

# An Efficient Kernel Extreme Learning Machine Approach for Bankruptcy Prediction

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**Abstract:** In recent years, many novel swarm intelligence algorithms have been proposed to apply in various fields. Kernel extreme learning machine (KELM) is combined kernel function with Extreme learning machine (ELM) algorithm. Then, KELM can reach the more robust and better generalization performance than the basic ELM. However, the performance of the method is determined by the crucial parameters in the practical cases. The key parameters of KELM are explored and the selection methods of the KELM-based swarm intelligence optimization are utilized. The FOA and GWO are intelligence computing methods which abstracts the math model from the hunting behavior of the creatures in the natural world. In order to further explore the ability of the FOA, crisscross strategy and GWO-based mechanism are introduced to FOA and called CGFOA. In this paper, a novel method of the CGFOA-KELM is proposed and successfully applied in financial bankruptcy prediction.

**Keywords:** Ente Kernel extreme learning machine, Parameter optimization, Fruit fly optimization, Bankruptcy prediction, Crisscross, Grey wolf optimization.

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## 1. Introduction

Optimization problems are everywhere, and researchers have never stopped studying optimization problems. Due to the complexity of optimization problems, there has never been a single method that can effectively solve all optimization problems. Since swarm intelligence optimization algorithm has been used to solve optimization problems, its many characters have attracted the attention of many researchers. The flexibility of swarm intelligence enables it to be applied to a wide range of optimization problems. Although it is not guaranteed that the global optimal solution can be obtained, the approximate solution of the global optimal solution can be obtained in most cases. In essence, optimization is suitable for finding an optimal solution or a group of optimal solutions of unknown variables [1]. Several swarm intelligence optimization algorithms, including moth-flame optimization (MFO) [2, 3], differential evolution (DE) [4], grey wolf optimization (GWO) [5, 6], genetic algorithm (GA) [7, 8], particle swarm optimization (PSO) [9], bacterial foraging optimization (BFO) [10], grasshopper optimization algorithm (GOA) [11], Harris hawks optimization (HHO) [12, 13] and artificial bee colony (ABC) [14], have been studied to determine the optimal parameter of the KELM model. However, these previously proposed optimizers introduce some specific parameters. Furthermore, as summarized by the 'no free lunch' (NFL) theorem, there is no best solution for all optimizations [15]. It has spurred the development of a wide variety of approaches with the goal of achieving superior optimization capabilities.

Never in recent memory has global growth been so clouded by uncertainty. Covid-19's full impact has been obscured by massive government intervention to bail out companies and support workers. Due to the impact of pandemic, many companies are going bankrupt or confronting the danger of dissolution. How to make a reasonable and accurate early warning before the official bankruptcy of the enterprises is of great practical significance. The financial crisis gets a lot of attention around the world. It is important to develop an

efficient method to predict company bankruptcy and assist to make accurate decision [16]. Bankruptcy prediction is generally a binary classification event and majority novel classification models have evolved [17-23]. The prediction of bankruptcy or non-bankruptcy is based on the model construction, while the input value of the classification model is the current financial situation of the enterprise, such as total assets, liabilities and surplus. There are two kinds of solution to the forecast problem of the enterprise bankruptcy. One way are typical mathematics and straightforward statistical methods in which to find the corresponding principle. A second are sophisticated artificial intelligence (AI) methods. Owing to the powerful capacities of coding with nonlinear data, the smart AI models generally outperform the analytical approaches in most performance attributes [16]. Besides, the increase big data [24] and AI techniques [25] have played an crucial role in the evolution of bankruptcy prediction. There are a variety of AI models utilized for bankruptcy prediction and financial decision making, including support vector machines (SVM) [26, 27], artificial neural networks (ANN) [28], decision trees (DT) [18], extreme learning machine (ELM) [21], kernel extreme learning machine (KELM) [5, 29], and other methods [17, 19, 20, 22, 30-33] and various hybrid approaches. Kerel Extreme Learning Machine (KELM) [28] is a new multi-class classifier developed on the ELM. In essence, extreme learning machine is a feedforward neural network with single hidden layer. Also, as a classification method, ELM [34] demonstrates superior performance compared to other state-of-the-art classifiers, including SVM [35]. While KELM [35], which is a method to extend ELM, can avoid the limitations of random assignment of weights in ELM for minimizing the fluctuation of accuracy and improving generalization performance. Owing to easy implementation, excellent efficiency, and fast training speed, KELM has been increasingly utilized in numerous fields including bankruptcy prediction [5], disease diagnosis [2, 36], regression tasks [37], image watermarking [4], spectra data classification [38], android electronic nose systems [39], tool condition monitoring [40], prediction of effluent quality [41],

digital mammogram classification [42], intrusion detection [43], tourist arrival forecasting [44] and action recognition [45]. Also, KELM performs well under complex imbalance classification circumstances [46] and large scale data classification [47]. Therefore, given KELM's merits and its widespread application, it is observed that KELM can be regarded as a promising classifier in bankruptcy prediction problem.

However, a lot of studies [2, 29, 47-50] have used metaheuristic algorithms to search for the best two parameters of the KELM model. The two critical parameters are kernel penalty parameter  $C$  and bandwidth  $\gamma$ . Liu et al. used quantum genetic algorithm to optimize KELM parameters. Wang et al. proposed a chaotic moth optimization strategy to optimize the parameters of KELM. In this study, an improved method of multi-population intelligent optimization algorithm is proposed, and the improved swarm intelligent optimization algorithm is applied to the optimization problem of machine learning model, and an effective prediction model is constructed according to the actual problem. Especially, the coefficient vector in GWO is used for crucial exploration, its randomness would lead to premature convergence in the detection of KELM optimal parameters. It means that there are still new optimizers that can solve problems better than previous optimizers [51]. The fact drives the development of considerable different approaches with the goal of achieving superior optimization capabilities. Many studies focused on modifying DE and PSO [52-59]. Besides, it provides a practical method for optimal design of fruit fly optimization. In addition, the research on swarm intelligence optimization algorithm improvement will also help other researchers in the field to enhance the original swarm intelligence algorithm, as many swarm intelligence algorithms face similar problems.

Pan [60] developed the classic fruit fly optimization algorithm (FOA) inspired by the foraging behavior of fruit flies in 2012. Like other intelligence algorithms, FOA has many advantages and has been applied in many real-world problems, such as searching for some feasible solutions [25, 61-68]. Due to the briefness in the calculation process and the simplicity in structure, FOA converted the foraging behavior into computer code easily and has attracted considerable attention since it was invented. Thus, to keep a balance in exploration and exploitation capacities, several improved FOA variants have been designed. As a result, FOA and its variants have been successfully used in many practical optimization fields [69-80]. Furthermore, FOA-based methods have been used for classification problems [48, 81-86]. Although the involved methods were employed to SVM, GRNN or LSSVM for parameter optimization, the works based on FOA-KELM for classification problems are worth developed. Zhang et.al [87] proposed a LSEOFOA-KELM towards bankruptcy prediction. Therefore, this study aims at developing an advanced FOA to optimize the KELM model for classification, and then to apply the acquired FOA-KELM classification model to predict bankruptcy, successfully and effectively. In the developed CGFOA, crisscross strategy and GWO-based mechanism are used to strengthen the randomness and exploration capability of the original FOA. The CGFOA is then used for optimizing KELM's two vertical parameters to advance the classification performance of the KELM model. Aimed at evaluating the performance of CGFOA on CEC 2017 test cases and bankruptcy prediction, several experiments are designed. As a result, the proposed CGFOA performs excellent compared to standard FOA and

other well-established algorithms. Besides, a KELM model based on CGFOA method obtains higher predictive accuracy than several other models.

The main contributions of this study are:

With crisscross strategy and GWO-based mechanism, a new enhanced algorithm CGFOA is proposed. In this section, crisscross strategy and GWO-based mechanism are illustrated, and the codes and flowchart of the CGFOA are presented.

The performance of CGFOA was demonstrated in a series of experiments on the CEC 2017 optimization assignments. Firstly, we discussed the one or two strategies which impact the outcomes on CEC2017 functions. Secondly, the CGFOA was compared with other improved FOA-based methods. Thirdly, several conventional algorithms as well as CGFOA were run in the same main function on CEC2017. Eventually, CGFOA was in comparison with several advanced optimizations on solving CEC2017 test functions.

The CGFOA-KELM is applied in financial bankruptcy prediction, finding the optimization problems with the optimal accuracy when compared to some other KELM-based swarm intelligence methods.

## 2. Proposed CGFOA

### 2.1. Fruit Fly Optimization Algorithm (FOA)

The Basing on the foraging behavior of fruit fly, FOA is a global search optimization. Fruit flies live in temperate as well as tropical climate and eat rotting fruit. Despite fruit flies are small, they have a sensitive sense of smell and vision which observe majority smells in the air successfully. Besides, they smell food source even far from 40 km away. They make use of smell sense to get close to the maximum smell concentration of the food and fly to the position successfully. Finally, they obtain the food. Simulating the fruit fly foraging for food, the FOA is divided into several steps as follows.

Step 1: Initialize parameters. Set the position  $(X_{axis}, Y_{axis})$  of fruit fly swarms randomly, as well as the maximal iterative number (MaxFEs). It is that the number of search agents (sizepop) and other parameters are initialized.

$$\begin{cases} X_{axis} = rands(1,2) \\ Y_{axis} = rands(1,2) \end{cases} \quad (1)$$

Step 2: Initialize individual. Each individual forages for food by the sense of smell and the vision, where  $i$  stands for the  $i$ th agent.

$$\begin{cases} X_i = X_{axis} + 2 \times R \times rand() - R \\ Y_i = Y_{axis} + 2 \times R \times rand() - R \end{cases} \quad (2)$$

Step 3: Individual evaluation. The distance ( $Dist_i$ ) is calculated as Eq. (3), and the smell concentration judgment value ( $S_i$ ) is evaluated as Eq. (4).

$$Dist_i = \sqrt{X_i^2 + Y_i^2} \quad (3)$$

$$S_i = 1 / Dist_i \quad (4)$$

Step 4: Define the smell. The function ( $Smell_i$ ) is determined by smell concentration judgment value ( $S_i$ ), and estimates each individual as Eq. (5).

$$Smell_i = Function(S_i) \quad (5)$$

Step 5: Determine the optimal. Order the  $Smell_i$  and find the maximum smell concentration of fruit fly swarm. It is the position that near the food and the expression is as follow.

$$[bestSmell \ bestIndex] = \max(Smell) \quad (6)$$

Step 6: Conserve the optimal position. The above best smell concentration is equal to the optimal concentration and the related position ( $X(bestIndex), Y(bestIndex)$ ) updates the fruit fly swarm position ( $X_{axis}, Y_{axis}$ ) in the next iteration.

$$Smell_{best} = bestSmell \quad (7)$$

$$\begin{cases} X_{axis} = X(bestIndex) \\ Y_{axis} = Y(bestIndex) \end{cases} \quad (8)$$

Step 7: Iteration loop. The above steps 2-5 are repeated in each iteration until the iteration gets to the maximum iteration or the smell function is equal to itself in the next iterative number. If ends, then go step 6.

After trial and error, the mentioned FOA algorithm falls into the convergence easily and early due to the next location only evaluated by the previous position. Besides, all the population share information with the best one and it easily falls into local optima. Therefore, to effectively avoid the limitation and enhance optimization capability, an enhanced FOA is proposed as follow.

## 2.2. Crisscross Strategy

Crisscross strategy (CC) is illuminated by the Confucian doctrine of the mean and the crossover steps of GA, which is made up of the horizontal crossover (HCS) and vertical crossover (VCS) mainly. The two crossover operations are introduced to the global search of FOA, which improve the explorative ability without slowing the convergence speed.

## 2.3. Grey Wolf Optimization

The grey wolf optimization (GWO) [88] is an efficient intelligence method has been widely used, which is proposed by Mirjalili et al. The algorithm is inspired by wolves in nature and simulates the hierarchical system as well as group hunting behavior existing in wolves. According to the hierarchical system, the wolf group is divided into Alpha ( $\alpha$ ), Beta ( $\beta$ ), Delta ( $\delta$ ) and Omega ( $\omega$ ). When the grey wolf rounds up the prey, the individual grey wolf in the group follows the position of three wolves to round up the prey.

## 2.4. The Proposed CGFOA

The original FOA is brief, simple and convenience in the iterations, which simulates the foraging behavior of fruit fly. Aimed at achieving the optimal agent, it generates a new location and converts the location into the smell concentration value randomly. But it traps into local optima easily. The crisscross operator and position update formula of GWO are introduced to the basic FOA. As crisscross operator strengthens the exploration and diversifies fruit fly swarm and GWO-based strategy prevents convergence and keeps balance in exploration and exploitation, a new enhanced FOA (CGFOA) is proposed. The entire procedure of the proposed CGFOA is provided in Figure 1, and the pseudocode is summarized as follow.

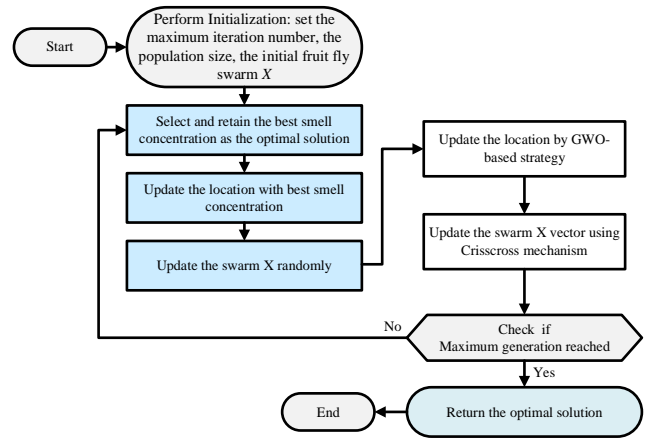


Figure 1. Flowchart of CGFOA

## 3. Experiments and Analysis

In this part, CGFOA was compared with other optimizers to verify its convergence ability. For a fair comparison, the whole experiments in this paper were conducted under the MATLAB R2018b software on the same computer equipped with Windows 10 (64 bit) operating system with Intel(R) Core (TM) CPU i7-10700 @ 2.90 GHz 2.90 GHz and 8 GB RAM.

To demonstrate the impact of only one or two strategies on the performance of the basic FOA, comparative experiments were designed in this experiment. The comparison result of CGFOA is shown in Table 1.

Table 1. Comparison outcome of CGFOA with FOA variants

	CGFOA	CFOA	GFOA	FOA
Avg	1.0333	2.3000	3.2000	3.4667
rank	1	2	3	4

## 4. Conclusion

Table 1 describes the average ranking outcomes by the Friedman test. As a result, CGFOA ranks the first, CFOA is the second, GFOA is worse than CFOA, and FOA owns low-ranking. This indicates that crisscross mechanism enhances the exploration skills of FOA to find the optimal solution obviously. Thus, the ranking results of the Friedman test are marked by 'AVR' in Table 5, CGFOA's 1.0333 ranks first with the best performance. Above all, it can be concluded that the crisscross as well as GWO-based strategies work well in FOA. Therefore, CGFOA obtain better outcomes than both CFOA and GFOA.

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