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Predicting Green Consumption Behaviors of Students Using Efficient Firefly Grey Wolf-Assisted K-Nearest Neighbor Classifiers

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ABSTRACT Understanding the green consumption behaviors of college students is highly demanded to update the public and educational policies of universities. For this purpose, this research is devoted to advance an efficient model for identifying prominent features and predicting the green consumption behaviors of college students. The proposed prediction model is based on the K-Nearest Neighbor (KNN) with an effective swarm intelligence method, which is called OBLFA_GWO. The optimization core takes advantage of the firefly algorithm (FA) and opposition-based learning (OBL) to mitigate the immature convergence of the grey wolf algorithm (GWO). In the proposed prediction framework, OBLFA_GWO is utilized to identify influential features. Then, the enhanced KNN model is used to identify the importance and interrelationships of features in samples and construct an effective and stable predictive model for decision support. Five other well-known algorithms are employed to validate the effectiveness of the proposed OBLFA_GWO strategy using 13 benchmark test problems. Also, the non-parametric statistical Wilcoxon sign rank and Friedman tests are conducted to validate the significance of the proposed OBLFA_GWO against other peers. Experimental results indicate that the FA and OBL can significantly boost the core exploratory and exploitative trends of GWO in dealing with the optimization tasks. Also, the OBLFA_GWO-based KNN (OBLFA_GWO-KNN) model is compared with four classical classifiers, such as kernel extreme learning machine (KELM), back-propagation neural network method (BPNN), and random forest (RF) and five advanced feature selection methods in terms of four standard evaluation indexes. The experimental results show that the classification accuracy of the proposed OBLFA_GWO-KNN can reach to 96.334 % on the real-life dataset collected from nine universities. Also, the proposed binary OBLFA_GWO algorithm has improved the classification performance of KNN compared to the other peers. Hopefully, the established adaptive OBLFA_GWO-KNN model can be considered as a useful tool for predicting students' behavior of green consumption.

INDEX TERMS K-nearest neighbor, firefly algorithm, grey wolf algorithm, opposition-based learning, green consumption behavior, feature selection.

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I. INTRODUCTION

The college student group has formed a considerable consumer market. Huge business opportunities are resulting from the green consumption behaviors of the college student, which assist us in understanding the social consumption fashions. However, due to factors such as environmental awareness, consumption environment, and economic development stage, it is difficult for college students to develop a rational and scientific consumption behavior. Therefore, it is necessary to conduct a big data empirical analysis on the green consumption behavior of college students and provide a reference for the scientific preparation of public policies based on the economic, environmental and educational aspects. In this work, we distributed 2020 questionnaires between students who studied in 9 colleges of Wenzhou city, including independent colleges, and accumulated a large amount of data. Through the analysis of these datasets, the typical factors affecting the green consumption behaviors of college students have been identified, and then the potential correlation between various attributes is further analyzed to predict the behavior of college students' green consumption, efficiently.

Up to now, few works of literature exploited machine learning techniques to establish an intelligent decision model to predict students' behavior of green consumption. KNN is one of the simplest classification approaches widely implemented in the field of machine learning. The current work of this paper aims to develop an intelligent decision model based on the KNN classifier. Compared with the traditional gradient descent algorithm [1], meta-heuristic algorithms, as a general solution of optimization problem, has the characteristics of fast convergence speed and strong global search ability [2]–[20]. The meta-heuristic algorithms such as bacterial colony optimization (BCO) [21], genetic algorithm (GA) [22], fruit fly optimization algorithm (FOA) [23], and particle swarm optimization (PSO) [24] have shown good performance in tackling with many tasks in the area of feature selection. A novel feature selection based on an enhanced GWO-based algorithm is used in this paper to identify the most critical features for the KNN model. Several kinds of research have been performed on the topic of the grey wolf algorithm (GWO) for feature selection in recent years [25]–[30]. In 2018, for obtaining the optimal size of the different system components, a novel multi-objective hybrid PSO–GWO optimization task was presented by Abdelshafy *et al.* [31]. Ibrahim *et al.* [32] presented an enhanced version of the GWO by merging it with the differential evolution (DE), the chaotic logistic map, the opposition-based Learning (OBL) and the disruption operator. The effectiveness of the proposed algorithm was evaluated by using the classical CEC2005, the CEC2014, and tasks of classification of the galaxy images. The results affirmed that COGWO2D was a promising approach and can outperform other algorithms in most cases. For realizing the high-precision wind speed prediction, the empirical wavelet transform decomposition, the regularized extreme learning machine (ELM) network combining with GWO was developed in [33].

A novel approach based on the GWO, the tent chaotic sequence, the nonlinear control parameter, and the particle swarm optimization (PSO) algorithm was presented to mitigate the immature convergence of the conventional GWO in [34]. The proposed algorithm was compared with some other improved algorithms on 18 benchmark functions. From the experimental results, the proposed approach shows higher performance with a better global optimal solution compared to other algorithms. In 2019, Fu *et al.* [35] adopted a hybrid optimization algorithm with GWO, sine cosine algorithm (SCA), and the mutation operator to select the parameters of support vector machine (SVM) for classifying different fault samples. For improving the multi-step short-term wind speed forecasting precision, a new optimization algorithm based on the multi-scale dominant ingredient chaotic analysis, the improved hybrid IHGWOSCA optimization strategy and extreme learning machine, was developed by Fu *et al* [36]. Comparative experiments indicate the superiority of the proposed hybrid model. Gu *et al.* [37] proposed an improved technique based on crossbreeding GWO with the OBL approach, the selection operation, cross-operation for dealing with the large-scale global optimization tasks. In order to deal with the bi-objective truck scheduling problem for the optimality via an epsilon-constraint method, a mixed-integer linear programming model with a hybrid algorithm combining the decomposition framework and the GWO was proposed by Peng and Zhou [38].

GWO has a limited capability in avoiding the local optima (LO) stagnation, and it also has a better performance in terms of convergence ability [39]. Generally, GWO has intensive exploitation trends, but during the optimization process and on some occasions, this algorithm cannot perform a well-distributed exploratory phase [40]. Table 1 records the review of recent works on the hybrid GWO algorithms. In this literature, GWO has the potential to fail in finding the global optimal in the majority of cases. While these hybrid techniques have some advantages in some aspects, but they improve the performance of GWO to some extent. Firefly algorithm (FA), one of the nature-inspired metaheuristic algorithms, mimics the fireflies' behavior of inter-attraction. The authors utilized the principle of 'the more brightness it has, the higher attractiveness [41], to promote the fireflies for communicating with each other and updating their positions. In this work, FA is used to generate new candidate solutions to increase the diversity of the population in GWO, simultaneously. The probability of falling into LO in GWO can be reduced due to the addition of FA as a new updating mechanism. Also, no one has made a systematic study on hybridizing GWO with FA to the best of our knowledge.

Hence, the hybrid of these two techniques is presented in this paper.

The basic FA was proposed in 2009 to solve optimization problems. Lieu *et al*. [42] combined the DE algorithm and FA for shape and size optimization of truss structures under multiple frequency constraints. To reduce the total electricity generation fuel cost, a novel algorithm based on FA was proposed in [43] for dealing with the task of the optimal operation of thermal generating units. Wang *et al*. [44] presented a new dynamic FA for demand estimation of water resources in Nanchang city of China. Yelghi and Kose [45] developed an enhanced version of FA that applies the tidal force formula as a strategy for a better exploration of the search space to obtain better positions. Evaluated with plate-shaped, steep ridges, unimodal, and multimodal benchmark functions, the empirical results indicate that, the proposed tidal force FA outperforms the other existing modified FAs in solving various complex problems. Zhang *et al*. [46] combine the FA, accelerated attractiveness, and evading strategies for classifier ensemble reduction. From the experimental results, the proposed FA model can bring significant improvements compared to the other FA's variants and recent state-of-the-art approaches in solving diverse complex unimodal and multimodal optimization cases and ensemble reduction problems. A novel approach based on the hypermutated FA for optimizing radial basis function neural network was proposed to improve the prediction accuracy of the hospitalization expense model [47]. Experimental results validate that the improved controller outperforms the conventional control methods.

Kaveh and Javadi [48] proposed to combine FA with a logistic map and Gaussian map respectively to improve the performance of the basic FA. An enhanced version of the FA with gender difference was presented by Wang and Song [49]. Le *et al* [50] adopted a hybrid optimization method with both Electromagnetism-like algorithm and FA to solve discrete structural optimization problems. The proposed approach has been verified over several constrained optimization problems and discrete optimization tasks, which demonstrated its superiority over other optimization algorithms in the literature. An improved FA was proposed to optimize the multi-target tracking method based on particle filter [51]. The experimental results indicate the effectiveness and tracking accuracy of the developed method.

In this research, an improved version of the GWO based FA algorithm and OBL mechanism [52] is presented to enhance the searching ability of the basic algorithm. For this purpose, the updating strategy of FA is combined with the core of the GWO to improve the exploration ability of the conventional method. Then, the OBL mechanism is used to generate new candidate solutions for increasing the diversity of the population. Hence, the search efficiency of this algorithm will be further improved. Also, the OBLFA_GWO algorithm is proposed to select the feature subset with the aid of KNN automatically, and then, the wrapped KNN classifier is utilized to identify the importance and inter-relationships of features in samples to construct a predictive model for decision support. By evaluating 13 standard benchmark functions, the numerical results indicate that the proposed OBLFA_GWO algorithm significantly outperforms the other 5 well-known search methods in solving unimodal and multimodal optimization problems. Additionally, the OBLFA_GWO based KNN (OBLFA_GWO-KNN) for predicting college students' green consumption behavior is compared with other peers on the base of four typical evaluation indexes [6]. The results demonstrate that the classification accuracy of the proposed OBLFA_GWO-KNN can reach to 96.334 % on the real-life dataset collected from nine Universities.

The paper is structured as follows. Section 2 presents brief descriptions of KNN, FA, GWO, the proposed OBLFA_GWO algorithm, and the hybrid OBLFA_GWO-KNN model. The trial background is described in detail in Section 3. Section 4 analyzes the simulation results of OBLFA_GWO on benchmark functions and the real-life dataset. Section 5 discusses the results. The conclusions and recommendations are delivered in Section 6.

II. METHODS

A. PREDICTION ENGINE: K-NEAREST NEIGHBOR (KNN)

In this work, the KNN classifier with standard Euclidian distance and the OBLFA_GWO algorithm are utilized to predict the students' behavior of green consumption and select the relevant features for the task, respectively. KNN is one of the simplest classification algorithms widely applied in the field of machine learning. When performing a new classification task, the number of neighbors (k) is the only parameter needed to determine in KNN. KNN is an instance-based learning method that tries to figure out the nearest training neighbors to the new instance based on the Euclidean distance, then the new instance is predicted based on the majority vote of the k-nearest neighbor category. Depending on the similarity measurement, the category of the new instance can be determined by the minimum distance from the new instance to the training points. The similarity index is widely utilized in the references measured by the Euclidean distance. The formula of the Euclidean distance in the KNN classifier is described as the following:

$$Dist\,(Q_1, Q_2) = (\sum\nolimits_{i=1}^{d} (q_1^i - q_2^i)^2)^{1/2} \tag{1}$$

where Q_1 and Q_2 indicate two points with d dimensions, k is set to 1 in this study.

B. FAGWO

The GWO algorithm can be considered as a population-based stochastic algorithm that has been employed to solve several mathematical and real-world optimization tasks in recent years. This algorithm is inspired by the behavior of the leadership hierarchy and hunting mechanism of wolves. Based

TABLE 1. Review of the hybrid GWO algorithms.

Description (Ref)	Method
Hybrid GWO and PSO [53]	In this paper, the PSO algorithm employs the best fitness value of the search agent and the best value of the grey wolf population to preserve the position of each wolf.
Hybrid GWO and PSO [54]	A new position update equation of search agents was proposed in this paper. The information of individual historical best solution in PSO is incorporated into the new updating equation to speed up convergence.
Hybrid GWO and PSO [55]	In this paper, to produce both variants' strength, the ability of exploitation in the PSO algorithm is improved with the help of the exploration in GWO.
Hybrid GWO and differential evolution (DE) [56]	A suitable initial population for the GWO algorithm is generated by DE, which makes the wolf pack have better solution ability.
Hybrid GWO and DE [32]	Through updating the population, the DE operator works as a local search technique to enhance the GWO algorithm's exploitation ability during the iterations.
Hybrid GWO and golden-section optimization [57]	To avoid unnecessary search and reduce the tracking time, the GWO technique is switched to golden-section optimization for a stronger ability of exploration at the later stage.
Hybrid GWO and artificial bee colony algorithm [58]	Wolves adapt the information-sharing strategy of the bee colony algorithm to promote their global search ability while wolves retain exploitation ability by keeping their original hunting strategy.
Hybrid GWO and Gravitational Search Algorithm [59]	GWO algorithm is utilized for optimizing the gravitational steady and enhancing the searching execution of the Gravitational Search Algorithm.
Hybrid GWO and Crow search algorithm [40]	To generate a promising candidate solution, this paper combines the strengths of both the algorithms effectively
Hybrid GWO and Cuckoo Search algorithm [60]	By introducing the global-search ability of the Cuckoo Search algorithm into GWO to update its best three solutions that are alpha-wolf, beta-wolf, and delta-wolf, the searching ability of GWO are strengthened, and the shortcoming of GWO is offset.

on the order of social status from high to low, the initial population is divided into four categories including alpha (α), beta (β), delta (δ) and omega (ω) wolves. The best solution in the grey wolf group is called α. The second and third fittest solutions are β and δ, respectively. The rest of the search agents, which are denoted as ω, should search promising areas of the search space to detect the optimal location by the following α, β, and δ. As grey wolves encircle prey during the hunt, the encircling behavior can be formulated as follows:

$$D = |C \cdot X_{prey}(t) - X(t)| \tag{2}$$

$$X(t+1) = X_{prey}(t) - A \cdot D \tag{3}$$

$$A = 2a \cdot R1 - a \tag{4}$$

$$C = 2 \cdot R2 \tag{5}$$

Here, t denotes the number of current iterations, X_{prey} refers to the position vector of prey, and X is the position vector of the search agent in the grey wolf population. A and C are coefficient vectors. Where $R1, R2 \in [0, 1]$ and a is linearly decreased from 2 to 0 during the whole iterative process. In the GWO algorithm, we suppose that the α, β and δ have better knowledge about X_{prey}. In this condition, the first three fittest candidate solutions obtained so far are saved for updating the rest of the positions. Hence, other search agents are obliged to update their positions according to the position of the optimal search agent. The mathematical model of hunting behavior could be calculated as follows,

$$\begin{cases} D_\alpha = |C1 \cdot X_\alpha - X| \\ D_\beta = |C2 \cdot X_\beta - X| \\ D_\delta = |C3 \cdot X_\delta - X| \end{cases} \tag{6}$$

$$\begin{cases} X_1 = X_\alpha - A1 \cdot D_\alpha \\ X_2 = X_\beta - A2 \cdot D_\beta \\ X_3 = X_\delta - A3 \cdot D_\delta \end{cases} \tag{7}$$

$$X(t+1) = (X_1 + X_2 + X_3)/3 \tag{8}$$

where X_α, X_β and X_δ indicate the positions of grey wolves α, β, and δ, respectively. D_α, D_β, and D_δ demonstrate the distances between the current position and α, β, and δ, respectively. After the distances have been computed, the final position of the search agent can be calculated by Eq. (8). In other words, the final position would be a random location which is determined by the positions of α, β, and δ.

Although GWO is an efficient optimization method, it may be trapped to LO when handling some problems. The advantages of other methods such as FA can help this optimizer to jump out of LO. FA [41] is one of the nature-inspired meta-heuristic algorithms proposed by Yang in 2009 for solving optimization problems. In FA, it is assumed that all fireflies are unisex. It means that individuals in FA are attracted to each other regardless of their gender. Also, the brightness of the firefly is dictated by its attractiveness. The more brightness it has, the higher attractiveness. The firefly with darker brightness in FA will move towards a more attractive one. Furthermore, the brightness of the firefly population is determined by the landscape of the fitness value. In the general design and implementation, the attractive function φ of FA is defined as follows,

$$\varphi(r) = \varphi_0 e^{-\gamma r_{ij}^2} (m \geq 1) \tag{9}$$

$$r_{ij} = \|x_i - x_j\| = \sqrt{\sum_{m=1}^{d} (x_{i,m} - x_{j,m})^2} \tag{10}$$

Here, φ_0 indicates the attractiveness of a search agent at $r = 0$, r shows the distance between two individuals in FA. γ refers to a fixed light absorption coefficient. $x_i(t)$ is the *i-th* search agent in the number of iteration t. The movement of a firefly i attracts to another higher attractiveness firefly j is calculated by [41]:

$$x_i(t+1) = x_i(t) + \varphi_0 exp^{-\gamma r_{ij}^2} \left(x_j(t) - x_i(t)\right) + \varepsilon(R3 - 1/2) \tag{11}$$

where ε is the randomization parameter. $R3 \in [0, 1]$ obeys the uniform distribution. $x_i(t)$ is the *i-th* search agent in the number of iteration $t + 1$.

C. OBLFA_GWO

The hybrid FAGWO algorithm is proposed by the combination of FA and GWO optimizers. Also, the OBL mechanism [52] was developed to improve the performance of the original FAGWO. The OBL method raised in 2005 regarded as a widely used mathematical concept within the computational intelligence community. In this paper, the OBL is used to compute the opposite solutions for all search agents. Under current conditions, the opposite solution can provide a new chance to get close to the best location according to the value of the specific objective function. In other words, there is an excellent opportunity to enhance the convergence rate and find the optimal solution with the help of the OBL mechanism. For a current search agent X_i in the proposed algorithm, the opposite solution X_i' can be generated as follows,

$$X_i' = l + u - X_i, \quad i = 1 \ldots n \tag{12}$$

where $X_i \in [l, u]$, n indicates the population size. l and u denote the lower and the upper boundaries of the search space, respectively. Remarkably, the new population is generated from the current swarm and the opposite solution based on the value of the specific fitness function. The OBL method is used to enhance the quality of the current population, then the individual in the proposed algorithm is updated with the combination of the FA and GWO algorithm. Therefore, the improved algorithm is called the OBLFA_GWO algorithm. In OBLFA_GWO, the population size is divided into two parts, and two update mechanisms are working together to find global optimal solution. For this purpose, the FA conducts as a new position updating mechanism to increase the diversity of the population. Therefore, the exploratory tendencies of the proposed optimizer is enriched, and the probability of falling into LO reduces. The pseudo-code of the whole procedure is given below.

Algorithm 1 Pseudo Code of OBLFA_GWO

Begin
Initialize the population $X_i (i = 1, 2, \ldots, n)$;
Initialize $\varepsilon, \varphi_0, \gamma$, and maximum number of iterations T;
Evaluate the fitness of all agents by KNN with agents as features;
Set the *Fbest* as the position of best search agent;
while $(t \leq T)$
X_α = the best search agent of X;
X_β = the second-best search agent of X;
X_δ = the third best search agent of X;
For $i = 1$: n
Calculate the oppositional position X_i' of X_i by Eq. (12);
Bring the X_i' back if it goes outside the boundaries;
Evaluate the fitness of current search agent by KNN with this agent as a feature;
End For
Update positions of $X_\alpha, X_\beta, X_\delta$;
Update population X by selecting the best n individuals from X' and X;
For $i = 1$: floor(n/4)
Update the position of the current search agent X_i by using Eq. (11);
Bring the current search agent back if it goes outside the boundaries;
End For
Update parameter A in GWO, according to Eq. (4);
For i = floor(n/4) + 1: n
Update the location vector of X_i by Eq. (8);
Bring the current search agent back if it goes outside the boundaries;
End For
Update *Fbest* if there is a better solution;
$t = t + 1$;
End while
return *Fbest* as the optimal position for KNN;
End

The computational complexity of the OBLFA_GWO mainly depends on the population size (n), dimensions of the specific optimization tasks (d), and the number of algorithm iterations (T). The overall computational complexity is O(OBLFA_GWO) = O(*Initialize*) + O(*Calculate the fitness values of the initial search individuals*) + O(*Sort the initial population*) + O(*Perform the oppositional operator in each iteration*) + O(*Sort the current population and the oppositional* search agents *in each iteration*) + O(*Obtain the new population from the current population and oppositional population in each iteration*) + O(*Update the new population in each iteration*). Different optimization cases have different time complexities so that there is no need for consideration of O(*Calculate the fitness values*). The time complexity for the process of initialization is $O(n \times d)$. *Sorting the initial population* is $O(n^2)$. The computational complexity of performing the oppositional operator is $O(T \times (2n \times d))$. Sorting the oppositional population and the original population in each generation is $O(T \times (4n^2))$. Obtaining new population from the current population and oppositional population in each iteration is $O(T \times (n \times d))$. The time complexity of updating the new populations is $O(T \times (n \times d))$. Hence, the total time complexity is as follows: $O(\text{OBLFA\_GWO}) = O(n \times d) + O(n^2) + T \times (5O(n \times d) + 4O(n^2))$.

D. OBLFA_GWO-KNN

In this section, the KNN classifier is introduced to assess the importance of the attributes in the dataset. Also, the binary OBLFA_GWO algorithm is proposed here as a feature selection tool to select the critical feature subset. The purpose of the feature selection problem is to select a few features and achieve higher classification accuracy as well. In the proposed OBLFA_GWO, it is required to transform the position of the individual and obtain a new binary solution with numbers of "0" and "1". For the feature selection method, "1" indicates that the feature is selected, and "0" means the corresponding feature is not selected. To transform the positions of individuals in the OBLFA_GWO algorithm into binary values, the central updating equation is shown as follows.

$$X_i(t+1) = \begin{cases} 1 & if\ sigMF\ (X_i) \geq rand \\ 0 & otherwise \end{cases} \tag{13}$$

$$sigMF\ (X_i) = 1/1 + exp^{-10(X_i - 0.5)} \tag{14}$$

Here, $rand \in [0, 1]$ obeys the uniform distribution. $X_i\ (t+1)$ is the binary position at iteration $t+1$. In this study, the feature information is obtained by the binary form of an individual. Both the selected number of features and the error rate are employed to assess the quality of the selected feature subset. We need to minimize the error rate and number of features [61]. Hence, the fitness function [62] is shown as follows,

$$Fitness = \partial \cdot error + \rho \cdot \frac{|L|}{|d|} \tag{15}$$

This paper builds a hybrid OBLFA_GWO-KNN model by combining the OBLFA_GWO method with the KNN classifier. Hence, *error* indicates the classification error rate obtained by KNN, $|L|$ is the total number of the selected indicators, and $|d|$ determines the entire attributes of the experiment dataset. ∂ and ρ are two parameters for weighing the importance of *error* and $|L|$. Also, $\partial = 0.99$ and $\beta = 0.01$ are set according to references [62], [63].

In this part, the prediction model named OBLFA_GWO-KNN is introduced. Figure 1 shows the framework of the hybrid approach. The first part is to normalize the data and establish an optimized KNN model with the enhanced binary OBLFA_GWO algorithm. In this part, the candidate feature set is obtained by the enhanced binary OBLFA_GWO approach, and at the same time, the feature importance is evaluated by the KNN model. The main aim of the two parts is to use the achieved optimal feature subset to predict new instances by the KNN model.

III. EXPERIMENTAL DESIGNS

A. DATA COLLECTION

The data in this paper is mainly collected from the students of Wenzhou University, Wenzhou Business College, Wenzhou Vocational College of Science and Technology, etc. and other six universities in Zhejiang Province. Two thousand twenty questionnaires are issued, and 2010 are taken back among which 1856 are valid. From these students, 1856 students are selected as research subjects, of which 1022 students have significant green consumption behaviors, and 834 students do not have.

Our selection of these attributes was based on the college students' personal background, environmental values, and understanding of environmental knowledge. According to the above major problems, F1-F52 questions have been collected. For each small problem, we set the different menu of options (see the last rows of the table 2 "Notes" for details). Each option corresponds to an element in the experimental dataset. For example, F2 (Gender (L1-L2)), the corresponding meaning is the gender of the research subject, the options refer to the Notes (F2: L1: Male students, L2: Female students). In this case, if the student is a male, the element of corresponding attribute in the data is 1, otherwise is 2. Then, all the recorded elements are imported into the data sheet. Again as an example, F21 (I do not buy or use non-degradable plastic bags (L1-L5)), the corresponding meaning is that whether the student will use or purchase non-degradable plastic bags. In this case, L1 (Never) indicates that the student will never use or buy non-degradable plastic bags, L5 (Always) means that the student always uses or buys. The corresponding element of L1 in data is 1, and 5 indicates the corresponding element of L5. Repeat these steps for the remaining questions.

The survey results of 1856 by 2020 questionnaires have been integrated to the experimental results as described above, of which 1022 students have significant green consumption behaviors (Label is set to 1), and 834 students do not have (Label is set to 0). The complete experimental data can be obtained by the above operations. Through the analysis of 52 attributes, this study intends to identify the most influential attributes of these 52 factors to construct a useful prediction tool. The detailed description of 52 factors is shown in Table 2.

B. EXPERIMENTAL SETUP

In this part, several competitive meta-heuristic algorithms, including the Lévy enhanced GWO (LGWO) [64], FA [41], GWO [65], bat algorithm (BA) [66], and Moth-flame optimization (MFO) [67] are considered to validate the effectiveness of OBLFA_GWO using several well-known benchmark functions. The parameters of LGWO, FA, GWO, BA,

TABLE 2. Description of 52 attributes.

Feature	Brief description	Mean	Std
F1	University (L1-L9)	5.39	2.95
F2	Gender (L1-L2)	1.65	0.48
F3	Educational background (L1-L4)	1.43	0.62
F4	Political orientation (L1-L4)	2.11	0.66
F5	Avg (L1-L4)	1.50	0.50
F6	Specialization at the university (L1-L10)	5.25	2.63
F7	Grade (L1-L5)	1.49	0.78
F8	Family background (L1-L3)	2.55	0.72
F9	Number of brothers and sisters (L1-L5)	1.87	0.84
F10	Monthly consumption capability (L1-L5)	2.88	1.06
F11	Annual household income (L1-L5)	2.40	1.16
F12	Parents' education background (L1-L5)	1.18	0.56
F13	I'll turn off the lights when leaving the room (L1-L5)	4.64	0.66
F14	I usually save water (L1-L5)	4.33	0.80
F15	I'll go out by walk, bicycle or public (L1-L5)	4.32	0.86
F16	I'll save electricity (L1-L5)	4.31	0.82
F17	I'll repair damaged articles (L1-L5)	3.29	1.06
F18	I'll turn down the screen brightness of my computer and mobile phone (L1-L5)	3.98	0.98
F19	I'll cut down on household waste (including less takeout to reduce lunch box waste) (L1-L5)	3.68	1.03
F20	I'll recycle the used items (L1-L5)	3.33	1.13
F21	I do not buy or use non-degradable plastic bags (L1-L5)	3.03	0.97
F22	I'll buy low phosphorus detergent (L1-L5)	3.25	1.08
F23	I'll buy products with green or packaging labels that are usable and recyclable (L1-L5)	3.60	0.96
F24	I'll choose energy-saving electronic products (mobile phones, notebooks, etc.) (L1-L5)	3.75	0.97
F25	I bring my own shopping bag when shopping (L1-L5)	2.92	1.20
F26	I'll classify domestic waste (L1-L5)	3.26	1.14
F27	I don't have any leftovers when eating in the canteen (L1-L5)	3.68	1.04
F28	Teachers mention green consumption in class (professional courses, ideological and political courses, etc.) (L1-L5)	4.40	0.75
F29	School youth league committee organizes environmental protection activities related to green consumption (such as recycling old batteries, recycling old clothes, etc.) (L1-L5)	4.22	0.86
F30	Green consumption is the theme of school party and league activities (theme class meetings, league day activities, party day activities, etc.) (L1-L5)	4.50	0.70
F31	I pay attention to the content of green consumption in the campus media (campus newspapers, websites, public numbers, etc.) (L1-L5)	4.51	0.68
F32	School facilities reflect green consumption elements (e.g. sidewalk environmental protection slogans, garbage cans with classified labels, office energy-saving tips, canteen restaurants with wall slogans, etc.) (L1-L5)	3.88	0.86
F33	I would like to buy degradable shopping bags (L1-L5)	4.57	0.65
F34	Choosing between organic food and regular food, I prefer to buy organic food (L1-L5)	4.25	0.78
F35	I think it is necessary to implement green consumption (L1-L5）	4.41	0.71
F36	I support environmental protection and think that college students should practice it (L1-L5)	4.23	0.81
F37	I know how to classify garbage (L1-L5)	4.27	0.79
F38	Pollution of the environment by waste batteries will do harm to human health (L1-L5)	4.32	0.74
F39	I can identify environmental signs (such as energy-saving signs, water-saving signs, etc.) (L1-L5)	4.13	0.89

TABLE 2. *(Continued.)* **Description of 52 attributes.**

F40	Green food is characterized by safety, nutrition, high quality and pollution-free (L1-L5)	4.08	0.86
F41	Consuming green products helps me make a good impression on others (L1-L5)	3.88	0.93
F42	Consumption of green products will make others feel that I have a sense of social responsibility (L1-L5)	3.81	1.05
F43	Consumption of green products helps me build a positive and healthy personal image (L1-L5)	4.24	0.76
F44	Consumption of green products can improve people's perception of me (L1-L5)	4.64	0.59
F45	My family and friends think I should buy green products (L1-L5)	4.64	0.60
F46	My classmates and friends often buy green products (L1-L5)	3.30	1.44
F47	My wasteful behavior will be criticized by others (L1-L5)	4.24	0.86
F48	People around me believe that we should practice economy (L1-L5)	3.77	0.97
F49	The earth's space and resources are limited (L1-L5)	3.93	0.89
F50	Man and nature must live in harmony for surviving (L1-L5)	3.94	0.91
F51	The seriousness and urgency of the environmental problem have been exaggerated (L1-L5)	3.94	0.91
F52	I'll be angry about the environmental pollution reported in the media (L1-L5)	4.14	0.80

Notes:

F1: L1: Wenzhou university, L2: Wenzhou university Oujiang college, L3: Wenzhou vocational college of science and technology, L4: Wenzhou business college, L5: Wenzhou medical university, L6: Wenzhou vocational & technical college, L7: Zhejiang college of security technology, L8: Zhejiang Dongfang polytechnic, L9: Zhejiang industry & trade vocational college

F2: L1: Male students, L2: Female students

F3: L1: Junior college students , L2:Undergraduate student, L3:Graduate student, L4:Others

F4: L1:Party member , L2:League member, L3:Masses, L4:Others

F5: L1:Under 20, L2:20-25, L3:26-40, L4:Others

F6: L1:Literature, L2:Science, L3:Engineering, L4:Management, L5:Economics, L6:Law , L7:Medicine, L8:Education, L9:Art, R10:Others

F7: L1:Freshman, L2:Sophomore, L3:Junior, L4:Senior, L5:Graduate student

F8: L1:City, L2:Cities and towns, L3:Countryside

F9: L1:0 , L2:1, L3:2, L4:3, L5:Others

F10: L1:Less than 800 yuan , L2:800-1,200 yuan, L3:1,201-1,600 yuan, L4:2,000 yuan or more

F11: L1:Less than 50,000 yuan, L2:50,000-100,000 yuan, L3:100,000-200,000 yuan, L4:200,000-300,000 yuan, L5:300,000 yuan or more

F12: L1:High school and below, L2:College specialty, R3:Undergraduate college, L4:Master degree, L5:Doctoral degree

F13-F32: L1: Never, L2:Rarely, L3:Uncertainly, L4:Usually, L5:Always

F33-F52: L1:Strong disapproval, L2: Disapproval, L3:Uncertainly, L4:Agreeable, L5:Strongly agreeable

MFO, and the proposed methods are set according to the values reported in Table 3. Then, the real-life dataset collected from nine universities in china is utilized to compare the quality of the OBLFA_GWO versus other metaheuristics. Also, the proposed OBLFA_GWO-KNN model is further compared against the original classifier KNN and several popular machine learning methods including kernel extreme learning machine (KELM), back propagation neural network method (BPNN), and random forest (RF) to study how the results change based on the selected classifier and verify the performance. All experiments have been performed on a Windows Server 2008 R2 operating system with Intel (R) Xeon (R) Sliver 4110 CPU (2.10 GHz) and 16GB of RAM. The tests are carried out under the MATLAB R2014b software.[1]

[1]The code of KELM and RF is obtained from http://www3.ntu.edu.sg/home/egbhuang, and https://code.google.com/archive/p/randomforest-matlab

TABLE 3. **Parameters setting for compared methods.**

Method	Other parameters
MFO	b=1; t=[-1 1]; a∈[-1 -2]
BA	A=0.5; r=0.5
GWO	a=[2,0]
LGWO	a=[2,0]
FA	$\varepsilon = 0.2$; $\varphi_0 = 1$; $\gamma = 1$
OBLFA_GWO	a=[2,0]; $\varepsilon = 0.2$; $\varphi_0 = 1$; $\gamma = 1$

The experimental data are scaled into $[-1, 1]$ prior to the construction of the classifier. In addition, the g-fold cross validation (CV) is used to gain an unbiased estimate of experimental results. The value of g is set to 10, which is commonly used in the literature [6], [68]. Thus, the experimental data

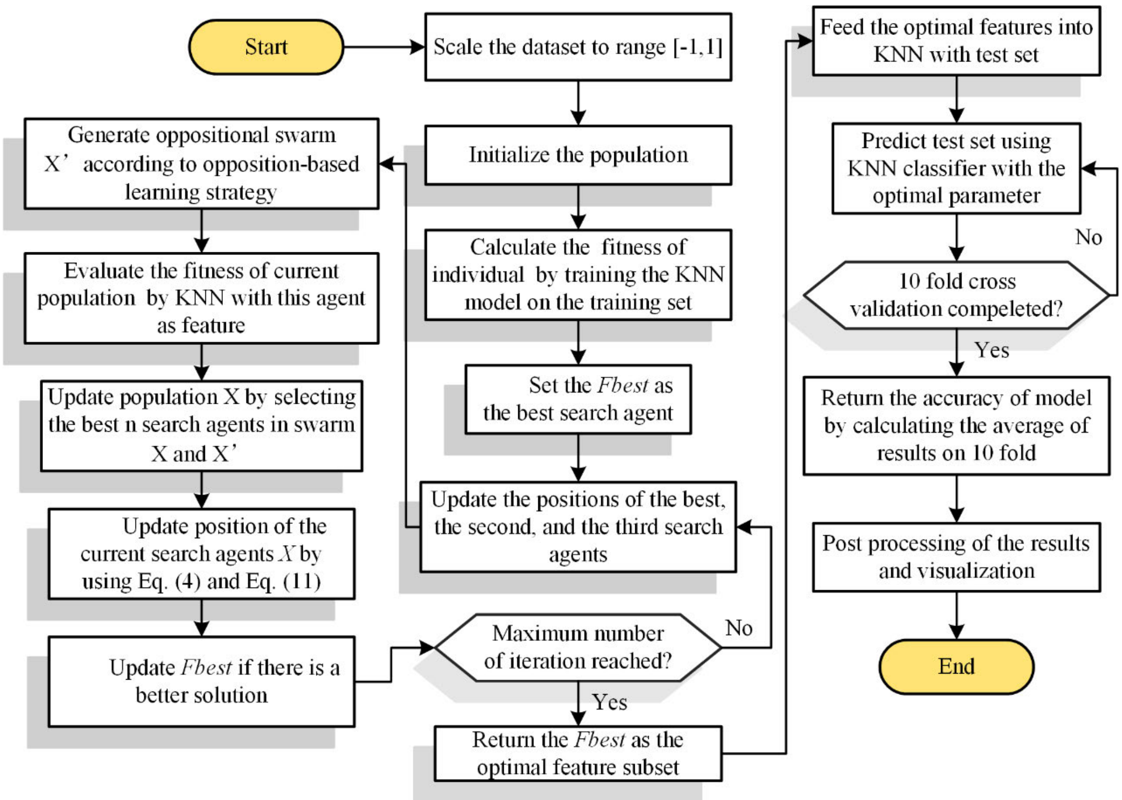

FIGURE 1. Flow chart of OBLFA_GWO-KNN.

TABLE 4. Unimodal benchmark functions.

Function	Dim	Range	f_{min}
$f_1(x)=\sum_{i=1}^{n} x_i^2$	30	[-100, 100]	0
$f_2(x)=\sum_{i=1}^{n}\lvert x_i\rvert+\prod_{i=1}^{n}\lvert x_i\rvert$	30	[-10, 10]	0
$f_3(x)=\sum_{i=1}^{n}(\sum_{j-1}^{i} x_j)^2$	30	[-100, 100]	0
$f_4(x)=max_i\{\lvert x_i\rvert, 1\le i\le n\}$	30	[-100, 100]	0
$f_5(x)=\sum_{i=1}^{n-1}[100(x_{i+1}-x_i^2)^2+(x_i-1)^2]$	30	[-30, 30]	0
$f_6(x)=\sum_{i=1}^{n}([x_i+0.5])^2$	30	[-100, 100]	0
$f_7(x)=\sum_{i=1}^{n} ix_i^4+random[0,1)$	30	[-1.28, 1.28]	0

TABLE 5. Multimodal benchmark functions.

Function	Dim	Range	f_{min}
$f_8(x)=\sum_{i=1}^{n}-x_i\sin(\sqrt{\lvert x_i\rvert})$	30	[-500,500]	-418.9829×N
$-f_9(x)=\sum_{i=1}^{n}[x_i^2-10\cos(2\pi x_i)+10]$	30	[-5.12,5.12]	0
$f_{10}(x)=-20\exp\left\{-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n}x_i}\right\}-exp\{\frac{1}{n}\sum_{i=1}^{n}\cos(2\pi x_i)\}+20+e$	30	[-32,32]	0
$f_{11}(x)=\frac{1}{4000}\sum_{i=1}^{n}x_i^2-\prod_{i=1}^{n}\cos\left(\frac{x_i}{\sqrt{i}}\right)+1$	30	[-600,600]	0
$f_{12}(x)=\frac{\pi}{n}\{10\sin(ay_1)+\sum_{i=1}^{n-1}(y_i-1)^2[1+10sin^2(\pi y_{i+1})]+(y_n-1)^2+\sum_{i=1}^{n}\mu(x_i,10,100,4)\}$ $y_i=1+\frac{x_i+1}{4}$ $\mu(x_i,a,k,m)=\begin{cases}k(x_i-a)^m & x_i>a\\ 0 & -a<x_i<a\\ k(-x_i-a)^m & x_i<-a\end{cases}$	30	[-50,50]	0
$f_{13}(x)=0.1\{sin^2(3\pi x_i)+\sum_{i=1}^{n}(x_i-1)^2[1+sin^2(3\pi x_i+1)]+(x_n-1)^2[1+sin^2(2\pi x_n)]+\sum_{i=1}^{n}\mu(x_i,5,100,4)$	30	[-50,50]	0

was split into 10 parts, with nine data parts used as training data and the last one used as the testing data in the experiment.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

A. BENCHMARK FUNCTION VALIDATION

To extensively investigate the performance of the proposed strategy, several competitive meta-heuristic algorithms, including the LGWO, FA, GWO, BA, and MFO are taken for comparison on 13 well-known benchmark functions. As shown in Tables 4-5, these unimodal and multimodal functions are utilized extensively in the literature. The dimensionality of the selected benchmark functions, the range of optimization variables, and the optimal values of functions in this table are abbreviated to Dim, Range, and f_{min}, respectively. In addition, the Dim, the population size, and the maximum number of iterations of 13 selected tasks are set to 30, 20, and 1000, respectively.

TABLE 6. Comparison results of the OBLFA_GWO algorithm and the other five peers.

Function	metric	LGWO	FA	GWO	BA	MFO	OBLFA_GWO
F1	avg	0.00E+00	6.13E-54	3.12E-03	8.46E-49	1.51E+01	**0.00E+00**
	stdv	0.00E+00	1.97E-53	1.17E-03	2.29E-48	2.29E+00	0.00E+00
F2	avg	0.00E+00	1.49E-33	1.32E-01	1.47E-29	3.96E+01	**0.00E+00**
	stdv	0.00E+00	1.78E-33	8.46E-02	1.62E-29	4.64E+01	0.00E+00
F3	avg	0.00E+00	2.99E-06	9.29E+02	2.99E-12	9.16E+01	**0.00E+00**
	stdv	0.00E+00	7.02E-06	4.22E+02	9.31E-12	2.46E+01	0.00E+00
F4	avg	0.00E+00	5.41E-07	7.04E-02	3.43E-12	3.11E+00	**0.00E+00**
	stdv	0.00E+00	2.25E-06	1.61E-02	3.55E-12	1.50E+00	0.00E+00
F5	avg	2.58E+01	2.66E+01	2.69E+02	2.72E+01	4.06E+03	**2.58E+01**
	stdv	3.12E-01	6.63E-01	5.34E+02	7.49E-01	1.08E+03	3.12E-01
F6	avg	4.83E-05	3.68E-01	2.85E-03	9.39E-01	1.54E+01	**4.83E-05**
	stdv	1.76E-05	2.28E-01	6.04E-04	3.49E-01	1.40E+00	1.76E-05
F7	avg	7.72E-05	1.51E-03	1.40E-02	1.20E-03	2.83E+01	**7.72E-05**
	stdv	7.27E-05	7.81E-04	7.05E-03	6.45E-04	1.57E+01	7.27E-05
F8	avg	-3.61E+03	-6.57E+03	-7.29E+03	-6.08E+03	**-7.20E+03**	-3.61E+03
	stdv	1.09E+03	1.04E+03	8.46E+02	8.58E+02	7.36E+02	1.09E+03
F9	avg	0.00E+00	1.46E+01	4.73E+01	3.59E-01	2.77E+02	**0.00E+00**
	stdv	0.00E+00	1.55E+01	1.50E+01	1.61E+00	1.88E+01	0.00E+00
F10	avg	1.78E-15	1.28E-14	1.24E-02	2.13E-14	5.24E+00	**1.78E-15**
	stdv	1.58E-15	5.06E-15	2.39E-03	4.87E-15	3.47E+00	1.58E-15
F11	avg	0.00E+00	4.03E-03	4.97E-03	7.04E-03	6.30E-01	**0.00E+00**
	stdv	0.00E+00	1.04E-02	2.28E-03	1.16E-02	4.69E-02	0.00E+00
F12	avg	9.17E-06	2.15E-02	2.48E-05	3.44E-02	1.31E+01	**9.17E-06**
	stdv	2.70E-06	3.01E-02	1.26E-05	1.41E-02	3.93E+00	2.70E-06
F13	avg	4.99E-03	**1.83E-01**	1.44E-03	7.60E-01	2.47E+00	4.99E-03
	stdv	2.18E-02	1.44E-01	3.45E-03	2.22E-01	4.23E-01	2.18E-02
	Ranking	3	2	4	6	5	1
	ARV	3.076087	2.997826	3.391304	5.467391	3.819565	2.247826

To assess the proposed method, OBLFA_GWO is compared with five well-known optimization algorithms, including LGWO, FA, GWO, BA, and MFO. The average results (avg) and the standard deviation (stdv) of the best position found by six methods over 30 independent runs are illustrated. For a fair comparison purpose, the same testing environment of competitors and the proposed algorithm are employed.

As shown in Table 6, OBLFA_GWO provides the lowest avg values for 11 functions. In other words, the proposed method has an evident superiority over other competitors on 11 problems in terms of avg index. The presented algorithm also has a fast convergence rate, and it achieves the optimal solutions for F1, F2, F3, F4, F9, and F11. Furthermore, the proposed method also obtains the highest quality solutions on F5, F6, F7, F10, and F12. Followed by MFO and FA, they provide the lowest mean value on one function.

The statistic results of the non-parameters statistical Friedman test are used to exhibit the average performance of the OBLFA_GWO over other competitive algorithms. As shown in Table 6, the ARV (the average ranking value) index is reported to rank the average performance of six algorithms for further statistical comparison. In terms of the statistic values of ARV, we can see that the developed OBLFA_GWO achieves the best performance for tackling these benchmark tasks, followed by FA, LGWO, GWO, and MFO, while BA has the worst search ability. To further estimate the significant improvement of the proposed OBLFA_GWO, the statistical results of the Wilcoxon sign rank test [69] are listed in Table 7. As can be seen from the table, the developed OBLFA_GWO is significantly better than LGWO and GWO on 12 out of 13 functions, and inferior to them in one case, respectively. Moreover, the results of the OBLFA_GWO algorithm are significantly better than those achieved by the well-known FA, BA, and MFO algorithms in dealing with all the selected functions. In short, the proposed OBLFA_GWO delivers the best search performance than the original FA, GWO, and two other competitors, and can avoid the LO very well.

Furthermore, to clearly demonstrate the superiority of the OBLFA_GWO algorithm, the convergence rates of LGWO, FA, GWO, BA, and MFO on 13 benchmarks are also showed in Figure 2. The experimental results show that the convergence curve of OBLFA_GWO is obviously enhanced compared with other popular algorithms under the same iteration

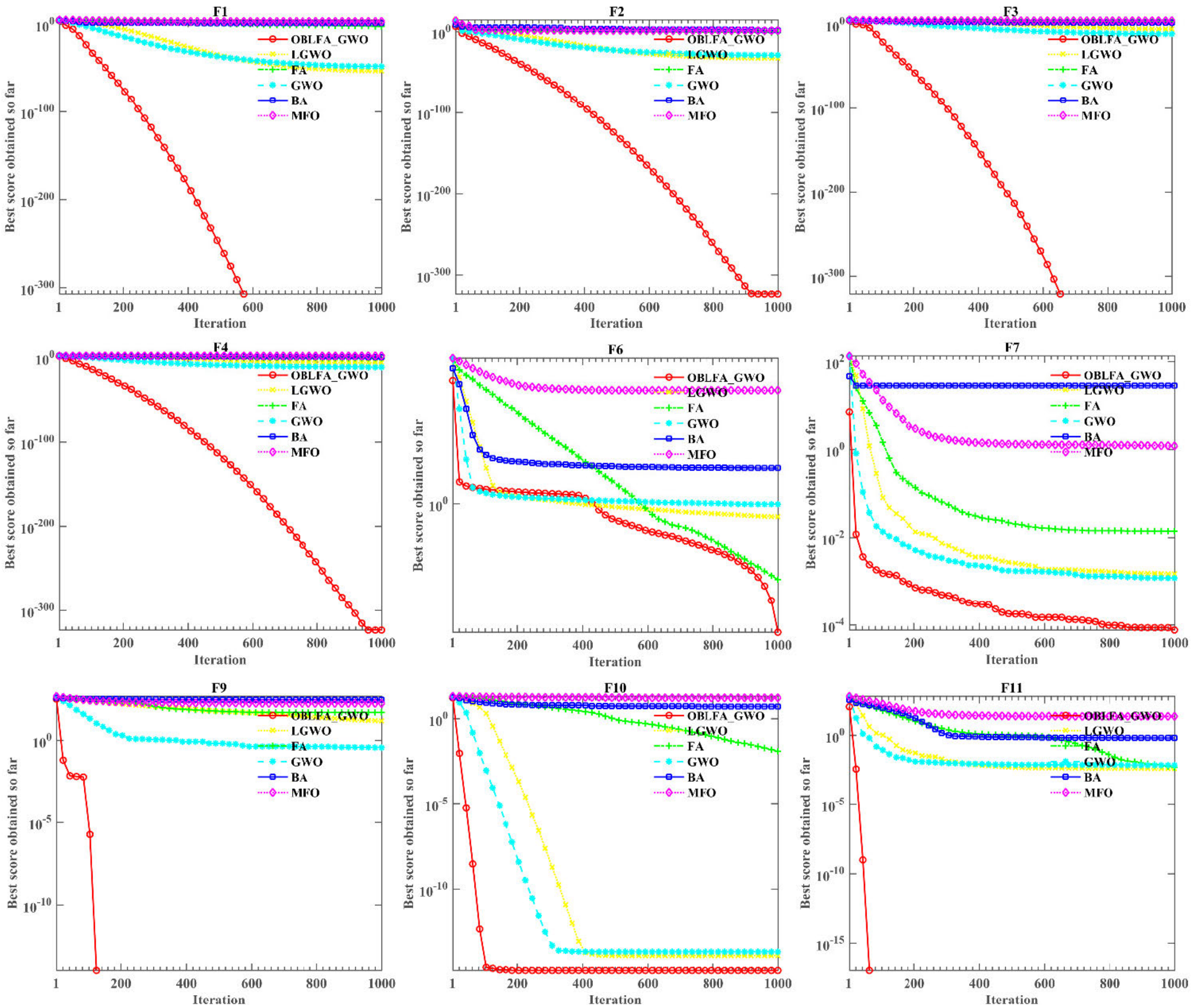

FIGURE 2. Convergence curves of 13 selected benchmark functions.

times on F1, F2, F3, F4, F6, F7, F9, F10, and F11. Also, it can be seen that the developed OBLFA_GWO algorithm achieves the optimal solution in dealing with F1, F2, F3, and F4. It should be noted that F9 and F11 belong to multimodal benchmark functions, and there are many LO. Under such circumstances, OBLFA_GWO can still converge to the optimal position with fast convergence speed. It indicates that OBL based FA_GWO has a strong ability to escape from the LO. Therefore, compared with the original GWO and FA, the developed OBLFA_GWO has a distinct advantage.

B. PREDICTION RESULTS OF STUDENTS' GREEN CONSUMPTION BEHAVIOR

The binary OBLFA_GWO algorithm is utilized to select the important feature subset, and the KNN classifier is employed to evaluate the importance of the attributes in the experiment dataset. The feature selection approaches including the binary OBLFA_GWO, binary PSO algorithm (BPSO) [70], binary ant lion algorithm (BALO) [63], binary salp swarm algorithm (BSSA) [71], and binary whale optimization algorithm (BWOA) [72] are included for comparison on the green consumption dataset. The parameters of BPSO, BALO, BSSA, BWOA, and the proposed methods are set according to the values reported in Table 8. In addition, the selected features of four binary optimization algorithms are combined with KNN to be compared against the performance of the proposed method. As can be seen from Figure 3, OBLFA_GWO with KNN can produce the best results among the five methods according to four indexes, including ACC, sensitivity, specificity, and MCC. Figure 4 shows the evolutionary curves of the developed OBLFA_GWO-KNN and the other four KNN-based binary optimization algorithms. To ensure the fairness of the comparison, the population size and the maximum iteration of the five optimization algorithms are set to 20 and 50, respectively. Through these figures, we can see that five fitness curves are gradually decreased with the

TABLE 7. Statistical comparison results of OBLFA_GWO with other peers by Wilcoxon test.

Function	LGWO	FA	GWO	BA	MFO
F1	8.86E-05	8.86E-05	8.86E-05	8.86E-05	8.86E-05
F2	8.86E-05	8.86E-05	8.86E-05	8.86E-05	8.86E-05
F3	8.86E-05	8.86E-05	8.86E-05	8.86E-05	8.86E-05
F4	8.86E-05	8.86E-05	8.86E-05	8.86E-05	8.86E-05
F5	3.38E-04	8.86E-05	1.03E-04	8.86E-05	8.86E-05
F6	8.86E-05	8.86E-05	8.86E-05	8.86E-05	8.86E-05
F7	8.86E-05	8.86E-05	8.86E-05	8.86E-05	8.86E-05
F8	8.86E-05	8.86E-05	1.40E-04	8.86E-05	8.86E-05
F9	2.93E-04	8.86E-05	**6.25E-02**	8.86E-05	8.86E-05
F10	7.65E-05	8.86E-05	7.28E-05	8.86E-05	8.86E-05
F11	**2.50E-01**	8.86E-05	1.56E-02	8.86E-05	8.86E-05
F12	1.03E-04	1.03E-04	8.86E-05	8.86E-05	8.86E-05
F13	1.20E-04	1.51E-03	8.86E-05	8.86E-05	8.86E-05
+/−/=	12/0/1	13/0/0	12/0/1	13/0/0	13/0/0

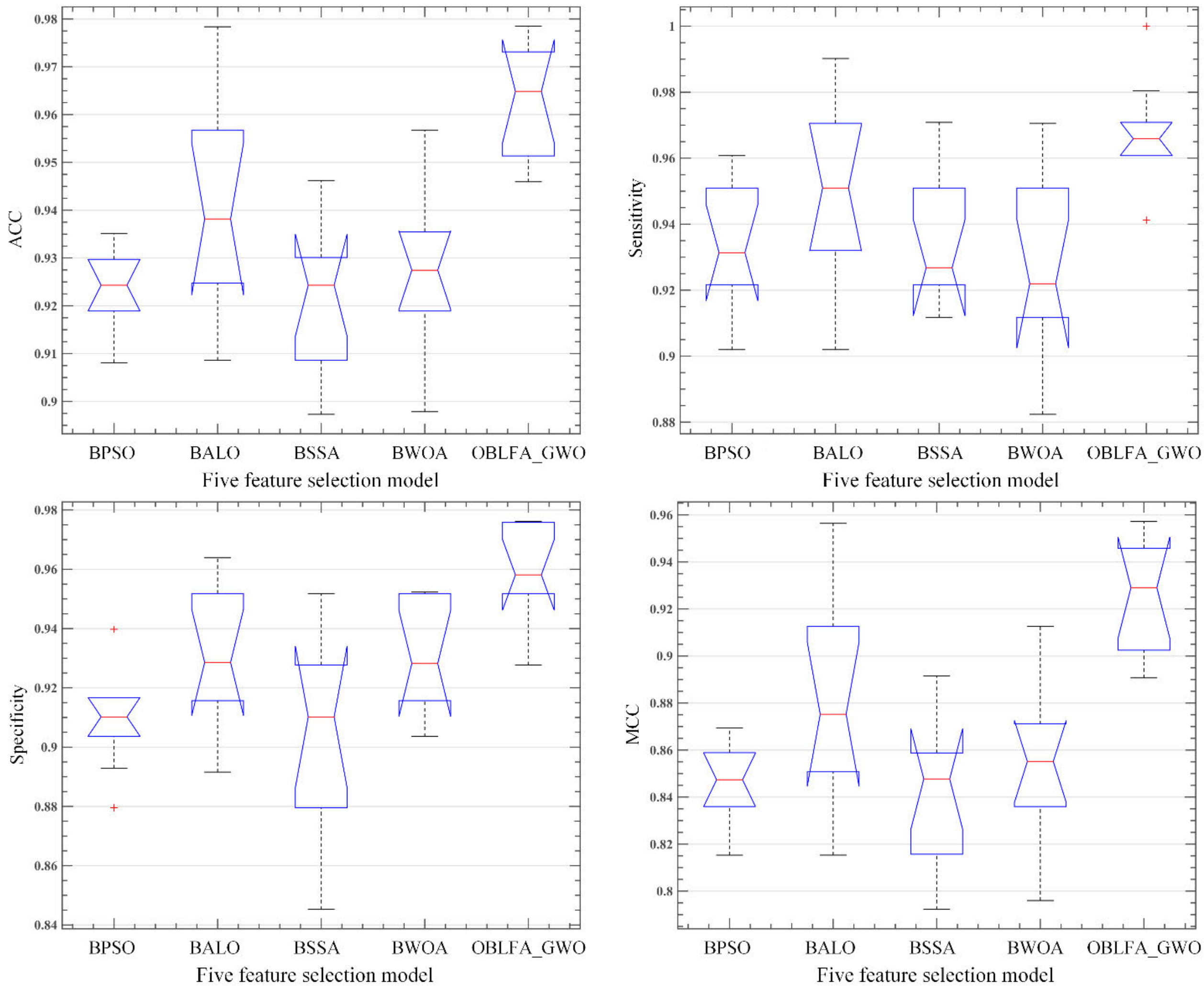

FIGURE 3. Boxplot of the five methods on four evaluation metrics.

increasing number of iteration. As can be seen from Figure 4, the suggested OBLFA_GWO-KNN model attains the finest convergence curve compared to other binary peers based on KNN for feature selection. It can be concluded that the proposed hybrid approach reveals a distinct advantage over the other four algorithms not only in terms of convergence

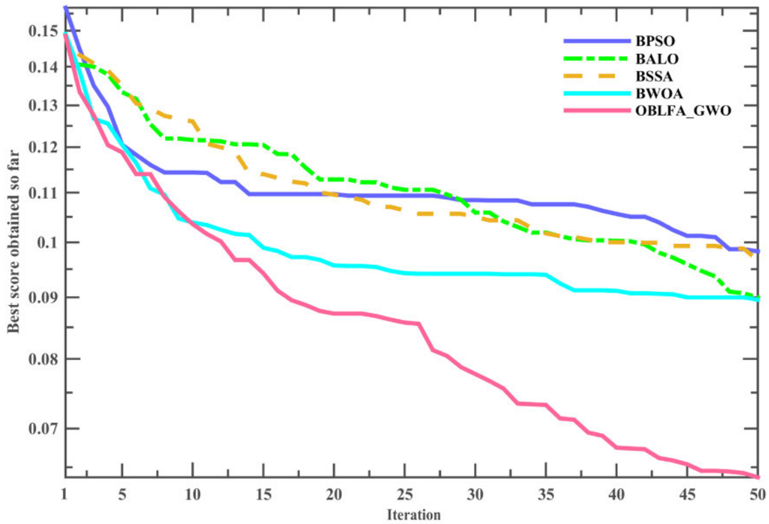

FIGURE 4. Convergence trend of five algorithms.

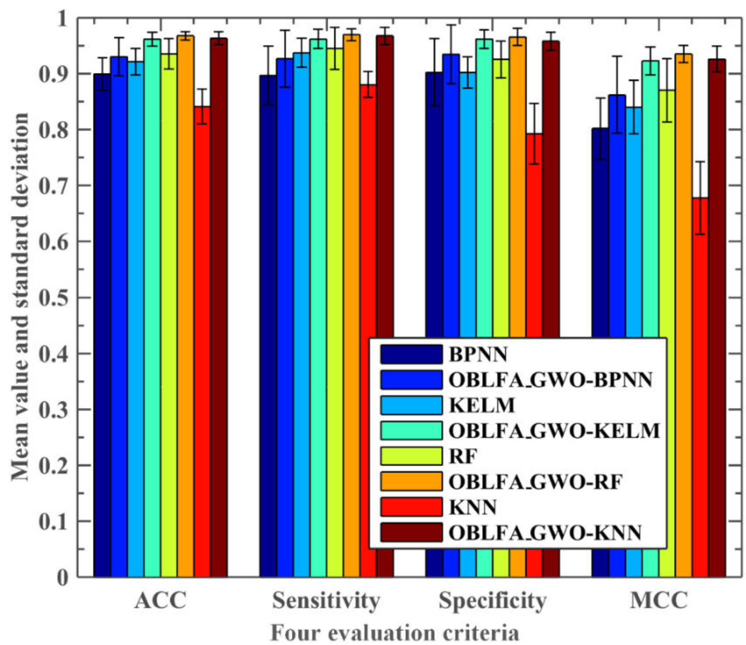

FIGURE 5. Comparison results between OBLFA_GWO-KNN and other peers.

rate but also the fitness value of the obtained optimal solution (subset). In short, the proposed binary OBLFA_GWO algorithm has improved KNN's classification performance compared to the rates obtained by other peers.

The advantage of the binary optimization method (OBLFA_GWO) was tested by comparing the well-known classifiers, including the original KNN, KELM, BPNN, and RF to these four classifiers with OBLFA_GWO. Table 9 shows the classification results of the hybrid OBLFA_GWO-KNN model over 10-fold cross-validation. From Table 9, we can find that the proposed OBLFA_GWO-KNN model can offer the results of 96.334% ACC, 96.771% sensitivity, 95.8% specificity, and 0.92612 MCC, while the original KNN produces results with an ACC of 84.11%, sensitivity of 88.05%, the specificity of 79.28%, and MCC of 0.6778. RF obtains the results of 93.59% ACC, 94.52% sensitivity, 92.57% specificity, 0.8709 MCC. The classical RF with the OBLFA_GWO model can offer the results of 96.77% ACC, 96.97% sensitivity, 96.55% specificity, and 0.9352 MCC. KELM yields the results of 92.13% ACC, 93.77% sensitivity, 90.23% specificity, 0.8404 MCC. The OBLFA_GWO-KELM model provides the results of 96.22% ACC, 96.23% sensitivity, 96.20% specificity, and 0.9229 MCC. BPNN achieves results with the ACC of 89.98%, sensitivity of 89.71%, the specificity of 90.26%, MCC of 0.8020. The OBLFA_GWO based BPNN model yields

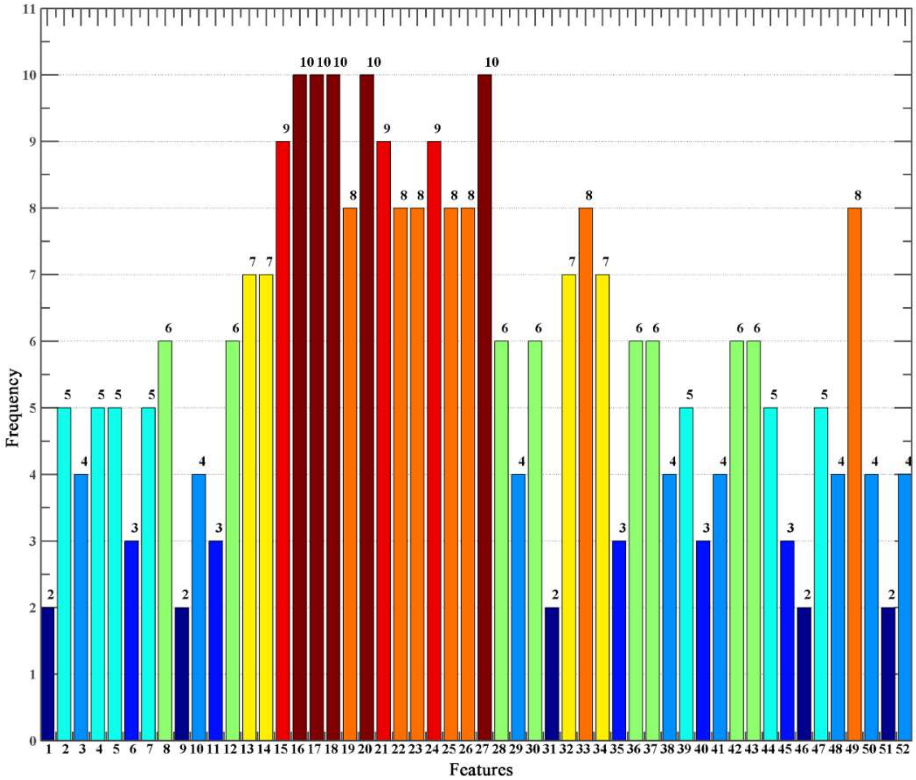

FIGURE 6. Frequency of 52 attributes selected by the OBL_GWO-KNN.

TABLE 8. Parameters setting for compared methods.

Method	Other parameters
BPSO	$c_1= c_2=2$; $vMax=6$; $wMax=0.9$; $wMin=0.4$
BALO	$k=500$
BSSA	$c_1\in[0\ 1]$; $c_2\in[0\ 1]$
BWOA	$a_1=[2,0]$; $a_2=[-2,-1]$; $b=1$
OBLFA_GWO	$a=[2,0]$; $\varepsilon = 0.2$; $\varphi_0 = 1$; $\gamma = 1$

the results of 93.05% ACC, 92.70% sensitivity, 93.47% specificity, 0.8622 MCC. For illustrating the experimental results, the performance of KNN, KELM, BPNN, and RF with the proposed feature selection algorithm and the original four classifiers are depicted in Figure 5 in terms of four criteria [6]. The experimental results demonstrate that the proposed OBLFA_GWO-KNN model obtains the best average results among four original methods via 10-fold cross-validation. Also, with the help of OBLFA_GWO, the four original classifiers can obtain more reliable solutions compared to the other well-known classifiers in terms of four indexes.

The statistical result of the frequency for each feature in Table 9 is depicted in Figure 6. Five attributes, including F16, F17, F18, F20, and F27 are the most common factors showed in ten selected feature combinations over the feature selection process. Therefore, the attributes 'saving energy', 'repairing damaged items', 'lowering the screen brightness of computers and mobile phones recycling old items', and 'having nod food left after eating in the cafeteria' are critical features in identifying the students' green consumption behavior. Therefore, we should pay more attention to these features to update the policies and rules for China's green consumption.

V. DISCUSSIONS

Based on the above experimental results, the most important characteristics of green consumption behavior are saving energy (F16), repairing damaged items (F17), lowering the screen brightness of computers and mobile phones (F18), recycling old items (F20) and having nod food left after eating in the cafeteria (F27). College students with these behavioral characteristics are more likely to engage in green consumption behavior. It can be seen that saving electricity and lowering the screen brightness of electronic products are all simple and feasible habits. Students with such living habits naturally pay more attention to energy conservation and environmental protection in other consumption cases. Repairing damaged items and eating in the canteen reflect the individual's consciousness of saving. With the advancement of the "optical action", garbage sorting, and other national actions, college students gradually accept that "resources are limited", "diligence and thrift are a virtue", etc. The concept of green consumption is becoming a trend. The second

TABLE 9. The detailed results obtained by OBLFA_GWO-KNN.

Fold	Selected feature subset	ACC	Sensitivity	Specificity	MCC
#1	{2, 3, 4, 6, 7, 11, 13, 14, 15, 16, 17, 18, 19, 20, 21, 23, 24, 25, 26, 27, 28, 30, 32, 33, 35, 36, 37, 41, 42, 43, 44, 46, 48, 49, 52}	0.97849	1	0.95238	0.95731
#2	{3, 6, 9, 14, 15, 16, 17, 18, 20, 21, 22, 23, 24, 25, 27, 32, 34, 37, 39, 40, 42, 44, 45, 46, 47, 49}	0.95722	0.96117	0.95238	0.91355
#3	{1, 2, 4, 5, 8, 10, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 24, 25, 26, 27, 28, 30, 33, 38, 39, 40, 48, 52}	0.97312	0.97059	0.97619	0.94584
#4	{5, 11, 12, 13, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 30, 31, 32, 33, 34, 37, 47, 50}	0.95135	0.94118	0.96386	0.90248
#5	{3, 5, 7, 8, 9, 12, 13, 14, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 29, 30, 33, 34, 36, 38, 39, 43, 44, 45, 48, 49}	0.97326	0.97087	0.97619	0.94608
#6	{2, 4, 6, 7, 11, 12, 15, 16, 17, 18, 19, 20, 22, 23, 24, 25, 26, 27, 33, 34, 36, 37, 39, 42, 43, 44, 45, 49, 50, 51}	0.96216	0.96078	0.96386	0.92366
#7	{1, 8, 13, 15, 16, 17, 18, 20, 21, 23, 24, 26, 27, 28, 29, 32, 35, 38, 39, 42, 43, 44, 47, 49, 51}	0.96757	0.98039	0.95181	0.93452
#8	{3, 4, 7, 8, 10, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 40, 41, 42, 47, 49}	0.94595	0.96078	0.92771	0.89071
#9	{2, 5, 8, 10, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 26, 27, 30, 32, 33, 34, 36, 37, 41, 43, 49, 50, 52}	0.95135	0.96078	0.93976	0.90161
#10	{2, 4, 5, 7, 8, 10, 14, 15, 16, 17, 18, 19, 20, 21, 22, 25, 26, 27, 28, 29, 32, 33, 34, 36, 41, 42, 43, 47, 48, 49, 50, 52}	0.97297	0.97059	0.97590	0.94549
avg	-	0.96334	0.96771	0.95800	0.92612
stdv	-	0.01137	0.01535	0.01634	0.02306

most crucial green consumption behavior is characterized by walking, cycling, or using public transportation (F15), not buying or not using disposable items (F21), and selecting energy-saving types of electronic products (mobile phones, notebooks, etc.) (F24). Green travel is an essential part of green consumption behavior, but the current green travel system in China is still not completed, and the convenience of green travel cannot meet the demand of the most ordinary people. The most typical of these is that the bus system in major cities is not perfect, and the proportion of citizens choosing to travel by bus is not high. The current development trend of the sharing economy represented by shared bicycles is unclear. Many shared bicycle companies have been unable to develop in China, which has affected the enthusiasm of college students in green travel. The same problem arises when you don't buy or use disposable goods. It is more convenient to use disposable items before there is a better alternative. Convenience is one of the most important factors for college students. Picking energy-saving types of electronic products may be related to energy prices. When purchasing such products, the average college students look for styles and prices, while energy labels are not much attention. Therefore, a college student who pays attention to energy conservation is generally the committed user of energy-saving products with a strong sense of green consumption.

In summary, college students with energy-saving, environmentally friendly habits and logical consumption concepts are more likely to implement green consumption. Green consumption is more acceptable only if it is balanced in economy and convenience. Thanks to the power of machine learning, China's green consumption level has much room for growth with the improvement of infrastructure and the educational systems.

VI. CONCLUSIONS AND FUTURE WORKS

An enhanced KNN-based framework was presented in this work to predict the students' behavior of green consumption. We proposed an improved OBLFA_GWO algorithm, which combined the idea of GWO, FA, and OBL mechanisms to enhance the exploratory and exploitation tendencies of the original GWO algorithm. We substantiated the modifications using 13 core benchmark functions. The experimental results indicate that the proposed OBLFA_GWO algorithm outperforms LGWO, FA, GWO, BA, and MFO in terms of average performance and running speed. Also, the enhanced binary OBLFA_GWO algorithm used to select the best combination of features in the experimental dataset. Hence, the OBLFA_GWO wrapper-based model was employed to predict the students' behavior of green consumption. On the one hand, the dataset of green consumption is utilized to compare the quality of the selected features obtained by OBLFA_GWO with other BPSO-KNN, BALO-KNN, BSSA-KNN, and WOA-KNN as feature selection approaches. Simulation results have shown that the proposed hybrid strategy can reveal a distinct advantage over the other four algorithms in terms of convergence rate and fitness values. On the other hand, the efficacy of the proposed binary method was tested against well-known classifiers such as KNN, KELM, BPNN over 10-fold cross-validation. Experimental results have shown that the classification performance with the proposed wrapper method was boosted compared to the other four original peers on the four indexes via 10-fold cross-validation.

It is noteworthy that this topic needs more efforts to be done. First, the involved attributes investigated in this paper are limited and obtaining the initial dataset is hard to process. More works should be conducted to investigate more factors that may influence students' behavior of green consumption in china or other countries. Second, to make an unbiased learning model, the experimental dataset needs to accomplish based on many kinds of universities for increasing the diversity of the experimental dataset. Also, building an expert system based on the OBLFA_GWO algorithm is one of our future research directions.

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