



# Vertex Imaging Hadron Calorimetry Using AI/ML Tools

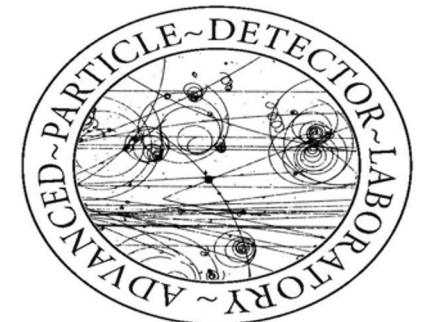
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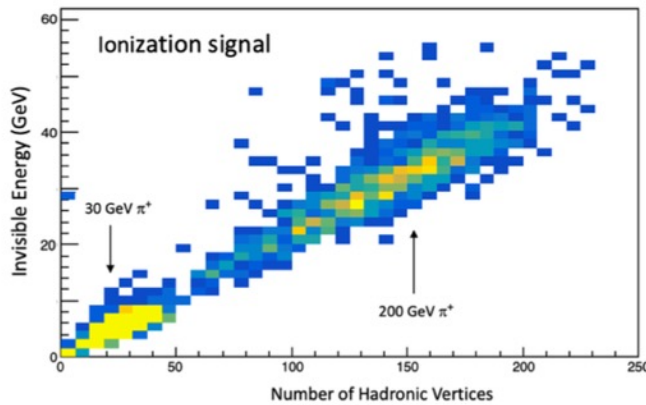
Department of Physics & Astronomy™



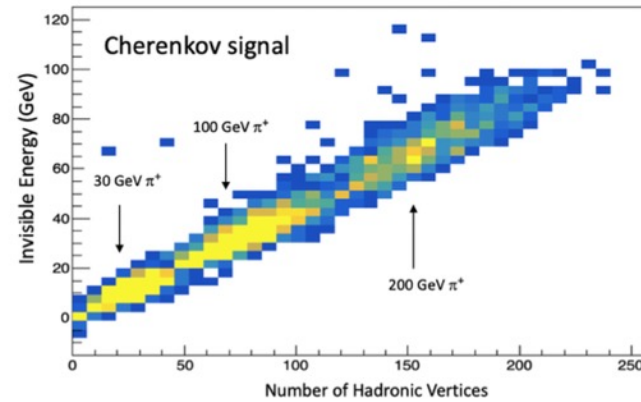
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# Vertex Imaging Calorimetry

We started the CaloX project at the Advanced Particle Detector Laboratory, TTU in 2019. Goal was to develop a novel calorimetry concept which utilizes new technologies- AI/ML techniques, high granularity of calorimeter, fast photo detector and high-density electronics.



(a)



(b)

In GEANT4 simulation study, we quickly noticed a strong correlation between the invisible energy and the number of inelastic hadronic vertices in absorber.

➔ Use ML to count and analyze the hadronic vertices to estimate the invisible energy.

Invisible energy = True energy – Measured energy

## Future calorimeter

### Desired feature

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- Fast
- High granularity
- Less neutrons

### Choice of simulation setup

=====

integration time < 5 ns  
 2x2x2 cm<sup>3</sup> cube structure  
 Cu absorber

### Consideration

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high collision rate  
 Molier radius (Cu 1.6 cm), memory size for CNN  
 least binding energy loss, minimize bg to tracker

# First ML Result

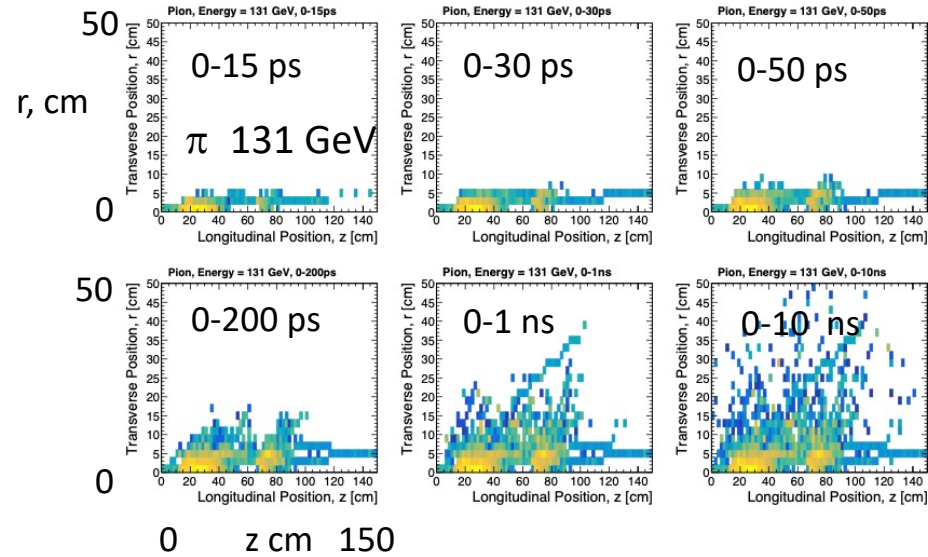
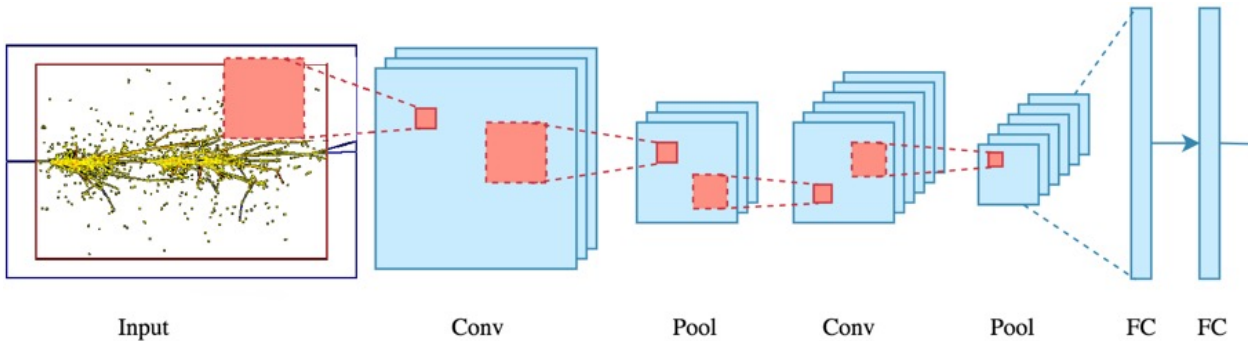
Ionization calorimeter

GEANT4: Cubic sampling structure  
 $2 \times 2 \times 2 \text{ cm}^3$ , Cu 1.7 cm, Si 0.3 cm  
 4-150 GeV pion, FTFP-BERT

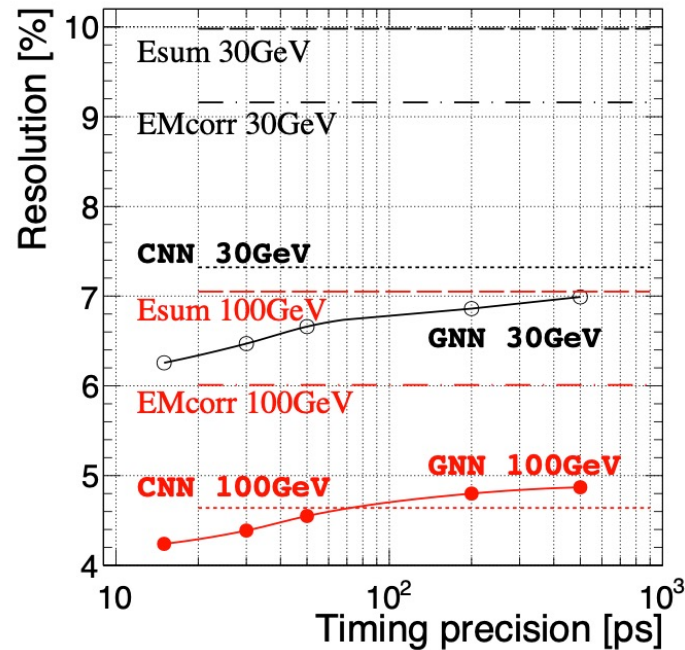
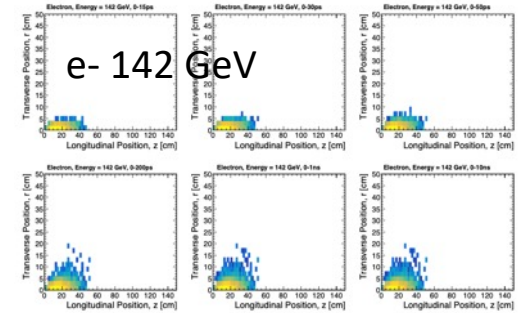
CNN: input (x, y, z, E) per cell in 5 ns  
 target (beam energy)

GNN: input(x, y, z, E, **time**) per cell in 6 time windows.

600k (training), 50k (validation), 300k (testing)  
 15 epocs



t: local time (TOF removed)  
 $t(G4) - z/c$



ML improved the resolution.

Fast shower images in 5 (0-10ns) were used.

Next → try Cherenkov signal which is ultimate fast signal.

# GNN Result on Fiber Calorimeter

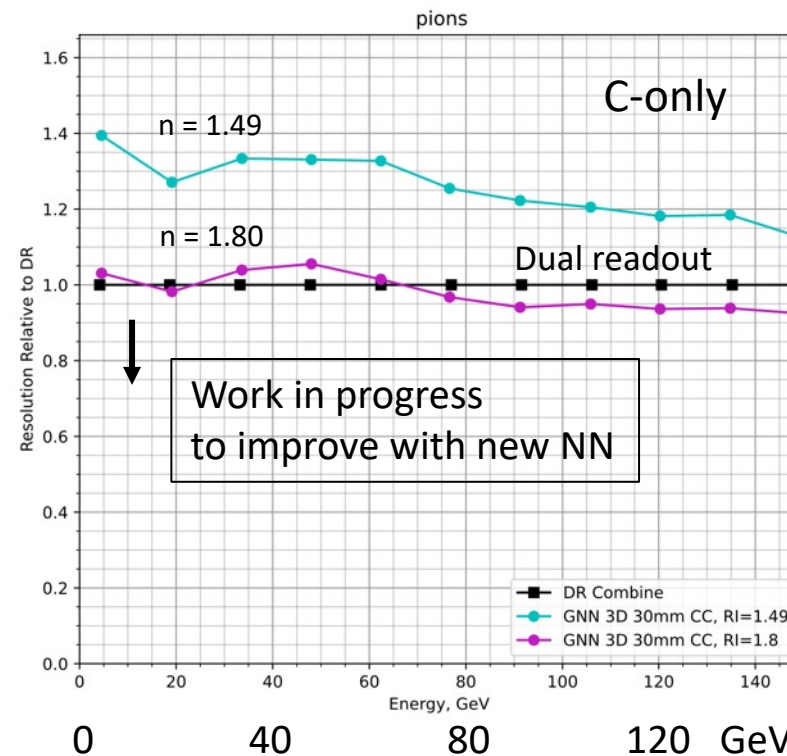
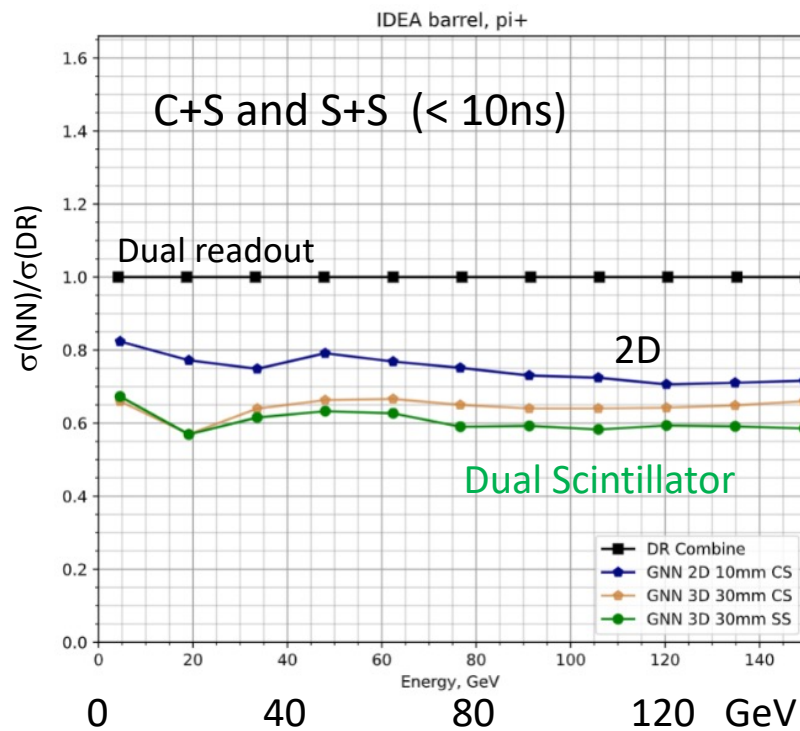
Calor2022: Cherenkov Fiber Calorimeter:  $\sigma/E$  13% (simple sum)  $\rightarrow$  4 % for 100 GeV pi+ [Ref-2]

Cu absorber (2 m deep), 1 mm  $\phi$  fibers, 1.5 mm spacing

readout segmentation: 1x1 cm<sup>2</sup> for 2D analysis, 3x3 cm<sup>2</sup> for 3D analysis

signal integration time: 10 ns

Resolutions: Dual-Read as reference:  $\sigma/E(\text{DR}) = 0.31/\sqrt{E} + 0.008$



Resolutions at 100 GeV

Dual Readout 10ns 4.0 %

Cherenkov (sum) 13.0 %

Cherenkov (1.49) 4.8 %

Cherenkov (1.80) 3.8 %

Scintillation 2.4 %

DREAM DR(2005) 2.6 %

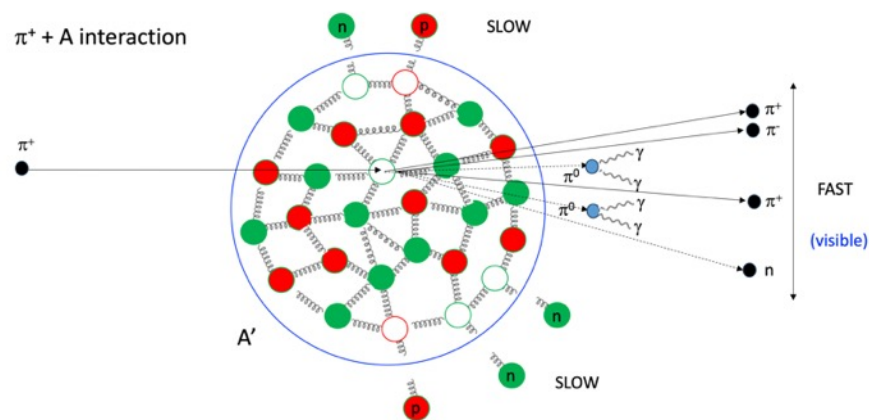
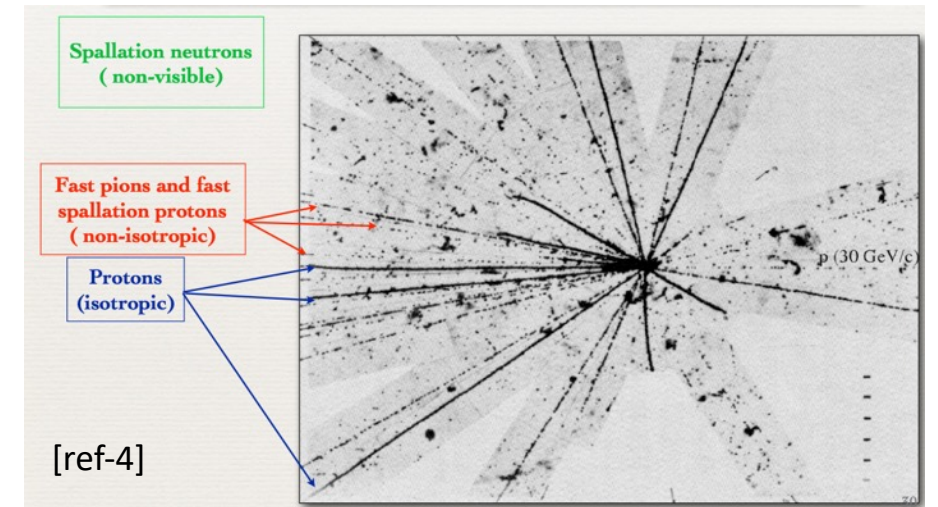
- long integration -

# Invisible Energy in Calorimeter

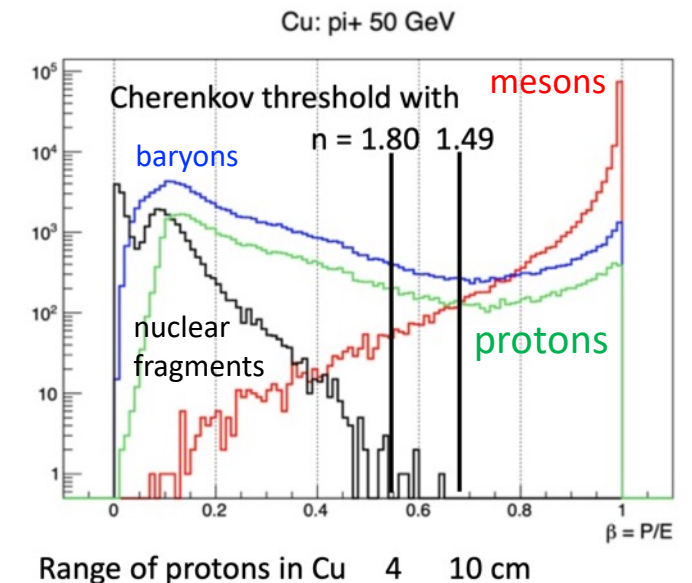
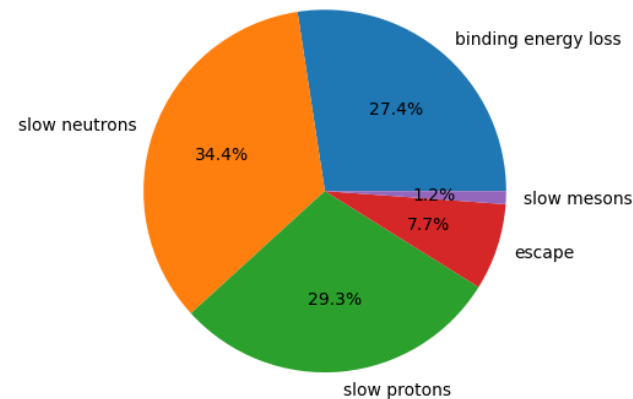
Main sources of invisible energy in hadron calorimetry are (1) binding energy loss, (2) undetected slow protons and neutrons and (3) escapes due to meson decay to leptons and absorption of mesons (mass).

Studies based on Class Activation Mapping revealed that energy correction is mostly derived by the CNN in regions near individual hadron interactions with traces from charged hadrons and just outside regions of substantial EM energy depositions. (Vertex Imaging) [Ref-1].

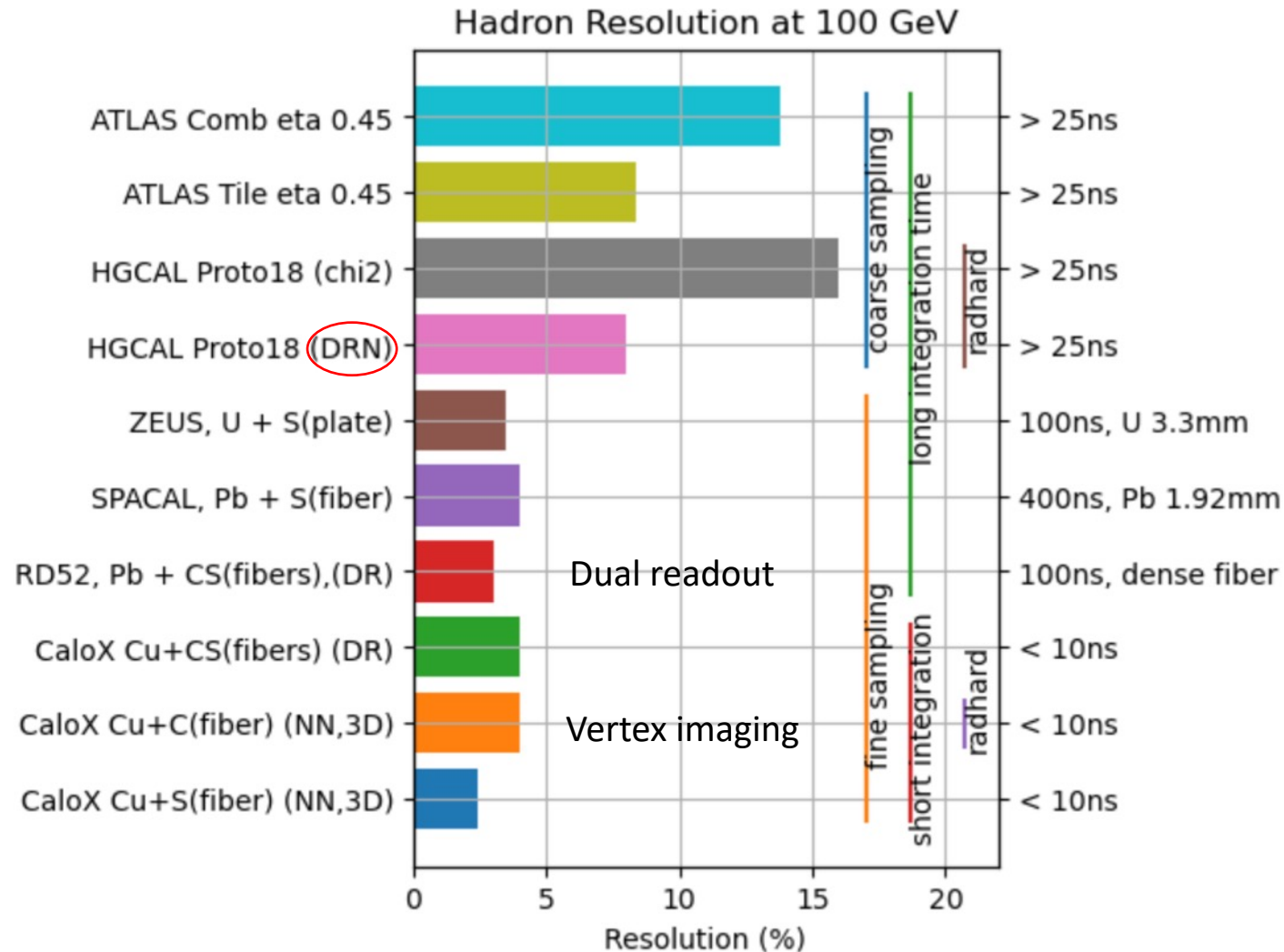
➔ Design NN friendly calorimeter.



50 GeV pi+ on Cu: Source of Invisible Energy (Average Visible Energy 69%)



# Features: Sampling Rate and Integration Time



Few key features of high-performance hadron calorimeter for future high rate collider experiments:

- [1] Fine sampling
- [2] Short integration time
- [3] Radiation hardness

Additional consideration:

- [4] absorber material  
Cu, Fe over Pb, W, U  
binding energy loss 16% (Fe) vs 32 % (PB)  
CU, Fe requires smaller correction.

- [5] homogeneous vs fine sampling

# Beyond Fibers: Imaging in Homogeneous Calorimeter

We simulated Cherenkov signal in a block of PbWO4 crystal ( $n=2.2$ ) and a Cu block, which is treated as an imaginary crystal of  $n=1.49$ .

Resolution from Cu is better than from PbWO4 with both Scintillation and Cherenkov imaging.

Segmented “Crystal” of  $2 \times 2 \times 2 \text{ cm}^3$  cubes does not provide very significant improvement in resolution over the densely packed fiber calorimeter. Looking for improvement... (work in progress)

Resolution of pion 100 GeV

= crystal cubes  $2 \times 2 \times 2 \text{ cm}^3$  CNN=

PbWO4 (S) 3.9 %

PbWO4 (C) 5.0 %

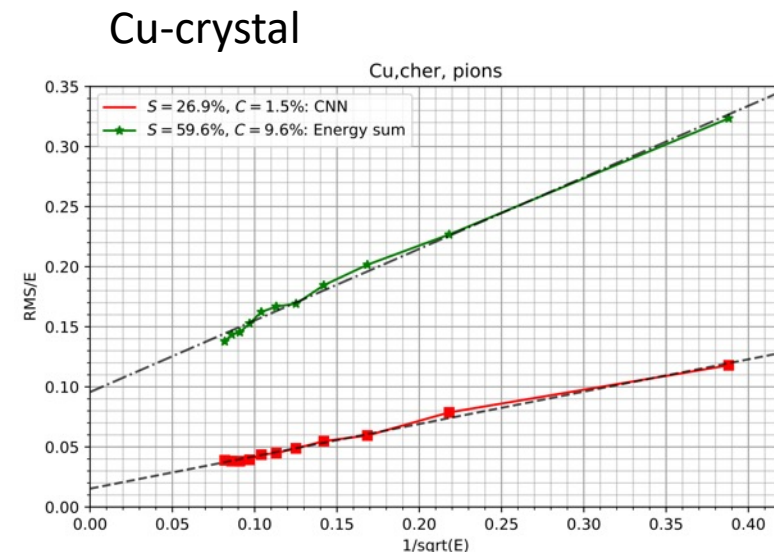
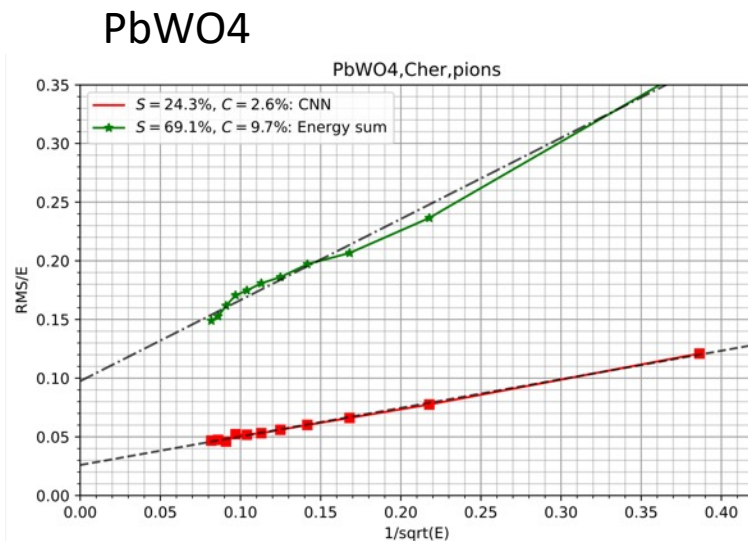
“Cu” (S) ionization 2.7 %

“Cu” (C)  $n=1.49$  4.1 %

= fiber calorimeter CNN=

Cu+Fiber(S/3D) 2.4 %

Cu+Fiber(C/3D) 4.0%



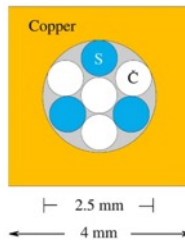
# HG-DREAM: 3D(xyz;E) fiber calorimeter

Test the Vertex Imaging of hadronic shower with refurbished DREAM module (HG-DREAM) with SiPM readout.

Challenge: 3D imaging with Cherenkov fibers. (Quartz  $n=1.458$ , Plastic  $n=1.49$ )

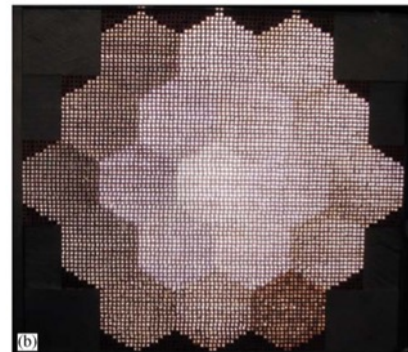
More challenging: 3D imaging with Scintillation fibers (SCSF-81J,  $n=1.59$ ,  $\tau=2.4$  ns)

N.Akchurin's talk  
on Thursday



DREAM (2003)

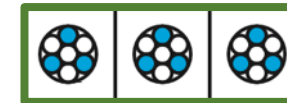
Cu Rod:  $4 \times 4$  mm<sup>2</sup>  
270 rods/PMT



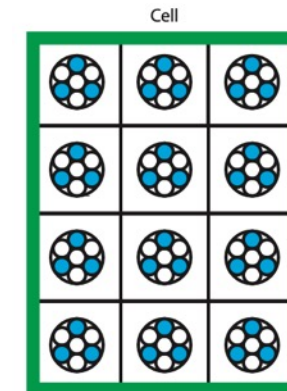
Refurbishing in progress



HGDREAM



Central region:  
3 rods/SiPM (3 mm)



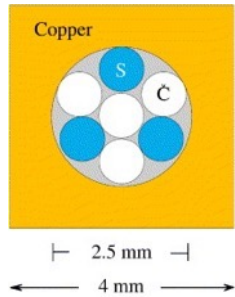
Outer region:  
12 rods/SiPM (6 mm)



# HG-DREAM: 4D(xyzt;E) Cherenkov Fiber Calorimeter

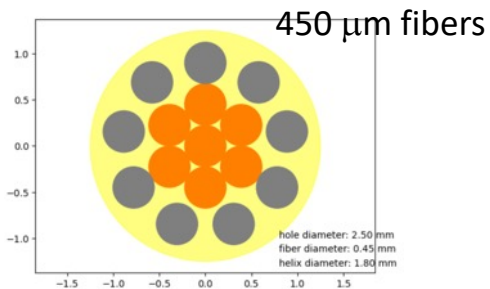
Very fast rise time of SiPM (< 10 ps) and prompt Cherenkov signal may provide absolute timing of signal and longitudinal position of shower in a full body of calorimeter with a pair of fibers, e.g. straight and helix or quartz and sapphire.

## HGDREAM-I: S+C

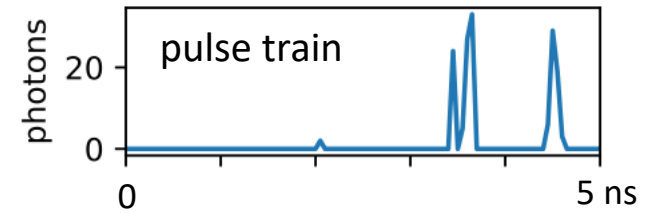
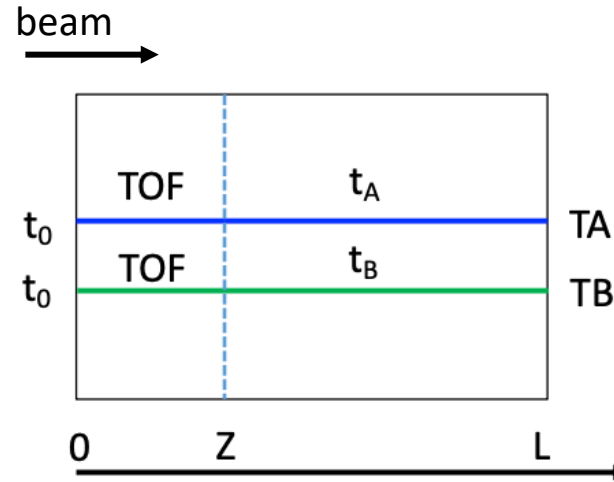
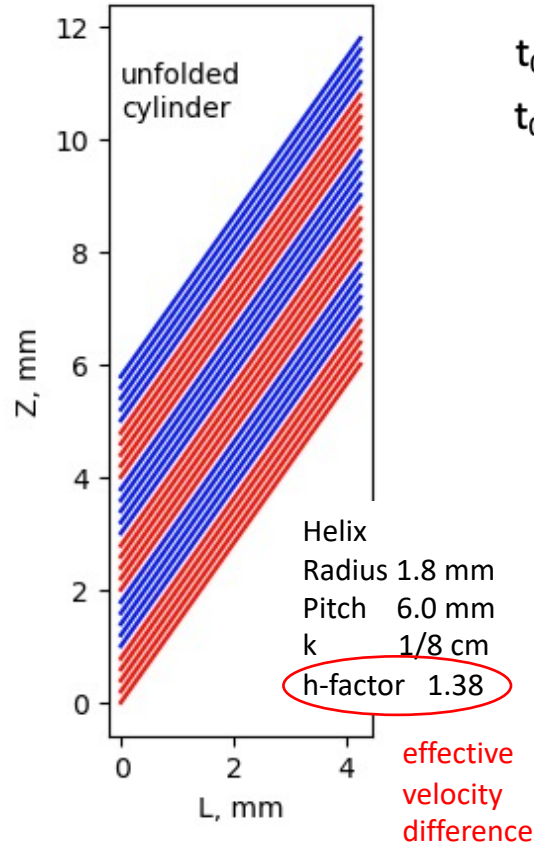


## HGDREAM-II: C+C

Fibers:  $\phi = 0.45$  mm  
Orange (core): straight  
Gray: helix



## Dual-helix fiber cable



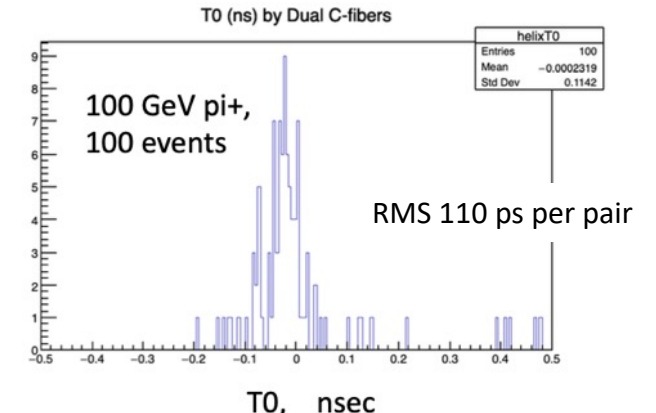
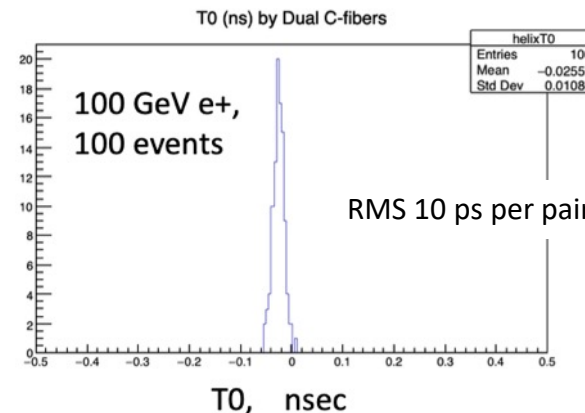
Light arrival time at SiPM-A (**core**)

Light arrival time at SiPM-B (**helix**)

$$TA = t_0 + Z/c + (L-Z)/(v)$$

$$TB = t_0 + Z/c + (L-Z) \cdot (\text{helix factor}) / (v)$$

## Reconstructed T0 in a pair of readout fibers (no SiPM simulation)



# Use of AI/ML. in case of Dual Cherenkov fiber readout

CNN trained with single hadron sample worked well to reconstruct the total energy of multi-particles (jet). (fig.1)  
 In case of more complex event structure, we need a sequential use of AI/ML tools to reconstruct events .

Channel-by-channel:	deconvolution of the pulse train to impulse structure per fiber (fig.2)
Pair of C-C channels:	translation of the impulse structure to series of T0 and Z coordinates in each pair
Global	3D clustering to reconstruct incident particles using clear image of shower from Cherenkov signal.

Fig-1 Energy regression with CNN, which has been trained with single particle sample. [Ref-1]

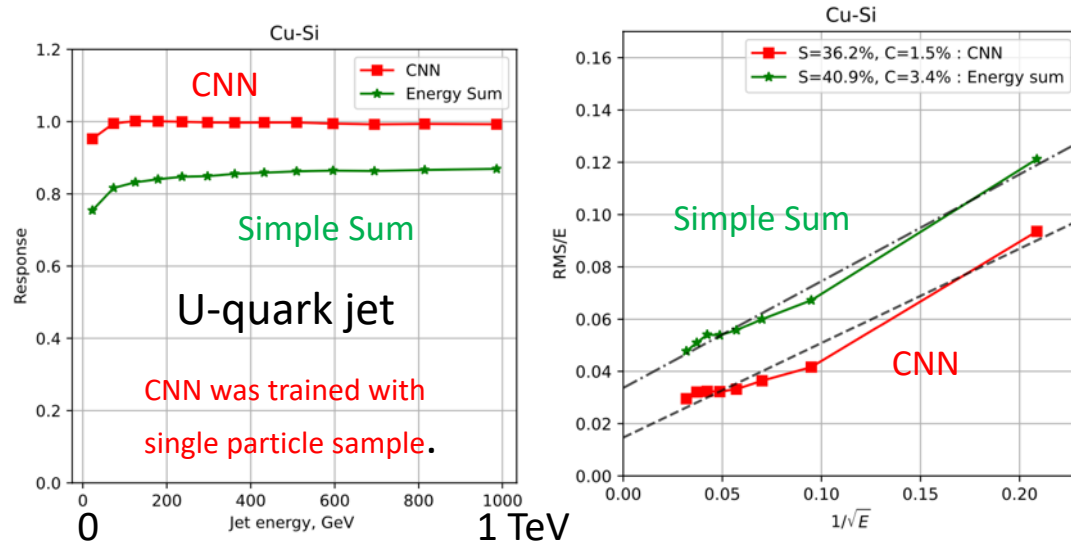
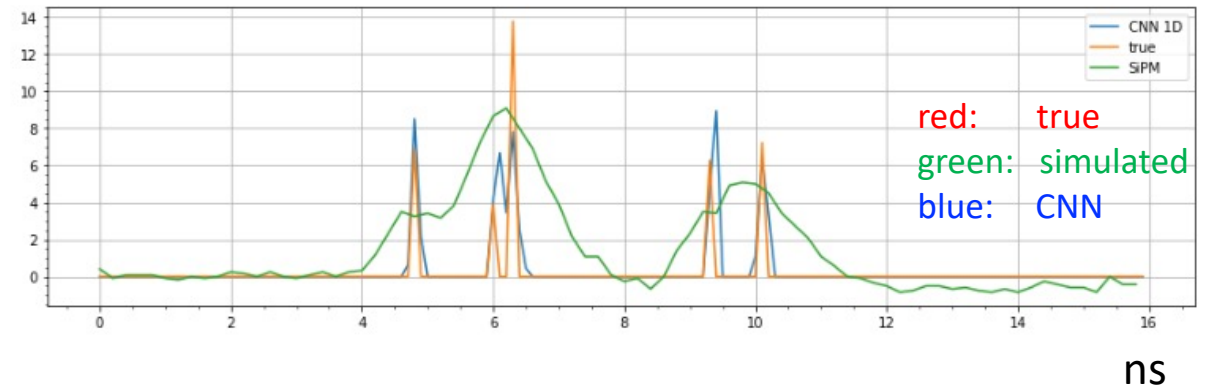


Fig-2 Deconvolution of pulse train arriving at SiPM at the end of fibers using CNN. (Candidate of on-detector data processing).

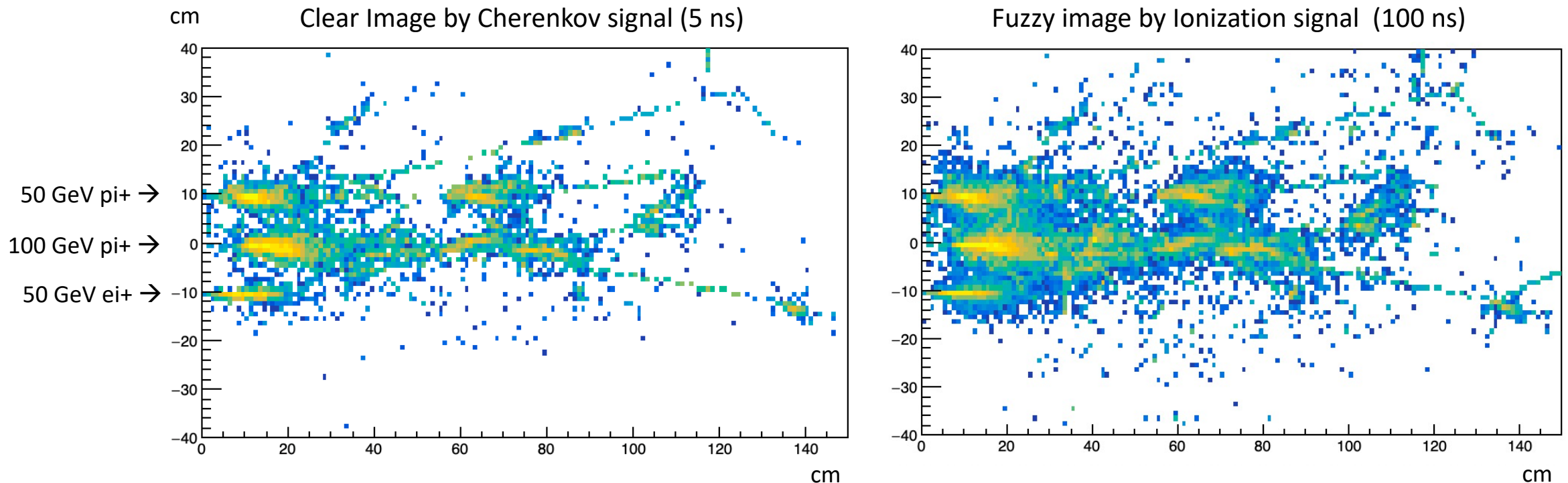


# Clustering of Hits in Jet

Cherenkov signal produces clear and narrow image of hadronic shower comparing to ionization signal. AI/ML may use such clean shower images for 3D pattern recognition of complex event structure.

- reconstruction of individual particle in jet (then, link to inner tracks for particle flow reconstruction).
- analysis of jet substructure to identify boosted W/ Z / top / Higgs.

Below is an example of “pseudo jet”. Three particles hit a calorimeter at 10 cm apart. Assignment of “hits” to particle may be done in both cases (Cherenkov and Ionization), but the Ionization case becomes difficult once the separation get smaller.



# Conclusion

Vertex Imaging Calorimetry using AI/ML may provide very fast hadron calorimetry to future collider experiments. The integration time of signal will be below 10 ns.

Dual Cherenkov Fiber Readout has a good potential to build a 4D (xyzt;E) imaging calorimeter with time resolution of  $O(10\text{ps})$  in its full body.

We used CNN and GNN in simple way. More effective use of AI/ML will bring further improvement to future calorimetry.

## References:

- [1] N. Akchurin, C. Cowden, J. Damgov, A. Hussain, S. Kunori, On the Use of Neural Networks for Energy Reconstruction in High-granularity Calorimeters, JINST 2021, 16, P12036, <https://doi.org/10.1088/1748-0221/16/12/P12036>
- [2] N. Akchurin, C. Cowden, J. Damgov, A. Hussain, S. Kunori, The (Un)reasonable Effectiveness of Neural Network in Cherenkov Calorimetry, Instruments 2022, 6, 43, <https://doi.org/10.3390/instruments6040043>
- [3] about CNN, GNN. See Ref[1] and [2].
- [4] G. Gaudio, M. Livan, Electromagnetic and hadronic showers development, The Art of Calorimetry Lecture II, [https://static.sif.it/SIF/resources/public/files/va2009/gaudio\\_0724-2.pdf](https://static.sif.it/SIF/resources/public/files/va2009/gaudio_0724-2.pdf)
- [5] ATLAS Collaboration, Study of energy response and resolution of the ATLAS barrel calorimeter to hadrons of energies from 20 to 350 GeV, Nucl Instr. Meth. A 621 (2010) 134, <https://doi.org/10.1016/j.nima.2010.04.054>
- [6] CMS collaboration, pi- energy reconstruction in HGCAL Beam Test prototype detector using Graph Neural Network, DP-2022/022
- [7] ZEUS collaboration, Test of the Zeus forward calorimeter prototype, Nucl Instr. Meth. A289 (1990) 115 [https://doi.org/10.1016/0168-9002\(90\)90253-3](https://doi.org/10.1016/0168-9002(90)90253-3)
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