IJNRD.ORG ISSN : 2456-4184
INTERNATIONAL JOURNAL OF NOVEL RESEARCH AND DEVELOPMENT (IJNRD) | IJNRD.ORG
An International Open Access, Peer-reviewed, Refereed Journal

An Artificial Neural Network Model for Predicting Distance Learning Students Performance in Nigeria

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ABSTRACT

The impact of education can never be underrated in every developed country. People acquire knowledge through education by different means, either by distance learning or online learning, or traditional conventional system. Distance learning education in Nigeria is primarily aimed for people to learn at their convenience outside the confines of the four walls of the traditional conventional system of education. The accurate prediction of distance learning student academic performance is of importance to institutions as it provides valuable information for decision making in the admission process and enhances educational services. Machine learning has been promising solution in prediction, therefore, this research has developed predictive model for predicting the performance of distance learning student, by the use of machine learning using Artificial Neural Network model. The data used in the developed system took into consideration factors that may affect distance learning student academic performance such as the students in their secondary school, cramming ability, assimilation rate, recall ability, financial strength etc. The data were pre-processed and trained with the Artificial Neural Network using gradient decent for backward propagation. The developed model was tested and evaluated using standard metrics and at the end, the result of the evaluation shows better performance in computational time, Mean Square Error, Root Mean Square Error and Correlation Coefficient.

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General Terms

Machine learning, Artificial Neural Network, Distance Learning.

Keywords

Machine learning, Artificial Neural Network, Distance Learning, computational time, Mean Square Error, Root Mean Square Error and Correlation Coefficient

1. INTRODUCTION

According to the National Population Commission of Nigeria, Nigeria reached a population of 167 million in 2011, occupying a landmass of about 923,768 square kilometers and with over 274 ethnic groups making up the federation. The social and economic dimensions of providing education for the population, within the context of prevailing national circumstances of dwindling financial and other resources in the face of developments needs are heavy.

Distance Learning is a system of education characterized by physical separation between the teacher and the learner in which instruction is deliver through a variety of media including print and other Information and Communication Technologies to learner who may either have missed the opportunity earlier in life or have been denied the face-to-face formal education due to socio-economic, career, family and other circumstances [1].

The new phenomenon in promoting distance education in Nigeria is the use of Mobile learning. Mobile learning is an evolving technology and a new research area that utilizes the advancements in mobile computing to enhance the education system. A mobile learning system is a mechanism that performs adaptation based on a learner model, and updates that learner model with the newly derived facts. A mobile learning application consists of interactive systems that deal with imprecise information [2]. M-learning uses wireless transmission and mobile devices such as Smartphones, tablets and PDAs instead of wired transmission and personal computers. This type of learning is dynamic as it increases learning capabilities with the opportunity to learn independent of time and location, therefore, it aids users to learn a course at anytime and anywhere and also provide the unique experience to the learners in terms of its flexibility [3].

However, one of the essences of distance learning education is to ensure students perform better in their studies in order to compete with other students in the labor market, therefore, prediction of students performance is very important to assist the students in improving their academic performance, to deliver high quality education and also important for the tutors to be able to recognize and locate students with a high probability of poor performance (students at risk) in order to

take precautions and be better prepared to face such cases. Soft computing has shown a promising concern in prediction.
There are several soft computing techniques used in this field such as Artificial neural networks. Artificial neural network (ANN) has been widely used. Therefore, this research work is set to develop a mobile learning model to predict the performance of distance learning students in higher institution in Nigeria using Artificial Neural Networks and considers some attributes that can affect the performance of students. Neural network is a soft computing technique and a tool for establishing intelligent systems.
Artificial Neural Networks (ANNs) are the form of artificial intelligence which is based on the function of human brain and nervous system. An artificial neural network has two types of basic components, namely, neuron and link. A neuron is a processing element and a link is used to connect one neuron with another. Each link has3 its own weight. Each neuron receives stimulation from other neurons, processes the information, and produces an output. Neurons are organized into a sequence of layers. The first and the last layers are called input and output layers, respectively, and the middle layers are called hidden layers. The input layer is a buffer that presents data to the network. It is not a neural computing layer because it has no input weights and no activation functions. The hidden layer has no connections to the outside world. The output layer presents the output response to a given input. The activation coming into a neuron from other neurons is multiplied by the weights on the links over which it spreads, and then is added together with other incoming activations. A neural network in which activations spread only in a forward direction from the input layer through one or more hidden layers to the output layer is known as a multilayer feed-forward network [4].

2. LITERATURE REVIEW

[5] presented participation-based student final performance prediction model through interpretable genetic programming: integrating learning analytics, educational data mining and theory. Building a student performance prediction model that is both practical and understandable for users is a challenging task fraught with confounding factors to collect and measure. Most current prediction models are difficult for teachers to interpret, these challenges motivated this project. The objective of the research was to develop a methodology to connect perspectives from learning analytics, EDM, theory and application. Data of 759 were collected from students in .txt format, in which the dataset was divided into two (testing and the training), 80% of the dataset was used for training and the remaining 20 % was used for training. Since the log data is centered on event types and the facilitation of measure construction, each event type was processed into four participation dimensions (Individual, Group, Event Types, Module Set) for each student. Participation-based student final performance prediction model was developed. The research did not did not consider the quality of ultimate artifacts or objects that may be generated at the end of a course.
[6] presented predicting distance learning student performance using machine learning techniques. The research work was motivated by the need to fill the gap between empirical prediction of student performance and the existing Machine Learning techniques. The objective of the research was to use the existing Machine Learning techniques to predict students' performance in a distance learning system. Data of 800 were collected from two distinct sources, the students' registry of the Hellenic Open University (HOU) and the records of the tutors. The dataset was divided into two (testing and the training), 50% of the dataset was used for training and the remaining 50% was used for training. The Naïve Bayes algorithm, Logistic Regression and Backward propagation were combined to improve the accuracy of the system. Predicting students' performance in distance learning using machine learning techniques was developed. The present work can only predict if a student passes the module or not, it cannot predict the student's marks.
[7] presented an Automated Recommender System for Course Selection. The research presents a collaborative recommender system that recommends university elective courses to students by exploiting courses that other similar students had taken. The research was motivated by the need to develop a collaborative recommender approach that employs association rule mining to discover courses' patterns in order to recommend courses. The objective of the research was to develop a collaborative recommender system that recommends university elective courses to students. 900 dataset of courses was collected from students, in which the dataset was divided into two (testing and the training), 80% of the dataset was used for training and the remaining 20% was used for training. After this, clustering technique on courses dataset was applied to group similar students to the same cluster. The research suffered the limitations of low precision and recall when the grade point is high and also low accuracy.
[8] present A Neuro-Fuzzy Model for Predicting Students Performance in Object-Oriented Programming Courses. The objective of the research was to design models and find a suitable methodology to predict the performance of students in object-oriented programming courses. The research was motivated by the need use Neuro-Fuzzy model to predict student performance in Object Oriented Programming courses. The system made use of object-oriented programming courses at Adekunle Ajasin University. The data was Analyzed using Neuro-Fuzzy Model in MATLAB, after which there was interpretation of the results of the data analyzed. The research work has low prediction performance.
[9] presented Student Performance Prediction Model using Machine Learning Approach: The Case of Wolkite University. The objective of the research work was to predicate the student performance particularly in college of computing student at Wolkite University based on the course the student took and GPA. The research was motivated by the need to predict the performance of students in Wolkite University. The system made use of result of six result in Information Technology at Wolkite university as the dataset. The system made use of WEKA software package. The dataset of 500 used for the research work is pre-processed in order to transform them into a suitable format to be used by the prediction tool. The dataset was divided into two parts of which 80% were used for training and 20% were used for testing. Tests were conducted using three algorithms' tests for the assessment of input variables: Neural Net (MLP), Naive Bayesian and Support Vector Machine. The limitation of the research is that the research work was limited to Wolkite University.

3. METHODOLOGY

The architecture of the system shows the step to step and this can be depicted in the figure 3.1 below. The descriptions of the various components that make up the system are also presented.

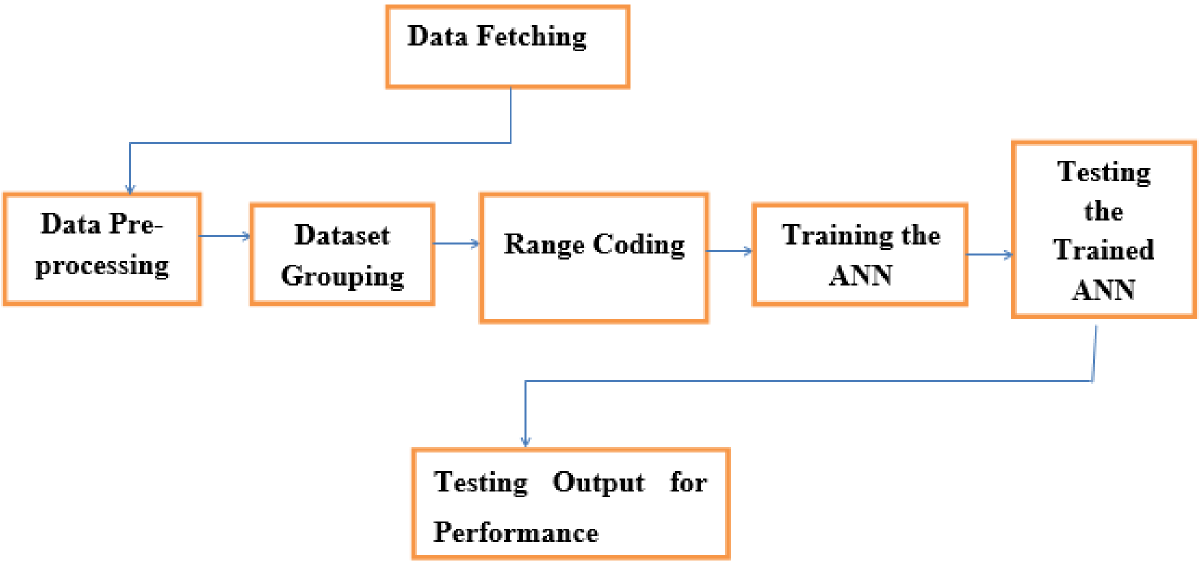

Figure 1: Architecture of the System

Data were collected from the online questionnaire with the help of google form. The link of the google form (https://docs.google.com/forms/d/1vaBujBTWii_djv9tbGJem TqBoaAEfWsdePrmuD5ZYs8/edit?chromeless=1) was administered to students doing distance learning in various higher institutions. The data take into consideration factors that may affect student academic performance such as the Online Class Participation (OCP), Assignment Submission (AS), Early/Late Registration (ELR), Parent/ Guardian Education (PGE), Performance in Secondary School (PSS), Online Practical Test (OPT), M_7 Fast Internet Service (FIS), M_8 represents Student Location (SL), M_9 represents Financial Assistance (FA). At the end, the total of 1000 data was used in this research work.

The data collected from the Google form were preprocessed. This is the process of transforming and mapping data from one "raw" data form into another format with the intent of making it more appropriate and valuable for a variety of downstream purposes such as analysis. The dataset was divided into two sets, namely the training set and the testing set. 80% of the dataset were allocated to the training set and 20% were allocated to the testing set. The training set enables the system to observe relationships between input data and resulting outputs, so that it can develop relationship between the input and the expected output. The testing set was used to validate the result of the result of the training set.

The attributes, which were valued as High, Medium and Low, are coded using 0 for Low, 1 for Medium and 2 for High using equation 1

$$\text{Code}=\begin{Bmatrix} x_1 - x_2 = 0 \\ x_3 - x_4 = 1 \\ x_5 - x_6 = 2 \end{Bmatrix} \qquad (1)$$

where x_1, x_3, x_5 are the lower limits of the class and x_2, x_4, x_6 are the upper limits of the classes.

A training algorithm finds a decision function that updates the weights of the network. Artificial Neural Network is designed using the fastest technique so as to get the minimum error between targeted and predicted value of output. There is no basic rule of choosing the learning rate, the momentum rate and the number of hidden layers in any network. It is rather trial and error process and up to the designer of the network.

Gradient descent was used in the back propagation, to minimized the loss function and achieving the desired target, which is to predict the performance of distance learning student, close to the original value. The input data was passed multiple times for the epoch until the minimum for that epoch is found Gradient descent uses the first derivative (gradient) of the loss function when updating the parameters.

$$w_i(k+1) = w_i(k) - \tau \nabla j_i(k) \qquad (2)$$

where τ is the learning rate, $\nabla j_i(k)$ is the gradient vector of the performance surface at iteration (k) for i th input node. Equation 2 was be used to calculate the performance surface (J).

$$J = \sum_P (d_p - y_p)^{2} \text{ and min } J = w_{opt} \qquad (3)$$

where w_{opt} is the optimal weight, d_p is the target output and y_p is the computed output of the p^{th} output neuron.
The training was stopped when Minimum Square Error or MSE is obtained, which is the minimum error between targeted and predicted. MSE is given by:

$$MSE = \frac{1}{n}\sum_l^n (y_p - y_l)^{2} \qquad (4)$$

where n is the total number of datasets, y_p is the predicted academic performance of the students and y_i is the desired academic performance of the students.

4. RESULTS

A feedback option was provided on the developed system for the students who have used the system and got recommendations to gauge the performance of the recommender system. A total of 1000 feedbacks from distance learning students, based on which the research work has evaluated the system with respect to five performance metrics: precision, recall, F1 score, specificity, and balanced accuracy.

Table 1 shows the confusion matrix of the feedback for the first 300 distance learning students, which shows the where the rating values greater than or equal to 3 are considered positive and the rating values smaller than 3 are considered negative.

Table 1: Confusion Matrix for 300 distance learning students

Confusion matrix	Positive ratings given by students (rating ≥ 3)	Negative ratings given by students (rating < 3)
Positive ratings recommended by system (rating ≥ 3)	True positive, TP (204)	False positive, FP (45)
Negative ratings recommended by system (rating < 3)	False negative, FN (21)	True negative, TN (30)

The five selected performance metrics used in the research work are analyzed below.

a. Precision

$$PPV = \frac{TP}{TP+FP} = \frac{204}{204+45} = \frac{204}{249} = 0.819 = 81.9\% \quad (5)$$

b. $Recall, TPR = \frac{TP}{TP+FN} = \frac{204}{204+21} = \frac{204}{225} = 0.907 = 90.7\%$ (6)

c. $F1Score = 2 \times \frac{Precision \times Recall}{Precision+Recall} = 2 \times \frac{0.819 \times 0.907}{0.819+0.907} = 2 \times \frac{0.743}{1.726} = 0.861 = 86.1\%$ (7)

d. $Specificity, TNR = \frac{TN}{TN+FP} = \frac{30}{30+45} = \frac{30}{75} = 0.40 = 40\%$ (8)

e. $Balanced\ Accuracy = \frac{TPR+TNR}{2} = \frac{0.907+0.40}{2} = 0.654 = 65.4\%$ (9)

Table 2 shows the confusion matrix of the feedback for 700 distance learning students, which shows the where the rating values greater than or equal to 3 are considered positive and the rating values smaller than 3 are considered negative.

Table 2: Confusion Matrix for 700 distance learning students

Confusion matrix	Positive ratings given by students (rating ≥ 3)	Negative ratings given by students (rating < 3)
Positive ratings recommended by system (rating ≥ 3)	True positive, TP (535)	False positive, FP (95)
Negative ratings recommended by system (rating < 3)	False negative, FN (38)	True negative, TN (32)

Table 2 shows the confusion matrix of the feedback for 700 prospective users, which shows the where the rating values greater than or equal to 3 are considered positive and the rating values smaller than 3 are considered negative.
The five selected performance metrics used in the research work are analyzed below.

a. Precision

$$PPV = \frac{TP}{TP+FP} = \frac{535}{535+95} = \frac{535}{630} = 0.849 = 84.9\% \quad (10)$$

b. $Recall, TPR = \frac{TP}{TP+FN} = \frac{535}{535+38} = \frac{535}{573} = 0.934 = 93.4\%$ (11)

c. $F1Score = 2 \times \frac{Precision \times Recall}{Precision+Recall} = 2 \times \frac{0.849 \times 0.934}{0.849+0.934} = 2 \times \frac{0.793}{1.783} = 0.90 = 90.0\%$ (12)

d. $Specificity, TNR = \frac{TN}{TN+FP} = \frac{32}{32+95} = \frac{32}{127} = 0.252 = 25.2\%$ (13)

e. $Balanced\ Accuracy = \frac{TPR+TNR}{2} = \frac{0.934+0.252}{2} = 0.593 = 59.3\%$ (14)

Table 3: Confusion Matrix for 1000 distance learning students

Confusion matrix	Positive ratings given by students (rating ≥ 3)	Negative ratings given by students (rating < 3)
Positive ratings recommended by system (rating ≥ 3)	True positive, TP (798)	False positive, FP (122)
Negative ratings recommended by system (rating < 3)	False negative, FN (57)	True negative, TN (23)

Table 3 shows the confusion matrix of the feedback for 1000 distance learning students, which shows the where the rating values greater than or equal to 3 are considered positive and the rating values smaller than 3 are considered negative.
The five selected performance metrics used in the research work are analyzed below.

a. Precision

$$PPV = \frac{TP}{TP+FP} = \frac{798}{798+122} = \frac{798}{920} = 0.867 = 86.7\% \quad (15)$$

b. $Recall, TPR = \frac{TP}{TP+FN} = \frac{798}{798+57} = \frac{798}{855} = 0.937 = 93.7\%$ (16)

c. $F1Score = 2 \times \frac{Precision \times Recall}{Precision+Recall} = 2 \times \frac{0.867 \times 0.937}{0.867+0.937} = 2 \times \frac{0.812}{1.804} = 0.900 = 90.0\%$ (17)

d. $Specificity, TNR = \frac{TN}{TN+FP} = \frac{23}{23+122} = \frac{23}{145} = 0.159 = 15.9\%$ (18)

e. $Balanced\ Accuracy = \frac{TPR+TNR}{2} = \frac{0.937+0.159}{2} = 0.548 = 54.8\%$ (19)

From table 3, 4 and 5, it can be observed that as the number of students increase, the precision value, F1 score and recall values increase. However, the values of specificity and balanced accuracy decreases as the number of students increase.

5. CONCLUSION AND RECOMMENDATION

The goal of distance learning education is to spread the reach of education to everyone irrespective of their distance or location; accessible to all, however, not everyone can survive in distance learning environment, therefore, the prediction of student's academic performance is crucial in order to know if students can excel in distance learning environment. In this research, an ANN model was developed to predict the academic performance of distance learning students using the following attributes: Online Class Participation, Assignment Submission, Early Registration, Parent/ Guardian Education, Performance in Secondary School, Online Practical Test, Fast Internet Service, Student Location, Financial Assistance. The developed system was tested using average computational time, Mean Square Error, Root Mean Square Error and Correlation Coefficient. The result shows that each of the attributes used contributed greatly to the academic performance of distance learning students, also, the result shows a very low computational time and high performance in Mean Square Error, Root Mean Square Error and Correlation Coefficient.

The developed model is recommended to students in distance learning program to help them predict their academic performance ahead of graduation. Future research could be done by extending the research work to other tertiary institution of learning. The system can also be improved by using deep learning models.

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