# Deep Learning based Radionuclide Identification for high temperature

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## 1. Introduction

In severe accidents at nuclear power plants, identifying radioactive isotopes emitted from a nuclear reactor can play an important role in understanding the progression of the accident. However, the high temperature environment surrounding a nuclear reactor can greatly influence the performance of radiation measurement systems. Additionally, the degradation of a radiation detector's output due to high temperatures can have a devastating effect on nuclide identification algorithms, which are based on the location of photopeaks in the spectrum.

In this study, we propose a deep learning-based radionuclide identification algorithm that can identify nuclear isotopes even with temperature fluctuations. To obtain radiation measurement data at high temperatures, we fabricated a radiation detector using a ruggedized PMT and Ce:GPS scintillator, which shows promising performance in high-temperature environments. Our proposed deep learning architecture consists of five hidden layers and one fully connected layer. The accuracy of the proposed radionuclide identification algorithm was verified using radiation sources of $^{137}$Cs, $^{57}$Co, and $^{133}$Ba in the temperature range of 20℃ to 150℃.

## 2. Materials and method

### *2.1 Gamma-ray spectrum measurements.*

We used a Ce:GPS scintillator (3×3×20 mm$^3$, OXIDE Corporation, Japan) coupled with a 19-mm-diameter Hamamatsu R3991A-07 photomultiplier tube (PMT) to detect gamma rays. The PMT was supplied with a voltage of 1500 V, and its anode signal was sent to a charge-sensitive preamplifier, which was then shaped/amplified and digitized using a high-speed DT5730 digitizer (500 MS/s, 14-bit resolution, CAEN). To obtain the gamma-ray spectra, we measured the $^{137}$Cs (2.79 ± 0.07 MBq), $^{57}$Co (2.83 ± 0.07 kBq), and $^{133}$Ba (540.52 ± 13.51 kBq) check sources and collected 100,000 pulses for each source while changing the temperature at 20℃, 50℃, 75℃, 100℃, and 150℃. Temperature measurements were taken using a long thermocouple probe inserted into the furnace as shown in Figure 1. Prior to each measurement, the scintillation crystal and PMT were allowed to stabilize for at least 30 minutes in the furnace. Optical compounds such as optical grease and epoxy were not applied between the scintillation crystal and PMT glass to avoid their properties changing due to heat.

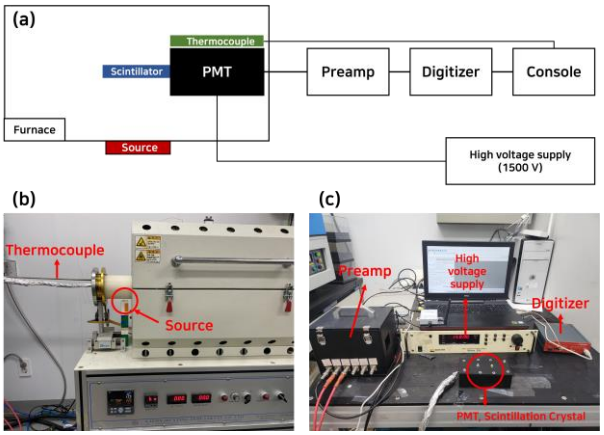


Fig. 1. (a) Schematic diagram for collecting radiation measurement data at high temperature. (b) The configuration of radiation detector, thermocouple, radiation source, and furnace. (c) The configuration of Charge sensitive preamplifer, High voltage supply, Digitizer and Console.

### *2.2 Training and Testing Dataset*

To identify the three types of radiation sources in this experiment, the dataset used for the deep learning model was divided into seven classes, as indicated in Table 1. Classes 0-2 consisted of 1200 gamma ray spectra generated using 100,000 pulses measured for one source at the same temperature. Of these, 1000 spectra were designated as the training dataset, while the remaining 200 spectra were designated as the test dataset.

For classes 3-6, the spectra were created by mixing 10,000 pulses randomly selected from the measured pulses for each source at the same temperature, ensuring that the proportion of pulses from any one source was at least 20%. For instance, in class 3, at least 2000 of the 10,000 pulses in a spectrum originated from measuring $^{137}$Cs.

Furthermore, to verify the temperature dependency of the deep learning model that could identify nuclides at temperatures for which it was not trained, the spectra obtained at 75℃ were used as only test datasets. Consequently, each class comprised 4000 spectra for training (25℃, 50℃, 100℃, and 150℃) and 1000 spectra for testing (25℃, 50℃, 100℃, 150℃, and 75℃).

Table I: Dataset used for deep learning

| *Class Number* | *Gamma-ray Sources* |
|---|---|
| 0 | $^{137}$Cs |
| 1 | $^{57}$Co |
| 2 | $^{133}$Ba |
| 3 | $^{137}$Cs, $^{57}$Co |
| 4 | $^{137}$Cs, $^{133}$Ba |
| 5 | $^{57}$Co, $^{133}$Ba |
| **6** | $^{137}$Cs, $^{57}$Co, and $^{133}$Ba |

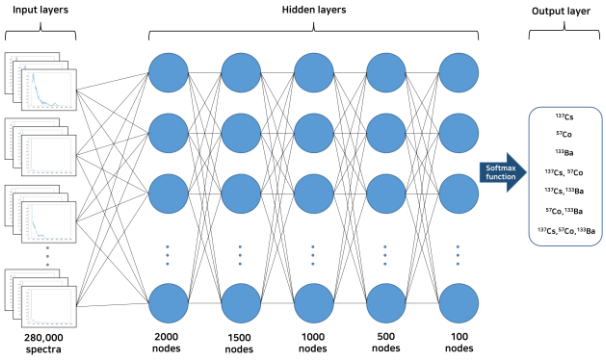


Fig. 2. Flowchart of the radionuclide identification base on Deep Neural Network.

*2.3 Architecture of Deep Neural Network (DNN)*

The DNN utilized in this study consisted of five stacked hidden layers and one Softmax layer, which can be shown in the flowchart illustrated in Figure. 2. The rectified linear unit (ReLU) served as the activation function for the five stacked hidden layers, each of which comprise 2000, 1500, 1000, 500, and 100 nodes. The output of the Softmax layer was used to assess the classification outcomes, and each node was fully connected. The architecture used in this study can be summarized as follows.

1) Configuration: Five layers and one Softmax layer (fully connected)
2) Activation Function for Hidden Layers: ReLU.
3) Optimizer: Adam optimizer (Adaptive Moment Estimation).
4) Learning Rate: 0.001.

To overcome the flaws of the traditional stochastic gradient descent technique, the Adam optimizer was employed as an optimization method.

In addition to the architecture of the DNN, the type of loss function utilized in this study is the categorical cross-entropy loss function. This loss function is commonly used for multi-class classification problems, where the goal is to minimize the difference between the predicted class probabilities and the true class probabilities.

## 3. Results and Discussion

As shown in Figure 3, it could be observed that shifts and changes in photopeaks occurred in the spectra as the temperature changed. These shifts could potentially have a negative impact on the identification of radionuclides. The spectra that contained these shifted photopeaks were utilized to train a deep learning model.

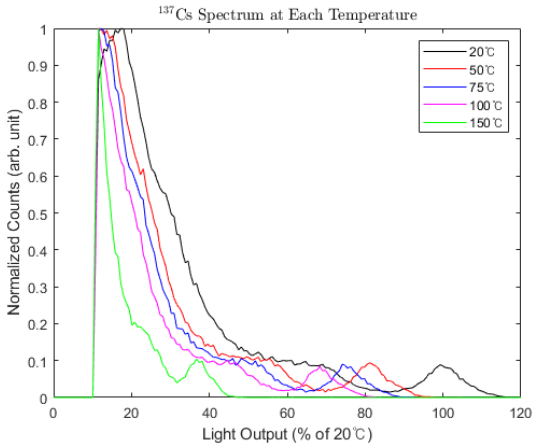


Fig. 3. $^{137}$Cs spectra at temperature of 20℃, 50℃, 75℃, 100℃, and 150℃.

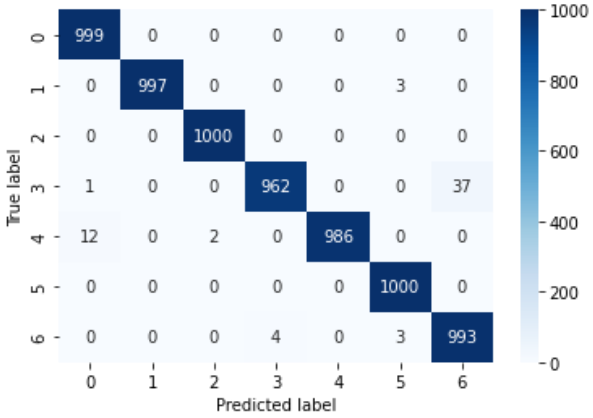


Fig. 4. Confusion matrix with accuracy of 99.11% for whole test dataset.

Table II: Classification accuracy by temperature.

| *Temperature* | *Accuracy* |
|---|---|
| 20°C | 100% |
| 50°C | 99.86% |
| 75°C | 95.93% |
| 100°C | 100%% |
| 150°C | 99.79% |
| **All** | 99.11% |

The trained deep learning model could identify all classes with a high accuracy of almost 100%, as evidenced in Figure 4. Notably, the trained deep learning model was able to identify nuclides with high accuracy regardless of temperature, from spectra obtained at 20°C, 50°C, 100°C, and 150°C. Furthermore, the trained deep learning model could identify radionuclide from spectra obtained at 75°C, which was not used for the train of the deep learning model, with an accuracy of 95.93% as shown in Table 2. This finding validates that our suggested deep learning

model can accurately identify nuclides, regardless of temperature fluctuations.

## 4. Conclusion

In this study, we proposed a deep learning model capable of identifying radionuclides irrespective of temperature variations. The proposed deep learning model exhibits high accuracy in identifying radionuclides, even when there are fluctuations in temperature. The proposed deep learning model demonstrated a 95.93% accuracy in identifying radionuclides with spectra obtained at temperatures which was not used for the training set. Future research will employ techniques such as interpolation to enhance the nuclide identification algorithm [3]. Additionally, we will assess the nuclide identification capabilities of the trained model on a more extensive range of nuclides.

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