Value of Timing in Calorimetry

Nural Akchurin, Christopher Cowden, Jordan Damgov, **Adil Hussain**, Shuichi Kunori

Texas Tech University

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Outline

- The focus of this study is the role of timing for specifically for calorimetry, and not what calorimeters can provide experiments for ‘global’ timing. We are focusing on ‘local’ timing ($t = t_{global} - z/c$)

1. Fast (< 5 ns) & precise (> 15 ps) timing in energy reconstruction and improvements gained by neural networks (CNN and GNN)

2. Longitudinal segmentation with timing in fiber calorimeters

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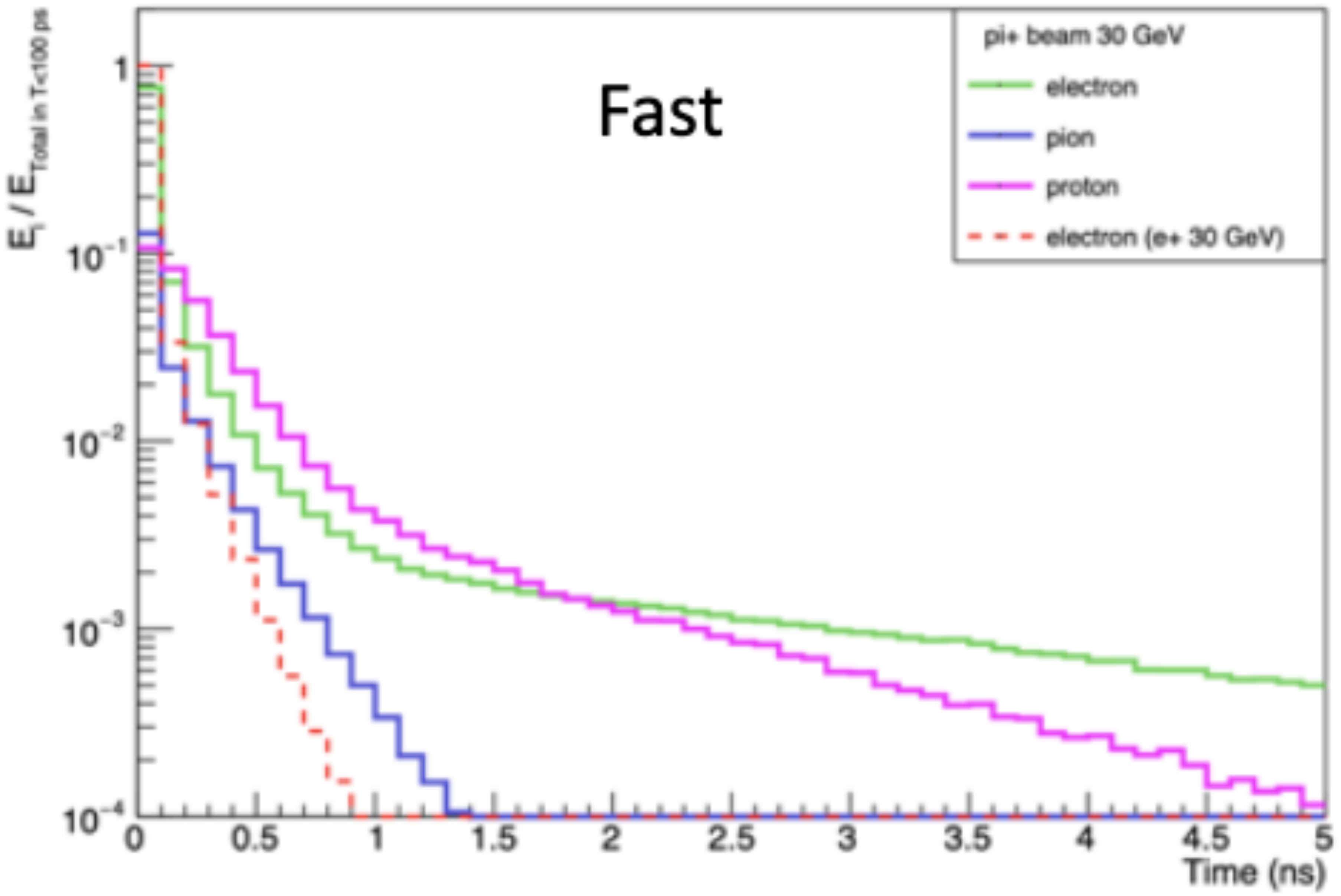
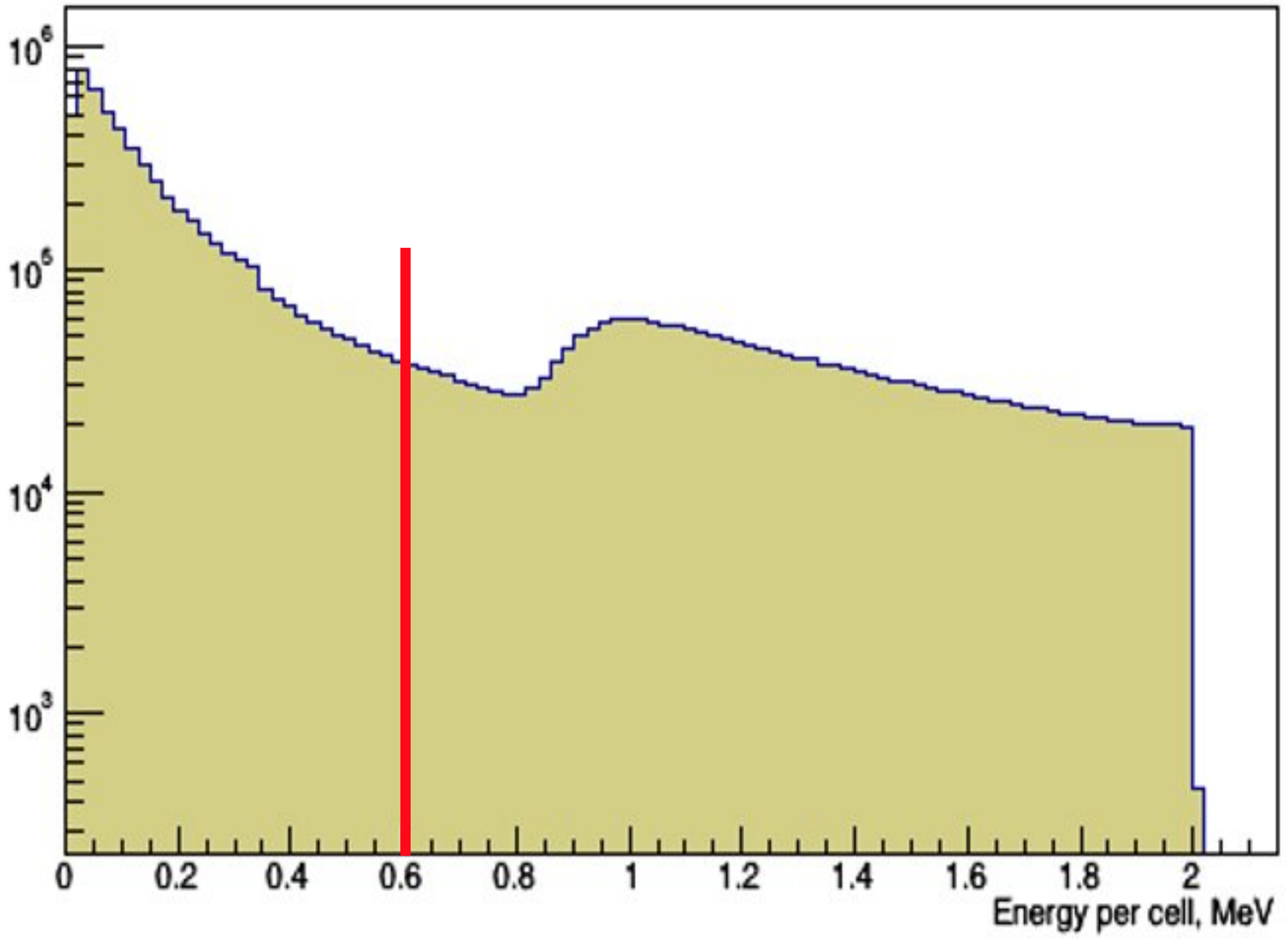
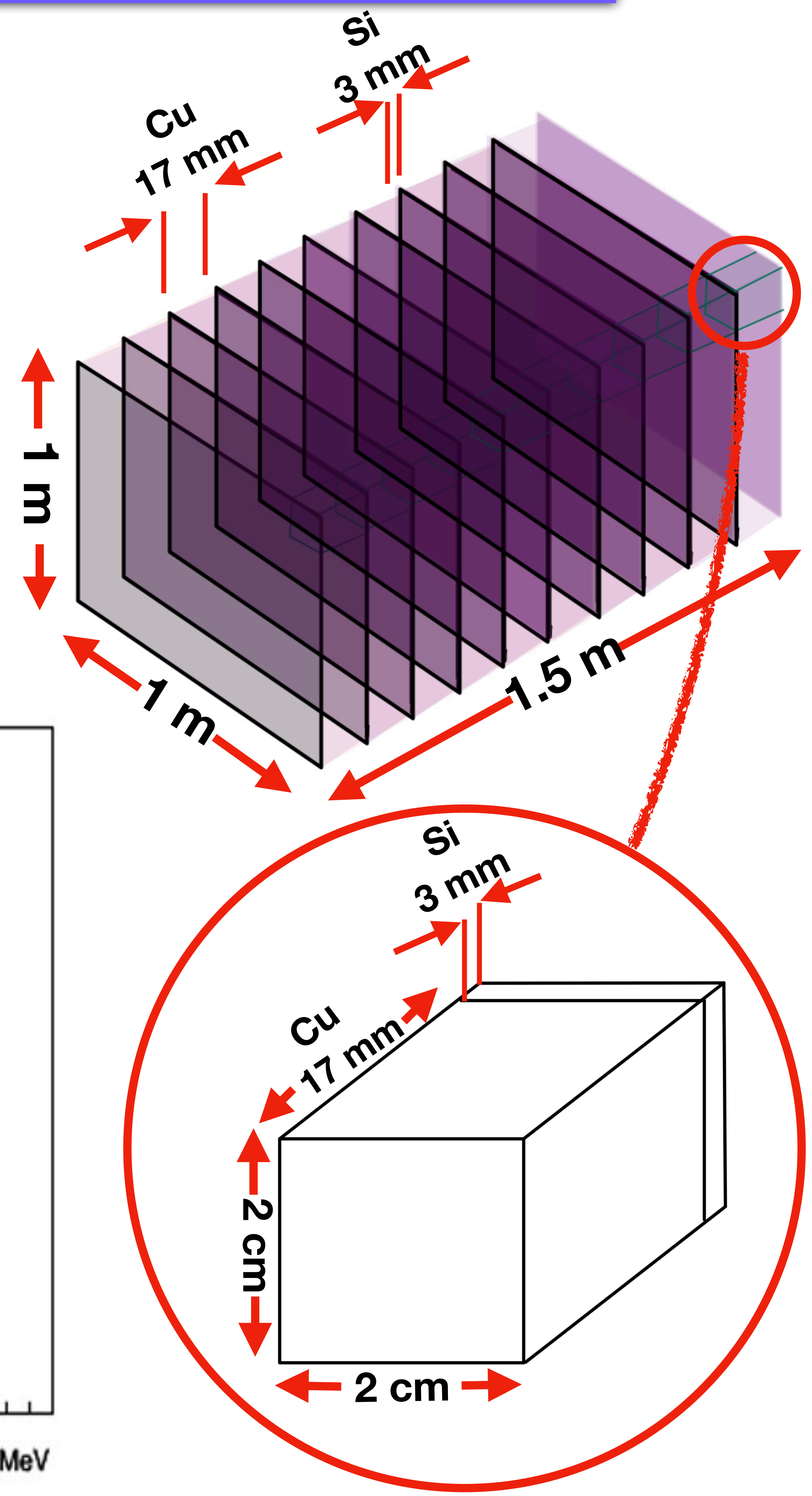
Simulation Set-Up

❖ Copper / Silicon sampling calorimeter is simulated with GEANT4

- Alternating Cu 17 mm (absorber), Si 3 mm (active) layers, with size of 1.0×1.0×1.5 m^3
- Readout granularity is 2×2×2 cm^3
- Signal is integrated over 5 ns local time
- Energy threshold of 0.6 MeV per cell is applied, with MIP MPV at about 1.0 MeV
- No electronics or noise included



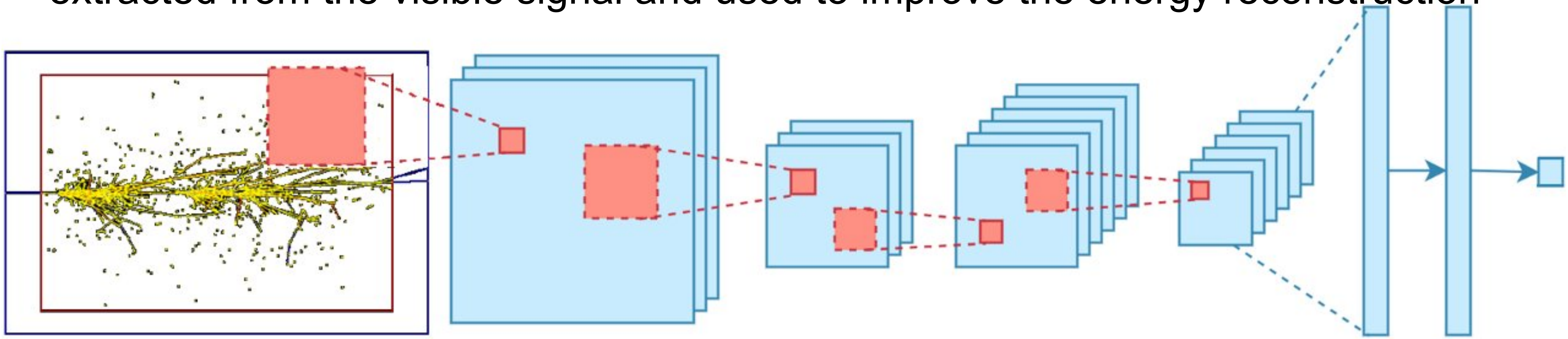




Shuichi Kunori's Talk on Friday

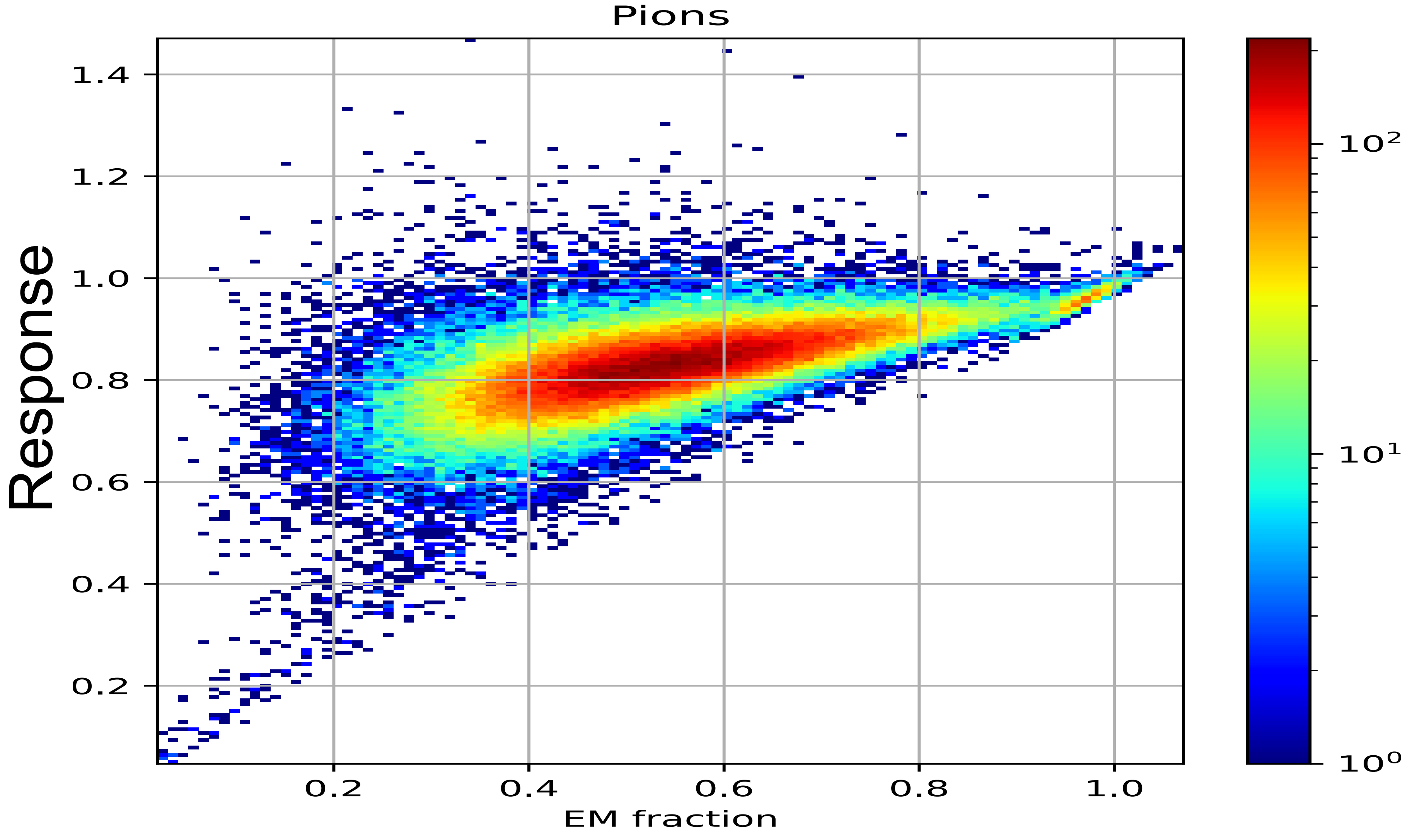
Convolutional Neural Network for Energy Reconstruction

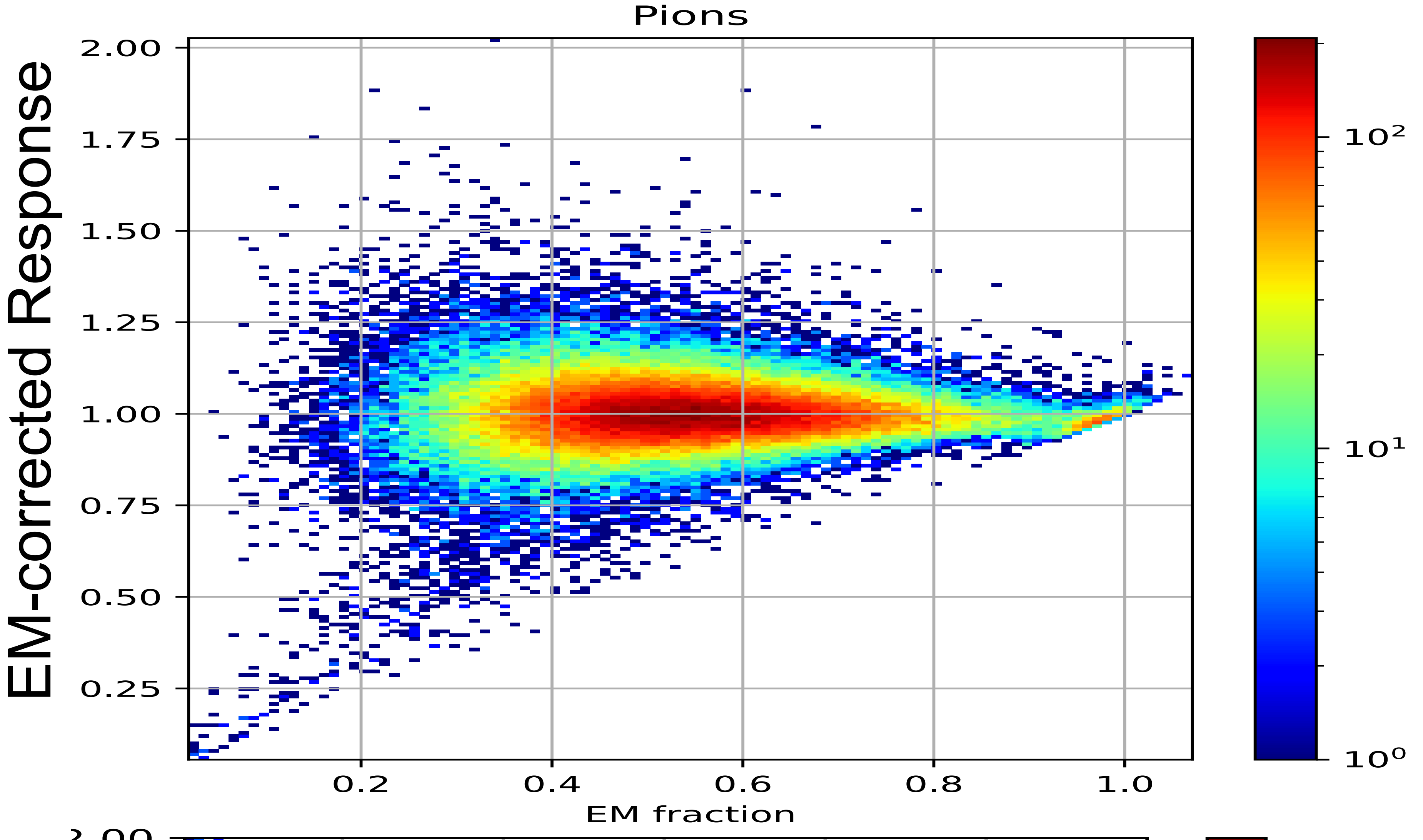
- ❖ Convolutional Neural Network (CNN) are very good at image classification
  - Raw images are used
  - Higher level features extracted using sequential convolutional operations
  - Regression performed
- ❖ Showers in high granularity calorimeters can be viewed as 3D images
  - Fiber calorimeters with depth segmentation by timing
- ❖ Detailed information on multiplicity and production angle of the secondaries can be extracted from the visible signal and used to improve the energy reconstruction



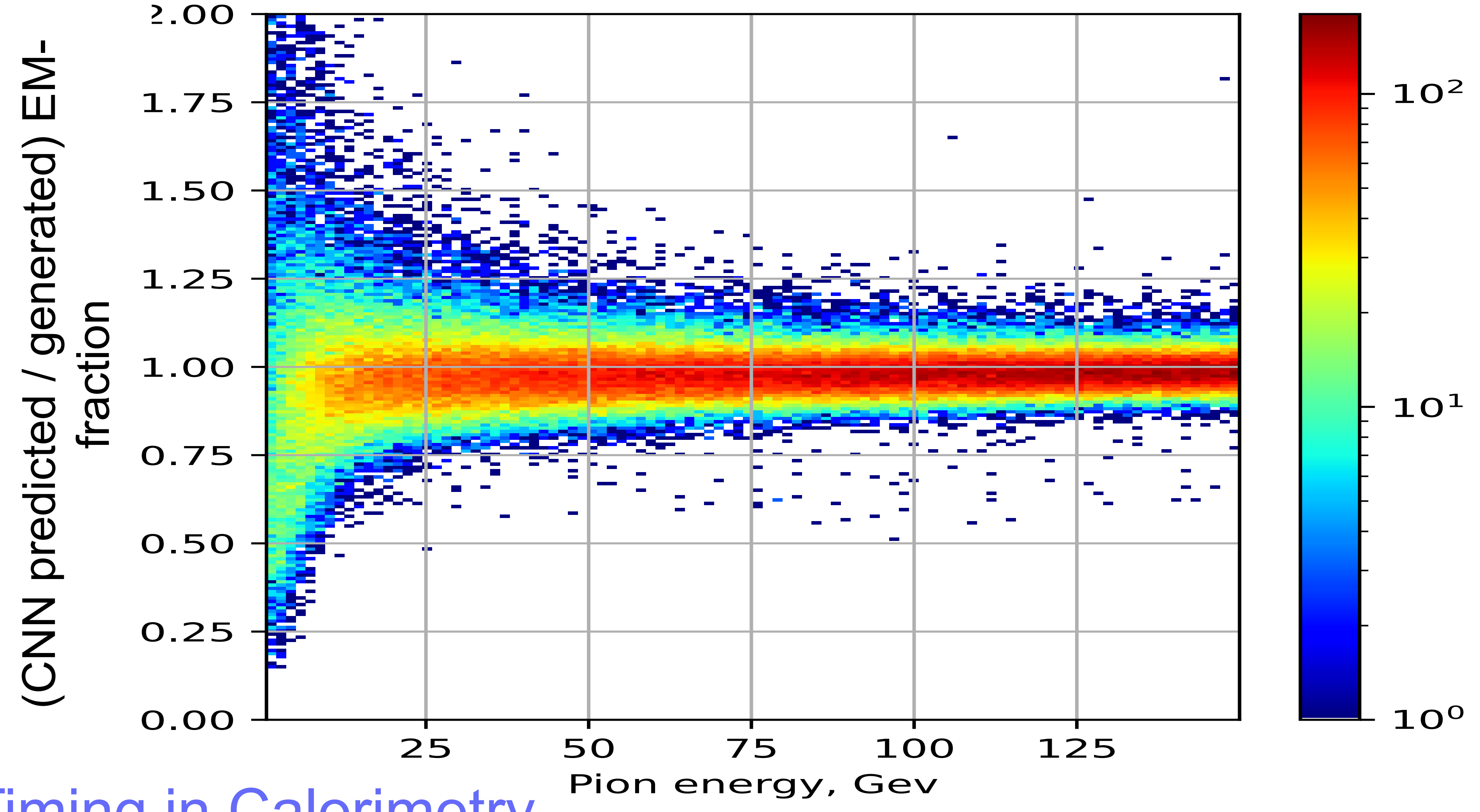
Energy Reconstruction with Traditional Techniques

❖ The performance of the energy reconstruction with CNN is compared to:
- Simple energy sum over all the channels in the volume
- Reconstruction with correction for fluctuation in the EM-fraction





CNN can estimate the EM- fraction in hadron showers



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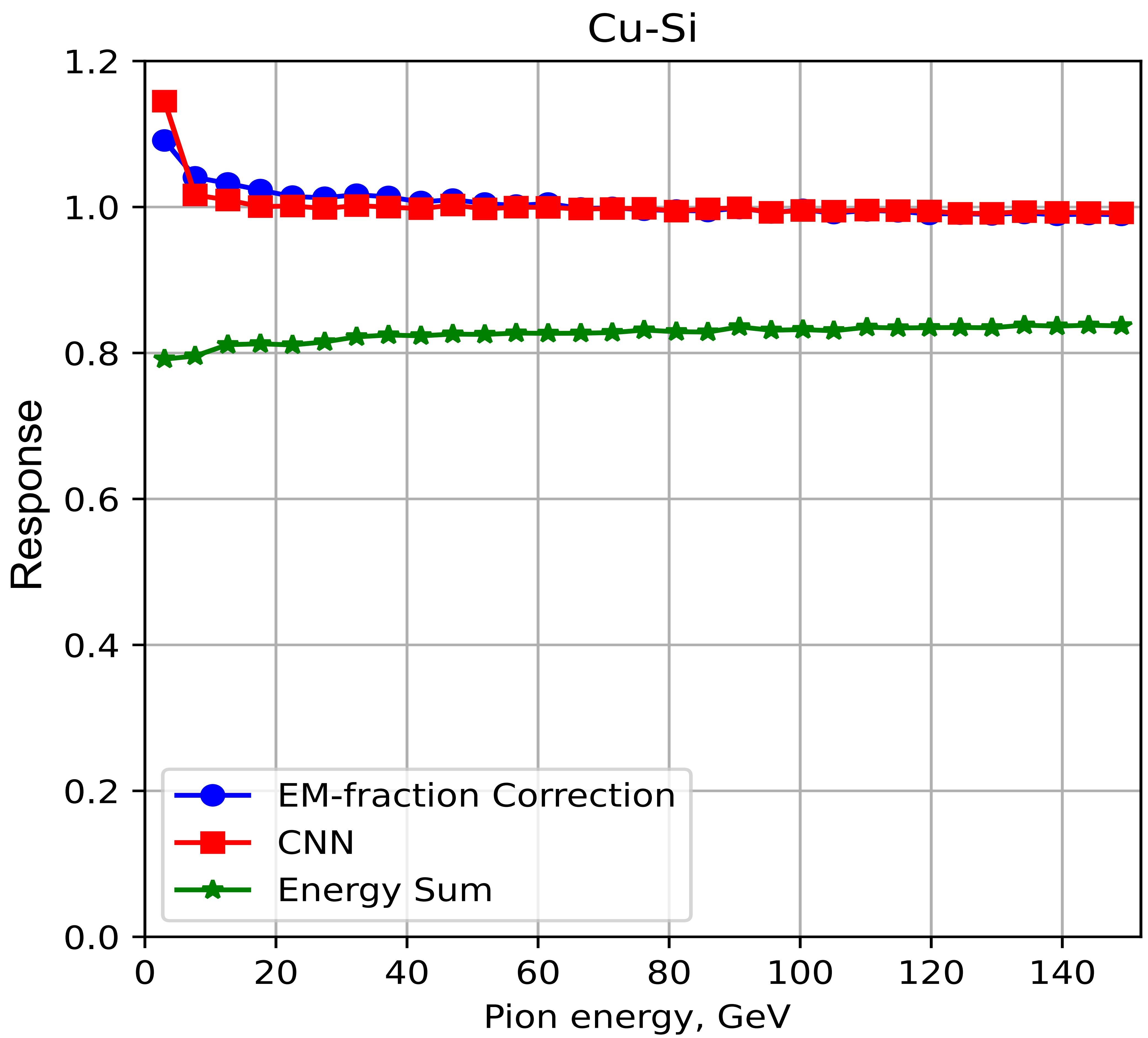
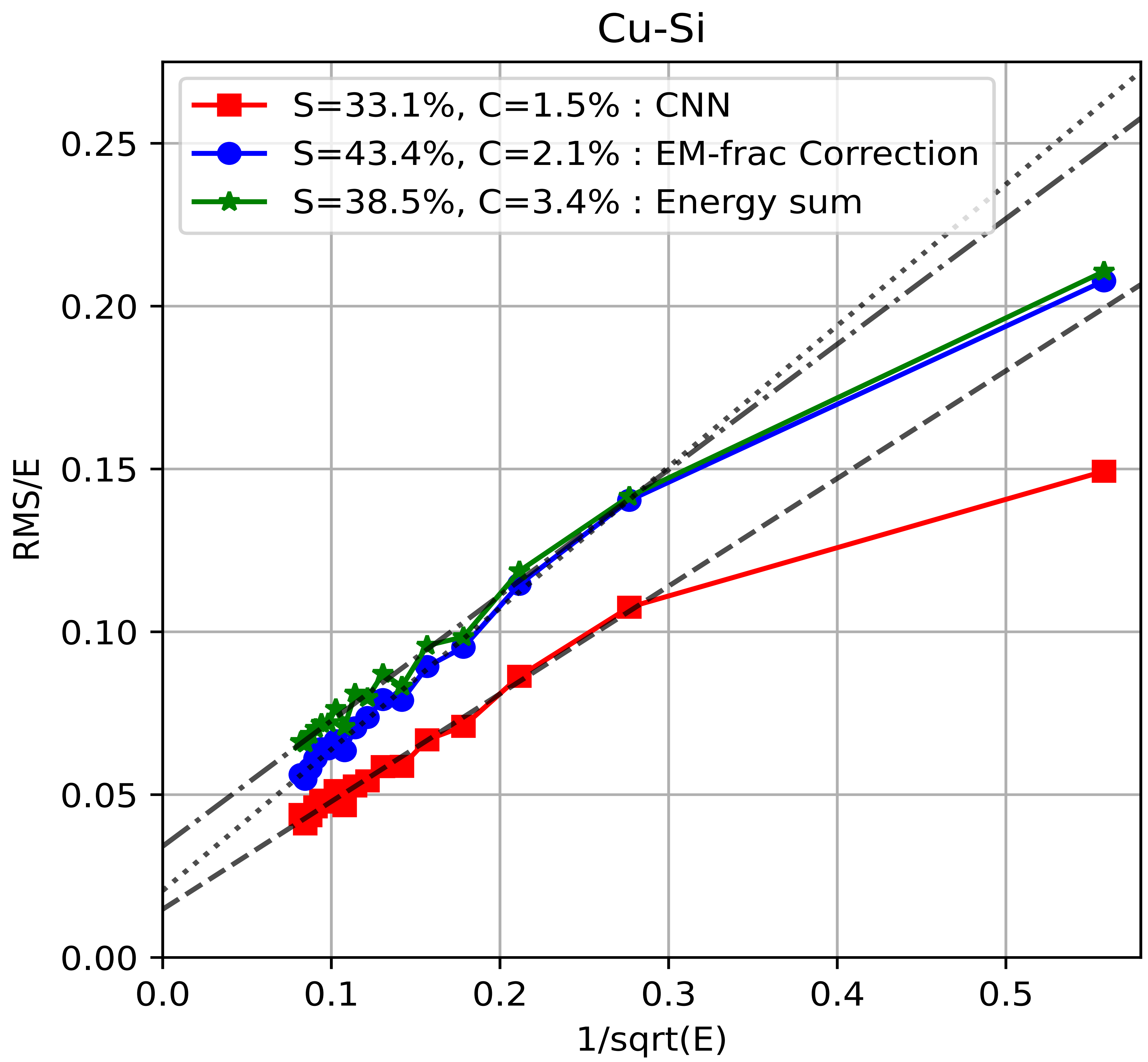
CNN Performance - Single Hadron

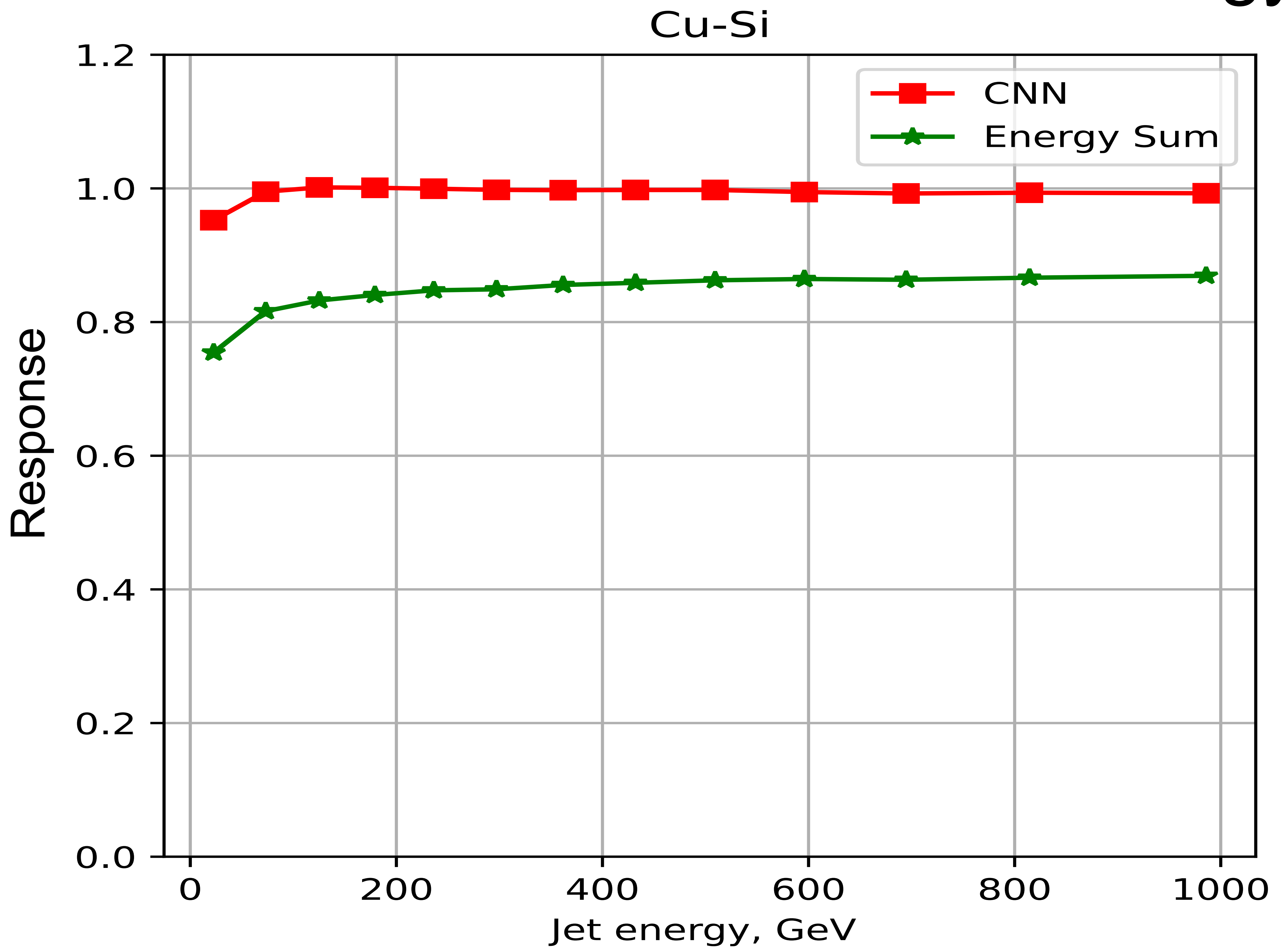
CNN trained with single pions (0.5 - 150 GeV) outperforms the conventional techniques for energy reconstruction

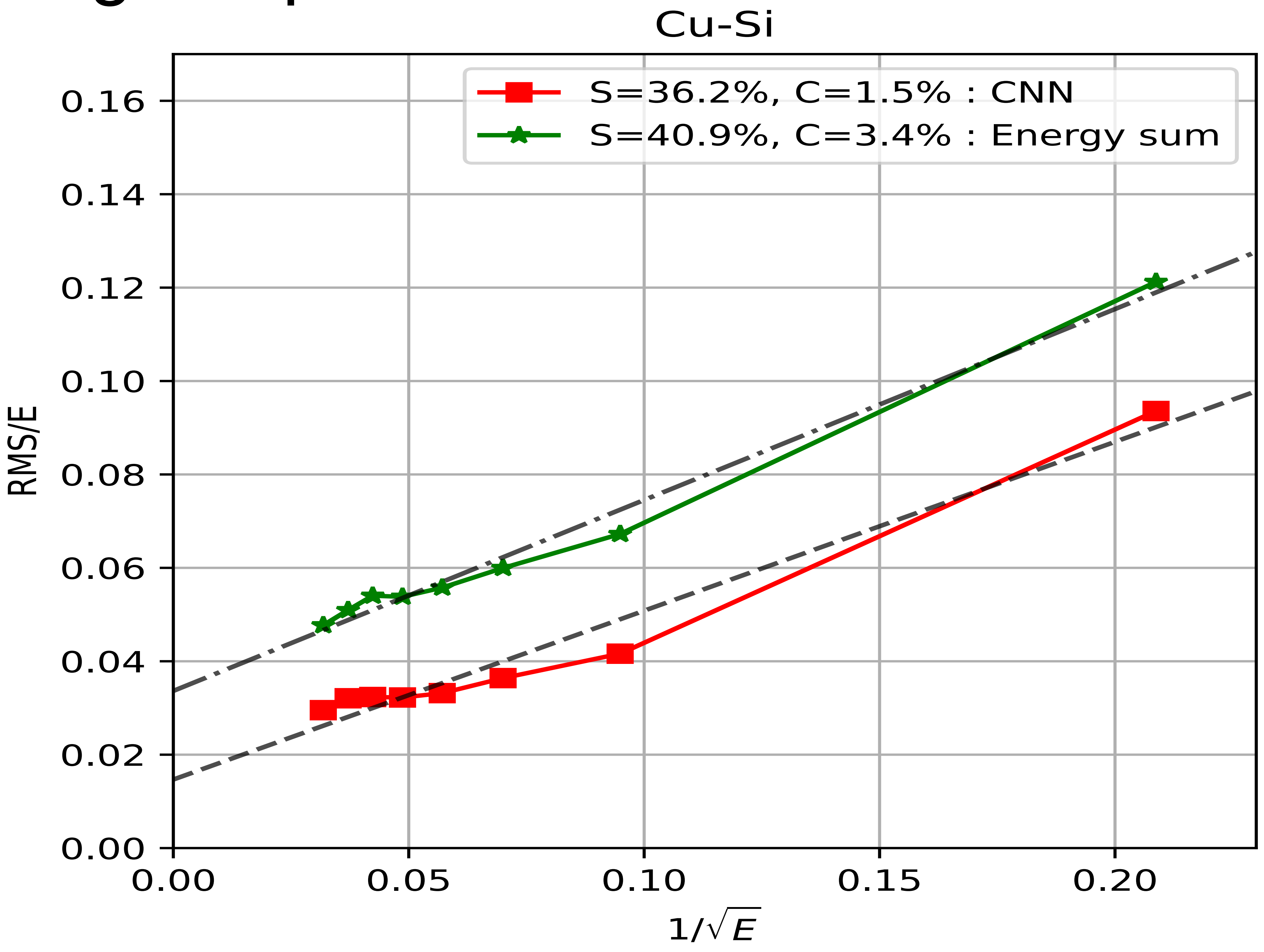




CNN Performance - u quark (Jet)

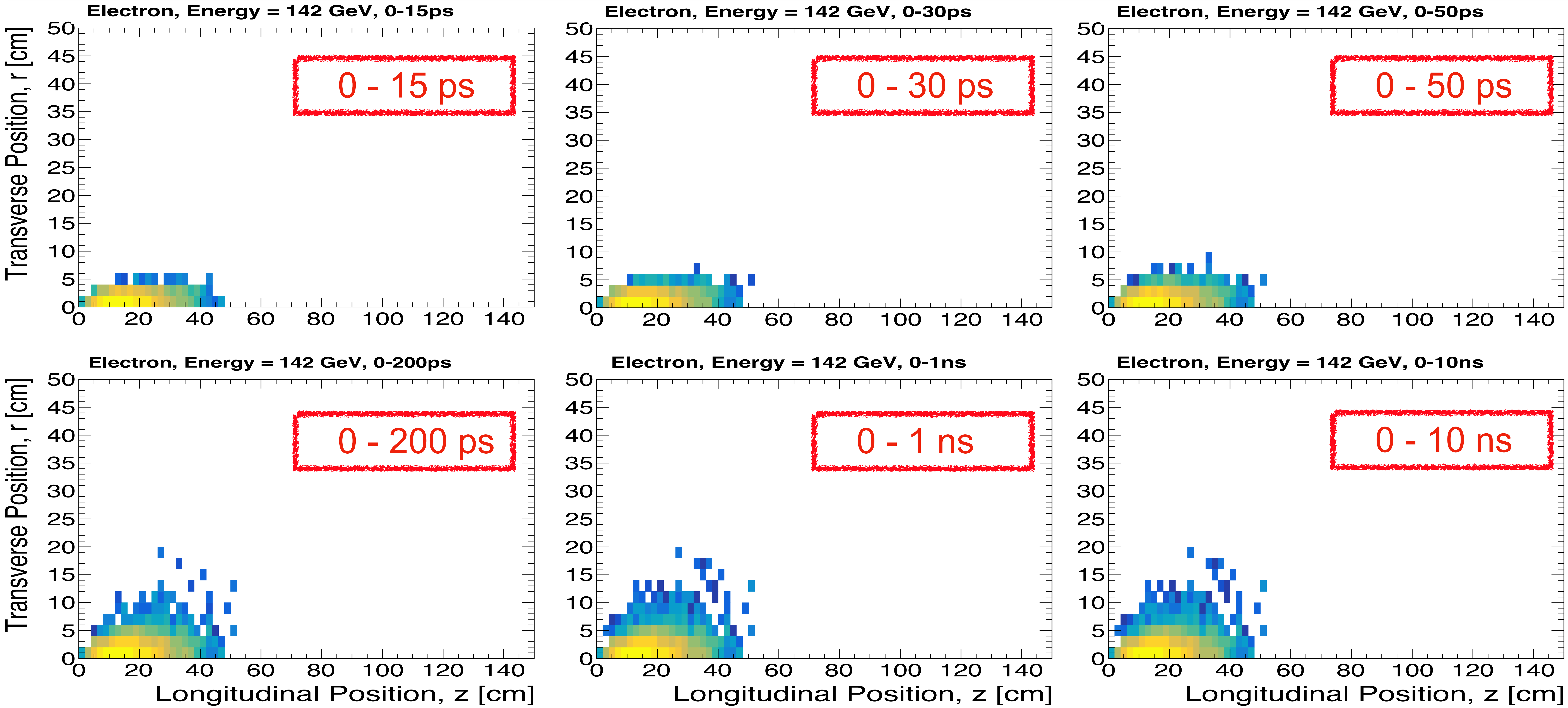
The CNN trained on single pions (0.5-150 GeV) performed very well with jet reconstruction in the extended energy range - up to 1 TeV





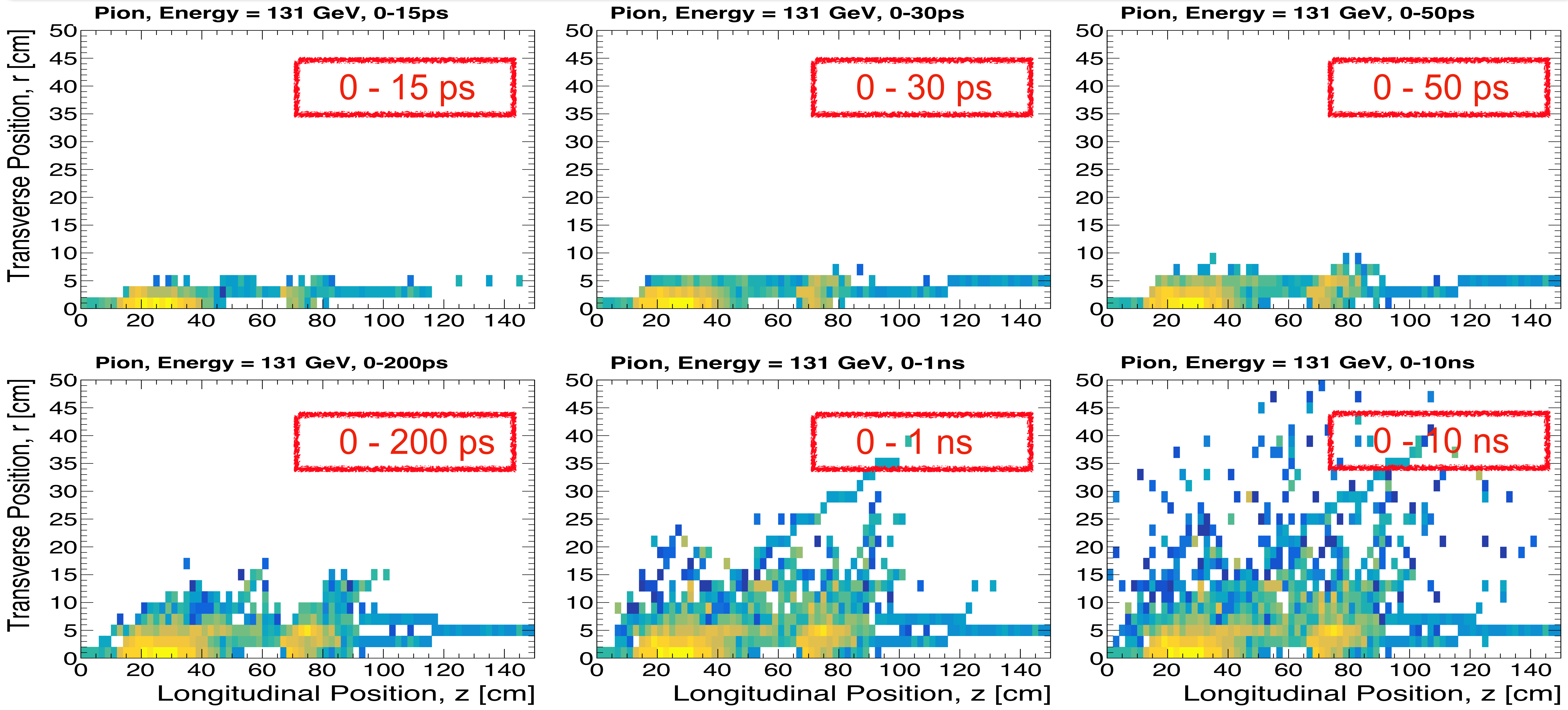
We also tested the CNN trained on single pions for electron energy reconstruction and it maintains good performance comparable to traditional techniques

Spatial Distribution of a Single Electron Shower



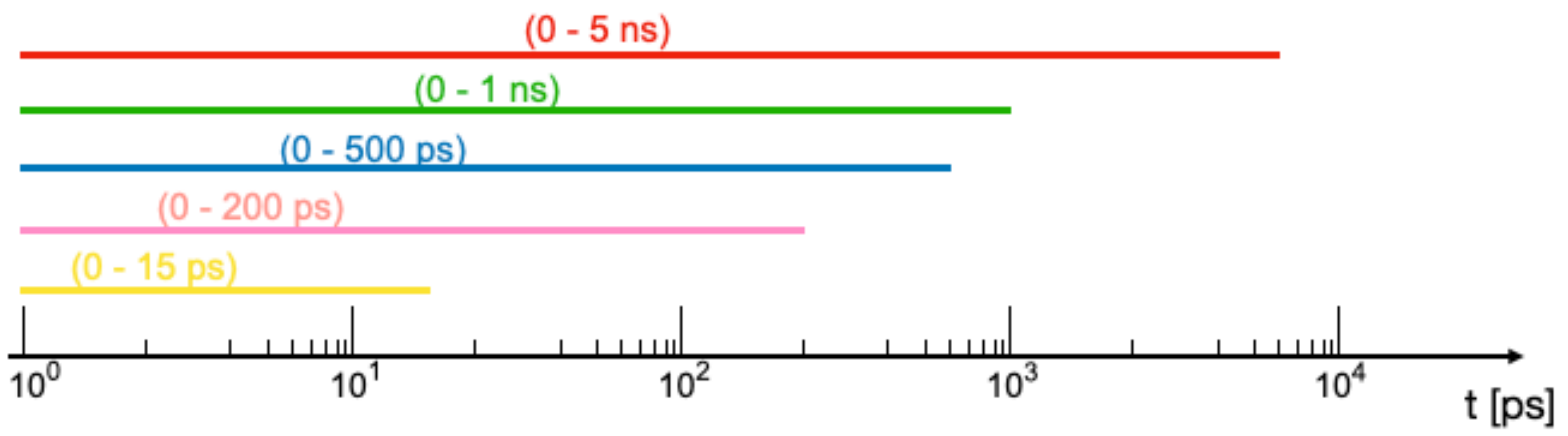
The energy deposits due to a single 142 GeV electron are shown in $r - z$ coordinates where the colors indicate deposited energy. As indicated on top of each each plot, the integration times gradually increase from 0-15 ps (top left) to 0-10 ns (bottom right). Time is 'local', in other words, it is corrected for the travel time, $t = t_{G4} - z/c$, along z-axis for all particles.

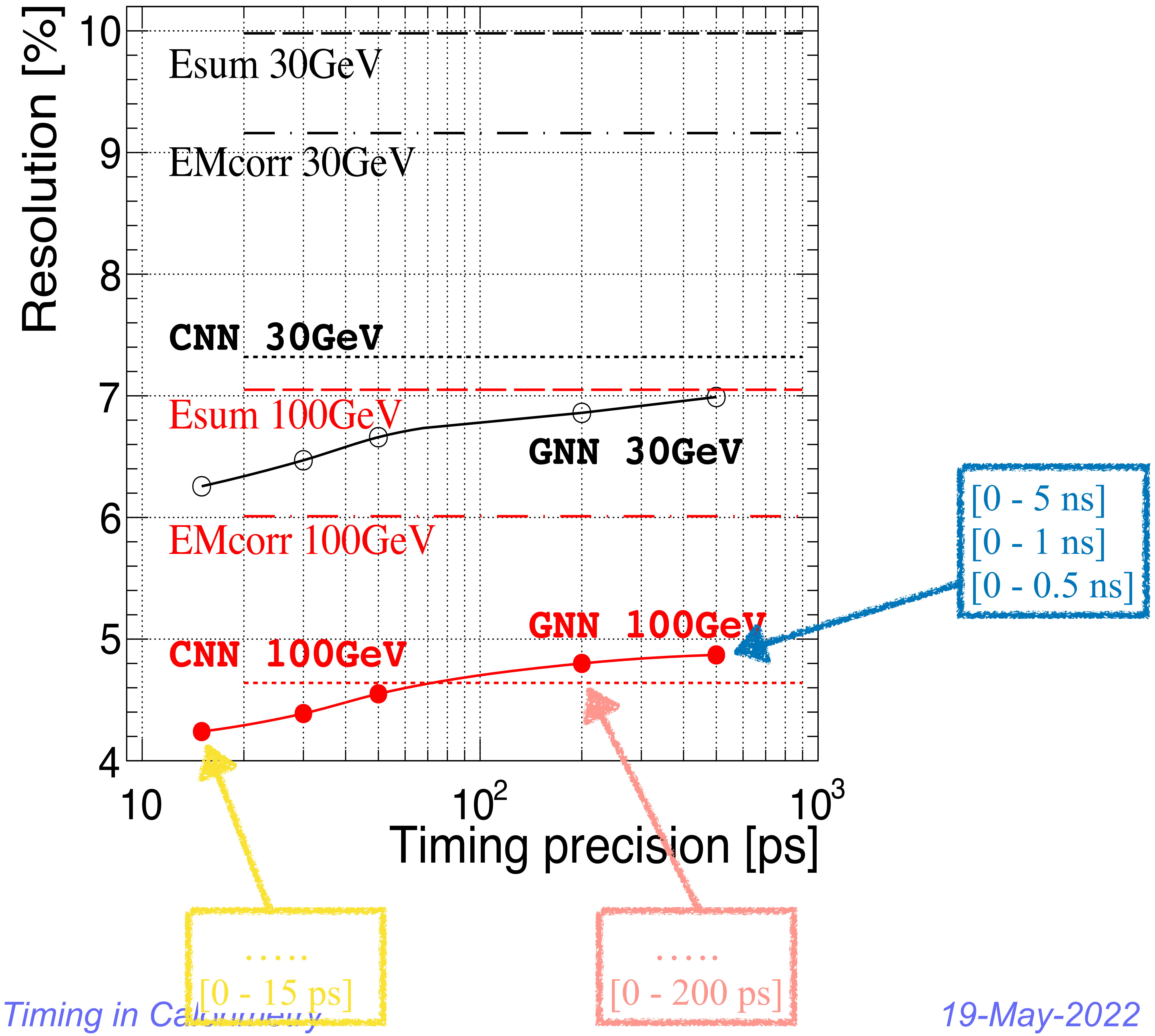
Spatial Distribution of a Single Pion Shower



The energy deposits due to a single 131 GeV charged pion are shown in $r - z$ coordinates where the colors indicate deposited energy. As indicated on top of each each plot, the integration times gradually increase from 0-15 ps (top left) to 0-10 ns (bottom right). Time is 'local', in other words, it is corrected for the travel time, $t = t_{G4} - z/c$, along z-axis for all particles.

Comparison of Performance using Timing information with Graph Neural Network (GNN)





The energy resolution (σ/E) for 30 GeV (black) and 100 GeV (red) pions. Simple energy sum (Esum), *f*em corrected energy sum (EMcorr), CNN and GNN reconstruction techniques. The horizontal axis indicates the assumed timing precision for the GNN technique. The energy resolutions obtained from different reconstruction techniques are also shown for comparison

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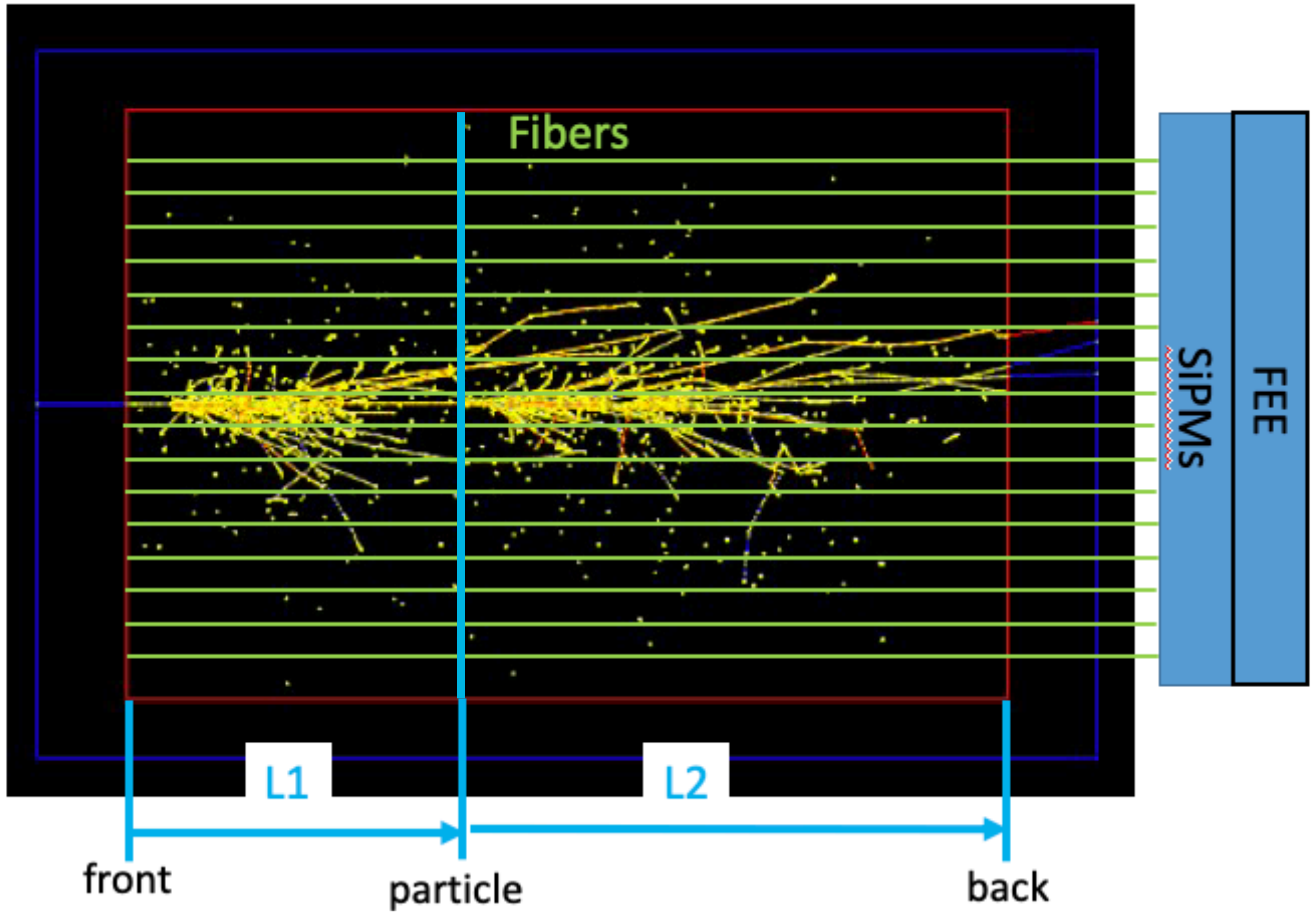
Longitudinal Segmentation with Timing



Signal time = L1/c + L2/v

c = velocity of particle

v = c/n, n = 1.46

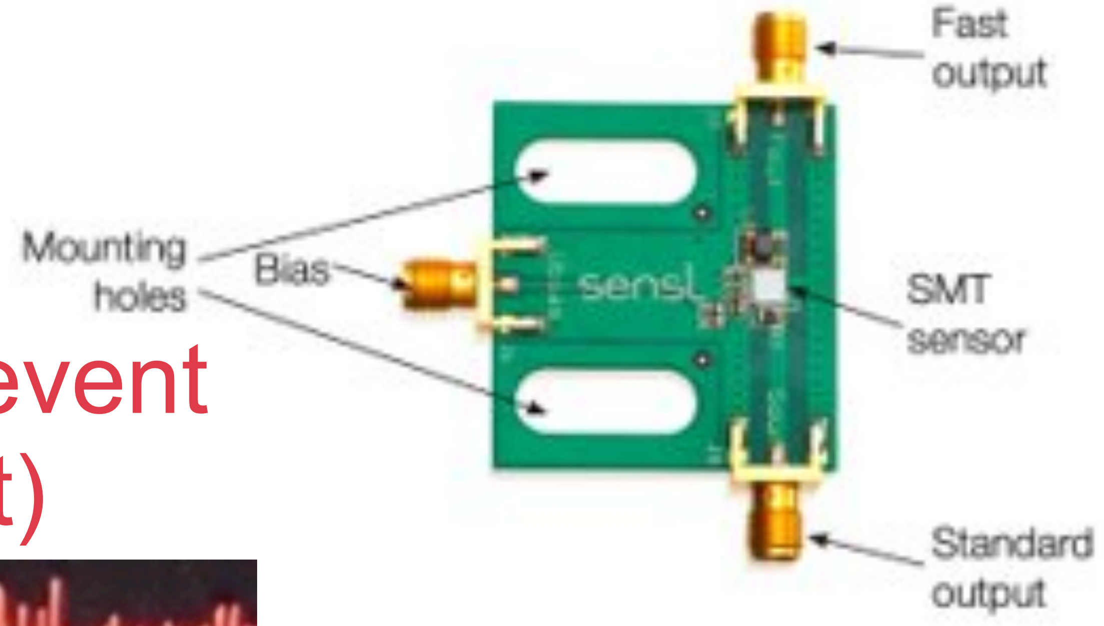
ΔL = 2 cm ≃ 44 ps

- ❖ 2D readout: fewer readout channels
- ❖ Effective 3D segmentation with timing
- ❖ Photo Detector and Front End Electronics (FEE) is on the back side of the detector, low radiations
- ❖ Easier signal collection
- ❖ The calibration is easier, no need to calibrate in depth

Separation of Two Signals Close in Time

SiPMs are excellent photon counting devices and have potential to map time structure of showers in calorimeter when used with high performance waveform digitizer

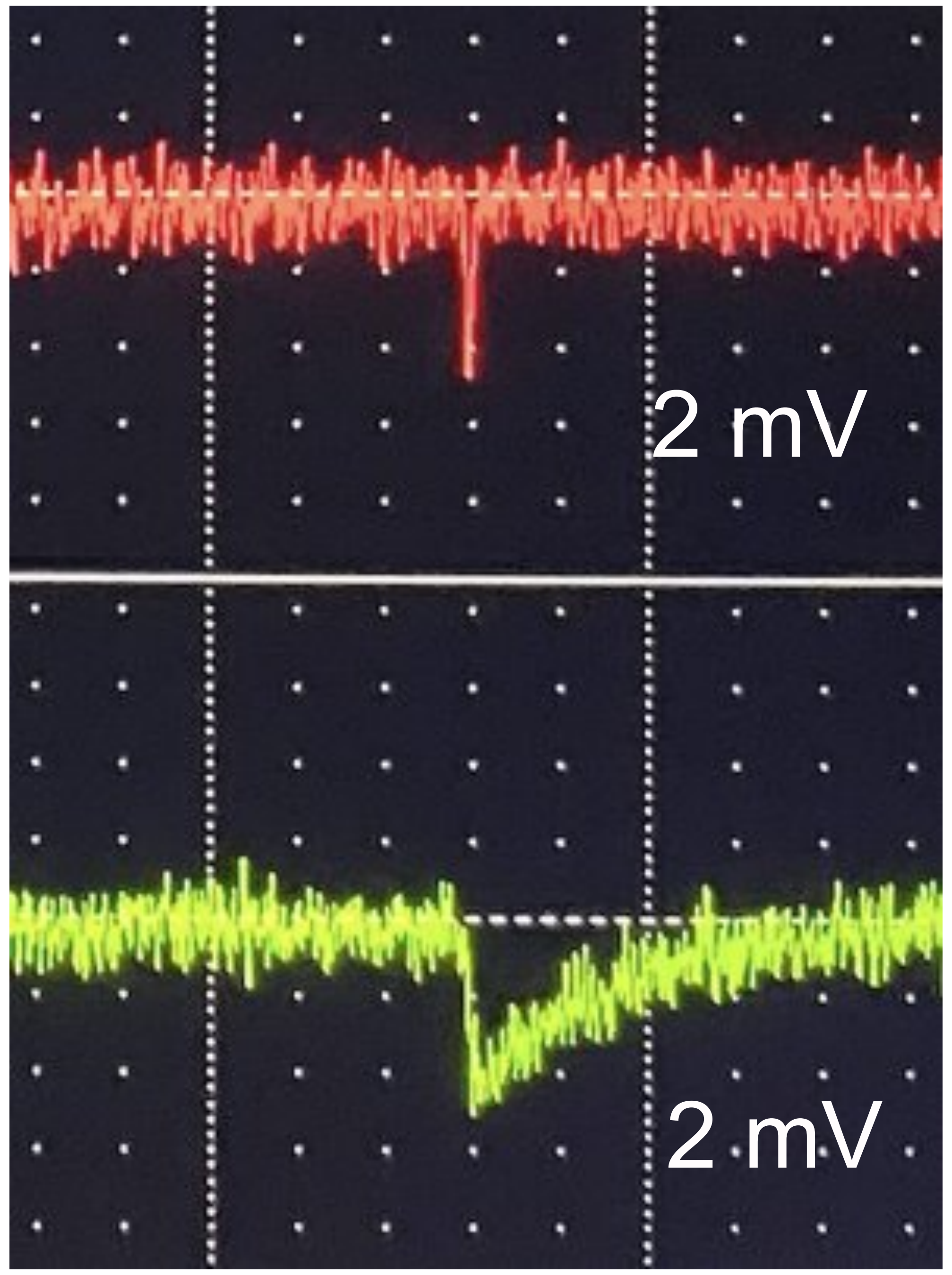
SensL (MicroFC-30020SMT) SiPMs have fast and standard outputs



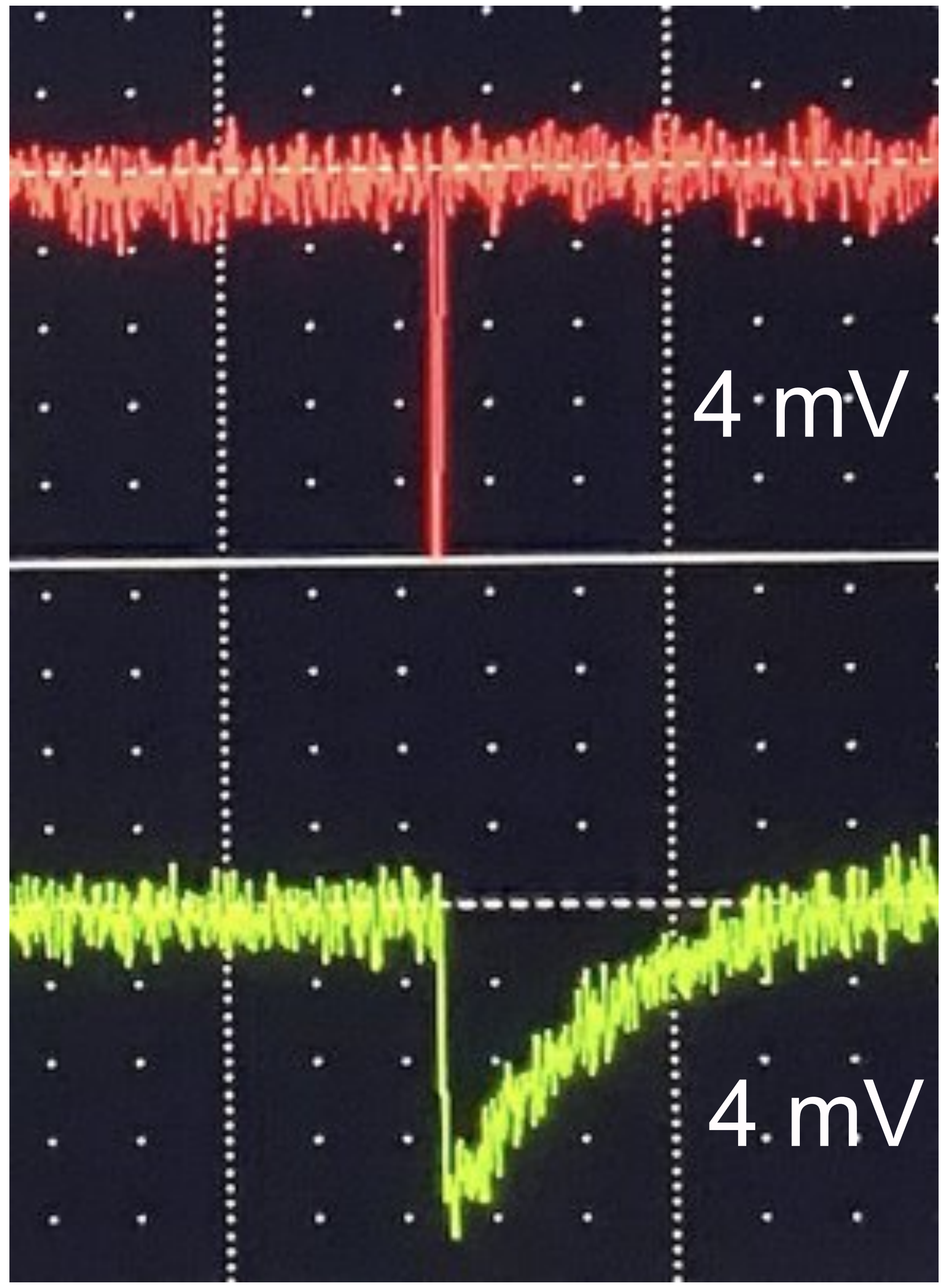
Fast Output (2 mV/photon)

Std Output (2 mV/photon)

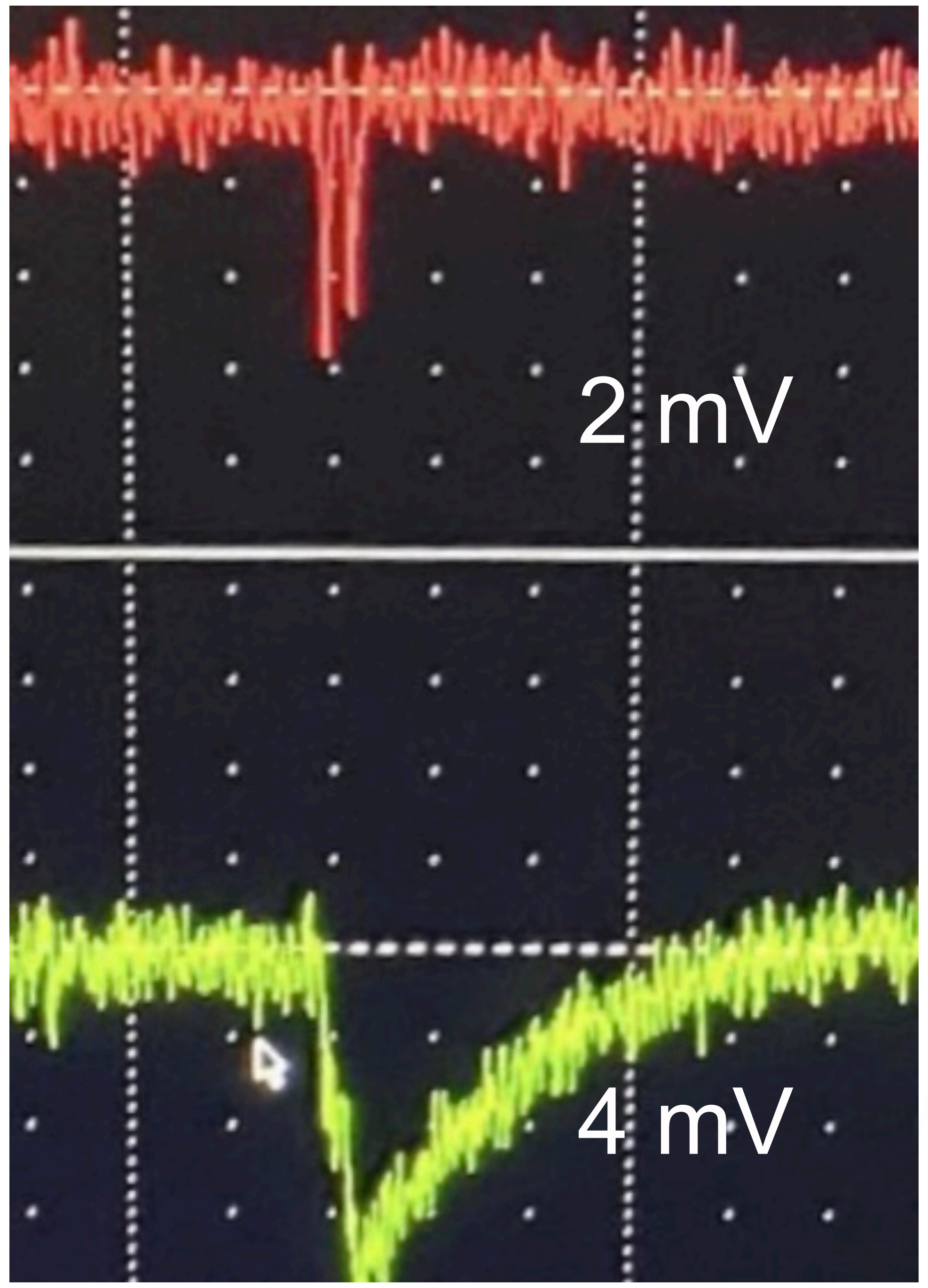
One photon event

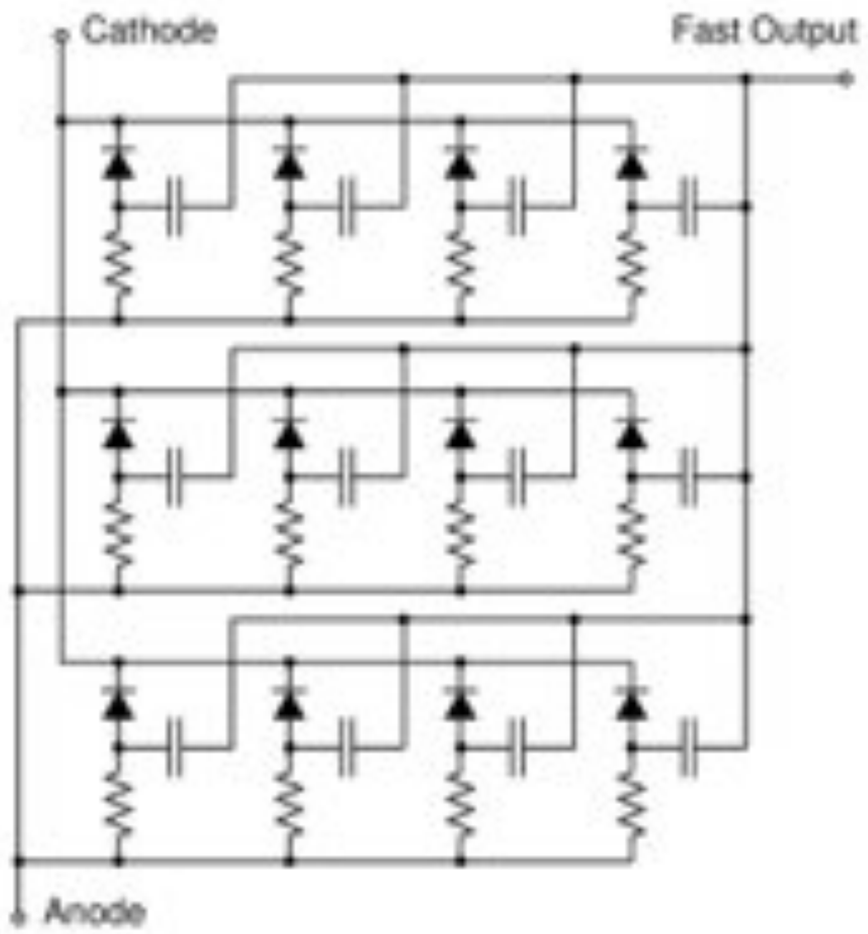


Two photons event (Simultaneous)

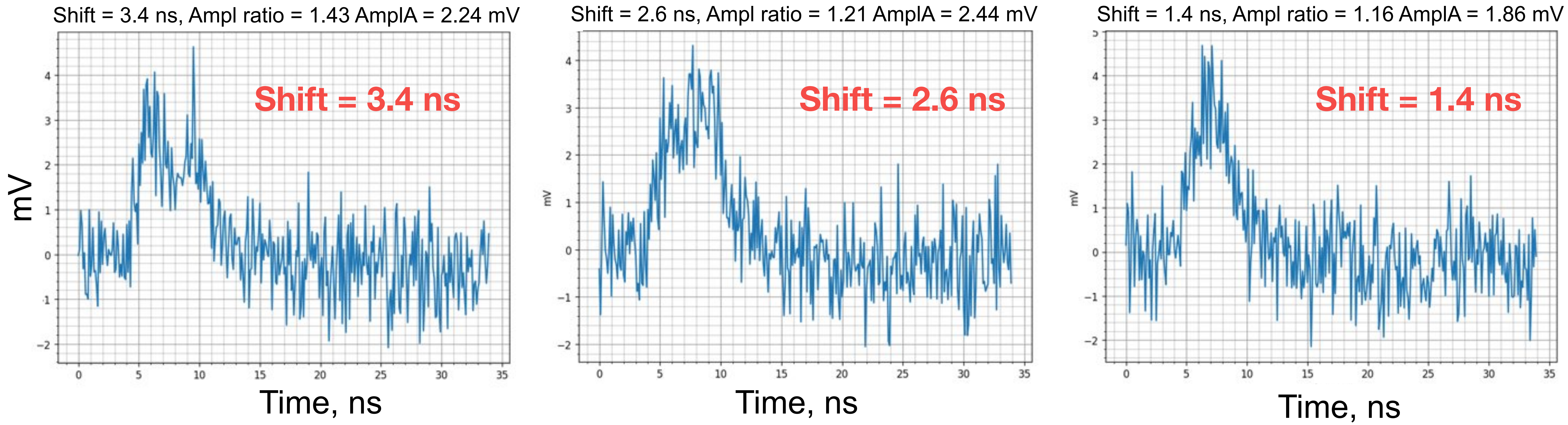


Two photons event (5 ns apart)

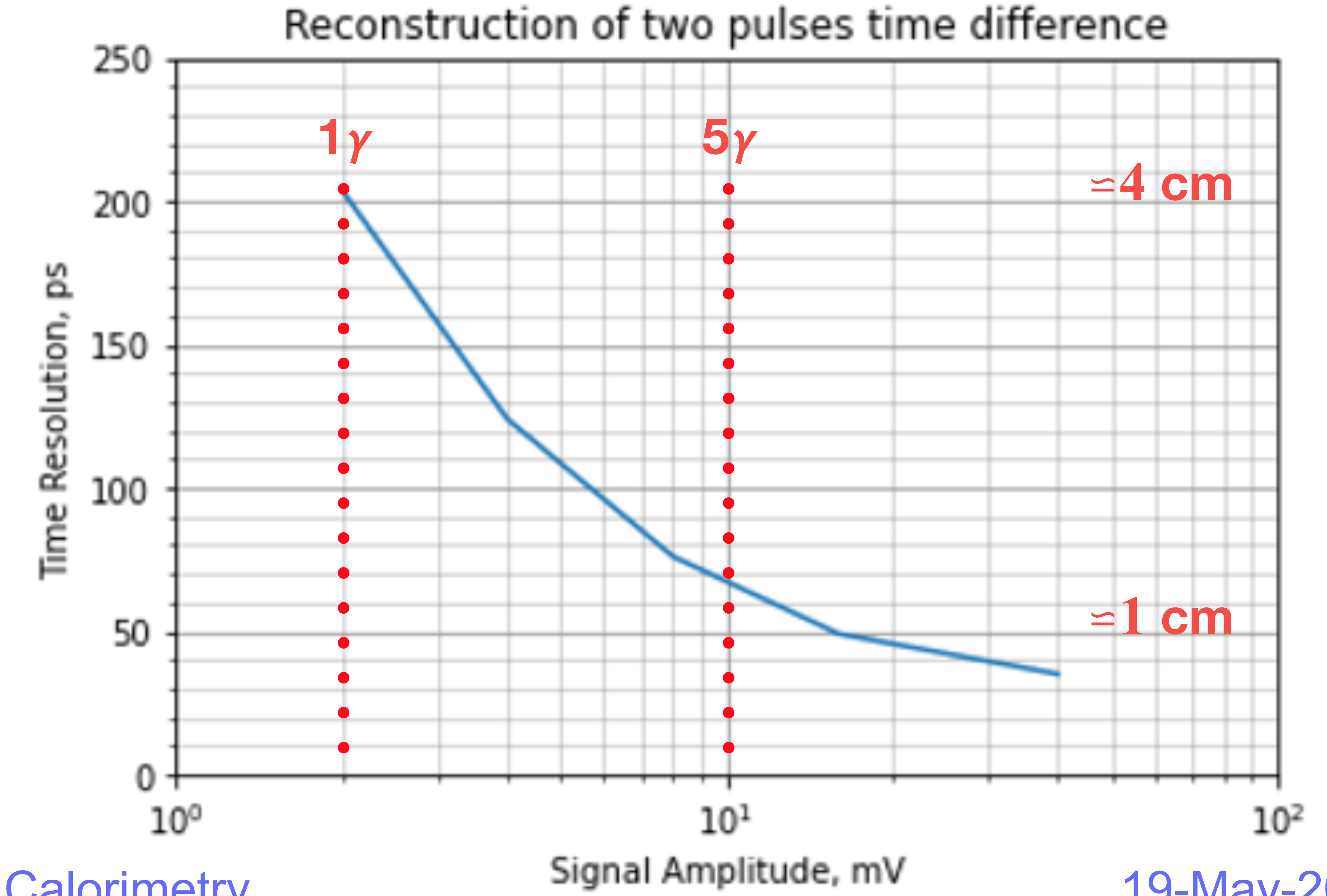




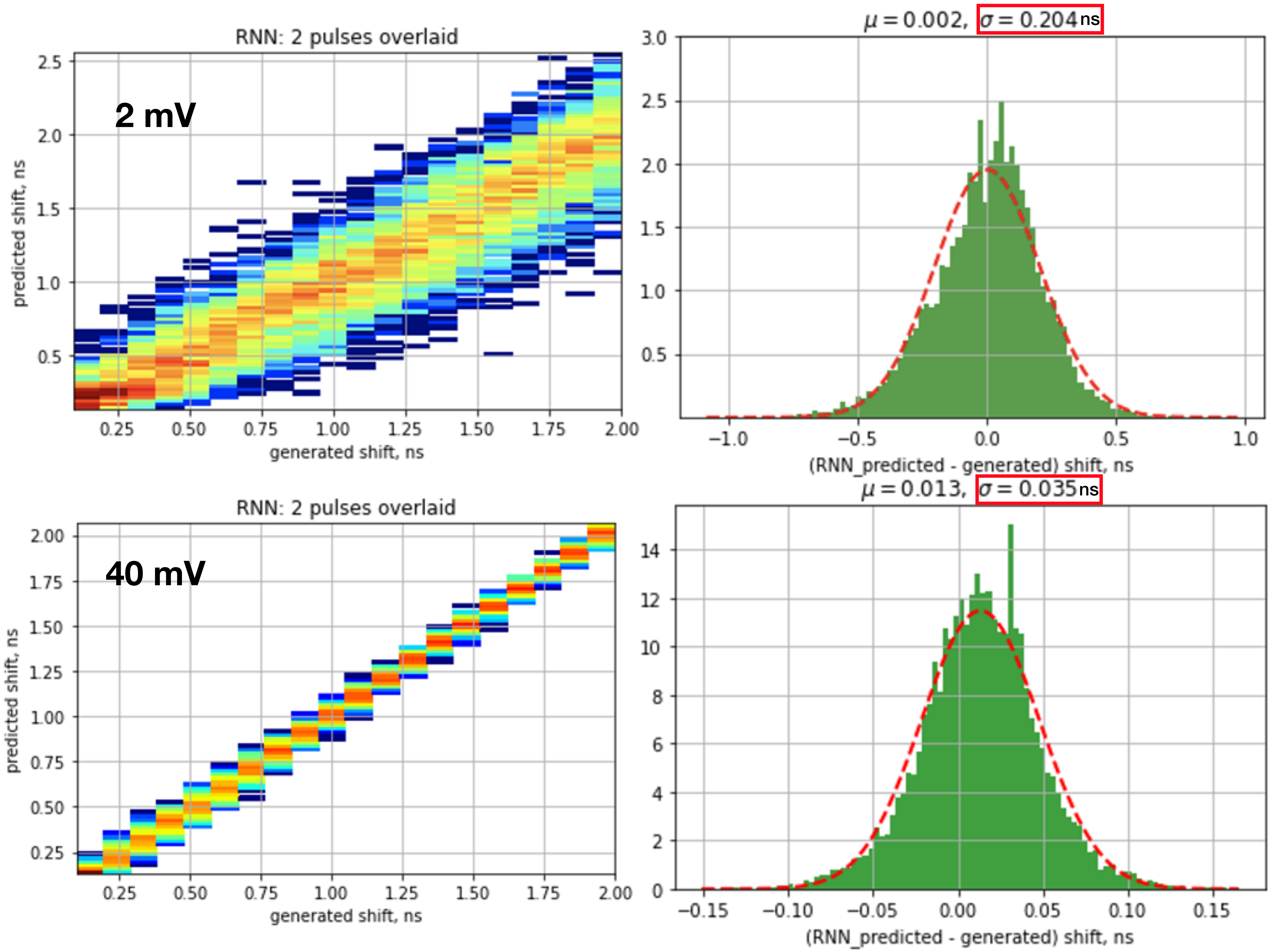
Timing Resolution at Single Photon Level Separation of Two Signals



- ❖ Pulse shape of single photon from SensL SiPM was measured with NALU's AARDVARC V3 and used to simulate waveforms of convoluted pulses of two photon events
- ❖ Recurrent Neural Network (RNN) was used to reconstruct the timing of two photons
- ❖ Resolution of 4 cm (1 cm) seem possible for 1 (5) photon equivalent signals on bench tests



Impact of Machine Learning at Timing Resolution



Recurrent Neural Network (RNN) adds significant resolving power in timing resolution

Clearly, more investigations are essential. It may be possible to implement these techniques in hardware in the future as appropriate

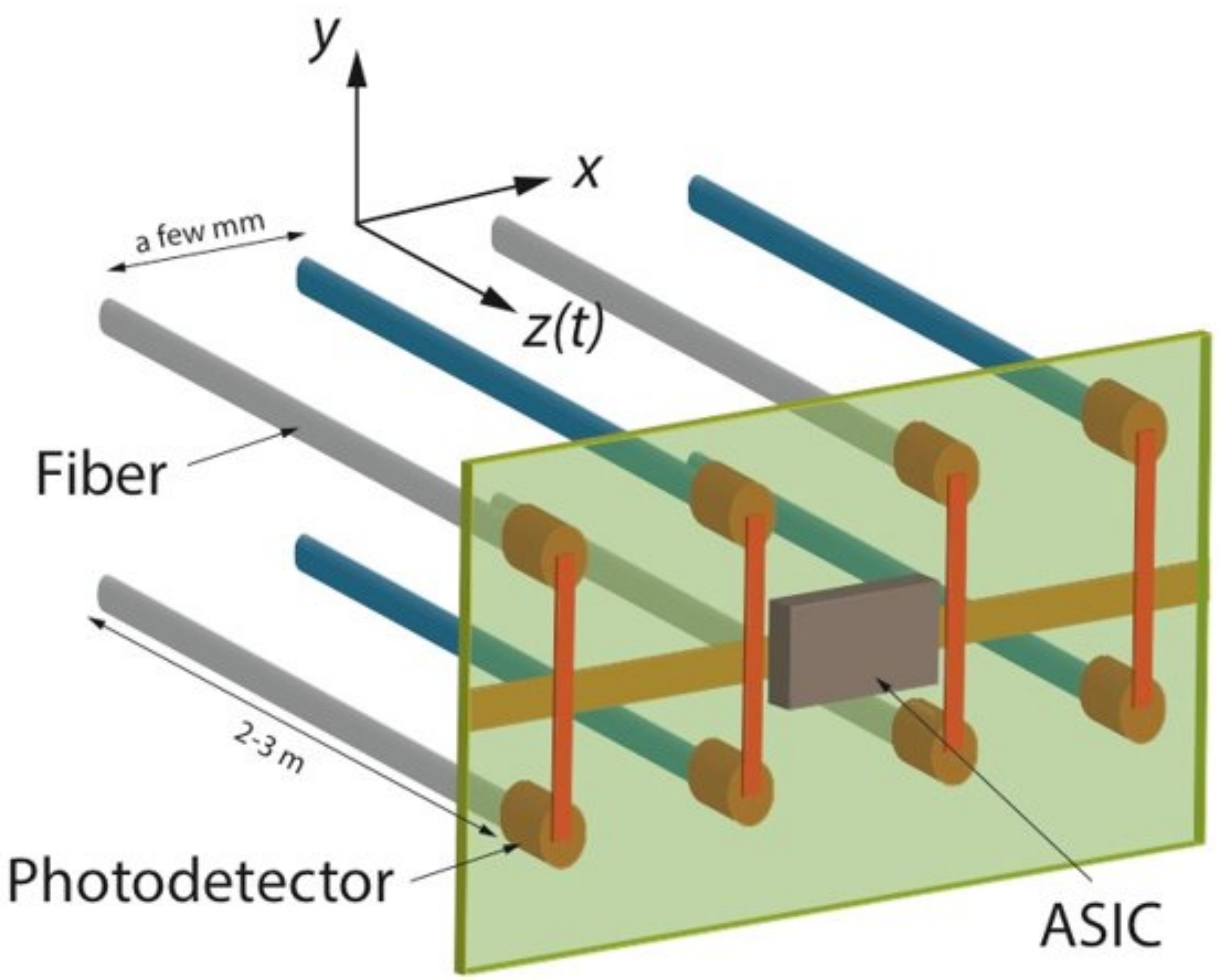
Conclusion

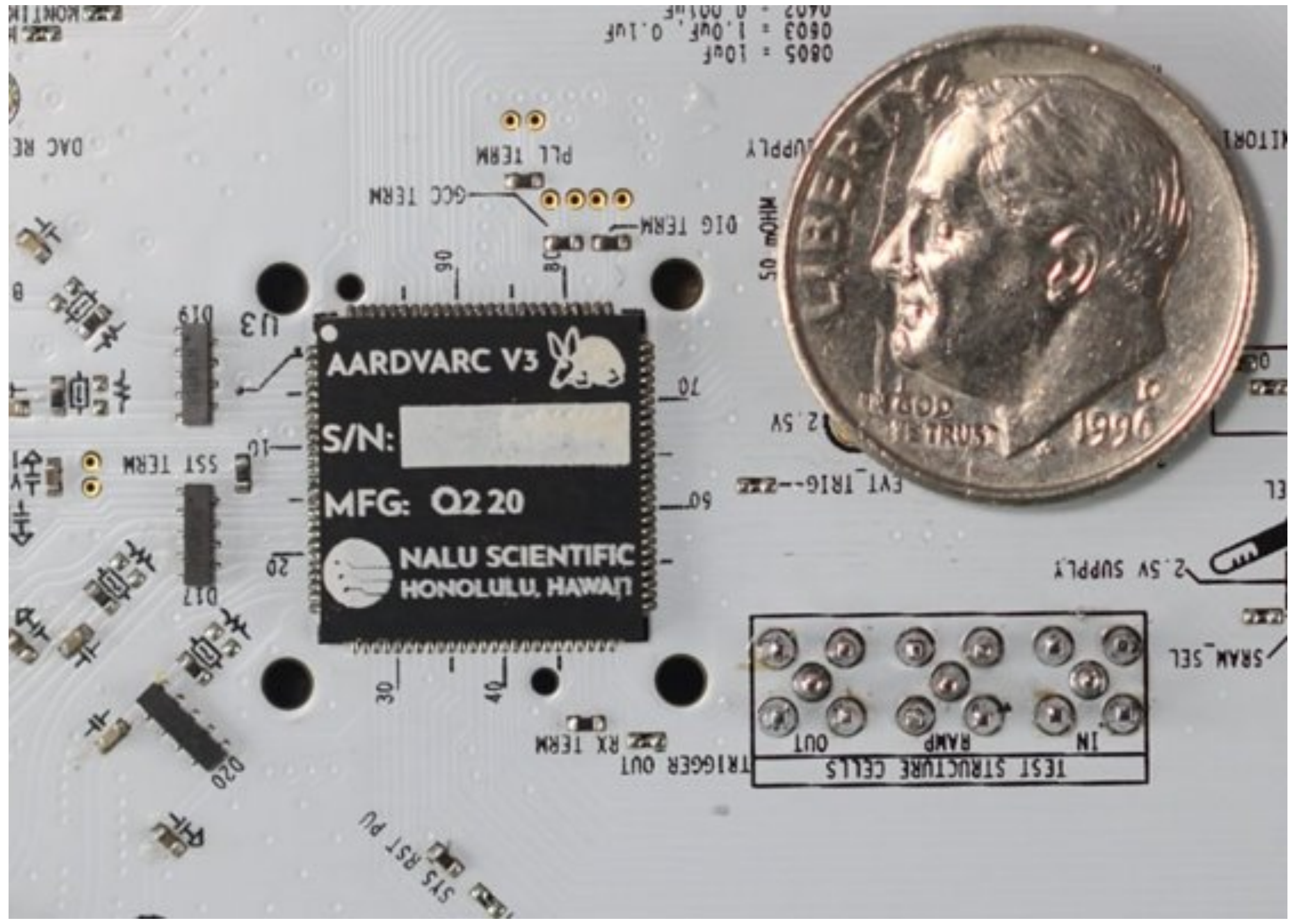
- We studied energy reconstruction in hadron calorimeters with CNN
  - We achieved improved precision of the energy reconstruction beyond the reach of commonly used techniques
  - CNN trained on cases with simulated single hadron showers performs well in a broad range of energy reconstruction task and can reconstruct energy of the jets and EM showers from photons
  - CNN based algorithm also correctly reconstructs the electromagnetic component in hadron showers
- Timing precision with GNN improves the energy resolution measurement
- Effective 3D segmentation is achievable by timing in fiber calorimeter
- Recurrent Neural Network (RNN) adds significant resolving power in timing resolution

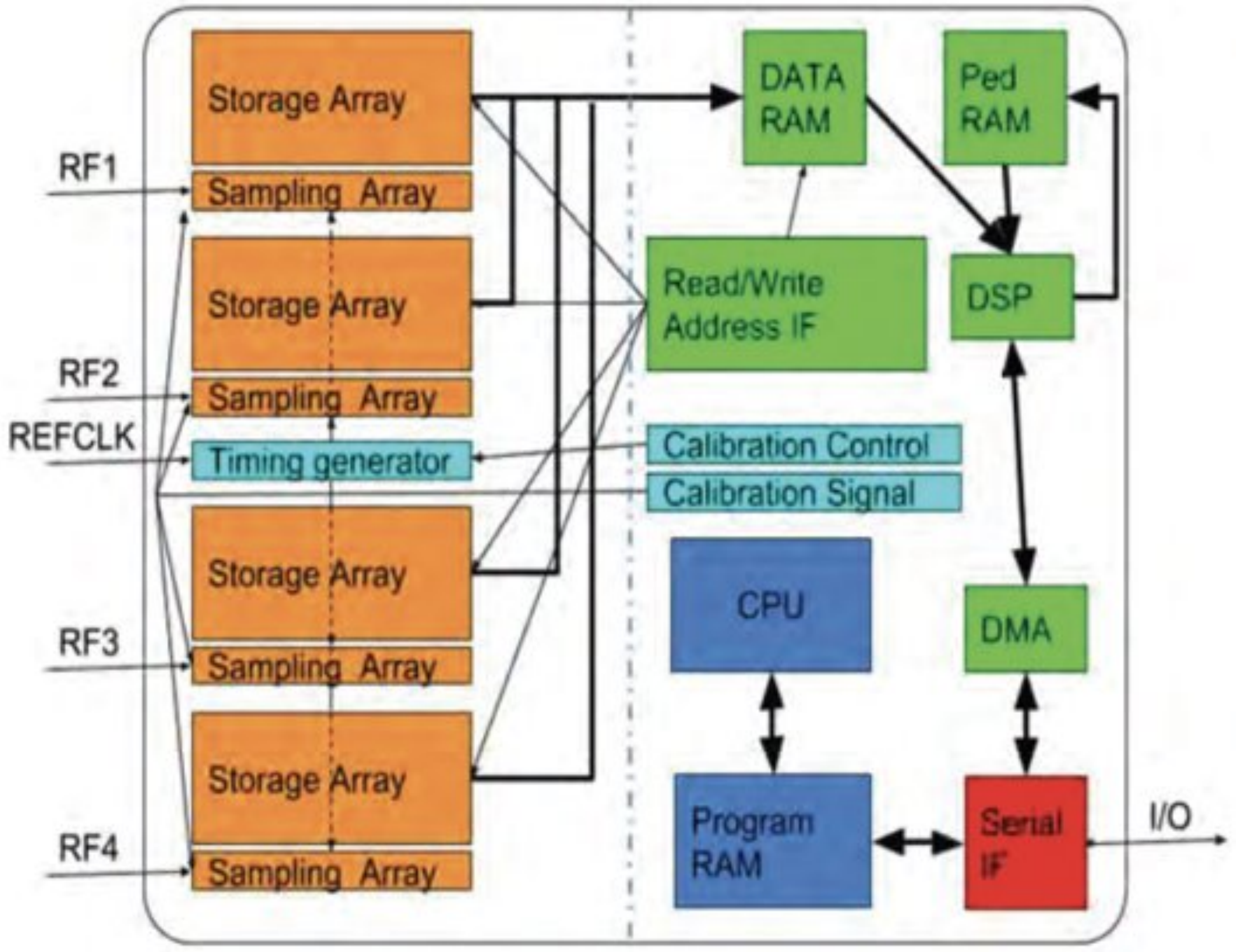
Backup

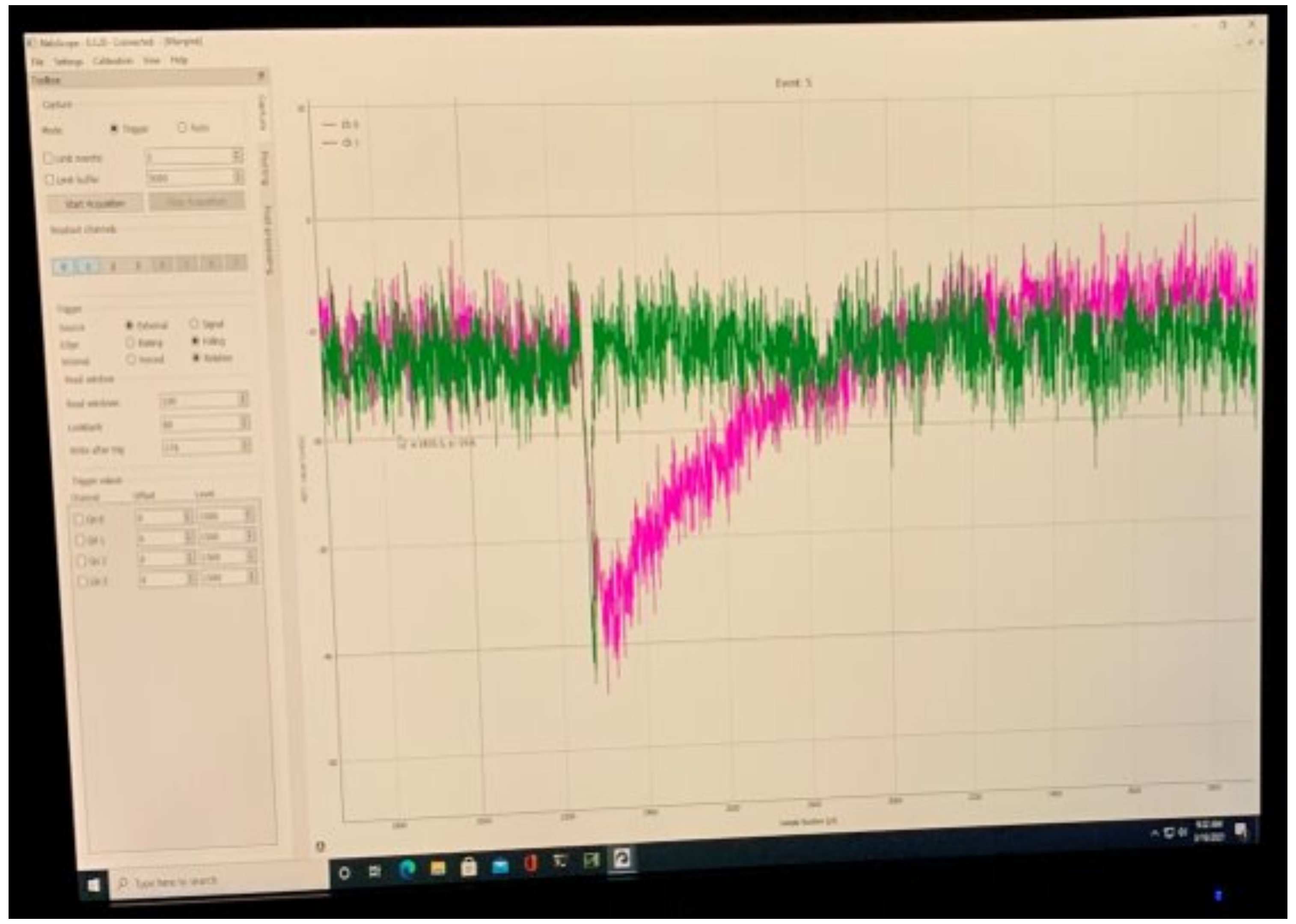
Digitizer AARDVARC V3

- Compact, high performance waveform sampling and ditizing
  - Sampling rate 10-14 GSa/s
  - 12 bits ADC
  - 4-8 ps timing resolution
  - 32 k sampling buffer
  - Bandwidth 2 GHz
  - Systen-on-chip (CPU)

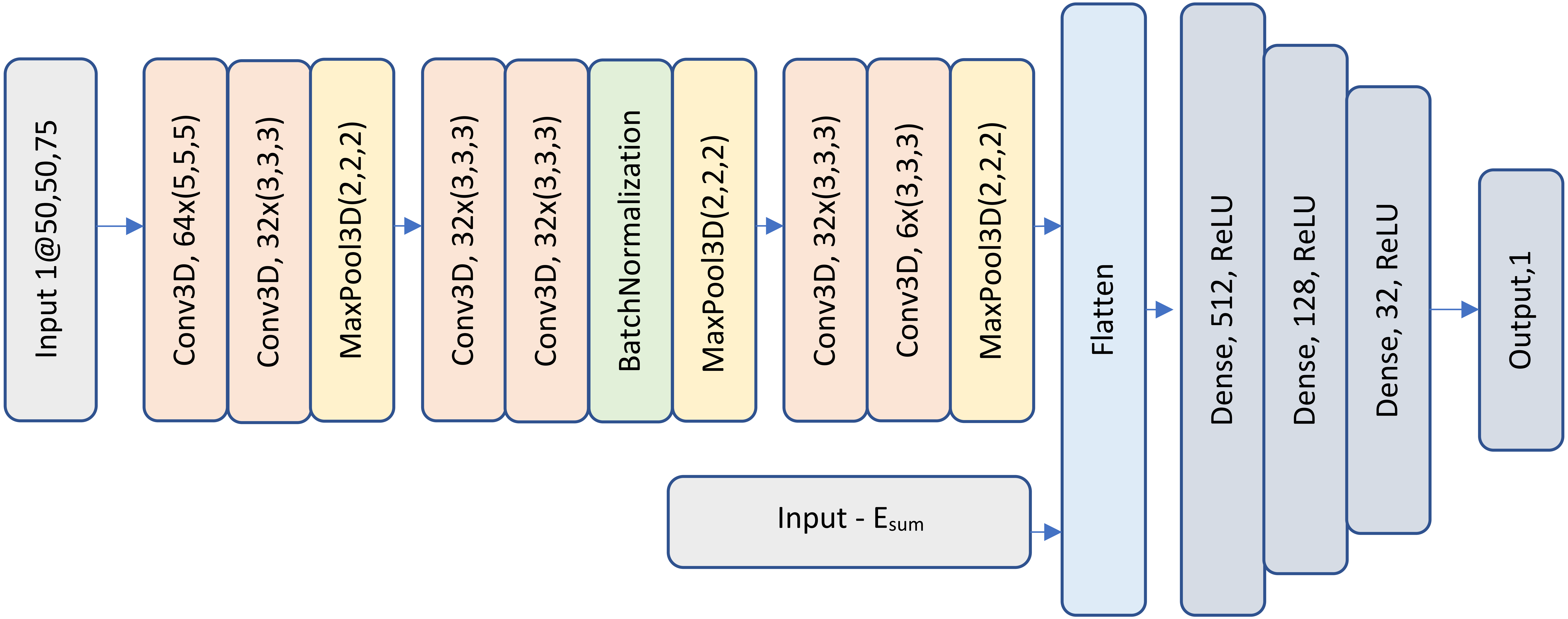








Convolutional Neural Network for Energy Reconstruction



Time vs Displacement Measurements with Beam