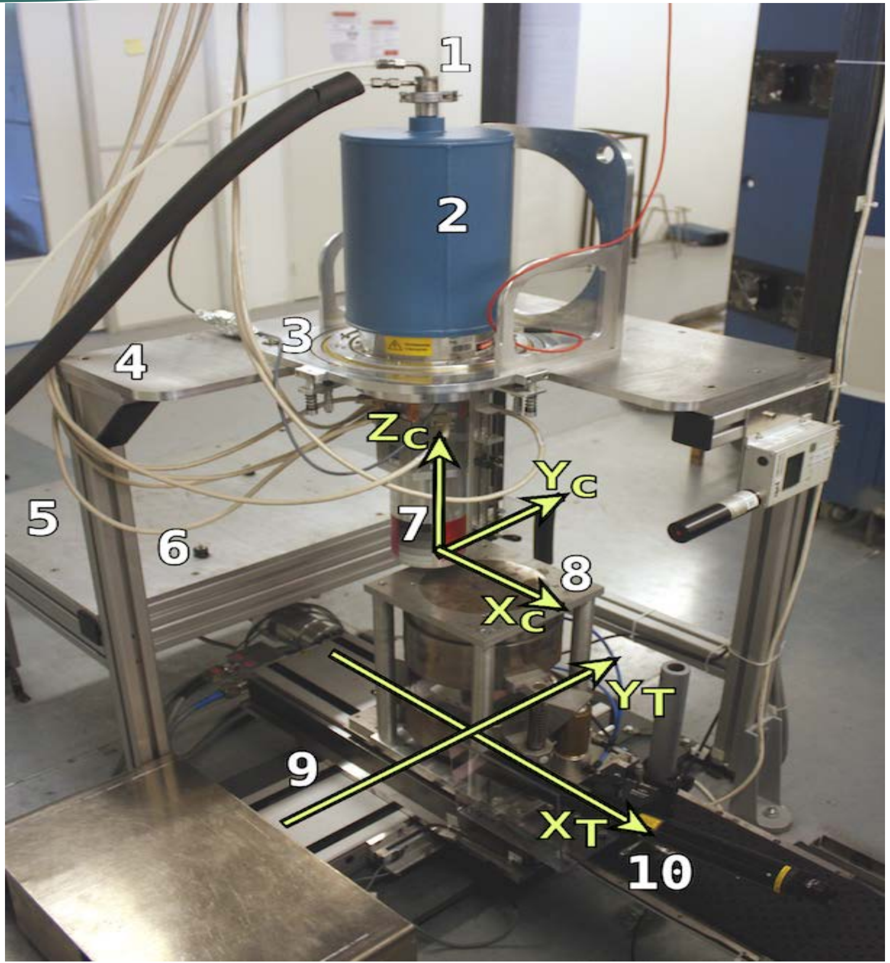
Utilizing Machine learning for the processing of Strasbourg scanning table data.

Mojahed Abushawish, Jeremie Dudouet, Guillaume Baulieu, Olivier Stezowski
Institut de Physique des deux infinis de Lyon (IP2I)

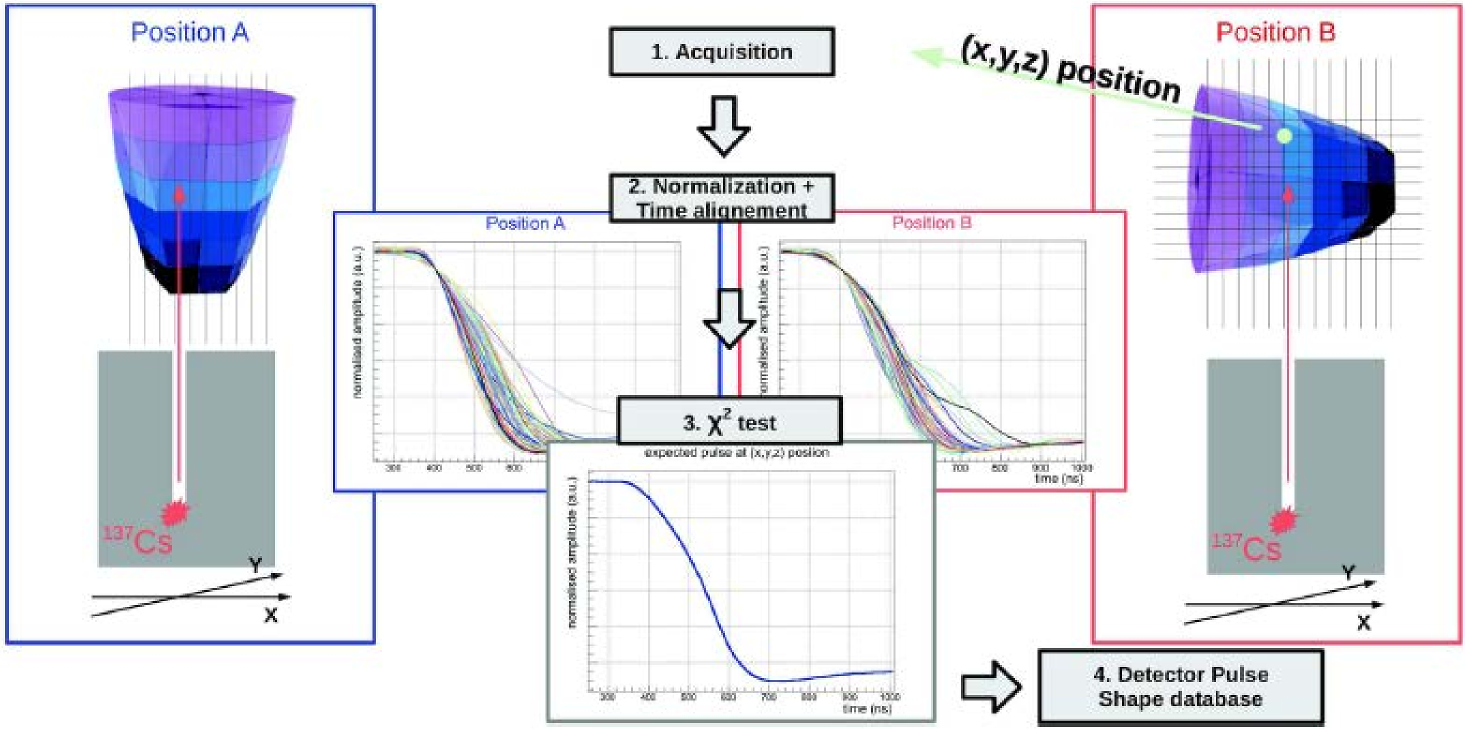
The Strasbourg scanning tables

- A motorized collimator with a 10μm precision.
- A system allowing the placement of the detector in vertical and horizontal positions.
- A laser alignment system.
- Detector scanned in this work: the symmetric S001 crystal, with a 137Cs source.



The scanning process

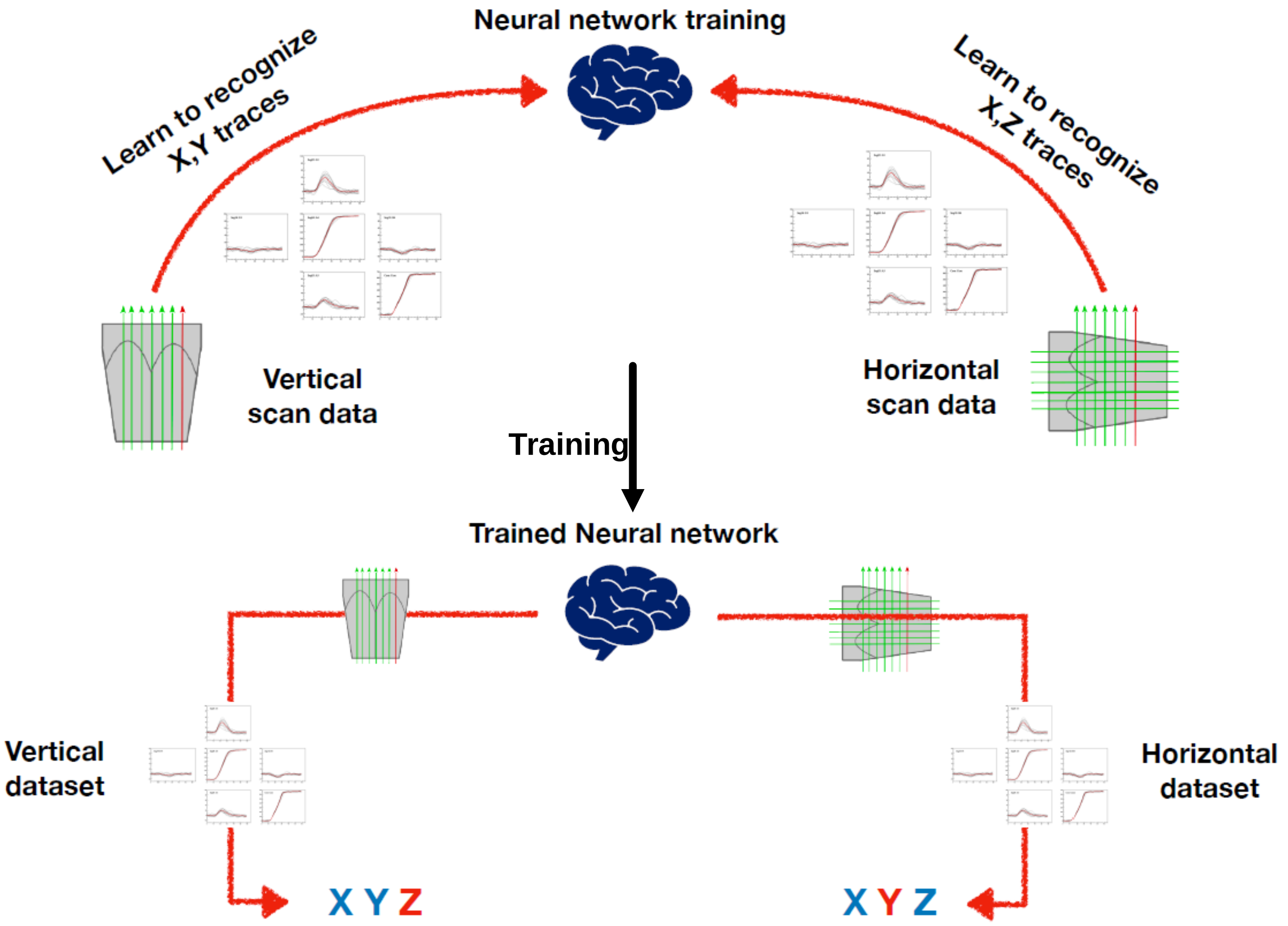
- 1 vertical (X,Y) and 1 horizontal(X,Z) scan.
- To get a 3D databases, a $\chi 2$ analysis of both datasets is done.
- This method has been validated and published but it's very time consuming (5 days for the PSCS analysis)



B. De Canditiis *et al.*, Eur. Phys. J. A 57 (2021), B. De Canditiis and G. Duchêne, Eur. Phys. J. A 56 (2020)

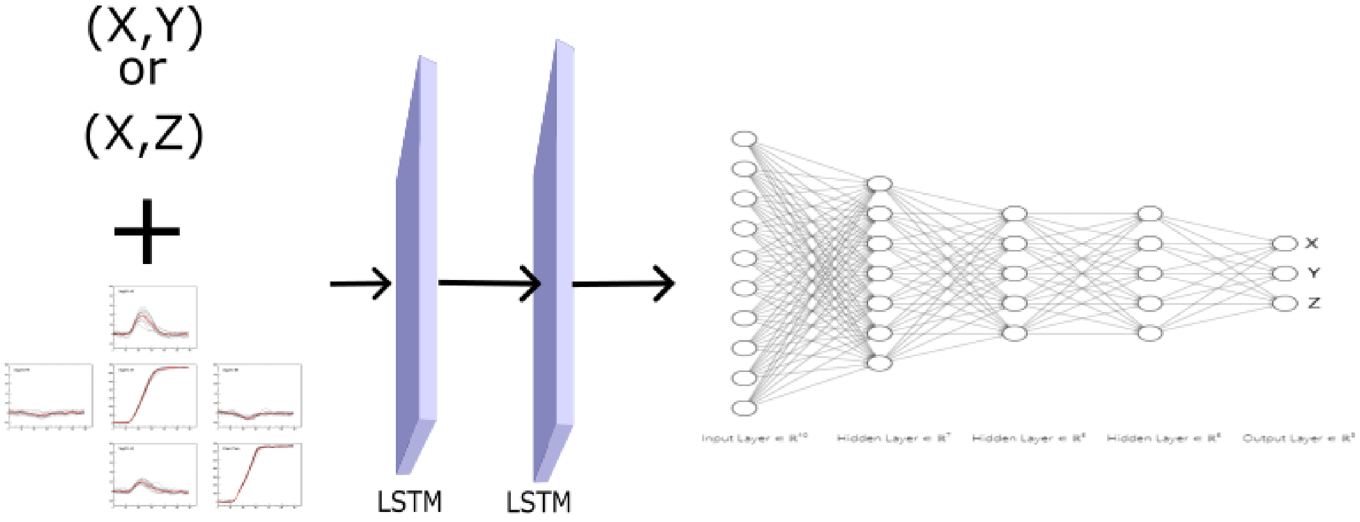
Picture from Michael Ginsz's PhD thesis

Neural networks to produce the 3D databases



Neural networks: LSTM

- 2 Long short-term memory (LSTM) layers were used.
  - ✓ LSTMs can process sequences of data like the signals.
  - ✓ Are very robust and are not affected by time misalignments.
- The loss function was calculated only for the two known axis, this allows the network to learn patterns of each dataset without affecting the other.

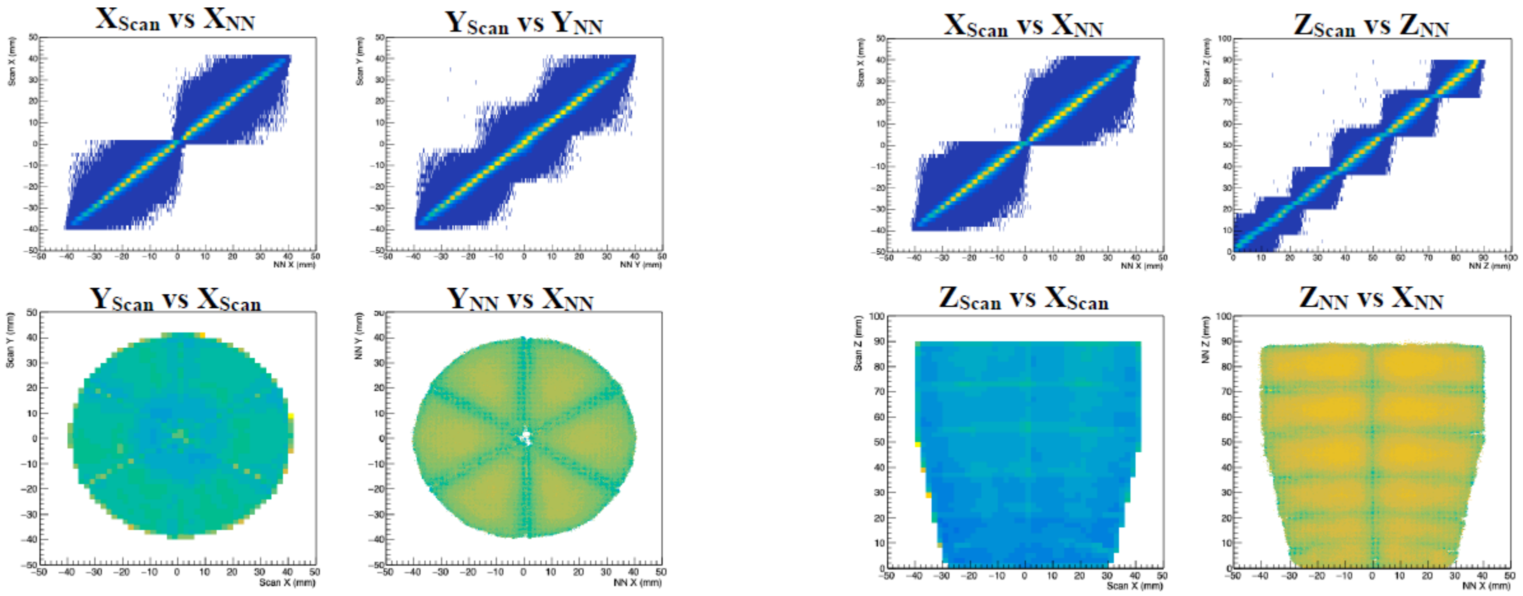


Data preparation

- The data must be homogenous to avoid bias from the neural network.
  - ✓ Only 10 signals/voxel are kept.
  - ✓ 500k signals per scan in total.
- Gate on the 662KeV photopeak and selection of segment multiplicity of 1.
  - ✓ To avoid Compton scattering signals and assure the signals at the right position.
  - ✓ This will favor double hits in one segment resulting in reduced number of signals at the segment borders.
- Remove dummy signals and filter bad signals.

Analysis of neural network results

- The two known axis are compared with the predictions of the network.
- The bad predictions can be due to bad signals.
- Only the predictions with error on the known axis of less than 1mm are kept.

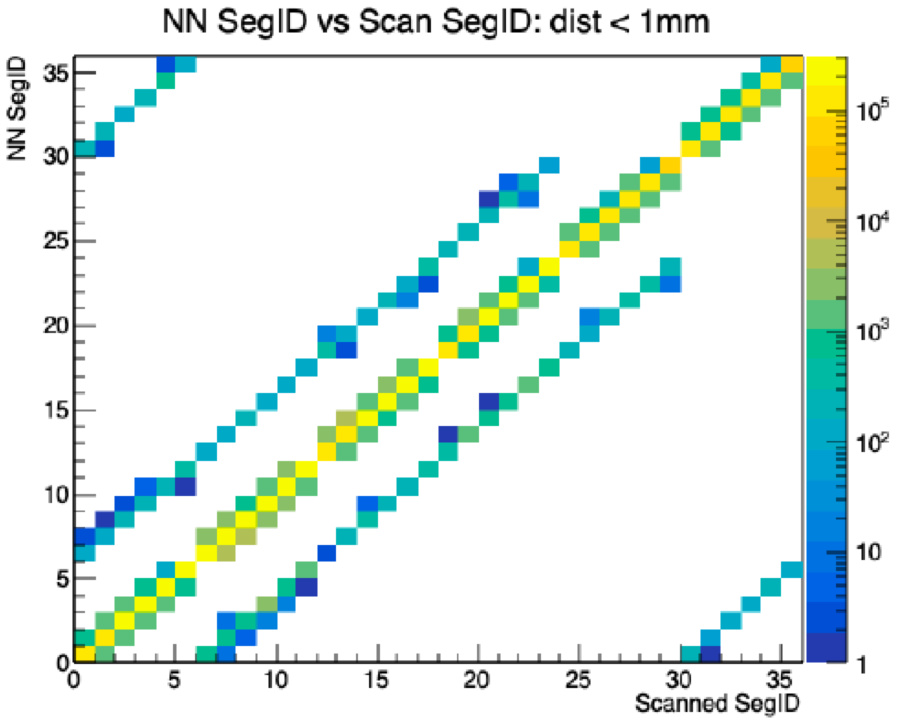


Training of the neural network

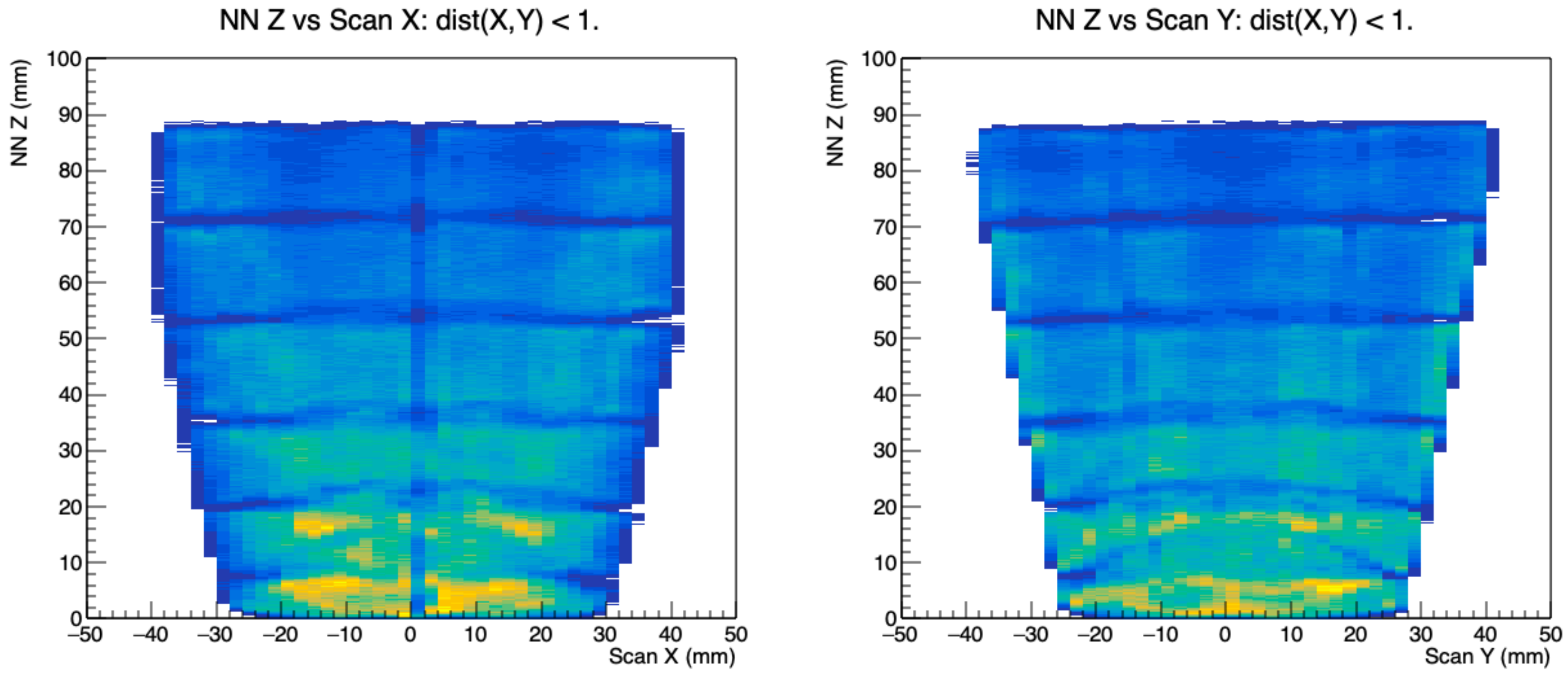
- Trained using RTX6000 GPU
- Using TensorFlow python library
- Took 30 minutes for training and 1 hour for inference

Analysis of neural network results

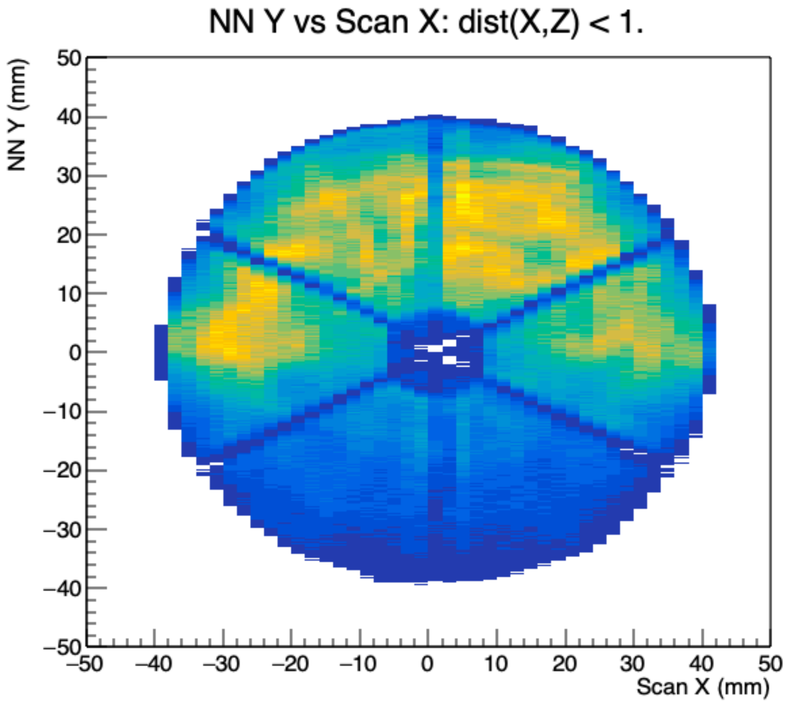
- Only 2% of the predicted segments were wrong.

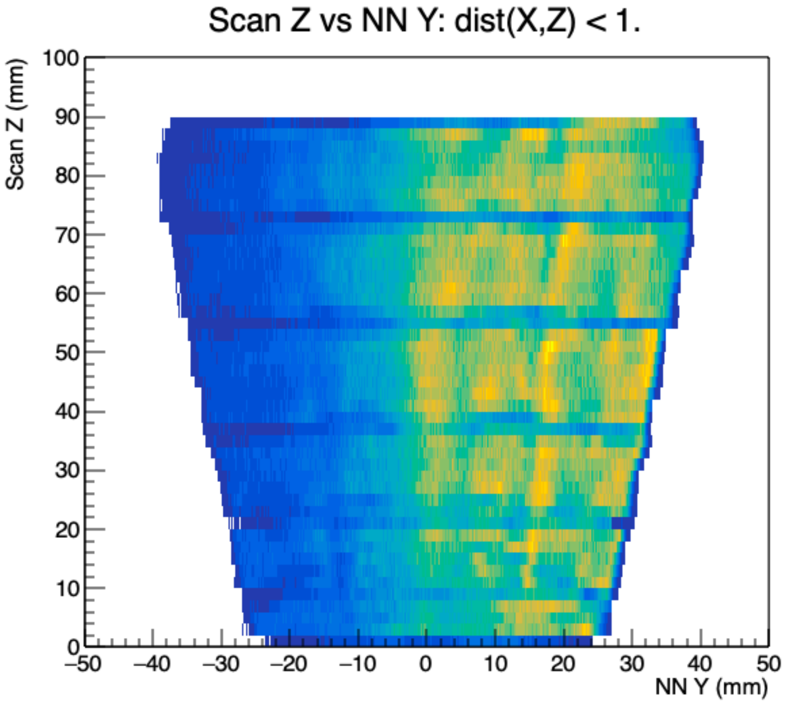


Neural network results: Vertical scan distribution

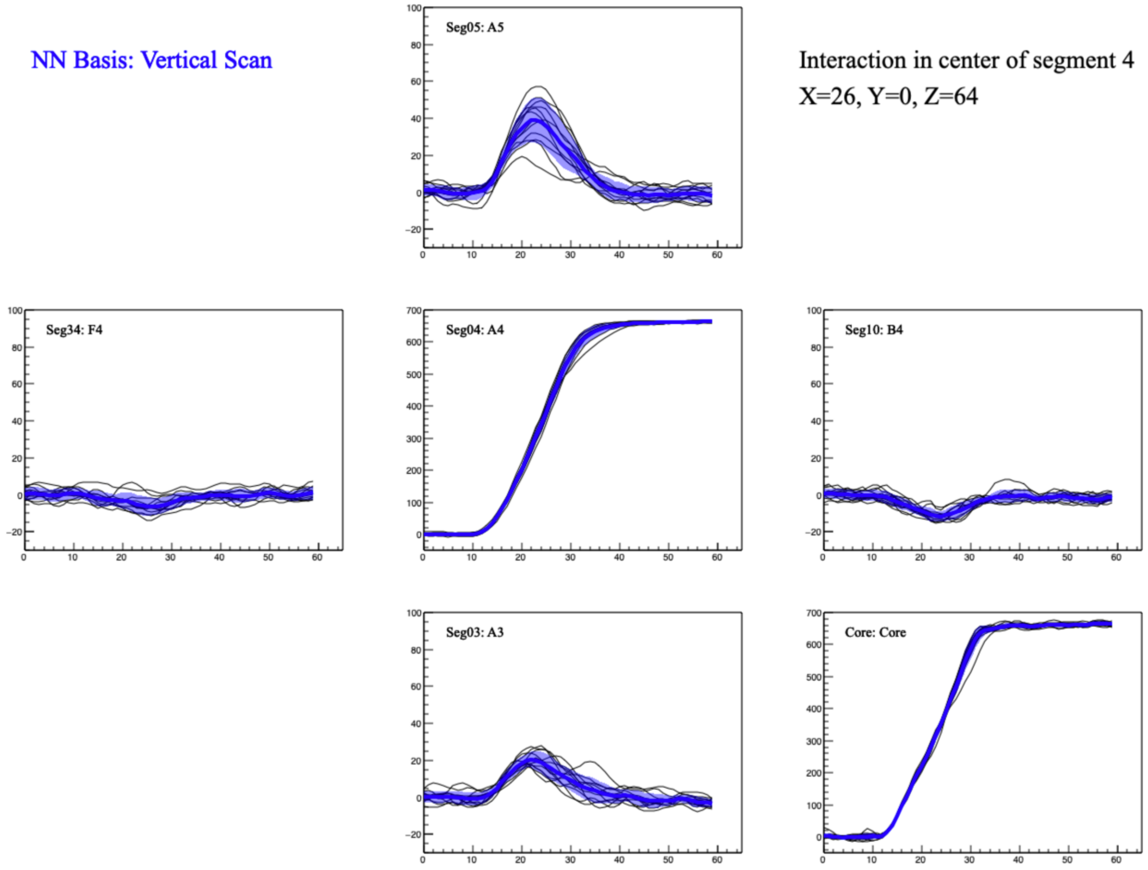


Neural network results: Horizontal scan distribution

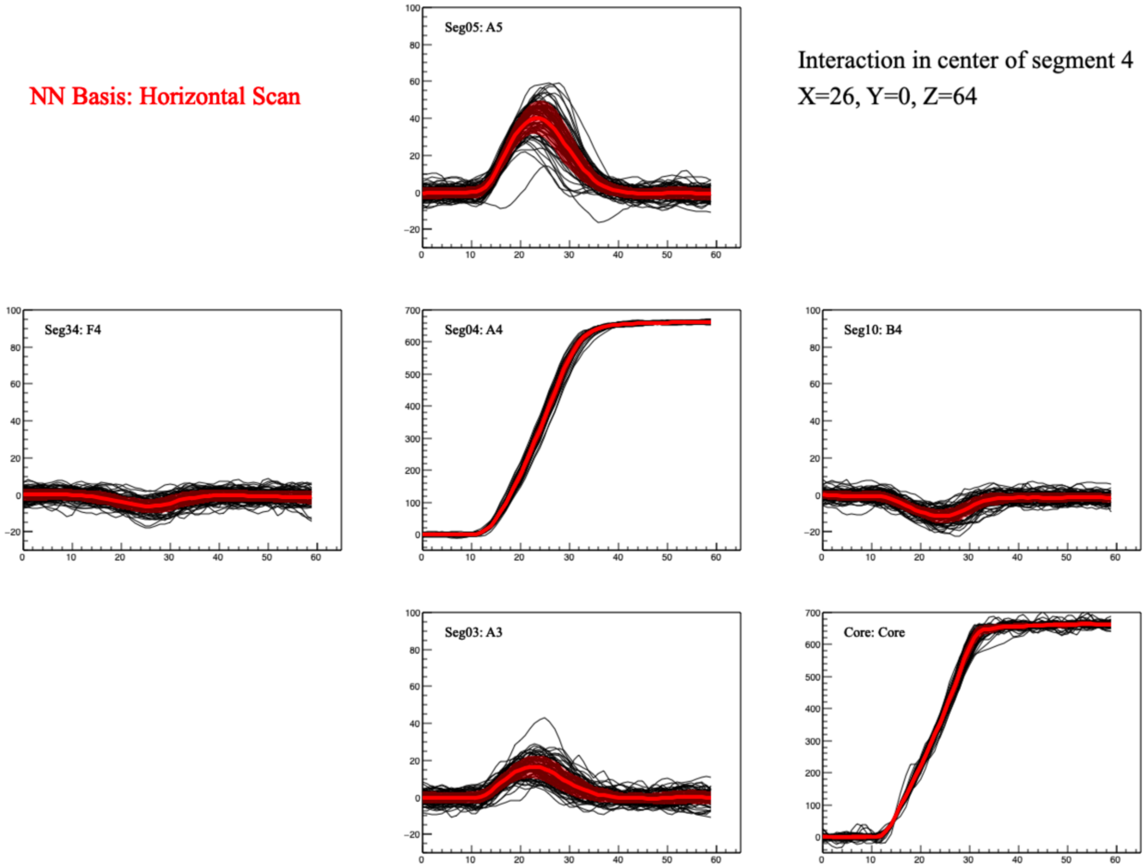




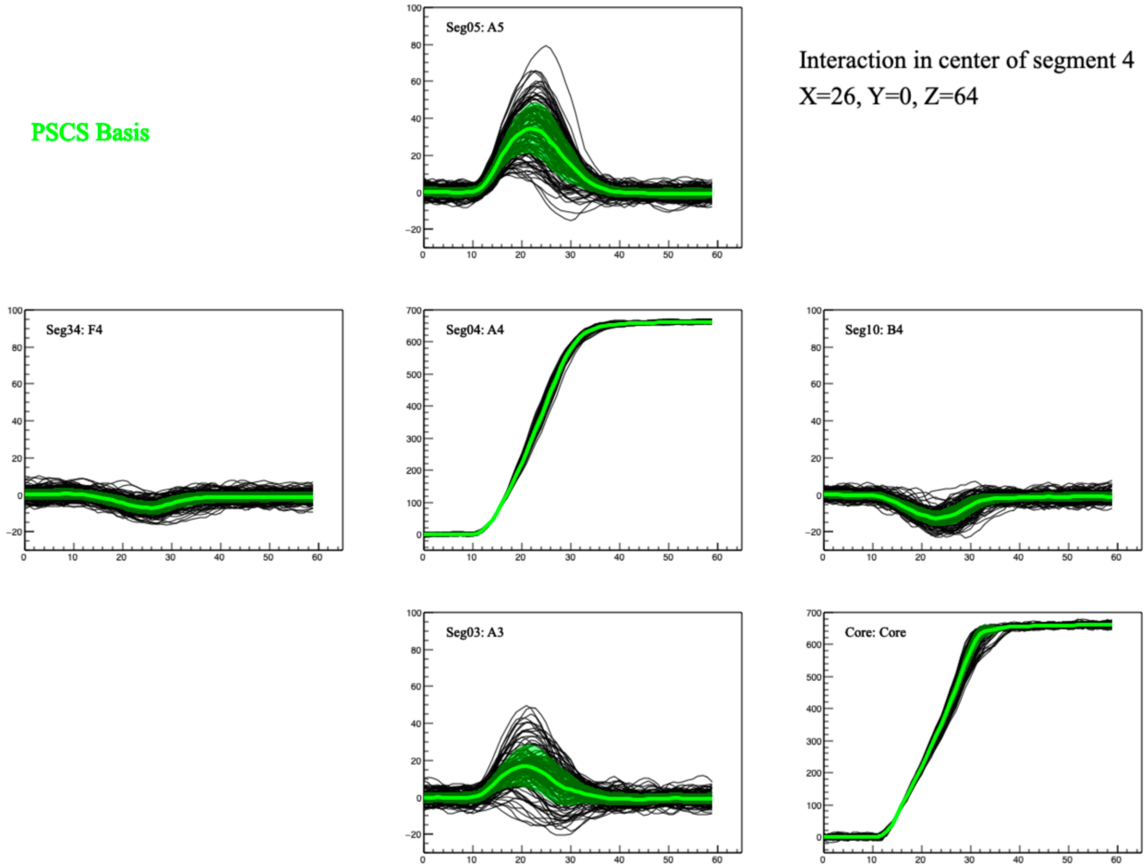
Neural network results: Vertical Signals



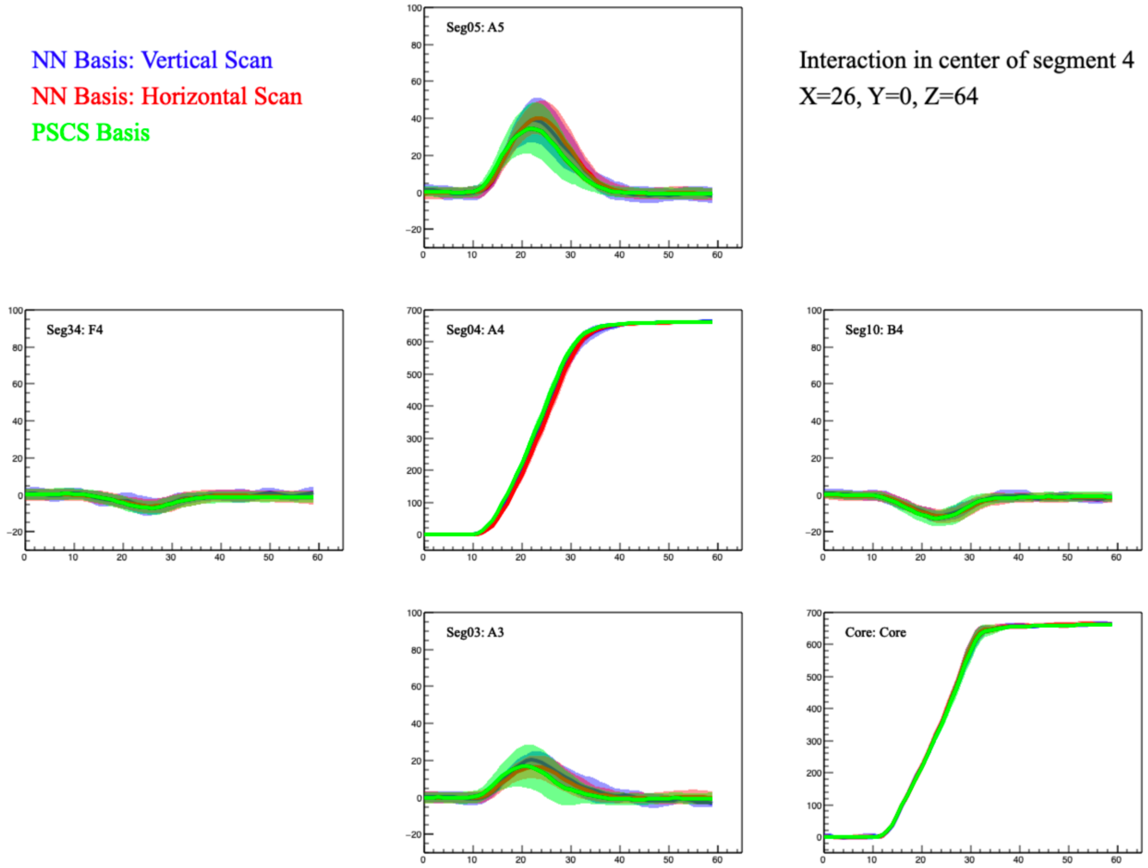
Neural network results: Horizontal signals



PSCS method signals



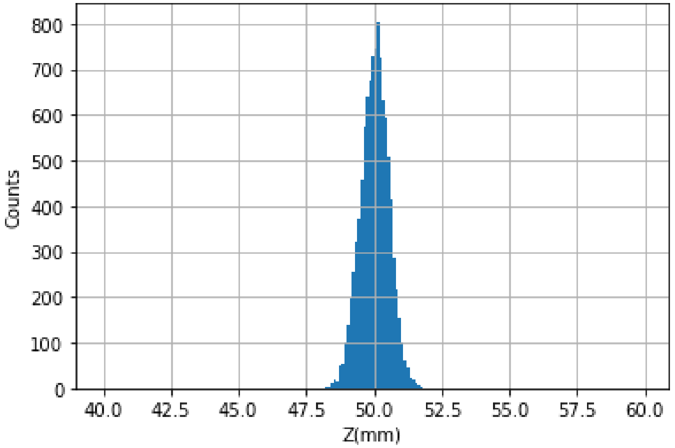
Neural network Vs PSCS



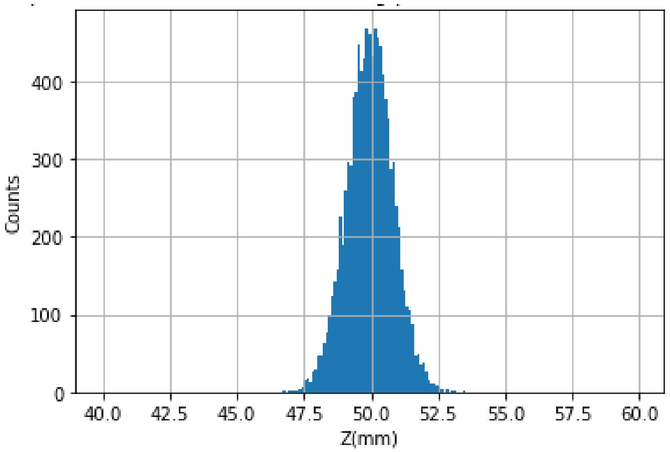
Imaging using Compton scattering

Imaging of a source located at (0,0,50)mm in the sphere of AGATA

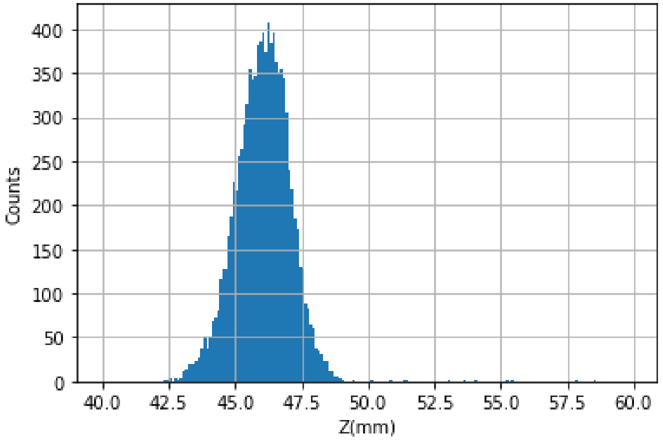
Experimental position error



Two times the experimental position error



Experimental position error with bad tracking



FWHM 1.3mm 2mm 2.4mm

Results: 3D signal basis reconstruction

Results

- Although this is still preliminary, the 3D signal basis seems to be compatible with the standard PSCS basis.

- The neural network 30 minutes for training and 1 hour to process the two scans compared to 5 day for the PSCS method.

Prospects

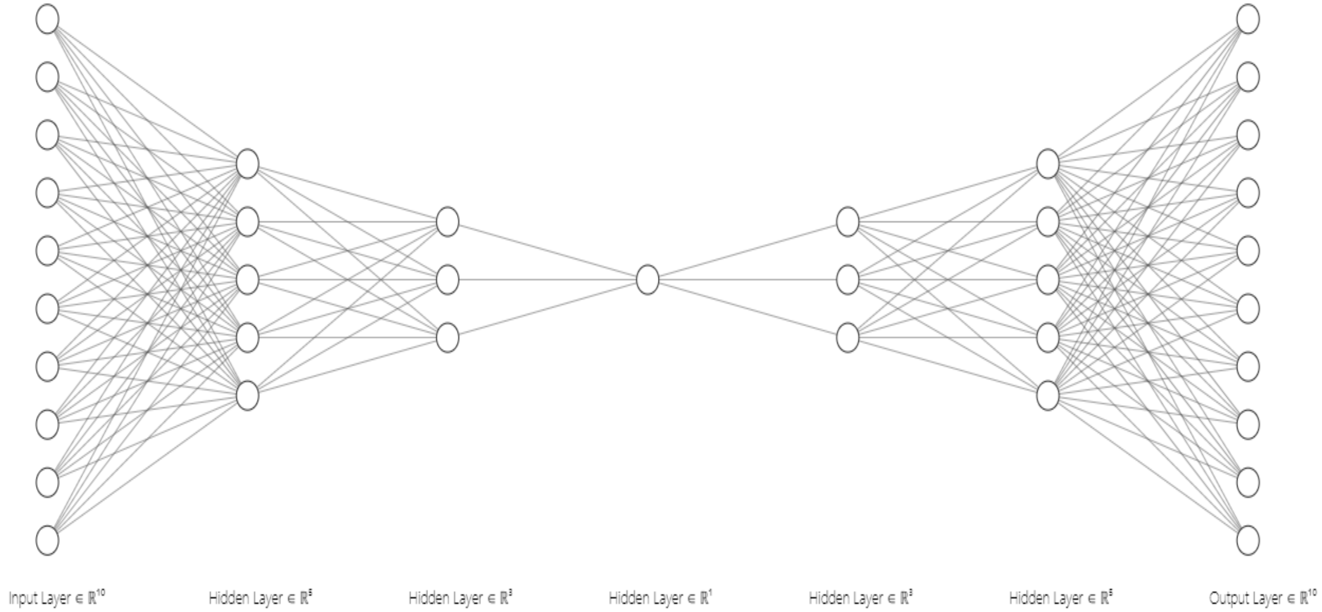
- The imaging method will be used to characterize the PSA and validate the neural network results.

- Reprocess the data taking 2 hits in the detector segments.

- Have a neural network and the validation method ready to apply it on the A005 crystal that will be scanned at Strasbourg.

Classifying and denoising bad signals using autoencoders

- It encodes the signal into a small latent space.
- Reconstructs the signal from this latent space removing the uncommon parts.
- We used 10 dense layers with latent space of 10.

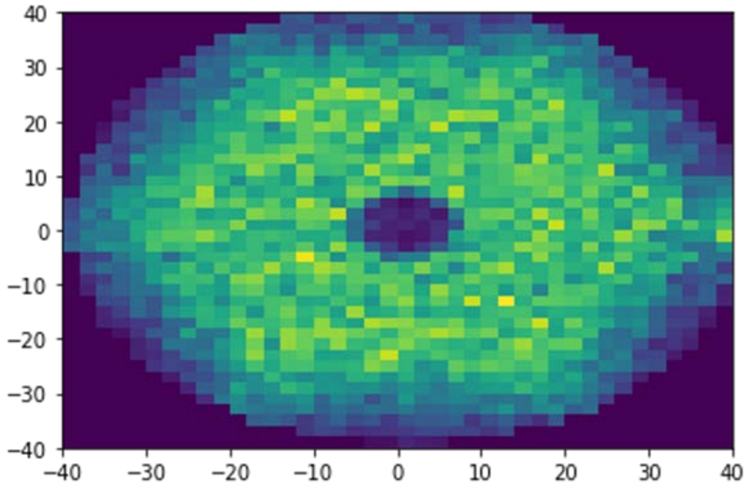


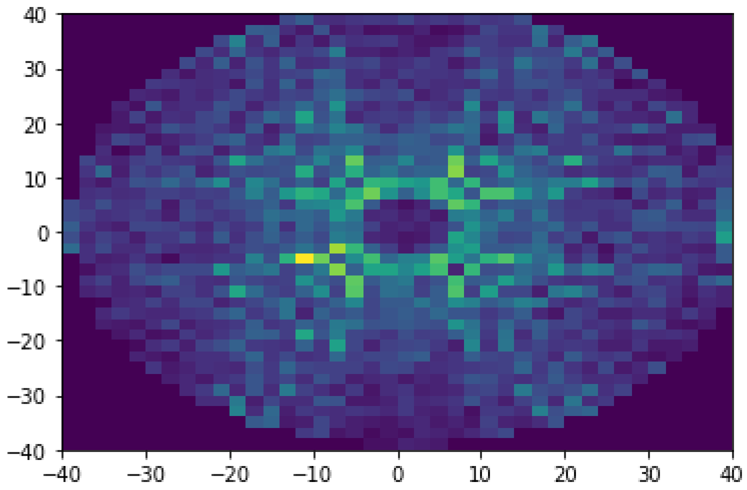
Training of the neural network

- Trained using RTX6000 GPU
- Using TensorFlow python library.
- The loss function used is mean squared error.
- Took 30 minutes for training.

Radial uniformity.

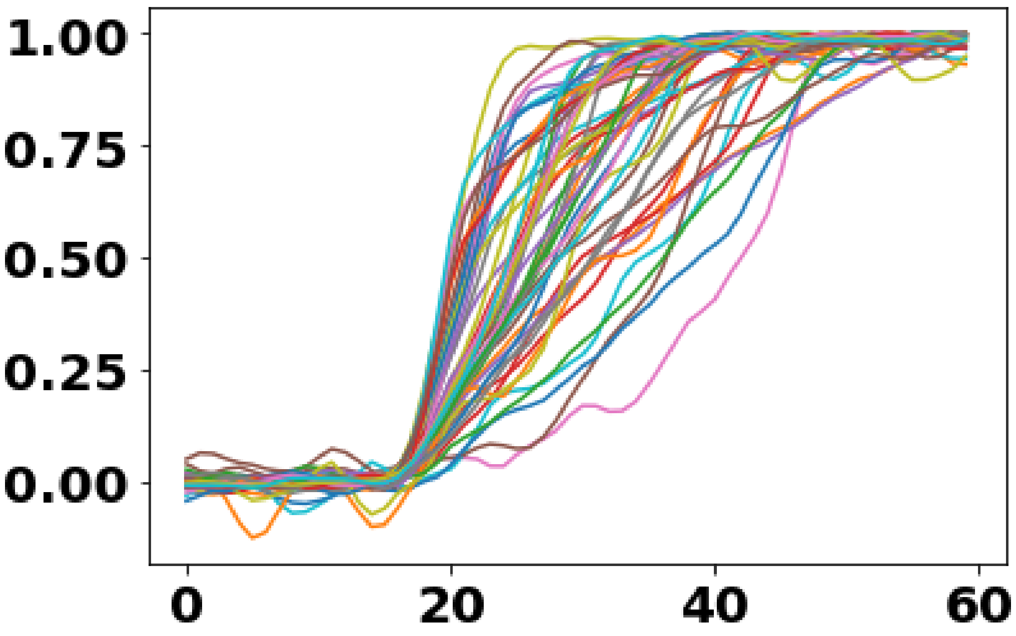
- The network was misclassifying the signals closer to the core.
- The signals closer to the core were uncommon for the network due to the global homogeneity function applied before.
- The data was reprocessed to apply a radial uniformity function.



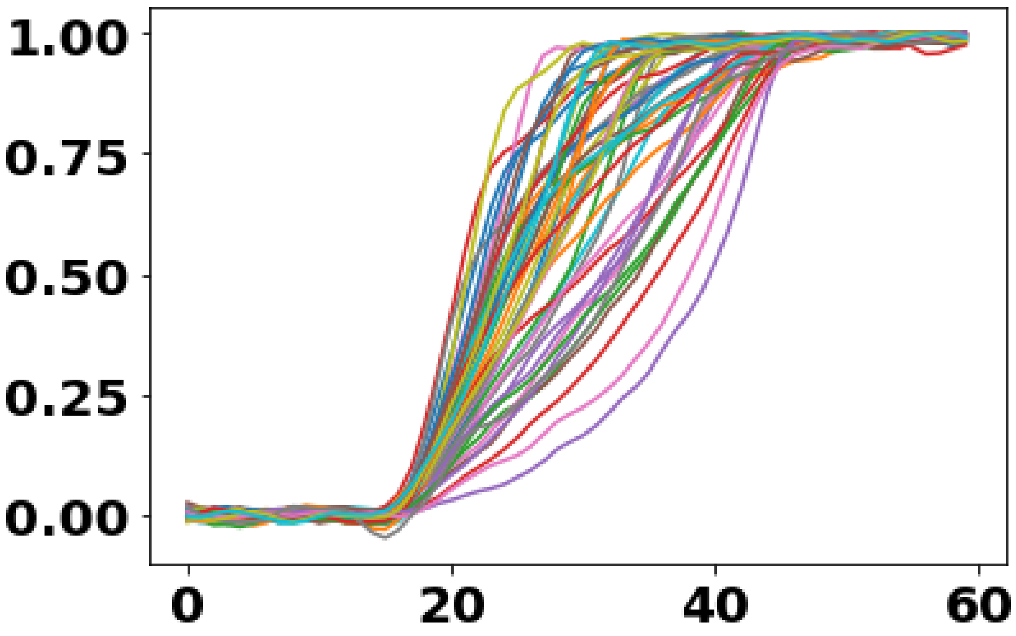


Autoencoder results.

The worst 2% reconstructed core signals



The normal core signals



Autoencoder limitations and prospects.

Limitations

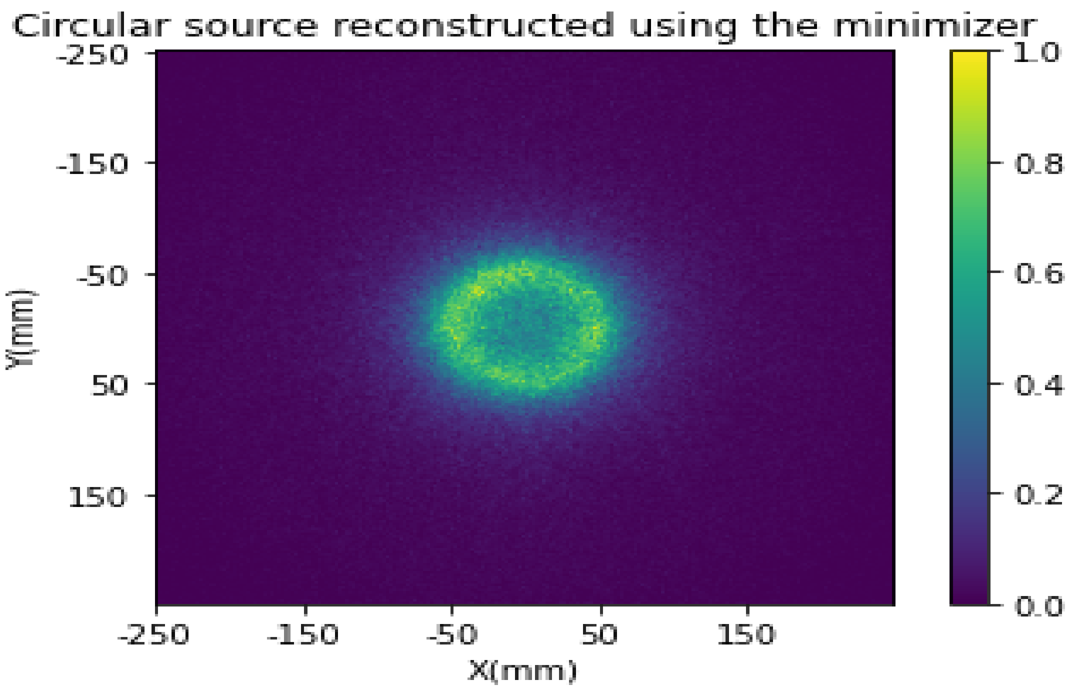
- Can't be sure of the validity of network due to lack of information on the ratio of bad signals in the dataset.
- The reconstructed signals must be validated.

Prospects

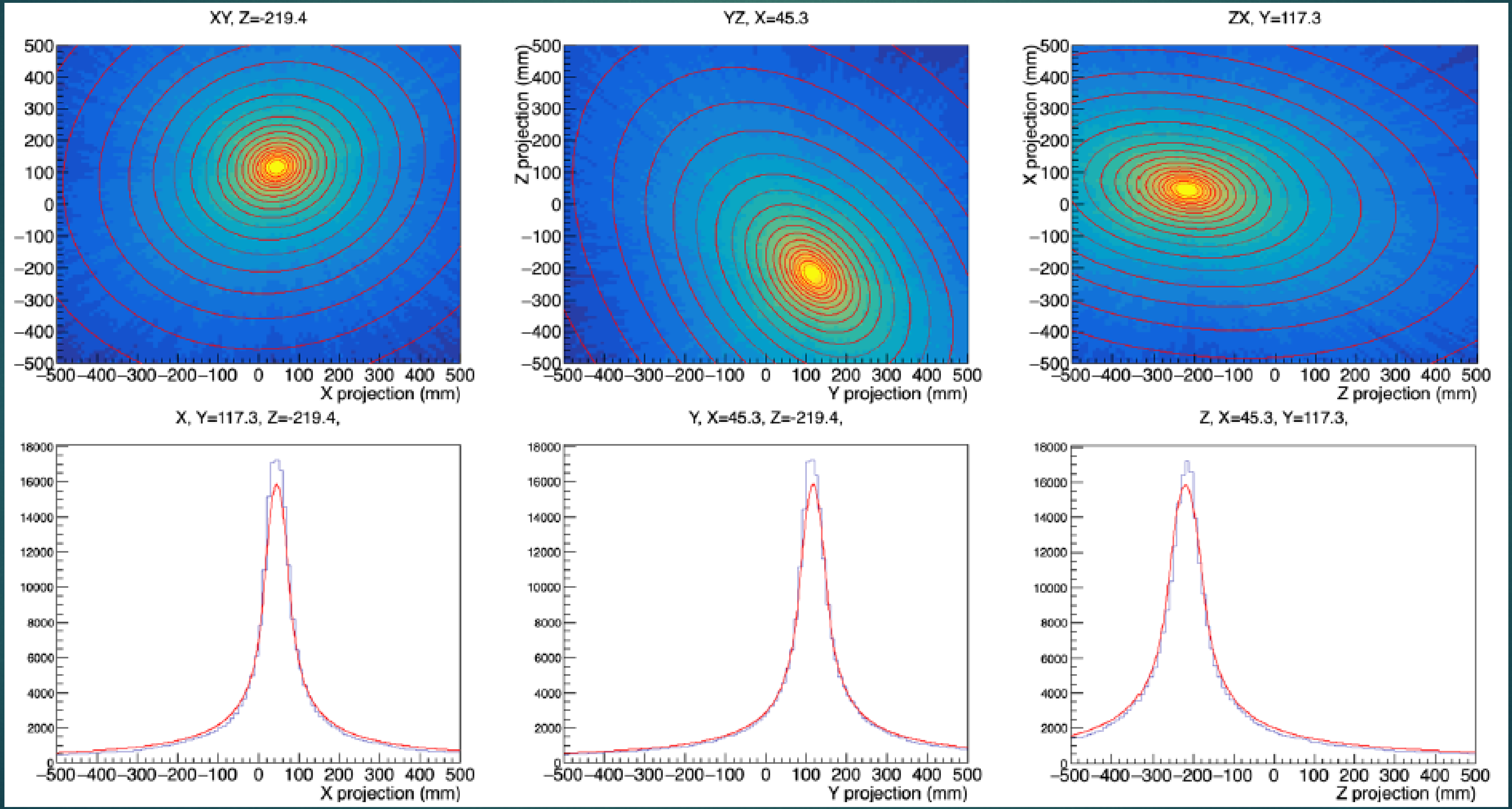
- The data will be reprocessed to remove filters on bad signals.
- One segment has particularly bad signals and will be used as a benchmark for the network.
- The reconstructed signals will be validated using the 3D basis neural network.

Thank you for your attention.

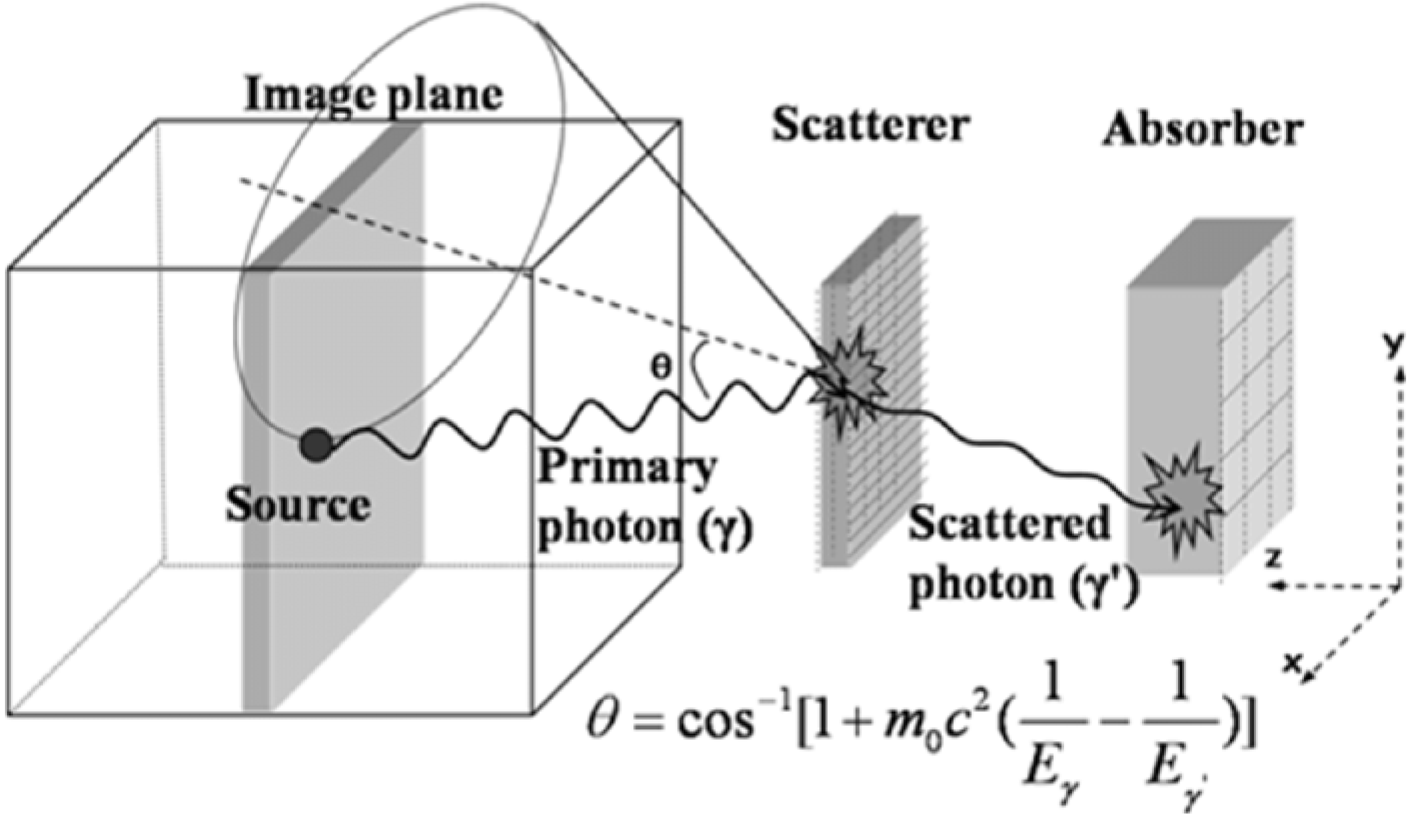
Imaging using Compton scattering



Imaging using 3D histograms

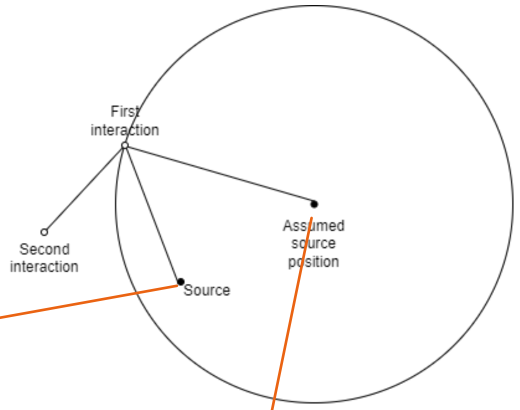


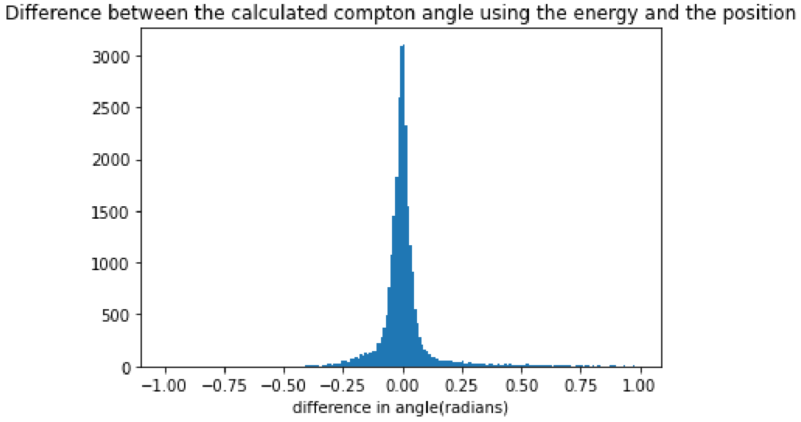
Imaging using Compton scattering

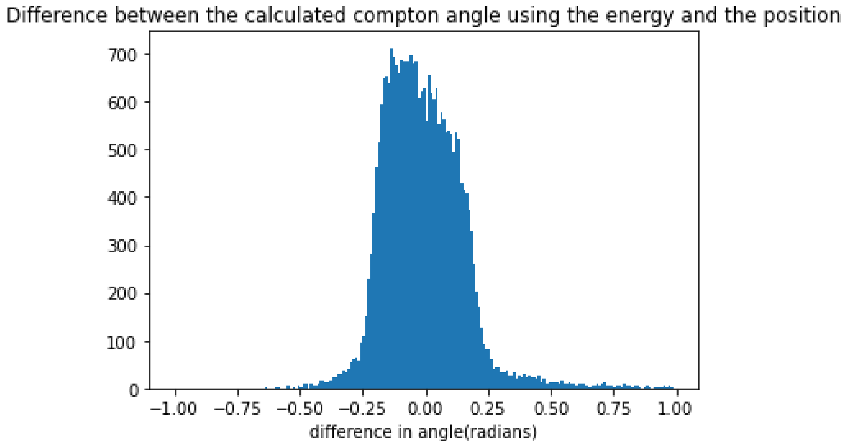


Imaging using an optimizer

- The scattering angle can be calculated from the energy and from the position.
- Minimizing the difference between the two will give the source position



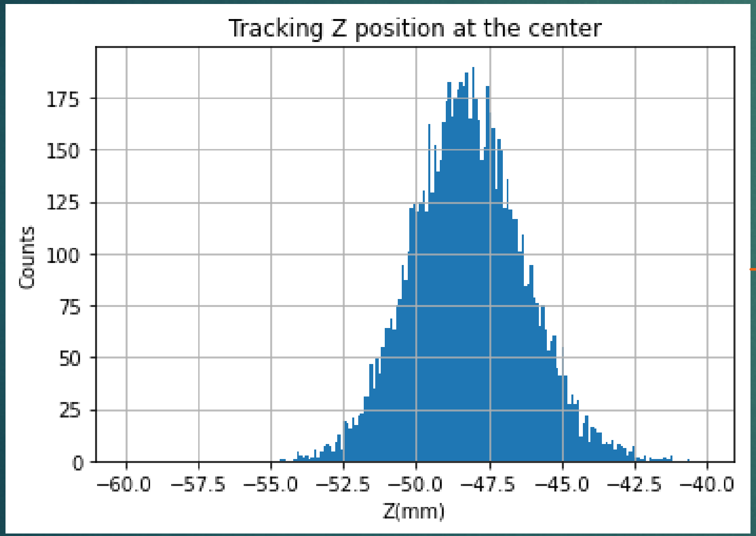




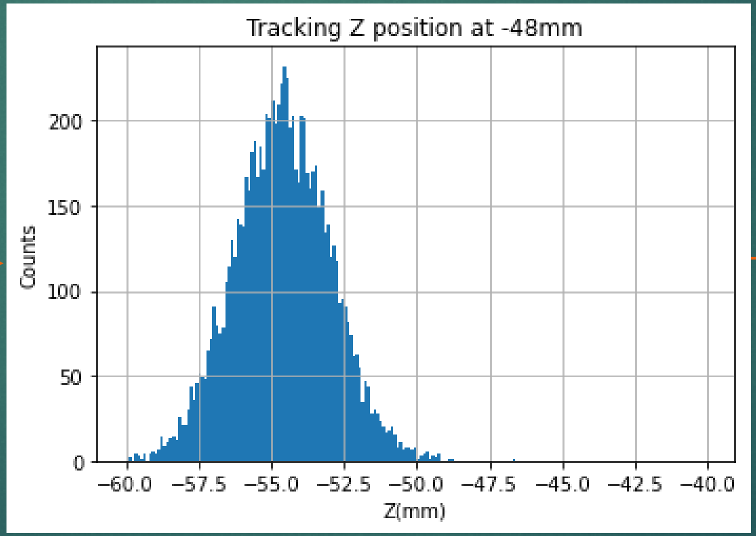
Results of the minimizer with experimental data

- This source run was conducted during GANIL campaign in the autumn of 2021.
- The source used is Eu located at (0,0,-55)mm.

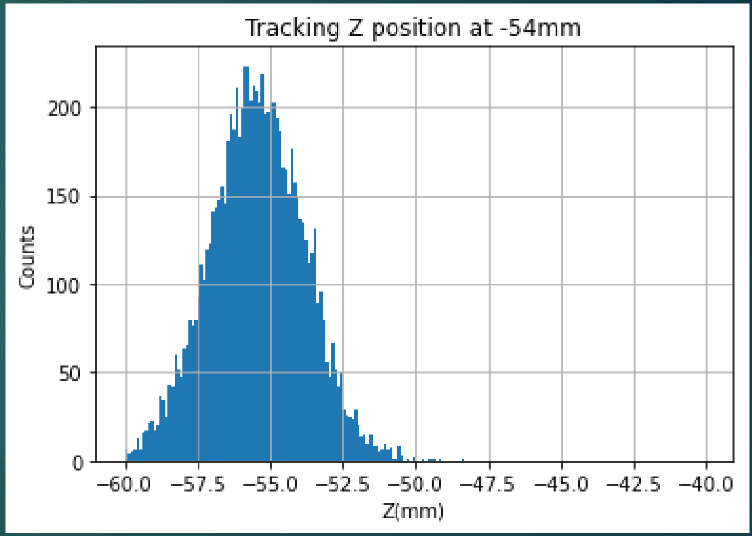
[-3.63   0.55 -48.23]



[-3.8   0.5 -54.58]



[-3.71   0.52 -55.46]



FWHM: 4.5mm 3.83mm 3.78mm

Neural network results