

Radioisotope identification with machine learning

**Nuclear Science and Instrumentation
Laboratory, IAEA**

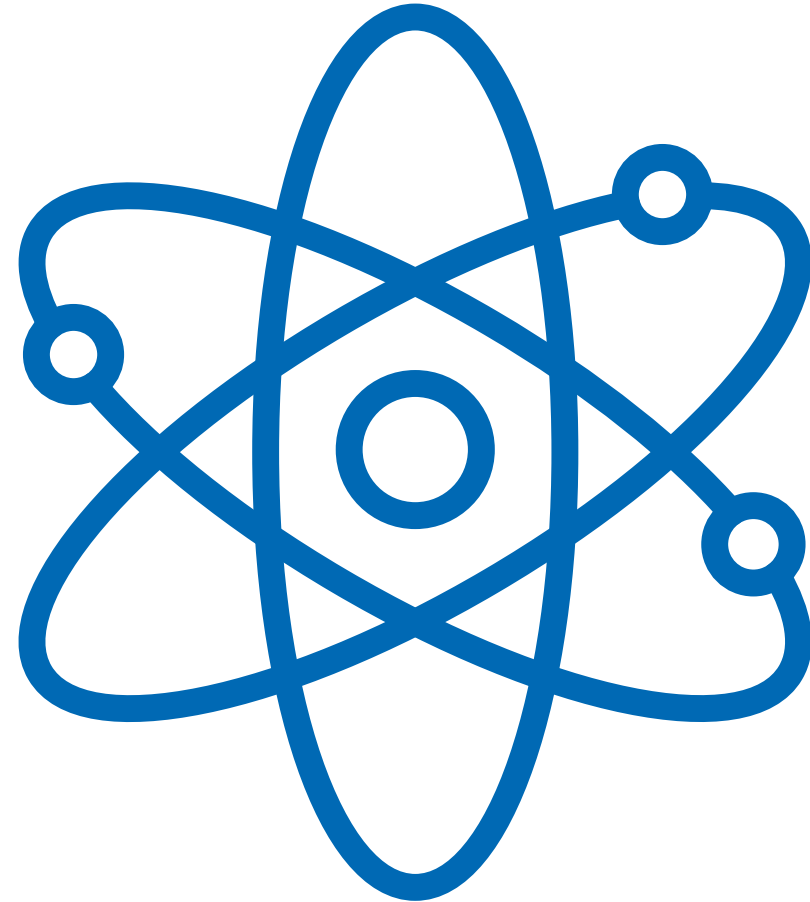
Ivan Morales

Joint ICTP-IAEA Workshop on Edge Artificial Intelligence for
Environmental and Radiation Sensing.
Bishkek, Kyrgyzstan, 14-18 September 2026.

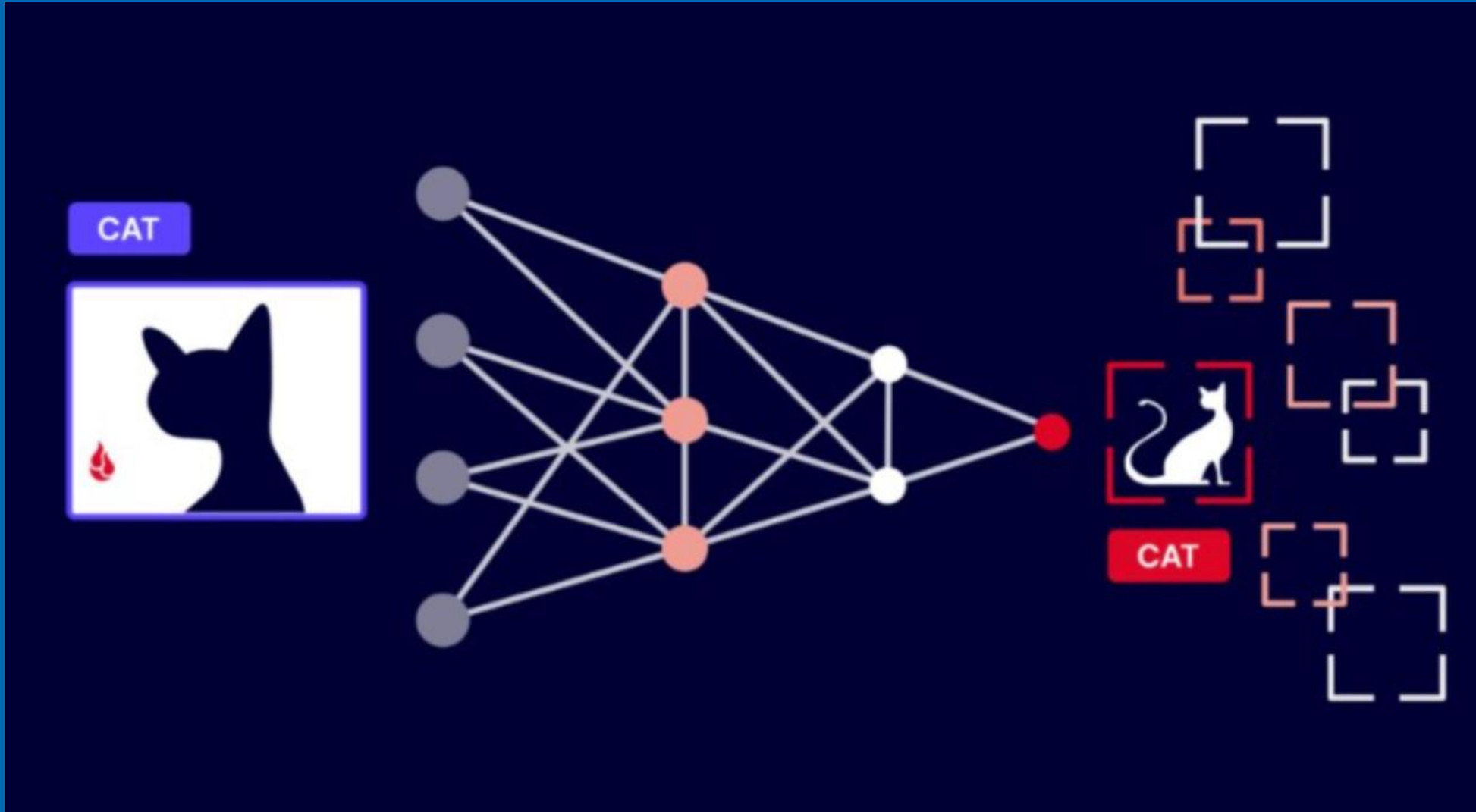


Outline

- Why machine learning
- From data to inference with ML
- Radioisotope ID with ML

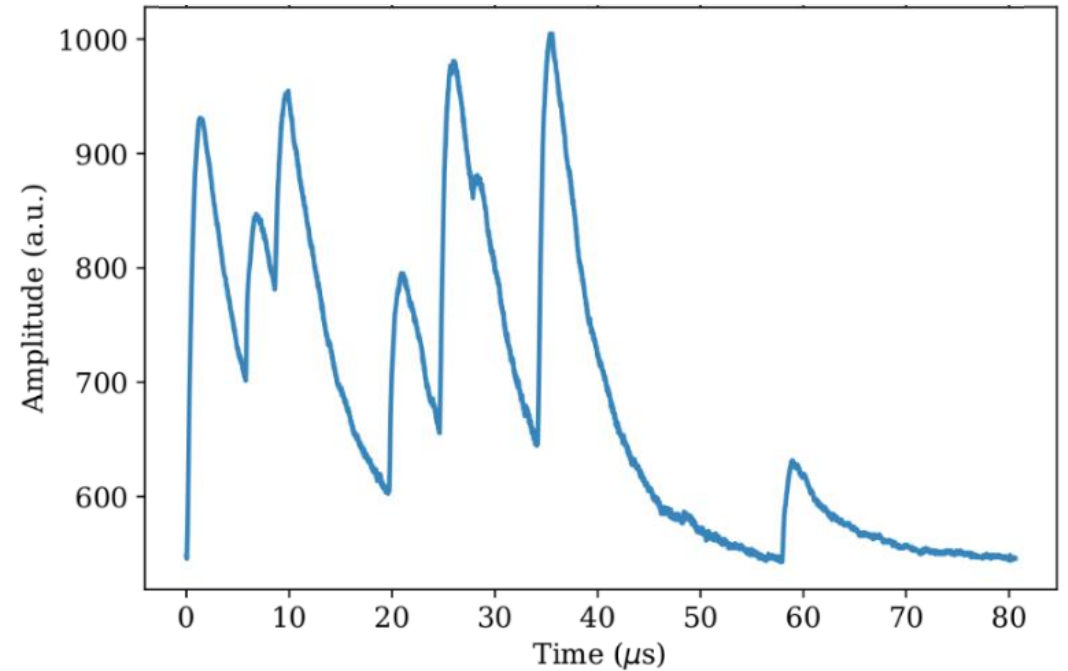
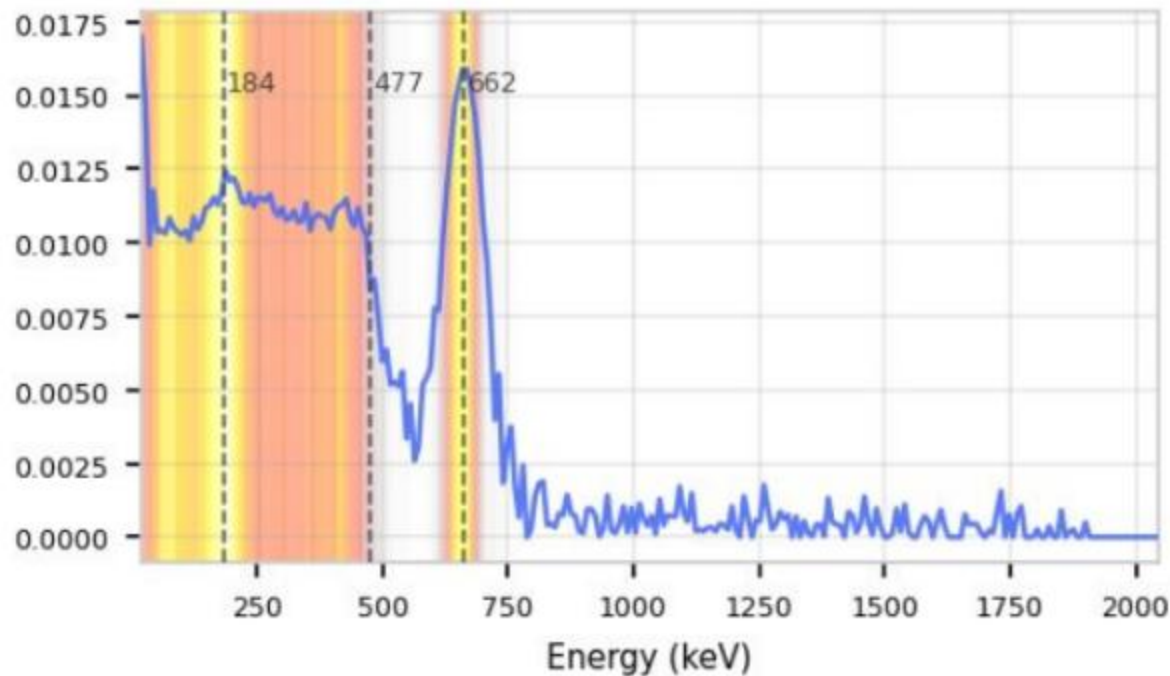


Why machine learning?

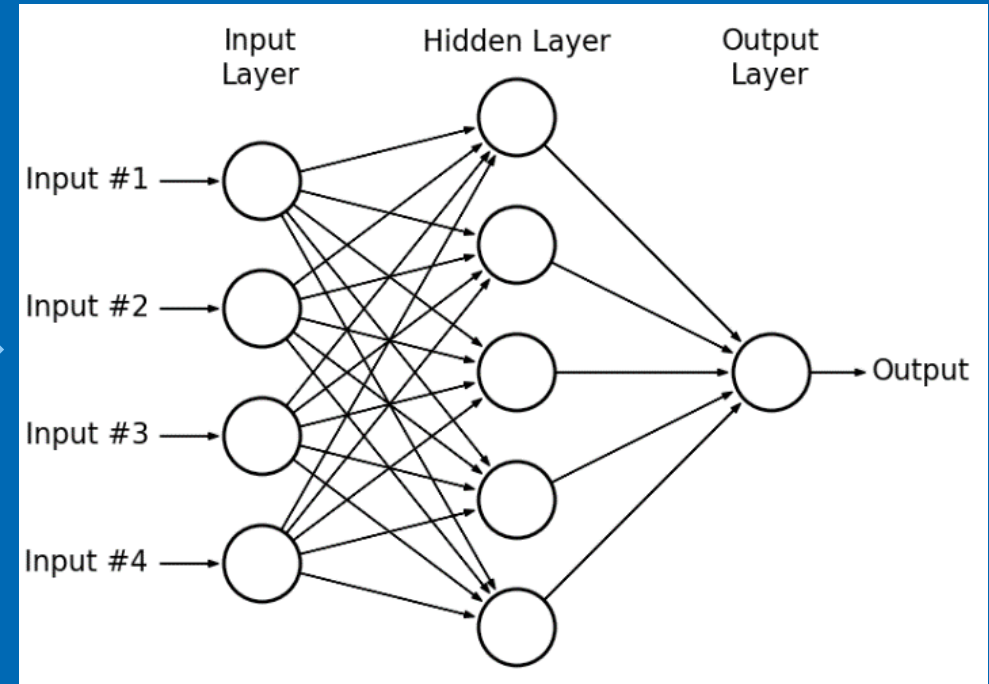
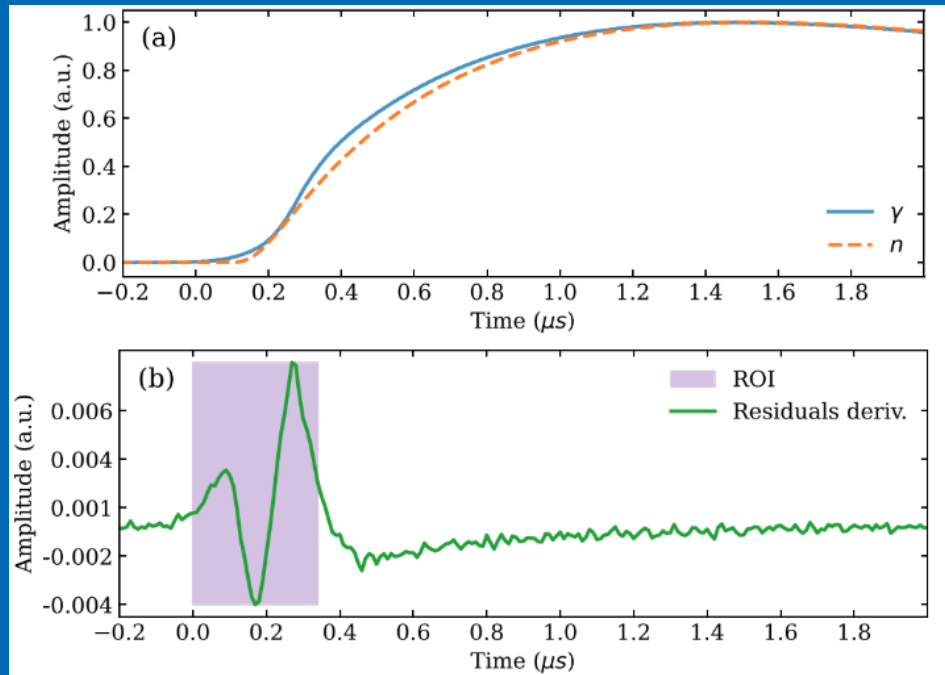


Why machine learning?

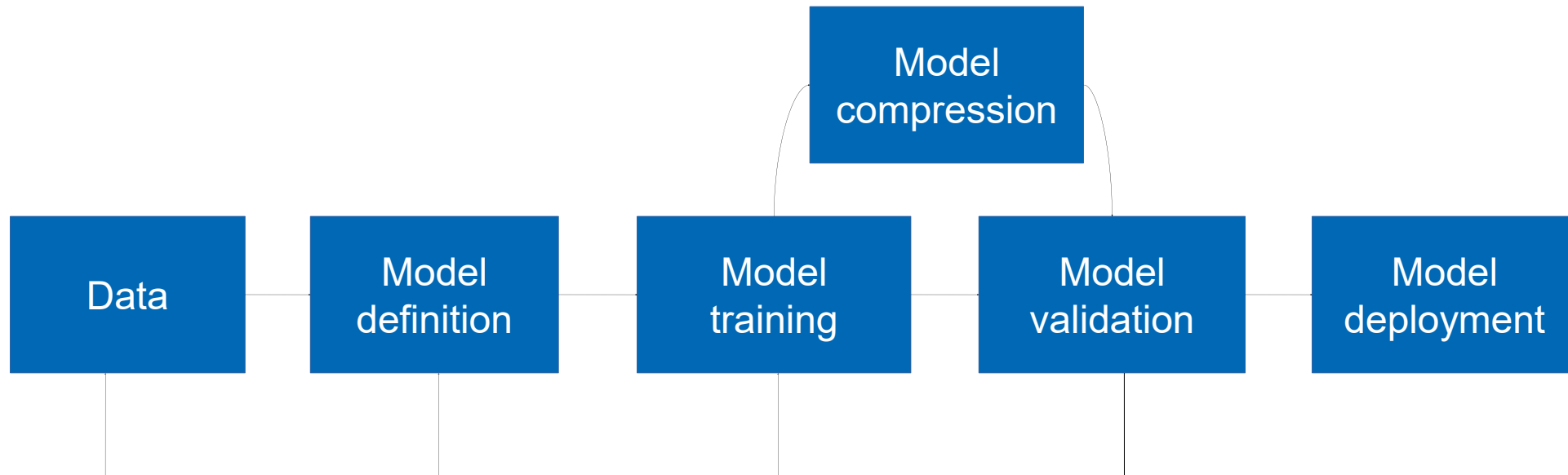
- Generalization/interpolation
- Leveraging unused features
- Overcoming issues with traditional methods



From data to inference with ML



From data to inference with ML



Data



Data sources

- Spectra, pulse shapes, other features
 - Experimental
 - Augmented
 - Synthesized

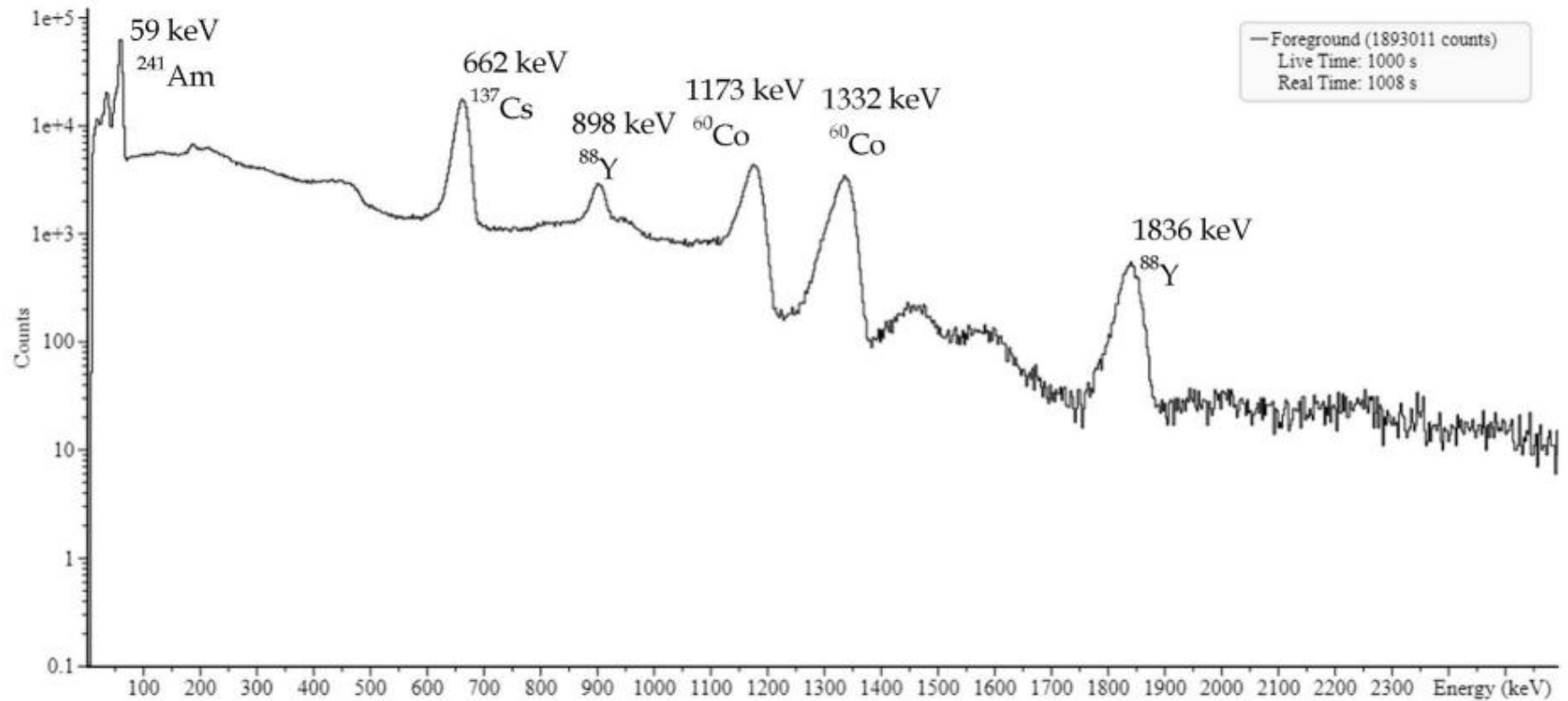
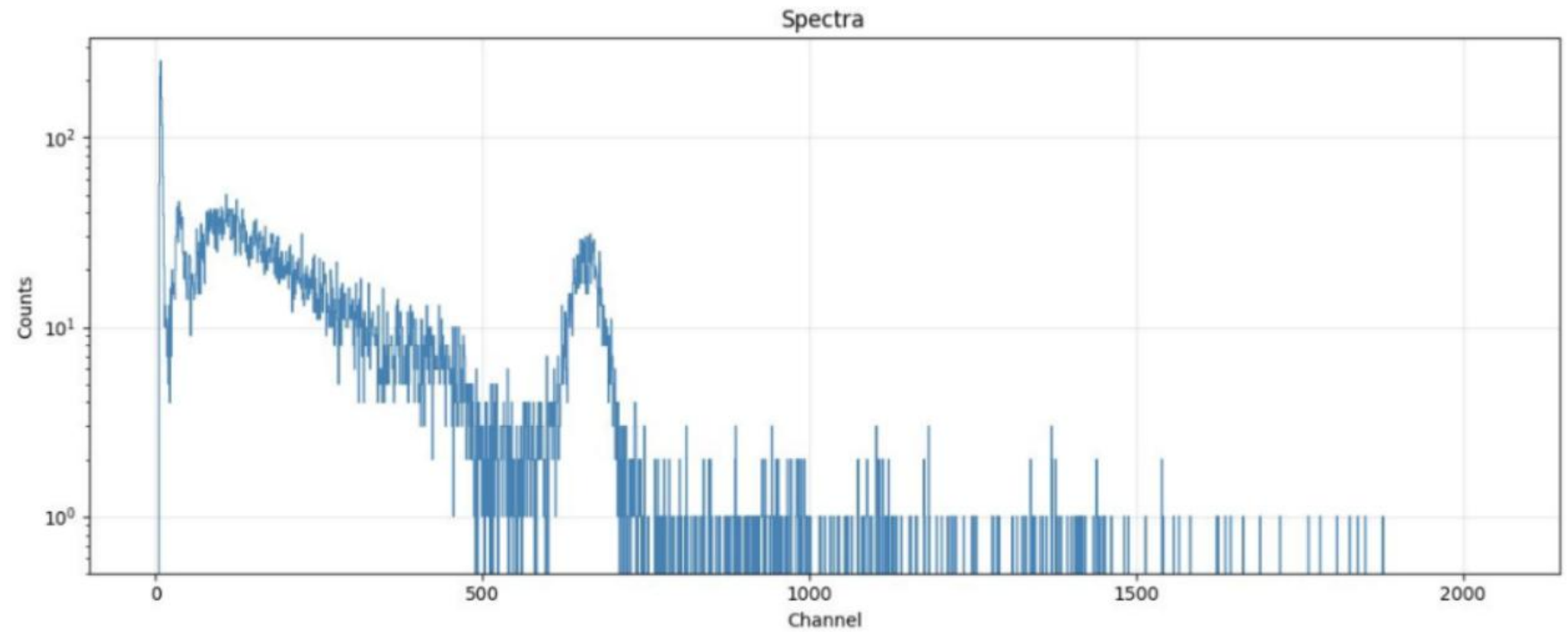


Figure from [1]

Data sources

- Spectra, pulse shapes, other features
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Data sources

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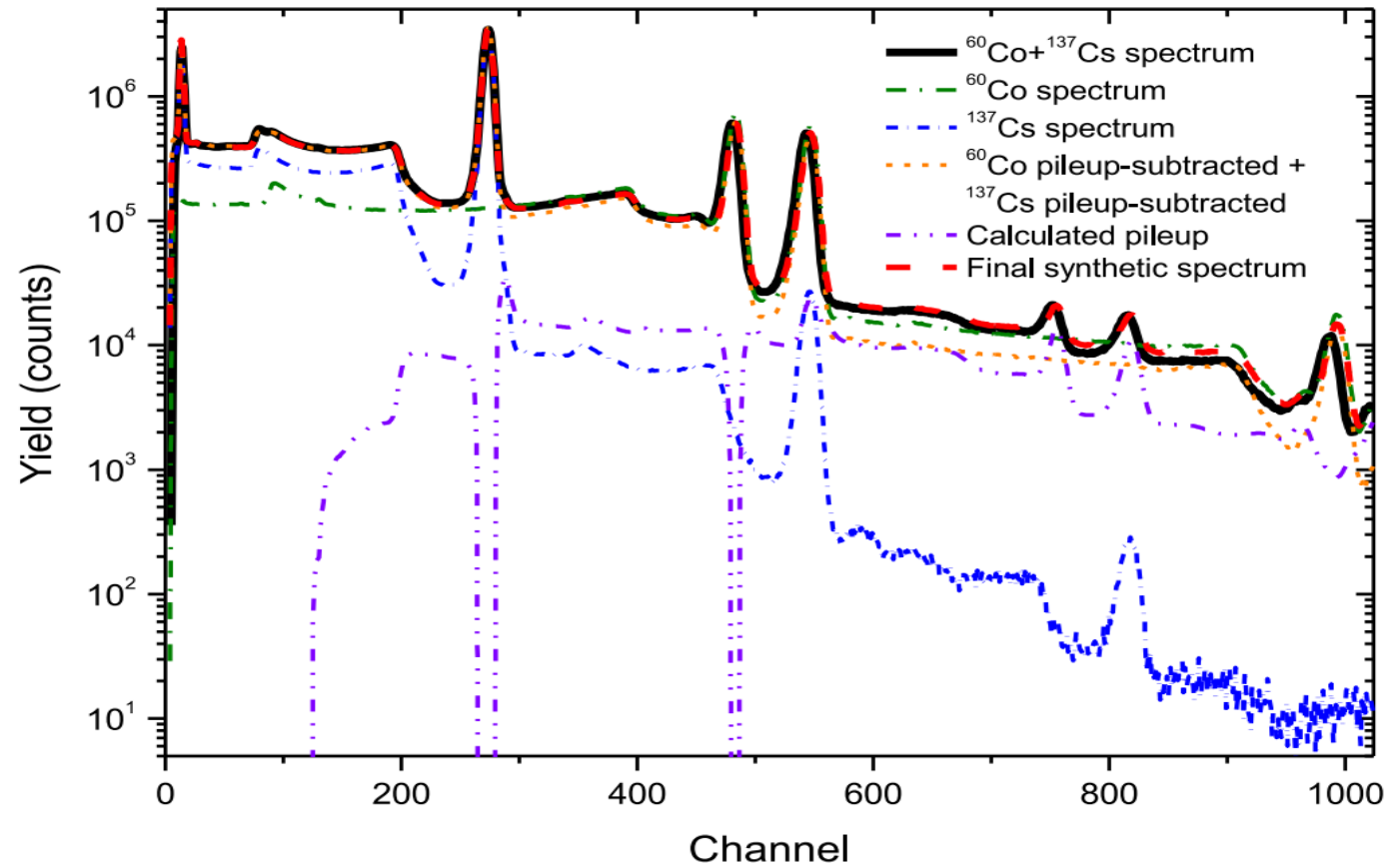
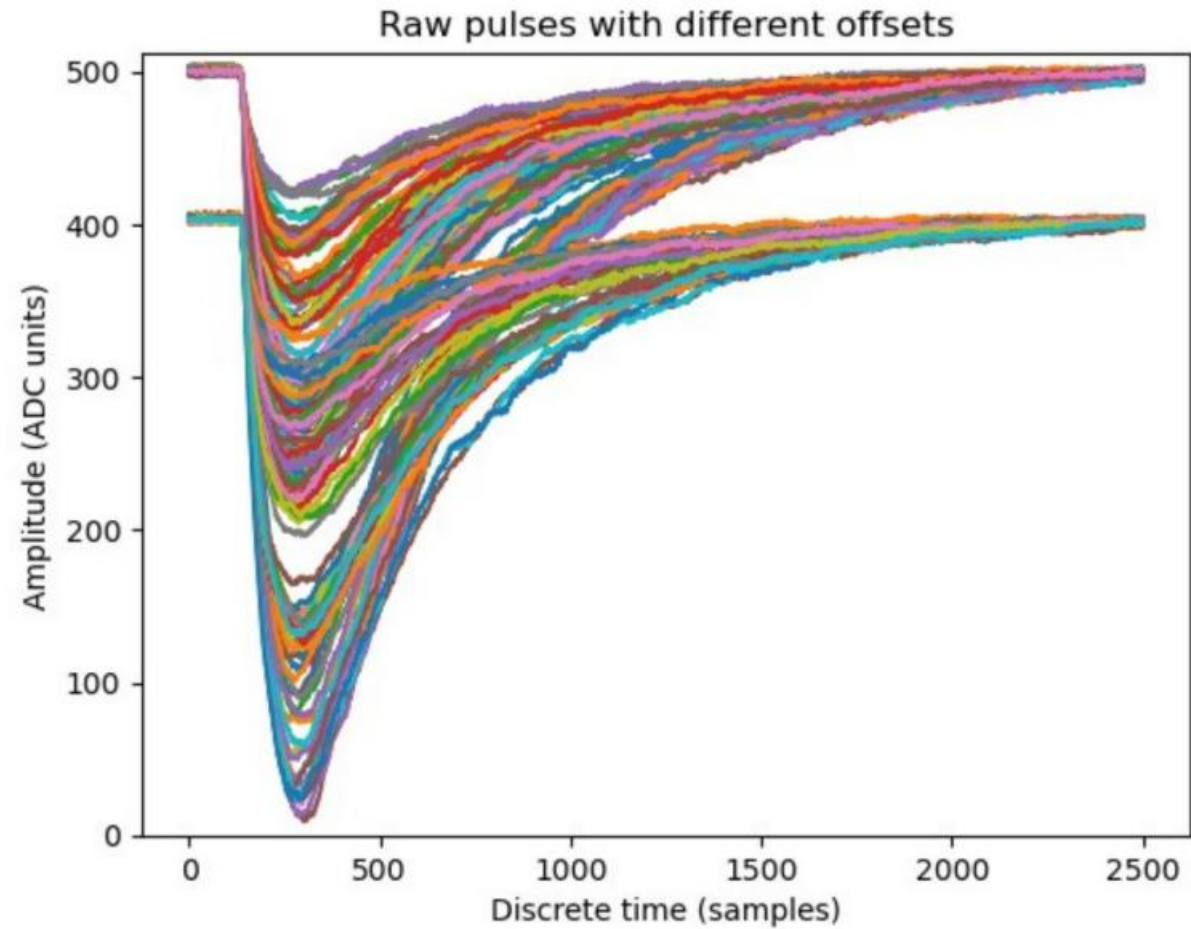


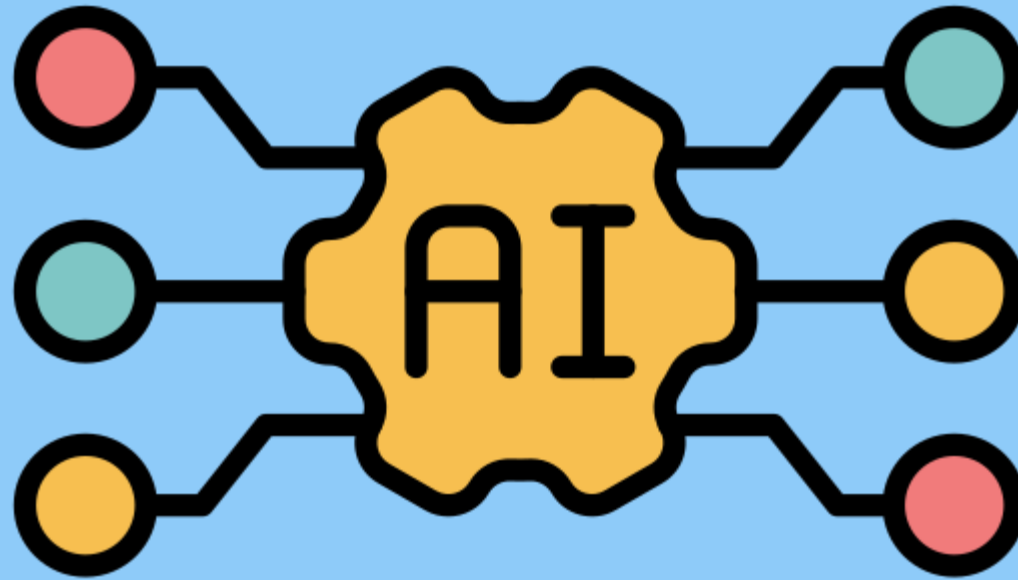
Figure from [1]

Data wrangling

- Data quality → model quality
- Unstructured → structured
- Cleaning
- Normalization



ML Model



Model definition

- ~~Pre-trained models~~ → general purpose (image segmentation/recognition, LLM, etc)
- Custom architectures: MLP, CNN, RF, ensembles
 - Layer types
 - Hyperparameters definition

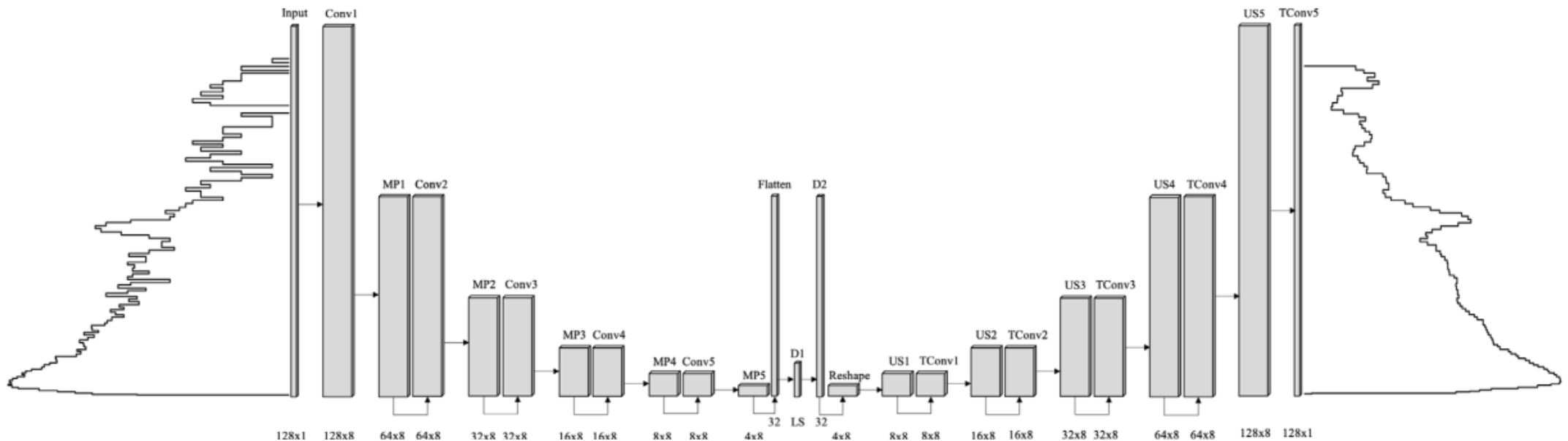
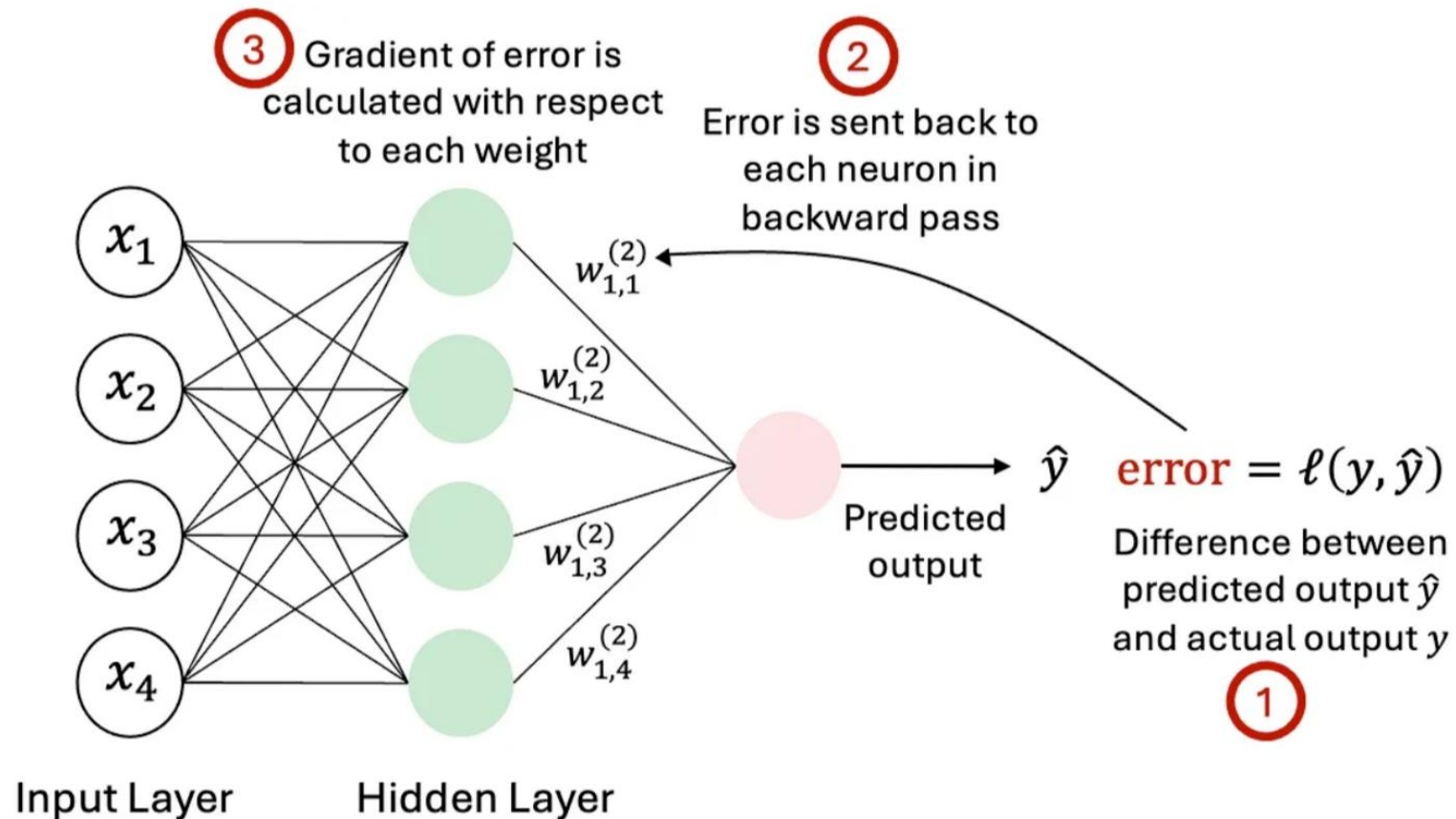


Figure from [2]

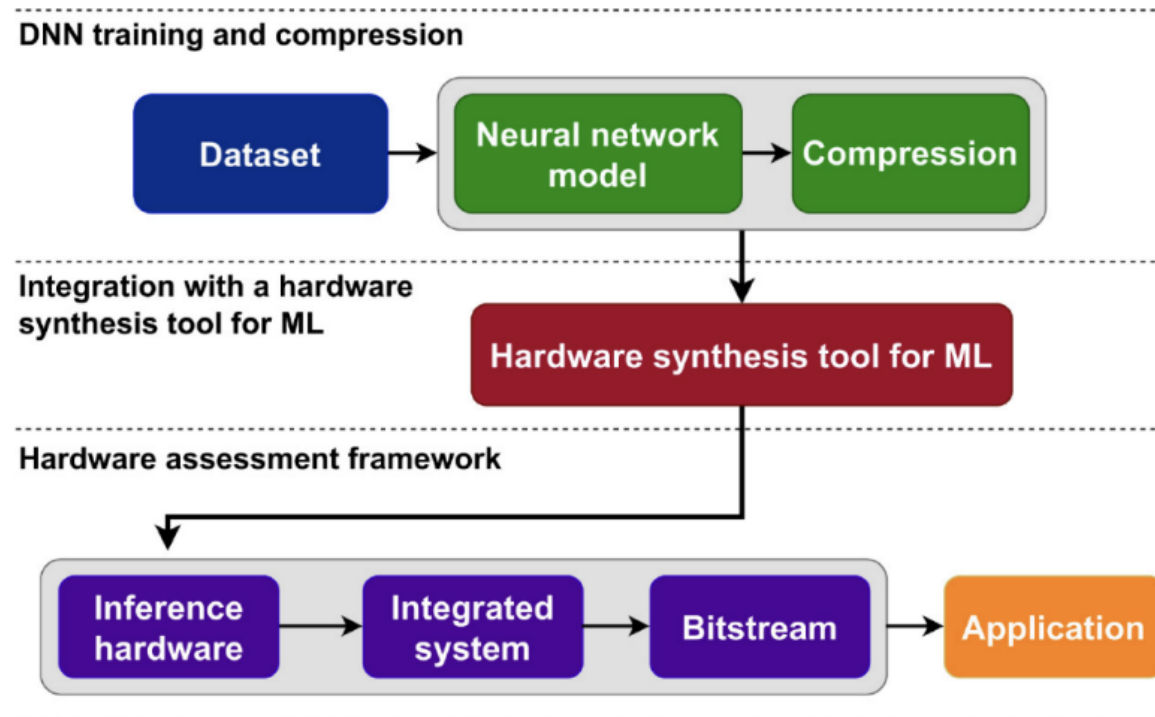
Model training

- Supervised/unsupervised
- Data-driven



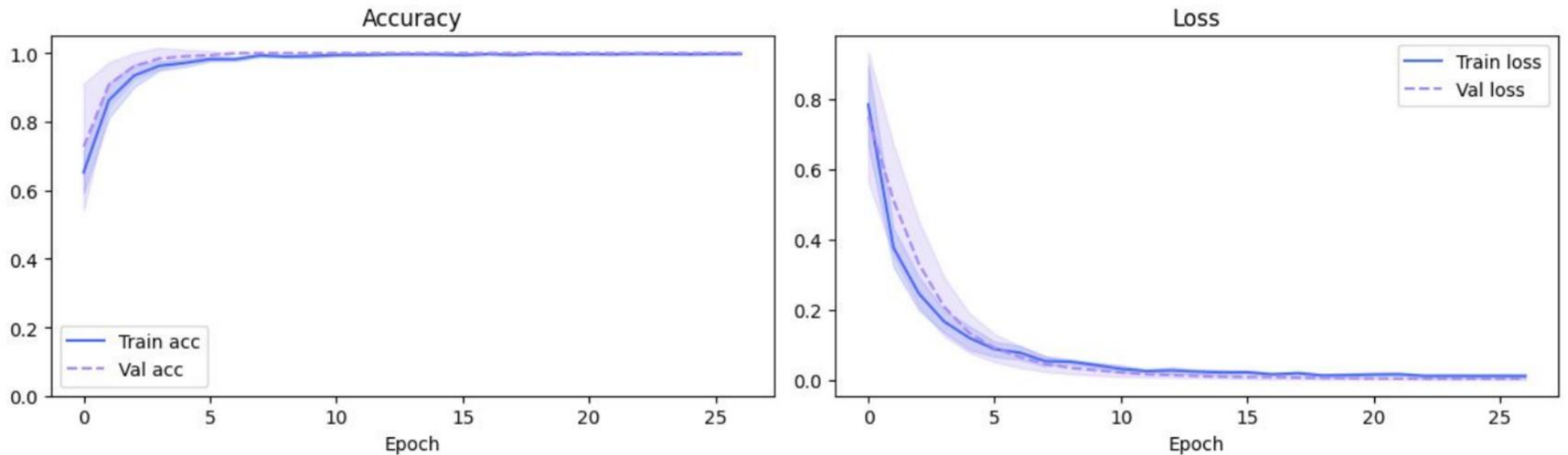
Model compression

- Reduces memory footprint and latency
- Slightly reduced precision
- Targeting the inference platform

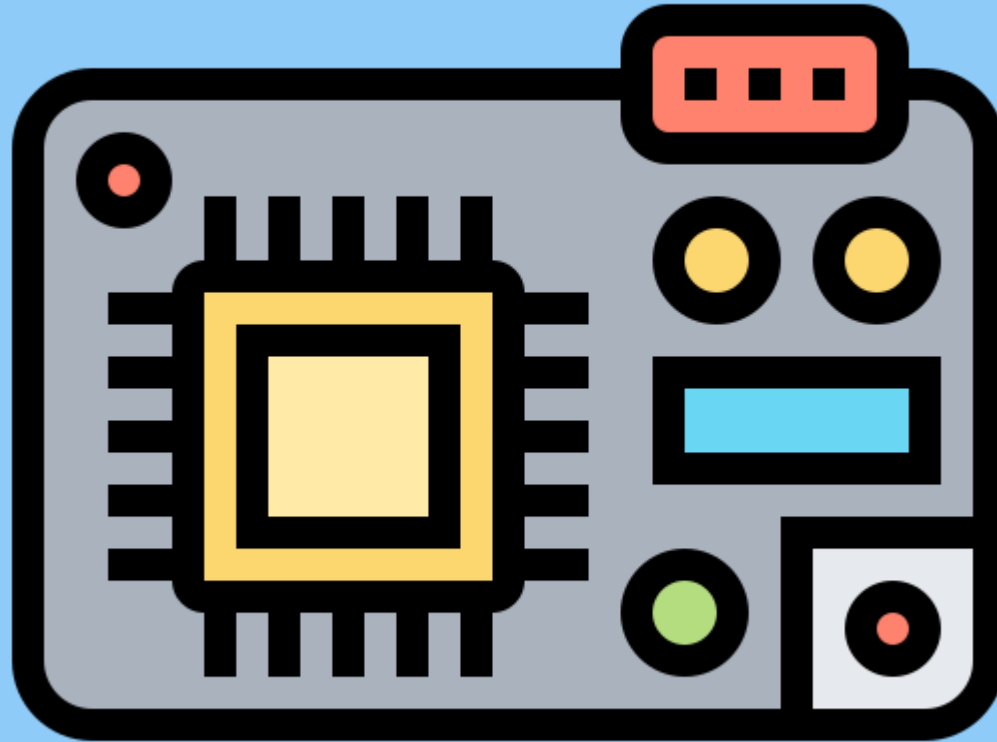


Model validation

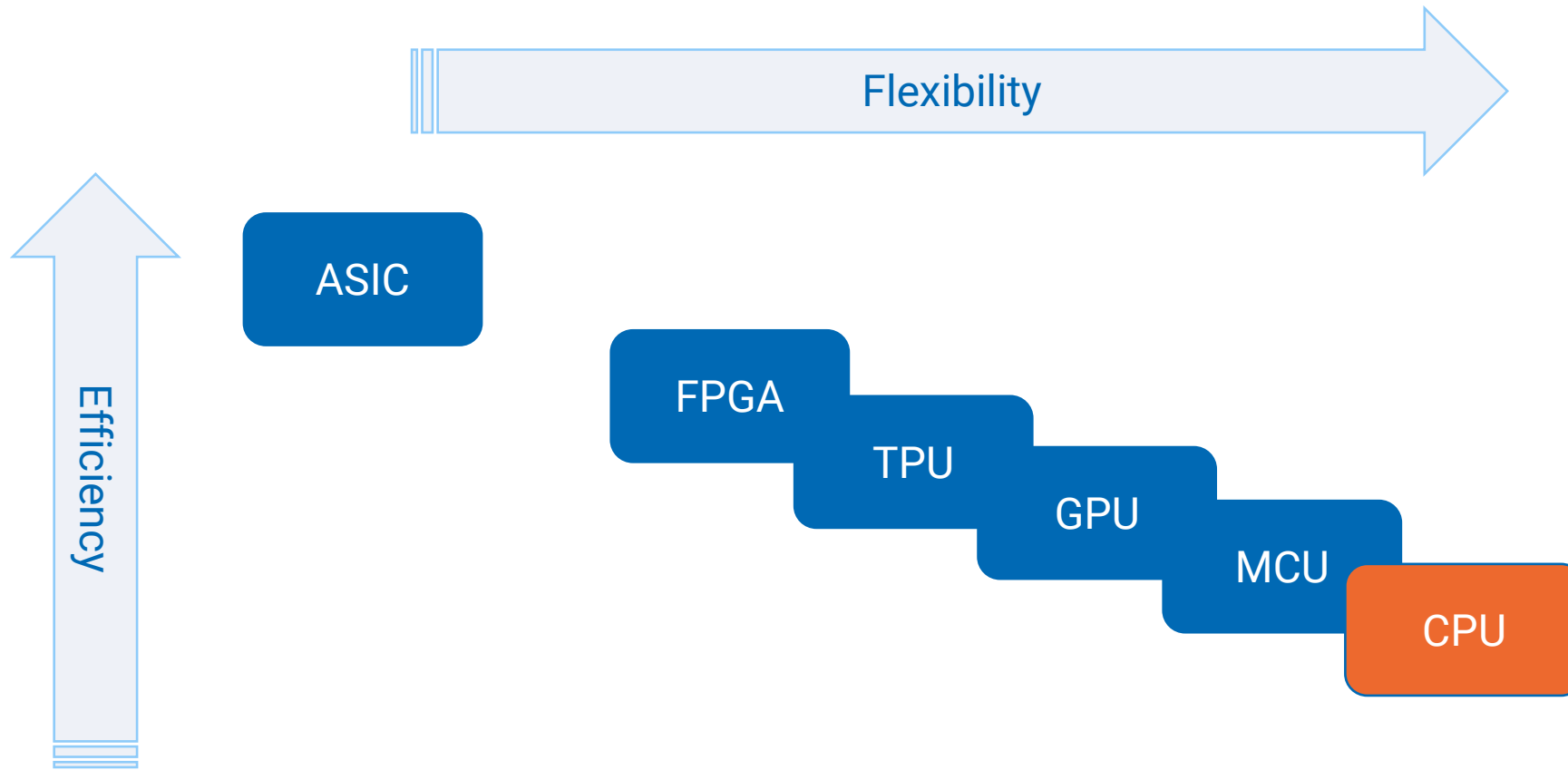
- Data split: training, test, and validation
- Validation after each training epoch
- Unseen data → checking generalization, overfitting



Model deployment



Model deployment - targets



Model deployment - requirements

- Real-time inference (+ on-the-edge)
- General-purpose systems
- Target-specific embedded systems
- Model size

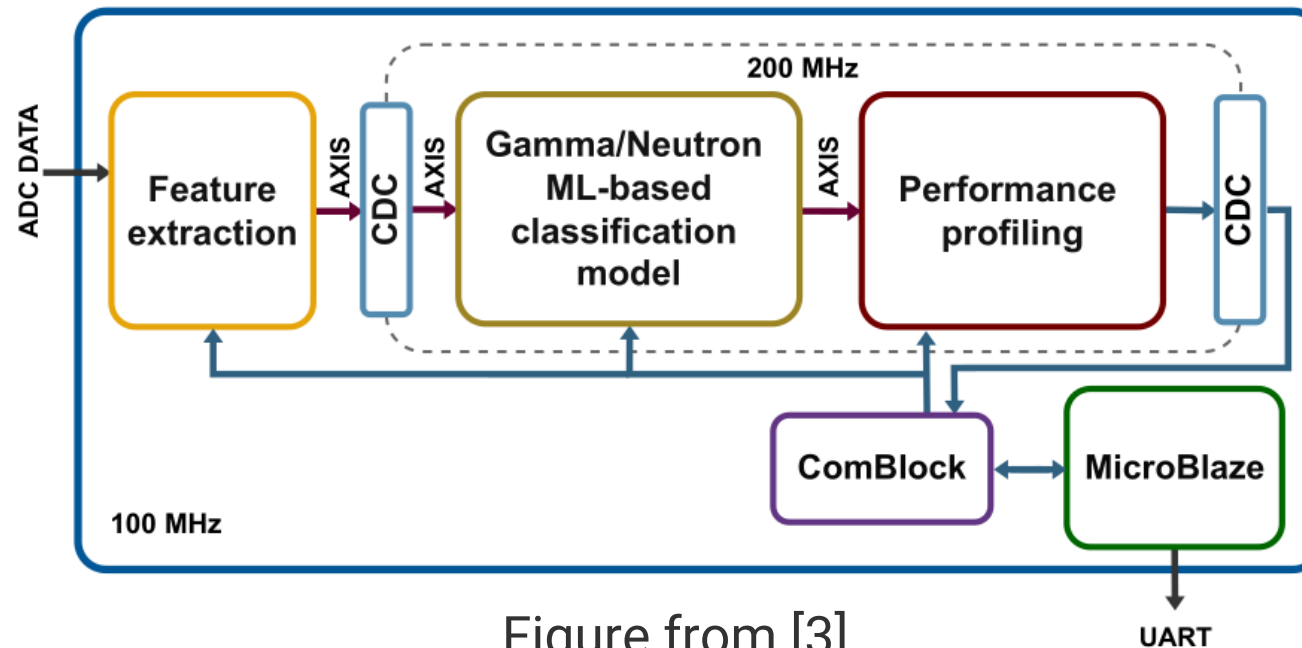
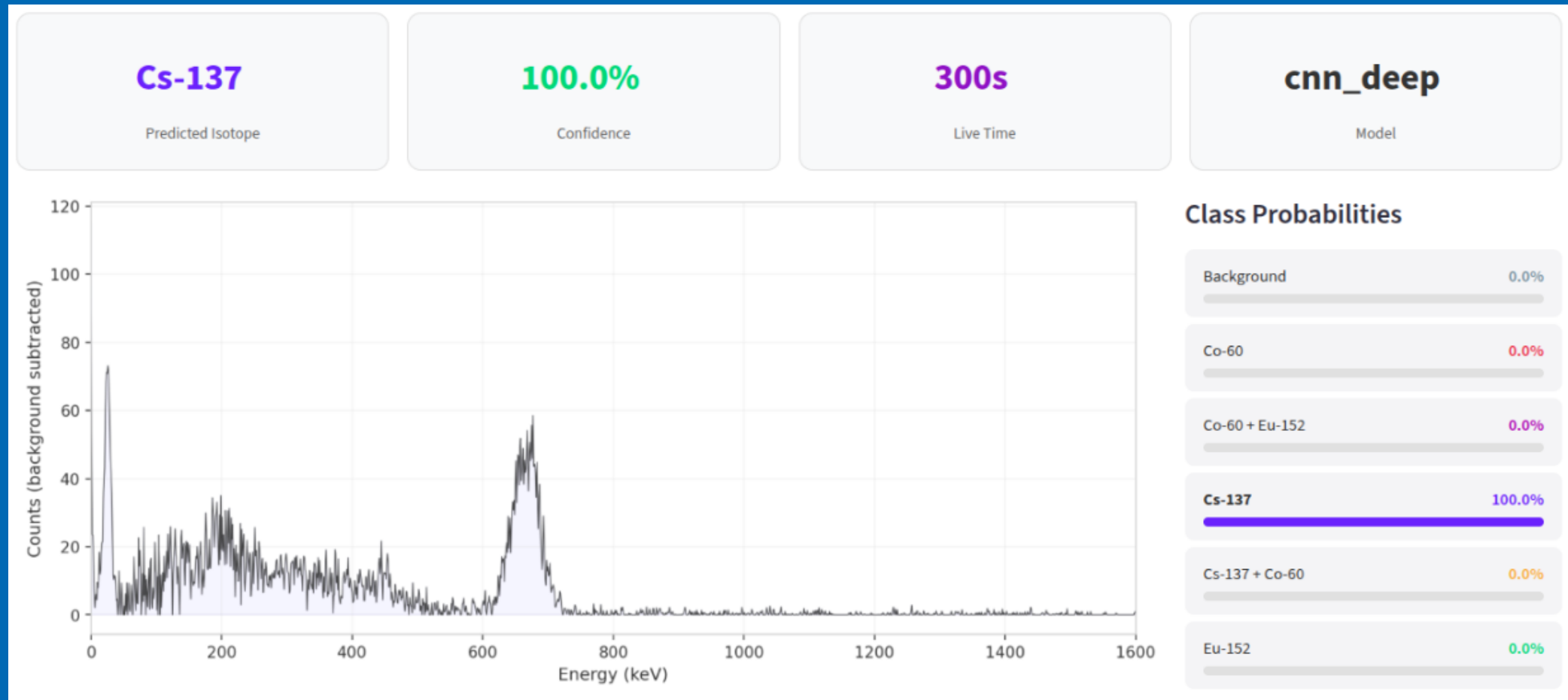


Figure from [3]

Radioisotope ID with ML

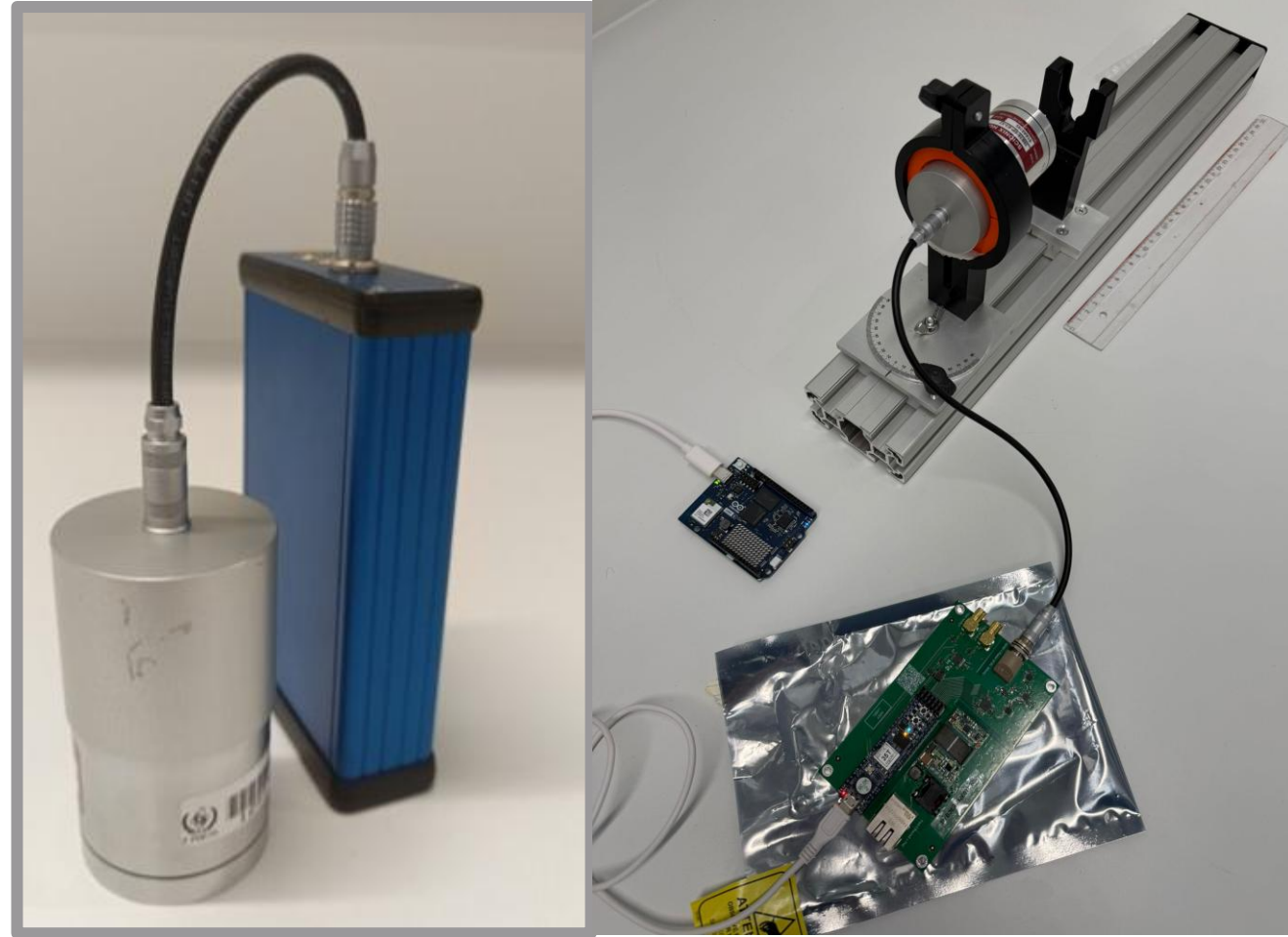


Portable spectroscopy system with RIID



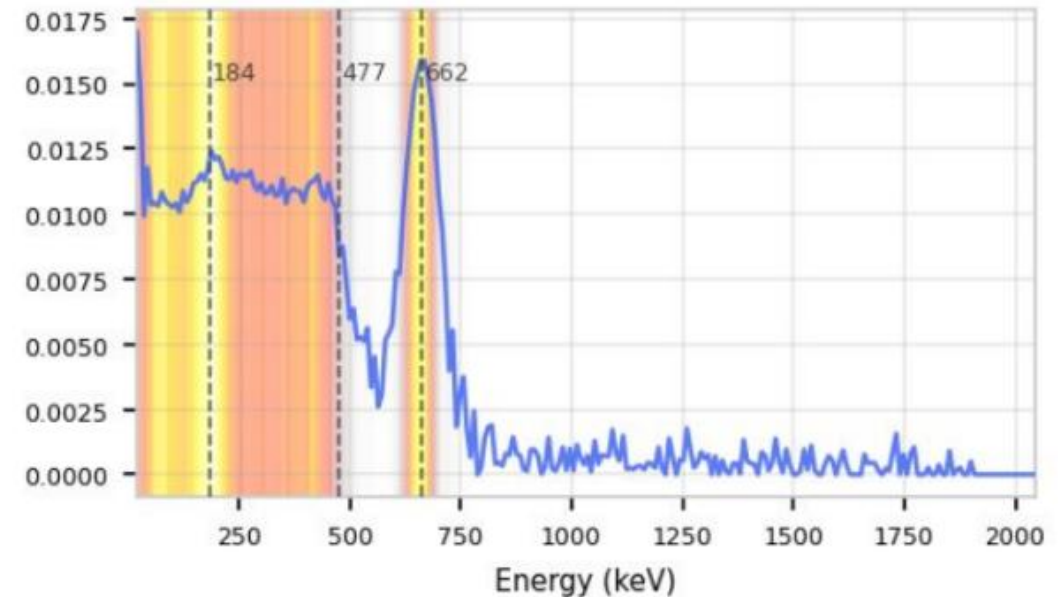
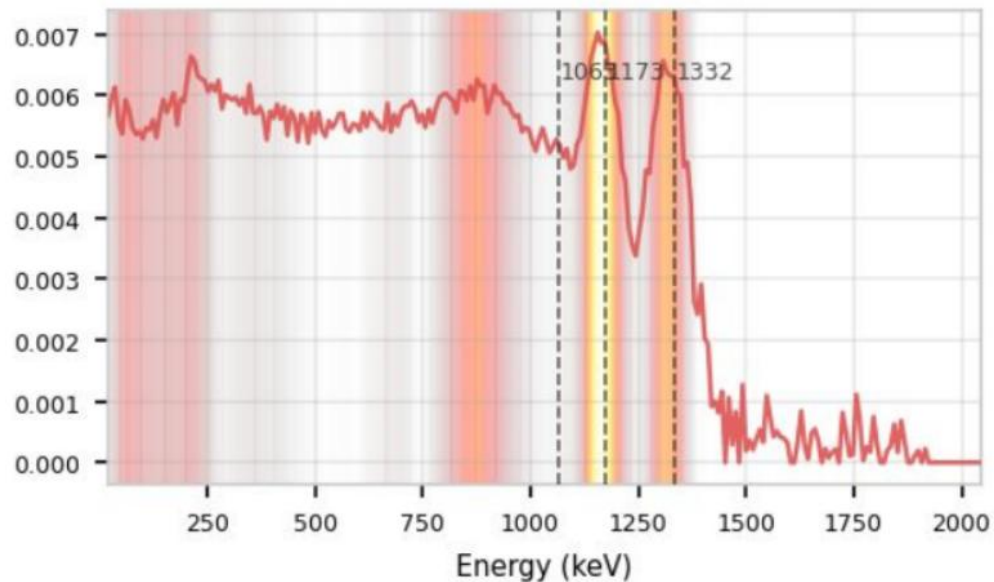
Online RIID with in-house MCA

- Target: **Edge CPU** (Arduino Uno Q's MPU)
- Portable device
- Training → full control
- Open-source
 - Hardware design: Schematics & PCB
 - FPGA firmware: real-time DSP
 - FPGA embedded processor: comms
 - MCU firmware: visualization
 - Python API (backend)
 - Python GUI (web-based)



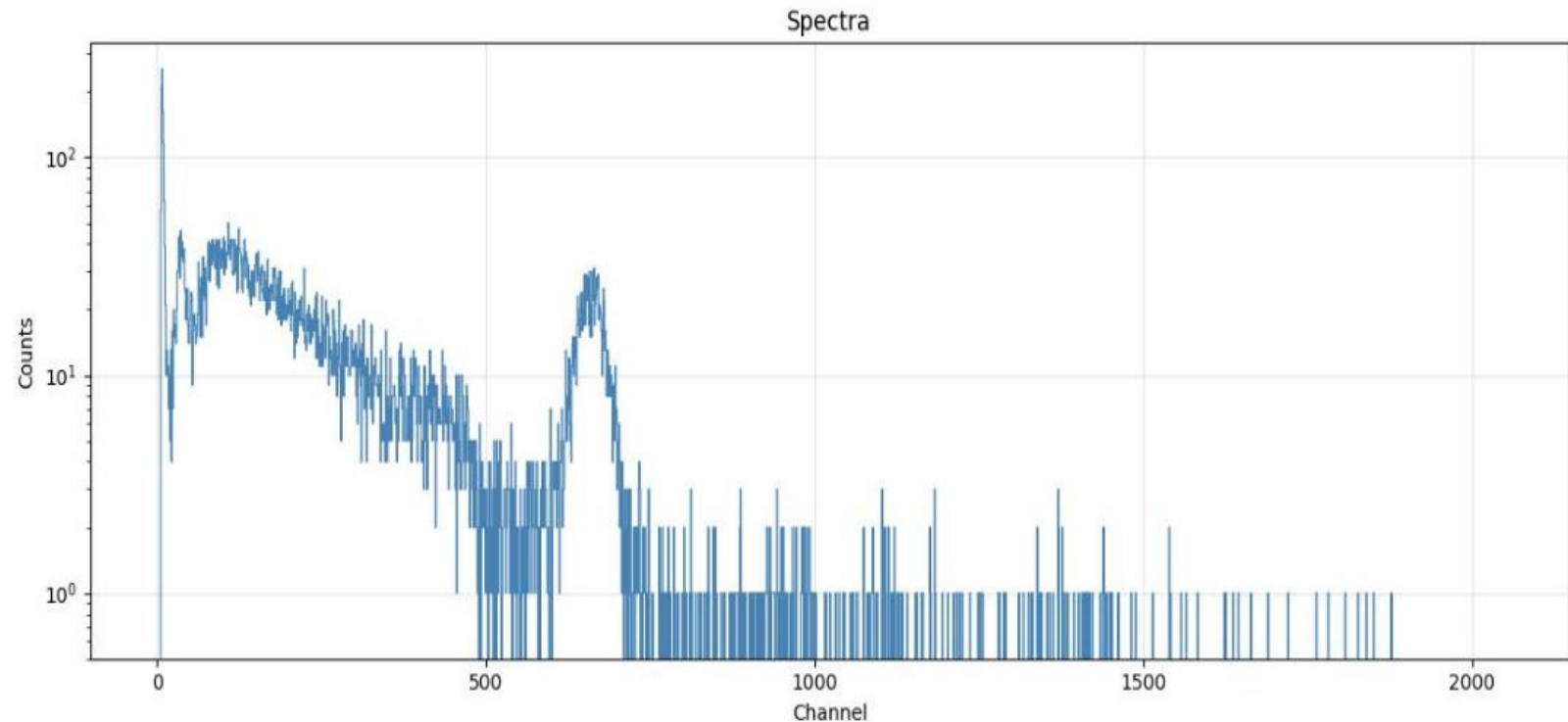
Advantages

- Leverages (typically) unused spectrum features
- Relaxed energy calibration
- Low resolution detectors

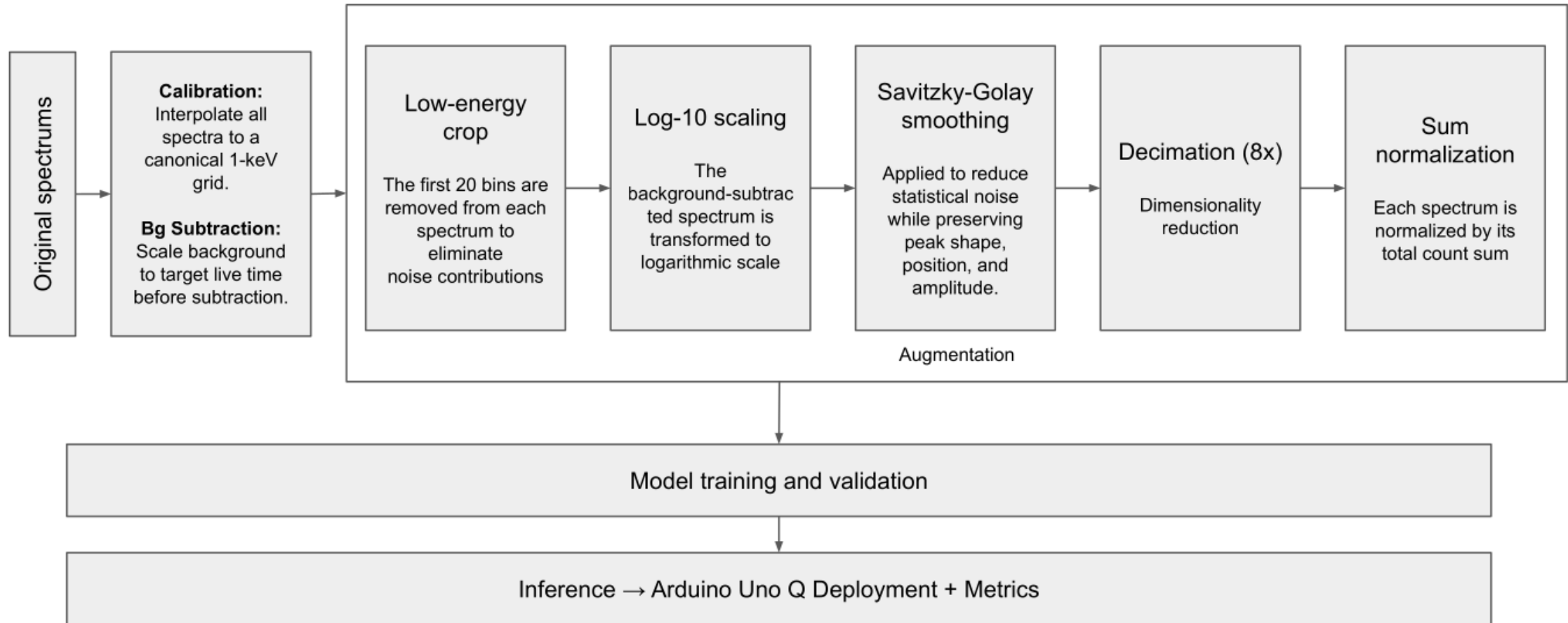


Data requirements for training

- Experimental variables
 - Radionuclides
 - Shielding
 - Detector geometry
 - MCA/detector
- Augmentation
 - Collection time
 - Distance
 - Calibration shift
 - Sources combination

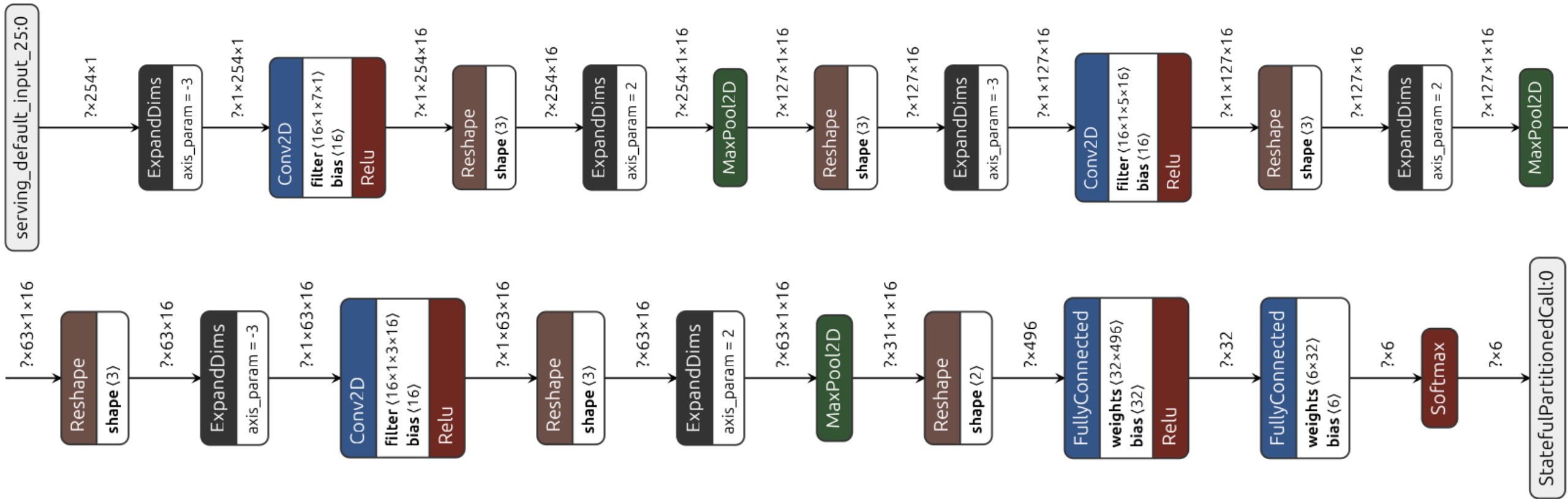


Preprocessing pipeline – training & inference

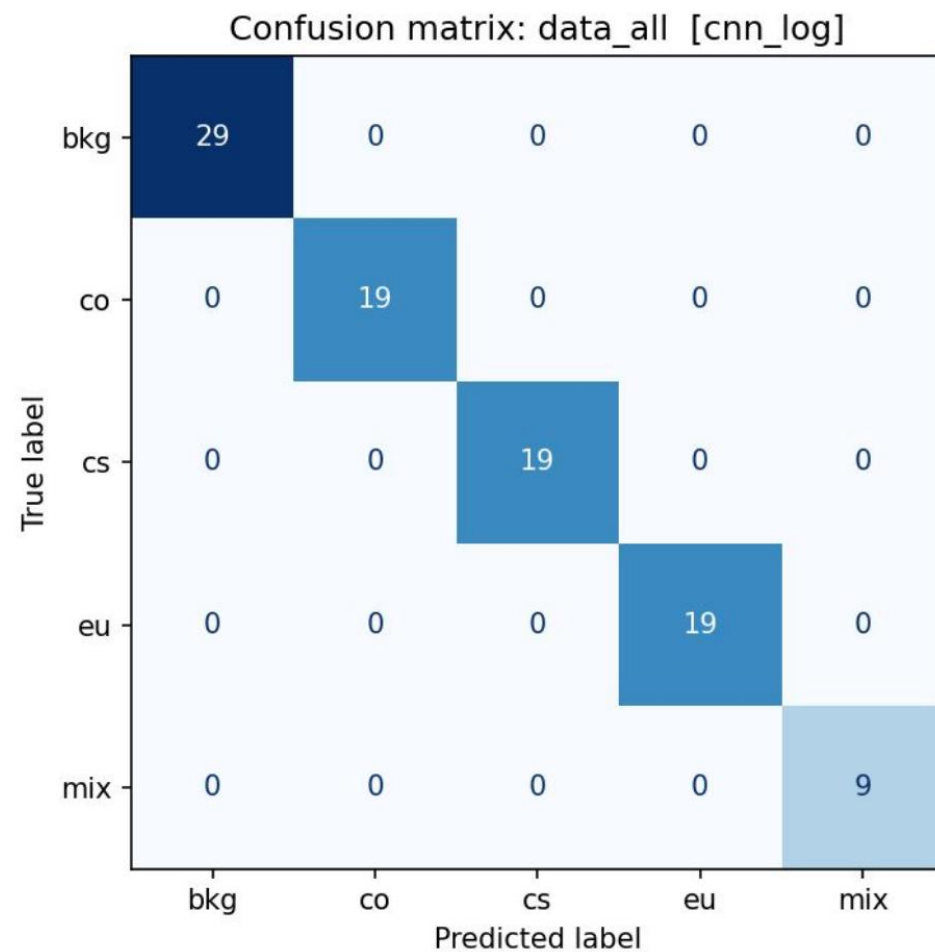
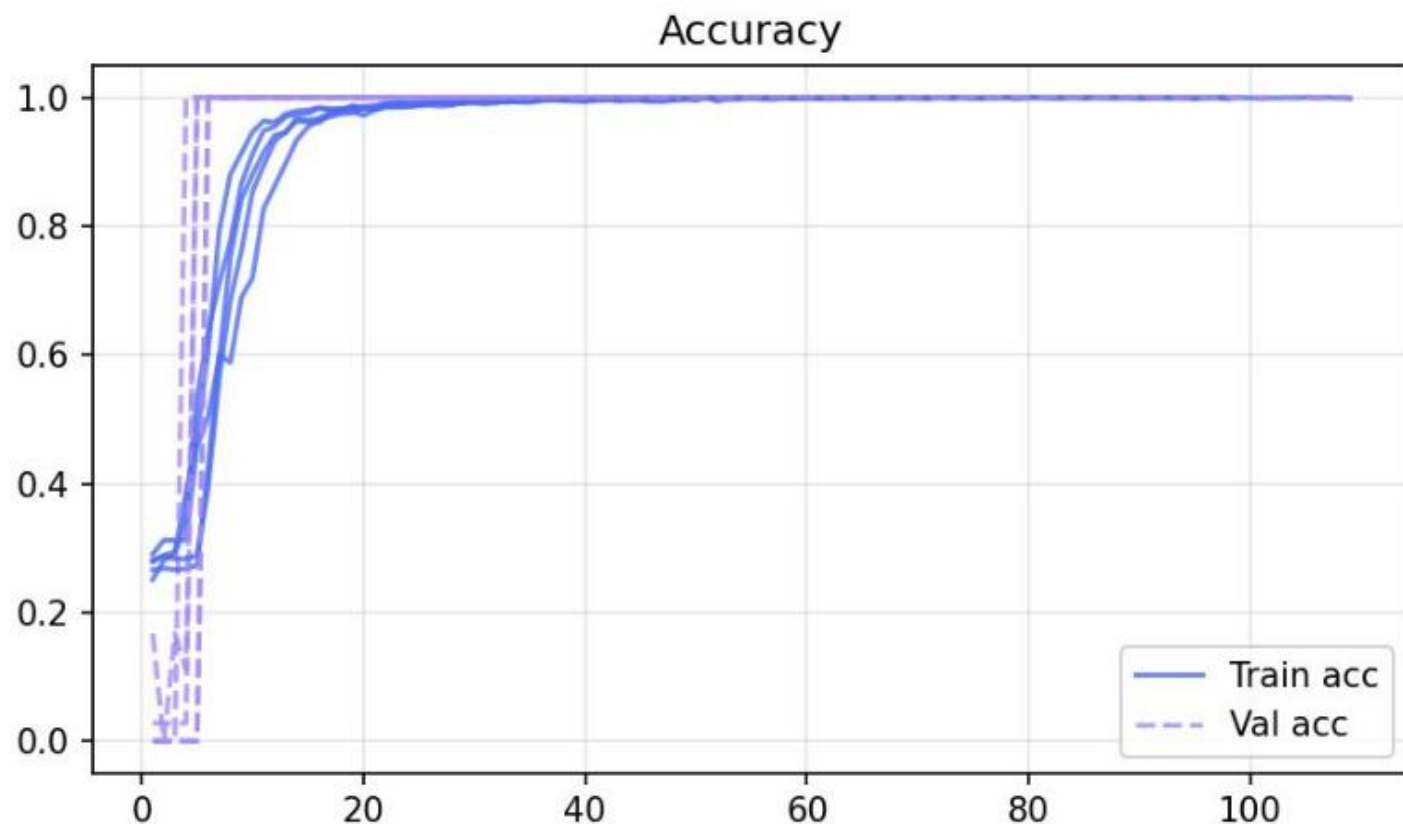


ML model

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



Model performance



Generalization capabilities

Cs-137 + Co-60

Predicted on Edge

99.0%

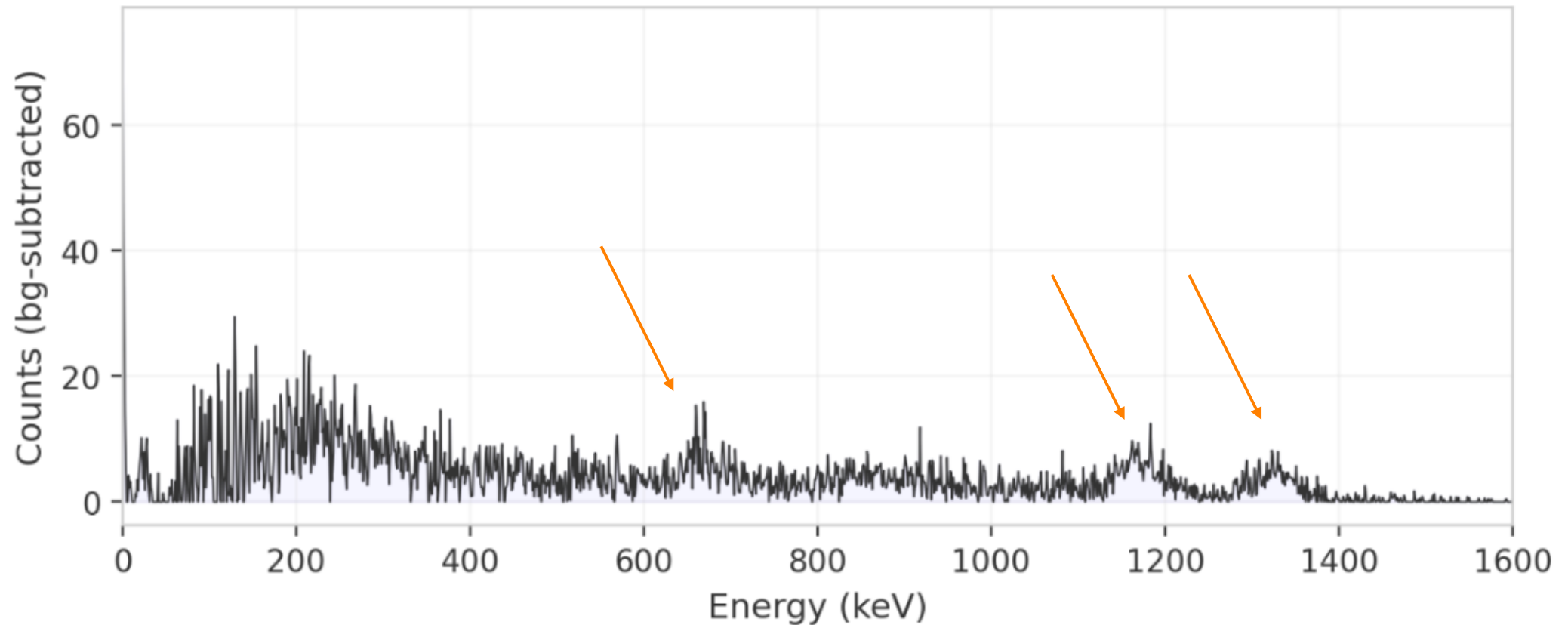
Confidence

0.46 ms

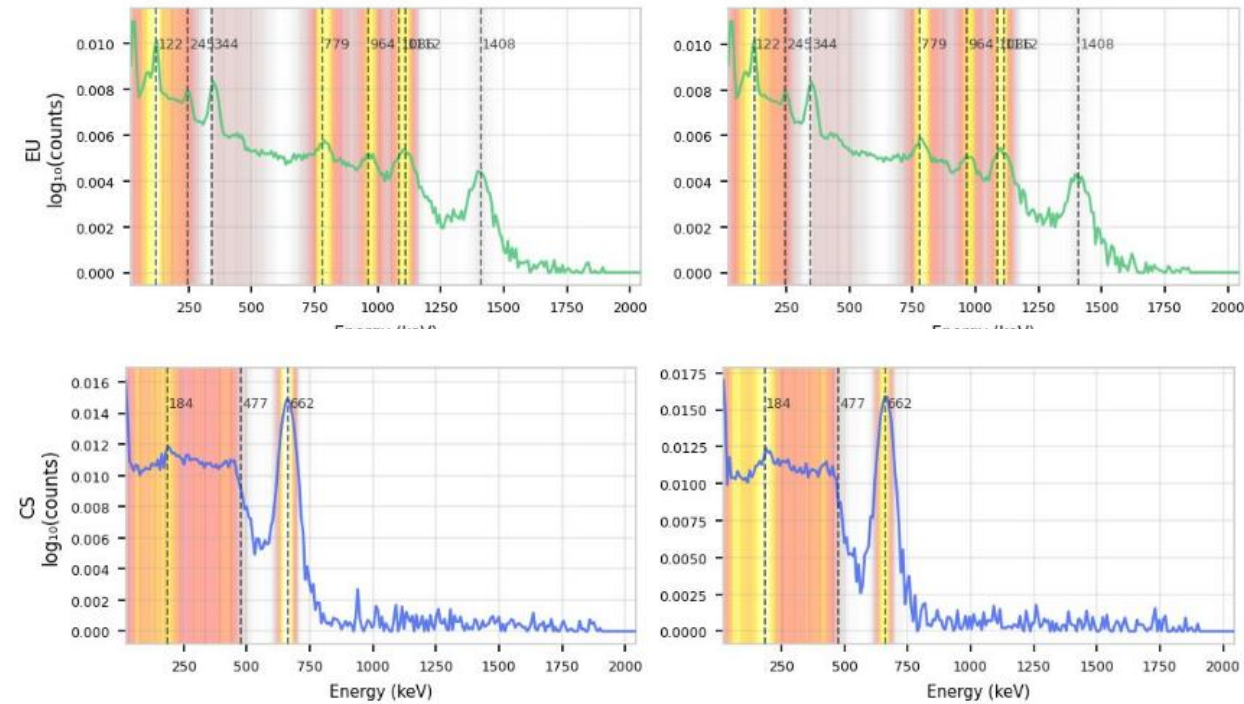
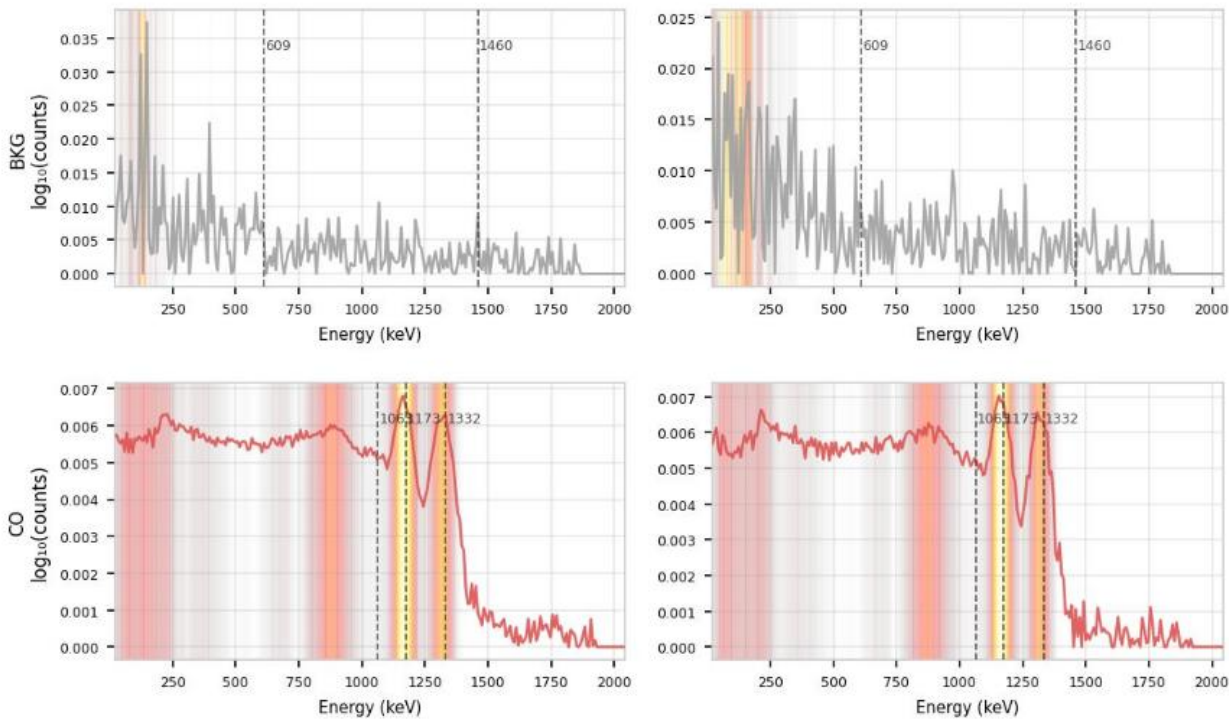
Model Latency

12.67 ms

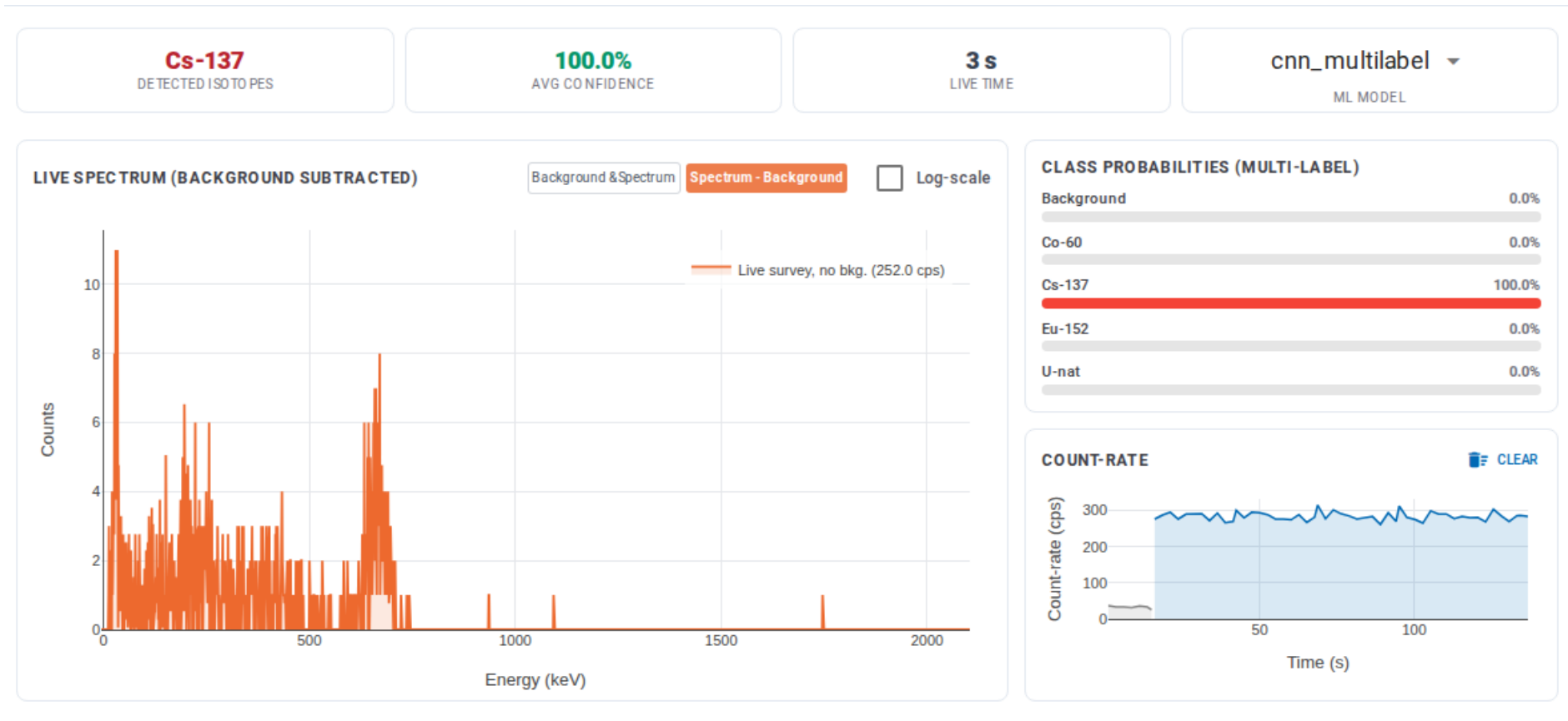
End-to-End Latency



Explainability – Integrated gradients



Graphical user interface



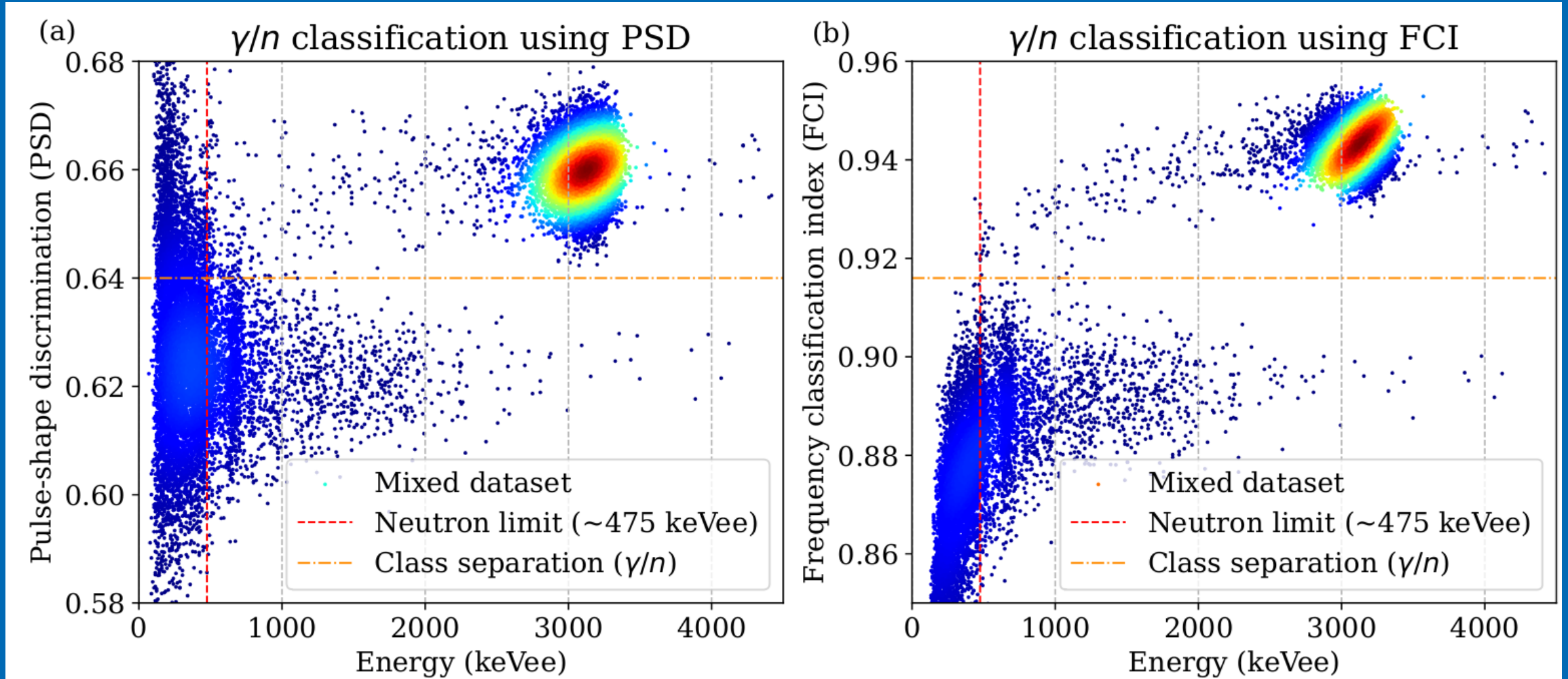


Thank you!

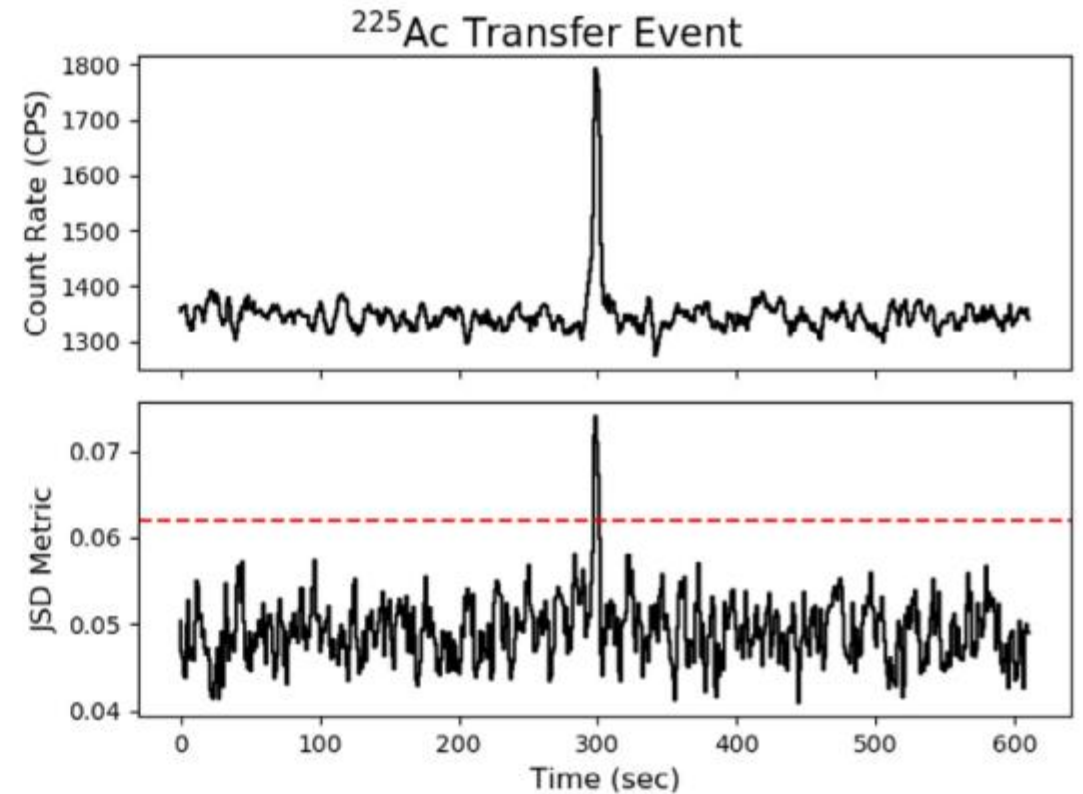
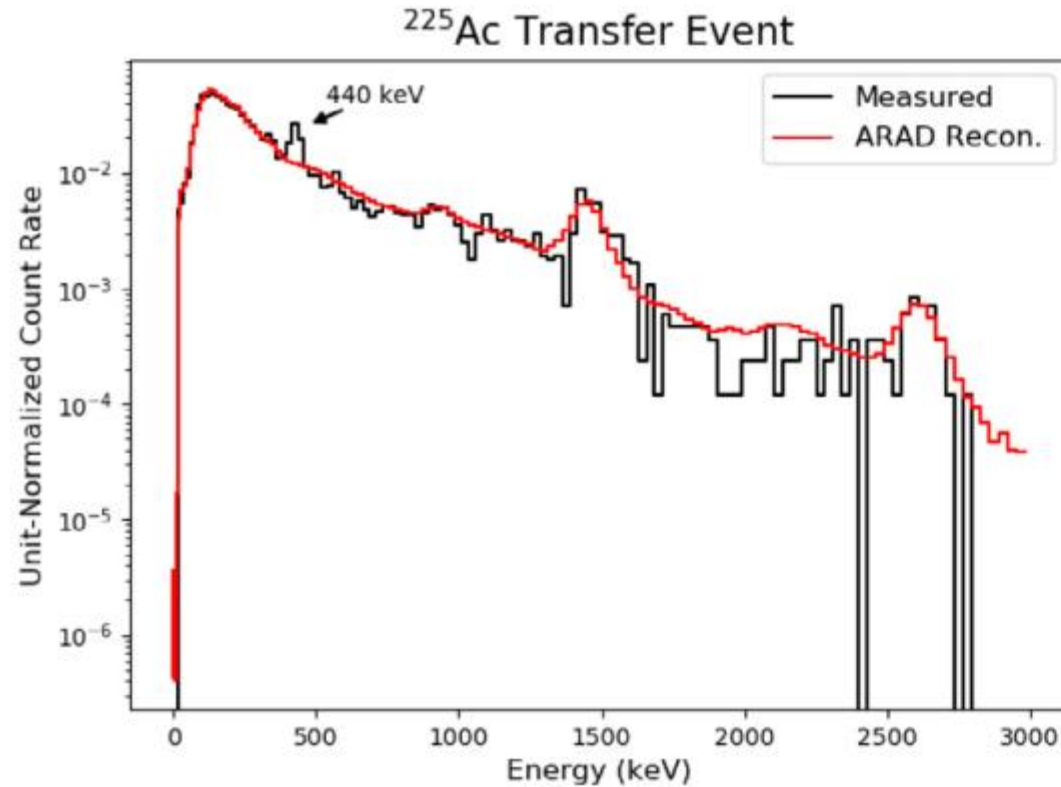
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Backup slides

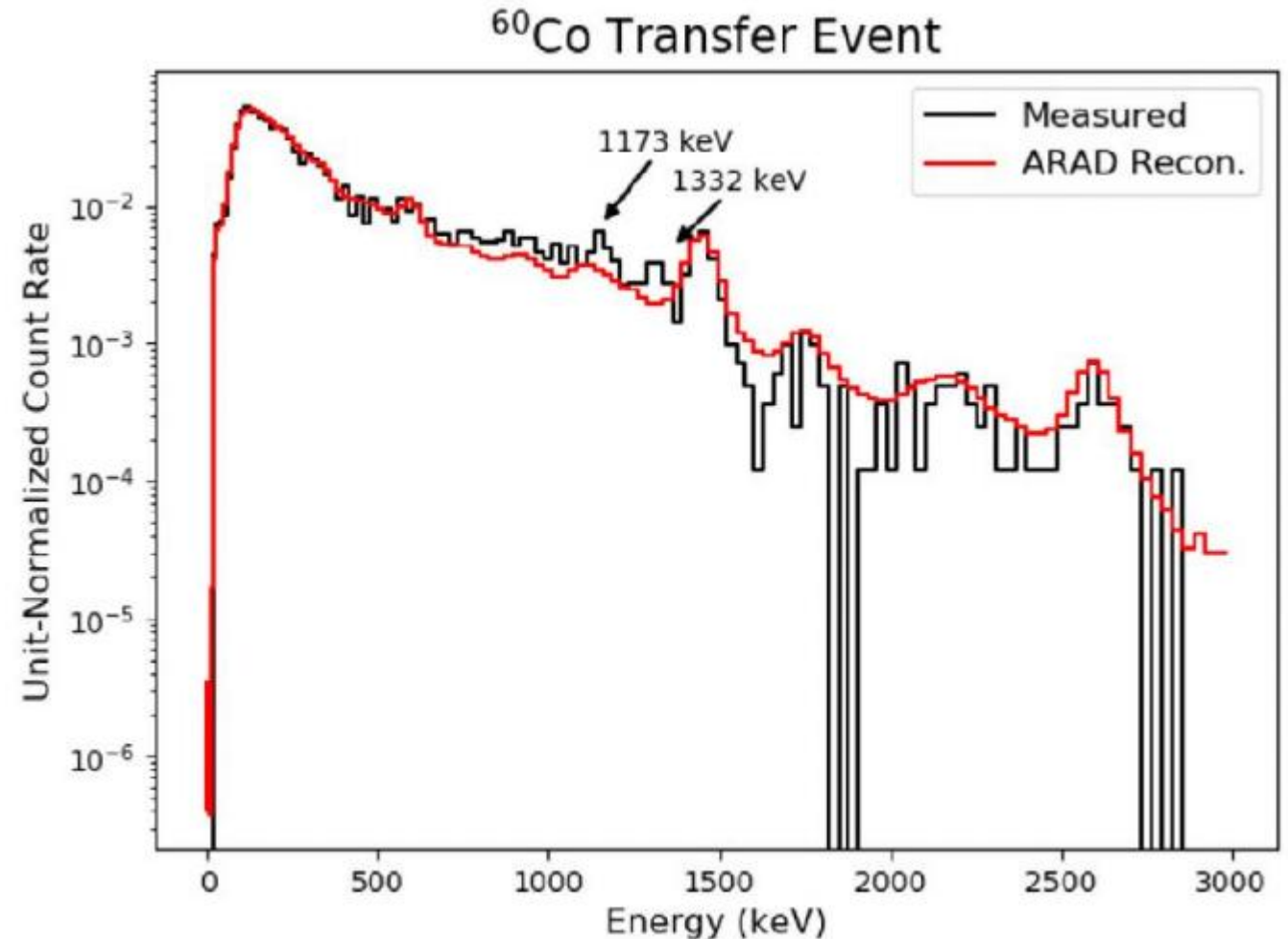


Applications – radiation detection



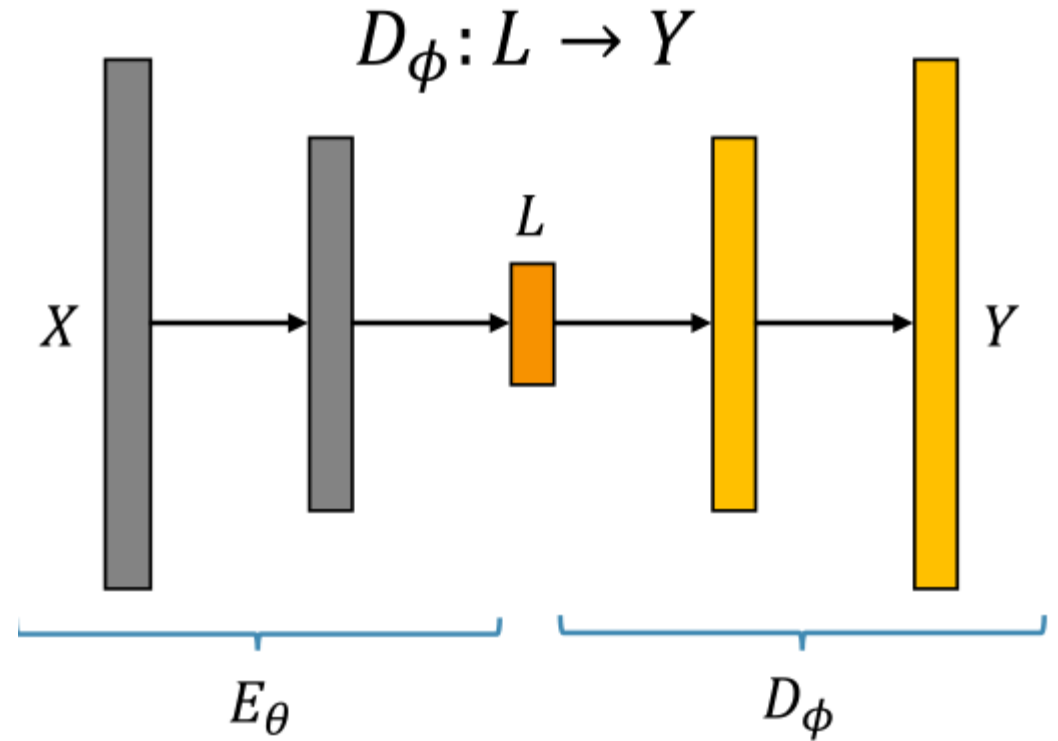
Background anomaly detection

- Target: **CPU**
- Dynamic background
- Shielded or fast-moving sources
- False alarm ratio < 1 / 2 hrs
 - ANSI N42.35-2016
- Unknown radionuclides
- Accumulation: 5 seconds
- NaI(Tl) – 2 Liters



ML model

- Autoencoder
- 1D CNN + FC
- Physics-informed:
 - Conv. layer filters trained to capture photopeaks $c(E)$
 - Loss function considers Log. relative intensities
 - Jensen-Shannon distance
 - Penalization with photopeaks



$$c(E) = c(\mu_E) \exp \left[-\frac{1}{2} \left(\frac{2\sqrt{2\ln 2}(E - \mu_E)}{R(\mu_E)\mu_E} \right)^2 \right]$$
$$R(\mu_E) = \frac{FWHM}{\mu_E} = \frac{2\sqrt{2\ln 2}\sigma}{\mu_E}$$

ML model

- Autoencoder for background reconstruction
- Goal → **Unsuccessful reconstruction** of background spectrum

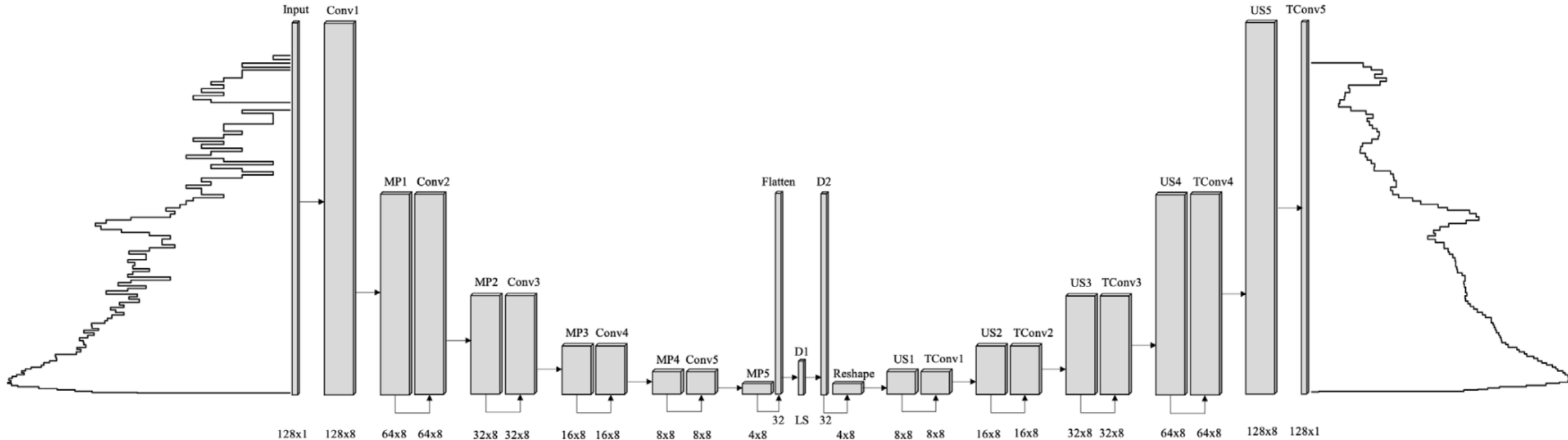


Figure from [2]

Anomaly detection – Clutter event

- Conventional threshold → alarm
- Anomaly detection → background spectrum shape reconstructed

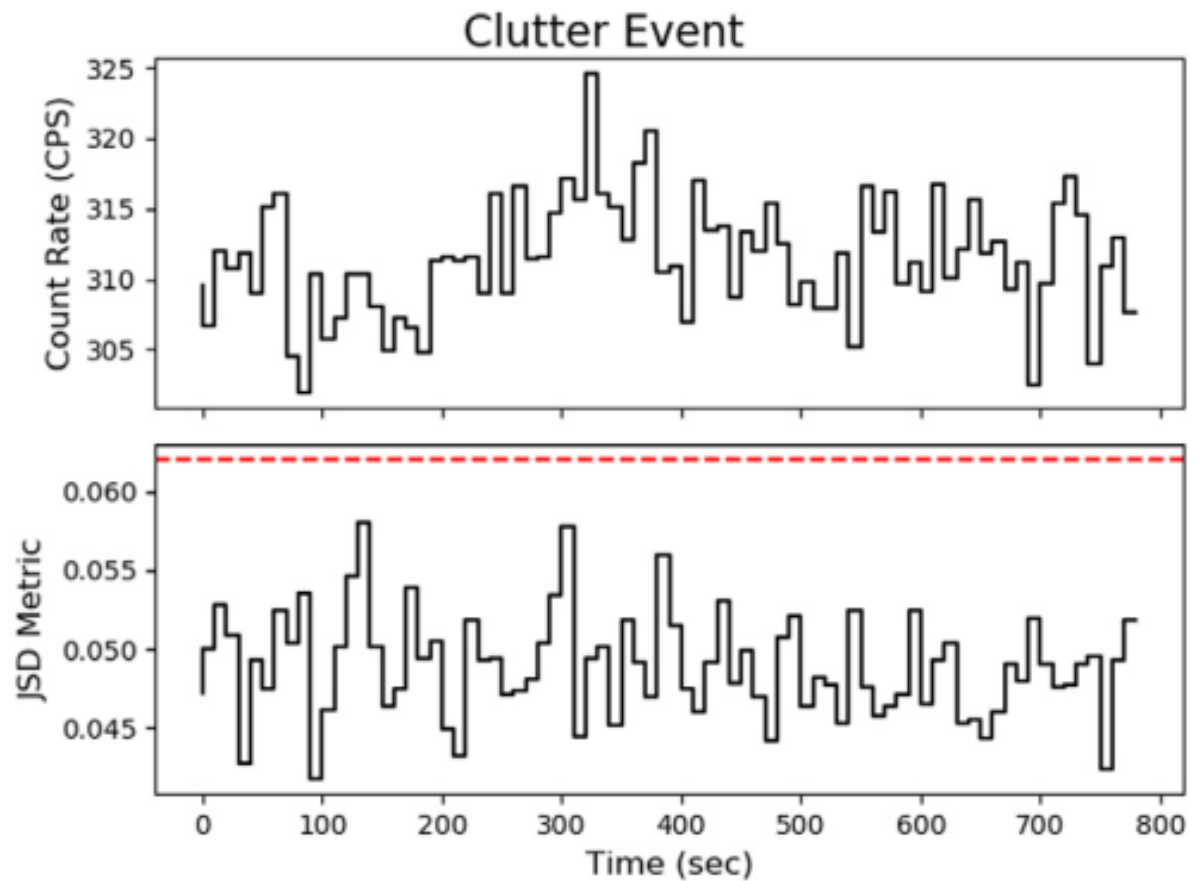


Figure from [2]

Anomaly detection – Radon washout

- Successful background reconstruction

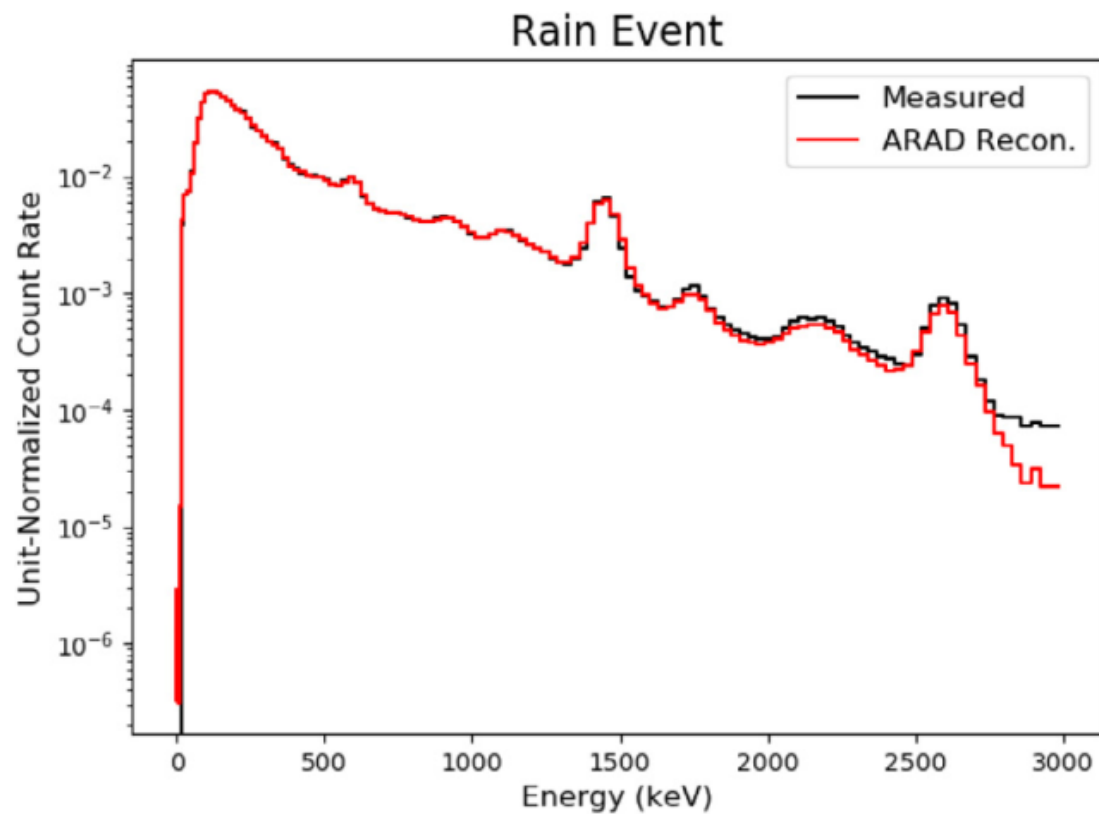


Figure from [2]

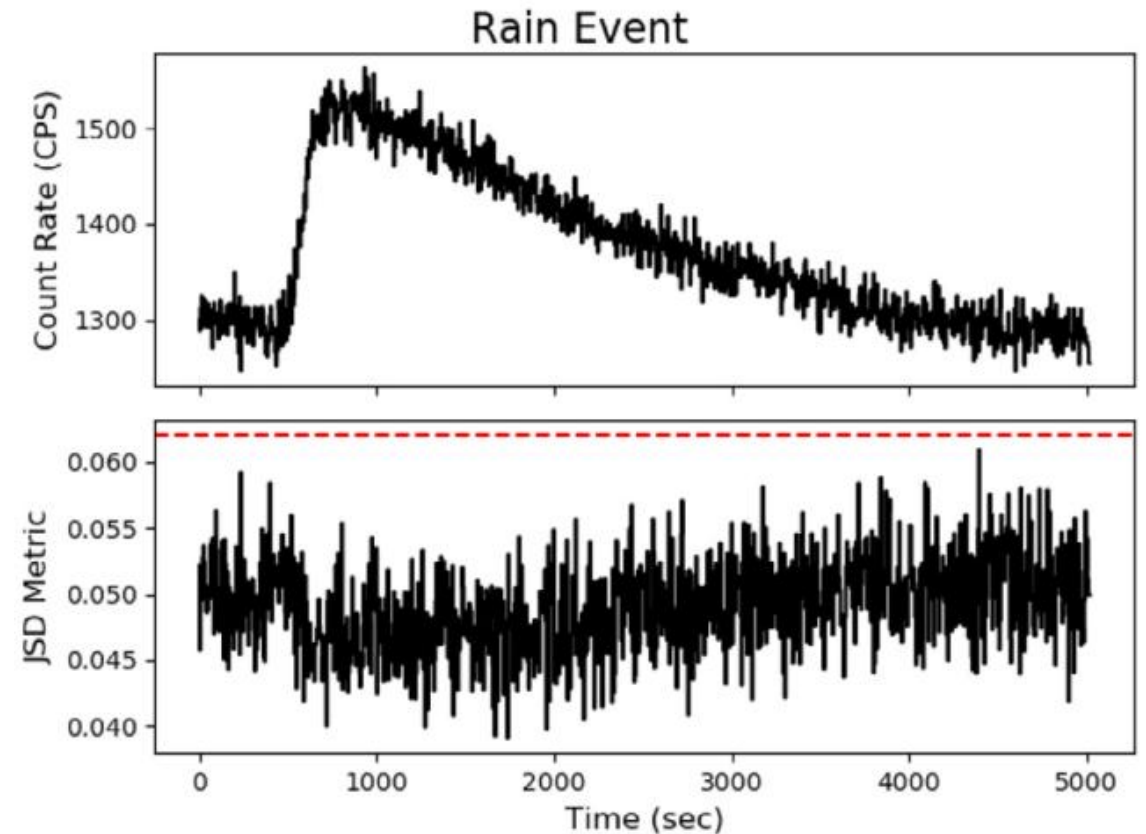


Figure from [2]

Anomaly detection – Co-60 transfer

- Unsuccessful background reconstruction

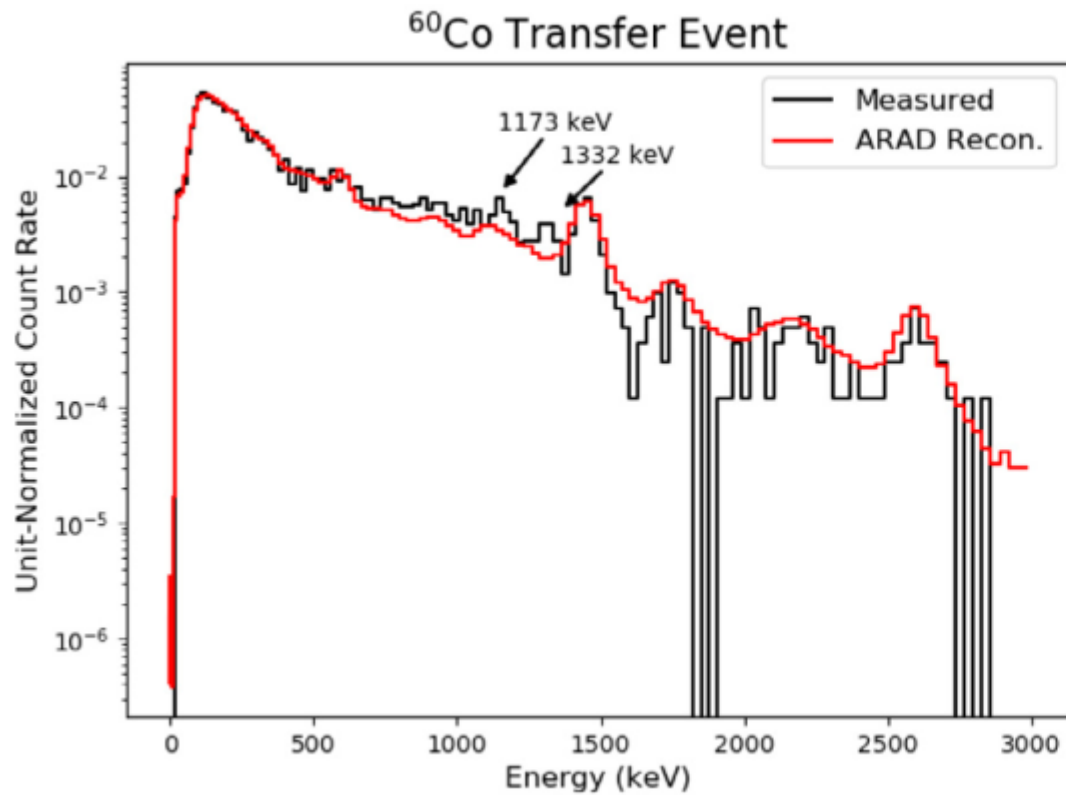


Figure from [2]

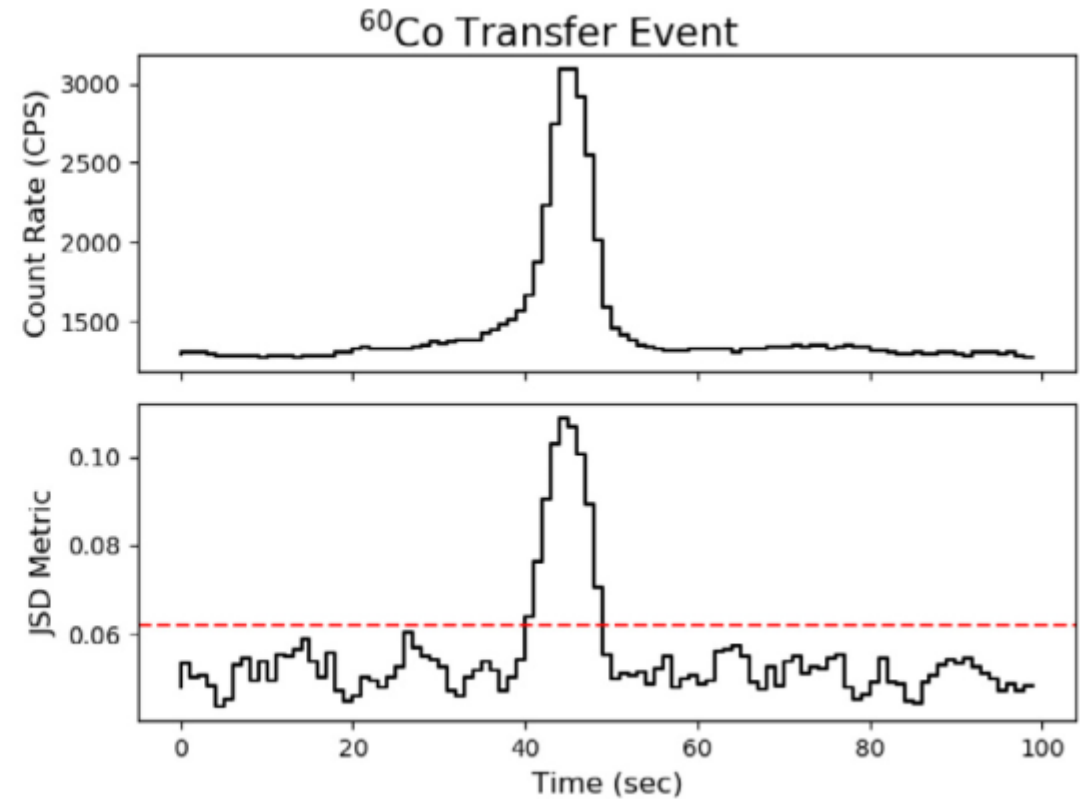


Figure from [2]

Anomaly detection – Ac-225 transfer

- Unsuccessful background reconstruction

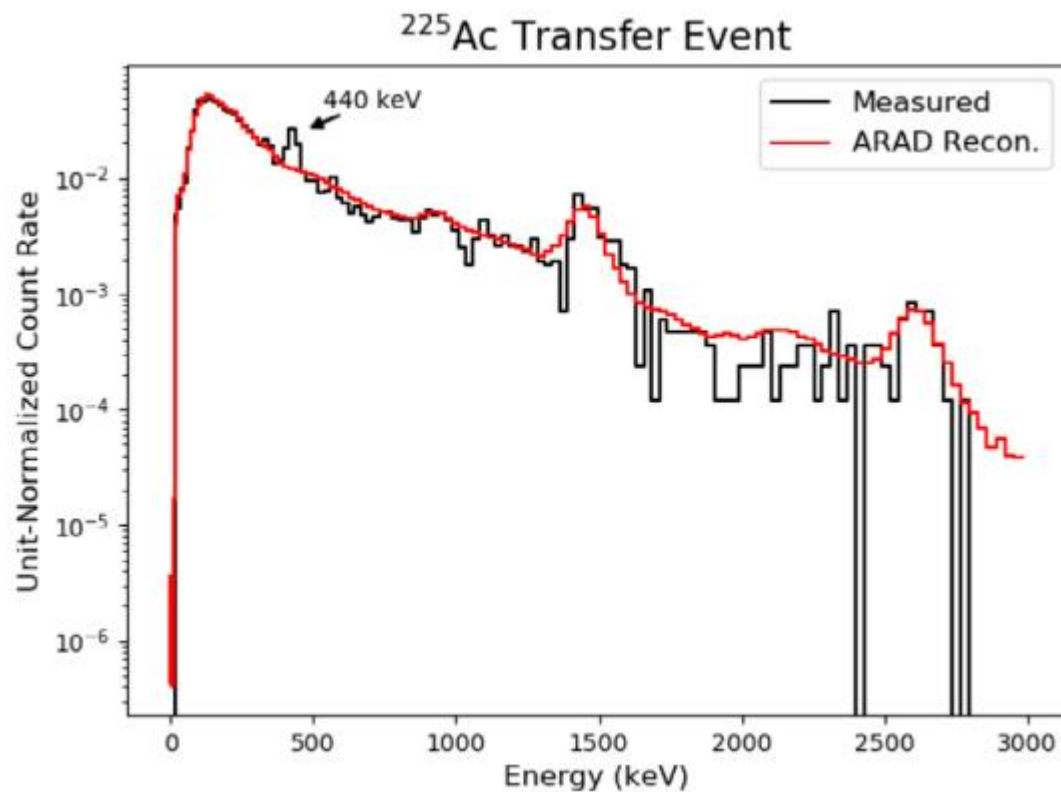


Figure from [2]

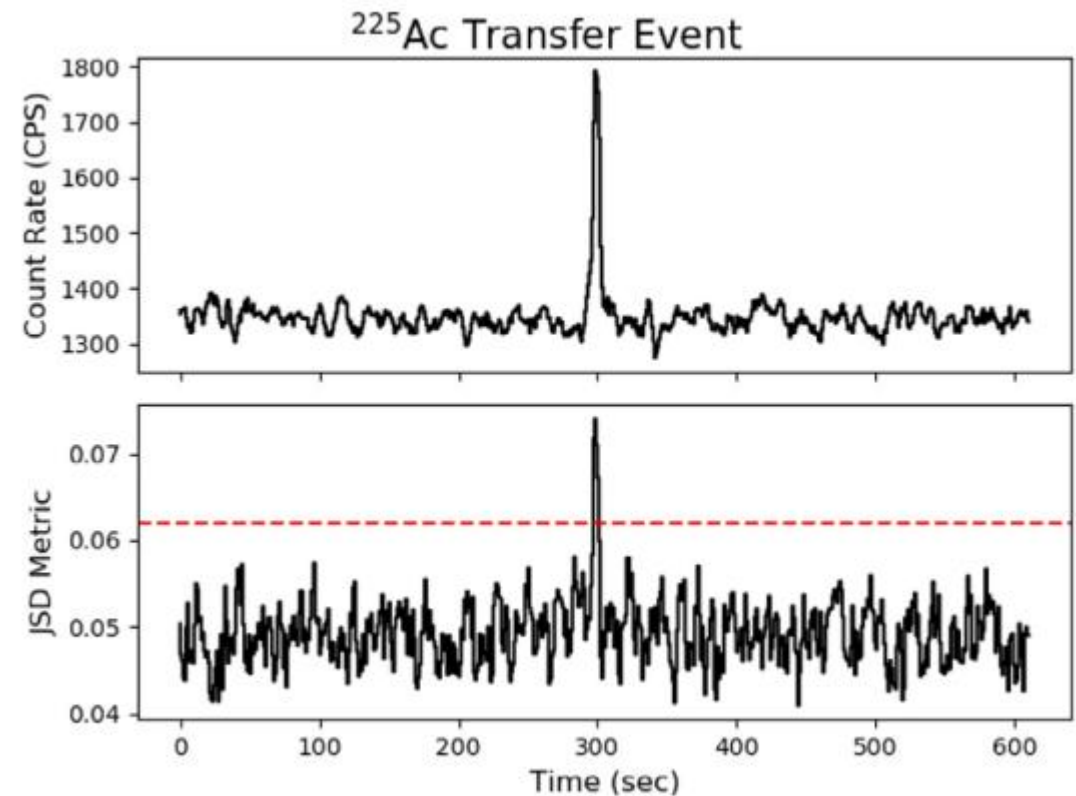


Figure from [2]

Anomaly detection – WGPu transfer

- Unsuccessful background reconstruction

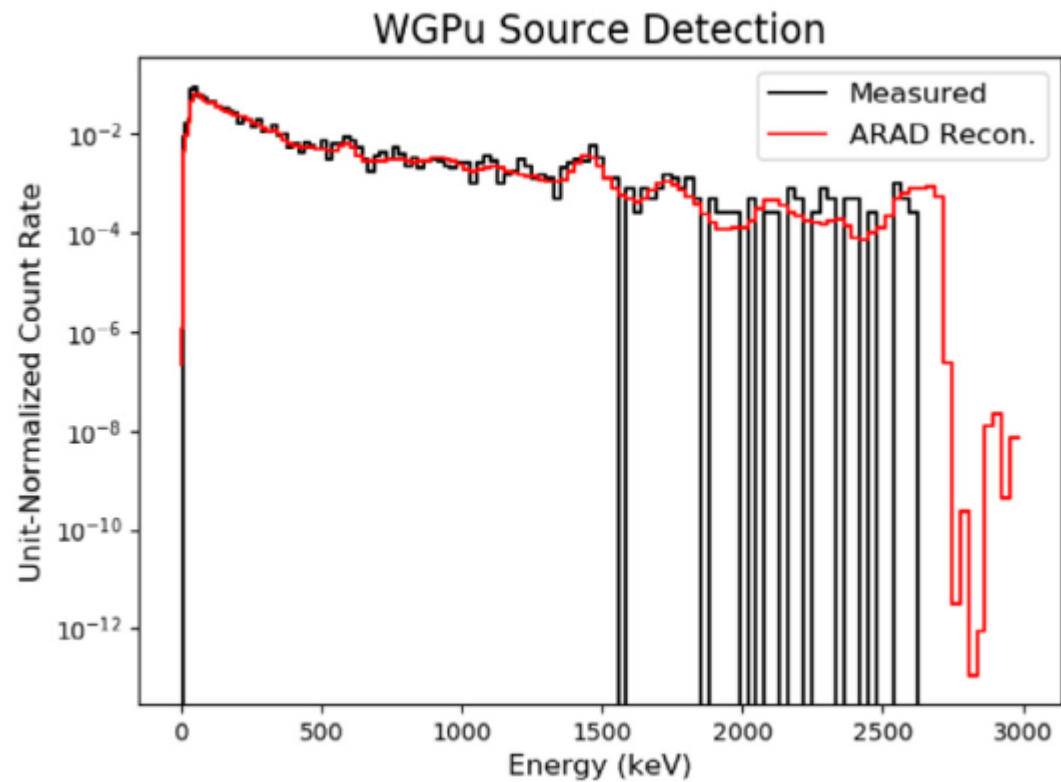


Figure from [2]

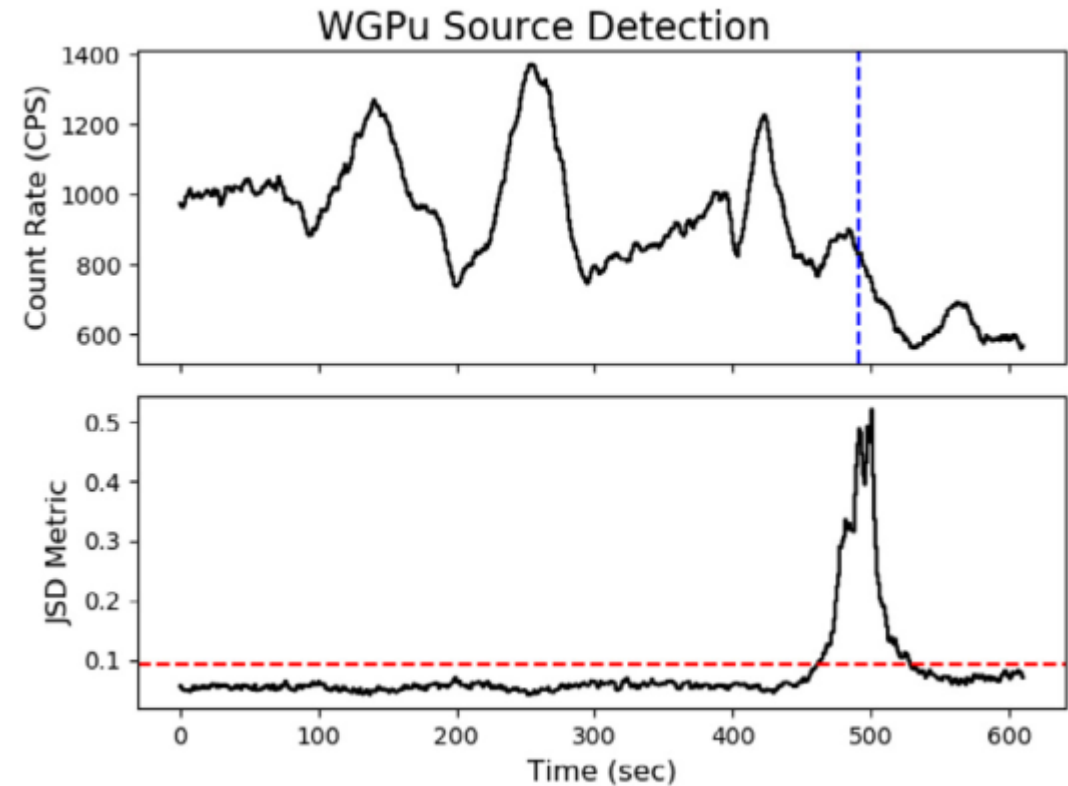


Figure from [2]

Applications – event discrimination

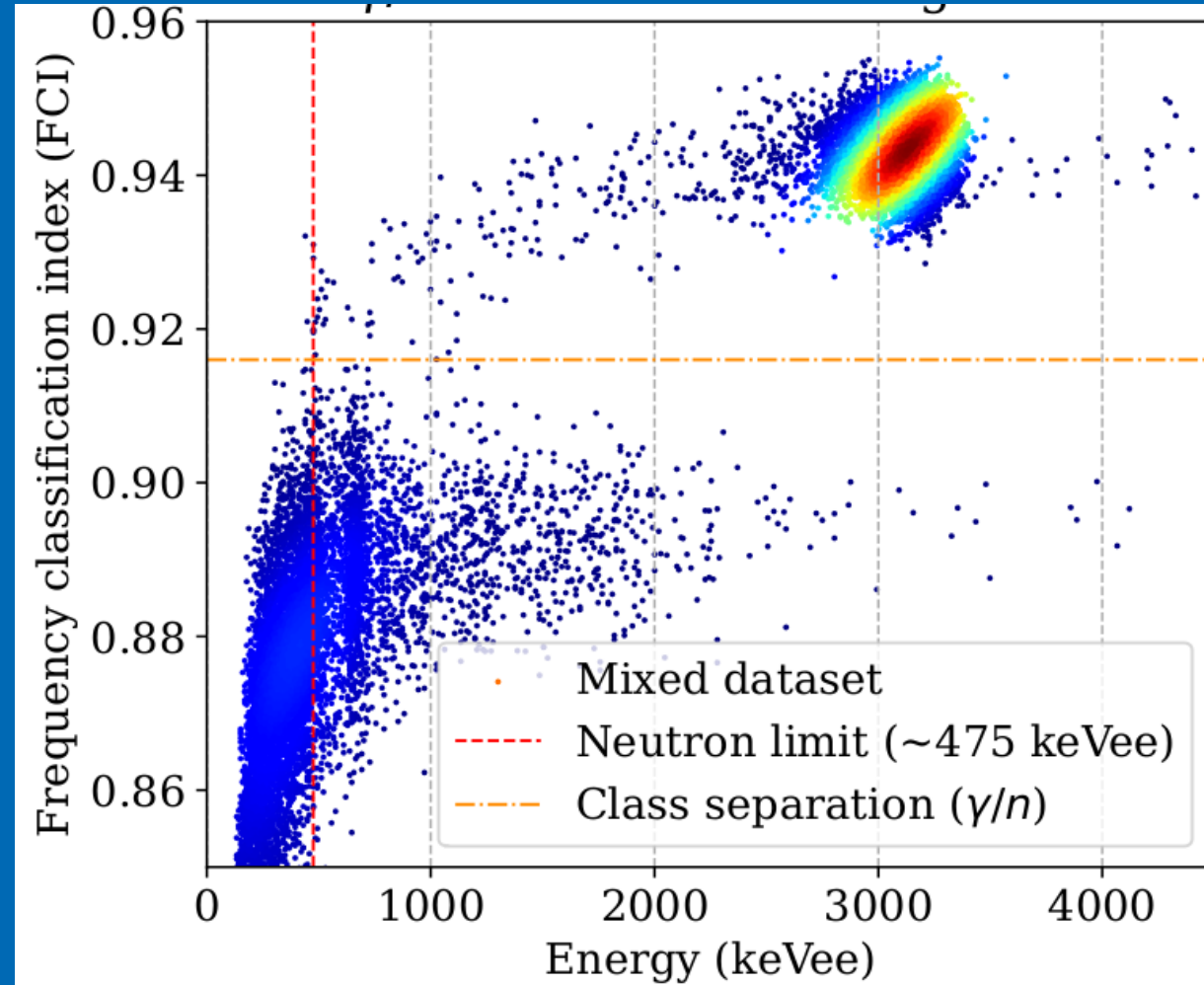


Figure from [3]

Gamma/neutron discrimination

- Target: **FPGA** (Artix-35T)
- Goal: g/n discrimination under pile-up distortion
- Real-time
 - Count-rate > 400 kcps
 - Dead-time < 2.5 μ s (limited by scintillator)
- Low-SWaP: portability
 - S: 0.56 Liters
 - W: 0.41 Kilograms
 - P: 1.5 Watt

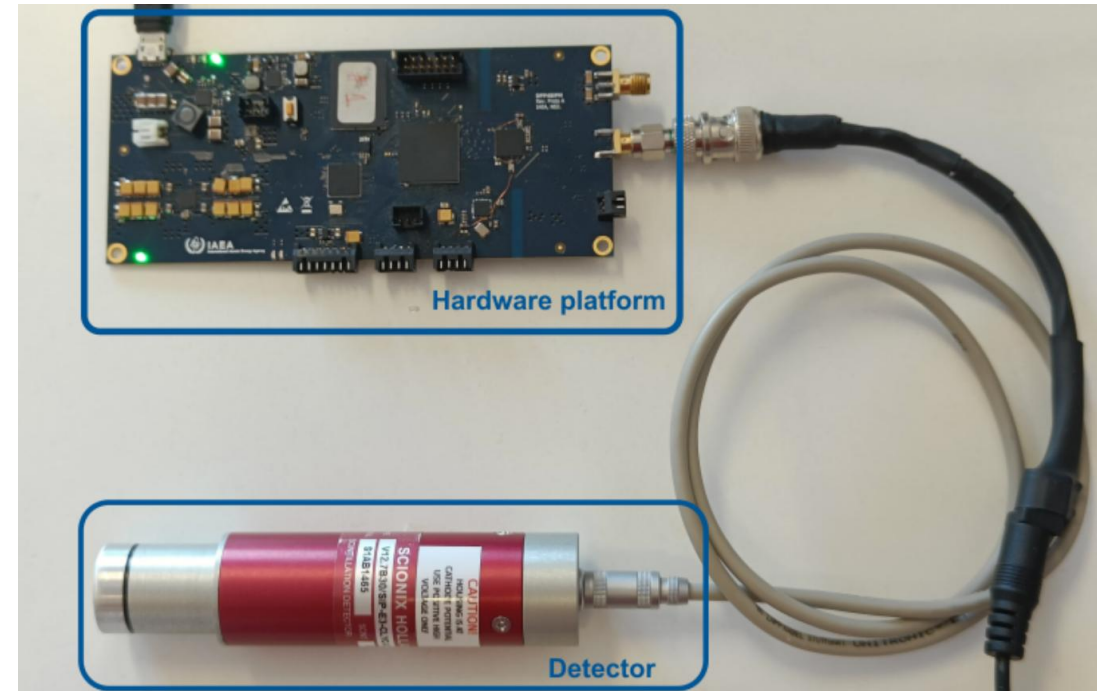


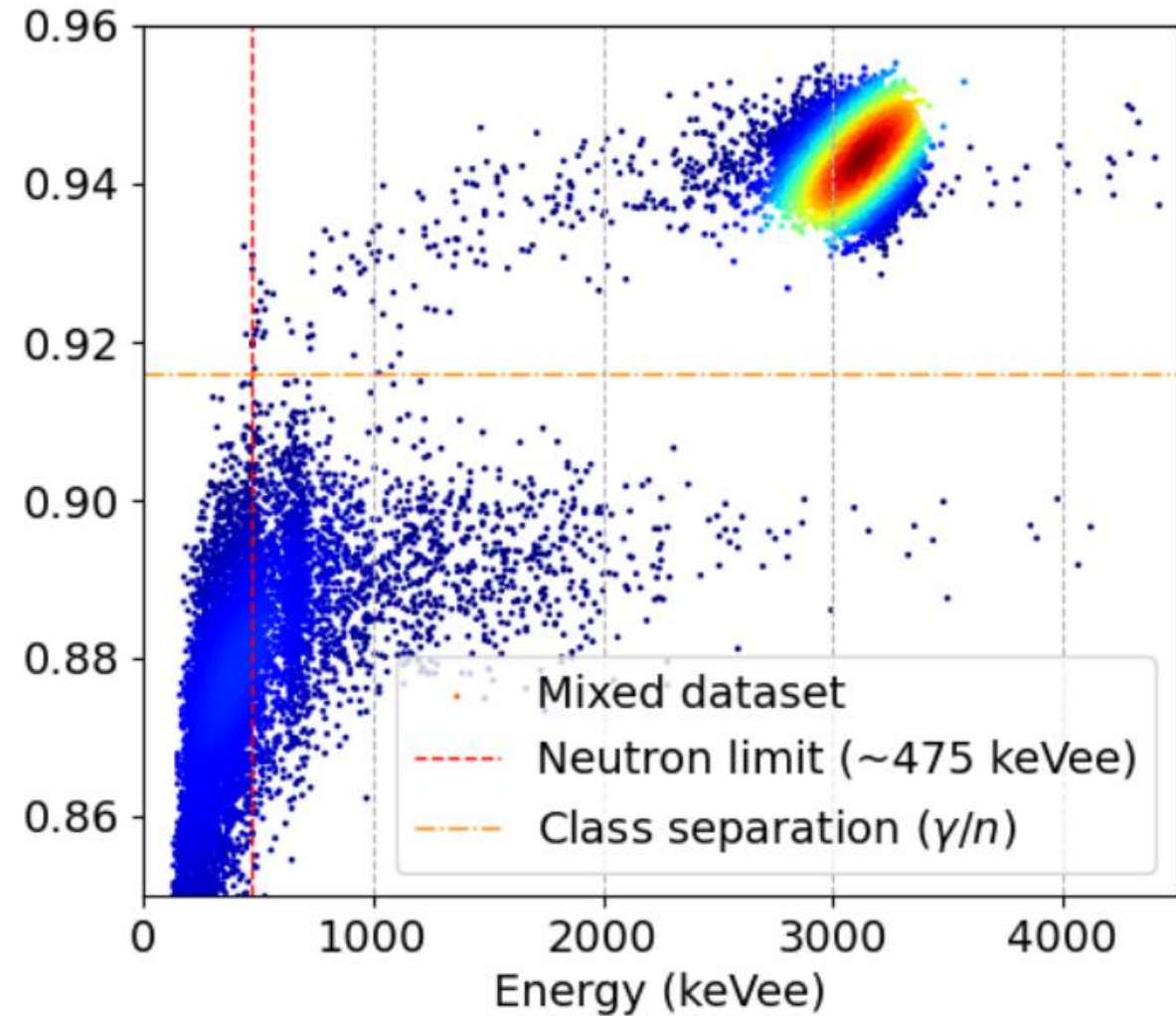
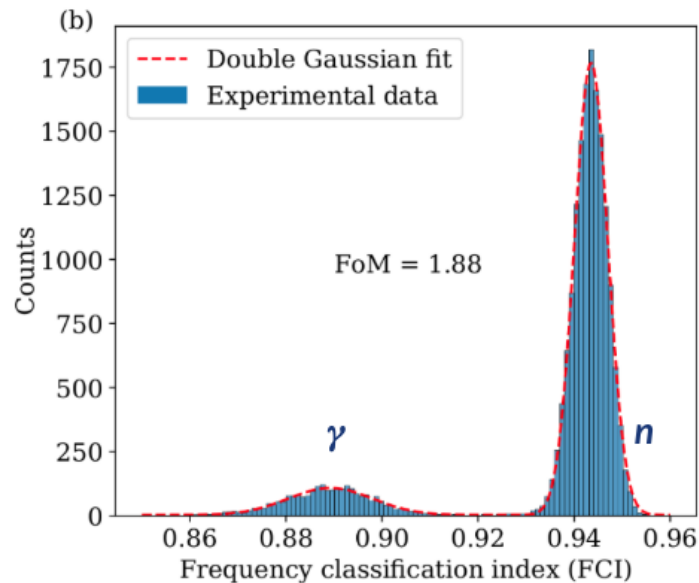
Figure from [4]

ML model



Data labelling

- Ground-truth discrimination [5]
- Two labels: gamma/neutron



ML model

Preprocessing pipeline

- CLYC detector: long pulses
- Pulse leading edge
- First 350 ns (pulse length $\sim 30 \mu\text{s}$)
- No time alignment required (CFD)
- 2nd derivative smoothed filter
 - IIR bandpass differentiator
- Python model
- VHDL real-time module for FPGA

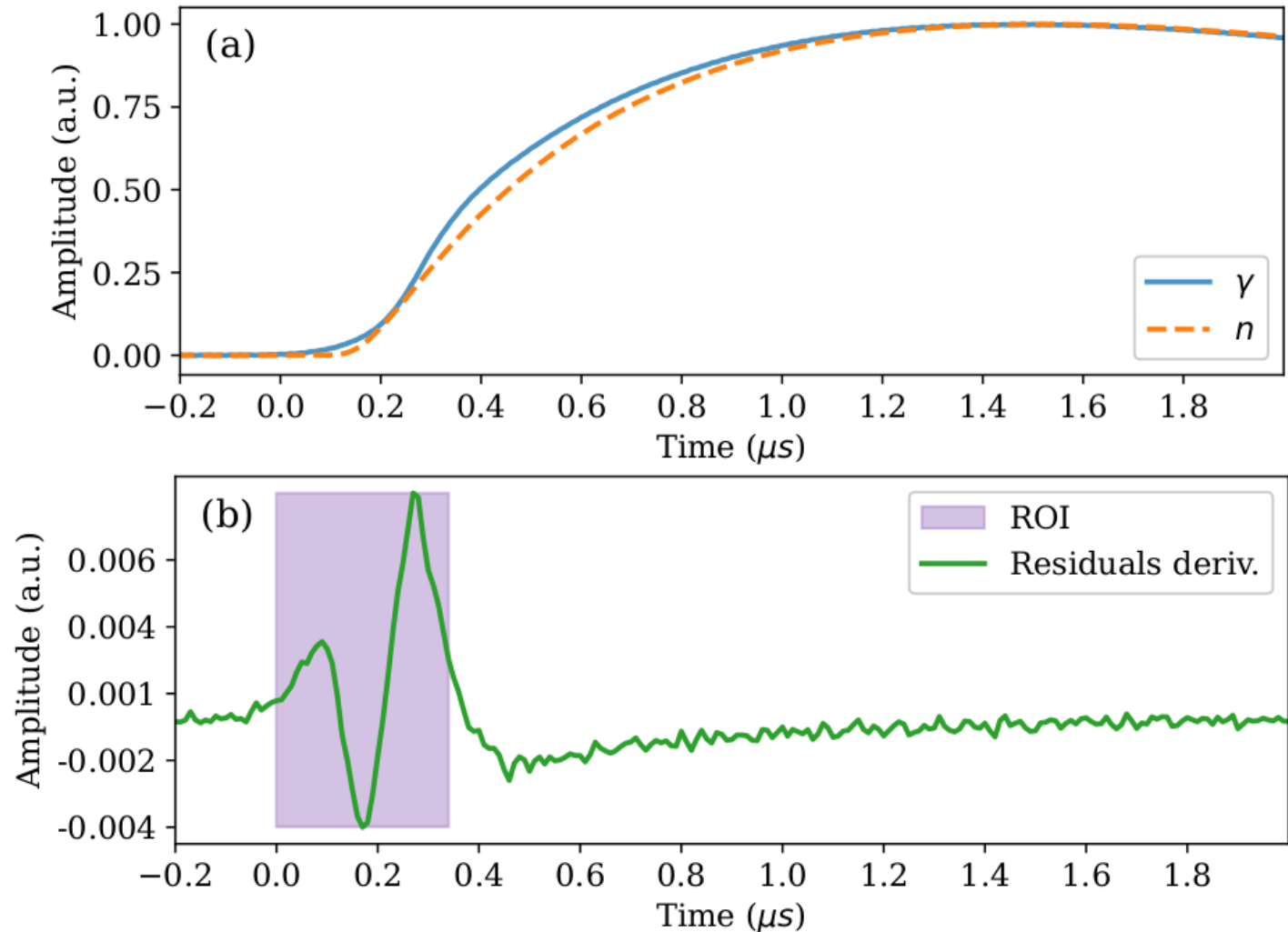


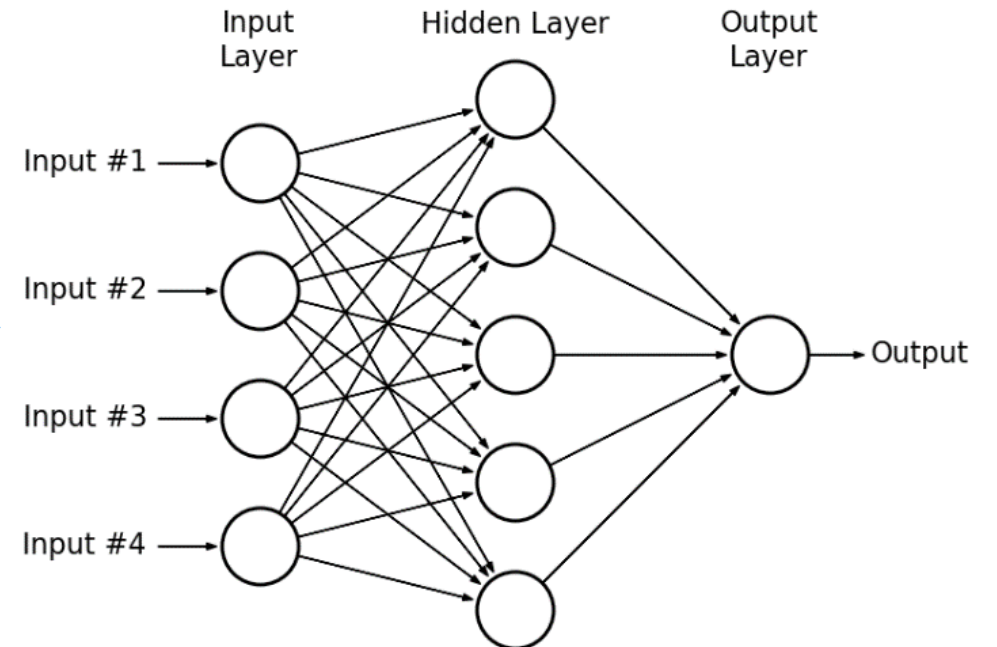
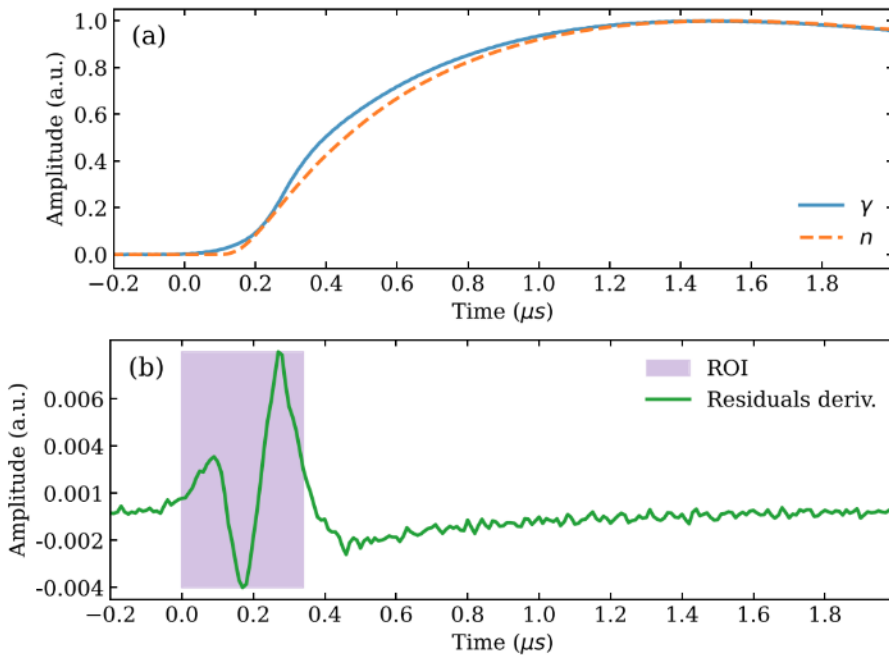
Figure from [4]

ML model

Inference pipeline

- 1) Python emulation
- 2) Real-time FPGA deployment

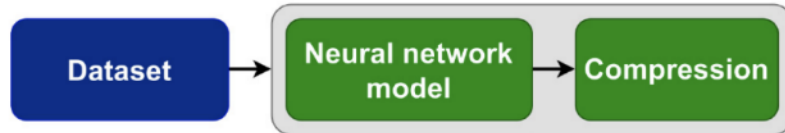
- Detector raw data stream
- Feature extraction
- Binary classification with MLP



ML model

Compression workflow [6]

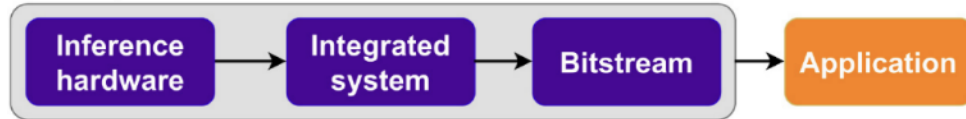
DNN training and compression



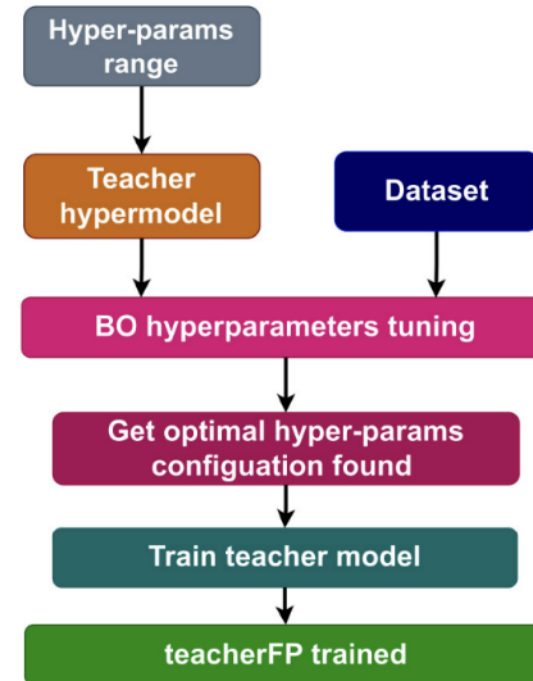
Integration with a hardware synthesis tool for ML

Hardware synthesis tool for ML

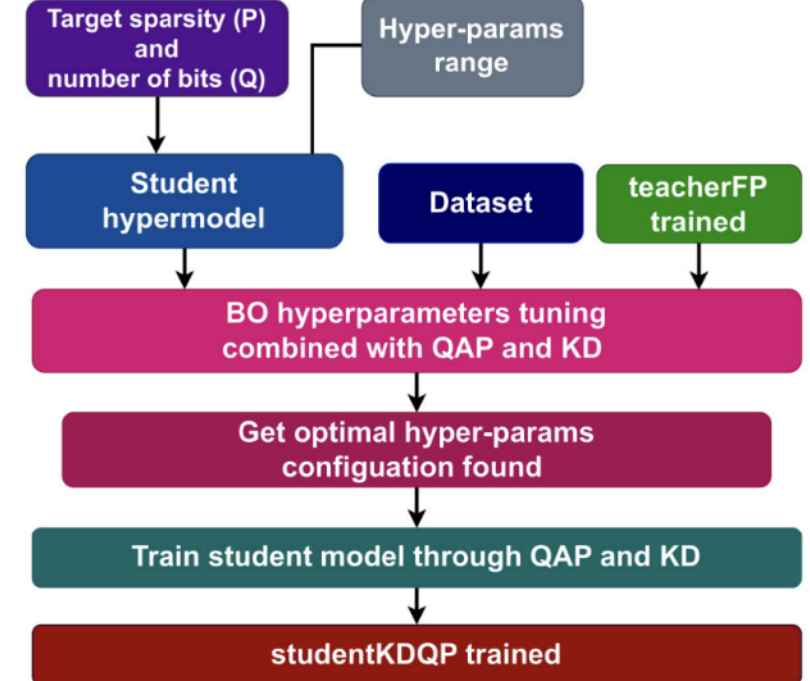
Hardware assessment framework



Stage 1



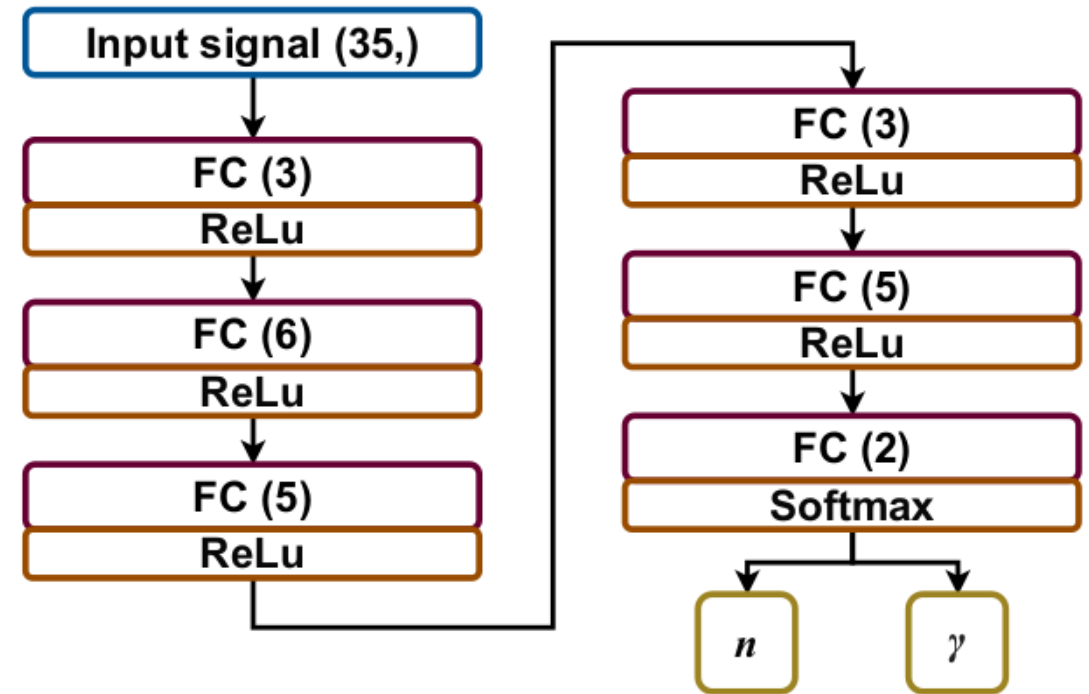
Stage 2



ML model

Deployed real-time model

- MLP: binary classifier (gamma/neutron)
- 8-bit fixed-point quantization
- 30% sparsity
- Distilled (student) model
- 217 parameters distributed in 6 hidden layers
- Overall accuracy 98.2%

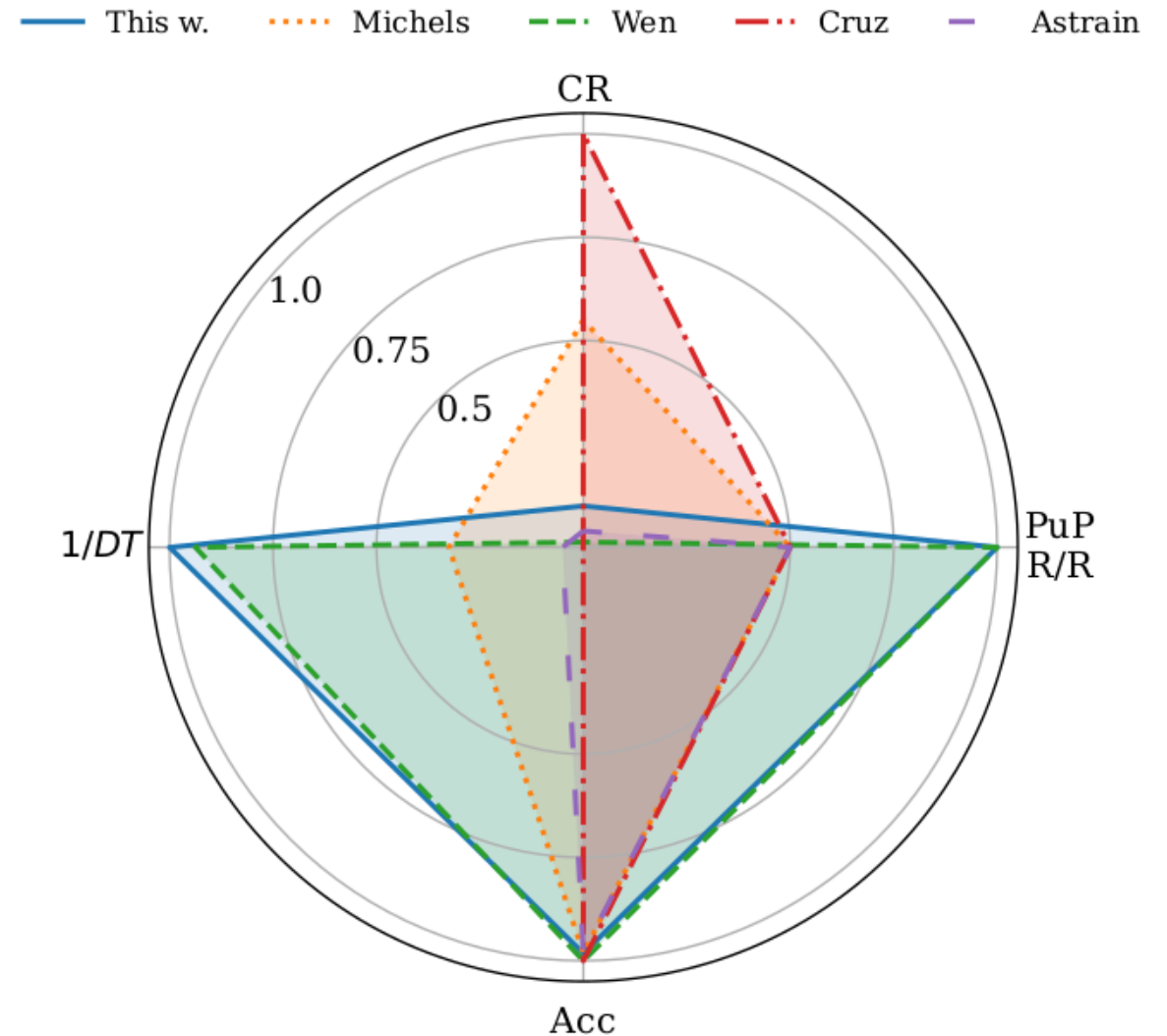


Results

Performance

- Count-rate (CR)
- Inverse of dead-time (1/DT)
- Pile-up recovery/rejection (PuP R/R)
- Overall accuracy (Acc)

Work	Overall perf.
This work	1.0
Michels et al.	0.89
Wen et al.	0.12
Cruz et al.	0.01
Astrain et al.	0.01



Michels et al. [doi:10.1109/ACCESS.2023.3298208](https://doi.org/10.1109/ACCESS.2023.3298208)

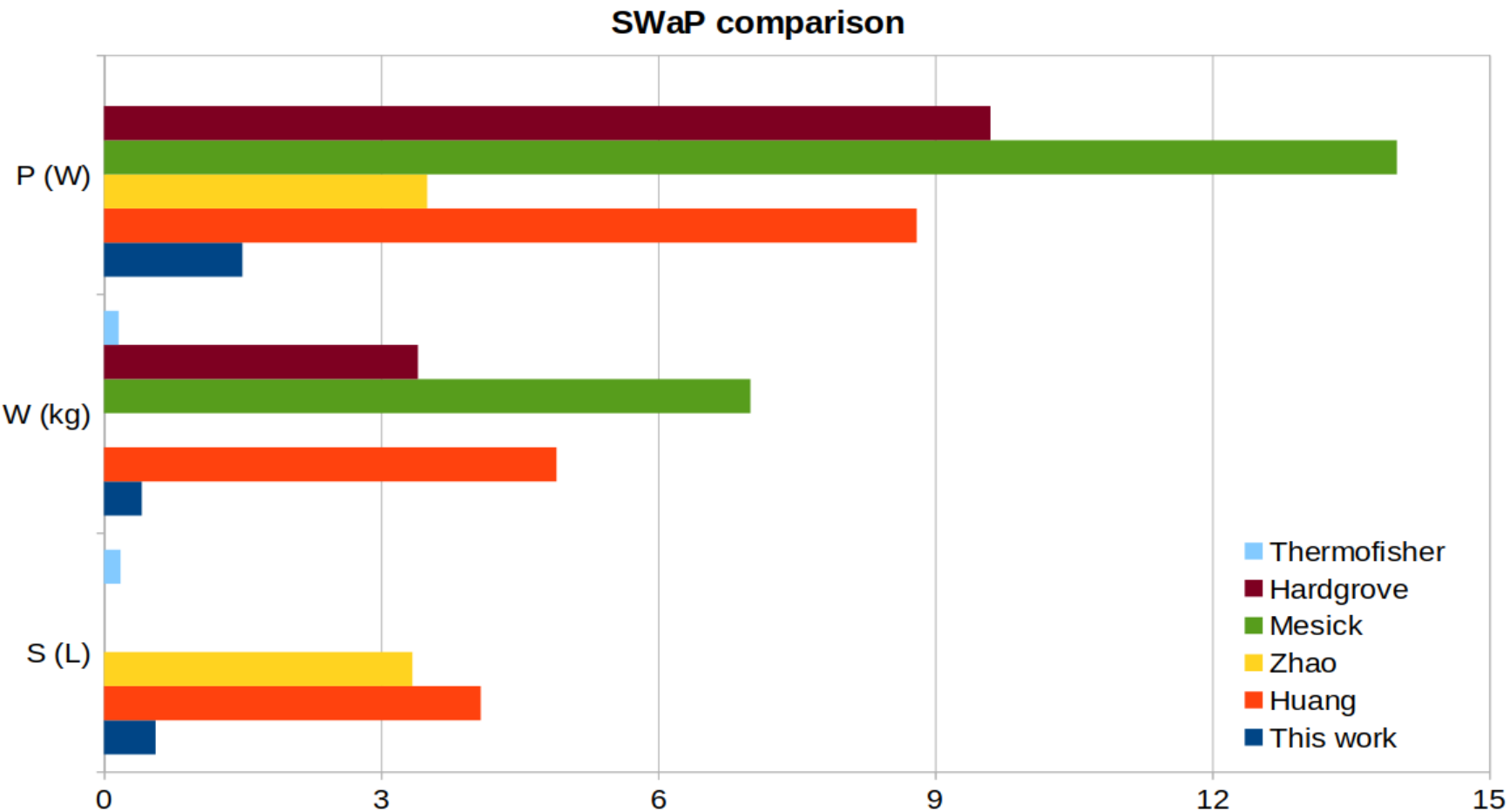
Wen et al. [doi:10.1016/j.nima.2017.06.007](https://doi.org/10.1016/j.nima.2017.06.007)

Cruz et al. [doi:10.1109/TNS.2019.2907056](https://doi.org/10.1109/TNS.2019.2907056)

Astrain et al. [doi:10.1109/TNS.2021.3090670](https://doi.org/10.1109/TNS.2021.3090670)

Results

Low SWaP



Thermo Fisher Scientific
<https://www.thermofisher.com/order/catalog/product/4250631>

Hardgrove et al.
[doi:10.1109/MAES.2019.2950747](https://doi.org/10.1109/MAES.2019.2950747)

Mesick et al.
<https://digitalcommons.usu.edu/smallsat/2020/all2020/118/>

Zhao et al.
[doi:10.1088/1748-0221/18/09/P09043](https://doi.org/10.1088/1748-0221/18/09/P09043)

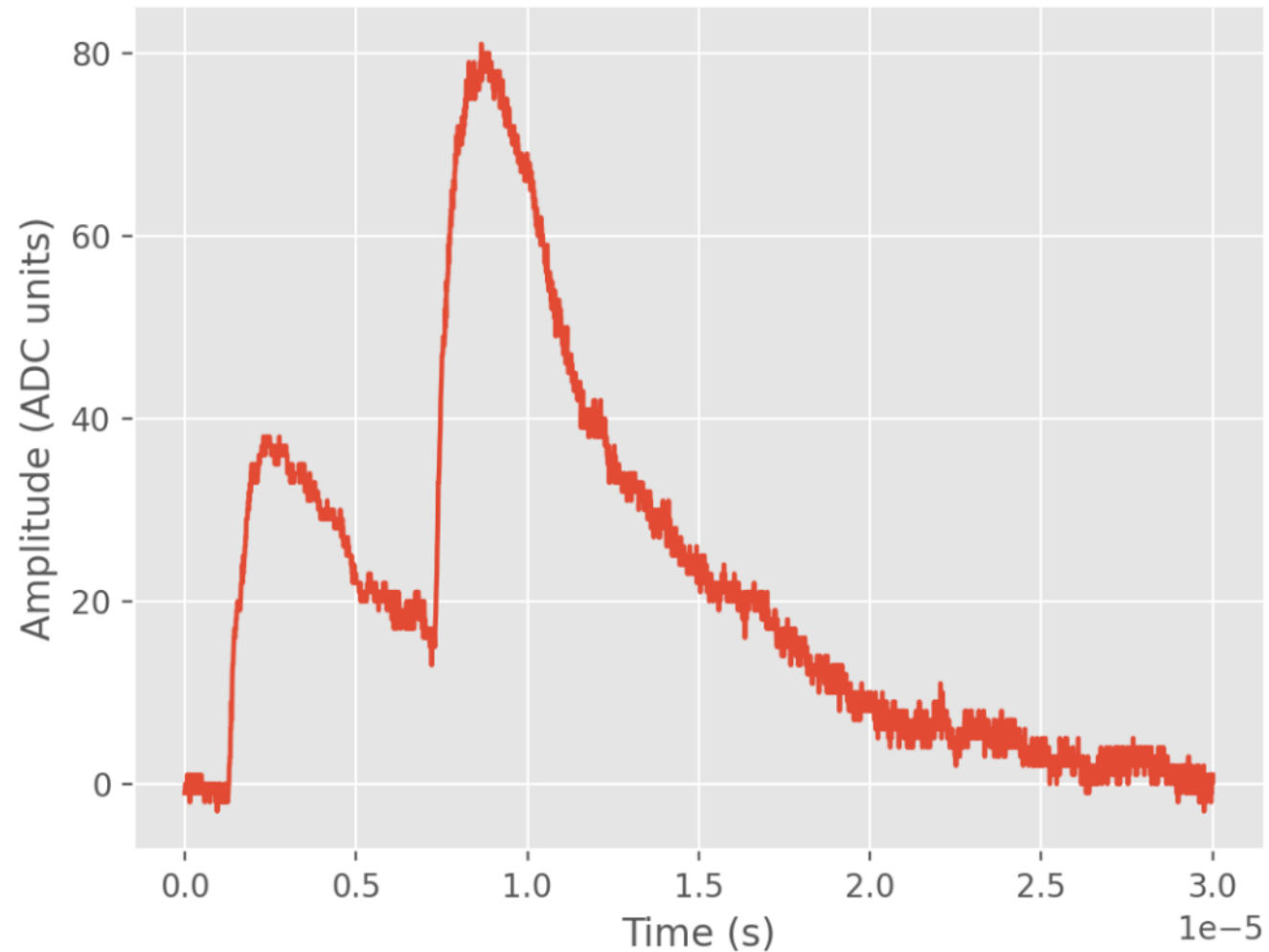
Huang et al.
[doi:10.2139/ssrn.4717223](https://doi.org/10.2139/ssrn.4717223)

References

- [1] Barradas, N. P., Vieira, A., Felizardo, M., & Matos, M. (2025). Nuclide identification of radioactive sources from gamma spectra using artificial neural networks. *Radiation Physics and Chemistry*, 232, 112692. doi:10.1016/j.radphyschem.2025.112692
- [2] Ghawaly Jr, J. M., Nicholson, A. D., Archer, D. E., Willis, M. J., Garishvili, I., Longmire, B., ... & Cook, M. T. (2022). Characterization of the autoencoder radiation anomaly detection (ARAD) model. *Engineering Applications of Artificial Intelligence*, 111, 104761. [doi:10.1016/j.engappai.2022.104761](https://doi.org/10.1016/j.engappai.2022.104761)
- [3] Morales Argueta, I. R. (2025). Embedded instrumentation platform on SoC/FPGA for mixed radiation fields. *Università degli Studi di Trieste*. PhD Thesis.
- [4] Morales, Ivan Rene, et al. "Gamma/neutron online discrimination based on machine learning with CLYC detectors." *IEEE Transactions on Nuclear Science* 71.12 (2024): 2602-2614. doi: 10.1109/TNS.2024.3498321
- [5] Morales, Iván René, et al. "Gamma/neutron classification with SiPM CLYC detectors using frequency-domain analysis for embedded real-time applications." *Nuclear Engineering and Technology* 56.2 (2024): 745-752.
- [6] Molina, R. S., Morales, I. R., Crespo, M. L., Costa, V. G., Carrato, S., & Ramponi, G. (2023). An end-to-end workflow to efficiently compress and deploy DNN classifiers on SoC/FPGA. *IEEE Embedded Systems Letters*, 16(3), 255-258. doi:doi.org/10.1109/LES.2023.3343030
- [7] Molina, R. S., Ballina, M. G., Crespo, M. L., & Carrato, S. (2026). Physics-Guided Neural Network for Pile-Up Rejection on SoC-FPGAs. *IEEE Transactions on Nuclear Science*. [doi:10.1109/TNS.2026.3681873](https://doi.org/10.1109/TNS.2026.3681873)

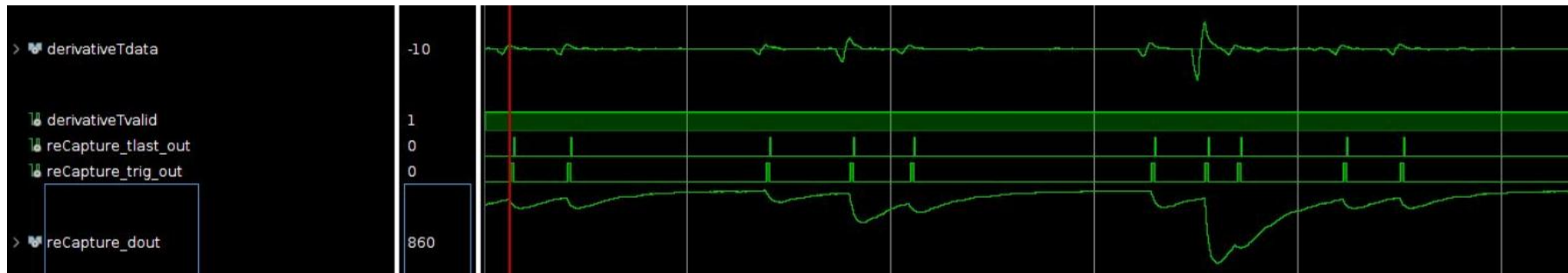
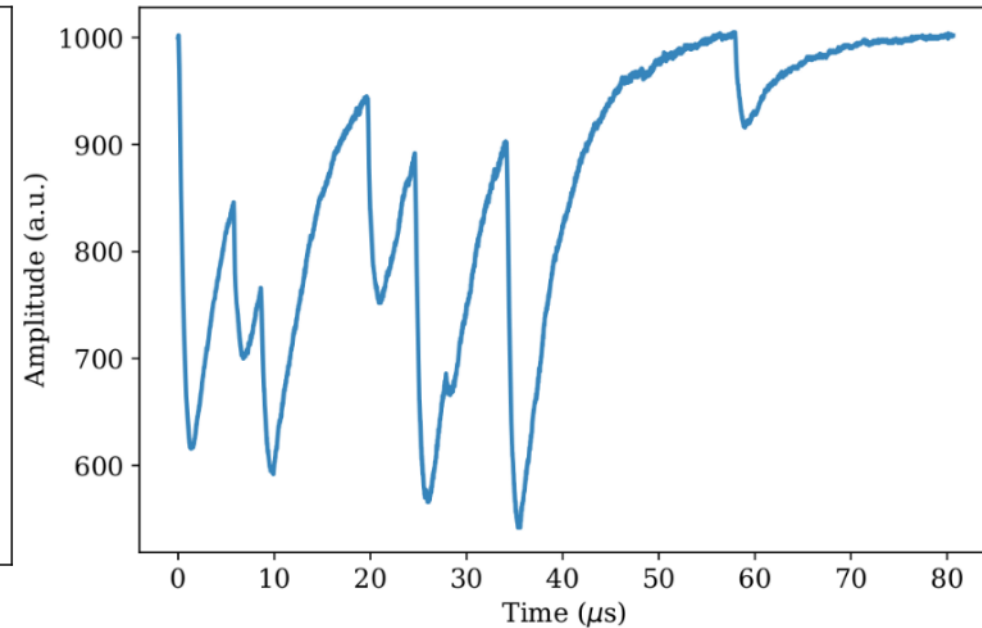
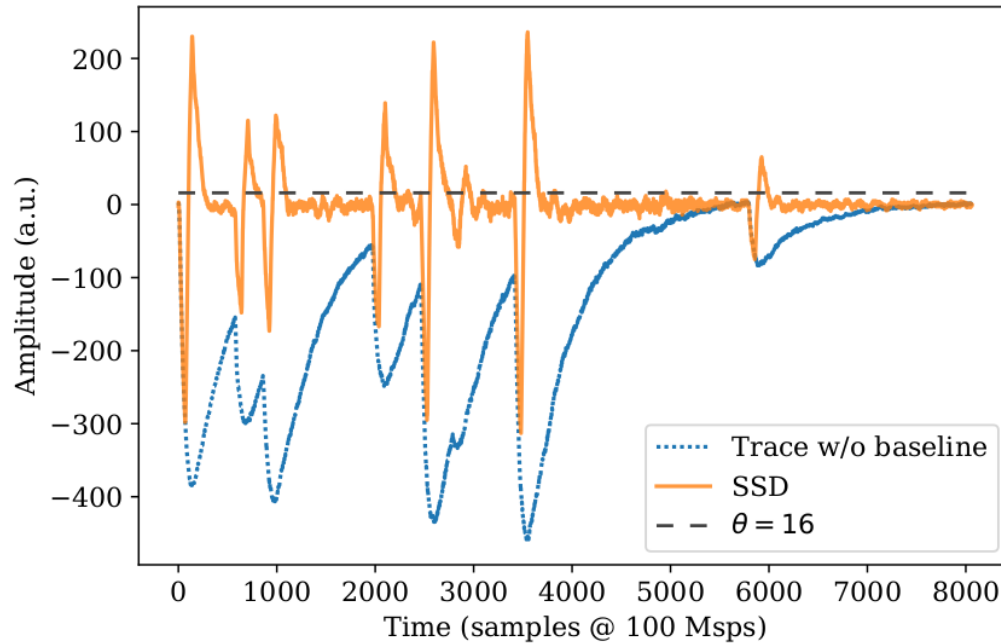
Example of piled-up trace

Gamma + neutron events



FPGA system architecture

Real-time feature extraction

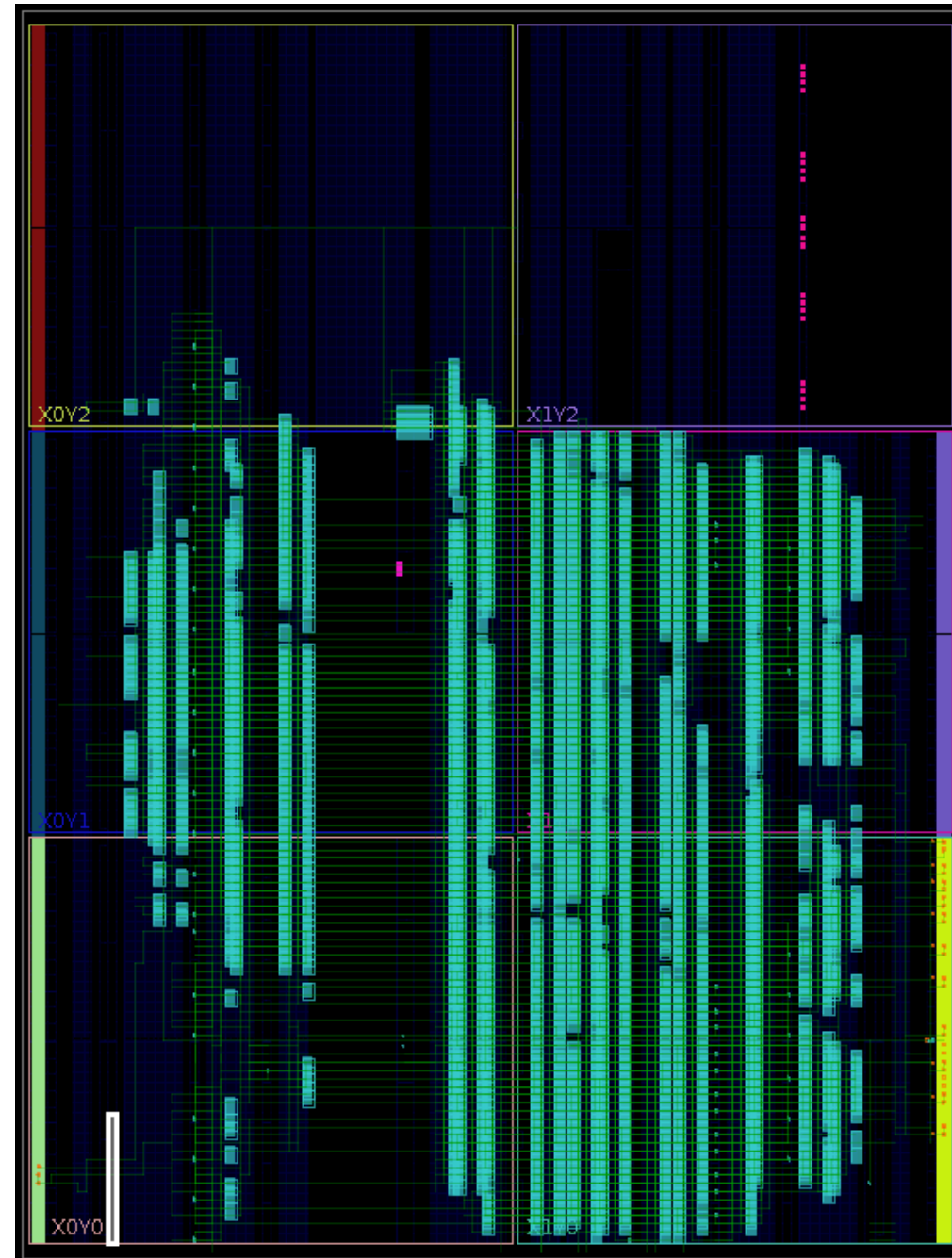


G/N discrimination

FPGA utilization

Low-end Artix-7 35T FPGA

- LUT: 30.4%
- Registers: 17.4%
- BRAM: 24.0%
- DSP: 17.8%



Validation

Gamma + neutron events

Recorded pulses from detector plugged into AFE

(a) Gamma events

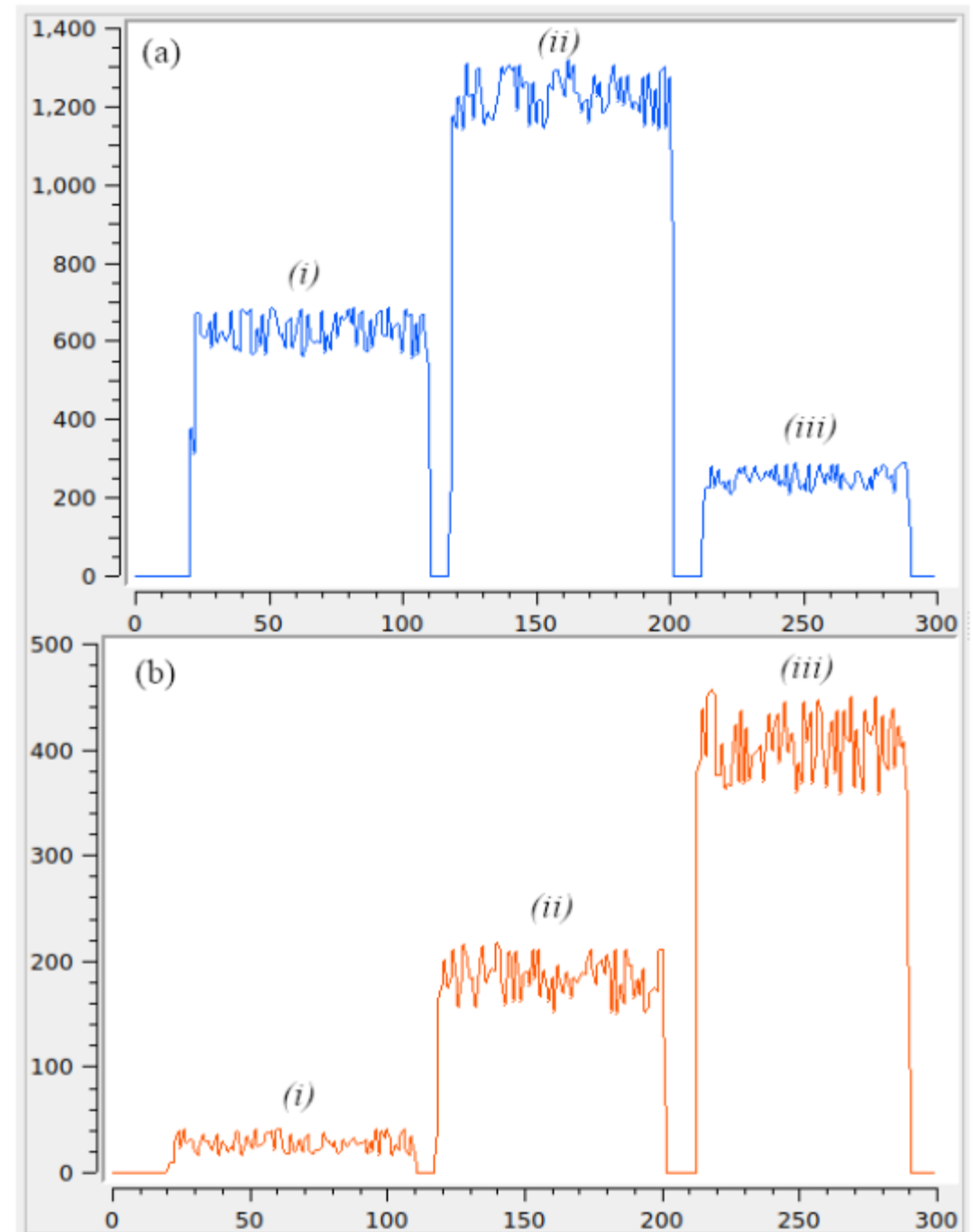
(b) Neutron Events

Runs

- i) Gamma-only events
- ii) AmBe + Cs-137 sources
- iii) DD generator + Cs-137

Neutron false alarms < 2.5%

Accuracy: 98.2%



Validation

Other detectors (without retraining)

Nal(Tl) with Co-60 source beside

- Accuracy 99.1%

Synthetic gamma events from fast plastic

- Absolute max. countrate ~ 1.01 Mcps
- Lowest dead-time 995 ns
- 129 ppm (missing events)

