3NID – An Advancement in Nuclide Identification

Arnaud Samie

Mirion Technologies, Lamanon, France

Introduction

Gamma spectroscopy is a proven and convenient non-destructive method allowing for the detection of radiological threats and the specific identification of radionuclides, of which spectrum features such as full energy peaks act as signatures. It is therefore consistently used in Homeland Security (HLS) scenarios by intervention forces or customs for border control. Mirion Technologies Security and Search (SnS) line offers a range of products responding to these use cases. Work done in the scope of the 3NID (Neural Network for Nuclide Identification) project aims at implementing CNN-based (Convolutional Neural Network) nuclide identification in these applications to improve their performance.

Automatic radionuclide identification has commonly been handled for decades by "classic" algorithms (i.e. non artificial intelligence (AI) based), whose performance typically depends on many internal and external factors, such as detector characteristics (dimensions, energy resolution), statistical value of the spectrum (number of counts, signal-to-noise ratio) or measurement geometry and configuration (source shielding, several sources with overlapping peaks). Recent breakthroughs in the field of AI and the success of CNN at pattern recognition, as well as object detection and facial recognition in imaging technologies, to which gamma spectroscopy can be easily related, lead both scientific research organisms and industrial actors to work on such applications.

Figure 1 - A few products from the Security & Search line.

Deep Learning and Neural Networks

Deep learning is a type of machine learning based on artificial neural networks (NN) in which multiple layers of processing are used to progressively extract higher level features from data. Its principle of operation mimics processes at work in the human brain, in a simplified way. When input data is injected, each layer of the NN, whose neurons (or nodes) are connected to the previous and next layers, successively performs specific mathematical operations, such as filtering in the case of a convolution layer, until the output layer is reached. Various parameters such as the weights of the inputs of all layers and values used in the mathematical operations are iteratively adjusted during the training process, making the neural network learn by itself from the provided input data and desired output, without any interaction from the operator. During execution, new input data (here, a gamma spectrum) is passed from layer to layer in the NN and an output is finally returned (here, radionuclide labels).

The 3NID Convolutional Neural Networks

In this project, various 3NID neural networks were developed using a popular machine learning framework, sharing a common structure as illustrated in Figure 2. The current network design was influenced by previous collaborations and similar applications found in literature, along with iterative testing of different configurations. The input data for 3NID consists of a 1024-channel spectrum.

The spectrum is processed through the first one-dimensional convolutional layer, where multiple filters are applied to the spectrum. Following this, a max pooling operation is applied, reducing the length of the filtered spectrum by half. Another convolutional layer with additional filters is then applied, followed by another max pooling layer.

The resulting values are flattened into a one-dimensional vector and passed to a dense layer. The output layer calculates independent probabilities for each of the radionuclides in the library. 3NID CNNs were trained with both raw and net (subtracted background) spectra separately, resulting in different networks for processing each type of spectrum, named 3NID-raw and 3NID-net respectively. During execution, 3NID returns probabilities for each possible output it was trained on. Values exceeding an adjustable threshold (usually 0.5) are considered identifications, and the associated radionuclide label and confidence level are reported on the user interface.

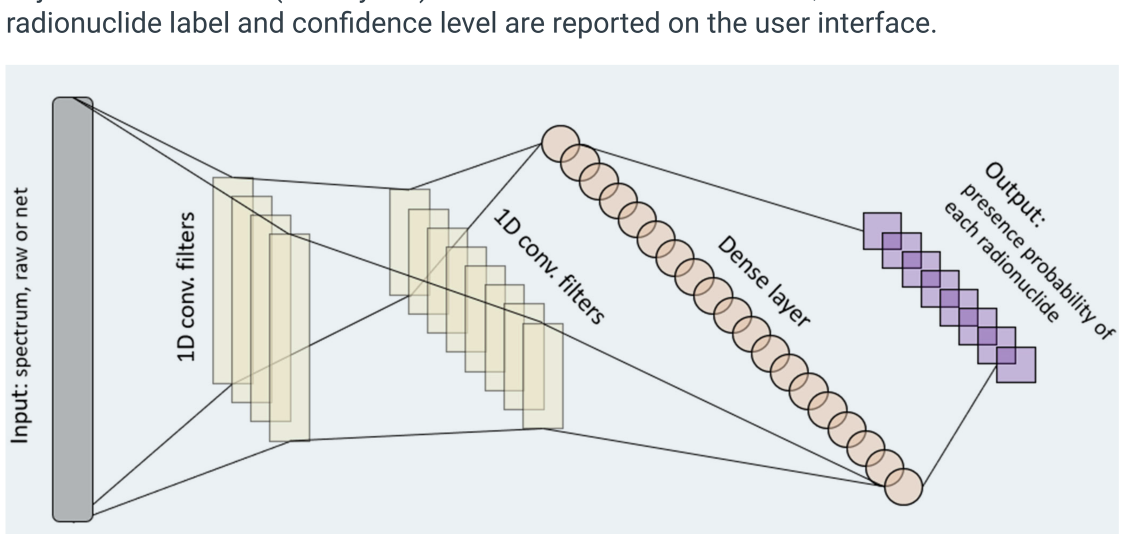

Figure 2 - General scheme of the 3NID convolutional neural network.

Targeted Use Cases

The feasibility study focuses on detection systems for the HLS market, addressing SNM (Special Nuclear Materials) illicit trafficking and "dirty bomb" radionuclides. Medical isotopes are the main false alarm drivers and must be separated from SNM. Masking scenarios involve SNM signals covered by medical or industrial radionuclides, requiring identification of both. The goal of 3NID is to outperform classical algorithms used in this field. Detection systems use mid-resolution scintillators like sodium iodide (NaI) or lanthanum bromide (LaBr3). This study focuses on SPIR-Pack, a backpack-type radiation detector with a NaI detector, intended for identifying a small number of radionuclides at a time.

Training of the Neural Network

The supervised training of a neural network involves iteratively adjusting network weights and parameters using input data to match the desired output. In this application, gamma spectra are used as input data, and the output identifies the radionuclides present in each spectrum. The output is represented as one-hot encoded vectors. Training continues until convergence, evaluated by loss and accuracy metrics. Part of the dataset is reserved for validation. After training, the NN's weights and parameters are fixed for execution. High-quality input data, built from Monte Carlo simulations only, is essential for optimal performance. Training typically takes a few hours on an average laptop equipped with a GPU.

Monte Carlo Simulations

All Monte Carlo simulations were run with MCNP6 [1]. A simplified SPIR-Pack detection system was modeled above the ground and in front of a PMMA phantom mimicking the operator carrying the backpack. Simulated sources are positioned in front of the detector, at different distances, except for background which is originating either from the ground or from a side position. Various geometries were modeled to cover the expected use cases of SPIR-Pack, as detailed in the table below. Each radionuclide and geometry produce a gamma spectrum as an output (total number of MCNP simulations is 480 for the most complete dataset). These MCNP spectra are then processed to build training and testing datasets.

Type	Geometry/source-to-detector distance (m)	Shielding (mm lead)	Radionuclides
Signal	1	0 to 200	All (HLS)
	1	In vivo	MED
	10	0	All (HLS)
	50	0	All (HLS)
Background	Ground	n/a	NORM
	Side	PMMA 80 mm	NORM

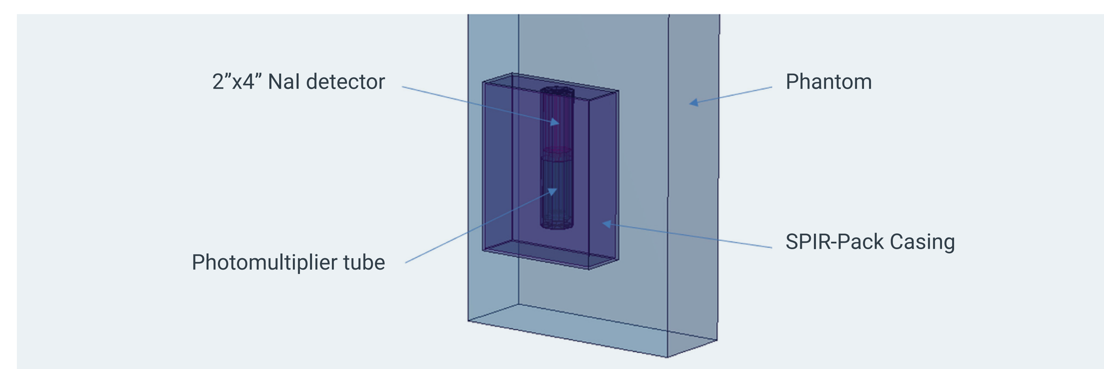

Figure 3 - MCNP model of SPIR-Pack.

Building Spectrum Datasets

The spectrum datasets for training and testing 3NID were created using Monte Carlo simulations. To ensure high performance in field applications, the data must be realistic. Various treatments are applied to the simulated spectra, including random sampling of parameters. A background spectrum is built from six different NORM sources, with dose rates ranging from 20 to 300 nSv/h. Measuring times are sampled from a list of discrete values. Signal spectra are prepared for single radionuclides and combinations (including SNM masking scenarios with medical and industrial isotopes), with net counts sampled from high or low signal distributions. The final spectra include energy resolution adjustments, statistical sampling, and energy gain adjustments. Each combination of radionuclides generates 400 spectra, resulting in datasets of around 350,000 spectra.

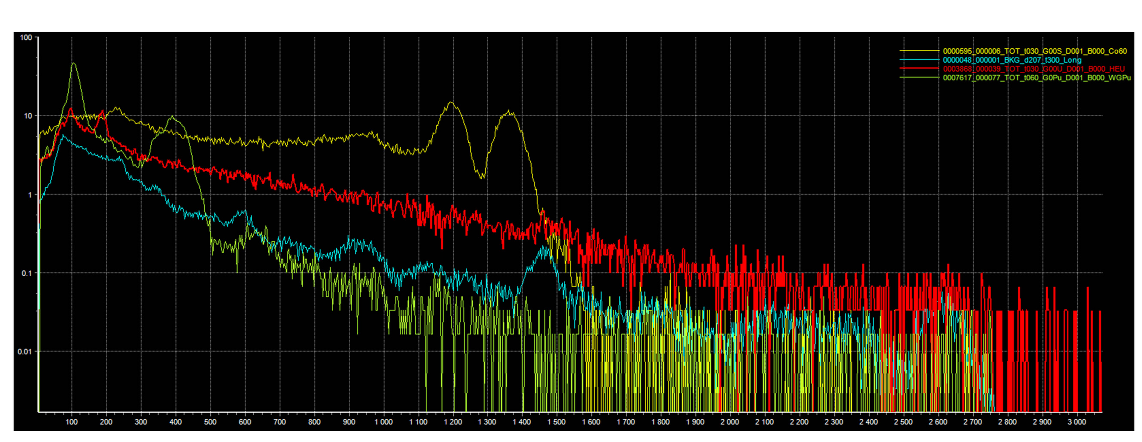

Figure 4 - A few spectra from the 3NID training dataset.

Test and Benchmark Campaign

A broad test campaign was run in 2022 at IB3 and PNNL laboratories to assess 3NID performance on measured SPIR-Pack spectra of SNM, medical and industrial radionuclides and benchmark it against classical algorithms. High counting statistics, single source spectra were acquired for long measuring times at controlled fluences in optimal laboratory conditions. Net signals were then extracted from these spectra and used to generate realistic spectra with variations of gain, measuring time, fluence and presence of other radionuclides to assess 3NID's identification performance in operational conditions. Two main approaches are proposed: limits of identification on single radionuclide spectra, and masking scenarios involving combinations of radionuclides.

Limits Of Identification On Single Radionuclides

To assess the limits of identification (LoID) of 3NID models and classical algorithms, for each measured radionuclide, 1000 spectra were generated with random time (usually 1 to 15 seconds) and fluence in a specified shielding configuration. Graphs below show the true positive rate as a function of the integrated fluence (measuring time multiplied by fluence): each curve shows the mobile mean over 50 data points – each data point value is either 1 or 0 (resp. true positive or no true positive). False positives are counted separately and shown as text on the graphs. Chosen performance indicators are integrated fluences at 50% and 90% true positive rate, and false alarm rate.

The 3NID algorithm, particularly the net model, generally outperforms the classical algorithm by requiring significantly lower fluences to achieve 50% and 90% true positive (TP) rates. The false alarm (FA) rates for 3NID-net are also lower than those exhibited by the classical algorithm, especially with MEDs. The performance of 3NID-net and raw models is comparable, with some variations depending on the source.

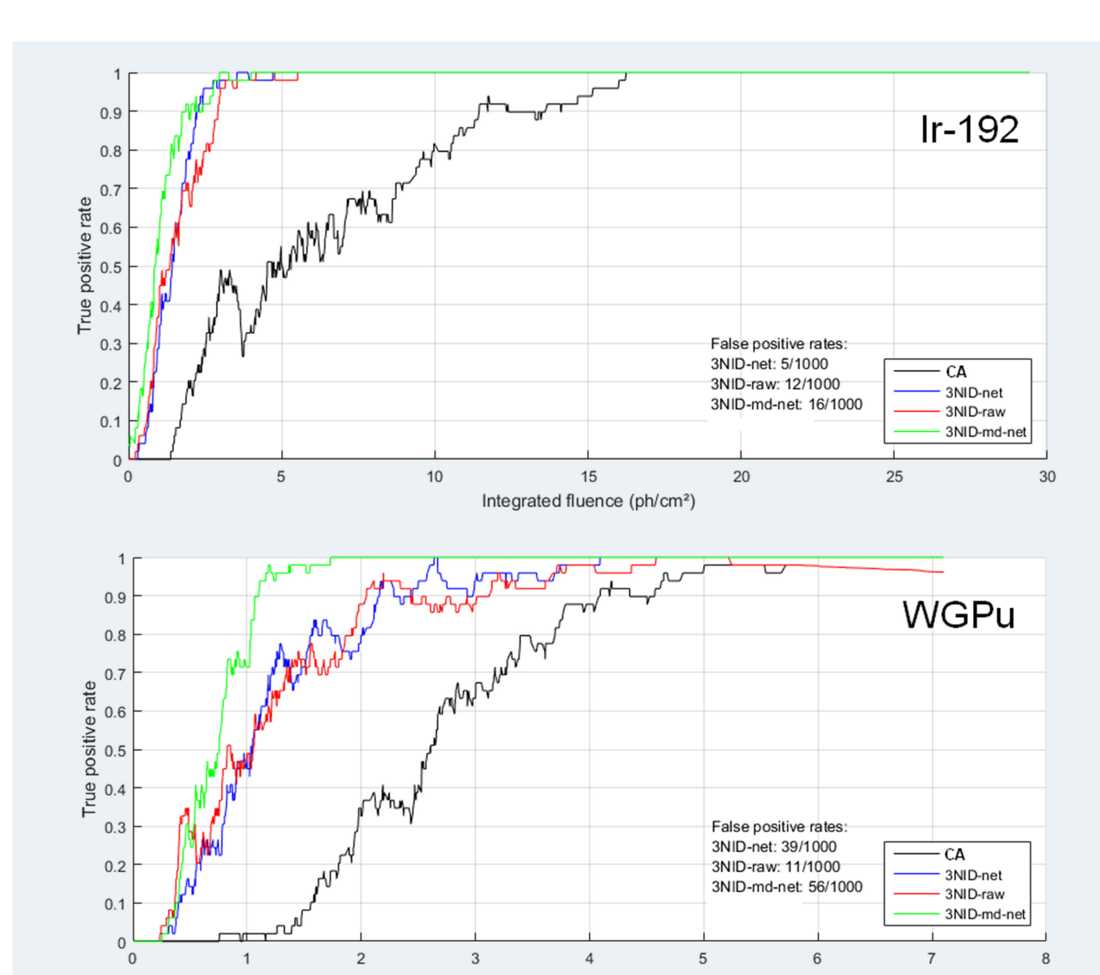

Figure 5 - Benchmark results: limits of identification.

Combined Identification On Masking Scenarios

For masking scenarios as described in TCS for backpacks [2], 5000 spectra were generated with a fixed measuring time of 60 seconds and random fluences in specified ranges for each isotope of the mix. Each spectrum is represented on graphs by a dot whose coordinates give the respective integrated fluences of the isotopes of the masking scenario. Color code is as follows – red: no TP; blue: 1 TP, green: 2 TP & 0 FA (perfect output), black: 1 or more FA.

In masking scenarios for backpacks, the 3NID models generally outperform the classical algorithm. The 3NID models have very low false alarm (FA) rates and achieve better two true positive (2TP) rates in several cases. The 3NID-raw model stands out with almost no FA on all tested spectra. Overall, 3NID models demonstrate superior performance, but further analysis is needed for specific scenarios.

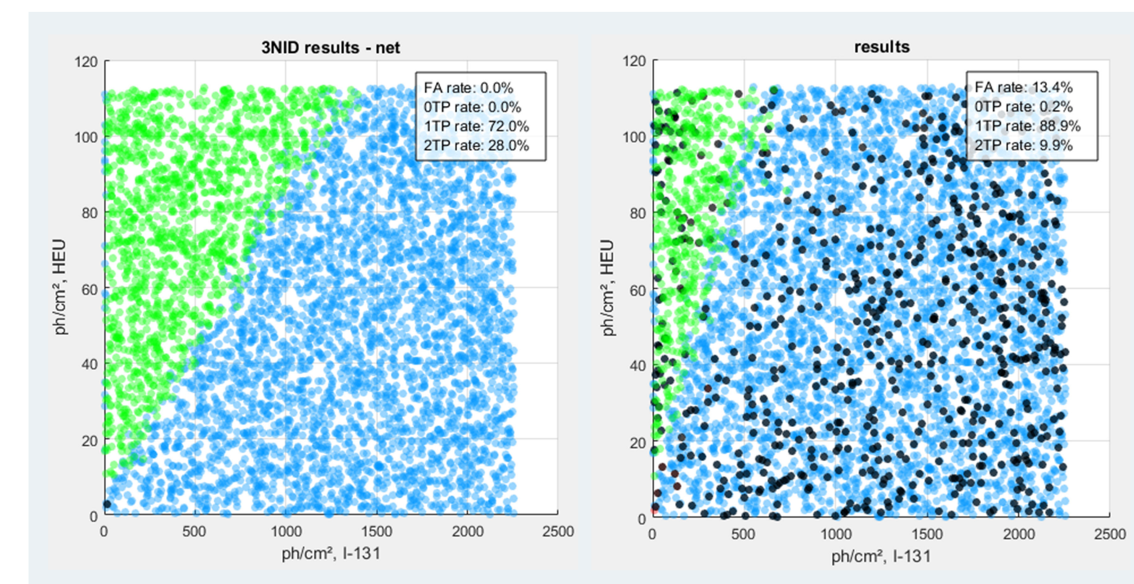

Figure 6 - Benchmark results (masking scenario: HEU + I-131). Left: 3NID, right: classical algorithm.

Current Stage of Developments

3NID is currently running on the microcontroller of a prototype based on a 2"x4" NaI detector and provides real time identification. It was also integrated into our desktop spectrum acquisition and visualization tool SMI.

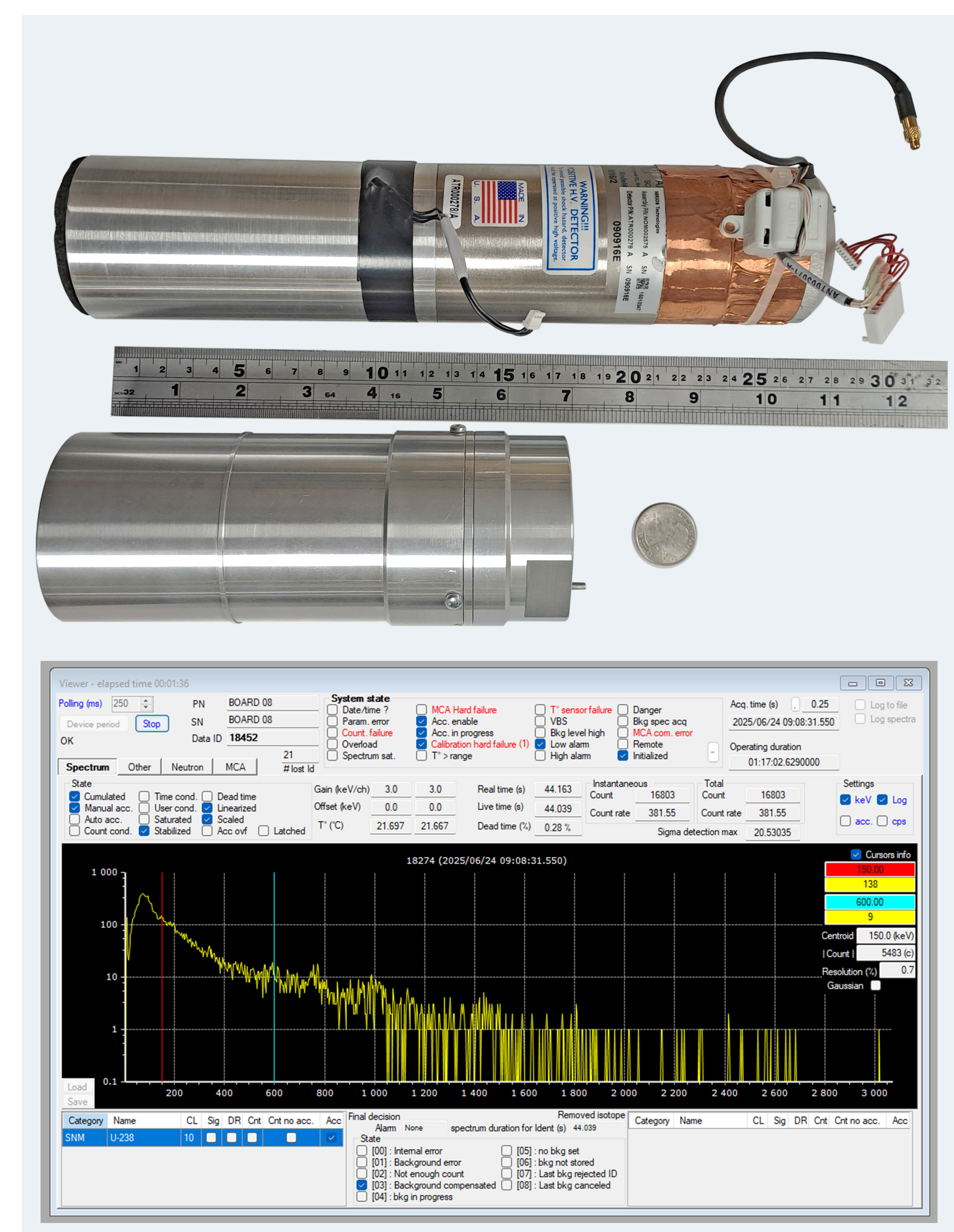

Figure 7 - Prototype and spectroscopy tool.

Conclusions

The 3NID (Neural Network for Nuclide Identification) project demonstrates the successful application of convolutional neural networks (CNNs) to gamma spectroscopy for homeland security (HLS) scenarios. Trained exclusively on Monte Carlo–simulated spectra, 3NID achieves:

- Superior identification performance compared to legacy classical algorithms, with significantly improved limits of detection and lower false alarm rates across a wide range of radionuclides and masking scenarios.
- Robust generalization to real-world measured data, validating the feasibility of AI-based nuclide identification in operational environments.
- Flexible integration into existing platforms.

References

1. A Monte-Carlo N-Particle (MCNP) transport code, v.6.1, Los Alamos National Laboratory.
2. Technical Capability Standard for Backpack Based Radiation Systems, Domestic Nuclear Detection Office, August 2013, US Department of Homeland Security.

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