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Swarm Optimized S-AAF: Enhancing Student Academic Performance Prediction with Swarm-Optimized Adaptive Binary Classifier

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ABSTRACT

Introduction: Predicting academic performance is crucial for educational institutions to implement timely interventions and strategies that enhance student success. Traditional predictive models often struggle with the nonlinear and high-dimensional characteristics of educational data, leading to suboptimal outcomes.

Objectives: This research aims to develop a more effective predictive framework that overcomes the limitations of conventional models by leveraging advanced optimization and classification techniques.

Methods: The work proposes the Swarm Optimized S-AAF model, which integrates Particle Swarm Optimization and Genetic Algorithm with a robust classifier called Sigmoid-plus Adaptive Activation Function . Particle Swarm Optimization optimizes parameters based on swarm intelligence, while GA uses evolutionary strategies to refine the solution space. Together, these algorithms enhance feature selection and improve the classification performance of the S-AAF model.

Results: Experimental evaluations demonstrate that the Swarm Optimized S-AAF model achieves superior predictive performance. It effectively identifies hidden patterns in student data and significantly outperforms existing state-of-the-art methods and standalone optimization algorithms in terms of accuracy and computational efficiency.

Conclusions: The integration of PSO and GA with the S-AAF classifier results in a powerful predictive model that addresses the complexity of educational data. The Swarm Optimized S-AAF model offers a promising approach for improving academic performance prediction and supports more informed decision-making in educational settings.

Keywords: S-AAF (Sigmoid plus – Adaptive Activation Function), Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Feature Selection, Prediction, Academic performance, Classification.

INTRODUCTION

Academic performance prediction is pivotal for educational institutions to refine student success rates and improve decision-making processes [1]. The field of machine learning has remodelled the way computers process and analyze data, allowing them to learn from experiences and improve their performance [2, 3]. Conventional predictive models struggle with non-linearity, high-dimensional data, and suboptimal feature selection, which often leads to decreased accuracy and interpretability. Most conventional models assume data normality and linear relationships, limiting their ability to obtain complex interactions among multiple academic, behavioral, and socioeconomic factors [4]. Moreover, these models lack an efficient mechanism to manage redundant features, resulting in overfitting and reduced generalizability when applied to different student populations [5]. To conquer these confines, this research recommends the Swarm Optimized S-AAF Model, which incorporates three

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components: Particle Swarm Optimization, Genetic Algorithm, and the S-AAF classifier. The PSO algorithm strengthens feature selection by simulating the collective behavior of swarms, ensuring adequate parameter tuning. Meanwhile, GA improves the optimization process among evolutionary strategies, allowing the model to strengthen feature importance dynamically [6] The S-AAF classifier improves upon traditional activation functions by adjusting its parameters adaptively, enabling better non-linearity handling and reducing model complexity. By incorporating these three components, the proposed model efficiently distinguishes hidden patterns in student datasets, enriches feature selection, and enhances classification accuracy [7]. The significance of the Swarm Optimized S-AAF Model lies in its ability to address the weaknesses of conventional models while providing a more adaptive and computationally efficient framework for academic performance prediction. This model guarantees enhanced feature selection, efficiently identifying the most applicable features while excluding redundant attributes, thereby enhancing accuracy. The inclusion of the Sigmoid plus Adaptive Activation Function allows the model to handle non-linearity more effectively, capturing complex student performance patterns that conventional models such as K-nearest neighbors [8], artificial neural networks [9], logistic regression [10], decision trees [11], and support vector machines [12] often fail to recognize. Despite these advantages, the proposed model also exhibits certain exceptions, such as increased computational complexity due to PSO-GA integration and the demand for hyperparameter tuning to optimize performance. However, these limitations are outweighed by the significant advancements in accuracy, interpretability, and robustness compared to conventional methods [13]. By combining metaheuristic optimization with machine learning, this model extends an efficient tool for educational institutions to forecast student performance and enforce tailored interventions. The structure of the paper is as follows: Section 2 reviews the related literature; Section 3 outlines the optimization and machine learning algorithms utilized in the paper; Section 4 presents an analysis of the results, examining their implications and importance. Finally, Section 5 concludes with a summary of the key findings.

RELATED WORK

Educational Data Mining uses statistics, machine learning, and data mining to examine educational data, aiming to enrich teaching and learning. A key focus is an early forecast of students' learning outcomes to distinguish potential issues, provide targeted support, and improve educational interventions, ultimately leading to better learning experiences and outcomes [14]. Educational Data Mining has accumulated meaningful attention due to its complexity and consequence. Various data mining algorithms and hybrid approaches [15] are used to address EDM challenges, with recent advancements incorporating optimization algorithms to enhance student performance prediction and improve outcomes.

Towfek et al. [16] introduces Particle Swarm Optimization - Whale Optimization Algorithm collaborative with Linear Regression. This method used PSO for feature selection and WOA for optimization, resulting in an accuracy of 87.5% on a Higher Education Student Survey dataset. However, the model is absent in handling high-dimensional datasets, leading to high computational complexity.

Chen & Zhai [17] conducted a comparative study on different machine learning models, including Support Vector Machines, Random Forest, and Neural Networks, for academic performance prediction. Their research exploited an educational dataset comprising student grades and behavioral attributes and reported an accuracy of 82.3%. While the study highlighted the strength of ML models in education, it also magnified that feature selection was a significant challenge. Additionally, the study found that imbalanced datasets significantly impacted prediction accuracy.

Khan et al. [18] introduces a conceptual framework for feature selection in student performance prediction models. Their work redefined various machine learning strategies but did not furnish an empirical evaluation. The research emphasized the importance of selecting optimal features and eliminating redundant attributes to improve prediction accuracy. While their framework furnished valuable theoretical perception, a major confine was the lack of experimental validation on real-world educational datasets.

Ahmed [19] evaluated different machine learning classifiers, including SVM, Decision Tree , Naïve Bayes , and KNN, for student academic performance prediction. The investigation used a University Student Data dataset and established that SVM attained the highest accuracy (96%), exceeding other classifiers. though, the research

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distinguished that Naïve Bayes performed poorly, struggling with datasets containing correlated features. Another limitation was that feature redundancy negatively impacted model efficiency, indicating the need for an optimized feature selection strategy to improve performance.

Charitopoulos et al. [20] investigated the application of Soft Computing techniques in Educational Data Mining, reviewing diverse fuzzy logic, genetic algorithms, and swarm intelligence methods. The work provided an extensive analysis of how soft computing techniques enhance prediction models. However, the research was largely theoretical, with finite real-time implementation. Without empirical validation, the proposed methods could not be equated against existing machine learning approaches for student performance prediction

Shami et al. [21] proposed a Hybrid PSO + GA Optimization Model for feature selection in academic performance prediction. Their study achieved 89.7% accuracy using open-source educational datasets. The research proved that integrating PSO and GA significantly advanced feature selection and model accuracy. However, the research also noted that the hybrid model suffered from a slower convergence rate when applied to large datasets, requiring additional tuning to enhance computational efficiency

Table 1 presents a comparative summary of related work on student performance prediction using various techniques. It emphasizes the strengths and weaknesses of various methodologies and emphasizes the need for models that balance accuracy, computational efficiency, and interpretability.

Table 1: Comparative Summary of Related Work

Author	Methods	Accuracy	Dataset	Limitation
Towfek et al	PSO-Guided Whale Optimization Algorithm (WOA) + Linear Regression	87.5%	Higher Education Student Survey Data	Struggles with high-dimensional datasets and interpretability
Chen & Zhai	Comparative study of ML algorithms (SVM, Random Forest, Neural Networks)	90.1%	Educational dataset (student grades, behavioral attributes)	Requires feature engineering; weak at handling imbalanced data
Ahmed	SVM, Decision Tree, Naïve Bayes, KNN	96%	University Student Data	Feature redundancy issues
Shami et al.	Hybrid PSO + GA Optimization for Feature Selection	89.7%	Open-source academic datasets	Slower convergence rate in large datasets

Problem Identification and Research Gap

Existing academic performance prediction models struggle with handling high-dimensional data, addressing non-linearity, and optimizing feature selection. Traditional machine learning models require extensive feature engineering and often fail on imbalanced datasets, resulting in poor accuracy and generalizability while PSO and GA have been explored for feature selection; they are mostly used independently, limiting their optimization potential.

Most existing models lack hybrid approaches, although few models combine them with classifiers to improve non-linearity handling and computational efficiency. Furthermore, current methods lack real-time adaptability, limiting their use in early intervention systems. The Swarm Optimized S-AAF Model bridges these gaps by integrating PSO and GA for feature selection and enhancing classification with an adaptive activation function, ensuring higher accuracy, better scalability, and improved adaptability.

METHODS

The proposed Swarm Optimized S-AAF method, as illustrated in Fig. 1, combines the strengths of Particle Swarm Optimization and Genetic Algorithm to significantly enhance the accuracy of academic prediction. This method

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comprises four interconnected tasks: Data pre-processing, PSO + GA utilization, S-AAF based classification, and performance measurement.

Initially, to normalize feature ranges and ensure data consistency Z-Score normalization is conducted. The proposed model is divided into three key stages, as in Fig. 2 and detailed in Algorithm1.

Stage 1: Particle Swarm Optimization is prone to enhancing a foremost population of candidate feature subsets by iteratively updating particles' positions and velocities to differentiate the extremely applicable combinations of features.

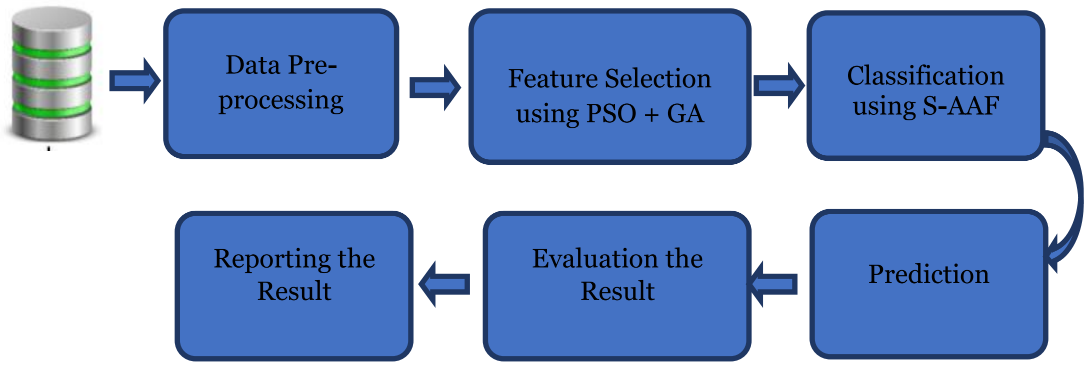

Fig. 1 Proposed Method

Stage 2: Genetic Algorithm further improves the feature subsets prompted by PSO among crossover and mutation operations, promoting diversity and aiding the search to escape local optima.

Stage 3: The optimal feature subset obtained from this hybrid optimization process is then passed to the S-AAF classifier to predict student performance.

The model is evaluated using multiple performance metrics such as accuracy, precision, and recall. This model incorporates several key steps like updating personal and global best values, which is outlined in Algorithm 2, adjusting particle velocities which is detailed in Algorithm 3, Algorithm 4 employing crossover and Algorithm 5 demonstrates mutation to ensure diversity and robustness. The combination of PSO and GA allows the system to exploit both global and local search capabilities, improving the robustness and accuracy of student academic predictions.

Data Preprocessing

Z-Score normalization is a standardization technique used to normalize data and this process eliminates numerical difficulties due to different ranges of values, prevents features with large ranges from dominating the model, and improves model convergence and performance. The proposed model employed Z-score normalization, as in Eq. (1) that transforms raw values into a normalized scale with a mean of 0 and a standard deviation of 1, ensuring equal feature contributions.

$$Z = \frac{X - \mu}{\sigma} \quad (1)$$

Z = Standardized value (Z-score), X = Original data point, μ = Mean of the dataset, σ = Standard deviation of the dataset

Stage 1:Particle swarm optimization algorithm

Particle Swarm Optimization is a nature-inspired algorithm that uses swarm intelligence to find optimal solutions. It mimics the collective behavior of bird flocks and fish schools to search for the best solution in complex problems [22]. In the Particle Swarm Optimization algorithm, a swarm of particles collaborates to find optimal solutions by navigating the search space with adaptive velocities. Each particle's movement is informed by its personal best experience (Pbest) and the swarm's collective best achievement (Gbest), allowing it to refine its position and

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velocity at each iteration. This dynamic interplay between individual and collective knowledge enables the swarm to converge towards the optimal solution, making PSO a powerful tool for exploring complex problem landscapes [23].

The input data is first pre-processed, and then the population of particles is initialized. In Particle Swarm Optimization, each particle is represented by a D-dimensional vector [24], denoted as Eq. (2):

$$x_i = (x_{i1}, x_{i2}, \dots, x_{iD}) \in S \tag{2}$$

Where, S is the search space. The initial population's velocity is randomly generated, with each particle having an initial velocity[6], as in Eq. (3)

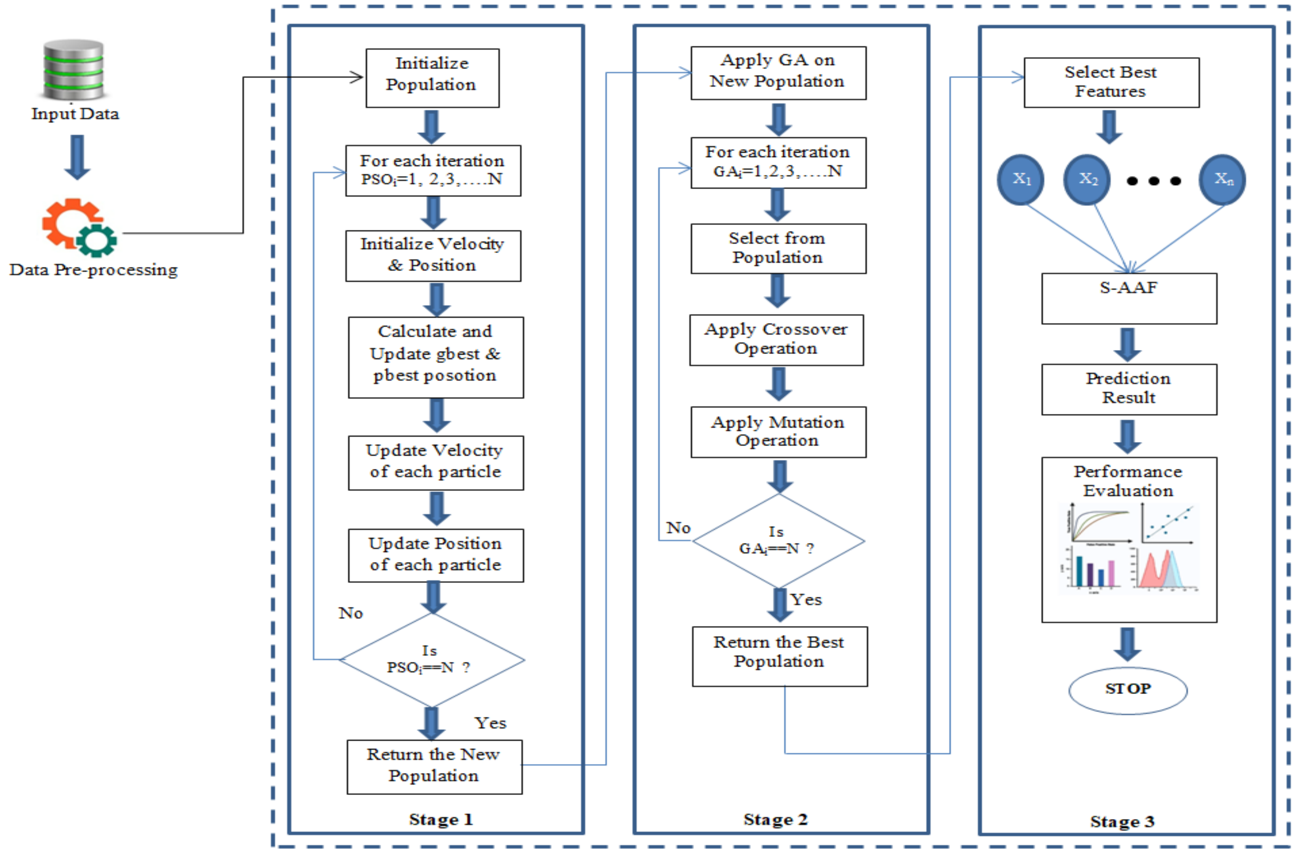

Fig. 2: Flowchart of the Swarm Optimized S-AAF

$$v_i = (v_{i1}, v_{i2}, \dots, v_{iD}) \tag{3}$$

The optimal local and global positions are established, where the best local position found by each particle[7] is specified in Eq. (4)

$$p_i = (p_{i1}, p_{i2}, \dots, p_{iD}) \in S \tag{4}$$

At each iteration, the particle adjusts its personal position according to the pbest and the gbest among particles in its neighbourhood[25], using the following update equations (5, 6)

$$x_i^{(t+1)} = x_i^{(t)} + v_i^{(t+1)} \tag{5}$$

$$v_i^{(t+1)} = v_i^{(t)} + c_1 r_{i1} \times \left(pbest_i^{(t)} - x_i^{(t)}\right) + c_2 r_{i2} \times \left(gbest - x_i^{(t)}\right) \tag{6}$$

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Where, c1 and c2 are acceleration constants, representing cognitive and social parameters, respectively , r1 and r2 are random vectors in [0, 1], $pbest_i^{(t)}$is the best local position encountered by particle i at iteration t, gbest is the overall best position among all particles in the neighbourhood. This process iterates for a predefined number of iterations, and after all iterations are complete, the algorithm returns a new population. This new population is passed to the stage 2 of the proposed model.

Stage 2: Genetic Algorithm

In the second stage, the Genetic Algorithm is applied to the new population generated by the PSO. GA starts by selecting a population of individuals, which are evaluated based on their fitness. Two individuals are then selected for reproduction using a selection method. The selected individuals undergo a crossover operation, where parts of their chromosomes (features) are exchanged [24]. This can be represented as in Eq.(7):

$$X_1 = \{x_1^1, x_2^2\},\ X_2 = \{x_2^1, x_1^2\} \tag{7}$$

Where X1 and X2 are the offspring produced by combining parts of the parents' chromosomes. After crossover, mutation is applied to introduce variability by randomly altering one or more genes in the offspring[7]. This can be represented as in Eq. (8):

$$x_j = x_j + \Delta_x \tag{8}$$

Where Δx is a small random change. This helps the algorithm explore new regions of solution space.The fitness of the offspring is then evaluated,the less fit individuals in the population are replaced by the new offspring based on fitness scores. The process of selection, crossover, and mutation is repeated for a predefined number of iterations. After GA completes its iterations, the best individuals (solutions) are selected, which represent the optimized features that are passed to the stage 3 for prediction and performance evaluation.

Stage 3: S-AAF Classifier

The S-AAF is an activation function, proposed for classification tasks. It demonstrates the capability to dynamically adjust both its shape and slope in response to the complexity and patterns in the input data, making it a powerful tool in machine learning models. By adapting the traditional sigmoid function, S-AAF introduces additional parameters that enhance its adaptability, allowing the function to more effectively model complex relationships in the data and improve overall performance, especially in classification problems [7].The standard sigmoid function is defined as in Eq. (9):

$$\sigma(x) = \frac{1}{1+e^{-x}} \tag{9}$$

Algorithm 1 : Swarm Optimized S-AAF Model

Input:

- Dataset D with features $X = \{x_1, x_2, \ldots x_{n\}}$ and labels Y
- Population size P
- Number of PSO iterations PSO_N
- Number of GA iterations GA_N

Output:

- New Population set $\{X_{best}\}$

Prediction results X_{pred}

Begin :

Initialize the positionX_i and velocity V_i for each particle i

$$X_i = (x_{i1}, x_{i2}, \ldots, x_{iD}) \text{ and } v_i = (v_{i1}, v_{i2}, \ldots, v_{iD})$$

FOR EACH iteration$t = 1\ 2, \ldots, PSO_N$

Update velocity using pbest and the gbest:

$$v_i^{(t+1)} = v_i^{(t)} + c_1 r_{i1} \times \left(pbest_i^{(t)} - x_i^{(t)}\right) + c_2 r_{i2} \times \left(gbest - x_i^{(t)}\right)$$

Update position: $x_i^{(t+1)} = x_i^{(t)} + v_i^{(t+1)}$

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Evaluate fitness of the updated particles: $\mathrm{Fitness}(x_i(t+1)) = f(x_i(t+1))$
IF $\mathrm{Fitness}(x_i(t+1)) = f(x_i(t+1)) <$ Fitness(pbest) then, Update pbest
IF $\mathrm{Fitness}(x_i(t+1)) = f(x_i(t+1)) <$ Fitness(gbest) then, Update gbest
FOR EACH GA iteration $t = 1\ 2, \ldots, GA_N$
Select individuals from the population
FOR EACH iteration $t = 1\ 2, \ldots, GA_N$
perform crossover to create offspring:

$$\mathrm{Offspring} = \{x_1^A, \ldots, x_k^A, x_1^B, \ldots, x_d^B\}$$

Apply Mutation to the offspring:

$$x_j = x_j + \Delta_x$$

Evaluate fitnessof the new offspring:

$$\mathrm{Fitness}(\mathrm{offspring}_i) = f(\mathrm{offspring}_i)$$

IF Fitness(offspring) < Fitness(pbest) then, Update pbest
IF Fitness(offspring) < Fitness(gbest) then, Update gbest
select features from the best population: $\{x_1, x_2, \ldots, x_n\}$
Apply S-AAF for classification:

$$S - AAF = \frac{1}{e^{\ln\left(e^{(z+T)} + e^{(z+T)^2+1}\right) - (z+T)}}$$

Evaluate the classification results using performance metrics.
End

Algorithm 2: Calculate pbest and gbest:
Input: Particles
Output: pbest and gbest
Set pbest = null, gbest = null, t = 0.
While t < max particles. size do:
If pbest[t] == null or pbest[t].get Fitness() > particles[t].get Fitness():
Set pbest[t] = particles[t]
If gbest == null or pbest[t].get Fitness()} <gbest. get Fitness()}:
Set gbest = pbest[t]
t = t + 1
Repeat until the last particle is processed

While the sigmoid function is widely used due to its simplicity and its ability to squash input values between 0 and 1, it suffers from limitations such as the vanishing gradient problem and lack of flexibility in adjusting to varied input data distributions. The S-AAF improves upon the sigmoid function by incorporating additional parameters to enhance its flexibility. The formula for S-AAF is presented as in Eq.(10):

$$S - AAF = \frac{1}{e^{\ln\left(e^{(z+T)} + e^{(z+T)^2+1}\right) - (z+T)}} \quad (10)$$

z- weighted input, T - Threshold value

This S-AAF function behaves similarly to the traditional sigmoid activation but is far more flexible due to the additional non-linearity introduced by the squared term and the logarithmic transformation. The parameters T and nonlinear components allow the function to adapt more dynamically to the input data, which can result in better classification performance. Finally, the prediction results are evaluated using performance metrics, such as accuracy, precision, recall, and F1-score. This stage provides the final output and performance evaluation of the model.

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Algorithm 3: Update Velocity using pbest and gbest:

```
Input: Velocity values
Output: Updated velocity values
Set t = 0 ; c1 = 1 ; c2 = 1.1 ;
While  t <max_particles.length} do:
        If Particle[t] ==pbest[t]  then
                velocity[t] -= c1 × rand(0, 1)
        Else
                velocity[t] += c1 ×rand(0, 1)
        If  Particle[t] == gbest [t] then
                velocity[t] -= c1 × rand(0, 1)
        Else:
                velocity[t] += c1 ×rand(0, 1)
        t = t + 1
```

Algorithm 4:Crossover Method

```
Input: Two chromosomes
Output :Offspring chromosome
Set c = random number between 0 and chromosome length
For  i = 0 to  c
  Offspring chromosome[i] = chromosome1[i]
For  i = c  to chromosome length:
Offspring chromosome[i] = chromosome2[i]
End
```

Algorithm 5 : Mutation Method

```
Input: Offspring chromosome (from crossover)
Output: New chromosome
Set mutationRate = 0.5
If random number ≤  mutationRate:
  Select random index p1 = random number ×chromosome length
  Select random index  p2 = random number ×chromosome length
If chromosome[p1] ≠ chromosome[p2]:
   Swap chromosome[p1] and chromosome[p2]
End
```

RESULTS AND DISCUSSION

Table 2 presents a comparative analysis of different optimization-based models, highlighting the effectiveness of various approaches in enhancing the performance of the S-AAF classifier. The proposed model

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
Proposed Model(PSO +GA+S-AAF)	94.11	94.06	93.56	93.42

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Table 2: Comparative Analysis of proposed model with optimization methods

SA + PSO + S-AAF	87.34	85.89	85.67	85.75
ACO + GA + S-AAF	90.75	90.06	92.01	90.05
CS + HS + S-AAF	86.55	85.95	87.76	86.27
GOA + DA + S-AAF	82.35	82.41	84.23	82.11

PSO - Particle Swarm Optimization, GA - Genetic Algorithm, SA - Simulated annealing, ACO -Ant colony optimization, CS - Cuckoo Search, HS- Harmony search, GOA - Grasshopper Optimization Algorithm, DA - Dragonfly Algorithm.

achieves the highest accuracy of 94.11% and maintains a well-balanced precision of 94.06% , recall of 93.56%, and F1-score of 93.42%, demonstrating its superior classification ability. This performance is attributed to the effect of PSO and GA, where GA effectively explores the feature space, and PSO refines solutions through swarm intelligence, leading to optimal feature selection and weight optimization. In comparison, SA + PSO + S-AAF achieve 87.34% accuracy, indicating that Simulated Annealing is less effective than Genetic Algorithm in optimizing model parameters. Similarly, ACO + GA + S-AAF achieves 90.75%, it performs better than SA-based optimization but still falls short of the proposed model, suggesting that Ant Colony Optimization is not as efficient as Particle Swarm Optimization in refining solutions. Other models, such as CS + HS + S-AAF achieves 86.55% and GOA + DA + S-AAF achieves 82.35%, exhibit even lower performance, indicating that Cuckoo Search, Harmony Search , Grasshopper Optimization Algorithm, and Dragonfly Algorithm do not optimize feature selection and classification as effectively as PSO and GA. Overall, the results clearly demonstrate that the PSO + GA + S-AAF model is the most effective, consistently outperforming other hybrid models across all evaluation metrics, proving its robustness in classification tasks.

Table 3 : Comparative Analysis with State of the art Methods

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
PSO + GA + S-AAF	94.11	94.06	93.56	93.42
PSO + GA + SVM	87.67	86.25	87.27	86.29
PSO + GA + KNN	83.03	84.11	78.44	80.22
PSO + GA + LR	88.56	86.49	89.06	87.6

SVM – Support Vector Machine, KNN – K Nearest Neighbour, LR – Logistic Regression.

Table 3 presents a comparative analysis of the proposed model against other state-of-the-art classification methods to assess its effectiveness. The proposed model achieves the highest accuracy and significantly outperforms the other models. It also maintains a well-balanced precision of 94.06%, recall of 93.56%, and F1-score of 93.42%, ensuring superior classification performance. Among the other models, PSO + GA + LR achieves 88.56% accuracy, making it the second-best performer, showing that Logistic Regression benefits from PSO and GA-based optimization but still falls short compared to S-AAF. PSO + GA + SVM follows closely with 87.67% accuracy, demonstrating that Support Vector Machine, while effective, does not perform as well as S-AAF in this context. The lowest accuracy is observed in PSO + GA + KNN , indicating that K-Nearest Neighbours struggle with classification despite optimization. Overall, these results emphasize that S-AAF, when optimized using PSO and GA, outperforms traditional classifiers. The superior accuracy and balanced performance metrics of the proposed model confirm its effectiveness in classification tasks, making it the best choice among the compared methods. The performance of the Feature Selection process in this model shows a significant improvement in classification accuracy by focusing on the most relevant features rather than using all the available features. Feature selection is an important step in optimizing machine learning models, as it helps eliminate irrelevant or redundant features that may add noise to the model, decrease performance, and increase computational complexity.

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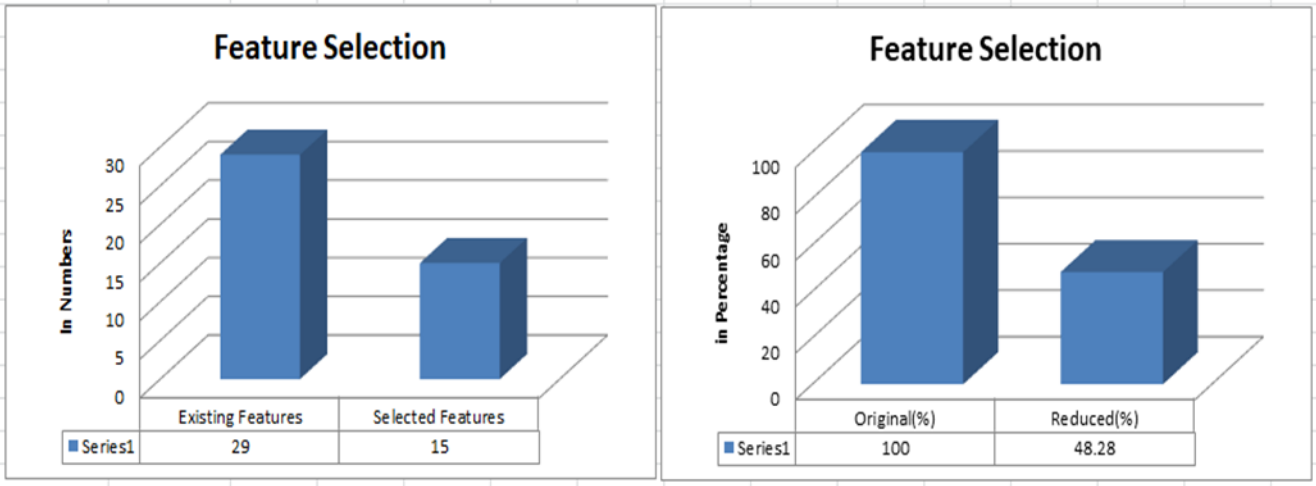

Fig.3 Selected Features from the dataset

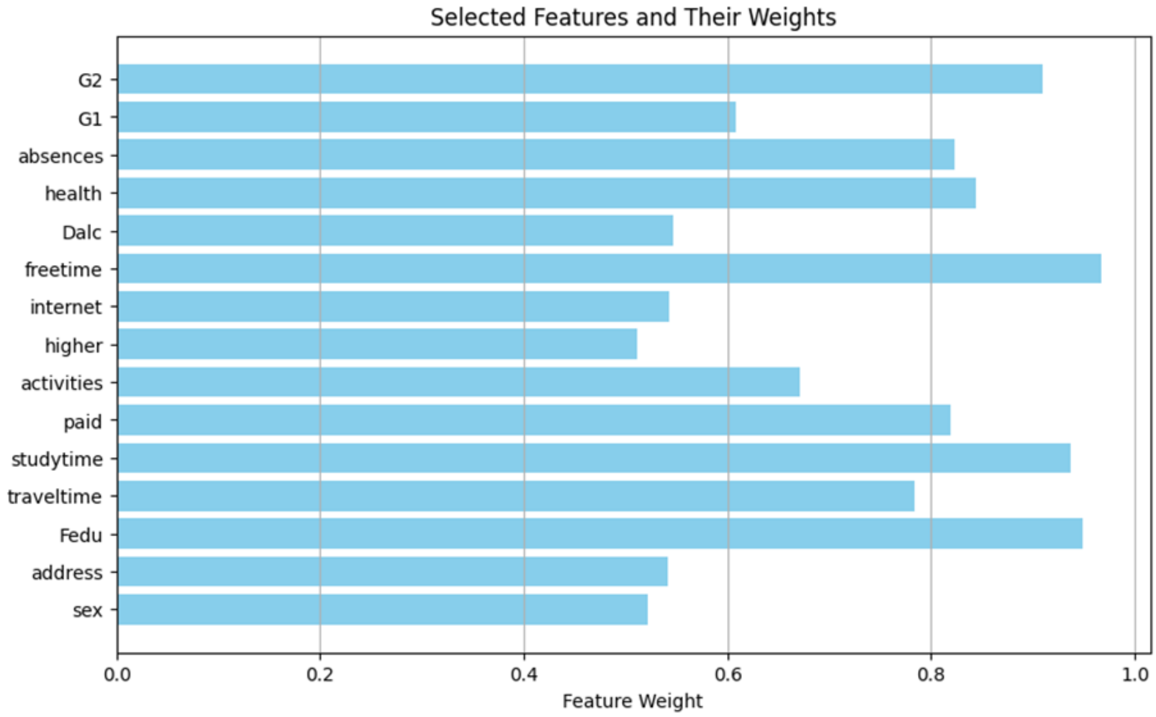

Fig.4 Selected Features and their Weights

From the results presented in Fig.3 & Fig.4, it is clear that the proposed approach effectively reduces the number of features while maintaining a high level of accuracy. The original dataset contains 29 features and after the feature selection process, only 16 features were selected. This represents a feature reduction percentage of 48.28%, meaning that nearly half of the features were deemed unnecessary for achieving high predictive performance. Despite this substantial reduction, the accuracy of the test set remained high at 94.11%, demonstrating the effectiveness of selecting the most important features for the model. The proposed model was tested on unimodal functions, shown in Table 4. These functions help assess the algorithm's ability to find the optimal solution. The model's faster convergence highlights the efficiency gained by the proposed model. The performance is assessed by plotting the function values versus the number of iterations, as illustrated in Figs. 5. These plots provide a visual comparison, with the dotted line representing the results of the standard algorithms, and the solid line representing the performance of the proposed hybrid model. In this context, the solid line for the proposed model demonstrates

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a faster convergence rate compared to the dotted line of the standard algorithms. Thus the proposed model improves the strengths of both Particle Swarm Optimization and Genetic algorithms.

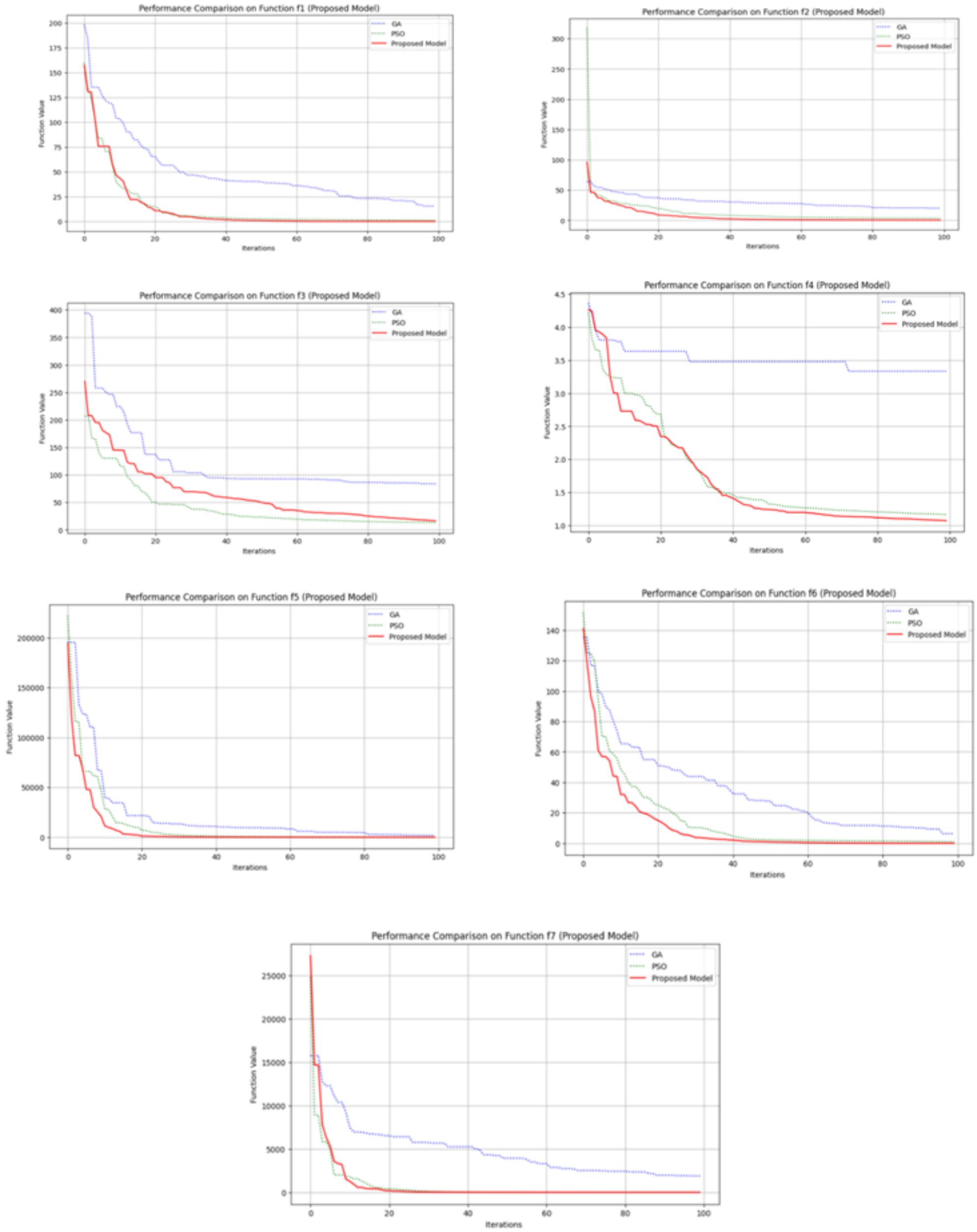

Fig. 5 The efficiency of proposed model on Unimodel function

Function	Formula
f1	$\sum_{i=1}^{d} x_i^2$

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Table 4: Unimodel Test Function

f3	$\sum_{i=1}^{d}(\sum_{j=1}^{i} x_j)^2$
f4	$\max_i \lvert x_i \rvert, 1 \le i \le d$
f5	$\sum_{i=1}^{d-1}[100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2$
f6	$\sum_{i=1}^{d}([x_i + 0.5])^2$
f7	$\sum_{i=1}^{d} ix_i^4 + \text{random}[0,1]$

Fig.6 shows the ROC-AUC curve of the proposed model, with an AUC of 0.9932, indicating excellent classification performance.

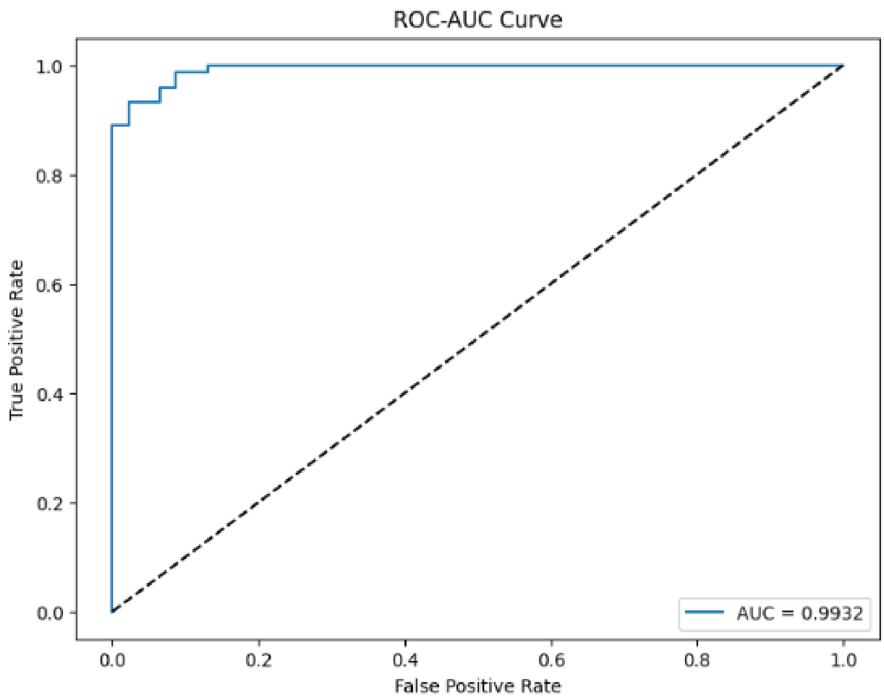

Fig. 6 ROC – AUC Curve

CONCLUSION

The proposed model for selecting significant features to enhance student academic predictions is achieving a high accuracy of 94.12% and outperforming existing state-of-the-art methods on the same dataset. By integrating Particle Swarm Optimization and Genetic Algorithm for feature selection, the model effectively identifies key features that boost predictive performance while significantly reducing the original feature count from 29 to 16, resulting in a 44.83% reduction. This reduction not only streamlines the input data but also enhances model interpretability, allowing stakeholders to gain valuable insights that influence student success. Additionally, the model employs the S-AAF classification method, which has been proven to further improve classification performance. The hybrid approach exhibits faster convergence compared to standard algorithms, validating the effectiveness of combining PSO and GA in optimizing feature selection while using S-AAF for robust classification. Future research could focus on optimizing computational efficiency, exploring diverse domains, integrating advanced machine learning techniques, and conducting longitudinal studies to assess long-term impacts. Overall, the proposed model represents a significant advancement in educational analytics, offering a robust framework for improving decision-making processes related to student performance while highlighting the need for further refinement and exploration.

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