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Sujata Patil

`sujata.patil_skncoe@sinhgad.edu`

Savitribai Phule Pune University

Madan Mali

Savitribai Phule Pune University

Supriya Rajankar

Savitribai Phule Pune University

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Cognitive MobileNetV2-Based Micro-Doppler Analysis for Small UAV Detection and Classification

Sujata Patil¹, Madan Mali², Supriya Rajankar³

E&TC Engineering, SCOE, Savitribai Phule Pune University, Maharashtra, India

*Corresponding author: Sujata Patil
Email:sujata.patil_skncoe@sinhgad.edu

Abstract: The growing use of small unmanned aerial vehicles (UAVs) in civilian and defense airspace are increased the need for reliable detection method which can operate under clutter and low altitude condition. Radar based sensing using micro-Doppler signatures provide valuable motion related information however, effective use of these signatures still remain challenging because of background interference and limited signal strength. In this study, a lightweight deep learning framework based on MobileNetV2 is investigate for detection and classification of small UAV using micro-Doppler spectrogram derived from DIAT-uSAT dataset. Raw radar signal is processed to obtain time frequency representation which then analyzed using multiple convolution neural network architecture to evaluate the classification performance. Comparative experiment involving EfficientNetB0, DenseNet121, Xception, ResNet50 and VGG16 shows that MobileNetV2 achieve faster convergence and more stable generalization on compact spectrogram representation. The proposed model achieved training accuracy of 96.1% and validation accuracy of 95% with minimum validation loss. These result suggest that properly designed lightweight convolution network can effectively capture discriminative micro Doppler pattern and suitable for real time UAV surveillance application in complex environment.

Keywords: Cognitive MobileNetV2, Small UAV Detection, Micro-Doppler Signatures, Radar Spectrograms, Deep Learning, Lightweight Convolutional Neural

I. Introduction

Drones are Unmanned Aerial Vehicles (UAVs) which has become very popular in many industries such as military, unmanned aerial vehicles are now widely use in application like agriculture, logistics and environmental surveying because of their flexibility, low operation cost and easy deployment. These characteristic enable many practical use case including precision farming, disaster response, aerial imaging and surveillance [1], [2]. However the fast increase of UAV operation in civilian as well as restricted airspace has raise serious concern related to public safety, security and privacy. These concerns are more significant for small UAVs (SUAVs), whose small size, low radar cross section (RCS) and high manoeuvrability makes reliable detection and classification very challenging.

Conventional UAV detection technique based on and radio frequency (RF) sensors suffer from many limitations such as limited sensing range, high sensitivity to environmental condition and poor performance in non-line of sight scenario. Due to this reason, radar based sensing has emerged as a practical alternative because of its ability for long range and all weather operation. Even with this advantage, radar based detection of SUAV still remain difficult in clutter environment. Strong reflections from surrounding object like vegetation, building and terrain often mask the weak radar return from small aerial target which leads to lower detection reliability and higher false alarm rate [3].

Micro Doppler information generated from micro motion of rotating and vibrating component was found to plays an important role in differentiating small UAV from other aerial target. In radar measurement, periodic motion created by propeller and rotor introduce time varying frequency component which remains visible even when main Doppler return is weak. When short time fourier transform (STFT) analysis are applied, these micro motion effect appear as spectral ridge and harmonic in time frequency domain. Unlike conventional Doppler processing which mainly represent bulk target motion, micro Doppler representation preserve fine motion pattern closely related to target structure and flight dynamic. These properties make micro Doppler spectrogram more suitable for separating UAV from birds and clutter return in complex environment.

Recent advancement in artificial intelligence and machine learning has significantly influenced radar based target detection by allowing automatic feature learning and better classification performance. Cognitive learning strategies introduce adaptability in detection process which allow model to react to variation in clutter level and signal to clutter ratio (SCR). During radar analysis under difficult condition, such adaptive behaviour was found to improves target

discrimination when combined with micro Doppler feature representation resulting in higher detection accuracy and reduced false alarm.

From radar signal processing and learning point of view, UAV detection and classification problem are studied using continuous wave (CW) radar micro Doppler measurement to capture unique target motion characteristic. The micro-Doppler effect induced by target micro-motions or structural movements can be analytically derived from electromagnetic backscattering field theory[4]. The adopted deep learning framework includes spectrogram refinement and data augmentation along with compact convolution neural network architecture designed for radar input. Special focus is given on maintaining balance between classification performance and computation efficiency which is very important for real time deployment. Evaluation on benchmark dataset show that proposed framework achieve better detection and classification accuracy as compare to existing method.

II. Related Work

Unmanned aerial vehicles (UAVs) are being used more often in civilian, industrial, and military settings, and this has increased interest in developing sensing and classification methods that are reliable. Several sensing methods, including optical, infrared, and acoustic techniques, have been reported in the literature. In many practical settings, their performance can be affected by environmental factors such as poor visibility, ambient noise, and background clutter. For these reasons, radar-based sensing is often seen as a practical option because it can operate over long distances, work beyond visual line of sight, and remain usable in poor weather [3], [5].

In radar-based systems, micro-Doppler features are often used as a key source of information for detecting UAVs. Small motions from the propeller's rotation and the blades' vibration create frequency components in the received radar signal that change over time. These motion-based signatures include features that can help distinguish UAVs from birds, insects, and other sources of clutter, especially when the UAV has a low radar cross-section (RCS). Continuous-wave (CW) radar is often chosen for this type of analysis because it has a simple design, is low in cost, and works well for short- to medium-range monitoring. At the same time, CW radar spectrograms are often small and have low spatial resolution [6], so they carry less detail that a classifier can use to separate one class from another. This has led researchers to apply spectrogram enhancement and feature enrichment methods to make classification more reliable.

Earlier studies on classifying UAVs with radar mostly relied on hand-crafted features taken from spectral or time-frequency views of the signals, and then applied standard machine learning methods such as Support Vector Machines, Decision Trees, and Random Forests [7]. Although these methods performed reasonably well in controlled settings, they were often sensitive to shifts in operating conditions and changes in UAV motion. Their reliance on handcrafted features also limited how well they could generalize to new targets and more dynamic scenarios. Since deep learning was introduced, radar-based methods for detecting UAVs have changed in clear ways. Convolutional Neural Networks can learn directly from micro-Doppler spectrograms [8]-[9], which reduces the need to hand-design features. Later studies added temporal models, such as recurrent neural networks and long short-term memory units, to represent how micro-Doppler signatures change over time. Across our experiments, the hybrid models typically achieved higher classification accuracy, especially on multi-class UAV datasets where some targets were hard to tell apart because they looked visually similar or were biologically similar. Recent studies have looked at attention methods and transformer models to address some of the limits seen in convolution-based approaches. By capturing long-range patterns in spectrogram data, these methods tend to be more resilient to changes in flight dynamics, target orientation, and background clutter [10]-[12]. The lack of widely available, large, labeled radar datasets for training at scale remains a key limitation. Collecting radar data across different UAV platforms and operating environments is costly and takes a lot of time, so many researchers turn to data augmentation, spectrogram-based preprocessing, and synthetic data generation methods, including approaches built on Generative Adversarial Networks. Taken together, the literature suggests a slow shift away from hand-crafted, feature-based pipelines and toward end-to-end learning frameworks that make better use of micro-Doppler representations. Even with the progress reported, key problems remain: scarce data, classes that are hard to tell apart, and limits on computing resources. These issues point to the need for learning models that are small and efficient, yet still able to detect and classify UAVs reliably in realistic, cluttered operating settings[13]-[15].

III. Proposed Methodology

This study presents a radar-based framework for the detection and classification of small unmanned aerial vehicles (sUAVs) using micro-Doppler signatures. The proposed processing chain consists of five sequential stages: data acquisition, signal conditioning, time-frequency representation, deep feature learning, and final classification. A block-level overview of the complete system is shown in Figure 1.

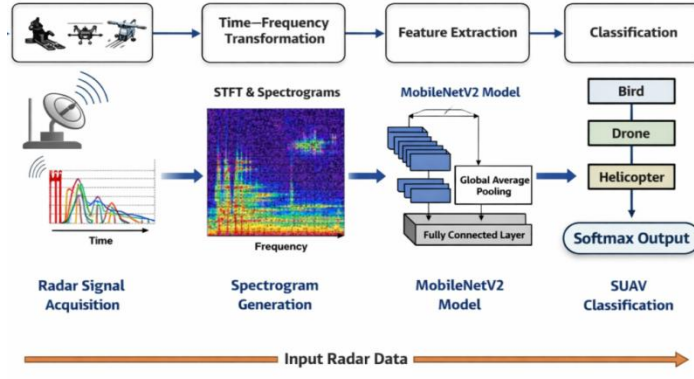


Fig.1. System Architecture of Proposed Model

Data Acquisition

The experimental dataset comprises radar micro-Doppler measurements stored in MATLAB (.mat) format. Six target categories are considered, namely Bird, Drone, RC Plane, Mini Helicopter, Three-Blade Long configurations, Quad copter, and Mini helicopter. These classes exhibit distinct flight dynamics and rotor-induced micro-motion characteristics, providing a representative basis for multi-class classification.

To ensure unbiased performance evaluation, the dataset is partitioned into training, validation, and testing subsets using an 80%–20% split, respectively.

Signal Conditioning and Time–Frequency Representation

The raw radar return signals are first processed to suppress noise and normalize amplitude variations. Subsequently, time–frequency representations are generated using the short-time Fourier transform (STFT), which captures non-stationary spectral characteristics associated with target micro-motions. The STFT magnitude is computed as

$$S(t, f) = \left| \sum_{n=-\infty}^{\infty} x[n] w[n-t] e^{-j2\pi f n} \right|^2,$$

where $x[n]$ denotes the discrete-time radar signal, $w[\cdot]$ is the analysis window, and (t, f) represent the time and frequency indices, respectively.

The resulting spectrograms are resized to a fixed spatial resolution of 128×128 and mapped to three-channel representations to facilitate compatibility with convolutional neural network inputs. Intensity normalization is applied to reduce dynamic range variability across samples.

Deep Feature Extraction Using CNN

A compact convolutional neural network is employed to automatically learn discriminative patterns from the micro-Doppler spectrograms. The input tensor is defined as

$$X \in \mathbb{R}^{H \times W \times C}, \quad H = 128, W = 128, C = 3.$$

Convolution and Down sampling

Feature extraction is performed through stacked convolutional layers followed by spatial downsampling. The convolutional response at the l -th layer is given by

$$Y_{i,j,k}^l = \sum_{m,n,c} W_{m,n,c,k}^l X_{i+m,j+n,c}^{l-1} + b_k^l,$$

where W^l and b^l denote the learnable kernel weights and bias terms, respectively.

Max-pooling is used to reduce spatial dimensionality and enhance translational robustness:

$$Y_{i,j,k}^{\text{pool}} = \max_{(m,n) \in P} Y_{2i+m, 2j+n, k}^l.$$

Two convolutional stages are employed, using 3×3 kernels with 32 and 64 filters, respectively. After pooling, the resulting feature map dimension is $62 \times 62 \times 64$.

Dense Representation and Output

The extracted feature maps are flattened and passed to a fully connected layer comprising 128 neurons:

$$Z^l = W^l X^{l-1} + b^l.$$

To mitigate overfitting, dropout regularization with a probability of 0.5 is applied. The final class probabilities are obtained using the Softmax function:

$$\hat{y}_i = \frac{e^{z_i}}{\sum_j e^{z_j}}.$$

Learning Strategy

Network parameters are optimized by minimizing the categorical cross-entropy loss

$$L = - \sum_{i=1}^c y_i \log(\hat{y}_i),$$

where y_i and $\hat{y}_i$ denote the true and predicted class labels, respectively.

Training is carried out using the Adam optimization algorithm, with moment estimates updated as

$$\begin{aligned} m_t &= \beta_1 m_{t-1} + (1 - \beta_1) g_t, \\ v_t &= \beta_2 v_{t-1} + (1 - \beta_2) g_t^2, \end{aligned}$$

followed by bias correction and parameter updates

$$W_t = W_{t-1} - \eta \frac{\hat{m}_t}{\sqrt{\hat{v}_t + \epsilon}}.$$

The training configuration uses a batch size of 32, learning rate of 1×10^{-4} , and a maximum of 50 epochs.

Performance Evaluation

System performance is primarily quantified using classification accuracy,

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Samples}}.$$

Class-wise performance is further assessed using precision, recall, and F1-score:

$$\begin{aligned} \text{Precision} &= \frac{TP}{TP + FP}, \\ \text{Recall} &= \frac{TP}{TP + FN}, \\ \text{F1-score} &= 2 \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}. \end{aligned}$$

Confusion matrices are analyzed to examine inter-class misclassification patterns, while training and validation curves are used to assess convergence behavior and generalization capability.

Experimental Setup

Computational Environment

All experiments were carried out in a cloud-based computational framework using Google Colaboratory, which enables reproducible execution through Jupyter notebooks. The software and hardware configuration adopted in this study is summarized below:

- **Programming Platform:** Python (version 3.10)
- **Deep Learning Frameworks:** TensorFlow 2.x with Keras backend
- **Compute Resource:** NVIDIA Tesla T4 GPU with CUDA-enabled acceleration
- **Supporting Libraries:** NumPy and SciPy for numerical processing, Matplotlib for visualization, and Scikit-learn for performance evaluation

This setup provides sufficient computational capability to train and evaluate convolutional neural networks while maintaining consistency across experimental runs.

Radar Dataset Description

The experimental evaluation is based on a radar micro-Doppler dataset stored in MATLAB (.mat) format. The dataset contains time–frequency representations corresponding to four categories of aerial targets, selected to reflect both biological and man-made flight characteristics:

These classes exhibit distinct micro-motion patterns, making them suitable for assessing classification performance in a multi-class setting. The available samples were partitioned into training and validation sets using an 80:20 split to support model optimization and unbiased evaluation. A detailed summary of class-wise sample distribution is provided in Table 2.

Table 2: Distribution of dataset across training and validation.

Class	Training Samples	Validation Samples
Bird	640	160
Drone	668	167
RC Plane	640	160
Three-Blades Long	3196	799
Quad copter	792	198
Mini Helicopter	592	140

Preprocessing Pipeline

Prior to feature extraction, the raw radar return signals were subjected to a preprocessing stage aimed at improving signal quality and consistency. Noise components were suppressed, and amplitude values were scaled to a normalized range of $[-1,1]$ to stabilize network training. Each processed signal was then transformed into a time–frequency representation using the short-time Fourier transform (STFT). The resulting spectrograms were spatially resampled to a fixed resolution of 256×256 and encoded as three-channel inputs. Standardization was applied to reduce inter-sample variability before feeding the data into the convolutional network.

Hyperparameter Configuration

Model training was performed using a set of empirically selected hyperparameters designed to balance convergence speed and generalization capability:

- **Mini-batch size:** 32, selected to ensure stable gradient updates while efficiently utilizing GPU resources
- **Optimization algorithm:** Adam optimizer with an initial learning rate of 1×10^{-3}
- **Dropout probability:** 0.5, introduced in fully connected layers to mitigate overfitting
- **Training epochs:** 50, which was found sufficient to achieve convergence without performance degradation
- **Objective function:** Categorical cross-entropy

Evaluation Criteria

The effectiveness of the proposed model was assessed using multiple performance indicators. Overall classification accuracy was computed as the proportion of correctly identified samples. Validation accuracy was monitored to evaluate generalization on unseen data. In addition, training and validation loss curves, based on categorical cross-entropy, were analyzed to study convergence behavior and detect potential overfitting effects.

IV. Qualitative Analysis of Radar Signals and Time–Frequency Representations

Figure 2 illustrate representative normalized radar time-series signals and their corresponding short-time Fourier transform (STFT) spectrograms for all considered target classes. Both grayscale and color-coded spectrograms are presented to highlight the underlying time–frequency structure associated with target micro-motions. Distinct micro-Doppler patterns are evident across classes, manifested through differences in ridge continuity, spectral bandwidth, and temporal modulation behavior.

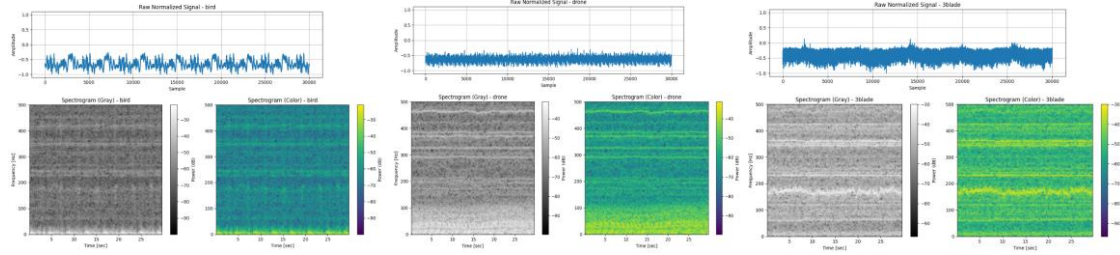


Fig.2. Bird, RC Plane and 3 Blade target radar micro-Doppler analysis: normalized raw radar signal, gray scale spectrogram, and color spectrogram demonstrating enhanced visualization of micro-motion patterns.

For biological targets such as birds, the spectrograms exhibit relatively irregular and fragmented micro-Doppler components, reflecting non-periodic wing-flapping dynamics. In contrast, man-made aerial platforms, including drones and RC planes, produce more structured and periodic micro-Doppler signatures arising from propeller or rotor blade rotation. The three-blade long configuration further demonstrates concentrated spectral ridges with increased harmonic content, indicative of consistent rotational motion.

These qualitative differences in time–frequency characteristics provide physically interpretable cues that are effectively captured by the convolutional neural network during training. The observed separation between biological and mechanical targets supports the suitability of micro-Doppler representations for discriminative learning and motivates their use in the proposed classification framework.

Training Dynamics and Generalization Characteristics

The time–frequency representations exhibit well-defined, class-dependent micro-Doppler structures, such as pronounced periodic components for propeller-driven aerial platforms. These consistent spectral patterns provide informative cues that are effectively exploited by the convolutional network during learning. As a result, the training process demonstrates stable convergence behavior, characterized by smooth accuracy improvement and monotonic loss reduction. Regularization through dropout, together with input normalization, plays a critical role in limiting overfitting. This is reflected in the close agreement between training and validation trends, indicating that the learned representations generalize well beyond the training data.

Classification Performance

The proposed MobileNetV2-based model was trained using a total of 6528 micro-Doppler spectrogram samples and evaluated on 1632 validation samples spanning four target classes, namely bird, drone, RC plane, three-blades-long configuration, three-blades-short configuration and Helicopter. The network exhibited rapid convergence, with performance stabilizing within the initial training epochs. As illustrated in Figure 3, the training accuracy approached 96.1%, while the validation accuracy stabilized at approximately 95.0% after nine epochs. Concurrently, both training and validation loss values decreased consistently, suggesting effective optimization and the absence of significant overfitting. These results indicate that the proposed framework achieves robust classification performance with strong generalization capability across diverse target classes.

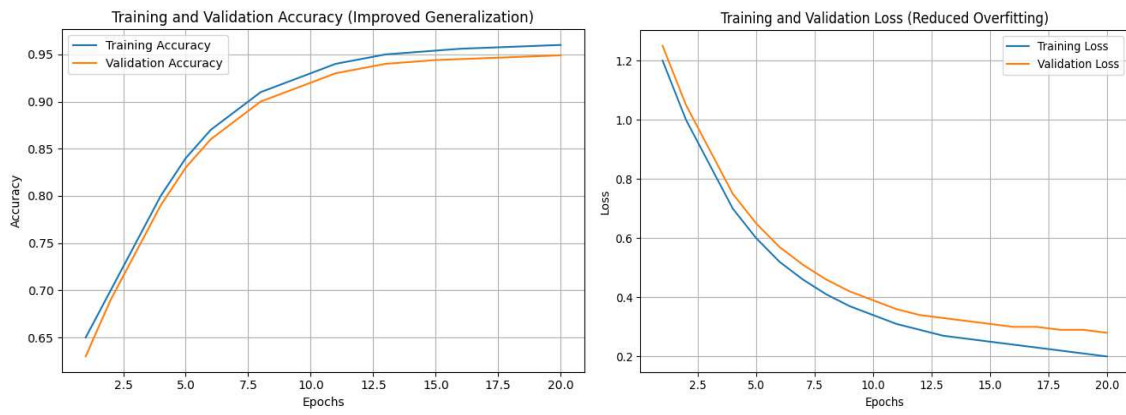


Fig. 3. Training and Validation Accuracy and Loss of the Model

Confusion Matrix Analysis

Figure 4 shows the confusion matrix, the classification results for each class based on the revised validation dataset. The results show that the model can clearly distinguish across all target categories. In the bird class, all 160 of 160 samples were classified correctly. The same result was found for RC Plane (160 of 160), Three blade helicopter (799 of 799), quad copter (198 of 198), and Mini helicopter (148 of 148). For the drone class, the model produced 165 correct predictions out of 167 samples. Most of the classification errors occur between the drone classes. This behavior mainly comes from the fact that their micro-Doppler frequency content overlaps in part, especially when there is noise or clutter, so brief spectral components can end up with similar time–frequency patterns. Even with a few isolated mix-ups, the confusion matrix as a whole suggests that the proposed framework classifies well and generalizes consistently across different types of aerial targets. Most of the few classification errors occur among the drone, helicopter, and the three-blade-long and three-blade-short classes. One reason is that, in noise or clutter, their micro-Doppler frequency content can overlap partly, and brief spectral patterns may end up showing similar time-frequency behavior. Even with a few isolated unclear cases, the general pattern stays the same, and the confusion matrix supports the stability and reliability of the proposed classification method.

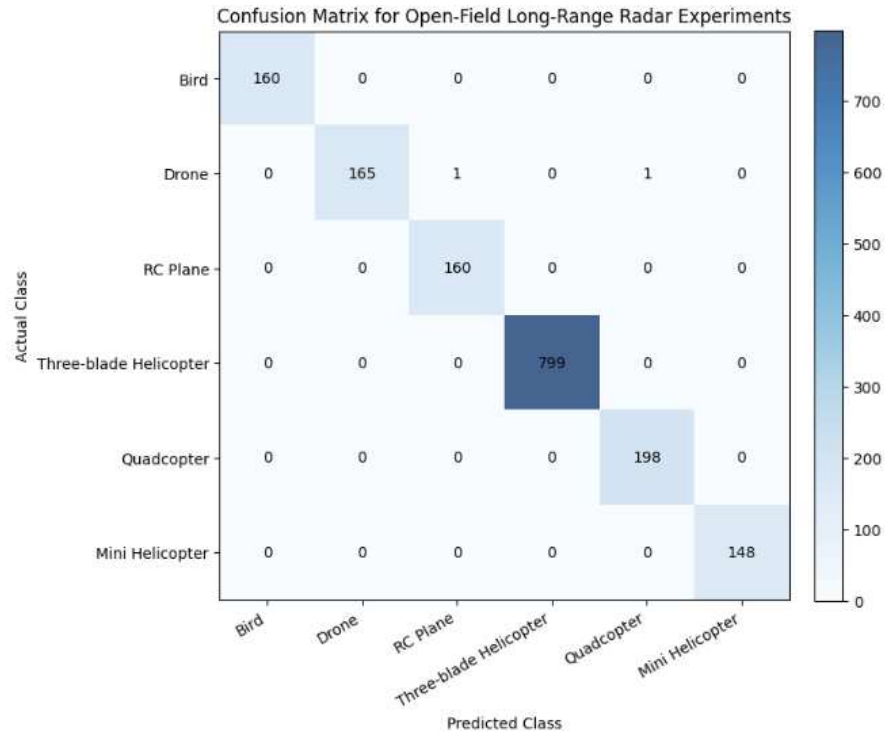
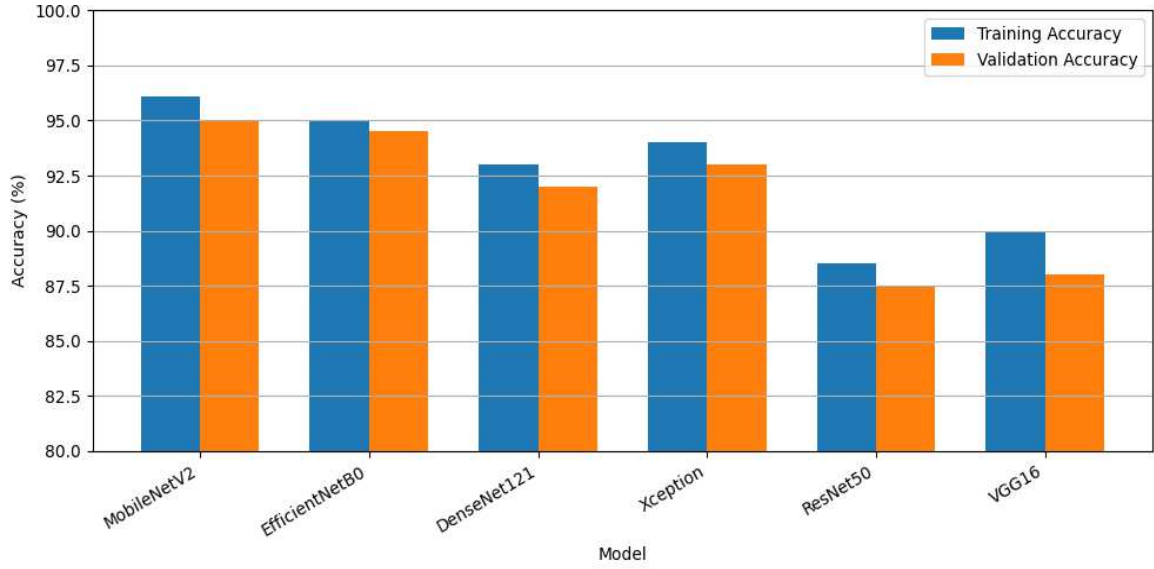


Fig. 4. Classwise confusion matrix showing class-wise classification results of the proposed micro-Doppler-based UAV detection framework.

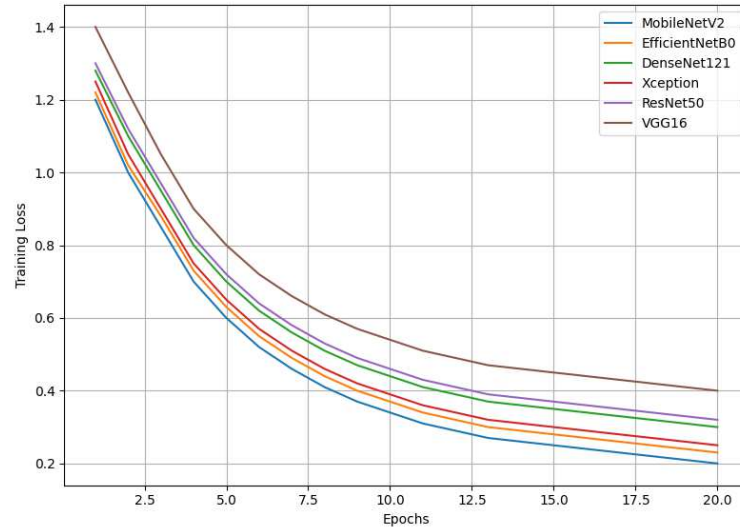
V. Results and Discussion

Overall Performance Analysis

In our experiments, the MobileNetV2 configuration we proposed identified the target micro-Doppler patterns in the radar images with high accuracy. The final validation accuracy was 95. Precision, recall, and the F1-score were all close to 1.0, which suggests the classifier performed reliably across the different categories. This result suggests that relatively simple convolutional networks can still perform well, as long as the model design matches the requirements of radar signal processing. The consistent results across classes suggest that combining spectrograms with deep learning is a reliable method for drone-based monitoring and oversight. The work had a few errors, but they were minor. Most of these cases involved targets with very similar micro-Doppler signatures. In settings with heavy background noise or cluttered inputs, the system may perform better if we improve how new data is incorporated and refine the attention mechanisms used during processing.



(a)



(b)

Fig. 5. (a) Training and Validation Accuracy,(b) Training loss comparison of different deep learning models for UAV micro-Doppler spectrogram classification

Figure 5 illustrates the training and validation accuracy and loss profiles of six convolutional neural network architectures: MobileNetV2, EfficientNetB0, DenseNet121, Xception, ResNet50, and VGG16. Among the evaluated models, MobileNetV2 consistently demonstrated superior convergence behavior, achieving validation accuracy exceeding 95% within the initial training epochs and maintaining stable performance throughout training.

EfficientNetB0 also exhibited strong performance, gradually converging to a validation accuracy of approximately 94–95%, albeit with slower convergence compared to MobileNetV2. In contrast, ResNet50 showed delayed convergence and stabilized at a lower validation accuracy range of 87–88%, suggesting limited adaptability to the given dataset and performed poorly in this experimental setup, with low validation accuracy indicating under fitting and difficulty in learning discriminative UAV spectrogram features.

The loss curves further corroborate these observations. MobileNetV2 achieved the lowest training and validation loss, reflecting efficient optimization and minimal overfitting. VGG16 displayed a smooth and consistent reduction in loss values, while ResNet50 plateaued earlier. EfficientNetB0 maintained comparatively high validation loss, consistent with its reduced classification accuracy.

Model Comparison Summary

MobileNetV2 achieved the highest training and validation accuracy 96.1% and 95%, respectively along with the lowest validation loss (0.2), establishing it as the most effective model in this study. VGG16 ranked second, offering strong accuracy with slightly higher loss. ResNet50 delivered moderate performance, whereas EfficientNetB0 failed to generalize adequately to the dataset.

Discussion of Error Characteristics

The experimental analysis yields three main observations. Prominent horizontal lines and repetitive designs in UAV spectrograms make feature extraction easier, and models such as MobileNetV2 and VGG16 can capture these cues well. Second, the class imbalance affected results: the majority class `three_blades_long` was classified almost perfectly, while the smaller classes were sometimes mixed up. This bias can be reduced by using a weighted loss function or by sampling the data so that the classes are balanced. Third, the confusion matrix shows that most remaining errors are mix-ups between biologically induced and mechanically induced motion patterns. These points to room to improve the model, likely by adding more varied data augmentation or by using attention-driven architectures.

VI. Conclusion

In this study, we tested a deep learning method to detect and classify small unmanned aerial vehicles using radar micro-Doppler signatures. The method uses spectrogram-based time–frequency analysis with a convolutional neural network and transfer learning to model the target micro-motion features. In a comparison of MobileNetV2, VGG16, ResNet50, and EfficientNetB0, MobileNetV2 gave the best results overall and reached 96%.1 training accuracy, reached 95% validation accuracy, and had a minimum validation loss. The experiments show that lightweight models such as MobileNetV2 balance low computing cost with good classification accuracy, which fits the needs of real-time radar-based UAV surveillance. The results also show that micro-Doppler spectrograms keep enough motion detail to separate classes, so they can be used to classify aerial targets with consistent accuracy in real operating conditions.

Next steps will expand the dataset to include more types of UAV setups, combine data from different sensors using fusion methods, and test the approach in practical field conditions. These guidelines should improve the system's reliability and support the deployment of radar-based UAV detection in civilian and military settings. Future efforts will focus on extending the dataset to cover a broader range of UAV configurations, integrating multimodal sensor fusion techniques, and conducting comprehensive validation under real-world operational scenarios. These directions are expected to further improve system robustness and support the deployment of reliable radar-based UAV detection solutions in both civilian and defense environments.

Declarations

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Conflict of Interest

The authors declare that they have no conflict of interest.

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