

Artificial Intelligence in Gamma Spectroscopy Systems

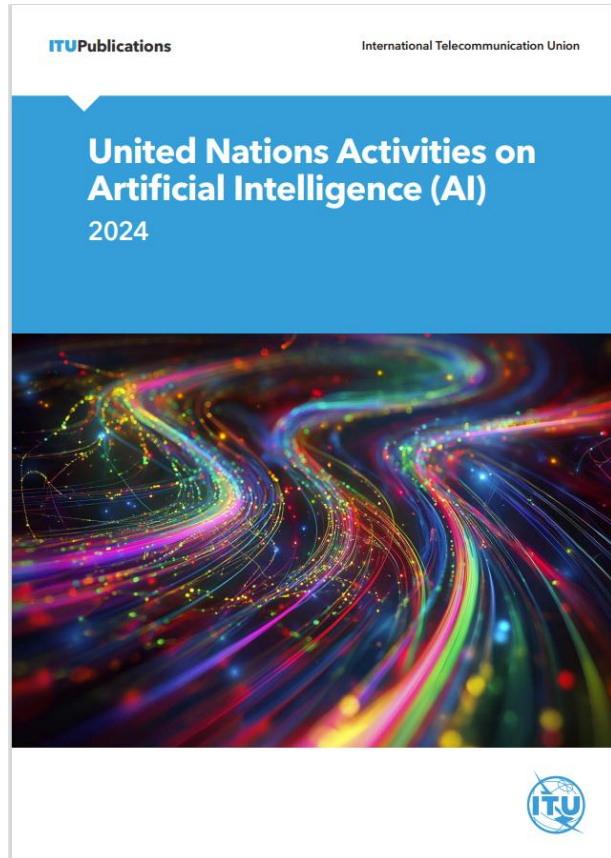
Milan Matos, Duriem Calderin

Technical Meeting on Advanced Technologies in
Nuclear Security Radiation Detection and Response

Wednesday June 24th 2026 Virtual

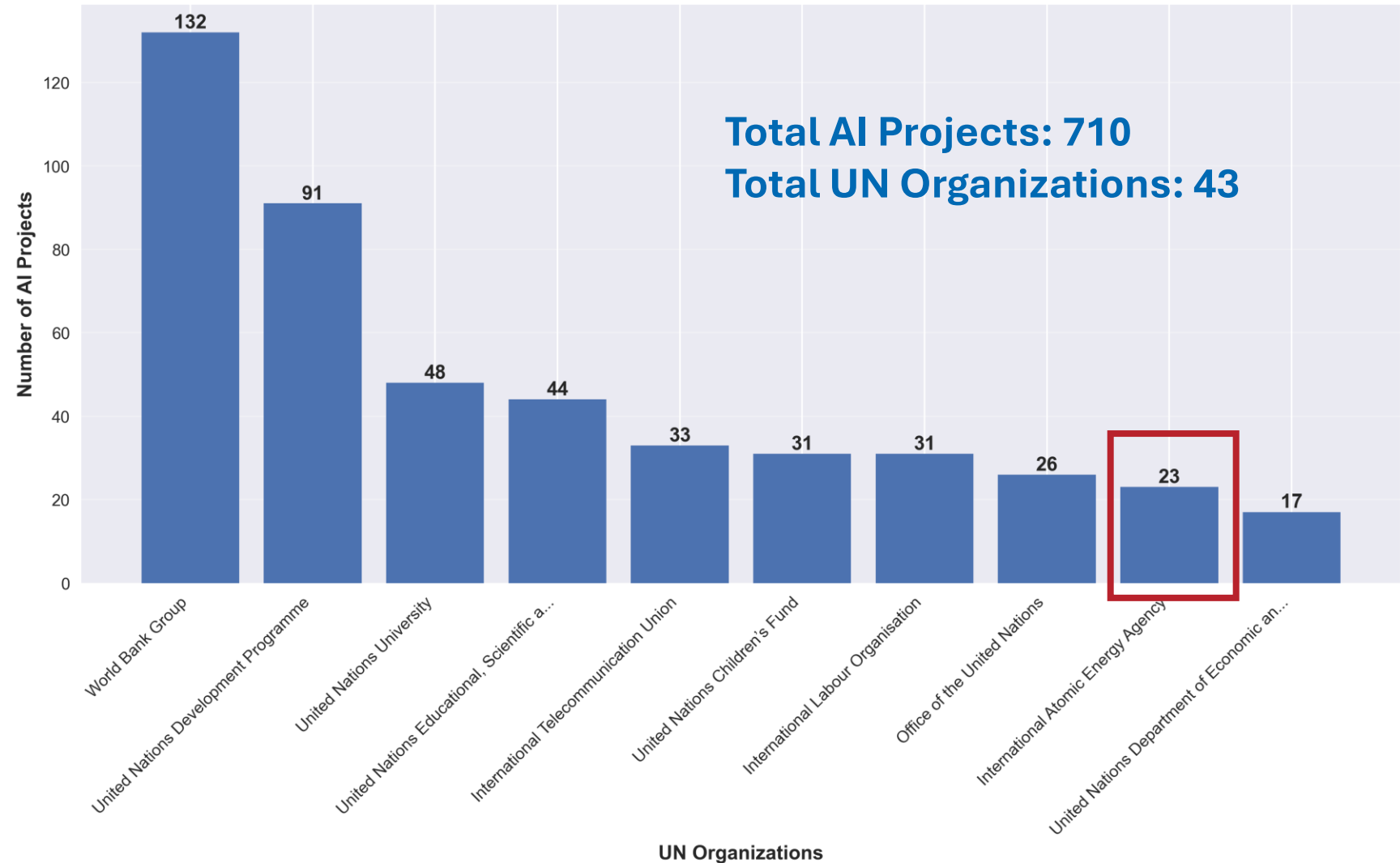


Artificial Intelligence (AI) at the United Nations



[United Nations Activities on Artificial Intelligence \(AI\)](#)

Top 10 UN Organizations by No. of AI Projects



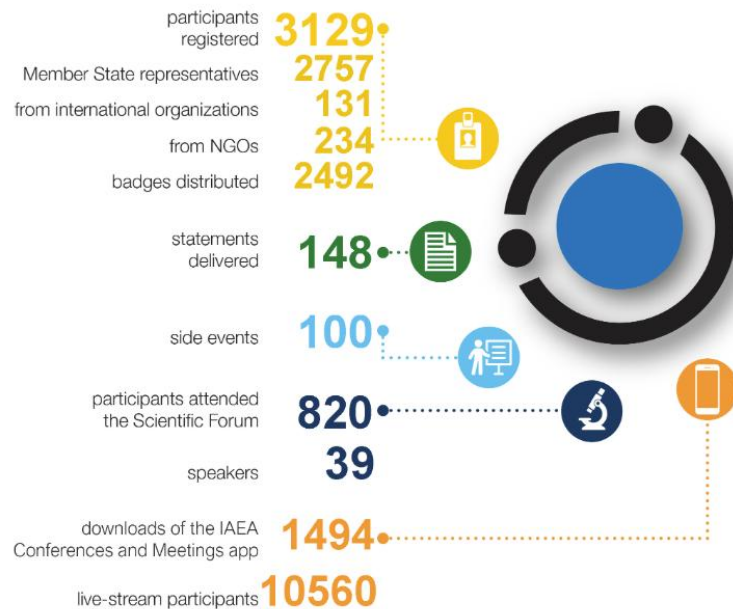


IAEA

AI is a mandate by Member States to Agency



GC in Numbers Day 4 - 18 September 2025



Nuclear and Radiation Safety: Conference Resolutions GC69

(r) Acknowledging that advances in science, technology and engineering present opportunities to enhance nuclear safety and that training and capacity building should continue to evolve in response, and recognizing potential benefits and challenges of emerging and innovative technologies, inter alia **artificial intelligence**, and the need for international cooperation in this regard,

5. Requests the Secretariat, in close consultation with Member States, to continue identifying potential benefits and challenges of **artificial intelligence** in support of nuclear safety, to provide relevant technical assistance to Member States upon request, and to keep Member States informed of any progress;

<https://www.iaea.org/about/governance/general-conference/gc69/resolutions>

Spectroscopic Detectors for Fast Nuclide Identification

Large
Backpacks



Medium
RIIDs



Small
SPRDs



Goals:

- Identify the nuclides (isotopes)
- Do it quickly (and it shall be easy)
+ portability

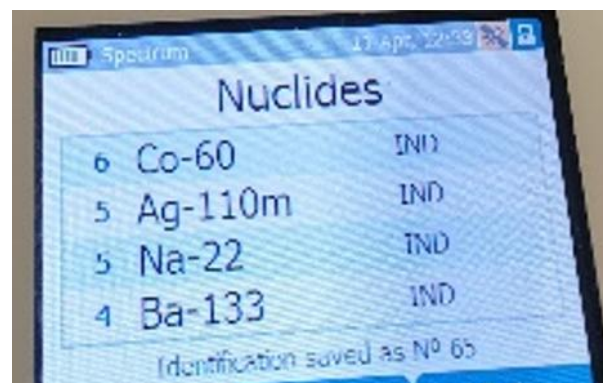
Patented QCC algorithm for fastest isotope ID

Patented and field-proven Discovery Technology

RadEAGLET advanced algorithms

Automatic identification on dose-rate warning

Advanced identification algorithms (DU, LEU, HEU)



Marinelli Beaker:

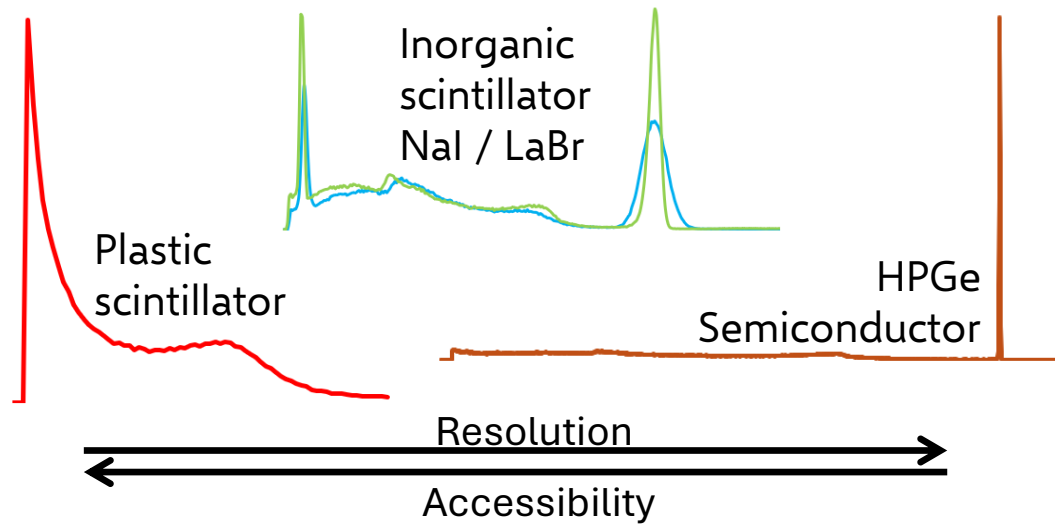
Am-241, Cd-109, Ce-139, Co-57,
Co-60, Cs-137, Ba-133, Sr-85,
Y-88, Cr-51

Laboratory			BKG subtraction +
IND	Y-88	10	
IND	Co-60	10	ⓘ
OTHER	508 keV		
OTHER	Ag-110m	6	
IND	Am-241	4	

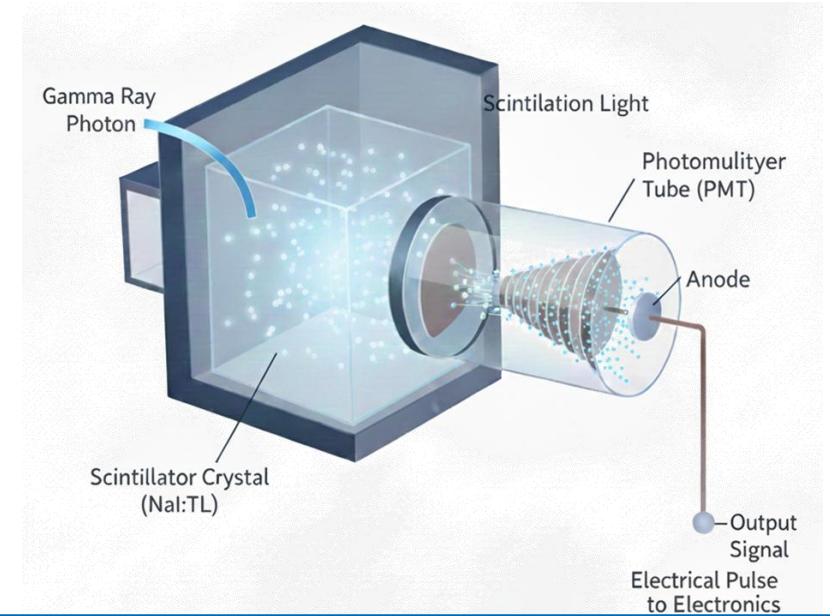
Gain: 3.00 Offset: 0 Live Time: 121.0		
IND	Y-88	10
IND	Co-60	10
IND	Ba-133	7
ORM	K-40	3
OTHER	Ru-106	3
Laboratory Miscellaneous No BKG subtraction		

Nuclide Detection and Identification Process

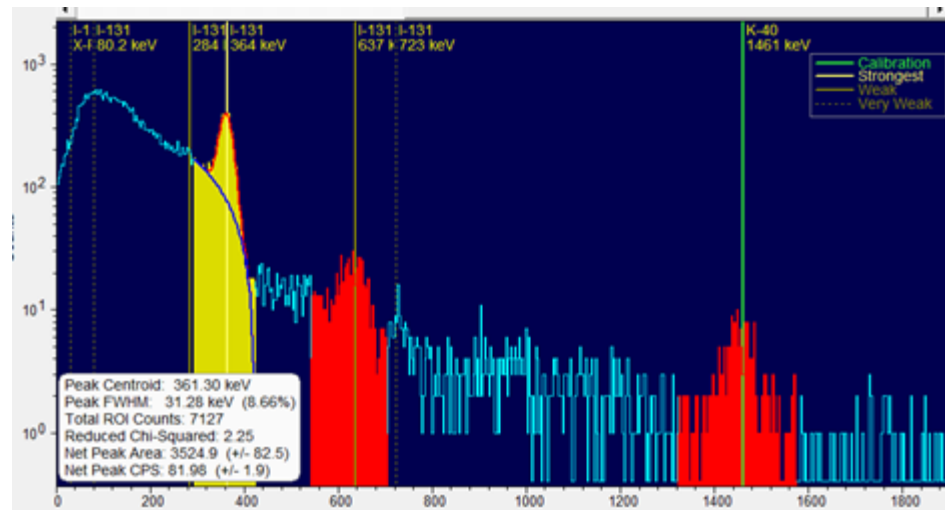
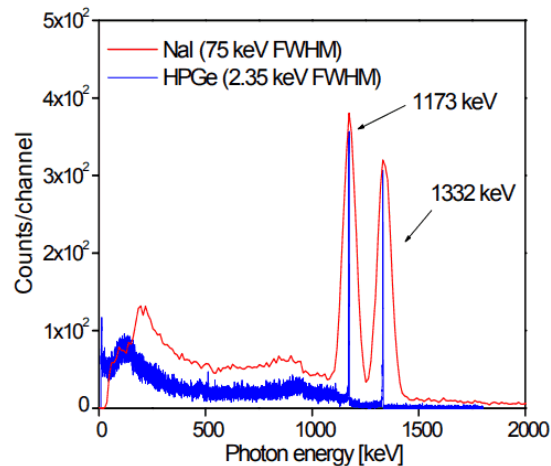
Gamma spectroscopic detectors



Detection in scintillators



Photopeak search



Nuclide ID using the photopeaks

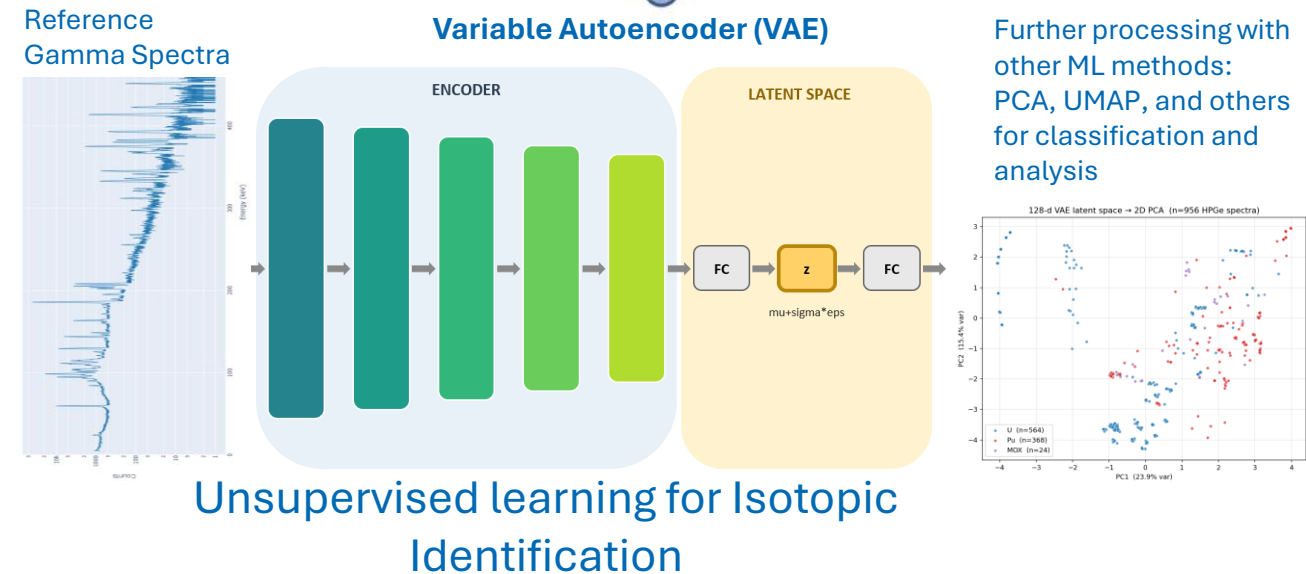
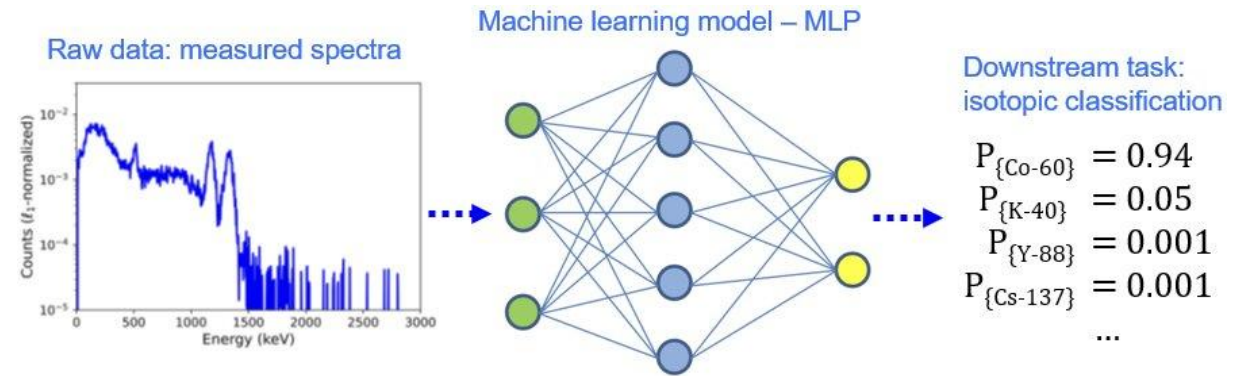
Outcomes of the Consultancy Meeting on AI Neural Networks Design Considerations to Support Survey Results During Gamma Spectroscopy

Challenge: Traditional approaches rely on identifying gamma spectra significant features, which may overlook critical elements for radionuclide identification (e.g. Compton scattering).

Solution: AI algorithms can be trained to look for additional robust features to assist domain experts during radionuclide identification.

Policy Limitation:

- Limited availability of open-source reference gamma spectroscopy data and machine learning algorithms.
- Lack of harmonized experience among Member States on physics-driven machine learning algorithms, testing and validation approaches for acceptance of results in safety applications.



Milan Matos, Duriem Calderin, Ivan Morales Argueta, Kalliopi Kanaki
ICTP, EPRI
Expert from Member States

Considerations for Radionuclide Identification with AI ML/Deep Learning

Data Governance: data verification, validation, quality control, and security.

Neural Network Architecture Definition, Training, Evaluation and Validation domain-specific

Deployment of Inference Model for Nuclide Identification

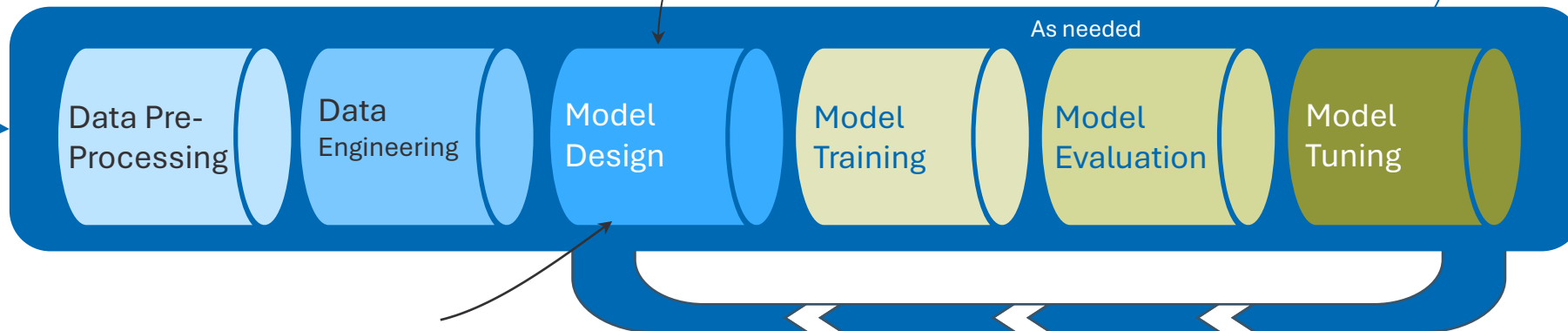
Real world Testing & Validation

Data Collection/
Synthetization

More data is needed



Define **standardized data** protocols, such as APIs.



e.g. Decision Trees, Random Forest

Pipeline

```
tokenizer = tokenizer.from_pretrained(model_id)
model = ModelForCausalLM.from_pretrained(model_id)

def generate_response(system_role, token_limit, user_input):
    # Combine system role and user input into a single prompt
    prompt = f"System: {system_role}\nAssistant: {user_input}"
    inputs = tokenizer(prompt, return_tensors="pt", truncation=True, max_length=token_limit)

    # Generate response
    outputs = model.generate(inputs, max_length=token_limit, do_sample=True, top_k=50, eos_token_id=tokenizer.eos_token_id)
    response = tokenizer.decode(outputs[0], skip_special_tokens=True)

    # Extract Assistant's reply
    assistant_reply = response.split("Assistant:")[1].strip()
```

Problem Statement (Data)

Data Libraries

- Experimental Data Sets
 - IAEA International Database of Reference Gamma Spectra
 - Berkeley Data Cloud
- Synthetic Data Sets and Generation Tools
 - ORNL Data for Training and Testing Radiation Detection Algorithms
 - RADAI Interactive Datasets
 - PyRIID – open-source tool for synthesizing spectra for ML training
 - GADRAS – application for the modelling of radiation detector responses
 - RASE – open-source tool for simulating spectra and evaluating available vendor algorithms
- Data augmentation: combination of experimental + synthetic data
 - Identify and document key attributes for data augmentation
 - Recommend formats, workflows, and meta data
 - Provide training and capacity building for dataset production
 - Centralized location to house data (data repository)



Data Governance: data verification, validation, quality control, and security

- Adopt standard data governance protocols
- Revise and add data governance protocols that are unique to gamma-ray datasets
- Standards: compliance with existing standards
 - Identify relevant standards

Agency Nuclear Science and Instrumentation Laboratory (NSIL) Data Collection (2024): Gamma Spectra

Detector: 1.5 × 1.5 in. LaBr₃(Ce)

Resolution: 3.6% at 662 keV

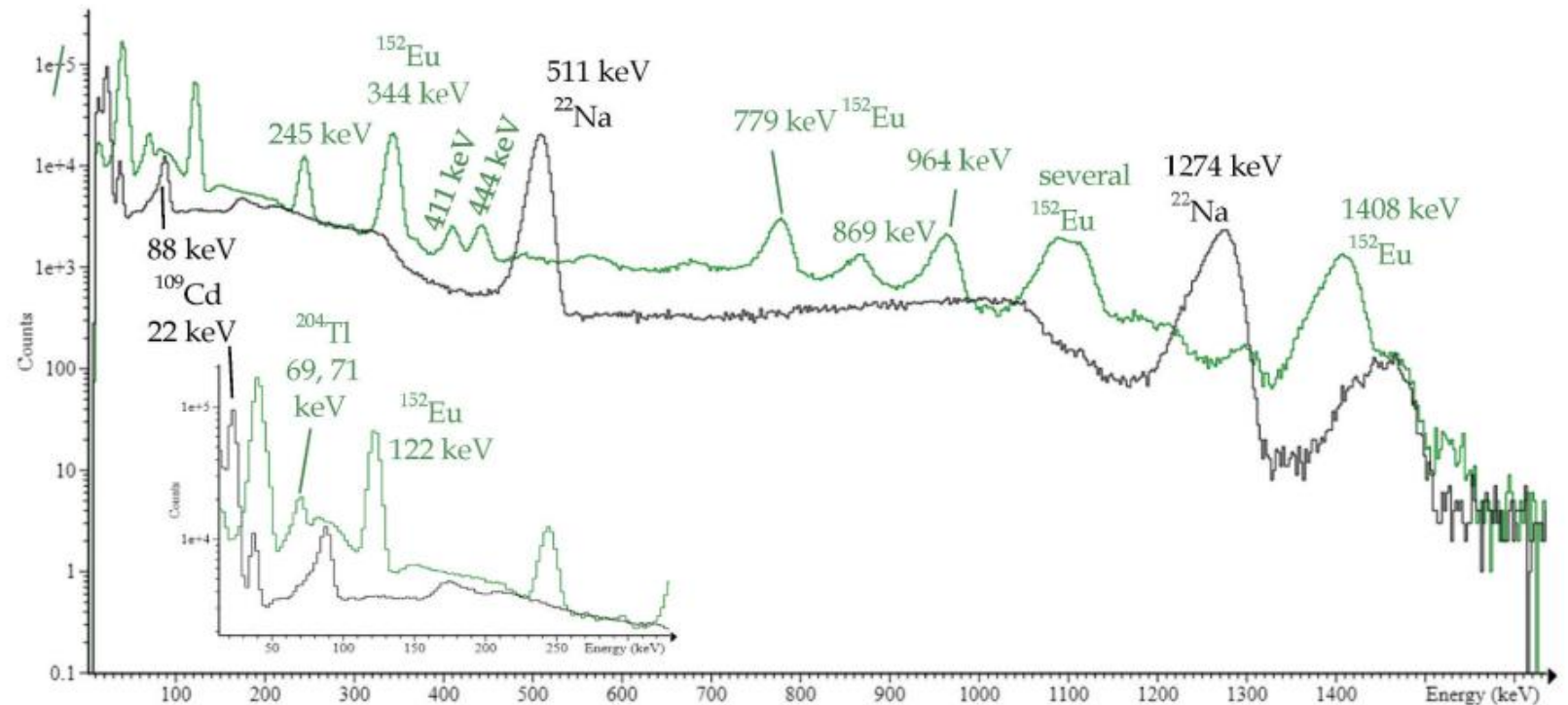
No. Spectra: 110

Configuration: 0-10 cm source detector distance

Shielding: 0,2,5 mm Pb

Sources used: (nuclide, activity)

- ²⁰⁴Tl (63.2 kBq)
- ¹³⁷Cs (566 kBq)
- ⁶⁰Co (324 kBq)
- ⁵⁷Co (6.43 kBq)
- ¹⁰⁹Cd (11.1 kBq)
- ¹⁵²Eu (408 kBq)
- ⁸⁸Y (0.5 kBq)
- ²⁴¹Am (464 kBq)
- ¹³³Ba (394 kBq)
- ²²Na (144 kBq)



black ¹⁰⁹Cd and ²²Na
green ²⁰⁴Tl and ¹⁵²Eu

Initial work on Neural Network for Gamma Spec Identification with NSIL dataset

Hypothesis: Neural networks can identify distinct features of the gamma spectra

Challenge: limited dataset (110 spectra) and experience finding the correct architecture

Solutions & Results:

- Expanded train and test sets with augmented spectra (50k)
- Selected Convolutional Neural Networks (CNNs) because they are designed for processing structured grid data.
- CNN were able to extra features from the spectra analysed
 - ANN Accuracy: **94%**
 - Human test: failed to identify a nuclide when was present **13%** more than ANN.



Contents lists available at [ScienceDirect](https://www.sciencedirect.com)

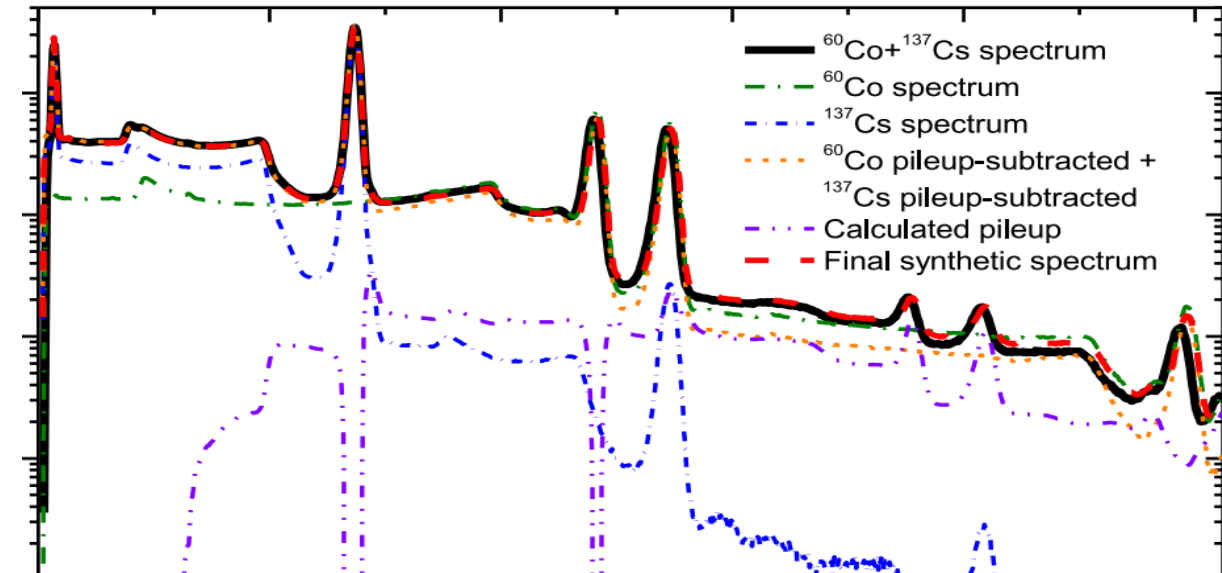
Radiation Physics and Chemistry

journal homepage: www.elsevier.com/locate/radphyschem



Nuclide identification of radioactive sources from gamma spectra using artificial neural networks

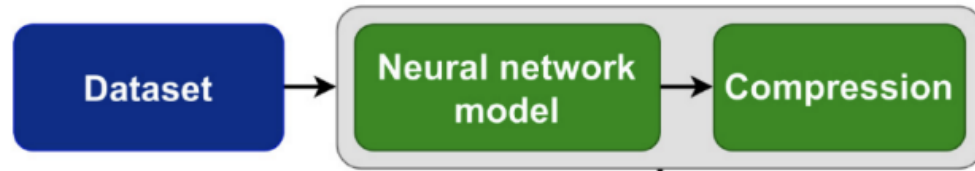
N.P. Barradas^{a,b,*}, A. Vieira^c, M. Felizardo^a, M. Matos^d



Current Approach for Gamma Spectra Identification with Neural Networks

- 1D CNN: 3x conv. layers + 2x fully connected. ~17k parameters
- Inference latency < 10 ms (Arduino Uno Q 4GB - CPU)

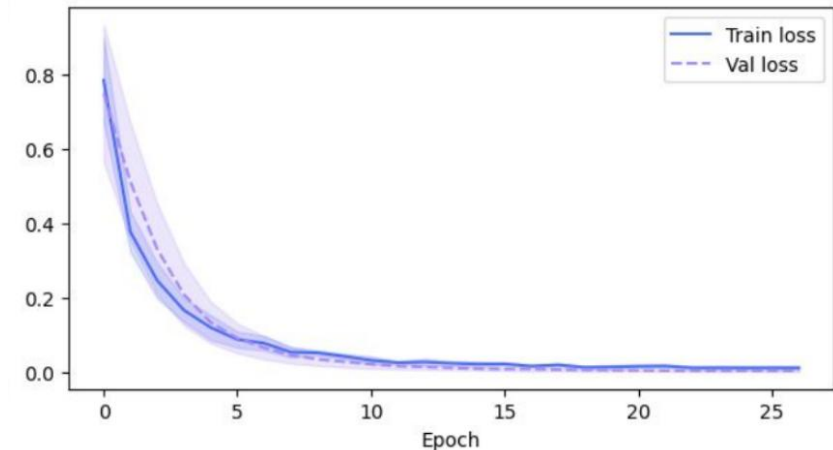
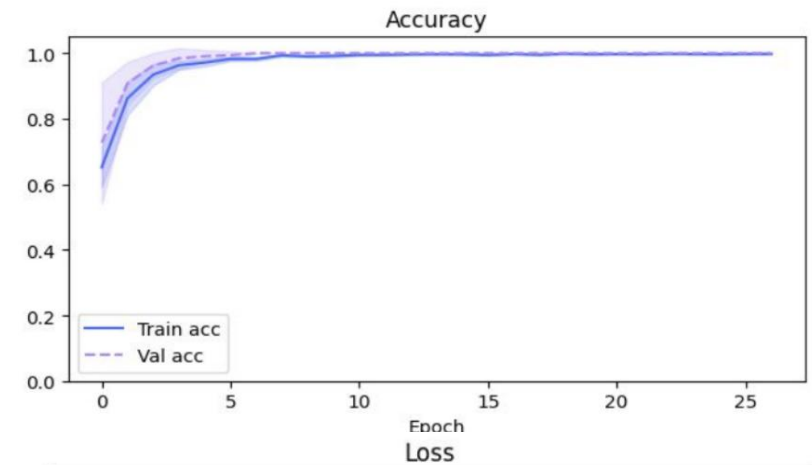
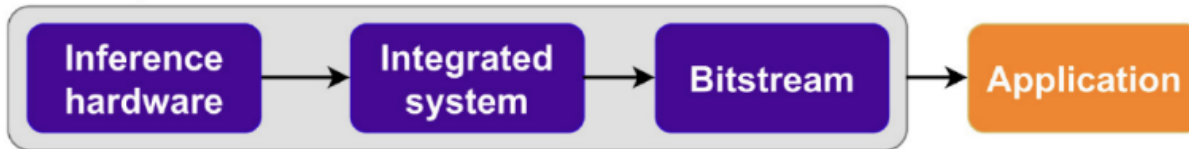
DNN training and compression



Integration with a hardware synthesis tool for ML

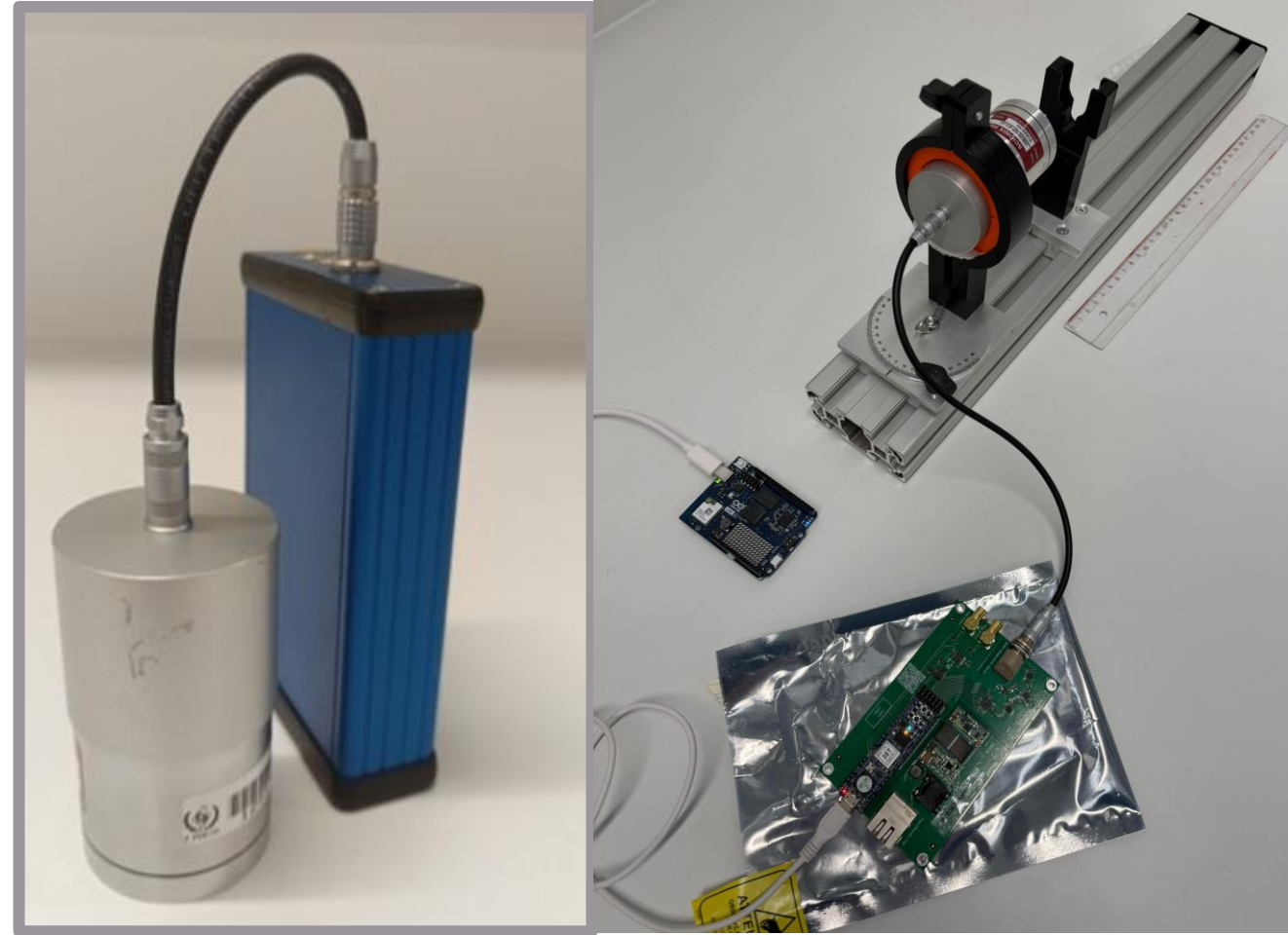
Hardware synthesis tool for ML

Hardware assessment framework

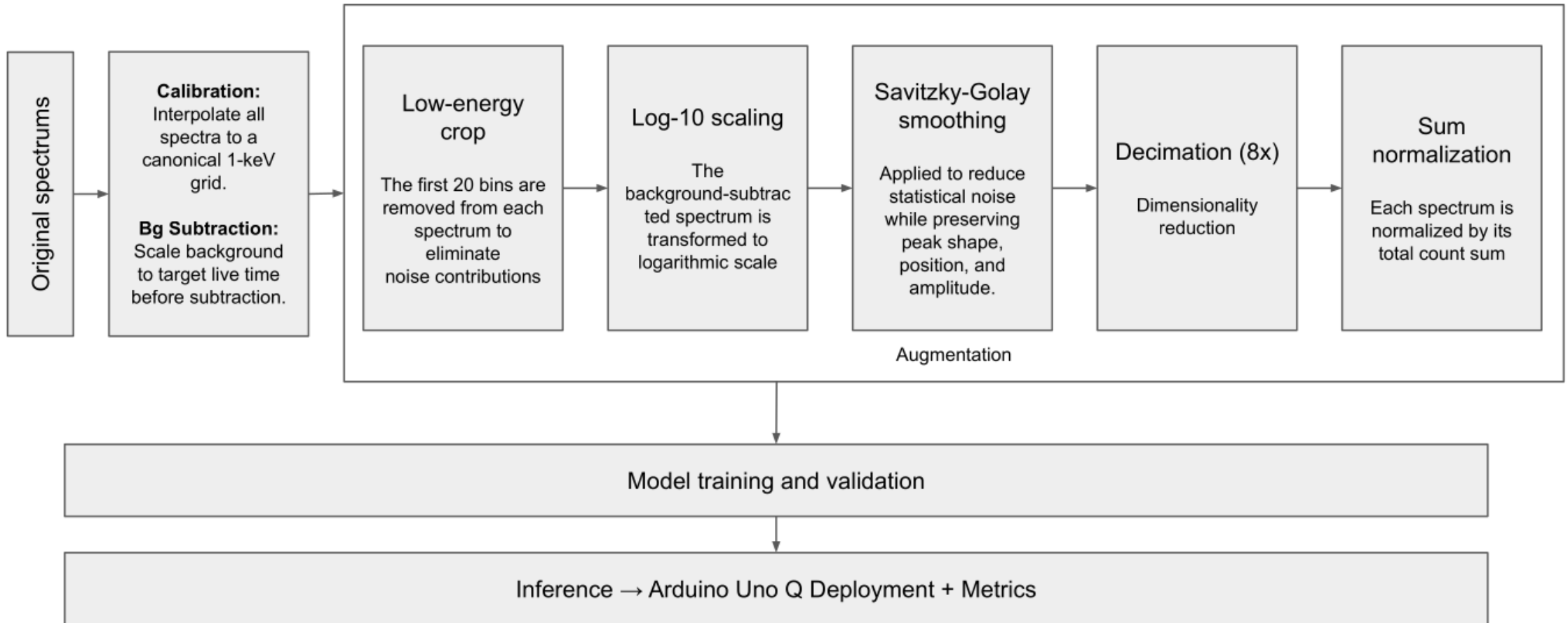


Current Approach for Gamma Spectra Identification with Neural Network

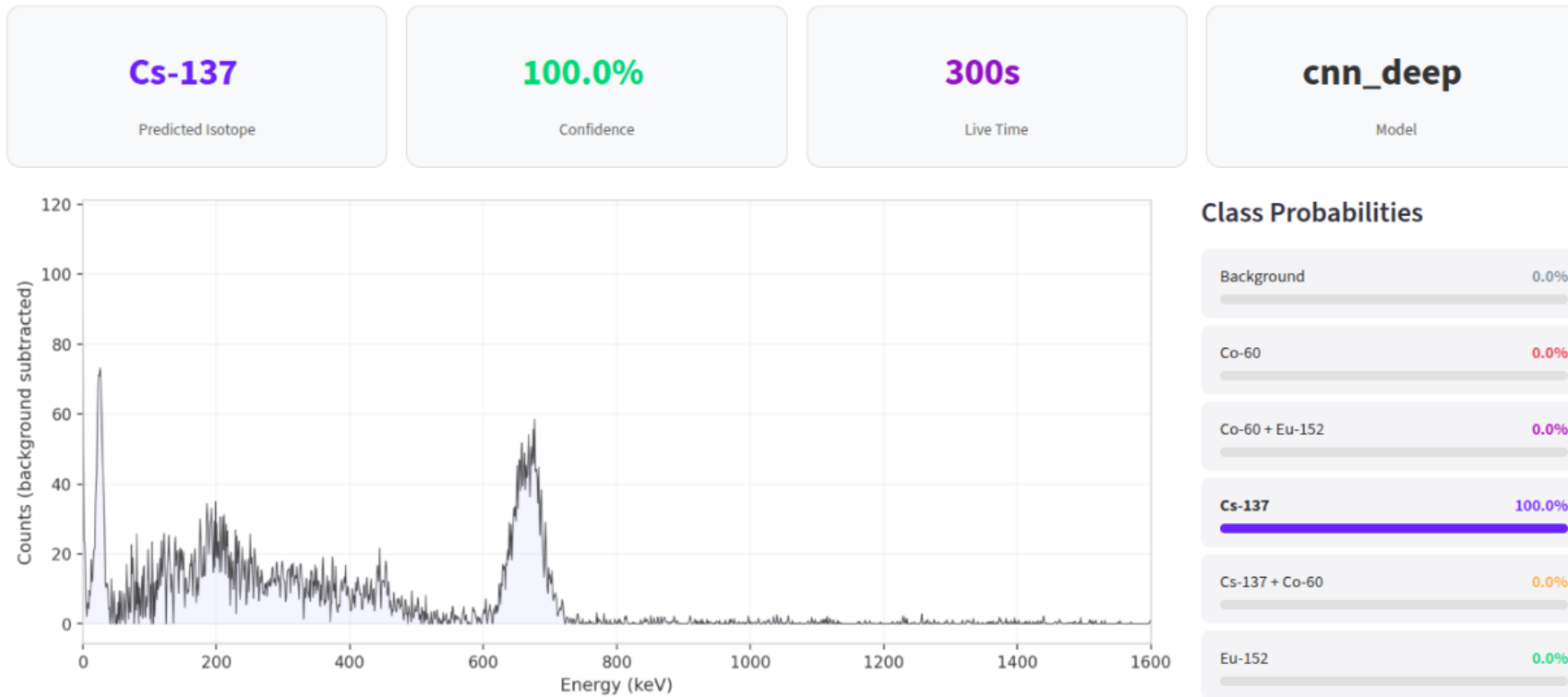
- Portable NaI+SiPM + built in-house MCA
- Inference Model: Arduino Uno Q
- Open-source
 - Hardware design
 - Firmware (FPGA, embedded processor)
 - Python API (backend)
 - Python GUI (web-based)
 - Desktop GUI (VC++ for Windows)



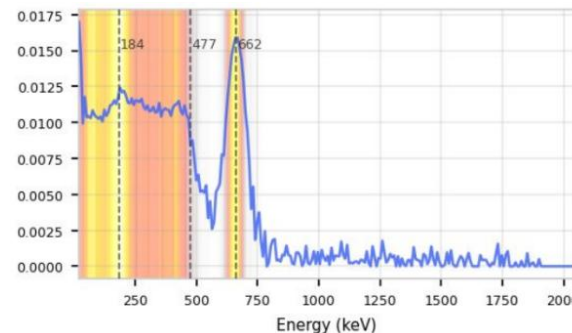
Preprocessing pipeline – training & inference



Current Approach for Gamma Spectra Identification with Neural Network (*cont.*)



Explainability – Integrated gradients



Generalization capabilities (under development)

Cs-137 + Co-60

Predicted on Edge

99.0%

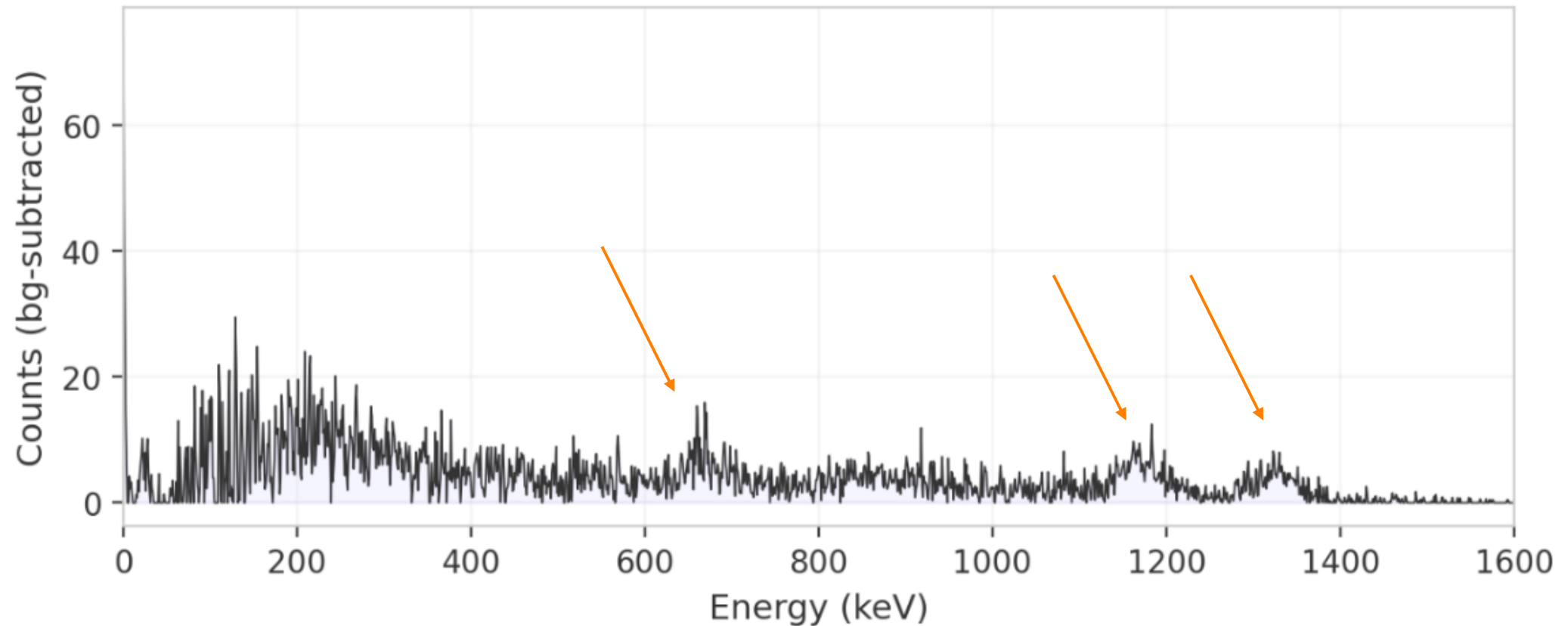
Confidence

0.46 ms

Model Latency

12.67 ms

End-to-End Latency





Conclusions and Path Forward

- Neural networks are showing potential for identifying spectral features, enabling radionuclide identification beyond traditional photopeak workflows.
 - Physics-informed approaches will be explored.
- Expand validated reference data, considering quality control and security.
 - Models will be able to generate synthetic data on the fly.
- Work on developing fully integrated systems (hardware, AI software, and experimental setup).
 - Robust architectures using domain-specific models will support reliable and secure AI systems.



IAEA

THANK YOU

Problem Statement (Data)

Data Libraries

- Experimental Data Sets
 - IAEA International Database of Reference Gamma Spectra



Search Datasets

This search form allows users to retrieve all datasets by default and refine their search criteria that describe the spectra. It provides access to all available metadata attribute options in the database.

The spectra that correspond to the search query will be listed in the results table. Additionally, users can retrieve all the details of a specific spectrum by clicking on its corresponding link.

Material metadata

① Material Type:

☐ U
☐ Pu
☐ MOX

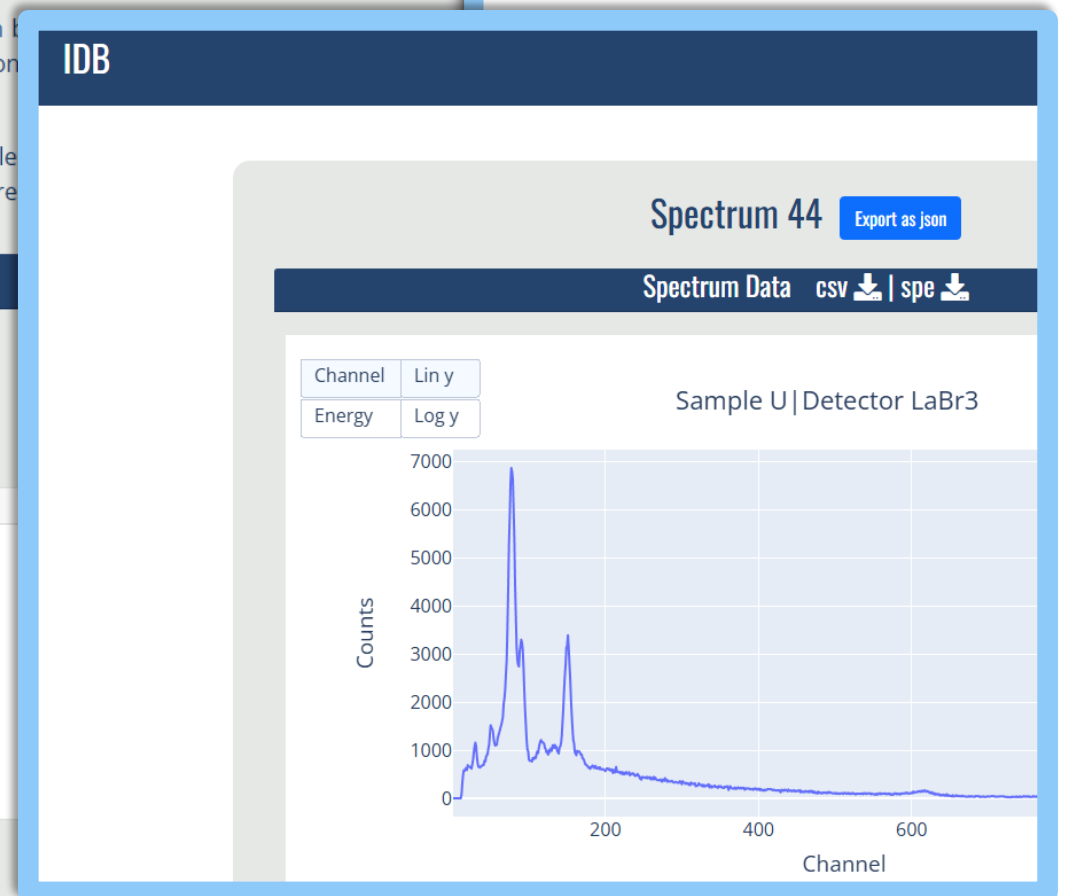
① Isotopic composition of material:

☐ ^{234}U	☐ ^{238}Pu
☐ ^{235}U	☐ ^{239}Pu
☐ ^{236}U	☐ ^{240}Pu
☐ ^{238}U	☐ ^{241}Pu
	☐ ^{242}Pu
	☐ ^{241}Am

① Form:

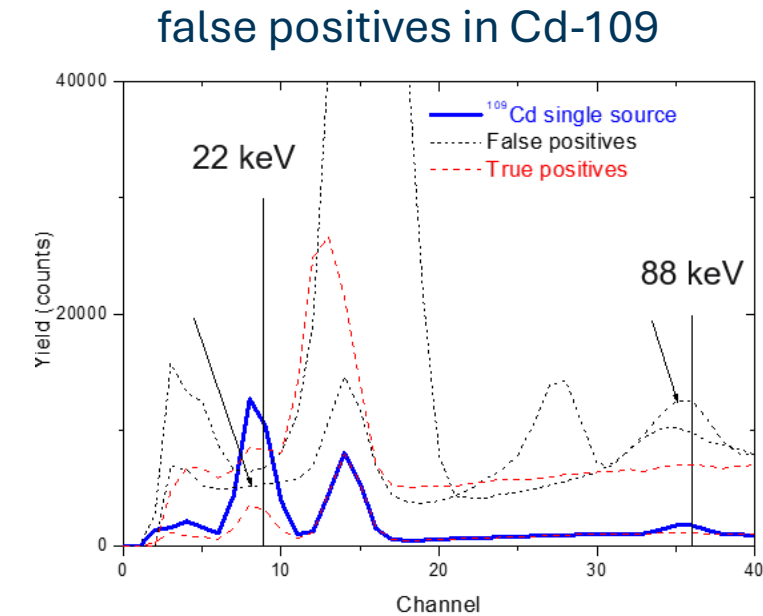
① Certificate data:

① Compound:



Proof of Principle - Convolutional Neural Networks

Radionuclide	Total positives in set	Total negatives in set	False Positives ANN	False Negatives ANN	False Negatives Human + Interspec
Co-60	25	45	0	0	0
Cs-137	26	44	0	0	0
Am-241	18	52	0	6	7
Y-88	21	49	0	4	4
Eu-152	21	49	1	0	0
Ba-133	15	55	0	0	0
Na-22	11	59	0	0	0
Co-57	11	59	4	4	4
Tl-204	10	60	4	3	3
Cd-109	29	41	2	13	16



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CNN (Convolutional Neural Network) + MLP (Multilayer Perceptron)

Explainability – Integrated gradients

