Soft Computing Hybrid System for Student Performance Evaluation

Eguavoen, V[a,1,*], Nwelih, E[b,2]

[a] Department of computer Science, Wellspring University, Benin City, Edo State, Nigeria
[a,b] Department of Computer Science, University of Benin, Benin City, Edo State, Nigeria
[1] victor_eguavoen@wellspringuni.edu.ng*; [2] emmanuel.nwelih@uniben.edu
* Penulis Korespondensi

ABSTRAK

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 quality of Categorizing information first utilizing Fuzzy C-Means and preparing ANFIS utilizing Particle Swarm Optimization was introduced which formed the Hybrid soft computing system (FCM-PSOANFIS). It demonstrated significantly, a robust predictive capability compared to other hybrid machine learning algorithms such as ANFIS and GANFIS. The results of the proposed Hybrid Soft Computing model (FCM-PSOANFIS) show a higher convergence when compare with ANFIS and GANFIS. The proposed model works better with bigger datasets than with smaller or fewer datasets, and it delivers higher predictive findings under settings that depict student learning capacities while assessing student academic achievement.

Check for updates

Kata Kunci
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 behaviours, 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, behaviours, 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 (POS) is considered in this analysis.

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

- Propose Soft Computing Clustering Expert Framework (FCM-PSOANFIS) for the evaluation of student performance
- 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. 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: BFGS, LM, RPROP, and 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], [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], [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. 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.

3.1. 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.

3.2. Data 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):

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

Where W1 and W2 are the weight coefficients of the absolute best and universal positions, $u_i(p+1)$ the current velocity of the ith particle, $s_i(p)$ is the location of an ith particle at time p, s_{gbest} is the renowned swarm position and s_i^{best} is the famous ith 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 neighbourhood. The particle Position is updated using the equation (2)

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

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.

3.2.1. 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)

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

Where:

M_1...M_i are linguistic variables for restriction values, and n is a significant indication in the datasets i, such as LMC, PSC, e.t.c, $R_{1..}R_i$ is continuous values for Academic data parameters i such as ACA, TCE, and $P_{1..}P_i$ are linguistic values for pre-entrance parameters i such as Sex, Age, e.t.c

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

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

Where:

A_i^1 is the i^{th} contribution from the first layer of neurons
x_i = Each parameter's input value

3.2.2. 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)

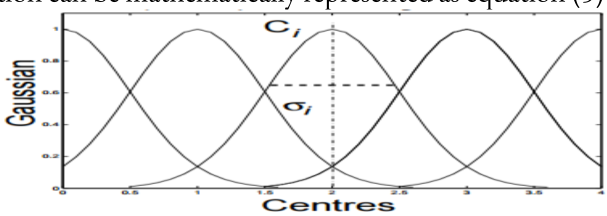

Figure 1. Membership function with a Gaussian distribution

Vol. 11., No. 2, Juni 2023, pp. 47-55 ISSN 2809-3399

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

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
$\mu(\mathrm{v})$ = 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).

$$\mathrm{A}_\mathrm{i}^3 = \mu(c_1) * \mu(c_2) * \ldots.\mu(c_n) \quad (6)$$

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.

$$\mathrm{A}_\mathrm{i}^4 = \frac{\mathrm{A}_\mathrm{i}^3}{\mathrm{A}_1^3 + \mathrm{A}_2^3 + \cdots + \mathrm{A}_\mathrm{n}^3} \quad (7)$$

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.

$$\mathrm{A}_\mathrm{i}^5 = \mathrm{A}_\mathrm{i}^4(d_i(c_i) + \mathrm{d}_2(c_2) + \cdots \mathrm{d}_n(c_n) + \mathrm{u}) \quad (8)$$

Where:

c_i is the vector n's resultant parameter.
u= bias
A_i^5 is the i^{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.

$$\mathrm{A}_\mathrm{i}^6 = \sum_{\mathrm{i}}^{\mathrm{n}} \mathrm{A}_\mathrm{i}^5 \quad (9)$$

Where:

A_i^5 is the i[th] neuron production from layer 5
A_i^6 is the i[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-PSOANFIS model.

3.3. 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.

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

Where:

m denotes the total number of samples to be analyzed.
j = sample index for research, j =1,2,3,...,n),
$\boldsymbol{S}_j^{real}$ denotes the current situation,
$\boldsymbol{S}_j^{prediction}$ denote the expected condition/outcome.

4. Results and Discussions

The PSO part and ANFIS was developed using the MATLAB platform. The PSO part was used to optimize and store the datasets. The ANFIS part was developed using Matrix Laboratory. The Hypertext Preprocessor (PHP) and Hypertext Markup Language (HTML) were used to develop the user interfaces. APACHE HTTP server was used to deploy all of the interfaces. MySQL was used to store all of the datasets and tables. The proposed algorithm was implemented with the help of MATLAB. The following subsections describe the operations of the model.

4.1. ANFIS Model Training and Testing

Table1 shows model performance on a training dataset of 91 students. It was observed that the proposed FCM-PSOANFIS has the least MSE and RMSE values. This implies that the FCM-PSOANFIS model performed optimally on the training dataset. Table2 shows model performance on a testing dataset of 39 students in 200 level. It was observed that the GANFIS slightly outperform the proposed FCM-PSOANFIS in terms of MSE and RMSE. It is therefore obvious that the proposed algorithm will meet standards to handle small and large datasets.

Table1. Model Performance for Training Dataset

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

Table2. Model Performance for Testing Dataset

MODEL TYPE	MEAN SQUARE ERROR (MSE)	ROOT MEAN SQUARE ERROR (RMSE)	NO OF TRAINING DATA
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, student performance is evaluated. 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). It provides fresh learners/new pupils with JIT (just in time) correct ideal responses supported by method verification. Last but not least, student performance evaluation with (FCM-PSOANFIS) is appropriate for use in theoretical classrooms, other educational contexts, including remote learning programs offered by Nigeria's National Open University system.

Daftar Pustaka

[1] D. Mertens, Research and Evaluation in Education and Psychology: Integrating Diversity With Quantitative, Qualitative, and Mixed Methods, SAGE Publications. https://books.google.com.ng/books?id=6RR7DwAAQBAJ, 9781544333748, 2019.

[2] O. L. B. B. &. A. R. M. Liu, "Measuring Learning Outcomes in Higher Education: Motivation Matters.," Educational Researcher 41(9), https://doi.org/10.3102/0013189X12459679, p. 352–362., 2012.

[3] E. Thandevaraj, N. Gani and M. Nasir, "A Review of Psychological Impact on Students Online Learning during Covid-19 in Malaysia," Creative Education, 12, 1296-1306. doi: 10.4236/ce.2021.126097, 2021.

[4] I. &. R. J. L. Boutakidis, "Academic motivation and engagement across three generations of Latino/a junior high school students," Journal of Latinos and Education. doi: 10.1080/15348431.2019.1674147 , 2019.

[5] J. Udeni, S. Ajantha and D. Anuja, "Student's Performance Evaluation in Online Education System vs Traditional Education system.," International COnfrerence on Remote Engineering and Virtuak Instrumentation. Bangkok, Thailand: IEEE., pp. 127-131, 2015.

[6] J. Tang, G. Liu and Q. Pan, "A Review on Representative Swarm Intelligence Algorithms for Solving Optimization Problems: Applications and Trends,"," IEEE/CAA Journal of Automatica Sinica vol. 8, no. 10, pp. 1627-1643, October 2021, doi: 10.1109/JAS.2021.1004129., pp. 1627-1643, 2021.

[7] C. Lin, "Optimization of Bearing Locations for Maximizing First Mode Natural Frequency of Motorized Spindle-Bearing Systems Using a Genetic Algorithm.," Applied Mathematics, 5, doi: 10.4236/am.2014.514208., pp. 2137-2152, 2014.

[8] M. Al-Faiz and S. Sadeq, "Particle Swarm Optimization Based Fuzzy-Neural Like PID Controller for TCP/AQM Router," Intelligent Control and Automation, Vol. 3 No. 1, doi: 10.4236/ica.2012.31009., pp. 71-77, 2012.

[9] L. Zajmi, F. Y. H. Ahmed and A. A. Jaharadak, "Concepts, Methods, and Performances of Particle Swarm Optimization, Backpropagation, and Neural Networks," Applied Computational Intelligence and Soft Computing Hindawi https://doi.org/10.1155/2018/9547212, 2018.

[10] M. S. Amirah, H. Wahidah and A. R. Nur'aini, "A Review on Predicting Student's Performance Using Data Mining Techniques.," Procedia Computer Science, Volume 72, https://doi.org/10.1016/j.procs.2015.12.157. (https://www.sciencedirect.com/science/article/pii/S1877050915036182), pp. 414-422, 2015.

[11] I. E. Livieris, K. Drakopoulou and P. Pintelas, "Predicting students' performance using artificial neural networks," 8th PanHellenic Conference with International Participation Information and Communication Technologies, pp. 321-328, 2012.

[12] G. Rao and K. Kumar, "Students Performance Prediction in Online Courses Using Machine Learning Algorithms," United International Journal for Research & Technology (UIJRT), 2(11), pp. 74-79, 2021.

[13] V. Oladokun, A. Adebanjo and O. Charles-Owaba, "Predicting Students Academic Performance using Artificial Neural Network: A Case Study of an Engineering Course," The Pacific Journal of Science and Technology. Volume 9. Number 1.

http://www.akamaiuniversityhttps://www.researchgate.net/publication/228526441_Predicting_Students_Academic_Performance_using_Artificial_Neural_Network_A_Case_Study_of_an_Engineering_Course, 2008.

[14] B. Yao, H. Hagras, M. J. Alhaddad and D. M. Al-Ghazzawi, "A fuzzy logic-based system for the automation of human behavior recognition using machine vision in intelligent environments," Soft Computing, 19, https://doi.org/10.1007/s00500-014-1270-4, pp. 499-506, 2015.

[15] S. H. J. Petrudi, M. Pirouz and B. Pirouz, "Application of fuzzy logic for performance evaluation of academic students," in 13th Iranian Conference on Fuzzy Systems (IFSC), doi: 10.1109/IFSC.2013.6675615., 2013.

[16] C. Cooper, "Students At Risk: The Impacts of Self-Efficacy and Risk Factors on Academic Achievement.," 2015.

[17] H. Petar, "Prediction of e-Learning Efficiency by Neural Networks," Cybernetics and Information Technologies 12(2), DOI: 10.2478/cait-2012-0015, 2012.

[18] S. T. Karamouzis and A. Vrettos, "An Artificial Neural Network for Predicting Student Graduation Outcomes," Proceedings of the World Congress on Engineering and Computer Science, October 22 - 24, 2008, San Francisco, USA ISBN: 978-988-98671-0-2 https://www.academia.edu/67409477/An_Artificial, 2008.

[19] A. U. a. H. H. Khasanah, "A Comparative Study to Predict Student's Performance Using Educational Data Mining Techniques," IOP Conference Series: Materials Science and Engineering, 215, 2017.

[20] S. &. F. N. Huang, "Work in progress — Prediction of students' academic performance in an introductory engineering course.," Frontiers in Education Conference (FIE), S4D-1-S4D-3., 2011.

[21] P. Mrinal and S. Taruna, "Towards the integration of multiple classifier pertaining to the Student's performance prediction.," Perspectives in Science, 8, Available online at www.sciencedirect.com ScienceDirect, p. 364—366, 2016.

[22] A. Al-Hmouz, J. Shen, R. Al-Hmouz and J. Yan, "Modeling and Simulation of An Adaptive Neuro-Fuzzy Inference System (ANFIS) for mobile learning.," IEEE Transactins on Learning Technologies, 5(3)., pp. 226-237, 2012.

[23] A. Kharola, "A hybid ANFIS techniques for Effective performance Evaluation.," PM World Journal, 4(9),, pp. 21-39., 2015.

[24] R. M. A. A. S. A. &. H. N. G. Asif, "Analyzing undergraduate students' performance using educational data mining," journal of Comput. Educ. volume (113), pp. 177-194 , 2017.