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A novel hybrid teaching learning based optimization algorithm for the classification of data by using extreme learning machines

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Abstract:
Data classification is the process of organizing data by relevant categories. In this way, the data can be understood and used more efficiently by scientists. Numerous studies have been proposed in the literature for the problem of data classification. However, with recently introduced meta-heuristics, it has continued to be riveting to revisit this classical problem and investigate the efficiency of new techniques. Teaching Learning Based Optimization (TLBO) is a recent meta-heuristic that has been reported to be very effective for combinatorial optimization problems. In this study, we propose a novel hybrid TLBO algorithm with Extreme Learning Machines (ELM) for the solution of data classification problem. The proposed algorithm (TLBO-ELM) is tested on a set of UCI benchmark datasets. The performance of the TLBO-ELM is observed to be competitive for both binary and multi-class data classification problems compared with state-of-the-art algorithms.

Key words: TLBO, ELM, meta-heuristic, classification, feature selection

1. Introduction

The data classification is a big challenge for scientists when they need to extract any useful knowledge it contains and answer some important questions related to the patterns of data [1, 2]. Many data mining and machine learning techniques have been proposed for the solution of this important problem. With the advent of big data era, the problem has gained more importance due to the dirty and redundant data features that negatively impact the performance of the decision systems (see Figure 1). Raw data (not preprocessed) may harm the accuracy level of data classification significantly [3]. Feature selection is a promising technique to make use of selected data where there exist large amounts of useless features [4]. Since the feature selection process is an NP-Hard problem, it becomes an intractable process for datasets with many features. Therefore, meta-heuristic approaches like evolutionary computation can be used as efficient tools to deal with this important problem [5].

A recent meta-heuristic Teaching Learning Based Optimization (TLBO) has been reported to be an efficient optimization tool that is inspired by the knowledge passing mechanism of teachers and learners in a classroom [6]. It has been applied to several well-known combinatorial optimization problems, producing good results [7]. Hybrid algorithms that use a heuristic approach and a machine learning technique are efficient tools for the classification of data. However, due to the huge number of fitness calculations, the optimization process

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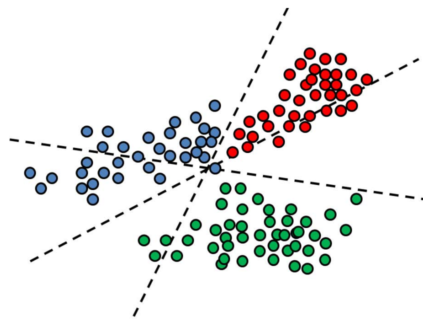

Figure 1. A picture of multi-class classification of data instances in a two dimensional space

of the classification can take a very long time with machine learning techniques that progress slowly. Hence, we propose a new hybrid TLBO algorithm that uses Extreme Learning Machines (ELM) that is one of the fastest and most successful machine learning techniques in literature [8–10]. The ELM is an outstanding machine learning technique with its fast and accurate evaluation process. Therefore, ELM becomes a very suitable tool in a hybrid optimization process that needs to calculate several fitness values during the data classification process. With this property of ELM, the accuracy of the classification process can be improved significantly as it is observed in our experiments while making comparisons with state-of-the-art algorithms in literature.

We have carried out comprehensive experiments on UCI benchmark datasets to show the effectiveness of our proposed algorithm. During the experiments, we tune the parameters (number of hidden nodes) of the ELM and use these well-tuned parameters in all of our subsequent experiments, which is a significant issue that greatly affects the performance of our proposed algorithm. To the best of our knowledge, our study is the first single objective TLBO algorithm that uses the ELM to solve the binary and multi-class data classification problem.

The rest our paper is organized as follows. Section 2 discusses the previous studies with TLBO, ELM, and data classification. In Section 3 we introduce our proposed algorithm, TLBO-ELM. Section 4 reports the observed results of our experiments. Finally, conclusion and future works are discussed in the last section.

2. Related Work

In this section, we give information about the previous studies related to the data classification problem, TLBO and ELM. There have been many studies in feature selection area till now [9–11]. In a study by Kohavi and John, the relevance of features are supervised at the beginning and weak/strong relevant features are concluded in order to capture the intuition better [10]. Algorithms proposed for the data classification can be categorized into two main types, *filtering* and *wrapper* algorithms. The main distinction between these two algorithms is that filtering algorithms select the feature subset before the application of any classification process. By using statistical properties, filtering approach eliminates less important features as it is applied in our algorithm.

The methods used are mainly beneficial with respect to an optimality rule and features are elected with respect to the specific learning algorithm. In a study by Kohavi and John, compound operators are used to apply a backward search, starting with the full set of features. Best-first search with compound operators are chosen to improve the methods, ID3, C4.5 and Naive-Bayes, in terms of accuracy and comprehensibility [10]. A study by Zexuan and Dash has fundamentally the same basis [11]. A filter method is developed and reported to be computationally more intensive than that of a wrapper. But wrapper methods generally outperform filter methods in terms of prediction accuracy. Stochastic, Multiple-Solution, Optimal and Node Pruning techniques are mostly discussed techniques for feature selection problem [9]. In particular, this study uses land images for the purpose of classification. Zexuan and Dash propose a hybrid wrapper/filter feature selection algorithm by using a memetic framework [11]. Solution representation for a candidate feature subset is encoded as a chromosome. Results show that the proposed method performs its search more efficiently and is capable of producing good classification accuracy with a small number of features simultaneously.

The method by Kohavi and John involves hill-climbing and best-first search engine [10]. Problem solution technique is claimed to be a simulated annealing approach. Xue et al. present a novel wrapper feature selection algorithm for classification problems [12]. The algorithm is a hybrid genetic algorithm with ELM (HGEFS). It uses evolutionary methods to wrap ELM to explore for the optimum set of features to improve the final prediction accuracy. Kashef and Nezamabadi-pour propose a novel feature selection algorithm based on Ant Colony Optimization (ABACO) [13]. The performance of the proposed ABACO is compared with the performance of Binary Genetic Algorithm (BGA), Binary Particle Swarm Optimization (BPSO), Catfish BPSO, Improved Binary Gravitational Search Algorithm (IBGSA) and some ACO-based algorithms for the feature selection. Experiments report good accuracy results on UCI Machine Learning Repository datasets [13]. Unler & Murat develop a discrete particle swarm optimization (PSO) algorithm for the feature subset selection problem [14].

TLBO is a competitive meta-heuristic with its outstanding performance. It is reported to outperform some of the well-known meta-heuristics regarding constrained benchmark functions, constrained mechanical design, and continuous non-linear numerical optimization problems [15]. It is also applied to discrete optimization problems successfully by previous studies and therefore it attracted our interest and we decided to evaluate its performance on feature selection problem in this study.

3. The Proposed Algorithm, TLBO-ELM

In this section of our study, we give details of our proposed algorithm, TLBO-ELM. The algorithm has two phases, the TLBO feature selection phase and the data classification phase with ELM technique (using the selected features). The TLBO-ELM algorithm uses ELM technique for the data classification. The TLBO-ELM is a member of filtering algorithms [8]. Initially, it selects subsets of features randomly, constructs learner individuals and then calculates the fitness value of each individual in the classroom. New solutions are generated by using the classical crossover and mutation operators and this process continues until the termination condition is met. The flowchart of TLBO-ELM algorithm is presented in Figure 2. The ELM phase classifies the data instances of the set with selected features that are sent by TLBO process of the TLBO-ELM algorithm.

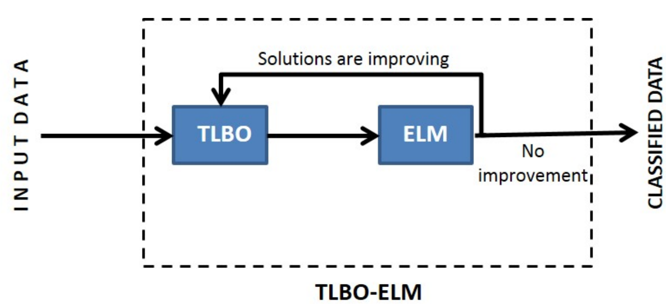

Figure 2. Flowchart of the TLBO-ELM Algorithm

TLBO phase uses the best individual at the classroom (population) as the teacher of students/learners. The teacher trains the learners and then the learners interact with each other to share the information they gain. This process goes on until the termination criterion is satisfied. Representation of a learner (individual in the classroom) structure of the TLBO-ELM algorithm is given in Figure 3. Crossover and mutation operators of the TLBO-ELM algorithm are presented in Figures 4 and 5 respectively.

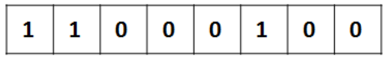

Figure 3. Representation of a learner (individual in a classroom) of the TLBO-ELM algorithm. Selected features are represented with value one whereas the others are zero.

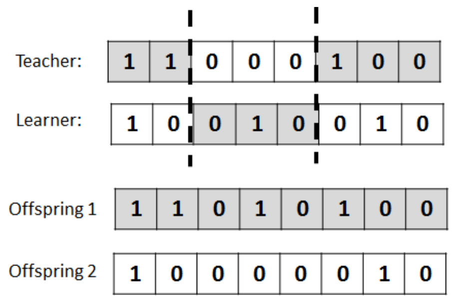

Figure 4. Crossover operator that produces two offsprings from two selected individuals

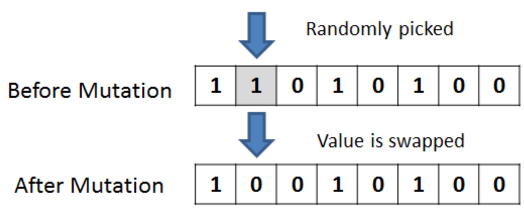

Figure 5. Mutation operator that swaps the genes of a chromosome

ELM phase of the algorithm: The output of Single-hidden Layer Feedforward Neural Networks (SLFN) having L hidden nodes is represented with Eq.1. The learning parameters of hidden nodes are a_i and b_i and the weight connecting the i^{th} hidden node to the output node is β_i. Function G(a_i , b_i , x) is the output of the i^{th} hidden node with respect to the input x.

$$f_L(x) = \sum_{i=1}^{L} \beta_i . G(a_i, b_i, x) \qquad x \epsilon \mathbf{R}^n, a_i, b_i \epsilon \mathbf{R} \tag{1}$$

Eq.2 describes the the activation function $G(a_i, b_i, x)$;

$$G(a_i, b_i, x_j) = g(a_i . x_j + b_i) = \mathbf{o}_j \qquad b_i \epsilon \mathbf{R}, j = 1, ..., N \tag{2}$$

In Eq.2, $a_i.x$ denotes the inner product of the vectors a_i and x where both are element of **R**. It is inferred that activation function G(x) can approximate these L samples with zero error is equal to $\sum_{j=1}^{L}\|\mathbf{o}_j - \mathbf{t}_j\| = 0$. This means that there exists β_i, a_i and b_i in Eq.3 such that;

$$\sum_{i=1}^{L}\beta_i.G(a_i.x_j + b_i) = \mathbf{t}_j \qquad j = 1, ..., N \tag{3}$$

N is the number of samples, i.e. inputs. We can rewrite this equation in another way as shown in Eq.4 for better understanding;

$$\mathbf{H}\beta = \mathbf{T} \tag{4}$$

where,

$$\mathbf{H}(a_1, ..., a_L, b_1, ..., b_L, \mathbf{x}_1, ..., \mathbf{x}_N) = \begin{bmatrix} g(a_1.\mathbf{x}_1 + b_1) & \cdots & g(a_L.\mathbf{x}_1 + b_L) \\ \vdots & \cdots & \vdots \\ g(a_1.\mathbf{x}_N + b_1) & \cdots & g(a_L.\mathbf{x}_N + b_L) \end{bmatrix}_{NxL} \tag{5}$$

$$\beta = \begin{bmatrix} \beta_1^T \\ \vdots \\ \beta_L^T \end{bmatrix}_{Lxm} \quad and \quad \mathbf{T} = \begin{bmatrix} \mathbf{t}_1^T \\ \vdots \\ \mathbf{t}_N^T \end{bmatrix}_{Nxm} \tag{6}$$

In Eq.5, $\mathbf{H}$ is the output of hidden layer matrix of the neural network. β^T is the transpose of a matrix or vector β in Eq 6. $\mathbf{H}$ is called the hidden layer output matrix of the network, the i^{th} column of $\mathbf{H}$ is the i^{th} hidden node's output vector with respect to inputs $x_1, x_2, ..., x_N$ and the j^{th} row of $\mathbf{H}$ is the output vector of the hidden layer with respect to input x_j. The number of hidden nodes is commonly less than the number of training data which causes the aggravation of the error ratio. Under the constraint of minimum norm least squares, i.e, $min\|\beta\|$ and $min\|\mathbf{H}\beta - \mathbf{T}|$, a simple representation of Equation 4 that is proven in studies [16–18] is presented in Eq.7.

$$\hat{\beta} = \mathbf{H}^{\dagger}\mathbf{T} \tag{7}$$

where $\mathbf{H}^{\dagger}$ is the Moore-Penrose generalized inverse [19] of the hidden layer output matrix $\mathbf{H}$. [18] had further shown that $\mathbf{H}$ is column full rank with probability one when $L \leq N$ if the N training data are distinct. In real applications, the number of hidden nodes is usually less than the number of training data, $L < N$. Thus, $\hat{\beta}$ can be written as $\left(\mathbf{H}^T\mathbf{H}\right)^{-1}\mathbf{H}^T$ which is clearly presented in [3, 16–18].

The pseudocode of the TLBO-ELM algorithm is presented in Algorithm 1.

Algorithm 1: TLBO-ELM Algorithm

Input: n is the number learners in the classroom, r is the rate of elitism.
Output: solution instance X

//Initialization
Generate n members of the classroom randomly;
for $\boldsymbol{i}$ = *1 to* $\boldsymbol{n}$ **do**
    Calculate hidden-layer output matrix $\mathbf{H}$;
    Calculate (β and $\mathbf{T}$);
    Evaluate $\mathbf{H}^{\dagger}$, i.e. the Moore–Penrose generalized inverse of matrix H;
    Evaluate the fitness of each instance i;
Sort the learners (individuals) in the classroom w.r.t. the fitness values;
while *(termination criterion is not met)* **do**
    Train learners with teacher (the best individual in the classroom);
    Train individuals with the other learners in the classroom;
    Generate new individuals using crossover and mutation operators;
    for $\boldsymbol{i}$ = *1 to* $\boldsymbol{n/2}$ **do**
        Calculate hidden-layer output matrix $\mathbf{H}$;
        Calculate (β and $\mathbf{T}$);
        Evaluate $\mathbf{H}^{\dagger}$, i.e. the Moore–Penrose generalized inverse of matrix $\mathbf{H}$;
        Evaluate the fitness of new instance $\mathbf{i}$;
    Truncate the worst $\boldsymbol{n/2}$ individuals and add the newly found $\boldsymbol{n/2}$ instances;
    Sort the solutions in the pool w.r.t. fitness values;
X = select the best learner in the classroom;
return X;

4. Experimental Setup and Evaluation of the Results

All our experiments are carried out on a PC having i5 1.60 GHz 64-Bit CPU with 8 GB of RAM. The TLBO-ELM algorithm is developed by using Java programming language and MATLAB (version 2015b). The parameter settings of the TLBO-ELM algorithm are presented in Table 1. All the results are the average values of 10 runs of tenfold cross-validation to lessen the impact of random factors. In the experiments, the dataset is first partitioned into 10 equal size sets and 9 out of 10 subsets are used for training while the final one is in turn used as the test dataset. Then, the mean of this 10 test dataset is used as our *Accuracy Value*.

Table 1. Parameters of the TLBO-ELM Algorithm

parameter	value
# learners	50
convergence ratio	95%
crossover type	truncate, 2-point
truncate ratio	50%
crossover ratio	0.6 (60%)
mutation ratio	0.02 (2%)

Datasets are selected to provide a fair comparison with other studies in literature [10, 12, 13]. There are 11 datasets (see Table 2 for details). The datasets have a wide range of features ranging from 4 to 279.

Number of hidden neurons of SLFN: is decided after some optimization experiments. This value is selected to be between 30 and 60. Table 3 gives the values of Hidden Neurons used for the datasets. We need to use different number of hidden neurons to obtain better accuracy levels for each dataset.

Table 2. Descriptive statistics of the selected datasets

Dataset	ID	# instances	# features	# classes
Vehicle	VEH	846	18	4
WDBC	WDB	569	32	2
Ionosphere	ION	351	34	2
Sonar	SON	208	60	2
Musk	MUS	476	168	2
Iris	IRI	150	4	3
Spambase	SPM	4601	57	2
Waveform	WAV	5000	21	3
Wisconsin B.C.(Or.)	WIS	699	10	2
Pima-Indian Diabetes	PID	768	8	2
Arrythmia	ART	452	279	16

In the first step of our experiments, we decide whether we are going to have any improvement on the accuracy of results with selected features instead of working with all the features of a dataset. Table 4 gives details of our experiments in terms of accuracy improvements when a subset of features is selected intelligently instead of working with all features. Improvements ranging from 3.82% to 41.6% are observed during the experiments. This shows us that working with related features can significantly improve the accuracy level of the data classification results. It is observed that it gets harder to achieve a higher fitness value as the number of attributes increases. Datasets with small number of attributes produce higher accuracy levels with selected features.

Table 3. Optimized number of hidden neurons for each dataset

ID	instance no	# hidden neurons
VEH	846	60
WDB	569	38
ION	351	30
SON	208	30
MUS	168	30
IRI	150	30
SPM	4601	60
WAV	5000	38
WIS	699	47
PID	768	51
ART	452	44

Table 4. Comparison of accuracy values with all feature set and selected features

ID	all features	selected features	improvement(%)
VEH	25.45	66.20	40.75
WDB	55.24	96.84	41.6
ION	79.06	92.60	13.54
SON	67.03	82.35	15.32
MUS	55.81	66.38	10.57
IRI	96.00	98.67	2.67
SPM	59.66	90.56	30.9
WAV	54.17	80.66	26.49
WIS	93.84	97.66	3.82
PID	52.98	76.30	23.32
ART	60.44	68.10	12.6

Table 5 shows the features that are selected by the TLBO-ELM algorithm for some of the datasets. The last column shows the selected features of the input data. For PID dataset, if we take consider the selected 3 attributes as reported in Table 5 rather than the whole set. We reach to 76.30% accuracy level. If we check Table 4, where the same process is performed by using all features, we can observe that the accuracy value is only 52.98%. It is possible to improve the accuracy level by 23.32% by selecting the features given in Table 5.

Comparison with state-of-the-art algorithms: In this section of our study, we compare our TLBO-ELM algorithm with state-of-the-art algorithms in literature (namely, HGEFS [12], ABACO [13], and ACOFS [13], Attribute Bagging (AB) [20], Multi-View Adaboost (MVA) [21], Random Subspacing Ensemble (RSE) [22], (CFS-SFS) [23], and C4.5 [24] algorithms). Table 6 gives comparison of our study with state-of-the-art algorithms in terms of accuracy (these were the only results we can obtain from the previous studies that are related to our proposed algorithm). The bold values are the best results obtained by the algorithms. The TLBO-ELM algorithm is competitive with other wrapper studies. It produces the best results for five of the compared 11 datasets. Two datasets are observed to be very close to the reported best values of related state-of-the-art algorithms [12, 13].

The execution times of the TLBO-ELM algorithm: is compared with the same kind of population based approaches. It is observed from the results of the previous studies [16–18] that the TLBO-ELM is a fast polynomial time algorithm (see Table 7). HGEFS [12], PSO-SVM [25] and GA-ELM [26] are the algorithms

Table 5. The selected features by the TLBO-ELM algorithm. The reported set of features provide the best results obtained by the TLBO-ELM algorithm.

ID	accuracy	selected features
VEH	66.20	0-1-0-0-0-1-0-0-1-0-0-0-0-0-0-0-0-0
WDB	96.84	1-0-0-0-1-1-0-1-1-1-1-0-0-0-1-1-0-1-0-1-0-0-0-0-1-0-1-1-1-0
ION	92.60	0-0-0-0-0-0-1-1-0-1-0-0-1-0-0-0-0-0-0-0-0-0-1-0-0-0-0-0-0-0-0-0-0-0
SON	82.35	1-0-0-1-0-0-1-0-1-1-1-0-0-0-1-0-0-1-1-1-1-0-1-0-0-1-0-1-1-1-0-0-1-0-0-0-1-1-0-1-0-1-0-0-0-1-1-0-1-1-1-0-0-0-0-1-0-1-0-0
		1-0-1-1-0-1-1-1-1-1-0-1-0-1-0-0-1-1-1-1-0-0-1-0-0-1-1-0-0-0-0-0-0-0-0-1-0-1-0-0-0-0-0-1-1-1-0-0-0-1-1-1-1-0-1-1-0-1-1-
MUS	66.38	0-0-0-1-1-1-0-0-0-0-1-0-0-1-1-0-0-1-0-1-1-0-1-0-0-0-1-0-1-0-0-0-0-1-0-0-1-1-1-0-0-1-1-1-0-0-0-0-1-0-1-0-1-1-1-0-1-0-0-0-
		1-1-0-1-1-1-0-0-0-1-0-1-0-0-1-0-1-0-0-0-1-1-0-0-1-0-1-0-0-1-1-0-0-1-0-1-0-0-0-0-0-1-0-1-1-0-0
IRI	98.67	1-1-1-1
SPM	90.56	0-0-0-0-1-0-1-0-1-0-0-0-0-0-0-1-0-0-0-0-0-0-1-1-1-1-1-0-1-1-1-0-0-1-0-0-0-0-1-0-0-1-0-1-1-1-1-0-0-0-1-1-1-0-0-0-0
WAV	80.66	0-0-0-0-0-1-0-1-0-1-1-0-0-0-1-1-0-0-0-0-0
WIS	97.66	1-1-1-1-0-1-1-0-0
PID	76.30	1-1-0-0-0-0-1-0

that we make comparison on *Arrythmia* dataset (ART) with 279 features and 452 instances. Since we integrate TLBO with ELM, our algorithm reaches/coverges the results quickly (The accuracy result of the ART dataset is 68.10%). The only parameter that can affect our execution time is the stopping criterion that can be decided by the user. The parameter settings we provide for the TLBO-ELM algorithm works well for the classification problem (see Table 1). The TLBO-ELM algorithm can be reported to be one of the fastest algorithms in its category due to the quick evaluation process of the ELM technique.

Table 6. Comparison of accuracy values with state-of-the-art algorithms

ID	AB [20]	MVA [21]	RSE [22]	CFS-SFS [23]	C4.5 [24]	HGEFS [12]	ABACO [13]	ACOFS [13]	TLBO-ELM
VEH	80.95	81.20	77.32	69.17	73.64	**82.02**	75.3	74.9	66.20
WDB	95.14	95.73	94.84	95.80	93.14	**97.10**	-	-	96.84
ION	89.54	90.14	89.01	89.06	91.16	91.33	-	-	**92.60**
SON	80.83	80.17	79.50	78.75	71.15	**83.00**	-	-	82.35
MUS	85.27	85.63	84.73	79.55	84.87	**88.13**	-	-	66.38
IRI	-	-	-	-	-	-	97.4	97.7	**98.67**
SPM	-	-	-	-	-	-	92.1	**92.2**	90.56
WAV	-	-	-	-	-	-	79.5	79.7	**80.66**
WIS	-	-	-	-	-	-	97.6	97.4	**97.66**
PID	-	-	-	-	-	-	-	-	**76.30**
ART	63.75	64.58	63.11	63.00	63.27	**68.30**	-	-	68.10

Table 7. Comparison of execution times (sec.)

Algorithm	execution (sec.)
HGEFS [12]	4936.7
PSO-SVM [25]	50493.1
GA-ELM [26]	4373.8
TLBO-ELM	4448.4

5. Conclusion and Future Work

In this study, we propose a novel hybrid algorithm for the data classification problem. To the best of our knowledge, the TLBO-ELM is the first algorithm designed by combining these two techniques for the data classification problem. We combine fast behaviour of the ELM for the first time with a recent meta-heuristic algorithm, TLBO, and produce a robust hybrid meta-heuristic algorithm. Even with datasets that have a large number of features (like SON dataset), the prediction accuracy level of the TLBO-ELM algorithm is among the best-performing algorithms with its prediction accuracy rate that is above 82.0%. With the datasets which we perform our experiments on, the TLBO-ELM algorithm can be reported as one of the top two algorithms in the literature. The TLBO-ELM uses the (near)-optimal parameter settings for the ELM. These parameter settings are reported in our study. The prediction accuracy performance of the TLBO-ELM algorithm is promising and competitive with state-of-the-art algorithms. It leads to the conclusion that, in the future, more specialized data classification problems can be solved by using this new algorithm. The multi-objective version of this algorithm might be another subject of research. Parallel execution of the TLBO-ELM with advanced GPU architectures can reduce the execution time and increase the exploration/exploitation capability of the algorithm significantly.

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