R&D of the EM Calorimeter Energy Calibration with Machine Learning based on the low-level features of the Cluster

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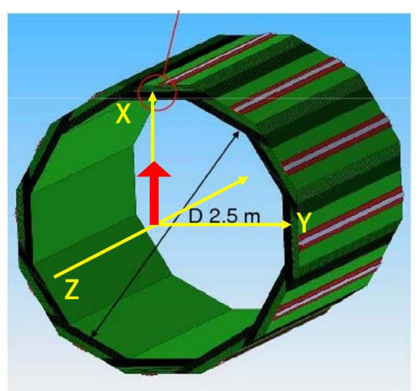
1. Outline

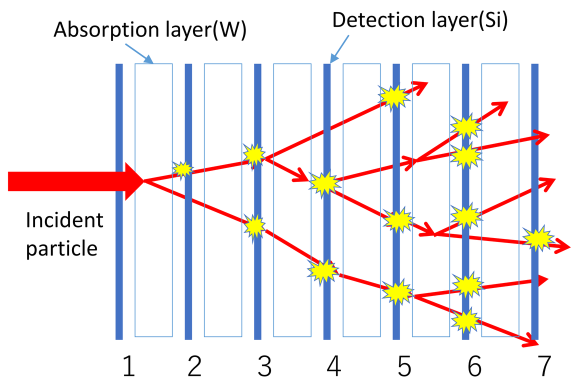
1-1. Introduction

We have developed the energy calibration method by using the machine learning for the ILC EM calorimeter (ECAL), a sampling calorimeter consisting with Silicon-Tungsten layers. In this method, we use deep neural network (DNN) to get the energy of the incident particle (energy calibration), as a regression problem, to improve the energy calibration resolution of ECAL. We have developed the DNN architecture here cluster hit data are input as low-level features of the cluster. We'll report the status of the R&D.

1-2. Electro magnetic CaLorimeter (ECL)

ECAL is a sampling type calorimeter and measure the energy of incident electrons and photons from energy loss.





inner radius of ECL barrel	1.27 m
maximum z of barrel	1.76 m
longitudinal profie	20 layers × 0.64 X_0
	10 layers × 1.30 X_0
EM energy resolution	$0.17/\sqrt{E} \oplus 1\%$
readout gap	1.25 mm (or less)
effective Molire radius(R)	14 mm

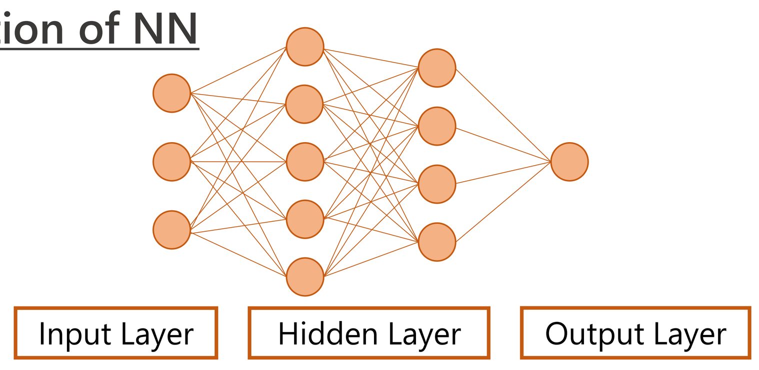
1-3. Neural Network

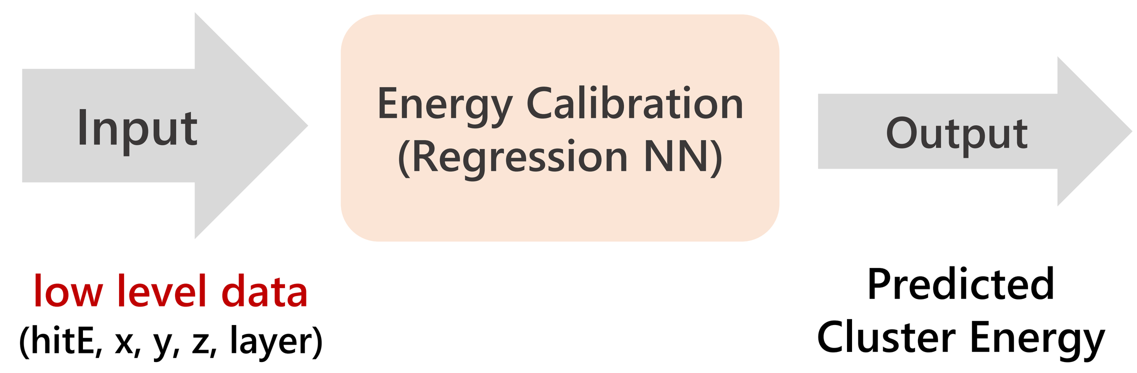
In this study, a regression model of NN is developed to predict the energy of incident particles by using the physical characteristics of the cluster as input parameters of NN.

Artificial Neural Network (NN) is one of the approaches to the machine learning. NN is a computational model based on smallest brain cell unit of information processing "neuron" and connection several sets in a model.

Regression is one of NN method, and predict the continuous value. In the energy calibration, we input the ECL cluster parameters to NN, and predict incident particle energy by NN regression.

Construction of NN





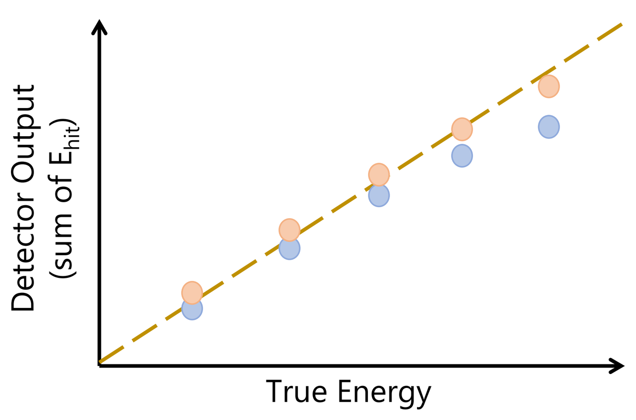
2. Energy Calibration by using the machine learning

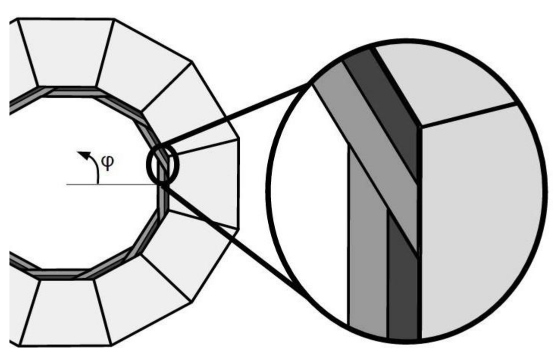
Three new regression models were developed, and the energy calibration accuracy of each model was compared with the energy resolution. Furthermore, energy calibration is performed when input data are made into electronic data, photon data, and mixed data, and the result is shown.

2-1. conventional energy calibration(simple recon)

【Some problems in ECL simple recon】

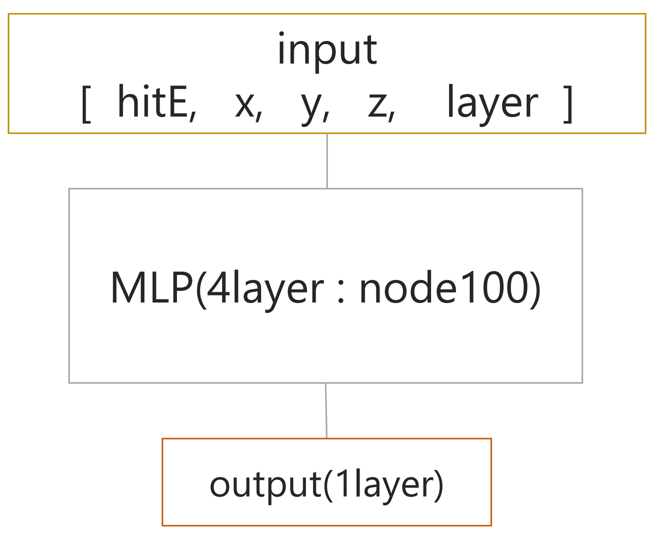
1. **Non-linear** detector response (due to the detector geometry, etc)
2. Different detector response for different particle(**particle-species dependence**)
3. **Angular dependence** due to the detector geometry





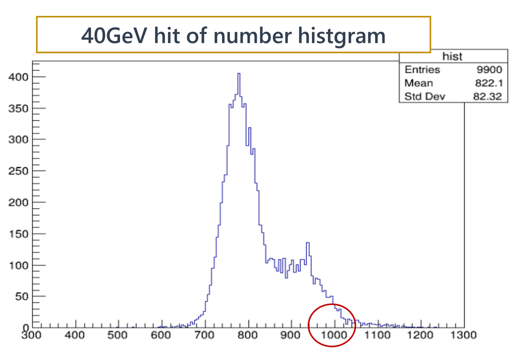
2-2. Energy calibration using a basic neural network

In the previous study, multiple feature quantities were processed in individual networks and finally combined, but this time, multiple feature quantities were processed as one data at a time to achieve a simple network structure.



make input data

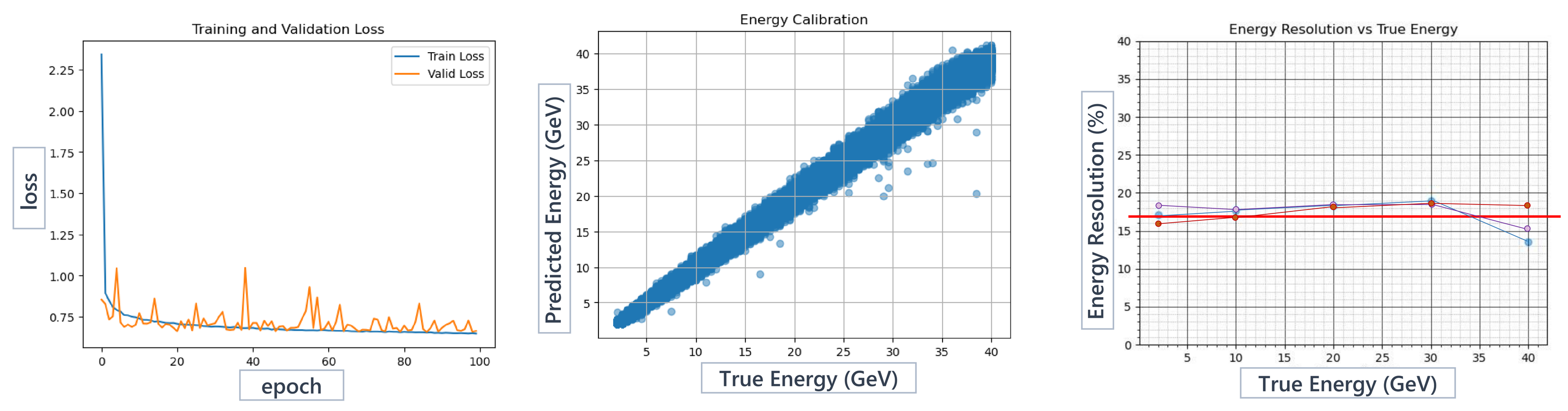
Fill in or cut the number of hits included in the cluster to align the number of data.The factors were applied to unify the influence of each element.



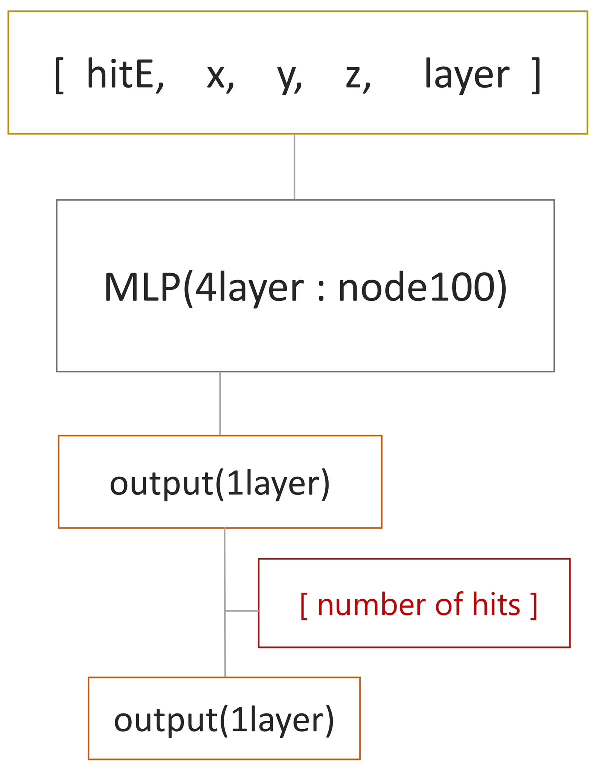
In this study, data ranging from 2 to 40 GeV (in 0.5 GeV increments) were used. From the histogram of the number of hits at the maximum energy of 40 GeV, the number of hits per cluster was set to 1000 hits, resulting in 9900 cluster data points being input into the neural network.

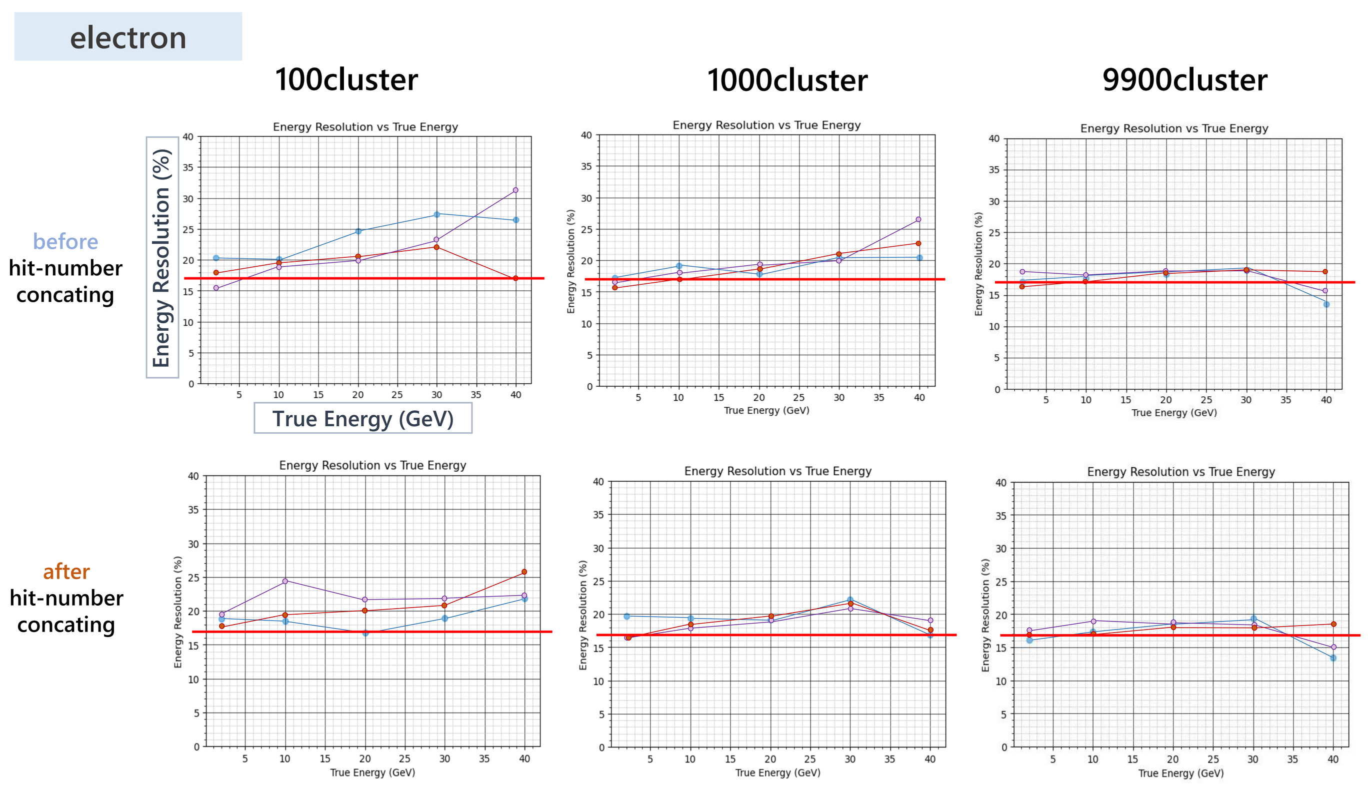
NN module	Pytorch
loss function	MSELoss
active function	Adam
batch size	128
epoch	100

electron (9900 cluster : train *0.8 / valid *0.1 / test *0.1)

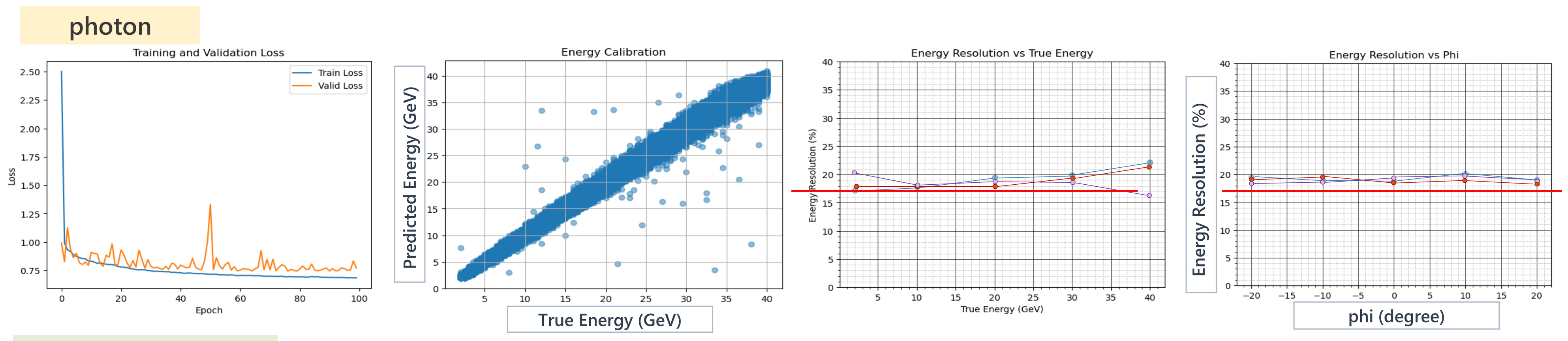


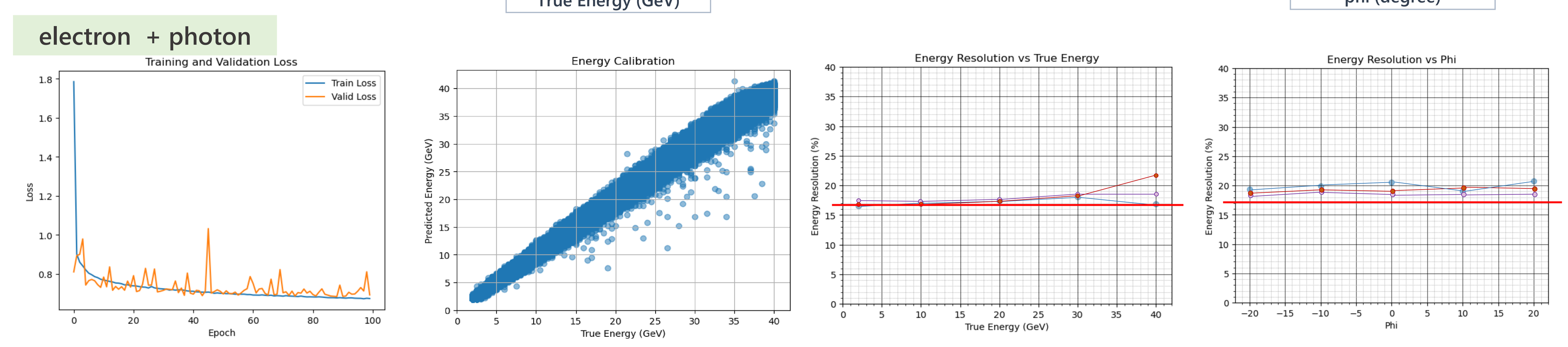
2-3. Energy calibration by NN concatenated number of hit information





The fewer the data points, the more the energy resolution is influenced by the number of hits, and incorporating the number of hits into the neural network brings the energy resolution closer to the ideal value. As the energy increases, the precision deteriorates.





1. By performing machine learning **using low-level-data directly**, ideal energy resolution (17(+1)%) can be achieved in the whole energy region of 2-40 GeV.
2. By directly inputting the location information of hit as low-level-data, energy resolution **independent of phi** is obtained.
3. A good energy accuracy was obtained even by using learning data **mixed with electron and photon**.

3. Conclusion

We have developed an energy calibration method using a regression NN with low-level data (hit data) for the electromagnetic calorimeter in the ILC experiment.

- Energy calibration with NN regression gives **the better energy calibration performance** over the simple recon since NN **expresses the non-linear detector response**.
- By concatenating the number of hits, it is possible to reduce errors in learning even with a small amount of data.
- **By using low-level data**, the network can learn the position information of each hit, resulting in **stable energy resolution with respect to the angle phi**.

Future prospects

- Similar application to the ILD design.
- Application of the different NN architecture, e.g. Graph NN to improve the energy calibration performance.

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