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Predicting Students' Academic Performance Using Neural Network

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ABSTRACT

Improving Students' academic performance has been a major challenge in the Nigerian Educational System, cutting across primary schools, secondary schools and higher institutions of learning. As a result, the need to determine the factors affecting students' academic performance has long been of interest to educational administrators. This study analyzes how factors such as family background, time management, financial management, religious activities, et-cetera, affect a student's performance using a neural network. Data was collected using questionnaire administered in two Nigerian universities-Bells University of Technology and Lagos State University (LASU). A Neural Network (NN) model was designed for predicting the students' academic performance based on the factors identified; a system was then developed that implemented the designed NN model. The Model was trained using 60% of the captured data; 30% was used to test and 10% for validation. The developed system interfaces provided for the display of these results. The model was thereafter used in predicting likely semester GPA of the captured students. From the result obtained, the system accurately predicted 6 out of 7 for the students that exhibited excellent patterns, 17 out of 24 for the students with good patterns, 44 out of 56 for the students with average patterns, 19 out of 20 for the students with fair patterns and 19 out of 19 for the students with poor patterns.

This research emphasizes the fact that different factors affect students in different ways and contributes in determining the students' academic performance.

Keywords: Prediction, Students' Academic Performance, Neural Network, GPA,

1. INTRODUCTION

Students' academic performance has been the subject of ongoing debate among educators, academics, and policy makers and there have been many studies that sought to examine this issue and studies are still ongoing (Hellas et al., 2018; Hijazi & Naqvi, 2006). The ability to predict students' academic performance in a course or program creates opportunities to improve educational outcome. Result from such prediction can be used in diverse ways, for instance, it will allows instructors and institutions allocate resources more accurately to foster better performance; it can be used for identifying student for counseling and close monitoring, used to motivate students and facilitate changes in students study and behavioral patterns, in addition to being applied into an academic pre-warning mechanism (Guo, Zhang, Xu, Shi, & Yang, 2015; Hellas, et al., 2018; Shana & Abdulla, 2015).

In Nigeria, poor academic performance of students has been blamed generally on some socio-economic, psychological and environmental factors and variables. These factors and variable are divers and participate with each other in complicated and nonlinear way, thereby making the student academic performance prediction process challenging (Guo, et al., 2015). How these factors affects students' academic performance is still being studied. This research aims to further this study by designing a neural network model for predicting students' academic performance.

2. REVIEW OF RELATED WORKS

(Uwaifo, 2008) indicated that factors such as student's internal state (intelligence, state of health, motivation, anxiety etc.) and their environment (availability of suitable learning environment, adequacy of educational infrastructure like textbooks and well-equipped laboratories) may be responsible for the declining quality of education in Nigeria. He showed that significant difference exist between students from students from single parent families and those from two-parent families in terms of attitude to examination malpractices, attitude to studies and academic performance. (Hijazi & Naqvi, 2006) quantified the relationship between the different factors that are considered responsible of affecting the students' performance, using private colleges as their case study. A sample of 300 students was taken from a group of colleges. Their research showed that empowerment to mothers on different fronts can lead to better educated society and those students who are with educated mothers are performing well as compared to those who are with illiterate mothers. (Brigman & Campbell, 2003) examined the impact of school-counselor-led interventions on student academic achievement and school success behavior. Their result showed that the combined school counselor intervention of group counseling and classroom guidance has a positive impact on students' academic achievement and behavior. (Sansgiry, Kawatkar, Dutta, & Bhosle, 2004) evaluated factors such as academic competency, test competency, time management, and study strategies, and demographic variables such as age, gender, race, marital status, and year of enrollment. The evaluation was done with the aim of determining the effect of academic progression on academic performance. The research was conducted on a total of 244 pharmacy students at 2 universities. Their result showed effect of academic progression on academic competency, time management, and study strategies, that academic progression may not positively influence academic competency, test competency, time management, and study strategies. From the above reviewed literatures and other (e.g., (Golding & McNamarah, 2005; Harb & El-Shaarawi, 2006; Zaidah & Daliela, 2007), the following factors were identified that can affect students' academic performance. These factors include:

(i) Family Variables (Family background, Father and Mothers' relationship, Parent's educational level, etc.) (Hijazi & Naqvi, 2006; Oladokun, Adebanjo, & Charles-Owaba, 2008; Urién, 2003).
(ii) Learning Infrastructural Variables (equipped library, availability of learning resources, School Counseling and classroom guidance etc.) (Brigman & Campbell, 2003; Uwaifo, 2008).
(iii) Environmental Variables: learning environment, adequate infrastructures, cafeteria, hostel, water, power, sport center, etc.) (Uwaifo, 2008).
(iv) Preferential Variables (Opinion of Program of Study, choice of school, study & learning styles, etc.) (Oladokun, et al., 2008; Sansgiry, et al., 2004; Urién, 2003).
(v) Personal Education Management Variables (Have study times, recreation times, attend lectures regularly, participate in class work, in laboratory works, in assignments, etc.) (Harb & El-Shaarawi, 2006; Sansgiry, et al., 2004).
(vi) Recreation and Social Variables (Relationship with teachers, kind of friend, etc.).
(vii) Educational Background Variables (kind of primary & secondary school education, WAEC and UME results, involvement in exam malpractice, etc.) (Bijayananda & Srinivasan, 2004; Harb & El-Shaarawi, 2006; Oladokun, et al., 2008; Sansgiry, et al., 2004; Urién, 2003).
(viii) Financial Variables (Financial adequacy, personal finance management
(ix) Religious & Conviction Variables (Attend religious services, etc.).

(x) Student's internal State & Health Variables: Intelligence, State of health, motivation, anxiety, etc. (Uwaifo, 2008).
(xi) Demographic Variables: Age, gender, race, marital status, year of enrolment. (Bijayananda & Srinivasan, 2004; Golding & McNamarah, 2005; Oladokun, et al., 2008; Sansgiry, et al., 2004).

Elements of the above identified and considered factors were used in the design of the neural network model. Some researches were neural network have been used for a similar purpose include:

(i) (Oladokun, et al., 2008) : they used neural networks to predicts the academic performance of a candidate being considered for admission into a university using factors based on the Nigerian education system
(ii) (Bijayananda & Srinivasan, 2004): used the neural network technique to classify applicants of Master of Business Administration (MBA) program into successful and marginal student pools based on undergraduate, GMAT scores, undergraduate major, age and other relevant data.
(iii) (Kohli & Puri, 2008) explored the use of neural networks in forecasting the performance of technical colleges in the counseling session before it actually takes place. Their result showed that compared to the other model types (i.e. logistic regression, discriminant analysis and classification and regression trees), using the exact same experimental conditions, neural networks performed significantly better.

The Neural Network

According to (Pattie & Snyder, 1996), neural networks are a right-brained approach to artificial intelligence that recognizes patterns based on previous training; neural networks are motivated by the human brain. According to (Hajek, 2005), a neural network is a massively parallel distributed processor that has a natural propensity for storing experiential knowledge and making it available for use. It resembles the brain in two respects: (i) Knowledge is acquired by the network through a learning process (ii) Interneuron connection strengths known as synaptic weights are used to store the knowledge. (Obe & Shangodoyin, 2010) defined a neural network as an artificial representation of the human brain that tries to simulate its learning process. The applications of neural networks include Pattern Recognition, Prediction, Grouping of elements that follow similar criteria, etc. (Singh & Chauhan, 2009) also stated fraud detection, telecommunications, medicine, marketing, bankruptcy prediction, insurance as some commercial applications of neural networks.

3. MATERIALS AND METHODS

From the review of literatures conducted, a number of factors were identified that affects students' academic performance. These factors, in addition to others served as a guide for developing a research instrument, a well-structured Likert-scale questionnaires, which was administered to students in two Nigerian universities. 19 factors that can affect a student's academic performance, whether positively or negatively, were considered. They include: (i) Opinion of study (that is the student's Major), (ii) Self-Organization and time management (iii) Study and Learning Style (iv) Personal facilities for studying and learning (v) Personal financial management (vi) Personal psychology (vii) Eating and resting (viii) Educational background (ix) Motivation and support (x) Relationships and socials (xi) Personal assessment of lecturers (xii) Educational malpractices (xiii) Personal response to study and lecturers (xiv) Choice of School (xv) Use of the library (xvi) Sporting, hostel and cafeteria facilities (xvii) Health (xviii) Religion and religious activities (xix) Family background. These factors were incorporated into a well-structured questionnaire. The designed Likert scale questionnaire used with the following values: 1 (Very Untrue), 2 (Untrue), 3 (Partly True), 4 (True) and 5 (Very Untrue).

Each factor represents a section in the questionnaire and each section has a number of questions under them. Data was collected from two universities; Bells University of Technology and Lagos State University. Students were required to fill in the questionnaire based on their level of agreement and disagreement. They were also required to fill in their Previous Grade Point Average (GPA) or grant access to it. This was also used as a predictor in a student's academic performance. The data collected was entered into the database implemented using Microsoft Access.

Thereafter, a neural network model was designed for use in predicting student's academic performance based on the factors identified. To allow for interactivity, a system that implements the neural network model was developed using Java. The neural network was trained using a subset of the data gathered. The model was then tested to determine its effectiveness and validity.

3.1 Neural Network Design

The multilayer perceptron with two hidden layers, was used in designing the Neural Network model because of its ability to solve nonlinear problems. The input layer contains twenty processing elements, each representing a factor. The twentieth processing element represents the previous GPA. The two hidden layers both have ten processing elements each while the output layer contains only one processing element Figure 1 is an illustration of the architecture of a multilayer backpropagation Neural Network (BP-NN) with two hidden layers. The Neural network model designed with 20 inputs using this architecture is captured in Figure 2. Figure 3 captures the implementation classes of the developed NN model.

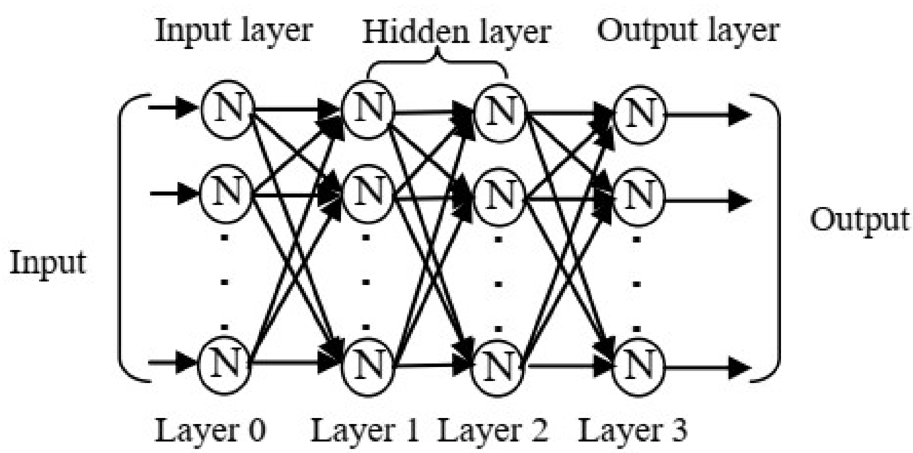

Figure 1: Structure of a two hidden layers BP-NN architecture

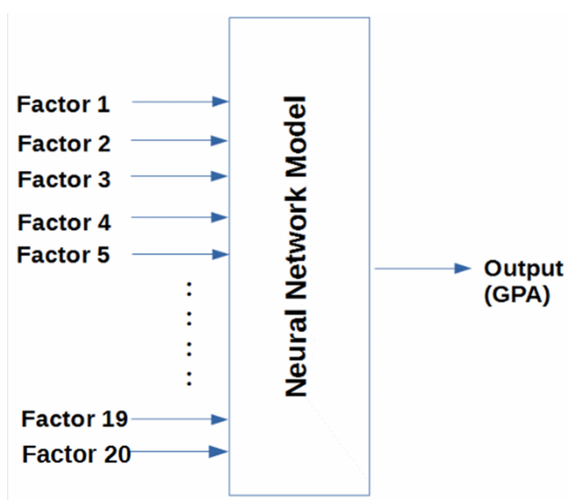

Figure 2: Input-output Schematic of the designed NN model.

The supervised training was chosen for this purpose with the back-propagation error correction as the learning algorithm. The back-propagation algorithm is considered to have converged when the absolute rate of change in the mean squared error per epoch is sufficiently small. Typically, the rate of change in the mean squared error is considered to be small enough if it lies in the range of 0.1 to 1 percent per epoch. The pattern mode of weight initialization was chosen here because it requires less local storage for each synaptic connection. The inputs of the neural network are the factors which represent the sections in the questionnaire. The sections have a number of questions under them.

The neural network analyzes and transforms the data for each section. For a section with n questions:

$$Section = \sum_{i=1}^{n} Optionvalue_i \quad \text{.. 1}$$

Where Option value equals 1,2,3,4 or 5.

The stages involved in the transformation of the data are:

(i) Collection of data
(ii) Inputting the data into the database
(iii) Uploading the data into the neural network based system
(iv) The neural network analyzes the data.

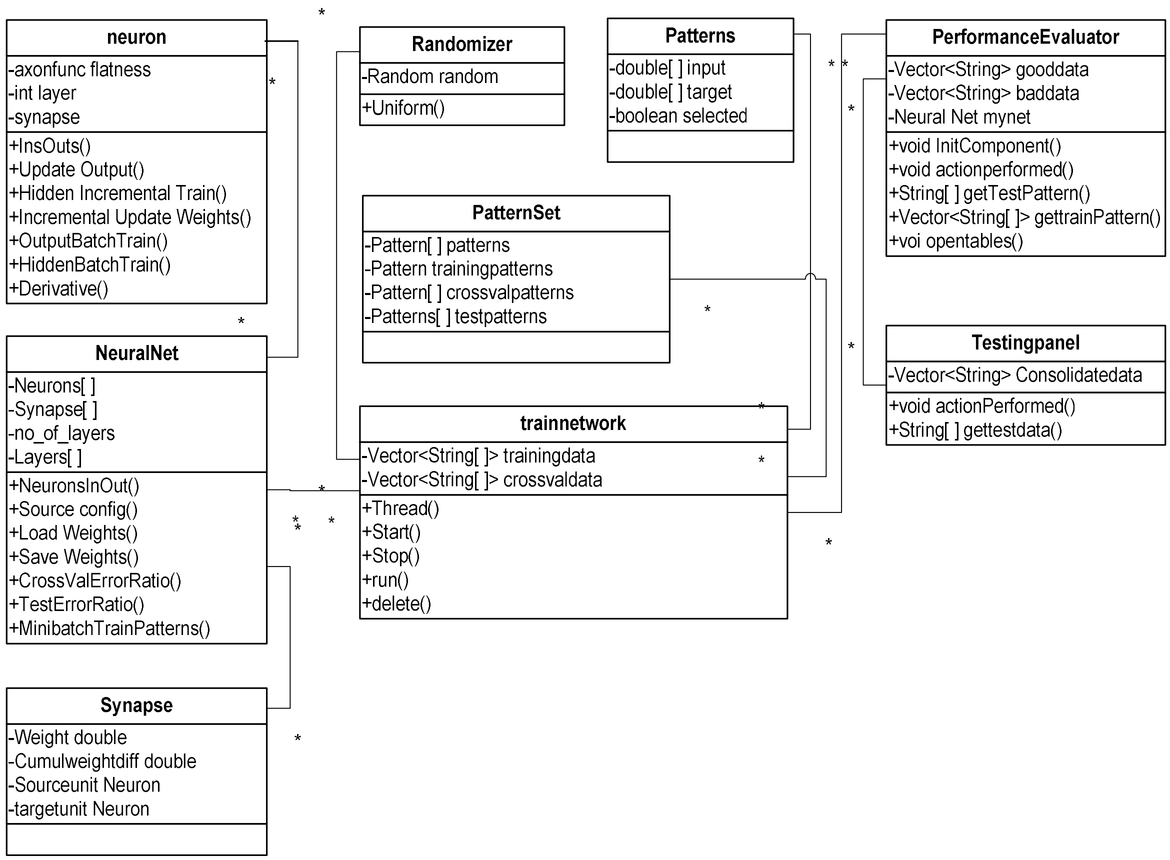

Figure 3: The System implementation classes of the developed Neural Network model

The output variable of the neural network represents the students' GPA at the end of the semester based on the ranges in the table below

Table 1: Result Classification

OUTPUT VARIABLE	GPA
Excellent	4.50 – 5.00
Good	3-50 – 4.49
Average	2.50 – 3.49
Fair	1.30 – 2.49
Poor	0.00 – 1.29

Using tanh activation function on all neurons of the network, the output of each neuron ranges between -1 and +1. Some training set in the training sample has a target value of 0.8 and some -0.8. Once the error at the output layer is at an acceptable level, the test data is fed into the network from the input layer and the output value is derived. The output -0.8 indicates a GPA of 0.00 and 0.8 indicates 5.0.

The corresponding GPA value for the test data is computed on this basis. A total of 422 students data were used in this analysis. 60% of the data (that is about 253 students) was used as the training set, 30% (about 126 students) was used as the testing set and 10% (42 students) was used as for cross validation.

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3.2 Neural Network-Based System Design

The Neural Network based system was designed using the following tools:

- Java
- Microsoft Access
- Computer System with Windows Vista Operating System

The architecture of the system is shown in Figure 4.

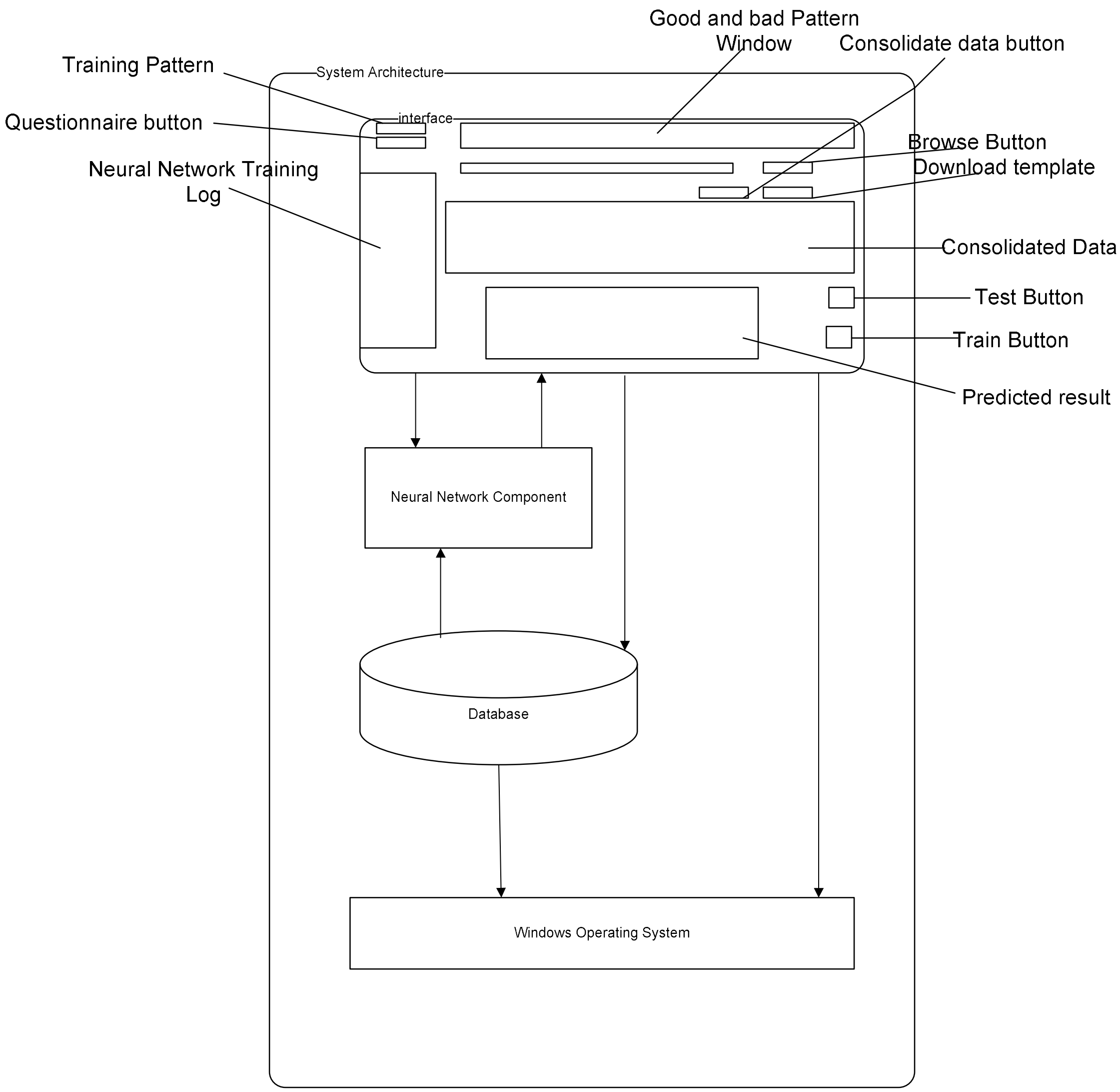

Figure 4: Neural Network Based System architecture.

3.2.1 The Interface

This is the point of communication between the user of the system and Neural Network based system. It was designed using Java and used to load data from the database into the neural network component.

3.2.2. The Neural Network Component

This component performs the Neural Network functions. Data was inputted via the user interface and it makes predictions based on the fed data. The result of the prediction is displayed on the user interface.

3.2.3 The Database

Microsoft Access was used in the implementation of the database used for the Neural Network processing and analysis. It serves as the database for the neural network. The class diagram for the database is shown in Figure 5.

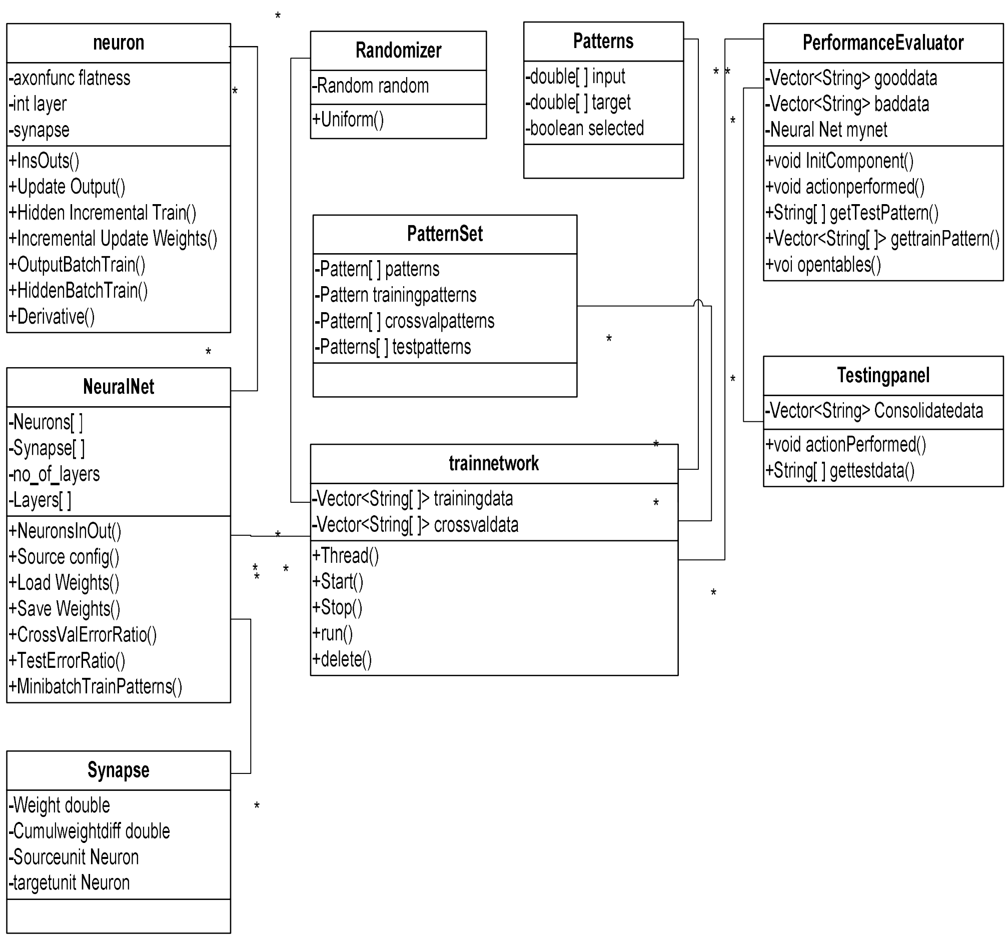

Figure 5: The Class Diagram for the Database Design

The class diagram shows the static structure of the classes in the system and how the classes are related to each other.

3.3 Training the Neural Network

Supervised Back propagation training algorithm was used to train the neural network because of its effectiveness towards pattern recognition. Training set comprise a portion of the data gathered. A training sample is a pair of input vector plus a desired output value (0.8 or -0.8). The network was provided with the training set and allowing it to learn by adjusting weights of its synapses using back propagation.

The algorithm is given below.

1. Identify number of input neurons (same as number of elements in the input vector)
2. Identify number of hidden layers and number of neurons on each layer. (Minimum required for back propagation is one hidden layer but for faster training we used two hidden layers with 10 neurons each).
3. Identify number of output neurons. We used one neuron on the output layer because we have one target value.
4. Initialize random weight values for the synapses connecting each neurons of preceding layer to the next layer. With backpropagation, weight values should be restricted to between -0.5 and +0.5.
5. Choose a random training set from the training sample and assign input vector to the input neurons.
6. Propagate all neurons in the forward direction to obtain output at the output layer.
   a. The output of each neuron is a function of its inputs. In particular, the output of the ***j*** th neuron in any layer is described by two sets of equations on the right:

$$U_j = \sum (X_i * w_{ij}) \quad \text{.. 2}$$

   b. For every neuron, ***j***, in a layer, each of the *i* *th* inputs, X_i, to that layer is multiplied by a previously established weight, w_{ij}. These are all summed together, resulting in the internal value of this operation, U_j. This value is then biased by a previously established threshold value, t_j, and sent through an activation function, F_{th} (tanh function).

$$Y_j = F_{th}(U_j + t_j) \quad \text{.. 3}$$

   c. The resulting output, Y_j, is an input to the next layer or it is a response of the neural network if it is the last layer.
7. Evaluate error values at the output neuron as the difference between obtained output and the desired output of the training set chosen.
8. Back-propagate the error, all the way up to the input layer.
   a. Backpropagation starts from the output layer with the following equation:

$$w_{ij} = w'_{ij} + LR * e_j * X_i \quad \text{....................................4}$$

   b. For the input of neuron in the output layer, the weight ***w*** is adjusted by adding to the previous weight value, w'_{ij}, a term determined by the product of a *learning rate*, ***LR***, an error term, e_j, and the value of the input, X_i. The error term, e_j, for the output neuron is determined by the product of the actual output, Y_j, its complement, $1 - Y_j$, and the difference between the desired output, d_j, and the actual output.

$$e_j = Y_j * (1 - Y_j) * (d_j - Y_j) \quad \text{...5}$$

9. Calculate and update weight values for all synapses such that the sum squared value of the error is minimized.
   a. Once the error term is computed and weights are adjusted for the output layer, the values are recorded and the next layer back is adjusted. A **revised weight adjustment process** was adopted for updating the weights following the equation below.

$$w_{ij} = w'_{ij} + (1 - M) * LR * e_j * X_j + M * (w'_{ij} - w''_{ij}) \quad \text{..............6}$$

   Momentum (M) basically allows a change to the weights to persist for a number of adjustment cycles. The magnitude of the persistence is controlled by the momentum factor. If the momentum factor is set to 0, then the equation reduces to that used to adjust the weight of the output layer. If the momentum factor is increased from 0, increasingly greater persistence of previous adjustments is allowed in modifying the current adjustment. This can improve the learning rate in some situations, by helping to smooth out unusual conditions in the training set.

   b. The error term is generated by a slightly modified version of the Equation in steps 9 above. This modification is:

$$e_j = Y_j * (1 - Y_j) * \sum (e_k * w'_{jk}) \quad \text{.. 7}$$

10. Choose another random training set from the training sample and repeat the steps above.
11. Train all training set in the training sample in a random selection order. A cycle through the training sample is called an epoch.
12. Stopping criterion is until the error obtained at the output layer is at an acceptable value. (0.05)

An activation function is used to obtain output from each neuron. Tangential Activation function was adopted. The equation is:

Y=tanh(X)………………………………………………………………………………….. 8

The flowchart below show how the neural network will work is shown in Figure 6.

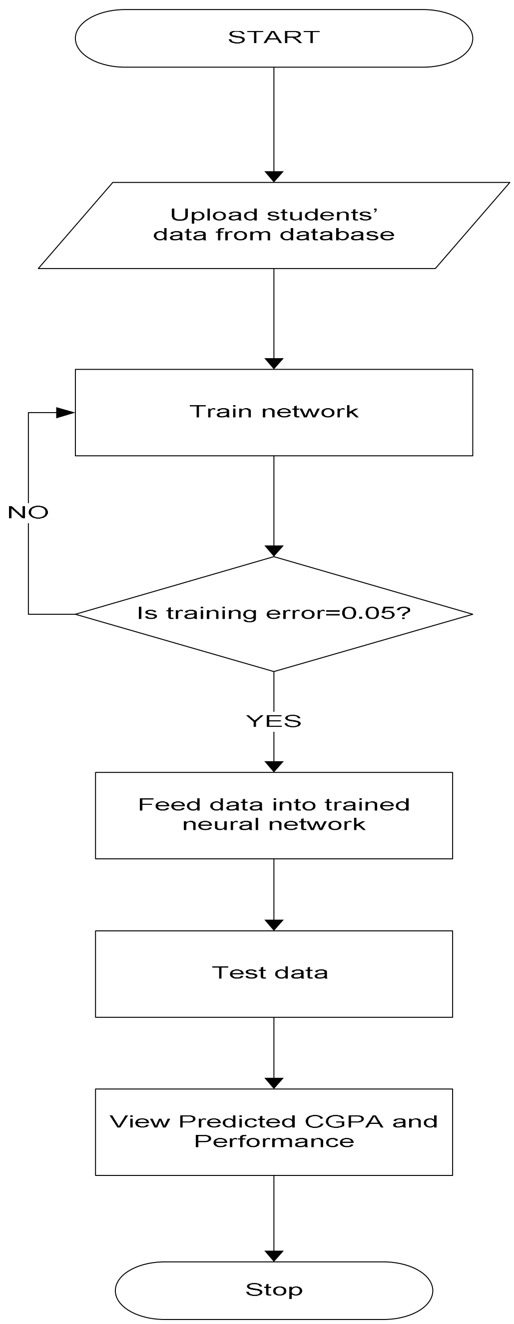

Figure 6: A Flowchart showing the computational stages of the Neural Network

3.4 Testing the Neural Network

The test data were used to test the network and this involves giving 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.

4. RESULT AND DISCUSSION

4.1 The System Interface

Screen shots of Figure 7, Figure 8 and Figure 9 show different views of the System built for using and displaying the result of the Neural Network model. Figure 7 is the main system interface used for displaying results of training, predicting and for data uploading. Figure 8 captures the interface showing the Training Pattern Button (for good and bad patterns), while Figure 9 is the interface for entering data from the Questionnaire.

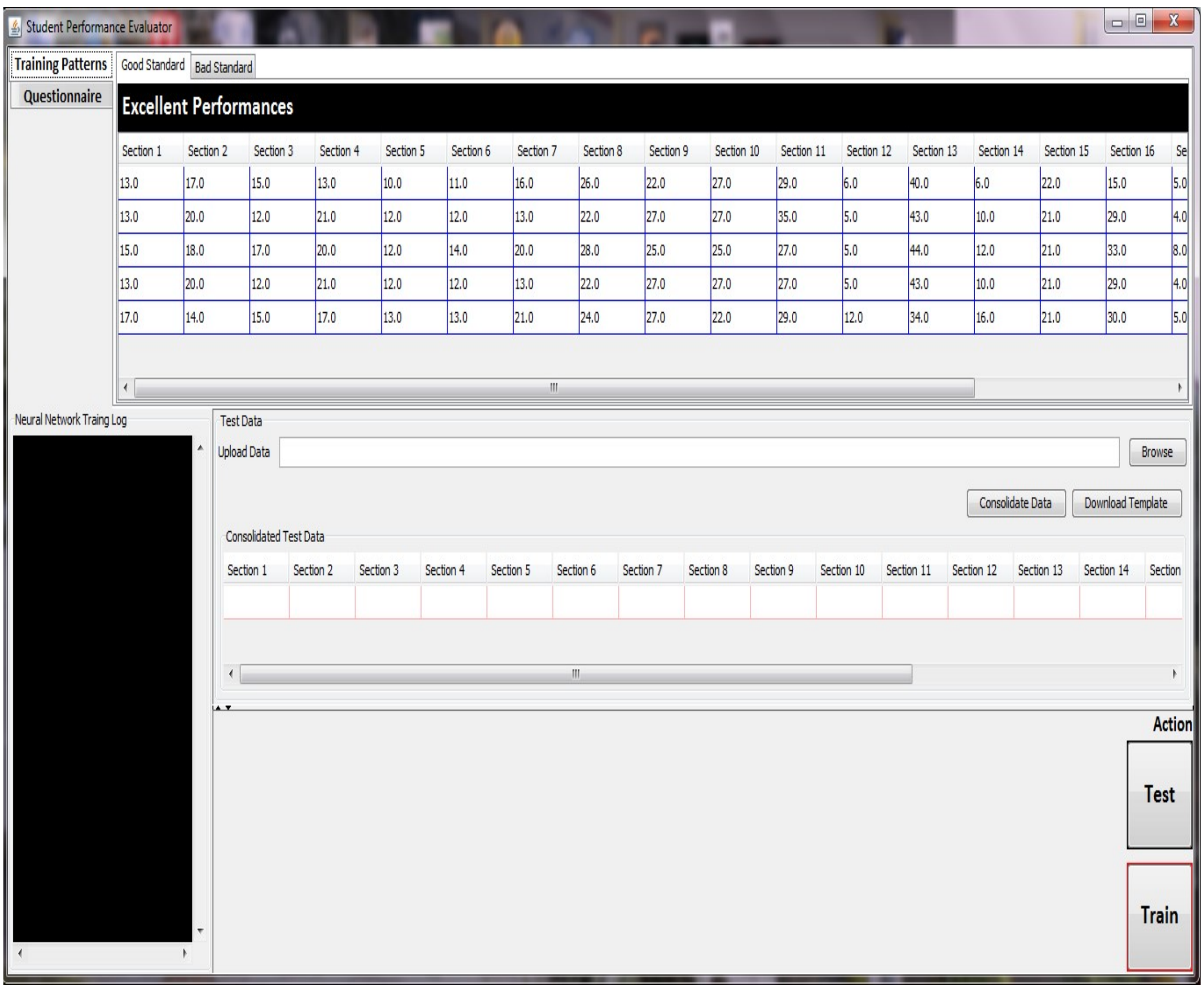

Figure 7: The Main System Interface.

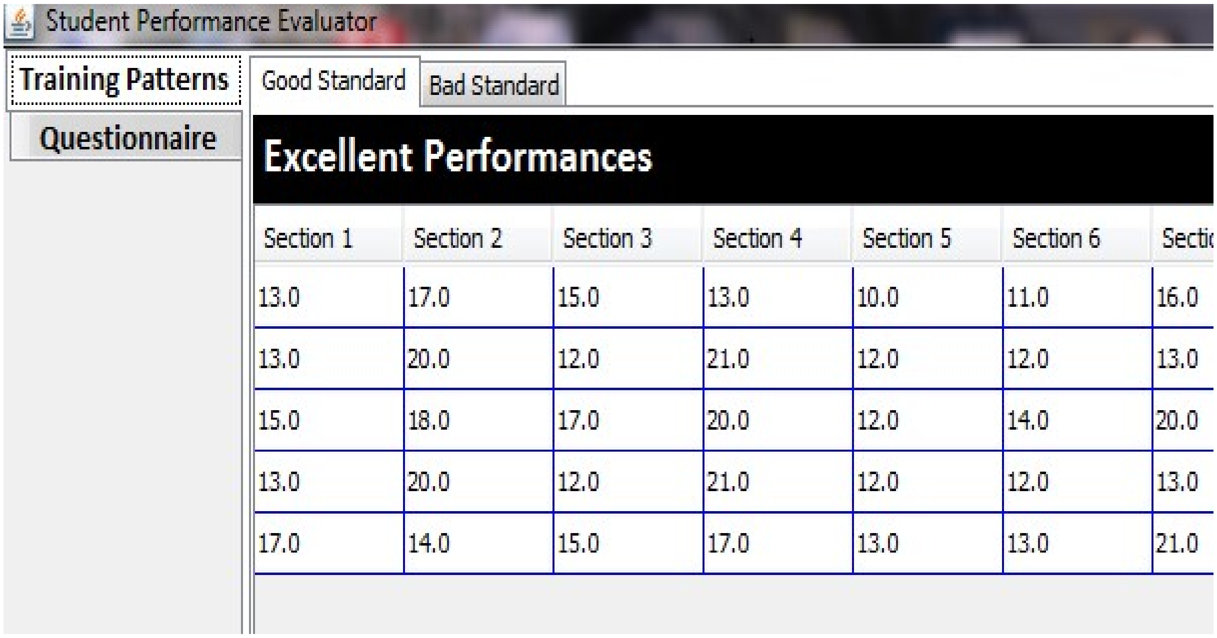

Figure 8: Interface showing the Training Pattern Button (for good and bad patterns)

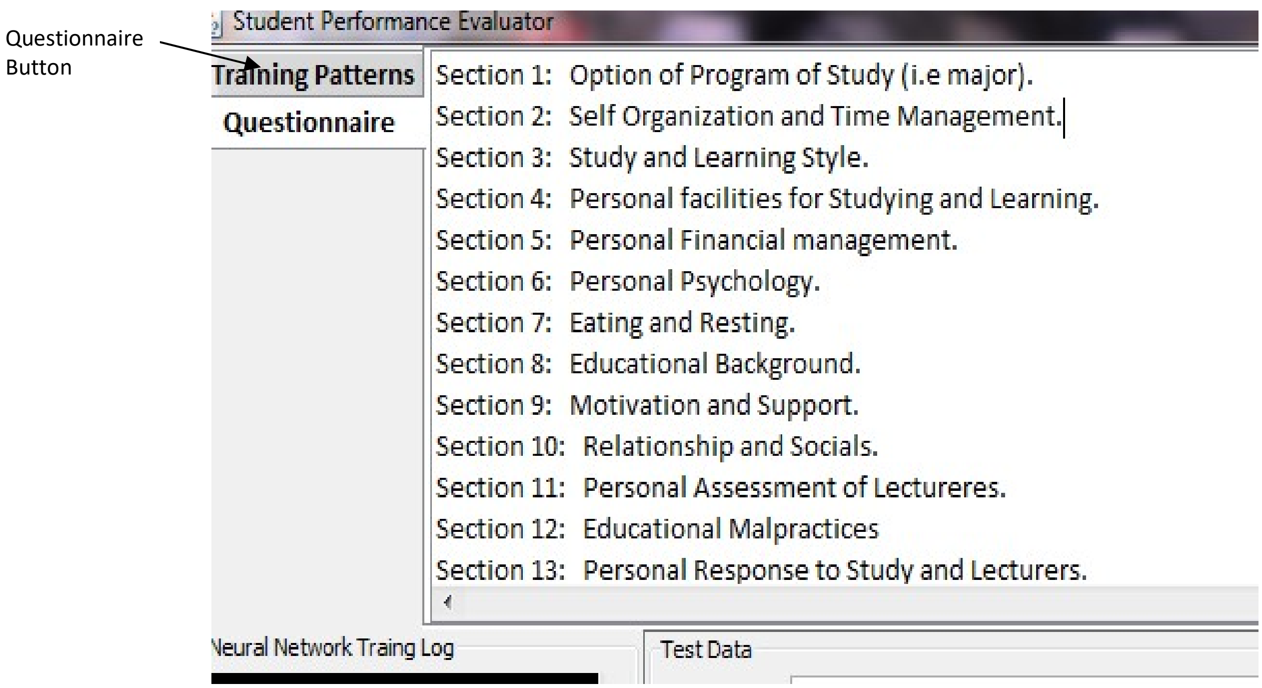

Figure 9: Interface for entering data from the Questionnaire.

4.2. Result

126 students' data (30% of the total data) was used to test the neural network. The predicted GPA is then compared to the previous GPA using the patterns used in designing the network. From our result, the neural network was able to predict 6 out of 7 for the students that exhibited excellent patterns, 17 out of 24 for the students with good patterns, 44 out of 56 for the students with average patterns, 19 out of 20 for the students with fair patterns and 19 out of 19 for the students with poor patterns correctly. The predicted results are shown in Appendix A and is based on answers provided in the questionnaire by each student.

5. CONCLUSION

This study analyzed how factors such as family background, time management, financial management, religious activities, et-cetera, affect a student's performance using a neural network and emphasizes the fact that different factors affect students in different ways and contribute in determining the students' academic performance. Unrealistic value obtained in the prediction in some instances could be due to insincere information obtained from students. A way of obtaining honest information from the student, without them being scared of being witch-hunted afterwards needs to be deduced.

However, the following limitation were noted regarding the research: (i) the result of the prediction could not be verified using the actual students' performance because the GPA for the current semester when the research was done was not available as at the conclusion of the research. The previous GPA was used instead (ii). The time for concluding the work was limited.

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APPENDIX A: Prediction Results

ID	Previous GPA	Predicted GPA	Performance
1	2.81	1.89	Fair
2	3.38	1.17	Poor
3	4.51	4.64	Excellent
4	4.43	4.25	Good
5	3.32	0.59	Poor
6	3.52	0.26	Poor
7	4.28	3.4	Average
8	3.88	1.04	Poor
9	1.48	0	Poor
10	3.6	3.08	Average
11	4.36	3.15	Average
12	3.83	3.82	Good
13	1.73	0	Poor
14	2.41	0	Poor
15	2.74	0.36	Poor
16	3.44	4.45	Good
17	3.62	3.12	Average
18	2.57	0.51	Poor
19	2.16	0	Poor
20	3.92	4.78	Excellent
21	2.94	1.9	Fair
22	2.59	1.05	Poor
23	3.04	2.18	Fair
24	1.94	0.16	Poor
25	3.54	4.25	Good
26	2.24	0	Poor
27	2.02	0	Poor
28	2.88	1.13	Poor
29	3.27	0.28	Poor
30	1.96	0	Poor
31	3.15	1.62	Fair
32	3.52	1.03	Poor
33	2.81	0.39	Poor
34	3.88	3.08	Average
35	3.38	1.34	Fair

ID	Previous GPA	Predicted GPA	Performance
36	4.22	4.64	Excellent
37	3.55	3.09	Average
38	3.23	3.68	Average
39	3.86	1.94	Fair
40	3.59	3.22	Average
41	3.76	3.57	Average
42	4.21	4.62	Excellent
43	3.54	3.04	Average
44	3.85	1.62	Fair
45	3.65	4.2	Good
46	4	4.82	Excellent
47	2.94	2.88	Average
48	3.89	4.26	Good
49	3.63	5	Excellent
50	4.35	5	Excellent
51	2.89	2.09	Fair
52	2.85	1.26	Fair
53	3.54	4.02	Good
54	3.65	4.34	Good
55	2.5	2.36	Fair
56	3.64	3.34	Average
57	2.75	4.17	Good
58	3.2	3.45	Average
59	4.25	0.47	Poor
60	4.3	4.25	Good
61	4.52	1.17	Poor
62	2.85	4.64	Excellent
63	3.51	4.25	Good
64	2.5	0.59	Poor
65	3.6	0.26	Poor
66	3.18	3.4	Average
67	3.21	1.04	Poor
68	3.59	0	Poor
69	2.59	3.08	Average
70	4.12	3.15	Average

ID	Previous GPA	Predicted GPA	Performance
71	3.98	3.82	Good
72	2.92	0	Poor
73	4.24	0	Poor
74	2.85	0.36	Poor
75	3.58	4.45	Good
76	3.5	3.12	Average
77	4.28	0.51	Poor
78	4.21	0	Poor
79		4.78	Excellent
80	2.85	1.9	Fair
81	4.52	1.05	Poor
82	4.25	2.18	Fair
83		0.16	Poor
84	4.25	4.25	Good
85	3.46	0	Poor
86	3.85	0	Poor
87	2.98	1.13	Poor
88	2.43	0.28	Poor
89	4.54	0	Poor
90	3.34	1.62	Fair
91	3.2	1.03	Poor
92	4.69	0.39	Poor
93	3.82	3.08	Average
94	3.67	1.34	Fair
95	3.98	4.64	Excellent
96	3.51	3.09	Average
97	3.56	3.68	Average
98	3.2	1.94	Fair
99	3.48	3.22	Average
100	4.62	3.57	Average

ID	Previous GPA	Predicted GPA	Performance
101	3.52	4.62	Excellent
102	3.98	3.04	Average
103	4.25	1.62	Fair
104	2.5	4.2	Good
105	3.21	4.82	Excellent
106	4.12	2.88	Average
107	4.5	4.26	Good
108	3.12	5	Excellent
109	4.62	5	Excellent
110	4.38	2.09	Fair
111	3.21	1.26	Fair
112	4.49	4.02	Good
113	3.13	4.34	Good
114	3.12	2.36	Fair
115	3.62	3.34	Average
116	3.75	4.17	Good
117	3.78	3.45	Average
118	3.64	2.87	Average
119	3.82	3.43	Average
120	2.87	3.61	Average
121	3.58	2.79	Average
122	3.27	3.26	Average
123	3.99	2.56	Average
124	3.98	3.54	Average
125	2.56	3.42	Average
126	3.67	2.96	Average