Front-end neural network filtering implemented in a silicon pixel detector

CPAD Workshop
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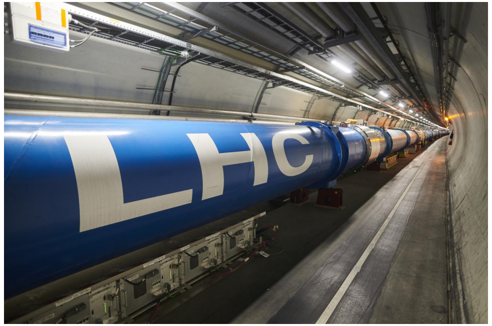
Motivation

- LHC upgrade requires technologies to deal with an increase in luminosity, pileup, & data, in a high radiation-environment
- LHC pp collisions occur at 40MHz, are selected by a trigger to read out events ~ 1MHz
- Currently, events with new physics only in the pixel data are not selected at all
- AI *embedded* on a chip can be used to filter data at the source, enabling data reduction AND taking advantage of pixel information to enable new physics measurements and searches

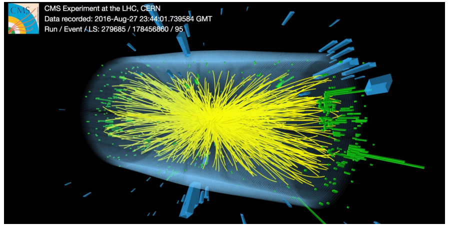


LHC Luminosity

- LHC design 10^{34} cm^{-2} s^{-1}
- LHC Runs 2/3: 2 x LHC
- HL-LHC: 5 to 7 x LHC

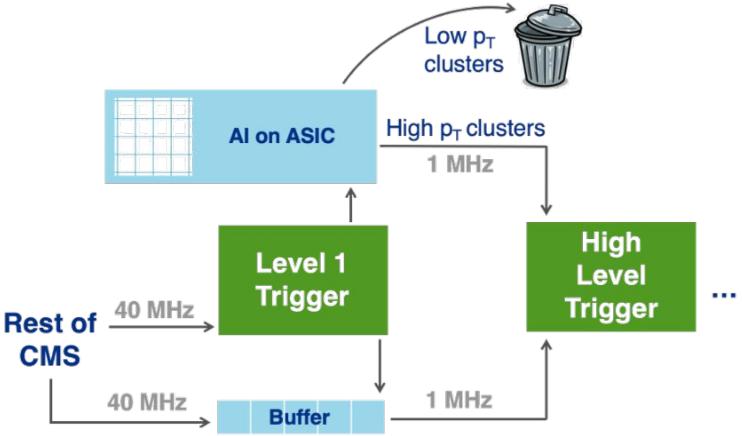
To Learn More:

- CPAD 2022: J. Dickinson, Smart pixels with data reduction at source
- CPAD 2023: B. Parpillon, Readout IC for future Phase III high luminosity upgrade of the large Hadron collider
- ICAD 2023: G. Di Guglielmo, Smart pixel sensors: towards on-sensor filtering of pixel clusters with deep learning



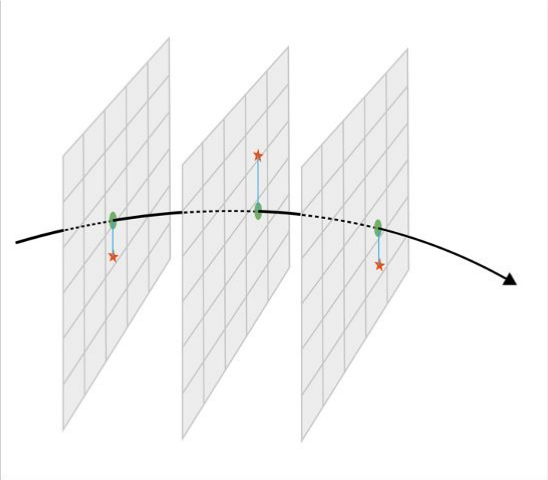
Data reduction

- Data reduction through
  - **Filtering** through removing low p_T clusters
  - **Featurization** through converting raw data to physics information
- Combination of approaches can reduce data rate enough to use pixel information at Level 1

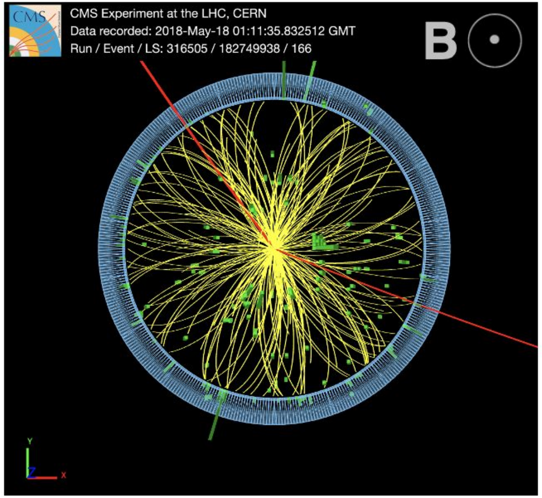


Particle tracks

- Reconstructing vertices is critical
- Connecting the dots between charge collected in different pixel layers creates a particle track
- Solenoid magnet immerses the pixel detector in a B-field, causing tracks to curve

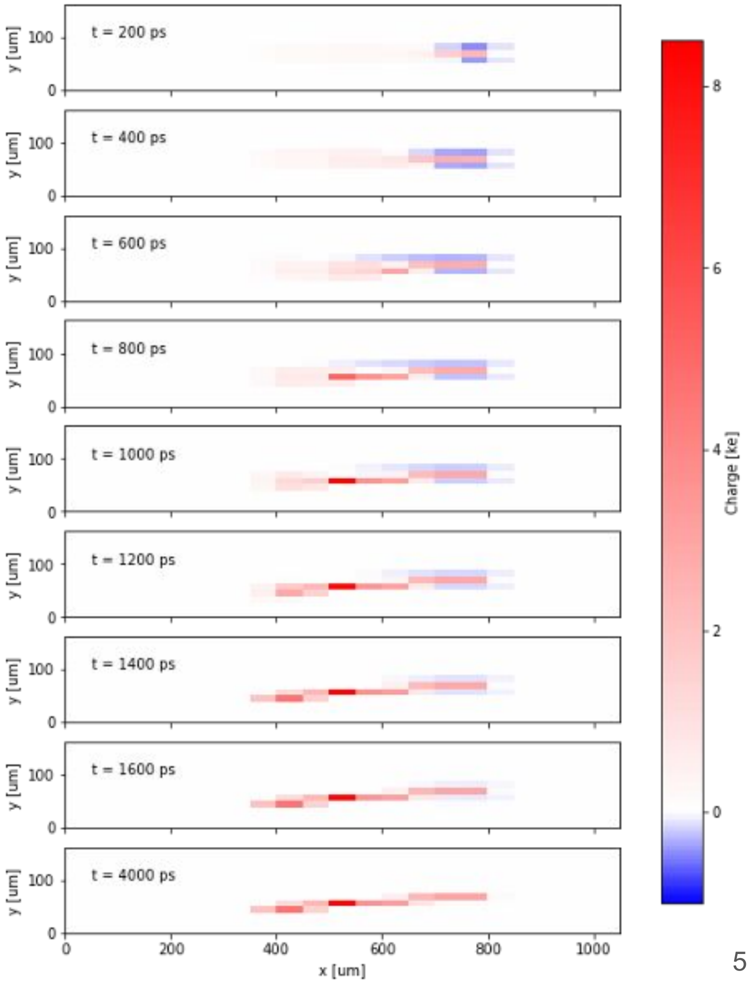


Very curved → low momentum
Almost straight → high momentum



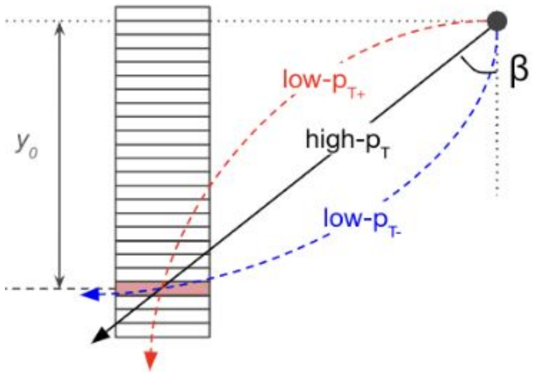
Simulated dataset (link)

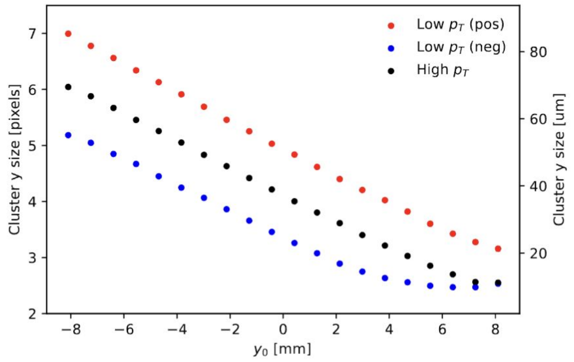
- Simulated charge deposition from pions
    - Initial conditions = fitted tracks from CMS
    - For a range of hit positions, incident angles
- Assume a futuristic pixel detector
    - 21x13 array of pixels
    - 50x12.5 µm pitch, 100 µm thickness
    - Located at radius of 30 mm
    - 3.8 T magnetic field
    - Time steps of 200 picoseconds



ML Inputs: y-position

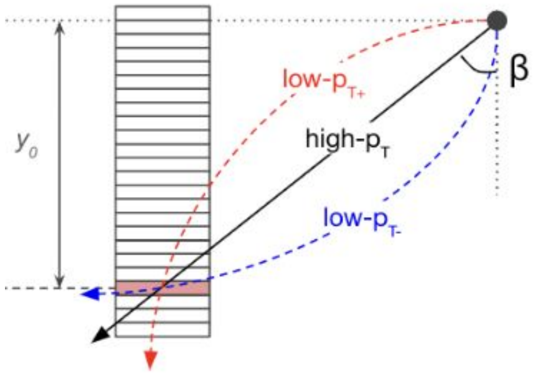
- The shape of the cluster is strongly correlated with its y-position (its azimuthal position with respect to the center of the sensor)
- Cluster y-size vs. y-position shows clear correlation between size & position
    - Decrease in cluster size from left to right is due to Lorentz drift
    - The final model chosen uses y-profile (not y-size) due to the former's better performance



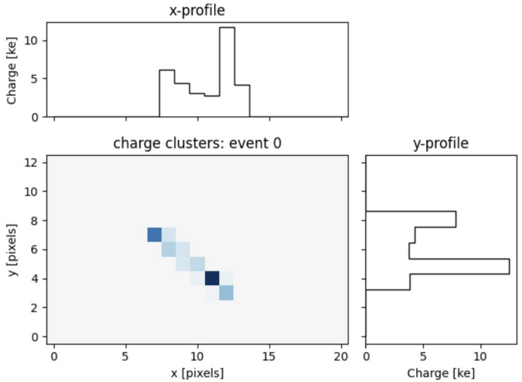


ML Inputs: y-profile

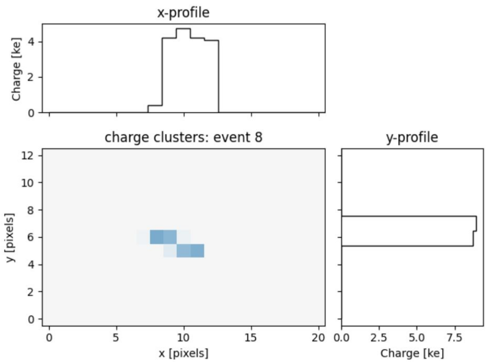
- We use ML due to complicated pulse shapes, and drift & induced currents
- y-profile (sum over pixel rows) projects the cluster shape on the y-axis and is sensitive to the incident angle β and thus the particle's p_T
- x-profile (sum over pixel columns) is parallel to B, and uncorrelated with p_T



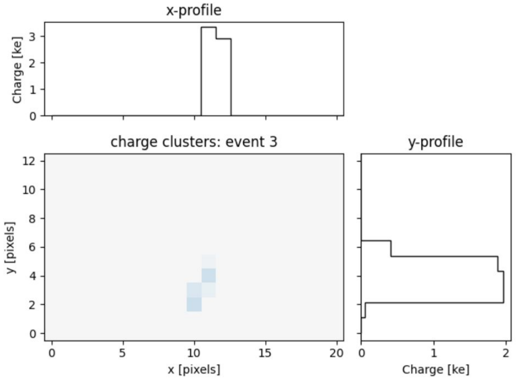
High p_T cluster



Low p_T positively charged cluster



Low p_T negatively charged cluster

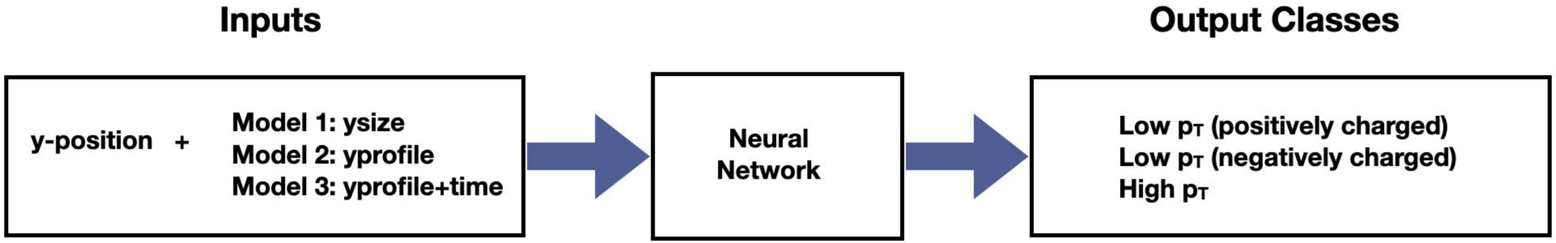


Classification Goals

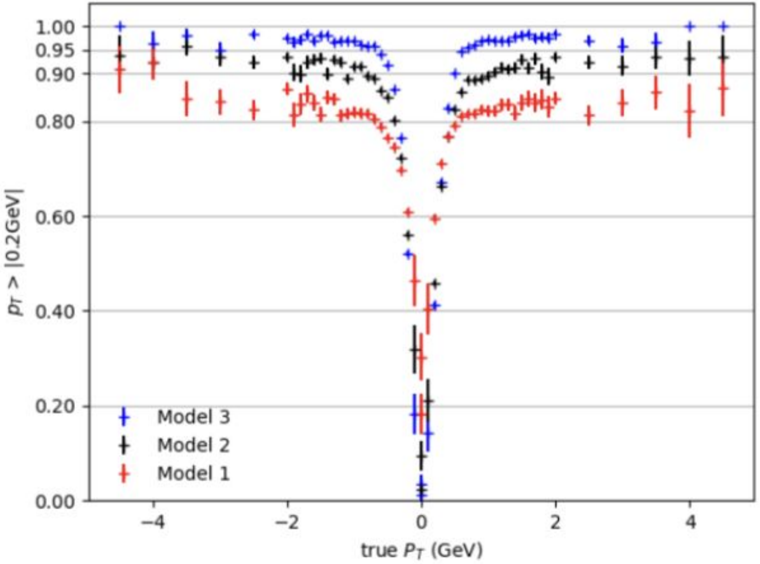
- Keep as many high p_T clusters as possible for physics
- Decrease data bandwidth

Baseline full precision model

```
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 flatten (Flatten)           (None, 14)                0

 dense (Dense)               (None, 128)               1920

 dense_1 (Dense)             (None, 3)                 387

=================================================================
Total params: 2,307
Trainable params: 2,307
Non-trainable params: 0
```



Metrics



$$Signal\ Eff. = \frac{\#\ clusters\ classified\ as\ high\ p_T}{\#\ clusters > 2\ GeV}$$

$$Bkg.\ Rej. = \frac{\#\ clusters\ classified\ as\ low\ p_T}{\#\ clusters < 2\ GeV}$$

Model	Sig. efficiency	Bkg. rejection
Model 1	84.8 %	26.6 %
Model 2	93.3 %	25.1 %
Model 3	97.6 %	21.7 %

Model 2 was chosen for implementation

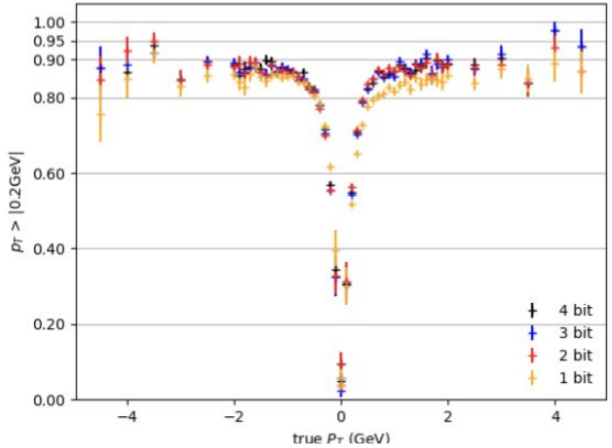
Data Reduction: Estimate 54.4% ~ 75.4%

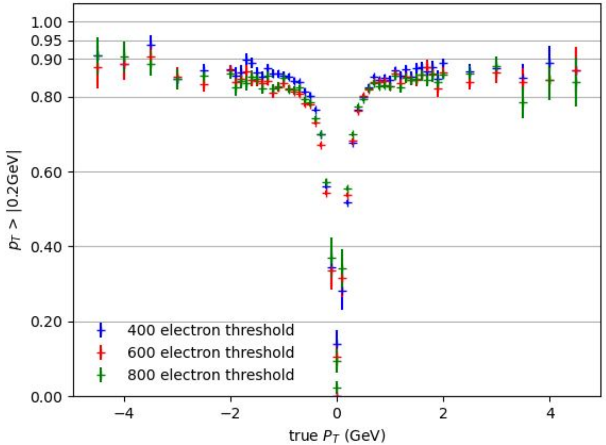
	Fraction of dataset	Rejection rate
Simulated tracks	40%	36.3%
Multi-pixel untracked	55%	61.9%
Single pixels	5%	100%

- Current detector only rejects single pixels; We can vastly improve on this!
- We reject 36.3% of simulated clusters (40% of dataset), 61.9% of multi-pixel untracked clusters (55% of dataset), and all single pixels (5% of dataset), giving a lower bound data reduction rate of 54.4%
- If we reject all untracked clusters, get an upper bound data reduction rate of 74.5%
- Since data readout is proportional to number of pixels in a cluster, if we reweight clusters by number of pixels, we reduce data by 54.4 ~ 75.4%

Model Quantization

- y-profile: 2-bit quantization chosen
- y-position quantized to 6-bit
- QKeras library for quantization-aware training
- Also, 400 e- electron threshold chosen

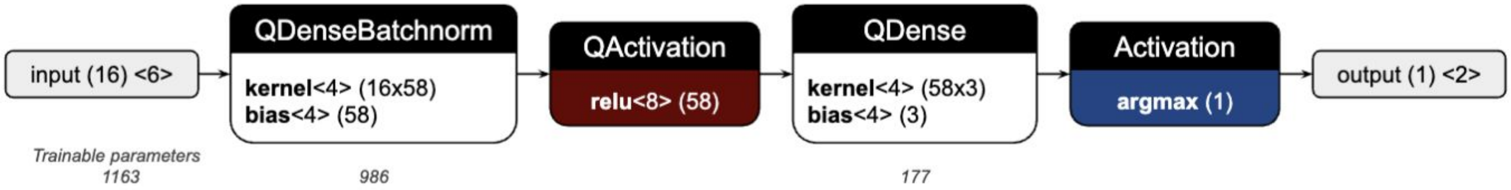




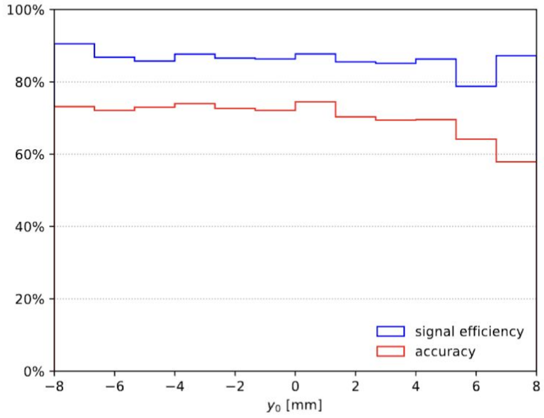
qkeras

On-chip implementation

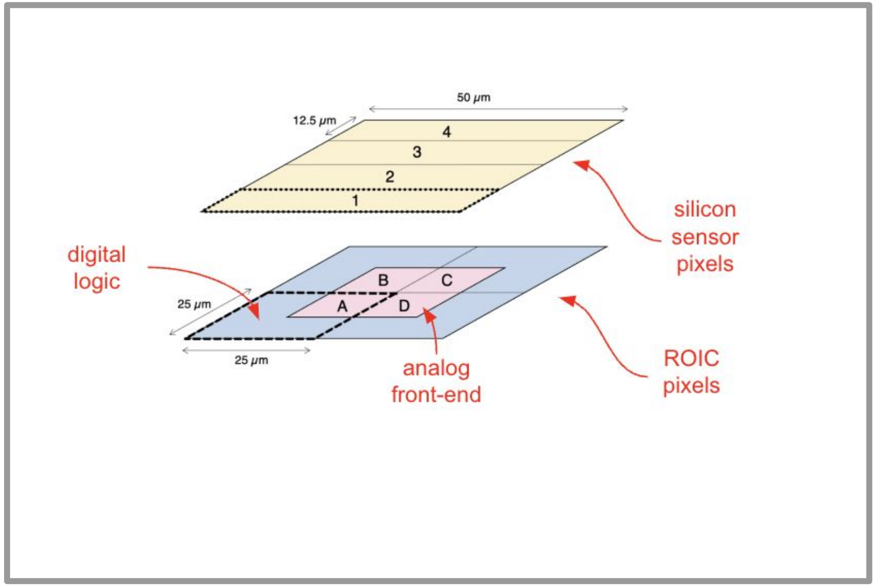
- Design space optimization

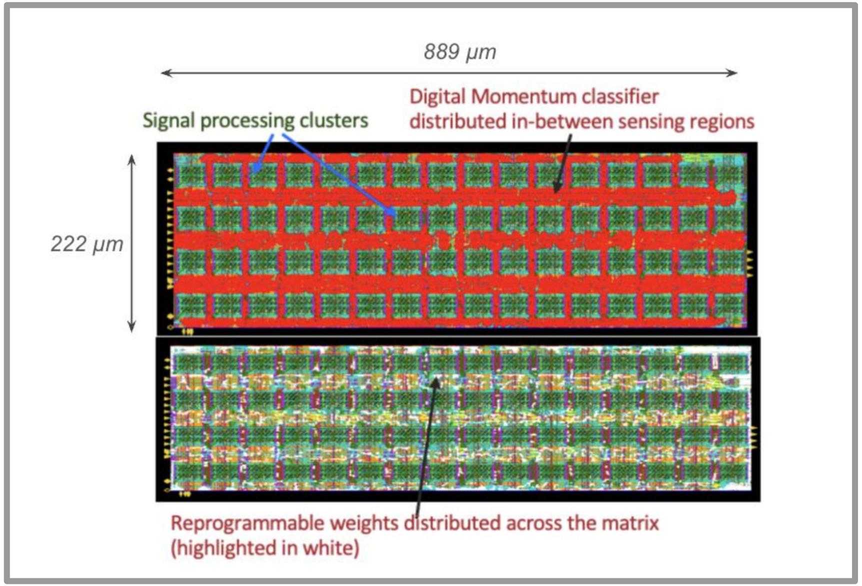


- Region specific implementation
  - 13 locally customizable (reprogrammable weights) neural networks implemented directly in the front-end
  - Reconfigurable weights so we can adapt to changing detector conditions



ROIC chip



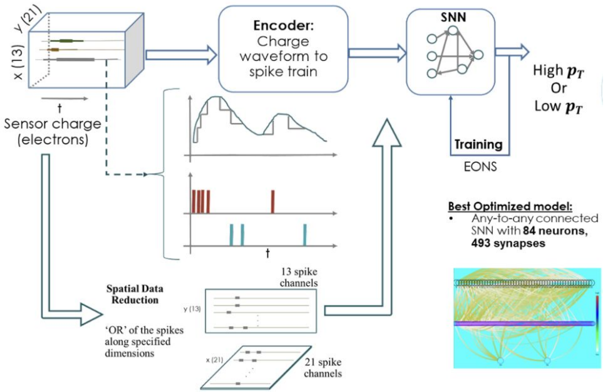


- 4 analog frontends, surrounded by a digital region
- Simulation: 13 x 21; Chip: 16 x 16

- Design expected to operate at < 300 µW
- Area < 0.2mm^2

Future Directions

- Hardware implementation
  - Tapeout expected by the end of this year
  - CPAD talk : Benjamin Parpillon: [Readout IC for future Phase III high luminosity upgrade of the large Hadron collider]
- Ongoing work
  - Studies on untracked clusters
  - Neuromorphic Approach with SNN
  - Regression studies: Train an algorithm to extract properties (positions, angles, and errors); expect further 5x improvement in data reduction!
  - Applications to other colliders (we're holding a workshop this Dec. Contact us for more info.!)
- Eventually enable improved AI performance through the ability to share data across layers (e.g., use photonic links)
- For more info!
  - Check out our preprint: https://arxiv.org/abs/2310.02474



Fig, by Shruti R. Kulkarni

Shruti R. Kulkarni et. al., On-Sensor Data Filtering using Neuromorphic Computing for High Energy Physics Experiments, ICONS '23: Proceedings of the 2023 International Conference on Neuromorphic Systems, Aug. 2023. https://dl.acm.org/doi/10.1145/3589737.3605976