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Security Supervision System of Agricultural Product Supply Chain Based on IoT Technology

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Abstract. The adaptive feature extraction capability of deep learning algorithms and the ability to collect data throughout the entire process of the Internet of Things provide technical support for efficient supervision of agricultural product supply chains. The research aims to build a safety supervision system for agricultural product supply chain through IoT technology, achieve food safety traceability, and improve the risk identification ability and supervision efficiency of agricultural product supply chain. The research adopts a hierarchical holographic modeling method to construct a risk indicator system, identifies agricultural product supply chain risks through backpropagation neural networks, and combines IoT technology for food safety traceability, thereby establishing a complete agricultural product supply chain safety supervision system. The results show that the average time to trace food safety issues before applying intelligent supervision is 15.9 days, while the average time to trace food safety issues after application is 4.2 minutes, with the maximum time spent being only 13.7 minutes, and it can effectively identify risks in the supply chain. The results indicate that the proposed agricultural product supply chain safety supervision system has improved the accuracy of risk identification in the agricultural product supply chain and achieved full traceability from production to consumption. The research results contribute to improving the quality and safety level of agricultural products and enhancing consumers' trust in agricultural products.

Keywords. Internet of things, agriculture products, supply chain, safety supervision, hierarchical holographic modeling, backpropagation

1. Introduction

The quick advancement of artificial intelligence has brought new solutions to the supervision of agricultural product quality and safety. There are many links in the agricultural product supply chain, and food safety incidents occur frequently, causing damage to consumers' physical health and having a huge impact on agricultural development [1]. Traditional agricultural product supply chain security supervision mainly relies on paper or electronic records, as well as manual sampling. This method has a strong warning effect and can play an effective regulatory role to a certain extent.

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However, this form of regulatory measures has problems such as low regulatory efficiency, opaque information, and difficulty in tracing. The Internet of Things (IoT) technology has been widely applied in various fields. IoT can collect various information data in real time and accurately, and applying it to the security supervision of agricultural product supply chains (APSCs) can improve the efficiency and accuracy of supervision [2-3]. IoT can obtain the full flow information of agricultural products, and this mechanism can help achieve food safety traceability. Backpropagation neural network (BP) can handle complex nonlinear problems and automatically extract patterns between data. It has high adaptability and self-learning ability, and exhibits high generalization ability, making it suitable for identifying risks in the supply chain [4]. Therefore, the study adopts the BP algorithm to identify risks in the APSC, and combines IoT technology for food safety traceability, in order to establish an IOT-BP based intelligent supervision system for APSC safety. The research aims to improve the quality and safety level of agricultural products and protect the rights and interests of consumers through an intelligent supervision system for APSC security based on IOT-BP. The innovation of the research lies in the use of BP algorithm in the process of supply chain risk assessment, which adopts hierarchical holographic modeling (HHM) method to construct a risk indicator system covering multiple links such as production, processing, circulation, and sales. This method improves the accuracy of BP algorithm for comprehensive risk assessment of APSC.

2. Research Foundation

The complexity and breadth of the agricultural supply chain make food safety a difficult issue to manage. IoT technology can collect data information from any link, providing technical support for the security supervision of APSC. The HHM method is widely used in risk prediction tasks, while the BP neural network is widely used in pattern recognition and classification tasks due to its powerful nonlinear mapping ability. Combining the two can effectively improve the accuracy of risk identification in the APSC. In addition, IoT technology can achieve comprehensive supervision of all links in the supply chain through real-time monitoring and data sharing, ensuring the safety of the entire process of food production and consumption. Therefore, building an IoT based APSC security supervision system can enhance the traceability and regulatory efficiency of food safety.

3. Method

3.1. Risk Identification Method for APSC based on Internet of Things and Improved BP Algorithm

The traditional APSC has problems such as low level of informatization and low degree of organization [5]. To address these issues, the introduction of IoT technology to build a new APSC system may also introduce risks such as information security and equipment failures [6-7]. The HHM method can comprehensively and systematically identify the sources of risks and is widely used in the field of risk management [8]. Therefore, the study used HHM to analyze the APSC from multiple perspectives and constructed a detailed risk evaluation index system. The risk index system of the APSC is divided into four main levels, each containing different types of risks. Firstly, there are eight types of perceived risks, including information infrastructure, distribution, cold chain transportation and storage, production and processing safety, transportation timeliness, information transmission timeliness, information errors, and warehousing. Next is the network layer risk, which involves five types of risks: information sharing degree, network stability, information security, IoT standards, and informatization level. The third is application layer risk, which covers five types of risks including market competition, cost, supply and demand, policy and regulation, and external collaboration. Finally, there are three types of risks, including natural disasters, corporate reputation, and socio-economic factors. After the construction of the risk assessment index system is completed, the study uses deep learning algorithms combined with risk index related data to identify risks in the APSC. BP neural network has high nonlinearity, less subjective influence, strong self-learning ability, and adaptability to uncertain information [9-10]. Therefore, the study introduces the BP algorithm to identify risks in the APSC. The calculation diagram of the BP algorithm is shown in Figure 1.

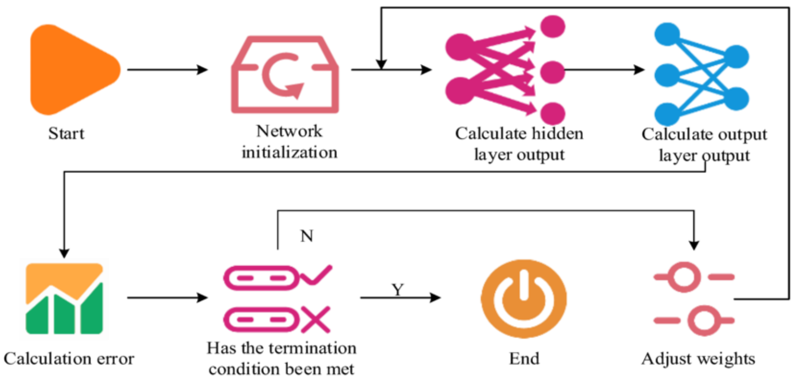


Figure 1. Schematic diagram of BP neural network algorithm

In Figure 1, during the forward propagation process of the BP neural network, initialization is first performed, and then the sample data enters the hidden layer for calculation using a transfer function. The result is then fed to the output layer, where the error and calculation result are calculated. Finally, the termination condition is reached and the prediction result is output. During the iteration process, if the termination condition is not met, backpropagation is performed, and the neural network updates the obtained training error to all neurons. Each neuron adjusts the weights and thresholds of the entire network based on the training error. If the training frequency reaches the set condition or the error reaches the minimum, the neural network ends. Otherwise, it enters the hidden layer to continue calculation until the condition is met and ends [11]. The calculation formula for the output of the forward propagation hidden layer is shown in equation (1).

$$r_q = f_1(H_{R\varphi}, E), \varphi = 1, 2, ..., l \tag{1}$$

In equation (1), o_s is the output layer output, E is the input sample, $H_{R\varphi}$ is the weight, l is the number of layers, and f_1 is the activation function. The calculation formula for the output o_s of the forward propagation output layer is shown in equation (2).

$$o_s = f_2(H_{\varphi s}, A), s = 1,2...,N \tag{2}$$

In equation (2), N means the amount of samples, $H_{\varphi s}$ means the weight, and f_2 is the activation function. The calculation formula for training error is shown in equation (3).

$$J = \frac{1}{2}\sum_{\varphi=1}^{N}\sum_{s}^{m}(i_{ns} - o_{ns})^2 \tag{3}$$

In equation (3), m refers to the amount of output layer nodes, n denotes the amount of input layer nodes, i_{ns} denotes the expected output of the network, and J represents the training error. The calculation formula for updating network weights is shown in equation (4).

$$\begin{cases} \varpi_{\vartheta s}^{\upsilon+1} = \varpi_{\vartheta s}^{\upsilon} + \psi\sigma_k^K r_q, s = 1,2,...,S; d = 1,2,...,L \\ \varpi_{g\vartheta}^{\upsilon+1} = \varpi_{g\vartheta}^{\upsilon} + \psi\sigma_d^L E_g, l = 1,2,...L; g = 1,2,...,G \end{cases} \tag{4}$$

In equation (4), $\varpi_{\vartheta s}^{\upsilon+1}$ represents the weight matrix of the hidden layer ϑ to the output layer s at the $\upsilon+1$ th iteration of the network, $\varpi_{g\vartheta}^{\upsilon}$ denotes the weight matrix of the input layer g to the output layer ϑ at the υ th iteration of the network, ψ is the learning rate, υ is the max amount of iterations, and E_g is the input sample [12]. To strengthen the nonlinear mapping ability of the BP algorithm, an improved Sigmoid function is utilized as the activation function, and the expression of the improved Sigmoid function is shown in equation (5).

$$\sigma(z) = \frac{1}{1+e^{-\beta z}} \tag{5}$$

In equation (5), z is the input value, e is the base of the natural logarithm, and β is an adjustable parameter that can control the slope of the function. $\sigma(z)$ is the output value of the Sigmoid function. By improving the Sigmoid function and adjusting the parameters to enhance the dynamic range of gradient, the problem of gradient disappearance is alleviated. This improvement measure can improve the prediction ability of BP algorithm.

3.2. Intelligent Supervision System for APSC Security Based on IoT-BP

The BP algorithm can evaluate the overall risk level of the APSC, and based on the results, targeted measures can be taken to reduce risks and improve the stability and efficiency of the supply chain. However, rapid traceability of food safety issues still cannot be effectively solved. Therefore, research is being conducted to establish a method for food safety traceability using IoT technology, combined the BP based supply chain risk identification method, to establish a complete intelligent supervision system for supply chain safety [13]. Taking the APSC in the research area as an example, the APSC process is shown in Figure 2.

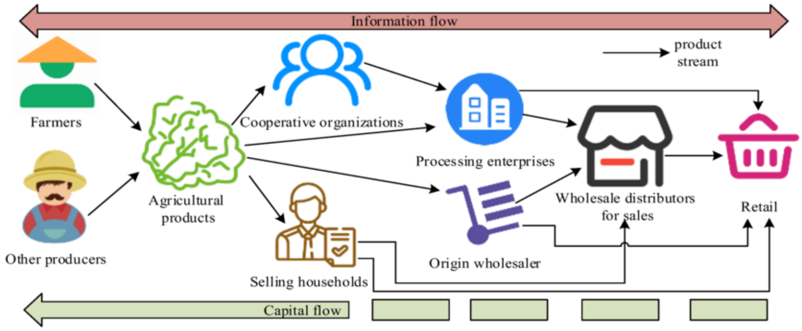


Figure 2. APSC process

In Figure 2, the vegetable supply chain is mainly distributed through channels from farmers to wholesalers and then to retail terminals, with sales accounting for over 65%. Individual business organizations account for 85% -93% of the total output of distributors, with 25% of the total output used for reprocessing. From Figure 2, it can be seen that the management technology of processing enterprises is the most mature. Research is needed to establish IoT communication and data links between various entities in the supply chain with such enterprises as the core, forming a tight agricultural product logistics system. The specific application methods of IoT technology include using RFID, sensors and other technologies to identify and track agricultural products, recording information about their production, processing, circulation and other links; By storing and analyzing the collected data through cloud platforms, information sharing among various links in the supply chain is achieved, which improves the efficiency of the supply chain [14-15]. As consumers, we can learn about the origin, production process, and other information of agricultural products through IoT platforms to improve product transparency. The combination of food safety traceability methods and BP based supply chain risk identification methods forms a complete supply chain supervision system, as shown in Figure 3.

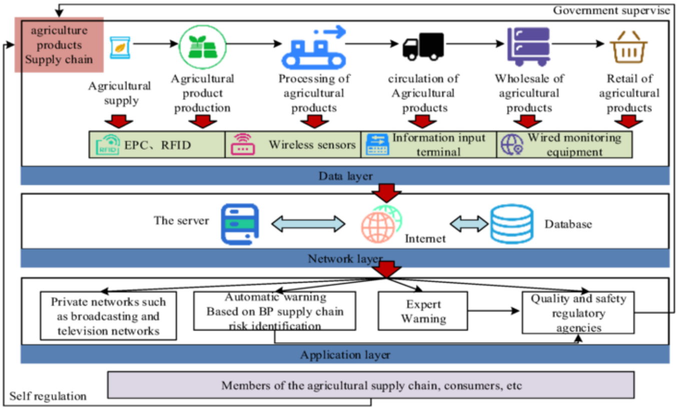


Figure 3. APSC security supervision system based on IoT-BP

In Figure 3, RFID, sensors, and other technologies are used to identify and track agricultural products in the circulation process, recording information about their production, processing, and circulation. Realize the whole process traceability of agricultural products, and improve product transparency through Internet information sharing. Regulatory agencies ensure food safety by monitoring the quality of agricultural products in real-time, and can also use supply chain risk identification technology based on BP algorithm to automatically warn of risks and take corresponding measures.

4. Testing

4.1. Performance Analysis of Improved BP Algorithm

To assess the effectiveness of the improved BP algorithm, a comparative test was conducted between the traditional BP algorithm and the improved BP algorithm. The study used 50 samples from the XOR operation dataset for network training, and the comparison findings during the training process are denoted in Figure 4.

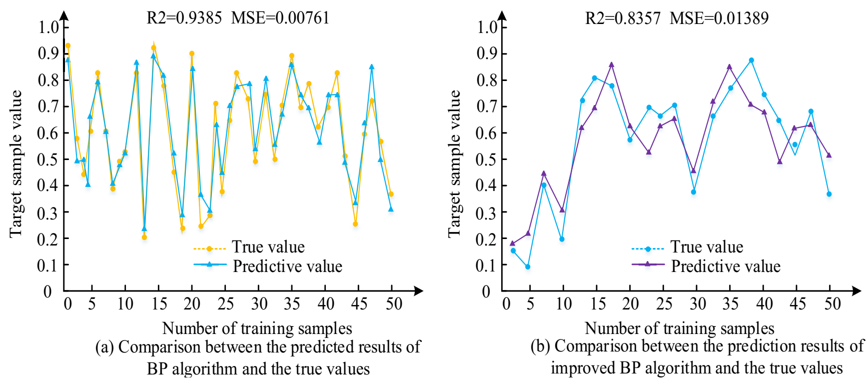
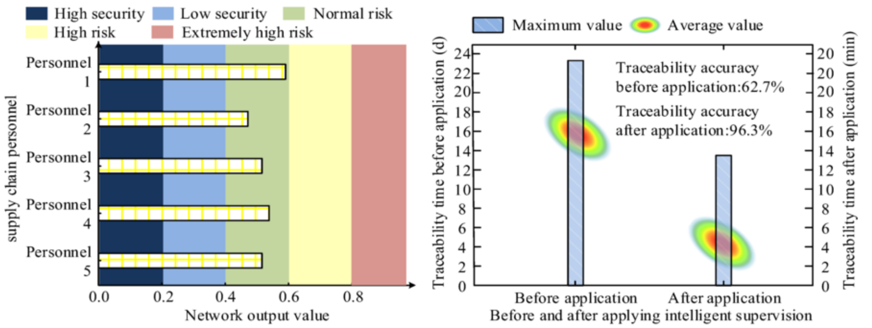


Figure 4. Comparison results of traditional BP and improved BP algorithms

In Figure 4 (a), the feature recognition results of the improved BP algorithm have a high degree of fit with the true values, with an R2 value of 0.9385 and an MSE value of 0.00761. In Figure 4 (b), the R2 value of the traditional BP test result is 0.8357, and the MSE value is 0.01389. The results indicate that the improved BP algorithm has better predictive ability than the traditional BP algorithm and can more effectively identify supply chain risks. From this, it can be seen that improving the Sigmoid function of the BP algorithm can alleviate the gradient vanishing problem and enhance its predictive ability.

4.2. Analysis of the Practical Application Effect of the IoT-BP based Intelligent Supervision System for APSC Security

To verify the practical application effect of the intelligent supervision system for APSC safety designed in the study, 13 complete supply chains related to agricultural products were selected for empirical analysis in the region, all participants in the supply chain meet the criteria for having experience in IoT agriculture. The risk identification of a single supply chain after the application of the intelligent supervision system, as well as the comparison of food problem traceability capabilities before and after the application of the intelligent supervision system in 13 complete supply chains, are shown in Figure 5.



(a) Single supply chain risk identification results (b) Comparison of traceability capabilities for food safety issues

Figure 5. Comparison of supply chain risk analysis and food issue traceability

In Figure 5 (a), the average risk assessments values of the five personnel on a single supply chain are 0.58496, 0.43627, 0.51759, 0.54773, and 0.51862, respectively, all within the normal risk range, indicating that the total risk of the supply chain is normal risk. In Figure 5 (b), the average time for tracing food safety issues before applying the intelligent regulatory system was 15.9 days, while the average time for tracing food safety issues after applying the intelligent regulatory system was 4.2 minutes, and the maximum time spent was only 13.7 minutes. In addition, the accuracy of tracing food safety issues after application has increased by 33.6% compared to before application. The results indicate that the intelligent regulatory system can predict risks for various participants in the supply chain, thereby completing risk assessments for each supply chain. At the same time, thanks to the efficient integration of data information in the Internet of Things, it can quickly and accurately trace food safety issues. From this, it can be seen that IoT technology can collect various information on the agricultural product supply chain in real time and accurately, providing favorable assistance for tracing food safety issues, and further strengthening the regulatory ability of supply chain risks by combining improved BP algorithm.

5. Conclusion

The issue of APSC security is becoming increasingly prominent, and establishing an efficient and precise regulatory system is of great significance. The research establish an intelligent supply chain security supervision method based on IoT technology, improve the quality and safety level of agricultural products, and protect consumer rights. The research adopts an improved BP algorithm to predict and identify risks, and uses IoT technology to achieve traceability of the entire process of agricultural products. The results showed that the R2 and MSE values for feature recognition using the improved BP algorithm were 0.9385 and 0.00761, respectively, which were higher than those of the BP algorithm; After applying the intelligent supervision method for APSC safety, the average time for tracing food safety issues is 4.2 minutes, which is much lower than the time before application, the accuracy of tracing food safety issues has also increased by 33.6% compared to before application, and the risk assessment of the supply chain can be automated. The results indicate that the system constructed by the research institute can quickly and accurately identify supply chain risks and trace food safety issues. Although the research has achieved certain results, there are still shortcomings. When food safety issues occur, the data collected by IoT devices may be tampered with, resulting in the inability to complete traceability. Future research can introduce blockchain technology into the regulatory system, further enhancing the security and immutability of data.

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