Deep Learning Techniques for Radioisotope Identification in Complex Gamma-Ray Spectra: A Comprehensive Survey

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Abstract: Fast nuclide identification with increased accuracy rates is an important demand in nuclear applications. So, effective spectrum identification techniques are established for low-resolution NaI(TI) scintillator and Si(Li) detector spectra. The goal of recent research is to identify X-ray and gamma complex spectra. Conventional spectrum analysis techniques often struggle with overlapping spectral peaks, background radiation, detector noise, and mixed-isotope settings, which limits their efficacy in real-world applications. This overview covers radioisotope identification methods from peak-based and statistics to machine learning algorithms and deep learning models for automated gamma-ray spectrum categorization. It also evaluates previous methods' accuracy, computing efficiency, generalization, and deployment practicality. The paper highlights explainable artificial intelligence, transfer learning, self-supervised learning, and lightweight edge-deployable models, as well as unsolved issues including limited annotated datasets and cross-detector adaptability. The findings can help researchers and practitioners develop reliable and intelligent radioisotope identification systems for nuclear threat detection, border security, radioactive waste management, emergency response, and nuclear medicine, including PET, SPECT, and radiopharmaceutical quality assurance.

Keywords: Radioisotope identification, Gamma-ray spectroscopy, Deep learning; Machine learning, Convolutional neural networks, Transformers, Nuclear security, Nuclear medicine.

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1. Introduction

Radioisotope identification (RIID) is an important and difficult job in gamma-ray spectroscopy [1]. It involves quantifying and identifying radioisotopes (RIs) using pulse-height spectra. Reliable RIID is critical for contamination control, decommissioning, environmental monitoring, nuclear nonproliferation, radioactive resource exploration, nuclear facility operation, and radio bioassays. Machine learning (ML) and condition-based RIID methods exist. The classical condition-based photopeak information approach

analytically detects RIs using spectrum photopeak energy information. This method uses RIID spectrum unfolding, spectral smoothing, energy linearity and resolution calibration, peak search, overlapping peak separation, background removal, peak area calculation, efficiency calibration, and library matching. This common procedure is difficult and requires expert help, especially with overlapping peaks. There are several analytical methods for overlapping peaks. These technologies need operator-defined parameters and have uneven precision, making them unsuitable for real-time and in situ applications. ML-based RIID approaches use the full spectrum pattern rather than individual peaks, avoiding complicated unfolding phases and expert participation. ML-based RIID can resolve mixes of numerous RIs with high accuracy, especially in real-time environments with complicated overlapping peaks, but it must first identify and label each RI's gamma-ray spectra [2]. Many scientific questions remain unanswered despite these developments. Many deep learning models need vast amounts of annotated spectral data, yet benchmark datasets are limited. Spectra acquired using differing detector technologies, energy resolutions, or environmental circumstances decrease model performance. Additionally, class imbalance, domain adaptability, explainability, computational complexity, and real-time deployment on edge radiation monitoring devices remain research issues. This paper reviews gamma-ray spectroscopy-based radioisotope identification methods in light of recent improvements.

In the early 1970s, researchers developed numerous quantitative NDA spectroscopic methods for uranium and plutonium isotopes. Currently, three NDA approaches evaluate 235U isotopic content. The IAEA's first method measures the 186 keV line of 235U in germanium or sodium iodide spectrometer spectra [4] and requires a known enrichment standard for calibration. The counting rate for the 185.7 keV peak is proportional to enrichment if the sample has the same shape and thickness as the reference and the measurement circumstances remain constant. This method has been used to infer 235U content, however it has significant drawbacks: The samples must meet the infinite thickness condition [5], be calibrated for various containers, and have wall thicknesses measured before enrichment [6].

2. Machine Learning Techniques for Radioisotope Identification

Gamma-ray spectra may help identify radioisotopes by reducing dimension. Therefore,[7] examined two dimensionality-reduction methods—principal component analysis as a linear technique and an autoencoder as a nonlinear method—for radioisotope identification, getting F1 of 0.99 and 0.91 for PCA. In [8] reduces Compton scattering via pulse classification and MLCSA using a convolutional neural network. kNN achieved over 90% accuracy on 5- and 14-isotope tasks, outperforming LR and NB as classes rose [9]. KNN inference was 1–3 orders of magnitude slower than other methods due to distance computations scaling with training data. Despite its accuracy, kNN is inappropriate for mobile or real-time deployments. SVMs confused near-degenerate emission lines in bigger libraries but had >90% accuracy on small libraries. SVM misidentified 87% of 235U (185.7 keV) as 226Ra (186.2 keV) in a 14-class assessment. Additionally, SVM incorrectly classified 24% of 137Cs as background under spectral drift. SVMs are intriguing for tiny libraries with clear features, but kernel choice and margin optimization cannot overcome peak-overlap physics without spectrum constraints. The second important method is algorithm adaptation, which changes current machine learning algorithms to accommodate multi-label classification directly. This is used in Knearest neighbors, logistic regression, decision trees, and SVMs. Deep learning models use sigmoid activation for the output layer and an average of binary cross-entropy (BCE) over all

radionuclides as the loss function. This method lets the network monitor all radionuclides and produce 0–1 values to identify them. arch, a hybrid CNN architecture, uses numerical values to predict radioisotope presence from signals. Fully calibrated detectors make sure that identification is done correctlyγ-ray spectrometry research has extensively utilized this method [10]. Recent works have examined Deep Learning loss function modifications such Focal Loss and Asymmetric Loss in multi-label categorization. Currently, these novel approaches are not used in γ-ray spectrometry.

Table 1. Literature Comparison of ML Techniques

Ref	Method	Performance	Limitations
[7]	PCA, Autoencoder	PCA: F1 = **0.99**; Autoencoder: **0.91**	Autoencoder performed worse than PCA.
[8]	CNN + MLCSA	Reduced Compton scattering and improved classification	Requires high computational resources.
[9]	kNN, LR, NB, SVM	kNN: **>90% accuracy**; SVM: **>90%** for small libraries	kNN is slow for real-time applications; SVM struggles with overlapping peaks.
[10]	Deep Learning (Sigmoid + BCE)	Effective for multi-label radionuclide identification	Does not handle class imbalance.

3. Deep Learning for Gamma-Ray Spectrum Classification

Conventional ML methods have been applied in γ-ray spectrometry literature for ML algorithms. Popular deep learning methods include multilayer perception (MLP) and convolutional neural network (CNN). The CNN architecture has shown higher performance and excellent accuracy in radioactive detection in recent investigations.

Table 2. Literature comparison with DL Methods

Ref	Method	Performance	Limitations
[11]	CNN (IRAND-Sim-02)	Achieved 99.97% accuracy	Applicable only on simulated dataset.
[12]	2D CNN	Calculated radioisotope proportions with low MAE	need specialised detector and training data.
[13]	Deep Neural Network (DNN)	Identified and quantified γ-ray spectra.	Depends on high-quality simulated and experimental datasets.
[14]	CNN	Generalized from single-/double-isotope training	Trained using simulated GADRAS-DRF spectra.

[15]	Hybrid CNN	Identified radioisotope using numerical signal features.	Requires calibrated detectors and feature engineering

4. Comparative analysis

Different gamma-ray detectors produce energy resolution, efficiency, and noise spectra. Thus, model design and input spectrum affect machine learning and deep learning algorithms performance. As shown in table-1, detector-wise study shows how detector features affect practical classification algorithm selection.

Table-1 Detector-wise Analysis

Detector	Resolution	Suitable Algorithm
HPGe	Very High	CNN, Transformer
NaI(Tl)	medium	CNN, SVM
CZT	high	CNN
LaBr3	high	CNN
Plastic Scintillator	low	Hybrid CNN

Figure 1 compares PCA, SVM, kNN, CNN, and Hybrid CNN robustness. PCA has the lowest robustness, scoring 60% for noise, 55% for peak overlap, 50% for mixed isotopes, and 58% for background radiation. These data show that PCA is vulnerable to spectrum distortions since it uses linear dimensionality reduction and cannot capture gamma-ray spectra's complicated nonlinear properties. SVM is somewhat robust, reaching 75% noise, 68% peak overlap, 65% mixed isotopes, and 70% background radiation. While SVM outperforms PCA, its robustness falls when spectra include overlapping energy peaks and many radionuclides. KNN outperforms PCA and SVM in noise, peak overlap, mixed isotopes, and background radiation, achieving 82%, 76%, 72%, and 78%, respectively.

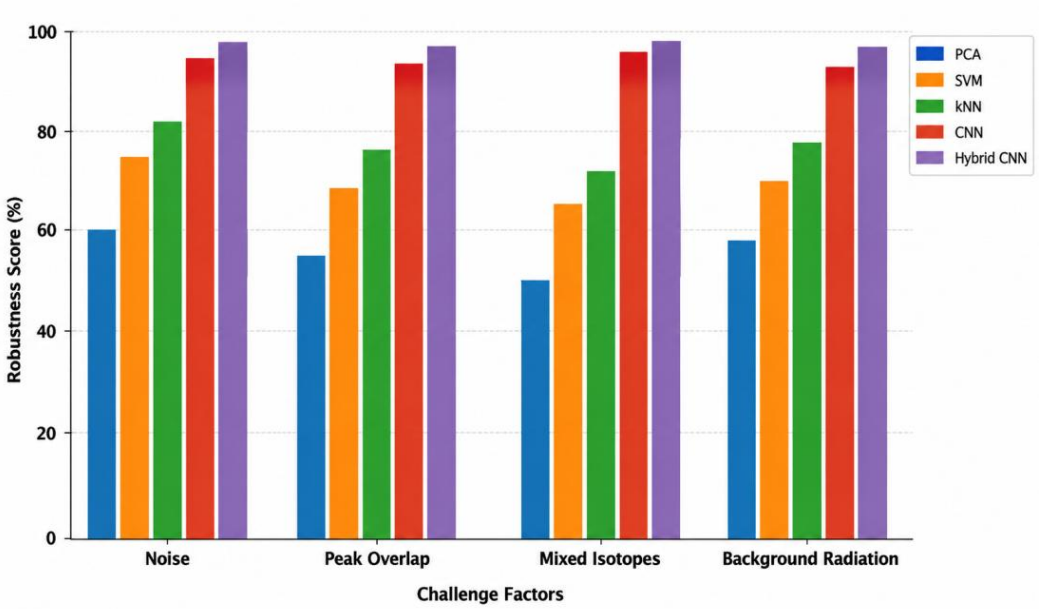

Figure 1. Performance of Different Models

Conclusion

This survey covered the progress of radioisotope identification methods for gamma-ray spectroscopy from spectrum analysis to machine learning and deep learning. Recent deep learning developments have improved radioisotope detection by automatically extracting hierarchical features from raw gamma-ray spectra. Specifically, compared to Conventional ML techniques, CNN and hybrid CNN architectures have shown greater resilience, classification accuracy, and generalization capabilities. Despite these achievements, several issues persist. Lack of publicly available benchmark datasets, domain adaptability across detector types, class imbalance, explainability of deep learning conclusions, computational complexity, and deployment on resource-constrained edge devices restrict practical implementation. The findings help researchers and practitioners choose appropriate identification methods and identify future research opportunities to develop accurate, reliable, and real-time radioisotope identification systems for nuclear security, radiation monitoring, environmental safety, and nuclear medicine.

References

1. Mustapha, I. (2022). Identification of Medical and Industrial Used Radioisotopes in Mining Sites of Nasarawa, Nasarawa State, Nigeria. *Journal of Oncology Research*.
2. Li, F., Gu, Z., Ge, L., Li, H., Tang, X., Lang, X., & Hu, B. (2019). Review of recent gamma spectrum unfolding algorithms and their application. *Results in Physics*, *13*, 102211.
3. J. Parker, T. Reilly, Plutonium isotopic determination by gamma-ray spectroscopy, Nuclear analysis research and development program status report.
4. T. Reilly, R. Walton, J. Parker, progress report la-4605-ms, Los Alamos National Laboratory, NNM (197) 19.
5. D. Reilly, N. Ensslin, H. Smith Jr, S. Kreiner, Passive nondestructive assay of nuclear materials, Tech. Rep. LA-UR-90-732, Office of Nuclear Regulatory Commission, Washington, DC, USA (1991).

6. T. E. Sampson, G. W. Nelson, T. A. Kelley, FRAM: A versatile code for analyzing the isotopic composition of plutonium from gamma-ray pulse height spectra, Tech. rep., Los Alamos National Lab.(LANL), Los Alamos, NM (United States) (1989)
7. Abdolpour, K., Masoudi, S. F., & Fathi, A. (2026). Comparison of nonlinear autoencoder and linear PCA dimensionality reduction in gamma-ray spectroscopy-based radioisotope identification. *Radiation Physics and Engineering*, e246488.
8. Lennon, K. S. (2026). *Applications of Machine Learning for Enhancing gamma-ray Spectrometry in Nuclear Fusion* (Doctoral dissertation, Sheffield Hallam University).
9. Qi S, Zhao W, Chen Y, et al. Comparison of machine learning approaches for radioisotope identification using NaI(Tl) gamma-ray spectrum. Appl Radiat Isot. 2022;186:110212. https://doi.org/10.1016/j.apradiso.2022.110212.
10. Paleti, B., & Sastry, G. H. (2024). Hybrid convolutional neural network approach for optimizing automatic identification of natural isotopes in gamma ray environmental sample spectra. *Neural Computing and Applications*, *36*(31), 19585-19595.