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How Deep Learning Affect Price Forecasting of Agricultural Supply Chain?

FEI JIANG[1], XIAO YA MA[2,+], YI YI LI[3], JIAN XIN LI[4], WEN LIANG CAO[4], JIN TONG[2], QIU YAN CHEN[2], HAI-FANG CHEN[2] AND ZI XUAN FU[2]

[1]*Guangxi International Business Vocational College, Nanning, China*
[1]*School of Management and Marketing, Faculty of Business and Law, Taylor's University Subang Jaya, 47500 Selangor, Malaysia*
[1]*Department of Logistics Management and Engineering Nanning Normal University, Nanning, 530023 China*
E-mail: 461425403@qq.com
[2]*Department of Logistics Management and Engineering, Nanning Normal University*
[2]*Guangxi Key Lab of Human-machine Interaction and Intelligent Decision*
[2]*Nanning Normal University, Nanning, 530023 China*
E-mail: drxyma@nnnu.edu.cn+; 1016769101@qq.com
[3]*Department of Logistics, Guangxi Vocational and Technical College, Nanning, Guangxi, 530023 China*
E-mail: 642823264@qq.com
[4]*School of Electronics Information, Dongguan Polytechnic Dongguan, Guangdong, 518172 China*
E-mail: 279149042@qq.com; caowl22@163.com

Due to the many factors that affect commodity prices, price forecasting has become a problematic research point. With the development of machine learning and artificial intelligence, some advanced ensemble algorithms and deep learning prediction methods based on time series have high accuracy and robustness. These algorithms have gradually become the inevitable choice for solving price prediction problems. Based on the National Bureau of Statistics of China data from January 2012 to December 2021, this study proposes deep learning combined forecasting model based on neural networks to predict wheat prices and fill the research gap in agricultural product price forecasting. Researchers utilize Python and Selenium to realize the automatic data acquisition of web pages to achieve the purpose of data collection and calculation. The final price result curve predicted by the price prediction model based on LSTM deep learning agrees with the actual price curve, and the mean square error MSE is only 0.00026. It shows that this prediction model based on time series influenced by multiple factors has an excellent application prospect in price prediction.

Keywords: machine learning, agricultural products, agricultural supply chain, BP-LSTM, price forecasting

1. INTRODUCTION

Many economic agents benefit from an understanding of wheat price movements. Wheat sales are one of the most important sources of earnings for the agricultural industry. According to the OECD and FAO study (2020), the aggregate worldwide value of wheat, maize, and rice output was above USD 500 billion in 2019 [1]. Wheat is an essential input in the manufacturing process of many other industries. Wheat exports account for a con-

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+ Corresponding author: drxyma@nnnu.edu.cn

siderable proportion of some countries' exports, so its prices will affect critical macroeconomic factors, such as the current account balance, terms of trade and exchange rates. What's more, agricultural commodity prices significantly influence food security, and hence poverty, across the world. As a result, comprehending the dynamics of agrarian product pricing and assessing the agricultural supply chain flexibility to anticipate price dynamics is critical for better economic decisions, particularly during emergency situations like the current COVID-19 pandemic. With the expansion of agricultural supply chain competition to include inter-chain competition, upstream suppliers and downstream distributors are now collaborating to create value for consumers. More recently, it was necessary to broaden the definition of flexibility beyond manufacturing to include supply chain scenarios [2]. The agricultural products price environment is characterized by uncertain demand and high volatility, which poses a formidable challenge to supply chain management. This context necessitates that firms utilize flexible supply chains that can readily respond to supply disruptions and agricultural product fluctuations in demand without impacting service delivery to consumers [3].

As a big country of grain production and consumption, China's agricultural products market is not only susceptible to market factors such as cost and economic environment but also vulnerable to non-market factors such as emergencies. [20]. This makes China's agricultural products market show different characteristics from the general commodity market, with flexible and changeable price fluctuations and certain complexity, and this complexity is the most representative characteristic of agricultural products market price. Therefore, it is of great significance to deeply analyze the flexibility and law of the agricultural product supply chain by selecting wheat as the research object, analyzing the fluctuation law of wheat market price and predicting the future trend of the wheat market price. Simultaneously, in recent years, the prices of agricultural products such as wheat in China have been in a relatively strong state of change, especially the short-term prices are affected by many factors, and the fluctuation law is complex, so it is difficult to predict them accurately. Currently, agricultural product price forecasting is a research field with many difficulties, and studying it is of great significance.

Due to the growing processing power, storage capabilities, and availability of big datasets, deep learning, a subset of machine learning, has become a popular technique in different areas. Deep learning has been utilized by many different researchers from many areas. Compared with the traditional prediction approaches, the neural network method in deep learning (DL) has been considered to complete better data prediction. Neural network has powerful nonlinear mapping ability, which can more accurately fit the data relationship. The research purposes of this paper are as follows: (1) Firstly, the deep learning method is used to predict the wheat price, and then the influencing factors of the flexibility and price fluctuation of China's agricultural products supply chain are analyzed; (2) Understand and analyze the neural network method under DL; (3) Construct a short-term forecast model of wheat price based on BP neural network, discuss and analyze its stability, reliability, possible problems and corresponding improvement measures in the actual forecast. This study is helpful to fill the gap in short-term forecasting methods of agricultural products' prices and lays the foundation for further research on the application of more advanced intelligent forecasting methods involving neural network theory in the agricultural products supply chain field.

The various novel contributions of this manuscript can be summarized as follows:

• Technical significance:

In this study, an artificial neural network, an intelligent method that has developed rapidly in recent years, is introduced into the short-term price forecasting of the agricultural products supply chain. It not only fills the gap of related research in this field but can also use the neural network's unique information processing mechanism and ability to solve short-term forecasting problems that traditional methods can't.

• Practical significance:

Realizing short-term price forecasts of agricultural products will significantly help producers and consumers obtain timely and reliable guidance information and minimize the harm caused by price fluctuation in the agricultural products supply chain. On the one hand, it can provide reference information for the production decision-making of the participants in the agricultural product supply chain, reduce the operational risk, and improve the interests of the participants in the agricultural product supply chain, which has a certain flexibility. On the other hand, this method can also effectively provide consumers with adequate consumption reference information and reduce their economic losses.

The rest of this research is structured into several sections as follows. Section 2 deliberates the literature on agricultural supply chain and DL with price forecasting. Section 3 introduces the system framework of this research. The data analysis and discussion is depicted in Section 4. Section 5 summarizes the results, and future work are described.

2. LITERATURE REVIEW

2.1 Agriculture Supply Chain and Flexibility

In many aspects, the agricultural supply chain is similar to the fast-moving customers' goods supply chain. Still, they vary widely in procuring raw materials and final merchandise. The essential components are gathered from the fields, and the result is designed for animal or human use. Before the final product reaches the final customers, the agricultural supply chain encompasses numerous processes such as manufacturing, storage, sales, and distribution [5]. Farmers, certifying traders, retailers, distributors, and end consumers are part of a typical agricultural supply chain. As a result, an agricultural supply chain's successful coordination necessitates activity management and decision-making at the strategic, tactical, and operational levels [6, 7]. An agricultural supply chain is more complicated than another supply chain since products perishability, high supply-demand fluctuations in this seasonal produce, and increasing customers' awareness to produce quality and safety [8].

Researchers need a deeper knowledge of the complex agricultural ecosystems to successfully deal with the ever-increasing issues of the agriculture supply chain [9]. This may be accomplished by utilizing today's disruptive technology platforms that allow continuous monitoring of the agricultural environment while simultaneously creating vast volumes of data [10]. Technologies such as the Internet of things (IoT) allow for actual data exchange and collecting via linked devices [11] coordination, communication, and collaboration amongst agriculture supply chain nodes, enhancing the agriculture supply chain. Wireless sensor technology can help close demand-supply gaps and handle crucial food quality and safety concerns [12]. Because so much data is created throughout the agriculture supply chain, analyzing it will allow farmers and businesses to gain useful insights, resulting in increased production through information decision-making [13]. On the other hand, the data-driven agriculture supply chain may provide a challenge to data collecting and visualization. Meanwhile, other issues such as data security, privacy, and accuracy are among the other concerns [14]. Furthermore, a digital gap develops between industrialized and developing countries due to a shortage of computing tools and appropriate skill sets [15].

Agricultural diseases and insect pests are the main biological disasters in agricultural production, seriously restricting the sustainable development of high-yield, high-quality, high-efficiency agriculture production. Applying the machine learning method to the early warning of agricultural pests and diseases can realize the intelligence of monitoring and early warning. As a popular research field in machine learning in recent years, deep learning has been increasingly used to monitor and early warn pests and diseases due to its robust data classification, recognition, and prediction capabilities. Especially in the image recognition of crop diseases and insect pests, it has the advantages of fast recognition speed and high accuracy [16]. Presently, industry 4.0 is improving flexibility in production, leading to the increased customization of merchandise [17]. Dynamic customer requirements and market competition have created pressure for the rapid response regarding the agricultural supply chain. The influence of the COVID-19 pandemic could significantly burden the agricultural supply chain and its supply chain regarding quality, managing costs, and responsiveness [18]. Developing flexibility in the supply chain is a common method applied by companies to tackle such challenges. Supply chain flexibility can represent the company's supply chain capability to implement adaptive, agile, and responsive measures to satisfy market requirements and guarantee the smooth flow of services and products throughout the supply chain against the backdrop of uncertain market conditions [19].

2.2 Deep Learning Application and Price Forecasting

Deep learning (DL) is a new research direction in the field of machine learning (ML). It is introduced into machine learning to make it closer to the original goal-artificial intelligence (AI) [20]. DL is to learn the inherent rules and representation levels of sample data. The information obtained in the learning process is of great help to the interpretation of data such as words, images and sounds. Its ultimate goal is to make the machine have the same analysis and learning ability as human beings and be able to recognize data such as words, images, sounds and so on [21]. It is a complex machine learning algorithm, and its effect on speech and image recognition is far superior to that of related technologies in the past [22]. Artificial Neural Network (ANN), Convolutional Neural Networks (CNN) and Recurrent Neural Network (RNN) are some of the learning algorithm models used in DL. It may be used to do tasks including prediction, clustering, classification, and pattern recognition, and its widespread application has resulted in significant efficiency gains in a variety of fields. More importantly. DL is a useful resource for research on utilizing deep learning to forecast the price of agricultural products. ANN simulates the behavioral characteristics of the biological neural network, composed of a large number of processing units (neurons) according to a specific topological structure and achieves the purpose of parallel processing of information by adjusting the interconnection between internal nodes. The particular operation principle of ANN is to grasp the potential laws between the two by analyzing a batch of input-output data provided in advance and calculating the output results with new input data according to these laws. Therefore, ANN has the characteristics of self-learning, memory and self-adaptation [23].

Traditional econometric methods often rely on the ability of designers to eliminate interference information from research data and screen out adequate information for research. The neural network method regards the research data as a system library composed of the most miniature information packets containing sufficient information and interference information [24]. When the information packet is input into the BP neural network for calculation, the pertinent data is given significant weight, while the interference information is provided with minimal weight [25]. Through this mechanism of automatic weight distribution, the influence of the interference information on the output is significantly reduced to achieve the purpose of automatically identifying information and improving prediction stability [26]. Generally speaking, even if the wrong information is input or the model environment changes, the BP neural network can remain relatively stable and operate, giving full play to its prediction performance.

Price forecasting is the foundation upon which an organization or system may perform management responsibilities such as planning, organization, coordination, and control. It is critical to many market players' decision-making and interests [27]. As a result, price forecasting is an essential aspect of the study of prediction based on deep learning. The most popular related literature is stock price forecasting in the financial area, which focuses on deep learning-based price forecasting. Nevertheless, these studies are relatively few in number and did not put forward a solid theoretical framework to outline both how DL application is developed to forecast prices in the agricultural supply chain with flexibility [28, 29].This research will seek to fill this gap utilizing the DL.

3. THE PROPOSED SYSTEM

The process of the combined BP-LSTM model can be seen as Fig. 3. First of all, in the same time range, the LSTM neural network can be directly used to train and learn. The corresponding price prediction model can be established so that the future price changes of agricultural products can be predicted. Because of time series problems, the relationship between time series is very close. The process of the combined BP-LSTM model can be seen as Fig. 1. First of all, in the same time range, the LSTM neural network can be directly

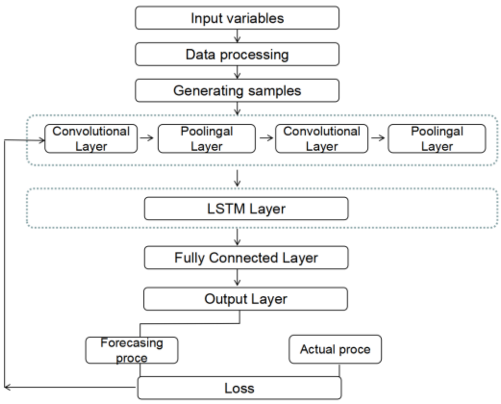

Fig. 1. Process of the combined BP-LSTM model.

used to train and learn. The corresponding price prediction model can be established so that the future price changes of agricultural products can be predicted. Because of time series problems, the relationship between time series is very close. For the price affected by multiple factors, the features extracted by the author cannot reflect all the practical information in the time series data well. Therefore, when using Python for data extraction, the researchers will use the convolutional neural network to process the input price data information through training and automatically extract the abstract feature information implicit in the given price data. In addition, for predicting changes in the price trend of agricultural products, researchers can use the characteristic information, including time and price, to establish a price prediction model. However, this information can only reflect the changes in the prices of agricultural products on the day. Still, it cannot reflect the changes in the prices of agricultural products in the future. Therefore, researchers need to use the data information of the past period to extract the feature vector information that can reflect the price changes of agricultural products in a certain period in the future. Meanwhile, due to the data at a particular moment being closely related to the data changes of the previous period, researchers can input the sequence data into the input layer of the long short-term memory neural network model in order of time. In addition, the prediction result of the next moment in the sequence is finally obtained through the transformation of multiple hidden layers. Secondly, it is necessary to fully consider the substructure of external factors, including freight volume, cargo turnover indicators, *etc.* This manuscript uses two fully connected layers to deal with this other factor. Finally, a linear layer is used to fuse the influence of time series features and other factors on the results, and the final prediction result of the model is given. Moreover, due to the data at a particular moment being closely related to the data changes of the previous period, researchers can input the sequence data into the input layer of the long short-term memory neural network model in order of time. In addition, the prediction result of the next moment in the sequence is finally obtained through the transformation of multiple hidden layers. Secondly, it is necessary to fully consider the substructure of external factors, including freight volume, cargo turnover indicators, *etc.* This manuscript uses two fully connected layers to deal with this other factor. Finally, a linear layer is used to fuse the influence of time series features and other factors on the results, and the final prediction result of the model is given.

4. DATA ANALYSIS

4.1 Dataset Collection

The relationship between the neural network prediction model and the research data is very close. The best neural network prediction model is the model that best matches the research data. Even some design links in the neural network prediction model need to be determined according to the characteristics of the research data. Therefore, the research data must be determined and processed before designing the BP neural network prediction model. This paper mainly studies and forecasts the market price of Chinese agricultural products (specifically wheat), and combines the factors affecting the flexibility of the supply chain, such as freight volume, turnover, express delivery, consumer price index, money supply and other related factors. It builds a prediction model based on CNN-LSTM through BP neural network. By consulting the China Statistical Yearbook, we obtained relevant data and historical data for a total of 10 years, from 2012 to 2021 (because the latest statistics released by the Chinese government are up to 2021). This paper selects ten years of historical data for analysis, considering factors such as data availability and timeliness. At the same time, this paper also refers to many research examples of using machine learning methods to predict freight volume, and uses ten years of data to test a good model.

However, some problems, such as data missing or abnormality in collecting raw price data, will directly affect the quality of future price prediction models when the researchers collect the data. Hence, performing operations such as cleaning and missing value completion on the original data is necessary. At the same time, to meet the needs of establishing a price forecast model, it is also essential to perform data conversion and standardization on the preprocessed data in combination with the actual tasks.

4.2 Experimental Environment

This manuscript uses Python and Selenium to realize the automatic data acquisition of web pages to achieve the purpose of data collection. Selenium is a testing framework commonly used in web programs and uses Web Driver to debug and communicate with the browser's interface. Wheat price data comes from crawling the official website of the National Bureau of Statistics of China. Since it is easy to have human or system problems during the recording process, data missing, duplication, outliers and other phenomena are caused. If it is not dealt with, it will quickly lead to the problem that the model is unsatisfied with the actual situation, and the prediction effect worsens. Hence, researchers need to assess whether or not there are missing data such as price and some outliers whose price is 0. For outliers, it is necessary to remove them by proximity-based methods to make them missing values, then use linear interpolation for missing values. Meanwhile, before performing prediction on the data, the data needs to be normalized since the normalized data will be more convenient and quicker in subsequent calculation and storage.

4.3 Parameters Setting

The mean square error (MSE) indicator is mainly used to evaluate the performance of the LSTM price prediction model based on multi-factor influence on the real agricultural product price data set. The formula for calculating MSE is as follows.

$$MSE = \frac{1}{n}\sum_{i=1}^{m}(y_i - \hat{y}_i)^2 \tag{1}$$

Due to BP neural networks are made up of three main components: neurons (BP neurons), network architecture (forward structure and architectural parameters), and learning rules, much as regular neural networks (BP algorithm). However, due to the BP algorithm's continuous derivation requirement, the hidden layer's neural activation function generally adopts the Sigmoid function of the nonlinear function. The main characteristic of the Sigmoid function (*s*-type function) is that the process itself and its derivatives are continuous. Sigmoid functions have many forms, and the following methods are more commonly used:

$$f(x) = \frac{1}{1+e^{-x}}. \tag{2}$$

The characteristic of the logarithmic Sigmoid function is that it has a nonlinear amplification function and uses different amplification ratios for any input signal. Using this function, the same neuron can process both small signals and large signals. Because the high derivative region in the middle of the function solves the problem of processing small signals, the low derivative regions extending to both sides are suitable for processing large signal inputs. Meanwhile, using

$$f'(x) = f(x) \times [1 - f(x)], \tag{3}$$

which can reduce the calculation difficulty and save the calculation time. For the above reasons, in this manuscript, when building a prediction model based on BP neural network, the activation function of neurons in the hidden layer adopts a logarithmic sigmoid function. This combination can realize any nonlinear mapping between input and output.

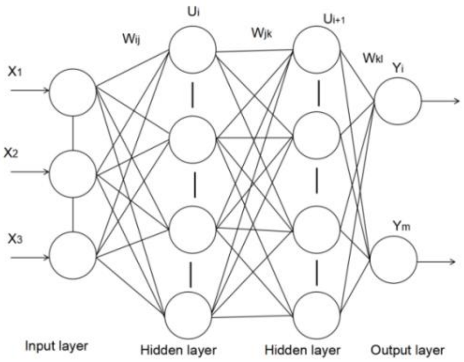

Fig. 2. Structural model of the BP neural network.

As seen in Fig. 2, the connection mode of the BP neural network belongs to the forward network structure, and it is grouped according to the input layer, hidden layer and output layer. There is no connection between neurons in the same group. The neurons in any group are connected with each neuron in the adjacent group, and then the basic tendency situation can be shown as below:

Fig. 3. Price tendency.

4.4 Performance Evaluation

The predicted wheat price results using the LSTM price model based on multi-factor influence are shown in Fig. 4.

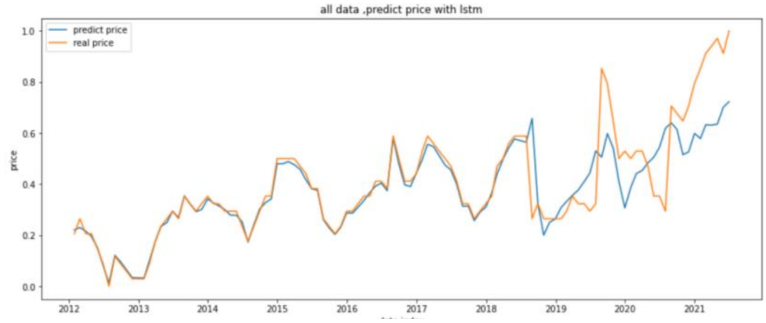

Fig. 4. Predict price with LSTM1.

Fig. 5. Predict price with LSTM2.

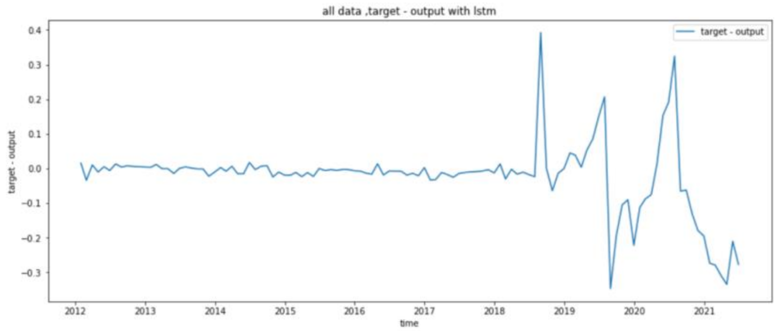

Fig. 6. Target output with LSTM.

From the prediction results in Fig. 3, we can analyze that: using LSTM based on multi-factor influence. The model can better predict the overall trend in the future and better capture the changes in certain moments of sudden price changes. Demonstrates the time series based on multi-factor influence. The LSTM neural network structure is suitable for price prediction influenced by many factors. In order to analyze the pros and cons of the prediction results, this paper uses the LSTM model based on multi-factor influence to compare the prediction results of LSTM and BP neural networks, which only consider the time information factor and as shown in Table 1.

Table 1. Comparison on MSE.

Model	MSE
LSTM based on multi-factor influence	0.00026
LSTM	0.00037
BP	0.00051

4.5 Discussion

The comparison between the results of the LSTM neural network and BP neural network for wheat price prediction in Table 1 can be analyzed as follows:

Firstly, the wheat price result curve predicted by the price prediction model based on LSTM deep learning agrees with the actual price curve, and the mean square error MSE is only 0.00026. It shows that the LSTM price prediction model based on time series influenced by multiple factors has an excellent application prospect in price prediction. Secondly, by comparing the price prediction results of the LSTM model based on deep learning with those of the LSTM model only considering time information, researchers can find that the price prediction results of the LSTM model only considering single time information are inaccurate. The mean square error MSE is only 0.00037. By combining the impact of external factors on price changes, it is found that the forecasting effect is significantly improved. Thirdly, the shallow learning model based on BP neural network has limited expressive ability for complex functions, which reduces the final prediction accuracy and the mean square error MSE is 0.00051. The BP neural network prediction model is only trained based on historical data, and there is no. It reflects the timing relationship, and there is no influence of the timing before and after. This reflects the significant deviation between the predicted price curve of the BP neural network and the actual price curve.

By analyzing the factors that affect price fluctuations and using the multi-factor-based LSTM forecasting model to forecast the wheat price, the forecast price in the series can be obtained at the next moment. At the same time, it is linearly fused with the results obtained by other factors through a linear layer, and finally, the predicted price trend of the price prediction model can be obtained. This paper uses the LSTM neural network model to obtain the characteristics of historical price data based on time series. According to the verification and analysis of the actual agricultural product price data, researchers can conclude that the multifactor-based LSTM prediction model can obtain highly accurate prediction results.

5. CONCLUSIONS

Price forecasting has always played an important role in agriculture. Based on this background, this paper conducts a pertinent and in-depth study on the field of price forecasting. This article will be about cutting-edge machine learning. Algorithms are at the heart of building price-prediction models. By analyzing the factors that affect product price changes, a multi-factor-based LSTM deep learning model, a general price prediction model, is established. Finally, China’s wheat price data is used as an experimental sample to demonstrate the price prediction model to verify the feasibility, accuracy and generalization of the price prediction model established in this paper.

This manuscript conducts targeted research in the field of price forecasting based on machine learning algorithms and establishes a multi-factor-based LSTM deep learning forecasting model. Since traditional forecasting algorithms cannot utilize the time series information of historical price data, the forecast results are not good. And BP-LSTM can finally get the prediction result of the next moment in the sequence through the transformation of multiple hidden layers. It solves the problem that the data of the previous time step in the recurrent neural network is used to predict the current time step. At the same time, we can use the special neural network structure of LSTM and two fully connected layers to deal with the impact of other factors on price changes. The final prediction result of the model is given by integrating the effects of time series features and other factors on the results through a linear layer. The LSTM price forecasting model based on multi-factors is used to forecast the price of vegetables and wheat, and a slight mean square deviation is obtained.

However, there are still some deficiencies in this study. For example, the data set of agricultural products obtained in this paper is relatively limited, so it is necessary to study further the influence of factors such as weather and average precipitation on changes in agricultural product prices. At the same time, since the deep neural network is very effective in other aspects such as image processing, theoretical research in regression prediction is relatively lacking, and further research in this area needs to be strengthened. At the same time, this paper has only initially realized the research and implementation of the price prediction model based on machine learning. The overall theoretical framework and practical experiments have proved the feasibility and versatility of the price prediction model. However, the understanding of algorithm theory still needs further study and research. It is also necessary to continuously improve the price prediction model so that it can achieve better feasibility and accuracy and achieve good results in various application fields.

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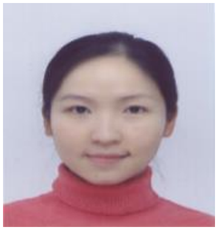

Fei Jiang (蒋菲) is currently pursuing a Ph.D. degree at Taylor's University. She also is an Associate Professor at the International Business College. Her research interest includes logistics and supply chain management.

Xiao-Ya Ma (马小雅) earned her Ph.D. degree in Business Management at Yunnan University. She is an Associate Professor and Postgraduate Tutor at the School of Logistics Management and Engineering, Nanning Normal University. Her research interests include logistics and supply chain management.

Yi Yi Li (李依依) is a Logistics Management and Engineering College Postgraduate student of Nanning Normal University. Her research interest includes logistics and supply chain management.

Jian Xin Li (李建新) Lecturer, postgraduate, his research interests include at machine vision algorithm, graphics and image processing, and data mining.

Wen Liang Cao (曹文梁) Associate Professor, postgraduate, his research interests include machine vision algorithm, graphics and image processing.

Jin Tong (童锦) is a Postgraduate student in Logistics Management and Engineering College of Nanning Normal University. Her research interest includes logistics and supply chain management.

Qiu Yan Chen (陈秋燕) Master Degree Candidate, studying in Nanning Normal University. Her research interest includes logistics and supply chain management.

Hai-Fang Chen (陈海芳) graduated from Nanning Normal University with a bachelor's degree, is currently an associate graduate student of the School of Logistics Management and Engineering, Nanning Normal University. Her research interest includes logistics and supply chain management.

Zi Xuan Fu (符紫萱) graduated from Nanning Normal University with a bachelor's degree, is currently an associate graduate student of the School of Logistics Management and Engineering, Nanning Normal University. Her research interest includes logistics and supply chain management.