

Advancing Drone Detection: Innovative Radio Frequency-CNN Fusion for Accurate Drone Detection and Identification

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ABSTRACT

The rapid growth of unmanned aerial vehicles (UAVs) has raised significant concerns about security, privacy, and unauthorized surveillance. This paper presents a proposed advanced Radio Frequency (RF)-Convolutional Neural Network (CNN) fusion model to improve the accuracy of UAV detection and identification. The proposed framework employs a deep 1D CNN trained on normalized RF amplitude data, with dropout regularization and 10-fold cross-validation to enhance generalization and result stability. The developed model can identify the signature of the UAV communication in the RF signal much better than the traditional detection strategy like radar and acoustic analysis through the application of deep learning tools on RF signal analysis and without the need for interpretation with RF signal analysis software. The suggested RF-CNN model has the highest accuracy and F1-score of 99.67% and 99.7 respectively, and that indicates its reliability and strength. Also, the UAV identification model achieves 88.39% accuracy with an F1-score of 88.4 which is better than the current RF-based UAV detection models. It has a low Root Mean Square Error (RMSE) of 0.003, indicating that the model has few classification errors; hence, it can be used in real-time drone monitoring. In contrast to the conventional techniques, the suggested RF-based deep learning model has scalable implementation, less computation complexity, and environmental adaptability. The results of this study provide practical implications to the airspace security, protection of critical infrastructure, and counter-drone technologies to facilitate the creation of sound AI-based surveillance systems on UAVs.

1. Introduction

The use of unmanned aerial vehicles (UAVs) has increased in popularity because high-end remote control, where frequency-hopping spread spectrum (FHSS) and orthogonal frequency-division multiplexing (OFDM) are utilized to facilitate stable long-range communication without constant human control [1, 2]. Recent UAVs are also distinguished by GPS-based navigation, real-time telemetry, and adaptive flight control systems, which incorporate inertial measurement units (IMUs) to provide better stability and accuracy of control. Such functions enable UAVs to perform precise autonomous flights under challenging, dynamic conditions. UAVs have numerous applications in military use, surveillance, research, and commercial applications [3]. They also have wide applications in remote sensing, disaster management and environmental monitoring [4]. The fact that logistics and delivery service providers are increasingly adopting large-scale commercial use of UAVs is further evidence of how UAVs are becoming more and more integrated into civilian life. Graphical processing units (GPUs) and field-programmable gate

arrays (FPGAs) have become widely used onboard processing units, greatly increasing UAV capabilities by enabling real-time data processing for functions such as object detection, terrain mapping, and automated decision-making. UAVs are used in agriculture for fertilization [4, 5], pesticide spraying [6], and crop monitoring [7], enhancing the efficiency and coverage of operations.

Even with these benefits, the rapid rise in UAV use has created significant problems with privacy, safety, and airspace management. Unauthorized UAV operations in restricted or sensitive airspace could interfere with manned aircraft, damage critical infrastructure, and facilitate criminal activities such as illegal surveillance or cyberattacks. There have been documented cases of unauthorized UAV flights near military and civilian aircraft. This demonstrates the importance of having reliable and effective UAV monitoring solutions [7, 8]. Contemporary UAV detection devices use multimodal sensing methods such as radio frequency (RF) signal detection, computer vision-based tracking, and radar-based detection. Sensing modalities have their own

benefits and limitations when used alone. Vision-based approaches have line-of-sight requirements and are susceptible to changes in illumination and weather conditions, whereas radar-based techniques tend to yield poorer detectability of small and low-altitude UAVs [5, 8–10]. The methods of acoustic detection are based on audio characteristics such as Mel-frequency cepstral coefficients (MFCCs) and zero-crossing rate (ZCR), although they fail in noisy conditions and at long detection distances [11–13]. Such constraints have led to rapid studies on anti-UAV systems with effective detection, classification, and responsive actions [9].

RF-based sensing methods have attracted a lot of attention lately because they use the unique communication signals exchanged between UAVs and their ground control stations to locate UAVs over long distances. RF-based detection doesn't require a direct line of sight to the target and is less affected by environmental changes. Recent improvements in deep learning-based RF signal classification have shown that it can easily distinguish UAV communication signals from those of other RF-emitting devices, such as Wi-Fi routers and mobile phones.

Machine learning (ML) and deep learning (DL) have played a transformative role in RF-based UAV detection. Convolutional neural networks (CNNs) are especially efficient at the hierarchical presentation of RF signal information to allow the correct classification of presence, type, and mode of operation of a UAV [14, 15]. Transformer-based models and recurrent neural networks (RNNs) have also been considered to represent time-dependencies in RF signal variations. Nevertheless, the issues pertain somewhat to adversarial RF interference, real-time processing bottlenecks, and the scarcity of annotated RF datasets.

Both DroneRF and RF100, among other large-scale datasets, are considered necessary to train powerful RF-based detection models [12]. However, manual annotation of RF signal data is time-consuming and resource-intensive, leading to a general shift toward data augmentation and transfer learning techniques to address data scarcity.

Given the extensive prior studies investigating ML-based UAV detection using radar, vision, audio, and RF signals [4–11], it is clear that the present study has a broad scope. Whereas these methods have been shown to be very accurate in the controlled lab set-up, they have been found to be weak when dynamic or noisy working conditions are taken into consideration. The RF-based analysis is a scalable and weather-resistant solution to continuous monitoring of UAVs compared to other sensing methods. Some of the studies [16–25] have examined RF signal pre-processing methods, such as the extraction of in-phase and quadrature (I/Q) components, spectrogram conversion, and CNN- and YOLO-based learning frameworks. YOLO-based formulations have demonstrated the potential for drone-type classification using center-frequency and bandwidth features [19]. Nevertheless, a significant number of currently avail-

able methods exhibit reduced robustness to real-world signal fluctuations or require substantial computational resources [26].

RF detection methods with deep learning summarized in Table 1 indicate classification accuracies of more than 95% on databases like DroneRF, RF100, and OpenSky-RF. Although these encouraging findings indicate that RFID has the potential to become a valuable resource, the issue of dataset imbalance and mode misclassification, along with RF signal resemblance among drone types, still have an impact on the reliability of real-time deployment [27–33]. To address these difficulties, this paper presents an RF-CNN fusion architecture designed to improve detection accuracy, identification capability, and operational resilience. The suggested framework is tested in three experimental tasks, i.e., UAV detection, UAV identification, and UAV mode classification, and it is compared to existing ones.

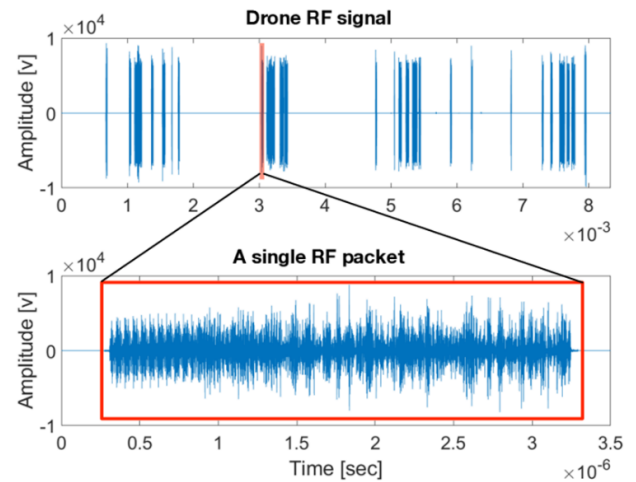


Fig. 1. Samples of the DroneRF dataset

Previous research has shown that the UAV detection and classification accuracy of deep learning-based RF signal analysis can be high across a number of benchmark datasets. The CNN-based methods are effective in capturing the spatial signal attributes, whereas recurrent and transformer-based models are aimed at capturing the temporal dependencies in RF transmissions. Nevertheless, current approaches often highlight constraints associated with dataset imbalance, confusion among similar drone types, and reduced resilience to RF fluctuations in real-life settings. Moreover, some methods are time-consuming because they require substantial computational resources, thereby reducing their applicability to real-time implementation. These facts encourage the development of an RF-CNN model that focuses on robustness, computational efficiency, and reliable performance under real operating conditions.

2. Proposed Methodology

The progress made in DL has greatly increased the accuracy and speed of detection, identification, and classification tasks, especially when working with large RF signal datasets. Recent research has shown that DL techniques can effectively extract discriminative features from RF signals, even under challenging con-

Table 1

Related work on RF-Based UAV Detection and Identification

Ref	Dataset Used	AI Model Used	Performance Metric	Contribution of Research	Limitation of Research
[28]	DroneRF	CNN	Accuracy: 98.3%, F1-score: 97.8%	RF-based CNN framework for UAV classification.	Limited dataset diversity; no real-time validation
[29]	RF100	LSTM	Accuracy: 95.2%, Recall: 94.7%	Temporal modeling of RF signals using LSTM	High computational cost; scalability concerns
[30]	DeepRF	ResNet-50	Accuracy: 96.8%, Precision: 96.5%	Transfer learning applied to RF-based UAV detection	Susceptible to adversarial RF interference
[31]	DroneDetect	YOLOv5+CNN	Accuracy: 97.5%, F1-score: 97.1%	YOLO-CNN integration for UAV identification	Reduced robustness in complex RF environments

ditions. DL-based models for UAV monitoring enable you to learn directly from raw RF signal representations without manual feature engineering. This section provides an overview of the dataset used, the preprocessing of RF signals, and the proposed CNN architecture, with a focus on design choices important for detecting and classifying UAVs.

2.1 Dataset and RF Signal Processing

This study uses the DroneRF dataset [12]. It includes 454 RF signal records that were taken on Bebop, AR, and Phantom drones and background RF activity. The recording consists of one million samples of the RF signal amplitude, which provides the possibility to characterize the temporal behavior of UAV communication in great detail. Data categories in the background are connected: hovering, flying, and recording of the UAV operation and non-UAV background signal. The recordings are mostly related to the UAV transmissions, approximately 82%, whereas the remaining 18.06% of the recordings are attributed to the background RF activity. Before training the models, RF signal amplitudes were normalized so that the numerical stability and the feature scaling of the samples were similar. No frequency-domain transforms like fast Fourier transform (FFT) or short-time Fourier transform (STFT) were used, and the CNN was free to learn the discriminative temporal features using only the normalized RF amplitude signals. The threshold-based criteria were used to remove the outlier signals and minimize the impact of severe noise artifacts and class imbalance.

2.2 CNN Architecture Design

CNNs were chosen because they are able to learn hierarchical representations using one-dimensional time signals. A one-dimensional CNN architecture was followed to retain the time-varying characteristics of RF amplitude sequences and maintain a smaller computational complexity as compared to two-dimensional time-frequency representations. The suggested architecture incorporates feature extraction and classification in one architecture and makes end-to-end learning possible.

The CNN consists of several convolutional, pooling and fully connected layers. A gradual increment in the filter depth (32 to 128 filters) was adopted to record low-

and high level RF signal properties. The use of five convolutional layers was empirically chosen to balance representational capacity and the risk of overfitting, given the size of the available dataset.

2.2.1 Convolutional Layer

Each convolutional layer extracts local temporal features from the RF input signal and is defined as:

$$h_l = \text{ReLU}(W_l * X_l + b_l) \quad (1)$$

where X_l denotes the input signal at layer l , W_l represents the learnable convolutional filters, b_l is the bias term, and $\text{ReLU}(\cdot)$ denotes the rectified linear unit activation function.

2.2.2 Pooling Layer

Pooling layers reduce feature dimensionality and computational load while retaining salient information:

$$p_l = \max_{i \in R} (h_l) \quad (2)$$

where R denotes the pooling region applied to the feature map h_l .

2.2.3 Fully Connected Layer and Classification

The extracted features are flattened and passed to fully connected layers for classification. For multi-class UAV identification, the SoftMax function computes class probabilities such as:

$$\hat{y} = \frac{e^{W_{fc}h_L + b_{fc}}}{\sum e^{W_{fc}h_L + b_{fc}}} \quad (3)$$

For binary UAV detection, the Sigmoid activation function is applied:

$$\hat{y} = \frac{1}{1 + e^{-W_{fc}h_L + b_{fc}}} \quad (4)$$

where h_L denotes the output of the final convolutional layer, and W_{fc} and b_{fc} are the weights and bias of the fully connected layer.

Figure 2 illustrates the CNN architecture used for binary UAV detection. The model consists of five one-dimensional convolutional layers followed by mean pooling and a dropout layer with a rate of 25%. This regularization mechanism was considered to offset overfitting by randomly turning off neurons during training while still keeping the model's generalization ability.

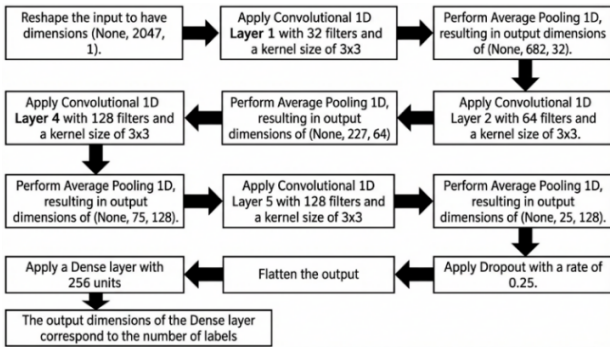


Fig. 2. Developed CNN architecture for UAV detection.

Figure 3 illustrates the CNN structure to be employed in identifying the UAVs and determining their mode of operations. The architecture contains four one-dimensional convolutional layers, two pooling layers, and an average pooling stage to increase feature aggregation. The identification of the drones needed a better extraction of features because of the similarity in the RF signals of UAVs; that is why further depth of the convolution was added to enhance the separability of classes. Early stopping of the model with a patience of 10 epochs was used to avoid overfitting by monitoring the validation loss. Dense layers were regularized using L2 regularization with $\lambda = 0.0001$ to prevent overweight increase and enhance generalization.

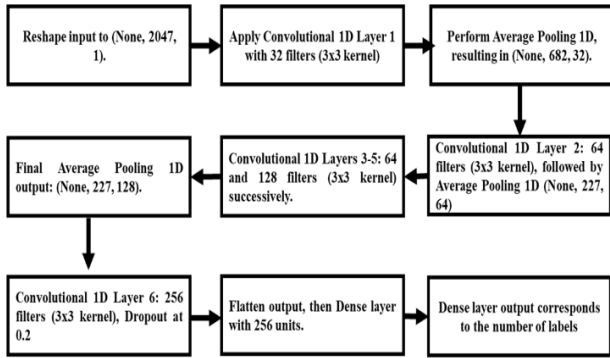


Fig. 3. Developed CNN architecture for UAV identification and mode classification.

2.3 Training Strategy and Implementation

The CNN models have been written in Python using the Keras API and trained in a workstation with Windows 10. Nvidia Titan V, Nvidia GTX 1070, Intel Xeon (2.10 GHz) and Intel Core i7 (2.7 GHz) were used as the hardware configuration. Training could be performed in a very efficient way with parallel computation through the use of the GPU acceleration and that decreased the convergence time of training and made it possible to perform the cross-validation experiments repeatedly. A support vector machine (SVM) classifier at the baseline was trained to assess the advantages of deep-learning-based RF signal representation.

2.4. Performance Metrics and Validation

Model performance was evaluated using accuracy, precision, recall, and F1-score metrics. These metrics are defined as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F1-Score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

where TP, TN, FP, and FN represent true positives, true negatives, false positives, and false negatives, respectively. The cross-validation approach was used in order to evaluate the model robustness and generalization (a ten-fold cross validation strategy). The standard deviation across folds indicated an accuracy deviation of 0.5%, implying that the performance was stable and not highly sensitive to data partitioning. The inference time per classification was also assessed, and it proved suitable for real-time UAV detection and identification.

Algorithm 1 RF-CNN Fusion-Based Drone Detection and Identification

Require: Dataset $D = \{(X_i, Y_i)\}$, batch size B , epochs E , learning rate η

Ensure: Trained CNN models for detection and identification

- 1: Load dataset D
- 2: Normalize RF signal features
- 3: Remove noisy and outlier samples
- 4: Split dataset:
- 5: $(X_{train}, Y_{train}), (X_{test}, Y_{test}) \leftarrow split(D, 0.2)$
- 6: Initialize CNN parameters W
- 7: **for** $l = 1$ to L **do**
- 8: $h_l \leftarrow ReLU(W_l * X_l + b_l)$
- 9: $p_l \leftarrow pool(h_l)$
- 10: **end for**
- 11: $\hat{y} \leftarrow softmax(W_{fc}h_L + b_{fc})$ {Multi-class}
- 12: $\hat{y} \leftarrow sigmoid(W_{fc}h_L + b_{fc})$ {Binary}
- 13: Compute loss:
- 14: $L(W) = -\sum [y \log(\hat{y}) + (1 - y) \log(1 - \hat{y})]$
- 15: **for** epoch = 1 to E **do**
- 16: **for** each mini-batch (X_b, Y_b) **do**
- 17: $W \leftarrow W - \eta \nabla L(W)$
- 18: **end for**
- 19: **end for**
- 20: Perform 10-fold cross validation
- 21: **for** $k = 1$ to K **do**
- 22: Train on $D \setminus F_K$
- 23: Validation on F_K
- 24: **end for**
- 25: Compute performance metrics:
- 26: Accuracy, Precision, Recall, F1-score
- 27: Construct confusion matrix:
- 28: $C = [TP \ FP \ FN \ TN]$

3. Results & Discussion

The CNN performance was tested using three experiments, i.e., drone detection, drone identification, and mode identification. The models have been trained on the DroneRF dataset, which contains 454 RF signal

records (82 percent UAV signals and 18.06 percent background RF activity). There are three types of drones, i.e., AR, Phantom, and Bebop, which are captured in various operational modes. The models have been implemented into Python via the Keras API and run on a Windows 10 workstation with Nvidia Titan V and Nvidia GTX 1070 chips. The CNN architecture comprises five one-dimensional convolutional layers and average pooling layers to extract discriminative RF temporal features. The network has 32, 64, and 128 filters with 3x3 kernels to represent features of different abstraction levels. To minimize overfitting a dropout layer with a rate of 0.25 was added and then a dense layer of 256 neurons. The output layer used SoftMax when dealing with multi-class tasks and sigmoid when dealing with binary detection. The Adam optimizer was used to conduct training.

The drone detection was trained in 100 epochs with learning rate equal to 0.001 and batches size equal to 50, and drone identification and mode classification were trained with learning rate equal to 0.00001 in 350 epochs and batches size equal to 50. Generalization performance was measured using a ten-fold cross-validation approach. Though the obtained results are reported with the use of the DroneRF dataset, the specified learning strategy is not necessarily dependent on the dataset. The model is trained on normalized RF amplitude sequences with no handcrafted features or dataset-specific signal transformations, therefore allowing it to be transferred to RF datasets collected in varying hardware settings, frequency bands, and operating conditions. The differences in dataset performance can be caused by variations in sampling rates, noise, and communication protocols. However, the consistent behavior of the stable performance of ten-fold cross-validation suggests that the learned temporal RF representations do capture the underlying transmission characteristics, which should be predictable over more than one benchmark. Cross-dataset testing, e.g., training on DroneRF, and testing on independent RF datasets but not on RF100 RF or OpenSky RF in particular, is thus suggested as a significant next step to further understand the robustness in real-world deployment conditions. In order to enhance interpretability, each of the experimental subsections presents the primary result of the classification, points out the main trends of confusion as shown by the confusion matrix, and giving a succinct conclusion about deployment implications. Confusion matrices of performance evaluation proved that the model is effective. To identify the mode (Fig. 4), the model achieved 99.8 percent accuracy for No Drone signals and 87.1 percent for Mode 3, with a mix of Mode 1 and Mode 2 due to similar RF properties. In the case of drone identification (Fig. 6), the Bebop drone was 88.4 percent accurate, whereas the Phantom was 91.1 percent accurate; some overlap was observed with AR. In the case of binary drone detection (Fig. 8), the model had 99.8 percent accuracy with a rate of 0.2 percent false negatives, so the model can be applied

in a real-time mode of detecting drones. Algorithm 1 summarizes the end-to-end training and evaluation workflow and is included in supporting reproducibility without interrupting the presentation of experimental results.

3.1. Experimentation for Identifying Drone Modes

This experiment is set to determine UAV operation modes, such as the connection or hovering of the UAV, flying, and recording. This activity is applicable in operational monitoring since errors in modes can affect the threat evaluation and response time. The proposed approach demonstrates improved performance compared to the baseline DL model reported in [10]. The model achieved 99.8% accuracy for ‘No Drone’ and 87.1% accuracy for Mode 3, with confusion primarily between Mode 1 and Mode 2. Mode 2 exhibited the highest misclassification rate (12.9%) with Mode 1, indicating overlapping RF characteristics in intermediate flight states, as shown in Fig. 4. This confusion suggests that adjacent operational states may produce similar RF temporal patterns, which can lead to delayed or incorrect mode-based decision logic in practice. Compared to [10], the model improves accuracy and F1-score by approximately 12%, with precision and recall increasing by 5% and 13%, respectively. To reduce the risk of overfitting, early stopping was applied during training; accuracy was observed to plateau after 350 epochs, and additional training epochs did not yield consistent improvements. Key takeaway: the model provides reliable mode separation for ‘No Drone’ and Mode 3, while Mode 1 and Mode 2 remain the primary ambiguity region due to RF similarity.

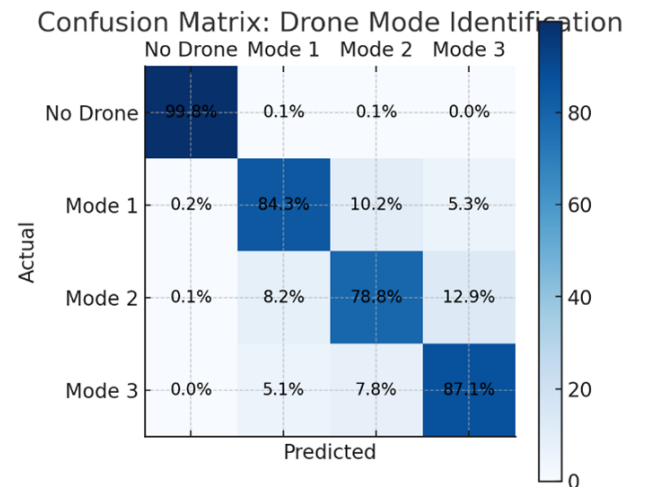


Fig. 4. Convolutional neural networks confusion matrix for drone mode.

3.2 Experiments for Identification of Drone

This experiment classifies four RF signal categories, including background RF activity and RF signals associated with AR, Bebop, and Phantom drones. The SoftMax activation function with a learning rate of 0.0001 and categorical cross-entropy loss achieved the best identification performance. The model classified ‘No Drone’ signals with 99.8% accuracy. Bebop and

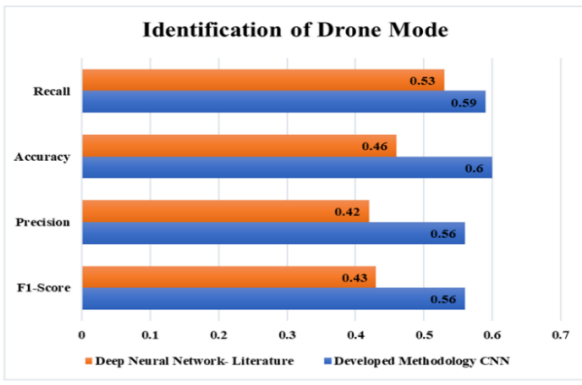


Fig. 5. Comparison between the related work (DNN) and the developed CNN.

AR drones exhibited misclassification rates of 7.2% and 6.1%, respectively. Phantom achieved the highest identification accuracy (91.1%), with confusion observed primarily with AR due to overlapping RF signal frequencies, as shown in Fig. 6. The CNN model improved accuracy by 1.3% compared to the DNN baseline, while the F1 score increased by 5.8%. Precision increased by 0.225%, and recall increased by 5.27%. Since these improvements are moderate in magnitude for multi-class identification, performance stability is further supported by the ten-fold cross-validation results reported in the methodology section. Misclassification errors were found to be in the Bebop and AR classes, as the RF signatures are similar. This point suggests that the main drawback of RF-only identification is apparent when UAV types work in the same or similar communication bands, which explains the desire to work on more elaborate RF representations and cross-dataset validation in the future. A comparison of the suggested CNN and the corresponding DNN approach is provided in Fig. 7.

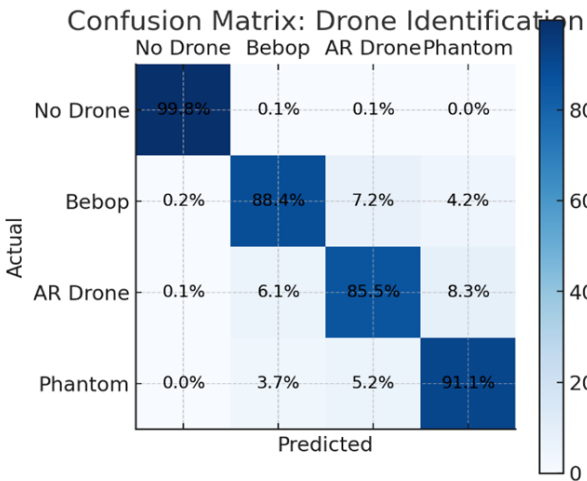


Fig. 6. Confusion matrix for drone identification using the CNN model.

3.3 Experiment for the Detection of Drone

This experiment addresses a binary classification task that distinguishes between background RF activity (Class 1) and drone RF communication signals (Class 2). The Sigmoid activation function was used as the output layer. The learning rate was set to 0.001, and the loss function was mean squared error (MSE). The CNN achieved 99.8% detection accuracy with an error

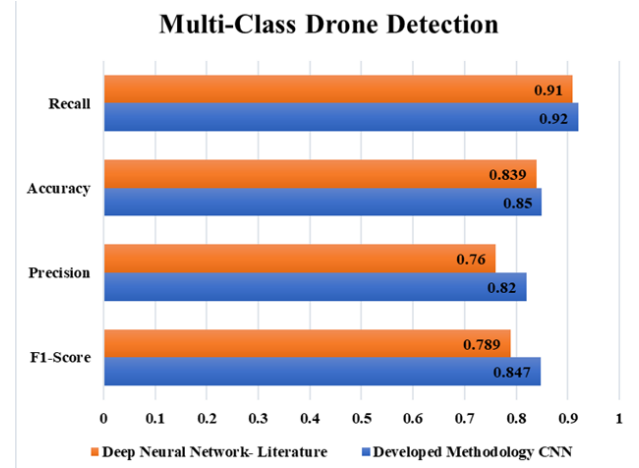


Fig. 7. Comparison between the related work (DNN) and the developed CNN

rate of 0.2%, as shown in Fig. 8. False positives and false negatives remained limited, supporting reliable detection for real-time monitoring. The model achieved an average F1 score of 99.7% across ten-fold cross-validation, with an error rate of 0.3%. Precision, false discovery rate (FDR), recall, and false negative rate (FNR) are summarized through the confusion matrix in Fig. 8.

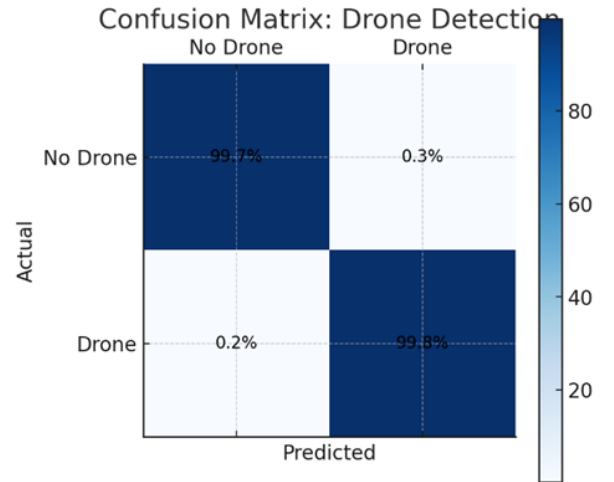


Fig. 8. Confusion matrix for binary drone detection using the CNN model.

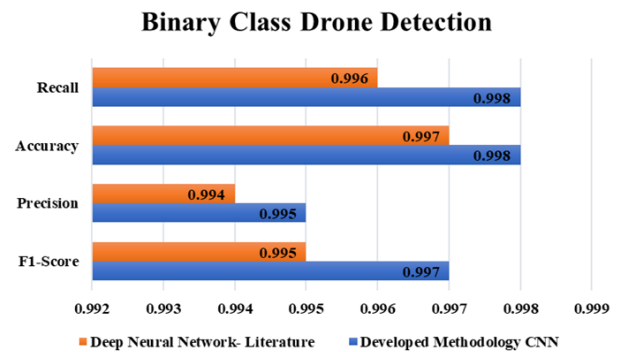


Fig. 9. Comparison between the related work (DNN) and the developed CNN

Fig. 9 compares the proposed CNN approach against the DNN baseline. Key takeaway: binary detection achieves near-perfect separation between UAV and background RF activity, which reduces the risk of missed detections in security-critical monitoring scenarios. Table 2 compares the proposed RF-CNN fusion model

with established RF-based UAV detection frameworks. For fair interpretation, the reported metrics for this work are obtained on the DroneRF dataset, while several compared studies report results on different datasets and experimental settings. In binary detection, the model achieves 99.8% accuracy with an RMSE of 0.003 [33, 34]. The model exceeds several conventional approaches in reported accuracy and F1-score, with improvements dependent on the dataset and test conditions. Compared to the transformer-based method, the model achieves comparable accuracy with reduced computational requirements, supporting real-time deployment on resource constrained platforms [1]. For multi-class drone identification, the model attains 88.4% accuracy and improves over the baseline DNN by approximately 1.3%, with dropout regularization and early stopping supporting generalization. Residual confusion between Bebop and AR remains due to overlapping RF spectra. The model also achieves 87.1% accuracy in mode classification, representing an approximately 12% improvement over [10], indicating effective learning of RF temporal patterns associated with UAV operational states.

4. Conclusion

This study described an RF-based convolutional neural network that detects UAVs, identifies drones, and classifies drone operational modes based on RF signal records of the DroneRF dataset. With the benchmark setting adopted, the proposed models performed 99.8% accuracy in binary detection of drones, 88.4% accuracy in drone identification, and 87.1% accuracy in classifying the drone operational mode. These findings show that the feature extraction of a one-dimensional CNN using normalized RF amplitude series can enable very reliable functioning in UAV monitoring under the conditions tested in the experiment. The proposed five layer one-dimensional convolutional architecture can learn discriminatory temporal RF signatures effectively and can be used to separate UAV-related transmissions and background RF activity without the use of handcrafted descriptors.

The consistency of the framework was also established based on tenfold cross-validation and confusion-matrix screening, which indicated consistent handling of classification and a significantly low rate of false negative (0.2) in binary detection activity. This is particularly important in safety and security-sensitive monitoring scenarios, where missed detections may have more serious consequences than false alarms [34]. Combined with the findings obtained, these results support the utility of RF-driven deep learning to UAV surveillance and indicate that RF sensing may also be a valuable alternative, or complementary modality, to radar-based and audio-based sensing in an environment where the practical relevance of traditional sensing systems is diminished by line of-sight considerations, acoustic interference, or environmental variation.

Simultaneously, there are a number of limitations that

can be noted in the current work. The experimental evaluation was done using one benchmark dataset and thus represents a limited variety of drone platforms, transmission conditions, and operating conditions. In spite of the fact that the suggested learning strategy is evidence-based and is not reliant on manually designed features, this does not necessarily ensure complete transfer to practical deployments. The real-world RF environments are heterogenous and can vary significantly by having differences in transceiver hardware, modulation properties, channel properties, interference sources, and propagation. Therefore, the good results on the benchmark must be viewed as the indication of methodological potential but not as the conclusive evidence of the deployment readiness in all the operational environments.

Systematic cross-dataset and cross-environment evaluation will then become an important next step in this context. Future research must examine transferability by retraining the framework on the DroneRF dataset and evaluating it on independent RF benchmarks or recently collected measurements, including and excluding limited fine-tuning, to measure robustness in heterogeneous RF settings. Further studies should also take into account the possibility of data collection in less controlled outdoor settings through the use of software-defined radio systems so as to be able to conduct an assessment of model behaviour under more realistic sensing conditions. Deployment wise, additional testing on resource-constrained embedded systems is also required to describe inference latency, memory footprint, and power consumption, which are critical issues of real-time field deployment.

The other potential research area is model interpretability. RF saliency analysis and convolutional filter activation inspection are lightweight explainable artificial intelligence methods that can potentially be used to enhance the transparency of model choices and build confidence in the security-focused UAV monitoring systems. This is especially the case with operational needs where automated decisions might require inspection, justification, or audit. In general, the latest developments in hybrid artificial intelligence and deep CNN-based classification schemes in various areas of application suggest that additional improvements can be attained by designing more complex models and learning processes [35–42].

Lastly, further research can be enhanced by expanding the current RF-only framework to multimodal sensing systems that consider RF data with the data provided by radar, infrared, or acoustics. These multimodal fusion schemes might be useful to improve resilience to RF ambiguity, discrimination within more complex operating scenarios, and the creation of more scalable and field-ready counter-UAV systems to be applied in real-world surveillance.

Table 2: Comparison with Existing Literature

Ref	AI Model Used	Dataset Used	Task	Accuracy (%)	F1-Score (%)	Remarks
[28]	CNN	DroneRF	UAV Classification	98.3	97.8	Lacked real-time testing
[29]	LSTM	RF100	Detection	65.2	94.7	High computational cost
[30]	ResNet-50	DeepRF	Detection	96.8	96.5	Susceptible to adversarial attacks
[31]	YOLOv5+CNN	DroneDetect	Identification	97.5	97.1	Limited robustness in dynamic environment
This work	CNN, RF-CNN Fusion	DroneRF	Detection/ Identification/ Mode Classification	99.8/ 88.4/ 87.1	99.7/ 88.4/ 87.0	Performance reported on DroneRF under ten-fold cross validation.

5. References

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