**Contract No:**

This document was prepared in conjunction with work accomplished under Contract No. 89303321CEM000080 with the U.S. Department of Energy (DOE) Office of Environmental Management (EM).

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# TRAINED DEEP CONVOLUTIONAL NEURAL NETWORK FOR ATTENUATED GAMMA-RAY DETECTION USING CdZnTeSe SPECTROMETER

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IEEE NPSS NUCLEAR & PLASMA SCIENCES SOCIETY

2021 IEEE NSS MIC

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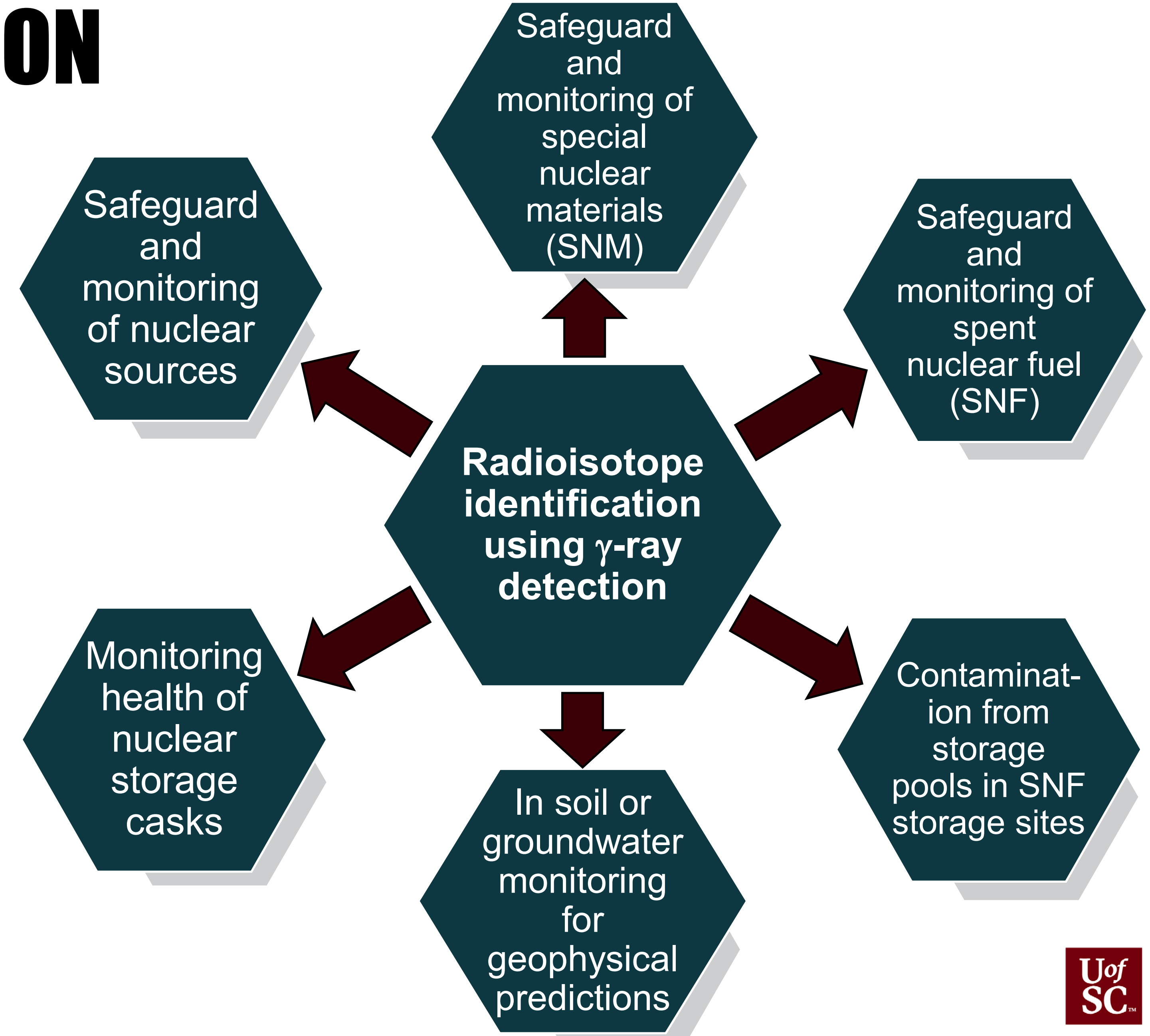
SRNL-STI-2021-00569

Session: N-21, Paper ID: 1171, Date: 10/21/2021

# INTRODUCTION

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# INTRODUCTION

$Cd_xZn_{1-x}Te_{1-y}Se_y$ (CZTS)[1-4]

Wide Bandgap $\geq$ 1.6 eV

High crystal growth yield ≥ 90%

Room temperature operation

Leads to lower production cost

[1]Roy et al., Sci. Rep. 9, 7303 (2019).
[2]Chaudhuri et al., J. Appl. Phys. 127, 245706 (2020).
[3]Chaudhuri et al., IEEE Electron. Dev. Lett. 41(9), 1336 (2020).
[4]Kleppinger et al., IEEE Trans. Nuclear Sci. 68(9), 2429 (2021).

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# INTRODUCTION

## Challenges in field applications

- Background radiation
- Noise in the detection system
- Attenuation and scattering of radiations
- Variation in the source-detector geometry
- Weak source strengths

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# INTRODUCTION

- Uncertainties involving radiation detection in such field applications cannot rely on simple peak detection algorithms and requires trained spectroscopist to manually analyze the detector signals to identify any anomalies.
- A cost-effective alternative is to employ trained algorithms, coupled to high resolution gamma detectors, to identify the gamma rays in less time, possibly durations as short as a few seconds.[1-3]
- A machine learning (ML) model that trains a convolutional neural network (CNN) to predict the energy of gamma rays has been developed.

[1]M. E. Medhat, Ann. Nucl. Energy 45, 73 (2012).
[2]W. P. Ford et al., arXiv: 1908.11207v1 (2019).
[3]M. Kamuda et al., IEEE Trans. Nucl. Sci. 64(7), 1858 (2017).

# INTRODUCTION

- Unlike the existing ML techniques for energy-based gamma-ray classification, which generally uses pulse height spectra to train the algorithm,[1-3] the present approach uses raw digital pulses from a spectrometer to train the CNN.
- The present technique has all the agility of digital spectroscopy and is expected to be versatile and time-efficient.
- The present scheme uses simulated charge pulses, resembling those obtained from gamma-ray interactions with a planar CdZnTeSe detector, to train a CNN.

[1]M. E. Medhat, Ann. Nucl. Energy 45, 73 (2012).
[2]W. P. Ford et al., arXiv: 1908.11207v1 (2019).
[3]M. Kamuda et al., IEEE Trans. Nucl. Sci. 64(7), 1858 (2017).

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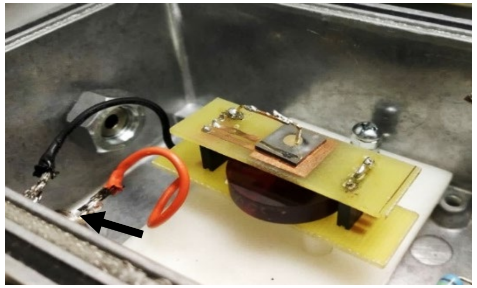
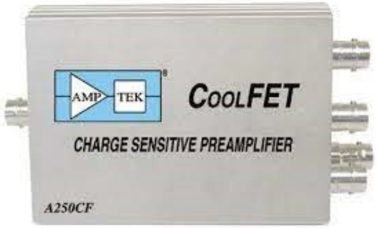
# DATA SIMULATION

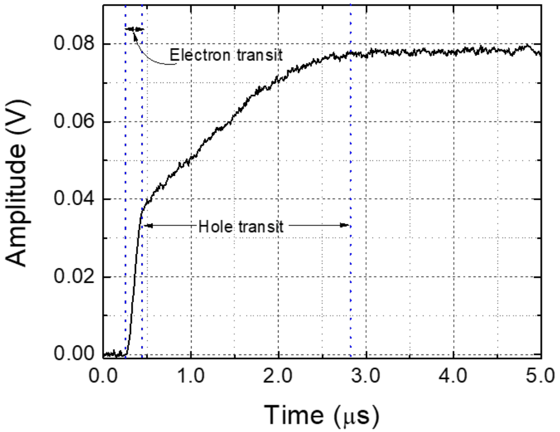


Detector-source assembly




Amptek A250CF pre-amplifier


NI PCI 5122 digitizer card




A typical charge pulse obtained from the CZTS detector exposed to 662-keV gamma rays.

- Charge pulses have been simulated to resemble the output of a digital spectrometer used in our laboratory as shown in the figure below.
- The simulation has been done using an in-house coded MATLAB program.
- Photoelectric and Compton events for different energies ranging from 5 keV to 5 MeV have been simulated.
- Each energy has 10000 pulses randomly generated to simulate a near-real situation.

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# DATA SIMULATION

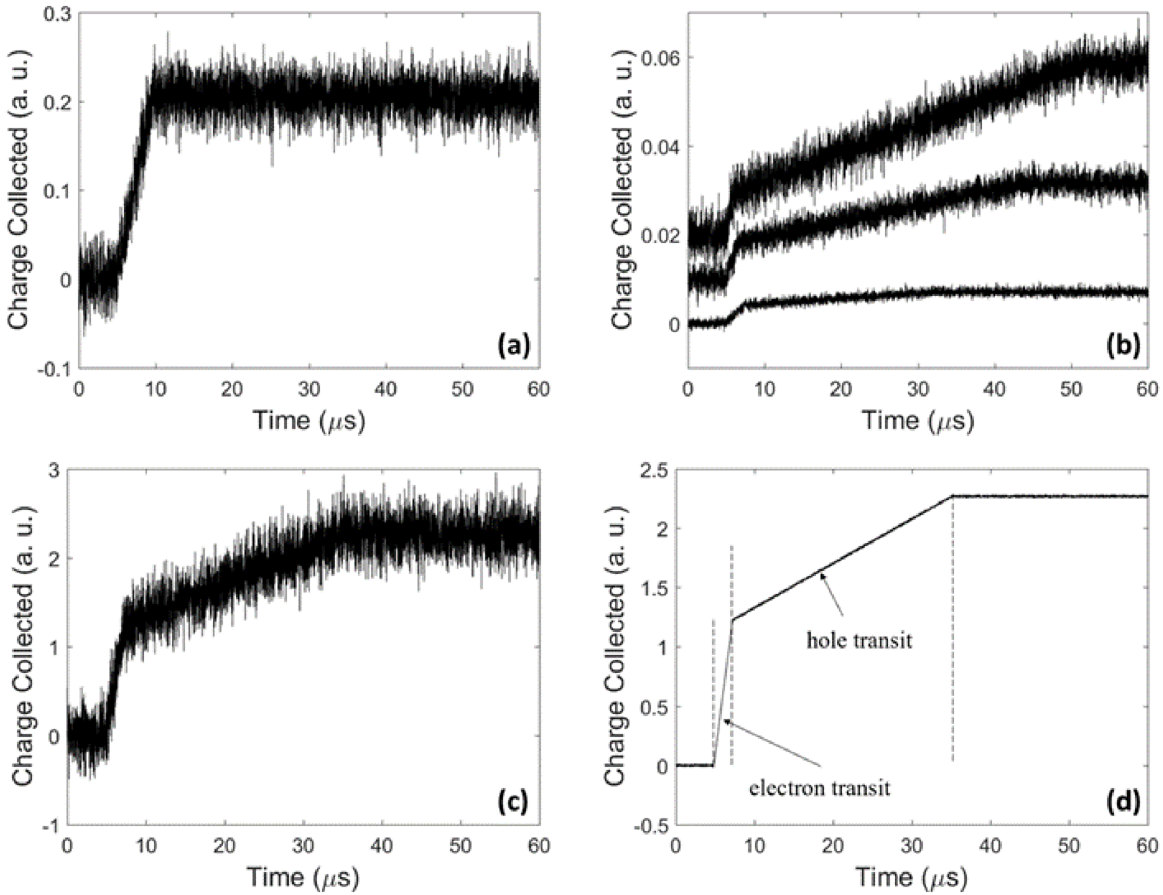


**Fig.** Simulated evolution of charge pulses for (a) Photoelectric absorption for 60-keV gamma rays; (b) Compton scattering of 60-keV gamma interaction; (c) Photoelectric absorption of 662-keV gamma rays with a SNR = 20; and (d) Photoelectric absorption of 662-keV gamma rays with a SNR = 50.

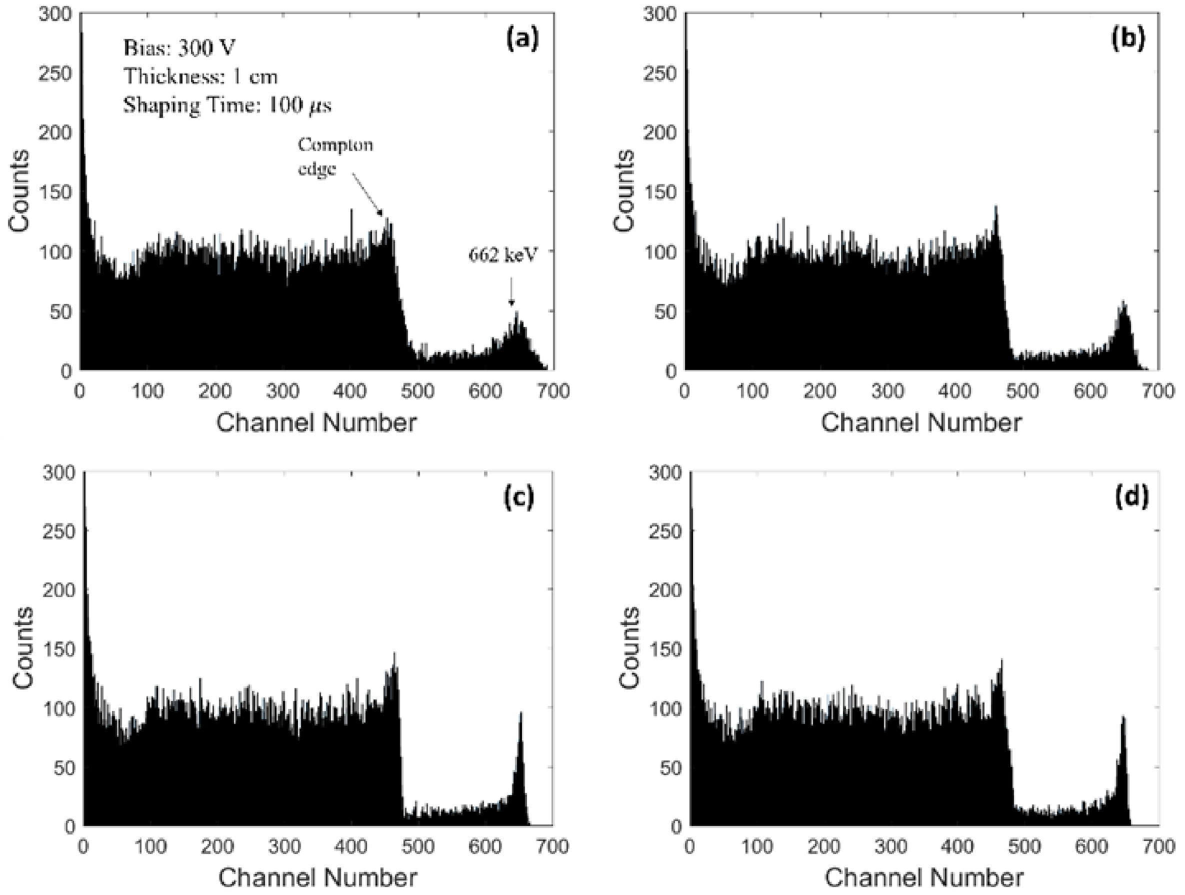


**Fig.** PHS generated using the simulated pulses with signal-to-noise ratios (a) 5, (b) 10, (c) 30, and (d) 70.

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# THE CONVOLUTIONAL NEURAL NETWORK

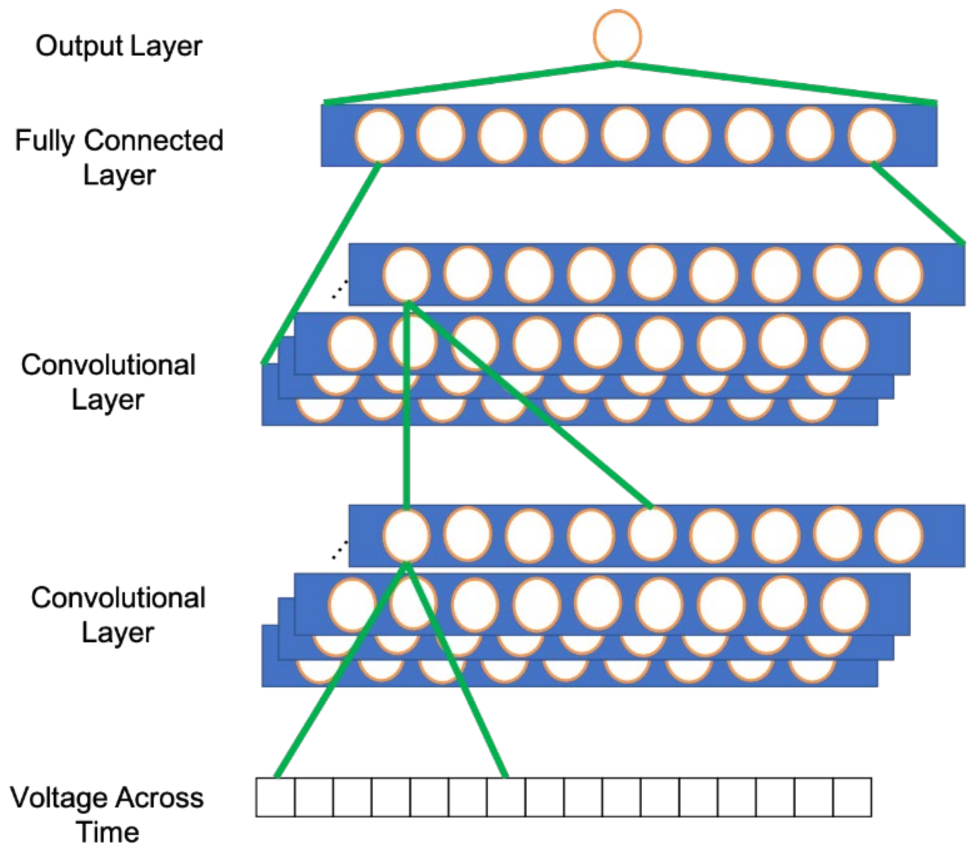


**Fig.** A one-dimensional convolutional neural network.

- The CNN has 7 1-dimensional convolutional layers with filters of size 11.[1]
- Each layer has 50 channels. The first 5 layers have a stride of 2, and the last two have a stride of 5.
- This is followed by a fully connected layer of size 1000 and another of size 1, which represents the energy prediction.

[1] Y. LeCun et al., Neural computation 1(4), 541-551, 1989.

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# THE CONVOLUTIONAL NEURAL NETWORK

- The CNN uses rectified linear activation functions[1] at all layers except the output layer, which is linear. The CNN also uses weight normalization[2] at all layers except the output layer.
- The CNN is trained for 1 million iterations using the ADAM optimizer.[3]
- The learning rate is initialized at 0.001 and is halved if the validation accuracy does not increase within 5,000 iterations.

[1]K. Jarrett et al., 2009 IEEE 12th International Conference on Computer Vision, pp. 2146-2153, 2009.

[2]T. Salimans et al., Weight normalization: A simple reparameterization to accelerate training of deep neural networks. Advances in neural information processing systems 29, 901-909, 2016.

[3]D. P. Kingma et al., A method for stochastic optimization. arXiv preprint arXiv:1412.6980, 2014.

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# VALIDATION OF THE CNN ARCHITECTURE

- A CNN was trained on the equivalent of 90% of the simulated data and validated on 10% worth of simulated data.
- The CNN estimates the energy level of the source using 0.28 msec of data.
- The results of our tests are shown in Fig. 5, which shows that the predictions of the CNN are within 0.3% of the actual energy except at lower energies where the percentage error is below 1%.

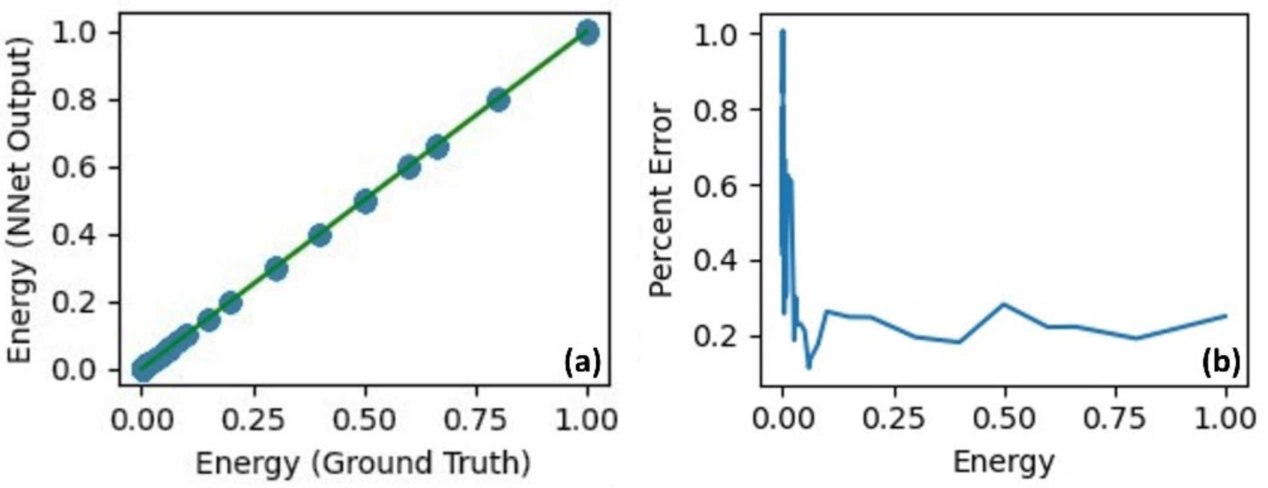


Fig. 5 (a) Correlation plot of the predicted energy [NNet (Neural Network) Output] and actual energy (Ground Truth).
(b) Dependence of the error of prediction on incident gamma energy.

# CONCLUSIONS

- A convolutional neural network (CNN) has been trained using simulated data resembling that obtained from a CdZnTeSe detector.
- CdZnTeSe detectors are a cost-effective alternative of expensive high-resolution CZT detectors.
- The simulated data resemble raw charge sensitive pre-amplifier pulses instead of shaped pulse height spectra.
- The digital approach is faster, cost-effective, and flexible than conventional machine learning approaches.
- The CNN architecture discussed in this presentation demonstrated an overall accuracy of less than 1% with a detection period of a fraction of a millisecond.

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# FUTURE PLANS

- The CNN will be evaluated for real detector data, currently being acquired and processed, that has photoelectric as well as Compton background.
- The CNN will be trained to identify gamma energies after being heavily attenuated by concrete/steel shielding as happens outside a nuclear spent fuel storage cask.
- This will help in monitoring SNF from outside the storage casks.

# ACKNOWLEDGMENTS


- This research was funded by the DOE Office of Nuclear Energy's Nuclear Energy University Program (NEUP), Grant Nos. DE-AC07-051D14517 and DE-NE0008662.

- The work has also been supported in part by the Advanced Support Program for Innovative Research Excellence-I (ASPIRE-I, Track 2) of the University of South Carolina (U*of*SC), Columbia, Grant# 155300-21-56895.


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# THANKS!

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