Journal of Al-Qadisiyah for Computer Science and Mathematics Vol. 14(4) 2022 , pp Math. 20–37

Available online at www.qu.edu.iq/journalcm

JOURNAL OF AL-QADISIYAH FOR COMPUTER SCIENCE AND MATHEMATICS

ISSN:2521-3504(online) ISSN:2074-0204(print)

Using Logistic Regression Models and Artificial Neural Networks to Study the Factors Affecting the Academic Achievement of University Student

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ARTICLE INFO

Article history:

Received: 10 /10/2022

Rrevised form: 06/11/2022

Accepted : 10 /11/2022

Available online: 01/12/2022

Keywords:

Academic Achievement, Prediction Model, Ordinal Logistic Regression, Artificial Neural Networks ANNs, Multi-Layer Perceptron MLP

ABSTRACT

This study aimed to identify the most important factors affecting the academic achievement of a university student and then build a predictive model using these factors to predict the student's academic status. The ordinal logistic regression method was used to identify the influencing factors, and neural network technique to build the prediction model. It was applied to a sample of 188 students at Al-Yamamah University in the Kingdom of Saudi Arabia. The analyzed data were collected using a questionnaire of three main axes: representing student related factors, family, and academic factors. The results of the logistic regression model showed that 10 variables had a significant effect on the student's academic achievement: age, cumulative average at high school, the distance of residence, work besides studying, daily study hours, frequent absences, fear of exams, the economic level of the family, parents divorce, and family follow-up. As for the MLP network model with architecture (18-28-3), whose inputs were the significant variables chosen by the logistic model, the values of all performance indicators were supportive of the model's quality and predictive ability, where the correct classification rate values in the training data reached 96%, validity 93% and testing 90%. The results of the classification table were also high, with the correct classification of the three categories of the target variable: 100% good, 91.95% fair, 82.35% poor. The total percentage of correct classification was 94.68%. All these indicators confirm the validity and feasibility of using this model as an initial tool for predicting the academic status of a university student.

MSC : 30C45 , 30C50

https://doi.org/10.29304/jqcm.2022.14.4.1093

1. Introduction

The student is at the center of the educational process in higher education institutions, where most of their efforts are directed towards providing scientific and cognitive training that will achieve the desired quality of their output. Therefore, these institutions are interested in identifying and analyzing the factors that can affect these outputs. The academic achievement of a university student during his academic years is measured by the cumulative points he scores in the final examinations of various courses. There are several factors affecting the progress of students' academic achievement. Identifying these factors and knowing their impact helps to predict the academic status of a student and to address many of the problems that may affect his academic achievement. To this end, an integrative method combining logistic regression LR models with neural networks NNs have been used. LR models are one of the statistical methods used in prediction studies. They are considered a special case of general regression models, and they are used when the dependent variable under study is qualitative. They can identify the significant independent variables that affect the dependent variable, measure and rank the amount of the effect [1]. NNs are one of the techniques of artificial intelligence being used as a mathematical method for building prediction models, classification, pattern recognition and other uses, in which independent variables are used as inputs to train the network so that they can produce output similar to the dependent or target variable [2].

The academic achievement of the university student is influenced, besides the IQ, by several other overlapping factors. There are factors related to the student, such as desire and motivation for studying, psychological and physical readiness, and others. Factors related to the family, its economic and social conditions, the educational level of parents and others are also to be considered, besides factors related to educational institutions, including policies, academic affairs, etc. All these factors combined have a clear impact on student's performance and academic achievement. The academic status of the student is usually measured by his cumulative average GPA, which represents overall academic achievement, upon which the student's performance can be classified as: good, fair or poor. We can summarize the problem of this study in the following questions: What are the most important factors affecting the academic achievement of a university student? Can the academic status of a student be predict by these factors?

The main objective of this study is to build statistical models using logistic regression methods and neural networks to identify the most important factors that affect the academic achievement of a university student, thereby predicting the academic status of a student (good, fair, poor). A sub-goal is for academically faltering students; early prediction of their academic status may help addressing some of their academic problems.

2. Methodology

The approach used in this study is the analytical, statistical method. Ordinal logistic regression OLR and artificial neural networks ANNs have been used to build statistical models to achieve the objectives of the study. First, the OLR model was used to identify the most important factors affecting the student's academic achievement. Second, based on the significant variables identified through the OLR, a prediction model was built using ANNs, via which student's academic status can be predicted. This was done through three phases: The first stage was the processing of missing and outliers data. The second phase subjected the study variables to the conditions of OLR, then the model was built, its performance was evaluated and the significant variables were identified. In the third phase, the ANN model was built based on the significant variables selected through the OLR model, then its performance was evaluated. The figure below shows the different stages and steps of the study.

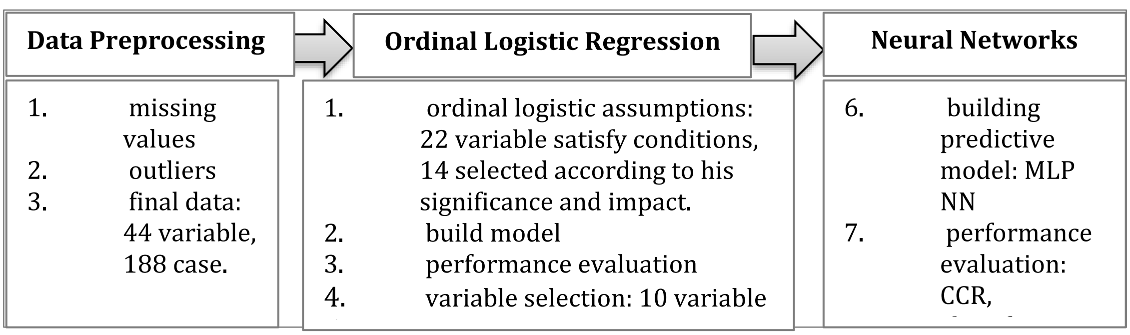

Figure (1): Study stages **(Source: prepared by researchers)**

The data for this study were collected from a sample of 188 students taken randomly from Al Yamamah University in the KSA at the Engineering and Business Administration Colleges during the academic year 1443 AH. The sample contained three categories of students: good, fair and poor. The data were collected using a questionnaire divided into a number of axes, that contain several of questions. The axes were: basic data, student-related factors, family factors, academic factors.

Variables of the Study: The study form contained 44 questions, 43 of which represented independent study variables, and one dependent variable. The dependent variable was the cumulative average GPA through which the student's academic achievement is measured, a quantitative variable converted into a categorical variable of three categories, which corresponds to the classification of students' performance to: good, fair and poor. Independent variables are represented by questions about factors affecting academic achievement and according to the conditions of the ordinal logistic regression, 22 variables have been identified, of which 14 have been selected based on their significant impact and their importance in building the logistic model. The following table represents the study variables and their coding.

Table (1): Study variables

Name	Variable label & Value
GPA	Student GPA: 1=good(3.5 to 4), 2=fair(1.75 to 3.49), 3=poor(≤1.74)
Q4_A	Age: 1=(≤20), 2=(21 to 25), 3=(≥26)
Q8_A	Cumulative average in high school: 1=(65 to 79.9), 2=(80 to 89.9), 3=(90 to 100)
Q10_A	The distance of residence in km: 1=(<30), 2=(30 to 50), 3=(>50)
Q11_B	The choice of specialization was made according to desire: 1=yes, 2=no
Q13_B	A job or any economic business besides studying: 1=yes, 2=no
Q16_B	Set aside hours for daily study: 1=yes, 2=no
Q17_B	Warning or deprivation, from some exams due to absences: 1=yes, 2=no
Q18_B	Fear of exams: 1=yes, 2=no
Q24_C	The economic level of the family: 1=low, 2=middle, 3=high
Q22_C	Father's education: 1=university, 2=secondary, 3=middle, 4=primary,5=uneducated
Q23_C	Mother's education: same as Q22_C
Q27_C	The parents are divorced: 1=yes, 2=no
Q29_C	Family obligations and responsibilities during study periods: 1=yes, 2=no
Q33_C	Family follow-up and supervision of your studies: 1=yes, 2=no

3. Literature Review

Many studies have been done through different statistical techniques to study the factors affecting the academic achievement of the university student. Some of these studies were summed up as follows:

[3], an ordinal logistic regression modelling technique was used to identify the main factors influencing the academic performance of undergraduate students at Njala University. The data were collected from 284 students using questionnaires. The factors that were found to influence students' academic performance is the number of study hours; father's income level; mother's educational level and mother's income level.

[4], they implement ANNs to predict academic performance and analyze the importance of several well-known predictors in higher education. The data were collected from 162,030 students from universities in Colombia. ANNs classify students' academic performance as either high (accuracy of 82%) or low (accuracy of 71%). Furthermore, it is found that prior academic achievement, socioeconomic conditions, and high school characteristics are important predictors of students' academic performance in higher education.

[5], used logistic regression to analyze the factors affecting the success of university students. The data was obtained from 360 university students. The variables found affecting academic success are gender, the university they studied, the way they chose their department, and their father's education. In addition, the variables such as counselling about their profession, support of

department's instructors, and communication with instructors have been found to be considerably effective on success.

[6], studied some factors that cause the low academic performance of undergraduate students, logistic regression and neural network were used, the data were collected from 300 students of the University of Gujrat, using a questionnaire. They found that the academic performance of students is directly linked with student competence in English, learning a skill, marks in the previous degree, family support, use of social media and role of teacher.

[7], used ANN to evaluate and predict the students' performance using the data about their socio-economic background and entrance examination results of the undergraduate students from a Chinese university. The accuracy prediction level achieved is 84.8%.

[8], used four data mining techniques: Support Vector Machine (SVM), ANN, Naïve Bayesian and Decision Tree to predict students' performance. The features used were demographic, social, and behavioral. The obtained results show that SVM outperforms others, and behavioral features have a good effect on students' performance.

[9], they identified the most common and widely studied factors that affect students' performance in higher education, as well as, the most common data mining techniques used to classify and predict students' performance. 36 research articles were reviewed. The results showed that the most commonly used factors are students' previous grades and class performance, students' e-learning activity, students' demographics, and students' social information. In addition, the most common data mining techniques are Decision Trees, Naïve Bayes and ANNs.

[10], used MLP-NN to predict student's performance at Katsina State Institute of Technology and Management, using students' personal information, academic information, and place of residence. A sample of 61 Computer Networking students' datasets was obtained from the department of networking and system security. The model correctly predicts 73.68% of students' performance and, specifically, 66.67% of the poor performing students.

[11], used MLP-NN model to predict the chance of students being at risk or not with respect to their degree based on CGPA at the end of 2nd semester, Study time. Previous degree marks, Home environment, study habits learning skills, hardworking and academic interaction. A sample of 300 students of social sciences studying in the 4th semester was selected from the University of Gujrat Hafiz Hayat. achieved a rate of correct classification of 95% in the training sample and 85% in the holdout sample.

[12], used MLP-NN model for prediction and classification of the academic performance of students in higher institutions. 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 97.07%.
[13], used decision tree and neural network to analyze factors affecting academic achievement that contribute to the prediction of students' academic performance. The data set comprised 1,600 students registered in the international program at a university in Thailand. The obtained results show that the decision tree classifier achieves high accuracy of 85%, which is higher than that of neural network classifier by 1.313%.
[14], compared Logistic Regression models (LR) and Neural Network (NN) on the academic failure data set. The data of 275 undergraduate students selected from schools of Hormozgan University of Medical Sciences. NN was a better performance compared with LR. The LR and ANN respectively classified 77.5% and 84.3% of the students correctly.
[15], used ANN model for predicting the students' performance in the Faculty of Engineering and IT at Al-Azhar University of Gaza. The data were obtained from student registration records. The ANN model can correctly predict the performance of more than 80% of prospective students.

Table (2): Comparison between the current study and related works

Similarities	The differences	advantages
1- This study agreed in its main objective with the previous studies in identifying the most important factors that affect the academic achievement of university students. 2- This study agreed with the previous studies in its use of the analytical statistical method to achieve the main objective of the study. 3- This study agreed with all previous studies in the similarity of the study population represented by university and higher institute students. 4- This study agreed with many previous studies in building a prediction model to predict the student's academic status and categorize it according to his academic status.	1- This study differed from some previous studies in the mathematical models that were used to build the prediction model. 2- This study differed from some previous studies in the size of the studied sample, as most of the previous studies were characterized by large sample sizes compared to this study. 3- This study differed from some previous studies in several factors affecting the	1- This study was characterized by using an integrative method between ordinal logistic regression and neural network technique to build a prediction model. 2- This study was characterized by a high percentage of accuracy in the network model, reaching 95% compared to most of the previous studies that used the neural network models. 3- The distinctive contribution of this study is the possibility of using this model in early prediction of the academic status of students who are academically stumbling, as this may help in the necessary

5- This study agreed with many previous studies in its usage of the questionnaire tool in to collect study data. 6- This study agreed with many previous studies on some factors affecting the student's academic achievement.	academic achievement of university students.	intervention to address some of the difficulties that hinder their academic achievement.

Source: prepared by researchers

4. Basic Concepts

4.1 Logistic Regression

Logistic regression models are a special case of general regression models. It is used to analyze the relationship between a categorical dependent variable and multiple independent variables, which could be continuous, ordinal or categorical, and used to predict the probability of an event occurring based on the values of explained variables that can be related to that event [16]. There are three sorts of logistic regression models, which are classified according to the sort of the dependent variable: Binary logistic regression BLR is used when the dependent variable is dichotomous. Multinomial logistic regression MLR is used when the dependent variable has multiple classes. Ordinal logistic regression OLR is used when the dependent variable is measured at the ordinal level. The OLR model is considered as a generalization of the BLR model. In the ordinal model, rather than demonstrating the probability of an individual event, as we do in logistic model, we are recognizing the probability of that event and all others above it in the ordinal positioning. We are worried about cumulative probabilities rather than probabilities for discrete classes [3].

For an ordinal dependent variable Y, P number of independent variables $(X_1, X_2, \ldots X_k)$, and for j=1,…,j-1, the ordinal logistic regression model can be composed as follows [3]:

$$logitP(Y \le j) = \beta_{j=0} - \beta_{j=1}X_1 + \beta_{j=2}X_2 + \ldots + \beta_{j=p}X_p \qquad (1)$$

This model uses cumulative probabilities up to a limit, consequently choosing the entire range of ordinal classes binary at that limit. Recognizing those levels of the dependent variable utilized in the ordinal regression analysis let Y=1,…,J with a natural ordering. Also, let (p0, p1, …, pj−1) be the related probabilities. The cumulative probability of a dependent Y≤j is given as [17]:

$$P(\mathrm{Y} \le \mathrm{j}) = \frac{\exp(\alpha_j + \beta X)}{1+\exp(\alpha_j + \beta X)} \quad ; \quad 0 < \mathrm{P} < 1 \qquad (2)$$

Where:

$$\log\left[\frac{\mathrm{P}(Y \le j)}{\mathrm{P}(Y > j)}\right] = \alpha_j - \beta X, \qquad j \in [1, J-1] \qquad (3)$$

α**j** is the intercept and is the log-odds of falling into category j or below. βk is the parameter that describes the effect of the independent variable Xi on the dependent variable Y.

The cumulative logit is given as [17]:

$$\log\left(\frac{\mathrm{P}(Y \le j)}{\mathrm{P}(Y > j)}\right) = \log\left(\frac{\mathrm{P}(Y \le j)}{1\text{-}\mathrm{P}(Y \le j)}\right) \qquad (4)$$

$$= \log\frac{p_1 + \ldots + p_j}{p_{j+1} + \ldots + p_j}$$

The cumulative logit measures how likely the response is to be in category j or below versus in a category higher than j.

Assumptions of ordinal logistic regression, for a model to be valid, need to fulfill specific assumptions: The fundamental assumptions are the dependent variable is ordinal. At least one of the independent variables are either continuous, categorical or ordinal. No multi-collinearity. The odds are proportional (parallel lines assumption), this implies that each independent variable has an identical effect at each cumulative part of the ordinal dependent variable. The parallel line assumption infers that there is one regression equation for each class with the exception of the last class [3].

4.2 Artificial Neural Networks

An artificial neural network ANN is a mathematical model of data processing that mimics the functioning of a biological neural network and is a non-linear model that relies on parallel information processing. The ANN consists of a set of units that are similar to the biological neurons found in the brain. These units process the information in the network [2]. The neurons calculate the average weights for each input of the processing unit. It doing that by multiplying each input value by its accompanying weight, then finding the sum for all the products, and then applying to it a certain activation function, the task of this function is to transform the product of the weighted addition process into a value limited to a given range, for example, (0, 1) or (-1, 1). The output of the neuron resulting from this process is then sent to other cells by the interconnections (Krose and Smagt, 1996). The following mathematical formula shows how information is processed within these units:

$$y_j = f\left(\sum_{i=1}^{n} w_{ji} x_i + w_j\right) \qquad (5)$$

Where: w_{ji} is weights, x_i is inputs, y_j is outputs, w_j is bias and f is activation function.

The general architecture of ANNs comprises a set of processing units distributed in a number of layers, which are associated with one another by interconnections, and in the various ways in which these units are associated, the various structures of neural networks are framed. The neural network usually comprises three layers: Input Layer, by which the network is fed with data from the outside. Output Layer, delivering the last result of the network. Hidden Layer, and is situated between the input and output layers and processes data from the input layer before being sent to the output layer. The network may contain one or more hidden layers, and there is some networks architecture that don't contain any hidden layers [18]. The following figure shows the design of a neural network with a single hidden layer.

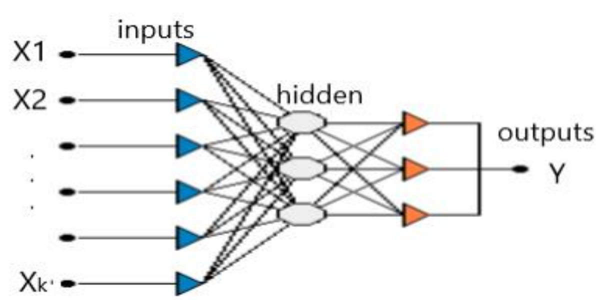

Figure (2): Artificial Neural Networks Structure

In carrying out its tasks, the ANN depends on the learning process. where a set of examples of the shape, pattern or task required of the network are presented, and the network, by adjusting the weights of the interconnections between its various units, forms an internal representation of the requested task and stores it in memory to be accessible for use thereafter. That is, it is the process of finding the appropriate weights for the network that enables it to reproduce the model it is required to represent, which is done through training or learning. There are three main ways to learn ANN: supervised learning, unsupervised learning and reinforcement learning. The neural network learning process depends on mathematical algorithms, many learning algorithms exist and the choice of the proper algorithm depends on the type of network. One of the most commonly used algorithms in training multi-layer neural networks is Back-Propagation Algorithm, which was used in this study to train the selected network. The work of this algorithm is to gradually reduce the error squares of the network output by adjusting weights in each training cycle. The algorithm is in three stages of operation: the forward feeding stage, the back-propagation stage and the weights update stage [19]. The following diagram shows the phases of operation of this algorithm.

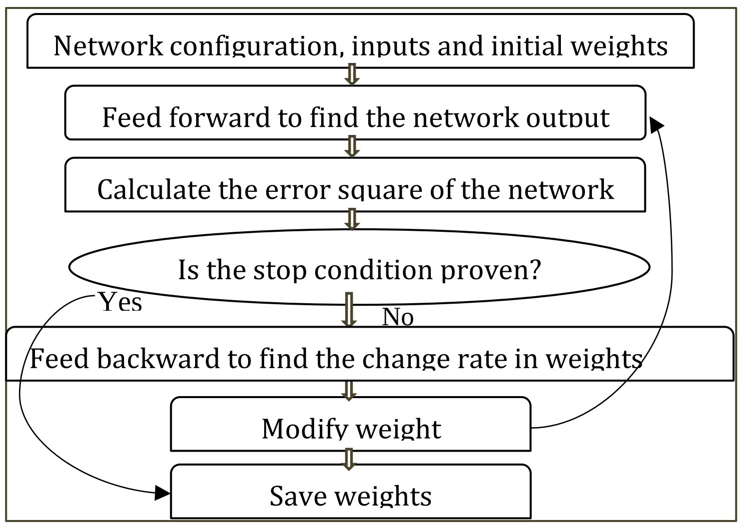

Figure (3): Back Propagation Algorithm

Neural network applications cover many areas in public life. Prediction, classification and pattern recognition are among the areas where NN models are most commonly used. The field of prediction has received many successful applications of NNs, and the results obtained from these applications have shown high accuracy compared to traditional methods of prediction. What distinguishes NN models from statistical models is that there are no assumptions or preconditions when applied in different fields, as in statistical methods, which must be realized before applying them.

In this study, we used a Multi-Layer Perceptron MLP network with a feed-forward back-propagation algorithm to train the network, a logistic activation function in the hidden layer and the output layer. It is the ideal form of networks used in prediction. MLP is one of the most frequently used networks in prediction models, and its results have shown high accuracy in this area.

The following mathematical formula shows how prediction values are calculated in the neural network model [20].

$$Y(t) = w_0 + \sum_{j=1}^{h} w_j \, f_j \left[\sum_{i=1}^{n} w_{ij} \; x(k-i) \right]_j + w_{j0} \ldots\ldots\ldots(6)$$

Where:- Y: network output, h: numbers of hidden layer units, n: numbers of input units, w_{ij}: weights between the inputs and the hidden layer, w_j: weights between the hidden and the output layer, $f_j(.)$: sigmoid activation function in hidden units (j_{th}).

5. Results and Discussion

To study factors influencing the academic achievement of the university student, and to build a predictive model based on the most influential factors, the ordinal logistic regression model was picked to study and identify factors and the MLP network to build a prediction model. The spss program was used to build the logistics model, and the Alyuda NeuroIntelligence program was used to build the MLP model. In the following will discuss the results obtained for the two models.

5.1 Ordinal Logistic Regression Model

The model was created based on enter method to determine the ability of the model to accurately specified the factors that affect academic achievement. The independent variables in the model were student, family and academic factors. The predictive variable was the student's academic status, which was represented by the GPA.

The size of the study sample included in analysis 188 cases, divided into three categories: good=84, fair=87, poor=17. All cases were selected and no missing values. The analysis results and discussion are as follows:

Table 3: Model-Fitting Information

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	332.553			
Final	196.869	135.684	10	.000

Table 3 shows the Chi-square test. It is used to test the null hypothesis "the model is not significant". The p-value (sig=.000<.001), which is significant at statistical value (.001), for that the null hypothesis is rejected, which means the model is significant.

Table 4: Goodness-of-Fit

Model	Chi-Square	df	Sig.
Pearson	275.224	244	.083
Deviance	199.849	244	.982

Link function: Complementary Log-log.

Table 4 shows the Pearson and Deviance chi-square tests, used to test the null hypothesis “the model represents the data well”. The p-value of two tests (sig.>.05), for that the null hypothesis is not rejected.

Table 5: Pseudo R-Square

Cox and Snell	.514
Nagelkerke	.608
McFadden	.386

Link function: Complementary Log-log.

Table 5 shows the Cox-Snell-R^2, the Nagelkerke-R^2 and the McFadden-R^2. From the table, between 39% and 61% of the variation in predicting academic achievement can be explained by the model. However, these measures are not considered as the R^2 in OLS regression due to the categorical nature of the dependent variable.

Table 6: Test of Parallel Lines[a]

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Null Hypothesis	196.869			
General	179.035	17.834	10	.058

Table 6 shows the Parallel Lines test. It is used to test the null hypothesis states that “the location parameters (slope coefficients) are the same across response categories”. The significance value of Chi-square (sig.=.058>.05), for that the null hypothesis is not rejected.

Table 7: Parameter Estimates

							95% Confidence Interval	
		Estimate	**Std. Error**	**Wald**	**df**	**Sig.**	**Lower**	**Upper**
Threshold	GPA=1	1.406	1.367	1.057	1	.304	-1.274	4.086
	GPA=2	4.612	1.452	10.081	1	.001	1.765	7.459
Location	Q4_A	-.605	.206	8.650	1	.003	-1.008	-.202
	Q8_A	.986	.231	18.292	1	.000	.534	1.438
	Q10_A	-.867	.201	18.674	1	.000	-1.260	-.474
	Q13_B	.684	.248	7.627	1	.006	.199	1.170
	Q16_B	.860	.258	11.132	1	.001	.355	1.365
	Q17_B	1.798	.321	31.450	1	.000	1.170	2.426
	Q18_B	1.571	.296	28.197	1	.000	.991	2.151
	Q24_C	-1.042	.271	14.753	1	.000	-1.573	-.510
	Q27_C	-1.012	.355	8.147	1	.004	-1.707	-.317
	Q33_C	.747	.271	7.574	1	.006	.215	1.278

Link function: Complementary Log-log.

Table 7 shows the estimated regression coefficients, standard error, Wald statistics and CI for the only significant variables included in the models. Consider Wald test and Sig. column. (sig.<0.05) for all these variables, which refer to the significant effect of these variables in predicting academic performance. Column (Estimate) contained the model coefficients by logit, which shows the effect of each predictor in predicting model.

By reference to regression coefficients, we note a negative impact of certain variables in student academic achievement, such as age Q4_A, residence distance Q10_A, family economic status Q24_C, and parents' divorce Q27_C.

5.2 Neural Network Model:

To build a prediction model for academic achievement, the MLP network was selected. The network inputs were the significant independent variables chosen by the ordinal logistic regression model, and these variables were the factors affecting the student's academic achievement. The target variable to be predicted was the academic achievement represented by GPA and contained three ranking categories: good, fair and poor. In order to train the network, the data entered into the network was randomly divided across the program into three groups, 128 items (68%) for the training set, 16 items (16%) for both validation set and test set. The data entered for the network were also adapted in the range between 1 and -1 for inputs, and between 0 and 1 for outputs. This is to help speed up training and eliminate the differences between data. The analysis results and discussion are as follows:

Table 8: Inputs Importance

Input column name	Importance %
Q18_B	17.99
Q10_A	15.41
Q33_C	13.67
Q16_B	12.23
Q8_A	9.81
Q24_C	8.93
Q4_A	7.92
Q17_B	7.48
Q13_B	4.41
Q27_C	2.15

Table8 shows the relative importance of the independent variables that have contributed to network training, and their impact on network performance. The impact of these variables is different. Some variables have contributed more than others to the network's learning stage. The highest degree of influence was for factor Q18_B at a rate of 17.99% and the lowest degree of effect was for factor Q18_C at a rate of 15.2%.

Table 9: Networks properties

Parameter	Value
Network architecture	18 – 28 – 3
Input activation FX	Logistic
Output name	GPA
Output error FX	Cross-entropy
Output activation FX	Logistic
Classification model	Winner-takes-all
Training algorithm	Quick Propagation
Iterations	1001

Table9 shows the general characteristics of the MLP network model used for study data. The architecture of the selected network consisted of three fully connected layers (18-28-3), which were determined by the best fitting during the trade-off between different structures. The processing units in these layers were distributed at 18 for the input layer, 28 for hidden and 3 for output, corresponding to the three target variable classes. All functions and statistical criteria used with this network until the training is completed are shown in the table. The network has been trained for 1001 repeated times until it has reached the acceptable level of learning, and the number of such iterations depends on the continuous devaluation of the error criterion accompanying the training process, and when we notice that the error value has slowed or stopped decreasing, then the training process is stopped [18].

Table 10: Network Errors

Absolute Error (AE)				Absolute Relative Error (ARE)			
Training	Validation	Test	All data	Training	Validation	Test	All data
0.034	0.097	0.174	0.063	0.068	0.089	0.539	0.138

Table 10 shows the values of AE and ARE. These criteria measure the quality of neural network training and are calculated based on network errors. The AE value is calculated by subtracting the current output values with the target output values of the network. The ARE value is calculated by dividing the difference between actual and desired output values by the module of the desired output value. In the two criteria, the smaller the network is, the better the network had been trained [21]. We note from the table, these values are small and near zero, with the largest value in the AE criterion being 0.174 corresponding to test data, and the largest value in the ARE criterion was 0.539 also corresponding to test data. It's good network learning.

Table 11: Network Accuracy

Avg training CCR, %	Avg validation CCR, %	Avg test CCR, %
96.09	93.33	90

Table 11 shows the Correct Classification Rate CCR criterion, which is used for classification tasks as a qualitative characteristic. It is calculated by dividing the number of correctly recognized records by the total number of records. It is measured in relative units or in percents ('Alyuda NeuroIntelligence User Manual', 2003). The high values of CCR in both training and validity data indicate the quality of the model, as does the high percentage in test data indicates the predictive capability of the model.

Table 12: Classification Table

		Predicted			
		Prediction			Percentage
Observed		good	fair	poor	Correct
Prediction	good	84	0	0	100
	fair	0	80	7	91.95
	poor	0	3	14	82.35
Overall Percentage					94.68

Table12 shows the percentage of correct classification by the network model for the categories of the target variable. The correct classification of the three categories was: 100% good, 91.95% fair and 82.35% poor. The overall correct percentage was 94.68% for 178 students out of 188 students representing the sample. These ratios are a good indicator of the model's performance and quality in prediction.

6. Conclusions

Ordinal logistic regression model OLR was used in this study to determine the significant factors affecting academic achievement, and then a neural network NN was used to build a model to predict the student's academic status. The results of the tests and statistical criteria of the OLR model are all supportive of the quality and validity of the model. According to the chi-square test in table3, the model is significant. Based on the chi-square test in table4, the model is a well-represented data. According to Wald's test in table7, there are 10 significant variables that affect academic achievement out of 14 variables making up the model. The significant variables are age, cumulative average in high school, the distance of residence, work besides studying, daily study hours, warning due to frequent absences, fear of exams, the economic level of the family, parents divorce, and family follow-up. Performance indicators' values of the neural network model were also supportive of the model's quality and its predictive ability. MLP-NN was used with a three-layer architecture (18-28-3), the network inputs were the significant variables chosen by the logistic model, and its output was the academic status of the student. The correct classification ratio of the three target variable categories, according to the results of the classification tables: good 100%, fair 91.95%, poor 82.35%. The total percentage of correct classification was 94.68%. We can infer from these indicators the quality and accuracy of this model and its highly predictive ability.

Through the performance indicators of the two models, we conclude that the quality of the network model and its predictability efficiency are largely due to the importance of the variables involved in its formation. This confirms the great efficiency of the logistic model in selecting significant variables, as well as the high degree of impact of these variables in predicting academic achievement. These variables are highly dependent on knowledge and prediction of a student's academic status. This combining model can be used as a primary tool for predicting the academic status of a university student. Getting knowledge of the influencing factors and predicting the student's academic status may help addressing some difficulties affecting student's academic achievement.

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