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Research paper

Efficient Feature Selection Method using Binary Teaching-learning-based Optimization Algorithm

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Abstract

High dimensionality is the biggest problem when working with large datasets. Feature selection is a procedure for reducing the dimensionality of datasets by removing additional and irrelevant features; the most effective features in the dataset will remain, increasing the algorithms' performance. In this paper, a novel procedure for feature selection is presented that includes a binary teaching-learning-based optimization algorithm with mutation (BMTLBO). The TLBO algorithm is one of the most efficient and practical optimization techniques. Although this algorithm has a fast convergence speed, and it benefits from exploration capability; there may be a possibility of trapping into a local optimum. Thus we try to establish a balance between exploration and exploitation. The proposed method is in two parts: First, we use the binary version of the TLBO algorithm for feature selection and add a mutation operator to implement a strong local search capability (BMTLBO). Secondly, we use a modified TLBO algorithm with the self-learning phase (SLTLBO) for training a neural network to show the application of the classification problem to evaluate the performance of the procedures of the method. The proposed method is tested on 14 datasets in terms of classification accuracy and the number of features. The results show that BMTLBO outperforms the standard TLBO algorithm, and proves the potency of the proposed method. The results are very promising and close to optimal.

1. Introduction

Data mining is the idea of finding hidden information, particular patterns, and relationships in a large amount of data. One of the biggest issues is dimensionality, and working with data by a large number of dimensions can increase the time and computational complexity of the algorithm; big data requires a pre-processing stage to find a lower dimensionality of the data and remove the redundant, noisy, unnecessary, and extra features from the dataset. Feature selection refers to this pre-processing stage. The main goal of feature selection is to find the best set of big data features with the highest level of classification accuracy. The feature selection methods are typically divided into three classes: filter, wrapper, and embedded. Based on the general characteristics of the dataset such as correlation with the dependent variable, the features are filtered using the filter method. When there are many features, it is usually the fastest and better approach [1] as in the case of filter-based ant colony optimization [2]. In embedded method, the feature selection process is integrated into the learning or model-building phases. The embedded approach is used in the development of hybrid genetic algorithms, wrapper-embedded feature approaches [3], and embedded-based genetic programming (GP) [4]. Algorithms for feature selection in the wrapper approach include the chaotic binary group search optimizer [5], the altruistic whale optimization algorithm [6], and the binary water wave optimization [7]. Additionally, a novel equilibrium optimization-based feature selection technique is presented [8]. Ramasamy *et al.*, have proposed a binary improved grey wolf optimizer approach based on wrappers to find the best possible set of features [9]. in order to find the ideal feature subset for a high dimensional classification, the adaptively balanced grey wolf optimization algorithm is suggested; gravitational search algorithm (GSA) is used for feature selection [10], which includes cross-over and mutation operators in a novel GSA-based algorithm [11]. Shojaee *et al.*, first establishes the relationship between the features, then chooses the most informative features with the aid of the particle swarm optimization algorithm and correlation functions[12]. Dynamic Salp swarm algorithm was combined with the K-nearest neighbor (KNN) classifier in a wrapper mode [13]. A multi-objective Salp swarm algorithm is developed that adopts two essential components: dynamic time-varying and local fittest solutions [14]. The TLBO algorithm is a relatively new, very widely used, low-parameter, and powerful in solving complex problems that have a high convergence speed. The Improved TLBO algorithm seeks to identify the best feature subset [15]. The binary TLBO algorithm is a wrapper-based feature selection technique that has emerged [16]. This algorithm also has a very high performance in combination with other algorithms such as a combined TLBO with a Salp swarm algorithm (SSA) to select the features [17].

In this paper, the evolutionary algorithms are presented with goals: minimize the number of features and maximize the classification accuracy from two different versions of TLBO [18]. The main advantages of the TLBO algorithm include the strong exploration capabilities, the quick convergence to the best solution, simplicity of implementation, and ease of use [19]. However, due to poor exploitation capacity, to prevent getting stuck in the local optima, two major improvements were added to the original TLBO algorithm. The first improvement with the aim of decreasing the time and the computational complexity and increasing the procedure accuracy consists of a binary version of TLBO with a local search, for feature selection problems (BMTLBO). The second is a modified TLBO algorithm for calculating the classification accuracy. In order to improve the best solution and the maintain population diversity during the search process, the self-learning concept is added to the basic TLBO algorithm (SLTLBO). Using 14 benchmark datasets from the UCI repository, the proposed method is compared with several optimization algorithms including (SSA, GA, PSO, GOA, and ALO).

The rest of the paper is organized as what follows. In Section 2, the proposed method, BMTLBO, and SLTLBO algorithm are described. In Section 3, the proposed method is evaluated and the results are described. Finally, in Section 4, the paper is concluded.

2. Proposed Method

The TLBO algorithm is a population-based heuristic algorithm with a great capability in solving the complex problems. This algorithm has easy concepts, simple implementation and execution, few parameters (requires figuring out the population size and how many iterations there will be), is flexible, and has a robust power of exploration. The algorithm's main steps strongly emphasize maintaining diversity and rapidly converge to the best solution. It can be said that this algorithm can produce the optimal solutions in a reasonable amount of time but in addition to all these benefits in solving some complex problems, there is a chance of convergence to the local optimum due to the basic algorithm's poor exploitation. This section presents two enhanced TLBO algorithms with two distinct goals to deal with this weakness. The BMTLBO algorithm is suggested for the feature selection to decrease the computational cost and improve the method's accuracy because working with big data is very expensive in terms of the time and the computational complexity. Including a potent local search in this algorithm has improved the exploitation capability, resulting in a balance between the exploitation, the exploration, and the rapid convergence to the global optimum. Due to the TLBO algorithm's superiority in comparison to other optimization techniques, another enhanced version of it called SLTLBO is used to train the neural network, and as a result, determine the classification accuracy in this paper. To balance the discovery and the exploitation, this algorithm attempts to strengthen its exploitation power by incorporating the ideas of self-learning and change into the basic algorithm's learning phase. As a result, this algorithm can train the neural network in the most effective manner and with the highest classification accuracy level in the big data.

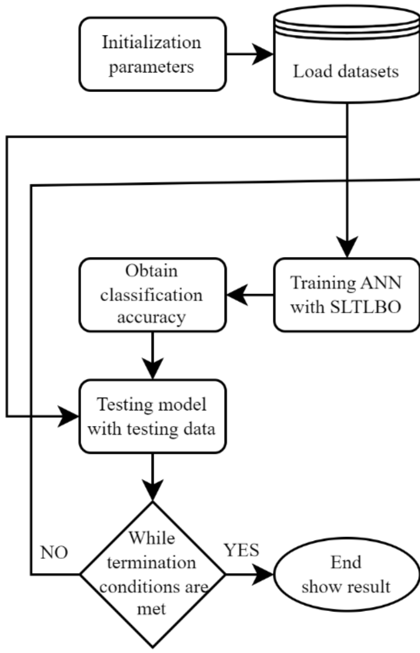

Figure 1. Flowchart of the proposed method.

2.1. Binary mutated teaching-learning-based optimization (BMTLBO)

A binary mutated TLBO is proposed for feature selection. The teacher phase and learner phase are the two phases of this algorithm. The following provides a brief explanation of the teacher phase and learner phase:

2.1.1. Teacher phase

In this stage, the classroom teaching procedure is demonstrated. According to each student's capacity, the teacher makes an effort to raise the students' knowledge level. The following Equation is used in this phase to update the learners' positions:

$$X_{new} = X_i + r \times \left(X_{teacher} - T_F \cdot X_{mean} \right) \tag{1}$$

where $X_{teacher}$ is the best learner, X_{mean} is the population positions average, and r is a random number in (0, 1) interval, and T_F is a teaching factor. The value of T_F is chosen randomly, and is calculated as follows:

$$T_F = \text{round}[1 + \text{rand}(0,1)] \tag{2}$$

2.1.2. Learner phase

In this phase, learners interact with each other to increase their knowledge. To further his or her understanding of Equations (3) and (4), a learner randomly interacts with other learners.

$$X_{new} = X_i + r \cdot \left| X_j - X_i \right| \quad \text{if} \quad f(X_i) > f(X_j) \tag{3}$$

$$X_{new} = X_i + r \cdot \left| X_i - X_j \right| \quad \text{if} \quad f(X_j) > f(X_i) \tag{4}$$

The learner's position in the typical TLBO is continuous values. We cannot directly apply feature selection into the proposed method due to its binary nature. The mapping from the continuous search space of the standard TLBO to the binary one is done by a transformation function. The mapping makes use of the hyperbolic tangent function:

$$V = \left| \tanh(X_i) \right|, \qquad X_{binary} = \begin{cases} 0 & rand < V \\ 1 & rand \geq V \end{cases} \tag{5}$$

where X_i is a continuous value, and the X_{binary} value can be 0 or 1.

2.1.3. Mutation operator

A mutation operator is proposed to improve the exploitation of the proposed algorithm. We propose a mutation operator to enhance exploitation capability in the learner phase of BMTLBO to prevent trapping in local minimums and to achieve a better balance between exploration and exploitation. Mutation applies to a fraction of the best learners. First, to reduce the number of selected features on the best learners, then to increase the number of selected features of the best individual with a probability only one feature is mutated. The new learner will be accepted if the classification accuracy improved.

2.2. BMTLBO for wrapper feature selection mode

This proposed BMTLBO algorithm is applied to a neural network classifier using wrapper mode for feature selection problems. BMTLBO will be used in the training dataset in each iteration to identify the feature subset that will be used to train the artificial neural network (ANN) classifier. In a feature selection problem, the selected and unselected features are represented by the binary values. The proposed method calculates the fitness values based on the neural network classification accuracy. The fitness value is evaluated by the neural network that has been trained by the SLTLBO algorithm. BMTLBO assigns, which represents the solution with the highest classification accuracy. The best solution will be returned by BMTLBO, and this represents the best feature subset that is selected by BMTLBO. The performance of BMTLBO on the testing dataset will finally be assessed using the features that were chosen in the best solution. Each step of the BMTLBO operates is shown in Figure 2.

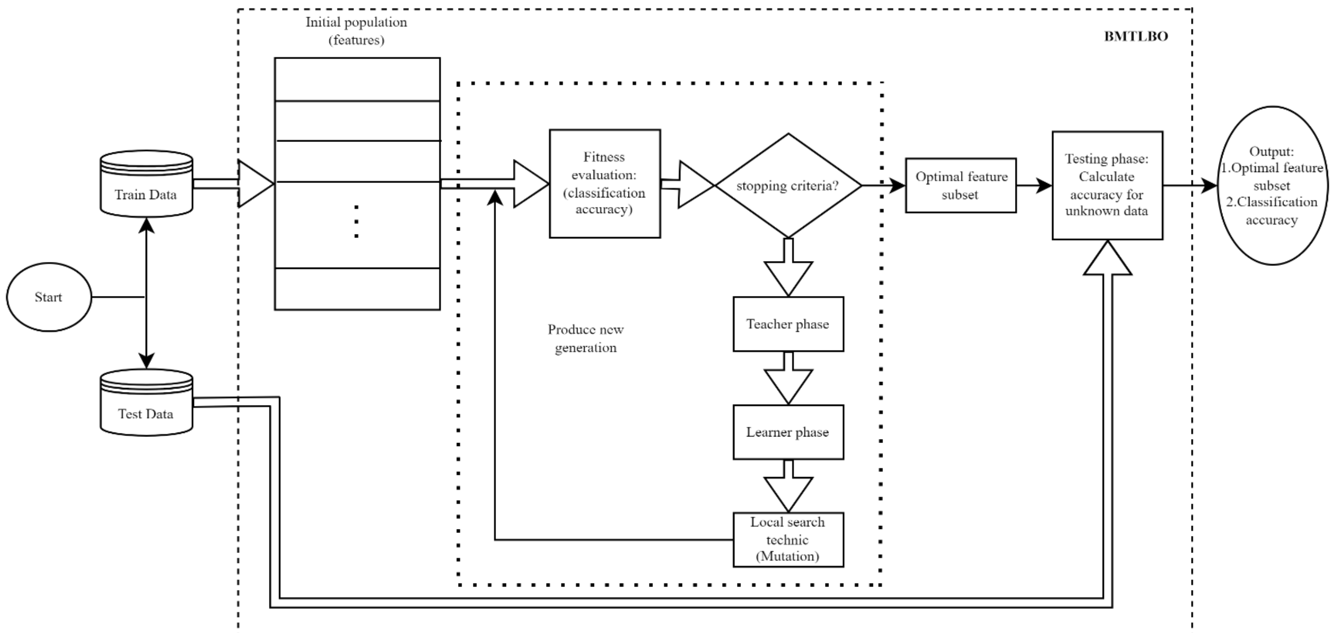

Figure 2. BMTLBO algorithm for feature selection.

2.3. Self-learning teaching-learning-based optimization (SLTLBO)

A self-learning TLBO is proposed for ANN training [5]; obviously, in the learner phase of this algorithm, the exploration capability is stronger than the exploitation capability. This problem is solved by SLTLBO with an enhancement to the fundamental TLBO. The learner phase is proposed by the concept of neighborhood. We are attempting to reduce the random choices, and use community resources for learning to increase the local search and the global search capability. The following are the main components of SLTLBO:

2.3.1. SLTLBO learner phase

Students may pick up knowledge from their peers or the top student in the class, so in the classroom, the learners can learn from the best learner around them. The idea of the neighborhood is used in the classroom to improve the exploitation skills and strike a balance between the exploration and the exploitation. Numerous neighbors who learn from the best learner exist for each student. After several iterations, each person's neighborhood is altered to maintain diversity. Update learner's positions are implemented with Equation (6).

$$X_{i,new} = X_{i,old} + r_2 \cdot \left(X_{teacher} - X_{i,old}\right) + r_3 \cdot \left(X_{i,teacher} - X_{i,old}\right) \quad (6)$$

where $X_{i,teacher}$ is the best learner in $X_{i,old}$ neighborhood, $X_{teacher}$ is the teacher, and r_2, r_3 are random numbers in the (0, 1) interval. If a learner's position remains unchanged over several successive generations, the individuals update their positions by the current teacher and the mean of the learners to improve the learners' ability to search.

Implementation of the update method looks like this:

$$X_{i,new}(t) = \text{normrnd}\left(\left(\frac{X_{teacher}(t) + X_{mean}(t)}{2}\right), \text{abs}(X_{teacher}(t) - r_5 \times X_{mean}(t))\right) \quad (7)$$

where r_5 when the position of the teacher is equal to the mean position of the students, increases performance by the distribution of new individuals.

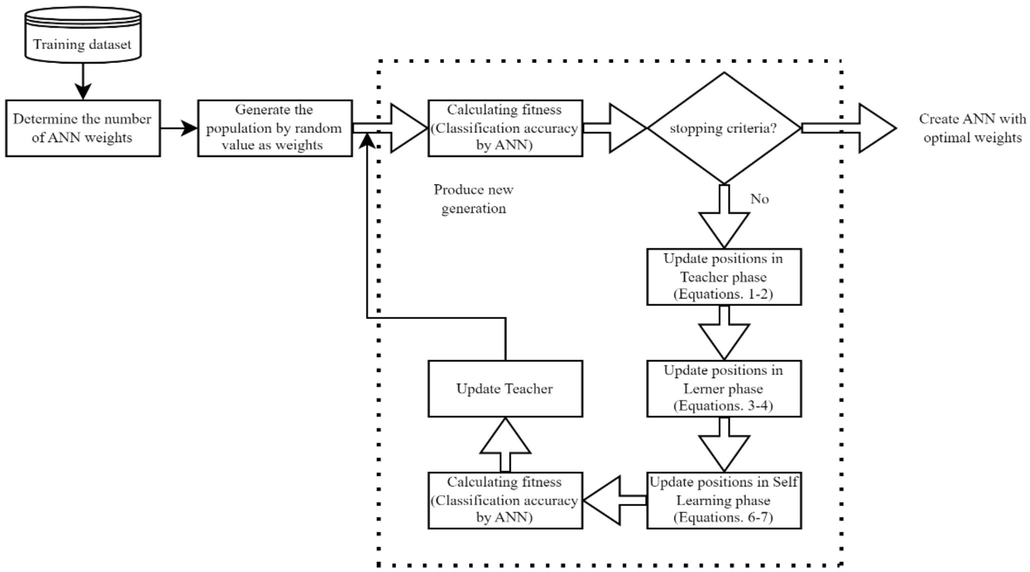

Figure 3. SLTLBO algorithm for a neural network's training purpose.

Pseudo-code for SLTLBO

Initialization parameters
Generate initial learner position and calculate objective function $f(X)$ for them
While (the termination requirements are not satisfied) %Teacher Phase
Calculate the mean of each design variable X_{mean}
Identify the best solution ($X_{teacher}$)
For i = 1... pop size
Calculate teaching factor T_F using Equation (**2**);
Modify solution based on best solution (teacher) using Equation (**1**);
Calculate objective function for new learner $f(X_{new})$
IF X_{new} is better than X_i
$X_i = X_{new}$
End if % Learner Phase
IF rand < Pc
Find the best learner around her/his, and update according to Equation (6)
Else
Randomly select another learner X_j , and update according to Equations (3), (4).
End if
IF the individual's position didn't change after some iteration
The position is updated according to Equation (7).
End if
IF new positions are better than the previous position replace them
End if %End of learner phase
IF mod(iteration, m) = 0
randomly rearrange all individuals
End if
End for
Set iteration = iteration + 1
End while
Post-process results and visualization

Figure 4. SLTLBO algorithm.

3. Experiment

3.1. Description of datasets

Utilizing MATLAB, all algorithms are implemented. In addition, 14 benchmark datasets from the UCI dataset repository are used in all experiments to assess and validate the performance of the proposed method in comparison to other research works. Table 1 contains the specifics of the used datasets.

3.2. Parameter settings

In every experiment that is done, the overall average result has been reported. In terms of the classification accuracy and the number of selected features, the results in Table 2 represent the average values over 50 runs. The proposed method is contrasted with the traditional TLBO, and other optimization algorithms like the Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Ant Lion Optimizer (ALO), and Grasshopper Optimization Algorithm (GOA). Additionally, the population size that is used for all algorithms is 20, and the maximum number of iterations for each optimization algorithm is 100.

Table 1. Datasets description

	Dataset		Number of features	Number of instances
1	Nsl-kdd	Train data	42	125974
		Test data	42	22545
2	Phishing		30	2457
3	Ionosphere		34	351
4	Credit		20	1000
5	Spambase		57	4601
6	Heart		13	270
7	Lymphography		18	148
8	Spect		22	267
9	Vote		16	300
10	Australian		14	690
11	Dermatology		34	366
12	Satellite		36	6435
13	Waveform		21	5000
14	Sonar		60	208

3.3. Result and analysis

The specifics and outcomes of every experiment are shown in this section. The proposed BMTLBO is compared to the standard TLBO in the first experiment. The second experiment compares the BMTLBO algorithm to other algorithms like GA, PSO, GOA, and ALO.

3.3.1. Comparison of BMTLBO and TLBO

This section compares the basic TLBO algorithm with the proposed BMTLBO algorithm. As shown Table 2, the classification accuracy and the number of selected features is demonstrated that BMTLBO model significantly improved the performance further than the original TLBO algorithm.

Table 2. Comparison between BMTLBO and TLBO based on average accuracy and average-number-of-selected features.

Dataset	Classification accuracy		Number of selected feature	
	BMTLBO	TLBO	BMTLBO	TLBO
Nsl-kdd	**97.64**	95.87	**27.5**	29.4
Phishing	**99.23**	97.45	**18.3**	20.7
Ionosphere	**99.85**	96.34	**10.9**	14.4
Credit	**80.97**	78.25	**7.9**	9.5
Spambase	**97.59**	93.47	**25.3**	27.4
Heart	**91.27**	85.84	**5.9**	7.3
Lymphography	**85.24**	71.93	**8.2**	10.5
Spect	**85.93**	77.65	**8.9**	11.2
Vote	**99.76**	98.37	**5.7**	7.9
Australian	**89.95**	86.54	**5.1**	8.3
Dermatology	**98.72**	92.45	**12.6**	16.7
Satellite	**94.65**	89.12	**17.5**	19.5
Waveform	**82.05**	80.34	**11.5**	13.8
Sonar	**98.91**	96.14	**15.7**	24.8

3.3.2. Comparison of BMTLBO with other optimization algorithms

Several optimization algorithms are chosen to demonstrate the superiority of the proposed method. In the past section, we compared BMTLBO and TLBO, and the result illustrated a superior performance for the BMTLBO algorithm in comparison to the standard version of TLBO. To show further superiority, we compare the proposed algorithm with other optimization algorithms. BMTLBO has been compared with the SSA, GOA, PSO, ALO, and GA algorithms. Table 3 shows the comparative results between BMTLBO and other optimization algorithms. From Table 3, it is clear that BMTLBO outperformed all other algorithms in terms of the classification accuracy but in the dermatology dataset, the SSA algorithm has better performance. Regarding the average number of selected features in 8 datasets, the proposed method has a lower amount, which means that the proposed method attempts to choose a smaller number of features for an optimal subset of features, which means it avoids searching among irrelevant features and then reduces the time complexity of the method. For more clarity on the superiority of the proposed method in comparison to other algorithms, in the following, we have compared the convergence curve of the proposed method comparison other algorithms. As shown in Figure 5, the proposed method has a higher exploration and exploitation capability. Furthermore, according to the convergence curves, the results of the proposed method are better than other algorithms in the most cases. This is proof of the ability to escape from trapping in the local optimum. But as it is clear from the Figure and the results, other algorithms are easily caught in the local optimal trap.

Table 3. Comparison between BMTLBO and other evolutionary algorithms based on average accuracy and average number of selected features.

Dataset	Metrics	BMTLBO	SSA	GOA	PSO	ALO	GA
Nsl-kdd	Accuracy	**97.64**	93.56	92.09	95.7	96.4	94.9
	Feature num	27.5	**25.9**	28.5	29.3	30.4	27.4
Phishing	Accuracy	**99.23**	96.45	94.78	87.34	89.76	88.9
	Feature num	**18.3**	19.6	21.8	19.2	25.4	20.7
Ionosphere	Accuracy	**99.85**	97.1	92.8	97.4	93.7	96.5
	Feature num	**10.9**	13.9	15.7	15.1	16.4	11.7
Credit	Accuracy	**80.97**	74.6	71.5	75.4	69.1	76.4
	Feature num	**7.9**	9.4	10	9.7	10	9.3
Spam base	Accuracy	**97.59**	93.4	90.6	93.8	90.4	93.4
	Feature num	25.3	26.3	28.7	30.1	29.5	**22.2**
Heart	Accuracy	**91.27**	85.9	78.8	86.2	75.5	84.4
	Feature num	5.9	5.6	6.4	6.2	5.9	**5**
Lymphography	Accuracy	**85.24**	68.1	54.8	72.2	54.5	68.5
	Feature num	8.2	7.9	8.2	8.5	8.7	**8**
Spect	Accuracy	**85.93**	81.6	70.4	81.6	72.6	81.3
	Feature num	**8.9**	10.5	10.8	10	11.2	10.5
Vote	Accuracy	**99.76**	98.3	96.2	97.3	96.3	97.6
	Feature num	5.7	6.2	7.7	7	7.6	**3.5**
Australian	Accuracy	**89.95**	84.0	78.8	83.7	76.0	84.3
	Feature num	**5.1**	5.9	5.9	6.9	6.7	5.2
Dermatology	Accuracy	98.72	**99.1**	96.7	98.8	95.1	**99.1**
	Feature num	**12.6**	15	16.8	15.9	16.5	13
Satellite	Accuracy	**94.65**	91.8	90.5	92.5	90.5	92.1
	Feature num	**17.5**	19.7	18.7	19.3	18	22
Waveform	Accuracy	**82.05**	80.2	76.5	80.0	77.4	79.8
	Feature num	11.5	12.6	**11.3**	11.5	11.6	13
sonar	Accuracy	**98.91**	96.1	90.3	96.6	90.3	97.5
	Feature num	**15.7**	26.4	29.6	26.9	29.3	22.6

4. Conclusion

In this paper, we proposed two novel TLBO algorithms called BMTLBO and SLTLBO for the feature selection and training a neural network simultaneously. The two improvements that are embedded into the standard TLBO are used to establish a balance between the exploration and the exploitation capability and to avoid trapping into local optima. Since the learner phase of the standard TLBO has a weak exploitation capability, in the BMTLBO algorithm for the reinforcement of this weakness a mutation operator is added to improve the local search, and also in SLTLBO we applied a self-learning part for the more optimal search of the search space. The proposed method is tested and evaluated in 14 datasets from the UCI repository. The proposed method evaluated by several well-known optimization algorithms (SSA, GA, PSO, GOA, and ALO) based on the classification accuracy, and the number of selected features. The effectiveness of the proposed method in comparison to other algorithms demonstrated through several experiments.

Future research can consider the application of the proposed approach in the real-world problems such as diagnosis of disease, cancer detection, and intrusion detection systems.

For the feature selection problems, the performance of the proposed method can be evaluated with other classification algorithms such as KNN and SVM.

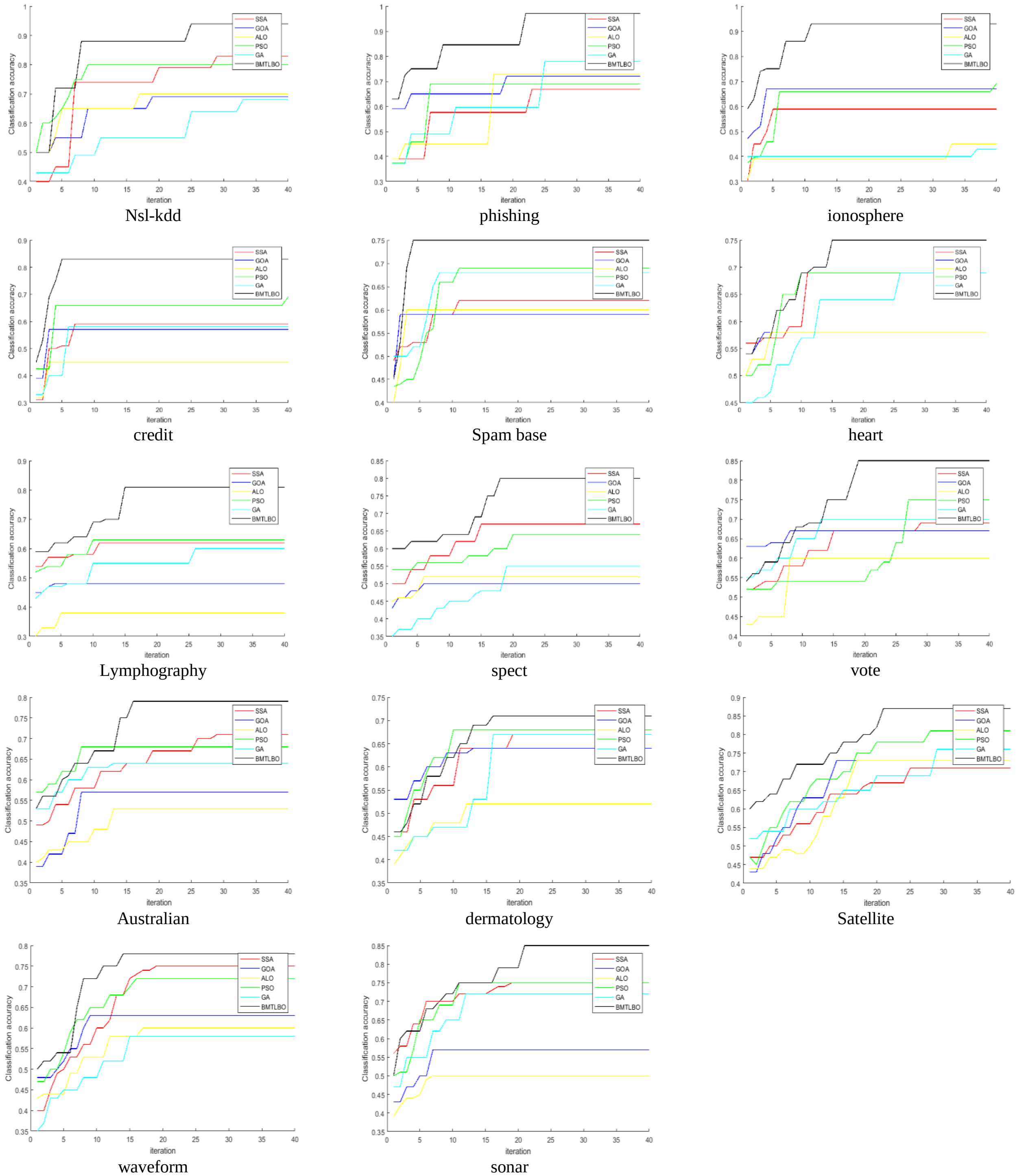

Figure 5. Convergence curve of the proposed method in comparison to other algorithms.

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روش انتخاب ویژگی کارآمد با استفاده از الگوریتم بهینه‌سازی آموزش مبتنی بر یادگیری باینری

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چکیده:

بزرگترین مسئله هنگام کارکردن با مجموعه داده‌های بزرگ، ابعاد بالای داده‌ها است. انتخاب ویژگی روشی برای کاهش ابعاد مجموعه داده‌ها از طریق حذف ویژگی‌های اضافی و نامربوط است. موثرترین ویژگی‌ها در مجموعه داده باقی می‌مانند و عملکرد الگوریتم‌ها را افزایش می‌دهند. در این مقاله، یک روش جدید برای انتخاب ویژگی ارائه شده است که شامل یک الگوریتم بهینه‌سازی مبتنی بر آموزش و یادگیری باینری همراه با یک عملگر جهش است(BMTLBO). الگوریتم TLBO یکی از کارآمدترین و کاربردی ترین تکنیک‌های بهینه‌سازی است. اگرچه این الگوریتم سرعت همگرایی بالایی دارد و از قابلیت اکتشاف بالایی برخوردار می‌باشد، اما احتمال به دام افتادن در یک بهینه محلی وجود دارد. بنابراین ما سعی می‌کنیم برای برطرف کردن این کاستی بین اکتشاف و بهره برداری تعادل برقرار کنیم. روش پیشنهادی شامل دو بخش متفاوت است: ابتدا، از نسخه باینری الگوریتم TLBOبه همراه یک عملگر جهش برای پیاده‌سازی قابلیت جستجوی محلی قوی، برای انتخاب ویژگی استفاده شده است (BMTLBO). سپس، از یک الگوریتم TLBO اصلاح شده به همراه فاز خودآموزی برای آموزش یک شبکه عصبی استفاده می‌کنیم که کاربرد مسئله طبقه‌بندی برای ارزیابی عملکرد روش پیشنهادی نمایش داده شود(SLTLBO). روش پیشنهادی بر روی ۱۴ مجموعه داده از نظر دقت طبقه‌بندی و تعداد ویژگی‌ها آزمایش شده است. نتایج نشان می‌دهند که BMTLBO از الگوریتم استاندارد TLBO به طرز قابل توجهی بهتر عمل می‌کند و ارزیابی‌ها قدرت روش پیشنهادی را اثبات می‌کند. نتایج بسیار امیدوارکننده و نزدیک به بهینه است.

کلمات کلیدی: انتخاب ویژگی، مسئله طبقه‌بندی، الگوریتم تکاملی، شبکه عصبی مصنوعی.