International Journal of Multidisciplinary Research and Development
www.allsubjectjournal.com
Online ISSN: 2349-4182, Print ISSN: 2349-5979, Impact Factor: RJIF 5.72
Received: 23-02-2021, Accepted: 24-03-2021, Published: 29-04-2021
Volume 8, Issue 4, 2021, Page No. 120-128

Adaptive neuro-fuzzy modelling and prediction of academic performance of online distance learners in the era of covid-19

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Abstract

The recent new normal occasioned by the outbreak of Covid-19 pandemic has brought online distance education system to limelight because it is one major protocol to containing the impact and spread of the deadly disease since it completely averts physical gathering. In this trend, monitoring and predicting learner's academic performance (LAP) becomes highly imperative so as to pay adequate attention to pertinent areas where necessary adjustments should be made concerning the learner's academic progression. Unlike the conventional mode of education, doing these is herculean task, therefore, this study developed a system that can efficiently predict LAP through Adaptive Neuro-Fuzzy Inference System (ANFIS) implemented on MATLAB 18.0 interface. Following the standard procedures, the structure of ANFIS model was optimized and utilized to predict the Cumulative Grade Point Average (CGPA) of learners. ANFIS-models were further used to investigate the interactions among the input variables and the corresponding effects on outputs, CGPA. Results showed accuracies of ANFIS-models based on the values of root-mean-square-errors (RMSE). Values obtained for RMSE ranged from 0.7999 to 28.6560 for all the ANFIS-models developed while the optimal model, ANFIS-Gaussmf, accurately predicted the LAP because it had the least RMSE value of 0.7999 at 100 epochs. Also, CGPA was found to depend majorly on the varying inputs in forms of scores in examination as direct proportional relationship was observed. T-test conducted to determine any significant difference between the collected and predicted data recorded p-value of 0.084, thus, signifying efficiency of the developed model. This study has established ANFIS-model to be a very reliable tool for prediction of LAP so as to ensure excellent results even on completion of study.

Keywords: ANFIS, prediction, modelling, CGPA

Introduction

Academic performance and the quality of candidates admitted into any higher institution affect the level of research and training within the institution, and by extension, on the overall nation's development, because these candidates eventually become key players in affairs of governance and economy of any nation (Oladokun, *et al.*, 2008) [16]. The recent new normal occasioned by the outbreak of Covid-19 pandemic has brought the distance education system to limelight such that it has become a popular and important concept in most countries due to the accompanying advantages (Zouhaier, 2020; Milena, 2020) [24, 14]. Online distance learning is one major Covid-19 protocol to containing the impact and spread of the deadly disease because it gives room for safe distance and averts physical gathering. Besides, it can be availed at any time at the learner's own convenience by logging in to access the courses (Colchester, *et al.*, 2017) [7]. It can share and offer teaching-learning materials in diverse formats such as slideshows, audios, videos, PDFs, e-mails, word documents and so on. Webinars and direct communications with tutors via various chat forums or messaging is also an open option in online learning process. Asides these, it also offers free access to certain e-manuals inform of PDF files while providing clear, easy, gradual instructions for better understanding of the learners. It is often regarded as the most suitable way for self-learning because it provides a wide range of materials for the learners that covers almost all topics and doubts (Bajaj and Sharma, 2018) [6]. Online distance education often provides an avenue for tutors to teach from, and the learners to learn at the comfort of their location across the world. This mode of learning is termed virtual learning also known as learning management system which is a platform for operation, where all the practices peculiar to the conventional mode (face-to-face) of learning are also in place and implemented, such as admission process, teaching, learning, classroom activities, quizzes, assignments, forum and various practical (Latah, 2016; Yildiz, *et al.*, 2014; Wolff, *et al.*, 2013) [13, 23, 22]. Other activities possible on the learning management system are marking and scoring, tracking of learners' academic records, regulation and moderation of the classes, etc. The learning management system, LMS is configured to be informative and interactive and ability to navigate it varies from individuals, depending on the role given, such as administrative, tutor, and learner rights. With this, just as in the conventional mode, there are limitations to where individuals can navigate through on the learning management system. According to Goga, *et al.*, (2015) [8] conventional educational systems enable the tutor to directly monitor the learner in the class environment and thus to take necessary precautions as a result of such observations.

However, unlike conventional education, the tutor does not see the learners face-to-face and cannot observe learner during distance education, meanwhile, lack of observation, considered a disadvantage for distance education, can be transformed into an advantage by analyzing the logs kept in the learning management system because LMS keeps logs of all learner-related activities (Yildiz, *et al.*, 2014; Huang, *et al.*, 2010) [23, 9]. During the last few years, the application of artificial intelligence in education has grown exponentially, spurred by the fact that it allows for new discovery, interesting and useful knowledge about learners and the world large (Naser, *et al.*, 2015) [15]. Application of artificial intelligence in educational settings is an emerging discipline, concerned with developing methods for exploring the unique types of data that come from educational context. While traditional database queries can only answer questions such as "*find the learners who failed the examinations*", data mining can provide answers to more abstract questions such as "*find the learners who will possibly succeed the examinations*" (Quang and Jeng-Fung, 2013) [18]. One of the key areas of the application of artificial intelligence is the development of learner models that would predict learner characteristics or performances in their educational pursuits (Shahiri and Husain, 2015) [20]. Hence, researchers have been investigating various data mining methods to assist educators towards evaluating and improving the structure of their course content as well as monitor the academic performance of learners (Ioannis, *et al.,* 2012) [11]. Accurate prediction of learner academic performance using artificial intelligence such as adaptive-neuro fuzzy inference system, ANFIS, artificial neural network, ANN, minitab, design expert, DX among others is useful in many different contexts of educational environments (Undavia, *et al.,* 2014) [21]. Candidates offered admission to study a particular course via an online distance platform, can have accurate predictions of their academic performance and this will assist them on the need to prepare ahead of examination in order to come out successfully. Failure to adequately prepare for examination may result in an unsuitable result. Since the quality of an educational institution is mainly reflected in its research and training, thus, quality of admitted candidates affects the quality level of an institution. Accurate prediction enables educational managers to improve learner academic performance by offering learners additional support such as customized assistance and tutoring resources (Colchester, *et al.,* 2017) [7]. Online distance learning education gives room for learners to be engaged in series of activities such as working, performing house chores, and a number of others which if not guided can always make learners go off concentration and this may have negative impact on their level of academic performance on semester grade point average (GPA) bases and by extension the cumulative grade point average (CGPA). Despite the level of previous studies in this area, there is still paucity of information on the use of artificial intelligence especially adaptive neuro-fuzzy inference system, ANFIS, for academic performance during this era of Covid–19, thus, it therefore becomes necessary to develop an intelligent system that is capable of assisting both the learners and school management in predicting academic performance. This promises to guide the learners in preparing for future semester examinations and inform them the minimum grades required for having desired CGPA.

Methodology

Consequent upon extensive search of the literature and leveraging on experts' opinions especially as it relates to learner's academic performance, a number of socio-economic, biological, environmental, academic, and other related factors that are considered to have influence on the performance of a university learner were identified. Consent and permission of the Institute for Open and Distance Learning Education, LAUTECH, Ogbomoso, Nigeria were sought for which led to the release of the data used for this research, since secondary data was necessary. The data collected were basically for 100 level learners since the target of coming out with good final CGPA at the end of the programme is dependent on the performances from the beginning of the programme. It is worthy to note that, the data collected cut across the general courses that the institute offer at 100 level and for the sake of confidentiality and not to infringe on privacy of the learners/institute, the names of the learners whose sessional results were cropped were not released along with the data. These included the results of four previous academic sessions, specifically the semesters' results in terms of grades for Mathematics, Physics, Biology, Chemistry and Computer Science. Also premise upon these, the respective candidate's CGPA was calculated, since it was the targeted output. These data were carefully studied and harmonized into a manageable number suitable for computer coding within the context of ANFIS modelling interface. These influencing factors were further categorized as input/output variables, and the factors were then transformed into a format suitable for ANFIS modelling, optimization and analysis.

ANFIS Theory

ANFIS is a Sugeno-type multilayer feed forward network that maps connections between the input–output data via a learning algorithm to adjust the parameters of the fuzzy inference system (Arora and Saini, 2013) [3]. ANFIS technique is fundamentally a fuzzy logic (FL) system where its parameters are optimized through neural network training. This adaptive technique benefits from the learning ability of Artificial Neural Network, ANN in order to determine the rules and membership functions of the FL system (Altaher, and BaRukab, 2017) [1]. The main reason here is to construct a network for achieving desired nonlinear mapping that is arranged by the set of data and that is made up of several input–output pairs of the target system, the data set utilized is referred to as training data. The procedure that occurs during training, which is known as data learning algorithm is the adjustment of parameters for performance improvement of the network (Ikuomola and Arowolo, 2012) [10]. In order to verify the generalization strength of the developed model, a test data set which had not been used in the training process was introduced to the system. The structure of ANFIS is composed of 5 layers as presented in model architecture shown in Figure 1. The two inputs (x, y) of the system are presented (ANFIS supports multiple inputs but single output systems). In Figure 1, square nodes (adaptive nodes) demonstrate that the parameters in these nodes are adjustable, to be learned, while the circle nodes (fixed nodes) demonstrate they are fixed

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Rule 1: If x is A_1 and y is B_1, then

$$f_1 = p_1 x + q_1 x + r_1 \qquad (1)$$

Rule 2: If x is A_2 and y is B_2, then

$$f_2 = p_2 x + q_2 x + r_2 \qquad (2)$$

ANFIS Modelling

ANFIS modelling required the use of existing data which prompted the data collected from the educational institute. In such modelling, there was need for specifying the pertinent factors that influence learner academic performance. Such data are referred to as the input variables while the targeted outcome is known as the output variable. It is worthy to note that, ANFIS model can only yield just an output, this suggested its suitability for this research, because the only output required was the CGPA. Input/ output mapping are as presented in the following sub-sections. ANFIS model for prediction of learner's academic performance was implemented in MATLAB (R2018a) interface.

The Input Variables

The input variables selected are those which can easily be obtained from the data collected, as scores/grades were as a result of learners' efforts, while CGPAs were calculated. Therefore, input variables are: Mathematics, Physics, Biology, Chemistry and Computer Science. Table 1.

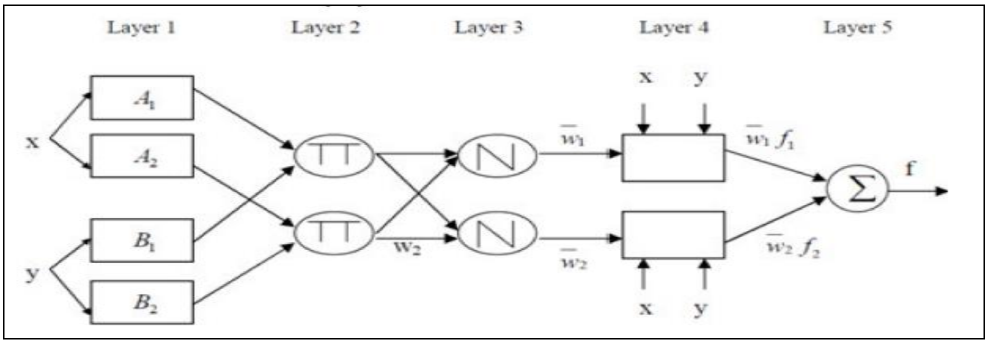


Fig 1: Model Architecture

The Output Variable

The output variable on the other hand represented the CGPA of learners which is in line with the levels of performance of a candidate in terms of the present school grading system. The CGPA was considered the premise for academic performance (See Table 2).

Classification of Output Variables

The classification of output variable domain is presented in Table 2, i.e., 1st class as 'distinction', 2nd class upper as 'good', 2nd class lower as 'average' while 3rd class and pass were 'poor'. This followed the practice of classifying candidates into these domains by the higher institution's grading system.

The Data Set Grouping

In supervised training, the data is divided into 3 categories; the training set, verification set and the testing set. The training set enables the system to observe relationships between input data and resulting outputs, so that it can model the relationship between input and expected output. A heuristic stated that the number of 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 (Bajaj and Sharma, 2018) [6]. Thus, the data collected was categorized into 3 such that 56%, 30% and 14% were implemented for training set, testing set and the validation set respectively.

ANFIS Model Prediction and Performance Evaluation

The membership functions, MFs used for fuzzification of input variables are; triangular MF (Trimf), Trapezium MF (Trapmf), Gaussian-bell MF (Gbellmf) and Gaussian MF (Gaussmf) respectively, and hybrid algorithm was selected for the learning method of input–output data of the process. After this, simulation study was conducted on the developed ANFIS architectures at different MFs for inputs and outputs, and the epoch numbers were studied to establish the best combination so that optimal model among all can be embraced. Root mean square errors, RMSEs of the generated models were respectively used as the bases for choosing the best model. Also the reliability of the models was evaluated through the coefficient of correlation, R-values obtained by statistically comparing the collected data and predicted data.

Comparison of Predicted and Cropped GPAs

In furtherance of validation, statistical package for social sciences, SPSS 20.0 version was used to be carry out T-test analysis, in order to statistically compare the results with a view to determining whether there were significant differences between the predicted CGPAs and the cropped CGPAs at the significance benchmark of $p \leq 0.05$.

Table 1: Details of Input and Output

S/N	Input Variables
1.	Mathematics
2.	Physics
3.	Biology
4.	Chemistry
5.	Computer Science
S/N	Output Variable
1.	CGPA

Table 2: Classification of Output Variables

S/N	Output Variable	Honors	CGPA
1.	Distinction	1st Class	4.50 – 5.00
2.	Good	2nd Class Upper	3.50 – 4.49
3.	Average	2nd Class Lower	2.40 – 3.49
4.	Poor	3rd Class	1.50 – 2.39
5.	Poor	Pass	1.00 – 1.49

Results and Discussion

Results of ANFIS-Models Developments

Four membership functions in respect of the input variables were used, these are; Trimf, Trapmf, Gbellmf and Gaussmf, for training the system while the output membership functions, constant and linear were tested against those of the inputs respectively so as to determine the one with least root mean square error (See Figure 2). The combination of these were used to generate the following ANFIS models such as; ANFIS-Trimf, ANFIS-Trapmf, ANFIS-Gbellmf and ANFIS-Guassmf respectively for both the constant and linear output membership functions. The ANFIS models were trained using the training data subset, (Figures 3 and 4) while the test data subset (Figure 5) was used to evaluate the prediction accuracy of the trained ANFIS models. The accuracy of each model was a factor of the average root mean square errors, RMSEs for both the training and testing data, upon which the optimal model was determined, these are shown Table 2. Figure 6 shows the reasoning procedure for a first order Sugeno fuzzy model. Each rule has a crisp output and the overall output is a weighted average (Figure 7). The ANFIS structure utilizes fuzzy clustering of the input and output data sets as well as the various membership functions (MFs) used. Thus, the number of rules equals to the number of output clusters. The equivalent rule viewer of the system is shown in Figure 8 while ANFIS model structure showing the interaction between input variables with the corresponding linguistics variables and the output membership function is shown in Figure 9.

ANFIS Models Performances and Evaluation

Table 3 shows the root mean square error values for the respective ANFIS-models developed. Considering the values as presented in the Table 3, it could be observed that, there are significant variations in terms of performance, reasons not unconnected to the type of membership function in use. Membership functions, MF are more or less the thinking faculty of the models, mode of thinking is dependent on the type of MF selected, so variations are acceptable. From Table 3, the testing root mean square error, RMSE obtained ranged from 0.7999 to 28.6560 for all the ANFIS-models developed. The accuracy of any ANFIS-model is evaluated based on the RMSE value (especially the average test error) as the lower the value the higher the accuracy of prediction (Altujjar, *et al.*, 2016) [2], hence, the optimal model ANFIS- Gaussmf (constant), accurately predicted the learner's academic performance because it had the least RMSE value of 0.7999 at 100 epochs. ANFIS-Trimf, followed with RMSE value of 1.0639 (constant), ANFIS-Gbellmf, 1.3305 (constant), ANFIS-Trapmf, 1.7441 (constant), ANFIS-Trapmf, 17.9196 (linear), ANFIS-Gbellmf, 25.9859 (linear), ANFIS-Trimf, 26.8848 (linear), and lastly, ANFIS-Gaussmf, 28.6560 (linear) reported the highest value of RMSE. In comparison and at the over all, it could be observed that non among the ANFIS-models developed with linear membership function selected for output had suitable root mean square error, unlike those with constant membership function selected for output. By implication, except that of ANFIS- Gaussmf (constant) with is optimally suitable, all others turned out to have huge inaccuracies and thus making them less inappropriate to be used for prediction of learner's academic performance. These results and interpretations technically match with those obtained for similar previous studies (Asif, *et al.*, 2017; Badr, *et al.*, 2016; Kolo, *et al.*, 2015; Ruby and David, 2014; Osmanbegovic, *et al.*, 2014) [4, 5, 12, 19, 17]. The three dimensional, 3D view of the input variables interactions are presented in Figures 10 to 13. These show the effects of the variables on one another relative to the output values. Results obtained, further showed that ANFIS can be used as a reliable tool for modelling and prediction of learner academic performance. The R-value obtained at 95% confidence level for the regression analysis to determine the relationship between the input and put variables 0.9886, thus, signifying strong correlation between the input and output variables. This justified the direct proportional relationship observed in the trend of the data, such that the higher the scores obtained in each course, the higher the CGPA becomes. The result of t-test conducted to determine any significant difference between the set of experimental (collected data) and predicted values gave p-value of 0.084, which by implication means there were no significant differences between the set of data, because the p-value obtained was greater than 0.05. This result further suggested the efficiency of the ANFIS model.

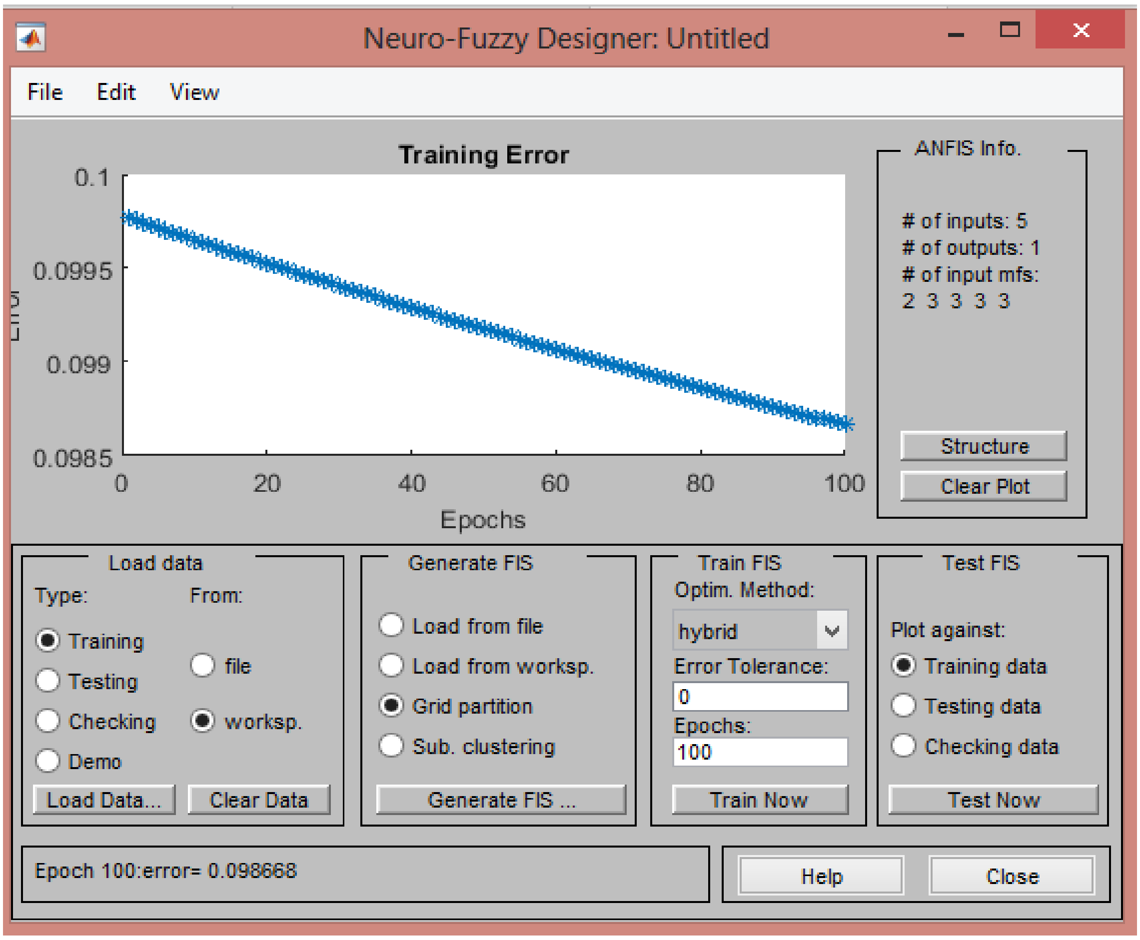


Fig 2: Input and output membership functions selection interface

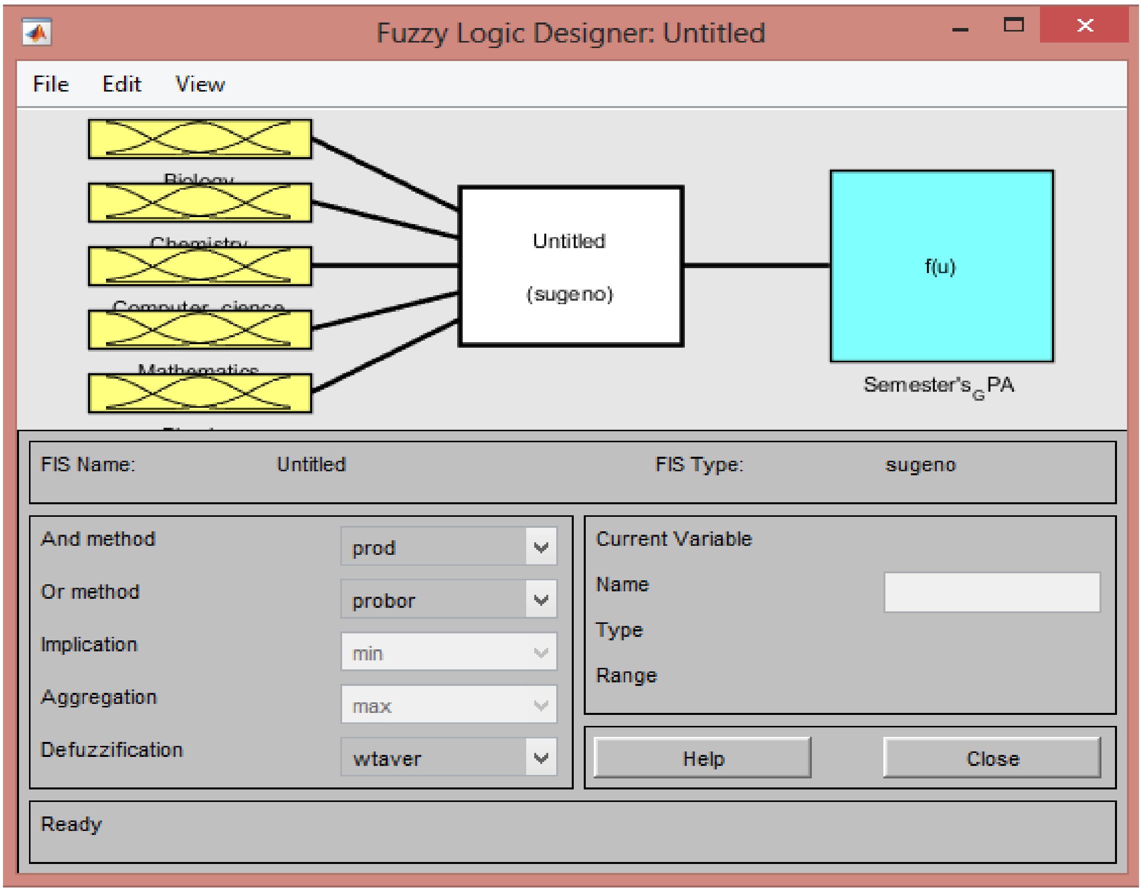
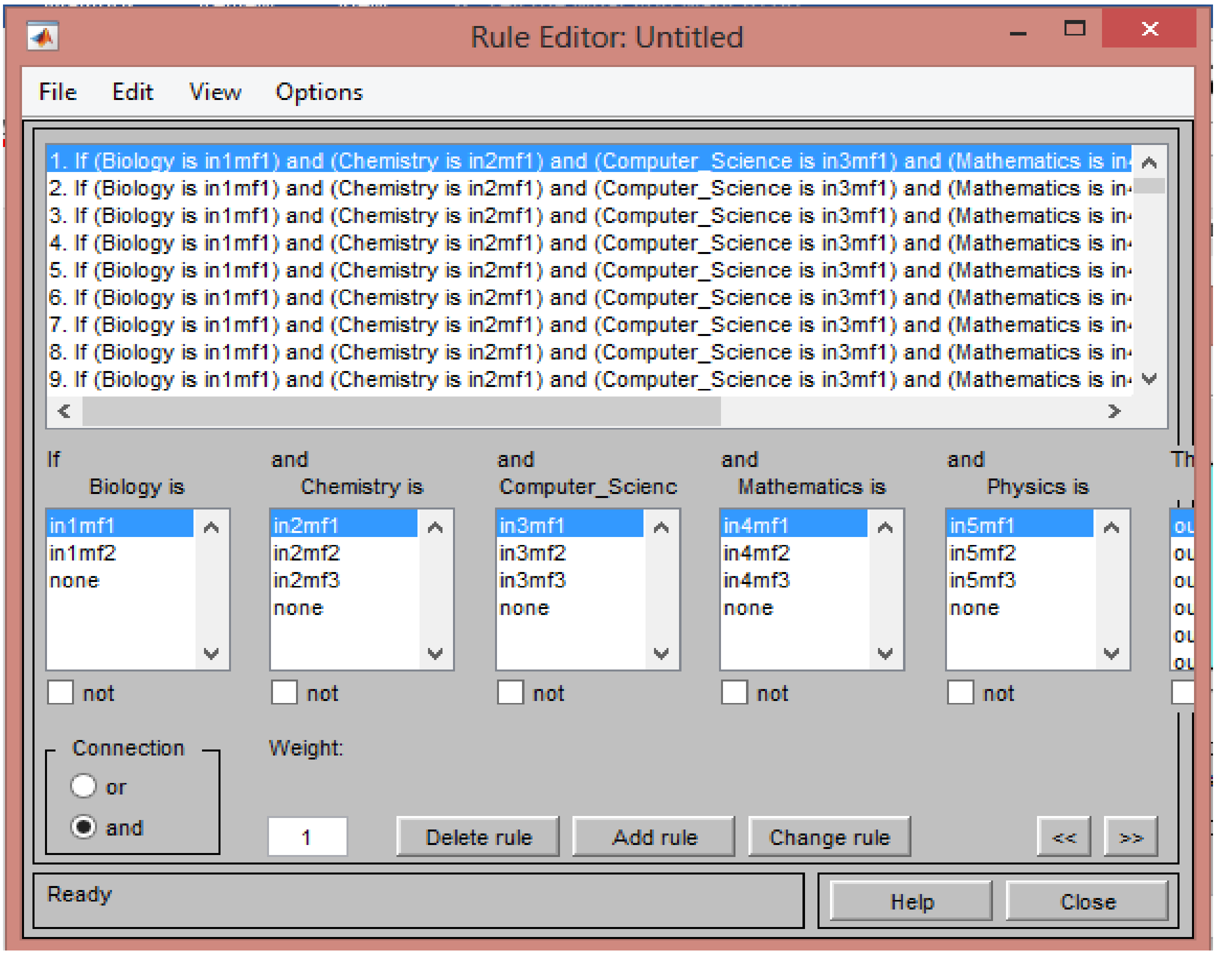


Fig 3: Training ANFIS model for semester's GPA predictions



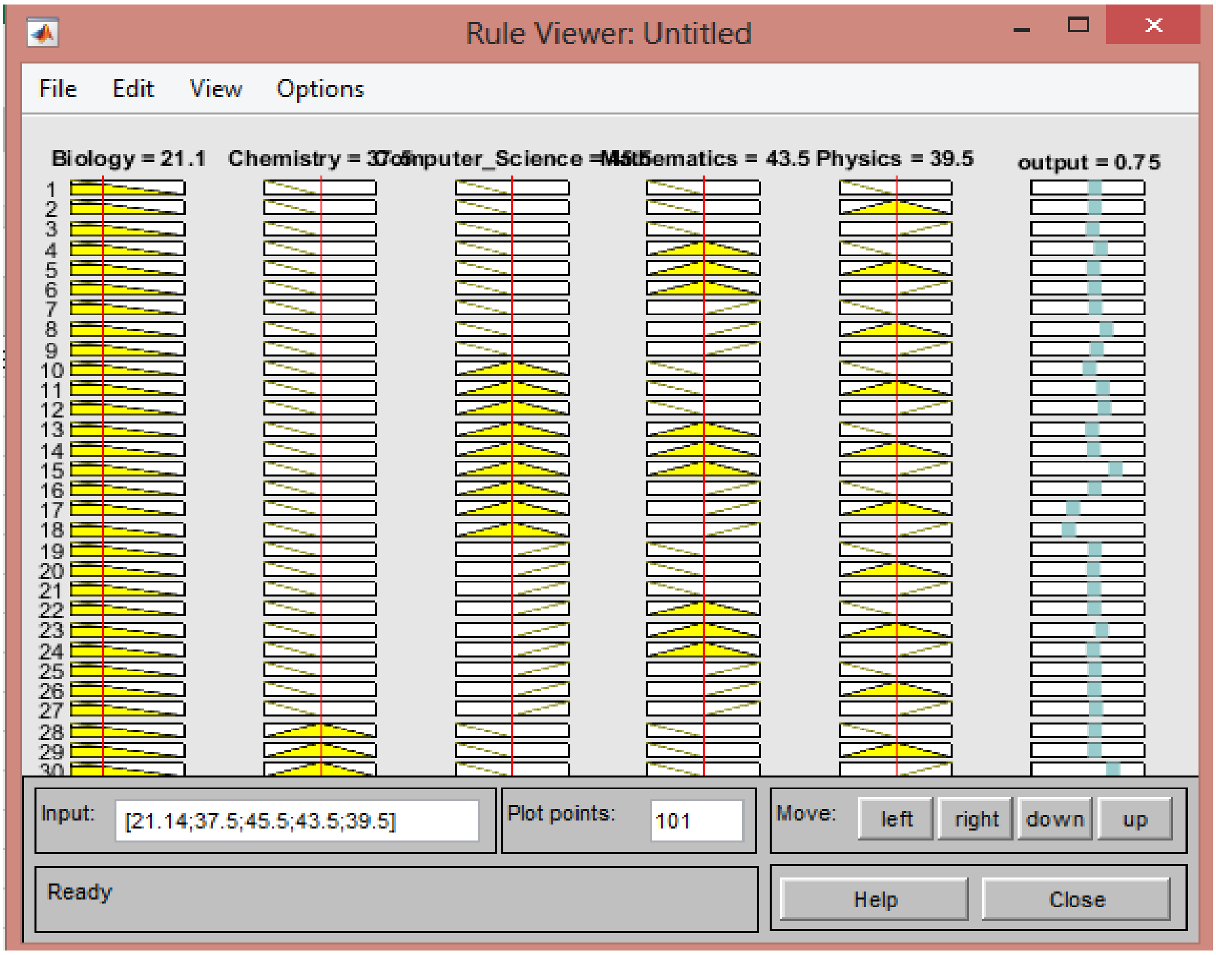


Fig 4: ANFIS training converges after 100 epochs

Table 3: Training and testing RMSE using different types of membership function with constant epoch no.

	Membership Functions		Root Mean Square Error, RMSE	
Epoch No	**Input**	**Output**	**Training Error**	**Average Test Error**
100	Trimf	Constant	0.0987	1.0639
100	Trapmf	Constant	0.2899	1.7441
100	Gbellmf	Constant	0.1034	1.3305
100	Gaussmf	Constant	0.0945	0.7999
100	Trimf	Linear	0.0124	26.8848
100	Trapmf	Linear	0.0359	17.9196
100	Gbellmf	Linear	0.0014	25.9859
100	Gaussmf	Linear	0.0020	28.6560

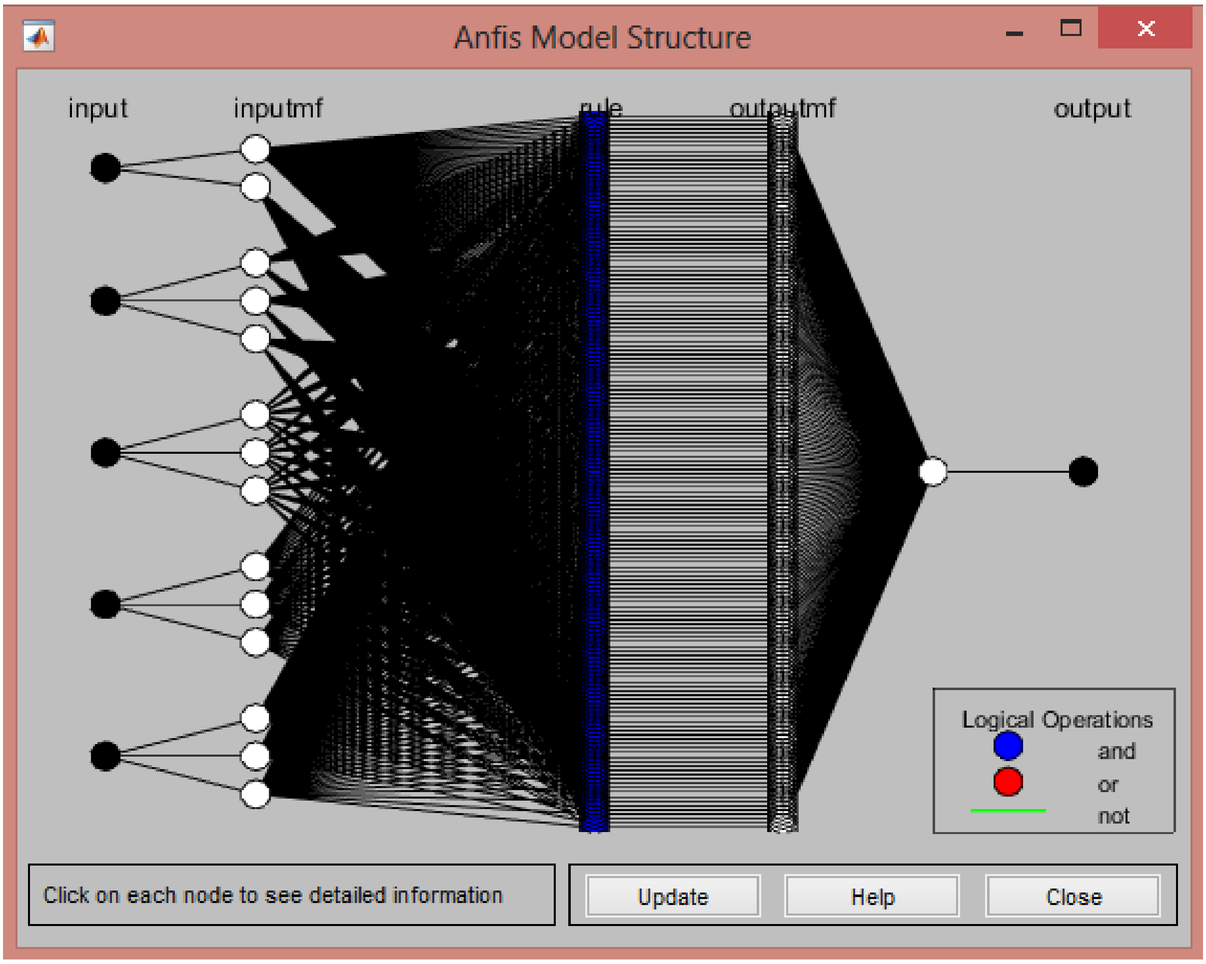


Fig 5: Testing ANFIS model for semester's GPA predictions

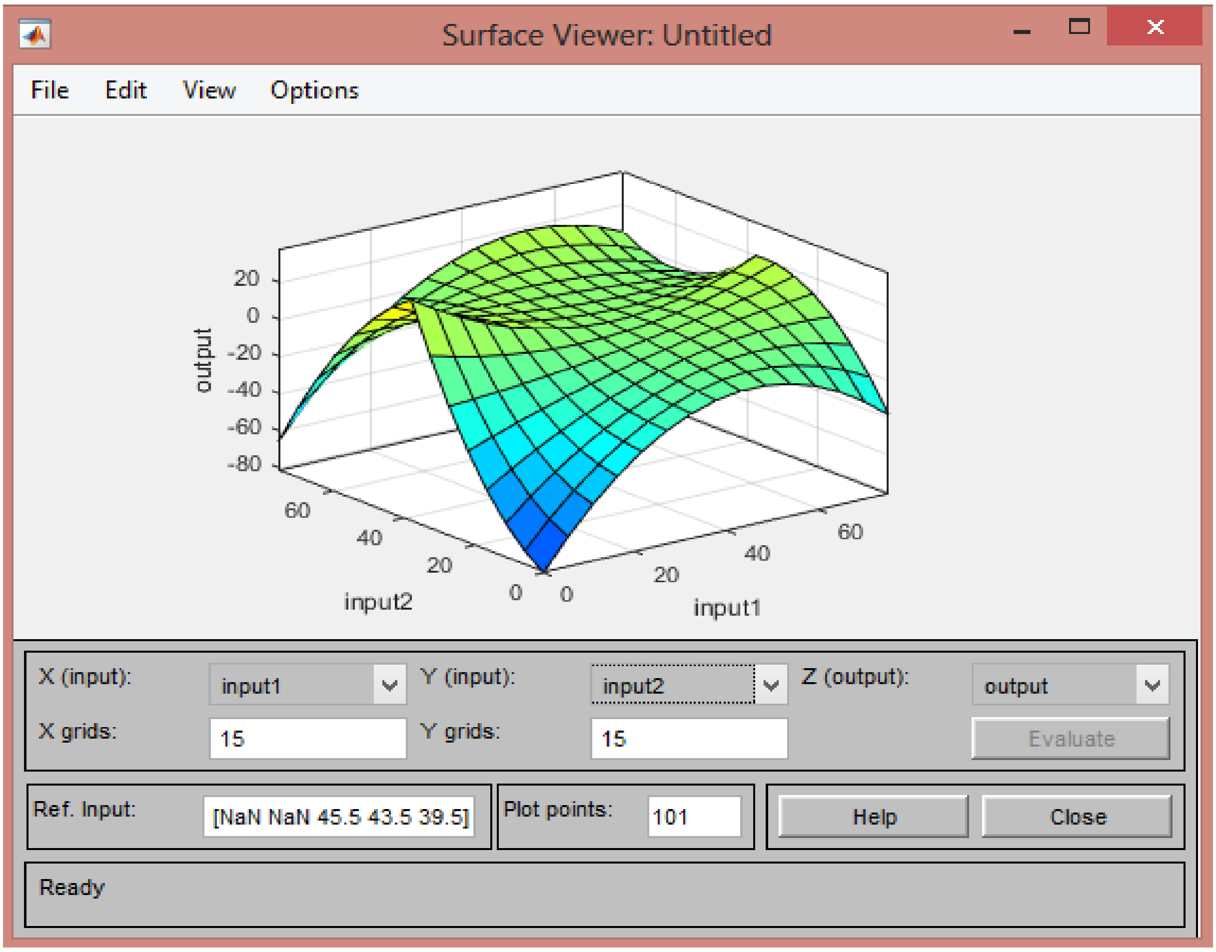


Fig 6: Screen shot of FIS with five input variables and one output

Conclusion and Recommendations

Conclusion

Advent of Covid-19 pandemic has made prediction of learner's academic performance more important. This study has established that adaptive neuro-fuzzy inference system, ANFIS is a very reliable tool that can be used by learners and school managements to predict academic performances so as to ensure excellent results on completion of study. Of all the membership functions and the hybrid algorithm used for developing as well as training the ANFIS models, Gaussian membership function (ANFIS-GaussMF) provided superior prediction of the learner's academic performance. The least average RMSE value of 0.7999 was recorded ANFIS-GaussMF in comparison to other MFs that recorded higher RSME values. The coefficient of correlation, R-value of 0.96 established the accuracy of the model while p-value of 0.084 obtained for comparison of the predicted and cropped data showed no significant difference.

Recommendations

This study recommended that adaptive neuro-fuzzy inference system, ANFIS be used to enhance learner's academic performance at all le as well as guide the school management and other educational stakeholders in taking appropriate decision on how to improve the learner performance through special provision and attention. It will also assist in the review of academic curriculum to attain the world class educational standard. A robust ANFIS model can be developed through the incorporation of data from a carefully designed oral interview administered to the learners as this may likely be an improvement over the present model.

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