Neural Network-Based Calibration in Phased Array Beamforming

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Introduction

- **Phased array radars** offer high-resolution, all-weather crop imaging that is well-suited for precision agriculture.
- **Hardware imperfections** like nonlinear phase shifts introduce beam pointing errors and increase side lobe levels, limiting ability to accurately map crop canopies.
- **Research Goal:** Train a neural network to predict phase coefficients that self-calibrate the beam pointing errors, restoring ideal beam performance.

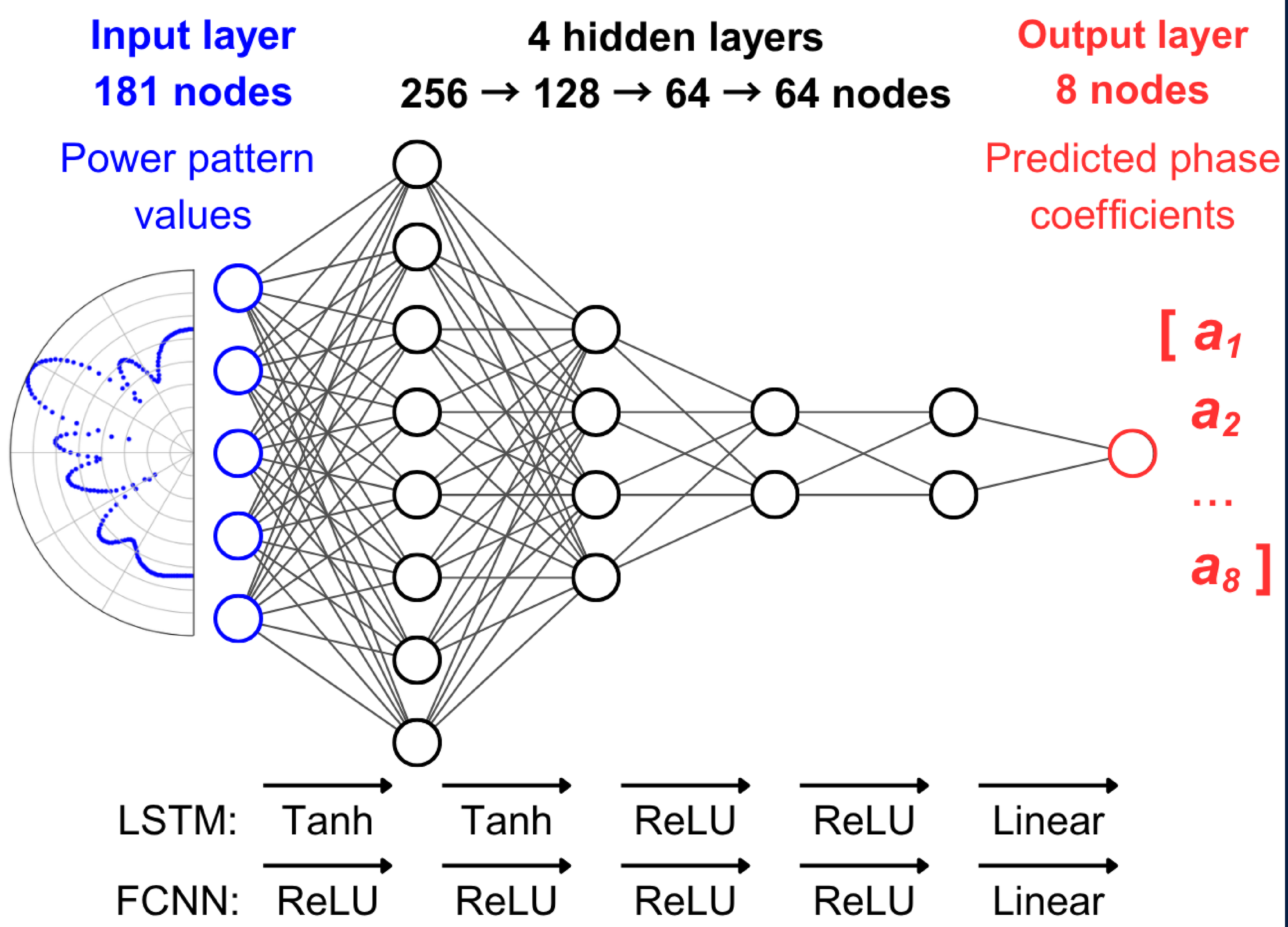
State-of-the-art Techniques

- **Genetic algorithms (GAs)** can optimize multiple objectives, such as minimizing SLLs while maximizing directivity.
  - GAs are iterative, require **"considerable computational time"** [1], and cannot be used for real-time phased array correction.
  - [2] presents another iterative calibration technique for an additive printed antenna array which is similarly time consuming.
- **Deep Learning (DL)** algorithms use multilayered NNs to learn complex relationships between data.
  - In [3], a deep NN trained on **1.25 million beam patterns** took **3.5 hours to train,** predicting phase coefficients with high accuracy.
  - DL models require increasingly large datasets and computational needs to maintain prediction accuracy as the problem gets more complex.
- **Convolutional Neural Networks (CNNs)** are good at processing spatial data, but require high quality, well-labeled training data to perform well.
  - Radar processing in [4] requires diverse datasets, much like how array calibration methods require a variety of gain, phase, and angle variations.

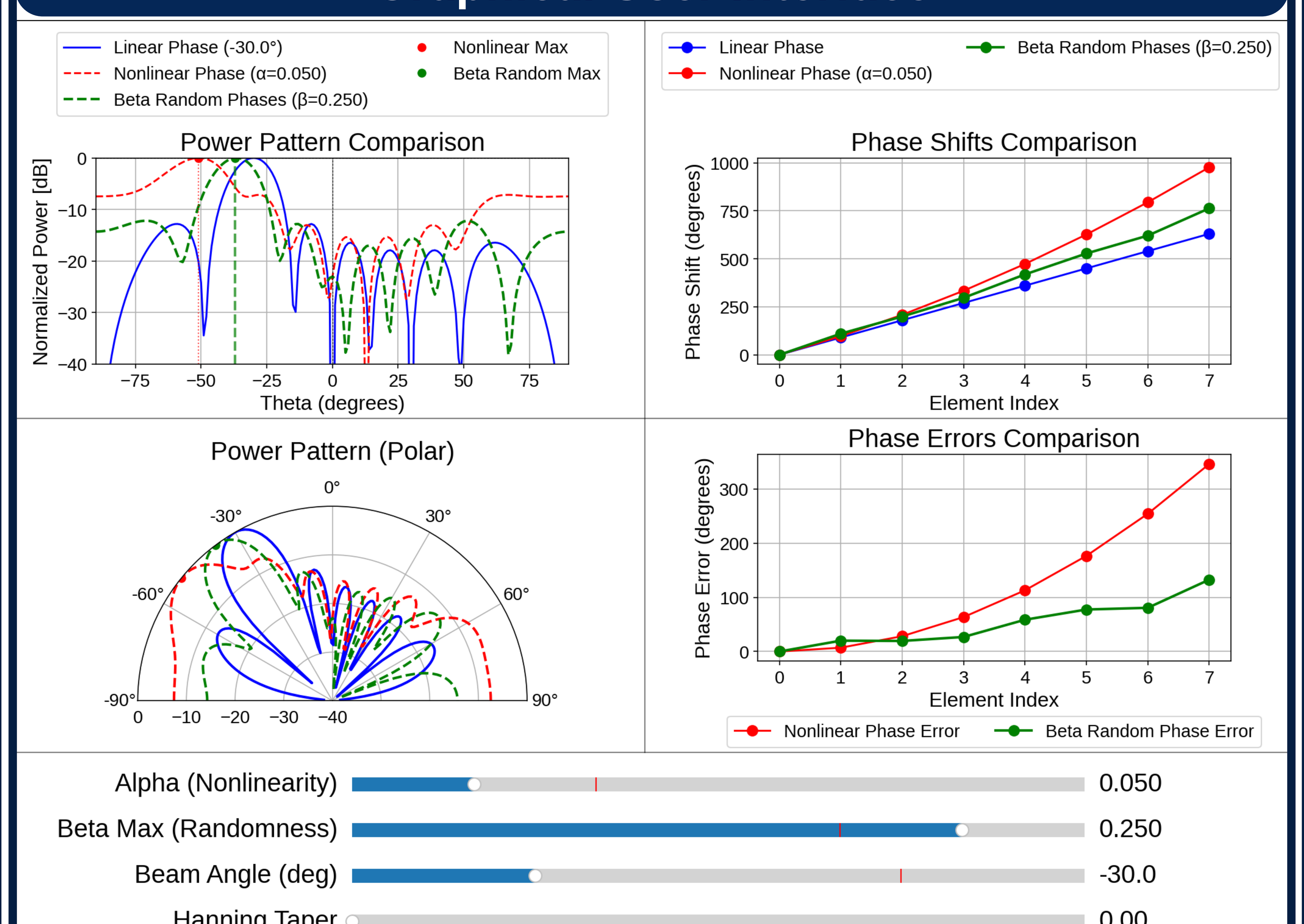
<u>Methods in this project:</u>

- **Fully Connected Neural Networks (FCNNs)** are simple to implement, train, and interpret the results. Compared to other methods, they are more efficient to train due to their simpler operations.
- **Long Short-Term Memory (LSTM)** models use memory cells and gates, allowing it to learn long-term dependencies and sequential data. In [1], the LSTM model outperformed the FCNN and 1D-CNN models at predicting amplitudes and phases of radiation patterns and exceled at synthesizing hypothetical power patterns.

Neural Network Structure

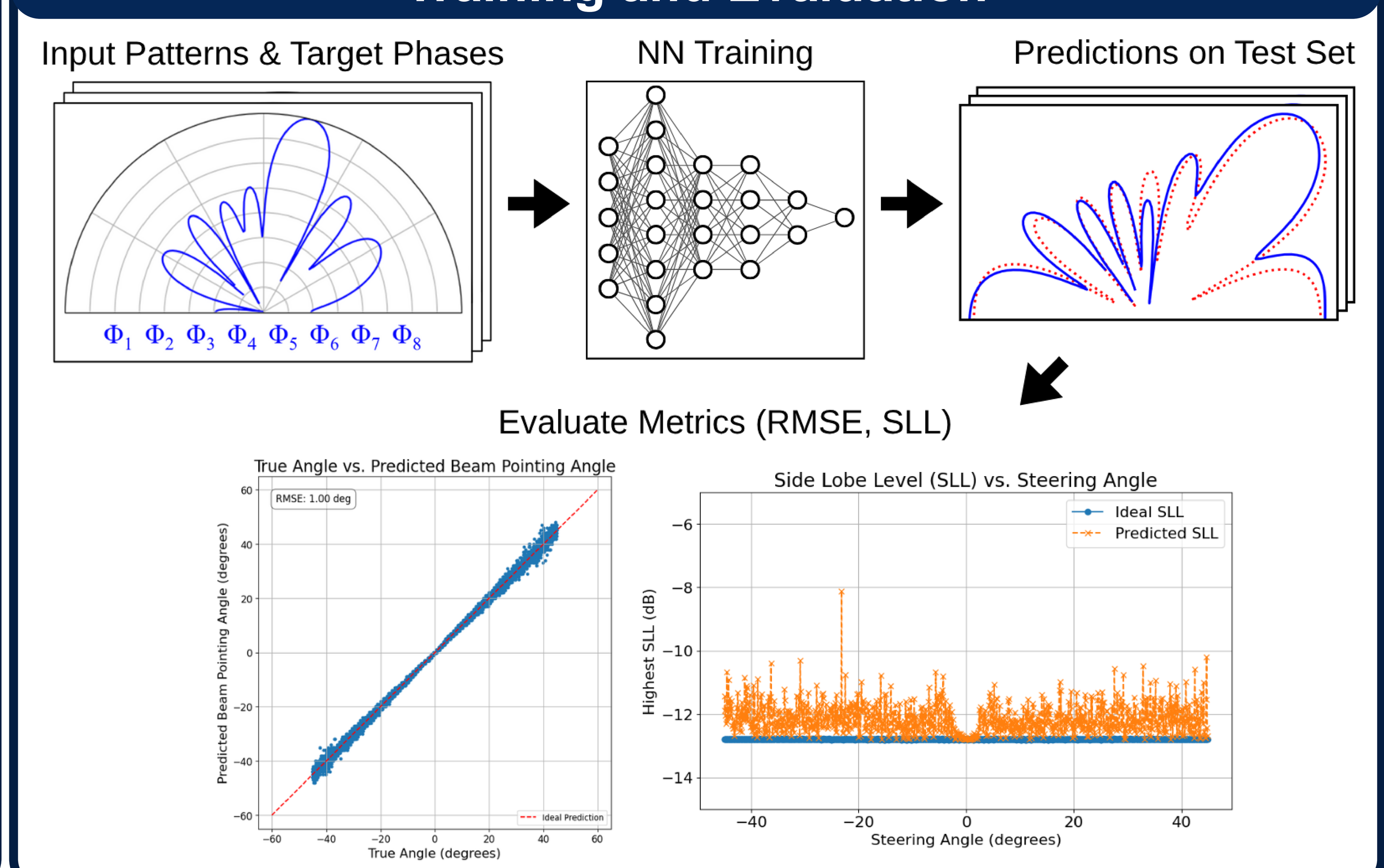


Graphical User Interface

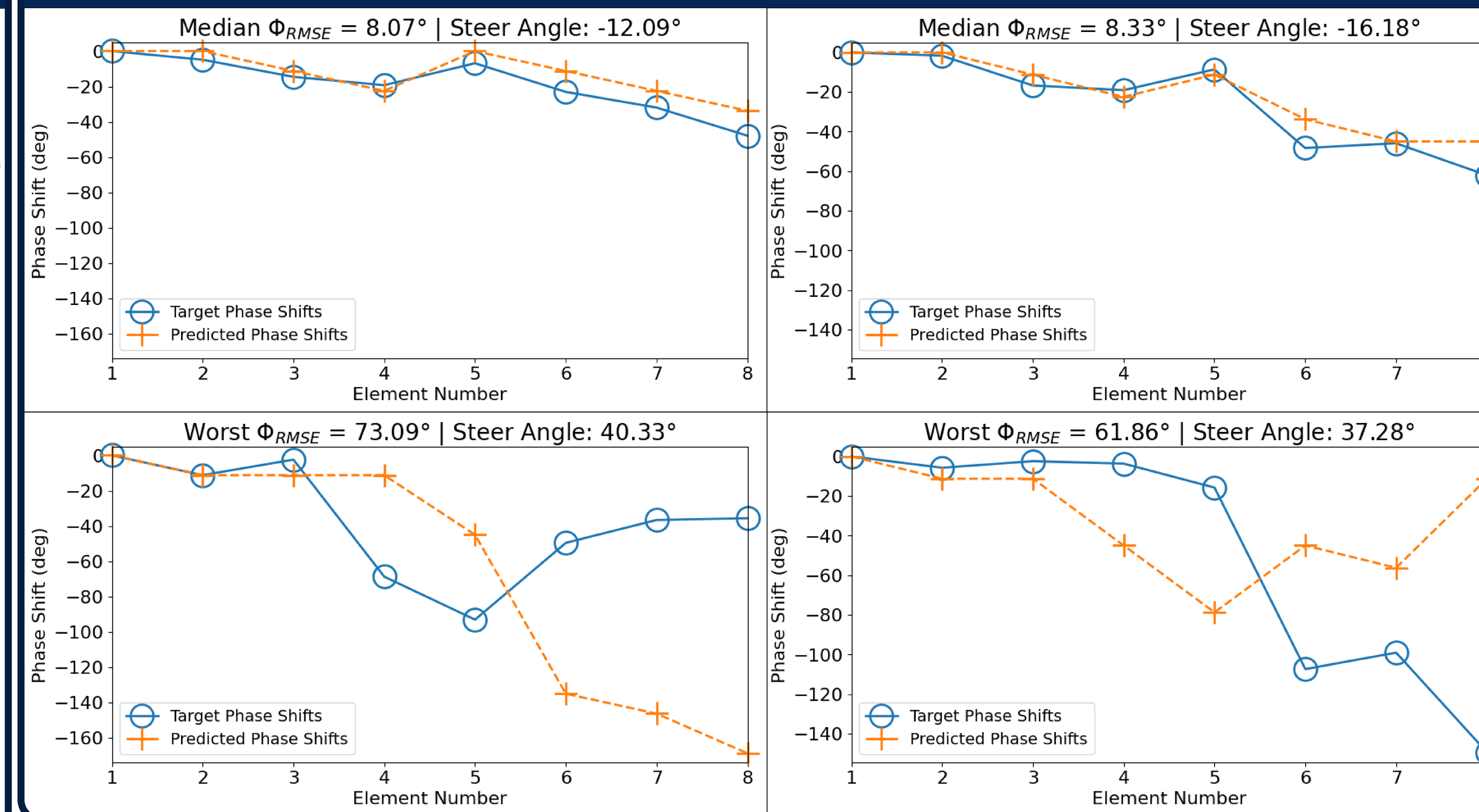


- GUI created with Python and the matplotlib library
- Visualize how phase nonlinearities change the beam pattern
- "Alpha": quadratic nonlinearity strength
- "Beta": maximum % random variation per element

Training and Evaluation



FCNN vs. LSTM Predictions



Results

	FCNN	LSTM
Angle RMSE	1.00°	1.02°
Avg SLL Difference	0.6895 dB	0.7142 dB
Avg Prediction Time	0.22 ms	1.48 ms
Model Size	365 KB	2585 KB

- Generated a training dataset of 20,000 power patterns steered between -50° and 50°. More patterns were generated near the bounds to better handle the nonlinear distortions at larger steering angles.
- The plots above show the median and worst-case predictions on a test set of 9000 power patterns between -45° and 45°. The LSTM model had a slightly higher median phase RMSE, but a lower worst-case phase RMSE.
- The FCNN slightly outperformed the LSTM in Angle RMSE and SLL difference, though this result may be due to the randomness in the test dataset generation.
- LSTM models have a more complex structure, which leads to greater computational overhead, larger model sizes, and slower inference times compared to an FCNN with the same number of layers and nodes.

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Conclusions

- **Neural networks can effectively self-calibrate a linear phased antenna array**, even under significant hardware nonlinearity and randomness.
- The FCNN and LSTM's achieved comparable performance, accurately restoring the main lobe direction within 1° of the ideal beam pattern.
- The main advantage of the FCNN is its **lower inference time and smaller model size**, though further hyperparameter tuning and model architecture experimentation may improve performance.

References

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