RESEARCH ARTICLE

Electromagnetic vibration energy modeling method for fruit cold chain logistics quality perception based on wireless sensor networks

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Fruit cold chain logistics has become an important way to transport fruits from different places with the convenience of transportation. Fruit is an extremely perishable variety, which requires continuous monitoring of fruit quality in the fruit cold chain logistics scheme. Traditional fruit cold chain logistics transportation uses relevant instruments to monitor the temperature, gas, and other quality characteristics of fruit, which consumes much time and material resources of operators and, therefore, limits the efficiency and time of fruit cold chain transportation. It is also difficult to monitor the changing laws of fruit quality in real time. This study designed an intelligent quality monitoring and control system using big data theory, wireless sensor technology, and electromagnetic vibration energy device for fruit cold chain logistics, which extracted three quality characteristics of fruit quality including temperature, humidity, and gas. The data extracted and collected by big data theory were transmitted to the computer for processing through wireless sensor technology. The results confirmed that an intelligent fruit cold chain logistics quality monitoring system based on big data theory, wireless sensor technology, and electromagnetic vibration energy device had been successfully designed and implemented. The system could accurately extract and predict key quality characteristics of fruits during cold chain transportation including temperature, humidity, and gas indicators using the multi path convolutional neural network (MPCNN)-long short-term memory (LSTM) method. Specifically, the multi-path architecture of MPCNN enabled it to efficiently capture feature information of different scales and levels from fruit images, thereby achieving accurate evaluation of fruit maturity. Combined with the unique gating mechanism of LSTM network, this system could effectively capture long-term dependencies in data and maintain high prediction accuracy even in the presence of noise or missing data.

Keywords: fruit cold chain; wireless sensor; electromagnetic vibration energy; big data.

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Introduction

In the early years, people could only taste the local specialties of fruits and were limited by transportation, which restricted not only the development of fruit growers, but also people's pursuit of different fruit types. Off-site fruit also has the disadvantage of higher price due to high transportation costs, which allows people to taste fruits from different regions, but increases people's demand for fruits. There is a relatively large risk in fruit transportation, which is prone to spoilage. Fruit transport requires efficient rates and certain measures of refrigeration [1]. In traditional cold chain logistics, environmental monitoring mainly relies on manual inspections and fixed sensors. However, this method is not only time-consuming and laborious, but also difficult to achieve real-time monitoring and precise control. In addition, due to the limited number of sensors, it is often impossible to fully cover the entire transportation process, resulting in inaccurate and incomplete monitoring data [2]. Therefore, how to achieve real-time monitoring and precise control of environmental factors in the cold chain logistics process has become an urgent technical challenge in the current cold chain logistics industry [3]. For some perishable fruits, people often use immature fruits for transportation, which limits people to taste fresher fruits. If fruit cold chain transportation cannot guarantee efficient timeliness, it will also cause certain economic losses to fruit suppliers. Therefore, reasonable refrigeration measures and the detection of fruit cold chain logistics are also crucial means. Fruit has the biological characteristics of fresh, tender, perishable, and senile, and it is a fresh commodity with great difficulty and risk in circulation [4]. Cold chain coupled preservatives or modified atmosphere technology have become one of the main forms of fruit logistics preservation [5]. It has transitioned from pure temperature perception to gas perception, which measures the quality of fruit by sensing the gas released by the fruit [6]. In cold chain logistics, wireless sensor networks can achieve real-time monitoring of key links such as transportation vehicles, cold storage, packaging boxes, *etc*. [7]. By deploying sensor nodes inside transport vehicles, cold storage walls, or packaging boxes, real-time collection and transmission of environmental parameters such as temperature and humidity can be achieved, providing data support for precise control of cold chain logistics [8]. In addition, wireless sensor networks also have advantages such as self-organization, scalability, and low power consumption, which can adapt to the complex and changing environmental requirements of cold chain logistics [9]. Although wireless sensor networks have many advantages in cold chain logistics, their energy consumption has always been a key factor restricting their widespread application [10]. Traditional wireless sensor nodes mainly rely on battery power supply, but the battery life is limited and the cost of replacing the battery is high, especially in environments such as cold chain logistics where manual intervention is difficult, battery replacement is almost impossible to achieve [11]. Therefore, how to provide durable and reliable energy supply for wireless sensor nodes has become a hot and difficult issue in current research on wireless sensor networks [12]. Meanwhile, different fruits will emit different gases during transportation in the cold chain, which brings certain difficulties to the quality perception in the fruit cold chain logistics scheme [13]. Fruit cold chain transportation workers often transport a variety of fruits. In the process of logistics and transportation, there will be a large error in measuring only one indicator [14]. The gas between different fruits will also be mixed. It is an inaccurate way to detect the quality of the cold chain logistics of fruits only by measuring the gas emitted by the fruits. In cold chain logistics, precise control of the temperature inside the transport carriage to maintain it within the optimal storage temperature range for fruits is the primary task in ensuring fruit quality [15].

Wireless sensor technology can monitor the relevant indicators from time to time, and the relevant parameters in the fruit transportation process can be transmitted through wireless sensors and local area network or blue-tooth technology [16]. Fruit cold chain logistics operators can always know the relevant indicators of fruit transportation in the cab, which avoids the tediousness of traditional mechanical measurement methods [17]. The electromagnetic vibration energy sensing device can start and stop related settings according to the temperature, humidity, gas, and other indicators measured by the sensor, which can maintain the freshness of the fruit during the cold chain logistics transportation. Meanwhile, it needs to intelligently classify the gas indicators, temperature, humidity, and other information measured by the sensor [18]. The core of big data theory lies in its powerful data processing and analysis capabilities. By deeply mining historical data, big data systems can learn and understand the specific temperature, humidity, and gas environment requirements of different types of fruits at different transportation stages [19]. Based on this, the system can tailor the optimal cold chain logistics solution for each type of fruit, achieving precise control and personalized service, thereby maximizing the freshness and quality of the fruit. Big data systems can self-learn and self-optimize [20]. With the continuous accumulation of data and iteration of algorithms, it can automatically adjust control strategies to adapt to new environments and demands. There is also a certain time correlation in the fruit cold chain logistics scheme, which requires the use of relevant algorithms for time extraction in big data theory [21]. The big data theory will include algorithms for spatial extraction and temporal feature extraction, which can learn not only the data correlation in the fruit cold chain logistics scheme, but also the time-related features of fruit-related indicators. Different researchers improved these two algorithms [22]. The quality monitoring of fruit cold chain transportation is more important to maintain the freshness and quality of the fruit. Temperature measurement and gas monitoring are common cold chain transportation methods for fruits [23]. Wu *et al*. believed that the cooling effect of the traditional fruit cold chain controlled by a single machine was less effective for the temperature control of fruit cold chain transportation. In the in-depth exploration of fruit cold chain logistics, temperature control chain was undoubtedly regarded as the core element affecting fruit quality. This understanding was based on extensive practical experience and strongly supported by scientific research [24]. To more accurately predict and manage temperature changes during cold chain transportation and their impact on fruit quality, researchers have introduced the innovative tool of virtual cold chain (VCC). By simulating the dynamic changes in the cold chain transportation environment and combining advanced computational fluid dynamics and mechanics methods, the advantage of this method was that it could identify potential temperature fluctuations and quality risks in advance, providing valuable warning and intervention opportunities for transporters, thereby effectively ensuring the final quality of fruits. However, despite the enormous potential of advanced tools such as VCC in improving cold chain management, Jiao *et al*. also revealed the limitations of intelligent algorithms in practical applications [25]. Especially, when pursuing the dual goals of short transportation time and minimum quality loss, existing intelligent control systems often face challenges, which is mainly because cold chain logistics is a complex multivariable system that involves the interaction of multiple factors such as temperature, humidity, gas concentration, transportation speed, packaging materials, *etc*., and the dynamic relationships between these factors are often difficult to fully describe with simple mathematical models. It also utilizes bacterial foraging algorithm to study the optimal transportation route according to different constraints. The research structure found an efficient and low-cost solution for fruit cold chain transportation. Further, scientists found that the strong convective cooling scheme was an important means for the control of fruit quality during the cold chain transportation of fruits, but the strong convective cooling scheme research on the computational fluid dynamics scheme was limited to small water cold chain transport packaging, which limited the performance of fruit cold chain transportation [26]. The study showed that the fruit cold chain quality loss was 23% higher in the presence of the cooling chain than that without the cooling chain. Wei *et al*. also found that manual methods and optical instruments were difficult to apply to the attenuation detection process of fruits. The handheld electronic nose (e-nose) simulated the working principle of the human olfactory system and used a sensor array to capture and identify volatile organic compounds (VOCs) emitted from fruits was investigated, which was a direct reflection of internal biochemical reactions in fruits, and the changes in their types and concentrations could reveal key information such as freshness, maturity, and disease status of fruits. Therefore, real-time monitoring of VOCs during cold chain transportation of fruits through e-nose could achieve non-destructive, rapid, and continuous evaluation of fruit quality. It also applied the successive projection method and weight sampling method to explore the characteristic relationship of fruit related indicators. The research results showed that the detection accuracy of this method was 95.83%. This method was a simple and non-destructive testing method for fruit quality measurement [27]. Wu *et al*. also found that refrigerated products such as fruit could minimize the degree of fruit decay during transportation and proposed a new algorithm to study the life cycle assessment of fruit cold chain transportation and the method of virtual cold storage. The results showed that this method could track the cooling history of fruit and use computational fluid dynamics to detect the transportation process of the whole cold chain [28].

The aim of this study was to design and implement an intelligent fruit cold chain logistics quality monitoring system, which combined wireless sensor technology, electromagnetic vibration energy devices, and big data theory to achieve real-time monitoring and control of temperature, humidity, and gas characteristics of fruits in the cold chain logistics process. Multi-path architecture of multi path convolutional neural network (MPCNN) was employed to effectively capture feature information of different scales and levels from fruit images, thereby achieving accurate evaluation of fruit maturity. Combined with the unique gating mechanism of long short-term memory (LSTM) network, this proposed system could effectively capture long-term dependencies in data and maintain high prediction accuracy even in the presence of noise or missing data.

Materials and methods

Electromagnetic vibration energy devices and applications of big data theory

The big data theory will extract quality monitoring of fruit cold chain logistics transportation, mainly including relevant indicators such as fruit temperature, gas, and humidity. The relationship between these indicators is quite complex, and big data theory will identify relevant features based on the characteristics of the corresponding indicators. Manually identifying these features will take a lot of time, which is also difficult for fruit cold chain transportation practitioners. The electromagnetic vibration energy device can control the switches of the relevant control units of the cold chain logistics transport vehicle based on the characteristics identified by big data theory, achieving a good temperature, humidity, and gas control environment, which can also achieve automatic intelligent control of the fruit cold chain logistics transportation environment. If relying solely on fruit cold chain logistics practitioners, it is difficult to consider transporting all fruits. Different fruits have different characteristics such as temperature, humidity, gas, *etc*., which makes it difficult to monitor the actual relevant indicators of different fruits and will limit the monitoring of fruit quality by fruit cold chain logistics and transportation practitioners.

Design of wireless sensor and electromagnetic vibration energy device in quality monitoring of fruit cold chain

An intelligent fruit cold chain logistics quality monitoring system was proposed using wireless sensors and electromagnetic vibration energy devices, which integrated big data theory to automatically classify the temperature, humidity, and gas characteristics of fruits. Wireless sensor technology wirelessly transmitted the collected fruit quality related information from fruit cold chain transport vehicles, enabling real-time monitoring and control of quality issues during fruit transportation. The electromagnetic vibration energy device received temperature, humidity, and gas characteristics extracted from big data theory, thereby further controlling the temperature, humidity, and gas control system of fruit cold chain logistics. Temperature, humidity, and gas sensors collected data on three indicators of fruit quality, and big data theory automatically classified and extracted relevant feature data for these three indicators. The relevant characteristic values were transmitted to electromagnetic vibration energy devices and wireless sensors. This network consisted of multiple sensors deployed inside the cold chain transport vehicle including temperature sensors, humidity sensors, and gas sensors. These sensors were responsible for real-time collection of key indicators such as oxygen and carbon dioxide concentrations in the fruit storage environment. The collected data was transmitted wirelessly to the data processing center, where big data theory was used for rapid processing and analysis of the data. The system could automatically identify and extract feature data closely related to fruit quality such as temperature fluctuation range, humidity level, and trends in gas composition changes. As the executing part of the system, this device intelligently adjusted the temperature, humidity, and gas control system inside the cold chain transport vehicle based on the feature data extracted by the data processing module. By using a vibration energy regulating device to change the air circulation inside the refrigerator, precise control of temperature and humidity could be achieved. Meanwhile, based on the analysis of gas composition, the operation of the ventilation system was adjusted to maintain the optimal gas conditions for fruit storage environment. During the cold chain transportation of fruits, wireless sensor networks continuously monitored various quality indicators of the storage environment and transmitted real-time data to the data processing center. The data processing module utilized big data algorithms to quickly analyze and extract features from the collected data to accurately evaluate the current quality status of the fruit. Subsequently, based on the extracted feature data, the electromagnetic vibration energy device intelligently adjusted the control parameters of the cold chain system to ensure that the fruit maintained its optimal quality throughout the entire transportation process. In this way, the intelligent fruit cold chain logistics quality monitoring system designed in this study could achieve real-time monitoring and intelligent control of fruit quality, effectively improving the efficiency of cold chain logistics and the quality assurance level of fruits.

Introduction of big data theory and wireless sensor technology

Wireless sensor is an instrument that combines various sensors, integrated digital processing units, and wireless transmission modules. It forms a self-organizing network transmission system. Wireless sensors can use portable multi-sensor systems to collect digital signals of research objects and transmit these signals to control gateways through wireless networks. These digital signals can be provided to managers for monitoring. It can also be sent to the processing system of the computer, which will perform feature extraction and related data extraction on these digital signals as illustrated in Figure 1.

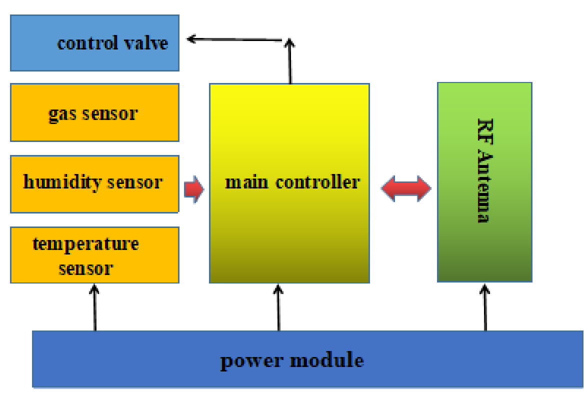

Figure 1. The application principle of wireless sensor technology.

For the intelligent fruit cold chain logistics quality monitoring system, big data theory provided reliable data support for wireless sensors and electromagnetic vibration energy devices. LSTM effectively captured long-term dependencies in data through its unique gating mechanism and maintained high prediction accuracy even in the presence of noise or missing data. This

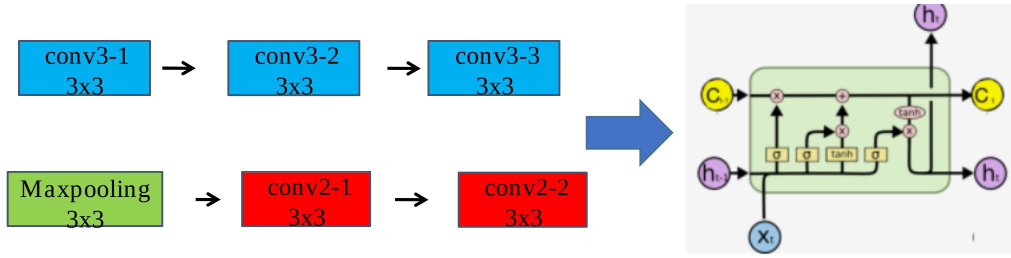

Figure 2. Application of hybrid MPCNN-LSTM neural network method in fruit quality characteristics.

characteristic is particularly important for predicting temperature, humidity, and gas indicators during cold chain transportation, as these indicators often exhibit complex dynamic changes over time. The workflow of the hybrid MPCNN-LSTM method intuitively reflected the deep integration of big data theory and deep learning techniques (Figure 2). In this process, big data was first used for data collection, cleaning, and preprocessing, providing high-quality input for subsequent analysis and modeling. Subsequently, MPCNN and LSTM neural networks worked together to process the spatial and temporal features of the data, and through steps such as feature fusion and decision optimization, ultimately output accurate predictions and evaluations of fruit quality. The temperature, humidity, and gas quality characteristic data of fruits were sequentially extracted and predicted using MPCNN and LSTM neural networks.

Relevant theories and expression explanations of big data theory

In this study, MPCNN and LSTM methods were designed to extract the temperature, humidity, and gas quality characteristics in the process of fruit cold chain logistics transportation, which used the convolution operation and the selection of time characteristics to extract. The following equations 1-3 respectively showed the form of data set for the three quality characteristics of fruit. All three datasets contained label data as well as input data. MPCNN-LSTM methods were all supervised learning methods, which would learn to establish a nonlinear relationship between the input data and the predicted data.

$$Train - \text{fruit quality} = \{(x_1, y_1), (x_2, y_2), \ldots\ldots (x_n, y_n), \ldots. (x_N, y_N)\} \quad (1)$$

where x_n was the feature vector of the i-th fruit. This vector might contain multiple dimensions such as color, size, shape, origin, *etc*. used to describe various fruits attributes. y_n was the quality or quality characteristic label of the *N*-th fruit, which was usually a numerical or categorical label used to measure or classify the quality of fruits. *N* was an index variable used to traverse all samples in the training set. From 1 to *N*, it indicated that there were *N* samples in the training set.

$$Test - \text{fruit quality} = \{(x_1, y_1), (x_2, y_2), \ldots\ldots (x_m, y_m), \ldots. (x_M, y_M)\} \quad (2)$$

Test-fruit quality was a test set used to evaluate the quality of fruits. $\{(x_1, y_1), (x_2, y_2)$ ..... (x_m, y_m), ... (x_M, y_M) represented multiple pairs of data in a set, each pair consisting of a feature value x and a corresponding quality value y. This was to express multiple different feature values x and their corresponding quality values y.

$$\hat{y} = \{\hat{y}_1, \hat{y}_2, \ldots\ldots, \hat{y}_m, \ldots\ldots, \hat{y}_M\} \quad (3)$$

The formula above was a representation of a vector. Where y was the vector name, y_1, y_2, ... y_m were components of the vector. Usually, the naming of vector components should be consistent. y was used as both the name of the vector and a possible component. The formula was intended to represent a vector containing three quality features, which should be written as

$y = (y_1, y_2, y_3)$, where y_1, Y_2, and y_3 respectively represented three different quality characteristics. If m was the number of samples in the dataset, rather than the number of components in the vector, then the formula should be reinterpreted. In this case, the formula itself did not directly represent the dataset, but might represent a specific calculation or transformation in the dataset. For the MPCNN method, its computational criteria were very similar to those of the CNN method. The difference between MPCNN and CNN was that it had two different paths. However, the convolution operation was a basic form of MPCNN. The convolution operation process of the MPCNN method was shown in equations 4-6, which included integral operation and summation operation with the integral operation form as follows.

$$\int_{-\infty}^{\infty} f(\tau)g(x-\tau)d\tau \quad (4)$$

Equation 4 represented the integration of the product of functions $f(\tau)$ and $g(x-\tau)$ over a certain interval. $f(\tau)$ and $g(x-\tau)$ were two functions, where t was the integral variable and dt was the derivative of t. The result of integration was a numerical value, which depended on the specific forms of $f(\tau)$ and $g(x-\tau)$, as well as the upper and lower limits of the integration.

$$\int_{0}^{\tau} f(x)g(\tau-x)dx \quad (5)$$

$$(f*g)(x) = \int_{-\infty}^{\infty} f(t)g(x-t)dt \quad (6)$$

Equation 5 represented a definite integral, where $f(x)$ and $g(\tau-x)$ were two functions. dx was the derivative of the integral variable x. This integral was the product of $f(x)$ and $g(\tau-x)$ over the range of 0 to t. In mathematics, such integral expressions could be used to calculate the weighted average or correlation between two functions over a certain interval.

$$S(x) = \frac{1}{1+e^{-x}} \quad (7)$$

Although mean squared error (MSE) performed well as a measure of model prediction accuracy in most cases, it was highly sensitive to outliers, i.e. values far from most data points. Since MSE calculated the average of the squared difference between predicted and actual values, outliers might significantly increase the error term, potentially dominating the value of the entire loss function, which might cause the model to overly focus on these outliers during training, while ignoring the learning of most normal samples. Therefore, in some cases, to mitigate the impact of outliers and more comprehensively evaluate model performance, it might be necessary to consider using more robust loss functions such as mean absolute error (MAE). In addition, when validating the proposed model, in addition to MSE and loss functions, F1 score was also a commonly used evaluation metric that could comprehensively consider the accuracy and recall of the model, providing a more comprehensive measure of model performance. In the optimization process, the gradient of MSE, i.e. the derivative of the loss function relative to the model parameters, was a linear function of the prediction error, which enabled optimization algorithms such as gradient descent to effectively adjust the model parameters to reduce errors. Due to the numerical difference between the predicted and actual values measured by MSE, it was particularly suitable for regression problems that required predicting continuous values. As mentioned earlier, MSE was sensitive to outliers and might lead to a decrease in model performance. In practical applications, this problem could be alleviated through data preprocessing such as outlier detection and processing or by selecting more robust loss functions.

$$L = MSE(q^{real}, q^{pre}) = \frac{1}{nm}\sum_{k=1}^{N}\sum_{j=1}^{M}(q_{kj}{}^{real} - q_{kj}{}^{pre})^2 \quad (8)$$

Equation 9 detailed the method and form of the convolution operation between biases, weights, and input data, while equation 10 showed the calculation method of the LSTM method to select historical state data with larger weight as the input of the next layer of network.

$$x_j^{\lambda} = f\left(\sum_{i \in M} x_i^{\lambda-1} * k_{ij}^{\lambda} + b_j^{\lambda}\right) \tag{9}$$

$$f_t = \sigma(w_f \bullet [h_{t-1}, P_t] + b_f) \tag{10}$$

The gradient descent algorithm was based on the concept of gradient in calculus, which referred to the direction in which the derivative of a function was maximized at a certain point. In optimization problems, the study aimed to find model parameters that minimized the loss function. Gradient descent determined the direction in which the loss function decreased the fastest by calculating the gradient of the loss function at the current parameter values, that was, the partial derivative vector of the loss function relative to the model parameters. Then, the algorithm updated the parameter values in the opposite direction of this gradient because the gradient pointed in the direction where the function value increased the fastest, the opposite direction movement to reduce the function value was expected to gradually approach the minimum value of the loss function.

$$i_t = \sigma(\omega_i \bullet [h_{i-1}, P_t] + b_i) \tag{11}$$

$$O_t = \sigma(w_o \bullet [\overset{\rho}{h}_{t-1}, P_t] + b_o) \tag{12}$$

The equation described the output O_t of a time step in a time series model. o was an activation function, which might be sigmoid, tanh, ReLU, *etc*., depending on the context of the model, used to convert the results of linear combinations into the desired output range. w was a weight vector or matrix that determined the importance of input features. In this formula, w was multiplied by a linear combination of input features to calculate the output. $\overset{1}{h}_{t-1}$ represented the hidden state of the previous time step, which was a part of the model's internal memory used to capture temporal dependencies in the time series. P might represent additional input features or contextual information for the current time step. This feature might be related to the current state of the time series and used by the model to generate more accurate outputs.

Dataset resources

The database content used Maersk Line's transportation chain as a reference. The dataset covered real-time monitoring data of various fruits during cold chain logistics transportation including temperature, humidity, gas concentration such as oxygen and carbon dioxide, and fruit quality indicators such as hardness, sugar content, acidity, *etc*. The data came from multiple transportation vehicles and warehouses of cold chain logistics company, ensuring the diversity and representativeness of the data.

Results and discussion

Temperature prediction

The performance of big data theory in extracting and predicting the temperature and quality of fruit cold chain transportation showed that the fluctuation range of fruit temperature quality was relatively large for different data samples, which might be due to the relatively large temperature range during transportation and required further precise temperature control. MPCNN and LSTM methods could accurately extract and predict temperature trends and data values during the cold chain transportation of fruits. The actual temperature values and predicted temperature values had a high degree of consistency, indicating that it was a more reliable method for fruit cold chain transport vehicles and could guide them to precise temperature control (Figure 3).

Prediction of humidity characteristics

The integration and analysis technology of big

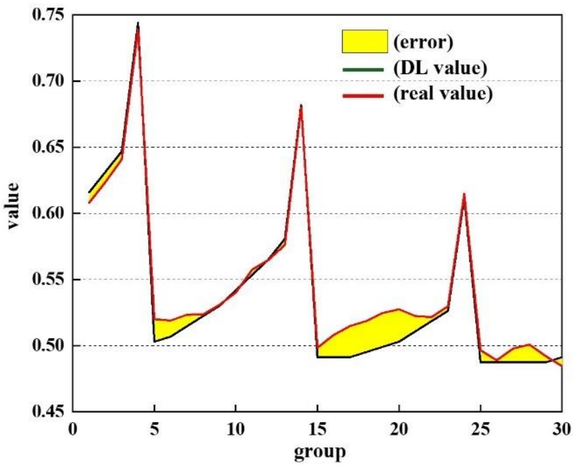

Figure 3. Characteristics of temperature and quality in the process of fruit cold chain logistics transportation.

data can capture multi-dimensional, gas concentration, and other transportation environments in real time, which is the key to understanding changes in fruit moisture. Through in-depth mining of these data, the inherent relationship and dynamic changes between water quality characteristics and transportation conditions can be revealed, providing scientific basis for precise control of fruit moisture content. In this study, error scatter plots were applied for detailed analysis of humidity characteristics during fruit cold chain transportation, which displayed the deviation distribution between the predicted and actual values of the model and revealed the variation patterns of prediction accuracy under different conditions. The error distribution of humidity characteristics demonstrated the high performance of the MPCNN-LSTM hybrid model in extracting and predicting humidity characteristics (Figure 4). The results not only validated the effectiveness of the model, but also further demonstrated the enormous potential of combining big data theory with deep learning techniques. It was worth noting that the MPCNN-LSTM hybrid model performed well in extracting humidity features due to its unique network structure and algorithm design. MPCNN could fully capture spatial features in data through multi-path parallel processing. The combination of the two preserved the spatial information in the data while considering the influence of time factors, thus achieving accurate prediction of humidity characteristics. Most humidity errors were distributed within 2% with only one set of humidity characteristics having an error exceeding 2%, but with Its value of only 2.24%. Some fruits also had humidity characteristics with an error of less than 1%. Through the distribution of humidity prediction errors, it suggested that the big data method designed in this study could accurately predict the humidity quality of fruit cold chain transportation, providing more accurate control data for electromagnetic vibration energy devices.

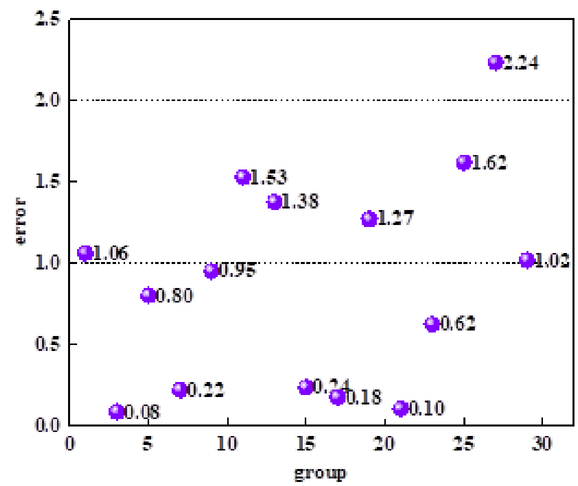

Figure 4. Humidity quality characteristic error in the process of fruit cold chain logistics transportation.

Prediction of gas characteristics

Gas is a more suitable evaluation indicator in the cold chain logistics transportation of fruits. Different fruits release different gases and have different gas range data values. By monitoring the gas quality of fruits, the quality status of different fruits can be understood more accurately. Since temperature can only measure the average temperature of all fruits, gas is a more specific quality monitoring indicator. The results showed that, although the gas quality characteristics of fruits had different peaks and fluctuations, the MPCNN-LSTM method could accurately grasp the gas quality characteristics

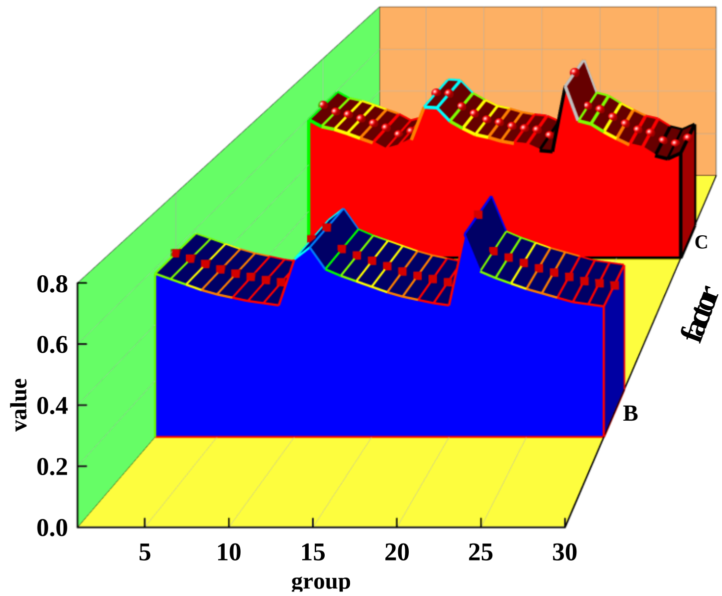

Figure 5. Trend of gas quality characteristics in the process of fruit cold chain logistics transportation. **Note:** "group" referred to the grouping of different types of fruits or the same fruit under different conditions. The numbers on the X-axis were the number of sampling points or time series.

emitted by different fruits, which could more effectively predict the changes and data values of fruit emission gas characteristic values (Figure 5). The results fully demonstrated that the big data theory designed in this study could provide more accurate gas characteristic data for wireless sensors and electromagnetic vibration energy devices, which was beneficial for the effective operation of electromagnetic vibration energy devices. The results showed that, although the gas quality characteristics of fruits in different groups exhibited different peaks and fluctuations, the MPCNN-LSTM method could still accurately capture and predict the changing trends and data values of these characteristics. To verify the superiority of the proposed method, MPCNN-LSTM was compared with traditional gas quality prediction methods. The traditional methods were usually based on simple statistical models or empirical formulas, which were difficult to accurately capture the nonlinear changes and complex trends of gas quality characteristics. In contrast, the MPCNN-LSTM method with its powerful feature extraction and prediction capabilities could more effectively predict changes in the characteristic values of fruit emission gases, providing more accurate data support.

Prediction through different fruit types

Considering that different types of fruits exhibit different temperature and humidity characteristics during cold chain transportation, which means that they each have specific temperature and moisture ranges, this variability places higher demands on the model's generalization ability and adaptability. Therefore, this study also aimed to explore the universal applicability of the model to different fruit types. The results indicated that the linear correlation coefficient distribution between the predicted fruit temperature and humidity using the MPCNN-LSTM method and the actual monitoring data showed a high linear correlation coefficient for any type of fruit with the linear correlation of fruit temperature characteristics higher than that of humidity quality characteristics (Figure 6). The results showed that linear correlation coefficient of fruit temperature characteristics reached 0.9887, while the correlation coefficient of humidity quality characteristics was 0.9876. Overall, the linear correlation coefficient of fruit temperature and humidity quality characteristics exceeded 0.95. The results suggested that big data methods had certain feasibility with the evidence that the correlation coefficients between temperature and humidity quality were both greater than 0.98, which further demonstrated that the MPCNN-LSTM method could provide more accurate data for wireless sensors and electromagnetic vibration energy devices.

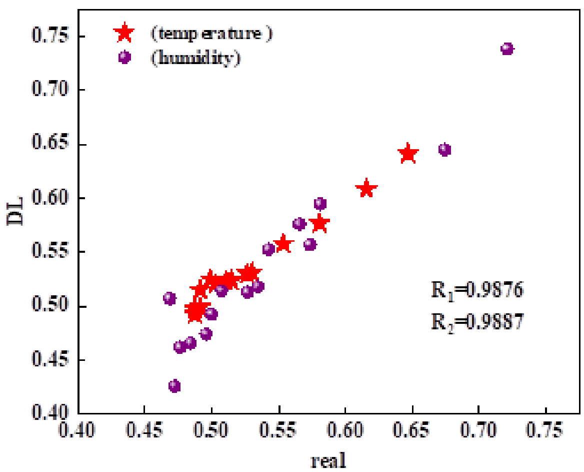

Figure 6. Linear correlation coefficient distribution for temperature and humidity characteristics.

Global error distribution

This study used different statistical parameters to analyze the performance of the proposed MPCNN-LSTM method under different temperature, humidity, and gas quality characteristics. The MPCNN part automatically extracted multi-level and multi-dimensional feature information from raw data through its multi-layer convolutional structure. These features not only cover direct readings of temperature and humidity, but also may include complex patterns derived from these basic data such as temperature fluctuation trends, humidity change rates, *etc*. This refined feature extraction provided richer and more comprehensive input data for subsequent prediction models. The MPCNN-LSTM method demonstrated a low average error in predicting the quality characteristics of fruit cold chain transportation with a maximum error of only 2.19% for gas characteristics, which not only verified the effectiveness of the method, but also demonstrated its high accuracy in practical applications. Gas characteristics are a more complex mass characteristic, which is a mixture of various gas characteristics. This error is reliable enough for quality monitoring of fruit transportation. The relative evaluation and prediction errors of temperature and humidity in cold chain transportation of fruits were 1.88% and 1.96%, respectively (Figure 7). From the perspective of global predictive performance, the MPCNN-LSTM method could provide more accurate data support for wireless sensors and electromagnetic vibration energy devices.

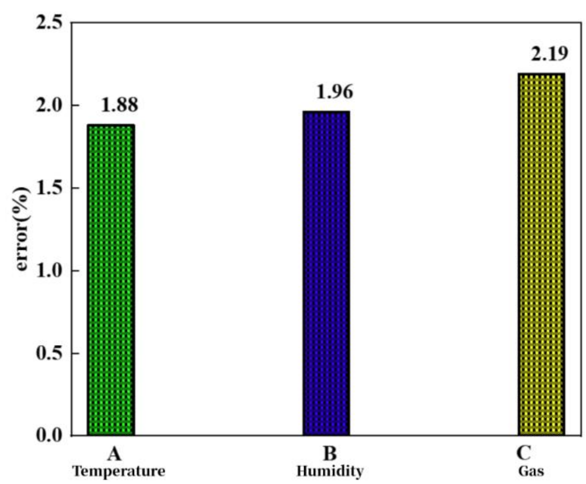

Figure 7. Prediction global error distribution of three qualities of fruit cold chain logistics.

Prediction errors

The results showed that the proposed method could monitor the quality indicators of fruits in real-time during cold chain transportation, improving the timeliness and accuracy of data. By utilizing big data theory to analyze monitoring data, potential quality issues and trends could be identified, providing scientific basis for decision-making. The prediction results based on MPCNN and LSTM methods could guide transport vehicles to perform precise temperature control, thereby improving the transportation quality and preservation effect of fruits. For the three characteristics of fruit quality, the largest prediction error was only 2.19%, while the errors in extracting the temperature and humidity quality features of fruits were only 1.88% and 1.96%, respectively. The results confirmed that this big data theory could provide more accurate data support for the work of wireless sensors and electromagnetic vibration energy devices. The proposed MPCNN-LSTM method could accurately extract the temperature, humidity, and gas change trends and related characteristic values during the transportation of fruit cold chain logistics.

Conclusion

This study proposed and implemented an electromagnetic vibration energy modeling method for fruit cold chain logistics quality perception based on wireless sensor networks. An intelligent fruit cold chain logistics quality monitoring system was developed by integrating big data theory, wireless sensor technology, and electromagnetic vibration energy devices. The proposed system was capable of real-time monitoring and extracting three key quality characteristics of fruits including temperature, humidity, and gas, providing strong data support for quality control during fruit cold chain transportation. The research used the advantages of MPCNN to effectively capture feature information of different scales and levels in fruit images through its multi-path architecture. This feature enabled the system to accurately determine the maturity of fruits, providing an important visual feature basis for quality evaluation in fruit cold chain logistics. The results showed that the system could maintain high prediction accuracy, especially in predicting fruit temperature and humidity with linear correlation coefficients exceeding 0.98, which fully verified the feasibility and effectiveness of the proposed method. Compared with traditional monitoring methods, the proposed method not only improved the accuracy and efficiency of monitoring, but also greatly reduced the time and material costs of operators, providing strong technical support for the sustainable development of fruit cold chain transportation.

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