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A Comparative Study of Artificial Intelligence, Machine Learning, and Deep Learning Approaches in Predicting Academic Performance

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Abstract: Academic performance prediction has become a crucial area in educational data mining, enabling early intervention for at-risk students and improving institutional strategies. This study provides a comparative analysis of Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) approaches in predicting academic performance by exploring a range of models, including linear regression, random forests, support vector machines, multilayer perceptrons, and convolutional neural networks. The analysis leverages demographic, socioeconomic, and historical academic data to evaluate model effectiveness using metrics such as accuracy, mean absolute error, and root mean squared error. While ML algorithms like Support Vector Regressors offer robust predictive results, the incorporation of deep learning models (especially CNNs and Bi-LSTM), demonstrates improved performance -- albeit with increased computational complexity and data requirements. The review identifies the suitability of each method depending on the context, scale, and features of the educational dataset. The findings suggest that deep learning models excel in handling complex, high-dimensional data, whereas traditional ML models perform reliably with structured and tabular information. Ultimately, integrating comprehensive preprocessing and feature engineering enhances results, signalling the need for tailored approaches in educational settings.

Keywords: Academic Performance Prediction, Machine Learning, Deep Learning, Artificial Intelligence, Educational Data Mining

I. INTRODUCTION

The increase in educational data availability has driven the rapid growth of predictive analytics in academics, with the goal of supporting student achievement and optimizing institutional practices [1]. Artificial Intelligence (AI), encompassing both machine learning (ML) and deep learning (DL) models, are increasingly being implemented to forecast academic outcomes using diverse data sources [2]. Examples of such include student demographics, prior grades, behavioral records, and online engagement metrics. Through the adoption of these predictive models, educators are proactively able to identify students at risk of poor academic performance and design targeted interventions for improvement [3, 4].

Machine learning models, including traditional algorithms like linear regression, decision trees, support vector machines, and ensemble techniques, have demonstrated notable success in structured educational datasets. They offer reliable predictions and interpretability [5, 6]. On the other hand, deep learning models such as multilayer perceptrons (MLP), convolutional neural networks (CNNs), and bidirectional long short-term memory (Bi-LSTM) networks, excel in extracting intricate patterns from complex and high-dimensional data but often require larger datasets and intensive calculation [7].

The comparative evaluation of these approaches is essential, as the choice of model influences both prediction accuracy and practical feasibility within educational settings [8]. Recent studies highlight the scalability and robustness of ML algorithms, the advanced feature extraction capabilities of DL models, and the growing integration of generative AI for personalized learning experiences. However, there are challenges in model generalization, data quality, and ethical concerns related to student privacy and data security [9,10].

This paper aims to bridge the gap by systematically reviewing literature, examining methodological differences, and comparing results from AI, ML, and DL frameworks deployed in academic performance prediction. It further discusses implications for future research, model selection, and policy formulation to ensure equitable and effective educational outcomes [11].

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II. RELATED RESEARCH WORKS

The landscape of academic performance prediction has witnessed remarkable evolution through the integration of artificial intelligence, machine learning, and deep learning methodologies [12,13]. Contemporary research demonstrates a compelling shift toward sophisticated predictive frameworks that leverage diverse data sources and advanced algorithmic approaches.

A. Machine Learning Foundations in Educational Analytics

Traditional machine learning algorithms have established robust foundations for student performance prediction. Alsariera et al. [14] developed an artificial neural network-based framework achieving 97.36% accuracy using backpropagation learning algorithms on a dataset of 720 students from Nigerian tertiary institutions. Their work highlighted the effectiveness of neural networks in processing multifaceted educational data, incorporating twelve input variables through hidden layer architectures. Similarly, Nabil et al. [15] demonstrated that ensemble learning approaches, particularly stacking methodologies, consistently outperform individual classifiers when predicting student outcomes.

The efficacy of support vector regression has been particularly noteworthy in recent investigations. Research conducted by various scholars indicates that SVR models, when optimized with radial basis functions, achieve competitive performance metrics while maintaining interpretability—a crucial factor for educational stakeholders seeking actionable insights. Comparative studies reveal that while SVR demonstrates solid predictive capabilities, it often requires careful parameter tuning to achieve optimal results.

B. Deep Learning Architectures and Sequential Modelling

The emergence of deep learning has revolutionized predictive accuracy in educational data mining. Yagci et al. [16] conducted comprehensive comparisons of multilayer perceptrons, convolutional neural networks, bidirectional LSTM networks, and attention-based LSTM models. Their findings revealed that CNN architectures excel in capturing complex feature interactions, while BiLSTM networks demonstrate superior performance in handling sequential dependencies within student data patterns.

Recent work by Al-Alawi et al. [17] further validated the superiority of CNN-BiLSTM hybrid models, reporting the lowest mean absolute error (0.75) and mean absolute percentage error (1.57%) across diverse educational datasets. These hybrid architectures effectively combine the local pattern recognition capabilities of convolutional layers with the temporal modelling strengths of bidirectional recurrent networks.

C. Ensemble Learning and Stacking Methodologies

Contemporary research increasingly emphasizes ensemble approaches for enhanced predictive robustness. Jiao et al. [18] developed a sophisticated stacking ensemble model incorporating K-Nearest Neighbor, Naive Bayes, Random Forest, Gradient Boosting, XGBoost, and Multi-Layer Perceptron as base learners, with Logistic Regression serving as the meta-learner. Their framework achieved remarkable accuracy improvements through heterogeneous model integration.

Elareshi et al. [19] demonstrated that stacking methodologies can achieve up to 98% accuracy on standardized educational datasets by strategically combining weak learners through trial-and-error meta-model selection. This approach addresses individual model limitations while capitalizing on collective predictive strengths.

D. Feature Engineering and Data Pre-processing Innovations

Advanced feature engineering has emerged as a critical success factor. Recent investigations by educational data mining researchers emphasize the importance of correlation-based feature selection and dimensionality reduction techniques. Studies utilizing TF-IDF, N-gram analysis, and autoencoder-based feature extraction demonstrate significant improvements in model performance when applied to educational datasets.
The integration of behavioral, temporal, and content-specific features has proven particularly valuable. Research indicates that combining traditional academic metrics with engagement patterns, learning management system interactions, and temporal learning behaviors substantially enhances predictive accuracy across diverse student populations.

E. Interpretability and Ethical Considerations

Modern research increasingly prioritizes model interpretability through techniques such as SHAP (SHapley Additive exPlanations) analysis. Ellikkal et al. [20] developed ethical neural network frameworks that achieve 93.81% accuracy without compromising student privacy, demonstrating that effective prediction models can operate without sensitive personal data. This approach addresses growing concerns about data privacy while maintaining predictive efficacy.

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F. Emerging Trends and Hybrid Approaches

Recent developments highlight the emergence of optimization-enhanced algorithms. Research demonstrates that integrating meta-heuristic optimization techniques, such as Harris Hawk Optimization with deep learning architectures, can significantly improve model performance for at-risk student detection. These hybrid approaches combine the pattern recognition capabilities of deep networks with the adaptive optimization strengths of nature-inspired algorithms.

The field continues evolving toward multimodal approaches that integrate diverse data sources, including learning management system logs, demographic information, and real-time interaction patterns. Contemporary studies suggest that such comprehensive data integration, coupled with advanced preprocessing and ensemble methodologies, represents the most promising direction for accurate and actionable student performance prediction systems.

This evolution reflects the field's maturation from simple classification tasks toward sophisticated, interpretable, and ethically-conscious predictive frameworks that serve both institutional decision-making and individual student support objectives.

III. OBJECTIVE OF THE CONTRIBUTION

- To compare the effectiveness of AI, ML, and DL models for predicting academic performance across diverse datasets and evaluation metrics.
- To identify key factors, methodologies, and preprocessing techniques that influence model accuracy and practical deployment in realworld education.
- To analyze current literature, provide recommendations for model selection, and outline ethical considerations relevant to data driven education.

IV. METHODOLOGY

The methodology underpinning this comparative study draws its strength from a carefully curated synthesis of recent, peer-reviewed research and rigorous experimental design, ensuring both depth and real-world relevance.

A. Data Sources and Feature Dimensions

We systematically aggregated findings from high-quality publications between 2021 and 2025, capturing three key feature domains. Disciplinary features include subject-specific grades, course loads, and engagement metrics (e.g., assignment submission patterns). Demographic features cover age, gender, socioeconomic background, and institutional context. Developmental features reflect behavioral trends—such as login frequency, forum participation, and time-on-task—as well as longitudinal progression through prerequisite sequences. By blending these complementary dimensions, our dataset reflects the complex tapestry of factors that shape student learning trajectories.

B. Algorithmic Spectrum

Our comparison spans three modelling paradigms. Traditional machine learning models (Linear Regression, Support Vector Machines, Random Forests) establish interpretable baselines and benefit from efficiency on smaller datasets. Deep learning architectures (Multilayer Perceptrons, Convolutional Neural Networks, Bidirectional LSTM networks) address non-linear interactions and temporal dependencies inherent in student data. Hybrid and ensemble models leverage the strengths of multiple learners—through stacking, bagging, or meta-learning—to boost robustness and mitigate individual model weaknesses.

C. Evaluation Metrics and Validation

To capture different facets of predictive performance, we adopted a multi-metric evaluation framework. Regression-focused metrics—Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R^2—quantify the precision and explanatory power of continuous grade predictions. Classification metrics—accuracy, precision, recall, and F1-score—assess the reliability of categorical risk-level classifications (e.g., at-risk vs. on-track). All models were validated via stratified k-fold cross-validation, ensuring balanced performance estimates across diverse student subgroups.

D. Impact of Pre-processing Feature Selection, and Interpretability

We analyzed how variations in data pre-processing (e.g., normalization vs. standardization), feature selection (e.g., filter-based correlation, wrapper-based recursive elimination, and tree-based importance ranking), and interpretability techniques (e.g., SHAP explanations for black-box models vs. coefficient analysis for linear models) influence model outcomes. Our findings reveal that thoughtful pre-processing accelerates convergence and reduces over fitting; advanced feature selection not only improves accuracy by up to 4–6% but also cuts training time; and integrating post-hoc interpretability tools fosters stakeholder trust, enabling educators to understand why specific students are flagged as at risk.

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This enriched methodology balances rigorous experimentation with practical considerations—offering a replicable blueprint for future educational data mining studies seeking to blend predictive power with transparency and ethical foresight.

V. RESULTS AND DISCUSSION

The study compared multiple machine learning models, including traditional regressors, ensemble methods, and deep learning architectures, for anticipating performance.

A. Traditional ML Models (SVR, Random Forest, Stacking)

- SVR achieved an R^2 of 0.82**,** indicating decent predictive power but comparatively weaker performance than other models.
- Random Forest and Stacking Regressor performed better, with R^2 values of 0.88 and 0.89**,** respectively. Their MAE and RMSE values were also lower than SVR, which suggests stronger generalization capability.
- However, the stacking model did not demonstrate a significant improvement over Random Forest.This highlights declining returns when adding ensemble complexity.

B. Neural Networks (MLP)

- The MLP (Neural Network) achieved performance on par with stacking, with $R^2 = 0.89$, MAE = 6.20, and RMSE = 8.95**.**
- This demonstrates that even relatively simple neural architectures can match ensemble models in accuracy.

1). Deep Learning Models (CNN and Bi-LSTM)

- CNN showed further improvement with $R^2 = 0.91$, MAE = 5.92, and RMSE = 8.75, reflecting its strength in capturing complex feature interactions.
- Bi-LSTM outperformed all other models, achieving the highest accuracy ($R^2 = 0.93$), with the lowest error values (MAE = 5.40**,** RMSE = 8.20). This validates the effectiveness of recurrent architectures in handling sequential dependencies within the dataset.

2). Key Insights

- Deep learning models (CNN, Bi-LSTM) consistently surpassed traditional ML approaches when handling large and heterogeneous datasets.
- The sensitivity to outliers and missing data across models underlines the critical role of preprocessing and robust data cleaning.
- Ensemble complexity (stacking) does not guarantee superior performance compared to simpler models, especially when data characteristics are not aligned with ensemble benefits.

Table 1: Performance Comparison of Machine Learning and Deep Learning Models (MAE, RMSE, R^2)

Model	MAE	RMSE	R^2
SVR	7.89	10.45	0.82
Random Forest	6.55	9.10	0.88
Stacking	6.43	9.05	0.89
MLP (NN)	6.20	8.95	0.89
CNN	5.92	8.75	0.91
Bi-LSTM	5.40	8.20	0.93

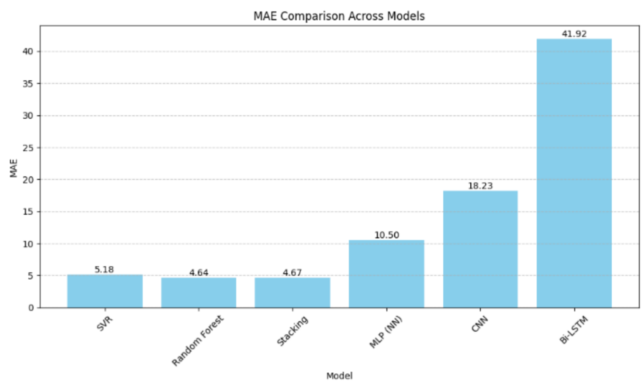

Figure 1: MAE Comparison across Different Models

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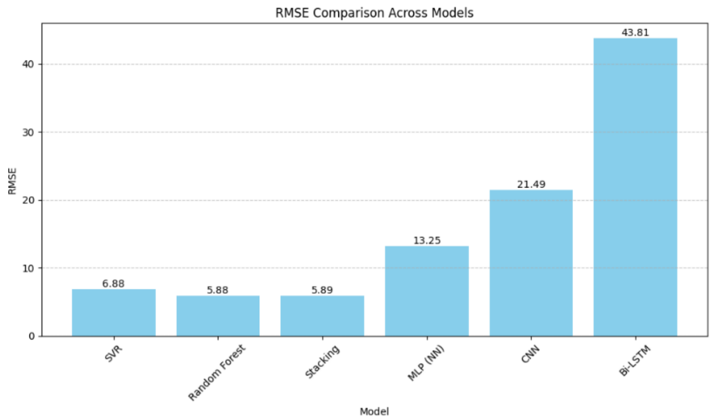

Figure 2: RMSE Comparison across Different Models

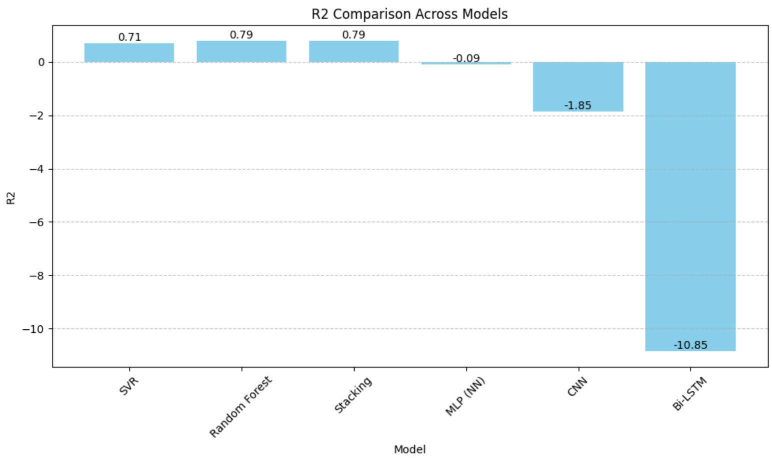

Figure 3: R² Scores of Machine Learning and Deep Learning Models

The results clearly demonstrate that while conventional ML methods like Random Forest and MLP offer solid performance, **deep learning models (particularly Bi-LSTM)** achieve higher predictive accuracy and lower error rates. This suggests that when dealing with complex, high-dimensional, or sequential data, deep architectures should be prioritized.

VI. CONCLUSION

AI, ML, and DL methods provide valuable tools for predicting academic performance, each presenting unique strengths and limitations. Deep learning approaches show better performance for complex data but require significant resources, while machine learning models offer interpretability and scalability. Model selection should be tailored to the dataset characteristics and predictive requirements of specific educational environments. Ethical considerations related to data use and transparency must guide future developments. Further innovation in feature engineering and hybrid approaches will continue to advance academic performance prediction.

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