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Preliminary Study of IR Sensor equipped Drone-based Nuclear Power Plant Diagnosis Method using Deep Learning

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1. Introduction

Safety is considered a top priority for nuclear power plants (NPPs) which consist of numerous components monitored by the operators. However, Three Miles Island (TMI) accident occurred in 1979 with malfunctioning of components and human error. The severe accident was caused by the failure of a measuring instrument with damage to the core. Therefore, supplementary inspection methods for components of NPP, without human intervention, should be proposed to prevent core damage. These inspection methods could help enhance NPP safety and reduce human error. Furthermore, a non-contact movable inspection method could help to reduce the cost by using a few inspection instruments comparing installation for all components. Currently, due to the radiation management regulation, the maintenance people cannot exceed 50 mSv per year with 100 mSv recommended for 5 years [1]. Considering, the maximum radioactivity of 2.6 mSv/hr for Kori Unit 1 [2], movable inspection by maintenance people is considered hard to realize. Therefore, a non-contact moving inspection instrument is required for improving safety and reducing the radiation exposure for workers.

Intuitive infrared (IR)-based diagnosis techniques for component monitoring have been proposed with performance verification [3]. Furthermore, with the development of artificial intelligence (AI), studies are being carried out to improve diagnostic performance by combining AI and IR technology. vibration-based component monitoring method is difficult to detect fluid-related malfunction, AI-based IR diagnostic method was proposed for a rotating baring [4]. In addition, the AI-based IR diagnosis method classified the condition of the radiator, which is a representative heat exchanger [5] with confirmation of the high performance. Additionally, the AI-based IR diagnostic method for component showed higher accuracy than the AI-based vibration diagnostic method for component [6]. AI-based IR condition monitoring has proven outstanding performance in several industries. However, if fixed IR cameras were used, they should be installed for all components constituting NPP causing significant cost. Therefore, for the diagnosis of NPPs, a method of inspecting numerous components using a single IR camera should be proposed for cost-efficiency.

With the development of robotics technology, movable devices have been proposed as the drone [7] and robot [8] with component diagnosis. Most of all, Drone has no limitation on height with mobility, comparing robot. Therefore, studies for drone inspection have been proposed. AI-based surface damage detection by drone for wind turbines was proposed, confirming the advantage in cost and time over inspection by maintenance people [9]. Furthermore, IR based monitoring method for photovoltaic power plants with drone was carried out to detect the defects of panels [10]. Although the drone-based inspection technique was carried out, only crack or damage detection was proposed. Since AI-based IR diagnoses have shown high performance, if combined with drone-based diagnosis technology, NPPs on a significant scale could be diagnosed.

AI-based IR monitoring methods have been confirmed significant performance. In addition, the drone inspection method has been carried out without limitation of height by enlarging the inspection range. Combining these technologies, this study suggests an AI-based IR inspection method with drone for NPPs. This preliminary study was carried out using the UNIST reactor innovative loop (URI-LO), thermal-hydraulic integral effect test facility of APR-1400. Drone inspection for NPPs is easy to data transmission and cost-efficient due to monitoring numerous components by a single IR sensor.

2. Experimental methods

The data used for training and testing AI were obtained by the operating condition of URI-LO. URI-LO was designed to 1/12 diameter ratio and 1/1152 volume ratio with 1/8 height ratio for APR 1400, a recent pressurized water reactor advanced in Korea [11]. The schematic of URI-LO is shown in Fig 1. with design features. Table 1. represents the normal operating condition of URI-LO designed by the three-level scaling method of Ishii and Kataoka [12]. In URI-LO operating conditions, thermal images acquired by IR sensor have a significant difference, comparing several states of main components. However, actual NPPs are covered by insulation materials decreasing heat loss. The AI-based IR diagnostic technique should be able to diagnose slight temperature changes in consideration of the insulation. Considering this condition, URI-LO was operated decreasing core power and operating temperature condition.

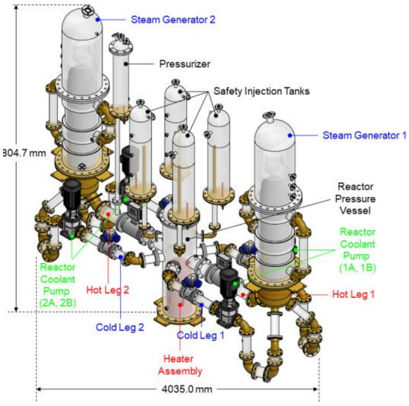

Fig 1. URI-LO schematic with design features [11]

Table I: Normal operating condition of URI-LO

Parameters	**Scaling ratios**	**URI-LO (water)**
Pressure [bar]	155.13	1.0
Core inlet temperature *[°K]*	-	347.2
Core outlet temperature *[°K]*	-	364.4
Temperature difference *[°K]*	0.5	17.2
Core flow rate *[kg/s]*	203.9 ($C_{p,oR} l_{oR}^{1/2} d_{oR}^{2}$)	2.7
Core power *[MW]*	407.3 ($l_{oR}^{1/2} d_{oR}^{2}$)	0.196
SG pressure *[bar]*	291.65	0.24

2.1 Configuration of Convolutional neural network

Convolutional neural networks (CNN) enhance the performance with the number of parameters lower than artificial neural network (ANN) [13]. CNN has outstanding performance processing the images, extracting the patterns of images by convolution layers. With the development of CNN, it has been classified with classification, segmentation, object detection, etc. AI-based IR inspection method using drone requires prompt and accurate performance about several components with movement. Among CNN, the object detection method is utilized for detection beyond a single object in real-time. Therefore, the object detection method was used for AI-based IR inspection through thermal images acquired by drone.

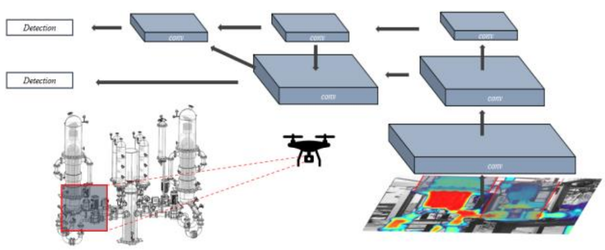

Fig 2. Simplified structure of Ai-based IR inspection using drone

Among real-time object detection algorithms, you only look once (YOLO) algorithms are representative with high performance [14]. YOLO algorithms have been developed, enhancing processing time and performance. The latest YOLO algorithm is YOLOv4 CSP compared with YOLOv1, YOLOv2, and YOLOv3. Therefore, AI-based IR inspection using drone is carried out with YOLOv4 CSP algorithm. A simplified structure used for AI-based IR inspection is shown in Fig 2.

When passing through the convolutional layer of CNN, the activation function is used to activate or deactivate the data. Depending on the utilized activation function, the output passed by the convolutional layer changes. Therefore, the activation function should be determined appropriately. Because sigmoid linear unit (SiLU) function, mish activation function [15], and sigmoid-weighted linear unit (Swish) function [16] are representative activation functions for the object detection algorithm, they are used as the selection of optimal activation function for AI-based IR inspection using drone. In this study, the form of activation function is based on PyTorch. Training epoch is 200 for demonstration of model performance with the small number of epochs. Adaptive momentum estimation (Adam) is utilized as the optimizer for IR inspection with 16 batch sizes. The training conditions for IR-based components inspection method are summarized in Table 2.

Performance evaluation of object detection method was conducted based on mean average precision (mAP). mAP is based on average precision (AP). AP is a single parameter, evaluating the precision and recall graph. Precision and recall are calculated by the confusion matrix which is used for the performance evaluation of the deep learning model. Furthermore, the intersection of union (IOU) is another representative indicator of performance evaluation and related to the object size. Because mAP is influenced by the IOU, mAP of object detection for IR-based Inspection was evaluated in accordance with IOU.

Table II: Training conditions of IR base inspection

Algorithm	YOLOv4-CSP
Activation function	SiLU Mish Swish
Optimizer	Adam
Loss function	Binary Cross-Entropy with Focal loss & Ciou
Batch size	16
Epoch	200
Hardware	GPU : Tesla-k80

3. Results and discussions

3.1 IR Thermography

The movable inspection method requires identification of the location of the fault component for maintenance. Therefore, the location identification performance was improved by combining the thermal image with the general image for training. In addition, the temperature range accepted by IR sensor was fixed to facilitate inspection through thermal images. The main components used for training are reactor coolant pumps (RCP), cold legs (CL), and steam generator water level. Thermal images acquired by IR sensor-equipped drone are shown in Fig 3 and Fig 4. Fig 3 (a) and (b) represent whether 1A RCP is operated or not. Fig 3(c) and (d) represent whether 1A CL is broken. Fig 4 shows thermal images of the steam generator water level for loop 1 in accordance with collapse. The number of thermal images including all RCP, CL, and steam generator water level was 17,213 with 28 classes. Thermal images of RCP have a significant difference between operation and non-operation conditions with a reduction of heat generation. Thermal images of CL are changed as soon as drain water. The difference among thermal images of water level is shown according to collapse. However, the immediate inspection could not be conducted by humans, because there was no significant difference for thermal images in each status. Therefore, AI was employed for components inspection enhancing accuracy.

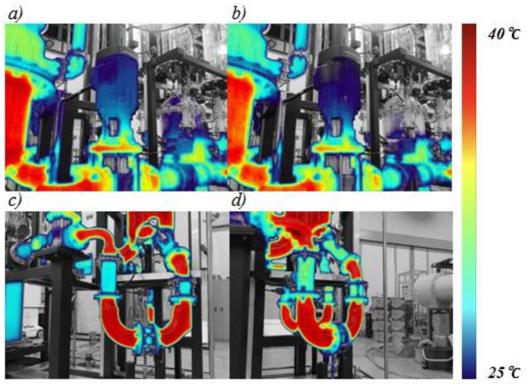

Fig 3. Thermal images of 1A RCP and 1A CL

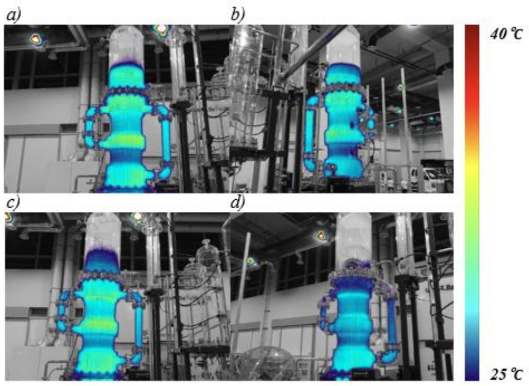

Fig 4. Thermal images of the steam generator water level of Loop 1

3.2 Performance evaluation of CNN

Floating point operations per second (FLOPS) and the number of parameters of the model were evaluated for computational performance. The performance of the IR-equipped drone-based inspection depended on the activation function. When YOLOv4 CSP was applied with Swish of the activation function, the overall mAP was high and demonstrated high performance even for small objects. There was no significant difference in test time according to the activation function, and it was 65.9ms per 16 batch size.

Table III: Performance evaluation metrics in accordance with activation function

	SiLU	*Mish*	*Swish*
mAP	***0.9888***	***0.9886***	***0.9891***
$mAP^{iou=0.95}$	***0.9598***	***0.953***	***0.9594***
$mAP^{iou=0.5}$	***0.995***	***0.995***	***0.995***
mAP^{small}	***0.4979***	***0.4691***	***0.4998***
mAP^{medium}	***0.9897***	***0.9892***	***0.9901***
mAP^{large}	***0.9904***	***0.9894***	***0.9902***
Parameters	***52.64M***		
FLOPs	***119.74G***		
Test time	***65.9ms***		

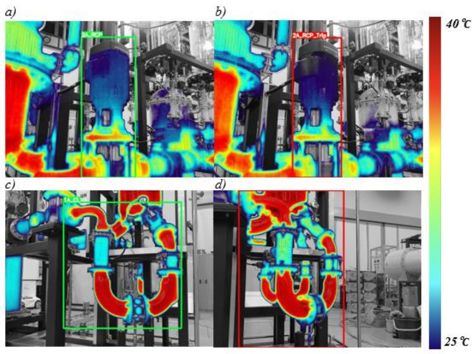

Fig 5. Inspection results of 1A RCP and 1A CL

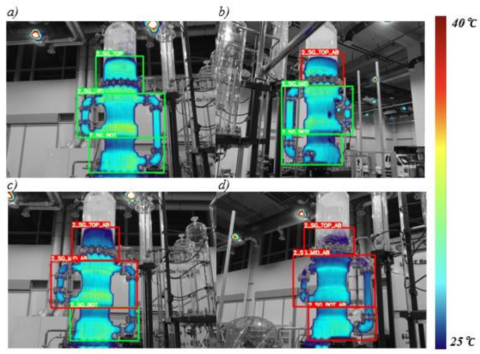

Fig 6. Inspection results of the steam generator water level of Loop 1

Fig 5. and Fig 6 represent the inspection result by the deep learning model. The AI-based IR diagnostic technique could inspect NPPs composed of numerous components with movement. The drone could properly inspect the main component by determining fault location instead of the maintenance people. The IR drone and AI based technique can reduce the radiation exposure and error caused by humans. Furthermore, because the movable inspection method requires fewer instruments than the fixed inspection method, it is cost-effective. As a result, the AI and IR equipped drone based inspection method shows a maximum overall mAP of 98.91% in real-time.

3. Conclusions

Additional component inspection methods are required to improve the safety of NPPs with the reduction of human error. Therefore, this study suggests AI and IR-equipped drone-based inspection method. The preliminary application was carried out with URI-LO. For AI inspection, CNN, effective for image processing, was utilized. Among CNN, the object detection method, which could be trained and tested with multiple objects, was applied for inspection. An optimal model was derived by changing the activation function based on the YOLOv4 CSP structure. When trained with the activation function Swish, it showed the maximum Map 98.91% in real-time. The drone-based nuclear power plant diagnosis method using deep learning equipped with IR sensor is considered to contribute to the improvement of nuclear power plant safety by reducing radiation exposure of workers, contributing to the reduction of human error, and providing additional inspection methods.

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