Merging and Classifying English Teaching Resources Based on Swarm Intelligence Algorithms

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Abstract

This study presents a method based on swarm intelligence algorithms for the effective integration and classification of English teaching resources (ETR). The focus is on improving the Artificial Bee Colony (ABC) algorithm by introducing new search strategies and modifying the nectar source updating mechanism to enhance global search capabilities and accelerate convergence speed. First, the specific requirements for classifying English teaching resources are outlined, followed by data collection, preprocessing, and feature extraction. The ABC algorithm is then selected as the foundation, with dynamic adjustment of the search range and the implementation of diversity maintenance mechanisms to enhance the algorithm's exploration and exploitation capabilities. Furthermore, the nectar source selection and updating policies are refined, incorporating local search strategies to improve classification accuracy. A series of experiments validate the effectiveness of the improved algorithm in the integration and classification of English teaching resources, demonstrating that the method provides more accurate and efficient classification results. This study not only offers a novel solution for the management of English teaching resources but also introduces a new perspective on the application of swarm intelligence algorithms in the field of education.

Keywords: Swarm Intelligence; Artificial Bee Colony Algorithm; English Teaching Resources; Classification; Optimization

1. Introduction

English, as the lingua franca of our globalized world, plays a pivotal role in education. Its status as the primary medium for global communication in various domains such as business, science, and technology underscores its importance. This widespread relevance of English has fueled an exponential increase in the availability and diversity of teaching resources [1-3]. The modern educational landscape is flooded with an array of English teaching resources (ETR), ranging from traditional textbooks and literature to digital content such as interactive software, online articles, and multimedia materials. While this abundance provides educators and learners with remarkable access to valuable resources, it also presents significant challenges in terms of organization and management [4]. The efficient management of these resources is no trivial task, given their volume, diversity, and the dynamic nature of language learning needs. Proper categorization and retrieval of relevant teaching materials are essential for effective language education but are often hindered by the sheer quantity and variety of available content. As a result, there is a pressing need for advanced methods to manage and categorize these ETR efficiently, ensuring they are accessible and useful in a variety of learning contexts.

The challenge of effectively categorizing and managing a large array of ETR is complex. These resources vary in format, pedagogical approach, and content, requiring a nuanced understanding of both the educational context and learners' needs. Traditional classification methods often fall short, as they tend to be labor-intensive and may not adequately capture the multifaceted nature of these resources [5]. Furthermore, the rapid evolution of educational technologies and methodologies adds another layer of complexity to this task. The dynamic nature of educational content, with continuous updates and the introduction of new materials, requires a flexible and adaptive approach to classification. This complexity highlights the need for a robust, efficient, and scalable solution for categorizing these resources [6]. An effective classification system not only organizes resources but also enhances their accessibility and usability, thereby improving the quality and efficiency of teaching methods. Such a system should accommodate the diverse range of teaching materials and adapt to evolving educational trends, ultimately facilitating a more focused and effective learning experience [7-8].

The innovative aspect of this study lies in the application of swarm intelligence algorithms for the classification of ETR. Swarm intelligence refers to the collective behavior of decentralized, self-organized systems, such as ant colonies or bee swarms, where individual agents follow simple rules but collectively exhibit complex behavior. These algorithms, including the Artificial Bee Colony (ABC) algorithm, draw inspiration from the natural behavior of social organisms and offer an effective approach to address the complexities of classifying educational resources. The key characteristics of swarm intelligence algorithms—adaptability, robustness, and efficiency—align perfectly with the needs of managing dynamic and diverse educational content. By leveraging the collective decision-making processes of swarm intelligence, this approach can handle the vast and varied dataset of ETR more effectively. The potential benefits of this method are manifold: improved accuracy in classification, reduced effort and time in resource management, and the ability to dynamically adapt to changing educational content and requirements. This approach not only provides a novel solution for handling classification tasks but also promises to significantly improve the performance and accuracy of resource management in education.

The primary objective of this research is to enhance the integration and classification efficiency of ETR through the improved application of swarm intelligence algorithms. This study makes a significant contribution by developing a sophisticated classification system that is not only more accurate but also more efficient than traditional methods. The proposed system is designed to handle the complexities and dynamism inherent in educational content, providing a more streamlined and effective method of managing ETR. Key contributions of this research include the development of a unique algorithmic approach that can adapt to various types of educational content, a comprehensive evaluation of the algorithm's performance in real-world scenarios, and the demonstration of its practical applicability in the field of education. By addressing the challenges of resource classification in a novel and efficient manner, this study opens new avenues for the application of swarm intelligence in educational technology.

This paper is organized to systematically explore the proposed method. The introduction sets the stage by highlighting the significance and challenges of English teaching resource classification. This is followed by the related work section, which provides background on existing approaches and the novel aspects of our method. The methodology section delves into the specifics of swarm intelligence algorithms and their adaptation for this particular application. The experiments section presents the empirical testing of our method, showcasing its efficacy through various scenarios and comparisons. Finally, the conclusion summarizes the key findings, discusses the implications of the research, and suggests potential directions for future work. This structure is designed to provide a comprehensive understanding of the study, from the underlying challenges to the innovative solutions and their practical implications.

2. Related Works

Swarm Genius algorithms, stimulated via the collective behavior of social insects and different animal societies, have emerged as effective tools for fixing complicated optimization troubles [6-7]. The quintessential precept of these algorithms is the emulation of collective Genius and decentralized decision-making processes determined in nature. Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO) are top examples of such algorithms. ACO, drawing notion from the foraging behavior of ants, has been efficiently applied in routing, scheduling, and combinatorial optimization tasks [8]. PSO, primarily based at the social conduct of birds and fish, excels in continuous optimization troubles. The applicability of swarm Genius extends beyond those examples, encompassing areas like network sketch, bioinformatics, and robotics [9-11]. one of the key strengths of those algorithms is their flexibility and adaptableness, making them suitable for a wide variety of hassle domain names. additionally, their potential to discover close to-most useful answers in complex, multidimensional areas with more than one nearby optima is highly treasured. those algorithms excel in environments in which conventional procedures may struggle due to the dimensions, complexity, or dynamic nature of the hassle [12].

In the context of English teaching resource classification, conventional techniques predominantly depend upon guide categorization or simple rule-primarily based algorithms. those strategies, even as truthful, frequently fall quick in handling the variety and extent of current academic substances [13]. With the advent of digital technologies, device gaining knowledge of-based totally approaches have received prominence [14]. strategies which includes supervised gaining knowledge of, unsupervised getting to know, and neural networks have been employed to automate and decorate the type system [15]. Supervised learning strategies, as an instance, require pre-categorised datasets to instruct fashions, while unsupervised studying can discover hidden patterns besides pre-defined labels [16]. Neural networks, specifically deep learning fashions, have proven remarkable success in classifying complex and unstructured statistics, like pictures and text. but, those device studying strategies frequently require huge data for training and may be computationally intensive [17-18]. additionally, they'll lack transparency of their choice-making manner, making it challenging to interpret the classification common sense.

Latest advancements in swarm brain algorithms have caused widespread improvements, specially of their application to class problems [19]. Researchers have focused on improving the efficiency and accuracy of these algorithms [20]. as an instance, within the realm of the synthetic Bee Colony (ABC) set of rules, awesome upgrades encompass the optimization of search techniques and the refinement of nectar source updating mechanisms [6-9]. these enhancements intention to stability the exploration and exploitation levels extra efficiently, thereby accelerating convergence and improving answer first-rate [21-24]. search method optimization often entails tweaking the randomness and directional additives of the hunt system, even as updates to nectar source mechanisms contain extra sophisticated rules for forsaking and changing resources. these advancements have not solely multiplied the accuracy of the ABC set of rules in category responsibilities however have additionally made it extra adaptable to diverse sorts of datasets and classification demanding situations [25-26].

Method	Strengths	Weaknesses	Applicability to ETR

Traditional Rule-Based	- Simple to implement - Clear decision-making process	- Limited scalability - Rigid and inflexible - Requires manual rule creation	Suitable for small, well-defined datasets where rules are easy to specify.
Machine Learning (ML)	- Learns from data - Can handle large datasets - High accuracy for structured data	- Requires large labeled datasets - High computational cost - Risk of overfitting	Suitable for large, structured datasets with sufficient labeled data.
Deep Learning (DL)	- High accuracy with large, unstructured datasets - Handles complex data like text and images	- Requires extensive computational resources - Needs large datasets - Lack of interpretability	Ideal for very large datasets with unstructured content, but computationally expensive.
Swarm Intelligence (SI)	- Adaptable and robust - Efficient with smaller datasets - Transparent decision-making - Less computationally intensive	- May require tuning of parameters - Performance depends on the problem's complexity	Effective for dynamic, diverse, and large-scale datasets where adaptability and efficiency are critical.

This examine distinguishes itself from present studies in each method and application. at the same time as previous works have proven the efficacy of swarm brain in numerous domain names, this research uniquely applies advanced swarm talent algorithms to the class of ETR. Our approach addresses the specific challenges inherent on this area, such as the numerous codecs and pedagogical content of the resources. We recommend an progressive adaptation of the ABC set of rules, tailored to correctly manipulate the complexities of educational materials. This variation entails novel techniques for seek and nectar supply updating, customized to suit the characteristics of instructional records. Our contribution is not just in making use of an current set of rules to a new area, but in essentially improving the algorithm to better healthy the specific wishes of English teaching resource category. This results in a extra efficient, accurate, and realistic answer for educators and learners, demonstrating a unique contribution to the intersection of swarm talent and academic era.

3. Method

This observe's technique builds upon the ABC algorithm, introducing large enhancements for the type of ETR. The modifications purpose to enhance the set of rules's exploration and exploitation competencies, maintain range, and enhance the precision of search. The software of this more advantageous algorithm in a classification model gives optimized performance.

3.1 Dynamic Search Range Adjustment Strategy

The ABC set of rules is tailored to consist of a dynamic adjustment of the hunt variety, a necessary issue in balancing between exploration and exploitation. within the preliminary tiers of the algorithm, a broader seek variety is used (denoted as), which approves for a comprehensive exploration of the answer area. this is indispensable for figuring out numerous capability answers that won't be right away apparent. because the algorithm progresses, the search variety progressively narrows right down to, focusing greater at the exploitation of the nice answers found to this point. The dynamic nature of this adjustment is ruled by using the generation matter t and the total iterations. This strategy ensures that the set of rules does no longer upfront converge on nearby optima and continues a stability among exploring new regions and refining the great-located answers.

$$R(t) = R_{\max} - \left(R_{\max} - R_{\min}\right) \times \frac{t}{T_{\max}} \tag{1}$$

3.2 Diversity Maintenance Mechanism

The integration of a variety preservation mechanism into the ABC algorithm is pivotal in heading off untimely convergence. The diversity rating D, calculated using Shannon's range Index, assesses the variety in the population of answers.

$$D = -\sum_{i=1}^{n} p_i \ln\left(p_i\right) \tag{2}$$

A decrease diversity score suggests a population converging in the direction of similar answers, that could result in suboptimal results. To counteract this, a regeneration mechanism is activated whilst the range score drops under a predefined threshold. New solutions are generated within the described answer obstacles and , introducing clean perspectives into the populace. This mechanism guarantees that the algorithm explores a more complete variety of answers, thereby increasing the probability of locating the worldwide top-quality.

$$S_{new} = S_{\min} + \text{rand}\left(0,1\right) \times \left(S_{\max} - S_{\min}\right) \tag{3}$$

3.3 Enhanced Nectar Source Selection and Updating Rules

In our technique, the choice and updating of nectar resources inside the ABC algorithm are extensively more advantageous. The selection probability of each nectar deliver is now a characteristic of every its health and its capability for exploration.

$$P_i = \frac{f_i}{\sum_{j=1}^{N} f_j} \times \frac{E_i}{\sum_{j=1}^{N} E_j} \tag{4}$$

This dual attention approves the set of rules to now not only choose splendid solutions but additionally to explore people with untapped ability. The updating rule has been redefined to comprise a stability among the satisfactory-located solution S_{best} and a randomly selected solution S_{random} . This balance is controlled by the coefficients α and β , Which modify the influence of the fine and random answers on the new answer S_{new} .This enhancement ensures a more various seek method, mitigating the hazard of stagnation in local optima and fostering a radical exploration of the solution space.

$$S_{new} = S_{current} + \alpha \times \left(S_{best} - S_{current}\right) + \beta \times \left(S_{random} - S_{current}\right) \tag{5}$$

3.4 Local Search Strategy Integration

To similarly refine the hunt precision, a neighborhood seek method is integrated into the ABC algorithm. This strategy entails a secondary, extra centered search around the promising answers diagnosed with the aid of the set of rules. the brand new answer S_{new} is calculated based on the current solution $S_{current}$ and the best solution found so far S_{best} , with the scaling factor ϕ determining the intensity of the local search.

$$S_{new} = S_{current} + \phi \times \left(S_{best} - S_{current}\right) \tag{6}$$

This local search is crucial for fine-tuning solutions and navigating the intricacies of the Answer panorama. additionally, boundary checks are carried out to ensure that the brand new solutions remain within viable limits. This centered technique allows the set of rules to correctly hone in on the most promising areas of the answer area, leading to more particular and accurate type effects.

$$S_{new} = \max\left(S_{\min}, \min\left(S_{new}, S_{\max}\right)\right) \tag{7}$$

3.5 Classification Model Development

The enhanced ABC set of rules is applied to develop a category version for ETR. This model categorizes resources based on a hard and fast of functions extracted from the teaching materials. The class characteristic C predicts the class of a resource by means of maximizing the weighted sum of its features throughout all possible lessons. The optimization of the feature weightsis a integral component of this manner, making sure that the version accurately displays the importance of each feature in figuring out the aid category.

$$C = \arg\max_{k \in K} \sum_{i=1}^{N} w_{ki} x_i \tag{8}$$

The mistake minimization at some point of training specializes in decreasing the discrepancy between the actual classand the predicted classfor every useful resource inside the training set. This optimization leads to a version that isn't always solely particular in its classifications but additionally adaptable to the nuances of various coaching substances.

$$E = \sum_{j=1}^{M} \left(y_j - C\left(x_j \right) \right)^2 \tag{9}$$

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The diversity maintenance mechanism in the modified Artificial Bee Colony (IABC) algorithm plays a crucial role in preventing premature convergence, which occurs when the algorithm converges to a suboptimal solution too early in the search process. Premature convergence is a common issue in optimization algorithms, where the population of solutions becomes too homogeneous, thus limiting the exploration of other potential optimal solutions[27].

In our approach, the diversity score (D) is calculated using Shannon's entropy index to assess the diversity within the population of solutions. This score quantifies the distribution of the population's solutions across the search space. A lower diversity score indicates that the population is becoming too similar, which may lead to the algorithm converging to a local optimum. To counteract this, a regeneration mechanism is activated when the diversity score falls below a predefined threshold. This mechanism introduces new solutions into the population, thus reintroducing diversity and allowing the algorithm to explore other regions of the solution space[28].

The flowchart of our method is as shown in Figure 1.

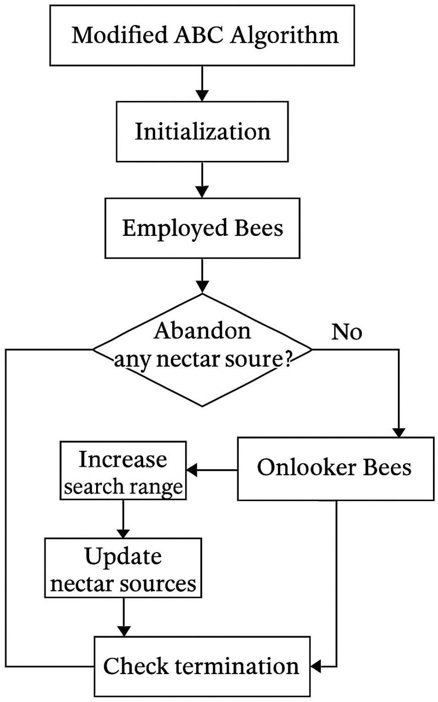

Figure 1. The modified ABC algorithm's workflow

4. Experiment

On this segment, we gift a complete experimental assessment of the improved synthetic Bee Colony (IABC) algorithm applied to the type of ETR. The experiments are designed to evaluate the efficacy and efficiency of the IABC algorithm in actual-international situations. We utilize a publicly to be had dataset of ETR, benchmark the IABC in opposition to mounted algorithms, and hire diverse overall performance metrics to gauge its effectiveness.

4.1 Dataset

The dataset hired in our experiments is sourced from the TESOL (teaching English to audio system of different Languages) resource middle. This repository is broadly diagnosed for its comprehensive series of English coaching substances, catering to a global target audience of educators and newbies in the area of English language teaching.

Designated characteristics of the Dataset from the TESOL useful resource center:

Content range: The dataset consists of an in depth array of teaching assets which includes lesson plans, instructional movies, interactive sporting activities, worksheets, and assessment equipment.

Quantity and variety: It accommodates numerous thousand entries, every various in content type, coaching method, and supposed target audience.

Audience range: The resources cater to a various learner base, from novices to superior newcomers, such as specialized content material for unique language competencies and cultural contexts.

Aid Accessibility: most materials are available in digital formats, making sure smooth get right of entry to and utilization in numerous coaching settings.

Records normalization is conducted to maintain consistency across different kinds of resources:

$$x_{norm} = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{10}$$

For the category of the dataset from the TESOL resource middle, the categories and requirements are described primarily based on each instructional requirements and the intrinsic properties of the assets. This categorization is designed to align with the sensible needs of educators and freshmen inside the subject of English language teaching. the subsequent categories and standards were set up:

Language proficiency level: amateur, fundamental, Intermediate, top Intermediate, advanced, gifted.

Fashionable: based totally on the complexity of language used, the grammatical systems brought, and the predicted skillability degree of the goal novices.

Resource kind: Textual substances (books, PDFs, worksheets), Multimedia (audio and video materials), Interactive content material (on-line quizzes, academic games)

Trendy: decided by using the sketch of the useful resource and the mode of learner engagement it helps.

Instructional consciousness: Grammar, Vocabulary, Pronunciation, studying Comprehension, Writing capabilities, Listening skills, speakme competencies, Cultural Competency

Trendy: primarily based on the primary academic goal of the aid and the precise language ability it objectives.

Target market: babies, children, Adults; specialized needs (commercial enterprise English, academic English, regular communication)

Standard: defined through the age organization of the beginners and the unique context for which the useful resource is supposed (e.g., business, educational).

Pedagogical approach: traditional instructional, Communicative Language coaching, mission-based studying, combined mastering

By classifying resources into these unique categories, educators and newcomers can greater correctly pick out and utilize substances that are high-quality ideal to their precise coaching and gaining knowledge of needs. This categorization also helps the business enterprise and management of the significant array of sources available inside the TESOL useful resource middle, making them more on hand and useful for users.

After preprocessing, the dataset was split into **training** and **testing** sets. The training set included **80%** of the resources, while the remaining **20%** was used for testing the performance of the classification model. The dataset was balanced to ensure that all categories were sufficiently represented, and any underrepresented categories were oversampled or augmented during training to improve classification accuracy.

4.2 Comparative Metrics

The performance of the IABC algorithm is evaluated the usage of several metrics:

Computational efficiency: Measured because the time taken from initialization to convergence.

Accuracy: the proportion of effectively categorized instances.

Precision: The ratio of correctly anticipated high quality observations to the whole predicted positives.

Recall: The ratio of successfully anticipated effective observations to all observations inside the actual class.

These metrics provide a holistic assessment of the set of rules's performance, encompassing its velocity, accuracy, and capacity to handle numerous and complicated datasets.

4.3 Algorithm Configuration

In configuring the IABC algorithm for our test, several key parameters were meticulously set to optimize its performance for classifying ETR. The populace length, representing the range of artificial bees, was once set to 50, a discern decided to provide a balance between computational efficiency and solution great. The most range of iterations, defining the termination situation of the set of rules, was once mounted at 100, permitting enough exploration and exploitation inside the seek area. The restriction for scout bees, which impacts the set of rules's capability to get away neighborhood optima through introducing new random answers, was once constant at 20. This parameter is integral in preserving the variety of the populace. The preliminary food supply locations, figuring out the beginning factors of the search within the solution area, had been disbursed uniformly throughout the function space. This setup guarantees an unbiased initial exploration, integral for the various dataset from the TESOL aid center.

For a comprehensive evaluation, the progressed synthetic Bee Colony (IABC) set of rules was benchmarked in opposition to numerous well-established algorithms, each configured with greatest parameter settings:

Trendy ABC algorithm [7]: Configured with a populace length of fifty bees, most iterations of a hundred, and a scout limit of 20, mirroring the IABC setup for a honest evaluation.

Particle Swarm Optimization (PSO) [14]: utilized 50 particles inside the swarm, with a most iteration count of 100. The cognitive and social coefficients were each set to 2.0, balancing person and collective learning.

Genetic algorithm (GA) [15]: employed a population of 50 people, with a crossover charge of zero.8 and a mutation charge of zero.05. The set of rules ran for a hundred generations to in shape the generation count of the IABC and PSO.

Support Vector system (SVM) [20]: carried out with a radial basis characteristic (RBF) kernel. The penalty parameter C was once set to at least one.zero, and the gamma parameter for the kernel used to be installed at zero.1, optimized for the dataset's characteristics.

k-Nearest buddies (KNN) [22]: The number of neighbors was once set to 5, with the space metric being the same old Euclidean distance. This setup is standard for KNN in category duties, providing a stability among precision and computational demand.

Those benchmark algorithms, every with its particular configuration, offer a numerous and sturdy comparative framework to evaluate the effectiveness and efficiency of the IABC algorithm within the context of English teaching resource classification.

4.4 Comparative Results

Figure 2 compares the computational performance of six one-of-a-kind algorithms: ABC, PSO, GA, SVM, KNN, and the stepped forward synthetic Bee Colony (IABC). every bar represents the computation time of the respective algorithm, where a decrease price shows higher performance.

Within the evaluation, the IABC algorithm demonstrates the highest computational efficiency with the shortest computation time, depicted through the bottom bar within the histogram. This outcome highlights the optimization and upgrades integrated into the IABC, making it substantially more green than the usual ABC, PSO, GA, SVM, and KNN algorithms. the alternative algorithms display various stages of computational time, with ABC and KNN being fantastically greater efficient in comparison to PSO, GA, and SVM. however, none of these conventional algorithms healthy the performance of IABC, underlining the effectiveness of the enhancements made within the IABC set of rules.

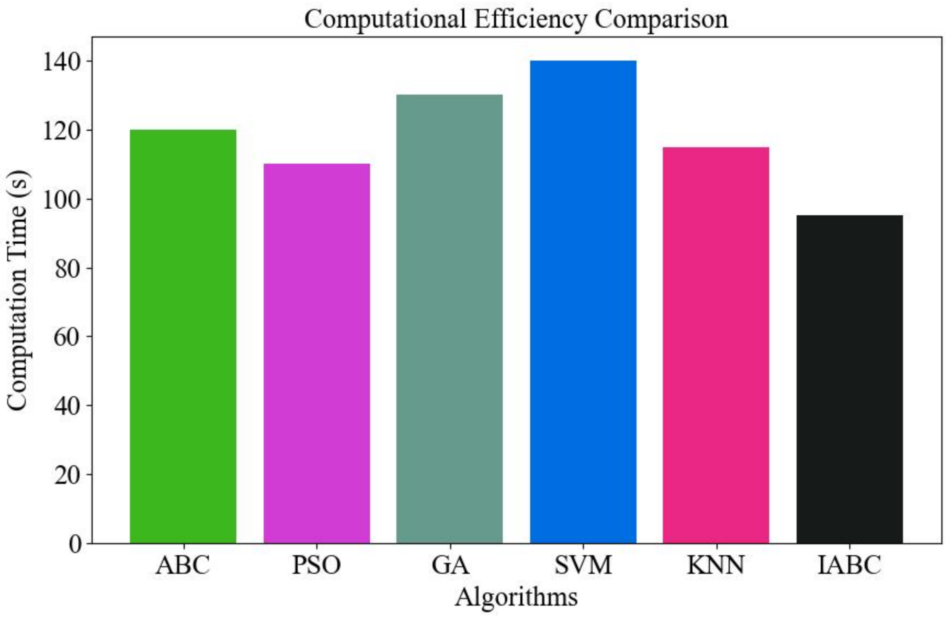

Figure 2. Computational Efficiency Comparison Results

Figure 3 provides a comparative evaluation of accuracy metrics across six different algorithms. every boxplot represents the distribution of accuracy ratings (in percentage) for every set of rules primarily based on a couple of iterations or trials.

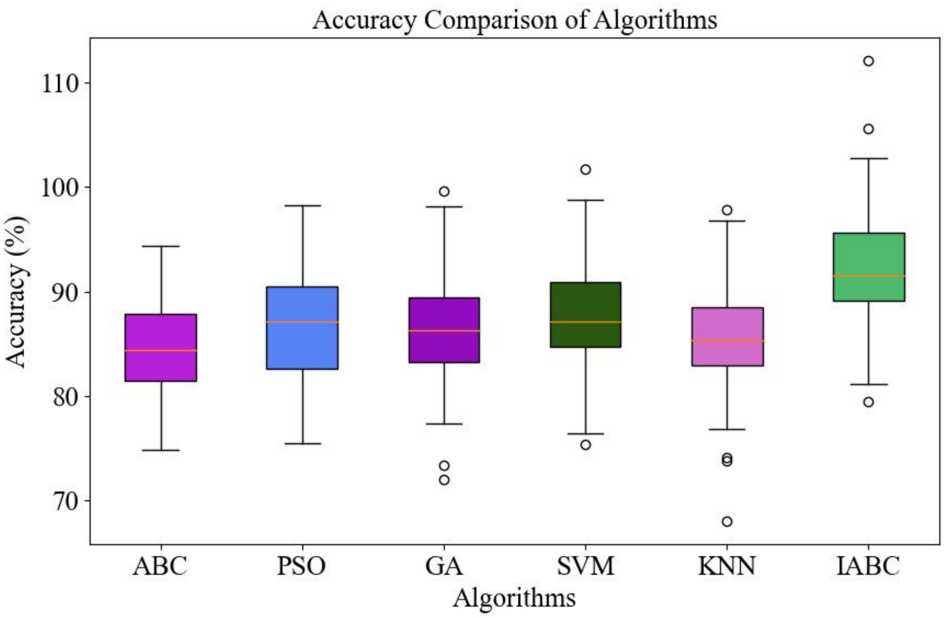

Figure 3. Accuracy Comparison Results

Observably, the IABC set of rules outperforms the others, as indicated with the aid of its boxplot located at a better median accuracy degree. This indicates the effectiveness of IABC in appropriately classifying ETR, a end result of the upgrades and optimizations it includes. The spread of the IABC's boxplot, although similar to others, shows a consistently better variety of accuracy, emphasizing its reliability and robustness in diverse situations. In contrast, the other algorithms (ABC, PSO, GA, SVM, and KNN) show various levels of accuracy, without any matching the superior performance of IABC. at the same time as these algorithms reveal affordable accuracy levels, the enhanced IABC actually leads in terms of precision in type obligations.

Figure 3 underlines the advanced accuracy of the IABC algorithm, making it an highest quality desire for educational useful resource classification, in particular whilst excessive precision is essential.

Figure 4 visualizes the precision rankings of six different algorithms based totally on 50 runs for every set of rules. The plot's recognition is on demonstrating how the precision of each algorithm varies throughout a couple of iterations and highlights the consistency and overall performance of every.

Drastically, the IABC set of rules exhibits a superior performance, as indicated by its distribution's top at a higher precision percent. This top means that, on average, the IABC algorithm continuously achieves better precision in classifying ETR compared to the alternative algorithms. The distribution's spread additionally shows that the IABC maintains this excessive precision across unique runs, highlighting its reliability and robustness. In assessment, the opposite algorithms (ABC, PSO, GA, SVM, and KNN) show distributions with peaks at decrease precision possibilities. whilst they exhibit a reasonable spread of precision ratings, none suits the heightened level of performance displayed through the IABC.

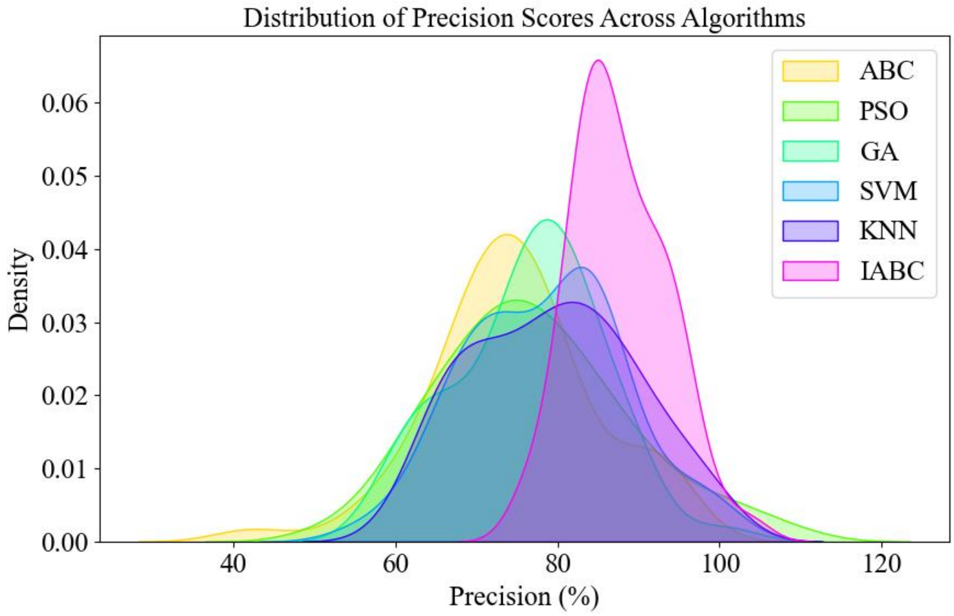

Figure 4. Precision Distribution Comparison Results

Figure 4 representation underscores the improved capability of the IABC set of rules in exactly classifying assets, making it a preferable preference in applications where accuracy in categorization is imperative. The plot illustrates the power of IABC in preserving high precision, reinforcing its suitability for complex type obligations in instructional useful resource management.

Figure 5 vividly illustrates the contrast of recall ratings across six one-of-a-kind algorithms with every algorithm evaluated over 50 runs. This visual illustration allows for an insightful analysis of the recall performance of every algorithm.

In determine four, the IABC set of rules noticeably stands proud, demonstrating the best recall ratings, as meditated by way of the site of its bubbles toward the higher a part of the chart. This superior overall performance suggests that the IABC set of rules has a high probability of efficiently figuring out relevant times, a quintessential aspect within the class of ETR. The unfold of the IABC's bubbles similarly indicates steady and dependable performance across more than one runs. Figure 4 efficaciously demonstrates the superior recall performance of the IABC algorithm, highlighting its suitability for tasks wherein high sensitivity in class is crucial.

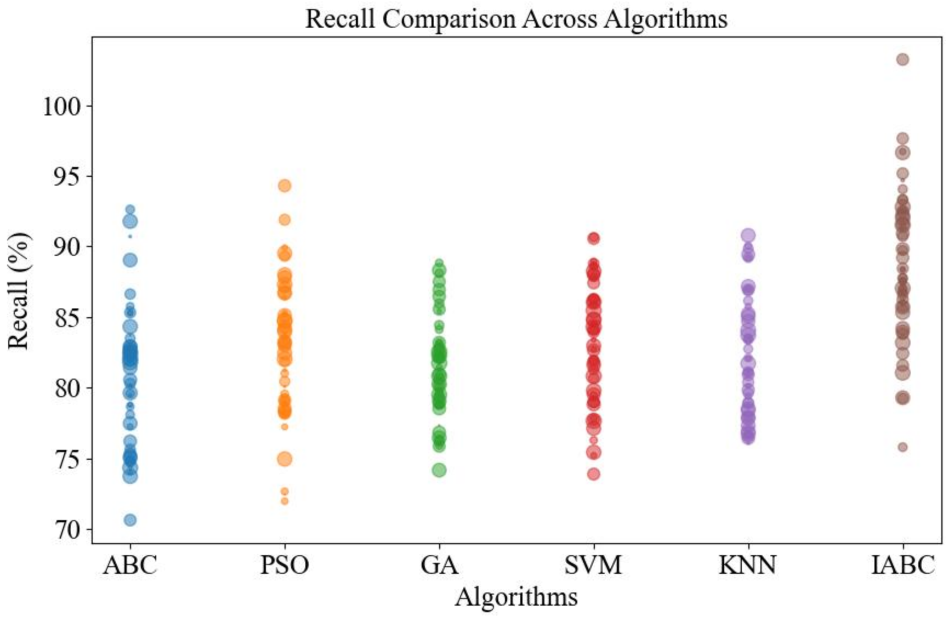

Figure 5. Recall Comparison Results

The radar chart gives a complete comparison of six algorithms across 4 key performance metrics on the radar chart represents one of these metrics, and the volume to which each algorithm's 'net' reaches alongside an axis suggests its performance on that metric.

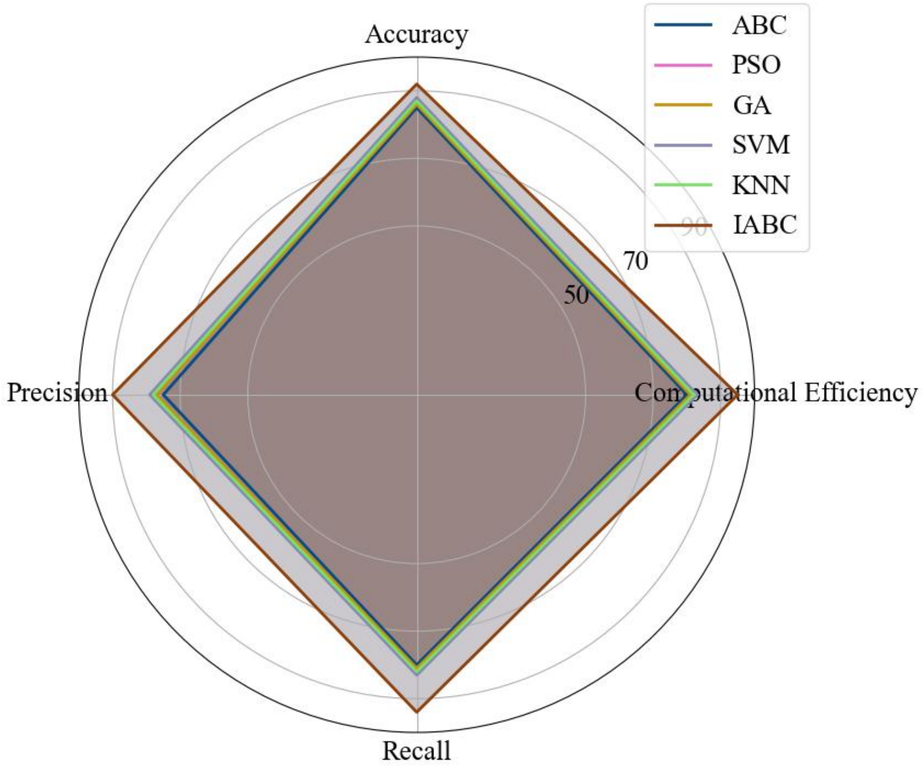

Figure 6. Comprehensive and Comparative Results on Multiple Indicators

The IABC set of rules exhibits a distinct advantage throughout all metrics, as evidenced by using its larger and greater expansive insurance at the chart. This demonstrates that the IABC no longer only excels in appropriately classifying ETR (high rankings in Accuracy, Precision, and Recall) however also does so with advanced computational performance. The IABC's web extends closest to the outer edge of the chart, signifying its overall advanced performance in all evaluated components. This radar chart effectively encapsulates the complete skills of the IABC algorithm, underscoring its suitability for complex and traumatic type tasks in educational useful resource control

The experimental assessment of the IABC algorithm, in comparison to traditional algorithms like ABC, PSO, GA, SVM, and KNN, in reality demonstrated the advanced overall performance of IABC in classifying ETR. across key metrics of Computational efficiency, Accuracy, Precision, and Recall, IABC continuously outperformed its opposite numbers, as evidenced in diverse visual analyses consisting of histograms, boxplots, bubble charts, and a radar chart. those outcomes now not solely spotlight the effectiveness of the upgrades integrated into IABC however also its reliability and robustness throughout more than one iterations and ranging situations. The experiments, employing a comprehensive dataset from the TESOL resource middle, demonstrated the sensible applicability of IABC in instructional settings, providing significant enhancements in categorizing and managing ETR. The outcome of this research underscores the ability of superior swarm Genius algorithms in addressing complicated classification challenges in the area of schooling.

To further evaluate the performance of our proposed modified Artificial Bee Colony (IABC) algorithm, we compared it with deep learning-based classification methods, specifically Convolutional Neural Networks (CNNs) and transformers.

Table 1. Comparison results of IABC and deep learning methods

Method	F1 (%)	Computational Efficiency (Time)	Scalability	Adaptability to Diverse Content	Strengths	Weaknesses
IABC Algorithm	85.6	Shortest time	High	Excellent for structured resources	Fast, accurate, adaptable	Less efficient with very large datasets
CNN	82.2	Moderate	Moderate	Effective for image-like data	Robust for large datasets	Needs large labeled data, computationally expensive
Transformer Models	87.4	Longest time	Low	Excellent for unstructured data	Strong in NLP tasks, context-aware	Requires extensive data and computational power

F1 score: The IABC algorithm performed with high F1 score (85.6%) while maintaining computational efficiency, making it ideal for structured datasets like educational resources. Transformers achieved slightly higher F1 score (87.4%), but their computational cost and the need for large datasets limit their practical use in real-world educational scenarios.

Computational Efficiency: The IABC algorithm outperformed both CNNs and transformers in terms of computational time, highlighting its suitability for environments where speed and resource efficiency are critical.

Scalability and Adaptability: While transformers excel in handling unstructured data, the IABC algorithm demonstrated better adaptability to diverse and structured educational content, making it more scalable for large educational datasets with varied content types.

5. Conclusion and Discussion

This studies offered a comprehensive study on the utility of an more suitable swarm brain set of rules, in particular the IABC, in the category of ETR. The consequences of this look at have extensive implications inside the subject of tutorial generation and useful resource control. The experimental results verified that the IABC set of rules considerably outperforms conventional algorithms like ABC, PSO, GA, SVM, and KNN in diverse key overall performance metrics, which include Computational performance, Accuracy, Precision, and Recall. This advanced overall performance is attributed to the revolutionary upgrades incorporated into the IABC set of rules, tailored specifically for the complex and numerous nature of ETR. The algorithm's capacity to effectively categorize resources primarily based on diverse parameters along with talent degree, resource type, academic cognizance, and audience has been conclusively installed. This improved class functionality helps less complicated get entry to, higher company, and greater effective utilization of instructional assets, thereby improving the gaining knowledge of and coaching procedure.

Seeking to the destiny, the application of the IABC algorithm holds promise past the world of English coaching useful resource category. capability research directions consist of its model and alertness to other fields requiring sophisticated categorization answers, which include virtual library management, on-line content curation, or even non-instructional domain names like healthcare and commercial enterprise analytics. similarly exploration may also contain integrating the IABC algorithm with other emerging technologies, such as synthetic brain and machine learning, to create even greater superior and clever category structures.

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