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Digital SiPM Neural Network Analysis in DREAM

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5D Calorimetry Meeting

May 13, 2025

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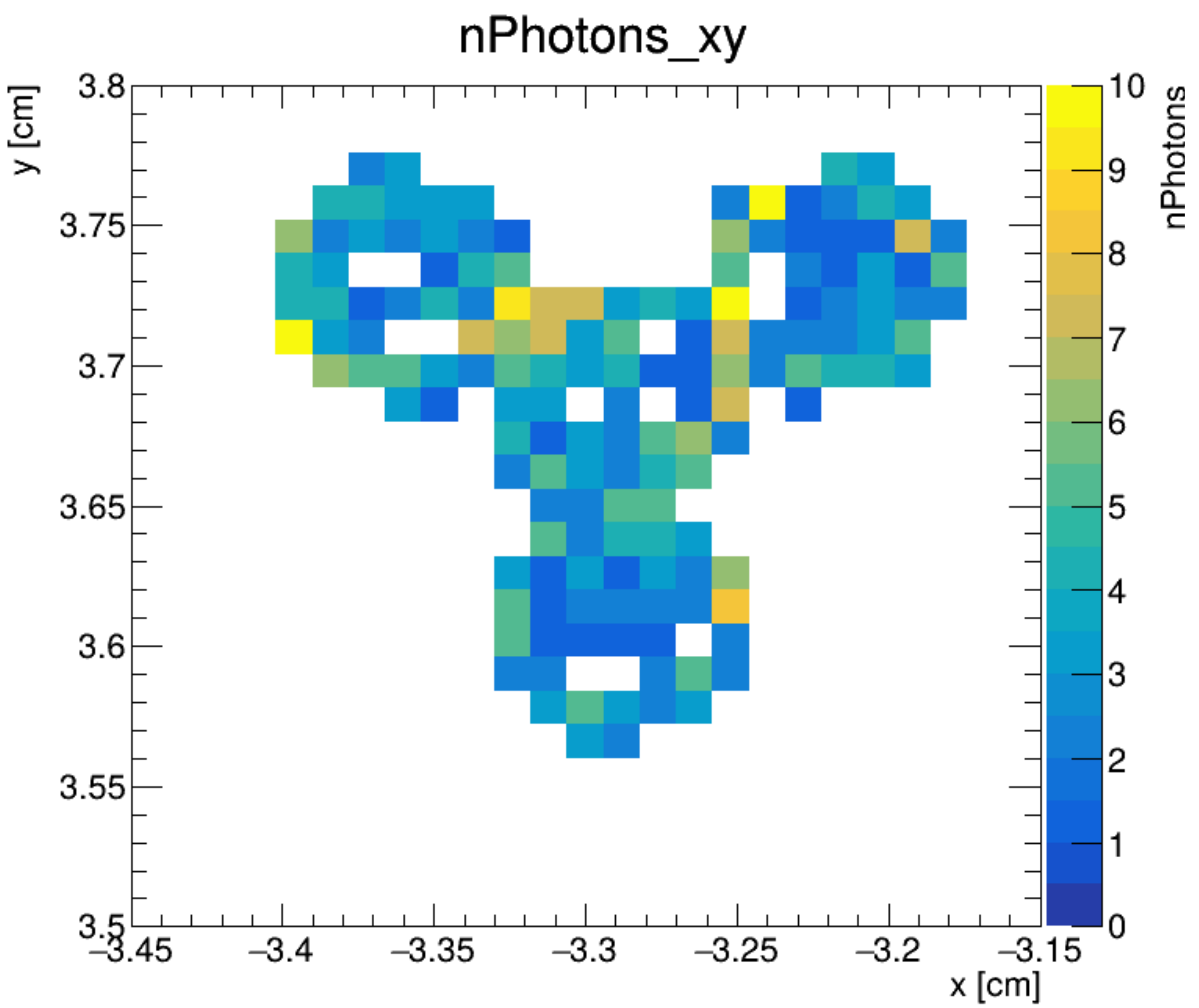
dSiPM Simulation Architecture

- Random-seed DREAM GEANT4 photon outputs as input to dSiPM simulation
- π^+ particles simulated with beam energies of 1 and 5 GeV, and 10-120 GeV at 10GeV steps. 28,000 events total used in analysis
- QE and deadtime modeled at five different SPAD sizes:
  - 20x20, 50x50, 100x100, 200x200 μm^2
- Python-based dSiPM simulation, with a PyTorch CNN used for energy reconstruction analyses



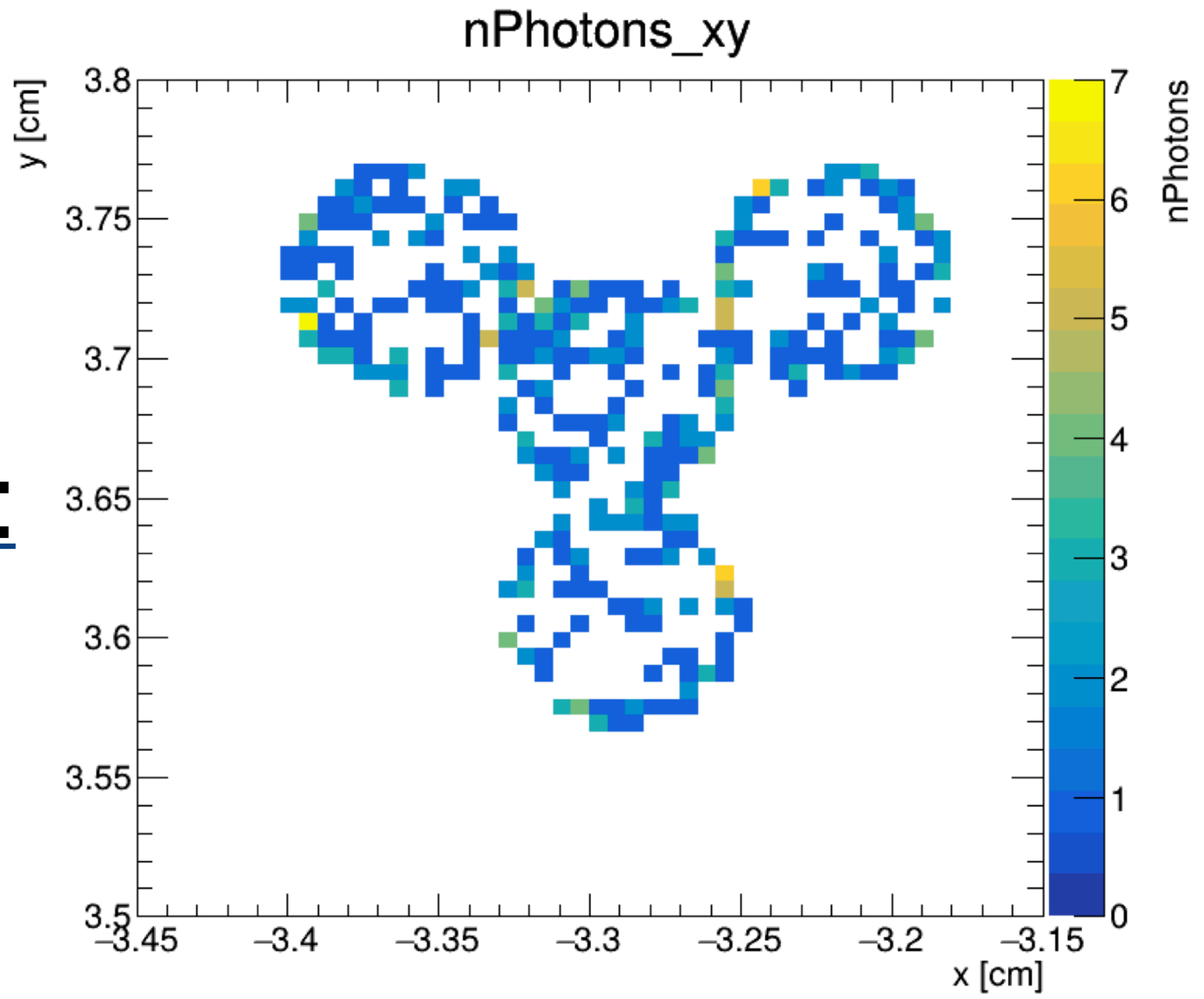
Motivation

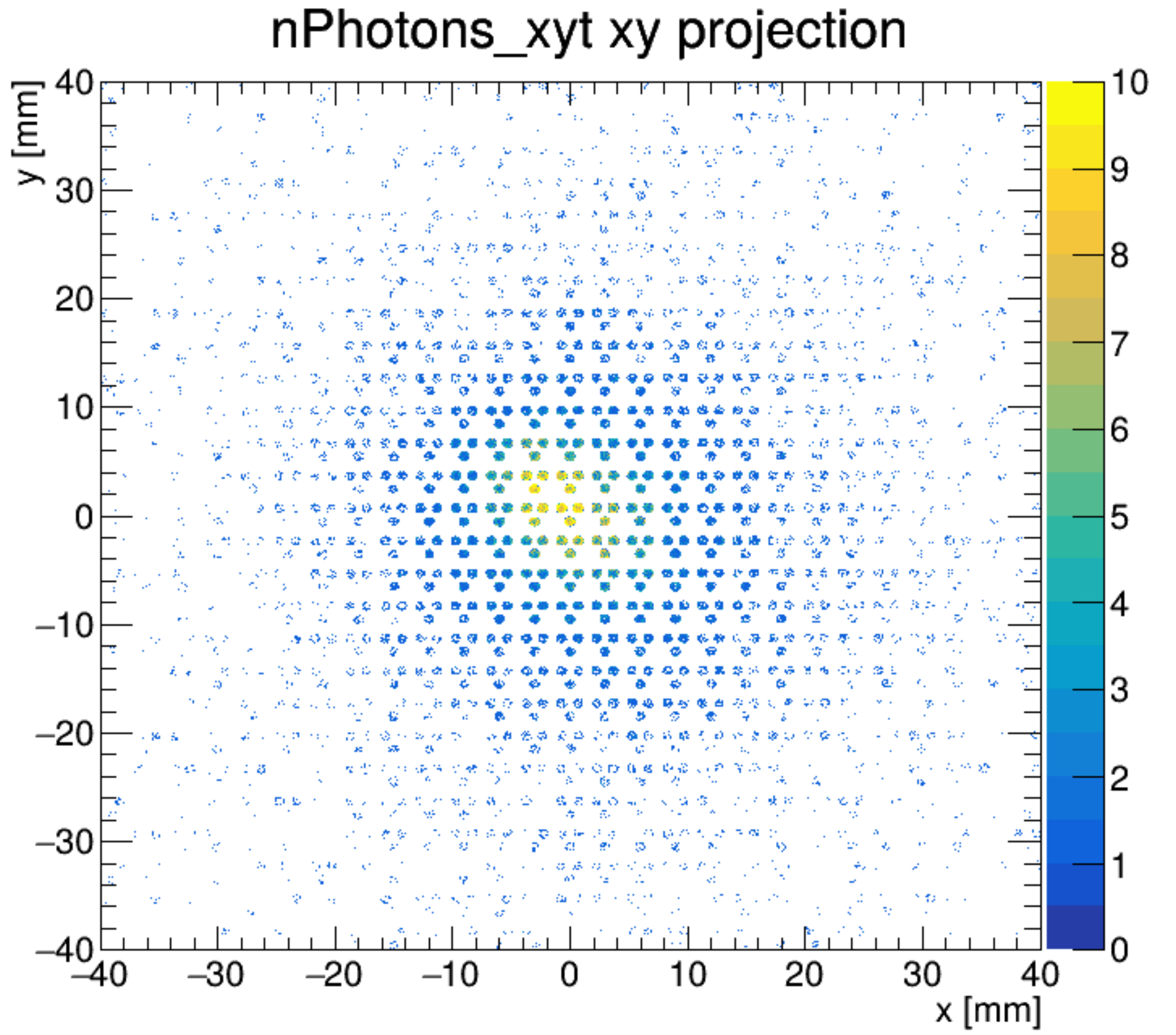
- Evaluate dSiPM readout in duel-readout fiber calorimetry
- Test preliminary energy regression methods using simulated data
- Test reconstruction capability variance under different SPAD sizes
- Explore dSiPMs as a possible implementation in DREAM

Idealized Fiber Layout

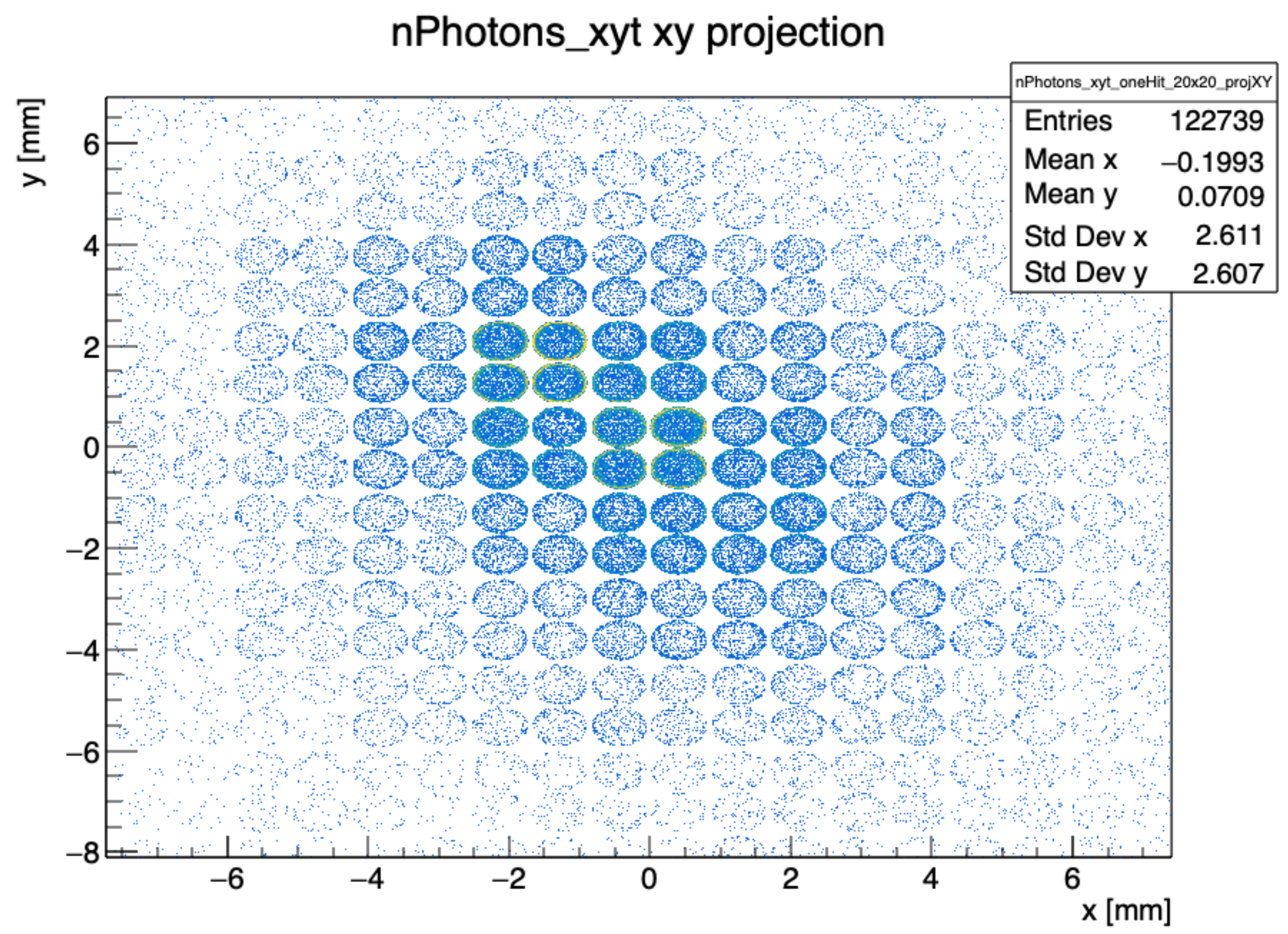
- Implemented fiber shift to minimize unused “white” bins
- Minimization of white space reduces the amount of always empty bins that are being trained to the NN, improving time and accuracy of energy regression.
- Modeled as ideal square compact layout

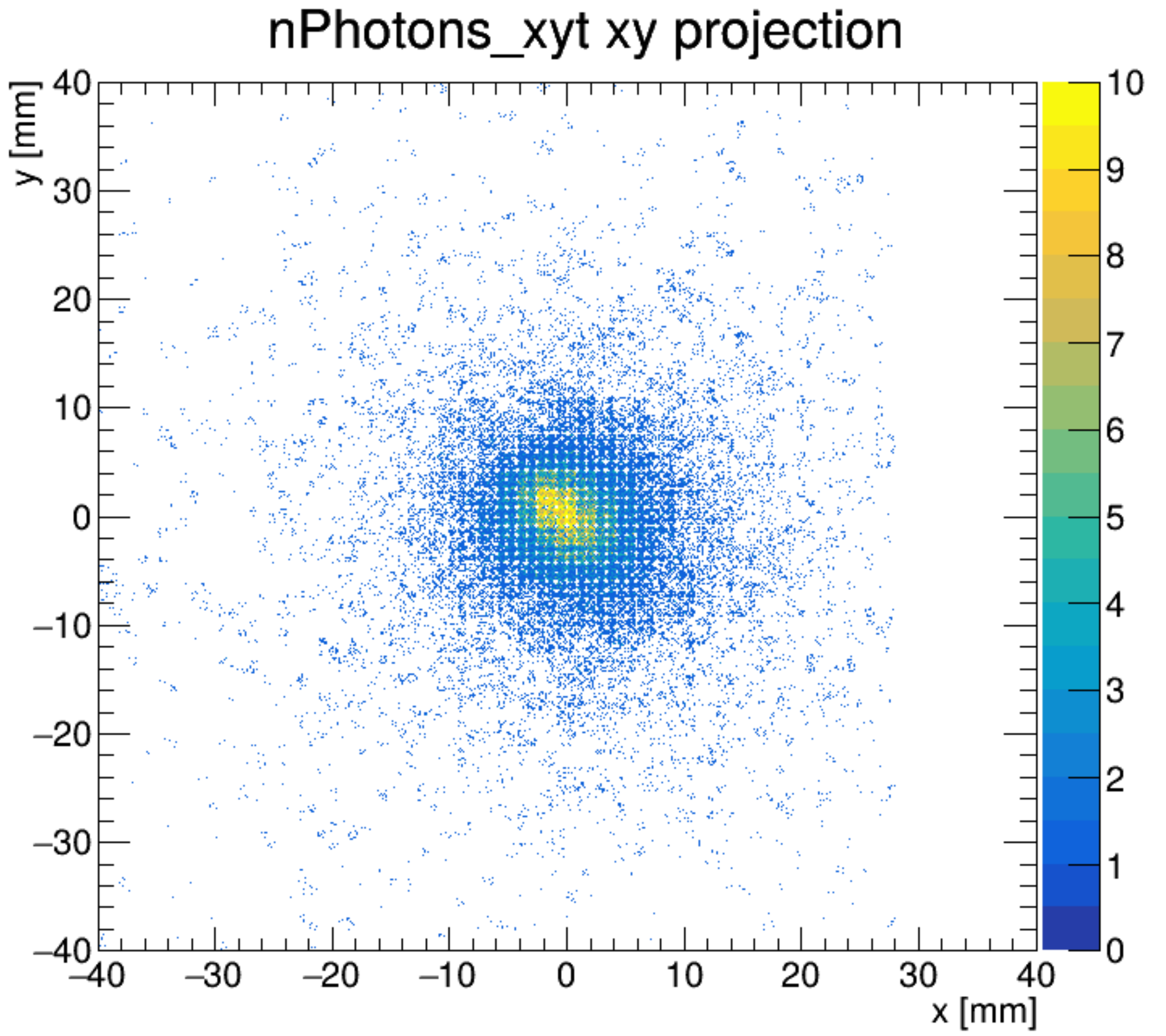
Before shift:





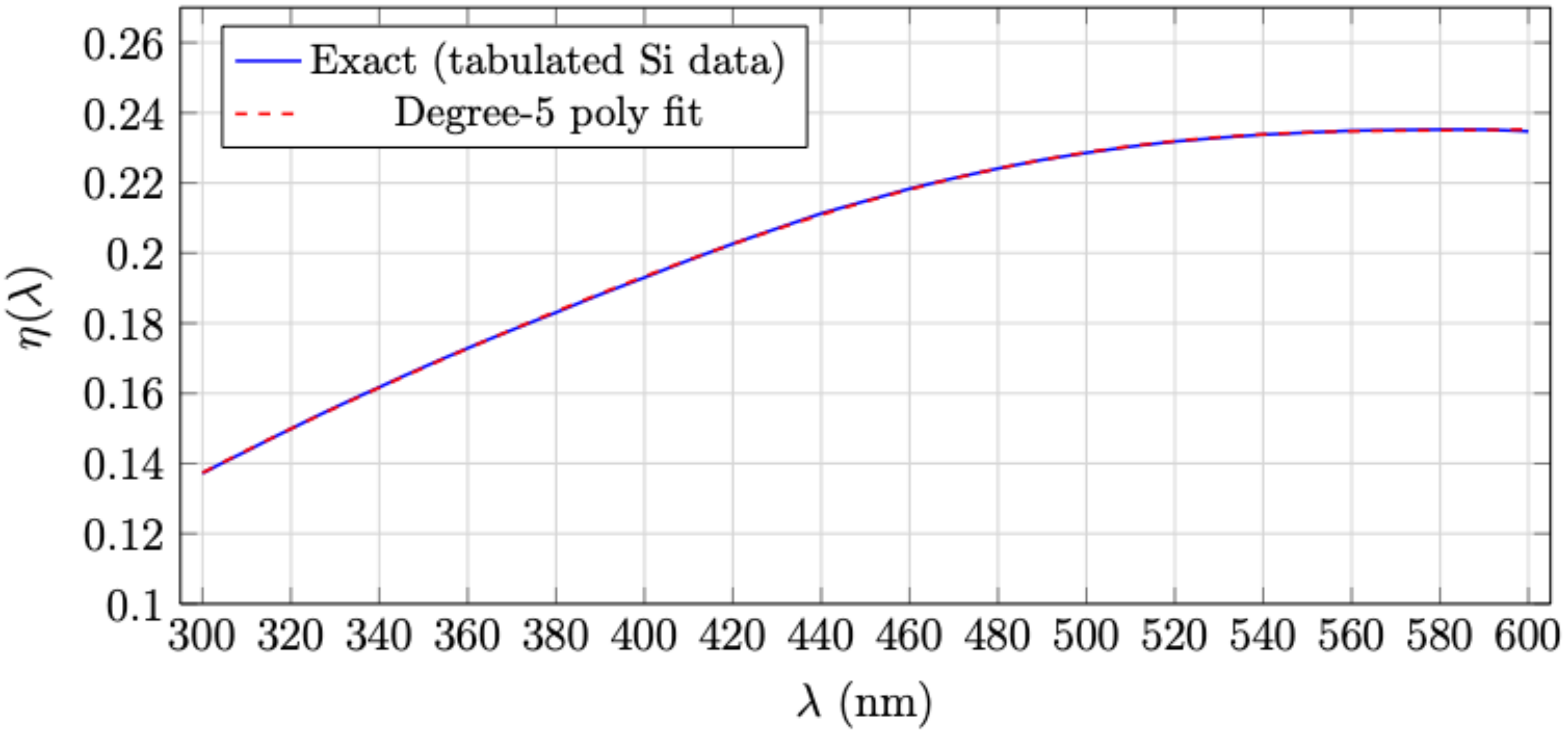
After shift:





Quantum Efficiency Modeling

- Quantum efficiency from the following equation:
  - $\eta(\lambda) = \mathscr{F}[1 - R(\lambda)]A(\lambda)$
- Table values needed for this formula taken as granular as possible, and used least-squares to fit a fifth-degree polynomial
- ~80% average photon reduction



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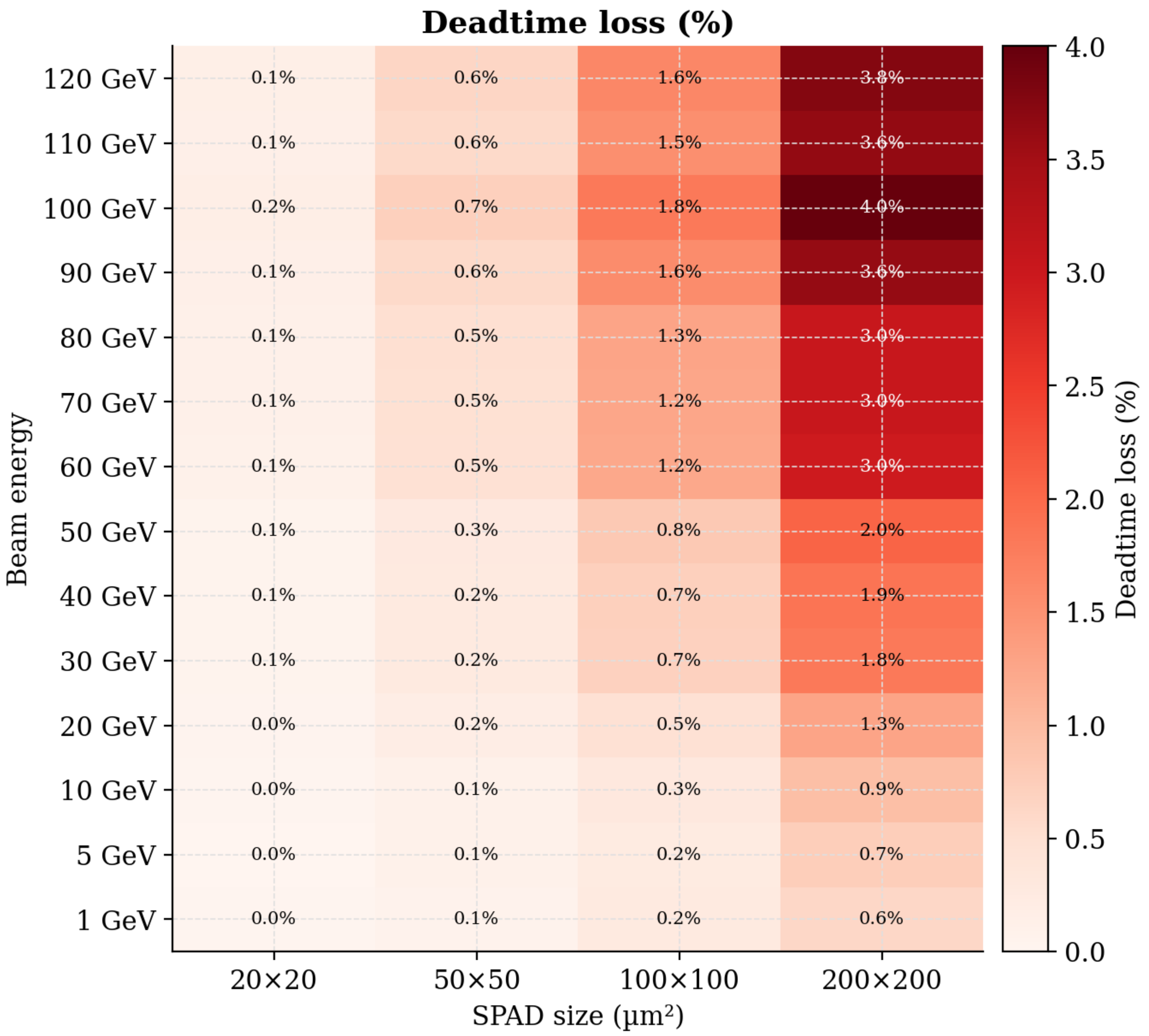
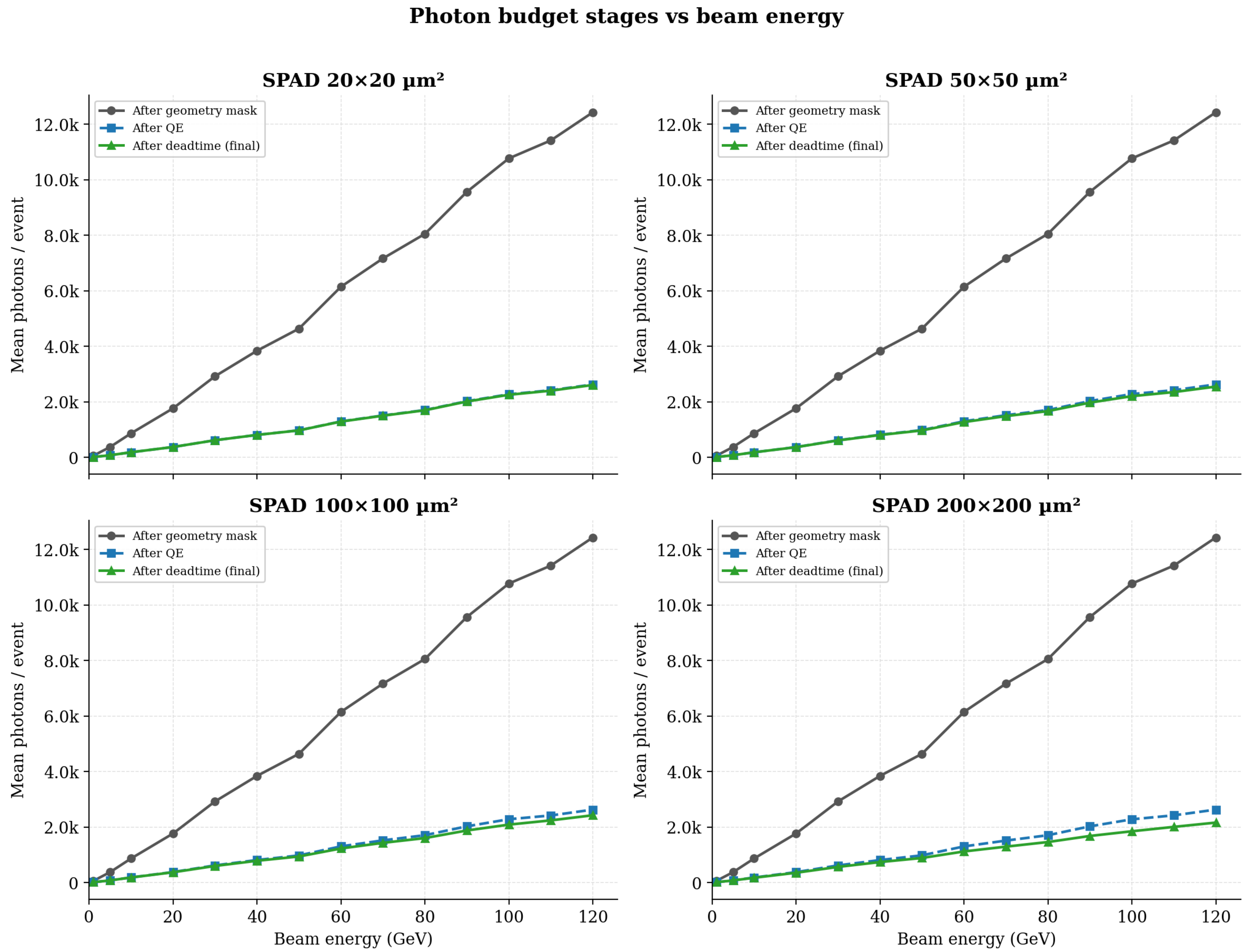
Deadtime Modeling

- Deadtime modeled as a per-event boolean
  - If SPAD hit, considered “dead” for the rest of the event
- Channel readout remains constant at $1 \times 1mm^2$, whereas SPAD size / count, and thus deadtime effect are variable.

Photon Distributions





- Loss is primarily dominated by QE, with deadtime loss rating from 0-4%.

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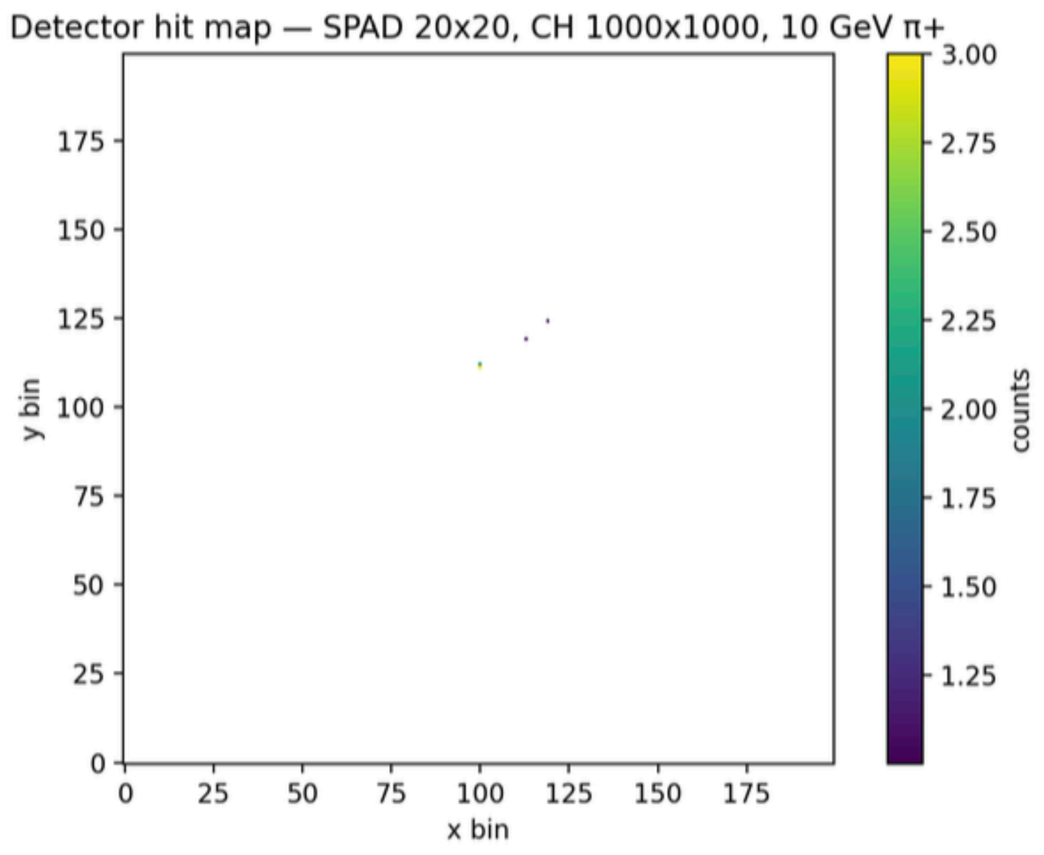
NN Framework

- 2-D time-sliced tensors as input to the convolutional neural network
- 70/30 validation split
- 14,000 events used for training and validation
- 14,000 events used for the energy resolution analysis

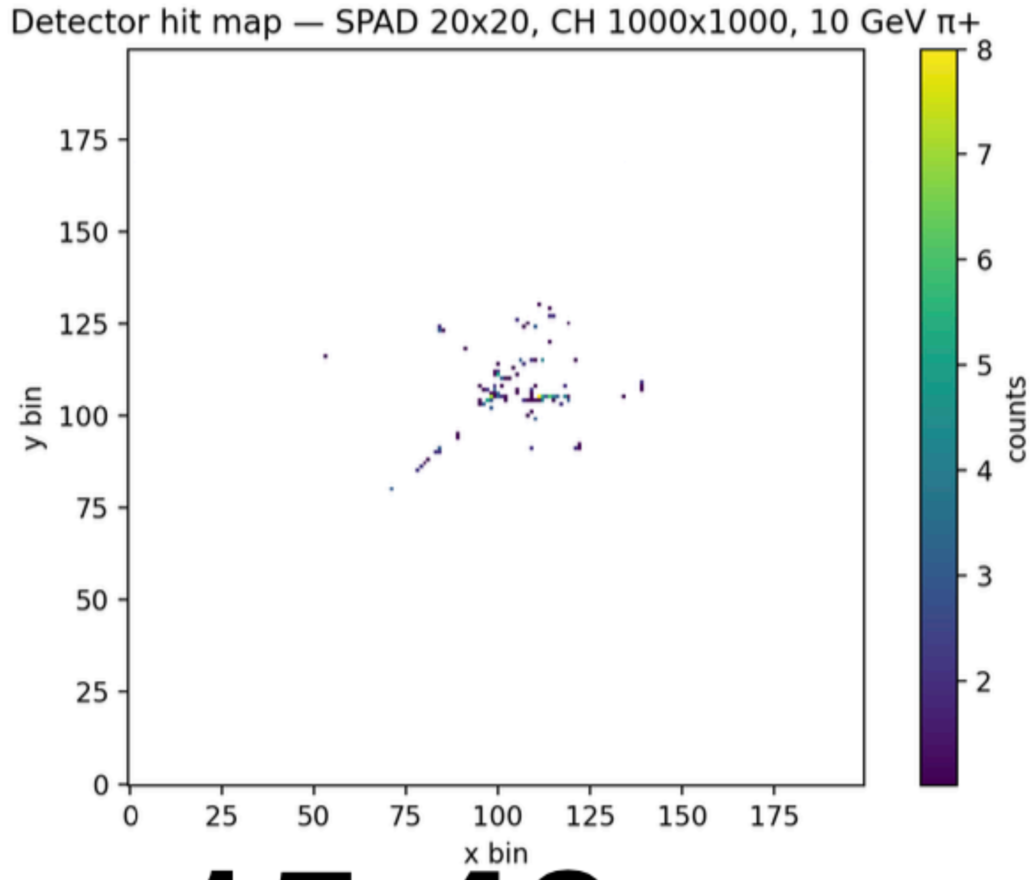
NN Example Input

- The five time slices from 0-40ns trained to the neural network along with beam energy.
- Energy regression performed using these event-level time slices, creating an energy reconstruction model.

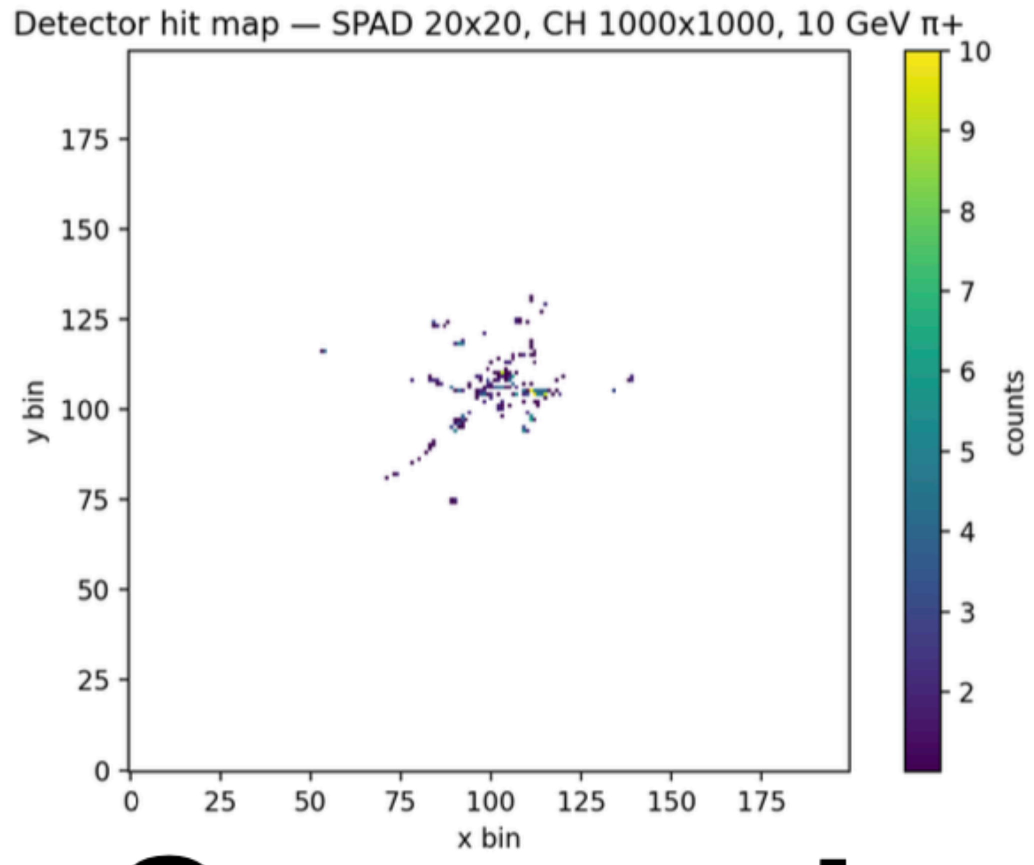
0-9ns



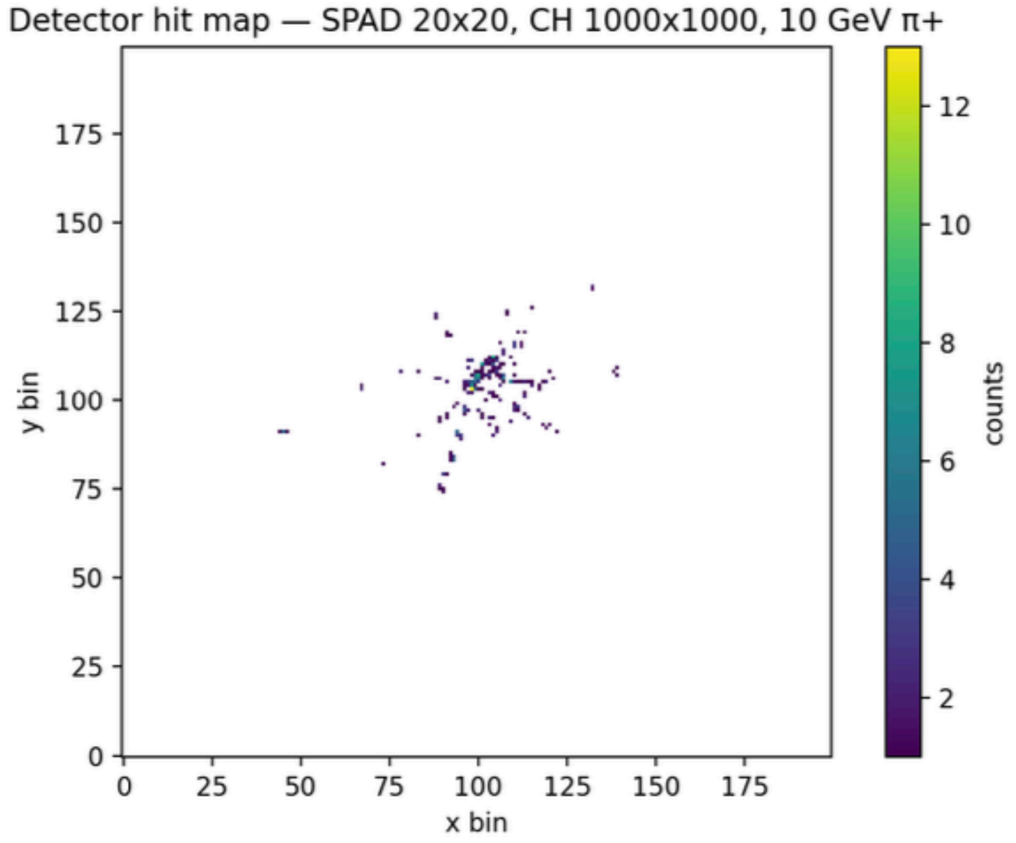
9-9.5ns



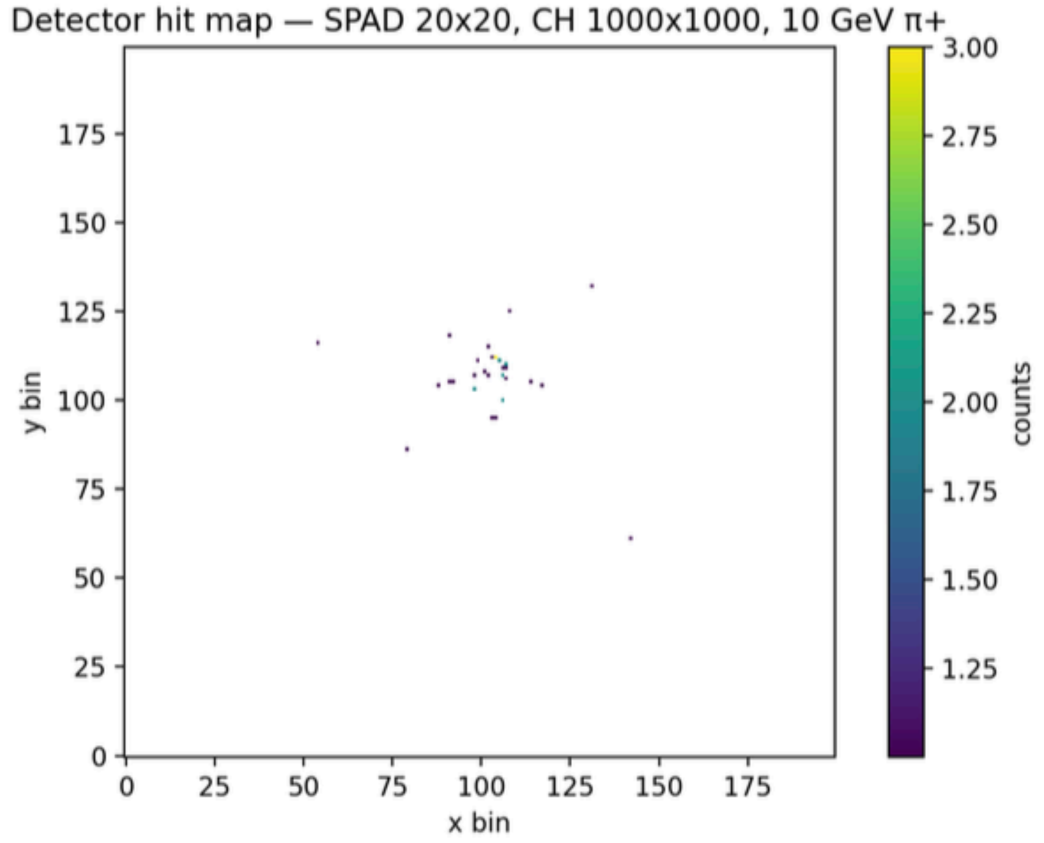
9.5-10ns



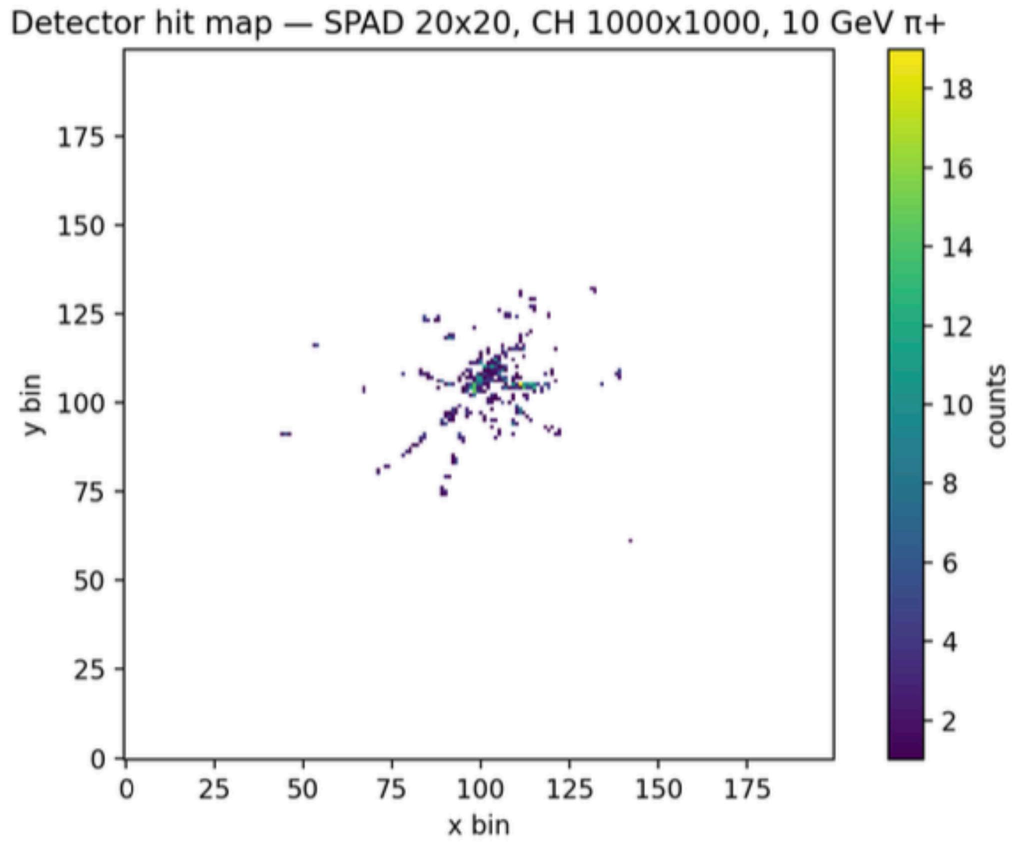
10-15ns



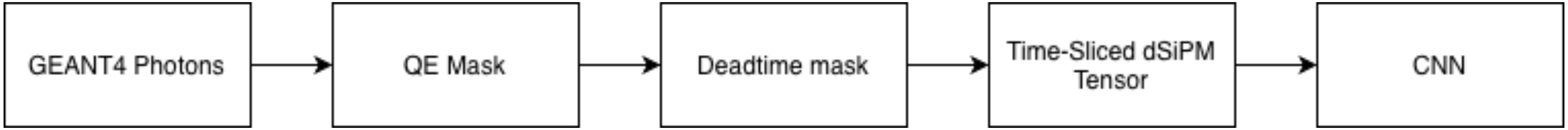
15-40ns



Summed



NN Workflow Overview:



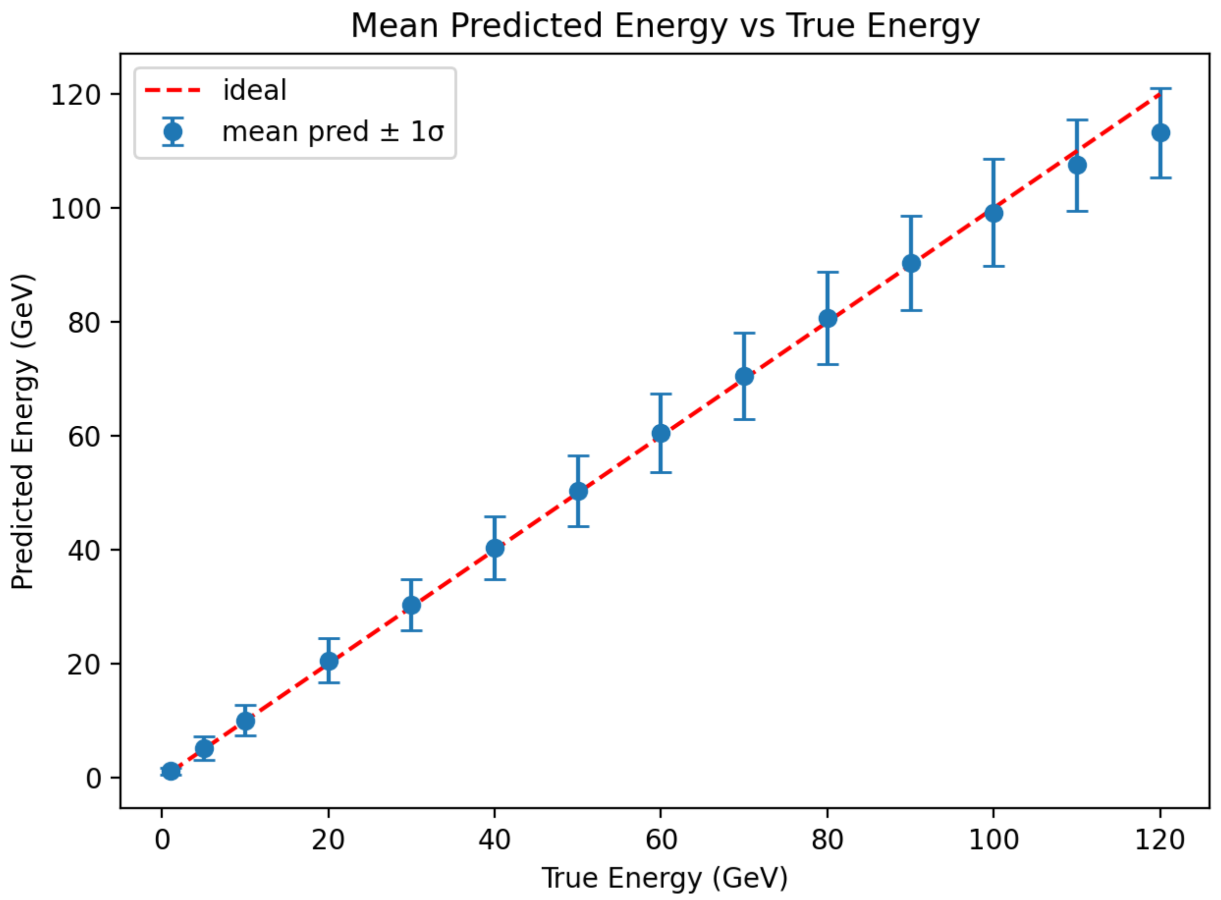
Example of QE/Deadtime Mask summary in smaller ($20 \times 20 \mu m^2$) SPADs:

"Event 92: 571764 raw photons
After geometry/timing mask: 16677 photons
QE (wavelength-dep): 3470/16677 survive (13207 discarded)
mean lambda = 465.3 nm | mean eta = 0.2117 | 0 photons outside 300-620 nm (eta=0)
Deadtime: in=3470, kept=3433, lost=37
Final photons used for tensor: 3433"

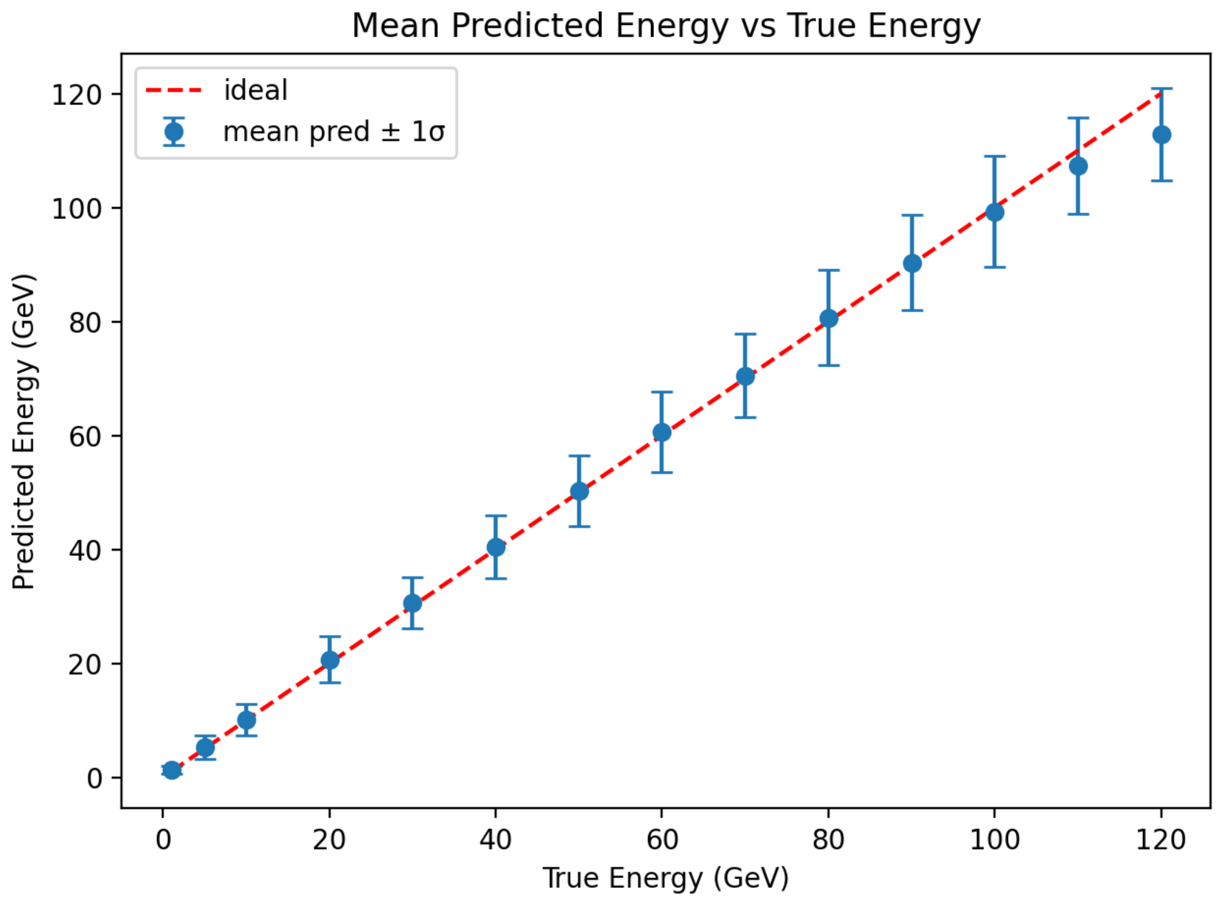
- ~16.7k photons hit dSiPMs
- 3,470 photons survive QE mask
- 3,433 photons survive deadtime

Neural Network Results

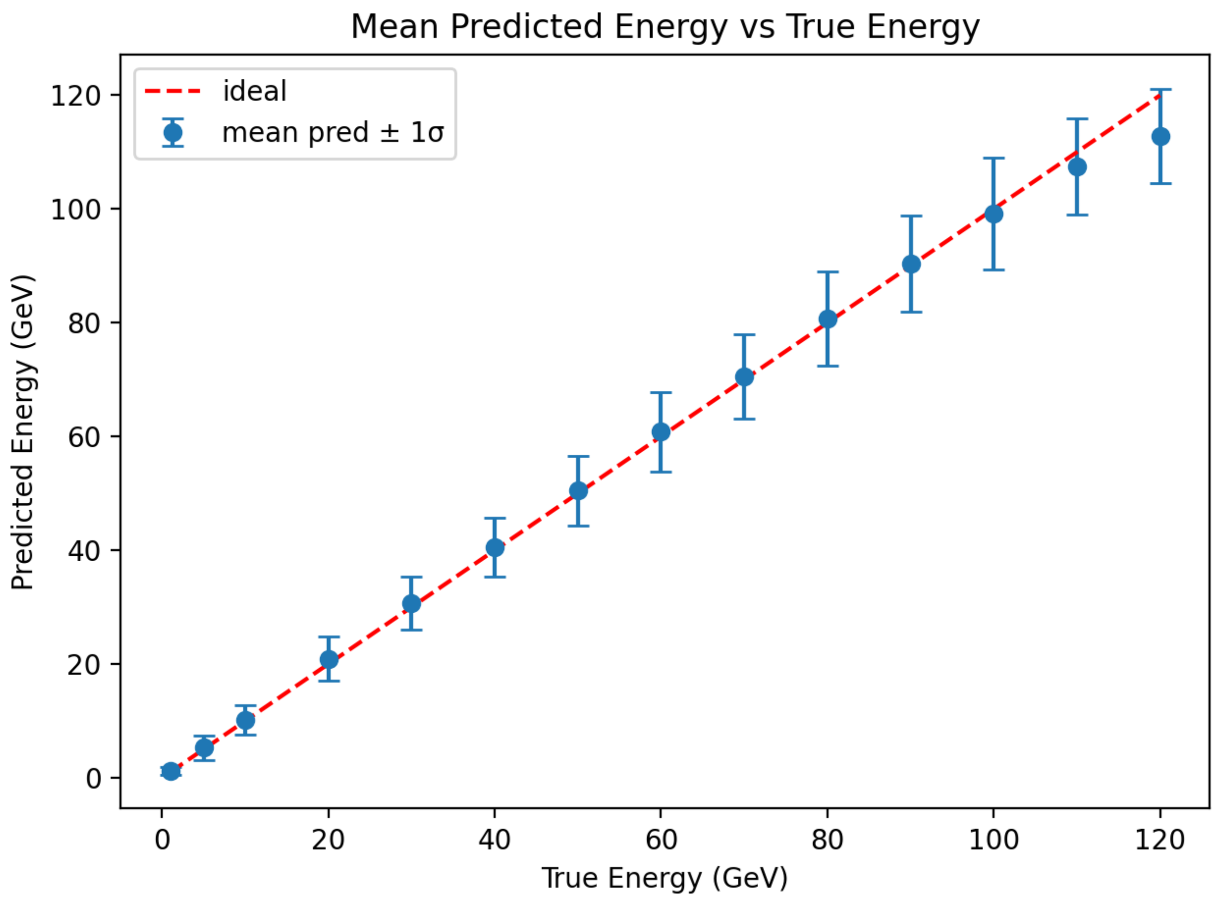
- Predicted energy vs. true beam energy plots shown. Perfect reconstruction y=x fit shown.
- Good reconstruction capabilities for all SPAD sizes. Similar mean values, slightly different standard deviation values.



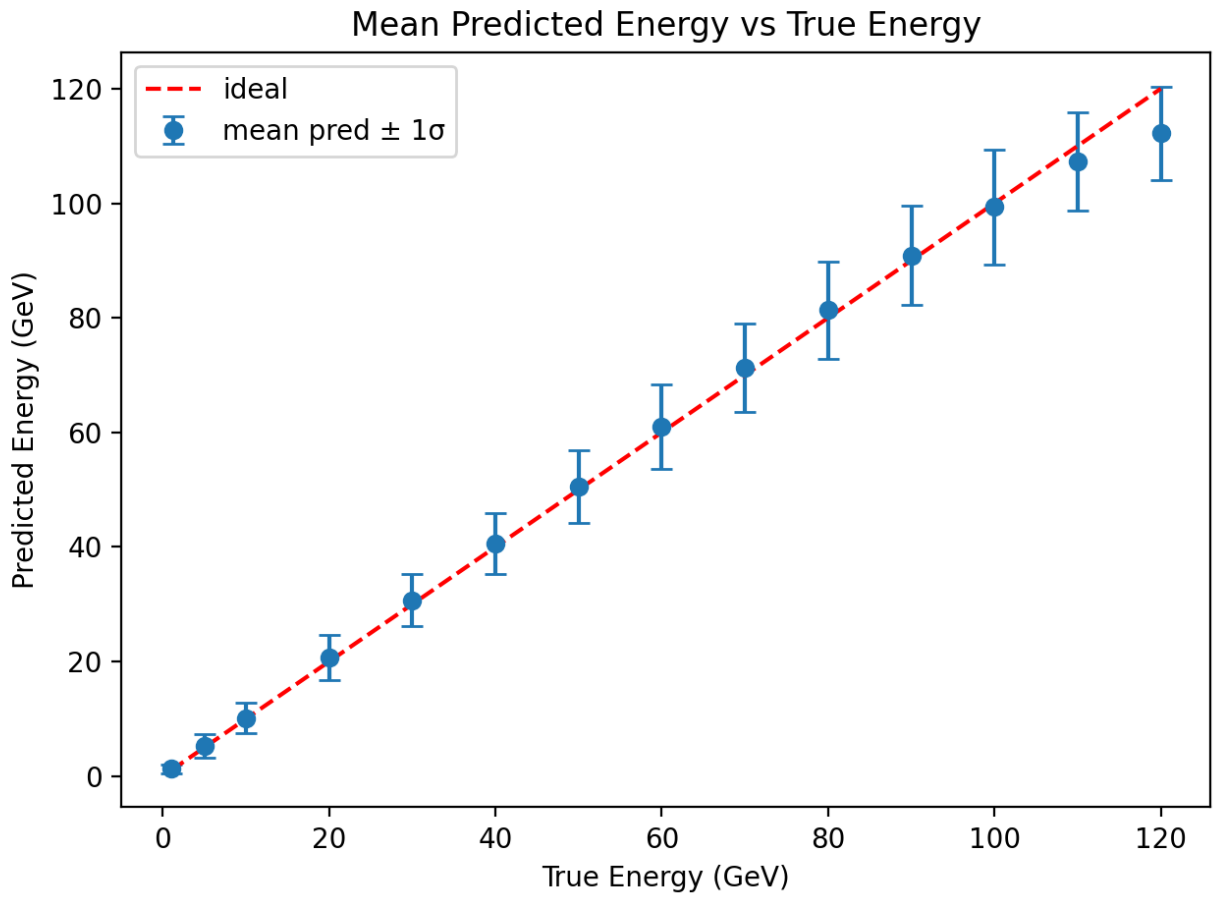
$20x20\mu m^2$



$100x100\mu m^2$



$50x50\mu m^2$



$200x200\mu m^2$

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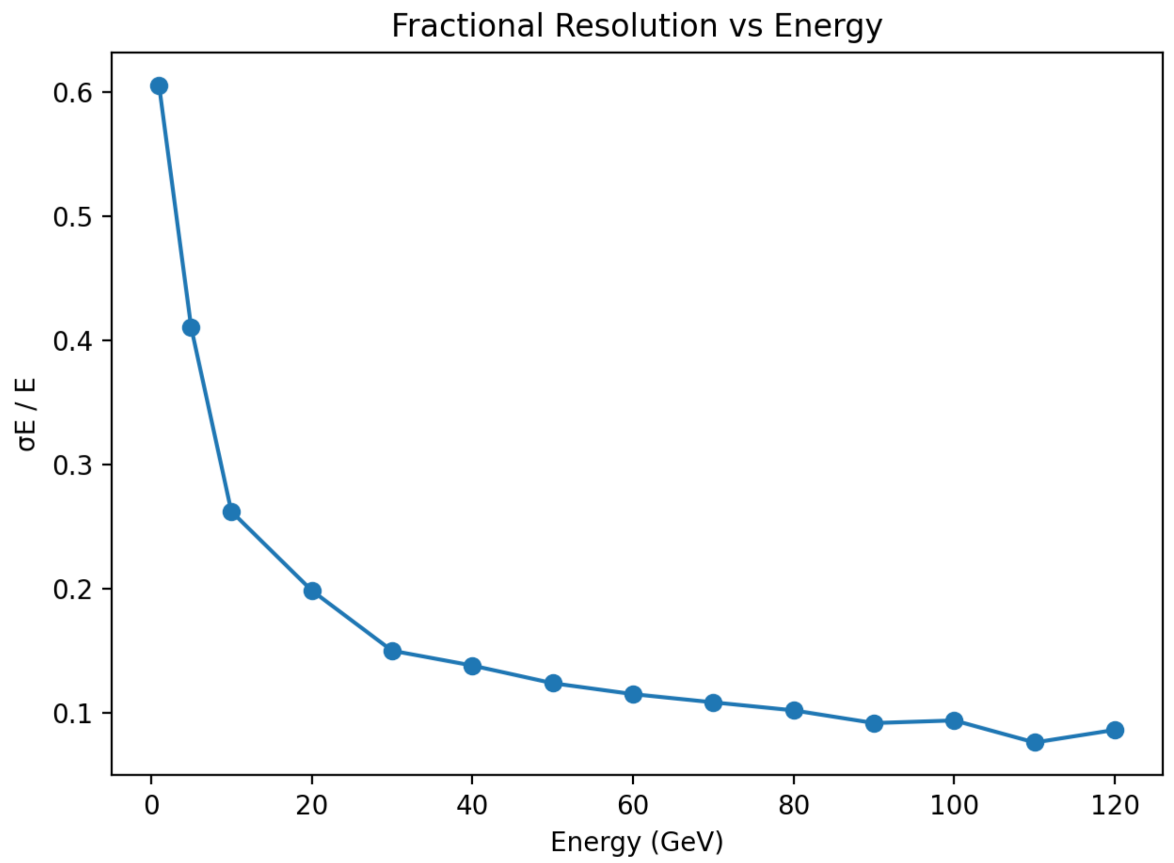
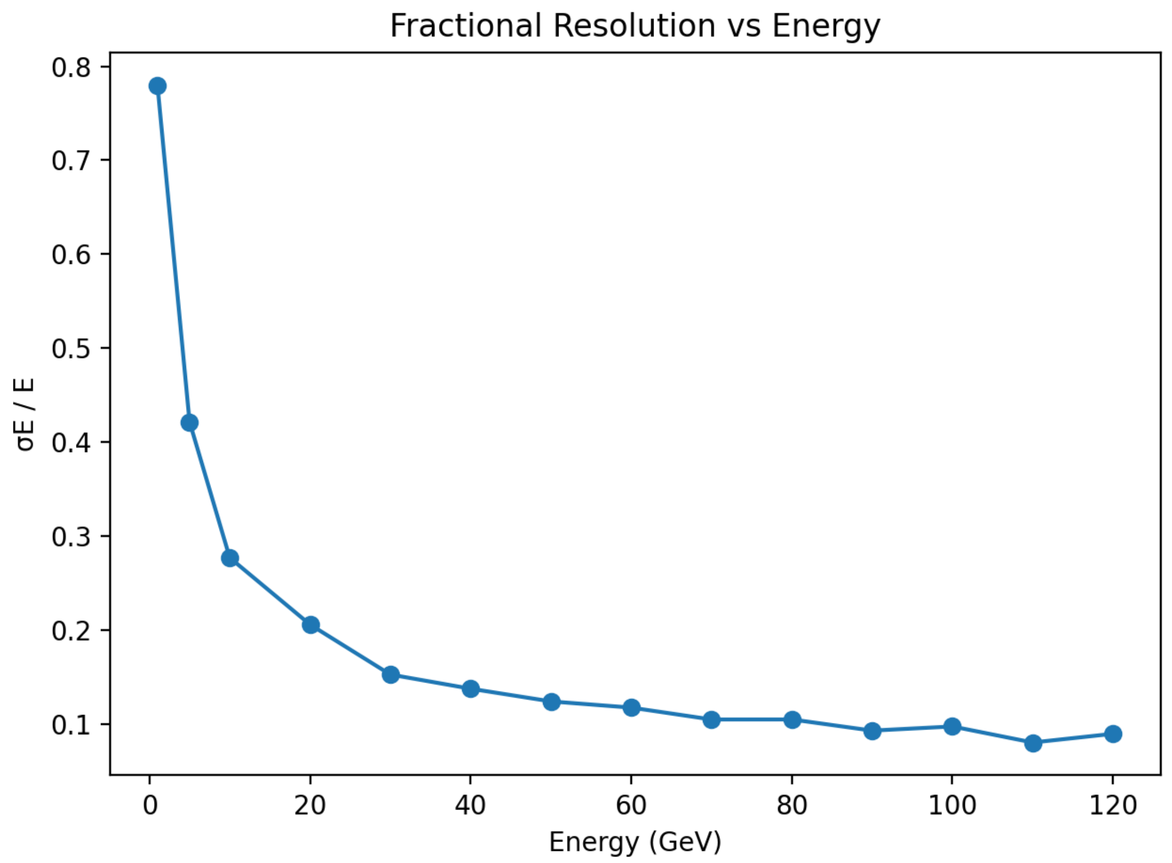
Neural Network Results

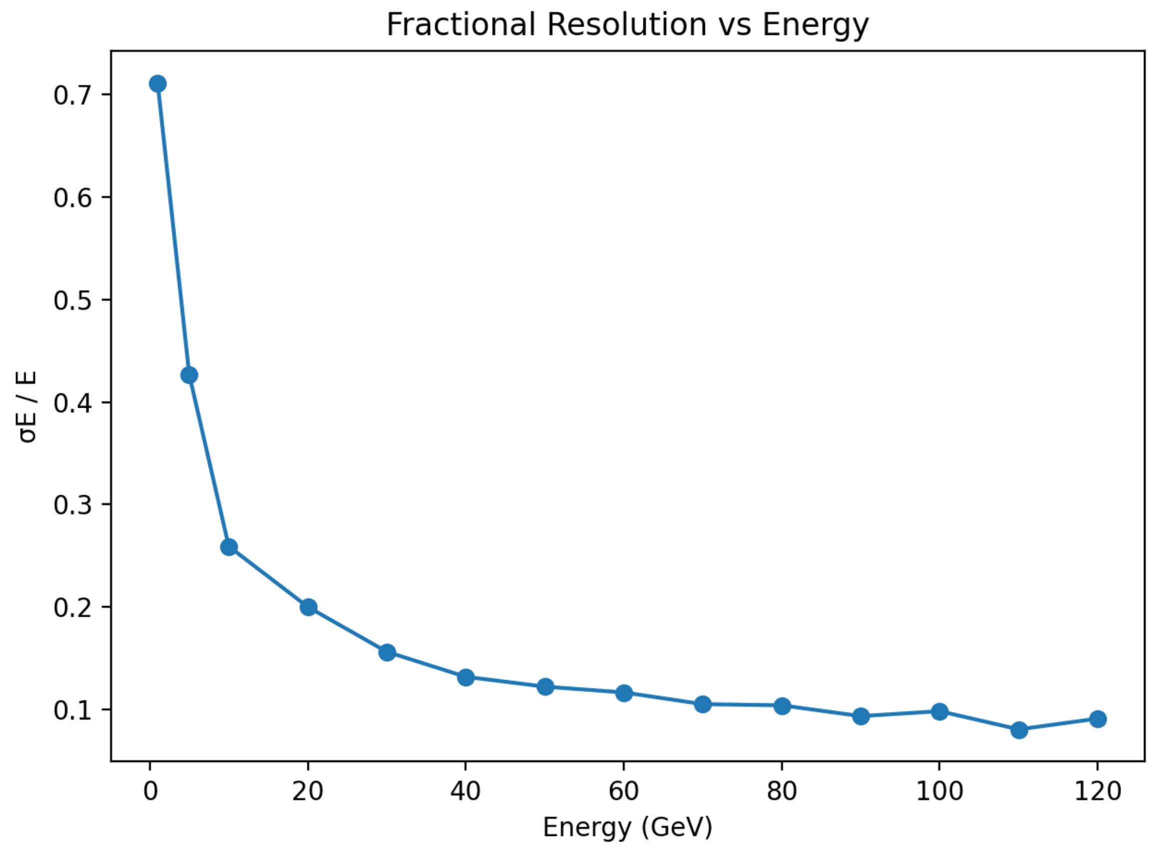
- Same general shape of fractional resolution
- Lower energies present biggest differences. At 1GeV:
  - $\frac{\sigma_E}{E} = 0.6$ $(20x20\mu m^2)$
  - $\frac{\sigma_E}{E} = 0.7$ $(50x50\mu m^2)$
  - $\frac{\sigma_E}{E} = 0.78$ $(100x100\mu m^2)$
  - $\frac{\sigma_E}{E} = 0.76$ $(200x200\mu m^2)$



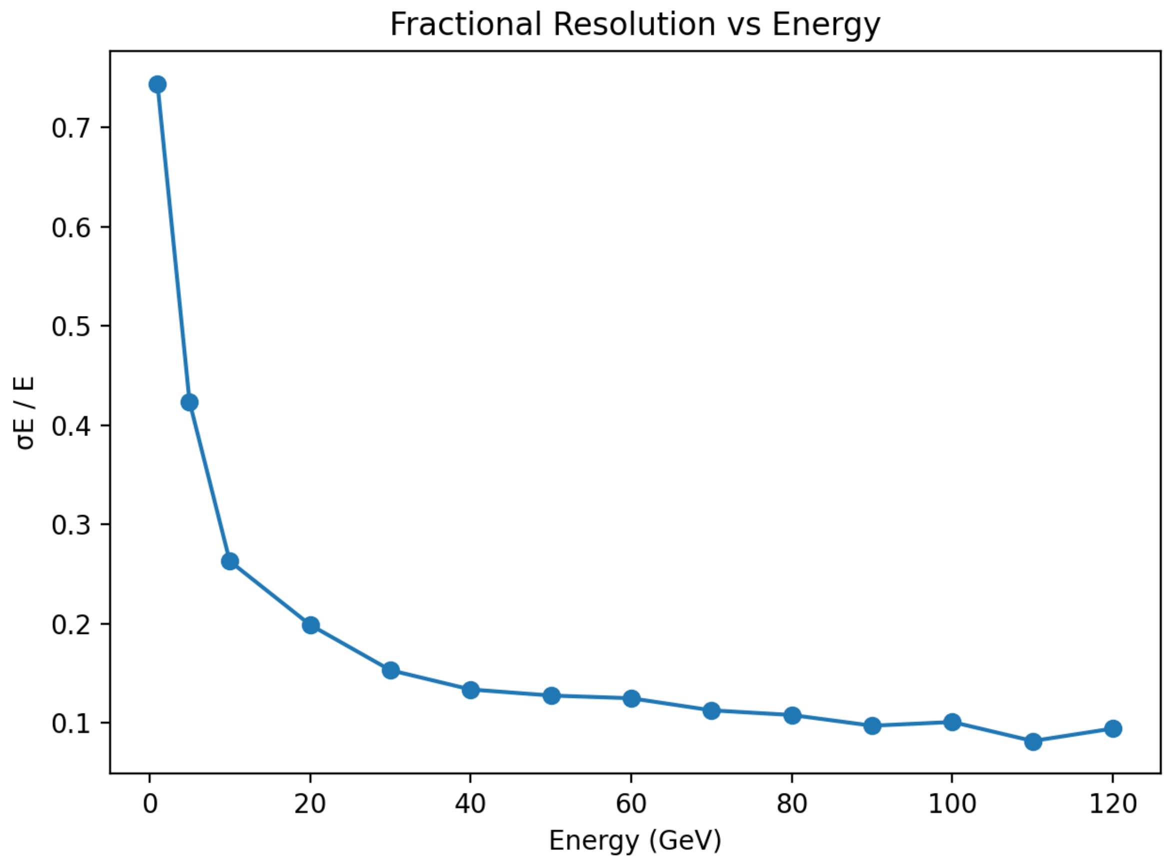
$20x20\mu m^2$



$100x100\mu m^2$



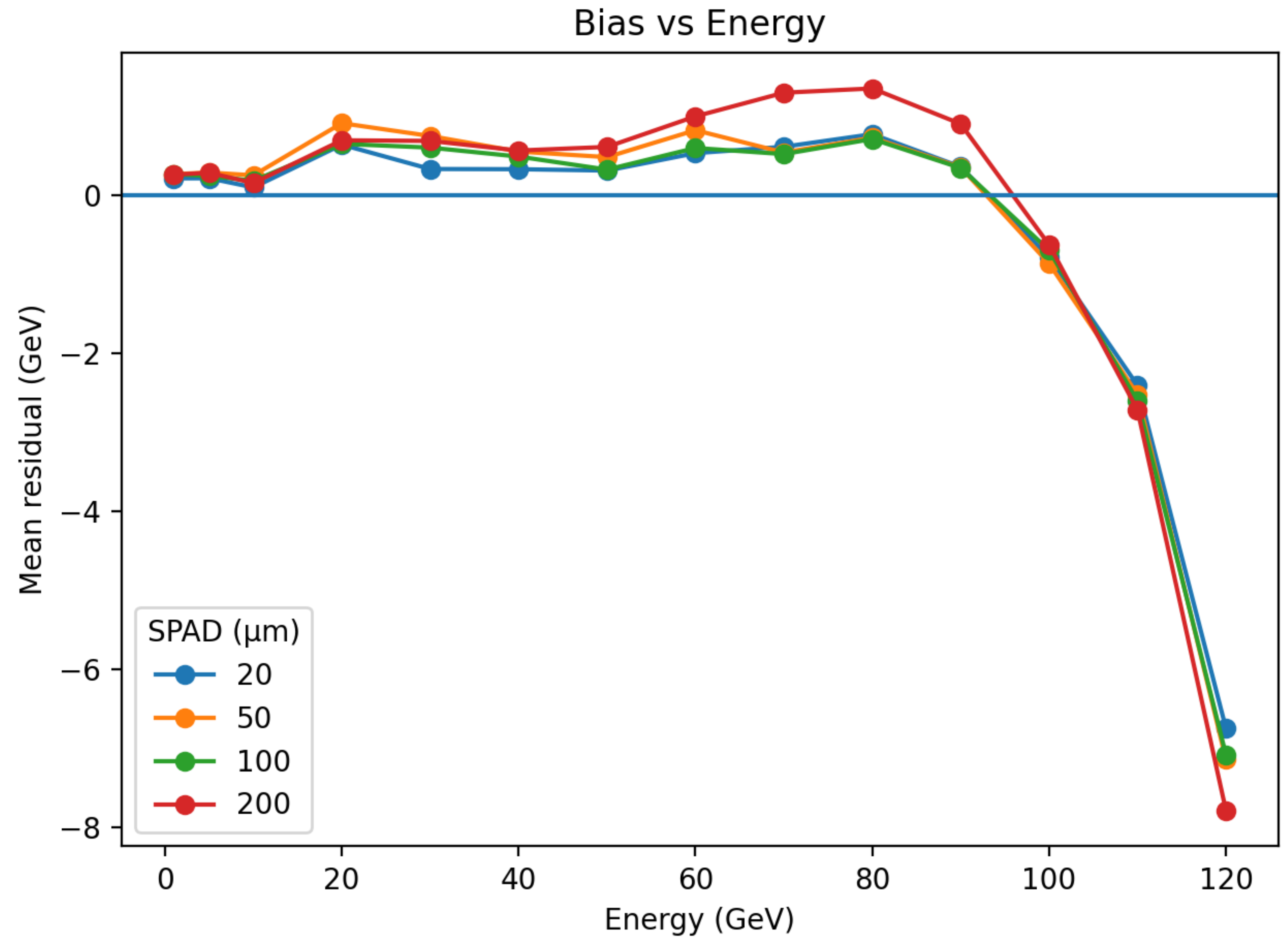
$50x50\mu m^2$



$200x200\mu m^2$

Neural Network Results

- Bias mostly consistent among mid/low SPAD sizes, with low magnitudes.
- CNN has major under-predictions at higher energies due to energy set bounds.
- Fractional resolution increases with SPAD size, other than a dip at $200 \times 200\mu m^2$, likely due to the neural network learning other features.



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Next Steps

- Add beam angle as a variable in the analysis.
- Finer energy steps at smaller energies
- Simulate different particles
- Implementing into IDEA simulation
- Physical dSiPM measurements on HG-DREAM

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Conclusion

- Photon losses in dSiPMs are predominantly by QE, with deadtime as a secondary but non-insignificant factor.
- The NN architecture is able to reasonably predict energy given dSiPM outputs in the form of time-sliced tensors.
- Smaller SPAD sizes generally give the network better reconstruction capabilities.