Performance Optimization of Support Vector Machine with Oppositional Grasshopper Optimization for Acute Appendicitis Diagnosis

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Abstract:
Preoperative differentiation of complicated and uncomplicated appendicitis is challenging. The research goal was to construct a new intelligent diagnostic rule that is accurate, fast, noninvasive, and cost-effective, distinguishing between complicated and uncomplicated appendicitis. Overall, 298 patients

with acute appendicitis from the Wenzhou Central Hospital were recruited, and information on their demographic characteristics, clinical findings, and laboratory data was retrospectively reviewed and applied in this study. First, the most significant variables, including C-reactive protein (CRP), heart rate, body temperature, and neutrophils discriminating complicated from uncomplicated appendicitis, were identified using random forest analysis. Second, an improved grasshopper optimization algorithm-based support vector machine was used to construct the diagnostic model to discriminate complicated appendicitis (CAP) from uncomplicated appendicitis (UAP). The resultant optimal model can produce an average of 83.56% accuracy, 81.71% sensitivity, 85.33% specificity, and 0.6732 Matthews correlation coefficients. Based on existing routinely available markers, the proposed intelligent diagnosis model is highly reliable. Thus, the model can potentially be used to assist doctors in making correct clinical decisions.

Keywords: Support vector machine; Feature selection; Grasshopper optimization algorithm; Appendicitis diagnosis; Opposition-based learning

1. Introduction

Among abdominal surgical emergencies, acute appendicitis is one of the most common [1]. The risk of suffering from acute appendicitis is approximately 7% [2], and approximately 16.5% of the appendix becomes gangrenous, perforated, and causes overt peritonitis[3]. Conservative management is a viable treatment alternative for selected patients with uncomplicated appendicitis (UAP) [4]. Several randomized trials have compared the efficacy of antibiotic therapy alone with surgery for acute appendicitis and showed that the two treatment options are safe and effective for patients with UAP [5, 6]. Unfortunately, it may cause various complications when a missed and delayed diagnosis of complicated appendicitis occurs in patients with acute appendicitis[7], such as intra-abdominal abscesses, wound infection, peritonitis, sepsis, small-bowel obstruction, and urinary retention, and results in higher morbidity and mortality rates [8, 9]. However, preoperative identification of complicated appendicitis (CAP) patients is an arduous task.

Several attempts with scoring systems, such as the Alvarado score and the more recent Appendicitis Inflammatory Response (AIR) score, have been created to increase diagnostic accuracy and decrease the degree of negative appendectomy [10]. Most of systems encompass symptoms, signs, and laboratory tests used to diagnose appendicitis among patients suspected of having appendicitis[11-14]. However, there are controversial conclusions concerning their sensitivity and specificity [15, 16]. Recent advances in imaging techniques, such as ultrasound and computed tomography (CT), have been shown to improve diagnostic accuracy [17, 18]. Salminen et al. [19] used CT-based criteria to distinguish UAP from CAP. However, ultrasound-based diagnosis accuracy is highly operator dependent, and CT accompanied by ionizing radiation may increase the lifetime risk of cancer [7]. In addition, some tests have demonstrated that diagnostic imaging may not increase the diagnostic accuracy or even put off the diagnosis of acute appendicitis [8].

Additionally, laboratory test results can be used to improve the differentiation between CAP and UAP. Appendicitis patients may have elevated blood markers, including neutrophil counts, CRP and white blood cell (WBC) counts, which may increase even more in patients with CAP[9]. Although these indices are weak in identifying appendicitis alone, combining them can provide a higher discriminatory ability[10], making machine learning appealing with its advantages. Previous literature has shown considerable performance for diagnosing acute appendicitis and may decrease unnecessary appendectomies[20-23]. Park et al. [24] found that artificial neural networks (ANNs) can diagnose acute appendicitis; their accuracy was significantly higher than that of the Alvarado clinical scoring system. Another work [25] combined an ANN with optimal input variables to diagnose acute appendicitis and achieved high classification performance. YOLDAS [25] was used as an effective tool for diagnosing acute appendicitis in the representation of ANNs as 100% sensitivity and 97.2% specificity were obtained. Regarding the diagnosis of acute appendicitis, Sakai [26] reported that the neural network model was more accurate than the logistic regression model. Hsieh [27] demonstrated that we can use random forest (RF) to accurately predict acute appendicitis. The results showed that the AUCs of random forest, support vector machine and ANN were 0.98, 0.96 and 0.91, respectively. Recently, Ting [28] showed that the decision tree that modifies the Alvarado scoring system is easier and more precise than the Alvarado scoring system. The sensitivity and specificity of the model are 0.945 and 0.805, respectively.

While emphasis has been placed on the confirmative diagnosis from suspected appendicitis, few studies have focused on the difference between UAP and CAP, and the latter is likely to fail conservative treatment and, therefore, must be discovered early. Therefore, establishing a safe and efficient rule to stratify suspicious patients properly is urgently needed. The present research attempted to examine the elements of ubiquitously available and inexpensive markers in the hope of developing cost-effective prognostic markers between UAP and CAP via an improved support vector machine (SVM) model. SVM [30, 31] is mainly based on the structural risk minimization principle as a popular artificial intelligence method. Since its introduction, SVM has performed well in many medical diagnostic tasks [29-35]. However, the hyperparameters in the model are the main parameters that affect the actual performance of the SVM. If these parameters are not properly chosen, good performance cannot be achieved. The purpose of the research was to establish a diagnostic model employing an enhanced SVM and determine the most important predictors in UAP and CAP discrimination. To further improve the diagnostic precision of acute appendicitis, this article attempts to construct an improved grasshopper optimization algorithm (GOA) to find the best parameters in SVM.

SVM is a supervised machine learning method proposed by Vapnik et al. [36] in the mid-1990s based on statistical learning theory. Although SVM has certain advantages in theory and application, appropriate parameters are the premise of realizing the advantages of SVM. Parameter selection directly impacts the SVM model's learning effect and generalization performance, so selecting the appropriate parameters has always been a research hotspot and difficulty of SVM. The traditional SVM parameter optimization methods mainly include cross-validation technology [37], gradient descent method [38], and grid search method [39]. Cross-validation technology tests the prediction error of nontraining samples under the condition of keeping the value of a certain parameter unchanged and constantly modifying the parameter value to minimize the test error. This method has a great amount of computation, and it is not easy to select more than two parameters. The basic principle of the gradient descent method is to minimize the upper bound of the decomposition of general errors to realize the optimization solution of SVM parameters. This method has advantages in calculation time and fast convergence speed, but it is sensitive to the initial value and requires the objective function to be differentiable with respect to parameters. The basic principle of the grid search method is to verify all the points within the grid range and finally select the grid point with the smallest error as the parameter of SVM. However, when there are many parameters or the range of parameters is large, this method requires considerable computation and is very time-consuming. To date, swarm intelligence (SI) algorithms have been used to solve different types of complex problems [40, 41]. SI algorithms have been applied in modeling complex dynamic systems. In detail, Gharehchopogh et al.[42] generated a tour using random-key encoding to solve the traveling salesman problem (TSP) by enhancing Harris hawks optimization (HHO). Gharehchopogh et al.[43] modified a new solution from neighborhoods produced by a modified farmland fertility (FFA) algorithm and improved the update functions in the FFA algorithm phases to solve a constrained engineering optimization problem. Goldanloo et al.[44] designed an improved opposition-based learning firefly algorithm (FA) and a symbiotic organisms search (SOS) algorithm to solve some optimization problems regarding exploration and early convergence of FA. Ghafori et al.[45] categorized the spotted hyena optimizer (SHO) algorithm based on hybridization, improvement, SHO variants, and optimization problems, and some experimental results demonstrated the effectiveness of this type of method in solving intricate and NP-hard problems. These methods seek solutions that are closer to the optimal value according to the corresponding updating rules in the solution space. In other words, when solving the minimization problem, the objective function of the problem is minimized by searching the optimal solution. Additionally, SI algorithms have found applications in many fields, such as engineering design problems [46-49], scheduling problems [50-54], image segmentation [55, 56], medical data classification [57-60], many-objective optimization problem [61], large-scale optimization problems [62], big data optimization problems [63], foreign fibers detection [64, 65], large-scale supply chain network design [66], virtual machine placement in cloud computing [67], design of power electronic circuits [68, 69], energy vehicle dispatch [70] and prediction problems in the educational field [71-75].

In this method, we used opposition-based learning (OBL) strategy to improve the exploration capability of classical GOA [76]. Similar to other metaheuristic algorithms, the GOA quickly falls into local optima, and the global search ability is insufficient. Thus, a boosted GOA with OBL is proposed to further ameliorate the performance, which is expected to show better convergence speed and higher convergence accuracy than the original GOA. The OBLGOA test was applied to identify the two critical parameters of SVM. The resultant model, OBLGOA-SVM, was validated on actual data samples collected from Wenzhou Central Hospital. In addition, the basic GOA-based SVM (GOA-SVM), grid search (GS)-based SVM (GS-SVM), extreme learning machine (ELM), kernel ELM (KELM), RF, and neural network based on the backpropagation algorithm (BPNN) were used for comparison. Promisingly, the developed OBLGOA-SVM method has achieved the highest prediction accuracy and Matthews's correlation coefficient (MCC).

The main contributions of this work are summarized as bellow: first, we used random forest methods to distinguish the most significant variables for appendicitis from appendicitis without CRP, heart rate, body temperature, and neutrophils compared to traditional diagnostic methods. Then, aiming at the deficiencies of GOA, an improved SVM based on GOA was designed to construct the diagnostic model of CAP and UAP. Finally, we test whether the proposed intelligent diagnosis model is highly reliable. Furthermore, through experimental verification, compared with some diagnostic methods, the method mentioned in this work has outstanding performance in key indicators, such as accuracy, specificity, sensitivity and MCC. Moreover, the robustness of the proposed method is satisfactory.

The remainder of this paper is structured as follows. Section 2 offers the details of the patients and data. The details of the suggested prediction model are presented in Section 3. Section 4 illustrates the detailed experimental designs. The simulation results of the suggested rule are shown in Section 5. Section 6 provides detailed discussions and limitations. Finally, the results are summarized in Section 7.

2. Patients and Data

This retrospective cohort study included all consecutive patients experiencing appendectomy because of acute appendicitis at Wenzhou Central Hospital (Zhejiang Province, China) from January 1, 2015, to December 31, 2016. Qualification criteria were histological reports showing appendicitis. Exclusion criteria included pathological reports indicating normal appendices or malignant tumors. We performed a retrospective analysis by reviewing all relevant medical records involving patients. The ethics committee of the institution approved the study, and informed consent was obtained from all patients.

Basic demographic data, including age, sex and vital signs, including body temperature and heart rate, were recorded. Furthermore, we collected preoperative laboratory markers, including WBCs, neutrophils, lymphocytes, eosinophils, monocytes, erythrocytes, hemoglobin, platelets, urea nitrogen, blood sugar, CRP, creatinine, and bilirubin. Patients were separated into two groups: the UAP group and CAP group. CAP is defined as gangrene or perforated appendicitis and/or diffuse peritonitis. Acute appendicitis was divided into CAP and UAP, and the results of surgical reports and appendicular histopathology were used as reference standards.

SPSS 16.0 was used for statistical analysis, Student's t test was employed to analyze measurement data, and Fisher's exact test was employed to analyze classification variables. A value of $P < 0.05$ was considered statistically significant. Table 1 lists the clinical and laboratory results for all patients with acute appendicitis. The CRP, temperature, heart rate, age, WBC count, lymphocytes, neutrophils, eosinophils, urea nitrogen, and blood sugar were statistically significant in the CAP group compared to the UAP group, in which the CRP was significantly greater. There were no significant differences with respect to sex, monocytes, hemoglobin, erythrocytes, platelets, creatinine, or bilirubin between the two groups.

Table 1. Detailed information of patients with acute appendicitis

Attributes	UAP(*n*=150)	CAP(*n*=148)	*P* value
Gender(n)	82	89	0.34
Age(y)	42.23±15.54	46.57±19.73	0.036
Temperature(℃)	36.98±0.56	37.50±0.85	0.000
Heart rate(bmp)	83.70±15.09	97.73±17.94	0.000
WBC($\times 10^9$/L)	13.89±4.03	15.42±5.04	0.004
Lymphocytes(%)	10.75±6.78	7.98±4.03	0.000
Neutrophils(%)	83.99±8.71	87.01±5.54	0.000
Monocytes(%)	4.53±2.09	4.51±2.04	0.941
Eosinophils(%)	0.40±0.82	0.21±0.44	0.014
Hemoglobin(g/L)	137.69±16.80	139.17±16.43	0.442
Erythrocytes($\times 10^{12}$/L)	4.89±3.65	4.61±0.58	0.355
Platelets($\times 10^9$/L)	212.84±51.88	209.72±62.62	0.640
Urea nitrogen(mmol/L)	4.48±2.76	5.93±7.48	0.028
Blood sugar(mmol/L)	6.18±2.10	6.93±2.02	0.002
Creatinine(μmoI/L)	81.46±19.99	88.40±56.86	0.160
Bilirubin(μmoI/L)	16.82±8.26	16.47±10.62	0.757
CRP(mg/L)	23.14±36.31	111.97±90.86	0.000

3. Methods

As shown in Fig. 1, this section introduces the proposed OBLGOA-SVM methodology for diagnosing acute UAP and CAP, containing two main phases. The first phase concerns the data preprocessing performed by the random forest. Through this step, the best features will be selected to prepare for subsequent classification. The second phase is mainly to introduce an opposition-based learning-based GOA strategy, named OBLGOA, to determine the two hyperparameters of SVM. In OBLGOA, the individuals constantly search for new solutions in the solution space according to the corresponding rules, making the classification accuracy of the SVM model as high as possible. When the termination condition is satisfied, the optimal parameters of the SVM model can be obtained. After the optimal SVM model is established, it is used to forecast new models. Notably, the entire procedure is performed through *k*-fold cross-validation (CV). The 10-fold CV is adopted for the outer classification performance evaluation, and the 5-fold CV is adopted for the inner parameter optimization procedure. This scheme has been adopted in many works [77, 78].

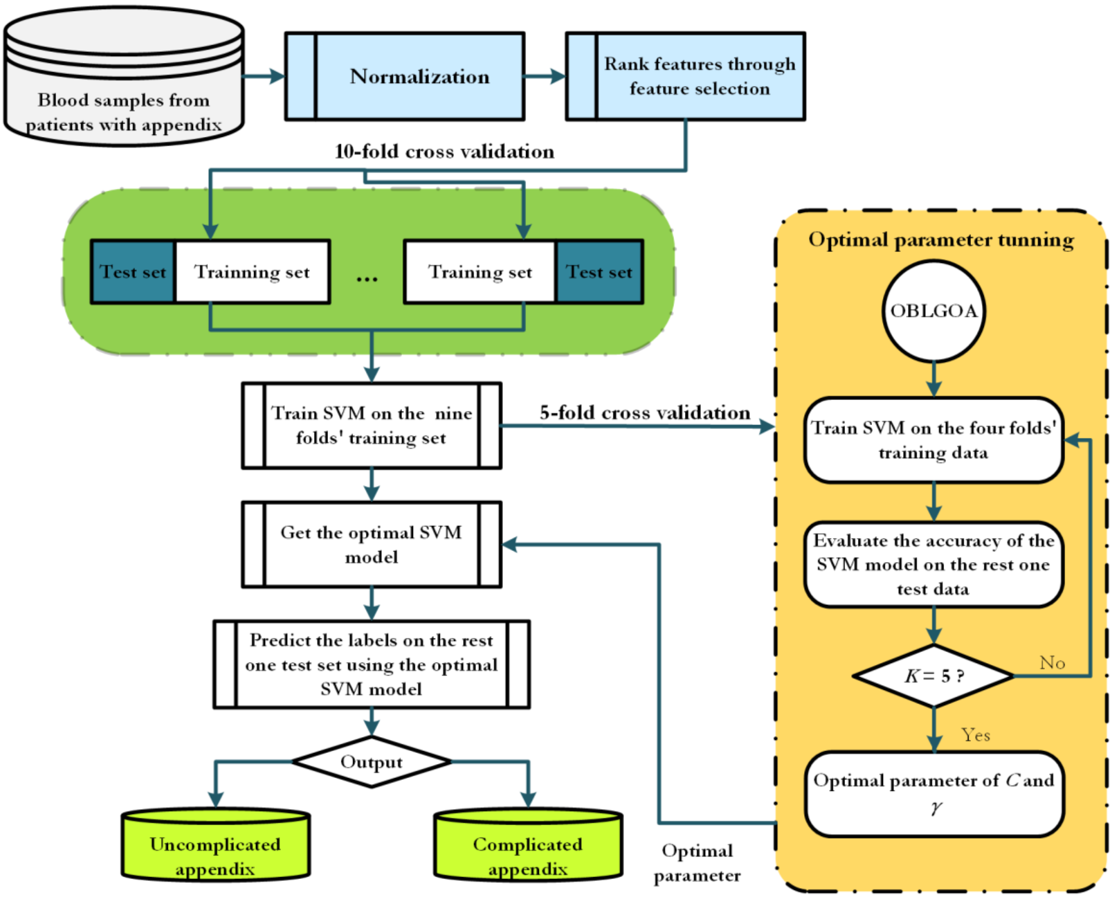

Fig. 1. Diagram of the proposed framework

3.1 Feature selection

Random forest (RF) [79], as a representative ensemble learning method, has been successfully applied in various fields since its inception. It is an ensemble learning method that builds multiple decision trees through bootstrapping and node random partitioning and obtains the final classification results by voting. RF can analyze the classification features of complex interactions. It has a faster learning speed and has good robustness to noisy data. It is widely used because its variable importance measure can be selected as a feature[80].

In this paper, the importance of each feature is mainly measured by the mean decrease accuracy. This method directly measures the influence of each feature on the accuracy of the model. The main idea is to interfere with the sequence of each feature and measure the influence of the change of the sequence on the accuracy of the model. Obviously, for unimportant features, the interrupt sequence will not significantly affect the accuracy of the model, but for important features, this operation will reduce the accuracy of the model.

3.2 Support Vector Machine (SVM)

SVM was first proposed by Cortes and Vapnik [81, 82]. The core idea of the SVM is to construct an optimal decision hyperplane, which maximizes the distance between two classes of samples on both sides of the hyperplane, thus providing a good generalization ability for supervised classification cases. SVM can cope with small samples and nonlinear pattern recognition and can be employed in various cases, such as function approximation and prediction [83-94].

The support vector in SVM means some training points are in the training sample set, which are closest to the classification decision-making surface and are the hardest data points to classify. When the distance between these points to the classification hyperplane reaches the maximum value, the best classification standard in SVM is reached.

For the linear binary classification problem, the expression of the SVM decision classification is as follows:

$$f(\boldsymbol{x}) = sgn\left(\sum_{i=1}^{n} \alpha_i y_i \boldsymbol{x}_i^T \boldsymbol{x} + b\right) \quad (1)$$

where b is the offset from the origin, y_i are the labels corresponding to samples x, and n is the quantity of support vectors.

SVM uses kernel techniques to change from this original linear space to a higher one in another dimension for nonlinear problems. In the high-dimensional linear space, the sample is divided according to a hyperplane. After the introduction of the kernel function, the decision formula is transformed as follows.

$$f(\boldsymbol{x}) = sgn(\sum_{i=1}^{n} \alpha_i y_i K(\boldsymbol{x}_i, \boldsymbol{x}) + b) \quad (2)$$

where $K(\mathrm{x}, \mathrm{x}_i)$ is a kernel function and the Gaussian kernel function is one of the most common kernel functions.

3.3 Grasshopper Optimization Algorithm (GOA)

Recently, many intelligent optimizers have been proposed to tackle global optimization problems, including hunger games search (HGS) [95], Harris hawks optimization (HHO) [96], Runge Kutta optimizer (RUN) [97], slime mold algorithm (SMA) [98], and colony predation algorithm (CPA) [99]. Inspired by grasshoppers' actions and social interaction, Saremi *et al.* proposed the GOA [76]. Although grasshoppers are one of the largest groups of insects, they often appear alone in nature. Young grasshoppers are slow to move, but adult grasshoppers can move long distances in a short time, forming colonies in the air. Looking for food is another characteristic of grasshoppers. Adult grasshoppers can obtain food quickly and accurately due to their fast-moving speed. Grasshopper behavior is affected by three factors: gravity, wind advection, and external forces. The influence of the first two factors can be neglected, the most important of which is the third one. The mathematical model of grasshopper colony behavior is as follows:

$$X_i^d = c\left(\sum_{\substack{j=1 \\ j\neq i}}^{N} c\frac{ub_d - lb_d}{2} s\left(\left|x_j^d - x_i^d\right|\right)\frac{x_j - x_i}{d_{ij}}\right) + \hat{T}_d \qquad (3)$$

where X_i represents the position of the *i*th agent, *N* represents the quantity of the agent population, ub_d and lb_d represent the upper and lower bounds of the d dimension, respectively, and $\hat{T}_d$ are the optimal solutions in the target value of the d dimension at present. *S* in the above equation is a function used to calculate the external force (attraction and exclusion), and the formula is as below:

$$s(r) = fe^{\frac{-r}{l}} - e^{-r} \qquad (4)$$

where *f* stands for the attraction intensity and *l* represents the scale of attraction length. In this work, we set $l = 1.5$ and $f = 0.5$ as in the original GOA. The last parameter c stands for the decreasing coefficient, and the calculation formula is as follows:

$$c = c_{\max} - t\frac{c_{\max} - c_{\min}}{L} \qquad (5)$$

where $c_{\max}$ and $c_{\min}$ represent the maximum and minimum values, *t* means the current iteration number, and *L* controls the maximum iteration number.

3.4 GOA with Opposition-based Learning (OBLGOA)

The essence of opposition-based learning (OBL) is to compare the current solution with the opposite solution simultaneously, and the better one is retained. We found that OBL could provide many benefits for soft computing methods when considering both randomness and opposition [100]. Several works have shown that the OBL mechanism can boost the performance of GOA [101-104]. If in the process of searching, the current solution and the reverse one are searched simultaneously, and the better solution is chosen as the guess solution, the algorithm's efficiency will be significantly improved. Since its introduction, the OBL strategy has attracted much attention in the academic and engineering fields because the convergence speed and quality of the optimization algorithm can be significantly improved. The OBL strategy has been introduced in many nature-inspired metaheuristic algorithms, including particle swarm optimization [105], differential evolution [106, 107], the krill herd algorithm [108], shuffled frog leaping [109], and the sine cosine algorithm [110].

OBL strategy is always defined as follows:

Suppose $Q = (x_1, x_2, x_3, \cdots, x_n)$ is a feasible solution in the *N*-dimensional search space. where $x_1, x_2, x_3, \cdots, x_n \in R,\ x_i \in [a_i, b_i]$; then, its opposite solution $Q^* = (x^*_1, x^*_2, x^*_3, \cdots, x^*_n)$ can be expressed as follows. In this work, the OBL ratio is set as 50% of the population.

$$x^*_i = a_i + b_i - x_i, i = 1, 2, \cdots, n \qquad (6)$$

In this article, to maintain the diversity of the agent population while preventing falling into a local optimum, the OBL strategy is introduced into GOA. The flowchart of the resultant method OBLGOA is displayed in Fig. 2.

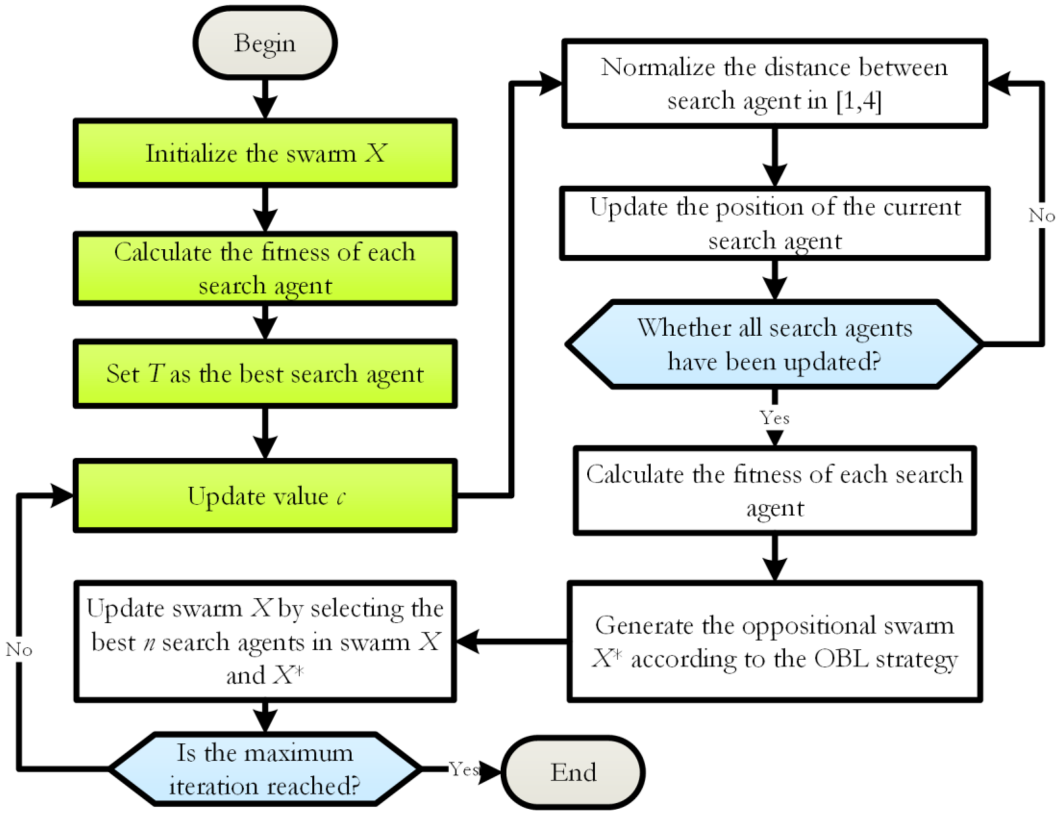

Fig. 2. Diagram of OBLGOA

4. Experimental Designs

We use MATLAB to realize the prediction system. The LIBSVM toolkit [111] was used for SVM implementation. The KELM technique available at http://ww3.ntu.edu.sg/home/egbhuang, was adopted for the KELM classification. To implement RF, we used a package from https://code.google.com/archive/p/randomforest-matlab. The Levenberg–Marquardt training algorithm embedded in the MATLAB toolbox was used to implement a backpropagation neural network (BPNN). OBLGOA, GOA, and GS were performed from scratch. This experiment was performed under the Windows 10 system using an Intel(R) Core (TM) i7-7500U processor (2.90 GHz) 32 GB RAM and MATLAB 2019b. For classification tasks, data were first scaled to [-1,1]. Stratified 10-fold cross-validation (CV) [112] was performed to ensure unbiased simulation results. The maximum number of iterations and group size were set to 100 and 25, respectively. Common performance indices, such as MCC, classification accuracy (ACC), specificity, and sensitivity, were used to judge the suggested method.

5. Results

5.1 Validation of benchmark function

To validate the performance of the proposed OBLGOA strategy, 12 benchmark functions were used to assess the results. The descriptions of these benchmark functions and brief descriptions of their characteristics can be seen in Tables 2 and 3, respectively. Notably, among these 12 functions, F01-F07 belong to single peak functions. These functions have only one global optimal solution. F08-F12 belong to multipeak functions, which are characterized by the existence of multiple local extremums.

Table 2. Description of unimodal benchmark functions

Function	Dimension	Range	$f_{\min}$
$f_1(x) = \sum_{i=1}^{n} x_i^2$	*n*	[-100,100]	0
$f_2(x) = \sum_{i=1}^{n} \lvert x_i \rvert + \prod_{i=1}^{n} \lvert x_i \rvert$	*n*	[-10,10]	0
$f_3(x) = \sum_{i=1}^{n} \left(\sum_{j-1}^{i} x_j \right)^2$	*n*	[-100,100]	0
$f_4(x) = max_i\{\lvert x_i \rvert, 1 \le i \le n\}$	*n*	[-100,100]	0
$f_5(x) = \sum_{i=1}^{n-1} [100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2]$	*n*	[-30,30]	0
$f_6(x) = \sum_{i=1}^{n} ([x_i + 0.5])^2$	*n*	[-100,100]	0
$f_7(x) = \sum_{i=1}^{n} i x_i^4 + random[0,1]$	*n*	[-128,128]	0

Table 3. Description of multimodal benchmark functions

Function	Dimension	Range	$f_{\min}$
$f_8(x) = \sum_{i=1}^{n} [x_i^2 - 10\cos(2\pi x_i) + 10]$	*n*	[-5.12, 5.12]	0
$f_9(x) = -20 \exp\left(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}\right) - \exp\left(\frac{1}{n}\sum_{i=1}^{n} \cos(2\pi x_i)\right) + 20 + e$	*n*	[-32,32]	0
$f_{10}(x) = \frac{1}{4000}\sum_{i=1}^{n} x_i^2 - \prod_{i=1}^{n} \cos\left(\frac{x_i}{\sqrt{i}}\right) + 1$	*n*	[-600, 600]	0
$f_{11}(x) = \frac{\pi}{n}\left\{10\sin(\pi y_1) + \sum_{i=1}^{n-1} (y_i - 1)^2[1 + 10\sin^2(\pi y_{i+1})] + (y_n - 1)^2\right\} + \sum_{i=1}^{n} u(x_i, 10,100,4)$ $y_i = 1 + \frac{x_i + 1}{4}$ $u(x_i, a, k, m) = \begin{cases} k(x_i - a)^m & x_i > a \\ 0 & -a < x_i < a \\ k(-x_i - a)^m & x_i < a \end{cases}$	*n*	[-50,50]	0
$f_{12}(x) = 0.1\left\{\sin^2(3\pi x_1) + \sum_{i=1}^{n} (x_i - 1)^2[1 + \sin^2(3\pi x_i + 1)] + (x_n - 1)^2[1 + \sin^2(2\pi x_n)]\right\} + \sum_{i=1}^{n} u(x_i, 5,100,4)$	*n*	[-50,50]	0

5.1.1 Comparison results with basic GOA

The behavior of OBLGOA is compared against that of basic GOA. For all the algorithms, the population size is set to 50, and the maximum number of iterations is set to 500. All algorithms are executed separately 30 times on each benchmark function, taking into account the random nature of each algorithm. Table 4 records the statistical values of each algorithm for each benchmark function involving the best, worst, average (Ave), and standard deviation (Std) values.

The detailed comparison results of OBLGOA and GOA for the twelve multidimensional benchmark functions are listed in Table 4. As shown, we can see that, on average, OBLGOA provided consistently better results than basic GOA in all cases. For the best solutions, OBLGOA also achieved superior results to basic GOA on all involved test problems. Comparing the worst results obtained by OBLGOA and basic GOA, OBLGOA's result is still better than GOA's result. Furthermore, the standard deviations of the two methods indicate that when facing all benchmark functions, OBLGOA has the smallest standard deviation, indicating that OBLGOA has better searching capability and performs more stably.

Table 4. Comparison results of OBLGOA and GOA

Function	OBLGOA				GOA			
	Best	Worst	Ave	Std	Best	Worst	Ave	Std
F01	8.76E-08	1.28E-02	5.35E-03	4.39E-03	1.03E+01	1.95E+02	5.78E+01	6.52E+01
F02	1.44E-01	2.29E+00	4.68E-01	6.44E-01	3.45E+00	1.79E+01	8.13E+00	3.91E+00
F03	2.30E-03	9.97E-03	6.62E-03	2.30E-03	1.14E+03	3.66E+03	2.21E+03	8.78E+02
F04	5.05E-05	3.04E-01	3.39E-02	9.54E-02	1.23E+01	1.94E+01	1.48E+01	2.45E+00
F05	2.87E+01	2.95E+01	2.90E+01	2.66E-01	1.16E+03	1.08E+04	5.56E+03	3.59E+03
F06	1.92E-08	1.21E-02	6.44E-03	3.85E-03	6.13E+00	8.11E+01	3.55E+01	1.98E+01
F07	2.65E-04	6.04E-03	1.68E-03	1.73E-03	2.28E-02	5.75E-02	4.16E-02	1.14E-02
F08	2.45E-09	9.36E+01	9.50E+00	2.95E+01	3.78E+01	1.24E+02	8.65E+01	2.75E+01
F09	1.04E-04	9.32E-02	6.39E-02	2.49E-02	3.61E+00	6.25E+00	4.86E+00	8.93E-01
F10	1.64E-07	2.86E-02	4.79E-03	9.25E-03	9.13E-01	1.35E+00	1.09E+00	1.21E-01
F11	4.54E-10	7.41E-05	3.55E-05	3.04E-05	4.01E+00	1.45E+01	9.99E+00	3.49E+00
F12	9.23E-09	1.36E-03	7.76E-04	4.26E-04	7.15E+00	6.15E+01	3.57E+01	1.71E+01

The convergence trends and ANOVA test of OBLGOA are depicted in Figs. 3-14. As shown, the OBLGOA both offered a fast convergence speed and achieved the best solution on twelve multidimensional benchmark functions. In Fig. 3, OBLGOA maintains a strong search ability throughout the iterative process. When the basic GOA falls into a local optimum, OBLGOA can still search for a better solution. After 500 iterations, the solution obtained by OBLGOA is better than the solution obtained by basic GOA. The ANOVA test for F01 reveals that the Std of OBLGOA is smaller than that of basic GOA, indicating that OBLGOA has stronger stability. In Fig. 4, both OBLGOA and basic GOA fall into a local optimum in the early iteration process. However, OBLGOA can safely avoid local minima and provide a better solution later. The Std of OBLGOA is still much smaller than that of GOA. The minimum standard deviation of OBLGOA after 30 independent operations indicates that the randomness of the algorithm has less influence on the final results of the model, which can reflect the strong robustness of the algorithm. Additionally, Figs. 3-14 show that OBLGOA has strong search ability and robustness on 12 benchmark functions, regardless of whether the function is unimodal or multimodal.

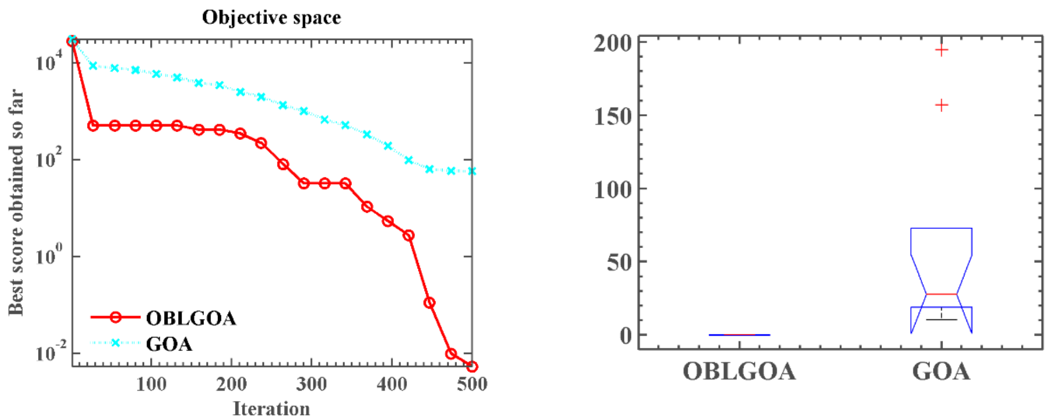

Fig. 3 Convergence plot and ANOVA test in F01

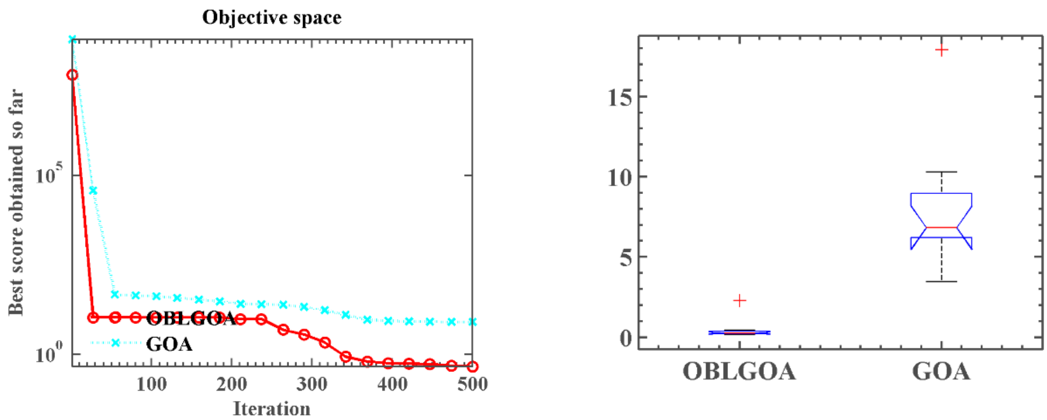

Fig. 4 Convergence plot and ANOVA test in F02

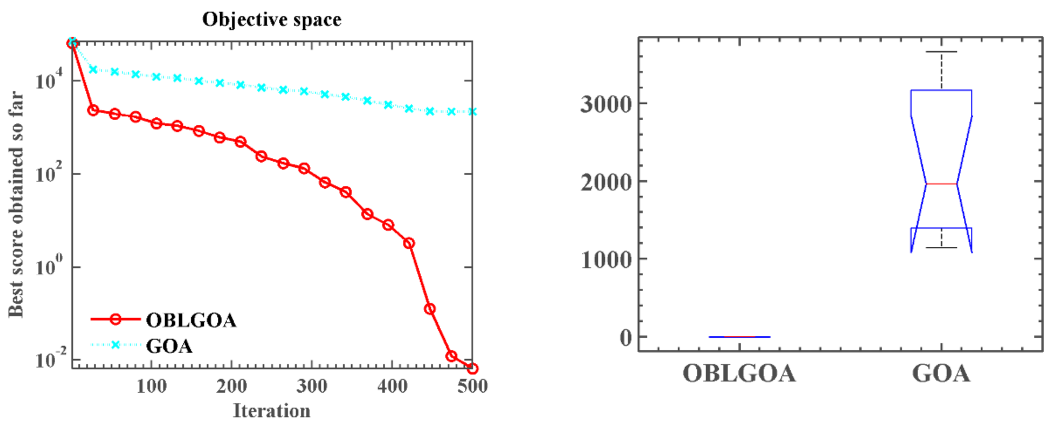

Fig. 5 Convergence plot and ANOVA test in F03

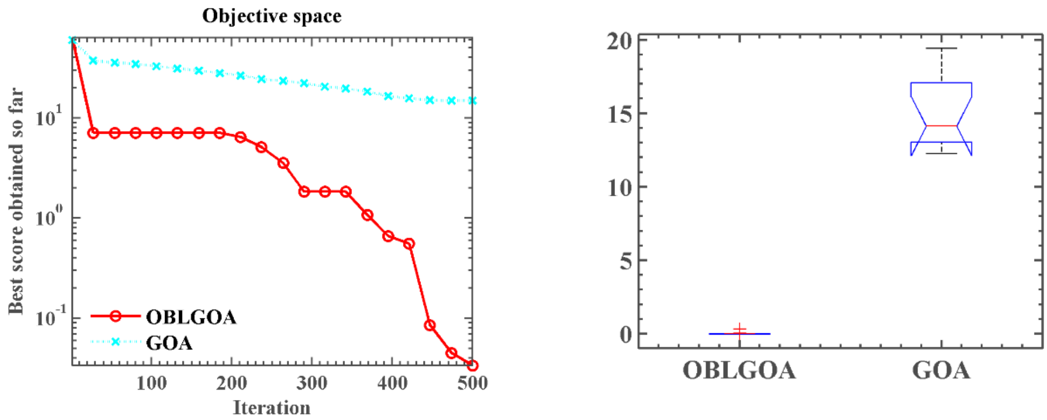

Fig. 6 Convergence plot and ANOVA test in F04

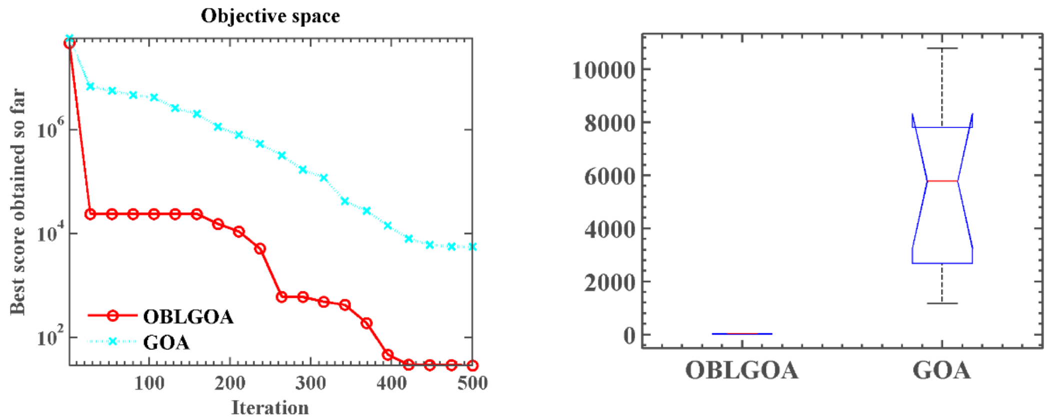

Fig. 7 Convergence plot and ANOVA test in F05

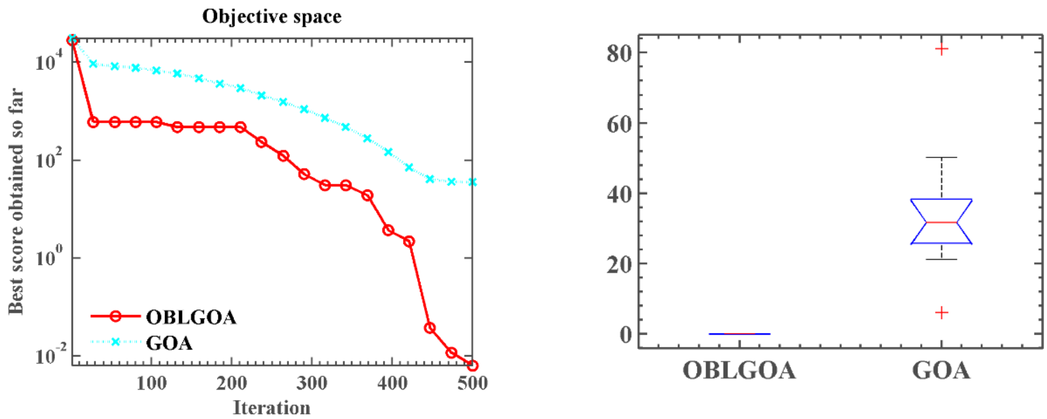

Fig. 8 Convergence plot and ANOVA test in F06

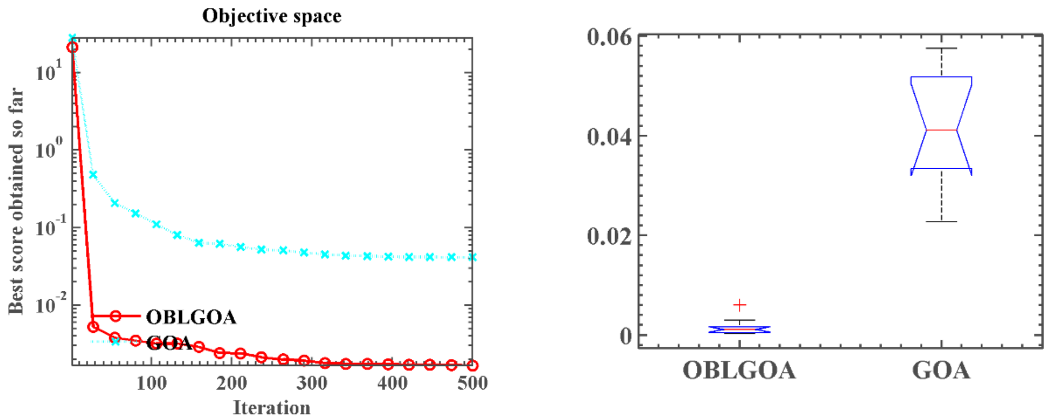

Fig. 9 Convergence plot and ANOVA test in F07

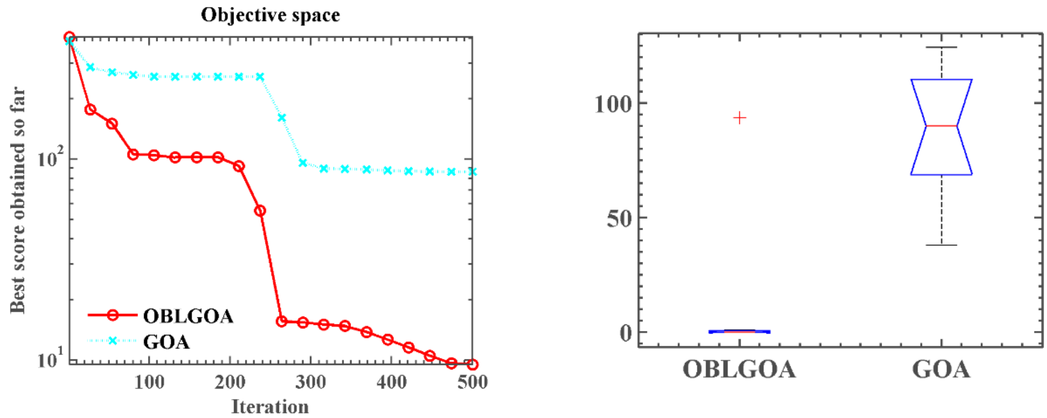

Fig. 10 Convergence plot and ANOVA test in F08

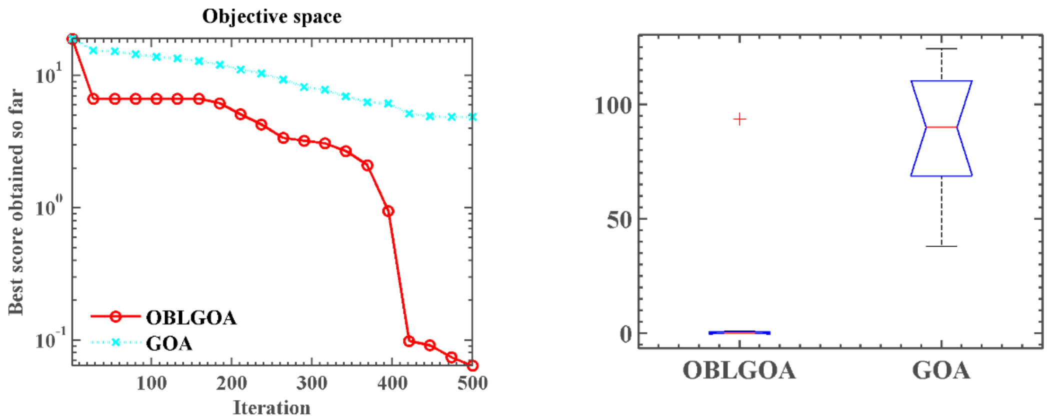

Fig. 11 Convergence plot and ANOVA test in F09

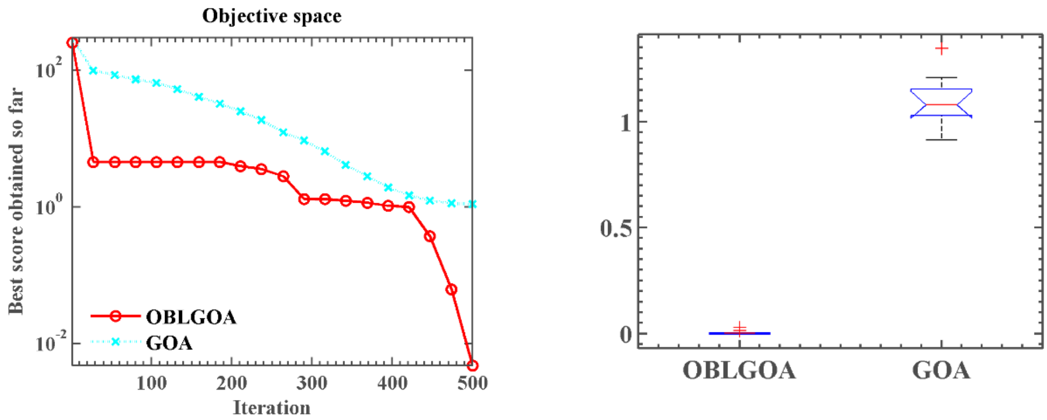

Fig. 12 Convergence plot and ANOVA test in F10

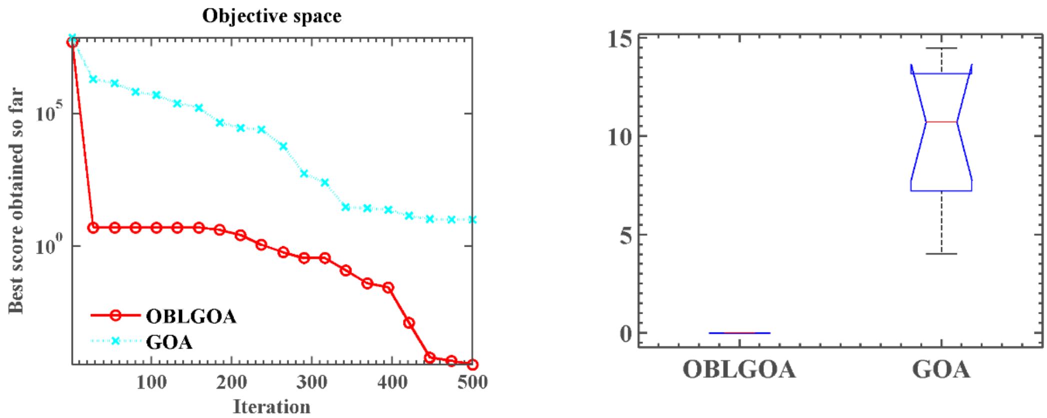

Fig. 13 Convergence plot and ANOVA test in F11

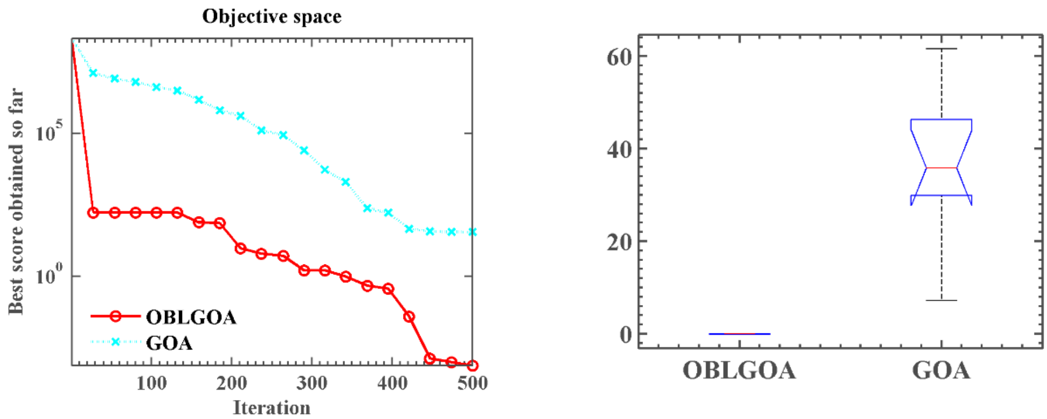

Fig. 14 Convergence plot and ANOVA test in F12

5.1.2 Comparison results with some champion algorithms

To further illustrate the effectiveness of the method proposed in this work, five champion algorithms, including ALCPSO, BLPSO, CLPSO, JDE and SADE, are selected as competing algorithms. To ensure the fairness of the experimental setting, each algorithm involved is executed 30 times independently, and the maximum number of iterations is set to 500. Additionally, the number of populations is 50. The comparison results of OBLGLA and other champion algorithms are presented in Table 5. Among them, Ave is the average value of the proposed algorithm in solving a type of problem, which can reflect the overall performance of the algorithm in solving the problem, and Std is the standard deviation that demonstrates the stability of the method in solving the problem. The Wilcoxon signed-rank test with a significance level of 0.05 is used as a measurement tool to prove that the proposed method is statistically significant. Specifically, the notation '+/=/-' makes it clear that OBLGOA is better, similar, and worse than competing algorithms.

From Table 5, we found that on all unimodal functions except F5 and F6, OBLGOA can always maintain the best performance regardless of optimization ability or stability. Simultaneously, when solving multimodal function problems, such as F8-F10, OBLGOA always has the best performance compared to other champion algorithms. Of course, the performance of OBLGOA is not always the best, but it is not far from the optimal results, which also lays the foundation for subsequent further research.

Table 5. Comparison results of OBLGOA and other champion algorithms

	F1		F2		F3	
	Ave	Std	Ave	Std	Ave	Std
OBLGOA	**1.01E-08**	**2.60E-08**	**2.13E-04**	**3.65E-04**	**8.84E-07**	**2.09E-06**
ALCPSO	6.83E-04	1.11E-03	2.46E-01	4.39E-01	4.39E+03	2.15E+03
BLPSO	6.19E+03	1.02E+03	3.76E+01	5.54E+00	1.98E+04	2.88E+03
CLPSO	6.09E+02	2.02E+02	7.56E+00	1.54E+00	1.77E+04	4.28E+03
JDE	3.44E-03	5.14E-03	2.37E-03	5.55E-03	1.97E+03	1.02E+03
SADE	1.88E+00	7.80E+00	7.45E-02	1.73E-01	1.35E+03	4.99E+02
	F4		F5		F6	
	Ave	Std	Ave	Std	Ave	Std
OBLGOA	**1.77E-03**	**7.50E-03**	1.02E+07	2.57E+07	2.61E+01	2.91E+01
ALCPSO	1.69E+01	4.65E+00	1.06E+02	**9.59E+01**	**2.21E-01**	9.83E-01
BLPSO	3.68E+01	3.42E+00	3.31E+06	9.23E+05	6.19E+03	1.23E+03
CLPSO	4.42E+01	3.67E+00	1.99E+05	1.24E+05	6.54E+02	2.34E+02
JDE	2.96E+01	7.68E+00	**2.32E+02**	1.56E+02	5.45E-03	**5.00E-03**
SADE	1.42E+01	3.04E+00	4.18E+02	3.33E+02	1.66E+00	6.51E+00
	F7		F8		F9	
	Ave	Std	Ave	Std	Ave	Std
OBLGOA	**8.07E-03**	**1.24E-02**	**6.23E-08**	**1.34E-07**	**2.73E-05**	**3.41E-05**
ALCPSO	1.54E-01	6.96E-02	7.49E+01	1.78E+01	2.24E+00	9.32E-01
BLPSO	2.17E+00	5.70E-01	2.44E+02	1.49E+01	1.37E+01	6.57E-01
CLPSO	3.75E-01	9.56E-02	5.07E+01	6.07E+00	9.89E+00	8.32E-01
JDE	7.94E-02	4.55E-02	1.68E+01	6.56E+00	5.37E-01	6.49E-01
SADE	8.61E-02	5.04E-02	4.75E+01	1.19E+01	2.26E+00	8.71E-01
	F10		F11		F12	
	Ave	Std	Ave	Std	Ave	Std
OBLGOA	**1.85E-08**	**4.21E-08**	1.83E+00	2.23E+00	4.69E+00	2.24E+00
ALCPSO	3.18E-02	3.21E-02	1.32E+00	9.87E-01	**3.32E-01**	**4.27E-01**
BLPSO	5.49E+01	8.17E+00	6.07E+05	4.09E+05	6.51E+06	2.50E+06
CLPSO	6.89E+00	1.64E+00	3.74E+01	2.20E+01	6.00E+04	6.00E+04

JDE	1.24E-01	2.54E-01	**2.83E-01**	**3.48E-01**	2.23E+03	6.98E+03
SADE	1.10E-01	1.07E-01	1.23E+00	1.64E+00	2.69E+01	6.14E+01

	overall		
	Ave	+/-/=	rank
OBLGOA	2.000000	~	**1**
ALCPSO	2.833333	8/3/1	3
BLPSO	5.833333	11/0/1	6
CLPSO	4.916667	11/0/1	5
JDE	2.500000	8/2/2	2
SADE	2.916667	9/1/2	4

To more intuitively present the performance of OBLGOA and related competing algorithms in the entire iteration process, the convergence curve is shown in Fig. 15. OBLGOA maintains the fastest convergence speed while satisfying the optimization accuracy in most of the benchmark functions. This result can fully prove that the introduction of OBL into the traditional GOA can significantly improve the search ability of individuals in the population.

In summary, believe that OBLGOA is a developable tool for solving unimodal and multimodal problems.

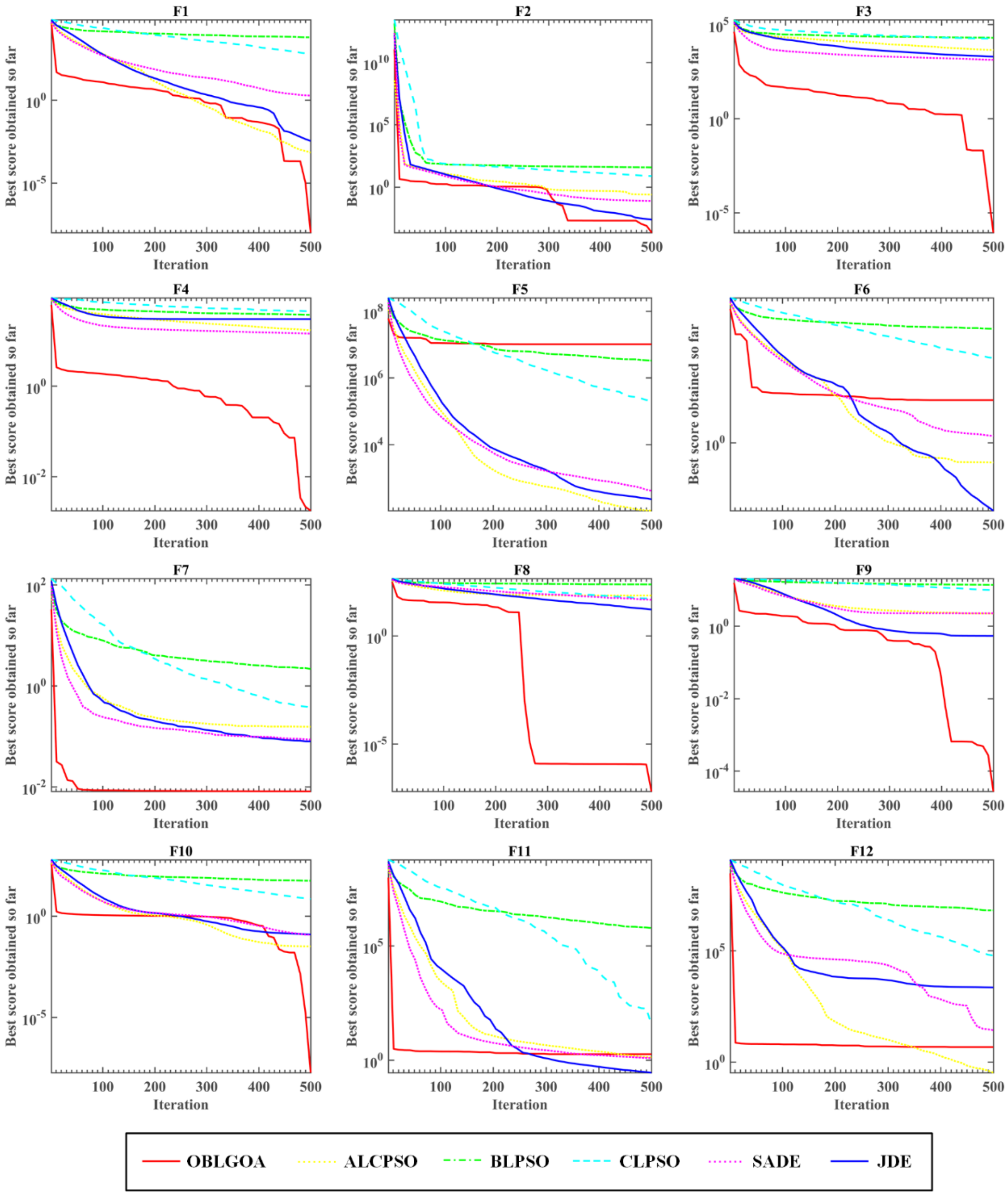

Fig. 15. Convergence plot of OBLGOA with other competitive algorithms on benchmark functions (dim = 30)

5.2 Classification results on the diagnosis of appendix

As mentioned above, the method is separated into two stages. The first stage is to select feature importance. The second stage uses the proposed improved GOA to identify two critical parameters of SVM and then distinguish appendicitis. First, the importance of the 17 features was assessed by the RF algorithm. As shown in Fig. 16, the top nine most important features were CRP, heart rate, body temperature, neutrophils, lymphocytes, eosinophils, blood sugar, urea nitrogen, and creatinine. By testing the feature combinations of these nine features by incremental selection, we found that a subset of the four most important features (CRP, heart rate, temperature, and neutrophils) had the best test results. Therefore, the best subset of features is fed into the learning model. Moreover, to clearly explain the competitive advantages of the proposed method over other competitive algorithms, we introduce four key indicators, including ACC, MCC, sensitivity, and specificity.

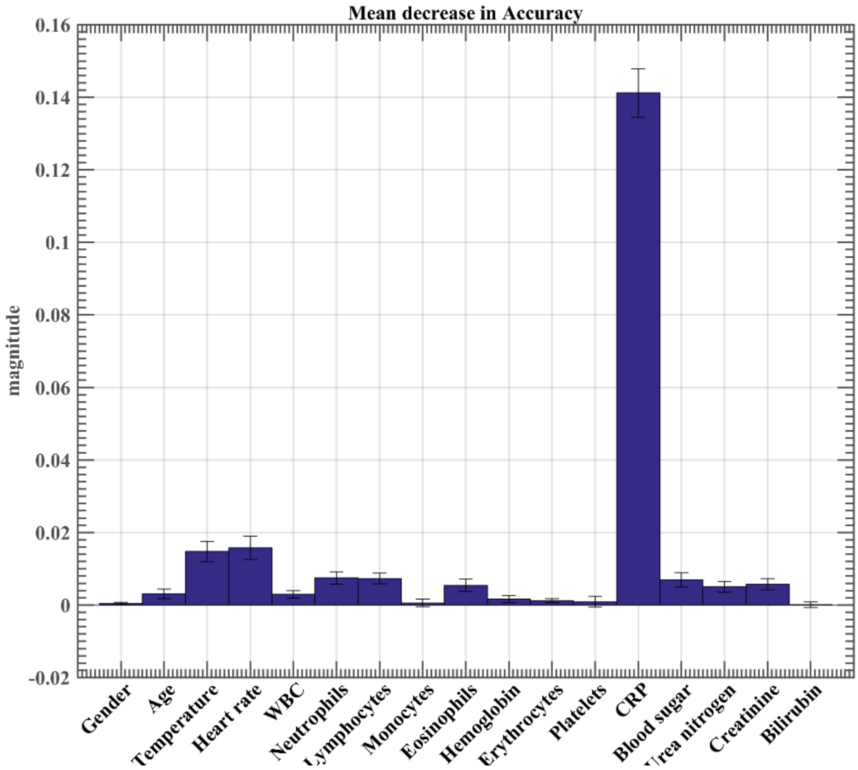

Fig. 16. The importance of the features evaluated by the RF

Table 6 shows the detailed results of OBLGOA-SVM based on the optimal five features. On average, OBLGOA-SVM achieved 83.56% classification accuracy, 67.32% MCC, 81.71% sensitivity, and 85.33% specificity. In addition, we can observe in the experiments that OBLGOA can automatically determine two parameters of SVM, which can be ascribed to the fact that these two parameters can be adaptively optimized by OBLGOA depending on the distribution of training data.

Table 6. Classification behavior of OBLGOA-SVM

Fold	MCC	ACC	Sensitivity	Specificity
#1	0.6555	0.8276	0.7857	0.8667
#2	0.7333	0.8667	0.8667	0.8667
#3	0.6054	0.8000	0.7333	0.8667
#4	0.6682	0.8333	0.8000	0.8667
#5	0.8667	0.9333	0.9333	0.9333
#6	0.4667	0.7333	0.7333	0.7333
#7	0.7333	0.8667	0.8667	0.8667
#8	0.6054	0.8000	0.8667	0.7333
#9	0.6682	0.8333	0.8000	0.8667
#10	0.7295	0.8621	0.7857	0.9333
Ave	0.6732	0.8356	0.8171	0.8533
Std	0.0530	0.1054	0.0645	0.0689

In the current study, many methods were used to diagnose appendicitis, such as RF-based methods

[113-117], SVM-based methods [118, 119], logistic regression-based methods [120-123], ELM-based methods [124], and neural network-based methods [116, 125-128]. These methods have achieved a satisfactory result in the diagnosis of appendicitis. To prove the effectiveness of the method proposed in this study, GOA-SVM, GS-SVM, RF, ELM, KELM, and BPNN were selected for comparative experiments. As displayed in Fig. 17, the results demonstrate that the OBLGOA-SVM model is superior to the classical GOA-SVM model in the four evaluation indices, and the variance is also smaller than that of the original GOA-SVM model. This finding indicates that the OBLGOA-SVM model has better performance and stability than the original GOA-SVM model. OBLGOA-SVM achieves the best results and minimum standard deviation on the ACC indicator. RF was second, followed by GOA-SVM, GS-SVM, KELM and ELM. BPNN is the worst. On the MCC indicator, OBLGOA-SVM performed the best. RF second, followed by GOA-SVM, GS-SVM, KELM, and ELM; BPNN was the worst. RF works best on sensitivity indicators. OBLGOA-SVM was second, followed by GOA-SVM and BPNN. The results of GS-SVM and ELM are very similar, while the KELM is the worst. GS-KELM achieved the best results regarding specificity. OBLGOA-KELM was second, followed by GOA-SVM, KELM, RF, and ELM. BPNN performed the worst. In conclusion, the established OBLGOA-SVM can obtain better results or very competitive results in four performance metrics than other involved methods.

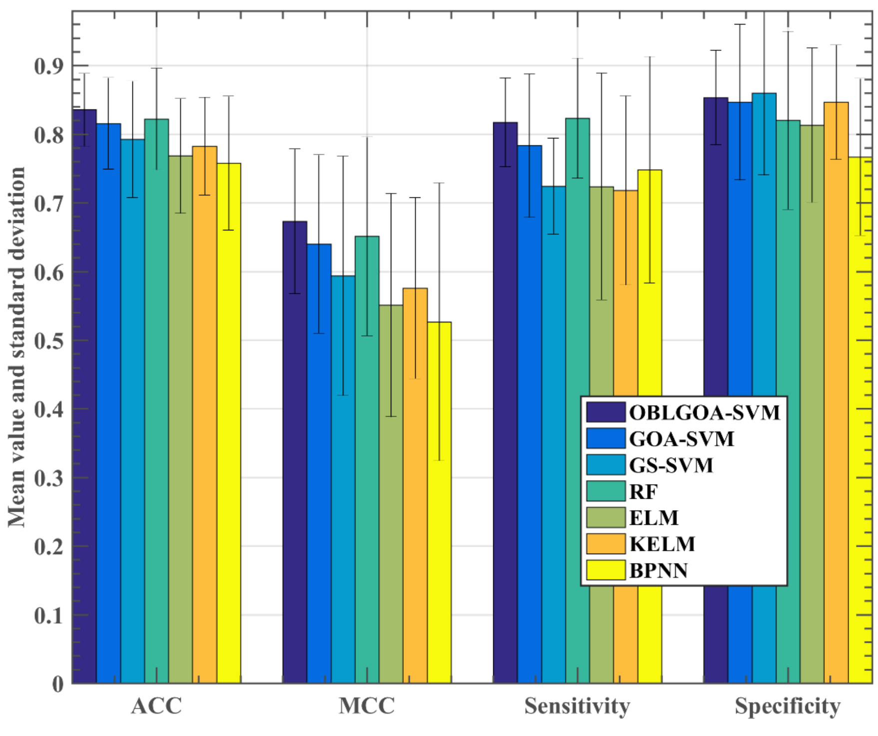

Fig. 17. Classification performance obtained by OBLGOA-SVM and six other methods

6. Discussions

Compared with UAP, the morbidity and mortality rate in patients with CAP is higher[129]. CAP is likely to fail conservative treatment and must be identified early for a successful outcome. Thus, it is of pivotal importance to create effective and safe methods to stratify patients appropriately. Most former studies focused on the evaluation of suspected appendicitis. In the current work, a new machine learning method was developed for a new scenario, i.e., the differential diagnosis between CAP and

UAP, aimed at directing decision-making in patients with confirmed appendicitis in the clinical setting. A few studies have shown that temperature, WBC count, CRP level, neutrophils, lymphocytes, neutrophil-to-lymphocyte count ratio, and bilirubin can distinguish between CAP and UAP [10, 130, 131]. In our study, demographic patient characteristics, thirteen laboratory markers, body temperature, and heart rate were employed to distinguish CAP from UAP. The results revealed that CRP, heart rate, temperature, and neutrophils were most significantly different between the two groups. However, this study neither included the clinical examination findings nor correlated them with the results; such an absence comes from our concern about the subjective findings' quality control. Nevertheless, the 83.56% accuracy outcome, seemingly satisfactory, may be further improved provided the clinical findings were included with good quality control. After all, our primary goal was to explore a reasonably more objective tool independent of individual doctors' experience and expertise, which varies significantly from surgeon to surgeon in rural areas.

The study discovered some interesting results. First, this study found that the WBC count, which has been more widely recognized and adopted as a superior predictor to aid the diagnosis of appendicitis [132], failed to indicate such superiority for the differential diagnosis of CAP and UAP. This fact might be explained by the inconsistency of the phase of the inflammation that the patients were at when they came to the clinic. Second, we found that the lymphocyte count was associated with the CAP. The significance of this finding is not clear, but it could suggest that lymphocytes are a more solid inflammatory response in patients with CAP so clinicians should pay more attention to it.

Of note, this study has two limitations that require further discussion. One limitation of this study is the failure to include radiological findings, such as ultrasound and CT scans, which also have distinguished merit for diagnosis, despite their drawbacks regarding their routine application. Other limitations included the insufficient volume of cases imputed from a single center and an uncontrolled and retrospective study. A multicenter, prospectively randomized control study with more cases is needed to validate the legitimacy of this diagnostic model.

In the near feature, the potential of the proposed OBLGOA can be further explored to solve problems including microgrid planning [133], video deblurring [134], human motion capture [135], image dehazing [136], kayak cycle phase segmentation [137], and location-based services [138, 139], video coding optimization [140], outlier detection [141], multi-view learning [142], multi-objective problems [143] and multivariate time series analysis [144].

7. Conclusions and future works

In this work, a new diagnostic framework, OBLGOA-SVM, was proposed to distinguish between CAP and UAP. The main novelty is constructing an improved GOA strategy to automatically determine two key parameters of the SVM model. Empirical experiments have demonstrated that the established methodology is significantly better than other competitors in various evaluation indicators. In conclusion, CRP, heart rate, body temperature, and neutrophils were found to be reliable predictors of CAP. Such an established decision support system could provide a clinical auxiliary diagnosis to identify patients with high-risk appendicitis, therefore facilitating early and necessary surgical interventions. However, the method proposed in this work does not give further consideration to radiological methods, and it is somewhat insufficient for the number of cases calculated by a single center and retrospective studies that are not subject to control. Although this does not affect the outstanding advantages of diagnosis, there are shortcomings in conventional applications, which will also be the basis for our further research on OBLGOA.

Additionally, in the future, we will further research OBLGOA to solve different and more complex problems, such as optimal power flow, wireless sensor networks, image segmentation, and discrete optimization problems.

Acknowledgments

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