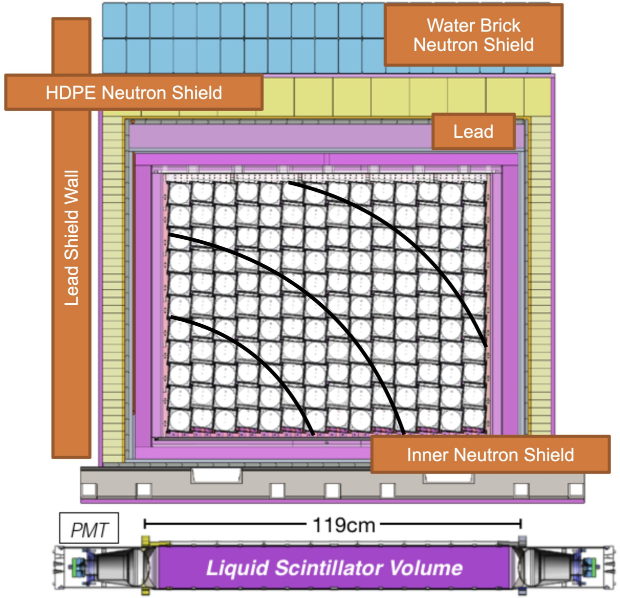
Machine Learning applications for Ortho-Positronium tagging in liquid scintillator for the PROSPECT experiment

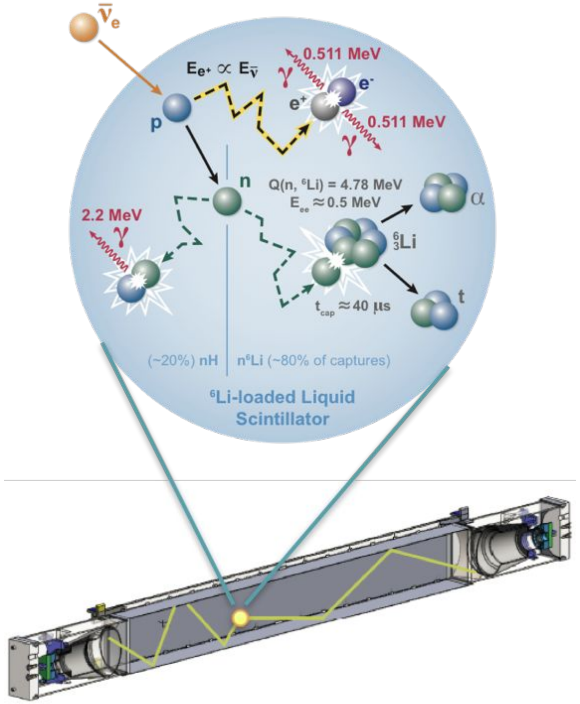
Blaine Heffron

Diego Venegas Vargas

PROSPECT Overview

PROSPECT took data at ORNL's High Flux Isotope Reactor from 2018-2019. It is a highly enriched uranium reactor with a compact core

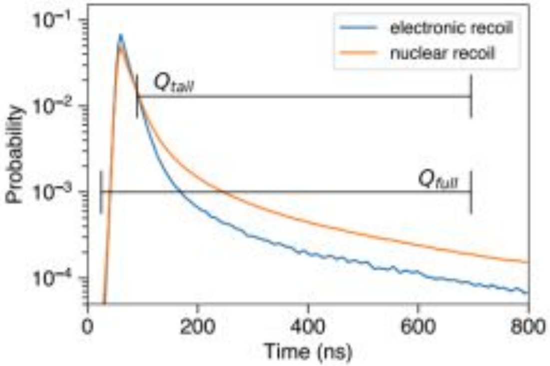


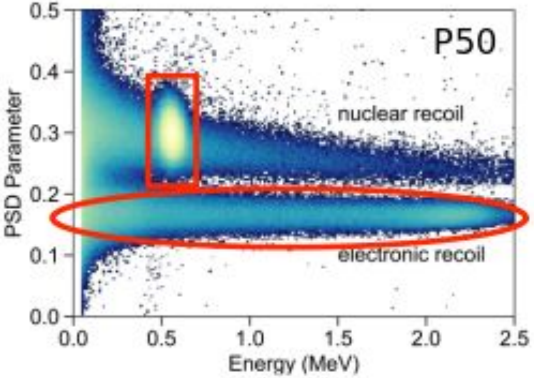


14 x 11 array of 6Li doped liquid scintillator for detecting inverse beta decay from reactor antineutrinos (6m from compact highly enriched uranium reactor core)

ML to improve analysis

- Currently use tail-fraction method for pulse shape discrimination method to discriminate particles (electron-like recoil vs nuclear recoils)
- PSD and energy can be used to separate nLi capture events quite well, but electrons, gammas, and positrons are difficult
- Positron tagging using topology, possible use of Ortho-positronium formation to improve this?

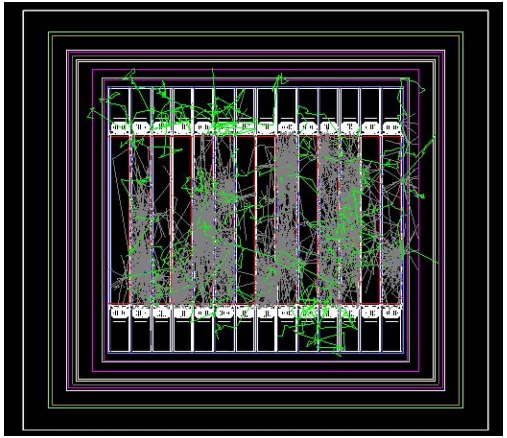


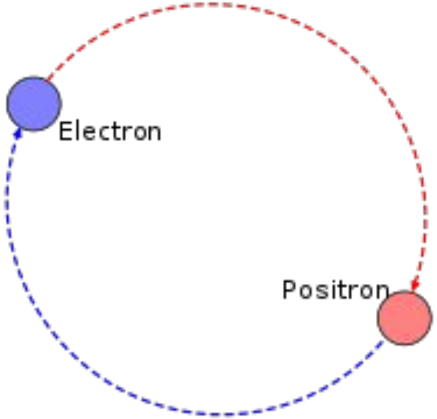


**See A. Delgado's talk for an overview of ML activities for PROSPECT and X. Lu's talk tomorrow at 11:06 for ML applications on single ended event reconstruction

Positron ID through o-Ps tagging

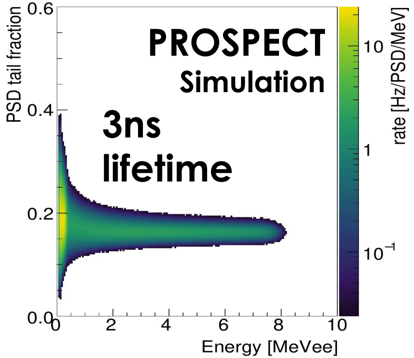
- Can we ID a subset of **positrons** though positronium formation?
- If the distortion in the **timing distribution** induced by **o-Ps** is not smeared by optical effects, we can use this feature as an extra handle for particle ID (P-ID).
- Initial optical simulations indicate that we are not sensitive to a 3ns OPs lifetime

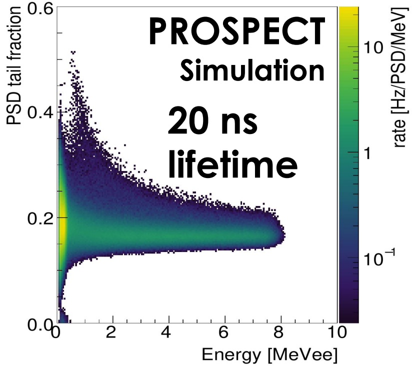




Para Positronium, (t=1, 2.5ns)

Ortho Positronium, (t=1,140ns)





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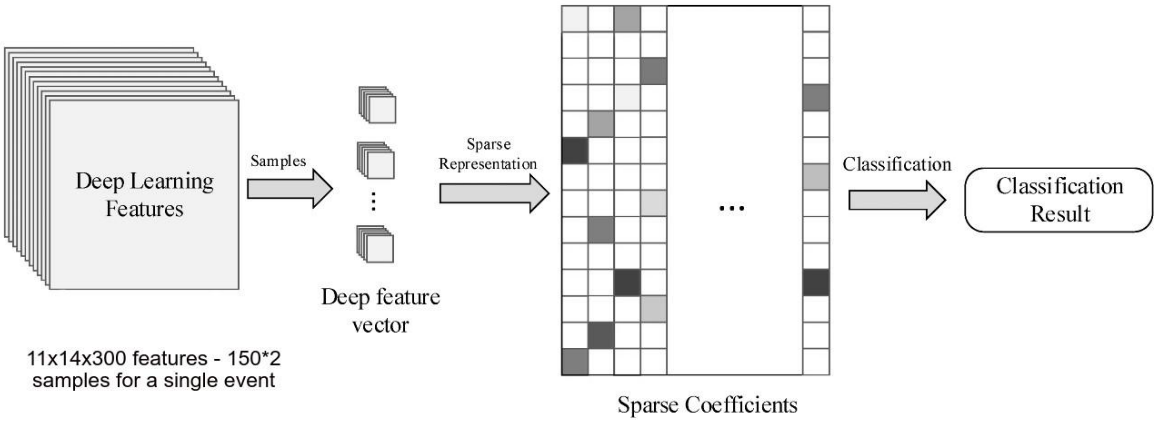
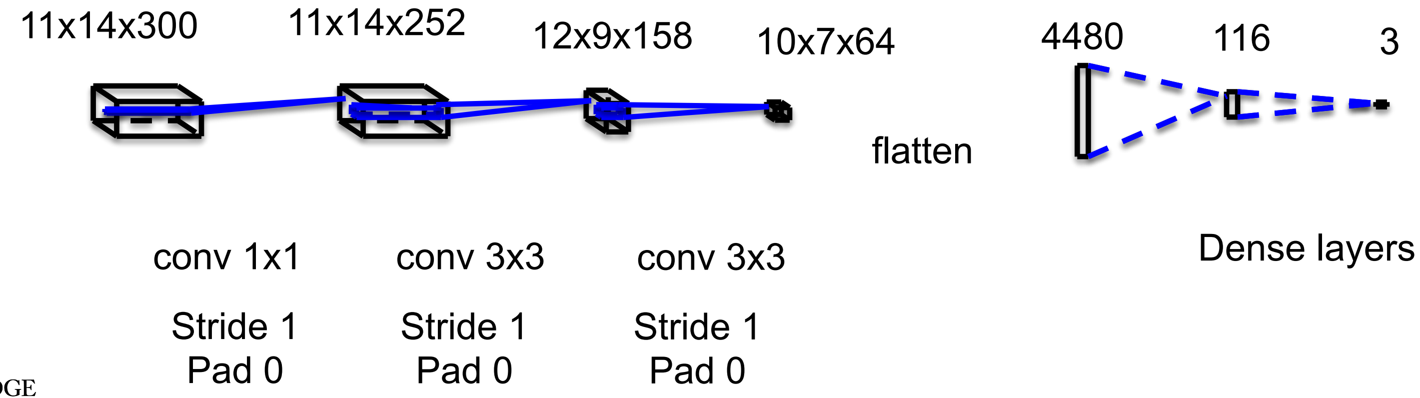
ML techniques

- Sparse convolutional neural networks are used to identify patterns in the energy deposition of various particles for particle discrimination
- PyTorch Lightning ML framework used for quick start to scalable multithreaded / GPU friendly code
- Spconv sparse convolutional library for pytorch
- Simulated gammas, electrons, positrons between 0-9 MeV randomly distributed within the detector

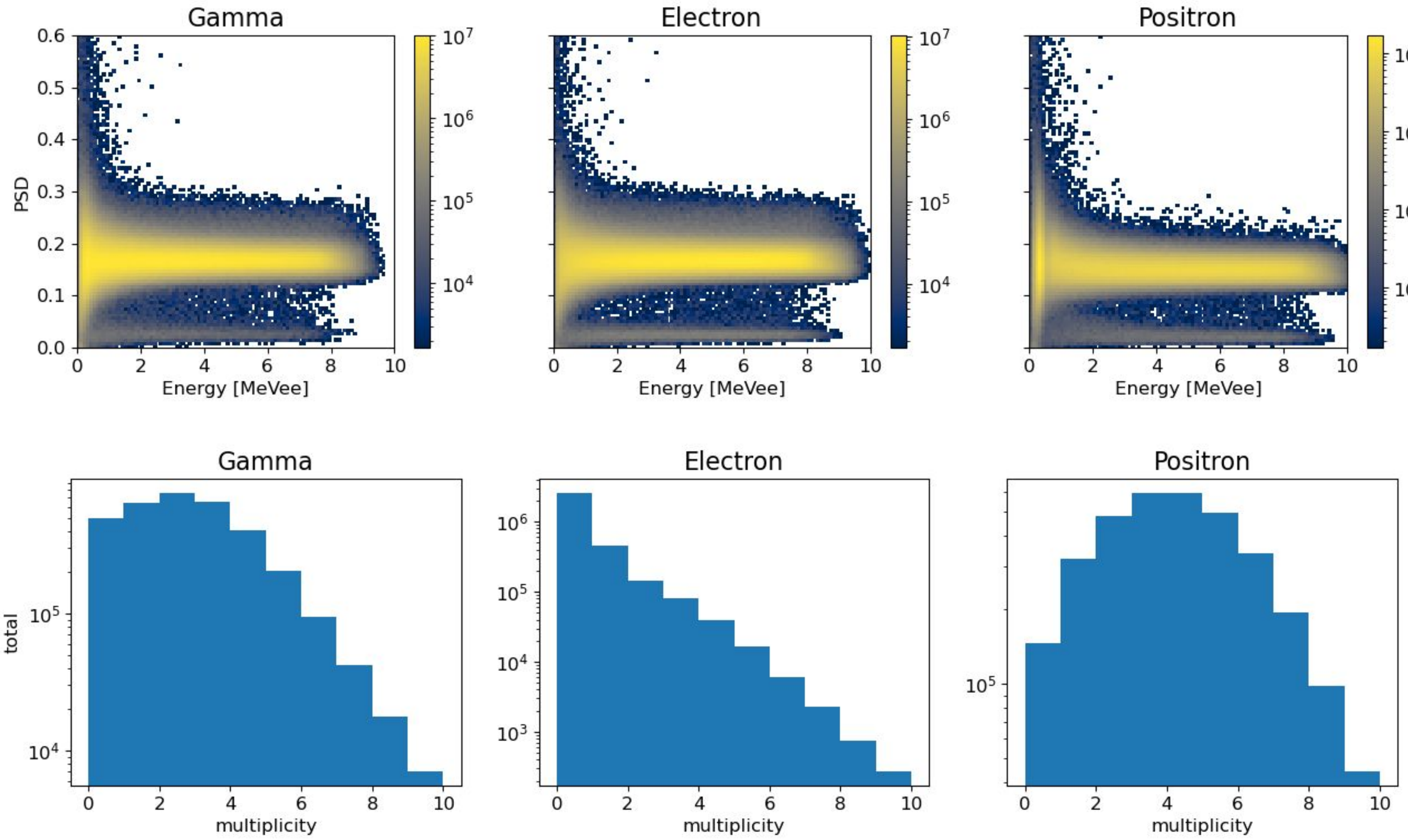
Particle Classification ML Architecture

- Sparse CNN -> linear
- Minimize cross entropy loss
- Stochastic gradient descent with Nesterov momentum

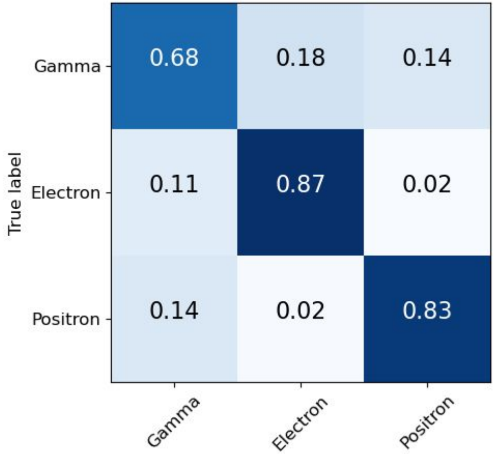




Simulated distributions



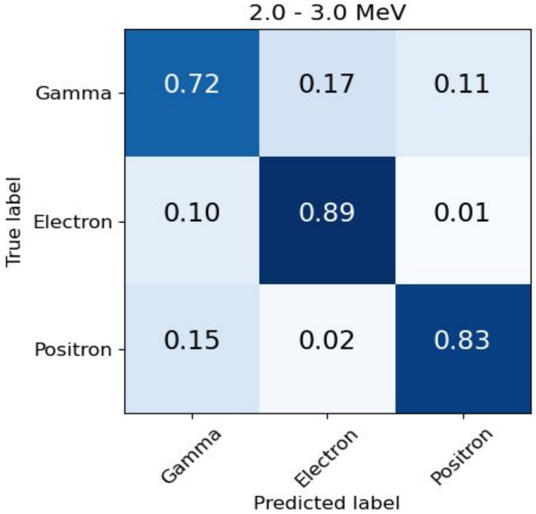
Best Trial Results

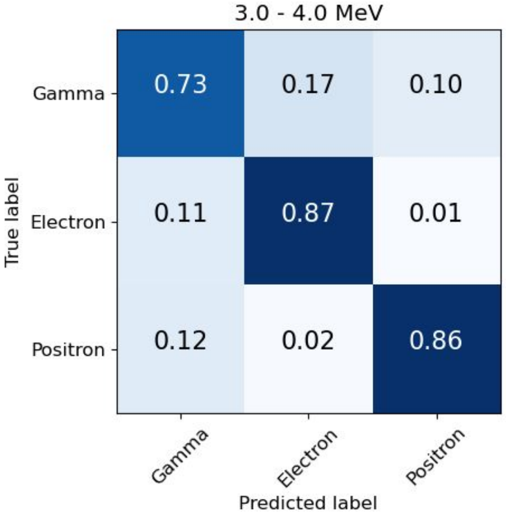


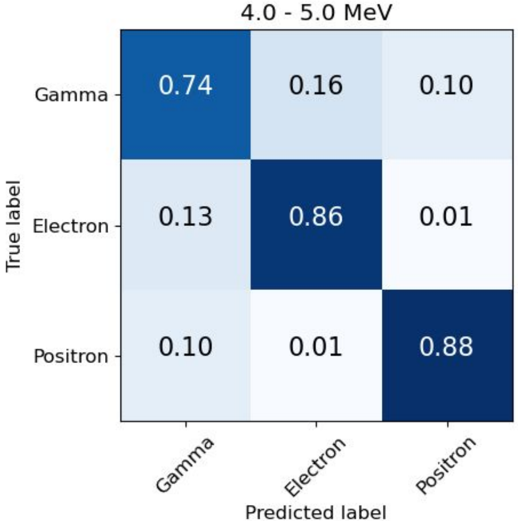
Best trial found after hyperparameter optimization (~ 100 trials)

Used Optuna optimization framework
Hyperparameters tuned:

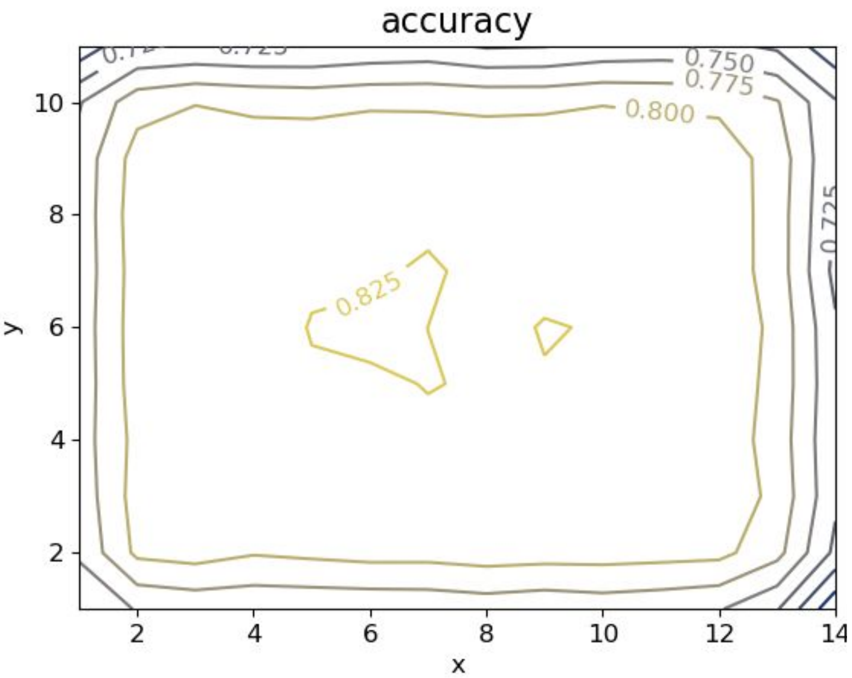
- number of convolutional layers
- number of linear layers
- number of output feature planes
- kernel size

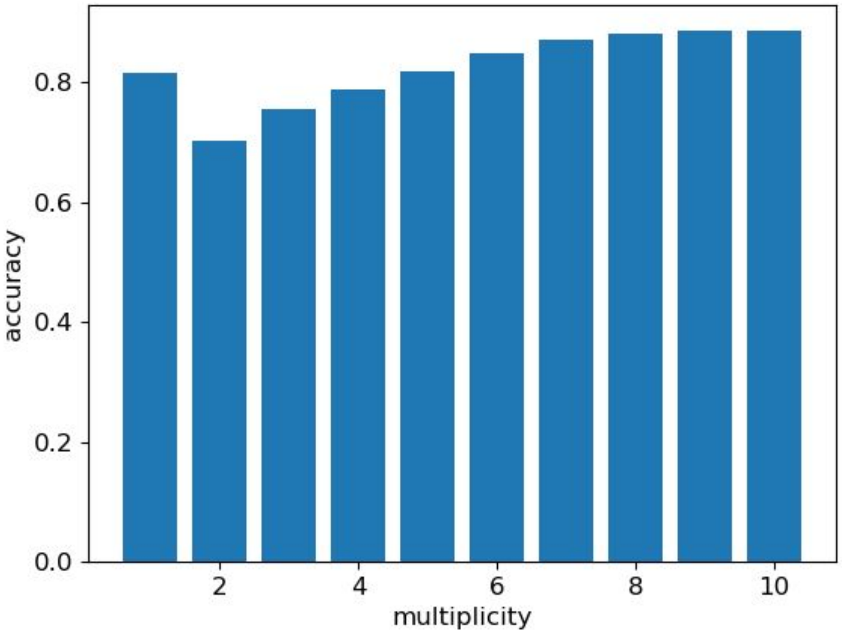




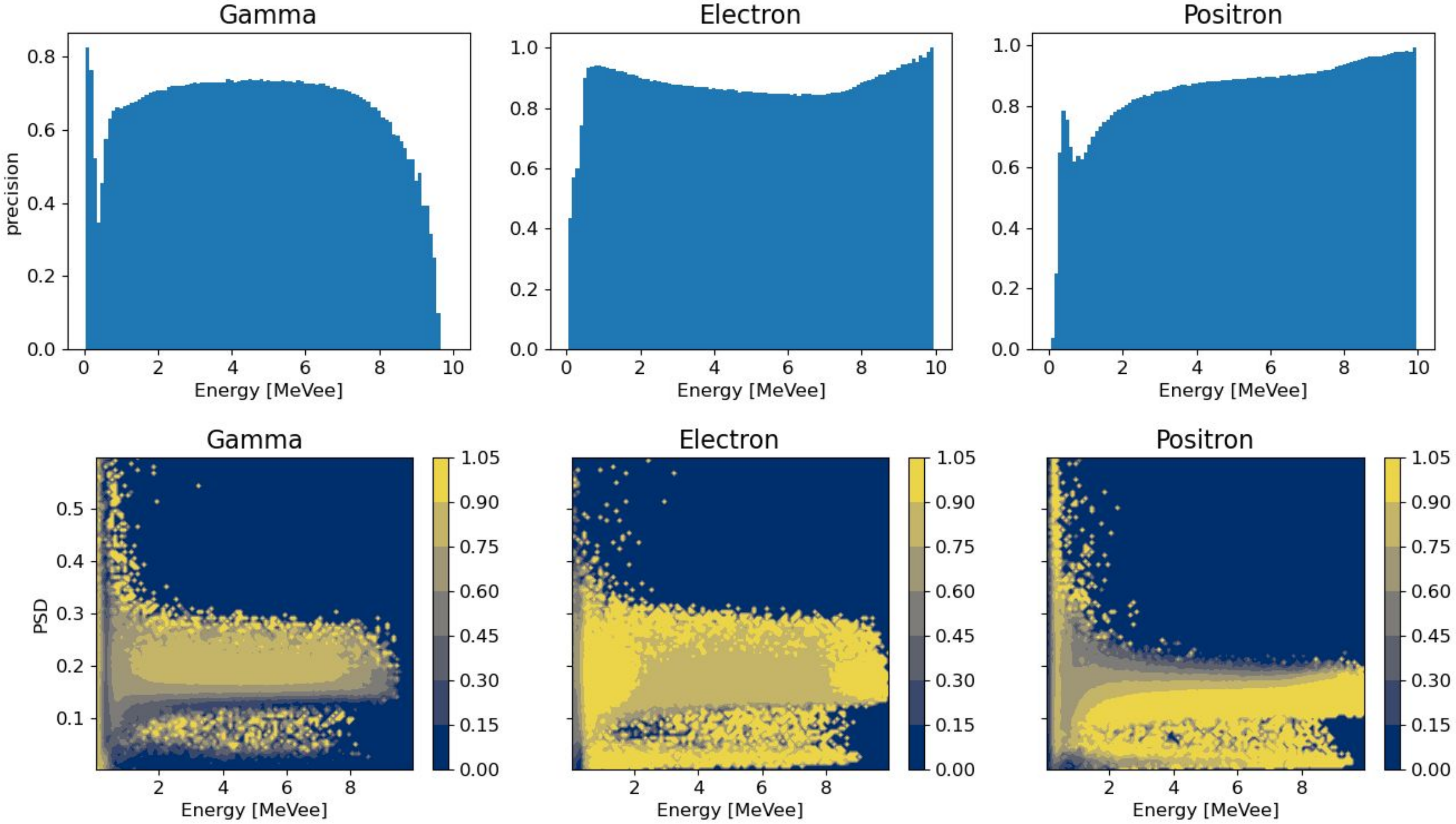


Accuracy Distributions



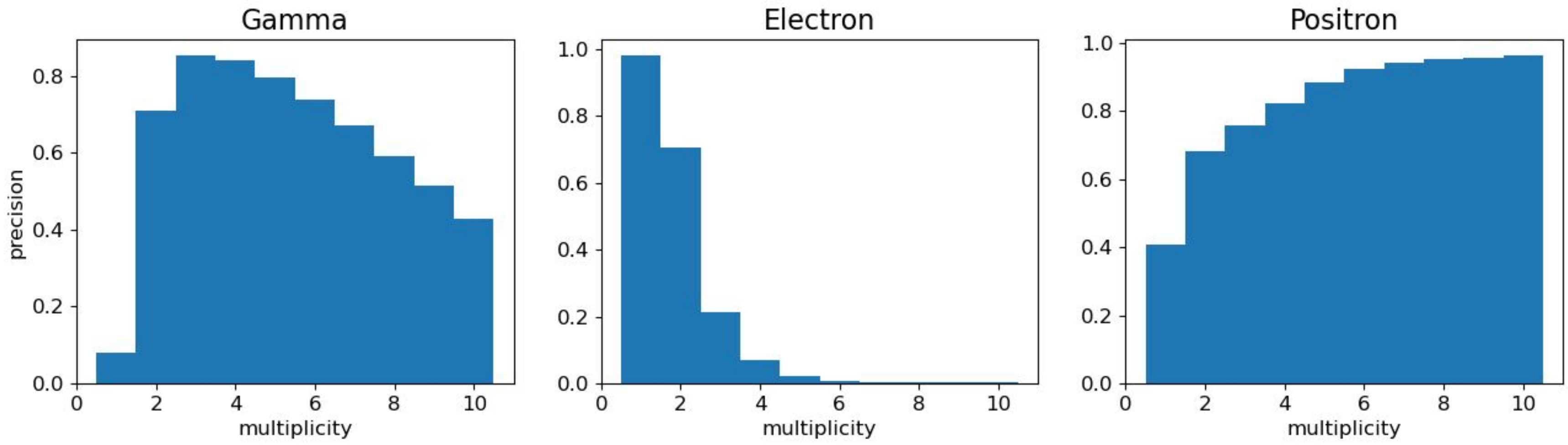


Precision vs Deposited Energy and PSD



Multiplicity Precision

- Multiplicity is important in the network's ability to distinguish
- More work needed to fully understand what the network is doing
  - Analyze statistical properties of pulses and topology of event



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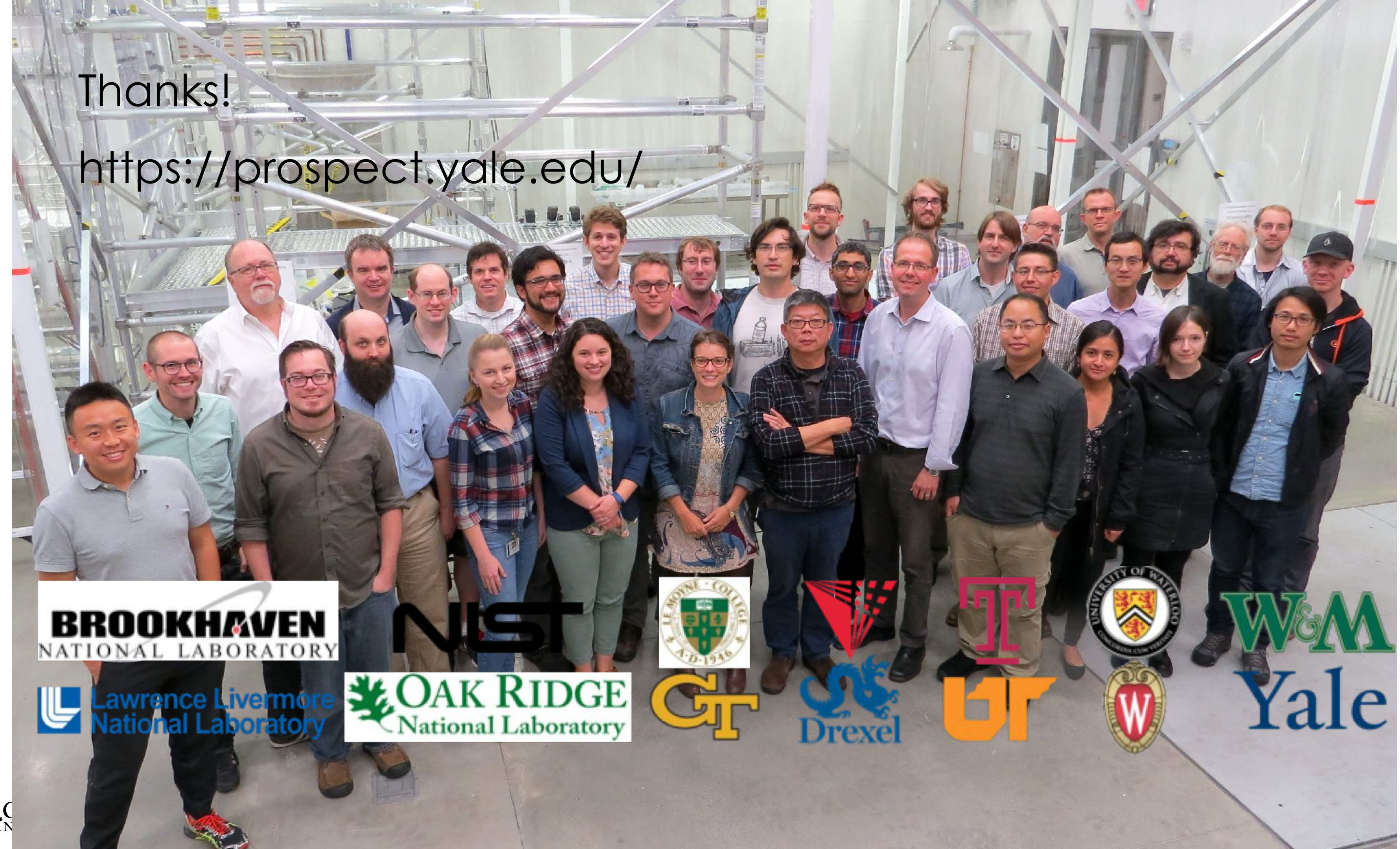
Conclusions / Future work

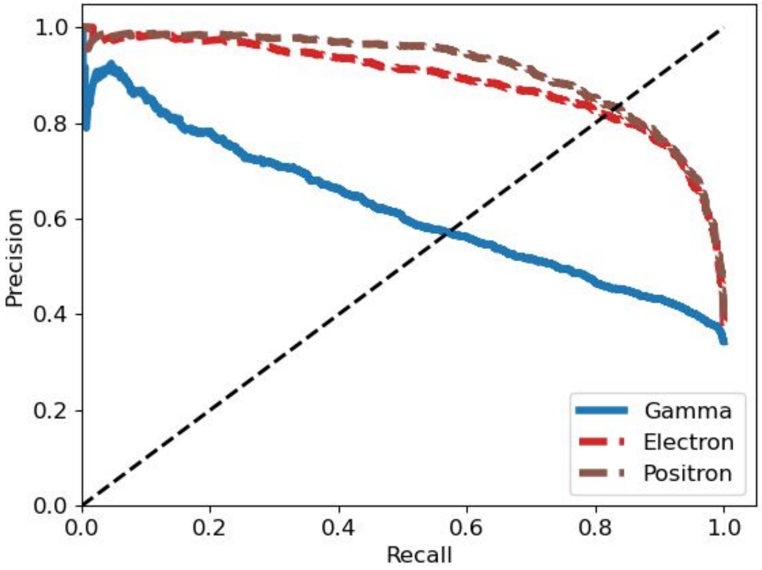
- Positrons within PROSPECT can be distinguished from gammas and electrons with up to 80% accuracy using sparse CNNs based on simulated waveform data
  - More work needs to be done to understand the physical signatures and if it is learning artifacts in the simulation
- We could not distinguish OrthoPositronium in PROSPECT based on simulation but could be a useful tag in gas based detectors or high temporal resolution detectors like TPCs
- Future work:
  - Try training on / classification of real pulse data from calibration runs
  - Incorporate sparse CNN information into classification of IBD candidates
  - Improve classification by utilizing image segmentation to identify different particles within a single event
  - Improve light simulation for more realistic simulated pulses

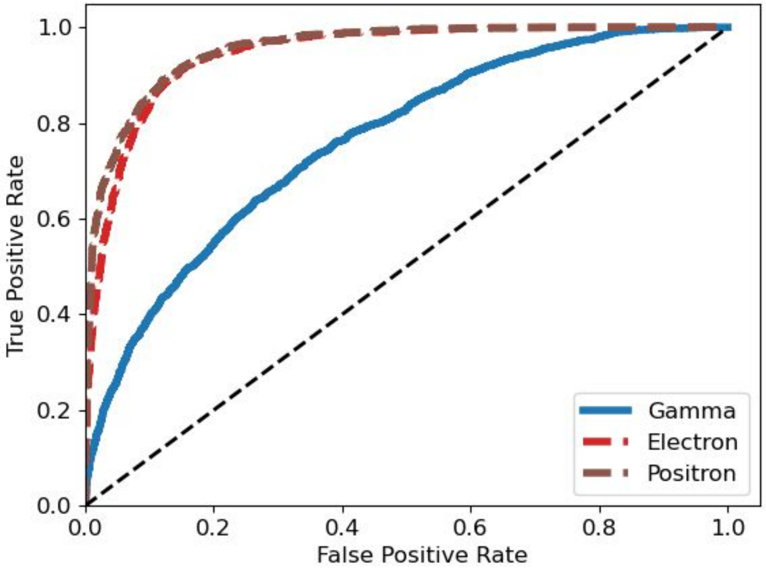
Thanks!

https://prospect.yale.edu/



Precision - Recall / ROC curves





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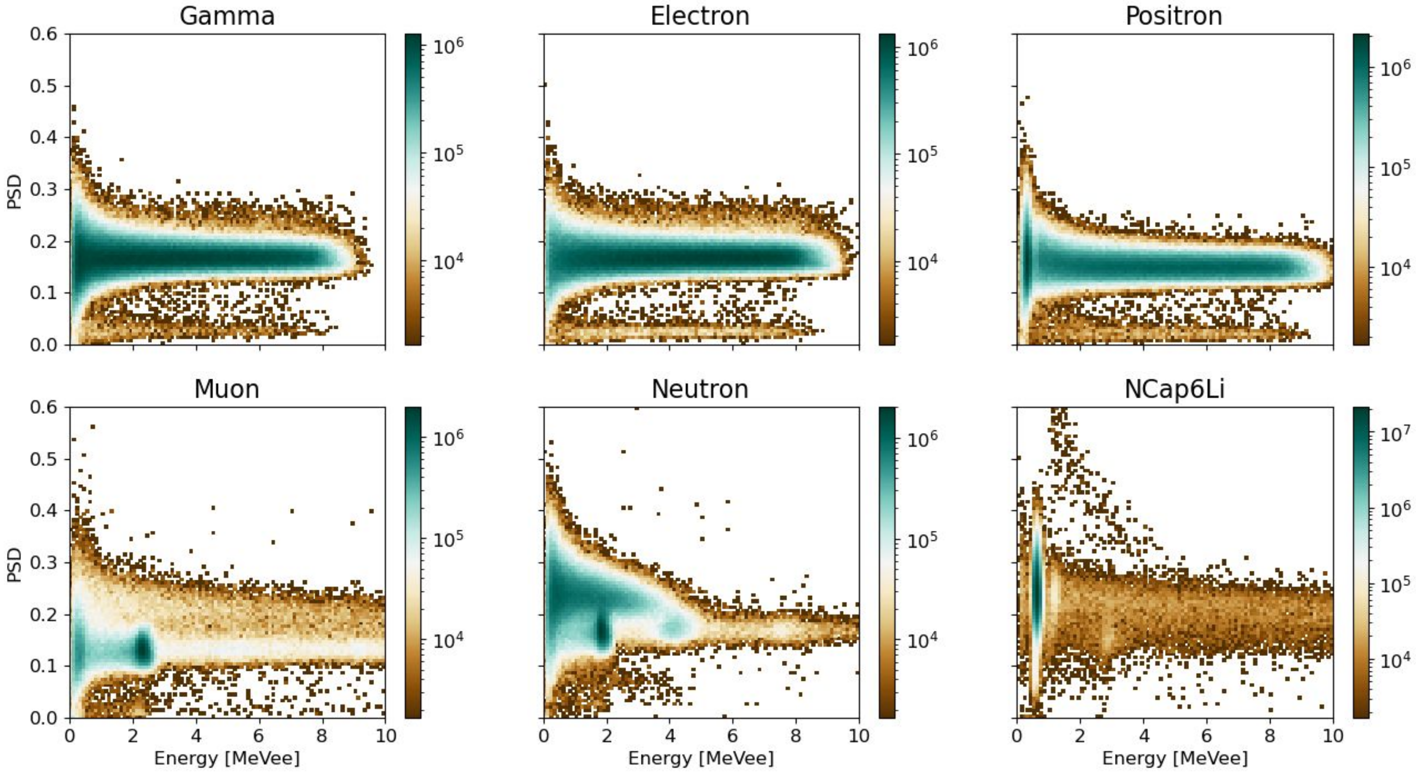
Simulated distributions



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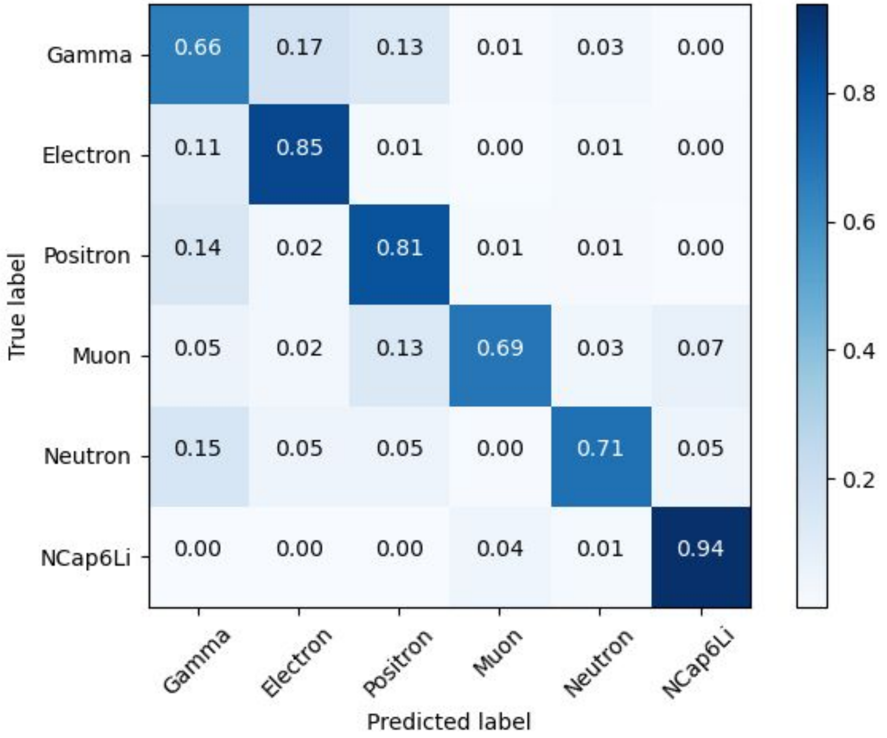
Best Trial Results

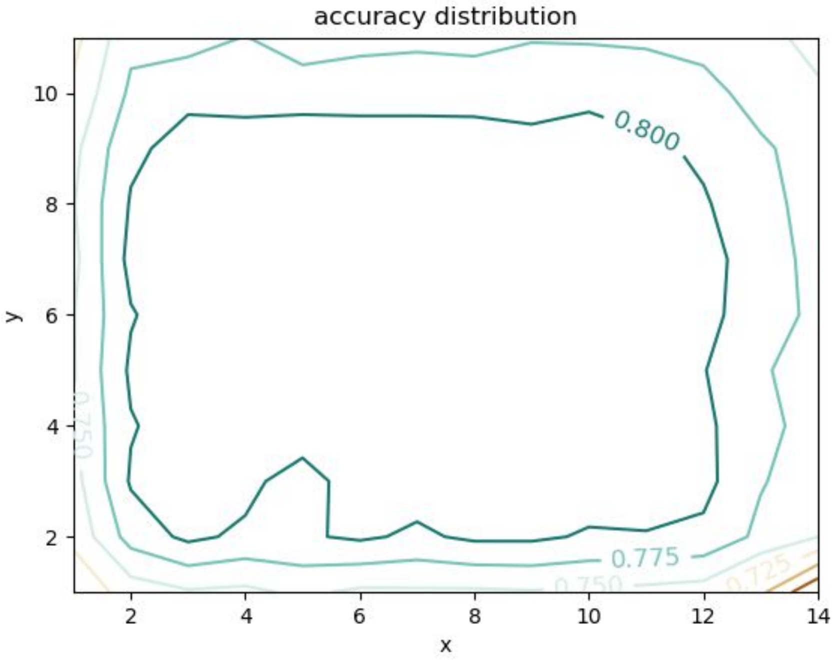


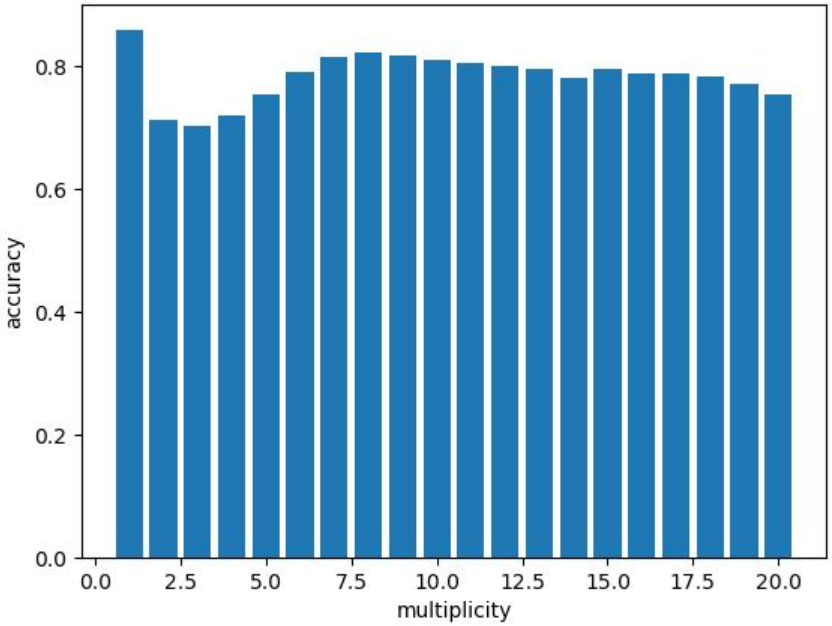
Best trial found after hyperparameter optimization (~ 100 trials)

Used Optuna optimization framework

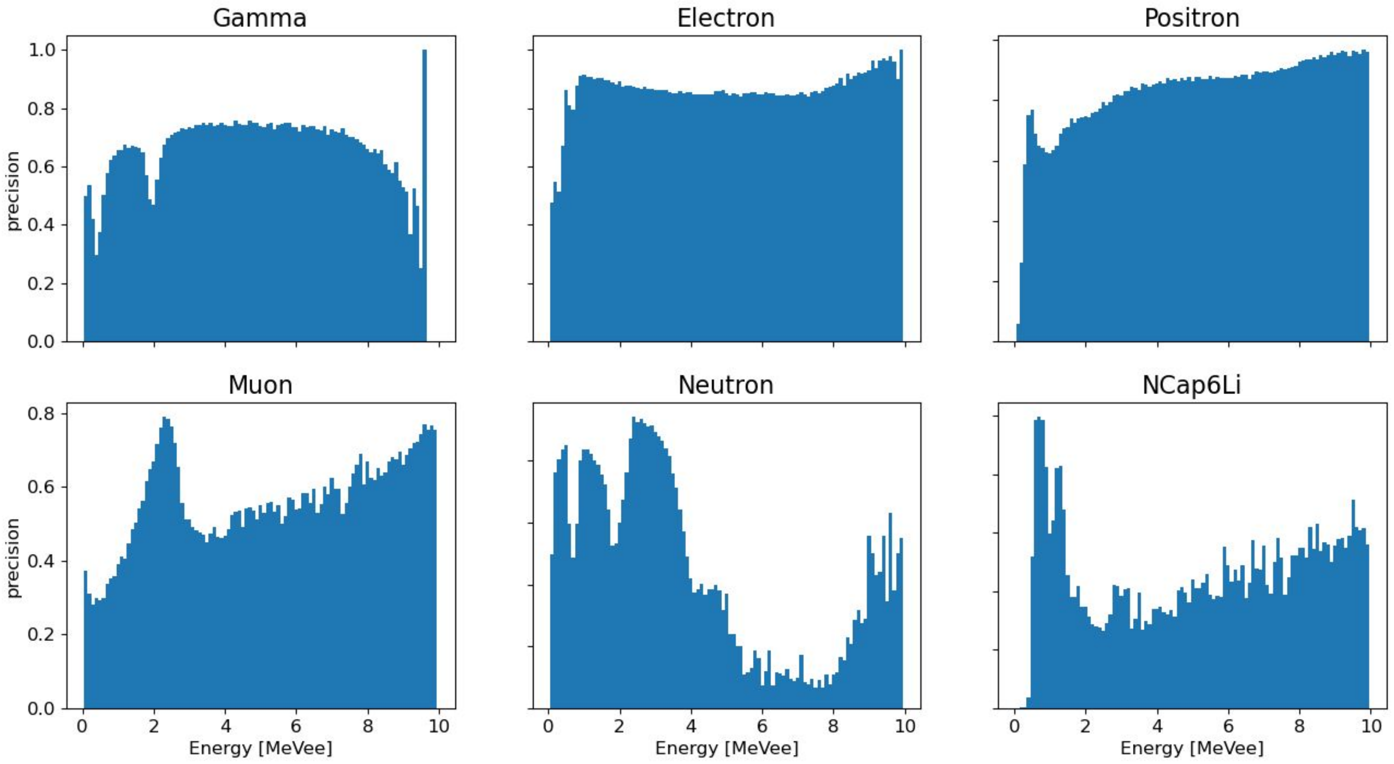
Varied number of convolutional layers, number of linear layers, number of output feature planes, padding, kernel size

Accuracy Distributions





Precision vs Deposited Energy



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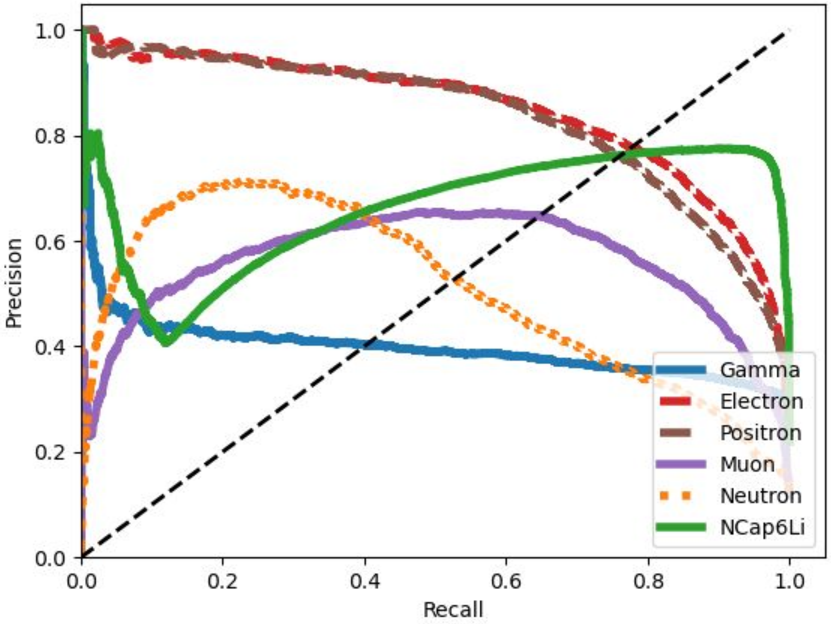
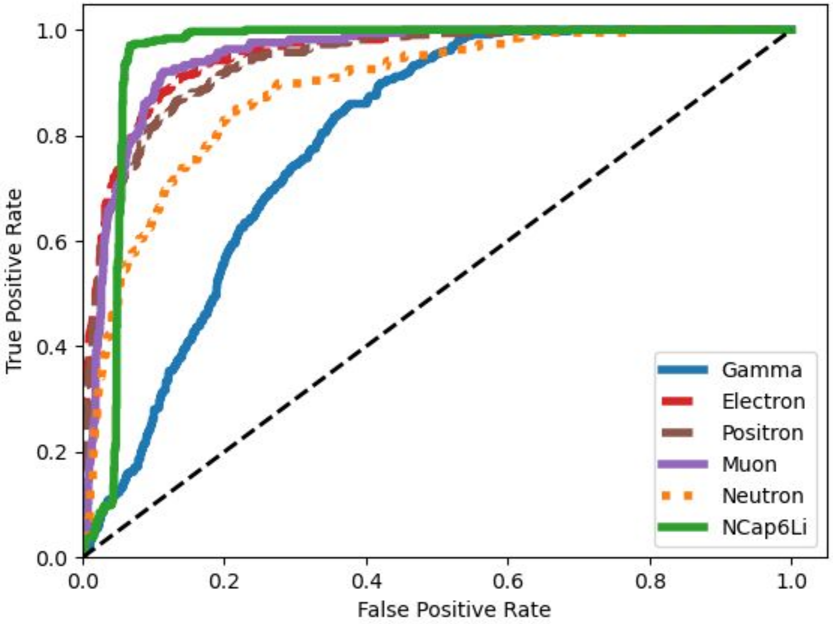
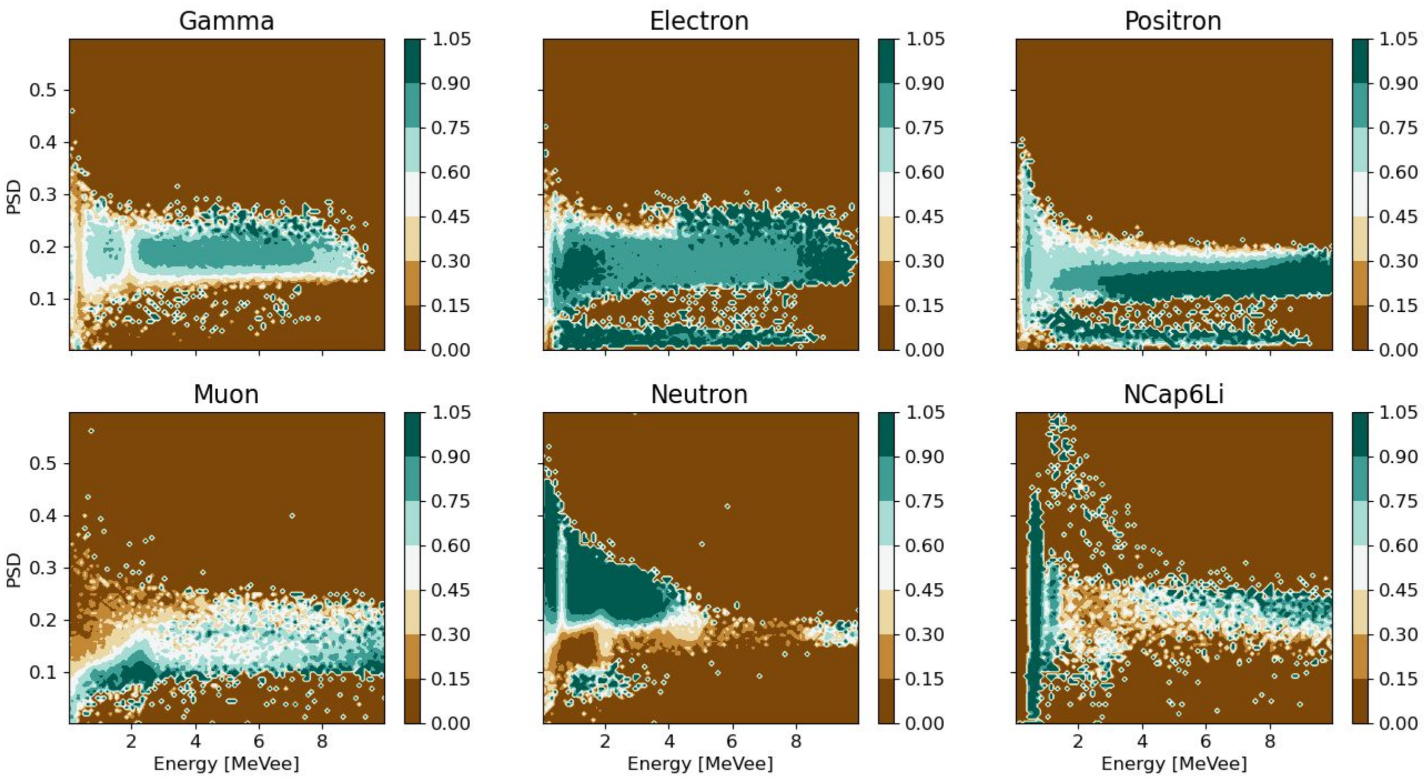
Precision - Recall & ROC curves





Precision Distribution (Energy - PSD space)



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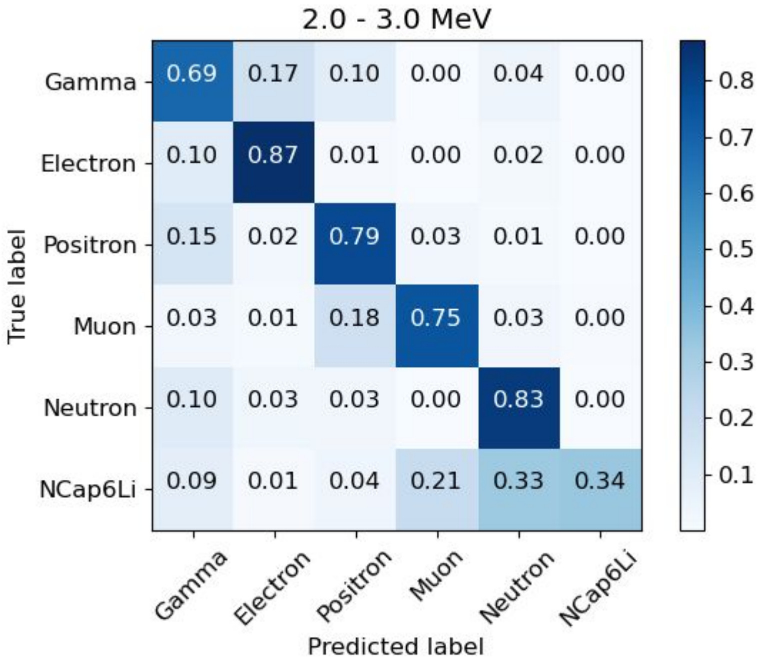
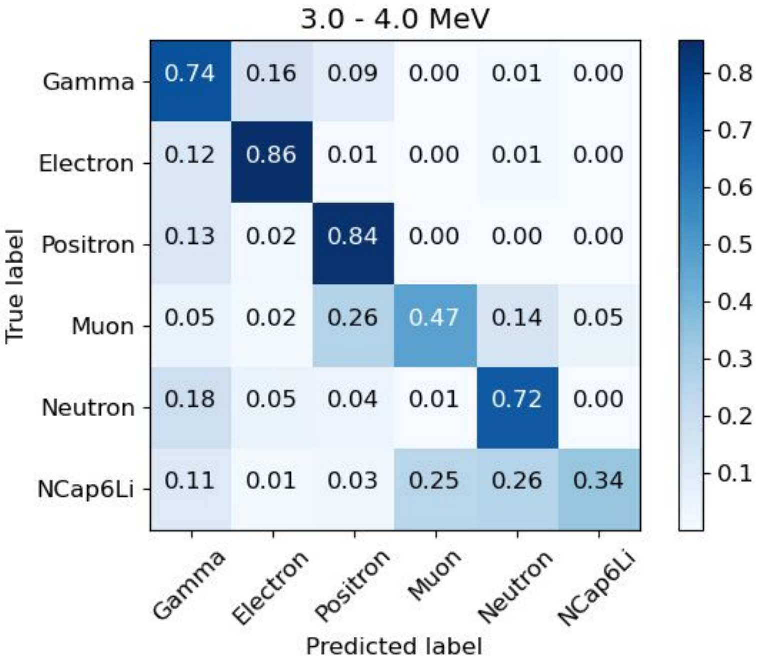
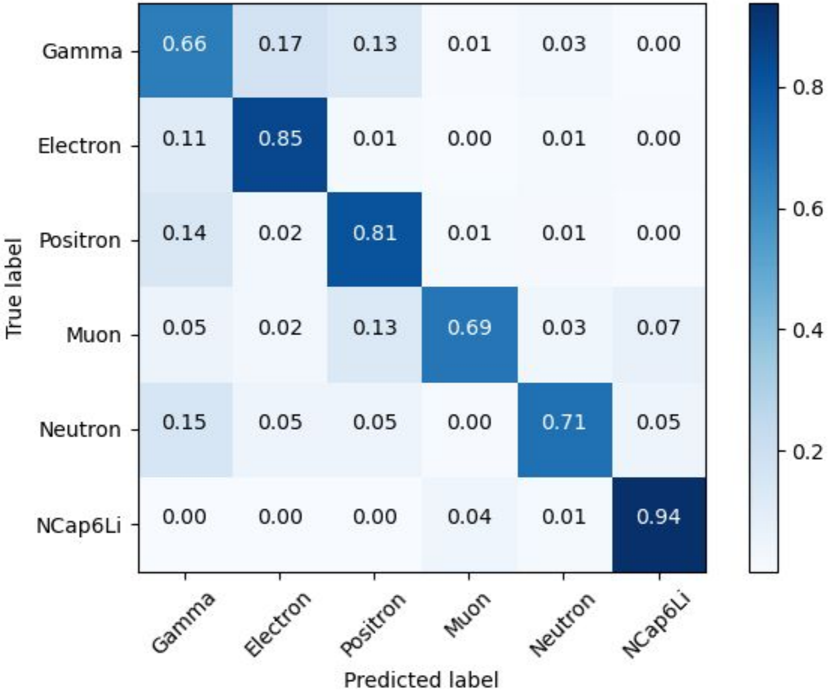
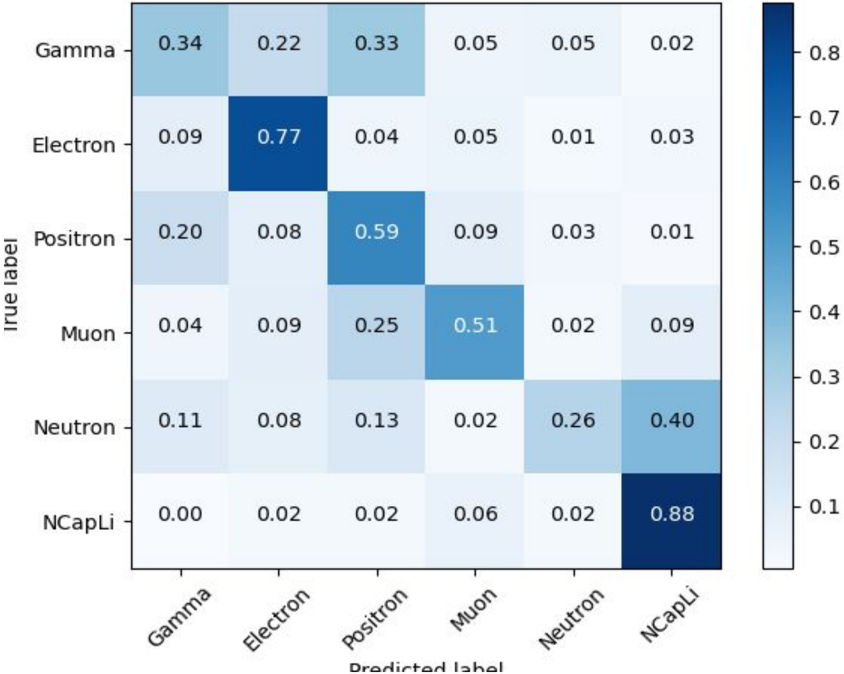
Confusion Matrix at selected energies





Comparison - Waveforms vs Extracted Features





Features: 2x150 16 bit samples (uncalibrated)

Features: Energy, total photoelectrons left and right PMT, rise time, relative start time, position along cell, PSD