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Retraction

Retracted: Intelligent Storage Data Classification System Based on the BP Neural Network

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

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[1] M. Li, "Intelligent Storage Data Classification System Based on the BP Neural Network," *Journal of Control Science and Engineering*, vol. 2022, Article ID 5771148, 7 pages, 2022.

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Research Article

Intelligent Storage Data Classification System Based on the BP Neural Network

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In order to solve the problem of multifeature recognition and classification of many kinds of pests, this study puts forward a method of pest feature classification using the BP neural network. Through the preprocessing of stored grain pest images, five characteristic parameters are obtained and optimized and input into the BP network for training. The experimental results show that sample 3 of flat grain thief and sample 4 of bark beetle are not well recognized. Because these two kinds of pests have small bodies and thin legs, some detailed features are eliminated after image processing, resulting in a low recognition rate. But the overall recognition rate can reach 95%. *Conclusion*. The experiment has obtained good recognition results. This method is accurate and effective for the classification and recognition of stored grain pests and provides a scientific basis for the scientific decision-making of controlling stored grain pests.

1. Introduction

China's grain warehouses have experienced the phased development process of grain hoarding, open air operation, house warehouse, and cave warehouse in the 1950s, earth round warehouse, underground warehouse, and house warehouse in the 1960s and 1970s, as well as low-temperature warehouse, portal roof truss warehouse, tall bungalow warehouse, and building warehouse widely used since the late 1990s. Since 1998, China's National Grain Reserve Depot has been built for many years since the founding of new China, with the largest investment, the largest construction scale, the most complete construction contents, and the most extensive use of advanced storage technology. It has realized the great leap forward development of China's grain storage, transportation, management, and technology, further improved the layout of National Grain Reserve Depots [1], and greatly improved the infrastructure conditions of grain circulation. Most granaries can take science and technology as the guide, comprehensively promote the use of new technologies, new warehouse types, and new equipment, greatly change the backward situation of low-level grain storage in the past [2], lay a good foundation for improving the scientific and technological content of grain storage facilities, and initially establish a more reasonable grain reserve system. With the continuous popularization and application of various new grain storage technologies, the quality management situation has been improved to a certain extent, and a series of rules and regulations, technical specifications, and operating procedures for grain management have been formulated one after another. However, the quality management of most enterprises is still relatively extensive, the operation level is low, the management is not standardized, the potential safety hazards still exist, there are still large defects and loopholes, and they do not have sufficient quality assurance ability [3]. Every year, we emphasize the safety of grain storage, but there is a sense of insecurity. Every year, we have to spend a lot of manpower, financial resources, and time on routine census and random inspection. Figure 1 shows the data classification architecture of intelligent warehousing.

2. Literature Review

The development of the grain storage system in foreign countries started earlier. Canada and Britain are one of the

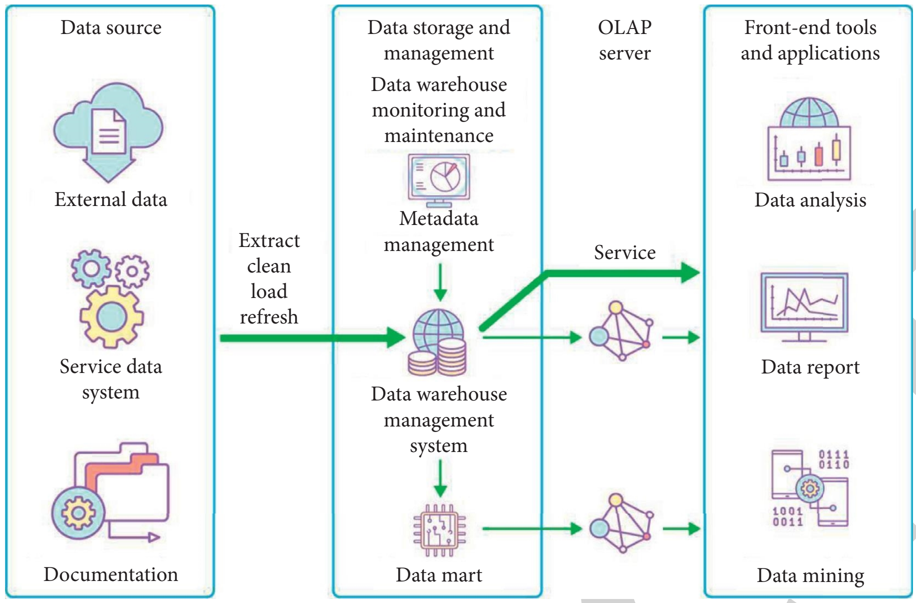

Figure 1: Intelligent warehouse data classification architecture.

countries that started earlier and achieved certain results, but they only stay in theoretical demonstration and do not use computer and other information technology. Sardjono and others made the finished product information system through practice [4]. Through computer programming, they established a grain storage management system based on the personal computer. The core function is to collect and monitor the temperature and humidity data in the granary in real time. However, due to the scientific and technological means at that time, there were many problems in the overall software system, such as serious software closure, long inspection time, and poor real-time performance. The BugSifter grain inspection system was developed by Naeem and others [5]. This system can achieve real-time monitoring of grain situation data and significantly mention the robustness and monitoring efficiency of the system. It can get rid of manual real-time marking, reduce labor costs, improve the original grain situation monitoring software framework, summarize and compare the data with wrong labels with the data with correct labels by summarizing and comparing the historical data, and increase the intelligent decision-making function. Although BugSifter has excellent grain condition monitoring function, the grain condition analysis function is not intelligent enough. Tufano and others developed a new grain storage ventilation model [6] and proposed a distributed parameter prediction model to realize the mechanical ventilation control in the granary by obtaining and comparing the grain condition parameters. The different areas of grain pile, such as surface, middle layer, bottom layer, side, air inlet, and air outlet, are divided into zones, and the prediction model of heat and mass transfer is established. Different thresholds and targets are set for grain piles in different regions. Through simulation experiments, the control effect of the model is verified, so that the temperature and moisture content of the whole grain pile can be effectively analyzed and controlled by grain condition data.

With the development of science and technology, machine vision, digital image processing, and pattern recognition technology have been developed and applied unprecedentedly and have also made fruitful applications in agriculture [7]. Because of its simple structure and strong plasticity, the BP neural network has been widely used in the fields of function approximation, pattern recognition, information classification, and data compression. Moreover, due to the introduction of the hidden layer of the BP neural network, the network can form any complex decision plane, which is very suitable for the classification of pests [8]. Using mathematical image processing, this study extracts the characteristics of four stored grain pests that have the greatest impact on the identification and classification and combines the BP neural network to accurately identify and classify stored grain pests, which lays a good foundation for effective pest control.

3. Research Methods

3.1. Image Preprocessing. In the actual stored grain pest detection, the original image obtained includes not only pests but also grain, and the proportion of grain is much larger than that of pests. Therefore, it is necessary to remove the influence of grain background and extract pest recognition targets, which requires image segmentation, and then, it is possible to extract various features of pests for recognition [9]. However, in practical application, the image obtained by CCD is sometimes not very satisfactory due to the stability and uniformity of external light, the vibration generated by motor operation, and the noise of space dust. Therefore, it is necessary to smooth and enhance the original image when necessary. The threshold h is automatically extracted by fuzzy set entropy and segmented to form a binary image. Finally, the mathematical morphology operator is used to filter out the noise such as holes and outliers.

After the above processing, the image basically meets the requirements of subsequent feature extraction and classification and recognition.

3.2. Feature Extraction and Normalization. There are more than 200 kinds of pests in the granary. The study found that the adults of pests are very similar in color, mostly brown [10], but there are great differences in morphological characteristics. At present, we have extracted more than 10 morphological features such as area, perimeter, complexity, rectangularity, duty cycle, circularity, and invariant moment as the original features of stored grain pests based on the binary images of four main pests: flat grain thief, rice weevil, pseudograin thief, and bark beetle [11, 12]. However, the fundamental task of feature extraction is how to find the most effective features from many features. After feature correlation analysis, category separability analysis, and repeated experiments, three features of area, perimeter, and complexity and two invariant moments φ_1 and φ_2 are selected.

3.2.1. Area. The number of pixels contained in the target area of stored grain pests has nothing to do with the change of the internal gray level. For the $N\times M$ size digital image whose gray value of the target pixel is "1", the calculation formula is the following formula [13].

$$A = \sum_{i}^{N}\sum_{j}^{M} f(i, j), \tag{1}$$

where M and N, respectively, represent the length and width of the image in pixels, and $f(i, j)$ represents the gray level of the binary image at point (i, j) (only "0″ or "1″).

3.2.2. Perimeter. The number of boundary pixels of the target area is in the stored grain pest image. It is particularly useful in distinguishing objects with simple or complex shapes. The calculation formula is the following formula [14].

$$L = A - \mathrm{SUM}(\mathrm{in}), \tag{2}$$

where A is the area of the target, and SUM (in) represents the total number of pixels whose pixel values are all target points.

The geometric feature area and perimeter of the pixel number statistics after image binarization are the two features that better reflect the characteristics of the target image, and their computation is small and the algorithm is easy to implement [15]. Generally, in the recognition system, these two features should be considered first.

3.2.3. Complexity. It describes the compactness of the object to a certain extent, and the calculation formula is the following formula:

$$C = \frac{L^2}{4\pi A}, \tag{3}$$

where L and A are the perimeter and area of pests, respectively. Under the same area condition, the circumference of the circle is the shortest, which can be called the most dense shape, $C = 1$. As the change of the concave convex of the perimeter intensifies, the perimeter increases and C increases. Therefore, complexity is often used as a measure of the discreteness of the region relative to the circle.

3.2.4. Two Moment Invariants. Among the seven moment invariants, moment invariants φ_1 and φ_2 have the best translation and rotation invariance, can accurately reflect the overall characteristics of pests, and are most suitable for identifying pests. Therefore, these two moment invariants are selected. The seven invariant moments are given in the following formula [16]:

$$\left.\begin{aligned}
\varphi_1 &= \eta_{2,0} + \eta_{0,2},\\
\varphi_2 &= \left(\eta_{2,0} - \eta_{0,2}\right)^2 + 4\eta_{1,1}^2,\\
\varphi_3 &= \left(\eta_{3,0} + 3\eta_{1,2}\right)^2 + \left(3\eta_{2,1} - \eta_{0,3}\right)^2,\\
\varphi_4 &= \left(\eta_{3,0} + \eta_{1,2}\right)^2 + \left(\eta_{2,1} + \eta_{0,3}\right)^2,\\
\varphi_5 &= \left(\eta_{3,0} - 3\eta_{1,2}\right)\left(\eta_{3,0} + \eta_{1,2}\right)\left[\left(\eta_{3,0} + \eta_{1,2}\right)^2 - 3\left(\eta_{2,1} + \eta_{0,3}\right)^2\right]\\
&\quad + \left(3\eta_{2,1} - \eta_{0,3}\right)\left(\eta_{2,1} + \eta_{0,3}\right) \times \left[3\left(\eta_{3,0} + \eta_{1,2}\right)^2 - \left(\eta_{2,1} + \eta_{0,3}\right)^2\right],\\
\varphi_6 &= \left(\eta_{2,0} - \eta_{0,2}\right)\left[\left(\eta_{3,0} + \eta_{1,2}\right)^2 - \left(\eta_{2,1} + \eta_{0,3}\right)^2\right]\\
&\quad + 4\eta_{1,1}\left(\eta_{3,0} + \eta_{1,2}\right)\left(\eta_{2,1} + \eta_{0,3}\right),\\
\varphi_7 &= \left(3\eta_{2,0} - \eta_{0,3}\right)\left(\eta_{3,0} + \eta_{2,1}\right)\left[\left(\eta_{3,0} + \eta_{1,2}\right)^2 - 3\left(\eta_{2,1} + \eta_{0,3}\right)^2\right]\\
&\quad + \left(3\eta_{1,2} - \eta_{3,0}\right)\left(\eta_{0,3} + \eta_{2,1}\right)\left[3\left(\eta_{3,0} + \eta_{1,2}\right)^2 - \left(\eta_{2,1} + \eta_{0,3}\right)^2\right]
\end{aligned}\right\} \tag{4}$$

where $\eta_{k,j}$ is the normalized central moment. In the process of feature description, because the dimensions of each eigenvalue are different, the magnitude is also very different. If the subsequent processing is carried out directly, it will have a great impact on the accuracy of recognition. In order to eliminate the difference of dimension and magnitude among features and make each index comparable, the sample eigenvalues of each feature are transformed into 0-1 by equation (5), that is, normalization.

$$x_{ij} = \frac{x_{ij} - \min_{ij}}{\max_{ij} - \min_{ij}}, \tag{5}$$

where x_{ij} and x'_{ij} are the data before and after the transformation of the characteristics of the stored grain pest, $\max_{ij}$ and $\min_{ij}$, respectively. They are the maximum and minimum values of the j^{th} characteristic of the i^{th} stored grain pest, respectively.

After normalizing the characteristic value data of pests to be identified, it is substituted into the network for simulation, and the species of pests can be determined according to the output of the network. The normalized characteristic values of pests to be identified are shown in Figures 2–6.

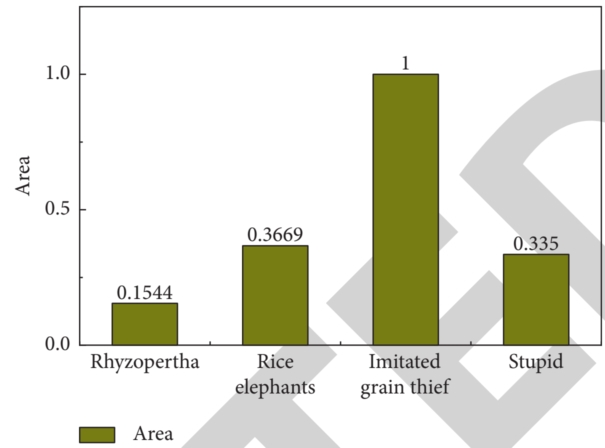

Figure 2: Normalized eigenvalue (area) of identified pests.

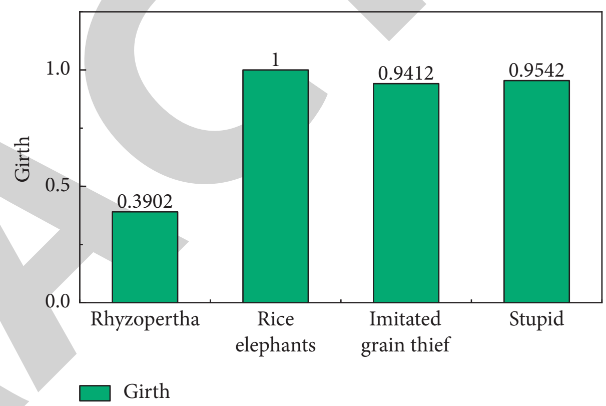

Figure 3: Normalized eigenvalue (perimeter) of identified pests.

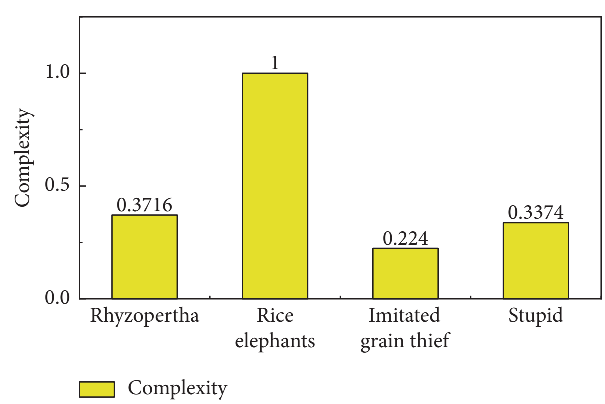

Figure 4: Normalized eigenvalues (complexity) of identified pests.

3.3. BP Neural Network Design

3.3.1. BP Neural Network. The artificial neural network, usually called the neural network, is a data processing model based on the biological neural network. The neural network connects a large number of artificial neurons (including input layer neurons, hidden layer neurons, and output layer neurons) to calculate [17] and changes its own structure according to external information. It mainly trains and models the input data by adjusting the network weight, so that it can finally have the ability to solve practical problems.

At present, there are many kinds of neural network models that have been proposed in academic circles, including the radial basis function network, Hopfield network, Boltzmann machine network, CMAC cerebellar model, BP neural network, and so on [18]. This work studies the BP neural network. The BP neural network is generally a multilayer. Another related concept is MLP, which has multiple hidden layers. MLP emphasizes the structure of the neural network, while the BP neural network adopts the BP algorithm to adjust the network weight on the premise of the multilayer network [14]. In most cases, MLP will use the BP algorithm for weight adjustment, so they generally refer to the same network.

Multilayer perceptron: due to the limitations of single-layer perceptron, academic circles continue to improve it. The concept of perceptron has been greatly expanded due to the proposal of the BP algorithm. MLP now refers to a multilayer feedforward neural network [19] with sigmoid (s) type function as the neuron transfer function of the hidden layer, which includes at least one hidden layer (except one input layer and one output layer). MLP is very suitable for solving the approximation problem of continuous integrable function. It is one of the most commonly used neural networks at present.

BP neural network: the BP neural network can deal with linear inseparable problems. It is a network containing one or more hidden layers. In history, because there has been no suitable learning algorithm for the multilayer neural network, the research of the neural network once fell into a downturn. Until the mid-1980s, Rumelhart, McClelland, and others established a parallel distributed processing group [20] and proposed the famous BP algorithm, which solved the weight updating problem of the multilayer neural network and promoted the development of the neural network to a great extent. Therefore, this neural network is also called BP neural network.

BP network: the back propagation network is called the error back propagation neural network. It is a kind of the neural network that can self-organize in the direction of meeting the given input/output relationship. In the forward propagation stage, the state of each layer of neurons only affects the state of the next layer of neurons. If the output layer cannot get the desired output result, it enters the back propagation stage of error. The error signal returns along the original connection path, and the network modifies the connection weight of each layer [21] according to the back propagation error signal to minimize the error signal, even if the actual output is as close as possible to the required index. A typical BP network consists of three parts: input layer, hidden layer, and output layer. The three parts are connected

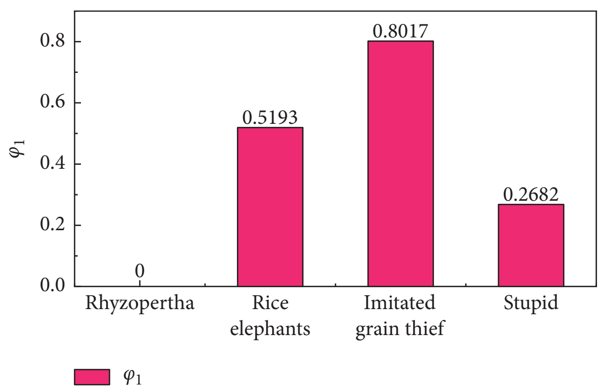

Figure 5: Normalized eigenvalues of identified pests (φ_1).

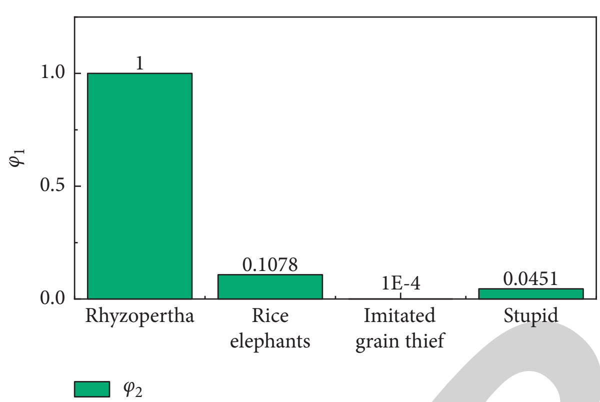

Figure 6: Normalized eigenvalues of identified pests (φ_2).

in turn through the connection weights between the nodes of each layer. A three-layer BP network can complete any dimension-to-dimension mapping.

BP neural network has the following characteristics:

(1) The BP neural network is composed of multiple layers. The neurons in the same layer are not connected, and the neurons between layers are completely connected with each other. This multilayer network structure design enables the BP neural network to mine more information from massive data, so as to complete more complex modeling tasks.

(2) The transfer function of the BP network must be differentiable. The BP network generally uses linear function or S-type function as transfer function. S function can be divided into log sigmoid function and Tan sigmoid function. If S-type function is selected, it depends on whether the output value contains the negative value. The nonlinear differentiability of S-type function makes it possible to use the gradient descent method. In the output layer, if the S-type function is used as the transfer function, the output value of the neural network will be limited to a small range. Therefore, the typical design of the BP neural network is that the hidden layer uses S-type function as the transfer function, while the linear function is used as the transfer function of the output layer.

(3) The error back propagation algorithm is used for learning. In the BP neural network, data propagate backward from input layer to input layer through hidden layer. When updating the network weight, start from the output layer and correct the connection weight of the network layer by layer along the direction of error reduction. With the continuous progress of network learning, the final error becomes smaller and smaller. When the error reaches the set threshold or the algorithm reaches the specified number of iterations, the network stops and completes the training.

3.3.2. Design of the Stored Grain Pest Identification Network. The development of the neural network includes the determination of the number of hidden layer neurons, neural network data source, data division, data preprocessing, and weight parameter initialization. The essence of an image recognition system is that the computer imitates the process of human recognizing and recognizing objects. Figure 7 shows the block diagram of the image recognition system of stored grain pests [22, 23]. It mainly consists of three parts: image preprocessing, feature extraction, and recognition and classification.

Here, the three-layer BP neural network composed of input layer, hidden layer, and output layer is trained with the sample set of four kinds of pests, and a $N \times 2N + 1 \times M$ three-layer BP network is used as the classifier [24], where n represents the number of components of the input eigenvector and M represents the total number of output categories. For this study, $N = 5$. (0, 0), (0, 1), (1, 0), (1, 1) are used to represent four kinds of stored grain pests: flat grain thief, rice elephant, pseudograin thief, and grain beetle. Thus, the BP network structure is as follows: there are 5 neurons in the input layer, 8 neurons in the hidden layer, and 2 neurons in the output layer. The transfer function of neurons in the hidden layer adopts the S-type tangent function tansig. Since the S-type logarithmic function is a 0-1 function [25], which just meets the output requirements of the classifier, the transfer function of neurons in the output layer selects the S-type logarithmic function logsig [26].

4. Result Analysis

Because the most common four kinds of pests are selected as the research object, 10 samples of each kind of pests are selected to form a sample set of 40 samples. The data of these 20 sample sets are used to train the BP network, and the output results are given in Table 1.

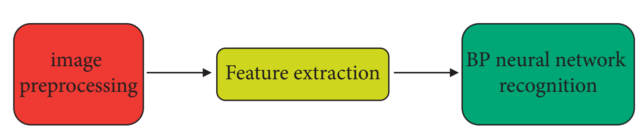

Figure 7: Composition block diagram of the grain pest image recognition system.

Table 1: Output of simulation experiment results.

Pest species	Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	Sample 6	Sample 7	Sample 8	Sample 9	Sample 10	Expected value
Flat valley thief	0.0212	0.0014	0.4516	−0.0072	0.0430	0.0024	0.0175	0.0054	0.0127	0.0037	(0, 0)
	0.1823	0.0010	0.2810	−0.0051	0.0385	0.0015	0.0081	0.0100	0.0031	0.0014	
Rice elephant	−0.0459	0.0521	0.0221	−0.0116	0.0074	0.0012	0.0072	0.0018	0.0102	0.0026	(0, 1)
	0.9345	0.9244	0.9452	1.0020	0.9998	−0.9850	1.0010	0.9700	0.9660	1.0002	
Pseudovalley thief	0.9995	1.0040	1.0052	0.9958	0.9900	0.9958	−1.0022	0.9908	0.9880	1.0002	(1, 0)
	0.0008	0.0952	−0.1035	0.0024	0.0042	0.0022	0.0005	0.0012	0.0008	0.0001	
Bark beetle	1.0842	0.9851	0.9813	1.1414	0.9900	1.0015	0.9956	1.0004	0.9902	−0.9997	(1, 1)
	0.9723	1.0147	0.9991	0.3874	0.9856	−0.9905	0.9980	0.9996	1.0023	1.0008	

According to the experimental results, it is found that sample 3 of flat grain thief and sample 4 of bark beetle are not well recognized. Because these two kinds of pests have small bodies and thin legs, some detailed features are eliminated after image processing, resulting in the low recognition rate. But the overall recognition rate can reach 95%.

5. Conclusion

In this study, the BP neural network is used to identify four main pests in granary. Different from the traditional information processing methods, the artificial neural network is adaptive and can be trained. It has the ability of self-modification, parallel processing, and parallel reasoning of information. In principle, it is much faster than the traditional methods and has many advantages, such as high nonlinearity, simulated parallelism, high fault tolerance, robustness, self-association, self-learning, and self-adaptation. In this study, the image recognition and classification technology based on the BP neural network are introduced into the recognition of stored grain pests, and the effective recognition rate is 95%. The recognition rate of the fuzzy recognition method in reference is more than 85%, and the recognition rate of this method is nearly 10% higher than that. The experimental results show that the method used in this study is accurate and effective in the classification and recognition of stored grain pests, which provides a scientific basis for the scientific decision-making of controlling stored grain pests.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

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