

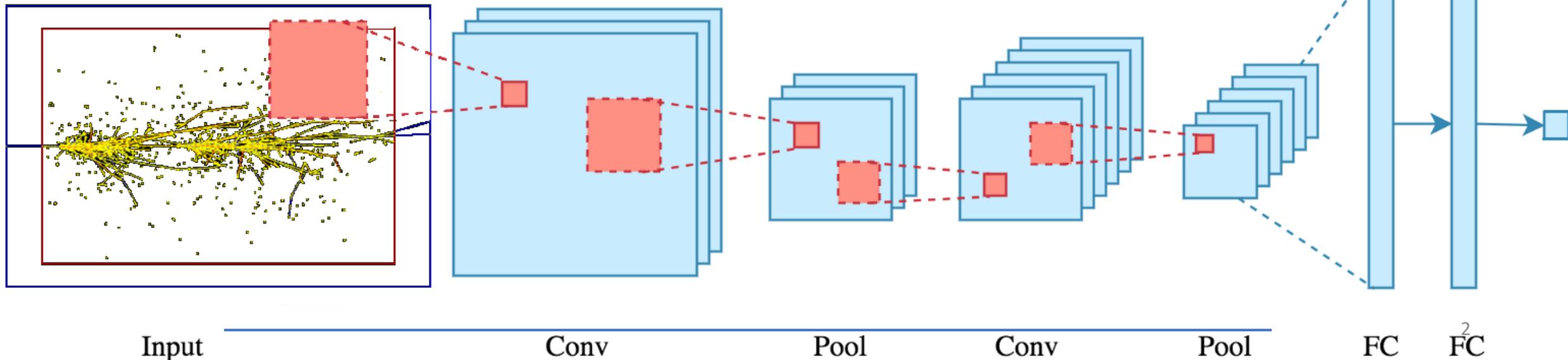
Energy Reconstruction using Convolutional Neural Networks in High Energy Calorimetry

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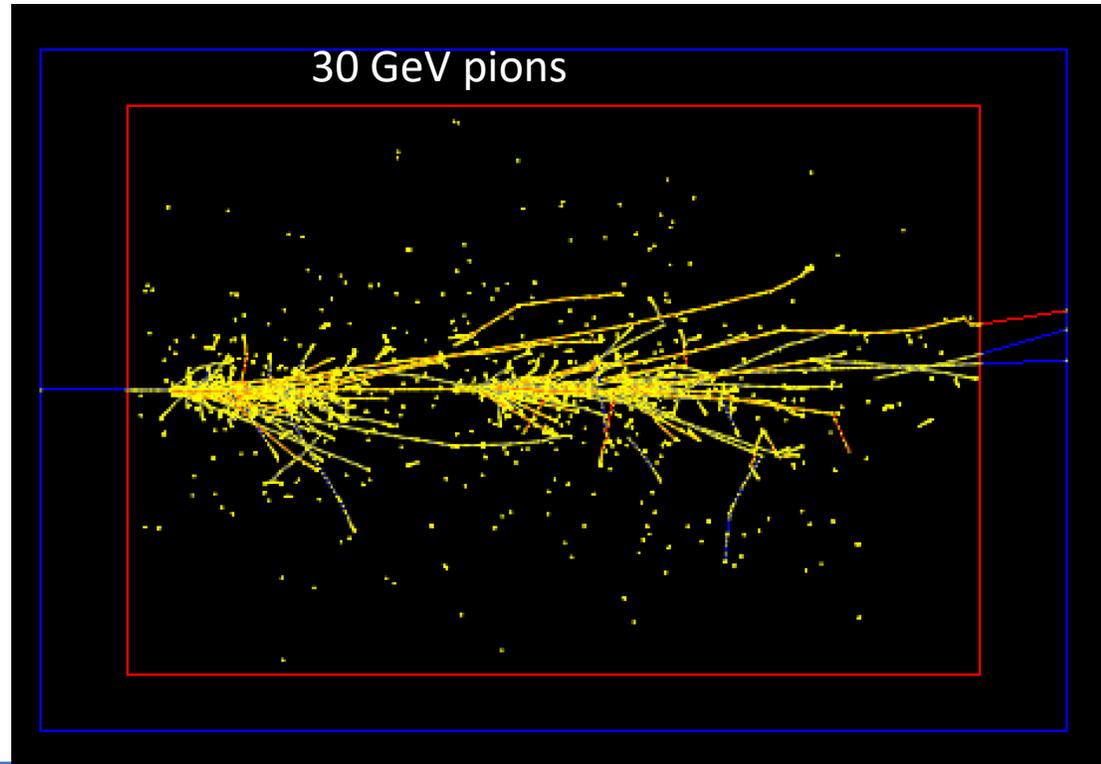
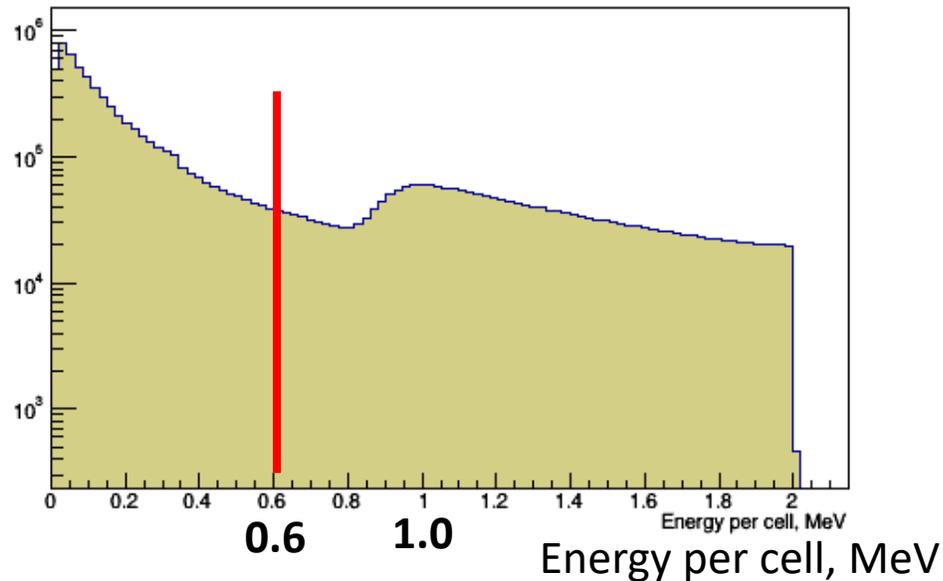
Convolutional Neural Network for energy reconstruction

- ❖ The showers in high granularity calorimeters can be viewed as 3D images
 - Fiber calorimeters with depth segmentation by timing
 - ❖ From the visible signal detailed information on *multiplicity and production angle of the secondaries* can be extracted and used to improve the energy reconstruction
- Convolutional Neural Networks(CNN) are very good at image classification
- Raw images are used
 - Extract higher level features using sequential convolutional operations
 - Can also perform regression



Standalone calorimeter setup (simulation)

- ❑ Copper / Silicon sampling calorimeter is simulated with GEANT4
 - Alternating Cu 17mm(absorber), Si 3mm (active) layers, with size of 1.0x1.0x1.5m³
 - Readout granularity is cells of 2x2x2cm³
 - Signal is integrated over 5ns with correction for the longitudinal propagation time.
 - Energy threshold of 0.6 MeV per cell is applied, with MIP MPV at about 1.0 MeV.
 - No electronics/noise is simulation



Convolutional Neural Network model

- ❖ **Input1 (50,50,75) in X,Y, and Z with beam being along Z**
- ❖ *Conv3D: 64 kernels, 5x5x5, ReLU*
- ❖ *Conv3D: 32 kernels, 3x3x3, ReLU*
- ❖ *MaxPool3D, 2x2x2*
- ❖ *Conv3D: 32 kernels, 3x3x3, ReLU*
- ❖ *Conv3D: 32 kernels, 3x3x3, ReLU*
- ❖ *MaxPool3D, 2x2x2*
- ❖ *Conv3D: 32 kernels, 3x3x3, ReLU*
- ❖ *Conv3D: 6 kernels, 3x3x3, ReLU*
- ❖ *MaxPool3D, 5x5x2*
- ❖ **Flatten + Input2(simple energy sum over the calorimeter volume)**
- ❖ **Dense layers: (256,ReLU), (128,ReLU), (32,ReLU,dropout=0.3)**
- ❖ **Output 1, linear**

Loss function:

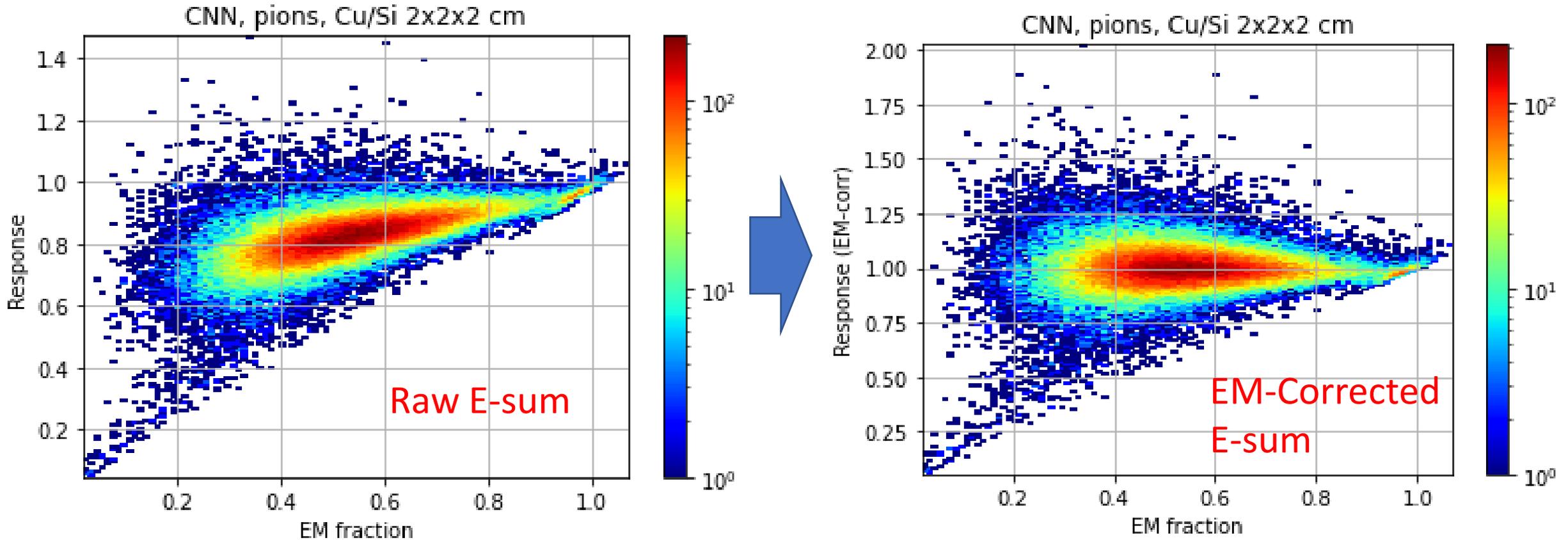
Mean squared logarithmic error

Trained on 800k single pions 0.5-150 GeV, validation on 100k, test 100-300k samples.

Energy reconstruction with more tradition techniques

The performance of the energy reconstruction with CNN is compared to:

1. Simple energy sum over all channels in the volume
2. Reconstruction with correction for the fluctuations in the EM-fraction

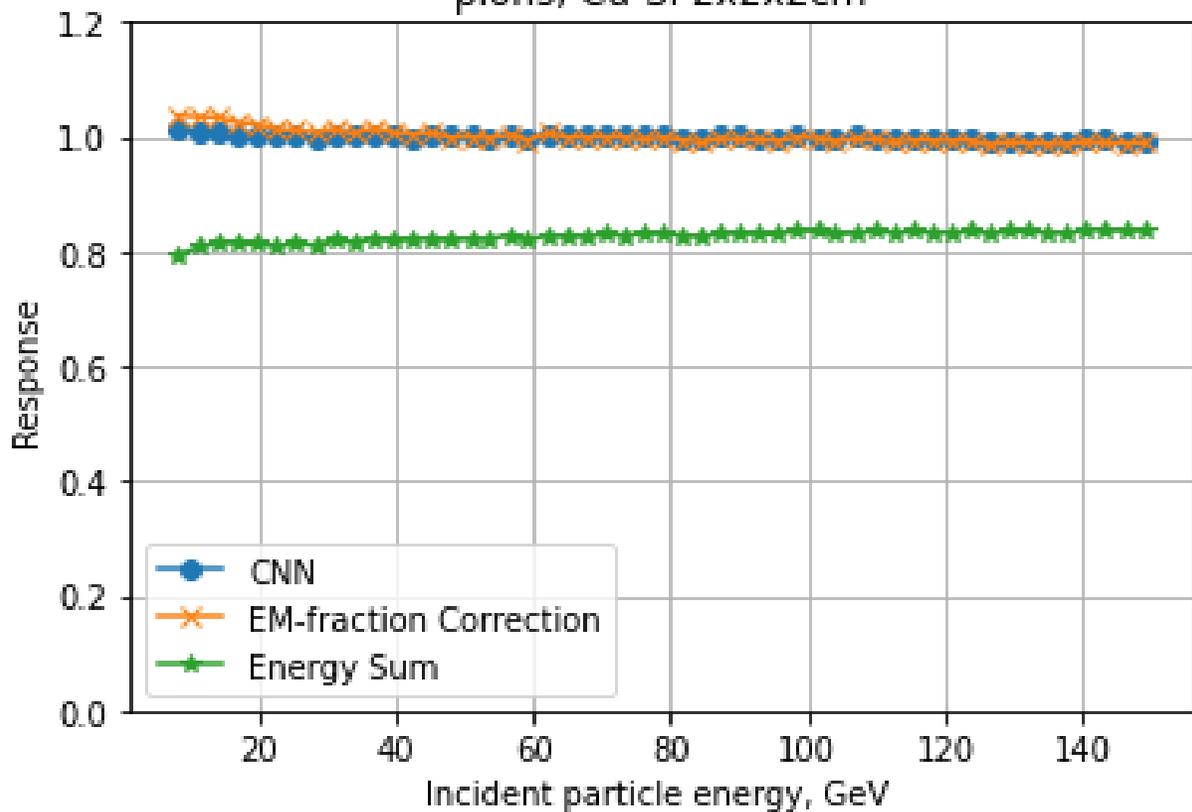


CNN performance – single hadron, Cu/Si

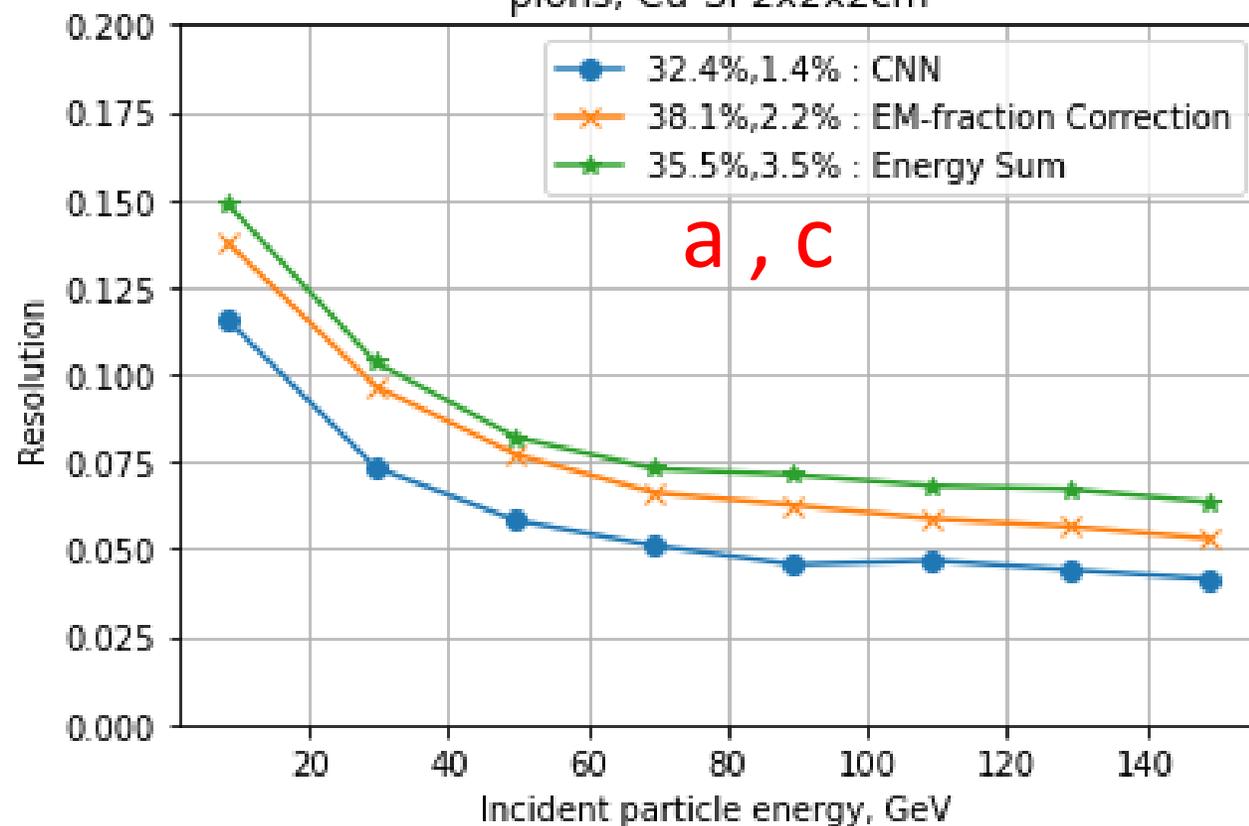
CNN trained with **single pions** outperforms other conventional methods for energy reconstruction.

$$\frac{\sigma}{E} = \frac{a}{\sqrt{E}} \oplus c$$

pions, Cu-Si 2x2x2cm

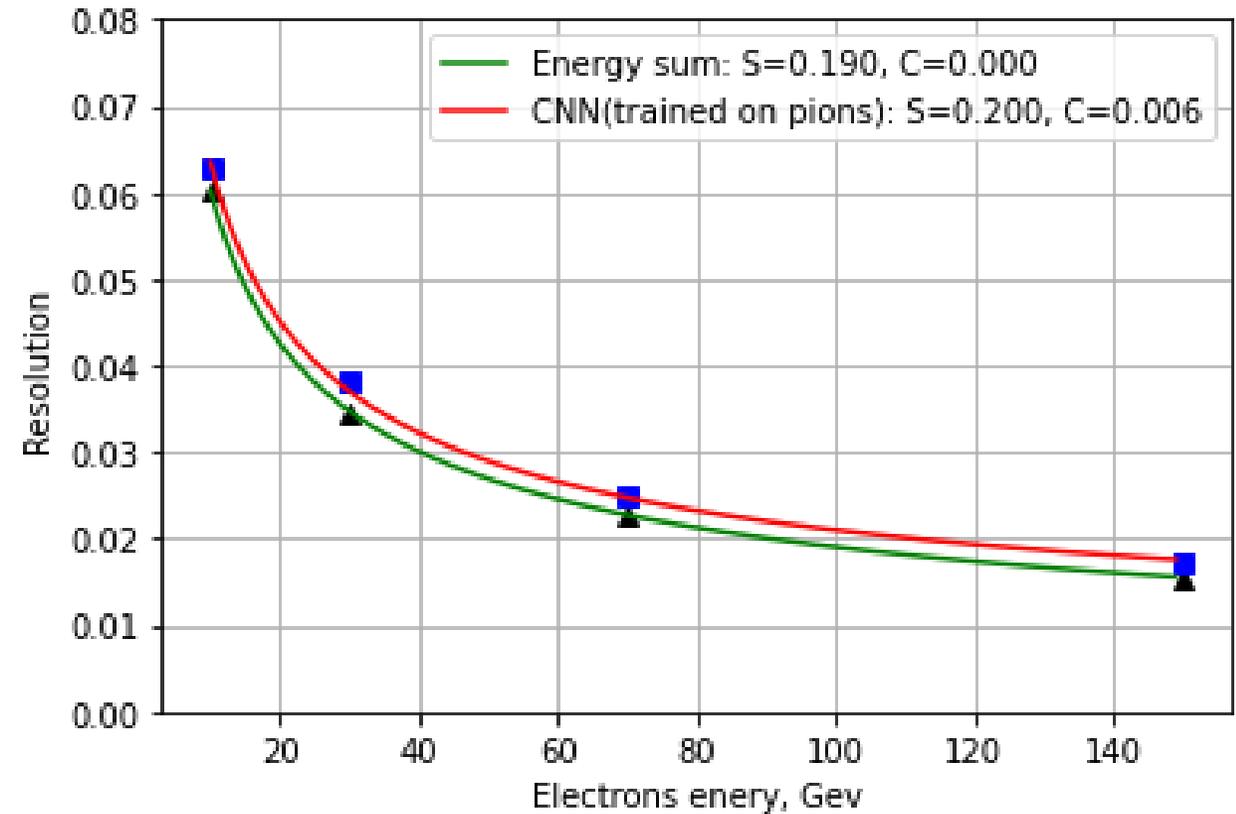
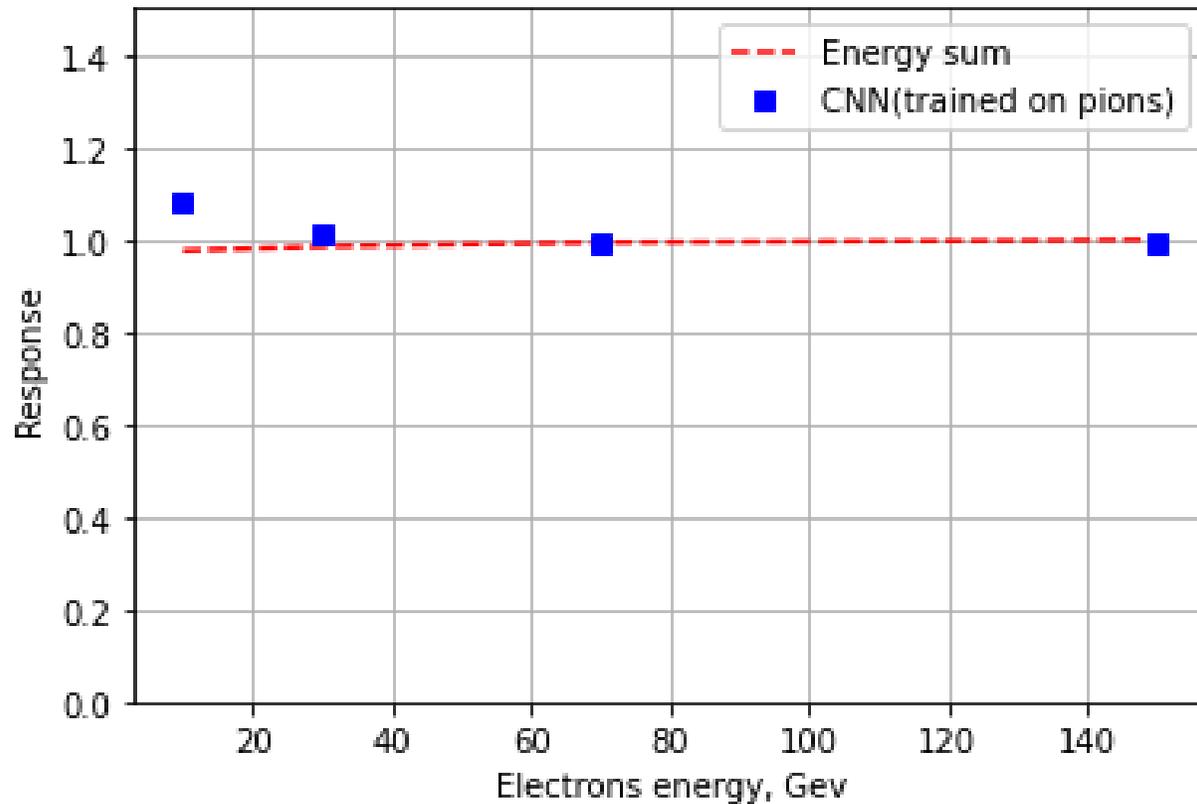


pions, Cu-Si 2x2x2cm



CNN test with electrons

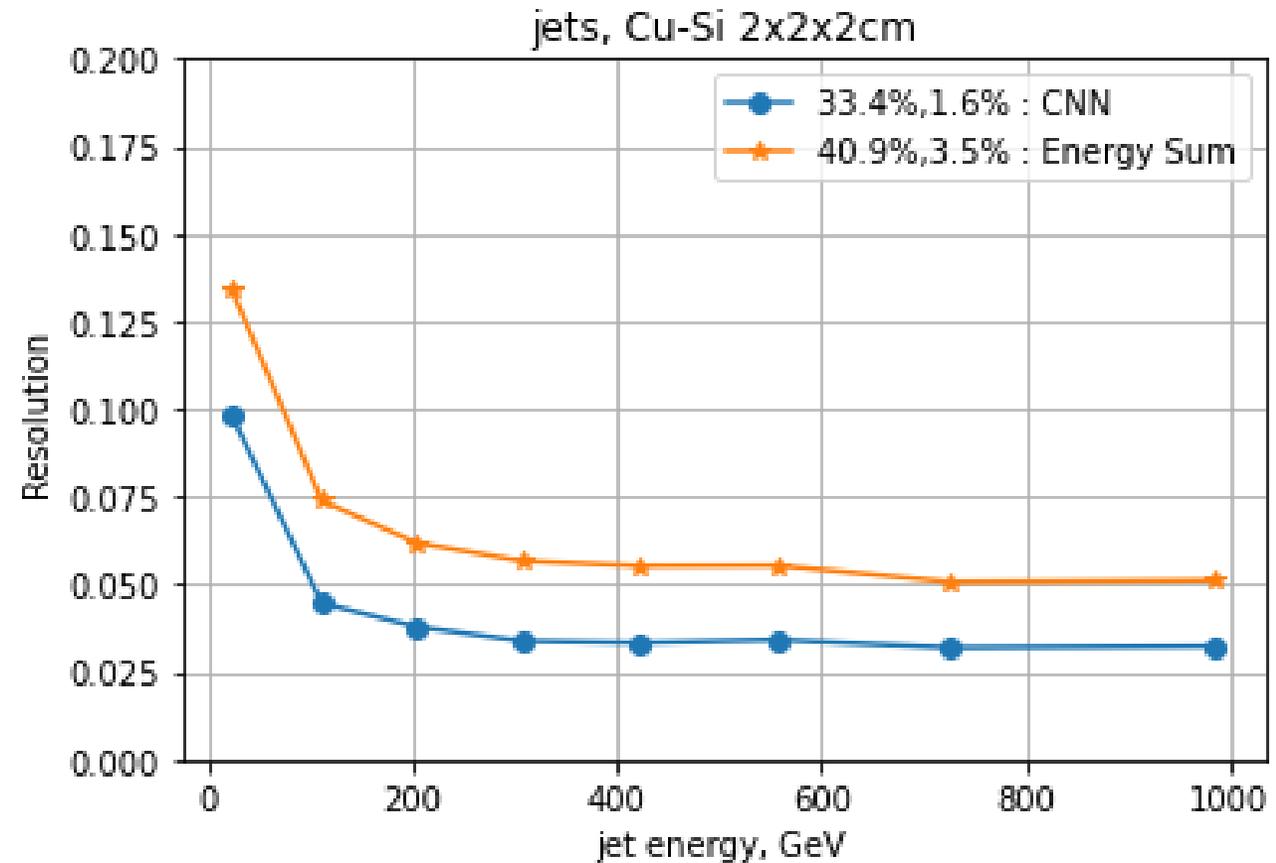
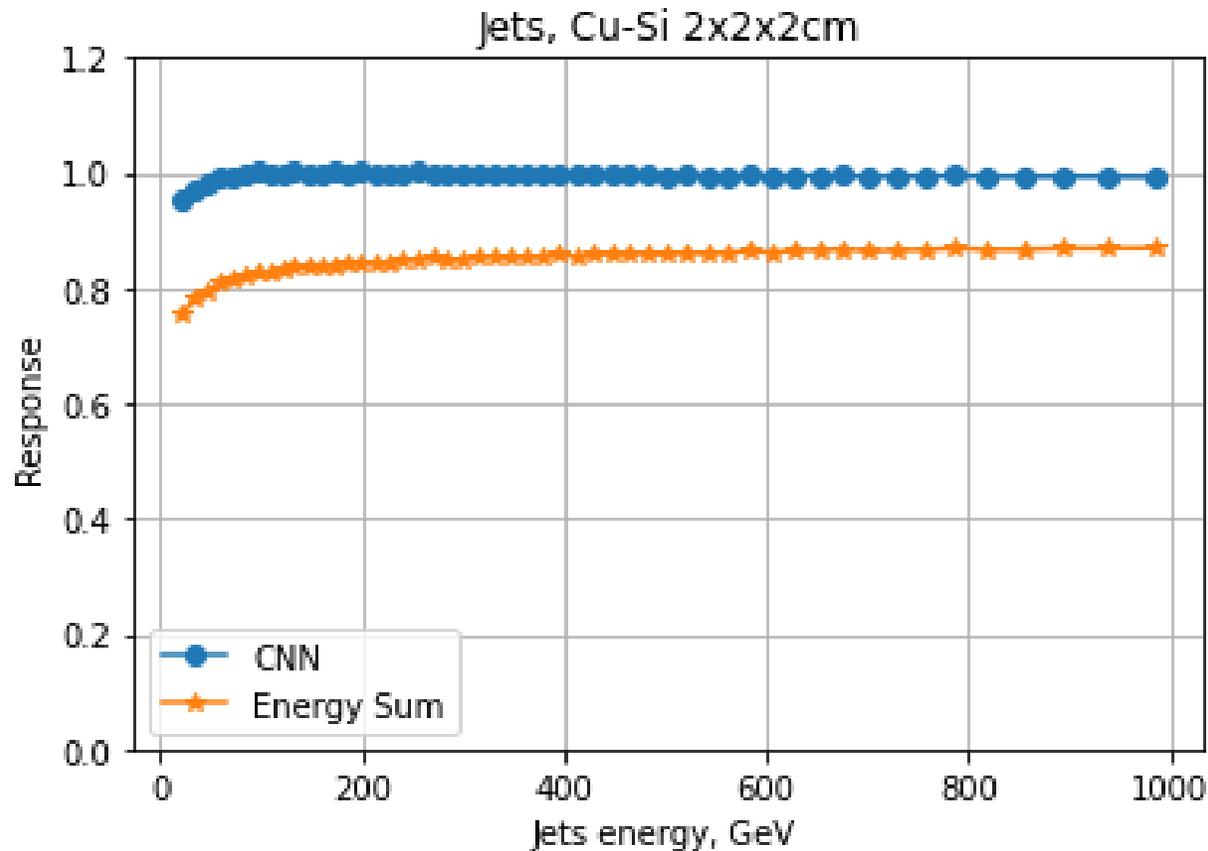
Electron reconstruction with CNN *trained on single pions*.



CNN maintains good performance for electrons reconstruction – comparable to the traditional technique.

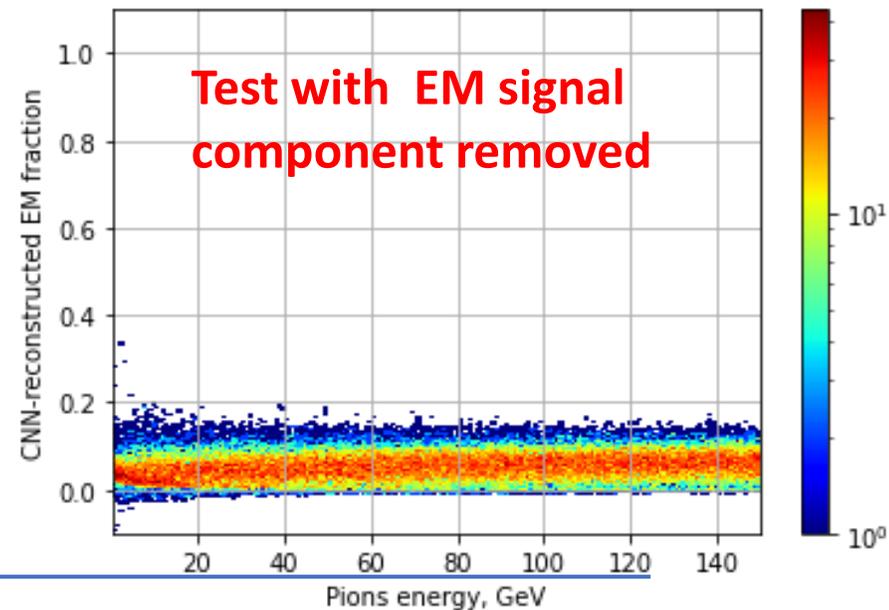
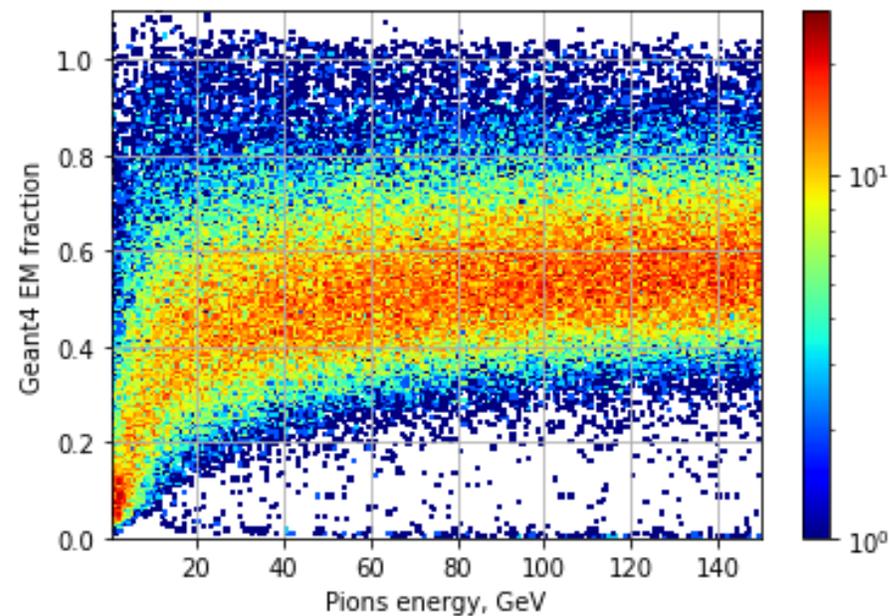
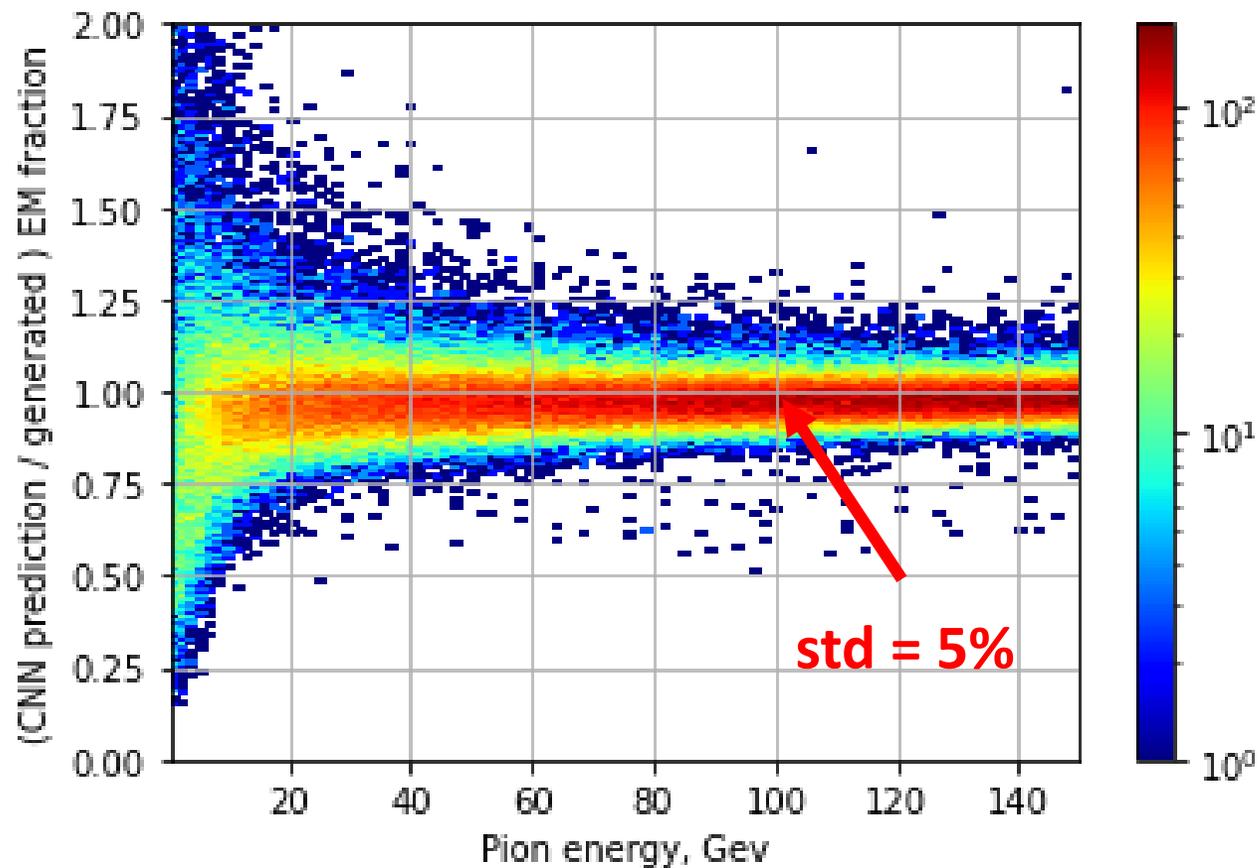
CNN performance – multi-particle showers: jets

CNN trained on *single pions* (0.5-150 GeV) performs very well on **jet reconstruction** in extended energy range – up to 1 TeV



Reconstructing the EM fraction with CNN

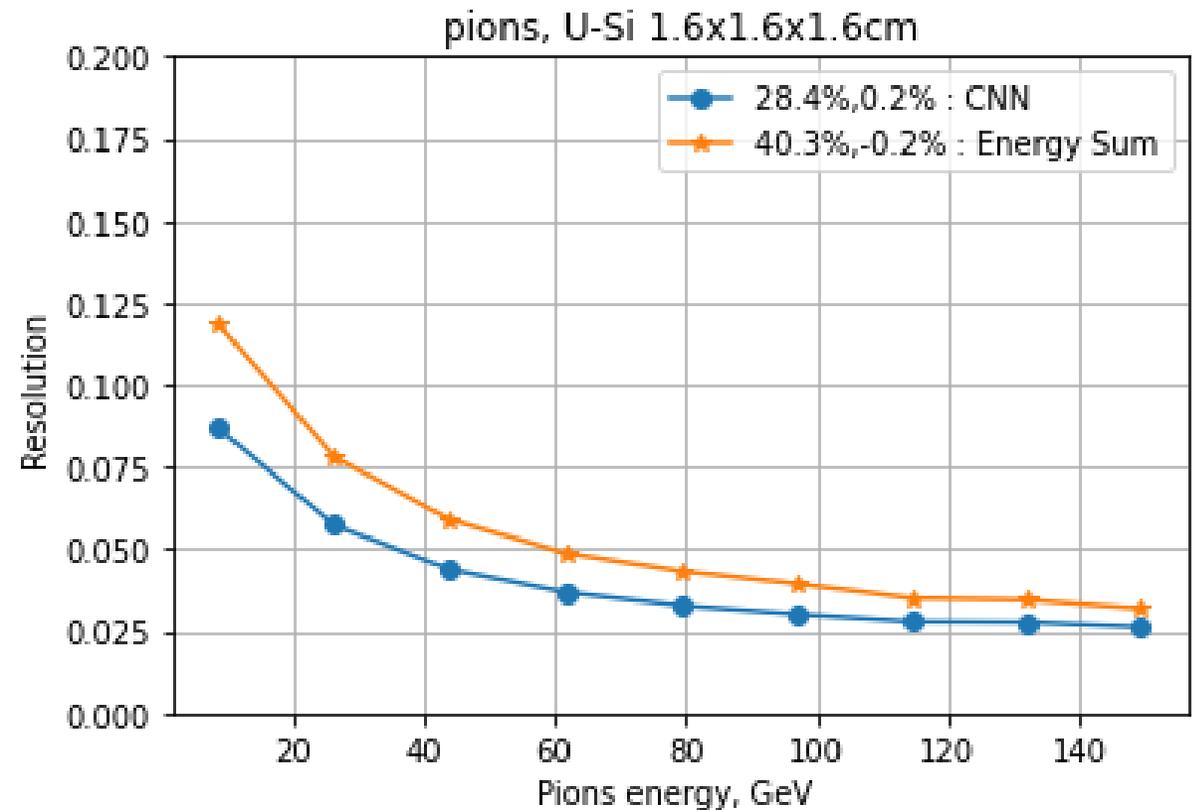
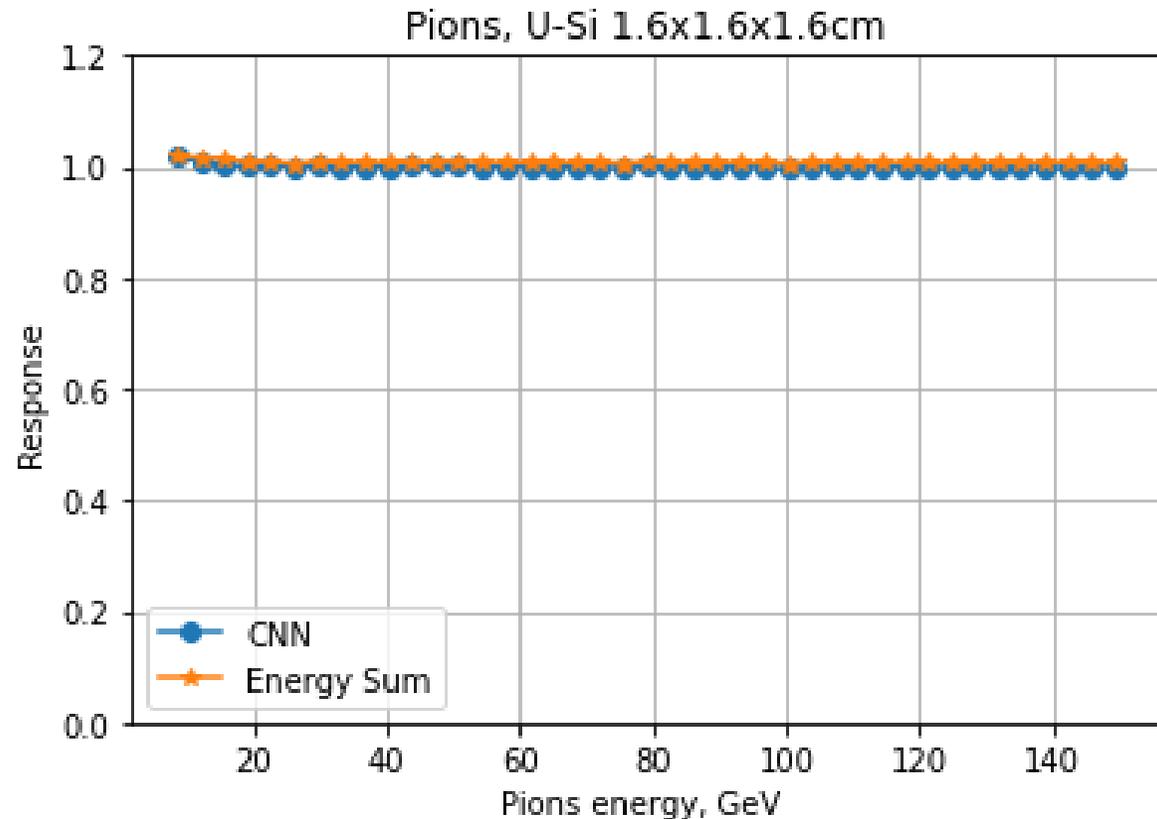
CNN can also be trained to reconstruct the EM-fraction in the hadron showers



CNN performance – compensating calorimeter

Uranium – Silicon sampling calorimeter. U-3.3mm, Si-0.7mm

Signal is integrated in 5ns and the cells are combined in $1.6 \times 1.6 \times 1.6 \text{cm}^3$ channels for the CNN reconstruction. CNN is trained on single pions 0.5-150 GeV.



Depth segmentation with timing

- Fast timing gives opportunity to explore timing-based depth segmentation in fiber calorimeters.
- CNN-like energy reconstruction techniques may contribute for further improvement in performance, using the 3D image of the showers

Recently developed *Waveform Digitizer*
By [NALU Scientific](#)

FEATURES	AARDVARC V3 ¹
SAMPLE BUFFER	32 k
CHANNEL	4-8 CHANNEL
BANDWIDTH	2 GHZ ANALOG
TIMING RESOLUTION	4-8 ps
SAMPLE RATE	10-14 GSa/s

Summary

- ❑ We studied energy reconstruction in high granularity hadron calorimeters with Convolutional Neural Network (CNN)

- ❑ We achieved improved precision of the energy reconstruction beyond the reach of commonly used techniques
 - The CNN performance was demonstrated on **Ci/Si (non-compensating) and U/Si (compensating) calorimeters**, using GEANT4 simulation.
 - CNN trained on examples with simulated **single hadron showers** performs well in a broader range of energy reconstruction tasks and can reconstruct energy of the **multi-particle showers from jets** and **EM-showers from photons**
 - CNN based algorithm also correctly **reconstructs the electromagnetic component** in hadron showers

- ❖ *Looking to expand the study to fiber calorimeters with **time-based longitudinal segmentation***

BACKUP

Energy loss vs charged pion multiplicity

