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FOUNDATIONS

Optimizing connection weights in neural networks using the whale optimization algorithm

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Abstract The learning process of artificial neural networks is considered as one of the most difficult challenges in machine learning and has attracted many researchers recently. The main difficulty of training a neural network is the nonlinear nature and the unknown best set of main controlling parameters (weights and biases). The main disadvantages of the conventional training algorithms are local optima stagnation and slow convergence speed. This makes stochastic optimization algorithm reliable alternative to alleviate these drawbacks. This work proposes a new training algorithm based on the recently proposed whale optimization algorithm (WOA). It has been proved that this algorithm is able to solve a wide range of optimization problems and outperform the current algorithms. This motivated our attempts to benchmark its performance in training feedforward neural networks. For the first time in the literature, a set of 20 datasets with different levels of difficulty are chosen to test the proposed WOA-based trainer. The results are verified by comparisons with back-propagation algorithm and six evolutionary techniques. The qualitative and quantitative results prove that the proposed trainer is able to outperform the current algorithms on the majority of datasets in terms of both local optima avoidance and convergence speed.

Keywords Optimization · Whale optimization algorithm · WOA · Multilayer perceptron · MLP · Training neural network · Evolutionary algorithm

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1 Introduction

Artificial neural networks (ANNs) are intelligent and non-parametric mathematical models inspired by the biological nervous system. In the last three decades, ANNs have been widely investigated and applied to classification, pattern recognition, regression, and forecasting problems (Schmidhuber 2015; Chatterjee et al 2016; Braik et al 2008; Linggard et al 2012; Huang et al 2015; Rezaeianzadeh et al. 2014). The efficiency of ANNs is highly affected by its learning process. For multilayer perceptron (MLP) neural networks, which are the most common and applied ANNs, there are two main categories of supervised training methods: gradient-based and stochastic methods. The back-propagation algorithm and its variants (Wang et al. 2015; Kim and Jung 2015) are considered as standard examples of gradient-based methods and the most popular between researchers. However, there are three main disadvantages in the gradient-based methods: tendency to be trapped in local minima, slow convergence, and high dependency on the initial parameters (Faris et al 2016; Mirjalili 2015; Anna 2012).

As reliable alternatives to the above-mentioned gradient-based approaches, heuristic search algorithms have been proposed in the literature for optimizing the MLP networks. In contrast to gradient algorithms, meta-heuristics show higher efficiency in avoiding local minima (Črepinšek et al. 2013; Gang 2013; Mirjalili et al. 2012). Evolutionary and

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swarm-based algorithms, which are the two main families of meta-heuristic algorithms, are among the most investigated methods by researchers in training MLP networks. These types of algorithms are population based, in which a number possible random solutions are generated, evolved, and updated until a satisfactory solution is found or a maximum number of iterations is reached. These algorithms incorporate randomness as the main mechanism to move from a local search to a global search, and therefore, they are more suitable for global optimization (Yang 2014).

Evolutionary algorithms were deployed in the supervised learning of MLP networks in three different main schemes: automatic design of the network structure, optimizing the connection weights and biases of the network, and evolving the learning rules (Jianbo et al. 2008). It is important to mention here that simultaneous optimization of the structure and weights of the MLP network can drastically increase the number of parameters, so it can be considered a large-scale optimization problem (Karaboga et al 2007). In this work, we focus only on optimizing the connection weights and the biases in the MLP network.

Genetic algorithm (GA) is a classical example of evolutionary algorithms and considered as one of the most investigated meta-heuristics in training neural networks. GA is inspired by the Darwinian theories about evolution and nature selection, and it was first proposed by Holland (1992), Goldberg (1989), and Sastry et al (2014). In Seiffert (2001), the author applied GA to train the connection weights in MLP network and argued that GA can outperform the back-propagation algorithm when the targeted problems are more complex. A similar approach was conducted in Gupta and Randall (1999) where GA was compared to back-propagation for the chaotic time-series problems, and it was shown that GA is superior in terms of effectiveness, ease of use, and efficiency. Other works on applying GA to train MLP networks can be found in Whitley et al. (1990), Ding et al. (2011), Sexton et al. (1998), and Randall (2000). Differential evolution (DE) (Storn and Price 1997; Price et al 2006; Das and Suganthan 2011) and evolution strategy (ES) (Beyer and Schwefel 2002) are other examples of evolutionary algorithms. DE and ES were applied in training MLP networks and compared to other techniques in different studies (Wdaa 2008; Ilonen et al. 2003; Slowik and Bialko 2008; Wienholt 1993). Another distinguished type of meta-heuristics that is getting more interest is the swarm-based stochastic search algorithms, which are inspired by the movements of birds, insects, and other creatures in nature. Most of these algorithms incorporate updating the generated random solutions by some mathematical models rather than the reproduction operators like those in GA. The most popular examples of swarm-based algorithms are the particle swarm optimization (PSO) (Zhang et al. 2015; Kennedy 2010), ant colony optimization (ACO) (Chandra 2012; Dorigo et al. 2006), and the artificial bee colony (ABC) (Karaboga et al. 2014; Karaboga 2005). Some interesting applications of these algorithms and their variations in the problem of training MLP networks are reported in Jianbo et al. (2008), Mendes et al (2002), Meissner et al. (2006), Blum and Socha (2005), Socha and Blum (2007), and Karaboga et al (2007).

Although a wide range of evolutionary and swarm-based algorithms are deployed and investigated in the literature for training MLP, the problem of local minima is still open. According to the no-free-lunch theorem (NFL), there is no superior optimization algorithm in all optimization problems (Wolpert and Macready 1997; Ho and Pepyne 2002). Motivated by these reasons, in this work, a new MLP training method based on the recent whale optimization algorithm (WOA) is proposed for training a single hidden layer neural network. WOA, a novel meta-heuristic algorithm, was first introduced and developed in Mirjalili and Lewis (2016). WOA is inspired by the bubble-net hunting strategy of humpback whales. Unlike previous works in the literature where the proposed training algorithms are tested on roughly five datasets, the developed WOA-based approach in this work is evaluated and tested based on 20 popular classification datasets. Also, the results are compared to those obtained for basic trainers from the literature including: four evolutionary algorithms (GA, DE, ES and the population-based incremental learning algorithm (PBIL) (Baluja 1994; Meng et al. 2014), two swarm intelligent algorithms (PSO and ACO), and the most popular gradient-based back-propagation algorithm.

This paper is organized as follows: A brief introduction to MLP is given in Sect. 2. Section 3 presents the WOA. The details of the proposed WOA trainer are described and discussed in Sect. 4. The experiments and results are discussed in Sect. 5. Finally, the findings of this research are concluded in Sect. 6.

2 Multilayer perceptron neural network

Feedforward neural networks (FFNNs) are a special form of supervised neural networks. FFNNs consist of a set of processing elements called 'neurons.' The neurons are distributed over a number of stacked layers where each layer is fully connected with next one. The first layer is called the input layer, and this layer maps the input variables to the network. The last layer is called the output layer. All layers between the input layer and the output layer are called hidden layers (Basheer and Hajmeer 2000; Panchal and Ganatra 2011).

Multilayer perceptron (MLP) is the most popular and common type of FFNN. In MLP, neurons are interconnected in a one-way and one-directional fashion. Connections are represented by weights which are real numbers that fall in the

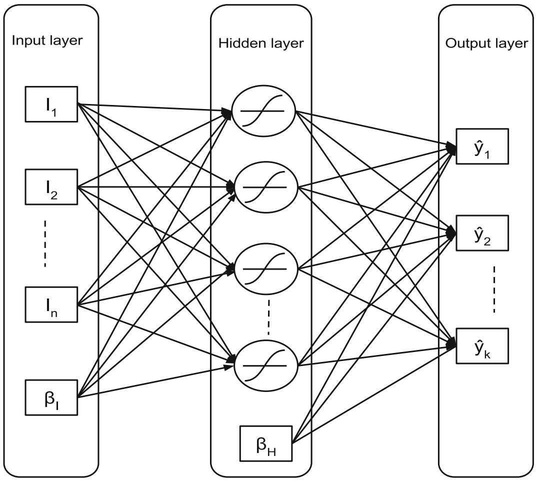


Fig. 1 Multilayer perceptron neural network

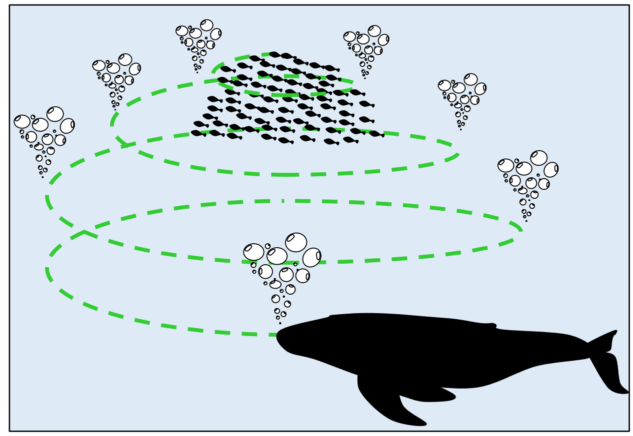


Fig. 2 Bubble-net hunting behavior

interval [−1, 1]. Figure 1 shows a general example of MLP with only one hidden layer. The output of each node in the network is calculated in two steps. First, the weighted summation of the input is calculated using Eq. 1 where I_i is the input variable i, while w_{ij} is the connection weight between I_i and the hidden neuron j.

Second, an activation function is used to trigger the output of neurons based on the value of the summation function. Different types of activation functions could be used in MLP. Using the sigmoid function, which is the most applied in the literature, the output of the node j in the hidden layer can be calculated as shown in Eq. 2 .

$$S_j = \sum_{i=1}^{n} w_{ij} I_i + \beta_j \tag{1}$$

$$f_j(x) = \frac{1}{1 + e^{-S_j}} \tag{2}$$

After calculating the output of each neuron in the hidden layer, the final output of the network is calculated as given in Eq. 3.

$$\hat{y}_k = \sum_{i=1}^{m} W_{kj} f_i + \beta_k \tag{3}$$

3 The whale optimization algorithm

Whale optimization algorithm (WOA) is a recently proposed stochastic optimization algorithm (Mirjalili and Lewis 2016). It utilizes a population of search agents to determine the global optimum for optimization problems. Similarly to other population-based algorithms, the search process starts with creating a set of random solutions (candidate solutions) for a given problem. It then improves this set until the satisfaction of an end criterion. The main difference between WOA and other algorithms is the rules that improve the candidate solutions in each step of optimization. In fact, WOA mimics the hunting behavior of hump back whales in finding and attacking preys called bubble-net feeding behavior. The bubble-net hunting model is shown in Fig. 2.

It may be observed in this figure that a humpback whale creates a trap with moving in a spiral path around preys and creating bubbles along the way. This intelligent foraging method is the main inspiration of the WOA. Another simulated behavior of humpback whales in WOA is the encircling mechanism. Humpback whales circle around preys to start hunting them using the bubble-net mechanism. The main mathematical equation proposed in this algorithm is as follows:

$$\mathbf{X}(t+1) = \begin{cases} \mathbf{X}^*(t) - \mathbf{AD} & p < 0.5 \\ \mathbf{D}' e^{bl} \cos(2\pi t) + \mathbf{X}^*(t) & p \geq 0.5 \end{cases} \tag{4}$$

where p is a random number in [0, 1], $\mathbf{D}' = |\mathbf{X^*}(t) - \mathbf{X}(t)|$ and indicates the distance of the ith whale the prey (best solution obtained so far), b is a constant for defining the shape of the logarithmic spiral, and l is a random number in [−1, 1], t shows the current iteration, $\mathbf{D} = |\mathbf{CX^*}(t) - \mathbf{X}(t)|$, $\mathbf{A} = 2\mathbf{ar} - \mathbf{a}$, $\mathbf{C} = 2\mathbf{r}$, $\mathbf{a}$ linearly decreases from 2 to 0 over the course of iterations (in both exploration and exploitation phases), and $\mathbf{r}$ is a random vector in [0, 1].

The first component of this equation simulates the encircling mechanism, whereas the second mimics the bubble-net technique. The variable p switches between these two components with an equal probability. The possible positions of a search agent using these two equations are illustrated in Fig. 3.

The exploration and exploitation are two main phases of optimization using population-based algorithms. They are both guaranteed in WOA by adaptively tuning the parameters a and c in the main equation.

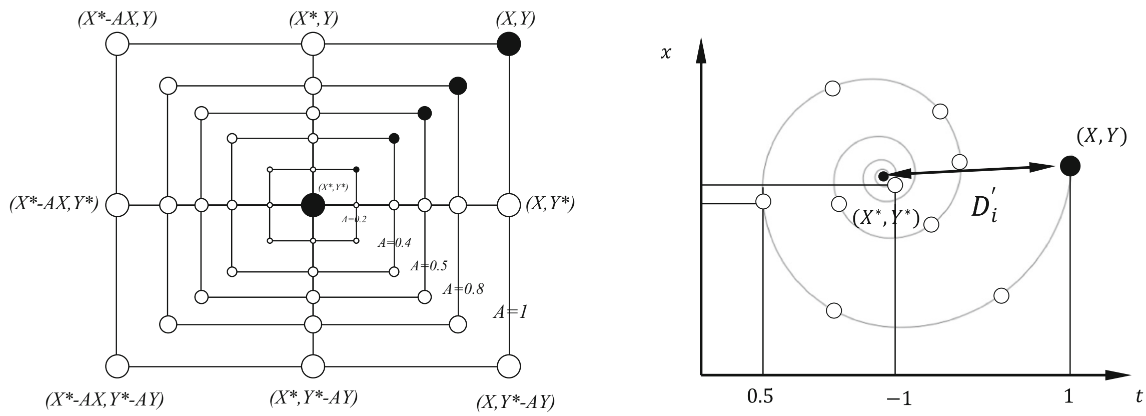


Fig. 3 Mathematical models for prey encircling and bubble-nethunting

The WOA starts optimizing a given problem by creating a set of random solutions. In each step of optimization, search agents update their positions based on a randomly selected search agent or the best search agent obtained so far. To guarantee exploration and convergence, the best solution is the pivot point to update the position of other search agents when $|\mathbf{X}| > 1$. In other situations (when $|\mathbf{X}| < 1$), the best solution obtained so far plays the role of the pivot point. The pseudocodes of the WOA are shown in Algorithm 1.

Algorithm 1 Pseudocodes of WOA

Initialize the whales population $X_i (i = 1, 2, 3, ..., n)$
Initialize a, A, and C
Calculate the fitness of each search agent
X^* = the best search agent
procedure WOA(Population, a, A, C, $MaxIter$, ..)
  $t = 1$
  while $t \leq MaxIter$ **do**
    for each search agent **do**
      if $|A| \leq 1$ **then**
        Update the position of the current search agent by the equation 2.6
      else if $|A| \geq 1$ **then**
        Select a random search agent $X_r and$
        Update the position of the current agent by the equation 2.8
      end if
    end for
    Update a, A, and C
    Update X^* if there is a better solution
    $t = t + 1$
  end while
  return X^*
end procedure

It was proven by the inventors of WOA that this algorithm is able to solve optimization problems of different kinds. It was argued in the main paper that this is due to the flexibility, gradient-free mechanism, and high local optima avoidance of this algorithm. These motivated our attempts to employ WOA as a trainer for FFNNs due to the difficulties of learning process. Theoretically speaking, WOA should be able to train any ANN subject proper objective function and problem formulation. In addition, providing the WOA with enough number of search agents and iterations is another factor for the success of this algorithm. The following section shows how to train MLPs using WOA in details.

4 WOA for training MLP

In this section, we describe the proposed approach based on the WOA for training the MLP network which will be named as WOA-MLP. WOA is applied to train an MLP network with a single hidden layer. Two important aspects are taken into consideration when the approach is designed: the representation of the search agents in the WOA and the selection of the fitness function.

In WOA-MLP, each search agent is encoded as a one-dimensional vector to represent a candidate neural network. Vectors include three parts: a set of weights connecting the input layer with the hidden layer, a set of weights connecting the hidden layer with the output layer, and a set of biases. The length of each vectors equals the total number of weights and biases in the network, and it can be calculated using Eq. 5 where is n is the number of input variables and m is the number of neurons in the hidden layer.

$$\text{Individual length} = (n \times m) + (2 \times m) + 1 \tag{5}$$

To measure the fitness value of the generated WOA agents, we utilize the mean square error (MSE) fitness function which is based on calculating the difference between the actual and predicted values by the generated agents (MLPs) for all the training samples. MSE is shown in Eq. 6 where y is the actual value, $\hat{y}$ is the predicted value, and n is number of instances in the training dataset.

$$\text{MSE} = \frac{1}{n} \sum_{i=1}^{n} (y - \hat{y})^2 \tag{6}$$

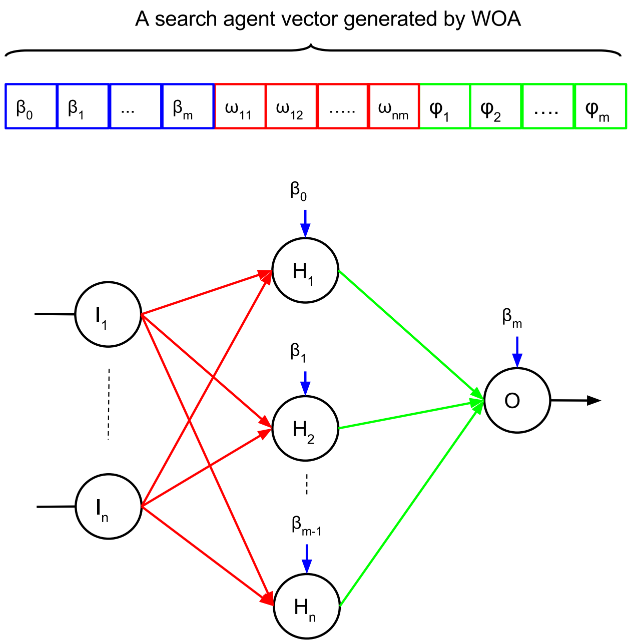


Fig. 4 Assigning a WOA search agent vector to an MLP

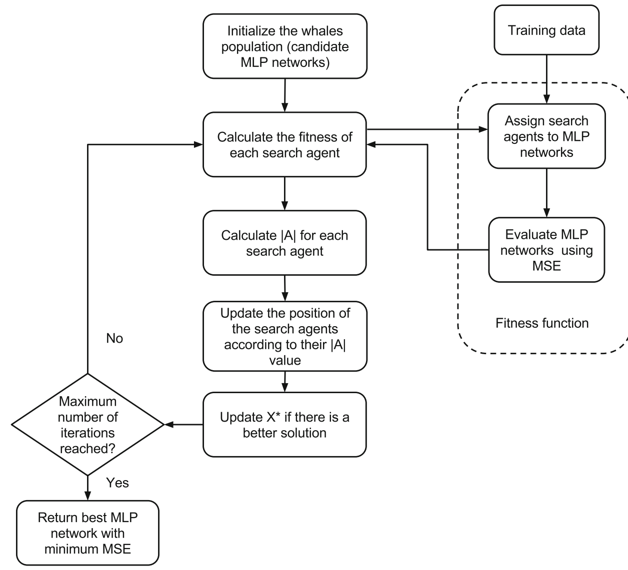


Fig. 5 General steps of the WOA-MLP approach

The workflow of the WOA-based approach applied in this work for training the MLP network can be described in the following steps:

1. Initialization: A predefined number of search agents are randomly generated. Each search agent represents a possible MLP network.
2. Fitness evaluation: The quality of the generated MLP networks is evaluated using a fitness function. To perform this step, the set of weights and biases that form the generated search agents vectors are first assigned to MLP networks, and then each network is evaluated. In this work, the MSE is selected, which is commonly chosen as a fitness function in evolutionary neural networks. The goal of the training algorithm is to find the MLP network with the minimum MSE value based on the training samples in the dataset.
3. Update the position of the search agents.
4. Steps 2 to 3 are repeated until the maximum number of iterations is reached. Finally, the MLP network with the minimum MSE value is tested on unseen part of the dataset (test/validation samples).

The general steps of the WOA-MLP approach are depicted in Fig. 5.

5 Results and discussions

In this section, the proposed WOA approach for training MLP networks is evaluated using *twenty* standard classification datasets, which are selected from the University of California at Irvine (UCI) Machine Learning Repository [1] and DELVE repository .[2] Table 1 presents these datasets in terms of the number of classes, features, training samples, and test samples. As can be noticed, the selected datasets have different numbers of features and instances to test the training algorithms in different conditions, which makes the problem more challenging.

5.1 Experimental setup

For all experiments, we used MATLAB R2010b to implement the proposed WOA trainer and other algorithms. All datasets are divided into 66% for training and 34% for testing using stratified sampling in order to preserve class distribution as much as possible. Furthermore, to eliminate the effect of features that have different scales, all datasets are normalized using min–max normalization as given in the following equation:

$$v' = \frac{v_i - \min_A}{\max_A - \min_A} \tag{7}$$

where v' is normalized value of v in the range $[\min_A, \max_A]$.

All experiments are executed for ten different runs, and each run includes 250 iterations. In WOA, there are two main parameters to be adjusted A and C. These parameters depend on the values of a and r. In our experiments, we utilize a and r the same way as used in Mirjalili and Lewis (2016); a is set to linearly decrease from 2 to 0 over the course of iterations,

[1] http://archive.ics.uci.edu/ml/.

[2] http://www.cs.utoronto.ca/~delve/data/.

Table 1 Classification datasets

Dataset	#Classes	#Features	#Training samples	#Testing samples
Blood	2	4	493	255
Breast cancer	2	8	461	238
Diabetes	2	8	506	262
Hepatitis	2	10	102	53
Vertebral	2	6	204	106
Diagnosis I	2	6	79	41
Diagnosis II	2	6	79	41
Parkinson	2	22	128	67
Liver	2	6	79	41
Australian	2	14	455	235
Credit	2	61	670	330
Monk	2	6	285	147
Tic-tac-toe	2	9	632	326
Titanic	2	3	1452	749
Ring	2	20	4884	2516
Twonorm	2	20	4884	2516
Ionosphere	2	33	231	120
Chess	2	36	2109	1087
Seed	3	7	138	72
Wine	3	13	117	61

Table 2 Initial parameters of the meta-heuristic algorithms

Algorithm	Parameter	Value
GA	• Crossover probability	0.9
	• Mutation probability	0.1
	• Selection mechanism	Roulette wheel
PSO	• Acceleration constants	[2.1, 2.1]
	• Inertia weights	[0.9, 0.6]
DE	• Crossover probability	0.9
	• Differential weight	0.5
ACO	• Initial pheromone (τ)	$1e{-}06$
	• Pheromone update constant (Q)	20
	• Pheromone constant (q)	1
	• Global pheromone decay rate (p_g)	0.9
	• Local pheromone decay rate (p_t)	0.5
	• Pheromone sensitivity (α)	1
	• Visibility sensitivity (β)	5
ES	• λ	10
	• σ	1
PBIL	• Learning rate	0.05
	• Good population member	1
	• Bad population member	0
	• Elitism parameter	1
	• Mutational probability	0.1

Table 3 MLP structure for each dataset

Dataset	#Features	MLP structure
Blood	4	4-9-1
Breast cancer	8	8-17-1
Diabetes	8	8-17-1
Hepatitis	10	10-21-1
Vertebral	6	6-13-1
Diagnosis I	6	6-13-1
Diagnosis II	6	6-13-1
Parkinson	22	22-45-1
Liver	6	6-13-1
Australian	14	14-29-1
Credit	61	61-123-1
Monk	6	6-13-1
Tic-tac-toe	9	9-19-1
Titanic	3	3-7-1
Ring	20	20-41-1
Twonorm	20	20-41-1
Ionosphere	33	33-67-1
Chess	36	36-73-1
Seed	7	7-15-1
Wine	13	13-27-1

Table 4 Accuracy results for blood, breast cancer, diabetes, hepatitis, vertebral, diagnosis I, diagnosis II, Parkinson, liver, and Australian, respectively

Dataset\Algorithm		WOA	BP	GA	PSO	ACO	DE	ES	PBIL
Blood	AVG	**0.7867**	0.6349	0.7827	0.7792	0.7651	0.7718	0.7835	0.7812
	STD	**0.0059**	0.2165	0.0089	0.0096	0.0119	0.0045	0.0090	0.0058
	Best	**0.7961**	**0.7804**	**0.7961**	0.7961	0.7765	0.7765	0.7922	0.7882
Breast cancer	AVG	**0.9731**	0.8500	0.9706	0.9685	0.9206	0.9605	0.9605	0.9702
	STD	**0.0063**	0.1020	0.0079	0.0057	0.0391	0.0095	0.0103	0.0085
	Best	**0.9832**	0.9706	**0.9832**	0.9748	0.9622	0.9706	0.9748	**0.9832**
Diabetes	AVG	**0.7584**	0.5660	0.7504	0.7481	0.6679	0.7115	0.7156	0.7366
	STD	**0.0139**	0.1469	0.0169	0.0307	0.0385	0.0290	0.0233	0.0208
	Best	0.7786	0.6908	0.7748	**0.7977**	0.7557	0.7519	0.7519	0.7634
Hepatitis	AVG	**0.8717**	0.7509	0.8623	0.8434	0.8472	0.8528	0.8453	0.8491
	STD	**0.0318**	0.1996	0.0252	0.0378	0.0392	0.0318	0.0306	0.0267
	Best	**0.9057**	0.8491	**0.9057**	0.8868	0.8868	**0.9057**	0.8868	0.8868
Vertebral	AVG	**0.8802**	0.6858	0.8689	0.8443	0.7142	0.7821	0.8472	0.8623
	STD	**0.0141**	0.1465	0.0144	0.0256	0.0342	0.0582	0.0239	0.0214
	Best	**0.9057**	0.8113	0.8868	0.8774	0.7642	0.8679	0.8679	0.8962
Diagnosis I	AVG	**1.0000**	0.8195	**1.0000**	**1.0000**	0.8537	0.9976	**1.0000**	**1.0000**
	STD	**0.0000**	0.1357	**0.0000**	**0.0000**	0.1233	0.0077	**0.0000**	**0.0000**
	Best	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**
Diagnosis II	AVG	**1.0000**	0.9073	**1.0000**	**1.0000**	0.8537	**1.0000**	**1.0000**	**1.0000**
	std	**0.0000**	0.0994	**0.0000**	**0.0000**	0.1138	**0.0000**	**0.0000**	**0.0000**
	Best	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**
Parkinson	AVG	0.8358	0.7582	**0.8507**	0.8463	0.7642	0.8239	0.8254	0.8388
	STD	0.0392	0.1556	**0.0233**	0.0345	0.0421	0.0384	0.0264	0.0336
	Best	**0.8955**	0.8657	0.8806	**0.8955**	0.8209	0.8806	0.8657	0.8806
Liver	AVG	**0.6958**	0.5407	0.6780	0.6703	0.5525	0.5653	0.6347	0.6636
	STD	**0.0284**	0.0573	0.0524	0.0263	0.0639	0.0727	0.0535	0.0461
	Best	0.7373	0.6525	0.7373	0.7034	0.6356	0.6695	**0.7458**	0.7203
Australian	AVG	**0.8535**	0.7794	0.8289	0.8241	0.7724	0.8232	0.8096	0.8355
	STD	**0.0159**	0.0528	0.0228	0.0255	0.0474	0.0311	0.0297	0.0166
	Best	**0.8772**	0.8289	0.8553	0.8596	0.8421	0.8816	0.8509	0.8553

while r is set as a random vector in the interval [0, 1]. The controlling parameters GA, PSO, ACO, DE, ES, and PBIL are used as listed in Table 2.

For MLP, researchers proposed different approaches to select the number of neurons in the hidden layer. However, in the literature, there is no standard method that is agreed about its superiority. In this work, we follow the same method proposed and used in Wdaa (2008), Mirjalili (2014) where the number of neurons in the hidden layer is selected based on the following formula: $2 \times N + 1$, where N is number of dataset features. By applying this method, the resulted MLP structure for each dataset is illustrated in Table 3.

5.2 Results

The proposed WOA trainer is compared with standard BP and other meta-heuristic trainers based on classification accuracy and MSE evaluation measures. Table 4 and Table 5 show the statistical results, namely average (AVG), and standard deviation (STD) of classification accuracy, as well as the most accurate result of the proposed WOA, BP, GA, PSO, ACO, DE, ES, and PBIL on the given datasets. As shown in the tables, WOA trainer outperforms all other trainers optimizers and BP for blood, breast cancer, diabetes, hepatitis, vertebral, liver, diagnosis I, diagnosis II, Australian, monk, tic-tac-toe, ring, wine, and seeds datasets with an average accuracy of 0.7867, 0.9731, 0.7584, 0.8717, 0.8802, 1.000, 1.000, 0.6958, 0.8535, 0.8224, 0.6733, 0.7729, 0.8986, and 0.8894, respectively.

The high average and low standard deviation of the classification accuracy obtained by WOA trainer give strong evidence that this approach is able to reliably prevent premature convergence toward local optima and find the best optimal values for MLP's weights and biases. In addition,

Table 5 Accuracy results for credit, monk, tic-tac-toe, titanic, ring, twonorm, ionosphere, chess, seed, and wine, respectively

Dataset\Algorithm		WOA	BP	GA	PSO	ACO	DE	ES	PBIL
Credit	AVG	0.6991	0.6933	**0.7133**	0.7100	0.6918	0.7018	0.7061	0.7124
	STD	0.0212	0.0196	**0.0200**	0.0132	0.0219	0.0261	0.0263	0.0270
	Best	0.7364	0.7273	**0.7545**	0.7364	0.7121	0.7303	0.7303	0.7333
Monk	AVG	**0.8224**	0.6517	0.8109	0.7810	0.6646	0.7592	0.7884	0.7966
	std	**0.0199**	0.0853	0.0300	0.0240	0.0659	0.0405	0.0320	0.0232
	Best	0.8571	0.7415	**0.8844**	0.8299	0.7551	0.8299	0.8299	0.8299
Tic-tac-toe	AVG	**0.6733**	0.5666	0.6353	0.6377	0.6077	0.6215	0.6383	0.6626
	STD	**0.0112**	0.0441	0.0271	0.0209	0.0347	0.0250	0.0313	0.0206
	Best	0.6840	0.6258	0.6687	0.6595	0.6810	0.6564	0.6748	**0.6902**
Titanic	AVG	0.7617	0.7377	0.7625	0.7605	0.7610	0.7622	0.7656	**0.7676**
	STD	0.0026	0.0387	0.0029	0.0049	0.0086	0.0072	0.0075	**0.0047**
	Best	0.7690	0.7690	0.7677	0.7677	0.7677	0.7690	0.7717	**0.7770**
Ring	AVG	**0.7729**	0.5502	0.7211	0.7091	0.6233	0.6719	0.6998	0.7393
	STD	**0.0084**	0.0513	0.0328	0.0118	0.0338	0.0230	0.0248	0.0176
	Best	**0.7830**	0.6526	0.7738	0.7266	0.6717	0.7075	0.7333	0.7655
Twonorm	AVG	0.9744	0.6411	**0.9771**	0.9303	0.7572	0.8556	0.8993	0.9574
	STD	0.0033	0.1258	**0.0010**	0.0155	0.0398	0.0240	0.0131	0.0050
	Best	**0.9785**	0.9046	0.9781	0.9551	0.8275	0.8907	0.9134	0.9642
Ionosphere	AVG	0.7942	0.7367	**0.8025**	0.7600	0.7067	0.7767	0.7358	0.7825
	std	0.0429	0.0385	**0.0157**	0.0242	0.0484	0.0340	0.0281	0.0240
	Best	**0.8667**	0.7833	0.8250	0.7917	0.8000	0.8417	0.7917	0.8333
Chess	AVG	0.7283	0.6713	**0.8088**	0.7160	0.6128	0.6695	0.6896	0.7733
	STD	0.0512	0.0471	**0.0238**	0.0218	0.0231	0.0289	0.0183	0.0196
	Best	0.8068	0.7259	**0.8500**	0.7479	0.6440	0.7259	0.7167	0.8040
Seed	AVG	**0.8986**	0.7986	0.8931	0.7903	0.5444	0.6347	0.7930	0.8583
	STD	**0.0208**	0.1277	0.0208	0.0580	0.1387	0.0747	0.0619	0.0375
	Best	**0.9306**	0.9167	0.9167	0.8889	0.7500	0.7361	0.8889	0.9028
Wine	AVG	**0.8894**	0.7697	**0.8894**	0.8227	0.6803	0.7576	0.7515	0.8667
	STD	**0.0335**	0.1153	0.0580	0.0474	0.1098	0.0763	0.0436	0.0557
	Best	**0.9545**	0.9091	0.9394	0.8939	0.8181	0.8788	0.8333	0.9091

the best accuracy obtained by WOA showed improvements compared to other algorithms employed.

Figures 6 and 7 show the convergence curves for the classification datasets employed using WOA, GA, PSO, ACO, DE, ES, and PBIL, based on averages of MSE for all training samples over ten independent runs. The figures show that WOA is the fastest algorithm for blood, diabetes, liver, monk, tic-tac-toe, titanic, and ring datasets. For other classification datasets, WOA shows very competitive performance compared to the best techniques in each case.

Figures 8 and 9 show the boxplots for different classification datasets. The boxplots are shown for 10 MSEs obtained by each trainer at the end of the training. In this plot, the box relates to the interquartile range, the whiskers represent the farthest MSEs values, the bar in the box represents the median value, and outliers are represented by the small circles. The boxplots prove and justify the better performance of WOA for training MLP.

The overall performance of each algorithm on all classification datasets is statistically evaluated by the Friedman test. The Friedman test is conducted to confirm the significance of the results of the WOA against other trainers. The Friedman test is a nonparametric test that is used for multiple comparison of different results depending on two impact factors, namely trainer method and the classification dataset.

Table 6 shows the average ranks obtained by each trainer using the Friedman test. The Friedman test shows that a significant difference does exist between the eight techniques (the lower is better). WOA has higher overall ranking in comparison with other techniques, which again prove the merits of this algorithm in training FFNNs and MLPs.

In summary, the results proved that the WOA is able to outperform other algorithms in terms of both local optima

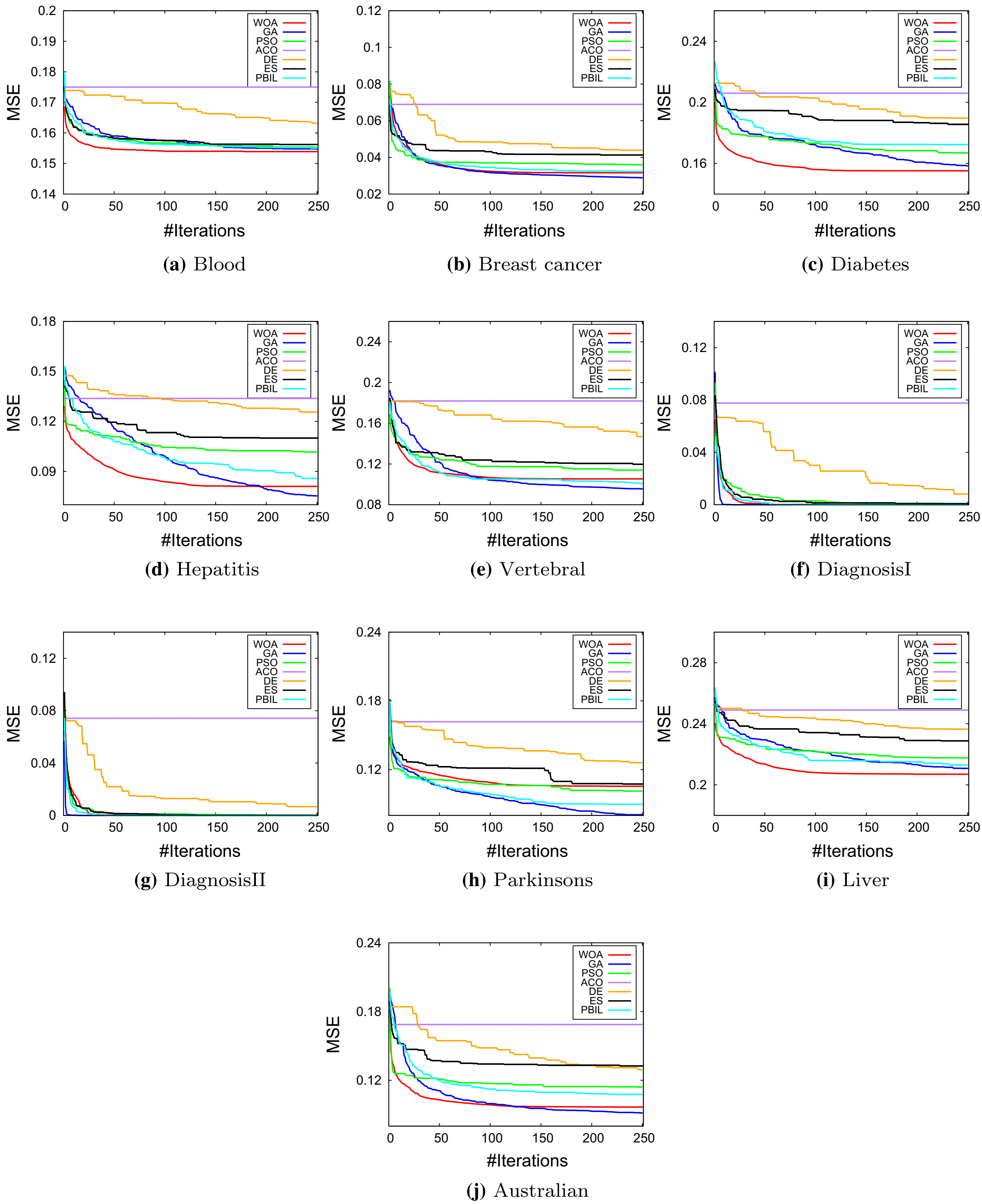
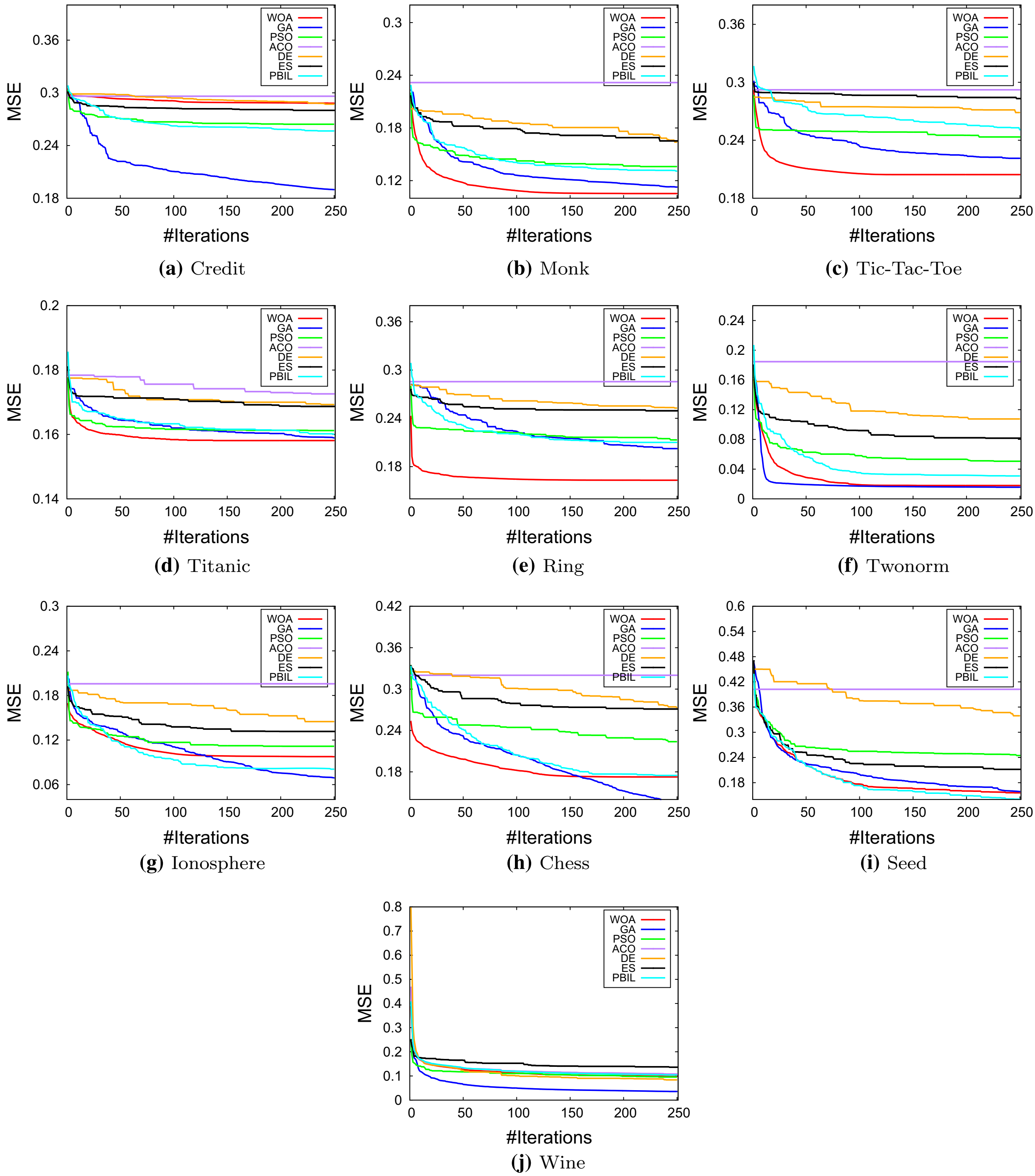
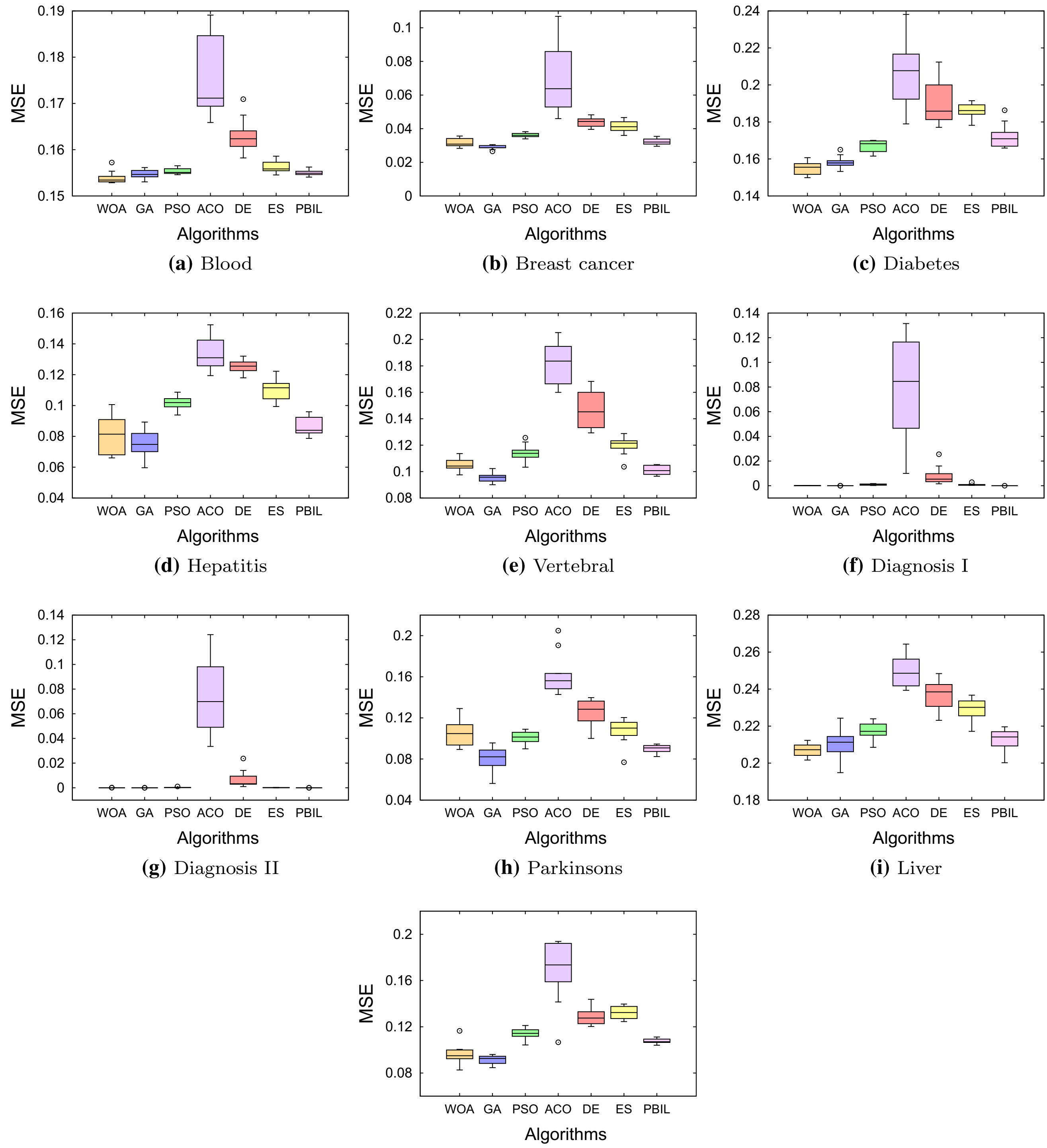


Fig. 6 MSE convergence curves of different classification datasets (a–j) MSE convergence curve for blood, breast cancer, diabetes, hepatitis, vertebral, diagnosis I, diagnosis II, Parkinson, liver, and Australian, respectively



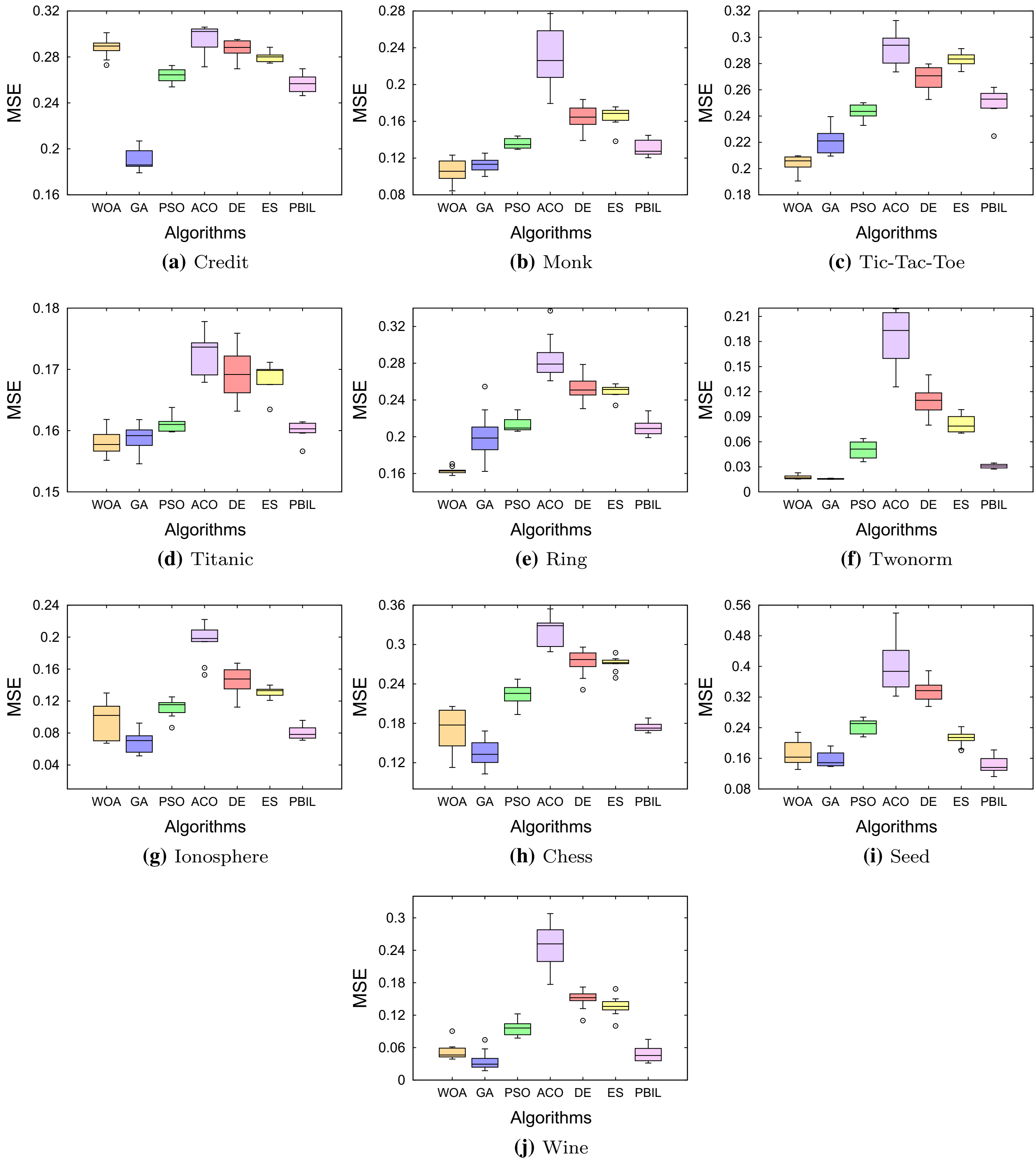
(a) Credit **(b)** Monk **(c)** Tic-Tac-Toe **(d)** Titanic **(e)** Ring **(f)** Twonorm **(g)** Ionosphere **(h)** Chess **(i)** Seed **(j)** Wine

Fig. 7 MSE convergence curves of different classification datasets (a–j) MSE convergence curve for credit, monk, tic-tac-toe, titanic, ring, twonorm, ionosphere, chess, seed, and wine, respectively



(a) Blood **(b)** Breast cancer **(c)** Diabetes **(d)** Hepatitis **(e)** Vertebral **(f)** Diagnosis I **(g)** Diagnosis II **(h)** Parkinsons **(i)** Liver **(j)** Australian

Fig. 8 Boxplot charts of different classification datasets (a–j). Boxplot charts for blood, breast cancer, diabetes, hepatitis, vertebral, diagnosis I, diagnosis II, Parkinson, liver, and Australian, respectively



(a) Credit **(b)** Monk **(c)** Tic-Tac-Toe **(d)** Titanic **(e)** Ring **(f)** Twonorm **(g)** Ionosphere **(h)** Chess **(i)** Seed **(j)** Wine

Fig. 9 Boxplot charts of different classification datasets (a–j). Boxplot charts for credit, monk, tic-tac-toe, titanic, ring, twonorm, ionosphere, chess, seed, and wine, respectively

Table 6 Average rankings of the algorithms (Friedman)

Algorithm	Ranking
WOA	2.05
BP	7.3
GA	2.2
PSO	4.275
ACO	7.2
DE	5.5
ES	4.6
PBIL	2.875

avoidance and convergence speed. The high local optima avoidance is due to the high exploration of this algorithm. The random selection of prey in each selections is the main mechanisms that assisted this algorithm to avoid the many local solutions in the problem of training MLPs. Another mechanism is the enemy encircling approach of WOA, which requires the search agents to search the space around the prey. The superior convergence speed of WOA-based trainer originates from the saving of the best prey and adaptive search around it. The search agents in WOA tend to search more locally around the prey proportional to the number of iterations. The WOA-based trainer inherits this feature from the WOA and managed to outperform other algorithm in the majority of the datasets.

Another interesting pattern is the better results of evolutionary algorithms employed (GA, PBIL, and ES, respectively) compared to the swarm-based algorithms (PSO and ACO). This is mainly because of the intrinsically higher exploration of evolutionary algorithms that assist them to show a better local optima avoidance. The combination of individuals in each generation causes abrupt changes in the variables, which automatically promotes exploration and consequently local optima avoidance. The local optima avoidance of PSO and ACO highly depends on the initial population. This is the main reason why these algorithm show slightly worse results compared to evolutionary algorithms. It is worth mentioning here that the results indicate that despite the swarm-based nature of the WOA, it seems that this algorithm does not show a degraded exploration. As discussed above, the reasons behind this are the prey encircling and random selection of whales in WOA.

6 Conclusion

This paper proposes the use of WOA in training MLPs. The high local optima avoidance and fast convergence speed were the main motivations to apply the WOA to the problem of training MLPs. The problem of training MLPs was first formulated as a minimization problem. The objective was to minimize the MSE, and the parameters were connection wights and biases. The WOA was employed to find the best values for weights and biases to minimize the MSE.

For the first time in the literature, a set of 20 test functions with diverse difficulty levels were employed to benchmark the performance of the proposed WOA-based trainer: blood, breast cancer, diabetes, hepatitis, vertebral, diagnosis I, diagnosis II, Parkinson, liver, Australian, credit, monk, tic-tac-toe, titanic, ring, twonorm, ionosphere, chess, seed, and wine. Due to different numbers of features in the datasets employed, MLPs with different numbers of inputs, hidden, and output nodes were chosen to be trained by the WOA. For the verification of the results, a set of conventional, evolutionary, and swarm-based training algorithms were employed: BP, GA, PSO, ACO, DE, and PBIL.

The results showed that the proposed WOA-based training algorithm is able to outperform the current algorithms on the majority of datasets. The results were better in terms of not only accuracy but also convergence. The WOA managed to show superior results compared to BP and evolutionary algorithm due to the high exploration and local optima avoidance. The results also proved that the higher local optima avoidance does not degrade the convergence speed in WOA. According to the findings of this paper, we conclude that firstly, the WOA-based trainer benefits from a high local optima avoidance. Secondly, the convergence speed of the proposed trainer is high. Thirdly, the trainer proposed is able to train FFN well for classifying datasets with different levels of difficulty. Fourthly, the WOA can be more efficient and highly competitive compared to the current MLP training techniques. Finally, the WOA is able to train FNNs with small or large number of connection weights and biases reliably.

For future works, it is recommend to train other types of ANNs using the WOA. The applications of the WOA-trained MLP in engineering classification problems are worth consideration. Solving function approximation datasets using the WOA-trained MLP can be a valuable contribution as well.

Compliance with ethical standards

Conflict of interest All authors declare that there is no conflict of interest.

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

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