J. Inf. Technol. Appl. Manag. 29(5): 27~37, October 2022
https://doi.org/10.21219/jitam.2022.29.5.027

ISSN 1598-6284 (Print)
ISSN 2508-1209 (Online)

Fuel Consumption Prediction and Life Cycle History Management System Using Historical Data of Agricultural Machinery

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Abstract

This study intends to link agricultural machine history data with related organizations or collect them through IoT sensors, receive input from agricultural machine users and managers, and analyze them through AI algorithms. Through this, the goal is to track and manage the history data throughout all stages of production, purchase, operation, and disposal of agricultural machinery. First, LSTM (Long Short-Term Memory) is used to estimate oil consumption and recommend maintenance from historical data of agricultural machines such as tractors and combines, and C-LSTM (Convolution Long Short-Term Memory) is used to diagnose and determine failures. Memory) to build a deep learning algorithm. Second, in order to collect historical data of agricultural machinery, IoT sensors including GPS module, gyro sensor, acceleration sensor, and temperature and humidity sensor are attached to agricultural machinery to automatically collect data. Third, event-type data such as agricultural machine production, purchase, and disposal are automatically collected from related organizations to design an interface that can integrate the entire life cycle history data and collect data through this.

Keywords : Agricultural Machinery, Long Short-Term Memory(LSTM), Fuel Consumption Prediction, History Maintenance System, Anomaly Detection, Historical Data

Received : 2022. 08. 30. Revised : 2022. 10. 26. Final Acceptance : 2022. 10. 26.
※ This research was supported by the Academic Research Fund of Hoseo University in 2020"(20200417)
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1. Introduction

When an agricultural machine user purchases an agricultural machine, the government provides a certain subsidy in Korea. Despite the government's support, the historical data over the life cycle of agricultural machinery has not been systematically managed. Therefore, this study collects historical data of agricultural machinery through IoT sensors or collects them in connection with related organizations, and then analyzes them to track and manage history data throughout all stages, such as production, purchase, operation, and disposal of agricultural machinery, and data-based life cycle. We would like to propose a management environment.

First, we want to predict the appropriate amount of oil used for agricultural machinery such as tractors and combines. Second, based on the manufactured sensor module, the history data of agricultural machinery is automatically collected to estimate the appropriate amount of oil used and to propose maintenance of consumables. Third, in order to collect agricultural machine history data, we will develop an algorithm that predicts the abnormalities of agricultural machines in advance by installing IoT sensors including GPS modules, gyro sensors, acceleration sensors, and temperature and humidity sensors on agricultural machines. Fourth, in cooperation with related organizations such as public data portals, we would like to suggest a development environment that can import and integrate historical data such as agricultural machine ownership status, agricultural machine safety information, agricultural machine certification report, etc. through OpenAPI.

2. Related Research

2.1 Vibration Analysis of Machines

Lee et al. [2012] constructed road surface models in different states and verified the usefulness of a method for analyzing the measured vehicle's vibration characteristics and ride comfort. It seems to be research data that meets the purpose of classifying vibration characteristics seen in farmland and general roads for the detection of fraudulent use of agricultural machinery. Jang et al. [2020] proposed a step-by-step anomaly symptom detection system through deep learning modeling based on LSTM prediction model simulation and collecting vibration trend data of facilities in real time to build a smart factory. Vibration detection sensors that can be attached to agricultural machinery stand out in the possibility of detecting abnormal signs of agricultural equipment in advance.

2.2 Domestic and International AI Technology Trends

Domestic artificial intelligence technology has a technology gap of 1-1.8 years lower than that of major countries (US, China, Japan, EU). Currently, the technology gap is 1.8 years in the US, 1.4 years in China, 1.4 years in Japan, and 1 year in the EU. The technology level compared to the US is 73.1% [KEIT, 2013], 75% [IITP, 2015], and 81.5% [IITP, 2017]. Unlike foreign countries, where commercial services are already active, technology interest is just beyond the level, and expert language and visual intelligence research and development (R&D) are at an early stage. The budget scale is remarkably low compared to major countries, and research manpower and research capacity to prepare for future demand are weak.

Kuk [2019] investigated and announced an international comparison of artificial intelligence research capabilities. The amount of artificial intelligence academic research is increasing significantly, especially in China, the United States, and India, and Korea ranks 9th out of 20 countries, with a very low growth rate. Korea is in an ambiguous position, ranking 12th to 14th in most indicators, so it is an important time to establish a future direction.

Domestic companies, such as Samsung, Naver, SK Telecom, and KT, have been active in AI development. Samsung has developed an artificial intelligence personal assistant, 'Visbig,' and is expanding support services such as knowledge search, financial services, and music recommendation playback. Naver developed voice search, face recognition camera, and conversational engine. SK Telecom developed its own natural language processing engine that distinguishes dialects, and KT, the same telecommunications company, developed voice processing technology incorporating machine learning, achieving recognition rates of 89~90% natural language processing accuracy and 95% voice recognition accuracy.

Overseas companies are actively developing artificial intelligence, centering on global companies (IBM, Google, Facebook, Amazon, MS, etc.). In particular, the development of machine learning and deep learning technologies in the field of artificial intelligence has accelerated. Google has provided state-of-the-art machine learning services along with pre-trained models and services, enabling customers to create customized models. Open source algorithm Tensorflow is disclosed, and solutions such as job search and search, video analysis, image analysis, and voice recognition are provided. Microsoft is working on the Adam Project, which provides real-time language translation on Skype and uses image recognition technology to recognize objects in images. Facebook has text translation and speech recognition technology that distinguishes people and objects in photos and provides newsfeed filtering. Amazon launched drone delivery, warehouse management by robots, and Alexa, a cloud-based speech recognition artificial intelligence. Finally, Baidu, a Chinese company, launched Stock Master, which predicts stock prices and theme stocks using news, stock market, and Baidu search engine data.

2.3 Failure Prediction and Anomaly Detection

Samsung SDS developed MAXIGENT, a monitoring solution that protects IT infrastructure. In order to respond to the complexity and rapid change of the data center, we have established an innovative failure analysis and prevention system based on big data analysis, and through this, we are creating new business. In addition, LGCNS describes a system that predicts IT infrastructure failures in advance with big data analysis in relation to ITOA (IT Operation Analytics), which is used for predicting and responding to infrastructure failures by combining big data analysis with infrastructure control.

Amazon provides monitoring of infrastructure, systems, applications, and business metrics through CloudWatch anomaly detection capabilities based on more than 12,000 internal models based on machine learning built on decades of experience. IBM disclosed PMQ, a process-related anomaly detection solution, and anomaly detection solutions using prediction/analysis techniques, such as SAP HANA and Pinterest's anomaly detection function, exist in the market.

Anomaly detection techniques using big data analysis and machine learning techniques have been developed by various companies in various fields, but most of them are simplified functions, and functions that provide detailed analysis have not been identified. Therefore, it is necessary to propose in-depth functions suitable for the site by seeking various functions including analysis of disability reports.

2.4 AIOps (Artificial Intelligent for IT Operations)

AIOps is a term that appeared in a 2014 Gartner report, and refers to making IT operations more intelligent and efficient by introducing AI into IT operations. The purpose of AIOps is to ensure stable service, reduce operator fatigue, and reduce operating costs by introducing AI as today's operating/controlling systems diversify and the amount of operational data such as metrics and logs rapidly increases.

In 2018, Gartner predicted that within the next 5 to 10 years, AIOps would be established as a technology or product in the market. The IDC Report also predicted AIOps to be the 10th most influential technology and trend in the domestic ICT market in 2019. AI-powered IT operations have no choice but to reduce IT spending, improve corporate IT agility, and accelerate innovation. 60% of CIOs will aggressively apply data and AI to IT operations, tools and processes by 2021.

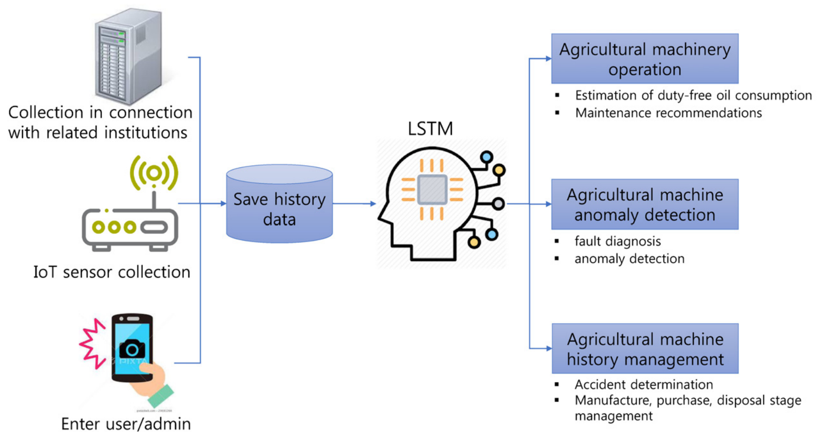
The AIOps market recorded US$ 1,270 billion in 2016 and US$ 1.730 billion in 2017. It is expected to grow by 36.2% annually from 2018 to 2025, and it is expected to become a market worth US$ 20,428 billion in 2025. The global AI infrastructure market is expected to grow at a CAGR of 23.1% by 2025, from USD 14.6 billion in 2019, driven by increasing adoption of cloud machine learning platforms, growing demand for AI hardware in high-performance computing data centers, and parallel computing in AI data centers. Increased concentration, increasing amount of data generated by industries such as automotive and healthcare, and co-improvement are the major factors driving the growth of the AIOps market [Coherent Market Insights, 2018].

Overseas, there are about 30 AIOps vendors, including the US, and among them, BMC and Splunk are making inroads into Korea. There are about 20 vendors such as AppDynamics, BMC, CA, Dynatrace, FixStream, IBM, InfluxData, Loom Systems, Moogsoft, Splun, VMware in the US, Micro Focus in the UK, StackState in the Netherlands, Anodot, There are VNT Software, etc., India has HCL, VuNet, etc., and Japan has Brains Technology, etc.

3. Research Methodology

3.1 Research Objectives

This study aims to track the final consumption of duty-free oil according to the time required for work and to detect fraudulent use by using gyro vibration data collected through a module attached to an actual agricultural machine and individual duty-free oil allocation data, as shown in 〈Figure 1〉. Using the agricultural machine data obtained through the manufactured module and the entered history data, future failures can be detected and



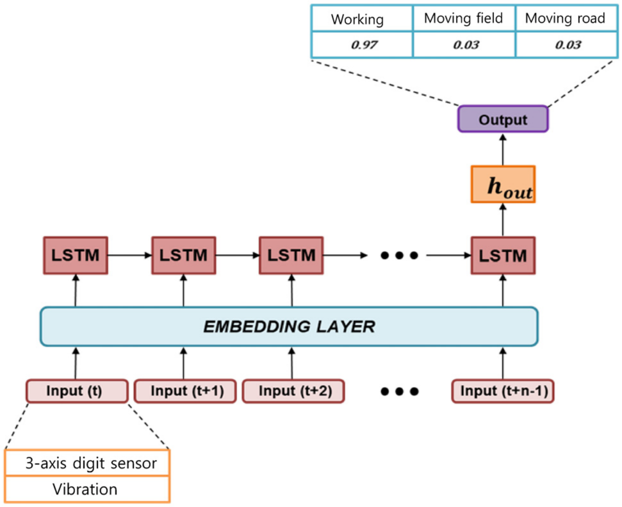
〈Figure 1〉 System Architecture

utilized to develop a model that helps maintenance in the use of agricultural machines. In addition, by using the vibration data of the agricultural machine obtained through the manufactured module, it is intended to develop a model that detects the accident situation of the agricultural machine and manages the agricultural machine's history data.

3.2 Duty-free Oil Misuse Detection Model Based on Vibration Data Extracted by 3-axis Gyro Sensor

The total vibration level of the riding vibration of the agricultural machine is determined by correcting the rms acceleration data on the x, y, and z axes obtained from the 3-axis gyro sensor according to the set frequency band. It is possible to develop a classification neural network model for whether the agricultural machine is 'at work', 'moving in the field', or 'moving on the pavement' by extracting the vibration generated when riding the agricultural machine through the 3-axis gyro sensor. The final duty-free oil consumption is tracked from the actual work hours calculated according to whether the neural network model is working or not and the duty-free oil consumption per unit working hour. It is possible to detect fraudulent use of agricultural machinery by comparing the maximum distance that can be moved according to 'tracked duty-free oil consumption' and 'personal duty-free oil allocation amount'.

The reference coordinate system for measuring riding vibration is the center of the seat as the origin, the forward direction of the tractor as the +x axis, the driver's left side as the +y axis in the forward direction, and the upper part of the xy plane consisting of the +x and +y axes to the +z axis. GPS (Global Positioning System) is the only global satellite navigation system that is currently fully operational and can check accurate location information regardless of the time of day. Information must be received at non-continuous regular intervals (1Hz), and in areas where GPS signal reception is difficult, such as tunnels, sensors that measure vehicle speed and motion are added to compensate for the shortcomings of GPS that accompany error in location information Estimate the location and moving distance of agricultural machinery to which the Kalman Filter is



〈Figure 2〉 Agricultural Machinery Work Type Classification Model

applied. Kalman Filter estimates the state of a dynamic system, uses the observed value of the error, can derive good results even in reception failures or weak signals, has excellent signal-to-noise separation, and can be easily implemented using a computer.

The classification model for agricultural machinery operation uses an RNN-based neural network model suitable for time series data, as shown in 〈Figure 2〉. In particular, we use LSTM Network, which complements the long-term dependency problem of vanilla RNN. LSTM Network introduces a structure of three gates (Forget, Input, Output) and can compensate for the long-term dependency problem of losing past information as it learns.

3.3 Anomaly Detection Model for Agricultural Machinery Based on C-LSTM Neural Network

Agricultural machinery is repaired 3.1 times a year on average, and follow-up management is emphasized as it is difficult to promote timely farming due to temporary breakdowns. However, the domestic post-management system is still operated as a modern management system of reporting failures, checking agency inventory, and visiting repairs. is not operating properly. Therefore, the necessity of developing a systematic follow-up management system that can continuously measure failures, transmit and manage information remotely, and provide it to farmers and mechanics is emerging.

In order to reduce the error due to the vibration of the sensor signal for fault diagnosis, a Kalman filter capable of predicting the measurement signal is used, and the sensor signal is analyzed to analyze the reproducibility and suitability of the fault diagnosis signal. Fault diagnosis is performed through multiple comparison analysis of the frequency signal of the acceleration sensor and the load signal of the load cell. By analyzing the collected data, we create a binary classification model by defining criteria for fault diagnosis.

The neural network structure of C-LSTM proposed in this model is as follows. The proposed system is composed of an end-to-end method and is designed to be directly applied to the actual anomaly detection field. The downside is that a large amount of data samples are required to train the system.

The value of the actually generated vibration data is converted into a value between 0 and 1 and goes through a normalization process. Next, a sliding window algorithm is applied to extract data samples as many as the set window size interval. Finally, we set the labels for the trace samples containing the outliers. A large amount of samples extracted through the above preprocessing process is used as an input to the convolution layer. In CNN, the convolution filter extracts local features while sliding the input data, and then delivers the output to the next layer through the process of compressing these features to the maximum value. In the LSTM layer, samples with reduced spatial information output through the convolution layer are used as inputs. LSTM is suitable for modeling time-series data with long-term dependence because it has the characteristic of memorizing learning data. In the proposed structure, the degree of time change decreases as it passes through the LSTM. In the proposed system, research is conducted to improve the classification performance of normal and abnormal for complex patterns of data by combining the advantages of modeling temporal information and spatial information.

3.4 Auto Encoder Neural Network Based Anomaly Detection Model

It is possible to build a model that can help maintenance by detecting outliers in agricultural machinery using unlabeled data. An auto encoder is an artificial neural network that simply regenerates inputs into outputs. It is a deep learning algorithm that has a simple structure and relatively small computational load and can be used for label-free unsupervised learning for diagnosis and monitoring. Despite being unlabeled training data, this algorithm was adopted as an anomaly detection diagnosis algorithm because it is possible to quantitatively express the performance as an error by comparing the input and the result of regenerating the input.

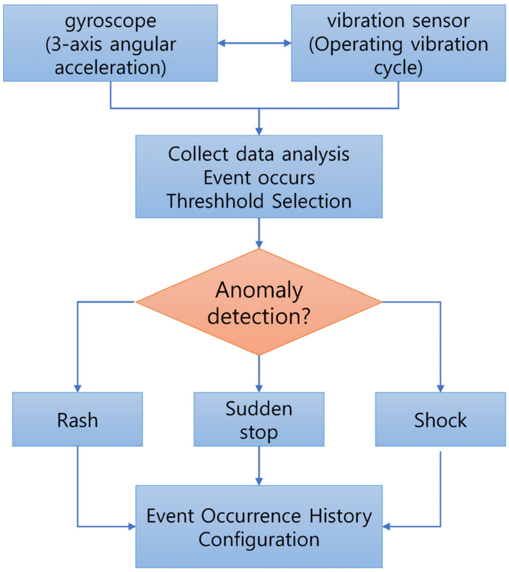
Auto encoder learns in the direction of minimizing reconstruction error, which is the difference between input and output. Reconstruction error, also called an outlier score, is the size of the error measured between input and output and is defined as the following formula.

$$J_{MSE}(\theta) = \frac{1}{m}\sum_{i=1}^{m} L_{MSE}(x_i, z_i) = \frac{1}{m}\sum_{i=1}^{m}\left(\frac{1}{2}\,||\,z_i - x_i\,||^{2}\right)$$

If it looks larger than the resulting error, it can be regarded as an abnormal state because it is judged that it has transitioned to a state different from the normal state.

3.5 Historical Data Collection Model

Among various agricultural machines, we focus on 'tractors', which account for the third highest accident rate after cultivators and harvesters. In this study, the movement and vibration data of the rotating shaft are collected and analyzed through the gyro sensor attached to the agricultural machine, as shown in ⟨Figure 3⟩. If an accident or major abnormality occurs, history management of agricultural machine history is performed by storing the number of times of the history and location through GPS. As above, vibration data is extracted through the gyro sensor attached to the tractor, and rotation speed and vibration period are collected. It is expected that it will be possible to derive a critical point that can be distinguished by defining 'emergency and accident occurrence' by comparing and learning data during normal operation and data during crash.



〈Figure 3〉 Agricultural Machinery History Management Model

4. Experimental Results

4.1 Key Performance Indicators

The division and contents of key performance indicators are shown in 〈Table 1〉 below.

〈Table 1〉 Key Performance Indicators

key performance	division	Contents
1. Accuracy of agricultural machine work classification model	indicator definition	Since the classification of agricultural machinery by work type is used as a basis for estimating oil consumption, the model's work classification accuracy is measured.
	target basis	$\frac{(\text{Actual task classification label} = \text{Model prediction classification label})\ \nu\text{mber of data}}{\text{Total }\nu\text{mber of data}}$
2. Accuracy of Agricultural Machinery Anomaly Detection Model	indicator definition	Based on the life prediction and history of agricultural machinery, how accurately the model predicts equipment abnormalities and failures, etc., measures the abnormality detection prediction accuracy.
	target basis	$\frac{(\text{Actual anormaly and failure occurence and Prection of anormaly and failure occurence})\ \text{number of data}}{\text{Total number of data}}$

4.2 Evaluation Method of Quantitative Targets

The evaluation items of the quantitative target and the evaluation method for each item are shown in 〈Table 2〉 below.

〈Table 2〉 Evaluation Method of Quantitative Targets

evaluation items	Evaluation method of quantitative target items
1. Accuracy of agricultural machinery work classification module	• Definition: Measurement of classification accuracy by work type of agricultural machinery • Performance measurement formula: The number of data in which the actual task classification label and the model-predicted classification label matched against the total number of data • Final performance target: 90% or more • Performance target basis: Quantitative values of classification data consistent with actual work for measuring classification accuracy • Performance evaluation tool: skikit-learn's accuracy calculation function
2. Accuracy of Agricultural Machinery Anomaly Detection	• Definition: Accuracy measurement of anomaly detection model of agricultural machinery • Performance measurement formula: The number of occurrences of actual

evaluation items	Evaluation method of quantitative target items
Model	anomalies and failures compared to the total number of data and data predicted to be failures • Final performance target: 50% or more • Grounds for performance targets: Numerical values that can quantitatively determine how accurately the model predicts equipment failures and failures based on life prediction and training of agricultural machinery • Performance evaluation tool: skikit-learn's accuracy calculation function

4.3 Evaluation Environment for Quantitative Target Items

The evaluation environment for each evaluation item of the quantitative target is shown in ⟨Table 3⟩ below.

⟨Table 3⟩ Evaluation environment for quantitative target items

evaluation items	Evaluation environment for quantitative target items
1. Accuracy of agricultural machinery work classification module	• Performance evaluation method: After inputting X pieces of acceleration data actually recorded during agricultural machine operation, classifying the type of operation, comparing it with actual operation information, calculating the accuracy of the agricultural machine work classification module with scikit-learn's accuracy calculation function
2. Accuracy of Agricultural Machinery Anomaly Detection Model	• Performance evaluation method: After inputting X pieces of readability data that are actually recorded during agricultural machine operation to determine whether or not there is an error, the accuracy of the agricultural machine anomaly detection model is calculated using the accuracy calculation function of skikit-learn by comparing it with the actual failure information. Calculate (Accuracy)

5. Conclusions and Implications

This study aims to develop an efficient method for determining usage patterns of agricultural machines and predicting failures based on usage history based on limited data collected from externally attached IoT sensors for overall management of agricultural machines. Equipment failure prediction in the existing anomaly detection field predicts complex aspects of equipment based on data measured from countless sensors and determines failures and failures based on this, but this is applied to agricultural machinery used in domestic agriculture. It was practically impossible to do. The development results of this study are expected to suggest a new methodology for efficient management of equipment and machines in other industries where it is difficult to obtain IoT sensor measurement data.

Based on the results of this study, from a technical point of view, it is possible to simplify the management technology using sensors attached to the outer walls of machines and equipment, and to develop management technologies for existing general equipment that are not equipped with sensors. From an economic point of view, maintenance costs can be reduced by using equipment life prediction technology for agricultural machinery. In addition, it is expected that the policy budget will be reduced by reducing unfair gains generated through the illegal use of duty-free oil. Looking at the social aspect, correct use and benefits of duty-free oil can be managed through detection of fraudulent use. In addition, accidents can be prevented through the occurrence and abnormality detection of agricultural machinery.

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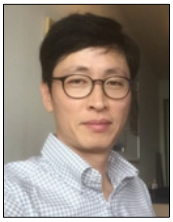

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