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ORIGINAL PAPER

Binary northern goshawk optimization for feature selection on micro array cancer datasets

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Abstract
Northern Goshawk Optimization (NGO) is a recently proposed swarm-based optimization method that hunts like a northern goshawk. However, while the approach excels with many benchmark functions, it is incapable of dealing with the binary optimization problem. We proposed a binary variation of NGO for feature selection (FS) issues in classification tasks. We employed S and V-shaped transfer functions (TF) to convert continuous data to binary values. The suggested model is evaluated based on six high dimensional micro array cancer datasets using the benchmark evaluation measures such as accuracy, fitness and number of features selected. To demonstrate the effectiveness of the suggested model, it is compared to traditional and recent binary versions metaheuristic algorithms. According to the findings, the S-shaped transfer function surpasses other transfer functions and classical models.

Keywords Feature selection · Micro array dataset · Binary optimization · Meta-heuristic optimization

1 Introduction

In machine learning (ML), FS is one of the well-known data pre-processing procedures (Tubishat et al. 2020). Its purpose is to reduce the number of features by deleting redundant and unnecessary elements. When doing feature reduction on a dataset, feature selection methods must take into account the accuracy of classification algorithms. In practice, FS is a typical strategy in ML for reducing dimensionality by eliminating unnecessary and redundant data from the raw dataset and reaching the ideal feature subset, which improves the speed and accuracy of classification algorithms (Nssibi et al. Jan. 2021). In reality, the purpose of feature selection is to choose a collection of m features from a total of n features that enhances the learning algorithm's performance in terms of learning speed or classification accuracy (Zheng et al. 2019).

Irrelevant and superfluous characteristics may be removed from datasets using FS. In addition to misleading the learning algorithm and degrading performance, irrelevant and duplicated learning features significantly increase the computational complexity and storage needs (Ibrahim et al. 2017). FS techniques are divided into two categories: filter and wrapper (Zhu et al. 2007). Apart from determining the error rate, the filter technique evaluates the suitable relevance of the features in the dataset (Lazar et al. 2012). The components with the lowest relevance score are eliminated from the dataset after comparing their relevance scores. Univariate and Multivariate are the types of filter methods (Tabakhi and Moradi 2015). The Univariate assesses each feature individually, whereas the Multivariate evaluates the features in reference to the connection between two or more qualities.

Feature scores may be evaluated using the filter method's (Aladeemy et al. 2020) Information Gain (IG) (Kamkar et al. 2015), Pearson correlation coefficient (Zheng et al. 2019), and Relief (Urbanowicz et al. 2018). The wrapper method searches the dataset for feature subsets and evaluates them (Abdel-Basset et al. 2021). The assessment requirements for the specified subset are met by employing learning algorithms to determine the feature subset with improved

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accuracy. The wrapper approach explains the feature selection procedure in detail. Wrapper feature selection approaches include Differential Evolution (DE) (Gao et al. 2012), ACO (Fahrudin et al. 2016), PSO (Shao et al. 2012), and Whale Optimization Algorithm (WOA) (Mirjalili and Lewis 2016). Wrapper strategies are more expensive than filter methods, but they are widely used to enhance the prediction approaches' performance because they interact with all of the dataset's features.

Researchers' curiosity was aroused by the discovery that metaheuristic (MH) algorithms had a lot of potential for solving the FS problem. The technique of merging random and local search methods is known as MH algorithms. Utilizing a heuristic method and a clever fusion of several different concepts, this approach investigates and utilizes the search space. No optimization strategy is adequate for all applications, as per No-Free-Lunch theorem. To solve an issue, you must produce a novel approach to enhance existing optimization approaches via hybridization. Wrapper approaches that include effective search space strategies serve to minimize time complexity and increase the predictive model's performance. Evolutionary Algorithm (EA) (Rostami et al. 2021), Physics-based Algorithm (Gao et al. 2020), Swarm-based Algorithm (Zheng et al. 2015), and Human-based Algorithm (Zhu et al. 2014) are the four types of population-based MH algorithms. Genetic Algorithm (GA) (Dhanalakshmi et al. 2009), Harmony Search (Diao and Shen 2012), Clonal Selection Algorithm (Ding and Li 2009), and Differential Evolution (Liu et al. 2020), which is inspired by natural evolution, are all part of the EA. Ions Motion Optimization (Javidy et al. 2015), MOA (Tayarani and Akbarzadeh 2008), and GSA (Rashedi et al. 2018) are physics-based approaches that claim to be the physical leaders of the natural world. PSO, WOA, and the Dragonfly Algorithm (Mirjalili 2016) are swarm-based algorithms. League Championship Algorithm (Husseinzadeh Kashan 2014), FA (Li et al. 2017), and MBA (Sadollah et al. 2012) are examples of human-based algorithms. However, fulfilling these objectives is difficult, especially if a strategy that can be extended to other domains is required. This encourages researchers to improve on previous techniques, which keeps the research area alive. When it comes to solving an optimization problem, multimodal functions have a lot of dimensions, making it difficult to find an ideal value for all of them at the same time. This is why researchers use meta-heuristic approaches to tackle these kinds of problems, with the objective of finding the best answer in a reasonable amount of time. In order to meet these needs, research is now underway. We used the northern goshawk optimization (NGO) (Dehghani et al. 2021) algorithm to create a hybrid meta-heuristic FS approach.

The northern goshawk is a raptor whose hunting approach is based on optimization. The northern goshawk uses this method to first pick and attack its target, after which it pursues the animal in a pursuit. This knowledge gap prompted the authors to create a novel optimization technique based on mathematical modelling of the northern goshawk's hunting tactics. It simulates the hunting behavior of northern goshawks. The suggested NGO algorithm's many phases are stated and then mathematically represented. It consists of two stages, in the first, it travels quickly towards the prey after spotting it, and next it chases the prey in a brief tail chase procedure. It outperforms cutting-edge MH algorithms in terms of exploration, exploitation, local optima, and premature convergence. Due to the advantages of NGO as well as the reality that it hasn't been applied to solve FS issues, getting the best features in FS is a challenging task, especially in wrapper-based methods. This is owing to the fact that each optimization step requires a learning algorithm. As a result, a suitable optimization technique is necessary; we provide a solution to the FS problem. Binary approaches are required to solve problems involving discreate search spaces.

We develop the binary NGO since the discrete search space cannot be solved by NGO. We suggest utilising a BNGO to handle the FS problem since binary arithmetic is simpler than continuous arithmetic and the search space may be specified in binary values [0, 1] depending on the nature of the FS probability.

The following are the primary findings of this study:

- There are two binary versions of the recommended NGO (V-BNGO and S-BNGO). Due to larger population variety, the continuous search space is mapped to utilising two transfer functions, which increases the NGO's present search capability.
- Six distinct benchmark datasets were tested on important features responsible for life-threatening disease.
- Assessment of suggested approach using, classification accuracy, p- statistical value, convergence rate, fitness function and complexity analysis.
- Validating the proposed methodology in comparison with conventional techniques such as HHO, SSA, SCA, MFO and classical NGO and binary versions such as Binary Harris Hawk Optimization, Binary Manta Ray Forging Optimization, Binary Atom search Optimization, Binary Marine Predator, Binary moth-flame optimization, Binary Gradient-based optimizer and Binary Artificial Algae Algorithm.

The remaining section organized as follows: Sect. 2 deals with the recent related work followed by Sect. 3 discuss the mathematical model of the NGO. Section 4 deals with the proposed binary NGO for feature selection followed by the experimental results and discussion on Sect. 5. The final Sect. 6 elaborates the conclusion and future scope.

2 Related works

Emary et al. (2016) proposed the binary-firefly algorithm, to solve FS issues based on threshold value. The recommended method underwent extensive testing and was able to come up with a straightforward approach to the issue. Taghian and Nadimi-Shahraki (2019) suggested a binary form of SCA for the FS issue that was designed specifically for medical data. Binary variations of the V and S-shaped binary sine cosine algorithms are suggested in this work. The recommended methods are compared to four of the most current binary optimization strategies on five medical datasets. The selected subset is evaluated using the K-nearest Neighbor (KNN) classifier. The experimental findings demonstrate that the suggested technique can match or even surpass current models on the largest datasets. In another work, binary version of the Jaya method for FS, based on binary similarity measurements. The usual two TFs are employed in this study, as well as a novel Jaccard similarity (JS) based approach. Furthermore, neighborhood search, a probability-based local search approach, is provided to balance exploration and exploitation. B Jaya-JS also has a faster convergence rate than competitive approaches across most datasets (Chaudhuri and Sahu 2021).

The authors presented a binary variation of the local search algorithm-hill climbing for FS in another paper. The S-shaped TF converts the data into binary form. A collection of 22 benchmark datasets is used to assess the suggested technique. Variable configurations, transfer function effect, used classifier effect, and comparisons to other local search-based approaches and population-based algorithms using the same UCI datasets are all part of the evaluation process. Three classifiers are employed to assess classification accuracy (KNN, Support Vector Machine (SVM) and Decision Tree (DT)). The K-NN is used in the recommended approach since it has the best performance (Ghosh et al. 2020). For FS issues, authors suggested a binary butterfly optimization algorithm (BBOA) in another work. BOA's two binary variants are utilised to find the optimum feature. The recommended binary algorithms are compared to five conventional approaches and four current high-performing optimization algorithms (Aroraa and Anand 2019). In the Binary Gravitational Search Algorithm (BGSA), the authors proposed a population based on clustering for FS. The authors presented a binary variation of Moth Flame Optimization for FS, which uses eight distinct TFs: S-shaped and V-shaped, to fit it inside the FS. For FS issues, the authors presented a binary form of the competitive swarm optimizer approach (Rashedi and Nezamabadi-pour 2009).

In another work authors introduces an improved grasshopper optimization algorithm (GOA) based on OBL and called as OBLGOA (Too and Saad 2019) to resolve major MH approaches. It involves two stages, first stage initializes population and its opposition using OBL and during its second stage, it applies OBL scheme to update the GOA population at each iteration. Totally, four engineering problems and 23 benchmarks functions are considered to measure the performance of proposed scheme and comparison is made with other MH algorithms to prove the proposed scheme's quality work. The Moth swarm algorithm (MSA) is enhanced by Diego Oliva et. al and address the limitation of MSA (Ghosh et al. 2021) like convergence ability and high complexity in selecting optimal feature set. This enhanced version of MSA merges OBL scheme to provide good exploration ability and faster convergence. The testing is done to solve three engineering problems and nineteen benchmark functions including unimodal, multimodal and composite functions. The comparisons done here are validated against other conventional methods and outcomes shows superior performance attained by proposed MDSA in all statistical measurement.

In another research, the authors (Rai et al. 2022a) examined Human-Inspired Optimization Algorithms (HIOAs) components, categorization, common structure, applications, and prior work. Using human behavior and cognition, it optimized Multi-Level Thresholding (MLT) for color satellite image segmentation using Tsallis' and t-entropy objective functions. The research found that several HIOAs' objective functions for color satellite image segmentation were suitable, with t-entropy's efficacy based on threshold levels. Increasing thresholds increased FSIM, PSNR, and SSIM for both objective functions. Despite threshold settings, all experimental HIOAs and PSO using Tsallis entropy as the objective function had high fitness values. These results demonstrate the potential of HIOAs to solve real-world optimization challenges, emphasizing the necessity for research methodologies to identify and choose suitable HIOAs. In another research, the authors (Rai et al. 2022b) reviewed image segmentation, Multilevel Thresholding (MLT) which is crucial, especially when analysing segmented parts of multidimensional pictures and dealing with complicated non-linear scenarios. Nondeterministic methods are required due to the complexity of the objective function in MLT, making it a difficult exponential combinatorial optimisation issue. Therefore, scientists have started using NIOAs (Nature-Inspired Optimisation Algorithms) to solve MLT problems. This research examines the most recent developments (from 2019 to 2021) in NIOA-based models for image multi-thresholding and the main problems connected with them. In another research, the authors (Dhal et al. 2022) introduce an enhanced version of Cuckoo Search (CS). This enhanced version involves allocating each solution in the population to one of two fuzzy sets based on its fitness. To improve the solutions, fuzzy collection centroids, recommendations from the best global solutions, and mutations based on the Lévy distribution are employed. The experimental study evaluates the performance of this approach using the CEC-2014 test suite and the domain of picture multi-level thresholding, utilizing widely recognized objective functions such as Otsu inter-class variance and Kapur's entropy. A comparison is made with several other algorithms which consistently delivers excellent results. The author presents (Rostami et al. 2021) a thorough examination of feature selection techniques in a separate study. This research encompasses an extensive overview, classification, and comparison of these techniques. Furthermore, the study focuses on the latest advancements in feature selection techniques that leverage cutting-edge algorithms inspired by swarm intelligence. The relative strengths and weaknesses of various swarm intelligence-based approaches for feature selection are analyzed and contrasted, providing valuable insights into their effectiveness.

Binary Particle Swarm Optimization (BPSO) is a suggested evolutionary computing technique that performs well in feature selection issues, according to a separate area of research. The transfer function is used to map the continuous search space onto the discrete one. In BPSO, transfer functions are crucial. This study presents a more effective BPSO by fusing V-shaped and U-shaped transfer functions, as well as introducing a novel learning method and a local search technique based on adaptive mutation. The enhanced BPSO has more optimization potential, especially when used to the feature selection issue. The experimental findings demonstrate that the enhanced BPSO outperforms competing algorithms in terms of its dimension reduction capability and classification performance (Chen et al. 2023).

In a separate study, the researchers proposed an enhanced search technique for MTS known as the Binary Whale Optimisation Technique (BWOA). The objective of this research is to provide an innovative approach for enhancing the efficacy of the Mahalanobis Taguchi System (MTS) via the development of a novel combination technique. Various MTS hybrid algorithms were also evaluated in terms of their efficacy in feature selection. The Biogeography-Based Optimisation Algorithm (BWOA) emulates the hunting behaviour of humpback whales via a systematic approach that involves exploration of unexplored regions within the solution space, incremental reduction of the search space, and refinement of the solution (Huan et al. 2023). Two wrapper feature selection (FS) methods were presented in another research; they use a hybrid version of the ant colony optimisation (ACO) algorithm. There has not been a lot of research done on HRO, a novel metaheuristic that mimics three-line hybrid rice breeding, for high-dimensional FS problems. During the first iteration of the hybridization, ACO is updated in a counterbalanced fashion with HRO, which is an evolutionary operator. The second kind of hybridization allows for two populations to evolve in parallel while sharing information about their own local search spaces. To enhance ACO's global search capabilities in identifying the smallest and most representative features, a problem-oriented heuristic factor assignment approach based on the knee point feature is applied prior to hybridization (Ye et al. 2023).

To aid with feature selection (FS) for classification tasks using datasets from the IoMT, the authors of another work offered a binary version of AO (BAO). We employed a total of 12 transfer functions (TF) designed in the shape of S, U, and V to convert continuous data into binary values. The analysis of the proposed transfer functions indicates that Baryon Acoustic Oscillation (BAO) techniques exhibit superior performance compared to other transfer functions, particularly S2-BAO. In contrast to conventional transfer functions, the proposed methodology, which involves the identification of optimal features, fitness values, and enhanced classification accuracy, achieves convergence to the global minimum over multiple iterations (Dhanalakshmi and Nallagorla 2022). In another work, the authors presented a BAVOA that uses an S-shaped and V-shaped eight-transfer function to change a continuous variable into a binary one. Using 14 standard data sets, 15 traditional binary metaheuristics algorithms are compared to the suggested method in terms of classification accuracy, fitness function, number of chosen features, and ability to converge. The Wilcoxon test is also used to interpret the data statistically. The results of comparing the S-shaped and V-shaped transfer functions show that BAVOA methods, especially S2-BAVOA, work better than other transfer functions(Balakrishnan et al. 2022).

3 Mathematical model of northern goshawk optimization

This section deals with the background and mathematical model of NGO.

3.1 Initialization

The approach is spirited into two parts, with the first stage consisting of a high-speed chase after spotting the prey, and the second stage consisting of a brief tail chase after spotting the prey. Each NGO population participant provides a potential response to the issue that generates the values of the variables. The population members in the search space are randomly initialised at the start of the procedure. Equation 1 is used to calculate the population matrix in the NGO method. Equation 2 may be used to express the values acquired for the objective function (OF) as a vector.

$$X = \begin{vmatrix} x_{1,1} \cdots & x_{1,d} \cdots & x_{1,m} \\ x_{i,1} \ddots & x_{i,d} \ddots & x_{i,m} \\ x_{N,1} \cdots & x_{N,d} \cdots & x_{N,m} \end{vmatrix} \tag{1}$$

$$V(X) = \begin{vmatrix} V_1 = V(X_1) \\ \vdots \\ V_i = V(X_i) \\ \vdots \\ V_N = V(X_N) \end{vmatrix} \tag{2}$$

where Vi is the OF value acquired by the ith suggested solution and V is the vector. It serves as a criterion for determining which option is the best. The better the recommended solution in minimization issues is the lower the objective function value, while the better the proposed solution in maximizing problems is the higher the objective function value.

3.2 Exploration

In the initial phase of hunting, The Northern Goshawk quickly launches an assault on a victim it chooses at random. This phase improves the NGO's ability for exploration because to the randomly chosen of prey in the search space. Equations 3–5 are used to mathematically model the notions provided in the first phase.

$$P_i = X_k \tag{3}$$

$$X_{ij}^{new,p1} = \begin{cases} x_{i,j+r(p_{i,j-Ix_{i,j}}} \\ x_{i,j+r(x_{i,j-p_{i,j}}} \end{cases} \tag{4}$$

$$xi = \begin{cases} X_{ij}^{new,p1}, V_i^{new,p1} < Vi \\ Xi, V_i^{new,p1} \geq Vi \end{cases} \tag{5}$$

where Pi is the ith northern goshawk's prey position.

3.3 Exploitation

The northern goshawk attacks the victim, which then makes an effort to escape. The northern goshawk thus keeps up its tail-and-chase hunting strategy. By imitating this behaviour, the algorithm's capability for local search of the search space is boosted. In the recommended NGO approach, this hunting is expected to be near to an attack point with a radius of R. Equation 6 through Eq. 8 is used to mathematically model the notions provided in the second phase.

$$X_{ij}^{new,p2} = x_{i,j} + R(2r - 1)x_{i,j} \tag{6}$$

$$R = 0.02\left(1 - \frac{t}{T}\right) \tag{7}$$

$$i = \begin{cases} X_{ij}^{new,p2}, V_i^{new,p2} < Vi \\ Xi, V_i^{new,p2} \geq Vi \end{cases} \tag{8}$$

4 The proposed binary northern goshawk optimization

Mirjalili and Lewis introduced TF for continuous method to binarization. Using Eq. (9). Kennedy and Eberhart initially designed an S-shaped TF, as shown in Fig. 1a, to convert

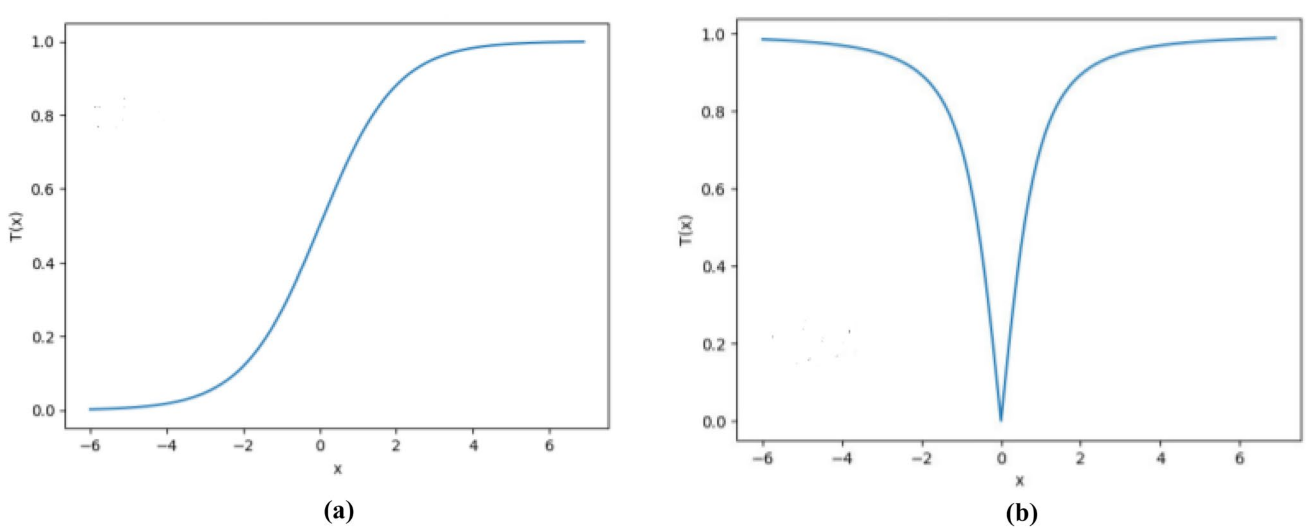

Fig. 1 **a** S-TFs and **b** V-TFs

continuous PSO to binary. For GSA binarization, use the V-shaped function shown in Fig. 1b in Eq. (10).

$$S(x_i^j(t) = \frac{1}{1 + e^{-x_i^j(t)}} \tag{9}$$

$$S(x_i^j(t) = \left|\tanh(x_i^j(t))\right| \tag{10}$$

The members of the feature subset in the future iteration are adjusted in the second stage using Eqs. (11) and (12).

$$x_i^j(t+1) = \begin{cases} 0 if rand < S(x_i^j(t+1) \\ 1 otherwise \end{cases} \tag{11}$$

$$x_i^j(t+1) = \begin{cases} \sim x_i^j(t) rand < S(x_i^j(t+1) \\ x_i^j(t) otherwise \end{cases} \tag{12}$$

S-BGNO and V-BGNO are two new binary whale optimization algorithms for feature selection. S-BGNO uses an S-shaped transfer function, while V-BGNO uses a V-shaped transfer function. The transfer functions are used to convert continuous values to binary values. The binary values are then used to represent the feature subset. The S-BGNO algorithm starts with a population of whales, where each whale represents a possible solution to the feature selection problem. The whales are then iteratively updated using a search strategy that is inspired by the bubble-net hunting strategy of whales. The bubble-net hunting strategy is a search strategy that is used by whales to catch prey. In the bubble-net hunting strategy, the whales create a bubble net around their prey. The bubble net traps the prey and makes it easier for the whales to catch. The V-BGNO algorithm is similar to the S-BGNO algorithm, but it uses a different transfer function. The V-BGNO algorithm uses a V-shaped transfer function, while the S-BGNO algorithm uses an S-shaped transfer function. The iteration process for both algorithms is the same. The iterative process involves the following steps:

1. Initialization: Initialize the population of binary solutions using S-BNGO or V-BNGO, depending on the chosen algorithm.
2. Fitness Evaluation: Evaluate the fitness of each binary solution in the population using the fitness function defined in Eq. (13). This fitness function considers both the robustness measure R(D) and the ratio of selected features to the total number of features (|R|/|N|).
3. Iteration: Perform iterative updates to improve the solutions. In each iteration, the transfer functions (Eqs. 9 and 10) are used to convert the continuous values to binary representations.
4. Feature Subset Selection: After each iteration, the feature subset is selected based on certain criteria. These criteria may include the minimal number of selected features and the highest rating accuracy, as mentioned earlier.
5. Termination: The iterative process continues until a stopping criterion is met, such as reaching a maximum number of iterations or achieving a desired level of convergence.

We compared the performance of S-BGNO and V-BGNO with other feature selection algorithms. The results showed that S-BGNO and V-BGNO outperformed the other algorithms in terms of fitness value and average number of selected features.We also investigated the impact of different parameters on the performance of S-BGNO and V-BGNO. The results showed that the performance of S-BGNO and V-BGNO is sensitive to the choice of parameters. We identified the optimal settings for the parameters using a grid search.

Figure 2 depicts the comprehensive process flow of the BNGO. The prediction model is evaluated using the KNN classifier. The reduced feature set is divided into two divisions using the tenfold cross-validation (CV) method: training and testing. Two opposing measures determine the acceptability of a subset of qualities: the minimal features selected and the greatest rating accuracy. The suggested algorithm's fitness function is defined by Eq. (13).

$$Fitness = \alpha\gamma R(D) + \beta\frac{|R|}{|N|} \tag{13}$$

5 Experimental results and discussion

5.1 Overview of the datasets

The National Center for Biotechnology Information (https://www.ncbi.nlm.nih.gov) and the public repository (http://csse.szu.edu.cn/staff/zhuzx/Datasets.html), were used to provide the datasets for this study (Too and Abdullah 2020) (Table 1).

5.2 Comparison of classical NGO, S-shaped and V-shaped B-NGO TFs

Table.2 shows the parameter settings of MH algorithms. In the general setting, the population size is set to 50, indicating the number of individuals in each iteration. The number of iterations is defined as 100, indicating the total number of times the algorithms will iterate. For the Whale Optimization Algorithm (WOA), the exploration factor (a) is set to 2, and the spiral updating coefficient (b) is set to 0. Additionally, the intensity of spiral updating is specified as

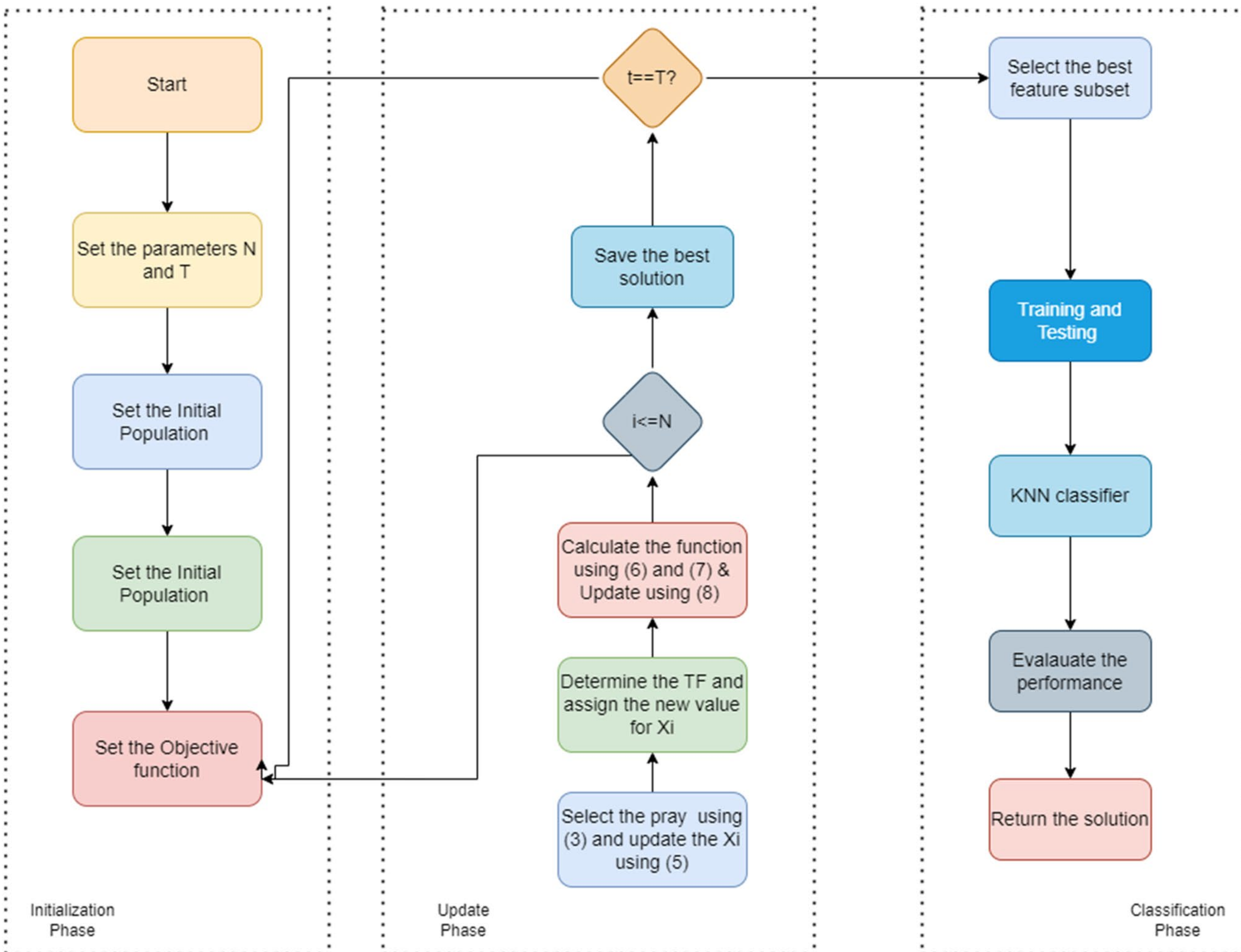

Fig. 2 Proposed binary NGO approach

Table 1 Dataset overview

	Name	Total features	Total samples
D1	Breast cancer	24,481	97
D2	Central nervous system (CNS)	7129	60
D3	Colon cancer	2000	60
D4	Leukemia	7129	72
D5	Oral squamous cell carcinoma (OSCC)	41,003	50
D6	Ovarian	15,154	253

Table 2 Parameter settings

General setting	Population size:	50
	Number of iterations:	100
WOA	a, b	(2, 0), 0.5
SSA	Initial search space, Leader score, leader position	No of columns in input data, $+\infty$, $(a_{i,j})1*D$, $\forall$ $a_{i,j}=0$, $j \in D$
HHO	B	1.5, $\lvert E \rvert \epsilon(0, 2)$
MFO	a, b	$[-2, -1]$, 1

0.5, which determines the strength of the spiral movement during optimization. In the Salp Swarm Algorithm (SSA), the initial search space is determined by the number of columns in the input data. The leader score is set as positive infinity (∞), indicating that the best score is not bounded. The leader position is defined as an array ($a_{i,j}$) of size 1*D, where $a_{i,j}$ represents an element at row i and column j. In this case, all elements are set to 0, and j ranges from 1 to the number of columns (D) in the input data. The Harris Hawks Optimization (HHO) algorithm incorporates a Beta (B) value of 1.5, regulating the degree of exploration and exploitation in the search process. Additionally, the epsilon (|E|) parameter is specified as a value between 0 and

2, exclusive, denoting a range of values that can be chosen within the defined bounds. In the Moth Flame Optimization (MFO) algorithm, parameter 'a' is represented by an array $[-2, -1]$, influencing the search behavior. The parameter 'b' is set to 1, determining the significance of the respective component in the optimization process. The ideal subset served as the basis for the trial-and-error determination of these parameters, and KNN predictions suggest that it is preferable to exactly eliminate the overfitting issue of the five subgroups.

Figures 3, 4 and 5 show the results of the two TF classes in terms of accuracy, selected characteristics and fitness metrics. Figure 2 shows the classification accuracy of the suggested model via classical MH approaches. From Fig. 2, the average accuracy value for NGO, S-bNGO and V-bNGO are 0.68, 0.79 and 0.75 respectively.

This indicates that there are almost 73% on an average of S-b and V-b NGO methods accurate positive predictions made for counterpart NGO algorithm. Among NGO, S-b and V-b NGO, S-b NGO outperforms the other counterpart algorithm by retaining 79% of prediction of correctly identified cases.

Figure 4 shows the number of features selected using NGO, S and V Shaped binary NGO. The average number of features selected for NGO, S-BNGO and V-BNGO are 10.77, 8.5 and 11.46 respectively. This indicates that there are almost 9% on an average of S-b and V-b NGO methods accurate features are selected against the counterpart NGO algorithm. Among all the algorithms outperforms the other counterpart algorithm by retaining least percentage 8% of features selected which indicates the high degree of dimensionality reduction.

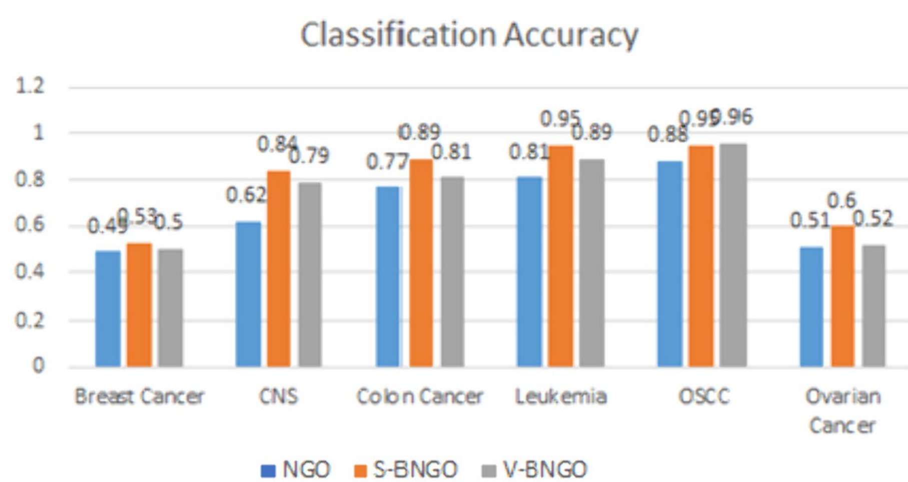

Fig. 3 Comparison of classification accuracy NGO, S-shaped and V-shaped TFs

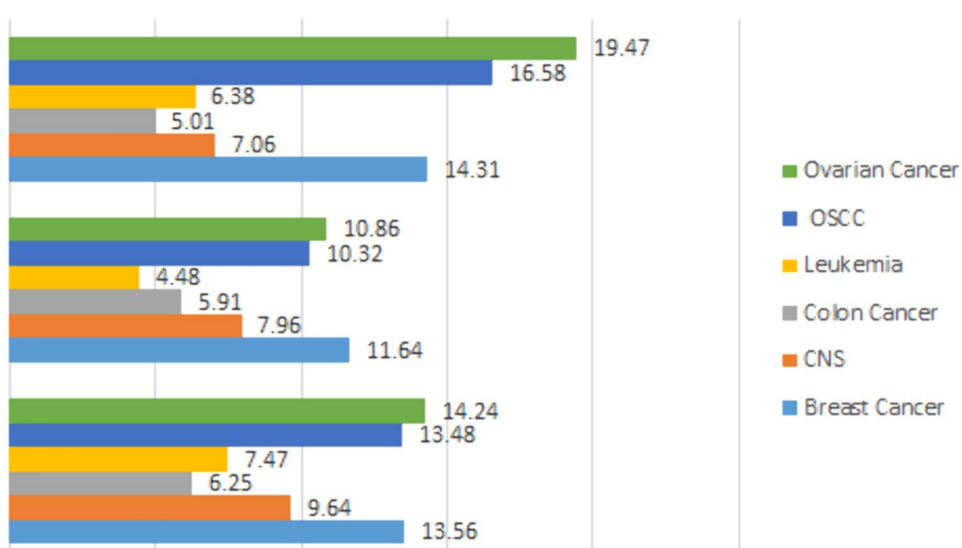

Fig. 4 Comparison of number of features selected in NGO, S-shaped and V-shaped TFs

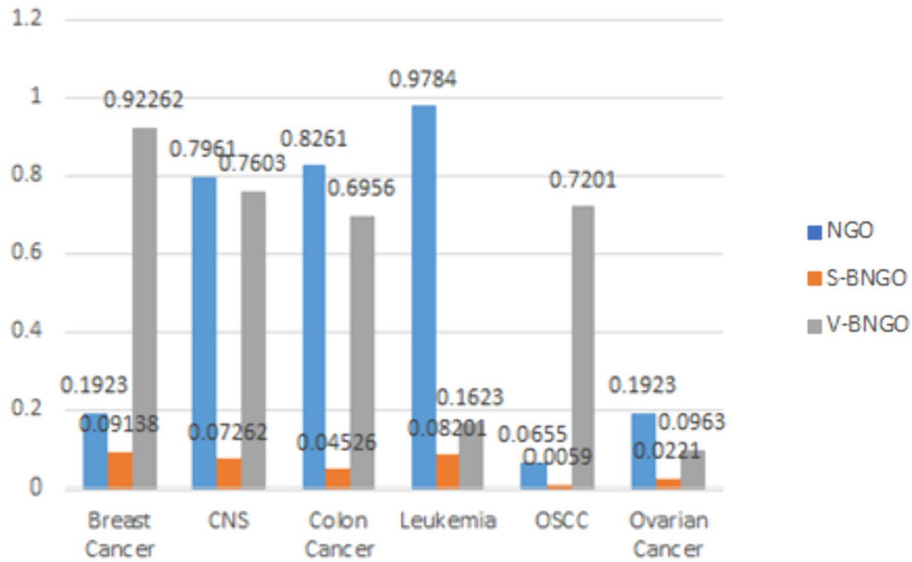

Fig. 5 Comparison of fitness value

Table 3 Parameter settings

S. no.	General	Population size:	50
		Max iter:	100
T1	BHHO	β	1.5
T2	BMRFO	–	–
T3	BASO	α, β, V_{max}	50, 0.2, 6
T4	BMPA	FADs, p	0.5, 0.5
T5	BMFO	b	1
T6	BGBO	α, β, k	0.99, 0.01, 5
T7	BAAA	Share force, e, adaptation	2, 0.2, 0.3

5.3 Comparison with recent binary MH approaches

In the next experiment, the evaluation of the suggested model is assessed with the different recent binary versions such as Binary Harris Hawk Optimization (Too and Saad 2019), Binary Manta Ray Forging Optimization (Ghosh et al. 2021), Binary Atom search Optimization (Too and Abdullah 2020), Binary Marine Predator (Elminaam et al. 2021), Binary moth-flame optimization (Nadimi-Shahraki et al. 2021), Binary Gradient-based optimizer (Jiang et al. 2021) and Binary Artificial Algae Algorithm (Bahaeddin Turkoglu and Uymaz 2022). Modern binary MH algorithms' parameter settings are displayed in Table 3. Table 3 presents the parameter settings for the different binary optimization algorithms being evaluated in the experiment. These settings play a crucial role in guiding the behavior and performance of each algorithm during the optimization process. To ensure a fair comparison, a common set of general parameters is applied to all algorithms. The population size is set to 50, determining the number of candidate solutions explored in each iteration. The maximum number of iterations is set to 100, defining the stopping criterion for the optimization process. For each specific algorithm, additional parameters are defined to fine-tune its behavior. The selection of these parameters is based on an ideal subset, which serves as a reference for determining the best values through a trial-and-error approach. In the case of Binary Harris Hawk Optimization (BHHO), the parameter β is set to 1.5. This value influences the exploration and exploitation balance within the algorithm, affecting the search space exploration capability. Binary Atom search Optimization (BASO) employs three parameters: α, β, and Vmax. α is set to 50, β to 0.2, and V_{max} to 6. These parameters control the movement and interaction of individuals within the population, guiding their search towards optimal solutions. Binary Marine Predator (BMPA) utilizes two parameters: FADs and p. FADs is set to 0.5, representing the fraction of population individuals acting as predators. The parameter p is also set to 0.5, determining the probability of prey individuals being captured by the predators.

Binary moth-flame optimization (BMFO) relies on a single parameter, b, which is set to 1. This parameter influences the movement of individuals towards the best solutions, balancing exploration and exploitation.

Binary Gradient-based optimizer (BGBO) incorporates three parameters: α, β, and k. α is set to 0.99, β to 0.01, and k to 5. These parameters govern the search direction and step size during the optimization process.

Lastly, Binary Artificial Algae Algorithm (BAAA) involves three parameters: Share Force, e, and adaptation. Share Force is set to 2, influencing the interaction between individuals. The parameter e is set to 0.2, affecting the exploration and exploitation trade-off. Adaptation, set to 0.3, determines the adaptability of individuals to changing environmental conditions.

The ideal subset served as the basis for the trial-and-error determination of these parameters, and KNN predictions suggest that it is preferable to exactly eliminate the overfitting issue of the five subgroups.

Figure 6 shows the classification accuracy reached by the proposed SBNGO technique versus traditional binary MH algorithms for each dataset. According to Fig. 6, the D5 datasets maintained the greater classification accuracy on BMPA while the S-BNGO kept the greatest classification accuracy on 5 datasets (D1-D4 and D6). The important adjustments are seen in relation to other traditional MH algorithms. The top spot is taken by S-BNGO, then BMPA. According to about 83% of the data, the suggested model maintained its superior classification accuracy.

Table 4 shows that, out of a possible six datasets, S-BNGO received the lowest fitness value. The D4 datasets in this investigation failed to attain the lowest fitness value. Here, the text's bold language highlights the finest fitness values. This leads us to the conclusion that S-BNGO scored the highest with 5 datasets, followed by BMPA with 2 datasets and BASO with 1. In this investigation, the best fitness value was attained for about 83.3% of the datasets. The remaining traditional binary MH algorithms in this situation were unable to produce the best outcomes in terms of fitness value. On the five datasets in Table 5, S-BNGO received the lowest score for the number of chosen features, with D2 receiving the next-lowest score. S-BNGO scored five datasets, followed by BMPA on one dataset, in terms of scoring. A modest number of the chosen characteristics on S-NGO were obtained by 83.3% of the datasets used in the study. We may thus draw the conclusion that S-NGO performs better than other

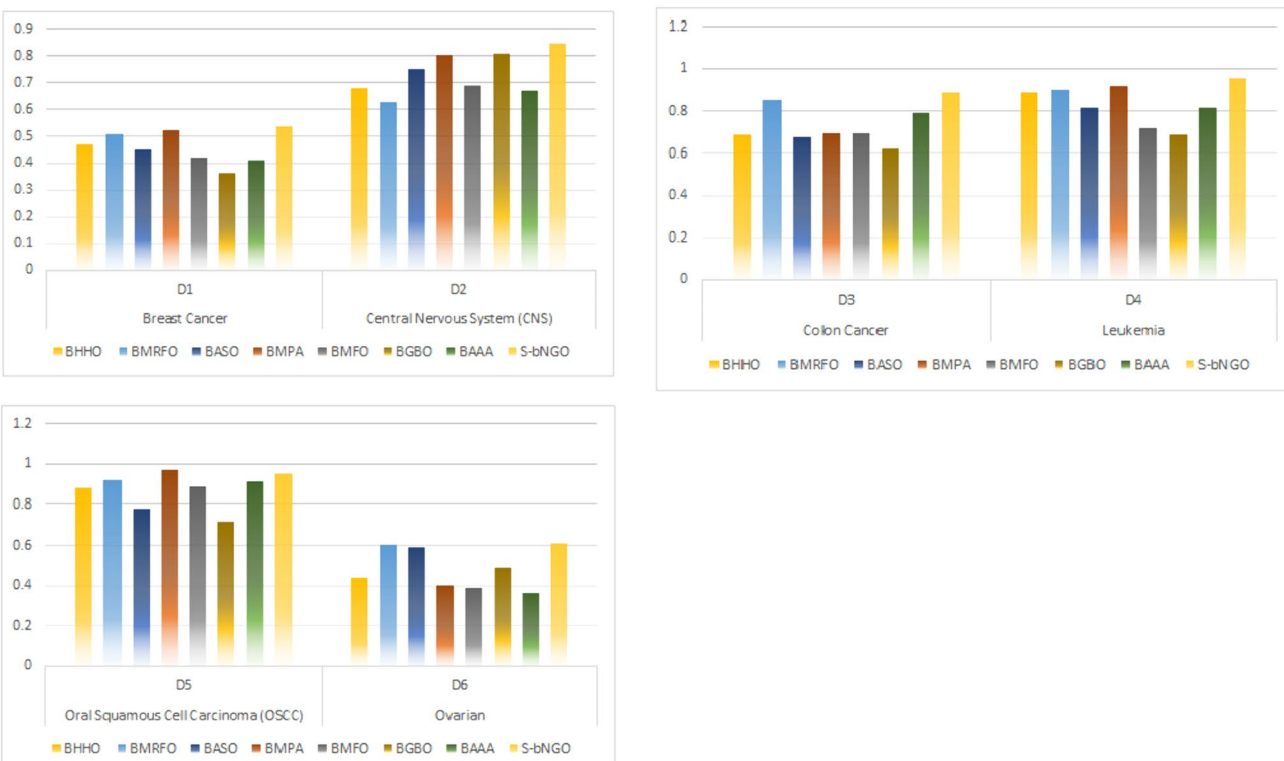

Fig. 6 Classification accuracy

Table 4 binary MH in terms of fitness value

Dataset	T1	T2	T3	T4	T5	T6	T7	S-BNGO
D1	0.152	0.65	0.203	0.098	0.18	0.5256	0.192	0.091
D2	0.087	0.563	0.281	0.092	0.11	0.892	0.325	0.072
D3	0.792	0.812	0.091	0.495	0.579	0.078	0.286	0.045
D4	0.725	0.689	0.012	0.203	0.252	0.012	0.354	0.082
D5	0.072	0.035	0.032	0.319	0.2	0.005	0.092	0.005
D6	0.481	0.625	0.095	0.175	0.355	0.081	0.125	0.022

Table 5 Comparison with binary MH in terms of average selected features

Dataset	T1	T2	T3	T4	T5	T6	T7	S-BNGO
D1	16.25	11.59	14.52	15.2	12.25	15.56	14.55	11.64
D2	14.25	11.59	8.93	12.87	11.51	7.25	9.28	7.96
D3	11.36	15.23	10.35	10.25	9.26	8.92	10.25	5.91
D4	10.55	12.25	14.26	7.9	10.55	5.26	7.9	4.48
D5	12.52	10.25	10.32	14.62	11.01	11.26	9.52	10.32
D6	12.56	15.94	12.03	13.39	11.38	10.86	10.99	10.86

binary MH methods in terms of fitness and average number of features selected.

Adapted from Fig. 7. It is deduced that the majority of the S-NGO dataset requires fewer operations to find the best answer, but other approaches are not even convergent, as seen by continual convergence. S-NGO, the suggested technique, pushes inexorably toward the best overall solution and produces considerable results. The convergence curve findings reveal that the proposed S-NGO technique outperforms in terms of speed, implying that S-NGO is better at finding optimal solutions for varied data sets in fewer epochs.

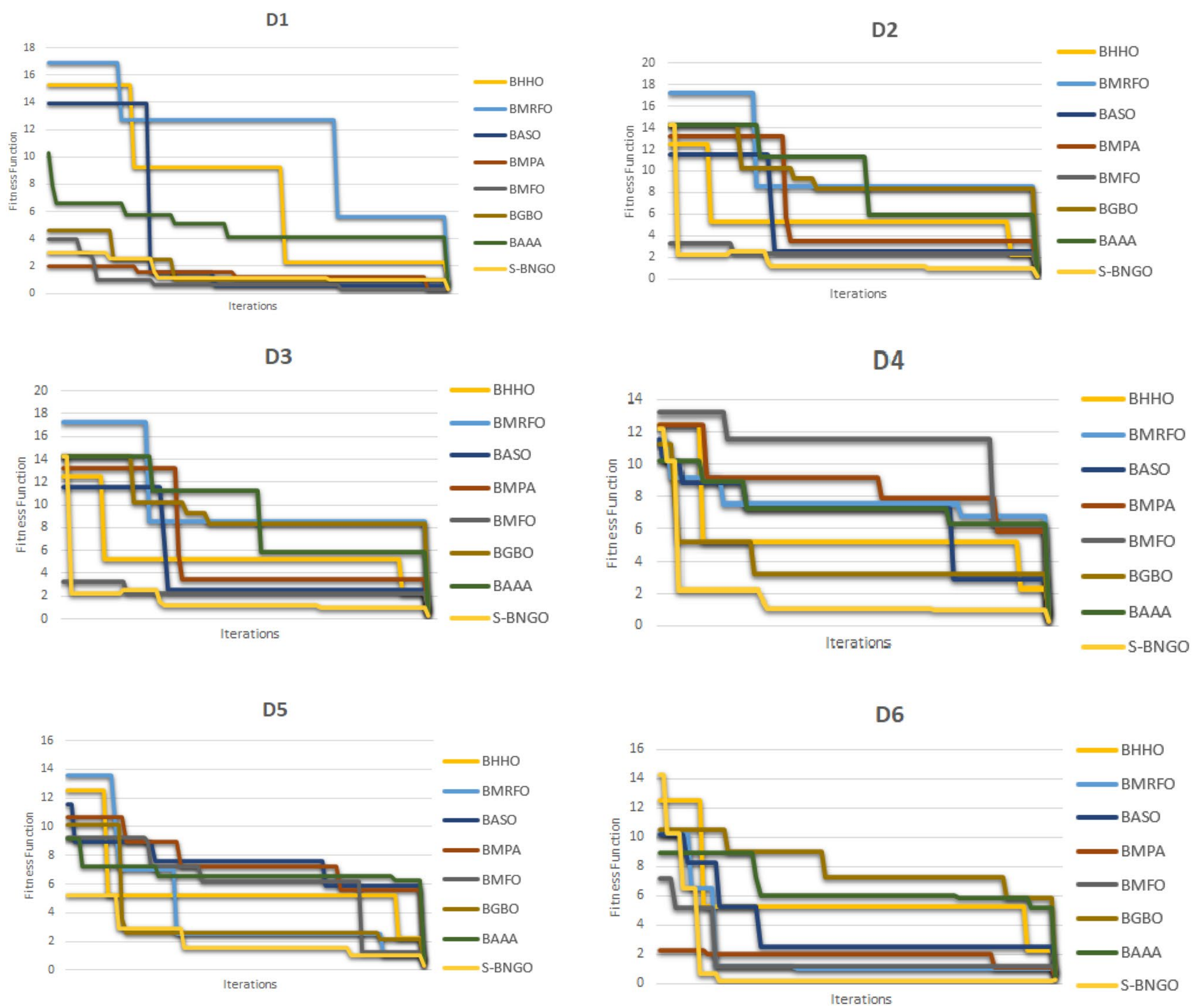

Fig. 7 converging ability

5.4 Comparison with recent MH approaches

Table.6 shows the comparison of various MH approaches for the average number of features.

Among the lowest range values, the proposed technique gives the lowest of the lowest values with an average of 8.52, indicating the closest solutions. The average difference in improvement between WOA and SSA, SSA and SCA, SCA and HHO, HHO and MFO, the proposed techniques is 1.9%, 2.0%, 1.4%, 0.9, 6.8% and 2.8% respectively. This shows that all algorithms have lower fitness function values. With the exception of the high-dimensional CNS data set, the proposed method scored lower fitness values than the conventional algorithms in all five data sets. Leukemia had the lowest fitness score of 5 records, followed by colon, CNS, OSCC, ovarian, and breast cancers.

From Table 7, SbNGO had a higher classification accuracy in the four datasets (OSCC, colon, leukemia and CNS). Based on the selected characteristics, SbNGO was observed to have superior performance on four datasets (OSCC, colon, leukemia and CNS). The average difference in improvement between WOA and SSA, SSA and SCA, SCA and HHO, HHO and MFO, the proposed techniques is 3%, 5%, 4%, 1.7%, 1% and 1.5% respectively. All algorithms have higher classification values of more than 45%, which indicates the common ground of choosing algorithms of similar performance for validating the efficacy of the proposed algorithm. The algorithms WOA and MFO have similar performance irrespective of the dataset. The potential of the suggested S-bNGO to effectively discover the solutions search space and discover the optimal feature subset with the maximum classification accuracy is demonstrated by having highest classification accuracy of 79% followed by WOA, and MFO algorithms.

Form Table 8, the proposed technique gives the lowest of the lowest fitness values with an average of 0.05, indicating the closest solutions. The average difference in improvement between WOA and SSA, SSA and SCA, SCA and HHO, HHO and MFO, the proposed techniques is 0.48, 0.34, 0.52, 0.47, 0.33 and 0.72 respectively. This shows that all algorithms have lower fitness function values. With the exception of the high-dimensional CNS data set, the suggested approach achieved lower fitness values than the other approaches in all five data sets. Leukemia had the less fitness followed by colon, CNS, OSCC, ovarian, and breast cancers for the S-BNGO proposed method.

Table 6 Comparison of MHs in terms of average number of selected features

Dataset	WOA	SSA	SCA	HHO	MFO	S-bNGO
D1	21.62	18.39	18.50	15.94	17.59	11.64
D2	8.96	14.94	8.39	7.98	9.53	7.96
D3	6.26	9.21	10.96	5.98	5.95	5.91
D4	8.85	18.26	8.56	9.29	5.26	4.48
D5	29.22	29.46	26.29	24.92	18.55	10.32
D6	14.62	21.59	16.69	12.56	19.86	10.86

Table 7 Comparison between S-bNGO of classification accuracy

Dataset	WOA	SSA	SCA	HHO	MFO	S-bNGO
D1	0.48	0.48	0.50	0.50	0.48	0.53
D2	0.61	0.71	0.39	0.57	0.62	0.84
D3	0.82	0.64	0.86	0.75	0.77	0.89
D4	0.71	0.86	0.74	0.74	0.81	0.95
D5	0.95	0.75	0.75	0.90	0.86	0.95
D6	0.49	0.50	0.49	0.51	0.50	0.60

Table 8 Comparison between S-bNGO with fitness value

Dataset	WOA	SSA	SCA	HHO	MFO	S-bNGO
D1	0.22486	0.52620	0.75262	0.20865	0.62515	0.09138
D2	0.28956	0.59232	0.10562	0.16528	0.19205	0.07262
D3	0.27826	0.15350	0.36265	0.16356	0.52326	0.04526
D4	0.26326	0.62051	0.47262	0.05916	0.09562	0.02201
D5	0.23381	0.39261	0.09520	0.09656	0.12692	0.05900
D6	0.15546	0.55684	0.082610	0.19567	0.13209	0.02210

5.5 Computational complexity analysis

This section looks at the computational difficulty of the BNGO FS approach that was put out in this study. The temporal complexity is summarised as follows:

Step 1: Initialization
O(n*d) time complexity is needed for initialization, where n is the population size of northern goshawks and d is the dimension space.
Step 2: Update function
Each induvial position of the population has to be updated, which O(n*d).
The amount of time required to map each population to the binary space O (n*d). o
The update phase also demands O(n*d*t) with the maximum iteration O(t)
The suggested model's computational complexity is O(n*d*t).

6 Conclusion and future scope

In conclusion, our study provides a binary NGO approach for feature selection in high-dimensional microarray cancer datasets. The recommended technique increases Binary NGO exploration and use by increasing population variation during startup. After each cycle, NGO balances global and local searches to find the global optimal without capturing the local ideal. V- or S-shaped TFs (eight functions) convert continuous NGO to binary. Six high-dimensional data sets from free sources were used to evaluate the recommended strategy and compare it to its next-generation rivals. S-shaped transfer functions outperform NGO and V-shaped transfer functions in accuracy, feature selection, and fitness. Five conventional metaheuristic optimisation approaches and seven current binary MH algorithms are compared to the S-shaped transfer function. Findings show that the S-shaped transfer function outperforms competing models. Additionally, the AVOA algorithm and KNN classifier effectively analyse the training data, reducing the cost of the feature set selected from the data set. The tenfold cross-validation approach enhances feature selection by (1) compressing training and validation accuracy and (2) balancing bias and variance. This helps avoid overfitting concerns. Binary NGO might be used for many public data sets and practical applications and coupled with other classifiers to improve current methods. Additionally, numerous MH algorithms may be hybridised to solve a variety of engineering multi-objective optimisation problems.

Declarations

Conflict of interest The authors declare that they have no conflicts of interest to report regarding the present study.

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