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Efficiency Evaluation of Food Safety Management based on Improved Hidden Markov Model

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ABSTRACT

Food safety management is crucial for social stability and is an important component of the country's long-term development strategy. Previous food safety management methods failed to achieve dynamic supervision of various links in the food production-to-sales process and lacked objectivity in food safety testing. Therefore, this paper introduces the Markov model into food safety management and optimizes it using the cuckoo search algorithm to improve parameter convergence speed and solve the global optimal solution problem. Experimental results demonstrate that the food safety management model based on the improved hidden Markov model can effectively achieve dynamic supervision of food safety and improve the accuracy of food safety risk assessment. In practical applications, it significantly enhances food management efficiency and improves technical and scale efficiency.

Keywords: Improved Hidden Markov, Food Safety, Safety Management, Efficiency Evaluation

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1. Introduction

Food safety is of paramount importance to people's physical and mental health and social stability, making it an integral part of the national strategy. With the increase in people's awareness of food safety, there is a growing demand for food safety management and testing, requiring corresponding food safety supervision measures at every stage from food raw materials planting and breeding to consumer purchase of related food. Among them, food safety risk assessment is a crucial part of food safety management, which not only concerns the safety of the food to be tested but also significantly impacts the efficiency of food safety management [1]. Food safety testing is one of the important means of food safety management, which focuses on key inspections of food according to safety standards to reduce the probability of safety risks. Previous food safety testing methods mainly checked whether the food safety standards were met and did not delve into the underlying risks hidden in the food safety information or eliminate potential risks and uncertainties [2]. Constructing a food safety risk assessment system can not only strengthen the prediction of food safety risks but also eliminate some deep safety risks, thereby enhancing food safety management performance, shortening food safety inspection time, and improving management efficiency.

Food safety data exhibits high dimensionality and nonlinear characteristics, with numerous testing indicators, missing data, noise, and other uncertain factors. Additionally, it has strong timeliness, requiring timely data processing within a short time. Currently, existing methods for food safety risk assessment suffer from significant errors due to the influence of various factors and still require manual assistance in judgment, leading to subjectivity and inability to meet dynamic data assessment. Furthermore, apart from food safety risk assessment, food safety management also requires supervision at every stage from production to sale, which cannot be achieved through manual methods and is relatively inefficient. Therefore, this paper introduces the improved hidden Markov algorithm into the food safety management system, constructs a food safety risk assessment module and an intelligent visual supervision module, and enhances the effectiveness and efficiency of food safety management. Finally, the DEA model is used to evaluate the efficiency of the food safety management system constructed in this paper, examining its practical application effect.

2. Current Research Status of Food Safety Management

The concept of food safety originated from industrialized countries in Europe and America in the 19th century and gradually came into people's attention. With the development of the economy and information technology, people's living standards have been continuously improving, leading to an increasing number of food safety issues exposed through online media, which has drawn widespread social attention and led to the emergence of the concept of food safety management [3]. Scholars have pointed out that food safety issues are diverse, with influences from various factors, requiring joint supervision and assistance from all levels of society. Based on this, researchers have studied the influencing factors, status, production chain, and government regulation of food safety and proposed the need to establish a corresponding safety system for food safety management, with the government playing a regulatory role [4]. Some scholars have focused on agricultural resources and the environment, studying food additives, market regulation, government supervision, and the impact of technology, and identified the abuse of pesticides and food additives as one of the causes of food safety problems [5].

To improve the effectiveness of food safety management, some scholars have proposed strengthening the intensity of food safety testing and using technological means to detect food safety. Accordingly, some researchers have introduced biotechnology into food testing, using DNA probe technology, biochip detection, and other techniques to enhance the efficiency and reliability of food testing [6]. Others believe that combining the HACCP system can enhance the efficiency of food supply chain safety management and ensure effective safety control of microbiological, chemical, and physical hazards in food [7]. In terms of food safety risk assessment, some researchers have combined risk management and decision-making departments to construct dynamic colony growth models, achieving quantitative analysis of food risks. Some have introduced fuzzy cluster analysis into prior risk probability to calculate the risk values of different attributes of food, thereby improving the accuracy of risk value prediction [8]. In terms of food safety management efficiency, some researchers argue that evaluating safety management efficiency can reflect the quality of food safety management, but the evaluation indicators lack uniformity. They have constructed a food safety management efficiency evaluation indicator system based on the characteristics of food enterprises and combined with the DEA model, and the results showed that DEA performed well in efficiency measurement [9]. Additionally, some scholars believe that past food safety incidents had a lag effect, and thus, they proposed the theory of preventive safety, which constructs a scientifically effective and operational indicator system with comprehensive and forward-looking security management [10].

3. Improved Hidden Markov Model for Food Safety Management

3.1. Improved Hidden Markov Model

The Hidden Markov Model (HMM) consists of a Markov chain that describes the state transition process and an observation process with the observation probability matrix. It can be described by five elements, expressed as, with the formulas for each element as shown in equation (1):

$$\begin{cases} Q=\{q_1,q_2,\ldots,q_n\} \\ O=\{o_1,o_2,\ldots,o_m\} \\ \pi=\{[\pi(i)_n]\pi(iq)=P(q_i)\} \\ A=\pi\left[a_{ij}\right]_{n*n}, a_{ij}=P(q_i \mid q_j) \\ B=\pi\left[b_j(h)\right]_{n*m}, b_j(h)=P(o_h \mid q_j) \end{cases} \tag{1}$$

Wherein the hidden model is denoted as the observed state, the probability matrix representing the initial state is denoted as the probability matrix with no state transition. The probability matrix for the transition of observed states is denoted as the probability matrix for the transition of observed states is *O*. The number of hidden layer states and observed features are denoted as ð and *O,* respectively. The hidden and observed sequence states are denoted as *B*.

Using the Hidden Markov Model to solve the evaluation problem involves calculating the probability of the observed sequence occurring in the model using the forward-backwards algorithm, that is, calculating the value of *B*. This can be divided into two parts: the forward probability and the backward probability. Let be the probability of the hidden state being at time and the observed state being at time, and let be the probability of the observed state sequence from time to time. Then, the final results for the forward probability and the backward probability are as shown in equation (2):

$$\begin{cases} P(O,\lambda)=\sum_{i=1}^{n} a_{T(i)} \\ P(O,\lambda)=\sum_{i=1}^{n} \pi_i b_i(o_1)\beta_1(i) \end{cases} \tag{2}$$

Where the forward probability is denoted as and the backward probability is denoted as.

At time, the probability of the given model and the observed sequence state being is shown in formula (3):

$$\gamma_t(i)=\frac{a_t(i)\beta_t(i)}{\sum_{i=1}^{n} a_t(i)\beta_t(i)} \tag{3}$$

At times and, the probability of the given model and the observed sequence state being is shown in formula (4):

$$\delta_t(i,j)=\frac{a_t(i)a_{ij}b_j(o_{t+1})\beta_{t+1}(j)}{\sum_{r=1}^{n}\sum_{s=1}^{n} a_t(r)\beta_{t+1}(s)a_{rs}b_s(o_{t+1})} \tag{4}$$

Using the Viterbi algorithm, the Hidden Markov Model solves the prediction problem by obtaining the state in the sequence that has the highest probability. The process for solving this is similar to the forward-backward algorithm, and the state sequence goes through initialization, recursion, termination, and output of the state sequence. Solving the learning problem in the Hidden Markov Model involves using the Baum-Welch algorithm to train the observed sequence and obtain the model with the maximum conditional probability. This process includes initialization, parameter updates, and termination. Let the initialized model parameters be denoted as B, and based on the forward-backward algorithm, calculate as shown in formula (5):

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$$\begin{cases} \pi_i = \gamma_1(i) \\ a_{ij} = \dfrac{\sum_{t=1}^{T-1} \delta_t(i,j)}{\sum_{t=1}^{T-1} \gamma_t(i)} \\ b_j(h) = \dfrac{\sum_{t=1, o_t = v_k}^{T} \gamma_t(i)}{\sum_{t=1}^{T-1} \gamma_t(i)} \end{cases} \quad (5)$$

Once the parameters in the formula reach the convergence state, the final calculation result is obtained. However, this algorithm is greatly influenced by the initial values. In order to reduce the dependence on the initial values, this paper introduces the CS algorithm to improve the initial parameters of the Hidden Markov Model. Through the Baum-Welch algorithm, local corrections can be made to achieve an improvement in convergence speed and obtain the global optimal solution. Figure 1 shows the flowchart of the improved Hidden Markov algorithm.

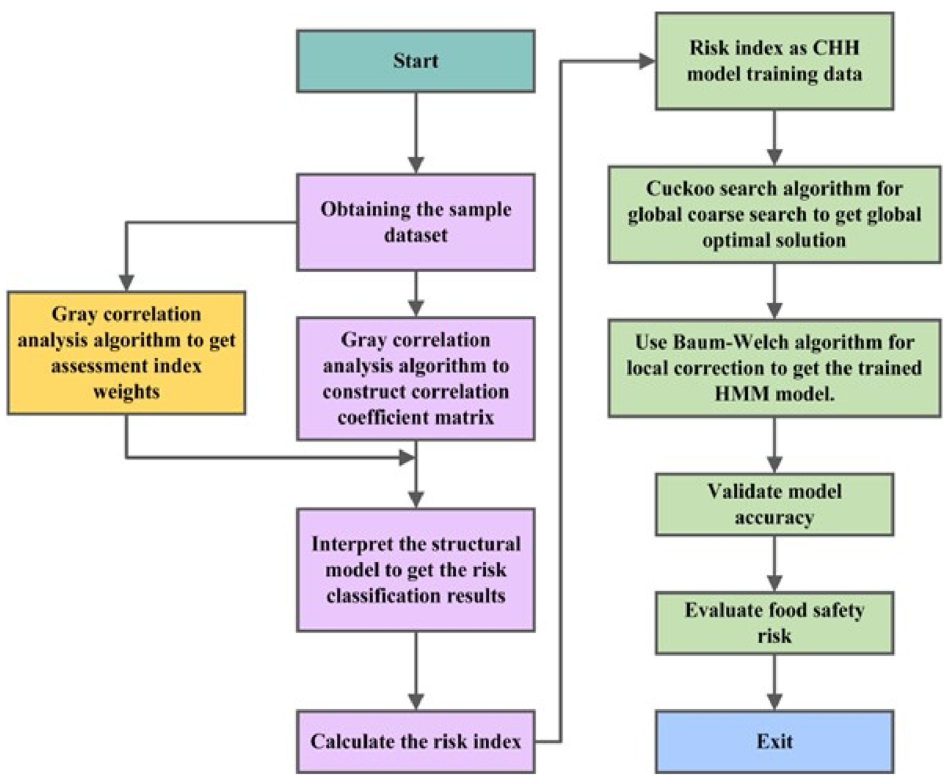

Figure 1. Flowchart of the Improved Hidden Markov Algorithm

3.2. Construction of Food Safety Management System

The food safety management system mainly considers the safety awareness and risk management in the food production and sales chain. Safety awareness refers to the safety of food processing, transportation, storage, planting, safety information feedback mechanisms, and the safety of relevant personnel throughout the process from planting to production to transportation. Risk management includes mechanisms for identifying hazards, food safety inspections, and safety emergency management. Therefore, the efficiency indicators for food safety management constructed in this paper are based on safety awareness and risk management. Both are primary indicators, which include specific content as secondary indicators. As safety awareness is the foundation of food safety management, its generation ensures the security of the food production chain. Safety awareness not only requires training and protection of relevant personnel but also needs safety supervision of every link in the production chain through appropriate measures. In this paper, an intelligent visual monitoring system based on the Hidden Markov Model is constructed, which analyzes human behavior based on the periodicity of human movement frequencies. If abnormal behavior occurs, the model identifies and predicts it accordingly, evaluating the safety risk of their behavior.

This process mainly includes the learning and training of the model and the behavior recognition steps. In the learning and training stage, the model needs to recognize the behavior feature sequence in the training set and build the test sequence based on it. The classification of human movement behavior using the Hidden Markov Model is to treat the given human behavior as an observation sequence and find its optimal description, achieving the classification of observation sequences. Then, the model encodes each key posture in the key posture set to form an action string and calculates the similarity between the key postures and the key posture feature values of human movement standard behaviors based on their included feature vectors. Next, the Viterbi algorithm is used to calculate the probability of the posture sequence generated by the test sequence. Based on the number of states and the length of the sequence, the state with the maximum probability is obtained, and thus the behavior category of the sequence is determined. Once the behave ior of relevant personnel is identified to belong to a category with a higher risk, supervisory personnel can promptly receive corresponding warning information, conduct inspections, or take appropriate measures in a short time. This module can reduce the supervision cycle time, achieve dynamic supervision, and promptly address problems in food safety management in daily management and inspection processes. Food safety risk assessment is based on risk indicators trained by the improved Hidden Markov Model to classify food safety risks, and the bird swarm search algorithm is used to optimize the model's global optimal solution. The Baum-Welch algorithm is used to make local corrections, thereby improving the accuracy of the model and reducing the error in food safety risk assessment.

4. Evaluation of Food Safety Management Efficiency Based on Improved Hidden Markov Model

In order to verify the evaluation effectiveness of the food safety risk assessment module based on the improved Hidden Markov Model, this paper adopts the matrix analysis model to judge the accuracy of the samples. Figure 2 shows the evaluation results of the Hidden Markov Model before and after improvement. For a more intuitive comparison, the actual risk assessment values of a certain food from 2019 to 2021 are selected for comparison. The results in the figure show that the overall trend of the risk assessment results of the Hidden Markov Model before and after improvement is basically consistent with the actual values. However, before the improvement, there is a significant difference between the assessment values and the actual values for the period from October 2020 to June 2021, and the error amplitude is relatively large. After improvement, the Hidden Markov Model has effectively reduced the error between its evaluation results and the actual values, with only a slight increase in error in 2020, which quickly converges to the actual values. This indicates that the Hidden Markov Model, after optimization with the CS algorithm, accelerates the convergence speed of the parameters and reaches a global optimal solution. At the same time, the improved Hidden Markov Model reduces the evaluation error, making the evaluation results more accurate and reliable. Additionally, when considering the time characteristics, it achieves better food safety risk assessment results, which are more in line with actual situations, effectively improving the quality of food safety and achieving the purpose of food safety management.

As shown in Figure 3, the trend chart of the food safety management efficiency value of a certain factory from 2014 to 2021, this factory applied the food safety management model based on the improved Hidden Markov Model in 2019. From the data in the figure, it can be seen that the overall trend of the food safety management efficiency curve is continuously increasing, indicating the effectiveness of the selected evaluation indicators. The scale efficiency curve remains at a slow growth trend, and the growth rate increases after 2020, indicating that the investment in food safety management in this factory is still insufficient.

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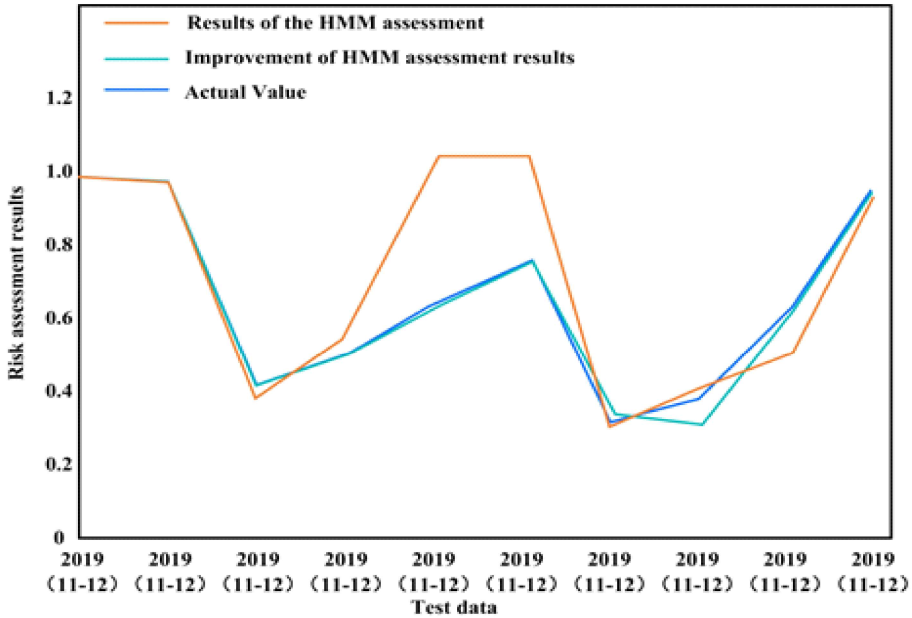

Figure 2. Evaluation Results of the Hidden Markov Model Before and After Improvement

Therefore, before 2017, the scale efficiency has been increasing year by year, reaching a relatively effective level in 2018, and then showing a relatively significant decline in 2019. This indicates that even with increasing management investment year by year, there was still a considerable part that did not generate scale efficiency. However, the increase after 2020 indicates that the application of the food safety management model based on the improved Hidden Markov Model effectively increased the scale efficiency. The technical efficiency curve, although overall showing a growth trend, initially decreased year by year and only started to rise slowly after 2016, until after 2020, it showed a significant increase, reaching a relatively effective state. It can be seen that before the application of the food safety management model based on the improved Hidden Markov Model, the performance of the factory in food safety management efficiency was not satisfactory, and both technical and scale efficiencies showed development instability. However, after the application, the management model effectively improved the management efficiency, achieved the enhancement of technical and scale efficiency, and demonstrated better comprehensive efficiency performance.

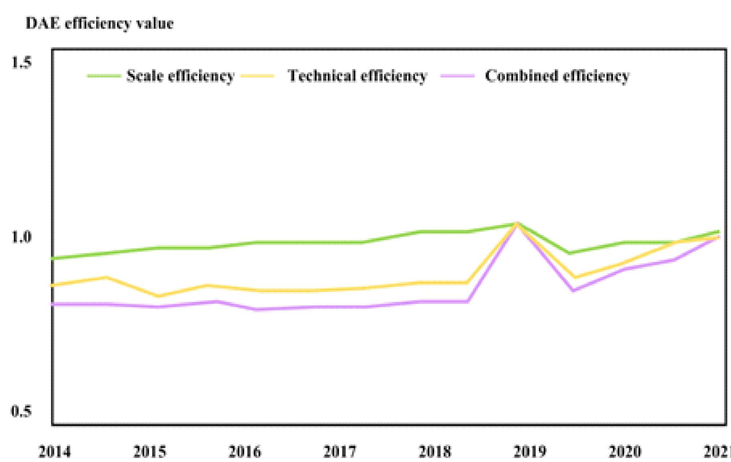

Figure 3. Trend Chart of Food Safety Management Efficiency in a Certain Factory from 2014 to 2021

In summary, after optimization with the Cuckoo Search algorithm, the Hidden Markov Model has improved the convergence speed of model parameters, solved the global optimal solution problem, and enhanced the accuracy and reliability of the food safety management model, providing assurance for its practical application effectiveness. According to the evaluation results of food safety management efficiency, it can be seen that the application of this model has effectively improved the quality and efficiency of food safety management.

5. Conclusions

Food safety has always been a focal point of people's lives and an important component of social and national long-term development strategies. The process of food production, from raw material cultivation and farming to final sales, involves many links, and each link carries certain food safety risks, requiring supervision from relevant personnel. However, manual supervision has inherent limitations and cannot achieve dynamic monitoring of every link. In addition, food safety testing is an essential means of ensuring food safety. To improve the efficiency and objectivity of food safety testing, this paper introduces the Hidden Markov Model in food safety management and optimizes it using the Cuckoo Search algorithm, enhancing the convergence speed of its parameters and solving the global optimal solution problem. Experimental results demonstrate that the improved Hidden Markov Model has better risk assessment performance with lower error and closer alignment to actual values. Moreover, the intelligent visual supervision system based on the improved Hidden Markov Model enables dynamic monitoring of food safety production, and the food safety risk assessment model reduces the error rate of risk assessment. The model effectively improves the technical and scale efficiency of management in practical application, enabling more effective transformation of management inputs and achieving the goal of enhancing food safety management quality.

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