FAULT PREDICTION MODEL OF CORN GRAIN HARVESTER BASED ON SELF-CODING NEURAL NETWORK

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基于自编码神经网络的玉米籽粒收获机故障预测模型

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ABSTRACT

The corn grain harvester serves as an example of complex farming machinery with a condition monitoring system that collects a lot of working condition data, making it challenging to identify the true change pattern due to the data coming from the equipment in various states. Firstly, the overall structure of the corn grain harvester is analysed, and the common causes and mechanisms of corn grain harvester failures are analysed, leading to the cutting table as the main research object; Secondly, the data is organized and pre-processed by collecting historical fault data as well as real-time fault information from corn grain harvesters. The processed data is trained using a self-coding network to extract internal features related to fault causes, based on feature fusion and prediction networks to construct a mapping between fault causes and fault phenomena; Finally, the future failure phenomena of the corn grain harvester are predicted according to different failure causes. The simulation analysis results show that the self-coding neural network fault prediction model can better predict the occurrence probability and types of faults, and provide data support for fault maintenance and decision making of agricultural machinery.

摘要

以玉米籽粒收获机为代表的复杂农机设备状态监测系统记录了大量的工作状态数据，由于数据来源于不同状态的设备导致其真实变化规律难以发现造成了传统故障预测模型准确率较低，因此我们提出了一种基于自编码神经网络的玉米籽粒收获机故障预测模型。首先分析了玉米籽粒收获机的整体结构，对玉米籽粒收获机故障的常见成因与机理进行分析，引出割台为主要研究对象；其次通过收集玉米籽粒收获机的历史故障数据和实时故障信息，对数据进行整理和预处理。将处理后的数据训练自编码网络，提取故障原因之间的内部特征。基于特征融合和预测网络来构建故障原因与故障现象间的映射；最后根据不同故障原因预测未来玉米籽粒收获机的故障现象。仿真分析结果表明，自编码神经网络故障预测模型能够更好的预测发生的故障概率及种类，为农业机械的故障维修与决策提供数据支持。

INTRODUCTION

Corn grain harvesters are very important equipment in the agricultural industry, and they are widely used in corn harvesting on farmland to help farmers improve harvesting efficiency. Research studies have shown that the direct factors inducing the failure of corn grain harvesters are mainly blockage due to excessive feeding and indirect factors mainly include the problem of parts damage due to aging of parts accumulated over time *(Shi, 2022)*. With the advancement of various instrumentation technologies, more harvester failure data were obtained, and most Chinese machinery companies collected and collated the causes of corn grain harvester failures, and used the collected failure cause data to analyse and improve the reliability of corn grain harvester, which has important engineering practical application value for the failure rate of corn grain harvester.

The approach to failure prediction has evolved rapidly over the last few decades. Firstly, the failure prediction techniques originated from the evolving aerospace systems. Initially, scholars used a series of dynamic equations as the mathematical theoretical basis to develop model-based prediction methods to reason about the mapping relationship between monitoring parameters and equipment failures, and this method of building an accurate model structure to simulate the pattern between parameter changes and equipment performance has many shortcomings.

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Some scholars *(Xu et al., 2011)* studied the mechanical wear period of CNC machine tools according to the groove curve law, and then established a mathematical model of non-flush Poisson process. Some scholars *(Liu et al., 2015)* obtained the mileage data corresponding to the moment of failure through the whole vehicle durability test, and based on the stochastic process theory, the mathematical model of the failure process of the test vehicle was established with a non-simultaneous Poisson process for reliability evaluation. By analysing the law of equipment failure occurrence and building the corresponding mathematical or physical model to deeply describe the equipment failure evolution mechanism model is more complex and poorly generalized, and it needs to consider the characteristics of different systems and perform task specificity in practical application, which is not universally applicable. In view of the drawbacks of poor generalization and small applicability of the analytical model, researchers have incorporated expert experience and fuzzy logic into fault prediction to form a knowledge-based prediction method, and some scholars *(Liu, 2023)* designed an expert system based on a diagnostic rule reasoner and constructed an experimental environment with the help of AMESim (Advanced Modeling Environment for performing Simulation of engineering systems) hardware to simulate various faults of the robotic arm by injecting different fault signals. The experimental data analysis proves that the designed fault diagnosis expert system can efficiently and accurately detect the faults of the robotic arm. The study improves the generalization of the analytical model by introducing the expert system and fuzzy logic reasoning, which can characterize the equipment fault severity and forecast the possible fault situations in time, and has a greater reference value for the state inference classification of the corn grain harvester in this paper, but the expert system is a rule base constructed by static knowledge, which has certain limitations and cannot express the failure process in time scale.

With the progress of communication technology, a large amount of industrial data can be uploaded to the platform database in time. For example, the corn grain harvester condition monitoring system records a great deal of working condition data, including machine operation status, sensor data, temperature vibration pressure, etc. *(Lian et al., 2022)*. Researchers have continuously modified the model by analysing the data and have proposed a data-driven approach based on it. Initially, signals such as equipment currents and vibrations were converted to the frequency domain range by introducing Fourier transforms to extract the features associated with faults in them and map them to the maintenance and repair of equipment. The development of communication technology laid the foundation for the later development of artificial intelligence.

In order to minimize downtime maintenance time through artificial intelligence learning algorithm research for fault prediction and feature extraction technology development has brought a new idea. Some scholars *(Gu et al., 2022)* proposed a fault diagnosis method of mining excavator engine based on an improved fruit fly optimization algorithm (IFOA) optimized RotGBM. RotGBM is generated by combining Rotation Forest and Light Gradient Boosting Machine (LightGBM), and a new fault diagnosis model is constructed and applied the method to mining excavator engine fault diagnosis with good fault diagnosis effect. Some scholars *(Zhao et al., 2021)* Zhao Hu, (2021). Fault prediction of key components of wind turbine based on BP neural net. *Power System Engineering*, Vol. 37, No. 2, 21-22.used back propagation (BP) neural network fault prediction model to predict the operating parameters of key components of wind turbines, and has good fault prediction effect on gear box bearing temperature. Some scholars *(Zhou et al., 2015)* used the learning method of support vector machine (SVM) to model the gas line failure of gas circuit and verified it with large sample data. Compared with the traditional way of human calculation to deal with faults, the deep learning model can give full play to the advantages of computer arithmetic, through a large amount of data training, gradually reduce the model prediction error, and continuously optimize the prediction results.

In this paper, a fault prediction of corn grain harvester is proposed. The model is a nonlinear mapping between the historical fault cause data and the fault phenomena of corn grain harvester established by self-coding neural network. The model is designed to accurately predict the type of corn kernel harvester failure based on the given fault data. At the same time, the data of failure cause of corn grain harvester were self-coded and analysed, and the internal relationship between the fault cause and maize harvester was obtained.

MATERIALS AND METHODS

Structure and fault analysis of corn seed harvester

As shown in the Fig. 1, the corn grain harvester consists of a cutting table, a lift, a detaching drum, a seed recovery device, an engine, a cab, and a grain bin. The harvesting process includes picking, threshing, separating, scavenging and conveying *(Li, 2016).* When the corn seed harvester is at work, the corn plant is separated from the stalks by cutting the ears through the cutting platform, and the lifters carry the ears into the detaching drum and finally send them to the grain bin *(Li, 2014).*

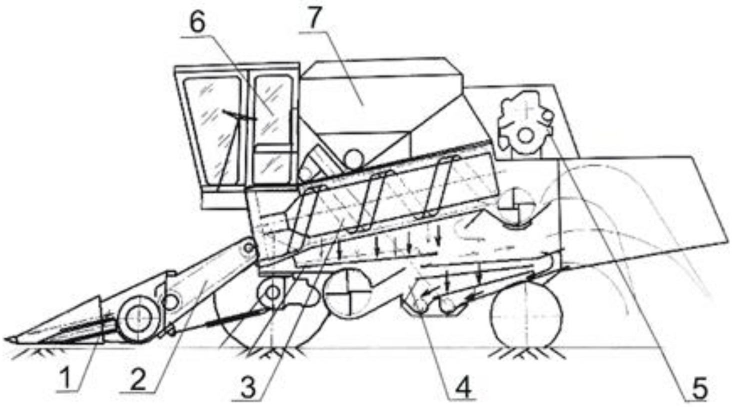

Fig. 1 – Structure of the whole machine of corn grain harvest
1. Cutting platform; 2. Lifting conveyor; 3. Threshing and separation apparatus with axial flow; 4. Grain recovery device; 5. Engine; 6. Cab; 7. Grain bin;

The corn grain harvester cutting table has the role to complete the cutting of corn stalks, clamping and conveying the cob, picking the cob, force feeding the stalk to the chopping mechanism, feeding power to the conveying unit, and providing a mounting platform for the conveying unit, chopping unit, and throwing unit. The structure of the corn grain harvester cutting table is shown in Fig. 2 which mainly includes the grain splitter, the spike picking unit, the conveying churn, the cutting table frame, and related transmission parts and lifting cylinders. The spike picking unit is the main working part of the cutting table, as shown in Fig. 3.

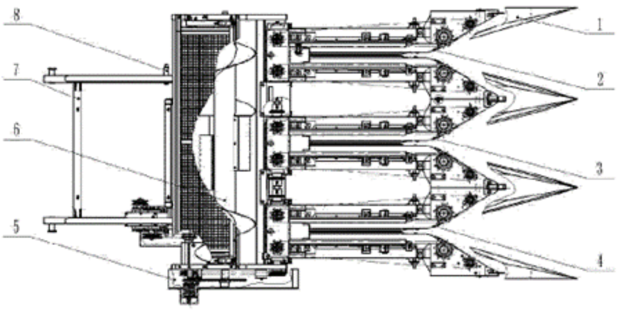

Fig. 2 – Cutting table structure diagram
1. Divider; 2. First unit body; 3. Second unit body; 4. Third unit body; 5. Cutting table rotation; 6. Conveyor churn; 7. Cutter frame; 8. Cutting table structure diagram

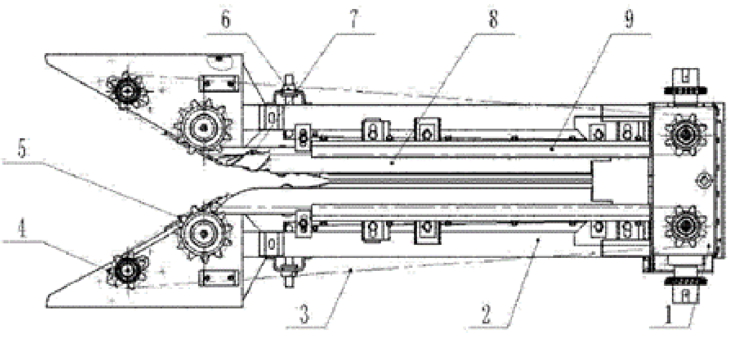

Fig. 3 – Unit structure
1. Spike tine box; 2. Spike rack; 3. Sprocket chain; 4. Tensioning sprocket; 5. Tiller chain driven wheel; 6. Stem pulling roller clearance adjustment handle; 7. Stem pulling roller; 8. Spike plate; 9. Cutting knife

The working process of the cutting table is that the corn plants are first divided by the grain splitter, and under the combined action of a set of paddle chains, the corn plants in front of the machine are guided to the stalk pulling rollers, fed into the working gap between the two stalk pulling rollers, and the ears are picked under the pulling force of the stalk pulling rollers and the blockage of the picking plate, and the ears are conveyed by the paddle chains, which pass the ears to the conveying churn and into the elevator. The rest of the picked ears of stems are drawn down for crushing.

There are many types of corn grain harvester failures, and the cutting platform is a fault-prone part of the corn grain harvester, the causes of failure are relatively complex, and the failure rate of the cutting platform accounts for a high percentage of the whole machine failure. The common failure of the cutter includes blockage of cutter parts, broken and aged parts, etc. *(Zhou, 2021).* The main reason for the above-mentioned failure of the cutter is the improper operation of the employees, which makes the feeding volume too large. The continuous high-intensity work of corn grain harvester makes the parts accelerate deformation and aging, making the harvest quality worse. Other failure mechanisms include inappropriate tension of the chain causing jumping or too tight making the chain and chain teeth wear seriously. The mismatch between the speed of the working parts and the forward speed of the machine can also cause a reduction in harvesting quality, blockage of the cutting table parts and excessive breaking of the corn kernels.

Therefore, this paper takes the corn grain harvester cutting table as the main fault research object, and predicts and classifies its faults.

Methodology Overview

The proposed method framework as shown in Fig. 4, which combines the selection of the fault phenomena of the corn seed harvester and the expected achievement of the fault prediction, is used to partition the difficult to learn by machine recognition data matrix into training and test segments, and the training data are used to train the self-coding neural network model to build a multi-scale fault prediction network *(Xu at al., 2020)*. The test dataset was validated; a fully connected layer with SoftMax classifier was used thereby establishing a mapping of fault data to corn seed harvester faults.

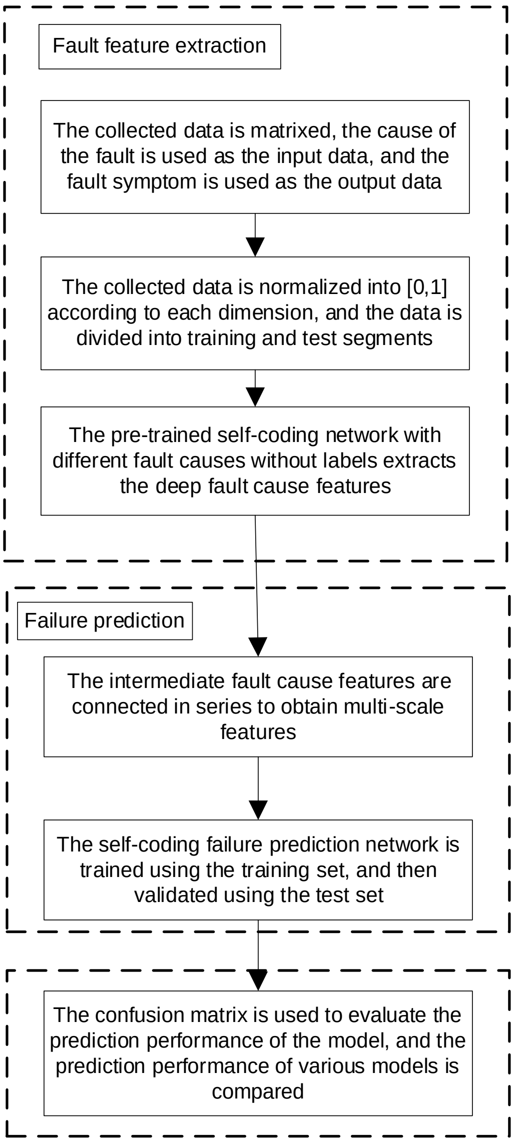

Fig. 4 - Technical route

Self-coding Network-based fault prediction of corn grain harvester

The research object of this paper is the corn grain harvester, through the field investigation of Shandong Dongfeng Agricultural Machinery Co., Ltd., combined with the historical fault database of the harvester obtained by some scholars *(Yang et al., 2022)* through data mining. Take this as the object of study, because the corn grain harvester is a large and complex mechanical equipment, the technician cannot collect all the status information, and the failure causes of the corn grain harvester are varied, this paper selects some fault causes and phenomena of the header for research, through the collection of a large number of historical faults in the corn grain harvester, the cause and symptom data determine the data types of the input and output, as shown in Table 1.

Table 1

Failure matrix

Sequence 1	Cause of fault (input data)	Sequence 2	Fault phenomenon (output data)
1	Excessive tool clearance	1	Cutter winding
2	Too small tool clearance	2	Harvest chain winding
3	The cutting platform rack is too high	3	Clogged rollers
4	The cutting platform rack is too low	4	Bridge blockage
5	The rolling speed is too high	5	Uneven chopping length
6	The rolling speed is too low	6	Stalk guide groove pulling roller is entangled by the plant
7	The chain tension is not appropriate	7	The churn clutch is disengaged, and the churn is not rotating
8	Chain deformation or wear	8	Stem churn conveyor is clogged
9	The speed of the working parts does not match the forward speed of the machine	9	Stem leaves accumulate in front of the stem churn
10	Unstable lifting speed of working parts	10	Corn grain broken too much
11	Cutting table row spacing and crop row spacing are not in line		
12	Large feeding volume		
13	Belt slippage		
14	Tool breakage		
15	Parts aging		
16	Loose parts		
17	Crop collapse		
18	Debris winding around the stem puller		
19	Fields weeds are unusually high		
20	Improper driving operation by staff		

As can be seen from Table 1, this paper uses 20 failure causes as input data and the resulting 10 failure phenomena as output data for the failure prediction of corn grain harvesters. In order to make the failure causes and failure phenomena data recognized by the computer, this paper constructs a matrix; the failure causes are input in a 1×20 matrix and output in a 1×10 matrix.

Pre-processing of database data, the collected historical fault information as well as database data are pre-processed, including the removal of outliers, normalization processing, feature dimensionality reduction, etc., to reduce the interference of noise to the model. For example, the size of the feed is scored by experts, the rest of the data are processed uniformly, and finally the data of each dimension collected is normalized, and the expression formula of normalization is:

$$x_{n'} = \frac{x_n - x_{min}}{x_{max} - x_{min}} \tag{1}$$

For example: $x = [x_1, x_2, \cdots x_n]$ for corn harvester feeding amount of the data collection; After x for normalization of data; x_{max} and x_{min} for corn harvester is one of the biggest feed rate and minimum feed rate.

Self-coding neural network

Autoencoder (AE) is a deep learning technique for learning the hidden representation of data for data generation and dimensionality reduction *(Wang et al., 2022).* The Autoencoder network consists of an encoder and decoder that learns the hidden representation by minimizing the input-output error *(Yu et al., 2020).* The encoder encodes the input data into a hidden representation and the decoder decodes the hidden representation into the output data.

Assuming the input data $\{A^{(1)}, A^{(2)}, \cdots A^{(n)}\}, A^{(i)} \epsilon R^n$, the self-coding network is trained unsupervised so that the encoding and decoding process makes the input data $A^{(i)}$ and the output data $B^{(i)}$ as identical as possible. A three-layer self-coding network structure contains an input layer, an implicit layer and an output layer as shown in Fig 5. The goal of the learning of the network is to approximate a constant function so that $A^{(i)} = B^{(i)}$. The corresponding coding and decoding process equation is expressed as:

$$h = f_c(A) = S(W_c A + d_c) \tag{2}$$

$$h = f_b(A) = S(W_b A + d_b) \tag{3}$$

$$B = f_e(A) = S(W_e A + d_e) \tag{4}$$

$$S(t) = \frac{1}{1+\exp(-t)} \tag{5}$$

Including f_c、f_b、f_e respectively encoding layer, hidden layer and decoding.

$S\,(t)$ as the Sigmoid activation function; W is the connection weight matrix; d is biased.

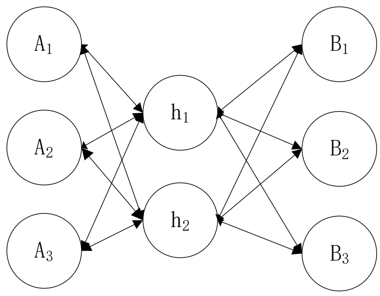

Fig. 5 - Three-layer autoencoding networks

In order to make the input data $A^{(i)}$ and the output data $B^{(i)}$ as identical as possible the cross-entropy error function is used to reconstruct the error $L(x, y)$ function *(Yan et al., 2023)* expressed as:

$$L(x,y) = -\frac{1}{n}\sum_{i=1}^{n}[x_i \ln y_i + (1-x_i)\ln(1-y_i)] + \frac{m}{2}\sum_{k=1}^{n_k}\sum_{j=1}^{s^l}\sum_{i=1}^{s^l+1}\left(W_{ij}^k\right)^2 \tag{6}$$

In the formula, $\frac{m}{2}\sum_{k=1}^{n_k}\sum_{j=1}^{s^l}\sum_{i=1}^{s^l+1}\left(W_{ij}^k\right)^2$ is a regular item, m as the attenuation coefficient of weight, each node weights between neurons for W_{ij}^k. By reducing the weight, overfitting is prevented when extracting deep features from self-coding.

The data selected in this paper have certain correlation, but the input data correlation features are not obvious. By using the fault causes as the input data for training, the deep feature relationships between the fault causes are extracted. The structure of multi-layer self-coding network contains several layers such as coding layer, feature transformation layer, and decoding layer. In this network, each layer consists of multiple neurons that are connected to each other to form a fully connected layer. Each neuron in the fully connected layer is connected to all neurons in the previous layer, and each neuron has a corresponding weight. These weights are used to convert the input data of the previous layer into the output data of the next layer. In this network, the Sigmoid activation function is used to map the output data of the fully connected layer to a range between 0 and 1 to produce probability distributions *(Lin et al., 2016)*.

These probability distributions can be used to represent the correlation between different features, thus helping the network for feature extraction and dimensionality reduction. As shown in Fig. 5, this paper uses a multilayer self-coding network. Input layer: for the dataset $x = [x_1, x_2, \cdots x_n]$ with n combined features, two coding layers are used for feature extraction and dimensionality reduction to obtain the dataset $\bar{x} = [\bar{x}_1, \bar{x}_2, \cdots \bar{x}_n]$. Feature exchange layer: deep feature mapping is extracted by feature transformation of the feature exchange layer data. Decoding layer: two decoding layers change the data into the resolution of the original signal. The network parameters are shown in Table 2.

In this paper, the two-layer coding layers and the two-layer decoding layers are used, and the network settings of each layer are shown in the Fig. 6.

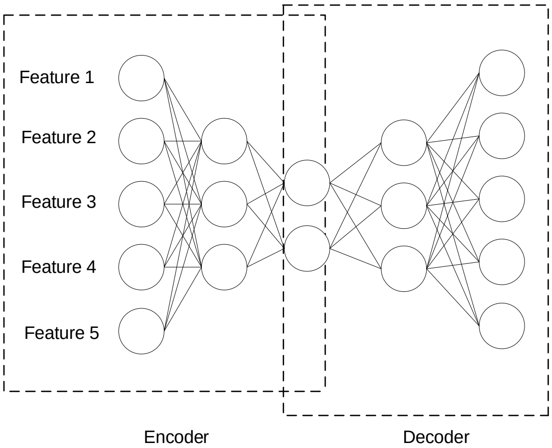

Fig. 6 - Basic structure of DAE

Among them, the two-layer coding layer performs feature extraction and dimensionality reduction on the data. The two-layer decoding layer reduces the original data type. In this paper, a total of 20 types of input data are taken, containing both 20 types of neurons. The input signal type differences are used to train the self-coding network using error functions so as to reconstruct the input signal to extract multi-scale features. The purpose of the self-coding network is to reconstruct the fault cause data to extract multi-scale features between fault causes. The self-coding network is trained by cross-entropy error function, considering that the input data are greatly influenced by the collection process and errors are unavoidable, making the network performance reduced. The self-coding network uses increasing noise perturbation to enhance the robustness of the network.

Table 2

Network parameter settings

One floor	two floors	three floors	four floors	five floors
{20,10}	{10,4}	{4,4}	{4,10}	{10,20}

Maize grain harvester fault prediction network

The internal feature relationships between the 20 causes of failure were obtained by the above feature extraction of the input data using a self-coding network but the phenomena of corn grain harvester failure could not be predicted. Next, the mapping between the causes of corn grain harvester failure and the phenomena of failure was established through fault prediction based on a self-coding neural network.

Fig. 7 - Prediction networks of Corn grain harvester

The maize seed harvester fault prediction network diagram is shown in Fig 7, for the constructed maize seed harvester fault prediction network firstly extracts the intermediate features of the cause of the maize seed harvester fault using a self-coding network, secondly concatenates the intermediate features to get the multi-scale features then uses a fully connected layer and a SoftMax classifier to get the phenomenon of the fault and the corresponding probability.

The 20 fault data outputs in the input table of the corn seed harvester fault prediction network are 10 fault phenomena, namely, cutter winding, harvest chain winding, clogged rollers, bridge blockage, uneven chopping length, stalk guide chute pulling stalk roller tangled by plant, disengaged churn clutch, churn not rotating, stalk churn conveyor clogged, stem leaves accumulate in front of the stem churn, and corn grain is broken too much. The coding and decoding layers of the fault prediction network use a self-coding network, and the fully connected part is trained using classification loss.

Simulation experiment

In order to verify the accuracy of self-coding neural network for fault prediction of corn grain harvester the corn grain harvester was tested in simulation experiments, the corn grain harvester was used as the test object for simulation experiments, the test platform was MatlabR2022a simulation software, and the method of fault prediction involved in this paper was input into the simulation software. A total of 500 sets of data were collected in this paper of which 450 sets were used as the training set and the remaining 50 sets were used as the test set. The historical failure data of the existing corn grain harvester was collected through research and data mining techniques to build a database. After normalizing the data, a self-coding network is used to mine the internal characteristics of the cause of the failure of the corn grain harvester, and a failure prediction network is used to predict the failure phenomena caused by the cause of the failure.

Establishing a confusion matrix and verifying the performance of corn grain harvester failure prediction by confusion matrix *(Wang et al., 2021).*

Table 3

Confusion matrix

Confusion Matrix		**True Value**	
		Positive	**Negative**
Predicted value	**Positive**	TP	FP
	Negative	FN	TN

Each column in Table 3 indicates the predicted category, and the numbers of data in each column indicates the number of data predicted to belong to that category. Each row indicates the real category to which the data belongs, and the numbers of data in each row indicates the number of instances of data in that category. The value in each column indicates the number of instances of the actual data predicted to belong to that category. TP, TN, FP, and FN in the table are the first-level base indicators of the confusion matrix with the following concepts: TP is the probability that a positive category is predicted to be positive; FP is the probability that a negative category is predicted to be positive; FN is the probability that a positive category is predicted to be negative; TN is the probability that a negative category is predicted to be negative. The formula and meaning of the confusion matrix are shown in Table 4.

Table 4

Equations and significance of confusion matrix

Abbreviation	**Formula**	**Implication**
Recall	$R = \frac{TP}{\lvert TP + FN \rvert}$	Model predicted positive class weights in all results where positive class is positive.
Precision	$P = \frac{TP}{\lvert TP + FP \rvert}$	Weight of model prediction positive class among all results with positive model prediction class
F1 score	$F = 2\frac{PR}{R + P}$	Coordinated average of model accuracy and recall, which reflects the stability of the model
Fowlkes-Mallows index	$FM = \sqrt{\frac{TN}{TN + FP} * \frac{TP}{TP + FN}}$	The geometric mean of the correct results of the classification samples, which can evaluate the overall classification performance of the algorithm.

RESULTS

Analysis of fault prediction results

In this paper, the final prediction of failure was made by comparing the probability of occurrence of the 10 conditions, i.e., cutter winding, harvest chain winding, clogged rollers, bridge blockage, uneven chopping length, stalk guide chute pulling stalk roller tangled by plant, disengaged churn clutch, churn not rotating, stalk churn conveyor clogged, stem leaves accumulate in front of the stem churn, and corn grain is broken too much. Fig. 8 shows the prediction results obtained by testing data from two different scenarios using the algorithm in this paper.

Fig. 8a shows that the probability of occurrence of the 10 fault phenomena for the given operating state of the fault cause condition is 2.7%, 28.17%, 48%, 12.33%, 3.54%, 1.9%, 2.03%, 0.32%, 0.14%, and 0.87%, respectively, which indicates that the probability of corn seed harvester cutter winding is the highest in the current state. Therefore, the output of the fault prediction is corn seed harvester cutter winding. Compared to the actual situation, the predicted results match the actual occurrence of the fault. Fig. 8b shows that the probability of occurrence of the 10 fault phenomena for the fault cause conditions of the given operating condition is 49.94%, 8.14%, 7.93%, 30.06%, 1.25%, 0.15%, 0.49%, 1.04%, 0.32%, and 0.68%, respectively, which indicates that the probability of bridge blockage and cutter winding of the corn seed harvester in the current condition is the highest. Therefore, the output of the fault prediction is that the corn seed harvester has overbridge blockage and cutter tangle. Compared with the actual situation, the predicted results match with the actual occurrence of faults. This shows that the prediction results of the self-coding neural network are consistent with the actual situation.

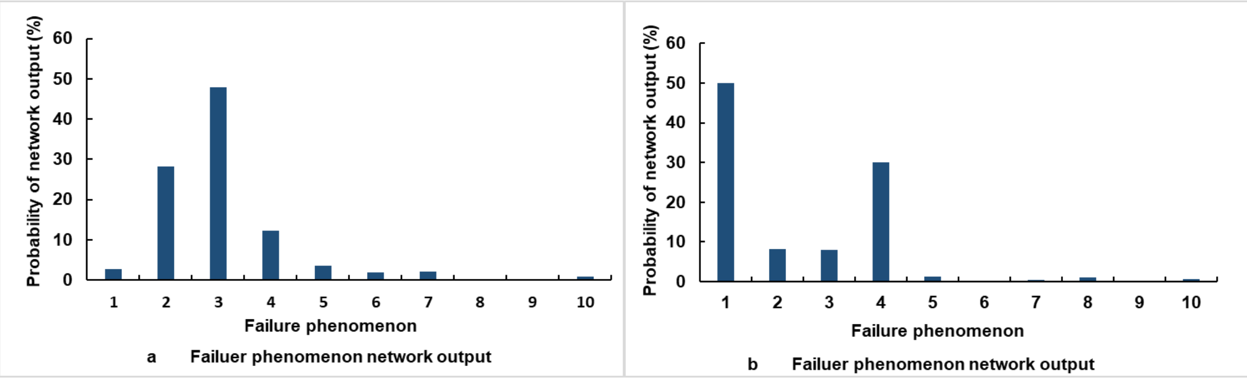

Fig. 8 - Output results of fault phenomenon networks with different data
a-Failure phenomenon network output; b-Failure phenomenon network output;

Algorithm comparison

To verify the effectiveness of the self-coding neural network algorithm, the algorithm was compared with the traditional self-coding network support vector machine classification, sparse self-coding, and Bayesian classification algorithms, using the same training data and test data in order to ensure the accuracy of the experiment. The prediction accuracy of the four models is shown in Table 5. From the table, it can be seen that the correct prediction of corn seed harvester faults by the self-coding neural network outperformed the other fault prediction models. Thus, it shows that the prediction results of the self-coding neural network have a greater improvement using multi-scale feature representation can improve the prediction accuracy of the network.

Table 5

Identification results of different models

Model	Accuracy rate	F	FM
Self-coding network	0.8668	0.8364	0.8472
Support vector machine	0.8507	0.8035	0.7963
Sparse self-coding network	0.9032	0.9079	0.9107
Bayesian classification algorithm	0.8319	0.8632	0.8768
Self-coding neural network	0.9384	0.9476	0.9197

CONCLUSIONS

In this paper, the cause of the fault is matrices, so that the computer can recognize and learn fault data better. Through a self-programmed network, the relationship between the fault causes can be understood, which can lead to a single failure phenomenon or multiple faults, so as to better explore the relationship between failure phenomena fault causes and failure phenomena, and to a certain extent predict the failure of corn grain harvester.

The shortcoming of this paper is that the limited data cannot predict the occurrence of malfunction to some extent, which provides new ideas for failure prediction, relevant references for the health management and maintenance of agricultural machinery, and new ideas for the development of corn grain harvester reliability.

A fault prediction model of corn grain harvester based on self-coding neural network is designed and simulation experiments are performed. Experimental results show that the error is less than a certain amount in different iterations of the test. Experimental results show that the proposed fault prediction model can not only improve the accuracy of prediction, but also reduce the time of fault repair and provide data support for the fault repair and reliability of agricultural machinery.

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