Intelligent Prediction Method for Agricultural Product Price

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Agricultural price prediction is a hot research topic in the field of agriculture, and accurate prediction of agricultural prices is crucial to realize the sustainable and healthy development of agriculture. Compared with econometric and mathematical-statistical methods, intelligent forecasting methods have fewer restrictions and assumptions in modeling and can effectively model nonlinear relationships in price series.

price forecasting combined models intelligent prediction methods

1. Support Vector Machine-Based Prediction Method

The support vector machine (SVM) is a machine learning approach rooted in statistical learning theory [1]. It hinges on VC dimensional theory, the principle of structural risk minimization [2][3], and represents the pioneering algorithm grounded in geometric distance [4]. Serving as a small-sample learning technique with a robust theoretical foundation, an SVM's final decision function is influenced by only a handful of support vectors. Its computational complexity hinges on these vectors rather than the sample space's dimensionality, sidestepping the so-called "dimensional disaster". Wang et al. [5] harnessed SVM to predict the nonlinear facet of garlic prices, coupling it with ARIMA for linear price prediction, yielding accurate results. Nevertheless, SVM does have drawbacks, including diminished performance when data features (dimensions) surpass the sample size, sensitivity to parameters and kernel functions. Consequently, approaches like parameter optimization are frequently employed to enhance SVM prediction performance. Duan et al. [6] employed a genetic algorithm to identify optimal parameter combinations for a support vector regression model. With these optimized parameters, they constructed a support vector regression model for predicting fish prices, yielding precise outcomes with minor errors. SVR's remarkable ability to manage high-dimensional, nonlinear, and small-sample data positions is a vital technique in agricultural price prediction.

2. Bayesian Network-Based Prediction Method

A Bayesian network is essentially a directed acyclic graph that uses probabilistic networks to make uncertainty inferences. The excellence of Bayesian networks in solving agricultural price forecasting as well as other agricultural problems stems mainly from the following key features: (1) Bayesian networks can handle incomplete datasets; (2) Bayesian networks allow one to understand the relationships between variables and quantify the strength of these relationships; (3) the ability to combine quantitative and qualitative data; (4) the ability to combine expert knowledge and data into Bayesian network; and (5) Bayesian methods can relatively easily avoid data overfitting during the learning process. Putri [7] used Bayesian network algorithms as a data mining classification method to predict pepper commodity prices in Bandung region based on weather information. One disadvantage of Bayesian networks is that they do not support ring networks [8], which would weaken the robust inference capability of the network, and this limitation is not friendly to static Bayesian networks. Dynamic Bayesian network (DBN) is a dynamic model amalgamating probability theory and influence diagram. It combines a time-varying hidden Markov model with a traditional static Bayesian network, capturing benefits from both while sidestepping their limitations through dynamic adaptability over time and the incorporation of new states [9]. Ma Zaixing [10] used the PC algorithm to learn from data, construct according to expert knowledge, and combine expert knowledge and PC algorithm to perform structural learning. After obtaining the initial structure, he adjusted the obtained initial structure to obtain the network structure of the model, and then used the EM algorithm to perform parameter learning. Moreover, he obtained a complete dynamic Bayesian network model for price prediction, and selected the best model based on the prediction results to predict the price and output of live pigs. The results show that the prediction effect is better than the control group's ARIMA, SVM, and BP neural network models.

3. Neural Network-Based Prediction Method

Neural networks are commonly referred to as artificial neural networks (ANN). They constitute a complex nonlinear network system composed of numerous processing units interconnected in a manner resembling biological neurons. Neural networks exhibit robust nonlinear fitting capabilities, enabling them to map intricate nonlinear relationships. Furthermore, their learning rules are simple, making them easily implementable on computers. They possess strong robustness, memory, nonlinear mapping abilities, and powerful self-learning capabilities, showcasing unique advantages in addressing agricultural commodity price prediction challenges. In 1987, Lapedes and Farber [11] pioneered the application of neural networks to forecasting, marking the inception of neural network predictions. In 1993, Kohzadi et al. [12] were among the first to employ feed-forward neural networks for predicting US wheat and cattle prices. They compared the predictive results with those from ARIMA, concluding that neural networks exhibited superior turning point prediction capabilities and achieved more accurate price forecasting.

As big data and artificial intelligence technology advance, neural networks find increasingly wide application in the agricultural domain [13]. In the realm of price prediction, prevalent neural network models are as follows (**Table 1**), along with examples, summarizes the applications of neural networks in agricultural commodity price prediction):

- Backpropagation (BP) Networks [14][15][16]: BP networks are easy to implement and understand. However, it is easy to fall into local optimal solutions and the training speed is relatively slow.

- Radial Basis Function Neural Networks (RBFNN) [17][18]: A BP network is a global approximation of a nonlinear mapping, whereas an RBF network is a local approximation of a nonlinear mapping and is faster to train. RBF can handle complex nonlinear relationships and has good generalization ability. However, it is sensitive to the network structure and hyperparameters, and the training and tuning are relatively complicated. When the problem involves complex nonlinear relationships and there is enough training data, you can try to use RBF neural network.

- Long Short-Term Memory Networks (LSTM) [19][20]: LSTM neural network is a special kind of recurrent neural network that solves the problems of long-term dependency and gradient vanishing by introducing structures, such as forgetting gates, input gates, and output gates, to control the flow of information through the unit states. LSTM neural networks have the ability to memorize and capture long-term dependencies. Therefore, LSTM is a good choice when the prediction problem involves time series data, especially with long-term dependencies.

- Convolutional Neural Networks (CNN) [21]: CNN is a multi-layer feed-forward neural network that extracts local and global features from data through structures, such as convolutional, pooling, and fully connected layers to enable automatic feature learning and abstraction. In price prediction tasks, CNNs can learn and capture important features, such as time series, data trends, periodicity, etc., in the input data. Market prices are usually affected by a combination of several factors, and CNNs can better handle these complex nonlinear relationships.

- Chaos Neural Networks (CNN) [22][23]: Chaos neural network (CNN) is a kind of intelligent information processing system that combines chaos theory and neural network. Chaotic neural networks exploit the sensitivity and unpredictability of chaotic phenomena to enhance the learning and generalization capabilities of neural networks, thus improving the accuracy of prediction and modeling. By introducing methods, such as chaotic noise or logistic maps, chaotic neural networks are able to avoid neural networks from falling into local minima to a certain extent, thus speeding up the training process and increasing the convergence rate.

- Extreme Learning Machines (ELM) [24]: The extreme learning machine is a feed-forward neural network that was first proposed by Professor Huang Guangbin of Nanyang Technological University in Singapore in 2006. ELM has the advantages of fast training, high generalization ability, and simple implementation.

- Wavelet Neural Networks (WNN) [25][26]: Wavelet neural network (WNN) is a method based on wavelet transform and neural network. By decomposing the original data into wavelet coefficients at different scales, it is able to effectively extract a variety of features in the data, such as trend, cycle, seasonality, etc. WNN combines the powerful fitting ability of neural networks, which is capable of nonlinear mapping, thus achieving accurate prediction of future prices. However, high complexity and high data requirements are the unavoidable drawbacks of this method.

Table 1. Application examples of neural network-based price forecasting for agricultural products.

Reference	[14]	[17]	[20]	[21]	[23]	[24]	[26]
Models/Algorithms	BPNN	RBFNN	LSTM	CNN	Chaotic neural networks	ELM	WNN
Characteristic	Strong nonlinear mapping	It has better approximation ability,	It effectively overcomes the problem	The effectiveness of CNN in	The output of the network not	The algorithm can	Wavelet neural network

	ability, high self-learning and self-adaptive ability, ability to apply learning outcomes to new knowledge, and certain fault tolerance. Research results show that the BP neural network model has the long-term prediction ability for the futures market.	classification ability, and learning speed than BP neural network, simple structure, concise training, fast learning convergence speed, can approximate any nonlinear function, and overcome the local minimum problem. Research results show that the influencing factors of soybean price are different at different price levels, and the construction of this model is beneficial to the prediction of soybean price.	of gradient vanishing caused by the increase in network layers in RNN. This model is especially suitable for tasks with very long time intervals and delays, and has excellent performance. Research results show that parameter tuning has a large impact on the prediction effect of LSTM network model, and the main parameters with large impact include iteration times, learning rate, window size, and network layers. Compared with ARIMA model, MLP model and SVR model, LSTM network model has higher accuracy in prediction results.	feature extraction and autonomous learning of nonlinear patterns makes it perform well in image classification and audio recognition tasks. This study reviews the factors that affect crop yield and proposes a 3D CNN model to predict future crop prices. The model helps decision-makers to better predict crop price trends and formulate strategic plans, select trade partners, reduce costs, and solve food insecurity issues.	only depends on the current input, but also on the past output. After training, the network will have better adaptability to nonlinear data and is very suitable for predicting complex, non-stationary, and nonlinear time series. The designed potato price time series prediction model based on dynamic chaotic neural network has clear advantages over ARMA model in prediction accuracy and performance.	randomly generate the input weights and hidden layer thresholds required by the neural network without multiple adjustments. As long as the number of hidden layer nodes is reasonable, a unique optimal solution can be obtained. Its parameter setting process is simple, does not need to be adjusted repeatedly, the training speed is significantly improved, and the prediction results are more accurate. Compared with traditional neural network learning algorithms (such as BP algorithm), it overcomes the disadvantage of falling into local optimum.	combines the advantages of neural network and wavelet function, using Morlet wavelet as the hidden layer basis function, which can extract local dynamic features, and can build a local approximation feed-forward neural network, reduce the interference between nodes, and improve the prediction accuracy. This study uses wavelet neural network to predict the prices of two kinds of Chinese medicinal materials, Radix Codonopsis and Angelica sinensis, and the results show that the prediction error is very small and the prediction accuracy is very high.

						This study uses PCA-ELM model to predict grain prices and achieves good prediction results.	
Agricultural Product	Egg	Soybeans	Soybeans	Five different Crops	Potato	Grain	Chinese herbal medicine
Observed Features	Soybean meal price, cull chicken price, corn price, egg seedling price, duck egg price	Domestic Soybean Production, Soybean Imports, Global Soybean Production, Domestic Soybean Demand, Consumer Price Index, Consumer Confidence Index, Money Supply, Imported Soybean Port Delivery Prices	Price time series	Environmental, economic, and commodity trading data	Price time series	Total grain production, per capita grain consumption, average grain production price index, per capita disposable income of urban residents, consumer price index, grain sown area	Planting area, yield, province's disaster area, hype factor, and market demand
Evaluation Method	Mean Absolute Percentage Error	Mean Absolute Percentage Error, Relative error	Mean Absolute Error, Root Mean Square Error, Mean Absolute Percentage Error, R-Square	Mean Absolute Error, Root Mean Square Error, Mean Absolute Percentage Error	Mean Square Error	Mean Square Error	Relative error

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