



Study of residual artificial neural network for PID using the CEPC AHCAL Prototype

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饮水思源·爱国荣校¹



- Motivation
- MC samples
- PID based on BDT
 - **PID based on ANN**
- PID application on Beam data



Motivation



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- Future Higgs/W/Z/Top factories require high jet energy resolution
 - Particle identification is essential for jet tagging and measurement.
 - Accurate differentiation between hadronic and electromagnetic showers is crucial for determining the energy and type of each particle.





CEPC in China



CLIC at CERN



FCC at CERN



Oct 27, 2023



Motivation



- **Exploration for ML PID methods in PFA-oriented calorimeters**
 - A major calroimetry option of future Higgs/W/Z/Top factories:
 - High granularity (imaging) -> A "camera".







Challenge:

- Hadronic showers may undergo secondary interactions and exhibit complex development patterns.
- Hadronic showers also contain EM component.
- Develop effective shower topology variables.





Introduction

- **CEPC AHCAL** prototype parameter - Geometry
 - 40 sampling layers.
 - 72cm \times 72cm in transversal plane.
 - 120cm in longitudinal direction.

- Absorber

- 2 cm thickness/layer steel.

- Sensitive cells

- -40mm $\times 40$ mm $\times 3$ mm scintillator tile coupled with SiPM (SiPM-on-tile).
- $18 \times 18 \times 40$ array.

Spatial distribution of hits viewed as a 3D image

Journal of Instrumentation, 2021, 16(03): P03001. Journal of Instrumentation, 2022, 17(11): P11034.





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Scintillato



Simulation set up

- the Geant4 11.1.1 Toolkit with the QGSP_BERT physics list was employed.
- 2 mm plastic scintillator + 0.25 mm \times 2 ESR + 20 mm Steel.
- Digitization:
 - Photon statistics: Poisson distribution concerning
 #detected photons (light output).
 - SiPM saturation : $response = \# pixel \times e^{-\frac{photon}{\# pixel}}$.
 - ADC error: assume 0.02%, very low.
 - Energy cut: 0.5 MIP.
- SiPM:
 - S14160-1315PS for first 38 layers.
 - EQR15 22-1313D-S for last 2 layers.







https://indico.cern.ch/event/847884/contributions/4831207/



GEANT4 Simulation

Generally, MC and Data are close in shower profile.

- Data come from beam test at SPS-H2, CERN.
- Several shower topology variables are reconstructed:
 - **Shower density**: Mean hits number in a 3×3 cell.
 - **Shower length**: Distance between the start of the shower and the layer with maximum RMS of hit transverse coordinates.











Monte Carlo Samples

- To study the separation power in HAD showers and EM showers.
- Training set : Validation set : Test set = 5:1:4.

Energy	5GeV	10GeV	30GeV	50 GeV	60GeV	80GeV	100GeV	120GeV
Electron	100k	100k	100k	100k	100k	100k	100k	100k
Pion-	100k	100k	100k	100k	100k	100k	100k	100k

Two machine learning methods



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- Boosted decision tree (BDT)
 - Need pre-reconstructed input.

Cell-based artificial neural networks (ANN)

• Treat spatial distribution of hits as images.





Neural networks



CEPC

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• Apply Extreme Gradient Boosting (XGBoost).

- 12 variables are reconstructed.
- Z depth, Shower radius, and Shower layers are top 3 variables.

														1 0 0
Shower Density	1.00	-0.68	-0.38	-0.05	0.21	0.35	-0.46	0.43	-0.05	-0.13	0.94	0.27		1.00
Shower Start	-0.68	1.00	0.65	-0.10	-0.39	-0.54	0.58	-0.42	-0.23	0.13	-0.73	-0.39	- (0.75
Shower Layer Ratio	-0.38	0.65	1.00	0.53	0.36	0.12	0.55	0.35	0.33	0.63	-0.24	0.33		0 5 0
Shower Length	-0.05	-0.10	0.53	1.00	0.77	0.56	0.02	0.69	0.68	0.90	0.15	0.72		0.50
Hits Number	0.21	-0.39	0.36	0.77	1.00	0.93	0.06	0.89	0.84	0.56	0.49	0.93	- (0.25
Shower Radius	0.35	-0.54	0.12	0.56	0.93	1.00	-0.03	0.81	0.80	0.33	0.60	0.88		0.00
FD ₁	-0.46	0.58	0.55	0.02	0.06	-0.03	1.00	-0.03	0.05	-0.05	-0.39	-0.00		0.00
FD ₆	0.43	-0.42	0.35	0.69	0.89	0.81	-0.03	1.00	0.68	0.54	0.67	0.92	- ,	-0.25
Shower End	-0.05	-0.23	0.33	0.68	0.84	0.80	0.05	0.68	1.00	0.55	0.23	0.84		0.50
Fired Layers	-0.13	0.13	0.63	0.90	0.56	0.33	-0.05	0.54	0.55	1.00	0.02	0.55		-0.50
Shower Layers	0.94	-0.73	-0.24	0.15	0.49	0.60	-0.39	0.67	0.23	0.02	1.00	0.54		-0.75
Z Depth	0.27	-0.39	0.33	0.72	0.93	0.88	-0.00	0.92	0.84	0.55	0.54	1.00		_1 00
														1.00

Correlation matrix

Rank: Variable	Variable weight
1: Z depth	0.532
2: Shower radius	0.186
3: Shower layers	0.073
4: Fired layers	0.065
5: Shower density	0.370
6: Shower start	0.026
7: Shower layer ratio	0.022
8: FD ₁	0.018
9: Hits number	0.013
10: FD ₆	0.012
11: Shower end	0.009
12: Shower length	0.006





Top 3 variables in separating between EM showers and HAD showers.

- **Z depth**: The RMS of the z-axis coordinates.
- Shower Radius: The RMS of the distance with respect to the z-axis.
- **Shower layers**: The number of layers in which the RMS of positions in the x-y plane exceeds 4 cm.







Fractal dimension: $FD_{\beta} = \left\langle \frac{\log(R_{\alpha,\beta})}{\log(\alpha)} \right\rangle$

FD Ref: PhysRevLett.112.012001

$$\left| - \right\rangle + 1$$
, where $R_{\alpha,\beta} = N_{\beta}/N_{\alpha}$.

- Hits number: The number of hits.

• N_{α} : number of hits scaled by α .



Take $\alpha = 2$ as an example



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BDT classifier performance

Pion efficiency	95%	96%	97%	98%	99%
Electron rejection (1/e efficiency)	16012.7	8734.2	3843.0	970.5	105.3









• We observe dependence of BDT performance on input variables

- Remove Shower End, Shower Layers, Fired Layers, and Z Depth to build BDT with 8 inputs.
- Further remove FD_1 and FD_6 to build BDT with 6 inputs.

- Feature engineering can be sometimes tricky.



• BDT optimization is still on going.





- Cell-based Artificial Neural Networks (ANN) make full use of highdimensional input.
 - Compile layers to extract features.
 - Input: Variable stands for events (Spatial distribution of hits).
 - **Output**: the likelihood of each particle type candidate.
 - After iteration, the mapping: **Input**->**Output** close to truth.







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• ANN-based PID: Taking the advantage of ResNet



ResNet Ref: He K, Zhang X, Ren S, et al. Deep residual learning for image recognition [C]//Proceedings of the IEEE conference on computer vision and pattern recognition. 2016: 770-778.



Particle Identification

- Executed on an NVIDIA V100 NVLink GPU.
- Loss: Cross Entropy.
- Hyper-parameter
 - Batch size= 64
 - lr=0.0001
 - epoch = 200

Algorithm 1 Artificial Neural Network.

Require: The batch size *m*, the epoch number *n*, initial learning rate lr, initial net parameters θ_0 .

1: Assign corresponding label y to data x.

2: for $t = 1, \cdots, k$ iteration steps **do**

3: **for** $i = 1, \dots, m$ **do**

4:
$$\hat{y} \leftarrow \operatorname{Net}(x, \theta)$$

5:
$$\operatorname{Loss}(y_i, \hat{y}_i)_{\theta}^{(i)} \leftarrow (-\log(\hat{y}_i))$$

$$\theta \leftarrow \text{SGD}\left(\nabla_{\theta} \frac{1}{m} \sum_{i=1}^{m} \text{Loss}_{\theta}^{(i)}\right)$$



pion-

True



Predicted

е



•

PID based on ANN



ANN classifier performance

Pion efficiency	95%	96%	97%	98%	99%
Electron rejection (ANN)	56012.7	48010.9	19769.2	9083.1	2154.3
Electron rejection (BDT)	16012.7	8734.2	3843.0	970.5	105.3
Improvement	199.8%	249.8%	393.8%	752.1%	1945.0%







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ANN PID cross-check using Cherenkov detectors

- Two CO2 Cherenkov detectors are available at PS (<15 GeV).
- 20,000 Electron and 20, 000 Pion samples are selected as truth.

W/O Ckv







• Achieve 90% Pion efficiency and 99% Pion purity at the same time.





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Beam composition is given by ANN classifier

- Trained on pre-selected data also tagged by Cherenkov detector.
- Pion beam purity: around 80% when beam energy is over 30 GeV.
- Electron beam purity: over 80% at each energy point.



AHCAL Prototype Performance



Purified beam data fitting

- ANN classier is first used for purifying the Pion beam.
- Crystal ball function is then used for fitting purified Pion Data.







1000

1250

[MeV]

1500

1750

2000

22

0.000

250

500

750





• ANN(ResNet) outperforms BDT in our cases.

- **Automatic feature extraction:** This allows ANN to make full use of all input information, and potentially uncover hidden patterns in the data that may be missed by BDT, which relies on limited reconstructed features.
- **Effective in handling large and high-dimensional inputs:** ANN is wellequipped to handle high-dimensional data and capture complex patterns within it.
- **Non-linearity:** ANN can model complex non-linear relationships in data more effectively than BDT.

More validation is still on going.









• SPS-H8: Oct 19 - Nov 2, 2022:

- μ^+ : 160 GeV (for calibration)
- π⁺: 10, 20, 30, 40, 50, 60, 70, 80, 90, 100, 120 GeV (~1M events each point)
- e⁺: 10, 20, 30, 40, 50, 60, 70, 80, 90, 100, 120 GeV (~0.3M events each point)

• SPS-H2: Apr 26 - May 10, 2023:

- μ^- : 100 GeV (for calibration)
- π⁻: 10, 15, 20, 30, 40, 50, 60, 70, 80, 100, 120, 350 GeV (~1M events each point)
- e⁻: 10, 20, 30, 40, 50, 60, 70, 80, 100, 120, 150, 250 GeV (~0.3M events each point)

• PS-T9: Apr 17 - May 31, 2023:

- μ^- : 10 GeV (for calibration)
- π⁻: 1, 2, 3, 4, 5, 6, 7, 8, 10, 12, 15 GeV (~0.5M events each point)
- e⁻: 1, 2, 3, 4, 5 GeV (~50K events each point)







Beam Test at CERN in 2022 & 2023

• Successful beam test for AHCAL and ScW-ECAL was conducted.

- Beam test at CERN SPS & PS in 2022, 2023.
- Beam: Muon, Electron, Pion, Proton (1-350GeV).







400

200

0

-200

-400

Y [cm]



Monte Carlo Samples & Test Beam Samples

CEPC AHCAL

+Icmj

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Monte Carlo Samples



- AHCAL only.
- Shower topology of the same particle type is similar between MC and Data.
- Shower type:
 - Muon: Non-showering track.
 - Electron: Electromagnetic shower.
 - Pion: Hadronic shower.





CEPC AHCAL Pion Simulation @100GeV



Test Beam Samples



CEPC AHCAL CERN SPS Test Beam Pion @100GeV



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Beam Test at CERN in 2022 & 2023





- First beam test at CERN SPS-H8: Oct-Nov, 2022.
- Beam: Muon, Electron, Pion (10-160GeV).
- Notice beam contamination issue.

- Beam: Muon, Electron, Pion, Proton (1-350GeV).
- Beam purity is better than 2022's.
- Available Cherenkov detectors (effective: E_{Beam} <30GeV).



GEANT4 Simulation

- Validation on High/Low Gain 0.5 MIP energy threshold
- Generally fit in High Gain; Need optimization in Low gain saturation correction.



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BDT input



- Fired layers: The number of layer with hits.
- **Shower density**: The average number of neighboring hits around one hit, including the hit itself, in a 3×3 cell area in a given event is calculated.
- **Shower end**: After the shower starts, the first layer of two consecutive layers without 2 hits. If no shower is formed, it is set to 42.





BDT input



- Shower layer ratio: Ratio of shower layers over fired layers.
- **Shower length**: The distance between the start of the shower and the layer where the maximum Root Mean Square (RMS) of hit transverse coordinates with respect to the z-axis occurs.
- **Shower start**: The first layer of the first three consecutive layers with at least 5 hits. For events without showers, the shower start layer is set to 42.



AHCAL Prototype Performance







Apply Extreme Gradient Boosting (XGBoost)

- 12 variables are reconstructed (Signal: π , Bkg.: e, μ) • MC samples to build BDT_{MC-12}, Data samples to build BDT_{Data-12}

	Data samples											
Shower density		-0.89	-0.65	-0.0012	0.62	0.64		0.68	0.36	-0.26	0.98	0.52
Shower start	-0.89		0.77	0.0073			-0.81	-0.69	-0.39	0.33	-0.9	-0.42
Shower layer ratio	-0.65	0.77		0.29	-0.17	-0.32	-0.42	-0.12	-0.12	0.57		-0.16
Shower length	-0.0012	0.0073	0.29	1	0.27	-0.085	0.18	0.35	-0.17	0.67	0.016	0.49
Hits number	0.62		-0.17	0.27		0.87	0.82	0.9	0.63	0.076		0.52
Shower radius	0.64		-0.32	-0.085	0.87		0.72	0.72	0.83	-0.072		0.51
FD ₁		-0.81	-0.42	0.18	0.82	0.72		0.78	0.45	-0.11	0.77	0.44
FD ₆ -	0.68	-0.69	-0.12	0.35	0.9	0.72	0.78		0.45	0.12	0.77	0.52
Shower end	0.36	-0.39	-0.12	-0.17	0.63	0.83	0.45	0.45		0.11	0.49	0.5
Fired layers	-0.26	0.33	0.57	0.67	0.076	-0.072	-0.11	0.12	0.11	1	-0.22	0.43
Shower layers	0.98	-0.9		0.016		0.75	0.77	0.77	0.49	-0.22		0.57
Z width	0.52	-0.42	-0.16	0.49	0.52	0.51	0.44	0.52	0.5	0.43	0.57	1





Correlation matrix

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MC training approach







Data training approach







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• We observe dependence of BDT performance on input variables

- Remove Shower End, Shower Layers, Fired Layers, and Z Width to build BDT with 8 inputs.
- Further remove FD_1 and FD_6 to build BDT with 6 inputs.
- Feature engineering matters in BDT
 - BDT optimization is on going.



Comparison between ANN and BDT

• We observe obvious improvement in terms of Background rejection when tested on two sets of samples.



Improvement

18.49%

163.12%

68.51%

103.65%

31.37%

251.14%





- Data samples are pre-selected by Cherenkov detectors and rough F.D. cut.
- MC and Data are close in Shower topology term .
- Obvious discrepancy in energy term.

Currently

✓ Do Research on PID approach.

Separate Data training and MC training.
 Trained on MC and then applied on Data.

- Discrepancy between Data and MC.
- Bridging gap is on going. Muon data: SPS_2023/100GeV_mu_Run25. Electron data: SPS_2023/100GeV_ e_run267. Pion data: SPS/100GeV_pi_run230.







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Apply Extreme Gradient Boosting (XGBoost)

- 12 variables are reconstructed (Signal: π , Bkg.: e , μ)
- MC samples to build BDT_{MC-12} , Data samples to build $BDT_{Data-12}$

Rank: Variable	Variable weight
1: Shower radius	0.377
2: Shower layers	0.232
3: Hits number	0.088
4: Fired layers	0.083
5: Shower start	0.080
6: Shower density	0.049
7: Z width	0.034
8: FD ₆	0.017
9: FD ₁	0.015
10: Shower layer ratio	0.014
11: Shower end	0.006
12: Shower length	0.006

MC samples

Data samples

Rank: Variable	Variable weight
1: Shower radius	0.379
2: Shower layers	0.228
3: Hits number	0.133
4: Shower density	0.058
5: Fired layers	0.058
6: Z width	0.042
7: Shower start	0.039
8: FD ₆	0.019
9: FD ₁	0.016
10: Shower layer ratio	0.010
11: Shower length	0.010
12: Shower end	0.008

Data pre-selection

- Collect pion samples in 20pion run files.
- Cut approach is guided by MC.



FD cut

MC

For data collected in 2023, SPS and PS

Data pre-selection

- Collect e samples in e run files.
- Cut approach is guided by MC.



FD cut

MC

For data collected in 2023, SPS and PS