Boosting HAWC's Sensitivity Through Efficient Deep Learning Classification

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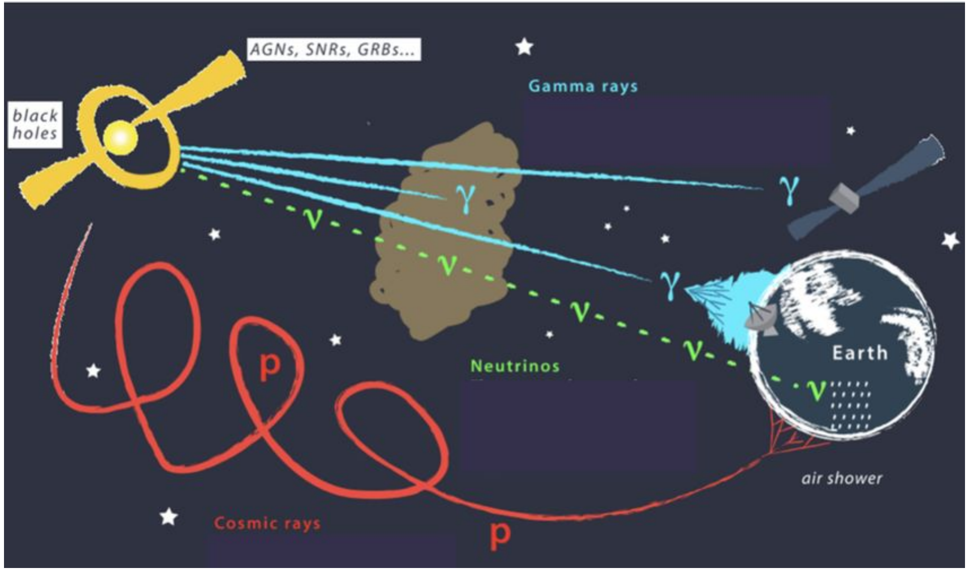
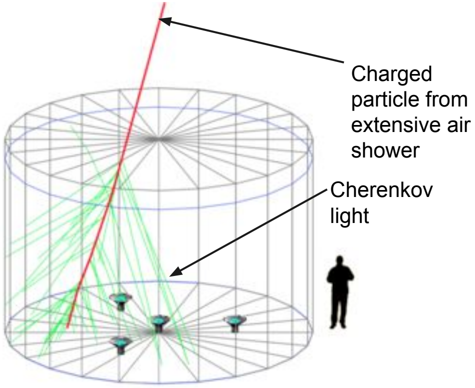
Gamma Rays in High-Energy Astrophysics



Multi-messengers from hadronic accelerators (credit J.A. Aguilar & J. Yang).

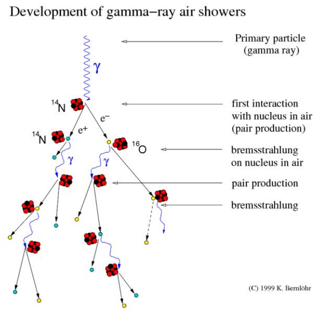
- Gamma rays play a crucial role in multi-messenger astronomy.
- Unlike cosmic rays, gamma rays from astrophysical source are not deflected by interstellar magnetic fields therefore can be traced back to the accelerator.
- The High-Altitude Water Cherenkov Gamma-Ray Observatory (**HAWC**) is a facility designed to observe gamma rays.

HAWC overview



- **Location**: HAWC is located on the flanks of the Sierra Negra volcano near Puebla, Mexico at an altitude of 4100 meters.
- **Detector Array**: 300 Water Cherenkov Detectors (WCDs or "tanks") covering ~22,000 m². Each tank contains 4 Photomultiplier Tubes (PMTs).
- **Water Cherenkov Detector**: Detects cherenkov light produced by charged particles from Extensive Air Shower (EAS).
- **Operation**: Wide Field-of-View (~2 sr), High Duty Cycle (>95%), ~25 kHz trigger rate. Sensitive to gamma rays and cosmic rays from **~300 GeV to >100 TeV**.

Extensive Air Shower (EAS)



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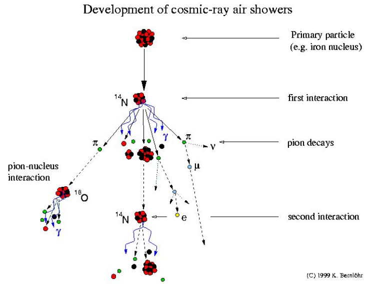
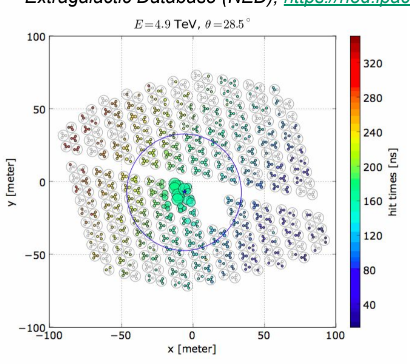
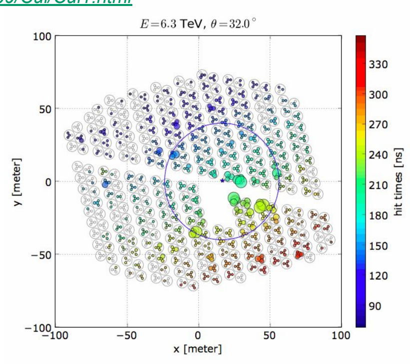


Images reproduced from Cui (2009), “Cosmic Rays and High-Energy Gamma Rays”, NASA/IPAC Extragalactic Database (NED), https://ned.ipac.caltech.edu/level5/Sept09/Cui/Cui1.html



Simulated Gamma-Ray Event



Simulated Cosmic-Ray Event

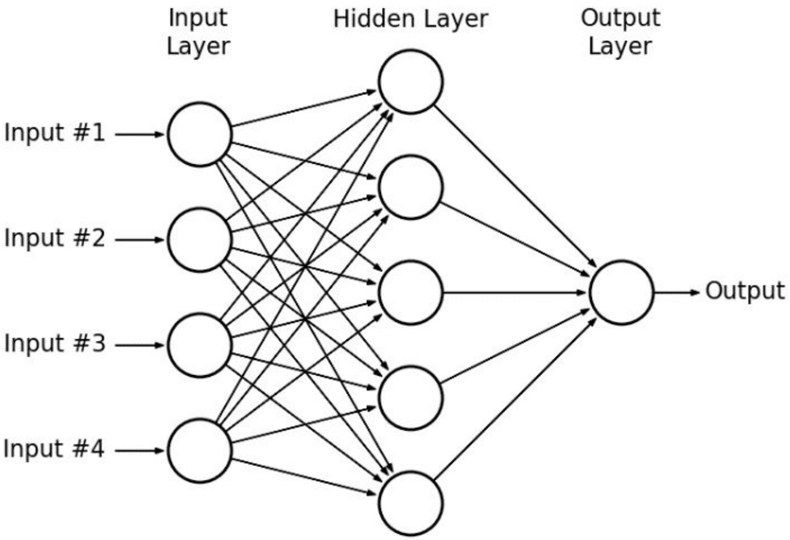
- Both gamma ray and cosmic ray produce EAS in the atmosphere.
- Gamma ray shower
  - Develops an cascade of electromagnetic (EM) particles through an alternating cycle of pair production and bremsstrahlung.
  - Almost pure EM shower.
  - Compact, symmetric around shower core.
- Cosmic ray shower
  - Rich with pions, muons, other hadronic secondaries.
  - High transverse momentum of hadronic secondaries leads to scattered high-charge hits far from the air shower’s core.

HAWC Standard Cut (SC) : Physics-based hard cut

- HAWC Standard Cut (SC) is defined as hard cut on two engineered feature sensitive to gamma/hadron separation.
- **LDFChi2**
  - Reduced χ^2 from fitting the measured photo-electron (PE) distribution with a lateral distribution function (LDF) based on a modified Nishimura–Kamata–Greisen (NKG) model, which describes the particle density of gamma-ray-induced air showers.
  - Lower value of LDFChi2 indicates better fit to a gamma-ray shower particle distribution.
- **Compactness**
  - Compactness = Nhit / Q_{40}
  - Nhit is the number of hit PMTs during the shower.
  - Q_{40} is the largest effective charge outside a radius of 40 meters from the shower core.
  - Compactness is smaller for hadronic events.

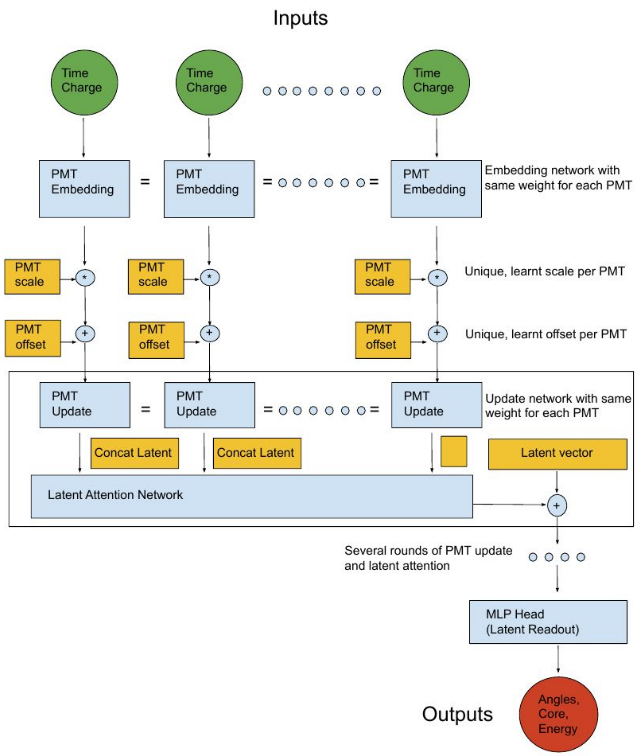
HAWC Standard Multilayer Perceptron (MLP) : Feature-based neural network

- A fast and computationally low-cost neural network which contains 4 layers of neurons.
  - Input layer accepts 20 input features.
  - Two hidden layers which take 128, 64 neurons, respectively.
  - Output layer is a single neuron with sigmoid activation.
- Input Features
  - Energy-related : fHit, fTank, NNEnergy, GPEnergy, LDFAmp
  - Shape-related : LDFChi2, PINCness, Compactness, fAnnulusQ0–Q9
  - Directional and positional features : R, Zenith
- It has higher performance than SC, adopted in the standard HAWC data analysis pipeline this year.



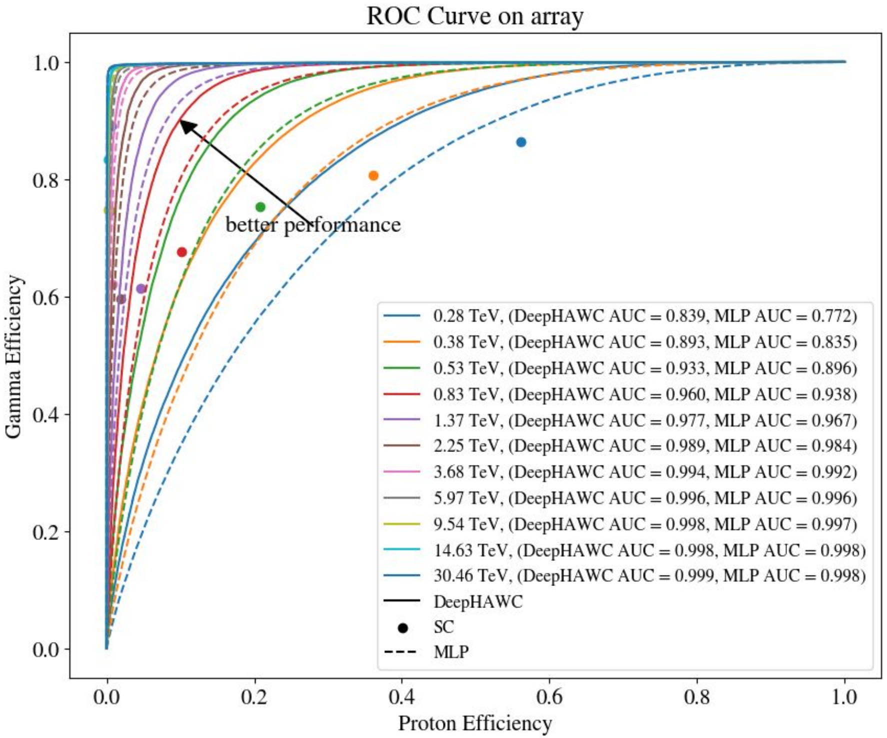
Scheme of MLP

DeepHAWC : Deep Learning Approach



- **Shift from engineered features to end-to-end learning.** We developed a custom attention-based network to process raw PMT data.
- Raw PMT hit information (time t_i, charge c_i) from the each PMT is transformed into a PMT-embedding vector.
- Learnable per-PMT adjustments implicitly encode detector geometry and calibration.
- **Iterative shower representation refinement**: A shower representation vector interacts with PMT-embedding vector via attention mechanisms over several steps.
- After all, deep learning model does feature extraction by itself.
- Shower representation vector is processed by final MLP head, then returns a gamma/hadron classification score.

ROC curve

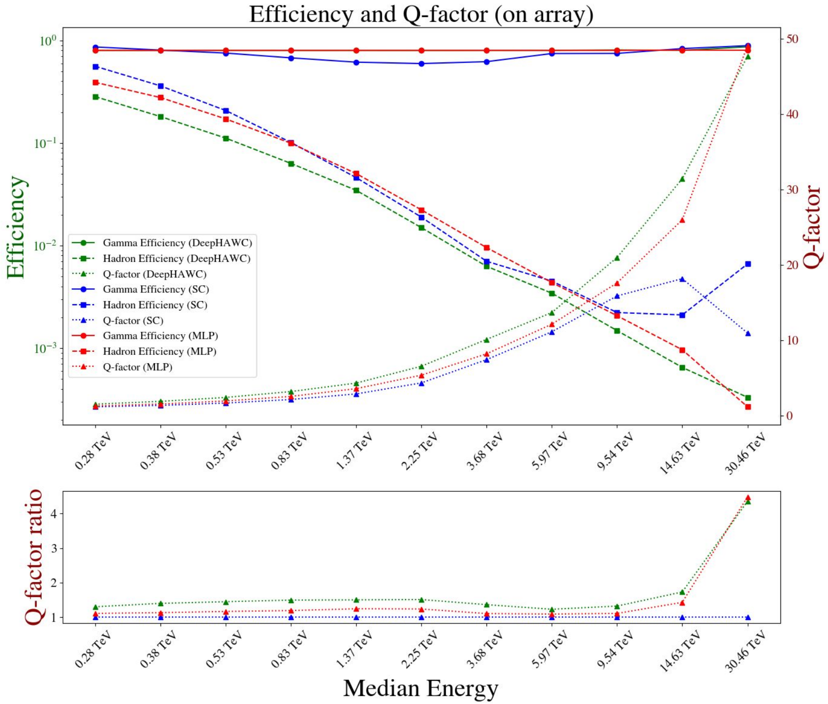


fHit Bins	Hit PMT Fraction	Median Energy (TeV) on-array(C0)
B0	2.7%–4.7%	0.28
B1	4.7%–6.8%	0.38
B2	6.8%–10.4%	0.53
B3	10.4%–16.1%	0.83
B4	16.1%–24.5%	1.37
B5	24.5%–35.1%	2.25
B6	35.1%–47.2%	3.68
B7	47.2%–59.9%	5.97
B8	59.9%–72.2%	9.54
B9	72.2%–82.2%	14.63
B10	82.2%–100.0%	30.46

(A. Albert et al., 2024, arXiv:2405.06050)

- **Fhit bin** is a proxy for the primary particle's energy, defined by the fraction of PMTs that records light during the event.
- **DeepHAWC** significance improves gamma/hadron separation especially in lower energy levels.

Efficiency / Q factor



Efficiency & Q factor
DeepHAWC and MLP optimized to 80% gamma-ray efficiency

- Q-factor = $\varepsilon_{gamma} / \sqrt{\varepsilon_{proton}}$
    - A standard metric of significance improvement.
- DeepHAWC achieves consistently higher Q-factors and better background rejection, indicating improved significance, except the highest energy level.

Conclusion

- We developed an **optimized attention-based network** for HAWC gamma/hadron separation.
- We achieved significant improvement over HAWC standard analysis with **higher AUC** & **higher Q-factor** especially significant in lower energy levels.
- This deep learning approach offers **enhanced sensitivity** for HAWC science.

Reference

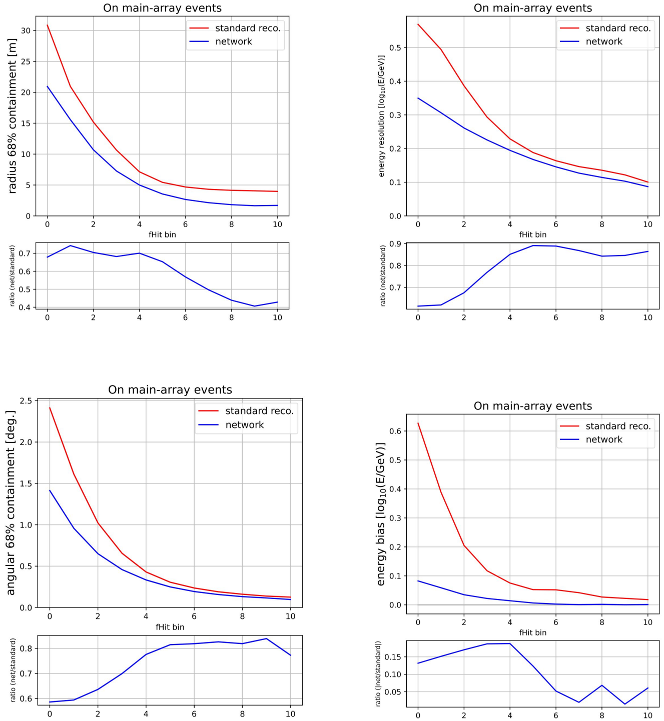
[1] Abeysekara, A. U., et al. "Observation of the crab nebula with the HAWC gamma-ray observatory." The Astrophysical Journal 843.1 (2017): 39.

[2] Albert, A., et al. "Performance of the HAWC observatory and TeV gamma-ray measurements of the Crab Nebula with improved extensive air shower reconstruction algorithms." The Astrophysical Journal 972.2 (2024): 144.

[3] Alfaro, R., et al. "HAWC Performance Enhanced by Machine Learning in Gamma-hadron Separation." The Astrophysical Journal 992.1 (2025): 156.

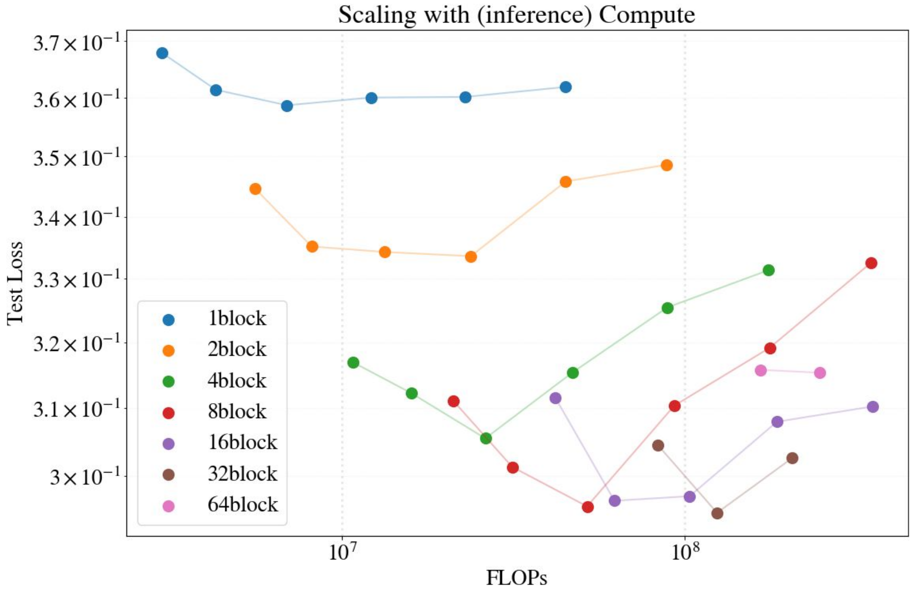
Backup

Shower Reconstruction Performance



- Assessed the performance of our attention-based architecture for reconstructing key air shower parameters.
- Parameters Reconstructed:
  - Shower radius
  - Arrival Direction (Azimuth, Zenith Angle)
  - Primary Particle Energy
- Results: The model demonstrates improved reconstruction accuracy compared to standard HAWC methods in all fhit bin range.

Scaling Law



- **Scaling Laws**: Model performance typically improves (lower test loss) with more parameters or compute, often following power laws ($L \propto N^{-a}$, $L \propto C^{-b}$).
- In this plot, for any number of blocks, the shower representation vector size follow a sequence that starts at 16 and doubles at each step, such as 16, 32, 64, and so on.
- Our model's performance follows an U-curve. As the model size increases, performance peaks and then declines. This is due to the limited size of our dataset.

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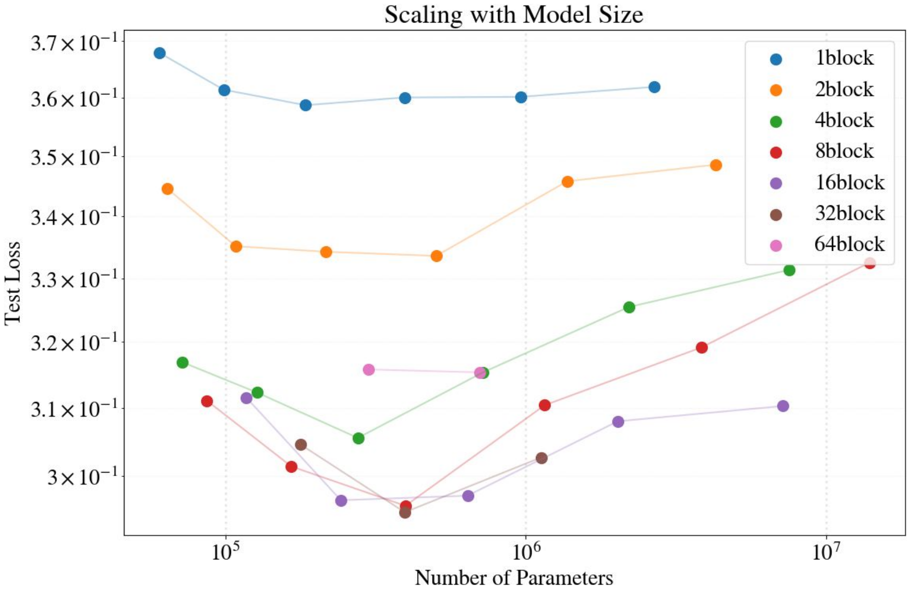

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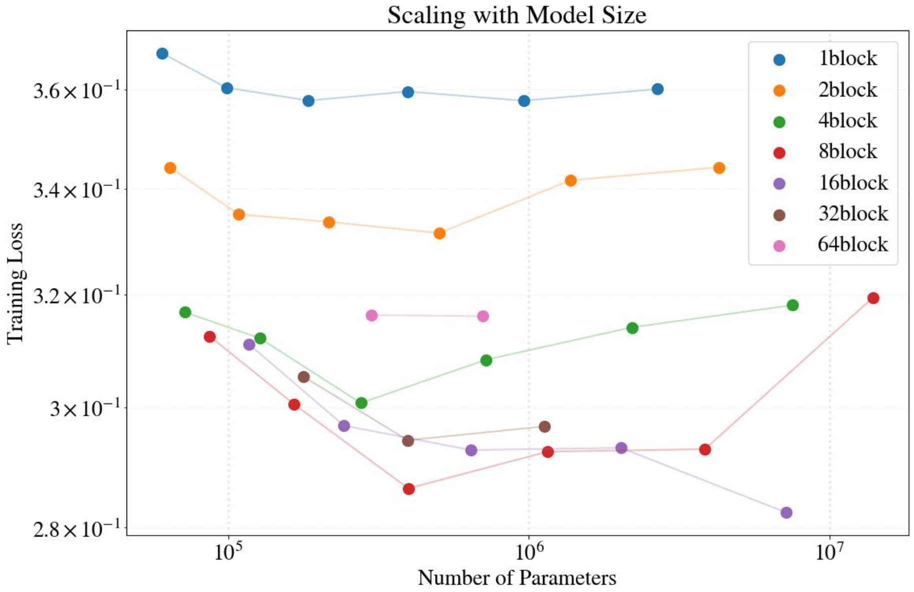

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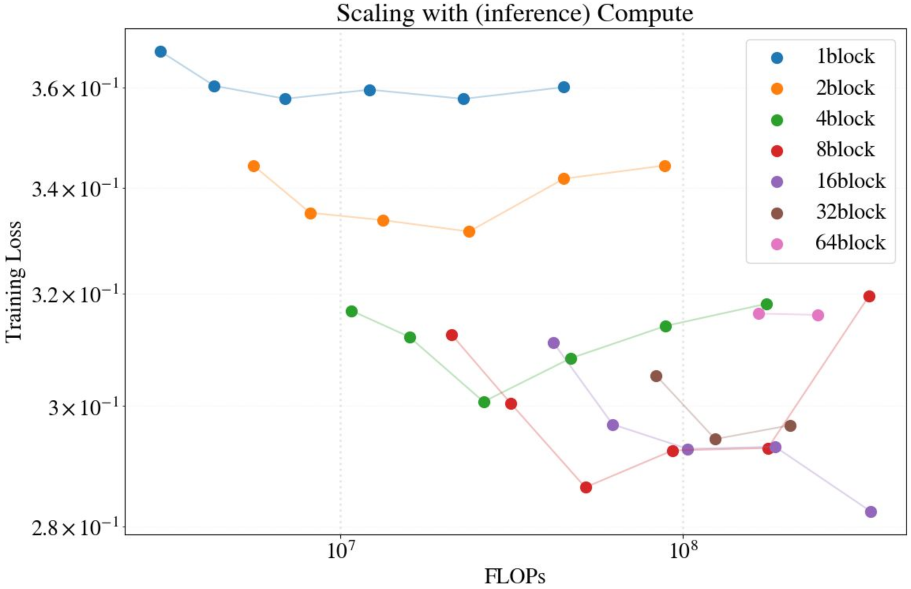

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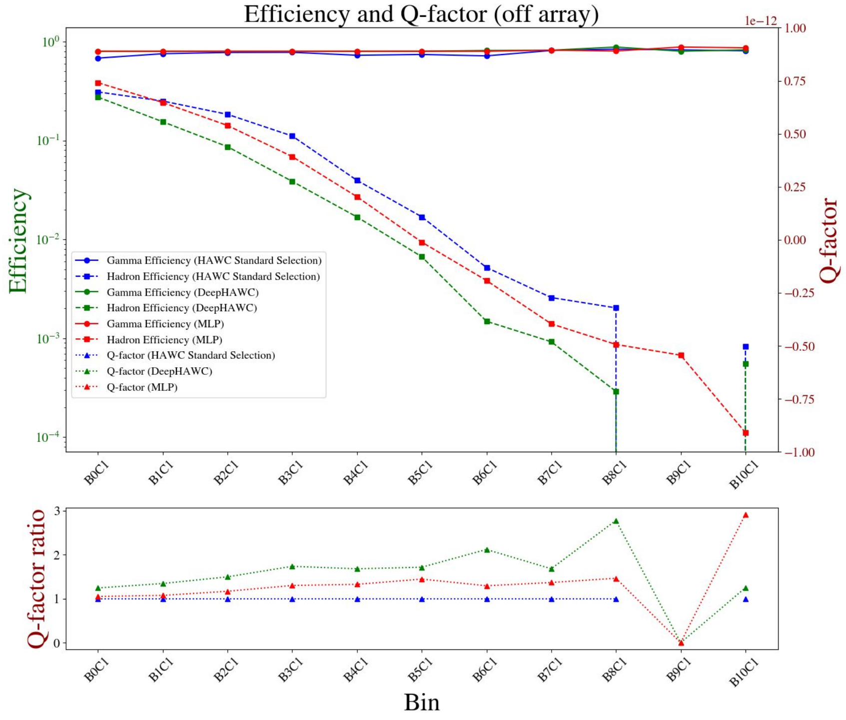
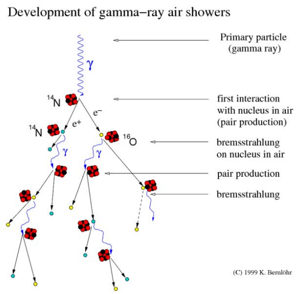
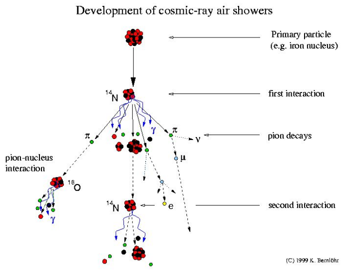
Efficiency and Q factor (Off array)



HAWC Standard Approach & Challenges



Differing shower physics



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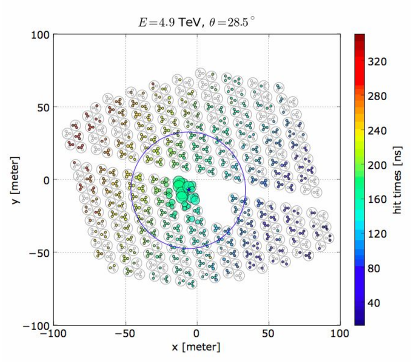

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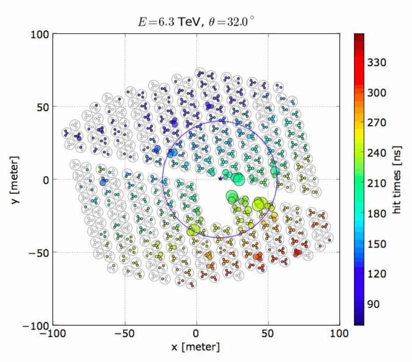

Simulated Cosmic-Ray Event

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- **Standard HAWC Reconstruction**:
  - Processes PMT data to estimate shower properties (e.g., arrival direction, core location, energy proxies).
  - Applies hard cuts or use MLP on parameters sensitive to gamma/hadron classification.
  - Cuts are optimized for each *fHit bins* depending on what fraction of PMTs were triggered during the event. It is sensitive to true energy of a source photon.
- **Our Deep Learning Goal**
  - Develop end-to-end models potentially enhancing standard reconstruction methods by learning optimal features directly from raw PMT responses.
  - Improved gamma/hadron classification.