Drone Detection Using DopplerNet Range-Doppler Radar

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***Abstract*—With the rapid advancements in drone technology and its diverse applications in military and industrial sectors, there's an imperative need for efficient drone detection mechanisms. This paper presents a solution using cost-efficient small radars, achieving a high accuracy rate of over 98% in drone detection. These radars address the challenges of minimal drone radar signatures, providing enhanced security and regulatory compliance. The project's code is available on GitHub https://github.com/eyalyakir159/radar_systems_eyal_project.**

I. Introduction

The advent of sophisticated drone technology, fueled by advancements in artificial intelligence, chips, and hardware, has revolutionized various sectors, including military and industrial domains. The reduction in drone prices has not only democratized their access but also diversified their applications, ranging from instruments of targeted destruction equipped with small explosives or weapons to efficient means of transporting goods. The proliferation of drones necessitates the development of robust, high-resolution detection and tracking systems to mitigate security risks and ensure adherence to regulations in both military and industrial contexts.

Drones, due to their compact size and minimal radar signature, pose substantial challenges in detection [5]. Their small radar signatures often resemble other entities such as birds and cars , complicating the differentiation process [6]. Current detection methodologies primarily rely on high-resolution cameras [7] coupled with intricate image detection models and radar systems [5]. However, these methods are often hindered by the limitations inherent to radar detection, including the need for multiple small radars instead of a singular large one to address the small and similar radar signatures of drones.

This paper aims to delve deeper into the complexities and challenges of drone detection, exploring innovative and cost-effective solutions to address the limitations of existing detection methodologies. The study focuses on the development of small, precise radars, detailing their capability to detect drones with over 98% accuracy and monitor their speed and location. The proposed small radars are designed to be economically viable, allowing for widespread deployment on cars, towers, streets, and more, to ensure comprehensive coverage and enhanced security measures.

The innovations and findings discussed in this paper are crucial for reinforcing security and regulation compliance in drone operations across military and industrial sectors. By addressing the challenges in drone detection and offering viable solutions, this study contributes to the ongoing discourse in drone technology and its implications, providing insights and directions for future research and development in the field.

II. Data Gathering and Processing

A. Radar Technology

The radar system utilized in this study is a 2D ubiquitous or persistent radar system developed by the microwave and radar group from the Universidad Politecnica de Madrid, called RAD–DAR (Radar with Digital Array Receiver). This radar system operates with an FMCW waveform, and a programmable signal generator provides the waveform, clock, and trigger signals. The system comprises a transmitting antenna and eight receiving antennas, each consisting of an array of eight elements, designed in microstrip technology. The antennas ensure a half-power beamwidth of 10° in the elevation plane and 90° in the azimuth plane.

TABLE I: Radar Parameters

Parameter	**Value**
Radar Frequency (f1)	8.75 GHz (X-band)
Bandwidth (f)	200 MHz
Ramp Period (Tm)	350 s
Ramp Frequency (fm)	2.86 kHz
Number of Samples per Ramp (Ns)	8192
Number of Integrated Ramps (Nd)	512
Number of Channels (Na)	8
Number of Range Bins (Nr)	4096
Dwell Time (Td)	0.1792 s
Number of Synthesised Beams	5 (40°, 20°,0°,20°,40°)
Sample Rate (fs)	32 MHz
Maximum Beating Frequency (fbmax)	16 MHz
Mean-time Gap Between Cubes	0.53 s

Note: In this paper, we did not construct the radar; we used data that was received from this radar. Understanding the source of the signals is crucial for comprehending the data processing and detection mechanisms involved in this study [4].

B. Data Processing

The data processing chain transforms the raw data acquired by the radar into a time-doppler matrix, which is crucial for detecting and extracting information about the object. This matrix is significant as it allows for the visual differentiation of targets based on their radar cross-section (RCS) and motion characteristics, enabling the distinction between drones, cars, and people.

The data is received as a 10×61 matrix, where each row represents a distance cell and each column represents a Doppler frequency. This matrix is obtained by applying a 2D Fast Fourier Transform (FFT) to the raw tensors acquired by the hardware, followed by beamforming and monopulse techniques.

The target range information is drawn from the beating frequency since the system uses an FMCW waveform. This frequency is the difference between transmitted and reflected frequencies. Mathematically, range information is estimated as in the equation below:

$$R = \frac{f_b \cdot c \cdot T_m}{2\Delta f}$$

where R is the range in meters, f_b is the beating frequency, T_m is the signal period, c is the speed of light, and Δf is the bandwidth of the signal.

Next, a second FFT is applied in the slow-time axis to obtain the Doppler information of the target. The equation for 2D FFT is given by:

$$X(k,l) = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} x(m,n) \cdot e^{-j2\pi\left(\frac{km}{M} + \frac{ln}{N}\right)}$$

where $X(k,l)$ is the 2D FFT of the input signal $x(m,n)$, and M and N are the dimensions of the 2D input signal.

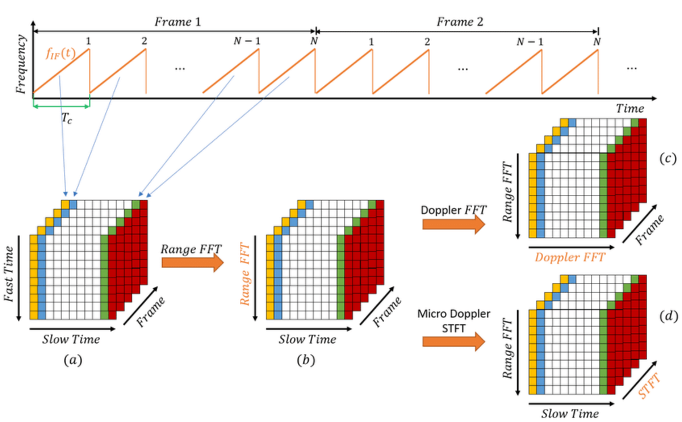
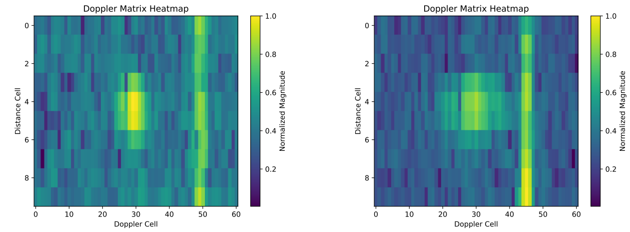


Fig. 1: Time–Doppler Cube

This meticulous processing and the subsequent formation of the time-doppler matrix are pivotal in enhancing the accuracy and reliability of object detection and classification in real-world scenarios.

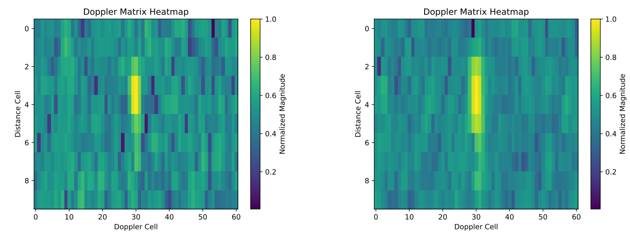
III. Simulations and Improvments

This section delineates the meticulous implementation and evaluation of both the existing Convolutional Neural Network (CNN) models and the proposed innovative models.



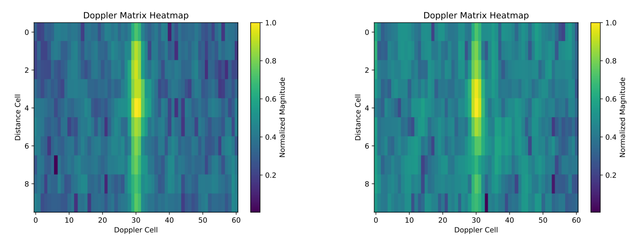
(a) Person Example 1 (b) Person Example 2

Fig. 2: Examples of People



(a) Drone Example 1 (b) Drone Example 2

Fig. 3: Examples of Drones



(a) Car Example 1 (b) Car Example 2

Fig. 4: Examples of Cars

A. Simulation of Existing CNN Networks

In this subsection, we replicate the CNN classifier as delineated in the DopplerNet study [4] to ensure consistency and reliability in comparative analysis. The objective is to gain insights into the foundational model's performance metrics and operational dynamics, providing a baseline for evaluating the innovations introduced in our proposed models.

The constructed network is meticulously designed, incorporating a singular convolutional neural network (CNN) layer endowed with 32 filters, followed by four linear processing layers. The CNN layer plays a pivotal role in the architecture, tasked with the extraction of salient features inherent in the data. This layer is instrumental in discerning intricate patterns and nuanced characteristics within the input, enabling the model to capture the underlying complexities of the dataset. Subsequent to the feature extraction phase, the linear layers undertake the responsibility of processing the acquired data. These layers are meticulously engineered to analyze the extracted features, synthesizing them to draw informed

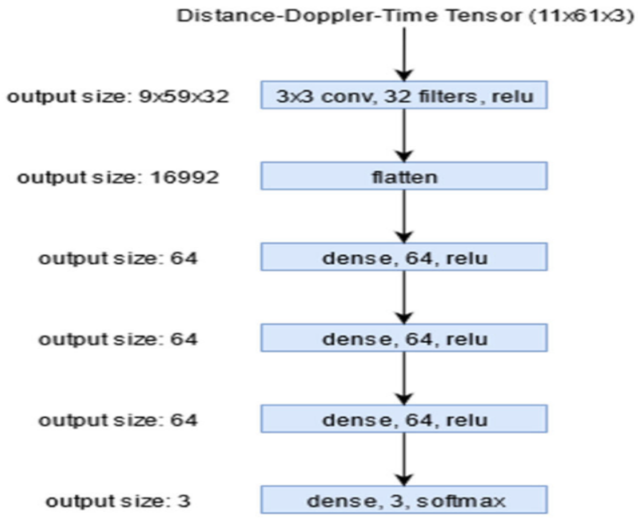


Fig. 5: Diagram of the DopplerNet Network

and accurate conclusions. This synergistic interplay between feature extraction and data processing allows the network to make robust and reliable predictions, ensuring the integrity and efficacy of the model in diverse applications.

B. Proposed Network and Improvements

In this subsection, we present and expound upon a novel network architecture, meticulously designed to navigate the intricate complexities inherent in the considered dataset. Additionally, recognizing that in real-world scenarios, radar predominantly encounters default terrain devoid of targets such as people, cars, or drones, we have incorporated an additional detection object—plain terrain (or the absence of significant objects). This inclusion is meticulously generated with respect to varying terrains, including mountains, sea, and grass, serving as a critical parameter to assess the model's discernment capabilities.

1) Enhanced U-Net Architecture: This architecture symbolizes the apex of our innovative endeavors, unveiling a model anchored in the U-Net [2] framework and augmented with specialized enhancements. The network is bifurcated into two core components: the encoder and the decoder. The encoder, employing deep convolutional layers, is tasked with feature extraction, downsampling, and the amplification of feature depth. Conversely, the decoder is dedicated to the synthesis of features while undertaking data upsampling.

Acknowledging the intricate nature of our dataset, we have instituted specialized connections, denominated as Time Doppler to Range Speed (TDRS), between each analogous layer in the encoder and the decoder. This innovation enables the decoder to assimilate both the refined features and the intrinsic, valuable data.

To culminate the architecture, a sequence of linear layers is integrated to synthesize the data extrapolated by the network and to render a conclusive detection outcome.

a) TDRS Block: The TDRS block, integral to the Enhanced U-Net Architecture, is devised to convert the time doppler matrix into a SPEED RANGE matrix through a linear processing layer transformation, mathematically represented as:

$$\text{output} = \text{linear}\left(\frac{f_b \cdot c \cdot T_m}{2\Delta f}\right)$$

where c represents the speed of light, and the definitions and elaborations of the other parameters are provided in Section 2 (Data Gathering and Processing).

This transformation enables the conversion of the extracted features into a more utilizable format, thereby enhancing the network's capability to draw accurate and reliable conclusions.

2) Terrain Data Generation: In this section, we elaborate on the generation of an additional detection modality for the model, representing standard terrains such as grass, sea, or mountain. This enhancement is pivotal for refining the model's discriminatory capabilities, enabling it to differentiate between significant targets and the prevalent terrains in real-world scenarios.

The terrain data is synthesized utilizing a specialized function designed to simulate radar signals corresponding to distinct terrain types. This function, denominated as `simulate_radar_signal`, accepts a terrain type and generates a simulated radar signal, represented as a 10×61 time doppler matrix, reflective of the specified terrain.

Algorithm 1 Pseudocode for Terrain Data Generation

```
procedure SIMULATERADARSIGNAL(terrain)
    assert terrain in ['mountain','grass','sea']
    Set seed for reproducibility
    Initialize signal with random noise of size 10 × 61
    if terrain == 'mountain' then
        Increase power in the first 20 frequency bins
    else if terrain == 'grass' then
        Increase power in the middle 20 frequency bins
    else if terrain == 'sea' then
        Increase power in the last 21 frequency bins
    end if
    return modified signal
end procedure
```

The function initializes the signal with random noise, under the foundational assumption that the signal is a random variable, and modifies it based on the specified terrain type. This simulated variation in radar signals is crucial for mimicking the discrepancies encountered across different terrains.

In this simulation:

- The sea terrain is associated with high frequencies, reflecting the smoother and more reflective surface of water bodies, which typically result in higher frequency returns.
- The grass terrain is assigned middle frequencies, symbolizing the intermediate roughness and reflectivity of grassy landscapes.

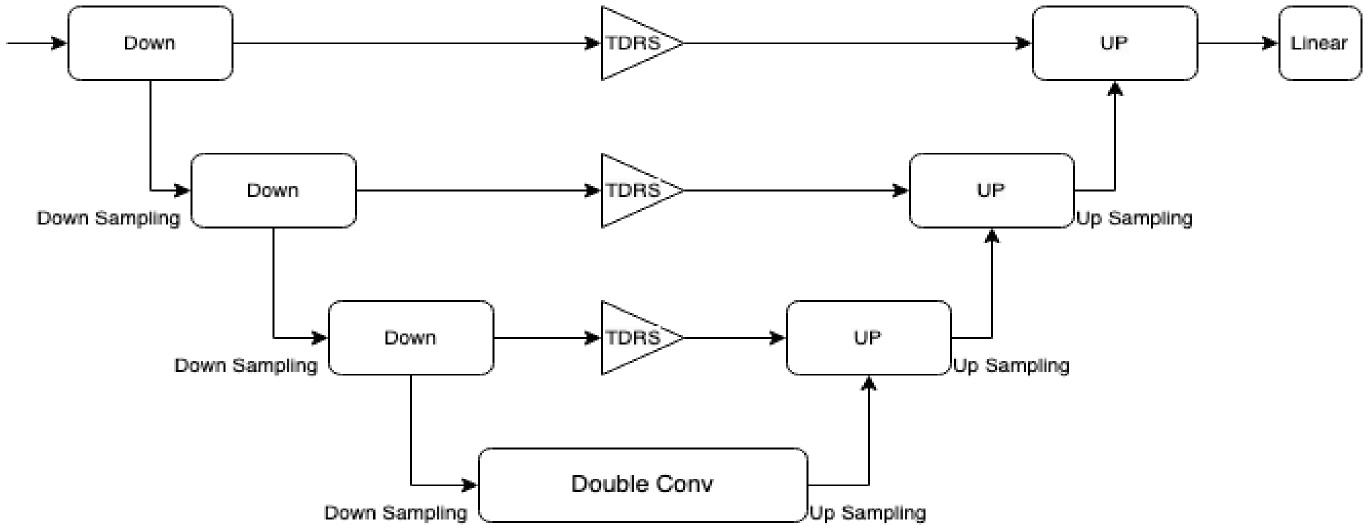


Fig. 6: Diagram of the U-net Network

- The mountain terrain is allocated low frequencies, representing the rugged and irregular surfaces of mountainous regions, which generally yield lower frequency returns.

Note: It is imperative to acknowledge that the data generated through this method does not represent real-world data. Instead, it serves solely as a synthetic dataset, constructed to assess the network's ability to distinguish between target and non-target entities within varied terrains.

This meticulous categorization and simulation of terrains serve as a foundational element for training the model to recognize and differentiate between various terrain types, thereby enhancing its precision and adaptability in diverse environmental contexts.

IV. Results

In this section, we showcase the performance outcomes of the DopplerNet Network and the augmented U-Net architecture, both with and without supplementary terrain data. Results are depicted via graphical false alarm illustrations and benchmarking tables comparing network metrics.

A. Training Environment and Parameters

Note: All networks were trained utilizing 8 GPU 1080ti for a duration of 60 minutes in Professor Haim Permuter's lab.

TABLE II: Training Parameters

Parameter	Value
Learning Rate	0.0002
Epochs	100
Batch Size	32
Optimizer	Adam
Criterion	BCE With LogitsLoss

B. Data

This subsection provides an overview of the datasets utilized in our study. The datasets encompass various data types, including car, drone, people, and terrain data. The specific quantities of each data type are detailed in Table III.

TABLE III: Amount of Data

Data Type	Amount
Car	5720
Drone	5065
People	6700
Terrain	5000

C. DopplerNet Network

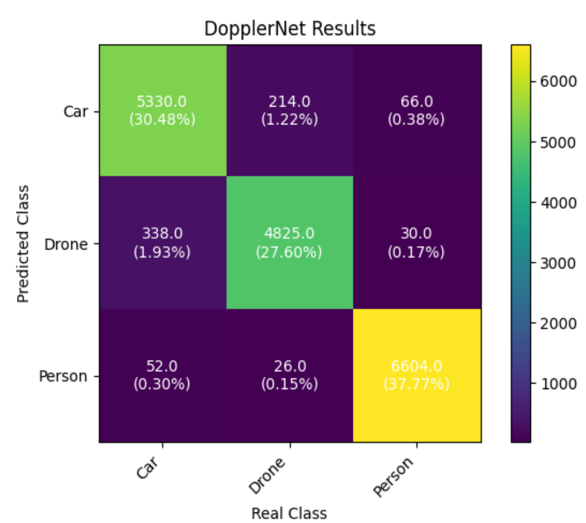


Fig. 7: False Alarm representation for DopplerNet Network without added terrain

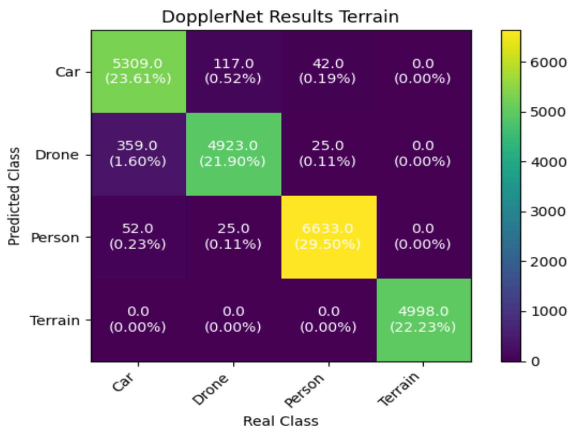


Fig. 8: False Alarm representation for DopplerNet Network with added terrain

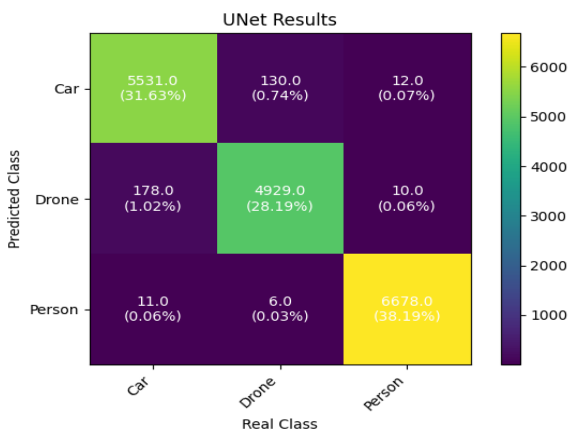


Fig. 9: False Alarm representation for Enhanced U-Net Architecture without added terrain

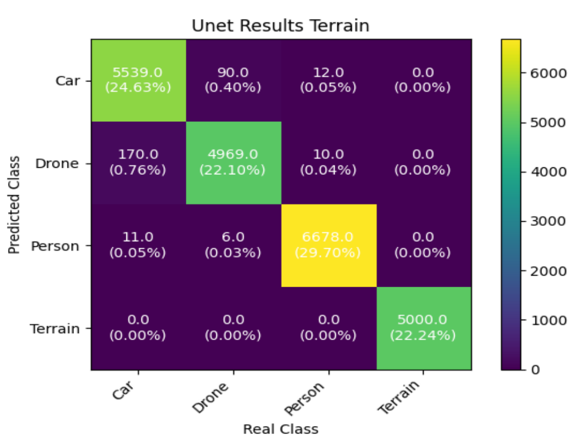


Fig. 10: False Alarm representation for Enhanced U-Net Architecture with added terrain

D. Unet Network

E. Benchmarking

Comparative analyses of the networks are presented in Tables VII and V, showcasing the performance metrics including Accuracy, Precision, and Recall for scenarios without and with added terrain respectively.

Accuracy: Accuracy is the ratio of correctly predicted instances to the total instances in the dataset. It can be calculated using the formula:

$$\text{Accuracy} = \frac{\text{Number of correct predictions}}{\text{Total number of predictions}}$$

Precision: Precision, also known as Positive Predictive Value, is the ratio of correctly predicted positive observations to the total predicted positives. The formula for precision is:

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives + False Positives}}$$

Recall: Recall, also referred to as Sensitivity or True Positive Rate, is the ratio of correctly predicted positive observations to all the actual positives. The formula for recall is:

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives + False Negatives}}$$

TABLE IV: Benchmarking of Networks without Added Terrain

Network	Accuracy	Precision	Recall
DopplerNet	95.85%	92.91%	95.26%
Enhanced U-Net	98.02%	96.33%	97.31%

TABLE V: Benchmarking of Networks with Added Terrain

Network	Accuracy	Precision	Recall
DopplerNet	97.24%	92.76%	97.20%
Enhanced U-Net	98.67%	96.50%	98.10%

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V. Discussion and Further Analysis

In our pursuit to understand the intricacies of the data and its amenability to various network architectures, we further explored two distinct neural network designs: a rudimentary linear network and a more sophisticated convolutional neural network (CNN). The rationale behind this exploration was twofold. Firstly, by employing a basic linear network, we aimed to ascertain if the data possesses inherent linearity, making it susceptible to simpler modeling techniques. Secondly, by juxtaposing the results with a complex CNN, we intended to gauge the potential improvements or nuances that arise from a more intricate architectural design.

A. Linear Network Analysis

The linear network has four decreasing-sized layers with intermittent dropout to prevent overfitting. Its results can indicate the data's simplicity, potentially negating the need for complex designs.

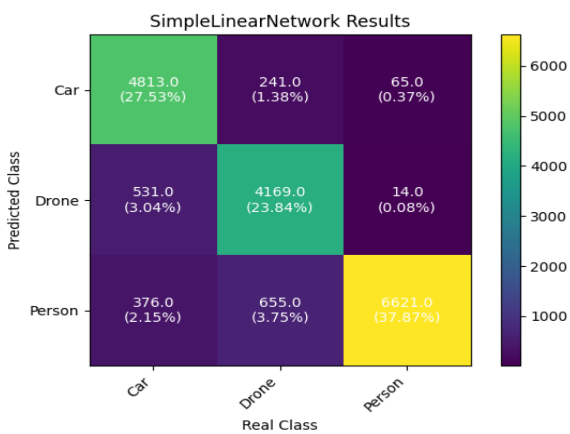

Fig. 11: Performance representation for the Linear Network without added terrain

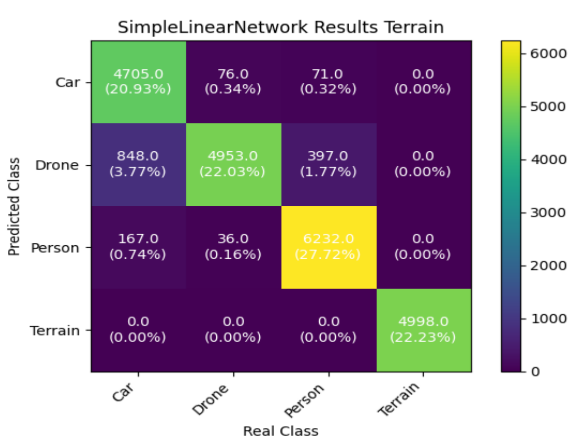

Fig. 12: Performance representation for the Linear Network with added terrain

B. Advanced CNN Analysis

The advanced CNN, with its layered design, aims to detect intricate data patterns. Comparing it to the linear network highlights the benefits and need for such complex architectures for the dataset.

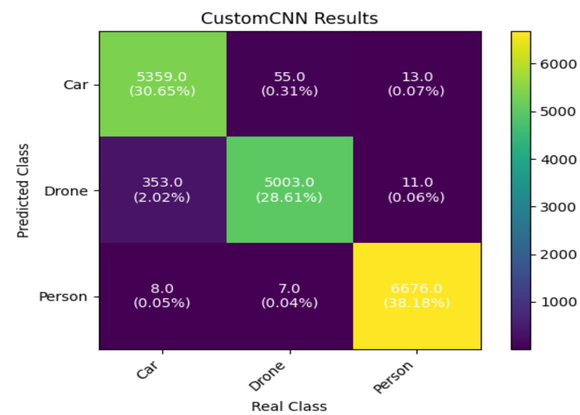

Fig. 13: Performance representation for the Advanced CNN without added terrain

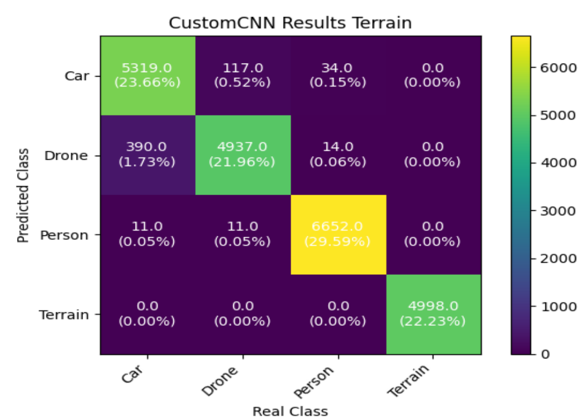

Fig. 14: Performance representation for the Advanced CNN with added terrain

TABLE VI: Benchmarking of Networks without Added Terrain

Network	Accuracy	Precision	Recall
DopplerNet	95.85%	92.91%	95.26%
Enhanced U-Net	98.02%	96.33%	97.31%
Linear	89.24%	88.44%	82.31%
Advanced CNN	96.44%	93.22%	96.78%

TABLE VII: Benchmarking of Networks with Added Terrain

Network	Accuracy	Precision	Recall
DopplerNet	97.24%	92.76%	97.20%
Enhanced U-Net	98.67%	96.50%	98.10%
Linear	92.91%	79.91%	97.79%
Advanced CNN	97.43%	92.44%	97.47%