

## Hybrid Soft Computing System for Student Performance Evaluation

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**Abstract.** *Education Institutions have deployed technology accelerated learning systems and innovations for effective learning outcomes. Evaluating student's performance in these systems must align with the cognitive, affective, and psychomotor learning domains. In this research, a Hybrid soft computing system comprising of the Clustering Algorithm, Machine learning technique, and Optimization algorithm were hybridized and implemented to evaluate student academic performance using academic, social, and economic data of students. The proposed model demonstrated the best results with the lowest mean square error (MSE) and root mean square error (RMSE) values of 0.17 and 0.41, respectively. Additionally, the GANFIS model achieved values of 0.25 and 0.50, respectively, which slightly outperformed the proposed FCM-PSOAN-FIS model. The proposed model works better with bigger datasets, and it delivers higher predictive findings under settings that depict student learning capacities while assessing student academic achievement.*

**Keywords:** *Hybrid; Soft Computing; Clustering Algorithm; Machine learning; Optimization Algorithm.*

### 1. Introduction

Several stakeholders, including educators, organizations, and communities, are concerned about how understudies are presented [1]. As a result, graduates must study harder for excellent reviews to progress to the desire for enlistment offices. Student assessment is critical in the education sector because it allows individual schools to monitor their student achievement, which aids university entrance commissions in evaluating individual students' abilities and results [2]. The term "evaluation" refers to the method of assessing a program critically. It comprises acquiring and analyzing data on a program's features, operations, and results. It aims to analyze



programs, increase their efficiency, and/or provide programming advice. In education, performance evaluation (PE) is a common mechanism for determining the degree or extent of a student's successful learning outcomes. It includes a wide range of tasks, from writing a brief response to conducting and analyzing a laboratory investigation, all of which involve students creating an original response that demonstrates their abilities and reasoning. They are used to evaluate high-level reasoning and problem-solving skills, as well as emotions or behaviors, environmental or psychological experiences, and the ability to apply learning to real-world problems [3].

Student Performance Evaluation (SPE) is a type of testing that allows students to complete a task rather than choose a response from a pre-determined list, after which experienced raters (either teachers or other professional staff) assess the quality of the student's work using a collection of established specifications. Traditional evaluation use CGPA as an output attribute for evaluating student success, which educational psychology and similar disciplines contend is unreliable in evaluating students' academic performance [4]. Without having to employ their long-term logical thinking abilities, students react to each question individually. Despite their ignorance of the topic at hand, they frequently pass up chances to demonstrate their logical thinking. This method does not allow for simple adjustment of student learning development because it does not allow for collaborative and innovative thinking, which has been shown to improve technical and professional skills. Since, to enhance learning processes, most educational institutions use Technological Accelerated Learning (TAL) systems in the form of e-learning, distance learning, m-learning, or online learning. When it comes to conventional learning programs, student success is often assessed using the cognitive domain, which includes understanding, comprehension, implementation, interpretation, and synthesis. Feelings, thoughts, behaviors, beliefs, motivations, physical expression, balance, motor, and sensory abilities are frequently overlooked in the Affective and Psychomotor domain. Performance Evaluation of students in TALs should envelop the learning domain such as the cognitive, affective, and psychomotor [5].

Soft Computing (SC) refers to a class of machine learning approaches that use AI and evolutionary theory to provide a simple and effective solution to extremely tough problems when analytical (hard computing) formulations are not possible. SC techniques like the Particle Swarm Optimization (PSO) and the bacterial foraging optimization (BFO) now incorporate swarm intelligence and biological population foraging behavior. [6]. Particle Swarm Optimization is a strategy that involves a group of particles moving together in order to maximize results. Researchers claim that while a bunch of particles migrates, the velocity vectors known as the vector are used to shift the positions of the particles. Real-world samples and social models were examined in the early stages of particle swarm optimization [7] [8]. Since PSO is part of Swarm Intelligence, swarms or neurons cooperate to find the best solution [9]. Since PSO's concept is based on natural phenomena like bird flocking and fish schooling, it is a population algorithm.

The existing approach of evaluating student performance/examinations from juvenile (first year) to the peak year (final year) focused solely on the cognitive learning domain. It evaluates learners using CGPA as an output attribute for measuring student success, which educational psychology and similar disciplines contend is unreliable in assessing students' academic performance. The emotional intelligence (affective), environmental conditions of institutions, and student mental well-being (psychomotor) were not been factored into use. In other to overcome this drawback, we factor in some affective and psychomotor constraints such as the learning material type used, the economic and social background of the learner, and the environmental conditions of the learning institution and the student. To solve this issue, we use the Fuzzy Clustering approaches to group students as cognitive, affective, and psychomotor domains. The output variable would be the classified outcome, making the proposed model stable and dynamic enough to be used in any educational framework. Supervised learning has many drawbacks, such as dimensions, and it took many training trials to determine the best parameter to use. However, due to the excessive use of data, measuring student performance is becoming more difficult [10]. Fashioning how best to implement this process will assist the department to make a viable learning environment that will address the poor level of attaining specialized skills in computer science. Hence the need for a scientific approach called soft computing to tackle the drawbacks of using an existing approach is required.

The imprecision or ambiguity associated with assessing student success that combines most of the drawbacks/constraints mentioned above can only be significant if they are well incorporated. Assume that linguistic categories such as high, medium, low, and so on would be used to express these shortcomings. These types of measurements are vague, necessitating the use of a Fuzzy Inference System (FIS). Furthermore, machine learning model that collects these parameters must be adaptive to reveal secret information that could be useful in decision-making. As a result, an Adaptive Neuro-Fuzzy Inference System (ANFIS) was introduced. Despite an impressive and robust power of ANFIS, determining better solutions that best predict the test dataset based on the training model requires many experiments (training) and model parameter reconfiguration, such as category of stimulation utilities, learning rate etc. This will necessitate a significant amount of time and space. These parameters can be tweaked to yield better performance. A more robust derivative, the Particle Swarm Optimization (PSO) is considered in this analysis.

The goal of this study is to create a Soft Computing Clustering Expert Framework, the Fuzzy C-Means - Particle Swarm Optimization ANFIS (FCM-PSOANFIS) for evaluating students' overall performance utilizing computer science from the University of Benin (UNIBEN) as an evaluator. The goals are to:

1. Propose Soft Computing Clustering Expert Framework (FCM-PSO-ANFIS) for the evaluation of student performance
2. Implement and evaluate the feasibility of the proposed model using both simulated and department of computer science datasets.

This research reveals a perception of the various issues associated with the current form of evaluating student academic performances.

## 2.1. Related Work

Several previous pieces of research based on the mathematical and predictive models developed for the prediction of student's success. [11]. [12] Proposed the Neural Network (NN) to develop a technique of predicting student performance in mathematics courses that assists educators in identifying disadvantaged kids. They use four separate training algorithms to assess the classification potential of neural networks: Broyden-Fletcher-Goldfarb-Shanno (BFGS), LevenbergMarquardt (LM), Resilient Backpropagation (RRBP) and modified spectral Perry (MSP). In comparison to the other classification techniques, the MSP-trained FNNs exhibit more consistent behavior and have greater generalization accuracy. [13] Used Artificial Neural Networks (ANN) to create a framework that utilized the Multilayer Perceptron Topology to determine why some Nigerian colleges have low student performance. The academic achievement of over 70 percent of incoming freshmen may be reliably predicted by the model using ANN, according to test data analysis, which took several factors into account.

[14] Developed a system based on fuzzy logic to estimate the threat progress of the students based on some basic knowledge about academic achievement to assess the risk level of students. The simulated model reveals that prior academic achievement is associated with a level of risk. The study's results showed that in order to enhance a student's learning ability, an instructor must pay more attention to their weaknesses [15] introduces a novel approach to performance evaluation that is based on fuzzy logic. It takes into account three factors for a single academic course and evaluates student performance using the Mamdani approach. The findings indicate that this method may be used to evaluate students' performance at universities.

Numerous academics have used neural networks to forecast student outcomes, and one of these researchers [16] proposed a decision-support tool based on the NN that identifies "at-risk" students who do not continue their academic progress in the next year. About 70% of pupils' permanence was appropriately predicted by the program. [17] Proposed the model that predict e-learning outcome indicators using the Balanced Scorecard and Neural Networks. The study addresses the problem of small sample size data by using interpolation and principal component analysis, and the

proposed method is shown to be effective and applicable through numerical experiments on real data. The author has obtained an error in the prognosis of 3-4 percent which is appropriate from a realistic perspective. [13] Used a NN to evaluate variables influencing pupils' performance. According to their conclusions, they classified the pupils into three classes. The forecast accuracy that the paper's authors were able to achieve was around 74%. [18] Used a three-layer MLPN with back propagation training to predict graduation levels for graduates. The network model builds of authors had 70.27 percent precision for competent learners and 66.29 percent accuracy for incompetent graduates. [19], a genetic algorithm was used to select highly influential attributes associated with student success. The author compared two classification algorithms: Bayesian Network (BN) and Decision Tree (DT). The findings showed that BN outperformed DT due to its greater precision rating, with student attendance and GPA in the first semester being among the best among all classification algorithms. [20] Focuses on the creation of predictive models using multivariate linear regression, multilayer perceptron neural networks, radial basis function neural networks, and support vector machines to forecast the academic performance of students in an introductory engineering course titled Engineering Dynamics. This course is made up of 239 undergraduate students. The findings demonstrate that, with an average prediction accuracy of 89.0%-90.9% and good predictions of 62.3%-69.0%, the support vector machine model gives the overall best forecasts.

From the studies it revealed that most of the researcher focuses on the cognitive domain in the evaluation of student performance using soft computing as cited by [21], [11], and [19]. Some attribute to attendance, previous knowledge or results as cited by [19], [13]. [22], [23] attributed it to size, dataset, teachers, environmental, personal, social, [24], [20]. The majority of these studies appear to concentrate on a particular topic or course as the factors that influence academic success [11], [19], and [13]. To improve prediction accuracy, [11] suggested that future studies should focus on other variables that may influence student academic performance, such as temperament, intellect, and psychological factors. While many research have been carried out to assess students' academic achievement globally, there are insufficient studies to assess students' performance based on the cognitive, emotional, and psychomotor domains. The vacuum in the literature must be filled. Hence, the study aims to evaluate student performance using a soft computing model called FCM-PSOANFIS in the cognitive, affective, and psychomotor domains of students.

### **3. 1. Methodology**

The proposed hybrid soft-computing model aims to incorporate multiple models of both conventional and technology-based learning systems that will solve several of the problems affecting the predictive and reasoning models. A hybrid of the

FCM-PSOANFIS model was used in this research to design an expert model of a multi-neuro-fuzzy system. The proposed model consists of knowledge databases, which stores pre-entrance, constraints, and academic records of students and stores optimized data. The PSO was integrated to identify solutions and parameters that best train the ANFIS model. The ANN in ANFIS streamlines the set of existing rules use for predicting academic achievement of the student grouping from FCM with necessary parameters and constraints retrieved from the learner database to solve a given new problem while the fuzzy logic part was adopted as a means for implying the imprecision in both constraint and education/academic records. These parameters, therefore, constitute the fuzzy parameter of the adaptive education mining system.

### 3.2. Proposed system’s dataset components and attributes

A specific record description contains three classes of data attributes which are Pre-entrance attributes; Constraint attributes and Academic data attributes. The reason for splitting the definition of the attributes into these classes is that it allows various constraints and requirements to be applied to particular entities and these constraints have to be met to conduct an effective mining operation. It also diminishes the effect of irrelevant or less-relevant attributes on the system performance and decomposes complex information in a more comprehensible manner. Table 1 and Table 2 show the pre-entrance attributes and academic data attributes.

**Table 1.** Pre-entrance attributes

S/N	Variable Name	Linguistic Variable Format	Variable Type
1	UTME Score (UTME)	3(Above 250), 2(200-250), 1(Below 200)	Categorical
2	Average Pre-Entrance or SSCE Result (Mathematics, English, Physics, Biology, Chemistry, etc.)	7(70 and Above), 6(60-69), 5(55-59), 4(50-54), 3(45-49), 2(40-44), 1(Below 40)	Categorical
3	SSCE Sitings (SS)	2(One sitting), 1(two Sitings)	Categorical
4	SSCE Exam Type (SST)	3(WAEC), 2(NECO), 1(NABTEB)	Categorical
5	Age of student at admission (Age)	3(Below 18 years), 2(18-23 years), 1(Above 23)	Categorical
6	Gender (Sex)	2(Male), 1(Female)	Categorical

**Table 2.** Academic data attributes

SN	Attributes/Variables	Description	Values	Type of attributes
1	Level	Level of student	100, 200, 300, 400, 500, 600, 700,800	Categorical
2	Subj1, Subj2 Subj3, Subj4, Subj5, Subj6, Subj7, Subj8, Subj9, Subj10	1 <sup>st</sup> Semester subjects scores	0 to 100	Continuous
3	Subj11, Subj12 Subj13, Subj14, Subj15, Subj16, Subj17, Subj18, Subj19, Subj20	2 <sup>nd</sup> Semester subjects scores	0 to 100	Continuous
4	Class	Class of Degree	1(Distinction), 2(upper Credit), 3(Lower Credit), 4(3 <sup>rd</sup> Class), 5(Fail)	Categorical

### 3.3. Component of particle swarm optimization (PSO)

Particles in the PSO algorithm move around the problem space, guided by their strongest prior position and the best prior position of the entire swarm or maybe a nearby neighbor. Every loop is modified by the particle's velocity in equation (1):

$$u_i(p + 1) = u_i(p) + \left( W_1 \times rand() \times (s_i^{best} - s_i(p)) \right) + \left( W_2 \times rand() \times (s_{gbest} - s_i(p)) \right) \quad (1)$$

Where  $W_1$  and  $W_2$  are the weight coefficients of the absolute best and universal positions,  $u_i(p + 1)$  the current velocity of the  $i$ th particle,  $s_i(p)$  is the location of an  $i$ th particle at time  $p$ ,  $s_{gbest}$  is the renowned swarm position and  $s_i^{best}$  is the famous  $i$ th particle location. The function  $rand()$  generates a variable  $[1,0]$  which is uniformly random. Variants on this update equation take into account the best locations of a particle in time  $t$  within the local neighborhood. The particle Position is updated using the equation (2)

$$s_i(p + 1) = u_i(p) + s_i(p) \quad (2)$$

Fuzzy Logic (FL) and Neural Network (NN), two powerful data mining approaches, are combined to create the Adaptive Neuro-Fuzzy Inference System, or ANFIS for short. The Adaptive Neuro-Fuzzy Inference System combines FL and NN as its FL

and NN elements. This mechanism is under the control of FL and NN intensity. ANFIS have six layers, each of which has a unique property. The architectural layers of ANFIS are as follows.

**3.3.1. Input/entering layer:** Users can access ANFIS through this layer, which also accepts pre-entrance numerical vectors, undergraduate information, and constraints in various language qualities as inputs. These vectors serve as representations of the significant parameter values and training cycle variables for the model. The letter “Z” stands in for the fuzzy word for parameters (also known as attributes) and has a collection of linguistic or continuous values that guarantee the appropriate evaluation of the constraints/attributes. The  $Z_{ni}$  ‘scale is written as shown in equation (3)

$$Z_{ni} = \{M_{n1}..M_{ni}, R_{n1}..R_{ni}, P_{n1}..P_{ni}\} \quad (3)$$

Where:

$M1...Mi$  are linguistic variables for restriction values, and  $n$  is a significant indication in the datasets  $i$ , such as LMC, PSC, e.t.c,  $R1...Ri$  is continuous values for Academic data parameters  $i$  such as ACA, TCE, and  $P1...Pi$  are linguistic values for pre-entrance parameters  $i$  such as Sex, Age, e.t.c

Equation (4) illustrates how this can be described numerically.

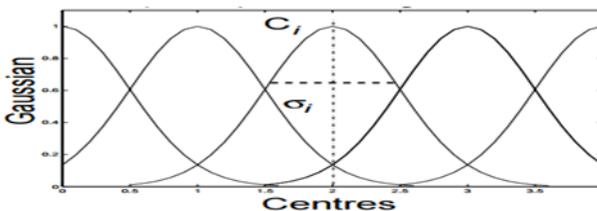
$$A_i^1 = c_i \quad (4)$$

Where:

$A_i^1$  is the  $i^{\text{th}}$  contribution from the first layer of neurons

$x_i$  = Each parameter’s input value

**3.3.2. Layer of membership-function:** The affiliate function, which maps inputs to fuzzy sets, is included in this layer. The Gaussian membership feature was used to assign parameters to the fuzzy scheme, Figure 1. Membership function with a Gaussian distribution can be mathematically represented as equation (5)



**Figure 1.** Membership function with a Gaussian distribution

$$\mu(v) = \exp\left(-\frac{(c_i - v)^2}{2A_i^2}\right) \quad (5)$$

Where:

$C_i$  is the  $i$ th fuzzy set's center or mean

$A_i$  = the  $i$ th fuzzy set's variance/width

$V$  = each input parameter's value

$\mu(v)$  =  $v$ 's membership function

Membership function with a Gaussian distribution was used to map linguistic variables (constraint, academic data, and pre-entrance data) to a collection of members in this layer.

The Rule layer specifies the result for each set of inputs. A second layer with an input value is added to such layers. This layer implemented the Takagi-Sugeno inference model, which can be represented mathematically as formula (6).

$$A_i^3 = \mu(c_1) * \mu(c_2) * \dots * \mu(c_n) \quad (6)$$

Where:

$\mu(c_n)$  = variable  $n$ 's membership function

$A_i^3$  is the  $i^{th}$  neuron's layer 3 output.

In the Layer of normalization, each neuron is paired exclusively with a rule-layer neuron. The standardization layer verifies the input from the preceding layer. Equation (7) illustrates how this can be interpreted mathematically.

$$A_i^4 = \frac{A_i^3}{A_1^3 + A_2^3 + \dots + A_n^3} \quad (7)$$

Where:

$A_i^4$  is the  $i^{th}$  neuron production from layer 4.

$A_i^3$  is the  $i^{th}$  neuron production from layer 3.

$n$  is the cumulative number of neurons in the third layer.

The normalization layer's input is all supplied into one neuron in the layer of defuzzification.

Defuzzification is the process of converting fuzzy values to actual values. Equation (8) illustrates how this may be expressed numerically.

$$A_i^5 = A_i^4(d_i(c_i) + d_2(c_2) + \dots + d_n(c_n) + u) \quad (8)$$

Where:

$c_i$  is the vector  $n$ 's resultant parameter.

$u$  = bias

$A_i^5$  is the  $i^{\text{th}}$  neuron production from layer 5.

$c_i, d_i$  = subordinate parameters

Layer of output generated results, and the number of neurons within the said layer decides how many outputs the system produces. Equation (9) illustrates how it can be expressed mathematically.

$$A_i^6 = \sum_i^n A_i^5 \quad (9)$$

Where:

$A_i^5$  is the  $i^{\text{th}}$  neuron production from layer 5

$A_i^6$  is the  $i^{\text{th}}$  neuron production from layer 6 respectively.

Creating student profile module allow the educationist to generate a student profile comprising of all attributes captured from the student information record submitted to the department either from the hardcopy form or from the online application. This ensures that appropriate data are captured for the ANFIS component. The database will hold information about the student in their respective departments and will also provide a mechanism for storage and result retrieval. While the view student profile component allow the student to view their results based on the FCM-PSO-ANFIS model.

### 3.4 Model performance validation function

The fitness function is the root mean square error (RMSE) or mean square error (MSE), a particular method used for classification. Equation (10) was utilized to validate model findings. A predictive model with a smaller root mean square error (RMSE) can provide more data.

$$RMSE = \sqrt{\frac{1}{m} \sum_{j=1}^m (S_j^{real} - S_j^{prediction})^2} \quad (10)$$

Where:

$m$  denotes the total number of samples to be analyzed.

$j$  = sample index for research,  $j = 1, 2, 3, \dots, n$ ,

$S_j^{real}$  denotes the current situation,

$S_j^{prediction}$  denote the expected condition/outcome.

## 4.1. Results and Discussions

MATLAB was used in the development of the PSO component and ANFIS to optimize and store datasets. The APACHE HTTP server was used to distribute the user interfaces, which were developed using PHP and HTML. Datasets and tables were stored in MySQL. The suggested solution made use of MATLAB and includes the Adaptive Machine Learning (ANFIS), Particle Swarm Optimization, and Fuzzy Clustering-Means algorithms. 91 and 31 datasets were utilized/used for training. Root mean square error (RMSE) findings for ANFIS, GANFIS, and FCM-PSOANFIS were 0.65, 0.50, and 0.41, and 0.74, 0.41, and 0.44 respectively. When these data were compared, FCM-PSOANFIS showed more convergence than ANFIS and GANFIS.

## 4.2. ANFIS Model Training and Testing.

The performance of different models was evaluated using a training dataset of 91 students (Table 1). The proposed FCM-PSOANFIS model demonstrated the best results with the lowest mean square error (MSE) and root mean square error (RMSE) values of 0.17 and 0.41, respectively. These values indicate that the FCM-PSOANFIS model performed optimally on the training dataset. Similarly, the models were tested on a separate dataset of 39 students in the 200 level (Table 2). In terms of MSE and RMSE, the GANFIS model achieved values of 0.25 and 0.50, respectively, which slightly outperformed the proposed FCM-PSOANFIS model with values of 0.19 and 0.44. This suggests that the proposed algorithm can effectively handle both small and large datasets, meeting the required standards.

**Table 1.** Model Performance for Training Dataset

<b>MODEL TYPE</b>	<b>MEAN SQUARE ERROR (MSE)</b>	<b>ROOT MEAN SQUARE ERROR (RMSE)</b>	<b>NO OF TRAINING DATA</b>
ANFIS	0.42	0.65	91
GANFIS	0.25	0.50	91
FCM-PSOANFIS	0.17	0.41	91

**Table 2.** Model Performance for Testing Dataset

<b>MODEL TYPE</b>	<b>MEAN SQUARE ERROR (MSE)</b>	<b>ROOT MEAN SQUARE ERROR (RMSE)</b>	<b>NO OF TRAINING DATA</b>
ANFIS	0.54	0.74	39
GANFIS	0.172	0.41	39
FCM-PSOANFIS	0.19	0.44	39

## 5. Conclusion

The aim of evaluating student performance is to assist teachers and students in strengthening their teaching and learning processes. In this study, we developed a hybrid software model that will help educators and administrators evaluate students' academic success based on both academic outcomes and economic and social status. We used the Fuzzy Clustering Algorithm (Fuzzy C-Means), Optimization algorithms (Particle Swarm Optimization), and Adaptive Machine Learning (ANFIS). The results from training and testing using root mean square error (RMSE) for ANFIS, GANFIS and FCM-PSOANFIS where 0.65, 0.50, 0.41 and 0.74, 0.41, 0.44 respectively which show a higher convergence for the FCM-PSOANFIS when compare with ANFIS and GANFIS. The proposed model will provide more predictive results in any conditions that portray the student learning abilities and when used in assessing student academic performance. Future research should explore the application and verification of a combined bootstrap educational mining model by utilizing contemporary nature-inspired optimization algorithms like Grey Wolf, Artificial Bees, and Whale Optimization Techniques. Furthermore, an advisory mechanism should be established to enhance students' learning patterns through specialized learning techniques, employing an SMS alert system.

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