Machine Learning Processing and Compression of Signal Shared AC-LGADs

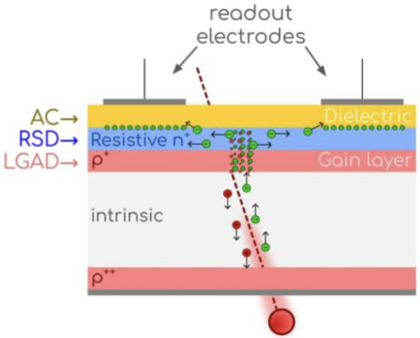
Diaolo Boye[2], Gabriele Giacomini[2], Vagelis Gkougkousis[4], Rohan Kher[1], Daniel Li[3], Matias Senger[4], **Samantha Sunnarborg[1]**, Jessica Tang[1], Alessandro Tricoli[2], Don Wong[1], Gaetano Barone[1]

Brown University[1], Brookhaven National Lab[2], Northwestern University[3], University of Zurich[4]

Introduction to ML with AC-LGADs

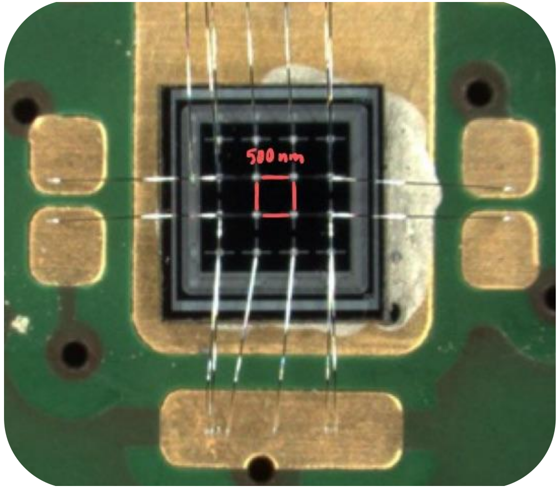
Goal: better leverage the spatial resolution of AC-LGADs with ML techniques extracting maximum information from full waveforms while allowing for compression of information

- Exploit charge sharing to accomplish spatial resolution
- Analytical methods are computationally challenging
- ML offers a regularized approach



BNL AC-LGAD Specs

- 4 readout channels
- Pitch: 500μm
- Pad Size: 200μm
- Active Thickness: 30μm



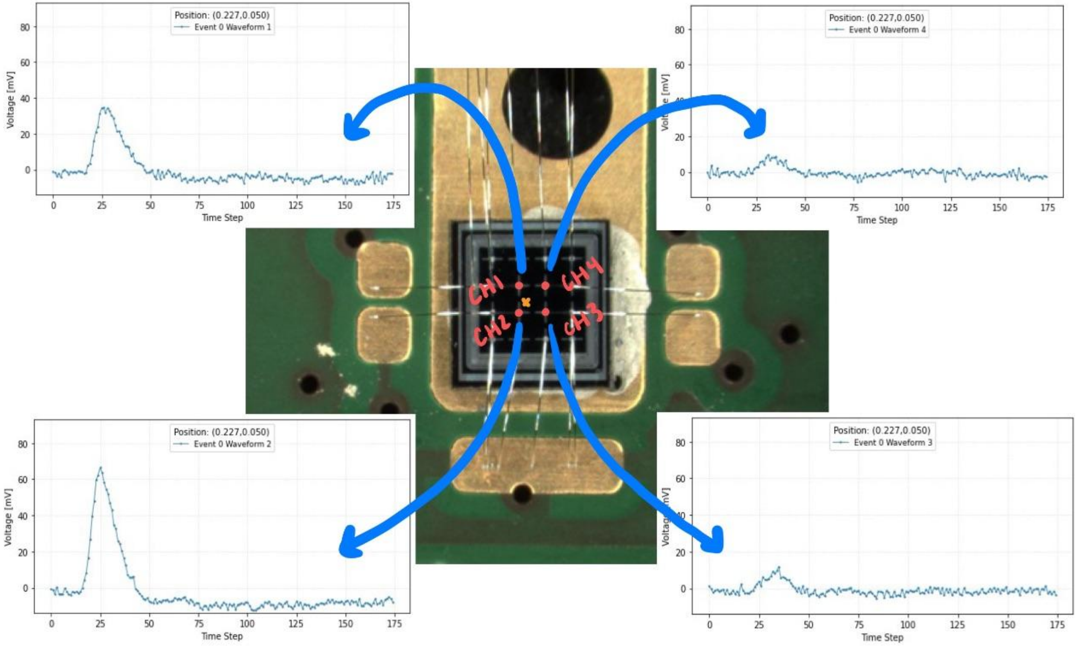
Methods and Techniques

Data collected using laser or test beam setups

Hit position inference error MSE

Techniques-

- Amplitude Matrix Inversion
  - MSE ~25µm (analytic)
- ML with Amplitudes
  - MSE ~20µm (DNN)
- **ML with Waveforms**

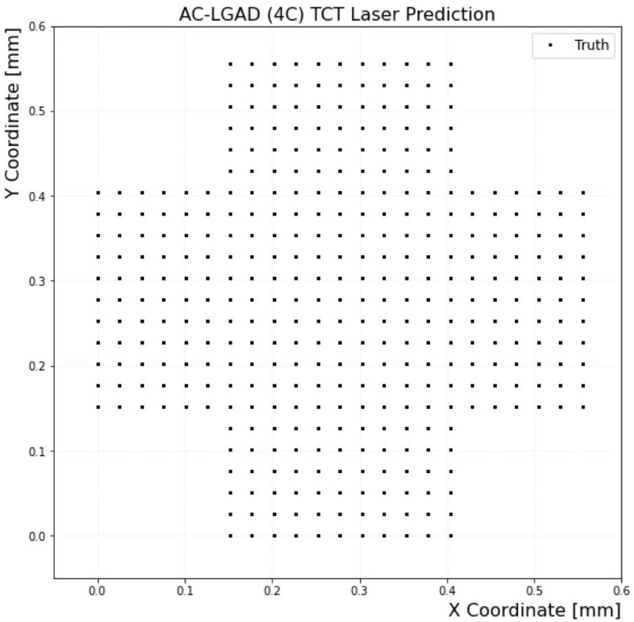


Transient Current Technique

TCT laser is utilized to collect waveforms with a well determined hit position

Specifications:

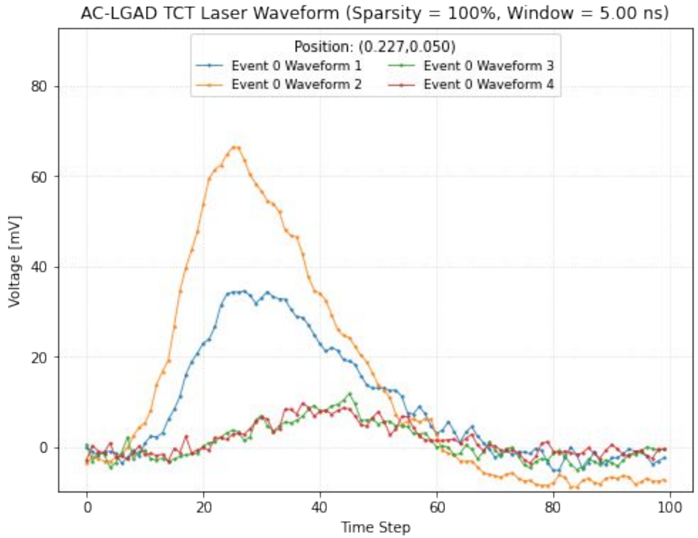
- 1064nm laser
- Laser intensity to roughly match one MIP
- Gaussian laser spot σ ~ 9μm
- Spatial resolution ~ 1μm
- 385 grid positions, 25μm x 25μm spacing

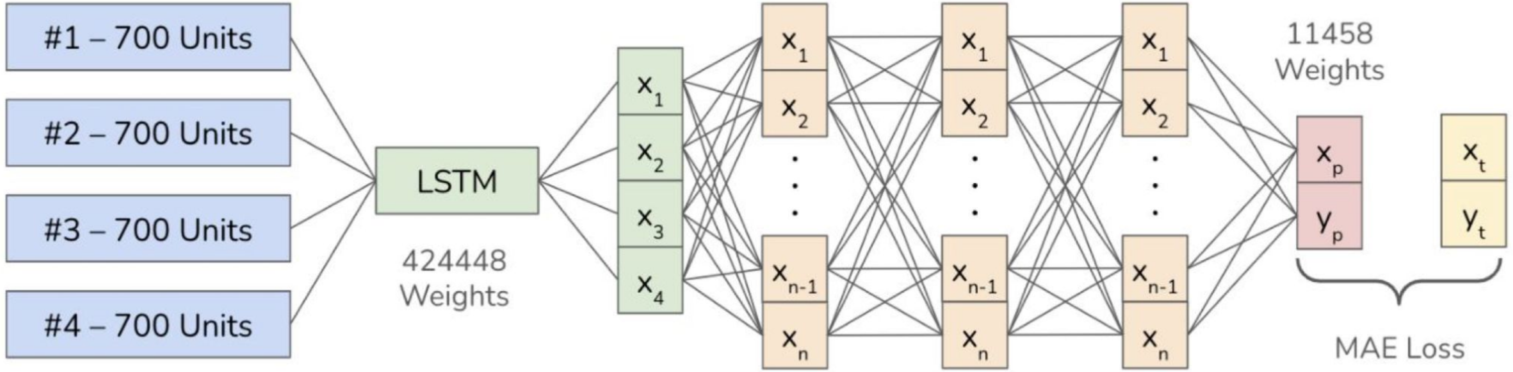


TCT ML Analysis

Recurrent Neural Network with four waveforms as input per event

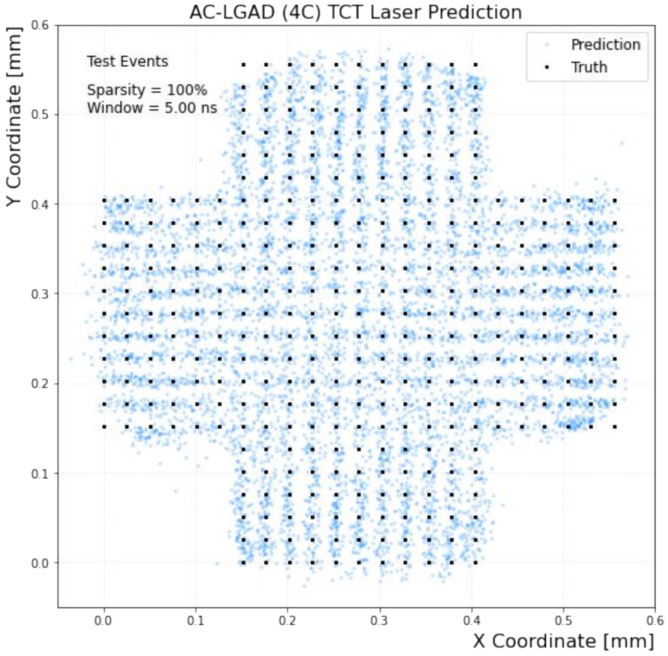
Allows the network to learn from small variations to enhance amplitude and timing information

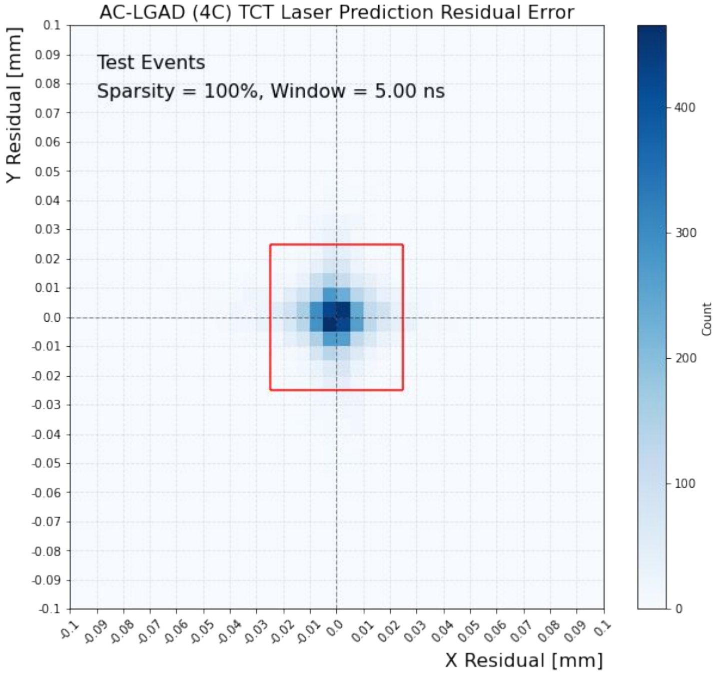




TCT ML Results

Roughly 33k events, 100 voltages in a window of 5ns





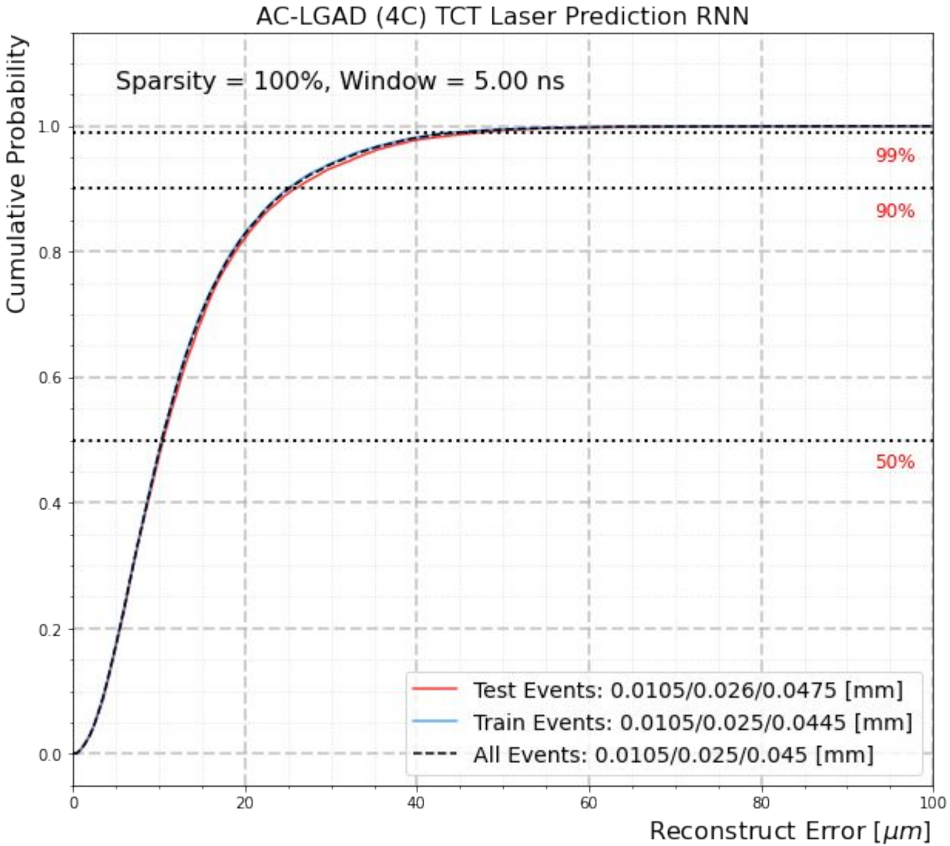
TCT ML Results

Achieved ~10μm mean reconstruction error

Great improvement from other TCT analysis methods

- amplitude ML ~20μm
- analytic methods ~25μm

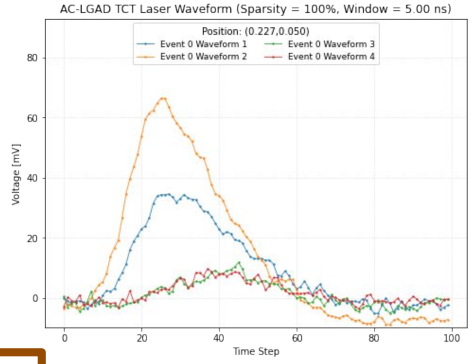
Prediction is precise enough to distinguish between grid points

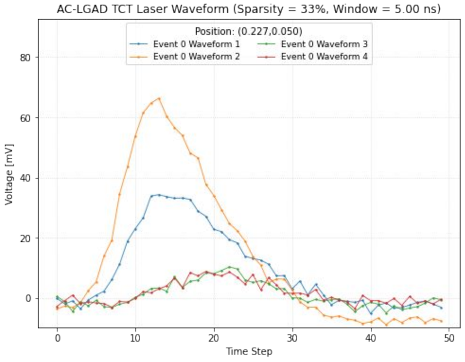


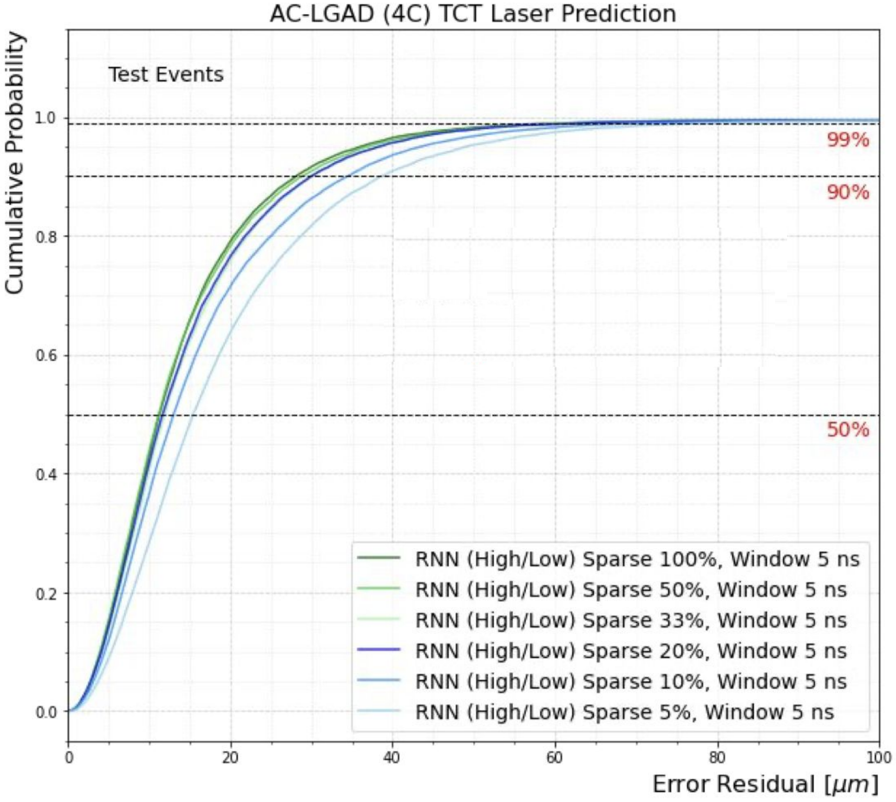
TCT Utilizing Sparsity

Sparsity utilized to lower number of computations per waveform

Performance maintained above sparsity of 33%



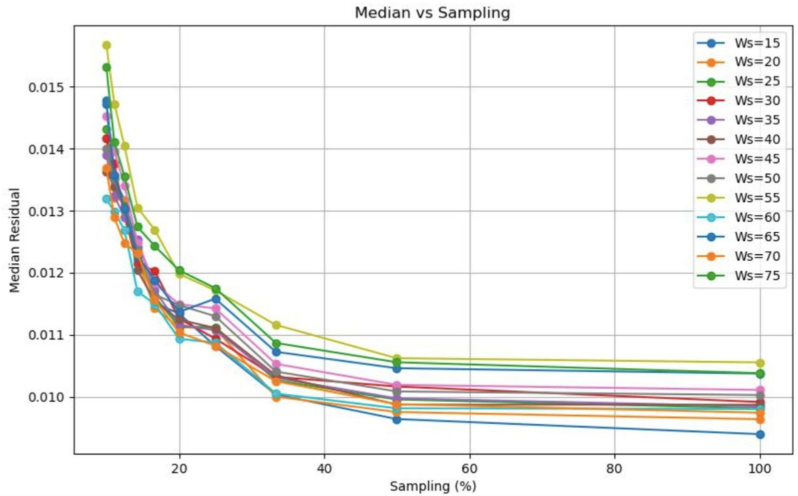


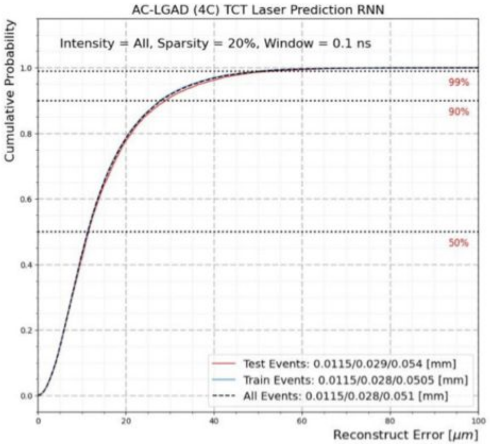


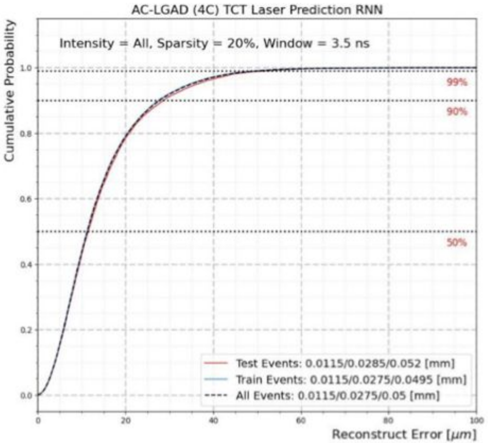
TCT Window Size

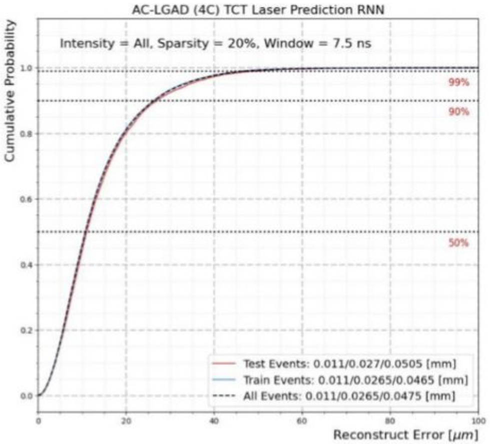
Window size has very small effect on position MSE

All window sizes diverge below 20%









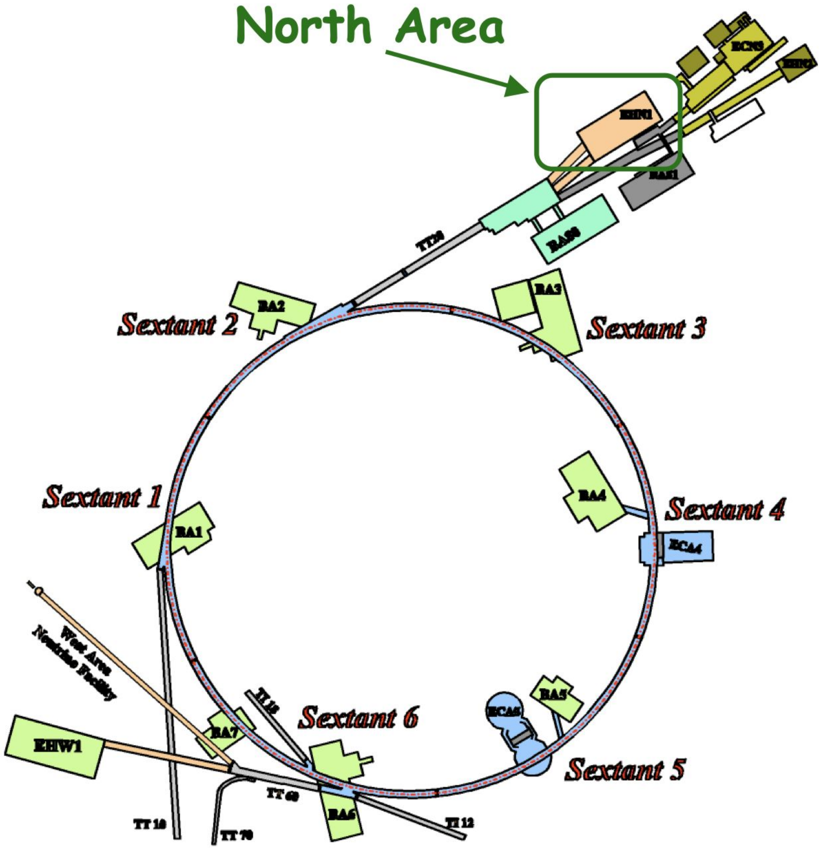
CERN H6 Test Beam

H6 120 GeV pion beam allows for collection of waveforms from MIPs including Landau fluctuations

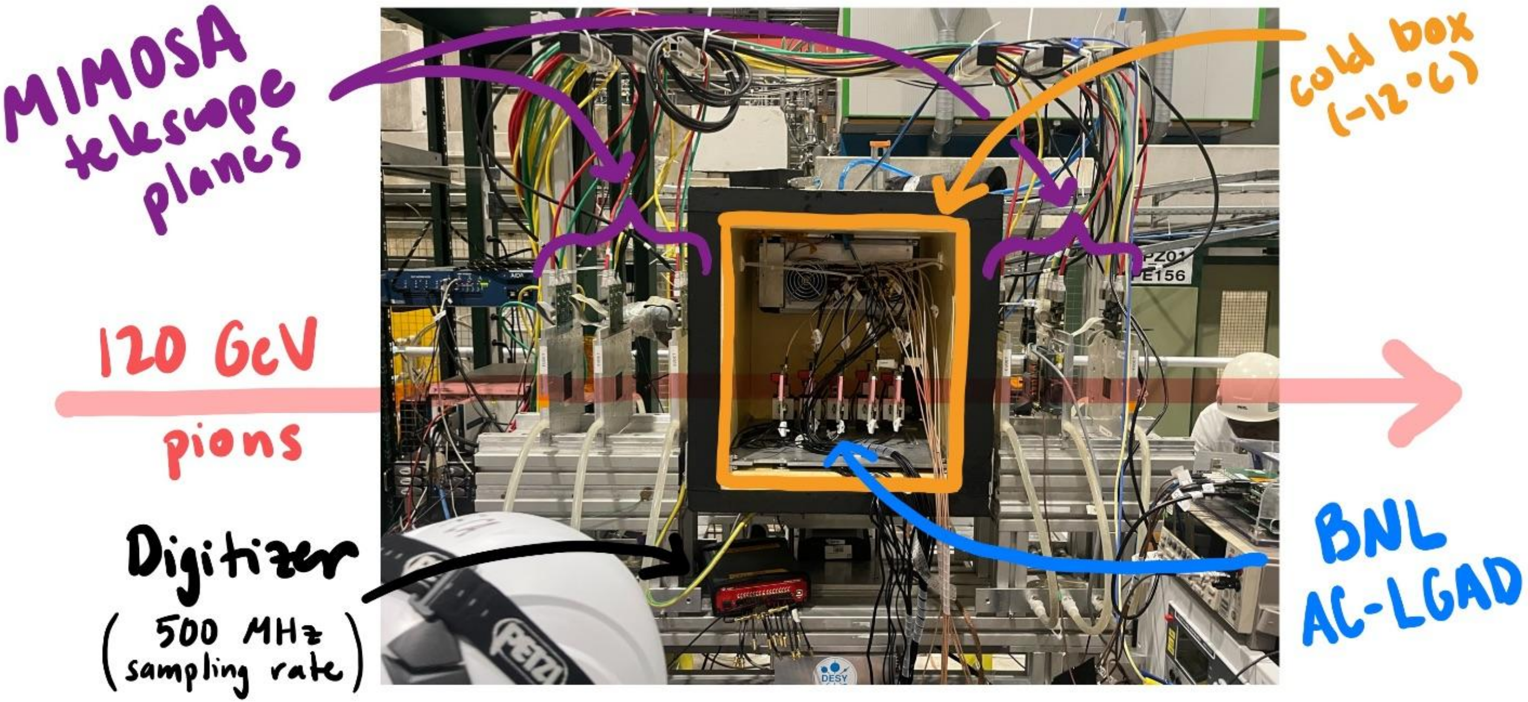
Previous studies:

- MSE ~45μm for DNN with fractional amplitudes

Data collected alongside UZH and BNL collaborators in June 2025



CERN H6 Test Beam Setup



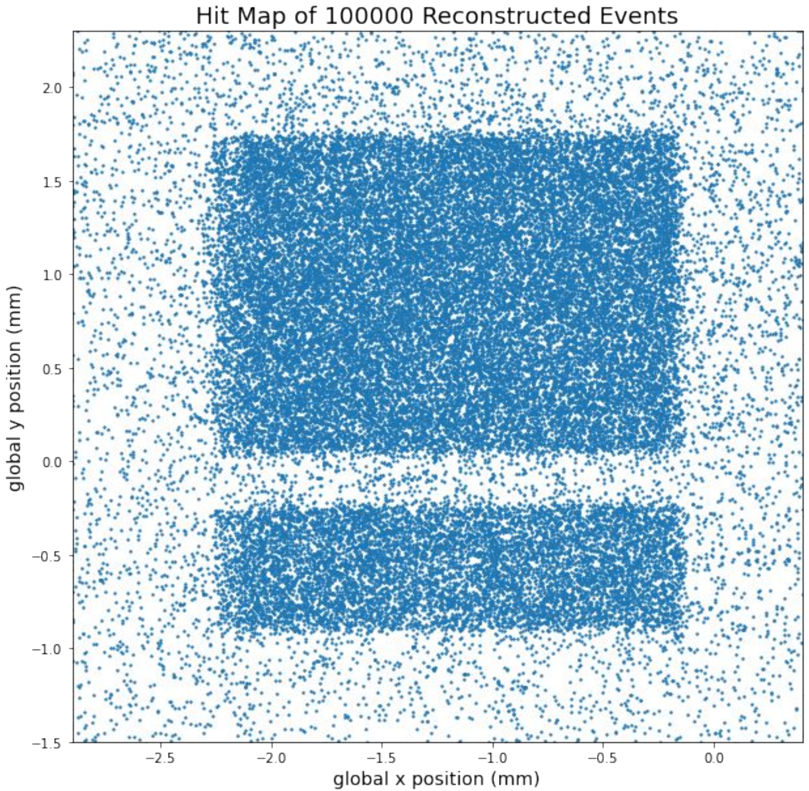
Test Beam Data Extraction

AC-LGAD hit positions are reconstructed using corryvreckan

A custom pipeline was created using TreeWriterDUT module

- Creates clusters on DUT plane to read hit position
- Alternative to using generalized reconstructed tracks

Incorrect CROC mask was used causing gap in hit positions

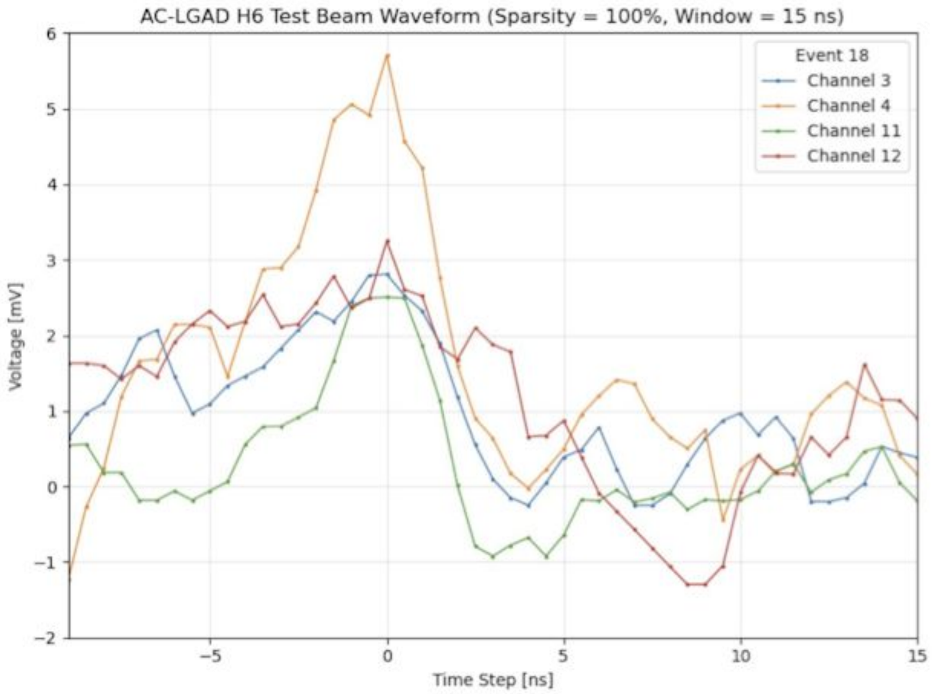


Test Beam Data Extraction

Waveforms are extracted from the oscilloscope for all DUTs upon trigger

Low efficiency and signal-to-noise ratio due to being under biased at 120V

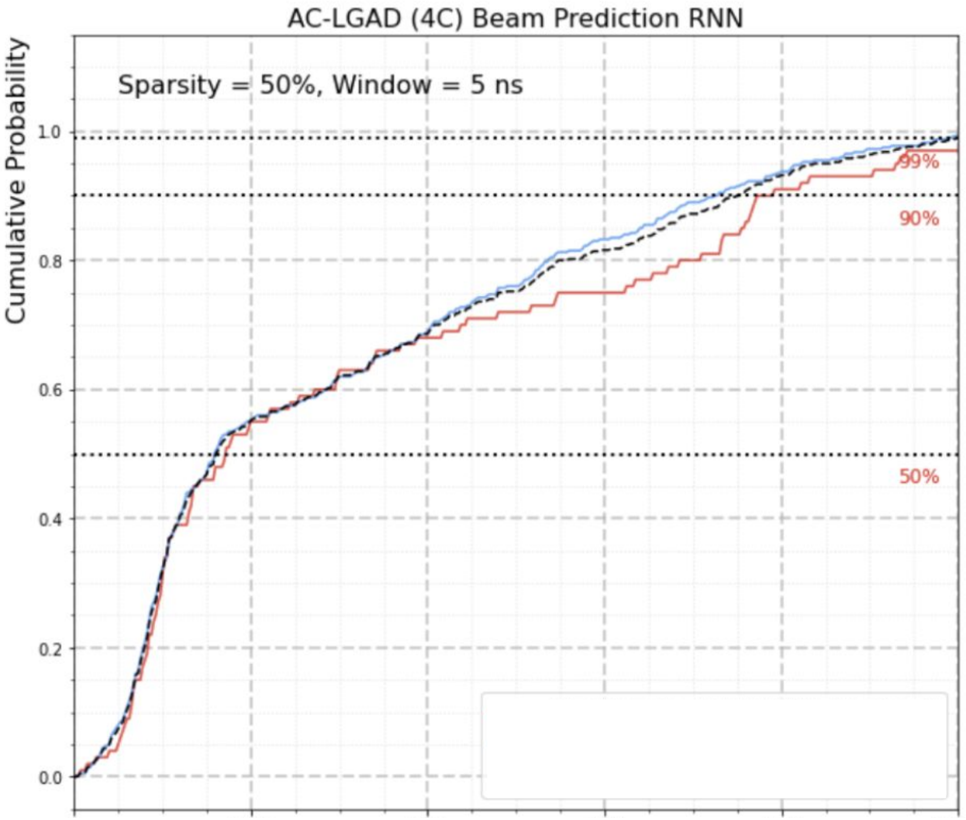
No default waveform-event association, requires further work



Preliminary RNN Results

Preliminary results using full TB waveforms on ~6k events

Proof of concept but requires a higher number of cleaner events



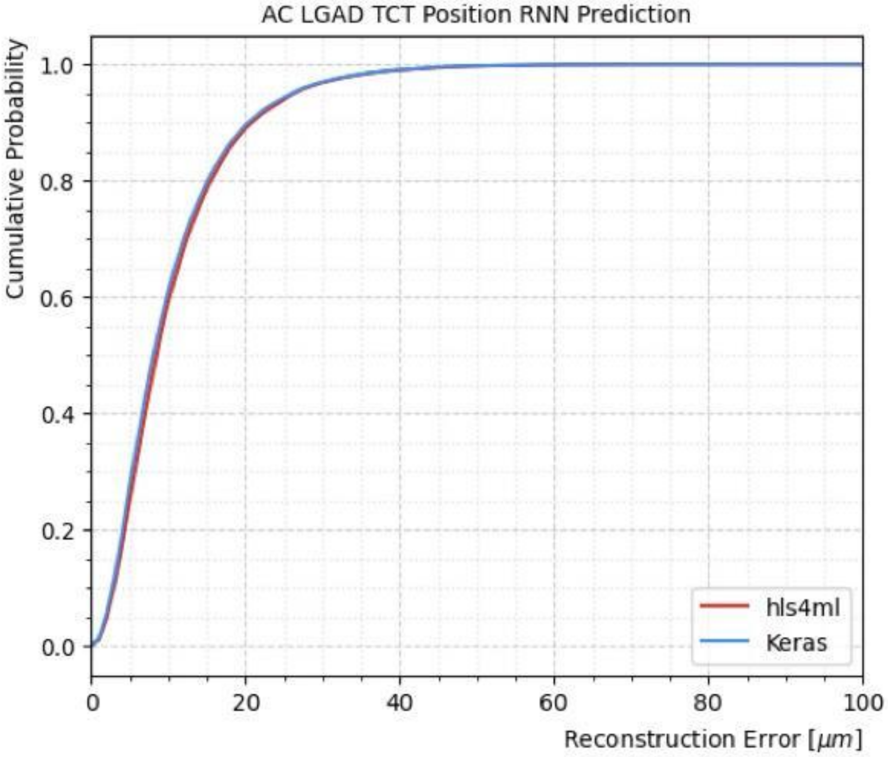
Ongoing Studies

Beginnings of implementation of models on electronics

Shown performance is maintained when compressed from a keras model to hls4ml to be deployed on FPGA

Preliminary studies on latency

Overall a proof of concept that requires further studies and development



Ongoing Studies

RNN architecture to be improved by expanding LSTM layer and laser as added input in TB data training

Same 4 channel AC-LGAD will be take part it another TB next week to provide more data with correct CROC mask and higher and varying bias voltages

Additional TCT data at bias voltages [60V, 120V] is been collected at UZH allowing for retraining on more data with voltage as variable

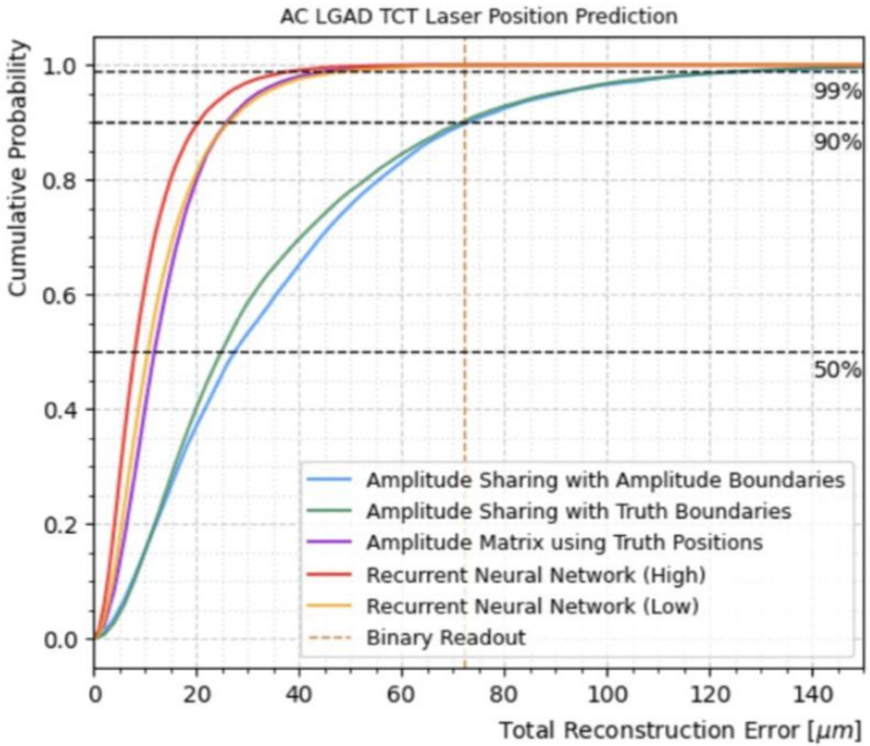
Investigation of variable geometries (widths, pad orientation, channel number)

Expanding our framework to improving timing performance

Conclusion and Outlook

Machine learning techniques (DNN or RNN) have been shown to improve spatial resolution of AC-LGADs with lower computational costs and compression of data to predicted hit positions. Our group has extended this work to extract maximal information from full waveforms.

Work is ongoing to improve and expand this architecture

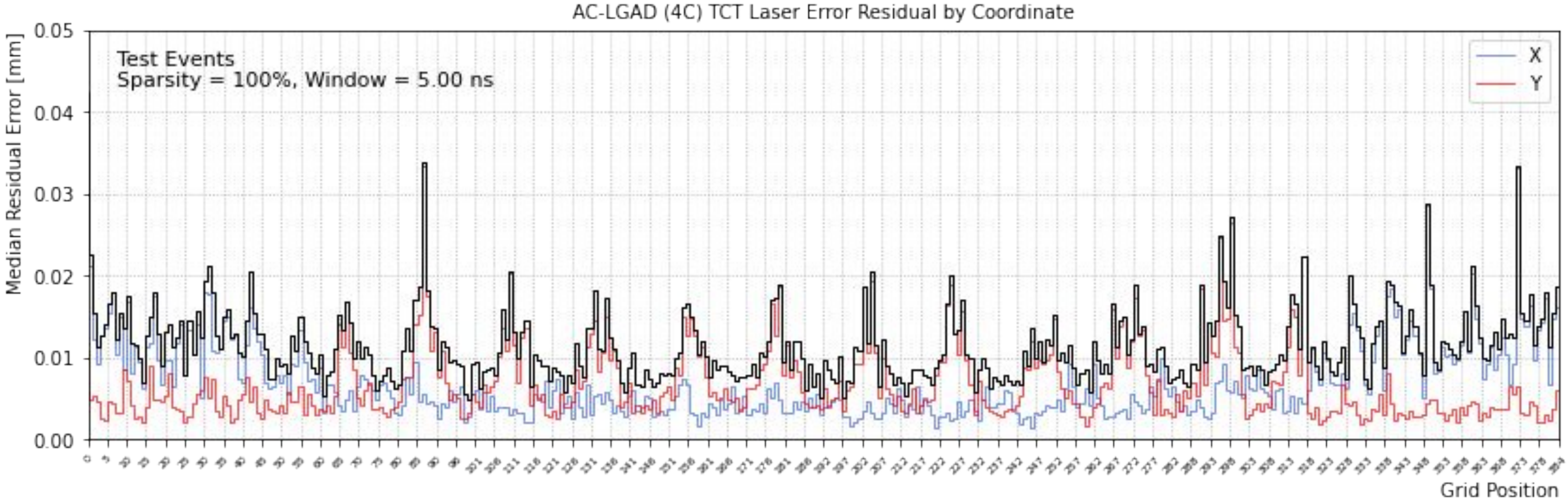


Previous Talks- [Don Wong Sept ‘25](), [Jessica Tang DRD3 June ‘25](), [Daniel Li DRD3 June ‘24]()

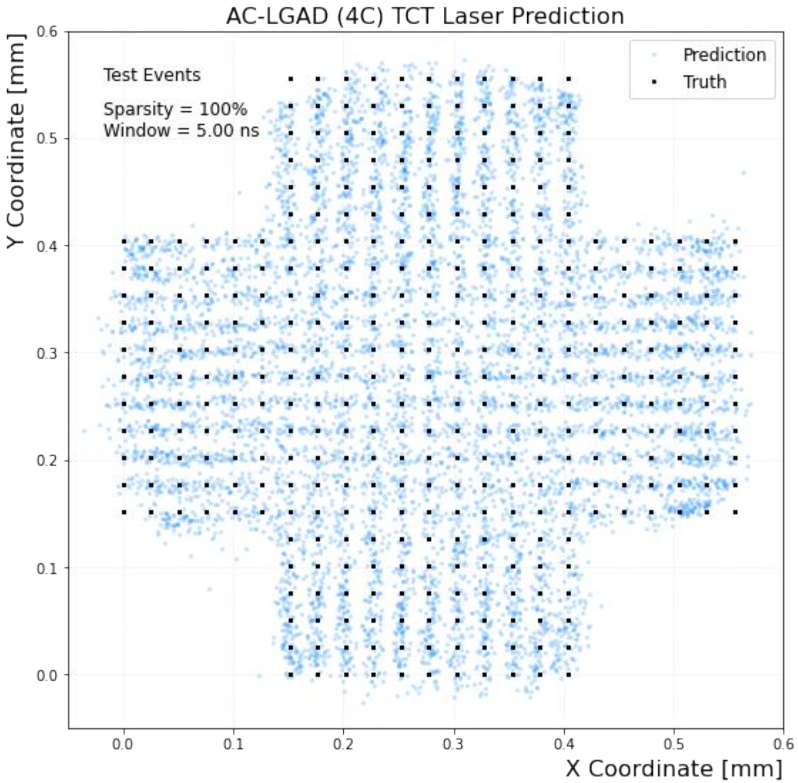
Backup Slides

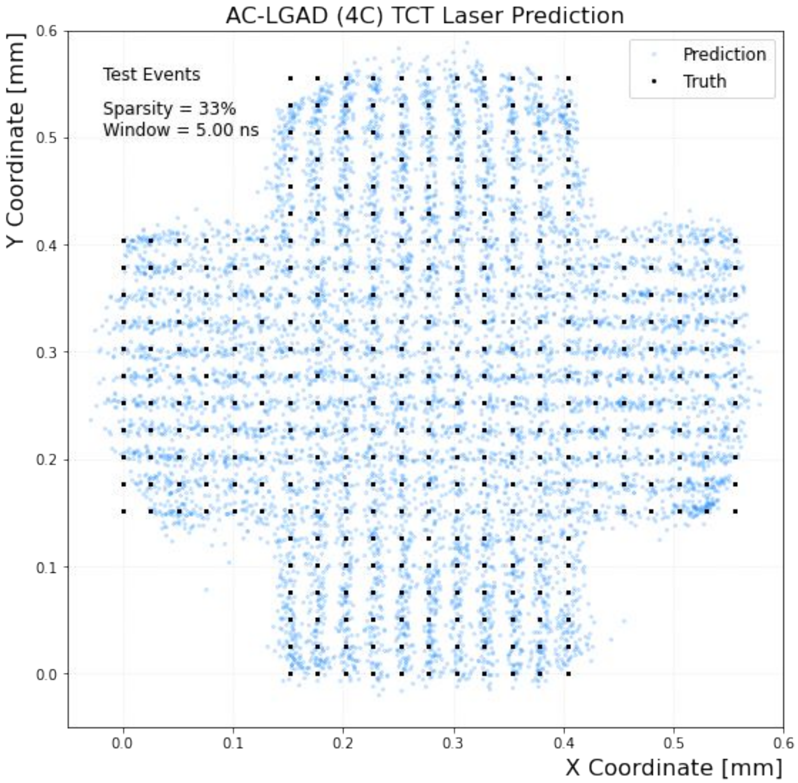
TCT ML Results

Roughly 33k events, 100 voltages in a window of 5ns



TCT Utilizing Sparsity



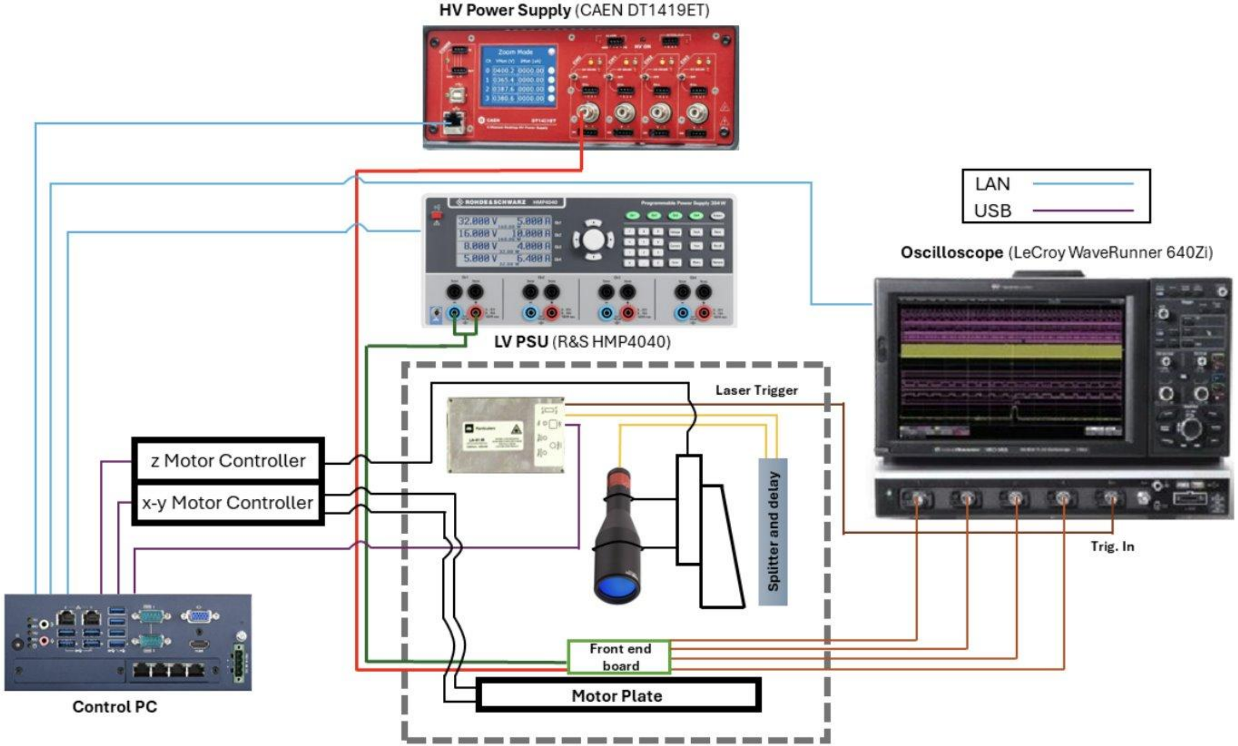


RNN Shape

Shape of the RNN for 100% sparsity 5ns waveforms (converged after ~500 epochs)

Layer (type)	Output Shape	Param #
input_layer (InputLayer)	(None, 4, 100)	0
lstm (LSTM)	(None, 8)	3,488
dense (Dense)	(None, 16)	144
dense_1 (Dense)	(None, 16)	272
dense_2 (Dense)	(None, 16)	272
dense_3 (Dense)	(None, 2)	34

TCT Setup



HV Power Supply (CAEN DT1419ET)
LAN
USB
Oscilloscope (LeCroy WaveRunner 640Zi)
LV PSU (R&S HMP4040)
Laser Trigger
z Motor Controller
x-y Motor Controller
Splitter and delay
Trig. In
Front end board
Motor Plate
Control PC

Model Latency