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Multi-Radioisotope Identification Using Convolutional Neural Networks Trained with Two-Dimensionally Transformed Gamma Spectrum Data Measured Using a CsI(TI) Spectrometer

Yong Hyun Kim, Dong Geon Kim, Kihong Pak, Jae Young Jeong, Sangmin Lee, Jae Chang Kim, Han Cheol Yang, Yong Kyun Kim* *E-mail: ykkim4@hanyang.ac.kr



Nar Se 한국원자력학회 Korean Nuclear Society

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Hanyang Univ. Nuclear Engineering dept. Radiation Instrument&Sensor engineering Lab. Yong Hyun Kim



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Radioisotope Identification (RIID) ?

• Quantification or identification of the radioactive materials in Gamma-ray spectroscopy



Neural Networks for RIID

• Energy Calibration X

• Unfolding X

(Unfolding : Smoothing, Background substraction, Peak search, Peak separation, etc)

- High Accuracy & Efficiency
- Multi-isotopes Identification (good resolving power for overlapped peaks)
- Powerful when using low-resolution detectors (Nal, Csl(Tl), etc)





How many Radioisotopes(RIs) can be identified in this spectrum?





-> ²⁴¹Am, ⁵⁷Co, ¹³⁷Cs, ⁶⁰Co, ²²Na, ¹³³Ba, ¹⁰⁹Cd, and ⁵⁴Mn can be identified and qua ntified relatively within 4~5% error when using Convolutional Neural Networks.







Purpose of the study

- For the development of CNNs for RIID, We use 2D transformed input data of RI mixtures for training of CNN model rather than use typical 1D spectrum data of RI mixtures.
- We compare the RIID performance of CNN models trained with 1D spectra and the transformed 2D inputs



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- The experimental setup to measure the energy spectrum to be used for learning of CNNs
- CsI(TI) crystal is coupled to silicon photomultipliers(SiPMs)
- Eight gamma-ray sources (²⁴¹Am, ⁵⁷Co, ¹³⁷Cs, ⁶⁰Co, ²²Na, ¹³³Ba, ¹⁰⁹Cd, and ⁵⁴Mn) used for generating single RI spectrum



1D spectrum data generation

2. Methods

Datasets are generated through data synthesis of • the spectra.

1. Introduction

Pulse height spectra s_i of single RI *j* are normalized to one 1.

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- 2. Each spectrum with 4096 channels is constructed to a spectrum wi th 1521 channels by discarding unnecessary front (noise: ~55) and rear (empty: ~1576) channel sections
- Normalized spectrum s_i' of single RI *j* is multiplied by the synthesi 3. s coefficient $c(0 \sim 1)$ that is randomly determined
- 4. Synthesized artificial spectrum S can be expressed as a linear com bination with the coefficient

$$S_i(x) = \sum_{j=1}^N c_{ji} s_j'(x) (\sum_j^N c_{ji} = 1)$$

N: the total number of RIs, 8

 c_{ii} : synthesis coefficient (relative activity) of RI *j* for the *i*th random generation(*i* : 1 ~ 15,000)

• 15,000 1D spectral data for multiple radiation sources in various ratios can be generated.

3. Results



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4. Conclusions

&Summarv

3. Results Contents 1. Introduction 2. Methods &Summary 2D transformed data generation

• We sequentially cut 39 channels in the 1D spectral data and arrange them to form 39 rows.





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4. Conclusions

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&Summaryp. 82D transformed data generation

- 15,000 1D spectral data and 15,000 2D data transformed from the 1D data are prepared
- We split each set of the 15,000 data into training, validation, and test sets in the ratio 67:13:20 through random splitting.

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Contents 1. Introduction 2. Methods 3. Results 4. Conclusions &Summary p. 9 CNNs for RIID

• Hyperparameters of both CNNs models are tuned to optimize the performance

Hyperparameters of the CNN models

| Parameter | Model trained with 1-D data | Model trained with 2-D data |
|---|-------------------------------------|-------------------------------------|
| Input size | height 1, width 1521 (1-D) | height 39, width 39 (2-D) |
| Filters per convolution layer | 32 | 32 |
| Dense layer nodes | 128 | 128 |
| Filter size | height 1, width 9 (1-D) | height 3, width 3 (2-D) |
| Pooling type | 1-D max pooling (height 1, width 4) | 2-D max pooling (height 2, width 2) |
| Dropout (pooling, dense layer) | 0.1 | 0.1 |
| Activation function (convolution, dense layer) | ReLU | ReLU |
| Activation function (output layer) | SoftMax | SoftMax |
| Optimizer | Adam | Adam |
| Loss function | Cross-entropy | Cross-entropy |
| Batch size | 64 | 64 |
| Number of classes (output size) | 8 | 8 |

• Evaluation of the performance of the trained CNN models

Mean Magnitude of Relative Error (MMRE):

$$M M R E_{f}(\%) = \frac{1}{n} \sum_{i=l}^{n} \left| \frac{(y_{ji} - \overline{y}_{ji})}{y_{ji}} \right| \times 100(\%)$$

 y_{ji} : the test value of the activity for RI *j* at the *i*th sampling \overline{y}_{ji} : the predicted values of the activity for RI *j* at the *i*th sampling *n* : the sampling number for the test set,







 The model trained with 2D data exhibits a higher p erformance except for ¹³⁷Cs isotope.
 (significantly a smaller MMRE and uncertainty for ¹⁰⁹Cd)

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- MMRE for ¹⁰⁹Cd decreases as the sampling range decreases
 - -> As relative activity increases, MMRE decreases
- For both models, the MMRE for ¹⁰⁹Cd is significantly larger than other RIs -> Because normalized spectrum of ¹⁰⁹Cd is smaller than other Ris
- The model trained with 2D data perfoms much better when activity is low

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&Summaryp. 11• We use two types of CNNs to identify and quantify RIs in a mixture of RIs through a gamma spectrum measure
d using a CsI(TI) spectrometer. (Two types: one is trained by 1D data and the other one is trained by 2D transfo
rmed data)

- The model trained with the transformed 2-D data outperforms the model trained with the 1-D data
- Proposed method of transforming 1-D spectra into 2-D data is a promising approach for training CNNs for RII
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Thanks for listening

Q & A





