Student Academic Performance Classification Using N-Valued Interval Neutrosophic Sets with Optimization Algorithms for Significant Feature Selection

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Abstract

The most effectual tools for demonstrating uncertainty in decision-making issues are the neutrosophic set (NS) and its additions, like interval NS (INS), complex NS (CNS), and interval complex NS (ICNS). NS delivers an effectual and precise method for defining an imbalance of information as per the data features. In present times, students' academic performances have been evaluated on the base of regular examinations or memory-related tests and by equating their performances to recognize the features for forecasting their academic excellence. The prediction of student academic performance is involved in Educational data mining (EDM), which mainly focuses on using data mining methods in the educational side. EDM progress models for finding data, which is a result of educational surroundings. This paper presents a Student Academic Performance Prediction Using N-Valued Interval Neutrosophic Sets and Optimization Algorithms (SAPP-NINSOA). The main intention of the SAPP-NINSOA technique is to provide a prevalent technology for predicting students' academic performance using an advanced optimization algorithm. At first, the data pre-processing stage applies Z-score normalization to convert input data into a beneficial format. Besides, the secretary bird optimization algorithm (SBOA) to select the relevant features from input data has executed the feature selection process. Next, the proposed SAPP-NINSOA model designs the N-Valued Interval Neutrosophic Sets (NVINS) method for the classification process. Finally, the arithmetic optimization algorithm (AOA) fine-tunes the parameter values of the NVINS model. An extensive range of experimentation was led to certify the performance of the SAPP-NINSOA technique. The simulation outcomes stated that the SAPP-NINSOA algorithm emphasized furtherance when compared to other existing systems.

Keywords: Student Academic Performance Prediction; Neutrosophic Sets; Feature Selection; N-Valued Interval; Arithmetic Optimization Algorithm

1. Introduction

The concept of neutrosophic set (NS) from a philosophical viewpoint is a generalization concept of IFS and FS [1]. Diverse IFS has no restriction on the membership functions in an NS, and the hesitancy degree is comprised in the NS [2]. However, NS is hard to implement in practical problems since the values of indeterminacy, falsity, and truth membership functions exist in [−0, 1+]. Therefore, this concept is lengthened to multiple NS whose falsity, indeterminacy, and truth membership functions take unique values from the closed interval [0, 1]. Currently, as an outcome of more competitive academic markets, most universities facing problems in appealing to possible learners [3]. The study of the academic accomplishments of students is of major importance in assisting the improvement of students and enhancing the quality of higher education finally improving reputation of institutions. The outcomes acquired from academic performance prediction might be utilized to classify learners, permitting the university to offer them additional support like tutoring resources or timely assistance [4]. Instructors may also utilize the result of prediction to recognize the more relevant learning behaviour for every

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student group and offer them added support intended for their necessities. Additionally, the prediction outcomes can aid learners to create knowledge about their execution, and then advance proper learning models [5]. A precise forecast of student achievement is unique way of upgrading academic quality and offering better service of education [6]. It is implemented effectively in various fields comprising medicine, business, and banking, and is now utilized for purpose of education known as Educational Data Mining (EDM). It is focused on removing a pattern to determine hidden data from educational information [7].

One of the major problems is to enhance the quality of educational procedures and improve performance of students [8]. In recent times, Deep Learning (DL) and Machine Learning (ML) methodologies have been employed to predict the academic performance of students [9]. The primary goal of DL and ML is to determine significant and hidden associations with the data having different features. Several approaches of these models originated to be effective for predicting the students' performance depending on the data stored in database of university [10]. The prediction of academic performance of students employing DL is advanced with the goal of automating the process of forecasting student's results.

This paper presents a Student Academic Performance Prediction Using N-Valued Interval Neutrosophic Sets and Optimization Algorithms (SAPP-NINSOA). At first, the data pre-processing stage applies Z-score normalization to convert input data into a beneficial format. Besides, the secretary bird optimization algorithm (SBOA) to select the relevant features from input data has executed the feature selection (FS) process. Next, the proposed SAPP-NINSOA model designs N-Valued Interval Neutrosophic Sets (NVINS) method for the classification process. Finally, the arithmetic optimization algorithm (AOA) fine-tunes the parameter values of the NVINS model. An extensive range of experimentation was led to certify the performance of the SAPP-NINSOA technique.

2. Literature Survey

Weng and Huang [11] developed a novel structure for recognizing learning patterns and forecasting the performance of learning. Dual modules, the DL prediction model (DNN), and the learning patterns identification modules are seamlessly combined with this structure to recognize the variance in performance of learning and precisely forecast performance of learning from the student's profile depending on multiple aspects. Feng et al. [12] project a student academic performance prediction method that depends upon the fusion of student's classroom behaviour images and educational information (BISAP). This paper includes training 3 DL methods to remove student behavioural features from SCBI that are categorized into negative and positive classes. In [13], a hybrid data-mining model called HDL-SP is projected to forecast the academic performance of students in e-learning settings and preclude dropouts. To minimize dimensions, a Teacher Learning-based Reactive Search Optimizer (TL-RSO) model chooses optimum aspects from an educational database. Classification and performance prediction are accomplished utilizing hybrid reverse transfer learning-based DBN.

Fazil et al. [14] present a method that is named ASIST: a new Attention-aware convolutional Stacked Bi-LSTM system for student representation learning to forecast their performance. ASIST advantages VLE click stream, student academic registry, and midterm continuous evaluation data for their behaviour representation learning. ASIST collectively learns the representation of students utilizing 5 behaviour vectors. It progresses the 4 sequential behaviour vectors utilizing a separate stacked Bi-LSTM system. It also utilizes the attention mechanism to assign weight to aspects depending on their significance. Afterward, 5 encoded vector features are coupled with the evaluation data. In [15], innovative DL classification and optimization models are applied in this paper. The most co-related aspects from the pre-processed schooling database are selected utilizing the War Strategy Optimizer (WStO) model to upgrade performance of prediction. To reliably and effectively assess the rate of student performance with some wrong predictions, a classification model that depends on the Bi-directional Gated Recurrent Neural Network (Bi-GRNNet) is implemented. The Arithmetic Operation Optimization Algorithm (AO2A) has been utilized to properly enhance the parameters of DL classifiers.

Muthuselvan et al. [16] developed an integrated Triple Voter Network and t-Self Improved Distribution-based Satin Bowerbird Optimizer (t-SIDSBO) to forecast student academic achievement. Now, the deep CNN, RNN, and LSTM methodologies, which depend on sophisticated feature prediction methods are employed for effectual classification and the finest features, were selected employing a t-SIDSBO-based FS approach. Fang et al. [17] project an improved Binary Snake Optimizer (MBSO) as a wrapped FS method and relate the MBSO FS approach with other feature models, the MBSO is capable of selecting aspects with strong co-relation to the students and the average count of student selected aspects have reached a minimum that significantly decreases the difficulty of student achievement prediction. Primarily, this method integrates the valuable point set initialization, adaptive t-distribution, and triangle-wandering approaches to attain the Modified Dung Beetle Optimizer (MDBO), then, it employs MDBO for enhancing the thresholds and weights of the BPNN.

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3. The Proposed Method

In this paper, we have presented a SAPP-NINSOA methodology. The main intention of the SAPP-NINSOA technique is to provide a prevalent technology for predicting student's academic performance using an advanced optimization algorithm. Fig. 1 represents the entire flow of the SAPP-NINSOA system.

3.1. Data Normalization

Initially, the data pre-processing stage applies Z-score normalization to convert input data into a beneficial format. This approach, otherwise recognized as standardization, is an extensively applied data normalization model in ML and statistical analysis [18]. It includes converting the data in such manner that the feature mean becomes 0 and the standard deviation becomes 1. These procedure midpoints the data near 0 and scales it to take a unit standard deviation (SD). The equation for this method for the feature x' is as demonstrated:

$$x' = \frac{x - mean(x)}{Std(x)} \tag{1}$$

Now, x refers to original value, x' stands for standardized value, $mean(x)$ symbolizes mean feature value χ, and $std(x)$ denote standard deviation of x. The major benefit of z-score standardization (normalization) is its sturdiness to outliers in comparison with other standardization techniques.

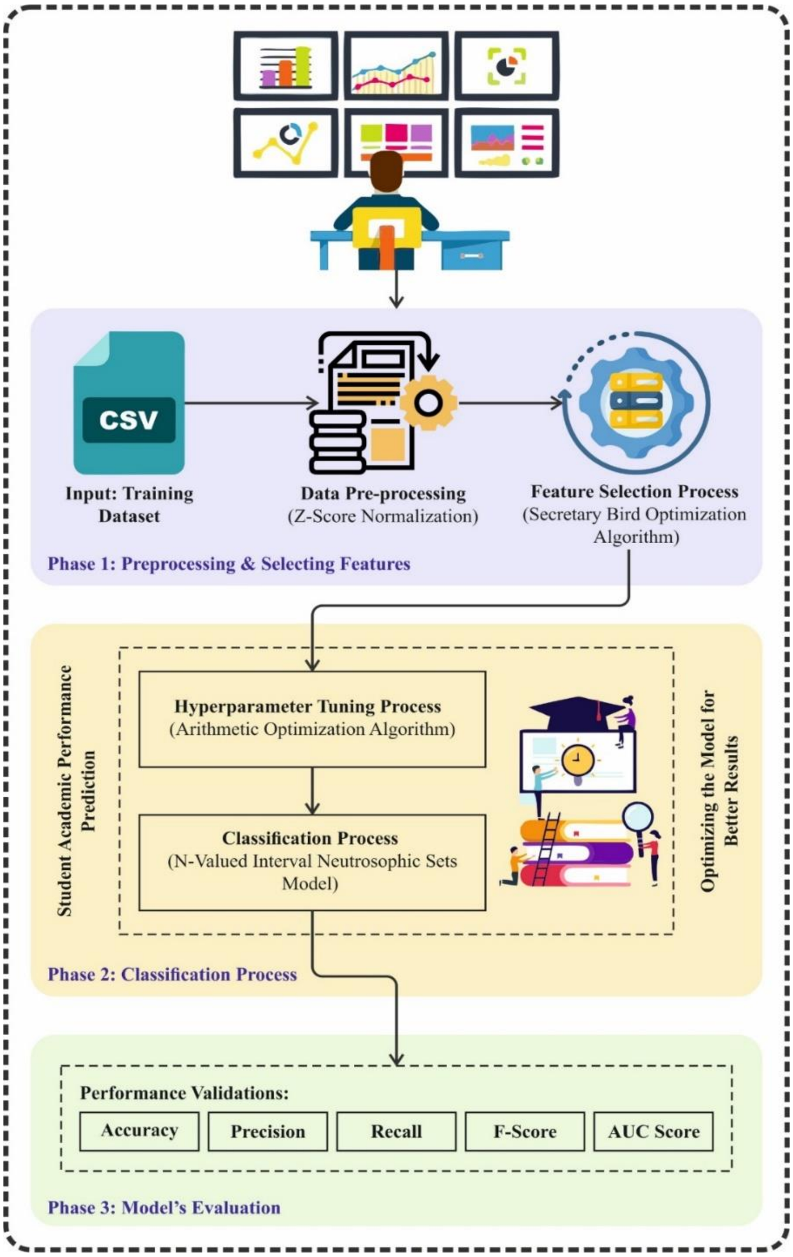

Figure 1. Overall flow of the SAPP-NINSOA system.

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3.2. SBOA-based Feature Selection

Besides, the FS process has been executed by the SBOA to select the relevant features from input data. The SBOA is a novel metaheuristic optimizer model with the benefits of robustness, higher efficacy, and faster convergence. It was stimulated by the secretary bird's searching behavior [19]. The model phases are as demonstrated:

Primarily, initialize the location of the secretary bird utilizing the succeeding equation:

$$X_{i,j} = lb_j + r * \left(ub_j - lb_j\right) \tag{2}$$

Whereas $X_{i,j}$ characterizes the $i\ th$ secretary bird value in the $j\ th$ dimension, lb_j and ub_j represents upper and lower limits of the $j\ th$ dimension, correspondingly, and r denotes a randomly generated number from the range of 0 and 1.

The SBOA characterizes the secretary bird group by the subsequent equation:

$$X = \begin{bmatrix} x_{1,1} & x_{1,2} & \cdots & x_{1,j} & \cdots & x_{1,Dim} \\ x_{2,1} & x_{2,2} & \cdots & x_{2,j} & \cdots & x_{2,Dim} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{i,1} & x_{i,2} & \cdots & x_{i,j} & \cdots & x_{i,Dim} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{N,1} & x_{N,2} & \cdots & x_{N,j} & \cdots & x_{N,Dim} \end{bmatrix}_{N\times Dim} \tag{3}$$

Here N signifies secretary bird counts and Dim refers to problem variable dimension, which is equivalent to 4. The SBOA has been applied to enhance the parameters of FMD: the filter length L, the mode counts n, the cycle period m, and the amount of frequency band cuts K. All secretary birds symbolize parameter combinations, and the value of the objective function is specified by the succeeding equation:

$$F = \begin{bmatrix} F_1 \\ \vdots \\ F_i \\ \vdots \\ F_N \end{bmatrix}_{N\times 1} = \begin{bmatrix} F(X_1) \\ \vdots \\ F(X_i) \\ \vdots \\ F(X_N) \end{bmatrix}_{N\times 1} \tag{4}$$

Now F denotes objective function value vector.

The fitness function (FF) reveals the accuracy of classifier and the quantity of chosen features. It exploits the classifier accuracy and declines the set dimension of preferred features. From this time, the below-mentioned FF has been exploited for evaluating a discrete solution, as exposed in Eq. (5).

$$Fitness = \alpha * \ ErrorRate + (1-\alpha) * \frac{\#SF}{\#All\_F} \tag{5}$$

While $ErrorRate$ is the classification rate of error by employing the chosen features. $ErrorRate$ is mainly computed as the proportion of incorrect, which classifies to a number of classifications made between 0 and 1. $\#SF$ denotes the amount of preferred features. $\#All\_F$ refers to a complete number of features in an original database. α is employed for controlling the impact of sub-set length and classifier quality. The value of α is 0.9 in this experiment.

3.3. Classification using NVINS Model

Next, the proposed SAPP-NINSOA model designs the NVINS method for the classification process. Following the n-valued NS (refined set or multi-set) and interval NS outlined, correspondingly [20]. In this section, offer the sets to n-valued interval-valued NSs.

Definition3.1. Assume X as a universe, the NVINS on X is described as demonstrated:

$$A = \{x, \begin{pmatrix} [\inf T_A^1(x), \sup T_A^1(x)], [\inf T_A^2(x), \sup T_A^2(x)], \ldots, \\ [inf T_A^p(x), \sup T_A^p(x)] \end{pmatrix},$$

$$\begin{pmatrix} [\inf I_A^1(x), \sup I_A^1(x)], [\inf I_A^2(x), \sup I_A^2(x)], \ldots, \\ [\inf I_A^p(x), \sup I_A^q(x)] \end{pmatrix},$$

$$[inf F_A^1(x), \sup F_A^1(x)], ([inf F_A^2(x), \sup F_A^2(x)], \ldots,$$

$$\left(\left[inf F_A^p(\mathrm{x}), \sup F_A^r(x)\right]\right): x \in X\}\}$$

Whereas

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$$infT_A^1(x), \inf T_A^2(x), \ldots, infT_A^p(x), \inf I_A^1(x), inf I_A^2(x), \ldots, \inf I_A^p(x), \inf F_A^1(x), inf F_A^2(x), \ldots, \inf F_A^q(x),$$

$$\sup T_A^1(x), \sup T_A^2(x), \ldots, \sup T_A^p(x), \sup I_A^1(x), \quad \sup I_A^2(x), \ldots / \sup I_A^q(x), \sup F_A^1(x),$$
$$\sup F_A^2(x), \ldots, \sup F_A^r(x) \in [O, 1]$$

in such a way that $0 \leq supT_A^i(x) + supI_A^i(x) + supF_A^i(x) \leq 3, \forall i = 1,2, \ldots, p$.

This paper generally concentrates on the case while $p = q = r$ represents interval truth-membership order, interval falsity-membership sequence, and interval indeterminacy-membership sequence of the component x, individually. Moreover, p is named the size of NVINS-A.

The collection of all n NVINS on X is represented by NVINS(X).

For instance3.2. Assume $X = \{X, X\}$ as a universe and A represents NVINS.

$$A = \{< x_1, \{[.1, .2], [.2, .3]\}, \{[.3, .4], [.1, .5]\}, \{[.3, .4], [.2, .5]\} >,$$
$$< x_2, \{[.3, .4], [.2, .4]\}, \{[.3, .5], [.2, .4]\}, \{[.1, .2], [.3, .4]\} >\}$$

Definition3.3. The complementary of A is represented by A^c and is delineated by

$$A^c = \{x, ([infF_A^1(x), \sup F_A^1(x), ([infF_A^2(x), \sup F_A^2(x)], \ldots,$$

$$([infF_A^p(x), \sup F_A^p(x)]),$$

$$\begin{pmatrix} [1 - \sup I_A^1(x), 1 - \inf I_A^1(x)], [1 - \sup I_A^2(x), 1 - \inf I_A^2(x)] \ldots, \\ [1 - \sup I_A^p(x), \inf I_A^p(x)], \end{pmatrix},$$

$$([inf\ T_A^1(x), \sup T_A^1\ [infT_A^2(x), \sup T_A^2(x)], \ldots,$$

$$[inf\ T_A^p(x), \sup T_A^p(x)]) : x \in X\}.$$

For instance3.4. Let's examine the instnace3.5. Next, we have,

$$A^c = \{< x_1, \{[.3, .4], [.2, .5]\}, \{[.6, .7], [.5, .9]\}, \{[.1, .2], [.2, .3]\} >,$$
$$< x, \{[.1, .2], [.3, .4]\}, \{[.5, .7], [.6, .8]\}, \{[.3, .4], [.2, .4]\} >\}$$

Definition3.5. For $\forall i = 1,2, \ldots, P$ if $infT_A^i(x) = \sup T_A^i(x) = 0$ and $nfI_A^i(x) = \sup I_A^i(x) = infF_A^i(x) = \sup F_A^i(x) = 1$, formerly A is named null NVINS signified by Φ, for every $x \in X$.

For instance3.6. Assume $X = \{x_1, x_2\}$ exist universe and A denote NVINS

$$\Phi = \{< x_1, \{[0,0], [0,0]\}, \{[1,1], [1,1]\}, \{[1,1], [1,1]\} >,$$
$$< x_2\ \{[0,0], [0,0]\}, \{[1,1], [1,1]\}, \{[1,1], [1,1]\} >\}.$$

Definition3.7. For $\forall\, i = 1,2, \ldots, P$ if $infT_A^i(x) = \sup T_A^i(x) = 1$ and $infI_A^i(x) = \sup I_A^i(x) = \inf F_A^i(x) = \sup F_A^i(x) = 0$, next A is entitled universal NVINS indicated by E, for each $x \in X$.

For instance3.8. Assume $X = \{x_1, x_2\}$ remain universe and A signifies NVINS

$$E = \{< x_1, \{[1,1], [1,1]\}, \{[0,0], [0,0]\}, \{[0,0], [0,0]\} >,$$
$$< x_2\{[1,1], [1,1]\}, \{[0,0], [0,0]\}, \{[0,0], [0,0]\} >\}.$$

Definition3.9. An NVINS-A included in the other NVINS $- B$, represented by $A \subseteq B$, if and only if

$$infT_A^1(x) \leq infT_B^1(x), infT_A^2(x) \leq infT_B^2(x), infT_A^p(x) \leq$$

$$infT_B^p(x),$$

$$\sup T_A^1(x) \leq \sup T_B^1(x), \sup T_A^2(x) \leq \sup T_B^2(x), \sup T_A^p(x) \leq$$

$$\sup T_B^p(x),$$

$$infI_A^1(x) \geq infI_B^1(x), infI_A^2(x) \geq infI_B^2(x), infI_A^p(x) \geq infI_B^p(x),$$

$$\sup I_A^1(x) \geq \sup I_B^1(x), \sup I_A^2(x) \geq \sup I_B^2(x), \sup I_A^p(x) \geq$$

$$\sup I_B^p(x),$$

$$infF_A^1(x) \geq infF_B^1(x), infF_A^2(x) \geq infF_B^2(x), infF_A^p(x) \geq$$

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$inf F_B^p(x)$,

$$\sup F_A^1(x) \geq \sup F_B^1(x), \sup F_A^2(x) \geq \sup F_B^2(x), \sup F_A^p(x) \geq \sup F_B^p(x)$$

for all $x \in X$.

For instance3.10. Assume $X = \{X_1, X_2\}$ stand universe and A and B are dual NVINSs

$$A = \{< x_1, \{[.1, .2], [.2, .3]\}, \{[.4, .5], [.6, .7]\}, \{[.5, .6], [.7, .8]\} >, < x_2, \{[.1, .4], [.1, .3]\}, \{[.6, .8], [.4, .6]\}, \{[.5, .6], [.6, .7]\} >\}$$

and

$$B = \{< x_1, \{[.5, .7], [.4, .5]\}, \{[.3, .4], [.1, .5]\}, \{[.3, .4], [.2, .5]\} >, < x_2, \{[.2, .5], [.3, .6]\}, \{[.3, .5], [.2, .4]\}, \{[.1, .2], [.3, .4]\} >\}$$

Formerly, we have $A \subseteq B$.

Definition3.11. Let A and B be dual n NVINS. Formerly, A and B are equivalent, signified by $A = B$ if and only if $A \subseteq B$ and $B \subseteq A$.

3.4. AOA-based Parameter Tuning

Finally, the AOA fine-tunes the parameter values of the NVINS model. AOA is a novel model that is applied with the aim of analysis and algebra [21]. The AOA is a meta-heuristic model with dual key conceptions, comprising exploration and exploitation, described below. Eq. (6) demonstrates that this procedure starts with the collection of candidate answers (X) formed arbitrarily. The best candidate outcome is received as the best-gained response or approximately the optimal as in all iterations.

$$X = \begin{bmatrix} x_{1,1} & \cdots & x_{1,j} & x_{1,n-1} & x_{1,n} \\ x_{2,1} & \cdots & x_{2,j} & \cdots & x_{2,n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{N-1,1} & \cdots & x_{N-1,j} & \vdots & x_{N-1,n} \\ x_{N,1} & \cdots & x_{N,j} & x_{N,n-1} & x_{N,n} \end{bmatrix} \quad (6)$$

The property of math optimizer accelerated (MOA) is computed by Eq. (7), applied in the main searching terms.

$$MOA(C_{Iter}) = Min + C_{Iter} \times \left(\frac{Max - Min}{M_{Iter}}\right) \quad (7)$$

Here, $MOA(C_{Iter})$ considered to be the function value in the t^{th} iteration, which can be computed by Eq. (7). M_{Iter} show the high iteration amounts, C_{Iter} among $[1 - M_{Iter}]$ is presented in the present iteration. Max and Min indicate the maximal and minimal values of the speeded-up function, correspondingly.

The simple rule that can make the Arithmetic operators behavior, is utilized. The following position updated computations for the searching parts.

$$x_{i,j}(C_{Iter} + 1) = \begin{cases} best(x_j) \div (MOP +) \times \left((US_j - LB_j) \times \mu + LB_i\right) r_2 < 0.5 \\ best(x_j) \times MOP \times \left((uB_j - LB_j) \times \mu + LB_j\right) Otherwise \end{cases} \quad (8)$$

Whereas $x_i(C_{Iter} + 1)$ displays the i^{th} answer in the following stage, $x_{i,j}(C_{Iter})$ state the j^{th} location of the i^{th} response in the current stage, and $best(x_j)$ refers to j^{th} location in the best response till now. Ɛ exhibits a small number, UB_j and LB_j define the lower and upper limits of the j^{th} location, correspondingly. μ points out controller parameter to fine-tune the searching process, which is available by 0.5 based on the problem estimated.

$$MOP(C_{Iter}) = 1 - \frac{C_{Itr}^{1/a}}{M_{Itr}^{1/a}} \quad (9)$$

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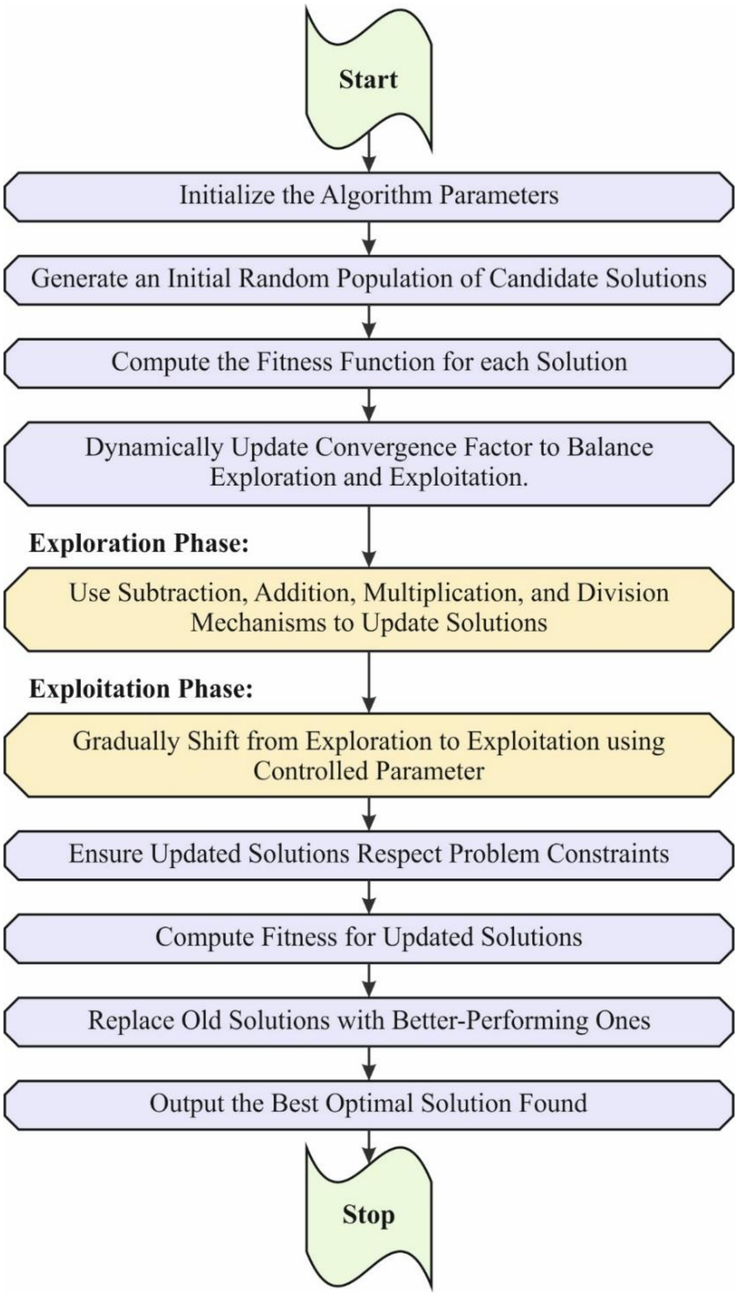

Figure 2. Flowchart of AOA

Whereas Math optimizer Probability (MOP) describes a coefficient, $MOP(C_{Iter})$ exhibits the function value at the r^{th} stage, and C_{Iter} defines the current phase and M_{Iter} denote maximal iteration. α explains a perceptive parameter and symbolizes the exploitation accurately over the stages. The searching stage is in condition through the MOA for the state of r_1 is smaller than or equal to the current $MOA(C_{Iter})$ value (Eq. 7).

In this method, the exploitation operators of AOA show the search spaces in-depth on larger compressed fields and use dual pivotal searching approaches to collaborate with the further appropriate response that is modeled. Fig. 2 illustrates the flowchart of AOA.

$$x_{i,j}(C_{Iter}+1)=\begin{cases} best(x_j)-MOP\times\left((U\mathcal{B}_j-L\mathcal{B}_j)\times\mu+LB_j\right) r_3<0.5 \\ best(x_j)+MOP\times\left((u\mathcal{B}_j-L\mathcal{B}_j)\times\mu+L\mathcal{B}_j\right) Otherwise \end{cases} \quad (10)$$

The AOA originates an FF for attaining an enhanced performance of classifier. It defines an optimistic number for signifying the improved efficiency of candidate solution. Here, the classification ratio of error reduction is reflected as FF.

$$fitness(x_i)=ClassifierErrorRate(x_i)$$

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$$= \frac{no.\,of\ misclassified\ samples}{Total\ no.\,of\ samples} * 100 \tag{11}$$

4. Experimental Validation

The performance evaluation of the SAPP-NINSOA system is studied under students' performance dataset [22]. This dataset contains 2392 samples under five grades as depicted in Table 1. There are 14 features, but only 11 are chosen.

Table 1: Details of Database

Grade	Description	No. of Samples
0	'A' (GPA >= 3.5)	107
1	'B' (3.0 <= GPA < 3.5)	269
2	'C' (2.5 <= GPA < 3.0)	391
3	'D' (2.0 <= GPA < 2.5)	414
4	'F' (GPA < 2.0)	1211
Total Samples		**2392**

Fig. 3 displays the classifier analysis of the SAPP-NINSOA technique. Figs. 3a-3b displays the confusion matrix through specific classification and identification of all classes under 70%TRAPHA and 30%TESPHA. Fig. 3c shows the PR examination, which notified enhanced performance over all class labels. Finally, Fig. 3d depicts the ROC study, exposing skilful solutions through great ROC values for different classes.

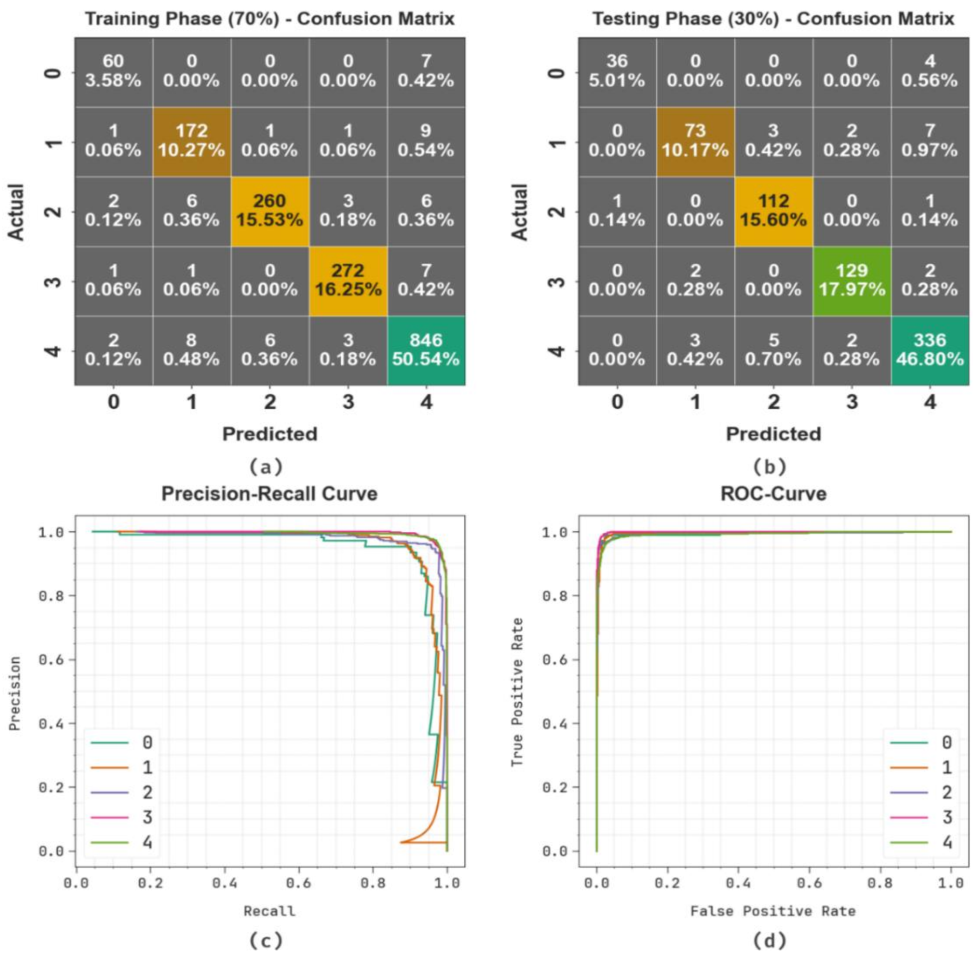

Figure 3. (a-b) Confusion matrices and (c-d) curves of PR and ROC

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Table 2 and Fig. 4 examine the students' performance detection of SAPP-NINSOA approach below 70%TRAPHA and 30%TESPHA. The performances stated that the SAPP-NINSOA method accurately categorized all the samples. Using 70%TRAPHA, the SAPP-NINSOA approach delivers average $accu_y$ of 98.47%, $prec_n$ of 94.89%, $reca_l$ of 94.30%, F_{score} of 94.58%, and AUC_{score} of 96.55%.

Furthermore, using 30%TESPHA, the SAPP-NINSOA algorithm provides average $accu_y$ of 98.22%, $prec_n$ of 95.44%, $reca_l$ of 93.65%, F_{score} of 94.47%, and AUC_{score} of 96.15%.

Table 2: Students' performance detection of the SAPP-NINSOA model under 70%TRAPHA and 30%TESPHA

Class Labels	$Accu_y$	$Prec_n$	$Reca_l$	F_{score}	AUC_{score}
TRAPHA (70%)					
0	99.22	90.91	89.55	90.23	94.59
1	98.39	91.98	93.48	92.72	96.24
2	98.57	97.38	93.86	95.59	96.68
3	99.04	97.49	96.80	97.14	98.15
4	97.13	96.69	97.80	97.24	97.11
Average	**98.47**	**94.89**	**94.30**	**94.58**	**96.55**
TESPHA (30%)					
0	99.30	97.30	90.00	93.51	94.93
1	97.63	93.59	85.88	89.57	92.55
2	98.61	93.33	98.25	95.73	98.46
3	98.89	96.99	96.99	96.99	98.15
4	96.66	96.00	97.11	96.55	96.67
Average	**98.22**	**95.44**	**93.65**	**94.47**	**96.15**

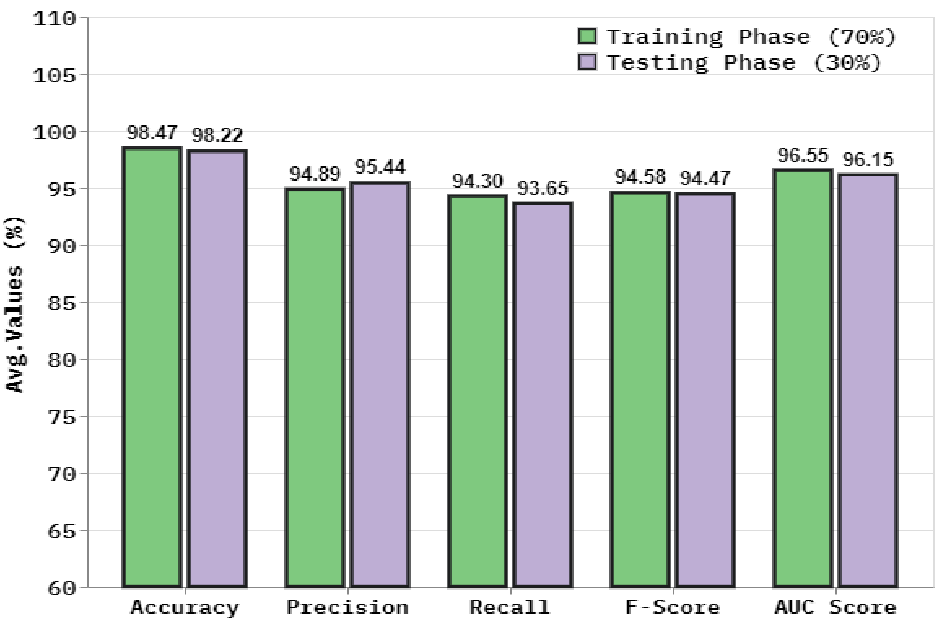

Figure 4. Average of SAPP-NINSOA technique below 70%TRAPHA and 30%TESPHA

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In Fig. 5, the training (TRAN) $accu_y$ and validation (VALN) $accu_y$ performances of the SAPP-NINSOA technique are depicted. The values of $accu_y$ are calculated through a time of 0-30 epochs. The figure underscored that the values of TRAN and VALN $accu_y$ expresses a growing tendency to notify the competency of the SAPP-NINSOA algorithm through maximum outcome over multiple replications. Furthermore, the TRAN and VALN $accu_y$ values remain close across the epochs, indicating diminished overfitting and presenting superior performance of the SAPP-NINSOA system, which guarantees reliable calculation on unseen samples.

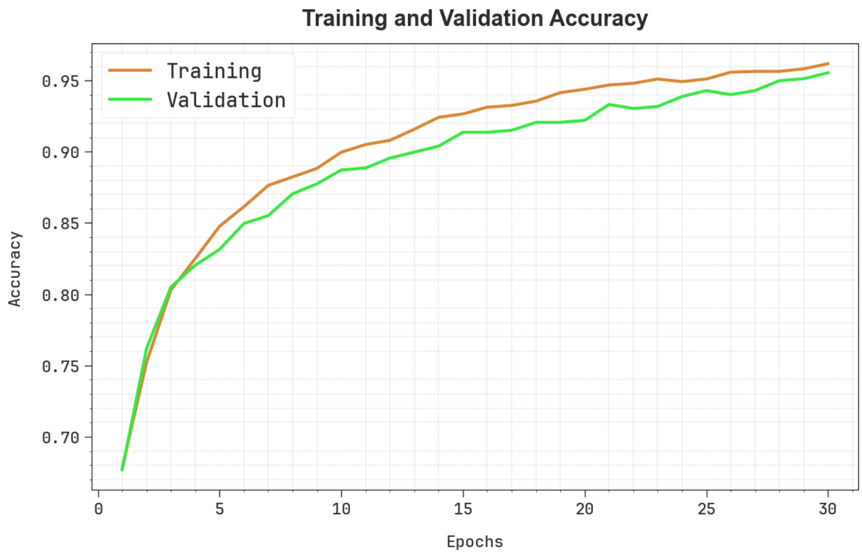

Figure 5. $Accu_y$ Curve of the SAPP-NINSOA algorithm

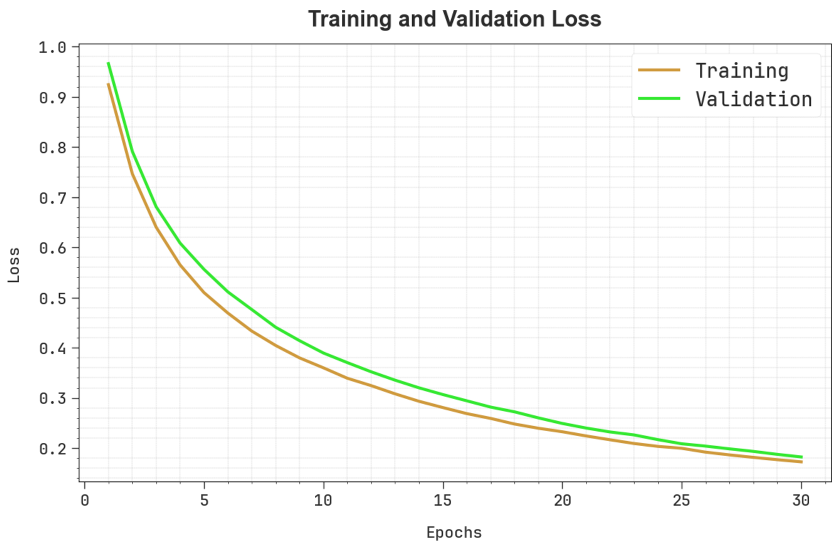

Figure 6. Loss curve of SAPP-NINSOA model

In Fig. 6, the TRAN loss (TRANLOS) and VALN loss (VALNLOS) graph of the SAPP-NINSOA method is showcased. The values of loss are computed through a time of 0-30 epochs. It is signified that the values of TRANLOS and VALNLOS demonstrate a declining propensity, indicating the capacity of the SAPP-NINSOA method in equalizing an equilibrium between generalization and data fitting. The sequential dilution in values of loss as well as assurances the increased performance of the SAPP-NINSOA algorithm and tune the calculation solutions after a while.

The comparative outcome of SAPP-NINSOA model through the existing approaches is illustrated in Table 3 and Fig. 7 [23-25]. The existing techniques namely TrialExamPure, LASSO, XGBoost, DGNN, DLM, CNN-LSTM, and GRU-RF algorithms have attained poorest performance. Additionally, the proposed system SAPP-NINSOA has gained superior performance with enhanced $accu_y, prec_n, reca_l$, and F_{score} of 98.47%, 94.89%, 94.30%, and 94.58%, respectively.

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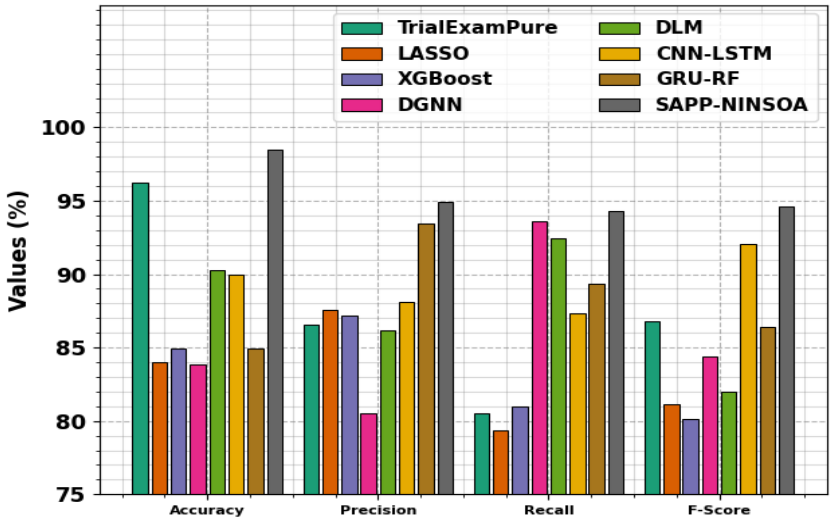

Figure 7. Comparative outcome of SAPP-NINSOA model with existing techniques

Table 3: Comparative outcome of SAPP-NINSOA model with existing models

Model	$Accu_y$	$Prec_n$	$Reca_l$	F_{score}
TrialExamPure	96.24	86.58	80.53	86.76
LASSO	84.03	87.59	79.34	81.17
XGBoost	84.92	87.20	80.96	80.14
DGNN	83.86	80.55	93.58	84.39
DLM	90.25	86.20	92.48	82.01
CNN-LSTM	89.95	88.10	87.34	92.08
GRU-RF	84.92	93.45	89.36	86.39
SAPP-NINSOA	98.47	94.89	94.30	94.58

Table 4 and Fig. 8 inspect the running time (RT) performances of SAPP-NINSOA technique with existing algorithms. According to RT, the SAPP-NINSOA method offers minimal RT of 10.20min while the TrialExamPure, LASSO, XGBoost, DGNN, DLM, CNN-LSTM, and GRU-RF approaches reach better RT of 14.25min, 14.40min, 24.22min, 17.86min, 22.78min, 12.14min, and 15.37min, respectively.

Table 4: RT outcome of SAPP-NINSOA model with existing techniques

Model	Running Time (min)
TrialExamPure	14.25
LASSO	14.40
XGBoost	24.22
DGNN	17.86
DLM	22.78
CNN-LSTM	12.14
GRU-RF	15.37
SAPP-NINSOA	10.20

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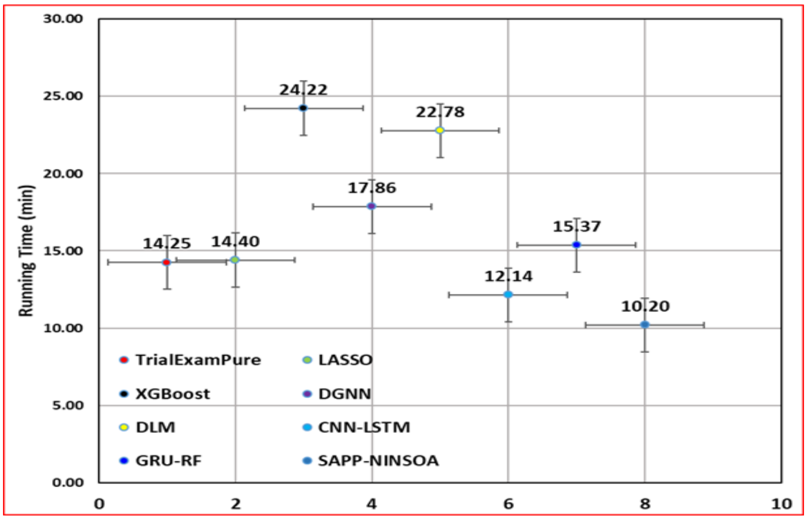

Figure 8. RT outcome of SAPP-NINSOA with existing approaches

5. Conclusion

In this study, we have presented a SAPP-NINSOA methodology. The main intention of the SAPP-NINSOA technique is to provide a prevalent technology for predicting students' academic performance using an advanced optimization algorithm. At first, the data pre-processing stage applies Z-score normalization to convert input data into a beneficial format. Besides, the FS process has been executed by the SBOA to select the relevant features from input data. Next, the proposed SAPP-NINSOA model designs the NVINS method for the classification process. Finally, the AOA fine-tunes the parameter values of the NVINS model. An extensive range of experimentation was led to certify the performance of the SAPP-NINSOA technique. The simulation outcomes stated that the SAPP-NINSOA algorithm emphasized furtherance when compared to other existing systems.

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