SAND2023-03955C

Sandia National Laboratories

Exceptional service in the national interest

LIST-MODE INFERENCE USING LINEAR CLASSIFIERS FOR NUCLEAR ARMS CONTROL VERIFICATION

May, 2023 Joint INMM/ESARDA Annual Meeting

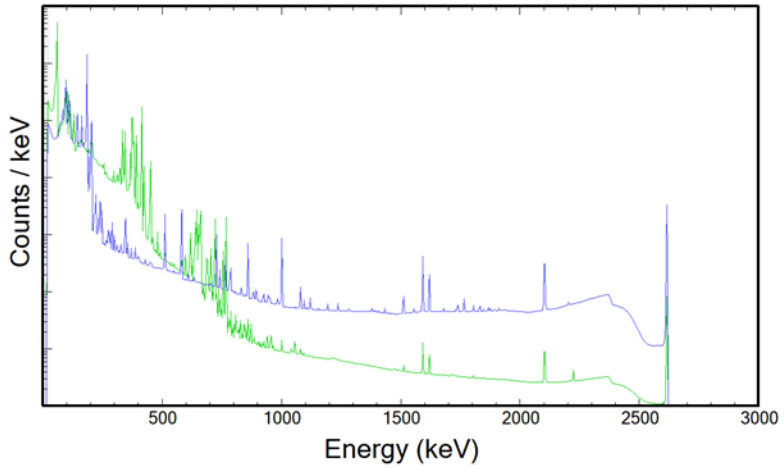
Eduardo Padilla, Heidi Komkov, Christopher Siefert, Ryan Kamm, Kyle Weinfurther, Jesus Valencia

Sandia National Laboratories is a multimission laboratory managed and operated by National Technology and Engineering Solutions of Sandia LLC, a wholly owned subsidiary of Honeywell International Inc. for the U.S. Department of Energy's National Nuclear Security Administration under contract DE-NA0003525.

Sandia National Laboratories is a multimission laboratory managed and operated by National Technology & Engineering Solutions of Sandia, LLC, a wholly owned subsidiary of Honeywell International Inc., for the U.S. Department of Energy's National Nuclear Security Administration under contract DE-NA0003525.

OUTLINE

- Motivation
- Concept
- Approach
- Conclusions
- Future Work



GADRAS-computed Gamma Spectra for weapons-grade Uranium (Blue) and Plutonium (Green)

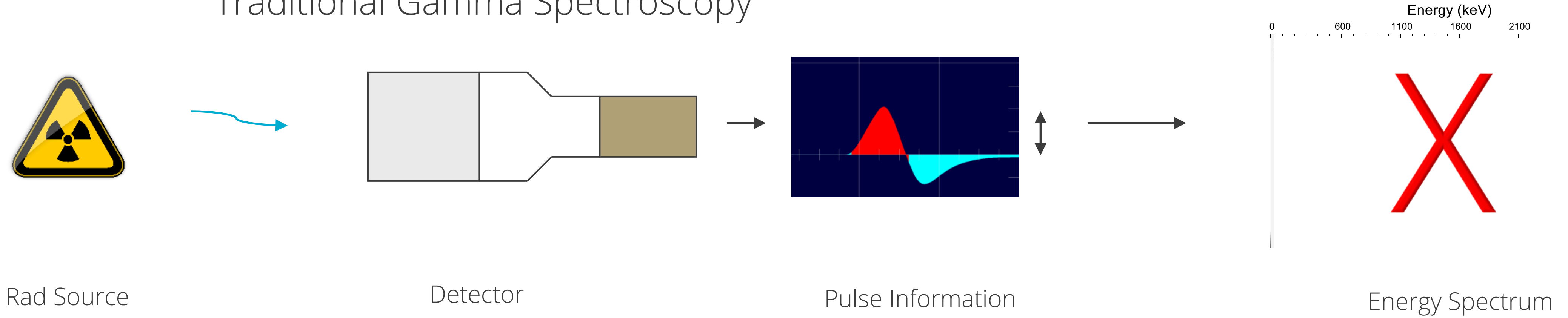
MOTIVATION

- Past nuclear arms control treaties have used limited radiation measurements for verification (gross neutron counting), but future treaties might rely on more effective, yet intrusive, measurements such as gamma-ray spectroscopy
- Typically, confidence in the verification measurement is directly proportional to the perceived risk of leaking sensitive information such as the spectroscopic gamma signature of a nuclear warhead; the collection of detailed, sensitive information allows for more thorough analysis and thus increased confidence

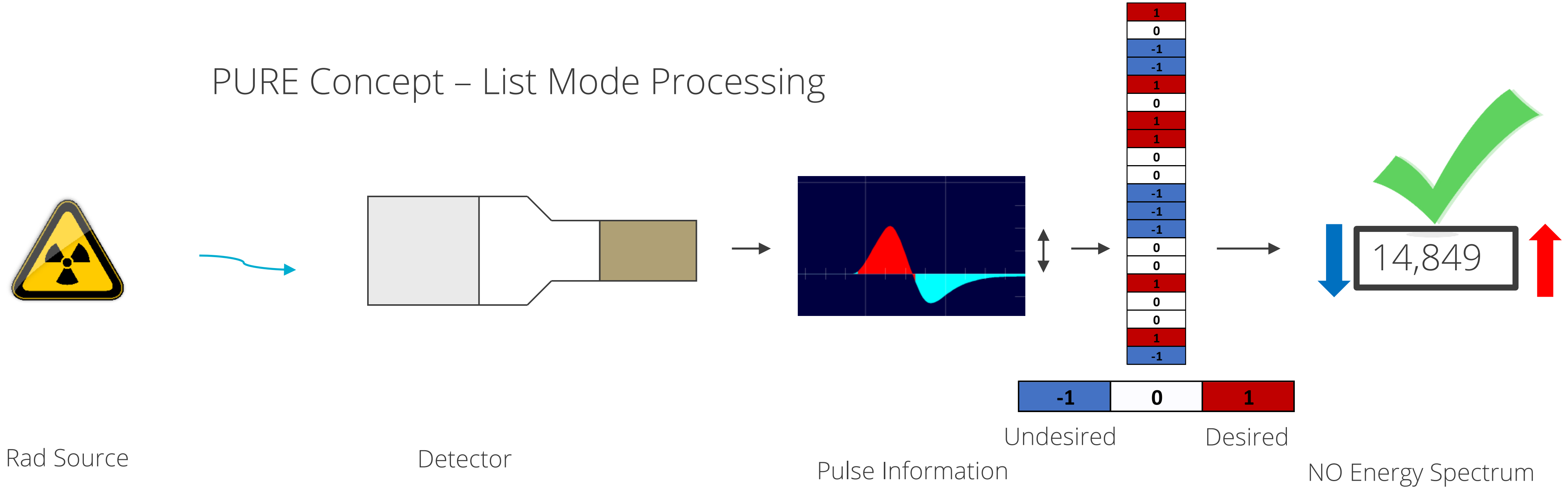
The impact of this project will be to develop an information barrier that enables the near-term deployment of a wide array of commercially available radiation detection systems for nuclear arms control verification, giving treaty negotiators much more latitude during negotiations.

CONCEPT: PLATFORM FOR UNCLASSIFIED RADIOISOTOPE EVALUATION (PURE)

Traditional Gamma Spectroscopy

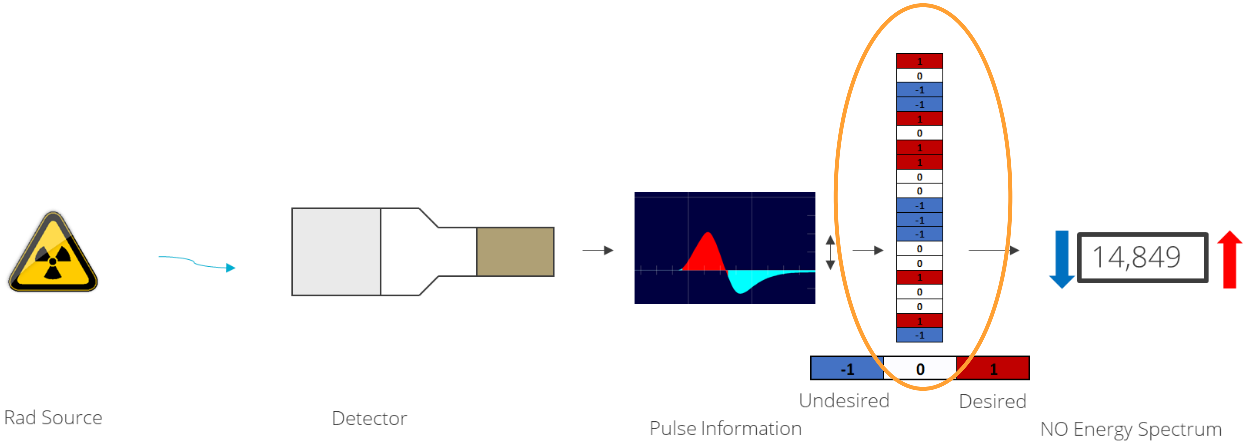


PURE Concept – List Mode Processing



APPROACH

- If we can optimize importance weighted arrays and analyze each pulse without collecting a spectrum (simply a counter), a large number of information security concerns could be alleviated
- The primary challenge is the generation and optimization of these weight arrays for a semi-infinite range of nuclear warhead signatures from a much larger semi-infinite range of non-nuclear warhead signatures
- **Goal is to develop and optimize these weight arrays using ML and DNN techniques such that we minimize the amount of administrative controls (such as count rates, assumed enrichments, etc.) needed for a practical implementation**



APPROACH: DATA SIMULATION

- Goal here is to create the LLNL "Spanning Set[1]," which has been openly shared. This set of "nuclear threat objects" spans a large array of fissile material objects from weapons grade plutonium and uranium, to reactor grade plutonium and low enriched uranium sources
  - In addition to the nuclear materials prescribed in the Nelson-Sokkappa paper, we also created sources of mixed radionuclides from most known medical, industrial and nuclear isotopes (100+)
- Initially utilizing GADRAS[2] inject tool to create hyper-realistic gamma spectra from a high-purity germanium detector (ORTEC Detective EX 100)
- Will be able to analyze the performance of other COTS detector systems as well (NaI, NaI + neutron, etc.)

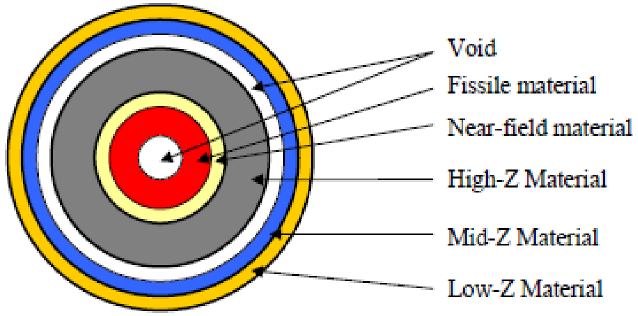


Figure 2-2. Modified 1-dimensional smuggled SNM model.

[1]Nelson, K., & Sokkappa, P. (Oct 2008). A Statistical Model for Generating a Population of Unclassified Objects and Radiation Signatures Spanning Nuclear Threats (LLNL-TR--408407). United States

[2]Gamma Detector Response and Analysis Software (GADRAS) v. 16.0. (2009). United States. [Online]. Available: https://www.osti.gov/biblio/1231259

APPROACH: DATA SIMULATION

- Class 0: Any source not defined as weapons grade
  - Contains sub-threshold SNM such as reactor grade Pu and <90% enriched U
  - Contains combinations (varying strengths and mixtures) of all known radioisotopes with practical half-lives (100+)
- Class 1: Weapons Grade Pu
- Class 2: Weapons Grade U
- Class 3: Layers of both Pu/U, one of which is weapons grade

Material	Very Highly Enriched Uranium	Highly Enriched Uranium (20-85%)	Weapons Grade Pu	Reactor Grade Pu 33 MWd/kg	Reactor Grade Pu 65 MWd/kg	^{233}U	Am	Np
Composition (weight %)	^{234}U, 0.70 ^{235}U, 85-92 ^{236}U, 0.3 ^{238}U, rest	^{234}U, 0.70 ^{235}U, 20-85 ^{236}U, 0.3 ^{238}U, rest	^{236}Pu, 5e-9 ^{238}Pu, 0.015 ^{239}Pu, 93.63 ^{240}Pu, 6.0 ^{241}Pu, 0.355	^{236}Pu, 3e-8 ^{238}Pu, 1.2 ^{239}Pu, 59.0 ^{240}Pu, 24.0 ^{241}Pu, 11.8 ^{242}Pu, 4.0	^{236}Pu, 4e-8 ^{238}Pu, 4.6 ^{239}Pu, 49.36 ^{240}Pu, 23.92 ^{241}Pu, 12.49 ^{242}Pu, 9.63	^{232}U, 3e-4 ^{233}U, rest	Am	Np
Age (y)	0-65	0-65	0-20	0-20	0-20	0-5	0-20	0-20
Mass (kg)	1 – *	1 – *	0.5 – 10	1 – 13	1 – 13	1-16	1 – 60	1 – 60
Density (g/cc)	18.95	18.95	15.75	15.75	15.75	18.95	12.0	20.45

* critical mass = $644f^2 - 1185f + 607$ where f is the fraction ^{235}U.

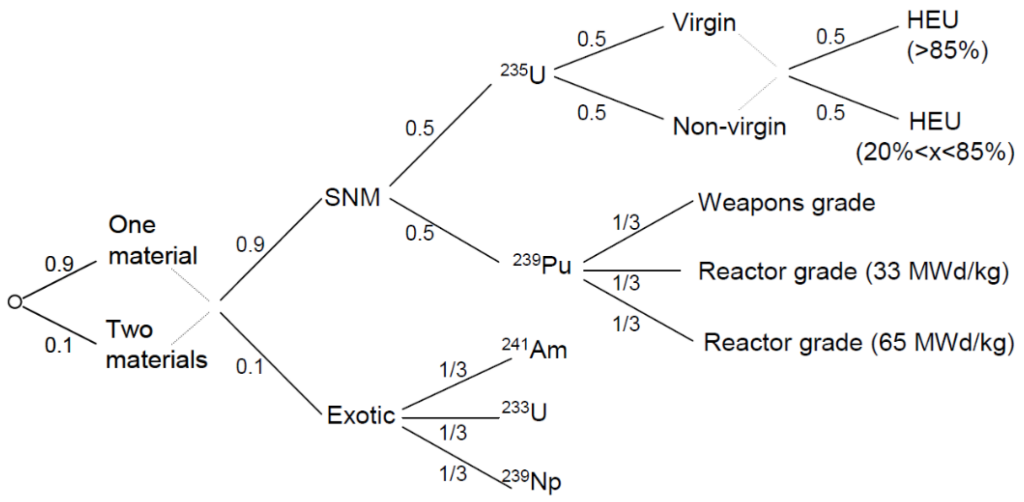
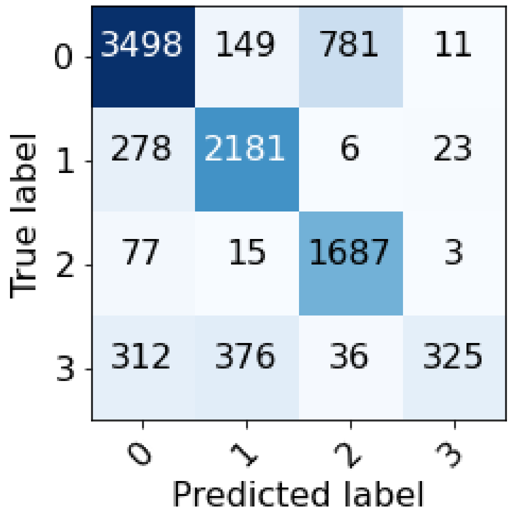


Figure 3-1. Tree diagram and probabilities for selecting fissile material.

Nelson, K., & Sokkappa, P. (Oct 2008). A Statistical Model for Generating a Population of Unclassified Objects and Radiation Signatures Spanning Nuclear Threats (LLNL-TR--408407). United States

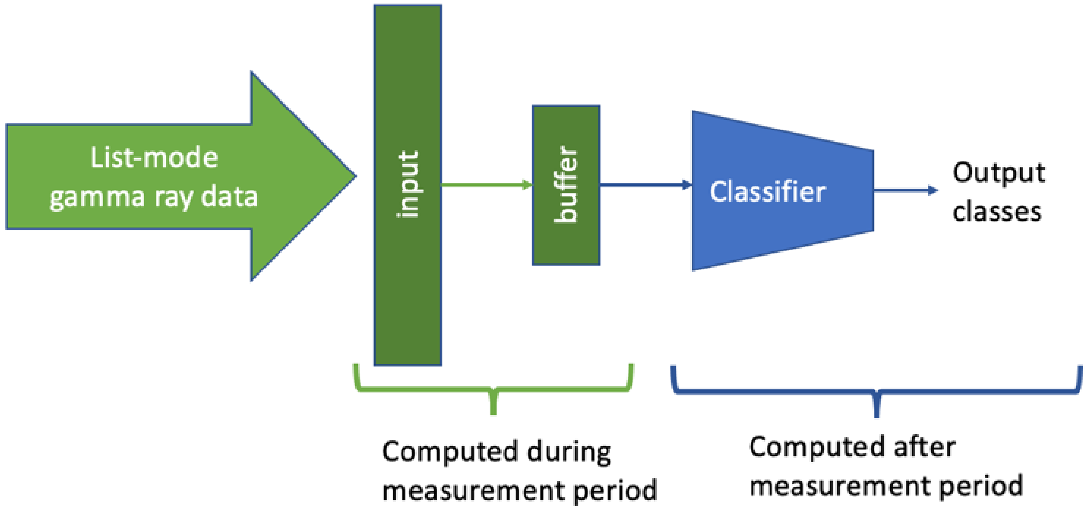
APPROACH: MACHINE LEARNING – LINEAR CLASSIFIER

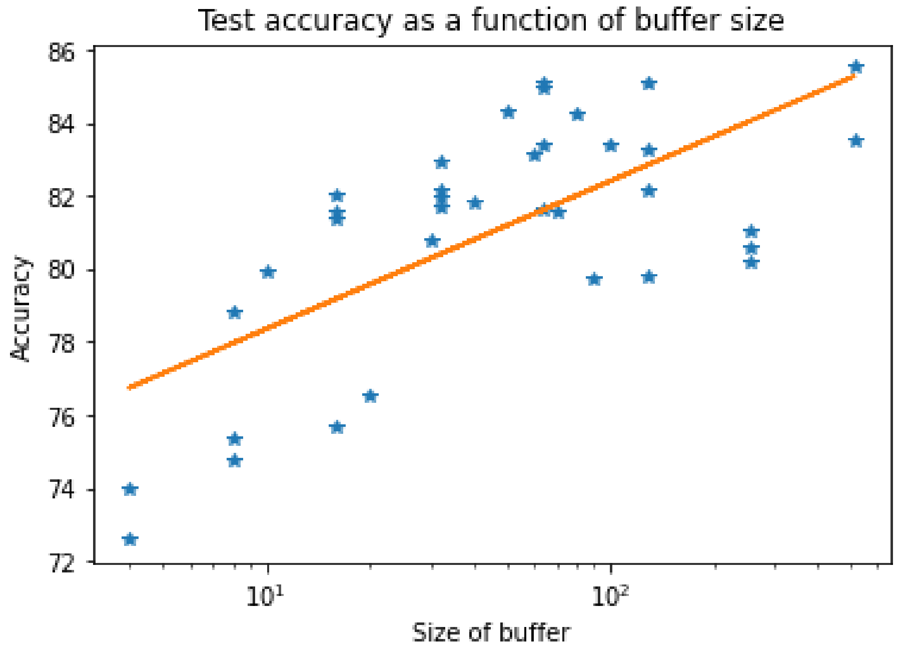
- With a model containing no nonlinear elements or convolutions, the weight arrays can be collapsed into a single weight array for each Class
- After a preset number of pulses (to physically normalize spectral features), the Class with the highest output score is declared as the result of the measurement
- The linear classifier achieved a "Red-Green" accuracy of 83.1%
  - Red-Green accuracy is how an inspector might view the system in a binary weapons-grade presence confirmation mode



APPROACH: MACHINE LEARNING – HYBRID MODEL

- In an attempt to create a nonlinear, neural model that is still list-mode compatible, a linear, fully connected neural network layer was used to project onto a buffer which is not practically recoverable
- Performance was demonstrated against buffers of different sizes
- A Red-Green accuracy of 85.5% was achieved with this method





APPROACH: MACHINE LEARNING – MATLAB LEARNER APP

- A summary of MATLAB's best performing models is shown below, compared with our linear classifier in the last row
- Class 3 forgiving (Class 3f) accuracy allows for model predictions of Class 1 or Class 2; with dual layers of SNM, it is expected that the outer layer has a much higher gamma signature than the interior layer due to self shielding

Accuracy:	Class-weighted	Red-Green	Class 3f
fineTree	70.40	83.07	86.87
medTree	65.28	78.62	84.82
coarseTree	54.66	74.15	76.92
fineKNN	65.94	79.87	77.22
medKNN	67.16	81.63	82.46
coarseKNN	66.07	80.51	84.70
cosineKNN	67.14	81.82	82.15
cubicKNN	67.21	82.04	82.65
weightedKNN	68.97	82.09	83.11
linear classifier	73.03	83.13	82.85

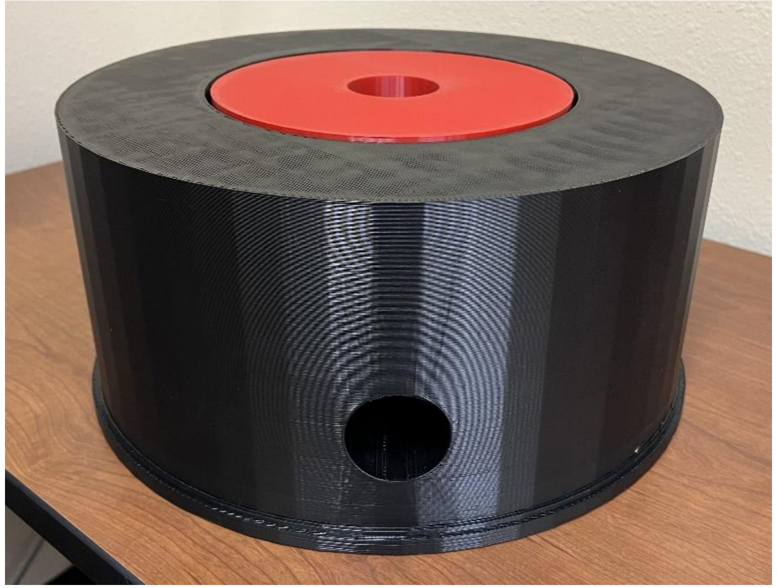
CONCLUSIONS

- Comparing our linear classifier to the state-of-the-art Matlab Classification Learner application results in nearly identical performance
- The hybrid model achieved slightly higher performance than the linear classifier, with a small penalty for the front end buffer (86% vs 89% accuracy)

Model	Red-Green Accuracy
Linear	83%
Hybrid	86%
Hybrid minus buffer (full nonlinear model)	89%
Matlab Learner	83%

FUTURE WORK

- Explore other detector response functions (NaI, CsI, LaBr, CLLBC, etc.)
- Add neutron information (count rates, multiplicity)
- Parametric studies leveraging data labels (minimum mass, isotopics, presence of HE, etc.)
- Prototype fabrication
- Incorporate in-situ authentication



QUESTIONS?