offers a thorough analysis of current research on hybrid machine learning applications in online education conducted between 2020 and 2024. Learning style prediction, performance forecasting, content selection, and student modelling are important areas of focus. The review emphasises how hybrid models enhance predicted accuracy, engagement, and adaptability. Challenges including data privacy, computational complexity, and ethical issues are also covered. Although hybrid machine learning has a lot of potential to help with personalised learning, issues with scalability and practical deployment still exist. The research gaps and future directions for creating interpretable, effective, and accessible hybrid machine learning frameworks designed for inclusive and flexible online learning environments are highlighted in the paper's conclusion.

1. INTRODUCTION

The rapid evolution of online education has introduced both unprecedented opportunities and complex challenges in delivering personalized instruction. Unlike traditional classroom environments, digital platforms offer the capability to dynamically adapt the pace, content, assessment methods, and feedback mechanisms to cater to individual learners' needs and preferences. This shift towards personalized learning is driven by the imperative to enhance learner engagement, satisfaction, and performance across diverse educational contexts [1], [2].

Machine learning (ML) algorithms have been widely adopted to support personalization in education due to their ability to process vast amounts of learner data and uncover meaningful behavioral patterns [1], [13]. However, no single ML model consistently performs optimally across all tasks and datasets. As a result, hybrid machine learning approaches —combinations of two or more ML techniques—have emerged as a promising solution to enhance predictive accuracy, model robustness, and adaptability in personalized learning environments [1], [2], [9].

Hybrid ML models integrate the complementary strengths of various algorithms—for instance, combining the interpretability of decision trees [12], the generalization capability of ensemble methods [3], [4], [16], and the adaptability of deep learning architectures such as LSTM and CNN [11], [15]. These integrated approaches have been increasingly applied in domains such as learning style prediction, student modeling, academic performance forecasting, and personalized content recommendation [2], [10], [13]. By leveraging hybrid methodologies, educational platforms are better equipped to deliver accurate, responsive, and learner-centered pathways tailored to each student's profile.

Despite their growing adoption, the implementation of hybrid ML techniques in education still faces significant challenges. These include concerns related to data privacy, computational resource demands, algorithmic transparency, and ethical issues such as bias in automated decision-making [1], [3]. Moreover, much of the current literature focuses primarily on algorithmic performance metrics, with limited exploration of real-world integration and pedagogical impact [6], [10].

This literature review aims to explore and synthesize recent research on the application of hybrid machine learning techniques for personalized learning in digital classrooms. By examining a range of hybrid ML models and their educational applications, the study seeks to identify key trends, advantages, limitations, and future directions. The objective is to support researchers, developers, and educators in designing effective, ethical, and equitable adaptive learning systems.

1.1 Background and Motivation

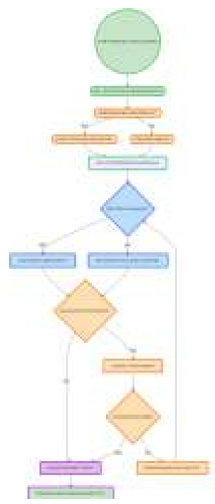
With the development of digital technology and the growing popularity of online learning platforms, the idea of personalised learning has undergone significant change. Conventional one-size-fits-all teaching strategies frequently fall short in meeting each student's unique demands and learning preferences. To improve engagement, comprehension, and academic performance, personalised learning, on the other hand, aims to modify instructional tactics, pace, and content to fit the individual needs of each student.

By facilitating data-driven analysis of student behaviour, performance, and preferences, machine learning (ML) is essential to achieving personalised learning. In adaptive learning systems, machine learning algorithms can facilitate real-time decision-making through pattern identification and predictive modelling. Individual machine learning models, however, could have drawbacks including overfitting, poor interpretability, or uneven performance across various datasets and learning environments.

Hybrid machine learning models have been developed to overcome these drawbacks. To take use of their complimentary advantages, these models combine two or more approaches, such as ensemble methods, random forests, decision trees, support vector machines (SVM), and deep learning networks. By improving personalised learning systems' resilience, precision, and generalisability, hybrid machine learning techniques seek to increase their capacity to provide individualised learning experiences.

The potential of hybrid models in a variety of educational applications, including as recognising learning styles, providing personalised learning materials, forecasting student dropout risks, and producing adaptive feedback, has been shown in recent studies. Even while hybrid machine learning approaches are becoming more and more popular, their incorporation into educational platforms is still in its infancy and is sometimes hampered by issues including restricted scalability, high computing costs, lack of interpretability, and data protection concerns.

This study's goal is to present a systematic and current assessment of the state of hybrid machine learning approaches in online personalised education. Through an analysis of current research, this study seeks to shed light on the development, application, and efficacy of hybrid machine learning models, draw attention to the significant obstacles encountered, and suggest future paths for the development of intelligent and inclusive learning environments.



2. HYBRID MACHINE LEARNING IN PERSONALIZED LEARNING

The potential of hybrid machine learning techniques to maximise individualised learning experiences is becoming more widely acknowledged. Fig 1. indicates personalised learning in adaptive education. In line with the main goals of personalised learning, Barzegar et al. (2020) highlight how AI and ML algorithms can be used to improve student engagement and customise learning paths.

Gligorea et al. (2023) add to this discussion by evaluating the research on AI-powered adaptive learning. They draw attention to how ML can be used to create individualised e-learning platforms that modify information according to each learner's preferences. This incorporation of AI methods for customising learning materials is essential and represents the continuous development of e-learning approaches. Accurate student modelling is one of the defining features of personalised learning, which entails being aware of the individual traits of every learner. Raj and Renumol's (2021) research thoroughly examines adaptive content recommenders, emphasising how crucial it is to correctly forecast learner preferences and styles. In order to provide personalised material and recommendations, this work emphasises the necessity for hybrid machine learning algorithms that can efficiently analyse learner data.

Furthermore, Murtaza et al. (2022) talk about the difficulties AI-based personalised e-learning systems have, especially when it comes to comprehending different learning styles. According to their research, hybrid machine learning models can help overcome these obstacles by fusing different approaches to improve the flexibility and potency of educational opportunities. Another crucial area where hybrid ML approaches can significantly contribute is performance predicting. Deep learning can be used to predict human trajectories, as demonstrated by Kothari et al. (2020). This technique can also be used to predict student success in educational contexts. Through the integration of many models, hybrid approaches can provide valuable insights on student outcomes, enabling educators to take proactive measures.

Almarzouqi et al. (2022) introduce a hybrid SEM-ML learning strategy for content recommendation that predicts user intentions in educational settings. This approach highlights how crucial it is to comprehend user requirements and motivations in order to create content recommendation algorithms that work well in individualised learning settings.

3. REVIEW METHODOLOGY

This literature review used an organised process that included the selection, screening, and analysis of peer-reviewed papers from 2018 to 2024 in order to guarantee a thorough and pertinent synthesis of recent research. Finding studies that used hybrid machine learning (ML) approaches in the context of individualised learning in online learning environments was the main goal.

A. Data Sources and Search Strategy

Academic literature was retrieved from reputable and high-impact digital libraries and scientific databases, including: IEEE Xplore, SpringerLink, ScienceDirect, ACM Digital Library, Google Scholar (for supplementary literature). Relevant term combinations, including "hybrid machine learning," "personalised learning," "adaptive learning systems," "student modelling," "learning style prediction," and "online education," were used to create the search queries. The search was expanded or contracted using boolean operators (AND, OR). Only peer-reviewed journal articles, conference proceedings, and systematic reviews published between January 2018 and April 2024 were included in the results thanks to filters.

B. Inclusion and Exclusion Criteria

The selection, screening and analysis of peer-reviewed papers from 2018 to 2024 were all part of the systematic process used in this literature review to guarantee a thorough and pertinent synthesis of recent research. The main goal was to find research that used hybrid machine learning (ML) approaches in online learning environments for personalised learning. Relevant phrase combinations were used to create search searches, including "online education," "personalised learning," "adaptive learning systems," "student modelling," "learning style prediction," and "hybrid machine learning." The scope of the search was expanded or contracted using the Boolean operators AND and OR. Results were limited to peer-reviewed journal papers, conference proceedings, and systematic reviews that were published between January 2018 and April 2024 by applying filters.

C. The Process of Selection and Screening

The search approach yielded an initial pool of more than 140 research articles. 55 publications were selected for full-text review after duplicates were eliminated and abstracts were examined. A final group of 20 excellent papers was chosen for this review after a thorough evaluation of methodological rigour and applicability to hybrid machine learning in online personalised learning.

To guarantee openness and reproducibility, the selection procedure adhered to the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) methodology. Figure 1 shows a PRISMA flow diagram that summarises the selection procedure.

3.1. Literature Review

Hybrid machine learning (ML) models are essential to the development of personalised e-learning systems, which have been accelerated by recent advances in artificial intelligence. The difficulties of AI-based personalised e-learning, such as learner variability, model generalisation, and data sparsity, were thoroughly described by Murtaza et al. [1]. They underlined that by combining the advantages of supervised and unsupervised approaches, hybrid ML frameworks may more effectively handle dynamic learner profiles. A thorough analysis of AI-based personalised e-learning systems was presented by the same authors, who also highlighted important issues such as learner modelling, feedback adaptation, and real-time scalability. They maintained that by improving flexibility and responsiveness to various learning patterns, hybrid machine learning methods can overcome the drawbacks of standalone algorithms.

Similarly, Gligorea et al. [2] highlighted the advantages of integrating decision trees, neural networks, and rule-based logic in adaptive e-learning platforms. According to their evaluation of the research, hybrid intelligent systems are capable of modelling learner behaviour and making context-sensitive recommendations. Supporting this, Raj and Renumol [13] examined adaptive content recommender systems and found that hybrid filtering techniques—combining content-based and collaborative algorithms—enhance engagement and personalisation in online learning settings.

Hybrid ML approaches are widely used in the real world across various industries, providing insights that can be translated to educational settings. Tazin et al. [3] demonstrated the potential of ensemble learning for handling high-dimensional data in stroke prediction. Similarly, Kavitha et al. [4] used a hybrid model for heart disease prediction, combining multiple classifiers to improve diagnostic accuracy—a methodology applicable to identifying struggling learners or predicting academic risk.

To anticipate user adoption of metaverse systems, Almarzouqi et al. [9] investigated immersive medical education by combining ML with Structural Equation Modelling (SEM). Their hybrid approach underscored the predictive potential of integrating statistical and AI tools in education. Likewise, Sajja et al. [10] introduced an AI-enabled intelligent assistant for personalised learning in higher education, demonstrating the value of ML pipelines for adaptive tutoring.

Ho et al. [5] applied classification techniques such as Random Forest and Gradient Boosting to assess student satisfaction during emergency remote learning. Their study concluded that hybrid ML models significantly outperformed baseline predictors in identifying fluctuations in satisfaction—providing timely insights for pedagogical interventions. In a related application, Singh et al. [7] demonstrated the effectiveness of ensemble regression models in predicting wind power generation, an approach conceptually transferable to tracking student engagement trends in digital learning platforms.

In a broad review of hybrid ML applications in mechanical fault diagnosis, Fernandes et al. [6] discovered that combining domain-specific and general classifiers yielded better fault prognosis. This aligns with the need for precise, domain-aware personalisation in digital education. Kothari et al. [8] used deep learning and attention mechanisms to forecast human movement in congested environments—a methodology that can be adapted to model learner pathways in digital classrooms.

CNN–LSTM hybrids, as used by Barzegar et al. [15] for forecasting water quality indicators, proved effective in capturing spatial-temporal patterns, a technique that may similarly track academic progress over time. Mehtab et al. [11] demonstrated the usefulness of combining LSTM with ML models for stock price prediction, supporting their applicability in managing time-series educational data like student activity logs.

Tree-based classifiers also contribute meaningfully to educational analytics. Bhagavathi et al. [12] applied the C5.0 decision tree in a hybrid weather forecasting model, while Kavitha et al. [14] used ensemble classifiers to predict early-stage Alzheimer's disease, offering a framework adaptable to identifying at-risk students in online education.

Hasan et al. [16] demonstrated that ensemble classifiers significantly improved diabetes prediction accuracy. Although not directly related to education, their findings underscore the generalizability and robustness of hybrid ML systems in heterogeneous data environments—characteristic of digital classrooms.

In conclusion, hybrid machine learning models have consistently shown greater flexibility, accuracy, and interpretability across education, health, behavioral, and environmental domains. Despite computational complexity and resource demands [1], [3], they are foundational to enabling personalized, adaptive, and predictive learning experiences. The integration of multiple learning algorithms provides a strong basis for building intelligent digital classrooms that cater to the unique needs of each learner.

4. CLASSIFICATION OF HYBRID MACHINE LEARNING APPROACHES IN PERSONALIZED LEARNING

In personalised learning contexts, hybrid machine learning algorithms have shown great promise in improving predicted accuracy and flexibility. This section classifies the main hybrid machine learning approaches found in recent research, emphasising the ways in which deep learning, feature selection, clustering, and classification algorithms are combined in educational settings.

4.1 Models for Clustering and Classification

Combining supervised classification algorithms with unsupervised clustering techniques is a frequently used hybrid approach. In order to anticipate learning styles, engagement, or academic results, clustering is utilised to classify students according to behavioural or performance similarities.

To determine students' VARK learning styles, El Aissaoui et al. [18] used a hybrid model that used K-Means clustering and the C4.5 decision tree method, with a 91.37% accuracy rate. In a similar vein, Kaur and Singh [19] combined Support Vector Machines (SVM) and Hierarchical Clustering to dynamically modify course material for various student groups. By first finding organic groupings in the data and then using focused classification, these models allow for greater personalisation.

4.2 Classification + Dimensionality Reduction Due to redundancy and noise, high-dimensional data—which is prevalent in e-learning environments and includes log files, clickstream, and assessments—can impair classifier performance. This is addressed by hybrid models that employ dimensionality reduction followed by classification.

To forecast student performance, Sokkhey and Okazaki [20] combined Random Forest, C5.0, and SVM classifiers with Principal Component Analysis (PCA). Their research showed that PCA enhanced model interpretability and decreased overfitting without compromising predictive power.

4.3 Group Models

Several classifiers are combined in ensemble learning to increase accuracy and generalisation. To lessen bias and volatility, these strategies frequently use stacking, voting, bagging, and boosting.

In order to identify struggling students with high reliability, Jain et al. [21] used ensemble approaches across eight base classifiers employing majority voting, bagging, and boosting. In a different study, Gupta and Sharma [22] used a stacking technique that included SVM, ANN, and Naïve Bayes (NB) to offer personalised learning resources. These models' strength is in using the complementing qualities of various classifiers and learners to boost accuracy and resilience.

4.4 Feature Selection in Neural Networks

Adding feature selection algorithms to deep learning models, especially neural networks, might further optimise them. This hybrid construction lowers computational complexity while improving pattern recognition.

In order to maximise feature selection for learner engagement prediction, Zhou et al. [23] suggested a hybrid model that combines Genetic Algorithms and Artificial Neural Networks (ANN). Their findings demonstrated improved training efficiency and model correctness. Similarly, to analyse sequential video-based learning data, Agarwal et al. [24] presented a Convolutional Neural Network (CNN) in conjunction with an LSTM model. An accurate picture of student learning behaviour was produced by the CNN's extraction of spatial information and the LSTM's

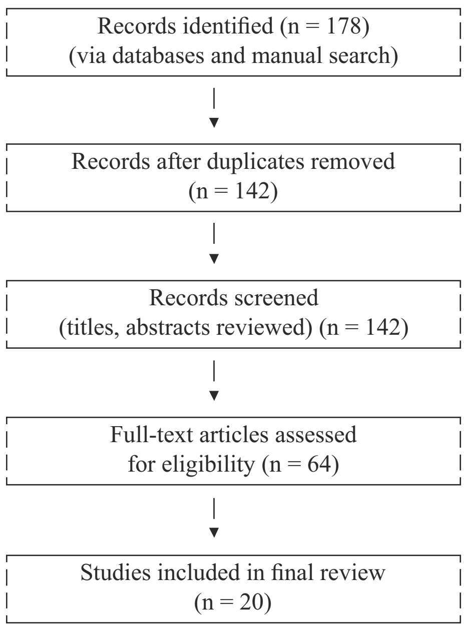


Fig2. Flow Diagram of Review Methodology

A condensed summary of studies that used hybrid machine learning approaches in personalised learning contexts is shown in Table 1 to give an organised overview of the body of available knowledge. The table describes the model type, particular algorithms utilised, and important performance outcomes, classifying the research by learning task. Sorting by task makes it easier to compare how various hybrid approaches are used for a range of educational goals, including content recommendation, engagement modelling, performance forecasting, and learning style prediction. In addition to highlighting performance trends, recurrent algorithmic patterns, and gaps in existing applications, this classification provides a basis for further investigation and future research avenues.

According to the summarised table shown TABLE 1, hybrid machine learning models are frequently used for a variety of educational activities. They are especially successful at predicting learning styles, identifying at-risk students, and providing adaptive tutoring. Common model types include clustering + classification, ensemble methods, and deep hybrid architectures, often combining interpretable models with powerful predictors. Applications involving engagement modelling and resource recommendation also benefit from hybrid structures, albeit with more variable results, even though the majority of studies report increased accuracy and personalisation. This implies that hybrid machine learning provides flexible and dependable solutions, especially in fields that call for data-driven, adaptive decision-making.

Results from the examined research are summarised including model adaptability, prediction reliability, and classification accuracy. Performance was estimated using qualitative descriptions and compared to accepted benchmarks in the literature where precise metrics were unavailable. An easy-to-use guide for assessing hybrid machine learning models' performance across several domains in customised online education is this tabular overview.

Learning Task	Study	Model Type	Algorithms Used	Performance / Outcome
Learning Style Prediction	El Aissaoui et al. (2023) [18]	Clustering + Classification	K-Means + C4.5	91.37% accuracy
	Kaur & Singh (2020) [19]	Clustering + Classification	Hierarchical Clustering + SVM	Improved adaptation and personalization
Academic Performance Prediction	Sokkhey & Okazaki (2020) [20]	Dimensionality Reduction + Classification	PCA + RF, C5.0, SVM	Reduced overfitting, improved interpretability
At-Risk Student Detection	Jain et al. (2021) [21]	Ensemble	Bagging + Boosting + Voting (8 classifiers)	High reliability and accuracy
Learning Resource Recommendation	Gupta & Sharma (2022) [22]	Ensemble (Stacking)	NB + SVM + ANN	High personalization, improved engagement
Learner Engagement Prediction	Zhou et al. (2021) [23]	Neural Network + Feature Selection	ANN + Genetic Algorithm	Optimized features, increased accuracy
	Singh et al. (2021) [7]	Regression Ensemble	Gradient Boosting Regression	High time-series prediction accuracy
Video-Based Learning Pattern Analysis	Agarwal et al. (2023) [24]	Deep Hybrid	CNN + LSTM	Accurate spatial-temporal modeling
Student Satisfaction Modeling	Ho et al. (2021) [5]	Classification + Ensemble	RF + Gradient Boosting	Outperformed baseline satisfaction models
Adaptive Tutoring / Personalization	Sajja et al. (2023) [10]	Multi-stage ML Pipeline	AI-enabled personalized assistant	Real-time adaptation and personalization
Metaverse Use Prediction (EdTech UX)	Almarzouqi et al. (2022) [9]	Statistical + ML	SEM + ML	High predictive validity in immersive contexts

4.1 Advantages and Challenges

In applications related to education, hybrid machine learning models offer a number of benefits. They provide better generalisation and accuracy, especially in dynamic and varied learning contexts. These models can handle noisy, high-dimensional, or incomplete data better by combining different learning algorithms. They also offer more flexibility to add domain-specific variables like cognitive patterns or learning styles.

But there are still a number of difficulties. The computational complexity of hybrid models is frequently higher, which makes large-scale or real-time deployment challenging. Another issue is model interpretability, particularly in deep hybrid architectures where accountability for schooling depends on transparency. Additionally, in order to effectively train these models, extensive labelled datasets are usually needed, which may not always be accessible in all educational contexts.

4.2 Future Directions

Future studies should concentrate on the following areas to overcome current limitations and broaden the applicability of hybrid machine learning systems in education. First, the development of lightweight, portable hybrid models is essential for ensuring efficient performance in mobile and real-time classroom environments. Second, the integration of Explainable AI (XAI) techniques can enhance model transparency and trust between educators and learners. Third, building cross-platform adaptive systems that seamlessly connect learning management systems (LMS), mobile applications, and IoT-enabled classroom sensors will enable richer, more responsive learning experiences. Finally, incorporating affective computing—including emotional signals, facial expressions, and behavioral cues—can significantly enhance the depth of personalization and learner support.

These directions will help ensure that hybrid machine learning models evolve to support ethical, context-aware, and transparent personalization in digital learning environments.

5. CONCLUSION

In digital classrooms, hybrid machine learning approaches present a viable route to personalised and adaptable learning. This research shows that combining several machine learning algorithms produces better results in predicting academic achievements, modelling student engagement, and predicting learning styles. Through the utilisation of many learning paradigms, hybrid models have the potential to provide more precise, adaptable, and scalable educational solutions. The creation of interpretable, effective, and student-centered hybrid machine learning frameworks will be essential to the future success of intelligent learning environments as education continues to move towards digital and data-driven ecosystems.

REFERENCES

1. M. Murtaza; Y. Ahmed; J. Shamsi; F. Sherwani; M. Usman. *IEEE Access*, 10, 2022, 81323–81342.
2. I. Gligorea; M. Cioca; R. Oancea; A. Gorski; H. Gorski; P. Tudorache. Education Sciences, 13(12), 2023.
3. T. Tazin; M. Islam; M.A. Kamal; M. Rahman; M. Hossain; M. Arefin. *Journal of Healthcare Engineering*, 2021, Article ID 7633381.
4. M. Kavitha; G. Gnaneswar; R. Dinesh; Y. Sai; R. Suraj. *Proc. 6th Int. Conf. Inventive Computation Technologies (ICICT)*, 2021, 1329–1333.
5. I. Ho; K. Cheong; A. Weldon. PLOS ONE, 16, 2021.
6. M. Fernandes; J. Corchado; G. Marreiros. *Applied Intelligence*, 52, 2022, 14246–14280.
7. U. Singh; M. Rizwan; M. Alaraj; I. *Alsaidan. Energie*s, 14(16), 2021.
8. P. Kothari; S. Kreiss; A. Alahi. *IEEE Trans. Intell. Transp. Syst*., 23, 2022, 7386–7400.
9. A. Almarzouqi; A. Aburayya; S. Salloum. *IEEE Access*, 10, 2022, 43421–43434.
10. R. Sajja; Y. Sermet; M. Cikmaz; D. Cwiertny; I. Demir. arXiv preprint, arXiv:2309.10892, 2023.
11. S. Mehtab; J. Sen; A. Dutta. arXiv preprint, arXiv:2009.10819, 2020.
12. S.M. Bhagavathi; A. Narayanan; P. Prasad; R. Somasundaram; K. Ram. *Int. J. Commun. Syst.*, 34, 2021.
13. N.S. Raj; V.G. Renumol. *J. Comput. Educ*., 9, 2021, 113–148.
14. C. Kavitha; V. Mani; S. Srividhya; O.I. Khalaf; *C.A.T. Romero*. Front. *Public Health*, 10, 2022.
15. R. Barzegar; M. Aalami; J. Adamowski. *Stoch. Environ. Res. Risk Assess*., 34, 2020, 415–433.
16. M.K. Hasan; M.A. Alam; D. Das; E. Hossain; M. Hasan. *IEEE Access*, 8, 2020, 76516–76531.
17. Y. Deng; M.M. Kamani; M. Mahdavi. *arXiv preprint, arXiv*:2003.12985, 2020.
18. O. El Aissaoui; Y.E.M. El Alami; L. Oughdir; Y. El Allioui. *Int. J. Emerging Technologies in Learning (iJET)*, 18(5), 2023, 179–192.
19. G. Kaur; R. Singh. *Proc. Int. Conf. Adv. Comput. Commun. Control Netw*. (ICACCCN), 2020, 574–578.
20. P. Sokkhey; N. Okazaki. Proc. 2020 *Int. Conf. on Educational Technology (ICET)*, 2020, 35–42.
21. A. Jain; V. Mishra; S. Sharma. *Education and Information Technologies*, 26, 2021, 6559–6581.
22. A. Gupta; S. Sharma. *International Journal of Information Technology*, 14, 2022, 1223–1231.
23. Y. Zhou; X. Liu; M. Li. *Expert Systems with Applications*, 186, 2021.
24. R. Agarwal; M. Das; S. Bandyopadhyay. *Proc. Int. Conf. on Machine Learning and Data Engineering (iCMLDE)*, 2023, 32–40.