Improved Drone Classification and Detection Using RF: A Cascaded Deep Learning Approach

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***Abstract*—In this research, we present a cascaded deep learning (DL) model to identify multiple drone radio frequency (RF) signals, leveraging the latest developments in DL technology. The model consists of a bi-directional long short-term memory (Bi-LSTM) model and a 1D-CNN. In this simulation experiment, the DroneRC dataset is employed. The raw RF data is initially preprocessed using the short-time Fourier transform and the power spectral density technique to identify the most relevant properties before being utilized to train the DL model. The simulation results demonstrate that the proposed DL model exhibits a low error rate and excellent classification accuracy.**

***Index Terms*—cascaded DL model, drone detection, RF signal classification, power spectral density**

I. Introduction

Unmanned aerial vehicles (UAVs), sometimes known as UAVs, have attracted a lot of interest lately. UAVs may be flown from kilometers away without a pilot present by using a remote controller. UAVs are valuable tools for several sectors, and they are being employed for many applications outside the military at the moment. For example, authorities use UAVs for environmental monitoring [1], remote sensing [2], and disaster prevention [3]. Privacy and safety issues are brought up by the growing usage of UAVs [4]. According to [5], the use of UAVs for terrorist attacks and unauthorized monitoring is the most worrying problem. To prevent the aforementioned occurrences, anti-UAV technology that can recognize, categorize, and destroy unauthorized UAVs gathering data using a variety of sensors is required [6].

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Deep learning (DL) techniques for UAV detection have gained the most significant attention in the scientific community. Several research works have looked at how to recognize UAVs using DL algorithms and a variety of modern technologies, including RF, thermal imaging, audio, video, and radar [7]. Since it can identify objects over significant distances and communicate across non-line of sight, radio frequency (RF)-based technology has drawn the most interest among all other technologies. As of right now, a lot of research has been done on the detection and classification of UAVs utilizing RF technology [8]–[12]. [8] presented a DL method based on RF to classify multiple UAVs. To achieve the detection and classification objectives, a supervised DL system was suggested by the authors. To prepare the RF signals, they employed the short-term Fourier transform (STFT). A significant contributing aspect to the enhanced efficiency of their technique was the first STFT data preparation in this investigation. The authors of [9] presented RF-UAVNet, a convolutional NN designed for UAV tracking systems that use RF signals to recognize and categorize UAVs.RF-based UAV identification and detection was investigated in [5]. To extract features, they employed the continuous wavelet transform and the wavelet scattering transform. They used principal component analysis in conjunction with many machine learning models, including SVM, kNN, and ensemble to complete classification and detection tasks with various levels of noise.

In this work, we have addressed a UAV detection and classification problem utilizing RF signal analysis based on a novel cascaded DL model called the CNN-BiLSTM to classify UAVs. The simulation study makes use of the DroneRC dataset. The raw RF data is initially preprocessed using the STFT and the power spectral density (PSD) technique to identify the most relevant properties before being utilized to train the DL model. The results of the simulation demonstrate that the suggested model offers low error rates and excellent classification accuracy.

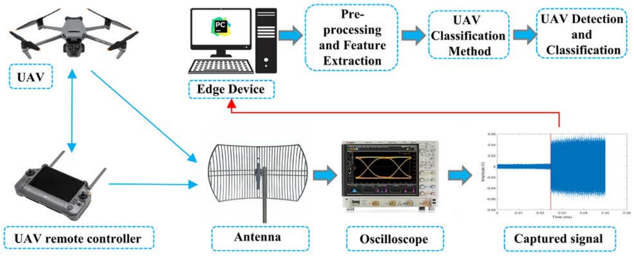

Fig. 1. The architecture of proposed RF-based UAV detection system.

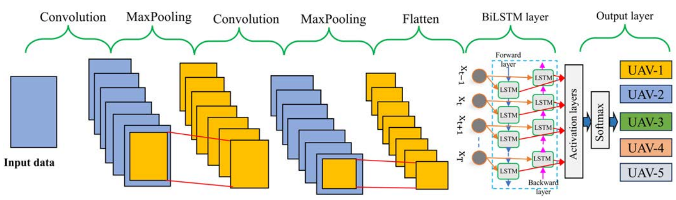

Fig. 2. The architecture of proposed cascaded CNN-BiLSTM model with different layers interconnection.

II. Datasets Description

This work uses the DroneRC dataset [13], a publicly accessible dataset that includes radio frequency (RF) signals from drone remote controllers (RCs) of various brands and types. A low-noise power amplifier, a directional grid antenna, and a high-frequency oscilloscope make up a passive RF surveillance system that records and intercepts the radio frequencies that the drone RCs send out to communicate with the drones. The drones were not moving while the data was being collected. The 2.4 GHz band is used by all drone remote controls to send signals. There are around 1000 worth of RF signals in each 17 drone RC, each lasting 0.25 milliseconds, and the drones are made by eight different manufacturers. Approximately 1000 RF signals in.mat format from the RCs datasets.Among them, we have used four drone datasets with different models for this study, such as the DJI (5) datasets for Inspire 1 Pro, Matrice 100, Matrice 600, and Phantom 3.

III. Methodology

The experimental configuration Fig. 1 displays the drone RC RF data recording arrangement. When it detects drone signals, a passive RF surveillance gadget records them. The setup consists of a Keysight MSOS604A oscilloscope with a 6 GHz bandwidth and a maximum sampling frequency of 20 GSa/s, a low-noise amplifier working in the 2–2.6 GHz range, and a 2.4 GHz 24dBi grid parabolic antenna. At distances ranging from 1 to 5 meters, RF signals were recorded in an indoor laboratory setting between the drone RC and the receiving antenna.

In this experiment, we have generated 500 signals with a 128×128 dimension size associated with each drone. Next, we propose an approach based on the energy-time-frequency domain. We employ the spectrogram approach to depict the RF signals in the energy-time-frequency domain. Generally speaking, the discrete-time STFT squared magnitude may be used to compute the spectrogram's signal as follows:

$$\text{Spectrogram}(n,\ \omega) = \left| \sum_{n=-\infty}^{\infty} y[m]\text{w}[n-m]e^{-j\omega n} \right|^2, \quad (1)$$

where $w[n]$ is a sliding window function that acts as a filter, $y[n]$ is the collected signal, ω is the frequency, and m is discrete-time. Furthermore, the spectrogram analysis of the recorded radio frequency data may reveal the signal's broadcast frequency as well as its frequency hopping patterns. The PDSs of the signals are computed using the periodogram technique to produce spectrogram images. Using this method, the time-domain signal $y[i]$ from a UAV is divided into successive blocks, and then each block's periodogram is created and averaged to estimate the PDS, i.e.,

$$y_g[i] = w[i]y[i + gR], \quad (2)$$

where G is the window dimension and $i = 0, 1, ..., G - 1$ defines the sample index. The window function represents $w[i]$, $g = 0, 1....K - 1$ is the window index, K is the total number of blocks, and R is the window's hop size, which modifies how much one window overlaps another. The periodogram of a block is then calculated as follows:

$$P_{y_g[i]}, G(w_k) = \frac{1}{G}|FFT_{N,k}(y_g)|^2 = \frac{1}{G}\left|\sum_{i=0}^{N-1} y_g[i]e^{-2j\pi ik/N}\right|^2 \quad (3)$$

Consequently, the PSD is calculated using the following formula:

$$\text{PSD} = \frac{1}{K}\sum_{g=0}^{K-1} P_{y_g[i]}, G(w_k) \quad (4)$$

In this case, the Hanning window is used to construct periodograms.

CNN and other DL algorithms are highly effective in applications involving image recognition and classification. CNNs are made up of layers, much like other NNs. Convolution layers are used to apply many filters to an image to extract features, independent of the location of those features within the image, in contrast to other DL. CNN performs effectively when dealing with 2D input.In comparison to other DNNs, it also needs less weight per neuron, which reduces processing complexity. Additionally, the BiLSTM network is a potent DL component that can learn the input characteristics in a two-directional fashion for the categorization of time series data. As a result, the proposed cascaded CNN-BiLSTM model gains strength and the classification task's accuracy rises. The proposed cacased DL model is shown in Fig. 2. Spectrophotograms of RF signals were utilized in this work as inputs for the CNN model and the output of CNN is fed to the BiLSTM network for further processing. The extracted RF features are trained using the proposed model with a minibatch size of 32 and a total epoch of 100. The entire dataset is divided into two subsets, with the training set accounting for 80% and the validation set for 20%, respectively. The test data

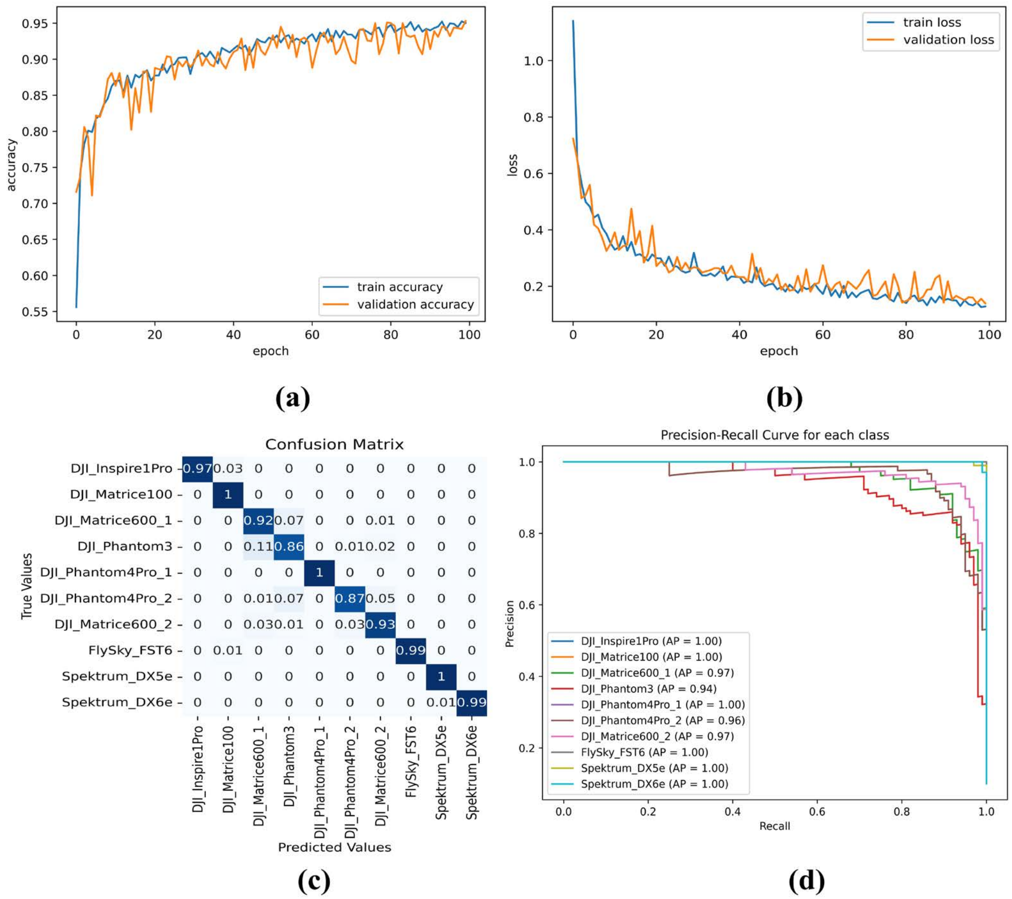

Fig. 3. (a) and (b) Training and validation accuracy versus loss for 10 classes of drone; (c) Confusion matrix results for 10 classes of drone; (d) Precision versus recall graph for 10 classes of drone.

is fed into a trained model for signal type categorization during the testing phase.

IV. Simulation Results

The model in the suggested system is trained using Python and the TensorFlow platform, while the datasets are created and preprocessed in the MATLAB R2022b environment. The suggested system application was run on a PC equipped with a 12th Gen Intel(R) Core(TM) i7-12700 2.10 GHz CPU and an Nvidia RTX3060 graphics processor unit. The performance of the suggested models is assessed by contrasting the real and anticipated values. In addition, we calculate values for false negatives (FN), true negatives (TN), true positives (TP), and false positives (FP). The formula is then used to determine the recall, accuracy, and precision as follows:

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

$$Precision = \frac{TP}{(TP + FP)} \tag{6}$$

$$Recall = \frac{TP}{(TP + FN)} \tag{7}$$

The effectiveness of the suggested model is assessed for 10 drone classes using a confusion matrix, precision, and recall analysis. We have illustrated the training and validation accuracy and loss to evaluate the performance of the suggested model with these 10 classes. Figures 3 (a) and (b) show the accuracy and loss for training and validation, respectively. As can be observed from Figures 3 (a) and (b), the model completes 100 epochs and achieves a validation accuracy of 95.30%, accompanied by a corresponding reduction in loss. These results demonstrate the success of the suggested model in learning from the proposed drone datasets.

The results of the confusion matrix for the situations with 10 classes are displayed in Fig. 3 (c). It can be observed from Fig. 3 (c) that, for the 10 drone classes, such as DJI_Inspire1Pro, DJI_Matrice100, DJI_Matrice600_1, DJI_Phantom3, DJI_Phantom4Pro_1, DJI_Phantom4Pro_2, DJI_Matrice600_2, FlySky_FST6, Spektrum_DX5e, and Spektrum_DX6e, the true and prediction values of the proposed model for the majority of classes are over 95%. However, the classification rates for several classes, such DJI_Matrice600_1, DJI_Phantom3, DJI_Phantom4Pro_2, and DJI_Matrice600_2, were 92%, 86%, 87%, and 93%, respectively. This indicates that there is no significant inaccuracy when considering the overall accuracy rate.

To determine the precision and recall values for ten classes of drone signals, we ran simulations as shown in Fig. 3 (d). The overall precision-recall accuracy of the suggested model produced encouraging results for the scenario involving ten classes of drones. The following DJI drones attained accuracies of 97%, 94%, 96%, and 97% respectively: DJI_Matrice600_1, DJI_Phantom3, DJI_Phantom4Pro_2, and DJI_Matrice600_2. The accuracy of the remaining classes was 100%. These findings demonstrate that the proposed model can predict drone signal classification with a high degree of accuracy and a low likelihood of errors.

V. Conclusion

In this paper, we propose an RF signal-based cascaded DL-assisted UAV detection and classification system. The configuration of the proposed model utilizes two DL models: CNN and BiLSTM. Compared to the state-of-the-art, the suggested model enhances detection and classification performance. This simulation study uses the DroneRC dataset. The raw RF data is initially preprocessed using the STFT and PSD techniques to identify the most relevant features before being used to train ML models. The results demonstrate that the suggested model has a low error rate and excellent classification accuracy.

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