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ENHANCING UAV CLASSIFICATION WITH RADIO FREQUENCY SIGNALS USING A HYBRID CONVOLUTIONAL-LSTM ARCHITECTURE

This research aims to automate the classification of small UAVs using radio frequency signals. ***The object of this research*** *is to classify UAVs by radio frequency signature using combined machine learning models. It focuses on a combination of machine learning-based models to achieve better classification results when efficient learning and high accuracy are difficult to achieve due to temporal dependency in complex signals.* ***This study aims*** *to enhance UAV classification models by optimizing a convolutional neural network architecture with the addition of recurrent layers.* ***Methods*** *described in this research propose a hybrid Convolutional Neural Network-Long Short-Term Memory (CNN-LSTM) model that combines convolutional and recurrent layers to extract spatially and temporally dependent features from UAV RF signals. Compared to traditional CNNs, the Convolutional Long-Short-Term Deep Neural Network (CLDNN) model reduces false positives across classes and improves classification performance (recall) for closely related or noisy signal classes. However, the complexity and computational costs of the CLDNN model are acknowledged, underscoring challenges for systems with limited processing power.* ***The tasks*** *of this research are as follows: 1) to review the current state-of-the-art approaches in the classification of small UAVs; 2) to outline the problem statement; 3) to create a test dataset for the proposed drone models; 4) to adapt CLDNN model for drone classification tasks; 5) to provide a comparison between CNN baseline and the proposed model.* ***Conclusions.*** *The experimental results show that the proposed CNN–LSTM model significantly improves classification accuracy compared with the baseline CNN architecture, especially for classes prone to misclassification. The integration of convolutional layers, which are effective at extracting local features, and recurrent LSTM layers, which are effective at modeling sequential dependencies, enables the combined architecture to reduce false positives. Accordingly, this hybrid structure is fairly effective for signal classification problems because it captures spatially localized features and temporal contextual information within the input. This study confirms that the CNN-LSTM model is efficient at classifying UAV radio-frequency signals and has great potential for practical applications. Possible future research directions include optimizing the model's computational efficiency by handling greater interference and noisier data.*

Keywords: *classification; convolutional neural network; unmanned aerial vehicles; radio-frequency analysis, drones; neural networks; machine learning.*

1. Introduction

1.1. Motivation

With production scaling up and the cost of UAVs for personal use decreasing, drones that were previously accessible only to professionals are now available to almost everyone. With advancements in camera integration and improved communication stability, drones can now reach many previously hidden objects. Information that could only be seen in low-resolution satellite images can now be viewed in real time. This creates new security challenges for counteracting small unmanned aerial vehicles that can be operated even by amateur users.

The task is complex, requiring the determination of the drone's location, classification, tracking, and destruction if necessary. One of the most common methods of controlling drones is via radio channels, with many manufacturers on the market and extensive experience in usage, adjustment, or customization, such as First Person View (FPV) drones. Therefore, this type of drone may be used more frequently than others due to its accessibility. In radio control, each drone has a unique RF signature during operation with a control station. This allows classification of drones using machine learning to automate human efforts, especially when operators face swarms of drones [1, 2], which significantly complicates threat identification.

In this work, a method for improving the classification of drones using a hybrid model capable of classifying drones even when operating on the same frequency is presented.

This approach, which allows distinguishing a specific type of drone among numerous similar devices, is especially relevant in a congested radio frequency environment where manual threat identification is no longer effective. The method is also helpful for relatively calm areas, where it is necessary to detect serial commercial drones that are accessible to anyone on time. Regularly updating datasets with new device samples maintains high algorithm accuracy and enables the system to adapt quickly to new models.

1.2. State-of-the-art

Given the security challenges posed by drones, research on effective detection, classification, and countermeasures is ongoing. Currently, modern systems face challenges such as determining whether a drone is friendly or hostile, whether it poses a security threat, identifying its unique characteristics, and distinguishing, monitoring, and tracking it. Several available methods can be used for both detection and classification tasks. Methods such as optical, acoustic, radar, and radio frequency provide engineers with options to choose a specific method or combine different ones for a more accurate airspace assessment. The issue addressed in this work is improving classification results based on one of the sources of data, as a component of countermeasures against drones for more detailed drone identification.

Optical classification methods can work within a limited field of view. The simplicity of this approach is that it relies on regular cameras, and the video processing is performed by CNN models, as listed in [3, 4]. It is a good choice for recognizing single and multiple objects in multiple-object tracking. In [5], an approach for target detection and tracking without prior knowledge of their locations was based on YOLOv6. One of the main challenges in drone detection is the lack of a publicly available dataset that could serve as a starting point for research. The existence of such datasets [6] simplifies researchers' work and provides more opportunities to explore new methods, thereby reducing the time required for data collection.

An example of non-LOS operations is acoustic methods for classifying noise sources, particularly drones. Such acoustic hardware for data collection is very cheap, making this a very effective and cost-efficient detection method. Studies on acoustic approaches have shown the efficacy of this method, for example, in [7, 8].

Radar-based approaches are typically more difficult but offer advantages such as longer detection ranges and more accurate trajectory and speed measurements. The application of micro-Doppler methods has shown efficient results as in [9], where the F1-score reached 95% and [10], which provided scores ranging from 85% to 95% depending on the experimental conditions.

The radio-frequency spectrum is used for the detection, identification, or classification of drones, offering benefits such as high accuracy even when drones operate on the same frequency. Furthermore, the long detection range and all-weather functionality enable the identification of both control mechanisms and video transmitters. The data from [11] and [12] contributed to experiments using many machine-learning methods available to researchers. The DroneRF dataset served as an excellent example in [13]. Further studies in [14] examined XGBoost because of its merit over conventional CNNs in the time-series data resolution. In addition, the utilization of LSTM described above in [15] proved how effective such models could be in terms of applications. Based on prior investigations, the decision was made to study the various alternatives found with CLDNN blended systems as one of the things that take advantage of the fact that these systems are CNN-like and the advantages of LSTM. These will automate drone classification instead of taking the long time required to train with the latter models. Recent studies have further demonstrated the effectiveness of hybrid models for RF-based drone classification. Sazdic-Jotic et al. [16] proposed FLEDNet, which combines fuzzy edge detection of RF spectrograms with CNN and convolutional recurrent networks. The authors reported accuracy improvements of 4.87%, 13.41%, and 7.26% for drone detection, drone-type identification, and multiple-drone detection, respectively. Rahman et al. [17] introduced a cascaded CNN-BiLSTM model using STFT/PSD spectrograms and evaluated it in the presence of WiFi and Bluetooth interference, reporting accuracies of 99.75%, 98.40%, and 99.57% for four, ten, and ten UAV classes, respectively. Huang et al. [18] proposed MD-Net, a lightweight MLP-LSTM dual-branch architecture with Adaptive Time-Frequency Masking, achieving an average accuracy of 85.58% on DroneRF, which is 5.27 percentage points above its baseline. Although these results were obtained using different datasets and experimental protocols, they demonstrate the value of time-frequency preprocessing, edge-based feature enhancement, recurrent temporal modeling, and feature fusion. These findings motivate the investigation of a spectrogram-based CLDNN architecture for RF drone classification in this study.

1.3. Objective and Approach

The overall objective of this paper is to upgrade the classification accuracy of the CNN-based methods of existing models by proposing the inclusion of the layers of the LSTM network into a CNN to exploit the time dependency of the drone signal. By integrating the relative strengths of CNNs and LSTMs, we aim to achieve a more robust and informative feature representation. The architecture leverages CNNs as an effective mechanism for capturing spatial or spectral features from the input data, thanks to convolutional filtering, while LSTM is good at temporal relation modeling by internally memorizing sequential input events. Considering the discussion above, this paper is structured around several sections. The proposed architecture enhancement to the standard CNN is first described in the "Materials and Methods of Research" section, beginning with an emphasis on the need to implement LSTM layers and an explanation of the overarching framework in detail. This includes appropriate hyperparameter descriptions, various network settings, and a strategy for input data preprocessing. Second, a systematic comparison is made between the proposed hybrid CNN-LSTM model and a simple baseline CNN in the "Experiments" section. Based on performance metrics such as accuracy, precision, recall, and F1-score, this comparison also

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explores computational complexity and training convergence behavior. The effectiveness and practical considerations of using the combined CNN-LSTM for classifying drone signals are proven from this comparative evaluation. Finally, in the sections "Discussion" and "Conclusions," the applied approach is briefly described, the experimental results are obtained, and further research steps and development directions are discussed.

2. Materials and research methods

The proposed approach uses a convolutional long short-term memory deep neural network (CLDNN) architecture [19] capable of performing multiclass classification. The proposed architecture combines convolutional processing, bidirectional recurrent learning, and temporal attention. The convolutional layers identify local patterns in the time-frequency representation, whereas the recurrent layer models dependencies between successive time frames [20]. The convolutional layers extract salient local patterns through their unique filtering mechanisms, while the recurrent LSTM layers preserve and exploit sequential information across successive time steps. This synergy provides not only enhanced classification accuracy but also extends the domains to which this approach applies, particularly those characterized by dynamic, time-dependent data. Hence, a more advanced hybrid CLDNN architecture with log-power spectral density spectrogram is calculated using the short-time Fourier transform, as shown in Fig. 1.

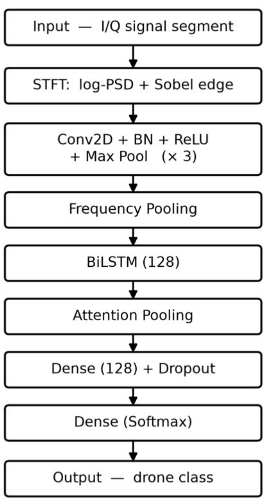

Fig.1. The Enhanced CLDNN architecture

The proposed Spec-CLDNN classifies the recorded drone signal using a short sequence of steps that follow the architecture shown in Fig. 1. First, the input is a segment of the baseband I/Q signal recorded on the drone–controller communication link. Second, using the short-time Fourier transform, this segment is transformed into a log-power spectral density (log-PSD) spectrogram, and a complementary Sobel-edge channel is added to emphasize the spectral contours, giving a two-channel time-frequency image. Third, a convolutional block of three consecutive two-dimensional stages with 32, 64, and 128 filters extracts local time-frequency patterns; each stage applies a 3 x 3 Conv2D layer, batch normalization, ReLU activation, and 2 x 2 max pooling. Fourth, adaptive average pooling is applied along the frequency axis, preserving the temporal dimension and producing a time-ordered sequence of feature vectors. Fifth, this sequence is processed by one bidirectional LSTM layer with 128 hidden units in each direction, so that every time frame is modeled from both its past and future contexts. Formula (1) gives the gate update for each t-th time step:

$$f_t = \sigma(W_f x_t^{pool} + U_f h_{t-1} + b_f), \tag{1}$$

where W_f is a weight matrix applied to current input x^{pool} used in the calculation of the forget gate;

U_f is the additional weight matrix used in the forget gate calculation for the previous hidden state $h_{t-1;}$

b_f is bias vector related to the forget gate;

h_t is the hidden state, which provides the output at time t;

X^{pool} is pooled input feature vector after applying a pooling layer.

Sixth, a temporal attention layer assigns greater weight to the most informative time frames and collapses the sequence into a single fixed-length vector. This vector is then passed to a fully connected (Dense) layer with 128 neurons and a ReLU activation, followed by a dropout layer with a coefficient of 0.5 to prevent overfitting. Finally, a softmax activation is applied to an output dense layer whose number of neurons equals the number of classes, which converts the outputs into a class-probability distribution. The model is compiled with the Adam optimizer at a low learning rate for stable convergence and is trained with the categorical cross-entropy loss, a proper measure for multiclass classification, given in formula (2); the accuracy metric is used to monitor the overall performance.

$$L = -\sum_{k=1}^{K} y_k \log\left(\frac{e^{s_k}}{\sum_{j=1}^{K} e^{s_k}}\right), \tag{2}$$

where y is the true label of a sample or segment of k class.

The performance of the model during training and validation is evaluated using the accuracy metric. The softmax function outputs the probabilities for each class, enabling multiclass classification, as described in formula (3):

$$f(s)_k = \frac{e^{s_k}}{\sum_{j=1}^{K} e^{s_k}}, \quad (3)$$

where K is total number of classes in the classification problem;

s_k is the output logit of the model for class k.

The dataset [21] contains baseband I/Q signal recordings for radio control and video signals of 10 consumer and prosumer drones. Figure 2 shows a visualization of the I/Q sample. The recordings are presented in an interleaved format (I1 Q1 I2 Q2 I3 Q3 ...) with 16-bit signed integers in little-endian format. Each recording contains 100 million samples, corresponding to a 0.5-second period.

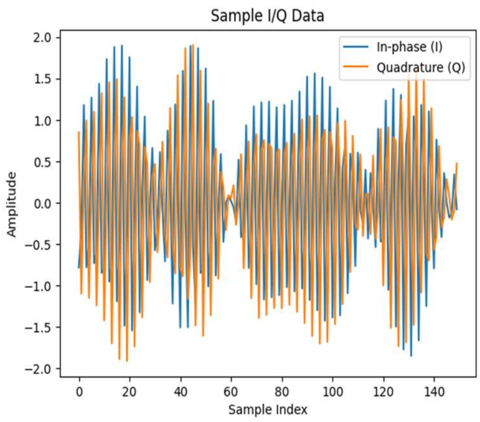

Fig. 2. Sample of RF drone's signal

The input data consist of raw I/Q samples representing as formula (4):

$$x_n = I_n + jQ_n, \quad (4)$$

where x_n is the n-th complex-valued sample;

I_n is the in-phase (real) component of the n-th sample;

Q_n is the quadrature (imaginary) component of the n-th sample.

Each sample is extracted from the RF signal's spectrum band through the communication link between the drone and the flight controller. Let $y \in D$, where D is the number of drones detected in some area. For training, we will need a prepared dataset represented as formula (5):

$$Z = \{(x_1, y_1), (x_2, y_2) \ldots (x_D, y_D)\}. \quad (5)$$

The selection used for this case included some particular drone models that are most popular in the market and are easily accessible online by an average buyer. Due to the obsolescence of some drones, we decided to remove them from the sample and focus on a smaller number. This allowed training on mid-range machines with up to 32 GB of memory capacity, which also positively impacts the reproducibility of the experiment. The key objective of this experimental study is to check the performance of drone classification with CNN and LSTM combined systems. The data include signal recordings of small drones that one person can deploy and ready for use. These drones weigh only 734–4,690 g, have a 335–643 mm diagonal wheelbase, and share similar characteristics for radio-control and video signals in the 2.4 GHz or 5.8 GHz frequency bands.

To train and validate our model correctly, the dataset was normalized using the following formula (6):

$$X_{norm} = \frac{X - \mu(X)}{\sigma(X)}, \quad (6)$$

where $\mu(X)$ is a mean value and $\sigma(X)$ is the standard deviation of the attribute X.

This approach, called Z-score normalization, converts all the values of an attribute from 0 to the attribute's standard deviation.

An important part of data preprocessing is segmentation, which involves dividing RF signals into small fixed-length chunks. This process helps obtain fixed-dimension inputs. Subsequently, the dataset was partitioned into training, validation, and test subsets, with proportions of 60%, 20%, and 20%, respectively.

Using measures that handle edge cases to evaluate the efficacy of the suggested CLDNN-based model for drone classification is essential. Precision assesses the accuracy of the positive predictions in formula (7). A false positive occurs when the algorithm incorrectly classifies an innocuous hobby drone as high-risk. This type of mistake could result in ineffective resource allocation and unnecessary countermeasure activation. Hence, accuracy is vital for the system's alert dependability.

$$\text{precision} = \frac{TP}{TP + FP}, \quad (7)$$

where TP is the number of incorrectly detected class k as positive, which is non-class k.

The second metric, expressed in formula (8) and referred to as recall, evaluates the proficiency of the model in recognizing all relevant instances of a class. A false negative occurs when the system fails to detect a specific drone category that is indeed present. In a security context, this error is often more critical because it implies that a potential threat could be overlooked or handled inappropriately.

$$\text{recall} = \frac{TP}{TP + FN}, \quad (8)$$

where FN is the number of wrongly detected class k, which is class k.

The F1-score, represented in formula (9), is an evaluation metric that combines two competing metrics, namely, the precision and recall scores of a model. An innate trade-off exists between minimizing false positives and false negatives in drone classification. A model that is too lenient might exhibit excellent recall but poor precision. In contrast, an overly careful model may achieve high precision at the cost of low recall.

$$F_1 = \frac{2TP}{2TP + FP + FN}. \quad (9)$$

3. Experiments

In this study, the proposed spectrogram-based CLDNN (Spec-CLDNN) is evaluated against the original CNN baseline and three reference models from the recent literature: CNN-BiLSTM, MD-Net, and FLEDNet-CRNN. All models were trained and evaluated using an identical approach: a contiguous 60/20/20 split by time position within each recording, per-segment normalization, and a clean (noise-free) test set. The performance is reported using standard classification metrics (precision, recall, F1-score, accuracy, and area under the ROC curve (AUC)), along with confusion matrices.

Training and evaluation were conducted on the Google Colab platform using an NVIDIA A100 GPU. Data preprocessing followed the pipeline described in the Materials and methods section, converting each I/Q segment into a log-power spectrogram with a complementary Sobel-edge channel. The original raw-I/Q CLDNN baseline achieved an accuracy of 86.5%, a macro-averaged F1-score of 0.866, and a mean AUC of 0.984 on the clean test set (Table 1).

The baseline errors concentrate on the drones that share the same frequency band, in particular DJI_matrice_210_5G (F1 0.85) and DJI_matrice_100 (F1 0.86), which are the classes most often confused with one another; the remaining classes are recognized more reliably.

Table 1

Summary of the compared models

Model	Precision	Recall	F1-score
CNN	0.87	0.87	0.87
CNN-BiLSTM	0.90	0.89	0.89
MD-Net	0.89	0.89	0.89
FLEDNet-CRNN	0.46	0.53	0.47
Spec-CLDNN	0.91	0.91	0.91

The proposed Spec-CLDNN, which operates on the spectrogram representation and adds a bidirectional LSTM with attention-based temporal pooling, clearly outperformed the baseline, reaching an accuracy of 90.9%, a macro-averaged F1-score of 0.909, and a mean area under the curve (AUC) of 0.995.

Across all evaluated models on clean data, the proposed Spec-CLDNN ranked first (accuracy, 90.9%; macro-F1, 0.909), ahead of the reference CNN-BiLSTM (89.9%), MD-Net (89.8%) models, the CNN baseline (86.5%), and FLEDNet-CRNN (52.7%), the last of which lacks the capacity to separate the classes. The Spec-CLDNN achieves this while remaining the most compact of the learned models (391 K parameters, compared with 2.42 M for CNN-BiLSTM and 2.13 M for the raw-I/Q baseline). It also achieves the most balanced per-class performance: even the two same-band 5.8 GHz drones - DJI_inspire_2_5G and DJI_matrice_210_5G - are separated with F1-scores of 0.91 and 0.90, well above the 0.74-0.78 obtained by MD-Net and CNN-BiLSTM for the same pair.

Combining convolutional feature extraction with a recurrent layer and attention pooling over the spectrogram enables the model to exploit both the spectral structure and the temporal dependencies of the signal, yielding higher and more uniform classification accuracy. The improvement is most pronounced for classes with overlapping spectral characteristics, precisely where the baseline and reference models struggle. For classification problems that require subtle time-dependent signal or object analysis and similar feature profiles.

4. Discussion

The results of this study show that a spectrogram-based CLDNN combining convolutional layers, a bidirectional LSTM, and attention pooling can classify closely related drone RF signals more accurately than both the original raw-I/Q CLDNN and competing architectures from the literature. The largest gains appear for classes that share the same frequency band and are therefore the hardest to distinguish, where the number of cross-class errors is reduced by the attention-weighted temporal representation.

More importantly, because the classification of complex signals involved temporal dependencies is challenging in practice, especially when it comes to efficient learning models with high accuracy and minimal processing time, the results of this training are shown in Fig. 3:

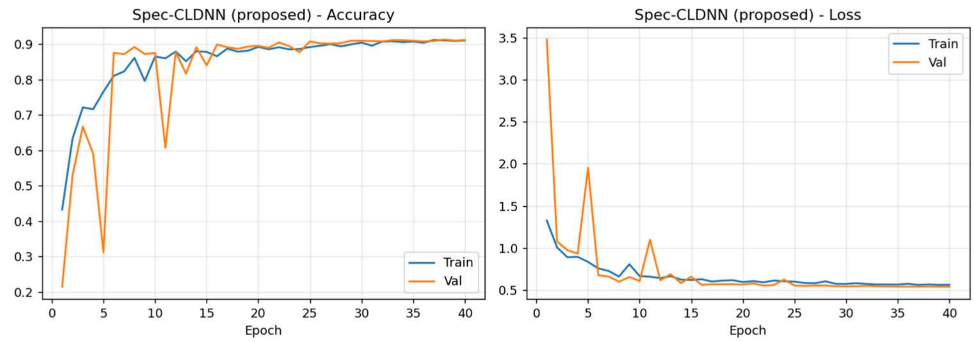

Fig. 3. Training and validation accuracy (left) and loss (right) of the proposed Spec-CLDNN across the training epochs.

In summary, moving from raw I/Q to a spectrogram representation and adding an attention-weighted recurrent stage proved to be effective: the Spec-CLDNN increased accuracy across the board, especially for the classes most easily confused with one another, while keeping the number of false predictions low. Nevertheless, some caveats of this approach should be mentioned.

From an architectural point of view, the spectrogram front-end keeps the model compact: the proposed Spec-CLDNN has only about 0.39 million parameters, which is roughly one-sixth of the reference CNN-BiLSTM (2.42 M), so the added recurrent and attention stages do not translate into a heavy computational or memory burden. Instead, the main practical cost lies in the input pipeline: forming the log-power spectrogram and the Sobel-edge channel adds a short-time Fourier transform and a per-segment normalization step ahead of the network, which must be considered in real-time deployment.

5. Conclusions

This study proposed a spectrogram-based CLDNN for classifying radio-frequency signals emitted between drones and their controllers. The scientific novelty lies in coupling a convolutional feature extractor over a log-power spectrogram (with a complementary edge channel) with a bidirectional LSTM and an attention-based temporal pooling stage to exploit both the spectral and the temporal structure of the signal. The proposed model achieved 90.9% accuracy and a 0.909 macro-averaged F1-score, outperforming the original CNN and the reference models while being markedly more compact. This approach is particularly effective at distinguishing closely related classes that occupy the same frequency band, a common weakness of classical CNN-based methods.

The practical significance of the results is twofold. First, the compactness and accuracy of the Spec-CLDNN make it well suited to the automated detection and identification of drone RF signals in security and surveillance systems, where reliable and timely recognition is required. Second, the study provides empirical evidence that the proposed spectrogram-based approach outperforms both the original CNN and competitive reference architectures on the same data, supporting its adoption in RF-based drone-recognition systems. By separating even same-band drone models more reliably, the method reduces false alarms and misclassifications, thereby strengthening its utility in real-world deployment.

Future work can extend the evaluation to noisy and low-SNR conditions to further characterize robustness and quantify statistical significance through multiple-seed training. Additional directions include richer time-frequency front-ends, transformer-based temporal modeling, the broadening of the signal set to other communication or radar sources, and the optimization of the pipeline for real-time operation. These steps would help establish the proposed Spec-CLDNN as a robust and flexible framework for RF signal classification beyond drone identification.

Another possible extension to this work would be to implement Sensor Fusion, a concept in which decisions or confidence levels regarding the presence of a drone from multiple individual sensors [22] (for example, radio-frequency communication and acoustic microphones) are combined in the last stages of signal processing; then these consolidated assessments are combined into the final decision. Because such diversity among sensors can also lead to increased overall precision in the reliability of the whole detection system, the late fusion will be crucial.

Contributions of authors: conceptualization, methodology – **Oleksii Shevchenko**, **Oleksandr Bezsonov**, **Oleg Rudenko**, formulation of tasks, analysis – **Oleksandr Bezsonov**, **Oleg Rudenko**; development of model, software, verification – **Oleksii Shevchenko**; analysis of results, visualization – **Oleksii Shevchenko**,

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Oleksandr Bezsonov; writing – original draft preparation, writing – review and editing – **Oleksii Shevchenko**, **Oleksandr Bezsonov**, **Oleg Rudenko**.

All authors have read and approved the final manuscript for publication.

Conflict of Interest

The authors declare that they have no conflict of interest in relation to this research, whether financial, personal, authorship or otherwise, that could affect the research and its results presented in this paper.

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Data Availability

Data will be made available upon reasonable request.

Use of Artificial Intelligence

The authors confirm that they did not use artificial intelligence or AI-assisted technologies in the preparation, writing, or editing of this manuscript.

References

1. Prymirenko, V., Demianiuk, A., Shevtsov, R., Bazilo, S., Pilipenko, A., & Vovchanskyi, M. Formation of a heterogeneous group of UAVS with a reasonable number of false and real drones. *Radioelectronic and Computer Systems*, 2024, vol. 3, pp. 80–95. DOI: 10.32620/reks.2024.3.06.

2. Fedorovich, O., et al. Modeling waves of a strike drones swarm for a massive attack on enemy targets. *Radioelectronic and Computer Systems*, 2024, vol. 2, pp. 203–212. DOI: 10.32620/reks.2024.2.16.

3. Selvi, S. S., Pavithraa, S., Dharini, R., & Chaitra, E. A Deep Learning Approach to Classify Drones and Birds. *Proceedings of the 2022 IEEE 2nd Mysore Sub Section International Conference*, 2022, pp. 1–5. DOI: 10.1109/MysuruCon55714.2022.9972589.

4. Brown, J., Gharineiat, Z., & Raj, N. CNN Based Image Classification of Malicious UAVs. *Applied Sciences*, 2023, vol. 13, article no. 240. DOI: 10.3390/app13010240.

5. Zhao, J., Zhang, J., Li, D., & Wang, D. Vision-Based Anti-UAV Detection and Tracking. *IEEE Transactions on Intelligent Transportation Systems*, 2022, vol. 23, pp. 25323–25334. DOI: 10.1109/TITS.2022.3177627.

6. Coluccia, A., et al. Drone-vs-Bird Detection Challenge at IEEE AVSS2021. *2021 17th IEEE International Conference on Advanced Video and Signal Based Surveillance (AVSS)*, 2021, pp. 1–8. DOI: 10.1109/AVSS52988.2021.9663844.

7. Anwar, M. Z., & Jamalipour, A. Machine Learning Inspired Sound-Based Amateur Drone Detection For Public Safety Applications. *IEEE Transactions on Vehicular Technology*, 2019, vol. 68, no. 3, pp. 2526–2534. DOI: 10.1109/TVT.2019.2893615.

8. Ohlenbusch, M., Ahrens, A., Rollwage, C., & Bitzer, J. Robust Drone Detection for Acoustic Monitoring Applications. *Proceedings of the 2020 28th European Signal Processing Conference (EUSIPCO)*, 2021, pp. 6–10. DOI: 10.23919/Eusipco47968.2020.9287433.

9. Liu, J., et al. Classification of bird and drone targets based on motion characteristics and random forest model using surveillance radar data. *IEEE Access*, 2021, vol. 9, pp. 160135–160144. DOI: 10.1109/ACCESS.2021.3130231.

10. Narayanan, R. M., Tsang, B., & Bharadwaj, R. Classification and Discrimination of Birds and Small Drones Using Radar Micro-Doppler Spectrogram Images. *Signals*, 2023, vol. 4, no. 2, pp. 337–358. DOI: 10.3390/signals4020018.

11. Al-lahham, M., Al-Sa'd, M., Al-Ali, A., Mohamed, A., Khattab, T., & Erbad, A. DroneRF dataset: A dataset of drones for RF-based detection, classification and identification. *Data in Brief*, 2019, vol. 26, article no. 104313. DOI: 10.1016/j.dib.2019.104313.

12. Medaiyese, O., Ezuma, M., Lauf, A., & Adeniran, A. Cardinal RF (CardRF): An Outdoor UAV/UAS/Drone RF Signals with Bluetooth and WiFi Signals Dataset. *IEEE Dataport*, 2022. DOI: 10.21227/1xp7-ge95.

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

14. Medaiyese, O. O., Syed, A., & Lauf, A. P. Machine Learning Framework for RF-Based Drone Detection and Identification System. *2nd International Conference on Smart Cities, Automation & Intelligent Computing Systems (ICON-SONICS)*, 2021, pp. 58–64. DOI: 10.1109/ICON-SONICS53103.2021.9617168.

15. Frid, A., Ben-Shimol, Y., Manor, E., & Greenberg, S. Drones Detection Using a Fusion of RF and Acoustic Features and Deep Neural Networks. *Sensors*, 2024, vol. 24, no. 8, article no. 2427. DOI: 10.3390/s24082427.

16. Sazdic-Jotic, B., Andric, M., Bondzulic, B., Simic, S., & Pokrajac, I. FLEDNet: Enhancing the Drone Classification in the Radio Frequency Domain. *Drones*, 2025, vol. 9, no. 4, article no. 243. DOI: 10.3390/drones9040243.

17. Rahman, M. H., Baik, J.-I., Aziz, M. A., Tabassum, R., Sejan, M. A. S., & Song, H.-K. Cascaded Learning Empowered Classification of UAVs Using Radio Frequency under Wireless Interference. *Alexandria Engineering Journal*, 2025, vol. 121, pp. 201–212. DOI: 10.1016/j.aej.2025.02.031.

18. Huang, M., Dou, L., & Sun, Q. MD-Net: A Lightweight Dual-Branch Network with Adaptive Time-Frequency Masking for Robust UAV RF Signal Classification. *Information*, 2026, vol. 17, no. 6, article no. 562. DOI: 10.3390/info17060562.

19. Sainath, T. N., Vinyals, O., Senior, A., & Sak, H. Convolutional, Long Short-Term Memory, fully connected Deep Neural Networks. *2015 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, South Brisbane, QLD, Australia, 2015, pp. 4580–4584. DOI: 10.1109/ICASSP.2015.7178838.

20. Aksan, F., Li, Y., Suresh, V., & Janik, P. CNN-LSTM vs. LSTM-CNN to Predict Power Flow Direction: A Case Study of the High-Voltage Subnet of Northeast Germany. *Sensors*, 2023, vol. 23, no. 2, article no. 901. DOI: 10.3390/s23020901.

21. Vuorenmaa, M., Marin, J., Heino, M., Turunen, M., & Riihonen, T. Radio-Frequency Control and Video Signal Recordings of Drones (1.0.1) [Dataset]. *Zenodo*, 2020. DOI: 10.5281/zenodo.4264467.

22. Cai, Y., Qin, Y., Ou, Y., & Wei, R. Intelligent Systems in Motion: A Comprehensive Review on Multi-Sensor Fusion and Information Processing From Sensing to Navigation in Path Planning. *International Journal of Semantic Web and Information Systems*, 2023, vol. 19, no. 1, pp. 1–35. DOI: 10.4018/IJSWIS.333056.

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ПОКРАЩЕННЯ КЛАСИФІКАЦІЇ БПЛА ЗА РАДІОЧАСТОТНИМИ СИГНАЛАМИ ЗА ДОПОМОГОЮ ГІБРИДНОЇ ЗГОРТКОВО-РЕКУРЕНТНОЇ АРХІТЕКТУРИ

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Це дослідження спрямоване на автоматизацію класифікації малих БПЛА за їх радіочастотними сигналами. ***Об'єктом*** *дослідження є процес класифікації БПЛА за радіочастотною сигнатурою з використанням комбінованих моделей машинного навчання. Предметом дослідження є комбінування моделей на основі машинного навчання для досягнення кращих результатів класифікації в умовах, коли ефективне навчання ускладнене, а висока точність досягається через часову залежність складних сигналів.* ***Метою*** *цієї роботи є вдосконалення моделей класифікації БПЛА шляхом оптимізації архітектури згорткової нейронної мережі шляхом додавання рекурентних шарів.* ***Методи****, описані в цьому дослідженні, допомагають створити гібридну модель на основі згорткової та довгої короткочасної пам'яті моделей (CNN-LSTM) шляхом поєднання згорткових шарів з рекурентними шарами, щоб мати можливість витягувати просторово-часові ознаки з радіочастотних сигналів БПЛА. Порівняно з традиційними штучними нейронними мережами (ШНМ), згорткова нейронна мережа довгої короткочасної пам'яті CLDNN зменшила кількість помилкових спрацьовувань у різних класах і підвищила ефективність класифікації для класів сигналів, які тісно пов'язані між собою або містять шум. Однак, складність і обчислювальні витрати, пов'язані з моделлю CLDNN, визнаються, що підкреслюють проблеми для систем з обмеженою обчислювальною потужністю.* ***Задачі*** *дослідження: 1) огляд сучасних підходів до класифікації малих БПЛА; 2) постановка задачі; 3) створення тестового набору даних для запропонованих моделей безпілотників; 4) адаптація моделі CLDNN для задач класифікації безпілотників; 5) порівняння базової моделі CNN та запропонованої моделі.* ***Висновки****. Експериментальна перевірка доводить, що запропонована модель CNN-LSTM значно покращує точність класифікації порівняно з базовою архітектурою CNN, особливо в класах, які є більш вразливими до помилок неправильної класифікації. Інтеграція згорткових шарів, які добре виділяють локальні особливості, і рекурентних LSTM-шарів, які добре моделюють послідовні залежності, дозволяє комбінованій архітектурі зменшити частоту помилкових спрацьовувань. Відповідно, така гібридна структура виявляється досить ефективною для задач класифікації сигналів, оскільки вона захоплює не тільки просторово локалізовані ознаки, але й часову контекстну інформацію на вході. Проведене дослідження підтверджує ефективність моделі CNN-LSTM для класифікації БПЛА на основі радіочастотних сигналів та підкреслює її потенціал для використання в практичних додатках.* ***Майбутні напрямки досліджень*** *включають оптимізацію обчислювальної ефективності моделі, застосування для більшої кількості завад і зашумлених даних.*

Ключові слова: *класифікація; згорткова нейронна мережа; безпілотні літальні апарати; радіочастотний аналіз; дрони; нейронні мережі; машинне навчання.*

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