International Journal of Electrical and Computer Engineering (IJECE)
Vol. 15, No. 2, April 2025, pp. 2282~2290
ISSN: 2088-8708, DOI: 10.11591/ijece.v15i2.pp2282-2290

Radionuclide identification system using convolution neural network for environmental radiation monitoring

Istofa[1,2], Gina Kusuma[2], Firliyani Rahmatia Ningsih[2], Joko Triyanto[2], I Putu Susila[2], Prawito Prajitno[1]
[1]Department of Physics, Faculty of Mathematics and Natural Sciences, Universitas Indonesia, Depok, Indonesia
[2]Research Centre for Nuclear Beam Analytics Technology, Research Organization for Nuclear Energy, National Research and Innovation Agency, Tangerang Selatan, Indonesia

Article Info

Article history:

Received Mar 10, 2024
Revised Oct 8, 2024
Accepted Oct 23, 2024

Keywords:

Convolutional neural network
Environmental radiation
Gamma spectrum image
Radionuclide identification
Rapid monitoring system

ABSTRACT

Radionuclide identification is an important task for nuclear safety and security aspects, especially to environmental radiation monitoring systems. This study aims to build an automatic radionuclide identification system that can be applied in environmental radiation monitoring stations. The gamma energy spectrum was obtained by varying radionuclide types, measurement time and source distance using a scintillation detector. The dataset was collected by converting gamma energy spectrum into images, data pre-processing by removing background noise and normalizing the gamma spectrum. Automatic identification is demonstrated as a development method based on convolutional neural network (CNN) algorithm, where the images come from gamma-ray spectrum in the form of photoelectric peak characteristic. Three CNN architectures are used to train the model, which are VGG-16, AlexNet and Xception. The performance of each model is evaluated using accuracy, precision and recall to find the appropriate architecture. The most optimum results are shown by VGG-16 with an accuracy of 97.72%, a precision of 97.75% and a recall of 97.71%. The models are critically reviewed and it is concluded that the developed models can be further implemented on embedded devices utilizing the tiny machine learning (TinyML) platform in environmental radiation monitoring systems.

Corresponding Author:

Prawito Prajitno
Department of Physics, Faculty of Mathematics and Natural Sciences, Universitas Indonesia
Depok, 16424, West Java, Indonesia
Email: prawito@sci.ui.ac.id

1. INTRODUCTION

Environmental radiation monitoring system around nuclear installations is a major concern for safety systems, such as source tracking [1], counter-terrorism, and emergency response, therefore detecting and identifying radioactive materials is crucial [2]. Speed and accuracy in identifying radionuclides that produce gamma-ray are challenging tasks, especially in emergencies when data interpretation requires complex calculations and expertise to obtain rapid and correct decisions before fatalities occur [3]. The key to successfully identifying radionuclide is data extraction of strong discriminative features, which bring specific and unique information of each nuclides [4].

The energy of gamma-ray spectrum contains a specific information of radionuclides, and becomes widely used on the identification system to discriminate the type of radionuclide [5]–[7]. Radionuclide identification system has various feature extraction techniques which have been employed, such as principal component analysis (PCA) [8], fuzzy logic algorithm [9], [10], Bayesian [11], Karhunen-Loeve transform

(K-L transform) [12], machine learning [13], [14], artificial neural network (ANN) [15]–[17], and convolution neural network (CNN) [18]–[22].

Research development and effort to overcome the challenges of radionuclide identification is summarizing in Table 1. Recently, there has been an increase in the use of machine learning approaches to quickly and precisely identify radionuclide from gamma-ray spectrum. Several researchers have taken note and made the first attempts to apply spectra extraction techniques utilizing machine-learning approaches. An ANN model was built on top of Monte Carlo simulation-based dataset, to identify 14 types of radionuclides using a 3×3-inch NaI detector. The results indicate that ANN has good generalization performance with average identification accuracy can be as high as 98% for specific condition [2]. Automation and fast identification of Cs-137 gamma source based-on CNN also presented by using Geant4 simulation data, and preserve confidence level of 90% [4]. In real measurement conditions, the accuracy might be decrease due to performance variations of detector affected by temperature changes, power supply noise, front-end circuit noise, and quantization errors on analog to digital converter (ADC) [23], [24].

Table 1. Research on the development of radionuclide identification system

Dataset	Method	Algorithm	Model Accuracy	Year	Ref
Monte-Carlo simulation	CNN	Energy-weighted	Cs-137: 84%; Co-60: 80%	2023	[14]
Monte-Carlo simulation	ANN	Back propagation	Cs-137: 96.5%; Co-60: 97.5%	2022	[2]
MAESTRO software based on SDK	R-L deconvolution and fuzzy	Peak search	Not mentioned, focused on confidence nuclide	2019	[10]
ANSI N42.34 library isotope peak energies	Wavelet transform for peak extraction	Bayesian statistic	Not mentioned, focused on peak measurement	2015	[11]

Most CNN models are designed and trained using datasets based-on particle simulations, and only a few studies use experimental data taken in the laboratory. In this study, we collect data taken from laboratory experiments by measuring the radiation spectrum of several radiation sources at different dose rates. Three CNN models with different architectures were constructed from large number of experimental data, which is the main contribution of this study. The performance of each model is evaluated using accuracy, precision, and recall to find the optimal architecture. The resulting model can then be implemented in an embedded device utilizing the tiny machine learning (TinyML) platform.

2. METHOD

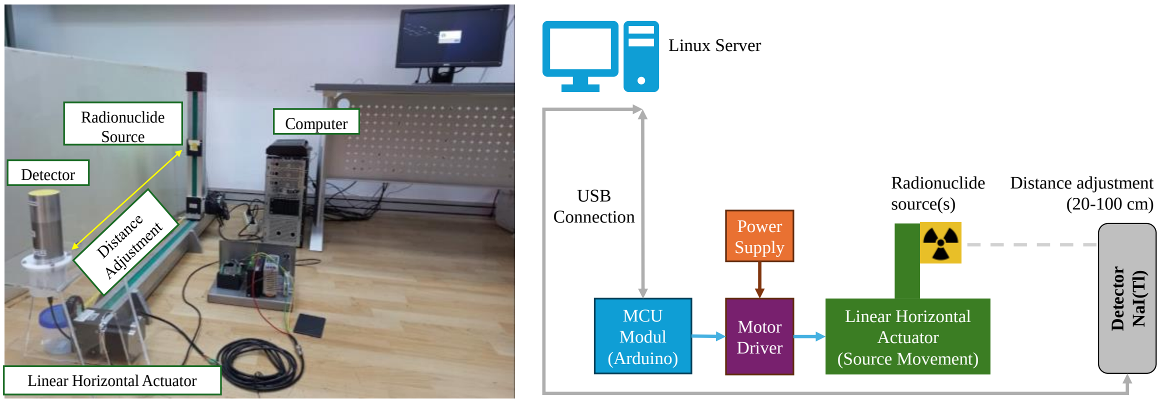
2.1. Acquisition of gamma energy spectrum

Gamma energy spectrum was collected through laboratory experiment using 2 inch R2D-NaI-2 NaI(Tl) scintillation detector, coupled with up to 2K channels of Int-1K-NaI-50 PMT-1000 multi-channel analyzer (MCA) from Bridgeport Instruments. High voltage supply, performance-enhancing field-programmable gate array (FPGA), and embedded ARM processor are integrated in the detector which is connected to computer through universal serial bus (USB). Radioactive sources used in this experiment are listed in Table 2. Figure 1 describes the configuration of the experiment. The detector is placed on a static detector stand, while the radionuclide source is placed on a radionuclide holder rod that can be adjusted back and forth driven by linear actuator. Arduino is used to control the movement of the linear actuator.

Table 2. Radionuclides used for dataset in October 2022

Radionuclides	γ Energy (keV)	Half-life (year)	Manufacture date (mm/dd/yy)	Initial activity (μCi)	Estimated activity (μCi)
^{137}Cs	662	30.05	01/01/19	0.10	0.09
^{60}Co	1,173; 1,332	5.27	04/01/19	1.00	0.59
^{134}Cs	569, 605, 796	2.06	08/01/15	0.77	0.07
^{152}Eu	122; 344; 779; 964; 1,086; 1,112; 1,408	13.54	04/01/12	0.93	0.56

A python-based application was developed to control the source movement and to collect the spectrum data through USB ports. In the experiment, variation of dose rate was obtained by acquisition of spectrum data at various distance starting from 20 to 100 cm with 10 cm interval, and measurement time from 5 to 60 seconds with 5 second increment. Spectrum data at each distance and time combination for certain radionuclide was taken 50 times to accommodate detector performance fluctuation. Variations of radionuclide sources are enumerated in the form of 4 radionuclides. Therefore, the collected spectrum for each radionuclide is 12×9×50=5,400 data, resulting total of spectrum was 21,600 data for 4 radionuclides.



(a) (b)

Figure 1. Gamma energy spectrum data collection system, (a) hardware components of the data collection system, and (b) block diagram that shows the connection between each component

2.2. Dataset preparation and network architecture

Spectrum images preparation is illustrated in Figure 2. The process begins with acquisition of gamma energy spectrum, using a scintillator detector which will produce radiation intensity data both for background and radionuclide stored into 1D vector. The average background and each radionuclide spectrum are normalized as shown by (1) in which

$$I_n^{'} = \frac{I_n \times 255}{I_{max}} \tag{1}$$

where $I_n^{'}$ is radiation intensity after normalized (count/second), I_{max} is the highest radiation intensity, I_n is intensity of the certain channel, and n is channel (keV). Each value in the histogram is multiplied by 255 (the range of pixel values in the image) and divided by the highest intensity I_{max}. This normalization process will result in redistributed values in the range of 0 to 255. As such, this function is designed to take a histogram of spectrum data and return a histogram that has been normalized to within the range of 0 to 255 values. Normalization is often applied to ensure that the data is within a range that subsequent algorithms or processes can effectively treat. Since the radiation spectrum data served the relation between energy and counts, no explanation regarding time measurement and distance correlation. The purpose of those treatment to increase the size of dataset, which can be reduced overfitting [19]. After obtaining the spectrum data distribution, it is mapped into 32×32 matrix, according to the number on the energy channel. There are several transformation methods from vector to matrix mapping, for instance Hilbert curve, z-order curve, vertical scanning and horizontal scanning [20]. Liang *et al.* [21] has been compared and analyzed based on those four transformation methods and found that Hilbert and z-order curve converged faster and smoother. Therefore, the z-order curved was used as a matrix transformation method for gamma-ray spectrum in this study.

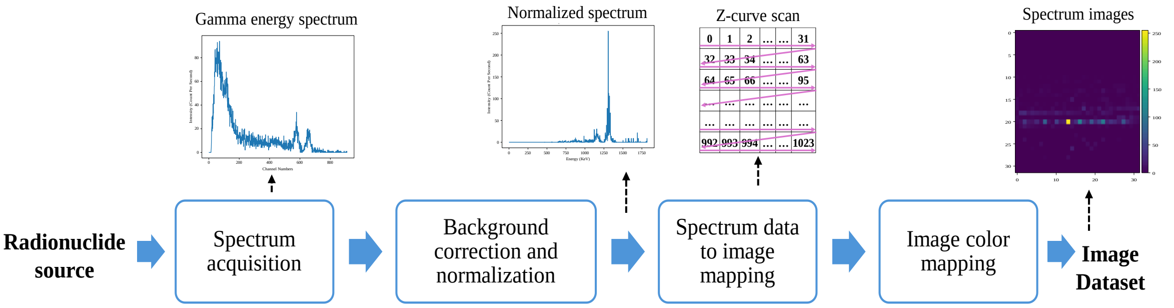


Figure 2. Block diagram of dataset preparation

The transformation program is designed to perform pre-processing of 1D spectrum vector. This function mainly aims to convert the 1D spectrum data into a two-dimensional array with a size of 32×32, which is saved as a 300×300 pixel PNG image file with Viridis color map. The 1D spectrum data contains 1,024 channels with maximum energy at 2048 keV, which means that each channel is equal to 2 keV of gamma energy. These 1024 channels are divided by 32 for each row, resulting in 32 rows and 32 columns. The first row from 0 to 31 represents the first row of the section. The second row from 32 to 63 is filled with information from the second section, and so on, resulting in a 32×32 image. The degree of color degradation in Viridis color map indicates the high-intensity information from the enumeration at that position. The highest intensity is shown in yellow and the lowest in dark blue. This image representation was used as a dataset to train and test classification model.

CNN is chosen to classify gamma radiation sources since it is a type of neural network well suited for processing structured arrays of data, employing multiple layers of linear and non-linear operations learned simultaneously in an end-to-end manner [25], [26]. We trained a CNN using prepared PNG image dataset as input layer to identify radionuclides. In this study, three CNN architectures are used to train the model, which are VGG-16, AlexNet and Xception as shown in Figure 3. In the context of deep learning, VGG-16, AlexNet, and Xception are prominent CNN architectures as shown in Figure 3(a)-(c), each representing distinct evolutionary stages in developing deep neural networks for image recognition tasks. These architectures vary significantly in their design principles, layer compositions, and computational complexities. As shown in Figure 3, Xception has more layers compared to VGG-16 and AlexNet primarily due to its architecture philosophy, which is centered around depth wise separable convolution. The choice between these architectures depends on the specific requirements of the task, including accuracy, computational efficiency, and resource availability.

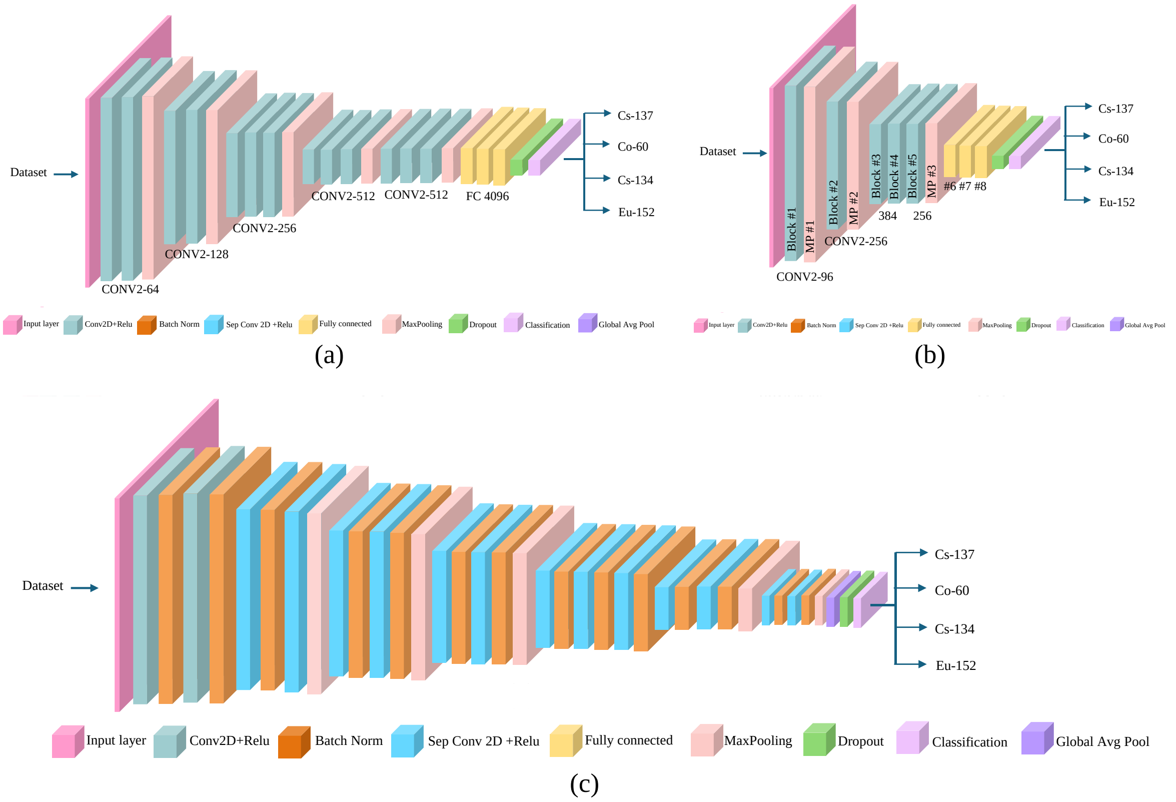


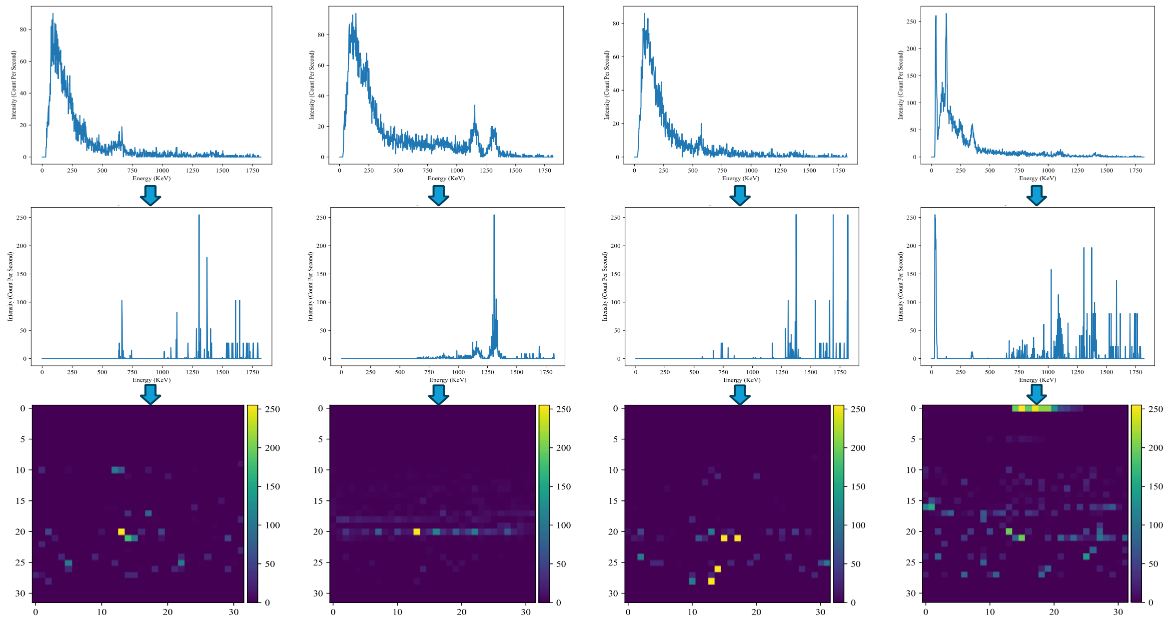
Figure 3. Illustration of three CNN architectures, (a) VGG-16, (b) AlexNet, and (c) Xception

In this study, the image dataset was divided with a ratio of 70% for training data, 20% for testing data, and 10% for validation data. The input size is 300×300×3 images entering the first filter layer. In VGG-16, layers refer to the different operations performed on the input data. These operations include convolution, activation, pooling, and fully connected layers. The convolution layer is the layer responsible for extracting features from the image. This layer uses filters to filter the image and generate a feature map. This feature map is then passed on to the next layer for processing. The pooling layer is responsible for reducing the size of the feature map. This construction is built to reduce the number of parameters that need to be learned by the network and to improve network performance. The kernel size or filter matrix is 3×3 considering the complexity of learned features. Max pooling layer with size 2×2 and three fully connected (FC) layers using 4,096 neurons. The fully connected layer is the layer responsible for making the final decision. It receives the output from the pooling layer and uses an activation function to generate the final output. At the ends of layers, Xception using global average pooling (GAP) to reduce numbers of parameters, different with VGG-16 and AlexNet which used dropout layers, because of regularization, to reduce the likelihood of overfitting.

3. RESULTS AND DISCUSSION

3.1. Transformation into image dataset

The transformation from radionuclide spectrum to image dataset is shown in Figure 4. This figure shows example of the transformation result of Cs-137, Co-60, Cs-134, and Eu-152 with source to detector distance of 20 cm and measurement time of 60 seconds. In the upper rows, original spectrum for each radionuclide and its peak for the corresponding energy as listed in Table 2 is shown. The second rows illustrate 1D normalized spectrum after correction using background spectrum as described in the method section. In the last rows, transformed images for each radionuclide is shown.

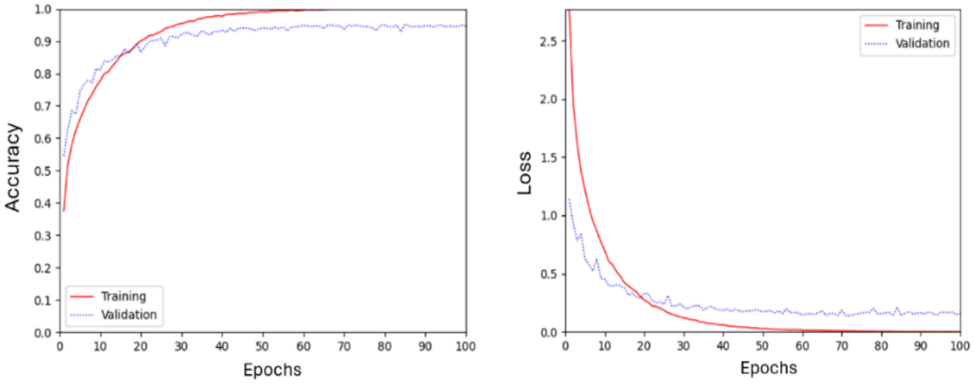


(a) (b) (c) (d)

Figure 4. Example of feature transferring from spectrum vector to image: (a) Cs-137, (b) Co-60, (c) Cs-134, and (d) Eu-152

3.2. Evaluation of training results

According to literature reviews, deep learning algorithms are particularly useful and frequently applied when the dataset consists of a collection of photos since they can extract complicated characteristics and perform classification with a high degree of accuracy [27]–[30]. One of indicator result based on deep learning CNN (DLCNN) is the training and validation graph as the epoch increases [30]. The training and validation process is shown in Figure 5, which is represented by an accuracy and loss function graph. An accuracy curve that tends to rise closer to 1 indicates that the model is getting better at learning data patterns and there is no overfitting. This is also in line with the loss function, which tends to decrease during the training process. The accuracy rate is close to 100% after 100 epochs, and the loss value curve approaches 0. The research used Hilbert-Huang transform (HHT-CNN) with 1D-CNN [28] showing that to obtain an optimal and stable accuracy, a higher epoch number is required compared to this research. Figure 5 makes it abundantly evident that the model may achieve optimal accuracy at approximately 20 epochs.



(a) (b)

Figure 5. The training and validation process of (a) accuracy and (b) loss

3.3. Model performance comparison

Three criteria are used to evaluate the performance of the model: accuracy, precision and recall [27], [29], [30]. Models have utilized DLCNN architectures with different filter, padding size, kernel size at the activation layer, learning rate and window size. Figure 6 explains that the VGG-16 model has the best testing accuracy, precision and recall values compared to other models, at 97.72%, 97.75% and 97.71% respectively.

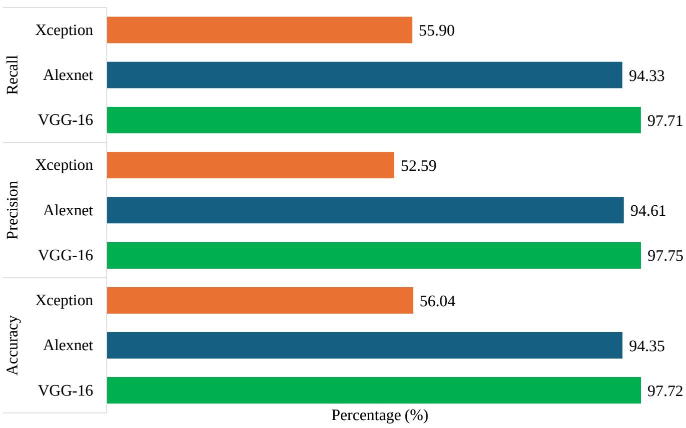


Figure 6. Output values of CNN for different model architecture

High accuracy results are proven in the confusion matrix, as shown in Table 3. The confusion matrix is a performance evaluation technique used in classification problems in machine learning and statistics. Its primary function is to provide a detailed breakdown of the performance of a classification model by presenting a matrix of actual versus predicted class labels. The table explains that the total of data correctly predicted by the model amounts to 1,025 data for the Co-60 class, 1,096 data for Cs-134 class, 1,053 data for Cs-137 class, and 1,063 data for Eu-152 class. Overall, the confusion matrix is a fundamental tool for evaluating, understanding, and improving the performance of classification models in various machine learning applications [20], [23]. It offers a granular view of classification results, enabling data scientists and practitioners to make informed decisions about model selection, optimization, and deployment.

Table 3. Confusion matrix of VGG-16 architecture

VGG-16		Prediction class			
		Cs-137	Co-60	Cs-134	Eu-152
Actual class	Cs-137	1,053	11	1	15
	Co-60	48	1,025	0	7
	Cs-134	0	0	1,096	0
	Eu-152	16	1	0	1,063

Recent study on the detection of radionuclide classification based-on machine learning demonstrate that the method can be implemented in embedded device utilizing TinyML platform [25]. Since an embedded device has limited resources in term of memory size and computational power, a proper classification method, reduction of model size and pre-processing method to reduce the input will be important for successful implementation. Therefore, in the future, studies on optimization of architecture and model size of the proposed method, as well as evaluation of pre-processing method to reduce the dimensions of spectrum image will be performed.

4. CONCLUSION

Radionuclide identification method based-on experimental dataset was designed for monitoring the environment radiation system. This study proposes an automatic system based on converting gamma-ray intensity to spectrum image as the dataset. The model performance was evaluated, and the results proved that the algorithm was suitable for an identification or classification system. Training the model by using three CNN architectures and obtained that VGG-16 has optimal accuracy values, and the loss function is very low. The results achieved the optimum accuracy at 97.72%, precision of 97.75% and recall 97.71%. Future work will develop the TinyML with additional gamma-ray data and embedded system technology. The direction of these findings is to contribute for providing an appropriate model of TinyML which can be embedded into radiation detection device.

REFERENCES

[1] I. P. Susila, A. Alfiansyah, I. Istofa, S. Sukandar, B. Santoso, and S. Suratman, "Development of mobile device for gamma radiation measurement utilizing lora as the communication means," *Jurnal Teknologi Reaktor Nuklir Tri Dasa Mega*, vol. 21, no. 2, p. 79, 2019, doi: 10.17146/tdm.2019.21.2.5432.

[2] S. Qi *et al.*, "Radionuclide identification method for NaI low-count gamma-ray spectra using artificial neural network," *Nuclear Engineering and Technology*, vol. 54, no. 1, pp. 269–274, Jan. 2022, doi: 10.1016/j.net.2021.07.025.

[3] C. Li *et al.*, "A new radionuclide identification method for low-count energy spectra with multiple radionuclides," *Applied Radiation and Isotopes*, vol. 185, Jul. 2022, doi: 10.1016/j.apradiso.2022.110219.

[4] G. Daniel, F. Ceraudo, O. Limousin, D. Maier, and A. Meuris, "Automatic and real-time identification of radionuclides in gamma-ray spectra: a new method based on convolutional neural network trained with synthetic data set," *IEEE Transactions on Nuclear Science*, vol. 67, no. 4, pp. 644–653, Apr. 2020, doi: 10.1109/TNS.2020.2969703.

[5] H.-L. Liu, H.-B. Ji, J.-M. Zhang, C.-L. Zhang, J. Lu, and X.-H. Feng, "A novel approach for feature extraction from a gamma-ray energy spectrum based on image descriptor transferring for radionuclide identification," *Nuclear Science and Techniques*, vol. 33, no. 12, p. 158, Dec. 2022, doi: 10.1007/s41365-022-01150-7.

[6] Y. Wang *et al.*, "Explainable radionuclide identification algorithm based on the convolutional neural network and class activation mapping," *Nuclear Engineering and Technology*, vol. 54, no. 12, pp. 4684–4692, Dec. 2022, doi: 10.1016/j.net.2022.08.011.

[7] S. M. Galib, P. K. Bhowmik, A. V. Avachat, and H. K. Lee, "A comparative study of machine learning methods for automated identification of radioisotopes using NaI gamma-ray spectra," *Nuclear Engineering and Technology*, vol. 53, no. 12, pp. 4072–4079, Dec. 2021, doi: 10.1016/j.net.2021.06.020.

[8] D. Boardman, M. Reinhard, and A. Flynn, "Principal component analysis of gamma-ray spectra for radiation portal monitors," *IEEE Transactions on Nuclear Science*, vol. 59, no. 1, pp. 154–160, Feb. 2012, doi: 10.1109/TNS.2011.2179313.

[9] M. Alamaniotis, S. Lee, and T. Jevremovic, "Intelligent analysis of low-count scintillation spectra using support vector regression and fuzzy logic," *Nuclear Technology*, vol. 191, no. 1, pp. 41–57, Jul. 2015, doi: 10.13182/NT14-75.

[10] Z. Wang *et al.*, "Spectrometry analysis algorithm based on R-L deconvolution and fuzzy inference," *Applied Radiation and Isotopes*, vol. 153, p. 108817, Nov. 2019, doi: 10.1016/j.apradiso.2019.108817.

[11] C. J. Sullivan and J. Stinnett, "Validation of a Bayesian-based isotope identification algorithm," *Nuclear Instruments and Methods in Physics Research Section A: Accelerators, Spectrometers, Detectors and Associated Equipment*, vol. 784, pp. 298–305, Jun. 2015, doi: 10.1016/j.nima.2014.11.113.

[12] L. Chen and Y.-X. Wei, "Nuclide identification algorithm based on K–L transform and neural networks," *Nuclear Instruments and Methods in Physics Research Section A: Accelerators, Spectrometers, Detectors and Associated Equipment*, vol. 598, no. 2, pp. 450–453, Jan. 2009, doi: 10.1016/j.nima.2008.09.035.

[13] G. Kusuma, R. M. Saryadi, S. K. Wijaya, S. Soekirno, P. Prajitno, and I. P. Susila, "Radionuclide identification analysis using machine learning and GEANT4 simulation," in *AIP Conference Proceedings*, 2021, p. 020033. doi: 10.1063/5.0067593.

[14] H. C. Lee *et al.*, "Radionuclide identification based on energy-weighted algorithm and machine learning applied to a multi-array plastic scintillator," *Nuclear Engineering and Technology*, vol. 55, no. 10, pp. 3907–3912, Oct. 2023, doi: 10.1016/j.net.2023.07.005.

[15] C. Bobin, O. Bichler, V. Lourenço, C. Thiam, and M. Thévenin, "Real-time radionuclide identification in γ-emitter mixtures based on spiking neural network," *Applied Radiation and Isotopes*, vol. 109, pp. 405–409, Mar. 2016, doi: 10.1016/j.apradiso.2015.12.029.

[16] M. Kamuda, J. Stinnett, and C. J. Sullivan, "Automated isotope identification algorithm using artificial neural networks," *IEEE Transactions on Nuclear Science*, vol. 64, no. 7, pp. 1858–1864, Jul. 2017, doi: 10.1109/TNS.2017.2693152.

[17] J. Kim, K. Park, and G. Cho, "Multi-radioisotope identification algorithm using an artificial neural network for plastic gamma spectra," *Applied Radiation and Isotopes*, vol. 147, pp. 83–90, May 2019, doi: 10.1016/j.apradiso.2019.01.005.

[18] A. Sharma, E. Vans, D. Shigemizu, K. A. Boroevich, and T. Tsunoda, "DeepInsight: a methodology to transform a non-image data to an image for convolution neural network architecture," *Scientific Reports*, vol. 9, no. 1, p. 11399, Aug. 2019, doi: 10.1038/s41598-019-47765-6.

[19] R. S. Saeed and B. K. O. C. Alwawi, "A binary classification model of COVID-19 based on convolution neural network," *Bulletin of Electrical Engineering and Informatics*, vol. 12, no. 3, pp. 1413–1417, Jun. 2023, doi: 10.11591/eei.v12i3.4832.

[20] F. Tempola, R. Wardoyo, A. Musdholifah, R. Rosihan, and L. Sumaryanti, "Classification of clove types using convolution neural network algorithm with optimizing hyperparamters," *Bulletin of Electrical Engineering and Informatics*, vol. 13, no. 1, pp. 444–452, 2024, doi: 10.11591/eei.v13i1.5533.
[21] D. Liang *et al.*, "Rapid nuclide identification algorithm based on convolutional neural network," *Annals of Nuclear Energy*, vol. 133, pp. 483–490, Nov. 2019, doi: 10.1016/j.anucene.2019.05.051.
[22] M. S. Naga Raju and B. S. Rao, "Colorectal multi-class image classification using deep learning models," *Bulletin of Electrical Engineering and Informatics*, vol. 11, no. 1, pp. 195–200, Feb. 2022, doi: 10.11591/eei.v11i1.3299.
[23] S. Jhung, S. Hur, G. Cho, and I. Kwon, "A neural network approach for identification of gamma-ray spectrum obtained from silicon photomultipliers," *Nuclear Instruments and Methods in Physics Research Section A: Accelerators, Spectrometers, Detectors and Associated Equipment*, vol. 954, no. December 2018, p. 161704, Feb. 2020, doi: 10.1016/j.nima.2018.12.019.
[24] C. Kim *et al.*, "Radiation resistance and temperature dependence of Ce:GPS scintillation crystal," *Radiation Physics and Chemistry*, vol. 183, no. June, p. 109396, Jun. 2021, doi: 10.1016/j.radphyschem.2021.109396.
[25] M. Altayeb, M. Zennaro, and E. Pietrosemoli, "TinyML gamma radiation classifier," *Nuclear Engineering and Technology*, vol. 55, no. 2, pp. 443–451, Feb. 2023, doi: 10.1016/j.net.2022.09.032.
[26] M. Kamuda, J. Zhao, and K. Huff, "A comparison of machine learning methods for automated gamma-ray spectroscopy," *Nuclear Instruments and Methods in Physics Research Section A: Accelerators, Spectrometers, Detectors and Associated Equipment*, vol. 954, no. October 2018, p. 161385, Feb. 2020, doi: 10.1016/j.nima.2018.10.063.
[27] K. H. Suradiradja, I. S. Sitanggang, L. Abdullah, and I. Hermadi, "Convolutional neural network for estimation of harvest time of forage sorghum (sorghum bicolor) cultivar samurai-1," *International Journal of Electrical and Computer Engineering*, vol. 14, no. 2, pp. 1730–1738, Apr. 2024, doi: 10.11591/ijece.v14i2.pp1730-1738.
[28] W. Zhao *et al.*, "Novel radionuclides identification method based on Hilbert–Huang transform and convolutional neural network with gamma-ray pulse signal," *Nuclear Instruments and Methods in Physics Research Section A: Accelerators, Spectrometers, Detectors and Associated Equipment*, vol. 1051, no. March, p. 168232, Jun. 2023, doi: 10.1016/j.nima.2023.168232.
[29] P. Kaur and R. Kumar, "Performance analysis of convolutional neural network architectures over wireless capsule endoscopy dataset," *Bulletin of Electrical Engineering and Informatics*, vol. 13, no. 1, pp. 312–319, Feb. 2024, doi: 10.11591/eei.v13i1.5858.
[30] A. R. Ajel, A. Q. Al-Dujaili, Z. G. Hadi, and A. J. Humaidi, "Skin cancer classifier based on convolution residual neural network," *International Journal of Electrical and Computer Engineering*, vol. 13, no. 6, pp. 6240–6248, Dec. 2023, doi: 10.11591/ijece.v13i6.pp6240-6248.

BIOGRAPHIES OF AUTHORS

Istofa is a researcher at Research Centre for Nuclear Beam Analytics Technology - Research Organization for Nuclear Energy - National Research and Innovation Agency, Indonesia. He obtained his bachelor's degree in nuclear engineering from Gadjah Mada University Indonesia in 2002. He is currently pursuing a master's degree in Department of Physics, Faculty of Mathematics and Natural Sciences, University of Indonesia. His research interests include electronics, nuclear instrumentation, embedded system and machine learning. He can be contacted at email: isto001@brin.go.id.

Gina Kusuma is a researcher at Research Centre for Nuclear Beam Analytics Technology – Research Organization for Nuclear Energy – National Research and Innovation Agency, Indonesia. Born in Bogor, West Java. He obtained his bachelor's degree in nuclear technophysics from Polytechnic Institute of Nuclear Technology – BATAN Yogyakarta in 2013 and then continuing his study in Magister Science, Physics Department, Universitas Indonesia, graduate in 2021. His research field is nuclear instrumentation, electronics, embedded system, desktop programming and artificial intelligence. He can be contacted at email: gina004@brin.go.id.

Firliyani Rahmatia Ningsih is a researcher at Research Centre for Nuclear Beam Analytics Technology. Born in Surabaya, East of Java. Graduated from bachelor program of Nuclear Engineering Universitas Gadjah Mada in 2015. After that continuing the study in magister science, Physics Department, Universitas Indonesia, graduation year of 2023. Currently active as an assistant researcher at National Research and Innovation Agency of Republic Indonesia. Research interests in technology of photon beam, radiation measurement, artificial intelligence and radiation imaging technique. She can be contacted at email: firl001@brin.go.id.

Joko Triyanto is a researcher at Research Centre for Nuclear Beam Analytics Technology. Born in Wonogiri, Central Java. Graduated from the undergraduate program in Nuclear Engineering Universitas Gadjah Mada in 1995. After that, he continued his studies at master of engineering, Department of Electrical Engineering, University of Indonesia, graduation year 2012. Currently active as a researcher at the National Research and Innovation Agency of the Republic of Indonesia. Research interest in nuclear instrumentation and control system, radiation measurement, and embedded systems. He can be contacted at email: joko019@brin.go.id.

I Putu Susila is a researcher at Research Centre for Nuclear Beam Analytics Technology–Research Organization for Nuclear Energy – National Research and Innovation Agency, Indonesia. He received his doctoral degree from Tohoku University Japan in 2009. His research interests include software developer, image processing, and embedded system in biomedical and health research. Particularly interested in developing healthcare equipment including hardware, software and developing open-source application. He can be contacted at email: iput001@brin.go.id.

Prawito Prajitno is a member of the teaching and research staff at the Electronic and Instrumentation Physics of the Department of Physics, University of Indonesia. He was born in Pekalongan on July 21st, 1960. He received his doctoral degree from University of Sheffield, England with the dissertation title neuro-fuzzy methods in multisensory data fusion. He is now active in the research area of artificial intelligence and embedded systems. He can be contacted at email: prawito@sci.ui.ac.id.