Machine Learning for Pion Identification and Energy Calibration with the ATLAS Detector

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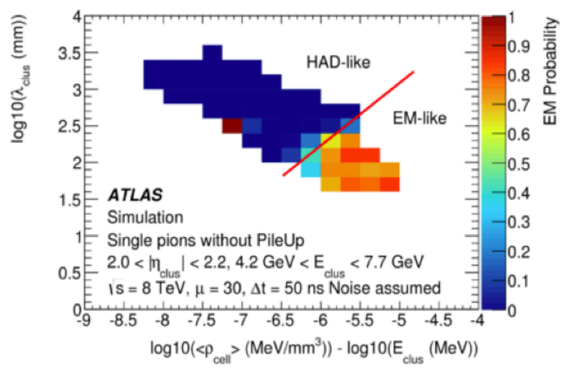
LC Pion Calibration Motivation

Classification of charged and neutral pions, as well as calibrating the pion energy response, is a core component of reconstruction in the ATLAS calorimeter. Machine-Learning-based calibrations, at the particle level, can significantly improve the quality of pion reconstruction in the ATLAS calorimeter. The more details of study could be found in the PUB note [1].



Calorimeter and Simulation

Only the central barrel of the detector is considered with $|\eta| < 0.7$.

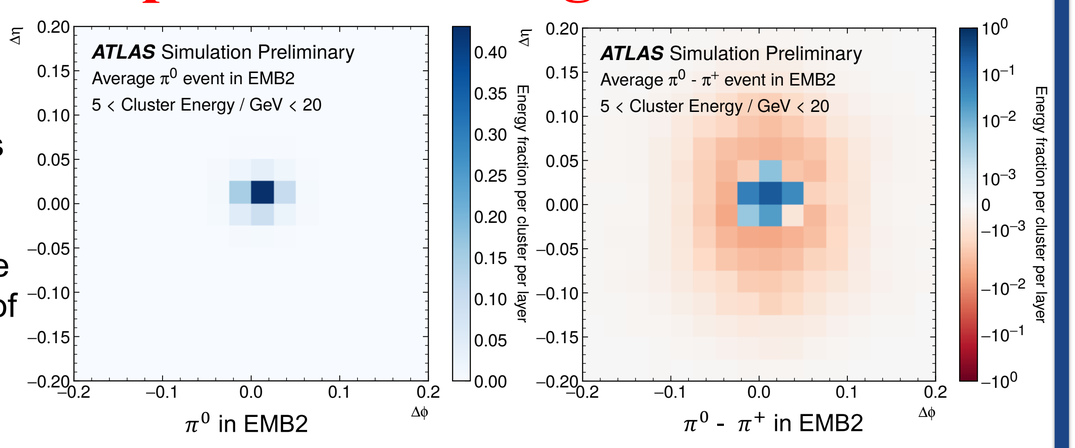
- Three layers of the EM calorimeter (EMB)
- Three layers of the hadronic calorimeter (Tile)

Single pion showers are simulated [2] in the ATLAS calorimeter based on Geant4 [3].

- Single π^0 and $\pi^{\pm}$ particles are simulated originating from the center of the detector with the logarithm of their energies in units of GeV sampled uniformly between 0.2 GeV and 2000 GeV.

Topo-Cluster Images

- Topo-Clusters [4] are three-dimensional objects that represent local particle showers in the detector and are built from the cells of the calorimeter.

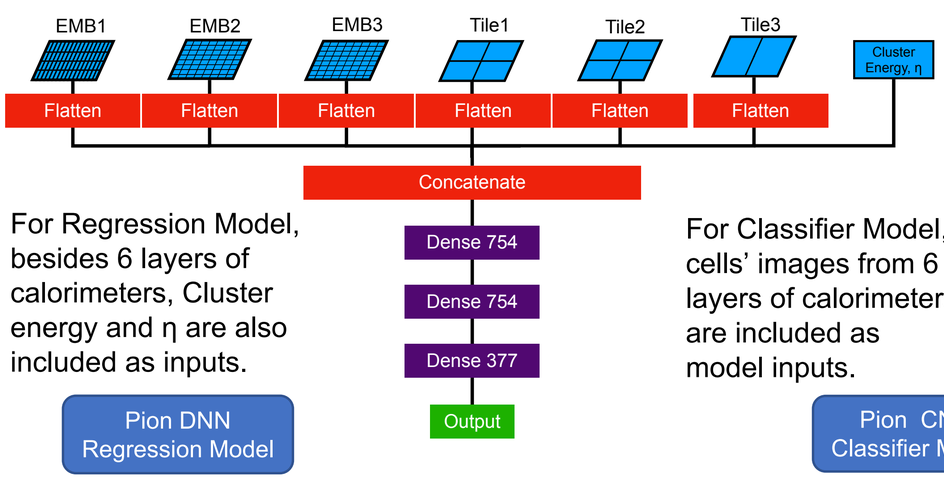


- Cells in a given sampling layer are projected on to a two-dimensional image in the (η, φ) plane with a Δη, Δφ range of 0.4 × 0.4 centered on the entire topo-cluster's centroid.

Neural Networks (NN)

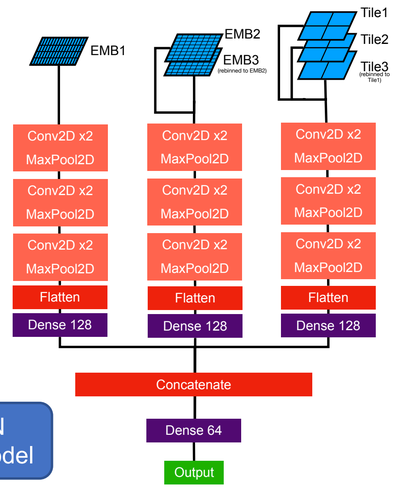
- Deep Neural Networks (DNN): using a flattened one-dimensional vector generated from Topo-Cluster cells' image. The model can learns from 1D raw information from cells' calorimeter.
- Convolutional Neural Network (CNN): uses the entire 2-D cell image from each of the calorimeter layers. The CNN model is typically used to withdraw features from images.
- Densely Connected Convolutional Network (DenseNet [5]) : Industry standard architecture for image classification.

Machine Learning Architectures



For Regression Model, besides 6 layers of calorimeters, Cluster energy and η are also included as inputs.

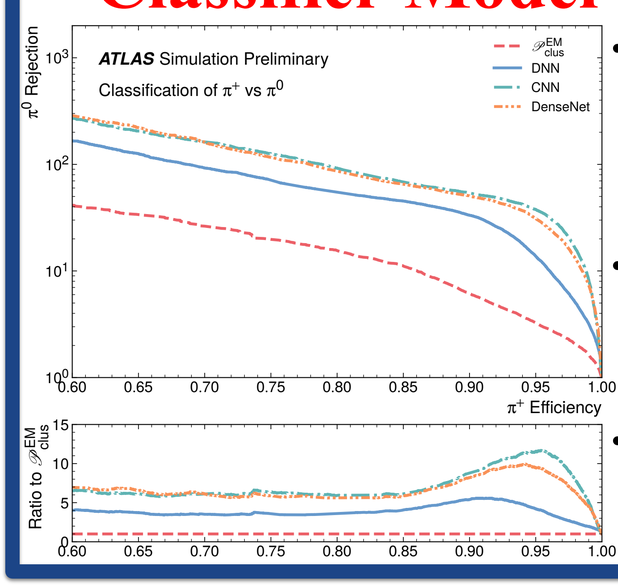
Pion DNN Regression Model



For Classifier Model, cells' images from 6 layers of calorimeters are included as model inputs.

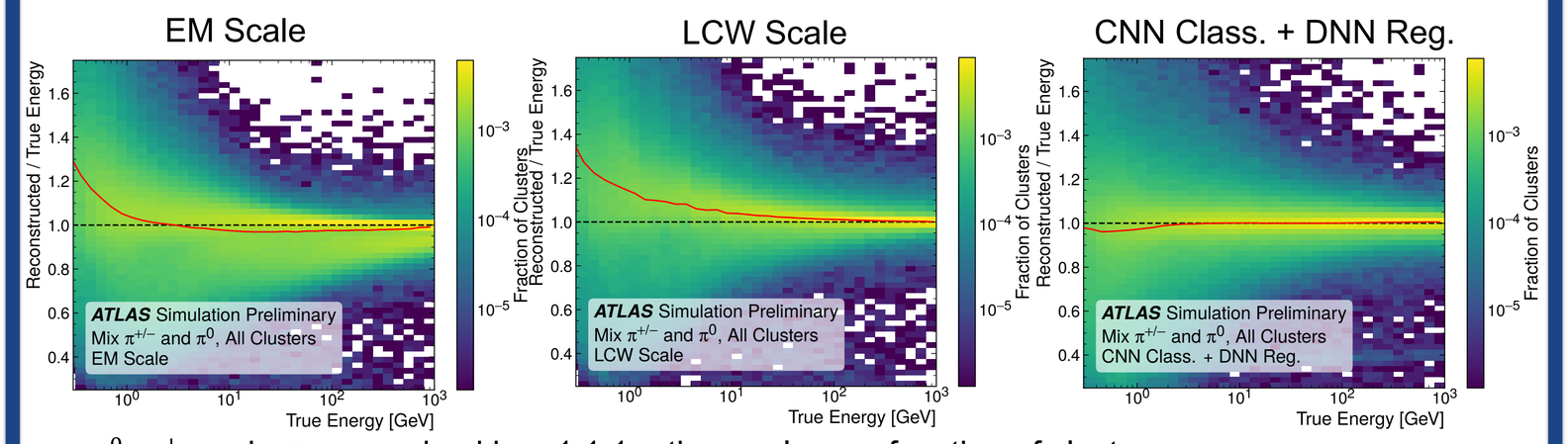
Pion CNN Classifier Model

Classifier Model Comparison



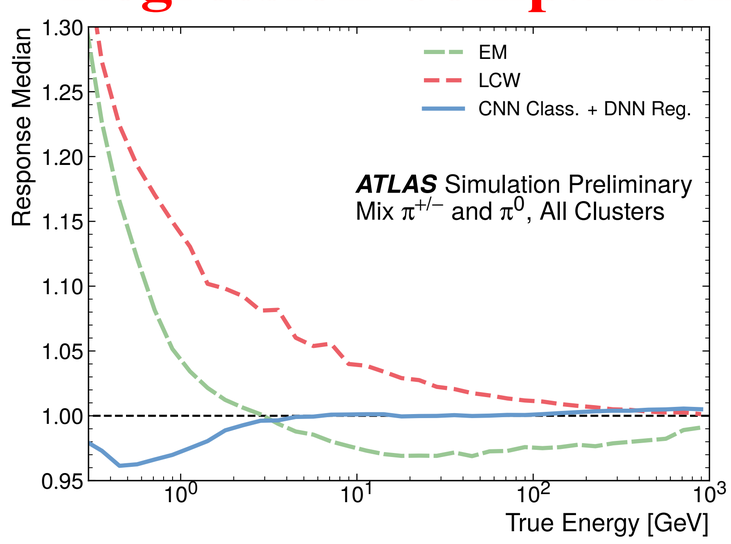
- The top panel shows the charged pion efficiency vs neutral pion rejection for the neural network models and $\mathcal{P}_{clus}^{EM}$.
- The bottom panel shows the ratio of the π^0 rejection of the NN models compared to the π^0 rejection of $\mathcal{P}_{clus}^{EM}$.
- $\mathcal{P}_{clus}^{EM}$ is the probability of topo-clusters classified as EM (in the LCW scheme).

Combined Classification Energy Regression Results



- π^0, π^+, and π^- were mixed in a 1:1:1 ratio evenly as a function of cluster energy.
- The maximum likelihood value of the classifier, is used to determine which regression to apply. Corresponding correct classification: 95% of π^0 and 95% of $\pi^{\pm}$.
- The combined CNN classifier and DNN regression, shown in top right figure, shows a consistent response at unity for nearly the entire range of true energy.

Regression Comparison



The response for the mixed pion sample for the EM, LC, and combined CNN classifier and DNN regression. The response is significantly improved over the full range of true energy.

Conclusion

- ML-based classifiers (i.e. DNNs, CNNs) can significantly improve the classification of topo-clusters originating from electromagnetic or hadronic showers by using more information contained in the longitudinal and transverse shower shapes through the complex and highly segmented ATLAS calorimeters.
- All the architectures are also able to significantly improve the energy scale and energy resolution for classified topo-clusters, particularly at low energies compared to traditional methods.

References

[1] ATLAS Collaboration, Deep Learning for Pion Identification and Energy Calibration with the ATLAS Detector. Technical Report ATL-COM-PHYS-2020-459, CERN, Geneva, Jul 2020
[2] ATLAS Collaboration, *The ATLAS Simulation Infrastructure*, Eur. Phys. J. C **70** (2010) 823, arXiv: 1005.4568 [physics.ins-det]
[3] S. Agostinelli et al., *Geant4 – a simulation toolkit*, Nucl. Instrum. Meth. A **506** (2003) 250
[4] ATLAS Collaboration, *Topological cell clustering in the ATLAS calorimeters and its performance in LHC Run 1*, Eur. Phys. J. C **77** (2017) 490, arXiv: 1603.02934 [hep-ex]
[5] G. Huang, Z. Liu, L. Van Der Maaten, and K. Q. Weinberger, "Densely Connected Convolutional Networks", 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2017 2261