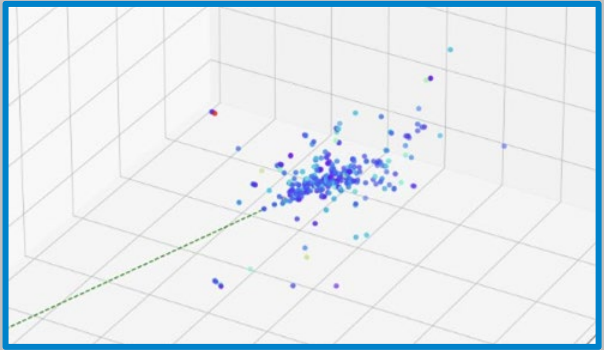
2nd AI4EIC Workshop, Oct. 10-14, William & Mary

ML Particle Identification with Measured Shower Profiles from Calorimetry



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U.S. DEPARTMENT OF ENERGY
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10/12/2022

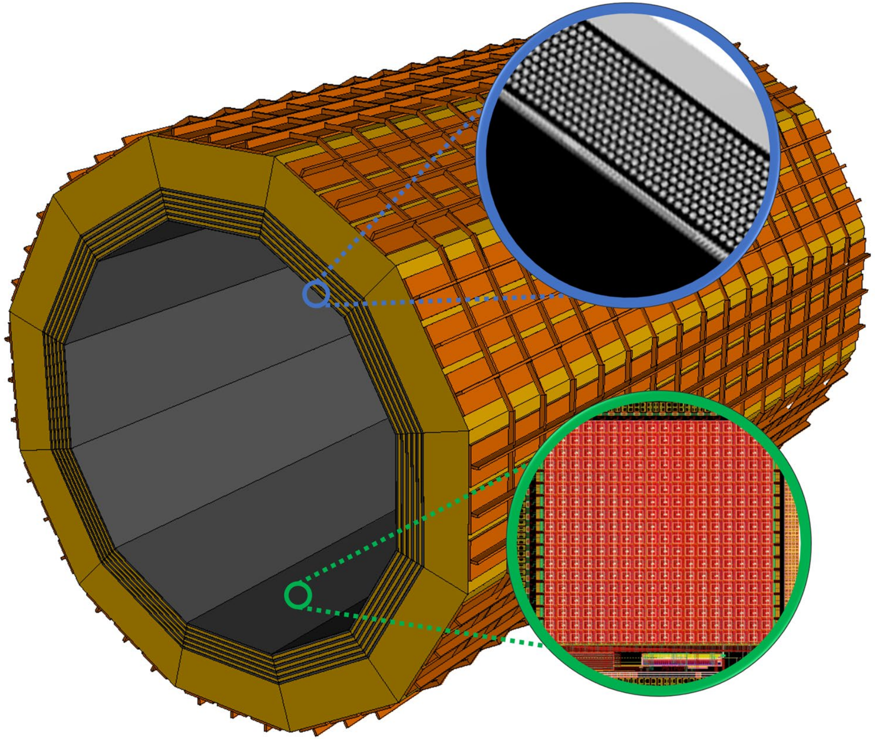
Imaging Calorimeter Concept

Hybrid Concept

- Monolithic Silicon Sensors **AstroPix** (NASA's AMEGO-X mission)
- Scintillating fibers embedded in Pb (**Pb/ScFi** similar to GlueX Barrel Ecal)

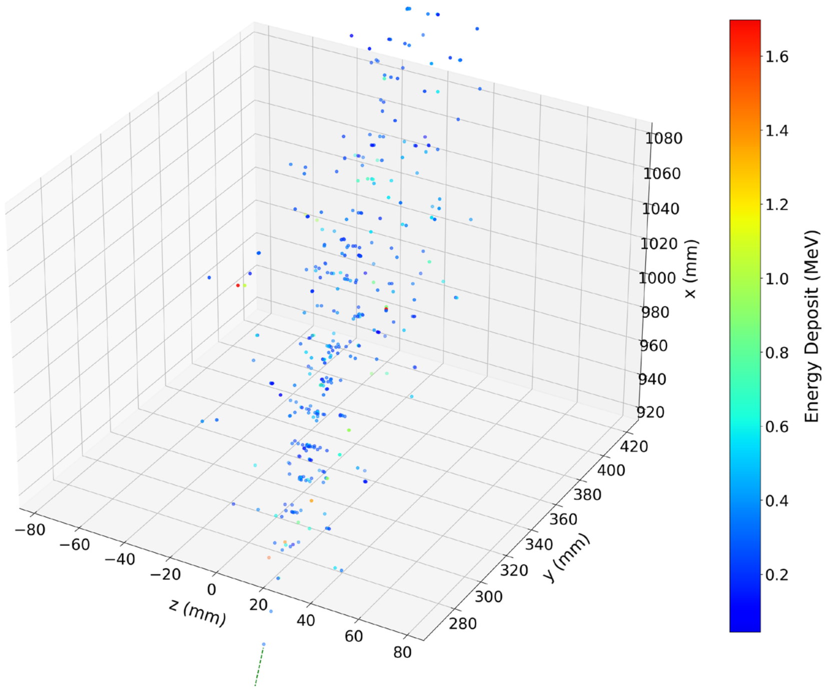
- "Sandwiched" 6 layers of AstroPix and 5 layers of Pb/ScFi (~1X_0) followed by a large chunk of Pb/ScFi
- Total thickness ~43 cm (~21 X_0)

- Excessive amount of data
  (3D shower imaging)
  0.5 x 0.5 mm^2 pixel from AstroPix
  ~2 x 2 cm^2 light guide from Pb/ScFi

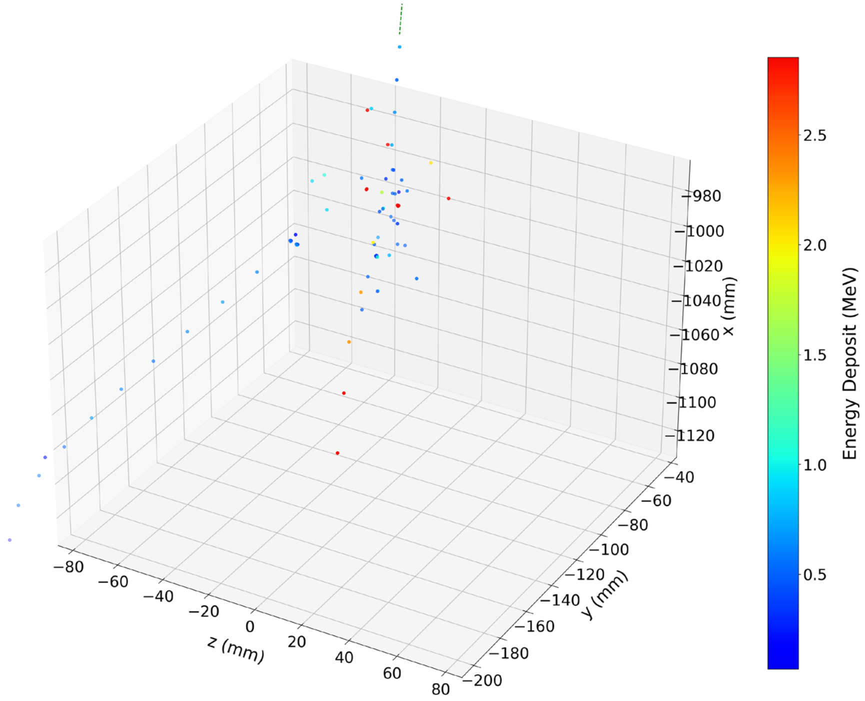


Event Sample (3D)

Electron Shower Sample

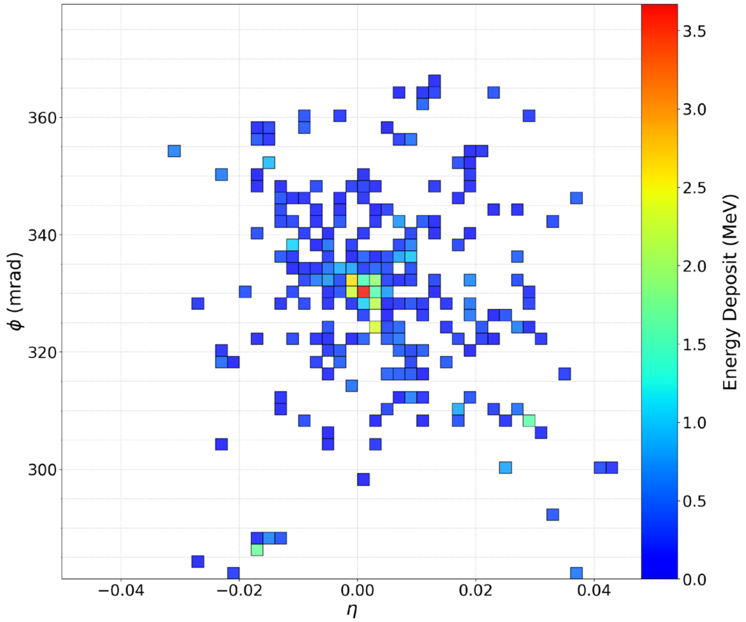


Pion Shower Sample

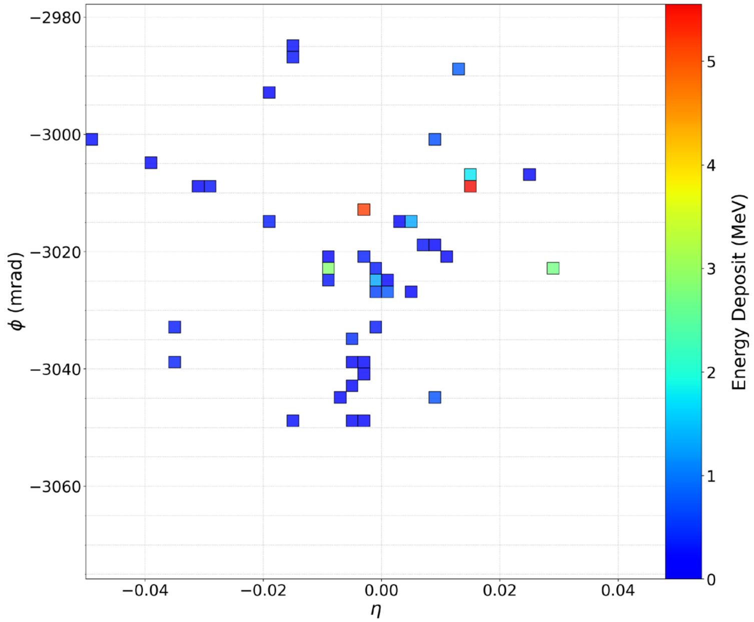


Event Sample (Projection)

Electron Shower Sample



Pion Shower Sample



Pion Rejection with Machine Learning

- Two-step process
  - Apply a “traditional” E/p cut first to clean up samples
  - ML model is applied to the leftover samples

- Combining hits from AstroPix layers and ScFi layers
  - Limited 20 hits per layer, sorted by energy deposit, zero padding
  - 5 features per hit (layer_type [0, 1], Edep, Rc, eta, phi)
  - Normalized all features to [0, 1]
  - Null eta values for ScFi hits (ignore z information from fibers)

- Adjust e:pi weighting in cost function to balance efficiency and rejection power

Pion Rejection with Machine Learning

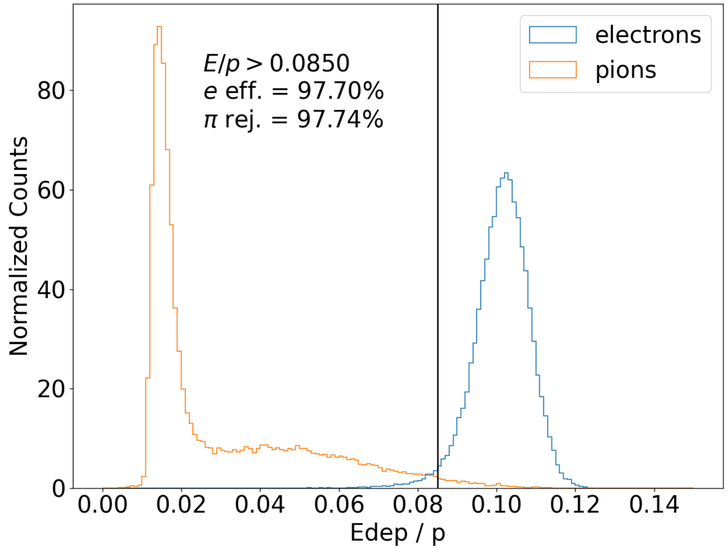
- Simple model
  - Sequential CNN + MLP
- 20 epochs of training
  - 100k events with 80% for training and 20% for validating
  - 100k events for benchmarking
- e-pi classification
  - Only two labels
  - Cut on P_π

```
Model: "sequential_75"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_225 (Conv2D)          (None, 29, 20, 48)        1008
_________________________________________________________________
max_pooling2d_225 (MaxPoolin (None, 14, 10, 48)        0
_________________________________________________________________
dropout_225 (Dropout)        (None, 14, 10, 48)        0
_________________________________________________________________
conv2d_226 (Conv2D)          (None, 14, 10, 96)        41568
_________________________________________________________________
max_pooling2d_226 (MaxPoolin (None, 7, 5, 96)          0
_________________________________________________________________
dropout_226 (Dropout)        (None, 7, 5, 96)          0
_________________________________________________________________
conv2d_227 (Conv2D)          (None, 7, 5, 48)          41520
_________________________________________________________________
max_pooling2d_227 (MaxPoolin (None, 3, 2, 48)          0
_________________________________________________________________
flatten_75 (Flatten)         (None, 288)               0
_________________________________________________________________
dense_225 (Dense)            (None, 128)               36992
_________________________________________________________________
dropout_227 (Dropout)        (None, 128)               0
_________________________________________________________________
dense_226 (Dense)            (None, 32)                4128
_________________________________________________________________
dense_227 (Dense)            (None, 2)                 66
=================================================================
Total params: 125,282
Trainable params: 125,282
Non-trainable params: 0
_________________________________________________________________
```

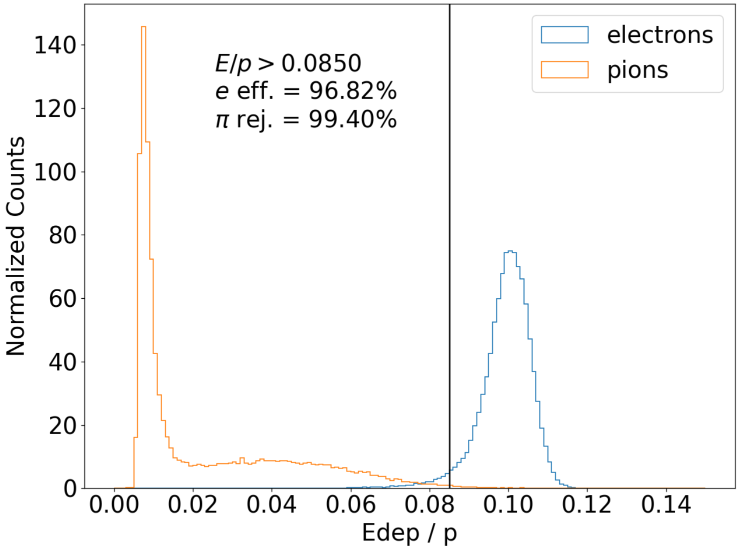
E/p Cut with Current Simulation

E/p cut at certain X_0

1.0 GeV/c particles, standalone BECal



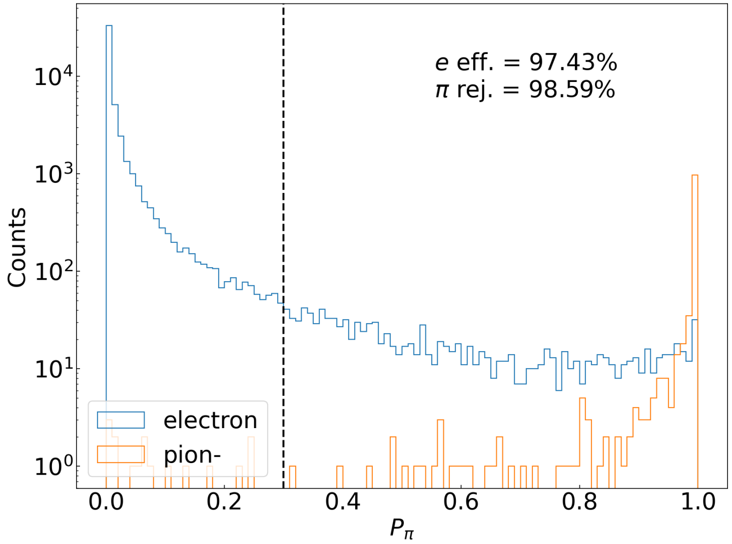
2.0 GeV/c particles, with MF and Mat.



Likelihood Cut on ML Output

Cut on probability of labeling

1.0 GeV/c particles, standalone BECal



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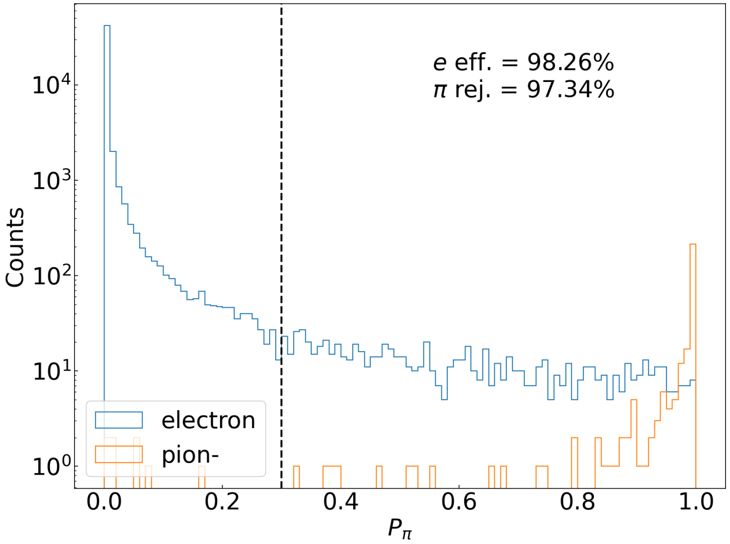


Pion Rejection with Standalone BECal

- Ideal case performance

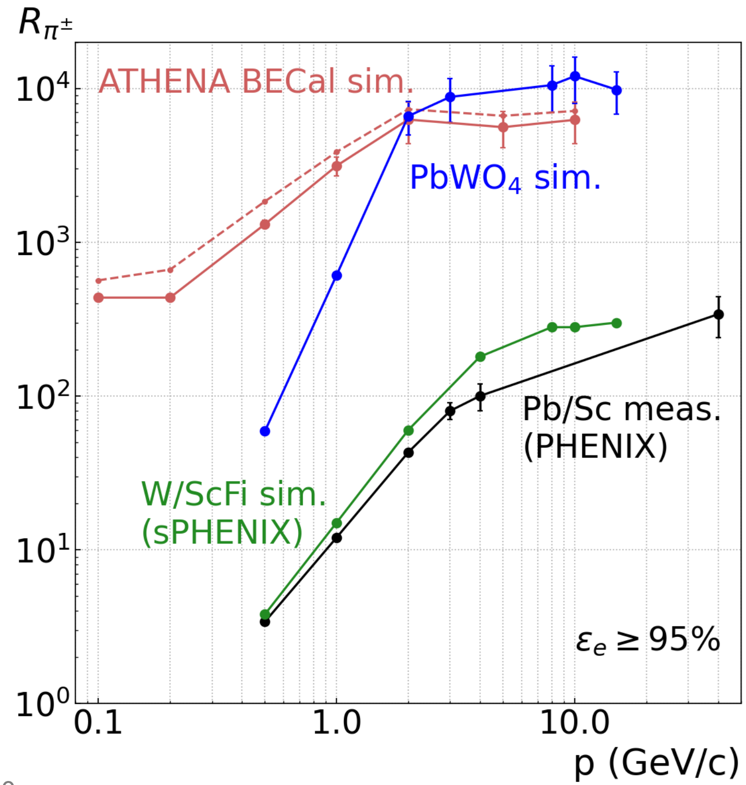
6 layers

p (GeV)	Edep/p cut			ML			Combined	
	Cut	e Eff.	pion Rej.	e:pion Weighting	e Eff.	pion Rej.	e Eff.	pion Rej.
0.1	> 0.055 @ $9X_0$	**99.83%**	**1.15**	1:10	**95.17%**	**378.54**	95.01%	436
0.2	> 0.070 @ $9X_0$	**99.49%**	**1.33**	1:15	**95.63%**	**328.44**	95.14%	436
0.5	> 0.085 @ $9X_0$	**97.26%**	**18.99**	1:20	**97.98%**	**68.89**	95.29%	1308
1	> 0.085 @ $9X_0$	**97.70%**	**44.28**	1:40	**97.43%**	**70.81**	95.19%	3136
2	> 0.085 @ $9X_0$	**96.82%**	**166.63**	1:40	**98.26%**	**37.63**	95.14%	6269
5	> 0.095 @ $20X_0$	**99.06%**	**184.44**	1:40	**96.58%**	**30.33**	95.67%	5595
10	> 0.095 @ $20X_0$	**98.61%**	**236.68**	1:40	**97.04%**	**26.38**	95.69%	6243

Pion Rejection with Standalone BECal

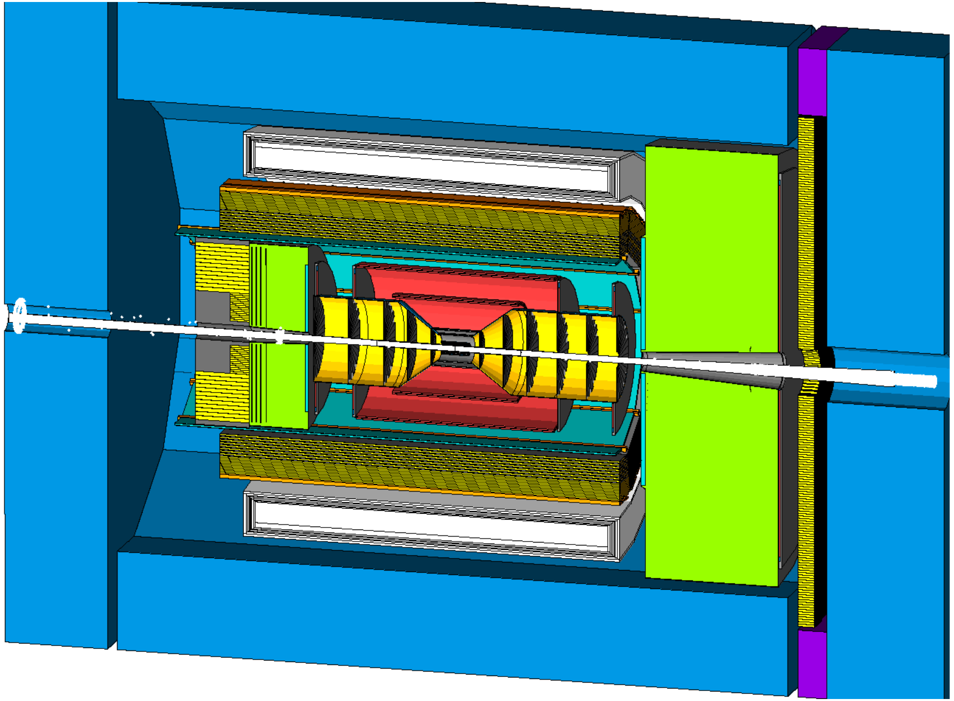
Solid line: 6 AstroPix Layers
Dashed line: 9 AstroPix Layers

- Best e/pi separation for p < 2 GeV/c
- Comparable to crystal calorimeter at higher momentum
- A factor of 30~100 boost on top of E/p cut for p > 1 GeV/c
- 500:1 rejection at lower momentum from when E/p does not work well



Effects from Materials and Magnetic Field

- Materials contributed from other PID detectors inside the barrel
- Major materials from DIRC frames
- Strong magnetic field ~3T
- Performance study with the realistic evironment



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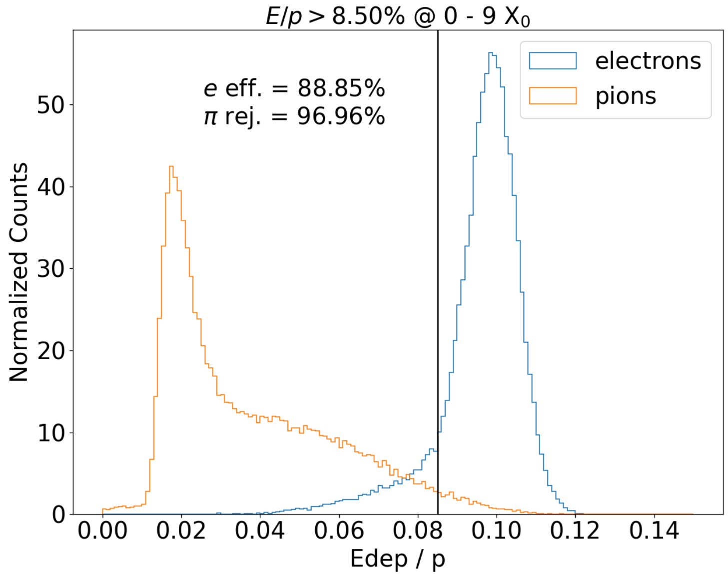

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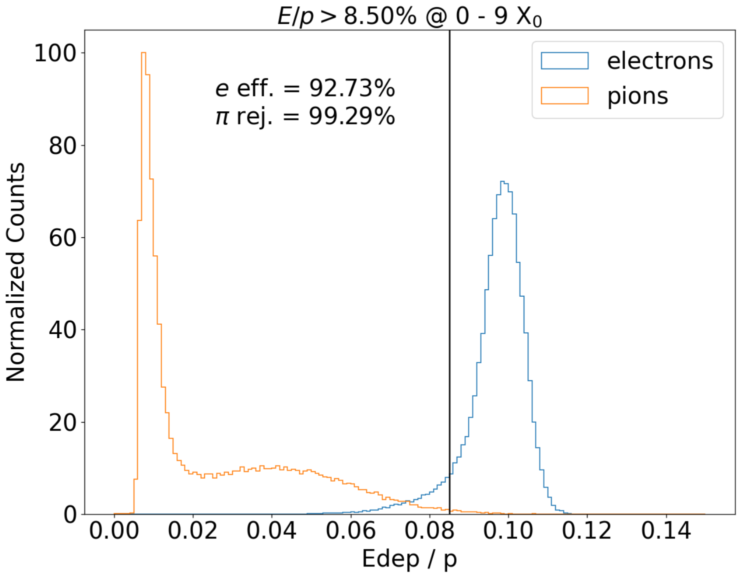

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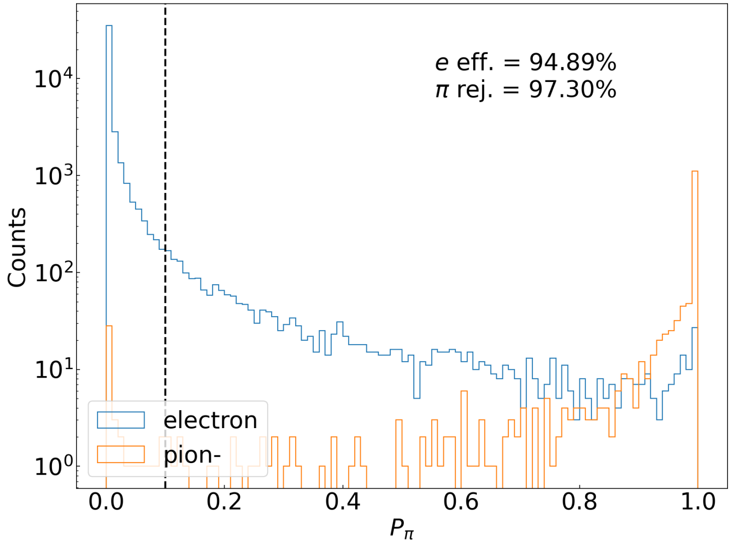

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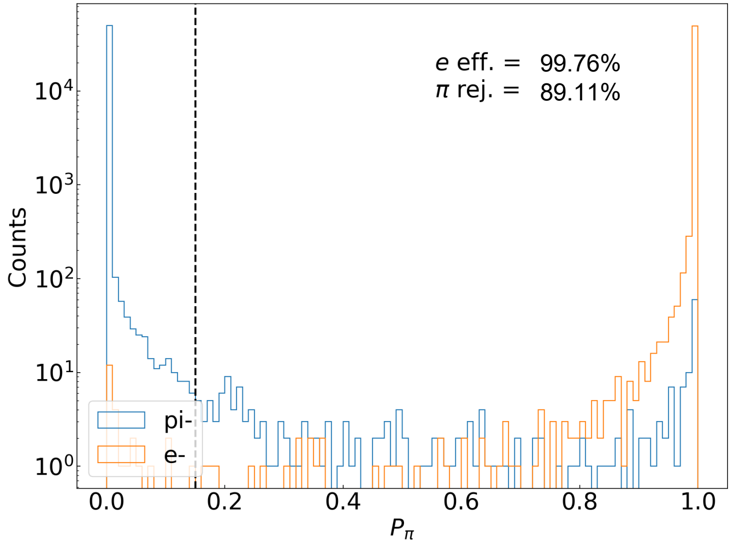
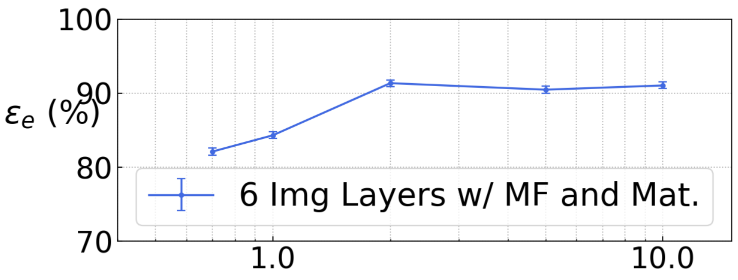
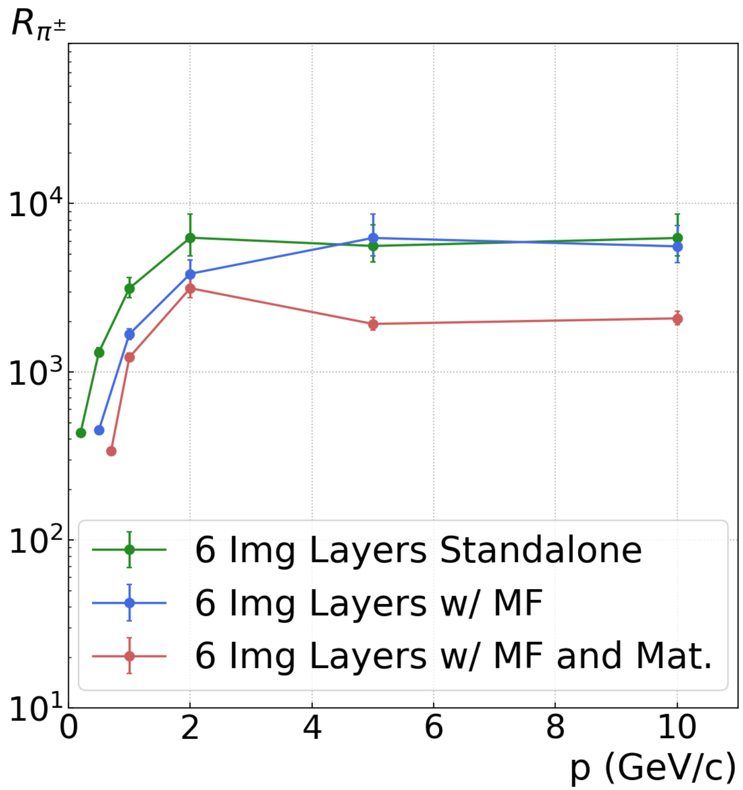


Effects from Magnetic Field and Materials

- Electron efficiency > 95% for "Standalone" and "w/ MF" simulations

- Electron efficiency is 82% to 92% for "w/ MF and Mat." simulation





Summary

- ML with shower imaging significantly improves particle identification
  - Boost pion rejection factor from traditional methods like E/p cut

- Possible future improvements
  - 2D cuts on dE/dx
  - Multi-views classification (More sophisticated NN model)
  - Generalize to more particles ($\pi^0, \mu, \ldots$)