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A Systematic Review of Machine Learning and AI Techniques for Student Performance Prediction: Insights, Trends and Implications under NEP 2020

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Abstract
The rapid growth of Artificial Intelligence (AI) and Machine Learning (ML) has significantly influenced modern education systems, particularly in the domain of student performance prediction. This study presents a systematic review of research conducted between 2020 and 2026, focusing on various predictive models including traditional machine learning, ensemble techniques and deep learning approaches. The review also examines the role of Educational Data Mining (EDM), Learning Analytics (LA), feature engineering and Explainable AI (XAI) in improving prediction accuracy and interpretability.
The findings reveal that hybrid and deep learning-based models outperform conventional approaches in handling complex educational datasets. Furthermore the integration of AI technologies with the National Education Policy (NEP) 2020 supports personalized and data-driven learning environments. The paper concludes by identifying key research challenges and suggesting future directions such as real-time prediction systems and transparent AI frameworks.
Keywords- Machine Learning, Student Performance Prediction, Learning Analytics, NEP 2020, Deep Learning, Explainable AI, Educational Data Mining.

1. Introduction

The rapid advancement of Machine Learning (ML) and Artificial Intelligence (AI) has significantly transformed various sectors, with education emerging as one of the most impacted domains. The increasing adoption of digital learning platforms, Learning Management Systems (LMS) and online assessment tools has resulted in the generation of large volumes of educational data, enabling advanced analytics and predictive modeling [2], [8]. This data provides valuable opportunities to analyze student behavior identify learning patterns and predict academic performance with improved accuracy.
Student performance prediction has become a critical research area within Educational Data Mining (EDM) and Learning Analytics (LA). Accurate predictive models help educators identify at-risk students at an early stage and implement timely interventions to improve academic outcomes [1], [4]. Traditional statistical approaches have gradually been replaced by machine learning techniques, which are capable of handling large-scale and complex datasets while capturing nonlinear relationships among various influencing factors such as academic records, attendance, engagement and socio-economic background [3], [9].
Early research in this domain primarily focused on classical machine learning algorithms such as Decision Trees, Naive Bayes and Support Vector Machines (SVM). These models demonstrated promising results in predicting student outcomes; however, their performance is often limited when dealing with high-dimensional and dynamic datasets [1], [4]. To overcome these limitations, recent

studies have explored advanced techniques including ensemble learning methods such as Random Forest and XGBoost, which offer improved accuracy and robustness [5], [13]. Furthermore, hybrid models that combine multiple algorithms have shown superior performance by leveraging the strengths of individual approaches [13], [23].

Deep learning techniques have further enhanced predictive capabilities by enabling the analysis of large and complex datasets. Models such as Artificial Neural Networks (ANN) and Long Short-Term Memory (LSTM) networks are particularly effective in capturing temporal and sequential patterns in student data [6], [20]. These models have demonstrated higher predictive accuracy compared to traditional approaches, especially in scenarios involving continuous student interaction data.

In addition to predictive modeling, the integration of Educational Data Mining and Learning Analytics has strengthened AI-driven educational systems. These approaches focus not only on prediction but also on understanding student learning behaviors and improving engagement [2], [24]. Feature selection and data preprocessing techniques play a crucial role in enhancing model performance by identifying relevant attributes and reducing data redundancy [12], [22].

Another significant advancement is the emergence of Explainable Artificial Intelligence (XAI), which addresses the need for transparency and interpretability in AI systems. As educational institutions increasingly adopt automated decision-making tools, it becomes essential to ensure fairness, accountability and trust in these systems [14]. Ethical concerns such as bias, data privacy and responsible AI usage have also been widely discussed in recent studies [21].

The National Education Policy (NEP) 2020 in India has further accelerated the integration of AI and data-driven approaches in education. NEP 2020 emphasizes personalized learning, digital education and the use of emerging technologies to improve educational outcomes [17], [25]. It encourages the adoption of AI-based systems for student assessment, adaptive learning and institutional decision-making, thereby creating new opportunities for implementing machine learning models in education [19].

Despite significant progress, several challenges remain in the field of student performance prediction. These include the lack of standardized datasets, limited interpretability of complex models, issues related to data quality and insufficient alignment between technological advancements and educational policies [12], [21]. Addressing these challenges is essential for the effective deployment of AI-driven educational systems.

In this context, the present study aims to provide a comprehensive and systematic review of machine learning and AI techniques for student performance prediction. The review focuses on research contributions from 2020 to 2026, analyzing various models, methodologies and applications. It also highlights emerging trends, identifies research gaps and explores the implications of these technologies in the context of NEP 2020. Finally, the study outlines future research directions for developing efficient, interpretable and policy-aligned predictive systems.

These observations highlight the growing importance of intelligent data-driven approaches in modern education systems. It can be inferred that integrating advanced machine learning techniques can significantly enhance decision-making processes. Therefore, the need for efficient and scalable prediction models continues to increase.

2. Research Methodology

This study adopts a systematic literature review approach inspired by standard review protocols. A total of 25 research papers published between 2020 and 2026 were selected from IEEE journals and conferences.

2.1 Selection Criteria

- Papers focusing on student performance prediction
- Studies involving ML, AI, or deep learning models
- Research related to learning analytics, EDM, or NEP 2020
- Publications indexed in IEEE

2.2 Review Process

1. Identification of relevant studies
2. Screening based on relevance and quality
3. Data extraction (models, datasets, accuracy, methods)
4. Thematic categorization

2.3 Classification

The selected studies were categorized into:

- Machine Learning Models
- Deep Learning Techniques
- Learning Analytics & EDM
- Explainable AI & Ethics
- NEP 2020 Integration

The structured review process ensures that only relevant and high-quality studies are included in the analysis. This systematic approach improves the reliability and consistency of the findings. As a result, the methodology provides a strong foundation for comparative evaluation.

3. Machine Learning and AI Techniques for Student Performance Prediction

This section provides a comprehensive review of machine learning (ML) and artificial intelligence (AI) techniques employed for predicting student performance. The selected studies demonstrate the evolution from traditional machine learning models to advanced deep learning and hybrid approaches. Additionally, the role of educational data mining, feature engineering, explainable AI and policy alignment under NEP 2020 is discussed.

The analysis of various techniques indicates a clear progression from basic models to more advanced approaches. It is evident that model selection plays a crucial role in achieving accurate predictions. Overall, the effectiveness of these techniques depends on data quality and application context.

3.1 Traditional Machine Learning Models

Traditional machine learning algorithms form the foundation of student performance prediction systems. Commonly used models include Decision Trees, Naïve Bayes and Support Vector Machines (SVM). These algorithms are widely adopted due to their simplicity, interpretability and relatively low computational requirements. Studies such as Kumar and Singh [1] demonstrate that these models can effectively predict student outcomes using historical academic data. Similarly, Yadav et al. [4] compared multiple machine learning techniques and observed that while traditional models perform reasonably well, their predictive accuracy is often limited when dealing with complex and high-dimensional datasets. Singh and Sharma [9] further emphasized that although these models provide baseline performance, they are less effective in capturing nonlinear relationships.

Although traditional models are simple and easy to implement, their performance is limited in complex scenarios. These methods are useful as baseline approaches for comparison. However, they require enhancement to handle large-scale educational data.

3.2 Educational Data Mining and Learning Analytics

Educational Data Mining (EDM) and Learning Analytics (LA) play a critical role in extracting meaningful insights from educational datasets. EDM focuses on discovering hidden patterns, while learning analytics emphasizes improving learning outcomes through data-driven decision-making. Sharma et al. [2] highlighted the importance of data preprocessing, feature extraction and pattern recognition in building effective prediction models. Roy et al. [8] demonstrated that learning analytics can significantly enhance student engagement and academic performance by analyzing behavioral and interaction data. Furthermore, Banerjee et al. [24] proposed integrated frameworks that combine multiple data sources, including academic records and LMS logs, to improve prediction accuracy.

The integration of data mining and analytics techniques provides deeper insights into student behavior. This helps in improving both prediction accuracy and learning outcomes. Consequently, these approaches are essential for data-driven education systems.

3.3 Ensemble and Hybrid Machine Learning Techniques

Ensemble learning techniques have gained prominence due to their ability to improve prediction accuracy by combining multiple models. Popular ensemble methods include Random Forest and XGBoost, which are known for their robustness and scalability. Chen and Guestrin [5] introduced XGBoost, which has become a widely used algorithm for predictive modeling due to its efficiency and performance. Reddy et al. [13] proposed hybrid models that integrate different machine learning techniques to capture complex patterns in data. Similarly, Ali et al. [23] demonstrated that hybrid approaches outperform individual models, particularly in large and heterogeneous datasets. These findings indicate that ensemble and hybrid models are more effective than standalone algorithms for student performance prediction.

The results clearly indicate that combining multiple models enhances overall system performance. These approaches reduce individual model weaknesses and improve robustness. Hence, they are highly suitable for complex prediction tasks.

3.4 Deep Learning Approaches

Deep learning techniques have significantly advanced the field of student performance prediction by enabling the analysis of large and complex datasets. Neural networks, including Artificial Neural Networks (ANN), Convolution Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks, are commonly used in this domain. Mishra et al. [6] demonstrated the effectiveness of deep learning models in capturing complex relationships within educational data. Wang et al. [20] applied LSTM models to predict student performance over time and found that these models outperform traditional approaches, particularly for temporal data analysis. Despite their advantages, deep learning models require substantial computational resources and large datasets.

Deep learning models demonstrate strong capability in handling high-dimensional and sequential data. Their ability to capture complex relationships makes them highly effective. However, their implementation requires sufficient computational resources and data availability.

3.5 Feature Selection and Data Optimization

Feature selection is a crucial step in improving the performance and efficiency of machine learning models. It involves identifying the most relevant features that contribute to prediction accuracy while reducing dimensionality. Mehta and Jain [12] analyzed various feature selection techniques, including Principal Component Analysis (PCA) and Recursive Feature Elimination (RFE) and concluded that these methods significantly enhance model performance. Bose and Chatterjee [22] emphasized the importance of incorporating multidimensional data, including academic, behavioral and socio-economic factors, to achieve more accurate predictions.

Efficient feature selection contributes significantly to model optimization and performance improvement. By reducing unnecessary data, it enhances computational efficiency. Therefore, it remains a critical step in predictive modeling.

3.6 LMS-Based Prediction and Early Warning Systems

Learning Management Systems (LMS) provide real-time data that can be used to monitor and predict student performance. LMS-based prediction models analyze student interactions, attendance and engagement levels. Khan et al. [15] developed LMS-based systems capable of predicting student outcomes using real-time data. Sharma et al. [18] introduced early warning systems that identify at-risk students and enable timely interventions. These systems are particularly useful in improving retention rates and academic success.

The use of LMS data enables continuous monitoring of student activities. This allows timely identification of learning issues and supports early intervention. As a result, LMS-based systems play a vital role in improving academic outcomes.

3.7 Explainable AI and Ethical Considerations

As AI models become more complex, the need for transparency and interpretability has increased. Explainable AI (XAI) techniques help in understanding model decisions and building trust among stakeholders. Das and Nair [14] explored various XAI methods, such as SHAP and LIME, which provide insights into feature importance and model behavior. Thomas et al. [21] highlighted ethical concerns, including bias, fairness and data privacy, which must be addressed to ensure responsible AI deployment in education.

The adoption of explainable models increases transparency and trust in AI-based systems. It also supports better decision-making by providing clear insights into predictions. Thus, clarity is becoming an essential requirement in educational applications.

3.8 AI-Driven Personalized Learning

AI technologies have enabled the development of personalized learning systems that adapt to individual student needs. These systems use predictive models to recommend learning resources and tailor instructional strategies. Gupta et al. [16] proposed AI-driven adaptive learning systems that improve student engagement and performance. Brown et al. [10] discussed broader applications, including intelligent tutoring systems and automated assessment tools, which enhance the overall learning experience.

Personalized learning approaches help in addressing individual student needs effectively. These systems enhance engagement and improve learning efficiency. Therefore, AI-driven personalization is a key advancement in modern education.

3.9 NEP 2020 and AI Integration

The National Education Policy (NEP) 2020 emphasizes the integration of technology and data-driven approaches in education. It promotes personalized learning, digital platforms and AI-based solutions. Agarwal and Joshi [17] analyzed the impact of NEP 2020 on digital education and highlighted the importance of AI adoption. Kulkarni and Deshmukh [25] discussed how AI can support outcome-based education and personalized learning. Sinha and Rao [19] emphasized the role of data-driven decision-making in improving educational outcomes. The alignment of AI-based prediction systems with NEP 2020 provides a strong foundation for transforming the Indian education system.

The alignment of AI technologies with NEP 2020 supports the transformation of the education system. It encourages the adoption of innovative and data-driven practices. Hence, policy integration plays a crucial role in large-scale implementation.

4. Emerging Trends and Research Gaps

4.1 Trends

- Shift from traditional ML to deep learning
- Use of hybrid and ensemble models
- Integration with LMS and real-time systems
- Adoption of Explainable AI

4.2 Research Gaps

- Lack of standardized datasets
- Limited clarity in deep learning
- Insufficient focus on ethical AI
- Need for NEP 2020 alignment

The identified trends indicate rapid technological advancement in this domain. However, existing gaps highlight the need for further research and improvement. Addressing these challenges is essential for future development.

5. Comparative Analysis of Machine Learning Models

Table: Comparative Analysis of Machine Learning Models for Student Performance Prediction

Author(s) & Year	Model Category	Techniques/ Algorithms	Performance Level	Key Strengths	Constraints	Suitable Use Cases
Kumar & Singh (2020) [1]	Traditional ML	Decision Tree, Naïve Bayes	Average (70–80%)	Simple, interpretable, fast execution	Lower accuracy for complex data	Basic prediction tasks
Yadav et al. (2021) [4]	Traditional ML	SVM, Decision Tree	Average	Easy implementation, reliable baseline	Limited scalability	Small datasets
Verma & Gupta (2021) [3]	Ensemble Learning	Random Forest	Strong (80–88%)	Handles noise, better accuracy	Computational overhead	Medium datasets
Chen & Guestrin (2022) [5]	Ensemble Learning	XGBoost	Strong (85–90%)	High efficiency, scalable	Complex tuning	Large structured datasets
Mishra et al. (2022) [6]	Deep Learning	ANN	Very Strong (85–92%)	Captures complex relationships	Requires large data	Large datasets
Wang et al. (2025) [20]	Deep Learning	LSTM	Very Strong (88–93%)	Handles temporal data	High computational cost	Sequential/ temporal data

Reddy et al. (2024) [13]	Hybrid Models	RF + ML combinations	Highest (90–95%)	Combines strengths, high accuracy	Complex architecture	Advanced predictive systems
Ali et al. (2026) [23]	Hybrid Models	AI-based hybrid models	Highest (92–96%)	Superior performance	Difficult implementation	Large-scale prediction systems
Khan et al. (2024) [15]	LMS-Based Models	LMS + ML	High (80–88%)	Real-time monitoring	Data dependency	Early warning systems
Sharma et al. (2025) [18]	LMS-Based Models	Early warning ML models	High	Identifies at-risk students	Requires continuous data	Intervention systems
Das & Nair (2024) [14]	Explainable AI	SHAP, LIME	Medium–High	Transparency, interpretability	Slight performance trade-off	Decision support systems
Thomas et al. (2025) [21]	Ethical AI / XAI	Explainable frameworks	Medium	Fairness and accountability	Implementation complexity	Policy-driven systems

Table presents a comprehensive comparison of various machine learning techniques along with their corresponding authors and contributions. The analysis shows that traditional models provide baseline performance, while ensemble and deep learning approaches improve prediction accuracy. Hybrid models achieve the highest performance by integrating multiple techniques. Additionally, LMS-based and Explainable AI models enhance real-time prediction and interpretability, making them suitable for practical educational applications.

The comparative evaluation provides a clear understanding of the strengths and limitations of different models. It helps in selecting the most suitable approach based on specific requirements. Overall, hybrid models show promising results in most scenarios.

6. Discussion

The findings of this study indicate that hybrid and ensemble models consistently outperform traditional machine learning approaches in predicting student performance. While deep learning models provide high accuracy, they require significant computational resources and large datasets [6], [20]. The integration of learning analytics and LMS-based systems enhances prediction capability by incorporating real-time data [15].

Furthermore, the adoption of Explainable AI techniques is essential for ensuring transparency and trust in educational systems [14]. The alignment of AI-based prediction models with NEP 2020 highlights the importance of policy-driven technological adoption in improving educational outcomes [17], [25].

The discussion highlights the practical implications of different machine learning approaches. It emphasizes the importance of selecting appropriate techniques for specific use cases. Additionally, it reflects the need for balancing accuracy and interpretability.

7. Conclusion

This study provides a comprehensive overview of machine learning and artificial intelligence techniques applied to student performance prediction. While conventional algorithms offer baseline results, advanced approaches such as ensemble and deep learning models demonstrate superior predictive capability. Hybrid models, in particular, achieve enhanced performance by leveraging the strengths of multiple techniques.

The integration of AI-driven solutions within the framework of NEP 2020 highlights the growing importance of personalized and data-centric education systems. However, challenges related to interpretability, data quality and ethical considerations must be addressed to ensure effective implementation. Future research should focus on developing transparent, scalable and real-time predictive models aligned with educational policies.

The study reinforces the significance of machine learning in improving educational outcomes. It also highlights the potential of advanced models in real-world applications. Ultimately, continuous research is required to enhance system effectiveness.

8. Future Research Directions

Future research should focus on developing explainable and interpretable models to enhance trust in AI systems [14]. The implementation of real-time prediction systems using LMS data is another promising direction [15]. Additionally, there is a need to develop standardized datasets and frameworks aligned with NEP 2020 to ensure scalability and practical applicability [17], [19].

Future research should focus on developing more efficient and interpretable models. There is also a need to incorporate real-time data for better prediction accuracy. Such advancements will further strengthen AI-based education systems.

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