

Forecasting Student Academic Performance Using Neuro-Fuzzy Model

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ABSTRACT

To achieve objective and precise forecasting of students' academic performance while keeping up with technological improvements and changes, this paper discusses a neuro-fuzzy technique for the prediction of student academic performance. The technique comprises a Neural Network (NN), Fuzzy Logic (FL), Knowledge Base (KB) and Rule Base (RB) subcomponents. The NN subcomponent uses a three-layered feed-forward architecture to acquire a large collection of interconnected units in some pattern for communications. The FL subcomponent is an extension of Boolean logic and it was used for establishing accurate selection processes and precise solutions to multivariable problems. The KB component forms the database of multi-level information while the RB comprises a set of if-then statements for decision-making. The inference engine subcomponent applies a pre-defined procedure on input from the rule base and fuzzy logic interfaces for final prediction. The proposed technique performs predefined procedures that are based on some input sets that store multi-level information derived from several pre-specified scores. Results from the implementation of the technique established its practical function.

Keywords: Academic performance, neural network, fuzzy logic, forecasting, variables

INTRODUCTION

Forecasting is the generation of a number, set of numbers, or scenario that relates to an upcoming event and is unequivocally indispensable for short and long-range scheduling. It is premised on pre-existing data, contrary to a prediction, which is more idiosyncratic and based on predisposition, gut feel or guesses. Both might refer to formal statistical methods employing time series, cross-sectional or longitudinal data, or to less formal judgmental methods (Stevenson, 2005). According to (Verboncu and Zalman, 2005), performance is a particular result obtained in management, economics, marketing, and so on that duplicates trait of

competitiveness, efficiency and effectiveness of the organization and its procedural and structural components. It can be measured by transforming complex reality into simplified numerical concepts that can be easily communicated and acted upon (Lebas, 1995). *Academic performance, otherwise known as the academic achievement* of a student focuses on the depth of ability, competence and skills which present how a student, teacher or institution has attained short or long-term *scholastic* aims. Completion of *educational* benchmarks such as secondary school diplomas and bachelor's degrees are some systems of academic success. Student performances are predisposed by social, psychological, economic, environmental and personal factors, though differ from individual to individual and country to country (Irfan and Shabana, 2012).

According to Raychauduri et al. (2010), academic performance is heavily reliant on several socio-economic factors such as attendance in class, family's educational and economic backgrounds, teacher-student ratio, qualification and proficiency of teachers, sex and age of student coupled with other external factors like proximity to the school. It is also noted that academic performance can be measured based on grade points earned from written works and examinations, on gradual and cumulative levels, as well as in oral presentations and seminars (Gudyalaka et al., 2018). Most institutions across the globe use Cumulative Grade Point Average (CGPA) to determine student performance (Galiher, 2006; Darling, 2005; Broh, 2000; Stephen & Schaban, 2002). There are also cases of student performance assessment through the results of specific subjects or the preceding year (Hijazi *et al.*, 2006; Hake, 1988). Education is one of the most important aspects of human resource development while poor academic performance presents the consequential effect of low self-esteem and trauma to the parents among others. This makes predictive measures based on some specialized soft computing techniques like fuzzy logic and neural network, very imperative for monitoring the student's academic performance.

Fuzzy logic is a computing approach that uses the degrees of truth aside from the normal "true or false" Boolean logic on which the modern computer is based to draw conclusions and inferences. Its main notion was first presented by Zadeh in 1964 (Zadeh, 1994). It contains a fuzzy logic controller that is used for imprecise, vague or missing data-based prediction of results (Mamdani, 1974). Fuzzy controllers are rule-based, reliable and widely used in forecasting weather, stock market, product market, health monitoring systems, aviation systems, temperature and pressure controllers in manufacturing industries and so on. Fuzzy logic has found its usefulness in addressing conventional logic failures due to the computational paradigm which is based on human thinking. An important concept in fuzzy logic is the application of linguistic variables that is, variables whose values are words or sentences in natural language (Iwasokun *et al.*, 2022). Its reasoning approach is notably used in designing some complex industrial and management systems which cannot be modelled precisely under various assumptions and approximations (Tzafestas and Tzafestas, 2001).

A fuzzy inference system (FIS) employs fuzzy if-then rules to acquire knowledge from human experts to deal with imprecise and vague problems and has been widely used in optimization, control, and system identification. Fuzzy systems do not usually learn and adjust themselves and this problem is often resolved using a neural network (NN) that can learn from its environment, self-organize and adapt in an interactive way. This often served as the basis for

the formulation of a neuro-fuzzy system that combines a fuzzy inference system and neural network as well as integrates the merits of the duo. It is implied that a neuro-fuzzy system is a fuzzy network system that is capable of overcoming the limitations of neural networks and fuzzy systems, due to its interpretable manner of learning and knowledge representation. Neuro-fuzzy classifier (NFC), combines the powerful description of FIS with the learning capabilities of NNs to partition a feature space into classes while NFCs have been commonly used for different problems, NFIS has been adapted successfully in applications such as control and classification.

LITERATURE REVIEW

In (Altyeb and Barukab, 2017), the practical value of adaptive neuro-fuzzy inference (ANFIS) system in the domain of performance monitoring is presented. The research attempted to provide a suitable platform to improve students' academic performances using an ANFIS that intelligently integrates the capability reasoning of fuzzy logic with the learning abilities of neural networks. The platform is based on ANFIS-GaussMF, ANFIS-TriMF and ANFIS-GbellMF that utilized various membership functions to generate accurate fuzzy rules for the prediction process. Implementation showed high accuracy of the platform as well as how it surpassed other models with improved Root Mean Square Error (RMSE). However, it was noted that with the three models, when the number of epochs reaches about 200 iterations, the training RMSE tends to a stable value, such that further training does not guarantee significant results in the prediction accuracy, leading to over-fitting. An automated system for the analysis and identification of the critical factors that affect the academic performance of students was designed by Ritu and Vishu (2016). The research focused on establishing the impact of the university environment, family issues, teaching and personal factors, among others on the overall performance of students. Focus was also on establishing a system for reducing the complex nature of the fuzzy expert system in performance assessment. The design was based on the integration of data mining and an expert system and the use of fuzzy logic and association rule mining techniques for estimation. The proposed system is reported to address the complexity of the fuzzy rule-based expert system in addition to reducing the computation time for the analysis of the student's performance. It is also reported to lack consideration for generalized association rules and some performance issues.

The authors in (Ashwani et al, 2016) presented a fuzzy logic reasoning model for the performance evaluation of students in schools or colleges. The model aimed at harnessing the academic as well as personality traits of students for improved evaluation of their performances. The fuzzy logic component of the model is based on the Matlab-Simulink model and a Mamdani-type FIS for performance evaluation while its membership functions (MFs) were anchored on the triangular shape-based analysis. The model used a stage-wise fuzzy reasoning approach for eliminating issues of rule expansion in a bid to establish its superiority over the traditional average method, though it is limited by its lack of consideration for some other optimization techniques like NN, ANFIS and Genetic algorithms (GA) which can be employed for building effective performance evaluation models. In (Sangita and Sudhir, 2018), a fuzzy logic and neural network decision and prediction model for e-learning was presented. The model uses existing e-contents that are based on the learning style, learning pattern, time, environment, psychology and mood of learners. The model could analyze the behavioural characteristics of online learners for enhancing learning and promote adaptivity and

personalization. It however requires face-to-face interaction between trainer and learners, which derails the principles of e-learning as well as failure to consider feedback from students. Veena et al. (2018) presented a Mamdani FIS and neuro-fuzzy model for the prediction of student academic performance. The model is based on network analysis, designing of rubrics, content delivery, auto-formulation of question papers, data collection and FIS and NF-based evaluations. The ability of the model to overcome the drawbacks of averaging method by evaluating learner performance the using scoring rubrics tool for network analysis is reported alongside its failure with increased training period and rules. The applicability of some of the existing machine learning algorithms and classifiers for performance evaluation was presented by Gudyalakar, et al. (2018). Focus was on the student's intellectuals, various parameters for evaluating student performance, the capability to study individually and collectively and the various types of soft computing algorithms for performance evaluation. Differentiation of the algorithms based on confusion matrix, RMSE, Training time and Accuracy was performed. The study established the level of performance of the existing algorithms as well as their growth in complexities with an increasing volume of data.

In (Solaf and Miran, 2015), a fuzzy rule-based model for grading online examinations is presented. The model aimed to find a model that provides a well-defined rule-based system to support student evaluation schemes in online tests. A fuzzy inference model based on the Mamdani technique was used for input variables and linguistic term selection, identification of fuzzy sets and membership functions, generation of rules set and application of rules and defuzzification. Results from the implementation exhibited improved grade classification and process performance, though face-to-face interaction is required between trainer and learners. Nidhi and Jatinderkumar (2013) presented a neural network model for the prediction of students' academic records. The model uses qualitative observations for handling reasoning with imprecise information and a fuzzy probabilistic neural network for achieving an easy-to-use and personalized performance prediction. Implementation of the model revealed how it outperformed traditional back-propagation neural networks and statistical models coupled with the issue of accuracy.

A fuzzy decision support refinement process model for forecasting student grades was proposed in (Zehra and Fevzi, 2014). The model focused on the evaluation of student abilities and bringing a solution to classical laboratory assessment problems using fuzzy logic. The model consolidates theoretical knowledge with practical applications to offer a better and more reliable evaluation system than classical systems in laboratory applications but its application is susceptible to noise-induced misclassification. The limitations of the works presented in (Mohd et al., 2017; Altyeb and Barukab, 2017; Ritu and Vishu, 2016; Ashwani et al, 2016; Sangita and Sudhir, 2018; Veena et al., 2018; Gudyalakar, et al, 2018; Solaf and Miran, 2015; Nidhi and Jatinderkumar, 2013; Zehra and Fevzi, 2014; Meenakshi and Pankaj, 2015) include instability of prediction accuracy, leading to over-fitting, insecurity, lack of consideration to non-academic factors, generalized association rules, feedback and virtuality with increased dataset leads to growth in complexities. The research is therefore motivated by the need to address some of the stated limitations based on a combination of neural networks and fuzzy logic.

PROPOSED NEURO-FUZZY FORECASTING SYSTEM (NFFS)

Fuzzy Inference System (FIS) is a useful soft computing technique for implementing the concepts of fuzzy set theory, fuzzy if-then rules, and fuzzy reasoning. The proposed NFFS was formulated to allow the integration of human expertise with adaptive learning and its architecture is presented in Figure 1 showing the knowledge base, inference engine, decision support engine and user interface as its major components. The *Knowledge Base* (KB) is made up of Database (DB) and Rule Base (RB). The DB sub-component stores multi-level information while the RB sub-component consists of a set of if-then statements that are useful for decision-making. The FL component performs predefined procedures that are based on some input set which are derived from several pre-specified scores. The Inference Engine (IE) applies a pre-defined procedure on its input from the RB and fuzzification interface to generate the final forecast.

The Knowledge Base

The *Knowledge Base* (KB) is a repository of structured and unstructured knowledge relevant to forecasting students' academic performances. The *structured knowledge* comprises organised facts, rules, events and attributes in the form of a network of semantically related static and dynamic objects each of which is modelled in a relational form. *Unstructured knowledge* represents the knowledge acquired through good practice, observations, guesses and judgements. The KB is formulated as an integrated collection of data warehouse, logic fuzzy and neural network.

Data Warehouse (DW)

DW integrates data marts which individually comprise key knowledge kind of stuff. It was designed based on the multi-dimensional star schemas shown in Figure 2.

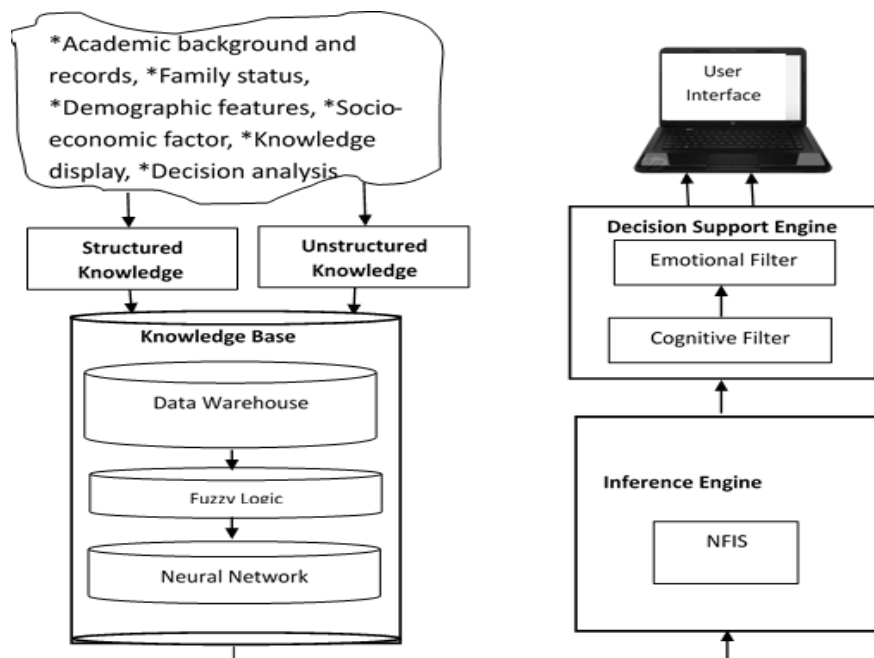


Figure 1: Architecture of the proposed

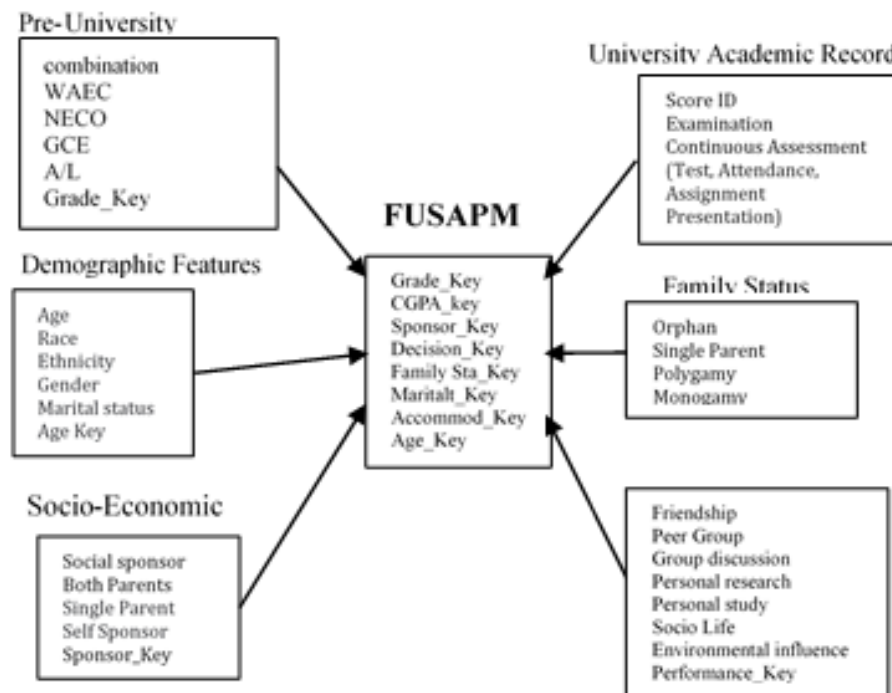


Figure 2: Star schema for system's facts

Fuzzy Logic (FL)

The FL component is an extension of Boolean logic and it was used for establishing accurate selection processes and precise solutions to multi-variable problems. The block diagram of the fuzzy logic component of the proposed system is depicted in Figure 3.

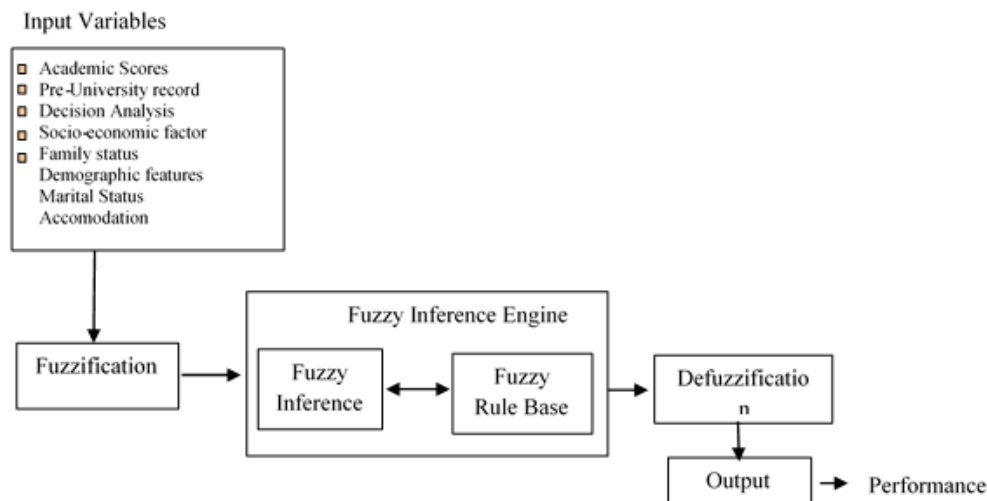


Figure 3: Block Diagram of Fuzzy Logic Inference Engine Components

In the fuzzification process, numeric data which are in the real-world domain are converted to linguistic terms in the fuzzy domain. The conversion is facilitated by the assignment of weights to variables. A crisp set of input data is converted to a fuzzy set using linguistic variables, fuzzy linguistic terms and membership functions. A triangular membership function is adopted given

its generality and simplicity. The linguistic input variables present data on demographic features, family status, and socio-economic factors, among others. The linguistic output terms are *first class*, *second class upper*, *second class lower*, *third class* and *fail* which were derived using Equation 1.

$$Weight(x) = \begin{cases} 0 & \text{if } x \text{ is fail non significant} \\ 2 & \text{if } x \text{ is 3rd class significant} \\ 3 & \text{if } x \text{ is 2nd class lower significant} \\ 4 & \text{if } x \text{ is 2nd class upper significant} \\ 5 & \text{if } x \text{ is 1st class significant} \end{cases} \quad (1)$$

x is the score variables which were assigned a weight based on relevance and contribution in the range $[0 - 5]$. Based on these ratings, the fuzzy sets were expressed as functions while the elements of the set were mapped to their degree of membership. In this research, the triangular MF is adopted for mapping the fuzzy set into linguistic values because it performs better than trapezoidal, Gaussian and generalized bell MFs in the task of prediction and classification (Inyang and Akinyokun, 2014; Iwasokun *et al.*, 2022). The degree of membership is used to map the output value specified in individual rules to fuzzy linguistic values which are “Fail”, “Third class”, “Second class lower”, “Second class upper”, and “First class”. The linguistic values of the variables denoted by x and the MF for the variable with 0, 2-, 3-, 4- and 5-point weights are derived as follows:

$$Var(v) = \begin{cases} Fail & \text{if } y < 0 \\ 3rd\ class & \text{if } 0 \leq y < 2 \\ 2nd\ class\ lower & \text{if } 1 \leq y < 3 \\ 2nd\ class\ upper & \text{if } 2 \leq y < 4 \\ 1st\ class & \text{if } 3 \leq y < 5 \end{cases} \quad (2)$$

Fuzzy Rule – Base:

The rule base for the system is characterized by a set of *IF-Then* rules in which the precursors (*IF* parts) and consequents (*THEN* parts) are presented as linguistic variables. The Mamdani fuzzy rule with a fuzzy controller involving in-input variables and one output variable for forecasting students’ academic performance is characterized by a set of IF-THEN rules. A rule intensity if any of its precedence parameters such as fail, 3rd class, 2nd class lower, 2nd class upper and 1st class evaluates to true, otherwise it does not fire. If the fuzzy scores of a student are represented as i and the fuzzy weight assigned to each attribute is represented by m , by inference, i is multiplied by m and each of the fuzzy points obtained in each category is summed to obtain the total fuzzy point.

Inference Engine

Mamdani’s Fuzzy Inference System was used to conclude a rule base. The fuzzy inference engine applies the inference mechanism to the set of rules in the fuzzy rule base to produce a fuzzy output set from a collection of the *IF-THEN* rules. This involves matching the input fuzzy set with the premises of the rules, activation of the rules to deduce the conclusion of each rule that is fired, and a combination of all activated conclusions using fuzzy set union to generate fuzzy set output. This mapping is the base from which decisions can be made. Fuzzy rule sets

usually have several antecedents that are combined using AND, OR and NOT fuzzy logical operators. AND uses the minimum weight of all the antecedents, while OR uses the maximum value. For this research, the aggregator operator AND is the minimum value of all the antecedents. The inference engine evaluates all the rules in the rule base and adds the weighted consequences of all the relevant (fired) rules into a single fuzzy set using the Root Sum Square (RSS) inferential techniques since it gives the best-weighted influence to all firing rules.

Defuzzification

Defuzzification is used to change a fuzzy output of the inference engine to crisp output. Its input process is the aggregated output fuzzy set and the output is a crisp number. The defuzzified output of the inference engine which is a fuzzy set is based on the Equation:

$$\delta = \sum_{i=1}^n wt_i r_{im} \quad (3)$$

δ is the crisp output and (wt_i) is the aggregated membership value of r_{im} .

Decision Support Engine (DSE)

The DSE of the System consists of cognitive and emotional filters as sub-components. The cognitive filter analyses the output of the NFIS system based on the objective judgment of undergraduate student performance forecast criteria while the emotional filter analyses the inputs based on the subjective feelings of the predictor. The cognitive filter uses the output of the NFIS system to objectively determine the course of actions to be taken in response to events on undergraduate student performance and its output was objectively stated as fail, third-class, second-class lower, second-class upper or first-class. A student with $\delta = 4.5$ or above 4.5 is First class, $3.5 \leq \delta \leq 4.49$ indicate Second class upper, $2.49 \leq \delta \leq 3.49$ are graded Second class lower, while $1.5 \leq \delta \leq 2.48$ are considered Pass and student with $0 \leq \delta \leq 1.49$ is graded fail. The emotional filter employs the subjective feelings of the predictor decision-making. A subjective feeling may be the decision to conclude on the performance of the student based on social and family status as well as a decision based on moral character and relationship.

Neural Network (NN)

The NN component of the KB uses a three-layered feed-forward architecture to acquire a large collection of units that are interconnected in some pattern for communications between units. The units are simple processors which operate in parallel and are referred to as nodes or neurons. The neurons are interconnected through connection links that are concomitant with a weight that bears the information on the input signal. Each neuron possesses an internal state known as the activation signal. The input signals and the activation rule are combined to produce the output signal, which consists of a bias 'b' with a weight of 1.

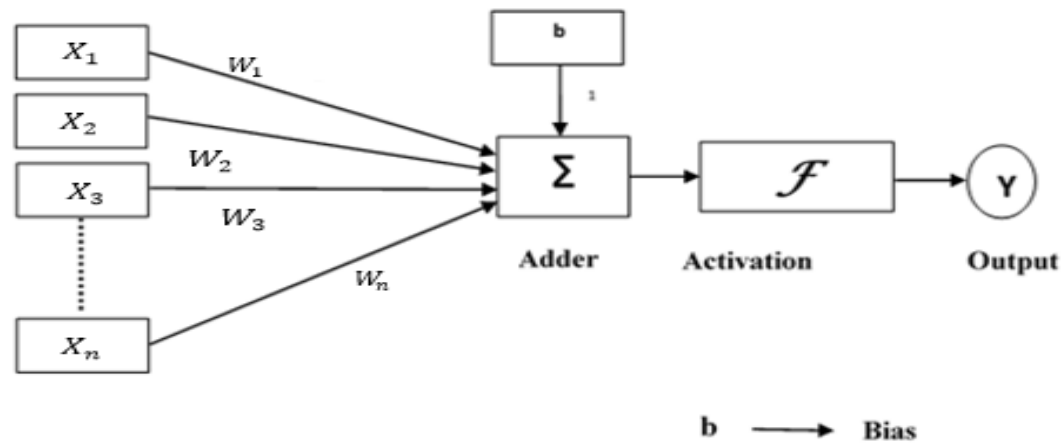


Figure 4: The neural network model

As shown in Figure 4 (Panagiotis, 2022), the input layer consists of data attributes and the hidden layer is located between the input and output of the algorithm as an intermediate layer that processes the data based on complex non-linear functions. These layers form the key component that enables the system to achieve complex tasks and reliable output based on the application of weights by the functions to the inputs and directs them through an activation function as the output.

The hidden layers equally carry out nonlinear transformations of the inputs. It is made up of six nodes that receive and process the signals from the input layer using the connection weights and hyperbolic transfer function. Adding a hidden layer between the input and output layers turns the perceptron into a universal approximator that essentially implies it is capable of capturing and reproducing extremely complex input-output relationships. The NN structure for the proposed system is depicted in Figure 5 (Robert, 2020).

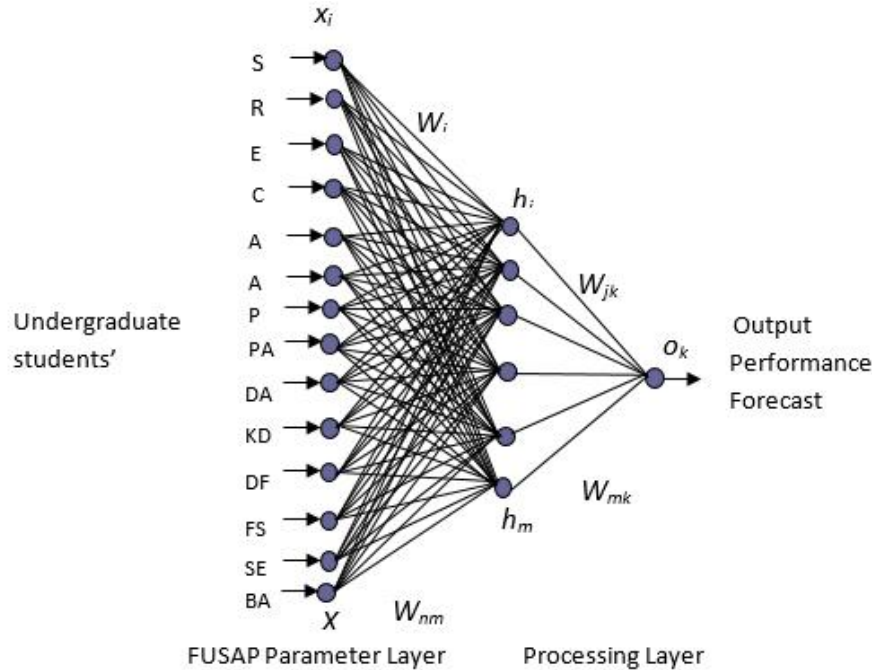


Figure 5: Neural Network of FUSAP

From the multilayer feed-forward schema presented in Figure 5, the network layers are represented as parameters X_i $i = 1, 2, \dots, n$ and processing layers h_j $j = 1, 2, \dots, m$. Given that h_j^* and o_k^* represent the output for the forecasting function at the hidden and output layers and W_{ij} be the matrix of weights on the connection from the j th node in the hidden layer to the i th node in the input layer, then the following Equations are formulated for the input and hidden layers.

$$\begin{aligned}
 w_{11}x_1 + w_{12}x_2 + \dots + w_{1n}x_n &= h_1^* \\
 w_{21}x_1 + w_{22}x_2 + \dots + w_{2n}x_n &= h_2^* \\
 &\vdots \\
 w_{m1}x_1 + w_{m2}x_2 + \dots + w_{mn}x_n &= h_m^*
 \end{aligned} \tag{4}$$

In terms of matrices, a system of Equations is represented as: $Wx = h^*$, where W is the matrix of weights, x is the activity detection input vector and h^* is the hidden layer pre-output and its compressed equivalent as shown in Equation (8) and Equation (9) respectively.

$$\begin{matrix} W & x & h^* \\ \begin{bmatrix} w_{11} & w_{12} & \dots & w_{1n} \\ w_{21} & w_{22} & \dots & w_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ w_{m1} & w_{m2} & \dots & w_{mn} \end{bmatrix} & \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} & = & \begin{bmatrix} h_1^* \\ h_2^* \\ \vdots \\ h_m^* \end{bmatrix} \end{matrix} \tag{5}$$

$$\sum_{j=1}^m \sum_{i=1}^n W_{ji}x_i = h_j^* \tag{6}$$

The actual output of hidden layer node h_j is obtained by exposing the pre-output in Equation (9) to the hyperbolic forecast function as shown in Equation (10).

$$h_j = \frac{e^{h_j^*} - e^{-(h_j^*)}}{e^{h_j^*} + e^{-(h_j^*)}} \quad (7)$$

Let W_{jk} be a matrix of weights that connects the k th-output layer node to the j th node in the hidden layer, the academic performance forecast shown in Equation (11) is composed in vector form presented in Equation (12) and compressed in Equation (13).

$$w_{11}h_1 + w_{12}h_2 + \dots + w_{1m}h_m = o_k^* \quad (8)$$

$$\begin{bmatrix} w_{11} & w_{12} & \dots & w_{1m} \end{bmatrix} \begin{bmatrix} h_1 \\ h_2 \\ \vdots \\ h_m \end{bmatrix} = o_k^* \quad (9)$$

$$\sum_{k=1}^p \sum_{j=1}^m w_{jk} h_j = o_k^* \quad (10)$$

The actual value of the output layer node o_k is obtained by subjecting the pre-output in Equation (13) to the sigmoid transfer function based on Equation (14).

$$o_k = \frac{1}{1 + e^{-(o_k^*)}} \quad (11)$$

The back-propagation learning procedure presented in (Inyang and Akinyokun, 2014; Udoh *et al.*, 2012) was used. The back-propagation algorithm commences by initializing the connection weights for all neurons to some random numbers between 0 and 1.

This is followed by using the input vector x_i as the output from the input layer of processing elements and then selecting the first training input and output pair (x, d) from the training pair vectors (x_i, d_k) . Consequently, the value of the hidden layer (h_j) and output layer (o_k) are computed as follows:

$$h_j = f\left(\left(\sum_{i=1}^m \sum_{i=1}^n W_{ij}x_i\right) + \theta_j\right) \quad (12)$$

$$o_k = f\left(\left(\sum_{j=1}^m w_{jk}h_j\right) + \theta_k\right) \quad (13)$$

The difference between the desire (d_k) and the computed (o_k) values is obtained while the output (e_k) and the hidden layer e_j errors are derived from:

$$e_k = (d_k - o_k) \quad (o_k)(1 - o_k) \quad (14)$$

$$e_j = h_j \left(1 - h_j \left(\sum_{k=1}^m w_{jk} e_k \right) \right) \quad (15)$$

If an error is greater than the predefined value, it is propagated back into the network by adjusting the weights connecting the output to the hidden layers and those connecting the hidden layers to the input layers.

The weights between k th output neurode and j th hidden neurode are adjusted thus:

$$w_{jk}(n+1) = w_{jk}(n) + h_j \beta e_k + \alpha \sum \Delta w_{jk} \quad (16)$$

n is the step in the training cycle, β and α are learning rate and momentum factors respectively.

The weights between the j th hidden neuron and the i th input neuron are adjusted using the formula:

$$w_{ij}(n+1) = w_{ij}(n) + x_i \beta e_j + \alpha \sum \Delta w_{ij} \quad (17)$$

The operations between selecting the first training input and output pair and weight adjustments are repeated as many cycles as needed until the Sum of Squared Error (γ) falls within a prescribed tolerance defined as follows:

$$\gamma = \sum_{k=1}^p (e_k)^2 \quad (18)$$

A trained NN is a veritable tool in proffering solutions to prediction and classification problems. It is also useful in the determination of input variable contributions to output as well as the extraction of fuzzy rules from the rule base. Rules or input variables with insignificant contributions to output are removed from the network thereby reducing computational complexity and enhancing the speed of deductive reasoning by the inference engine.

Experimental Study

The experimental study of the model was carried out on Pentium IV Computer System with a 2.0 GHZ Duo Core Processor, 2 GB of RAM, and 300GB hard disk size. The frontends include Python 3, Pandas 1.0.3, Jupyter notebook 1.0.0, Tensorflow 1.14.0, Neurotechnology concept and MatLab 7.10 (R2010a).

MYSQL Database from Wamp Server 2.2 served as the backend in Microsoft Windows 8 Operational environment. The experimental study included the implementation phase that focused on converting the model into a software solution or program module and it was based on the dataset shown in Table 1. The dataset was obtained from the Department of Software Engineering, Federal University of Technology, Akure, Nigeria. The choice of the dataset was premised on its availability, relevance, adaptability and variability.

The dataset also enjoys academic and research-related permission. Its features include *Matriculation Number, Pre-University Qualifications, Age, Economic Status, Personal Study Mode, Marital Status, Family Status, Accommodation, Current CGPA, Semester and Level. Matriculation*

Number represents the unique identifier of the students and serves no computational purpose. The experimental data are classified into criteria, attributes, crisp and alternative.

Criteria data contains code, name, attribute, and weight which determines the importance. Attributes present the significance of the data in terms of benefits and cost. Crisp data contains criteria, descriptions, and weight codes. Alternative data provides options for the calculation and selection.

Table 1: The experimental dataset

Matriculation Number	Pre-Uni.	Age	Economic status	PS Mode	Marital Status	Family Status	Accommodation	CGPA	Semester	Level
SEN/18/2001	A/L	21	BP	GD	S	Mo	Ho	4.60	First	300
SEN/18/2002	A/L	24	SP	PS	S	SP	Oc	2.73	First	300
SEN/18/2003	A/L	27	SS	GD	S	Mo	Ho	4.00	First	300
SEN/18/2004	A/L	17	BP	GD	S	Mo	Oc	3.67	First	300
SEN/18/2005	GC	20	SS	PS	M	Po	Oc	3.36	First	300
SEN/18/2006	A/L	18	BP	GD	M	Po	Oc	3.32	First	300
SEN/18/2007	CO	14	SS	PG	S	Mo	Oc	2.49	First	300
SEN/18/2008	WA	17	SS	GD	M	Po	Sq	2.45	First	300
SEN/18/2009	GC	23	SS	GD	S	Or	Ho	4.33	First	300
SEN/18/2010	CO	20	BP	GD	S	Mo	Ho	3.67	First	300
SEN/18/2011	A/L	19	SP	GD	S	Po	Ho	3.11	First	300
SEN/18/2012	A/L	23	SS	PS	S	Or	Ho	2.13	First	300
SEN/18/2013	CO	17	SS	GD	S	SP	Sq	3.34	First	300
SEN/18/2014	GC	15	BP	PG	S	Po	Or	2.28	First	300
SEN/18/2015	NE	17	BP	PG	M	Po	Or	1.47	First	300
SEN/18/2016	A/L	18	SP	PS	M	Po	Ho	2.60	First	300
SEN/18/2017	WA	22	BP	PS	S	Mo	Ho	3.15	First	300
SEN/18/2018	CO	23	SP	GD	S	Po	Ho	3.04	First	300
SEN/18/2019	CO	20	SS	GD	S	Mo	Oc	3.86	First	300
SEN/18/2020	CO	17	BP	GD	M	Po	Oc	3.00	First	300
SEN/18/2021	WA	24	SP	PG	S	Mo	Ho	2.85	First	300
SEN/18/2022	WA	20	SS	GD	S	SP	Oc	3.50	First	300
SEN/18/2023	NE	19	SS	GD	S	Mo	Ho	4.68	First	300
SEN/18/2024	WA	17	SP	PS	S	Po	Sq	2.24	First	300
SEN/18/2025	NE	25	SS	PG	S	Or	Ho	0.93	First	300
SEN/18/2026	A/L	21	SS	GD	S	SP	Ho	3.59	First	300
SEN/18/2027	GC	16	BP	PS	S	Mo	Ho	3.38	First	300
SEN/18/2028	GC	19	SS	GD	S	Po	Ho	2.76	First	300
SEN/18/2029	GC	18	BP	PS	S	Po	Ho	3.82	First	300
SEN/18/2030	GC	20	SS	GD	S	Mo	Ho	4.77	First	300

On the dataset displayed in Table 1, A/L indicates 'Advanced Level', NE indicates 'NECO', WA indicates 'WAEC', CO indicates 'combination of two or more results', BP indicates 'both parents', SP indicates 'self-sponsor', SS indicate 'social support', GD indicates 'group discussion', PG indicates 'peer group', PS indicates 'personal study', S represents 'single', M represents 'married', Mo represents 'monogamy', Po represents 'polygamy', Ho represents 'Hostel', Oc indicates 'off campus', Sq indicates 'squatting' and Or represents 'orphan'. The dataset was divided into three parts; training, validation and testing sub-datasets in the ratio of 8:1:1

respectively. Table 2 presents the fuzzy weight, scores and scales attached to the forecasting variables. Because a student's academic performance (CGPA) ranges between 0 and 5, the fuzzy scores were computed such that the sum of the peak value for the 10 variables is 5. The inference engine evaluates all the rules in the rule base and combines the weighted consequences of all the relevant (fired) rules into a single fuzzy set using the root sum square inferential technique because it gives the best-weighted influence to all firing rules as shown in Equation (21). The results of the application of the fuzzy scale on the dataset are presented in Table 3.

Table 2: The Variables Attributes (E = Excellent, V = Very Good, G=Good, H=High, M = Moderate, L = Low, P = Poor and F = Fail)

S/N	Attribute	Variables	Fuzzy weight	Fuzzy score	Scale
1	CGPA (Cumulative Grade Point Average)	Fail	5.0	0.00	P
		Third Class		0.8	A
		Second Class Lower		1.1	G
		Second Class Upper		1.2	V
		First Class		1.9	E
2	Pre-certificate	Combination: (2 Sittings - NABTEB+ WAEC) +/NECO	0.5	0.05	L
		WAEC or NECO		0.10	M
		GCE		0.15	H
		Advanced Level (A/L)		0.20	V
3	Age	14 – 15	0.8	0.10	L
		16 – 18		0.16	M
		19 – 20		0.22	H
		20 and above		0.30	V
4	Economic status	Self	2.2	0.10	L
		Single Parent		0.40	M
		Both Parents		0.70	H
		Social/Scholarship		1.00	V
5	Study mode	Peer	1.0	0.05	L
		Personal Study		0.35	M
		Group Discussion		0.60	H
6	Marital Status	Married	0.1	0.03	L
		Not Married		0.07	H
7	Family Status	Orphan	1.0	0.04	L
		Single Parent		0.15	M
		Polygamy		0.25	H
		Monogamy		0.56	V
8	Accommodation	Squat	0.4	0.05	L
		Off-Campus		0.12	M
		Hostel		0.23	H
9	Semester	First	0.1	0.03	L
		Second		0.07	H
10	Level	100	0.15	0.01	L
		200		0.02	M
		300		0.05	H
		400 or higher		0.07	V

Table 3: Operational Weight of Attributes

Student.	Pre-Uni.	Age	Social Economic	PS Mode	Marital Status	Family Status	Accommodation	CGPA	Level	Semester
SEN/18/2001	V	V	H	H	H	V	H	E	H	L
SEN/18/2002	V	V	M	M	H	M	M	M	H	L
SEN/18/2003	V	V	L	L	L	V	M	M	H	L
SEN/18/2004	V	M	H	H	H	V	M	H	H	L
SEN/18/2005	H	H	L	M	L	H	M	M	H	L
SEN/18/2006	V	M	H	H	L	H	M	M	H	L
SEN/18/2007	L	L	M	L	H	V	M	M	H	L
SEN/18/2008	M	M	L	H	L	H	L	L	H	L
SEN/18/2009	H	V	L	H	H	L	H	H	H	L
SEN/18/2010	L	H	H	H	H	V	H	H	H	L
SEN/18/2011	V	H	M	H	H	H	H	M	H	L
SEN/18/2012	V	V	L	M	H	L	H	L	H	L
SEN/18/2013	L	M	V	H	H	M	L	M	H	L
SEN/18/2014	L	L	L	L	H	H	L	L	H	L
SEN/18/2015	M	M	L	L	L	L	M	P	H	L
SEN/18/2016	V	M	M	M	L	H	L	M	H	L
SEN/18/2017	M	V	H	M	H	M	L	M	H	L
SEN/18/2018	L	V	M	H	H	H	H	M	H	L
SEN/18/2019	L	H	V	H	H	V	M	H	H	L
SEN/18/2020	L	M	H	H	L	H	L	M	H	L
SEN/18/2021	M	V	M	M	H	V	H	M	H	L
SEN/18/2022	M	H	V	H	H	H	M	H	H	L
SEN/18/2023	M	M	H	M	H	V	L	M	H	L
SEN/18/2024	M	V	L	M	H	H	L	L	H	L
SEN/18/2025	M	V	L	L	H	L	H	P	H	L
SEN/18/2026	V	V	M	H	H	M	H	H	H	L
SEN/18/2027	H	M	H	M	H	V	H	H	H	L
SEN/18/2028	H	H	L	H	H	H	H	M	H	L
SEN/18/2029	H	M	H	M	H	H	H	M	H	L
SEN/18/2030	H	H	V	H	H	V	H	E	H	L

As shown in Table 2, the scores and weight were set based on a mutually agreed order of importance to academic performance forecasting. CGPA score was set to 5.0 and weights of 0.00, 0.8, 1.1, 1.2 and 1.9 were assigned to 'Fail', '3rd Class', '2nd Class Lower', '2nd Class Upper', and 'First Class' respectively. This indicates that forecasting gives the greatest preference to student academic performance over other attributes because it demonstrates the student's ability and intelligence. Economic status was set to 2.2 and variable weights are 0.10, 0.40, 0.70 and 1.00 for self-sponsor, single parent, and both parent and social support respectively. The setting was based on the premise that the academic performance of a student is highly dependent on his/her financial status. The Family Status shows the level of home support which often initiates performance capability. The score is set at 1.0 and the weights assigned to attributes are 0.04, 0.15, 0.25 and 0.56 respectively. Pre-University score represents the student's prior academic qualification. A student with Advanced Level (A/L) degree enjoys the highest points compared to others. The score for the study mode was set to 1.0 and distributed

among peers, personal study and group discussion. Age score was set to 0.8 and weight 0.10, 0.18, 0.22, and 0.30 and it indicates the level of maturity of mind and reasoning.

Neuro-Fuzzy Implementation

In setting up the Neuro-fuzzy system, a hybrid system was developed using Mamdani fuzzy inference technique with the combination of gradient descent and least-square estimate learning algorithm. In the testing phase, 30 records in the dataset were divided into three (training, validation and testing) in a ratio of 8:1:1 respectively. 24 records were used for training, 3 records were used for validation and 3 records were used for testing. The degree to which the output of the system matches the actual data set was used to evaluate the system's forecasting ability. The Mamdani FIS was constructed using a triangular membership function for all records and the input and output variables were scored as poor, low, moderate, high and excellent. The method integrates the elementary features of the Mamdani model-based Neuro-fuzzy inference system (M-NFIS) into forecast evaluation, which has ten inputs and one output, as shown in Figure 6.

The triangular MF was adopted as presented in Table 2. The NFIS procedure was invoked with the MATLAB editor. The Mamdani's inference mechanism was adopted with *Min* and *Max* operators for implication and aggregation operations respectively. Five linguistic terms for dependent and independent variables defined for input are *Excellent*, *High*, *Moderate*, *Low* and *Poor* and for output are *First class*, *Second Class Upper*, *Second Class Lower*, *Third Class* and *Fail*. The Inference system enables the choice of membership function and the formation of fuzzy rules. The rule editor enables the formation of rules for deductive reasoning. Some of the fuzzy decisions, obtained fuzzy weights and the grade forecasts based on the attributes are presented in Table 4.

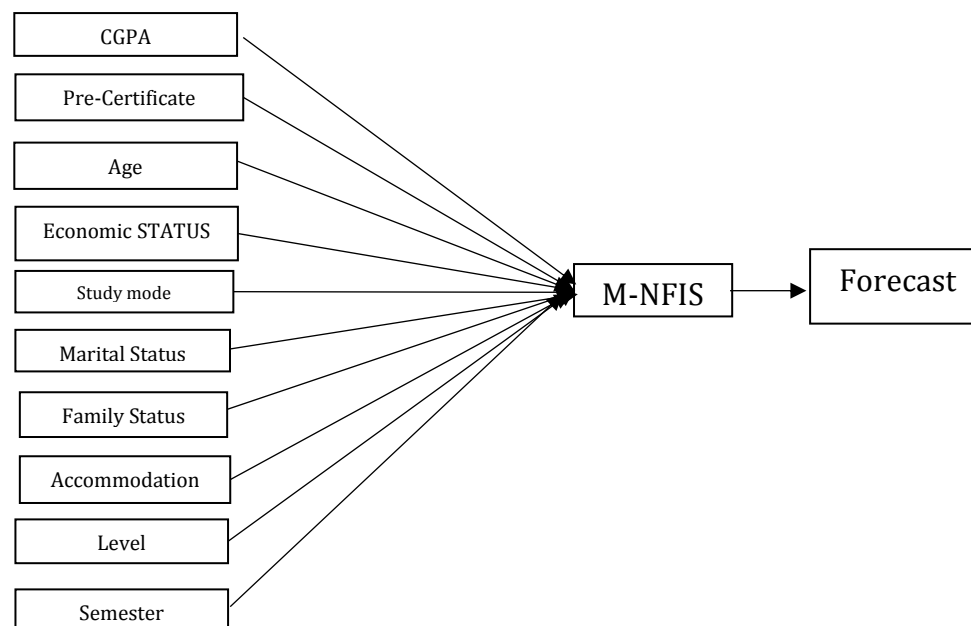


Figure 6: Mamdani NFIS for forecast evaluation

Table 4: fuzzy decisions, obtained fuzzy weight and the grade forecast based on the attributes

S/N	Matric No.	Attribute	Fuzzy decision	Fuzzy weight	Grade forecast
1.	SEN/18/2001	advance level, age (21 years), both parent sponsor, group discussion, single, hostel and excellent	0.2, 0.3, 0.7, 0.6, 0.07, 0.56, 0.23, 1.9	4.60	First class
	SEN/18/2023	WAEC, age (16 years), community sponsor, group discussion, single and excellent	0.1, 0.18, 1.0, 0.6, 0.07, 0.56, 0.23 and 1.9	4.68	
	SEN/18/2030	GCE, age (19 years), social sponsor, group discussion, single, hostel and academic excellent	0.15, 0.22, 1.0, 0.6, 0.07, 0.56, 0.23 and 1.9	4.77	
2.	SEN/18/2003	Advanced level, age (25 years), self-sponsor, group discussion, single, monogamy, hostel with academic excellent	0.2, 0.3, 0.1, 0.6, 0.07, 0.56, 0.23, and 1.9	4.00	2 nd class upper
	SEN/18/2009	GCE, age (21 years), social sponsor, group, discussion, single, orphan, single parent, hostel and academic excellent	0.15, 0.3, 1.0, 0.6, 0.07, 0.04, 0.23 and 1.9	4.33	
	SEN/18/2010	Combination, age (17 years), social sponsor, group discussion, single, monogamy, hostel and academic high	0.05, 0.22, 0.7, 0.6, 0.07, 0.56, 0.23 and 1.9	3.67	
	SEN/18/2026	A/L, age (24 years), self-sponsor, group discussion, single, single parent, hostel and academic excellent	0.2, 0.3, 0.1, 0.6, 0.07, 0.15, 0.23 and 1.9	3.59	
	SEN/18/2029	NECO, age (16 years), both parents, personal study, single, polygamy, hostel with excellent academic	0.1, 0.18, 0.7, 0.35, 0.07, 0.25, 0.23 and 1.9	3.82	
3.	SEN/18/2002	A/L, age (23 years), self-sponsor, personal study, single, single parent, off-campus and moderate academic	0.20, 0.3, 0.4, 0.35, 0.07, 0.15, 0.12 and 1.1	2.73	2 nd class Lower
	SEN/18/2017	WAEC, age (22 years), both parents, personal study, single, monogamy, hostel and low academic	0.1, 0.3, 0.7, 0.35, 0.07, 0.56, 0.23 and 0.8	3.15	
	SEN/18/2020	Combination, age (16 years), both parents, group discussion, married, polygamy, off-campus and moderate academic	0.05, 0.18, 0.7, 0.6, 0.03, 0.25, 0.12 and moderate academic.	3.07	
4.	SEN/18/2008	Combination, age (17 years), self-sponsor, group discussion, married, orphan, squat and moderate academic	0.1, 0.18, 0.1, 0.6, 0.03, 0.25, 0.05, 0.03 and 1.1	2.45	3 rd class
	SEN/18/2014	GCE, age (14 years), both parents, peer group, single, polygamy, off-campus with low academic	0.15, 0.1, 0.7, 0.05, 0.07, 0.25, 0.12 and 0.8	2.28	
	SEN/18/2024	WAEC, age (18 years), single parent, personal study, single, polygamy, squat and low academic	0.1, 0.18, 0.4, 0.35, 0.07, 0.25, 0.05 and 0.8	2.24	
5.	SEN/18/2015	NECO, age (18 years), both parents, peer group, married, polygamy, off-campus, and poor academic	0.1, 0.18, 0.4, 0.35, 0.07, 0.25, 0.05 and 0.0	1.47	Fail
	SEN/18/2025	WAEC, age (26 years), self-sponsor, peer group, single, orphan, hostel and poor academic	0.1, 0.3, 0.1, 0.05, 0.07, 0.04, 0.23, and 0.0	0.93	Fail

Table 5 presents the overall Neuro-Fuzzy forecast grade for the 30 students. The Table presents the FL scores (based on Equations 6-20) on the dataset derived from the weighted influence on all firing rules on the forecasting parameters (attributes). Each of the attributes was weighted and scored based on its assigned fuzzy score.

Table 5: The overall Neuro-Fuzzy forecast for the 30 students

Mat No.	Pre-University	Age	Social Economic	Decision Analysis	Marital Status	Family Status	Accommodation	CGPA weight	Level	Semester	Output	Remark	Forecast Grade
SEN/18/2001	0.20	0.30	0.7	0.60	0.07	0.56	0.23	1.9	0.03	0.01	4.60	Excellent	First class
SEN/18/2002	0.20	0.30	0.4	0.35	0.07	0.15	0.12	1.1	0.03	0.01	2.73	Moderate	2 nd class lower
SEN/18/2003	0.20	0.30	0.1	0.60	0.07	0.56	0.23	1.9	0.03	0.01	4.00	High	2 nd class upper
SEN/18/2004	0.20	0.18	0.7	0.60	0.07	0.56	0.12	1.2	0.03	0.01	3.67	High	2 nd class upper
SEN/18/2005	0.15	0.22	1.0	0.35	0.03	0.25	0.12	1.2	0.03	0.01	3.36	Moderate	2 nd class lower
SEN/18/2006	0.20	0.18	0.7	0.60	0.03	0.25	0.12	1.2	0.03	0.01	3.32	Moderate	2 nd class lower
SEN/18/2007	0.05	0.10	0.4	0.05	0.07	0.56	0.12	1.1	0.03	0.01	2.49	Moderate	2 nd class lower
SEN/18/2008	0.10	0.18	0.1	0.60	0.03	0.25	0.05	1.1	0.03	0.01	2.45	Low	3 rd class
SEN/18/2009	0.15	0.30	1.0	0.60	0.07	0.04	0.23	1.9	0.03	0.01	4.33	High	2 nd class upper
SEN/18/2010	0.05	0.22	0.7	0.60	0.07	0.56	0.23	1.2	0.03	0.01	3.67	High	2 nd class upper
SEN/18/2011	0.20	0.22	0.4	0.60	0.07	0.25	0.23	1.1	0.03	0.01	3.11	Moderate	2 nd class lower
SEN/18/2012	0.20	0.30	0.1	0.35	0.07	0.04	0.23	0.8	0.03	0.01	2.13	Low	3 rd class
SEN/18/2013	0.05	0.18	1.0	0.60	0.07	0.15	0.05	1.2	0.03	0.01	3.34	Moderate	2 nd class lower
SEN/18/2014	0.15	0.10	0.7	0.05	0.07	0.25	0.12	0.8	0.03	0.01	2.28	Low	3 rd class
SEN/18/2015	0.10	0.18	0.7	0.05	0.03	0.25	0.12	0.0	0.03	0.01	1.47	Poor	Fail
SEN/18/2016	0.20	0.18	0.4	0.35	0.03	0.25	0.05	1.1	0.03	0.01	2.60	Moderate	2 nd class lower
SEN/18/2017	0.10	0.30	0.7	0.35	0.07	0.56	0.23	0.8	0.03	0.01	3.15	Moderate	2 nd class lower
SEN/18/2018	0.05	0.30	0.4	0.60	0.07	0.25	0.23	1.1	0.03	0.01	3.04	Moderate	2 nd class lower
SEN/18/2019	0.05	0.22	1.0	0.60	0.07	0.56	0.12	1.2	0.03	0.01	3.86	High	2 nd class upper
SEN/18/2020	0.05	0.18	0.7	0.60	0.03	0.25	0.05	1.1	0.03	0.01	3.00	Moderate	2 nd class lower
SEN/18/2021	0.10	0.30	0.4	0.35	0.07	0.56	0.23	0.8	0.03	0.01	2.85	Moderate	2 nd class lower
SEN/18/2022	0.10	0.22	1.0	0.60	0.07	0.15	0.12	1.2	0.03	0.01	3.50	High	2 nd class upper
SEN/18/2023	0.10	0.18	1.0	0.60	0.07	0.56	0.23	1.9	0.03	0.01	4.68	Excellent	First class
SEN/18/2024	0.10	0.18	0.4	0.35	0.07	0.25	0.05	0.8	0.03	0.01	2.24	Low	3 rd class
SEN/18/2025	0.10	0.30	0.1	0.05	0.07	0.04	0.23	0.0	0.03	0.01	0.93	Poor	Fail
SEN/18/2026	0.20	0.30	0.1	0.60	0.07	0.15	0.23	1.9	0.03	0.01	3.59	High	2 nd class upper
SEN/18/2027	0.15	0.18	0.7	0.35	0.07	0.56	0.23	1.1	0.03	0.01	3.38	High	2 nd class upper
SEN/18/2028	0.15	0.22	0.1	0.60	0.07	0.25	0.23	1.1	0.03	0.01	2.76	Moderate	2 nd class lower
SEN/18/2029	0.10	0.18	0.7	0.35	0.07	0.25	0.23	1.9	0.03	0.01	3.82	High	2 nd class upper
SEN/18/2030	0.15	0.22	1.0	0.60	0.07	0.56	0.23	1.9	0.03	0.01	4.77	Excellent	First class

Figure 7 also presents the plot of the overall forecast of the student based on the neuro-fuzzy score.

According to the forecast, students with Matriculation Number SEN/18/2001, SEN/18/2023 and SEN/18/2030 are likely to graduate with first class while students with matriculation number SEN/18/2015 and SEN/18/2025 are likely to fail.

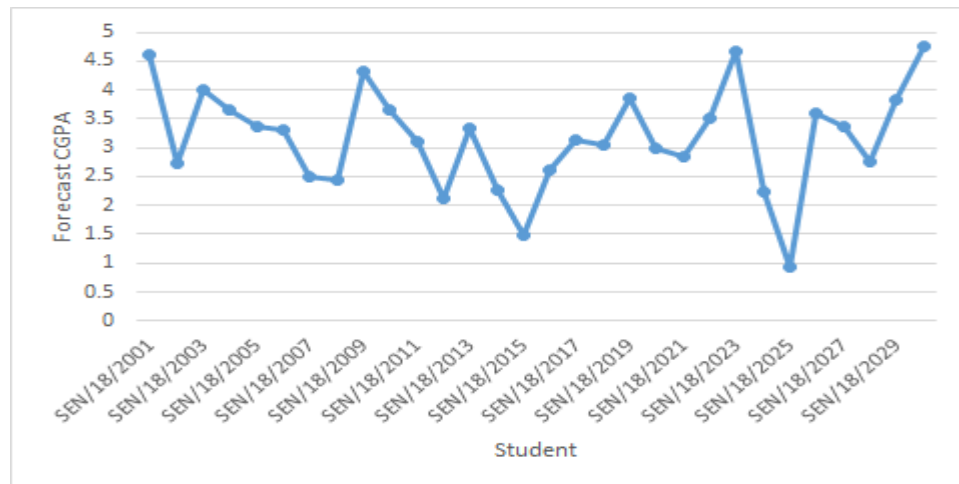


Figure 7: Plot of the forecast CGPA

System Evaluation

The experimental data for the evaluation of the system were derived based on the administration of a questionnaire that featured related questions on users' experiences and responses were based on five-point scaled variables; namely '*Strongly Agree (SA)*', '*Agree (A)*', '*Fairly Agree (FA)*', '*Indifferent (ID)*', and '*Don't Agree (DA)*'. The Questionnaire alongside responses for 100 assessors of students' performance that were randomly surveyed is presented in Table 6.

Table 6: Questionnaire on users' experiences

Index	SA	A	FA	ID	DA	TOTAL
The forecast is very likely to match the final performance	69	11	10	3	7	100
The system drew the correct forecast	78	13	5	1	3	100
The user interface is friendly	81	12	3	2	2	100
The operational system is highly responsive	83	9	1	4	3	100
The system promotes ease of use	87	7	3	3	0	100
The system promotes reliability	82	12	0	2	4	100
students' performance forecasting by the system is consistently accurate	84	7	3	4	2	100
The system meets the user's satisfaction	84	9	3	2	2	100
The system is recommended for use	87	5	5	2	1	100
The system promotes objectivity above subjectivity	90	7	1	0	2	100

The evaluation of the system was based on *Accuracy (A)*, *Precision (P)*, *Recall (R)* and *F-measure (F)*. While *Accuracy* presents how a measurement comes to its true value and it is important because bad equipment or facility, poor data processing or human error can lead to misleading results that deviate from the truth, *Precision* on its shows the closeness among a series of measurements of the same attribute to each other. Precision also qualifies the number of positive predictions that belong to the positive class. *Recall* qualifies the number of positive class

predictions made out of all positive examples in a dataset while *F-Measure* gives a mono score that balances the concerns of precision and recall in a single number. Accuracy, Precision, Recall and F-measure obtained as follows (Iwasokun *et al.*, 2022):

$$A = \frac{\rho + \sigma}{\rho + \beta + \gamma + \sigma} \quad (22)$$

$$P = \frac{\rho A}{\rho A + \gamma C} \quad (23)$$

$$R = \frac{\rho A}{\rho A + \beta B} \quad (24)$$

$$F = \frac{2 * P * R}{P + R} \quad (25)$$

ρ is the number of students that satisfy a certain requisition out of those forecasted by the system, β is the number of students that satisfy a certain requisition but are not correctly forecasted by the system, γ is the number of students that do not satisfy a certain requisition through correctly forecasted by the system and σ is the number of students that do not satisfy a certain requisition and not correctly forecasted by the system. The measure of *Accuracy*, *Precision*, *Recall* and *F-measure* based on the opinion of the 100 surveyed individuals is shown in Figure 8. It is revealed that 76%, 80%, 67% and 78% were recorded for Accuracy, Precision, Recall and F-Measure respectively. This shows that the system performed well. The comparison of the proposed system based on *Flexibility*, *Accuracy*, *Scalability* and *User Feedback* with other related works is presented in Table 7. While 0 implies not available, 1 means available. It is evident from Table 7 that output from the current study possesses all the attributes while output from each of the other studies failed in one attribute or the other.

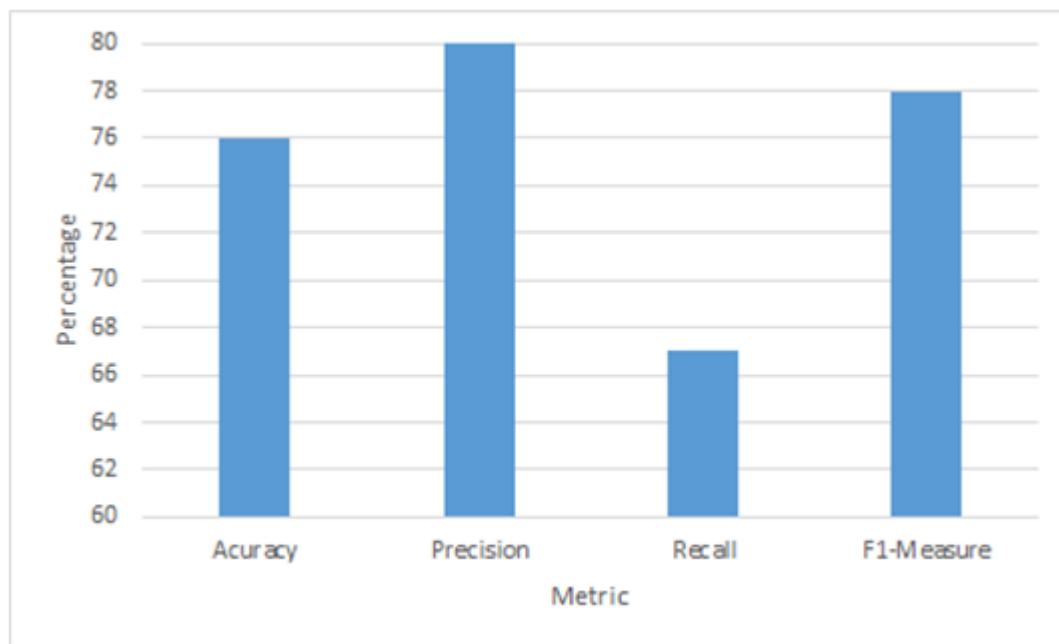


Figure 8: System performances based on standard metrics

Table 4.4: Comparison of Research Work with other Existing Systems

Attribute	Solaf and Miran (2015)	Umar (2019)	Ikuomola A.J. and Arowolo (2020)	Boyinbode et al (2020)	Current system (2019)
Flexibility	1	1	0	1	1
Accuracy	0	0	1	0	1
Scalability	1	1	0	1	1
User Feedback	1	1	1	1	1

DISCUSSION

The aim of forecasting student academic performance is to evaluate the ultimate grade of a student if he or she continues to maintain the existing status as provided by some forecasting variables. It provides support in the selection of courses and the designing of the appropriate study guide and mechanisms for students. It also allows students to play an active role in the forecasting process, which experts have discovered could lead to increasing the attainment of set goals. Most of the existing methods for the prediction of students' academic performances fall within data mining (clustering, classification and association rule) and machine learning. According to reports, these methods are confronted with the challenges of instability of prediction accuracy, leading to over-fitting, insecurity, lack of consideration to non-academic factors, generalized association rules, feedback and virtuality with increased dataset leads to growth in complexities (Mohd et al., 2017; Altyeb and Barukab, 2017; Ritu and Vishu, 2016; Ashwani et al, 2016; Sangita and Sudhir, 2018; Veena et al, 2018; Gudyalakar, et al, 2018; Solaf and Miran, 2015; Nidhi and Jatinderkumar, 2013; Zehra and Fevzi, 2014; Meenakshi and Pankaj, 2015). On this note, this research adopted neuro-fuzzy inferencing, which is a machine learning technique for the development of a student performance prediction system that addresses some of these challenges and provides an objective platform for the seamless forecast of academic performances. The existing and the new techniques are scientific in nature

and offer a systemic approach to overcoming some human-related bottlenecks in performance prediction and evaluation.

The new technique is a forecasting processing mechanism that is devoid of human interference and influence, hence the issue of subjectivity or emotional intervention in prediction is effectively eliminated. According to Wu *et al.* (2020) and Rinsum and Verbeeten (2012), the negative impacts of subjectivity on performance forecasting include reduced perceived mission clarity, and diminishing levels of trust, with a consequential effect of reduction in motivation. As exhibited in the experimental study, the proposed model is scalable, adaptive and hence suitable for the inclusion of other academic performance prediction-related variables, thereby serving predictive and evaluation purposes. This is in agreement with the opinion of Saa *et al.* (2019), Levin (1998) and Heather (2020) that an academic performance prediction system must meet predictive and other evaluation criteria. Analysis of results from the experimental study also revealed the positive impacts of the application of neuro-fuzzy for establishing standard definitions for linguistic variables. These impacts include timeliness, high accuracy and good precision levels, which according to Ekwoaba *et al.* (2015), United Nations (2013) and APA (2018) are some of the key potentials that any good evaluation and performance system must possess. The conclusion on the high responsiveness of the system by its evaluators establishes its computational simplicity thereby satisfying the opinion of Lievens and Chapman (2019) and Ekwoaba *et al.* (2015) on the need for evaluation systems to be computationally responsive and unassuming. The adaptive nature of the system is in agreement with Wang (2007) and Bachinger *et al.* (2021) who opined that for effectiveness, predictive systems must exhibit dynamic adaptation to the needs of the stakeholders, the problem domain, and to the decision context. Since different organizations use a variety of approaches in different environments and legal frameworks, an adaptive system is required to facilitate suitable prediction of performances as well as limit the functional overheads to the minimum. The adaptive attribute of the system also places it in agreement with Angelopoulos *et al.* (2015) and Almutairi *et al.* (2021), who opined that adaptability should be one of the key principles for validating the outcome of any predictive system. Huilgol (2023) and Powers (2011) argued that for wide acceptability and reliability, a predictive system must score high on accuracy, precision, recall and f-measure evaluation metrics.

The experimentally obtained values of 76%, 80%, 67% and 78% for accuracy, precision, recall and f-measure respectively are based on the opinion of surveyed individuals and hence justified the high acceptability and functional reliability of the proposed system. Furthermore, results on the user's evaluation of the system show significant advancement of the new model over the existing ones in areas of flexibility, accuracy, scalability and user feedback which according to Power (2002), Podvesovskii *et al.* (2021) and Ko *et al.* (2022) are key criteria for a good performance forecasting system. This advancement implies the new system stands to gain higher preference from organizations on educational assessments. The obtained scoring weights are specific to the research dataset obtained from the Department of Software Engineering, Federal University of Technology, Akure, Nigeria. Different weights could be recorded for datasets from any other Department or institution, implying that the scoring weights are domain dependent and not generic.

CONCLUSION

The limitations of some of the existing works on the application of scientific methods to forecasting students' academic performance currently pose a research gap. These limitations include prediction inaccuracy, leading to over-fitting, data insecurity, lack of consideration for non-academic factors, non-existence of generalized association rules, poor feedback and growth in complexity with the increased dataset. Hence, this paper presented a report of cutting-edge research to fill the gap by addressing the pre-listed limitations as well as lessen the doubt and burdens that presently confront most predictive processes for students' academic performance. The proposed model encompasses neural network, fuzzy logic, inferencing and fuzzification subcomponents. While the neural network component uses a three-layered feed-forward architecture to acquire a large collection of units that are interconnected in some pattern for communications between units, the fuzzy logic sub-component used Boolean logic for establishing an accurate selection process and precise solutions to multi-variable problems. The inferencing unit used a preset objective procedure on input from the rule base for forecasting. The fuzzification interface was used to generate the final and objective forecasting. The model is fortified with features for attaining a scalable, adaptive and computation-friendly system that is devoid of subjectivity and complexities. The originality of the model is presented through its cleverly picking of weights for the forecasting variables in precedence to rational evaluation. The model is also unique in its offering of selective and adaptive variable assessment mode in contrast to the predetermined and static style of the existing performance forecasting models. The system that arose from the implementation of the model sufficiently overcome some human-related challenges through fool-proof and error-free performance prediction. Such challenges include a lack of apparent statistically significant differences in the thoughts and opinions on valid and invalid criteria in the context of identifying the critical aspects of the prediction and lack of deep reasoning skills and poor handling of uncertainties. The new technique offered a performance predictive procedure that is free of human interference and influence, thereby promoting highly objective output. On the social implications, its high objectivity suggests it will be very much useful for monitoring the performance trend of students anywhere it is adopted. Analysis of results from the experimental study of the model also revealed how the application of neural network and fuzzy logic established timeliness, high accuracy and good precision levels based on standard definitions for the linguistic variables. The conclusion that the system is highly responsive by its evaluators equally established its user-friendliness and computational simplicity. The system also scores high on accuracy, precision, recall and f-measure evaluation metrics based on the opinion of surveyed individuals. This means the system enjoys high acceptability and is adjudged to be functionally reliable. Further evaluation of the system also showed its significant advancement over some of the existing ones in areas of flexibility, accuracy, scalability and user feedback. This advancement implies the new system is poised to enjoy greater patronage from various organizations for the forecast of academic performances.

Further Research

Further research aims at implementing the model with multi-source, bigger and wider variables datasets. Towards an effective classification of variables and optimality of results and predictions, future research will also focus on combining neural networks with other machine learning techniques such as genetic algorithms.

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