Using 1D-CNN for Reconstruction

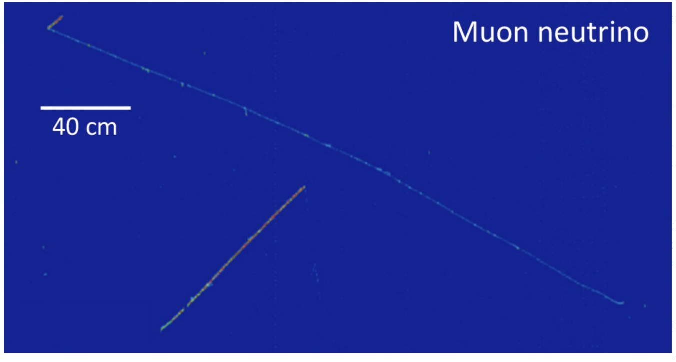
By: Gabriel Soto, SULI Intern
Supervisors: Minerba Betancourt & Bruce Howard

Overview

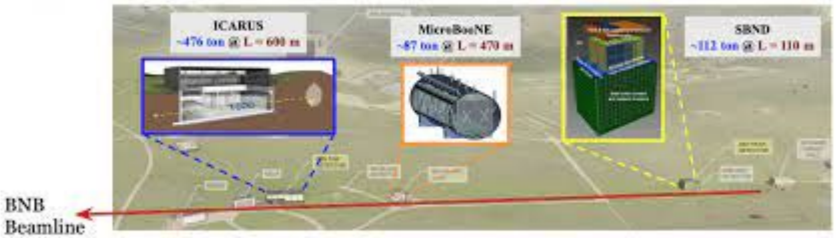
- Introduction
- List Samples
- Training using Ar39 without Coherent Noise
- Testing Model with Muons
- Testing Model with Noise
- Summary

Introduction

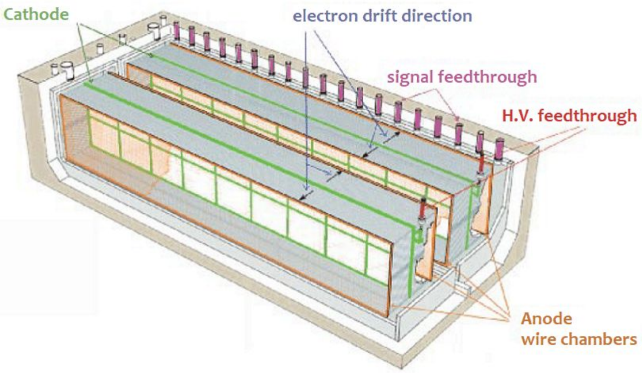
- Fermilab has a rich neutrino program, here reconstruction is used for experiments in neutrino interactions and background.
- We want to use a deep learning method called convolutional neural network (CNN) in data reconstruction for low energy particle physics.
- Using ICARUS data and Monte Carlo simulations we can train a model using CNN to do so. (Why?)
- Traditionally, the presence of signals in raw wire waveforms is based on an over threshold algorithm. CNN attempts to change this.
- Our deep learning approach (1D-CNN) uses convolution and pooling techniques in order to classify the one dimensional image input.



ICARUS Layout



- Neutrino detector.
- Uses Liquid Argon Time Projection Chambers (LArTPC).
- Filled with 760 tons of Liquid Argon.
- LArTPC’s consist of cathode planes in the middle, where the signals drift away from them towards the planes.
- Measures neutrino cross sections in LAr.
- Measures both appearance and disappearance channels.



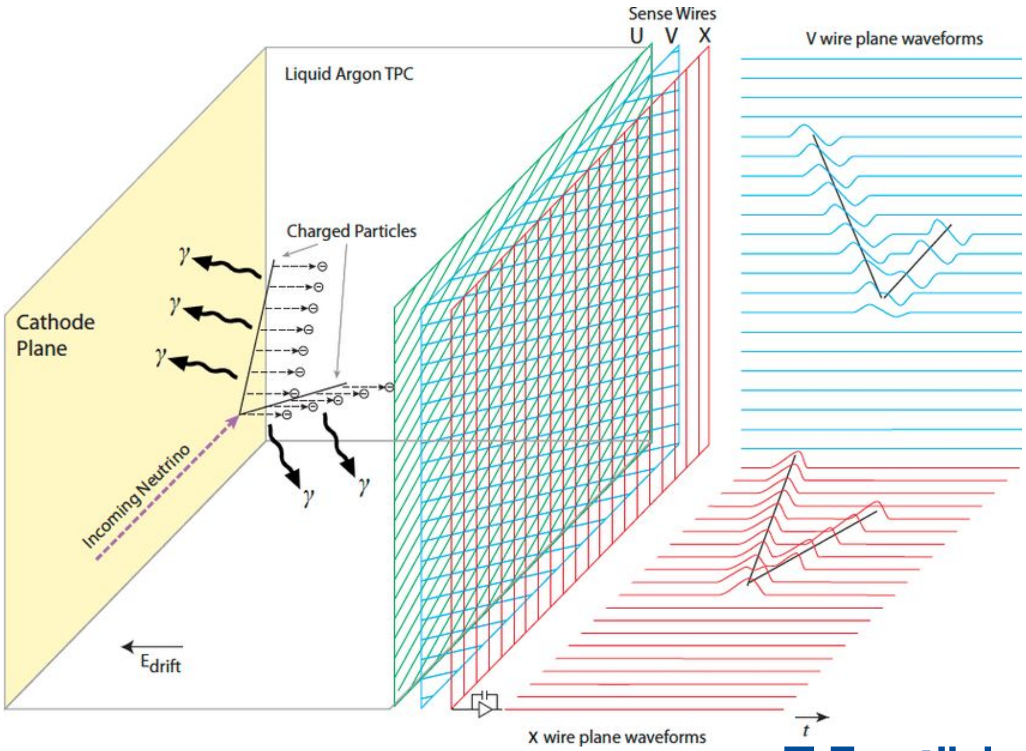
Time Projection Chamber and Wireplanes

Time Projection Chamber:

- Neutrino interaction in LAr produces ionization and scintillation light.
- Electric field causes the charged ions to drift away from the cathode plane.
- Read out charges and light are produced using precision wires and PMT's.

Three wire planes that ionizations and light are recorded on:

- 1 Collection, records unipolar waveforms.
- 2 Induction, records bipolar waveforms.



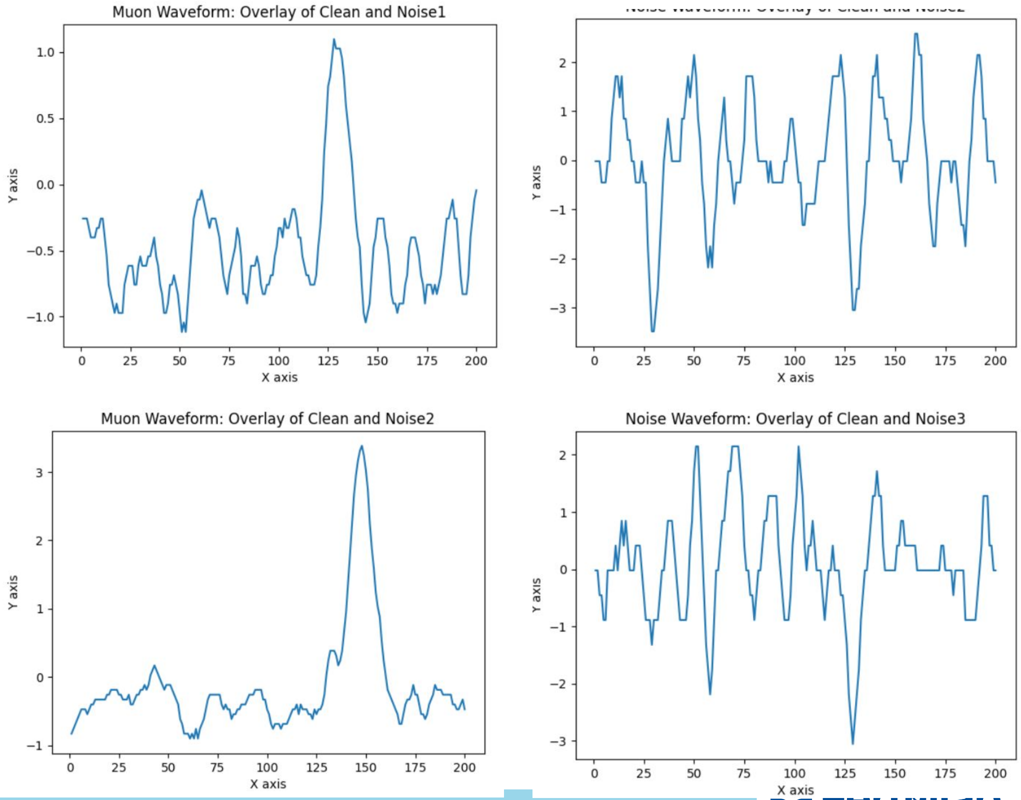
Samples (Collection Plane)

Training:

- Argon 39 without coherent noise sample trained with ADC > 3 and 877483 waveforms (Simulation)

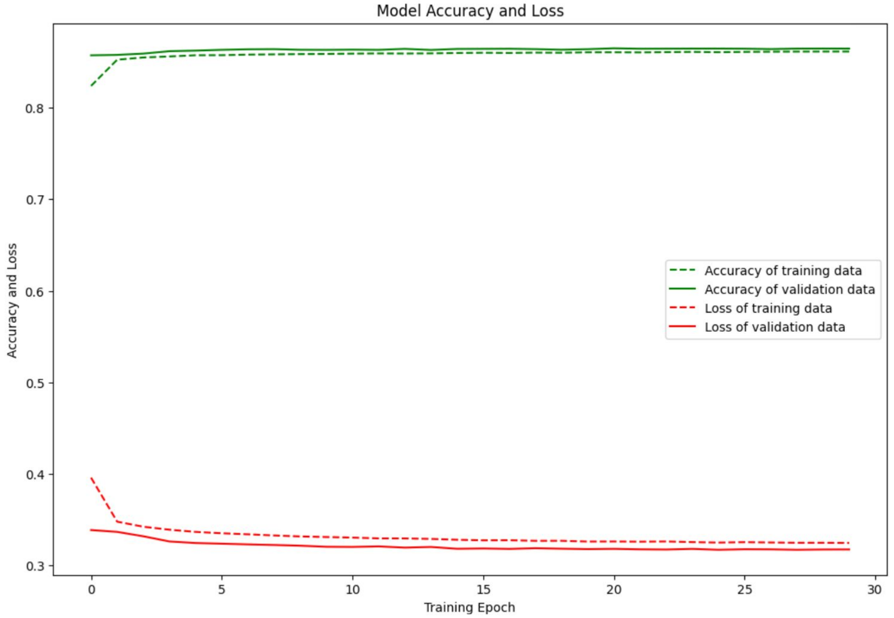
Testing:

- Single Muon data sample (Has coherent noise removed, and is simulated)
- Noise data sample (real data)



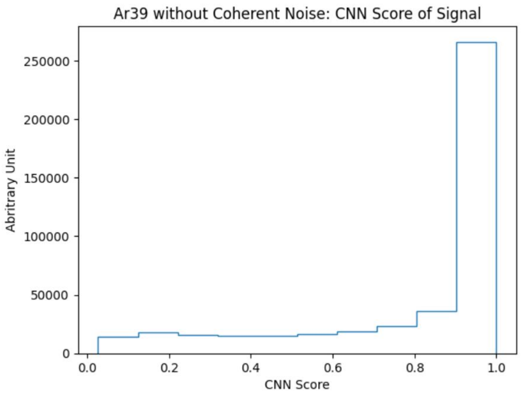
Argon 39 without Coherent Noise sample trained with ADC > 3 and 877483 waveforms (simulation)

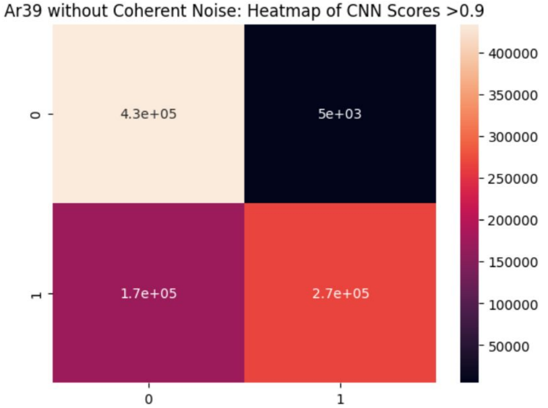
- This Accuracy and Loss plot provides us with how well the model is performing. We look for towards 1 for the Accuracy and 0 for the Loss. Here we can see that the plot are approaching the ideal areas and they don’t have a big displacement.

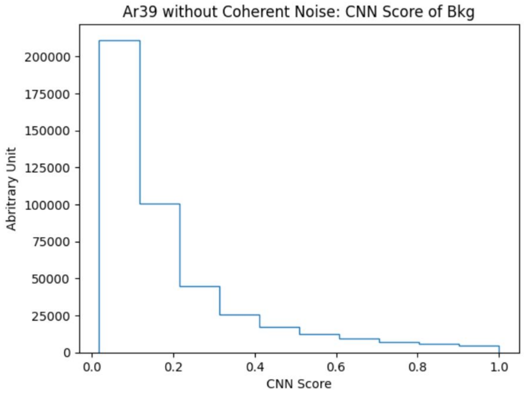


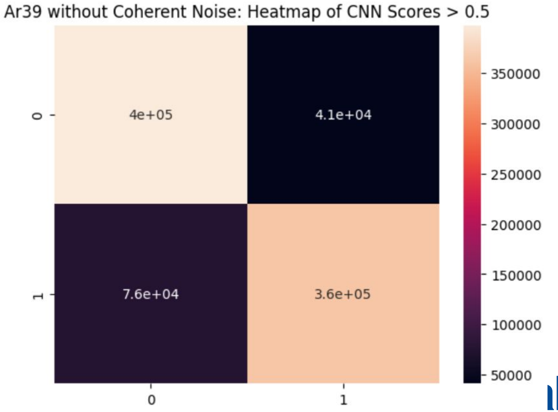
Argon 39 without Coherent Noise sample trained with ADC > 3 and 877483 waveforms: CNN Plots

- CNN Scores: Here we are looking for the signal plot to be at 1, and the background plot to be at 0. We can see some promise here.
- Heatmaps: Here we compare the actual signal with the predicted. Efficiency and precision is not too bad.

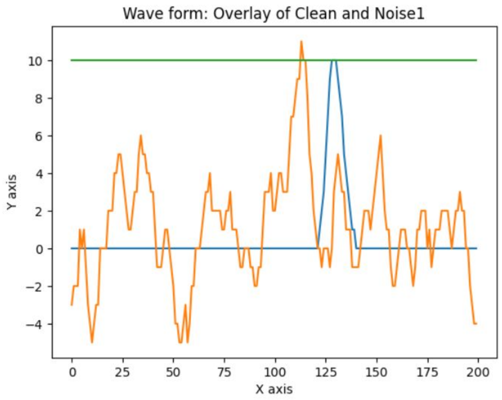


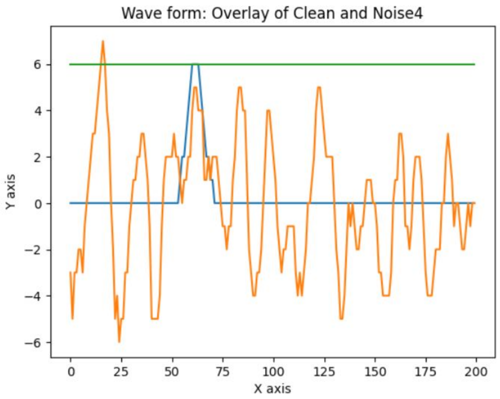




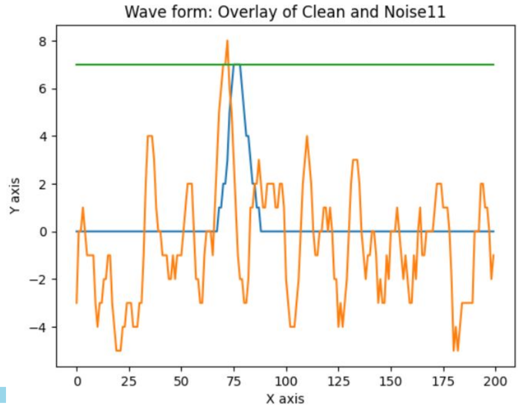


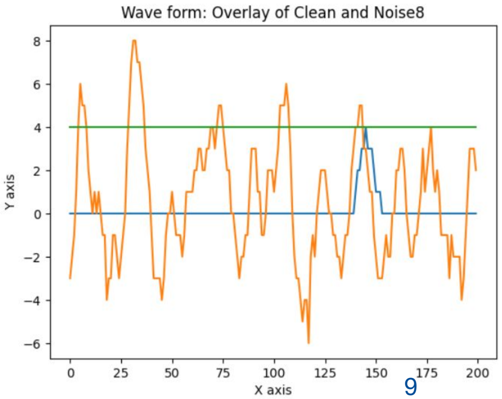
Argon 39 without Coherent Noise sample trained with ADC > 3 and 877483 waveforms: Waveforms





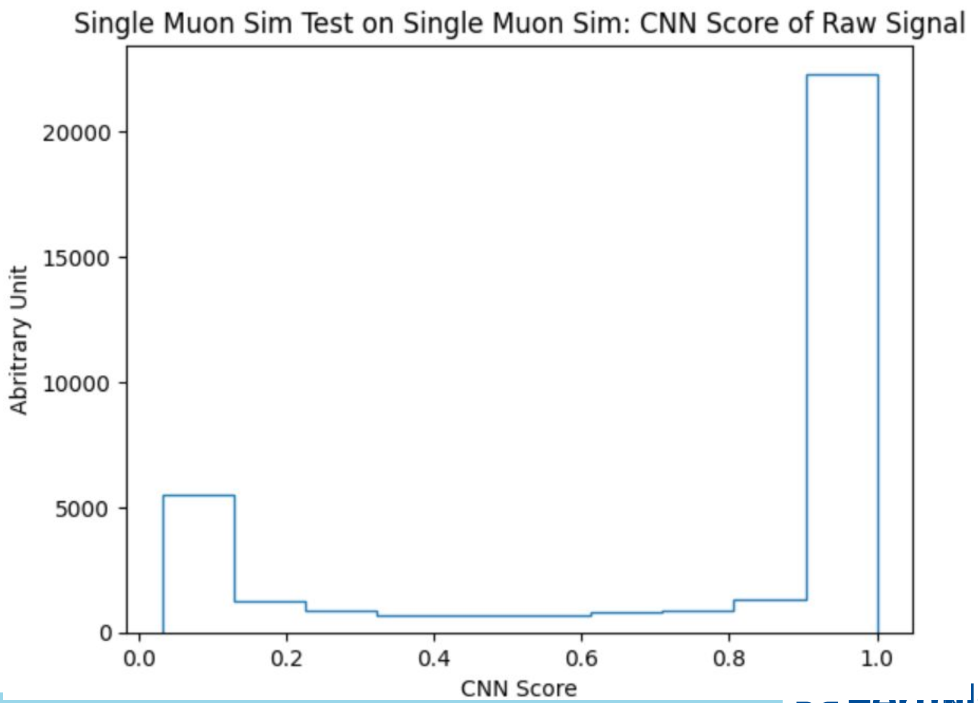
- Orange is our signal and noise.
- Blue is the clean waveform signal.
- For the training sample the signal is a little difficult to distinguish and it the clean signal waveform did not always line up perfectly with signal waveform due to noise distortion.





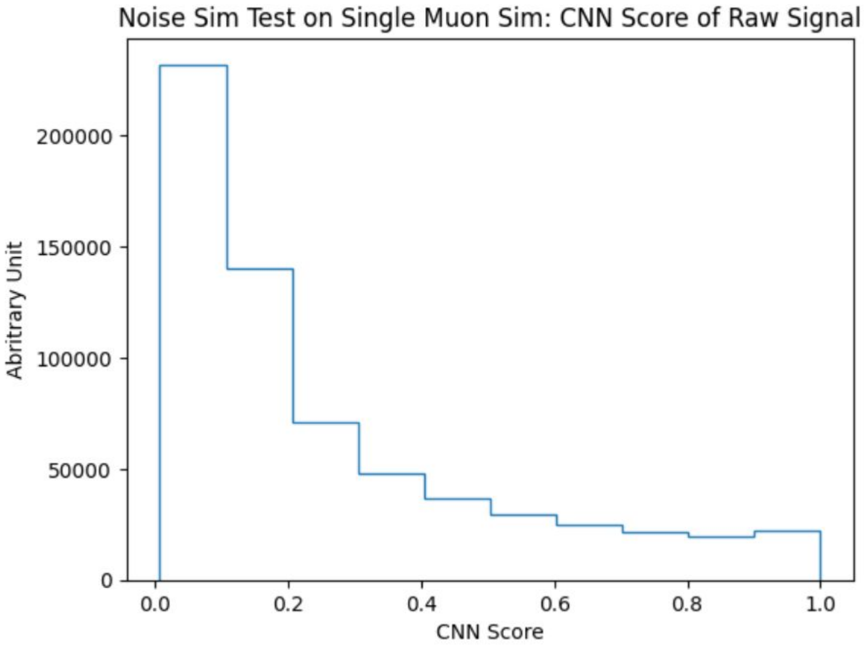
Argon 39 without Coherent Noise sample trained with ADC > 3 and 877483 waveforms: Single Muon Sample 34920 waveforms (simulation)

- Here we have CNN Score for the single muon sample and does a good identifying signal.
- Although we do have a small peak at 0 but it is almost insignificant compared to the right peak.



Argon 39 without Coherent Noise sample trained with ADC > 3 and 877483 waveforms: Noise Sample 646000 waveforms (real data)

- We can see here that we do have some stragglers but overall did a fine job.



Summary

- From our data it seems that adc 3 has the best results but other thresholds should be investigated further along with other datasets.
- We have a range from about 10-20 ADC, where the training has trouble identifying signal waveforms.
- Continue checking gaps in tracks to get a better idea of how well the training does compared to default method.
- Try different data samples.
- Investigate issue with the induction training.

Results of Internship

- Worked and was paid full time with Fermilab physicists and post-docs.
- Gained new knowledge of python, machine learning methods, and Fermilab gpvm.
- Learned new methods of critical thinking and troubleshooting when working with computational problems.

References

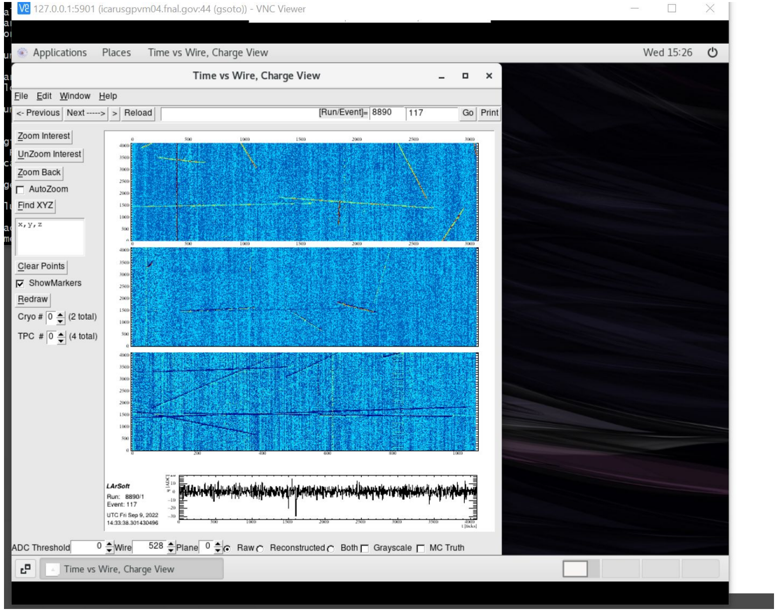
1. Uboldi, L. et al. Extracting low energy signals from raw lartpc waveforms using deep learning techniques — a proof of concept. Nuclear Instruments and Methods in Physics Research Section A: Accelerators, Spectrometers, Detectors and Associated Equipment 1028, 166371 (2022).
2. Acciarri, R. et al. A deep-learning based raw waveform region-of-interest finder for the liquid argon time projection chamber. Journal of Instrumentation 17, (2022).

Back up

Other ADC Thresholds for the Ar39 sample without Coherent Noise

- We also tried other ADC the thresholds:
  - 5
  - 7
  - 9
- These thresholds didn't improve the machine learning algorithm much. It reduced the amount of data being used and didn't seem to improve with identifying the signal waveforms.
- Furthermore, the resulting cnn scores and accuracy and loss plots did not improve compared to ADC 3.

Testing Model Further



We want an even better signal and background identifier.
Using the an event from the an off-beam dataset, we used LArSoft to hand pick certain waveforms and assign them as either signal or noise.
After doing so, Bruce used this information to extract the waveform information in order for us to have our model to make a prediction.
From the prediction our model gave us, we noticed that our model had issues predicting signals with peaks in the range 10-20 ADC.