11TH INTERNATIONAL SCIENTIFIC CONFERENCE ON DEFENSIVE TECHNOLOGIES
OTEH 2024
Serbia, Tara, 9-11 October 2024

SIMPLE ENERGY DETECTOR FOR TWO-STAGE CLASSIFICATION FOR ANTIDRONE SYSTEMS

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Abstract: *Signal detection theory, a fundamental concept in various scientific disciplines, involves mandatory measuring of the signal features. This theory finds applications in telecommunications, radar technology, medical devices, automation and process control, geophysical research, biometric systems, and security systems, emphasizing its broad significance. Likewise, drone detection in the radio-frequency domain is necessary for signal detection and ensures efficient and reliable communication, surveillance, and security. The recent conflict between Russia and Ukraine has underscored the crucial role of drones in modern warfare. Our research can improve the detection of any malicious drones that pose a threat, thereby underlining the significance of the proposed methodology in modern electronic warfare. This is a specialized approach to drone signal detection based on two-stage classification with two key components: a method based on spectrogram energy detection and deep learning classification. Energy detection on the spectrograms is particularly effective when the signal's energy characteristics differ significantly from the surrounding noise. The practical applicability of our proposed method was evaluated using the publicly available VTI_DroneSET dataset, which contains a diverse range of signals from three types of drones. Furthermore, we conducted tests with the VTI_DroneUSRP dataset and signals from the NI-USRP-2954 receiver, demonstrating the effectiveness and practicality of the proposed method in real situations. The successful detection and identification of Wi-Fi, Bluetooth, and drone signals in both ISM frequency bands were performed, proving the method's reliability. The proposed approach improved execution times and energy savings, indicating that applying the energy detector on the spectrograms in a two-stage classification significantly enhances the performance of ADRO applications for real-time drone detection. Furthermore, we conducted a comparative analysis of different deep learning algorithms at the outset of two-stage classification, which is a potential basis for adopting this approach.*

Keywords: *artificial intelligence, deep learning, detection, drone, energy detector, receiver.*

1. INTRODUCTION

Drones have emerged as a significant threat in contemporary military operations. Their small size, speed, and agility enable them to execute various combat maneuvers and cause substantial damage. Consequently, military entities heavily invest in developing effective antidrone (ADRO) systems and measures. The first step in any ADRO system involves a procedure that aims to detect all drones in the area of interest. The next step is the identification of detected drones, with the main task of separating malicious drones. Modern ADRO systems might have a direction-finding or radar device to localize detected drones, which can help further analysis. These steps are essential to electronic warfare (EW) and are particularly challenging because they are realized in the complex and demanding battlefield domain.

Operating in an environment saturated with multiple signals from different users of the electromagnetic spectrum, an ADRO system faces a unique challenge in distinguishing between threats. It must effectively differentiate between commercial signals like Wi-Fi, Bluetooth, NFC, and LoRa and identify malicious drones amidst the noise of friendly ones. Distinguishing between different signals is crucial for ADRO systems that use

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DOI: 10.5937/OTEH24066Z

receivers as primary sensors. The goal is to detect signals quickly and with a high probability of accuracy, even if it means there might be some false alarms. One standard detection method is energy detection, also used in this paper. This method allows the ADRO system to quickly determine if a signal exists in the monitored frequency spectrum. By combining an energy detection method on spectrograms (EDS) with more advanced deep learning-based detectors, exceptional results can be achieved. Furthermore, using two-stage classifiers is also possible, as it can help reduce resources and speed up the detection and identification process. Considering the information provided, this research paper explores the potential of using the EDS method and deep learning (DL) algorithms to enable an ADRO system to detect and identify drones promptly.

This paper is structured as follows: Section 2 provides an overview of the literature on drone classification. Sections 3 and 4 present the methodology and discuss our experimental results, and the study conclusion is given in the last section.

2. LITERATURE REVIEW

According to existing studies, various classification techniques utilizing radio-frequency sensing systems are employed to achieve a common objective: identifying and accurately characterizing potential threats. As discussed in the Introduction section, enhancing input data accuracy can be achieved by applying multiple sensing modalities related to energy detection. Research in energy detection is predominantly associated with cognitive radio performance, explicitly focusing on estimating unused spectrum. In [1] and [2], the authors explore methods for identifying unused spectrum in the presence of signals from primary users, intending to perform spectrum reallocation without introducing harmful interference to existing users. This paper employs a similar methodology but with an inverted approach. In the detection process, spectrum sensing can be seen as a binary hypothetical testing problem with hypotheses H0 and H1 defined as nonexistent and existent signals of interest, which in binary form represents a state with no threat and a state with threat. In [3] the authors address the false alarm occurrence in the signal determination process. In this paper, the authors propose a preprocessing for detection to prescreen the false alarms by investigating the energy of the received signal. Whereas the conventional solutions to mitigate false alarms are in-decoder schemes, energy-based detection can be performed before the decoding trial. The false alarms described in the energy detection and classification process originate from ambient noise, including Bluetooth and Wi-Fi signals, and additional interference sources operating in the observed frequency ranges. Several approaches to extracting ambient noise have been applied in different studies. In [4] author proposed a solution for detecting and classifying radio-frequency signals from different UAV controllers in the presence of Bluetooth and Wi-Fi interference by developing multistage models supported by the a priori knowledge of Bluetooth and Wi-fi signal specification that is well standardized. The first step in deciding whether the detected signal is Wi-fi interference is performing bandwidth analysis. In [4], [5] are given detailed specifications on Bluetooth and Wi-Fi features. Following the bandwidth analysis, if a conclusive decision cannot be reached, the model proceeds to additional analysis, including modulation comparison and a detailed signal decomposition to identify the signal source accurately. Subsequent processing involves digital forensics analysis using a dataset of radio-frequency fingerprints for various drone types. Aside from selecting appropriate techniques, the primary challenge in classification processes is the limited access to drone signal datasets. In [6], the author reviews the existing literature on drone classification within the radio-frequency spectrum, focusing specifically on detection and identification. This review examines passive radio-frequency sensors, classification techniques, and datasets, shedding light on the associated challenges, presents a new categorization system, and comprehensively analyzes publicly available drone classification techniques. The results of this study demonstrate that DL algorithms are currently the most effective approach for addressing the challenge of drone classification within the radio-frequency domain. A major impediment is the need for a comprehensive, standardized framework for drone classification in this context, which should be tailored to end-user requirements. Additionally, findings from two ablative experiments underscore the importance of preprocessing raw I/Q radio signals as a critical step in the drone classification process. This paper applies machine learning and DL algorithms to input data obtained through energy detection and subsequent signal preprocessing.

3. METHODOLOGY

During our research, we followed a structured approach that involved multiple steps. Firstly, we accessed data from the datasets. Then, we utilized an EDS method and applied DL algorithms. For an in-depth understanding, refer to Figure 1, which provides a comprehensive overview of the methodology employed.

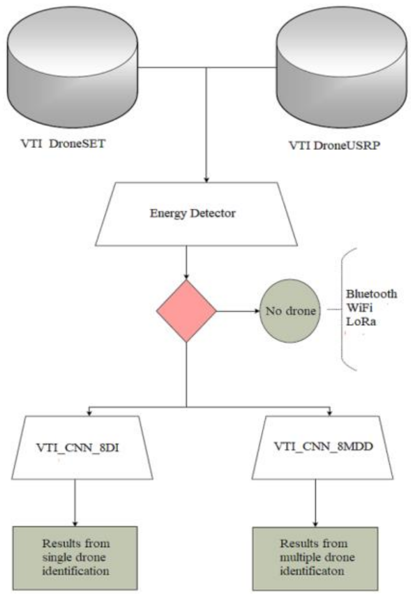

Figure 1. An overview of the methodology.

Figure 1 shows our research methodology, explaining the sequence of experiments realized with the EDS method and DL algorithms. Moreover, the input data consists of two datasets. The main idea of the EDS method is to reduce the number of spectrograms in the DL algorithms by jointly rejecting spectrograms with Wi-Fi and Bluetooth signals. Next, the methodology is presented by describing datasets, the EDS method, and DL algorithms.

3.1. Datasets

This research used two separate datasets: the VTI_DroneSET introduced in [7] and VTI_DroneUSRP. The VTI_DroneSET is a radio-signal drone dataset created for research and development purposes for new ADRO systems. This dataset was verified through various research papers in [6], [8], [9], [10], [11], [12], [13] and will be used as a benchmark dataset. This dataset contains signals from drones and flight (operational) control. For the equipment under test (EUT), three different drones (DJI Phantom IV, DJI Mavic Zoom, and DJI Mavic 2 Enterprise) were used. Drones operated independently (one drone per experiment) and simultaneously (two and three per experiment). This dataset was obtained in laboratory conditions using Tektronix Real-Time Spectrum Analyzer, two receiving antennas (for two separate frequency bands) with corresponding cables and connectors. The Real-Time Spectrum Analyzer instantaneous records bandwidth of 110 MHz within 2.4 or 5.8 GHz ISM (Industrial, Scientific, and Medical) frequency bands and saves records directly in a *.mat format suitable for loading and analyzing the MatLab application. Figure 2 shows the spectrogram of one example from the VTI_DroneSET dataset.

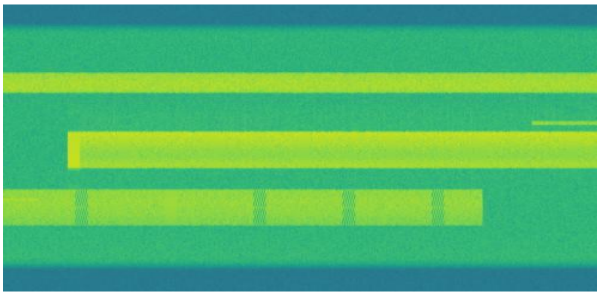

Figure 2. The spectrogram of three drones operating simultaneously (source: VTI_DroneSET dataset).

Figure 2 shows one example of a spectrogram of three drones operating simultaneously. It is essential to notice that the acquisition length of each signal was 450 ms, and the sampling frequency was 150 MSample/s for an instantaneous bandwidth of 110 MHz. All spectrograms were obtained using a short-time Fourier Transform (STFT) with 2048 frequency bins on zero mean (without DC component) segments of signals from the VTI_DroneSET dataset. It is important to note that each recording from the dataset was segmented into 100,000 samples, identical to the time of acquisition of 0.67 ms.

The VTI_DroneUSRP is a new dataset of frequency signals from drones and flight (operational) control recorded outdoors with the NI-USRP-2954 receiver [14]. The recording was made with 200 MHz bandwidth within the 433MHz, 880MHz, 2.4GHz, and 5.8GHz ISM frequency bands. For the EUT, seven different drones (DJI Phantom IV, DJI Mavic 3T, DJI Mavic 2 Enterprise, DJI Mini 3, DJI Matrice 30T, DJI Matrice 300, and DJI Matrice 350RTK) were used. Drones operated independently (one drone per experiment) and simultaneously (up to four per experiment). The receiver has an FPGA module that processes the received signal with morphological operations to binarize the output and represent it in a spectrogram form with dimensions 2048x1000 pixels. The fast Fourier transformation length N=2048 bins and the frame size F=1000 are the output spectrograms' dimensions. This implies that the acquisition time is 10.24 ms for each spectrogram from the FPGA module. However, due to the necessary time for the signal processing, the FPGA module produces only four spectrograms per second. Figure 3 shows the spectrogram of one example from the VTI_DroneUSRP dataset.

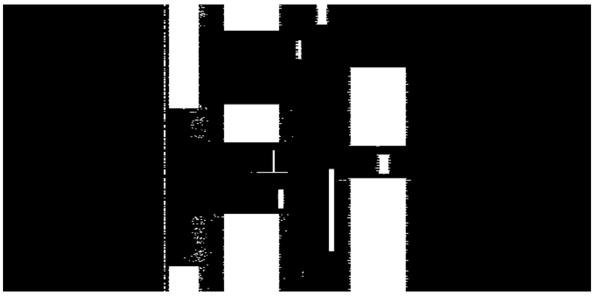

Figure 3. The spectrogram of three drones operating simultaneously (source: VTI_DroneUSRP dataset).

Figure 3 shows one example of a spectrogram of three drones operating simultaneously. All spectrograms were obtained using a short-time Fourier Transform (STFT) with 2048 frequency bins on zero mean (without DC component) segments of signals from the FPGA module. It is important to note that Figure 2 represents the whole recording from the VTI_DroneSET dataset (450 ms), while Figure 3 is a spectrogram of 1000 frames (10.24 ms). The spectrogram in Figure 3 is rotated 90 degrees for better user experience, waterfall effect, and visibility. Table 1 presents the summarized key dataset aspects for a better overall presentation.

Table 1. The dataset statistics.

Dataset name	VTI_DroneSET	VTI_DroneUSRP
Number of recordings	50	> 10,000
Length of recordings	450 ms	10.24 ms
Number of drones	3	7
Multiple drones	Yes (2 and 3)	Yes (2,3, and 4)
ISM bands	2.4/5.8	2.4/5.8
Environment	Laboratory	Outdoor
Type of data	Raw I/Q data	Spectrograms

3.2. Energy detection on spectrograms (EDS)

Energy detection strategies are primarily used for spectrum sensing. These strategies involve establishing a threshold based on the noise floor to differentiate and detect signals. Energy detection approaches are popular for spectrum sensing (detection of primary and secondary users of the radio frequency bands) because of their low computational complexity [15].

The proposed simple EDS method operates very simply. Its input data is an image generated by transforming the detected signal, a spectrogram from the receiver, into an array of numbers. Given numerical arrays are normalized to values within the range [0,1]. This step scales the image's pixel values to ensure consistency and comparability. After that, a binary array is created from the normalized array. The binary array is then summed up to calculate the signal's energy value. This sum represents the total number of pixels originally at maximum intensity in the image. The resulting sum provides the energy value of the detected signal, which can be used for further analysis or decision-making. The proposed EDS method was applied to the VTI_DroneSET and the VTI_DroneUSRP datasets to enhance the detection and identification. Another reason was to evaluate the resources (RAM, energy, and time) needed for the two-stage classification procedure. The maximum and minimum energy values of the signal of interest (drone signals) were obtained by applying the EDS method to the datasets. The main issue is correctly setting the threshold to separate signals of interest. The threshold is set empirically through measurements on both datasets for all samples of radio signals.

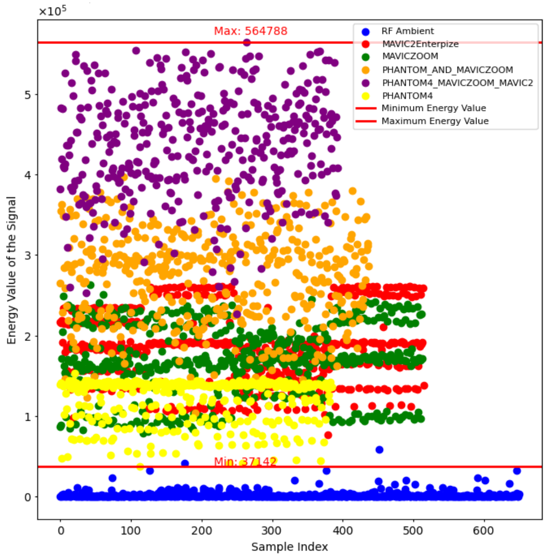

Figure 4. An example of a statistical analysis of the energy of the signals from VTI_DroneSET.

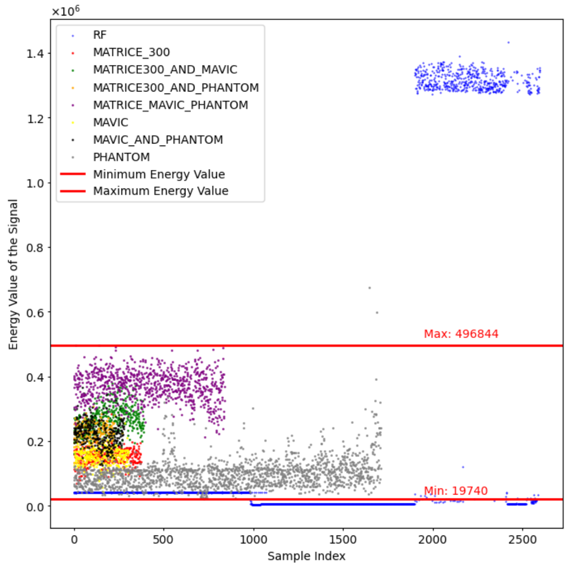

Figure 5. An example of a statistical analysis of the energy of the signals from VTI_DroneUSRP.

Figures 4 and 5 show the results of applying the EDS method to the VTI_DroneUSRP and the VTI_DroneUSRP.

Figure 4 shows the results from the EDS method of the signals for seven distinct types of drones individually. The visualization of energy detection of spectrograms shown in Figure 4 provided a clear view that applying the EDS method makes it possible to separate the ambient noise from the signal of interest. In Figure 4, it can be seen that the energy value of the signal of interest ranges between 37,142 and 564,788. In Figure 5, it can be seen that the energy value of the signal of interest is between 19740 and 496,844. The EDS method was applied by setting the obtained threshold values. The EDS method first engages the signal spectrogram to determine its energy value. If the energy value falls within the predefined range of the signal of interest, the signal is sent to the model; otherwise, it is discarded.

It is essential to note that the proposed EDS method can effectively distinguish radio-frequency ambient (Bluetooth or Wi-Fi signals in the observed frequency ranges marked with blue color in Figures 4 and 5).

3.3. Deep learning models

The final stage involves engaging the two DL models to estimate the best practical implementation. However, both models consist of three convolutional blocks, fully connected layers, and a final softmax layer. The first three layers represent convolutional blocks with ReLU activation, batch normalization, and max pooling. These convolutional layers gradually increase the number of feature maps, starting with sixteen, thirty-two, and finally sixty-four output channels. After the final convolutional layer, the resulting feature maps are flattened and passed through three fully connected layers with ReLU activation and dropout regularization to reduce the likelihood of overfitting. The model concludes with a softmax layer providing either six or eight outputs, depending on the number of classes the network is designed to classify, which is adapted to the specific cases of training data and the model's task.

The first DL model is the VTI_CNN_DI model trained for drone identification. This model is designed in one version with six output classes. The second model is the VTI_CNN_MDD model, which is trained to determine the number of drones and their identification. This model is designed in two versions, with six and eight output classes. The reason is that, within the VTI_DroneSET dataset, there are at most six classes, so we must adopt this model to fit the presented problem. Both models were trained on both datasets for ten epochs using a batch size of thirty-two and the Adam optimizer. After the training, the DL models were used for inference to conduct experiments in real scenario applications.

4. RESULTS

The objective of evaluating the impact of the EDS method and DL models is to minimize the time required to analyze incoming signals from the receiver and maximize the classification accuracy (identification of the type of drone) from the spectrogram. Additionally, the goal is to evaluate the usage of the proposed methodology on platforms where resources are limited. This adaptation was examined by measuring the energy consumption and average emission of CO2-equivalent (expressed in kg emitted per kWh of electricity), which is a limiting factor in real-world applications.

The evaluation was conducted for two scenarios - using the EDS method with a threshold specific to the given dataset and without the EDS method - to demonstrate the effectiveness of this approach. Each model, combined with or without the EDS method, was assessed on two datasets with ambient samples (samples of radio-frequency ambient containing noise and Wi-Fi and Bluetooth). It is important to note that this is intentionally done because most received radio signals in real applications are from ambient). The samples of other classes are equally distributed, creating an unbiased problem. Table 2 presents duration, consumed energy, and average emissions to realize comprehensive analyses of the general performances of engaged two-stage classification.

Tables 3 to 5 show accuracies for both models with different scenarios in the inference process, using 782 spectrograms (the VTI_DroneSET dataset) and 1140 spectrograms (the VTI_DroneUSRP dataset). These results are used for a comparative analysis of accuracies for different classes.

Table 2. The overall performance of two-stage classifications during the inference process.

Model	EDS	Dataset	Number of spectrograms for prediction	Number of spectrograms for input in DL model	Average / Total execution time [s]	Execution time improvement [%]	Emissions of CO2-eq [kg]	Consumed energy [kWh]
VTI_CNN_6MDD 6 classes	No	VTI_DroneSET	782	/	0.017 / 13.02	65.8	0.00000077	0.00032
	Yes			624	0.007 / 4.45		0.00000007	0.00003
VTI_CNN_8DI 8 classes	No	VTI_DroneUSRP	1140	/	0.013 / 15.33	59.7	0.00014	0.00022
	Yes			828	0.007 / 6.18		0.00003	0.00005
VTI_CNN_8MDD 8 classes	No			/	0.015 / 16.96	65.8	0.00017	0.00027
	Yes			855	0.007 / 5.79		0.00003	0.00005

Table 3. The accuracy [%] of two-stage classifications during inference for the eight classes from VTI_DroneUSRP.

Model	EDS	Dataset	Ambient	One drone			Two drones			Three drones	Total
				Matrice 300	Mavic 2Ent	Phantom 4	Matrice 300 Mavic 2Ent	Matrice 300 Phantom 4	Mavic 2Ent Phantom 4	Matrice 300 Mavic 2Ent Phantom 4	
VTI_CNN_8MDD 8 classes	No	VTI_DroneUSRP	100	80	95	100	95	100	85	100	99.21
	Yes		100	80	95	100	95	100	85	100	99.21

Table 4. The accuracy [%] of two-stage classifications during inference for the eight classes from VTI_DroneUSRP.

Model	EDS	Dataset	Ambient	One drone							Total
				Matrice 30T	Matrice 350 RTK	Mavic 3T	Mini 3pro	Phantom 4	Matrice 300	Mavic 2Ent	
VTI_CNN_8DI 8 classes	No	VTI_DroneUSRP	97	100	90	100	100	100	100	100	97.19
	Yes		97.5	100	90	100	100	100	100	100	97.63

Table 5. The accuracy [%] of two-stage classifications during inference for the eight classes from VTI_DroneUSRP.

Model	EDS	Dataset	Ambient	One drone			Two drones	Three drones	Total
				Mavic 2Ent	Mavic Zoom	Phantom 4	Matrice 300 Mavic 2Ent	Matrice 300 Mavic 2Ent Phantom 4	
VTI_CNN_6MDD 6 classes	No	VTI_DroneSET	99.7	100	100	100	100	100	99.74
	Yes		100	100	100	100	100	100	100

Applying both models with and without the EDS method demonstrates the effect of energy detection. As previously mentioned, a much larger number of spectrograms obtained from receivers lack significant information. The EDS method effectively filters out many such spectrograms, thereby reducing the load on the DL model. In this case, the time required to process all incoming signals is significantly reduced - from 15 seconds for all inference data to 6 seconds, representing a 60% acceleration, while 73% of the total input data, i.e., 83% of the radio-frequency ambience, was discarded. In addition to reducing the time crucial for real-time drone detection, this approach significantly reduces carbon dioxide emissions into the atmosphere. The energy consumption is also substantially reduced, making this system applicable in real-scenario applications with limited power sources. If the proposed two-stage classification is used continuously for 24 hours, energy consumption without the EDS method, where four signal spectrograms are generated per second, amounting to 0.0667 kWh, while with the EDS method, it is 0.0152 kWh, which represents a significant saving. It is essential to note that this component is part of a more complex system, and every energy saving is necessary.

It is also important to note that the VTI_CNN_MDD model with the VTI_DroneSET dataset has the best accuracy due to the quality of the drone signals when more drones are present in the image, making them more distinguishable by the EDS method. The VTI_DroneSET dataset contains laboratory samples of drone signals, so a higher efficiency of this approach is expected compared to real-scenario applications for the other cases.

After the EDS method stage, spectrograms enter the DL model, which predicts the drone type and number. The EDS method indicates that the drone signal is possibly present in the spectrogram, while the model predicts classes. The model efficiently recognizes distinct types of drones in the images and provides information about the presence, number, and type of drones captured by the receiver in both time and space. All models deliver near state-of-the-art results, with the model being slightly more sensitive to specific drone types due to the lack of high-quality training data, as evidenced by the laboratory example of the VTI_CNN_MDD model with the VTI_DroneSET dataset, where an accuracy of 100% was achieved in two-stage classification.

5. CONCLUSION

This study demonstrates the usefulness of the EDS method in aiding the DL models in improving their predictions. This approach minimizes resource consumption in terms of time and energy by reducing harmful gas emissions and enabling efficient drone detection based on recorded signals from the datasets. The proposed DL models were evaluated by applying two datasets (VTI_DroneSET and VTI_DroneUSRP) with and without the EDS method. The obtained results indicate a significant reduction in the execution time when the EDS method is engaged in the two-stage classification process - specifically, 65,8% for the VTI_CNN_MDD model and 59,7% for the VTI_CNN_DI model. By reducing the number of input spectrograms obtained from the USRP receiver for the proposed DL models, energy consumption and CO2-eq emissions have decreased. These execution times and energy savings suggest that applying the EDS method in a proposed two-stage classification effectively optimizes the performance of ADRO applications in real-time drone detection, where speed and accuracy of detection are of great importance. Further research should focus on expanding the VTI_DroneUSRP dataset by collecting new data and improving the scope of two-stage or multistage classification.

Acknowledgements

This work was by Serbian Ministry of Defense and Serbian Ministry of Education, Science and Technological Development, Grant No 451-03-66/2024-03/200325.

References

[1] J. Luo, G. Zhang, and C. Yan, “An Energy Detection-Based Spectrum-Sensing Method for Cognitive Radio,” *Wirel Commun Mob Comput*, vol. 2022, no. 1, p. 3933336, Jan. 2022, doi: 10.1155/2022/3933336.

[2] A. Nasrallah, A. Hamza, G. Baudoin, B. Toufik, and A. M. Zoubir, “Simple improved mean Energy Detection in spectrum sensing for cognitive radio,” in *2017 5th International Conference on Electrical Engineering - Boumerdes, ICEE-B 2017*, Institute of Electrical and Electronics Engineers Inc., Dec. 2017, pp. 1–4. doi: 10.1109/ICEE-B.2017.8192177.

[3] H. Ju, E. Cho, and S. H. Kim, “Energy-Detection based False Alarm Reduction in Polar-Coded Uplink Control Channel Transmission in 5G-NR,” in *IEEE Vehicular Technology Conference*, Institute of Electrical and Electronics Engineers Inc., Apr. 2021. doi: 10.1109/VTC2021-Spring51267.2021.9448973.

[4] M. Ezuma, F. Erden, C. K. Anjinappa, O. Ozdemir, and I. Guvenc, "Detection and classification of UAVs using RF Fingerprints in the Presence of Wi-Fi and bluetooth interference," *IEEE Open Journal of the Communications Society*, vol. 1, pp. 60–76, 2020, doi: 10.1109/OJCOMS.2019.2955889.

[5] L. Ophir, Y. Bitran, and I. Sherman, "WI-FI (IEEE802.11) and bluetooth coexistence: Issues and solutions," in *IEEE International Symposium on Personal, Indoor and Mobile Radio Communications, PIMRC*, 2004, pp. 847–852. doi: 10.1109/pimrc.2004.1373819.

[6] B. Sazdić-Jotić, I. Pokrajac, J. Bajčetić, and N. Stefanović, "Review of RF-based drone classification: Techniques, datasets, and challenges," *Vojnotehnicki glasnik*, vol. 72, no. 2, pp. 764–789, Apr. 2024, doi: 10.5937/vojtehg72-49286.

[7] B. M. Sazdić-Jotić *et al.*, "VTI_DroneSET," Mendeley Data. Accessed: Nov. 01, 2020. [Online]. Available: https://data.mendeley.com/datasets/s6tgnnp5n2/1

[8] T. Šević, V. Joksimović, I. Pokrajac, B. Radiana, B. Sazdić-Jotić, and D. Obradović, "Interception and detection of drones using RF-based dataset of drones," *Scientific Technical Review*, vol. 70, no. 2, pp. 29–34, 2020, doi: 10.5937/str2002029S.

[9] M. Mokhtari, J. Bajčetić, B. Sazdić-Jotić, and B. Pavlović, "RF-based drone detection and classification system using convolutional neural network," in *29th Telecommunications Forum (TELFOR)*, IEEE, 2021, pp. 1–4. doi: 10.1109/TELFOR52709.2021.9653332.

[10] B. Sazdić-Jotić, I. Pokrajac, J. Bajčetić, B. Bondžulić, and D. Obradović, "Single and multiple drones detection and identification using RF based deep learning algorithm," *Expert Syst Appl*, vol. 187, Jan. 2022, doi: 10.1016/j.eswa.2021.115928.

[11] Y. Xue *et al.*, "UAV signal recognition of heterogeneous integrated KNN based on genetic algorithm," *Telecommun Syst*, vol. 85, no. 4, pp. 591–599, Apr. 2024, doi: 10.1007/s11235-023-01099-x.

[12] S. Dafrallah and M. Akhloufi, "Malicious UAV detection using various modalities," Jan. 01, 2024, *Canadian Science Publishing*. doi: 10.1139/dsa-2023-0049.

[13] A. Famili, A. Stavrou, H. Wang, J. M. Park, and R. Gerdes, "Securing Your Airspace: Detection of Drones Trespassing Protected Areas," Apr. 01, 2024, *Multidisciplinary Digital Publishing Institute (MDPI)*. doi: 10.3390/s24072028.

[14] . Ettus Research, "USRP Software Defined Radio (SDR)," Ettus Research. Accessed: Sep. 05, 2024. [Online]. Available: https://www.ettus.com/

[15] . N. Ibadik, A. F. Ashari, D. D. Ariananda, and W. Dewanto, "Frequency Domain Energy Detection for Multiband Spectrum Sensing in Cognitive Radio System," in *ICITEE 2022 - Proceedings of the 14th International Conference on Information Technology and Electrical Engineering*, Institute of Electrical and Electronics Engineers Inc., 2022, pp. 7–12. doi: 10.1109/ICITEE56407.2022.9954120.