DREAM FOR FUTURE

# Particle Identification for Dual-readout Calorimeter using Deep Learning

YunJae Lee from University of Seoul

on behalf of the Dual-Readout Calorimeter R&D team

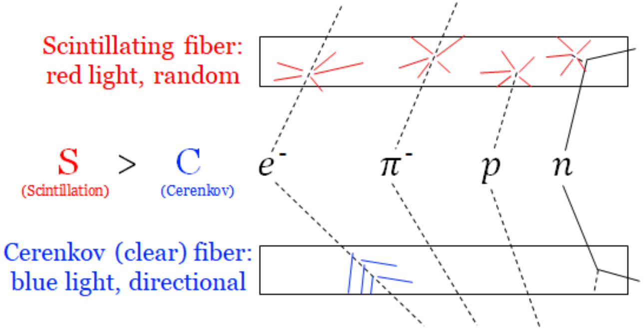
CALOR 2022 - 19th International Conference on Calorimetry in Particle Physics

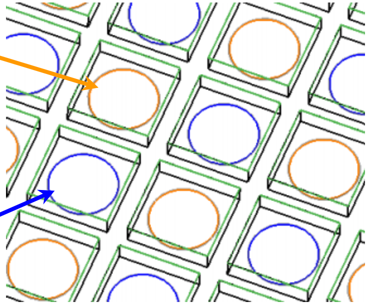
18 May 2022

E-mail: yunjae.lee@cern.ch

# Dual-Readout Calorimeter

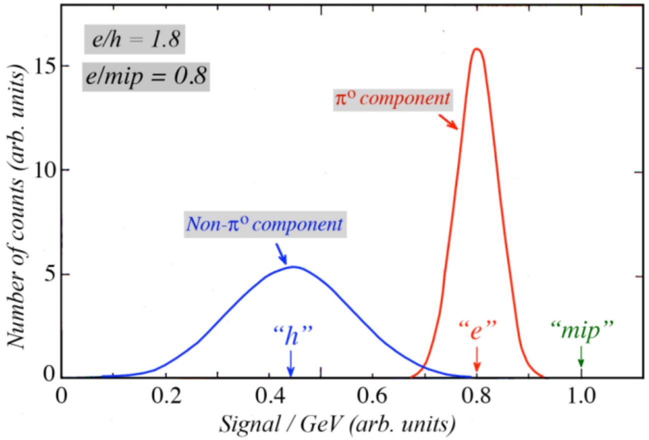
- Dual-readout calorimeter is considered of detector for FCC-ee and CEPC due to its great hadronic energy resolution.
- Dual-readout calorimeter has two different, Scintillation and Cerenkov fibers components.
  - Scintillation fibers react to both EM and hadronic particle, Cerenkov fiber reacts to EM particle only.
- Ratio of hadronic component and EM component $\boldsymbol{h/e}$ is differed by Scintillation part $(\boldsymbol{h/e})_S$ and Cerenkov part $(\boldsymbol{h/e})_C$.



Array of fibers

Distributions of signal for shower components[1)]




Normalized to the response for minimum ionizing particles ("mip")
The average values of hadronic response(h) is smaller than EM response(e)

1) Lee, S., Livan, M. and Wigmans, R. (2018) Nucl. Instr. and Meth. A882, 148

# Dual-Readout Calorimeter

- Scintillation signal S and Cerenkov signal C are measured with optical photon.
  - Cerenkov signal is smaller than scintillation signal for hadronic showers.
- EM shower fraction($f_{em}$) is directly measured by scintillation and Cerenkov responses.
  - $f_{em} = 1$ for EM shower, $f_{em} < 1$ for hadron shower
  - Hadronic energy can be measured with better resolution.

$$f_{\rm em} = \frac{(h/e)_C - (C/S)(h/e)_S}{(C/S)[1-(h/e)_S] - [1-(h/e)_C]}$$

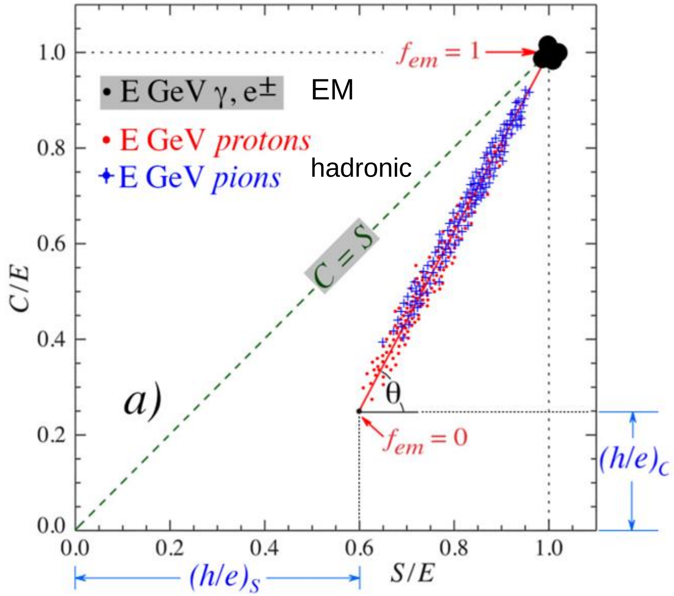
$$E = \frac{S - \chi C}{1 - \chi}$$

$$S = E\left[f_{\rm em} + \frac{1}{(e/h)_S}(1 - f_{\rm em})\right]$$

$$C = E\left[f_{\rm em} + \frac{1}{(e/h)_C}(1 - f_{\rm em})\right]$$

$$\cot\theta = \frac{1-(h/e)_S}{1-(h/e)_C} = \chi$$

Signal from a dual-readout calorimeter [1)]

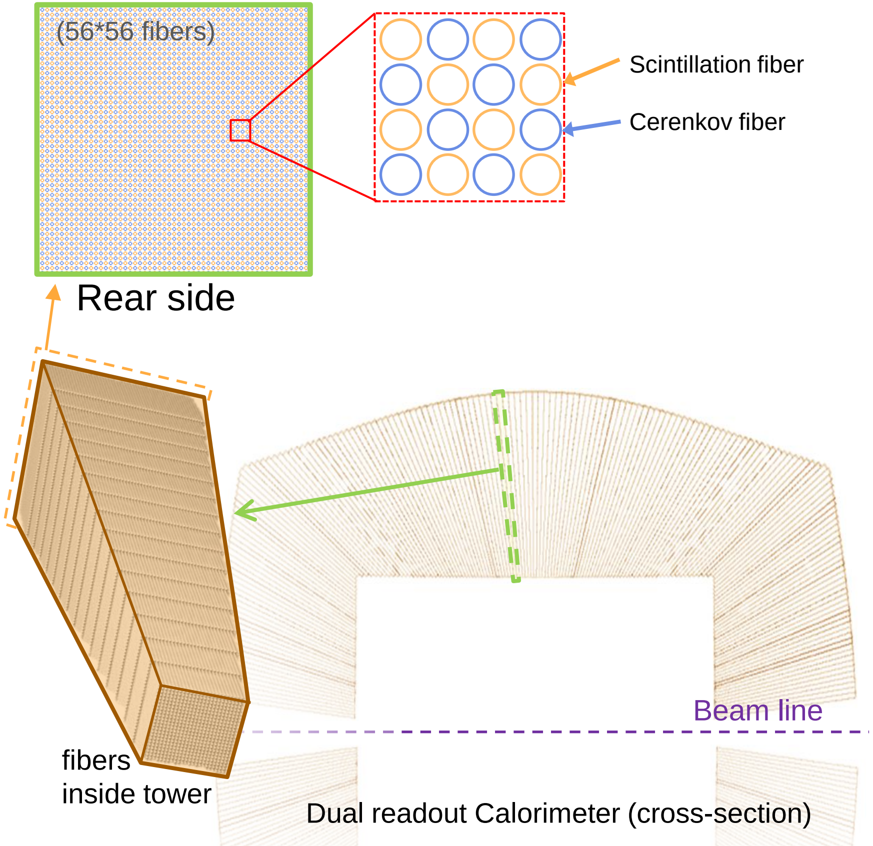



Signal is calibrated with electron of known Energy E.
Cerenkov signal is smaller than scintillation signal with hadron showers.

1) Lee, S., Livan, M. and Wigmans, R. (2018) Nucl. Instr. and Meth. A882, 148

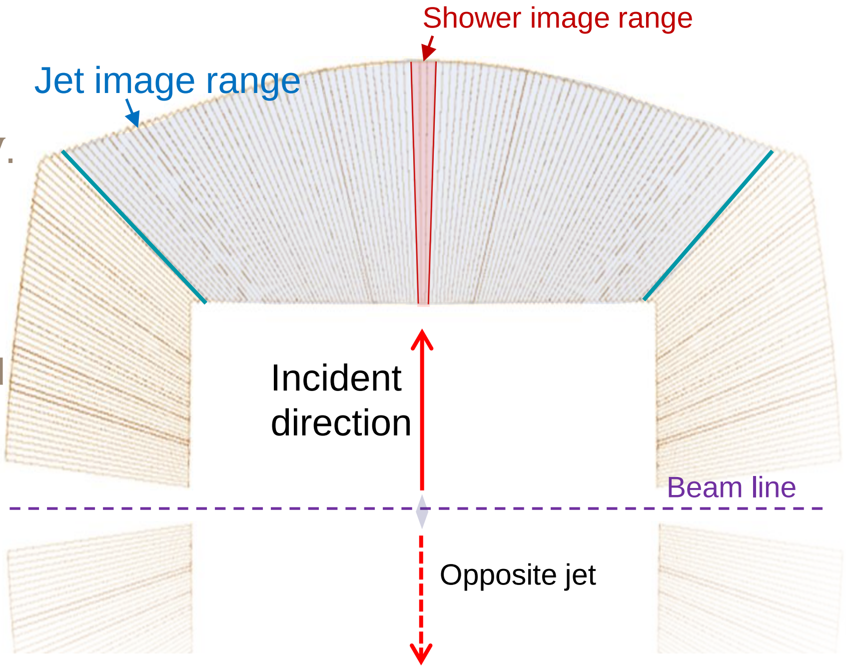
# Simulation setup

- The calorimeter geometry for simulation study.
  - Calorimeter structure consists of column shaped copper towers.
  - 56*56 array of (Cerenkov(28) and scintillation(28)) fibers are implanted in copper towers.
  - MC energy deposits to fibers are reconstructed by optical photon coming out to rear end of fiber.
- Monte Carlo Simulation
  - Dual-readout calorimeter only – no other structure.
  - No magnetic field applied.
  - Hadronization of jet is simulated by Pythia8.
  - Calorimeter and shower are simulated by GEANT4.



# Data setup

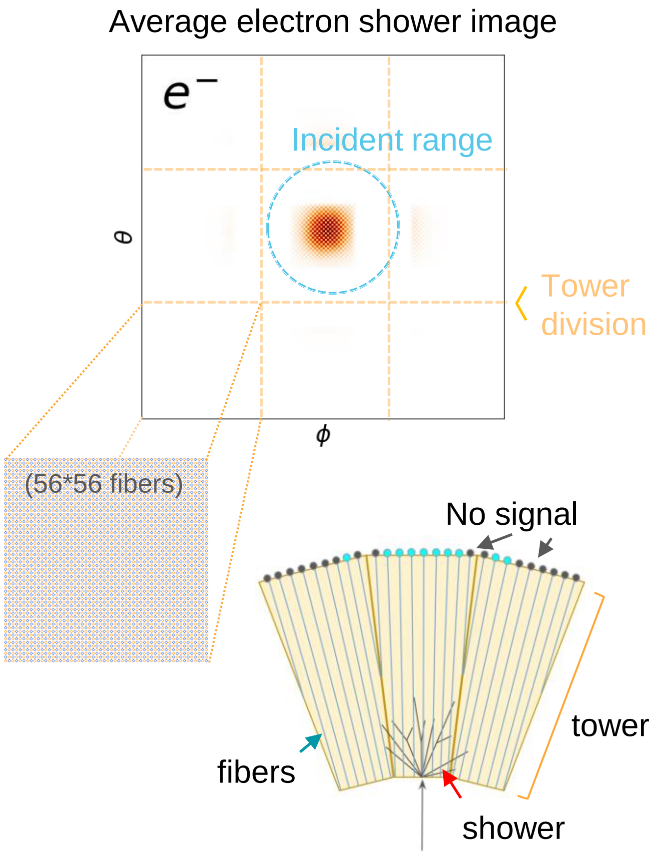
- Particles are generated at center of calorimeter with certain energy with directed to middle of barrel.
- $e^-$, gamma, $\pi^+$, $\pi^0$, $K^+$, $K_L^0$, proton and neutron
  - Incident particle energy range between 10 ~ 100 $\mathrm{GeV}$.
- Quark and gluon jets
  - Back-to-back quark-antiquark or gluon-gluon are generated because of color confinement.
  - Quark(u, d) and gluon jets with energy at 50 $\mathrm{GeV}$ and 70 $\mathrm{GeV}$.
- Reconstructed scintillation and Cerenkov energy distribution of shower or jet are processed to 2 channel image.
  - Energy reconstructed by number of optical photon from fiber which generated by shower.




Dual readout Calorimeter (cross-section)

# Image of reconstructed energy

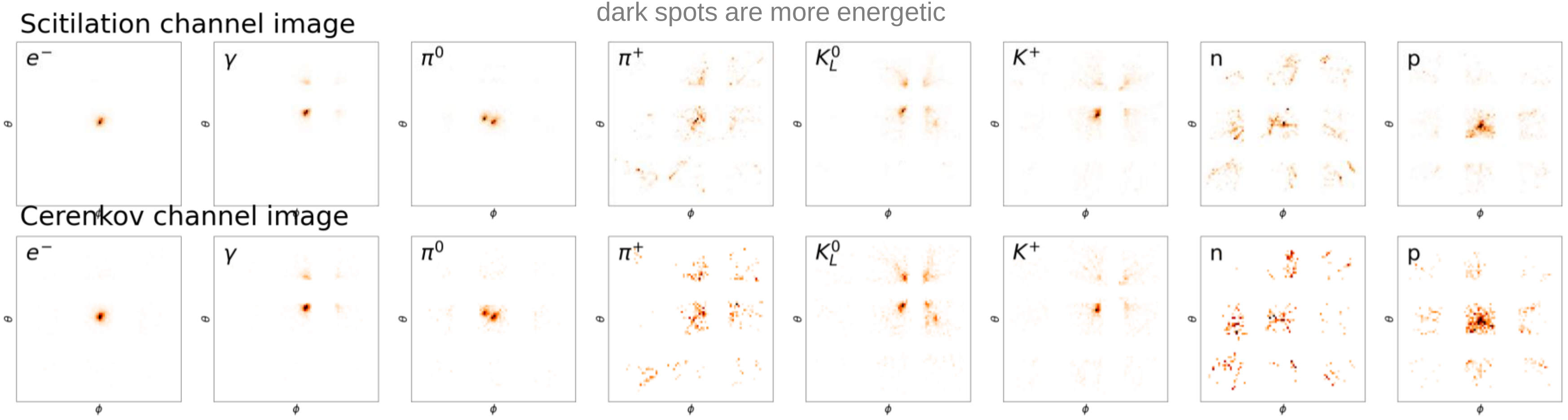
- Reconstructed energy pixelized by position of fiber.
  - Pixelized by rear end of fiber, axis direction is $\theta$, $\phi$.
  - Image have 2 channel of reconstructed scintillation and Cerenkov.
  - More fibers at rear than front, fibers around tower border get signal when shower get through enough depth.
- Maximum image resolution is 56*56 pixel per a tower, but reduced image resolution is used as input because image are very sparse.



# Image of reconstructed energy

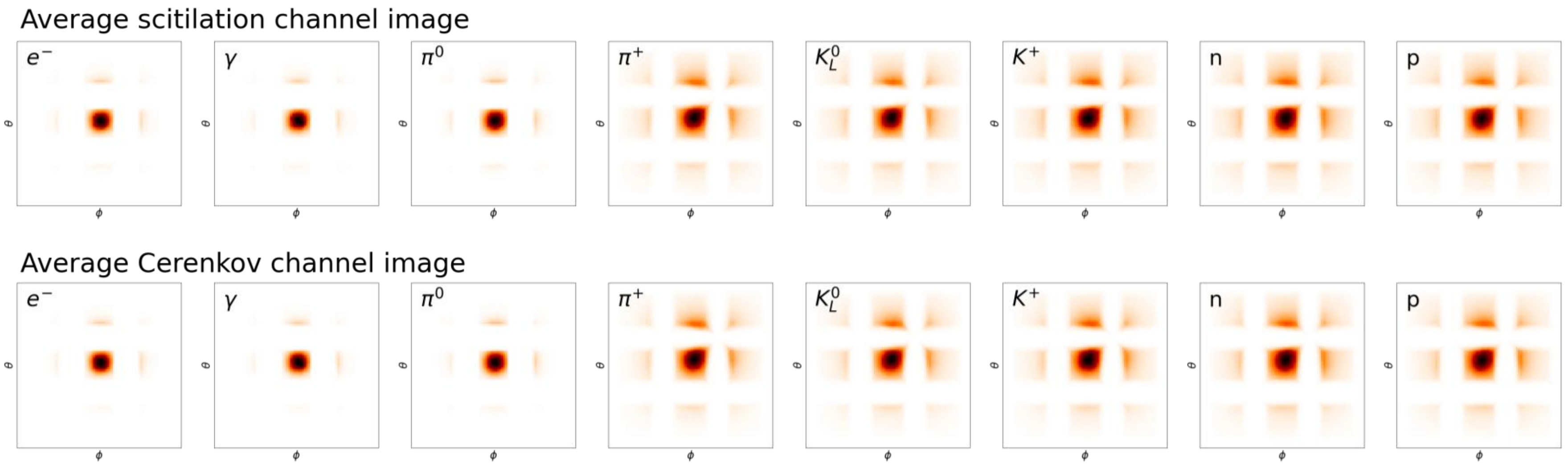
- Shower image(84*84pixels) covers 3*3 towers range with resolution of 28*28 pixels per a tower.
- EM($e^-$, gamma, $\pi^0$) shower images show narrow spread, hadron shower images show more wider spread.
- $\pi^0$ shower shows separated cluster, according to opening angle of its decay.

dark spots are more energetic



# Image of reconstructed energy

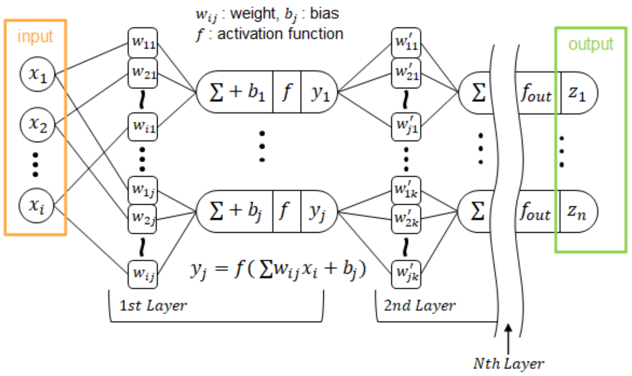
- Average images of every shower image from same particle shows tendency of shower.
  - Average images are mostly same for each EM and hadron showers.
- EM shower deposited in a tower(85% when incident to tower center), while hadron shower spread over beside towers.



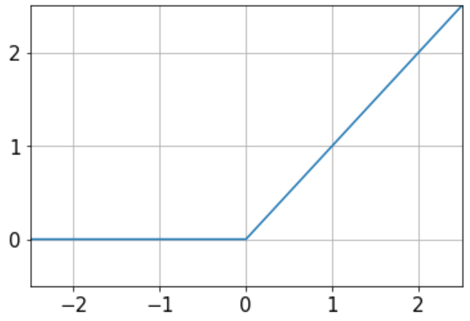
# Deep Learning Methods

- One of ML methods, which are based on neural networks
  - In each layer, weighted sum of inputs and bias are passed through activation function to outputs for subsequent layer.
  - Non-linear activation function provide non-linearity to model.
  - Multi-layer structured model can approximate arbitrary function.
- Deep learning model is trained to produce target outputs.
  - Loss function expresses error between model outputs and target outputs.
  - Weights are optimized with gradients of loss respect to weights.
- Deep learning methods are implemented with Keras of TensorFlow.

Neural Networks




Rectified Linear Unit

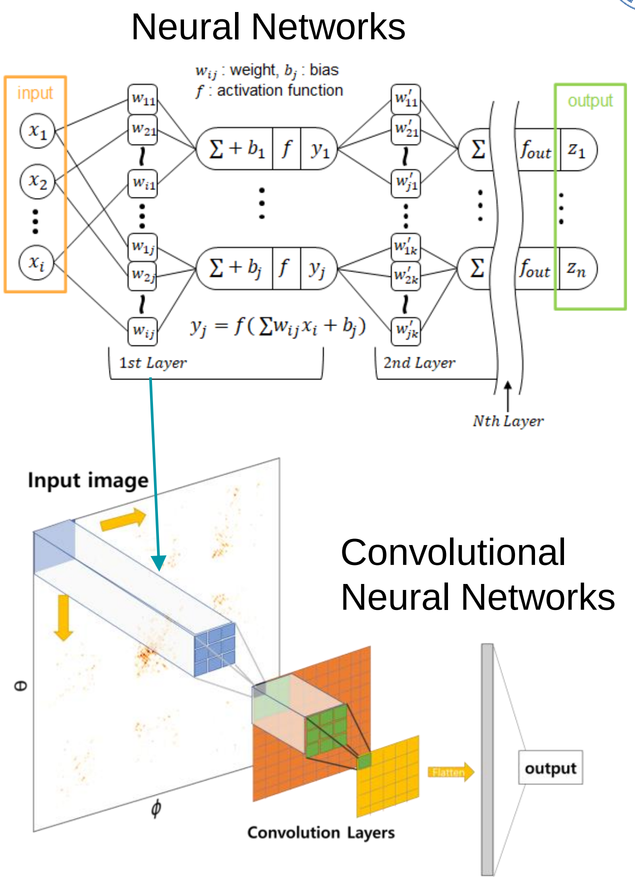


# Deep Learning Methods

- Convolutional neural networks(CNN) have weight matrix of certain size.
  - Weight matrix convolute certain window over input image.
  - Output is also array and the weight matrix work as convolution filters finding contour or shape features over image.
- Binary classifications are performed between two particle.
  - Softmax function for output to return between 0(background) to 1(signal).
  - Cross entropy loss as loss function for binary classification between particles.

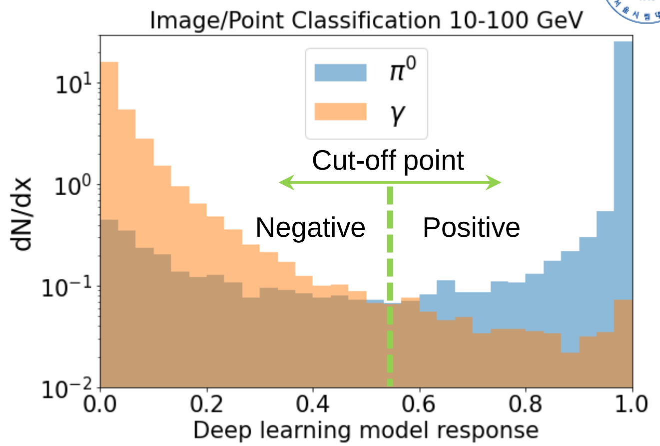
$$\mathrm{loss(y, p)} = -(y \log p + (1-y) \log(1-p))$$

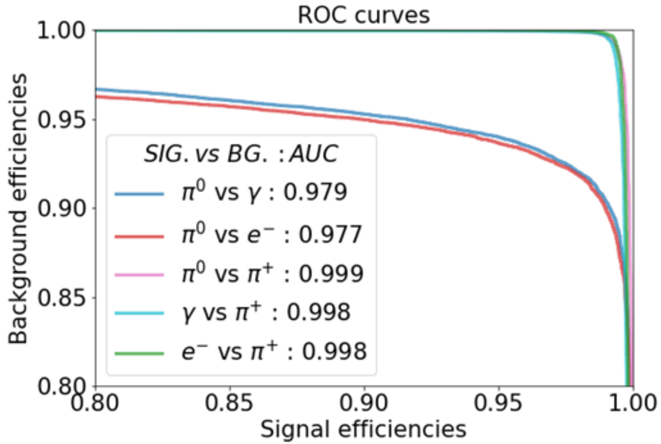
( y is target value, p is prediction value )



# Particle Identification

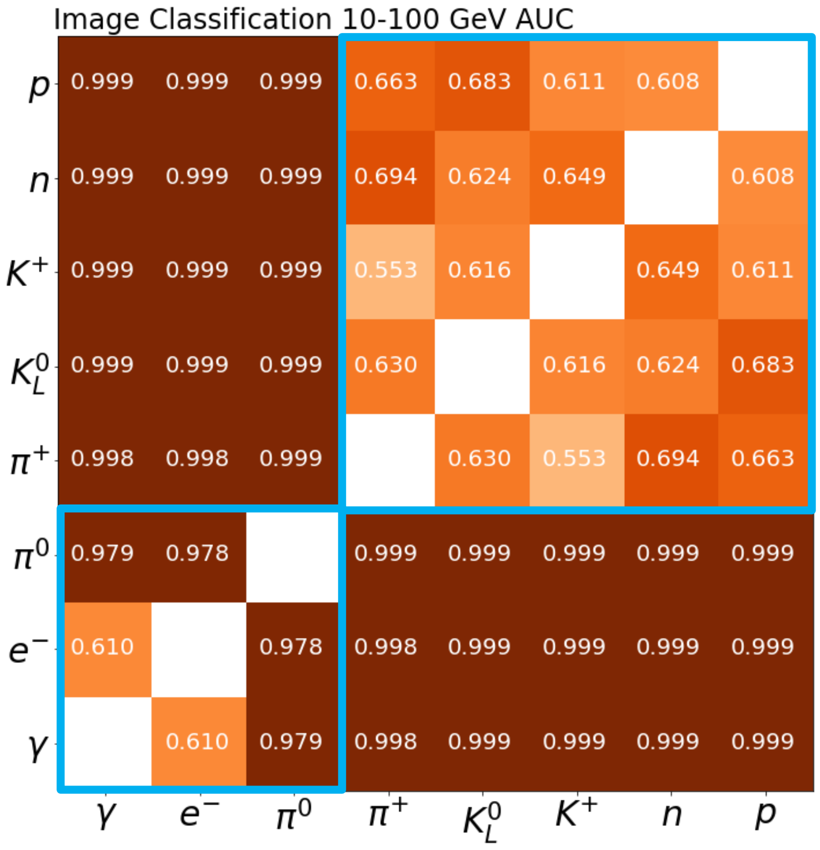
- After training model, model responds to input data between 1.0(signal) to 0.0(background).
  - As $\pi^0$ decays to two gamma, some having very narrow opening angle are misidentified as gamma shower.
- Receiver operating characteristics(ROC) curve drawn with signal and background efficiencies.
  - $\text{signal efficiency} = \frac{\#\ of\ signal}{\#\ of\ positive\ reponse}$ ,$\text{background efficiency} = \frac{\#\ of\ background}{\#\ of\ negative\ reponse}$
  - Positive and negative responses are decided by certain cut-off point.
- Area under ROC curve(AUC) close to 1.0 implies high signal and background efficiencies, performance of classification are compared by AUC value.
  - AUC 0.97 - 93% efficiencies, AUC 0.99 - 99% efficiencies.



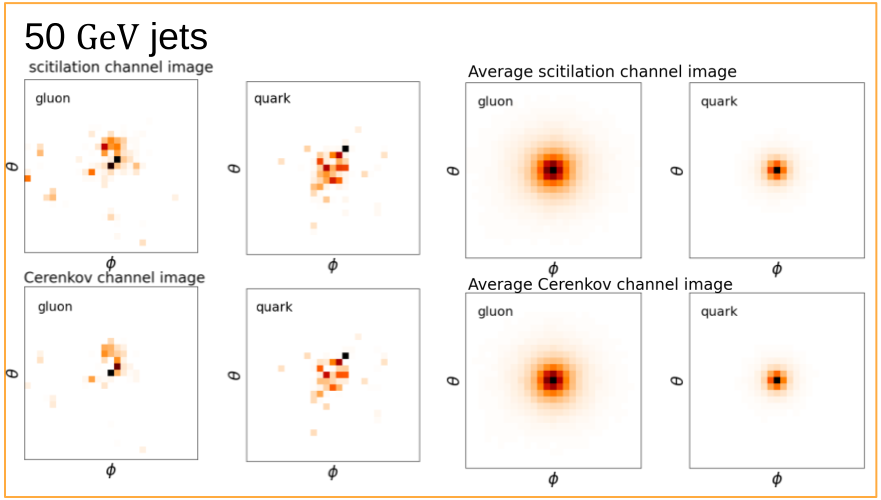
# Particle Shower Identification

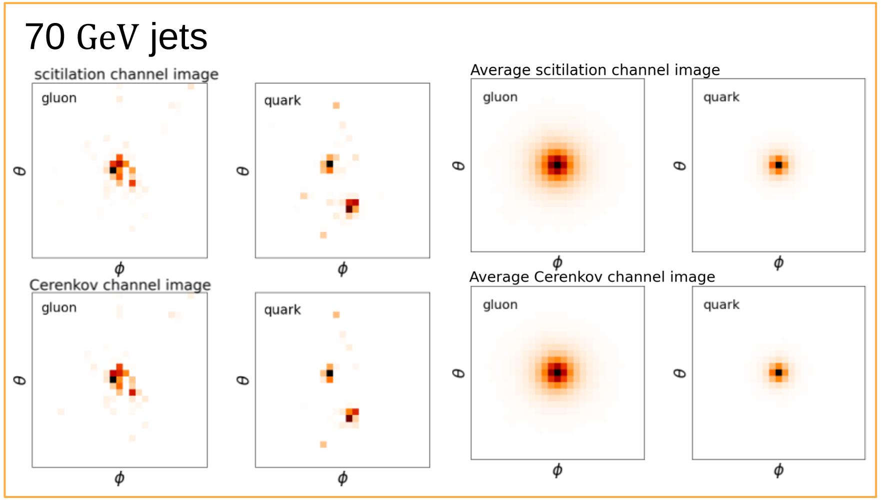
- Binary classification performed for particle showers with energy between 10-100 GeV.
- Cells show AUC values for classification between shower particles labeled at row and column.
  - AUC for $\pi^0$ vs gamma is 0.979
  - Lower than 0.7 means not classified practically.
    - $e^-$ vs gamma, hadron vs hadron
- EM showers and hadronic showers discriminated strongly with each other.
- Classification Hadronic shower model mostly doesn't discriminate but performance varied by charge and between meson and baryon.



# Image of reconstructed energy

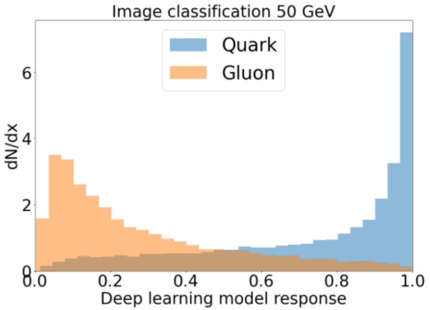
- Jet image(27*27pixels) covers 81*81 towers range(quarter of barrel) with resolution of a pixel per 3 towers.
- Because of hadronization, jets have irregular shape. But gluon jet have tendency to have more hadronization process because color factor of gluon(3) is larger than quark($\frac{4}{3}$).
- Average images shows gluon jets have larger spatial size than quark jets.

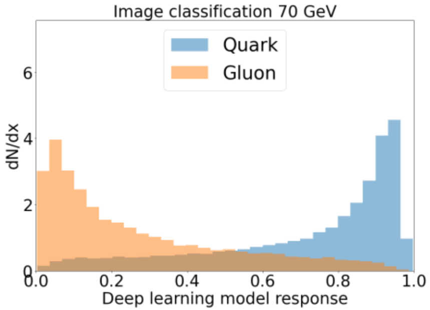


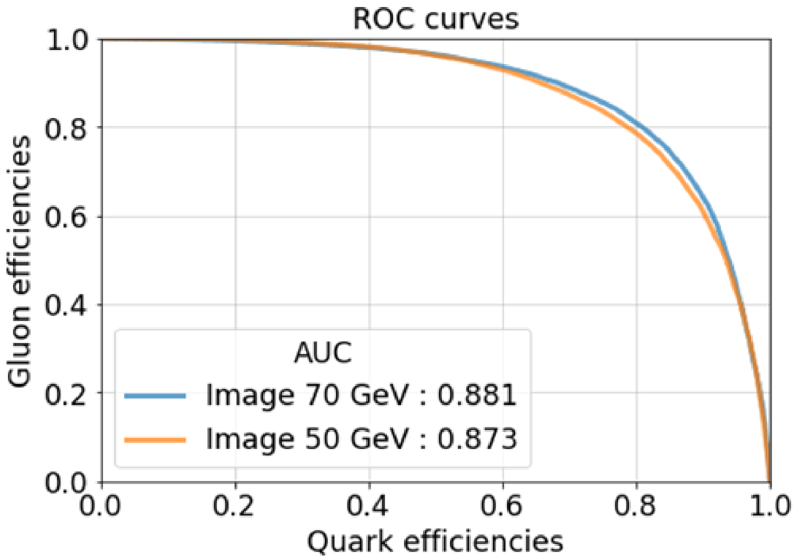



# Quark and Gluon Jet Identification

- Image based model(Image) used for classification between quark(u,d) and gluon jets at 50 GeV and 70 GeV.
- Distributions of model responses show separated quark side and gluon side.
- Quark efficiency and gluon efficiency can be achieved about 79% at 50 GeV, 80% at 70 GeV.



# Summary

- Particle identifications are demonstrated using image-based deep learning method with scintillation and Cerenkov channel images from dual-readout calorimeter.
- Hadron showers and EM showers are discriminated with 99% efficiency and $\pi^0$ shower also can be discriminated with other EM shower with 93% efficiency at energy between 10-100 $\mathrm{GeV}$.
- Quark and gluon jet can be separated with image-based model(79~80% efficiency).
- Deep learning application will be extended and optimized for the dual-readout calorimeter system.

# Backups

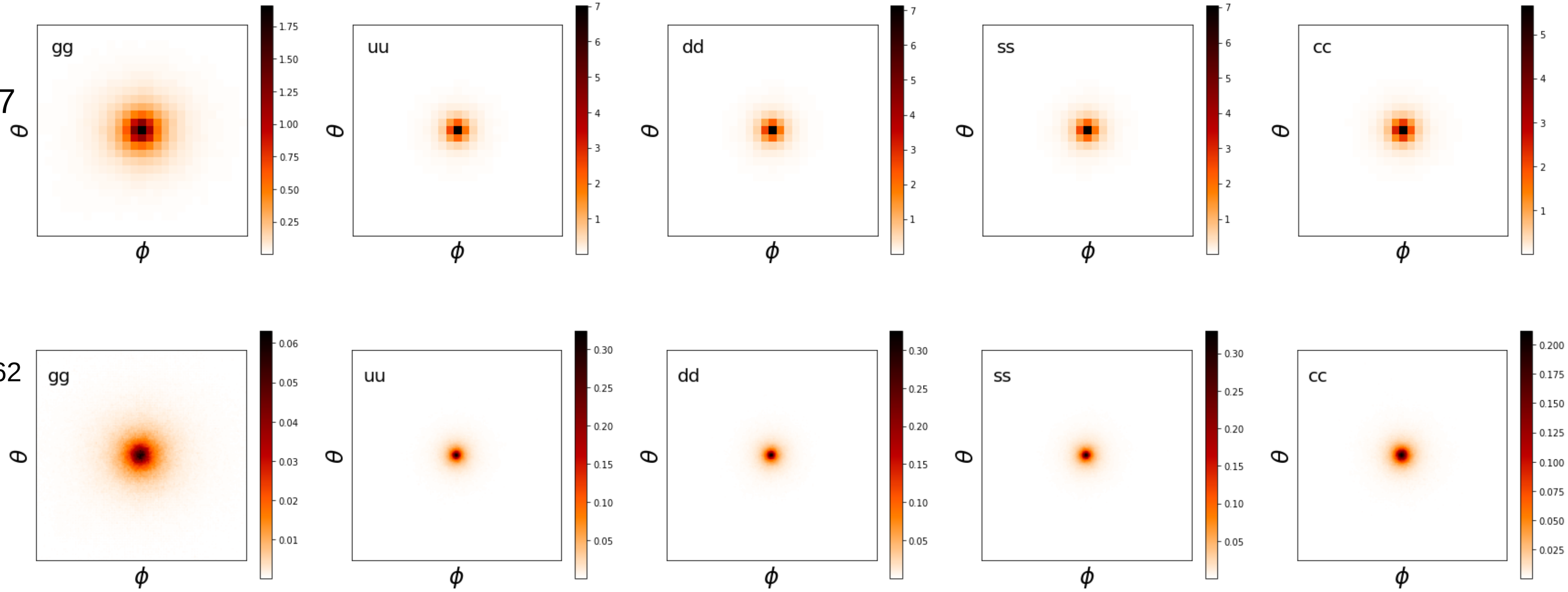

16

# Jet image – 50 GeV

- Average Scintillation energy deposits

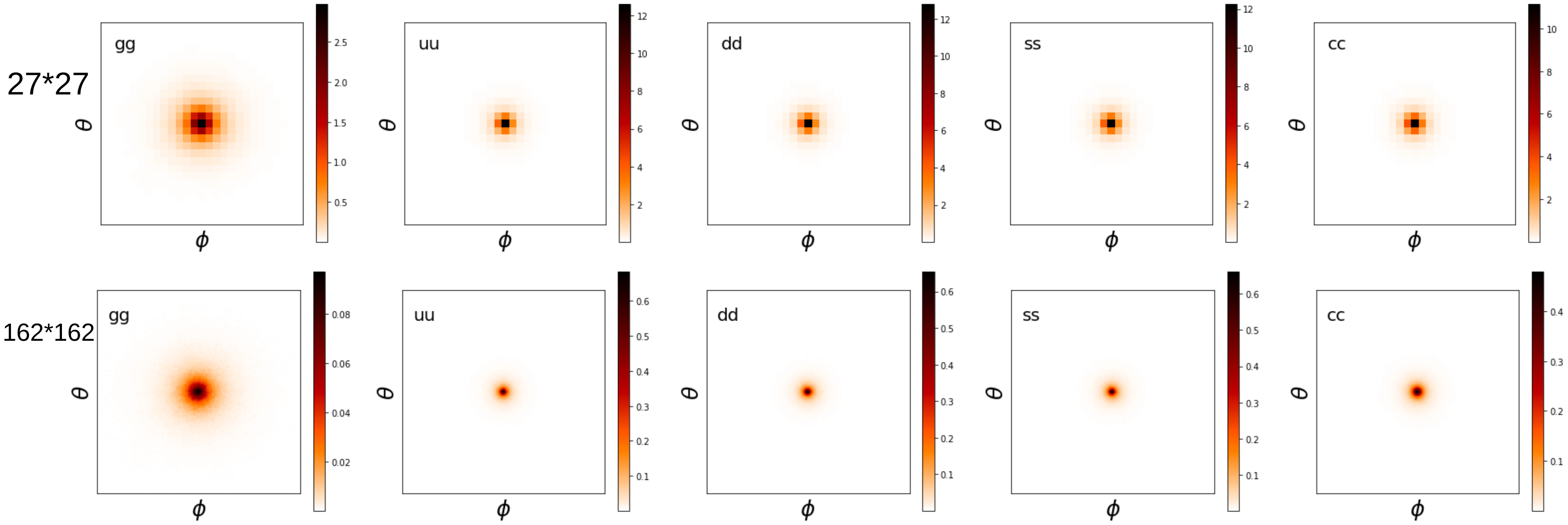
27*27

162*162



# Jet image – 70 GeV

- Average Scintillation energy deposits



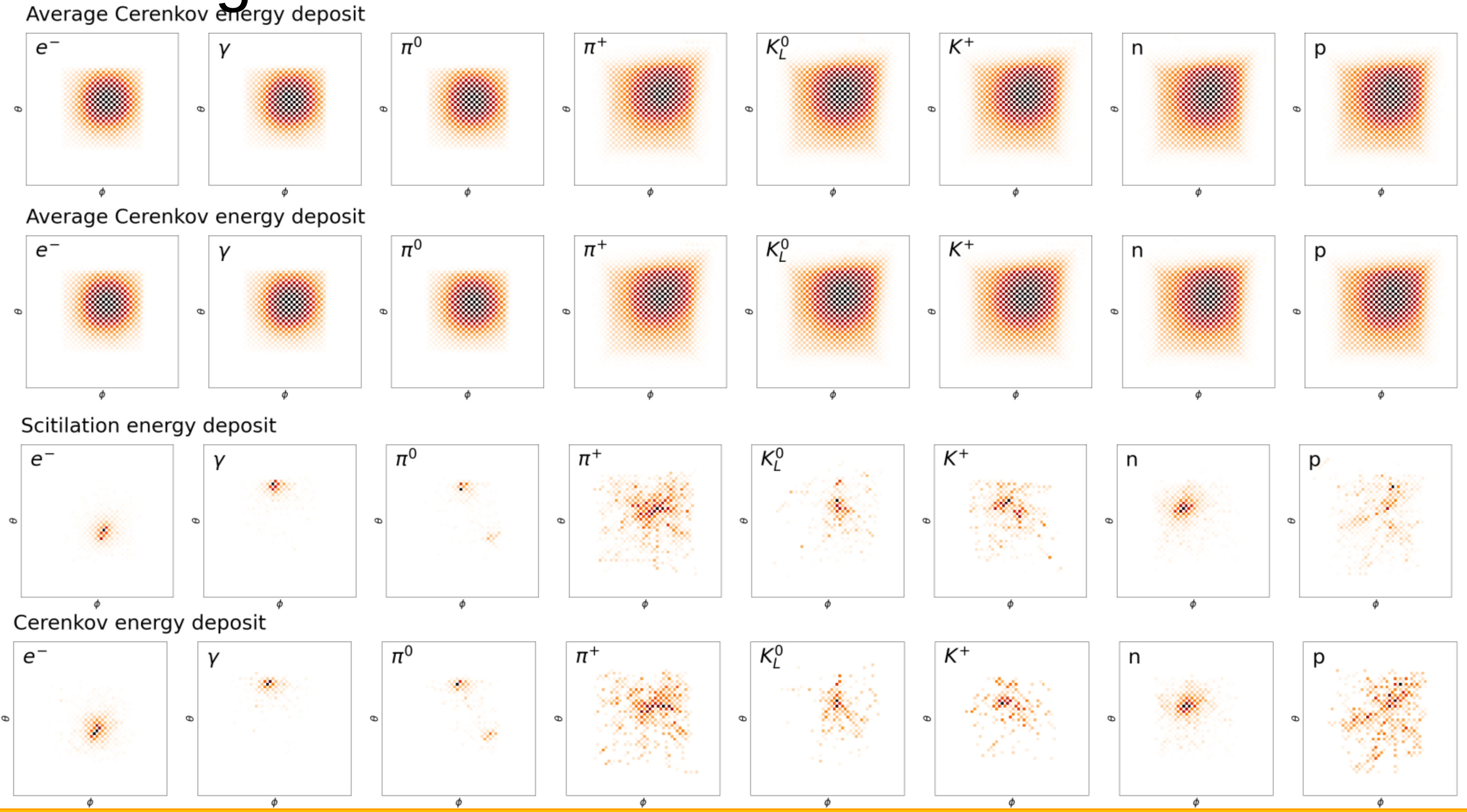
# Deep learning Details

- Environment
  - OS : CentOS7
  - Training with GPU : V100 Nvidia GPU
  - DL library : Keras 2.4.0 with Tensorflow 2.4.0
- Data set division
  - Training 50%, validation 20%, test 30% - 140K total
- Loss function
  - Categorical cross-entropy for classification

Adam optimizer(learning rate=0.0003)

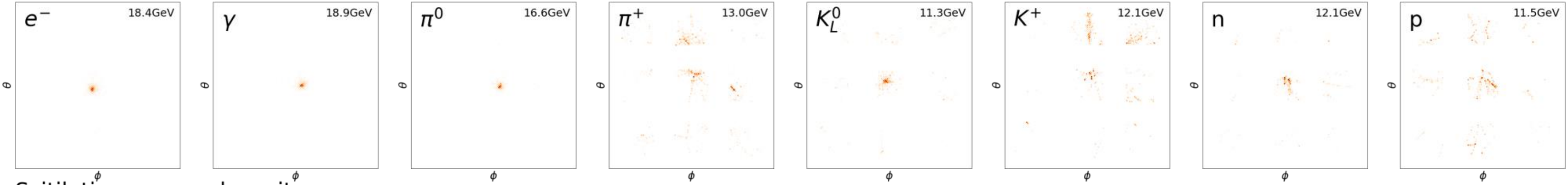
- Process time
  - Image 0.7ms/shower 45 mins 50epochs to train enough around 15 epochs get best model
- Data size
  - 30M/1k showers image (sparse array reduced storage size 30%)

# Average 1 tower

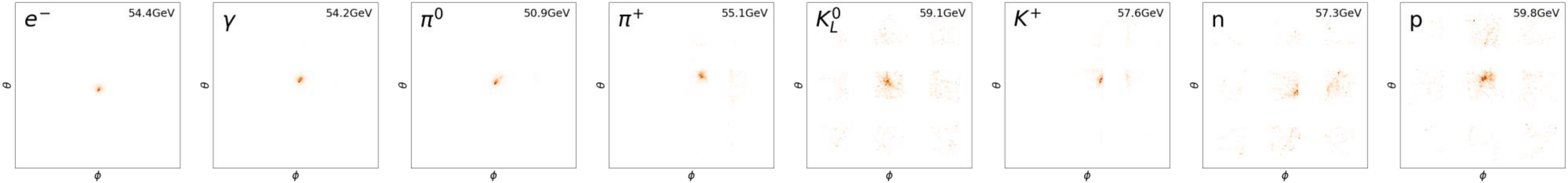


# shower Energy

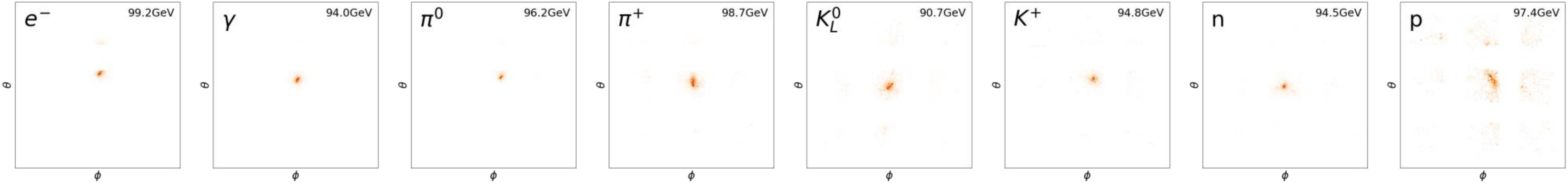
Scitilation energy deposit



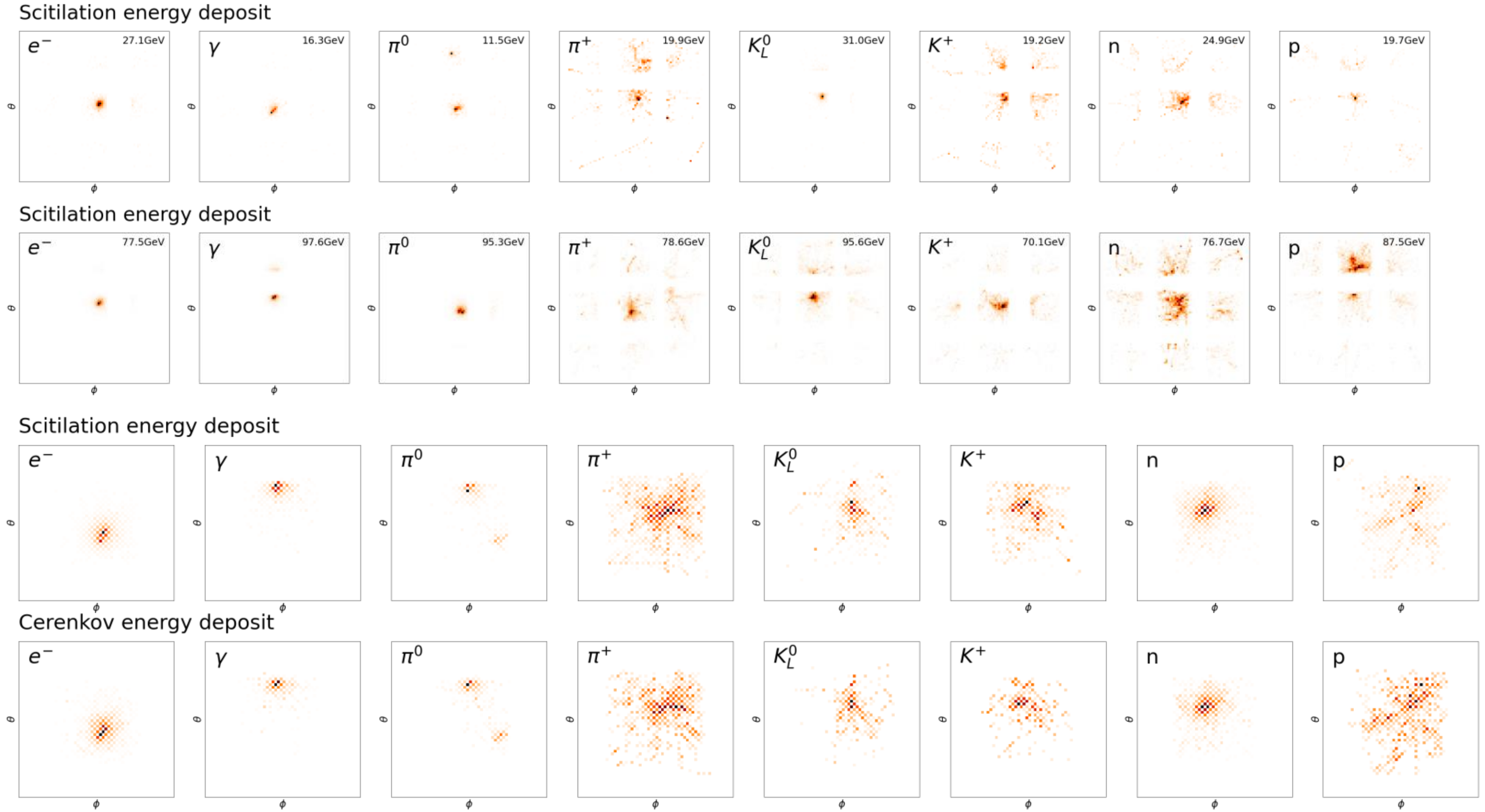

Scitilation energy deposit



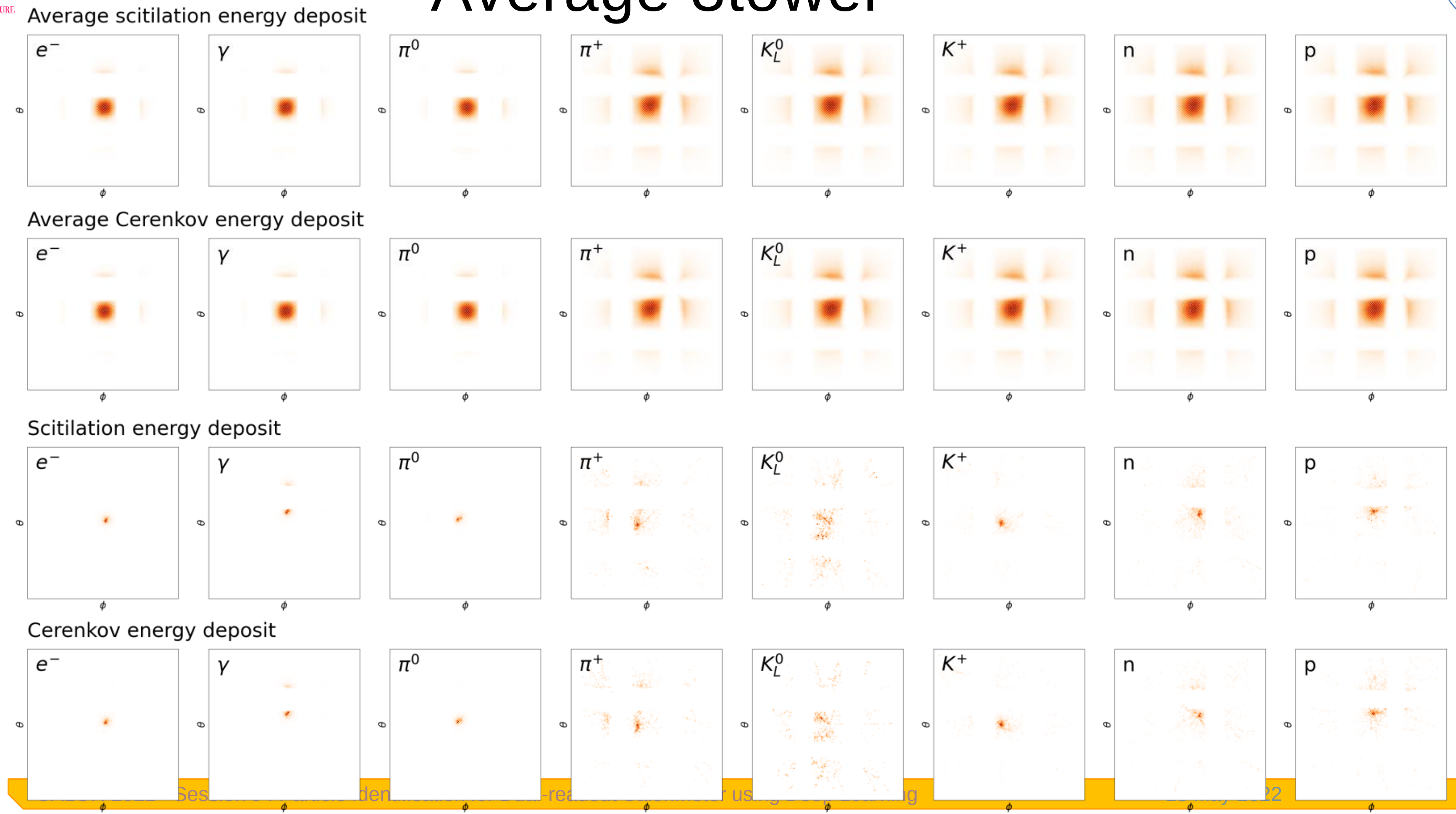

Scitilation energy deposit



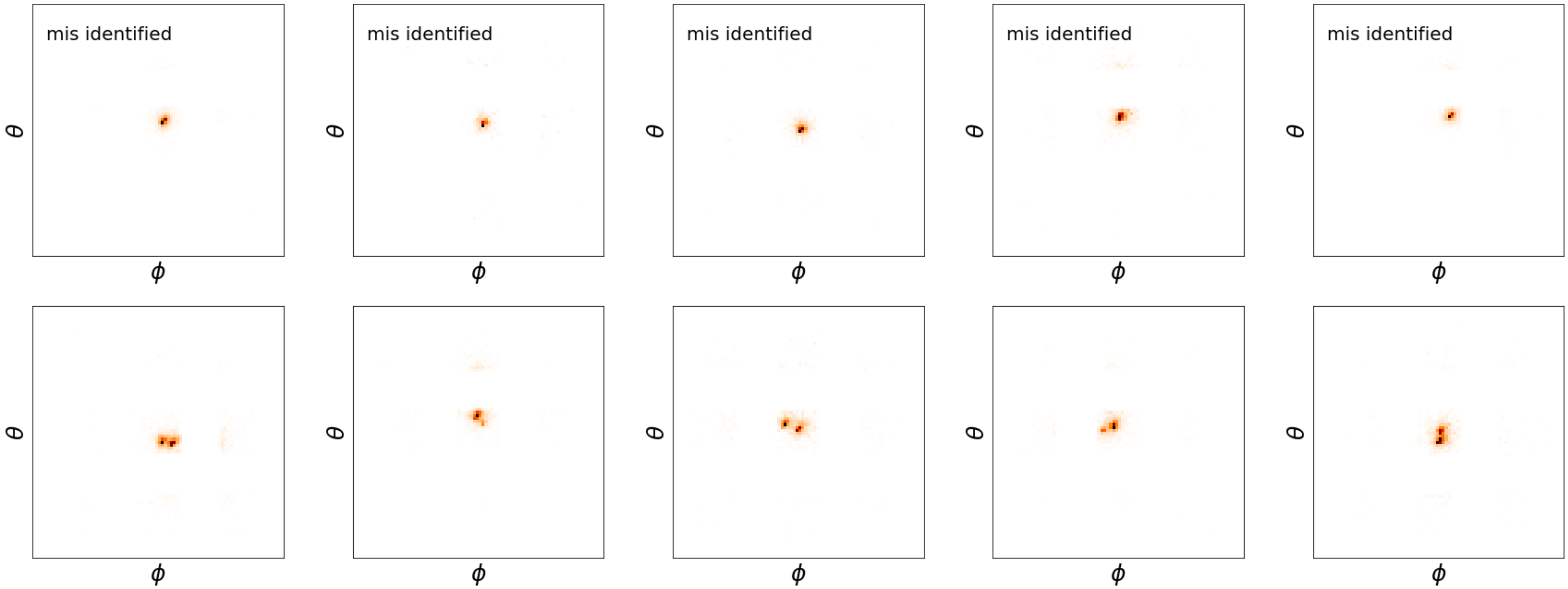
# Shower image by channel



# Average 3tower



# Mis identified $\pi$0 images



# Jet variable comparison