

Agentic AI for Real-Time Expedited Discovery from High-Complexity EIC Data Streams

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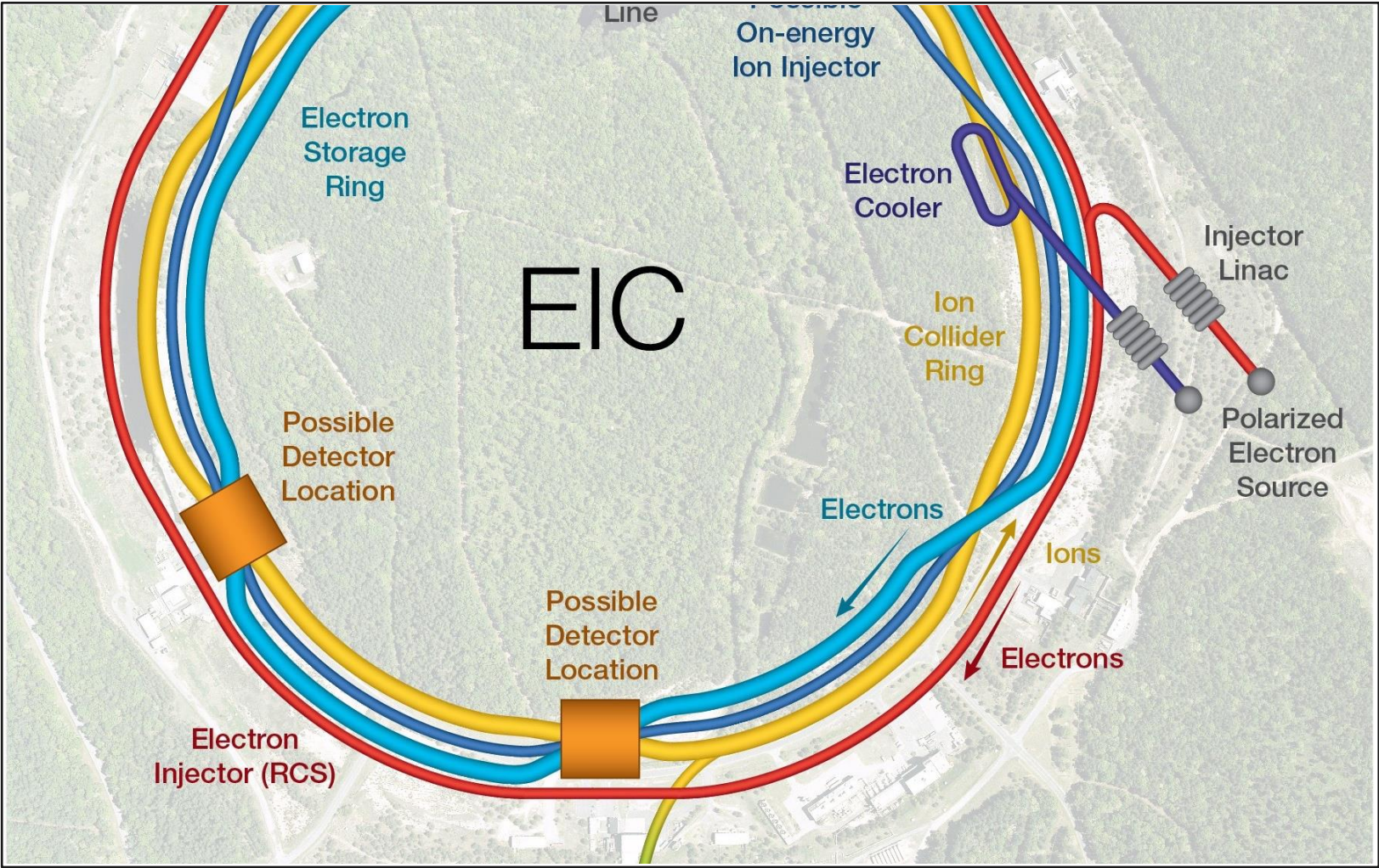
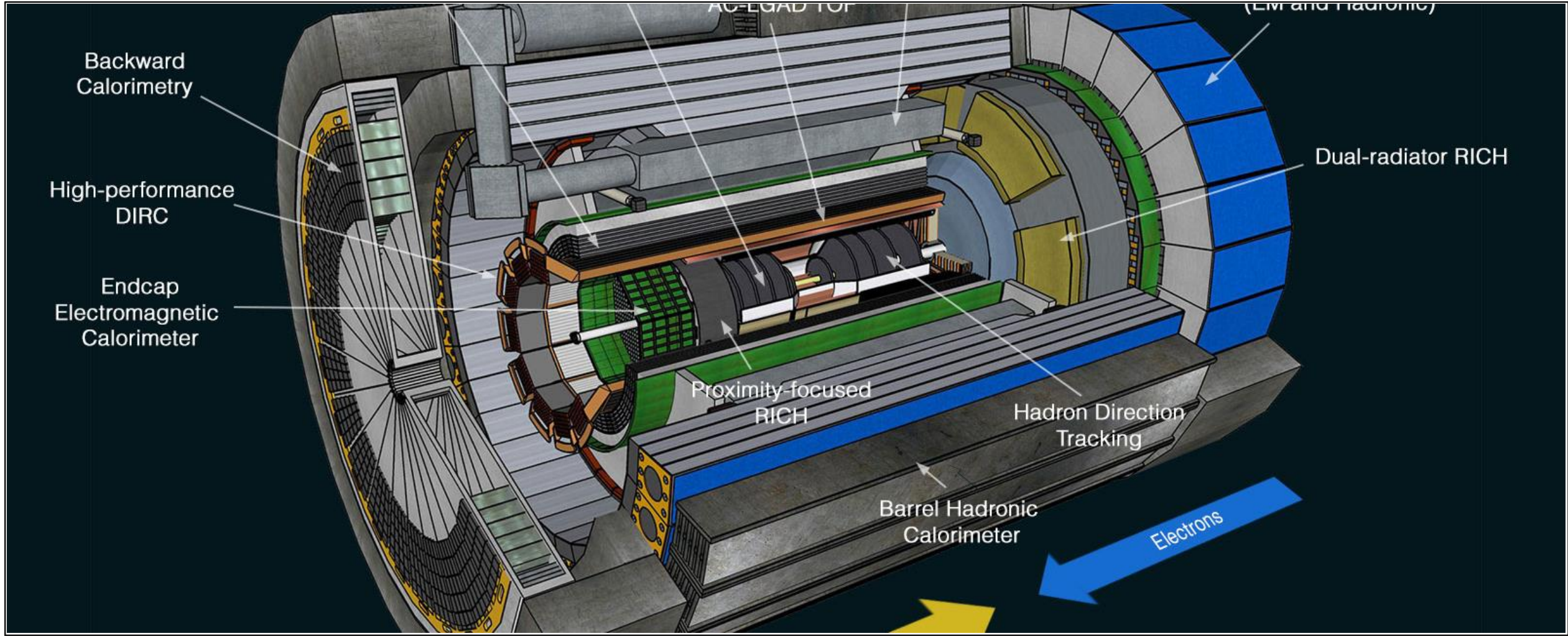


Fig. 1 — Left: ePIC detector cutaway. Right: the planned EIC accelerator complex at Brookhaven National Laboratory, showing the electron and ion storage rings and the two possible detector locations. The innermost silicon-pixel tracking layers are where synchrotron and beam-gas background first saturate the data stream — the point of intervention targeted by this proposal.

Motivation

At the future Electron-Ion Collider, synchrotron and beam-gas backgrounds in the innermost silicon pixel layers will exceed GHz rates — orders of magnitude above the true DIS signal, which sits at hundreds of kHz. Left unmitigated, this saturates readout bandwidth, data movement, storage, and downstream reconstruction, restricting the physics reach of the experiment.

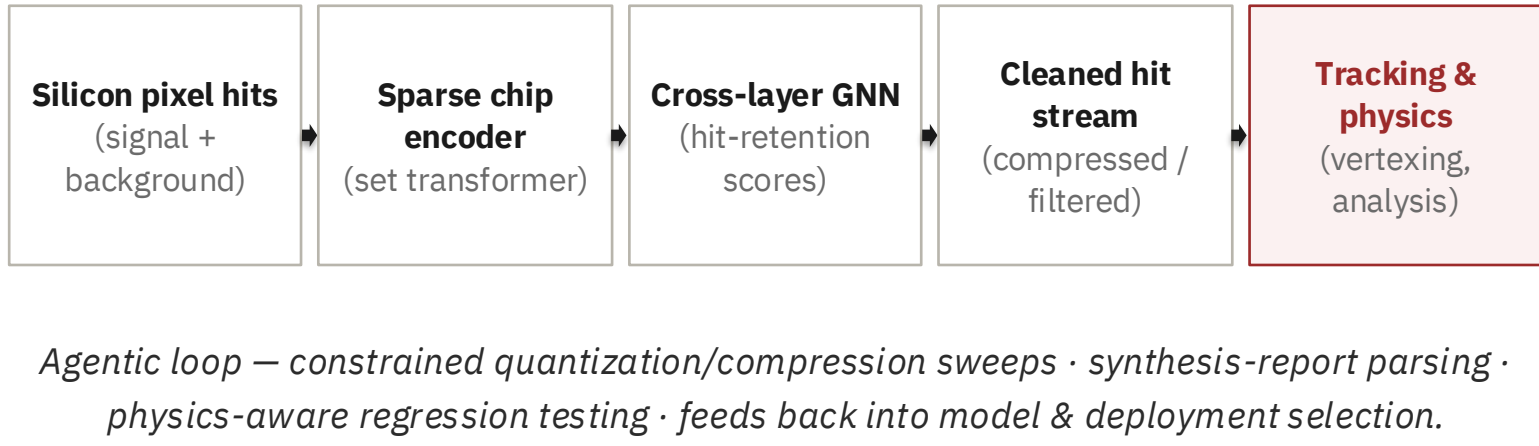
Key Question

Can hardware-optimized sparse AI models significantly reduce EIC beam-gas backgrounds and thus downstream data volumes while preserving downstream physics performance within the experimental bandwidth constraints? Furthermore, can a bounded agent-assisted workflow measurably shorten the path from model training to an optimized hardware-integrated implementation?

Approach

- 01 Benchmarks & evaluation framework:** Establish realistic EIC benchmarks — datasets, baselines, and evaluation protocols — for high-complexity silicon-pixel streams under synchrotron/beam background.
- 02 Sparse representation & low-latency models:** Develop physics-preserving sparse-data models, from sensor level to physics analysis, that suppress or compress background while retaining tracking/vertexing utility.
- 03 Agentic co-optimization & deployment:** Test bounded agent-assisted workflow components and demonstrate measurable AI advantage on one integrated deployment path.

Sensor-to-Physics Pipeline



Timeline

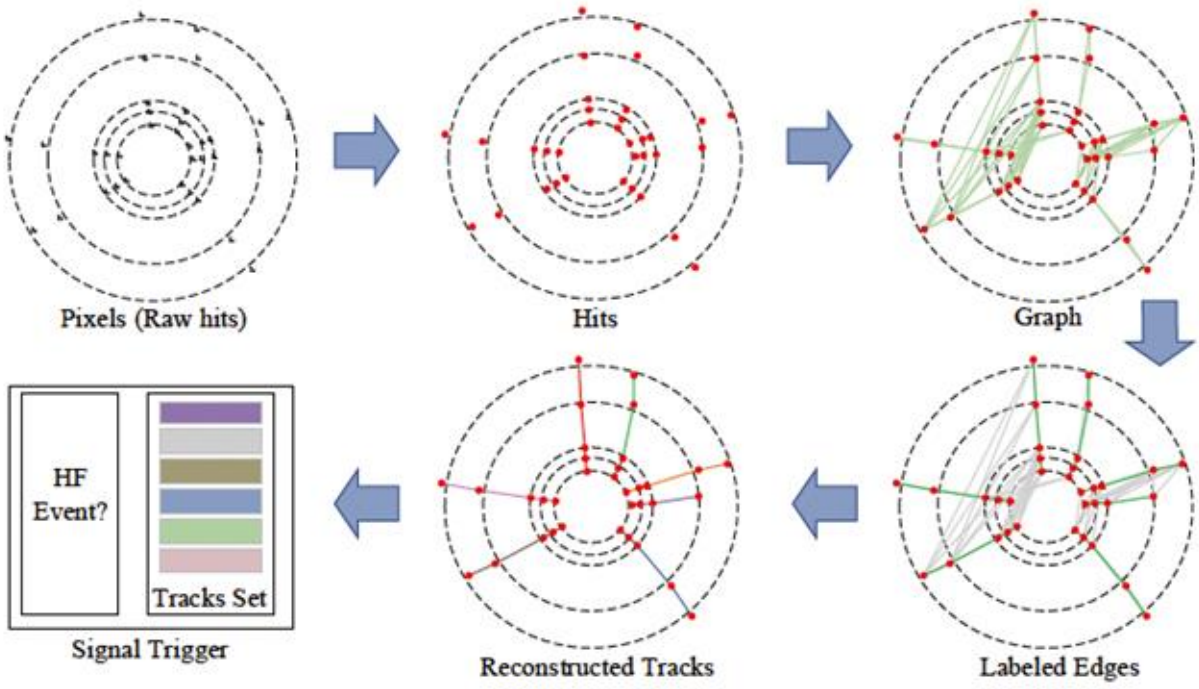
- MONTHS 1–2** Finalize use case, benchmark spec & dataset splits, non-AI baselines.
- MONTH 3** Benchmark v1 release; GPU/FPGA/hybrid deployment screening.
- MONTHS 4–5** Train & compare sparse models; down-select primary model.
- MONTH 6** Integrate agentic pipeline with performance, robustness, deployment profile towards candidate architecture.

Performance Metrics

- ≥10×** background/data-volume reduction (≥2× best non-AI baseline, matched retention)
- ≥95%** signal retention, ≤2% downstream performance loss
- Sustained** benchmark stream rate within latency & resource budget
- Scaling** advantage over best conventional baseline per unit compute
- ≥30%** faster iteration or ≥3× more design points via agentic workflow

Prior work

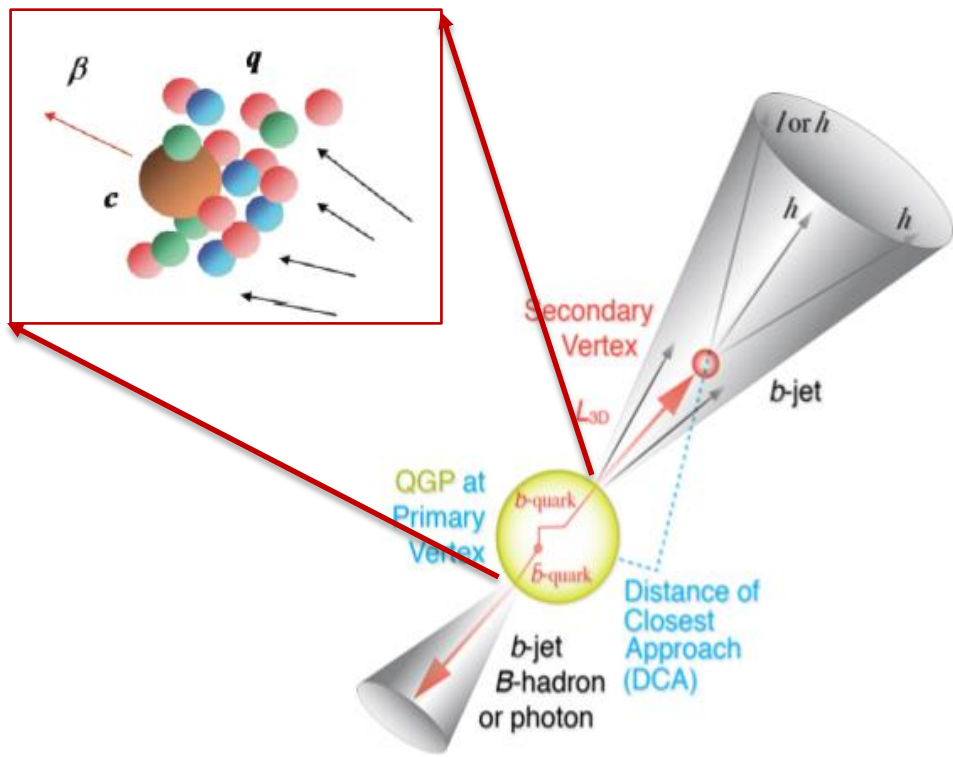
Conceptual flow for GNN based tracking



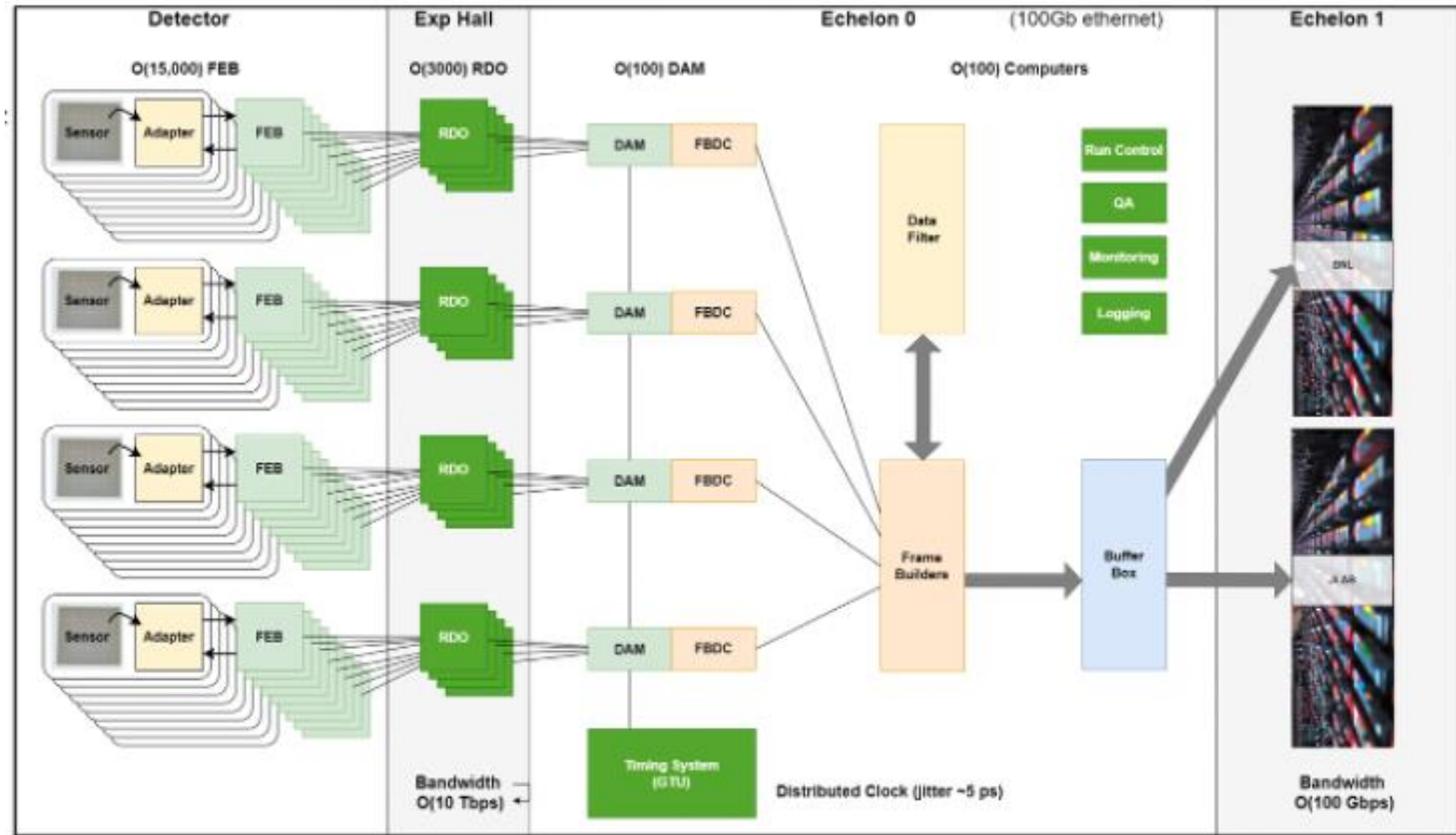
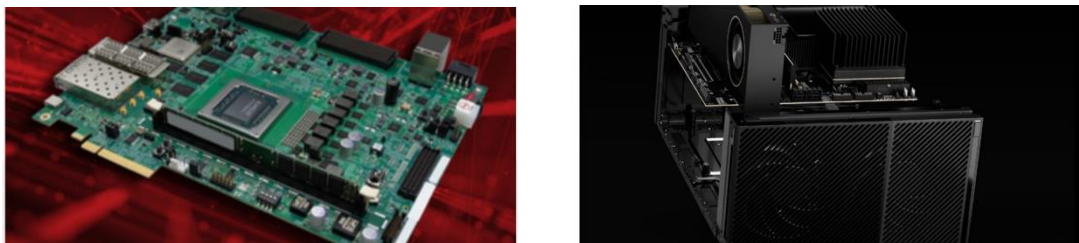
Initial sPHENIX model comparison

Model	with track radius estimation			without track radius estimation		
	# Parameters	Accuracy	AUC	# Parameters	Accuracy	AUC
Set Transformer	299,266	86.40%	91.92%	298,882	72.04%	78.92%
GarNet	284,210	86.22%	91.81%	284,066	72.59%	79.61%
PN+SAGPool	780,934	86.25%	92.91%	780,678	69.22%	77.18%
BGN-ST	363,426	87.56%	93.22%	363,170	74.13%	81.81%

Experiment Dataflow



Exploring hardware architectures for streaming AI acceleration



Related Work

Kvapil et al., “Intelligent experiments through real-time AI,” PoS ICHEP2024 (2025) 1033 [arXiv:2501.04845] — FPGA/hls4ml real-time AI for sPHENIX & EIC, the deployment foundation this proposal extends to sensor-level background suppression.