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RESEARCH ARTICLE

# How to Guarantee Food Safety via Grain Storage? An Approach to Improve Management Effectiveness by Machine Learning Algorithms

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## ABSTRACT

The purpose of grain storage management is to dynamically analyze the quality change of the reserved grains, adopt scientific and effective management methods to delay the speed of the quality deterioration, and reduce the loss rate during storage. At present, the supervision of the grain quality in the reserve mainly depends on the periodic measurements of the quality of the grains and the milled products. The data obtained by the above approach is accurate and reliable, but the workload is too large while the frequency is high. The obtained conclusions are also limited to the studied area and not applicable to be extended into other scenarios. Therefore, there is an urgent need of a general method that can quickly predict the quality of grains given different species, regions and storage periods based on historical data. In this study, we introduced Back-Propagation (BP) neural network algorithm and support vector machine algorithm into the quality prediction of the reserved grains. We used quality index, temperature and humidity data to build both an intertemporal prediction model and a synchronous prediction model. The results show that the BP neural network based on the storage characters from the first three periods can accurately predict the key storage characters intertemporally. The support vector machine can provide precise predictions of the key storage characters synchronously. The average predictive error for each of wheat, rice and corn is less than 15%, while the one for soybean is about 20%, all of which can meet the practical demands. In conclusion, the machine learning algorithms are helpful to improve the management effectiveness of grain storage.

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## INTRODUCTION

Grain is an important strategic material of our country and a necessity for people's lives. The safe storage and circulation of food is an important guarantee for national stability, is related to the national economy and people's livelihood, and is the top priority of food work. In the process of storage and management of grain, its quality declines with the number of years. When the quality drops to a certain level, it will be inedible, causing serious food waste. In the storage process, low temperature, drying, chemical fumigation and other technical means should be adopted as much as possible to prevent grain diseases, insect pests and mildew, so as to slow down the process of grain quality degradation and extend the storage life. Grain that has deteriorated too quickly needs to be shipped out of the warehouse and put on the market early, and new grains must be purchased for storage. There are many factors that affect grain quality changes in the process of grain storage management, including region, weather, season, temperature, humidity, etc. The influence of



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these external factors is directly reflected by the changes in the internal attributes of the grain quality inspection data. China has a vast territory with obvious climate differences in different regions and the grain storage in different areas will form an obvious grain storage ecosystem. Researchers divide these grain storage ecosystems into seven parts [1]. The conclusions of changes in grain quality obtained through experimental extraction methods are limited to the area studied, and it is difficult to expand the application [2-5]. The initial level of grain is different for each ecoregion and each warehouse. If the food storage characteristics of each ecological area and each warehouse are obtained through experiments, the efficiency will be greatly reduced and the manpower and material resources will be wasted. Therefore, how to quickly predict the changes in grain quality in each ecological area is of great significance for evaluating the grain storage conditions in each ecological area.

With the rapid development of information technology, machine learning has entered the stage of deep learning in the era of big data. That is more effective training through massive data to obtain accurate classification [6]. The advent of deep learning algorithms makes machine learning reach a new peak, which is widely used in many fields. Machine learning is an approach to the realization of artificial intelligence. It can quickly process computer data through algorithms, and the ability to predict and classify problems with statistical models [7]. Artificial Neural Network (ANN) and Support Vector Machine (SVM) are both machine learning algorithms. ANN shows some skill characteristics by constructing a mathematical model and continuously adjusting the interconnection relationship between most internal nodes. The error back-propagation algorithm is a commonly used algorithm in the artificial neural network. Its simulation learning process includes forward propagation of input signals and back propagation of error signals. The hidden layer weight of the network is adjusted through continuous error feedback so that the actual output value gradually approaches the expected value. It is widely used in the fields of prediction analysis [8,9], pattern recognition [10] and signal processing [11], etc. SVM shows many advantages in solving small samples, nonlinear, and high-dimensional pattern [7-12]. SVM has good stability and strong generalization ability for unknown data, especially when the amount of data is small, it has better performance than other traditional machine learning algorithms. It has been applied in many fields, such as image recognition and processing [13-15], face recognition [16], speech recognition [17], handwritten digital recognition [18], text classification [19], and biomedicine [20], etc. However, there are few reports on the application of machine learning algorithm in the quality prediction of stockpiled grains. A few reports have been applied in the prediction of grain yield [21,22] and the identification of pests and diseases [23,24]. Shang used data mining technology was used to construct a model to predict whether the grain storage quality will change over time [25].

Therefore, in this research, we have made full use of the machine learning algorithms in the era of big data to build a prediction model for food safety and grain storage characteristics, and overcome the shortcomings of the existing experimental extraction technology. According to the previous quality data and temperature and humidity data of grain during the storage period, and the mathematical model was innovatively established by using BP neural network algorithm and SVM algorithm. Deep mining and analysis of huge grain storage data, and 25 intertemporal prediction models and 25 synchronous prediction models of grain storage character in different regions were constructed. 6 intertemporal prediction models of the grain storage character were constructed based on temperature and humidity. It provides data support for exploring the quality standards and reasonable rotation cycle of different varieties of grains in different regions, and theoretical support for grain quality protection technology in different regions.

## METHODOLOGY

### Data collection

The results of the 2014-2018 spring and autumn quality data of the SINOGRAIN were selected as sample data. About 180, 000 pieces of data were processed through big data sorting, screening, and deduplication. A total of 169,100 valid data were obtained, including 61, 300 wheat data, 37, 500 corn data, 63,800 rice data (23,900 japonica rice, 39,900 indica rice), and 60,500 soybean data. At the same time, the temperature and humidity data of some silos (including the average temperature of the grain surface, in-warehouse temperature, in-warehouse humidity, and out-warehouse humidity) were selected. The indexes of grain storage character were: wheat for water absorption of gluten, rice and corn for fatty acid value, soybean for crude fatty acid value and protein soluble ratio. The grain quality indicators are all indicators specified by national standards.

### Data normalization

Many studies have shown that data of different dimensions have a greater impact on model accuracy and prediction results [26,27]. The units of each quality indicator in grain are different and the values are also large. In order to eliminate the impact of different dimensions between different indicators on model analysis, the sample data needs to be standardized. The data were normalized by the formula (1):

$$x'_{ij} = \frac{x_{ij} - min(x_{ij})}{max(x_{ij}) - min(x_{ij})} \quad (1)$$

## Construction of prediction models

**Establishment of BP neural network model for intertemporal prediction:** BP neural network is a non-linear multilayer forward network, which is composed of the input layer, hidden layer, Dropout layer, Dense layer, and output layer. The hidden layer can be one layer or multiple layers. This study was a double layer. The dropout layer in order to prevent the trained model from overfitting. The Dense layer is a fully connected layer.

After the data input to the input layer, the output of the first hidden layer $f_1$ is obtained through the formula (2), the output of the second hidden layer $f_2$ is obtained through the formula (3), and the output of the output layer is obtained through the formula (4).

$$f_1 = relu((W_{f1} * X) + b_o) \quad (2)$$

$$f_2 = relu((W_{f2} * f_1) + b_o) \quad (3)$$

$$output = (W_{output} * f_2) + b_{output} \quad (4)$$

where $W_f$ is the weight matrix of the current, $b_o$ is the bias term of the current layer, relu is the activation function. The input data of the BP neural network is a 2D matrix with the shape (samples, timesteps) samples represent the number of samples and timesteps represents the dimension of the input data. When the dimension is 4, the storage character of the fourth period was predicted based on three consecutive periods of storage character. The formula is: $y_t = F(y_{t-3}, y_{t-2}, y_{t-1},)$, the model is shown in figure 1.

In the BP neural network model established in this study, the three parameters of the data dimensions of the training and testing sets, the number of network layers, and the number of neural units in the network hidden layer need to be optimized. The data dimension is the number of periods of data required to build the model. According to the actual situation of storage of various grains, the data dimension is between 3 and 5. The number of network layers, the test results showed that there is no significant difference between the double hidden layer and the three hidden layers, but the training time of the three hidden layers was much longer than the double hidden layer, so the double hidden layer was selected. Based on the principle of minimum MSE, the number of neural units is determined.

**Establishment of storage character intertemporal prediction model based on temperature and humidity:** Based on the quality and storage character data in March and the temperature and humidity data from April to September, the storage character in September is predicted, as shown in formula (5):

$$Y_t = F(X_{1,t-1}, \ldots, X_{6,t-1}, Y_{t-1}, Z_{1,t-1}, \ldots, Z_{6,t-1}) + \varepsilon_t \quad (5)$$

where $Y_t$ and $Y_{t-1}$ are the storage character data of September and March, $X_{1,t-1}$~$X_{6,t-1}$ are the temperature and humidity data from April to September, $Z_{1,t-1}$~$Z_{6,t-1}$ are the quality indexes data such as moisture and impurities in March the model is shown in figure 2.

**Establishment of SVM model for synchronous**

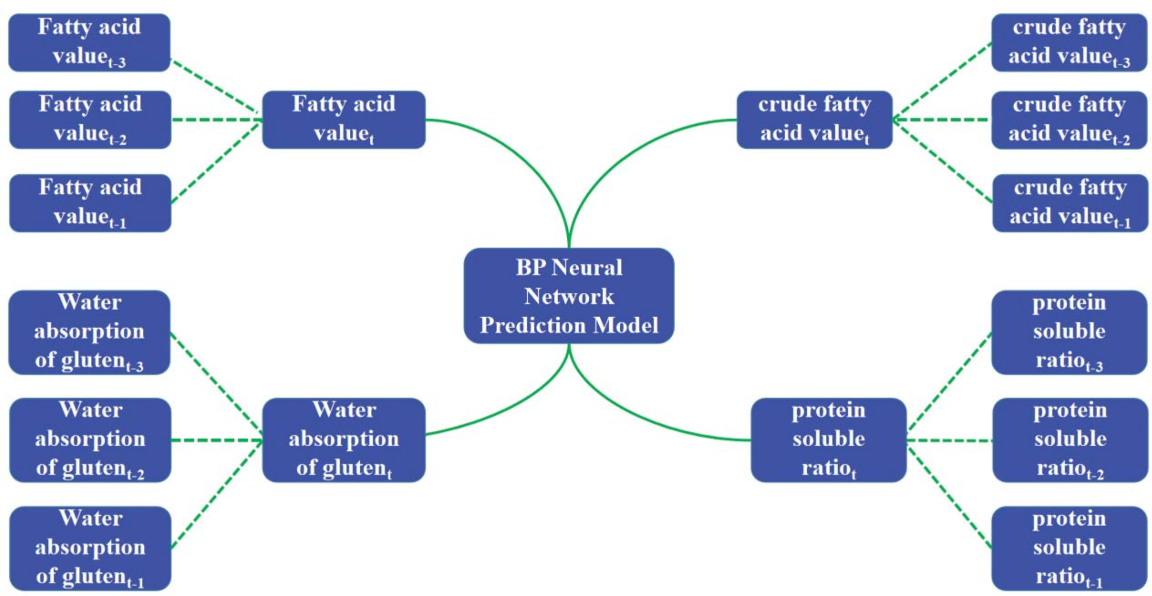


**Figure 1** Diagram of BP neural network prediction model.

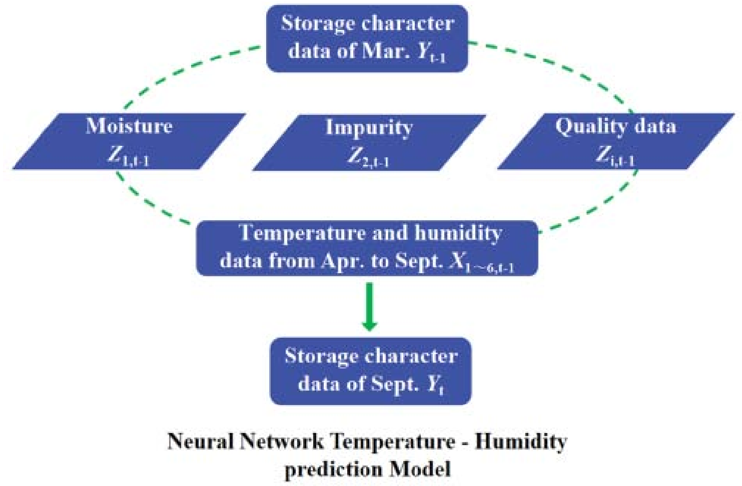


**Figure 2** Diagram of Temperature and humidity-storage character prediction model.

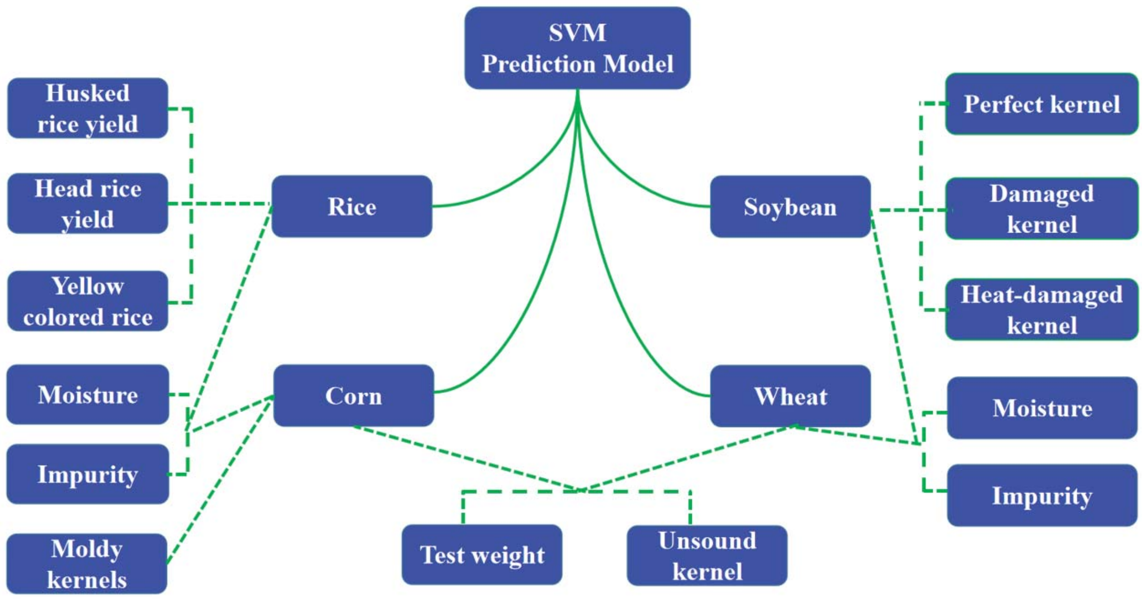


**Figure 3** Diagram of SVM prediction model.

**prediction:** For the relationship between the input value ($x_{ij}$) and the output value ($y_i$), it is assumed that there is a non-linear mapping relationship f such that $y_i = f(x_{ij})$. SVM was used to solve the regression equation $f(x)=\sum_{i=1}^{k}\left(\alpha^*_i-\alpha_i\right)K\left(x_i.x\right)+b^*$, and the predicted value of the grain quality index was obtained from the regression equation. The model is shown in figure 3.

In the SVM model established in this study, only the type of kernel function needs to be adjusted, and other parameters are determined by grid-search, and the optimal prediction model is selected among 1000 models by adjusting the parameters.

## Model evaluation

In this paper, the results of the model are displayed by fitting the trend of the predicted value and the real value, and the results of the model were evaluated by the Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) [28,29]. The calculation formula is shown in Equation 6 and Equation 7.

$$RMSE=\sqrt{\frac{\sum_{i=1}^{n}\left(P_i-O_i\right)^2}{n}} \quad (6)$$

$$MAPE=\frac{1}{n}\sum_{i=1}^{n}\frac{\left|P_i-O_i\right|}{O_i} \quad (7)$$

Where P is the prediction value, O is the real value, n is the number of samples. The above two indexes can be used to reflect the overall model prediction effect.

## RESULTS AND DISCUSSION

### The construction and error analysis of intertemporal prediction model of BP neural network for grain in different ecological regions

Taking wheat, corn, rice, and soybean as the research objectives, according to the chronological order form 3 ~ 5 data dimension, and the BP neural network intertemporal prediction model of each grain species was constructed by ecological regions. Randomly select 80% of the data as model training data and 20% of the data as test data to predict the accuracy of the model. The comparison results between the predicted and tested values of the storage character values of various varieties in different ecological regions, as shown in table 1.

As can be seen from table 1, rice and soybean predictions are more accurate. The average prediction error of rice was less than 10%. The average error of soybean crude fat value was about 20%. The prediction accuracy of water absorption of gluten and corn fatty acid values in different ecological regions were quite different. But the average prediction error is better, the water absorption of gluten was less than 5%, the corn fatty acid values are basically below 10%.

### The analysis of storage character intertemporal prediction model based on temperature and humidity

Grain quality is closely related to storage conditions, especially temperature and humidity. Therefore, the temperature and humidity of grain and warehouse were introduced into the model. The model is built on the quality data from March and on the temperature and humidity data from April to September, to predict the grain storage character in September. The predicted results were shown in table 2.

As can be seen from table 2, The Rooted-Mean-Square-Error (RMSE) and the Mean-Absolute-Percentage-Error (MAPE) of the prediction results of the storage character of

**Table 1:** The prediction results of BP neural network in each grain storage ecosystem.

| Varieties | Ecosystem | Data dimension | The first hidden layer units | The second hidden layer units | RMSE | MAPE (%) |
|---|---|---|---|---|---|---|
| Wheat | First ecosystem | 4 | 1 | 24 | 9.97 | 0.75 |
| | Second ecosystem | 3 | 3 | 25 | 43.3 | 2.71 |
| | Third ecosystem | 3 | 5 | 7 | 19.75 | 1.66 |
| | Fourth ecosystem | 5 | 7 | 21 | 92.17 | 3.55 |
| | Fifth ecosystem | 4 | 13 | 3 | 59.56 | 2.74 |
| | Sixth ecosystem | 4 | 13 | 21 | 4.04 | 0.86 |
| | Seventh ecosystem | 3 | 27 | 14 | 54.76 | 3.01 |
| Corn | Second ecosystem | 4 | 19 | 22 | 34.95 | 9.32 |
| | Third ecosystem | 4 | 19 | 28 | 45.85 | 9.44 |
| | Fourth ecosystem | 4 | 16 | 20 | 35.01 | 10.21 |
| | Fifth ecosystem | 4 | 12 | 8 | 32.66 | 9.48 |
| | Sixth ecosystem | 3 | 4 | 2 | 15.43 | 7.61 |
| | Seventh ecosystem | 3 | 22 | 3 | 6.08 | 4.69 |
| Japonica rice | Third ecosystem | 4 | 1 | 4 | 6.14 | 7.56 |
| | Fourth ecosystem | 3 | 5 | 4 | 2.72 | 5.38 |
| | Fifth ecosystem | 4 | 2 | 15 | 4.86 | 7.64 |
| | Sixth ecosystem | 3 | 3 | 21 | 1.96 | 5.67 |
| Indica rice | Fourth ecosystem | 4 | 7 | 29 | 2.88 | 6.48 |
| | Fifth ecosystem | 4 | 2 | 19 | 7.28 | 9.13 |
| | Sixth ecosystem | 4 | 17 | 8 | 3.39 | 6.20 |
| | Seventh ecosystem | 4 | 28 | 2 | 4.53 | 6.29 |
| Soybean | Second ecosystem | 3 | 5 | 23 | 0.20 | 20.91 |
| | Third ecosystem | 4 | 3 | 4 | 0.27 | 22.28 |
| | Fourth ecosystem | 3 | 13 | 23 | 0.08 | 9.94 |
| | Fifth ecosystem | 3 | 27 | 18 | 0.45 | 22.71 |

**Table 2:** The prediction results of prediction model based on temperature and humidity.

| Varieties | Indexes | The first hidden layer units | The second hidden layer units | RMSE | MAPE (%) |
|---|---|---|---|---|---|
| Wheat | Water absorption of gluten | 23 | 6 | 12.46 | 15.41 |
| Corn | Fatty acid value | 20 | 5 | 1.52 | 6.57 |
| Japonica rice | Fatty acid value | 22 | 8 | 9.20 | 13.32 |
| Indica rice | Fatty acid value | 28 | 4 | 8.23 | 15.04 |
| Soybean | Crude fatty acid value | 5 | 14 | 1.69 | 7.73 |
| Soybean | Protein soluble ratio | 5 | 16 | 2.66 | 8.11 |

each grain variety were within acceptable ranges, which can meet the actual business needs. Using the prediction results of this model can provide theoretical support for the next quality inspection and provide a basis for the focused and targeted grain quality inspection.

## The construction and error analysis of synchronous prediction model of SVM for grain in different ecological regions

Using the current grain quality index data, the SVM algorithm was introduced to construct a predictive model of the storage character in the same period. The comparison between the predicted results and the tested values is shown in table 3.

From the prediction results of the model, there are individual ecological regions and individual species models with poor simulation results. There are two main reasons. One is that the amount of data for grain varieties is small due to differences in different ecological regions, and there are even only dozens of valid data in the individual ecological regions. Another one is that the data comes from multiple storage sites and even multiple provinces. The data fluctuates greatly due to the variety difference, the difference among the testing institutions, the poor quality of the year caused by natural disasters, and the error of prediction was large. In subsequent research, further data should be collected to further optimize the model to minimize the above-mentioned adverse effects.

## Model validation

Grain quality-storage character intertemporal prediction model and grain quality-storage character synchronous prediction model established by using BP neural network algorithm and SVM algorithm using grain quality detection data from 2014 to 2018, respectively. In order to verify the prediction effect of the model after data update, a total of 865 samples of more than 120 stocks were collected from the third, fourth, and fifth ecological regions for four consecutive periods of detection (all including 2019 annual test results). The data of the relevant ecological regions were input into the BP neural network model and the SVM model respectively, and the predicted data were compared with the actual detection results.

**Validation of BP neural network intertemporal prediction model:** The data of the first 3 periods of water absorption of gluten, rice fatty acid value, and corn fatty acid value were input into the corresponding intertemporal prediction model, and the results of the 4th period were obtained, and then compared with the measured values of the 4th period.

In the third ecological region, the average forecast error of corn fatty acid value was 8.11%. That is, for corn samples with fatty acid values around 60, the model deviations can be controlled within 5 units. In the third and fourth ecological regions, the average forecast error of fatty acid value with japonica rice was 7.06% and 9.18%, respectively. That is, for japonica rice samples with fatty acid values around 25,

**Table 3:** The prediction results of SVM in each grain storage ecosystem.

| Ecosystem | Wheat | | Japonica rice | | Indica rice | | Corn | | Soybean | |
|---|---|---|---|---|---|---|---|---|---|---|
| | RMSE | MAPE (%) | RMSE | MAPE (%) | RMSE | MAPE (%) | RMSE | MAPE (%) | RMSE | MAPE (%) |
| First ecosystem | 5.58 | 2.27 | - | - | - | - | - | - | - | - |
| Second ecosystem | 30.60 | 3.68 | - | - | - | - | 6.72 | 11.58 | 0.26 | 21.61 |
| Third ecosystem | 5.10 | 2.03 | 3.22 | 13.49 | - | - | 6.32 | 10.20 | 0.43 | 30.40 |
| Fourth ecosystem | 78.22 | 12.03 | 3.00 | 11.71 | 3.49 | 12.73 | 6.91 | 12.10 | 0.41 | 29.44 |
| Fifth ecosystem | 26.51 | 3.69 | 3.72 | 12.60 | 3.30 | 12.03 | 7.37 | 14.33 | 0.45 | 19.03 |
| Sixth ecosystem | 9.71 | 3.78 | 2.77 | 10.02 | 3.73 | 13.58 | 6.30 | 10.11 | - | - |
| Seventh ecosystem | 9.72 | 3.75 | - | - | - | - | 6.84 | 12.21 | 0.03 | 15.61 |

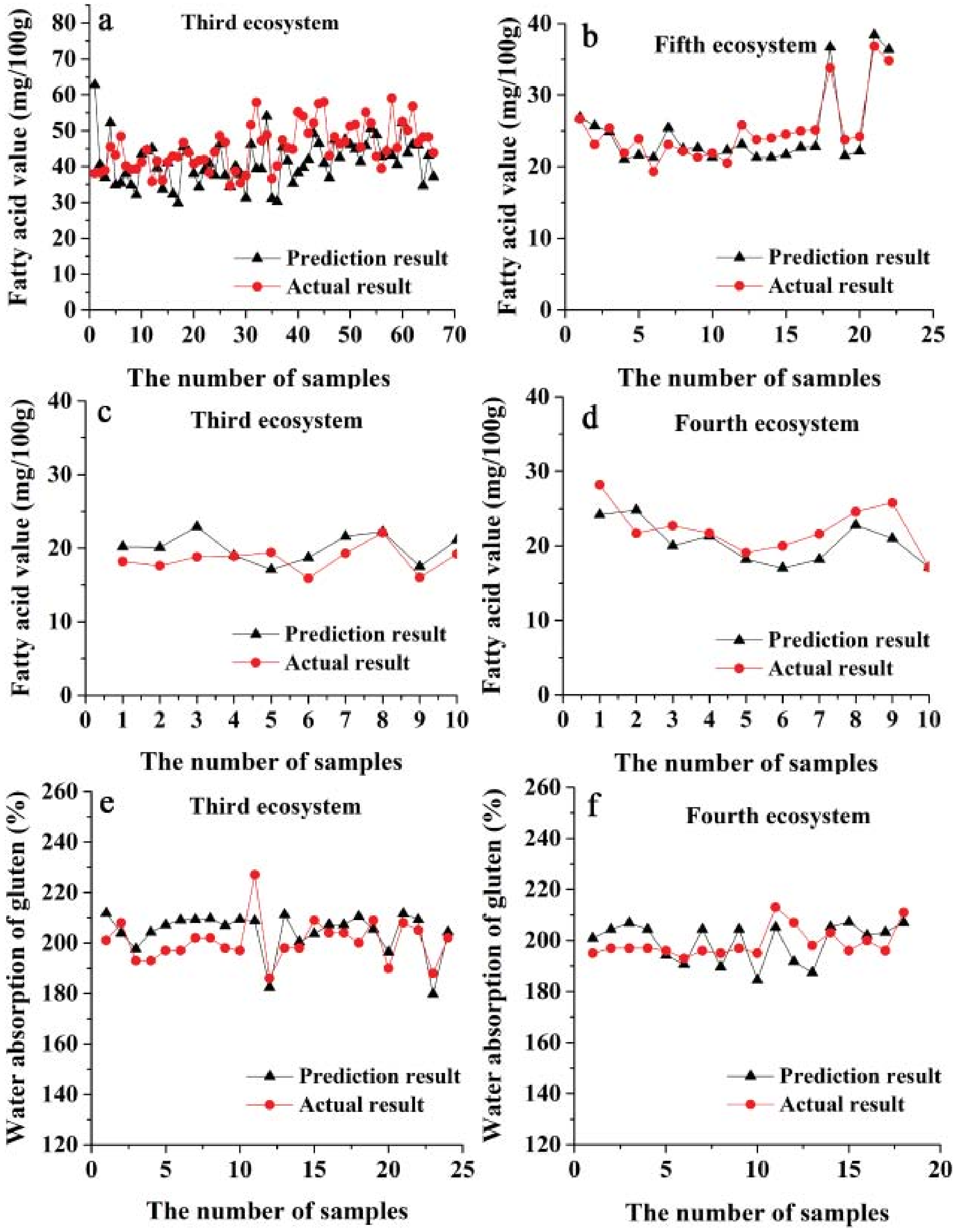


**Figure 4** Contrast diagram of storage character model intertemporal prediction results and actual results. (a) corn in the third ecological; (b) indica rice in the fifth ecological; (c) japonica rice in the third ecological; (d) japonica rice in the fourth ecological; (e) wheat in the third ecological; (f) wheat in the fourth ecological.

the model deviations can be controlled within 3 units. In the fifth ecological region, the average forecast error of indica rice fatty acid value was 7.73%. That is, for indica rice samples with fatty acid values around 30, the model deviations can be controlled within 3 units. In the fourth and fifth ecological regions, the average forecast error of water absorption of gluten was 3.68% and 3.58%, respectively. That is, for wheat samples with water absorption of gluten around 200, the model deviations can be controlled within 8 units. The comparison results between the predicted value and the measured value are shown in figure 4.

**Validation of SVM synchronous prediction model:** The current quality index data of rice, corn, and soybean are input into the SVM synchronization forecast model of the corresponding ecological region, the results of the same period were obtained and then compared with the measured values of the current period.

The japonica rice samples were selected for verification in the third and fourth ecological regions, the average forecast errors were 10.82% and 12.38%, respectively. That is, for japonica rice samples with the fatty acid value of about 25, the model deviations can be controlled within 3 and 4

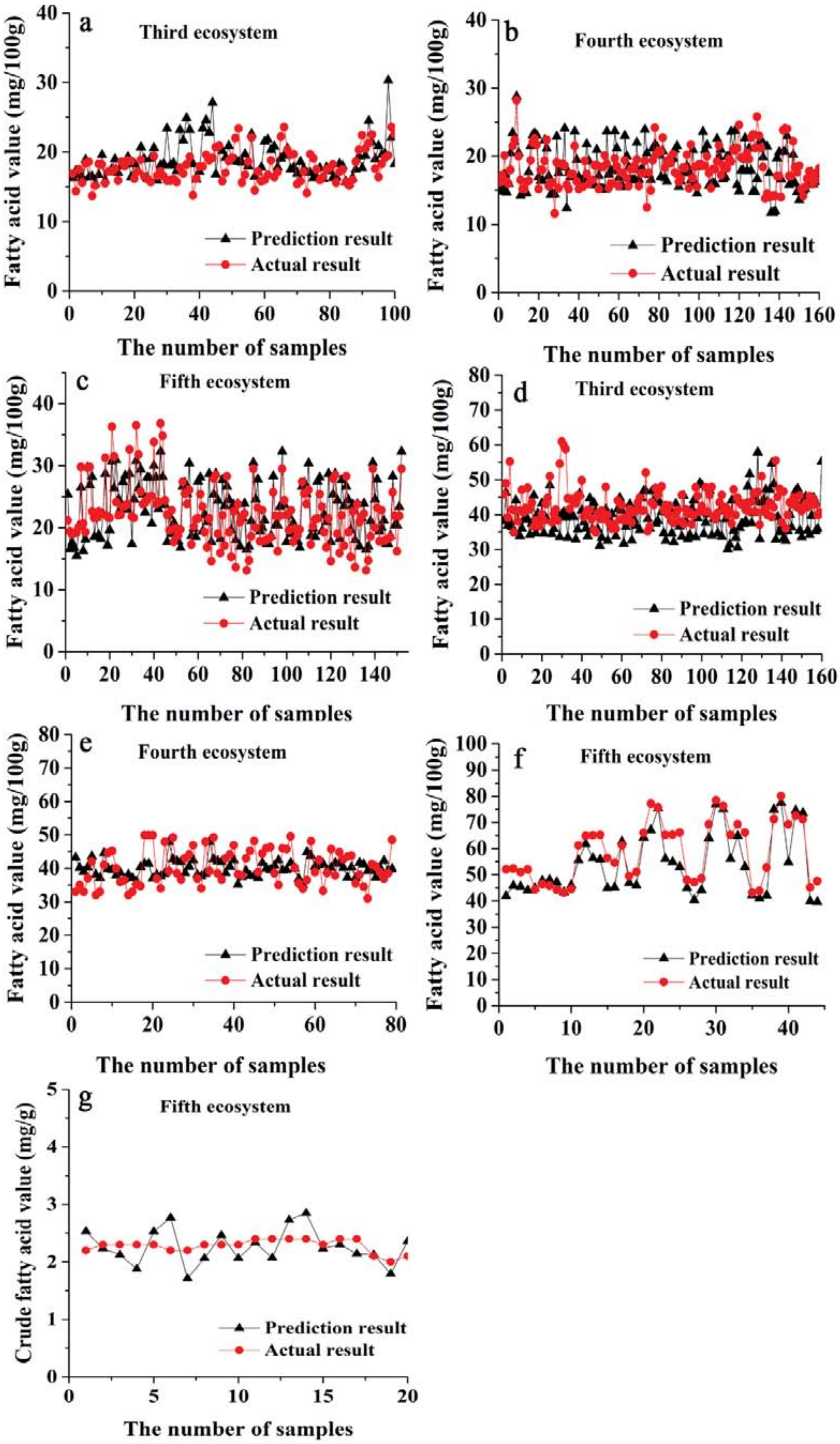


**Figure 5** Contrast diagram of storage character model synchronous prediction results and actual results. (a) japonica rice in the third ecological; (b) japonica rice in the fourth ecological; (c) indica rice in the fifth ecological; (d) corn in the third ecological; (e) corn in the fourth ecological; (f) corn in the fifth ecological; (g) soybean in the fifth ecological.

units, respectively. The indica rice sample was selected for verification in the fifth ecological regions, the average forecast error was 13.01%. That is, for indica rice samples with the fatty acid value of about 30, the model deviations can be controlled within 4 units. The corn samples were selected for verification in the third, fourth, and fifth ecological regions, the average forecast errors were 8.11%, 11.32% and 10.89%, respectively. That is, for corn samples with the fatty acid value of about 60, the model deviations can be controlled within 5, 7 and 7 units, respectively. The soybean samples were selected for verification in the fifth ecological region, the average forecast error was 11.19%. That is, for soybean samples with the crude fatty acid value of about 3, the model deviations can be controlled within 0.4 units. The comparison results between the predicted value and the measured value are shown in figure 5.

Based on the verification results obtained above, Using BP neural network algorithm and SVM algorithm to build a prediction model, using the results of the grain quality and storage character, can more accurately predict the storage character of grain during storage. The prediction error can be controlled within 15%. These results showed promising applications of the method of constructing grain storage character prediction based on machine learning algorithms.

## CONCLUSION

This paper introduces machine learning algorithms in the era of big data based on the previous quality data of grain during the storage period. Grain quality-storage character intertemporal prediction model and grain quality-storage character synchronous prediction model established by using BP neural network algorithm and SVM algorithm were constructed in various varieties in different ecological regions. The prediction model was trained with a large amount of data, and then tested with a part of the data and selected new data for verification. The results showed that using BP neural network algorithm and SVM algorithm to predict the storage character of grain, the model simulation is good, the prediction error is within the acceptable range, which can meet the needs of practical applications.

The application model established in this article was based on the grain quality index, storage character index, temperature, and humidity to predict the storage character in the different period or in the same period. The intertemporal prediction model can provide theoretical support for the next quality inspection and provide a basis for the focused and targeted grain quality inspection. The simultaneous prediction model can be applied to the acquisition of grain. Quickly judging the storage character by testing the quality index, it can greatly shorten the time for grain acquisition, improve work efficiency. It has a certain guiding significance for grain acquisition and storage management.

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### Data Availability Statement

All data, models, and code generated or used during the study appear in the submitted article.

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