Available online www.unicrossjournals.com

UNICROSS JOURNAL OF SCIENCE AND TECHNOLOGY, UJOST

RESEARCH ARTICLE VOL. 4(4) DECEMBER, 2025 ISSN:2814-2233

Date Approved December 31, 2025 Pages 34 – 46

PREDICTING STUDENT ACADEMIC PERFORMANCE USING ARTIFICIAL NEURAL NETWORKS: A DATA-DRIVEN APPROACH TO ENHANCING ADMISSION DECISIONS IN NIGERIA

Ogunbanwo, Afolakemi Simbo
Department of Computer Science
Tai Solarin University of Education,
Ijagun, Ogun State, Nigeria.
Email: **ogunbanwoas@tasued.edu.ng**

Abstract

This study explores the use of Artificial Neural Networks (ANNs) to predict student academic performance and enhance admission decisions in Nigerian tertiary institutions. Using 480 student records obtained from the Kalboard 360 Learning Management System, which served as a proxy dataset due to limited access to real institutional data. The dataset comprises of 16 demographic and academic features, the data was preprocessed and split into 75% training and 25% testing sets. An ANN model was developed in Python with Scikit-learn, achieving 80% overall accuracy. The model showed balanced performance across three student categories: moderate performers (Class 1) had the highest F1-score of 0.83, while low (Class 0) and high performers (Class 2) scored 0.79 and 0.77 respectively. These results highlight ANNs' effectiveness in accurately predicting student outcomes. The results suggest potential for integrating machine learning approaches like ANNs into Nigerian tertiary education decision-making, providing a data-driven method to optimize student selection and resource management. However, the relatively small size of the proxy dataset limits the model's generalizability, indicating the need for larger, institution-specific datasets to improve robustness and real-world applicability.

Keywords: Student Academic Performance, ANN, Predictive Modeling, Admission Systems, Data-driven Admissions, Nigeria

1. Introduction

Predicting student academic performance has emerged as a significant focus in educational research, particularly in light of the increasing demand for accountability and efficiency in academic admissions (Dung *et al*., 2023; Liu & Yang, 2025). Admission decisions shape both student success and institutional reputation. Traditionally, admission decisions in Nigeria have been based on a combination of standardized test scores such as UTME and Post-UTME, as well as secondary school results like WAEC. However, these processes make limited use of advanced computational techniques to assess candidate suitability. These conventional methods often fall short in accurately forecasting academic outcomes, resulting in the admission of students who may struggle academically (Baashar *et al*., 2022).

Artificial Neural Networks (ANNs), as a branch of machine learning, offer a promising alternative. They are computational models inspired by the structure and function of the human brain, capable of learning complex patterns from large datasets. They have demonstrated strong performance in fields such as medicine, finance, and engineering, particularly in tasks involving classification and prediction (Baashar *et al*., 2022; Al-azazi & Ghurah, 2023). In the educational domain, their capacity to analyze multifactorial inputs makes them suitable for modeling academic performance, which is inherently influenced by numerous interrelated factors.

Despite global advances in applying ANNs to student performance prediction, Nigerian institutions have not fully embraced these technologies in admission processes (Adeniyi *et al*., 2021; Oladokun *et al*., 2008; Olaniyan *et al.*, 2021). There exists a pressing need to explore and evaluate the use of ANN models in the Nigerian education system, particularly to support data-driven decision-making in admissions.

This study builds on existing research by developing and evaluating an ANN-based model for predicting student academic performance using structured pre-admission data within the Nigerian tertiary education context. Previous studies in Nigeria have shown that ANNs can be applied to academic performance prediction; however, much of this work has concentrated on post-admission or course-level outcomes rather than on pre-admission decision-support applications (Oladokun *et al.*, 2008; Adeniyi *et al.*, 2021). In this respect, the present study places emphasis on multi-class prediction, model transparency, and computational efficiency, factors that are relevant for practical adoption in admission processes, particularly in resource-constrained institutional settings.

2. Related Studies

In 2022, Baashar *et al*. presented a comprehensive approach to predicting student academic performance using Artificial Neural Networks (ANNs). The study demonstrated the significant advantages of ANNs in handling complex educational data, where traditional machine learning models often faltered. Baashar and colleagues showed that ANNs can adapt and learn from large datasets, making them highly effective in predicting academic success with a high degree of accuracy. Their work underscored the potential of ANNs in identifying at-risk students and offering early interventions. However, the study’s limitation lies in its reliance on large datasets, which may not be available in many educational institutions especially in low-resource contexts this thereby hindering the model’s scalability.

In a similar vein, EL Habti *et al.* (2025) explored the effectiveness of machine learning algorithms in predicting student performance in e-learning environments. Their study compared Random Forest and Support Vector Machines, finding that Random Forest achieved an impressive 91% accuracy rate. This study highlighted the growing significance of AI in online learning settings, where traditional classroom tools may fall short. The study's results demonstrated that machine learning, particularly Random Forest, could significantly enhance the prediction of student outcomes in digital education platforms. But its scope is restricted to online environments, limiting its generalizability to traditional or hybrid academic settings.

As AI techniques evolve, so does their ability to handle more complex data challenges. Liu and Yang (2025) introduced a Generative Adversarial Network (GAN) model designed to improve student performance prediction by addressing data imbalance. In the context of blended learning environments, the GAN model used short text data to improve prediction accuracy and generalization. This innovation paved the way for multimodal approaches in predicting student performance, combining different types of data to provide a more holistic view of a student's potential. However, GAN architectures are computationally demanding and difficult to tune, which may present practical implementation challenges in resource-constrained educational systems.

Dung *et al.* (2023) further strengthened the case for ANNs in predicting student performance by showcasing how these models can successfully handle real-world educational data. The study highlighted how factors such as attendance, participation, and academic history could all be integrated into ANN models to predict performance more accurately. The authors demonstrated that ANNs are particularly effective when multiple input features are involved, showcasing the model's adaptability and power in predicting a student's academic trajectory.

Al-azazi & Ghurah, (2023) proposed an ANN-LSTM model to predict student performance. By combining Long Short-Term Memory (LSTM) networks with ANNs, the model significantly outperformed traditional Recurrent Neural Networks (RNNs) and Gated Recurrent Units (GRUs) in multi-class classification tasks. This hybrid deep learning model highlighted the growing trend of deep learning techniques in addressing the challenges of large-scale educational platforms, promising higher prediction accuracy in online learning ecosystems. Even though the hybrid model demonstrated superior performance, its complexity requires significant computational resources and deep expertise, limiting its use in institutions without advanced technical infrastructure.

In another study, Wang *et al.* (2021) introduced a graph-based ensemble machine learning method that combined supervised and unsupervised learning techniques to enhance the stability and accuracy of student performance predictions. By leveraging graph-based algorithms, the study demonstrated how these methods could improve prediction outcomes, especially when working with diverse datasets. This innovative approach showcased the potential of combining different machine learning techniques to enhance the robustness of student performance prediction models. This method improved prediction robustness across diverse datasets, but the integration of graph-based algorithms increases methodological complexity, making implementation and replication difficult for non-specialists.

Delianidi *et al.* (2021) focused on dynamic neural models for predicting student performance, comparing Time Delay Neural Networks (TDNN) with Recurrent Neural Networks (RNNs). The study concluded that RNNs were superior in predicting student responses over time, making them particularly useful for tracking performance across multiple academic terms. This finding further emphasizes the importance of incorporating temporal elements in AI models to improve long-term student performance predictions.

Baashar *et al.* (2022) and Dung *et al.* (2023) both provide strong evidence supporting the effectiveness of Artificial Neural Networks (ANNs) in predicting student academic performance, yet their findings emphasize different strengths of ANN-based models. Baashar *et al.* (2022) highlights the capacity of ANNs to learn from large and complex datasets, demonstrating superior performance compared to traditional machine learning approaches. In contrast, Dung *et al.* (2023) shows that ANNs also perform exceptionally well when trained on diverse, real-world educational features—such as attendance, participation, and academic history—underscoring their adaptability to multidimensional inputs. While both studies converge on the usefulness of ANNs in academic prediction contexts, Baashar *et al.* (2022) focus primarily on scalability with respect to data volume, whereas Dung *et al.* (2023) stresses the importance of feature richness in enhancing prediction accuracy. This distinction reveals complementary insights: ANNs are not only powerful when abundant data is available but also highly effective when working with complex, multifactorial datasets. Together, these findings contribute to a broader understanding of ANN applicability in education while also highlighting the need for improved interpretability to support practical adoption in institutional settings.

Random Forest’s strong performance (El Habti *et al*., 2025) reflects the characteristics of the specific e-learning dataset, which favors tree-based models. However, ANN approaches typically excel with larger, more complex, or multi-modal data (Baashar *et al.*, 2022, and Dung *et al.*, 2023). Thus, neither method is universally superior; model effectiveness depends on dataset size, feature complexity, nonlinearity, and learning context, making performance inherently context-dependent rather than absolute. In nutshell, Random Forest may outperform ANN in some structured, tabular contexts, but ANNs remain more suitable for complex or large-scale datasets. Thus, model superiority is context-specific rather than absolute.

While AI has shown promise in predicting student performance, most studies rely on single data modalities, limiting their ability to capture complex learning behaviors. Few have integrated multi-modal data encompassing both online and offline contexts, such as classroom interactions, assignments, and digital activity. This study addresses this gap by leveraging heterogeneous data sources to develop more robust, holistic, and context-aware predictive models.

3. Methodology

This study aims to predict students' academic performance using a machine learning algorithm, focusing on the design and implementation of a predictive model. The methodology discussed the acquiring and preparing a diverse and relevant dataset, development of an ANN-based predictive model with robust training/testing protocols and employing thorough evaluation metrics to measure the model’s predictive effectiveness

The study used a real-world dataset sourced from the Kalboard 360 LMS, which provides a rich set of 480 student records across demographic, academic, and behavioral features. This multi-dimensional dataset supports the complex modeling of academic performance, reflecting the multifactorial nature of student success as stated in the introduction. The preprocessing steps involved handling missing data, cleaning, removing irrelevant features, and structuring data which are crucial to enhance the dataset's quality, directly supporting the objective of preparing data for effective model training. This ensured that the ANN learns from relevant and accurate information, minimizing noise and bias and directly contributes to achieving the objective of preparing a robust dataset for effective model training.

During model development, the study employed Python with the Scikit-learn library to implement a Multi-Layer Perceptron (MLP)-based ANN. The final model configuration included one input layer with 16 neurons (corresponding to the selected features), two hidden layers with 32 and 16 neurons respectively, and an output layer with three neurons representing the student performance classes. ReLU (Rectified Linear Unit) activation was used in the hidden layers to improve learning efficiency and address vanishing gradient issues, while the softmax activation in the output layer enabled multi-class probability predictions. The model was trained using the Adam optimizer, selected for its adaptive learning rate and computational efficiency, and a learning rate of 0.001, which balances convergence speed and training stability. The training process incorporated 100 epochs to allow the ANN sufficient iterations to learn underlying patterns without overfitting. These methodological choices align with established best practices in ANN-based classification and directly reinforce the study's objective of employing advanced computational techniques to improve predictive accuracy.

Splitting the data into 75% training and 25% testing aligns with best practices for ensuring that the model generalizes well to unseen data, avoiding overfitting. NumPy and Pandas libraries were employed to facilitated efficient data handling and manipulation, crucial for feeding the ANN model with well-structured inputs. The methodology centers on implementing the ANN model, underscoring the study's commitment to advanced machine learning approaches as alternatives to traditional admission decision tools. Also, the Epoch training was incorporated to improve model convergence and learning stability addresses practical concerns about model complexity and performance refinement, supporting the objective of building a reliable predictive model.

The Confusion Matrix was adopted for evaluating model performance, this provided detailed insights beyond simple accuracy by including precision, recall, and F1-score. These metrics are vital for understanding the model's predictive power, especially in educational settings where false positives or negatives (e.g., misclassifying a student's potential) have significant implications. The use of these metrics allows a robust and nuanced evaluation, supporting the objective to critically assess how well the ANN distinguishes students' academic potentials. While accuracy provides a general measure of performance, precision and recall are particularly critical in educational contexts, where misclassifying an at-risk student could lead to missed interventions.

Ethical and practical considerations were addressed by using anonymized student records obtained from a publicly available dataset, ensuring that no personally identifiable information was disclosed. Potential biases arising from demographic or class imbalance were mitigated through careful preprocessing, including data cleaning and balanced evaluation metrics, to promote fairness and reliability in the model's predictions.

4. Result and Discussions

The dataset underwent meticulous preprocessing to enhance its suitability for predictive modeling. Figure 1 and Figure 2 illustrate the dataset before and after preprocessing, respectively. These measures ensured the dataset's analytical robustness and reliability for subsequent modeling. Figure 1 highlights issues such as missing values, inconsistent scales, and unstructured inputs, which could adversely affect model learning. While Figure 2 demonstrates the impact of preprocessing steps—data cleaning, normalization, and appropriate encoding—resulting in a refined dataset suitable for ANN training. These steps are critical for improving model stability, convergence, and predictive reliability.

	gender	Nationality	StageID	GradeID	SectionID	Topic	Semester	Relation	raisedHands	VisitedResources	Ar
0	M	Kuwait	lowerlevel	G-04	A	IT	F	Father	15	16	
1	M	Kuwait	lowerlevel	G-04	A	IT	F	Father	20	20	
2	M	Kuwait	lowerlevel	G-04	A	IT	F	Father	10	7	
3	M	Kuwait	lowerlevel	G-04	A	IT	F	Father	30	25	
4	M	Kuwait	lowerlevel	G-04	A	IT	F	Father	40	50	

Figure 1: Before Pre-processing

	raisedHands	VisitedResources	AnnouncementsView	Discussion	gender_F	gender_M	Nationality_Egypt	National
0	15	16	2	20	0	1	0	
1	20	20	3	25	0	1	0	
2	10	7	0	30	0	1	0	
3	30	25	5	35	0	1	0	
4	40	50	12	50	0	1	0	

Figure 2: After Pre-processing

```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix, classification_report
from sklearn.neural_network import MLPClassifier
from sklearn import preprocessing
```

Figure 3: Showing the imported libraries

The ANN model was developed using the imported Python libraries, as shown in Figure 3. Figure 3 shows the Python libraries imported for model development, underscoring the use of standard, widely adopted machine learning tools. This enhances the reproducibility and practical applicability of the study. The dataset was partitioned into 75% for training and 25% for testing. Figure 4 displays the trained ANN model, which was structured to capture complex patterns and interactions within the dataset's multifactorial inputs. Thus, Figure 4 presents the architecture of the trained ANN model, designed to capture non-linear relationships and interactions among multiple academic and behavioral features. The model structure reflects a balance between complexity and computational efficiency.

```
model = MLPClassifier(random_state=42, max_iter=1000)
```

```
model.fit(train_X, train_y)
```

```
MLPClassifier
MLPClassifier(max_iter=1000, random_state=42)
```

```
pred_y = model.predict(test_X)
```

```
pred_y
```

Figure 4: The ANN Model

Model performance was assessed through a confusion matrix (Figure 5), with a corresponding heatmap (Figure 6) to facilitate intuitive visualization of prediction accuracy across different classes. Figures 5 and 6 present the confusion matrix and its heatmap visualization, respectively. These figures provide insight into the model's classification behavior across the three performance classes, highlighting areas of correct prediction as well as misclassification patterns. The heatmap in Figure 6 improves interpretability by visually emphasizing prediction strengths and weaknesses across classes.

```
cm = confusion_matrix(test_y, pred_y)
cm
```

```
array([[22,  0,  6],
       [ 0, 27,  7],
       [ 7,  4, 47]])
```

Figure 5: Confusion matrix of the model

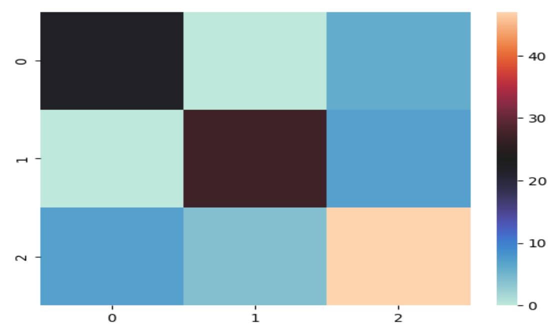

Figure 6: Heatmap of the Confusion Matrix

Finally, Figure 7 and Table 1 summarize the classification report, detailing precision, recall, and F1-scores for each class. These results demonstrate balanced model performance, with Class 1 achieving the highest F1-score, indicating strong predictive capability for moderate-performing students. Overall, the figures collectively validate the effectiveness and robustness of the ANN model.

Table 1: Classification report of the experiment

Metric/ Class	Precision	Recall	F1-score	Interpretation
Class 0	0.76	0.79	0.77	Slightly lower precision, balanced recall, moderate F1-score
Class 1	0.87	0.79	0.83	High precision, moderate recall, best F1-score among classes
Class 2	0.78	0.81	0.8	Balanced precision and recall, good F1-score
Overall Accuracy	—	—	—	80.0% accuracy (96 out of 120 predictions correct)
Macro Average	0.804	0.797	0.8	Equal weight to each class; reflects balanced performance across classes
Micro Average	0.8	0.8	0.8	Aggregates all outcomes globally; matches overall accuracy
Weighted Average	0.802	0.8	0.801	Weighs classes by sample size; accounts for class imbalance realistically

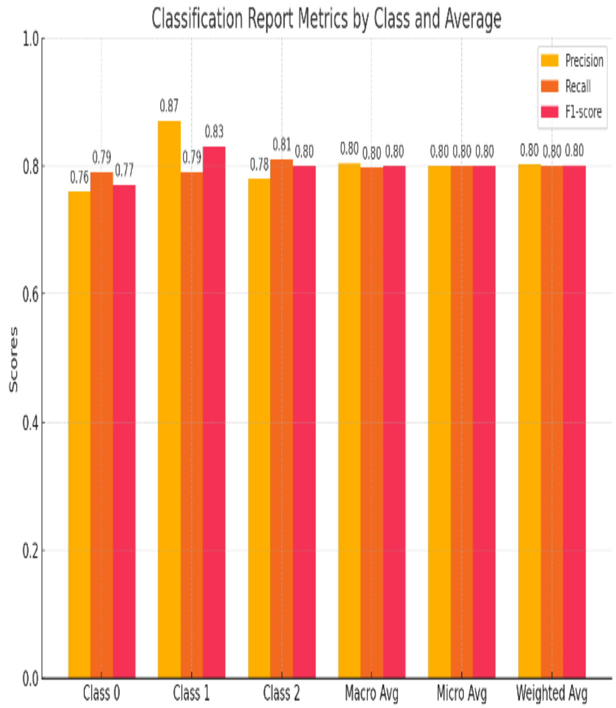

Figure 7: Classification report of the experiment

5. Interpretation of the Results

The model performs reasonably well across the three classes, with class 1 showing the highest precision (0.87) and F1-score (0.83), indicating it is the class for which the model is most confident and balanced in correct predictions. Class 0, while having slightly lower precision (0.76), maintains a solid recall (0.79), suggesting that while the model may generate some false positives for this class, it still successfully identifies most actual instances. Class 2 exhibits a well-balanced performance with precision and recall close to 0.8, reinforcing the model's consistent behavior across classes.

The macro average scores, which treat each class equally regardless of size, confirm that the model maintains balanced performance across all classes with F1-score around 0.80. The micro average, equivalent to overall accuracy here, reflects the aggregate performance considering all predictions together. The weighted average adjusts for the influence of class distribution, and its close proximity to the macro and micro averages suggests the model handles class imbalance effectively. Overall, these metrics demonstrate a reliable, balanced model with consistent predictive capability across different classes.

6. Discussion

The study employed a diverse dataset from the Kalboard 360 LMS that included demographic, academic, and behavioral features—such as educational stage, grade level, attendance, class participation, and parental involvement—as input variables for the Artificial Neural Network (ANN) as model. Following thorough preprocessing to ensure data quality, the model achieved an overall accuracy of 80%, with Class 1 (moderate performers) exhibiting the highest F1-score (0.83) and precision (0.87). The superior performance observed for this class may be attributed to the relatively balanced and well-represented nature of moderate-performing students within the dataset. Additionally, their academic and behavioral attributes tend to exhibit clearer and more consistent patterns. Unlike extreme high or low performers, whose outcomes may be influenced by atypical or unobserved factors, moderate performers often exhibit stable engagement and performance trends. This stability makes them more predictable by ANN models.

These findings indicate that the selected combination of academic background and behavioral factors significantly contributed to accurate performance predictions. These findings align with those of Baashar *et al.* (2022) and Dung *et al.* (2023), who also identified multifactorial inputs like attendance, prior academic records, and parental involvement as key predictors of student success. While Liu and Yang (2025) introduced short-text data into GAN-based models to enhance feature richness, this study relied solely on structured tabular data, underscoring the continued relevance and effectiveness of well-curated structured inputs in educational performance prediction.

The ANN model further demonstrated consistent macro, micro, and weighted F1-scores around 0.80 across three distinct student performance classes. This indicates a robust and balanced classification capability. This stability suggests that the model effectively minimized class bias and maintained reliable performance across categories, reinforcing its suitability for educational decision-support applications. Notably, the relatively simple ANN architecture adopted in this study provides a computationally efficient and more interpretable alternative to complex deep learning models, enhancing its feasibility for deployment in traditional educational environments with limited technical infrastructure.

Furthermore, the developed Artificial Neural Network (ANN) model demonstrated strong predictive effectiveness in distinguishing suitable candidates for academic programs by accurately classifying students into three performance levels. The model achieved relatively balanced precision, recall, and F1-scores across the classes, with particularly high accuracy for Class 1 (moderate performers) and respectable F1-scores of approximately 0.77 and 0.80 for Classes 0 and 2, respectively. This balanced performance highlights the model's capability to go beyond binary classification and effectively identify students who may either excel or require additional support. Visual evidence from the confusion matrix heatmap and classification report further supports the model's robustness in handling multi-class predictions, enhancing its value as a decision-support tool in the admissions process. Unlike earlier studies such Delianidi *et al.* (2021), which relied on temporal data to track academic progression, this study's focus on pre-admission data makes the predictive results particularly noteworthy, as forecasting academic performance prior to enrollment is inherently more difficult.

Despite these encouraging results, the relatively small dataset size of 480 student records presents a limitation in terms of external validity and generalizability. A limited sample may not fully represent the heterogeneity of student populations, academic structures, and institutional practices across Nigerian tertiary institutions. Consequently, the model's predictive performance may vary when applied to larger or institution-specific datasets, underscoring the need for future studies using broader and more diverse data sources.

Overall, this study effectively demonstrates that Artificial Neural Networks (ANNs) can serve as accurate and interpretable tools for predicting student academic performance prior to admission, particularly in contexts where traditional evaluation methods are limited. The model's performance not only aligns with but in some instances approaches that of more complex techniques such as Generative Adversarial Networks (GANs) and hybrid deep learning models, yet it does so with significantly lower computational demands and easier integration into existing educational infrastructures. The model's performance not only aligns with, but in some instances approaches, that of more complex techniques such as Generative Adversarial Networks (GANs) and hybrid deep learning models. However, it achieves this with significantly lower computational demands and easier integration into existing educational infrastructures.

This balance between predictive effectiveness and practical deployability positions ANN-based models as viable tools for data-driven admission decision-making in resource-constrained educational environments. In the Nigerian tertiary education context, ANN models are particularly appropriate due to their relatively low computational requirements, scalability, and ease of implementation using widely accessible platforms such as Python and Scikit-learn. Unlike more complex deep learning architectures, ANN models can be trained efficiently on modest hardware while still achieving reliable and competitive predictive performance.

7. Conclusion

This study demonstrates the feasibility and effectiveness of applying Artificial Neural Networks (ANNs) to predict student academic performance using pre-admission data within the Nigerian tertiary education context. The ANN model, developed using structured academic and behavioral features from the Kalboard 360 Learning Management System, achieved strong multi-class classification performance, confirming its capacity to model complex, non-linear relationships among predictors. The findings are consistent with prior studies (Al-azazi & Ghurah, 2023; Baashar *et al*., 2022; Dung *et al.*, 2023) that highlight the effectiveness of ANN-based approaches in leveraging multifactorial inputs such as academic history, attendance, and student engagement to predict academic outcomes.

Compared to traditional linear and rule-based admission methods, the proposed ANN model exhibited greater adaptability and predictive capability by accounting for interaction effects among multiple indicators. Although advanced machine learning architectures which include Generative Adversarial Networks, LSTM-based models, and ensemble techniques, have reported higher accuracy in certain contexts, their computational complexity often limits practical deployment. In contrast, this study shows that a relatively simple ANN trained on structured pre-admission data can achieve competitive performance while remaining suitable for resource-constrained educational environments.

The study contributes to educational data mining by providing an interpretable, scalable, and low-resource predictive model that supports multi-class classification. This enables institutions to identify high-potential students and anticipate those who may require early academic support, thereby improving admission decisions and resource allocation. However, the use of a small proxy dataset limits generalizability, suggesting the need for larger and more diverse datasets in future research. Overall, the study underscores the value of integrating machine learning into admission policies to promote data-driven, equitable, and context-sensitive decision-making in Nigerian tertiary education.

8. Further Study

Future research could enhance predictive accuracy by incorporating additional features, such as socio-economic status, psychological factors, and prior extracurricular involvement, to capture a broader range of influences on student performance. Integrating real-time data and online learning environments could further enable the development of more dynamic and adaptable models. Additionally, exploring hybrid approaches that combine ANNs with other artificial intelligence techniques such as genetic algorithms or support vector machines, may improve both predictive performance and robustness.

Future work should also address ethical considerations, including fairness, transparency, and potential biases in admission decisions, to ensure that predictive models support equitable and responsible educational practices.

References

Adeniyi, J. K., Adeniyi, A. E., Ogundokun, R. O., Gupta, H., & Misra, S. (2021). Prediction Of Students' Performance with Artificial Neural Network Using Demographic Traits. *Electrical Engineering: Recent Innovations in Computing (pp. 613–624)*. Springer Nature Singapore. OUCI

Baashar, Y., Alkawsi, G., Mustafa, A., Alkahtani, A. A., Alsariera, Y. A., Ali, A. Q., Hashim, W., & Tiong, S. K. (2022). Toward Predicting Student's Academic Performance Using Artificial Neural Networks (ANNs). *Applied Sciences, 12*(3), 1289. https://doi.org/10.3390/app12031289

Delianidi, M., Diamantaras, K., Chrysogonidis, G., & Nikiforidis, V. (2021). Student Performance Prediction Using Dynamic Neural Models. *arXiv preprint arXiv:2106.00524*. https://arxiv.org/abs/2106.00524

Dung, S. T., Thomas, G., & Oyerinde, Y. (2023). Predicting Students' Academic Performance Using Artificial Neural Networks. *International Journal of Computer Applications*, *185*(19), 1–7. https://doi.org/10.5120/ijca2023922889

EL Habti, F. E., Hiri, M., Chrayah, M., Bouzidi, A., & Aknin, N. (2025). Enhancing Student Performance Prediction in E-Learning Ecosystems Using Machine Learning Techniques. *International Journal of Information and Education Technology*, *15*(2), 301–311.

https://doi.org/10.18178/ijiet.2025.15.2.2243

Al-azazi, F. A., & Ghurah, M. (2023). ANN-LSTM: A Deep Learning Model for Early Student Performance Prediction in MOOC. *Heliyon*, *9*(8), e15382. https://doi.org/10.1016/j.heliyon.2023.e15382

Liu, J., & Yang, Y. (2025). A Student Performance Prediction Model Based on Multimodal Generative Adversarial Networks. *International Journal of Sensor Networks*, *43*(3), 186–198. https://doi.org/10.1504/IJSNET.2025.144630

Oladokun, V. O., Adebanjo, A. T., & Charles-Owaba, O. E. (2008). Predicting Students' Academic Performance Using Artificial Neural Network: A Case Study of An Engineering Course. *The Pacific Journal of Science and Technology*, *9*(1), 72–79. repository.ui.edu.ng

Olaniyan, O. M., Oloyede, A. O., Aremu, I. A., Babatunde, R. S., & Adeyemi, B. M. (2021). Predicting Student Academic Performance Using Artificial Neural Network. *LASU Journal of Research and Review in Science*, *8*(1), 1–7.

Wang, Y., Ding, A., Guan, K., Wu, S., & Du, Y. (2021). Graph-Based Ensemble Machine Learning for Student Performance Prediction. *arXiv preprint arXiv:2112.07893*. https://arxiv.org/abs/2112.07893