Pakistan J. Zool., vol. 56(3), pp 1305-1314, 2024 DOI: https://dx.doi.org/10.17582/journal.pjz/20220905020912

Application of UAV Image Detection Based on CBPSO Algorithm in Crop Pest Identification

Li Tian[1]*, Chun Wang[2], Hailiang Li[2], Haitian Sun[2] and Chang Wang[3]

[1]*College of Information and Electrical Engineering, Heilongjiang Bayi Agricultural University, Daqing, 163319, China*
[2]*South Subtropical Crops Research Institute, Chinese Academy of Tropical Agriculture Science, Zhanjiang, 524000, China*
[3]*College of Science, Heilongjiang Bayi Agricultural University, Daqing, 163319, China*

Article Information
Received 05 September 2022
Revised 20 December 2022
Accepted 18 October 2022
Available online 08 May 2023 (early access)
Published 17 April 2024

Authors' Contribution
LT, CW and HL conceived the research idea and designed the study. HS and CW visited the dairy farms and collected the data. LT and CW performed data analysis. LT and HL wrote the paper.

Key words
CBPSO algorithm, Image detection, Identification of pests and diseases, Fitness, Character screening

ABSTRACT

In order to quickly control crop diseases and insect pests, chaos theory is used to optimize PSO, and CPSO algorithm is proposed. In the practical application of crop diseases and insect pests identification, CBPSO algorithm is obtained by binary operation of CPSO, and its performance and application are analyzed. The experimental results show that the classification accuracy of CBPSO-SVM algorithm is 98.22% and 97.78% respectively in gray spot disease and algal spot disease, higher than that of PCA-SVM (82.5% and 83.67%). In addition, the average classification accuracy of CBPSO-SVM is 91.26%, better than that of PCA-SVM (81.83%). At the same time, through the comparison of CBPSO algorithm, BPSO algorithm and PSO algorithm, it is found that CBPSO algorithm has great adaptability, the maximum fitness is 0.99, and the average fitness is 0.97. Therefore, CBPSO algorithm has good effect on global optimization, and its convergence speed is faster, and its execution task and efficiency are higher. In addition, among the five particle swarm optimization algorithms, the CBPSO algorithm performs best in the 20 dimension, with the minimum value of 1.0008 and the minimum value of variance of 8.4206. Therefore, it is determined that the search efficiency of the CBPSO algorithm in the 20 dimension is the best. Compared with other algorithms, the stability and accuracy of the CBPSO algorithm have been greatly improved, and it has high robustness in the actual UAV image detection and crop pest identification.

INTRODUCTION

Crop diseases and insect pests are a natural disaster faced by farmers, which not only cause serious harm to agricultural production, but also affect the quality of agricultural products (Xiao *et al*., 2018). With the continuous development of computer vision technology, these problems have been gradually solved. The application of the above technologies to detect and identify pests and diseases can lay a theoretical foundation for future prevention and control work. Therefore, scholars at home and abroad have carried out extensive research on it. Paula *et al*. (2021) confirmed the mutant of soybean aphids by studying soybean genes, and the mutation helps to improve the resistance of soybean aphids, thus providing help for soybean aphid control using the complete mitochondrial gene structure to establish a maximum likelihood evolutionary tree, which provided a data basis for the control of nematodes. Chen *et al*. (2021) used a digital image recognition and counting algorithm based on three-step deep learning, which reduces the recognition time of wheat mites in wheat fields, thereby avoiding the loss of wheat fields. Khadatkar *et al*. (2021) used practical application of some traditional knowledge technologies to provide a basis for pest reduction and sustainable agricultural development. Based on this, the research obtained the chaotic binary particle swarm optimization (CBPSO) algorithm by combining chaos theory with the particle swarm optimization (PSO) algorithm and binary processing, which was actually applied to crop diseases and insect pests. In identification, the aim is to improve the efficiency and accuracy of UAV image detection in the identification of pests and diseases through the CBPSO algorithm, thereby reducing the loss of agricultural production.

Abriviations used:
CBPSO, Chaotic binary particle swarm optimization; PSO, Particle swarm optimization; UAV-IS, UAV integrated system

* Corresponding author: tllbj19781015@126.com
0030-9923/2024/0003-1305 $ 9.00/0

Related work

Computer vision technology has a good application prospect in the detection and identification of crop diseases and insect pests, and it is a research hotspot at present. However, due to the variety and disorder of pests, it is very difficult to identify pests in real time. There are still limitations in monitoring and controlling pests by using mechanical vision technology only. Therefore, the majority of domestic and foreign scholars have done a lot of research on the identification technology of crop diseases and pests. These studies have enhanced the recognition and classification accuracy of rice diseases by using network learning technology, and also improved the recognition efficiency (Nageswari *et al*., 2020), analyzed the data of bacteria in cocoa beans to reduce the insect invasion of cocoa bean trees and improve their yield (Simamata *et al*., 2020), confirmed that intestinal bacteria play an important role in insecticide resistance in cotton bollworm population by detecting 11 bacterial isolates of cotton bollworm, thus improving the quality of pesticides (Madhusudhan *et al*., 2021), by expounding the application of deep learning and bionic technology in the agricultural field promoted the intelligent development of agriculture and provided help for crop classification and disease insect identification. Tu *et al*. (2021) introduced the application of artificial intelligence technology in integrated pest control, so as to transfer integrated pest management (IPM) technology to remote areas around the world, providing a good solution for agricultural disease pest control (Srikanth *et al*., 2020). Hunter *et al*. (2020) combined unmanned weed map and unmanned spray device in UAV integrated system (UAV-IS) to improve the efficiency of pest management. These studies introduced a method for classification and early diagnosis of soybean diseases by using computer automatic vision technology, and sent disease information to farmers by using mobile phone computing to reduce the threat of diseases and pests (Devaraj *et al*., 2017).

In addition, Peng *et al*. (2017) proposed the particle swarm optimization (CBPSO) algorithm based on the basic principles of fuzzy mathematics, and established a multi-objective fuzzy optimization model with correlation constraints, thus reducing the cost of microgrid; effectively reduced the complexity of the communication system by using the CBPSO algorithm, thereby reducing the cost and increasing the system capacity (El-khamy *et al*., 2017). Shahbeig *et al*. (2018) used chaos theory and particle swarm optimization to obtain binary particle swarm optimization (BPSO) algorithm, which improved the accuracy and flexibility in classification and recognition. They used the multi-scale UAV image data source to provide help for finding an efficient fracture extraction technology suitable for the surface conditions of Jinchuan copper nickel ore (Geng *et al*., 2022). They verified that single canopy detection can provide important information for ecology and economy through the research on UAV photogrammetry technology of single canopy (Tahar *et al*., 2021); Effectively identified the defects of high-voltage transmission lines by using the deep learning method by identifying and classifying the images collected by UAVs (Zheng *et al*., 2021); The impact of intermittent cicada occurrence on broad-leaved mixed forest was evaluated by using UAV images, so as to reduce the large-area loss in forest area (Hentz and Strager, 2018).

Through the research of domestic and foreign scholars, it can be found that UAV image detection technology can effectively improve the efficiency of disease and pest identification, and particle swarm optimization algorithm can also improve its accuracy in classification and identification. Therefore, it is necessary to study the application of UAV image detection based on cbpso algorithm in disease and pest identification.

MATERIALS AND METHODS

Identification technology of crop diseases and insect pests based on CBPSO algorithm

Analysis of PSO algorithm based on chaos theory

In order to quickly prevent crop diseases and insect pests, and at the same time reduce the damage of pesticides to the ecological environment, on the basis of PSO, in view of the shortcomings of its slow convergence speed, chaos theory is introduced to obtain the CPSO algorithm, and then binary processing is performed according to actual needs to obtain CBPSO algorithm and its performance analysis in crop disease and insect pest image recognition. The PSO algorithm simulates the process of bird foraging, the optimization problem is bird foraging, the search space is the activity space of birds, and the particle is a bird that seeks the solution of the optimization problem in the search space (Wang *et al*., 2017). It is assumed that the particle is a volume less point, moving in the search space, using its own experience and the experience of its partners to dynamically adjust the speed, thereby changing its direction and position, and using the iterative method to find the best solution. After each iteration, the particle will use two extreme values to update itself, and the individual extreme value is the best result that the particle itself can find, and the whole value is the best result of the particle swarm. The PSO algorithm process as shown in Figure 1.

As can be seen from Figure 1, the PSO algorithm process is first to initialize the particle swarm; secondly, to evaluate the particles; then to update the individual best and the global best of the particles, and to ensure that when the particle fitness value is *pbest* better than *gbest* replace the current position; then update the particle according to Equations 4 and 5; finally determine whether the number of iterations exceeds the set threshold, if not, re-evaluate the particle, if so, output the optimal solution to terminate the loop.

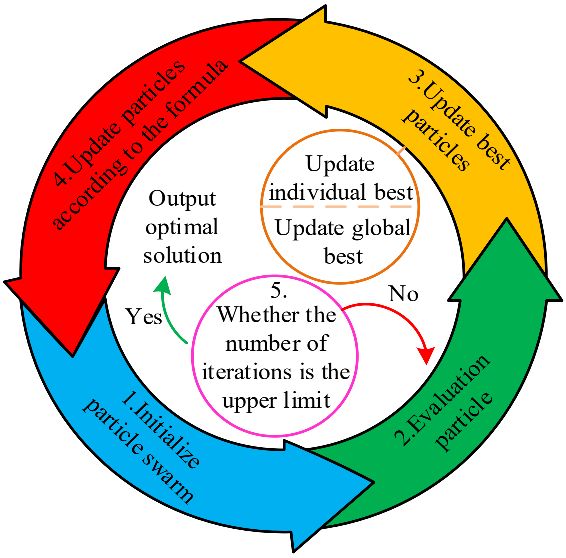

Fig. 1. Flow chart of PSO algorithm.

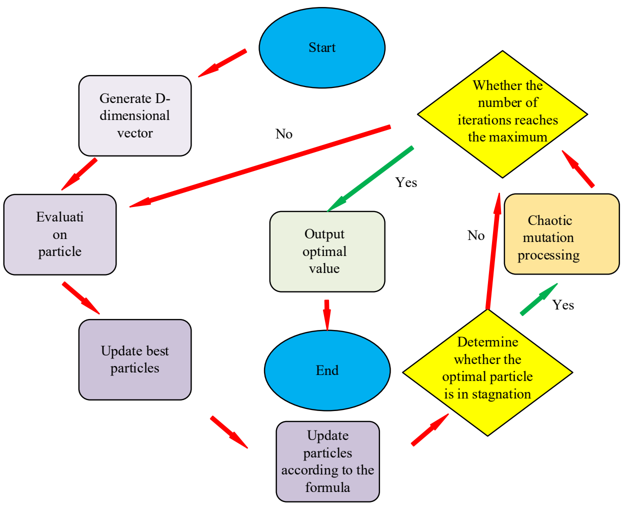

Fig. 2. CPSO algorithm flow chart.

Due to some limitations of PSO, such as the uncertainty of initializing the population, and the PSO algorithm is easy to generate local optima in the middle and late iterations. Therefore, in order to solve these problems, the research introduces the chaotic principle and proposes the CPSO algorithm. The core of the CPSO algorithm is to introduce the chaotic principle into the population when initializing the population. The algorithm flow is shown in Figure 2.

As can be seen from Figure 2, the algorithm flow is firstly to randomly generate a D vector of dimension y under the group initialized by chaos theory, so as to complete the initialization process; secondly, to evaluate the particles. When evaluating the particles, it is necessary to adapt to the degree function calculates the appropriate value; then update the individual best and the global best; then update the position and velocity of the particle according to Equations 4 and 5; then determine whether the particle is stagnant, and if so, for the particle Perform chaotic mutation processing and then proceed to the next step. If not, do not do the processing and proceed to the next step; finally, determine whether the number of iterations reaches the maximum. If not, re-evaluate the particles and continue the loop. If so, output the optimal value to end the loop. In the step of generating a vector in the algorithm, the formula of the vector is shown in Equation 1.

$$x_1 = x_{11}, x_{22}, \ldots, x_{1D}, x_{1j} \in (0,1), j \in (1,D) \ldots(1)$$

In formula 1, it *j* represents the number of dimensions. On this basis, the logistic mapping regression equation is needed to generate N vectors, and the logistic mapping regression equation is shown in Equation 2.

$$x_{i+1}, j = 4x_{ij}(1 - x_{ij}), i = 1,2,..,N-1, j = 1,2,..,D \ldots(2)$$

Equation 2, the *j* dimension is represented. Therefore, in the optimal problem, *xj* each component carrier is within the value range of the variable, and its range formula is shown in Equation 3.

$$z_{ij} = l_j + (u_j - l_j)x_{ij} \ldots(3)$$

In Equation 3, *z* represents the value range of the variable, *l* and *u* both represent the value range of a certain dimension. In addition, when updating the particle, its velocity update formula is shown in Equation 4.

$$v_{id}^{k+1} = \omega v_{id}^{k} + c_1 r_1 (p_{id}^{k} - x_{id}^{k}) + c_2 r_2 (g_{id}^{k} - x_{id}^{k}) \ldots(4)$$

In Equation 4, *v* represents the iteration speed; *i* represents the particle; *d* represents the number of dimensions; represents the number of *k* iterations; ω represents the inertia weight; *c* represents the learning factor; *r* represents the random number, whose value range is (0, 1); *P* represents the individual extreme value; *g* represents indicates the best position of the particle. The formula for updating the position of the particle is shown in Equation 5.

$$x_{id}^{k+1} = x_{id}^{k} + v_{id}^{k+1} \ldots(5)$$

In Equation 5, it *x* represents the iteration position. In the chaotic mutation processing, a vector with the *So* same dimension will be randomly generated D, and after updating its speed according to Equation 4, it is generated using the formula $S1$, and its generation formula is shown in Equation 6.

$$x_{n+1} = \begin{cases} 2x_n, 0 \le x_n \le 0.5 \\ 2(1-x_n), 0.5 \le x_n \le 1 \end{cases} \quad \ldots(6)$$

Equation 6, it n represents the number of features. In this technique, each $S1$ component is one-to-one corresponding to the disturbance interval [-β, β], so as to obtain the disturbance quantity formula as shown in Equation 7.

$$\square\gamma = -\beta + 2\beta s_{1j} \quad \ldots(7)$$

In Equation 7, □γ represents the disturbance amount and s_{lj} represents the vector of s_l the first j dimension.

Improved algorithm CBPSO algorithm based on CPSO algorithm

On this basis, in order to maintain the diversity of groups as much as possible and improve the search efficiency, to overcome the inability of traditional chaotic particle swarm algorithm to solve discrete problems effectively. The research proposes the CBPSO algorithm. The core idea of the CBPSO algorithm is to encode each particle as a binary vector, and set the particle velocity within a certain range, so as to avoid the SF from being too large by modifying the Sigmoid Function (SF). The formula for particle update is shown in Equation 8.

$$P_{ij} = \begin{cases} 1, rand() \le S(v_{ij}) \\ 0, \quad otherwise \end{cases} \quad \ldots(8)$$

In Equation 8, P represents the historical optimal solution; i represents the i^{th} particle; represents the jth element $S(vij)$ of the current particle; j represents the S shape limiting conversion function. In addition, the definition formula of SF is as shown in Equation 9.

$$S(v_{ij}) = \frac{1}{1+e^{-v}} \quad \ldots(9)$$

In Equation 9, it e represents a natural constant. According to the research needs, the maximum speed is set to 4 according to this formula, so the modified SF formula is shown in Equation 10.

$$S(v_{ij}) = \begin{cases} 0.98, v > 4 \\ \frac{1}{1+e^{-v}}, -4 \le v \le 4 \\ 0.02, v < -4 \end{cases} \quad \ldots(10)$$

Therefore, according to the modified formula of SF, the formula for updating the position of the binary particle swarm is shown in Equation 11.

$$\begin{cases} x_{id}^{k+1} = 1, \rho_{id}^{k+1} < S(v_{id}^{k+1}) \\ x_{id}^{k+1} = 0, \rho_{id}^{k+1} \ge S(v_{id}^{k+1}) \end{cases} \quad \ldots(11)$$

In Equation 11, it ρ_{id}^{k+1} represents a positive real number, and its value range is fixed between (0, 1). The purpose of CBPSO is to improve the defects of PSO algorithm in solving discrete problems, so as to improve the efficiency of traditional chaotic particle swarm optimization, optimize its results, and improve the performance of the algorithm. In general, the particle variable is a binary vector, while the chaotic variable is a real number ranging from 0 to 1, so when using it, the two variables must be interacted. From the previous step to the next step, the binary transformation of the previous step must be into decimal, and then divide by 2^l-1 (l representing binary digits) to obtain a particle variable. This process is the process of transforming the mixture variable into a particle variable. The flow of the CBPSO algorithm is shown in Figure 3.

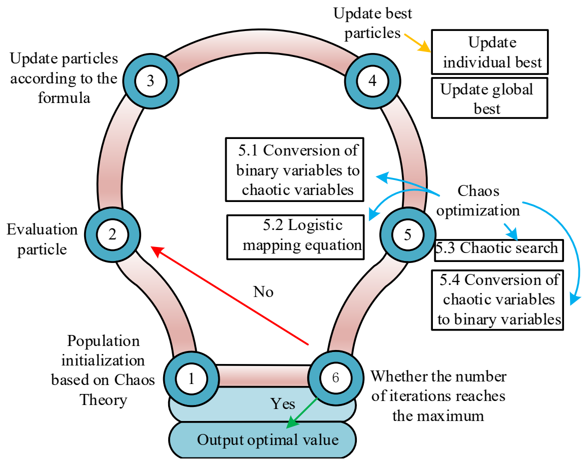

Fig. 3. CBPSO algorithm flow chart.

As can be seen from Figure 3, the CBPSO algorithm first initializes the population according to the chaos theory; secondly, it evaluates the particles; then updates the particles; If the fitness value of the particle is better than the current particle position, P_{best} it will be used P_{best} instead of the current particle position, and when the global update is performed, a judgment is required to select the next step. If the particle fitness value is better than that g_{best}, it will be judged to be premature, and the g_{best} current particle position will be replaced by chaotic execution. Optimize the operation, otherwise go to determine whether the number of iterations reaches the threshold. In the chaotic optimization step, the first step is to transform binary variables into chaotic variables, and secondly, the logistic mapping equation formula, chaotic search and transformation from chaotic variables to binary variables are used; the algorithm finally determines whether the number of iterations reaches the previously set value. If not, re-evaluate the particles, repeat the process, and output the optimal value if it is reached, and end the cycle. Among them, the logistic mapping equation formula is shown in Equation 12.

$$x_i^l = \alpha_i + (b_i - a_i)z_i^l \quad \ldots(12)$$

In Equation 12, α_i, b and a both represent relevant parameters and z_i^l represent chaotic variables. During the chaotic search, it will x^k be set to obtain the fitness value $F(x^k)$, and its setting formula is shown in Equation 13.

$$x^k = (x_1^{l+k}, x_2^{l+k}, \cdots, x_n^{l+k}) \quad \ldots(13)$$

In Equation 13, k represents the number of iterations. On the basis of the fitness value, it is initialized, and then chaos search is performed according to Equation 14.

$$x_{i+1} = 4x_i(1 - x_i) \quad \ldots(14)$$

After the chaotic search, the result is binary discrete to obtain the variable $g^{best\text{-temp}}$. If at this time $g^{best} < g^{best\text{-temp}}$, it needs to g^{best} be updated.

Multi feature selection analysis of CBPSO algorithm in UAV crop diseases and insect pests

In practical application, an important problem of pest identification is feature extraction. The core work of feature extraction is to analyze the image characteristics of various pests and diseases, and determine the corresponding features, so as to achieve the purpose of improving the classification accuracy of pests and diseases (Tanno *et al.*, 2017). In the feature set, more key features are identified, and redundant features are excluded, and the process of avoiding interference is called feature selection. Through the feature selection of images, the classification accuracy of images can be improved (Garcia-Chimeno *et al.*, 2017). Therefore, when performing feature selection, the first problem to be solved is to obtain a correct set of feature subsets. In addition, the problem of feature selection is often the problem of particle swarm optimization. Therefore, the study uses the CBPSO algorithm to extract the characteristics of pests and diseases, including the problem of particle design and parameter conversion. Binary particle swarm optimization is usually described as a binary bit string, and its internal particle structure is shown in Figure 4.

Figure 4 depicts a binary representation, which consists of penalty parameters, kernel parameters, and feature bits. Among them, $C_1 \sim C_N$ represents the binary representation of the penalty parameter, $R_1 \sim R_N$ represents the binary representationof the kernel parameter, and $F_1 \sim F_L$ represents the binary representation of the feature bit. It can be seen from the figure that all three parameters have been binarized, and each binary corresponds to a feature. If the value of the binary is 1, it means that the selected feature parameter is locked; otherwise, if it is not equal to 1, then indicates that it is not locked.

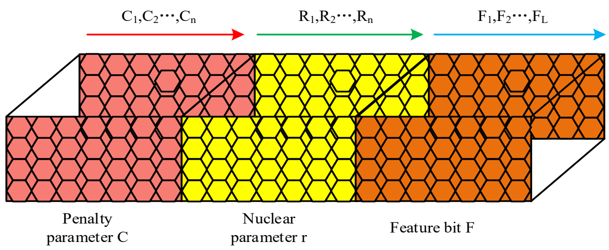

Fig. 4. Particle structure diagram.

In addition, since the particle variable is a binary vector, and the chaotic variable is a real number in the range of (0, 1), in practical applications, the binary of the two variables must be converted into a decimal, and then divided by 2^l-1. The numerical value of a chaotic variable can be obtained, wherein, l represents a binary number, which corresponds to a particle variable, and its conversion formula is shown in Equation 15.

$$P = \frac{\min p + d \times (\max p - \min p)}{2^{l-1}} \quad \ldots(15)$$

In Equation 15, P represents the decimal value of the min p parameter, represents the minimum value of the max p parameter, represents the maximum value of the parameter, l represents the length of the binary number, and represents the decimal value in the binary number d.

RESULTS

Application analysis of CBPSO algorithm in UAV crop disease and pest identification

In order to verify the performance of the CBPSO algorithm, the research selected longan diseases and insect pests among crop diseases and insect pests as the research object through comprehensive consideration, and selected three of them as research data by collecting disease species, as shown in Figure 5, which is the research data set.

In Figure 5, the study selected three common longan diseases, the ratio of which is gray spot, Ascospora leaf spot and algal spot disease. In the overall data, there are 53 gray spot diseases and 60 Ascoidi leaf spot diseases. 60 algal spot diseases, 35 of them were selected as training samples, and the rest were test samples. At the same time, a total of 9 color features, 16 texture features and 12 shape features were selected according to the requirements.

After the sample selection is completed, in order to more clearly see the advantages of the CBPSO algorithm in the identification of crop diseases and insect pests, the study introduces the principle component analysis (PCA) method to rank the three samples in pairs, so as to obtain the The core features, the optimized feature items obtained after optimization are shown in Figure 6.

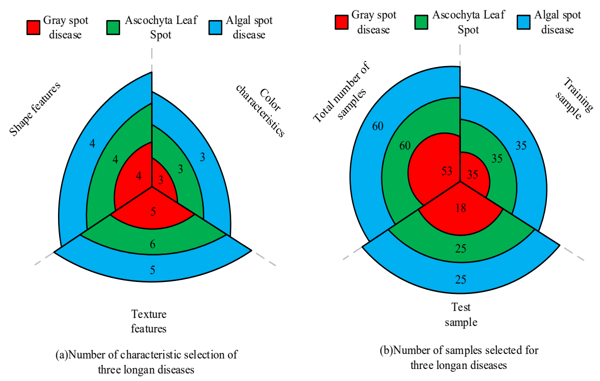

Fig. 5. Partial examples of three longan diseases.

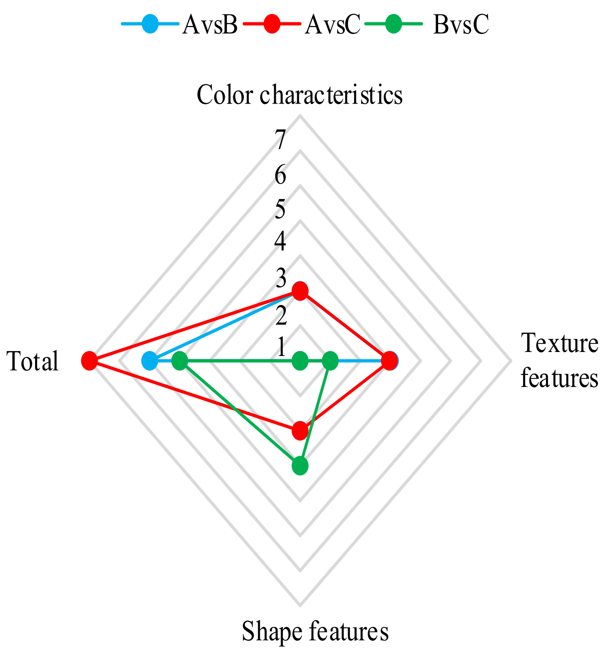

Fig. 6. Optimized feature item map obtained after optimization.

As can be seen from Figure 6, in the screening of traits of gray spot and Ascoidiosis leaf spot, 5 optimal features were obtained, including 3 texture features and 2 color features, which were different from the actual gray spot It is grey and the Ascospora leaf spot is golden. In addition, by screening the traits of gray spot and algal spot, seven optimal characteristics were obtained, including 2 morphological characteristics, 3 texture characteristics and 2 color characteristics. There are also differences in the size of the spots, so there is a clear difference in morphology. Through the screening of Ascoidiosis leaf spot and algal spot disease, 4 optimal characters were screened, of which 1 had texture characteristics and 3 morphological characteristics. Since these two diseases and insects did not have much difference in color difference, but very different in shape. In summary, a total of 7 features were obtained by using the PCA method, including 3 shape features, 2 texture features and 2 color features. These features are mainly used for later classification, such as the support vector machine (SVM) classifier. Figure 7 is the classification accuracy result map of CBPSO-SVM. The method of selecting rotation orthogonality is studied for experiments.

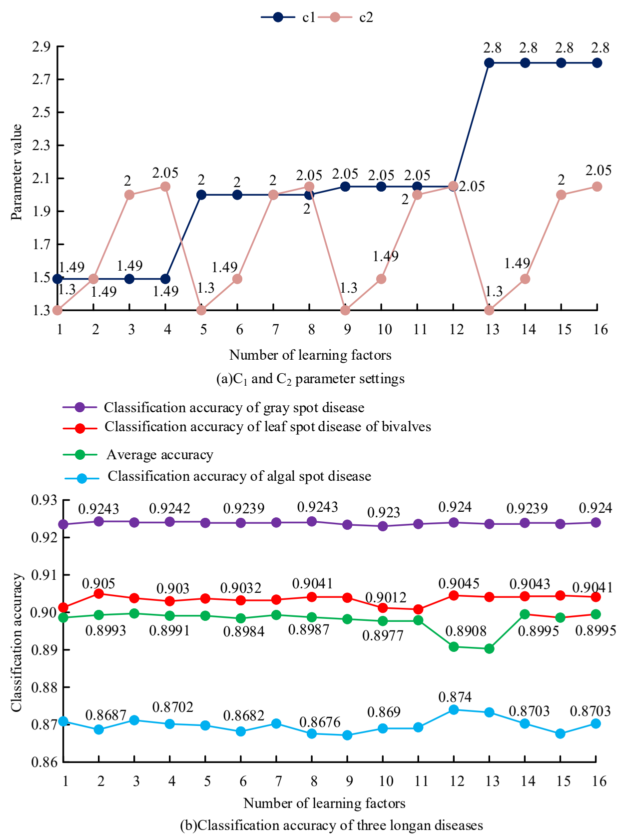

Fig. 7. Comparison of classification accuracy of three longan diseases.

Figure 7a is the setting value of the learning factor parameter, represented by C1 and C2, respectively, and Figure 7b is the comparison result of the classification accuracy of three longan diseases. As can be seen from

Figure 7, when the two types of learning have equal values, the classification accuracy appears to be the best, with the accuracy rates of 92.4%, 90.45%, and 87.4%, respectively, and the average classification accuracy is 89.08%. On this basis, the research compares PCA-SVM with CBPSO-SVM, and selects 37 optimal features and uses them f_1 to f_{37} represent them, respectively. In the particle swarm algorithm, 1 is set as selected, and 0 is set as unselected. Therefore, after using the CBPSO algorithm, the optimal particleization path is obtained, where f_2 to f_6, f_{14} to f_{18} and f_{28} to $f30$ are the optimal feature sets obtained by optimization. Therefore, PCA-SVM and CBPSO-SVM are used to reduce the dimensionality of the comprehensive features of the images and remove redundant information. At the same time, the comprehensive features of 37 images are used for classification. The images are classified, and the obtained classification results are shown in Figure 8.

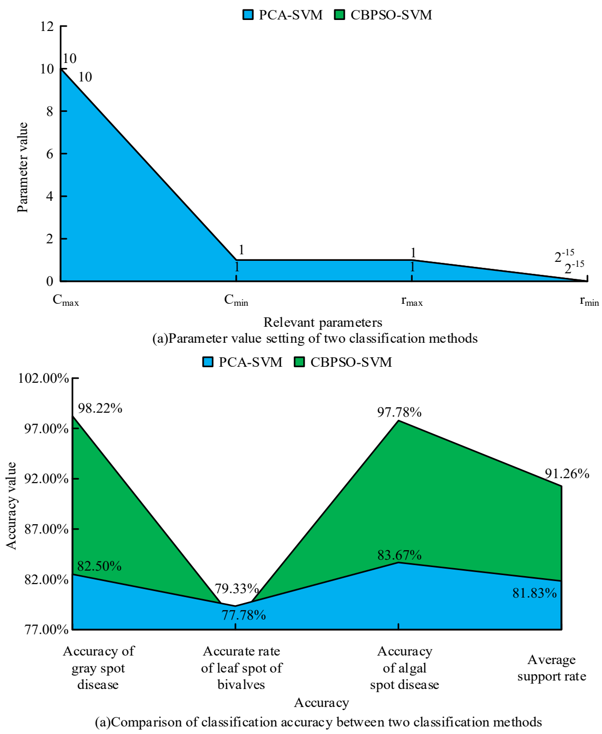

Fig. 8. Classification results of two classification methods.

Figure 8a is the parameter setting of SVM, and Figure 8b is the classification accuracy comparison of the two classification methods. It can be seen from Figure 8a that the PCA-SVM classification method has the same parameter settings as the CBPSO-SVM classification method, the maximum penalty parameter is 10, and the maximum kernel parameter is 1. It can be seen from Figure 8b that the CBPSO-SVM classification method has higher accuracy than PCA-SVM for both gray spot and algal spot among the three longan diseases, and ascoidi leaf spot is lower than that of PCA- SVM. Among them, the accuracy rate of gray spot disease is 98.22%, which is higher than 82.5% of PCA-SVM, algal spot disease is 97.78%, which is higher than 83.67% of the latter, and the average accuracy rate is 91.26%, which is much higher than that of PCA-SVM. 81.83%.

Overall, the results of both classification methods are better than the image classifier without dimensionality reduction operation, which indicates that there are indeed redundant features in the synthetic features, which need to be screened. Compared with the PCA-SVM classification method, the CBPSO-SVM classification method has higher classification accuracy and stability, and the CBPSO-SVM classification method optimized on the basis of SVM has better robustness. Therefore, the proposed method can effectively improve the classification accuracy of the classifier and enhance the generalization performance of the classifier.

Performance analysis of CBPSO algorithm

Through comprehensive analysis, the study fixed the weights of PSO algorithm, CBSO algorithm and CBPSO algorithm, which were 0.75, 0.9, 0.9, respectively. On this basis, the study introduced the binary particle swarm optimization (BPSO) algorithm. The three algorithms are compared in terms of convergence speed, task execution time and load balance to judge their search efficiency and accuracy. The results are shown in Table I.

It can be seen from Table I that in the fitness value, the CBPSO algorithm can reach a maximum of 0.99, and its average value is 0.97, which is significantly higher than that of BPSO and PSO; in terms of execution time, CBPSO takes the shortest time, with an average of 1375ms, it is far lower than BPSO's 1560ms and PSO's 1700ms; in terms of load balance, CBPSO's average is 0.23, lower than BPSO's 0.31 and PSO's 0.36. In general, the CBPSO algorithm shows good performance in global optimization, and has good convergence performance. The task execution time of the system is short, and it has high work efficiency, so as to determine its search accuracy and Efficiency is better.

In order to further test its performance, the study sets the dimension between, by comprehensively comparing the mean and variance of the best fitness values of different particle swarm algorithms to verify the optimal dimension of CBPSO (here the adaptive chaos is introduced Particle swarm (Adaptive chaotic particle swarm Optimization) algorithm and Linear Decreasing Weight Particle Swarm Optimization (LDW-PSO) algorithm), the results are shown in Figure 8.

Table I. Comparison results of three algorithms.

Iteration times and task time	Fitness			Execution time (ms)			Load balance		
	CBPSO	BPSO	PSO	CBPSO	BPSO	PSO	CBPSO	BPSO	PSO
20	0.88	0.87	0.86	600	600	600	0.2	0.35	0.4
40	0.93	0.91	0.89	900	900	900	0.15	0.3	0.35
60	0.95	0.94	0.92	950	1000	1100	0.2	0.25	0.3
80	0.99	0.96	0.94	1000	1100	1300	0.3	0.35	0.45
100	0.99	0.97	0.95	1100	1300	1400	0.15	0.35	0.4
120	0.99	0.97	0.93	1350	1500	1650	0.2	0.25	0.35
140	0.99	0.97	0.93	1450	1600	1700	0.25	0.3	0.3
160	0.99	0.97	0.93	1700	2000	2150	0.3	0.3	0.35
180	0.99	0.97	0.93	2100	2500	2800	0.25	0.35	0.4
200	0.99	0.97	0.93	2600	3100	3400	0.3	0.3	0.3

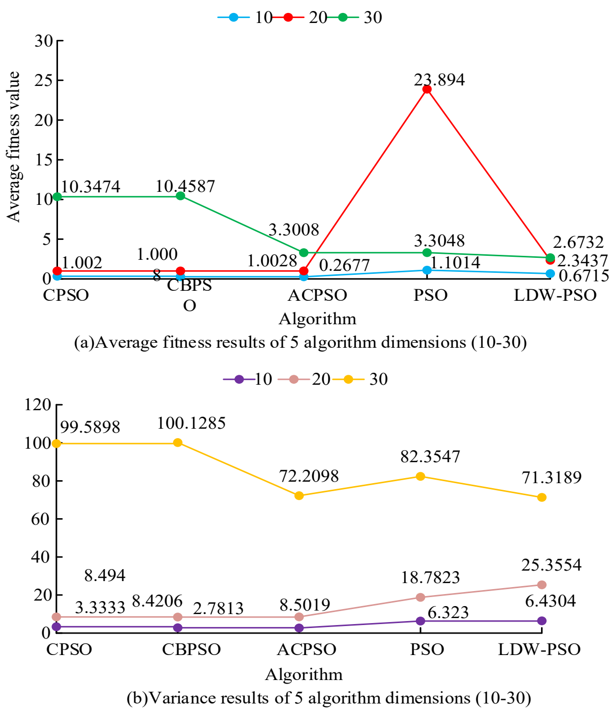

Fig. 9. Comparison chart of 5 algorithm dimensions (10-30).

As can be seen from Figures 9, in 10 dimensions, the average fitness value of the ACPSO algorithm is the lowest, and its stability is the highest. At this time, the accuracy of the CBPSO algorithm is slightly lower than that of the ACPSO algorithm, but higher than other algorithms. The variance of the CBPSO algorithm is 2.7813, It is also lower than other algorithms and higher than the ACPSO algorithm; when the dimension is 20, the average fitness of the CBPSO algorithm reaches the minimum, which is 1.0008, and the variance also reaches the minimum, which is 8.4206; when the dimension is set to 30, the average fitness of the CBPSO algorithm is 30. The highest is 10.4587, and the highest variance is 100.1285, which shows that the effect is not good, and the search results are not ideal. Therefore, the optimal dimension of the CBPSO algorithm is set to 20 dimensions. At this time, the CBPSO algorithm has certain advantages compared with other algorithms, and its optimization effect is better, and the accuracy and stability are greatly improved.

CONCLUSION

In order to prevent and control crop diseases and insect pests and reduce the harm caused by pesticides to the ecological environment, based on the PSO algorithm, the CPSO algorithm is proposed by using the chaos principle, and then the binary operation is carried out according to the actual situation to obtain the CBPSO algorithm, which is applied in UAV image detection in image recognition of crop diseases and insect pests. The experimental results show that the classification accuracy of CBPSO-SVM classification method is 98.22% in gray spot and 97.78% in algal spot, which is higher than 82.5% and 83.67% of PCA-SVM, and its average accuracy is 91.26%, which also outperforms PCA-SVM by 81.83%. In addition, after comparing the CBPSO algorithm with the introduced BPSO algorithm and the PSO algorithm, it is found that the highest fitness value is 0.99, and the average value is 0.97. Under the characteristics of high efficiency, its search accuracy and efficiency are significantly higher. At the same time, in the comparison of the five particle swarm optimization algorithms, the CBPSO algorithm is the best when the dimension is 20. At this time, the average fitness is the smallest, which is 1.0008, and the variance is also the smallest, which is 8.4206. Therefore, it is judged that its optimization effect reaches. The best, compared with other algorithms, the stability and accuracy have been significantly improved. However, the number of samples collected for the study is not enough, and the current research on the types of pests and diseases is not enough, so it can be considered to increase the number of images collected to facilitate subsequent image processing.

Funding

The research is supported by: Research on recognition method of maize crop nutrition status based on UVA Hyperspectral Imaging Technology (No. ZRCPY202017); Program for Young Scholars with Creative Talents in Heilongjiang Bayi Agricultural University (No. CXRC2017017).

IRB approval

This research was carried out with the approval of Research Guidance Workshop Committee (College of Information and Electrical Engineering, Heilongjiang Bayi Agricultural University).

Ethical statement

This article does not contain any studies with human participants performed by any of the authors.

Statement of conflict of interest

The authors have declared no conflict of interest.

REFERENCES

Chen, P., Li, W.L., Yao, S.J., Ma, C., and Liang, D., 2021. Recognition and counting of wheat mites in wheat fields by a three-step deep learning method. *Neurocomputing*, **437**: 21-30. https://doi.org/10.1016/j.neucom.2020.07.140

Devaraj, P., Arakeri, M.P., and Kumar, B., 2017. Early detection of leaf diseases in beans crop using image processing and mobile computing techniques. *Adv. Comput. Sci. Tech.*, **10**: 2927-2945. https://www.ripublication.com/acst17/acstv10n10_02.pdf.

El-Khamy, S., Moussa, K., El-Sherif, A., and El-Sherif, A., 2017. A smart multi-user massive MIMO system for next G wireless communications using evolutionary optimized antenna selection. *Telecom. Syst.*, **65**: 309-317. https://doi.org/10.1007/s11235-016-0232-9

Garcia-Chimeno, Y., Garcia-Zapirain, B., Gomez-Beldarrain, M., Fernandez-Ruanova, B., and Garcia-Monco, J.C., 2017. Automatic migraine classification via feature selection committee and machine learning techniques over imaging and questionnaire data. *BMC Med. Inform. Decis. Mak.*, **17**: 1-10. https://doi.org/10.1186/s12911-017-0434-4

Geng, S., Zhang, W., Tian, S., Zi, Y., Miao, J. and Shen, R., 2020. Study on UAV image extraction of surface crack information technology in goaf. *Open Access Lib. J.*, **9**: e8675.1-e8675.15. https://doi.org/10.4236/oalib.1108675

Hentz, Â.M.K., and Strager, M.P., 2018. Cicada (Magicicada) tree damage detection based on UAV spectral and 3D data. *Nat. Sci.*, **10**: 31-44. https://doi.org/10.4236/ns.2018.101003

Hunter, J., Gannon, T., Richardson, R., Yelverton, F., and Leon, R., 2020. Integration of remote-weed mapping and an autonomous spraying unmanned aerial vehicle for site-specific weed management. *Pest Man. Sci.*, **76**: 1386-1392. https://doi.org/10.1002/ps.5651

Khadatkar, A., Deb, R., Sah, R.P., Basak, S., and Jumrani, J., 2021. Application of indigenous knowledge for control of insects-pests in field crop and diseases in livestock. *J. Ext. Educ.*, **56**: 181-184. https://doi.org/10.5958/2454-552X.2020.00033.X

Li, Z., Wang, W., Xiao, Y., and Zhang, L., 2021. Characterization of the mitochondrial genome of spodoptera exempta (Lepidoptera: Noctuidae) from South Africa. *Mitochondrial DNA B*, **6**: 370-372. https://doi.org/10.1080/23802359.2020.1869619

Madhusudhan, S., Jalali, S.K., and Sibi, G., 2021. Molecular identification of insecticide degradation by gut bacteria isolated from *Helicoverpa armigera* of Cotton plants. *J. appl. Nat. Sci.*, **13**: 641-653. https://doi.org/10.31018/jans.v13i2.2678

Nageswari, C.S., Raveena, C., Yogashree, E., and Vasaknavi, M., 2020. Identification and classification of paddy ailments by modified inception architecture using network learning technique. *J. Crit. Rev.*, **7**: 506-513.

Paula, D.P., Lozano, R.E., Menger, J.P., Andow, D.A., and Koch, R.L., 2021. Identification of point mutations related to pyrethroid resistance in voltage-gated sodium channel genes in Aphis glycines. *Ent. Gen.*, **41**: 243-255. https://doi.org/10.1127/entomologia/2021/1226

Peng, L., Xu, D., Zhou, Z., Lee, W.J., and Bo, Z., 2017. Stochastic optimal operation of microgrid based on chaotic binary particle swarm optimization. *IEEE Trans. Smart Grid*, **7**: 66-73. https://doi.org/10.1109/TSG.2015.2431072

Shahbeig, S., Rahideh, A., Helfroush, M.S., and Kazemi, K., 2018. Gene selection from large-scale gene expression data based on fuzzy interactive multi-objective binary optimization for medical diagnosis. *Biocybern. Biomed. Eng.*, **38**: 313-328. https://doi.org/10.1016/j.bbe.2018.02.002

Simarmata, R., Widowati, T., Dewi, T.K., Lekatompessy, S.J.R., and Antonius, S., 2020. Isolation, screening and identification of plant growth-promoting endophytic bacteria from theobroma cacao. *Biosaintifika J. biol. Biol. Educ.*, **12**: 155-162. https://doi.org/10.15294/biosaintifika.v12i2.21280

Srikanth, R., Rekha, S., Kiran, R., and Reddy, P.V.R., 2020. Online published (Preview). *Indian J. Ent.*, **82**: 609-616. https://doi.org/10.5958/0974-8172.2021.00005.5

Tahar, K.N., Asmadin, M.A., Sulaiman, S., Khalid, N., and Razali, M.H., 2021. Individual tree crown detection using UAV orthomosaic. *Eng. Technol. appl. Sci. Res.*, **11**: 7047-7053. https://doi.org/10.48084/etasr.4093

Tanno, N., Yang, T.W., Wazawa, T., and Suzuki, M., 2017. 3P131 Hydration study of aqueous solutions of alkyl- sulfonates and carboxylates by microwave dielectric relaxation spectroscopy (Water and Hydration and Electrolyte, The 48th Annual Meeting of the Biophysical Society of Japan). *Trans. Chin. Soc. Agric. Eng.*, **31**: 175-180. https://doi.org/10.2142/biophys.50.S168_1

Tu, C., Li, J., Wang, X., Cheng, S., and Li, J., 2021. Bionic technology and deep learning in agricultural engineering: Current status and future prospects. *Am. J Biochem. Biotechnol.*, **17**: 217-231. https://doi.org/10.3844/ajbbsp.2021.217.231

Wang, X., Zhang, L., Du, X., and Sun, Y.L., 2017. Evolving cooperation in spatial population with punishment by using PSO algorithm. *Nat. Comp.*, **16**: 99-117. https://doi.org/10.1007/s11047-016-9546-5

Xia, J.A., Wang, Y.Y., Xin, C.H., Qi, K.Y., and Wei, C.G., 2018. Performance analysis of clustering method based on crop pest spectrum. *Eng. Agric.*, **11**: 84-89. https://doi.org/10.1016/j.eaef.2018.02.004

Zheng, X., Jia, R., Aisikaer, Gong, L., and Dang, J., 2021. Component identification and defect detection in transmission lines based on deep learning. *J. Intell. Fuzzy Syst.*, **40**: 3147-3158. https://doi.org/10.3233/JIFS-189353