



# A Comprehensive Review of Machine Learning and Deep Learning Approaches for Student Failure Rate Prediction: Towards an Enhanced Hybrid and Explainable Framework

Babandi Usman<sup>1</sup>, Salim Ahmad<sup>2</sup> and Zahraddeen Safyanu<sup>3</sup>

<sup>1</sup>Department of Computer Science, Jigawa State Polytechnic Dutse, Nigeria.

<sup>2</sup>Department of Information Technology, Federal University Dutse, Jigawa State, Nigeria.

<sup>1,3</sup>Department of Computer science, Federal University Dutse, Jigawa State, Nigeria.

Corresponding Author Email: [babandee@gmail.com](mailto:babandee@gmail.com)

**Abstract-** Student academic failure remains a persistent challenge in higher education, particularly in developing countries where late identification of at-risk students limits timely intervention. Recent advances in Educational Data Mining and Learning Analytics have enabled predictive modelling of student performance; however, many existing models suffer from poor interpretability, data imbalance, and limited integration of behavioral and socio-economic variables. This study presents a comprehensive review and synthesis aimed at guiding the development of an enhanced algorithm for student failure rate analysis. A systematic review methodology was employed, involving structured literature collection, screening, categorization of predictive techniques, and comparative analysis of statistical, machine learning, ensemble, and deep learning approaches. Algorithms were evaluated using established performance metrics including accuracy, precision, recall, F1-score, and ROC-AUC, alongside qualitative criteria such as interpretability, scalability, and real-time applicability. The analysis reveals that while ensemble and deep learning models achieve superior predictive accuracy, they often lack transparency and struggle with imbalanced educational datasets. Based on these findings, the research proposes a hybrid and explainable predictive framework that integrates ensemble learning, neural networks, imbalance-handling techniques, and explainable AI methods. The review demonstrates that hybrid approaches provide the most promising balance between accuracy, interpretability, and early detection capability. The major contribution of this research lies in synthesizing fragmented literature into a unified framework for enhanced student failure prediction, identifying critical research gaps, and establishing a methodological foundation for developing a scalable, interpretable, and real-time predictive system to support data-driven academic interventions.

**Keywords:** Student Failure Prediction, Educational Data Mining, Learning Analytics, Hybrid Machine Learning, Explainable AI, Academic Performance Analytics

## I. INTRODUCTION

Student failure and dropout continue to pose significant challenges in higher education systems worldwide, with the impact being particularly severe in developing countries. Limited institutional resources, large student-teacher ratios, and persistent socio-economic inequalities contribute to an environment where many students struggle to achieve academic success (Quiles et al., 2023). Traditionally, universities rely on reactive strategies to

address poor academic performance, identifying struggling students only after examination results are released. Such delayed intervention reduces the likelihood of meaningful academic recovery and increases the risk of dropout, ultimately affecting institutional performance and national human capital development (Smith et al., 2022). The rapid advancement of data analytics has transformed this landscape by enabling the emergence of predictive education systems capable of identifying at-risk students at an early stage. Educational Data Mining (EDM) and Learning Analytics (LA) have become key research



domains that leverage large volumes of institutional and behavioural data to understand and forecast student performance. These approaches draw on diverse data sources, including academic records, Learning Management System (LMS) interaction logs, attendance patterns, engagement indicators, and socio-economic and demographic characteristics, thereby providing a more holistic view of the factors influencing academic outcomes.

Despite these advancements, existing predictive systems still face several important limitations. Many models operate as black-box systems with limited interpretability, making it difficult for educators and administrators to trust and adopt their predictions (Rane et al., n.d.). Additionally, educational datasets are often imbalanced, leading to poor identification of at-risk students. Current approaches also tend to rely on single-model techniques rather than hybrid modelling strategies, and they frequently underutilize behavioural and psychological factors that strongly influence learning outcomes (Apolinar, 2024).

Against this backdrop, this review aims to establish a comprehensive foundation for the development of an enhanced algorithm for student failure rate analysis by synthesizing existing research, identifying critical gaps, and highlighting opportunities for more accurate, interpretable, and scalable predictive solutions.

## **II. LITERATURE REVIEW**

### **Evolution of Student Performance Prediction**

Research on student performance prediction has undergone a clear methodological evolution over the past decades. Early studies relied heavily on traditional statistical modelling techniques, primarily regression-based approaches, to estimate the likelihood of academic success or failure (Obahiagbon et al., 2023). While these methods provided foundational insights and were valued for their interpretability, they were limited in their ability to capture the complex and nonlinear relationships present in educational data. With the growth of computational power and the availability of large educational datasets, the field transitioned into the machine learning era. Techniques such as Support Vector Machines, Decision Trees, and Random Forests became widely adopted due to their improved predictive accuracy and ability to model nonlinear patterns (Attaoui et al., 2024). These methods significantly enhanced the reliability of student performance prediction and demonstrated the potential of data-driven decision-making in education.

More recently, the emergence of artificial intelligence and deep learning has further transformed the field. Advanced models such as Artificial Neural Networks, Recurrent Neural Networks, and Long Short-Term Memory networks have been applied to capture complex behavioural and temporal learning patterns, particularly from Learning Management System data (SHRIPAD Pujari Bharati Vidyapeeth et al., 2024). This progression reflects a shift from simple predictive modelling toward more sophisticated systems capable of analysing multidimensional and time-dependent learning behaviours.

### **Statistical Approaches**

Initial research in student performance prediction was dominated by statistical techniques, particularly linear regression, logistic regression, and survival analysis. These models were attractive due to their simplicity, transparency, and ease of implementation. They enabled researchers and institutions to identify relationships between academic performance and variables such as attendance, prior grades, and demographic characteristics (Anthi et al., 2021). Despite their advantages, statistical models rely heavily on assumptions of linear relationships among variables, which limits their effectiveness when dealing with the complex and multidimensional nature of educational data. Student learning is influenced by numerous interacting academic, behavioural, and socio-economic factors that rarely follow linear patterns.

Consequently, several limitations of statistical approaches have been identified. These models struggle to capture nonlinear interactions among variables, often resulting in lower predictive accuracy. They are also sensitive to noisy or incomplete datasets, which are common in educational environments. As a result, the limitations of traditional statistical methods paved the way for the adoption of more advanced machine learning and artificial intelligence techniques in student failure prediction research.

### **Machine Learning Approaches**

The adoption of machine learning techniques marked a significant advancement in student performance prediction, offering improved accuracy and the ability to model complex, nonlinear relationships within educational datasets. Unlike traditional statistical approaches, machine learning algorithms can automatically learn patterns from large volumes of academic and behavioural data, making them highly suitable for predictive analytics in education. Several supervised learning algorithms have been widely applied in the literature (Ummah, 2019). Decision Tree models are valued for their transparency and



ease of interpretation, enabling educators to understand how predictions are generated. However, they are prone to overfitting, particularly when dealing with noisy or high-dimensional data. Random Forest, an ensemble extension of decision trees, addresses this limitation by combining multiple trees to improve generalization and predictive accuracy, though it comes with increased computational requirements. Support Vector Machines (SVM) have also demonstrated strong performance, particularly in smaller or high-dimensional datasets, due to their ability to construct optimal decision boundaries (Lange et al., 2023). Nevertheless, SVM models are often considered difficult to interpret, which can limit their adoption in educational decision-making contexts. Other algorithms such as k-Nearest Neighbour (k-NN) offer simplicity and ease of implementation but become computationally inefficient as dataset size increases. Naïve Bayes classifiers provide fast and scalable predictions; however, their assumption of feature independence rarely holds in real educational scenarios.

Overall, empirical studies consistently report that ensemble-based approaches such as Random Forest and margin-based methods like SVM outperform traditional statistical models in terms of predictive accuracy and robustness, making them foundational techniques in modern student failure prediction research.

### III. ENSEMBLE LEARNING

#### Ensemble Learning

Ensemble learning has become one of the most influential advancements in student failure prediction because it improves predictive performance by combining the outputs of multiple models rather than relying on a single algorithm. Educational datasets are often noisy, heterogeneous, and imbalanced; therefore, ensemble methods provide robustness, stability, and improved generalization (Khone & Ulagamuthalvi, 2022). The three major ensemble techniques widely applied in educational data mining are bagging, boosting, and stacking.

Bagging (Bootstrap Aggregating) focuses primarily on reducing variance and improving model stability. In this approach, multiple subsets of the training dataset are generated through random sampling with replacement, and separate models are trained on each subset (Wu & Weng, 2021). The final prediction is obtained by aggregating the outputs of all models, typically through majority voting or averaging. Random Forest is a well-known bagging-based algorithm that has been extensively used in student performance prediction. Its success lies in its ability to

reduce overfitting while maintaining strong predictive power. Bagging is particularly effective when dealing with noisy educational datasets where small variations in data can significantly affect model performance.

Boosting takes a different approach by focusing on reducing bias and improving the learning capability of weak learners. Instead of training models independently, boosting trains models sequentially, where each new model gives more attention to previously misclassified instances. Algorithms such as AdaBoost, Gradient Boosting, and Extreme Gradient Boosting (XGBoost) fall into this category (Ghorbani et al., 2025). Boosting methods are highly effective for educational datasets because they can capture complex feature interactions and improve classification of minority classes, such as students at risk of failure. Among these methods, gradient boosting has consistently demonstrated state-of-the-art performance in student performance prediction due to its ability to optimize model accuracy iteratively.

Stacking (Stacked Generalization) represents a more advanced ensemble strategy that combines multiple diverse models using a meta-learner. In stacking, several base models such as decision trees, support vector machines, and neural networks are trained simultaneously, and their predictions are used as inputs to a higher-level model that produces the final output (Ibrahim et al., 2024). This approach leverages the complementary strengths of different algorithms and often yields superior predictive performance compared to individual models or simpler ensembles. Stacking is particularly useful in educational data mining because it enables the integration of models that capture different aspects of student behaviour, academic performance, and engagement patterns. In addition to these core techniques, ensemble learning also supports hybridization with deep learning models, enabling the integration of neural networks with traditional machine learning algorithms. Such hybrid ensembles are increasingly being explored to balance accuracy, robustness, and interpretability.

Overall, ensemble learning techniques have demonstrated substantial improvements in accuracy, robustness, and scalability in student failure prediction. Their ability to address overfitting, bias, and dataset imbalance makes them a critical component in the development of enhanced predictive algorithms for educational analytics.

**Table 1: Shows the ensemble techniques**

Method	Advantage
--------	-----------



Bagging	Reduces variance
Boosting	Reduces bias
Stacking	Combines best models

Boosting algorithms (e.g., gradient boosting) achieve state-of-the-art performance in educational datasets.

### Deep Learning Approaches

Deep learning has recently emerged as a powerful paradigm for modelling complex and high-dimensional educational data. Unlike traditional machine learning techniques that rely heavily on manual feature engineering, deep learning models can automatically learn hierarchical representations from raw data. This capability makes them particularly suitable for analysing large-scale student data generated from Learning Management Systems, online learning platforms, and institutional databases. Artificial Neural Networks (ANN) are among the earliest deep learning models applied to student performance prediction. They are capable of modelling nonlinear relationships between multiple academic and behavioural variables, making them effective for tasks such as Grade Point Average prediction and course outcome classification. By learning complex feature interactions, ANN models often outperform traditional machine learning methods when sufficient data is available. Recurrent Neural Networks (RNN) introduced the ability to model sequential and time-dependent learning behaviours. Student learning is inherently temporal, involving patterns of study, engagement, and assessment over time. RNN models are therefore well suited for analysing sequences of student activities, such as weekly engagement patterns or continuous assessment trends. However, traditional RNNs struggle with long-term dependencies due to issues such as vanishing gradients.

Long Short-Term Memory (LSTM) networks were developed to address this limitation by incorporating memory cells that retain long-term information. LSTM models have proven particularly effective for analysing LMS interaction logs, capturing patterns such as frequency of logins, time spent on learning resources, and progression through course materials. These models enable more accurate modelling of behavioural trends that influence academic success or failure. Despite their strong predictive capability, deep learning approaches present several challenges in educational contexts. They typically require large datasets to achieve optimal performance, which may not always be available in smaller institutions. Additionally, deep learning models are often considered

“black-box” systems, lacking transparency and interpretability, which can limit their acceptance by educators and policymakers. Furthermore, the high computational cost associated with training deep neural networks can be a barrier for institutions with limited technological infrastructure.

Consequently, while deep learning offers significant potential for improving student failure prediction, its limitations highlight the need for hybrid and explainable approaches that balance accuracy, efficiency, and transparency.

**Table 2: Deep Learning Models and Their Applications in Student Performance and Behaviour Analysis**

Model	Application
ANN	GPA prediction
RNN	Sequential learning behaviour
LSTM	LMS interaction analysis

### Limitations

- Require large datasets
- Lack interpretability
- High computational cost

### Feature Engineering in Student Failure Prediction

Prediction accuracy strongly depends on selected features.

### Categories

**Table 3: Categories of Features Used in Student Failure Rate Prediction and Their Examples**

Category	Examples
Academic	GPA, assignments
Behavioural	LMS logins
Demographic	Age, gender
Socioeconomic	Family income
Psychological	Motivation

Behavioural features from LMS logs significantly improve accuracy.

### Identified Research Gaps

Despite the rapid progress in student performance prediction, the existing body of research still reveals several critical gaps that limit the practical deployment and effectiveness of predictive systems in real educational

environments. Addressing these gaps is essential for developing more reliable, interpretable, and institutionally applicable student failure prediction models. One major limitation is the lack of hybrid modelling approaches. Many existing studies rely on single algorithms, either statistical, machine learning, or deep learning techniques. While individual models may perform well under specific conditions, no single technique simultaneously satisfies the requirements of accuracy, scalability, robustness, and interpretability. This highlights the need for hybrid models that combine multiple techniques to leverage their complementary strengths.

Another significant gap is the limited explainability of predictive models. Modern high-performing algorithms, particularly ensemble and deep learning models, often operate as black-box systems. Educational institutions require transparent and interpretable predictions to support academic decision-making, policy formulation, and targeted interventions. Without clear explanations of why students are predicted to be at risk, institutional adoption of predictive systems remains limited. A further challenge is the poor handling of imbalanced educational datasets. In most academic settings, the number of students who fail is typically much smaller than those who succeed. This imbalance leads to biased models that favour majority classes and struggle to accurately identify at-risk students the very group that predictive systems aim to support. Existing models also demonstrate weak real-time prediction capability. Many studies rely on historical or end-of-semester data, which restricts their usefulness for early intervention. Real-time or near-real-time prediction is essential for enabling timely academic support and preventing failure before it occurs. Finally, there is limited integration of socio-behavioural and psychological data. Most research focuses primarily on academic performance indicators, while factors such as engagement, motivation, learning behaviour, and socio-economic background are often underutilized. Incorporating these multidimensional factors is crucial for building holistic and more accurate predictive systems.

These identified gaps provide strong justification for the development of an enhanced, hybrid, and explainable algorithm capable of delivering accurate, interpretable, and real-time student failure prediction.

#### **IV. METHODOLOGY**

This review adopts a systematic review methodology.

#### **Research Process**



**Figure 1: Shows the systematic review methodology adopted in the research**

#### **Data Sources Reviewed**

To ensure a comprehensive and balanced review, this study relied on a wide range of scholarly and technical sources that cover the interdisciplinary nature of student failure prediction, spanning education, data science, and artificial intelligence. The literature selection process prioritised high-quality, peer-reviewed publications and widely recognised research outlets to guarantee the credibility and relevance of the reviewed works. A substantial portion of the reviewed literature was obtained from major academic digital libraries and indexing databases. These databases provide access to peer-reviewed journal articles, conference proceedings, and technical reports related to educational data mining, learning analytics, and predictive modelling. The search strategy focused on keywords such as student performance prediction, educational data mining, learning analytics, academic failure prediction, machine learning in education, and dropout prediction. Priority was given to publications from the last decade to capture the most recent developments in artificial intelligence and data analytics. In addition, specialised Educational Data Mining and Learning Analytics journals formed a core source of information for this review. These journals publish domain-specific research that explores the application of data mining, machine learning, and artificial intelligence techniques to educational datasets. Articles



from these outlets provided valuable insights into feature engineering, dataset characteristics, intervention strategies, and practical deployment challenges in academic environments.

The review also incorporated findings from machine learning and artificial intelligence conference proceedings, which are often the primary venues for cutting-edge research in predictive modelling and algorithm development. Conferences in data mining, artificial intelligence, and learning analytics frequently introduce new algorithms, hybrid models, and evaluation techniques before they appear in journal publications. Including these sources ensured that the review reflects the most recent methodological advancements and emerging trends.

Furthermore, relevant institutional reports, theses, and technical white papers were considered where appropriate, particularly when they provided real-world case studies or implementation insights that complement academic research. By combining these diverse sources, the study ensures a comprehensive and multidisciplinary perspective on student failure prediction research.

**Comparative Evaluation Criteria**

To systematically analyse and compare the diverse predictive techniques reviewed in this study, a set of evaluation criteria was established. These criteria were selected to reflect both the technical performance of predictive models and their practical applicability within real educational environments. While many studies focus primarily on prediction accuracy, institutions require solutions that are not only accurate but also interpretable, scalable, and capable of supporting early intervention.

The chosen criteria therefore provide a balanced framework for assessing how well different approaches address the core requirements of student failure prediction systems. Accuracy measures the effectiveness of a model in correctly predicting outcomes, while interpretability evaluates the extent to which stakeholders can understand and trust the model’s decisions. Scalability considers the ability of the model to handle large and growing educational datasets, and real-time usability assesses whether predictions can be generated early enough to enable timely academic interventions. Together, these criteria ensure a comprehensive and meaningful comparison of existing techniques.

**Table 4: Evaluation Criteria for Assessing Student Failure Prediction Models**

Criterion	Description
Accuracy	Prediction performance

Interpretability	Model transparency
Scalability	Big data capability
Real-time usability	Early prediction ability

**Analysis**

**Comparative Performance of Algorithms**

A comparative analysis of the major algorithmic approaches used in student failure prediction reveals important trade-offs between predictive performance, transparency, and practical deployment. While advances in machine learning and deep learning have significantly improved prediction accuracy, no single technique currently satisfies all the key requirements needed for real educational environments. Institutions require models that are not only accurate but also interpretable and scalable for large and continuously growing datasets. Traditional statistical models such as logistic regression remain highly interpretable and easy to implement, which makes them attractive for academic decision-making. However, their limited ability to model nonlinear relationships reduces predictive accuracy. Decision tree models improve prediction performance while maintaining high interpretability, but they can suffer from overfitting and limited generalization. Ensemble approaches such as Random Forest demonstrate strong predictive performance and scalability, making them suitable for large institutional datasets. Nevertheless, their interpretability is lower than simpler models because predictions are derived from multiple decision trees. Support Vector Machines also achieve high accuracy, particularly with high-dimensional data, but their mathematical complexity makes them difficult to interpret for non-technical stakeholders.

Deep learning models achieve the highest predictive accuracy and scalability due to their ability to model complex behavioural and temporal patterns. However, they are typically considered black-box systems, offering limited transparency and requiring significant computational resources.

**Table 5: Comparative Evaluation of Machine Learning and Deep Learning Algorithms for Student Failure Prediction**

Algorithm Type	Accuracy	Interpretability	Scalability
Logistic Regression	Low	High	Medium



Decision Tree	Medium	High	Medium
Random Forest	High	Medium	High
SVM	High	Low	Medium
Deep Learning	Very High	Low	High

**Key Insight**

The analysis highlights a critical research challenge: no single algorithm simultaneously satisfies the requirements of high accuracy, strong interpretability, and high scalability. This trade-off strongly motivates the development of hybrid and explainable predictive models.

**Table 6: Identified Weaknesses of Existing Models**

Weakness	Impact
Data imbalance	Misclassification of at-risk students
Black-box models	Hard institutional adoption
Static models	Late prediction
Limited features	Reduced accuracy

**Need for Hybrid and Explainable Models**

Hybrid models combine strengths of multiple approaches. Proposed components:

- Ensemble learning for accuracy
- Deep learning for pattern extraction
- Explainable AI for transparency

**V. RESULTS AND DISCUSSION**

**Proposed Enhanced Hybrid Framework**

Based on the analysis of existing literature and identified research gaps, this study proposes an enhanced hybrid predictive framework designed to improve student failure rate analysis. The framework integrates ensemble learning, deep learning, and explainable artificial intelligence into a unified architecture capable of delivering accurate, interpretable, and real-time predictions.

The proposed system begins with the aggregation of heterogeneous student data sources, including academic records, behavioural logs from Learning Management Systems, and socio-demographic information. This data undergoes preprocessing, feature engineering, and class-imbalance handling before being processed by a hybrid prediction engine that combines ensemble models and

neural networks. An explainable AI module is incorporated to provide transparent reasoning behind model predictions, enabling educators and administrators to trust and act upon the results. Ultimately, the framework supports an early-warning system capable of triggering timely academic interventions.

**Expected Improvements**

**Table 7: Expected Performance and Institutional Benefits of the Proposed Student Failure Prediction Framework**

Area	Improvement
Prediction Accuracy	Higher than single models
Early Detection	Real-time capability
Interpretability	Explainable predictions
Institutional Decision Support	Actionable insights

**Evaluation Metrics**

**Table 8: Evaluation Metrics for Assessing the Performance of Student Failure Prediction Models**

Metric	Purpose
Accuracy	Overall performance
Precision	Correct failure prediction
Recall	Identifying at-risk students
F1 Score	Balanced metric
ROC-AUC	Model robustness

Hybrid models are expected to achieve highest F1 and ROC-AUC scores.

**VI. DISCUSSION**

The integration of ensemble learning, deep learning, and explainable artificial intelligence presents a well-balanced and robust solution to the limitations observed in existing student failure prediction systems. While individual approaches such as statistical models, standalone machine learning algorithms, or deep learning networks offer certain advantages, they often fall short when simultaneously evaluated on accuracy, interpretability, scalability, and practical usability within educational environments. Ensemble learning contributes significantly by improving

predictive stability and overall accuracy through the combination of multiple models, thereby reducing both bias and variance. Deep learning complements this by capturing complex, nonlinear, and temporal patterns in student behaviour that traditional models often fail to represent. However, the inherent black-box nature of these models necessitates the inclusion of explainability mechanisms. Explainable AI techniques, therefore, play a critical role in bridging the gap between high-performance prediction and institutional trust. By providing clear and interpretable justifications for model outputs, they enable educators, administrators, and policymakers to understand the underlying factors contributing to student risk classification. This transparency is essential for actionable decision-making in academic environments.

In summary, educational institutions require systems that are not only highly accurate but also interpretable and actionable. This makes explainable hybrid models the most suitable and sustainable direction for future research and practical deployment in student failure prediction systems.

## VII.CONCLUSION

This review has critically examined the evolution and current state of student failure prediction research, tracing its development from traditional statistical methods to modern machine learning and advanced artificial intelligence techniques. The analysis reveals a clear progression in methodological sophistication, where early linear and logistic models provided limited predictive capability, while recent machine learning and deep learning approaches have significantly enhanced prediction accuracy and pattern recognition capabilities within complex educational datasets. However, despite these improvements, several persistent challenges remain unresolved. These include limited model interpretability, poor handling of imbalanced datasets, and insufficient support for real-time or early-stage prediction. Additionally, many existing systems fail to fully integrate behavioural, psychological, and socio-economic factors that strongly influence student academic performance, thereby limiting the comprehensiveness of their predictions. To address these limitations, this study proposes a hybrid and explainable predictive framework that integrates multiple complementary techniques. Specifically, ensemble learning is employed to enhance predictive accuracy and model stability, deep learning is utilized to capture complex behavioural and temporal learning patterns, and explainable artificial intelligence is incorporated to ensure transparency and interpretability of

predictions. The combination of these approaches provides a more balanced, robust, and institutionally applicable solution to student failure prediction.

In conclusion, this research establishes a strong conceptual and methodological foundation for the development of an enhanced algorithm for student failure rate analysis. Such a system has the potential to transform academic support mechanisms by enabling early identification of at-risk students, supporting data-driven interventions, and ultimately improving student retention and academic success rates.

## REFERENCES

1. Anthi, E., Williams, L., Rhode, M., Burnap, P., & Wedgbury, A. (2021). Adversarial attacks on machine learning cybersecurity defences in Industrial Control Systems. *Journal of Information Security and Applications*, 58(February), 102717. <https://doi.org/10.1016/j.jisa.2020.102717>
2. Apolar, M. (2024). Using Decision Tree Algorithm to Predict Student Performance. February 2019. <https://doi.org/10.17485/ijst/2019/v12i5/140987>
3. Attaoui, A. El, Hami, N. El, & Koulou, Y. (2024). Android malware detection using the random forest algorithm. *Indonesian Journal of Electrical Engineering and Computer Science*, 36(3), 1876–1883. <https://doi.org/10.11591/ijeecs.v36.i3.pp1876-1883>
4. Ghorbani, S., Ghorbany, S., & Noorzai, E. (2025). Development of a data-driven framework to predict waste generation and evaluate influential factors: Machine learning innovations in construction waste management. *Cleaner Waste Systems*, 11(April), 100299. <https://doi.org/10.1016/j.clwas.2025.100299>
5. Ibrahim, A. M., Aliyu, M. S., & Safyanu, Z. (2024). Hybrid Framework for Network Intrusion Detection System. 3(2), 52–64.
6. Khonde, S. R., & Ulagamuthalvi, V. (2022). Hybrid intrusion detection system using blockchain framework. *Eurasip Journal on Wireless Communications and Networking*, 2022(1). <https://doi.org/10.1186/s13638-022-02089-4>
7. Lange, A., Smolyakov, D., & Burnaev, E. (2023). Sequential Minimal Optimization algorithm for one-class Support Vector Machines with privileged information. *IEEE Access*, PP, 1. <https://doi.org/10.1109/ACCESS.2023.3331685>



8. Obahiagbon, E. G., Nwankwo, N., & Olaniyi, T. K. (2023). Qualitative Analysis of Social Media Influencers Impact On Sustainable Brand Equity: A Case Study of Small Businesses in Nigeria. *Advances in Multidisciplinary and Scientific Research Journal Publication*, 37(December), 69–82. <https://doi.org/10.22624/aims/accracrossborder2023v2p6>
9. Quiles, O., Galdón-López, S., & Lendínez-Turón, A. (2023). Factors contributing to university dropout: a review. *Frontiers in Education*, 8. <https://doi.org/10.3389/educ.2023.1159864>
10. Rane, N. L., Mallick, S. K., Kaya, Ö., & Rane, J. (n.d.). Machine learning and deep learning architectures and trends : A review (Issue 2024).
11. SHRIPAD Pujari Bharati Vidyapeeth, R., Sahasrabuddhe, D., Pujari, R., Suguna, R., Vinmathi, M. S., P, J. A., & Vinay Sahasrabuddhe, D. (2024). Integrating IoT and Machine Learning for Enhanced Construction Safety Management *International Journal of INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING* Integrating IoT and Machine Learning for Enhanced Construction Safety Management. Original Research Paper *International Journal of Intelligent Systems and Applications in Engineering IJISAE*, 2024(20s). <https://www.researchgate.net/publication/382003116>
12. Smith, T. E., Thompson, A. M., & Maynard, B. R. (2022). Self-management interventions for reducing challenging behaviors among school-age students: A systematic review. *Campbell Systematic Reviews*, 18(1), e1223. <https://doi.org/10.1002/cl2.1223>
13. Ummah, M. S. (2019). No 主観的健康感を中心とした在宅高齢者における健康関連指標に関する共分散構造分析 Title. *Sustainability (Switzerland)*, 11(1), 1–14. [http://scioteca.caf.com/bitstream/handle/123456789/1091/RED2017-Eng-8ene.pdf?sequence=12&isAllowed=y%0Ahttp://dx.doi.org/10.1016/j.regsciurbeco.2008.06.005%0Ahttps://www.researchgate.net/publication/305320484\\_SISTEM\\_PEMBETUNGAN\\_TERPUSAT\\_STRATEGI\\_MELESTARI](http://scioteca.caf.com/bitstream/handle/123456789/1091/RED2017-Eng-8ene.pdf?sequence=12&isAllowed=y%0Ahttp://dx.doi.org/10.1016/j.regsciurbeco.2008.06.005%0Ahttps://www.researchgate.net/publication/305320484_SISTEM_PEMBETUNGAN_TERPUSAT_STRATEGI_MELESTARI)
14. Wu, L., & Weng, S. (2021). Ensemble Learning Models for Food Safety Risk Prediction. 1–26.
- 15.