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Evaluation on Frozen Shellfish Quality by Blockchain Based Multi-Sensors Monitoring and SVM Algorithm During Cold Storage

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ABSTRACT IoT-enable monitoring can provide valuable information for the shellfish quality evaluation during cold storage condition. However, IoT based information storage relies on the centralized platform, it is possible to tamper. In this paper, we establish blockchain based multi-sensors (WSN) monitoring system to collect quality parameters and verify captured information for improving transparency and trust during cold storage. The implementation of the K-means and SVM algorithms were used in quality evaluation applications to classify and predict the quality loss of frozen shellfish. The results show blockchain based WSN monitoring can achieve the dynamic indicators continuous monitoring and ensures the data security and reliability. The proportion of the training set and the test set in the allowable deviation range is 88.89% and 87.17%. The root mean square error (RMSE) of training set and test set are 0.1502 and 0.1793 by SVM model. The performance of the K-means and SVM model has higher accuracy than BP model. This paper could help to reduce the risk of food losses and improve quality and safety management of frozen shellfish during cold storage.

INDEX TERMS Blockchain, cold storage, frozen shellfish, K-means and SVM, IoT.

I. INTRODUCTION

Shellfish products is rich in nutritional value which is popular seafood throughout the world for market consumption. With the demands of convenience and healthiness, the sales quality of shellfish products is rapidly increasing [1], [2]. However, shellfish products are vulnerable and highly perishable, and their quality deterioration usually occurs within a short period of time. The storage life of shellfish is restricted by various factors, such as different storage conditions, production handling and species which affect the freshness loss and deterioration pattern of shellfish products. The main issue was a high rate of ambient dynamic changes during cold storage [3], [4].

Currently, the quality and safety issues of shellfish products have drawn the considerable attention, which have also brought great challenges for quality and safety control in seafood industry [5], [6]. Many countries are making efforts to improve the quality and safety of perishable products. Therefore, it has great importance value for the quality dynamic monitoring and prediction of shellfish products to ensure quality meets consumers' requirements.

Cold storage is used to be an effective strategy to maintain the freshness and safety from production to consumption [7], [8]. In order to ensure delivery of safe, fresh, high-quality products to customers, strict time and storage ambient condition (temperature, relative humidity and gases.) control are special requirements which must be incorporated during cold chain logistic. Among them, temperature control has always been the highest essential issue that affects the food deterioration and shelf life [9], [10]. Therefore, ambient parameters monitoring and control along cold food supply chains (FSCs) are very essential for maintaining the optimum temperature and relative humidity for freshness during warehouse storage, distribution, cold chain transportation and sales display.

Wireless sensor network (WSN) technology has a significant impact on the way cold chain management operated. It is low-cost, low-power and high-resolution cold chain monitoring measures for enabling real time ambient data along the supply chain [11]–[14]. Data acquisition is the key

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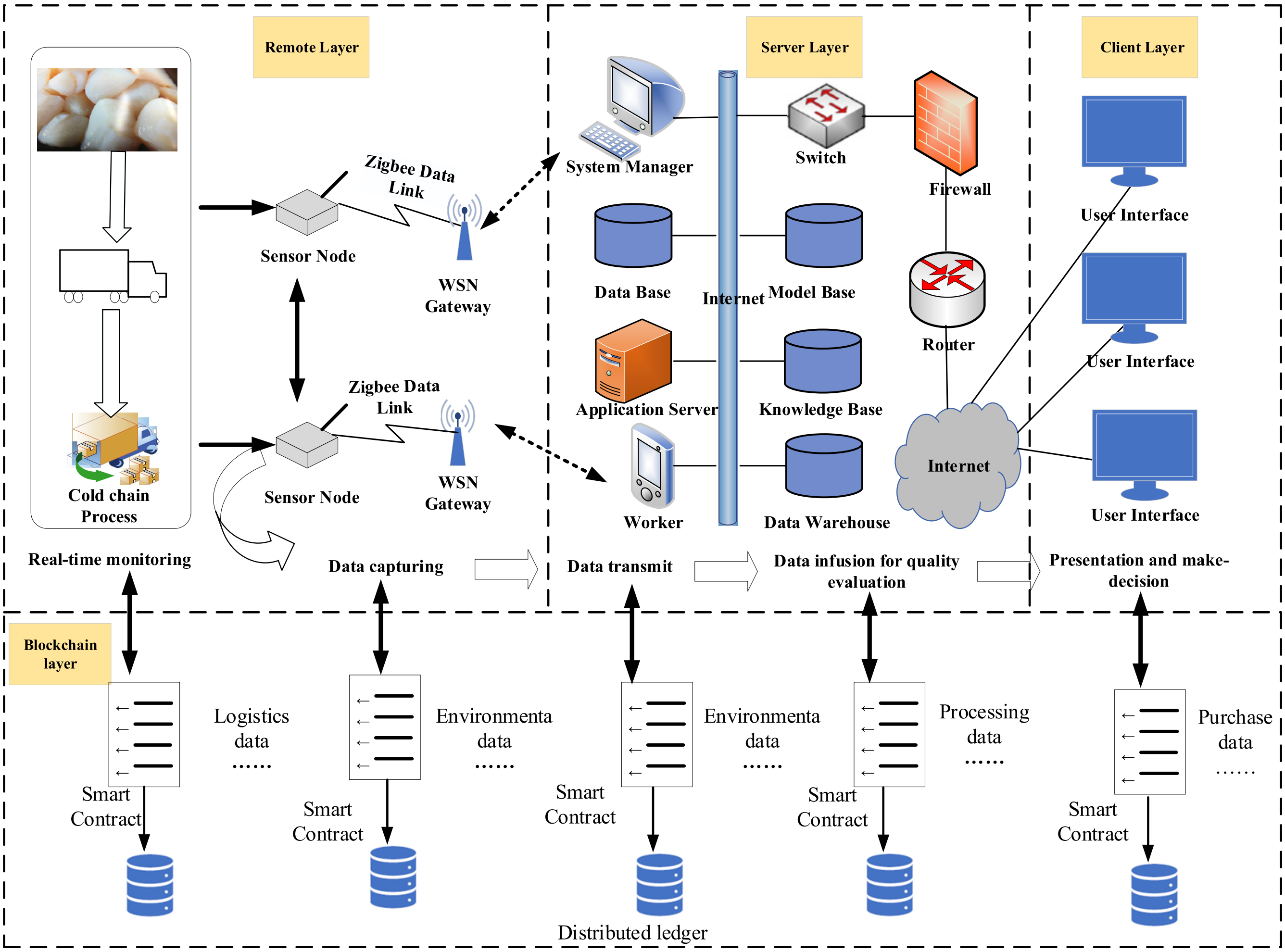

FIGURE 1. Architecture of blockchain based multi-sensors monitoring system.

to quality evaluation and prediction. The implementation of WSN is used to record specific history data (such as temperature, humidity, location and gas content), thus providing an unbroken information chain. it can help to improve cold chain logistic management and decision-making strategies of quality control, such as through First-Expired-First-Out inventory management, dynamic expiry dates and dynamic pricing systems [4], [15]. However, the information is stored in a heavily-centralized cloud infrastructures. This means its databases are also at greater risk of attack and not be able to ensure the information record from maliciously modified. Blockchain is regarded as a promising and tremendous potential technology to build trust for preventing data to be tampered [16]. Therefore, we establish blockchain based WSN monitoring system to collect ambient parameters (temperature, humidity, gas etc.) during cold storage and improve transparency and safety.

After data acquisition has been completed, a model can be created to evaluate and predict the class or the value of perishable products quality (freshness, shelf life, weigh loss) for any future samples. Therefore, statistical and artificial intelligence algorithms are significant sensed data processing approaches as they are able to build and predict appropriate models for the evaluation and prediction of quality. Multiple Linear Regression (MLR), Genetic algorithm (GA), SVM, PCA, K-means, neural networks and decision tree algorithm have been widely applied to classify and predict in many quality assessment applications of perishable products [17]–[19].

The objective of this study was to establish blockchain based WSN monitoring system to capture ambient parameters (temperature, humidity, gas etc.) during cold storage and improve transparency. The acquired sensor data will serve as input sets for quality evaluation and prediction. The K-means and SVM algorithms were implement to frozen shellfish quality attributes applications. The results can help to enable dynamic quality prediction and increase cold storage management trust.

II. MATERIALS AND METHODS

A. SYSTEM DESIGN AMD IMPLEMENTATION

1) ARCHITECTURE DESIGN OF BLOCKCHAIN BASED MULTI-SENSORS MONITORING SYSTEM

The blockchain based multi-sensors (WSN) monitoring system adopts a four-layer architecture. Fig.1 shows a 4-layer

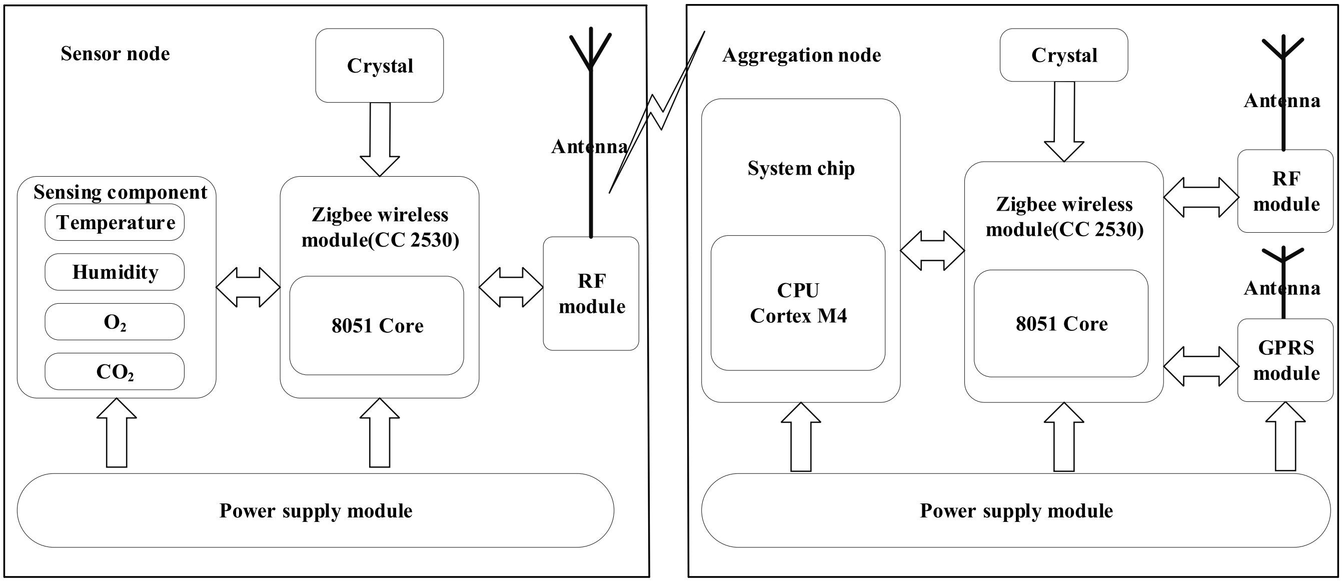

FIGURE 2. Architecture of WSN node.

computing architecture in blockchain based WSN quality and safety monitoring system for frozen shellfish products.

- The Remote Layer: includes sensor nodes specially designed for application, which is responsible for receiving data at the remote terminal.

ZigBee is used in the wireless sensor networks design. The remote node which is a ZigBee wireless temperature sensor node is deployed at the transport vehicles or cold storage to sense the real-time temperature data and then send them to the network coordinator during cold chain logistics. The network coordinator would process data and send them to the remote center via the GPRS. Zigbee is considered as the most suitable solution for wireless sensor networks because of its low power consumption and simple networking configuration [13], [20]–[22]. Zigbee adds network, security and application software according to the IEEE 802.15.4 standard. The data are encapsulated in packets which are transmitted in the form of multi-hop via a self-organized and self-configured Zigbee network to the WSN gateway. The gateway collects data from the nodes in packets and sends them to a database server via the internet [23]–[25].

- The Server Layer: is mainly responsible for sensor data reception/storing, which is the pipeline connecting the users and wireless sensor nodes.

The server layer provides an integrated and reliable data access services. In the WSN-based monitoring system, the server layer consists in a database server, an application server, the switches, the routers and the firewalls. A PostgreSQL service is running on the database server. All data include the temperature, position, vehicle and driver information are uploaded from the WSN gateway [26], [27]. The application server reads data in the database server and uses them to predict the quality of frozen shellfish products.

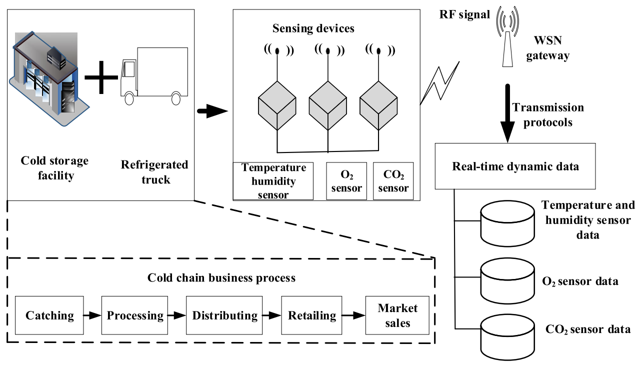

FIGURE 3. The process of multi-sensors real-time data capturing.

All data are treated as input of business logic in the monitoring system and the feedback of automatic control system from both transport vehicles and Internet.

- The blockchain Layer: this layer aims to facilitate data transparency and improve security of frozen shellfish products. With the quality data, smart contracts can implement real-time quality monitoring and control in blockchains. With the logistics data, smart contracts are able to plan logistics automatically [28], [29]. It is also able to provide the consumers with a way to indelibly record a list of transactions indicating how products have flowed through a commercial network, from producers to processors to distributors to grocers.
- The Client Layer: is mainly responsible for providing an operation interface for users. This layer providers users with visualization environment and graphical user interface(GUI), which is convenient for end-user to manage and use data. The real-time information can be provided to users, and the system managers can easily use friendly operation and configuration interface.

2) WSN NODES DESIGN AND IMPLEMENTMENT

The design of WSN for real-time quality and safety monitor includes the sensor nodes, the aggregation node, the architecture and the prototype of the WSN is demonstrated in Fig.2.

The sensor nodes are equipped with temperature, humidity, O2, CO2 sensing components, each node is an independent operating EndDevice. It is deployed at the shellfish products container or cold storage for capturing real-time dynamic ambient data. The captured data was transmitted through the Zigbee CC2530, which is composed of the 8051 microprocessor and IEEE 802.15.4 standard RF module for running ZigBee protocol and control sensor [30].

The aggregation node consists of the ARM Cortex-M4 central processor, the network coordinator and the GPRS module. The coordinator is responsible for launching and coordinating the WSN network and processing returned data from all sensor nodes [12]. The process of WSN real-time data capturing is shown in Fig.3. The obtained sensor data can unload into the blockchain, which can be automated through smart contracts. Furthermore, data records cannot be tampered with and deleted.

ARM Cortex-M4 central processor is adopted as the hardware architecture of the embedded system, which is used to communicate with the CC2530, the GPRS module using UART protocol. The router aims to relay the sensor data from parental nodes to the next node. The Router and Coordinator are powered by regular 3.6V power for the operation of the sensor nodes, it can be connected to the power supply system of the transportation vehicle or the active power supply from the warehouse.

3) SOFTWARE DESIGN AND IMPLEMENTATION

The software for the WSN-based monitoring system is composed of the user application interface software, the business data processing software and the database management software, as shown in Fig.4. It is responsible for preserving and maintaining the received sensor data, visualization diagram analysis of system data and shelf-life prediction for the frozen products during the cold chain logistics.

- User application interface for PC and mobile phone is responsible for displaying the ambient information from all sensor nodes to the end-users. They can view the dynamic fluctuation diagram of real-time temperature data and model processing results in the cold chain logistics.
- Business data processing is the key to the WSN- based monitoring system. It is mainly responsible for realizing real-time sensor monitor, data transmission processing, data visualization diagram analysis and shelf-life prediction. The real-time temperature data is exchanged between the sensor monitor module and data management within the system components. Data operating would reorganize sampled data and present the shellfish products shelf-life information based on the model and knowledge of WSN-based monitoring system, then send the results to the user application interface for visual display.

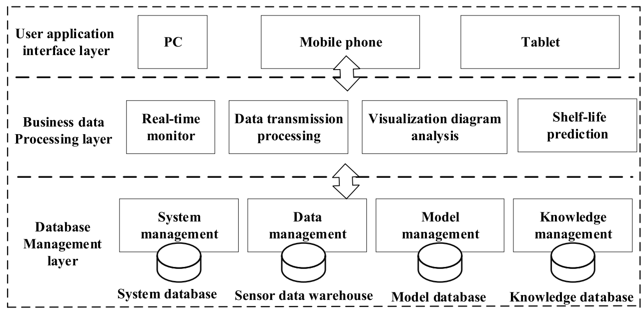

FIGURE 4. Software architecture of WSN-based monitoring system.

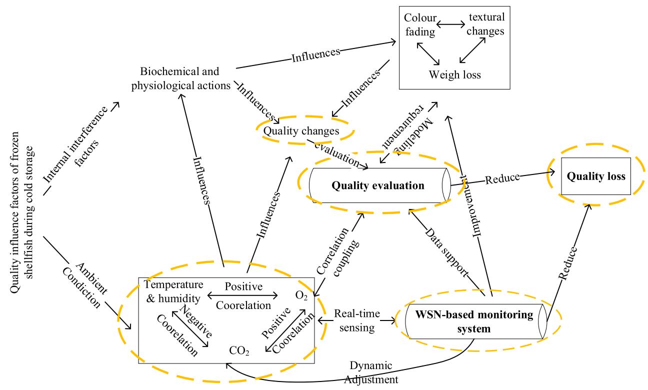

FIGURE 5. Quality critical parameters analysis and evaluation framework.

- Database management is composed of 4 independent databases, which communicate with each other and are driven by driven by related database of business data processing.

The overall system is integrated by the C# application in Microsoft Visual Studio 2013. The database is designed with MS SQL Server2008. All the real-time ambient parameters data from different WSN monitoring locations will be sent back by a relay of sensor nodes and collected by the system. Then the Data processing component will be integrated with the returned WSN data and dynamically display change diagram and quality evaluation results. The overall quality status of frozen products can thus be easily visualization presentation.

B. QUALITY CRITICAL PARAMETERS AND EVALUATION METHODS

1) QUALITY CRITICAL INDICATORS ANALYSIS AND EVALUATION FRAMEWORK

Quality critical indicators analysis and digital evaluation are very important strategy for improve quality of frozen shellfish during cold storage. The quality critical parameters analysis and evaluation framework is shown in Fig.5.

Preservation of quality of food products is affected by many complex factors, these main include internal interference factors and ambient conditions. Therefore, an efficient quality monitoring and evaluation has become great requirement to reduce quality loss. According to the principles of HACCP, quality critical indicators including storage ambient conditions (temperature, humidity, O2 and CO2) weight loss are most requirement during cold storage. The temperature, humidity, oxygen and carbon dioxide concentration are easy to fluctuate ambient parameters that affect the quality attributes, especially temperature. It should be uninterrupted-temperature controlled at −18°C in refrigerating cabinet and refrigerated truck during cold storage.

However, real-time ambient parameters monitoring and control system are the most critical points for ensuring the quality and safety of frozen shellfish products. It should be maintained an appropriate and stable storage condition. The pathogenic bacteria may be contaminated or reproduced due to improper control of time and temperature. Therefore, the management of critical points might be improved by applying the real-time monitoring system and quality evaluation modelling. Quality loss may be reduced with a better ambient parameters control, and finally ensure the quality and safety of frozen shellfish during cold storage.

2) WEIGHT LOSS

Weight loss is one of the physical properties of food that affects the texture and sensory properties of frozen shellfish products. Weight loss (%) was determined by calculating difference of shellfish weight before and after storage, as follows:

$$\text{Quality loss}(\%) = \frac{W_b - W_a}{W_b} \times 100\%$$

where, W_b represents the sample weight before storage, W_a represents the sample weight after storage.

3) PREDICTION MODEL FOR QUALITY INDICATOR UNDER COLD STORAGE BY KNN AND SVM

In this section, we adopted K-means clustering and support vector machine (SVM) algorithms to predict quality indicator during cold storage periods for frozen shellfish products. They are useful in decision-making and classification situations [31]–[33]. The flow chart of algorithms is shown in Fig.6.

K-means clustering is a simple and effective method for classification according to the closest training examples in the feature space [34], [35]. K-means algorithm is for unsupervised pre-clustering problems. It is a prototype-based, partitioned dynamic clustering method that evaluates the similarity by calculating the Euclidean distance between the sample and initial center. The sample will be sorted into the corresponding cluster based on thresholds.

SVM is a supervised learning algorithm for solving classification and regression prediction problems based on statistical learning theory [36], [37]. The main task is finding the smallest subset data for prediction, identifying outliers and derivations in sample space.

C. THE EXPERIMENTAL SAMPLE

Frozen shellfish samples were directly obtained from the local supermarket (Box horse fresh, Beijing, China). The frozen shellfish was kept in cardboard packaging with

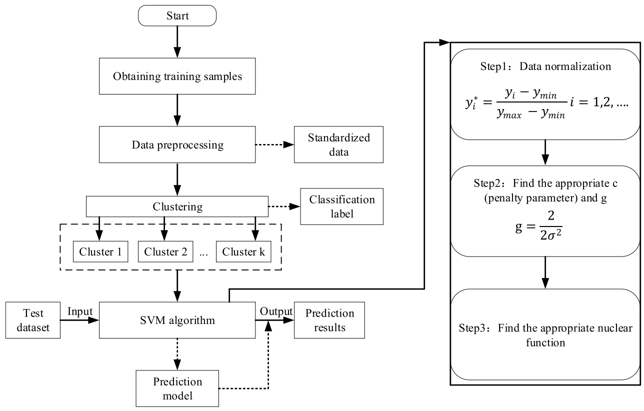

FIGURE 6. Flow chart of K-means and SVM algorithm.

HDPE film with the average net weight of 200g. The samples were transported during refrigeration to the laboratory within 40 mins. They were placed in a foam box of 30 cm×20 cm×15 cm. Then they were kept during cold storage at −18° ± 2 °C for 15 days.

The sensor is symmetrically placed at the center of the foam box. The sensor integrated temperature and humidity parameters, O_2 and CO_2 gas content were performed in real time. After 15 days, the samples were taken out from the foam box and weigh.

D. STATISTICAL ANALYSIS

The data were analyzed by One-Way ANOVA processing using SPSS 21.0 (SPSS Inc., Chicago, IL, USA). The differences at p-values ($p < 0.05$) were considered significant. The Clustering Algorithm (K-means) and the Support Vector Machines Algorithm (SVM) were conducted by MATLAB environment.

The optimal model was evaluated with the least root mean square error (RMSE) and mean relative errors (MRE) between observed and predicted.

The root mean square error (RMSE) is used to evaluate the accuracy for a given value, it represents the extent to which the measured data deviates from the actual value, as follows:

$$\text{RMSE} = \frac{\sum_{i=1}^{n} (Y_{predict,i} - Y_{obs,i})^2}{n}$$

$$\text{MRE} = \frac{\sum_{i=1}^{n} \left| \frac{Y_{predict,i} - Y_{obs,i}}{Y_{obs,i}} \right|}{n}$$

where, RMSE is the mean squared error calculated for a given ambient sensor data, MRE is the mean relative errors calculated for a given ambient sensor data. $Y_{obs,i}$ is the observed value, $Y_{predict,i}$ is the predicted value.

III. RESULTS AND DISCUSSION

A. AMBIENT INDICATORS DYNAMIC CHANGES ANALYSIS

1) CHANGES OF TEMPERATURE AND HUMIDITY DURING COLD STORAGE

Frozen shellfish products have strict temperature requirements during cold storage, which of great value for

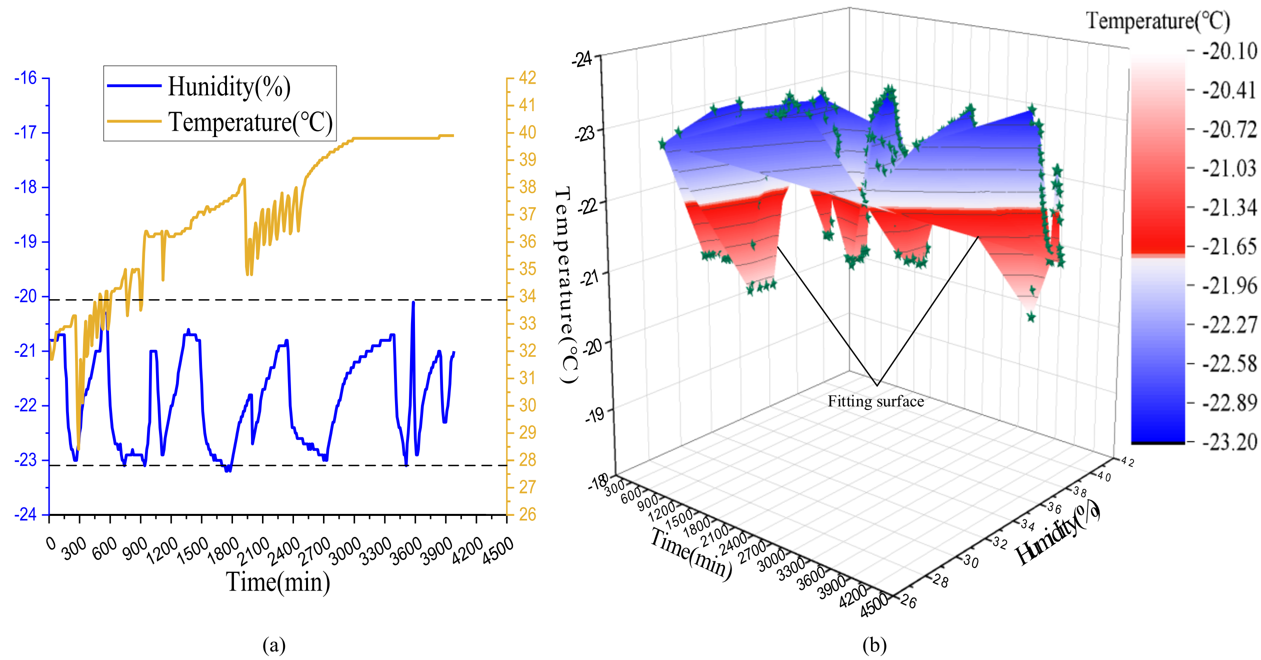

FIGURE 7. **(a) Temperature-humidity changes profile. (b) Temperature-humidity fit curve.**

monitoring and evaluating quality changes. Ambient temperature changes could influence the relative humidity. A real scenario was studied in a 15-day cold storage time. Through WSN based monitoring of temperature and humidity changes along with the time of frozen shellfish that is shown in Figure 7a and 7b.

The temperature changes wildly, ranged from about −23.2 C to −20.1 (minus −18°C). the temperature profile showed an amplitude of temperature values of less than 3 °C. Temperature changes is affected by multi-dimensional factors, such as the space, position change, and external ambient temperature change, etc. The humidity curve is basically rising during cold storage. In the beginning, humidity changes slowly, next has a small drop, then rise to 40.2%. This is mainly due to the influence of the ambient temperature changes from the frozen shellfish products. Maintaining the stable temperature range is an effective way to reduce weight loss.

2) CHANGES OF O_2 AND CO_2 DURING COLD STORAGE

O2 and CO2 also affect the freshness of frozen shellfish products during cold storage. Changes in ambient gas (O2 and CO2) is shown in figure 8. The concentration of gas (O2 and CO2) increases over time during cold storage. At the beginning of the cold storage, the concentration of CO2 was 178.13 ppm and the concentration of O2 was 20.87%. Then rose sharply. The accumulation concentration of CO2 was 6965.62 ppm. The concentration of O2 was 32.37%. The changes of gas concentration is affected by cold storage time, temperature, humidity and the inner factors of frozen shellfish.

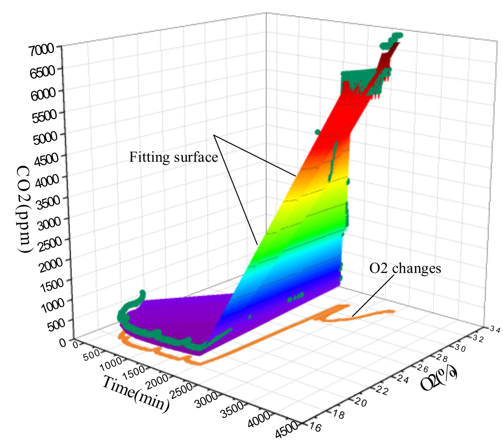

FIGURE 8. **Changes of gas concentration during cold storage for frozen shellfish.**

B. WEIGHT LOSS EVALUATION

The weight loss of frozen shellfish samples during storage at minus −18°C is shown in Fig. 9. Generally, the weight loss should be less than 5% during the cold storage for frozen shellfish products. The weight of frozen shellfish varies with temperature changes. In this work, the values of weight loss showed no significant differences throughout cold storage period. The weight loss value changes very small. However, the results showed an upward trend during the whole cold storage period, the samples underwent 0.12 ± 0.04% loss of initial weight, and ending at 0.40 ± 0.07%. Therefore, weight loss is related to product type, temperature and cold storage space. These reduced values should be explained by a well-controlled cold storage temperature.

TABLE 1. Frozen shellfish monitoring characteristic analysis for system evaluation during cold storage.

Content	Evaluation results	Implementation efficiency	Suggestion	System performance
Continuous cold chain micro-ambient monitoring	Monitoring in real time	The higher efficiency of WSN-enabled monitoring system	Improving the data quality	Functional performance
Efficiency of data transmission	Efficiency of monitoring system	Efficient	Improving with low power consumption and battery-free wireless sensing	Functional performance
Processing control	The system can realize the function of the computer-based processing control	Medium speed	Improving with high speed to process data and operate	Functional performance
Blockchain based information storage mechanism	Prevent data tampering	More secure and transparent	Improve blockchain development of consensus algorithm, transaction capacity and data accessibility	Functional performance
Sensors deployment	Sensors are easy to deploy and use	More efficient	Deploying with more simply and easy way	Nonfunctional performance
System stability and scalability	System can run stably and can have well- scalability	Relatively stable	Improve the system operation efficiency	Nonfunctional performance
Cost and size of sensor system	The system cost is out of expectation		Reduce the cost and size of WSN based sensor system	Nonfunctional performance

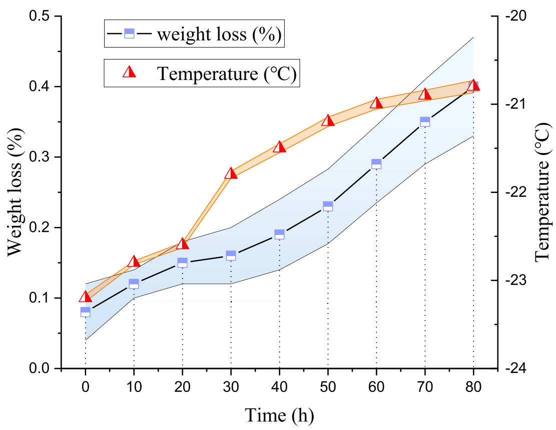

FIGURE 9. Weight loss evaluation during cold storage period for frozen shellfish.

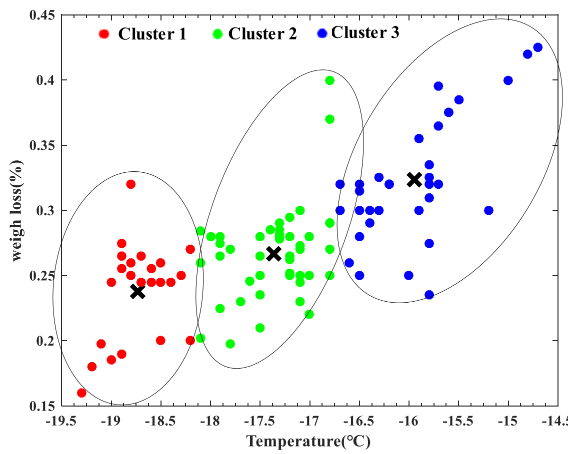

FIGURE 10. Clustering results of sample set.

C. RESULTS AND PERFORMANCE EVOLUTION OF MODEL

The training sample set is clustered by k-means clustering algorithm, 100 sample data were used in our model. Three training subsets were obtained, and the number of samples for each class was 23, 46, 31 respectively. Clustering results of sample set is shown in Fig.10.

The prediction of frozen shellfish's quality loss were performed by using SVR, 70 sample data were used to model training, and 18 sample data were used to verify the reliability of the model. The most important is to find the best parameters for high-accuracy. In this work, we used the grid method to optimize parameters. LibSVM package of MATLAB provides the capability of cross validation. The penalty factor **c** was 132.34 and the **g** was = 0.008215, which were used to predict weigh loss of the test set. The prediction results of training set and test set are shown in Fig. 11 (a) and (b). The mean relative errors (MRE) of training set and test set are shown in Fig. 12 (a) and (b).

As is shown in Fig. 11, the root mean square error (RMSE) of training set and test set are 0.1502 and 0.1793, respectively. The correlation coefficient (R-squared) of the training set and test set are 0.9472 and 0.9385, respectively.

This indicates that a good linear relationship of the quality loss predicted values and measured values. In Fig. 12, the training set maximum of mean relative errors (MRE) is 2%. The test set maximum of mean relative errors (MRE) is 12%. The proportion of the training set and the test set in the allowable deviation range is 88.89% and 87.17%.

In order to verify the accuracy of the prediction model, we compare it with BP neural network, the BP prediction result is shown in Fig. 13. The root mean square error (RMSE) is 0.2716, R-squared is 0.8913. The SVM prediction model has higher accuracy by comparison with the BP model.

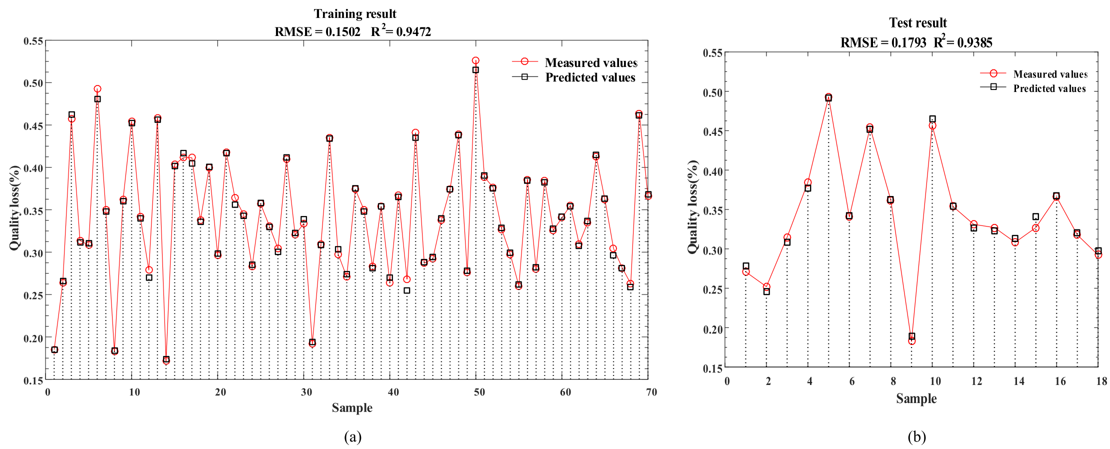

FIGURE 11. (a) The prediction results of training set. (b) The prediction results of test set.

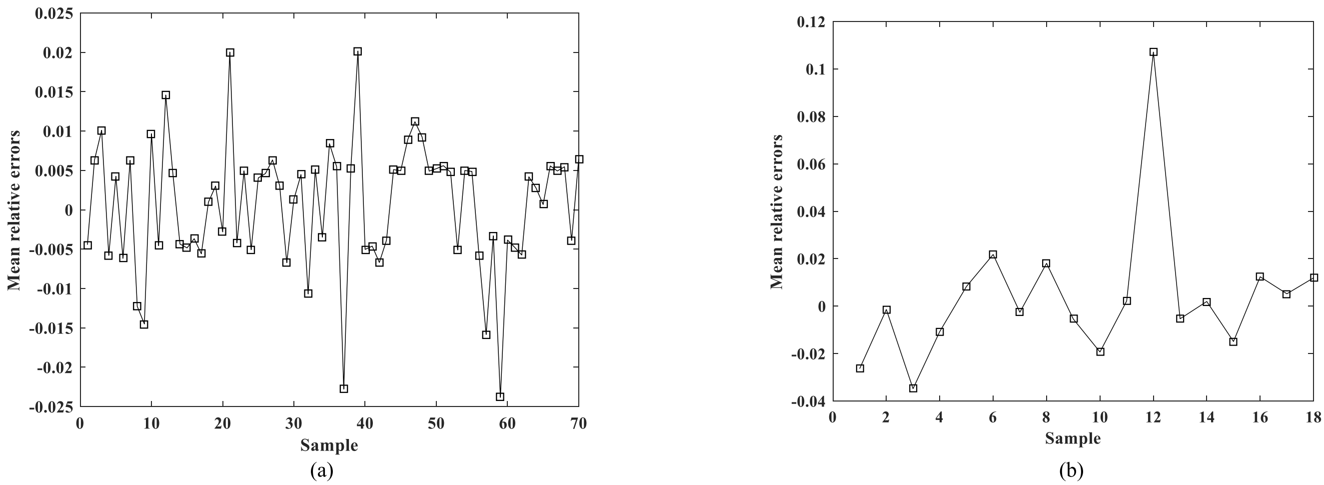

FIGURE 12. (a) Mean relative errors (MRE) of training set. (b) Mean relative errors (MRE) of test set.

Therefore, the results indicate feasibility of sample data and model.

D. SYSTEM EVALUATION

The purpose of the system evaluation is to discuss and measure the system operation performance and to collect the feedback from users. System evaluation provides the optimization and improvements of on real-time data collection, data security, technological capacity and actual performance before and after deploying monitoring system for the frozen shellfish products quality monitoring and evaluation during cold storage.

According to the experiment scenario, system evaluation was undertaken by the managers and workers from the enterprise to discuss how the system should be perfected to help enable effectively dynamic monitoring and control. Table 1 shows the evaluation performance and suggestions for the improvement the monitoring accuracy and efficiency.

IV. CONCLUSION

This paper presented the model and evaluate of blockchain based multi-sensors (WSN) monitoring and algorithm-based quality prediction for frozen shellfish during cold storage. A blockchain based WSN monitoring system was used for capturing actual micro-ambient changes data and preventing data tampering. The implementation of the K-means and SVM algorithms were used in quality evaluation applications to classify and predict the quality loss of frozen shellfish.

The results show blockchain based WSN monitoring can achieve the dynamic indicators continuous monitoring and ensure the data security and reliability. Reliable estimations and prediction of the quality loss could be performed. This could help to improve the information transparency during cold storage.

The implementation of the K-means and SVM algorithms could achieve dynamic quality loss prediction. The root mean square error (RMSE) of training set and test set are

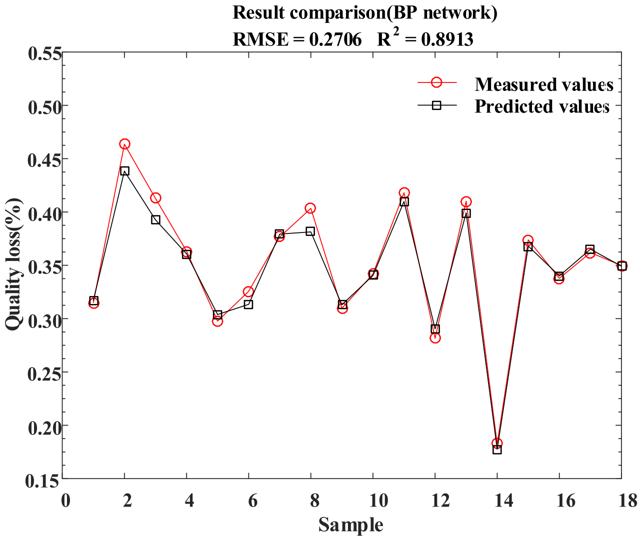

FIGURE 13. Result comparison with BP prediction

0.1502 and 0.1793, respectively. The performance of the K-means and SVM method has higher accuracy than BP model (RMSE is 0.2716). This could reduce the risk of food losses and improve quality and safety management of frozen shellfish during cold storage.

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