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A novel binary modified beluga whale optimization algorithm using ring crossover and probabilistic state mutation for enhanced bladder cancer diagnosis

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ABSTRACT

Bladder cancer (BC) remains a significant global health challenge, requiring the development of accurate predictive models for diagnosis. In this study, a new Binary Modified White Whale Optimization (B-MBWO) algorithm is proposed to address the BC problem. The proposed method utilizes circular transitivity optimization and the Probabilistic State Mutation Algorithm (PSMA) to enhance its optimization performance. The new method is called the BBWORCPS algorithm. High-dimensional and complex medical datasets pose challenges to the original optimization algorithms in addressing the BC problem, motivating the proposed modifications to the original Beluga Whale Optimization algorithm. These enhancements, including quantum-inspired mutation and circular crossing, aim to improve solution space exploration and enhance the algorithm's effectiveness in handling intricate feature spaces. Through comprehensive experiments on BC datasets, the superiority of the BBWORCPS algorithm in terms of feature selection accuracy and computational efficiency is demonstrated compared to existing optimization methods. The obtained findings suggest that BBWORCPS offers a promising approach for developing more precise and reliable predictive models for bladder cancer analysis.

1. Introduction

Bladder cancer (BC) is the 10th most universal cancer worldwide for both men and women [1]. The International Agency for Research on Cancer (IARC) of the World Health Organization published the worldwide cancer statistics for 2020, revealing that cancer was responsible for around 10 million fatalities [2]. In 2019, over 17,600 individuals in the United States succumbed to Bladder Cancer, representing 2.9 % of all deaths associated with cancer [1]. The symptoms of bladder cancer are dysuria, everyday urination, pain in urination, low

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back pain, abdominal pain, and severe painless hematuria [3]. In adults, undetectable blood in urine occurs in about 2–7% of men and 3–15 % of women [4], rendering extensive assessment for bladder cancer efficiently impossible. The early stages of bladder cancer may often be confused with cystitis due to intersecting symptoms such as dysuria, urgency, hematuria, and comparisons in medical imaging. The identified imaging sign of eosinophilic cystitis, which involves a thickening or mass in the bladder wall, is identical to that of bladder cancer, which makes early diagnosis difficult.

Traditional diagnosis and monitoring of BC are principally relevant to invasive approaches approximating cystoscopy, biopsy, and tumor resection for pathological examination. These approaches have limitations in accuracy and sensitivity, often causing discomfort, comorbidities, and side effects. However, the gold standard technique for diagnosing bladder cancer is cystoscopy, with a specificity of 77.1–97 % and a sensitivity of 88–100 % [5]. The accuracy of identifying bladder tumors during cystoscopy significantly depends on the skill of the examiner, making advancements in cryptoscopic tumor recognition crucial for surgical outcomes and patient prognosis. At the same time, a major non-invasive method is cytology, with only 38 % sensitivity but high specificity [5]. In typical cytology-based diagnosis, a cytologist examines the morphological characteristics of patient cells under a microscope. This process is highly subjective, depending on the cytologist's experience, knowledge, and mental state, which affects diagnostic accuracy [6]. Thus, there is an urgent need for a screening method to diagnose bladder cancer with high specificity and sensitivity.

In clinical laboratories, the main diagnostic screening tests are urine analysis and clinical chemistry tests [7]. Any change in the chemical analysis and urine analysis, such as color, specific gravity, and clarity, can be interpreted as a relationship with the disease. Chemical analysis and urine sediment examination are typically used to check for glucose, pH, occult blood, ketones, protein, and bilirubin [8,9]. Abnormal results in chemical analysis may indicate certain diseases; for example, hematuria indicates bleeding in the urinary tract, while ketonuria can be found in the urine of diabetic patients [10]. Furthermore, urine sediment analysis may reveal white blood cells, red blood cells, bacteria, tubules, and crystals that provide more information about the urinary tract system. So, depending only on clinical test interpretations can result in incorrect diagnosis [11].

In response to this severe need, the field of artificial intelligence (AI) and machine learning (ML) presents a beacon of expectation. The potential of ML to revolutionize BC diagnostics is grounded in its prowess for deciphering complex data patterns, offering a leap in diagnostic accuracy and efficiency [12]. Noteworthy advancements, such as ML-enhanced CT urography [13] and predictive analytics using clinical laboratory data [14], exemplify the transformative impact of AI in this field. Our proposed Binary Modified Beluga Whale Optimization (B-MBWO) algorithm stands at the forefront of this revolution, ingeniously designed to navigate the intricate landscapes of medical data with unparalleled Precision.

To address these challenges, this research proposes the Binary Modified Beluga Whale Optimization Algorithm (B-MBWO), a novel approach specifically tailored for BC diagnostics. This study is poised to make seminal contributions to the BC diagnostic. By harnessing the novel quantum-inspired mutations and circular crossings within the B-MBWO algorithm, we transcend the capabilities of traditional optimization techniques. By integrating quantum-inspired mutations and circular crossings into the traditional Beluga Whale Optimization (BWO) algorithm, B-MBWO aims to enhance solution space exploration and algorithmic efficiency. These modifications allow for more effective handling of intricate feature spaces inherent in medical datasets, facilitating the development of precise and dependable predictive models for BC. Furthermore, the integration of advanced metaheuristics with proven ML algorithms like Random Forest, complemented by sophisticated data processing and feature selection techniques, heralds a new era in BC diagnostics. The introduction of the Probabilistic State Mutation Algorithm (PSMA) and Ring crossover (RC) into our methodology amplifies the efficacy of our approach, promising significant strides in medical diagnostic algorithms.

This work makes several key contributions to the field of medical diagnostics and computational optimization, which are as follows.

1. The Beluga Whale Optimization (BWO) algorithm faces challenges with diversity, risking entrapment in local optima.
2. Integration of transfer functions into BWO enhances its speed, robustness, and overall efficacy for complex optimizations.
3. Exploration is broadened by investigating new potential areas for BWO, utilizing Naive Bais and Probabilistic State Mutation Algorithm (PSMA).
4. The combination of PSMA and Ring crossover to modify the Binary Whale Optimization BWO diversifies the solution pool and ensures solution reliability, leading to the Novel Binary Modified Beluga Whale Optimization with Ring Crossover and Probabilistic State Mutation Algorithm (BBWORCPS) strategy.
5. BBWORCPS excels in global optimization challenges, particularly with clinical laboratory data for biomedical classification tasks.
6. Utilizing a Naïve Bayes (NB) classifier, BBWORCPS has been rigorously tested across seven diverse illness datasets, showcasing its effectiveness in medical diagnostics.

The remainder of this paper is organized as follows: Section 2 explores the background, highlighting the limitations of current BC diagnostic methods and setting the stage for the B-MBWO algorithm's introduction. Section 3 details the methodology, focusing on the B-MBWO algorithm's structure and the key preprocessing steps necessary for effective feature selection and classification in BC diagnostics. Section 4 presents a thorough evaluation of matrices to validate the B-MBWO algorithm's performance compared to other optimization techniques. Section 5 discusses the broader implications of the findings, considering the B-MBWO algorithm's potential application in various medical diagnostic areas and its impact on healthcare outcomes. Section 6 concludes the paper with a summary of significant findings and contributions, also suggesting future research directions to enhance diagnostic models with advanced computational algorithms.

2. Related work

In this section, the significant studies proposed for the BC are reviewed and summarized. In addition, the BWO is highlighted by presenting the most considerable studies that adapt and utilize it.

2.1. Bladder cancer

BC continues to be a significant health concern worldwide prompting extensive research into utilizing accurate diagnostic and prognostic tools. In this section, previous studies focusing on bladder cancer diagnosis and highlighting their methodologies were reviewed, along with findings and limitations. Our exploration begins with an examination of various studies, each contributing distinct insights into bladder cancer diagnosis. Recent improvements in bladder cancer diagnostics have resulted in the use of a variety of approaches to improve detection accuracy and efficiency [15]. used classic machine learning algorithms on a bladder cancer dataset, including Neural Networks, Random Forests, Regression Trees, Naive Bayes, and Logistic Regression, to achieve the greatest F1 score of 92.5 % with Logistic Regression. However, this study did not investigate the possibilities of optimization or hyperparameter tuning, which are frequently required to maximize model performance.

Conversely, some studies demonstrated remarkable achievements in bladder cancer diagnosis [16]. used Radial Basis Function (RBF) Neural Networks to discriminate between Transitional Cell Carcinoma (TCC) and non-TCC cases, reporting an 85 % accuracy. Despite its contribution, the study was restricted by its low accuracy and the lack of optimization

Table 1
Research Gaps and Contributions of Previous Authors on Blader cancer.

Author.	**Data Source**	**Methods**	**Best Result**	**Limitations**
[15]	Bladder Cancer Dataset	Neural Network, Random Forest, Regression Tree, Naive Bayes, Logistic Regression	F1 of 92.5 % using LR	No optimization or hyperparameter tuning
[16]	Bladder Cancer Dataset (TCC vs. non-TCC)	RBF Neural Networks	Accuracy of eighty-five%	Low accuracy, no optimization or hyperparameter tuning
[17]	Cystoscopic Cancer Images	Deep Learning Networks (LeNet, AlexNet, GoogLeNet), EasyDL	Accuracy of 96.9 % with EasyDL	No limitations stated
[18]	Bladder Cancers in Hong Kong	ANN	Overall accuracy of 77.8 %	Small sample size, limited follow-up, need for multi-center trials, lack of a cancer database, limited clinician knowledge in statistics
[19]	Malignant Pathological Slice Images	Machine Learning	AUC of 96.3 %, 89.2 %, 94.1 %	No comparisons with other studies or ML methods, no method modification
[20]	Brightfield and Fluorescence Cystoscopy Images from Rats	SERS with Machine Learning	Accuracy of 99.6 %	Not stated
[21]	Bladder Cancer	InfoGain and Ranker for Feature Selection, ML	LightGBM accuracy of 84.8 %–86.9 %	Not stated
[22]	Bladder Cancer Images	VGG16 and ResNet-34	Accuracy of 96.9 %	Not stated

or hyperparameter modifications [17]. used Deep Learning Networks such as LeNet, AlexNet, GoogLeNet, and EasyDL on cystoscopic cancer images, achieving a high accuracy of 96.9 % using EasyDL. While intriguing, the study did not disclose any limitations, which may be significant for contextualizing the findings.

[18] investigated bladder tumors in the Hong Kong region using Artificial Neural Networks (ANN) and reported an overall accuracy of 77.8 %. Their study had several limitations, including a small sample size, the need for multi-center trials, the lack of an established cancer database, and insufficient physician expertise in statistical analysis [19]. used machine learning algorithms to interpret malignant pathological slice images and reported AUC scores of 96.3 %, 89.2 %, and 94.1 %, respectively. However, their work lacked a comparative examination with other studies or machine learning approaches, and no changes were reported to the methodologies used.

[20] used Surface-Enhanced Raman Scattering (SERS) and machine-learning approaches to diagnose bladder cancer in rats, with an accuracy of 99.6 %. They examined both brightfield and fluorescence cystoscopy pictures. The limitations of this study were not disclosed, which could have provided information about the practical applications and replicability of the findings [21]. used Information Gain and Ranker algorithms for feature selection in conjunction with machine learning, specifically LightGBM, and achieved an accuracy range of 84.8 %–86.9 % on bladder cancer datasets. They did not identify any limitations to their approach, as have several other research.

In this study [22], the authors applied well-known Deep Learning architectures, VGG16 and ResNet-34, to bladder cancer images, attaining an accuracy of 96.9 %. Despite its great accuracy, the study did not address any potential limits. This review of current research identifies a trend of combining machine learning and medical diagnostics, with a strong emphasis on deep learning and feature selection approaches. The majority of research produces promising results, but they frequently lack complete information on limits, which is required for a thorough evaluation and subsequent refinement of the proposed methodology.

While numerous studies have made commendable strides in bladder cancer diagnosis, they are not devoid of limitations. Common shortcomings include the absence of optimization or hyperparameter tuning, small sample sizes, and limited comparisons with other methodologies. To address these limitations, our proposed Modified Beluga Whale Optimization Algorithm aims to optimize feature selection, thereby enhancing diagnostic accuracy and contributing to the advancement of bladder cancer diagnosis. Through this STUDY, we gain valuable insights into the landscape of bladder cancer diagnosis research, paving the way for future endeavors in this critical area of healthcare. An overview of the given studies is presented in Table 1.

One significant gap in bladder cancer diagnosis research is the lack of optimization and hyperparameter tuning in diagnostic models. Many studies overlook these crucial steps, potentially leading to suboptimal performance and hindering the achievement of higher accuracy rates. By integrating optimization techniques and fine-tuning model parameters, researchers can enhance the effectiveness of diagnostic algorithms.

Another gap is in the limited differences made between different diagnostic methodologies. Numerous studies fail to assess their methods against existing approaches or alternative ML algorithms. Without comparative analysis, it becomes challenging to determine the relative efficacy and efficiency of different techniques, impeding progress in the field.

Furthermore, several studies suffer from small sample sizes, controlling the generalizability and strength of their findings. Larger and more different datasets are critical to ensure that diagnostic models are completed effectively across diverse patient populations and clinical settings. Moreover, studies with limited follow-up periods may fail to capture long-term outcomes and disease progression accurately, the importance of the need for longitudinal research designs.

On the other hand, several limitations impact the consistency and applicability of existing diagnostic models. Data quality problems, such as noise, artifacts, and missing data, can introduce biases and errors into the analysis, compromising the validity of diagnostic results. Furthermore, the lack of interpretability in some diagnostic models, specifically those based on deep learning algorithms, poses challenges in understanding the underlying decision-making process, hindering clinical adoption. Resource needs represent another limitation, as certain diagnostic approaches may demand significant computational resources or specialized hardware. These resource constraints can impede the implementation of diagnostic tools in real-world clinical settings, particularly in resource-constrained settings. Finally, validation and external generalization are critical aspects often overlooked in bladder cancer diagnosis research. Many studies lack robust validation procedures, leading to overfitting or inflated performance estimates. Ensuring proper validation of independent datasets is essential for assessing the real-world applicability of diagnostic models.

Several research gaps are evident, including the prevalent neglect of optimization processes and comparative analyses. Several research gaps are evident, including the prevalent neglect of optimization processes and comparative analyses. Addressing these gaps, particularly through the application of optimization techniques and expanding dataset sizes, can significantly enhance the accuracy and applicability of bladder cancer diagnostics, paving the way for more reliable and effective clinical tools.

Table 2
The variants of the BWO algorithm.

Authors	Variant	Abbreviation & Name	Description	Area	Results
[23]	Modification	OBWO: OBWOD	Enhances BWO with OBWO, KNN, and DCS for faster search and diverse solutions.	Biomedical	Outperforms seven algorithms with 85.17 % accuracy on medical datasets.
[24]	Hybridization	HBWO	Integrates QOBL and Nelder-Mead with BWO for improved multidimensional problem-solving.	Engineering Problems	Superior to BWO and others in real-world problems.
[25]	Modification	IBWO with GAS	Expands BWO for better exploration/exploitation and convergence.	Optimization Problems	Effective in global optimization.
[26]	Modification	FDBBWO	Improves BWO with fitness-distance balance to prevent early convergence.	Optimization Problems	Enhances performance by mitigating early convergence.
[27]	–	IBWO with AMC-Deeplabv3+	Merges AMC-Deeplabv3+ with IBWO for hyperparameter optimization in segmentation.	Aerial Images	High segmentation accuracy and dice coefficients.
[28]	–	BWO-RF	Refines Random Forest with BWO for flood risk assessment.	Regional Flood Disaster Risk	Superior optimization efficiency and stability.
[29]	Hybridization	HBWO-JS	Merges BWO with Jellyfish Search for better convergence accuracy and solution quality.	Engineering Applications	Competitive advantage and stable scalability performance.
[30]	–	Deep-CNN using BWO	Applies BWO for hyperparameter optimization in Deep-CNN for emotion recognition.	Speech Emotion Recognition	Significant SER accuracy improvements on datasets.
[31]	Multi-objective	IBWO for DG Planning	Improves BWO for multi-objective DG planning, reducing costs and power loss.	Power Quality	Reduces comprehensive cost, voltage deviation, and power loss.
[32]	Modification	MBWO	Enhances BWO's real-world problem-solving capabilities.	Engineering Problems	Effective in finding optimal solutions for diverse challenges.
[33]	–	IBWOA-FIMS	Employs enhanced BWO with fuzzy-based monitoring for the visually impaired and elderly.	Remote Monitoring of Disabled & Elderly	Improves monitoring accuracy, reliability, and efficiency for the disabled and elderly in smart homes.

2.2. Beluga whale optimization (BWO) algorithm

In the landscape of optimization algorithms, the Beluga Whale Optimization (BWO) algorithm has attracted considerable interest for its adeptness in tackling intricate problems. However, researchers have acknowledged the potential for further refinement and customization to address specific challenges across various domains. Table 2 presents an overview of several BWO algorithm variants proposed by different authors, each tailored to meet specific needs and applications.

In 2023 [23], presented OBWOD, a BWO variant that combines OBWO with KNN and DCS to improve search speed and solution diversity. This variation was developed exclusively for biomedical applications and demonstrated its usefulness by outperforming seven other algorithms on medical datasets with an accuracy of 85.17 %. This development illustrates the potential of OBWOD in medical data processing and diagnosis, resulting in faster and more accurate biomedical solutions [24]. work in the same year introduced HBWO, which combines Quantum-inspired Opposition-Based Learning (QOBL) and Nelder-Mead techniques with BWO to address multidimensional engineering challenges. The hybridized algorithm outperformed both classic BWO and other approaches, particularly in addressing real-world engineering difficulties. This hybridization exemplifies the trend of combining metaheuristic algorithms with other optimization techniques to solve complex problems more effectively.

IBWO and GAS broadened BWO's capabilities in terms of exploration, exploitation, and convergence while addressing global optimization difficulties [25]. Their approach was proven effective in large-scale optimization problems, marking a significant step toward improving the BWO algorithm's robustness and convergence speed [26]. adapted BWO to add a fitness-distance balance under the name FDBBWO. This variation was created to address the prevalent problem of early convergence in optimization algorithms, hence improving performance by giving more trustworthy solutions across multiple optimization scenarios [27]. combined IBWO with AMC-Deeplabv3+ for hyperparameter tuning in image segmentation tasks. The use of this advanced technology on aerial pictures resulted in high segmentation accuracy and dice coefficients, suggesting a successful optimization of the segmentation process.

Collectively, these advancements underline the dynamic evolution of BWO and its applications. The modifications and hybridizations enhance computational performance in specific problem domains, ranging from medical diagnostics to engineering and image processing, showcasing a continued commitment to optimizing algorithmic efficiency and applicability. In 2023, authors revealed how well-calibrated optimization algorithms can considerably improve computer performance in complicated problem domains [28].

In the same year, Hussien et al. used BWO to modify the Random Forest algorithm, resulting in BWO-RF, which was specifically designed for flood risk assessment [24]. This use of BWO in regional flood disaster risk assessment resulted in higher optimization efficiency and stability, demonstrating the algorithm's utility in real-world environmental applications. The modification provides a potential path for more precise and dependable flood risk projections, which are critical for disaster preparedness and mitigation activities [29]. presented HBWO-JS, a hybrid of BWO and the Jellyfish Search algorithm. This combination tries to leverage the capabilities of both algorithms in order to improve convergence accuracy and solution quality. Their expertise has been used in several technical applications, providing a competitive advantage and steady scalability performance. This indicates the hybrid algorithm's capability to efficiently navigate the search space and arrive at high-quality solutions stably.

Wang et al. [30] used BWO to optimize hyperparameters in Deep Convolutional Neural Networks (Deep-CNN) for speech emotion recognition. Their implementation resulted in considerable gains in SER accuracy on datasets, highlighting the necessity of adjusting hyperparameters to improve the performance of deep learning models in properly perceiving human emotions from speech. These studies highlight the novel ways in which BWO is being adjusted to satisfy the specific requirements of diverse, complex systems, ranging from engineering and environmental risk assessment to cutting-edge sectors like affective computing. Through these changes and hybridizations, BWO remains at the vanguard of optimization algorithm research, giving significant insights and tools for addressing a wide range of computational difficulties.

Deepika and Kuchibhotla [31] introduced a multi-objective form of the Beluga Whale Optimization algorithm that was specifically built for Distributed Generation (DG) planning. This new approach, known as IBWO for DG Planning, is designed to handle numerous objectives at the same time, most notably lowering overall costs and power loss while also regulating voltage deviation. The use of this variation in the domain of power quality represents a significant advancement in optimizing the

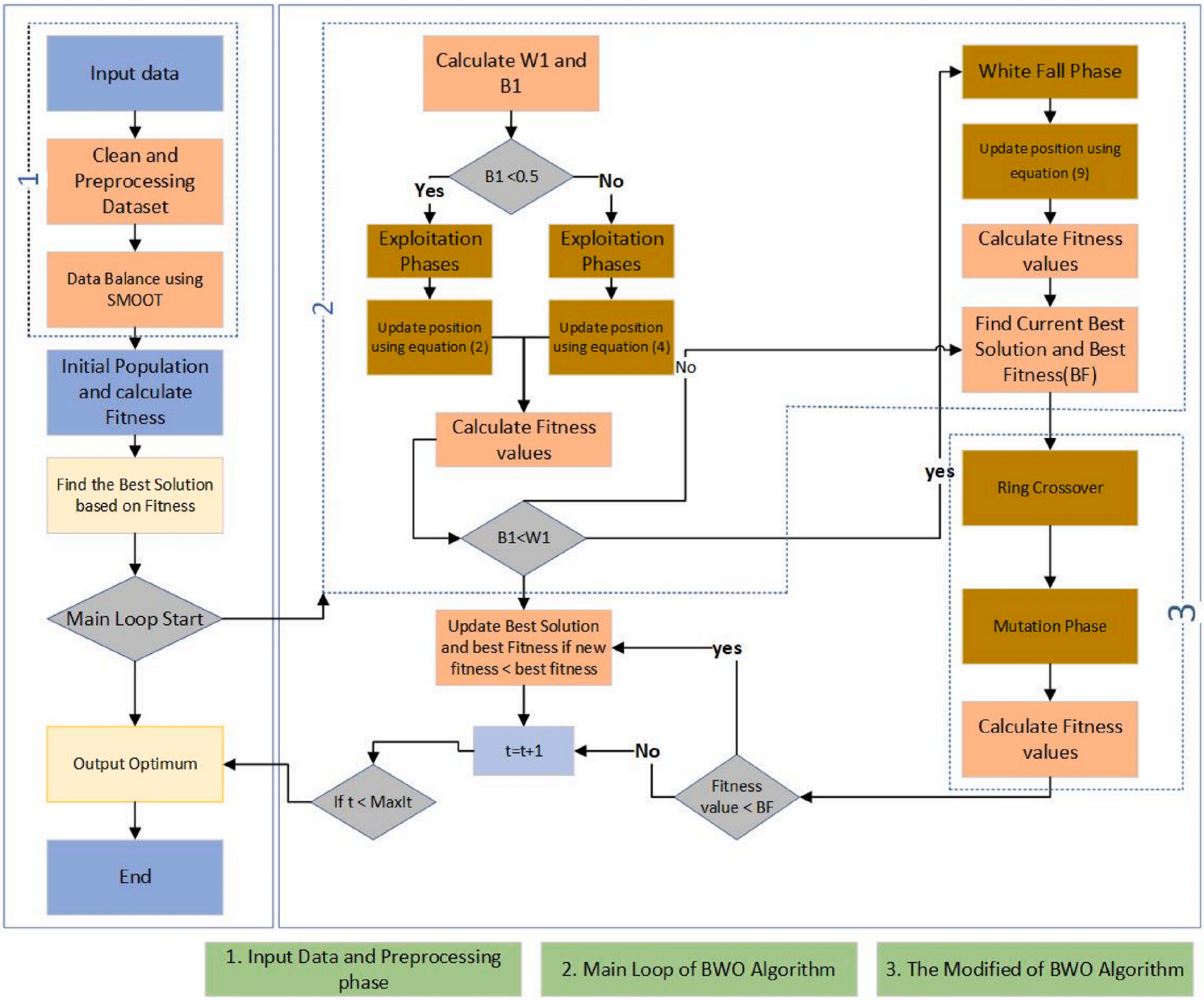

Fig. 1. Flowchart of modified BBWORPS

complicated balance of economic and technical aspects in power systems, resulting in more efficient and reliable energy distribution [31].

Li et al. [32] contributed to the body of work with their variation, MBWO. This update aims to improve the BWO's ability to address real-world engineering challenges. Their findings demonstrate the MBWO's efficiency in identifying optimal solutions to a wide range of technical difficulties. This broad application illustrates the BWO framework's adaptability to various contexts, highlighting its significance as a tool for complicated issue resolution. Jia et al. [33] investigated the use of BWO in a socially significant context by creating a system known as IBWOA-FIMS, which stands for Improved BWO Algorithm with Fuzzy-based Intelligent Monitoring System. Their solution is specifically designed to improve the living conditions of the visually impaired and elderly, particularly in smart home contexts. They developed a monitoring system that increases accuracy, reliability, and efficiency by combining BWO and fuzzy logic. The IBWOA-FIMS demonstrates how optimization algorithms can benefit assistive devices by creating a safer and more responsive environment for vulnerable people.

Collectively, these works demonstrate the trend of optimization algorithms moving beyond traditional computational boundaries and into multifaceted, real-world applications. Whether it's upgrading energy systems, solving complex technical challenges, or improving the well-being of specific demographic groups, BWO, and its derivatives continue to demonstrate their value as potent tools in the continual pursuit of scientific innovation and social progress.

Similarly, the HBWO variant introduces a hybridization approach by integrating QOBL and Nelder-Mead with BWO to improve multidimensional problem-solving, particularly in engineering contexts. The results have been promising, with HBWO demonstrating superiority over traditional BWO and other algorithms in real-world applications. Such hybridization strategies highlight the importance of leveraging complementary techniques to optimize algorithm performance across diverse problem domains. However, despite the advancements offered by these variants, several gaps and limitations remain to be addressed. One common limitation observed across various variants is the lack of comprehensive optimization or hyperparameter tuning. For instance, in the case of the OBWO: OBWOD variant, while it excels in providing diverse solutions, the absence of optimization or hyperparameter tuning may restrict its ability to achieve optimal performance in certain scenarios. Similarly, the HBWO variant, despite its success in engineering applications, may encounter challenges when applied to more complex problem domains that require fine-tuned parameters.

Moreover, some variants exhibit limitations related to specific application areas. For example, the IBWO with AMC-Deeplabv3+ variant, aimed at hyperparameter optimization in segmentation tasks, may face challenges in scenarios requiring real-time processing or dealing with large-scale datasets (Author, Year). Additionally, while the MBWO variant shows promise in addressing real-world engineering challenges, its effectiveness in highly dynamic or uncertain environments remains to be fully explored.

In conclusion, while the variants of the BWO algorithm present promising advancements in optimization techniques, there exist notable gaps and limitations that warrant further research attention. Addressing these gaps, such as through comprehensive optimization strategies and robust parameter tuning, will be crucial in unlocking the full potential of BWO variants across diverse application domains. By overcoming these challenges, researchers can pave the way for more effective and versatile optimization algorithms tailored to meet the evolving needs of complex problem-solving tasks.

3. Proposed methodology

In the proposed methodology, an enhanced variant of the BWO algorithm is introduced, drawing inspiration from the social and hunting behaviors of beluga whales. The methodology comprises several carefully designed phases, as shown in Fig. 1. The first phase involves Input Data and Preprocessing, where the raw data undergoes thorough cleansing to eliminate inconsistencies and anomalies, resulting in a robust dataset. To address class imbalances, the SMOOT technique, derived from the Synthetic Minority Over-sampling Technique (SMOTE), is employed to ensure adequate representation of minority class instances.

Next, an Initial Population is created, consisting of potential solutions. Each solution is evaluated for its fitness, indicating its adherence to the optimization criteria. The fittest solution is identified as the leader of the population. The subsequent phase, known as the Main Loop, mirrors the foraging strategies of beluga whales by dynamically balancing exploration and exploitation. The algorithm determines whether to explore new territories or exploit existing solutions based on a threshold value. During the exploration phase, solutions' positions are updated using a specific equation to uncover new potential areas in the solution space. In the exploitation phase, solutions' positions are meticulously adjusted using another equation to approach the optimal solution.

A distinctive feature of the BWO algorithm is the Whale Fall Phase, triggered by specific conditions simulating the sudden influx of a new resource, similar to a whale carcass falling to the ocean floor. This phase prompts the repositioning of solutions and a re-evaluation of their fitness. To further enhance the algorithm's performance, the Modified BWO Algorithm incorporates principles from genetic algorithms. It introduces the "Ring Crossover" mechanism, a novel concept that mimics genetic crossover within the BWO context, thereby generating a diverse mix of solutions with potentially superior traits. Additionally, a mutation phase is included, injecting stochastic variations into the population to increase the diversity of the solution space, akin to natural genetic mutations. The main loop iterates, comparing the current solutions against the best solution found thus far and adopting any solution with superior fitness. This iterative improvement process continues until the maximum number of iterations (MaxIt) is reached.

Finally, the algorithm concludes by yielding the optimum solution, representing the culmination of the evolutionary process. The termination of the algorithm signifies not only the end of the computational routine but also the achievement of an iterative quest for perfection inspired by the natural intelligence and adaptive strategies of beluga whales.

3.1. Patient cohort and data preprocessing

Mackay Memorial Hospital collected clinical laboratory test data from different patient cohorts From January 2017 to February 2020. The first cohort was based on two hundred patients with uterine cancer, all of whom were female and had a typical age of 60.86 ± 10.26. The second cohort consists of 591 patients with bladder cancer, comprising 386 males and 205 females with an average age of 66.73 ± 9.4. The third cohort contained two hundred patients with kidney cancer, 138 males and 62 females, with an average age of 63.41 ± 10.45. Finally, the fourth cohort involved 144 patients with cystitis, comprising 88 males and 56 females with an average age of 60.12 ± 11.99 [21].

To prepare the dataset for analysis, several preprocessing steps were

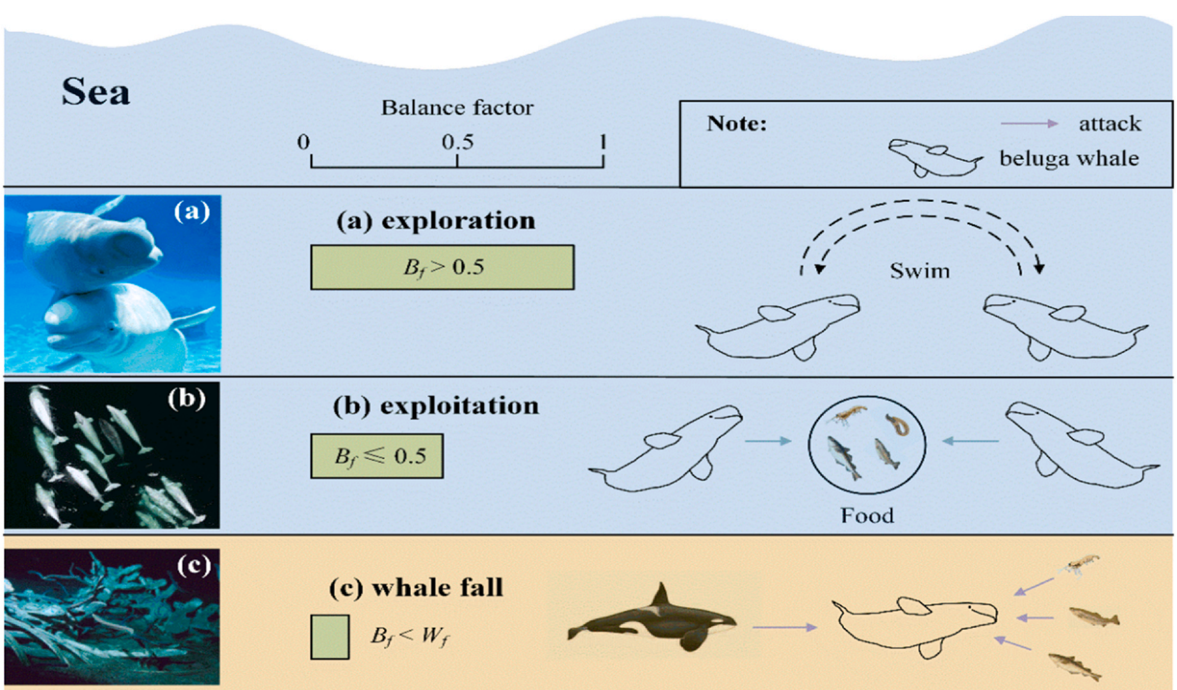

Fig. 2. Behaviors of beluga whales.

performed. The first step involved data cleaning to enhance the quality of the data. Missing values, identified as "NULL," were replaced with the most frequent values or modes to ensure the integrity of the data.

Next, feature engineering was conducted. This step included converting categorical replies into binary parallels. Categorical variables were converted into binary variables, with "1″ indicating the presence of a particular category and "0″ indicating its absence. This conversion facilitates computational processing and analysis. Additionally, equation (1) was utilized during the feature engineering process. The specific details and purpose of equation (1) were not provided in the given context, so further information is required to understand its application and significance in the preprocessing stage.

$$X' = (X - X_{min}) / (X_{max} - X_{min}) \tag{1}$$

Here, x is an original value, X' is the normalized value. X_{min} is the lowest value and X_{max} is the highest value. Data enhancement further involves data transformation, where the labeled data is converted into digital form using label encoders, making it suitable for algorithmic processing.

Finally, we used Oversampling with SMOTE (Synthetic Minority Oversampling Technique). This technique addresses the issue of class imbalance by generating synthetic samples from the minority class. SMOTE works by randomly selecting a point from the minority class and computing the k-nearest neighbors of this point. Then, artificial points are added between the selected point and its neighbors. This approach not only balances the categories in our dataset but also enriches our dataset with new and plausible examples.

3.2. Mathematical representation original beluga whale optimization algorithm

The BWO algorithm is a swarm-based algorithm inspired by the behaviors of beluga whales derived from three phases of exploration, exploitation, and whale fall. The exploration phase performs a global search in the design space, and beluga whales are randomly selected, while the exploitation phase controls the local search in the design space. The search operators in BWO are belugas because of the population-based BWO process, and each beluga is a candidate solution that is updated during optimization. In addition, the possibility of whales falling is taken into account. Search agent positions are represented by Equation (2).

$$X = \begin{bmatrix} X_{11} & \cdots & X_{1d} \\ \vdots & \ddots & \vdots \\ X_{n1} & \cdots & X_{nd} \end{bmatrix}, \tag{2}$$

Where n and d are the population size and dimension of design variables, respectively.

3.2.1. Exploration phase

When the exploration phase begins, the swimming behaviors of beluga whales in the ferries are considered. Beluga whales can assume various positions when performing sexual behaviors, as shown in Fig. 2.

Thus, the positions of the search agents are updated based on the pair swimming of the whales and are represented mathematically by Equation (3).

Table 3
Parameter setting employed in constrained optimization algorithms.

Algorithm	Parameters
BWO	WF = (0.1, 0.05), kk = (1, 0.5)
BBWORCPS	WF = (0.1, 0.05), kk = (1, 0.5), mutation_rate = 0.3
RTH	A, R0, r = 15, 0.5, 1.5
SCA	a = 2, r1 = (2, 0)
WOA	a = (2, 0), a2 = (−1, −2)
HGS	VC2 = 0.03, shrink = (2, 1)

$$X_{i,j}^{T+1} = \begin{cases} X_{i,p_j}^T + \left(X_{r,p_1}^T - X_{i,p_j}^T\right)(1+r_1)\sin(2\pi r_2), j = even \\ X_{i,p_j}^T + \left(X_{r,p_1}^T - X_{i,p_j}^T\right)(1+r_1)\cos(2\pi r_2), j = odd \end{cases}, \tag{3}$$

where $X_{i,j}^{T+1}$ is the new position for the $i-th$ beluga whale on $j-th$ diminution, T is the current iteration, X_{i,p_j}^T and X_{r,p_j}^T are the current positions of the $i-th$ and $r-th$ beluga whales on p_j diminution, r_1 and r_2 are random numbers between $(0,1)$.

To move from the exploration stage to the exploitation stage, we rely on the balance factor B_f, which is represented mathematically, as shown in Equation (4).

$$B_f = B_0(1 - T / 2 \times Max\_it) \tag{4}$$

3.2.2. Exploitation phase

Exploitation is inspired by behavior derived from predation by beluga whales. Beluga whales move based on the location of nearby beluga whales, and they feed cooperatively. The Levi's flight strategy is used in the exploitation phase. The mathematical model is expressed as shown in Equation (5).

$$X_i^{T+1} = r_3 X_{best}^T - r_4 X_i^T + C_1 \times L_F \times \left(X_r^T - X_i^T\right) \tag{5}$$

$$C_1 = 2 \times r_4 \frac{1-T}{Max\_it} \tag{6}$$

$$L_F = 0.05 \times \frac{u + \sigma}{|v|^{1/\beta}} \tag{7}$$

$$\sigma = \left(\frac{\Gamma(1+\beta) \times \sin(\pi\beta/2)}{\Gamma((1+\beta)/2) \times \beta \times 2^{(\beta-1)/2}}\right)^{1/\beta} \tag{8}$$

In equation (5), X_i^{T+1} is the new position of the $i-th$ beluga whale, X_r^T and X_i^T are the current position for the $i-th$ and random beluga whale, T expresses the current iteration, r_3 and r_4 are random numbers between 0 and 1, C_1 calculated using equation (6). L_F is Levy flight function Levy and calculated using equation (7).

β in the equation is a default constant equal to 1.5, u and v are normally distributed random numbers, and σ calculated using equation (8) u and v calculated using equations (9) and (10).

$$u = randn(1, dim) \times \sigma \tag{9}$$

$$v = rand(1, dim) \tag{10}$$

3.2.3. Whale fall phase

The probability of whales falling is used to simulate small changes in the population as they are assumed to fall into the deep sea based on 12 simulations. The location is updated using the whales' positions and the whales' fall stride size. The location update is mathematically expressed in equation (11).

$$X_i^{T+1} = r_5 \times X_i^T - r_6 \times X_r^T + r_7 \times X_{step}^T \tag{11}$$

$$X_{step}^T = (u_b - l_b) \times e^{-C_2 \times \frac{T}{Max\_it}} \tag{12}$$

$$C_2 = 2 \times W_f \times n \tag{13}$$

$$W_f = 0.1 - 0.05 \times \frac{T}{Max\_it} \tag{14}$$

u_b *and* l_b in equation (12) are the lower and upper bound X_{step}^T is calculated using equation (12). C_2 in equation (12) is calculated using equation (13) and equation (14) using to calculate W_f which is used in equation (13)

Table 4
Experimental runs' details.

Item	Setting
Lower bound	−5
Upper bound	5
Max iteration	20
Population size	50
Variable number (number of features)	Number of features
Number of runs	30

3.3. *Modified beluga whale optimization (BWO) algorithm*

In the quest for efficient optimization techniques, the Modified BWO algorithm stands out for its incorporation of innovative strategies such as transfer functions, ring crossover, the Probabilistic State Mutation Algorithm (PSMA), and a fitness function. These components collectively contribute to the algorithm's ability to navigate complex optimization landscapes and yield superior results.Table. 3

3.3.1. *Transfer functions*

This is a frequently used technique to translate a continuous position into a binary position. Eight S- and V-shaped transfer functions were proposed by (Mirjalili and Lewis, 2013). The mathematical expression for the eight functions is displayed in Table 4; according to Lemus-Romani et al. (2023), the functions operate based on one denoting determination and 0 indeterminacy. The transfer function was selected because of its low computational cost. Using the experimental approach of eight functions, we will identify the function that yields the best outcome in this study. x is the chance of either 0 or, denoted b x_i^j.

S-Shaped	Function	V-Shaped	Function
S1	$\frac{1}{1+e^{-2x}}$	*V1*	$\left\lvert erf\left(\frac{\sqrt{\pi}}{2}x\right)\right\rvert$
S2	$\frac{1}{1+e^{-x}}$	*V2*	$\lvert tan(x)\rvert$
S3	$\frac{1}{1+e^{\frac{-x}{2}}}$	*V3*	$\left\lvert\frac{x}{\sqrt{1+x^2}}\right\rvert$
S4	$\frac{1}{1+e^{\frac{-x}{3}}}$	*V4*	$\left\lvert\frac{2}{\pi}arctan\left(\frac{\pi}{2}x\right)\right\rvert$

3.3.2. *Ring crossover*

Ring Crossover is a fundamental genetic operator employed in evolutionary algorithms to produce offspring from two parent chromosomes. This technique, as given in Fig. 3, is essential in genetic algorithms and is designed to combine genetic material from parent chromosomes to generate new solutions with potentially improved characteristics. The procedure includes several progressive steps, each contributing to the design of diverse and possibly advantageous progenies. Firstly, the process starts with the selection of parent chromosomes, which are the basis for creating the offspring. These parent chromosomes represent potential solutions to the optimization problem at hand. The parent chromosomes are subjected to the ring crossover operation, which comprises four main steps. Firstly, the two parent chromosomes are initialized and prepared for the crossover process. This step involves extracting the genetic material from each parent that will contribute to the making of the offspring.

In the second stage, the genetic material from the parent chromosomes is joined in the form of a ring structure. This ring structure act as a circular arrangement of genetic material. The exact point at which the ring is cut to separate the genetic material is determined randomly, introducing variability into the process. Following the creation of the ring structure, the third step involves generating a random number to determine the position of the cut point along the length of the combined parental chromosomes. Once the cut point is established, two children are created by selecting genetic material from each parent chromosome. The selection process follows a specific pattern, with one child inheriting genetic material in a clockwise direction and the other in a counter-clockwise direction from the cut point. Finally, the transposition and reversion processes are applied to the offspring chromosomes. In the transposition process, a subset of genes between the crossed parents is replaced, promoting diversity in the offspring population. Simultaneously, the reversion process reverses the remaining genes, further enhancing the variability of the offspring.

3.3.3. *The Probabilistic State Mutation Algorithm (PSMA)*

The mutation is imperative to underscore the potential of mutation in resolving intricate optimization issues, especially in scenarios where conventional algorithms may encounter difficulties. In addition to encouraging a more varied investigation of the solution space, the probabilistic mutation offers a way out of local optima. The algorithm is a unique and potentially potent tool in the field of optimization and evolutionary algorithms because of its quantum-inspired methodology, which also enables it to take advantage of ideas from quantum computation. The PSMA relies heavily on the quantum_inspired_mutation function. In the context of classical computing, it simulates the uncertain and non-deterministic behavior of quantum systems. The function works with a population of people, where each person is a set of characteristics, or "genes," that are all numerically represented. Each gene in an individual is subject to a mutation process with a certain probability (mutation_rate). The mutation process is mathematically formulated as an equation (15)

$$g_i^{'} = g_i + \Delta \tag{15}$$

For each gene g_i in an individual, a random number R is generated. If R < mutation_rate, the gene is mutated. In equation (15), $g_i^{'}$ is the mutated gene, Δ is random value drawn from a uniform distribution, U (−0.5,0.5).

The quantum ideas of superposition and state transition served as the inspiration for this mutation process. A particle exists in several states until it is seen in quantum mechanics. Comparably, every gene in PSMA possesses the capacity to 'jump' to a new value, emulating a shift in the

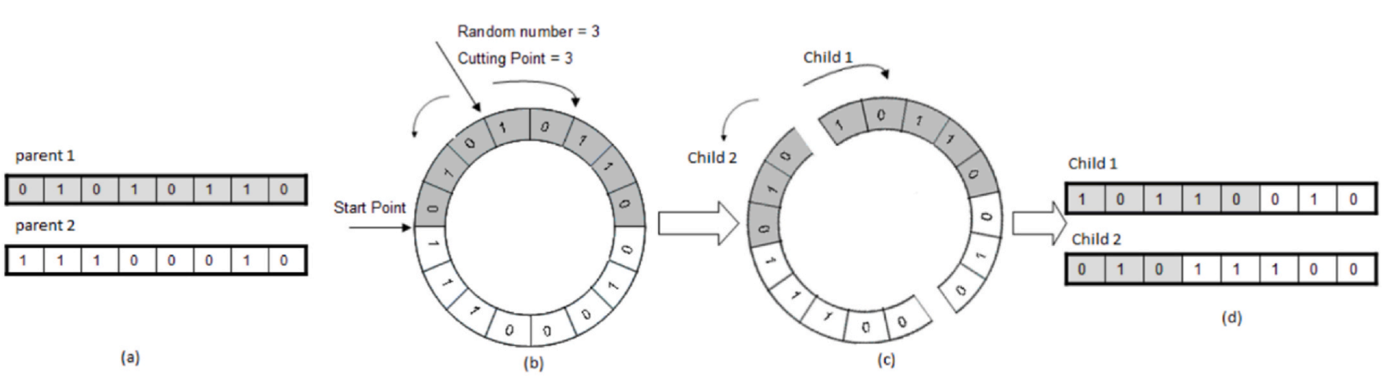

Fig. 3. Flow chart describes how ring crossover work.

quantum state. By introducing a degree of exploration and randomness, this method helps to avoid local optima and more thoroughly explore the solution space.

3.3.4. Fitness function

In the context of the Beluga Whale Optimization (BWO) algorithm, the fitness function serves as a crucial component for evaluating the performance of potential solutions. Specifically tailored for feature selection tasks, the fitness function aims to identify the subset of features that maximizes performance while minimizing the number of selected features. The subset of features is evaluated using the following fitness function (16).

$$F = h1\frac{|s|}{|f|} + h2Error(D) \tag{16}$$

The fitness function aims to strike a balance between minimizing the misclassification rate (indicative of predictive accuracy) and minimizing the number of selected features (to prevent overfitting and improve computational efficiency). By optimizing this fitness function, the BWO algorithm can effectively identify an optimal subset of features that maximizes predictive performance while minimizing complexity.

Algorithm 1. Pseudo-code of BBWORCPS Algorithm

```
Input: Define parameters (population size, Max_it)
Output: Best population and best solution
1.  Initialize the population, calculate fitness values, then initialize the best solution (P*) and
    best fitness (BF)
2.  While T ≤ Max_it Do
3.     Calculate whale fall W_f using Equation (14) and balance factor B_f using Equation (4)
4.     For all beluga whale (Xi) Do
5.        If B_f(i) > 0.5
6.           // Exploration phase
7.           From dimension generate pj (j = 1,2,,d) randomly
8.           Choose a beluga whale X_r randomly
9.           Update the new position of i − th beluga whale using Equation (4)
10.       Else If B_f(i) ≤ 0.5
11.          // Exploitation phase
12.          Update C1 and calculate L_F using equation (7)
13.          Update the new position of i − th beluga whale using equation (5)
14.       End If
15.       Evaluate current fitness values of new position and update (P*) and BF if current
          fitness < BF
16.    End For
17.    For all beluga whale (Xi) Do
18.       // whale fall phase
19.       If B_f(i) ≤ W_f
20.          Update the C_2 using equation (13)
21.          Calculate X_step^T using equation (12)
22.          Update the new position of i − th beluga whale using Equation (11)
23.          Evaluate current fitness values of new position and update (P*) and BF if current
             fitness < BF
24.       End If
25.    End For
26.    Update population using ring crossover.
27.    Define R as a random () and mutation_rate as a constant value
28.    If R < mutation rate
29.    // Mutation phase
30.       Define Δ as random (U (-0.5,0.5))
31.       Update population using equation (15)
32.    Evaluate current fitness values of new position and update (P*) and BF if current fitness
       < BF
33.    Find the current best solution P* and best fitness (BF)
34.    T = T+1
35. End While
36. Output the best solution
```

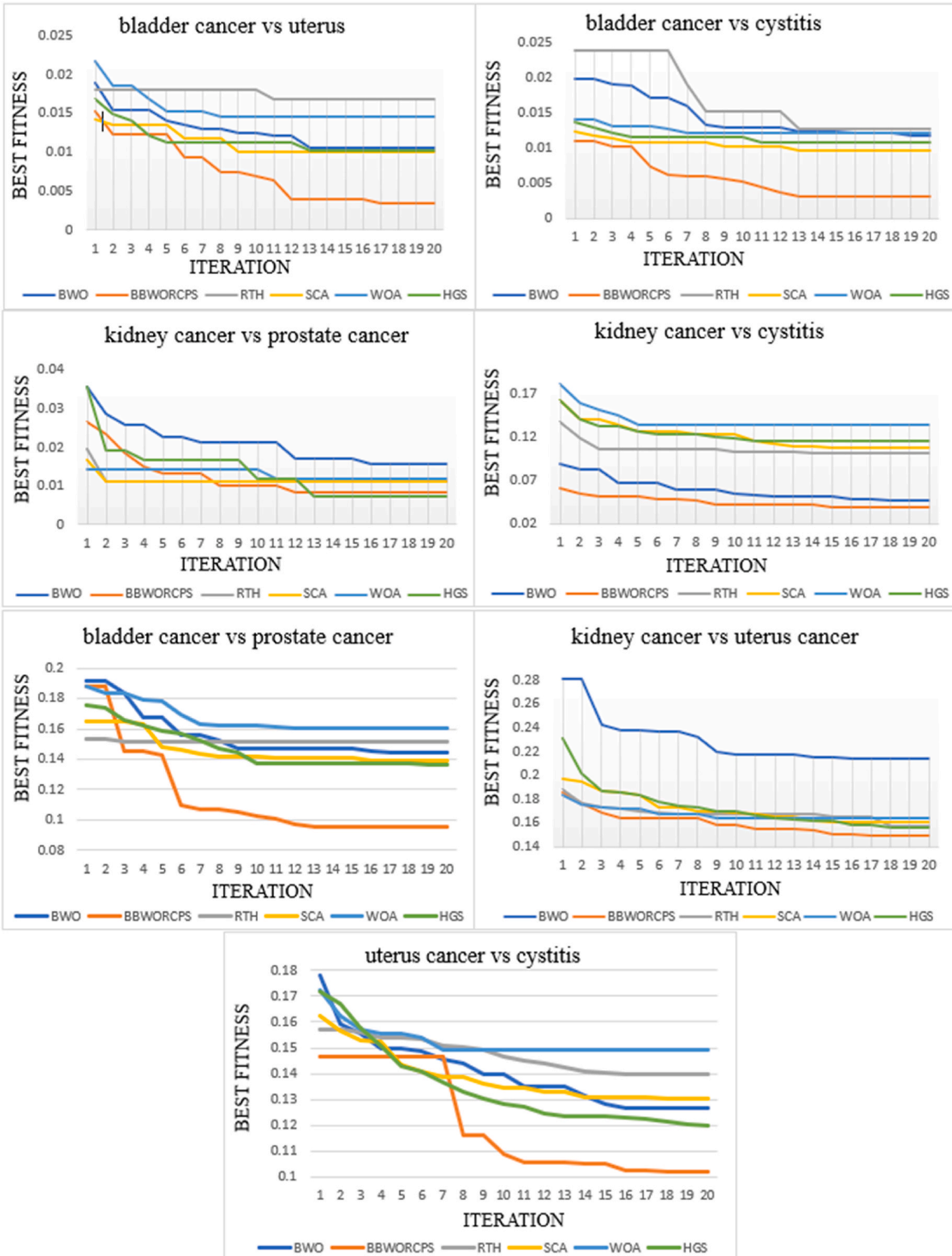

Fig. 4. Convergence curves of the proposed BBWORCPS and other optimization algorithms.

The pseudo-code outlines these steps, which include initialization, exploration, exploitation, whale fall, mutation, and evaluation processes. The main steps involve updating the position of beluga whales based on exploration and exploitation phases, incorporating whale fall effects, performing crossover and mutation operations, and evaluating fitness values.

The algorithm iterates until reaching a predefined maximum number of iterations (Max_it), ultimately outputting the best solution found. This algorithmic framework facilitates the effective application of the BWO algorithm to feature selection tasks, enabling the identification of feature subsets that optimize predictive performance while minimizing computational complexity. Through iterative refinement guided by the fitness function, the BWO algorithm can systematically explore the solution space and converge towards an optimal feature subset tailored to

Table 5
Comparison of the mean of best fitness.

Dataset	BWO		BBWORCPS		RTH		SCA		WOA		HGS	
	$\mu_{fitness}$	$\sigma_{fitness}$	$\mu_{fitness}$	$\sigma_{fitness}$	$\mu_{fitness}$	$\sigma_{fitness}$	$\mu_{fitness}$	$\sigma_{fitness}$	$\mu_{fitness}$	$\sigma_{fitness}$	$\mu_{fitness}$	$\sigma_{fitness}$
Data1	0.0118	0.0035	0.0031	0.0008	0.0127	0.0035	0.0096	0.0008	0.0122	0.0018	0.0108	0.000
Data2	0.1445	0.0162	0.0952	0.0070	0.1514	0.0303	0.1393	0.0092	0.1602	0.0091	0.1361	0.0165
Data3	0.0106	0.0020	0.0034	0.0011	0.0168	0.0017	0.0101	0.000	0.0145	0.0039	0.0103	0.0013
Data4	0.0468	0.0096	0.0397	0.0062	0.1017	0.0033	0..1074	0.0135	0.1350	0.0140	0.1157	0.0202
Data5	0.0157	0.0053	0.0083	0.0000	0.0111	0.0039	0.0111	0.0034	0.0119	0.0034	0.0071	0.0000
Data6	0.2142	0.0480	0.1488	0.0157	0.1570	0.0091	0.1603	0.0084	0.1645	0.0104	0.1560	0.0100
Data7	0.1266	0.0117	0.1020	0.0188	0.1397	0.0171	0.1301	0.0123	0.1493	0.0144	0.1198	0.0074

Table 6
Comparison of the number of FS.

Dataset	BWO		BBWORCPS		RTH		SCA		WOA		HGS	
	μ_{FS}	σ_{FS}	μ_{FS}	σ_{FS}	μ_{FS}	σ_{FS}	μ_{FS}	σ_{FS}	μ_{FS}	σ_{FS}	μ_{FS}	σ_{FS}
Data1	19.2	1.7436	17.2	2.0881	26.0	9.2736	15.7	0.9428	21.0	1.6330	17.7	1.2472
Data2	21.2	1.4697	17.4	1.6248	39.0	0.000	16.3	2.6247	19.3	4.1899	17.0	0.8165
Data3	22.4	4.4091	17.8	1.7205	20.3	2.3570	19.7	1.8856	24.7	7.3636	19.0	2.1602
Data4	18.4	1.0198	15.8	3.5440	16.3	2.4944	20.0	0.8817	16.3	6.1824	15.3	1.6997
Data5	20.0	3.4059	19.8	2.4819	19.8	1.6997	16.0	2.9439	20.0	0.0000	16.0	1.4142
Data6	21.4	2.9394	21.4	3.8262	20.0	2.5298	20.4	1.7436	17.8	5.2688	18.0	1.8974
Data7	19.8	2.6382	15.8	1.9391	23.0	4.8990	16.8	3.6	15.6	8.2122	16.4	2.9394

Table 7
Comparison of the accuracy.

Dataset	BWO		BBWORCPS		RTH		SCA		WOA		HGS	
	μ_{ACC}	σ_{ACC}	μ_{ACC}	σ_{ACC}	μ_{ACC}	σ_{ACC}	μ_{ACC}	σ_{ACC}	μ_{ACC}	σ_{ACC}	μ_{ACC}	σ_{ACC}
Data1	0.9882	0.0035	0.9969	0.0008	0.9845	0.0072	0.9904	0.0008	0.9878	0.0018	0.9892	0.0000
Data2	0.8556	0.0163	0.9048	0.0070	0.8180	0.0091	0.8607	0.0092	0.8398	0.0091	0.8639	0.0165
Data3	0.9894	0.0019	0.9966	0.0011	0.9832	0.0017	0.9899	0.0000	0.9855	0.0039	0.9897	0.0013
Data4	0.9532	0.0096	0.9603	0.0062	0.8983	0.0033	0.8926	0.0135	0.8650	0.0140	0.8843	0.0202
Data5	0.9843	0.0053	0.9917	0.0000	0.9889	0.0039	0.9889	0.0039	0.9881	0.0034	0.9929	0.0000
Data6	0.7858	0.0480	0.8512	0.0157	0.8430	0.0091	0.8397	0.0084	0.8355	0.0104	0.8440	0.0100
Data7	0.8734	0.0117	0.8986	0.0180	0.8603	0.0171	0.8699	0.0123	0.8507	0.0144	0.8802	0.0074

the specific problem domain.

4. Evaluation matrices

The effectiveness of the classification process can be examined using the assessment criteria provided below, which can categorize findings as True Positive (TF), True Negative (TN), False Positive (FP), or False Negative (FN). Among other metrics, these four features can be used to assess recall, f1-score, Precision, and accuracy.

The accuracy assessment is defined as the percentage of accurately predicted samples among all predicted samples. Total, true negative (TN), and true positive (TP) indicate the total number of forecasts.

$$Accuracy = \frac{T_p + T_N}{T_p + T_N + F_p + F_N} \tag{17}$$

Accurate classification numbers are penalized, whereas the correct number is calculated with Precision.

$$Precision = \frac{T_p}{T_p + F_p} \tag{18}$$

The recall metric estimates the number of accurate categories that have missing entries.

$$Recall = \frac{T_p}{T_P + F_N} \tag{19}$$

The F-score is the harmonic average of measurement accuracy and recall rate.

$$F_1 - Score = 2 \times \frac{precision \times Recall}{Precision + Rrecall} \tag{20}$$

5. Experimental result and discussion

The performance of the proposed BBWORCPS algorithm is tested using seven datasets, and the results are compared with the other five comparable metaheuristic algorithms. First, the details of medical problems are provided, and the experimental setup and compared algorithms are presented. In this study, the performance of the BBWORCPS approach was evaluated against five renowned optimization algorithms: the Red Tail Hawk (RTH) algorithm, the Sine Cosine technique (SCA), the Whale Optimization Algorithm (WOA), and the Hunger Games Search (HGS). The Red red-tail hawk (RTH) method effectively explores and exploits the search space to address complex optimization problems, drawing inspiration from the hunting strategy of red-tail hawks (Ferahtia et al., 2023). The Sine Cosine Algorithm (SCA) has proven to be effective in engineering design and feature selection tasks. It achieves this by exploring the search space using mathematical sine and cosine functions (Mirjalili, 2016). The Whale Optimization Algorithm (WOA) is derived from the bubble-net hunting method employed by humpback whales. It is well-known for its robustness in tackling various optimization problems (Mirjalili and Lewis, 2016). The Hunger Games Search (HGS) algorithm is a relatively new technique that is particularly effective in machine learning and data mining applications. It emulates the competitive behavior of individuals in an environment with limited resources (Nd, 2021). The selection of these

Table 8
Comparison of the precision.

Dataset	BWO		BBWORCPS		RTH		SCA		WOA		HGS	
	μ_P	σ_{PVV}	μ_P	σ_{PVV}	μ_P	σ_{PVV}	μ_P	σ_{PVV}	μ_P	σ_{PVV}	μ_P	σ_{PVV}
Data1	0.9881	0.0033	0.9968	0.0008	0.9848	0.0068	0.9901	0.0008	0.9879	0.0018	0.9728	0.0000
Data2	0.8655	0.0090	0.9090	0.0066	0.8396	0.0027	0.8771	0.0055	0.8643	0.0037	0.8825	0.0086
Data3	0.9895	0.0019	0.9965	0.0011	0.9773	0.0044	0.9861	0.0000	0.9859	0.0036	0.9859	0.0029
Data4	0.9535	0.0095	0.9603	0.0062	0.9004	0.0044	0.8922	0.0136	0.8741	0.0213	0.8862	0.0195
Data5	0.9848	0.0050	0.9915	0.0000	0.9897	0.0036	0.9897	0.0036	0.9886	0.0032	0.9932	0.0000
Data6	0.8100	0.0255	0.8490	0.0130	0.8505	0.0117	0.8566	0.0066	0.8662	0.0033	0.8556	0.0111
Data7	0.8758	0.0118	0.9004	0.0184	0.8831	0.0128	0.8872	0.0087	0.8772	0.0093	0.8920	0.0068

Table 9
Comparison of the recall.

Dataset	BWO		BBWORCPS		RTH		SCA		WOA		HGS	
	μ_R	σ_R	μ_R	σ_R	μ_R	σ_R	μ_R	σ_R	μ_R	σ_R	μ_R	σ_R
Data1	0.9882	0.0037	0.9970	0.0009	0.9842	0.0075	0.9909	0.0008	0.9877	0.0017	0.9934	0.0000
Data2	0.8607	0.0146	0.9075	0.0069	0.8221	0.0050	0.8648	0.0087	0.8379	0.0095	0.8688	0.0156
Data3	0.9892	0.0019	0.9967	0.0012	0.9764	0.0079	0.9861	0.0000	0.9852	0.0041	0.9845	0.0009
Data4	0.9530	0.0098	0.9603	0.0062	0.8988	0.0040	0.8933	0.0139	0.8599	0.0126	0.8868	0.0199
Data5	0.9841	0.0056	0.9919	0.0000	0.9883	0.0041	0.9883	0.0041	0.9879	0.0034	0.9926	0.0000
Data6	0.8092	0.0393	0.8652	0.0135	0.8436	0.0091	0.8405	0.0083	0.8304	0.0115	0.8408	0.0101
Data7	0.8764	0.0118	0.9005	0.0182	0.8627	0.0169	0.8720	0.0120	0.8488	0.0147	0.8841	0.0073

Table 10
Comparison of the F1-score.

Dataset	BWO		BBWORCPS		RTH		SCA		WOA		HGS	
	μ_{F-1}	σ_{F-1}	μ_{F-1}	σ_{F-1}	μ_{F-1}	σ_{F-1}	μ_{F-1}	σ_{F-1}	μ_{F-1}	σ_{F-1}	μ_{F-1}	σ_{F-1}
Data1	0.9881	0.0035	0.9969	0.0008	0.9845	0.0072	0.9904	0.0008	0.9878	0.0018	0.9827	0.0000
Data2	0.8553	0.0167	0.9048	0.0070	0.8161	0.0090	0.8599	0.0095	0.8364	0.0104	0.8631	0.0172
Data3	0.9894	0.0019	0.9966	0.0011	0.9767	0.0034	0.9861	0.0000	0.9855	0.0040	0.9852	0.0019
Data4	0.9531	0.0096	0.9603	0.0062	0.8982	0.0034	0.8924	0.0136	0.8625	0.0135	0.8843	0.0202
Data5	0.9843	0.0054	0.9917	0.0000	0.9888	0.0040	0.9888	0.0040	0.9881	0.0034	0.9928	0.0000
Data6	0.7849	0.0489	0.8486	0.0152	0.8423	0.0089	0.8380	0.0090	0.8302	0.0123	0.8416	0.0102
Data7	0.8734	0.0117	0.8986	0.0180	0.8586	0.0177	0.8688	0.0127	0.8474	0.0156	0.8799	0.0075

algorithms for analyzing the BBWORCPS method was based on their established effectiveness in optimization, providing a thorough and reliable benchmark. The numerical data produced by the BBWORCPS approach and other competing algorithms were statistically examined using the Friedman test. The performance of the BBWORCPS algorithm and other optimization algorithms was compared using the Friedman test for the *mean* and *STD* of the best solutions. The effectiveness of the BBWORCPS algorithm was evaluated on seven disease datasets with various feature. The final row is ranked in each of the results tables using Friedman's rank. The Naive Bayes (NB) classifier was used to evaluate the performance of the BBWORCPS algorithm. The data was split into 80 % for training and 20 % for testing to ensure robust evaluation. In the following tables, the labels $\boldsymbol{\mu}$ and $\boldsymbol{\sigma}$ refer to the mean and standard deviation of the function values, respectively. The bold type represents the best values.

5.1. Algorithm configurations

5.1.1. Parameter settings

Table 3 demonstrates the parameter setting employed in constrained optimization algorithms. To find all possible solutions, BWO, BBWORCPS, Red-Tailed Hawk (RTH), Sine Cosine Algorithm (SCA), Whale Optimization Algorithm (WOA), and Hunger Game Search (HGS) have to be effectively repeated. A total of 30 runs were performed for this purpose, with each run having a maximum number of iterations.

To determine which optimization approach was the most effective, we ran each under identical conditions, as given in Table 4. It is the straightest approach to determine how well a classification problem is performing when the result can include two or more different types of classes.

5.1.2. Performance models

In this study, a modified version of the BWO method is presented. This improved technique uses ring crossover and the PSMA to improve bladder cancer diagnosis accuracy. The modified algorithm, known as BBWORCPS, was rigorously tested against the standard BWO as well as other well-established algorithms such as RTH, SCA, WOA, and HGS across seven different datasets involving bladder cancer and other conditions such as cystitis, prostate cancer, kidney cancer, and uterine cancer. The generated curves from iterative simulations show that the BBWORCPS method continuously maintains a lower best fitness value than its alternatives, as shown in Fig. 4, implying greater diagnostic Precision across the iterations.

The figures clearly show the efficacy of the proposed algorithm, particularly in the datasets comparing bladder cancer to prostate cancer and cystitis, where the BBWORCPS consistently outperforms other algorithms throughout the iterations. The convergence curves in the bladder cancer versus cystitis and kidney cancer versus uterine cancer datasets, in particular, show a rapid and stable convergence to optimal solutions, demonstrating the modified BWO's robustness and reliability in distinguishing nuanced differences between closely related conditions. The study's findings are promising, indicating that the BBWORCPS algorithm has the potential to dramatically improve the computational diagnosis of bladder cancer, providing medical

Table 11
Comparative freedman ranking of optimization algorithms across various performance metrics.

Measurements	BWO	BBWORCPS	RTH	SCA	WOA	HGS
Fitness	4.14	1.14	4.50	3.21	5.43	2.57
Accuracy	4.14	1.14	4.50	3.21	5.43	2.57
Precession	4.14	1.71	4.50	2.93	4.36	3.36
Recall	3.86	1.14	4.50	3.50	5.14	2.86
F1-score	3.71	1.14	4.36	3.36	5.00	3.43
FS	5.00	2.71	4.57	2.93	3.71	2.07

Table 12
P-values from wilcoxon signed-rank tests comparing BBWORCPS with other optimization algorithms across different performance metrics.

Measurements	BWO	RTH	SCA	WOA	HGS
Fitness	0.0156	0.0156	0.0156	0.0156	0.0313
Accuracy	0.0156	0.0156	0.0156	0.0156	0.0313
Precession	0.0156	0.0313	0.0781	0.1094	0.0781
Recall	0.0156	0.0156	0.0156	0.0156	0.0313
F1-score	0.0156	0.0156	0.0156	0.0156	0.0313

professionals with a valuable tool for early and accurate disease detection.

The collective performance of these algorithms illustrates the diverse capabilities within the field of optimization, reinforcing the idea that the choice of algorithm can significantly impact the outcome of problem-solving in complex, real-world situations.

This study involved a comprehensive assessment of the effectiveness and dependability of seven optimization algorithms, using mean fitness (μ_fitness) and standard deviation (σ_fitness) of fitness as essential measures. The proposed BBWORCPS is a considerable advance over the original BWO and the other four competing algorithms: RTH, SCA, WOA, and HGS. Table 5 shows that the proposed BBWORCPS, for example, outperforms BWOs on the first dataset by 0.0031 and 0.0008, compared to 0.0118 and 0.0035 for μ_fitness and σ_fitness, respectively. This improved performance and consistency trend is seen in a range of datasets. On the sixth dataset, for example, BBWORCPS scores 0.1488 with a 0.0157, which is substantially higher than BWO's 0.2142 and 0.0480 for μ_fitness and σ_fitness, respectively. The overall results suggest that BBWORCPS is more robust and efficient in optimization tasks. They also underline the major benefits of adding probabilistic state mutation and ring-crossing approaches into the algorithmic architecture.

The comparison of four other optimization algorithms (RTH, SCA, WOA, and HGS) with the BWO algorithm and its improved version, BBWORCPS, reveals important new information about feature selection capabilities across seven datasets. Notably, in terms of feature selection efficiency, BBWORCPS regularly outperforms the original BWO and the other algorithms, selecting fewer features while maintaining or improving consistency. As shown in Table 6, BBWORCPS chooses 17.2 features from the first dataset, surpassing BWO's 19.2 and an average of 1.7436. This trend indicates the strategic advantage of BBWORCPS in selecting a condensed but relevant feature set, as it achieves a lower mean feature count while preserving or enhancing selection stability across all datasets. It illustrates BBWORCPS's superior optimization efficacy. This is corroborated by the Friedman position, which reveals that BBWORCPS and BWO are tied for first place, showing superior performance in terms of feature selection reliability and efficiency, as well as demonstrating the advantages of integrating ring crossover and probabilistic state mutation approaches.

The proposed BBWORCPS algorithm exceeds the original BWO and the other four competitive algorithms on seven datasets in terms of mean accuracy and standard deviation, as shown in Table 7. As seen by its performance on Data1, where it reaches an outstanding 0.9969 while maintaining an even more remarkable low of 0.0008, BBWORCPS frequently surpasses its predecessor and the other algorithms in terms of accuracy. Data2 and Data5, which suggest that BBWORCPS is resilient and trustworthy, mirror this growing accuracy and consistency trend by reporting higher values of 0.9048 and 0.9917, respectively, while maintaining lower levels. The Friedman ranking affirms BBWORCPS' dominance by illustrating its effectiveness as well as the huge impact of adding ring crossover and probabilistic state mutation techniques. This in-depth research indicates that BBWORCPS can achieve not just high accuracy but also noteworthy consistency over a variety of datasets, confirming the algorithm's improved optimization capabilities and cementing its place as a top solution in the field of computational optimization.

This table presents a comparison of the accuracy performance metrics of various metaheuristic optimization methods, including BBWORCPS. Table 8 presents the mean precision values and the standard deviation of precision values for each dataset and technique, offering a comprehensive assessment of the effectiveness and consistency of different approaches. BBWORCPS demonstrates strong performance across a wide range of datasets, with a high mean positive predictive value and a low standard deviation of positive predictive value. These results indicate that BBWORCPS is both reliable and robust for optimization tasks.

Table 9 shows that BBWORCPS consistently has excellent recall ratings. BBWORCPS outperforms BWO, RTH, SCA, WOA, and HGS, all of which experienced recalls ranging from 0.9842 to 0.9934. This tendency to outperform persists in subsequent datasets. BBWORCPS maintained a substantial competitive edge in Data2 and Data3, with recall rates of 0.9075 and 0.9967, respectively. The recall figures exemplify the reliability and effectiveness of BBWORCPS in many situations, as well as its ability to recognize all important elements accurately. The BBWORCPS recall consistently exhibits low standard deviations, showing its durability and consistency in performance across many situations. The Friedman rankings consistently place the BBWORCPS algorithm at a higher position compared to other algorithms, indicating its superior performance.

The proposed BBWORCPS typically outperforms or competes with other metaheuristic algorithms on several datasets, according to an analysis of the dataset's F1-score performance as in Table 10. Notably, BBWORCPS has a strong balance of Precision and recall, with high F1-scores of 0.9969 in Data1 and 0.9966 in Data3. This performance exceeds that of BWO, RTH, SCA, WOA, and HGS. BBWORCPS, in particular, has the lowest score variability, as indicated by the smallest standard deviation values, as well as the greatest F1-score. BBWORCPS's robustness is shown by its constant and reliable performance, even on tough datasets, such as Data 6 and Data 7.

The proposed BBWORCPS outperforms almost all statistical measures across the datasets. In comparison to the standard BWO and other algorithms, including RTH, SCA, WOA, and HGS, BBWORCPS consistently has lower mean fitness values, indicating better optimization performance.

In terms of accuracy, the BBWORCPS once again surpasses the rival algorithms, with greater mean accuracy rates and lower standard deviations, showing that it is effective at correctly diagnosing the conditions provided in the datasets. Similarly, the mean F1 score for BBWORCPS is often higher, indicating improved diagnostic performance by combining Precision and recall. Across the datasets, BBWORCPS consistently outperforms other algorithms, confirming it as a powerful tool for accurately and reliably detecting medical disorders.

5.1.3. Statistical analysis of optimization algorithms

In our investigation, we compared the performance of various optimization methods using metrics like Fitness, Accuracy, Precision, Recall, F1-score, and Feature Selection. Table 11 displays the results in the form of Freedman rankings, which allow a reliable statistical comparison of non-parametric data. The BWO method was modified to incorporate ring crossover and probabilistic state mutation techniques, resulting in the BBWORCPS. This change was intended to improve the algorithm's efficiency and accuracy by improving its explorative and exploitative capabilities in binary search spaces.

Significantly, the BBWORCPS algorithm outperforms nearly all assessed measures, regularly earning the highest rankings (lowest Freedman rank values). Specifically, it ranks #1 in Fitness, Accuracy, Precision, Recall, and F1-score. This is a significant improvement over the original BWO, which rates much worse in these criteria.

The statistical rankings reflect the success of the changes made to BBWORCPS. The utilization of ring crossover introduces a regular flow of information between individuals, increasing diversity while preventing premature convergence. Meanwhile, probabilistic state mutation aids in escaping local optima by allowing for random but guided changes in the solution state based on probabilistic criteria.

These enhancements contribute to BBWORCPS's robust performance, outperforming other algorithms such as RTH, SCA, WOA, and HGS in most metrics. The results substantiate the potential of combining crossover mechanisms and adaptive mutation techniques in binary optimization algorithms, setting a precedent for future research in algorithmic design and application.

Following the examination of Freedman rankings, which provided preliminary insights into the comparative performance of the optimization algorithms, additional statistical tests were carried out to confirm these results. Wilcoxon signed-rank tests were used to assess the significance of differences between the BBWORCPS algorithm and the other algorithms in terms of several performance measures such as fitness, accuracy, Precision, recall, and F1-score.

The results of these tests, given in Table 12, show statistically significant differences in performance across practically all parameters. For example, when comparing BBWORCPS to algorithms like BWO, RTH, SCA, and WOA, the p-values are consistently 0.0156 across parameters such as Fitness, Accuracy, and Recall, showing a statistically significant gain in performance. These data confirm that the enhancements integrated into the BBWORCPS, such as ring crossover and probabilistic state mutation, significantly boost its effectiveness.

In criteria like Precision, while BBWORCPS still outperforms most algorithms, the differences are less evident when compared to SCA and WOA, as evidenced by higher p-values of 0.0781 and 0.1094, respectively. This implies that while BBWORCPS generally outperforms other algorithms, its dominance varies depending on the element of performance.

The only other algorithm that occasionally performs better than BBWORCPS is HGS, which has a p-value of 0.0313 in metrics like Fitness and F1-score, indicating a moderately significant difference. This demonstrates HGS's competitive capabilities in specific cases, though not consistently across all parameters.

6. Conclusion

This study pioneered the binary adaption of the BWO algorithm, resulting in the creation of the BBWORCPS. This novel approach was developed expressly to improve feature selection for bladder cancer diagnosis, representing a substantial advancement in the use of optimization algorithms in medical diagnostics. The BBWORCPS algorithm, which incorporates ring crossover and the Probabilistic State Mutation Algorithm into the newly binary BWO, not only addresses the original algorithm's diversity restrictions but also considerably minimizes the chance of entrapment in local optima. The adjustments significantly enhanced the algorithm's resilience, efficacy, and speed, especially in complicated optimization scenarios like feature selection in huge datasets. In a comparison of five established optimization algorithms—RTH, SCA, WOA, and HGS—across seven different datasets, BBWORCPS consistently outperformed the competition, demonstrating its effectiveness and efficiency in dealing with high-dimensional data and improving diagnostic accuracy.

Given BBWORCPS's success in biomedical data analysis, future research could look into its application in other critical areas of healthcare, such as genetic data processing and personalized medicine, where feature selection is critical for interpreting complex biological information. Furthermore, given the rapid advancements in computational methods for health informatics, further improvements to the BBWORCPS algorithm, such as the inclusion of more sophisticated transfer functions and mutation mechanisms, may improve its adaptability and performance in a variety of dynamic environments. Continuous comparison studies with new and developing optimization techniques will be required to keep the algorithm's competitive advantage and relevance in the rapidly changing world of biomedical research and healthcare technology.

Ethical approval

This article does not contain any studies with human participants or animals performed by any of the authors.

Informed consent

Informed consent was obtained from all individual participants included in the study.

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Declaration of competing interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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References

[1] Saginala K, Barsouk A, Aluru JS, Rawla P, Padala SA, Barsouk A. Epidemiology of bladder cancer. Medical sciences 2020;8(1):15.
[2] Ferlay J, Colombet M, Soerjomataram I, Parkin DM, Piñeros M, Znaor A, Bray F. Cancer statistics for the year 2020: an overview. Int J Cancer 2021;149(4):778–89.
[3] Huang XJ, et al. Aspartate aminotransferase (AST/GOT) and alanine aminotransferase (ALT/GPT) detection techniques. Sensors 2006;6(7):756–82. https://doi.org/10.3390/s6070756.
[4] Kamat AM, Hahn NM, Efstathiou JA, Lerner SP, Malmström P-U, Choi W, Guo CC, Lotan Y, Kassouf WJTL. Bladder Cancer 2016;388(10061):2796–810.
[5] Zhu CZ, et al. A review on the accuracy of bladder cancer detection methods. J Cancer 2019;10(17):4038–44. https://doi.org/10.7150/jca.28989.
[6] Al Mamlook RE, et al. Classification of cancer genome atlas glioblastoma multiform (TCGA-GBM) using machine learning method. IEEE international conference on electro information technology, 2023-may(may). 2023. p. 265–70. https://doi.org/10.1109/eIT57321.2023.10187283.
[7] Chovancova B, et al. Role of sodium/calcium exchangers in tumors. Biomolecules 2020;10(9):1–10. https://doi.org/10.3390/biom10091257.

[8] Maclagan NF. Laboratory data. Bmj 1966;1(5486):531–2. https://doi.org/10.1136/bmj.1.5486.531-c.
[9] Waxman SG. Mechanisms of Disease: sodium channels and neuroprotection in multiple sclerosis—current status. Nat Clin Pract Neurol 2008;4(3):159–69. https://doi.org/10.1038/ncpneuro0735.
[10] Oettl K, et al. Oxidative damage of albumin in advanced liver disease. Biochim Biophys Acta (BBA) - Mol Basis Dis 2008;1782(7–8):469–73. https://doi.org/10.1016/j.bbadis.2008.04.002.
[11] Nelson JJ, et al. Serum albumin level as a predictor of incident Coronary heart disease: the Atherosclerosis Risk in Communities (ARIC) study. Am J Epidemiol 2000;151(5):468–77. https://doi.org/10.1093/oxfordjournals.aje.a010232.
[12] Martin H. Laboratory measurement of urine albumin and urine total protein in screening for proteinuria in chronic kidney disease. Clin Biochem Rev 2011;32(2):97–102.
[13] Echeverry G, Hortin GL, Rai AJ. Introduction to urinalysis: historical perspectives and clinical application. The urinary proteome: methods and protocols 2010:1–12.
[14] Lillian A, Mundt KS. Chemical analysis of urine. Graff's Textbook of Routine Urinalysis and Body Fluids 2010;1:35–53. Lippincott Williams & Wilkins: Philadelphia, PA, USA.
[15] Shakhssalim N. In: Lifestyle and occupational risk assessment using machine learning methods and development a web- based nomogram for prediction of bladder cancer Short title : risk assessment and nomogram to predict bladder cancer; 2022.
[16] Ji W, Naguib RNG, Ghoneim MA. Neural network-based assessment of prognostic markers and outcome prediction in bilharziasis-associated bladder cancer. IEEE Trans Inf Technol Biomed 2003;7(3):218–24. https://doi.org/10.1109/TITB.2003.813796.
[17] Yang R, et al. Automatic recognition of bladder tumours using deep learning technology and its clinical application. Int J Med Robot Comput Assist Surg 2021;17(2). https://doi.org/10.1002/rcs.2194.
[18] Lam KM, He XJ, Choi KS. Using artificial neural network to predict mortality of radical cystectomy for bladder cancer. Proceedings of 2014 International Conference on Smart Computing 2014:201–7. https://doi.org/10.1109/SMARTCOMP.2014.7043859. SMARTCOMP 2014, (August.
[19] Chen S, et al. Clinical use of machine learning-based pathomics signature for diagnosis and survival prediction of bladder cancer. Cancer Sci 2021;112(7):2905–14. https://doi.org/10.1111/cas.14927.
[20] Lee S, et al. Early-stage diagnosis of bladder cancer using surface-enhanced Raman spectroscopy combined with machine learning algorithms in a rat model. Biosens Bioelectron 2024;246(December 2023):115915. https://doi.org/10.1016/j.bios.2023.115915.
[21] Tsai IJ, et al. Machine learning in prediction of bladder cancer on clinical laboratory data. Diagnostics 2022;12(1). https://doi.org/10.3390/diagnostics12010203.
[22] Freitas NR, et al. Detection of bladder cancer with feature fusion, transfer learning and CapsNetsI. Artif Intell Med 2022;126(February). https://doi.org/10.1016/j.artmed.2022.102275.
[23] Alzahrani JS, Rizwanullah M, Osman AE. Piece-wise linear chaotic mapping-based beluga whale optimization algorithm-based indoor activity monitoring for elderly and visually impaired persons. Journal of Disability Research 2023;2(2):112–9. https://doi.org/10.57197/jdr-2023-0030.
[24] Houssein EH, Sayed A. Dynamic candidate solution boosted beluga whale optimization algorithm for biomedical classification. Mathematics 2023;11(3). https://doi.org/10.3390/math11030707.
[25] Huang J, Hu H. Hybrid beluga whale optimization algorithm with multi-strategy for functions and engineering optimization problems. Journal of Big Data 2024;11(1). https://doi.org/10.1186/s40537-023-00864-8.
[26] Chen H, et al. An improved multi-strategy beluga whale optimization for global optimization problems. Math Biosci Eng 2023;20(7):13267–317. https://doi.org/10.3934/mbe.2023592.
[27] Paçaci S. Improvement of beluga whale optimization algorithm by distance balance selection method. Journal of Yalvaç Academy 2023;8(1):125–44. https://doi.org/10.5712/yalvac.1257808.
[28] Hussien AG, et al. Novel memetic of beluga whale optimization with self-adaptive exploration–exploitation balance for global optimization and engineering problems, Soft Computing. Berlin Heidelberg: Springer; 2023. https://doi.org/10.1007/s00500-023-08468-3.
[29] Yuan X, et al. HBWO-JS: jellyfish search boosted hybrid beluga whale optimization algorithm for engineering applications. Journal of Computational Design and Engineering 2023;10(4):1615–56. https://doi.org/10.1093/jcde/qwad060.
[30] Wang C, et al. Development and application of a comprehensive assessment method of regional flood disaster risk based on a refined random forest model using beluga whale optimization. J Hydrol 2024;633(April 2023). https://doi.org/10.1016/j.jhydrol.2024.130963.
[31] Deepika C, Kuchibhotla S. Deep-CNN based knowledge learning with Beluga Whale optimization using chaogram transformation using intelligent sensors for speech emotion recognition. Measurement: Sensors 2024;32(January):101030. https://doi.org/10.1016/j.measen.2024.101030.
[32] Li LL, et al. Multi-objective distributed generation hierarchical optimal planning in distribution network: improved beluga whale optimization algorithm. Expert Syst Appl 2024;237(PA):121406. https://doi.org/10.1016/j.eswa.2023.121406.
[33] Jia H, et al. Modified beluga whale optimization with multi-strategies for solving engineering problems. Journal of Computational Design and Engineering 2023;10(6):2065–93. https://doi.org/10.1093/jcde/qwad089.