

Research Article

An Enhanced Optimization-Based Support Vector Machine for Urolithiasis Prediction with Topological Guidance and Reflective Learning

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Abstract

Urolithiasis, a condition characterized by the formation of stones in the urinary tract, is influenced by a confluence of factors, including genetic predispositions, dietary habits, and inadequate hydration. This condition can lead to urinary obstruction and pain, elevate the risk of infections, and, in severe cases, potentially impair kidney function. Early identification and prediction are crucial for preventing the formation of urinary stones and mitigating their consequent impacts. In this study, a machine learning model, named bTRWOA-SVM, was developed utilizing data from 1027 suspected patients at the First Affiliated Hospital of Wenzhou Medical University. This model synergizes the whale optimization algorithm (WOA) with the support vector machine (SVM) and introduces enhancements through the triangular topological search strategy and reflective learning operator to augment the search proficiency of the WOA, resulting in a variant termed TRWOA. Comparative analysis against a range of contemporaries using the CEC 2017 benchmark suite substantiated TRWOA's effective optimization capabilities and convergence precision. Furthermore, the constructed bTRWOA-SVM model, when applied to clinical data about urolithiasis, achieved a predictive accuracy of 98.830% and a specificity of 97.665%. Conclusively, the model also identified critical features influencing urolithiasis prediction, including urinary bilirubin, total protein, pH value, creatinine, and direct bilirubin, thereby providing a scientific basis for the early diagnosis and treatment of urolithiasis.

Keywords

Urolithiasis, Machine Learning, Support Vector Machine, Whale Optimization Algorithm, Predictive Modeling, Feature Selection

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1. Introduction

Urolithiasis is the most common disease in urology, and its incidence has been increasing globally in the past few decades [1, 2]. The first symptoms of urolithiasis are mainly sustained severe colic in the lower back and hematuria. If the patient is accompanied by a urinary obstruction, it may even damage the kidney function [3]. Therefore, rapid and accurate determination of the existence of calculi has important guiding significance for prevention and treatment [4]. Since computed tomography (CT) was first applied in urological diagnosis in 1955 [5], it has become the gold standard for the diagnosis of suspected urinary calculi. Its advantage is that it not only accurately determines the location, size, and shape of the stone, but also analyzes the severity of urinary tract obstruction as well as other diseases of the urinary system [6]. Therefore, CT has been widely used in clinical diagnosis and treatment. However, it has some disadvantages, such as high cost and the possibility of cancer induced by excessive radiation [7]. Moreover, the use of CT does not seem to improve the prognosis of patients with urolithiasis [8]. To optimize the clinical diagnosis ability and develop a patient-centered multidisciplinary collaborative diagnosis and treatment mode as the starting point, several clinical prediction tools have been developed. The STONE score proposed by Moore et al. [9] is one of the most representative ones. In the STONE score, five factors were found to be most predictive of ureteral stone: male sex, short duration of pain, race, presence of nausea or vomiting, and microscopic hematuria, which yield a score of 0-13.

Therefore, the development of an accurate diagnosis for urolithiasis is crucial for disease management and prognosis. With the rapid advancement of artificial intelligence technology, machine learning (ML) based diagnostic techniques have demonstrated immense potential in the medical domain. ML operates by analyzing complex patterns and issues through dynamic algorithms on pre-labeled datasets, subsequently generating useful predictive outputs, thus providing effective decision support for healthcare professionals. In the realm of urinary stone disease, numerous researchers have already established predictive models. Chen et al. [10] proposed a predictive model for urolithiasis based on the decision tree, random forest (RandomF), model, extreme gradient boosting, and others. Results on the collected dataset of urolithiasis patients indicated that the predictive model based on the RandomF model achieved the highest accuracy. Furthermore, an analysis of significant features affecting the formation of infected stones (such as gender, urine leukocytes, and urine pH) was conducted based on this model. Haifler et al. [11] utilized XGBoost to develop a predictive model for urinary stones smaller than 5mm based on a dataset collected from 471 urinary stone patients. The model ultimately achieved an 80% prediction accuracy on the collected dataset. Lopez-Tiro et al. [12] compared the performance of six ML

methods and three deep-learning methods for identifying urinary stone types. Experimental results demonstrated that the XGBoost classifier outperformed others, achieving a 96% accuracy rate.

Moreover, Zheng et al. [13] constructed an infectious stone identification model using Fourier transform infrared spectroscopy and multivariate logistic regression analysis. Radiological features were extracted from patient images using Fourier transform infrared spectroscopy, followed by logistic regression to construct the identification model. Experimental results on the dataset indicated that the model built in this study could serve as an effective tool for identifying urinary tract infection stones. Based on 252 collected urine stone samples, Li et al. [14] utilized ex vivo infrared spectroscopy for feature extraction and constructed a urine stone classification decision model using multi-criteria weighted fusion. Chmiel et al. [15] established a stone composition prediction model using gradient boosting machines and logistic regression models, evaluating the model performance using kappa scores. Experimental results indicated that urea, blood uric acid, and carbonate were the three most influential predictive factors. Wu et al. [16], based on a dataset of 1168 urinary stone patients, employed five ML algorithms, including support vector machine (SVM), multilayer perceptron, decision tree, RandomF classifier, and adaptive boosting (AdaBoost) to construct predictive models for urolithiasis. These five predictive models all demonstrated good prediction accuracy.

Although many ML-based urinary stone prediction models have been proposed, in practical applications, medical data often contain noise and irrelevant features, which may effect the classification performance of the models. Therefore, incorporating feature selection (FS) into urinary stone prediction can not only eliminate redundant features but also choose the most relevant features for interpretable diagnosis of the disease. FS methods can be classified into three types: wrapper-based, filter-based, and embedded methods. Among them, wrapper-based FS methods, which select features based on the evaluation metric of classifier performance, can obtain better feature subsets than the other two FS methods. However, when searching for feature subsets in a dataset with many features, this search process is often considered an NP-hard problem [17]. In recent years, many researchers have combined metaheuristic algorithms (MAS) with wrapper-based FS methods due to their powerful search capabilities [18]. By integrating MAS with wrapper-based FS methods, MAS based FS method can effectively explore the search space and find the optimal feature subset within a reasonable amount of time, thereby efficiently reducing feature dimensionality.

Commonly used particle swarm optimization (PSO) [19], Harris hawks optimization (HHO) [20], slime mould algo-

rithm (SMA) [21, 22], sine cosine algorithm (SCA) [23], colony predation algorithm (CPA) [24], rime optimization algorithm (RIME) [25], weighted mean of vectors (INFO) [26], Runge Kutta optimizer (RUN) [27], ant colony optimization (ACO) [28], etc. The whale optimization algorithm (WOA) [29] is a metaheuristic algorithm inspired by the foraging process of whales. Due to its simplicity and few parameters, WOA has been utilized in various disease prediction models to achieve data dimensionality reduction. Atimbire et al. [30] proposed a heart disease risk prediction model using WOA for FS. Betshrine Rachel et al. [31] employed WOA for FS on extracted lung tissue texture and shape features, followed by classification using SVM. Experimental results demonstrated an accuracy of 88.94% for the proposed diagnostic model. Chatterjee et al. [32] introduced a variant of WOA based on an opposition-based learning strategy for FS on diabetes datasets. Govindamoorthi et al. [33] proposed a maximum likelihood swarm WOA for extracting critical features of atherosclerosis. Nadimi-Shahraki et al. [34] proposed an enhanced variant of WOA to address the limitations of the original WOA and applied the proposed algorithm for optimal feature subset selection on medical disease datasets. Furthermore, Kundu et al. [35] presented a WOA variant based on the concept of altruism and performed FS on high-dimensional microarray datasets. Experimental results validated the effectiveness of the proposed method. Tair et al. [36] proposed an enhanced variant of WOA based on chaotic and oppositional-based learning strategy and applied the algorithm for extracting critical features of diabetes and psoriasis. Devi et al. [37] embedded mutation and crossover operations into the original WOA to improve its performance, and then used the proposed algorithm for FS on gene expression data.

Although the WOA has been applied to FS for various diseases to improve the performance of subsequent disease diagnosis models, there has been limited research on using WOA for selecting critical features from urinary stone data.

Therefore, this study aims to predict urinary stone formation based on a collected dataset using the SVM classifier, combined with an FS algorithm based on the WOA, to assist doctors in making clinical decisions in the future. To enhance the optimization performance of the original WOA, the triangulation topology search (TTS) strategy and the reflective learning operator (RLO) strategy inspired by the cooperative search algorithm are proposed. The TTS strategy improves the search efficiency of solutions by utilizing the conversion between polar and Cartesian coordinate systems. The RLO strategy maintains population diversity by promoting communication and cooperation among population individuals, thus preventing the algorithm from falling into local optima. The WOA variant embedded with TTS and RLO strategies is named TRWOA. The effectiveness of the proposed strategies is validated on the CEC 2017 benchmark functions, and the performance of the proposed algorithm is further compared experimentally with 11 state-of-the-art (SOTA) algorithms to validate its performance. Subsequently, a wrapper-based FS model (bTRWOA-SVM) is proposed using the binary version of TRWOA (bTRWOA) and the SVM classifier for urinary stone data FS. bTRWOA-SVM is compared with other MAS-based FS methods and classical classifiers on the collected urinary stone dataset. In summary, the main contributions of this study are as follows:

- 1) The TTS strategy and RLO strategy are introduced into WOA to enhance the optimization capability of the original algorithm.
- 2) The performance of TRWOA is validated using 29 CEC 2017 benchmark functions and compared with existing methods.
- 3) The FS capability of TRWOA is tested on the collected urinary stone dataset.
- 4) Using the minimization of feature subset size and classification error rate as the objective function, bTRWOA-SVM is compared with existing methods on the urinary stone dataset.

2. Materials and Methods

2.1. Urolithiasis Dataset

Table 1. List of the features used in this study and their definitions number.

NO.	Features	Abbr.	NO.	Features	Abbr.
C1	Age	/	C19	Total cholesterol	TC
C2	Sex	/	C20	High-density lipoprotein cholesterol	HDL-C
C3	Hemoglobin	Hb	C21	Low-density lipoprotein cholesterol	LDL-C
C4	Absolute lymphocyte count	ALC	C22	PH value	/
C5	Absolute monocyte count	AMC	C23	Nitrite	Nit

NO.	Features	Abbr.	NO.	Features	Abbr.
C6	Absolute neutrophil count	ANC	C24	Glucose	Glu
C7	Platelet count	PLT	C25	Specific gravity	SG
C8	Red blood cell count	RBC	C26	Protein qualitative	Pro
C9	White blood cell count	WBC	C27	Urobilinogen	Ubg
C10	Total bilirubin	TBil	C28	Bilirubin in urine	Bil
C11	Direct bilirubin	DBil	C29	Ketone bodies	Ket
C12	Total protein	TP	C30	Urinary leukocytes	U-WBC
C13	Albumin	Alb	C31	Casts	/
C14	Glucose	Glu	C32	Epithelial cell count	ECC
C15	Urea	/	C33	Red blood cells in urine	RBC/u
C16	Creatinine	Cr	C34	Pathological casts	/
C17	Uric acid	UA	C35	Crystals	Cry
C18	Triglycerides	TG			

Our patients' data came from the First Affiliated Hospital of Wenzhou Medical University, which is a large general hospital in a large city of more than nine million people. This retrospective study included a total of 1029 samples from 2017 to 2022, which included 289 patients with urolithiasis and 740 patients without urolithiasis. Patients without urolithiasis mean no previous history of urolithiasis and no radiographic indication of the presence of urolithiasis. Patients with urolithiasis have clear imaging evidence. All patients are adults (>18 years) and patients without urinalysis or blood biochemistry tests are excluded. Clinical variables (sex, age), blood chemistry results, and routine urine test were collected for all included patients by 3 urologists through the hospital information system. The detail of the data is shown in [Table 1](#).

All clinical examinations and data collection of patients were conducted in accordance with the Declaration of Helsinki and approved by the Medical Ethics Committee of the First Affiliated Hospital of Wenzhou Medical University.

2.2. Support Vector Machine

When dealing with classification problems, the basic concept behind SVM is to find a hyperplane that maximizes the margin between two classes [38]. However, the original SVM is only capable of solving some simple linear classification problems. To address more complex nonlinear classification problems, researchers have introduced the notion of kernel functions, which map samples from the original space to a higher-dimensional feature space [39]. This mapping renders the samples linearly separable in the higher-dimensional feature space. Commonly used kernel functions include linear kernel functions, polynomial kernel functions, and radial basis

function (RBF) kernels. Among these, the RBF kernel possesses universal approximation capability and, by tuning γ , can smoothly transition between nearly linear and highly nonlinear decision boundaries. Moreover, compared with the polynomial kernel, it entails a more parsimonious hyperparameterization. In this study, the SVM based on the RBF kernel is used to classify the data. The expression of the hyperplane is as follows:

$$x = w^T K(x_i, y_i) + b \quad (1)$$

$$w = \sum_{i=1}^n \alpha_i y_i x_i \quad (2)$$

$$K(x_i, x_j) = \exp\left(\frac{-\|x_i - x_j\|^2}{\gamma}\right) \quad (3)$$

where x denotes the input sample. y is the label w^T is a weight vector, which is described as shown in Eq. (2). and b is a bias. α_i is a Lagrangian multiplier. γ is a nuclear parameter.

2.3. Whale Optimization Algorithm

The WOA constitutes a meta-heuristic algorithm that emulates the foraging behavior of humpback whales, introduced by Mirjalili and Lewis in the year 2016 [29]. This algorithm is predominantly employed in addressing optimization challenges, demonstrating its efficacy, particularly in the identification of global optima. The inspiration behind the algorithm is rooted in the distinctive hunting strategy of humpback whales, especially their utilization of the bubble-net feeding technique during prey capture. The WOA process can be

broadly categorized into three phases: the encircling prey, the spiral updating, and the search for prey phase, with specific formulas presented in Table 2. For a comprehensive exposi-

tion of the WOA procedure, one is advised to refer to Literature [29].

Table 2. Specific formulas in WOA.

Process	Formulas	No.
Encircling prey phase	$X(t+1) = X_{best} - A \times D$	(4)
	$D = C \cdot X_{best} - X(t) $	(5)
	$A = 2 \cdot a \cdot r - a$	(6)
	$C = 2 \cdot r$	(7)
Spiral updating phase	$X(t+1) = D' \cdot e^{fl} \cdot \cos(2\pi l) + X_{best}$	(8)
	$D' = X_{best} - X(t) $	(9)
	$X(t+1) = \begin{cases} X_{best} - A \times D, p < 0.5 \\ D' \cdot e^{fl} \cdot \cos(2\pi l) + X_{best}, \text{otherwise} \end{cases}$	(10)
Search for prey phase	$X(t+1) = X_{rand} - A \times D$	(11)
	$D = C \cdot X_{rand} - X(t) $	(12)

2.4. Proposed Algorithm and Model

2.4.1. Proposed TRWOA Algorithm

The pseudocode for the TRWOA is delineated in Algorithm 1. Within the framework of the proposed TRWOA, the whale population is initially instantiated through a random initialization process. Subsequently, the optimization of individuals within the current evaluation cycle is facilitated by the assessment of fitness values, followed by an update to these values. During position updating, the TTC enables each whale to interact with multiple neighbors rather than a single leader, which enhances local search ability and prevents premature convergence. Afterward, the RLO generates mirrored candidate solutions across the search space, improving global exploration and reducing the risk of being trapped in

local optima.

The computational complexity of the TRWOA algorithm is represented by the notation $O(TRWOA)$. This quantification is predicated upon the amalgamation of three principal computational constituents, namely $O(WOA)$, $O(TTC)$, and $O(RLO)$. Within this framework, the complexity of $O(WOA)$ is defined by the formula $O(MaxFes \times N \times D + 2 \times N \times D)$, which incorporates the maximum number of function evaluations ($MaxFes$), the population size (N), and the dimensionality of the problem space (D). Furthermore, the complexities associated with $O(TTC)$ and $O(RLO)$ are respectively articulated through the expressions $O(MaxFes \times N \times Dim)$. Consequently, the comprehensive computational complexity of the TRWOA algorithm is encapsulated by the expression $O(MaxFes \times N \times (N + 2Dim) + N \times Dim)$.

Algorithm 1: TRWOA framework.

Input: D : the dimensionality of the problem;

N : population size;

ub : Search the upper boundary of space;

lb : Search the lower boundary of space;

$MaxFes$: maximum number of evaluations;

Output: optimal individual X_b and its fitness value $f(X_b)$.

Parameter settings including Fes and $MaxFes$;

Initialize the population X and calculate the fitness value Fit ;

$Fes \leftarrow Fes + N$;

while $Fes \leq MaxFes$ do

Sorted in ascending order by fitness value Fit ;

Update X_b and $f(X_b)$;

```

for  $i = 1$  to  $N$  do
  Generate new members  $X_i$  using Eq. (10) by WOA;
  Calculate the fitness value  $f(X_i)$  for  $X_i$ ;
  if  $f(X_i) < Fit_i$ 
    Update individual  $X_i$  and its fitness  $Fit_i$ ;
  end if
  # Triangular topological search strategy
  if  $rand < 0.5$ 
    Generate new members  $X_\mu$ ,  $X_\nu$ , and  $X_\psi$  using Eqs. (13)-(15) by TTC strategy;
    Calculate the fitness values for  $X_\mu$ ,  $X_\nu$ , and  $X_\psi$ ;
     $[Fit_i, index] \leftarrow \min(f(X_\mu), f(X_\nu), f(X_\psi), Fit_i)$ ;
    Update individual  $X_i$ ;
  end if
end for
# Reflective learning operator
for  $i = 1$  to  $N$  do
  Generate new individual  $X_{RLO}$  using Eq. (18) by RLO;
  Calculate the fitness value  $f(X_{RLO})$  for  $X_{RLO}$ ;
  if  $f(X_{RLO}) < Fit_i$ 
    Update individual  $X_i$  and its fitness  $Fit_i$ ;
  end if
end for
Update to the current position of the  $X_b$  and its fitness value  $f(X_b)$ ;
end while
return  $X_b$  and  $f(X_b)$ .

```

2.4.2. Triangular Topological Search Strategy

In the resolution of optimization problems, the adoption of efficient search strategies emerges as quintessentially critical. The TTS strategy exemplifies an innovative approach by integrating the transformation between polar and Cartesian coordinate systems, thereby enhancing the efficacy and precision of the search process [40]. Within the spherical coordinate system, the commencement of the search is instantiated by the current search agent, denoted as the initial vertex X_i . This point, serving as the genesis of the search endeavor, underpins subsequent transformations. Following this, the application of trigonometric function transformations facilitates the conversion of positions within the spherical coordinate system to their corresponding points in the Cartesian coordinate system. This operation yields a new directional vector with a magnitude of $l \cdot \psi$, where l represents the original vector's length and ψ embodies a magnification factor designed to adjust the vector's magnitude. The terminus of this vector, identified as the second vertex and marked as X_μ , delineates a pivotal step in the search trajectory.

Further, to encompass a broader expanse within the solution space, the generated directional vector undergoes a counterclockwise rotation of $\pi/3$. This rotation is executed based on the original vector X_μ . After the rotation, a transformation back into the coordinate system yields the third

vertex, denoted as X_ν . This procedure not only amplifies the coverage of the search space but also enhances the diversity within the search process by leveraging geometric relationships.

Lastly, by conducting a linear weighting within the ensemble of vertices (X_i , X_μ , and X_ν), a fourth vertex, denoted as X_ψ , is constituted. This step is achieved through the computation of a weighted average of the preceding three vertices, to probe potential solutions within the triangular domain formed by these vertices. This methodology ensures that the search process is not solely fixated on the peripheries of the solution space but also delves into its internal regions, thereby potentially uncovering superior solutions.

The expression for the generation of vertices (X_μ , X_ν , and X_ψ) is articulated as follows:

$$X_\mu = X_i + l \cdot \psi(\vec{\theta}) \quad (13)$$

$$X_\nu = X_i + l \cdot \psi(\vec{\theta} + \pi/3) \quad (14)$$

$$X_\psi = r_1 \cdot X_i + r_2 \cdot X_\mu + r_3 \cdot X_\nu \quad (15)$$

within this framework, l governs the search radius of the current search agent X_i , where $l = 9 \cdot e^{-FES/MaxFES}$. Here, FES denotes the current number of evaluations, and $MaxFES$ signifies the maximum number of evaluations. The

parameter l diminishes as the number of evaluations increases. Moreover, $\psi(\vec{\theta})$ and $\psi(\vec{\theta} + \pi/3)$ represent the directional vectors of the other two edges guided by the cur-

rent search agent X_i , with their expressions delineated as follows:

$$\psi(\vec{\theta}) = [\cos \theta_1, \cos \theta_2, \dots, \cos \theta_D] \quad (16)$$

$$\psi(\vec{\theta} + \pi/3) = [\cos(\theta_1 + \pi/3), \cos(\theta_2 + \pi/3), \dots, \cos(\theta_D + \pi/3)] \quad (17)$$

where $\vec{\theta} = [\theta_1, \theta_2, \dots, \theta_D]$, and $\theta_j \in \vec{\theta}$ denotes a random number within the value range of $[0, \pi]$. Moreover, D signifies the dimensionality of the search space.

2.4.3. Reflective Learning Operator

The concept of the RLO is derived from the cooperative search algorithm [41], which enhances search efficiency and the quality of solutions through mutual aid and cooperation among populations. Regarding the WOA, although its inspiration originates from the hunting behaviors of humpback whales in nature and has demonstrated its superior performance across numerous optimization challenges, its efficiency and effectiveness encounter obstacles when addressing highly complex optimization problems. Specifically, WOA exhibits certain limitations in averting premature convergence

and in maintaining diversity within the search population.

RLO, by integrating an experience-based learning mechanism, synthesizes its experiences in the opposite direction, thereby acquiring new knowledge. This experience-based learning mechanism enables the WOA to autonomously adjust its search way, achieving a more optimal balance between exploring uncharted territories and exploiting known information. Through this methodology, RLO significantly reduces the risk of premature convergence of the algorithm, while simultaneously fostering information exchange and experience sharing within the population. RLO effectively maintains the diversity of the population, thereby enhancing the global search capabilities of the algorithm. Its mathematical model is as follows:

$$X_{RLO}^j = \begin{cases} q_j, & \text{if } X_i^j \geq c_j \\ p_j, & \text{otherwise} \end{cases} \quad (18)$$

$$q_j = \begin{cases} \phi(ub_j + lb_j - X_i^j, c_j), & \text{if } |X_i^j - c_j| < \phi(0, 1) \cdot (ub_j - lb_j) \\ \phi(lb_j, ub_j + lb_j - X_i^j), & \text{otherwise} \end{cases} \quad (19)$$

$$p_j = \begin{cases} \phi(c_j, ub_j + lb_j - X_i^j), & \text{if } |X_i^j - c_j| < \phi(0, 1) \cdot (ub_j - lb_j) \\ \phi(ub_j + lb_j - X_i^j, ub_j), & \text{otherwise} \end{cases} \quad (20)$$

$$c_j = (ub_j + lb_j)/2 \quad (21)$$

where X_{RLO}^j represents the j th dimension of the newly generated solution through reflection upon X_i^j , where X_i^j denotes the j th dimension of the current search agent. ub_j and lb_j respectively signify the upper and lower bounds of the search space in the j th dimension. $\phi(L, U)$ is a function employed to generate a random number uniformly distributed within the $[L, U]$.

2.5. Proposed bTRWOA-SVM Model

2.5.1. The Framework of bTRWOA-SVM

Figure 1 illustrates the flowchart of the proposed bTRWOA-SVM model. To better evaluate the performance of the proposed model and reduce the risk of overfitting, ten-fold cross-validation is employed to train the model. This

involves partitioning the given dataset into ten equally sized subsets, with nine subsets used as training data and one subset as validation data. During the feature subset search process, bTRWOA is utilized to search for the optimal feature subset. The model is trained based on the searched feature subset and SVM classification. Subsequently, the quality of the feature subset is evaluated using an adaptive function based on the number of features and the classification accuracy of the model. A greedy selection strategy is then employed to choose the current optimal feature subset, ultimately outputting the optimal feature subset. After finding the optimal feature subset, the performance of the classification model is evaluated using the validation set based on the optimal feature subset and the SVM classifier. This process is repeated ten times, and the average of the ten evaluation results is used as the performance metric of the model to more accurately assess its generalization ability.

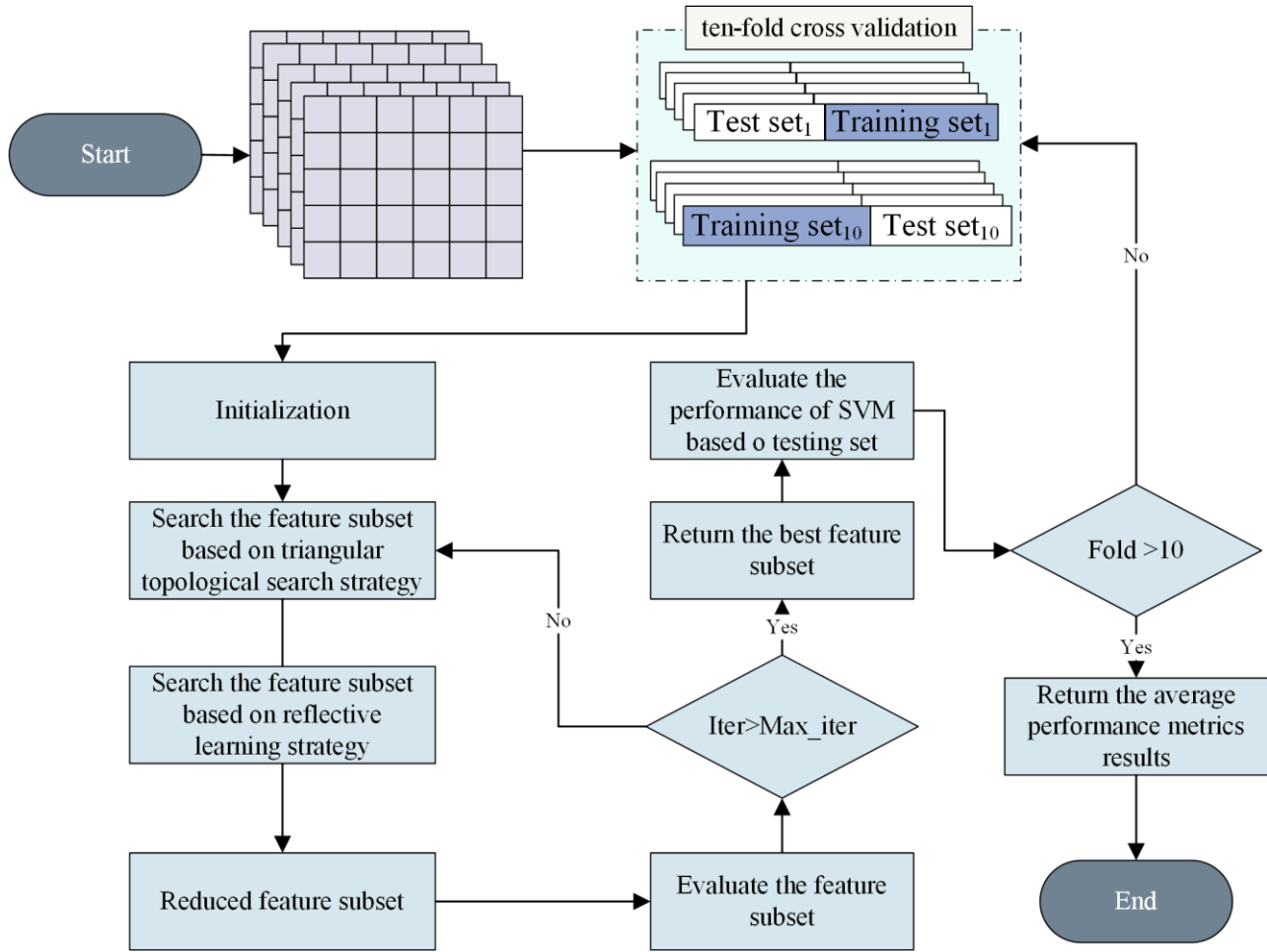


Figure 1. Flowchart of the bTRWOA-SVM model.

2.5.2. Transfer Function

The proposed TRWOA in Section 3.1 is suitable for continuous space, while FS operates in a discrete space where “1” indicates the current feature is selected and “0” indicates the current feature is not selected. Therefore, a transfer function (TF) is required to map the position of the search individual to binary space. For the current search agent X_i , the TF as described in Eq. (23) is used to map its position to binary form bX_i .

$$bX_i = \begin{cases} 1 & S(X_i) > rand \\ 0 & \text{otherwise} \end{cases} \quad (22)$$

$$S(x) = \frac{1}{1 + e^{-2x}} \quad (23)$$

where $rand$ is a random number within the range $[0,1]$.

2.5.3. Fitness Function

During the process of using bTRWOA to search for the optimal feature subset, a fitness function is required to evaluate the quality of the currently selected feature subset. Minimizing the number of selected features (F_n) and maximizing the classification accuracy (Acc) are the two key objectives in FS problems. Therefore, to simultaneously satisfy these two objectives, this study adopts Eq. (24) as the fitness function.

$$Fitness = \alpha \times (1 - Acc) + \beta \times \frac{|F_n|}{|N|} \quad (24)$$

where α and β are two control parameters, with values set to 0.99 and 0.01 respectively.

3. Results

3.1. Experiments on Benchmark Functions

3.1.1. Benchmarks Validation

Table 3. The parameter setting of comparison algorithms.

Algorithm	Reference	Parameter information
TRWOA	Presented	$b = 1; p = [0,1]$
CGPSO	[42]	$1 = c2 = 2; W_{max} = 0.9; W_{min} = 0; W_{min} = 0.2; V_{max} = 6$
ASCA-PSO	[43]	$V_{max} = 6; w_{Max} = 0.9; w_{Min} = 0.2; c1 = 2; c2 = 2$
ALGSA	[44]	$p = 0.5; limit = 2$
CCMWOA	[45]	$m = 1500$
CDLOBA	[46]	$Q_{min} = 0; Q_{max} = 2$
SCADE	[47]	$beta_{min} = 0.2; beta_{max} = 0.8; Pcr = 0.8$
BMWOA	[48]	$b = 1; p = [0,1]$
CGSCA	[49]	$a = 2; delta = 0.1$
ISNMWOA	[50]	$a_1 = [0,2]; a_2 = [-2, -1]; alpha = 0.5$
RCBA	[51]	$Q_{min} = 0; Q_{max} = 2$
MWOA	[52]	$p = [0,1]; p2 = [0,1]$

To validate the performance of the proposed TRWOA, it is tested using the CEC 2017 benchmark functions [53]. The CEC 2017 benchmark functions comprise four different types of functions: unimodal, multimodal, hybrid, and composition functions, providing a comprehensive assessment of algorithm performance. Additionally, 11 SOTA algorithms are selected for performance comparison with TRWOA. *Table 3* lists the parameter settings for the proposed TRWOA and other algorithms. To ensure experimental fairness and effectiveness, the population size, maximum evaluation times, and test problem dimensions for all algorithms are set to 30, 30×10^4 , and 30, respectively. Furthermore, all algorithms are independently run 30 times, and the average fitness value (Avg) and standard deviation (Std) of these 30 runs are calculated to rank algorithm performance. Additionally, the Wilcoxon signed-rank test (WST) [54], and Friedman test (FRT) [55], and the Bonferroni post-hoc test (BP) [56] are conducted for significance analysis of the experimental results.

3.1.2. Ablation Study

To validate the effectiveness of the TTS and RLO strategies and their impact on algorithm performance, variants corresponding to these two strategies (TTSWOA and

RLOWOA) are designed using sensitivity analysis. Comparative experiments are conducted among TRWOA, TTSWOA, RLOWOA, and WOA using the CEC 2017 test functions. The Avg and Std results are presented in Supplementary Material S1, where the optimal results are highlighted in bold. From the results in the table, it can be observed that both TTSWOA and RLOWOA outperform the original WOA on the benchmark functions, indicating that the TTS and RLO strategies enhance the optimization capability of the original WOA to some extent. The TRWOA algorithm, which combines the TTS and RLO strategies, ultimately achieves the smallest Avg on 15 benchmark functions and the second smallest Avg on 13 benchmark functions, suggesting that the combination of TTS and RLO strategies can better enhance the optimization capability of the original WOA. *Table 4* illustrates the final average rankings of each algorithm, where a smaller ranking indicates better performance. TRWOA achieves the best average ranking of 1.52, ranking first. TTSWOA and RLOWOA achieve average rankings of 2.34 and 2.55, respectively, ranking second and third, indicating that the contributions of the TTS and RLO strategies to TRWOA are significant. The original WOA ranks last.

Table 5 presents the WST results for these four algorithms. In the table, “+”, “-”, and “=” represent TRWOA's perfor-

mance being better than, worse than, and similar to the comparison algorithms on the current benchmark function, respectively. The last row of the table, “S+/S-/S=”, summarizes the number of test functions that TRWOA is better than, worse than, and similar to the comparison algorithms across all benchmark functions. From Table 6, it can be observed that for most test functions, TRWOA's optimization performance is significantly better than that of WOA. Compared to TTSSWOA and RLOWOA, TRWOA's performance is significantly superior on 11 and 16 test functions, respectively. In summary, both TTS and RLO strategies contribute to improving the performance of WOA from different perspectives, and the performance improvement of TRWOA, which combines TTS and RLO, is the most significant.

Figure 2 presents the average ranking results of FRT for TRWOA and the other three algorithms. The curves in the figure indicate that the proposed TRWOA achieves the smallest average ranking value. TTSSWOA and RLOWOA are positioned second and third, respectively, reaffirming the effectiveness of the TTS and RLO strategies.

To visually analyze the convergence ability of the pro-

posed algorithms, Figure 3 and Figure 4 respectively depict the convergence curves and corresponding violin plots of these four algorithms on six test functions. Observing Figure 3, it can be noted that TRWOA exhibits the fastest convergence speed and highest convergence accuracy compared to TTSSWOA, RLOWOA, and WOA, indicating the effectiveness of the TTS and RLO strategies in significantly improving the algorithm's convergence speed and performance. Figure 4 illustrates the distribution of the best fitness values obtained by the algorithms in 30 independent experimental runs. In the violin plot, the solid dot in the middle represents the mean of the data. The width of the plot indicates the density of the data at that position, with wider widths indicating denser data points. The ends of the violin plot represent the extremes of the data, and the extended lines denote the range of the data. The results in the figure indicate that TRWOA achieves higher distribution results compared to TTSSWOA, RLOWOA, and WOA in most instances, demonstrating the superior stability of TRWOA. In summary, the TTS and RLO strategies effectively enhance the convergence speed and accuracy of the original WOA.

Table 4. The average rank of TRWOA, TTSSWOA, RLOWOA, and WOA is based on Avg and Std. “Mean Rank” means the average rank based on the Avg and Std results. “Rank” means the final rank results.

Algorithm	Mean Rank	Rank
TRWOA	1.52	1
TTSSWOA	2.34	2
RLOWOA	2.55	3
WOA	3.59	4

Table 5. WST results of TRWOA, TTSSWOA, RLOWOA, and WOA based on Avg and Std. “+”, “-”, and “=” represent TRWOA's performance being better than, worse than, and similar to the comparison algorithms on the current test function, respectively. “S+/S-/S=” is the total number of test functions that TRWOA is better than, worse than, and similar to the comparison algorithms across all benchmark functions.

	TTSSWOA			RLOWOA			WOA		
F1	3.06500E-04	-		6.14315E-01	=		1.73440E-06	+	
F2	6.83586E-03	-		1.73440E-06	+		1.73440E-06	+	
F3	8.29013E-01	=		3.40526E-05	+		1.36011E-05	+	
F4	4.86026E-05	+		1.20445E-01	=		1.05695E-04	+	
F5	4.86026E-05	+		5.17048E-01	=		1.73440E-06	+	
F6	3.93334E-01	=		1.92092E-06	+		1.73440E-06	+	
F7	3.06500E-04	+		2.05888E-01	=		3.37885E-03	+	
F8	3.58884E-04	+		7.97098E-01	=		6.98378E-06	+	
F9	7.49871E-01	=		1.03568E-03	+		6.42421E-03	+	
F10	6.42421E-03	+		1.35908E-01	=		1.73440E-06	+	

	TTSWOA		RLOWOA		WOA	
F11	5.03833E-01	=	4.28430E-01	=	1.73440E-06	+
F12	5.19307E-02	=	1.04444E-02	+	1.73440E-06	+
F13	1.52861E-01	=	8.46608E-06	+	1.92092E-06	+
F14	9.75387E-01	=	2.71155E-01	=	2.35342E-06	+
F15	3.16034E-02	+	1.04444E-02	+	4.07151E-05	+
F16	3.06500E-04	+	1.75184E-02	+	7.51366E-05	+
F17	6.87136E-02	=	4.90798E-01	=	9.31566E-06	+
F18	3.28571E-01	=	4.52807E-01	=	1.73440E-06	+
F19	5.44625E-02	=	6.88359E-01	=	3.60943E-03	+
F20	3.31726E-04	+	3.00099E-02	+	2.84342E-05	+
F21	5.31968E-03	+	4.11403E-03	+	5.70644E-04	+
F22	3.85424E-03	+	1.10792E-02	+	8.58958E-02	=
F23	2.45190E-01	=	6.88359E-01	=	4.77947E-01	=
F24	2.70292E-02	-	4.38962E-03	+	6.31976E-05	+
F25	8.93644E-01	=	8.30707E-04	+	4.07023E-02	+
F26	1.98610E-01	=	2.61343E-04	+	3.49346E-01	=
F27	3.28571E-01	=	9.31566E-06	+	1.73440E-06	+
F28	1.60464E-04	+	4.11403E-03	+	1.14992E-04	+
F29	5.03833E-01	=	1.30592E-01	=	1.73440E-06	+
S+/S-/S=	11/3/15		16/0/13		26/0/3	

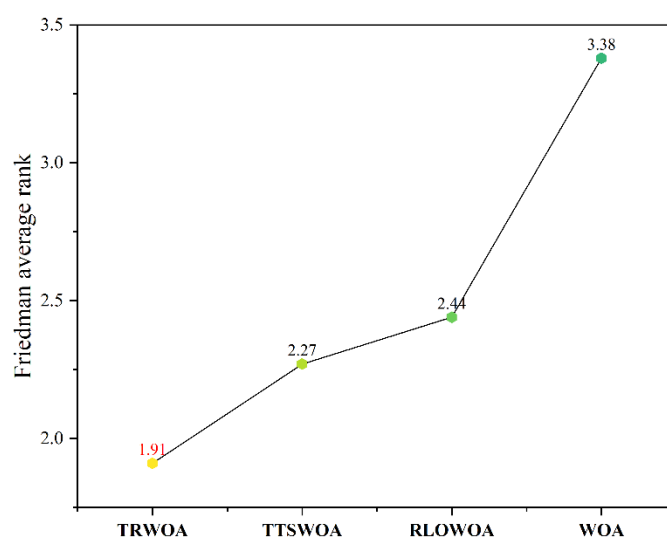


Figure 2. FRT average rank of TRWOA, TTSWOA, RLOWOA, and WOA.

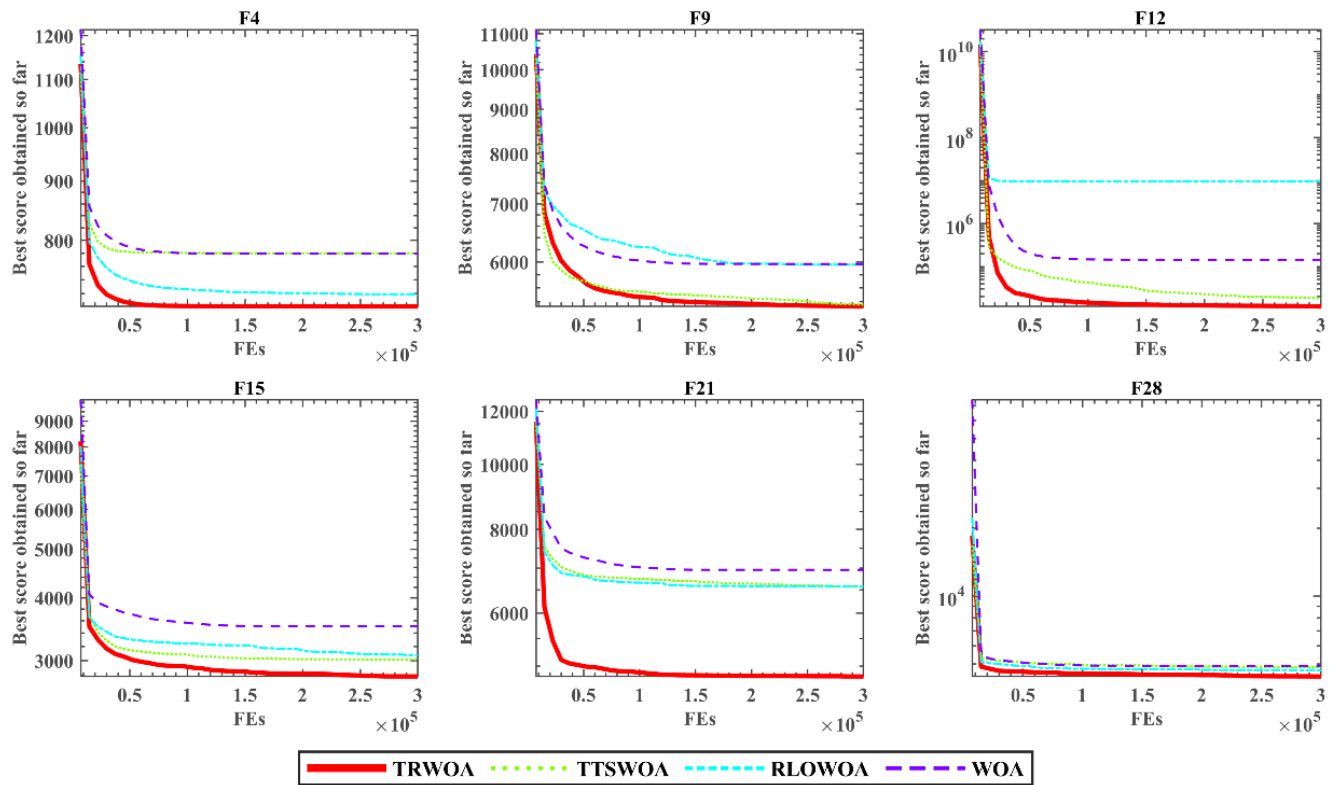


Figure 3. Convergence curves of TRWOA, TTSWOA, RLOWOA, and WOA.

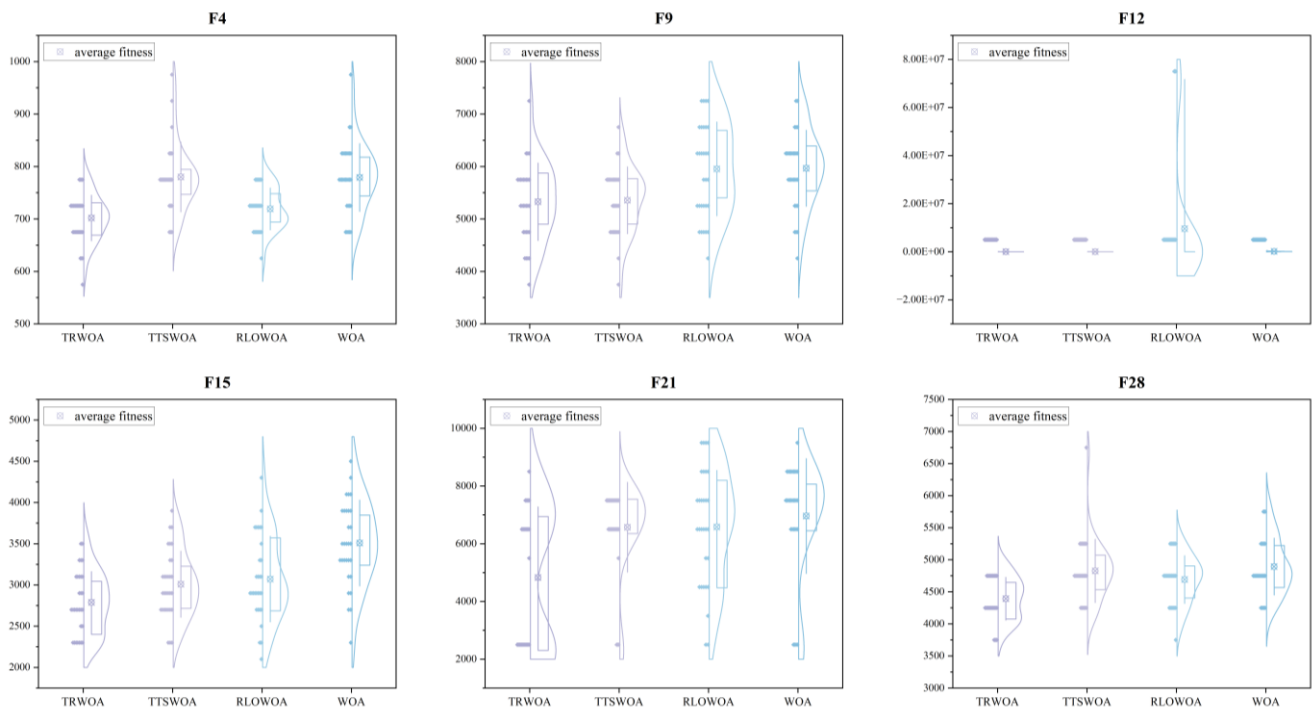


Figure 4. Violin plot of TRWOA, TTSWOA, RLOWOA, and WOA.

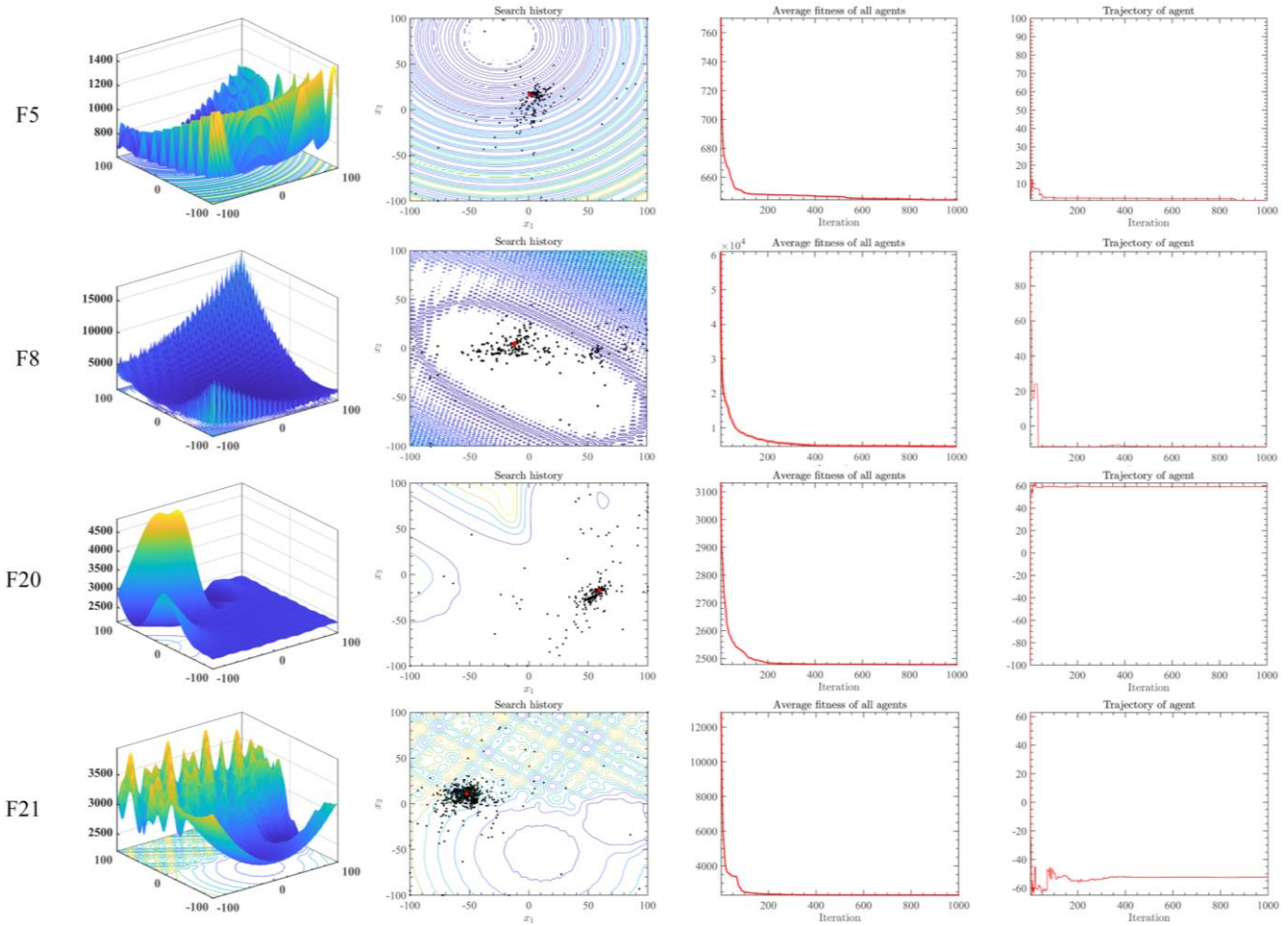


Figure 5. Qualitative analysis of TRWOA on four test functions.

3.1.3. Qualitative Analysis of TRWOA

This section discusses the qualitative results of TRWOA in handling different test functions. Figure 5 presents four indicators: the search space of different test functions, search history, trajectory curves, and average fitness values.

The first column plots three-dimensional illustrations of F5, F8, F20, and F21, revealing that the surfaces of these four functions are uneven and have multiple local optima, thereby better validating the optimization capability of the proposed algorithm. From the trajectory curves in Figure 5, it can be observed that TRWOA experiences oscillations of varying amplitudes during the initial stages of seeking the optimal solution, which gradually diminish in the later iterations, eventually converging to the optimal position. Considering the search history in the second column, it can be noticed that the majority of black dots representing search individuals are clustered around the red dot representing the optimal solution, with only a small fraction of black dots being distant from the

red dot. This demonstrates the robust search capability of TRWOA. Furthermore, observing the average fitness results in the third column, the variation of TRWOA throughout the entire iteration process demonstrates the positive impact of adopting the TTS and RLO strategies on fitness. These two strategies assist the algorithm in rapidly converging toward the vicinity of the optimal solution, thus exhibiting rapid descent in the early iterations.

3.1.4. Comparison Experiments with SOTA

In this section, TRWOA is compared with the SOTA algorithms on the CEC 2017 benchmark functions. Supplementary Material S2 provides the best results obtained by each algorithm on each function. From the data in the table, it is evident that TRWOA achieves better results than the comparison algorithms for most functions. TRWOA obtains the top-ranking results on functions F4, F7, F9, F10, F12, F15, and F19, and secures the second-best results on functions F5, F6, F8, F14, F16, F17, F20, and F29.

Table 6. The average rank of TRWOA and SOTA algorithms based on Avg and Std. “Mean Rank” means the average rank based on the Avg and Std results. “Rank” means the final rank results.

Algorithm	Mean Rank	Rank
TRWOA	3.00	1
ASCA-PSO	4.17	3
CGPSO	3.86	2
ISNMWOA	4.83	4
SCADE	8.34	10
CCMWOA	9.07	11
CDLOBA	6.97	9
BMWOA	6.07	6
CGSCA	6.86	7
RCBA	6.03	5
ALGSA	6.90	8
MWOA	11.90	12

Table 7. WST result and FRT average rank of TRWOA and SOTA algorithms. “S+/S-/S=” is the total number of test functions that TRWOA is better than, worse than, and similar to the comparison algorithms across all benchmark functions.

Algorithm	WST S+/S-/S=	FRT	
TRWOA	\	3.52	1
ASCA-PSO	13/6/10	4.47	2
CGPSO	17/6/6	4.65	4
ISNMWOA	13/10/6	4.62	3
SCADE	26/1/2	8.45	10
CCMWOA	29/0/0	8.89	11
CDLOBA	22/3/4	6.44	8
BMWOA	24/2/3	6.32	7
CGSCA	24/2/3	7.33	9
RCBA	17/6/6	5.86	5
ALGSA	19/5/5	6.24	6
MWOA	29/0/0	11.21	12

Table 6 records the final average ranking results for these 12 algorithms. Compared to the other comparison algorithms, TRWOA effectively enhances the optimization performance of the algorithm by incorporating the TTS and RLO strategies. Therefore, TRWOA ultimately ranks first with an average ranking of 3.00. CGPSO and ASCA-PSO closely follow. The optimization performance of CCMWOA and MWOA is

comparatively weaker among these algorithms.

Table 7 records the results obtained by TRWOA and the SOTA algorithms in terms of the WST and the average ranking results obtained by the FRT. From the table, it can be observed that TRWOA achieves effective and significant results on most test functions. The performance of TRWOA is significantly better than MWOA and CCMWOA on all test

functions. Additionally, TRWOA significantly outperforms SCADE, BMWOA, CDLOBA, CGSCA, and ALGSA on 26, 24, 22, 24, and 19 test functions, respectively. It is worth noting that the optimization performance of ASCA-PSO and ISNMWOA is comparable to that of the proposed TRWOA. TRWOA significantly outperforms ASCA-PSO and ISNMWOA on only 13 test functions, and its performance is significantly weaker than ASCA-PSO and ISNMWOA on 6 and 10 functions, respectively. Supplementary Material S3 presents the p-value results obtained by TRWOA and the comparison algorithms in the WST. The p-values for most test functions in the table are less than 0.05, indicating significant differences in performance between TRWOA and the comparison algorithms on most test functions.

On the other hand, the average ranking results obtained from the FRT in Table 7 once again demonstrate that the performance of the proposed TRWOA surpasses that of the comparison algorithms, with an FRT average ranking of 3.52, ranking first. Based on the FRT results, a BP test is conducted. The BP test helps control the type I error rate and determines whether there are significant differences between the proposed algorithm and the comparison algorithms based on the

corrected significance level. Figure 6 illustrates the BP results with significance levels of 0.05 and 0.1. The solid and dashed lines represent the threshold lines for significance levels of 0.05 and 0.1, respectively. If the FRT average ranking of a comparison algorithm exceeds the threshold, it indicates that there is a significant difference in performance between TRWOA and that particular comparison algorithm at the given significance level. The results in the figure indicate that at both significance levels, there are significant differences in performance between TRWOA and SCADE, CCMWOA, CDLOBA, BMWOA, CGSCA, ALGSA, and MWOA, while no significant differences exist between TRWOA and the other comparison algorithms.

Figure 7 and Figure 8, respectively, illustrate the convergence curves and corresponding violin plots of the TRWOA and SOTA algorithms across six test functions. From Figure 7, it is evident that TRWOA performs well on these six test functions, exhibiting fast convergence speed and high convergence accuracy. The violin plots depicted in Figure 8 indicate that TRWOA possesses better stability. In summary, the proposed TRWOA in this study demonstrates strong competitiveness in terms of optimization performance.

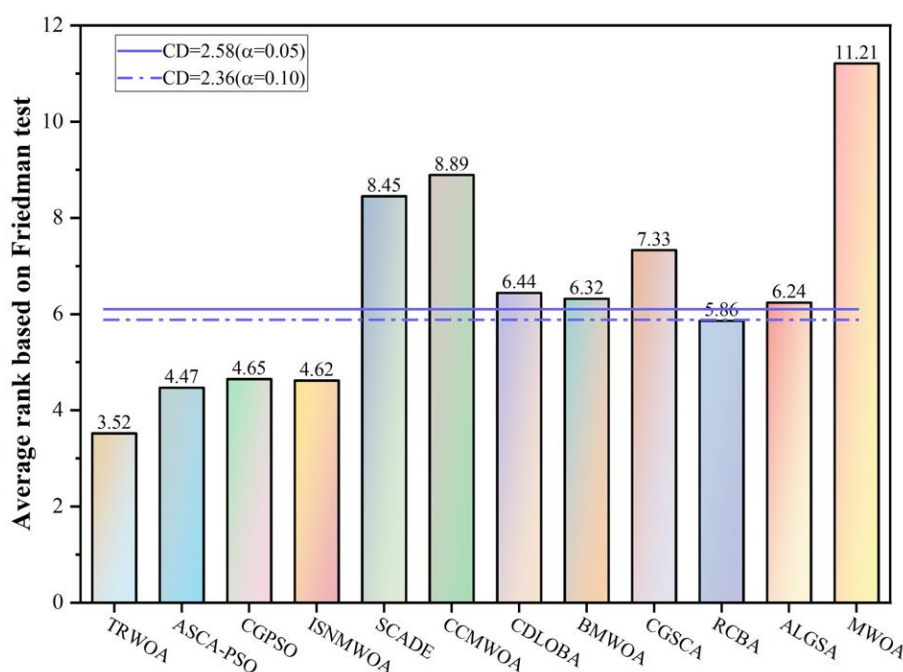


Figure 6. BP results of TRWOA and SOTA algorithms. The solid and dashed lines represent the threshold lines for significance levels of 0.05 and 0.1, respectively.

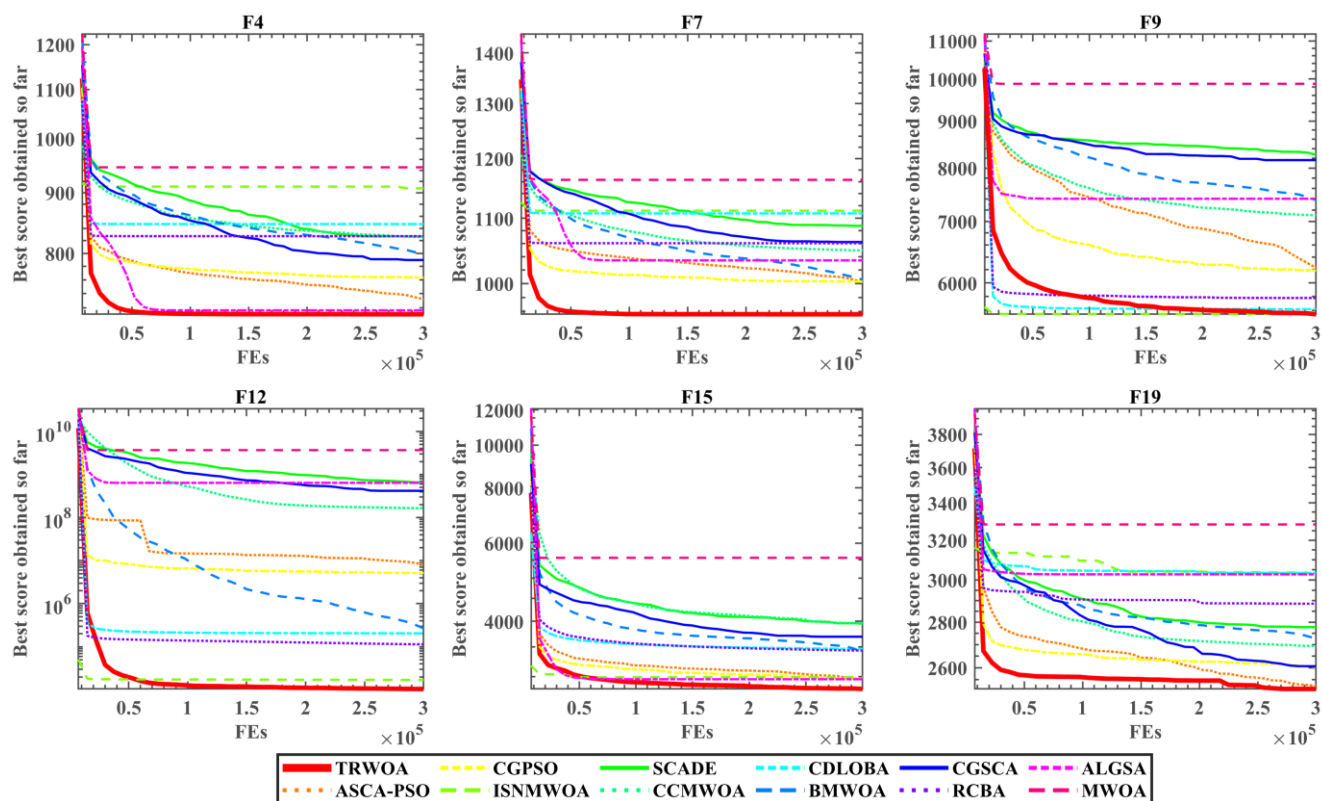


Figure 7. Convergence curves of TRWOA and SOTA algorithms.

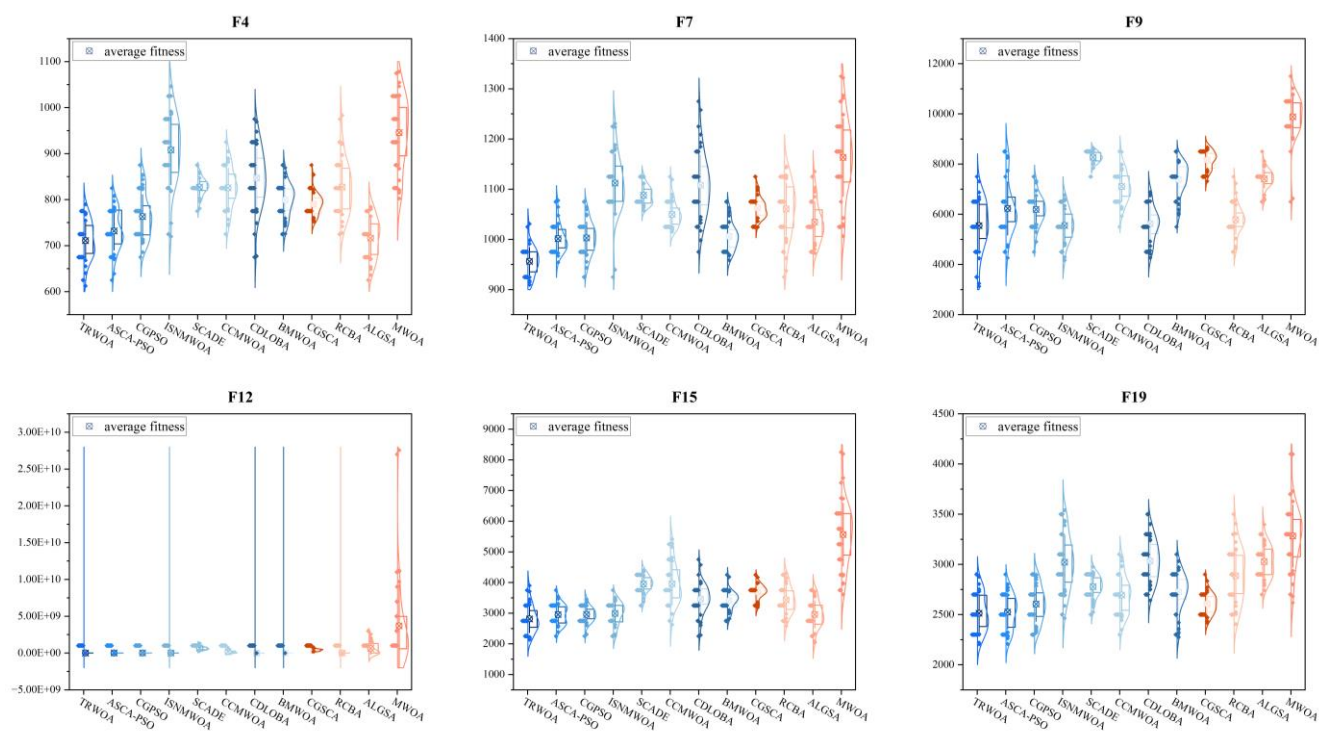


Figure 8. Violin plots of TRWOA and SOTA algorithms.

3.2. Urolithiasis Classification Prediction Experiments

3.2.1. Experiment Setup

This portion of the study focuses on evaluating the effectiveness of the bTRWOA-SVM model in the prediction of urolithiasis. The urolithiasis dataset, upon which this study is predicated, has been thoroughly described in section 2.1. To comprehensively evaluate the model's performance, six widely recognized performance metrics were employed: accuracy, specificity, sensitivity, precision, the Matthews correlation coefficient (MCC), and the F-measure [57, 58].

The bTRWOA-SVM model under examination was initially contrasted with a variety of both traditional and modern machine learning models, including AdaBoost, RandomF, fuzzy k-nearest neighbors (FKNN), classification and regression trees (CART), SVM, k-nearest neighbors (KNN), and backpropagation neural network (BP), all of which were configured using their default parameter settings. Furthermore, comparisons were made with recently proposed FS algorithms, encompassing bHHOSRL [59], PbGSK_V4 [60], and bRFACO [61], as well as with classic FS algorithms such as bACO [28], bABC [62], bRIME [25], and bWOA [63]. All these FS algorithms were integrated with an SVM classifier to evaluate the performance of the selected feature subsets, adopting parameter settings as recommended in the original publications.

To ensure the experiments were both fair and standardized, the experimental design adhered to strictly defined guidelines. The population size for the FS algorithms was uniformly set at 20, with their dimensions determined by the number of features in the urolithiasis dataset, and the number of iterations for the experiments was fixed at 50. Considering the potential impact of experimental randomness on result accuracy, this study conducted ten independent experimental runs to enhance the reproducibility of the results and to mitigate the effects of random errors.

3.2.2. Comparison of Different Transformation Functions

Recent research has illuminated the central role TFs play in augmenting the classification efficacy of models, a relevance extending from gene selection [64] to the prediction of diseases [65, 66]. Consequently, this study aims to individually evaluate the integration of various TFs with the bTRWOA-SVM model to ascertain the TF most conducive to the accurate prediction of urolithiasis.

Figure 9 presents a histogram of average errors for the bTRWOA-SVM model's predictions of urolithiasis under different TFs. Overall, the combination of all evaluated TFs with the bTRWOA-SVM model achieves an accuracy exceeding 95% in predicting urolithiasis. Among these, the S3-type TF exhibits relatively inferior performance in terms of sensitivity, while the S2 falls slightly short on other evaluation metrics. Notably, the integration of S1-type TF with the bTRWOA-SVM model demonstrates superior performance in predicting urolithiasis compared to other TFs.

More detailed outcomes are presented in Table 8, which offers a quantitative analysis of the performance of the bTRWOA-SVM model in the task of predicting urolithiasis using TFs, covering the Avg and Std across six evaluation metrics. Significantly, the bTRWOA-SVM-S1 showcases exceptional performance across all metrics, with an accuracy of 98.830%, sensitivity of 97.665%, specificity of 99.340%, and precision of 98.239%, where the MCC and F-measure are 97.138% and 97.897%, respectively. These figures emphatically demonstrate the model's high accuracy, stability, and superior performance in predicting urolithiasis. The results not only underscore the capability of bTRWOA-SVM-S1 in precisely identifying patients with and without urolithiasis but also highlight the optimal efficacy of the S1-type TF for the bTRWOA-SVM prediction of urolithiasis.

From the analysis above, it can be concluded that the combined use of the bTRWOA-SVM model with the S1-type TF exhibits a significant advantage in predicting urolithiasis. Subsequent comparative experiments will involve analyzing the integration of S1 and bTRWOA-SVM with other models.

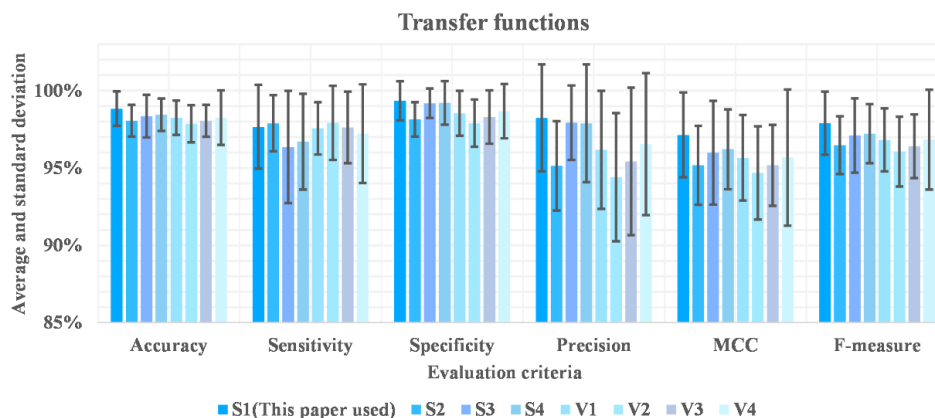


Figure 9. Performance comparison of bTRWOA-SVM on different TF.

Table 8. Avg and Std of the bTRWOA-SVM for predicting urolithiasis at different TF.

Methods	Accuracy		Sensitivity		Specificity	
/	Avg	Std	Avg	Std	Avg	Std
bTRWOA-SVM-S1	98.830%	0.011	97.665%	0.027	99.340%	0.013
bTRWOA-SVM-S2	98.055%	0.010	97.892%	0.018	98.139%	0.011
bTRWOA-SVM-S3	98.348%	0.014	96.353%	0.036	99.189%	0.010
bTRWOA-SVM-S4	98.441%	0.010	96.698%	0.031	99.210%	0.014
bTRWOA-SVM-V1	98.248%	0.011	97.559%	0.017	98.542%	0.015
bTRWOA-SVM-V2	97.856%	0.012	97.913%	0.024	97.891%	0.015
bTRWOA-SVM-V3	98.049%	0.010	97.621%	0.023	98.294%	0.017
bTRWOA-SVM-V4	98.248%	0.018	97.224%	0.032	98.675%	0.018
Methods	Precision		MCC		F-measure	
/	Avg	Std	Avg	Std	Avg	Std
bTRWOA-SVM-S1	98.239%	0.035	97.138%	0.027	97.897%	0.020
bTRWOA-SVM-S2	95.135%	0.029	95.170%	0.025	96.471%	0.019
bTRWOA-SVM-S3	97.931%	0.024	95.986%	0.034	97.101%	0.024
bTRWOA-SVM-S4	97.894%	0.038	96.210%	0.026	97.212%	0.019
bTRWOA-SVM-V1	96.170%	0.038	95.653%	0.028	96.815%	0.020
bTRWOA-SVM-V2	94.397%	0.041	94.676%	0.030	96.060%	0.023
bTRWOA-SVM-V3	95.419%	0.048	95.171%	0.026	96.408%	0.021
bTRWOA-SVM-V4	96.539%	0.046	95.669%	0.044	96.829%	0.032

3.2.3. Comparison Experiment of Predictive Models

To evaluate the performance of bTRWOA-SVM in predicting urolithiasis, a comparative analysis was conducted against seven other FS models constructed based on SVM, as well as against seven widely recognized classification models. The SVM-based models included in this analysis are

bHHOSRL-SVM, PbGSK_V4-SVM, bRFACO-SVM, bACO-SVM, bABC-SVM, bRIME-SVM, and bWOA-SVM. In parallel, the comparison extended to well-known classification models, encompassing AdaBoost, RandomF, FKNN, CART, SVM, KNN, and BP.

Table 9. Avg and Std of the bTRWOA-SVM with other models predicting urolithiasis.

Methods	Accuracy		Sensitivity		Specificity	
/	Avg	Std	Avg	Std	Avg	Std
bTRWOA-SVM	98.830%	0.011	97.665%	0.027	99.340%	0.013
bHHOSRL-SVM	97.955%	0.011	95.974%	0.034	98.785%	0.008
PbGSK_V4-SVM	97.275%	0.015	96.837%	0.029	97.492%	0.016
bRFACO-SVM	89.665%	0.099	73.290%	0.390	90.435%	0.102
bACO-SVM	96.396%	0.010	93.805%	0.024	97.461%	0.014
bABC-SVM	97.566%	0.013	97.138%	0.022	97.745%	0.014

Methods	Accuracy		Sensitivity		Specificity	
bRIME-SVM	97.762%	0.012	96.607%	0.032	98.266%	0.012
bWOA-SVM	98.248%	0.014	97.603%	0.027	98.551%	0.017
AdaBoost	97.958%	0.021	96.628%	0.041	98.534%	0.018
RandomF	96.103%	0.025	94.207%	0.060	96.944%	0.019
FKNN	91.040%	0.022	85.504%	0.069	93.373%	0.022
CART	89.670%	0.030	81.880%	0.067	92.710%	0.016
SVM	94.351%	0.018	91.170%	0.043	95.620%	0.018
KNN	91.039%	0.029	85.307%	0.064	93.379%	0.026
BP	88.807%	0.068	80.234%	0.288	89.301%	0.067
Methods	Precision		MCC		F-measure	
/	Avg	Std	Avg	Std	Avg	Std
bTRWOA-SVM	98.239%	0.035	97.138%	0.027	97.897%	0.020
bHHOSRL-SVM	96.872%	0.020	94.997%	0.026	96.380%	0.018
PbGSK_V4-SVM	93.387%	0.044	93.230%	0.037	95.014%	0.028
bRFACO-SVM	69.138%	0.379	67.940%	0.370	70.946%	0.381
bACO-SVM	93.350%	0.039	91.079%	0.026	93.511%	0.020
bABC-SVM	94.089%	0.036	93.934%	0.033	95.556%	0.025
bRIME-SVM	95.468%	0.033	94.484%	0.030	95.979%	0.022
bWOA-SVM	96.182%	0.045	95.680%	0.034	96.815%	0.025
AdaBoost	96.170%	0.048	94.979%	0.052	96.341%	0.038
RandomF	91.983%	0.052	90.394%	0.061	92.963%	0.045
FKNN	82.562%	0.061	77.817%	0.055	83.727%	0.038
CART	81.145%	0.043	74.348%	0.074	81.481%	0.053
SVM	88.522%	0.049	85.944%	0.045	89.724%	0.033
KNN	82.586%	0.074	77.754%	0.072	83.698%	0.054
BP	68.350%	0.253	68.605%	0.255	73.692%	0.267

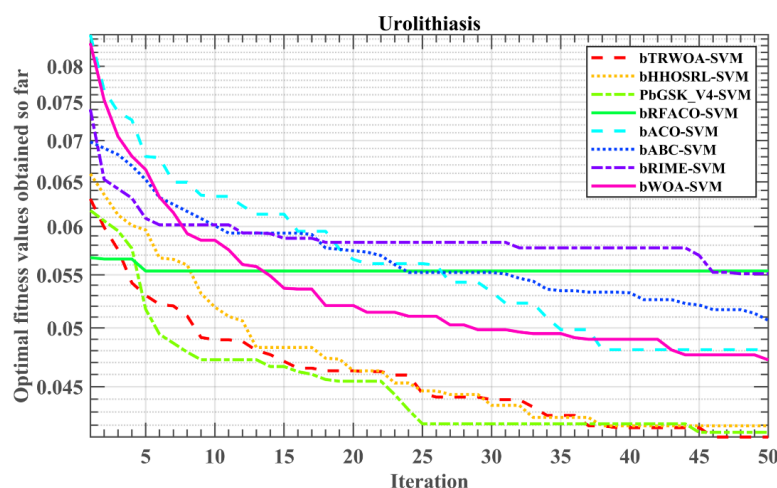


Figure 10. Convergence trend of fitness values of bTRWOA-SVM with its peers in predicting urolithiasis.

Table 9 presents the Avg and Std of the performance metrics for bTRWOA-SVM alongside other models in predicting urolithiasis. The metrics include accuracy, sensitivity, specificity, precision, MCC, and F-measure. Notably, bTRWOA-SVM exhibits exceptional performance with an accuracy of 98.830% (± 0.011), sensitivity of 97.665% (± 0.027), and specificity of 99.340% (± 0.013), underscoring its superior predictive capability. Precision and MCC stand at 98.239% (± 0.035) and 97.138% (± 0.027), respectively, with an F-measure of 97.897% (± 0.020), indicating high reliability and predictive quality.

Comparatively, models like bHHOSRL-SVM, PbGSK_V4-SVM, and bWOA-SVM also demonstrate commendable performances but do not match the accuracy and balance achieved by bTRWOA-SVM. In particular, bRFA-CO-SVM shows a notable drop in performance metrics, especially in sensitivity ($73.290\% \pm 0.390$) and precision ($69.138\% \pm 0.379$), highlighting its limited predictive accuracy.

Among the well-known classification models, AdaBoost closely mirrors the high performance of bTRWOA-SVM with an accuracy of 97.958% (± 0.021) and a precision of 96.170% (± 0.048). Conversely, algorithms like FKNN, CART, and BP exhibit significantly lower performance across all metrics, with CART and BP showing a pronounced decrease in sensitivity and precision, which may affect their applicability for reliable urolithiasis prediction.

Additionally, **Figure 10** provides insight into the convergence trends of models during the process of identifying the optimal feature subset. Analyzing the speed of model convergence and the fitness values ultimately achieved offers a comparative perspective on each model's capability in feature subset detection. Specifically, the bTRWOA-SVM, bHHOSRL-SVM, and PbGSK_V4-SVM models exhibit faster convergence rates compared to other models, indicating their efficiency in locating the optimal feature subsets. Among these, the bTRWOA-SVM ultimately achieves the lowest fitness value, further evidencing its superior performance in the feature subset detection process. This finding reveals that the bTRWOA-SVM model excels not only in predictive stability but also in the execution efficiency and

effectiveness of the optimization algorithm, providing a potent tool for the accurate prediction of urolithiasis.

In summary, through an in-depth analysis and comparison of the performance of different models in predicting urolithiasis, the bTRWOA-SVM model has been found to exhibit significant advantages and high stability across multiple key performance indicators. Relative to similar and well-known classifiers, it not only leads to predictive accuracy but also demonstrates outstanding performance in model stability and feature subset detection capability. Notably, the bTRWOA-SVM's rapid convergence capability and the achievement of a low fitness value in the process of identifying the optimal feature subset further confirm its efficacy and reliability as a predictive tool for urolithiasis.

3.2.4. Feature Importance Analysis

To discern which features exert a decisive impact on the prediction of urolithiasis, this study employed the bTRWOA-SVM model and subjected it to ten-fold cross-validation ten times. This method aims to quantitatively assess the relative importance of each feature in predicting urolithiasis by analyzing the frequency of FS within the urolithiasis dataset.

Figure 11 illustrates the results of analyzing the importance of features for predicting urolithiasis using the bTRWOA-SVM model. It was observed that the features C28 (Bil), C13 (TP), C22 (PH value), C16 (Cr), and C11 (DBil) were selected with descending frequencies, achieving selection rates of 100, 83, 83, 82, and 80 times, respectively. Notably, Bil was selected with a frequency of 100%, underscoring its significance in the diagnosis of urolithiasis. Abnormal levels of Bil may indicate liver dysfunction or issues within the biliary system, which are potentially linked to the occurrence of urolithiasis. The relatively high selection frequencies of TP, PH value, Cr, and DBil further suggest their association with the urolithiasis formation process, such as renal function status, the body's acid-base balance, and the health of the biliary system.

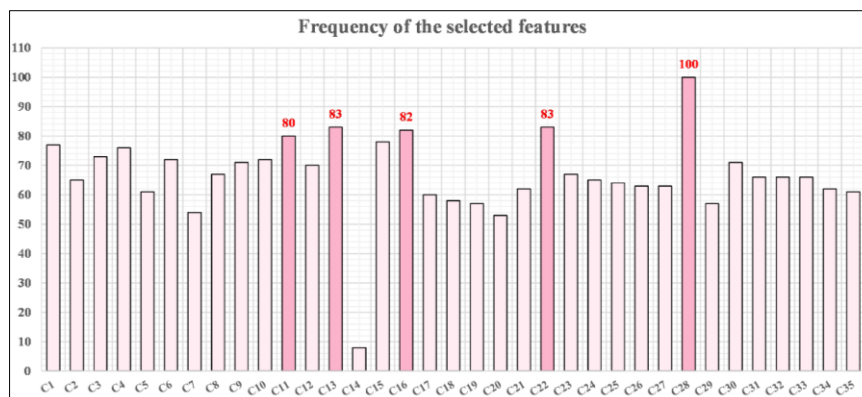


Figure 11. Selected features of the bTRWOA-SVM in the 100 FS.

4. Discussion

This retrospective study included 1029 samples, which included 289 patients with urolithiasis and 740 patients without urolithiasis. We collected and compared the blood routine, blood biochemical, and urine routine results of the two groups of patients. The machine learning approach was used to screen out 5 factors highly related to the stone occurrence from 35 test results: urobilinogen, albumin, creatinine, direct bilirubin (DBIL), and Urine pH. These indicators have their meanings in the urinary system, and this paper links them together as a whole for the first time. The main components of urinary calculi are 90% inorganic crystals and 2-5% organic components [67]. The supersaturation of inorganic crystals, such as oxalates, urates, phosphates, etc., in the human body is only one of the conditions for stone formation, rather than a decisive factor. In metabolic abnormalities and disease conditions, the increased concentrations of albumin may press the accelerator key for stone formation [68]. Elevated serum creatinine levels may indicate urolithiasis leading to high urinary obstruction, and the predictive validity of creatinine levels was also validated by Kim's modified stone score [69, 70]. What's more, many studies have shown that the pH of the urine in the phosphate and apatite groups was significantly higher, and the urine pH of patients in the uric acid and oxalate groups was significantly lower [71]. In addition, our model included urobilinogen and serum direct bilirubin, which had not been previously associated with urinary calculi. However, Song et al. found that high urinary urobilinogen indicates acute hepatic porphyria in patients with abdominal pain [72]. As a routine physical examination item in China, urobilinogen and direct bilirubin have great potential to become new indicators for stone prediction. It is important to note that although urine leukocytes, urine crystals, and other tests are abnormal in many patients with urinary calculi [73], they do not seem to show a specific correlation in our scoring model.

In previous studies, most scoring models tend to cover clinical symptoms. Such as the STONE score, Moore et al. proposed five factors highly associated with stones, which were associated with integer point values. male sex, short duration of pain, race, nausea or vomiting, and hematuria, yielding a total score ranging from 0-13. Scores ranging from 0-5, 6-9, and 10-13 represent a low, moderate, and high probability of urolithiasis, respectively [9]. Patients with high STONE scores may be able to avoid CT altogether or perform a reduced-dose CT. The main aim of the STONE score was to be involved in the imaging decision of suspected urolithiasis to decrease exposure to radiation and over-utilization of imaging. In addition, Kim et al. added CRP and previous history of urinary calculi based on Moore's work, and the final modified calculi score showed better sensitivity and specificity of the score [69]. Although the study of the STONE score points to a very low rate of missed diagnoses, it seems unrealistic to forgo more accurate CT tests for patients based on stone

scores alone. CT examination conforms to the secondary prevention strategy in China, which means "early detection, early diagnosis, and early treatment". CT examination is not only a clear diagnosis of urinary calculi, but also a "physical examination" of the chest, abdomen, and pelvic structure [74, 75].

Different from previous studies, the main purpose of our prediction model is not to reduce the amount of CT radiation received by patients with suspected urolithiasis. The main purpose of our prediction model is to predict whether a patient is at risk of urolithiasis just through blood routine, biochemical, and urine routine results. The main target population is those who do not have clinical symptoms such as urinary obstruction, low back pain, and hematuria, and imaging methods do not indicate the presence of urinary stones. Based on this prediction model, people at high risk of urinary stone formation can take preventive measures in advance to prevent stone formation. It is also an extremely beneficial tool for patients with recurrent urinary stones. Nevertheless, some limitations should be acknowledged. First, the current model is classifier dependent, and its performance may vary if other machine learning algorithms are applied. Second, the sample size of the dataset is relatively limited, which may restrict the generalizability of the results. However, these limitations do not detract from the overall quality and potential impact of our research, and future studies with larger and more diverse datasets as well as alternative classifiers are warranted to further validate and improve the model.

5. Conclusions

This study investigates a wrapper-based FS method for urinary stone data. To overcome the limitations of traditional WOA, TTS, and RLO strategies are proposed. The TTS strategy expands the search range of solutions by converting between polar and Cartesian coordinate systems and employing a rotational search method. The RLO strategy promotes information exchange among population individuals to maintain population diversity. TRWOA is compared with existing methods on the CEC 2017 benchmark functions, and the experimental results demonstrate that TRWOA has advanced local and global search capabilities, leading to improved optimal solutions. For the urinary stone data FS problem, a wrapper-based FS method using bTRWOA as the search strategy and SVM as the classifier is proposed. bTRWOA-SVM is compared with existing methods, and experimental results on the urinary stone dataset show better improvement in accuracy. Furthermore, the experimental results indicate that TP, PH value, Cr, and DBi are the key features affecting urinary stone formation.

Although the proposed method achieves satisfactory results, there are still some limitations. Firstly, since a wrapper-based FS model is used, the quality of the feature subset depends largely on the choice of classifier. Therefore, designing an

evaluation function independent of classifier performance to assess the quality of the feature subset could be considered in the future. Additionally, the relatively small sample size of the urinary stone data used in the experiments may lead to model overfitting. Therefore, collecting more urinary stone data for model updating in the future is also needed.

Abbreviations

CT	Computed Tomography
ML	Machine Learning
RandomF	Random Forest
AdaBoost	Adaptive Boosting
SVM	Support Vector Machine
FS	Feature Selection
MAS	Metaheuristic Algorithms
PSO	Particle Swarm Optimization
HHO	Harris Hawks Optimization
SMA	Slime Mould Algorithm
SCA	Sine Cosine Algorithm
CPA	Colony Predation Algorithm
RIME	Rime Optimization Algorithm
INFO	Weighted Mean of Vectors
RUN	Runge Kutta Optimizer
ACO	Ant Colony Optimization
WOA	Whale Optimization Algorithm
TTS	Triangulation Topology Search
RLO	Reflective Learning Operator
TRWOA	WOA Embedded with TTS and RLO
SOTA	State-of-the-art
bTRWOA	Binary TRWOA
bTRWOA-SVM	A FS Model Based on Btrwoa and SVM
RBF	Radial Basis Function
TF	Transfer Function
Avg	Average Fitness Value
Std	Standard Deviation
WST	Wilcoxon Signed-rank Test
FRT	Friedman Test
BP	Bonferroni Post-hoc Test
MCC	Matthews Correlation Coefficient
FKNN	Fuzzy k-nearest Neighbors
CART	Classification and Regression Trees
KNN	K-nearest Neighbors
BP	Backpropagation Neural Network

Supplementary Material

The supplementary material can be accessed at <https://doi.org/10.11648/j.acm.20251406.13>

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Data Availability Statement

The data involved in this study are all public data, which can be downloaded through public channels.

Conflicts of Interest

The authors declare no conflicts of interest.

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