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A METHOD FOR MONITORING RICE SEED LOSS BASED ON WOA-BP ALGORITHM

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KEYWORDS

combine harvester, seed loss rate, WOA-BP, online monitoring.

ABSTRACT

The combine harvester is a widely used piece of agricultural equipment in modern agriculture, and the seed loss rate is one of the important indexes used to measure its operational performance, so the monitoring of the seed loss rate is crucial for adjusting the operational parameters of combine harvesters and improving the quality of grain harvesting. Aiming at the problems of the slow response speed and low monitoring accuracy of the existing domestic seed loss rate monitoring models, this paper proposed a rice seed loss rate monitoring method based on the whale optimization algorithm-back propagation neural network (WOA-BP). The loss rate monitoring device consisted of a piezoelectric ceramic sensor module, charge amplification circuit, band-pass filter circuit, analog-to-digital (AD) converter, main control unit, etc. The WOA-BP algorithm, which has a high accuracy and fast response speed, was used to classify and count the signals to realise seed loss rate monitoring. The indoor test results showed that the relative errors of the monitoring results are less than 8.5% under the condition of a conveying speed of 1.3–2.1m/s, and the relative errors showed an increasing trend as the proportion of straw increased.

INTRODUCTION

Combine harvesters are widely used in grain harvesting; they can complete the operations of cutting, threshing, separating, and cleaning all at once, but there is also a certain degree of grain loss (Li, 2024). According to the China Grain Statistics Administration, annual cereal production reached over 640 million tons in 2023. With such a large production base, reducing grain harvest losses has become an effective measure to enhance food security (Mu & Wu, 2023). With the increasing maturity of electronic information technology and sensor technology, agricultural mechanization equipment is gradually developing in the direction of artificial intelligence. Seed loss monitoring has become one of the key issues in the intellectualization of agricultural machinery (Zhao et al., 2023).

There are three main forms of grain losses incurred during combine harvester operation: cutter losses, entrainment losses, and scavenging losses. In response to different forms of grain losses, drivers need to adjust the operating conditions of combine harvesters according to the loss rate in order to minimize harvesting losses. Since scavenging losses account for the largest share of the total losses, this paper mainly focuses on the monitoring of scavenging losses (Li et al., 2020).

Many companies in Europe and the United States have conducted research concerning the loss problem of combine harvesters, and the related technologies have been applied in the loss rate monitoring of combine harvesters. Many combine harvesters are equipped with grain loss monitoring devices, including the Italian New Holland TX64 combine harvester and the American John Deere 9660STS combine harvester (Tang et al., 2012). To reduce grain losses during harvester operation, foreign researchers have studied the loss rate monitoring of combine harvesters. Craessaerts et al. (2010) installed four piezoelectric sensors in the back half of the scavenging screen to monitor the load of the scavenging sieve, and a fuzzy model for loss prediction was developed based on the load. Omid et al. (2010) designed a fuzzy logic controller to realize the automatic adjustment and control of the harvester to minimize grain loss by controlling the speed

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of the scavenging fan and the forward speed of the machine, among other things.

Compared with foreign countries, domestic real-time monitoring methods are not mature. The traditional method of calculating the loss rate is still used in China; it relies on manpower to manually sift the grains and straw after the combine harvester stops operating, and then the loss rate is calculated. The results of this method are relatively accurate, and it is usually used when testing the performance of a combine harvester (Wang et al., 2024a). However, the method is inefficient and time-consuming. Domestic seed loss monitoring technologies are mainly of two types: one is based on visual monitoring using images and the other is based on piezoelectric principle monitoring (Nie, 2021). The visual monitoring method using images was able to monitor the rate of seed loss more accurately in the early stages of harvesting. However, as the working time of the combine harvester increases, dust begins to cover the camera, resulting in a significant decrease in the monitoring accuracy. For monitoring based on the piezoelectric principle, scholars have proposed utilizing various methods for classification and identification, such as neural networks, support vector machine (SVM), decision trees, etc.

Ge et al. (2019) combined the harvester forward speed, paddle wheel speed, scavenging fan speed, and disengagement drum speed into a variable input matrix and used a neural network to calculate the grain harvest loss rate in real time. Wang et al. (2018) utilized an SVM multi-classification algorithm to classify the impact signals. The method realized the real-time monitoring of the seed loss, and the monitoring accuracy reached 91%. Lian et al. (2021) utilized a decision tree algorithm to identify and classify materials, and then they calculated the loss rate. The recognition accuracy of the system could reach 90% through indoor testing.

Domestic combine harvester loss rate monitoring devices are still in the research stage; the lack of online monitoring devices, the monitoring accuracy, and the response speed need to be further improved. Decision tree, SVM, and BP neural network algorithms have shorter training times, but the comprehensive classification effect is poorer. The whale optimization algorithm-BP (WOA-BP) method has a higher accuracy and faster response speed compared with other algorithms; it also has stronger optimization capabilities, and the comprehensive classification effect is better. Therefore, in order to improve the accuracy and response speed of monitoring the seed loss rate during the working process of the combine harvester, this paper proposes a seed loss rate monitoring method based on the WOA-BP algorithm, aiming at the real-time monitoring of the seed scavenging loss rate of the combine harvester.

MATERIAL AND METHODS

Principle of scavenging loss monitoring

In the process of combine harvester operation, the rice plant is placed in the paddle wheel support, and it is cut by the cutting platform cutter. The cut crop is transported to the threshing drum by the scraper in the conveying trough, and then the crop experiences a spiral movement under the joint action of the threshing drum and the concave plate sieve of threshing. Under the effect of centrifugal force, the threshed seeds and light straw are separated by the concave plate sieve and fall to the cleaning sieve, and the light straw is blown out of the machine through the cooperation of the fan and the vibrating sieve. During the above process, fewer grains will be blown out of the machine, resulting in less seed clearing, which directly affects the operation quality and grain yield of the combine harvester.

The mathematical model of the combine harvester loss rate is the ratio of the mass of seeds lost to the mass harvested per unit of time. The mass lost per unit of time t is the number of lost seeds multiplied by the thousand kernel weight. The harvested mass at this time is obtained from parameters such as the forward speed, yield per square metre, and width of the cut of the harvester operation (Liu et al., 2020). Thus, the mathematical model of the loss rate is calculated as follows:

$$L = K\frac{nq}{vyct} * 10^{-6} * 100\% \tag{1}$$

Where:

L – the rate of the scavenging loss;

K – the correction factor;

v – the forward speed of the harvester, m/s;

y – the yield per square metre, kg/m^2;

c – the cutting width of the harvester, m;

n – the number of seeds monitored;

q – the amount in terms of the thousand kernel weight of the seeds, g.

Construction of the monitoring system

The seed loss rate monitoring device mainly includes the scavenging loss sensor, charge amplification circuit, bandpass filter circuit, embedded processor, and controller area network (CAN) bus communication and other modules. A schematic diagram of the hardware structure is shown in Figure 1.

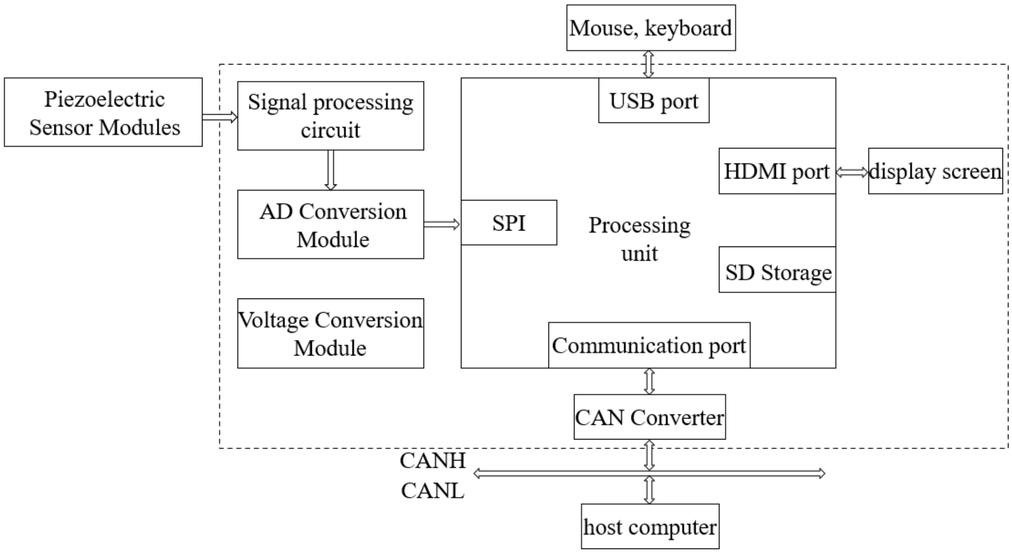
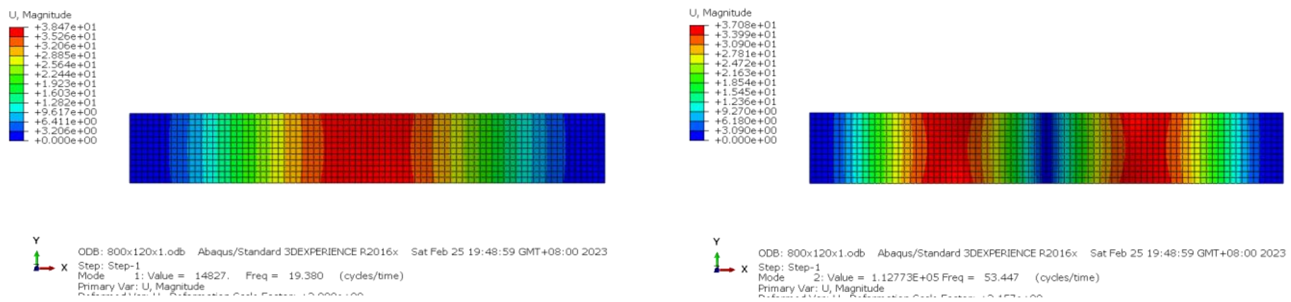


FIGURE 1. Schematic diagram of hardware structure.

According to the small deflection thin plate theory, the collision vibration of the seeds and the sensitive plate conforms to the transverse vibration equation of the thin plate, and the various orders of the intrinsic frequency and vibration pattern of the sensitive plate are mainly related to its structure (Feng et al., 2011). ABAQUS 2016, a finite element analysis software developed and produced by SIMULIA, a company of Dassault Systèmes, USA, is used to carry out modal analysis of the sensitive plate and study its vibration characteristics. In the analysis process of the ABAQUS software, the characteristic properties of the sensitive plate are set; the material of the sensitive plate is 304 stainless steel, with dimensions of 800 mm (length) × 120 mm (width) × 1 mm (thickness), the density ρ = 7930 kg/m^3, Young's modulus E = 194 GPa, Poisson's ratio μ = 0.3, and the yield strength σ_s = 205 MPa. The results of the modal analysis of the sensitive plate are obtained after sequentially performing the main steps, such as creating the module, setting the constraint region, creating the step, meshing, submitting the job, etc., and the results are shown in Figure 2.

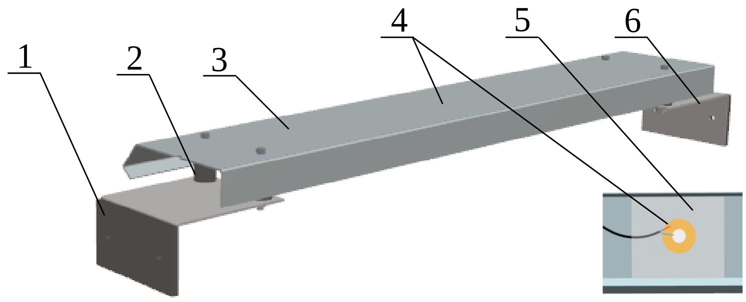


(a) 1st-order mode shapes

(b) 2nd-order mode shapes

FIGURE 2. Isogram of modal shape of sensitive plate.

From the modal analysis, it is known that at different modal frequencies, the maximum response position of the sensitive plate structure vibration is different, and the sensitivity of the piezoelectric sensor is directly related to the amplitude of the sensitive plate. Figure 2(a) shows that closer to the center of the sensitive plate, the amplitude is larger, and the amplitude is smallest at the fixed position of the sensitive plate. Figure 2(b) shows that installing a sensor where the vibration pattern has large amplitudes may cause large displacements and pressures, which can lead to damage to the sensor or affect the sensor monitoring accuracy. Therefore, mounting the sensor in the middle of the sensitive plate can better capture the dynamics of the impact signal, and at the same time it can avoid the monitoring error caused by the uneven force on the edge of the sensitive plate (Wang et al., 2009). The scavenging loss sensor adopts a four-point fixed support structure. It adopts a double-stud rubber vibration damper to connect the sensitive plate and connecting frame, and 6-mm-thick rubber is set at the connection between the connecting frame and the end of the cleaning sieve. This constitutes a two-way vibration isolation structure, and it reduces the transverse and longitudinal vibration transmission path of the connecting frame (Wu & Dai, 2009). The structure of the scavenging loss monitoring sensor is shown in Figure 3.



1 – Vibration isolation rubber, 2 – Double-stud rubber vibration damper, 3 – Sensitive plate, 4 – Piezoelectric sensor, 5 – Butyl rubber, 6 – Connection frame

FIGURE 3. Structure of the scavenging loss monitoring sensor.

The impact response signals of different seeds and straw after the amplification circuit processing were studied, several groups of tests were conducted to take the average value of each group, and the response signals of seeds and straw were recorded. It was found that the voltage amplitude of the seed signal was generally concentrated from 1.2–6.0 V, and the voltage amplitude of the straw signal was generally lower than 2 V; additionally, the faster the impact speed, the larger the voltage amplitude.

When the seeds and straw impact the sensitive plate, the piezoelectric ceramic sensor outputs the corresponding electrical signal and transmits this signal to the loss rate monitoring device, which is mainly composed of a charge amplifier, bandpass filter, AD module, CAN communication module, data storage module, voltage converter, and other modules. The charge amplifier circuit amplifies impact signals to within 10 V. Band-pass filtering circuitry allows signals in the 3–20 kHz band to pass through, filtering out signals in other bands (Liang et al., 2013). The analogue-to-digital converter module is centered on the AD7606 chip, and the sampling frequency is 40 kHz. It converts the acquired digital signals into analogue signals and transmits them to the NVIDIA Jetson TK1 embedded processor master unit. The processor performs software filtering and feature extraction on the signals; then, it recognizes and counts the feature signals using the recognition model based on the WOA-BP algorithm, and it calculates the loss rate of rice by using the monitored number of lost seeds and the mathematical model of the loss rate. For this process, the CAN communication module needs to be mounted on the CAN bus of the host computer to realize data transmission, and the monitoring results are stored in the SD card for offline data analysis.

Seed recognition model based on WOA-BP

Whale optimization algorithm

The whale optimization algorithm is a new intelligent optimization algorithm based on simulating the feeding behavior of humpback whales. Whales generally capture prey using three strategic behaviors: encircling the prey, spouting bubbles to repel the prey, and feeding on the prey. Similarly, the whale optimization algorithm is divided into three phases: encircling prey, bubble netting, and searching for prey. The WOA generates several individual whales in the search space; the group updates the position of each whale according to the current optimal individual and finally obtains the optimal position through loop iteration (Wu & Wen, 2021).

(1) Encircling the prey

The size of the whale population is set to N, and the position of the i_{th} whale in the space is $X_i = (x_i^1, \ldots, x_i^d)$; d represents the spatial dimension of the search. The optimal position of the prey in the group is the global optimal solution, and other whales gradually surround this position, updating the position according to [eq. (2)] and [eq. (3)]:

$$D = \left| CY(t) - X(t) \right| \tag{2}$$

$$X(1+t) = Y(t) - AD \tag{3}$$

Where:

t – the current number of iterations;

$Y(t)$ – the current position of the prey;

$X(t)$ – the current position of the individual;

D – the distance between the whale and the prey;

A and C – the positional coefficients, which can be defined by [eq. (4)] and [eq. (5)]:

$$A = 2\alpha r_1 - \alpha \tag{4}$$

$$C = 2r_2 \tag{5}$$

Where:

r_1 and r_2 – random values in [0,1];

α – the convergence factor, which can be defined by the following expression:

$$\alpha = 2 - \frac{2t}{T} \tag{6}$$

Where:

T – the maximum number of iterations.

(2) Bubble netting

The spiral update position method is utilized to update the positional distance between the whale and its prey. The following equation is established based on the process of the whale's spiral attack on the prey:

$$X(t+1) = \begin{cases} Y(t) - AD, p < 0.5 \\ D^{'}e^{bl}\cos(2\pi l) + Y(t), p \geq 0.5 \end{cases} \tag{7}$$

Where:

$D^{'}$ – the distance between the whale and the prey, $D^{'} = \left| X_p(t) - X(t) \right|$;

b – a constant that defines the spirals;

l – a random number between [-1,1].

During the continuous optimization process, the spiral position update probability p is set to 0.5 in order to simulate whales contracting to encircle their prey as they follow the path of the spiral.

(3) Searching for prey

In order to improve the global search ability of the algorithm and avoid falling into local optimality, the algorithm carries out a stochastic search for the location of the prey when $A \geq 1$. The expression for this phase is

$$D = \left| C\bar{X}(t) - X(t) \right| \tag{8}$$

$$Y(1+t) = \bar{X}(t) - AD \tag{9}$$

Where:

$\bar{X}(t)$ – the position of a randomly selected whale in the whale group.

Training process of WOA-BP network

BP neural networks have the characteristics of the forward transfer of data and the backward transfer of errors. In the forward transfer process, the data enter the network from the input layer， and the network generates an output signal at the output layer after calculations using each layer. If there is an error between the output signal and the desired output, it is transferred to the reverse transfer process, and the weights and threshold are adjusted according to the error. After training, the predicted output should gradually approximate the desired output (Ge et al., 2019). BP neural networks are widely used, but they have their own limitations. For example, the network structure is not easy to determine, and the convergence speed is slow; therefore, the whale algorithm is used to optimize the BP neural network to obtain the optimal threshold and weights. Compared to other algorithms, this algorithm has strong optimization-seeking capabilities (Li et al., 2022). A flowchart of the WOA-BP algorithm is shown in Figure 4.

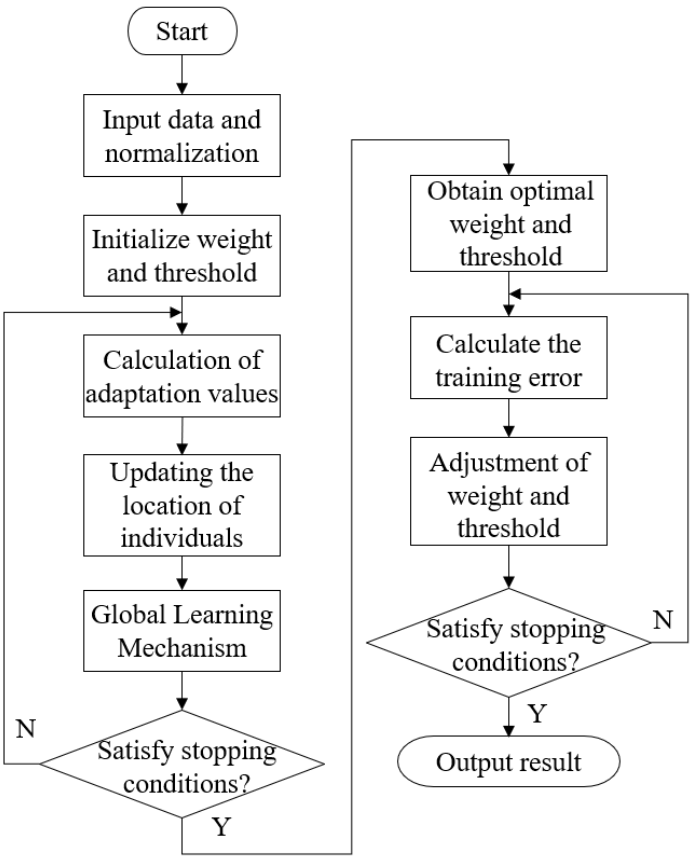


FIGURE 4. Flowchart of the WOA-BP algorithm.

After data preprocessing, feature extraction and normalization are performed. Scaling the data to a specific range reduces the difference in the speed of updating weights and thresholds, which in turn improves the convergence speed and generalization ability of the WOA-BP model. The extracted time-domain features include the root-mean-square (RMS) value, peak value, and variance, and the frequency-domain features include the center of gravity frequency, frequency variance, and signal energy. Signal features are stored in two dataset files, using the category ordinal numbers 1 and 0 to represent seeds and straw. Each dataset file contains 500 sets of samples, where column 1 is the category label and the remaining six columns are signal features. Since the BP neural network has a strong fitting ability, it will remember the order of the samples if this order is not disrupted, which affects the generalization ability, so after combining two files into one file, the order of the samples is disrupted. Finally, the dataset is randomly divided into training and testing sets using a ratio of 7:3.

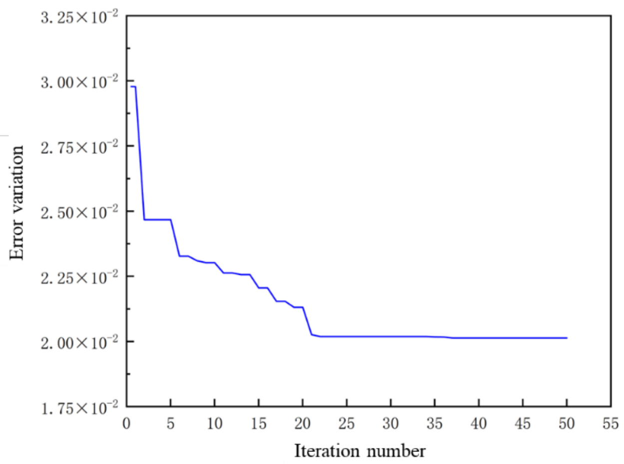


FIGURE 5. Evolution curve of WOA-BP algorithm.

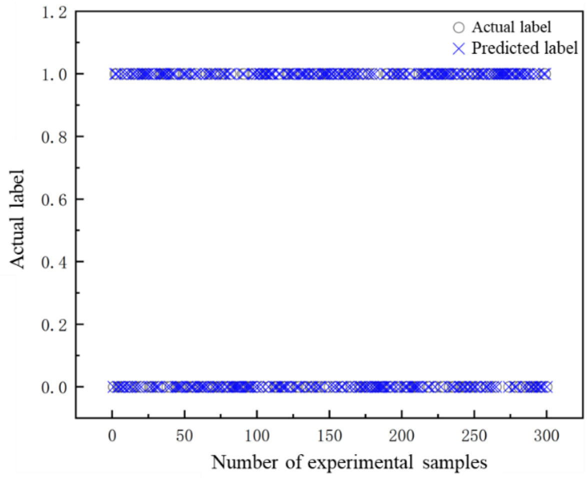


FIGURE 6. Comparison between predicted values and actual values of test dataset.

The WOA-BP parameters are initialized as follows: a three-layer neural network structure is used; the input, hidden, and output layers have 6, 12, and 2 nodes, respectively; the number of whales is 25; the maximum number of evolutions is 50; the minimum error of the training objective is 0.0001; the learning rate is 0.01; and the maximum number of iterations is set to 1000. The RMS error is used as the fitness function, and the optimal weights and threshold are output if the number of iterations is satisfied or the error accuracy is reached during the training process (Nabavi & Zhang, 2017). As the number of iterations increases, the RMS error gradually decreases, and after 21 iterations, the RMS error stabilizes and reaches the best performance, as shown in Figure 5. The validation results of the test set are shown in Figure 6; the rate of correct seed recognition is 95.93%, which indicates that the WOA-BP algorithm model has good seed recognition capabilities.

Quantitative evaluation of algorithmic model

At present, a variety of algorithmic models have been used in the field of agricultural machinery intelligence to monitor the rate of seed loss, including decision trees, SVM, BP neural networks, etc. In learning classification tasks, five metrics are commonly used to measure the performance of an algorithmic model, including the accuracy, precision, recall, F1-score, and training time (Wang et al., 2024b). In addition, the area under curve (AUC) value is selected to assess the classification effect of the model; the larger this value is, the better the classification effect is.

The feature array dataset is constructed. It contains 1000 samples, and it is divided into a training dataset and a testing dataset based on a 7:3 ratio. Classification performance comparisons based on the accuracy, precision, recall, F1-score, and training time are performed, and the results are shown in Table 1.

TABLE 1. Classification model performance comparison.

Classification model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	Training time (s)
Decision tree	91.67	91.89	91.28	91.58	0.97
SVM	94.33	93.42	95.30	94.35	1.75
BP network	94.67	95.39	93.55	94.46	1.98
WOA-BP	96.33	96.10	96.73	96.42	3.89

From Table 1, it can be seen that the training time for the decision tree, SVM, and BP neural network algorithms is relatively short, but the accuracy, precision, recall, and F1-score are low, indicating that the comprehensive classification effect of these algorithms is poor. In contrast, the WOA-BP algorithm has a relatively long training time, but the other four indicators are higher, indicating that it is significantly superior compared to the other classification models and has better recognition capabilities than the remaining three algorithms. The receiver operating characteristic curve (ROC) of the WOA-BP algorithm model is plotted in Figure 7.

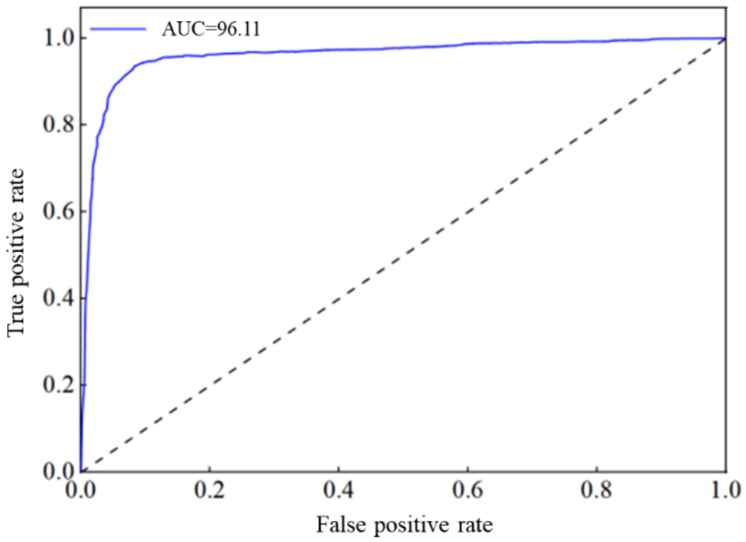


FIGURE 7. ROC curve of the WOA-BP algorithm model.

From Figure 7, the AUC value is equal to 96.11%, which is close to 1, indicating that the algorithm performs classification better and is able to reliably perform classification tasks.

Test method

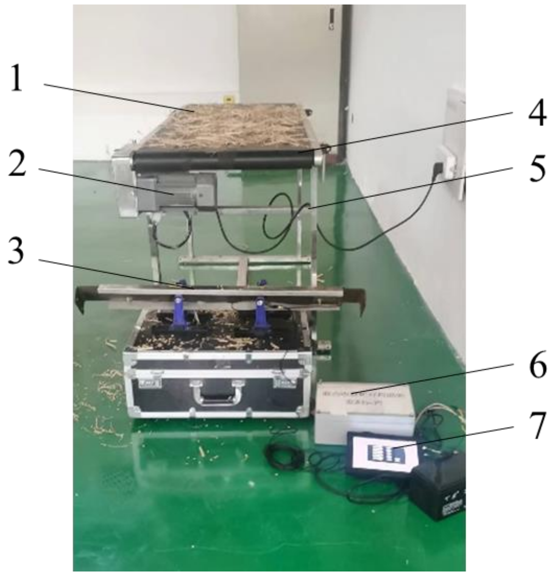
To test the accuracy of the seed loss rate monitoring device, a conveyor belt test bed was set up indoors to simulate the scavenging loss process of the combine harvester. The test bench consists of a conveyor belt, a motor, and a frame, and the conveying speed is adjustable according to different test conditions. The test object is the seeds and straw of rice of the Nan Japonica 52 variety; the material samples are shown in Figure 8.

(a) Seeds

(b) Straw

FIGURE 8. Material samples.

In order to facilitate the collection of material signals, the scavenging loss sensor was placed within a certain height range below the conveyor test bed and set at an angle to avoid the accumulation of seeds and straw on the scavenging loss sensors, which would affect the test results. In the indoor test, the scavenging loss sensor was mounted at different angles and heights for testing, multiple sets of repetitive tests were conducted, and the test results were recorded and systematically analyzed to determine the optimal test conditions. The indoor platform was constructed as shown in Figure 9.



1 – Material, 2 – Motor, 3 – Scavenging loss sensor, 4 – Conveyor belt, 5 – Frame, 6 – Monitoring device box, 7 – Display screen

FIGURE 9. Indoor platform construction.

The results of the tests with the scavenging loss sensor mounted at different heights and angles relative to the conveyor test bed are shown in Figure 10. When the scavenging loss sensor was installed at a height of 56 cm from the tabletop of the test bench and at an angle of 45º, the test results were better, and the recognition accuracy was 94.35%. Therefore, the indoor tests were conducted under these conditions.

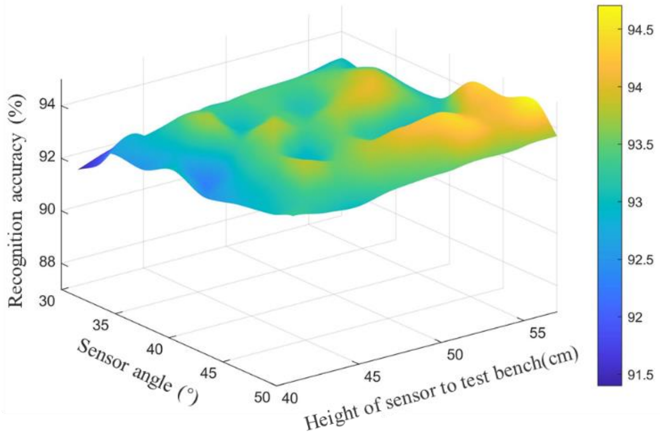


FIGURE 10. Indoor test of sensor module at different heights and angles.

The test data are evaluated using the relative error, which is calculated from [eq. (10)]:

$$\varepsilon_i = \frac{|n_i - n_o|}{n_o} \cdot 100\% \tag{10}$$

Where:

ε_i – the relative error at the i_{th} time;

n_i – the number of seeds monitored at the i_{th} time;

n_o – the number of seeds actually measured manually at the o_{th} time.

RESULTS AND DISCUSSION

Prior to the experiment, the parameters of the seed loss rate monitoring device were adjusted, and the seeds and straw of several NJ 52 rice varieties were collected. The moisture content of the material was measured to be 22.8%, and the thousand kernel weight of the seeds was measured to be 29.6 g. The test samples were divided into three groups according to the mass ratio of the seeds and straw, and the mass ratios used were 1/2, 1/2.5, and 1/3. The total mass of material in each group was 20 g. The three groups were labelled C1, C2, and C3. The scavenging loss sensor was placed at a height of 56 cm from the top of the conveyor test bed at an angle of 45º. With other test conditions consistent, tests were conducted at different conveyor speeds, and the manual identification of the actual number of seeds was used as a control. The results are shown in Table 2.

From Table 2., it is clear that for the test samples with different seed and straw mass ratios, the relative errors of the test results were less than 8.5% at conveying speeds ranging from 1.3 m/s to 2.1 m/s. When the seed and straw mass ratio was 1/2, the relative error at different conveying speeds was smaller. As the proportion of straw increased (when the mass ratio of seeds to straw was 1/2.5 and 1/3), the relative error showed an increasing trend. Due to the increased percentage of straw, seed signal characteristics were difficult to distinguish, so there was a range of errors between the actual seed counts and the monitored values.

TABLE 2. Results of the indoor test.

Conveying speed (m/s)	Group	Actual number	Number monitored	Relative error (%)
1.3	C1	246	258	4.88
	C2	206	217	5.34
	C3	181	191	5.52
1.7	C1	239	252	5.44
	C2	212	225	6.13
	C3	186	199	6.99
2.1	C1	251	267	6.37
	C2	215	231	7.44
	C3	189	205	8.47

The test results were compared with the results of the indoor test of the SVM-based seed loss rate monitoring device (Wang et al., 2018) and the results of the indoor test of the decision tree-based seed loss rate monitoring device (Lian et al., 2021). Because of the differences between the test programs, test conditions, and test subjects, the maximum relative error and average monitoring period were selected for comparison; the results are shown in Table 3.

From Table 3, it is clear that each of the three devices has its own advantages. The decision tree-based seed loss rate monitoring device performed better, with a relative error of less than 12% and an average monitoring period of 2 s. The SVM-based seed loss rate monitoring device performed relatively poorly, with a relative error of less than 15% and an average monitoring period of 4 s. Compared with the previous two methods, the relative error of the seed loss rate monitoring device proposed in this paper was less than 8.5%, and the average monitoring period was 3 s. When using the seed loss rate monitoring device, the balance between the monitoring period and the relative error must be considered; therefore, the rice seed loss rate monitoring device proposed in this paper had a lower relative error and a shorter monitoring period, and the monitoring of the rice loss rate has a better feasibility.

TABLE 3. Comparison of indoor test results of this research device with existing equipment.

Type of seed loss rate monitoring device	Maximum relative error (%)	Average monitoring periodicity (s)
Decision tree-based seed loss rate monitoring device	11.82	2
SVM-based seed loss rate monitoring device	15.00	4
WOA-BP-based seed loss rate monitoring device	8.47	3

CONCLUSIONS

(1) In order to obtain the rice seed loss rate during combine harvester operation in real time, an online monitoring method for combine harvester loss rate was investigated. The rice seed loss rate monitoring device was designed, the recognition processing algorithm for seed and straw was established, the feature signals of rice and miscellaneous surplus were extracted and classified, and the test set results showed that the recognition accuracy of seeds was 95.93%. Three previously proposed algorithmic models for the grain seed loss rate, including the decision tree, SVM, and BP neural network models, were selected, and their performance was compared with that of the WOA-BP model. The results showed that the five performance indicators of WOA-BP, the accuracy, precision, recall, F1-score, and training time, were 96.33%, 96.10%, 96.73%, 96.42%, and 3.89 s, which indicated that the WOA-BP algorithm had a better comprehensive classification effect.

(2) The scavenging loss sensor was mounted at a height of 56 cm from the top of the conveyor table at an angle of 45º, and indoor trials were conducted with samples of different seed-straw proportions at different conveying speeds. The results showed that the relative error of the monitoring results was less than 8.5% when the conveying speed in the range of 1.3 m/s to 2.1 m/s. This study realized the online monitoring of the rice loss rate, which can contribute to the further study of the seed loss of combine harvesters, reduce the grain harvesting loss, and improve economic benefits for farmers.

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