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AI Machine Vision based Oven White Paper Color Classification and Label Position Real-time Monitoring System to Check Direction

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Abstract: We develop a vision system for batch inspection by oven white paper model color by manufacturing a machine vision system for the oven manufacturing automation process. In the vision system, white paper object detection (spring), color clustering, and histogram extraction are performed. In addition, for the automated process of home appliances, we intend to develop an automatic mold combination detection algorithm that inspects the label position and direction (angle/coordinate) using deep learning.

Keywords: angle; color image processing; coordinate determination; machine vision; optimal operation; production management

1 INTRODUCTION

We support the process system of manufacturing companies to increase sales and promote employment through the successful technological advancement of companies. It is time to support the development of process automation systems in line with the 4^{th} industrial revolution. It has secured significant technological accumulation and IoT solution development technology through government R&D projects of small and medium-sized enterprises that have created artificial intelligence convergence complexes. Appropriate government support is needed to overcome difficulties such as high risks in the subsequent commercialization stage and lack of self-commercialization capacity [1]. The driving force behind the machine vision market includes challenges that need to be addressed due to the lack of user awareness of the rapidly changing machine vision technology, such as growth accelerators, growth restraints, and market opportunities. Overcoming limitations in label position inspection and visual inspection of white paper color classification of products based on artificial intelligence. This is because it is important to increase the productivity by improving the reliability and speed of inspection. It is urgent to develop and commercialize low-cost machine vision systems and automation software solutions suitable for small and medium-sized enterprises (SMEs), as it is required to avoid such qualitative judgments and establish quantitative judgment standards. In order to improve domestic manufacturing productivity and competitiveness, it is necessary to make smart production sites [2].

Technologies such as vision, AI, and robot control are essential fields that must be promoted along with the wave of the global 4^{th} industrial revolution. The government is also focusing on key areas such as the Ministry of Industry's smart factory supply project, smart industrial complex creation project, and the Ministry of SMEs and Startups' DNA (Data, Network, AI) Korea construction project. Although these technologies are currently showing great results in global companies such as Dassault Systèmes and Siemens, they are mostly applied to large corporations. For small and medium-sized enterprises (SMEs) to apply, it is a field that has limited entry due to size and cost limitations. In addition, although manufacturing innovation that converges each independent unit technology is essential for smart factories, it is not easy to apply in small and medium-sized enterprises (SMEs), and although government-level support measures are being implemented. They are still insufficient products to be applied to the manufacturing process using AI are being introduced competitively by various companies, but it is difficult to compare and evaluate them as products for general consumers as it requires customization and grafting of know-how to suit the situation of the target company. Currently, technologies for controlling robots by grafting vision are being developed and introduced by many companies and research institutes under the category of digital twin. In Korea, there is an attempt to build a production line that incorporates this in the actual manufacturing process, but it is very difficult for small and medium-sized enterprises to apply this technology without government support as they are built mainly by large companies.

By using AI-based object recognition algorithm, the position of the spring on the hinge is identified to increase the accuracy of product identification. Based on the histogram of the image obtained when identifying the corner, the reference value for judging the product was selected as the learned result. Smart factory-related technologies, such as product shape recognition, discrimination using AI, and robot control technology through simulation, are applied to actual processes and a system that can contribute to productivity improvement has been established.

This paper is the development of a real-time monitoring system that inspects artificial intelligence based home appliances.

In Chapter 2, the vision inspection system design and Chapter 3 develops a machine vision system for the automated process of home appliances, In Chapter 4, an automatic mold defect detection algorithm using deep learning was developed [3, 4, 17].

2 RELATED WORKS
2.1 Real-Time Monitoring Platform Design

We designed the infrastructure to configure the hardware of the real-time quality control monitoring system for home appliances based on AI machine vision. As shown in Fig. 1, design H/W for optical and real-time Auto-Focus inspection processing that inspects product appearance. We are going to implement an inspection image processing system for development and segmentation of product injection mold appearance and image processing [5].

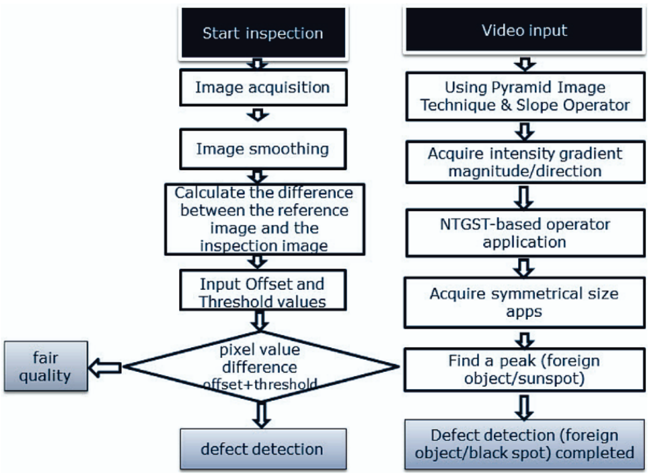

Figure 1 System logic

AI-based vision inspection algorithms learn and analyze images. We develop solutions to improve process efficiency and inspection accuracy by detecting difficult- to-detect defects, fast speed, and low errors. Design an integrated big data management platform architecture such as data collection, storage, exchange, and security for AI-based analysis by building a database for developing AI models for bad prediction [6]. Decision tree, random forest, naive Bayes, SVM, gradient boosting, etc. are used to utilize classification algorithm in the development of data set quality inspection module for AI-based automatic reading of quality information. PCA principal component analysis uses AI-based quality prediction modeling using quality inspection data and collected data [7, 8]. Defect occurrence prediction and predictive modeling results are linked in designing the monitoring system [9, 10]. Labeling is performed on various types of defects leaked from here.

2.2 Design of Vision Inspection System to Acquire Appearance Information

In Fig. 2, it is implemented as an integrated structure that can inspect both appearance inspection and Cabi curvature at the same time by designing and implementing the exterior vision inspection system infrastructure [11, 12, 18].

The inspection object is classified through the result of comparing/ analyzing/ processing images taken according to the vision inspection algorithm. As for the inspection object, we develop an injection mold exterior vision device that judges the status of good or defective products (scratches, dents, foreign substances detection, etc.) within 1 minute [13, 14, 19]. Optical and real-time Auto-Focus processing H/W technology is applied as shown in Fig. 3 to obtain results obtained by comparing, analyzing, and processing images taken according to the vision inspection algorithm. This is to develop an injection mold exterior vision equipment that judges the condition of the inspection object as good or defective (scratches, dents, foreign substances detection, etc.) within 1 minute. Here, the optical and real-time Auto-Focus inspection processing H/W design that inspects the curvature of home appliances is reflected.

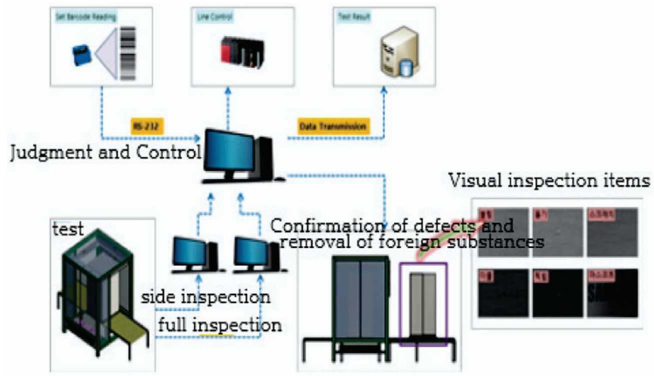

Figure 2 Facade Vision Inspection System Design

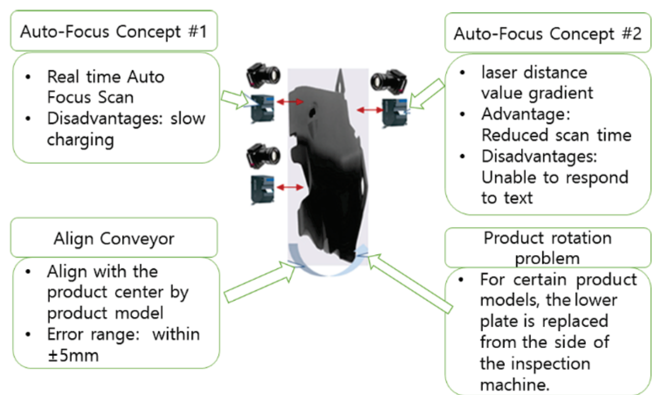

Figure 3 Optical and real-time Auto-Focus processing H/W technology

In Fig. 4, the defect calculation and judgment result are output using the blob area of the binarized image by removing the afterimage by adjusting the contrast from the image acquired by the scratch S/W algorithm.

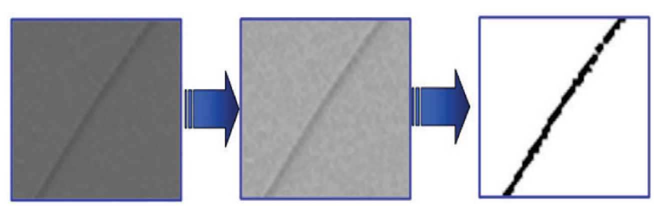

Figure 4 Scratch S/W technology

In Fig. 5, the afterimage is removed by adjusting the contrast from the image acquired by the foreign substance or sunspot S/W algorithm. By calculating the binarized image on the removed image, the binarized blob area is obtained, and foreign substances are detected in the image with gradation, and the found foreign substances are displayed in real time [15].

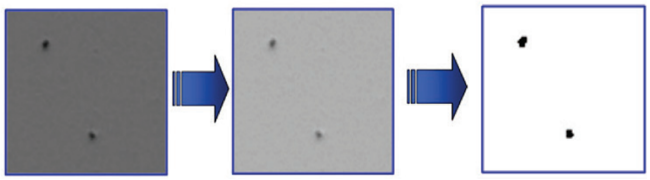

Figure 5 Scratch S/W technology

In Fig. 6, the standard deviation S/W algorithm calculates the standard deviation of the averages within the inspection area to set the range for non-defective products. Here, an area having an average value out of the range is judged as defective and displayed [16].

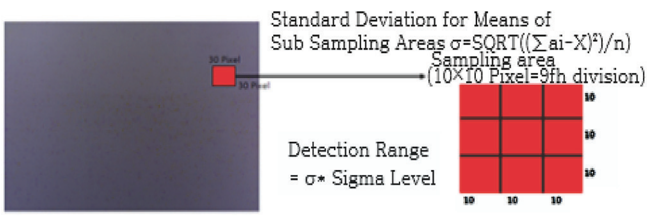

Figure 6 Standard deviation S/W technology

3 RESEARCH METHODS AND CONTENTS

3.1 Machine Vision Systems for Oven Manufacturing Automation Processes

Fig. 7 is a color classification system for classifying white paper models for oven doors. Oven doors are heavier than doors of general home appliances due to heat resistance and the like, and an internal spring is used to support them. The color and size of the white paper spring used for each model in the automated process are different.

After acquiring the image of the spring part using the machine vision system, we plan to identify the model by classifying the size and color of the spring. This is to detect the spring size of white paper by applying an object detection algorithm.

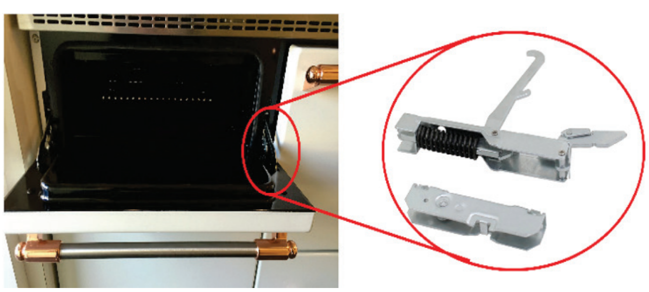

Figure 7 White paper for oven door

3.2 Vision Alignment System for Product Labeling

Object detection (spring) is to extract only the spring part from white paper by applying the image object detection algorithm. Color clustering removes distorted information caused by light reflections and the like through color clustering. Here, histogram extraction is to extract the main color range by obtaining an RGB-related histogram based on the clustered image. By combining these two algorithms, the color detection algorithms are listed in Fig. 8 to identify the whiteness of the product being worked on and to check whether the product is currently being put into assembly.

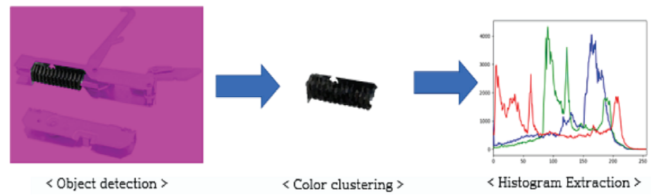

Figure 8 Color detection algorithm

3.3 Edge S/W Algorithm

In Fig. 9, FOV and Fixel values of the inspection effective part are given as an image processing S/W technology for image segmentation and image processing in the development of the interlocking system. The operating PC is designed to be able to respond immediately when abnormal conditions such as distributed processing speed and line scan inspection speed occur.

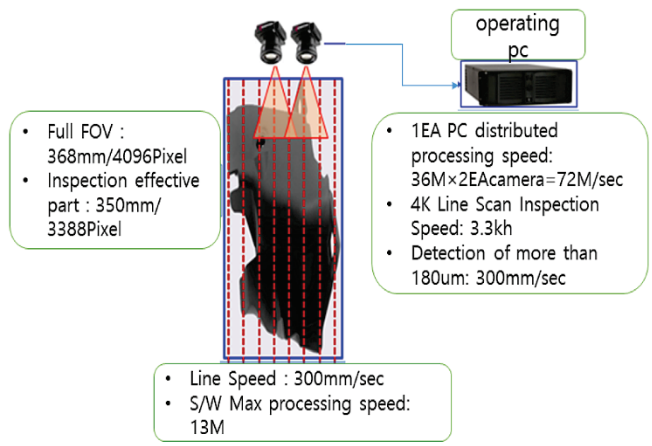

Figure 9 Image Processing Inspection image processing S/W technology

Fig. 10 shows the Edge S/W algorithm, and it is an image to which Sub Pixel is applied. In the primary differential method, the number of pixels in the original image is 5, and the edge is detected by the differential method in the enlarged image using sub pixels.

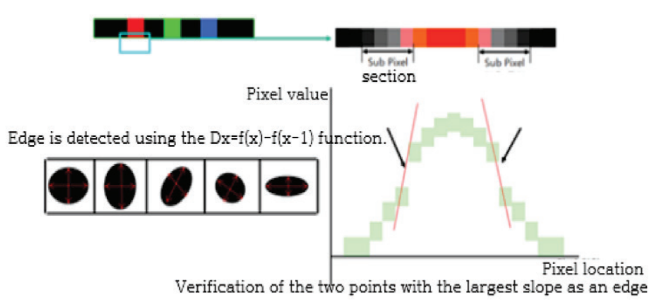

Figure 10 Edge S/W Algorithm

3.4 Big Data Management Platform Architecture

Design an integrated big data management platform architecture such as data collection, storage, exchange, and security for AI-based analysis. It is to analyze and store a large amount of structured and unstructured data generated in the manufacturing process in real time and provide it to users. Design and use a big data management platform as shown in Fig. 11 [11, 12].

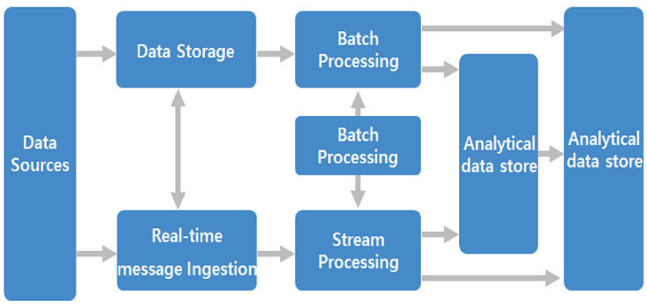

Figure 11 Big Data Management Platform Architecture

4 EXPERIMENTAL RESULTS

4.1 Development of Automatic Mold Defect Detection Algorithm Using Deep Learning

In order to predict product defects from the data acquired in the inspection process for vision inspection, the most suitable predictive model is implemented for the training data. The learning data is targeted for 24-hour cumulative data of the day when the defect occurred. It is estimated by using the decision tree model under which conditions a defect occurs, and the composition of the variables is shown in Tab. 1 below.

Table 1 Composition of variables

Variables	Description
Date	data generation time
Model No	Model Number
Statics	color, material, propose
Defect factor	Defective quantity Defect factor

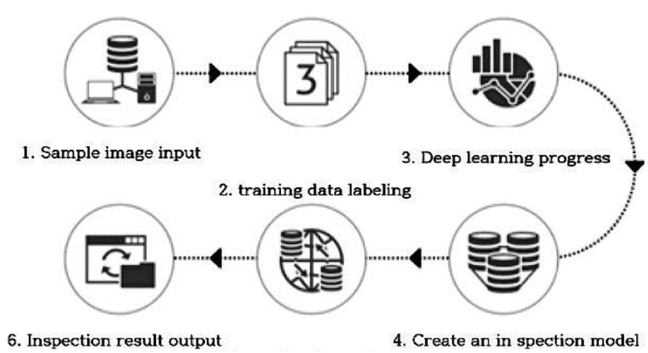

Figure 12 Automatic Mold Defect Detection Algorithm Using Deep Learning

In developing the methodology for deriving optimal control variables, log data generated from the process model is acquired through a vision sensor. The data manager pre-processed the data, and it was used as a model to suggest improved process variables based on empirical data and knowledge. For the process variable control model, an ensemble classification model that derives the optimal process variable region (process window) through voting of four classification models was applied. The optimal process variable region defines the margin border of the variable where defects occur. We use a regional ensemble classification model that combines optimal process variables that do not cause defects. First, if a defective product image is input, additional training data is generated as needed to label each defect type. A deep learning model with optimal conditions is created through the learning steps according to the selected mode and requirements. When the final model is created, the inspection image of the mass-produced product on the actual production line is input to determine whether it is a good product or a defective product. As shown in Fig. 12, the related information is an automatic mold defect detection algorithm using deep learning.

4.2 Edge Acquisition Algorithm

4.2.1 Hinge Recognition Unit

Fig. 13 shows the different types of oven hinges used. An algorithm was developed to classify the spring part of the equipment based on the size and color. After recognizing the spring using the object recognition algorithm, the length is measured. In addition, by analyzing the color distribution through the histogram, the oven hinge of the selected model is distinguished.

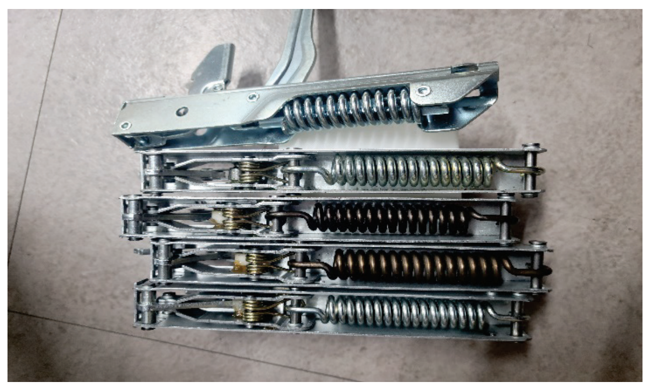

Figure 13 Oven hinges

4.2.2 Corner Recognition Unit

Fig. 14 is the result of recognizing the corners of the oven. After recognizing the corners of the top and sides of the oven, the exact location is derived on the image based on this. A black and white camera is used to acquire the image of the product, and the top and side are distinguished based on the black and white histogram. Based on the recognized line, two intersections are recognized as edges. Recognized edges calculate the exact product edge location based on the actual distance per pixel. Based on the value of the actual distance obtained in this way, a barcode label is later attached using a robot.

For edge recognition, the above figure and algorithm are implemented on the Region of Interest, the outline of the top and side of the product is recognized. The intersection point is calculated on the image, and the actual distance is calculated based on the calculated distance value per pixel by performing calibration. Based on this actual distance, it is possible to attach a barcode at a desired location on the product in the real coordinate system.

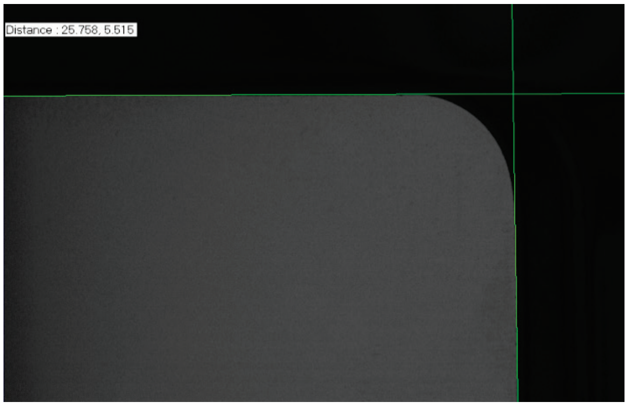

Figure 14 Edge recognition result

4.3 AI Exterior Vision Monitoring System Establishment

When a model that satisfies all the requirements for inspection is created through learning, a system for monitoring the quality of the exterior in real time at the actual manufacturing site is built. It provides name node and data node system information through a dashboard-type monitoring environment. In Fig. 15, the number of Map·Reduce jobs and program success/failure information are provided, and system progress monitoring and log events are tracked.

Figure 15 Application of AI injection mold exterior vision monitoring system

4.4 Color Classification and Label Attachment Position Alignment System

Fig. 16 is an oven hinge color classification and label attachment position alignment system applied with machine vision technology. Using two machine vision systems, images of hinges and edges for ovens are acquired, and image processing is used to recognize hinge models and edges for labeling. The oven hinge color classification and label attachment position alignment system to which this machine vision technology is applied is a system for deriving performance test results.

Figure 16 Oven hinge color classification and label attachment position alignment system

4.5 Hinge Model Grasp Speed

After preparing 5 different hinges according to the test conditions and methods, one or more hinges are put into the equipment. In addition, after acquiring the external image of the input hinge through the machine vision system, the object recognition algorithm measures the time to recognize the currently selected model among the input hinges. The criterion for decision was within 400 ms, and a result value of 282 ms was obtained as a vision response time. Detailed test results are shown in Tab. 2.

Table 2 Detailed test results

Exam conditions	Number	Vision response time (ms)
Hinge recognition speed	1 time	279
	Episode 2	285
	average	282

5 CONCLUSION

In this study, the final inspection of the manufactured product is carried out to improve the manufacturing process. By significantly lowering inspection time and cost, productivity and management convenience of the process line have been increased. By securing the base technology, a technological foundation was prepared that could dramatically lower the production cost of products, which had previously been a problem. This created the effect of further enhancing the degree of completion of commercialization.

These research results have improved quality and reliability, increasing quality satisfaction due to the introduction of a one-stop quality inspection system from the manufacturing stage to completion. The speed, stability, and accumulation of inspection results have made it possible to realize smart factories through big data in production and manufacturing processes. Through real-time process status monitoring, changes in the process capability index are immediately detected, and the process utilization rate is improved by shortening the processing time of abnormal factors such as registration, notification, and processing in case of abnormalities. Therefore, it has a relatively shortened inspection time and cost reduction effect and it is possible to conduct automatic discrimination inspection linked to the established product-specific database for future product line additions.

Based on the improvement of the quality of the products produced by the manufacturing company, it can be of great help to the growth of the company based on the increase in corporate reliability. In the inspection of parts such as automobile bearings, where safety is important, human error (human error) of the visual inspector was minimized and expectations were raised for improved accuracy in various inspection fields. In addition, healthcare, mail sorting, intelligent transportation system (ITS), intelligent security CCTV, autonomous vehicles, etc. It is expected that machine vision technology will be widely used in a wide range of fields, and eventually almost all inspections that can be done with the eyes can be replaced with machine vision.

In addition, through multidimensional analysis of process data, quality problems were detected in advance to increase production efficiency by improving the defect rate. By acquiring and analyzing mold data and defect data in real time, the optimal combination of process variables that do not cause defects was derived. In addition, the flexibility of inspection work for process variable recombination is improved and costs are reduced.

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6 REFERENCES

[1] Sarmah, S. S. (2020). An efficient IoT-based patient monitoring and heart disease prediction system using deep learning modified neural network. *IEEE Access*, 8, 135784-135797. https://doi.org/10.1109/ACCESS.2020.3007561

[2] Sung, K. K. (2017). A study on the IoT technology trend and utilization plan. *Journal of Next-generation Convergence Technology Association, 1*(3), 121-127.

[3] Pickell, P. D., Chavardes, R. D., Li, S., & Daniels, L. D. (2021). FuelNet: An artificial neural network for learning and updating fuel types for fire research. *IEEE Transactions on Geoscience and Remote Sensing, 59*(9), 7338-7352. https://doi.org/10.1109/TGRS.2020.3037160

[4] He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 770-778. https://doi.org/10.1109/CVPR.2016.90

[5] Masoumi, S., Baum, T. C., Ebrahimi, A., Rowe, W. S. T., & Ghorbani, K. (2021). Reflection measurement of fire over microwave band: A promising active method for forest fire detection. I*EEE Sensors Journal, 21*(3), 2891-2898. https://doi.org/10.1109/JSEN.2020.3025593

[6] Choi, S. Y. & Shin, S. J. (2021). A study on expansion proposal of data dividend qualification based on the contribution of platform workers. *The Journal of the Institute of Internet, Broadcasting and Communication (JIBC), 12*(6), 267-272. https://doi.org/10.7236/JII

[7] Jeon, J. S., Koo, J. K., & Park, C. M. (2015) Outlier detection in time series monitoring datasets using rule based and correlation analysis method. *Journal of the Korean Geo-Environmental Society, 16*(5), 43-53. https://doi.org/10.14481/jkges.2015.16.5.43

[8] Bor, M., Edward, J., & Roedig, U. (2016). LoRa for the Internet of Things. *Proc. International Conference on Embedded Wireless Systems and Networks,* Graz, Austria, 361-366.

[9] Roh, T. H. (2021). Accuracy analysis of road alignment reconstruction convergence technology based on mobile laser scanning technology. *Journal of Next-generation Convergence Technology Association, 5*(3), 426-436. https://doi.org/10.33097/JNCTA.2021.05.03.426

[10] Kang, G. C., Kim, B. J., Hong, S. W., & Yim, Y. C. (2017). Improving reliabilities of dam displacement based on monitoring given points by total station. *Journal of Korean Geosynthetics Society, 16*(1), 1-8. https://doi.org/10.12814/jkgss.2017.16.1.001

[11] Sharifi, M., Fathy, M., & Mahmoudi, M. T. (2002). A classified and comparative study of edge detection algorithms. *International Conference on Information Technology: Coding and Computing*, 117-120. https://doi.org/10.1109/ITCC.2002.1000371

[12] Lee, K. J., Kim, J. H., Ha, M. S., & Cho, K. H. (2020). Measurement management system using Lora, sensor node, and cloud platform. *Journal of the Korean Society of Hazard Mitigation, 20*(6), 143-150. https://doi.org/10.9798/KOSHAM.2020.20.6.143

[13] Yoo, C. H., Kim, I. H., Lee, S. J., Hwang, J. S., & Baek, S. C. (2018). Basic study on monitoring system of reservoir and leeve using wireless sensor network. *Journal of the Korean Geo-Environmental Society, 19*(1), 25-30. https://doi.org/10.14481/JKGES.2018.19.1.25

[14] Yoon, S. Y. & Lee, Y. W. (2022). UTOPIA smart city AI middle ware and person detection. *Journal of Next-generation Convergence Technology Association, 6*(5), 750-759. https://doi.org/10.33097/JNCTA.2022.06.05.750

[15] Canny, J. (1986). A computational approach to edge detection. *IEEE Transactions on Pattern Analysis and Machine Intelligence, TPAMI-8*(6), 679-698. https://doi.org/10.1109/TPAMI.1986.4767851

[16] Prachi, P., Rashmi, G., & Ashwani, K. (2019). Neural networks for facial age estimation: A survey on recent advances. *Artificial Intelligence Review, 53*(5), 3299-3347. https://doi.org/10.1007/s10462-019-09765-w

[17] Al-Eiadeh, M. R. (2021). Automatic Lung Field Segmentation using Robust Deep Learning Criteria. *International Journal of Hybrid Information Technologies, 1*(1), 69-82. https://doi.org/10.21742/ijhit.2653-309X.2021.1.1.06

[18] Barthelemy, A. M. & Suter, G. (2021). Highly Intelligent Recommendation Algorithm based on Matrix Filling. *International Journal of Hybrid Information Technologies, 1*(1), 83-96. https://doi.org/10.21742/ijhit.2653-309X.2021.1.1.07

[19] Park, H.-K. (2016). Development of Machine Vision Monitoring System for Semiconductor Package Sorter. *International Journal of Control and Automation, NADIA, 9*(4), 63-72. https://doi.org/10.14257/ijca.2016.9.4.07

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