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A Data-Driven Approach to Small UAV Detection using Micro-Doppler Signatures and Deep Convolutional Architecture

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Abstract - Detecting and classifying Small Unmanned Aerial Vehicles (SUAVs) remains a complex task for radar systems due to their compact size and radar cross-section, which often resemble those of birds, insects, or background clutter. As SUAVs are increasingly used in security-sensitive contexts, improving detection methods is essential for defence and airspace monitoring. Traditional radar approaches often fall short in reliably distinguishing SUAVs from similar targets. However, micro-Doppler signatures derived from Continuous Wave (CW) radar offer valuable motion-based features that can help overcome this challenge. In this study, we propose a method to increase the size of micro-Doppler signatures obtained from Continuous Wave (CW) radar, aiming to enhance the discriminative capabilities of radar-based UAV detection systems by augmenting the collected radar data and employing advanced signal processing techniques. This enhancement captures subtle motion characteristics that are key to differentiating SUAVs. We further leverage recent advancements in Artificial Intelligence (AI), particularly Deep Learning (DL), to enable automatic feature extraction and classification. Our experimental results indicate that the proposed approach improves detection robustness, achieving a classification accuracy and balanced performance across precision, recall, and F1-score. These findings underscore the potential of our method to strengthen radar-based UAV detection systems in clutter and noise environments.

***Key Words*:** Artificial Intelligence (AI), Airspace Security, Continuous Wave (CW) Radar, Deep Learning (DL), Micro-Doppler Signatures,

1. INTRODUCTION

Unmanned Aerial Vehicles (UAVs), commonly referred to as drones, have seen rapid adoption across a range of sectors, including defense, agriculture, logistics, and aerial imaging. While their utility is undeniable, their growing presence in public and restricted airspaces raises significant concerns related to safety, privacy, and unauthorized operations. Detecting and classifying UAVs, particularly smaller variants (SUAVs), remains a critical challenge—especially when they operate in areas where they ma, y interfere with manned aviation or breach secure zones.

Radar-based systems offer a robust solution for UAV detection, as they can operate in various environmental conditions and detect objects beyond visual line of sight. Among the radar features leveraged for target discrimination, **micro-Doppler signatures** have gained prominence. These signatures capture subtle frequency modulations caused by the motion of rotating parts (e.g., propellers), enabling the differentiation of UAVs from birds, insects, or clutter.

Continuous Wave (CW) radar systems are frequently employed in this context due to their continuous transmission and cost-effectiveness. However, a significant limitation is the relatively low resolution and small size of micro-Doppler signatures derived from CW radar, which can reduce the performance of classification algorithms. Addressing this limitation is vital for improving the reliability of radar-based UAV detection systems.

2. RELATED WORKS

Recent advancements in radar signal processing and deep learning have led to notable progress in micro-Doppler-based Automatic Target Recognition (ATR). Ufer et al. [1] explored various deep learning architectures, including convolutional neural networks (CNNs) and transformers, to evaluate their performance on complex micro-Doppler datasets. Their findings suggest that model architecture plays a crucial role in effective target classification.

Yang and Cheng [2], [3] proposed a time-frequency analysis approach based on short-time parametric sparse representation (STPSR), which demonstrated improved parameter estimation over conventional Hough transform methods. Their simulations confirmed the method's potential for accurate micro-Doppler analysis.

Other studies have examined the extraction of micro-Doppler features using wavelet transforms, inverse Radon transforms, and adaptive time-frequency representations. These techniques have been applied to distinguish UAVs from other targets such as birds and rotating mechanical structures, with promising results for both military and civilian applications [14], [20], [23], [34].

Despite this progress, several research gaps remain. Specifically:

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- **Micro-Doppler Signature Augmentation**: Few studies focus on increasing the size or enhancing the resolution of micro-Doppler signatures from CW radar returns, limiting classification performance [1].
- **Underutilization of Cognitive AI**: Most existing approaches rely on traditional ML or DL techniques, with limited exploration into cognitive AI methods that could improve contextual decision-making [15].
- **Sensor Fusion Limitations**: While multi-sensor integration has been proposed, comprehensive studies combining radar with electro-optical and acoustic sensors are scarce [16].
- **Lack of Real-World Testing**: Many experimental validations are conducted in controlled settings, and there remains a need for real-world trials across diverse operational scenarios [21].
- **Dataset Availability**: The absence of large, open-access datasets with labeled micro-Doppler UAV signatures impedes benchmarking and reproducibility of new methods [25].

This study seeks to address these gaps by introducing a methodology to enhance micro-Doppler signature resolution through signal processing and data augmentation. By increasing the temporal and spectral richness of radar returns, we aim to extract more detailed motion features and improve UAV classification accuracy. The approach is validated through extensive experimentation, comparing baseline and augmented models.

Ultimately, this work contributes toward more sensitive and reliable radar-based SUAV detection systems, supporting security operations in both civilian and defense contexts.

3. METHODOLOGY

In this study, a Convolutional Neural Network (CNN) is designed for classification tasks. The model shown in Figure 1 consists of convolutional layers for feature extraction, pooling layers for dimensionality reduction, and fully connected layers for classification.

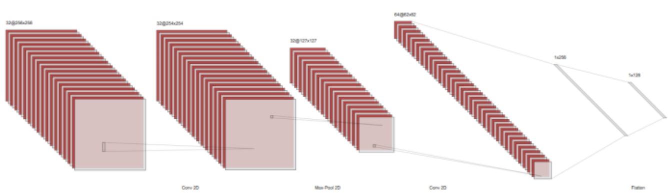

Figure 1: CNN Model Architecture

3.1 Input Layer

The input image can be expressed in the following equation (1):

$$X \in \mathbb{R}^{H \times W \times C} \qquad (1)$$

where H = 256, W = 256, and C = 3 (RGB channels).

3.2 Convolutional and Pooling Layers

First Convolutional Block as given in equation (2), Conv2D operation applies $N_1 = 32$ filters of size 3 × 3, generating feature maps. The convolution operation at layer l is given by:

$$Y^{\{l\}}_{\{ijk\}} = \sum_{m=0}^{K-1} \sum_{n=0}^{K-1} \sum_{c=0}^{C-1} W^{L}_{mnc}\ X^{l-1}_{i+m,j+n,c} + b^{l}_{k} \qquad (2)$$

Where $Y^{l}_{i,j,k}$ is the output feature map at location (i,j) and channel k.

$W^{l}_{m,n,c,k}$ is the filter weight.

b^{l}_{k} is the bias term.

$X^{(L-1)}_{i+m,j+n,c}$ represents the input from the previous layer.

Since stride = 1 and padding = valid, the output feature map size is:

$$H' = \frac{H-K}{S} + 1, \quad W' = \frac{W-K}{S} + 1$$

A MaxPooling layer with a 2 × 2 filter and stride = 2 is applied using the equation (3)

$$Y^{pool}_{i,j,k} = \max_{(m,n) \in P} Y^{l}_{2i+m,2j+n,k} \qquad (3)$$

A second Conv2D layer applies $N_2 = 64$ filters of size 3 × 3, producing an output size of 125 × 125 × 64.

A MaxPooling layer with 2 × 2 reduces it further to 62 × 62 × 64.

3.3 Fully Connected Layers

The output from the last convolutional layer is flattened into:

Flatten Size = 62 × 62 × 64 = 246016

A Dense layer with 128 neurons is applied as per the equation (4),

$$Z^{l} = W^{l} X^{l-1} + b^{l} \qquad (4)$$

Where Z^{l} is the pre-activation output, $W^{l}$is the weight matrix,$X^{l-1}$is the input from the previous layer, and b^{l} is the bias vector.

A dropout layer with 50% dropout is added. Finally, the dense output layer with a softmax activation function given in equation (5) is applied:

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$$\hat{y}_i = \frac{e^{zi}}{\Sigma_j e^{zj}} \qquad (5)$$

Where $\hat{y}_i$ is the probability of class i.

3.4 Loss Function and Optimization

The model is trained using categorical cross-entropy loss as per equation (6),

$$L = -\Sigma y_i \log(\hat{y}_i) \qquad (6)$$

Where y_i is the true label and $(\hat{y}_i)$ is the predicted probability.

The Adam optimizer is used, updating weights expressed in the following equations (7 to 10):

$$m_t = \beta_1 m_{t-1} + (1-\beta_1) g_t \qquad (7)$$

$$v_t = \beta_2 v_{t-1} + (1-\beta_2) g_t^2 \qquad (8)$$

$$\hat{m_t} = \frac{m_t}{1-\beta_1^t} \quad , \hat{v^t} = \frac{v_t}{1-\beta_2^t} \qquad (9)$$

$$W_t = W_{t-1} - \frac{\eta}{\sqrt{v_t + \epsilon}} \hat{m_t} \qquad (10)$$

where m_t, v_t are the first and second-moment estimates, g_t is the gradient at time t, β_1, β_2 are momentum terms, η is the learning rate.

3.5 Performance Metrics

The model is evaluated using equation (11):

Training Accuracy: $\text{Accuracy} = \frac{\text{Correct Predictions}}{\text{Total Samples}}$ (11)

• Validation Accuracy: Computed on unseen data.

• Training and Validation Loss: Measured using cross-entropy.

4. RESULT ANALYSIS

The training and validation accuracy graphs shown in Figures 2 and 3 indicate a consistent rise in performance over the epochs, stabilizing around 0.95, which demonstrates that the model successfully converged without signs of underfitting or overfitting. Similarly, the training and validation loss graphs exhibit a decreasing trend, converging to low values and indicating a reduction in errors as the training progresses. Table 1 summarizes the training and validation of the model.

The model achieved an impressive test accuracy of 93.58%. The classification report highlights strong performance for both classes. For the "Bird" class, the precision, recall, and F1-score were 0.97, 0.90, and 0.94, respectively, while for the "Drone" class, the corresponding metrics were 0.90, 0.97, and 0.93.

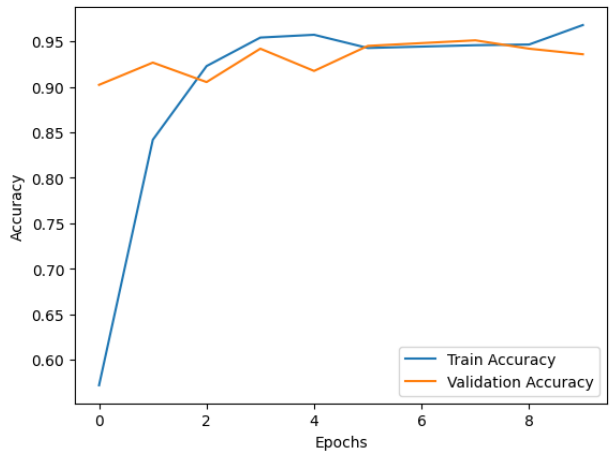

Figure 2: Training and Validation Graph

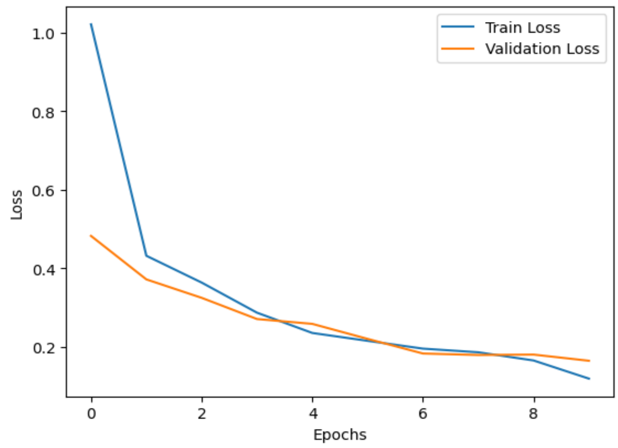

Figure 3: Loss Trends

Table 1: Summary of Training and Validation

Metric	Trend	Observation
Training Accuracy	Increasing, Stabilizing ~0.95	The model effectively learns from training data and reaches ~95% accuracy.
Validation Accuracy	Increasing, Stabilizing ~0.95	The model generalizes well to unseen data, maintaining ~95% accuracy.
Training Loss	Decreasing, Converging to low values	The error rate reduces as the model learns, resulting in low loss.
Validation Loss	Decreasing, Converging to low values	The model's error rate on unseen data also decreases, confirming effective learning.

The balanced macro and weighted averages of precision, recall, and F1-scores (all at 0.94) further validate the robustness of the model across the classes summarized in Table 2. The support values reflect that the dataset was fairly balanced with 172 samples for "Bird" and 155 samples for "Drone." This indicates that the high accuracy is not a result of class imbalance, but rather effective learning by the model. Overall, the results confirm the suitability of the trained model for accurately distinguishing between birds and drones.

Table 2: Training and Validation Metrics Trends

Metric	Bird	Drone
Precision	0.97	0.90
Recall	0.90	0.97
F1-Score	0.94	0.93

The confusion matrix shown in Figure 4 provides a detailed view of the model's performance for the classification task between birds and drones. Table 3 explains the results: **True Positives (155)**: These are correctly classified instances where the actual class was "Bird," and the model also predicted "Bird."

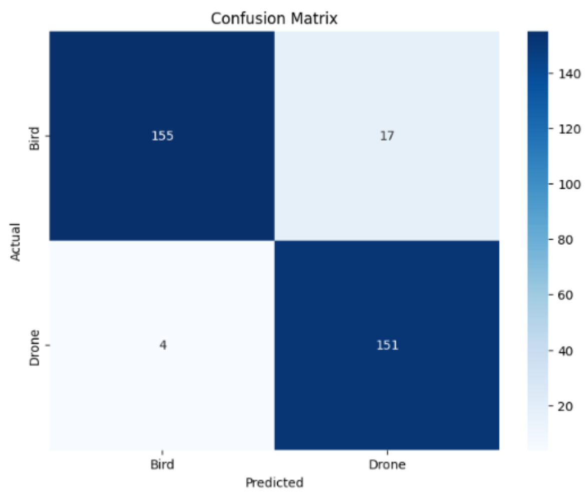

Figure 4: Confusion Matrix of the model

True Negatives (151): These are cases where the actual class was "Drone," and the model correctly predicted "Drone."**False Positives (17)**: These represent instances where the model incorrectly predicted "Drone" when the actual class was "Bird. **"False Negatives (4)**: These cases represent instances where the model incorrectly classified actual "Drone" samples as "Bird." Despite these misclassifications, the confusion matrix overall reflects the robustness of the model, as both classes are handled with high accuracy, and the errors remain minimal and evenly distributed

Table 3: Prediction Data

Prediction	Actual Bird	Actual Drone
Predicted Bird	155 (TP)	4 (FN)
Predicted Drone	17 (FP)`	151 (N)

5. CONCLUSION

This study demonstrates the effectiveness of data augmentation techniques in improving the detection and classification of small unmanned aerial vehicles (SUAVs) using radar-based micro-Doppler signatures. By applying methods such as random translation, scaling, rotation, noise injection, and flipping, we significantly expanded the dataset without compromising the integrity of the original signal characteristics. These enhancements contributed to measurable improvements in classification performance, as reflected in key metrics like accuracy (93.58%), precision, recall, and F1-score (each approximately 0.94).The confusion matrix analysis confirms the model's robustness, with minimal and balanced misclassifications. Notably, the low number of false negatives (4) for drone classification indicates strong sensitivity, while a slightly higher number of false positives (17) for birds suggests potential areas for further optimization, possibly in feature extraction or threshold calibration. Overall, the model exhibits reliable generalization and performs well in distinguishing drones from birds, underscoring its potential for deployment in real-world security and surveillance scenarios.

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