



Machine Learning Processing of BNL AC-LGAD Sensors Readout with Signal Sharing

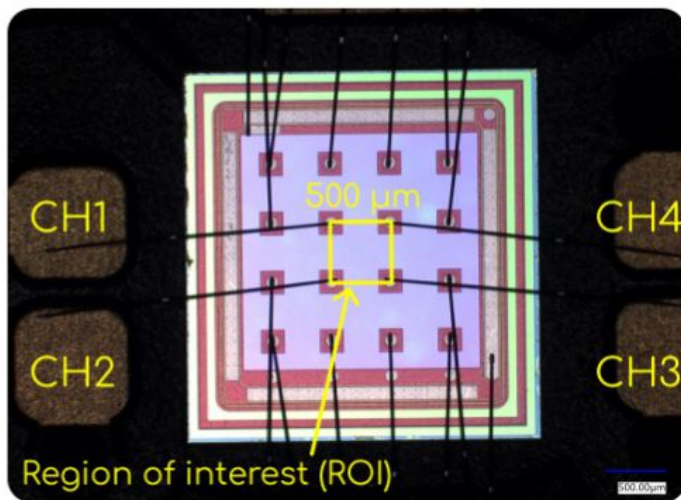
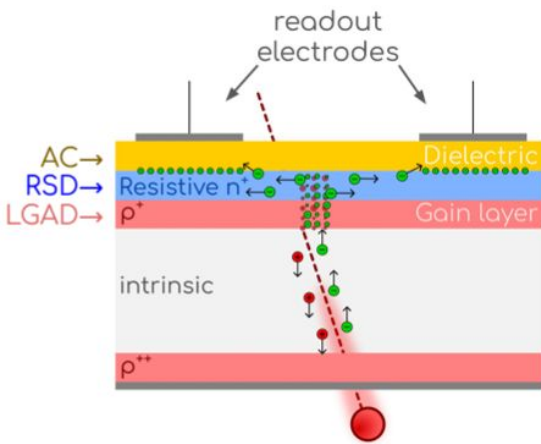
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Introduction and Overview

Goal: Accurate and precise prediction of charged particle hit coordinates using machine-learning methods taking AC-LGAD waveforms as inputs

- Unique exploit is charge sharing between electrodes \rightarrow improved spatial resolution
- Limited ROI for study utilizing four electrodes $\rightarrow 570 \mu\text{m} \times 570 \mu\text{m}$



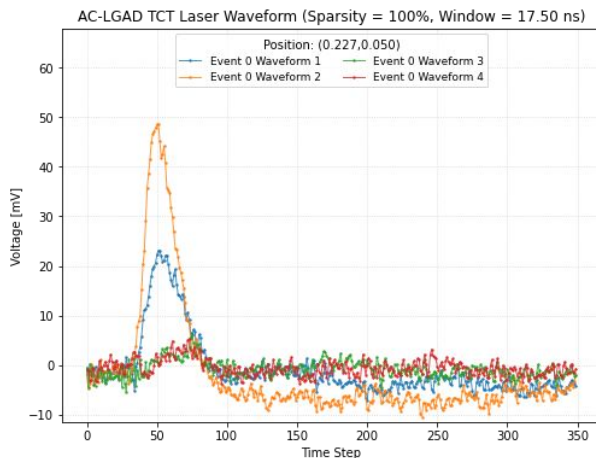
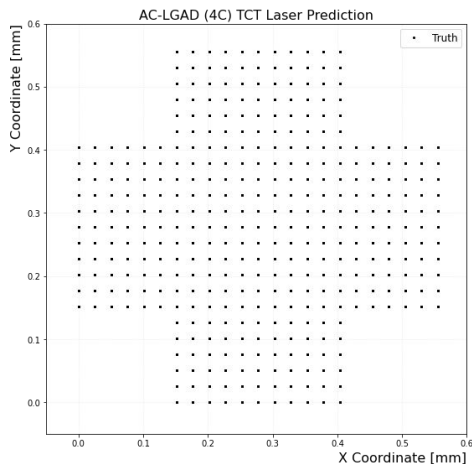
Specifications:

- Manufactured at BNL
- Active thickness: $30 \mu\text{m}$
- Pad size: $200 \mu\text{m}$
- Pitch: $500 \mu\text{m}$

Using TCT laser to extract waveforms (without Landau fluctuations)

- TCT waveform dataset collected by Dr. Matias Senger from UZH
- Two available intensities (through attenuation) → “high” and “low”
- 385 grid positions with $25 \times 25 \mu\text{m}^2$ spacing and 111 events per position

Charge sharing exemplified in waveform shape → correlated to hit-to-pad proximity



Specifications:

- 1064 nm laser
- Laser spot Gaussian with $\sigma \sim 9 \mu\text{m}$
- $\sim 1 \mu\text{m}$ spatial resolution
- Laser intensity match 1 MIP
- Two pulses separated by 100 ns

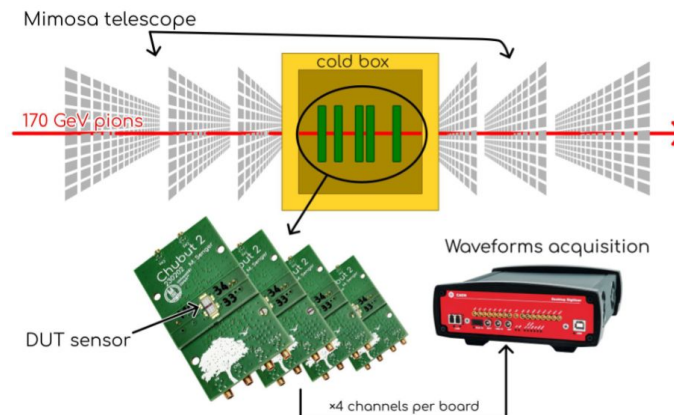
Summary of Previous Studies with Test Beam

Dr. Senger previously studied a DNN trained on “higher-level” waveform information

- Using relative amplitudes
- Best TCT median MSE achieved $\sim 20 \mu\text{m}$
- Comparison to analytic charge sharing methods

CERN H6 test beam with $O(100)$ MeV pions \rightarrow “AIDAInnova”

- Mimosa telescope
- Chubut 2, 4 channels readout board
- CAEN DT5742 digitizer, 500 MHz @ 5 GS/s
- Cold box ($-12 \text{ }^\circ\text{C}$) for irradiated DUTs



| Method | TCT | Test Beam |
|----------------------------------|-----------------------|-----------------------|
| Analytic Peak Relative Amplitude | $\sim 25 \mu\text{m}$ | $\sim 50 \mu\text{m}$ |
| DNN Peak Relative Amplitude | $\sim 20 \mu\text{m}$ | $\sim 44 \mu\text{m}$ |



Proof of Concept with Recurrent Neural Networks



Pre-processing of waveforms to remove noise and keep “interesting” portions around peak

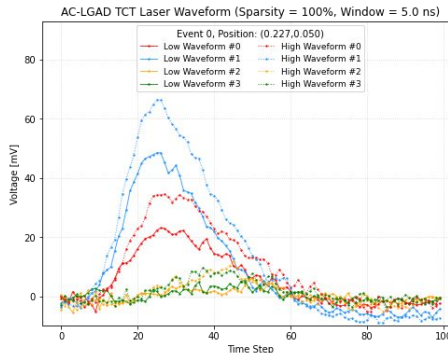
- 100 time steps for each (4) waveform
- Train on both high and low intensity waveforms

Long Short-Term Memory (LSTM) layer # weights scales with series length

- Fewer weights desirable for future application (latency, memory usage)

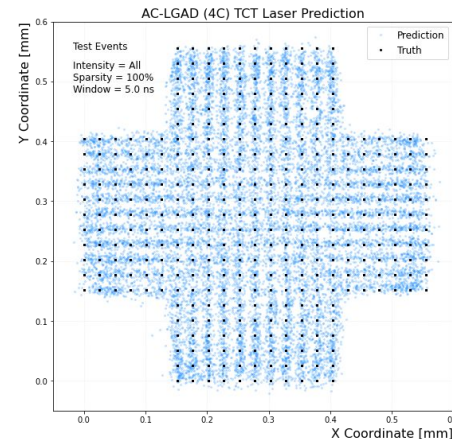
Model architecture “lightly” tuned to have fewer weights → training regulators included

- Converges ~150 epochs with Adam(0.001)
- Batch size \approx # grid points → 2^9 (512)

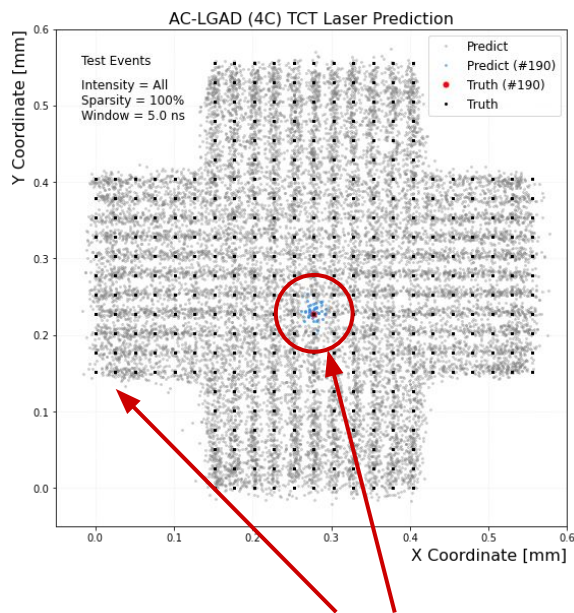


Fixed input series length

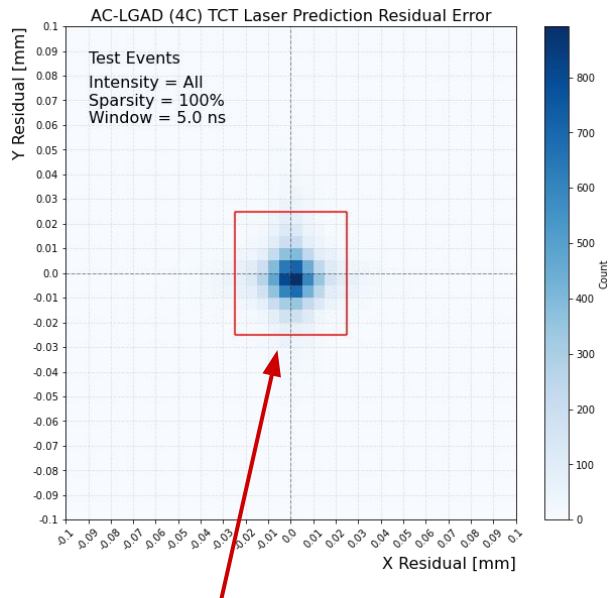
| Layer (type) | Output Shape | Param # |
|-------------------------------------|------------------|---------|
| input_1 (InputLayer) | [(None, 4, 100)] | 0 |
| lstm (LSTM) | (None, 32) | 17024 |
| dense (Dense) | (None, 32) | 1056 |
| dense_1 (Dense) | (None, 32) | 1056 |
| dense_2 (Dense) | (None, 32) | 1056 |
| dense_3 (Dense) | (None, 2) | 66 |
| ----- | | |
| Total params: 20258 (79.13 KB) | | |
| Trainable params: 20258 (79.13 KB) | | |
| Non-trainable params: 0 (0.00 Byte) | | |



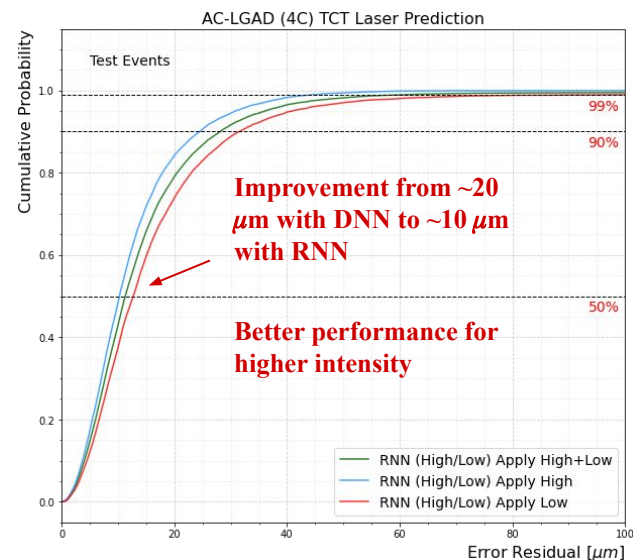
Metrics for Performance



Central regions perform better than the edges



Accurate and precise enough to distinguish two grid points



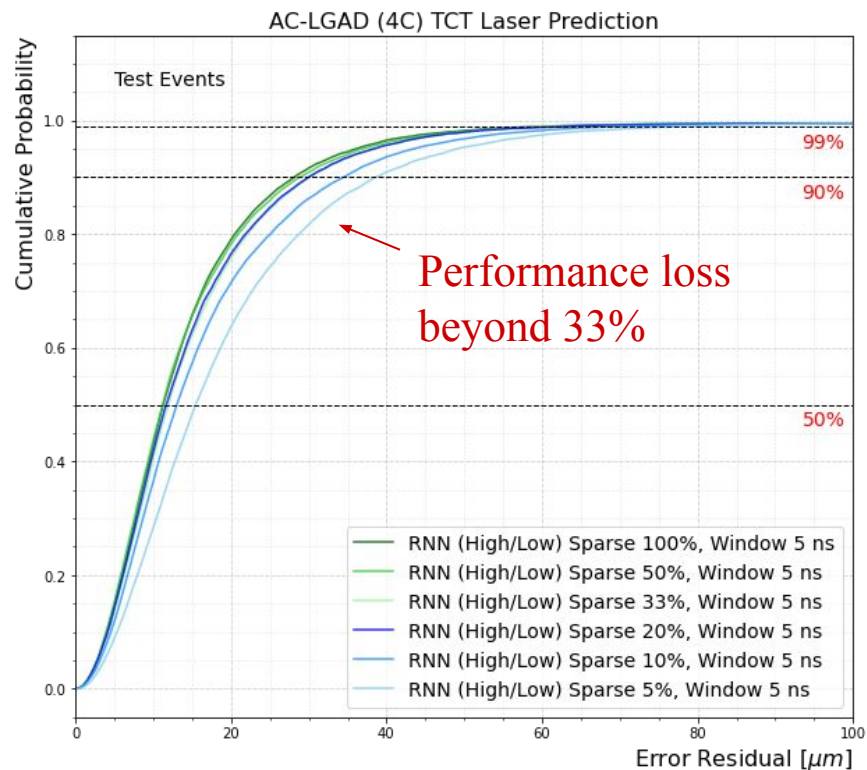
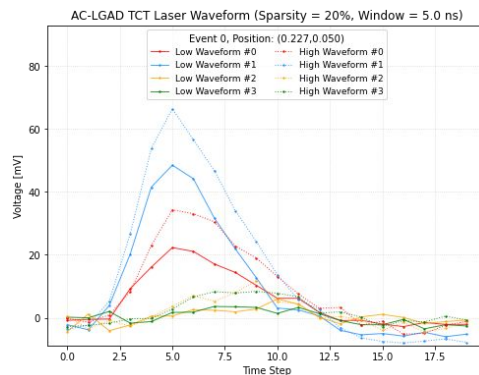
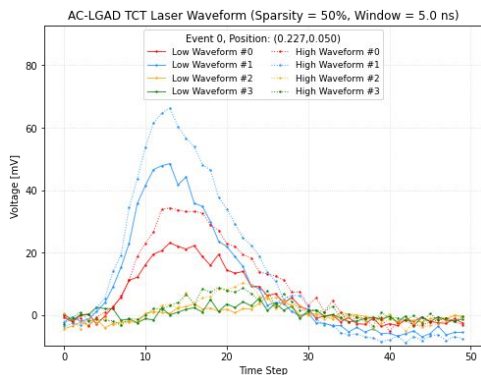
Quantitative metric to compare various methods

Waveform Rasterization Studies

Main parameter of optimization is amount of information necessary to keep from waveforms

- Benefits having fewer LSTM weights

Rasterize the waveform input at a few thresholds of 100/50/33/20/10/5%



Comparison to Analytic Methods

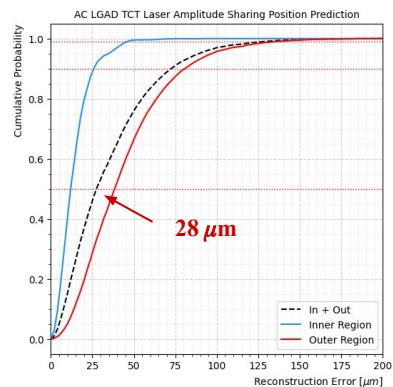
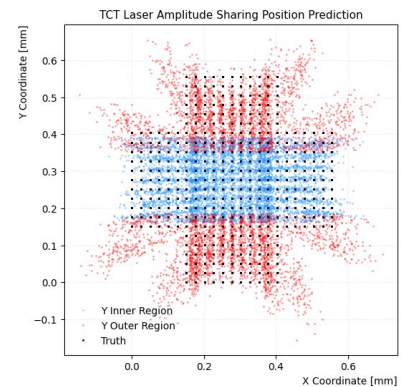
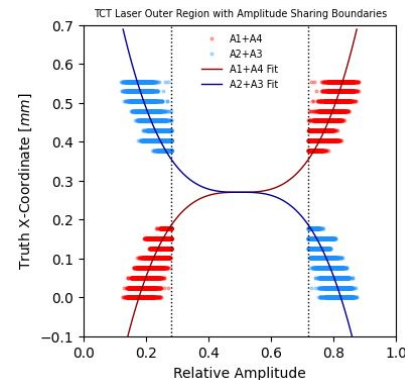
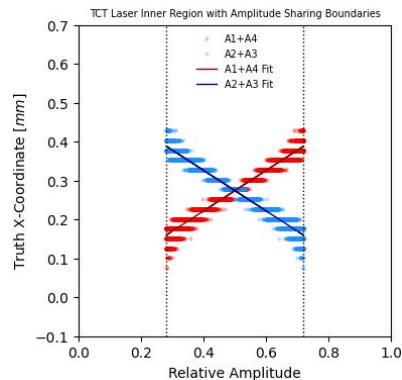
Traditional approach of estimating hit position with strip sensors and charge sharing uses *only* the waveform peak value

- 1-dimensional problem with linear regression using relative amplitudes

For 2D grid, higher-order (3rd) regression required in “outer” region

- Define regions by relative amplitudes

Inner region predictions expectedly accurate but outer regions (majority) very inaccurate





Summary and Outlook



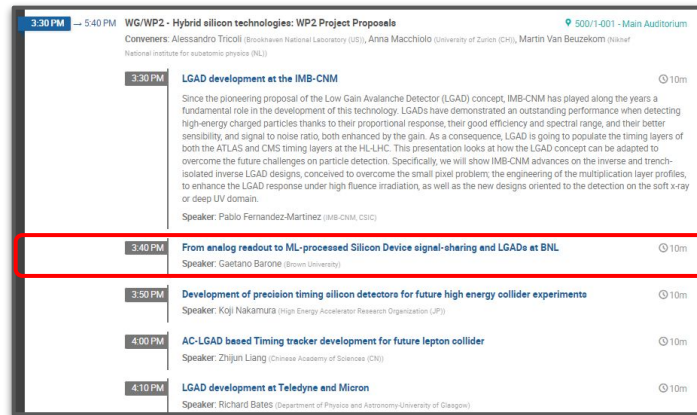
Improved hit reconstruction with RNN using “full” waveform at median MSE $\sim 10 \mu\text{m}$

- Peak amplitude with DNN $\sim 20 \mu\text{m}$
- Peak amplitude analytic method $\sim 25 \mu\text{m}$
- Projected improved performance with test beam

Performance maintained at 33% rasterization and spatial interpolation achievable (not shown)

Future and ongoing work:

- Expanding beyond 4 channels
- Test beam and incorporating Landau noise
- HLS conversion and application on FPGA



Join Gaetano Barone's talk this afternoon for a deeper discussion regarding the “bigger” picture and more technical hardware details

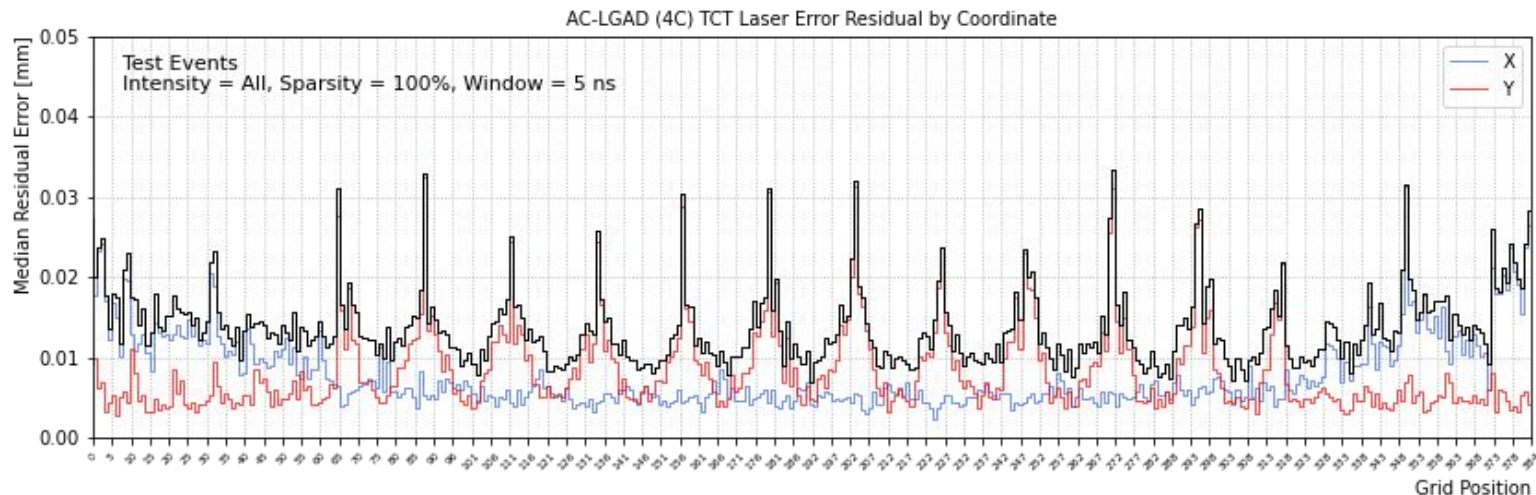


Thank you for your attention—Questions?

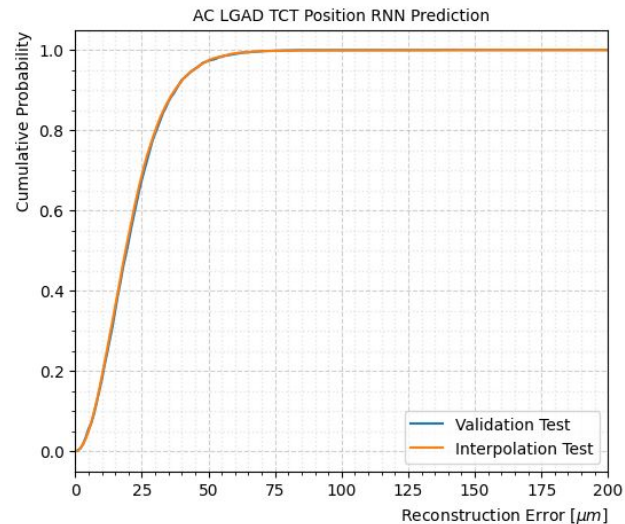
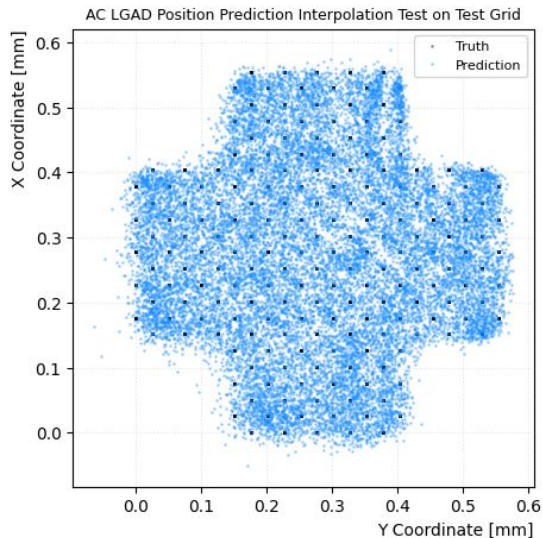
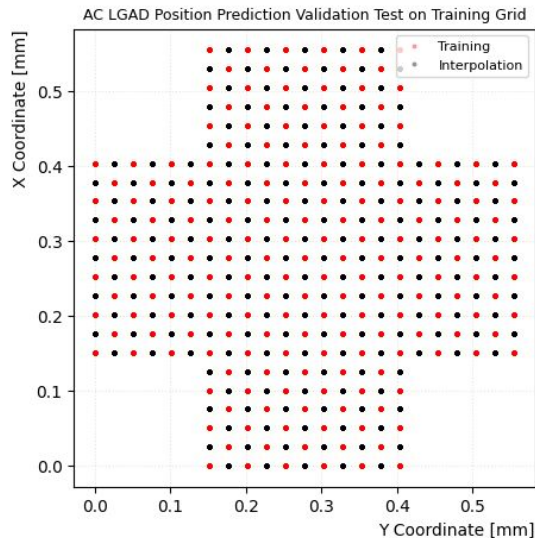


Backup Slides

Characterization of RNN Prediction

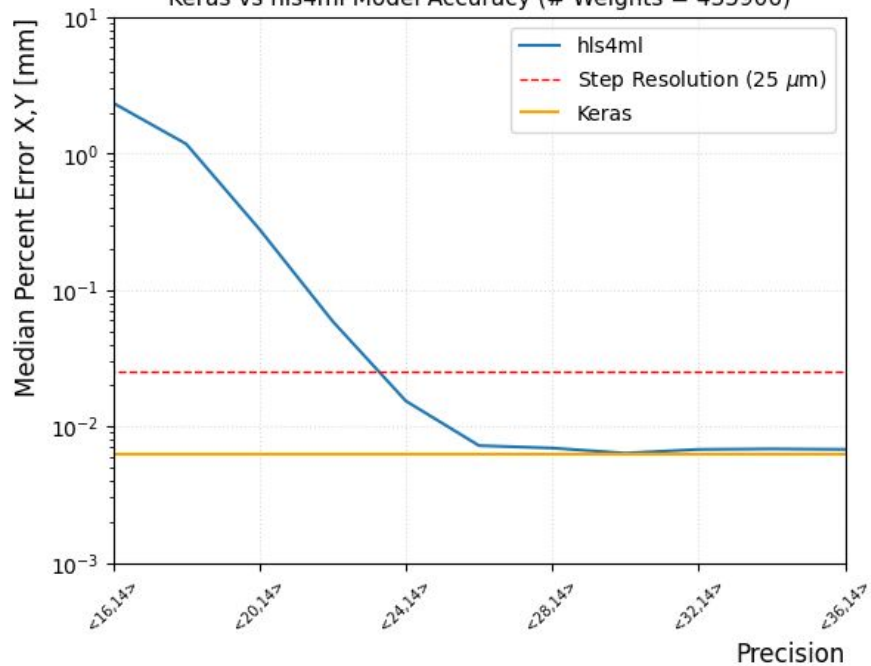


Interpolation Studies

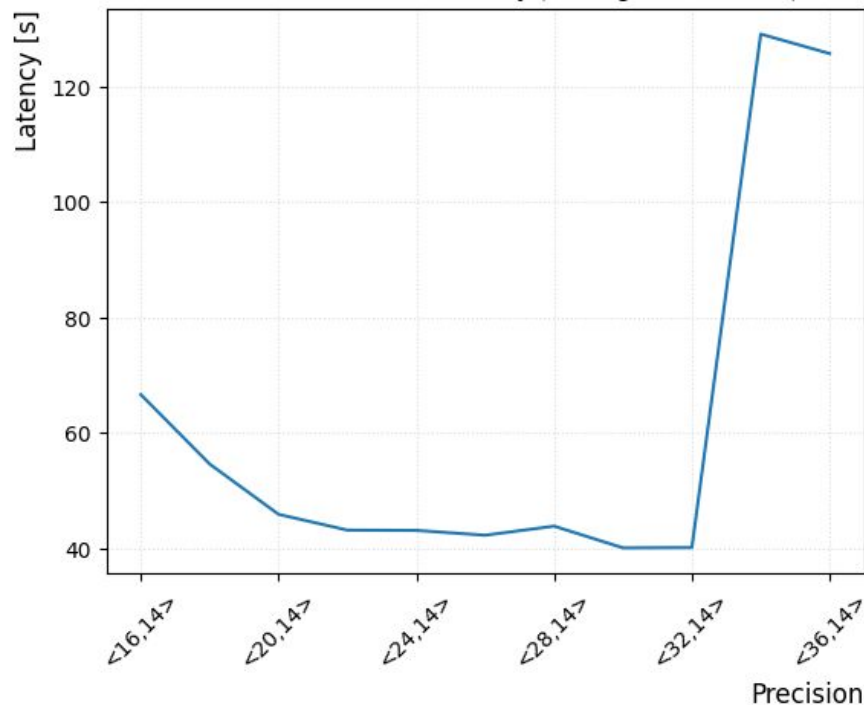


The network is trained to interpolate within a $25 \mu\text{m}$ step size \rightarrow can target finer levels of precision with closer grid spacing

Keras vs hls4ml Model Accuracy (# Weights = 435906)



Keras vs hls4ml Model Latency (# Weights = 435906)



hls4ml Keras Conversion

