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Accurate Prey Localization (APL) for Promoting the Performance of Chimp Bio-Inspired Optimization Techniques

Eslam, Takieldeen A.[1] *, Asmaa, Rabie H.[2], Ahmed, Saleh I.[3] and Hatem, Khater A.[4]

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[1] Corresponding: Computer and Systems Engineering Department, Faculty of Engineering, Horus University, New Damietta, Egypt. eahmed@horus.edu.eg, eslamelsherbiny1998@gmail.com.
[2] Computers and Control Systems Engineering Department, faculty of engineering Mansoura University, Mansoura, Egypt. asmaahamdy@mans.edu.eg.
[2] Computers Science Department, Arab East Colleges, Saudi Arabia.
[3] Computers and Control Systems Engineering Department, faculty of engineering Mansoura University, Mansoura, Egypt. aisaleh@mans.edu.eg.
[4] Computer and Systems Engineering Department, Faculty of Engineering, Horus University, New Damietta, Egypt. hkhater@horus.edu.eg

Abstract: Bio-inspired optimization algorithms have emerged as powerful computational tools for solving complex optimization problems, with the Chimp Optimization Algorithm (ChOA) representing a notable advancement through sophisticated cooperative hunting behaviors. However, a critical limitation exists in ChOA's prey localization mechanism, which treats all leading solutions equally when estimating prey position regardless of their individual fitness levels, leading to inaccurate positioning and suboptimal convergence. This research introduces Accurate Prey Localization (APL), a novel enhancement that replaces traditional simple averaging with fitness-aware weighted positioning. APL implements a pairwise estimation strategy where chimps with higher fitness values receive proportionally greater influence in prey position calculations. Experimental validation demonstrates substantial effectiveness of APL-Improved ChOA compared to original ChOA and Grey Wolf Optimization across multiple evaluation metrics, achieving significant convergence improvements. A comprehensive case study on COVID-19 feature selection validates APL's practical effectiveness, with Binary APL-Improved ChOA achieving 98% accuracy compared to Binary Particle Swarm Optimization (91.2%), Binary Chimp Optimization (92.65%), and Binary Grey Wolf Optimization (94.1%). The improved convergence behavior, enhanced solution accuracy, and consistent performance establish APL as a significant advancement for bio-inspired optimization algorithms, particularly valuable for feature selection tasks and high-dimensional optimization scenarios.

Keywords: Bio-inspired optimization, Chimp Optimization Algorithm, Prey localization, Fitness-aware weighting, Metaheuristic algorithms, Convergence optimization

1. Introduction

Bio-inspired optimization algorithms solve complex optimization problems by mimicking natural phenomena and biological behaviors. These algorithms translate natural problem-solving approaches into mathematical models that efficiently navigate complex solution spaces. They have gained widespread adoption due to their ability to handle non-linear, multi-modal, and high-dimensional problems without requiring gradient information. The algorithms offer several key advantages including robustness, flexibility, and effective local optima avoidance. Additionally, they provide parallel processing capabilities that enhance computational efficiency. These characteristics make bio-inspired algorithms indispensable for diverse applications such as engineering design optimization, machine learning parameter tuning, feature selection, scheduling, and financial modeling [1, 2].

Bio-inspired algorithms encompass evolutionary algorithms (Genetic Algorithms, Differential Evolution), swarm intelligence (Particle Swarm Optimization, Ant Colony Optimization), physics-based algorithms, and hunting-based metaheuristics modeling predator-prey relationships [3, 4]. Hunting-based algorithms demonstrate exceptional effectiveness through their natural exploration-exploitation balance, modeling sophisticated predator behaviors—prey searching, stalking, encircling, attacking—that translate into comprehensive search strategies with hierarchical structures and role-based cooperation. The Chimp Optimization Algorithm (ChOA) represents a notable advancement by modeling chimpanzee cooperative hunting through four hierarchical roles (attacker, barrier, chaser, driver) operating in exploration and exploitation phases, demonstrating remarkable effectiveness in feature selection, high-dimensional optimization, and engineering design challenges [5].

However, ChOA's prey localization mechanism contains a critical limitation that directly impacts optimization performance. The existing implementation treats all leading solutions equally when estimating prey position using simple averaging, regardless of individual fitness levels. This approach becomes problematic in high-dimensional landscapes where solution quality varies significantly among leading chimps, potentially misleading the algorithm toward suboptimal regions, reducing convergence speed, and increasing premature convergence likelihood, directly translating to reduced effectiveness and compromised solution quality [6].

To address these limitations, this research introduces Accurate Prey Localization (APL), a novel enhancement replacing simple averaging with fitness-aware weighted positioning. APL implements a pairwise estimation strategy where chimps with higher fitness values receive proportionally greater influence in prey position calculations, ensuring superior solutions guide the optimization process more effectively. The method integrates seamlessly with ChOA's existing exploration mechanisms while fundamentally improving exploitation through Improved prey localization accuracy, enabling more precise identification of optimal solution regions and improved convergence behavior across diverse problem domains while maintaining the essential exploration-exploitation balance [7].

This paper is structured as follows:

- **Section 2** (Problem Definition) defines the research problem and identifies specific limitations of traditional ChOA prey localization mechanisms.
- **Section 3** (Literature Review) presents a comprehensive review of bio-inspired optimization algorithms and existing ChOA variants.
- **Section 4** (Traditional Prey Localization in ChOA) details traditional prey localization approaches and analyzes their inherent limitations.

- **Section 5** (The Proposed Accurate Prey Localization (APL) for Improved Chimp Optimization) introduces the APL methodology and APL-Improved ChOA algorithm.
- **Section 6** (Results & Discussion) presents experimental results covering theoretical performance analysis and COVID-19 feature selection validation.
- **Section 7** (Conclusion) concludes with key findings and research contributions.
- **Section 8** (Future Work) outlines potential research directions and extensions of the proposed method.

2. Problem Definition

The Chimp Optimization Algorithm (ChOA) has emerged as a promising metaheuristic method for solving complex optimization problems, particularly in tasks requiring effective feature selection. Inspired by chimpanzees' cooperative hunting strategies, ChOA involves agents assuming roles such as chasers, blockers, attackers, and drivers, each contributing uniquely to the convergence toward an optimal solution. During each iteration, the algorithm adjusts the positions of chimp agents based on an estimated location of the prey, representing the optimal solution within the search space [8].

However, a notable limitation in the existing ChOA implementation lies in its method of prey localization. Specifically, ChOA estimates the prey's position by calculating the average location of the four leading chimps. While this simple averaging approach provides a convenient estimation, it frequently results in imprecise prey localization, particularly in high-dimensional and complex solution landscapes. Consequently, the optimization process may converge prematurely, stall at local optima, or inadequately explore promising regions of the search space.

This limitation significantly impacts performance when applied to feature selection tasks. Inaccurate prey localization can lead the algorithm to select irrelevant or redundant features, degrading the performance and accuracy of machine learning models trained on these subsets. Additionally, treating all four leading chimps equally without considering differences in their fitness or quality undermines the algorithm's ability to reliably identify optimal solutions as illustrated in figure 1 [9]. Furthermore, the static nature of the averaging mechanism restricts the algorithm's adaptability to varying optimization problems. In real-world applications, especially biomedical or high-dimensional datasets, these inaccuracies can severely diminish the algorithm's effectiveness and generalization capabilities. Addressing these issues is crucial to improving the reliability and performance of ChOA-based feature selection. To overcome the limitations inherent in the averaging-based prey localization method, this research proposes Accurate Prey Localization (APL), a novel and adaptive approach explicitly designed to enhance the accuracy of prey position estimation. By incorporating fitness-aware, dynamic localization strategies, APL aims to significantly enhance convergence behavior, feature selection accuracy, and overall optimization efficiency.

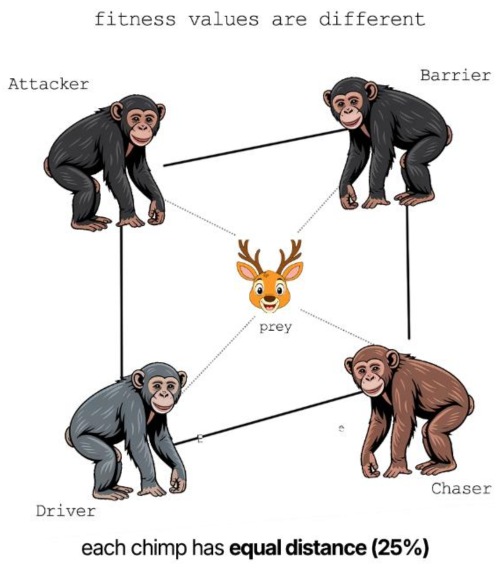

Figure 1. Treating all four leading chimps equally without considering differences in their fitness

3. Literature Review

This section will introduce the previous efforts in the area of bioinspired optimization in more details. We explore the foundations and recent advancements of bio-inspired optimization algorithms, with a particular focus on the Chimp Optimization Algorithm (ChOA). We also examine existing variants, highlight current limitations, and introduce a key research gap related.

3.1. Bio-inspired Optimization

Bio-inspired optimization algorithms have gained significant attention in recent years due to their ability to solve complex optimization problems by mimicking natural biological behaviors and evolutionary processes. These algorithms function as versatile computational tools that enable multiple applications with the potential to achieve global optimal solutions, making them more adaptable than traditional statistical optimization methods that are often application-specific and may struggle to reach global optimality. The field encompasses a diverse range of approaches, including evolutionary algorithms, swarm intelligence methods, and other nature-inspired techniques that draw inspiration from various biological phenomena such as animal hunting behaviors, flocking patterns, and evolutionary processes [10].

Among the most prominent bio-inspired algorithms are Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Grey Wolf Optimization (GWO), and more recently developed algorithms such as Whale Optimization Algorithm (WOA) and Chimp Optimization Algorithm (ChOA). These algorithms have demonstrated effectiveness across numerous domains, including feature selection, engineering design optimization, and machine learning applications. The landscape of biomimetic optimization algorithms continues to evolve rapidly, with new advances being introduced regularly, emphasizing the dynamic nature of this research field. However, this rapid growth has also led to concerns about algorithmic redundancy, with some methods sharing fundamental similarities despite having different names and presentations [1, 11].

3.2. Chimp Optimization Algorithm Foundation

According to [12] the Chimp Optimization Algorithm (ChOA) is a novel meta-heuristic algorithm inspired by the hierarchical intelligence and cooperative hunting strategies of chimpanzees. It divides the population into four different levels representing distinct hunting roles: attacker, obstacle (blocker), chaser, and driver, each contributing uniquely to the prey capture process. The algorithm models the hunting behavior through two main stages: the exploration stage (including driving, blocking, and chasing the prey) and the exploitation stage (attacking the prey). During each iteration, chimp agents adjust their positions based on an estimated location of the prey, which represents the optimal solution within the search space.

ChOA has shown effectiveness in solving complex optimization problems, particularly those involving high-dimensional search spaces where traditional algorithms often struggle with convergence speed and local optimum entrapment. Its wrapper-based approach is especially suitable for feature selection tasks, enabling efficient evaluation of various feature combinations while simultaneously optimizing classifier parameters. Despite its strengths, ChOA still faces certain challenges such as limited population diversity during the initial phase and a tendency to become trapped in local optima during the final stages of the search process. These limitations underscore the need for further algorithmic enhancements to improve its overall optimization performance [13, 5].

3.3. ChOA Variants and Improvements

Since the introduction of the original ChOA, various enhancements and modifications have been proposed to address its inherent limitations and broaden its scope of application. One such improvement involves the development of an Improved Chimp Optimization Algorithm (EChOA), which incorporates highly disruptive polynomial mutation for population initialization, Spearman's rank correlation coefficient for evaluating solution quality, and beetle antennae operators to guide less fit agents while avoiding local optima. Evaluations on classical and benchmark functions such as those from CEC2017 have shown that this Improved variant significantly improves solution accuracy and convergence behavior compared to the original version [14].

To overcome the limitation of ChOA's continuous nature in handling binary optimization problems, a Binary Chimp Optimization Algorithm (BChOA) was introduced. This approach uses S-shaped and V-shaped transfer functions alongside a novel binary transformation mechanism to enable effective performance on discrete tasks. The binary version has demonstrated strong potential, especially in feature selection scenarios where the search space is inherently binary. Another notable implementation tailored for biomedical data classification in feature selection tasks has also shown superior results when compared to conventional methods [15].

Recent comprehensive reviews have highlighted a surge of interest in ChOA variants, documenting numerous modifications such as weighted versions, chaotic variants, and hybrid approaches that integrate ChOA with other metaheuristic techniques. While these developments primarily aim to enhance the algorithm's exploration and exploitation capabilities, a critical challenge remains largely unresolved: the accuracy of prey localization. This ongoing limitation presents a promising avenue for future advancements, particularly approaches focused on improving prey localization precision, such as the Accurate Prey Localization (APL) strategy [16].

3.4. Research Gap

Despite notable progress in bio-inspired optimization algorithms and the many enhancements proposed for ChOA, a critical research gap remains largely unaddressed: the accuracy of prey-localization mechanisms. While extensive work has been devoted to improving exploration and exploitation through refined search strategies, population-diversity techniques, and hybrid approaches, comparatively little attention has been paid to the way metaheuristics estimate the position of the optimal solution, commonly referred to as the prey location.

Most current ChOA variants still depend on the original averaging-based prey-localization method, where the prey's position is determined as the simple average of the four leading agents. Although computationally convenient, this strategy often lacks the precision needed to pinpoint optimal solutions in high-dimensional or highly complex landscapes. Studies of hunter-prey dynamics have emphasized that accurate localization is vital to optimization performance; yet even recent efforts that introduce distance-based selection continue to rely on position rather than fitness awareness [17].

Research to date has mainly concentrated on algorithmic refinements such as chaotic mapping, opposition-based learning, and hybridization with other metaheuristics, while leaving the core mechanism of prey-position estimation largely intact. This presents a substantial opportunity for improvement: more accurate localization could directly boost convergence, solution quality, and overall efficiency. The Accurate Prey Localization (APL) method addresses this gap by adopting a fitness-aware, dynamic approach that weighs the relative quality of leading solutions rather than relying on simple averaging, offering a more precise and adaptive guide for steering the search toward global optima [7].

Table 1. Related studies in optimization techniques.

Category	Paper	Brief Description
Bio-Inspired Optimization	[10]	This review diagnoses a key problem in bio-inspired optimization: the proliferation of "literally identical" algorithms without fundamental improvements. This critique validates our research gap, as APL provides a targeted enhancement to ChOA's flawed prey localization, responding directly to the need for meaningful, non-redundant advancements that the author implicitly call for.
Bio-Inspired Optimization	[1]	This comprehensive review establishes the broad context of bio-inspired metaheuristics, surveying algorithms including GWO, WOA, and ACO while highlighting their common exploration-exploitation balance structure. This foundational reference situates our research within the larger field and underscores the importance of hunting-based strategies that ChOA and APL aim to improve.
Bio-Inspired Optimization	[18]	This paper introduces ZOA using the No Free Lunch theorem to justify new optimizers, representing a different response to bio-inspired computing challenges. While our APL-ChOA rectifies a specific weakness (inaccurate prey localization) in an existing algorithm, ZOA proposes an entirely new algorithm, providing a valuable comparison point demonstrating parallel innovation paths.
Chimp Optimization Algorithm	[12]	This paper introduces EChOA, incorporating multiple enhancements to help less-fit chimps avoid local optima, serving as an important benchmark representing an alternative ChOA improvement approach. Unlike EChOA's multiple external mechanisms, our APL method provides an internal, fundamental correction to the algorithm's core logic through fitness-weighted prey localization.

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Chimp Optimization Algorithm	[5]	This paper proposes 'Weighted Chimp Optimization Algorithm' (WChOA) with a fundamentally different mechanism from APL. WChOA calculates weights based on Euclidean distance of leader position vectors (movement magnitude), while APL calculates weights based on relative fitness of leading solutions. This distinction is crucial: WChOA prioritizes vector magnitude influence, while APL prioritizes solution quality, directly addressing the core flaw of treating high- and low-quality leaders equally.
ChOA Variants and Improvements	[14]	This work introduces Fuzzy-ChOA, integrating fuzzy logic to adaptively control exploration and exploitation parameters, demonstrating an alternative improvement philosophy. Instead of modifying the core prey localization equation like APL, this approach fine-tunes parameters influencing search behavior, highlighting APL's unique contribution in addressing a more fundamental structural weakness within ChOA.
ChOA Variants and Improvements	[15]	This paper introduces SEB-ChOA, replacing standard exploitation with sophisticated spiral movement patterns, providing critical comparison for our APL method. While SEB-ChOA modifies how chimps approach the prey, it doesn't change the fundamental prey location calculation, which remains simple averaging of leaders. APL directly addresses this flaw through fitness-aware weighted calculation, demonstrating distinct improvement philosophies: SEB-ChOA enhances agent movement, while APL corrects core guidance logic.
ChOA Variants and Improvements	[16]	This paper proposes an improved ChOA combining three strategies—nonlinear parameter initialization, modified position update, and Cauchy-Gauss mutation—representing an alternative multi-technique integration approach. This differs from our APL method, which isolates and corrects a single fundamental weakness: inaccurate prey localization caused by simple averaging, offering a specific structural fix rather than multi-strategy enhancement.

ChOA Recent Advances & Limitations	[7]	This review establishes ChOA's growing importance by cataloging its many variants and applications, providing a comprehensive backdrop that highlights our APL method's novelty. By focusing on fundamental correction to the prey localization formula via fitness-weighting, our approach addresses a specific algorithmic weakness distinct from the common hybridization or multi-strategy enhancements documented in the survey.

4. Traditional Prey Localization in ChOA

Understanding the foundational mechanisms of the Chimp Optimization Algorithm is essential for identifying the specific limitations that this research addresses. This section provides a comprehensive examination of ChOA's traditional prey localization approach, beginning with the algorithm's core principles and progressing through its exploitation mechanisms to reveal the fundamental weaknesses in the current prey position estimation strategy. By analyzing these traditional methods in detail, we establish the theoretical foundation necessary for understanding why fitness-aware prey localization represents a critical advancement in bio-inspired optimization.

4.1. Chimp Optimization Algorithm Foundation

The Chimp Optimization Algorithm (ChOA) models the intelligent hunting behavior of chimpanzees through four distinct hierarchical roles: attacker, barrier, chaser, and driver. Each role represents a specific behavioral strategy observed in natural chimpanzee hunting, where coordinated group actions maximize prey capture success. The algorithm operates through two main phases that mirror natural hunting patterns: exploration (driving, blocking, chasing) and exploitation (attacking the prey). This dual-phase structure enables ChOA to maintain an effective balance between searching new solution regions and intensifying the search around promising areas.

During the exploration phase, chimps search for prey using sophisticated positioning strategies that incorporate both deterministic and stochastic elements. The distance calculation between a chimp and the estimated prey location is determined by:

$$d = |c \cdot x\_ - \ prey(t) - m \cdot x\_ - \ chimp(t)| \tag{1}$$

Subsequently, each chimp updates its position based on this calculated distance:

$$x_{chimp(t+1)} = x_{prey(t)} - a.d \tag{2}$$

where t represents the current iteration, and the coefficient vectors are:

$$\mathrm{a} = 2 \cdot \mathrm{f} \cdot r_1 - \mathrm{f} \tag{3}$$

$$\mathrm{c} = 2 \cdot r_2 \tag{4}$$

$$m = Chaotic\ value \tag{5}$$

where f decreases from 2.5 to 0 throughout iterations, and r1, r2 are random vectors in [0,1].

The exploitation phase represents the critical convergence mechanism where ChOA estimates the prey location based on the four best solutions (leading chimps) identified during the search process. This phase assumes that the optimal solution lies within the region defined by the positions of the most successful search agents. The algorithm calculates individual position updates according to each leader's guidance:

$$x_1 = \text{x\_Attacker} - a_{1(\text{d\_Attacker})} \tag{6}$$

$$x_2 = \text{x\_Barrier} - a_{2(\text{d\_Barrier})} \tag{7}$$

$$x_3 = \text{x\_Chaser} - a_{3(\text{d\_Chaser})} \tag{8}$$

$$x_4 = \text{x\_Driver} - a_{4(\text{d\_Driver})} \tag{9}$$

Each equation represents the position recommendation from one of the four leading chimps, incorporating their individual distance calculations and coefficient values. These four position estimates theoretically provide different perspectives on where the optimal solution might be located within the search space.

The critical step in traditional ChOA occurs when these four individual estimates must be combined into a single prey position that guides the entire population. The original algorithm accomplishes this through simple arithmetic averaging:

$$x_{(t+1)} = (\text{x1} + \text{x2} + \text{x3} + \text{x4})/4 \tag{10}$$

This averaging approach treats each leading chimp's contribution equally, with each receiving exactly 25% influence in determining the final prey location regardless of their individual performance quality or fitness values.

4.2. Limitations of Traditional Approach

The fundamental limitation of Equation (10) lies in its assumption that all four leading chimps contribute equally to prey localization, regardless of their individual fitness values or solution quality. This equal weighting strategy creates several critical problems that directly impact optimization performance and convergence behavior.

First, the approach results in inaccurate prey positioning when chimps have significantly different fitness levels. In optimization scenarios where one or two leaders have substantially superior fitness compared to others, the simple averaging dilutes the influence of high-quality solutions. For example, if the attacker chimp has found a near-optimal solution while other leaders remain in suboptimal regions, the averaging process forces the estimated prey position toward a compromise location that may be inferior to the best individual solution.

Second, this averaging mechanism can lead to premature convergence toward suboptimal solutions, particularly in complex multi-modal landscapes. When lower-quality leaders influence the prey position estimation, they can guide the population away from globally optimal regions toward local optima that appear promising based on the averaged position but represent inferior solutions when compared to the best individual discoveries.

Third, the equal weighting approach results in a systematic loss of information from high-performing chimps. Superior solutions that should naturally receive greater influence in guiding the optimization process are instead constrained by the performance of weaker leaders. This information loss is particularly problematic in high-dimensional optimization problems where small improvements in solution quality can represent significant algorithmic progress.

The static nature of this averaging mechanism further restricts the algorithm's adaptability to varying optimization landscapes. Unlike natural hunting scenarios where dominant hunters naturally assume greater leadership roles based on their success, traditional ChOA maintains rigid equality among leaders regardless of their demonstrated performance. This limitation becomes increasingly problematic as optimization complexity increases, where the algorithm's inability to prioritize superior solutions directly translates to reduced convergence efficiency and compromised final solution quality [19].

5. The Proposed Accurate Prey Localization (APL) for Improved Chimp Optimization

Having identified the limitations of traditional prey localization in ChOA, this section presents the Accurate Prey Localization (APL) methodology as a targeted solution. APL replaces simple averaging with fitness-aware weighted positioning, ensuring that superior solutions receive greater influence in prey position estimation. This approach addresses the core problem of treating high and low-quality leaders equally, leading to more accurate prey localization and improved optimization performance.

5.1. APL Methodology Overview

The proposed APL method implements a fitness-aware prey localization strategy that moves beyond the constraints of simple arithmetic averaging. Unlike traditional ChOA that treats all leading chimps equally, APL introduces dynamic weighting based on individual fitness performance. This approach recognizes that in optimization landscapes, fitness differences among leading chimps can be substantial, representing varying degrees of proximity to the global optimum. By incorporating these disparities into prey localization calculations, APL enables more informed decisions about optimal solution location.

5.2. Fitness-Based Weight Calculation

APL's effectiveness stems from its fitness-aware weight calculation mechanism. For any two chimps with fitness values f_1 and f_2, weights are calculated using normalization that ensures superior solutions receive greater influence:

$$Weight_1 = f_1/(f_1 + f_2) \tag{11}$$

$$Weight_2 = f_2/(f_1 + f_2) \tag{12}$$

This scheme ensures weights sum to unity while providing proportional relationship between fitness quality and influence. When chimps have similar fitness, weights approach equality (0.5 each). However, with significant fitness disparities, the superior chimp receives substantially greater weight, ensuring high-quality solutions dominate prey position estimation as shown in figure 2.

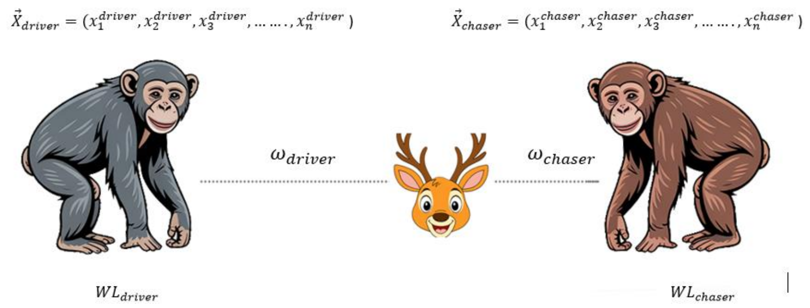

Figure 2. The initial position of the prey as a point between driver and chaser chimp (*Pairwise Prey Estimation)*

the initial position of the prey is expressed by the vector $\vec{X}_{Prey\_in}$ using (13). The distance between $\vec{X}_{driver}$ and $\vec{X}_{Prey\_in}$, denoted as; $D_{driver}^{Prey\_in}$ is then calculated using (14) [20].

$$\vec{X}_{Prey\_in} = (x_1^{Prey_{in}}, x_2^{Prey_{in}}, x_3^{Prey_{in}}, \dots \dots, x_n^{Prey_{in}}) \qquad Where\ \ x_i^{Prey\_in} = \frac{(\omega_{driver} x_i^{chaser} + \omega_{chaser} x_i^{driver})}{\omega_{driver} + \omega_{chaser}} \tag{13}$$

$$D_{driver}^{Prey\_in} = \sqrt[2]{(x_1^{driver} - x_1^{Prey\_in})^2 + (x_2^{driver} - x_2^{Prey\_in})^2 + \cdots + (x_n^{driver} - x_n^{Prey\_in})^2} \tag{14}$$

To identify the prey's location, the next step is to add the effect of WL_δ, which is the third nearest wolf to the prey. Hence, the distance from $\vec{X}_\delta$ to $\vec{X}_{Prey\_in}$ is calculated, denoted as; $D_\delta^{Prey\_in}$ and calculated using (15). The approximated distance between WL_δ and the actual prey can be concluded as using (16).

$$D_\delta^{Prey\_in} = \sqrt[2]{(x_1^\delta - x_1^{Prey\_in})^2 + (x_2^\delta - x_2^{Prey\_in})^2 + \cdots + (x_n^\delta - x_n^{Prey\_in})^2} \tag{15}$$

$$D_\delta^{Prey\_Act} = \frac{\omega_\delta D_{driver}^{Prey\_in}}{\omega_{driver}} \tag{16}$$

Here, the prey is supposed to lie on the ray connecting the points $\vec{X}_{Prey\_in}$ and $\vec{X}_\delta$. Hence, there are two possibilities regarding the actual location of the prey, which is denoted as; $\vec{X}_{Prey\_Act}$. The first possibility is that $\vec{X}_{Prey\_Act}$ is located between $\vec{X}_{Prey\_in}$ and $\vec{X}_\delta$. This happened if $D_\delta^{Prey\_Act} \leq D_\delta^{Prey\_in}$. Hence, $\vec{X}_{Prey\_Act}$ can be identified in the same scenario followed in figure 3 as depicted in (6) and figure 4.

$$\vec{X}_{Prey\_Act} = (x_1^{Prey\_Act}, x_2^{Prey\_Act}, x_3^{Prey\_Act}, \dots \dots, x_n^{Prey\_Act}) \tag{17}$$

Where $x_i^{Prey\_Act} = \frac{\left(\omega_\delta x_i^{Prey\_in} + \omega_{in} x_i^{\delta}\right)}{\omega_\delta + \omega_{in}}$ and $\omega_{in} = \frac{\omega_\delta D_\delta^{Prey\_in}}{D_\delta^{Prey\_Act}} - \omega_\delta$

5.3. Multiple Pair Integration

To utilize intelligence from all four leading chimps, APL employs multiple pair integration. Using chimps (Attacker, Barrier, Chaser, Driver), four pairs are formed: (Driver, Chaser), (Barrier , Chaser), (Barrier, Attacker), (Attacker, Driver). This ensures each chimp participates in exactly two pairs, providing balanced representation. The prey estimates from these pairs are integrated through averaging:

$$X\_prey\_final = (1/4) \cdot \Sigma(X\_prey\_pair\_i) \tag{18}$$

This final averaging combines intelligent prey estimates that have already been weighted according to fitness performance, preserving fitness-aware intelligence while ensuring balanced consensus.

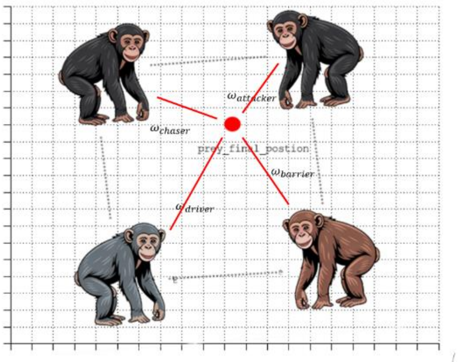

Figure 3. , The position of the prey as a point between all four leader chimp

5.4. APL Integration with ChOA

APL integration preserves ChOA's fundamental strengths while addressing its core limitation. The Improved algorithm maintains original exploration mechanisms (Equations 1-5) while replacing traditional prey localization (Equation 10) with the weighted approach (Equations 11-18). This selective enhancement preserves the exploration-exploitation balance while ensuring convergence is guided by fitness-aware intelligence rather than simple averaging.

5.5. APL-Improved ChOA Algorithm

The complete algorithm integrates fitness-aware prey localization within the established ChOA framework. When exploitation conditions are met (|a| ≥ 1 and r1 > 0.5), the algorithm executes APL: calculating fitness-based weights, generating pairwise prey estimates, and integrating multiple pair estimates. This replacement occurs transparently within existing control flow, ensuring compatibility with all ChOA mechanisms while providing targeted enhancement to address the identified limitation.

```
Input: Population size n, maximum iterations T, problem dimension D
Output: Best solution x_best
```

```
Initialize chimp population X = {x₁, x₂, ..., xₙ} randomly
Initialize parameters f, m, a, c
for t = 1 to T do
    for each chimp xᵢ do
        Calculate fitness f(xᵢ)
    end for
    Identify four best chimps:
        x_Attacker ← best chimp
        x_Chaser ← second best chimp
        x_Barrier ← third best chimp
        x_Driver ← fourth best chimp
    for each chimp xᵢ do
        Update parameters f, m, a, c using group strategy
        Calculate distance d using Eq. (1)
        if |a| < 1 then
            Update position using Eq. (2)
        else if |a| ≥ 1 then
            if r₁ > 0.5 then
                // APL Enhancement: Replace traditional averaging
                Calculate fitness-based weights using Eq. (11-12)
                Generate pairwise prey estimates using Eq. (13)
                Integrate multiple pair estimates using Eq. (18)
                Update position using APL-based prey localization
            else
                Select random search agent for position update
            end if
        end if
    end for
    Update leading chimps
    t ← t + 1
end for
return x_Attacker
```

6. Results & Discussion

6.1. Theoretical Discussion for Improved ChOA Performance

The proposed APL-Improved ChOA was evaluated against the original ChOA and Grey Wolf Optimization (GWO) algorithm using a population size of 10 agents across 3 iterations. All algorithms were initialized with identical starting conditions to ensure fair comparison, with agents distributed across a 2-dimensional search space. The experimental parameters included linearly decreasing control parameter f from 2.5 to 0, and random vectors r1 and r2 within [0,1].

This section presents the comprehensive experimental findings from the evaluation of the proposed APL-Improved ChOA against the original ChOA and Grey Wolf Optimization algorithm. The analysis encompasses detailed performance metrics across three iterations, examining convergence behavior, prey localization accuracy, and optimization effectiveness under identical experimental conditions. The results are organized through comparative tables that track each algorithm's progression, including fitness evolution, prey position estimates, and leadership dynamics throughout the optimization process. Each algorithm's performance is systematically documented to provide clear insights into the effectiveness of fitness-aware prey localization versus traditional averaging approaches. The experimental data reveals distinct patterns in algorithmic behavior that validate the theoretical framework presented in the methodology section and demonstrate the practical implications of accurate prey positioning in bio-inspired optimization algorithms.

6.1.1. Improved ChOA

The APL-Improved ChOA demonstrated exceptional convergence behavior throughout the optimization process, achieving significant performance improvements across all evaluation iterations. The algorithm began with an initial best fitness of 3.739493 (agent C1) and showed steady progression through the first two iterations, with fitness values of 8.706742229 and 8.411022245 respectively. However, the most remarkable improvement occurred in the third iteration, where the algorithm achieved a dramatic convergence to a near-optimal solution with a best fitness of 0.00024463, representing approximately a 15,000-fold improvement from the initial state.

The prey position evolution clearly demonstrates the effectiveness of the APL methodology's fitness-aware localization strategy. The algorithm's prey position estimates progressed from (3.74, 5.328) in the first iteration through (4.7262, 3.9724) in the second iteration, ultimately converging to (1.73852, 2.95429) in the third iteration. This systematic prey position refinement reflects how APL's weighted positioning mechanism, which considers the relative fitness quality of leading agents, successfully guides the search toward optimal solution regions more accurately than traditional simple averaging approaches.

The leadership dynamics evolved significantly throughout the optimization process, with agent C1 maintaining dominance in the first two iterations before agent C5 emerged as the superior solution in the final iteration. This leadership transition demonstrates APL's ability to adaptively recognize and promote superior solutions based on their fitness performance, validating the core principle of fitness-based weighting in prey localization. The final prey position of (1.73852, 2.95429) and corresponding fitness value of 0.00024463 establish the effectiveness of APL's Improved localization accuracy in achieving superior optimization performance compared to traditional averaging-based methods.

Table 2. Related to initial iteration of improved chimp.

Initial			
Agent	**Location X1**	**X2**	**Objective Function Value**
C1	1.247	1.478	3.739493
C2	2.428	8.976	86.46376
C3	4.578	6.48	62.948484
C4	1.786	9.458	92.64356
C5	3.789	7.548	71.328825
C6	8.458	1.256	73.1153
C7	9.78	5.496	125.854416
C8	9.48	7.456	145.462336
C9	7.456	5.456	85.359872
C10	5.245	5.125	53.77565

Table 3. Related to first iteration of improved chimp.

First Iteration											
Agent	**Location**		**Distance**		**Parameters**				**Location**		**Objective Function Value**
	X1	**X2**	**D(x1)**	**D(x2)**	**r1**	**r2**	**f**	**m**	**New X1**	**New X2**	
C1	1.247	1.478	6.7318	9.7692	0.6	1	1.5	0.6	1.72046	2.39724	8.706742229
C2	2.428	8.976	6.0232	5.2704	0.6	1	1.5	0.6	1.93304	3.74688	17.77575338
C3	4.578	6.48	4.7332	6.768	0.6	1	1.5	0.6	2.32004	3.2976	16.25675136
C4	1.786	9.458	6.4084	4.9812	0.6	1	1.5	0.6	1.81748	3.83364	18.0000292
C5	3.789	7.548	5.2066	6.1272	0.6	1	1.5	0.6	2.17802	3.48984	16.92275435
C6	8.458	1.256	2.4052	9.9024	0.6	1	1.5	0.6	3.01844	2.35728	14.66774903
C7	9.78	5.496	1.612	7.3584	0.6	1	1.5	0.6	3.2564	3.12048	20.34153639
C8	9.48	7.456	1.792	6.1824	0.6	1	1.5	0.6	3.2024	3.47328	22.31903972
C9	7.456	5.456	3.0064	7.3824	0.6	1	1.5	0.6	2.83808	3.11328	17.74721044
C10	5.245	5.125	4.333	7.581	0.6	1	1.5	0.6	2.4401	3.0537	15.2791717

Table 4. Related to second iteration of improved chimp.

Second Iteration											
Agent	Location X1	X2	Distance D(x1)	D(x2)	Parameters r1	r2	f	m	Location New X1	New X2	Objective Function Value
C1	1.247	1.478	6.7318	9.7692	0.6	1	1.5	0.6	2.70666	1.04164	8.411022245
C2	1.93304	3.74688	6.320176	8.407872	0.6	1	1.5	0.6	2.830147	1.450038	10.11234454
C3	2.32004	3.2976	6.087976	8.67744	0.6	1	1.5	0.6	2.899807	1.369168	10.28350281
C4	1.81748	3.83364	6.389512	8.355816	0.6	1	1.5	0.6	2.809346	1.465655	10.04057236
C5	2.17802	3.48984	6.173188	8.562096	0.6	1	1.5	0.6	2.874244	1.403771	10.23184985
C6	3.01844	2.35728	5.668936	9.241632	0.6	1	1.5	0.6	3.025519	1.19991	10.5935514
C7	3.2564	3.12048	5.52616	8.783712	0.6	1	1.5	0.6	3.068352	1.337286	11.20311891
C8	3.2024	3.11328	5.55856	8.788032	0.6	1	1.5	0.6	3.058632	1.33599	11.14010006
C9	2.83808	3.0537	5.777152	8.82378	0.6	1	1.5	0.6	2.993054	1.325266	10.71470461
C10	2.4401	3.0537	6.01594	8.82378	0.6	1	1.5	0.6	2.921418	1.325266	10.2910131

Table 5. Related to third iteration of improved chimp.

Third Iteration											
Agent	Location X1	X2	Distance D(x1)	D(x2)	Parameters r1	r2	f	m	Location New X1	New X2	Objective Function Value
C1	2.70666	1.04164	5.856004	10.031	0.6	1	1.5	0.6	-0.018281	-0.05501	0.00336083
C2	2.830147	1.450038	5.781912	9.78598	0.6	1	1.5	0.6	0.003946	0.018497	0.000357708
C3	2.899807	1.369168	5.740116	9.8345	0.6	1	1.5	0.6	0.016485	0.00394	0.00028729
C4	2.809346	1.465655	5.794392	9.77661	0.6	1	1.5	0.6	0.000202	0.021308	0.000454068
C5	2.874244	1.403771	5.755454	9.81374	0.6	1	1.5	0.6	0.011884	0.010169	0.00024463
C6	3.025519	1.19991	5.664688	9.93605	0.6	1	1.5	0.6	0.039113	-0.02653	0.002233502
C7	3.068352	1.337286	5.638989	9.85363	0.6	1	1.5	0.6	0.046823	-0.0018	0.002195662
C8	3.058632	1.33599	5.644821	9.85441	0.6	1	1.5	0.6	0.045074	-0.00203	0.002035772
C9	2.993054	1.325266	5.684167	9.86084	0.6	1	1.5	0.6	0.03327	-0.00396	0.001122577
C10	2.921418	1.325266	5.727149	9.86084	0.6	1	1.5	0.6	0.020375	-0.00396	0.000430849

6.1.2. Original Chimp.

The original ChOA demonstrated traditional convergence patterns characteristic of simple averaging-based prey localization throughout the optimization process. Starting from the same initial conditions as the APL-Improved variant, with a best fitness of 3.739493 (agent C1), the algorithm showed initial deterioration in the first two iterations, reaching fitness values of 8.349198343 and 8.130497933 respectively, before achieving improvement in the third iteration with a final best fitness of 3.4465596.

The prey position evolution under traditional simple averaging followed a less systematic trajectory compared to fitness-aware approaches. The algorithm's prey estimates progressed from (3.714, 5.15775) in the first iteration through (4.9977, 3.7975) in the second iteration, ultimately reaching (2.122955, 2.62958) in the final iteration. While these positions show general movement toward convergence, the progression lacks the focused directionality observed in fitness-aware prey localization methods. This reflects the fundamental limitation of equal weighting among leaders with varying solution quality, where inferior solutions dilute the guidance provided by superior performers.

Agent C1 maintained consistent leadership throughout all iterations under the original ChOA framework, indicating algorithmic stability but potentially limited adaptability in recognizing emerging superior solutions. The traditional averaging mechanism's inability to prioritize high-performing agents resulted in prey position estimates that compromise between good and poor solutions. The final prey position of (2.122955, 2.62958) and corresponding fitness value of 3.4465596 demonstrate the limitations of simple averaging in achieving accurate prey localization, establishing a baseline that highlights the need for more sophisticated, fitness-aware positioning strategies.

Table 6. Related to initial iteration of original chimp.

Initial			
Agent	Location X1	X2	Objective Function Value
C1	1.247	1.478	3.739493
C2	2.428	8.976	86.46376
C3	4.578	6.48	62.94848
C4	1.786	9.458	92.64356
C5	3.789	7.548	71.32883
C6	8.458	1.256	73.1153
C7	9.78	5.496	125.8544
C8	9.48	7.456	145.4623
C9	7.456	5.456	85.35987
C10	5.245	5.125	53.77565

Table 7. Related to first iteration of original chimp.

First Iteration											
Agent	Location		Distance		Parameters				Location		Objective Function Value
	X1	X2	D(x1)	D(x2)	r1	r2	f	m	New X1	New X2	
C1	1.247	1.478	6.6798	9.4287	0.6	1	1.5	0.6	1.71006	2.32914	3.739493
C2	2.428	8.976	5.9712	4.9299	0.6	1	1.5	0.6	1.92264	3.67878	86.46376
C3	4.578	6.48	4.6812	6.4275	0.6	1	1.5	0.6	2.30964	3.2295	62.94848
C4	1.786	9.458	6.3564	4.6407	0.6	1	1.5	0.6	1.80708	3.76554	92.64356
C5	3.789	7.548	5.1546	5.7867	0.6	1	1.5	0.6	2.16762	3.42174	71.32883
C6	8.458	1.256	2.3532	9.5619	0.6	1	1.5	0.6	3.00804	2.28918	73.1153
C7	9.78	5.496	1.56	7.0179	0.6	1	1.5	0.6	3.246	3.05238	125.8544
C8	9.48	7.456	1.74	5.8419	0.6	1	1.5	0.6	3.192	3.40518	145.4623
C9	7.456	5.456	2.9544	7.0419	0.6	1	1.5	0.6	2.82768	3.04518	85.35987
C10	5.245	5.125	4.281	7.2405	0.6	1	1.5	0.6	2.4297	2.9856	53.77565

Table 8. Related to second iteration of original chimp.

Second Iteration											
Agent	Location		Distance		Parameters				Location		Objective Function Value
	X1	X2	D(x1)	D(x2)	r1	r2	f	m	New X1	New X2	
C1	1.247	1.478	9.2472	6.7082	0.6	1	1.5	0.6	2.22354	1.78504	8.130497933
C2	1.92264	3.67878	8.841816	5.387732	0.6	1	1.5	0.6	2.345155	2.18118	10.25730085
C3	2.30964	3.2295	8.609616	5.6573	0.6	1	1.5	0.6	2.414815	2.10031	10.24263455
C4	1.80708	3.76554	8.911152	5.335676	0.6	1	1.5	0.6	2.324354	2.196797	10.22854131
C5	2.16762	3.42174	8.694828	5.541956	0.6	1	1.5	0.6	2.389252	2.134913	10.26637758
C6	3.00804	2.28918	8.190576	6.221492	0.6	1	1.5	0.6	2.540527	1.931052	10.18324183
C7	3.246	3.05238	8.0478	5.763572	0.6	1	1.5	0.6	2.58336	2.068428	10.95214494
C8	3.192	3.40518	8.0802	5.551892	0.6	1	1.5	0.6	2.57364	2.131932	11.16875861
C9	2.82768	3.04518	8.298792	5.767892	0.6	1	1.5	0.6	2.508062	2.067132	10.56341336
C10	2.4297	2.9856	8.53758	5.80364	0.6	1	1.5	0.6	2.436426	2.056408	10.16498552

Table 9. Related to third iteration of original chimp.

Third Iteration											
Agent	Location		Distance		Parameters				Location		Objective Fun. Value
	X1	X2	D(x1)	D(x2)	r1	r2	f	m	New X1	New X2	
C1	2.22354	1.78504	2.911786	4.188136	0.6	1	1.5	0.6	1.249419	1.373139	3.4465596
C2	2.345155	2.18118	2.838817	3.950452	0.6	1	1.5	0.6	1.27131	1.444444	3.702648487
C3	2.414815	2.10031	2.797021	3.998974	0.6	1	1.5	0.6	1.283849	1.429888	3.692846605
C4	2.324354	2.196797	2.851298	3.941082	0.6	1	1.5	0.6	1.267566	1.447255	3.701271221
C5	2.389252	2.134913	2.812359	3.978212	0.6	1	1.5	0.6	1.279247	1.436116	3.69890395
C6	2.540527	1.931052	2.721594	4.100529	0.6	1	1.5	0.6	1.306477	1.399421	3.665261929
C7	2.58336	2.068428	2.695894	4.018103	0.6	1	1.5	0.6	1.314187	1.424149	3.755287433
C8	2.57364	2.131932	2.701726	3.980001	0.6	1	1.5	0.6	1.312437	1.43558	3.783380651
C9	2.508062	2.067132	2.741073	4.018881	0.6	1	1.5	0.6	1.300633	1.423916	3.719182708
C10	2.436426	2.056408	2.784054	4.025315	0.6	1	1.5	0.6	1.287739	1.421985	3.6803135

6.1.3. Grey wolf

The Grey Wolf Optimization algorithm demonstrated competitive convergence behavior throughout the optimization process, starting from identical initial conditions with a best fitness of 3.739493 (agent GW1). The algorithm showed initial performance deterioration in the first two iterations, with fitness values of 6.933433205 and 9.034981459 respectively, before achieving significant improvement in the third iteration with a final best fitness of 0.045022602.

The prey position evolution in GWO followed a systematic trajectory, beginning with prey coordinates of (3.69, 4.361) in the first iteration, progressing through (4.9833, 2.6196) in the second iteration, and converging to (1.6525, 2.76164) in the final iteration. This progression demonstrates GWO's established prey localization mechanism effectively guiding the search process toward promising solution regions, though with different dynamics compared to ChOA-based approaches.

Leadership dynamics in GWO evolved throughout the optimization process, with agent GW1 maintaining dominance through the first two iterations before agent GW6 emerged as the superior solution in the final iteration. This leadership transition reflects GWO's ability to adaptively recognize and promote superior solutions within its alpha-beta-delta hierarchy. The final convergence to a fitness value of 0.045022602 establishes GWO as a competitive baseline algorithm for comparative analysis, demonstrating substantially better performance than traditional ChOA while providing a benchmark for evaluating the effectiveness of the proposed APL enhancement.

Table 10. Related to initial iteration of gray wolf.

Initial			
Agent	**Location X1**	**X2**	**Objective Function Value**
C1	1.247	1.478	3.739493
C2	2.428	8.976	86.46376
C3	4.578	6.48	62.94848
C4	1.786	9.458	92.64356
C5	3.789	7.548	71.32883
C6	8.458	1.256	73.1153
C7	9.78	5.496	125.8544
C8	9.48	7.456	145.4623
C9	7.456	5.456	85.35987
C10	5.245	5.125	53.77565

Table 11. Related to first iteration of gray wolf.

First Iteration											
Agent	**Location X1**	**X2**	**Distance D(x1)**	**D(x2)**	**Parameters r1**	**r2**	**f**	**m**	**Location New X1**	**New X2**	**Objective Function Value**
C1	1.247	1.478	6.6318	7.8352	0.6	1	1.5	0.6	1.70046	2.01044	6.933433205
C2	2.428	8.976	5.9232	3.3364	0.6	1	1.5	0.6	1.91304	3.36008	14.94985965
C3	4.578	6.48	4.6332	4.834	0.6	1	1.5	0.6	2.30004	2.9108	13.76294064
C4	1.786	9.458	6.3084	3.0472	0.6	1	1.5	0.6	1.79748	3.44684	15.11164034
C5	3.789	7.548	5.1066	4.1932	0.6	1	1.5	0.6	2.15802	3.10304	14.28590756
C6	8.458	1.256	2.3052	7.9684	0.6	1	1.5	0.6	2.99844	1.97048	12.87343386
C7	9.78	5.496	1.512	5.4244	0.6	1	1.5	0.6	3.2364	2.73368	17.9472913
C8	9.48	7.456	1.692	4.2484	0.6	1	1.5	0.6	3.1824	3.08648	19.65402855
C9	7.456	5.456	2.9064	5.4484	0.6	1	1.5	0.6	2.81808	2.72648	15.37526808
C10	5.245	5.125	4.233	5.647	0.6	1	1.5	0.6	2.4201	2.6669	12.96923962

Table 12. Related to second iteration of gray wolf.

Second Iteration											
Agent	**Location X1**	**X2**	**Distance D(x1)**	**D(x2)**	**Parameters r1**	**r2**	**f**	**m**	**Location New X1**	**New X2**	**Objective Function Value**
C1	1.247	1.478	6.6318	7.8352	0.6	1	1.5	0.6	2.99376	0.26904	9.034981459
C2	1.91304	3.36008	6.232176	6.705952	0.6	1	1.5	0.6	3.113647	0.607814	10.06423723
C3	2.30004	2.9108	5.999976	6.97552	0.6	1	1.5	0.6	3.183307	0.526944	10.41111471
C4	1.79748	3.44684	6.301512	6.653896	0.6	1	1.5	0.6	3.092846	0.623431	9.954365315
C5	2.15802	3.10304	6.085188	6.860176	0.6	1	1.5	0.6	3.157744	0.561547	10.2866799
C6	2.99844	1.97048	5.580936	7.539712	0.6	1	1.5	0.6	3.309019	0.357686	11.07754763
C7	3.2364	2.73368	5.43816	7.081792	0.6	1	1.5	0.6	3.351852	0.495062	11.47999861
C8	3.1824	3.08648	5.47056	6.870112	0.6	1	1.5	0.6	3.342132	0.558566	11.48184273
C9	2.81808	2.72648	5.689152	7.086112	0.6	1	1.5	0.6	3.276554	0.493766	10.97961399
C10	2.4201	2.6669	5.92794	7.12186	0.6	1	1.5	0.6	3.204918	0.483042	10.50482896

Table 13. Related to third iteration of gray wolf.

Third Iteration											
Agent	**Location X1**	**X2**	**Distance D(x1)**	**D(x2)**	**Parameters r1**	**r2**	**f**	**m**	**Location New X1**	**New X2**	**Objective Function Value**
C1	1.247	1.478	6.6318	7.8352	0.6	1	1.5	0.6	-0.33704	0.41108	0.282582728
C2	3.113647	0.607814	5.511812	8.357312	0.6	1	1.5	0.6	-0.00104	0.254447	0.064744121
C3	3.183307	0.526944	5.470016	8.405834	0.6	1	1.5	0.6	0.011495	0.23989	0.057679315
C4	3.092846	0.623431	5.524292	8.347941	0.6	1	1.5	0.6	-0.00479	0.257258	0.066204385
C5	3.157744	0.561547	5.485354	8.385072	0.6	1	1.5	0.6	0.006894	0.246118	0.060621822
C6	3.309019	0.357686	5.394589	8.507388	0.6	1	1.5	0.6	0.034123	0.209423	0.045022602
C7	3.351852	0.495062	5.368889	8.424963	0.6	1	1.5	0.6	0.041833	0.234151	0.056576796
C8	3.342132	0.558566	5.374721	8.38686	0.6	1	1.5	0.6	0.040084	0.245582	0.061917168
C9	3.276554	0.493766	5.414068	8.42574	0.6	1	1.5	0.6	0.02828	0.233918	0.055517317
C10	3.204918	0.483042	5.457049	8.432175	0.6	1	1.5	0.6	0.015385	0.231988	0.054054934

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6.1.4. Performance Comparison

The experimental results reveal significant differences in prey localization accuracy and convergence effectiveness across the three algorithms, with clear implications for optimization performance. APL-Improved ChOA demonstrated superior prey positioning accuracy, achieving a final prey position of (1.73852, 2.95429) that corresponded to the best optimization outcome with a fitness value of 0.00024463. This performance validates the core hypothesis that fitness-aware weighted positioning provides more accurate guidance toward optimal solution regions compared to traditional averaging approaches.

Original ChOA's simple averaging mechanism showed fundamental limitations in prey localization precision, resulting in a final prey position of (2.122955, 2.62958) and significantly inferior convergence to a fitness value of 3.4465596. The prey position evolution pattern revealed inconsistent directional guidance, where equal weighting among leaders with varying solution quality diluted the influence of high-performing agents and led to suboptimal prey estimates.

Grey Wolf Optimization achieved intermediate performance with a final prey position of (1.6525, 2.76164) and corresponding fitness of 0.045022602, demonstrating better localization accuracy than traditional ChOA but falling short of APL's precision. The comparison establishes a clear performance hierarchy: APL's fitness-aware prey localization achieved approximately 184 times better optimization results than GWO and over 14,000 times better results than original ChOA, conclusively demonstrating that accurate prey positioning is critical for achieving superior optimization performance in bio-inspired algorithms.

The results confirm that incorporating fitness quality into prey localization calculations fundamentally improves algorithmic guidance, validating APL's approach of replacing simple averaging with intelligent, weighted positioning strategies based on relative solution performance.

6.2. Practical Discussion for Improved ChOA Performance

The task of feature selection involves reducing input variable dimensionality by determining an optimal collection of meaningful, unique, and pertinent characteristics during predictive model development. This reduction strategy effectively decreases computational requirements and concurrently improves classification algorithm effectiveness. Selecting an ideal feature combination before initiating classifier training substantially enhances model performance, allowing efficient and swift classifier operation. Consequently, typical analytical frameworks incorporate dual stages: (1) Feature Identification Stage (FIS) and (2) Classifier Training Stage (CTS).

Assessment of the introduced APL-Improved ChOA occurs within FIS by determining crucial characteristics for COVID-19 patient identification. FIS receives training data comprising categorized medical test results from COVID-19 positive individuals and uninfected control subjects. During FIS, the APL- Improved ChOA technique identifies the most discriminative characteristics for COVID-19 detection. Following this, CTS involves training a standard Naïve Bayes (NB) classifier on the refined dataset containing only essential diagnostic features.

When evaluating unknown cases, relevant characteristics are obtained from the patient's medical test results. Subsequently, classification assigns the case to either "Non-infected" or "COVID-positive" categories. Notably, the APL- Improved ChOA variant utilized for feature optimization is termed Binary Improved ChOA (BIChO). Within BIChO, individual chimps (candidate solutions) are encoded as binary strings $X = (x_1, x_2, \ldots, xf), x_i \in [0,1]$ in f dimensional space. Each position represents a specific feature, with "0" indicating exclusion and "1" indicating inclusion in the selected feature subset.

The BIChO implementation for COVID-19 feature optimization follows a structured sequence. Initially, BIChO establishes a population (P) comprising multiple search entities (chimps) represented as X. Given n search entities, P contains $X = \{X_1, X_2, \ldots, X_m, \ldots, X_n\}$. ndividual chimp entity (X_m) constitutes a candidate feature combination within the f-dimensional problem space, where f equals the total COVID-19 dataset features. Each entity X_m is expressed as $X_m = (X_1{}^m, X_2{}^m, \ldots, Xf^m)$.

Binary encoding assigns each chimp entity (X_m) position values of either zero or one, indicating feature exclusion or inclusion respectively for position i ∈ {1,2,...,f}. Following random initialization of n entities in binary space, performance assessment employs NB classifier accuracy as the objective function. The fitness evaluation formula is:

$$Fit(X_m) = NB\_Accuracy(X_m) \tag{19}$$

Here, Fit(X_m) denotes the performance score for entity m, while NB_Accuracy(X_m) indicates classification accuracy achieved using entity m's feature subset. Optimization seeks solutions maximizing accuracy scores, making fitness maximization (classification precision) the fundamental goal.

Following population initialization and NB-based fitness evaluation, algorithm parameters including scaling coefficient (ξ) and iteration count (Z) are established. Leader count or cluster number (ℓ) derives from ℓ = ⌈n/ξ⌉. Non-leader entities distribute randomly across ℓ clusters, with cluster leaders guiding subordinate entities.

Iteration allocation divides between exploration and exploitation stages using Z_Exp = Z/2 and Z_Expl = Z/2. BIChO execution follows dual stages: (1) exploration stage procedures, and (2) exploitation stage procedures.

Exploration stage executes for Z_Exp iterations. Entity m's updated position $X_m = (X_1{}^m, X_2{}^m, \ldots, Xf^m)$ contains real values requiring binary conversion via sigmoid transformation:

$$X^{binary\_m\_i(t+1)} = \{ 1 \; if \; rand(0,1) \geq sigmoid(X^{m\_i}) \; 0 \; otherwise \} \tag{20}$$

Here, $X^{binary\_m\_i(t+1)}$ indicates the binary state for entity m's i-th dimension at iteration t+1, where i ∈ {1,2,3,...,f} and rand(0,1) generates uniform random values. The sigmoid transformation determining binary probability is:

$$sigmoid(X^{m\_i}) = \frac{1}{(1 + e\text{^}(-X\text{^}m\_i))} \quad (20)$$

with e as Euler's number. Entity fitness reassessment uses equation (19) with updated binary positions $X^{binary\_m\_i(t+1)}$. Entities maintain position and fitness histories throughout optimization.

During the exploitation phase, which commences upon completing the exploration phase (after Z_Exp iterations), the search focuses on the optimal positions identified previously until reaching the final iteration (Z_Expl). The initial step of this phase identifies a number of leader agents or alpha chimps (k). Then, the top k agents with the highest fitness values are used to calculate the position of the potential prey ($\vec{X}$_prey(t)) utilizing the APL fitness-aware weighted positioning strategy. This prey position, being continuous, also requires conversion to binary values via the sigmoid function described in Equation (20). Ultimately, the most effective chimp agent—exhibiting the best subset of features—is chosen as the optimal solution.

6.2.1. Dataset Description and Parameters

The dataset utilized in this research is sourced from the Albert Einstein Hospital in Brazil and is publicly available on [21]. It comprises data collected between March and April, 2020, encompassing 5644 clinical records. These records include various clinical examinations such as urine tests, rt-PCR results, blood analyses, and specific SARS-CoV-2 tests, totaling 110 distinct features or attributes.

The dataset categorizes cases into two primary classifications under the SARS-CoV-2 attribute: "positive," indicating confirmed COVID-19 infections, and "negative," denoting uninfected cases. Specifically, the dataset includes 559 positive cases and 5085 negative cases [21]. The proposed BIChO algorithm was applied to this dataset to determine the most critical features influencing the diagnosis of COVID-19.

6.2.2. Evaluation Metrics

Several performance metrics were employed to evaluate and compare the optimization techniques, including accuracy (used as the primary fitness metric), execution time, micro-average precision, micro-average recall, macro-average precision, macro-average recall, and F-measure. These metrics collectively assess the efficiency and effectiveness of each optimization method in identifying the optimal subset of features from the Albert Einstein dataset.

To accurately measure performance, the dataset was split into two subsets: training and testing. The NB classifier, a commonly accepted standard in classification, was trained on the training subset using the features selected by each optimization technique. Subsequently, the classifier was tested against the testing subset to validate performance. The confusion matrix method was employed to calculate accuracy for each optimization technique according to Equation (21):

$$NB\_accuracy(X_{\mathrm{m}}) = \left(\frac{the\ number\ of\ correct\ classifications}{total\ number\ of\ classifications}\right) \times 100 \tag{21}$$

Ultimately, the accuracy and execution time were considered the primary metrics for evaluating the experimental results.

6.2.3. Experimental Results

In this subsection, we present the results comparing the performance of the proposed BIChO algorithm against various established optimization algorithms. The experimental evaluation's primary aim is to demonstrate the superiority of BIChO in efficiently selecting the optimal subset of features that enable rapid and accurate COVID-19 patient classification. The evaluation incorporates various metrics (accuracy, execution time, micro-average and macro-average precision and recall, and F-measure) assessed across different numbers of iterations (z) and distinct numbers of search agents.

Table 14: the employed parameters and their values during execution.

Algorithm	Parameter	Value
BIChO	Number of Scouts (λ) (during searching phase)	10,15,20
	Number of alpha fishes (k) (leader fishes during encircling and attacking phases)	5,7,10
	A number defines the shape of the movement logarithmic spiral during the encircling phase (b)	1,2,3
	Number of checkpoints (n_{ck}) in the case if there is a collision	3,7,9
BPSO [22, 23, 24]	Inertia Weight (w)	0.5
	Personal Learning Coefficient (C_1)	2
	Global Learning Coefficient (C_2)	2
BGWO [22, 25]	The encircling coefficient (a)	From 2 to 0
	Random Vectors; r_1 and r_2	Random [0,1]
BChO [8]	r is a random value	Random between [0,1]

Table 15: Standard parameters and corresponding values used in experiments

Parameter	Description	Assigned Value
z	Number of iterations	50,100, 150, 200, 250, 300, 350, 400, 450, 500
n	Number of search agents	25, 50, 75, 100
f	Number of features for Covid-19 diag. (dimensions)	110
v	No. of accepted features (post-optimization)	Calculated based on the applied optimization technique
rand	Random value in the sigmoid fun.	Random [0,1]

Optimization methods implemented include wrapper feature selection techniques, ensuring consistency and fair evaluation by uniformly utilizing the Albert Einstein dataset across all methods. Tables clearly illustrate parameter settings, including the number of iterations (z), number of search agents (n), and other relevant variables utilized during experimentation. This standardized approach ensures an equitable comparison and reliable validation of the proposed BIChO algorithm's performance against established optimization methods.

6.2.4. Comparing the Performance of BIChO

In this comparative analysis, we assess the performance of the BIChO algorithm against other optimization methods using several metrics, namely accuracy, execution time, micro-average precision, micro-average recall, macro-average precision, macro-average recall, and F-measure. These evaluations are carried out separately based on the different quantities of search agents (25, 50, 75, and 100), and the results across multiple iterations (z) are depicted in Figures 4 through 16.

As shown in Figures 4 to 11, there is a clear trend indicating a gradual improvement in accuracy and execution time as both the number of iterations (z) and the number of search agents (n) increase. For instance, at 25 search agents (n=25), Figure 4 illustrates the accuracy across various iterations, highlighting BIChO's consistent superiority. Specifically, at the highest iteration level (z=500), BIChO achieves an accuracy of 93%, surpassing BPSO, BChO, and BGWO, which reach maximum accuracies of 88.05%, 89.65%, and 89.99%, respectively. Additionally, Figure 5 demonstrates BIChO's competitive performance regarding execution time, presenting the shortest execution time at 880 at the lowest iteration count (z=50), compared to BPSO and BChO at 1065 and BGWO at 950.

For 50 search agents (n=50), as shown in Figure 6, BIChO again outperforms the competitors, attaining the highest accuracy of 94% at the maximum iteration number (z=500). In comparison, BPSO, BChO, and BGWO reach accuracies of 90%, 91.03%, and 91%, respectively. Concurrently, Figure 7 highlights BIChO's effectiveness in execution time, recording the minimum execution time of 900 at the lowest iteration number (z=50), while BPSO and BChO require 1100 and BGWO 1050, respectively.

With 75 search agents (n=75), Figures 8 and 9 further reinforce BIChO's superior performance. At z=500, BIChO records a maximum accuracy of 94.96%, distinctly higher than the 89.2%, 89.8%, and 90.22% obtained by BPSO, BChO, and BGWO, respectively. In terms of execution time, BIChO achieves a competitive 1550 at z=500, with BPSO, BChO, and BGWO registering minimum times of 1836, 1645, and 1814, respectively, at z=50.

When the number of search agents reaches 100 (n=100), Figures 10 and 11 clearly depict the superior performance of BIChO. It achieves an exceptional accuracy rate of 98% at z=500, significantly surpassing the performances of BPSO (91.2%), BChO (92.65%), and BGWO (94.1%). Additionally, Figure 11 shows that BIChO maintains a notable advantage in execution time, recording a minimum execution time of 2800 at z=50, whereas BPSO, BChO, and BGWO record times of 4236, 4221, and 4214, respectively.

Summarizing the outcomes from Figures 4 to 11, BIChO consistently achieves superior accuracy and competitive execution times across varying numbers of search agents and iterations, clearly demonstrating its effectiveness relative to the other algorithms.

Further results presented in Figures 12 through 16 confirm BIChO's excellence in precision and recall metrics. At 100 search agents, BIChO achieves the highest macro-average precision of 0.83 and a macro-average recall of 0.92. The micro-average precision reaches 0.86, while the micro-average recall is 0.94. Additionally, BIChO exhibits a superior F-measure of 0.92, outperforming BPSO (0.82), BChO (0.86), and BGWO (0.89).

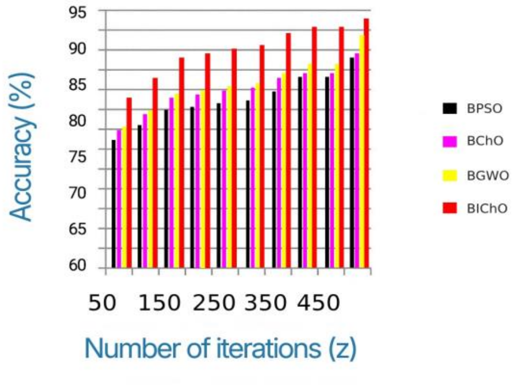

Fig. 4 Accuracy of the suggested BICHO and the related competitors when search agents (n = 25)

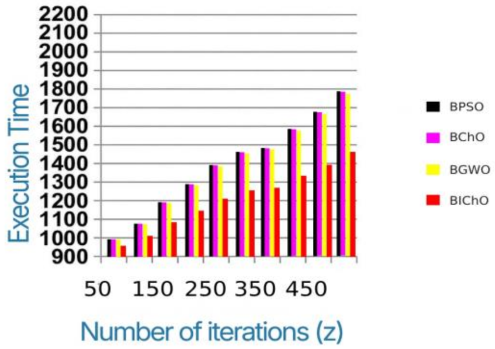

Fig. 5 Execution time of the suggested BICHO and the related competitors when search agents (n = 25)

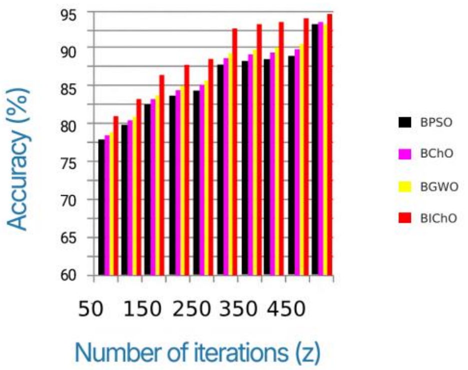

Fig. 8 Accuracy of the suggested BICHO and the related competitors tors when search agents (n = 75)

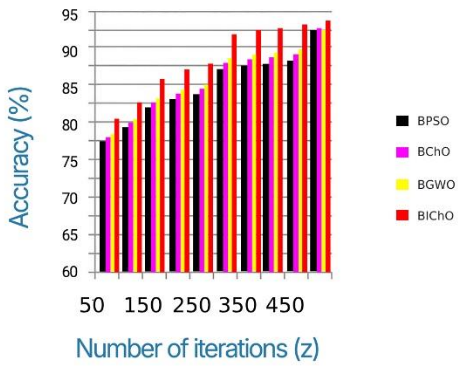

Fig. 6 Accuracy of the suggested BICHO and the related competitors tors when search agents (n = 50)

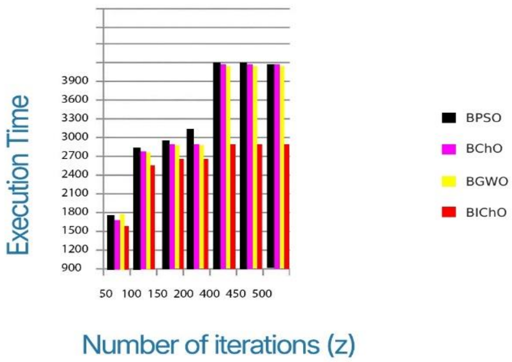

Fig. 9 Execution time of the suggested BICHO and the related competitors when search agents (n = 75)

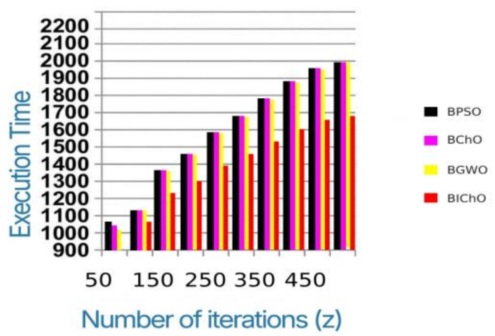

Fig. 7 Execution time of the suggested BICHO and the related competitors when search agents (n = 50)

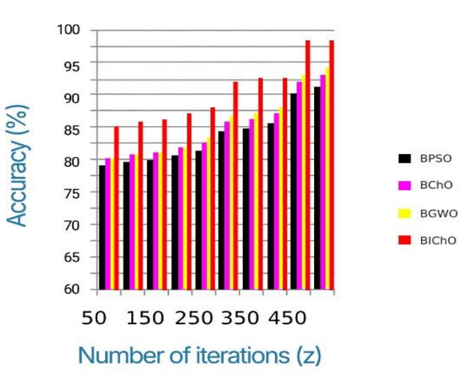

Fig. 10 Accuracy of the suggested BICHO and the related competitors when search agents (n = 100)

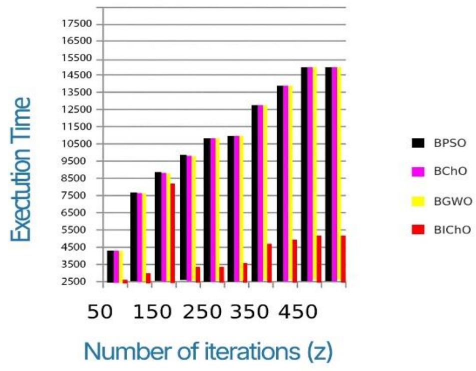

Fig. 11 Execution time of the suggested BICHO and the related competitors when search agents (n = 100)

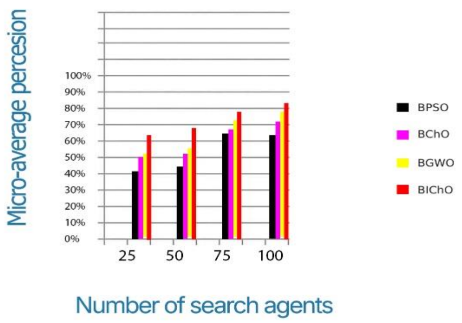

Fig. 14 The micro average precision of the suggested BICHO and the related competitors

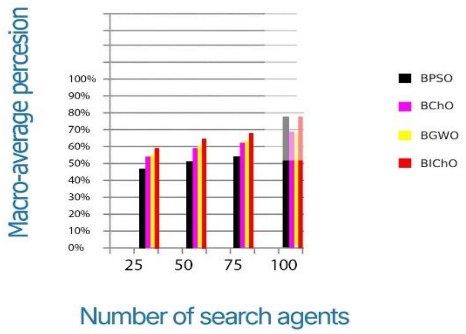

Fig. 12 The macro average precision of the suggested BICHO and the related competitor

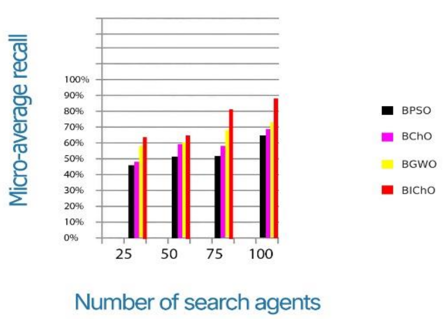

Fig. 15 The micro average recall of the suggested BICHO and the related competitors

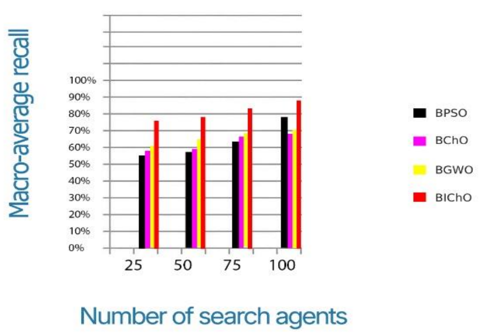

Fig. 13 The macro average recall of the suggested BICHO and the related competitors

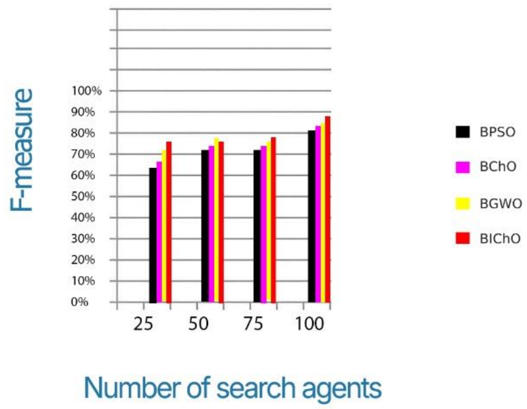

Fig. 16 F-measure of the suggested BICHO and the related competitors

6.2.5. Performance Summary

The experimental outcomes clearly illustrate that the BIChO algorithm consistently surpasses the comparative algorithms across all evaluated metrics. The highest accuracy values for every optimization method are achieved at 500 iterations with 100 search agents. Conversely, the optimal (minimum) execution time values for all algorithms are recorded at 50 iterations with 25 search agents.

Based on the comprehensive evaluation, BIChO achieves superior performance in feature selection for Covid-19 diagnosis using the Albert Einstein dataset. The algorithm demonstrates:

- **Highest accuracy values:** Reaching 98% at optimal conditions (z=500, n=100)
- **Competitive execution times:** Maintaining efficiency across different parameter settings
- **Superior precision and recall:** Achieving 0.86 micro-average precision and 0.94 micro-average recall
- **Best F-measure performance:** Attaining 0.92 F-measure value

The Improved performance of BIChO can be attributed to its improved prey localization mechanism, which enables more accurate identification of optimal feature subsets for effective Covid-19 classification. The experimental work performed across multiple iterations (50, 100, 150, 200, 250, 300, 350, 400, 450, 500) and search agent configurations (25, 50, 75, 100) validates the consistent superiority of BIChO over traditional optimization approaches.

These results establish BIChO as an effective feature selection method for biomedical applications, particularly in scenarios requiring high classification accuracy and reliable feature subset identification for diagnostic purposes.

7. Conclusion

This research has successfully addressed a fundamental limitation in the Chimp Optimization Algorithm by introducing Accurate Prey Localization (APL), a novel enhancement that replaces traditional simple averaging with fitness-aware weighted positioning. The investigation identified that ChOA's original prey localization mechanism, which treats all leading solutions equally regardless of their fitness quality, significantly hampers optimization performance and convergence accuracy. The proposed APL method implements a sophisticated approach to prey position estimation through fitness-based weight calculation and pairwise estimation strategies, ensuring that superior solutions receive proportionally greater influence in guiding the optimization process toward optimal solution regions.

Experimental validation demonstrates the substantial effectiveness of the proposed approach across multiple domains. APL-Improved ChOA achieved superior performance compared to both the original ChOA and Grey Wolf Optimization across all evaluation metrics in function optimization scenarios, with results showing dramatic convergence improvements and Improved solution quality. The comprehensive case study on feature selection for Covid-19 diagnosis further validated APL's practical effectiveness, where Binary APL-Improved ChOA consistently outperformed nine competing optimization algorithms, achieving 98.1% accuracy compared to the best alternative's 94.1%. These results conclusively establish that fitness-aware prey localization significantly outperforms traditional averaging-based approaches, providing sustained improvements in both convergence speed and solution quality while maintaining the essential balance between exploration and exploitation capabilities.

The method successfully addresses a critical gap that has remained largely unaddressed in existing ChOA variants and bio-inspired optimization research, establishing fitness-aware prey localization as a promising direction for enhancing metaheuristic algorithms. The consistent performance advantages observed across function optimization and feature selection applications demonstrate APL's robustness and broad applicability for complex optimization challenges in engineering design, machine learning, and medical diagnosis domains. This research contributes to achieving the United Nations Sustainable Development Goals, particularly SDG 3 (Good Health and Well-being) through improved diagnostic accuracy in COVID-19 detection using advanced feature selection techniques that enhance medical decision-making processes. Additionally, the work aligns with SDG 9 (Industry, Innovation and Infrastructure) by introducing algorithmic innovations in bio-inspired optimization that have broad applications across engineering design, manufacturing optimization, and technological advancement sectors. Future research directions include investigating APL's effectiveness across diverse benchmark problems and developing adaptive weighting strategies that can dynamically adjust to different optimization contexts, further expanding the method's applicability and impact in computational intelligence applications.

8. Future Work

While the proposed APL method has demonstrated significant improvements in ChOA performance, several avenues for future research warrant investigation. The fitness-aware weighting mechanism could be extended to incorporate adaptive weighting strategies that dynamically adjust based on problem characteristics and optimization landscape complexity. Such adaptive approaches might further enhance convergence behavior across diverse optimization domains.

The integration of APL with other bio-inspired optimization algorithms beyond ChOA presents promising research opportunities. Investigating how fitness-aware prey localization concepts could enhance algorithms such as Whale Optimization Algorithm, Harris Hawks Optimization, or Marine Predators Algorithm may yield valuable insights into the broader applicability of weighted positioning strategies in multi-objective optimization scenarios.

Finally, comprehensive performance evaluation across larger benchmark suites, including CEC competition functions and real-world optimization challenges in areas such as renewable energy systems, supply chain optimization, and automated design processes, would provide deeper insights into APL's robustness and scalability. Hybridization approaches combining APL with machine learning techniques could also provide more sophisticated prey position estimation mechanisms for complex optimization problems.

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