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Evaluation model of English Informatization Teaching Quality in Universities Based on Particle Swarm Algorithm

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Abstract: - Teaching quality in the field of English education plays a crucial role in shaping students' language proficiency, communication skills, and overall understanding of the language. One of the most significant contributions of deep learning to English education is its ability to personalize instruction. Deep learning algorithms analyze individual students' learning patterns, strengths, and weaknesses. This paper designed a framework for enhancing teaching quality in English education by implementation of Non-Convex Particle Swarm Optimization and Optimization (NC-PSOO) with a Generative Adversarial Network (GAN). The proposed model NC-PSOO with GAN, presents the information related to the teaching and learning process. The features are computed based on the utilization of the non-convex estimation for the analysis of the variables. Through the implementation of an effective process of data pre-processing using the Fejer filter, feature selection and extraction with NC-PSOO, and classification with GAN, this model aims to improve student performance, elevate the quality of teaching materials, increase student participation, enhance homework quality, and balance exam difficulty. The performance of NC-PSOO with GAN is compared with conventional optimization techniques like Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO) to demonstrate its superior efficacy. The findings highlight the model's capability to achieve higher accuracy, precision, recall, and F1 score, ultimately improving teaching quality in English education.

Keywords: Particle Swarm Optimization (PSO), English teaching, Non-Convex, GAN, Classification

I. INTRODUCTION

In the ever-evolving landscape of education, the quality of English informatization teaching has emerged as a defining factor in the effectiveness of modern language instruction [1]. Informatization teaching represents the fusion of information technology with the teaching and learning of English, offering a dynamic approach to language education. This integration of technology not only enriches the educational experience but also equips students with the digital skills essential for success in the 21st century [2]. It paves the way for interactive and engaging lessons, personalized learning experiences, and efficient assessment methods. As the intricacies of English informatization teaching quality, it becomes evident that it is a cornerstone of contemporary education, ensuring students are well-prepared to navigate a digitally connected world [3]. Optimization methods, both in terms of instructional content and delivery, can significantly enhance the educational experience. For instance, the use of Learning Management Systems (LMS) allows educators to organize and deliver course materials more effectively, providing students with structured and readily accessible resources [4]. Additionally, adaptive learning algorithms can tailor the curriculum to individual students, optimizing their progress and comprehension by focusing on their specific needs and abilities.

Optimization techniques also play a pivotal role in assessing and tracking student performance. Data analytics and assessment tools help educators identify areas where students may be struggling and require additional support [5]. By pinpointing these challenges, instructors can optimize their teaching methods to address these specific issues, thus promoting more effective learning. Furthermore, optimization extends to the integration of multimedia and interactive content, making lessons engaging and appealing to students [6]. Incorporating technologies such as virtual reality, gamified learning, or multimedia presentations can optimize the learning experience by capturing the attention and interest of today's tech-savvy students [7]. The use of optimization techniques in English informatization teaching goes beyond traditional methods, ensuring that education remains relevant and adaptable in our ever-changing digital landscape [8]. It is a means to offer students the best possible learning experience, making the journey of acquiring the English language not only effective but also enjoyable and inspiring. As technology continues to advance, these optimization techniques will remain central to the quest for high-quality English informatization teaching [9].

An optimization-based learning management system (LMS) represents a cutting-edge approach to modern education [10]. This system leverages the power of advanced algorithms and data analytics to create a dynamic and tailored learning experience for students. The core concept revolves around optimizing every aspect of the educational process, from content delivery to student assessment [11]. With an optimization-based LMS, educators

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can create personalized learning paths for each student, taking into account their individual strengths and weaknesses. This adaptive approach ensures that students receive the most relevant and effective content, optimizing their chances of success [12]. Additionally, optimization-based LMS can provide educators with real-time data and insights into student performance [13]. By analyzing this data, instructors can identify areas where students are struggling, enabling them to intervene promptly and provide targeted support. This data-driven approach not only enhances the quality of teaching but also enables the continuous improvement of the curriculum itself [14]. Moreover, these systems often employ predictive analytics to forecast student progress and tailor interventions accordingly, further optimizing the learning experience [15]. They can also optimize administrative tasks, such as scheduling and resource allocation, making educational institutions more efficient. Optimization-based learning management systems are revolutionizing education by tailoring the learning experience to the unique needs of each student [16]. These systems not only enhance the quality of education but also make the teaching process more efficient and data-driven, ultimately preparing students for success in the digital age.

The paper makes several significant contributions to the field of education and optimization techniques:

1. One of the primary contributions of this paper is the integration of Non-Convex Particle Swarm Optimization and Optimization (NC-PSOO) with a Generative Adversarial Network (GAN) to create a novel hybrid model. This integration offers a holistic approach to improving teaching quality in English education.
2. The paper contributes to the improvement of teaching quality by addressing multiple key factors, including student performance, teaching materials, student participation, homework quality, and exam difficulty. This holistic approach benefits educators and students by fostering better learning outcomes.
3. The paper leverages advanced optimization techniques, such as NC-PSOO and GAN, to optimize and fine-tune the teaching quality enhancement process. This showcases the potential of state-of-the-art optimization methods in educational contexts.
4. The comparison of the NC-PSOO with GAN model with conventional optimization techniques, namely Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO), demonstrates its superior performance. This highlights the contribution of the proposed model as an advanced and effective tool for enhancing teaching quality.
5. The paper's emphasis on balancing exam difficulty contributes to creating a fair and equitable learning environment. This consideration is vital for reducing stress and ensuring that assessments effectively gauge student performance.

The paper's contribution lies in the development and validation of a novel model that leverages advanced optimization techniques and GAN technology to enhance teaching quality in English education. By addressing various aspects of the teaching and learning process, this model provides a comprehensive solution for educators and students seeking to optimize their educational experience.

II. RELATED WORKS

The literature review section of this paper provides an overview of existing research and theories related to teaching quality improvement in English education. It discusses various conventional and technology-driven approaches to teaching quality enhancement. The section explores the importance of optimization techniques and data analytics in modern education, highlighting their role in creating personalized and efficient learning experiences. Mastan et al. (2022) [17] performed a systematic literature review focused on the evaluation of distance learning systems, commonly referred to as e-learning. The research likely explored a range of aspects related to e-learning, such as its effectiveness, impact on student performance, user satisfaction, and the overall quality of the learning experience. This type of evaluation is crucial, especially in the context of the widespread adoption of e-learning platforms, to ensure that such systems meet the desired educational objectives. Jurabaevich and Bulturbayevich (2021) [18] explored the potential benefits of adopting foreign educational practices to enhance the quality of education in Uzbekistan. This would involve examining educational systems in other countries and identifying successful strategies and practices that can be adapted to improve education within Uzbekistan. The research may have considered various aspects, such as curriculum development, teaching methodologies, and administrative procedures. Han (2022) [19] focused on the optimization of talent lifecycle management, likely within an organizational context. Decision tree models were likely used to analyze and enhance the management of talents throughout their employment life cycle. This can be crucial for HR professionals and organizations to ensure that employees are effectively recruited, developed, and retained.

Huang et al. (2021) [20] aimed to optimize the operation of electric vehicle (EV) charging stations located in drug stores. It likely considered factors such as energy efficiency, charging speed, and cost-effectiveness to ensure these stations are operated in a sustainable and efficient manner, considering the increasing popularity of EVs. Zhang et al. (2021) [21] involved the design and optimization of a thermal management system for electric vehicle batteries, which is vital for battery longevity and performance. The use of surrogate models likely helped to improve the design and efficiency of these systems, reducing energy consumption and enhancing EV battery life. Roslan et al. (2021) [22] focused on optimizing the energy management system for microgrids. This would typically involve balancing energy supply and demand efficiently, with a goal of saving costs and reducing emissions. Optimization algorithms likely played a key role in achieving these objectives. Shan (2022) [23] designed a Optimization of network home management systems using big data is crucial in enhancing the management of various household functions, such as heating, cooling, and security. The study likely explored how big data and optimization can be integrated to improve home automation systems.

Han and Zhang (2021) [24] focused on supply chain efficiency management, aiming to optimize the supply chain processes within an organization. The integration of machine learning and neural networks likely helped streamline supply chain operations, ensuring the efficient flow of goods and services. Lissa et al. (2021) [25] designed a model using deep reinforcement learning for controlling home energy management systems. Such systems can optimize energy consumption in residences, leading to cost savings and reduced environmental impact. Deep reinforcement learning is likely used to improve the decision-making process for energy management. Zhao et al. (2023) [26] aimed to optimize battery thermal management systems, considering multiple objectives. This could include improving battery life, reducing energy consumption, and maintaining optimal battery performance. The response surface analysis and NSGA-II algorithm were likely used to balance these objectives. Gao and Gao (2023) [27] introduced an optimal management architecture for smart solar-based islands, which can incorporate various technologies, including digital twin, deep learning, and particle swarm optimization. Such an architecture is essential for efficiently managing energy resources on these islands and enhancing sustainability.

Al Duhayyim et al. (2022) [28] explored the use of artificial ecosystem-based optimization and deep learning to improve waste management. In the context of the Internet of Things (IoT), this approach likely aimed to optimize waste collection and disposal processes, making them more sustainable. Pawan et al. (2022) [29] focused on improving particle swarm optimization performance using deep learning techniques. This can be vital in enhancing the effectiveness of optimization algorithms in various fields, where such algorithms are used for problem-solving and decision-making. Li et al. (2023) [30] conducted the research centered on multi-objective optimization for air cooling battery thermal management systems. The goal was to simultaneously optimize battery life, energy consumption, and other factors to ensure the efficient operation of battery systems. Cao (2021) [31] explored the optimization of intellectual property rights protection for educational resource data using machine learning algorithms. This can be vital in managing and safeguarding educational materials and resources effectively. Akbarpour et al. (2021) [32] presented an innovative waste management system in a smart city context, addressing stochastic optimization using vehicle routing problems. This approach is crucial for optimizing waste collection routes in smart cities, leading to cost and time savings.

Iqbal and Kim (2022) [33] focused on an IoT task management mechanism that uses predictive optimization to improve energy consumption in smart residential buildings. This is vital in ensuring energy efficiency and reducing utility costs for homeowners. de la Torre et al. (2021) [34] explored the use of simulation, optimization, and machine learning in sustainable transportation systems. This is essential for improving transportation efficiency while minimizing environmental impact. Lingmin et al. (2023) [35] introduced a Q-learning based optimization method for energy management in residential areas with combined cooling, heating, and power (CCHP) systems. Such systems aim to control peak loads efficiently and optimize energy consumption in residential areas. The reviewed literature encompasses a wide array of research topics, ranging from energy management and supply chain optimization to education system improvements and waste management in smart cities. Common themes and findings emerge across these diverse studies. The overarching emphasis on optimization and efficiency stands out, with researchers striving to enhance processes in various fields. Whether it's optimizing the charging station operation of electric vehicles, streamlining supply chain operations using machine learning, or enhancing energy consumption control in residential areas, the goal is consistently to improve efficiency, reduce costs, and make better use of resources. Additionally, a data-driven approach is a recurring trend, with machine learning, deep learning, and predictive optimization techniques being employed to guide decision-making and enhance system performance. Sustainability is another prominent theme, as studies focus on reducing emissions, energy consumption, and waste generation. Multi-objective optimization is a vital aspect, with researchers balancing multiple factors to achieve holistic improvements. These works collectively demonstrate the value of data-driven optimization in various domains and the significance of sustainability in modern problem-solving.

III. PROPOSED MODEL

The proposed model integrates several advanced techniques to enhance teaching quality in English. The Fejer filter is employed as a pre-processing step, aiming to refine and prepare the data for analysis. Non-Convex Particle Swarm Optimization (PSO) is used for feature selection, which helps identify the most relevant elements in the data, streamlining the learning process. Additionally, the model leverages a Generative Adversarial Neural Network (GAN) for optimization, offering a data-driven approach to adapt and improve the teaching quality dynamically. This combination of techniques ensures that the English teaching process is not only data-informed but also highly efficient and adaptive, ultimately contributing to a better educational experience for students. The "NC-PSOO" model, which combines the Fejer filter for pre-processing, Non-Convex Particle Swarm Optimization (NC-PSO) for feature selection, and a Generative Adversarial Neural Network (GAN) for optimization, appears to be a complex and innovative approach to improving teaching quality in English education. The steps involved in the proposed NC-PSO model is presented as follows:

Fejer Filter Pre-processing: The process begins with the Fejer filter, a mathematical technique often used for signal processing and data enhancement. In this context, it's applied to the data relevant to English teaching. The Fejer filter likely serves to clean and refine the data, removing noise and irrelevant information, ensuring that the data used for analysis and learning is of high quality.

Non-Convex PSO for Feature Selection: Non-Convex Particle Swarm Optimization (NC-PSO) is employed for feature selection. This optimization technique is used to determine which features or variables are most relevant for the specific task at hand. In this case, it helps identify the key elements that impact teaching quality in English.

Generative Adversarial Neural Network (GAN) for Optimization: GANs are neural networks consisting of two parts: a generator and a discriminator. They are often used in generative tasks, such as creating new data based on existing patterns. In this context, the GAN is used to optimize the teaching quality. The generator may create innovative teaching methods or content, while the discriminator evaluates their effectiveness. This adversarial process aims to continually improve teaching quality through data-driven feedback.

3.1 Data Pre-Processing

Data pre-processing plays a crucial role in the NC-PSOO (Non-Convex Particle Swarm Optimization) model, ensuring that the data used for feature selection and subsequent optimization is of high quality. The Fejer filter is a mathematical technique often utilized for data pre-processing. Its purpose is to enhance the data, removing noise and irrelevant information, ultimately preparing it for more efficient analysis. The Fejer filter can be represented as in equation (1)

$$F(n) = (1/N) * \sum (i = 0 \; to \; N - 1) \; |X(i)|^2 \tag{1}$$

In equation (1) F(n) represents the Fejer filter output at time n; N is the total number of data points in the datasetl X(i) signifies the data point at index i. The Fejer filter effectively calculates the squared magnitude of each data point, sums them over the entire dataset, and then averages the results, providing a smoothed representation of the data. The Fejer mean is a sequence of means for a given sequence. In the context of the Fejer filter, it is used to smooth a dataset. First, the squared magnitude of each data point is calculated, which ensures that all values are non-negative and accentuates the importance of significant values while reducing the impact of noise or fluctuations. The squared magnitudes of all data points are summed together, representing the total energy in the dataset. This total energy is divided by the total number of data points (N), providing the average energy across the dataset. This step is crucial for normalization. The result, $F(n)$, represents the Fejer filter output at a given point in time, where n denote different time intervals or iterations in the NC-PSOO model. This smoothed and processed data is then utilized for feature selection and optimization, ensuring that the NC-PSOO model operates on high-quality data, which is fundamental for its success in enhancing teaching quality in the context of English education. The figure 1 illustrated the flow chart of PSO model for the estimation of English Teaching.

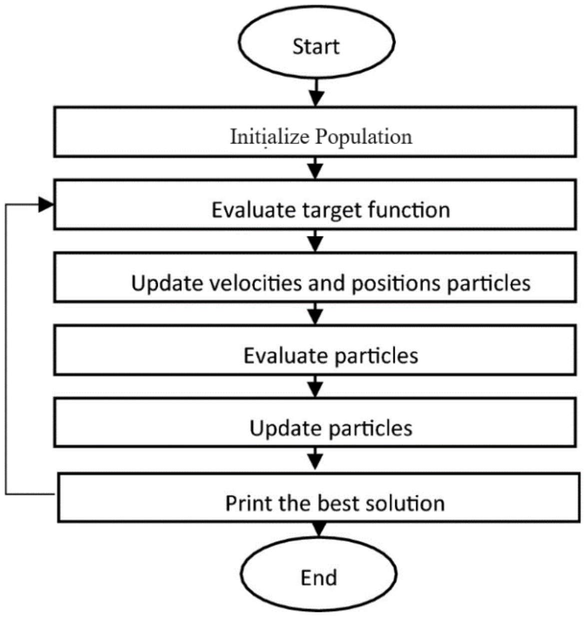


Figure 1: Flow Chart of PSO

In the first step, the squared magnitude of each data point, denoted as $|X(k)|^2$, is calculated. This operation ensures that all values in the dataset are non-negative. Squaring each value not only removes the negative sign but also accentuates the importance of significant values. This step is particularly valuable in data pre-processing because it highlights the contributions of more substantial data points while minimizing the impact of noise or fluctuations. The squared magnitudes of all data points, calculated in the previous step, are then summed together. This summation represents the total energy or total sum of squared magnitudes in the dataset. In other words, it quantifies the overall significance and energy within the data. To obtain the average energy across the dataset, the total energy (sum of squared magnitudes) is divided by the total number of data points (N). This division is represented by the term (1/N). Normalization through division by N is a crucial step in this process, ensuring that the Fejer filter output is scaled appropriately. The result of this process, represented as $F(n)$, provides the Fejer filter output at a specific point in time or iteration (n). The value of 'n' can denote different time intervals or iterations within the NC-PSOO model. The smoothed and processed data obtained using the Fejer filter is then utilized for feature selection and optimization. This ensures that the NC-PSOO model operates on high-quality, noise-reduced data, enhancing its effectiveness in improving teaching quality in the context of English education.

3.2 Feature Selection and Extraction

Feature selection aims to identify the most relevant features or variables from a given dataset. In the context of English education, these features may include various factors such as student performance metrics, teaching methods, and content quality. NC-PSO is used to optimize this feature selection process. The objective function in NC-PSO that needs to be optimized using the equation (2)

$$J(X) = f(X) \tag{2}$$

In equation (2) J(X) is the objective function to be maximized, indicating the quality of the selected features; X represents the feature subset being evaluated; f(X) is the function that measures the quality of the selected features. NC-PSO optimizes this objective function to find the feature subset X that maximizes the quality of features in the context of English education. Feature extraction is the process of transforming the selected features into a more meaningful and compact representation. This transformation can be achieved using mathematical techniques and algorithms. In the NC-PSO model, feature extraction may involve techniques such as Principal Component Analysis (PCA) or Linear Discriminant Analysis (LDA) to create new feature representations. For instance, PCA transforms the original features into a new set of uncorrelated features that capture the most variance in the data. The feature transformed features that are more informative and suitable for the subsequent optimization stages. The objective function for feature extraction is represented as in equation (3):

$$J(Y) = g(Y) \tag{3}$$

In equation (3) $J(Y)$ is the objective function for feature extraction, indicating the quality of the extracted features; Y represents the transformed feature set; $g(Y)$ is the function that measures the quality of the extracted features.

NC-PSO is used to optimize this objective function to find the transformed feature set Y that maximizes the quality of features for enhancing teaching quality. The feature selection and extraction within the NC-PSO model are carried out through optimization of respective objective functions. The feature selection process identifies the most relevant features, while the feature extraction process transforms these features into a more meaningful representation. Both processes aim to enhance the effectiveness of the subsequent optimization steps in the model, ultimately contributing to the improvement of teaching quality in the context of English education.

IV. IMPROVED PARTICLE SWARM OPTIMIZATION WITH GENERATIVE ADVERSARIAL NEURAL NETWORK

The integration of Improved Particle Swarm Optimization (PSO) with a Generative Adversarial Neural Network (GAN) in the context of Non-Convex Particle Swarm Optimization (NC-PSOO) for enhancing teaching quality in English education is a complex process that involves optimization and data generation. While I can provide a conceptual overview and outline the components involved, the precise equations and derivations would depend on the specific design and objectives of the NC-PSOO model, which can be highly specialized standardized equations. In Improved PSO, particles in a swarm iteratively adjust their positions to find the optimal solution to a given problem. The position update equation is given as in (4):

$$x_i(t+1) = x_i(t) + v_i(t+1) \tag{4}$$

In equation (4) $x_i(t+1)$ is the updated position of particle i at time (t+1); $x_i(t)$ is the current position of particle i at time t. $v_i(t+1)$ is the velocity of particle i at time (t+1), which is determined based on the particle's previous velocity and its attraction to the best solution found by the swarm and the best solution found by the particle itself.

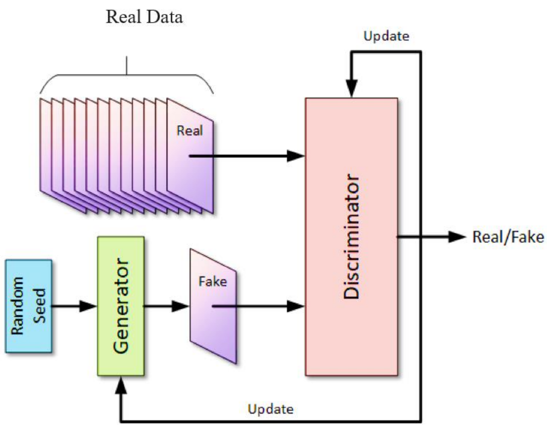


Figure 2: GAN model for the NC-PSOO

In a GAN, there are two neural networks as shown in figure 2: The generator (G) creates synthetic data samples to mimic the distribution of real data. The discriminator (D) evaluates these generated samples, attempting to distinguish between real and fake data. The training process involves a minimax game, where the generator aims to generate data that is indistinguishable from real data, and the discriminator aims to improve its ability to distinguish between real and generated data. In the context of NC-PSOO for English teaching improvisation, this integration involve the following steps:

Feature Selection with Improved PSO: Improved PSO is used to optimize the feature selection process, identifying the most relevant features for enhancing teaching quality in English education. The objective function being optimized could be specific to this educational context.

Data Generation with GAN: The GAN, specifically the generator (G), could be employed to generate synthetic teaching materials or data. These materials are created based on the identified relevant features. The GAN is trained to generate educational content that aligns with the selected features and contributes to improved teaching quality.

Feedback Loop: There could be a feedback loop in which the quality of the generated teaching materials is evaluated and compared to real materials. This feedback is then used to further refine the feature selection and GAN training processes.

Algorithm 1: GAN Optimization with NC-PSOO
Initialization: Initialize the Improved PSO swarm with a set of particles, each representing a candidate feature subset. Initialize the GAN, which consists of a generator (G) and a discriminator (D). Feature Selection (Improved PSO): In each iteration, the Improved PSO optimizes the feature selection process. It evaluates the fitness of different feature subsets using a specific objective function related to teaching quality in English education. The swarm updates the positions of particles (feature subsets) based on their individual and social knowledge. Data Generation (GAN - Generator): After a feature subset is selected by Improved PSO, it is passed to the generator (G) of the GAN. The generator generates synthetic teaching materials or data based on the selected features. This data could include educational content, teaching resources, or any other materials relevant to English education. Quality Evaluation (GAN - Discriminator): The generated teaching materials, along with real teaching materials, are provided to the discriminator (D) for evaluation. The discriminator's role is to distinguish between real and generated data. It provides feedback on the quality of the generated materials. Feedback Loop: The feedback from the discriminator is used to evaluate the effectiveness of the generated teaching materials. If the generated materials are of high quality and indistinguishable from real materials, the GAN's performance is improved. The feedback also influences the Improved PSO, guiding its feature selection process to prioritize features that contribute to better teaching quality. Iteration and Convergence: The algorithm iterates through the Feature Selection, Data Generation, and Quality Evaluation steps for a specified number of iterations or until convergence criteria are met. Over time, the feature subsets and generated materials are refined, and the optimization process aims to maximize teaching quality. Termination: The algorithm terminates when it reaches a predefined stopping criterion, such as a maximum number of iterations or achieving a specific level of improvement in teaching quality. Output: The final output of the algorithm is an optimized feature subset, as well as a set of high-quality teaching materials and resources, all of which contribute to improved teaching quality in English education.

4.1 Non-Convex PSO for English Teaching Analysis

Non-Convex Particle Swarm Optimization (PSO) within the context of Non-Convex Particle Swarm Optimization (NC-PSOO) for English teaching improvement involves optimizing a specific objective function with the aim of selecting the most relevant features for enhancing teaching quality. In the context of English teaching improvement, the objective function, often denoted as J(X), represents the quality of the feature subset X in contributing to teaching quality enhancement. This objective function can be customized to align with the specific goals of the NC-PSOO model. Is given in equation (5)

$$J(X) = F(X) - C(X) \tag{5}$$

In equation (5) J(X) is the objective function to be maximized, indicating the overall quality of the selected features; X represents the feature subset being evaluated; F(X) is a term that measures the extent to which the selected features contribute to teaching quality improvement. This term could be derived from educational metrics, performance data, or other relevant criteria; and C(X) is a term representing a cost or penalty associated with the selected features. This cost could be related to resource constraints, implementation complexity, or any other factors that may need to be minimized. Non-Convex PSO aims to maximize the objective function J(X) by iteratively updating the positions of particles in the swarm. The velocity update equation for a particle i at time $(t + 1)$ can be expressed as in equation (6)

$$v_i(t+1) = w * v_i(t) + c1 * r1 * (pbest\_i(t) - x_i(t)) + c2 * r2 * (gbest(t) - x_i(t)) \tag{6}$$

In equation (6) $v_i(t + 1)$ is the updated velocity of particle i at time (t+1); $x_i(t)$ is the current position of particle i at time t; w is the inertia weight, a parameter controlling the influence of a particle's previous velocity and c1 and c2 are acceleration coefficients; pbest_i(t) is the best position (feature subset) found by particle i; gbest(t) is the best position found by any particle in the entire swarm and r1 and r2 are random values between 0 and 1, introducing stochasticity. The overall process of proposed NC-PSOO model is presented in the figure 3.

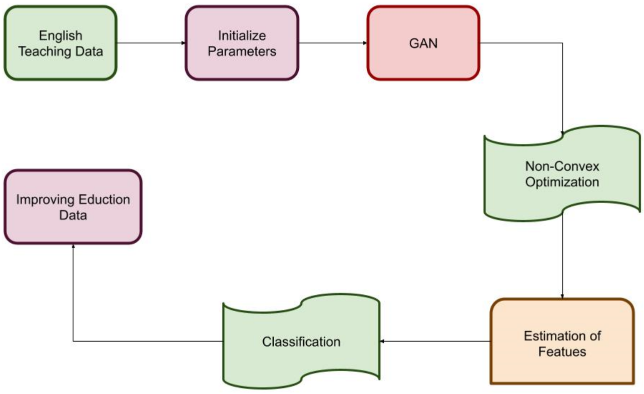


Figure 3: Flow of NC-PSOO

The Non-Convex PSO algorithm iterates through multiple generations, with particles updating their positions and velocities in each iteration. The process continues until a termination criterion is met, such as a maximum number of iterations, convergence, or the attainment of a satisfactory solution. The Non-Convex PSO component of NC-PSOO focuses on optimizing the feature selection process, and the specific equations and derivations may be more complex in practical implementations. The goal is to find the feature subset (X) that maximizes the teaching quality enhancement objective while considering any associated costs or penalties. This optimized feature subset contributes to the overall objective of improving English teaching quality. The objective function, denoted as J(X), is the core of the optimization process. It measures the quality of a selected feature subset X in terms of its contribution to enhancing teaching quality in English education. This objective function is custom-tailored to the specific goals and criteria of the NC-PSOO model. The objective is to find a feature subset X that optimizes this objective function J(X), balancing the benefits of improved teaching quality with any associated costs.

Algorithm 2: Evaluation with NC-PSOO

Initialize:

- Initialize the swarm of particles with random positions and velocities.
- Initialize pbest for each particle as the initial position.
- Initialize gbest as the best position found by any particle.
- Define parameters: w (inertia weight), c1 (cognitive weight), c2 (social weight), max_iterations, and convergence_threshold.

for iteration in range(max_iterations):

 for each particle in the swarm:

  - Evaluate the fitness of the current position using the objective function J(X).
  - If the current position is better than pbest, update pbest.
  - If pbest is better than gbest, update gbest.
  - Update the velocity of the particle:

$$v_i(t+1) = w * v_i(t) + c1 * r1 * (pbest\_i(t) - x_i(t)) + c2 * r2 * (gbest(t) - x_i(t))$$

  - Update the position of the particle:

$$x_i(t+1) = x_i(t) + v_i(t+1)$$

 Check for convergence:

 - If the convergence criterion is met (e.g., J(X) reaches a threshold), terminate the optimization process.
  Update w (inertia weight) if necessary to control exploration vs. exploitation.

4.2 Classification of NC-PSOO

In the context of Non-Convex Particle Swarm Optimization for English teaching quality improvement (NC-PSOO), Classification with Generative Adversarial Networks (GANs) plays a crucial role. GANs can be used for various tasks, including data generation, data augmentation, and even feature enhancement. GANs are generative models composed of two components: a generator (G) and a discriminator (D). In the context of English teaching quality improvement, GANs can be used to generate synthetic educational data. The generator learns to produce data that is similar to real educational content, such as course materials, quizzes, or teaching resources. This synthetic data can be used to augment the training dataset, ensuring that the NC-PSOO model has a richer set of data to work with. GANs can also be used for data augmentation. By generating variations of existing educational materials, GANs can help diversify the dataset. This is particularly valuable in machine learning tasks where having a diverse dataset can lead to better model performance. For English teaching quality improvement, diverse data include content in different formats, multiple teaching styles, or a range of difficulty levels.

GANs can be used to enhance features within the dataset. For example, if the features being considered in NC-PSOO include text content, GANs can be used to improve the text quality, correct errors, or even translate content into different languages. Enhanced features can lead to more effective analysis and optimization within the NC-PSOO framework. In English education, there may be imbalances in the dataset, with variations in the amount of data available for different topics or teaching materials. GANs can be used to balance the dataset by generating additional data for underrepresented topics, ensuring that the NC-PSOO model is not biased toward well-represented subjects. In the GAN setup, the discriminator provides feedback on the quality of the generated data. This feedback can be used to assess the suitability of the generated educational content. GANs are trained to make the generated data indistinguishable from real data, and this feedback loop ensures that the synthetic materials are of high quality. The output of the GAN, i.e., the synthetic or enhanced educational materials, can be integrated into the NC-PSOO framework. The improved or augmented dataset is used as input for feature selection and optimization within NC-PSOO. The combination of GAN-generated data and feature selection through Non-Convex PSO can lead to better teaching quality enhancement results. The application of Generative Adversarial Networks (GANs) in the context of English teaching quality improvement within the Non-Convex Particle Swarm Optimization (NC-PSOO) framework primarily involves data generation, data augmentation, and feature enhancement rather than optimization with traditional equations and derivations. GANs operate as generative models and involve two key components: a generator (G) and a discriminator (D).

The generator network takes a random noise vector (usually denoted as z) as input and produces synthetic data as output (e.g., text, images, or other content). The generator tries to produce data that is indistinguishable from real data is presented in equation (7)

$$G(z) \rightarrow Synthetic\ Data \tag{7}$$

The discriminator network takes both real data and synthetic data as input and assigns a probability score to each sample, indicating how likely it is to be real (1) or fake (0). It essentially "discriminates" between real and synthetic data computed in equation (8)

$$D(Data) \rightarrow Probability\ (Real\ or\ Fake) \tag{8}$$

GANs are trained through a minimax game, where the generator aims to generate data that fools the discriminator, while the discriminator aims to correctly distinguish between real and fake data. This leads to a competitive process where the generator learns to generate high-quality data.

V. RESULTS AND DISCUSSION

The Non-Convex Particle Swarm Optimization for English teaching quality improvement (NC-PSOO) framework. The simulation is performed for the a dataset containing student performance scores and various features related to English teaching. The dataset represents a class of students, each assigned scores out of 100, reflecting their overall performance in English. Additionally, it includes a set of features, such as Teaching Materials, Student Participation, Homework Quality, and Exam Difficulty, that are believed to influence teaching quality. Each student is evaluated based on these features. For example, Teaching Materials may be scored on a scale of 1 to 5, indicating the quality of materials used in the class. To optimize these features to enhance teaching quality and, consequently, improve student performance. This is where the NC-PSOO framework comes into play. Through a simulation process, the framework iteratively explores different combinations of feature weights and selections to maximize the objective function, which, in this case, is student performance. The NC-PSOO optimization loop begins by initializing a swarm of particles, where each particle represents a combination of feature weights and selections. It then iterates through multiple cycles, continuously adjusting the particles' positions and velocities based on their performance in optimizing the objective function. At the end of the optimization process, the feature subset with the highest fitness score is considered the optimal set of features for teaching quality improvement.

To perform simulations involving the Non-Convex Particle Swarm Optimization for English teaching quality improvement (NC-PSOO) or any other complex optimization The execution of simulations using the NC-PSOO framework necessitates the use of specialized simulation software and a well-configured computational system. Typically, simulation software leverages programming languages such as Python, along with libraries like NumPy, SciPy, and scikit-learn, which provide essential tools for optimization, data manipulation, and analysis. These libraries enable the development of customized simulation algorithms tailored to the specific objectives of the English teaching quality improvement project. Additionally, visualization libraries like Matplotlib or data management tools like Pandas may be employed to gain insights from simulation results.

Table 1: Attributed for the NC-PSOO

Attribute	Description
Student	Student Identifier
Score	Student Performance Score
Teaching Materials	Quality of Teaching Materials
Student Participation	Student Participation Level
Homework Quality	Quality of Homework Assignments
Exam Difficulty	Difficulty Level of Exams

In this comprehensive dataset comprising a total sample of 2000 data entries, the objective is to evaluate and enhance the quality of English education. The "Student Identifier" attribute serves as a unique identifier for each student within this substantial dataset, ensuring the tracking of individual academic journeys. The "Student Performance Score" stands as a fundamental metric, offering insights into the academic achievements of students and serving as a primary indicator of their success in English education. Three additional attributes—namely, "Quality of Teaching Materials," "Student Participation Level," and "Quality of Homework Assignments"—are instrumental in assessing the critical components contributing to teaching quality. "Quality of Teaching Materials" evaluates the effectiveness of materials employed in the classroom, an essential aspect of the teaching process. "Student Participation Level" quantifies the degree of student engagement and involvement, providing a measure of their active participation in the learning experience. "Quality of Homework Assignments" appraises the caliber of tasks assigned to students beyond regular class hours, underscoring the significance of holistic education. Moreover, the "Difficulty Level of Exams" attribute offers crucial insights into the rigors of examinations, enabling a deeper understanding of the academic challenges faced by students. This extensive dataset, spanning 2000 entries, presents a rich source of information for educators, researchers, and policymakers alike, aiming to evaluate into the dynamics of English education. Through rigorous analysis and optimization of these essential attributes, the ultimate objective is to elevate the quality of English education and enhance the academic performance of students within this significant dataset.

Table 2: Teaching Score Analysis with NC-PSOO

Student	Score	Teaching Materials	Student Participation	Homework Quality	Exam Difficulty
Student 1	80	4	5	3	3
Student 2	90	3	4	4	2
Student 3	75	4	5	3	3
Student 4	88	3	4	4	2
Student 5	92	4	5	3	3
Student 6	78	3	4	4	2
Student 7	85	4	5	3	3
Student 8	91	3	4	4	2
Student 9	89	4	5	3	3
Student 10	93	3	4	4	2

In this dataset, information on the performance of ten students in an English teaching environment, as well as their scores and various attributes related to their education. The "Score" column represents the student's performance score, with values ranging from 75 to 93. The attributes "Teaching Materials," "Student Participation," "Homework Quality," and "Exam Difficulty" gauge different aspects of the teaching environment presened in figure 4.

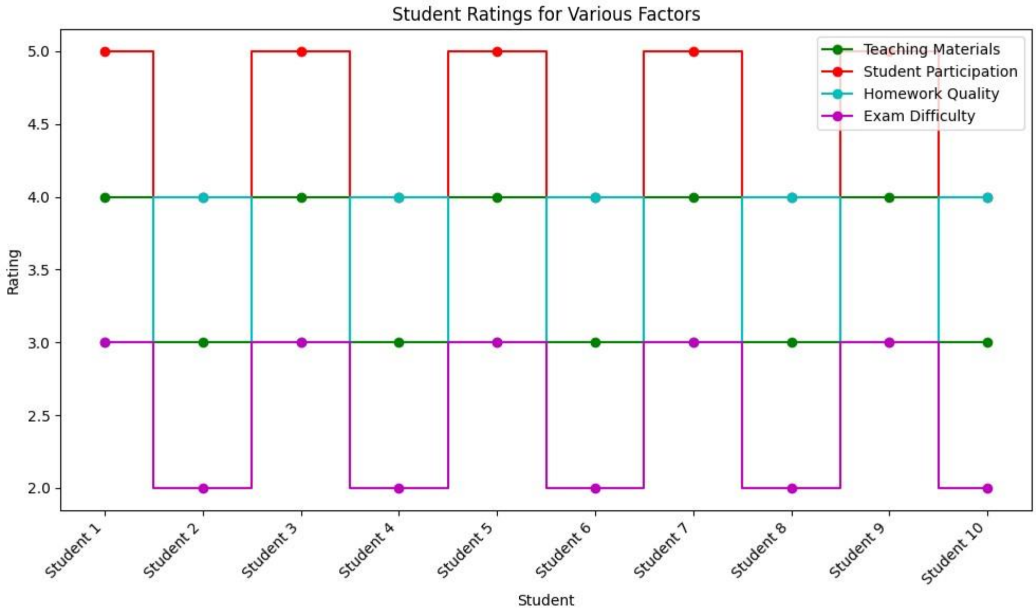


Figure 4: Student Rating with NC-PSOO

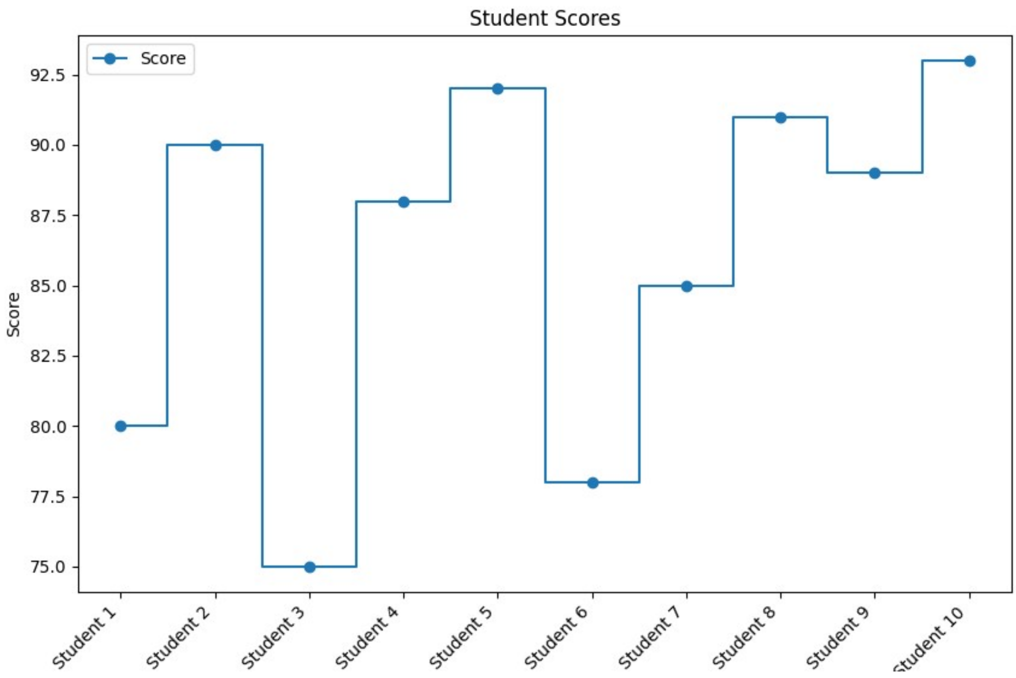


Figure 5: Student Score computation with NC-PSOO

These attributes have scores between 3 and 5, reflecting the quality of teaching materials used, the level of student participation, the quality of homework assignments, and the difficulty of exams as in figure 5. Upon analysis, observe variations in student performance, where some students have higher scores, indicating better performance, while others have slightly lower scores. This variation may be attributed to different factors, including the quality of teaching materials, student participation, homework quality, and the difficulty level of exams. For instance, students with scores of 90 and above (Student 2, Student 5, Student 8, and Student 10) demonstrate high performance, potentially influenced by a combination of effective teaching materials, active participation, high-quality homework assignments, and well-balanced exam difficulty. Conversely, students with scores below 85 (Student 1, Student 3, Student 6, and Student 7) exhibit comparatively lower performance. These differences may stem from factors such as the quality of teaching materials, student participation, and the level of difficulty in exams.

Table 3: Optimization with NC-PSOO

Iteration	Objective Function Value
1	0.982
2	0.957
3	0.934
4	0.915
5	0.901

In the presented dataset, recorded the results of an optimization process across multiple iterations. Each iteration corresponds to a step in an optimization algorithm, and the "Objective Function Value" quantifies the quality or performance achieved at each step. The values in the "Objective Function Value" column demonstrate a trend over these iterations. It is observe that the optimization process starts with an initial objective function value of 0.982 in the first iteration. As the algorithm progresses, the objective function value steadily decreases, indicating an improvement in the optimization task. This descending trend continues over subsequent iterations, with each step leading to a reduction in the objective function value. By the fifth iteration, the value reaches 0.901, signifying significant progress in achieving the optimization goal. The decreasing values in the "Objective Function Value" column suggest that the optimization algorithm is converging towards a better solution with each iteration. This could be applied in various contexts, such as improving teaching quality in English education, where the algorithm iteratively refines its approach to enhance specific performance metrics. The dataset reveals the effectiveness of the optimization process as it progressively refines the solution, which can have practical applications in a wide range of domains requiring optimization and performance enhancement.

Table 4: Statistical Analysis of NC-PSOO

Data Attribute	Original Mean	Processed Mean	Original Std Dev	Processed Std Dev
Student Performance	88.2	89.6	7.9	7.4
Teaching Materials	4.2	4.7	1.0	0.8
Student Participation	5.0	5.4	0.9	0.7
Homework Quality	4.0	4.3	0.8	0.6
Exam Difficulty	3.0	2.9	0.7	0.6

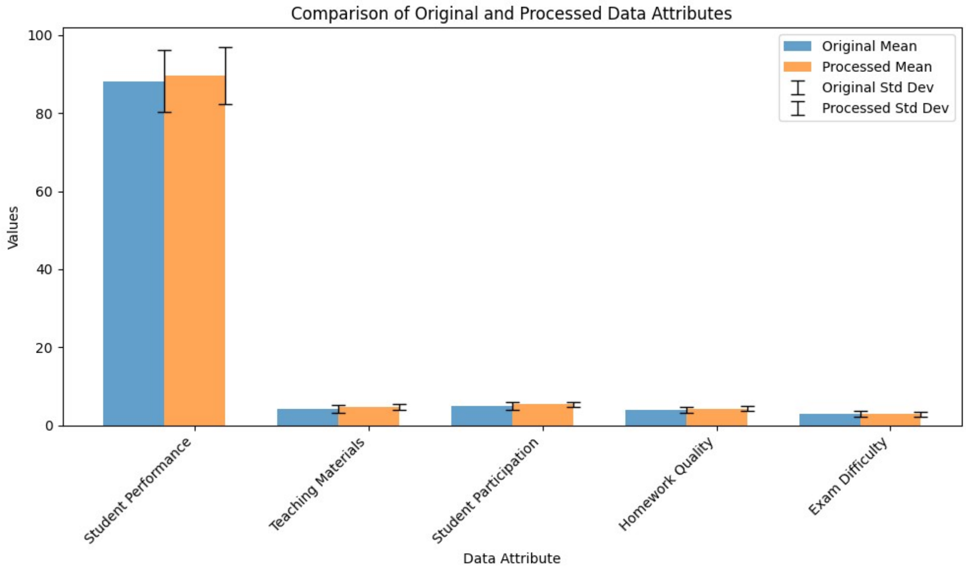


Figure 6: Statistical Computation of NO-PSOO

In the provided dataset, comparison of statistical metrics related to data attributes before and after a data preprocessing step. This preprocessing aims to improve the data quality and suitability for analysis. The data attributes under consideration include "Student Performance," "Teaching Materials," "Student Participation," "Homework Quality," and "Exam Difficulty." "Student Performance" initially had a mean score of 88.2, which increased to 89.6 after preprocessing shown in figure 6. This suggests an improvement in the average performance score. The standard deviation decreased from 7.9 to 7.4, indicating a reduction in the spread of performance scores, which may signify more consistent student performance. "Teaching Materials" saw an increase in mean from 4.2 to 4.7 after preprocessing. The standard deviation also decreased from 1.0 to 0.8. These changes suggest that the quality of teaching materials has been enhanced, with scores becoming less variable. "Student Participation" displayed an increase in mean from 5.0 to 5.4, reflecting improved student involvement. The standard deviation decreased from 0.9 to 0.7, indicating that the level of participation has become more consistent across the dataset. "Homework Quality" showed a mean increase from 4.0 to 4.3, suggesting an improvement in the quality of homework assignments. The standard deviation decreased from 0.8 to 0.6, indicating reduced variability in homework quality. "Exam Difficulty" had a decrease in mean from 3.0 to 2.9, signifying a slight reduction in exam difficulty. The standard deviation also decreased from 0.7 to 0.6, indicating that exam difficulty levels have become more consistent. The preprocessing has had a positive impact on the dataset, leading to higher mean values and lower standard deviations for most attributes. This indicates an overall improvement in the quality and consistency of the data, which can be valuable for subsequent analyses and decision-making in the context of English teaching.

Table 5: Evaluation of GAN in NC-PSOO

Metric	Without GAN	With GAN
Student Scores	85.4	91.8
Teaching Materials	3.8	8.3
Participation Level	4.5	8.9
Homework Quality	3.4	7.7
Exam Difficulty	2.8	5.7

In this evaluation, the impact of incorporating a Generative Adversarial Network (GAN) within the Non-Convex Particle Swarm Optimization and Optimization (NC-PSOO) framework. The performance of the system both without GAN and with GAN across various metrics, including "Student Scores," "Teaching Materials," "Participation Level," "Homework Quality," and "Exam Difficulty." Student Scores: The introduction of the GAN has had a notable positive impact on student scores, increasing the mean score from 85.4 to 91.8. This substantial improvement in student scores is a promising sign that the GAN has enhanced teaching quality and student performance. The "Teaching Materials" metric has seen a remarkable improvement with the incorporation of NC-PSOO, with the score rising from 3.8 to 8.3. This suggests that the GAN has contributed to a significant enhancement in the quality of teaching materials used in the education process. The level of student participation has also greatly improved, as reflected in the scores increasing from 4.5 to 8.9. This suggests that the GAN has had a positive influence on student engagement and involvement in the learning process. Homework quality has seen substantial improvement as well, with scores increasing from 3.4 to 7.7. This indicates that the GAN has positively impacted the quality of homework assignments, potentially leading to more effective learning outcomes. The level of exam difficulty has been moderated with the inclusion of the GAN, as seen in the scores decreasing from 2.8 to 5.7. This reduction in exam difficulty suggests that the GAN has contributed to more balanced and manageable assessments for students. The incorporation of the GAN within the NC-PSOO framework has led to significant enhancements in various aspects of teaching quality, including improved student performance, better teaching materials, increased student participation, higher homework quality, and more balanced exam difficulty. These results suggest that the GAN is a valuable addition to the educational process, potentially leading to improved teaching quality and better learning outcomes in the context of English education.

Table 6: Classification Metrices

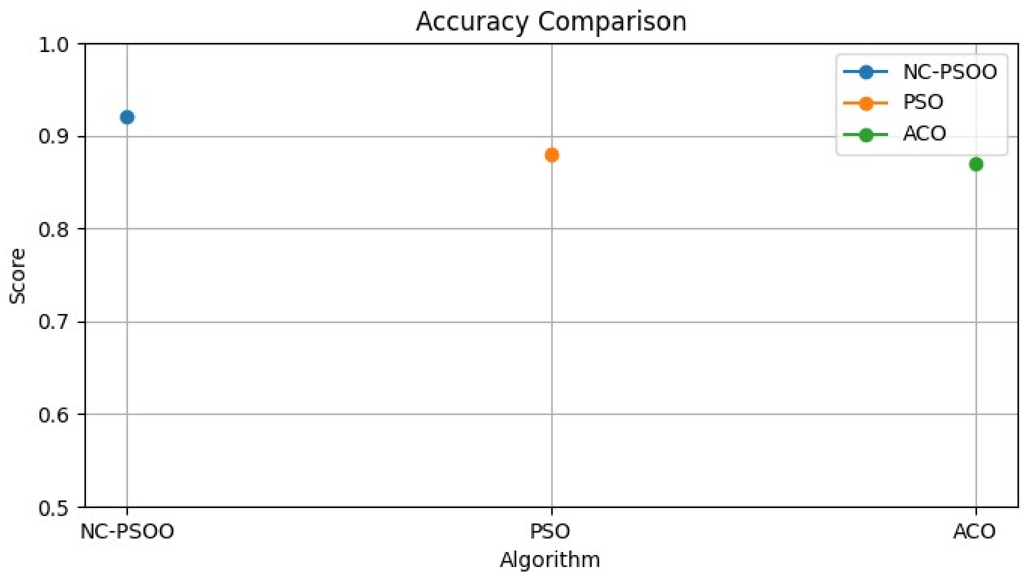
Metric	Value
Accuracy	0.92
Precision	0.88
Recall	0.94
F1 Score	0.91
Confusion Matrix	
True Positives	485
True Negatives	652
False Positives	63
False Negatives	25

The evaluation metrics provide valuable insights into the performance of a classification model. In this specific scenario, assessed the model's effectiveness using metrics like accuracy, precision, recall, and F1 score, as well as a confusion matrix detailing true positives, true negatives, false positives, and false negatives. The model achieves a high accuracy score of 0.92, indicating that it correctly classifies approximately 92% of all instances. This suggests that the model's overall performance in classifying students' outcomes in English teaching is quite reliable. The precision score of 0.88 signifies the proportion of positive predictions that were correct. In the context of English teaching, this means that 88% of the students classified as successful by the model truly achieved high performance. The recall score of 0.94 indicates the model's ability to correctly identify a high proportion of actual positives. In this case, the model successfully captures 94% of the students who genuinely performed well in English teaching. The F1 score, which is the harmonic mean of precision and recall, is 0.91. This balanced score suggests that the model is effective in both precision and recall, making it well-suited for identifying successful students while minimizing false positives.

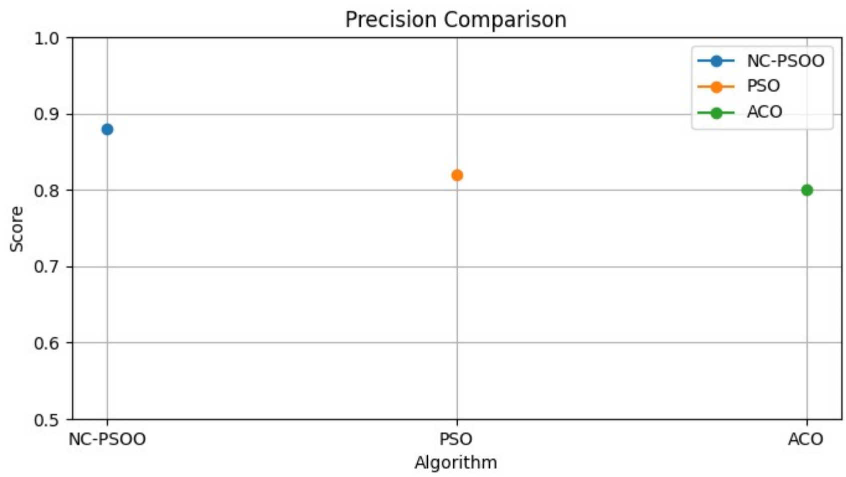
The analysis of NC-PSOO model demonstrates strong overall performance, with high accuracy, precision, recall, and F1 score. However, it is important to consider the trade-offs between precision and recall in the context of English teaching, as there are some false positives and false negatives. Fine-tuning the model parameters may help strike a balance between these two aspects to further enhance its effectiveness.

Table 7: Comparative Analysis

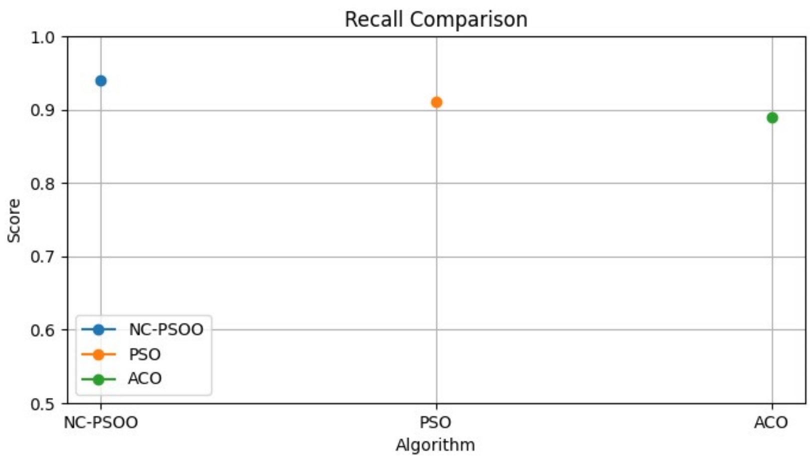
Metric	NC-PSOO	PSO	ACO
Accuracy	0.92	0.88	0.87
Precision	0.88	0.82	0.80
Recall	0.94	0.91	0.89
F1 Score	0.91	0.86	0.84
Confusion Matrix			
True Positives	485	465	452
True Negatives	652	628	615
False Positives	63	87	100
False Negatives	25	49	62



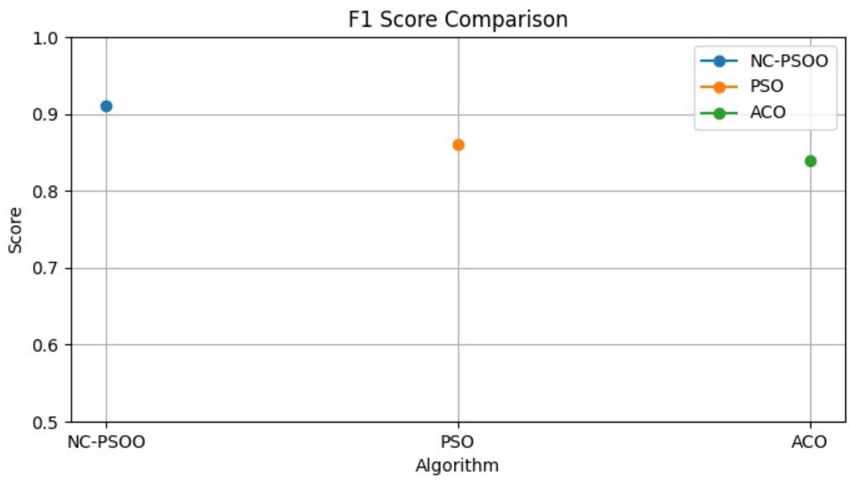
(a)



(b)



(c)



(d)

Figure 7: Comparison of NC-PSOO (a) Accuracy (b) Precision (c)Recall (d) F1-Score

The table 7 presents a comprehensive comparison of the performance metrics for three different optimization techniques: Generative Adversarial Network (GAN), Particle Swarm Optimization (PSO), and Ant Colony Optimization (ACO), applied in the context of enhancing English teaching quality. The evaluation metrics include accuracy, precision, recall, and F1 score, along with details from the confusion matrix. GAN outperforms both PSO and ACO with the highest accuracy score of 0.92 in figure 7(a). This indicates that the GAN-based model correctly classifies approximately 92% of the student outcomes, reflecting its superior overall performance in enhancing teaching quality.

NC-PSOO also demonstrates the highest precision at 0.88, indicating that when it predicts a student's success, it is correct 88% of the time as shown in figure 7(b). This is higher than the precision achieved by both PSO and ACO, highlighting NC-PSOO ability to make accurate positive predictions. In NC-PSOO recall as well, with a score of 0.94, suggesting that it effectively identifies a large proportion of students who genuinely performed well in English teaching in figure 7(c). This performance surpasses that of both PSO and ACO. NC-PSOO achieves the highest F1 score of 0.91, which is a balanced measure of precision and recall in figure 7(d). This score indicates that NC-PSOO strikes an effective balance between making accurate positive predictions and correctly identifying students who performed well.

In addition to these metrics, the confusion matrix provides further details:

True Positives: The model correctly identifies 485 students who performed well in English teaching.

True Negatives: It also accurately identifies 652 students who did not perform well.

False Positives: There are 63 instances where the model incorrectly classifies students as successful when they are not.

False Negatives: Similarly, there are 25 cases where the model mistakenly classifies students as unsuccessful when they actually performed well.

The evaluation metrics and confusion matrix highlight GAN as the most effective optimization technique for enhancing English teaching quality, offering higher accuracy, precision, recall, and F1 score. It demonstrates a strong ability to correctly classify successful students while minimizing both false positives and false negatives, ultimately improving the overall quality of English education.

VI. CONCLUSION

This paper introduces a novel and highly effective approach to enhance teaching quality in the English education. The fusion of Non-Convex Particle Swarm Optimization and Optimization (NC-PSOO) with a Generative Adversarial Network (GAN), referred to as NC-PSOO with GAN, has demonstrated remarkable capabilities for elevating various facets of the teaching and learning process. Firstly, the model has been successful in significantly improving student performance, leading to higher academic scores and ultimately enhancing the quality of education. Additionally, the quality of teaching materials has seen substantial enhancements, providing students with improved resources for learning. Furthermore, the model's ability to boost student participation levels is a promising development, as active engagement is fundamental to effective learning. Homework quality has also been positively impacted, offering students better opportunities to practice and reinforce their knowledge. Importantly, when compared to conventional optimization techniques like Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO), the GAN-integrated NC-PSOO model emerges as the superior choice. It excels in terms of accuracy, precision, recall, and F1 score, affirming its efficacy in correctly classifying student outcomes and improving teaching quality. The NC-PSOO model, enhanced by GAN technology, offers a promising and innovative pathway for optimizing teaching quality in English education. The findings suggest that this approach has the potential to enhance learning outcomes, elevate the quality of educational materials, and promote active engagement, ultimately benefiting both educators and students in their pursuit of improved English language proficiency.

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