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Brief Report

Design of a Nuclear Monitoring System Based on a Multi-Sensor Network and Artificial Intelligence Algorithm

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Abstract: Nuclear power is a sustainable energy source, but radiation management is required for its safe use. Radiation-detection technology has been developed for the safe management of radioactive materials in nuclear facilities but its performance may vary depending on the size and complexity of the structure of nuclear facilities. In this study, a nuclear monitoring system using a multi-sensor network was designed to monitor radioactive materials in a large nuclear facility. Additionally, an artificial-intelligence-based localization algorithm was developed to accurately locate radioactive materials. The system parameters were optimized using the Geant4 Application for Tomographic emission (GATE) toolkit, and the localization algorithm was developed based on the performance evaluation of the Artificial Neural Network (ANN) and Decision Tree (D-Tree) models. In this article, we present the feasibility of the proposed monitoring system by converging the radiation detection system and artificial intelligence technology.

Keywords: multi-sensor network; artificial intelligence; radiation monitoring; nuclear energy; radioactive material

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1. Introduction

According to the policy briefing of the World Summit on Sustainable Development (WSSD), the energy sector is emerging as a key topic for sustainable development. Recent energy-related policies emphasize stability and the possibility of sustainable development in environmental, social, and economic aspects. In particular, governments around the world are researching the sustainable use of natural energy such as coal, gas, and crude oil while striving to develop and distribute new energy technologies [1].

A new technology to obtain energy safely and sustainably is nuclear power plant energy. Currently, nuclear power accounts for more than 11% of global electricity [2,3]. However, nuclear power plants have a disadvantage in that follow-up management is required due to nuclear fuel and radioactive waste generated in the process of using nuclear materials. For the continuous and safe supply of nuclear energy, it is important to prevent accidents and conduct research on safety-related technology to protect people, the environment, and workers from radiation hazards [4]. Various radioactive materials such as nuclear fuel and waste exist in the nuclear energy production process, and their safe management is essential to prevent illegal nuclear use such as nuclear terrorism. In order to prevent accidents, technology that can quickly and accurately monitor nuclear facilities is needed.

In this study, we intend to design a high-precision radiation monitoring system that integrates measurement equipment and artificial intelligence technology to monitor natural uranium (UO_2), which is a material for nuclear fuel. This thesis contains research contents on the design optimization stage for the development of a monitoring system.

1.1. Radiation-Monitoring Technology

Uranium compounds such as UO_2 are used and stored in loading facilities to provide nuclear fuel for nuclear power plants. According to the International Atomic Energy Agency (IAEA), uranium compounds must be safely managed in a series of enrichment, fuel manufacturing, and storage processes. Therefore, accurate monitoring of uranium-filled facilities is necessary to detect and regulate the use of nuclear materials [5,6].

Gamma rays emitted from ^{235}U (143.7, 163.3, 185.7, 205.3 keV, etc.) are not detectable by the naked eye. Thus, the use of radiation detection equipment is essential to identify and prevent radiation leakage accidents.

Recently, research on radiation-monitoring technology has aimed to develop new detection devices and software that can measure radiation with high accuracy rates for very low amounts of radiation while at the same time serving as a form of radiation-measurement technology for a wide range of environments and facilities [7].

Several radiation detection instruments have been used for decades, including gamma spectrometers, gas-based ion chambers, and gamma cameras [8]. A gamma spectrometer can determine radionuclides by measuring gamma-ray counts and energy, and a gas-based ion chamber can measure radiation dose rates. However, these two methods have limitations in tracking the location of the radionuclide [9–13]. Although a gamma camera can be used to monitor the distribution of radionuclides, its detection efficiency is low and large-area monitoring is limited due to the use of a collimator and scintillator coupled to photomultiplier tubes (PMTs) [14,15].

However, new designs of detectors, applications, and software have been developed and studied by many researchers to improve performance and shortcomings in the field of radiation-monitoring systems. Representatively, many studies on wireless-based monitoring systems have been conducted to reduce unnecessary radiation exposure [16–19].

The advances in hardware technology such as materials, processes, and software including AI will be utilized as technological elements to improve the accuracy of radiation detection systems and to ensure the safety of workers, the environment, and people.

1.2. Artificial Intelligence (AI)

Artificial intelligence is a key technology that can quickly analyze and derive results using data sets in various research fields such as education, agriculture, finance, medicine and human-judgement assistance [20–22].

Research utilizing artificial intelligence is conducted in the field of radiation monitoring. The research of unstructured data such as supervision of an object-detection method using a deep convolutional neural network (DCNN) in a loading facility of radioactive materials is currently underway [23].

Artificial neural network (ANN) technology is one of these technologies, which connects of numerous neurons and builds multiple layers of neurons, just like the nervous system of a living organism, to increase the learning ability of a neural network. An artificial neural network uses input and output layers as weighting values to train and connect synapses of neurons. Each layer optimizes the training data to produce accurate answers. UO_2 powder storage facilities targeted in this study require various measurement variables to standardize the location, size (volume), energy, and radioactivity of the target nuclear material. The structure of the nuclear material storage facility was investigated in advance and described through simulation. In addition, an artificial-intelligence-based model was implemented and trained for various environmental variables according to the monitoring location. Then, a location-tracking algorithm was developed and applied to the monitoring system to quickly and accurately locate radioactive materials.

1.3. Radiation-Monitoring System Using Multiple Sensors and AI

The system is proposed to monitor a storage facility housing natural uranium UO_2 powder used for nuclear fuel. The UO_2 powder storage facility is a low-level radiation facility with a low criticality risk. However, the standards for theft and loss control including monitoring and management must be thorough due to its nuclear fuel properties.

In this study, in order to overcome the limitations of existing radiation-monitoring systems, we developed a nuclear facility monitoring system using a multi-sensor network using multiple gamma spectrometers and artificial intelligence data analysis technology. The multi-sensor network is based on a database obtained from networked gamma spectrometer data. The data obtained depending on the configuration of the sensor network was analyzed with an AI training mechanism to determine the location of the radioactive source. Various cases of monitoring environments for a UO_2 radioactive source were simulated. The simulated count rates of each detector module were built into a database. The database was used as training and validation data for AI-based algorithms. The performance evaluation of the AI algorithm was performed by measuring the localization accuracy of the missing UO_2 radioactive source.

2. Materials and Methods

2.1. Configuration of Monitoring System Using AI and Multi-Sensor Network

Figure 1 shows the schematic diagram of the proposed unmanned large-area nuclear facility monitoring system composed of a multi-sensor network, signal processing circuits, and AI-based data- and image-processing algorithms.

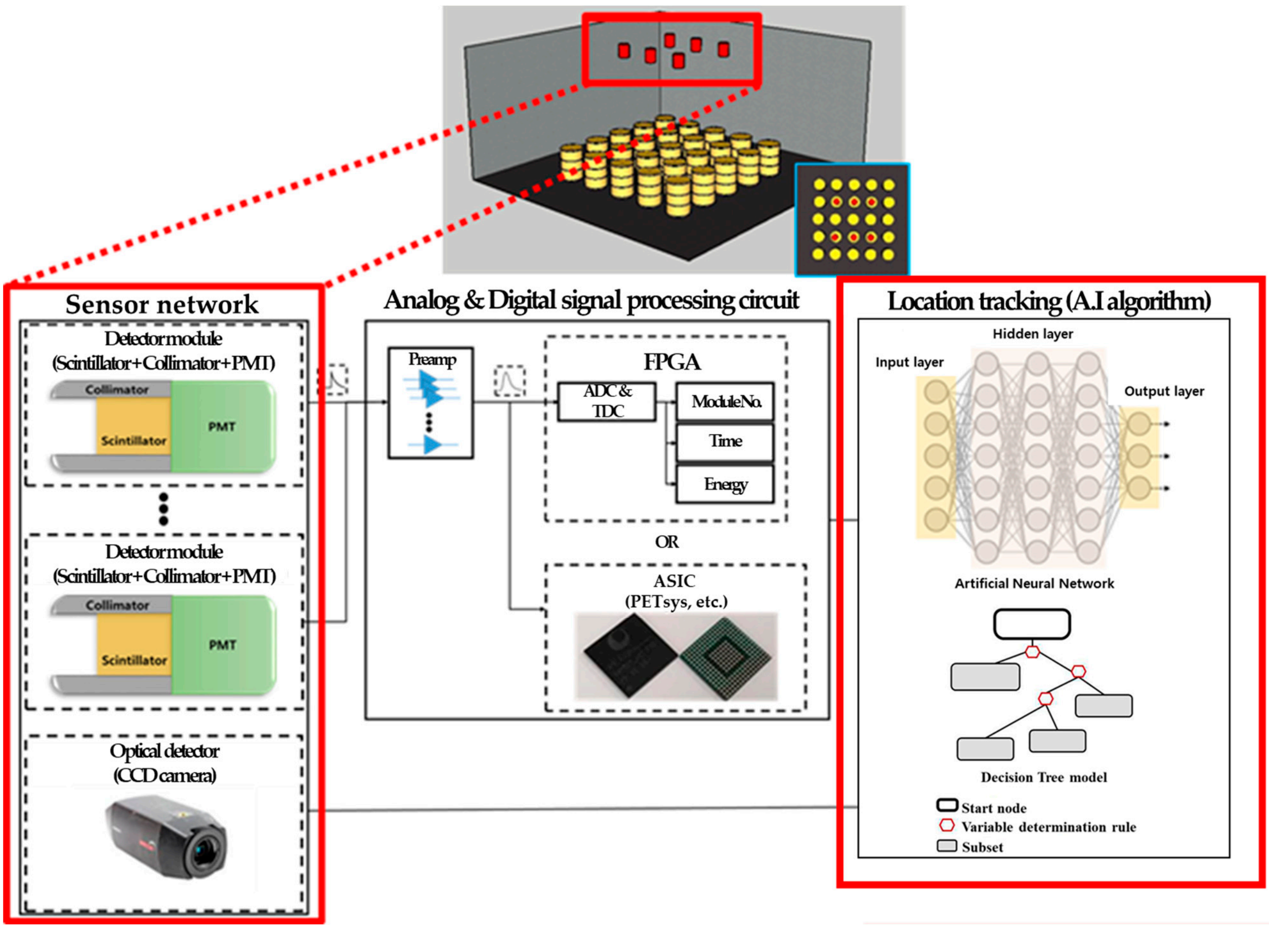


Figure 1. Configuration of radioactive-material-monitoring system using artificial intelligence and sensor network.

The designed system uses a multi-sensor network to track the location of the radioactive source and identify the radionuclide type. The multi-sensor network consists of several detector modules, and a single detector module is composed of a scintillator, PMT, and lead collimator, thus allowing radionuclide identification and limiting the effective field of view. The multi-sensor network was configured using an array of detector modules according to the geometry of the monitoring environment. The count rate of each detector module is acquired and digitized through analog and digital signal processing circuits and used to track the location of the UO_2 radioactive source. The measurement time, detector module number, and energy of each radiation signal data are acquired by a field programmable gate array (FPGA) and implemented in AI training to track the location of the radioactive source.

2.2. Modeling of UO_2 Powder Drums and Storage Facility Using GATE Tool

In this study, the database was obtained through Monte Carlo simulations to develop an AI-based algorithm using the multi-sensor network, and the accuracy of the proposed AI-based algorithm was evaluated.

The Geant4 Application for Tomographic Emission (GATE) tool was used to evaluate the AI-based algorithm. Figure 2 shows the monitoring environment of a UO_2 drum storage facility and the multi-sensor network designed using GATE.

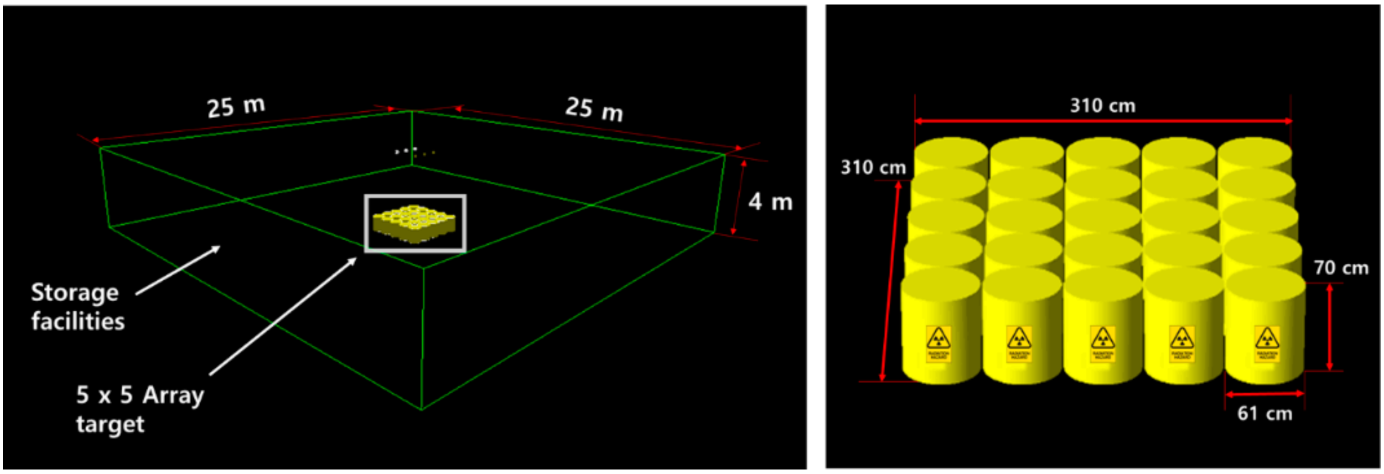


Figure 2. Geometry of a UO_2 drum storage facility (**Left**) and 5 × 5 drum array (**Right**) simulated by GATE tool.

The UO_2 drum storage facility was designed with a size of 2500 m^3 (25 × 25 × 4 m^3) to accommodate 40 × 40 UO_2 drums according to the 'Low-Level Radioactive Waste Repositories' published in 2011 [24]. The cylindrical UO_2 drum is 61 cm in diameter and 70 cm in height and can store 200 L of UO_2 powder. Each drum was placed on a 62 cm pitch. UO_2 drums and detectors were arranged in a uniformly repeating pattern. The count rate obtained from each detector was constant for a given condition. Therefore, to reduce the repetitive execution time of the computational simulation, a simulation environment was established by designating 5 × 5 drums as the minimum unit.

In the initial storage state, the loaded drum was set to be stored in a fixed state in order to track the abnormal position caused by the change in radiation dose. The initial state was set with all 25 drums present in the storage. The simulation was performed with a missing number of drums to obtain the database.

2.3. Design of Radiation Detector Module Using Multi-Sensor Network

Figure 3 shows the detector module modeled in the GATE simulation. A NaI(Tl) scintillator coupled to a lead collimator was used as the detector module to measure the gamma-rays and minimize the effective field of view. The diameter and height of the cylindrical scintillator were both set to 2.54 cm. The thickness of the lead collimator was set to 1 cm to shield background and fission product radiation.

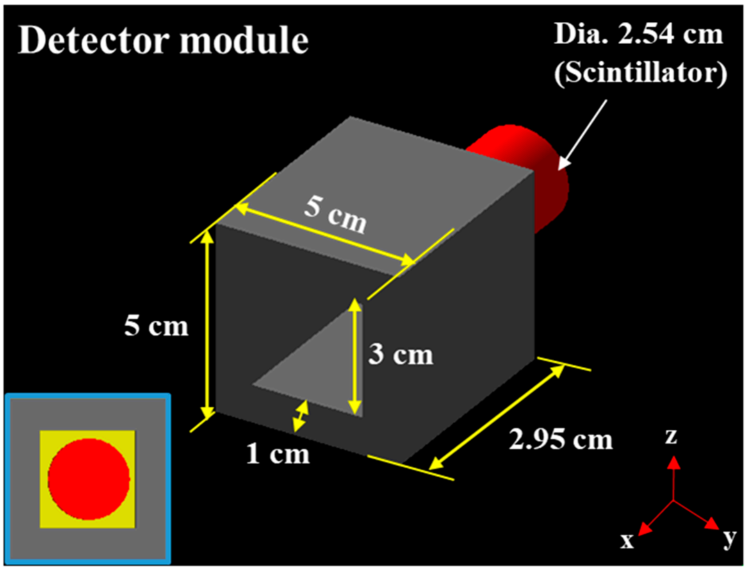


Figure 3. Structure of a single detector module designed for the measurement of radioactive materials.

Figure 4 shows the multi-sensor network configuration used for monitoring the storage environment. The yellow circles represent the UO_2 drums placed on the floor, and the red squares inside the yellow circles represent the locations of each of the six detector modules installed in the ceiling. The six detector modules were arranged in a 2 × 3 array. Each detector module monitored a 3 × 3 drum array with an effective field of view. For example, the detector module 1 monitored 01, 02, 03, 06, 07, 08, 11, 12, and 13 UO_2 drums. Detector modules 1 and 2 were positioned adjacently, and the effective field of view of each partially overlapped. The experiment was designed in such a way as to make a difference in the radiation count rate according to the geometrical arrangement of the detector module and the UO_2 drums, thus enabling detailed location analysis according to the combination of these factors in the sensor network.

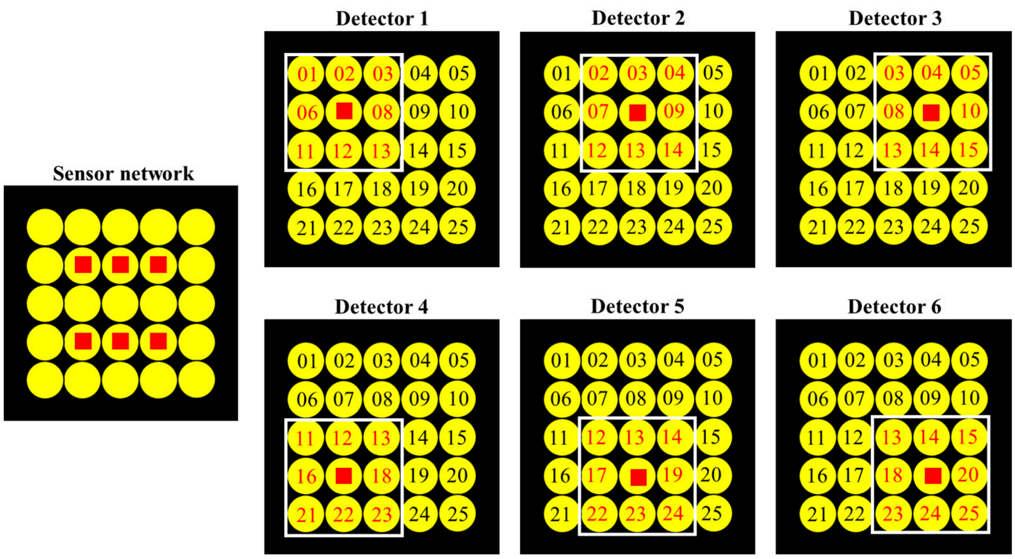


Figure 4. Field of view of a single detector module (each detector monitors a 3 × 3 are of drums).

2.4. D-Tree and ANN Model for Location Tracking

Each UO_2 drum was removed to obtain a database of various simulation cases and to evaluate the positioning accuracy of the algorithm. In this study, D-Tree and ANN models, which show high performance in vector format data, were used.

Figure 5 demonstrates the process of the D-Tree model. D-Tree is a machine learning program based on a classification algorithm that classifies data by creating rules based on the uniformity of the data. Then, the data is applied to classification and prediction [25–27]. A defect classification model based on the D-Tree algorithm was developed using the decreasing count value measured by the detector that monitors the missing drum. The algorithm model features the count values obtained from the six detectors as input to produce the probability of a missing drum as the output.

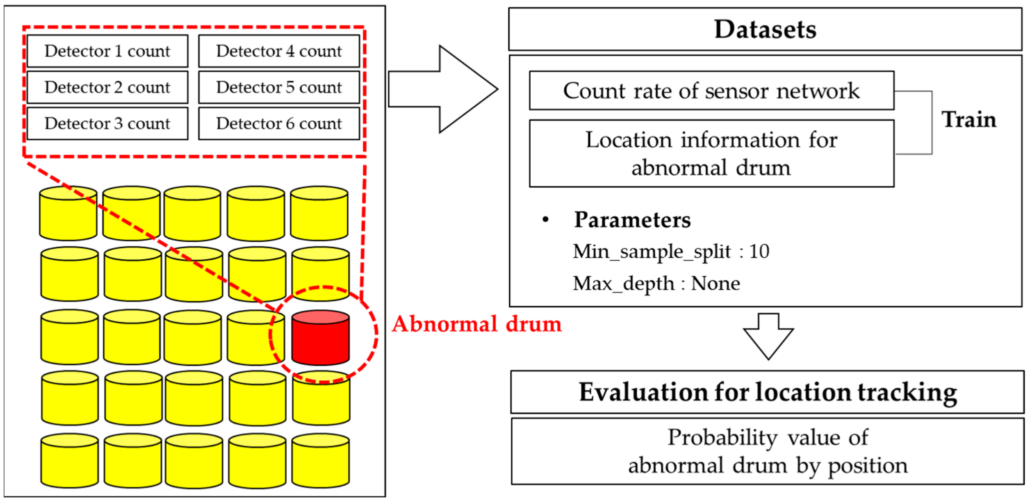


Figure 5. Process of D-Tree model.

Table 1 shows the parameters used in the D-Tree model. The gini that demonstrates the degree of data congestion is used as the criterion for splitting the data. The learning process generates decision rules to minimize impurities. At this time, as a parameter, the degree of splitting until the class is completely classified (max_depth) is set and the minimum number of samples (min_sample_split) to be split by the node is set to 10 to prevent data overfitting. This generates rules for reliable decision-making by constructing an algorithm that trains to the maximum depth until it contains a small number of samples.

Table 1. Parameters for D-Tree model.

Parameter	Explanation	Option
Criterion	Indicator of impurity	Gini
Min_sample_split	Minimum number of samples for segmentation	10

An ANN is a learning algorithm that mathematically models the human nervous system [28,29]. The system makes predictions using various weights in a network that connects neurons in layers. The algorithm consists of three structures: an input layer, a hidden layer, and an output layer. The neuron maps the sum of input signals received from the previous layer in a non-linear form through an activation function and transmits them to the neuron of the next layer. As training progresses, the model learns the optimal connection weight between neurons. Figure 6 shows the process of the ANN model using the count rates obtained from six detectors. The parameters of the ANN used in this study are as follows: the input layer consists of six neurons corresponding to the input signals of the six detector modules, and the hidden layer consists of 512 neurons and two layers, respectively. The output layer consists of 25 nodes, which is the number of all UO_2 storage drums. The activation function of each layer used tanh, and the activation function of the last output layer was constructed using sigmoid.

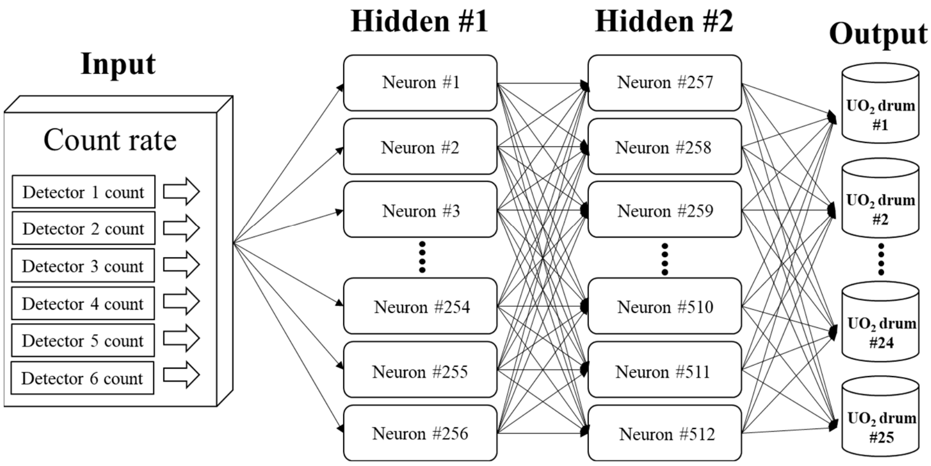


Figure 6. Process of ANN model.

Figure 7 A,C show some of the simulated cases where the loaded drums are removed one by one, and the removed location is circled in red. A total of 26 cases were considered with one case containing all 25 UO_2 drums and 25 different cases with one UO_2 drum removed. We ran 100 simulations for 26 cases each to generate a total of 2600 datasets. Data from 2600 simulations were acquired and preprocessed with count rate, module numbers, and energy information. The preprocessed data were converted into a database on a case-by-case basis.

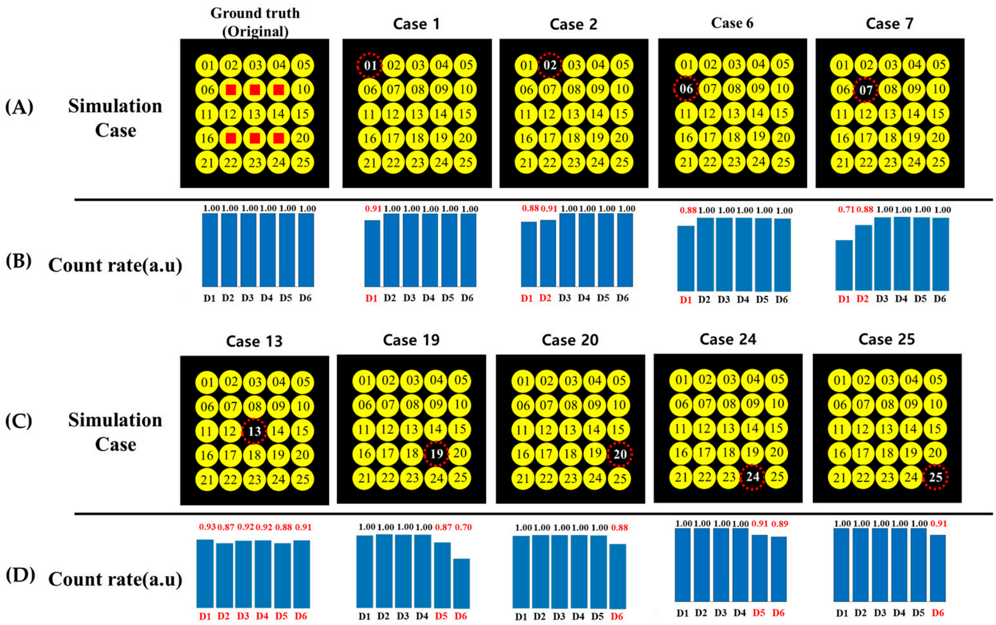


Figure 7. Simulation cases of one drum removal (**A**,**C**) and count rate comparison of each detector module (**B**,**D**).

The cross-validation method was used to evaluate the reliability of the simulation. The data was divided into training data (1820) and verification data (780) at a ratio of 7:3. The accuracy of D-Tree and the ANN-based positioning algorithm was derived through the following data division. Table 2 and Equation (1) show the evaluation indicator for the accuracy of each algorithm. The evaluation was classified using actual and predicted values. A true positive (TP) predicts an actual true value as true, a false positive (FP) predicts an actual false value as true, a false negative (FN) predicts an actual true value as false, and a true negative (TN) predicts an actual false value as false.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

Table 2. Indicator for the evaluation of AI-based positioning algorithm.

		Actual Value	
		True	**False**
Predicted value	True	True Positive	False Positive
	False	False Negative	True Negative

Accuracy was calculated by counting the number of TP + TN over the total number of all prediction cases (TP + TN + FP + FN).

3. Results

Figure 7 shows the count rates of the six detector modules for each simulated case. It was confirmed that the count rates of each detector module were different due to the positional relationship between the detector module and the removed UO_2 drum.

For case 1, the count rate decreased due to source loss within the FOV for detector number 1(D1), but not for D2-6. This shows that the location of the missing UO_2 drum can be identified by analyzing different count rates using the geometric location arrangement between the detector module and the UO_2 drum. For case 2, the count rates of detector modules 1 and 2 were 88% and 91% of the mean count rate of detector modules 3 to 6, respectively. Compared to D2, D1 was relatively more affected by the drum removal because it was closer to the missing UO_2 drum.

The count rates obtained from each detector module were used as training data to find missing UO_2 drum for both D-Tree and ANN algorithms. Figure 8 shows the accuracy of localization according to the training and validation data of D-Tree and ANN training models. It shows that the accuracy of the two models is similar, and no overfitting of the data was identified.

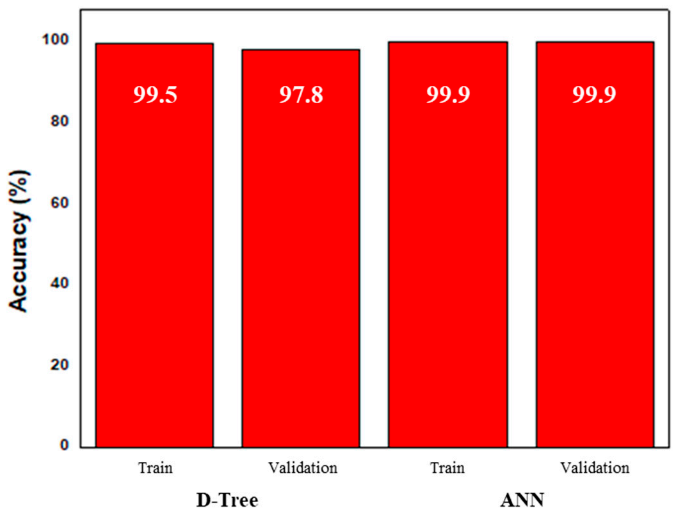


Figure 8. Accuracy evaluation of D-Tree and ANN model.

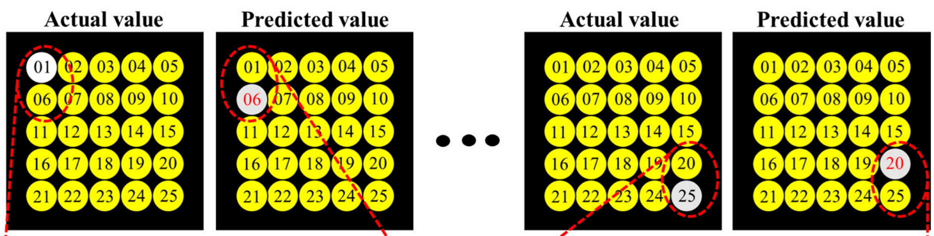
The accuracy of training and validation were 99.5% and 97.8% for the D-Tree model, respectively. Both the training and validation accuracies of the ANN model were 99.9%, which was higher than that of the D-Tree model.

Both D-Tree and ANN models are representative artificial intelligence algorithms that show good performance in solving classification problems. However, D-Tree tends to be less efficient in multi-class classification problems than in binary classification problems [30,31]. Because of these characteristics, the ANN model shows higher accuracy than the D-Tree model in this study.

4. Discussion

The database obtained using the Monte Carlo simulation was applied to the D-Tree and ANN-based algorithmic models to improve the accurate localization of removed UO_2 drums in nuclear and radioactive material storage facilities. In this study, a multi-sensor network arranged in a 2×3 array was positioned to monitor a 5×5 array of UO_2 drums. We trained an AI-based algorithm to track the location of missing sources using the count rate of each detector module constituting the multi-sensor network. The training and validation accuracies of the D-Tree model were 99.5% and 97.8%, respectively. The ANN algorithm model achieved 99.9% accuracy in both training and validation, confirming that the localization of a removed UO_2 drum is possible. In both training and validation, the ANN model showed higher accuracy performance than the D-Tree model. As a result of deriving various rules from the raw data of neurons configured in the ANN, it showed higher performance than D-Tree.

Figure 9 represents the errors encountered during the localization. The location of UO_2 drum 1 was incorrectly predicted as drum 6, and drum 25's location was incorrectly predicted as drum 20. The lack of count rate data resulted in incorrect position predictions for adjacent drums located in the corners of the storage facility. This misplacement error can be solved by increasing the number of cases in further studies.



Location # 1	Train (%)	Validation (%)
D-Tree	99.5	96.1
ANN	99.8	99.8

Location # 6	Train (%)	Validation (%)
D-Tree	99.5	92.6
ANN	99.7	99.7

Location # 20	Train (%)	Validation (%)
D-Tree	99.3	93.3
ANN	99.7	99.4

Location # 25	Train (%)	Validation (%)
D-Tree	99.5	96.8
ANN	99.8	99.7

Figure 9. Cases of error that occurred in the AI localization process.

Further studies are ongoing into various abnormal situations, including multiple missing UO_2 drums. The accuracy of the localization of radioactive materials in an AI-based monitoring system can be improved when it continuously learns by considering various variables in the measurement environment.

5. Conclusions

In this study, a nuclear material monitoring system based on a multi-sensor network and AI algorithm was implemented through Monte Carlo simulations. Performance tests were conducted to evaluate the accuracy of the system. It was confirmed that the developed

D-Tree and ANN-based algorithm showed high performance in determining the location of missing sources in radiation and nuclear facilities.

In further research, the proposed monitoring system will be developed and evaluated through experiments in radioactive source storage facilities. The fabrication of a detector module consisting of a PMT and a 2.54 cm sized diameter and thickness scintillator will be conducted to verify the simulation. The energy resolution and sensitivity of the detector module will be evaluated to identify the type of radiation source in the storage facility and to utilize the multi-sensor network, respectively. In addition, concealed sources such as Co-57 and Cs-137 will be placed in a test storage facility to configure a measurement environment. The obtained data for each source location can be applied to the algorithm to evaluate the location tracking accuracy. The data can also be used to develop a software-based program tool that applies to the monitoring system. Additionally, although structured data are currently used as input data for the AI model, we want to evaluate the possibility of location tracking using unstructured data such as images.

The proposed research can be used for safe nuclear power plant management through accurate detection and localization of nuclear materials by converging the existing radiation monitoring system and artificial intelligence technology. Based on the following research, public awareness of nuclear safety and radioactive waste management will guide nuclear power as a safe and sustainable energy source in the future.

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