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On the Establishment of LSTM-based Predictive Maintenance Platform to Secure The Operational Reliability of ICT/Cold-Chain Unmanned Storage

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Abstract

Recently, due to the expansion of the logistics industry, demand for logistics automation equipment is increasing. The modern logistics industry is a high-tech industry that combines various technologies. In general, as various technologies are grafted, the complexity of the system increases, and the occurrence rate of defects and failures also increases. As such, it is time for a predictive maintenance model specialized for logistics automation equipment. In this paper, in order to secure the operational reliability of the ICT/Cold-Chain Unmanned Storage, a predictive maintenance system was implemented based on the LSTM model. In this paper, a server for data management, such as collection and monitoring, and an analysis server that notifies the monitoring server through data-based failure and defect analysis are separately distinguished. The predictive maintenance platform presented in this paper works by collecting data and receiving data based on RabbitMQ, loading data in an InMemory method using Redis, and managing snapshot data DB in real time. The predictive maintenance platform can contribute to securing reliability by identifying potential failures and defects that may occur in the operation of the ICT/Cold-Chain Unmanned Storage in the future.

Keywords: *ICT/Cold-Chain Unmanned Storage, Predictive Maintenance, Long Short-Term Memory(LSTM), System Reliability*

1. Introduction

Recently, due to the development of enterprise commerce technology, the expansion of the delivery and logistics industry is underway. Therefore, it is time to develop various types of pickup tower-based unmanned delivery storage device technology that reflects logistics trends such as product loss, convenience of goods due to change of mind, prevention of delivery-related crimes, and activation of early morning delivery infrastructure to ensure the safety of fresh food. In addition, the prevention of courier-related crimes is increasing the anxiety of courier customers through the diversification of intelligent crimes disguised as courier drivers using criminal methods such as theft, phishing, and smishing. In addition, the cold chain, a series of value chains that thoroughly maintain temperature/humidity during the process from harvesting raw materials to reaching consumers in the product supply chain, has the characteristic of growing together as trade of fresh

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products and medicines between countries becomes more active. In line with these environmental changes, the unmanned delivery goods storage device control technology is Cold/Frozen Container for delivery, intelligent cold chain logistics environment data sensor, intelligent cold chain product quality prediction platform, low temperature maintenance status measurement for fresh food, and basic information on delivery goods. It is applied as a combination of the management platform for external information and the appearance information, and the development of unmanned delivery goods storage devices is in progress. In this way, ICT/Cold-Chain Unmanned Storage, which are new concept logistics services using convergence/combined technology, are established as key elements to secure economic power in the logistics industry in modern times. ICT/Cold-Chain Unmanned Storage include technology where robots automatically store items on shelves by applying unmanned storage box control technology. All items can be stored within the size of the item that can be stored, and the space can be efficiently allocated and stored according to the height of the item. These product storage features include the function of selecting a shelf loaded with cargo through a rotating and vertical moving transfer robot, receiving the cargo and loading it into the allocated space, and automatically detecting the size and weight of the product for use in loading decision- making. ICT/Cold-Chain Unmanned Storage can monitor the storage status of cargo through a control system, and apply ICT technologies such as Bluetooth, NFC, and QR code to confirm receipt of goods and recipients, and enable delivery of delivery towers without touching the storage box. Automatic loading and unloading of goods is possible through access or remote control using a smartphone app. The storage capacity is 18 ㎡ and can store about 50 boxes of the maximum size. The maximum size of stored items is 0.5m x 0.7m x 0.6m, and the insertion and discharge speed of stored items is 5 to 7 seconds. The number of shelves for storing goods is 200 to 300, and the external size of the ICT/Cold-Chain Unmanned Storage is 3.3m x 3.34m x 6.2m. In addition, the ICT/Cold-Chain Unmanned Storage can be installed both outdoors and indoors, and includes a function to maintain constant temperature/humidity inside, and specific spaces are separated into refrigeration/freezing sections. It can be used to store fresh food, etc. This includes the application of cold chain technology that passes fresh logistics temperature management standards. As such, ICT/Cold-Chain Unmanned Storage that must perform various functions must ensure electrical/mechanical safety and must be developed as a durable unmanned storage platform that satisfies reliability in complex storage environments. Figure 1 below shows a conceptual diagram of ICT/Cold-Chain Unmanned Storage.

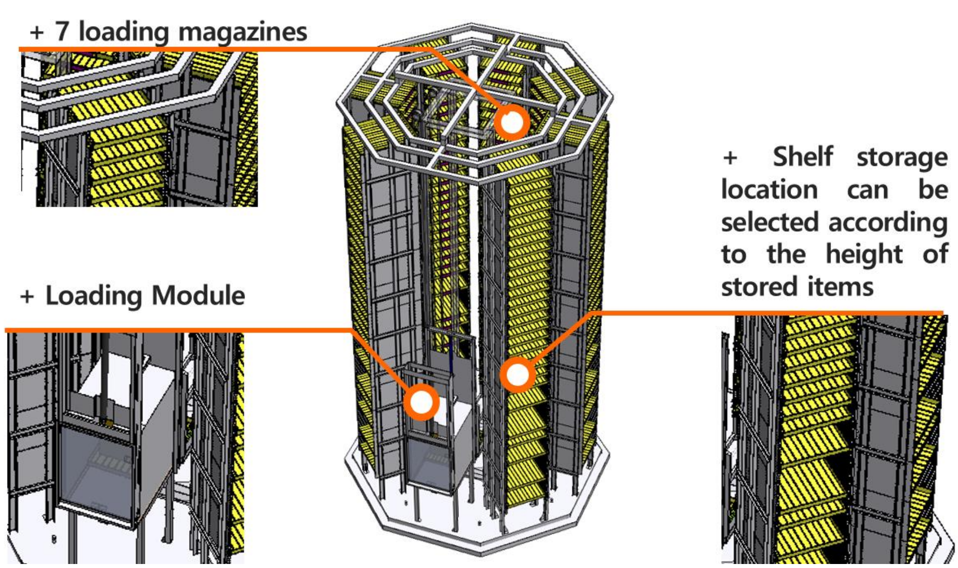

Figure 1 Concept of ICT/Cold-Chain Unmanned Storage

ICT/Cond chain storage is a complex system using convergence/complex technologies. In general, the more complex the system, the higher the probability of failure. In order to reduce the probability of failure, an efficient method of predicting failures and defects is needed. LSTM models can be used as a way to predict potential failures and defects. LSTM is a model that predicts future data by learning existing data based on time series data. Additionally, in order to utilize LSTM, a data platform is needed to collect, analyze, and monitor data in real time. Therefore, this paper selected ICT/Cond chain storage as the research object and conducted it for the purpose of building an LSTM-based predictive maintenance platform as a method to predict potential failures and defects in advance.

2. Related works

The ICT/Cold-Chain Unmanned Storage is a convergence type system in which various technologies are grafted. Therefore, efforts in various fields are required to predict failures and defects. Previously, in the field of reliability analysis research, research was conducted to predict the life cycle of a system or component by using the MTTF (Mean Time To Failure) methodology. Currently, with the development of technology, research is being conducted to graft MTTF or perform artificial intelligence-based predictive maintenance. In this section, predictive maintenance research was analyzed to build a predictive maintenance platform for predicting failures and defects of the ICT/Cold-Chain Unmanned Storage. Hwang has conducted a text analysis study of LNG ship dock repair items for the development of a ship predictive maintenance model [1]. Through text analysis, a result was derived showing that although the devices are included in different parts and operate separately, they can have interrelationships at the same time. [2]. He judged that through the development of MPdM(Maritime Predictive Maintenance), if the technology for performing predictive maintenance based on the judgment of anomalies was implemented, it would contribute to accident prevention and cost reduction by improving ship operation efficiency. Hong conducted a study on the application of predictive maintenance using artificial intelligence and big data based on NASA data repository [3]. He concluded that if Mahalanobis distance and principal component analysis are used, it is possible to detect anomalies before failures as well as detect prognostic symptoms that occur before failures. Cheon studied machine predictive maintenance methods using explainable AI, and presented an explainable XGBoost model, an explainable AI technique, to explain failure risks and failure situations by collecting past failure histories of high-pressure compressors [4]. Lee conducted a study on Youngin rail vehicle parts maintenance data analysis and condition-based predictive maintenance method [5]. He concluded that it is necessary to develop technology and software that automatically determines whether or not a part is defective and predicts its lifespan by analyzing the state information collected through the sensors installed on the target part in order to build a highly reliable CBM system. Lee conducted a study on smart factory predictive maintenance through machine learning-based vibration anomaly signal analysis [6]. He proposed a model for detecting anomalies in rotating equipment and classifying defects using vibration signals collected from vibration sensors attached to rotating equipment. Park conducted a study on the predictive maintenance of 5-axis processing machines for large aircraft parts [7]. He performed real-time monitoring of the current applied to the spindle motor using a CT current sensor. He also presented a method to perform predictive maintenance by judging the abnormal condition of the tool using a machine learning-based abnormality detection algorithm for the collected current signal. Lee conducted a study on artificial intelligence-based anomaly detection and defect classification for gearbox predictive maintenance [8]. He came to the conclusion that it is necessary to study a technique to build a model using small but significant variables by separately extracting specific frequencies (fault frequencies, harmonics, etc.) that represent information on faults for each facility. Kim proposed a model for predicting the remaining useful life of a turbofan engine using k-NN [9]. It was concluded that if only the sensor is attached, it can be generally applied not only to turbofan engines but also to other equipment and devices based on machine learning, and it is possible to understand the causal relationship. In relation to predictive maintenance, Kim conducted a machine learning-based anti-equipment repair parts demand forecasting model [10]. In this study, a data mining-based demand forecasting model was proposed by collecting demand data for repair parts for army anti-aircraft equipment for the past five years and extracting various structured data items including unstructured data such as maintenance details. As such, the field of predictive maintenance is being carried out through various approaches for each industry, such as defense and aviation. In this paper, a predictive maintenance platform was established for the purpose of securing reliability by identifying failures and defects that may occur in the operation of the ICT/Cold-Chain Unmanned Storage.

2.1 Definition of problem

ICT/Cold-Chain Unmanned Storage is a system for a new concept logistics service that applies convergence/combined technologies. In general, as various technologies are combined, the complexity of the system increases and the rate of occurrence of defects and failures also increases. ICT/Cold-Chain Unmanned Storage can be used in various spaces and for various purposes along with the expanding delivery and logistics industry. In other words, if this system is used domestically or even abroad, problems related to maintenance may result. Because existing traditional maintenance activities rely on the experience and judgment of workers, they are highly subjective, and additional costs, such as training new employees, are incurred in passing on the maintenance technology. In addition, it may be unclear whether regular inspection cycles and replacement parts are appropriate, and sudden stoppages due to failures and lack of preparation for adjustment may result in a company-wide impact on business and operations as the failure cannot be identified and the scale of the failure expands. You can. To solve this problem, it is necessary to automate maintenance activities to prevent problems in company-wide operations by collecting and analyzing sufficient data related to failures and defects.

2.2 Procedure of research

This paper was conducted with the goal of establishing a predictive maintenance platform based on failure and defect prediction in order to secure operational reliability of the ICT/Cold-Chain Unmanned Storage. Chapter 1 of this thesis discusses the background of the logistics industry and describes the increase in demand for logistics automation equipment due to the expansion of the logistics industry. In addition, we discussed the background of the ICT/Cold-Chain Unmanned Storage and the core functions and configurations of our system. Chapter 2 discusses the general predictive maintenance model. In general, it was found that predictive maintenance can be classified into machine learning, deep learning, etc., and that NLP(Natural Language Processing) can also be used depending on the utilization. And, the necessity of establishing a predictive maintenance model specialized for logistics automation equipment was discussed. In Chapter 3, we discussed the method and process for building a predictive maintenance model specific to the ICT/Cold-Chain Unmanned Storage. In this paper, the main conveyor motor was selected and the LSTM model was applied. In Chapter 4, a detailed discussion was conducted on the construction of a predictive maintenance platform using LSTM. In Chapter 5, the meaning and expected effects included in this thesis and the future connection were discussed. Figure 2 shows the procedure for building a predictive maintenance platform specialized for ICT/Cold-Chain Unmanned Storage, which is the content of Chapter 3 of this paper.

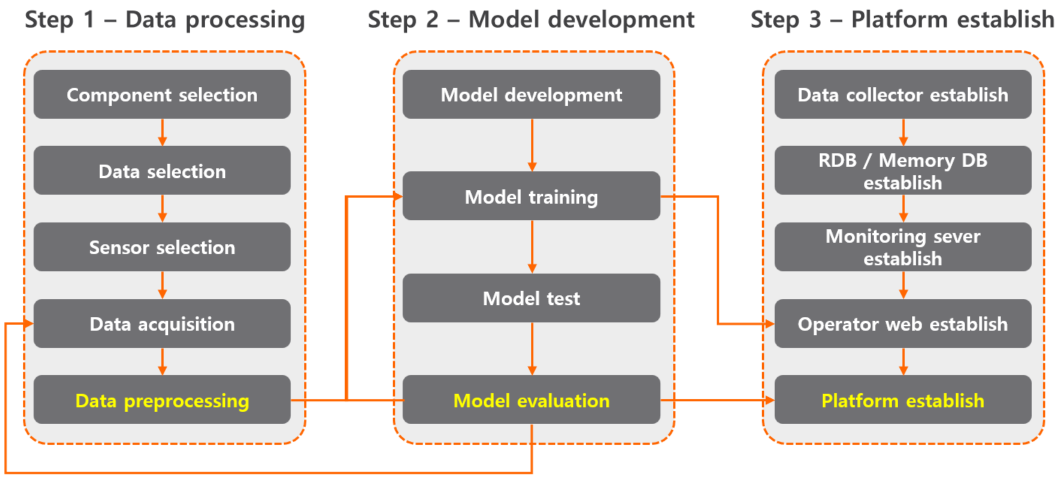

Figure 2. Procedure of predictive maintenance platform

3. Predictive maintenance for ICT/Cold-Chain Unmanned Storage

3.1 Long short-term memory

Existing RNN (Recurrent Neural Network) has a long-term dependence problem in which the depth of the neural network becomes deep when learning long sequence data, causing loss of technology. LSTM is a technique devised to solve these disadvantages of RNN [11]. Chi Nguyen recognized the need to supplement network data speed, latency, and requirements, and used a fusion algorithm combining CNN (Convolutional Neural Network)-LSTM [12]. Xu Gao used the Graph Convolution Network (GCN)-LSTM model with the goal of achieving efficient resource performance of 5G networks [13]. The results showed that the proposed model effectively improves spectrum data throughput. Xianyun Wen has used Attention-incorporated LSTM to effectively calculate the interrelationships between sequence data [14]. This paper concluded that it can be effectively applied to improve the accuracy of data prediction. In this way, LSTM is derived and used as a variety of methodologies in various fields. This paper examines the specificity of data analysis using basic LSTM and plans to apply derived LSTM to compare later. Figure 3 below shows the structure of LSTM. C, t, x, and h in Figure 3 mean the cell state, time step, input value, and output value, respectively, and f, i, and o mean the forget gate, input gate, and output gate, respectively. LSTM solves the long-term dependency problem of RNN through three gates and cell state. Here, the cell state of LSTM plays a role in forwarding information to the next LSTM cell as it is. The formulas for operations performed in LSTM, including these cell state operations, are as follows. Here, W and b in Equations 1, 2, 3, and 4 represent a weight matrix and a bias vector, respectively. Equation 1 means the forgetting gate operation, and plays a role in determining the information to be forgotten among the cell state information received from the previous point. The forget gate receives h_{t-1}, the hidden state at the previous time, and x_t, the input at the current time, as inputs, and takes the sigmoid function and has the value as output. The output of this forgetting gate has a value between 0 and 1 because the sigmoid function is applied. The larger this value, the longer the cell state information is maintained, and the smaller this value, the faster the information disappears. Equation 2 means the input gate operation, and plays a role in determining the information to be used among the cell states at the previous time when it is received. $\tilde{C}_t$ in Equation 4 corresponds to new candidate values to be added to the cell state, and the output of the input gate is multiplied by $\tilde{C}_t$ in Equation 5 to determine the information to be used. Equation 3 means the output gate operation, and plays a role in determining the value to be exported in the updated cell state. Finally, in Equation 5, element-wise-product is performed on the output value of the forget gate and the cell state at the previous time to determine the information to be used in the cell state at the previous time, and the output value of the input gate and the candidate values to be added to the cell state Element-wise-product is performed to determine information to be used among candidate values. Element-wise-product is performed on the value taken by the hyperbolic tangent function on the cell state updated with these two values and the output value of the output gate, and the output value at the current point in time is calculated and transferred to the next point in time. This calculation is performed at each time point, and the result of the calculation performed at the last time point corresponds to the predicted value. In this paper, the LSTM model was used to predict failures and defects of the ICT/Cold-Chain Unmanned Storage.

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \tag{1}$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{2}$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{3}$$

$$\tilde{C}_t = tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \tag{4}$$

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t \tag{5}$$

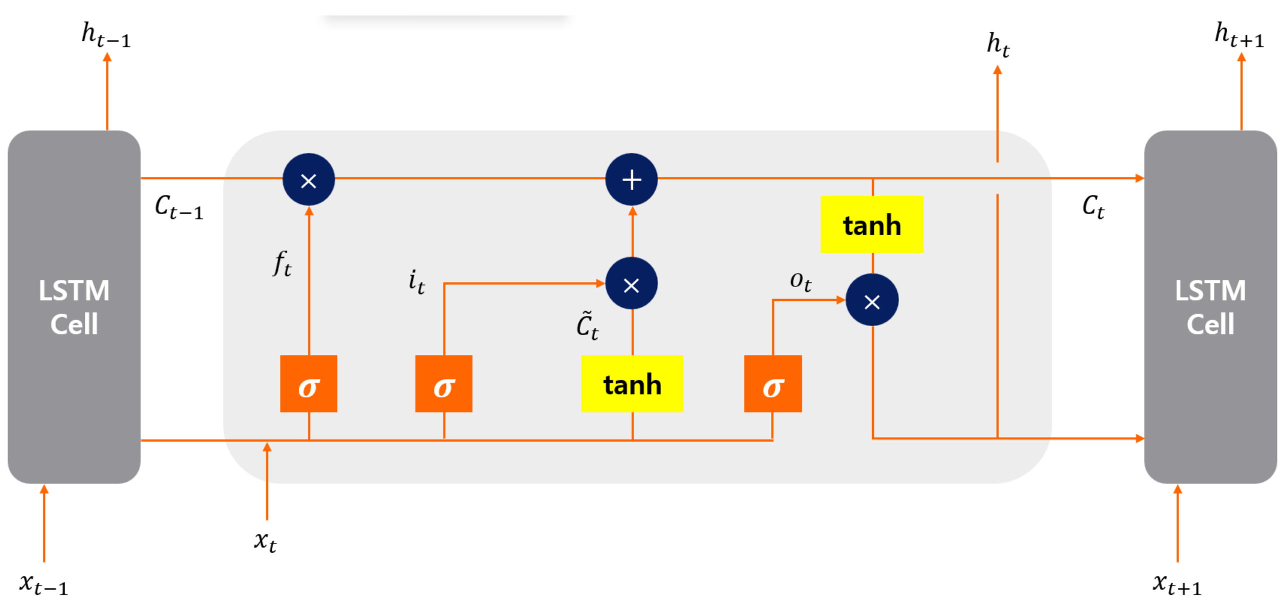

Figure 3. Long short-term memory model

3.2 Predictive maintenance platform

Predictive maintenance can make maintenance of target systems extremely efficient. Breaking away from the conventional method of maintenance as planned regardless of the state of the system, equipment with a high potential for actual failure can be serviced first, and excessive maintenance such as unnecessary replacement of parts can be prevented. First, data collection is the work of collecting data to analyze data or to use in decision making. Data collection also includes the processing and storage of data. In order to collect data, it is necessary to consider the frequency of data to be collected and the form of storage. In order to perform predictive maintenance, it is necessary to collect raw data corresponding to failures and defects. In this paper, 3-axis acceleration and gyro data were collected for the conveyor main motor, which is a key element of the ICT/Cold-Chain Unmanned Storage. Collection In this paper, a server for data management, such as collection and monitoring, and an analysis server that notifies the monitoring server through data-based failure and defect analysis are separately distinguished. First, in order to collect raw data, a data collection element based on the context format in the form of json was used. Context in the form of Json can provide basic information of collected data such as meta data. The collected raw data passes through the data collection element, which is a detailed element of the data collector, and is delivered to RDB(Relational Database) and Memory DB(Database), respectively. A separate java framework was used for the framework delivered to RDB. Memory DB was used for data monitoring and management, such as real-time data collection, and RDB was used for predictive maintenance data analysis, such as failure and defect prediction. Data correlation was performed through the raw data stored in the RDB for predictive maintenance analysis such as breakdowns and defects, and through this, the correlation between each data was reviewed. The raw data collected in real time is transferred to the LSTM model, and time-series-based data analysis is performed according to the specific number and period of analysis. In addition, in order to improve the failure and defect prediction performance of LSTM, a separate correction model was used to correct the LSTM model based on the Bayesian model. Through data analysis delivered to RDB in real time, the analysis server performs the function of notifying the monitoring server in case of failure or defect. Lastly, the monitoring server was configured as a web for operational efficiency. Figure 4 shows a predictive maintenance platform of ICT/Cold-Chain Unmanned Storage.

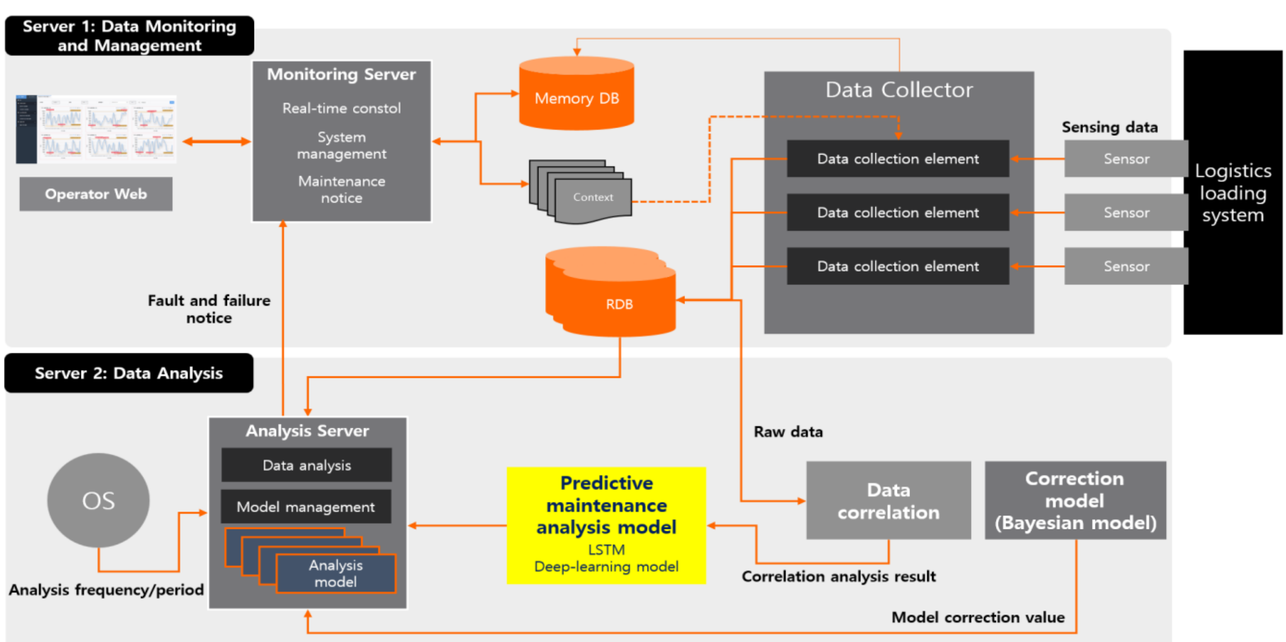

Figure 4. Predictive maintenance platform architecture

In order to implement a predictive maintenance platform, the corresponding functions must be defined. First, functions can be classified into equipment data generation and alarm data generation. Equipment data generation is a function of requesting equipment data per minute (requesting data to RabbitMQ) that generates equipment data through a batch scheduler, a data transmission function that transmits data to Rabbit MQ (saving data in Redis in an InMemory method), and equipment through a batch scheduler. It includes a function to save data per minute to perform a snapshot request (save the requested snapshot data in the DB), and a data merge function per hour to request the data per minute for each device stored in the DB (convert the data per minute to hourly data and store it in the DB). Alarm data creation is an alarm data request function that requests an alarm through API from the algorithm server (alarm request through RabbitMQ), an alarm data reception function that receives an alarm through Web socket (receives an alarm and stores it in the alarm history DB), and a Web socket. Includes a received alarm web service function that receives an alarm message through socket (displays the received alarm message on the main web screen). Table 1 shows the main functions for implementing the predictive maintenance platform of the ICT/Cold-Chain Unmanned Storage. In addition to the main function, each DB includes sub-functions. Each DB stores user information, classifies and manages general users and system administrators, a user table, an alarm table that stores alarm information and manages alarms generated by equipment, and a table that stores equipment information and stores equipment specifications. It consists of an equipment table that provides a structure change function, a equipment data per minute table that stores equipment data per minute information, and provides a table structure change function according to data collection information. In addition, the web service function includes a site management function that performs site management and equipment mapping management, a system management function that performs category management and group management, and a monitoring management function that provides minute and hourly monitoring status in chart form. The ICT/Cold-Chain Unmanned Storage predictive maintenance process in this paper starts with two batch executions on the platform server. The first batch execution is a batch execution that requests RabbitMQ SW to create equipment data every minute, requests merge of equipment data collected every minute, and saves it in the web service DB. The second batch execution requests device snapshot data from Redis SW every minute and receives it from the web service DB. When the analysis algorithm server predicts anomalies in the ICT/Cold-Chain Unmanned Storage, it sends an alarm message through the queue to RabbitMQ SW and Web server. During this process, the alarm message web socket is saved as an alarm history in the web service DB. In addition, RabbitMQ SW receives queue equipment and alarm data back to the web server, and the web server requests Redis SW to store equipment data in memory. In this process, the web server propagates an alarm message to the connected client in real time, and the client can receive the message. Figure 5 shows a functional flow diagram for performing predictive maintenance of the ICT/Cold-Chain Unmanned Storage.

Table 1. Predictive maintenance platform function

Classification	Function	Contents
Generate equipment data	Data request per minute	- Equipment data generation through batch scheduler - Data request with RabbitMQ
	Receive Data	- Receive data with RabbitMQ - Storing data in Redis (InMemory)
	Save data per minute	- Equipment Snapshot request via Batch Scheduler - Save requested Snapshot data to DB
	Data merge per hour	- Data requests per minute per equipment stored in DB - Data per minute → Save to DB after converting hour data
Generate	Request alarm data	- Alarm request through API from algorithm server - Alarm request through RabbitMQ
	Receive alarm data	- Receiving alarms via WebSocket

alarm data		- After receiving an alarm, it is stored in the alarm history DB
	Received alarm web service	- Receive alarm message via WebSocket - Received alarm message displayed on the web main screen

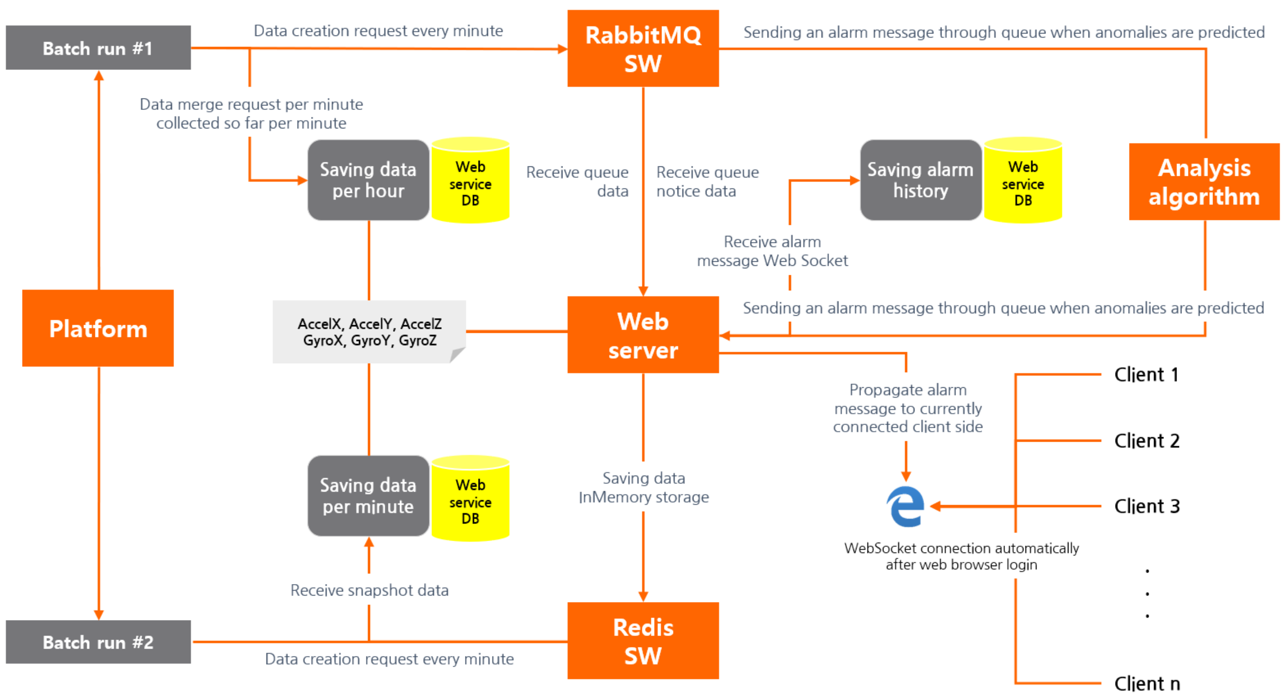

Figure 5. Predictive maintenance platform function flow diagram

4. Result of research

Figure 6 shows a web configuration that can provide notification services for failures and defects through the data collection and monitoring screen of the platform for predictive maintenance of the ICT/Cold-Chain Unmanned Storage. Figure 6 collects normal/abnormal data, receives data based on RabbitMQ, loads data in InMemory method using Redis, and executes snapshot data DB in real time. First, the corresponding data implemented a function to express the data received in the equipment selected on the basis of the search date in the form of a chart. Data items are displayed on the chart based on 6 points corresponding to the 3 axes of acceleration and gyro, and if it is determined to be an outlier among the displayed contents, the corresponding point is highlighted in red. The criteria for displaying outliers are the high interval (high interval (95%): measured value > maximum value – (median value * 5%)) and low interval (low interval (less than 5%): measured value < minimum value + (median value * 5%)) 2 cases were calculated. Data is displayed on the screen through automatic renewal by default by requesting new data on a per-minute basis.

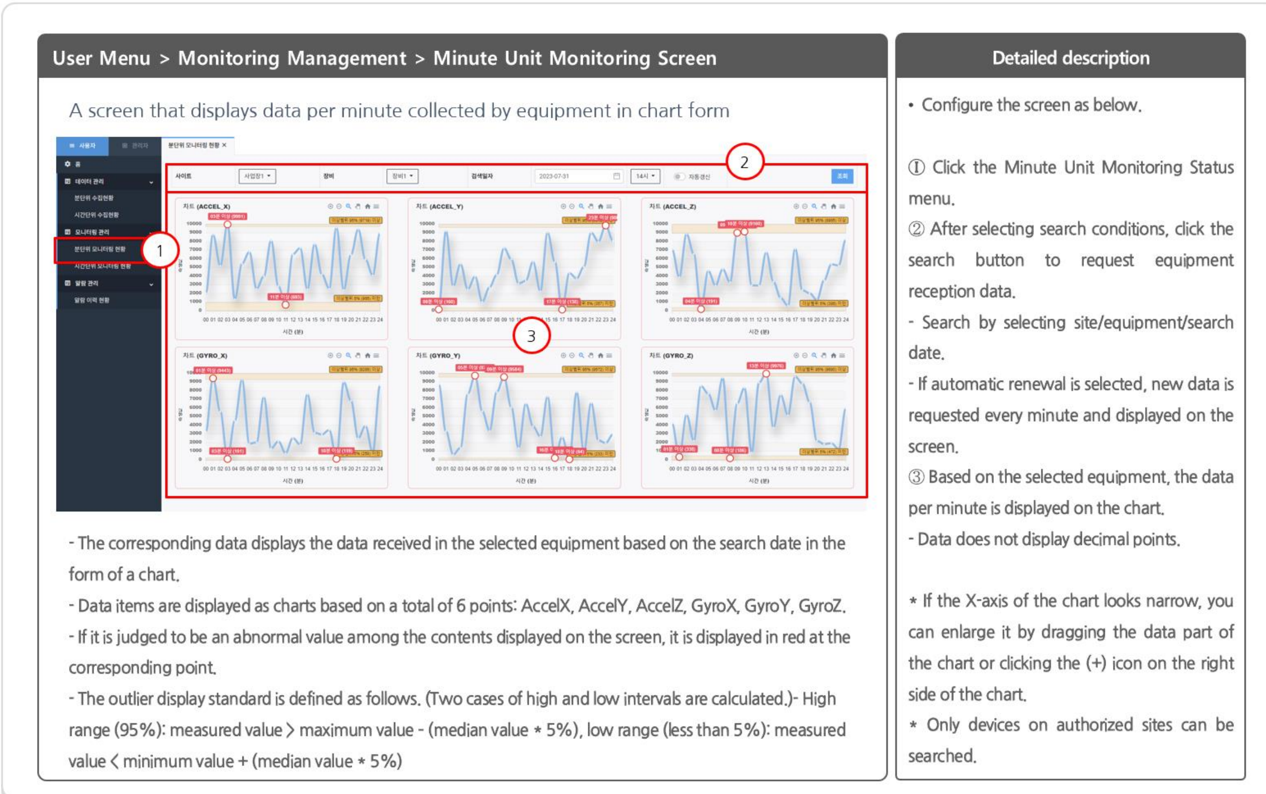

Figure 6. Predictive data acquisition and notice web

Since the ICT/Cold-Chain Unmanned Storage, which is the subject of this thesis study, will be deployed in several logistics centers, each management is required. Therefore, in addition to the data collection and notification web shown in Figure 6, a predictive maintenance platform was built including functions to perform DB history status, management, and control for each system. Figure 7 shows the data monitoring and abnormal data notification event points. The collected data can be monitored from various perspectives, such as data per second, data per minute, and data per hour, by determining the scope of collection. A function to designate a range based on a specific point or to emphasize a specific value has been added. In addition, by displaying three or more points at the same time, a function was added to check the relationship between the points.

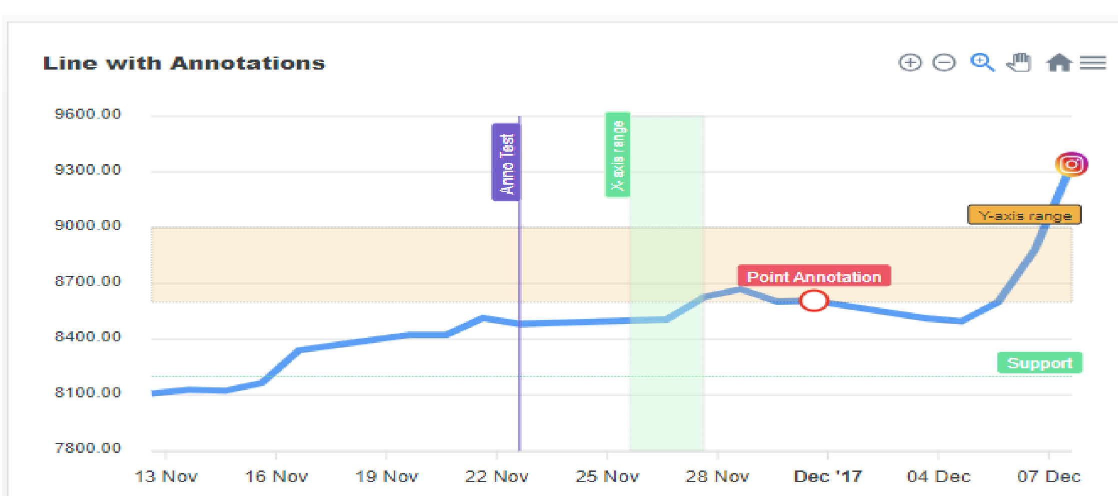

Figure 7. Data monitoring and abnormal data notification event points

5. Conclusion

Recently, due to the development of enterprise commerce technology, the expansion of the delivery and logistics industry is underway. Therefore, it is time to develop various types of pickup tower-based unmanned delivery storage device technology that reflects logistics trends such as product loss, convenience of goods due to change of mind, prevention of delivery-related crimes, and activation of early morning delivery infrastructure to ensure the safety of fresh food. In line with these environmental changes, the unmanned delivery goods storage device control technology is Cold/Frozen Container for delivery, intelligent cold chain logistics environment data sensor, intelligent cold chain product quality prediction platform, low temperature maintenance status measurement for fresh food, and basic information on delivery goods. ICT/Cold-Chain Unmanned Storage is a system for a new concept logistics service that applies convergence/combined technologies. In general, as various technologies are combined, the complexity of the system increases and the rate of occurrence of defects and failures also increases. ICT/Cold-Chain Unmanned Storage can be used in various spaces and for various purposes along with the expanding delivery and logistics industry. In other words, if this system is used domestically or even abroad, problems related to maintenance may result. In this paper, we built a platform for collecting, analyzing, and processing normal/abnormal data, which is the base data for predicting failures and defects of the ICT/Cold-Chain Unmanned Storage in advance. In addition, in order to secure operational reliability of the ICT/Cold-Chain Unmanned Storage through this, we implemented a predictive maintenance system that can predict failures and defects in advance with pre-learned big data based on artificial intelligence and deep learning LSTM models. As for the details for predictive maintenance, 3-axis acceleration and gyro data were collected for the conveyor main motor, which is a key element of the ICT/Cold-Chain Unmanned Storage. Collection In this paper, a server for data management, such as collection and monitoring, and an analysis server that notifies the monitoring server through data-based failure and defect analysis are separately distinguished. The predictive maintenance platform presented in this paper collects normal/abnormal data for the ICT/Cold-Chain Unmanned Storage, loads data in an InMemory method using Redis through RabbitMQ-based data reception, and creates a snapshot data DB in real time. do and work The predictive maintenance platform can contribute to securing reliability by identifying potential failures and defects that may occur in the operation of the ICT/Cold-Chain Unmanned Storage in the future.

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