Deep Learning-Based Isotope Identification for Radiological Crime Scene Investigations Using Convolutional Neural Networks

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Introduction

Accurate identification of radioactive isotopes is vital for nuclear security, environmental monitoring, and emergency response, yet traditional gamma-spectroscopy techniques (peak fitting, template matching, expert analysis) often falter with low resolution, limited counting statistics, and high background—challenges that are especially acute for field-portable 3″ NaI(Tl) detectors. To overcome these hurdles, we developed a one-dimensional convolutional neural network that directly ingests raw gamma spectra, eliminating the need for extensive preprocessing. The CNN was trained on Monte Carlo–simulated spectra for 35 isotopes with real background measurements from an actual NaI(Tl) detector added to each simulation to replicate realistic field conditions. Our model achieved a global classification accuracy of 94%, demonstrating the promise of deep learning for robust isotope identification in challenging environments.

Data Generation

- A 3″ NaI(Tl) detector was simulated in GEANT4 and irradiated with the following isotopes: **^{241}Am, ^{133}Ba, ^{109}Cd, ^{57}Co, ^{60}Co, ^{51}Cr, ^{137}Cs, ^{152}Eu, ^{67}Ga, ^{123}I, ^{131}I, ^{111}In, ^{192}Ir, ^{40}K, ^{177}Lum, ^{54}Mn, ^{99}Mo, ^{22}Na, ^{237}Np, ^{239}Pu, ^{240}Pu, ^{226}Ra, ^{75}Se, ^{153}Sm, ^{89}Sr, ^{99}Tcm, ^{232}Th, ^{201}Tl, ^{204}Tl, ^{233}U, ^{235}U, ^{238}U, WGPu, ^{133}Xe**
- **Background** has been sampled from a real background distribution taken using a 3″ NaI(Tl) detector
- Detector energy response was recorded and **smeared to account for detector resolution.**
- 2500 histograms with 1024 bins up to 1600keV per isotope were created
- Histograms include a random number of events ranging from 5×10^3 to 10^5
- **Signal-to-background ratios** (Signal/(Signal+Background)) were chosen randomly, following a uniform distribution from 0.1 to 1.

Deep learning

- Convolutional Neural Networks (CNNs) are a class of deep learning algorithms designed to process data with a grid-like topology, such as images or, in this case, spectral histograms
- Extract features by applying filters (kernels) that detect patterns, such as peaks or edges, in the input data.
- Effective for analyzing localized features in gamma-ray spectra or images.
- Automatically detect important patterns without manual feature engineering.
- Handle noise and variability in input data, such as overlapping signatures or smeared energy distributions.

CNN Architecture

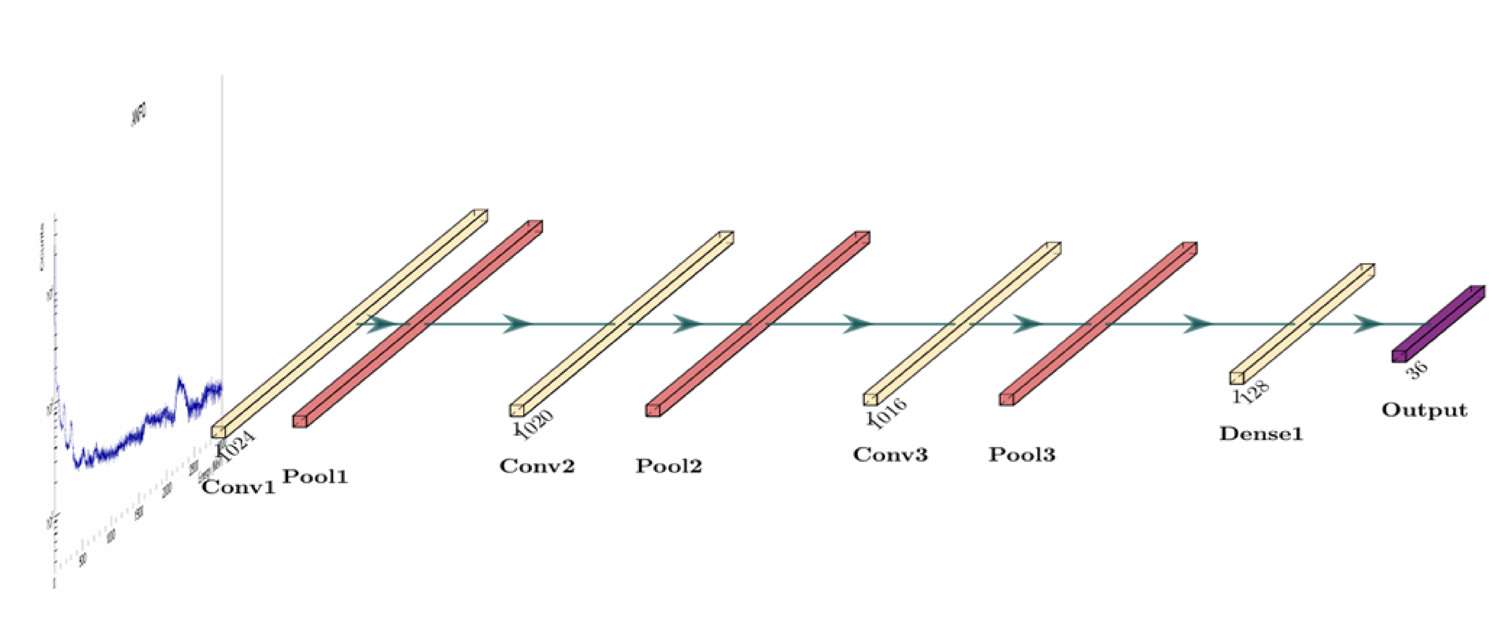

Figure 1. A 1D-CNN with three convolution–pooling blocks (32→64→128 filters, kernel/pool size 3), a 128-unit dense layer, and a 36-unit softmax output for isotope classification.

Layer	Configuration	Purpose
Convolutional Feature Extractors (1D)	• 3 layers with ReLU activation • Filters: 32 → 64 → 128 • Kernel size: 3, stride: 1	Learn low- to high-level spectral patterns
Max-Pooling Stages	• 3 layers (one after each convolution) • Pool size: 3, stride: 1	Dimensionality reduction and noise suppression
Fully Connected Layer	• 128 units with ReLU	Integrate extracted features for discrimination
Output Layer	• 36 units (35 isotopes + background) • Softmax activation for multi-class classification	Multi-Class Classification

Table 1. Layer configurations for the 1D-CNN architecture, detailing convolutional filters, pooling parameters, dense units, and output classes.

Training Details

Parameter	Value
Training Set	60%
Validation Set	20%
Testing Set	20%
Batch Size	128
Epochs	5
Preprocessing	• Spectra Histograms normalized to the total counts • Bin Transformation: Z-Score
Loss Function	• Categorical Cross Entropy

Table 2. Training configuration parameters, including dataset split proportions, batch size, number of epochs, preprocessing steps, and chosen loss function.

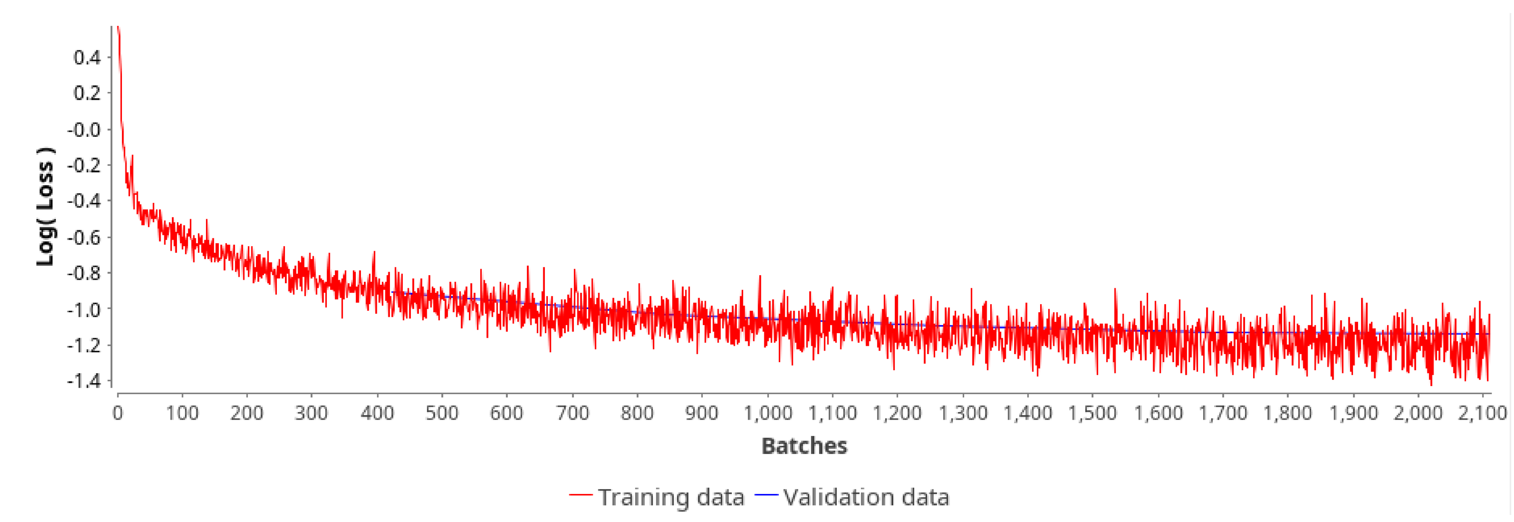

Figure 2: Evolution of the logarith of the loss function vs batch number, with training loss shown in red and validation loss in blue; the close alignment of the validation curve with the training curve indicates consistent learning without significant overfitting.

Results

Isotope \ Pr...	Am-241	Ba-133	Cd-109	Co-57	Co-60	Cr-51	Cs-137	Eu-152	Ga-67	I-123	I-131	In-111	Ir-192	K-40	Lum-177	Mn-54	Mo-99	Na-22	Np-237	Pu-239	Pu-240	Ra-226	Se-75	Sm-153	Sr-89	Tcm-99	Th-232	Tl-201	Tl-204	U-233	U-235	U-238	WGPu	Xe-133	U-238_Pa-2...	bgr
Am-241	499	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Ba-133	0	527	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Cd-109	0	0	510	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Co-57	0	0	0	477	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Co-60	0	0	0	0	521	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Cr-51	0	0	0	0	0	505	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Cs-137	0	0	0	0	0	0	498	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Eu-152	0	0	0	0	0	0	0	509	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Ga-67	0	0	0	0	0	0	0	0	511	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2
I-123	0	0	0	0	0	0	0	0	0	514	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
I-131	0	0	0	0	0	0	0	0	0	0	478	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
In-111	0	0	0	0	0	0	0	0	0	0	0	481	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Ir-192	0	0	0	0	0	0	0	0	0	0	0	0	519	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
K-40	0	0	0	0	0	0	0	0	0	0	0	0	0	504	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Lum-177	0	0	0	0	0	0	0	0	0	0	0	0	0	0	476	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Mn-54	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	501	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Mo-99	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	509	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Na-22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	487	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Np-237	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	527	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	3
Pu-239	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	372	0	0	0	0	0	0	0	0	0	0	0	0	126	0	0	0
Pu-240	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	509	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Ra-226	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	481	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Se-75	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	473	0	0	0	0	0	0	0	0	0	0	0	0	0
Sm-153	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	516	0	0	0	0	0	0	0	0	0	0	0	0
Sr-89	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	454	0	0	0	0	0	0	0	0	0	0	0
Tcm-99	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	488	0	0	0	0	0	0	0	0	0	0
Th-232	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	488	0	0	0	0	0	0	0	0	1
Tl-201	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	428	95	0	0	0	0	0	0	0
Tl-204	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	15	460	0	0	0	0	0	0	0
U-233	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	488	0	0	0	0	0	4
U-235	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	513	0	0	0	0	0
U-238	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	485	0	0	0	2
WGPu	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	126	0	0	0	0	0	0	0	0	0	0	0	0	370	0	0	0
Xe-133	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	482	0	0
U-238_Pa-...	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	512	0
bgr	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	544

Table 3. Confusion matrix computed on the held-out test dataset for all 36 classes (35 isotopes + background), illustrating per-class accuracy and the most frequent misclassifications.

- The confusion matrix for all 36 classes (35 isotopes + background), computed on a held-out test dataset never seen during training. The strong diagonal dominance indicates that the 1D-CNN correctly classifies the vast majority of spectra, yielding an overall test accuracy of 0.97. Per-class recall exceeds 0.96 for 31 of the 35 isotopes and reaches 1 for the background class.
- These results on unseen data confirm that our network not only achieves high overall accuracy but also maintains robust, consistent performance across a diverse set of radionuclides and realistic background conditions.

Conclusions and Future Work

A 1D CNN trained on raw, low-resolution NaI(Tl) spectra—augmented with real background measurements—achieves 97 % accuracy on 35 isotopes plus background in held-out tests, even under low-count and high-background conditions. By learning discriminative features end-to-end on realistic Monte Carlo simulations, the method shows promise for mixed-isotope samples and direct estimation of isotope ratios—capabilities currently under investigation. Future work will verify the algorithm with actual isotope standards and extend the framework to small-form-factor CZT detectors, leveraging their higher resolution while addressing limited volume and statistical-noise challenges.

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