VOL. 11 NO. 9,
FEBRUARY, 2026
E-ISSN 3026-958X
P-ISSN 3027-1169

African Scholar Publications & Research International
www.africanscholarpub.com

Journal of Science Innovation & Technology Research (JSITR)

Students' Performance Prediction using Artificial Neural Network

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DOI: https://doi.org/10.70382/ajsitr.v11i9.083

Abstract

The increasing availability of educational data has created opportunities for applying advanced machine learning techniques to improve student outcomes. This study focuses on predicting students' academic performance using Artificial Neural Networks (ANN). The aim is to develop a predictive model that accurately estimates student performance based on academic, behavioural, and socio-demographic factors, such as attendance, IQ, study habits, and prior academic records. The data for the study contained both primary and secondary data to ensure data triangulation. The primary data collected through a questionnaire was obtained from 720 respondents from Adamawa State Polytechnic, Yola. Secondary data containing mainly students' cumulative grade point average (CGPA) was obtained from the students' academic record division of the school management information system (MIS) office. The structured dataset collected was pre-processed to ensure data quality, including normalization and handling of missing values. The ANN model was designed with input, hidden, and output layers, and trained using backpropagation to learn complex relationships within the data. The model's performance was evaluated using a confusion matrix. The prediction accuracy of 97.36% and the standard deviation of 0.52% was obtained. The results indicate that the ANN model achieved a high level of prediction accuracy, outperforming traditional statistical approaches in capturing non-linear patterns among variables. This study demonstrates that Artificial Neural Networks can serve as an effective tool for early identification of students at risk of poor academic performance. The findings provide valuable insights for educators and institutions seeking to implement data-driven strategies for improving

student success. Future work is recommended to enhance model transparency and incorporate hybrid approaches for improved predictive performance.

Keywords: Artificial Neural Networks, Machine Learning, Predictive Modelling, Student Performance Analysis, Educational Data Mining, Classification.

Introduction

Student academic performance is a key indicator of an institution's success (Ahmed, 2024). The goal of every academic institution is to provide quality teaching to its students, and while one of the necessary indicators of education is academic performance, this is one of the highest priorities for any study centre (Bithari et al., 2020). However, a growing trend of declining student performance is emerging, raising serious concerns for education systems (Gutiérrez-de-Rozas et al., 2022). Academic performance is influenced by multiple factors, including students' learning styles, teacher quality, family background, infrastructure, and peer effects (Briones et al., 2022). Improving academic performance is a major challenge for universities, especially in increasingly competitive environments where outcomes impact reputation and student retention (Ha et al., 2020).

Many students struggle with high failure and dropout rates, which pose significant challenges for educators and administrators. For ages, student performance has stood as a prime axis of education systems for improving teaching styles and learning outcomes. It is based on static evaluations and, hence, cannot give an extensive view of student progress by traditional methods of assessments. With advancements in machine learning and deep learning, new opportunities arise to model these complexities more effectively, enabling a deeper exploration of how variables such as gender, ethnicity, parental education, lunch status, and test preparation impact student test scores (Badal and Sungkur, 2023).

The motivation for this study comes as a result of the high rate of student withdrawal from Adamawa State Polytechnic due to poor academic performance. It is also sad that even spill over students that came to clear their carry-over courses end up on the withdrawal list. As a departmental exam officer seeing these scenarios motivated the researcher to carry out this research.

Predicting student performance enables early intervention to address learning gaps and supports diverse learning strategies (Teoh et al., 2022). This helps educators monitor and improve the efficiency of the learning process, where current technologies allow data to be analyzed in a didactic way (Nabil et al., 2022). Educational data mining (EDM) has emerged as a powerful approach for analyzing student data and predicting academic outcomes. Through the application of data mining techniques, statistical models, and machine learning algorithms, EDM enables institutions to identify at-risk students, optimize educational resources, and implement targeted interventions to support student success (Pecuchova and Drlik, 2024).

Machine learning one of the EDM algorithm is an effective strategy by having the ability to adapt to the user's needs. So, in the field of education, by extracting student data and assessing gaps in learning, you can identify areas where teachers are outnumbered and create solutions in real ways, such as practice tests in additions (Sandra et al., 2021). Machine learning is an artificial intelligence method used for the creation and classification of profiles, Thus, several machine learning algorithms have been used, including Logistic Regression, J48, Multilayer Perceptron, Naive Bayes, Support Vector Machine, Random Forest, etc., for predicting students' academic performance based on comparisons to obtain their accuracy and other metrics (Balaji et al., 2021). This study uses a dataset from Adamawa State Polytechnic, Yola Adamawa State Nigeria and applies machine learning techniques to improve model performance in predicting academic performance.

Related Works

This section is concerned with related work carried out by other researchers on students' academic prediction. Albreiki et al. (2021) systematically reviewed the literature on student performance prediction and hence endorsed that machine learning approaches, particularly with regard to Decision Trees, are the current flavour of education, and further went on to comment on the trend among students towards AI-based tools fostering personalised learning. El-Keiey et al. (2022), in their study, analysed the performance of students in relation to the time they spend on their activities, in which they used 3 machine learning algorithms: KNN, Decision Tree, and Random Forest. Taking into account a dataset of 500 students, the data was divided: 70% for training and 30% for testing, where a precision of 85% was obtained, as well as an F1 Score of 84% when using a Decision Tree. Ghorbani and Ghousi (2020), in their study, made a comparison of several resampling techniques (SMOTE-ENN, Random Over Sampler, SMOTE-Tomek, etc.), using 2 different data sets and using machine learning algorithms, including Random Forest, KNN, and XGBoost, among others, where the results show that XGBoost was the one that obtained high values of the metrics, these being accuracy and recall of 69.24%, precision of 64.85%, and an F1 score of 66%, taking into account 2 countries (Iran and Portugal) and unbalanced data. Asselman et al. (2023) obtained an accuracy of 78.75%, precision of 75.12%, recall of 78.75%, and F1-score of 73.48%. Ojajuni et al. (2021) employed Extreme Gradient Boosting (XGBoost), which is a machine learning algorithm, for higher accuracy prediction of students' academic performance over their traditional methods. The results further established that ensemble learning techniques would be competent in handling complex datasets from an education perspective.

Singh and Pal (2020) developed a model combining the Bagging and Boosting algorithms to predict student performance, using the following machine learning techniques: KNN, Naive Bayes, Decision Tree, and ExtraTREE, for which a dataset of 1000 instances and 22 attributes was used. where the results reported a recall of 81.55%, precision of 82.89%, and F1-score of 72.78% using Naive Bayes; however, Bagging achieved the best accuracy value = 91.76%.

The work of Leelaluk et al. (2024) is notable. The authors proposed an Attention-Based Artificial Neural Network (Attn-ANN) to identify at-risk students. They evaluated their model on a university dataset and reported promising results, achieving 89.5% accuracy, an F-score of 83.4%, and an AUC of 92.8%. However, their study was limited by the small and imbalanced dataset, which could affect the model's generalizability. Hussain et al. Nabil et al. (2021) presented a deep artificial neural network integrated with several resampling approaches, such as SMOTE, ROS, ADASYN, and SMOTE-ENN, to predict students' academic performance. The data obtained from a public university was used to evaluate the models. The model was compared with various ML methods, including DT, RF, gradient boosting (GB), LR, SVM, and KNN algorithms. The results revealed that DNN outperformed other algorithms, with an accuracy of 89%, an F1-score of 89%, and a sensitivity of 89%. Kala et al. (2024) proposed a hybrid method that combines particle swarm optimisation (PSO) and deep neural networks for predicting student academic performance. They used the widely known XAPI-academic dataset, which covers various courses. The performance of the method was compared with various machine learning algorithms, including LR, DT, SVM, ANN, RF, and KNN, as well as a standalone DNN. According to the author, the proposed model achieved a 63% accuracy rate. However, the proposed model's accuracy is lower but performs 6% better than the traditional algorithms.

Yunus et al. (2023) proposed a predictive framework that combines improved feature selection techniques with a BiLSTM model to predict students' academic performance. Their model achieved an accuracy of 90.16%, with precision, recall, and F-score values of 86.16%, 90%, and 90%, respectively. Song et al. (2024) proposed an ANN-BiLSTM approach that integrates artificial neural networks for feature extraction with BiLSTM for sequential learning for student academic performance prediction. Evaluated using the OULAD dataset, this model outperformed several baselines, including RNN, GRU, and ANN-LSTM, achieving an accuracy of 73%, a precision of 79%, a recall of 56%, and an F-score of 65%. Manigandan et al. (2024) developed a BiLSTM-CRF hybrid model to predict student success based on historical academic performance. The model achieved 90.6% accuracy, 92.7% precision, 89.7% recall, and 92.4% specificity. Rahman et al. (2025), then, pushed forward with reviews of potential uses of artificial intelligence, in which it is majorly machine learning predictive application within the performance of students. Their study had addressed different approaches regarding supervised learning methods, which included decision trees and linear models and were backed by an academic context under which maximisation of learning output would be attained.

Methods and Materials

This section presents the methodology employed in this study, detailing the key steps involved. It includes a description of the datasets, data preprocessing approach, the proposed method, experimental setup, baseline models, and performance metrics used to assess the model's effectiveness.

Research Framework

The research framework is represented in diagram 1 as shown below.

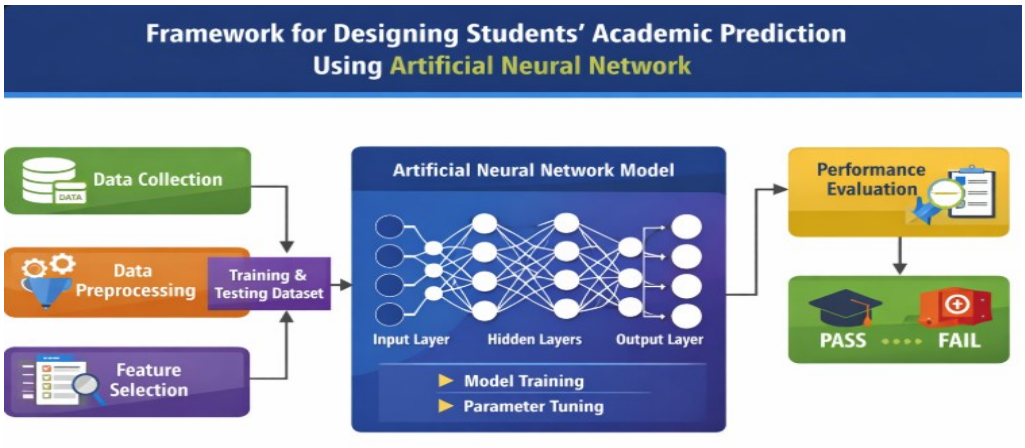


Figure 1: Represent the Framework of the Research Work

I. **Data Collection (Green Box)**
   - This is the first step where relevant student information is gathered.
   - Examples of data include demographics (age, gender), past grades, attendance records, and engagement metrics (e.g., participation in online learning platforms).
   - The collected data forms the raw input for the predictive model.

II. **Data Preprocessing (Orange Box)**
   - Preprocessing involves cleaning and preparing the raw data for analysis.
   - This may include handling missing values, normalizing numerical features, encoding categorical data, and removing outliers.
   - Proper preprocessing ensures the ANN model receives high-quality, consistent input.

III. **Feature Selection (Purple Box)**
   - Not all collected variables contribute equally to predicting academic performance.
   - Feature selection identifies the most relevant attributes to reduce complexity, improve model efficiency, and avoid overfitting.

IV. **Training & Testing Dataset (Purple Arrow)**
   - After preprocessing and feature selection, the dataset is split into training and testing subsets.
   - The training set is used to teach the ANN model patterns in the data, while the testing set evaluates the model's predictive accuracy on unseen data.

V. **Artificial Neural Network Model (Blue Box)**

- **Input Layer:** Receives the selected student data features.
- **Hidden Layers:** Perform complex computations to learn relationships between input variables and the target outcome. The diagram shows multiple hidden layers, indicating a deep learning approach.
- **Output Layer:** Produces the final prediction, such as whether a student will pass or fail, or their expected grade.
- **Model Training & Parameter Tuning:** The ANN adjusts its internal weights and biases iteratively to minimize prediction errors.

VI. **Performance Evaluation (Yellow Box)**

- After training, the model is evaluated for accuracy, precision, recall, or other relevant metrics to assess how well it predicts student outcomes.

VII. **Prediction Outcome (Green Box)**

- The final step shows the practical output: a classification of students' academic performance, typically as exceptional, High, low and poor performance.
- These predictions can be used by educators to identify students at risk and provide timely interventions

Dataset Description

The dataset employed in this study consists of 720 records, each containing information about a student's demographics, parental background, and educational experiences from the academic division in Adamawa State Polytechnic, Yola, Adamawa State, Nigeria.

Two sets of instruments were used in data collection, which included a structured questionnaire and documentation (historical data) that was collected from the school database through a request. These data constitute academic records and socioeconomic and behavioural features of the students. The study collected academic performance data from final-year students of each of the sampled institutions. This implies that the study made use of five (5) years (2021-2025) of students' academic records. This study obtained a total of 720 students' academic records with raw data of 43 columns. An appropriate data size is essential for obtaining a precise and reliable outcome of a study.

Table 1: Showing Variables Collected and Sources

Variable	Source(s)
Sex	Departments & Students
Pre-ter status	Students (questionnaire)
Parental Socio. Econ	Students (questionnaire)
Studying Style	Students (questionnaire)
Qua.Edu. Environment	Students (questionnaire)
HRs Study per Day	Students (questionnaire)
Personality traits	Students (questionnaire)
Festivity	Students (questionnaire)

Variable	Source(s)
Regularity to Class	Students (questionnaire)
Health status	Students (questionnaire)
IQ	Students (questionnaire)
CGPA	Departments
Class	Codified from CGPA

S/N	Variable	Description of the variable with property
1	Sex	Male (1), female (2)
2	Pre-ter sch st	Urban, suburban, or rural (U,S,R)
3	Parent socio-econ st	1 (high), 2 (moderate), 3 (low)
4	Studying style	Group (0), single (1), both (2)
5	Qual of Edu Env	From 1 (very low) to 5 (very high)
6	Hrs study per Day	1 (<3 hrs), 2 (3 to 6 hrs), 3 (7 to 9 hrs), 4 (>9 hrs)
7	Regularity to Class	1 (high) 2 (moderate) 3 (low)
8	Festivity	From 1 (very low) to 5 (very high)
9	Personality Traits	From 1 (very low) to 5 (very high)
10	Health	From 1 (very bad) to 5 (very good)
11	IQ	From 1 (very low) to 5 (very high)
12	CGP	From 1 (poor) to 4 (exceptional)

Data Preprocessing

To prepare the dataset for input into the deep learning models, several preprocessing steps were applied to ensure that the data is in a suitable format and scale. First, categorical variables, including gender. Raw data on students' academic performance records were collected from Adamawa State Polytechnic, Yola, in Adamawa State, Nigeria. A total of 720 academic records were from the institution. The initial raw data collected had 43 columns. This is shown in Table 3. The collected data includes additional variables that incorporate personality traits and socio-psychological factors of the student. This enables the study to achieve its objectives.

Table 3: Pre-processed Students records for academic performance Prediction

```
In [1]: import pandas as pd
        dataframe = pd.read_csv("PerformancePredictData.csv")
        #dataframe[dataframe.Class=='Poor']
        dataframe
```

Out[1]:

	Sex	Pre-ter_Status	Parent_socio_econ	Studying Style	Qua.Edu. Evironment	HRs Study per Day	personlity traits	Festivity	Regularity to Class	Health	I.Q	CGPA	Class
0	0	0	3	2	3	2	2	4	2	4	4	2.36	Poor
1	1	0	2	2	3	3	2	5	3	5	5	1.71	Poor
2	0	0	3	2	3	1	2	2	1	5	1	1.73	Poor
3	0	0	1	2	5	1	1	3	2	5	5	2.80	Low
4	0	1	3	2	3	1	2	3	2	3	3	2.66	Low
5	1	0	3	2	3	3	1	5	1	5	4	2.19	Poor
6	0	0	1	0	1	2	1	1	2	5	3	2.55	Low
7	1	0	2	1	5	2	2	1	3	4	5	3.22	High
8	1	1	2	1	2	2	2	3	3	5	5	4.19	High

Model Architecture

After data preparation, a design choice about the model architecture needs to be made. The research used a supervised learning method, that is, the architecture that was chosen for the research was a Multilayer Perceptron and Feedforward Neural Network (FFN) with fully connected hidden layers and the architecture of the model will be determined through experiments on the data set obtained as shown in Figure 2

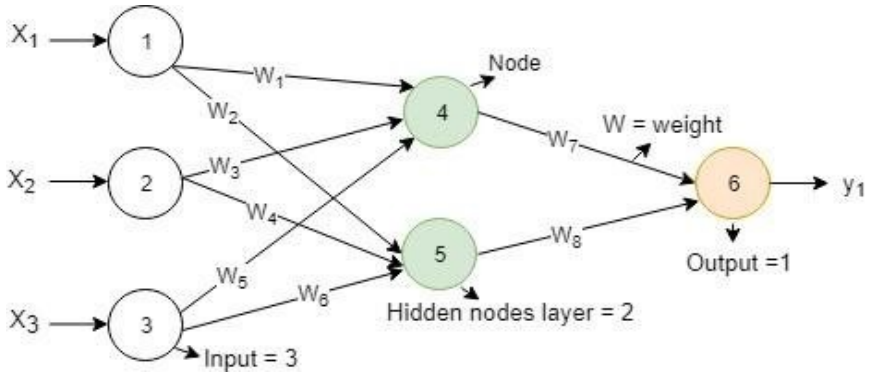


Figure 2: The Architecture of Multilayer Feed-Forward Neural Network

Procedure for Artificial Neural Network Design

The procedure for building a neural network which is a subset of the machine learning method comprises the following steps: Features selection, building the database (data cleaning and pre-processing), training and verification of the database using ANN (network type and architecture, training algorithm, verification and robustness of ANN–based approaches) and testing in predicting students' academic performance.

Model Development

Jupyter Notebook, a Python Anaconda development platform for Artificial Neural Network was used in modelling this students' academic performance prediction.

Generally, the artificial neural network architecture is usually in layers and each layer are made up of neurons. The pictorial representation of the final model of the neural network is as shown below in Figure .3 This also represents the neural network model for students' academic performance.

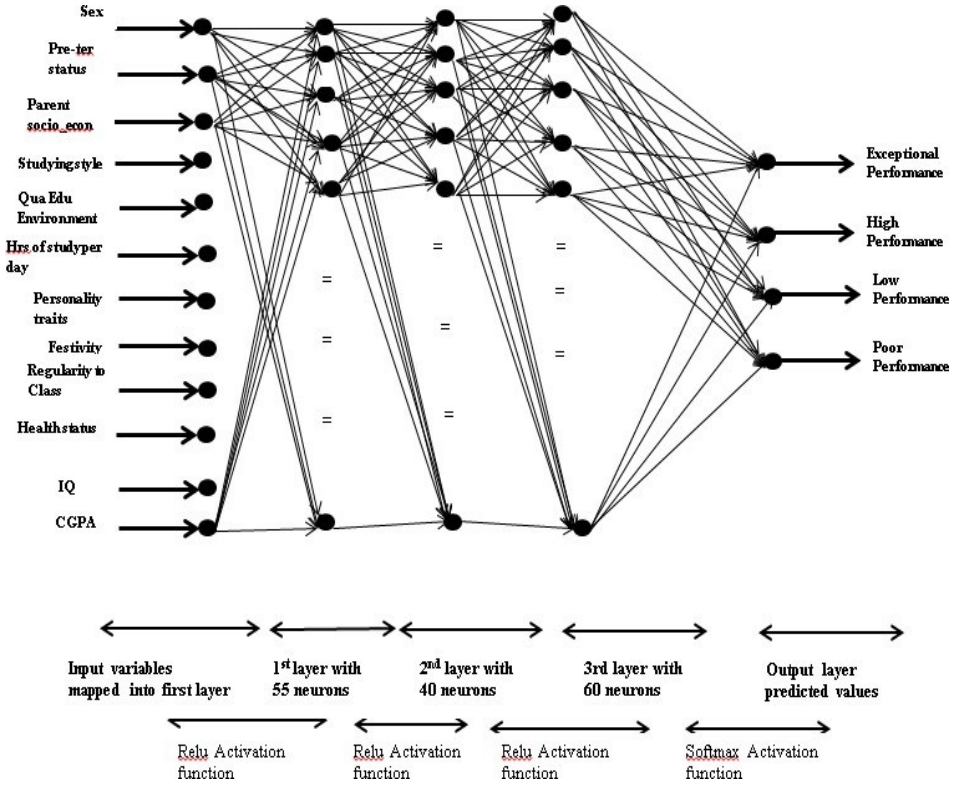


Figure 3: Artificial Neural Network Architecture for Students' Academic Performance

The model accuracy is computed using the 4x4 matrix also shown below.

	precision	recall	f1-score	support
class 0(Exceptional)	0.00	0.00	0.00	6
class 1(High)	0.84	0.98	0.90	42
class 2(Low)	0.99	0.96	0.97	78
class 3(Poor)	0.99	1.00	0.99	90
avg / total	0.93	0.95	0.94	216

```
[[ 0  6  0  0]
 [ 0 41  1  0]
 [ 0  2 75  1]
 [ 0  0  0 90]]
```

The model evaluation is further represented in Table 4.

Algorithm	Accuracy	Precision	Recall	F1Score
Artificial Neural Network	97.36%	0.99	1.00	0.99

The behaviour of the training and testing dataset partition as well as the model accuracy and loss values as shown below

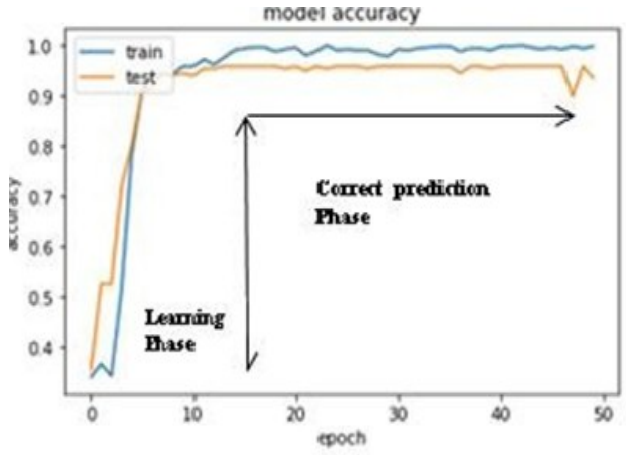


Figure 4: Model Accuracy Graph

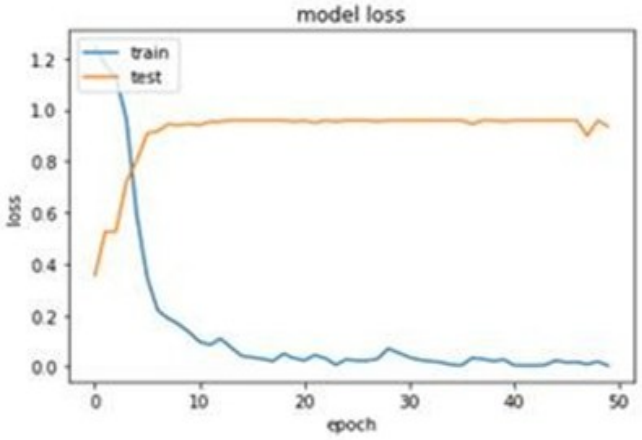


Figure 5: Model Loss Graph

From the graphical representations above in Figure 4, the model started making correct predictions after epoch 10. The learning phase was smaller compared to the correct prediction phase. This implies that the model learns faster to be able to make correct predictions on the dataset. The two-coloured graphs showed the performance of the dataset's partitions for the training and testing datasets. The two dataset partitions performed well and had almost the

same patterns in the graph. After 10 epochs or iterations, as seen in the graph, both dataset partitions started performing at more than 90% accuracy.

Figure 5 shows the model loss values in graphical form. The loss value of the model for the training datasets performs better and is consistent with the model learning behaviour, as expected for a good model. The testing dataset slants downward from the upper left at a value of about 1.2 model loss value to the downward right at almost zero loss value, showing the reduction of incorrect predictions as the model encounters more data. However, the model loss for the test dataset started from 0.4 and plateaued at about 0.8, denoting that the test dataset, despite having a prediction accuracy of 97%, did not learn as fast as the training dataset. The result of the training and model loss agrees with the backpropagation learning algorithm (BPP), which was used to train the datasets by default in the artificial neural network.

From the literature review, it is important to note that the present study shows significant improvement with a data set of 720 respondents compared to the work of other scholars. The model accuracy of 97.3% obtained in this study shows significant improvement and better results than the study conducted by Heyul et at. (2023) that predicted students' success rate using an artificial neural network. The results of their study obtained a model accuracy of 93.8% without considering personal data. Leekaka et al. (2024) implemented an artificial neural network to predict the academic performance of senior students. The study obtained an accuracy of 89.5%.

A study carried out by Aseelman et al. (2023) implemented several models to predict students' academic performance. Random forest, artificial neural network, SVM, logistic regression, Naive Bayes and KNN were used for the model. The results of the study show that the Artificial Neural Network provided the best results with an accuracy of 78.75%. The study fails to use students' personal data. The study only used students' midterm and final exam grades, career path and academic department as information. The 97.36% obtained in this research indicated an improvement compared to the work of Asselman et al. (2023).

Discussion

The findings of this study demonstrate that Artificial Neural Networks (ANNs) are effective tools for predicting students' academic performance based on multiple input variables. The model was able to have a prediction accuracy of 97.36%.

One of the key observations from this study is that variables such as attendance, studying style, health status, and educational environment. Personality traits, IQ, and previous academic records had a strong influence on prediction accuracy.

The performance evaluation of the model showed satisfactory accuracy, indicating that ANN can serve as a reliable predictive tool in educational settings. Compared to simpler models, the neural network demonstrated improved generalisation ability, especially when handling large and complex datasets.

Another limitation is the issue of interpretability. Unlike linear models, ANNs are often described as "black-box" systems, making it difficult to clearly explain how specific inputs

influence the final prediction. This lack of transparency may reduce trust among educators and stakeholders who require clear justification for decision-making processes.

From a practical perspective, the implementation of ANN-based prediction systems in educational institutions could provide significant benefits. Early identification of at-risk students would enable timely interventions, such as academic support programs or counselling, thereby improving overall student outcomes. Furthermore, such systems can assist administrators in making data-driven decisions regarding curriculum design and resource allocation.

Conclusion

Student success plays a vital role in educational institutions, as it is often used as a metric for the institution's performance. Early prediction of students' performance, along with preventive measures, can drastically improve their success and learning outcomes. To improve the performance of the predictive model, that is, the accuracy of prediction, an Artificial Neural Method was used for this study. The prediction accuracy was 97.36%, and a standard deviation of 0.52%, the performance of the model was evaluated. This study concludes that while artificial neural has high predictive capabilities in students' academic success prediction based on the dataset used, factors such as intelligence quotient, regularity to class, hours of study by the student, and health status of the student should be considered as major determinants in student academic success modelling.

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