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Building an Intelligent Food Safety Inspection System Based on the Internet of Things

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Abstract
In order to make it more convenient and fast for people to obtain the production information of dairy food and consume dairy food with confidence, a dairy food safety testing system based on the Internet of Things (IoT) is proposed in the study. Firstly, an ISM-AHP-RBF neural network-based risk assessment method for dairy products is proposed, and then the design of an IoT-based dairy milk production method is proposed using the information transmission and data collection functions of the IoT. The performance of the model is validated by comparing it with traditional neural network models. The results show that the ISM-AHP-RBF neural network can quickly iterate to a stable state and converge better than the other two traditional models; the results of risk prediction and assessment of milk components using the model are close to the real values and can accurately predict the riskier components, thus ensuring the food safety of dairy products.

Keywords
Food Safety, Internet of Things, Neural Networks, Safety Testing

1. Introduction

Food is essential to human life, but in recent years there have been various concerns about food safety. Concern about food safety has grown from individuals to major regulatory bodies, and the Food and Drug Administration has taken a number of steps from many perspectives to improve food safety concerns [1]. The safety of dairy products, an essential part of the daily diet, is an issue that needs to be addressed. At present, China's food safety testing system is still in its infancy, and we still need to learn from nations that have done better in food safety in order to build on this foundation and construct a safety testing system that is appropriate for China's current food situation [2]. The dairy sector differs from other industries in that its supply chain is long and complicated, and it is difficult to trace its origin due to the many factors that influence quality [3]. In general, dairy products have to pass through six stages before reaching the consumer: dairy farming, milk production, milk processing, storage, transport and sale, each of which is prone to quality degradation because it is difficult to ensure the quality and safety of the entire dairy supply chain. The Internet of Things is being used in a wide range of applications, including logistics monitoring, medical education, intelligent transport and digital education. Internet of Things (IoT) technology is being used in an increasing number of sectors to provide quick information

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transmission and data storage [4]. In order to better optimize the detection effect of the current dairy products detection system in China, this research combines the IoT technology and neural networks to jointly build a dairy products risk assessment model and a dairy products production detection system. This research aims to achieve a highly automated and accurate dairy inspection system using IoT technology and artificial intelligence neural networks, to better control every link in the dairy production and transport process, and to ensure that dairy products transported to market meet quality standards.

2. Related Works

With the continuous development of Internet technology, IoT is gradually being widely used in more and more fields in the form of information carriers based on the development of the Internet [5]. Qiu et al. [6] proposed an event-aware backpressure scheduling scheme for large-scale emergency IoT based on event-awareness, aiming to solve the problem of long packet paths caused by routing in traditional backpressure scheduling schemes. Through extensive experiments, this paper showed that the proposed backpressure scheduling scheme is able to reduce end-to-end latency and increase the forwarding percentage. By introducing IoT deep learning capabilities into edge computing, along with a new set of offloading policies to optimize the performance of IoT applications with edge computing capabilities and deep learning capabilities, Li et al. [7] found through performance evaluation that the scheme IoT deep learning outperformed other learning solutions. Siow et al. [8] proposed a hierarchical taxonomy based on IoT data collection to analysis that can provide insights with adaptability for use in the data analysis process and in turn form technical support for IoT analysis and IoT architectures. Xu et al. [9] analyze and compare battery-free backscatter with various other backscatter for small devices such as sensors in fifth generation mobile communications and summarize a treatment scheme aimed at solving the existing battery problem. Lima et al. [10], considering the limitations of the environment in which IoT applications are validated, reviewed and compared the latest technologies related to test beds for wireless sensor networks and IoT applications, and finally analyzed the advantages and limitations of the test bed required for IoT experiments based on the respective performance differences. Based on the above-mentioned domestic and international research status, this study proposes an IoT-based dairy food safety inspection system, taking into account the current development of the IoT and a series of problems in food safety.

3. Model Construction of a Dairy Food Safety Inspection System based on the IoT

3.1 Design of an RBF Neural Network-based Risk Assessment Method for Dairy Products

With the development of the economy, there has been a new demand for the traditional mode of clothing, food, housing, and transportation, followed by food safety issues that only increase without decreasing [11]. Among the numerous food safety issues in China, the safety of dairy products has always been high. At present, the monitoring methods for the composition of dairy products are inefficient and have low accuracy. Therefore, this study combines neural networks to propose a new intelligent detection and evaluation method for dairy product safety. Radial basis function (RBF) neural networks are artificial neural networks commonly used for pattern recognition, approximate function fitting, and nonlinear data modelling. RBF networks are advantageous in dealing with certain types of problems, especially when there are nonlinear distributions in the input space or complex nonlinear relationships in the objective function. RBF is an improvement on backpropagation (BP) neural networks. RBF is an improvement on BP neural networks in that the RBF neural network is trained and adjusted to the weights of some factors that have an impact on the local output. Therefore, the training time is shorter and the computational accuracy is higher than the traditional BP neural network. The current dairy food safety detection system is not perfect enough and needs to be further optimized by combining artificial intelligence technology.

In recent years, the hybrid evaluation method that combines qualitative and quantitative evaluation has gradually gained popularity among more and more scholars due to its excellent evaluation performance. Therefore, this study mainly combines the interpretative structural modeling (ISM) method and analytic hierarchy process (AHP) to construct a RBF neural network risk assessment model that can be qualitatively and quantitatively analyzed for risk assessment of dairy products. ISM is mainly used to analyze the relationships between various variables. In order to simplify the problem, directed graphs and correlation matrices are used to represent the relationships between various influencing factors. The formula used to express the results is shown in Eq. (1) [12]:

$$H = (V, E), V = m, E = n \tag{1}$$

In Eq. (1), m is the number of vertices, n is the number of edges and the relationship between the elements of each variable can be found through the directed graph. The relationship between two nodes in the directed graph H can be represented by the adjacency matrix $A = (a_{ij})$ of $m \times m$.

$$a_{ij} = \begin{cases} 1, < v_i, v_j > \in E, & 1 \le i, j \le o \\ 0, \quad other \end{cases}. \tag{2}$$

In Eq. (2), o is the number of elements that make up the directed graph and is 0 when $a_{ij} < v_i, v_j >$ is irrelevant and a_{ij} is 1 when $< v_i, v_j >$ is relevant. The $n \times n$ reachable matrix $B = (b_{ij})$ is defined in the directed graph H as shown in Eq. (3):

$$b_{ij} = \begin{cases} 1, When < v_i, v_j > PASS, & 1 \le i, j \le o \\ 0, \quad other \end{cases}. \tag{3}$$

The flow chart of the RBF risk assessment model based on the ISM and AHP algorithms is shown in Fig. 1.

3.2 Methodological Design of an IoT-based Dairy Milk Production System

In addition to intelligent testing and risk assessment of dairy products, it is also necessary to consider their traceability system. At present, China's dairy traceability system is still in its infancy, with immature technology and an incomplete traceability system [13]. Considering that milk production is a relatively important part of the whole traceability system, this study will take advantage of the powerful data capabilities of IoT on the traditional traceability system to build an IoT-based dairy milk production system to facilitate intelligent monitoring of the quality and safety of dairy products. The overall architecture of the IoT-based dairy production system is shown in Fig. 2.

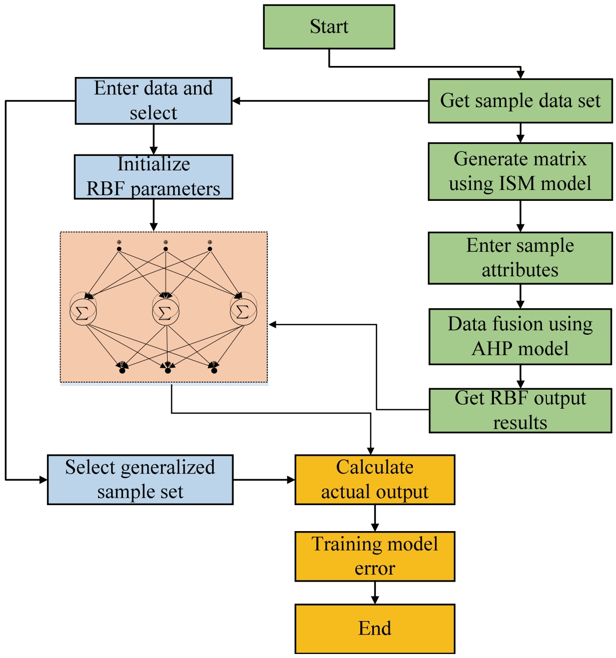

Fig. 1. Flow chart of the RBF risk assessment model based on ISM and AHP algorithms.

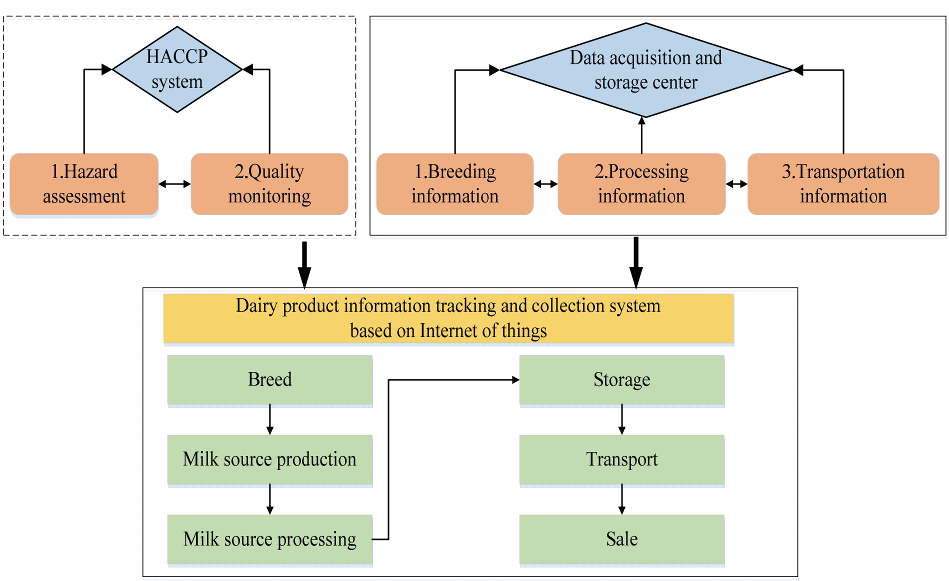

Fig. 2. IoT-based dairy milk production system.

The IoT-based dairy milk production system, as shown in Fig. 2, is separated into two parts: the hazard analysis critical control point (HACCP)-based dairy hazard assessment and quality monitoring system, and the IoT-based milk production information tracking, collection, and data processing system. The traditional traceability process includes a total of six parts, namely breeding, milk production, milk processing, storage, transportation, and sales [14]. The three common measures of food traceability systems are traceability breadth, traceability depth and traceability accuracy, and the higher the requirements for the three measures, the more time and cost will be invested. Due to the complexity of the dairy food production supply chain, it is unrealistic to trace all processes. In this paper, the HACCP system is used to analyze the quality hazards of the dairy milk production, and the key control points are shown in Table 1 [15].

As can be seen from Table 1, at the raw material production stage of dairy products, they are basically biological hazards, most of which are microbial infections and all are significant hazards that accompany the entire raw milk production process. If left uncontrolled, they are likely to lead to food safety problems. Key point control is an effective way of determining whether the hazards at each stage are significant, and then determining whether that stage is capable of reducing the risk and ensuring food quality and safety based on current technology. In addition to raw milk production, the same principles of HACCP key point control apply to other stages of the process. The traceability code provides clear information on several key stages of the production process so that users can obtain specific information about the product in a timely manner. The code composition of the traceability code provides the basis for the IoT information collection, which enables the timely collection of dairy product information through the automatic identification and unlimited transmission of the IoT.

Table 1. Hazard analysis of the dairy milk production chain

	Dairy cow cleaning	Equipment disinfection	Personnel cleaning	Disinfection of containers	Filter cloth cleaning	Cooling operations	Fresh milk transport
Type of hazard	Biological hazards	Biological hazards	Biological hazards	Biological hazards	Biological hazards	Biological hazards	Biological hazards
Is the harm significant	Yes	Yes	Yes	Yes	No	Yes	No
Is it HACCP	Yes	Yes	Yes	Yes	No	Yes	No
Are the sources of harm traceable	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Availability of preventive measures	Yes	Yes	Yes	Yes	Yes	Yes	Yes

4. Performance Comparison of ISM-AHP-RBF Neural Network Models and Analysis of Results

In order to verify the validity of the RBF network model (later denoted as ISM-AHP-RBF) fusing the interpreted structural model method and the hierarchical analysis method, several UCI standard datasets were used to test the model, in which the bias correlation thresholds of the structural model method used in the three datasets were 0.05, 0.05, and 0.5, respectively, and the number of layers obtained by the hierarchical analysis algorithm was 3. The model constructed by the study was then compared with a traditional BP neural network model (later notated as BP), and a BP neural network model incorporating the interpreted structural model method and the hierarchical analysis method (later notated as ISM-AHP-BP), and the iterative results of the three algorithms are shown in Fig. 3.

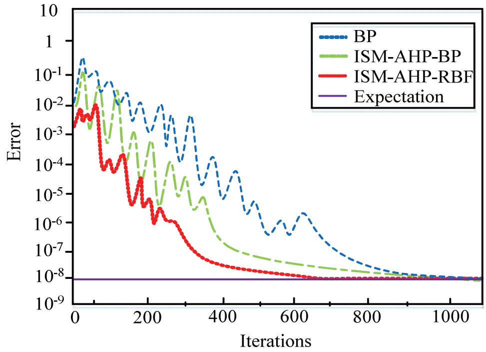

Fig. 3. Comparison of training effects of three models.

As shown in Fig. 3, which shows a plot of the iterations under the three algorithms, the ISM-AHP-RBF model has a more pronounced downward trend in training error than the other two models and is able to reach the desired value quickly after 689 iterations; the ISM-AHP-BP model has a slightly flatter downward trend than the ISM-AHP-RBF model and reaches the desired value after the number of iterations. The traditional BP model had a slower decrease in training error than the other two models, but reached the desired value only after 1,132 iterations. A sample of 100 commercially available milk brands was randomly selected as the milk to be tested. To clarify the range of risk indicators, standard risk values were set according to the national standards GB2762-2012 and GB25190-2010. Six ingredients commonly found in milk were selected for evaluation and the ISM-AHP-RBF model was used to train the limits for the six ingredients and the results obtained are shown in Table 2.

Table 2. National standard limits of common ingredients in dairy products

	Ingredient					
	1	**2**	**3**	**4**	**5**	**6**
Component	Fat	Protein	N-fat solid	Acidity	Calcium	Lead
Limit value	≥3.0	≥2.8	≥8.0	11–17	≥0.08	≤0.04
Reference	GB25190-2010	GB25190-2010	GB25190-2010	GB25190-2010	GB2762-2012	GB2762-2012
Unit	g/100 g	g/100 g	g/100 g	T	mg/kg	mg/kg

As can be seen from Table 2, each milk component under the ISM-AHP-RBF model can meet the national standard after training. In order to further verify the predictive ability of the model while obtaining more accurate prediction results, the milk samples to be tested were divided into top-level indicators, middle-level indicators and bottom-level indicators. Twenty sets of data were randomly selected for risk assessment experiments, and the risk prediction assessment of the model was determined based on the monitoring values of the three indicators.

Fig. 4 illustrates how the risk threshold values as a whole had a trend of rising and subsequently falling values. Within the corresponding components of the top-level indicators, the risk values before the data modification were below the risk threshold, but the risk values after the modification were above the risk threshold. Prior to the data modification, the values of the three risk indicators for the 20 datasets to be measured were all below the risk threshold; however, after the data modification, the values of the risk indicators as a whole tended to gradually decrease. This suggests that among the top-level indicators, a comparable risk component has evolved.

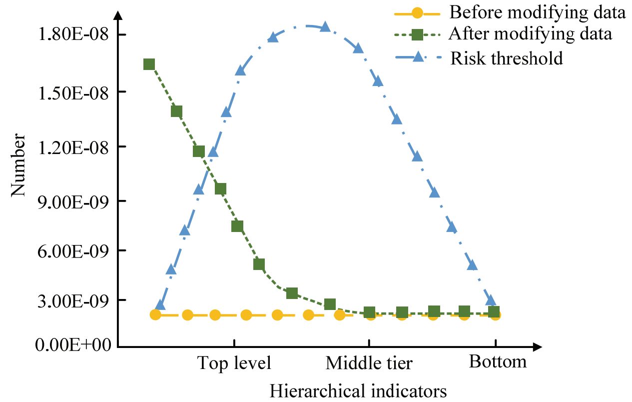

Fig. 4. Comparison of risk assessment index results.

5. Conclusion

Aiming at the existing quality and safety problems of milk source production of dairy food in China, this paper first evaluates the risk of dairy products by using ISM-AHP-RBF neural network, then intelligently monitors the safety of dairy food by using RFID technology of IoT, and finally proposes the design of milk source production method based on IoT. The results are as follows. The downward trend of the training error of the ISM-AHP-RBF model is more obvious than that of the other two models, with fewer iterations and faster convergence speed, which shows that the training results of the model constructed by the Institute are better than the traditional model, and can be applied to the component safety risk assessment of dairy products. At the same time, the IoT-based dairy food safety detection system was analyzed, and it was found that the risk of non-fat milk solids was high. In its single value quality control chart, the mean line in the quality control chart was 9.54, while the single value of non-fat milk solids finally floated up and down around the quality control mean and tended to be stable; in its range quality control chart, the mean line in the quality control chart is 0.35. Except for the first point, which fluctuates greatly, the other points float in a small range below the quality control mean, and the data fluctuation is relatively stable. In conclusion, it shows that the system can be used to detect the actual quality control value of risk components in dairy food, can truly evaluate the risk situation of each component, and make prevention in advance, so as to further achieve the purpose of food safety detection.

6. Future Work

Future research can expand and broaden the study to increase the precision, efficacy, and applicability of dairy food safety evaluation and monitoring. The following are potential paths for further research.

First, the risk assessment model needs to be improved. Although the ISM-AHP-RBF model in this paper does a good job of assessing the safety of dairy foods, it can still be further optimized in terms of parameter settings, data processing, and feature selection. It is possible to think about adding more data characteristics, growing the model's input layer, etc. Second, multi-modal data fusion—data from many sources, including sensor data, manufacturing records, environmental monitoring, etc., are used to ensure modern food safety. The safety status of dairy production may be better understood by combining data from many sources to create a more comprehensive risk assessment model. Third, intelligent monitoring system optimization—the IoT-based intelligent monitoring system can be further improved and optimized. Consideration can be given to introducing more sensors to monitor all aspects of dairy production in real time, including raw material storage, production and processing, transportation, etc., to achieve more comprehensive food safety monitoring. Fourth, risk early warning and response—in the field of dairy food safety, early detection of risks and timely response are crucial. Future work can explore how to reduce the incidence of safety incidents by establishing an early warning mechanism and realizing timely identification and response to potential risks based on the output of the model. In conclusion, future work can continue to explore in depth the areas of algorithm optimization, data fusion, practical application validation and food safety early warning to further improve the level of dairy food safety assessment and monitoring to protect public food safety and health.

Conflict of Interest

The authors declare that they have no competing interests.

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