mathematics

MDPI

Article

Binary Whale Optimization Algorithm for Dimensionality Reduction

Abdelazim G. Hussien [1], Diego Oliva [2,3], Essam H. Houssein [4], Angel A. Juan [2] and Xu Yu [5,*]

1 Faculty of Science, Fayoum University, Faiyum 63514, Egypt; aga08@fayoum.edu.eg
2 IN3-Computer Science Department, Universitat Oberta de Catalunya, 08018 Barcelona, Spain; diego.oliva@cucei.udg.mx (D.O.); ajuanp@uoc.edu (A.A.J.)
3 Departamento de Ciencias Computacionales, Universidad de Guadalajara, CUCEI, Guadalajara 44430, Mexico
4 Faculty of Computers and Information, Minia University, Minia 61519, Egypt; essam.halim@mu.edu.eg
5 School of Information Science and Technology, Qingdao University of Science and Technology, Qingdao 266061, China
* Correspondence: yuxu0532@qust.edu.cn

Received: 20 September 2020; Accepted: 12 October 2020; Published: 17 October 2020

check for updates

Abstract: Feature selection (FS) was regarded as a global combinatorial optimization problem. FS is used to simplify and enhance the quality of high-dimensional datasets by selecting prominent features and removing irrelevant and redundant data to provide good classification results. FS aims to reduce the dimensionality and improve the classification accuracy that is generally utilized with great importance in different fields such as pattern classification, data analysis, and data mining applications. The main problem is to find the best subset that contains the representative information of all the data. In order to overcome this problem, two binary variants of the whale optimization algorithm (WOA) are proposed, called bWOA-S and bWOA-V. They are used to decrease the complexity and increase the performance of a system by selecting significant features for classification purposes. The first bWOA-S version uses the Sigmoid transfer function to convert WOA values to binary ones, whereas the second bWOA-V version uses a hyperbolic tangent transfer function. Furthermore, the two binary variants introduced here were compared with three famous and well-known optimization algorithms in this domain, such as Particle Swarm Optimizer (PSO), three variants of binary ant lion (bALO1, bALO2, and bALO3), binary Dragonfly Algorithm (bDA) as well as the original WOA, over 24 benchmark datasets from the UCI repository. Eventually, a non-parametric test called Wilcoxon's rank-sum was carried out at 5% significance to prove the powerfulness and effectiveness of the two proposed algorithms when compared with other algorithms statistically. The qualitative and quantitative results showed that the two introduced variants in the FS domain are able to minimize the selected feature number as well as maximize the accuracy of the classification within an appropriate time.

Keywords: whale optimization algorithm; WOA; Binary whale optimization algorithm; bWOA-S; bWOA-V; Feature selection; Classification; Dimensionality reduction

1. Introduction

The datasets from real-world applications such industry or medicine are high-dimensional and contain irrelevant or redundant features. These kind of datasets then have useless information that affects the performance of machine learning algorithms; in such cases, the learning process is affected. Feature selection (FS) is a powerful rattling technique used to select the most significant subset of features, overcoming the high-dimensionality reduction problem [1], identifying the relevant features and removing redundant ones [2]. Moreover, using the subset of features, any machine learning algorithm can be applied for classification. Therefore, several studies have taken into consideration that the FS problem is an optimization problem, hence the fitness function for the optimization algorithm has been changed to classifier's accuracy, which may be maximized by the selected features [3]. Moreover, FS has been applied successfully to solve many classification problems in different domains, such as data mining [4,5], pattern recognition [6], information retrieval [7], information feedback [8], drug design [9,10], job-shop scheduling problem [11], maximizing lifetime of wireless sensor networks [12,13], and the others where FS can be utilized [14].

There are three main classes of FS methods: (1) The wrapper, (2) filter and (3) hybrid methods [15]. The wrapper approaches generally incorporate classification algorithms to search for and select the relevant features [16]. Filter methods calculate the relevant features without prior data classification [17]. In the hybrid techniques, the compatible strengths of the wrapper and filter methods are combined. Generally speaking, the wrapper methods outperform filter methods in terms of classification accuracy, and hence the wrapper approaches are used in this paper.

In fact, a high accuracy classification does not depend on a large selected features number for many classification problems. In this context, the classification problems can be categorized into two groups: (1) binary classification and (2) multi-class classification. In this paper, we deal with the binary classification problem. There are numerous methods that are applied for binary classification problems, such as discriminant analysis [18], decision trees (DT) [19], the K-nearest neighbor (K-NN) [20], artificial neural networks (ANN) [21], and support vector machines (SVMs) [22].

On the other hand, the traditional optimization methods suffer from some limitations in solving the FS problems [23,24], and hence nature-inspired meta-heuristic algorithms [25] such as the whale optimization algorithm (WOA) [26], moth–flame optimisation [27], Ant Lion Optimization [28], Crow Search Algorithm [29], Lightning Search Algorithm [30], Henry gas solubility optimization [31] and Lévy flight distribution [32] are widely used in the scientific community for solving complex optimization problems and several real-world applications [33–35]. Optimization is defined as a process of searching the optimal solutions to a specific problem. In order to address issues such as FS, several nature-inspired algorithms have been applied; some of these algorithms are hybridized with each other or used alone, others created new variants like binary methods to solve this problem. A survey on evolutionary computation [36] approaches for FS is presented in [37]. Several separate and hybrid algorithms have been proposed for FS, such as hybrid ant colony optimization algorithm [38], forest optimization algorithm [39], firefly optimization algorithm [40], hybrid whale optimization algorithm with simulated annealing [41], particle swarm optimization [42], sine cosine optimization algorithm [43], monarch butterfly optimization [44], and moth search algorithm [45].

In addition to the aforementioned studies to find solutions for the FS problem, other search strategies called the binary optimization algorithms have been implemented. Some examples are the binary flower pollination algorithm (BFPA) in [46], binary bat algorithm (BBA) in [47], binary cuckoo search algorithm (BCSA) in [48]; all of them evaluate the accuracy of the classifier as an objective function. He et al. have presented a binary differential evolution algorithm (BDEA) [49] to select the relevant subset to train a SVM with radial basis function (RBF). Moreover, Emary et al., have proposed the binary ant lion and the binary grey wolf optimization [50,51], respectively. Rashedi et al. have introduced an improved binary gravitational search algorithm version called (BGSA) [52]. In addition, a salps algorithm is used for feature selection of the chemical compound activities [53]. A binary version of particle swarm optimization (BPSO) is proposed [54]. A binary whale optimization algorithm for feature selection [55–57] has also been introduced. As the NO Free Lunch (NFL) theorm states, there is no algorithm that is able to solve all optimization problems. Hence, if an algorithm shows a superior performance on a class of problem, it cannot show the same performance on other classes. This is the motivation of our presented study, in which we propose two novel binary variants of the whale optimization algorithm (WOA) called bWOA-S and bWOA-V. In this regard, the WOA is a nature-inspired population-based metaheuristics optimization algorithm, which simulates the humpback whales' social behavior [26]. The original WOA was modified in this paper for solving FS issues. The two proposed variants are (1) the binary whale optimization algorithm using S-shaped transfer function (bWOA-S) and (2) the binary whale optimization algorithm using V-shaped transfer function (bWOA-V). In both approaches, the accuracy of K-NN classifier [58] is used as an objective function that must be maximized. K-NN with leave-one-out cross-validation (LOOCV) based on Euclidean distance is also used to investigate the performance of the compared algorithms. The experiments results were evaluated on 24 datasets from UCI repository [59]. The results of the two proposed algorithms were evaluated versus different well-known algorithms famous in this domain, namely (1) particle swarm optimizer (PSO) [60], (2) three versions of binary ant lion (bALO1), bALO2, and bALO3) [51], (3) binary gray wolf Optimizer bGWO [50], (4) binary dragonfly [61] and (5) the original WOA. The reason behind choosing such algorithms is that PSO, one of the most famous and well-know algorithms, as well as bALO, bGWO, and bDA, are recent algorithms whose performance has been proved to be significant. Hence, we have implemented the compared algorithms using the original studies and then generated new results using these methods under the same circumstances. The experimental results revealed that bWOA-S and bWOA-V achieved higher classification accuracy with better feature reduction than the compared algorithms.

Therefore, the merits of the proposed algorithms versus the previous algorithms is illustrated by the following two aspects. First, bWOA-S and bWOA-V confirms not only feature reduction, but also the selection of relevant features. Second, bWOA-S and bWOA-V utilize the wrapper methods search technique for selecting prominent features, and hence the idea of these rules is based mainly on high classification accuracy regardless of a large number of selected features. The purpose of wrapper method is used to maintain an efficient balance between exploitation and exploration, so correct information of the features is provided [62]. Thus, bWOA-S and bWOA-V achieve a strong search capability that helps to select a minimum number of features as a subset from the most significant features pool.

The rest of the paper is organized as follows: Section 2 briefly introduces the WOA. Section 3, describes the two binary versions of whale optimization algorithm (bWOA), namely bWOA-S and bWOA-V, for feature selection. Section 4, discusses the empirical results for bWOA-S and bWOA-V. Eventually, conclusions and future work are drawn in Section 5.

2. Whale Optimization Algorithm

In [26], Mirjalili et al. introduced the whale optimization algorithm (WOA), based on the behaviour of whales. The special hunting method is considered the most interesting behaviour of humpack whales. This hunting technique is called bubble-net feeding. In the classical WOA, the solution of the current best candidate is set as close to either the optimum or the target prey. The other whales will update their position towards the best. Mathematically, the WOA mimics the collective movements as follows

$$\vec{D} = |\vec{C} \cdot \vec{X}^*(t) - \vec{X}(t)| \tag{1}$$

$$X(\vec{t+1}) = \vec{X}^*(t+1) - \vec{A} \cdot \vec{D} \tag{2}$$

where t refers to the current number of iterations, X refers to the position vector, X^* is the best solution position vector. C and A are coefficient vectors and can be calculated from the following equations

$$\vec{A} = 2 \cdot \vec{a} \cdot \vec{r} - \vec{a} \tag{3}$$

$$\vec{C} = 2 \cdot \vec{r} \tag{4}$$

where r belongs to the interval [0, 1] and a decreases linearly through the iterations from 2 to 0. WOA has two different phases: exploitation (Intensification) and exploration (diversification). In the diversification phase, the agents are moved for exploring or searching different search space regions, while in the intensification phase, the agents move in order to locally enhance the current solutions.

The intensification phase: the intensification phase is divided into two processes: the first one is the shrinking encircling technique which can be obtained by reducing a values using Equation (4). Note that a is a stochastic value in the interval $[-a, a]$. The second phase is the spiral updating position in which the distance between the whale and the prey is calculated. To model a spiral movement, the following equation is used in order to mimic the movement of the helix-shaped.

$$\vec{X}(t+1) = \vec{D}^l e^{bl} \cdot \cos(2\pi l)) + \vec{X}^*(t) \tag{5}$$

From Equation (5), l is a randomly chosen value between $[-1, 1]$ where b is a fixed. A 50% probability is used for choosing either the spiral model or shrinking encircling mechanism, as assumed. Consequently, the mathematical model is established as follows

$$\vec{X}(t+1) = \begin{cases} \vec{X}^*(t) - \vec{A} \cdot \vec{D} & if p < 0.5 \\ \vec{D^l}^{bl} \cdot \cos(2\pi l) + \vec{X}^*(t) & if p \geq 0.5 \end{cases} \tag{6}$$

where p is a random number in a uniform distribution.

The exploration phase: In the exploration phase, A used random values within $1 \prec A \prec -1$ to force the agent to move away from this location mathematically, formulated as in Equation (7).

$$\vec{D} = |\vec{C} \cdot \vec{X}_{rand} - \vec{X}| \tag{7}$$

$$\vec{X}(t+1) = X_{rand} - \vec{A} \cdot \vec{D} \tag{8}$$

3. Binary Whale Optimization Algorithm

In the classical WOA, whales move inside the continous search space in order to modify their positions, and this is called the continuous space. However, to solve FS issues, the solutions are limited to only $\{0, 1\}$ values. In order to be able to solve feature selection problems, the continuous (free position) must be converted to their corresponding binary solutions. Therefore, two binary versions from WOA are introduced to investigate problems like FS and achieve superior results. The conversion is performed by applying specific transfer functions, either the S-shaped function or V-shaped function in each dimension [63]. Transfer functions show the probability of converting the position vectors' from 0 to 1 and vice versa, i.e., force the search agents to move in a binary space. Figure 1 demonstrates the flow chart of the binary WOA version. Algorithm 1 shows the pseudo code of the proposed bWOA-S and bWOA-V versions.

3.1. Approach 1: Proposed bWOA-S

The common S-shaped (Sigmoid) function is used in this version. The S-shaped function is updating, as shown in Equation (11). Figure 2 illustrates the mathematical curve of the Sigmoid function.

3.2. Approach 2: Proposed bWOA-V

In this version, the hyperbolic tan function is applied. It is a common example of V-shaped functions and is given in Equations (9) and (10).

$$y^k = |tanhx^k| \tag{9}$$

$$X_i^d = \begin{cases} sel_d^t & if rand < S(x_i^k(t+1)) \\ org_d^t & otherwise \end{cases} \tag{10}$$

$$y^k = \frac{1}{1 + e^{-x_i^k(t)}} \tag{11}$$

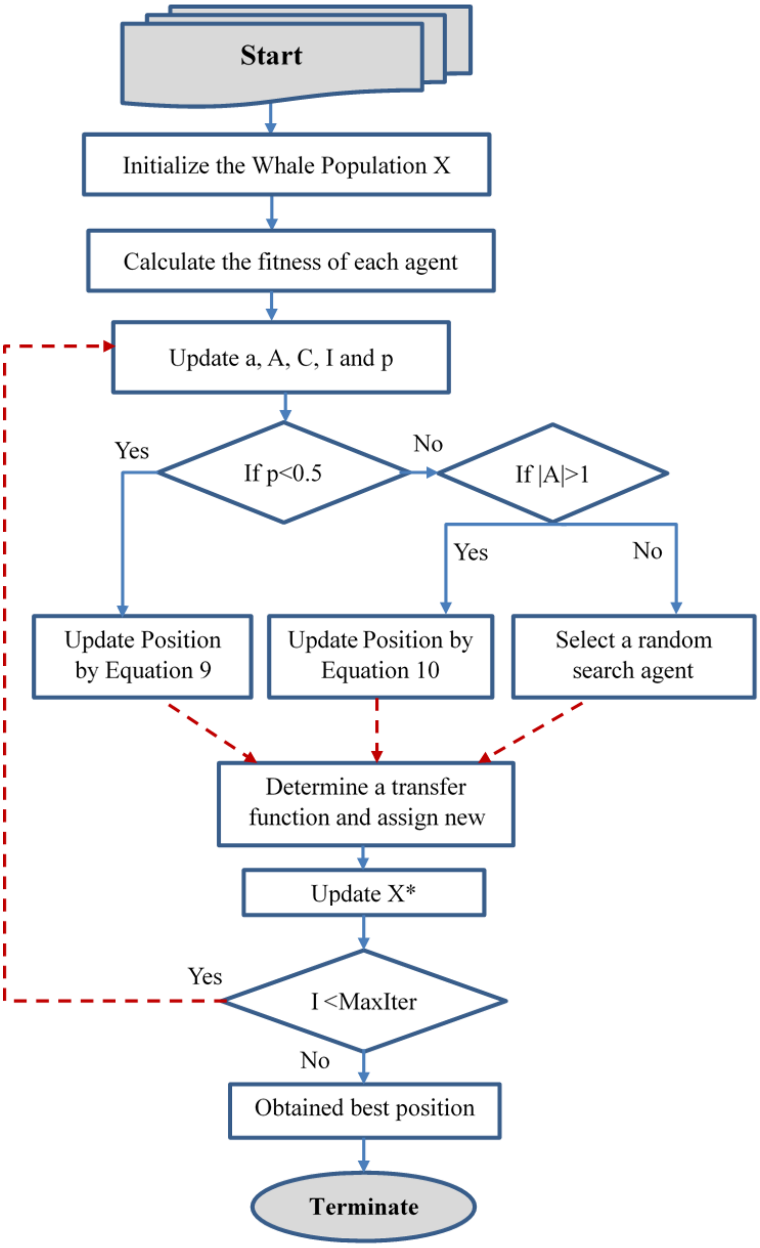


Figure 1. Binary whale optimization algorithm flowchart.

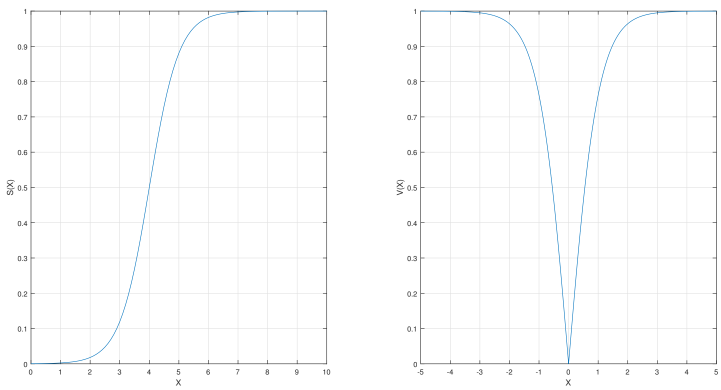


Figure 2. S-shaped and V-shaped transfer functions.

Algorithm 1 Pseudo code of bWOA-S & bWOA-V

Input: n whales number in the population.
$MaxIter$ maximum iteration number.
Output: position of the optimal whale.
Initialize a and n.
Calculate X^*.
while current iter $<$ maximum iteration number **do**
  for Each Whale **do**
    Calculate a; A, C, p and l.
    if $p < 0.5$ **then**
      if $(|A| < 1)$ **then**
        Update the position of whale using Equation (2).
      else$(|A| \geq 1)$
        Choose a random search agent (X_{rand})
        Update the position of whale using (8).
      end if
    else$(p \geq 0.5)$
      UUpdate the position of whale using (5).
    end if
    Update $\vec{X}(t+1)$ using Equation (11) or (9)
  end for
  Update $X*$ if there is a better solution.
  $t++$
end while

3.3. bWOA-S and bWOA-V for Feature Selection

Two binary variants of whale optimization algorithm, called bWOA-S and bWOA-V, are employed for solving the FS problem. For a feature vector size, if N is the number of different features, then the combination number would be 2^N, which is a huge feature number to search exhaustively. Under such a situation, the proposed bWOA-S and bWOA-V algorithms are used in an adaptive feature space search and provide the best combination of features. This combination is obtained by achieving the maximum classification accuracy and the minimum selected features number. The following Equation (12) shows the fitness function accompanied by the two proposed versions to evaluate individual whale positions.

$$F = \alpha \gamma_R(D) + \beta \frac{|C - R|}{|C|} \tag{12}$$

where F refers to Fitness function, R refers to the length of the selected feature subset, C refers to the total features number, $\gamma_R(D)$ refers to the classification accuracy of the condition attribute set R, α and β are two arguments that are symmetric to the subset length and the accuracy of the classification, and can be calculated as $\alpha \in [0, 1]$ and $\beta = 1 - \alpha$. This will lead to the fitness function that achieves the maximum classification accuracy. Equation (12) can be converted to a minimization problem based on the error rate of classification and selected features. Thus, the obtained minimization problem can be calculated as in Equation (13)

$$F = \alpha E_R(D) + \beta \frac{|R|}{|C|} \tag{13}$$

where F refers to Fitness function, $E_R(D)$ is the classification error rate. According to the wrapper methods characteristic in FS, the classifier was employed as an FS guide. In this study, K-NN classifier is used. Therefore, K-NN is applied to ensure that the selected features are the most relevant ones. However, bWOA is the search method that tries to explore the feature space in order to maximize the feature evaluation criteria, as shown in Equation (13).

4. Experimental Results and Discussion

The two proposed bWOA-S and bWOA-V methods are compared with a group of existing algorithms, including the PSO, three variants of binary ant lion (bALO1, bALO2, and bALO3), and the original WOA. Table 1 reports the parameter settings for the cometitior algorithms. In order to provide a fair comparison, three initialization scenarios are used and the experimental results are performed using 24 different datasets from the UCI repository.

Table 1. Parameter setting.

Parameter	Value
No of search agents	8
No of iterations	70
Problem dimension	No. of features in the data
Data Search domain	[0, 1]
No. repetitions of runs	20
Inertia factor of PSO	0.1
Individual-best acceleration factor of PSO	0.1
α Parameter in the fitness function	0.99
β Parameter in the fitness function	0.01

4.1. Data Acquisition

Table 2 summarizes the 24 datasets from the UCI machine learning repository [59] that were used in the experiments. The datasets were selected with different instances and attribute numbers to represent various kinds of issue (small, medium and large). In each repository, the instances are divided randomly into three different subsets, namely training, testing, and validation subsets. The proposed algorithms were tested over three gene expression datasets of colon cancer, lymphoma and the leukemia [64–66]. The K-NN is used in the experimental tests using the trial and error method, and 5 is the best choice of K. Meanwhile, every position of whale produces one attribute subset through the training process. The training set is used to test and evaluate the performance of the K-NN classifier in the validation subset throughout the optimization process. The bWOA is employed to simultaneously guide the FS process.

Table 2. List of datasets used in the experiments results.

No.	Name	Features	Samples
1	Breastcancer	9	699
2	Tic-tac-toe	9	958
3	Zoo	16	101
4	WineEW	13	178
5	SpectEW	22	267
6	SonarEW	60	208
7	IonosphereEW	34	351
8	HeartEW	13	270
9	CongressEW	16	435
10	KrvskpEW	36	3196
11	WaveformEW	40	5000
12	Exactly	13	1000
13	Exactly 2	13	1000
14	M-of-N	13	1000
15	vote	16	300
16	BreastEW	30	569
17	Semeion	265	1593
18	Clean 1	166	476
19	Clean 2	166	6598
20	Lymphography	18	148
21	PenghungEW	325	73
22	Colon	2000	62
23	lymphoma	96	4026
24	Leukemia	7129	72

4.2. Evaluation Criteria

Each algorithm carried out 20 independent runs with a random initial positioning of the search agents. Repeated runs were used to test the capability of the convergence. Eight well-known and common measures are recorded in order to investigate the algorithms performance in a comparative way. Such metrics are listed as follows:

- Best: The minimum (or best for a minimization problem) fitness function value obtained at different independent runs, as depicted in Equation (14).

$$Best = Min_{i=1}^{M} g_*^i \tag{14}$$

- Worst: The maximum (or worst for a minimization) fitness function value obtained at different independent operations, as shown in Equation (15).

$$Worst = Max_{i=1}^{M} g_*^i \tag{15}$$

- Mean: Average calculation performance of the optimization algorithm applied M times, as shown in Equation (16).

$$Mean = \frac{1}{M}\sum_{i=1}^{M} g_*^i \tag{16}$$

where g_*^i is the optimal solution obtained in the i-th operation;
- Standard deviation (Std) can be calculated from the following Equation (17).

$$Std = \sqrt{\frac{1}{M}\sum (g_*^i - Mean)^2} \tag{17}$$

- Average classification accuracy: Investigates the accuracy of the classifier and can be calculated by Equation (18).

$$AvgeragePerformance = \frac{1}{M}\sum_{j=1}^{M}\frac{1}{N}\sum_{i=1}^{N}Match(C_i, L_i) \tag{18}$$

where C_i refers to classifier output for instance i; N refers to the instance number in the test set; and L_i refers to the reference class corresponding to instance i;
- Average selection size (Avg-Selection) measures the average reduction in selected features from all feature sets and is calculated by Equation (19)

$$AvgerageSelectionSize = \frac{1}{M}\sum_{i=1}^{M}\frac{size(g_*^i)}{N_t} \tag{19}$$

where N_t is the total number of features in the original dataset;
- Average execution time (Avg-Time) measures the average execution time in milliseconds for all comparison optimization algorithms to obtain the results over the different runs and calculated by Equation (20)

$$R_a = \frac{1}{M}\sum_{i=1}^{M}RunT_{a,i} \tag{20}$$

where M refers to the run number for the optimizer a, and $RunT_{a,i}$ is the computational time for optimizer a in milliseconds at run number i;
- Wilcoxon rank sum test (Wilcoxon): a non-parametric test called Wilcoxon Rank Sum (WRS) [67]. The test gives ranks to all the scores in one group, and after that the ranks of each group are added. The rank-sum test is often described as the non-parametric version of the t test for two independent groups.

The two proposed versions of whale optimization algorithm (bWOA-S and bWOA-V) are compared with three common algorithms that are famous in this domain. Four different initialization methods/techniques are used to guarantee the two proposed algorithms' ability to converge from different initial positions. These methods are: (1) a large initialization is expected to evaluate the capability of locally searching a given algorithm, as the search agents' positions are commonly close to the optimal solution; (2) a small initialization method is expected to evaluate the ability of a given algorithm to use global searching as the initial search; (3) mixed initialization is the case in which some search agents are close enough to the optimal solution, whereas the other search agents are apart. It will provide diversity of the population frequently. since the search agents are expected to be apart from each other. (4) random initialization.

4.3. Performance on Small Initialization

The statistical average fitness values of the different datasets obtained from the compared algorithms using the small initialization methods are shown in Table 3. Table 4 shows average classification accuracy on the test data of the compared algorithms using small initialization methods. From these tables, we can conclude that both bWOA-S and bWOA-V achieve better results compared with other algorithms.

4.4. Performance on Large Initialization

The statistical average fitness values of the different datasets obtained from the compared algorithms using the large initialization methods are shown in Table 5. Table 6 shows average classification accuracy of the test data of the compared algorithms using small initialization methods. From these tables, we can conclude that when using large initialization methods, both bWOA-S and bWOA-V achieve better results compared with other algorithms.

4.5. Performance on Mixed Initialization

The statistical average fitness values on the different datasets obtained from the compared algorithms using the large initialization methods are shown in Table 7. Table 8 shows average classification accuracy of the test data of the compared algorithms using small initialization methods. As is notable from this table, we can conclude that both bWOA-S and bWOA-V achieve better results compared with other algorithms.

Table 3. Statistical mean fitness measure on the different datasets calculated for the compared algorithms using small initialization.

No.	WOA	bWOA-S	bWOA-v	BALO1	BALO2	BALO3	PSO	bGWO	bDA
1	0.061	0.049	0.051	0.079	0.095	0.088	0.060	0.035	0.031
2	0.327	0.224	0.313	0.345	0.352	0.334	0.333	0.243	0.210
3	0.247	0.133	0.220	0.411	0.395	0.416	0.249	0.127	0.058
4	0.933	0.908	0.937	0.955	0.960	0.953	0.926	0.880	0.877
5	0.345	0.295	0.340	0.351	0.391	0.375	0.362	0.276	0.253
6	0.337	0.203	0.315	0.374	0.372	0.369	0.303	0.154	0.188
7	0.137	0.123	0.131	0.175	0.177	0.184	0.141	0.098	0.125
8	0.297	0.251	0.273	0.294	0.302	0.288	0.282	0.195	0.169
9	0.381	0.361	0.379	0.391	0.397	0.394	0.402	0.354	0.338
10	0.391	0.081	0.375	0.421	0.418	0.419	0.421	0.079	0.052
11	0.436	0.196	0.437	0.499	0.498	0.517	0.432	0.181	0.187
12	0.322	0.297	0.337	0.347	0.332	0.334	0.314	0.314	0.208
13	0.245	0.244	0.239	0.237	0.264	0.240	0.243	0.244	0.237
14	0.291	0.135	0.299	0.359	0.351	0.352	0.289	0.133	0.075
15	0.125	0.068	0.140	0.151	0.155	0.174	0.130	0.062	0.054
16	0.051	0.047	0.059	0.087	0.084	0.083	0.051	0.038	0.030
17	0.097	0.035	0.097	0.095	0.094	0.096	0.099	0.025	0.033
18	0.298	0.150	0.298	0.357	0.375	0.367	0.294	0.110	0.141
19	0.087	0.044	0.087	0.128	0.131	0.134	0.086	0.035	0.043
20	0.294	0.203	0.275	0.376	0.317	0.379	0.309	0.183	0.165
21	0.461	0.181	0.444	0.614	0.602	0.606	0.446	0.148	0.176

Table 4. Average classification accuracy for the compared algorithms on the different datasets using small initialization.

No.	WOA	bWOA-S	bWOA-v	BALO1	BALO2	BALO3	PSO	bGWO	bDA
1	0.863	0.648	0.745	0.834	0.814	0.842	0.867	0.966	0.758
2	0.652	0.781	0.670	0.598	0.599	0.584	0.620	0.743	0.685
3	0.740	0.843	0.770	0.457	0.471	0.442	0.588	0.862	0.817
4	0.041	0.057	0.026	0.014	0.011	0.017	0.033	0.088	0.033
5	0.624	0.663	0.606	0.566	0.557	0.550	0.583	0.705	0.640
6	0.632	0.712	0.658	0.547	0.548	0.549	0.609	0.832	0.696
7	0.845	0.835	0.838	0.780	0.779	0.761	0.820	0.890	0.828
8	0.674	0.645	0.632	0.602	0.592	0.604	0.653	0.793	0.658
9	0.585	0.584	0.587	0.557	0.540	0.572	0.565	0.629	0.584
10	0.586	0.919	0.606	0.517	0.519	0.519	0.545	0.916	0.782
11	0.556	0.804	0.552	0.398	0.402	0.392	0.392	0.817	0.742
12	0.635	0.668	0.618	0.588	0.622	0.619	0.656	0.656	0.640
13	0.725	0.722	0.703	0.744	0.692	0.704	0.724	0.728	0.710
14	0.699	0.845	0.845	0.720	0.723	0.708	0.814	0.932	0.873
15	0.864	0.915	0.838	0.720	0.723	0.708	0.814	0.932	0.873
16	0.899	0.694	0.724	0.808	0.821	0.833	0.893	0.963	0.780
17	0.897	0.964	0.890	0.876	0.902	0.903	0.898	0.971	0.956
18	0.685	0.815	0.674	0.593	0.582	0.589	0.641	0.875	0.796
19	0.909	0.957	0.908	0.847	0.848	0.842	0.884	0.965	0.952
20	0.674	0.734	0.654	0.513	0.553	0.523	0.616	0.799	0.706
21	0.491	0.748	0.493	0.285	0.295	0.300	0.415	0.809	0.729

4.6. Discussion

Figure 3 shows the effect of the initialization method on the different optimizers applied over the selected datasets. The proposed bWOA-S and bWOA-V can reach the global optimal solution in almost half of the datasets, compared to the algorithms in all initialization methods. The limited search space in the case of binary algorithms explains the enhanced performance due to the balance between global and local searching. The balance between local and global searching assists the optimization algorithm to avoid early convergence and local optimal values. The small initialization keeps away the initial search agents from the optimal solution; however, in the large initialization, the search agents are closest to the optimal solution, although they have low diversity. While the mixed initialization method improves the performance of all compared algorithms, the two proposed algorithms are superior even in a high-dimensional dataset as in Table 9.

Table 5. Statistical mean fitness measure calculated on the different datasets for the compared algorithms using large initialization.

No.	WOA	bWOA-S	bWOA-v	BALO1	BALO2	BALO3	PSO	bGWO	bDA
1	0.133	0.127	0.164	0.183	0.146	0.223	0.160	0.036	0.032
2	0.215	0.207	0.209	0.241	0.248	0.243	0.204	0.211	0.209
3	0.149	0.138	0.139	0.168	0.129	0.182	0.171	0.101	0.076
4	0.928	0.928	0.929	0.938	0.937	0.924	0.925	0.907	0.882
5	0.316	0.312	0.314	0.322	0.320	0.312	0.314	0.303	0.249
6	0.303	0.289	0.293	0.273	0.298	0.288	0.277	0.258	0.197
7	0.168	0.163	0.180	0.162	0.177	0.166	0.160	0.150	0.127
8	0.349	0.337	0.349	0.341	0.358	0.346	0.345	0.288	0.171
9	0.400	0.403	0.390	0.403	0.403	0.388	0.397	0.375	0.343
10	0.069	0.073	0.072	0.073	0.071	0.073	0.069	0.067	0.051
11	0.193	0.192	0.192	0.196	0.193	0.191	0.188	0.189	0.187
12	0.303	0.309	0.312	0.305	0.305	0.304	0.302	0.305	0.207
13	0.259	0.259	0.260	0.260	0.266	0.264	0.258	0.256	0.241
14	0.138	0.131	0.138	0.143	0.137	0.133	0.121	0.121	0.068
15	0.087	0.090	0.086	0.089	0.093	0.094	0.086	0.084	0.053
16	0.217	0.220	0.156	0.108	0.155	0.205	0.200	0.043	0.030
17	0.044	0.043	0.044	0.043	0.042	0.045	0.046	0.036	0.033
18	0.187	0.186	0.189	0.182	0.195	0.190	0.189	0.170	0.138
19	0.052	0.052	0.053	0.052	0.051	0.052	0.051	0.049	0.043
20	0.238	0.232	0.222	0.248	0.235	0.233	0.234	0.228	0.147
21	0.260	0.246	0.273	0.274	0.262	0.273	0.232	0.227	0.183

Table 6. Average classification accuracy on the different datasets for the compared algorithms using large initialization.

No.	WOA	bWOA-S	bWOA-v	BALO1	BALO2	BALO3	PSO	bGWO	bDA
1	0.616	0.619	0.615	0.679	0.693	0.666	0.748	0.959	0.780
2	0.792	0.799	0.798	0.740	0.738	0.742	0.748	0.760	0.668
3	0.833	0.839	0.832	0.811	0.847	0.798	0.817	0.890	0.787
4	0.059	0.056	0.054	0.048	0.050	0.062	0.060	0.084	0.033
5	0.664	0.670	0.668	0.663	0.668	0.674	0.668	0.688	0.643
6	0.692	0.703	0.698	0.719	0.696	0.705	0.720	0.741	0.704
7	0.830	0.836	0.819	0.838	0.821	0.832	0.839	0.852	0.819
8	0.645	0.654	0.637	0.648	0.630	0.639	0.642	0.697	0.653
9	0.593	0.583	0.598	0.581	0.580	0.593	0.586	0.620	0.589
10	0.934	0.930	0.932	0.918	0.925	0.923	0.931	0.939	0.777
11	0.810	0.808	0.810	0.804	0.807	0.810	0.813	0.815	0.740
12	0.693	0.683	0.685	0.680	0.680	0.679	0.684	0.689	0.648
13	0.740	0.741	0.741	0.728	0.723	0.724	0.734	0.737	0.712
14	0.861	0.865	0.862	0.831	0.833	0.834	0.856	0.866	0.721
15	0.907	0.908	0.905	0.907	0.903	0.901	0.906	0.917	0.881
16	0.612	0.610	0.613	0.715	0.697	0.656	0.714	0.938	0.766
17	0.963	0.964	0.963	0.964	0.965	0.962	0.962	0.971	0.958
18	0.814	0.818	0.812	0.820	0.807	0.812	0.812	0.834	0.807
19	0.956	0.956	0.955	0.955	0.957	0.956	0.956	0.959	0.953
20	0.742	0.754	0.762	0.736	0.746	0.752	0.745	0.770	0.717
21	0.742	0.755	0.731	0.729	0.742	0.730	0.769	0.773	0.731

The standard deviation in the obtained fitness values on the different datasets for the compared algorithms averaged over the initialization methods is given in Table 10. As shown in this table, the proposed bWOA-V can reach the optimal solution better than compared algorithms, regardless of the initialization used.

With regard to the time consumption for optimization of these 11 test datasets, Table 11 presents the results of the average time obtained by the two proposed versions and other compared algorithms with 20 independent runs. As can be concluded from Table 11, bWOA-V ranks first among the algorithms. bWOA-S ranks fifth, but it is better than PSO and bALO, as it significantly outperforms the other compared algorithms with a little more time consumption.

Table 7. Statistical mean fitness measure calculated on the different datasets for the compared algorithms using mixed initialization.

No.	WOA	bWOA-S	bWOA-v	BALO1	BALO2	BALO3	PSO	bGWO	bDA
1	0.054	0.052	0.079	0.100	0.099	0.076	0.031	0.035	0.032
2	0.220	0.207	0.215	0.245	0.252	0.246	0.204	0.215	0.209
3	0.153	0.148	0.120	0.183	0.146	0.141	0.078	0.096	0.071
4	0.925	0.928	0.910	0.935	0.938	0.938	0.884	0.903	0.882
5	0.313	0.307	0.289	0.319	0.321	0.312	0.242	0.280	0.255
6	0.304	0.286	0.254	0.278	0.298	0.285	0.168	0.235	0.194
7	0.159	0.158	0.152	0.156	0.169	0.165	0.113	0.141	0.124
8	0.328	0.308	0.259	0.319	0.324	0.308	0.158	0.233	0.167
9	0.389	0.380	0.372	0.393	0.397	0.384	0.337	0.359	0.341
10	0.071	0.074	0.081	0.074	0.072	0.074	0.040	0.061	0.053
11	0.193	0.193	0.195	0.198	0.195	0.193	0.182	0.187	0.188
12	0.303	0.308	0.301	0.301	0.307	0.308	0.151	0.272	0.226
13	0.241	0.244	0.252	0.237	0.244	0.253	0.238	0.244	0.243
14	0.139	0.133	0.155	0.151	0.150	0.136	0.022	0.112	0.072
15	0.084	0.084	0.081	0.089	0.090	0.085	0.048	0.069	0.052
16	0.081	0.058	0.062	0.086	0.088	0.086	0.033	0.057	0.031
17	0.044	0.043	0.037	0.043	0.043	0.044	0.032	0.034	0.030
18	0.191	0.187	0.176	0.184	0.192	0.197	0.136	0.158	0.149
19	0.052	0.052	0.049	0.051	0.052	0.052	0.041	0.044	0.042
20	0.235	0.230	0.223	0.258	0.243	0.237	0.138	0.211	0.160
21	0.260	0.244	0.242	0.276	0.262	0.274	0.149	0.217	0.180

Table 8. Average classification accuracy on the different datasets for the compared algorithms using mixed initialization.

No.	WOA	bWOA-S	bWOA-v	BALO1	BALO2	BALO3	PSO	bGWO	bDA
1	0.785	0.619	0.628	0.740	0.725	0.726	0.802	0.962	0.789
2	0.787	0.799	0.786	0.686	0.681	0.686	0.720	0.764	0.673
3	0.841	0.839	0.822	0.656	0.706	0.680	0.789	0.900	0.779
4	0.065	0.056	0.053	0.039	0.033	0.031	0.039	0.086	0.031
5	0.678	0.670	0.664	0.635	0.623	0.625	0.656	0.707	0.649
6	0.698	0.703	0.703	0.645	0.639	0.647	0.721	0.765	0.705
7	0.835	0.836	0.831	0.819	0.803	0.802	0.835	0.860	0.827
8	0.656	0.654	0.652	0.625	0.621	0.623	0.668	0.751	0.652
9	0.598	0.582	0.595	0.573	0.559	0.577	0.589	0.631	0.571
10	0.936	0.930	0.918	0.766	0.765	0.757	0.794	0.943	0.754
11	0.812	0.808	0.804	0.642	0.649	0.647	0.763	0.816	0.747
12	0.687	0.683	0.691	0.644	0.656	0.648	0.664	0.706	0.642
13	0.738	0.740	0.735	0.733	0.711	0.703	0.723	0.735	0.712
14	0.865	0.865	0.833	0.734	0.732	0.744	0.761	0.883	0.728
15	0.915	0.908	0.900	0.829	0.823	0.829	0.884	0.930	0.866
16	0.761	0.610	0.615	0.730	0.744	0.727	0.810	0.944	0.769
17	0.964	0.964	0.965	0.924	0.939	0.925	0.956	0.972	0.959
18	0.815	0.818	0.803	0.729	0.720	0.724	0.806	0.845	0.791
19	0.956	0.956	0.955	0.908	0.910	0.911	0.953	0.962	0.952
20	0.756	0.755	0.749	0.639	0.672	0.659	0.705	0.786	0.709
21	0.744	0.755	0.725	0.553	0.568	0.563	0.765	0.781	0.730

Table 9. Results for high dimensional datasets.

Dataset	Accuracy	STDEV	Fitness			Time	SelSize
			Avg	Min	Max		
Colon							
WOA	0.67083	0.02710	0.52313	0.18933	0.33625	5.77346	0.52313
bWOA-S	0.66667	0.03066	0.45386	0.18940	0.31566	15.37727	0.45386
bWOA-V	0.66667	0.03003	0.49724	0.23179	0.35564	9.87549	0.49724
bALO1	0.62250	0.03513	0.46110	0.20995	0.35688	3.52489	0.46110
bALO2	0.62584	0.04386	0.47458	0.23059	0.37749	39.64500	0.47458
bALO3	0.62084	0.03544	0.49837	0.27183	0.35686	37.76940	0.49836
PSO	0.66084	0.02626	0.48793	0.16870	0.31424	3.52425	
bGWO1	0.79584	0.03536	0.35911	0.12644	0.27228	44.10091	0.35911
bDA	0.65167	0.02854	0.43856	0.16915	0.25231	6.72146	0.43856
Lymphoma							
WOA	0.42628	0.06076	0.47314	0.38451	0.72184	13.73907	0.47314
bWOA-S	0.35435	0.06035	0.44921	0.17422	0.71399	52.34015	0.44921
bWOA-V	0.39457	0.05754	0.49642	0.37169	0.80664	22.35106	0.49642
bALO1	0.41973	0.06194	0.51039	0.42877	0.73545	8.27976	0.510395
bALO2	0.39939	0.06230	0.44844	0.33482	0.74161	77.97951	0.44844
bALO3	0.39923	0.05861	0.48594	0.41489	0.76677	81.05818	0.48594
PSO	0.46635	0.05212	0.47878	0.18666	0.71151	7.31112	
bGWO1	0.48642	0.05491	0.28062	0.26272	0.71343	89.87190	0.28062
bDA	0.40717	0.03993	0.37595	0.32643	0.84836	16.47820	0.37595
Leukemia							
WOA	0.82353	0.08431	0.64732	0.15909	0.21848	30.54245	0.64732
bWOA-S	0.82353	0.08471	0.69674	0.07869	0.15941	85.80836	0.69674
bWOA-V	0.84647	0.07902	0.57925	0.09967	0.20281	45.17051	0.57925
bALO1	0.72500	0.08793	0.62512	0.14453	0.23919	14.68936	0.62511
bALO2	0.72471	0.09272	0.62429	0.15182	0.23920	171.695	0.62429
bALO3	0.73029	0.08913	0.62491	0.12273	0.23192	182.292	0.62491
PSO	0.85059	0.08055	0.80121	0.06281	0.1652	15.26511	
bGWO1	0.94588	0.07589	0.47347	0.02565	0.09169	205.829	0.47348
bDA	0.83706	0.07626	0.48777	0.02671	0.06319	31.56270	0.48777

Table 10. Standard deviation fitness function on the different datasets averaged for the compared algorithms over the three initialization methods.

No.	WOA	bWOA-S	bWOA-v	BALO1	BALO2	BALO3	PSO	bGWO	bDA
1	0.013	0.013	0.011	0.028	0.012	0.013	0.009	0.009	0.007
2	0.053	0.045	0.058	0.056	0.056	0.057	0.058	0.047	0.048
3	0.033	0.017	0.040	0.046	0.041	0.042	0.018	0.020	0.015
4	0.205	0.208	0.200	0.208	0.212	0.214	0.202	0.200	0.199
5	0.061	0.073	0.066	0.072	0.080	0.064	0.075	0.072	0.052
6	0.074	0.053	0.062	0.067	0.064	0.071	0.049	0.042	0.046
7	0.027	0.030	0.030	0.035	0.043	0.035	0.026	0.035	0.028
8	0.060	0.060	0.057	0.061	0.062	0.058	0.052	0.054	0.039
9	0.084	0.084	0.079	0.087	0.092	0.089	0.080	0.075	0.076
10	0.034	0.015	0.028	0.035	0.036	0.043	0.033	0.017	0.012
11	0.058	0.043	0.067	0.061	0.061	0.062	0.058	0.041	0.040
12	0.065	0.070	0.067	0.068	0.066	0.068	0.061	0.071	0.045
13	0.055	0.058	0.055	0.055	0.070	0.055	0.051	0.051	0.051
14	0.037	0.033	0.041	0.043	0.054	0.042	0.038	0.021	0.012
15	0.022	0.016	0.023	0.024	0.027	0.030	0.022	0.013	0.010
16	0.037	0.031	0.009	0.011	0.033	0.013	0.026	0.010	0.006
17	0.012	0.009	0.012	0.012	0.011	0.013	0.011	0.007	0.007
18	0.054	0.032	0.042	0.052	0.050	0.050	0.044	0.027	0.034
19	0.013	0.010	0.014	0.013	0.017	0.016	0.012	0.009	0.009
20	0.049	0.041	0.031	0.067	0.055	0.067	0.050	0.039	0.040
21	0.051	0.071	0.056	0.069	0.071	0.087	0.046	0.020	0.040

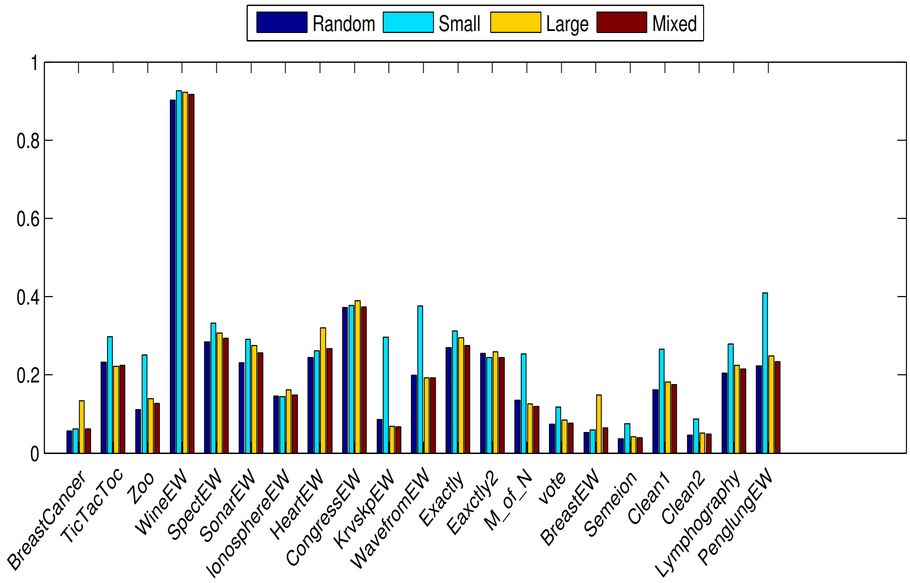


Figure 3. Statistical mean fitness averaged on the different datasets for the different optimizers using the different initializers.

Table 11. Average execution time in seconds on the different datasets for the compared algorithms averaged over the three initialization methods.

No.	WOA	bWOA-S	bWOA-v	BALO1	BALO2	BALO3	PSO	bGWO	bDA
1	4.722	4.243	4.467	4.896	4.703	4.42890	6.172	7.177	4.629
2	9.747	8.784	9.114	7.791	7.468	6.81349	8.253	10.149	6.720
3	3.712	3.460	3.741	4.019	4.010	3.89503	3.822	4.771	3.859
4	11.094	10.557	12.450	11.934	10.94404	10.779	11.804	14.946	11.225
5	3.725	3.364	4.072	4.158	4.195	3.92277	4.423	5.218	3.654
6	3.835	3.540	3.816	3.673	5.014	4.83652	4.316	5.756	3.599
7	4.139	4.220	4.376	4.030	4.978	4.73393	4.456	5.670	4.033
8	3.714	3.124	3.642	3.614	3.796	3.87177	4.029	5.339	3.616
9	4.353	3.719	4.680	4.130	4.502	4.66121	4.411	133	4.477
10	78.311	78.516	77.182	65.795	64.663	57.458	39.671	78.063	51.987
11	180	2122	3449	157	153	140	112	199	116
12	6.610	8.068	8.672	8.004	7.259	6.740	6.287	7.011	6.468
13	7.210	8.422	9.819	8.554	6.946	6.554	6.783	6.720	7.123
14	7.334	8.638	6.957	8.169	6.332	6.519	7.789	7.856	6.569
15	3.281	3.901	3.307	4.267	3.668	3.717	4.213	3.695	3.303
16	4.248	4.600	3.919	5.464	4.751	4.294	4.995	5.090	3.813
17	107	139	144	91.552	95.185	77.564	86.140	99.636	122
18	9.497	11.970	17.209	8.412	10.710	11.481	8.893	10.474	5.933
19	2672	1996	1733	985	1018	858	920	2053	1281
20	3.593	3.932	3.917	3.605	3.683	3.396	3.809	3.941	3.087
21	4.830	6.478	5.522	3.993	10.437	10.220	4.407	7.852	4.183

On the other hand, Tables 12 and 13 summarize the experimental results of the best and worst obtained fitness for the compared algorithms over 20 independent runs.

The mean selected features obtained from the compared algorithms are shown in Table 14.

Table 14 reports the ratio of mean selected features obtained from the compared algorithms. In Table 14, the performance of bWOA-V is superior in keeping its good classification accuracy by selecting a lower number of features.

This reveals the outstanding performance of bWOA-V in searching for both features' reduction and enhancing the optimization process.

Table 12. Best fitness function on the different datasets averaged for the compared algorithms over the three initialization methods.

No.	WOA	bWOA-S	bWOA-v	BALO1	BALO2	BALO3	PSO	bGWO	bDA
1	0.032	0.031	0.031	0.033	0.038	0.038	0.025	0.022	0.020
2	0.201	0.185	0.186	0.234	0.225	0.233	0.195	0.192	0.172
3	0.023	0.046	0.065	0.093	0.074	0.123	0.057	0.015	0.004
4	0.853	0.861	0.873	0.884	0.862	0.877	0.849	0.830	0.812
5	0.250	0.247	0.230	0.275	0.274	0.249	0.225	0.218	0.216
6	0.218	0.182	0.190	0.213	0.208	0.220	0.175	0.132	0.137
7	0.108	0.123	0.107	0.122	0.128	0.124	0.088	0.077	0.083
8	0.229	0.214	0.207	0.241	0.247	0.214	0.168	0.140	0.125
9	0.334	0.343	0.324	0.346	0.342	0.339	0.328	0.328	0.310
10	0.103	0.057	0.097	0.117	0.125	0.126	0.106	0.038	0.038
11	0.212	0.179	0.196	0.262	0.258	0.261	0.200	0.171	0.177
12	0.273	0.186	0.281	0.276	0.278	0.283	0.144	0.185	0.026
13	0.222	0.225	0.220	0.221	0.226	0.226	0.217	0.216	0.217
14	0.131	0.085	0.123	0.154	0.133	0.170	0.061	0.046	0.012
15	0.045	0.042	0.036	0.050	0.038	0.046	0.029	0.043	0.027
16	0.028	0.028	0.029	0.039	0.040	0.035	0.024	0.023	0.018
17	0.049	0.030	0.045	0.044	0.042	0.045	0.040	0.022	0.024
18	0.150	0.128	0.161	0.179	0.191	0.185	0.143	0.092	0.109
19	0.051	0.041	0.049	0.056	0.060	0.062	0.049	0.037	0.038
20	0.180	0.150	0.116	0.196	0.161	0.183	0.115	0.119	0.115
21	0.136	0.122	0.174	0.206	0.184	0.238	0.111	0.071	0.046

Table 13. Worst fitness function on the different datasets averaged for the compared algorithms over the three initialization methods.

No.	WOA	bWOA-S	bWOA-v	BALO1	BALO2	BALO3	PSO	bGWO	bDA
1	0.171	0.239	0.339	0.251	0.341	0.282	0.151	0.145	0.047
2	0.304	0.264	0.322	0.345	0.338	0.330	0.271	0.262	0.238
3	0.301	0.256	0.267	0.360	0.331	0.326	0.290	0.238	0.154
4	0.978	0.993	0.961	0.981	0.985	0.993	0.945	0.956	0.922
5	0.377	0.356	0.394	0.384	0.417	0.421	0.401	0.328	0.288
6	0.375	0.387	0.356	0.365	0.389	0.372	0.290	0.286	0.256
7	0.214	0.176	0.215	0.204	0.222	0.213	0.190	0.182	0.165
8	0.376	0.360	0.386	0.411	0.407	0.383	0.301	0.347	0.198
9	0.442	0.419	0.446	0.480	0.455	0.436	0.433	0.399	0.375
10	0.211	0.106	0.224	0.234	0.231	0.222	0.194	0.142	0.064
11	0.315	0.207	0.321	0.301	0.301	0.322	0.273	0.199	0.198
12	0.354	0.333	0.365	0.371	0.372	0.379	0.324	0.335	0.294
13	0.303	0.276	0.278	0.282	0.345	0.286	0.287	0.275	0.262
14	0.220	0.198	0.277	0.264	0.265	0.255	0.197	0.181	0.127
15	0.190	0.124	0.198	0.150	0.203	0.192	0.118	0.118	0.077
16	0.314	0.183	0.343	0.334	0.328	0.251	0.148	0.235	0.046
17	0.072	0.050	0.069	0.065	0.066	0.071	0.062	0.041	0.042
18	0.284	0.222	0.261	0.280	0.286	0.279	0.233	0.202	0.185
19	0.069	0.056	0.069	0.080	0.082	0.082	0.061	0.049	0.048
20	0.337	0.305	0.303	0.374	0.352	0.394	0.289	0.274	0.202
21	0.440	0.381	0.462	0.474	0.481	0.528	0.433	0.365	0.312

In order to compare each runs results, a non-parametric statistical called Wilcoxon's rank sum (WRS) test was carried out over the 11 UCI datasets at 5% significance level, and the p-values are given in Table 15. From this table, p-values for the bWOA-V are mostly less than 0.05, which proves that this algorithm's superiority is statistically significant. This means that bWOA-V exhibits a statistically superior performance compared to the other compared algorithms in the pair-wise Wilcoxon signed-ranks test.

Table 14. Average selection size on the different datasets averaged for the compared algorithms over the three initialization methods.

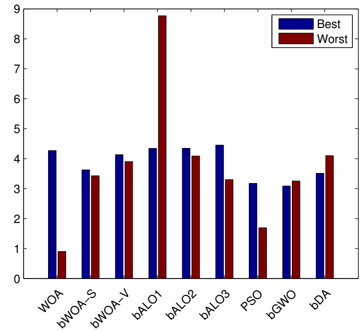
No.	WOA	bWOA-S	bWOA-v	BALO1	BALO2	BALO3	PSO	bGWO	bDA
1	0.60875	0.63875	0.56750	0.47500	0.50250	0.50875	0.636	0.63875	0.50625
2	0.77500	0.97083	0.75555	0.61806	0.63750	0.62083	0.520	0.79167	0.80417
3	0.66172	0.76328	0.60625	0.62031	0.61797	0.62500	0.609	0.59141	0.47109
4	0.62596	0.69904	0.58365	0.55865	0.56154	0.54231	0.643	0.58269	0.47019
5	0.64602	0.73920	0.59148	0.54432	0.59886	0.56989	0.568	0.62898	0.45966
6	0.64729	0.66396	0.55667	0.60563	0.60566	0.62396	0.520	0.62146	0.43854
7	0.60221	0.66875	0.59265	0.54522	0.55699	0.54081	0.564	0.61213	0.40625
8	0.55577	0.54519	0.54134	0.51731	0.45769	0.47885	0.611	0.57596	0.41730
9	0.53281	0.58438	0.54609	0.50859	0.52578	0.50469	0.427	0.62891	0.44219
10	0.70417	0.90347	0.67951	0.61909	0.62535	0.62361	0.578	0.76314	0.53368
11	0.73344	0.90500	0.70750	0.62656	0.63156	0.63062	0.750	0.79906	0.58656
12	0.64038	0.72693	0.69712	0.51635	0.54231	0.54231	0.475	0.62212	0.61827
13	0.49904	0.46731	0.61538	0.39423	0.40385	0.44615	0.475	0.42981	0.17885
14	0.72404	0.87884	0.69135	0.62212	0.60865	0.62115	0.695	0.76442	0.63462
15	0.66719	0.74609	0.60234	0.59141	0.56640	0.61016	0.520	0.61094	0.37813
16	0.57250	0.62375	0.60250	0.51875	0.49500	0.51000	0.552	0.60750	0.48875
17	0.66788	0.79953	0.59774	0.62183	0.62538	0.62363	0.856	0.64108	0.50028
18	0.69247	0.79488	0.58893	0.62146	0.61942	0.62387	0657	0.64932	0.48532
19	0.66822	0.77086	0.57515	0.62432	0.62402	0.62771	0.781	0.68577	0.48735
20	0.66250	0.72708	0.60069	0.60555	0.58958	0.59028	0.499	0.62569	0.50486
21	0.64835	0.71131	0.53630	0.62142	0.62111	0.62312	0.550	0.49126	0.47477

Table 15. The Wilcoxon test for the average fitness obtained by the compared algorithms.

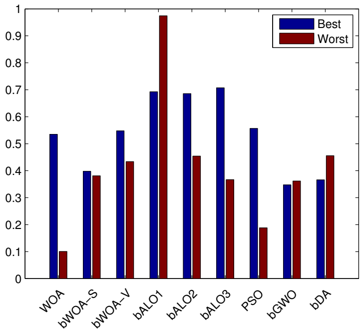
Algorithms	bWOA-S			bWOA-V		
	Small	Mixed	Large	Small	Mixed	Large
WOA	0.0606	0.4756	0.4201	0.4178	0.4352	0.5640
bALO1	0.0000	0.4006	0.4609	0.1191	0.2180	0.4480
bALO2	0.0038	0.2736	0.4248	0.0754	0.2036	0.5881
bALO3	0.0947	0.0596	0.6410	0.3404	0.0725	0.4672
bGWO	0.0589	0.0532	0.879	0.654	0.0587	0.0.300
bDA	0.0439	0.0298	0.1406	0.4892	0.0584	0.400

Moreover, Figure 4 outlines the best and worst acquired fitness function value averaged over all the datasets, using small, mixed and large initialization. Figure 5 shows the classification accuracy average. From these figures, it can be proven that the bWOA-V performs better than other compared algorithms, such as PSO and bALO, which confirms bWOA-V's searching capability, especially in the large initialization.

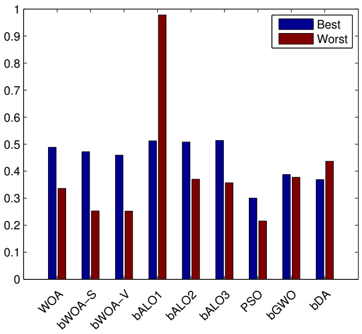
In order to show the merits of bWOA-S and bWOA-V qualitatively, Figures 6–8, show the boxplots results for the three initialization methods obtained by all compared algorithms. According to these figures, bWOA-S and bWOA-V have superiority since the boxplot of bWOA-S and bWOA-V are extremely narrow and located under the minima of PSO, bALO, and the original WOA. In summary, the qualitative results prove that the two proposed algorithms are able to provide remarkable convergence and coverage ability in solving FS problems. Another fact worth mentioning here is that the boxplots show that bALO and PSO algorithms provide poor performance.



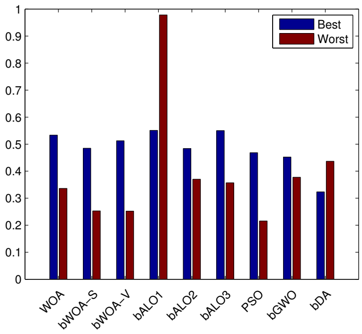
(**a**) Random initialization



(**b**) Small initialization

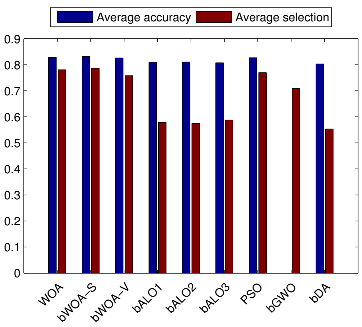


(**c**) Mixed initialization

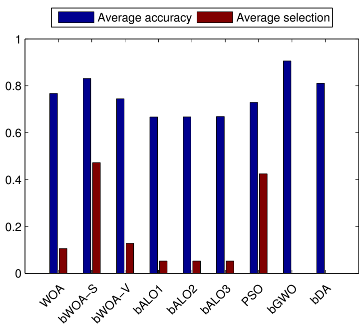


(**d**) Large initialization

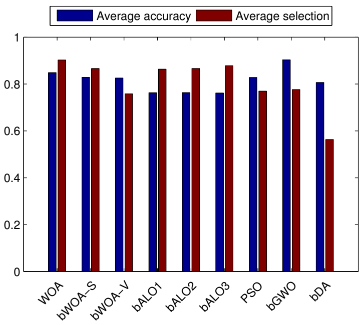
Figure 4. Best and worst fitness obtained for the compared algorithms on the different datasets averaged over the four initialization methods.



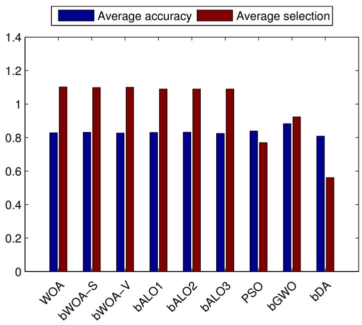
(**a**) Random initialization



(**b**) Small initialization



(**c**) Mixed initialization



(**d**) Large initialization

Figure 5. Average classification accuracy and average selection size obtained on the different datasets averaged for the compared algorithms over the three initialization methods.

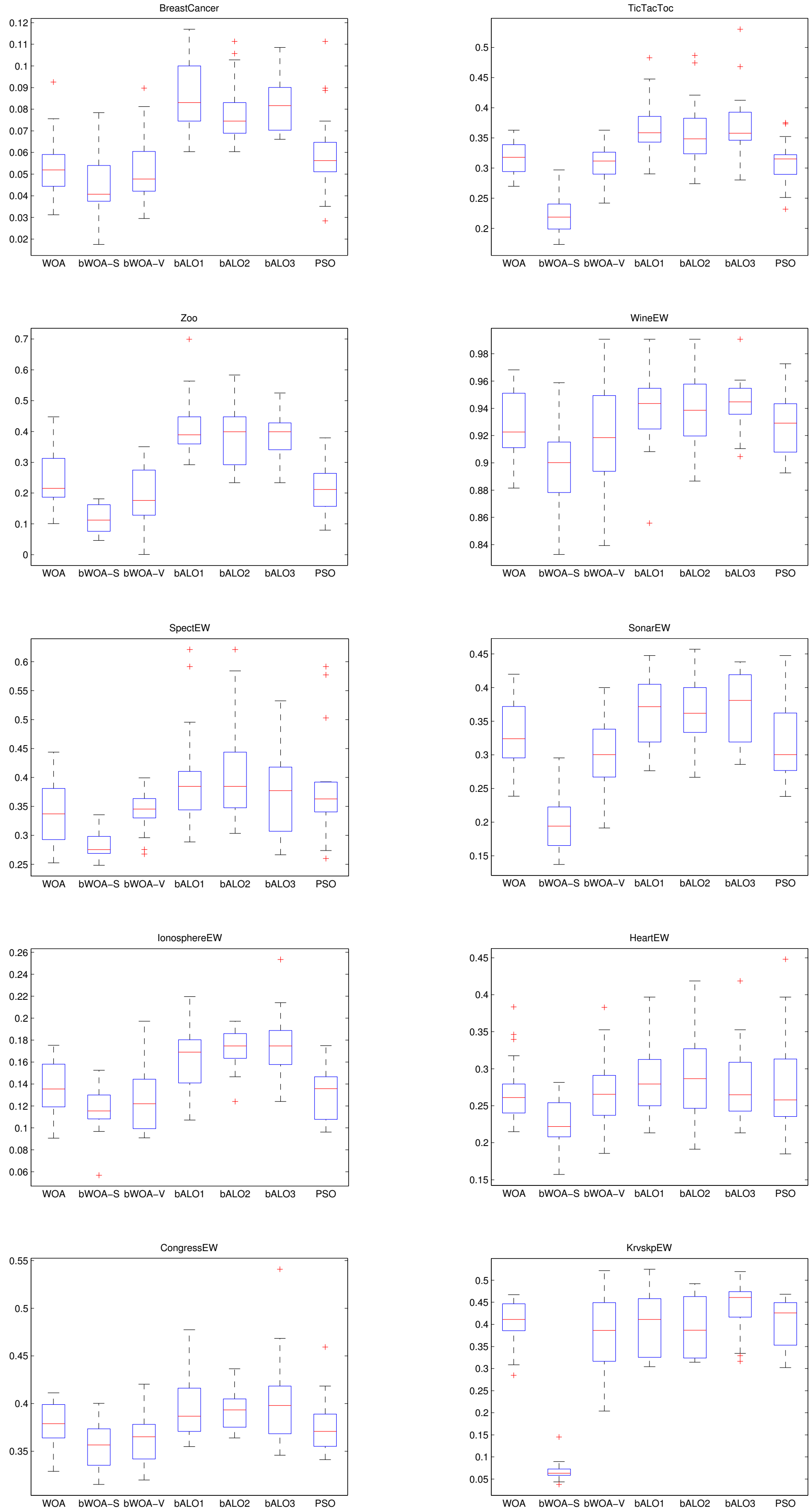


Figure 6. Small initialization boxplot for the compared algorithms on the different datasets.

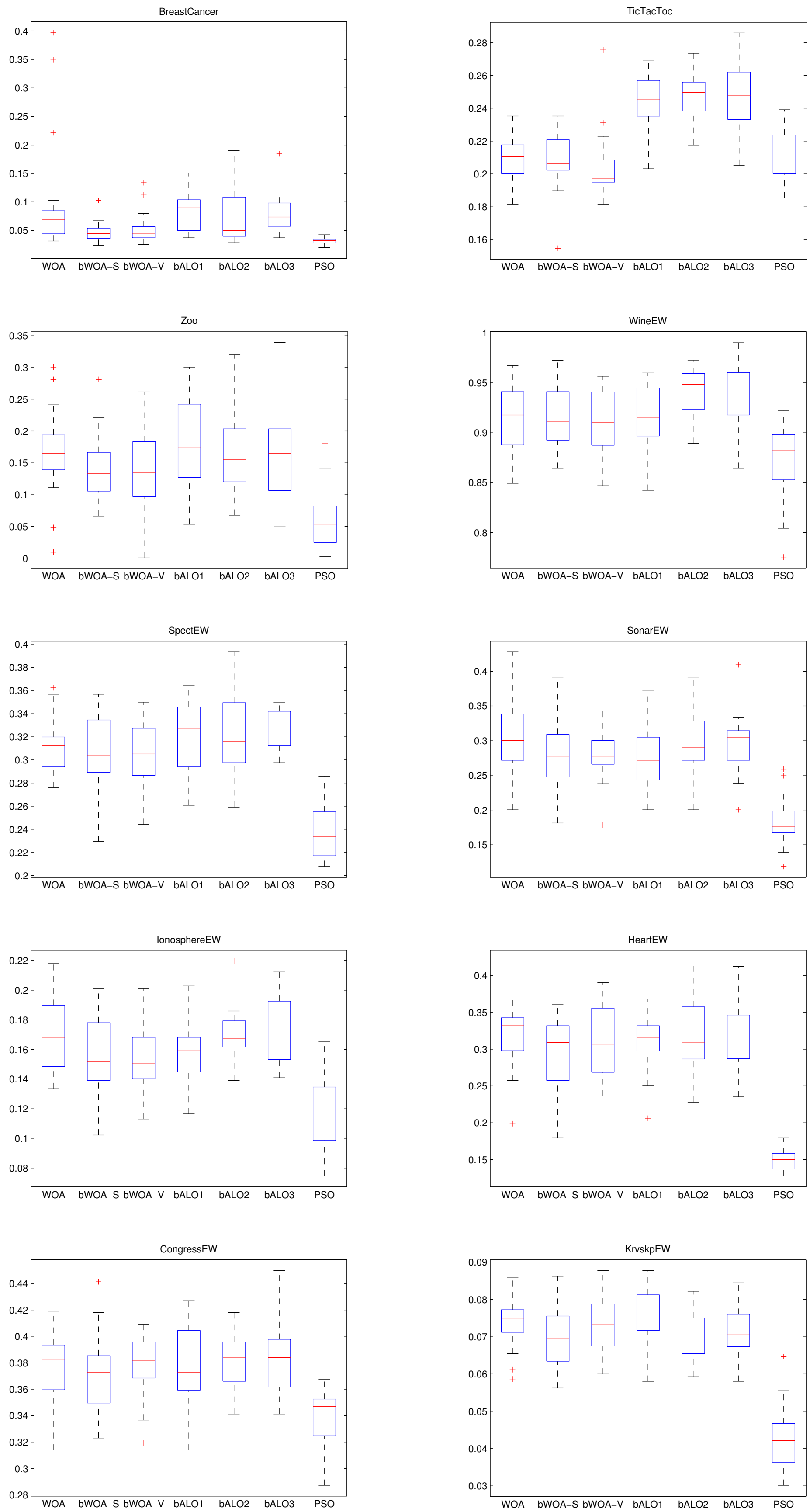


Figure 7. Mixed initialization boxplot for the compared algorithms on the different datasets.

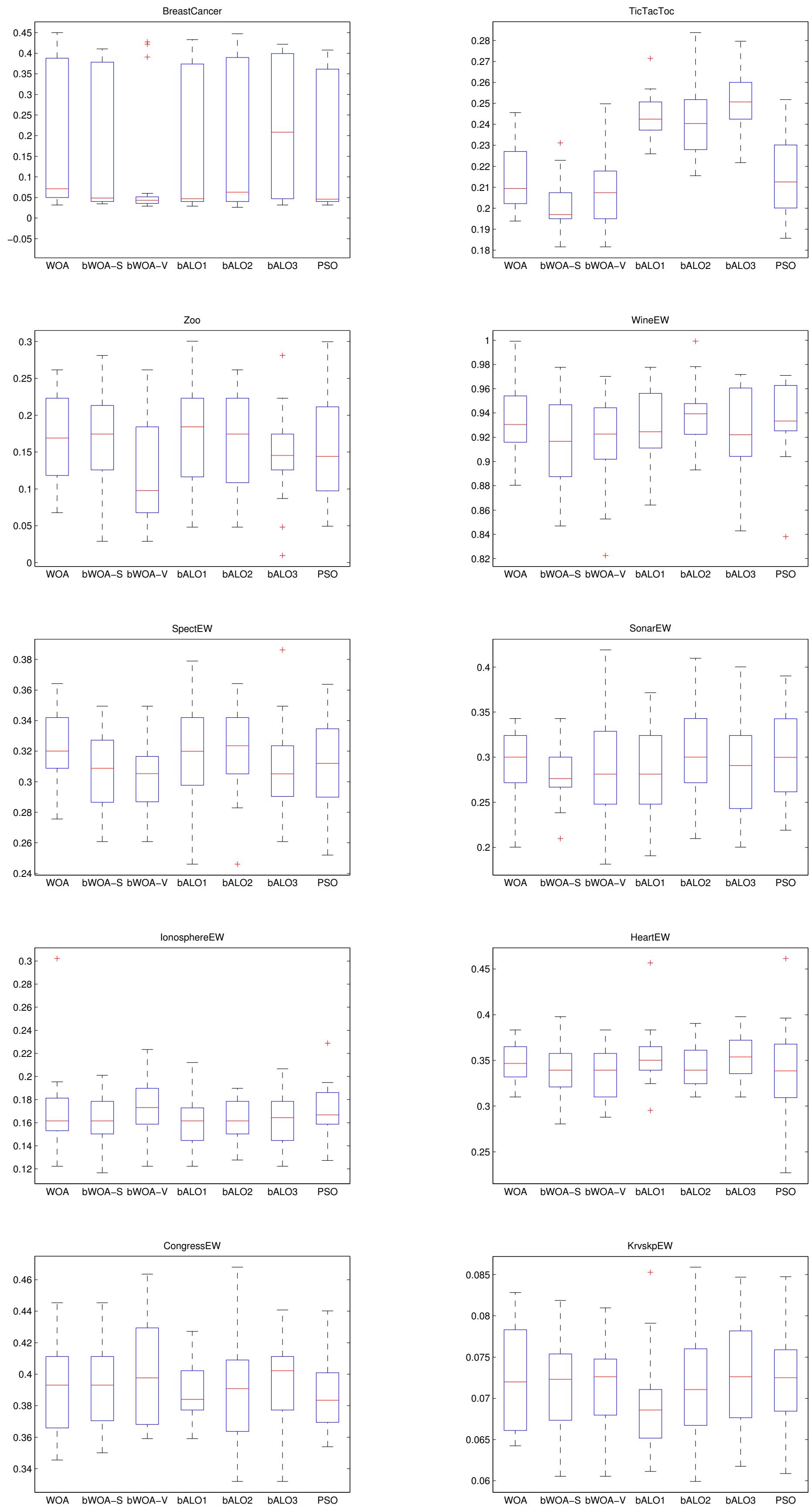


Figure 8. Large initialization boxplot for the compared algorithms on the different datasets.

5. Conclusions and Future Work

In this paper, two binary version of the original whale optimization algorithm (WOA), called bWOA-S and bWOA-V, have been proposed to solve the FS problem. To convert the original version of WOA to a binary version, S-shaped and V-shaped transfer functions are employed. In order to investigate the performance of the two proposed algorithms, the experiments employ 24 benchmark datasets from the UCI repository and eight evaluation criteria to assess different aspects of the compared algorithms.The experimental results revealed that the two proposed algorithms achieved superior results compared to the three well-known algorithms, namely PSO, bALO (three variants), and the original WOA. Furthermore, the results proved that bWOA-S and bWOA-V both achieved smallest number of selected features with best classification accuracy in a minimum time. In addition, the Wilcoxon's rank-sum nonparametric statistical test was carried out at 5% significance level to judge whether the results of the two proposed algorithms differ from the best results of the other compared algorithms in a statistically significant way. More specifically, the results proved that the bWOA-s and bWOA-V have merit among binary optimization algorithms. For future work, the two binary algorithms introduced here will be applied to high-dimensional real-world applications and will be used with more common classifiers such as SVM and ANN to verify the performance. The effects of different transfer functions on the performance of the two proposed algorithms are also worth investigating. This algorithm can be applied for many problems other than FS. We can also investigate a multi-objective version.

Author Contributions: A.G.H.: Software, Resources, Writing—original draft, editing. D.O.: Conceptualization, Data curation, Resources, Writing—review and editing. E.H.H.: Supervision, Methodology, Conceptualization, Formal analysis, Writing—review and editing. A.A.J.: Formal analysis, Writing—review and editing. X.Y.: Formal analysis, Writing—review and editing. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external fundin.

Conflicts of Interest: The authors declare that there is no conflict of interest.

References

1. Yi, J.H.; Deb, S.; Dong, J.; Alavi, A.H.; Wang, G.G. An improved NSGA-III algorithm with adaptive mutation operator for Big Data optimization problems. *Future Gener. Comput. Syst.* **2018**, *88*, 571–585. [CrossRef]
2. Neggaz, N.; Houssein, E.H.; Hussain, K. An efficient henry gas solubility optimization for feature selection. *Expert Syst. Appl.* **2020**, *152*, 113364. [CrossRef]
3. Sayed, S.A.F.; Nabil, E.; Badr, A. A binary clonal flower pollination algorithm for feature selection. *Pattern Recognit. Lett.* **2016**, *77*, 21–27. [CrossRef]
4. Martin-Bautista, M.J.; Vila, M.A. A survey of genetic feature selection in mining issues. In Proceedings of the 1999 Congress on Evolutionary Computation-CEC99 (Cat. No. 99TH8406), Washington, DC, USA, 6–9 July 1999; Volume 2, pp. 1314–1321.
5. Piramuthu, S. Evaluating feature selection methods for learning in data mining applications. *Eur. J. Oper. Res.* **2004**, *156*, 483–494. [CrossRef]
6. Gunal, S.; Edizkan, R. Subspace based feature selection for pattern recognition. *Inf. Sci.* **2008**, *178*, 3716–3726. [CrossRef]
7. Lew, M.S. *Principles of Visual Information Retrieval*; Springer Science & Business Media: Berlin, Germany, 2013.
8. Wang, G.G.; Tan, Y. Improving metaheuristic algorithms with information feedback models. *IEEE Trans. Cybern.* **2017**, *49*, 542–555. [CrossRef] [PubMed]
9. Houssein, E.H.; Hosney, M.E.; Elhoseny, M.; Oliva, D.; Mohamed, W.M.; Hassaballah, M. Hybrid Harris hawks optimization with cuckoo search for drug design and discovery in chemoinformatics. *Sci. Rep.* **2020**, *10*, 1–22. [CrossRef] [PubMed]
10. Houssein, E.H.; Hosney, M.E.; Oliva, D.; Mohamed, W.M.; Hassaballah, M. A novel hybrid Harris hawks optimization and support vector machines for drug design and discovery. *Comput. Chem. Eng.* **2020**, *133*, 106656. [CrossRef]

11. Gao, D.; Wang, G.G.; Pedrycz, W. Solving fuzzy job-shop scheduling problem using de algorithm improved by a selection mechanism. *IEEE Trans. Fuzzy Syst.* **2020**. [CrossRef]
12. Houssein, E.H.; Saad, M.R.; Hussain, K.; Zhu, W.; Shaban, H.; Hassaballah, M. Optimal sink node placement in large scale wireless sensor networks based on Harris' hawk optimization algorithm. *IEEE Access* **2020**, *8*, 19381–19397. [CrossRef]
13. Ahmed, M.M.; Houssein, E.H.; Hassanien, A.E.; Taha, A.; Hassanien, E. Maximizing lifetime of large-scale wireless sensor networks using multi-objective whale optimization algorithm. *Telecommun. Syst.* **2019**, *72*, 243–259. [CrossRef]
14. Chandrashekar, G.; Sahin, F. A survey on feature selection methods. *Comput. Electr. Eng.* **2014**, *40*, 16–28. [CrossRef]
15. Liu, H.; Yu, L. Toward integrating feature selection algorithms for classification and clustering. *IEEE Trans. Knowl. Data Eng.* **2005**, *17*, 491–502.
16. Kohavi, R.; John, G.H. Wrappers for feature subset selection. *Artif. Intell.* **1997**, *97*, 273–324. [CrossRef]
17. Liu, H.; Setiono, R. A probabilistic approach to feature selection-a filter solution. In Proceedings of the 13th International Conference on Machine Learning, Bari, Italy, 3–6 July 1996; Volume 23, pp. 319–327.
18. Hastie, T.; Tibshirani, R.; Friedman, J. *The Elements of Statistical Learning: Data Mining, Inference, and Prediction;* Springer: New York, NY, USA, 2002.
19. Safavian, S.R.; Landgrebe, D. hastie2002elements. *IEEE Trans. Syst. Man, Cybern.* **1991**, *21*, 660–674. [CrossRef]
20. Dasarathy, B.V. *Nearest Neighbor ({NN}) Norms:{NN} Pattern Classification Techniques*; IEEE Computer Society Press: Washington, DC, USA, 1991.
21. Verikas, A.; Bacauskiene, M. Feature selection with neural networks. *Pattern Recognit. Lett.* **2002**, *23*, 1323–1335. [CrossRef]
22. Vapnik, V.N.; Vapnik, V. *Statistical Learning Theory*; Wiley: New York, NY, USA, 1998; Volume 1.
23. Khalid, S.; Khalil, T.; Nasreen, S. A survey of feature selection and feature extraction techniques in machine learning. In Proceedings of the Science and Information Conference (SAI), London, UK, 27–29 August 2014; pp. 372–378.
24. Wang, G.G.; Guo, L.; Gandomi, A.H.; Hao, G.S.; Wang, H. Chaotic krill herd algorithm. *Inf. Sci.* **2014**, *274*, 17–34. [CrossRef]
25. Hassanien, A.E.; Emary, E. *Swarm Intelligence: Principles, Advances, and Applications*; CRC Press: Boca Raton, FL, USA, 2016.
26. Mirjalili, S.; Lewis, A. The whale optimization algorithm. *Adv. Eng. Softw.* **2016**, *95*, 51–67. [CrossRef]
27. Hussien, A.G.; Amin, M.; Abd El Aziz, M. A comprehensive review of moth-flame optimisation: Variants, hybrids, and applications. *J. Exp. Theor. Artif. Intell.* **2020**, *32*, 705–725. [CrossRef]
28. Assiri, A.S.; Hussien, A.G.; Amin, M. Ant Lion Optimization: Variants, hybrids, and applications. *IEEE Access* **2020**, *8*, 77746–77764. [CrossRef]
29. Hussien, A.G.; Amin, M.; Wang, M.; Liang, G.; Alsanad, A.; Gumaei, A.; Chen, H. Crow Search Algorithm: Theory, Recent Advances, and Applications. *IEEE Access* **2020**, *8*, 173548–173565. [CrossRef]
30. Shareef, H.; Ibrahim, A.A.; Mutlag, A.H. Lightning search algorithm. *Appl. Soft Comput.* **2015**, *36*, 315–333. [CrossRef]
31. Hashim, F.A.; Houssein, E.H.; Mabrouk, M.S.; Al-Atabany, W.; Mirjalili, S. Henry gas solubility optimization: A novel physics-based algorithm. *Future Gener. Comput. Syst.* **2019**, *101*, 646–667. [CrossRef]
32. Houssein, E.H.; Saad, M.R.; Hashim, F.A.; Shaban, H.; Hassaballah, M. Lévy flight distribution: A new metaheuristic algorithm for solving engineering optimization problems. *Eng. Appl. Artif. Intell.* **2020**, *94*, 103731. [CrossRef]
33. Hashim, F.A.; Houssein, E.H.; Hussain, K.; Mabrouk, M.S.; Al-Atabany, W. A modified Henry gas solubility optimization for solving motif discovery problem. *Neural Comput. Appl.* **2020**, *32*, 10759–10771. [CrossRef]
34. Fernandes, C.; Pontes, A.; Viana, J.; Gaspar-Cunha, A. Using multiobjective evolutionary algorithms in the optimization of operating conditions of polymer injection molding. *Polym. Eng. Sci.* **2010**, *50*, 1667–1678. [CrossRef]
35. Gaspar-Cunha, A.; Covas, J.A. RPSGAe—Reduced Pareto set genetic algorithm: Application to polymer extrusion. In *Metaheuristics for Multiobjective Optimisation*; Springer: Berlin/Heidelberg, Germany, 2004; pp. 221–249.

36. Avalos, O.; Cuevas, E.; Gálvez, J.; Houssein, E.H.; Hussain, K. Comparison of Circular Symmetric Low-Pass Digital IIR Filter Design Using Evolutionary Computation Techniques. *Mathematics* **2020**, *8*, 1226. [CrossRef]
37. Xue, B.; Zhang, M.; Browne, W.N.; Yao, X. A survey on evolutionary computation approaches to feature selection. *IEEE Trans. Evol. Comput.* **2016**, *20*, 606–626. [CrossRef]
38. Kabir, M.M.; Shahjahan, M.; Murase, K. A new hybrid ant colony optimization algorithm for feature selection. *Expert Syst. Appl.* **2012**, *39*, 3747–3763. [CrossRef]
39. Ghaemi, M.; Feizi-Derakhshi, M.R. Feature selection using forest optimization algorithm. *Pattern Recognit.* **2016**, *60*, 121–129. [CrossRef]
40. Emary, E.; Zawbaa, H.M.; Ghany, K.K.A.; Hassanien, A.E.; Parv, B. Firefly optimization algorithm for feature selection. In Proceedings of the 7th Balkan Conference on Informatics Conference, Craiova, Romania, 2–4 September 2015; p. 26.
41. Mafarja, M.M.; Mirjalili, S. Hybrid Whale Optimization Algorithm with simulated annealing for feature selection. *Neurocomputing* **2017**, *260*, 302–312. [CrossRef]
42. Xue, B.; Zhang, M.; Browne, W.N. Particle swarm optimization for feature selection in classification: A multi-objective approach. *IEEE Trans. Cybern.* **2013**, *43*, 1656–1671. [CrossRef]
43. Hafez, A.I.; Zawbaa, H.M.; Emary, E.; Hassanien, A.E. Sine cosine optimization algorithm for feature selection. In Proceedings of the 2016 International Symposium on INnovations in Intelligent Systems and Applications (INISTA), Sinaia, Romania, 2–5 August 2016; pp. 1–5.
44. Wang, G.G.; Deb, S.; Cui, Z. Monarch butterfly optimization. *Neural Comput. Appl.* **2019**, *31*, 1995–2014. [CrossRef]
45. Wang, G.G. Moth search algorithm: A bio-inspired metaheuristic algorithm for global optimization problems. *Memetic Comput.* **2018**, *10*, 151–164. [CrossRef]
46. Rodrigues, D.; Yang, X.S.; De Souza, A.N.; Papa, J.P. Binary flower pollination algorithm and its application to feature selection. In *Recent Advances in Swarm Intelligence and Evolutionary Computation*; Springer: Berlin/Heidelberg, Germany, 2015; pp. 85–100.
47. Nakamura, R.Y.; Pereira, L.A.; Costa, K.; Rodrigues, D.; Papa, J.P.; Yang, X.S. BBA: A binary bat algorithm for feature selection. In Proceedings of the 2012 25th SIBGRAPI Conference on Graphics, Patterns and Images (SIBGRAPI), Ouro Preto, Brazil, 22–25 August 2012; pp. 291–297.
48. Rodrigues, D.; Pereira, L.A.; Almeida, T.; Papa, J.P.; Souza, A.; Ramos, C.C.; Yang, X.S. BCS: A binary cuckoo search algorithm for feature selection. In Proceedings of the 2013 IEEE International Symposium on Circuits and Systems (ISCAS), Beijing, China, 19–23 May 2013; pp. 465–468.
49. He, X.; Zhang, Q.; Sun, N.; Dong, Y. Feature selection with discrete binary differential evolution. In Proceedings of the 2009 International Conference on Artificial Intelligence and Computational Intelligence, Shanghai, China, 7–8 November 2009; Volume 4, pp. 327–330.
50. Emary, E.; Zawbaa, H.M.; Hassanien, A.E. Binary ant lion approaches for feature selection. *Neurocomputing* **2016**, *213*, 54–65. [CrossRef]
51. Emary, E.; Zawbaa, H.M.; Hassanien, A.E. Binary grey wolf optimization approaches for feature selection. *Neurocomputing* **2016**, *172*, 371–381. [CrossRef]
52. Rashedi, E.; Nezamabadi-Pour, H.; Saryazdi, S. BGSA: Binary gravitational search algorithm. *Nat. Comput.* **2010**, *9*, 727–745. [CrossRef]
53. Hussien, A.G.; Hassanien, A.E.; Houssein, E.H. Swarming behaviour of salps algorithm for predicting chemical compound activities. In Proceedings of the 2017 Eighth International Conference on Intelligent Computing and Information Systems (ICICIS), Cairo, Egypt, 5–7 December 2017; pp. 315–320.
54. Nezamabadi-pour, H.; Rostami-Shahrbabaki, M.; Maghfoori-Farsangi, M. Binary particle swarm optimization: Challenges and new solutions. *CSI J. Comput. Sci. Eng.* **2008**, *6*, 21–32.
55. Hussien, A.G.; Houssein, E.H.; Hassanien, A.E. A binary whale optimization algorithm with hyperbolic tangent fitness function for feature selection. In Proceedings of the 2017 Eighth International Conference on Intelligent Computing and Information Systems (ICICIS), Cairo, Egypt, 5–7 December 2017; pp. 166–172.
56. Hussien, A.G.; Hassanien, A.E.; Houssein, E.H.; Bhattacharyya, S.; Amin, M. S-shaped Binary Whale Optimization Algorithm for Feature Selection. In *Recent Trends in Signal and Image Processing*; Springer: Berlin/Heidelberg, Germany, 2019; pp. 79–87.
57. Hussien, A.G.; Hassanien, A.E.; Houssein, E.H.; Amin, M.; Azar, A.T. New binary whale optimization algorithm for discrete optimization problems. *Eng. Optim.* **2020**, *52*, 945–959. [CrossRef]

58. Chuang, L.Y.; Chang, H.W.; Tu, C.J.; Yang, C.H. Improved binary PSO for feature selection using gene expression data. *Comput. Biol. Chem.* **2008**, *32*, 29–38. [CrossRef]
59. Dua, D.; Graff, C. UCI Machine Learning Repository. 2017. Available online: http://archive.ics.uci.edu/ml (accessed on 28 September 2020).
60. Eberhart, R.; Kennedy, J. A new optimizer using particle swarm theory. In Proceedings of the Sixth International Symposium on Micro Machine and Human Science, Nagoya, Japan, 4–6 October 1995; pp. 39–43.
61. Mafarja, M.M.; Eleyan, D.; Jaber, I.; Hammouri, A.; Mirjalili, S. Binary dragonfly algorithm for feature selection. In Proceedings of the 2017 International Conference on New Trends in Computing Sciences (ICTCS), Amman, Jordan, 11–13 October 2017; pp. 12–17.
62. D'Angelo, G.; Palmieri, F. GGA: A modified Genetic Algorithm with Gradient-based Local Search for Solving Constrained Optimization Problems. *Inf. Sci.* **2020**, *547*, 136–162. [CrossRef]
63. Mirjalili, S.; Hashim, S.Z.M. BMOA: Binary magnetic optimization algorithm. *Int. J. Mach. Learn. Comput.* **2012**, *2*, 204. [CrossRef]
64. Alon, U.; Barkai, N.; Notterman, D.A.; Gish, K.; Ybarra, S.; Mack, D.; Levine, A.J. Broad patterns of gene expression revealed by clustering analysis of tumor and normal colon tissues probed by oligonucleotide arrays. *Proc. Natl. Acad. Sci. USA* **1999**, *96*, 6745–6750. [CrossRef] [PubMed]
65. Alizadeh, A.A.; Eisen, M.B.; Davis, R.E.; Ma, C.; Lossos, I.S.; Rosenwald, A.; Boldrick, J.C.; Sabet, H.; Tran, T.; Yu, X.; et al. Distinct types of diffuse large B-cell lymphoma identified by gene expression profiling. *Nature* **2000**, *403*, 503–511. [CrossRef] [PubMed]
66. Golub, T.R.; Slonim, D.K.; Tamayo, P.; Huard, C.; Gaasenbeek, M.; Mesirov, J.P.; Coller, H.; Loh, M.L.; Downing, J.R.; Caligiuri, M.A.; et al. Molecular classification of cancer: Class discovery and class prediction by gene expression monitoring. *Science* **1999**, *286*, 531–537. [CrossRef] [PubMed]
67. Wilcoxon, F. Individual comparisons by ranking methods. *Biom. Bull.* **1945**, *1*, 80–83. [CrossRef]