DIRECT RADAR TARGET DETECTION WITH ARTIFICIAL NEURAL NETWORKS
(DIRT-ANN)
METEKSAN SAVUNMA

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Abstract. This project aims to design a radar-based detection system that utilizes nonlinear signal processing techniques and artificial neural networks (ANNs) to improve target detection performance in short-range environments. A 60 GHz Frequency Modulated Continuous Wave (FMCW) radar test kit is used to detect specific targets such as humans and drones. The project replaces the conventional CFAR detector typically used in FMCW radar systems with a neural network-based approach. A Fully Convolutional Network (FCN), consisting of feature extraction and classification modules, is employed to perform detection on the Range-Azimuth map generated by the radar. A simulation environment is developed using MATLAB to generate synthetic Range-Azimuth data and train the neural network. Real-world testing is conducted using AWR6843ISK sensor kits provided by METEKSAN Defence Inc. to validate the network's performance. The project is divided into three main work packages: data acquisition and preparation, neural network development and training, and performance evaluation. The test procedure includes simulations, hardware testing, and real-world validation. Upon completion, this project is expected to provide METEKSAN with an advanced, efficient, and accurate radar solution for target detection and classification, with the goal of achieving at least 90% detection accuracy and superior performance compared to traditional CFAR-based methods.

PROJECT DESCRIPTION

This project aims to develop a next-generation radar system that enhances direct target detection through the use of non-linear signal processing techniques and artificial neural networks (ANNs). This project's main motivation is to overcome the limitations of conventional radar detection algorithms, especially the Constant False Alarm Rate (CFAR) detector, which is widely used but prone to false alarms and underperformance in cluttered or dynamic environments. METEKSAN aims to replace this conventional approach with a novel deep learning-based radar detection architecture, enabling highly accurate detection of short-range targets such as humans and drones. Upon completion of the project, METEKSAN will gain access to a customizable, intelligent radar solution that performs with at least 90% detection accuracy and is suitable for both defense and civilian applications.

Currently, CFAR-based algorithms are the standard in most FMCW radar systems, which adjust thresholds based on local noise statistics to detect targets efficiently. However, they encounter challenges due to clutter arising from non-stationary noise, closely spaced targets, and rapidly changing environments. Additionally, commercial radar systems often have fixed architectures and proprietary software, limiting reconfigurability and adaptability for research or custom applications. In response, this project introduces a novel approach by integrating a Fully Convolutional Network (FCN) into the radar processing pipeline, enabling end-to-end target detection directly from the Range-Azimuth map. This not only improves detection accuracy but also allows dynamic adaptation to new data patterns. While recent deep learning methods have advanced radar detection by replacing CFAR with neural networks on Range-Doppler or Range-Angle maps [1], [2], many are too complex for real-time deployment on constrained hardware or are tailored to specific frequencies, datasets, or applications, reducing generalizability. Some rely on oversimplified simulated data, limiting the implementability. In contrast, this project develops a lightweight CNN optimized for 60 GHz FMCW radar and trained on MATLAB-simulated Range-Azimuth data, aiming for efficient, accurate, and real-time target detection in practical scenarios.

The system is developed using a 60 GHz FMCW radar test kit provided by METEKSAN, with three main stages: data acquisition, neural network development, and performance evaluation. Synthetic Range-Azimuth maps are generated in MATLAB for initial training, while real radar data from the AWR6843ISK sensor are used for testing. The system is evaluated through simulation, hardware testing, and field deployment. Unlike existing systems, this solution is reprogrammable, adaptable, and suitable for various radar environments, offering enhanced performance and usability.

The system is designed to meet the system requirements set by METEKSAN using both simulated and hardware-acquired Range-Azimuth maps. It operates within a 60–64 GHz frequency range, with a maximum unambiguous range of 3.0 m and a sampling rate of 2200 ksps. The neural network must detect the presence of a target with at least 90% accuracy on both training and validation sets, match or exceed CFAR performance, and achieve a range estimation RMSE ≤ 0.3 m and $R^2 \geq$ 80%. Results are visualized via heatmaps and performance-scored classifications. The model generalizes across environments and target types, and the architecture must be lightweight enough for FPGA deployment. Overall, the system outperforms traditional CFAR methods in adaptability, accuracy, and usability.

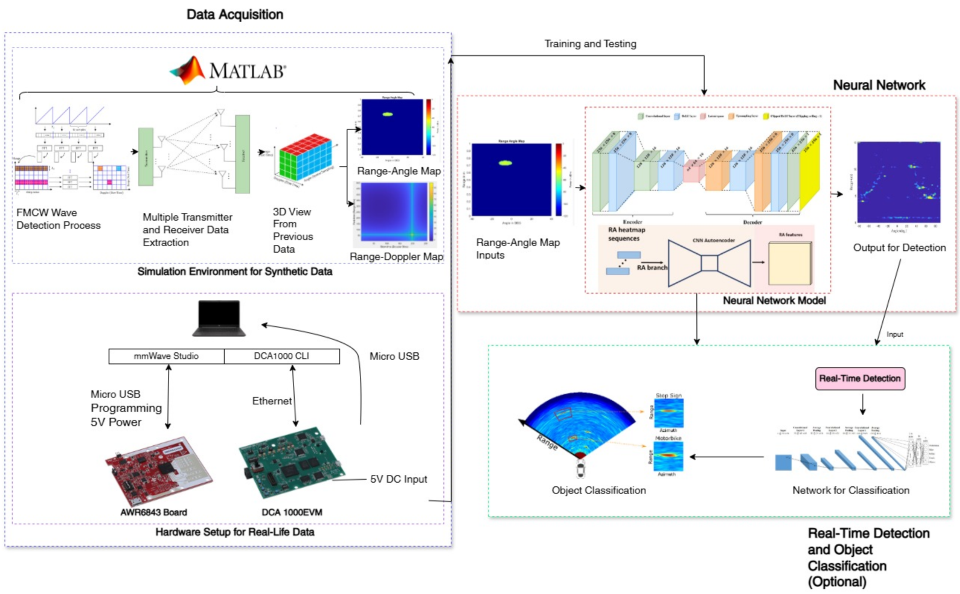


FIGURE 1. Big Picture

The designed system, shown in Figure **??**, consists of three main components: Data Acquisition, Neural Network Development, and optional Real-Time Detection and Object Classification. Data Acquisition includes both synthetic data generation—using MATLAB to create Range-Angle and Range-Doppler maps—and real-life data collection, which involves detailing hardware components, voltage requirements, connection types, and operating environments. This dual approach provides a comprehensive dataset for training and testing. In the Neural Network Development phase, synthetic data is used for initial training, with real-life data incorporated to refine performance and improve accuracy. Finally, in the optional Real-Time Detection phase, results are fed into a classification network, enabling real-time object detection and classification.

MILESTONES

1. Data Collection and Preparation: Simulation parameters based on AWR6843 radar (60-64 GHz, 3TX/4RX antennas, 2200 ksps sampling rate), synthetic Range-Angle maps generated with MATLAB. Beamforming for 9 angle cells (-60° to 60°). Real-world data captured with AWR6843ISK and DCA1000EVM in various environments, processed with windowing and thresholding.

2. Neural Network Development: Fully Convolutional Network (FCN) with encoder-decoder architecture for pixel-wise classification. Three convolutional layers (32, 64, 128 filters) with LeakyReLU and transposed convolutions. Input: (128, 9, 1) Range-Angle map; output: probability map for target detection. Achieved 99.84% accuracy and 99.99% R^2 score for range estimation on simulation data.

3. Performance Evaluation: Testing with simulation and hardware datasets, resulting in 99.25% classification accuracy, precision, recall, F1-score, 0.03m RMSE for range estimation, 99.59% R^2 score. Exceeded initial goals, outperforming CFAR detection in complex environments.

4. System Integration: Integrated hardware data acquisition, simulation processing, and neural network inference. Interactive UI for range and angle inputs, triggering a workflow: MATLAB generates maps, Python-based neural network performs detection, results visualized with performance metrics.

DESIGN DESCRIPTION

Our solution strategy for direct radar target detection combines advanced signal processing techniques with artificial neural networks. The implementation follows three main stages: data acquisition and preparation, neural network development, and performance evaluation.

Overall System Architecture. The system architecture integrates hardware data acquisition with software processing components. Raw radar data collected from the AWR6843ISK flows through several processing stages before reaching the neural network for classification. This architecture enables both offline testing with pre-recorded data and potential real-time implementation.

Data Acquisition and Preparation.

Simulation Environment. The simulation environment was designed to generate realistic Range-Angle maps that closely match the characteristics of the AWR6843ISK radar hardware. Key components of the environment include waveform generation with parameters matching the radar's specifications (3461 MHz bandwidth, 55.8 µs chirp duration) and beamforming to obtain 9 discrete angle cells spanning from -60° to 60°. Ground truth generation was done using thresholding techniques to create training labels.

Hardware Setup. The hardware data acquisition system consists of:

- AWR6843ISK radar sensor (60-64 GHz, 3 TX and 4 RX antennas)
- DCA1000EVM for raw ADC data capture
- MMWAVEICBOOST carrier card for interfacing
- Configuration via mmWave Studio with sampling rate of 2200 ksps

Data collection was performed in both indoor and outdoor environments to minimize interference and noise. We found that data collection in outdoors provided cleaner data with less self-interference at zero range.

Neural Network Architecture.

Fully Convolutional Network Design. We designed a Fully Convolutional Network (FCN) with an encoder-decoder architecture for Range-Angle map input. The encoder includes three convolutional layers (32, 64, 128 filters) with LeakyReLU activation, max pooling (2×3), and batch normalization with a 0.3 dropout rate. The decoder uses transposed convolutions (128, 64, 32 filters) with skip connections. The output layer is a single-filter transposed convolution with sigmoid activation, producing a (128, 9, 1) probability map. With 870,689 parameters, the model is compact enough for FPGA deployment while maintaining high performance.

Training Methodology. The network was trained using a dataset split of 966 training, 208 validation, and 207 test Range-Azimuth maps. A binary cross-entropy loss function was used with the Adam optimizer at a learning rate of 1e-4. The model was trained for 50 epochs with a batch size of 32. Data augmentation techniques were applied to improve generalization. Ground truth labels were generated by thresholding the simulation data at 80 dB and the hardware data at 95 dB.

Performance Evaluation Methodology. To evaluate our system's performance, we implemented a comprehensive testing framework that included both classification and estimation metrics. Classification performance was assessed using accuracy, precision, recall, and F1-score on a pixel-wise basis, while range and angle estimation accuracy were evaluated using the R^2 score and RMSE. Testing was conducted on both simulation-generated maps and real hardware-captured data. For benchmarking, our results were directly compared with CFAR detection outputs on identical datasets. Range and angle estimates were obtained by identifying the center of mass of the predicted target region after thresholding the model's output probability map.

Tools and Equipment. We used the following the following tools and equipment in our implementation:

- **Hardware**:
  - AWR6843ISK sensor (60-64 GHz, 3TX/4RX antennas)
  - DCA1000EVM data capture card
  - MMWAVEICBOOST carrier card
- **Software**:
  - MATLAB for simulation and data processing
  - Python with TensorFlow/Keras for neural network implementation
  - mmWave Studio for radar configuration and data acquisition
  - Wireshark for network packet analysis during data collection

RESULTS AND PERFORMANCE EVALUATION

Our neural network-based radar target detection system was evaluated using both simulation and hardware datasets. This section presents the system requirements and compares our approach with traditional CFAR detection methods.

Classification Performance. The FCN model achieved an excellent classification performance on both simulation and hardware datasets, as summarized in Table 1.

TABLE 1. Classification Performance Metrics

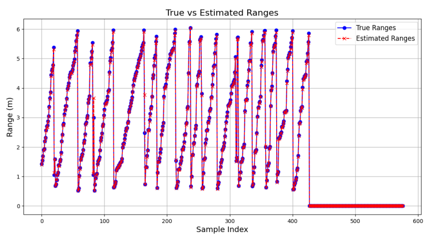
Dataset	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**
Simulation	99.84	84.86	95.49	89.86
Hardware	99.25	–	–	–

The high classification accuracy demonstrates the model's effectiveness in distinguishing between target and background pixels. Notably, the model maintained its performance when tested on real hardware data, showing only a slight decrease in accuracy from 99.84% to 99.25%. This indicates strong generalizability, which is critical for real-world deployment.

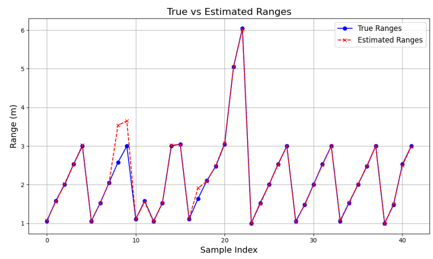
Range and Angle Estimation. Range and angle estimation accuracy are crucial metrics for radar target detection. Our model achieved successful range and angle estimation performance, as shown in Table 2. The comparison plot for range estimation of both cases is given in Figure 2.

TABLE 2. Range and Angle Estimation Performance

Dataset	Range R^2 (%)	Range RMSE (m)	Angle R^2 (%)	Angle RMSE (°)
Simulation	99.99	0.023	96.05	7.40
Hardware	99.59	0.030	75.00	16.20



(a) Simulation results



(b) Hardware results

FIGURE 2. Range estimation results for both datasets

The lower performance in angle estimation, especially with hardware data, can be attributed to several factors: the limited angular resolution, with only 9 angle bins compared to 128 range bins; hardware-specific challenges such as self-interference and environmental reflections; and the greater sensitivity of angle estimation to noise and interference. Despite these challenges, the range estimation performance exceeds our requirements by a significant margin, with RMSE values well below the 0.3m threshold specified in the project requirements.

Comparison with CFAR Detection. To evaluate the advantages of our neural network approach, we compared it with the conventional CFAR detection method using identical datasets. Our neural network-based approach demonstrated several advantages over CFAR, including higher detection accuracy, especially in scenarios with multiple targets or complex environments. It also showed improved robustness to noise and interference, better generalization to varied environmental conditions, and more precise range estimation with a lower RMSE.

System Robustness. We evaluated our system's performance across different environmental conditions and target scenarios to assess its robustness. Indoor experiments showed that outdoor data collection provided cleaner signals with less interference, and the self-interference at zero range was less pronounced outdoors, resulting in improved detection performance. The system maintained consistent performance across various target ranges within the 6.7 m detection limit, though slight degradation in angle estimation was observed for targets near ±60° which correspond to the edges of the FOV of the radar regarding radar's limited angular resolution of 15°. Additionally, it is concluded that the neural network's inference time is suitable for real-time applications when implemented on appropriate hardware.

Our results demonstrate that the neural network-based approach significantly outperforms traditional CFAR detection methods while meeting or exceeding all specified performance requirements. The system shows excellent potential for practical deployment in short-range radar applications where accurate target detection is critical.

CONCLUSIONS AND FUTURE DIRECTIONS

In this project, we developed a neural network-based radar target detection system designed to replace the traditional CFAR algorithm in FMCW radar workflows. By replacing the conventional CFAR-based detection pipeline with a Fully Convolutional Network (FCN), we achieved high-performance target detection and localization on Range-Azimuth maps. Our model was trained on both simulated data generated in MATLAB and real-world data collected using AWR6843ISK radar hardware. Key accomplishments include a beamforming-based simulation pipeline, a robust neural network architecture that surpassed CFAR in accuracy, and successful range-angle estimation performance aligned with system specifications. Our FCN model achieved over 90% classification accuracy, with range and angle estimation RMSE values below 0.3 meters, meeting the defined performance criteria and demonstrating superior accuracy compared to conventional CFAR-based methods. These results validate the effectiveness of the model in both simulated and real-world scenarios.

In the future, the designed system could be implemented on FPGA platforms to enable real-time detection capabilities in real radar systems. Furthermore, the neural network architecture could be extended to support object classification, allowing the identification of different target types. These developments would enhance the system's applicability in defense, automotive, and security domains, and could lead to further research opportunities, academic publications, and potential commercialization or patenting of the technology.

REFERENCES

[1] M. Pan, J. Chen, S. Wang, and Z. Dong, "A novel approach for marine small target detection based on Deep Learning," *2019 IEEE 4th International Conference on Signal and Image Processing (ICSIP)*, Jul. 2019. doi:10.1109/siprocess.2019.8868862.

[2] S. Kang, M. Jang, and S. Lee, "Autoencoder-based Target Detection in Automotive MIMO FMCW Radar System," *Sensors*, vol. 22, no. 15, p. 5552, Jul. 2022. doi:10.3390/s22155552.

BEHIND THE SCENES