LA-UR-20-21612
Approved for public release; distribution is unlimited.

Title: MAD using INRAD and Radiography

Author(s): Klasky, Marc Louis
Watkins, Yijing Z.
Skau, Erik West
Stults, Katrina Ann
Hung, Li-Wei

Intended for: Presentation

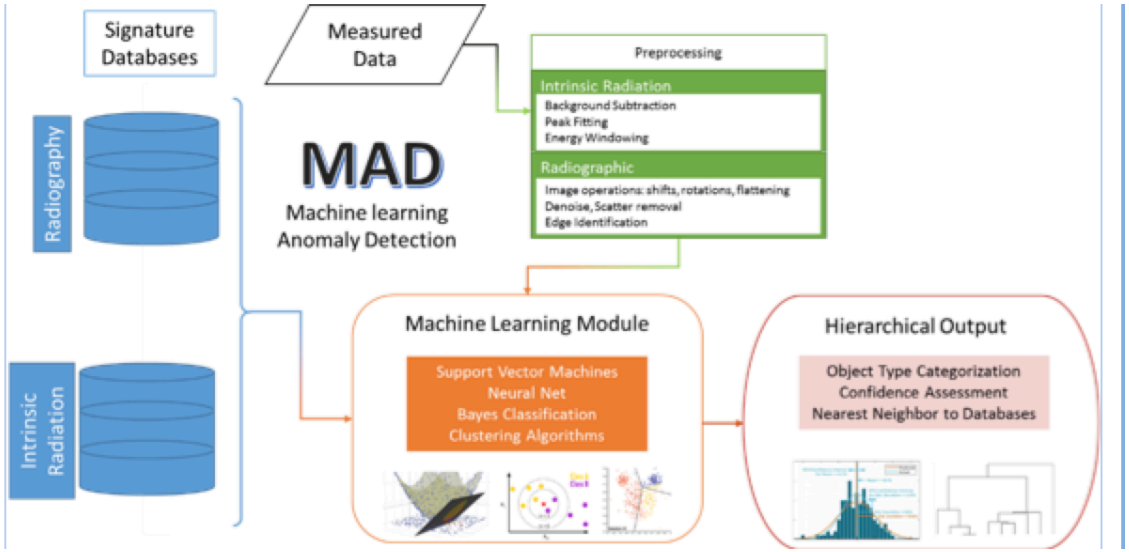
Issued: 2020-02-19

Disclaimer:
Los Alamos National Laboratory, an affirmative action/equal opportunity employer, is operated by Triad National Security, LLC for the National Nuclear Security Administration of U.S. Department of Energy under contract 89233218CNA000001. By approving this article, the publisher recognizes that the U.S. Government retains nonexclusive, royalty-free license to publish or reproduce the published form of this contribution, or to allow others to do so, for U.S. Government purposes. Los Alamos National Laboratory requests that the publisher identify this article as work performed under the auspices of the U.S. Department of Energy. Los Alamos National Laboratory strongly supports academic freedom and a researcher's right to publish; as an institution, however, the Laboratory does not endorse the viewpoint of a publication or guarantee its technical correctness.

MAD using INRAD and Radiography

Application of Machine Learning Algorithms to Radiation Portal Monitor (RPM) Threat Detection

Marc Klasky(PI) P-23, Yijing Watkins P-23, Erik Skau CCS-3, Katrina Stults NEN-2, Li Wei Hung P-Div



January 21, 2019

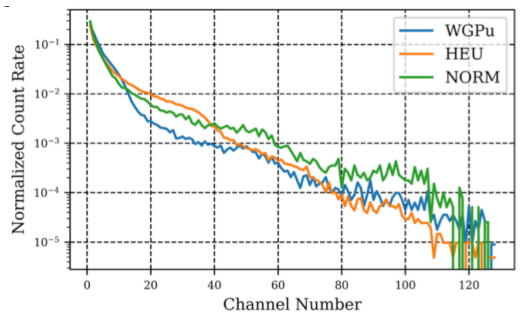
Outline of Talk

- **Project Objective and Background**
- **Methodology**
  - **Intrinsic Radiation**
  - **Radiography**
- **Results**
  - **Intrinsic Radiation**
  - **Radiography**
- **Program Impact**
- **Pentachart**

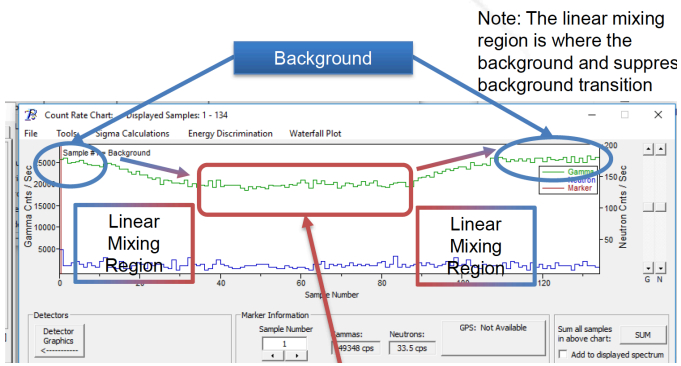
Los Alamos National Laboratory

Project Objective and Background

- **Background**
  - We have previously evaluated Intrinsic Radiation Detection Algorithms from vendors for the Department of Homeland Security.[1,2,3] These algorithms have limited spectra capability due to both the relatively low spectral content of the signal due to the use of PVT in the Radiation Portal detectors as well as relatively simple algorithms which are based on energy windowing and other simple algorithms to perform classification of Special Nuclear Material.
  - Current detection algorithms are suceptible to nuissance alarms due to Naturally Occuring Radiation (NORM) and variations in background suppression.



PVT normalized energy spectra from an example of NORM, HEU, WGPu.

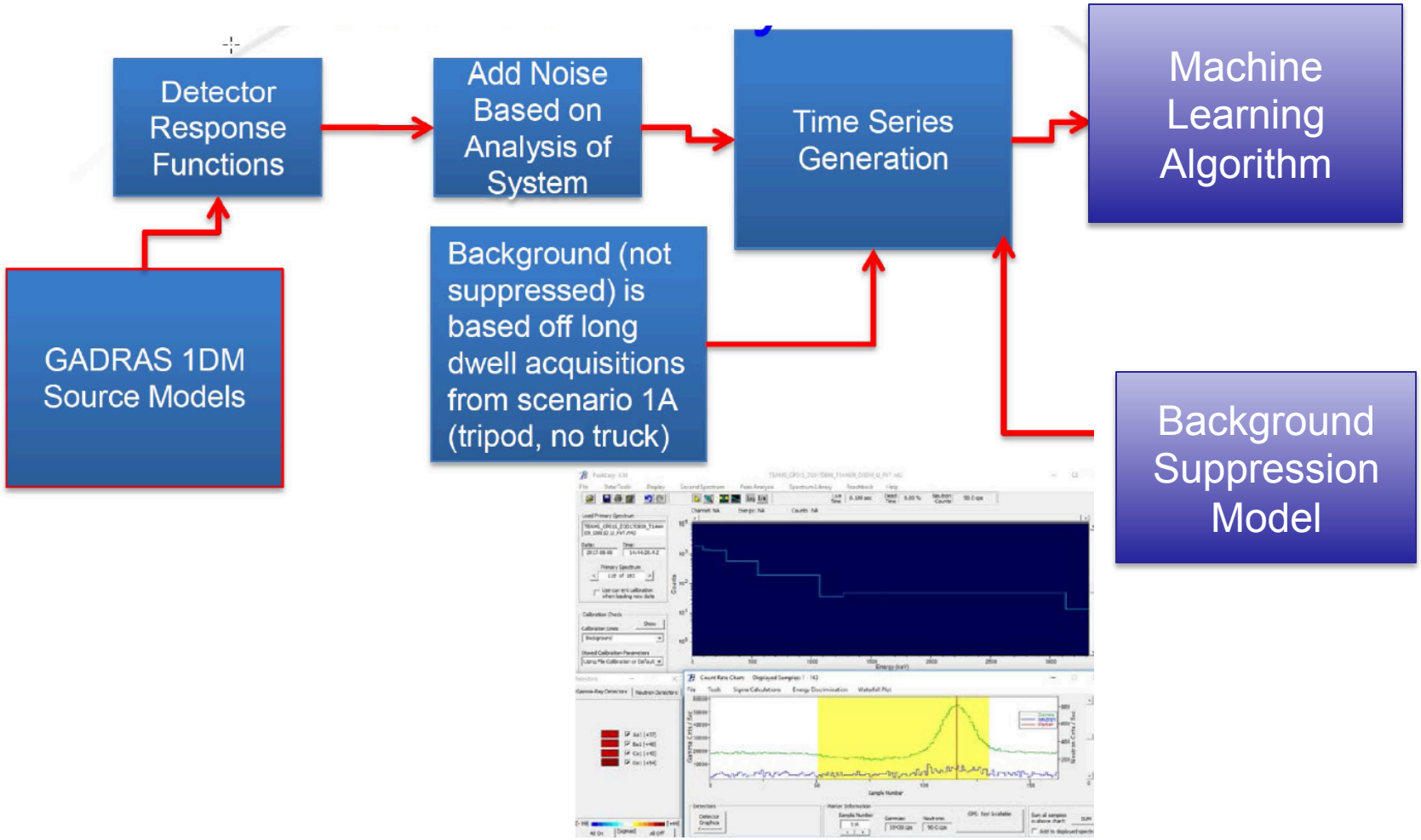


- **Objectives**
  - We propose to fuse the intrinsic radiation and radiographic data in conjunction with well-established machine learning algorithms to developed enhanced Threat Object detection capability.
    - Perform ML intrinsic radiation classification Threat (SNM)/ Non-Threat that out perform existing algorithms for Radiation Portals.
    - Evaluate Detectability of Threat Items using automated algorithms using radiographic data(Canny Edge/Hough Transform)
    - Evaluate the utility of combined intrinsic radiation and radiography for Radiation Portal Detection

Intrinsic Radiation

- **Construction of training data sets utilized to perform machine learning algorithms play a fundamental role in the performance for intrinsic radiation classification algorithms. Two issues that were examined to address this aspect of the problem were:**
  - Generation of synthetic data
  - Selection of data sets
- **Generation of Training Data**
  - Experimental data typically is not available to provide training.
    - Simulations using both MCNP and GADRAS were examined to generate data for intrinsic radiation machine learning.
- **Experiments have been performed to examine the ability of both MCNP and GADRAS to match experimental data.[1,2]**
  - MCNP: Monte Carlo method in which both the source and the detector are modeled.
  - GADRAS: Utilizes deterministic transport combined with empirical fitting to calibration test sources for detector response.

Data generation for injection into machine learning algorithm for intrinsic radiation classification



Overview of Training Data utilized in Machine Learning Algorithms for Intrinsic Radiation Classification

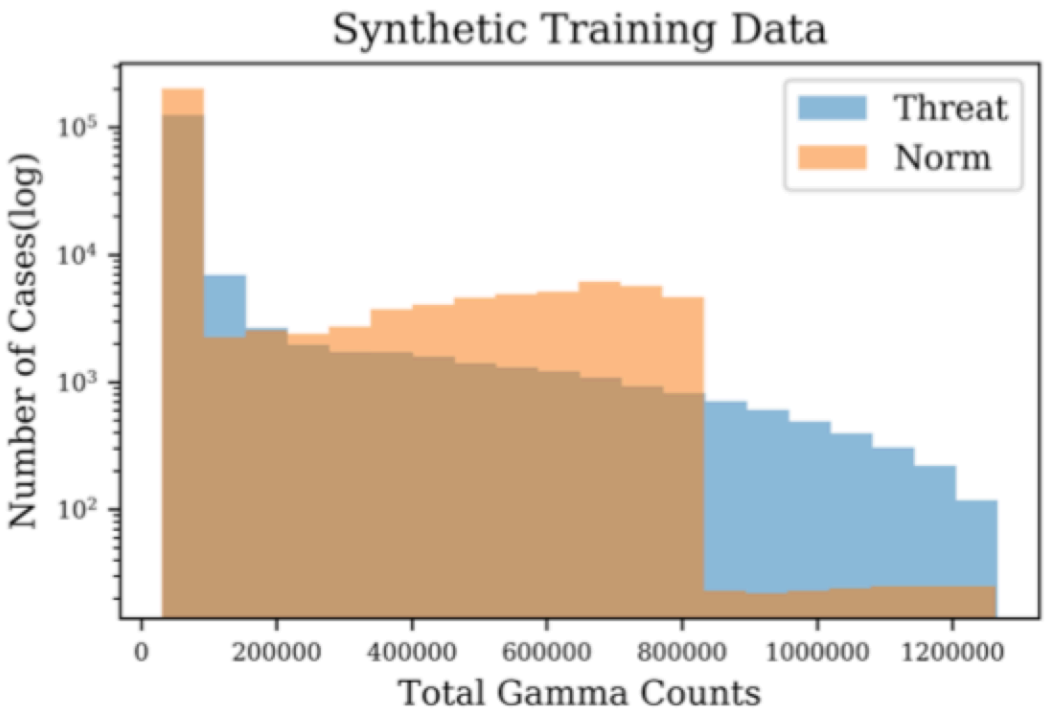
Synthetic Training Data Set

Number of total training sets: 401806 cases

- Number of threat sets: 150895 cases
  - Number of Pu:65124
    - Shielded: 39717
    - Bare: 25407
  - Number of HEU: 85771
    - Shielded: 69517
    - Bare: 16254
- Number of NORMs/background sets: 250911 cases
  - Number of backgrounds: 150000
  - Number of NORMs with shield: 916 cases
  - Number of NORMs without shield: 249995 cases

Training Materials :

- Threat: 'Plutonium', 'HEU','Plutonium with water', 'Plutonium with plywood', 'Plutonium with iron', 'HEU with water', 'HEU with plywood', 'HEU with iron', 'Plutonium with Du', 'HEU with Du'.
- Norm/Background: 'Silicon Oxide', 'Weld Pod 2% Th', 'Weld Pod 2% Th with iron', , 'Potassium Chloride (KCl)', 'Ho-166m', 'I-131', 'Tc-99m', 'Bare background', 'Lightly shielded background', 'Heavily shielded background'.



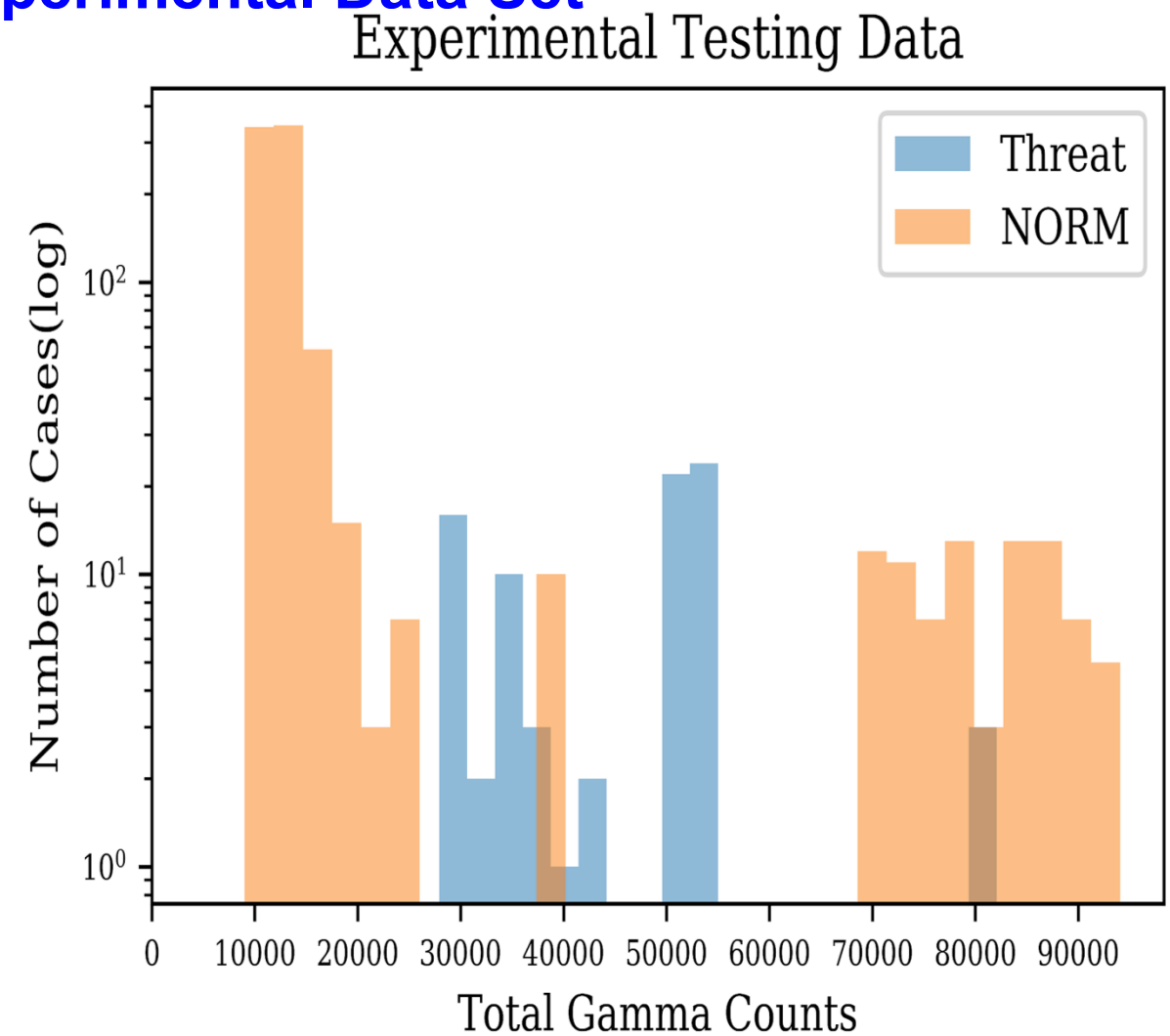
Testing of Machine Learning Algorithms with Experimental Data Set

Number of total testing sets: 944 cases

- Number of threat sets: 80 cases
- Number of non-threat sets: 864 cases

Testing Materials :

- Non-Threat: 'Am-241', 'Cd-109', 'Cf-252 1-cm poly', 'Cf-252 4 cm poly', 'Co-60', 'Co-60 W Shield', 'Cs-137', 'Cs-137 W shield', 'DU plates', 'DU spheres (4pc) in 0.5" steel', 'Ho-166m', 'I-131', 'K + Cs-137', 'Low-density NAM', 'Ra + Cs-137 W Shield', 'Tc-99m', 'Th + Co-60'.
- Threat: 'HEU (2.5 kg) in DU Spheres (2pc)', 'HEU (25 kg bare)', 'HEU 25 kg in Al', , 'WgPu Puck', 'WgPu Puck in DU spheres (2pc)', 'WgPu Sphere .5 steel'.



Machine Learning Algorithms Investigated for Intrinsic Radiation Classification

- Random Forest
- Support Vector Machine (SVM)
- K-nearest neighbors (KNN)
- Neural Networks

Automated Object of Interest Detection of Radiographic Objects

Objective:

- **Develop an algorithm to determine if an "object of interest" is present in a given radiographic scene.**
- **Radiographs and intrinsic radiation signatures are generated self consistently.**

- **Assumption:**
  - Object of interest is assumed to be 3 or more concentric spheres.

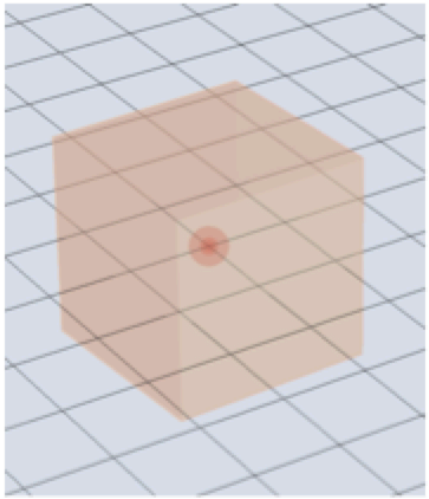
Threat Object Detection using Radiography

- Scripts written to generate random objects within a box, with different shapes, materials, of different sizes and positions/orientations.
- Ray trace code ASTRA 3D utilized to produce with specified gain + scatter level and Poisson noise.

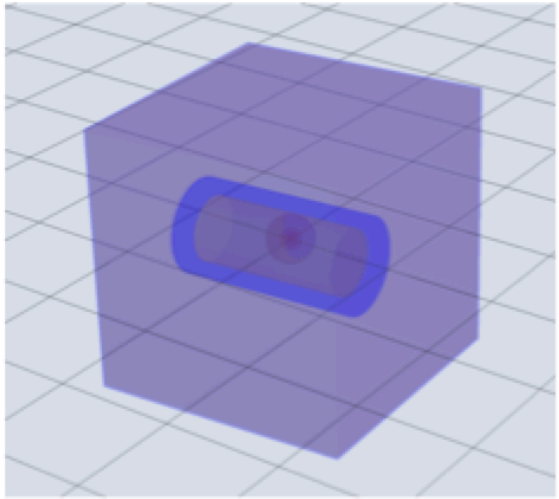
Steps in Automating Threat Object Detection using Radiography

- Canny Edge Finding used to determine edges.
- Hough Transform taken to locate object of interest (three concentric spheres)

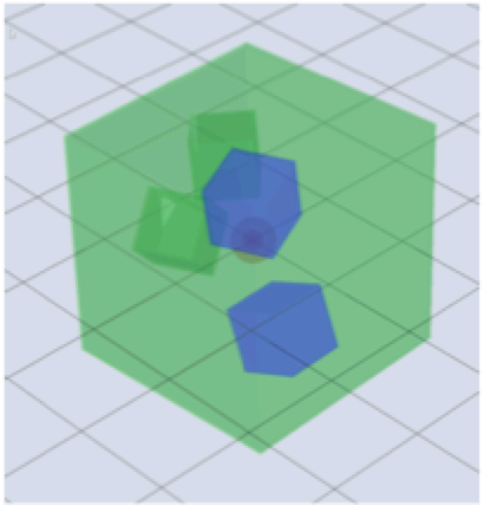
Examples of Radiographic Identification of Objects of Interest in Different Scenes



Three Concentric Spheres in Iron Truck Size Container



Three concentric Spheres concealed in Cylinder in Iron Truck Size Container

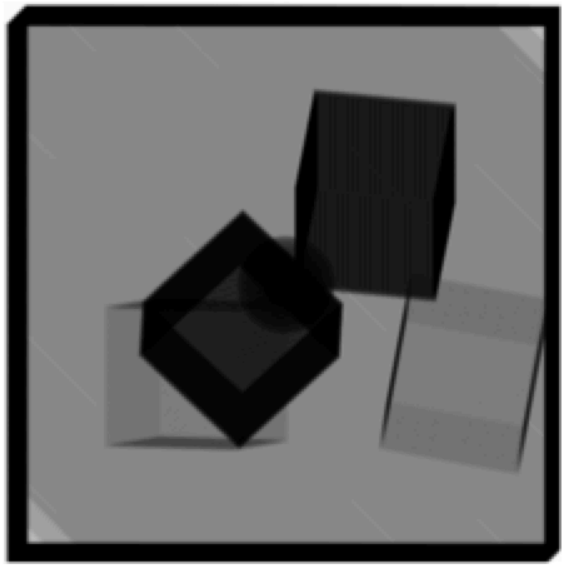


Three concentric Spheres occluded in Iron Truck Size Container

Examples of Radiographs from different Scenes

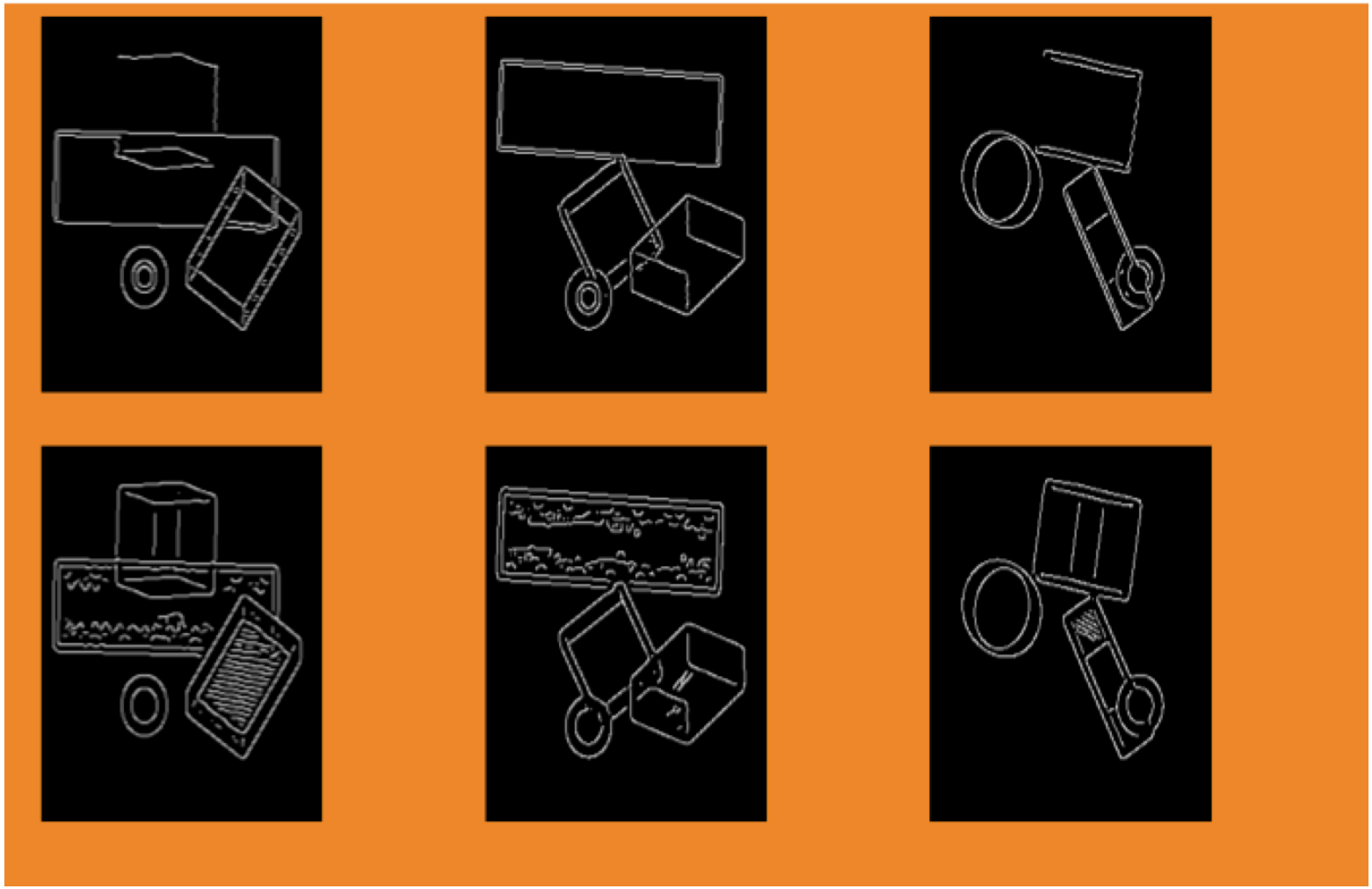
Three Concentric Spheres in Iron Box

Three concentric Spheres concealed in Cylinder

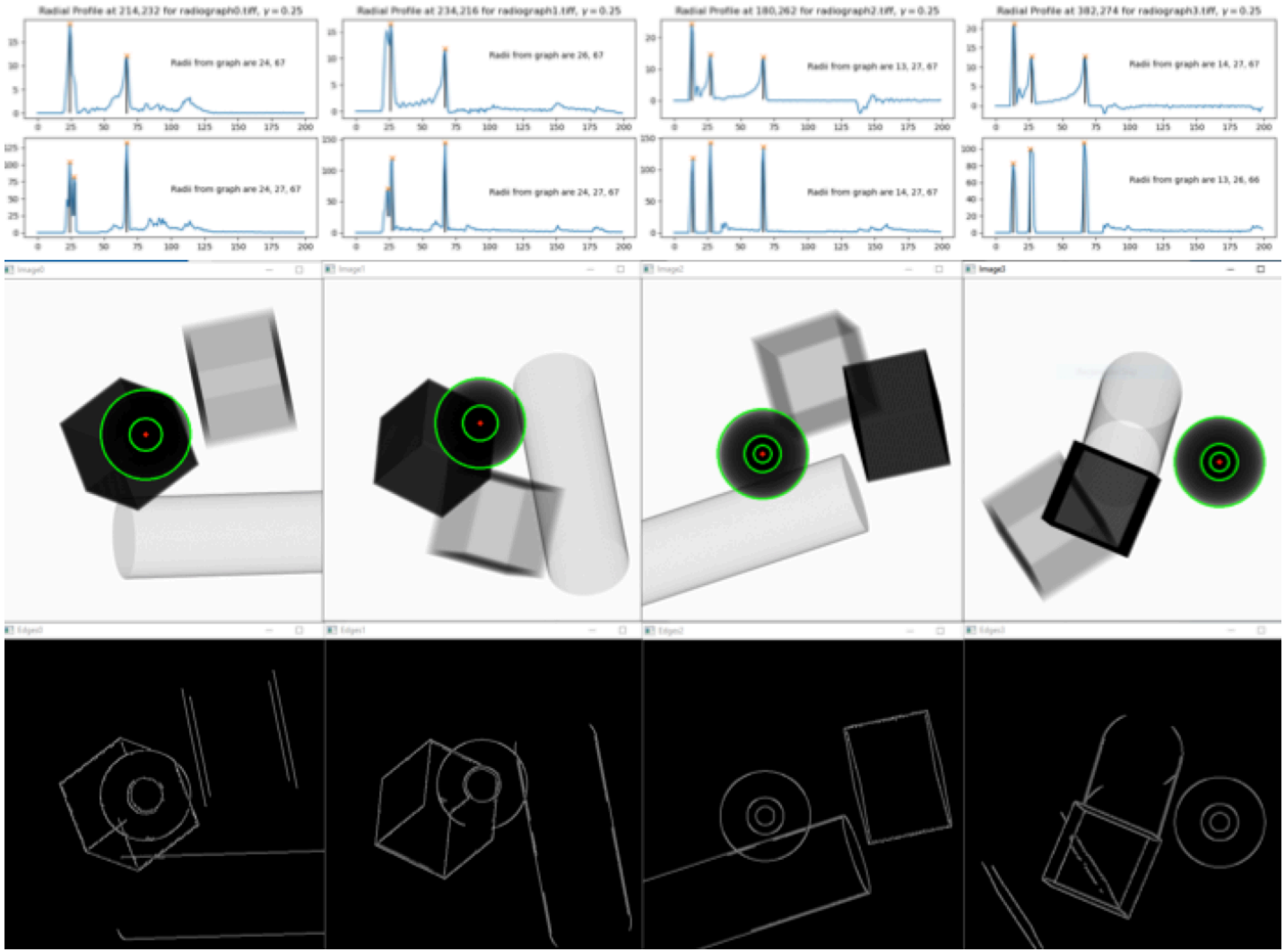


Three concentric Spheres occluded

Canny Edge Detector

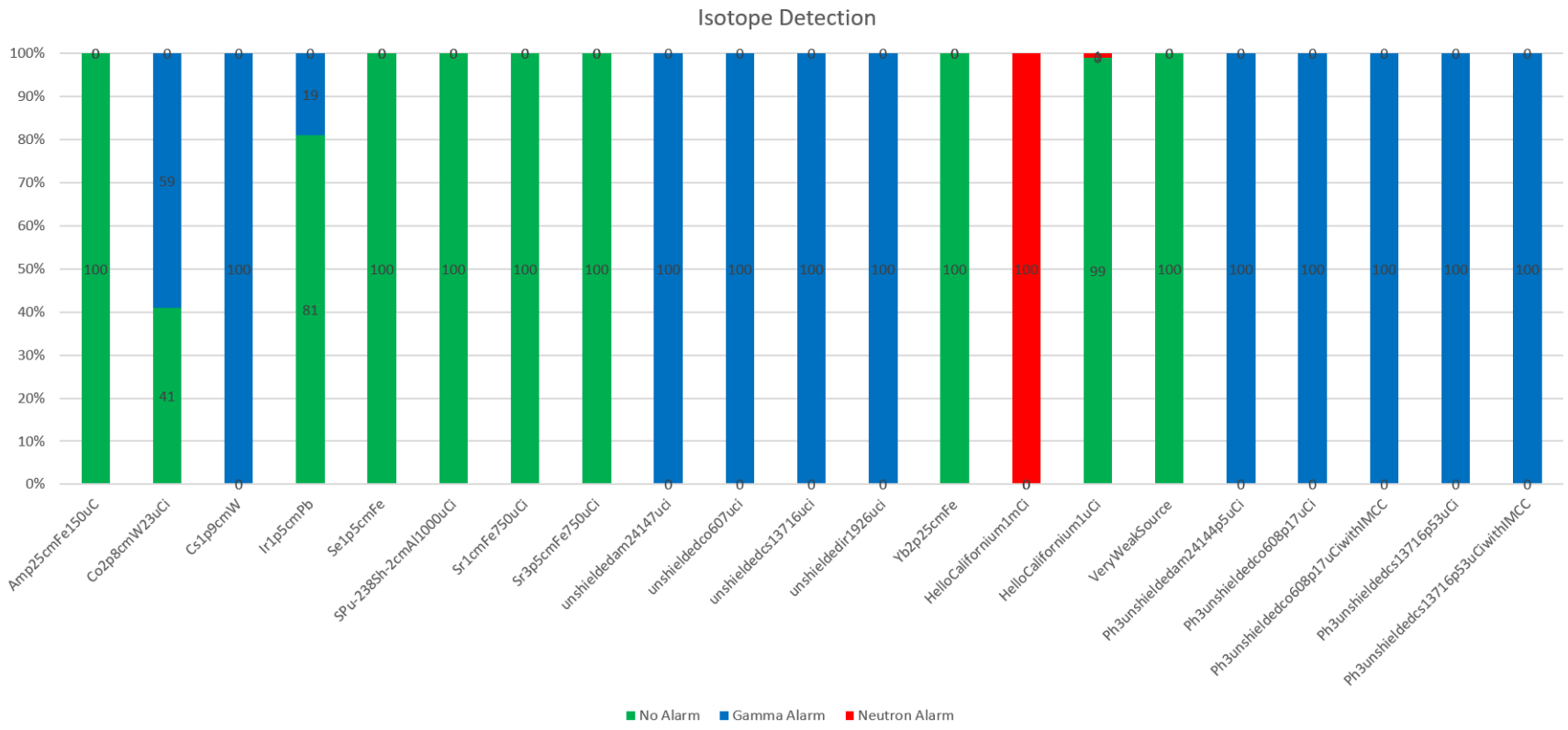


Application of Hough Transform

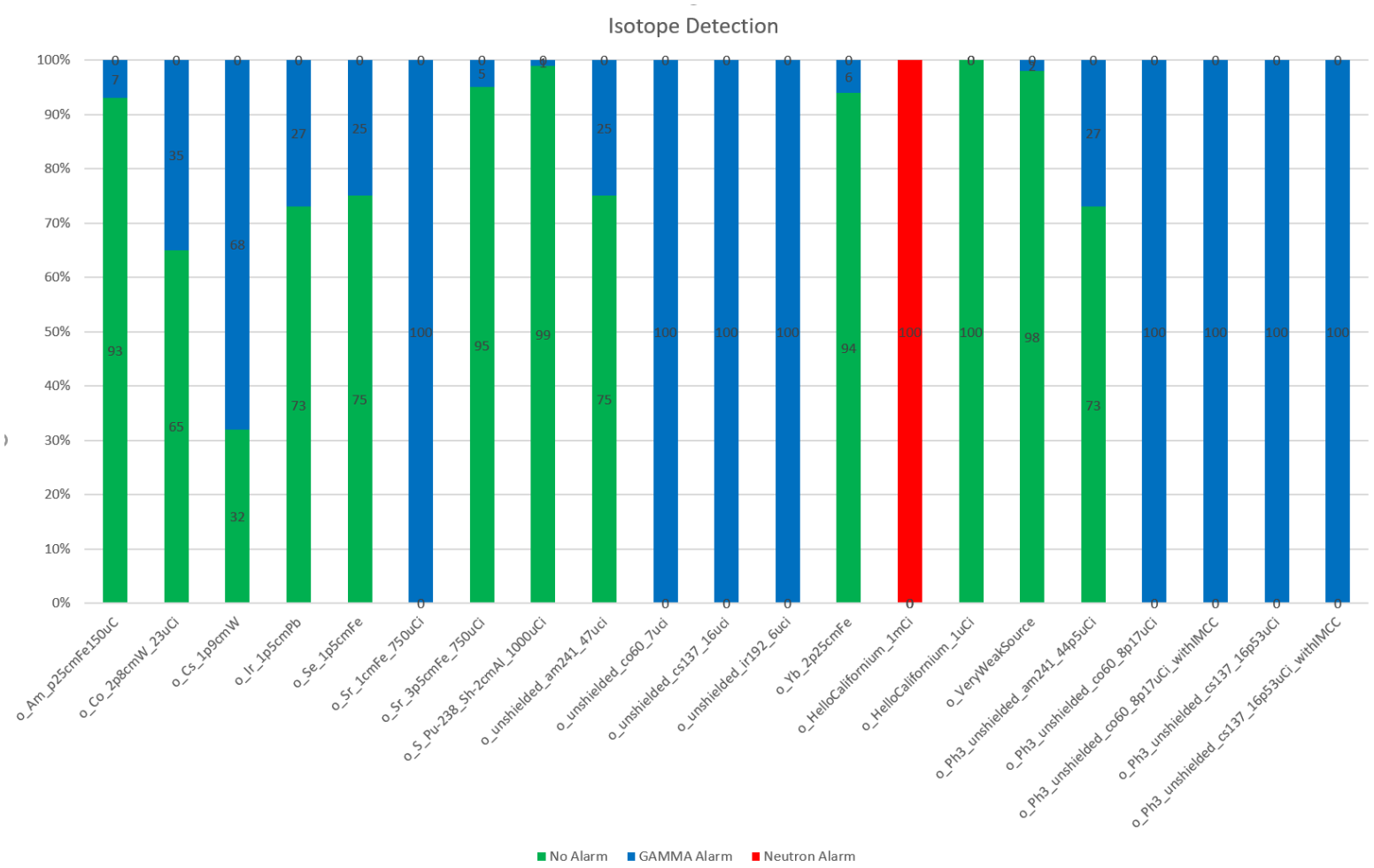


Vendor Results of Classification of Experimental Intrinsic Radiation Measurements

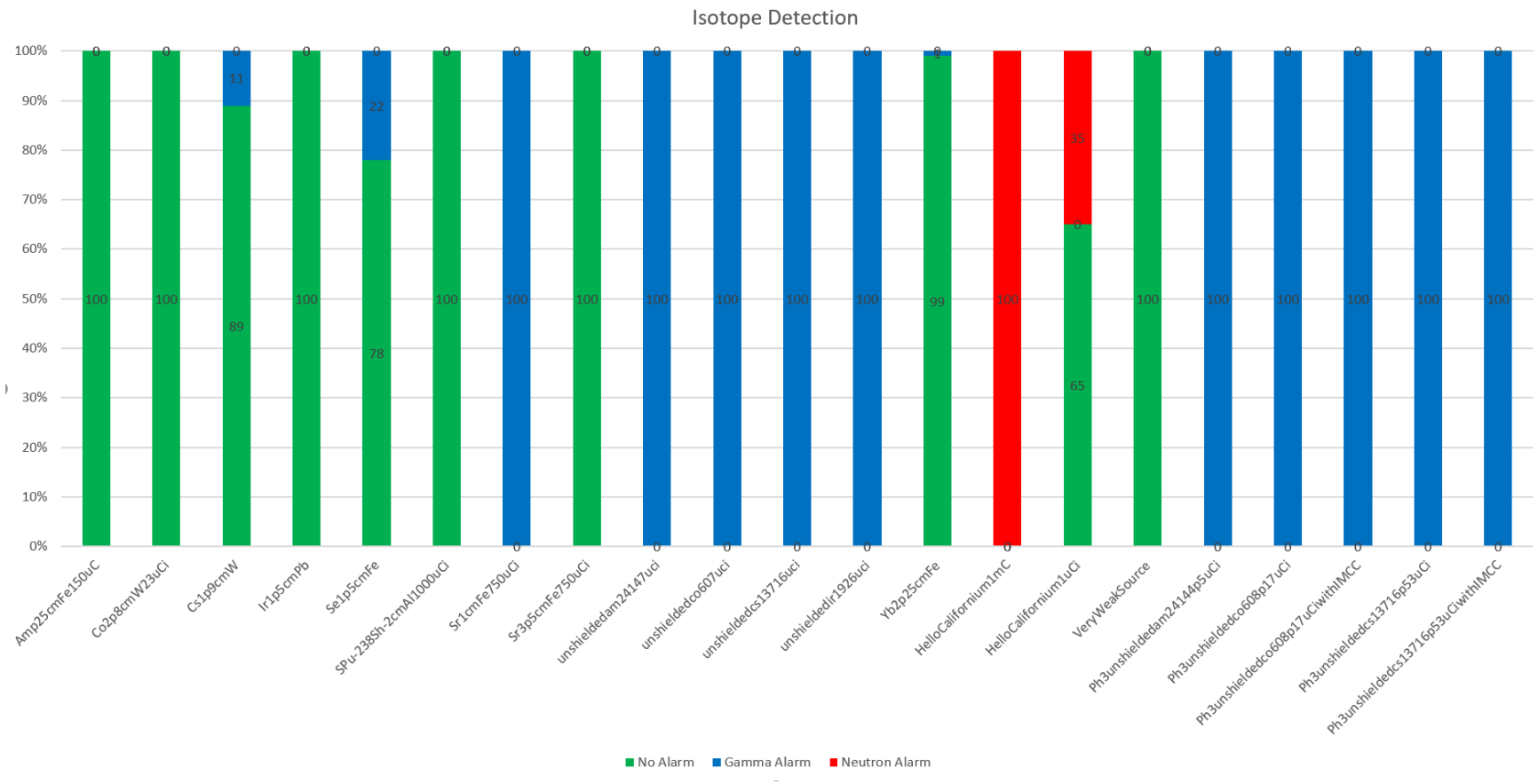
Vendor System 1



Vendor System 2



Vendor System 3



Our Experimental CT classification results

Training Materials with Labels :

- Threat: 'Plutonium', 'HEU','Plutonium with water', 'Plutonium with plywood', 'Plutonium with iron', 'HEU with water', 'HEU with plywood', 'HEU with iron', 'Du plates'(100x10).
- Non-Threat: 'Silicon Oxide', 'Weld Pod 2% Th', 'Weld Pod 2% Th with iron', 'Potassium Chloride (KCl)', 'Bare background', 'Lightly shielded background', 'Heavily shielded background', 2 cases of CT 'Ho-166m', 1 case of CT 'Tc-99m'.

Testing set: 944 cases, 80 threat cases, 864 norm cases. Divide all cases' energy count by 4 because 4 detectors.

- Threat: Pu, HEU. Non-Threat: Ho-166m,Tc-99m, I-131 and others

Training Accuracy: 1.0,Testing Accuracy: 0.9989,False Positive Rate 0,True Positive Rate 0.9880

83/83 threat correct: 16/16 HEU (25 kg bare), 15/15 WgPu Puck, 15/15 WgPu Sphere .5 steel, 3/3 HEU 25 kg in Al, 16/16 HEU (2.5 kg) in DU Spheres (2pc) and 15/15 WgPu Puck in DU spheres (2pc), 3/3 DU plates.

861/861 Non Threats correct: Cf-252 4 cm poly,Cs-137,Am-241,Co-60,KCl Fr-65-obj,Welding Rods Fr-65-obj,Zircon Sand Fr-65-th,KCl Fr-65-th,Zircon Sand Fr-65-obj ,Th + Co-60,Co-60 W Shield,Cs-137 W shield,KCL MVV, Cd-109,Welding Rods MVV,Zircon Sand MVV,Ra + Cs-137 W Shield,K + Cs-137,DU spheres (4pc) in 0.5" steel,Cf-252 1-cm poly,High-density NAM,Bare,Low-density NAM,DU plates,10/10 Ho-166m, 85/85 Tc-99m, 99/99 I-131.

0/83 Threat incorrectly!

Analysis of Combined Radiographic & Intrinsic Radiation

- A set of 2000 cases were generated to test Intrinsic Radiation Machine Learning algorithms based on training data produced from self-consistent radiographic/GADRAS simulations.

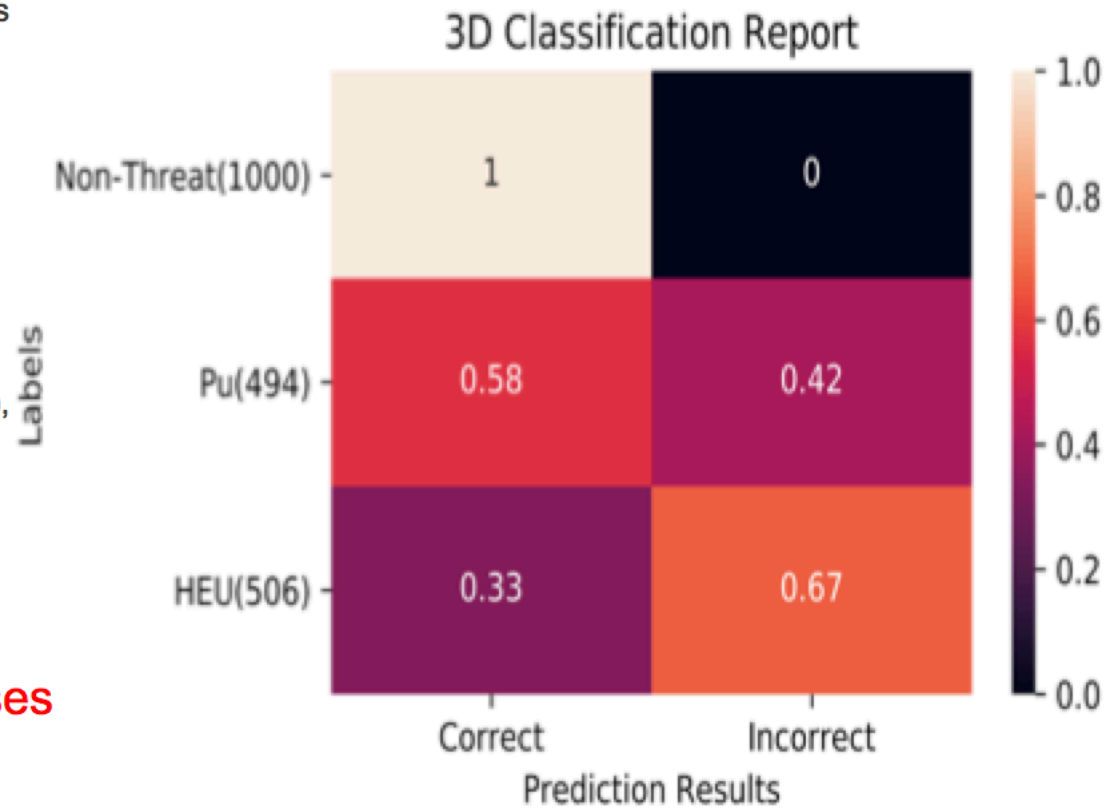
- Most of these are very heavily shielded objects with obstructions in field of view.

Testing with 3D Synthetic Gamma

Label: Threat: Pu, HEU Non-threat: Backgrounds

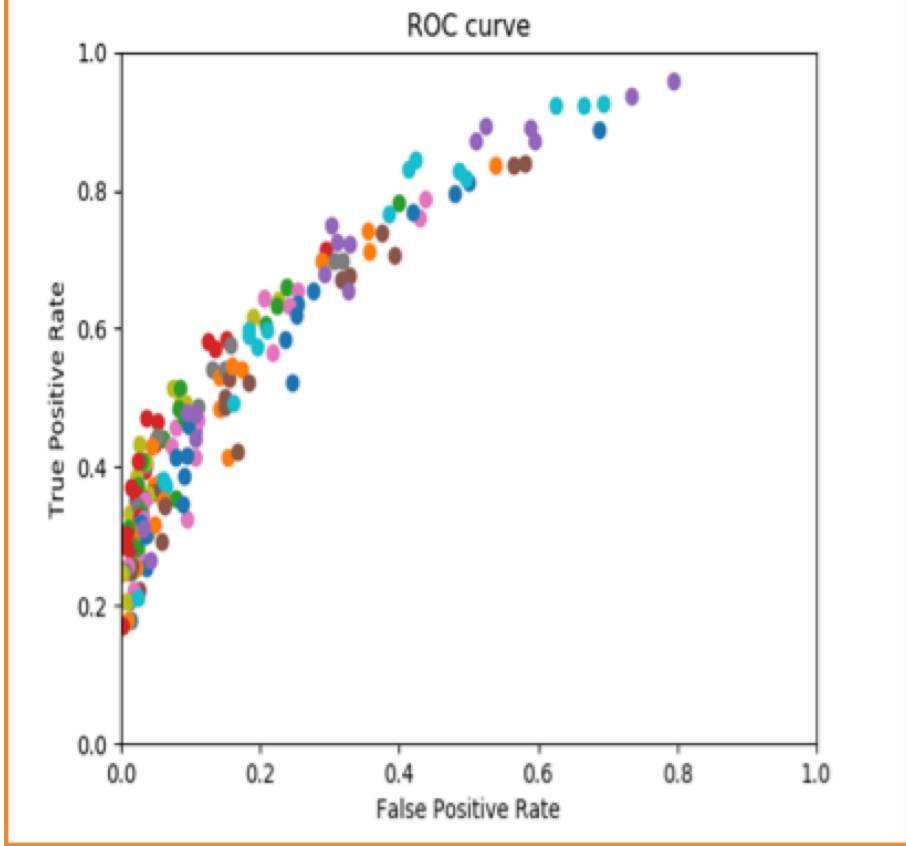
HEU Classification Results:

- False Positive Rate: **0%**
- True Positive Rate: **33%**
  - Wrong classified HEU cases: 337,
    - Four level of shields:94,
    - Three Level of shields:98,
    - Two level of shields:88,
    - One level of shield: 0(water), 29(W), 28(Fe), 0(Wood)



Using Neutron results all PU cases are correctly identified

Determination of Canny & Hough Transforms Parameters



Train with a set of “void” containers, meaning filled with air, to detect the number of concentric spheres outside of the outermost “dense” sphere.

Picked point:
TPR = 0.3203125
FPR = 0.017735

With the Canny parameters:
Sigma = 1.5
Low_threshold = 0.0
High_threshold = 0.1

And the circle detection parameters:
Vote_threshold = 0.36,
Radial_threshold = 3
Spatial_threshold = 5

Radiography Analysis of 3D Objects Results

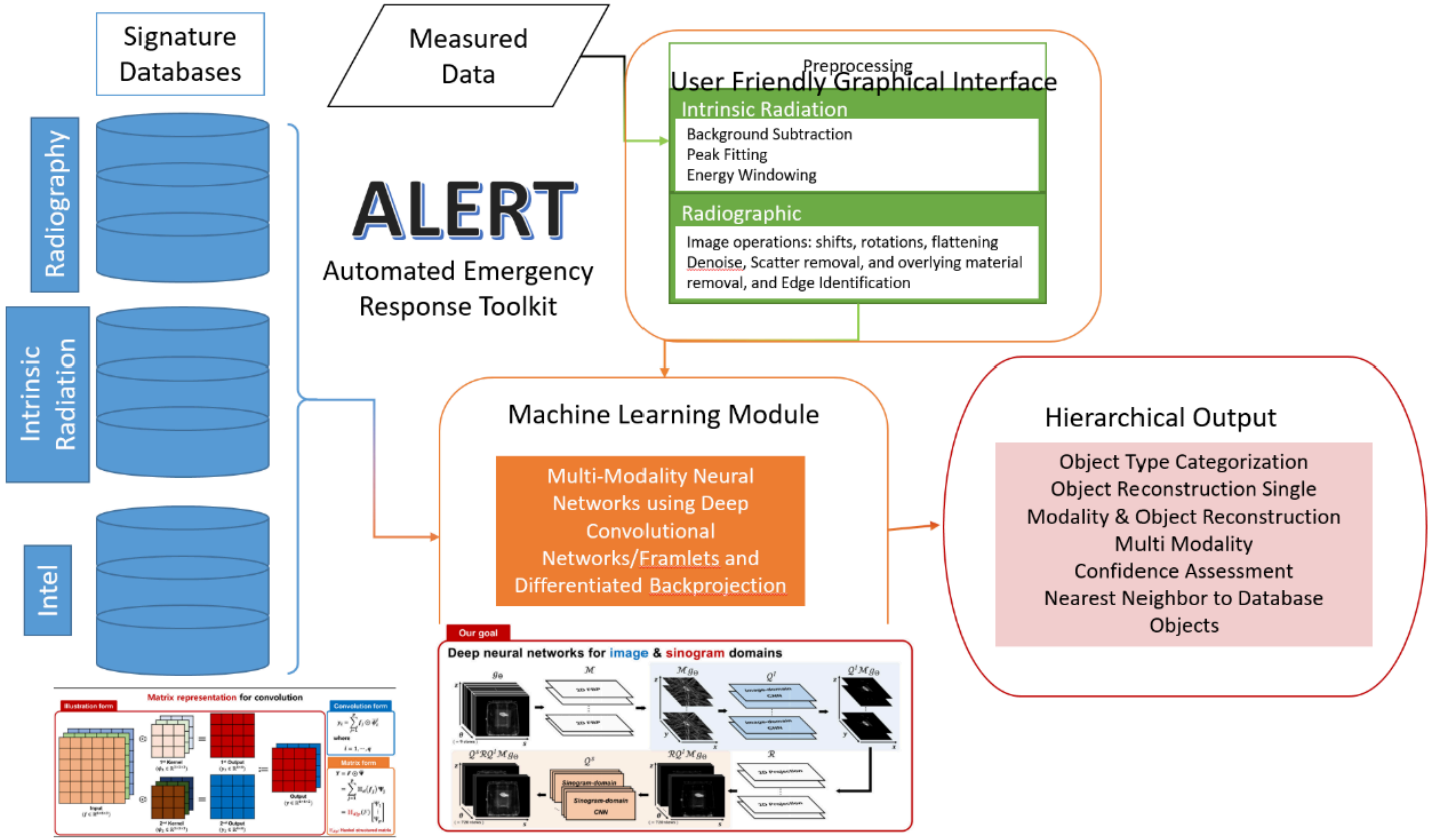
- 616 Objects of the 2000 had Three or More Concentric Spheres.
- 53/616 Threat Objects Correctly Detected with Radiography
- 563/616 Missed Threats
- 20 False Positives

- 33 Additional Cases all containing HEU are detected with Radiographythat were previously undetected.

Program Impact

- **Potential Customers for Intrinsic Radiation and Radiography Machine Learning Algorithms Identified:**
  - **DHS**
  - **DTRA**
  - **NNSA Hydrodynamic Program**
- **Joint DTRA/NNSA NA-82 Proposal successfully written to address Rapid Device Reconstruction for Emergency Response Applications using Machine Learning (Intrinsic Radiation and Radiography) 2.5 M/4 yrs Awarded FY 20**
- **Numerous discussions with Hydro Program Manager Jonathan Morgan to fund the development of Advanced Radiographic Reconstruction code using Physics based Neural Network (Scatter/ Hydrodynamics) have taken place. Funding likely**
- **DHS (Scott White)**

DTRA Proposal For Object Reconstruction using Radiography and IntrinsicRadiation



Details (I)

1. Feature identification:
   - Adaptive Hough-circle transformation
     - Canny edge detection with automated hysteresis thresholding:
       - High threshold (Ht) start from midway of grayscale depth (e.g. 120 for 8bit), low level = 0.4* Ht
       - Step down 5 until identify circles.
       - Back up 2 before number of circles drop to 0 to ensure more prominent circles are picked (weed out false positives)
2. Radial profile averaging
   - Calculate average radial profiles from each centers of circles from step 1 for –
     - Gradient maps
     - Edge maps
   - Idea is to reduce noise from the interference of other objects

Details (II)

3. Peak picking:
   - Peak picking algorithm is used
   - Identify radial profiles containing 2 to 3 peaks above empirical prominent levels.
   - Profiles not meeting the above requirement are discard
   - Two profile for each map to crosscheck to improve accurracy
4. Center optimization (optional)
   - At times peaks less than 2-3 pixels (twin peaks) were observed in radial profiles of edge maps.
   - This indicated that that center determined in step 1 were slightly off
   - Local grid search shifting center +-2 pixels in both X and Y directions to detect if a single high peak are observed – more accurate centers
5. Report
   - Report centers and peaks corresponding to centers and radii of desired features – projection of layered spheres as concentric circles
6. Automation
   - The program carried all the above procedures without human intervention for the results shown in the previous slides
   - 0.5-0.8s per image including disk i/o for intermediate results. Can be faster if without.

Details (II)

3. Peak picking:
   - Peak picking algorithm is used
   - Identify radial profiles containing 2 to 3 peaks above empirical prominent levels.
   - Profiles not meeting the above requirement are discard
   - Two profile for each map to crosscheck to improve accurracy
4. Center optimization (optional)
   - At times peaks less than 2-3 pixels (twin peaks) were observed in radial profiles of edge maps.
   - This indicated that that center determined in step 1 were slightly off
   - Local grid search shifting center +-2 pixels in both X and Y directions to detect if a single high peak are observed – more accurate centers
5. Report
   - Report centers and peaks corresponding to centers and radii of desired features – projection of layered spheres as concentric circles
6. Automation
   - The program carried all the above procedures without human intervention for the results shown in the previous slides
   - 0.5-0.8s per image including disk i/o for intermediate results. Can be faster if without.

Canny Edge Operator

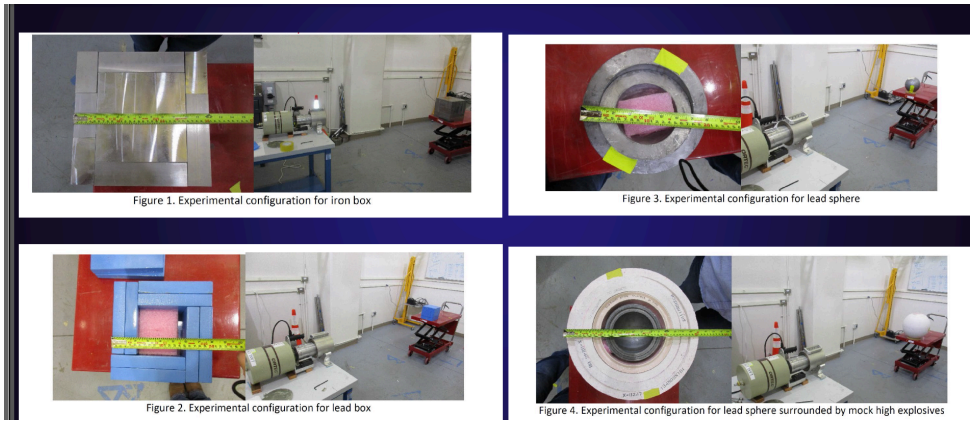
- Smooth image *I* with 2D Gaussian: $G * I$
- Find local edge normal directions for each pixel

$$\overline{\mathbf{n}} = \frac{\nabla(G * I)}{|\nabla(G * I)|}$$

- Compute edge magnitudes $|\nabla(G * I)|$
- Locate edges by finding zero-crossings along the edge normal directions (**non-maximum suppression**)

$$\frac{\partial^2 (G * I)}{\partial \overline{\mathbf{n}}^2} = 0$$

Experiments performed at Los Alamos to assess performance of GADRAS and MCNP



Small Scale Shielding Experiments NISC

Large Scale Experiments TA-16

Experimental and GADRAS Spectral Comparisons

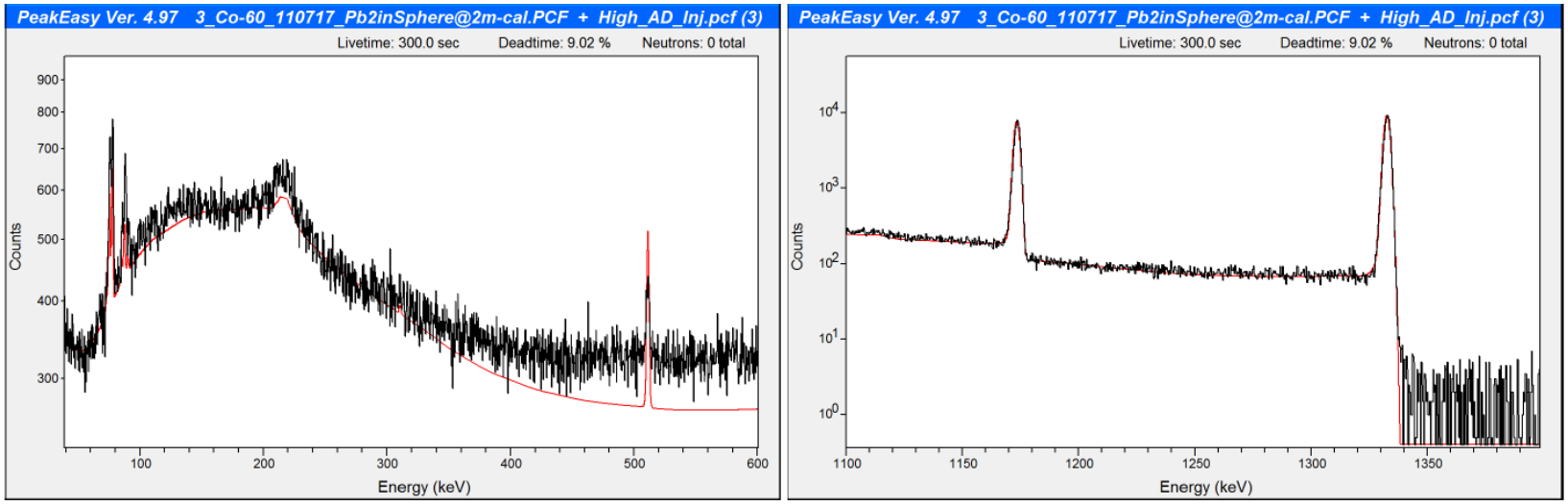


Figure 11. Spectral overlay, Pb- 2” sphere, Measured (Black) vs Synthetic (Red)

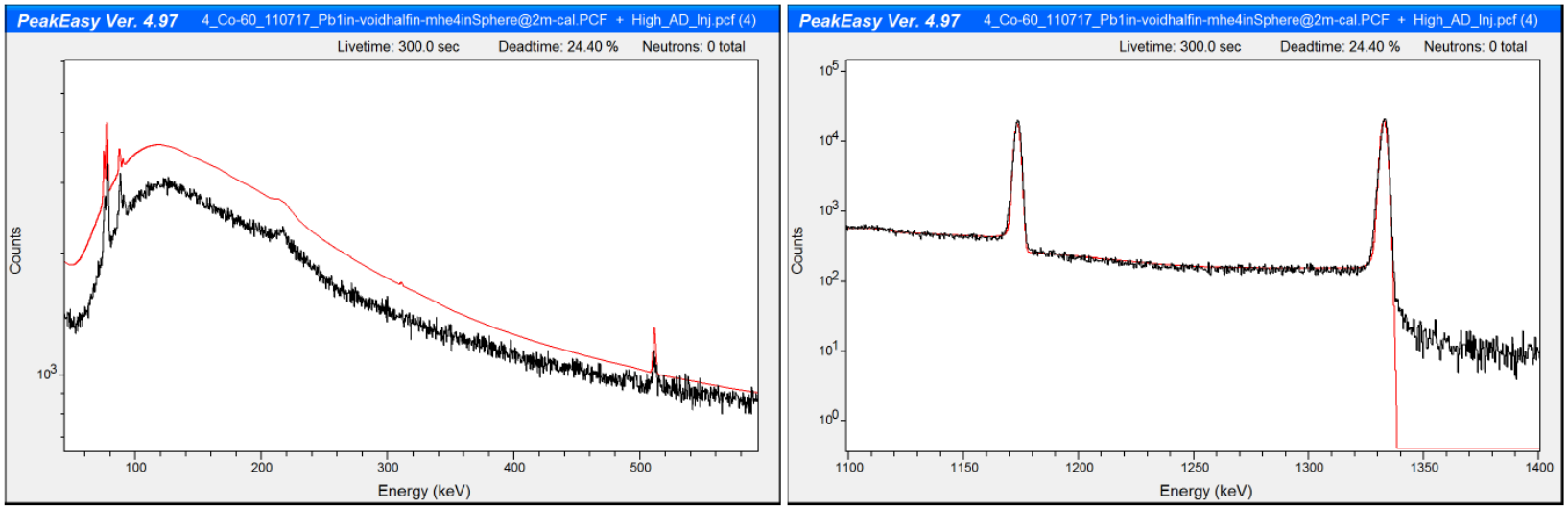


Figure 12. Spectra overlay, Pb- 2” sphere in MHE- 4” sphere, Measured (Black) vs Synthetic (Red)

GADRAS PVT Experimental Validation

Los Alamos Large Scale Validation Experiments

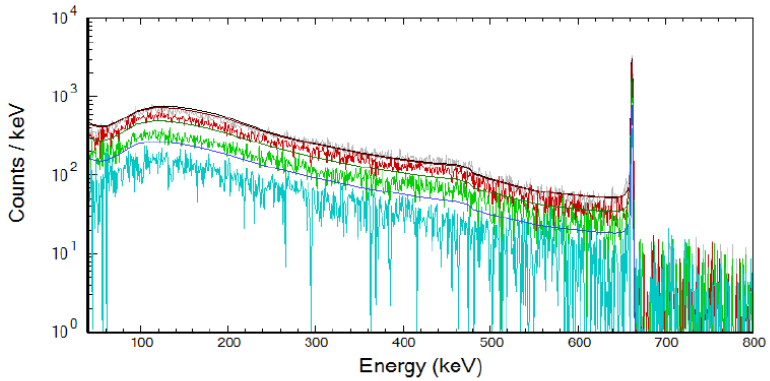


Figure 8. Comparison of measured and computed spectra based on SimpleA for ^{137}Cs at displacements of 0, 2, 4, and 6 feet relative to the detector normal position.

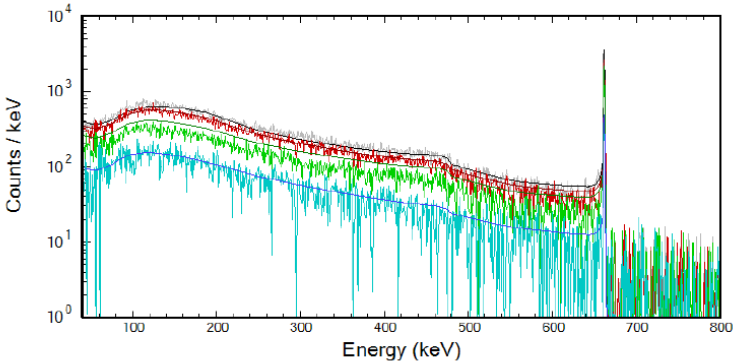


Figure 7. Comparison of measured and computed spectra based on ConfigA for ^{137}Cs at displacements of 0, 2, 4, and 6 feet relative to the detector normal position.

Comparisons of MCNP and GADRAS with Experimental Data

Table 1. Quantitative Comparison between Measured and Synthetic Spectra- High Areal Density Shielding Measurements

Config	Absolute % Difference	Average % Difference	Chi Square	% More than 3 σ Difference	Gamma cps % Difference	% Difference, 1173 keV peak	% Difference, 1332 keV peak
Fe box (AD=80)	34.5%	27.7%	112.87	41.1%	45.3%	-3.4%	-3.0%
Pb box (AD=58)	25.7%	16.5%	38.74	38.5%	16.7%	-3.5%	-2.6%
Pb sphere (AD=58)	11.0%	-9.1%	5.17	19.2%	-8.5%	-0.8%	-0.2%
Pb-MHE sphere (AD=47.6)	11.1%	8.0%	39.00	35.8%	11.8%	-13.2%	-10.0%

Table 2. Quantitative Comparison between Measured and Synthetic Spectra- High Areal Density Shielding Measurements

Config	Absolute % Difference	Average % Difference	Chi Square	% More than 3 σ Difference	Gamma cps % Difference	% Difference, 1173 keV peak	% Difference, 1332 keV peak
Fe box (AD=80)	12.4%	-6.4%	6.58	17.5%	-4.6%	2.4%	6.1%
Pb box (AD=58)	19.5%	-17.7%	12.73	52.2%	-15.3%	-9.9%	-4.9%
Pb sphere (AD=58)	20.5%	-18.7%	17.17	59.7%	-16.3%	-6.9%	-2.0%
Pb-MHE sphere (AD=47.6)	22.6%	-18.7%	62.02	93.4%	-11.1%	-25.0%	-19.8%

Table 5. Quantitative Comparison between Measured and Synthetic Spectra- Increasing Polyethylene Shielding with Co-60 Measurements

Config	Absolute % Difference	Average % Difference	Chi Square	% More than 3 σ Difference	Gamma cps % Difference	% Difference, 1173 keV peak	% Difference, 1332 keV peak
Co-60_unshielded	10.6%	-0.9%	2.22	2.2%	-2.3%	-0.4%	0.1%
Co-60_2.5"PE	10.3%	1.6%	1.90	3.1%	0.4%	-5.0%	-4.6%
Co-60_3.5"PE	10.8%	1.6%	1.96	3.5%	0.6%	-4.7%	-4.0%
Co-60_4.5"PE	11.1%	2.3%	1.97	3.4%	1.5%	-6.2%	-5.2%

Table 6. Quantitative Comparison between Measured and Synthetic Spectra- Increasing Polyethylene Shielding with Co-60 Measurements

Config	Absolute % Difference	Average % Difference	Chi Square	% More than 3 σ Difference	Gamma cps % Difference	% Difference, 1173 keV peak	% Difference, 1332 keV peak
Co-60_unshielded	28.3%	-26.7%	12.15	43.9%	-18.0%	-6.8%	-1.7%
Co-60_2.5"PE	22.9%	-20.8%	8.40	28.5%	-14.1%	-6.6%	-1.9%
Co-60_3.5"PE	22.3%	-19.5%	8.14	27.3%	-12.7%	-5.9%	-0.7%
Co-60_4.5"PE	21.1%	-17.6%	7.52	22.0%	-10.6%	-7.0%	-1.7%

GADRAS

MCNP

Experimental CT KNeighbors Classifier results

Training Materials with Labels :

- Threat: 'Plutonium', 'HEU','Plutonium with water', 'Plutonium with plywood', 'Plutonium with iron', 'HEU with water', 'HEU with plywood', 'HEU with iron', 'Du plates'(100x10).
- Non-Threat: 'Silicon Oxide', 'Weld Pod 2% Th', 'Weld Pod 2% Th with iron', 'Potassium Chloride (KCl)', 'Bare background', 'Lightly shielded background', 'Heavily shielded background', 2 cases of CT 'Ho-166m', 1 case of CT 'Tc-99m'.

Testing set: 944 cases, 80 threat cases, 864 norm cases. Divide all cases' energy count by 4 because 4 detectors.

- Threat: Pu, HEU. Non-Threat: Ho-166m,Tc-99m, I-131 and others

Training Accuracy: 0.9560,Testing Accuracy: 0.928,False Positive Rate 0.0,True Positive Rate 0.181

15/83 threat correct: 0/16 HEU (25 kg bare), 14/15 WgPu Puck, 0/15 WgPu Sphere .5 steel, 1/3 HEU 25 kg in Al, 0/16 HEU (2.5 kg) in DU Spheres (2pc) and 0/15 WgPu Puck in DU spheres (2pc), 0/3 DU plates.

861/861 Non Threats correct: Cf-252 4 cm poly,Cs-137,Am-241,Co-60,KCl Fr-65-obj,Welding Rods Fr-65-obj,Zircon Sand Fr-65-th,KCl Fr-65-th,Zircon Sand Fr-65-obj ,Th + Co-60,Co-60 W Shield,Cs-137 W shield,KCL MVV, Cd-109,Welding Rods MVV,Zircon Sand MVV,Ra + Cs-137 W Shield,K + Cs-137,DU spheres (4pc) in 0.5" steel,Cf-252 1-cm poly,High-density NAM,Bare,Low-density NAM,DU plates,10/10 Ho-166m, 1/85 Tc-99m, 99/99 I-131.

67/83 Threat incorrectly: 16/16 HEU (25 kg bare), 1/15 WgPu Puck, 15/15 WgPu Sphere .5 steel, 2/3 HEU 25 kg in Al, 16/16 HEU (2.5 kg) in DU Spheres (2pc) and 15/15 WgPu Puck in DU spheres (2pc), 3/3 DU plates.

Experimental CT MLP Classifier results

Training Materials with Labels :

- Threat: 'Plutonium', 'HEU','Plutonium with water', 'Plutonium with plywood', 'Plutonium with iron', 'HEU with water', 'HEU with plywood', 'HEU with iron', 'Du plates'(100x10).
- Non-Threat: 'Silicon Oxide', 'Weld Pod 2% Th', 'Weld Pod 2% Th with iron', 'Potassium Chloride (KCl)', 'Bare background', 'Lightly shielded background', 'Heavily shielded background', 2 cases of CT 'Ho-166m', 1 case of CT 'Tc-99m'.

Testing set: 944 cases, 80 threat cases, 864 norm cases. Divide all cases' energy count by 4 because 4 detectors.

- Threat: Pu, HEU. Non-Threat: Ho-166m,Tc-99m, I-131 and others

Training Accuracy: 0.93,Testing Accuracy: 0.737,False Positive Rate 0.288,True Positive Rate 1.0

83/83 threat correct: 16/16 HEU (25 kg bare), 15/15 WgPu Puck, 15/15 WgPu Sphere .5 steel, 3/3 HEU 25 kg in Al, 16/16 HEU (2.5 kg) in DU Spheres (2pc) and 15/15 WgPu Puck in DU spheres (2pc), 3/3 DU plates.

248/861 Non Threats correct:

613/861 Threat incorrectly: 85 Tc-99m, 83 I-131, 26 Cf-252 4cm poly, 14 Weld Rods MVV, 10 Ho-166m, 10 Cf-252 1cm poly, 2 Cs-127, 2 Weld Rods Fr-65-obj, 1 Zircon Sand Fr-65-obj

Experimental CT AdaBoost Classifier results

Training Materials with Labels :

- Threat: 'Plutonium', 'HEU','Plutonium with water', 'Plutonium with plywood', 'Plutonium with iron', 'HEU with water', 'HEU with plywood', 'HEU with iron', 'Du plates'(100x10).
- Non-Threat: 'Silicon Oxide', 'Weld Pod 2% Th', 'Weld Pod 2% Th with iron', 'Potassium Chloride (KCl)', 'Bare background', 'Lightly shielded background', 'Heavily shielded background', 2 cases of CT 'Ho-166m', 1 case of CT 'Tc-99m'.

Testing set: 944 cases, 80 threat cases, 864 norm cases. Divide all cases' energy count by 4 because 4 detectors.

- Threat: Pu, HEU. Non-Threat: Ho-166m,Tc-99m, I-131 and others

Training Accuracy: 0.929,Testing Accuracy: 0.912,False Positive Rate 0.0,True Positive Rate 0.0

0/83 threat correct:

861/861 Non Threats correct:

83/83 Threat incorrectly: 16/16 HEU (25 kg bare), 15/15 WgPu Puck, 15/15 WgPu Sphere .5 steel, 3/3 HEU 25 kg in Al, 16/16 HEU (2.5 kg) in DU Spheres (2pc) and 15/15 WgPu Puck in DU spheres (2pc), 3/3 DU plates.

Experimental CT Decision Tree Classifier results

Training Materials with Labels :

- Threat: 'Plutonium', 'HEU','Plutonium with water', 'Plutonium with plywood', 'Plutonium with iron', 'HEU with water', 'HEU with plywood', 'HEU with iron', 'Du plates'(100x10).
- Non-Threat: 'Silicon Oxide', 'Weld Pod 2% Th', 'Weld Pod 2% Th with iron', 'Potassium Chloride (KCl)', 'Bare background', 'Lightly shielded background', 'Heavily shielded background', 2 cases of CT 'Ho-166m', 1 case of CT 'Tc-99m'.

Testing set: 944 cases, 80 threat cases, 864 norm cases. Divide all cases' energy count by 4 because 4 detectors.

- Threat: Pu, HEU. Non-Threat: Ho-166m,Tc-99m, I-131 and others

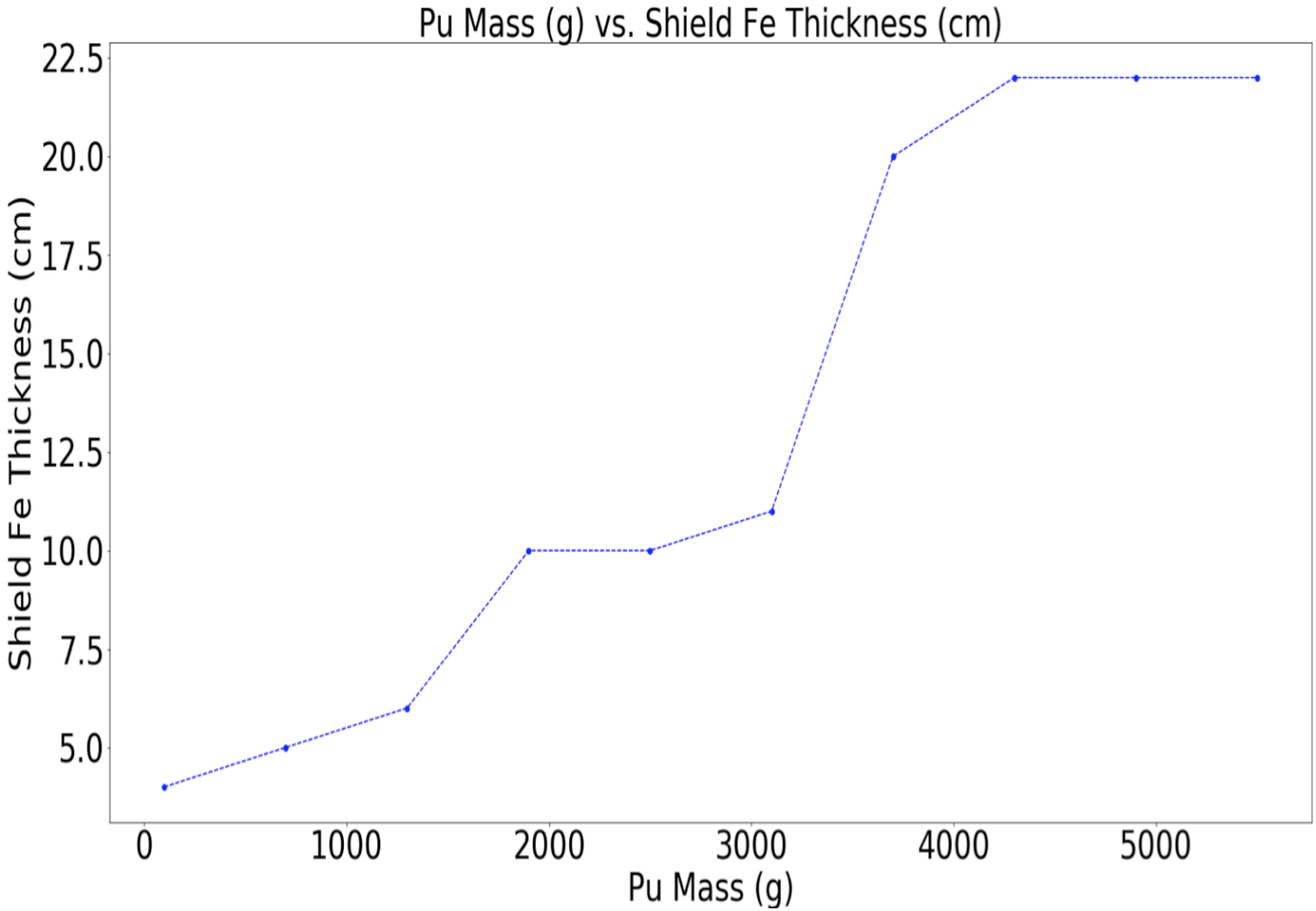
Training Accuracy: 1.0,Testing Accuracy: 0.1557,False Positive Rate 0.8873,True Positive Rate 0.6024

50/83 threat correct: 16 HEU (2.5 kg) in DU Spheres (2pc), 15 WgPu Sphere .5 steel, 15 WgPu Puck in DU spheres (2pc), 3 DU plates, 1 WgPu Puck.

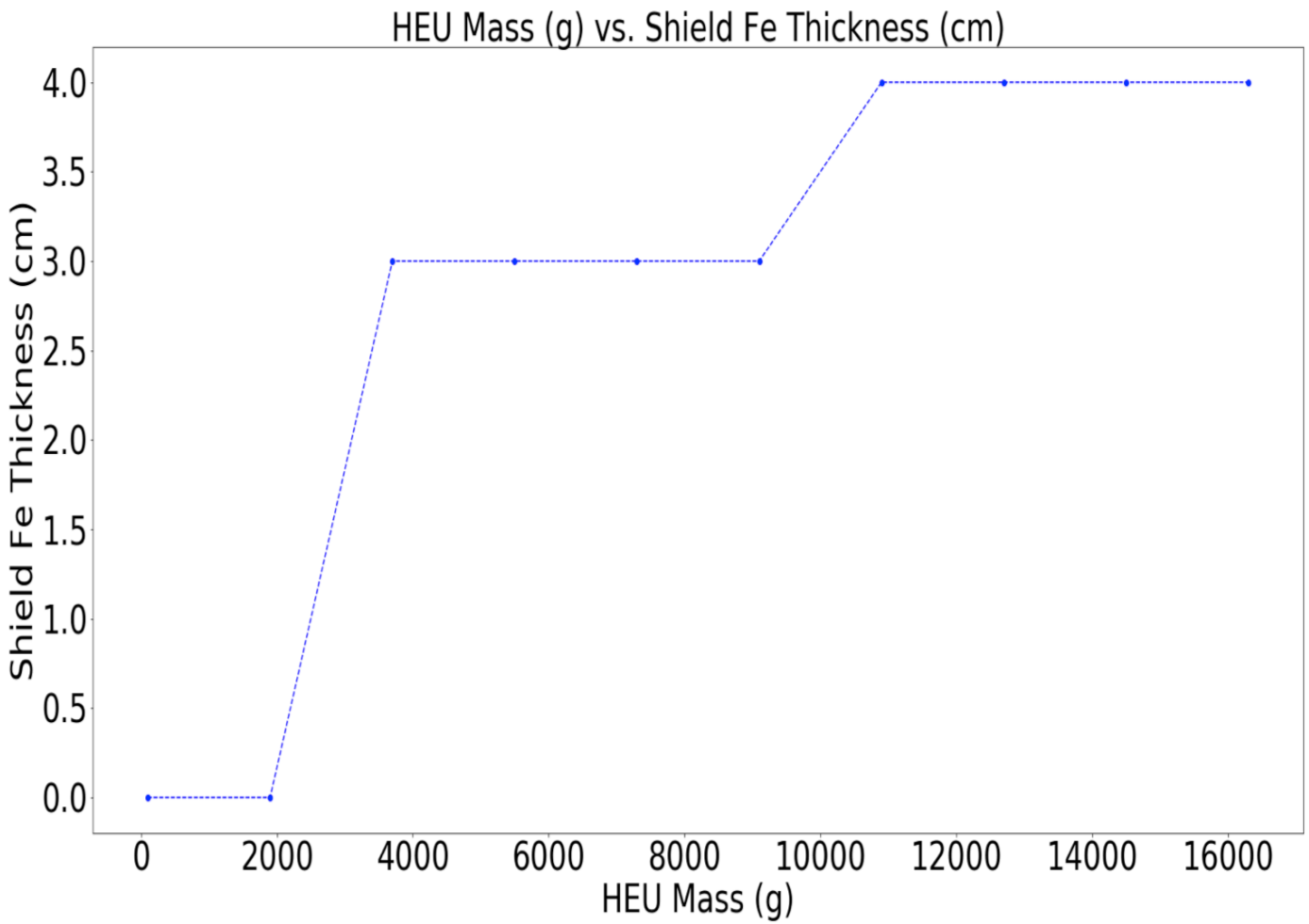
97/861 Non Threats correct: 84 Tc-99m, 10 Ho-166m, 2 Th + Co-60, 1 Co-60

33/83 Threat incorrectly: 16/16 HEU (25 kg bare), 14/15 WgPu Puck, 0/15 WgPu Sphere .5 steel, 3/3 HEU 25 kg in Al, 0/16 HEU (2.5 kg) in DU Spheres (2pc) and 0/15 WgPu Puck in DU spheres (2pc), 0/3 DU plates.

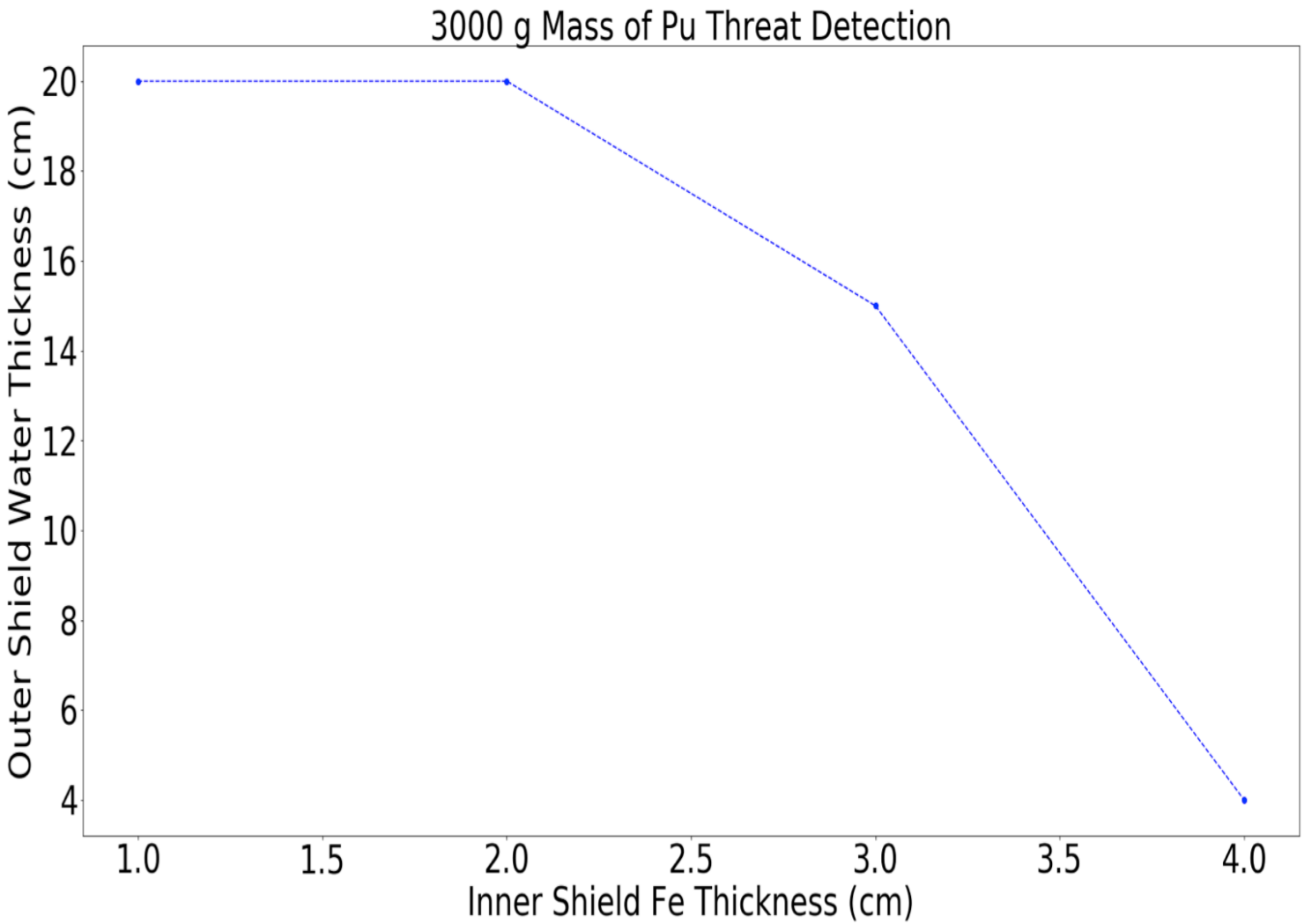
Pu with Fe Shielding Threat Detection
Only train and test using Gamma features



HEU with Fe Shielding Threat Detection
Only train and test using Gamma features

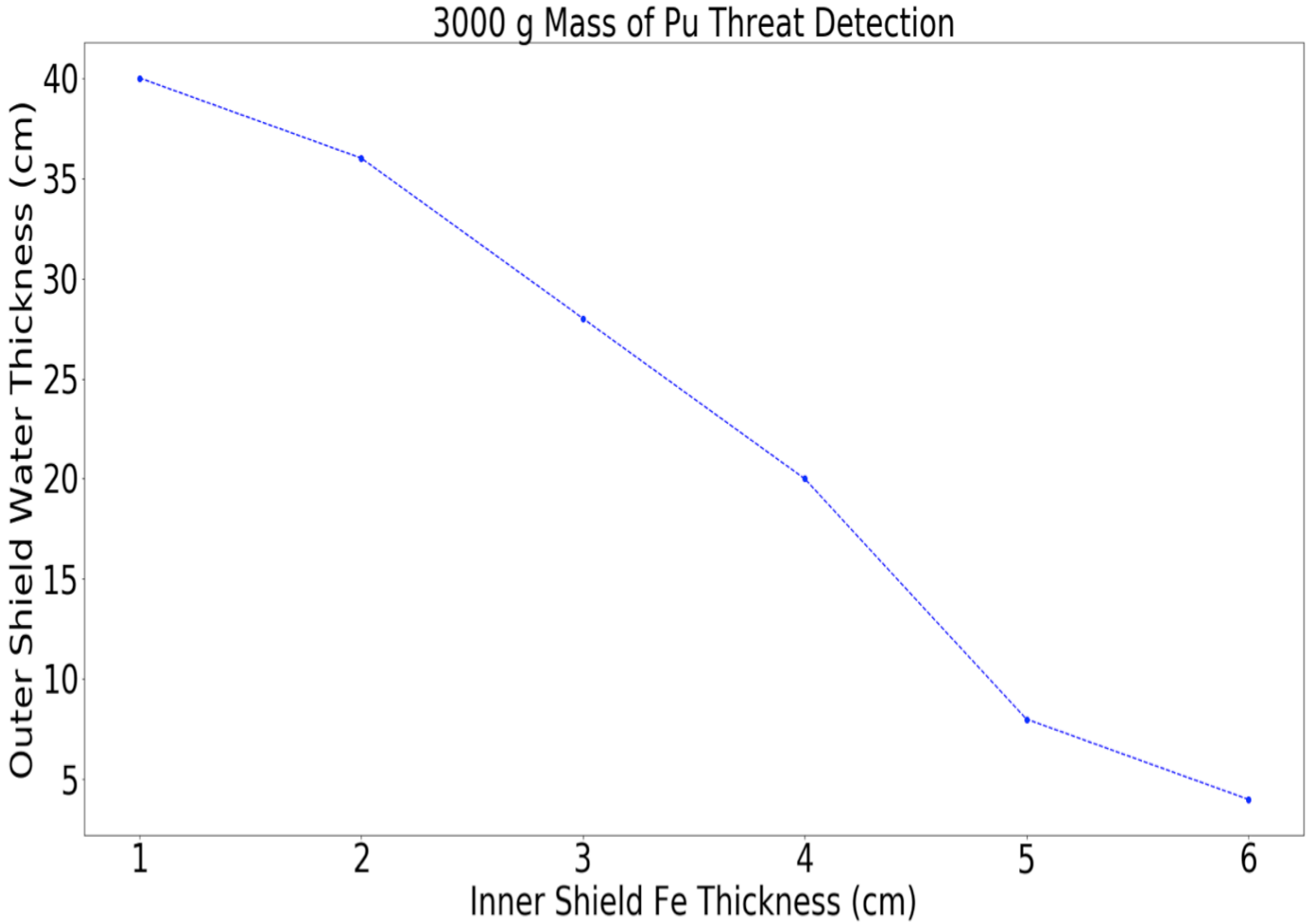


3000g of Pu with Fe and Water Shielding Threat Detection
Only train and test using Gamma features

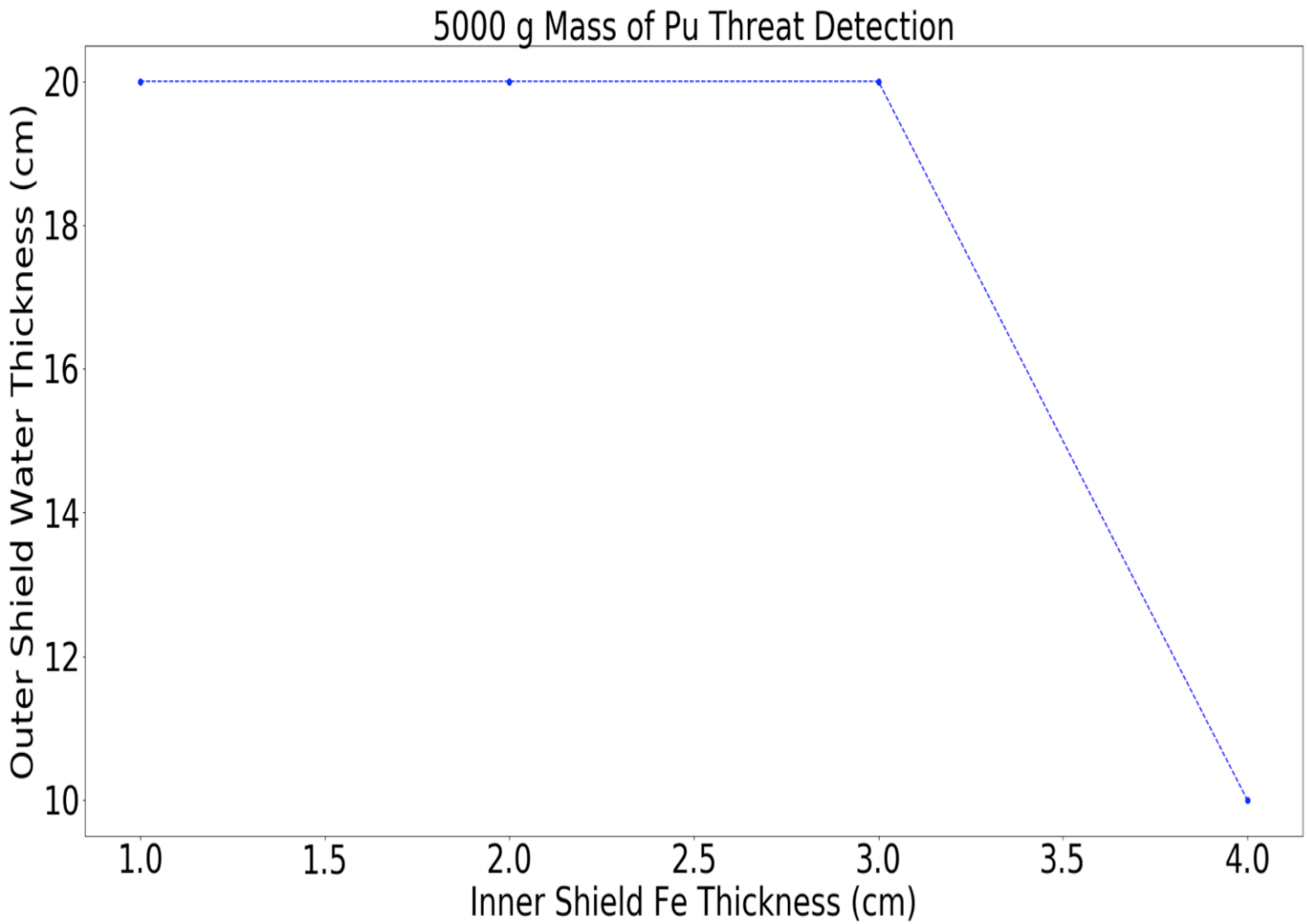


3000g of Pu with Fe and Water Shielding Threat Detection

Only train and test using Neutron features when testing cases are not included in the training

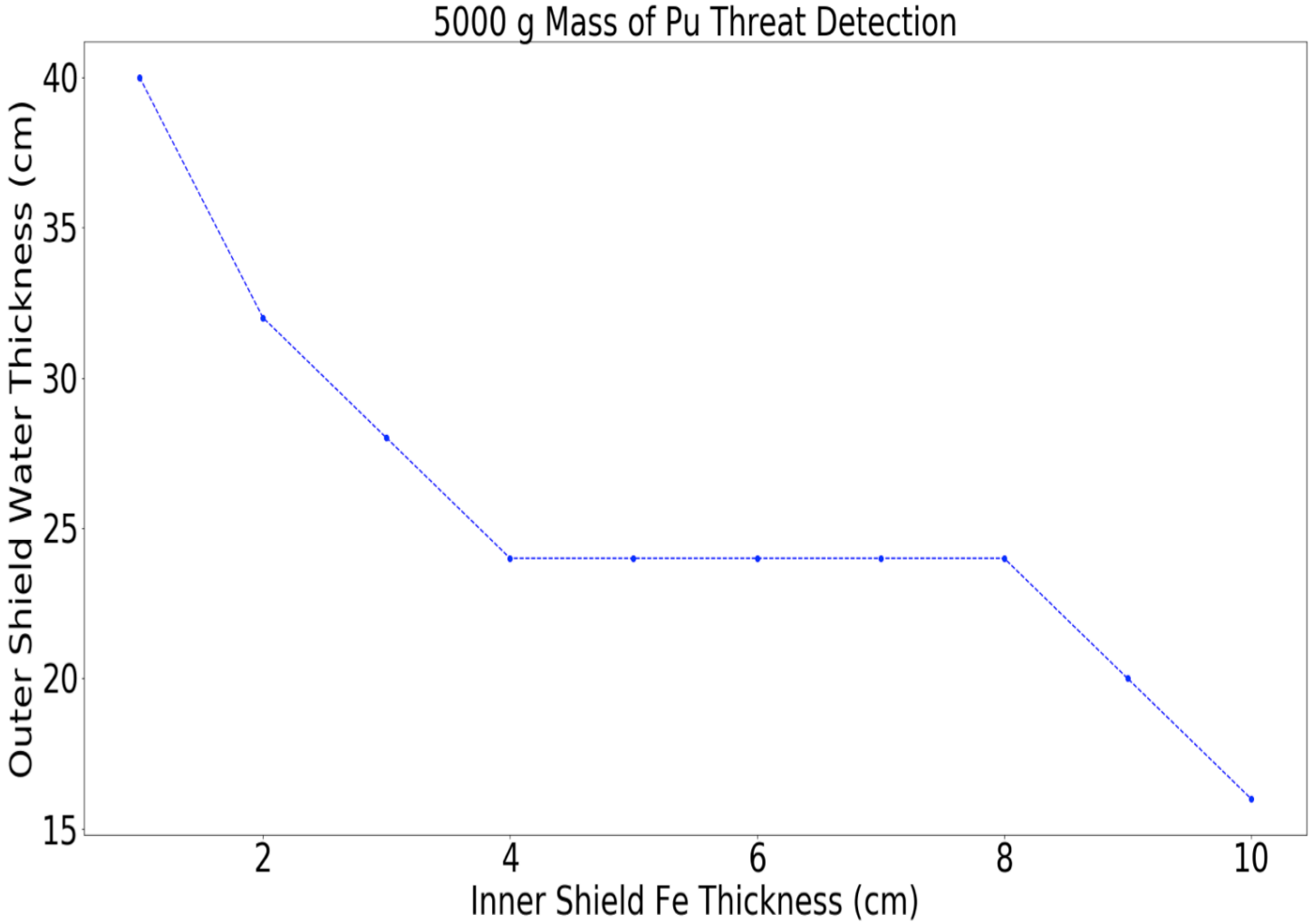


5000g of Pu with Fe and Water Shielding Threat Detection
Only train and test using Gamma features



5000g of Pu with Fe and Water Shielding Threat Detection

Only train and test using Neutron features when testing cases are not included in the training



Pu with Fe and Water Shielding Threat Detection
Only train and test using Neutron features

After All 3000/5000g Pu with 1-10 cm inner Fe shielding and 4-40 cm outer Water shielding cases are included in the training set, all the cases were classified as threat.