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Development of an artificial intelligence model for predicting students' performance in an engineering department of a Nigerian university.

Kelechi Favour Francis, Victor Oluwasina Oladokun and Adekunle Kolawole*
Department of Industrial and Production Engineering, University of Ibadan, Nigeria
*Corresponding Author's E-mail: kolawole_adekunle@yahoo.co.uk

Abstract

Students seeking admission into Nigerian tertiary institutions are required to possess some requirements. However, the efficacy of these requirements in predicting students' performance has been a subject of discussion. This study examines the effectiveness of current admission requirements in predicting academic performance among engineering students in a Nigerian university. Using data from 340 students admitted between 1996 and 2016, variables such as age, gender, UTME scores, O'Level results, and final CGPA were analysed. With Microsoft Excel and Python, Data pre-processing was carried out. Multiple machine learning models that include Support Vector Machine, Decision Tree, Random Forest, Naïve Bayes, and K-Nearest Neighbours were developed using 311 training samples. To enhance classification accuracy, a One-Vs-One binary classifier based on Decision Tree networks was implemented for three performance categories. Pearson correlation analysis indicated a very weak relationship (0.0075) between UTME scores and CGPA, signifying that UTME alone is a poor predictor of academic performance. But, WAEC scores (0.32), year of birth (0.31), and year of O'Level examination (0.29) showed relatively stronger correlations with CGPA. The exploratory analysis confirmed that the current admission criteria may be inadequate, and a combination of other factors are likely to be better predictors of students' performance. The resulting ML model which explored broader variables offers a more effective decision support tool for processing undergraduate admissions in Nigerian universities.

Keywords: Classification models, Students' performance prediction, undergraduate admission, Machine learning, Binary classifier

1. Introduction

The quality of graduates from Nigerian tertiary institutions has been a subject of concern in recent times. Several factors have been highlighted as the causes of the poor quality of undergraduates students in Nigeria among which is the quality of candidates selected for admission (Ibanga 2015; Jonathan 2018; Nwosu and John 2017; Pitan, 2016). This causal factor follows general industrial engineering principles, given that the quality of input fed into a system has a major influence on the quality of the output that would emanate from the system (Salam 2015).

Despite the number of concerns regarding the mode of selection for undergraduate admissions in Nigeria, the same methods are still being used. Some authors have examined students' performance in the examination used for undergraduate admissions and their grades while in the University (Marycynthia et al., 2025 and Olaniyan et al., 2022). Some were found to have a negative correlation, attesting to the hypothesis that some of those examinations are not good determinants of students' ability. Many methods of selecting candidates for undergraduate admission have been explored over the years, but the responsible boards and councils in the country appear not to consider as necessary the fourth industrial revolution technological tools in the selection process.

This study explores the efficacy of predicting students' academic performance using artificial intelligence (machine learning and deep learning models) and the possibility of using the best-performing models as a selection tool for applicants to undergraduate programmes in Nigerian universities. The variables used in training the models are of a wider variety than those currently used in the admissions process, considering that those other variables play a role in determining a student's performance. Data of students obtained from an engineering Department of a Federal University in South Western Nigeria, were used in training and testing the models with Python programming language. The models were thereafter vetted using various model performance metrics so as to know the best model for the problem.

There is ample research covering the usage of machine and deep learning algorithms to predict students' performance. For example Xiao (2025) utilised combination of Multi-Layer Perceptron (MLP), Long Short-Term Memory (LSTM), and Transformer models to predict student academic performance. The study was able to ascertain the growing importance of deep learning methods in educational mining. Also, Turkmenbayev et al., (2025) scrutinized some studies that involved undergraduate engineering students and discovered the strength of artificial intelligence (AI), machine learning (ML) and deep learning (DL) methods in enhancing student performance in university engineering education. Furthermore, Gharkan et al., (2025) stressed the application of key techniques analytics and machine learning to examine historical data and accurately forecast future performance of student. These authors buttress the importance AI related methods in addressing issues that have to do with predicting students' performance. This research is however distinguished from others by its application in the Nigerian education system. While several studies have applied machine learning and deep learning models to predict students' academic performance globally, the novelty of this study lies in its dual contribution to both the field of educational data mining and the Nigerian university admissions system. Unlike existing works such as (Xiao (2025); Aldowah et al., (2019); Almasri et al., (2020); Turabieh et al., (2021) that appear to focus more on in-programme performance prediction, this study targets the pre-admission stage, utilising admission requirement data to predict a candidate's eventual class of degree on graduation. It also considers the problem of the admissions system from an industrial engineering point of view by taking into consideration that the university is a system that needs to have its input assiduously selected to avoid wastage of resources and ensure the best quality of output.

The university education can be regarded as a system that has its inputs, processors, outputs and feedback mechanisms. As with any service or manufacturing system, the goal is to produce the best quality of output given the available input and resources. The inputs of the university system are the students granted admission into the university. The processors are the academic staff and other supporting staffs who employ various teaching methods to impart knowledge and skill. The feedback and quality control mechanisms are the tests and examinations administered to the students to ascertain their level of reception and understanding of the concepts being taught. Finally, the outputs are the graduates who are churned out from the system at the end of every academic year.
It can be said that one factor that can affect the quality of outputs generated from a system is the quality of input allowed into the system from the start of the process. While the quality of graduates can be attributed to several other factors, one element that can be acted upon is ensuring that only the students with the highest potential for excellence are granted admission (Ibanga 2015 and Okebukola 2015)

In Nigeria, the predictive power of the examinations currently used as determinants for admission has been interrogated, considering that many students who perform brilliantly in those examinations seem not to sustain that excellent performance till the end of their undergraduate studies (Okebukola 2015. Further studies by Owan (2017) using correlation analysis show a weak correlation between some admission-qualifying examinations and students' final year performance. What then could probably be the best method for selecting candidates to be granted admission into Nigerian higher institutions? As more individuals pass through the system, a huge amount of data is generated. Aldowah et al., (2019) and Almasri et al., (2020) stated that the large volume of data being produced by the university system is relevant to solving the problems encountered in the educational sector. With the advent of big data and with various options of data processing technologies available at this time, there are opportunities to mine crucial information from available data (Adekitan and Noma-Osaghae (2019); Jalota and Rashmi (2019).

The ability to predict students' performance is now possible, given past data and relevant data analysis tools and models. If the models used for these predictions are computed to attain a high level of accuracy, they would be useful in improving selection methods for undergraduates seeking admission and valuable in identifying drawbacks in the admissions system (Jalota and Rashmi (2019). Hence, the objective of this study is to provide an artificial intelligence model that might better predict the class of degree that candidates seeking admissions into first year in an engineering department of a Nigerian university may graduate with.

This research covers the possibility of the application of artificial intelligence to Unified Tertiary Matriculation Examination (UTME) undergraduate admissions in an engineering department of a university in Nigeria. A review of existing literature reveals that while the application of educational data mining for predicting students' performance is well established generally, its deployment within the Nigerian university admissions context have not been fully explored. Most documented studies focus on institutions in Europe, Asia, and North America, with very limited adaptation to the peculiarities of the Nigerian tertiary education system, including its unique admission structure involving UTME, PUTME, and O'Level administered by JAMB, Universities and WAEC respectively. Hence the need for this study. An innovative aspect of this work lies in the implementation of a One-Vs-One binary classifier built on Decision Tree networks, which apparently demonstrated superior accuracy over conventional models. It can be deployed as an accessible decision support tool for admissions process which offers a replicable framework that can be extended to other departments and institutions across Nigeria. It explores different machine learning and deep learning models and how they can be used to forecast students' class of degree when programme is completed. It takes features such as West African Examination Council (WAEC) grades, UTME scores, age at application for admission, sex, number of years between completing secondary school and gaining admission, type of secondary school, and zone of secondary school attended, among others as input features for model training. The outputs (the class of degree) from the model are classified into three. First Class and Second Class upper as Good while Second Class lower is Average and third class together with Pass as Poor.

2.0 Methodology

The data used for model training and testing were collected from an Engineering Department in a Federal government-owned University in South Western Nigeria from 1996 to 2016. The subject matter of the study are the graduates from the above-mentioned graduating classes. Graduates' data were selected for this study as the method of model training used was supervised learning. Supervised learning requires output data to be available, which in this case, are the final degree classes obtained by the graduates upon completion of their programme. Python programming language was used for analysis on Jupyter Notebook, the Integrated Development Environment (IDE) used for code writing, editing and execution. K-Nearest Neighbour, Decision Tree, Naïve Bayes, Random Forest and Support Vector Machines are the models explored for prediction in this work. The study is focused on 100-level admissions through the UTME and does not extend to Direct Entry (DE) admissions due to data sufficiency constraints. Also, 100-level UTME students take up to about 90% of undergraduate admissions, justifying the focus on this set of students' admission. Following literature survey, it could be deduced that the concept of machine and deep learning are widely applied to predict students' performance and improve student learning (Adekitan and Noma-Osaghae 2019; Oladokun *et al.*, 2008; Ouyang, *et al.*, 2023; Shrestha and Pokharel 2021; Turabieh et al., 2021; Turkmenbayev et al., 2025)

2.1 Data Collection

A total of 326 entries were collected for training and testing, but were reduced to 311 after cleaning. An extra 14 samples were collected for cross-validation of the model. The data from the students' files were manually retrieved and entered into Microsoft Excel spreadsheets. The data include information on admission requirements of students as well as their final CGPA. The final CGPA was used as the bases for determining their class of degree, as shown in Table 1. This classification is widely applied in grouping of results to class of degree- First class and Second class upper as "good or excellent", Second class lower as "average" and Third class and Pass as "poor" (Oladokun *et al.*, 2008). Input Data collected can be seen in Table 2. These input data were selected based on the consideration that they may directly or indirectly influence a student's performance (Oladokun *et al.*, 2008). Output data includes each student's class of degree, based on his or her final CGPA upon graduation. Both the input and output data were sourced from the department's archives.

Table 1: Classification based on final CGPA and Class of degree.

S/N	Output	Class of Degree	CGPA
1.	Good	First Class	6.0 – 7.0
		Second Class Upper	4.6 – 5.9
2.	Average	Second Class Lower	2.4 – 4.5
3.	Poor	Third Class	1.8 – 2.3
		Pass	1.0 – 1.7

Source: Oladokun, *et.al*. (2008)

Data size for the development of the model was determined using the "10 rule of thumb", as seen in Collins et al., [2021]. The rule of thumb states that "the size of the dataset must be greater than or equal to ten times the number of variables in the data". There are 23 variables, which implies that at least 230 data set are required. In this study, there are 311 data set satisfying the condition of Collins et al., (2021).

2.2 Data Cleaning and Pre-Processing (Feature Engineering)

Python 3.10 was used as the programming language on the Jupyter Notebooks IDE. Microsoft Excel 2016 was explored to perform the first phase of the pre-processing which included data cleaning and two transformation types: one-hot and ordinal encoding. Power BI was used in the visualization stage for extracting insights from the data. Data transformation methods were applied to each of the variables as shown in Table 2. These transformations were applied at the second stage of pre-processing using Python. Other libraries used at the pre-processing stage include; Pandas, MatPlotLib and Seaborn. The feature selection method employed, was determined by the data type of the input variable. However, during pre-processing, all input variables were transformed into numerical type data to allow for an efficient learning and model training process. Table 2 shows the transformation method applied to each of the data set, making them numerical data and enabling for numerical input-numerical output feature selection method. For all input, Pearson coefficient was employed.

Table 2: Transformation and feature selection method applied to each input variable.

S/N	Input Variable	Data Type	Values	Transformation	Name in Model
1.	Age	Numerical	Positive Integers $x \geq 16$	Normalization	AdAge
2.	Sex	Categorical	Male Female	One-hot Encoding	Sex
3.	UTME Score	Numerical	Positive Integers $180 \leq x \leq 400$	Standardisation	UTME
4.	O'Level Result For English, Chemistry, Mathematics and Physics	Categorical	Grades A1-F9 For four compulsory science subjects	Ordinal Encoding	WAEC_ENGLISH WAEC_MATHS WAEC_CHEM WAEC_PHY
5.	Knowledge of Technical Drawing	Boolean	Yes or No	Binary Logic	TD
6.	Knowledge of Technical Drawing	Boolean	Yes or No	Binary Logic	WAEC_F/MATHS
7.	Combination of results to meet O'Level Credit Requirement	Boolean	Yes or No	Binary Logic	COMBINE
8.	Exam Year	Numerical	Positive Integers $x \geq 2016$	Ordinal Encoding	ExamYear
9.	Zone of Secondary School Attended	Categorical	NW, NE, NC, SW, SE, SS	One-hot Encoding	ZoneSecSch
10.	Type of Secondary School Attended	Categorical	Private Public	One-hot Encoding	TypeSecSch
11.	Final CGPA group (Target variable)	Categorical	Good Average Poor	Ordinal Encoding	CGPA

Synthetic Minority Oversampling Technique (SMOTE) resampling technique was applied to inhibit the effects of the imbalance observed in the data.

2.3 Model Training

To select the models that are best fit for the data, it was based on HuggingFace's AutoTrain as recommended by Rothman (2024) and Thakur (2024). The models suggested by AutoTrain were further analysed and modified, and the one with the best performance was selected for the work. About 81% of the data was used for model training. The models trained include the following: Support Vector Machine (SVM), Decision Trees, Random Forest, Naïve Bayes, K-Nearest Neighbours (KNN). Further analysis of the results from the AutoTrain showed that a One-Vs-One binary classifier using decision trees had the best potential for high accuracy. Three binary classifiers were trained to determine whether or not an entry belonged to any of the three classes- 'GOOD', 'AVERAGE' or 'POOR', their results are shown in Table 3. The binary classifiers made use of Decision Trees as the base model for classification.

Table 3: Binary classifiers, their respective model names and the predicted class/group.

Classifier	Model	Class/Group
Binary classifier #1	Model_0	GOOD
Binary classifier #2	Model_1	AVERAGE
Binary classifier #3	Model_2	POOR

2.4 Model Evaluation

Model evaluation analyses the model's performance with the testing data. Approximately 14% of the data was used for testing, while about 5% was used for cross-validation. The following evaluation metric Eq. (1) was employed on the models;

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

From equation (1); TP, TN, FP and FN denote True Positives, True Negatives, False Positives and False Negatives respectively.

2.5 Model Deployment

When selecting a deployment tool for a machine learning project, key considerations include the tool's user interface flexibility, accessibility for end users, and cost of hosting. Streamlit was used in this study because it allows rapid development and deployment of interactive web applications directly from Python scripts, without requiring extensive web development knowledge. Other tools that can be used for model deployment include Gradio and Dash. These platforms can be used to host the model and enable ease of use for end users.

3.0 Results and Discussions

The results obtained are summarised and discussed in this section.

3.1 Results and Insights from Exploratory Data Analysis

The data collected showed a heavy dominance of male students over female students as shown in Figure 1. This is generally expected as data were obtained from an engineering department that is usually male-dominated in Nigerian Universities. This observation appears to be in agreement with the study of Ndewu (2022). Ndewu (2022) discovered that enrolment of female students for Engineering and Mathematics courses at Nigerian tertiary institutions are at a lower rate compared to their male counterpart demonstrating a gender gap despite the significance of these courses to economic and societal growth. More awareness and orientation are needed to encourage female students to get interested in engineering and science based programmes.

Another occurrence of dominance can be seen in Figure 2, where students with group classification 'POOR' were very low.

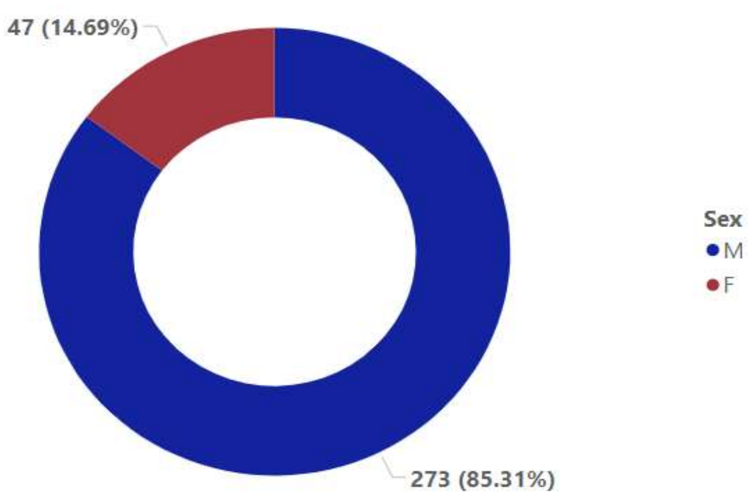

Figure 1: Percentage frequency of male versus female students.

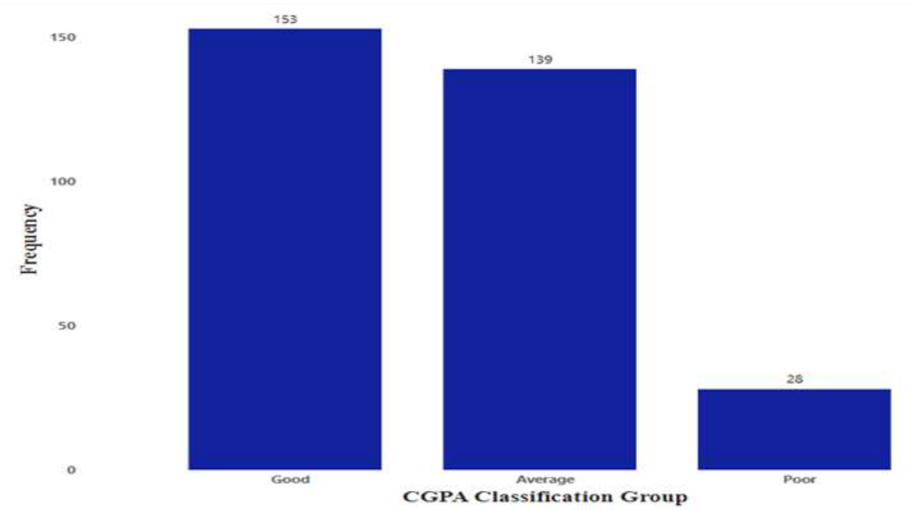

Figure 2: Frequency distribution of CGPA classification groups; 'GOOD', 'AVERAGE', 'POOR'.

The implication of this underrepresentation of some groups led to the severe imbalance of the data which if left untreated, could affect the performance of the model. Imbalance affects the model such that it does not properly learn to predict scenarios with the underrepresented group, causing it to falsely classify entries from such groups during testing and cross-validation. The trend of students' average age at admission over the years was also investigated and the result indicated in Figure 3. It can be deduced that the students' being admitted into the department are relatively younger than those admitted in the earlier years of the department.

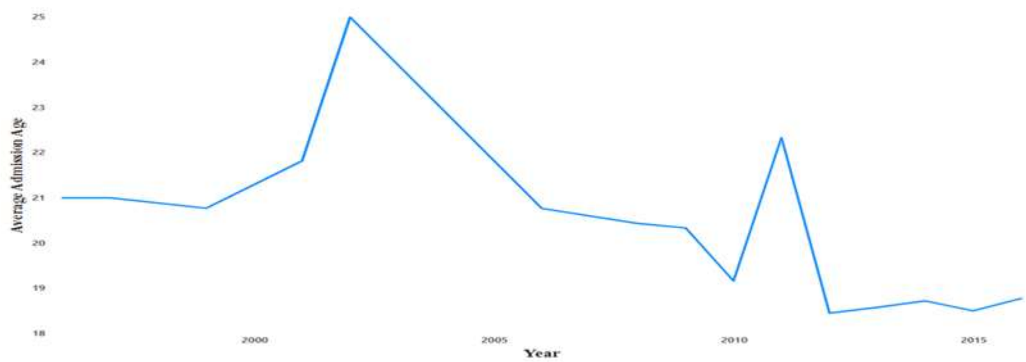

Figure 3: Trend of average admission age from 1996 till 2016.

Figure 4 shows the result of the investigation of the trend in students' performance as measured by their CGPA. It shows a climb in the average performance of students over the years. In Figure 5, the trend of average final CGPA per year was superimposed on the average age at admission and there exists an inverse relationship as seen in the figure. While CGPA is on an upward trend, age at admission shows a downward trend. This observation corresponds with the relatively strong negative correlation observed between final CGPA and admission age in Table 4

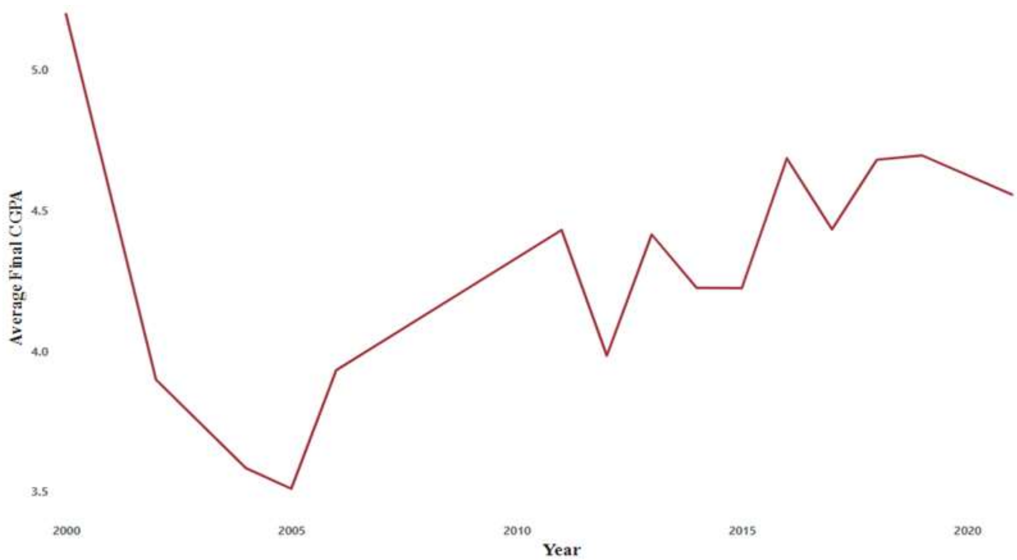

Figure 4: Trend of final CGPA from 2000 till 2021.

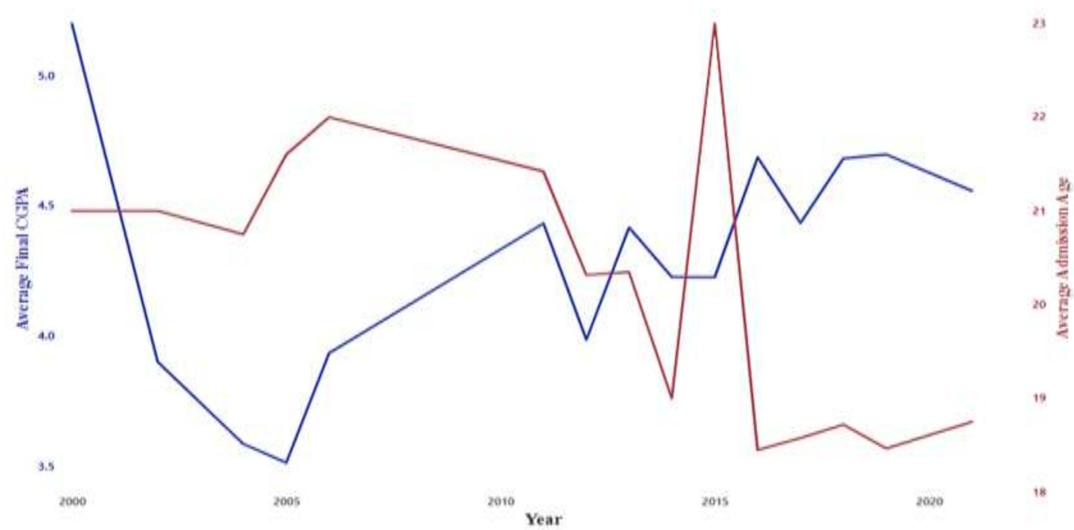

Figure 5: Superimposed trends of final CGPA and admission age to show opposite relationship.

The efficacy of predicting students' performance through UTME in the university was also investigated with the data. The result as shown in Figure 6 reveals little to no correlation and this can be confirmed by the correlation coefficient of UTME and final CGPA in Table 4. This outcome may have justified the conduct of post-UTME screening by many Universities in Nigeria and one of the reasons to widening admission criteria beyond UTME. The works of Olaniyan et al., (2022) and Marycynthia et al., (2025) have also substantiated justification not to rely on UTME alone for the purpose of admission in Nigerian Universities.

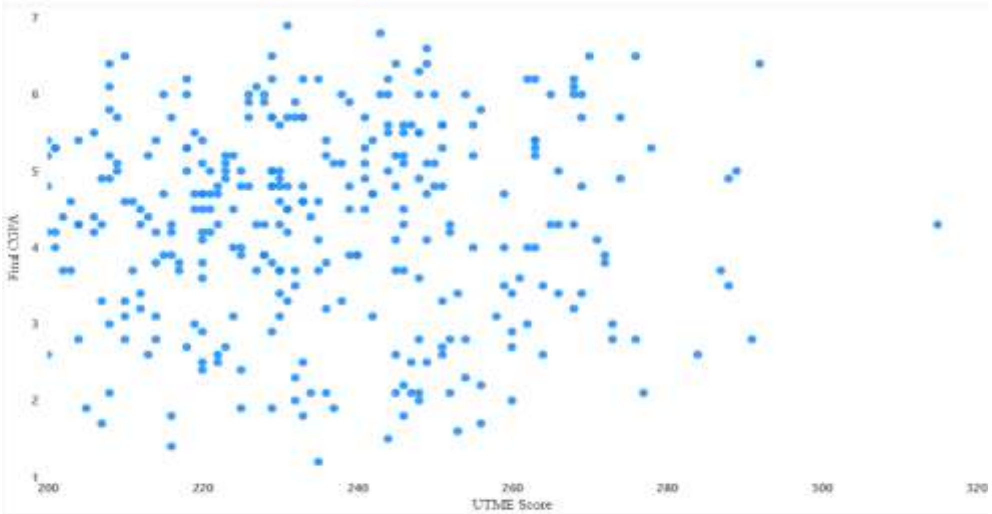

Figure 6: Scatter plot showing low correlation between final CGPA and UTME score

3.2 Results from Pre-processing of Data

Data cleaning was conducted to prepare the data for modelling. The reduction of the entries from 326 to 311 showed a relatively high level of data completeness, given that only about 4.6% of the data was lost after cleaning. This metric also shows that the data can be trusted to correctly model the problem for a real-life application.

Table 4 shows the Pearson correlation coefficient for all the variables. This step aided the feature selection process to indicate which variables are the most and least correlated with students' CGPA. As seen in the Table, WAEC_SCORE, an aggregated score of all four compulsory O'Level subjects, demonstrates the highest correlation with CGPA, with a 32% correlation. Interestingly, UTME score shows the least correlation with 0.75% correlation; this low correlation can also be seen in the scatter plot in Figure 6. This corroborates previous studies of Afu and Ukofia (2017) as well as Kennedy and Ebuwa (2020), where the efficacy of the UTME examination as a basis for predicting students' potential was found to be low. Other variables which have significant correlation to the final CGPA include year of birth (YYYY), O'Level examination year (ExamYear) and admission year (AdYear) with 31%, 29% and 25% correlation respectively. This shows a better/higher average CGPA performance in more recent years. In Figure 4, the trend of CGPA over the years is indicated and the trend line corroborates the positive correlation between CGPA and the year of admission (and by extension, graduation year).

The relatively strong positive correlation of CGPA with year of birth can either be interpreted as better performance for younger students or as a strengthened performance of students in recent years, as shown in Figure 5. Negative correlation of admission age (AdAge) with CGPA of 27.8% emphasises that younger students appear to be performing better than older students. It also shows the potential of age as a performance predictor and possibly proving that the recent advocate or policy of raising admission age may probably be counterproductive.

Table 4: Input variables and their respective correlation coefficient to CGPA.

S/N	Input Variable	Correlation Coefficient
1.	YYYY	0.310761
2.	AdYear	0.254942
3.	UTME	0.007548
4.	WAEC_ENGLISH	0.174502
5.	WAEC_F/MATHS	0.188547
6.	WAEC_MATHS	0.201692
7.	WAEC_CHEM	0.222681
8.	WAEC_PHY	0.291023
9.	TD	0.136138
10.	COMBINE	-0.193048
11.	ExamYear	0.293088
12.	ZoneSecSch	-0.012288
13.	TypeSecSch	-0.069086
14.	AdAge	-0.277823
15.	WAEC_SCORE	0.320528
16.	Score	0.268303
17.	Final CGPA	1.000000

3.3 Results from Model Training and Evaluation

Following the automatic training of models using an online AI tool, Table 5 shows the models which had the best potential for success based on their accuracies.

Table 5: Models trained on the students' record dataset and their respective performance.

Model	**Results**
SVM	55.3%
Decision Tree	74.5%
Random Forest	68.1%
Naïve Bayes	55.3%
KNN	57.4%

From Table 5, the Decision Tree model was the most promising and it was further optimised for accuracy using the One-Vs-One classifier method. The three binary classifiers had accuracies of 93.6%, 76.6%, 87.2%. The accuracy of the One-Vs-One classifier, using decision trees as a whole is 80.9%.

4.0 Conclusion and Recommendation

This study considered exploring an artificial intelligence (AI) model to accurately predict the graduating class of degree of candidates seeking admissions into an engineering department of a Nigerian university. Data were obtained using a manual data entry method and then cleaned, pre-processed and trained using Microsoft Excel 2016 and the Pandas library with Python programming language. Some AI models - SVM, Decision Tree, Random Forest and Naïve Bayes, were trained before One-Vs-One classifier using decision trees was selected. The final accuracy of this model was 80.9%. The results indicated that UTME result alone has a weak relationship to final CGPA of students considered, indicating that combination of other factors would be better predictors of students' performance.

This study would be beneficial to the undergraduate admissions system in Nigerian universities, providing an alternative where artificial intelligence can be used to improve the existing process. The model can further be trained with data from other departments and schools across the country to achieve higher accuracy. Other relevant variables like Post UTME data, which was not used in the development of this model, can also be used to further explore its performance. It may also be beneficial to expand the usage of the model by making use of data from Direct Entry (DE) candidates. This work provides an alternative for the admission grading system that relies only on O'Level results and UTME scores by exploring more potential predictors of students' performance using artificial intelligence models.

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