TPC tracking study using CNN

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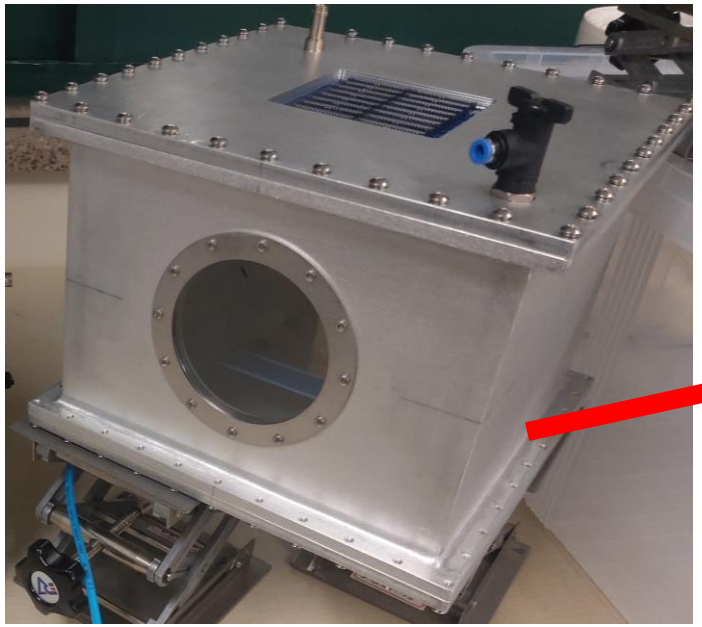
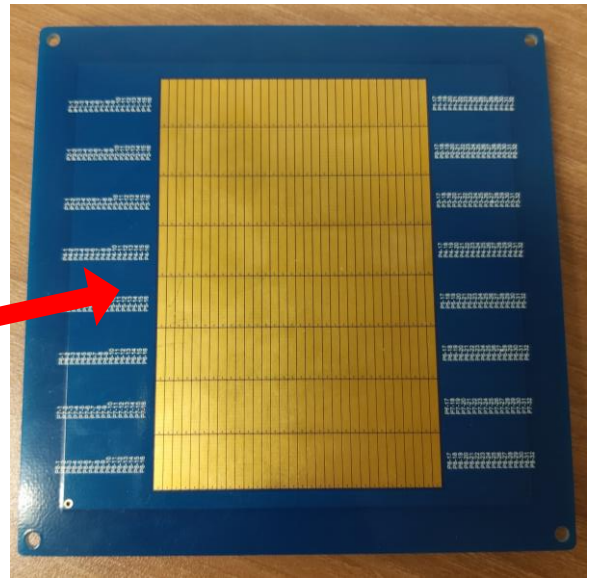
Introduction

Introduction

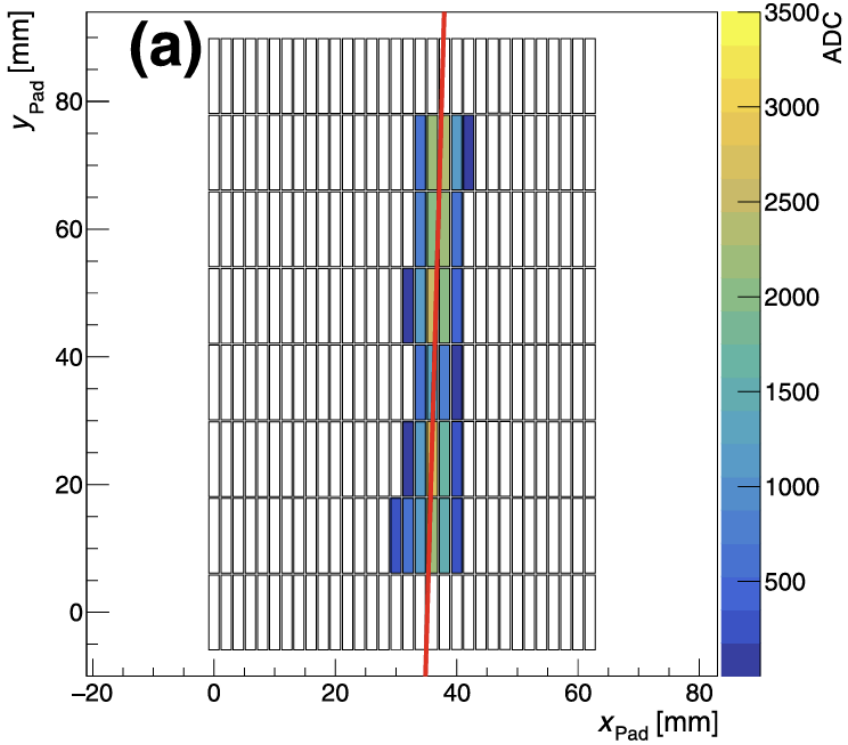
AT-TPCs for HIMAC





Triple GEM base

Layer: 32
Row: 8
Channel: 256



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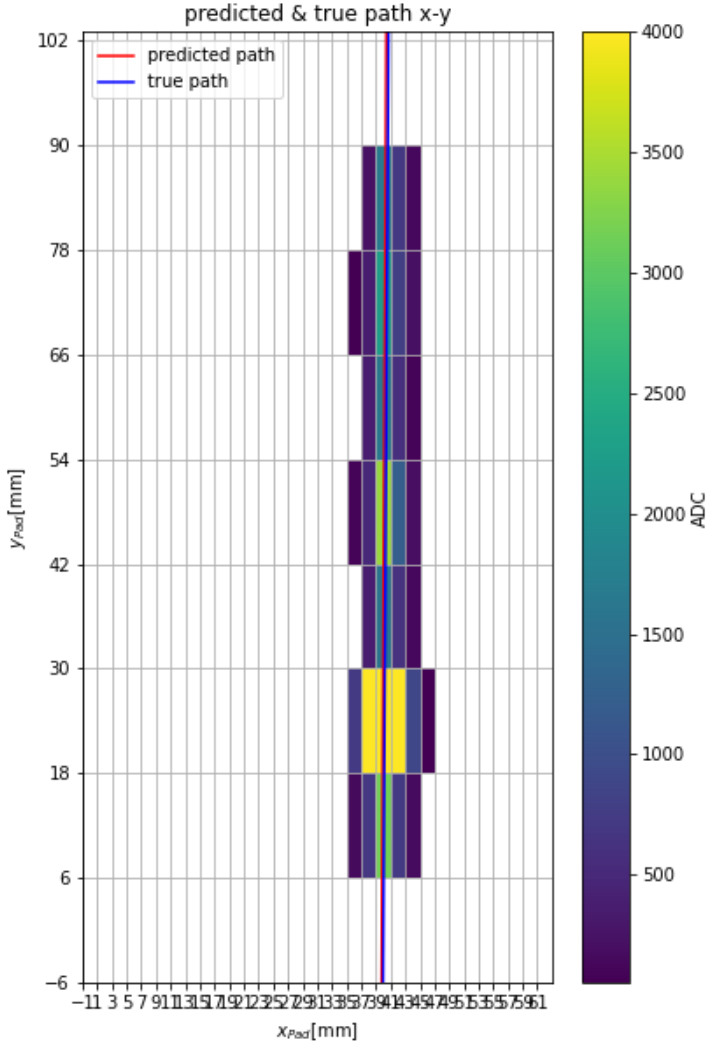


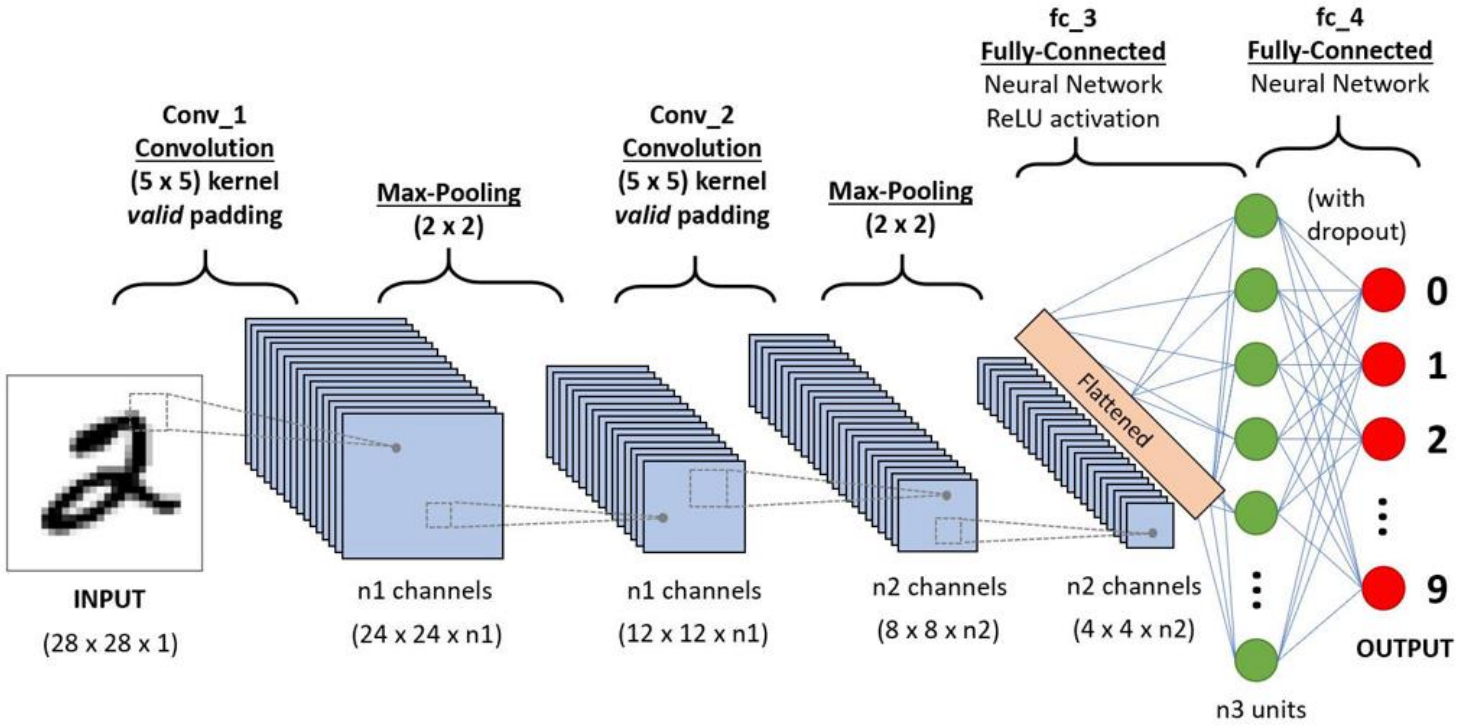
Motivation

To develop more efficient tracking method for charged particles for AT-TPC experiment.

Method

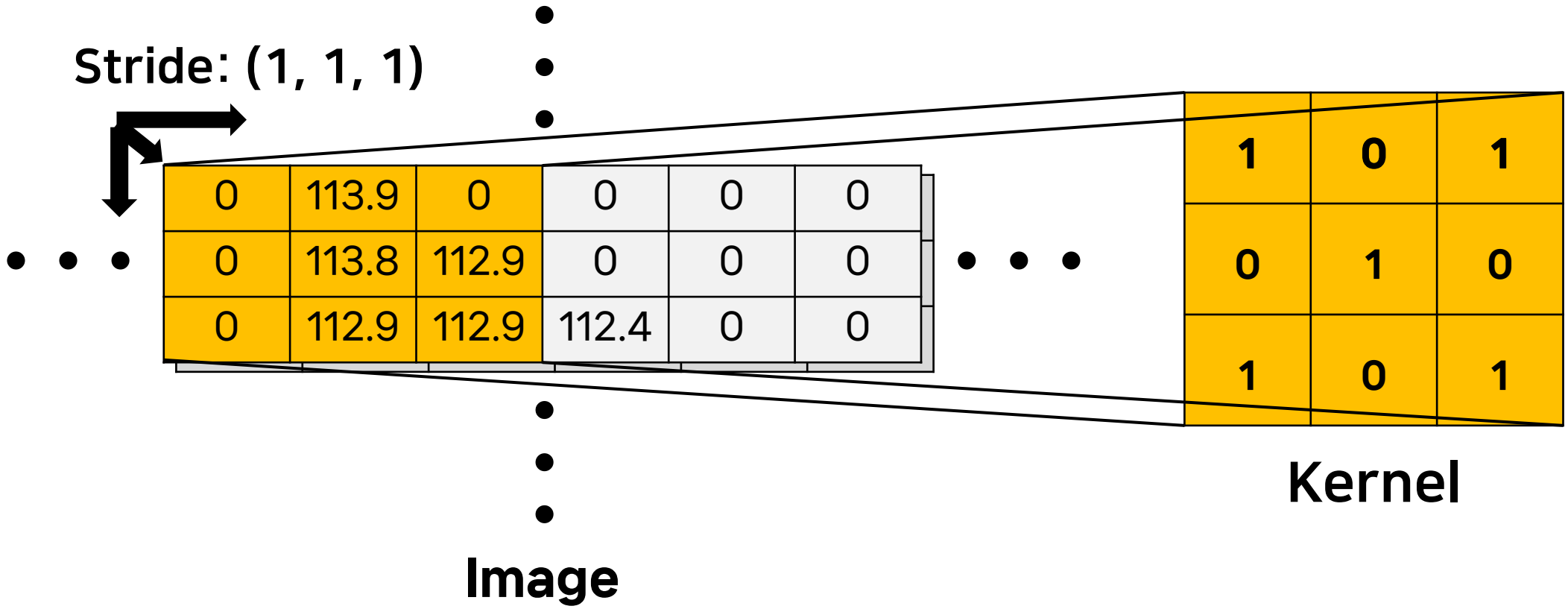
: 3D CNN(Convolution Neural Network)

Deep learning model specialized for 3D image learning

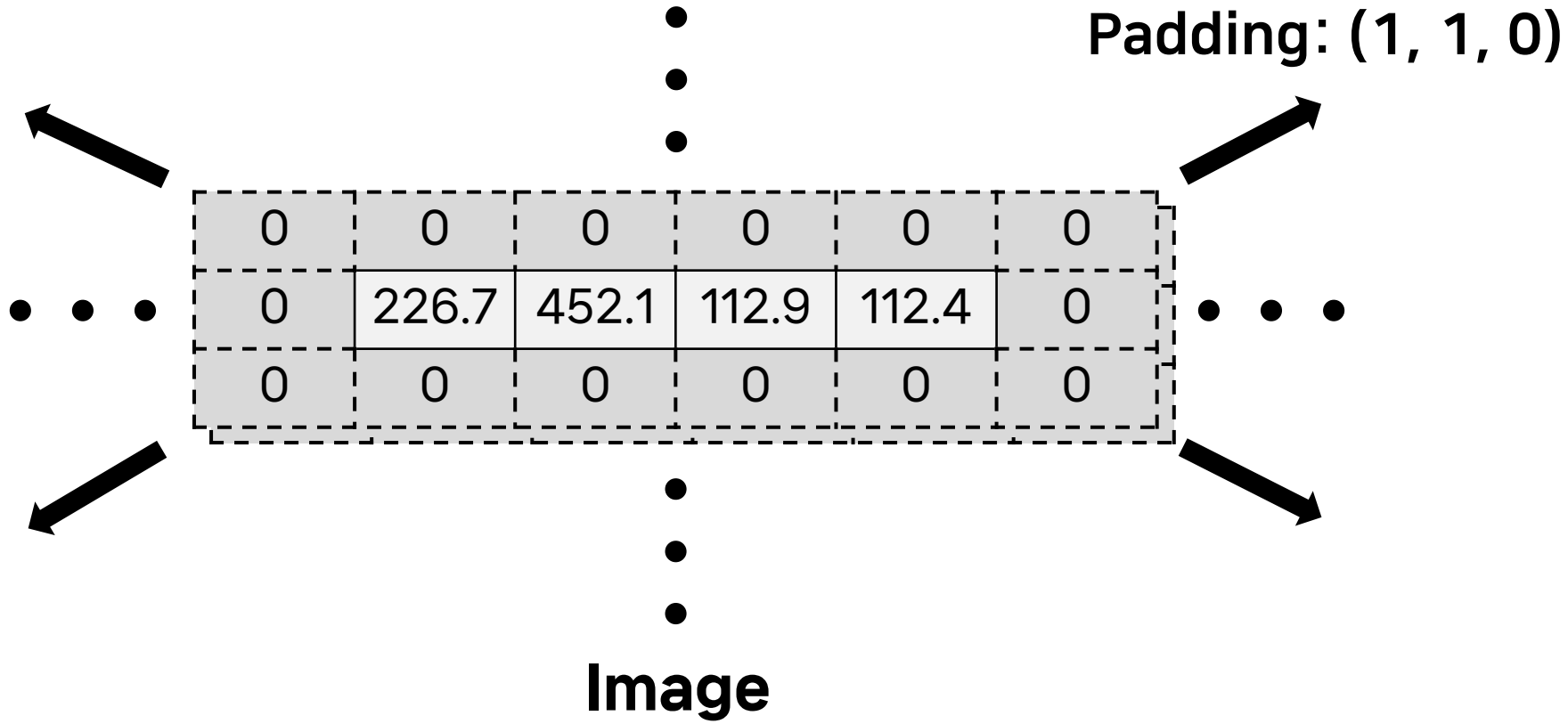


A CNN sequence to classify handwritten digits

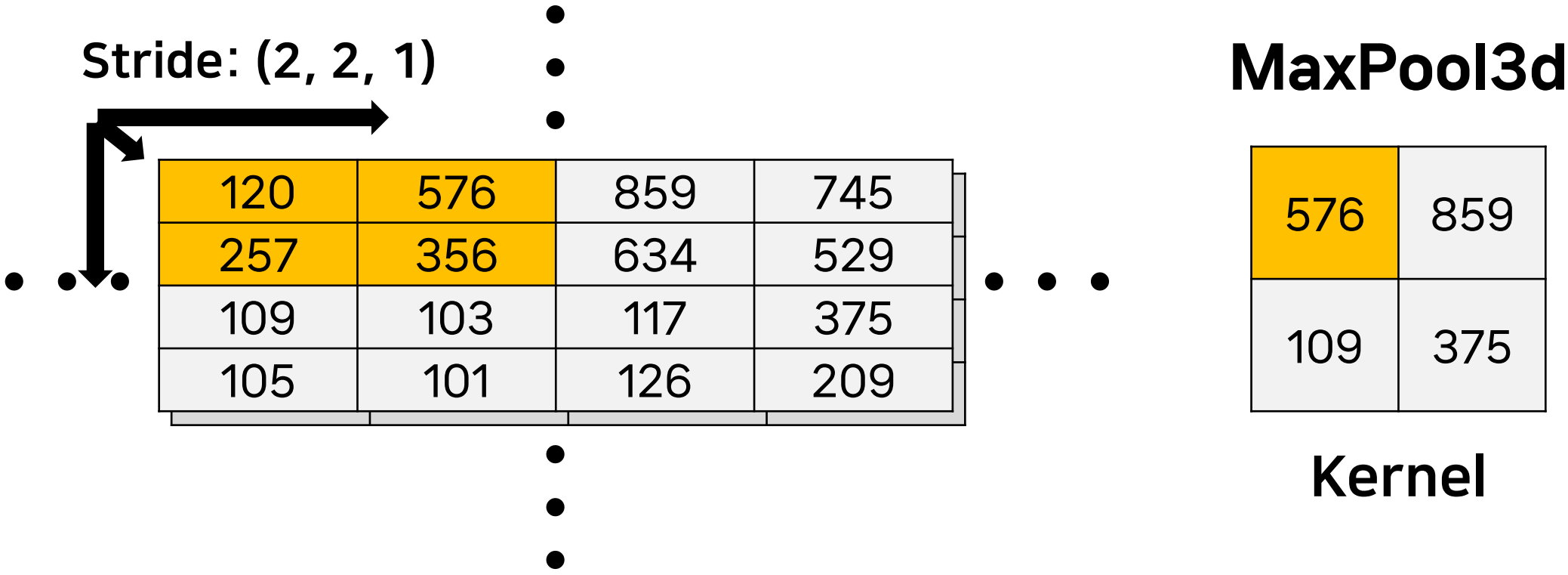
1) Convolution layer



1) Convolution layer

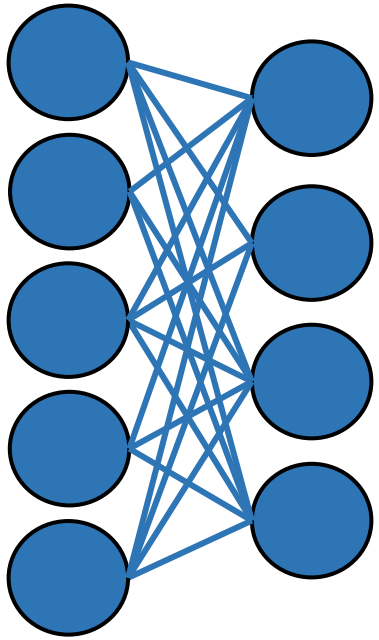


2) Pooling


Stride: (2, 2, 1)
120
576
859
745
257
356
634
529
109
103
117
375
105
101
126
209
MaxPool3d
576
859
109
375
Kernel

3) FC layer

Flatten → Activation function → output



Study

Image Reconstruction for CNN

Beam: Proton (120MeV)

Gas: p10 (760torr)

Angle: from y position -550mm, About ±10°

Before

(Xpos, Ypos, Z, ADC)

Answer: x, z pos at y = 0, 100

#100,000

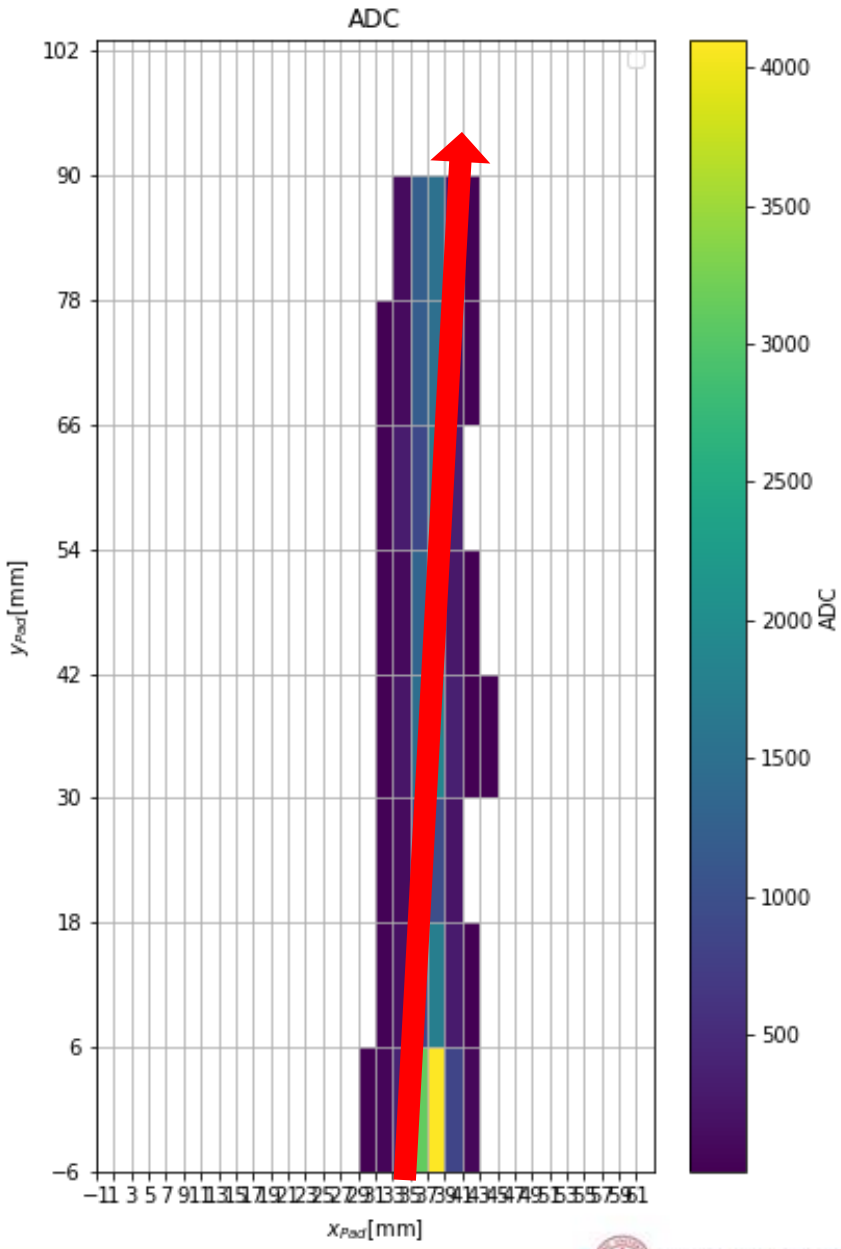


Image Reconstruction for CNN

After

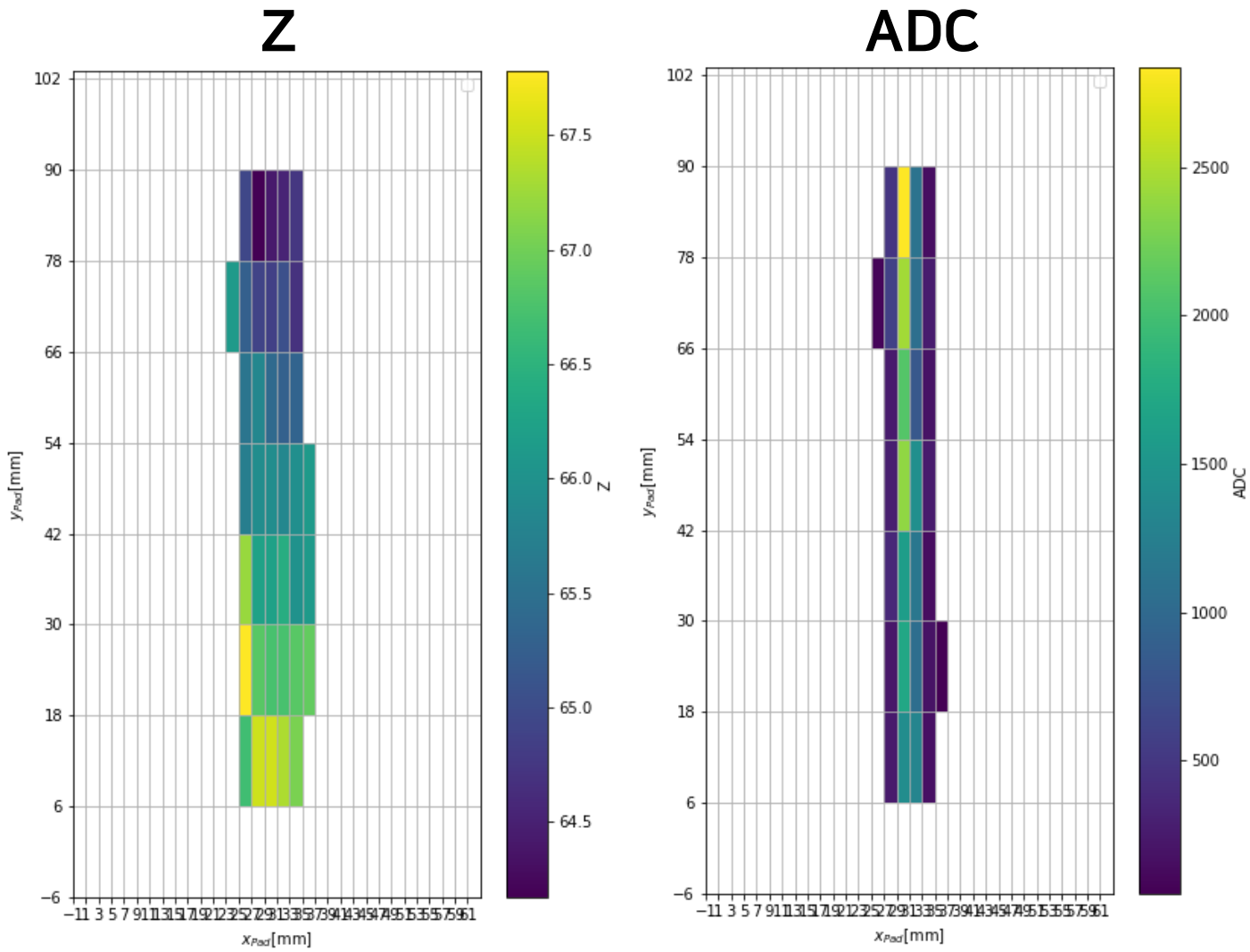
Image size: (32, 9, 2)

=(xpos, ypos, (Z, ADC))

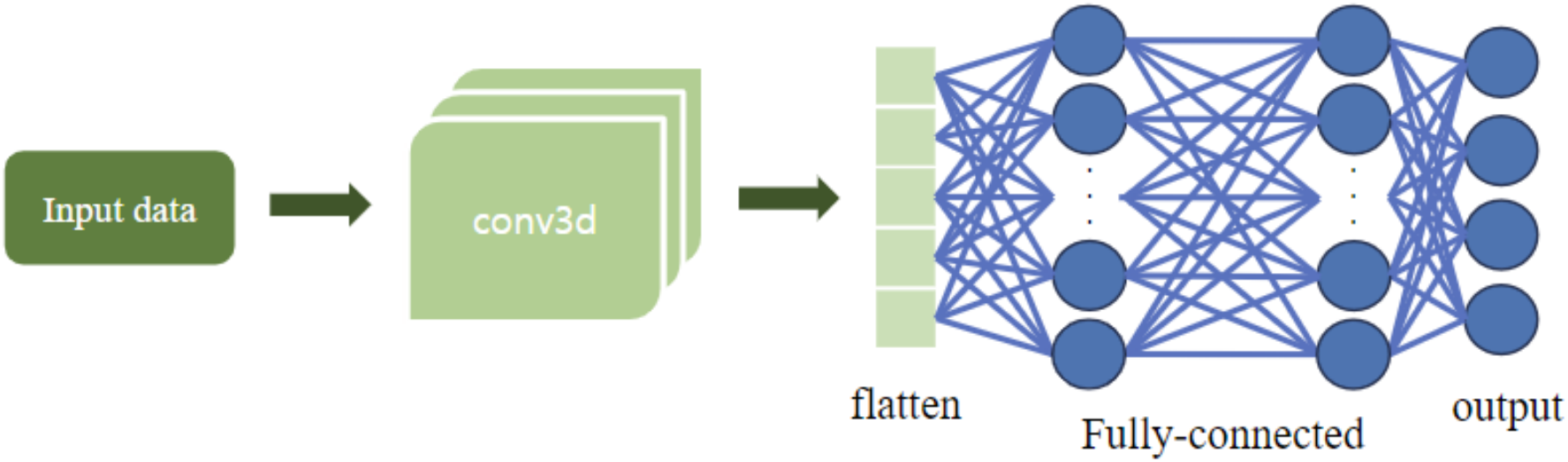
 # 73586

+ Add gaussian noise

Noise image : Raw image = 1 : 1



CNN Construction



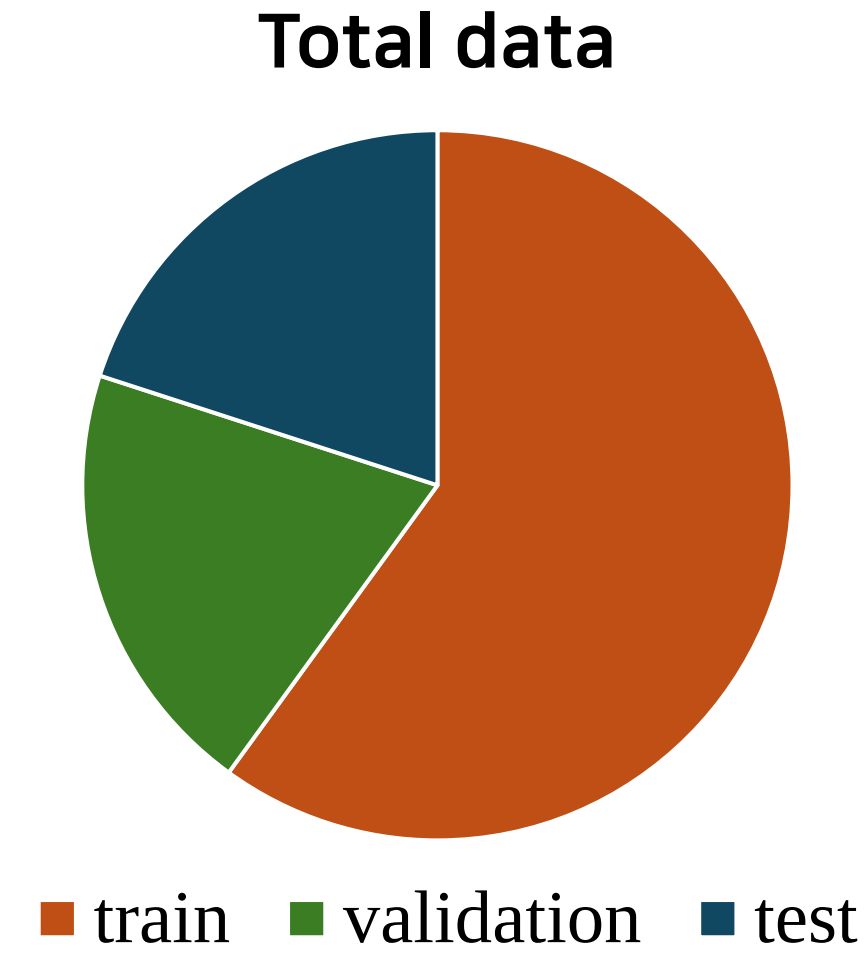
Hyper parameters

Hidden layer: 3

FC layer: 1

Output: 4

1) Train/Test Data Split

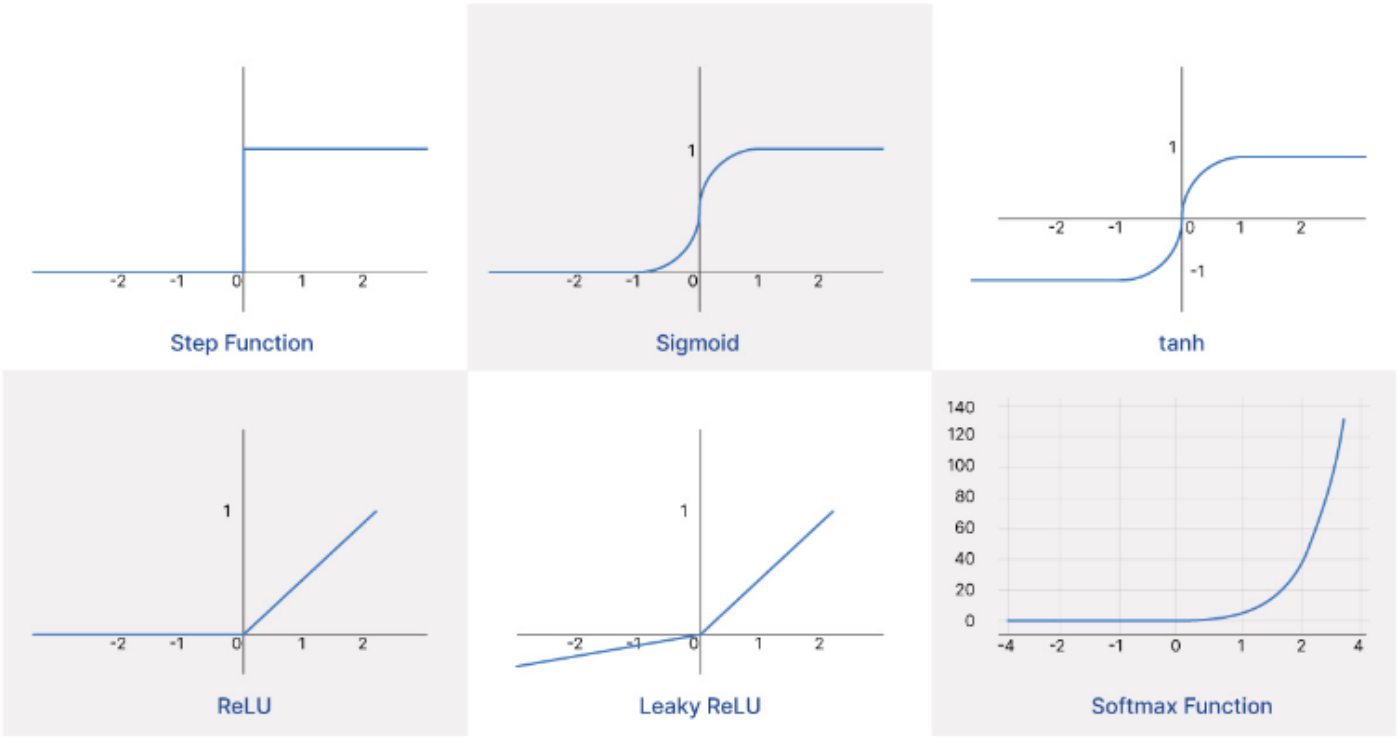


Train : Validation : Test = 3 : 1 : 1

Batch size: 64

Training epoch: 17

2) Activation function



Leaky ReLU

$$y = \begin{cases} x, & \text{if } x > 0 \\ \alpha x, & \text{otherwise} \end{cases}$$

Preserving some activity in the neurons

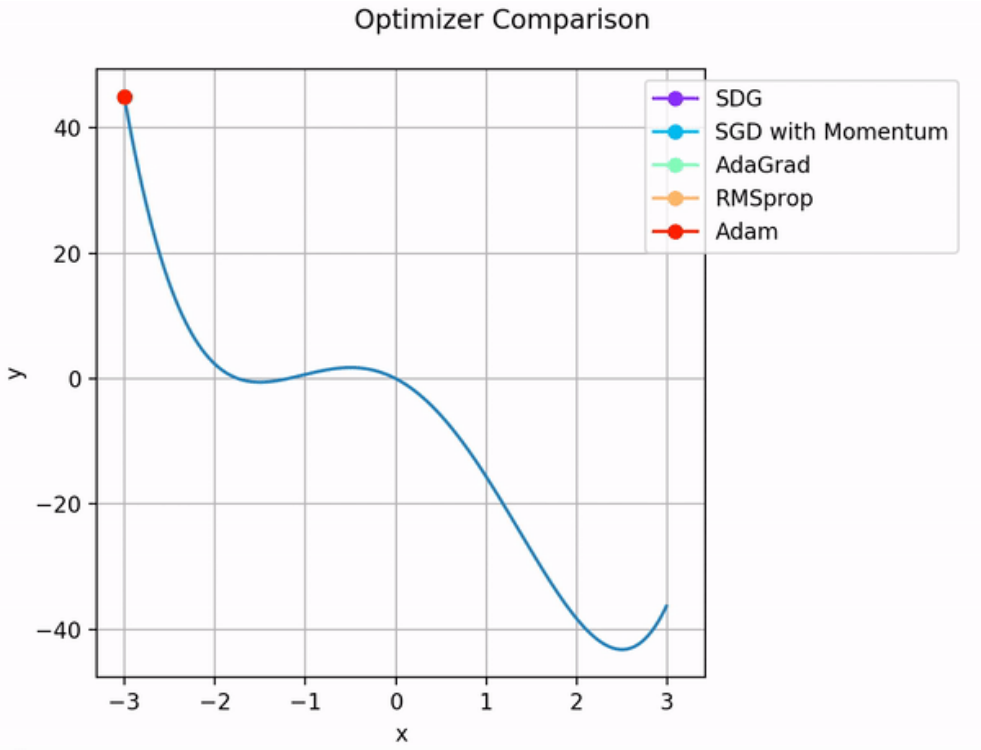
(Negative slope = 0.05)

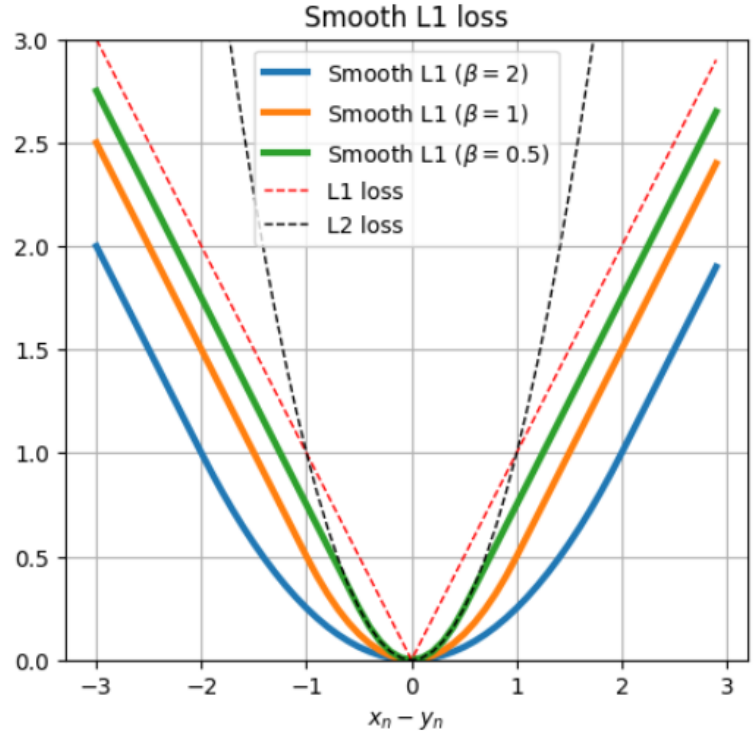
3) Training

Optimizer : Adam

Loss function : Smooth L1 Loss

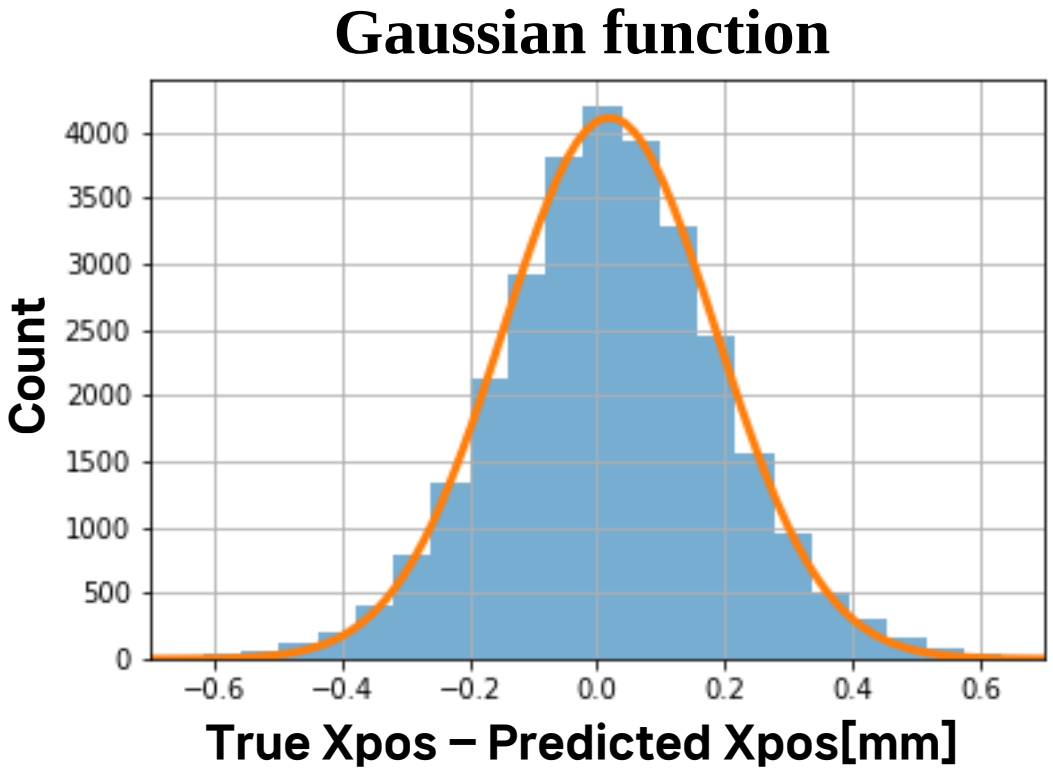
Using the Learning Rate Scheduler





Result

1) Gaussian function & Evaluation



Gaussian distribution

σ: 185μm

Deep Learning evaluation index

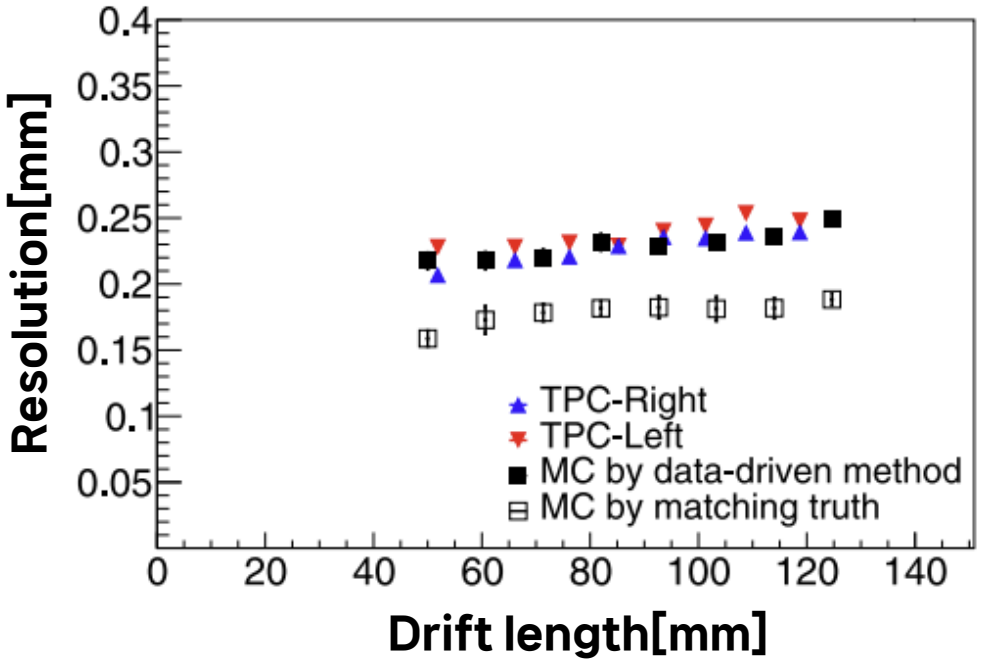
Mean Absolute Error (MAE): 0.009

Mean Squared Error (MSE): 0.009

R^2 Score: 0.964

2) Spatial Resolution by Drift Length

Conventional



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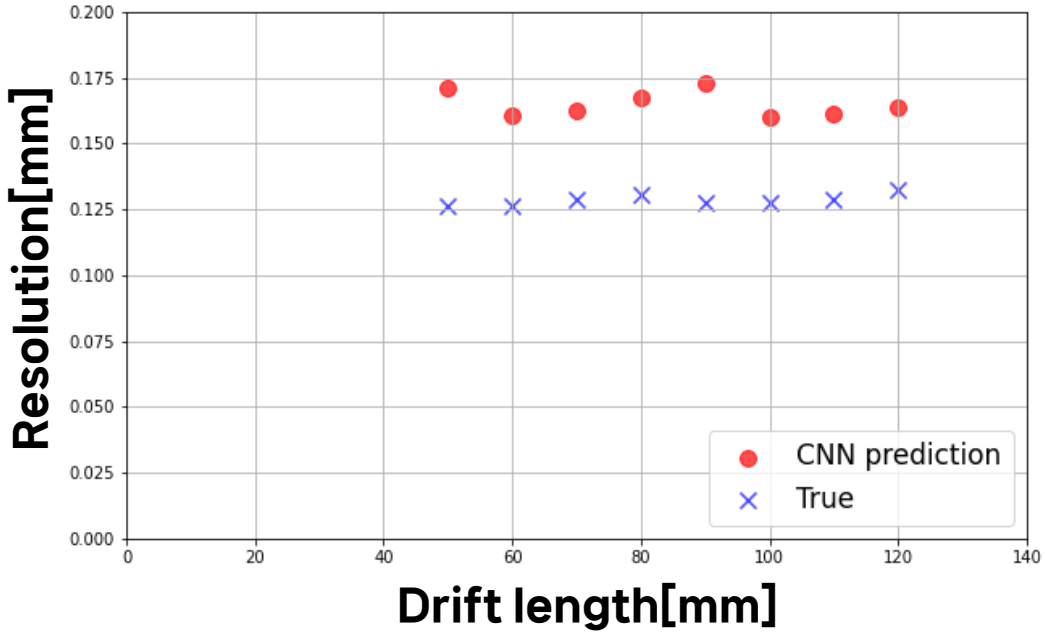
CNN

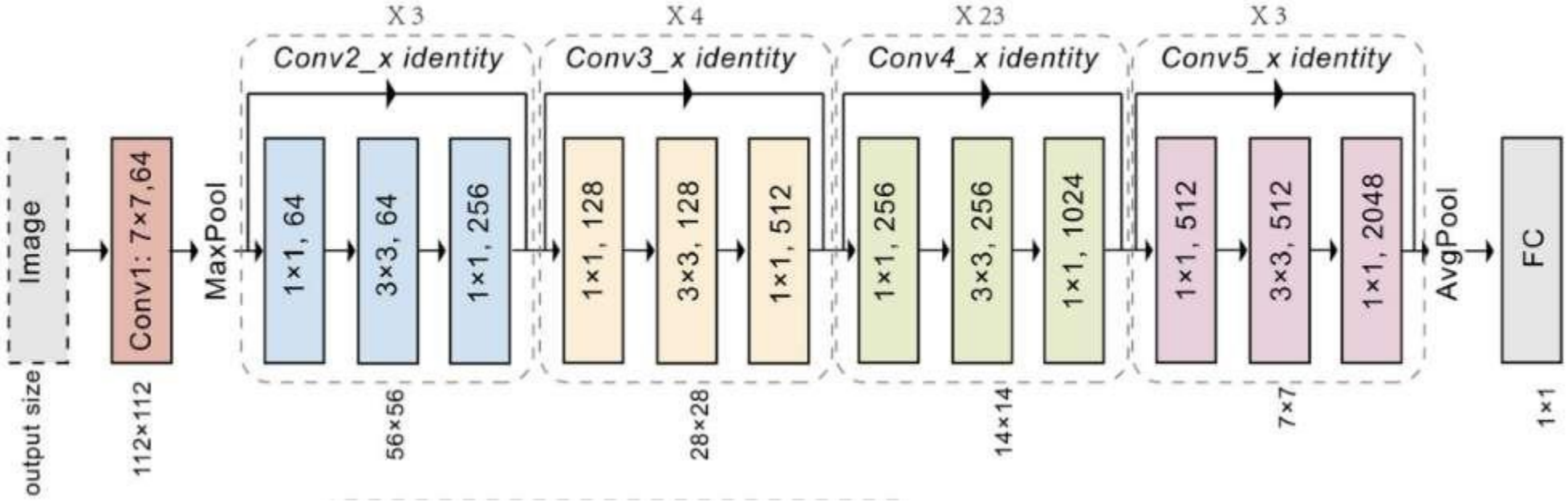


※ because data setting is different,
true data resolutions are also not same.

3) Further Study

- Apply ResNet
- Increase data numbers

ResNet Structure



Summery

- We studied about the way to use CNN model for AT-TPC data tracking.
- CNN model has good evaluation value and spatial resolution.
- After applying ResNet,

    (1) We can reanalyze HIMAC data.

    (2) The model will be used for TPC-Drum and AT-TPC.

    (3) This study will be used for Low energy LAMPS.

Reference

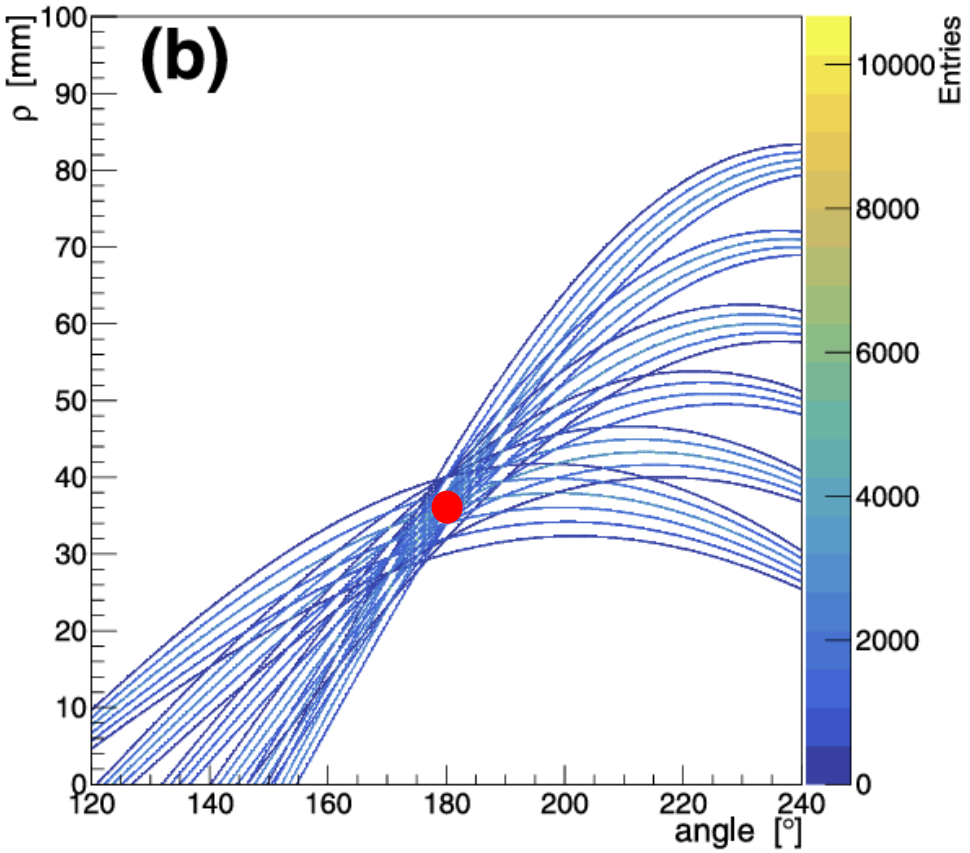
WU, Huangkai, et al. Nuclear Instruments and Methods in Physics Research Section A: Accelerators, Spectrometers, Detectors and Associated Equipment, 2023, 1055: 168528. Machine learning method for 12C event classification and reconstruction in the active target time-projection chamber.

R2 score

$$R^2 = \frac{\text{RegSS}}{\text{TSS}} = \frac{\sum_i \left(\hat{y}_i - \bar{y}\right)^2}{\sum_i \left(y_i - \bar{y}\right)^2}$$

$\bar{y}$: mean of y value
$\hat{y}$: prediction value

Hough Transform



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