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Research article

Evaluation of student failure in higher education by an innovative strategy of fuzzy system combined optimization algorithms and AI

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ABSTRACT

This research suggests two novel metaheuristic algorithms to enhance student performance: Harris Hawk's Optimizer (HHO) and the Earthworm Optimization Algorithm (EWA). In this sense, a series of adaptive neuro-fuzzy inference system (ANFIS) proposed models were trained using these methods. The selection of the best-fit model depends on finding an excellent connection between inputs and output(s) layers in training and testing datasets (e.g., a combination of expert knowledge, experimentation, and validation techniques). The study's primary result is a division of the participants into two performance-based groups (failed and non-failed). The experimental data used to build the models measured fourteen process variables: relocation, gender, age at enrollment, debtor, nationality, educational special needs, current tuition fees, scholarship holder, unemployment, inflation, GDP, application order, day/evening attendance, and admission grade. During the model evaluation, a scoring system was created in addition to using mean absolute error (MAE), mean squared error (MSE), and area under the curve (AUC) to assess the efficacy of the utilized approaches. Further research revealed that the HHO-ANFIS is superior to the EWA-ANFIS. With AUC = 0.8004 and 0.7886, MSE of 0.62689 and 0.65598, and MAE of 0.64105 and 0.65746, the failure of the pupils was assessed with the most significant degree of accuracy. The MSE, MAE, and AUC precision indicators showed that the EWA-ANFIS is less accurate, having MSE amounts of 0.71543 and 0.71776, MAE amounts of 0.70819 and 0.71518, and AUC amounts of 0.7565 and 0.758. It was found that the optimization algorithms have a high ability to increase the accuracy and performance of the conventional ANFIS model in predicting students' performance, which can cause changes in the management of the educational system and improve the quality of academic programs.

1. Introduction

The advancement of information and communication technology (ICT) has been continuous across various domains, leading to transformative changes in how we communicate, work, and live. ICT constantly impacts life's social, cultural, and economic facets. Through infrastructure and regulations, several nations are attempting to succeed in committing to the information society to foster knowledge acquisition and create intelligent societies [1]. The rapid expansion of technical networks and smart devices has led to the emergence of numerous learning management system (LMS) solutions in the academic setting [2]. The COVID-19 pandemic has made

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it necessary for academic users to become oriented toward distance education and e-learning, and they are becoming more persuaded of the significance of these new learning trends. In fact, due to government-imposed lockdown measures and the requirement for social distancing, institutions worldwide have transitioned from face-to-face instruction to purely online learning. To ensure the educational process's continuity, most educational institutions look to entirely online or mixed learning models [3,4]. The outcomes indicate that various students are unfamiliar with this new environment and are stressed, in addition to the rising rate of use of unique teaching and learning approaches [5,6]. In fact, according to several research studies, dropout and failure rates are rising [7,8]. This is mainly because exams and resources are inappropriate for kids with teaching and learning challenges. Today, one of the key research topics under discussion in the educational sector is online teaching and learning effectiveness.

In this situation, numerous academics have focused on creating fresh approaches to handle these difficulties. The first wave of researchers focused on adaptive learning mode and suggested systems like [9–11] to remedy these problems. They claim that using individualized learning environments (i.e., teaching strategies, resources, and assessments) and adaptive educational systems may greatly support students' academic performance. However, these systems face substantial difficulties concerning the caliber of instructional strategies and course contents [12–16].

The second group of researchers looked for ways to forecast school student failures. The improvement of several prediction approaches based on LMS and electronic online assessment tools has been made more accessible by the growth of artificial intelligence (AI). During learning, teaching, and assessment, faculty members are free to intervene and prevent the failure of students [17–21]. Arsad and Buniyamin presented an ANN-based approach for early performance forecasting. Also, much research has been performed on using advanced neural networks in pattern recognition, image analysis, or even robot selection [22–26].

A Malaysian university hosted the study's engineering participants. The cumulative grade point average was used to gauge academic performance in semester eight. Additionally, Ref. [27–29] examined the impact of cognitive and psychological factors on the academic performance of secondary school pupils using a feed-forward neural network. The authors concluded that utilizing ANN to group students into different groups based on their performance is an effective technique that enables curriculum designers and planners to deliver better educational services. The authors of [30–33] used student grouping and data mining to find patterns and explain academic dropout. Registered students for two admission seasons at the Universidad Tecnologica Indoamerica in Ambato, Ecuador, contributed data for the study. K-means was used to categorize and characterize the performance patterns, and a support vector Machine (SVM) approach was used to provide predictions for brand-new pupils. The study presented by Zhang et al. [34] makes grade predictions and suggests a deep learning model comprising fully linked, convolutional neural and distributed attention layers. Information on grades, student demographics, and course descriptions was also acquired. The suggested model produced predictions with an accuracy of 81% and failed forecasts with an accuracy of 85%, and it also offered a possible justification for the result. Ragab et al. [35] highlighted that machine learning techniques enhance the estimates of prior student performance and explain how a student's performance reaches a particular score. Additionally, it offers a visual method to help identify the variables that impact the experiment's score most, allowing teachers to spot at-risk pupils early and encourage them appropriately.

In this sense, Kalyani et al. [36] used a convolutional neural network (CNN) approach to predict and evaluate student performance. As predictor factors, researchers looked at the student's study time and their level of class participation. Okubo et al. [37] employed the recurrent neural network (RNN) approach to forecast the final grade. Compared to a multiple regression analysis approach, it was used to predict the results of 108 students early on and proved effective.

Comparative research was conducted to forecast students' academic achievement using a single performance indicator [38]. Generalized regression neural network (GRNN) and multilayer perceptron neural network (MPNN) learning methods are used on information gathered from student transcript records and documents. The results show that GRNN outperforms the MPNN Multilayer Perceptron approach with a 95% accuracy in terms of overall performance. The research also concluded that instructors could predict students' academic achievement using GRNN based on a single performance indicator.

Most of these studies have issues with performance, particularly with low accuracy, and use no more than one predictive technique. To address this problem, ensemble learning approaches are utilized; however, it is crucial to balance the complexity, the number of systems involved, and the desired results. Combining the predictions of numerous learners in an ensemble learning setting improves overall accuracy. The three most popular learning strategies are stacking, boosting, and bagging. The capacity of layered generalization for classification is utilized in this work to ensure that teaching and learning assignments are tailored. The learner's aptitudes, competencies, passions, and requirements can be used as classification criteria. To overcome learning limitations and ensure success, each student's class follows a distinct learning route [39].

More and more people are questioning the value of online learning, particularly in the post-pandemic period. Today's educational institutions are asked to create novel, time- and space-independent educational approaches. Through blended learning, e-learning, online education, and mobile learning, they must develop engaging learning environments and methods to match these objectives. Teachers are also urged to provide exercises that let students actively research and deepen their understanding of a subject. They ought to be successful in their online classes. To enable students to advance at accelerated rates, they must also flexibly arrange learning and activities assignments while offering feedback [40–42]. Several research studies [43–45] have focused on the principles and recommendation methodology of e-learning systems in the context of educational adaptation. As stated, the method of e-learning systems involves the systematic design, development, implementation, and evaluation of digital learning environments.

In this study, different machine learning algorithms, including the Earthworm Optimization Algorithm (EWA) and the Harris Hawk's Optimizer (HHO), along with conventional adaptive Neuro-Fuzzy Inference System (ANFIS), are used to improve students' classification performance and result prediction. The suggested approach enables dropout forecasting and intervention by providing many learning pathways to ensure students' success and lower failure. The structure of this essay is as follows: The established database used in this study is shown in Section 2. The research's methodology is described in Section 3. In Section 4, where we discuss the effectiveness of our suggested technique, results analyses are given. The study of this proposed system's conclusion is presented in Section 5.

2. Established database

A trustworthy database containing information and factors influencing the students' failure performance is required when using artificial intelligence algorithms to evaluate students' failure performance, such as the Harris Hawk's Optimizer (HHO), Earthworm Optimization Algorithm (EWA), and Adaptive Neuro-Fuzzy Inference System (ANFIS). Based on past studies, 4424 records and 14 variables influencing students' failing performance were ultimately identified. Seventy percent (3097) of the data is allocated to the training phase, and the remaining 30% (1327) is for testing. After the Bologna Procedure was applied to higher education in Europe, the information relates to enrollment records for students who started attending during the academic years 2008/2009 and 2018/2019. Displacement, gender, age at enrollment, debtor, nationality, educational special needs, current tuition costs, scholarship holder, unemployment, inflation, GDP, application order, day/evening attendance, and admission grade were established as input factors. Tables 1 and 2 present each variable's definition and statistical aspects. The histograms for the input variable are shown in Fig. 1.

A two-dimensional representation of multivariate data can be depicted using an Andrews plot, a data visualization tool used in statistics. The graphic illustrates each data point as a curve, with the curves being grouped individually according to the data points' Fourier coefficients. These curves can be broken up into a multitude of parallel axes. Each data is represented by a curve in an Andrews plot; that curve's shape is determined by the values of the variables being plotted. The position of the curve can be estimated using the data's mean amount, and the breadth of the curve can be used to measure the amount of variation in the data. Fig. 2 displays an Andrews plot that describes the input layers and the result.

3. Methodology

3.1. Adaptive neuro-fuzzy inference systems (ANFIS)

Adaptive Neuro-Fuzzy Inference System (ANFIS) is a versatile computational model that combines fuzzy logic and neural networks to create a hybrid system capable of learning and making predictions or decisions. ANFIS models can take different forms based on the number and arrangement of fuzzy rules and the type of membership functions used. In the current study, we used the First-Order Sugeno Model. The kind of ANFIS depends on the nature of the data, the complexity of the relationships to be modeled, and the application's specific requirements. Practitioners often experiment with different ANFIS configurations to find the most suitable model for a given task. Here are some common types of ANFIS:

First-Order Sugeno Model: In the first-order Sugeno model, each rule in the fuzzy system has a linear consequent part. The output of the system is a weighted sum of the rule consequences. This type of ANFIS is straightforward and commonly used in various applications.

Table 1
Variables utilized by variable's class.

Class of Attribute	Attribute	Type	Description
Demographic data	Displaced	Numeric/binary	1 – yes 0 – no
	Gender	Numeric/binary	1 – male 0 – female
	Age at enrollment	Numeric/ discrete	Age of student at enrollment
	International	Numeric/binary	1 – yes 0 – no
Socioeconomic data	Educational special needs	Numeric/binary	1 – yes 0 – no
	Debtor	Numeric/binary	1 – yes 0 – no
	Tuition fees are up to date	Numeric/binary	1 – yes 0 – no
	Scholarship holder	Numeric/binary	1 – yes 0 – no
Macroeconomic data	Unemployment rate	Numeric/ continuous	Unemployment rate (%)
	Inflation rate	Numeric/ continuous	Inflation rate (%)
	GDP	Numeric/ continuous	GDP
Academic data at enrollment	Application order	Numeric/ ordinal	Application order (between 0 - first choice and nine last choice)
	Daytime/evening attendance	Numeric/binary	1 – daytime 0 - evening
	Admission grade	Numeric/ continuous	Admission grade (between 0 and 200)
Target	Target	Categorical	The problem is formulated as a three-category classification task (dropout, enrolled, and graduate) at the end of the expected duration of the course.

Table 2
Variables' statistical aspects.

Attribute	Mean	Median	Dispersion	Min.	Max.
Displaced	0.548	1	0.907	0	1
Gender	0.352	0	1.358	0	1
Age at enrollment	23.130	20	1.358	17	70
International	0.025	0	6.262	0	1
Educational special needs	0.012	0	9.260	0	1
Debtor	0.114	0	2.792	0	1
Tuition fees are up to date	0.881	1	0.368	0	1
Scholarship holder	0.248	0	1.739	0	1
Unemployment rate	11.566	11.100	0.230	7.600	16.200
Inflation rate	1.228	1.400	1.126	−0.800	3.700
GDP	0.002	0.320	1152.820	−4.100	3.500
Application order	1.730	1	0.760	1	9
Daytime/evening attendance	0.891	1	0.350	0	1
Admission grade	126.9781	126.1	209.6809	95	190
Target		Graduate	1.02		

Higher-Order Sugeno Model: Higher-order Sugeno models extend the first-order model by allowing the rule consequences to be higher-order polynomials rather than just linear. This increases the expressive power of the ANFIS system, enabling it to capture more complex relationships.

Takagi-Sugeno-Kang (TSK) Model: TSK models generalize the Sugeno models by allowing non-linear consequent parts. In a TSK model, each rule has a fuzzy set antecedent, and the resultant part is a function that takes the input variables and produces an output. This type of ANFIS is more flexible in representing complex relationships.

Hybrid Model: Hybrid ANFIS models combine different types of fuzzy systems within the same structure. For example, a hybrid model might include first-order and higher-order Sugeno rules, allowing it to capture linear and non-linear relationships in the data.

ANFIS with Elliptic Membership Functions: The choice of membership functions for the fuzzy sets in the antecedent part of ANFIS is crucial. While Gaussian membership functions are commonly used, elliptic ones can also be employed. Elliptic membership functions offer a different shape and can be helpful in specific applications.

ANFIS with Bell-Shaped Membership Functions: Bell-shaped membership functions, such as triangular or trapezoidal shapes, can be used in the fuzzy sets of the antecedent part. The choice of membership functions depends on the characteristics of the input data and the problem being addressed.

ANFIS with Custom Membership Functions: ANFIS models can be extended to include custom membership functions tailored to the specific characteristics of the data. This customization allows practitioners to better capture the underlying patterns in the dataset.

Multi-Objective ANFIS: Multi-objective ANFIS models consider multiple conflicting objectives simultaneously. These models aim to optimize several criteria simultaneously, making them suitable for problems with diverse and competing goals.

In the current study, we used Fuzzy C-Means (FCM) clustering, which was integrated into ANFIS to enhance its learning process. FCM is a clustering algorithm that falls under the broader category of fuzzy clustering techniques. It was introduced by Bezdek et al. [46] and is an extension of the traditional K-Means clustering algorithm. As in the calculation process, the FCM aims to minimize the objective function, representing the sum of the squared differences between data points and cluster centers weighted by their fuzzy membership values.

FCM is widely used in pattern recognition, image segmentation, medical imaging, and data clustering applications where data points may belong to multiple categories simultaneously [47–50]. It allows data points to belong to multiple clusters with varying degrees of membership rather than assigning each point to a single cluster. Indeed, the genfis3 function in MATLAB is commonly used to generate a Fuzzy Inference System (FIS) structure based on input-output training data. ["fis = genfis3(x,t,'sugeno',nCluster, fcm_options); "]. The genfis3 function in MATLAB is part of the Fuzzy Logic Toolbox and is used to generate a fuzzy inference system (FIS) using the subtractive clustering method. This method helps in creating a fuzzy system with a set of rules based on input-output data. The resulting FIS can be employed for system modeling, control, and decision-making tasks in fuzzy logic applications.

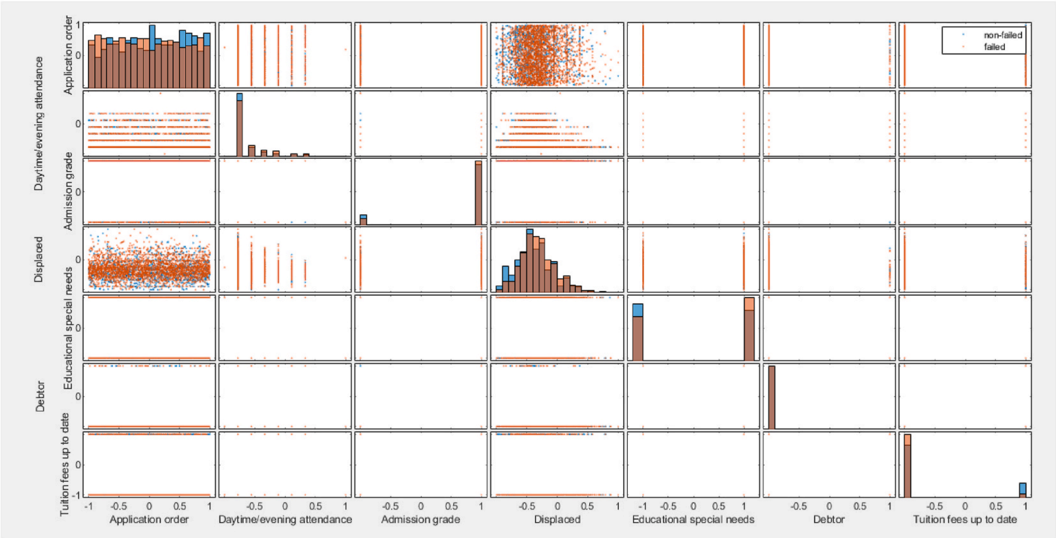
As shown in Fig. 3, the ANFIS method employs a Takagi Sugeno fuzzy inference model with a linear output function and six layers. The first layer is for crisp input, the second is a layer of fuzzification with parameters known as premise or antecedent parameters, the third is a layer of rules, the fourth is a layer of normalization, the fifth is a layer of defuzzification with subsequent parameters, and the final layer is an output layer with a single summation neuron [51].

The input layer, which is the initial layer, only transmits clear signals to the subsequent layer (Equation (1)):

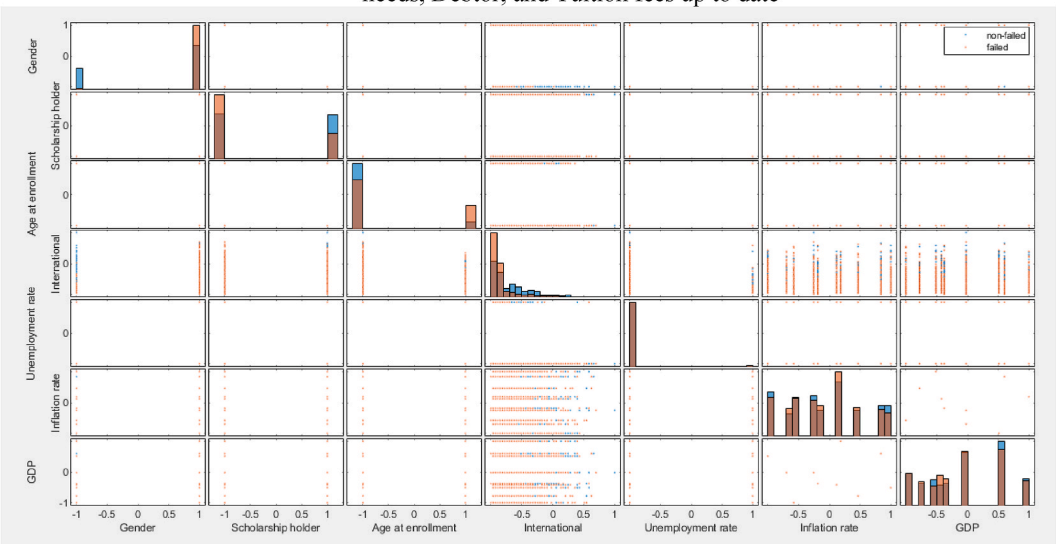
$$y_i^{(1)} = x_i^{(1)} \tag{1}$$

The bell activation function of the fuzzification neurons in the second layer is illustrated as Equation (2):

$$y_i^{(2)} = \frac{1}{1 + \left(\frac{x_i^{(2)} - a_i}{c_i}\right)^{2bi}} \tag{2}$$



(a) Application order, Daytime/evening attendance, Admission grade, Displaced, Educational special needs, Debtor, and Tuition fees up to date



(b) Gender, Scholarship holder, Age at enrollment, International, Unemployment rate, Inflation rate, and GDP

Fig. 1. Input variable's histograms, (a) Application order, Daytime/evening attendance, Admission grade, Displaced, Educational special needs, Debtor, and Tuition fees up to date, and (b) Gender, Scholarship holder, Age at enrollment, International, Unemployment rate, Inflation rate, and GDP.

The operator product, the third output of neuron (i) in the third layer (Equation (3)), is used to compute the strength of the Sugeno-type fuzzy rule.

$$y_i^{(3)} = \prod_{j=1}^{k} x_{ji}^{(3)} \tag{3}$$

The fourth layer, which determines how strong a normalized rule is, works as Equation (4):

$$y_i^{(4)} = \frac{x_{ji}^{(4)}}{\sum_{j=1}^{n} x_{ji}^{(4)}} = \frac{\mu_i}{\sum_{j=1}^{n} \mu_i} = \overline{\mu}_i \tag{4}$$

Where n is the total number of rule neurons and $x_{ji}^{(4)}$ represents the input from layer three neuron j to layer four neuron i. The fifth

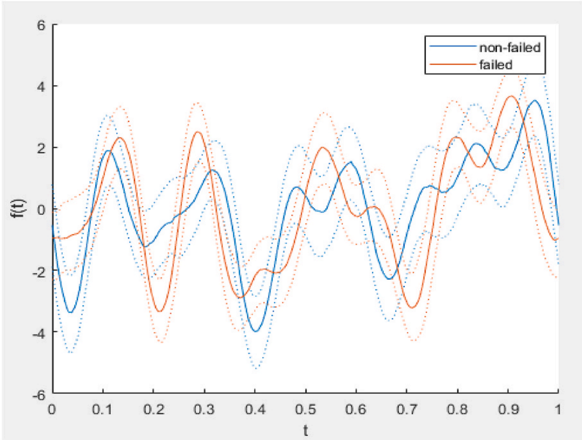


Fig. 2. Description of the Andrews plot for input and output layers.

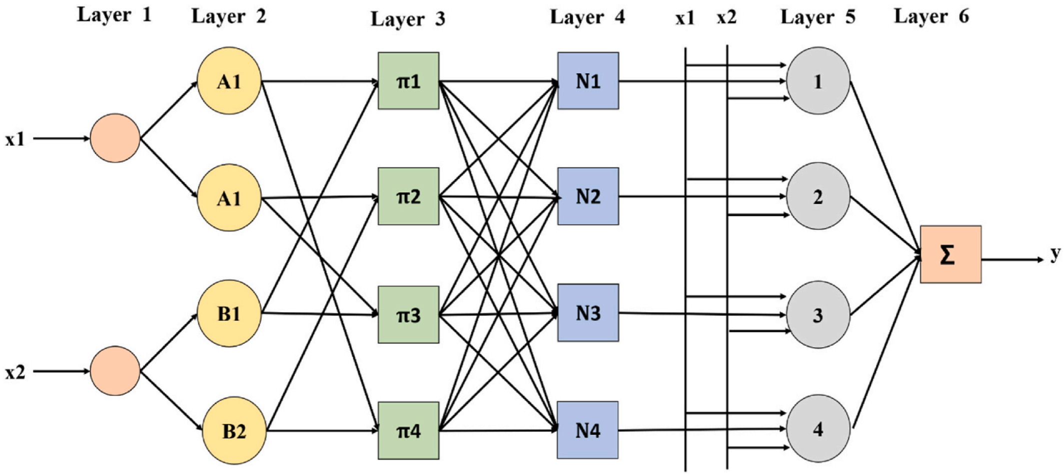


Fig. 3. Adaptive neuro-fuzzy inference system (ANFIS).

layer's defuzzification operation is determined by Equation (5):

$$y_i^{(5)} = x_i^{(5)}[k_{i0} + k_{i1}x_1 + k_{i2}x_2] = \overline{\mu}_i^{(5)}[k_{i0} + k_{i1}x_1 + k_{i2}x_2] \tag{5}$$

Where $x_i^{(5)}$ is the input, $y_i^{(5)}$ is the output of Layer 5's defuzzification neuron i and k_{i0}, k_{i1} and k_{i2} are a group of the rule i's subsequent parameters.

A single summation neuron makes up layer 6, as seen below in Equation (6):

Table 3
Main parameters of the initial ANFIS model.

Specification	Proposed ANFIS model
Type	Sugeno
Inputs/outputs	14/1
No. of MFs for each input	10
No. of output MFs	10
Input MF type	Gaussian
Output MF type	linear
No. of fuzzy rules	10
No. of nonlinear parameters	160
No. of linear parameters	50
No. of epochs	150

$$y_i^{(6)} = \sum_{i=1}^{n} x_i^{(6)} = \sum_{i=1}^{n} \overline{\mu}_i [k_{i0} + k_{i1}x_1 + k_{i2}x_2] \tag{6}$$

The input parameters for the membership functions used by ANFIS are determined using the back-propagation learning process, and the subsequent parameters are determined using the least mean square method. Each iteration of the learning algorithm entails the following two steps: Two methods of parameter refinement are (i) taking all antecedent parameters as fixed parameters and using the minimal squared approach to refine the subsequent parameters and (ii) using the back-propagation learning algorithm to refine the antecedent parameters. The main parameters of the initial ANFIS model are shown in Table 3.

3.2. Hybrid model development

Combining ANFIS with nature-inspired optimization algorithms involves integrating the strengths of both approaches to enhance the modeling and optimization capabilities [54–61]. This integration approach allows for the creation of a hybrid system that benefits from the modeling capabilities of ANFIS and the optimization power of nature-inspired algorithms, potentially leading to improved model accuracy and generalization. The general guide on how ANFIS combined with nature-inspired optimization algorithms is illustrated below.

- ANFIS is a hybrid system that integrates fuzzy logic and neural networks. Nature-inspired optimization algorithms mimic natural processes like evolution, swarm behavior, or genetic processes to find optimal solutions to complex problems. On the other hand, standard nature-inspired optimization algorithms include genetic algorithms (GA), particle swarm optimization (PSO), ant colony optimization (ACO), differential evolution (DE), and others. This study employed two of the most recently developed EWA and the HHO methods [62–65].
- Define the optimization objective, such as tuning the parameters of the ANFIS model or optimizing the structure of the fuzzy system.
- Initialize the parameters of the ANFIS model, including fuzzy rule parameters, membership function parameters, and neural network weights. This serves as the initial solution for the optimization algorithm [66–69].
- Formulate an objective function that represents the optimization goal. This function should be based on the performance of the ANFIS model, such as minimizing prediction error, maximizing accuracy, or optimizing rule parameters.
- Choose a nature-inspired optimization algorithm based on the problem characteristics and requirements. The selected algorithm will be responsible for updating the parameters of the ANFIS model [70,71].
- Integrate the nature-inspired algorithm with the ANFIS model by using it to evaluate the objective function. The optimization algorithm guides the exploration and exploitation of the solution space.
- Utilize the optimization algorithm to update the parameters of the ANFIS model iteratively. The algorithm explores the solution space to find optimal or near-optimal parameter values [72–74].
- Define stopping criteria for the optimization process, such as a maximum number of iterations or reaching a satisfactory level of performance. This helps prevent overfitting or unnecessary computation.
- Retrieve the best solution obtained by the optimization algorithm. These optimal parameters can be applied to the ANFIS model.
- Implement integration of the nature-inspired optimization algorithm with the ANFIS model using a programming language or a modeling tool that supports both functionalities.
- Validate the combined ANFIS and nature-inspired optimization model using separate validation datasets. Fine-tune parameters as needed to achieve the desired level of performance [75–78].

As for assessing the proposed models, four statistical indices were computed for the training and testing models. Equations (7) and (8) describe the MSE and mean absolute error (MAE). The accuracy of calculated models was estimated using these statistical metrics. For instance, MSE and MAE were used to assess the model's accuracy, and AUC and ROC were used to evaluate its robustness [79–81]. In this instance, y_k represents the measured value and (y_k) represents the expected value. The number of samples is n.

$$MSE = \frac{\left(\sum_{k=1}^{n} (\widehat{y}_k - y_k)^2\right)}{n} \tag{7}$$

$$MAE = \frac{1}{n}\left(\sum_{i=1}^{n} (\widehat{y}_k - y_k)^2\right) \tag{8}$$

3.2.1. Harris Hawks optimization (HHO)

Heidari et al.'s HHO is a novel optimization technique that mimics the cooperative behavior of Harris hawks in optimization problems [52]. In this algorithm, hawks use three primary phases to pursue their prey: exploration, transfer, and exploitation. Waiting, looking for, and discovering potential prey are constants during exploration. Equation (9) pinpoints where hawks are:

$$Y(iter+1) = \begin{cases} Y_{rand}(iter) - r_1 |Y_{rand}(iter) - 2r_2 Y(iter)| & q \geq 0.5 \\ (Y_{prey}(iter) - Y_m(iter)) - r_3 (LB + r_4(UB - LB) & q < 0.5 \end{cases} \tag{9}$$

where Y_{prey} represents the location of the prey, Y_{rand} represents a randomly chosen existing hawk and $r_i(i = 1, 2, 3, 4, n)$ represents a random value between 0 and 1. The symbol denotes the average position Y_m and is calculated as Equation (10):

$$Y_m(iter) = \frac{1}{N}\sum_{i=1}^{N} Y_i(iter) \tag{10}$$

The energy of the prey is described in the transition stage as $E = 2E_0\left(1 - \frac{iter}{T}\right)$, where T and $E_0 \in (-1,1)$, indicating that the energy of the prey decreases as it flees. By calculating E, the hawk determines whether to explore new areas or focus on the immediate vicinity of the solutions, beginning the exploration phase when $|E| \geq 1$ and engaging in immediate neighborhood exploration when $|E| < 1.0$. Hawks choose whether to apply a mild or strong besiege once they are in the exploiting phase based on the value of $|E|$. A soft besiege is effective since $|E| \geq 0.5$ indicates that the prey has sufficient energy to flee but fails due to some deceptive jumps. Harris' hawks, on the other hand, scarcely encircle their prey to conduct the surprise pounce when ultimately $|E| < 0.5$ because the prey is too exhausted to flee [50]. Readers can see Heidari et al. [50] for comprehensive HHO operation information.

3.2.2. Earthworm Optimization Algorithm (EWA)

The Earthworm Optimization Algorithm (EWA) is a nature-inspired metaheuristic algorithm for optimization problems [53]. It is inspired by the behavior of earthworms, specifically their movement and burrowing patterns. EWA aims to mimic the earthworm's ability to find optimal paths through complex environments [54].

Mathematically, EWA can be described as follows.

1. Initialization:
   - Set the population size, N.
   - Randomly initialize N earthworms in the search space.
   - Define the maximum number of iterations, MaxIter.
2. Evaluation:
   - Evaluate the fitness function of each earthworm in the population.
3. Sorting:
   - Sort the earthworms based on their fitness values in ascending order.
4. Movement:

   Update the position of each earthworm using the following equation:

$$X(t+1) = X(t) + S(t) \times d(t) \tag{11}$$

Here, $X(t+1)$ represents the new position of the earthworm at time step $t+1$.

- $X(t)$ is the current position of the earthworm at time step t.
- $S(t)$ represents the step size determined by the fitness value of the earthworm.
- $d(t)$ is a random direction vector.

5. Boundary Handling:
   - Check if the new position of an earthworm violates any boundary constraints.
   - If it does, apply appropriate boundary-handling techniques (e.g., reflection, wrapping, or random repositioning) to keep the earthworm within the search space.
6. Fitness Update:
   - Recalculate the fitness value for each earthworm based on their new positions.
7. Sorting and Selection:
   - Sort the earthworms based on their updated fitness values.
   - Select the top-performing earthworms to form the next generation.
8. Termination:
   - Check if the termination condition is met (e.g., the maximum number of iterations reached or a satisfactory solution is obtained).
   - If the termination condition is not met, go back to step 4.

The step size, $S(t)$, is typically determined based on the fitness value of each earthworm. Higher fitness values result in larger step sizes, allowing the earthworm to explore the search space extensively.

EWA combines exploration and exploitation strategies by allowing earthworms to explore new regions of the search space while exploiting promising areas [82]. The algorithm's performance depends on the fitness evaluation, step size determination, and boundary handling techniques, which can be customized based on the problem.

It is important to note that the Earthworm Optimization Algorithm's specific formulation and implementation details may vary depending on the research papers and variations proposed by different authors.

4. Results and discussion

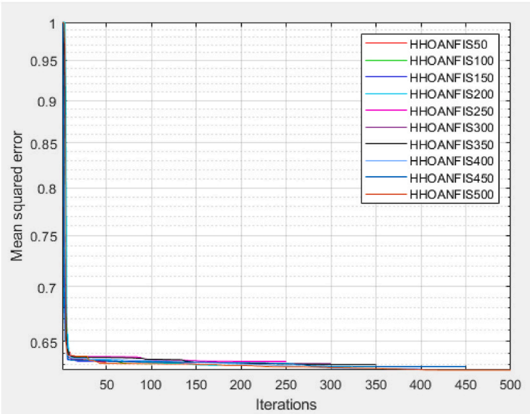
Several hybrid predictive networks have been created to find the best layout—the models' accuracy changes when the typical ANFIS's main parameter is altered. The initial optimization findings are where various optimization strategies start. The model provides the best prediction network with the highest score. The evaluations were based only on how well the model predicted the future. For instance, a lower MSE increases the score for the suggested model—however, a higher AUC results in a higher score for the AUC. The results of these networks are thus used in the following sections. The MSE changes for each strategy are shown in Fig. 4.

The underlying principles of the ensuing optimization strategies will be drawn from the initial optimization discovery phase. The outputs of these networks are therefore used in the following parts. It is shown that prediction accuracy is higher in architectures with lower MSE. Predicted values are the suggested model because they can be utilized to address regression and classification findings more specifically. The proposed designs for forecasting student failure for various hybrid HHO-ANFIS and EWA-ANFIS structures are shown in Fig. 4 (a) and (b) to vary in MSE versus iterations. The HHO-ANFIS and EWA-ANFIS have concluded that 400 and 400 (N_{pop}) constitute the best choice in light of these factors.

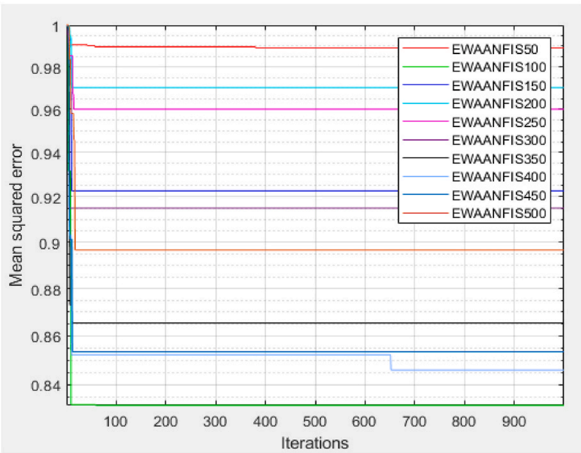
The Receiver Operating Characteristic (ROC) curve is a tool used to evaluate the precision of a continuous measurement to make a binary outcome prediction. This is the primary use of the ROC curve. The most accurate classifier will have an area under the curve (AUC) value near 1. The AUC for each of the conventional ANFIS (i.e., first-order Sugeno Model) and both employed hybrid classifiers can be seen in Figs. 5–7 below. Two of the three classifiers performed excellently, while the third had subpar performance.

The AUC and accuracy values acquired from this experiment were used to determine that the neural networks method is the most suitable for predicting academic success for this study. The performance of EWA-ANFIS (Fig. 7 (a, b)) came after the performance of HHO-ANFIS (Fig. 6 (a, b)). It is, therefore, possible to conclude that the HHO-ANFIS algorithm was superior to the EWA-ANFIS algorithm in terms of the classification of academic performance.

During the evaluation process, AUC chooses the most successful hybrid configurations. A swarm population of 400 individuals is necessary for testing and training predictive modeling outputs in the optimum hybrid technique for student failure. This refers to the



a) HHO-ANFIS



b) EWA-ANFIS

Fig. 4. The best-fit model for the (a) HHOANFIS and (b) EWAANFIS.

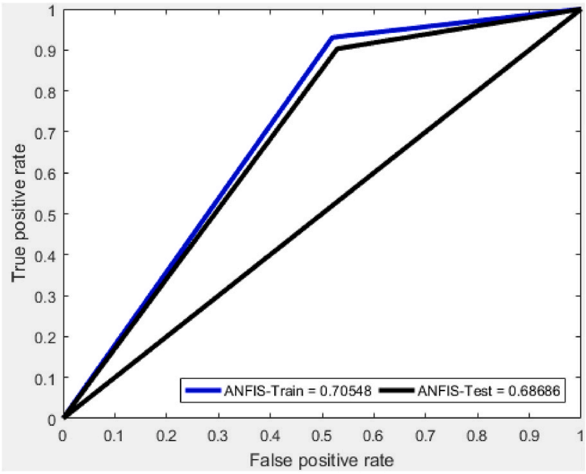


Fig. 5. ROC curve and AUC results of non-hybridized ANFIS first-order Sugeno Model.

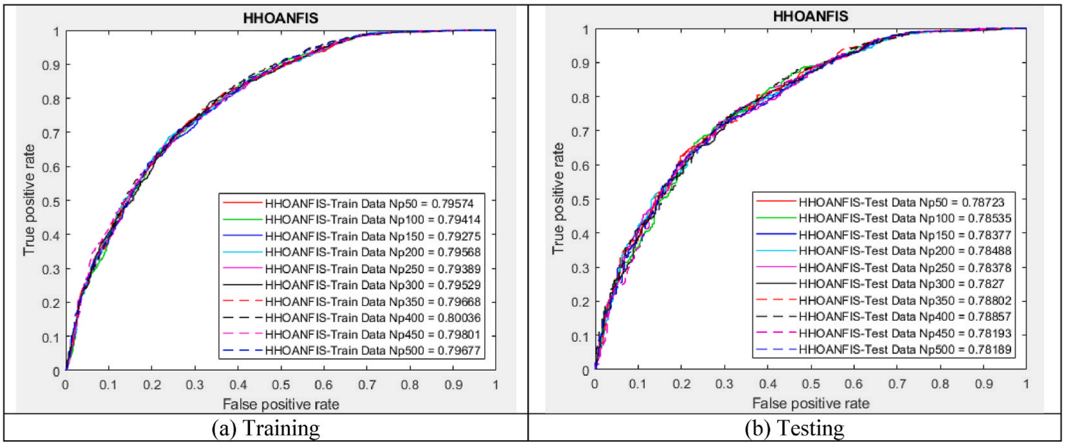


Fig. 6. Regression results for the HHOANFIS method in training and testing datasets, (a) Training and (b) Testing.

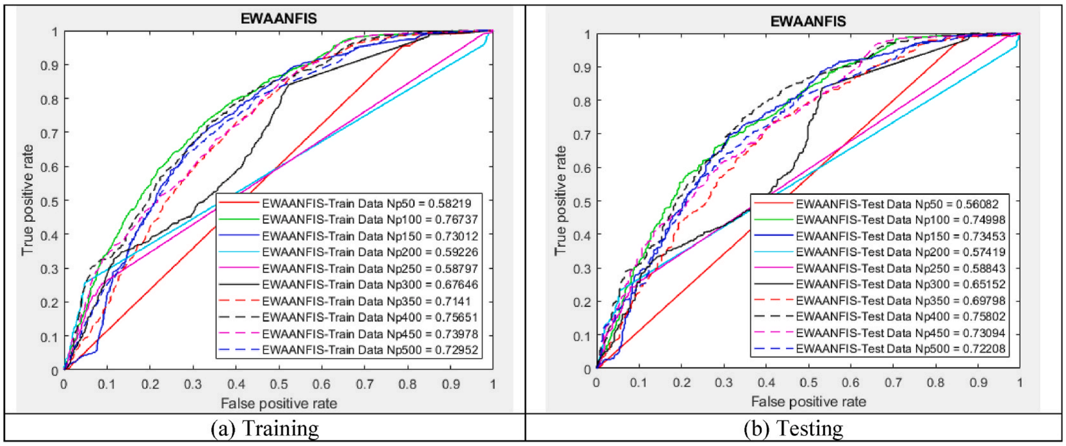


Fig. 7. Regression results for the EWAANFIS method in training and testing datasets, (a) Training and (b) Testing.

accuracy with which the algorithm can estimate the likelihood of student failure. In addition, it demonstrates how closely the outcomes of step two mirror those of phase one. Tables 4 and 5 list the network results obtained from a selection of HHO-ANFIS and EWA-ANFIS. According to the data presented in these tables, the AUC values for HHO-ANFIS and EWA-ANFIS were 0.8004 and 0.7565 during the training phase and 0.7886 and 0.758 during the testing phase (Tables 4–5).

Fig. 8 (a, b) and Fig. 9 (a, b) shows the frequency of mistakes in the best-fitted structures for HHO-ANFIS and EWA-ANFIS, respectively. The figures also show the least significant number of errors. The findings collected from the testing and training datasets indicate a high degree of concordance between the observed and estimated measurement of the student's failure. During the training period, the HHO-ANFIS and EWA-ANFIS acquired respective MAE values of 0.64105 and 0.70819, respectively. In addition, the MAE testing amounts for the HHO-ANFIS and the EWA-ANFIS are 0.65746 and 0.71518, respectively. These values can be found in the table below. Error ranges of [0.0030126, 0.79189] and [−0.026067, 0.84556] are achieved for HHO-ANFIS and EWA-ANFIS during the training phase. During the testing phase, error ranges of [−0.0088957, 0.81018] and [−0.017809, 0.84734] are obtained, respectively.

4.1. Discussion

We used MATLAB programming language to implement the proposed system. The methods used by MATLAB are described in Table 6. The proposed HHO-ANFIS has achieved fewer prediction errors than EWA-ANFIS. As for the level prediction performance listed in Table 5, the HHO-ANFIS and EWA-ANFIS algorithms work well on this essentially multiple classification problem. On the contrary, HHO-ANFIS can better use the input characteristics by its connection layer and obtain a better result. Hence, we propose an HHO-ANFIS algorithm for academic course performance prediction, which achieves the best result in our ablation study.

The application of optimization algorithms such as the Earthworm Optimization Algorithm (EWA) and Harris Hawk's Optimizer (HHO) combined with the Adaptive Neuro-Fuzzy Inference System (ANFIS) for assessing student failure in higher education presents an exciting research area. However, several research gaps can be identified in this context.

While there is a considerable body of research on student performance prediction and classification in higher education, the specific focus on assessing student failure is relatively limited. There is a research gap in exploring the use of optimization algorithms, such as EWA and HHO, in combination with ANFIS for accurately and effectively assessing student failure in higher education settings. Another research gap is conducting performance comparisons between optimization algorithms, such as EWA and HHO, for assessing student failure. Comparative studies that evaluate the strengths and weaknesses of these algorithms in terms of accuracy, efficiency, and robustness can provide insights into their suitability for student failure assessment tasks. Identifying the most suitable algorithm or combination of algorithms for this specific application can be valuable for improving prediction accuracy and intervention strategies.

While ANFIS has been widely used for various prediction and classification tasks in education, there is a research gap in investigating the integration of optimization algorithms like EWA and HHO with ANFIS for assessing student failure. Research in this area can focus on developing hybrid models that leverage the strengths of both optimization algorithms and ANFIS to enhance the accuracy and interpretability of student failure assessment systems. Exploring feature selection techniques and methods to improve the interpretability of the prediction models can also be the gap. Optimization algorithms can be employed to identify the most relevant features or optimize the feature subset for student failure assessment. Additionally, research focusing on model interpretability and explanations for the prediction outcomes can enhance the trust and acceptance of assessment systems in educational institutions.

While there have been studies on student failure assessment in higher education, there is a gap in real-world validation and deployment of optimization-based models. Validating the performance of EWA and HHO combined with ANFIS on large-scale datasets from diverse educational institutions can provide insights into their practical applicability, generalizability, and scalability.

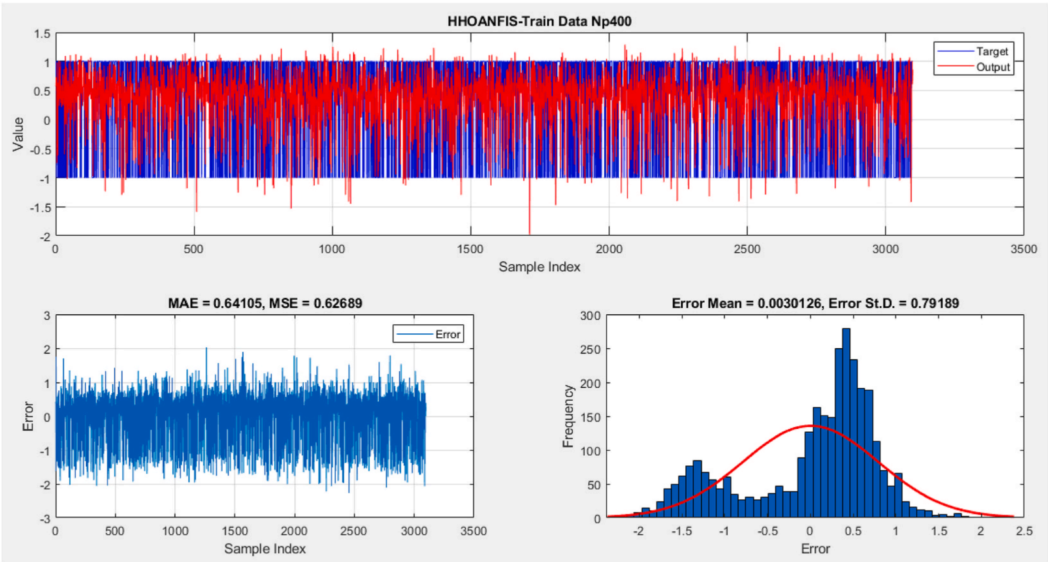
Addressing these research gaps can contribute to the development of accurate and reliable student failure assessment systems in higher education. Furthermore, it can enhance interventions and support systems to improve student success rates and retention, leading to positive outcomes for students and educational institutions.

Table 4
Results of network based on AUC for different proposed HHOANFIS swarm sizes.

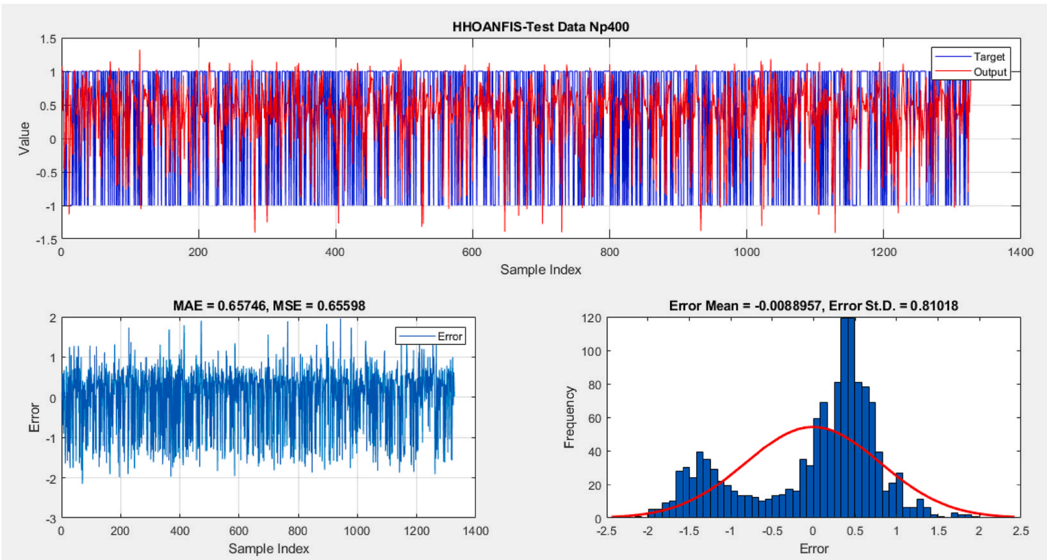
Population size	Network AUC results		Scoring		Total score	RANK
	Training	Testing	Training	Testing		
50	0.7957	0.7872	5	8	13	3
100	0.7941	0.7853	3	7	10	5
150	0.7928	0.7838	1	4	5	10
200	0.7957	0.7849	5	6	11	4
250	0.7939	0.7838	2	4	6	9
300	0.7953	0.7827	4	3	7	8
350	0.7967	0.788	7	9	16	2
400	0.8004	0.7886	10	10	20	1
450	0.798	0.7819	9	1	10	5
500	0.7968	0.7819	8	1	9	7

Table 5
Results of network based on AUC for different proposed EWAANFIS swarm sizes.

Population size	Network AUC results		Scoring		Total score	RANK
	Training	Testing	Training	Testing		
50	0.5822	0.5608	1	1	2	10
100	0.7674	0.75	10	9	19	1
150	0.7301	0.7345	7	8	15	3
200	0.5923	0.5742	3	2	5	8
250	0.588	0.5884	2	3	5	8
300	0.6765	0.6515	4	4	8	7
350	0.7141	0.698	5	5	10	6
400	0.7565	0.758	9	10	19	1
450	0.7398	0.7309	8	7	15	3
500	0.7295	0.7221	6	6	12	5

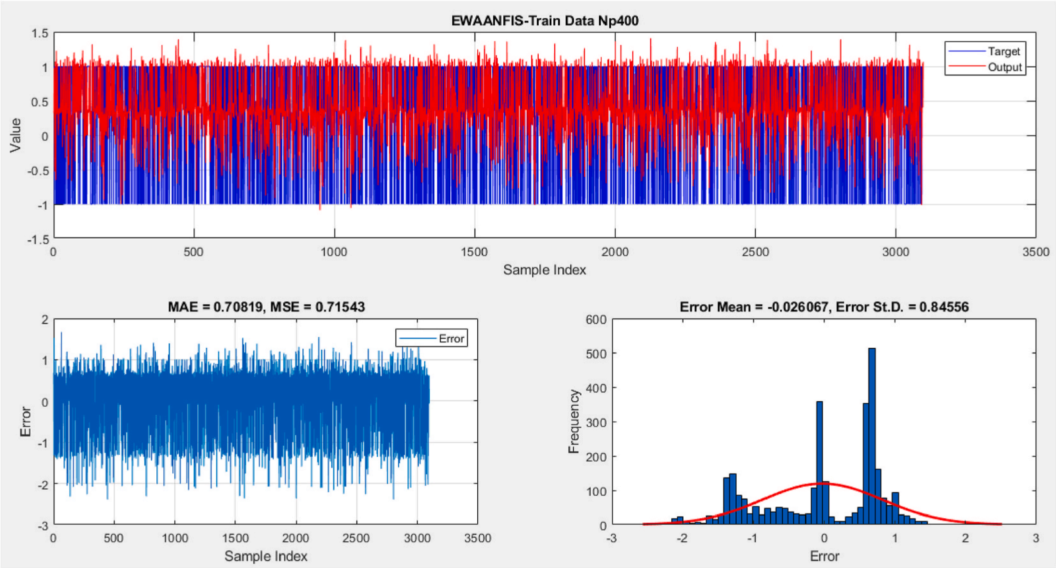


(a) HHOANFIS 400-training

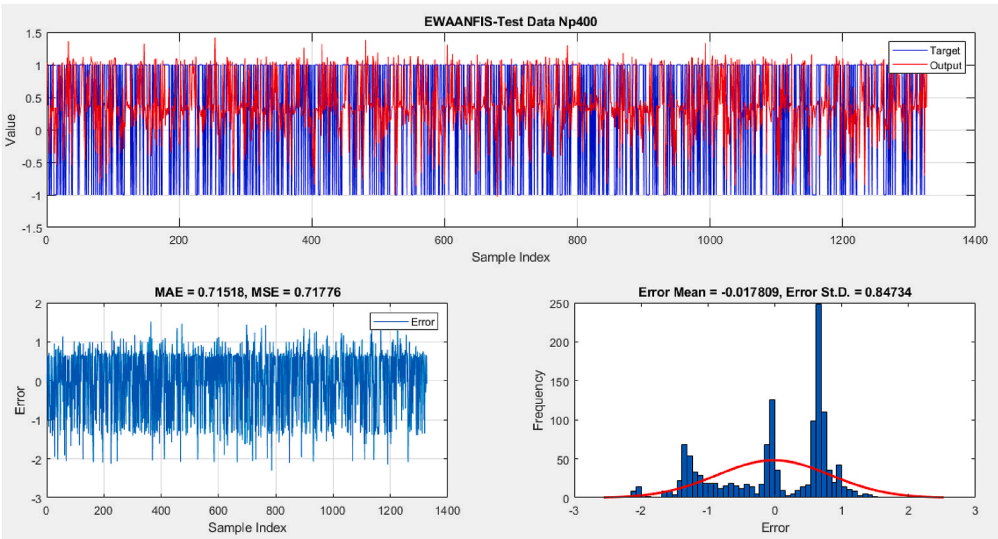


(b) HHOANFIS 400-Testing

Fig. 8. The MAE error and frequency for the best fit HHOANFIS structure, (a) Training, and (b) Testing.



(a) EWAANFIS 400-training



(b) EWAANFIS 400-Testing

Fig. 9. The MAE error and frequency for the best fit EWAANFIS structure, (a) Training, and (b) Testing.

5. Conclusions

In this study, we suggested a neuro-fuzzy method for predicting students' failure in higher education institutions. This study used the EWA, HHO, and ANFIS to assess student failure in higher education. Displacement, gender, age at enrollment, debtor, nationality, educational special needs, current tuition costs, scholarship holder, unemployment, inflation, GDP, application order, day/evening attendance, and acceptance grade were considered when evaluating the conditioning criteria. 70% of the observed student failure is used to train the suggested models, while the remaining 30% assesses the models' accuracy. MSE, MAE, and AUC metrics were used to evaluate the forecasting models' accuracy. The precision indicator of the MSE, MAE, and AUC showed that the HHO-ANFIS is more accurate than the EWA-ANFIS, which has MSE amounts of 0.71543 and 0.71776, MAE amounts of 0.70819 and 0.71518, and AUC amounts of 0.7565 and 0.758. The HHO-ANFIS has values of 0.64105 and 0.65746, 0.64105 and 0.8004, and 0.8004 and 0.7886.

Hybridization with deep learning techniques is also recommended for future work. Explore the integration of EWA, HHO, ANFIS, and other algorithms with deep learning techniques, such as convolutional neural networks (CNNs) or recurrent neural networks (RNNs). Hybrid models that combine the strengths of optimization algorithms and deep learning can potentially improve the accuracy and predictive power of student failure assessment tasks. Also, techniques should be developed to provide transparent explanations for

Table 6
Method results used in the proposed system.

Methods	Swarm size	AUC		MAE		MSE		Scoring						Total Score	Rank
		Training	Testing	Training	Testing	Training	Testing	Training			Testing				
HHOANFIS	400	0.8004	0.7886	0.64105	0.65746	0.62689	0.65598	2	2	2	2	2	2	12	1
EWAANFIS	400	0.7565	0.758	0.70819	0.71518	0.71543	0.71776	1	1	1	1	1	1	6	2

the prediction outcomes, enabling educators and administrators to understand the factors influencing student failure. This can lead to better decision-making and targeted interventions to address the identified risk factors.

Ethics statement

All ethical responsibilities are considered regarding this paper's publication. We confirm that informed consent was obtained from all participants for this study.

Consent to publish

The author has read and agreed to the published version of the manuscript.

Data availability statement

The data presented in this study are publicly available at https://doi.org/10.5281/zenodo.5777339 (accessed on 10 October 2022). Also, the data that support the findings of this study are available from the corresponding author (h.ahmadi005@ut.ac.ir), upon reasonable request.

CRediT authorship contribution statement

Junting Nie: Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Hossein Ahmadi Dehrashid:** Writing – review & editing, Writing – original draft, Software, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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