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Of Students Academic Performance Rates Using Artificial Neural Networks (ANNs)

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Abstract A model based on the multilayer perception algorithm was programmed. The result from the test data evaluation showed that the programmed Artificial Neural Network model was able to correctly predict and classify the performance of students with Mean Correct Classification Rate CCR of 97.07%.

Keywords: *mean correct classification rate, Artificial Neural Networks (ANNs), Predictive models*

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1. Introduction

Universities and higher institutions of learning have been known as a breeding and grooming field for students' academic pursuit. That is why the path of the students' academic performances are necessary to be checked, in order to help sustain the important roles students play in the society upon graduation, which maybe either to continue their studies into the post-graduate program or become the man power for the industry, government and private sectors. Thus, the students' academic performances are critical in ensuring that those significant roles the students' play in the society are maintained. This has motivated some higher institutions of learning to developed interest in predicting the paths of students, thus identifying which students will require assistance in order to graduate at the stipulated time or maintain their studies or even drop out of the school. This is brought about by the academic failure rate among students, which has fed to a large number of debates [5].

In this paper, a Soft computing technique, which artificial neural network is part of, has been recognized as attractive alternatives to the standard, well-established hard computing paradigms. Soft computing techniques, which emphasize gains in understanding system behavior in exchange for unnecessary precision, have been proven to be able to efficiently solve complicated problems. Soft computing techniques have also enabled the development of more efficient models which predicts student academic performance more accurately than previously possible. There are several soft computing techniques popularly known and used: Artificial Neural Networks, Decision Tree, and K-Mean clustering.

However, the main objective of this work is to evaluate the accuracy of the Artificial Neural Network Model Architecture developed under a statistical programme (Matlab 2009) as a classifier, using its Mean Correct Classification Rate CCR (%), among others is: to report the order of predictor's significance to the model programmed.

Several researchers have conducted studies on students' academic performances: [13,16,19] and so many others have carried out a scholarly research on prediction of academic performance of students. Whereas others like: [3,21]; have used Artificial Neural Networks to model, predict and classify, using number of factors which influences academic performance of university students. [12] utilized a Multilayer Perception Neural Networks to predict student performance. They used the average point scores of grade 12 students as inputs and the first year college results as output. Their research showed that Artificial Neural Networks-based model is able to predict student performance in semester one with high accuracy. [14] used a Multiple Feed-Forward Neural Networks to predict students' final achievements and to group them into two groups.

2. Materials and Methods

The data used in this work were secondary data collected from the students files of the faculty of veterinary medicine, University of Ibadan from 2009-2013. All students' record with blank fields or incomplete information was deleted from the compiled data. A total number of 420 records were collected and used.

Through extensive review of literatures, a number of socio-economic, biological, environmental, academic, and other related factors like pre-admission requirements that were considered to have influence on the academic performance and promotion rates of university students were identified. Some of these factors can be seen in some literatures like [4,7,9,10,15,17].

These factors gender, parents marital status, parents educational status, parents occupation, O'level result, age at entry, time delay before admission, type of secondary school attended, location of secondary school attended, post UMTE, physically impaired and performance outcome were collected from the students' records were carefully studied and harmonized into a manageable number suitable for computer coding with the context of the Artificial Neural Network modeling. These influencing factors were categorized as input variables (units). The output variables on the other hand will represent the performance rate (students that were promoted to final years, students that repeated fifth year and students that dropped down to fourth year). That is, the output was categorically classified. MatLab R2009a was used as a statistical tool for the analysis.

A Multi-Layer Artificial Neural Network (ANN) model with a Logistic Transfer Function, trained with back-propagation algorithm was programmed; the model was able to predict and classify students into three categories: those that were promoted to final years, those that repeated class and those that were demoted to fourth year. A six years course was considered in this work and the consideration was based on the extension of a research work done by [20] which recommended that the work be extended to other discipline and many more other influencing factors which affect students' academic performance or pre-admission status be considered as well.

3. The Neural Network Model

Artificial Neural Network (ANN) model proposed by [2] was used in this research work. The model is given below with consideration of logistic transfer function.

$$y = f(X,W) + e_i \qquad \text{i}$$

$$y = f(X,W) + e_i = \alpha X + \sum_{h=1}^{H} \beta_h \, g\left(\sum_{i=0}^{I} \gamma_{h_i} x_i\right) + e_i \qquad \text{ii}$$

$$y = f(X,W) + e_i$$

$$= \alpha X + \sum_{h=1}^{H} \beta_h \left(1+e^{-x}\right)^{-1} \left(\sum_{i=0}^{I} \gamma_{h_i} x_i\right) + e_i \qquad \text{iii}$$

$$g(.) = \frac{1}{1+e^{-x}} = \left(1+e^{-x}\right)^{-1} \qquad \text{iv}$$

where: $X = (x_0 = 0, x_1, ..., x_I)$; $W = (\alpha, \beta, \gamma)$;

y is the ouput variable;

X is the input variables;

α is the weight of the input unit(s);

β is the weight of the hidden unit(s);

γ is the weight of the output unit(s),

$g(.)$ is the logistic transfer function;

e_i is the error term.

4. Network Architecture and Design

Multilayer Perceptions (MLPs) are layered feed forward networks typically trained with static back propagation. These networks have found their way into countless applications requiring static pattern classification. Therefore, given the computational capabilities of a multilayer perception as a classifier, a three-layered feed forward neural network was programmed in this research work. The first layer (input level) comprised of 17 neurons (processing elements) - one for each profile parameter (input). The third layer (output level) comprised of 3 neurons - one for denoting "promoted students", another one for "repeating students" and the other for the "dropped down student" as seen in fig 1.

However, based upon recommendations from [6] and [11] that one hidden-layer network is sufficient to model any complex system, the designed network model will have only one hidden layer. See fig 1.

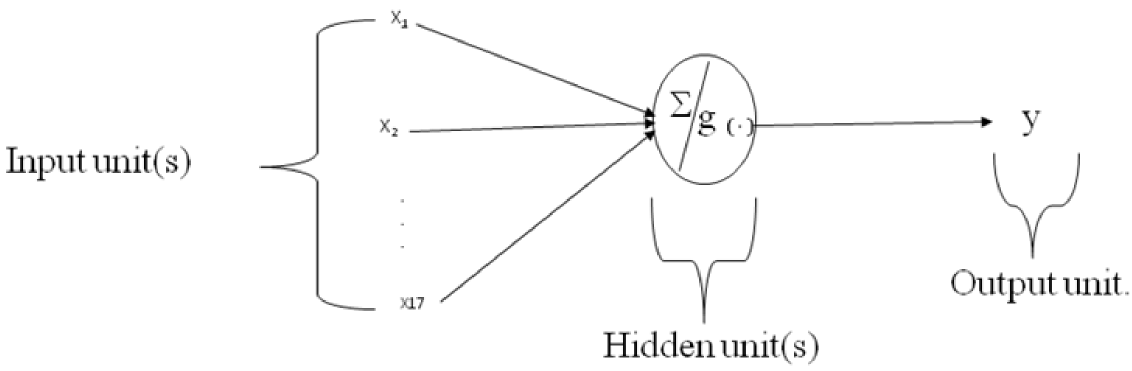

Figure 1.

In this work, we decided to have 70 neurons in the hidden layer as the network performance was best at this number. The back-propagation learning algorithm was used for training the network. The logistic activation function was used at the hidden layer, which can be seen inside the shape in the hidden layer together with the symbol of the summing unit and the identity activation function was used at the output layer.

5. The Data Set Grouping

In supervised training, the data is divided into 3 categories; the training set, verification set (hide out) and 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.

A heuristic statement is that the number of the training set data should be at least a factor of 10 larger than the number of network weight to accurately classify test data with 90% accuracy [1]. A total of 420 students records were used in the analysis. About (58.8%) of the total data (i.e. 247 candidates) were used as the training set, (31.0%) (i.e. 130 candidates) as the testing set, and (10.2%) (i.e. 43 candidates) was used for cross validation as each network was run for 100 epochs.

6. Model Performance Measures

There can be many performance measures for predictors; the most important measure of performance is the prediction accuracy that can be achieved with the training data. The most frequently used is the Mean Correct Classification Rate (CC_R), [8,18] which is defined as

$$CC_R = \frac{\sum_{k=0}^{C-1} CC_R}{n} \qquad \text{v}$$

where CC_R is the number of corectly classified observations

and n is the number of observations in the class

A model with a high Correct Classification Rate has a better performance. In general, CC_R is used to judge the functional network classifier performance. The better classifier is the one with a high CC_R value.

7. Results

After the training and cross validation, the network was tested with the test data set and the following results were obtained. This involves given the input variable data to the network without the output variable results. The output from the network is then compared with the actual variable data and the mean correct classification rate was evaluated using equation v. The comparison is summarized in the matrix bellow.

Table 1. Results from Testing

Students Performances	**Promoted**	**Repeated**	**Demoted**
Promoted	83 (100%)	0 (0%)	0 (0%)
Repeated	6 (37.5%)	10 (62.5%)	0 (0%)
Demoted	2 (6.5%)	0 (0%)	29 (93.5%)
Mean Correct Classification Rate CCR = 97.07%			

From Table 1 above, each row represents a case of interest and each cell represents the number of the cases of the interest in the rows as evaluated by the classifier. The network was able to predict accurately 83 out of 83 for promoted students (which represents candidates which were promoted to final year), 10 out of 16 for the repeated students (which represents candidates that repeated class), and 29 out of 31 for the demoted students (which represents candidates that were demoted) used to test the Network's topology. This gives an accuracy of 100% for promoted students, 62.5% for repeated students, and 93.5% for the demoted students. This indicates a Mean Correct Classification Rate or accuracy of about 97.07% for the Artificial Neural Network model architecture developed which shows a good performance according to results from some literatures is like: [1], [17] and [20].

8. Conclusion

This paper has shown the potential of the Artificial Neural Network for accurate prediction and classification of the academic performance of students in higher institution of learning, especially the considered case study by its CCR value. The model was developed based on some selected input variables from the pre admission data contained in the student's records. It achieved an accuracy of over 97.07%, which shows the potential efficacy of Artificial Neural Network as a prediction tool and a selection criterion for classifying students according to their rates of performances.

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APPENDIX

Those factors that were considered in this work are listed in the Table below;

No.	**Variables descriptions**	**Data type**	**Location**	**Code**
1	Gender	Categorical	Input	1=male, 0=female
2	Parents Marital Status	Categorical	Input	0= Married and living together 1= Father die 2= Mother die 3= Mother & father die 4= Married but living apart because of occupation 5= Married but living apart because other reasons 6 = Divorced
3	Father's Education	Categorical	Input	0 = Uneducated 1= Primary school 2 = Secondary school 3 = Degree 4 = Vocational 5 = Diploma 6 = Masters degree 7= Doctors degree
4	Mother's Education	Categorical	Input	0 = Uneducated 1 = Primary school 2 = Secondary school 3 = Degree 4 = Vocational 5 = Diploma 6 = Masters degree 7 = Doctors degree
5	Fathers Occupation	Categorical	Input	0 = Government service(govt. officer) 1 = Government service(temporary) 2 = State enterprise employee 3 = Company employee 4 = Ownership 5 = Farmer, fisher 6 = Freelance 7 = Unemployed 8 = Others
6	Mother's Occupation	Categorical	Input	0 = Government service(govt. officer) 1 = Government service(temporary) 2 = State enterprise employee 3 = Company employee 4 = Ownership 5 = Farmer, fisher 6 = Freelance 7 = Unemployed 8 = Others

7	O' Level Results	Categorical	Input	English: 0 = A1-A2 1 = A3-C4 2 = C5-C6 Mathematics: 0 = A1-A2 1 = A3-C4 2 = C5-C6 Chemistry: 0 = A1-A2 1 = A3-C4 2 = C5-C6 Physics: 0 = A1-A2 1 = A3-C4 2 = C5-C6 Biology: 0 = A1-A2 1 = A3-C4 2 = C5-C6
8	Age at Entry	Categorical	Input	0 = Below 23 years 1 = 23 years and above
9	Time delay before admission	Categorical	Input	0=1year 1=2years 2=3years and above
10	Type Of Secondary School Attended	Categorical	Input	0= Private 1= State 2= Federal
11	Location of Secondary School attended	Categorical	Input	0=Urban 1= Rural
12	Post UTME	Numerical	Input	True value
13	Physically impaired	Categorical	Input	0 = Disable 2 = Not disable
14	Performance outcome	Categorical	output	1 = Promoted students 2 = Repeating students 3 = Demoted students

Appendix: Table containing both response and predictor variables considered in this work and the appropriate code.