上海交通大學
SHANGHAI JIAO TONG UNIVERSITY

Final Report

飲水思源 愛國榮校

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Group 2 – Project 2

Date:September 8th, 2024

CONTEXT

01

Overview of offline research

What did we do collectively?

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brainstorm

learn new models

presentation

Stage 1: Research design and methodology development

a. Literature review
b. brainstorm related methodology
c. design simple networks, e.g. MLP, CNN

Stage 2: Model training and optimization

a. train different models and tuning
b. after getting new datasets and training, we optimize old models and put forward new ones

Stage 3: Visualiation and analysis

a. plot result graphs and error pictures
b. results analysis and draw conclusions
c. deal with jets

What did we do individually?

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Zhang Han

1. data preprocessing and code organization
2. design architectures of CNN, U-Net, U-Net with Attention

Lin Shengxiang

1. literature review
2. deal with jets, e.g. run the pythia and write algorithm for jets reconstruction

Zhang Yangguang

1. literature review
2. design architectures of MLP, RNN

Zhang Xingyi

1. train the models and optimize all models
2. design architectures of CNN and try noval models

Wang Yu

1. train the models and optimize all models
2. do the visualization

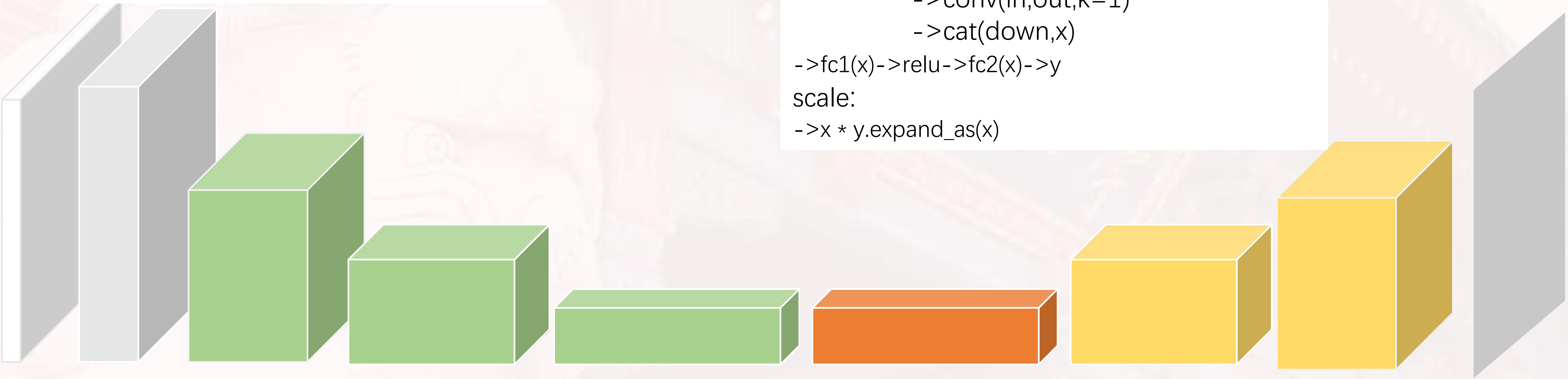
02

Model descriptions

CNN

Downsample->conv(in,out,k=2,s=2)
->LeakyReLU

Upsample->interpolate(x, scale_factor=2, mode='nearest')
->conv(in,out,k=1)
->cat(down,x)
->fc1(x)->relu->fc2(x)->y
scale:
->x * y.expand_as(x)

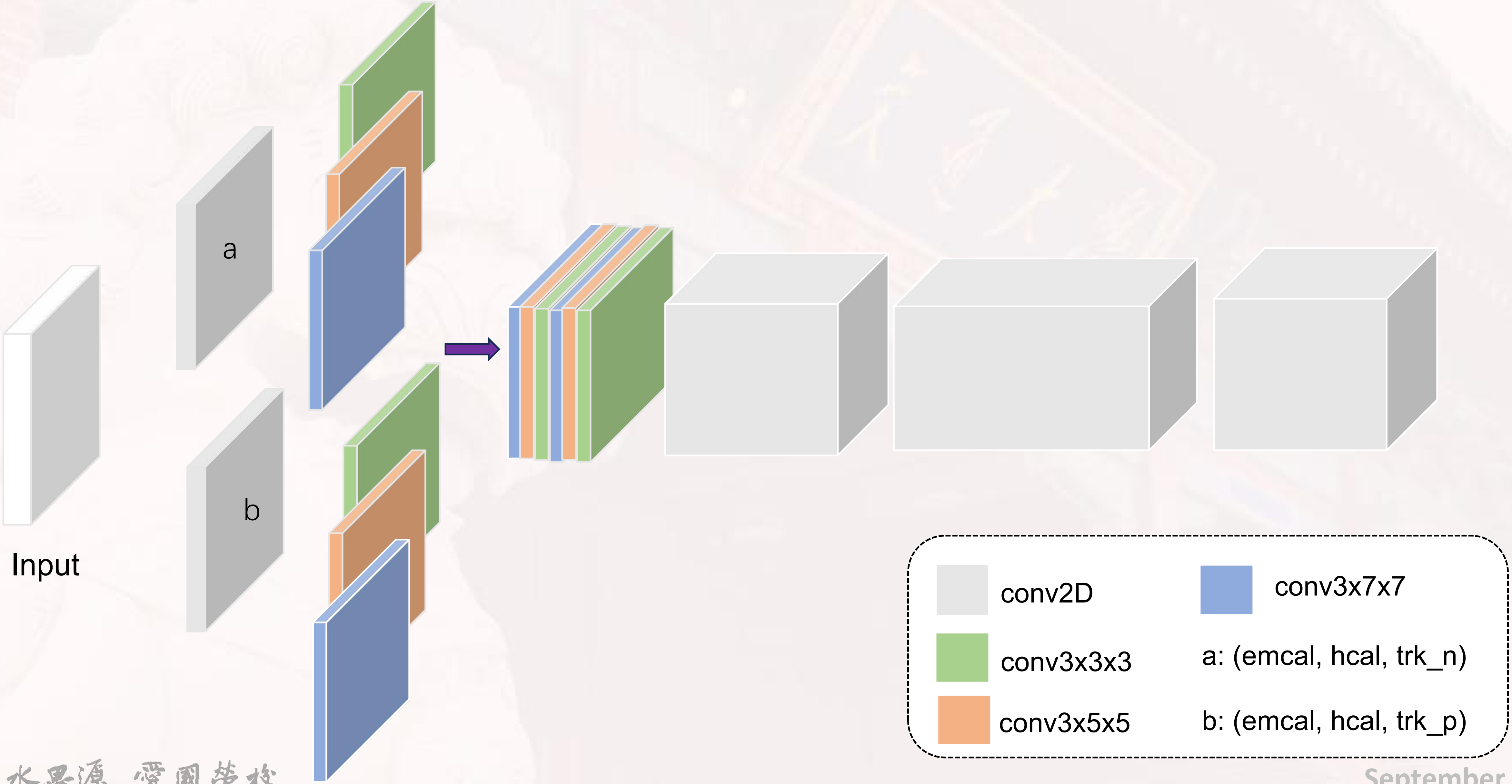


Output

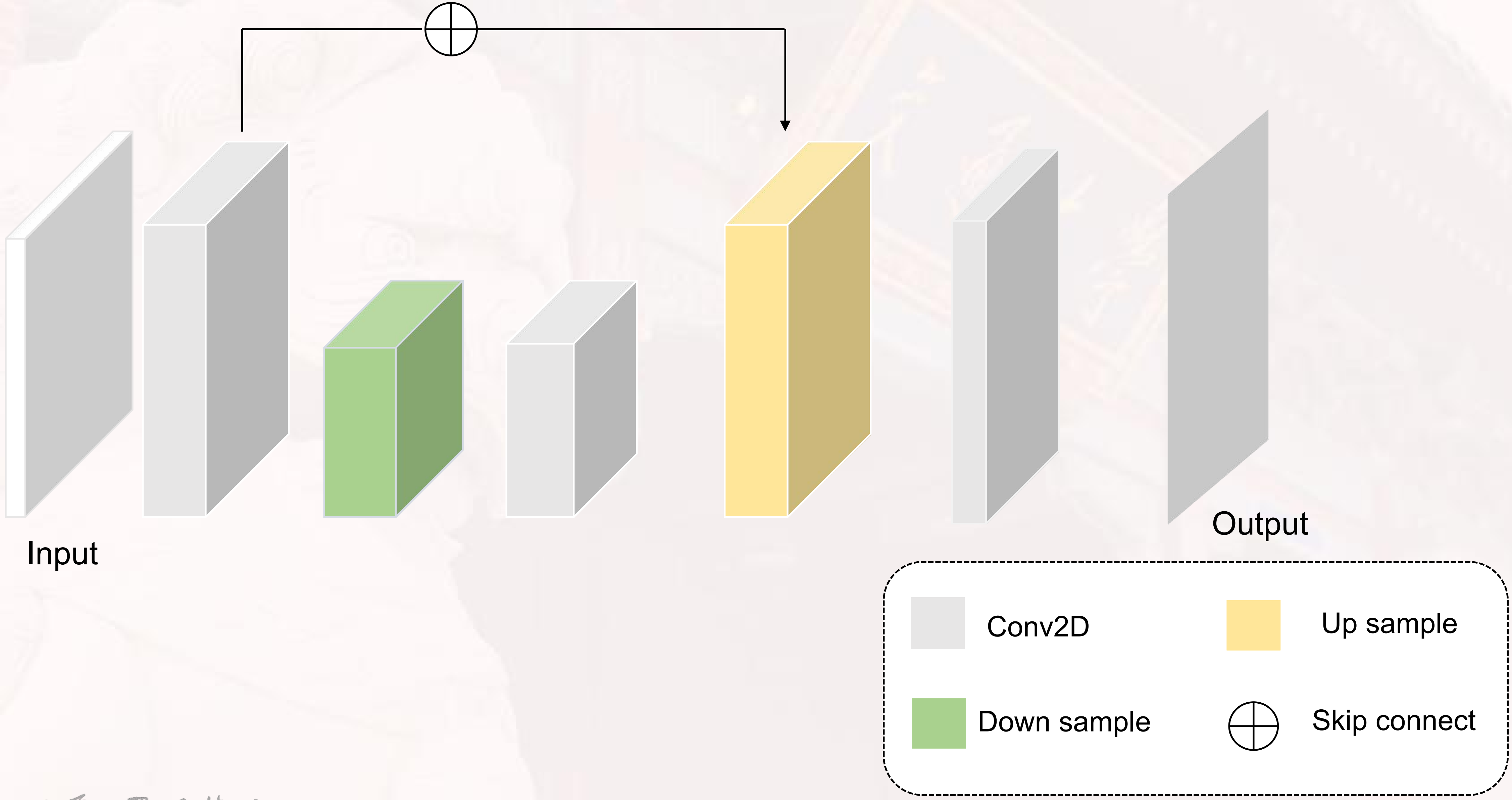
Conv2D->conv(c_in,c_out,k=3,s=1,p=1)
->batchnorm(c_out)
->dropout(0.3)
->LeakyReLU

Conv2D
DownConv
UpConv
SEBlock
Skip connect

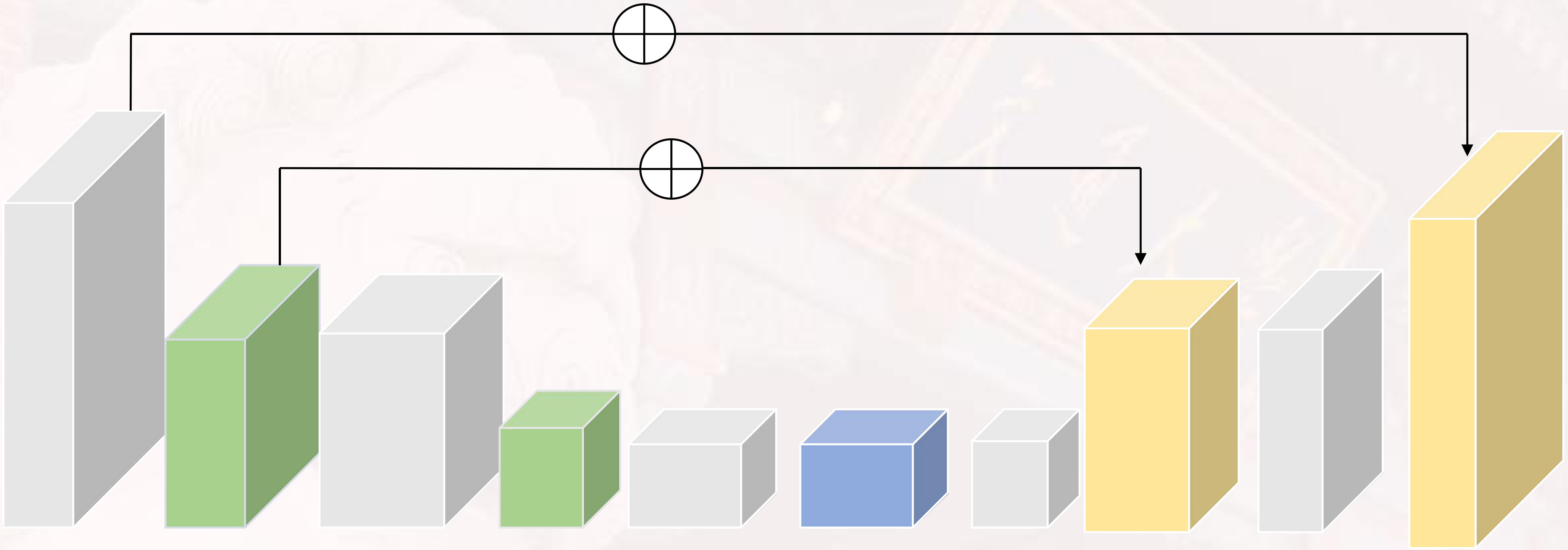
3DCNN


a
b
Input
conv2D
conv3x7x7
conv3x3x3
a: (emcal, hcal, trk_n)
conv3x5x5
b: (emcal, hcal, trk_p)

U-Net



U-Net with Attention

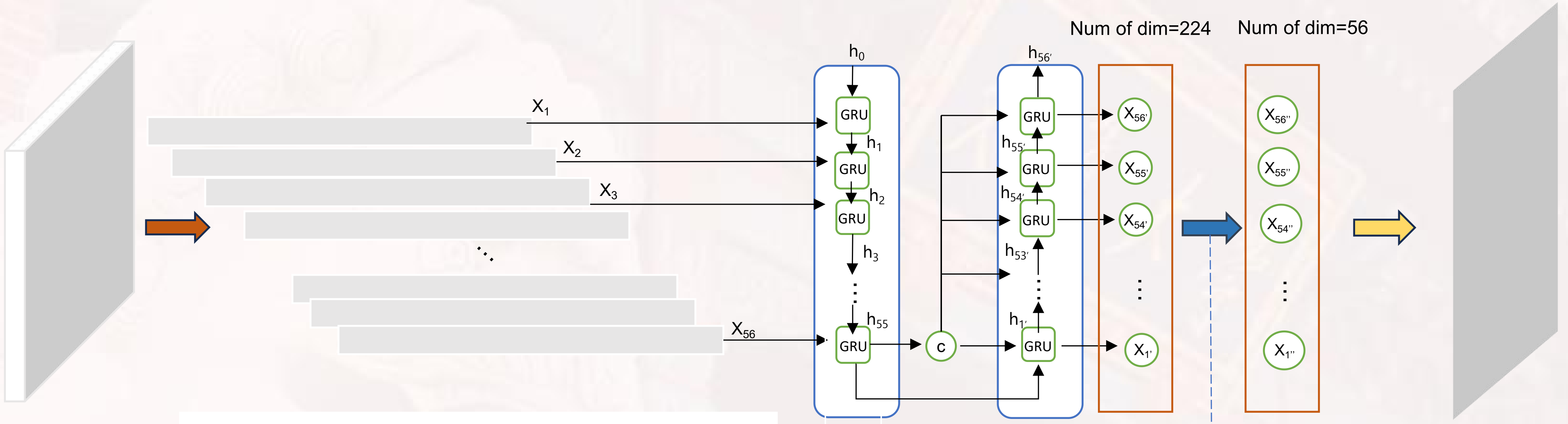


self attention:

```
query=conv(x)  #kernal_size=1
key=conv(x)    #kernal_size=1
value=conv(x)  #kernal_size=1
atten=q*transpose(k)
score=atten*value
```

- Conv2D
- Up sample
- Self attention
- Down sample
- Skip connect

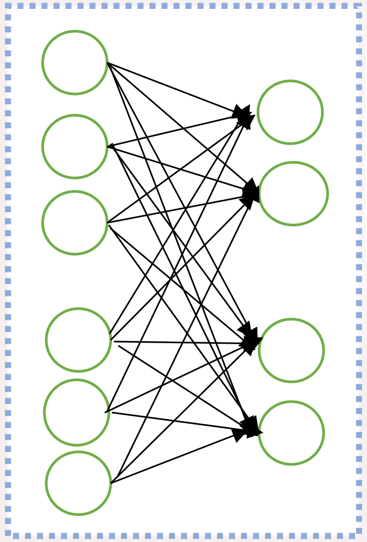
RNN



Input

Output

embedding:
(4,56,56)-->(4*56,56)



dimensionality reduction:
input_nodes=4*56
output_nodes=56

- embedding
- dimensionality reduction
- connect by columns

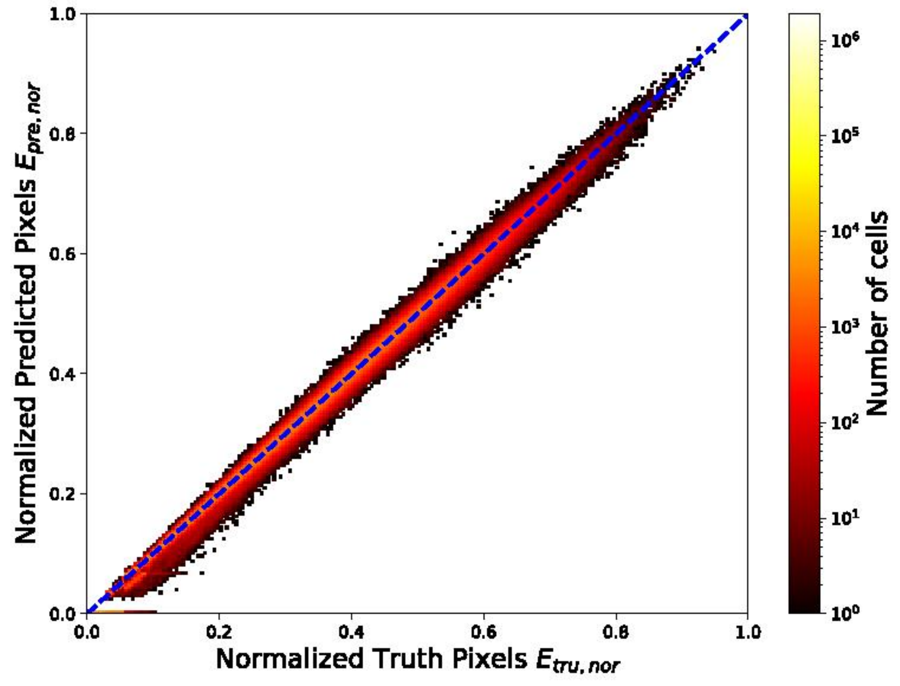
03

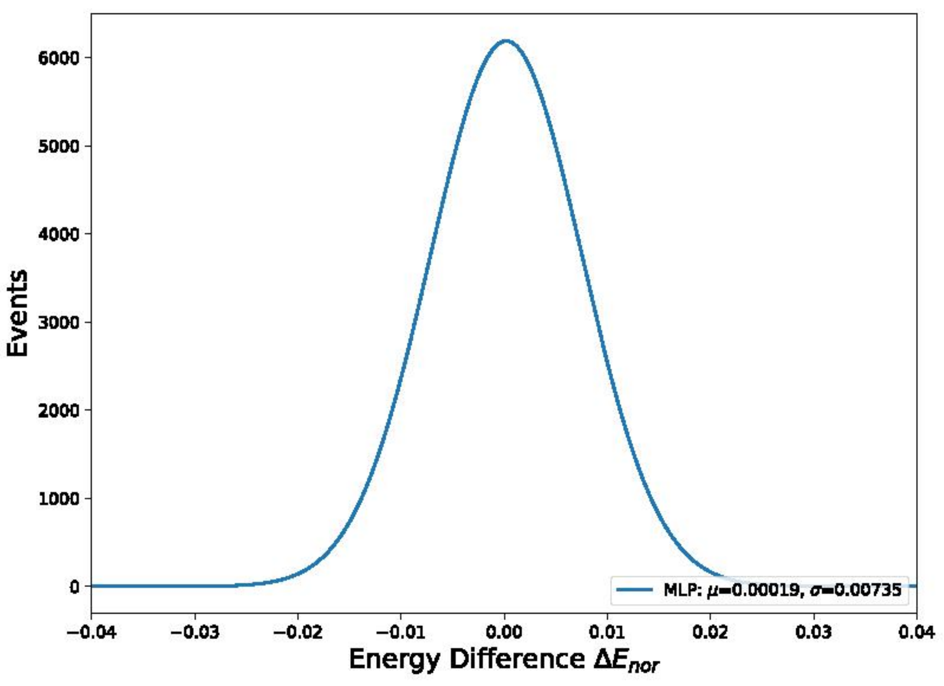
Results analysis

Results on the datasets without jets

1. The normalized energy difference:

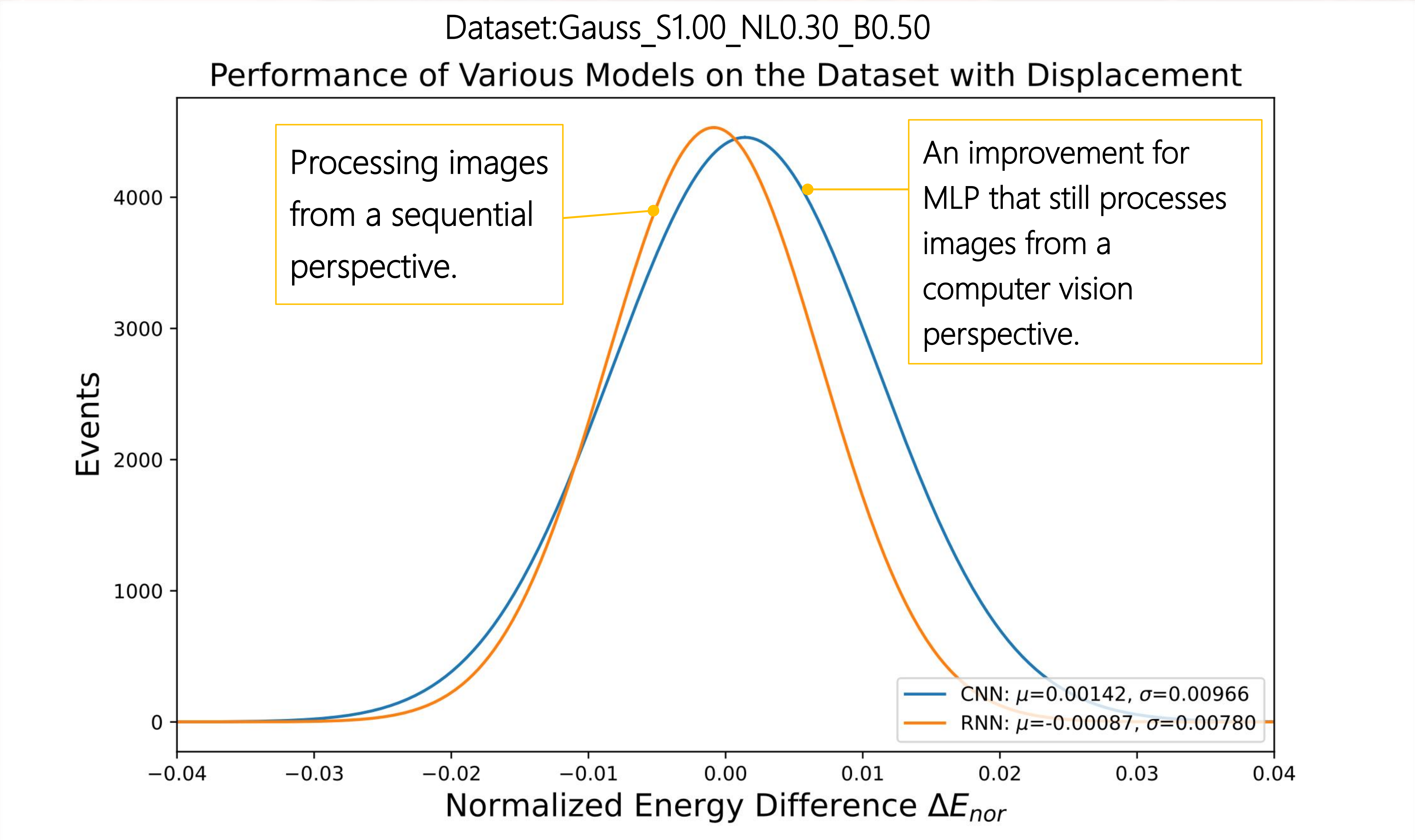
$$\Delta E_{nor} = E_{pre,nor} - E_{tru,nor}$$



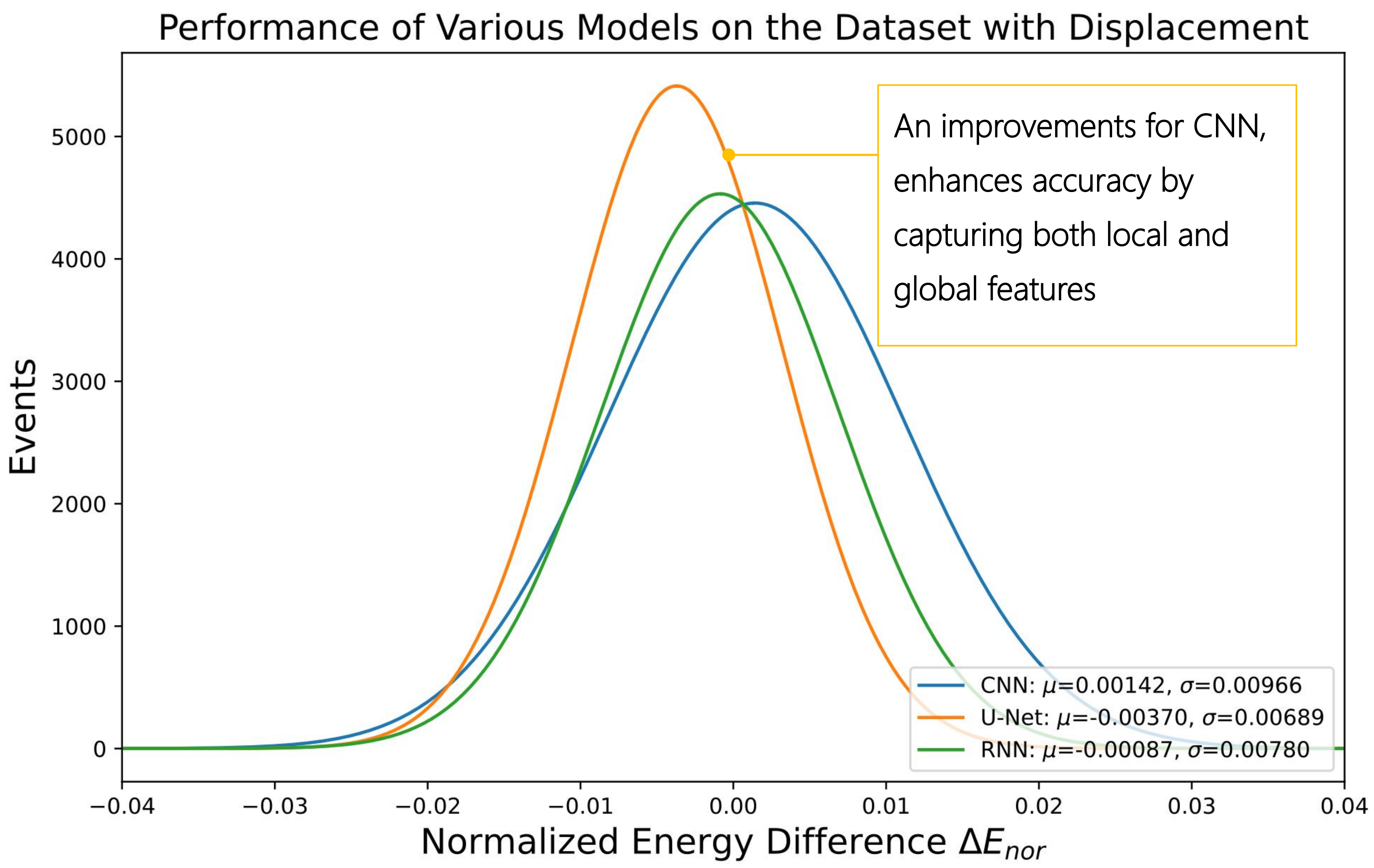


2. Benchmark: The performance of the MLP model on the Gauss_S1.00_NL0.30_B0.00 .It will be considered the best-case scenario preset for our model, whose normalized errors follows a perfect Gaussian distribution with a peak value exceeding 6000.

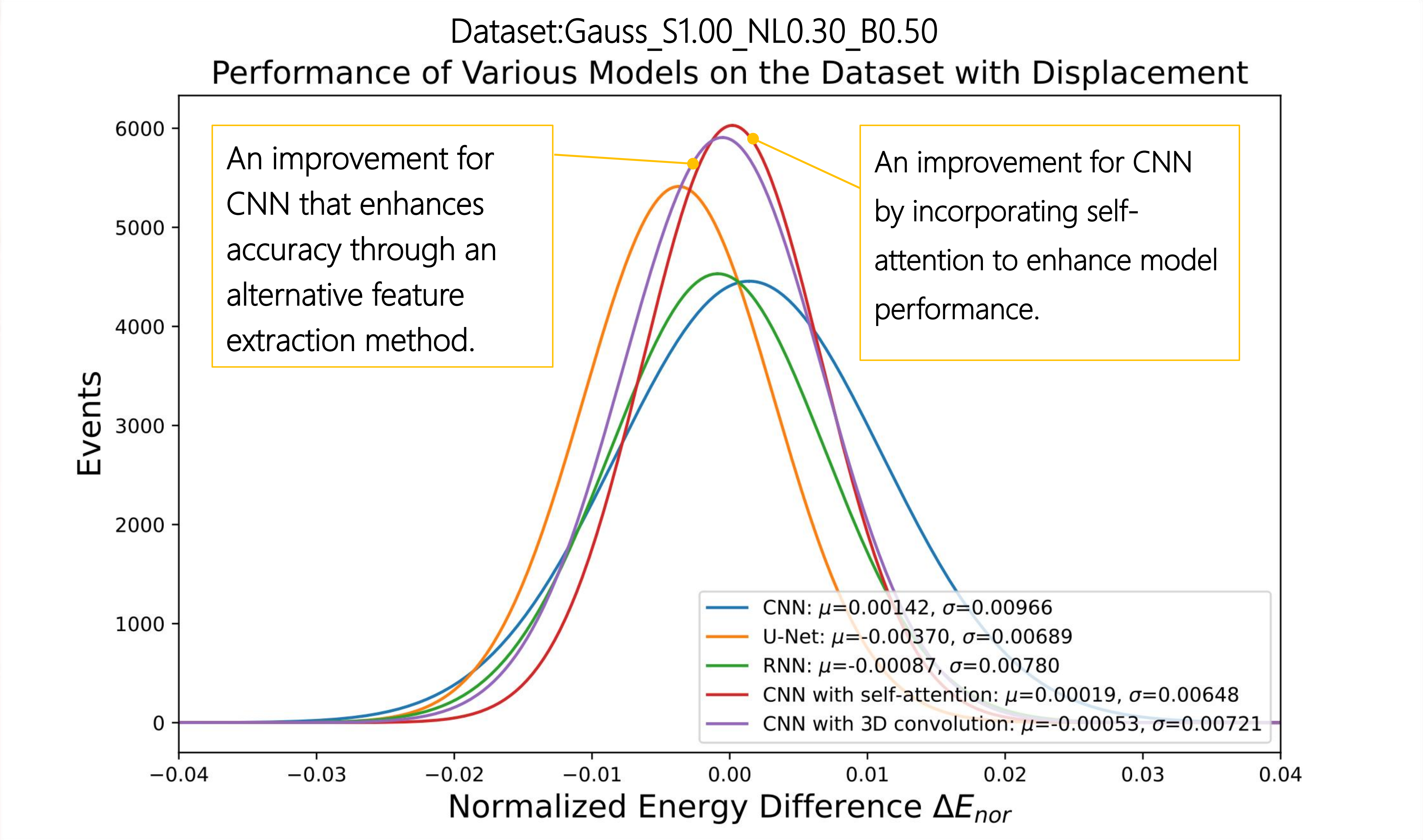
Results on the datasets without jets



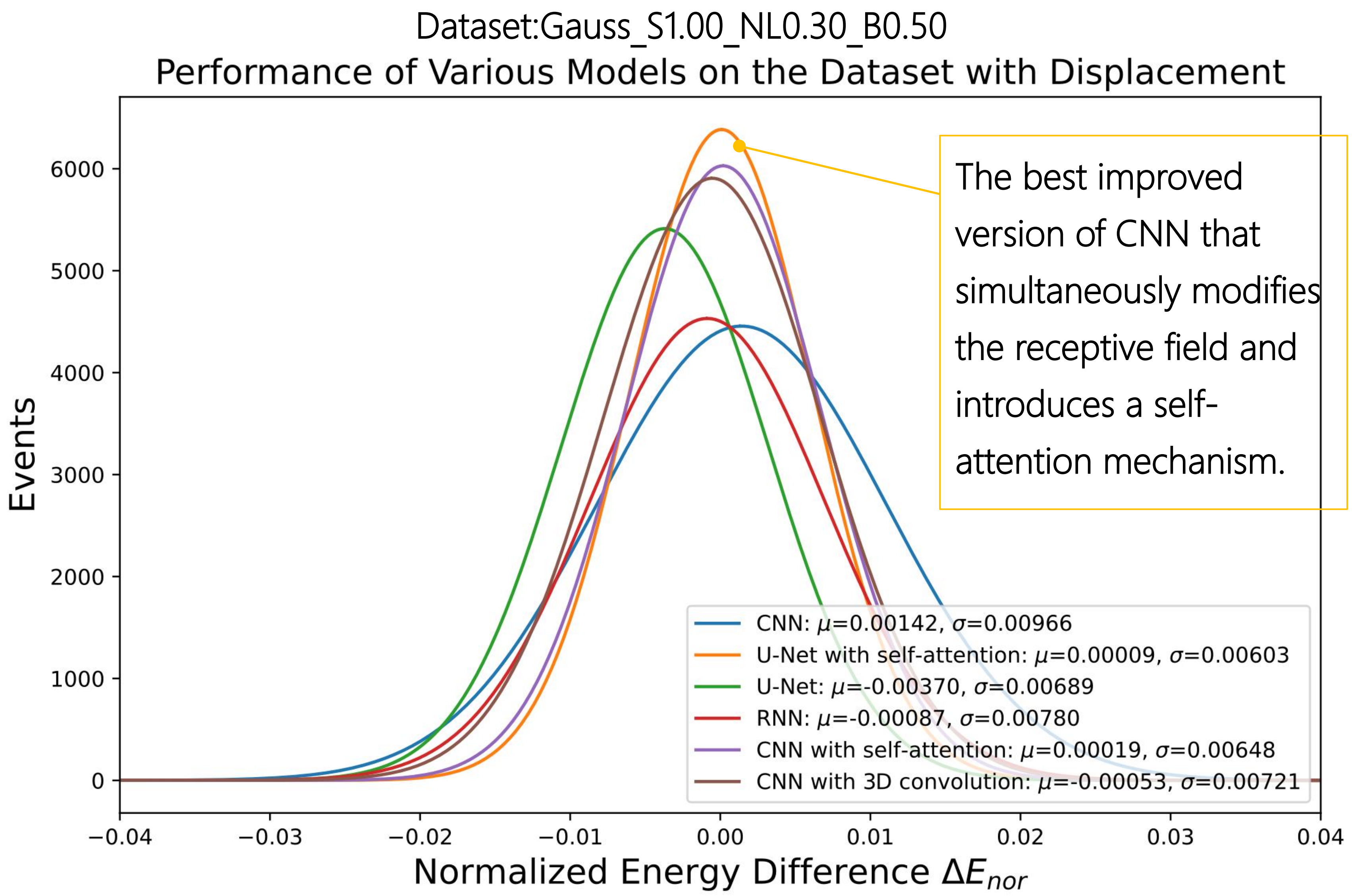
Results on the datasets without jets



Results on the datasets without jets



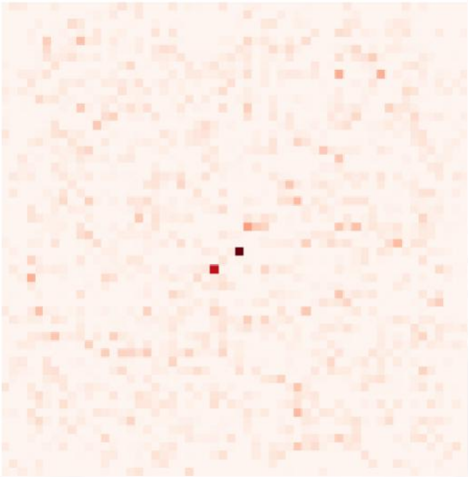
Results on the datasets without jets



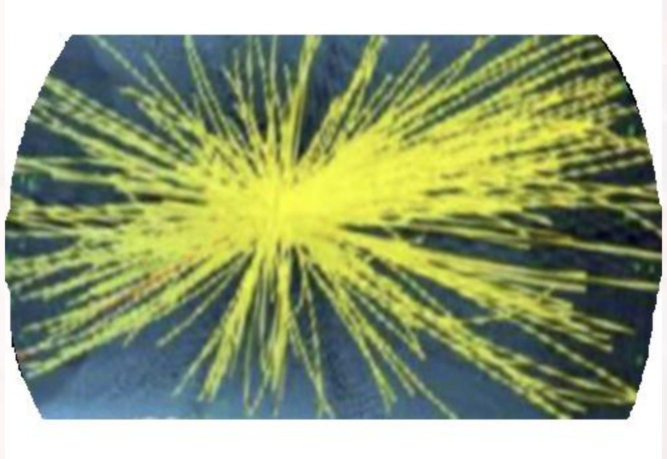
The best improved version of CNN that simultaneously modifies the receptive field and introduces a self-attention mechanism.

Results on the datasets with jets

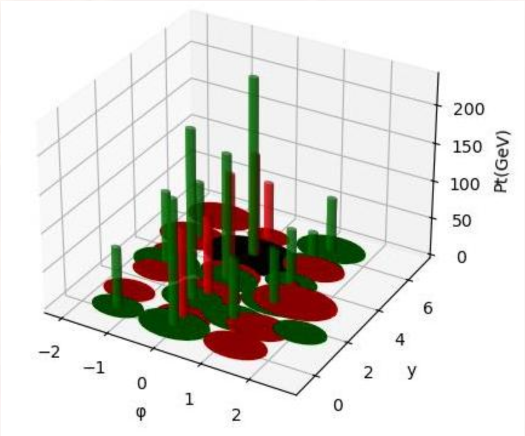
Extract 2D image plane information



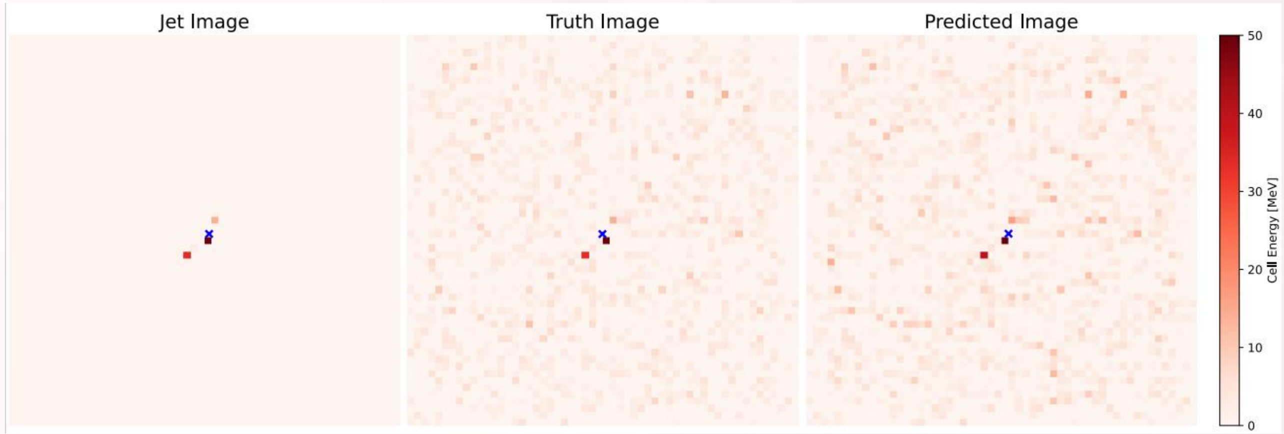
Translated into the momentum of the particle in the stereogram



The anti-kt algorithm was used to obtain information about the jet's rap, phi, pts, and E

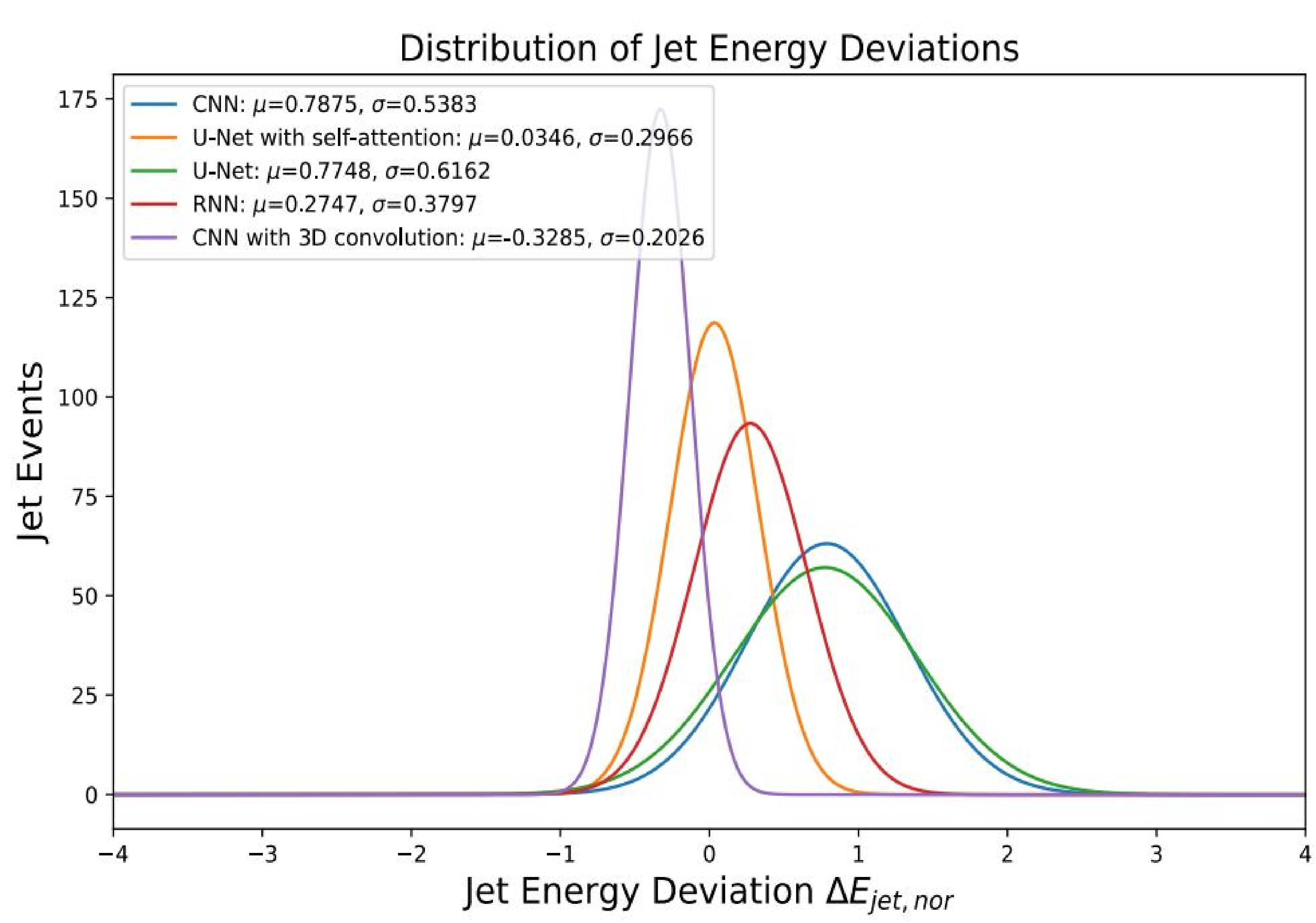


The 3D coordinates of the jet center are obtained from the information of rap, phi, pts, E

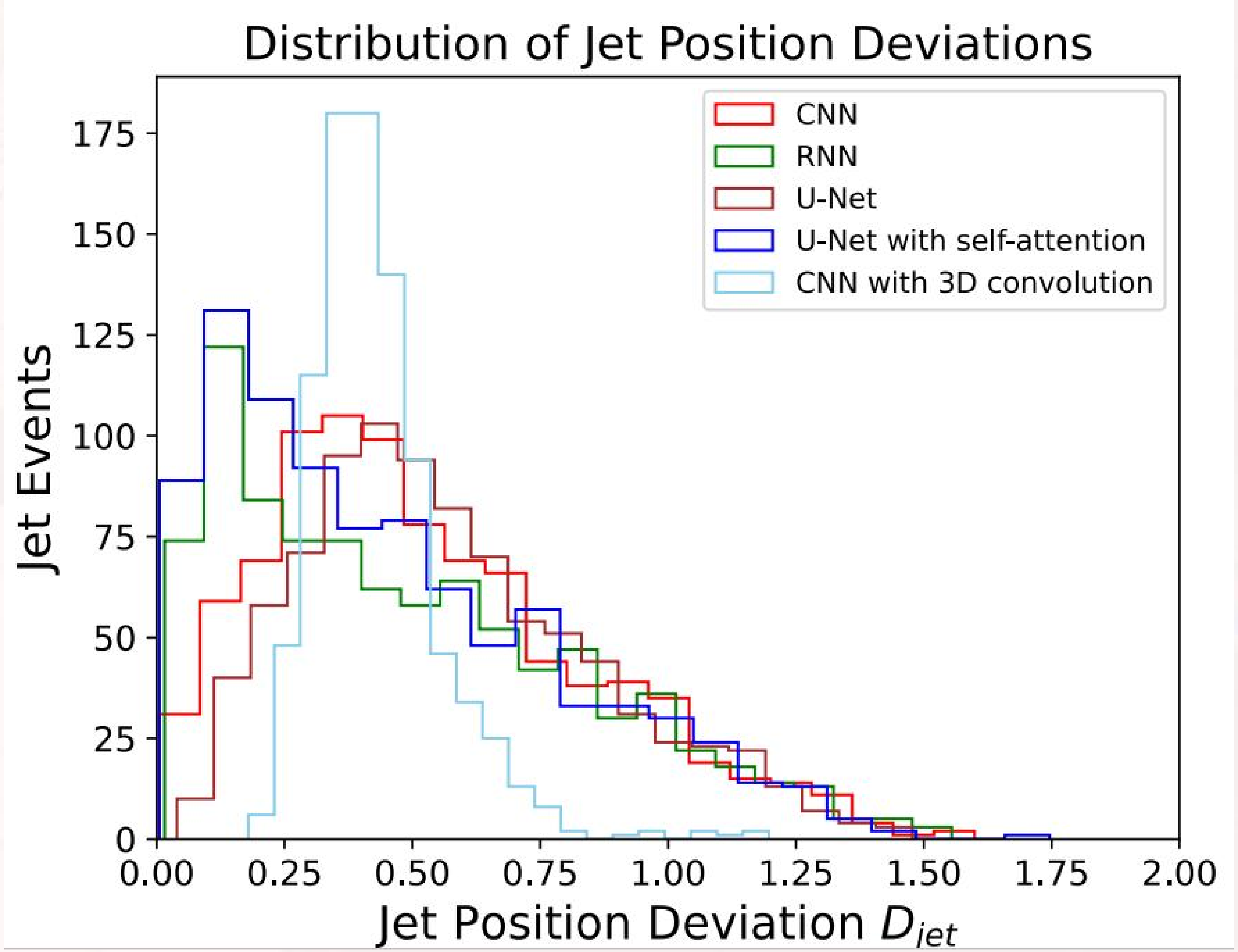


Projecting the 3D position of the jet center onto a 2D plane

Results on the datasets with jets



Results on the datasets with jets



04

Conclusion and outlook

Conclusion

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1

This study presents **significant progress** in applying deep learning techniques to particle flow reconstruction in high energy physics, particularly in enhancing jet reconstruction in the LHC experiment.

2

By integrating more **complex methods**, the models' sensitivity to complex features, such as particle shifts, has been significantly improved, leading to **more accurate** particle energy reconstructions.

3

In our model, **UNet with Self-Attention** is undoubtedly the best performer.

Outlook

The following is our outlook, arranged from lower to higher levels.
We have already started exploring most of these aspects, but the results are not yet good enough to be presented at this time, so we have included them in there.

Model optimization

Some CNN networks can still be optimized, especially 3D convolutional models that exhibit strong robustness.

Train a GNN

Comparing to machine vision, representing particles as point clouds and usingGNNs, namely edge conv could increase data density.

Transformer-based models

Transformers demonstrate higher sensitivity to anomalous events, such as jets. Applying transformer variants, such as U-shaped transformers holds potential for further exploration.

Monte Carlo simulated datasets

This will allow for rigorous testing and further enhancement of the models' generalization capabilities.

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Thank You For Listening

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