https://dx.doi.org/10.4314/dujopas.v8i4b.10
ISSN (Print): 2476-8316
ISSN (Online): 2635-3490
Dutse Journal of Pure and Applied Sciences (DUJOPAS), *Vol. 8 No. 4b December 2022*

Development of an Optimised Neural Network Model for RF Based UAV Detection and Identification

Rexcharles Enyinna Donatus[1,2], Mustapha Deji Dere[4], Ifeyinwa Happiness Donatus [3], Ubadike Osichinaka chiedu [1], Muhammad Bashir Abdulrazaq[2], Monday F. Ohemu[5]

[1]Department of Aerospace Engineering,
Airforce Institute of Technology,
Kaduna, Nigeria

[2]Department of Computer Engineering,
Ahmadu Bello University, Zaria, Nigeria

[3]Department of Computer Science,
Kaduna State University. Kaduna, Nigeria

[4]Department of Artificial Intelligence,
National Open University of Nigeria, Abuja, Nigeria

[5]Department of Electrical and Electronics Engineering,
Airforce Institute of Technology, Kaduna, Nigeria

Email: charlly4eyims@yahoo.com

Abstract

The rapid popularity of Unmanned Aerial Vehicles (UAVs) or drones is due to its great promise for various commercial and recreational applications. Moreover, technological advancements has made UAVs both affordable and versatile, it is able to perform task considered difficult and dangerous with high mobility, low cost and safely. Despite these advantageous applications and future potentials, UAVs are regrettably also used for malicious activities such as cyber-attack (i.e., eavesdropped the mobile phone of unsuspecting users), terrorism, drug trafficking and violation of security of restricted or sensitive areas. In order to overcome these aforementioned challenges, various UAV detection and identification techniques were developed by researchers in the past. Conventional techniques have inherent weakness such as poor performance in the presence of low visibility, less effective in an environment with high ambient noise and are also adversely affected by weather conditions. All these and more constitute major setback in UAV detection and identification. Similarly, RF sensing employed are usually based on traditional machine learning and statistical methods which are less effective in their capacity to successfully capture the rich information present in complex unstructured RF signal. To this end, a deep learning approach is proposed as a possible solution that is capable of achieving high accuracy in detection with less training time. To verify the effectiveness of our proposed convolutional neural network architecture, it was evaluated on the popular open source dataset, the DRONE RF dataset. Our empirical results demonstrates that our proposed CNN model outperformed state-of- the -art results using the same DRONE RF dataset.

Keywords: Convolutional neural network, radio frequency signal, UAV detection, UAV identification

**Author for Correspondence*

INTRODUCTION

Unmanned Aerial vehicles (UAVs) also known as drones have proven to be very useful in a wide variety of military applications such as reconnaissance operation, espionage, and search and rescue operation (Swinney & Woods, 2020). Similarly, over the past few years, there has also been rapid growth in the application of UAVs to numerous domains leading to its popularity. The pervasiveness of UAVs is primarily due its relative reduction in price and the technological advancement in precision sensors. These sensors such as motion sensors and gyroscope found in modern UAVs that aid its guidance, navigation, and control have contributed in stimulating the increasingly applications of UAVs in various domains. For instance UAVs are used for recreational activities, disaster management (Restas, 2015), surveillance (Nemer *et al*., 2021), courier delivery (Kosolyudhthasarn *et al.,* 2018), cinematography, environmental monitoring, agriculture monitoring (Bisio *et al*., 2019), remote sensing, search and rescue missions (Nguyen *et al.*, 2016) and lot more. Notably, UAVs are seen as promising substitute for satellite based systems or in some instance used to complement it. In reality, UAV usage could potentially promote and facilitate economic growth (Nemer *et al*., 2021). In addition, there still exist great promises for new use-case of UAVs in the future.

Even though UAVs have many advantageous applications, it is also used for illicit purposes that pose significant threat to the public safety (Swinney & Woods, 2021) and national infrastructure (Solodov *et al*., 2018) .Recently, some rebels violated the security of national infrastructures by flying UAVs into airport and nuclear reactor (Solodov *et al*., 2018). For instance in 2018 Gatwick airport and network liberty international airport were shut down for hours due to UAVs invasion (Zhang, 2021). Similarly, UAVs are used to carry out cybercrimes, for instance , utilizing UAV to eavesdrop on mobile phone users and hence violating the confidentiality of unsuspecting users sensitive data (Alajmi *et al.,* 2017) . In addition, UAV can be used for a variety of illegal activities e.g., spying, terrorism (Chamola *et al.,* 2021), illegal surveillance (Medaiyese *et al.,* 2021), drug trafficking, fire arm smuggling and so on.
With the current rise of UAVs misuse, these have open doors to a new era where finding effective and intelligent UAV detection and identification becomes a research challenge. Many literatures have attempted various methods by using various sensing mechanism that includes radar, video, audio and RF based and so on.

Jeon *et al*., (2017) conducted a research by investigating how unique sound signature produces by UAVs could be captured and analyzed by deep neural network. They implemented and compared Gaussian mixture model (GMM), recurrent neural network (RNN) and CNN for sound classification and drone identification. Their empirical results showed them that RNN was the best performing in drone detection with a short processing of 240ms. Hence it proved that their proposed technique is suitable for application in real time scenario. In (Muhammad *et al*., 2020; Unlu *et al*., 2019) UAV detection was achieved using computer vision approach. They demonstrated that camera can be placed at strategic position for video surveillance of specific area. The video and images captured could form a dataset for UAV detection. These dataset can be used to train a deep learning model, and the model will automatically extract features which will aid in identifying UAVs. Parameter such as UAV appearance or it motions could serve as a distinguishing different UAVs. The author argued that for quick detection multiple cameras can be used for wider visualizations. (Taha & Shoufan, 2019) has also provided review on many work where radar sensing mechanism are applied with difference Machine learning (ML) approach for UAV detection .The empirical result from these works showed that drone identification can be achieved with accuracy comparable with state-of the art and also outperform it. From these literatures reviewed, these mainstream sensing mechanism have inherent weakness such as poor performance in the present of low light visibility, less effective in an environment with high ambient noise and negatively influence by weather condition. All these and more has been the major setback in UAV detection and identification using the aforementioned sensing mechanisms.

RF signals have emerged as one of the reliable sensing mechanism for UAV detection and identification. Use of RF signals have also proven to be adequate for real-life scenarios (Azari *et al*., 2018). It is considered the best sensing technique when detection at a distance is the objective (Swinney & Woods, 2020) . In addition, RF based UAV detection and identification facilitates high accuracy , capable of determining UAVs make or models and its modes of operation, which can potentially aid forensic investigations (Al-Emadi & Al-Senaid, 2020). Few literatures have also addressed the problem of UAV identification using RF signals. This sensing mechanism is usually based on experiments that involve intercepting the RF signal transmitted between UAVs and its flight controller during mission.

Ezuma *et al*., (2019) investigated the detection and classification of micro-UAV by using raw RF signals transmitted from the flight controller to the micro-UAV. In their proposed technique the RF signal is converted to frames during the pre-processing step. They employed the wavelength domain analysis for the purpose of data size reduction and removal of bias present. A naive Bayes classifier is then applied for detection of UAV from signal frames and also for the classification of UAV types. In addition, they utilized energy transient signals which are robust to various noises and easy to modulate. Although their technique had significant improvement over existing machine learning techniques, however the inherent draw back with their technique is that it depends on hand crafted features which is costly. In another work by (Al-Sa'd *et al.,* 2019)**,** they proposed using deep neural network model on raw RF signal for the purpose of detecting and identifying UAV. The proposed algorithm successfully identified the presence of UAV, the specific type of UAV. In addition their algorithm also detected UAV operation mode (i.e., power on/off, hovering, video recording and flying). They achieved an average accuracy of 97.7%, 84.5% and 46% in the three difference classification. Notably, their work built the pioneering DRONE RF database. A database that was made available to the public to foster research in RF based UAV and detection and identification. Even though their work was ground breaking, their technique was computationally expensive and their DNN algorithm was feed with large dimension of input vector. Ezuma *et al*., (2020) in a recent work implemented a multiphase detector to identify UAV signal in the presence of other RF interference i.e., wireless technology such as WiFi and Bluetooth. Their proposed approach involves a machine learning (ML) classifier used to classify any UAV detected. In addition a multiphase detector consisting of two detectors was used. Firstly, by using Naive Bayes algorithm based on Markov model they were able to determine whether the captured data has an RF signal or Not. The second phase is initiated for the purpose distinguishing whether an RF signal detected is an interference or UAV control signal. The basis of distinction between the two categories of RF signal is the band and modulation characteristic of the RF signal. The ML classifier is fed with only UAV control signals from the multi-phase detector, for further processing to determine the UAV model and make of the controller. Their experimental evaluation achieved an accuracy of 98.13% using K-Nearest Neighbour classifier with 25dB SNR. Though their result high accuracy, classical machine learning is quickly becoming unreliable with the increasingly complexity of real life data.

Swinney & Woods, (2020) explored the use of power spectral density in frequency domain on the popular DRONE RF data set. In this work VGG16 CNN a form of transfer learning was used for feature extraction. The significant feature from VGG16 is feed to three machine learning classifiers namely support vector machine (SVM), logistic regression (LR) and

random forest (RF). Based on their experimental evaluation and comparison the authors argued that Power spectral density (PSD) has higher accuracy than time domain spectrograms on the dataset. Their study has shown that LR performed better than RF and SVM. However the difference was marginal. Their proposed approach produced 40% increase when benchmark against (Al-Sa'd *et al.*, 2019). In addition, they noticed a drop of 37.7% when the classification was increases from 4classes to 10 classes. However, the drawback of their work was that it is time consuming.
Medaiyese *et al.*, (2021) developed a system for UAV detection and classification that is effective even in the presence of other wireless signal. Their technique exploited steady state RF signals transmitted by UAV and it flight controller. Their technique employed a semi supervised learning approach that combined stack denoising auto encoder (SDAE) and local outlier factor algorithms. In order to make their approach robust to all form of channel noise the SDAE transforms the signal into latent representation by compressing the signal. The output from the SDAE is fed into a local outlier factor (LOF) algorithm which essentially detects the UAV signal, by distinguishing it from all other wireless signals i.e., WIFI and Bluetooth. The detected UAV signal is further analysed to facilitate the classification into different category such as type of UAV, UAV model type and flight mode of the UAV. The drawback of the proposed technique is that it is time consuming and it is computationally expensive.

To the best of our knowledge no literature has proposed a robust UAV detection and identification system. The problem of finding effective and intelligent system that adequately handle the issue of UAV detection, To this end, we implement a convolutional neural network (CNN), an advance technique for the detection and identification of UAV utilizing RF fingerprints. CNN when optimized is a possible solution that is capable of achieving comparable state-of-the-art result accuracy in detecting UAVs with reduced training time.
.

PROPOSED NEURAL NETWORK MODEL

Our proposed neural network model architecture is cost-efficient. Fig. 2 shows the implemented architecture, a CNN used for an efficient drone identification and detection. CNN is not just one network but a combination of algorithms in different layers. The common structure of a CNN contains several succeeding convolutional layers with pooling and normalization, after which there are a couple of fully linked layers (perceptron). Figure 1 shows a conceptual model:

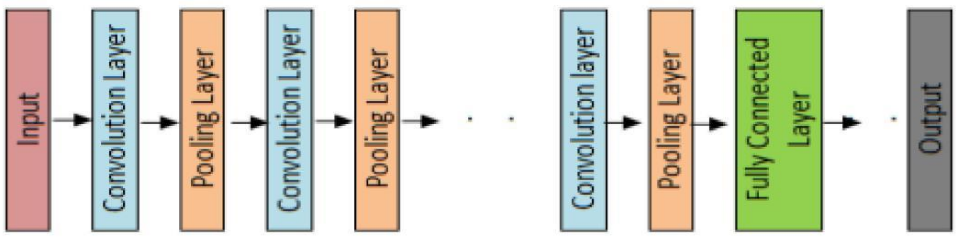

Figure 1. Conceptual model of CNN (Sultana *et al.*, 2018)

We deployed a two-dimensional (2D) convolutional layer in our network architecture to properly process the RF signal dataset and extract features. The proposed CNN model architecture consists of six two-dimensional convolution layers with different hyper-parameters suitable for the analyses of the correlations of raw RF signal and extracting highlevel features. Figure 2 shows illustration of the final design of our neural network architecture for the proposed CNN model.

To validate the effectiveness of our proposed neural network architecture using the RF database. A preprocessed raw RF signal is fed to the convolution layer. The convolutional layer is the central building block of CNN, and it conveys the major portion of the computational load in the network. In other words it is responsible for extracting features from input data. It is made up of several kernels (also known as filters). The filter primary purpose is to perform convolution operation over the input data and compute different feature map. Consequently, Convolution layer reduces the number of learning parameters to a great degree by using many set of kernels (filters).

The feature map obtained from convolution layer can be mathematically expressed as,

$$h_i = \sum_{I=1}^{N} x_i y_i + b_i \qquad (1)$$

Here $h_i$represent the feature map at the two dimensional coordinates i, of input signal which is computed through the summation of multiplication of the input channel y_i and the corresponding convolutional kernel x_i of same input channel. b_i is considered the bias.
The input for convolution are primarily shaped in the form of (height * weight * channel. The input to the first convolution layer was shaped in terms of (data * channels*1) to match the requirement of the convolution layers (Tsinganos *et al.*, 2018). The model includes both a batch and layer normalization layer. Batch normalization ensures that the mean is always close to 0 and the standard deviation is relative to 1. This is very necessary to avoid gradient explosion. Furthermore, we adopted rectified linear unit as an activation function following the convolutional layer is an activation function, we adopted rectified linear unit (ReLU). The ReLU requires very minimal computation load compared to others. The mathematical representation of ReLU is:

$$f(x)_{ReLU} = max(0, x) \qquad (2)$$

The reason of selection ReLU activation is because of its ability to solve vanishing gradient problem and make a better learning approach for the proposed CNN model. Furthermore, pooling layer has been included after the ReLU layer after each convolution layer. The pooling layer has an important property that reduces the number of parameter and computational load by sub sampling the input, hence handling the problem of over fitting. In addition, a flatten layer has be added to further reduce the spatial dimension of input signals to correspond to the initial channel dimensions. Lastly, our proposed CNN has fully connected layer followed by a softmax layer. The key important of the fully connected layer is to combine all the learned features obtained from the previous layer. The fully connected layer helps to map the representation between the input and the output layers. The fully connected layer performs a combination of matrix multiplication and a bias effect. It is mathematically expressed as follows:

$$F = W\,Z + \, b_f \qquad (3)$$

As shown in equation 3 Z if the input and W is the weight matrix. b_f is the bais of the fully connected layer. . Accordingly, a softmax transfer function is performed over the net feature map of fully connected layer as follows

$$X = \frac{\exp{(t)}}{\sum exp\;(t)} \qquad (4)$$

Here X represent the output and where (t) is the input feature map of the softmax layer. Finally, the feature map of softmax layer is received by the classification layer. Here, the cross entropy loss function performs to allocate each input to one of the mutually exclusive class. In other words, the Softmax activation function gives individual classes a probability that is used by the loss function and back propagated through the network architecture. The hyper parameters used to tune the model are highlighted in the Table 1. It is worth noting that to obtain these hyper parameters that give the optimal performance for the proposed CNN model, time was taken in carrying out numerous experiments with different values of hyper parameters using grid-search model until best accuracy is achieved.
Finally, the summary of our proposed CNN model configuration used during the 4-class classification which is identification of UAVs types is reported in Table 3. It is worth noting that this outcome of number of layers and neuron as seen in Table 3 was a result of several simulations which was done to achieve an optimal solution The implementation of the proposed CNN model was carried out in python script using Pandas, MatplotLib, Numpy, scikit learn and popular deep learning API keras and Tensorflow framework.

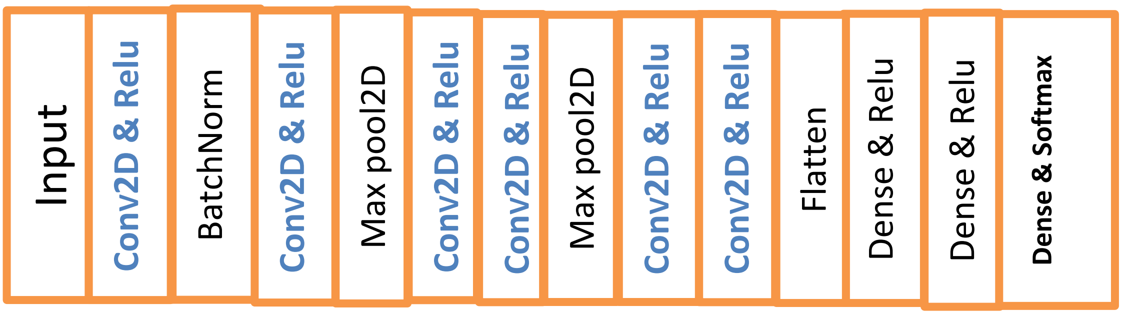

Figure 2. Illustration of the final network architecture of our Proposed CNN model

Table 1. Optimal values of hyper parameter used to tune the Proposed CNN Model

Hyper parameters	Values
Learning Rate	0.0001
Weight decay	0.00001
Batch size	32
K-fold	10
Loss	Sparse Cross-entropy

DATASET DESCRIPTION

The dataset used for this work was produced from the experimentation performed by (Al-Sa'd *et al.*, 2019) which comprises of three UAVs namely DJI phantom 3,parrot AR, and Parrot Bebop.

The dataset is consisting of 227 segments of RF signals that were obtained from the three different drones. The RF signal segment has two frequency bands i.e. low and high and each consist of I million samples of raw RF signals. During the experiment to build the dataset the author experimented using different flight modes such as ON and Connected, OFF, Hovering, flying, and video recording. Furthermore the details of different categories of classification that are facilitated using the dataset are as shown in Table 2.

Table 2. Drone Classification Types

1.	Drone detection: this is a binary classification.(2-class) i.e., UAV or No- UAV
2.	Drone identification: this is a multi-class experiment(4-class) i.e., no UAV, Bebop AR, Phantom,
3.	Drone mode Identification: this essentially has to do with identifying drone type and it mode of operation (10-classes).Flight modes involves (e.g., mode 1 switch on and connected to controller, mode 2 hovering automatically, mode 3 flying without video, mod 4 flying with video

Table 3. Proposed CNN model Network configuration for UAV identification

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	[(None, 10, 2048, 1)]	0
conv2d (Conv2D)	(None, 10, 2048, 64)	640
batch normalization (BatchNo	(None, 10, 2048, 64)	256
conv2d_1 (Conv2D)	(None, 10, 2048, 32)	8224
max_pooling2d (MaxPooling2D)	(None, 10, 2048, 32)	0
conv2d_2 (Conv2D)	(None, 8, 2046, 32)	9248
conv2d_3 (Conv2D)	(None, 8, 2046, 32)	4128
max_pooling2d_1 (MaxPooling2	(None, 8, 2046, 32)	0
conv2d_4 (Conv2D)	(None, 6, 2044, 32)	9248
conv2d_5 (Conv2D)	(None, 4, 2042, 32)	9248
flatten (Flatten)	(None, 261376)	0
dense (Dense)	(None, 200)	52275400
dense_1 (Dense)	(None, 32)	6432
dense_2 (Dense)	(None, 4)	132

Total params: 52,322,956
Trainable params: 52,322,828
Non-trainable params: 128

EMPIRICAL RESULTS AND DISCUSSION

In order to prove and demonstrate the effectiveness our proposed model, we used a popular open source dataset called "DRONE RF dataset" that was made public by (Al-Sa'd *et al.*, 2019) to foster research in UAV detection and identification. In our experiment using these dataset, it facilitated three type of classification problem as shown in Table 2. The proposed model overall graphical experimental result for accuracy and loss for drone detection, drone identification and drone mode identification is as shown in Fig. 3, Fig. 4a and Fig. 4b respectively. To show that our proposed model is effective we compared it performance with state-of-the-art (Al-Sa'd *et al.*, 2019; Swinney & Woods, 2020) using accuracy in terms of UAV detections, it types and flight modes as summarized in Table 4. The evaluation metric chosen for our models is accuracy. The equation for the calculating accuracy is given as

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (5)$$

Where TP = True Positive, TN= True Negative, FP= False Negative and FN = False Negative. Our accuracy result achieved as demonstrated in Table 4, when compared with state of the art shows that there was great performance improvement using proposed model in the identification of drone types i.e., the 4-class classification problem. Furthermore, our model has also demonstrated the effectiveness of using raw RF data input and not handcrafted features as used in (Swinney & Woods, 2020).

We also evaluated our proposed model by comparing it with (Al-Sa'd *et al*., 2019) in terms of its time complexity as shown in Table 5. Our result demonstrates that the proposed model had a reduced training time, hence energy efficient. We also had an improved classification accuracy achieving 94.15% for the 4-class classification problem, which was 5.4% and 10.8%. better than (Swinney & Woods, 2020) and (Al-Sa'd *et al*., 2019) respectively.

Table 4. Performance Evaluation Metric of existing and Proposed Model

Accuracy achieved in percentage				
Models	(Al-Sa'd et al., 2019)	(Swinney & Woods, 2020) Spectrogram	PSD	Proposed CNN Model
2 -class	99.70%	82.70%	100.00%	99.70%
4-classes	84.50%	70.30%	89.20%	94.15%
10-classes	46.80%	67.40%	87.50%	81.50%

Table 5. Time Complexity Analysis of existing and Proposed Model

Time Complexity		
Models	Al-Sa'd *et al*., (2019)	Proposed CNN Model
Total number of epochs	200	50

Figure 3. UAV Detection accuracy and loss

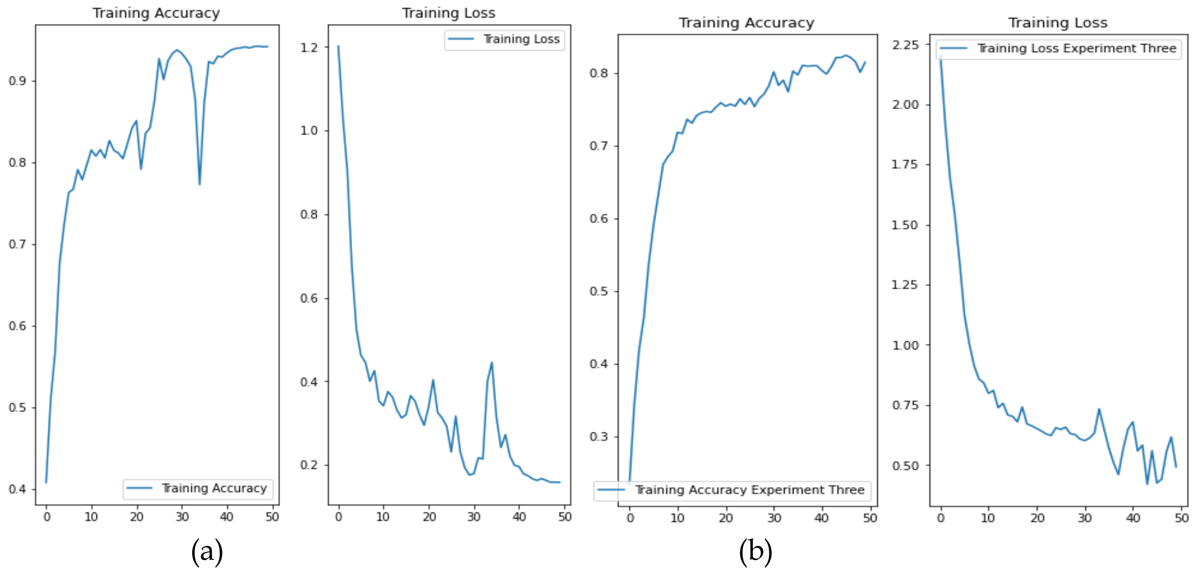

Figure 4. (a). UAV types Identification and (b) UAV flight mode Identification accuracies and Loss

CONCLUSION

The potential threats to the public and national infrastructure from the malicious use of UAVs are undoubtedly an issue of serious concern that demands urgent solution. In this work, we proposed a technique that leverages high performing CNN as possible solution that is capable of achieving high accuracy in detecting UAV presence, its types and flight modes with less training time. We have compared our simulation results with prior work in term of being energy efficient and accuracy in classification, our proposed neural network model performed better. Moreover, we have also demonstrated the effectiveness of using raw data input in our model compared to handcrafted features.

REFERENCES

Al-Emadi, S., & Al-Senaid, F. (2020). Drone Detection Approach Based on Radio-Frequency Using Convolutional Neural Network. *2020 IEEE International Conference on Informatics, IoT, and Enabling Technologies, ICIoT 2020*, 29–34. https://doi.org/10.1109/ICIoT48696.2020.9089489

Al-Sa'd, M. F., Al-Ali, A., Mohamed, A., Khattab, T., & Erbad, A. (2019). RF-based drone detection and identification using deep learning approaches: An initiative towards a large open source drone database. *Future Generation Computer Systems*, *100*, 86–97. https://doi.org/10.1016/j.future.2019.05.007

Alajmi, A. A. A., Vulpe, A., & Fratu, O. (2017). UAVs for Wi-Fi Receiver Mapping and Packet Sniffing with Antenna Radiation Pattern Diversity. *Wireless Personal Communications*, *92*(1), 297–313. https://doi.org/10.1007/s11277-016-3851-2

Azari, M. M., Sallouha, H., Chiumento, A., Rajendran, S., Vinogradov, E., & Pollin, S. (2018). Key Technologies and System Trade-offs for Detection and Localization of Amateur Drones. *IEEE Communications Magazine*, *56*(1), 51–57. https://doi.org/10.1109/MCOM.2017.1700442

Bisio, I., Garibotto, C., Lavagetto, F., Sciarrone, A., & Zappatore, S. (2019). Blind detection: Advanced techniques for WiFi-based drone surveillance. *IEEE Transactions on Vehicular Technology*, *68*(1), 938–946. https://doi.org/10.1109/TVT.2018.2884767

Chamola, V., Kotesh, P., Agarwal, A., Naren, Gupta, N., & Guizani, M. (2021). A Comprehensive Review of Unmanned Aerial Vehicle Attacks and Neutralization Techniques. *Ad Hoc Networks*, *111*. https://doi.org/10.1016/j.adhoc.2020.102324

Ezuma, M., Erden, F., Anjinappa, C. K., Ozdemir, O., & Guvenc, I. (2019). Micro-UAV Detection and Classification from RF Fingerprints Using Machine Learning Techniques. *IEEE*

Aerospace Conference Proceedings, *2019-March*. https://doi.org/10.1109/AERO.2019.8741970

Ezuma, M., Erden, F., Anjinappa, C. K., Ozdemir, O., & Guvenc, I. (2020). Detection and classification of UAVs using RF Fingerprints in the Presence of Wi-Fi and bluetooth interference. *IEEE Open Journal of the Communications Society*, *1*(January), 60–76. https://doi.org/10.1109/OJCOMS.2019.2955889

Jeon, S., Shin, J. W., Lee, Y. J., Kim, W. H., Kwon, Y. H., & Yang, H. Y. (2017). Empirical study of drone sound detection in real-life environment with deep neural networks. *25th European Signal Processing Conference, EUSIPCO 2017*, *2017-Janua*, 1858–1862. https://doi.org/10.23919/EUSIPCO.2017.8081531

Kosolyudhthasarn, P., Visoottiviseth, V., Fall, D., & Kashihara, S. (2018). Drone Detection and Identification by Using Packet Length Signature. *Proceeding of 2018 15th International Joint Conference on Computer Science and Software Engineering, JCSSE 2018*, 1–6. https://doi.org/10.1109/JCSSE.2018.8457352

Medaiyese, O. O., Ezuma, M., Lauf, A. P., & Adeniran, A. A. (2021). *Hierarchical Learning Framework for UAV Detection and Identification*. 1–12. http://arxiv.org/abs/2107.04908

Muhammad, K., Hussain, T., Tanveer, M., Sannino, G., & De Albuquerque, V. H. C. (2020). Cost-Effective Video Summarization Using Deep CNN with Hierarchical Weighted Fusion for IoT Surveillance Networks. *IEEE Internet of Things Journal*, *7*(5), 4455–4463. https://doi.org/10.1109/JIOT.2019.2950469

Nemer, I., Sheltami, T., Ahmad, I., Yasar, A. U. H., & Abdeen, M. A. R. (2021). Rf-based UAV detection and identification using hierarchical learning approach. *Sensors*, *21*(6), 1–23. https://doi.org/10.3390/s21061947

Nguyen, P., Ravindranathan, M., Nguyen, A., Han, R., & Vu, T. (2016). Investigating cost-effective RF-based detection of drones. *DroNet 2016 - Proceedings of the 2nd Workshop on Micro Aerial Vehicle Networks, Systems, and Applications for Civilian Use, Co-Located with MobiSys 2016*, 17–22. https://doi.org/10.1145/2935620.2935632

Restas, A. (2015). *Drone Applications for Supporting Disaster Management*. *October*, 316–321.

Solodov, A., Williams, A., Al Hanaei, S., & Goddard, B. (2018). Analyzing the threat of unmanned aerial vehicles (UAV) to nuclear facilities. *Security Journal*, *31*(1), 305–324. https://doi.org/10.1057/s41284-017-0102-5

Sultana, F., Sufian, A., & Dutta, P. (2018). Advancements in image classification using convolutional neural network. *Proceedings - 2018 4th IEEE International Conference on Research in Computational Intelligence and Communication Networks, ICRCICN 2018*, 122–129. https://doi.org/10.1109/ICRCICN.2018.8718718

Swinney, C. J., & Woods, J. C. (2020). Unmanned Aerial Vehicle Flight Mode Classification using Convolutional Neural Network and Transfer Learning. *16th International Computer Engineering Conference, ICENCO 2020*, 83–87. https://doi.org/10.1109/ICENCO49778.2020.9357368

Swinney, C. J., & Woods, J. C. (2021). *Deep Residual Learning Feature Extraction*. 1–23.

Taha, B., & Shoufan, A. (2019). Machine Learning-Based Drone Detection and Classification: State-of-the-Art in Research. *IEEE Access*, *7*, 138669–138682. https://doi.org/10.1109/ACCESS.2019.2942944

Tsinganos, P., Skodras, A., Cornelis, B., & Jansen, B. (2018). Deep Learning in Gesture Recognition Based on sEMG Signals. *Learning Approaches in Signal Processing*, *Ml*, 471. https://doi.org/10.1201/9780429061141-23

Unlu, E., Zenou, E., Riviere, N., & Dupouy, P. E. (2019). Deep learning-based strategies for the detection and tracking of drones using several cameras. *IPSJ Transactions on Computer Vision and Applications*, *11*(1). https://doi.org/10.1186/s41074-019-0059-x

Zhang, Y. (2021). RF-based Drone Detection using Machine Learning. *2021 2nd International Conference on Computing and Data Science (CDS)*, 425–428. https://doi.org/10.1109/CDS52072.2021.00079