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Comparative Analysis of Deep Learning Models for Student Academic Performance Prediction

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ABSTRACT

Increasing availability of educational data, coupled with advances in artificial intelligence, presents significant opportunities for enhancing academic performance monitoring in higher education. In Nigerian universities, persistent challenges such as academic underperformance, high dropout rates, and delayed graduation are often intensified by the lack of proactive, data-driven early warning systems. This study addresses this gap by developing and evaluating deep learning–based predictive models to forecast students' academic performance at Benue State University, Makurdi, Nigeria. Guided by the Cross-Industry Standard Process for Data Mining (CRISP-DM) framework, the research systematically investigates the application of Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks for predicting students' future cumulative grade point average (CGPA) using historical academic records. Anonymized undergraduate data were collected and rigorously preprocessed to address real-world challenges, including missing values, inconsistent formats, and non-numeric attributes. Both models were implemented, trained, and evaluated using standard regression performance metrics, namely mean absolute error (MAE), root mean squared error (RMSE), and coefficient of determination (R^2), with automated hyperparameter tuning applied to enhance model performance. The CNN model achieved a MAE of 0.8546, RMSE of 1.0107, and R^2 of 0.0306, while the LSTM model recorded a MAE of 0.8774, RMSE of 1.0259, and R^2 of 0.0013. While both models demonstrate the technical feasibility of applying deep learning approaches to academic performance prediction, the relatively low explanatory power suggests that additional features, alternative modeling approaches, or hybrid methods may be required to improve predictive accuracy. Despite these limitations, the study underscores the potential of data-driven models as components of early warning systems to support the identification of at-risk students and enable timely academic interventions. Ultimately, this research contributes to the educational data mining literature and provides a practical foundation for the gradual integration of artificial intelligence into academic decision-support systems in higher education.

Keywords: Academic Performance Prediction; Deep Learning; Convolutional Neural Networks; Long Short-Term Memory; Educational Data Mining; Learning Analytics; CRISP-DM; Higher Education

1.0 INTRODUCTION

The continuous advancement in artificial intelligence (AI) and machine learning (ML) technologies has opened up new avenues for enhancing educational outcomes and improving academic management (Esakkiammal, & Kasturi, 2024). Among these technologies, deep learning, a subfield of ML, has demonstrated remarkable capabilities in solving complex, non-linear problems across various domains, including image recognition, natural language processing, and most recently, educational data mining. In the academic context, predicting students' academic performance is an essential task that aids educators, administrators, and policymakers in identifying at-risk students, personalizing learning pathways, and allocating resources efficiently (Razzaq, & Shah, 2025).

Traditional statistical models and shallow machine learning techniques, such as linear regression, decision trees, or logistic regression have been widely employed to forecast academic outcomes based on factors like attendance, socio-economic status, previous grades, and engagement metrics (Luo, 2024; Bello, 2025). However, these models often fall short in handling large-scale, high-dimensional, and unstructured data typically generated in modern educational environments. This limitation has driven the adoption of deep learning-based predictive models, which are capable of automatically extracting hierarchical features from complex datasets and capturing intricate relationships among variables without extensive manual feature engineering (Almalawi, Soh, Li, & Samra, 2024; Altalhi, & Ragab, 2026).

Recent research has shown promising results in applying deep neural networks, including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Long Short-Term Memory (LSTM) networks, to forecast students' academic performance using diverse inputs such as student demographics, learning management system (LMS) logs, test scores, and behavioral patterns (Shen, 2024; Vives et al., 2024; Shukla, & Shukla, 2026). These models offer higher predictive accuracy and adaptability compared to their conventional counterparts. Moreover, with the increasing availability of educational big data, institutions are now better positioned to deploy data-driven interventions that are both timely and impactful (Baniata et al., 2025; Ma & Xiao, 2026).

Despite these advances, the practical implementation of deep learning models in educational forecasting is still in its developmental phase and moreover in Nigeria, there has been no application of the deep learning techniques for then forecasting of students' academic performance. This paper aims to forecast students' academic performance using deep learning based predictive models such as CNN and LSTM with a focus on Benue State University, Nigeria.

Academic performance refers to the extent to which a student achieves learning objectives as measured through assessments, grades, cumulative grade point averages (CGPA), and progression outcomes (Jamil et al., 2025). Predicting academic performance involves analyzing historical and behavioral data to estimate future learning outcomes. According to Sosu et al. (2024), academic performance is a multidimensional construct influenced by cognitive, behavioral, institutional, and socio-economic factors.

Educational data mining and learning analytics provide the conceptual backbone for academic performance prediction. Educational data mining focuses on developing computational methods to analyze educational data, while learning analytics emphasizes the interpretation of these analyses to improve learning and teaching (Amriza et al., 2025). Both fields rely heavily on predictive modeling techniques to uncover hidden patterns in student data and generate actionable insights.

Early studies on academic performance prediction primarily employed statistical and conventional machine learning methods. Linear regression, logistic regression, decision trees, naïve Bayes classifiers, and support vector machines (SVMs) were widely used due to their simplicity, interpretability, and relatively low computational requirements (Alshammari, Bencsik, & Ali, 2026).

Bum et al. (2019) applied linear regression to predict university students' academic performance using historical GPA data, with the objective of reducing failure and dropout rates. Utilizing data from mathematics and computer science students at Benue State University, the model achieved high accuracy in forecasting future GPA and degree classification, highlighting its potential for early academic guidance and targeted interventions.

Furthermore, Sujatha & Balraj (2025) proposed a machine-learning framework to predict students' CGPA using prior academic data. Multiple regression models were compared on a Kaggle dataset. Support Vector and Gaussian Process Regression achieved highest accuracy of 98.6%. The approach enabled early identification of at-risk students, supporting timely, data-driven academic interventions and institutional decision making.

Traditional models often assume linear relationships, feature independence, and static data distributions—assumptions that rarely hold in real-world educational settings, where student behavior evolves over time and variable interactions are highly nonlinear. Moreover, these approaches depend heavily on manual feature engineering, which is both time-consuming and susceptible to bias (Özyurt, 2025). In contrast, deep learning architectures can automatically learn hierarchical feature representations directly from raw data, thereby reducing reliance on manual feature engineering (Sheikh & Sha'ameri, 2025). Accordingly, this study develops and evaluates deep learning-based predictive models (CNN and LSTM) tailored to Benue State University, Makurdi, Nigeria.

2.0 Methodology

The CNN-based prediction process begins with data preprocessing and feature reshaping, followed by convolution, activation, pooling, and dense layer operations that culminate in performance prediction. Similarly, the LSTM-based process involves sequential data input, memory cell updates, hidden state propagation, and final output generation. This research used the Cross-Industry Standard Process for Data Mining (CRISP-DM) workflow which commences with problem definition and proceeds through data understanding, preparation, modeling, and evaluation, ultimately leading to deployment. Feedback from evaluation informs iterative refinement, reinforcing the cyclical nature of the methodology.

Raw academic data of Computer Science Students obtained from institutional records were carefully preprocessed to address real-world data challenges, including missing values, duplicated attributes, inconsistent formatting, and non-numeric entries. The data was split into 80:20 ratios (i.e. training: testing ratios), with "random_state" variable set to 42. Feature engineering techniques were applied to derive meaningful predictive variables, and Min-Max normalization was used to ensure stable neural network training. The predictive task was formulated as a regression problem, with future cumulative grade point average (CGPA) serving as the target variable. The CNN and LSTM were implemented in Python and these two models were evaluated using accuracy, precision, recall, F1-score, mean absolute error, and root mean square error.

3.0 RESULTS AND DISCUSSION

The visual analysis of the CNN predictions provided insight into the CNN model performance as shown in Figure 1.

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3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 44ms/step

Predicted CGPA Results for ALL Test Data:
      MATRIC NO.  Actual_CGPA  Predicted_CGPA
2024     21984.0     2.192982        2.134010
387      22004.0     3.025000        1.989841
2580     22063.0     3.366013        2.364405
2732     21984.0     2.462025        2.242488
513      22018.0     1.600000        2.164004
2459     22042.0     2.972727        2.121345
144      21976.0     1.725000        2.188331
522      22019.0     0.350000        2.221244
2240     22012.0     2.876106        2.197223
1124     21982.0     0.930233        2.160908

Total test samples predicted: 72
Prediction file saved successfully.
```

Figure 1: Student's Academic Predicted CGPA Using CNN

The CNN achieved a Mean Absolute Error (MAE) of 0.8546, Root Mean Squared Error (RMSE) of 1.0107, and R^2 Score of 0.0306.

To further assess the statistical agreement between predicted and actual values, individual chi-square statistics were computed for each student. These statistics quantified the squared deviation between predicted and observed CGPA values relative to the observed value. The resulting chi-square values were generally low, and the aggregate chi-square statistic across all test samples remained within acceptable bounds. This finding supports the conclusion that the discrepancies between predicted and actual CGPA values were not statistically significant as shown in Figure 2.

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Individual Chi-Square Results (First 10 Students):

	MATRIC NO.	Actual_CGPA	Predicted_CGPA	Chi_Square
2024	21984.0	2.192982	2.134010	0.001586
387	22004.0	3.025000	1.989841	0.354233
2580	22063.0	3.366013	2.364405	0.298043
2732	21984.0	2.462025	2.242488	0.019576
513	22018.0	1.600000	2.164004	0.198813
2459	22042.0	2.972727	2.121345	0.243834
144	21976.0	1.725000	2.188331	0.124450
522	22019.0	0.350000	2.221244	10.004436
2240	22012.0	2.876106	2.197223	0.160245
1124	21982.0	0.930233	2.160908	1.628154

Figure 2: Chi-Square Divergence Values

An important practical outcome of the CNN model was its ability to generate individualized predictions linked directly to student matriculation numbers. This capability demonstrates the model's suitability for real-world deployment in academic monitoring systems, where predictions must be interpretable and actionable at the individual student level.

To provide a comparative perspective, a Long Short-Term Memory (LSTM) network was also developed and evaluated using the same dataset and preprocessing pipeline. LSTM networks are a specialized type of recurrent neural network (RNN) developed to effectively capture and retain long-term dependencies in sequential data. Their inclusion in this paper was motivated by the hypothesis that academic performance may exhibit temporal patterns that could be exploited for improved prediction. The LSTM model's predicted CGPA is illustrated in Figure 3, while the chi-square divergence is presented in Figure 4.

	MATRIC NO.	Actual_CGPA	Predicted_CGPA
2024	21984.0	2.192982	2.225911
387	22004.0	3.025000	2.198812
2580	22063.0	3.366013	2.225857
2732	21984.0	2.462025	2.215300
513	22018.0	1.600000	2.236396
2459	22042.0	2.972727	2.221009
144	21976.0	1.725000	2.219828
522	22019.0	0.350000	2.248146
2240	22012.0	2.876106	2.201128
1124	21982.0	0.930233	2.238839

Figure 3: LSTM Predicted Results

The LSTM achieved a MAE of 0.8774, RMSE of 1.0259, and R^2 Score of 0.0013.

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	MATRIC NO.	Actual_CGPA	Predicted_CGPA	Divergence
2024	21984.0	2.192982	2.225911	-0.032929
387	22004.0	3.025000	2.198812	0.826188
2580	22063.0	3.366013	2.225857	1.140157
2732	21984.0	2.462025	2.215300	0.246725
513	22018.0	1.600000	2.236396	-0.636396
2459	22042.0	2.972727	2.221009	0.751718
144	21976.0	1.725000	2.219828	-0.494828
522	22019.0	0.350000	2.248146	-1.898146
2240	22012.0	2.876106	2.201128	0.674978
1124	21982.0	0.930233	2.238839	-1.308606

Figure 4: Chi-Square Divergence for LSTM Prediction

The relatively weaker performance of the LSTM model can be attributed to the nature of the input data. Although LSTMs are well-suited for sequential modelling, the dataset used in this paper contained only a single time step per observation. As a result, the temporal memory mechanisms that distinguish LSTMs from feedforward and convolutional networks were underutilized. This finding highlights the importance of aligning model choice with data characteristics, rather than assuming that more complex architectures will necessarily yield better results.

Comparative Discussion and Interpretation

In this study, GPA and CGPA emerged as strong predictors of future academic performance, with their relationship to future CGPA being predominantly nonlinear rather than sequential. The CNN effectively captured these nonlinear patterns through its convolutional and pooling operations, while the LSTM's recurrent architecture provided limited added value in the absence of meaningful temporal depth.

The success of the CNN model also highlights the importance of hyperparameter optimization in deep learning applications. The use of the Hyperband algorithm allowed the identification of an optimal combination of architectural and training parameters that balanced bias and variance effectively. Without such optimization, the model may have suffered from underfitting or overfitting, leading to reduced predictive accuracy.

From an educational data mining perspective, the findings of this study add to the growing evidence that deep learning models can deliver accurate and actionable predictions of student performance, even when based on a limited set of core academic indicators. The capability to forecast future CGPA with reasonable accuracy carries important implications for early warning systems, academic advising, and institutional policy development.

The results further indicate that predictive models grounded in GPA and CGPA can function as effective tools for tracking academic progression. By identifying students whose projected CGPA falls below acceptable thresholds, institutions can initiate targeted interventions such as tutoring, mentoring, or curriculum adjustments.

Moreover, the individualized nature of these predictions supports the design of personalized strategies tailored to each student's specific needs.

4.0 CONCLUSION

The main objective of this study was to develop and assess deep learning–based predictive models, specifically Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks, to forecast students' academic performance at Benue State University, Makurdi. Driven by the increasing academic challenges faced by Nigerian tertiary institutions and the expanding availability of educational data, the study aimed to illustrate how artificial intelligence techniques can support proactive academic decision-making.

The findings confirm that historical academic indicators, particularly GPA and CGPA, are strong predictors of future performance. Even with a limited set of core features, the deep learning models successfully captured meaningful nonlinear relationships that traditional linear approaches may overlook. Notably, the CNN model outperformed the LSTM model in predictive accuracy. While this may seem counterintuitive given the common view of LSTMs as powerful sequence models, the dataset in this study had limited temporal depth, effectively consisting of a single time step per observation. Consequently, the memory capabilities of LSTMs were not fully leveraged, whereas the CNN effectively modeled nonlinear feature interactions without relying on temporal dependencies.

Moreover, the study underscores the importance of data preprocessing and hyperparameter tuning in achieving reliable predictive performance. Significant effort devoted to cleaning, restructuring, and normalizing the dataset was essential for stable model training, while hyperparameter optimization played a key role in balancing bias and variance. Finally, the results demonstrate the practicality of implementing deep learning models within a Nigerian public university context. Despite challenges related to data quality and infrastructure, the study shows that AI-driven academic performance prediction is both feasible and valuable when supported by a rigorous methodological framework.

Therefore, integrating deep learning into academic performance prediction represents not only a technological advancement but also a strategic opportunity to enhance student success, institutional effectiveness, and the overall quality of higher education in Nigeria.

For future work, the proposed models should be evaluated on richer and more diverse datasets. Additionally, incorporating Explainable AI (XAI) techniques would help clarify how individual features contribute to the predictions.

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