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Integrating PSO with Butterfly Optimization for Efficient Feature Selection: An IBFPSO Approach

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ABSTRACT

Feature selection is an effective way to decrease dataset dimensions and increase classification accuracy. But feature selection is a complex and challenging procedure that needs a highly efficient algorithm. The collective behavior of decentralized, self-organized natural or artificial systems is known as swarm intelligence (SI). The migration patterns of butterflies serve as the inspiration for the Butterfly Optimization algorithm, a type of swarm intelligence metaheuristic algorithms. In this enhanced Butterfly Optimization algorithm (BOA-PSO), the issue of feature selection is initially conceptualized and subsequently transformed into a fitness function. Next, we proposed an IBFPSO to address the issue of feature selection. In order to enhance the BOA and expand its applicability to feature selection issues, we integrated PSO into the BOA. Ultimately The proposed algorithm IBFPSO is benchmarked against , binary PSO (BPSO), Binary dragonfly algorithm (BDA), Binary grey wolf optimization approach (BGWO), Binary bat algorithm (BBA) and enhanced binary bat algorithm (EBBA). To evaluate these algorithms, five datasets were sourced from the UC Irvine Machine Learning Repository. The experimental findings reveal that the IBFPSO algorithm outperforms other comparative algorithms across all datasets. In the Breastcancer dataset, the accuracy rate for IBFPSO was (0.9886) compared to the closest algorithm's (0.9786). In the BreastEW dataset, the accuracy rate for IBFPSO was (0.9843) compared to the closest algorithm's (0.9614). In the Congress dataset, the accuracy rate for IBFPSO was (0.9874), whereas it was (0.9793) for the nearest algorithm. In the SpectEW dataset, the accuracy rate for IBFPSOwas (0.8556) compared to the nearest algorithm where it was (0.7407). In the tic-tac-toe dataset, the accuracy rate was (0.9791), while the closest algorithm's was (0.8521).

1. Introduction

Over recent years, there has been a significant increase in the volume of high-dimensional data that is available and accessible online. Consequently, machine learning algorithms have a hard time dealing with enormous amounts of data. To use machine learning technology effectively, data must be preprocessed [1,2]. Strategies for selecting features prove invaluable in supervised learning, aiming to optimize particular functions to boost predictive accuracy by identifying and selecting

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features pertinent to a specific class label [3,4] . In many applications, including text classification, spam classification, picture classification, intrusion detection, sentiment analysis, cancer detection, medical applications, and many more, feature selection is an essential first step. When all of the features in the dataset are used in these applications, performance will suffer and computational costs will rise[5,6]Click or tap here to enter text. .SI studies group behavior in decentralized systems, simulating natural swarms like insects, elephants, birds, fish, and bees. Ant colony optimization (ACO) is a popular technique for SI. [7] , particle swarm optimization (PSO) [8], artificial bee colony (ABC) [9].

Metaheuristic optimization techniques have the capability to explore the entirety of the search space and employ a global search strategy, significantly enhancing the ability to discover high-quality solutions within a feasible time frame[10].Arora and Singh (2019) developed the swarm intelligence-based Butterfly Optimization Algorithm (BOA) to tackle global optimization issues, inspired by butterflies' sense of smell for finding food sources and potential partners. The BOA algorithm simulates butterflies' senses of smell, sight, taste, touch, and hearing to locate food and potential mates, with smell being the most significant. The BOA algorithm uses butterflies as search agents, with their fitness correlated to fragrance production intensity. They communicate and build a global search network, detecting scents from each other over long distances [11].

The Butterfly Optimization Algorithm (BOA) is a versatile, derivative-free, flexible, and scalable SI algorithm that has been widely applied for optimization issues, including feature selection [12]. BOA outperforms other optimization techniques using benchmark functions and engineering problems, but may become trapped in local optima and struggle with diversity in solutions.Eberhart and Kennedy (1995) introduced the particle swarm optimization (PSO) algorithm, a stochastic optimization method based on swarm [13] . The PSO algorithm, a cooperative food gathering system, mimics the social behavior of animals like insects, fish, birds, and herds. Its design concept is linked to evolutionary algorithms and artificial life studies, allowing it to simultaneously search large parts of the optimization function's solution space [11].

In our study, we incorporate a PSO with the BOA specifically for feature selection, a method we've named IBFPSO. This novel approach merges the strengths of the hybrid The butterfly optimization algorithm (BOA) and Particle swarm optimization (PSO) algorithm to create a more effective algorithm. we can combine the exploration capabilities of BOA with the exploitation abilities of PSO, further enhancing the algorithm's performance. Simulations, utilizing openly available datasets from the UC Irvine machine learning repository, were executed to validate the problem-solving prowess of the proposed IBFPSO method. For a comprehensive evaluation, IBFPSO was benchmarked against several standard algorithms. Subsequently, we demonstrate the efficacy of the improvements incorporated into IBFPSO, highlighting its enhanced performance.

The structure of this study is outlined as follows: Section 2 delves into an examination of pivotal works related to swarm intelligence algorithms and feature selection . In Section 3, we introduce the Enhanced butterfly optimization algorithm (IBFPSO) and elaborate on the factors that have been optimized. Section 4 is dedicated to presenting the outcomes of our simulations. Finally, Section 5 concludes this work.

2. Related Works

Metaheuristic algorithms have proven their efficacy across a wide range of applications. The challenge of feature selection, inherently a multi-objective optimization problem, strives to achieve a dual goal: maximizing classification accuracy while minimizing the number of selected features. To address this, numerous metaheuristic approaches have been employed, effectively tackling feature selection challenges, and a selection of these will be reviewed.

Furthermore, a variety of heuristic algorithms, inspired by the mechanisms of biological and physical systems found in nature, have been introduced. These algorithms stand out as robust solutions for global optimization tasks, showcasing the innovative application of natural phenomena to solving complex computational problems.

Sadeghian *at el.,* [15] presented the Information Gain Binary Butterfly Optimization Algorithm (IG-bBOA), which focuses on mutual information and classification accuracy maximization. The Ensemble Information Theory based Binary Butterfly Optimization Algorithm (EIT-bBOA) selects optimal feature subsets with minimum redundancies more efficiently when IG-bBOA is incorporated. Utama *et al.,* [16] created the Hybrid Butterfly Optimization Algorithm (HBOA) to reduce distribution costs in G-VRP, which combines BOA with local search and tabu search techniques. It demonstrated superior computation time and cost savings when evaluated with different vehicle speeds and compared to current approaches. Abdel-Basset *et al.,* [17] have innovatively combined the Grey Wolf Optimizer algorithm with a two-phase mutation strategy to address the challenge of feature selection. Ghanem *et al.,* [18] used the multi-objective BAT algorithm (MOBBAT) to develop an algorithm of a proficient wrapper approach-based feature selection.

Li *et al.,* [19] proposed an improved version of the sticky binary PSO (ISBPSO) algorithm aimed at boosting evolutionary performance. The ISBPSO incorporates three innovative approaches built upon the sticky binary particle swarm optimization (SBPSO), a novel variation of the binary PSO that was recently introduced. J. Feng *et al.,* [20] have put forward an Enhanced Binary Bat Algorithm (EBBA) specifically tailored to tackle feature selection problems. To augment the capabilities of the Bat Algorithm (BA) and extend its suitability for feature selection challenges, they have integrated a trio of sophisticated techniques into EBBA: a global search strategy based on Lévy flight, a technique to improve population diversity, and a chaos-based method to adjust. Anter and Ali [21] suggested the hybrid crow search optimization algorithm(CFCSA)for feature selection in medical diagnostics which combines chaos theory and fuzzy c-means . Tawhid and Dsouza [22] introduced a new hybrid binary version of the bat and an improved particle swarm optimization approach (HBBEPSO) to solve the issue of feature selection. Nakamura *et al.,* [23] suggest a novel feature selection method, Bat Algorithm combined with Optimum-Path Forest classifier to find the best combination of features. Remeseiro *et al.,* [24] reviewed the most recent feature selection techniques designed and used in medical problems. El-Kenawy *et al.,* [25] introduced a hybrid methodology that merges the Gray Wolf Optimization (GWO) and Particle Swarm Optimization (PSO) algorithms.

This innovative approach is designed to pinpoint essential features while discarding those that are redundant and reducing complexity in the process. Praveena *et al.,* [26] introduced an improved artificial bee colony optimization algorithm for feature selection, followed by classification with a stacked autoencoder. Mahdi and Yuhaniz [27] introduced an Improved Binary Sparrow Search Algorithm (IBSSA) for feature selection in clinical texts to enhance COVID-19 patient categorization. Hussein *et al.,* [28] suggest an algorithm combining a discrete grey wolf optimizer with Q-learning (DGWO-QL) for the green vehicle routing problem (GVRP), focusing on environmental impact and computational efficiency. Kumar *et al.,* [29] proposed an innovative approach that combined firefly and harmony search algorithm for energy-efficient and secure VM allocation in cloud data centers. A new hybrid algorithm inspired by butterfly behavior in food search enhances Particle Swarm Optimization (PSO) by calculating nectar probability based on node degree [30]. Integrating these changes improves PSO performance in finding optimum values. Results on benchmark functions show improved performance based on butterfly sensitivity and nectar probability.

3. Methodology
3.1 Butterfly Optimization Algorithm

BOA is a metaheuristic algorithm inspired by butterflies' food foraging and mate selection. They use chemoreceptors to detect food, flowers, and mates, producing varying scents as they move. The BOA algorithm uses scent to guide search agents, butterflies. If no scent is detected, butterflies engage in exploitation and move randomly based on scent intensity. Exploration occurs when detecting scent of best butterfly for global search. Eq. (1) in BOA method calculates scent based on stimulus intensity.

$$f = cI^a \tag{1}$$

The fragrance emitted by a Butterfly is determined by stimulus intensity (I), sensory modality power exponent (an), and fragrance magnitude (f). The amount of aroma absorption is controlled by stimulus intensity. Butterflies' positions in BOA can be adjusted using two formulae based on the fragrance magnitude. Eq. (2) is responsible for global search, while Eq. (3) handles local search.undaunted, all equations | irrespective of their hides align the intrinsic.

$$X_i^{t+1} = X_i^t + (r^2 * g^* - X_i^t) * f_i \tag{2}$$

$$X_i^{t+1} = X_i^t + \left(r^2 * X_j^t - X_k^t\right) * f_i \tag{3}$$

where X_j^t represents the jth butterfly, X_k^t represents the kth butterfly of the space of possible solutions, r represents a random value over the interval (0, 1), and g^* value is the best solution at the current iteration.

Despite having strong parameters, the Bayesian Optimization Algorithm (BOA) faces issues like slow convergence, local optima, and uneven exploration vs. exploitation balance, which can hinder it from finding optimal solutions. Several iterations have been proposed to address these challenges and improve the BOA's performance across different search spaces [31].

3.2 The Particle Swarm Optimization Technique

Particle Swarm Optimization is a type of Swarm Intelligence technique [32]. Kennedy and Eberhart proposed the particle swarm optimization in 1995 [33]. PSO is a popular optimization method based on population search. It uses a stochastic technique to optimize the behavior of a simulated swarm, inspired by social behavior in animals. Particles are assigned random velocities to navigate the search space with task-specific constraints. Fitness is evaluated based on the objective function. Each particle represents progress made. They move at set speeds within the defined area. Particle updates direction and velocity using best past experiences from memory and social influence [34] . Particle moves towards favorable area in hunting field or space[35]. Particle positions updated based on velocity during current iteration, determining next iteration's position. In dimension d, the k-th particle is at coordinates xk1, xk2, xk3. with velocity vk1, vk2, vk3. Eq. (4) and Eq. (5) update particle velocities [36].

$$v_{k+1} = w * v_k + c_1 r_1 (pbest_k - currentpostion) + c_2 r_2 (gbest_k - currentpostion) \tag{4}$$

$$x_{k+1} = x_k + v_{k+1} \tag{5}$$

Where

r_1, r_2 : two random numbers between (0, 1).

c_1, c_2 : the cognitive and social scaling parameters.

3.3 Proposed IBFPSO

To improve the Butterfly Optimization Algorithm (BOA) with Particle Swarm Optimization (PSO), we can combine the exploration capabilities of BOA with the exploitation abilities of PSO. During each iteration, update the positions of the butterflies (particles) using the PSO update rules for velocity and position. This approach incorporates the PSO update rules for velocity and position into the existing BOA optimization loop. It leverages the strengths of both algorithms to potentially improve the optimization process.

In the optimization loop, for each iteration, we update each butterfly's position using BOA and PSO principles. For BOA, we calculate the step size and new position based on the global best or a random butterfly. For PSO, we update the velocity using inertia, cognitive, and social components, and then update the position. The new positions are evaluated using the fitness function, and if they improve the fitness, the butterflies' positions and fitness values are updated.

The steps of IBFPSO are summarized in Algorithm 1 as follows:

Algorithm 1: IBFPSO

Initialization

i. Butterfly Positions and Velocities: Initialize a binary matrix representing the positions of butterflies (solutions) and a uniform random matrix for their velocities.
ii. Personal and Global Bests: Evaluate the fitness of each butterfly. Set the global best position and fitness based on the best-performing butterfly. Initialize personal best positions and fitness values to the current butterflies' positions and fitness values.

Optimization Loop

i. Iteration: For each iteration, update the position of each butterfly.
    a) PSO Update: Adjust velocities and update positions based on PSO equations (equation 4 for velocities and equation 5 for positions).
    b) BOA Update: Compute a step size using equation 1 and update positions according to equation 2 of the BOA.
    c) Combine Positions: Combine the positions from PSO and BOA by averaging them.
ii. Fitness Evaluation: Calculate the fitness of the new combined position and the new position derived solely from PSO.
iii. Position Update:
    a) If the fitness of the new combined position is better than the current fitness, update the butterfly's position.
    b) If the fitness of the new PSO position is better, update the position based on PSO.
iv. Best Position Updates:
    a) Update personal best if the current fitness surpasses the personal best fitness.
    b) Update global best if the current fitness exceeds the global best fitness.

Output

Return the best feature subset and corresponding fitness value found by the algorithm.

4. Simulations

In this section, we conduct simulations to assess the effectiveness of the approached IBFPSO. Initially, we present the datasets and configurations used for the evaluation. Following this, we compare the performance of IBFPSO against a range of other algorithms. Lastly, we demonstrate the effectiveness of the enhancements integrated into IBFPSO.

Table 1
Datasets [37]

Dataset	No. of Features	No. of Instance
Breastcancer	10	699
BreastEW	30	569
Congress	16	435
SpectEW	22	267
tic-tac-toe	9	958

4.1 Datasets and Setups

This work introduces five datasets sourced from the UC Irvine Machine Learning Repository [37], with Table 1 offering key details about these datasets. In addition, a 6th Gen Intel (R) CoreTM i3-6006U @ 2.00 GHz CPU and 4 GB of RAM are utilized. We implement the simulation codes using Python, and we use a Forests classifier. Moreover, this paper benchmarks the proposed IBFPSO against several notable algorithms, including binary PSO (BPSO) [38], BGWO[39] , BDA [40], BBA [23], ,and EBBA [20] are introduced as benchmarks. It's important to note that both the IBFPSO and the benchmark algorithms share a uniform configuration of a population size of 24 and a total of 100 iterations. Additionally, a wrapper approach to feature selection is employed throughout this paper.

In our study, we opt for the Random Forest classifier due to its simplicity, ease of application, high accuracy with complex datasets, and its capability to mitigate overfitting. By integrating a wrapper method with this straightforward yet cost-effective classification algorithm, we can secure a robust feature subset well-suited for intricate classification challenges. Conversely, if a more sophisticated classification technique were employed for wrapper-based feature selection, the resultant feature subset might not perform as well with simpler classification models. This discrepancy arises because advanced classification algorithms tend to influence the wrapper approach's learning algorithm, such as the proposed IBFPSO, to adapt to the nuances of the classification technique itself, rather than discerning the intrinsic relationships among various features.

4.2. Simulation Results

The accuracy rate optimization results for several techniques are displayed in Table 2. Take note that the values that rank highest across all comparison methods are bolded. It is evident that, out of the five datasets, the proposed IBFPSO gets the highest accuracy rate. It indicates that the proposed IBFPSO performs better than all benchmark algorithms, making it a better choice for handling feature selection issues (see Figure 1 to Figure 5).

Table 2 The optimization outcomes obtained from several algorithms are presented, with the highest-performing values distinctly marked in bold. This notation emphasizes the algorithms that achieved the most favorable results in comparison to their counterparts [20].

Dataset	Breastcancer	BreastEW	Congress	SpectEW	tic-tac-toe
BBA	0.9786	0.9613	0.9793	0.7379	0.8493
BDA	0.9767	0.9589	0.9743	0.7185	0.8099
BGWO	0.9767	0.9532	0.9750	0.7219	0.8465
BPSO	0.9786	0.9612	0.9785	0.7335	0.8521
EBBA	0.9786	0.9614	0.9793	0.7407	0.8521
IBFPSO	0.9886	0.9843	0.9874	0.8556	0.9791

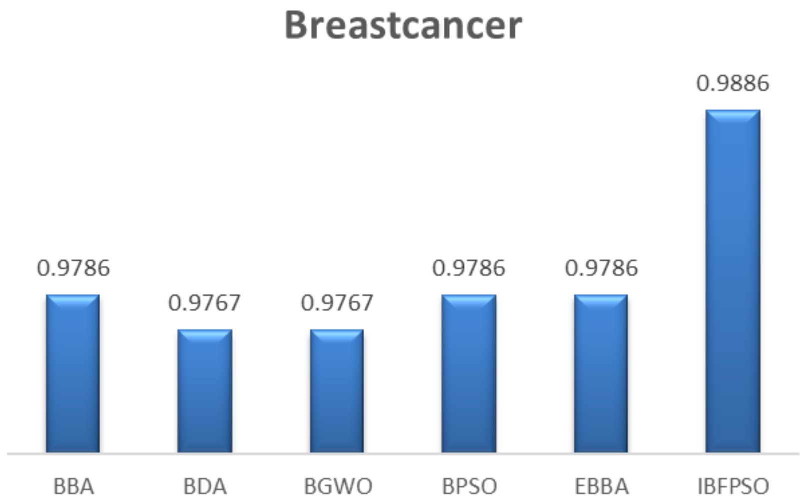

Fig. 1. Illustrates the comparative accuracy rates attained by diverse algorithms when applied to the breast cancer dataset

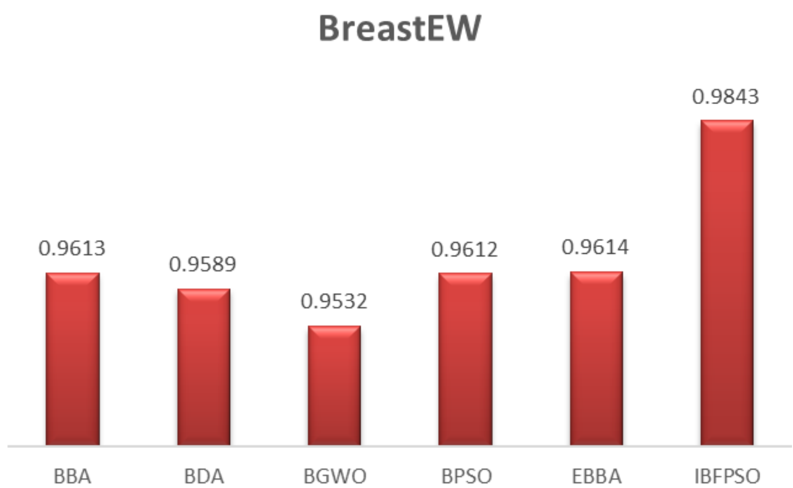

Fig. 2. Illustrates the comparative accuracy rates attained by diverse algorithms when applied to the BreastEW dataset

Fig. 3. Illustrates the comparative accuracy rates attained by diverse algorithms when applied to the Congress dataset

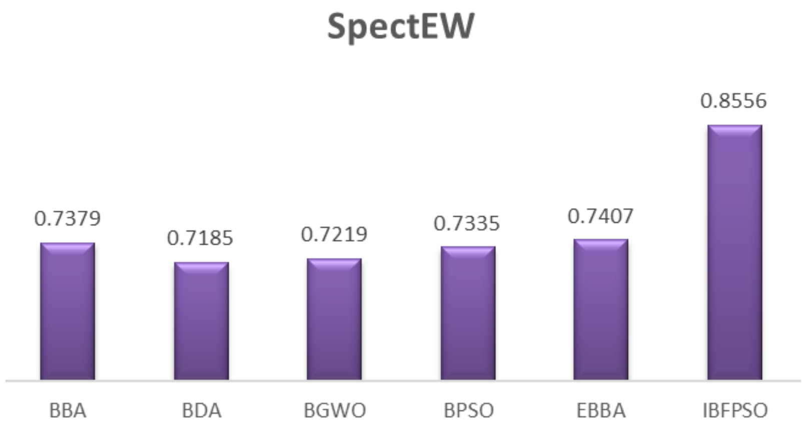

Fig. 4. Illustrates the comparative accuracy rates attained by diverse algorithms when applied to the Congress dataset.

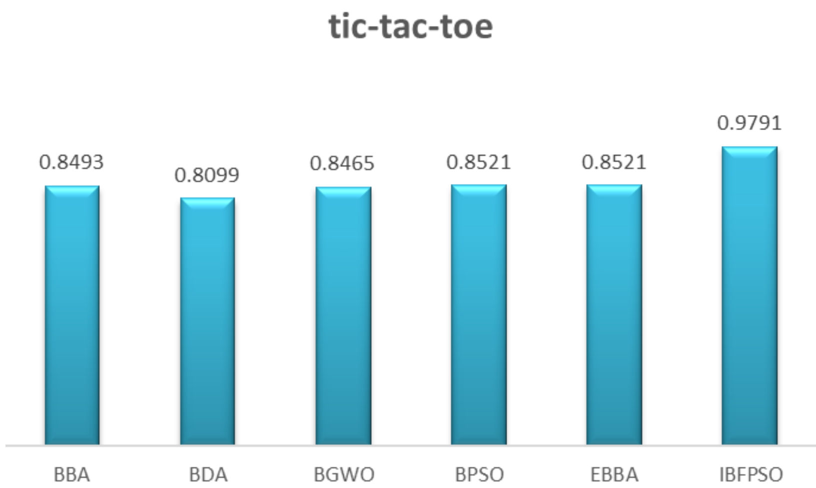

Fig. 5. Illustrates the comparative accuracy rates attained by diverse algorithms when applied to the tic-tac-toe dataset

Utilizing diverse classification algorithms, the IBFPSO methodology surpasses other comparative approaches, demonstrating its effectiveness across varying factors regardless of the classification technique employed. This leads to consistent robust performance in scenarios prone to both overfitting and underfitting, highlighting the adaptability and strength of the IBFPSO strategy.

5. Conclusions

This paper examines feature selection issues that have the potential to improve classification and decrease data dimension. Initially, we conceptualize the feature selection dilemma and subsequently reformulate it into a fitness function. Next, we approach an IBFPSO to address the issue of feature selection. In IBFPSO, we improved the BOA and expanded its applicability to feature selection issues by integrating PSO into it. Ultimately, the approach IBFPSO is tested using simulations, and the outcomes show that it performs better than alternative comparative benchmarks. We plan to assess the approached IBFPSO using more realistic datasets in the future.

Conflicts of Interest

The authors declare that there is no conflict of interest that occurred when conducting this research paper.

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