
AirGuard: Micro-Doppler-Based Target Classification Using Edge AI

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Abstract.

In recent years, identifying the difference between drones and birds has become increasingly difficult in low-altitude airspace monitoring systems. Therefore, the study proposed as a micro-Doppler-based approach that was combined with deep learning techniques in order to address these challenges. Here, the radar signals have been transformed into time-frequency representations by using the Short-Time Fourier Transform (STFT), which is used to capture unique motion characteristics like rotor movement and wing flapping. These spectrograms are then used to train a YOLOv11-based model to support a real-time classification process. The proposed system was observed to achieve approximately 96% accuracy while also maintaining low latency parameters, making it suitable for deployment purposes on edge devices. Overall, these approaches are seen to provide an efficient and scalable solution supporting real-time aerial object classification.

Keywords. Micro-Doppler Radar, Edge AI, YOLOv11, Drone Detection, Bird Classification, STFT, Spectrogram Analysis, Real-Time Target Classification.

1. INTRODUCTION

The rapid growth in the usage of drones has thereby made an airspace monitoring system to seem more complex. One of the key challenges among all of them is the differentiation of drones from birds, as both of them are seen to generate similar radar signatures.[1][8]. Traditionally the techniques like Radar Cross Section (RCS) were used, which often failed to provide reliable results hence leading to misclassification [3][7]. In order to overcome this limitation as a solution micro-doppler signatures have been utilized to capture fine-grained motion patterns also including rotor dynamics in drones and wing movements in birds effectively [1]. The recent advancements in deep learning have further improved classification accuracy by the convergence of radar signals into spectrogram images therefore allowing the automatic feature learning process[5][9][10].

2. LITERATURE SURVEY

Many researchers were found to look into the micro-Doppler techniques for the purpose of classifying aerial targets. Where the earlier studies demonstrated that these signatures could effectively distinguish drones from birds using the radar data [1]. Along with deep learning performance has improved significantly, especially when the radar signals have been converted into spectrogram images also making the feature extraction step easier [9]. Models like Convolutional Neural Networks (CNNs) have been popular because they are used to extract important patterns from these spectrograms [8]. Recently, YOLO-based models have gained attraction among all due to their capabilities like speed and real-time detection [10]. The Data augmentation techniques has also helped to improve model accuracy and thereby reduce overfitting [7]. Despite of all these advancements the challenges remained such as performance drop in the noisy conditions and the limitations with small datasets [6][5]. Thus, a more robust and efficient system was still needed for reliable real-time aerial target classification.

3. PROPOSED SYSTEM / METHODOLOGY

Radar Signal Working: Radar signals of the and birds are collected from the available datasets or radar-based sensing systems.

Pre-processing: The collected radar signals are processed in order to reduce the noise and disturbances using the methods such as normalization and segmentation.

Spectrogram Analysis: The pre-processed radar signals are then converted into spectrograms using the Short-Time Fourier Transform (STFT) to capture the micro-doppler patterns such as rotor movement in drones and the wing movements in birds.

Model Training: YOLOv11 is trained using the generated spectrogram images to automatically learn the distinguishing patterns between drone and bird signatures and then perform target classification.

Edge AI Integration: After the classification of the aerial targets is done, the trained model is then considered for the deployment on an edge or mobile device. Then the system will provide fast and low-latency real-time classification of drones and birds.

4. ARCHITECTURAL DIAGRAM

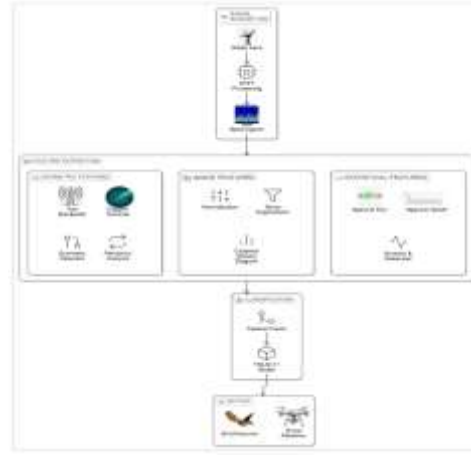


Figure 4.1. System Architecture of the proposed micro-doppler system

The above system first processes to collect raw radar signals and then clean them by removing noise in order to enhance quality. These signals are then converted into spectrograms using the STFT, which helps in extraction of useful features. These features are then applied as input to the YOLOv11 model for real-time classification.

5. DATASET DESCRIPTION:

Radar signatures of drones and birds were obtained from standard radar datasets used in aerial target classification and micro-Doppler analysis research [1], [3]. The collected radar data represents different motion patterns of drones and birds, including rotor movements and wing-flapping patterns. Due to the limited availability and variability of real-world radar samples, data augmentation techniques were used to increase the diversity of the available data. Techniques such as time shifting, noise addition, and scaling were applied to generate additional samples [7].

6. MATHEMATICAL MODEL:

Mathematical representation of our system:

The STFT is represented as:

$$X(t, f) = \int x(\tau) w(\tau - t) e^{-j2\pi f\tau} d\tau \quad (1)$$

Feature extraction function:

$$F = \phi(X) \quad (2)$$

The output class:

$$Y = f(F; \theta) \quad (3)$$

$X(t)$ = Input raw radar signal, X' = Pre-processed radar signal, $X(t,f)$ = STFT-generated spectrogram, F = Extracted micro-Doppler features from the spectrogram, Y = Model prediction (Drone or Bird), θ = Trained YOLOv11 model parameters.

7. RESULT ANALYSIS:

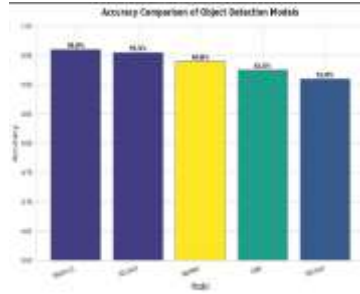


Figure 2: Accuracy Comparison



Figure 3: Application Interface

8. CONCLUSIONS:

In this work we have presented the micro-Doppler-based system for classifying drones and birds utilizing STFT and a YOLOv11 model. The results are seen to promise us with the model achieving approximately 96% accuracy while supporting the real-time edge deployment. Using the spectrogram-based features we improved overall classification performance. Nonetheless, there is still some room for the enhancement, especially with the noisy data and the unfamiliar situations.

9. REFERENCES:

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Biographies



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