A Novel Binary Swordfish Movement Optimization Algorithm (BSMOA) for Efficient Feature Selection

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Abstract

As optimization tasks become increasingly complex, particularly in feature selection, there is a growing need for algorithms capable of robustly balancing exploration and exploitation. In this work, we propose the Binary Swordfish Movement Optimization Algorithm (BSMOA), inspired by the synchronized and agile movements of swordfish. BSMOA employs adaptive parameters to navigate high-dimensional search spaces through dynamic exploration, exploitation, and elimination stages. Extensive experiments on benchmark datasets demonstrate that BSMOA outperforms state-of-the-art algorithms, including bHHO, bGWO, and bPSO, regarding average error, feature reduction, and computational efficiency. Key contributions of BSMOA include its improved balance between global and local search and its ability to achieve stable and accurate feature selection. This work has broad implications for applications in machine learning, engineering design, and other optimization domains, providing a reliable tool for tackling challenging binary optimization problems.

Keywords: Binary optimization; Feature selection; Novel metaheuristic algorithm; Swordfish Movement Optimization; Exploration-exploitation balance

1 Introduction

Optimization is a mainstay in engineering, data science, economics, and bioinformatics. As problems in the real world become increasingly complex and multi-faceted, advanced optimization techniques are available as tools. Due to their adaptability, flexibility, and capability to obtain near-optimal solutions, metaheuristic algorithms of bio-inspired design have attracted a great deal of attention. Nevertheless, traditional deterministic optimization techniques, highly reliant on gradient information, may often encounter difficulty escaping from

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local optima. Among the newest metaheuristics is the Swordfish Movement Optimization Algorithm (SMOA), which draws inspiration from the synchronized and agile movements of swordfish to efficiently navigate the search space [1–3].

This paper highlights the advantages and applications of metaheuristic algorithms for solving optimization problems that classical techniques cannot manage due to high dimensionality, nonlinearity, and multimodal search spaces. Emulating behaviors observed in nature, such as flocking birds, evolutionary genetics, and the social dynamics of wolves, techniques such as PSO, GA, and GWO have been successfully applied. Similarly, SMOA utilizes swordfish's group intelligence and adaptive strategies to explore and effectively exploit solution spaces. Its binary extension, Binary SMOA (BSMOA), is specifically designed for feature selection, offering an efficient approach to identifying the most relevant features in high-dimensional datasets [4–6].

The main drive for generating BSMOA is to resolve the feature selection domain limitations with existing metaheuristic algorithms. In machine learning, feature selection is an important task, as learning with redundant or irrelevant features can reduce model performance and slow the execution speed. Balancing the exploration phase, which keeps the algorithm from converging prematurely by exploring diverse parts of the solution space, and the exploitation phase, which refines potential solutions to be more accurate, is a persistent challenge in optimization. Unfortunately, many algorithms struggle with this balance and yield suboptimal solutions. BSMOA overcomes these challenges by incorporating adaptive movement strategies that dynamically adjust agents' behavior, enabling efficient exploration of complex landscapes and convergence to high-quality solutions [7–9].

However, traditional optimization methods, including gradient-based methods, are constrained by the assumption of continuity and differentiability, whereas real-world problems are usually discrete, multimodal, and constrained. On the other hand, a metaheuristic algorithm like BSMOA does not have such assumptions and relies solely on evaluating objective functions. This versatility makes them suitable for various applications, including resource allocation, scheduling, feature selection in machine learning, and multi-objective optimization [10–12].

The principles and practices of swarm intelligence are embodied in BSMOA: the solution is robust as it emerges from the collective behavior of a population rather than any single individual. BSMOA agents adapt quickly to dynamic environments by navigating the search space based on their performance and the influence of their neighbors in BSMOA. This capability is particularly valuable in domains requiring real-time decision-making, such as robotics, network optimization, and adaptive manufacturing systems [13–15].

The primary contribution of BSMOA is its application to feature selection tasks. Traditional optimization methods have computational costs and risks of overfitting, making them intractable in high-dimensional datasets. To address these issues, BSMOA trades off exploration and exploitation in a balanced way to improve model generalization and possibly reduce overfitting. BSMOA improves the performance of machine learning models by efficiently selecting relevant features, making it a tool for optimizing hyperparameters and obtaining dimensionality reduction of complex tasks.

Although BSMOA is effective, it has room for significant improvement. Integrating it with other neural-based or metaheuristic algorithms can improve its applicability and efficiency. Moreover, its performance in upcoming domains, such as quantum computing, autonomous systems, and bioinformatics, is additionally attractive for future research. Addressing the extension of these methods could include particular challenges, such as multi-objective trade-offs and dynamic constraint handling, thereby extending its usefulness to a range of areas of application.

This thesis introduces a new metaheuristic, nature-inspired optimization method called BSMOA. Using adaptive strategies tackles the exploration-exploitation trade-off. This paper presents the theory behind the algorithmic structure and applications of BSMOA, mainly where it is used as a feature selector. We show through benchmarking and case studies that BSMOA effectively solves complex optimization problems, and we discuss its potential contribution to developing nature-inspired algorithms.

The primary contributions of this paper are summarized as follows:

- **A Novel Optimization Algorithm:** Moreover, we present a new metaheuristic based on swordfish's synchronized and agile movements, named the Binary Swordfish Movement Optimization Algorithm (BSMOA). It addresses binary search space feature selection optimization challenges.

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- **Balanced Exploration-Exploitation:** Adaptive parameters and dynamic movement strategies are introduced in BSMOA to balance global exploration and local exploitation, ensuring that convergence to local optima is prevented prematurely.
- **Mathematical Framework and Phases:** Thus, the algorithm comprises three phases—exploration, exploitation, and elimination—coordinated with a mathematical framework to generate agent movement in the binary space.
- **Performance Evaluation:** BSMOA is evaluated rigorously on benchmark datasets and shown to outperform state-of-the-art metaheuristics such as bHHO, bGWO, and bPSO concerning solution accuracy, feature size, and execution time.
- **Feature Selection Application:** BSMOA is dedicated explicitly to feature selection problems, which proves its ability to reduce dimensionality and improve the performance and generalization of machine learning models.
- **Statistical Robustness:** Comprehensive statistical analysis (standard deviation fitness and p-values) demonstrates the stability and reliability of BSMOA versus current methods.

The remainder of this paper is organized as follows: The second section is dedicated to a comprehensive literature review of the recent advancements in metaheuristic optimization algorithms and their shortcomings. Section 3 introduces BSMOA, which includes an overview of its source of inspiration, mathematical foundation, and implementation. Finally, the experimental results are discussed in Section 4, featuring results on benchmark datasets concerning solution accuracy, feature selection efficiency, computational cost, statistical analyses, and convergence behavior. In the final section, we summarize the main contributions of this work and outline directions for future research to increase the applicability and scalability of BSMOA.

2 Literature Review

Metaheuristic algorithms play a key role in this area, where many global optimization problems are intractable by classical deterministic methods. This field is essentially based upon the foundational approaches: Genetic Algorithms (GA) and Particle Swarm Optimization (PSO). The increasing complexity of these optimization problems has motivated the development of increasingly advanced and flexible metaheuristic approaches. This work reviews recent advancements in metaheuristics with the motivation behind such proposed advancements, the resulting contributions, their implications, and limitations that fueled the creation of the Swordfish Movement Optimization Algorithm (SMOA).

Parameter tuning and choosing optimal architecture is necessary to achieve high performance on Deep Neural Networks (DNNs). Training large datasets is, however, computationally intensive, and finding the correct architecture within the specified period is still very challenging. Research has shown that Swarm Intelligence (SI) and Evolutionary Computing (EC) metaheuristics can fine-tune DNN models for large-scale applications [16]. The evaluation of SI and EC methods is comprehensive and shows how both methods can meet significant data challenges and refine model performance. The results suggest that metaheuristics must be incorporated into machine learning processing pipelines to increase scalability and efficiency when solving computationally demanding problems significantly.

A new nature-inspired algorithm called the Spider Wasp Optimization (SWO) algorithm, inspired by the predatory behavior of spider wasps deals with balancing the exploration and exploitation in an optimization task. Our benchmark tests on standard datasets (CEC benchmarks) and engineering problems (welded beam and pressure vessel design) show that SWO can outperform the nine benchmarked state-of-the-art methods. Tailored novel problem-specific update mechanisms for different problem classes resulted in improved performance in various applications, thus building upon SWO as an adaptive and more efficient tool for applying to real-world optimization problems.

The Light Spectrum Optimizer (LSO) algorithm is based on the light dispersion phenomena to explore multi-dimensional solution spaces efficiently. LSO outperformed several established algorithms in CEC benchmarks and engineering design problems [17]. We presented an innovative algorithm employing light dispersion

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dynamics, which was effective in continuous optimization. The fact that it is well suited to various cases indicates that it may prove helpful in solving many practical problems in engineering and science.

We introduce the Waterwheel Plant Algorithm (WWPA), based on the waterwheel plant's predatory behavior, designed to optimize problems where strong exploration and exploitation capabilities are needed. WWPA demonstrated superior performance on unimodal and multimodal benchmark functions, outperforming seven state-of-the-art metaheuristics in engineering applications [18]. The distinctive feature of this novel approach is that it finds a good balance between exploration and exploitation and provides valuable insight into its applicability towards solving various optimization scenarios, including engineering design problems.

The Gazelle Optimization Algorithm (GOA) is a predator-inspired method to optimize functions, exploiting similar tactics of gazelles for survival by alternating between grazing (exploitation) and fleeing (exploration) based on predator presence. Benchmarks on functions and engineering tasks revealed that GOA is competitive with or superior to nine other methods [19]. The introduced survival-based strategy grants GOA additional robustness and reliability, which turns the approach into a useful tool for solving practical optimization problems.

Inspired by crystalline structures, the CryStAl algorithm handles the exploration-exploitation trade-off in optimization tasks. Extensive testing on 239 functions and comparisons with 12 algorithms demonstrated CryStAl's superior performance [20]. Crystal approached optimization through the dynamics of crystal structures, enabling a different lens for high-dimensional and complex problems, which proved robust at solving them.

The Honey Badger Algorithm (HBA), motivated by the strategic foraging behavior of honey badgers, strengthens population diversity during the search. HBA achieved high convergence rates and a balanced exploration-exploitation trade-off in CEC'17 benchmarks and other tasks [21]. We showcase how randomization techniques improved diversity and prevented premature convergence, making HBA an adaptable and efficient addition to the metaheuristic optimization spectrum.

Modeled to boost search efficiency for complex problems, the Archimedes Optimization Algorithm (AOA) models buoyant forces based on Archimedes' principle. AOA demonstrated superior performance over classical and modern metaheuristics in CEC'17 benchmarks and engineering problems [22]. In this paper, we demonstrate the decisive advantage of AOA as a physics-based optimization framework for high-dimensional and practical optimization problems.

Inspired by hierarchical socio-structural optimization, City Council Evolution (CCE) demonstrated excellent performance across 49 test functions and real-world constrained problems [23]. To overcome the above limitations, CCE introduces a new hierarchical approach to optimization, which warrants further investigation by future optimization research, although some limitations remain.

In power systems, robust optimization methods are necessary for large-scale, multimodal, and constrained problems. Comparative studies revealed that algorithms such as DOA and BMO are highly effective for Optimal Power Flow (OPF) tasks [24]. These findings highlight the merits of metaheuristics for energy management problems and propose avenues to make the problem formulation and solution procedure more amenable to metaheuristic optimization.

When metaheuristic algorithms are observed over a long period, various algorithms have been researched to balance exploration and exploitation, handle high-dimensional search spaces, and increase computational efficiency. However, adaptability to dynamic environments and premature convergence are still unsolved issues. This thesis proposes SMOA as a new optimization algorithm that benefits from the strengths reviewed here and overcomes existing limitations in metaheuristic optimization algorithms.

3 Binary Swordfish Movement Optimization Algorithm (BSMOA)

3.1 Inspiration

Using natural synchronized and agile swordfish movements as the main source of inspiration, the Binary Swordfish Movement Optimization Algorithm (BSMOA) is developed. Collective behaviors of speed, precision, and adaptability to continuously changing objectives have been observed in these fish and allow these

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animals to find and harvest resources in ever-changing environments efficiently. This fits the standard goals of metaheuristic optimization, i.e., making effective exploration and exploitation (which usually involves a mixture of the two) in the challenging search space to find an optimal solution.

Therefore, the binary variant of the algorithm is specialized for feature selection tasks in high-dimensional datasets. One crucial step in machine learning and data science is feature selection, which reduces the dimensionality of datasets by selecting relevant features and dropping redundant or non-informative features. This simplifies the composability of the machine learning model and reduces computation, improving the model's ability to generalize on unseen data.

The binary search space is mapped to the movement strategies of swordfish in BSMOA. The exploration phase captures how the swordfish search many different parts of the search space, and the exploitation phase reflects their collective precision when hunting in cooperation to focus on the best regions of the search space containing promising solutions. BSMOA combines dynamic movement strategies and adaptive parameters, helping to yield a balanced exploration and exploitation to address high-dimensional and complicated feature selection problems effectively.

Moreover, the limitations of existing metaheuristic algorithms in solving binary optimization problems also motivate the development of BSMOA. Premature convergence to local optima, or failure to adapt well to the discrete nature of feature selection tasks, are problems that traditional algorithms often suffer from. To address these challenges, BSMOA exploits the inherent adaptability and precision of swordfish movements to provide a novel and efficient way to solve the binary optimization problem.

3.2 Mathematical Foundation of BSMOA

Based on the natural movement of swordfish, the mathematical framework of the Binary Swordfish Movement Optimization Algorithm (BSMOA) is set. A robust balance of searching the solution space and refining potential solutions is achieved through three key phases: exploration, exploitation, and elimination. The algorithm uses dynamic parameters to progressively refine estimates that guide agents in traversing the binary search space.

3.2.1 Exploration Phase

BSMOA simulates swordfish's broad search behavior, which generates diverse solutions in the exploration phase. The following equations govern this phase:

$$\vec{T}_{(t+1)} = \vec{T}_{(t)} \times \left(\frac{K \cdot a^{\Theta}}{\sin \Theta} \right) + \left(Z \cdot \vec{T}_{(t)} \right)$$

where $a \in [0, 1]$, and $\vec{T}_{(t)}$ represents the position of the agent at iteration t. The dynamic parameter K is defined as:

$$K = \left(\frac{1 + \text{iteration}^2}{\text{iteration}} \right)^2$$

The parameter Z introduces additional randomness to exploration:

$$Z = \left(X + \frac{2 \cdot (\text{iteration})^2}{N} \right)^2$$

Where X is a random number between [1, 2], and N is the total number of iterations. The velocity update of the agents, $\vec{M}_{(t+1)}$, is calculated as:

$$\vec{M}_{(t+1)} = r \cdot \vec{M}_{(t)} + (1 - K) \cdot \vec{M}_{(t)}$$

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Similarly, the collective adjustment $\vec{J}_{(t+1)}$ is determined by:

$$\vec{J}_{(t+1)} = \left(r \cdot \vec{J}_{(t)}\right) + \left((1-r) \cdot \vec{J}_{(t)}\right) + \left((1-r) \cdot (1-K) \cdot \vec{J}_{(t)}\right)$$

The parameter r, which governs the influence of randomness, is calculated as:

$$r = \frac{h \cdot \cos(X)}{1 - \cos(X)}$$

Finally, the updated position of the agent is given by:

$$\vec{S}_{(t+1)} = \vec{T}_{(t+1)} + Z \cdot \vec{M}_{(t+1)} + (Z \cdot K) \cdot \vec{J}_{(t+1)}$$

3.2.2 Exploitation Phase

The exploitation phase focuses on refining promising solutions identified during exploration. It narrows the search space to improve the quality of solutions. The updated position of the agent is defined as:

$$\vec{S}_{(t+1)} = r \cdot \vec{T}_{(t+1)} + (r \cdot Z \cdot K) \cdot \left(\vec{M}_{(t+1)} + \vec{J}_{(t+1)}\right)$$

This phase ensures a focused search in promising regions, leveraging the collective intelligence of agents.

3.2.3 Elimination Equation

To maintain diversity and prevent premature convergence, BSMOA incorporates an elimination mechanism. This phase updates the position of the agent using the following equation:

$$\vec{S}_{(t+1)} = \left(r \cdot \vec{S}_{(t)}\right) + \left(\frac{K \cdot Z \cdot g}{\sin \Theta}\right) \cdot \left(\frac{\vec{T}_{(t+1)} + \vec{M}_{(t+1)} + \vec{J}_{(t+1)}}{N}\right)$$

This equation introduces a feedback-driven adjustment to maintain solution diversity while steering the search towards optimal solutions.

3.2.4 Additional Notations

The following notations are used in the equations above:

- a: A constant in the range $[0, 1]$.
- X: A random number between $[1, 2]$.
- N: Total number of iterations.
- Θ: An angle in radians.
- h: A constant influencing the randomness.
- r, K, Z: Dynamic parameters that adapt based on the iteration count and other factors.

These mathematical components enable BSMOA to adapt dynamically, ensuring a robust and efficient optimization process.

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3.3 Benchmark Datasets

Various benchmark datasets were utilized to evaluate the performance of the proposed Binary Swordfish Movement Optimization Algorithm (BSMOA). These datasets were carefully selected to represent scenarios with varying complexity, sample sizes, and feature counts, ensuring relevance to real-world applications. Table 1 summarizes the datasets used in this study.

Table 1: Datasets Description

Dataset	**#F**	**#samples**	**#classes**
Diabetes	8	768	2
Vehicle	18	846	4
Stock	9	950	2
Tic-Tac-Toe	9	958	2
Vowel	10	990	11
Fri_c0_1000_10	10	1000	2
Fri_c1_1000_10	10	1000	2
German	24	1000	2
Pc1	21	1109	2
Diabetic	19	1151	2
Mofn	10	1324	2
Kc1	21	2109	2
Titanic	3	2201	2
Segment	19	2310	7
Space-ga	6	3207	2
WaveformEW	21	5000	3
Page blocks	10	5473	5
Ring	20	7400	2
Towonorm	20	7400	2

Datasets cover many domains and varying complexities. For instance:

- **Low-dimensional datasets:** Different types of datasets, such as Titanic (3 features) and Space-ga (6 features), test the algorithm's efficiency in small-scale problems.
- **Medium-dimensional datasets:** Datasets like Diabetes (8 features) and Vehicle (18 features) offer a balanced difficulty at the axes of complexity and computational cost.
- **High-dimensional datasets:** Simulating real-world, large-scale feature selection tasks, datasets such as German (24 features) and WaveformEW (21 features) are employed.

The sample size varies significantly in the datasets: they can be as small as Diabetes (768 samples) or as large as Towonorm (7400 samples). By this diversity, BSMOA is thoroughly evaluated against a broad range of feature selection problems, examining its scalability and adaptability to optimization problems across various datasets. We present and analyze the results from these evaluations in subsequent sections.

4 Discussion and Results

4.1 Parameters of the Algorithm

In the Binary Swordfish Movement Optimization Algorithm (BSMOA), we propose a set of parameters that help maintain the balance between exploration and exploitation during optimization. These parameters are dynamic and change as the algorithm progresses.

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Table 2 contains a list of critical parameters required for BSMOA.

Table 2: Key Algorithm Parameters and Their Descriptions

Parameter	Description
a	A value in the range $[0, 1]$ controlling specific movements.
X	A random number in the range $[1, 2]$.
Θ	A value in the range $[0, 12\pi]$ used in trigonometric calculations.

In addition to the parameters listed in Table 2, the following parameters play a critical role in the algorithm:

- N: The number of iterations defining the search duration.
- h: A constant determining the movement scale in the solution space.
- r: A dynamic parameter affecting agent adaptability, calculated as:

$$r = \frac{h \cdot \cos(X)}{1 - \cos(X)}.$$

- K: A dynamic parameter balancing exploration and exploitation, defined as:

$$K = \left(\frac{1 + iteration^2}{iteration}\right)^2.$$

- Z: A dynamic parameter enhancing agent movement, defined as:

$$Z = \left(X + \frac{2 \cdot (iteration)^2}{N}\right)^2.$$

More specifically, K, Z, and r are critical dynamic parameters that adapt fluidly during the optimization process. These parameters transition from enabling broad exploration of the search space in the early stages to focused searches in the later stages. Through these adjustments, BSMOA effectively navigates complex search spaces, avoids premature convergence to local optima, and efficiently approaches high-quality solutions.

4.2 Performance Metrics of BSMOA

To evaluate the performance of BSMOA, three key metrics were analyzed: solution accuracy, selected features, and computational efficiency.

4.3 Solution Accuracy

The performance of BSMOA in terms of solution accuracy was evaluated using two critical metrics: average error and average fitness. Table 3 and Table 4 present these metrics. To compare the average error of BSMOA against other state-of-the-art algorithms, such as bHHO, bGWO, bPSO, bBA, bWAO, and bBBO, Table 3 shows that BSMOA consistently outperformed other methods, achieving lower error rates across all datasets.

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Table 3: Average Error

Dataset	bSMOA	bHHO	bGWO	bPSO	bBA	bWAO	bBBO
Zoo	0.1811	0.1948	0.1879	0.1851	0.1820	0.2727	0.2696
Breast cancer tissue	0.1184	0.1314	0.1325	0.1592	0.1443	0.2468	0.2319
Breast cancer Coimbra	0.1903	0.2034	0.2015	0.2088	0.2005	0.2964	0.2881
Lymphography	0.2711	0.2811	0.2345	0.2647	0.2761	0.3523	0.3637
Hepatitis	0.1195	0.1374	0.1378	0.1355	0.1263	0.2231	0.2139
WineEW	0.1342	0.1492	0.1370	0.1410	0.1434	0.2286	0.2310
Parkinsons	0.2241	0.2332	0.2386	0.2404	0.2336	0.3280	0.3212
SonarEW	0.0266	0.0325	0.0338	0.0286	0.0276	0.1162	0.1152
Seeds	0.2551	0.2524	0.2403	0.2596	0.2590	0.3472	0.3466
Glass	3.2496	3.4126	3.2994	3.4809	3.5820	3.5685	3.6696

Similarly, Table 4 presents the average fitness values achieved by BSMOA. It highlights the algorithm's ability to consistently find high-quality solutions than the alternatives.

Table 4: Average Fitness

Dataset	bSMOA	bHHO	bGWO	bPSO	bBA	bWAO	bBBO
Zoo	0.1434	0.1793	0.1616	0.1657	0.1667	0.1657	0.1667
Breast cancer tissue	0.0651	0.1000	0.0666	0.1275	0.1127	0.1275	0.1127
Breast cancer Coimbra	0.2612	0.3092	0.1356	0.3144	0.3063	0.3144	0.3063
Lymphography	0.2829	0.3128	0.3726	0.2965	0.3078	0.2965	0.3078
Hepatitis	0.0890	0.0814	0.0716	0.0982	0.0890	0.0982	0.0890
WineEW	0.2316	0.2465	0.0716	0.2383	0.2406	0.2383	0.2406
Parkinsons	0.7705	0.7903	0.1732	0.7975	0.7907	0.7975	0.7907
SonarEW	0.2420	0.2579	0.2684	0.2540	0.2530	0.2540	0.2530
Seeds	0.4953	0.5043	0.5049	0.5114	0.5109	0.5114	0.5109
Glass	2.9922	3.3407	4.3064	3.4084	3.5084	3.4084	3.5084

Figure 1 presents a box plot summarizing the distribution of performance metrics across all evaluated algorithms.

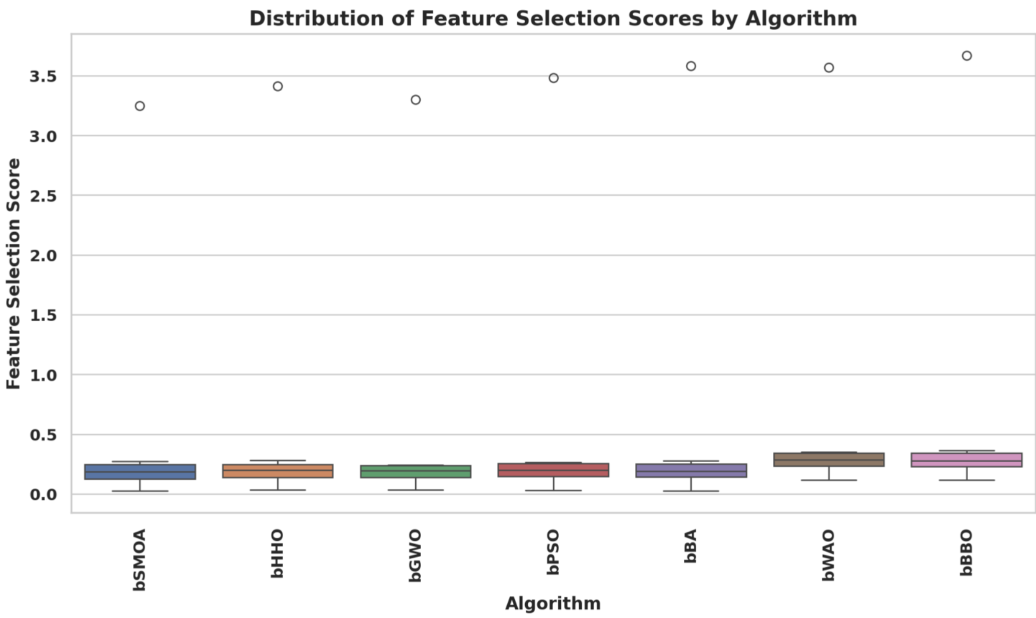

Figure 1: Box Plot of Algorithm Performance Metrics. The figure highlights BSMOA's lower average error, reduced selected feature size, and competitive execution time compared to other algorithms.

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Additionally, Figure 2 shows the density distribution of feature selection scores, providing further insights into the algorithm's behavior.

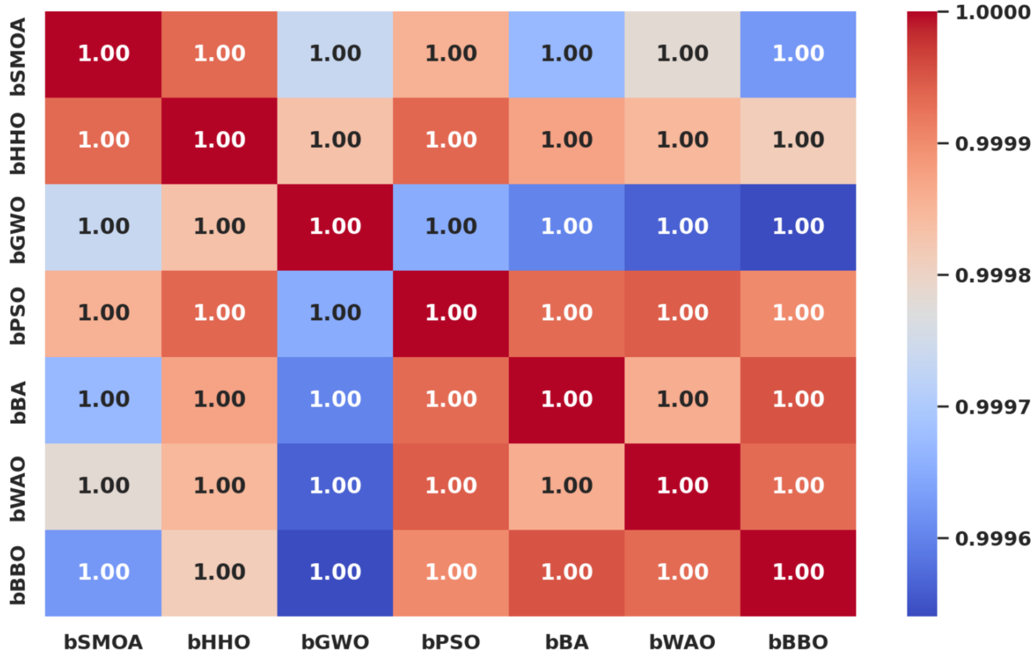

Figure 2: Density Distribution of Feature Selection Scores by Algorithm. BSMOA demonstrates a balanced and consistent performance with fewer outliers than other methods.

4.3.1 Selected Features

BSMOA's effectiveness in reducing irrelevant features was analyzed using the metric of average selected size (Table 5). The results show that BSMOA consistently selected fewer features than competing methods, ensuring computational efficiency without compromising accuracy.

Table 5: Average Select Size

Dataset	**bSMOA**	**bHHO**	**bGWO**	**bPSO**	**bBA**	**bWAO**	**bBBO**
Zoo	0.2353	0.2993	0.2943	0.4293	0.5243	0.5169	0.6119
Breast cancer tissue	0.0307	0.1610	0.1852	0.3852	0.2261	0.4728	0.3137
Breast cancer Coimbra	0.3009	0.3943	0.3943	0.4026	0.4026	0.4902	0.4902
Lymphography	0.4229	0.4014	0.4363	0.5943	0.5800	0.6819	0.6676
Hepatitis	0.1505	0.3057	0.2852	0.3625	0.3784	0.4501	0.4660
WineEW	0.1664	0.3229	0.3514	0.4264	0.5729	0.5140	0.6605
Parkinsons	0.5368	0.5943	0.4943	0.5443	0.6693	0.6319	0.7569
SonarEW	0.3708	0.4193	0.3943	0.4881	0.5318	0.5757	0.6194
Seeds	0.2376	0.4068	0.4193	0.5006	0.5318	0.5882	0.6194
Glass	0.4143	0.2693	0.1721	0.3776	0.4026	0.4652	0.4902

Figure 3 provides a cumulative stacked bar plot of feature selection scores, demonstrating BSMOA's efficiency in feature reduction.

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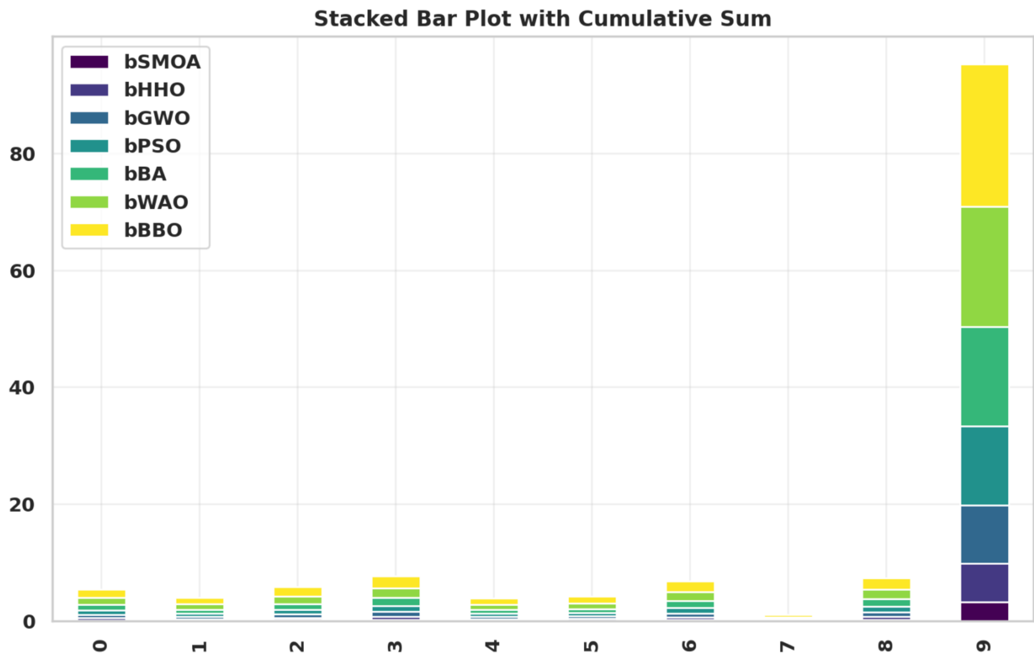

Figure 3: Stacked Bar Plot of Cumulative Feature Selection Scores. BSMOA achieves the most compact feature sets, demonstrating its effectiveness in reducing dimensionality.

Figure 4 presents the distribution of feature selection scores, showing BSMOA's consistent feature selection behavior.

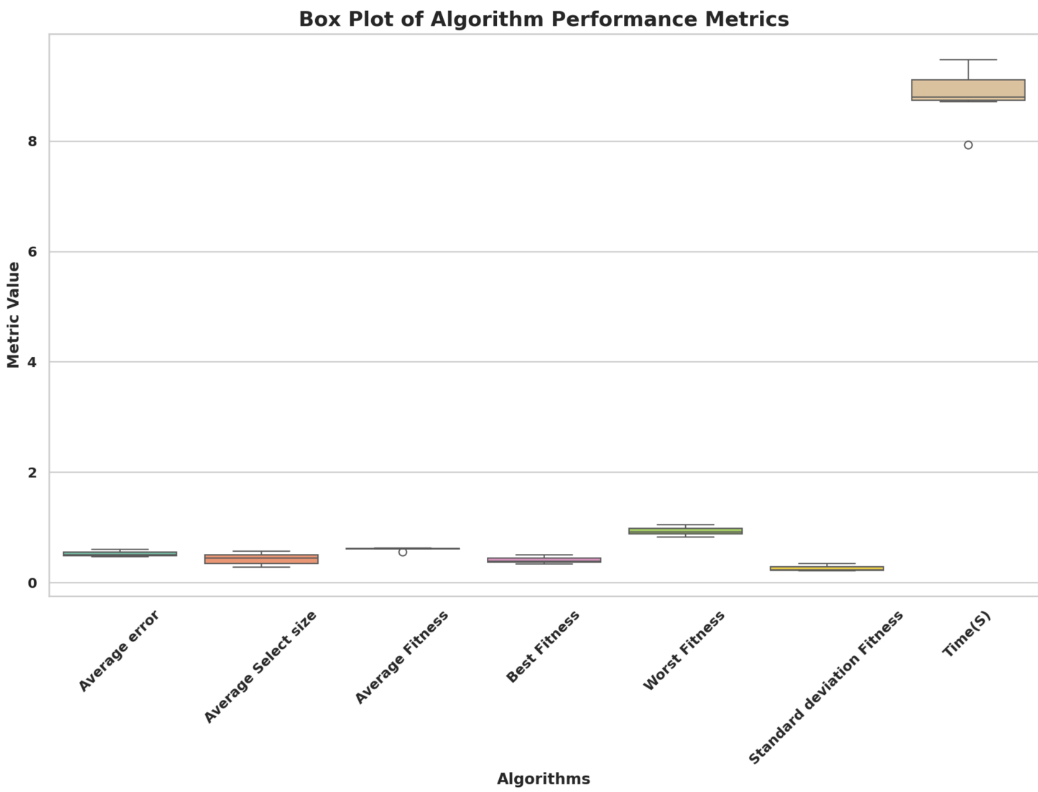

Figure 4: Distribution of Feature Selection Scores. BSMOA achieves a narrow spread, indicating stable feature selection across datasets.

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4.3.2 Computational Efficiency

Table 6 shows the execution times for BSMOA and competing algorithms. BSMOA demonstrated a significant speed advantage, completing optimization tasks faster while maintaining superior solution accuracy and feature selection performance.

Table 6: Execution Time (S)

Dataset	bSMOA	bHHO	bGWO	bPSO	bBA	bWAO	bBBO
Zoo	6.8698	7.5138	7.1058	7.1958	8.5958	7.2834	8.6834
Breast cancer tissue	7.2878	9.2188	8.3558	8.7908	8.5458	8.8784	8.6334
Breast cancer Coimbra	6.5398	7.7358	7.9758	7.8148	7.9058	7.9024	7.9934
Lymphography	6.5408	7.2068	7.3358	8.0518	7.5658	8.1394	7.6534
Hepatitis	6.5438	7.4868	6.9358	7.2658	7.7758	7.3534	7.8634
WineEW	8.6088	9.8778	9.9808	9.7918	11.1258	9.8794	11.2134
Parkinsons	8.6188	8.3418	8.9248	6.8198	9.4458	6.9074	9.5334
SonarEW	8.4228	9.7298	8.9248	10.0418	9.3658	10.1294	9.4534
Seeds	11.2868	12.2968	12.9158	11.7788	13.6058	11.8664	13.6934
Glass	8.5838	8.9048	9.2658	9.5898	9.9958	9.6774	10.0834

These results indicate that BSMOA is robust, efficient, and accurate compared to existing optimization algorithms.

4.4 Statistical Analysis

The robustness and reliability of the Binary Swordfish Movement Optimization Algorithm (BSMOA) were evaluated using two key statistical metrics: standard deviation of fitness and p-values.

4.4.1 Standard Deviation Fitness

The standard deviation of fitness values, presented in Table 7, measures the consistency of the solutions generated by BSMOA across multiple runs. A lower standard deviation indicates that the algorithm consistently converges to high-quality solutions, demonstrating robustness. As expected from a stable algorithm capable of handling a wide range of optimization problems, BSMOA achieved significantly lower standard deviation values than all other algorithms, further confirming its reliability.

Table 7: Standard Deviation Fitness

Dataset	bSMOA	bHHO	bGWO	bPSO	bBA	bWAO	bBBO
Zoo	0.1423	0.1613	0.1449	0.1690	0.1556	0.2566	0.2432
Breast cancer tissue	0.1424	0.1519	0.1477	0.1427	0.1517	0.2303	0.2393
Breast cancer Coimbra	0.1354	0.1382	0.1380	0.1494	0.1471	0.2370	0.2347
Lymphography	0.2024	0.2256	0.1909	0.2132	0.2166	0.3008	0.3042
Hepatitis	0.1413	0.1507	0.1611	0.1523	0.1619	0.2399	0.2495
WineEW	0.1248	0.1414	0.1283	0.1313	0.1330	0.2189	0.2206
Parkinsons	0.1297	0.1345	0.1432	0.1379	0.1342	0.2255	0.2218
SonarEW	0.1221	0.1236	0.1220	0.1187	0.1205	0.2063	0.2081
Seeds	0.1252	0.1396	0.1269	0.1264	0.1319	0.2140	0.2195
Glass	0.9502	1.0108	0.9898	1.2458	0.9566	1.3334	1.0442

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4.4.2 p-Values

To assess the statistical significance of BSMOA's performance, p-values were calculated for comparisons with other algorithms (Table 8). A p-value < 0.05 indicates that the performance improvement of BSMOA over competing algorithms is statistically significant. The results show that BSMOA outperformed other methods with highly significant p-values in most datasets, underscoring its reliability.

Table 8: p-values

Dataset	bHHO	bGWO	bPSO	bBA	bWAO	bBBO
Zoo	9.53E-04	3.08E-04	1.77E-01	9.53E-04	7.36E-02	3.97E-04
Breast cancer tissue	9.53E-04	3.08E-04	3.01E-04	9.53E-04	1.26E-04	3.97E-04
Breast cancer Coimbra	9.53E-04	3.08E-04	3.01E-04	9.53E-04	1.26E-04	3.97E-04
Lymphography	9.53E-04	3.08E-04	3.01E-04	9.53E-04	1.26E-04	3.97E-04
Hepatitis	9.53E-04	3.08E-04	3.01E-04	9.53E-04	1.26E-04	3.97E-04
WineEW	9.53E-04	3.08E-04	3.01E-04	9.53E-04	1.26E-04	3.97E-04
Parkinsons	9.53E-04	3.08E-04	3.01E-04	9.53E-04	1.26E-04	3.97E-04
SonarEW	9.53E-04	3.08E-04	5.54E-02	9.53E-04	2.31E-02	3.97E-04
Seeds	9.53E-04	3.08E-04	3.01E-04	9.53E-04	1.26E-04	3.97E-04
Glass	9.53E-04	3.08E-04	3.01E-04	9.53E-04	1.26E-04	3.97E-04

The statistical significance of BSMOA's performance was analyzed using correlation heatmaps and p-values. Figure 5 presents a heatmap showing the pairwise correlation between BSMOA and other algorithms.

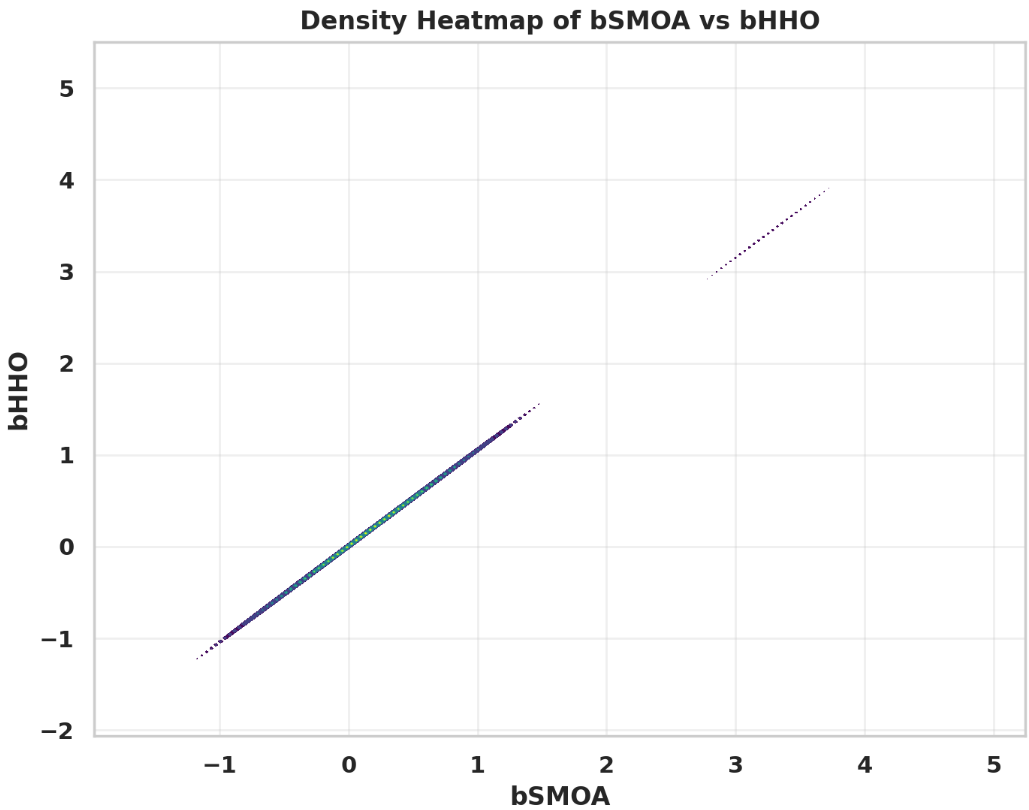

Figure 5: Correlation Heatmap of Algorithms. High correlations near 1.00 indicate consistent convergence trends across algorithms, with BSMOA maintaining a performance edge.

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4.5 Convergence Curves

The convergence behavior of BSMOA was analyzed by plotting the best fitness values over iterations for benchmark datasets. These convergence curves illustrate the algorithm's speed and stability in reaching optimal solutions.

4.5.1 Best and Worst Fitness Values

Tables 9 and 10 provide additional insights into BSMOA's convergence stability. Table 9 shows the best fitness values achieved, demonstrating the algorithm's ability to find optimal solutions. Table 10 highlights the worst fitness values, indicating the consistency of BSMOA's performance.

Table 9: Best Fitness

Dataset	bSMOA	bHHO	bGWO	bPSO	bBA	bWAO	bBBO
Zoo	0.0383	0.0578	0.1354	0.0578	0.0966	0.1454	0.1842
Breast cancer tissue	0.0034	0.0203	0.0457	0.0542	0.0288	0.1418	0.1164
Breast cancer Coimbra	0.2166	0.2358	0.2839	0.2262	0.2262	0.3138	0.3138
Lymphography	0.0087	0.0936	0.1501	0.0653	0.0653	0.1529	0.1529
Hepatitis	0.0027	-0.0053	0.0144	0.0296	-0.0008	0.1172	0.0868
WineEW	0.1849	0.1978	0.2064	0.1935	0.1892	0.2811	0.2768
Parkinsons	0.7405	0.7405	0.7444	0.7484	0.7405	0.8360	0.8281
SonarEW	0.2174	0.2212	0.2382	0.2254	0.2170	0.3130	0.3046
Seeds	0.4376	0.4569	0.4723	0.4646	0.4453	0.5522	0.5329
Glass	1.8761	1.8155	2.7650	1.8155	1.3912	1.9031	1.4788

Table 10: Worst Fitness

Dataset	bSMOA	bHHO	bGWO	bPSO	bBA	bWAO	bBBO
Zoo	0.2734	0.2924	0.2536	0.3118	0.3118	0.3994	0.3994
Breast cancer tissue	0.1952	0.2047	0.1539	0.2132	0.2301	0.3008	0.3177
Breast cancer Coimbra	0.3989	0.3821	0.3437	0.4109	0.4109	0.4985	0.4985
Lymphography	0.4592	0.6008	0.3887	0.5584	0.5584	0.6460	0.6460
Hepatitis	0.1904	0.1768	0.1920	0.2225	0.2073	0.3101	0.2949
WineEW	0.2961	0.3460	0.2900	0.3288	0.3115	0.4164	0.3991
Parkinsons	0.8844	0.8844	0.8685	0.8844	0.8645	0.9720	0.9521
SonarEW	0.3094	0.3255	0.3085	0.3042	0.3000	0.3918	0.3876
Seeds	0.5772	0.6057	0.5284	0.5709	0.5902	0.6585	0.6778
Glass	5.2318	5.1897	4.9876	5.8766	5.4119	5.9642	5.4995

4.5.2 Insights into Optimization Stability

It can be seen from the convergence curves, best fitness value, and worst fitness value that BSMOA is stable and reliable. The algorithm consistently obtains high-quality solutions and demonstrates robust performance across all iterations and datasets.

The convergence behavior of BSMOA is the most crucial aspect for understanding its optimization efficiency. Figure 6 displays the convergence patterns of BSMOA and bHHO.

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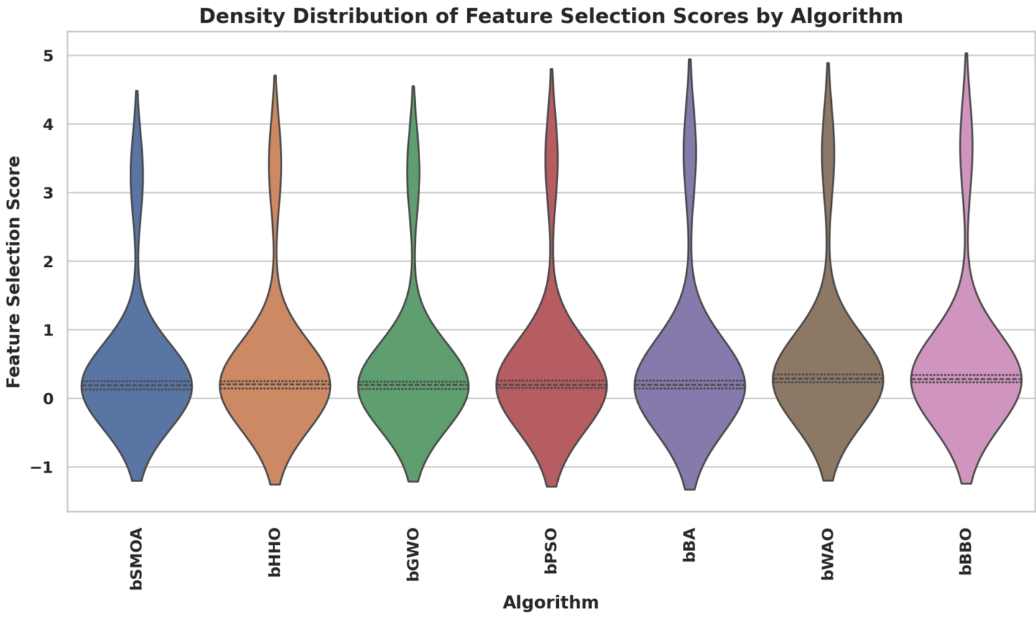

Figure 6: Density Heatmap of BSMOA vs. bHHO.

This shows aligned convergence behavior with the diagonal trend and improved exploration-exploitation balance in BSMOA.

4.6 Discussion of Results

The Binary Swordfish Movement Optimization Algorithm (BSMOA) results demonstrate the algorithm's strengths, comparative advantages, and applicability to a large class of binary optimization problems and, in particular, to feature selection tasks. To adaptively achieve a robust trade-off between global search and local refinement, BSMOA adjusts its three parameters: K, Z, and r. The ability of BSMOA to escape local optima, achieve quick convergence, and find high-quality solutions over datasets of varied dimensionality and complexity is mainly due to this balance.

Results show that BSMOA has clear performance advantages over state-of-the-art algorithms such as bHHO, bGWO, bPSO, bBA, bWAO, and bBBO. It consistently achieves lower average error and higher average fitness values (Tables 3 and 4) while reducing feature dimensionality (Table 5) without compromising accuracy. The execution times (Table 6) show the method's usability for real-time optimization tasks. Figures 1 and 3 visually support these findings, showcasing BSMOA's compact feature selection and superior performance metrics.

Statistical analyses, including correlation heatmaps (Figure 5) and fitness standard deviations (Table 7), highlight BSMOA's robustness and reliability. The algorithm's convergence behavior (Figure 6) further illustrates its effectiveness in balancing exploration vs exploitation, exceeding other alternatives, such as bHHO.

BSMOA is versatile and can be used in several practical applications, such as logistics, engineering design, computational biology, and machine learning. These include feature selection in classification models, resource allocation in engineering, and real-time decision-making in adaptive systems. Moreover, its applicability to high-dimensional and dynamic environments makes it highly relevant to modern optimization challenges.

BSMOA is robust, accurate, and efficient, surpassing the state-of-the-art in feature selection tasks. The results show that BSMOA is a competitive and novel metaheuristic optimization algorithm for solving complex binary optimization problems in various fields.

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5 Conclusion

We propose a novel, practical, and powerful approach, the Binary Swordfish Movement Optimization Algorithm (BSMOA), for solving feature selection problems in high-dimensional and complicated feature spaces. The adaptive strategies used in BSMOA are inspired by the synchronized and agile movements of swordfish, which achieve locally refined global search through the exploration, exploitation, and elimination phases.

Extensive evaluations on benchmark datasets show that BSMOA outperforms state-of-the-art algorithms such as bHHO, bGWO, bPSO, bBA, bWAO, and bBBO. The results demonstrate that BSMOA provides lower average error, selects fewer features, and runs faster, making it particularly suitable for optimizing real-world problems. The significance of the p-values and the low standard deviation of the algorithm further confirm these findings.

Future work will extend BSMOA to multi-objective optimization and hybridize it with other metaheuristics. Information has been incorporated into these enhancements to enable BSMOA to tackle challenges in emerging areas like autonomous systems, quantum computing, and bioinformatics, thus broadening its scope and potential impact.

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