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Drones Identification and Classification using Fingerprints in Spectrograms

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***Abstract*— The rapid proliferation of drones and Wi-Fi-enabled devices has revolutionized various sectors, including agriculture, entertainment, security, and surveillance. However, this also has magnified the threat space in terms of security, privacy, and efficient spectrum management. Detecting and classifying these devices accurately is crucial to address potential threats to public safety. To alleviate this issue, this paper proposes an advanced signal classification framework to identify drones base on their unique fingerprint. This is done by using spectrogram images of different drones and Wi-Fi devices operating within the 2.4 GHz spectrum which give unique patterns to identify drones fingerprint. The approach combines the features generated by Principal Component Analysis (PCA) with a modulation index to enhance classification accuracy and robustness of different machine learning classifiers. Two tasks are considered in this paper: i) multi-class classification of different drone models and ii) binary classification of drones and Wi-Fi signals. The proposed framework is rigorously tested and challenged using different hyperparameters configurations and ablation studies. The results demonstrate the robustness of the proposed approach in identifying drones accurately.**

I. Introduction

Drones are becoming a key technology in diverse smart living and transportation applications [1]–[3]. The low-cost of drones and their span of applications have opened multiple beneficial applications where humans do not have easy access or they are high risky. Drones will use a variety of 4G, Wi-Fi to future 6G telecoms to transmit command and control data, where the data is mixed with other non-drone transmissions. Separating and classifying these data streams is crucial to locating drones, operators, and understanding their risk profile. Here, the negligent or malicious usage of drones pose critical challenges in security and protection of critical national assets. Current counter-drone systems [4], [5] are based on detection systems based on cameras, radars or LiDARs which are highly prone to false positives due to lightning conditions [6], [7]. Other approaches have focused on analysing time-series data of the trajectories followed by aerial vehicles [8]–[10]. However, this signals by themselves do not provide information about the drone for threat triaging [8], [11], [12]. Furthermore, these methods often struggle in environments with high noise levels or when dealing with small agile drones. Consequently, there is growing interest in leveraging advanced signal processing techniques and machine learning algorithms to enhance the accuracy and robustness of these detection systems [13].

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Fingerprint has appeared as a useful tool to give a unique feature linked to an object, e.g., in face recognition. This raises a question of how we can uncover the unique fingerprint of drones such that is easier to classify drones without high-resolution cameras or time-series analysis. Fingerprint approaches use spectrogram analysis [14], [15], which provide a time-frequency representations of signals. By converting signals into spectrograms, it becomes possible to visualise and analyse the distinct frequency patterns and temporal variations of different devices. This visualisation aids in extracting meaningful features that can be used for classification purposes.

Despite the advances in this field, several challenges are still open. One of the primary challenges is the dynamic and often unpredictable nature of radio-frequency (RF) environments [16]. Signals from different sources can overlap, leading to interference and making it difficult to distinguish between them [17], [18]. Additionally, the variations in signal strength and quality due to distance, obstacles, and other environments factors pose significant hurdles [19].

A. Related work

The literature review explores various methodologies and models used in signal classification [20], [21], specifically focusing on distinguishing between drone and Wi-Fi signals. Wavelet transform has been used to enhance spectrogram analysis of RF-based UAV detection [22]. Wavelet transforms, unlike traditional Fourier transforms, provide multi-resolution analysis, capturing both frequency and temporal information with high precision. The study experimented with discrete, continuous, and wavelet scattering transforms. Notably, the wavelet scattering transform excelled by capturing steady features of RF signals, which are pivotal in distinguishing drones from other RF sources like Wi-Fi devices. These transformed features are subsequently fed into a pre-trained convolutional neural network (CNN), specifically SqueezeNet, achieving a commendable classification accuracy of 98.9% at a signal to noise ratio of 10dB. This underscores the efficacy of integrating advanced spectrogram analysis techniques with deep learning models.

Authors in [15] delved into enhancing spectrogram-based signal classification through transfer learning. By leveraging pre-trained CNNs and fine-tuning them on spectrogram data specific to drone and Wi-fi signals, the study capitalized on the rich feature extraction capabilities of deep networks. The approach recognized that spectrograms, when processed through layers of convolutional filters, unveil intricate patterns and temporal dynamics inherent to specific signal

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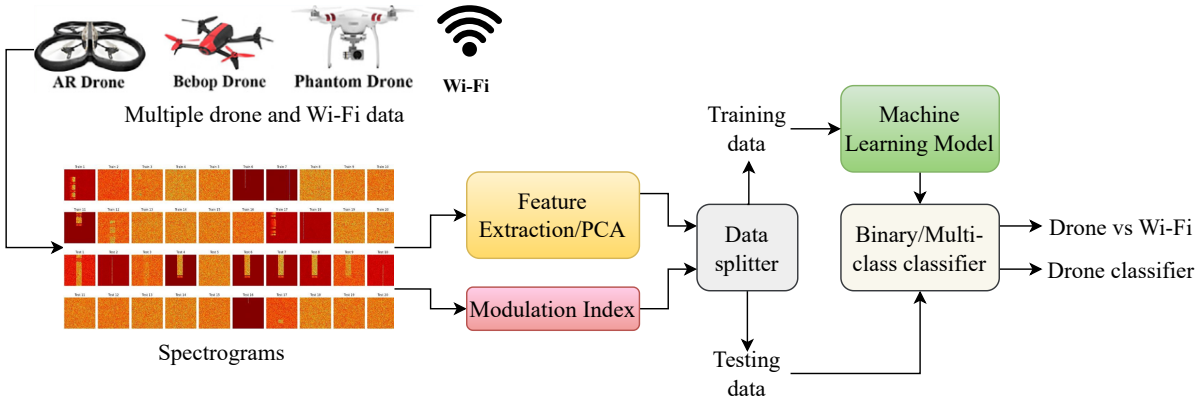


Fig. 1. High-level diagram of the proposed methodology

types [23]. This methodology not only expedited the training process but also bolstered classification accuracy, showcasing the adaptability of spectrogram analysis in conjunction with modern deep learning techniques.

Contrastingly, [24] adopted a more traditional route, employing manual feature extraction from spectrograms. Features such as signal energy distribution, frequency peaks, and temporal variations are meticulously extracted and then classified using a support vector classifier (SVC). Whilst this approach is less computationally demanding, it often falls short in capturing the nuanced differences between overlapping signals, especially in scenarios where drone and Wi-Fi transmissions coexist. The study highlighted the limitations of manual feature extraction, emphasizing the need for automated and sophisticated techniques to navigate the complexities of modern signal environments.

In [25], a principal component analysis (PCA) is proposed as a dimensionality reduction tool to streamline spectrogram features. By identifying principal components that capture the majority of variance in the data, PCA effectively reduces the feature space. When combined with spectrogram analysis, PCA distilled the most salient features, which are then classified using traditional machine learning models. While this approach achieved reasonable accuracy, it underscored a trade-off between computational efficiency and the depth of feature representation, especially when juxtaposed with deep learning methodologies.

B. Contributions and Outline

This paper aims to provide a framework to identify drones using fingerprinting in spectrograms. We observed that the spectrograms provide unique features for drone identification. PCA is used as a dimensionality reduction and feature extraction algorithm to capture only the main features that allows to classify drones in a lower dimensional representation. These features are further enhanced by considering the modulation index that allows to transform the nonlinear separable classification problem into an almost linear separable classification problem. Two main tasks are considered in this paper: i) a multi-classifier between of different drone models and ii) a binary classifier between drones and Wi-Fi signals. Exhaustive experiments are conducted to verify the effectiveness of the approach under different machine learning models and hyperparameters.

II. Methodology

The proposed methodology is depicted in Fig. 1. The diagram consists in radio-frequency data obtained from different drones and Wi-Fi signals operating within the 2.4 GHz spectrum. From these data, spectrograms are extracted and analysed to uncover unique fingerprint of these devices using PCA as feature extraction and the modulation index. These features are concatenated and split into training and testing data for both the training and evaluation of machine learning models that will be discussed in future sections. The models are trained for both binary (drone vs Wi-Fi) and multi-task classification (Drone classifier) tasks.

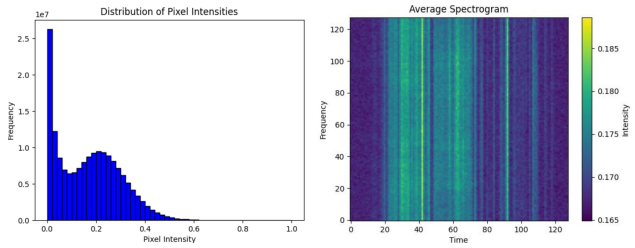
A. Dataset

We used the drone signals dataset produced in [18]. The dataset covers a range of drone signals that includes nine different drone signals and one Wi-Fi signal, all operating at the 2.4 Ghz frequency band. This dataset contains in total 15,000 samples. We split these samples into training and testing datasets with 10,500 and 4,500 samples, respectively.

B. Spectrogram analysis

The spectrograms reveal the unique characteristics of each signal [17], [26] that allows to understand the underlying patterns in the data, as well as the challenges posed by different levels of noise and interference. To better understand the spectrograms of the dataset, we proceed to analyse the distribution of pixel intensities as shown in Fig. 2(a).

The histogram suggests that many pixels have low-intensity values (first peak), indicating the prevalence of background noise or weaker signal components in the recordings. However, the presence of a secondary peak suggests that certain segments of the data contain stronger signals, which are critical for distinguishing between different devices. Understanding this distribution is essential for preprocessing the data, such as through normalisation or contrast enhancement, to ensure that the key features are adequately



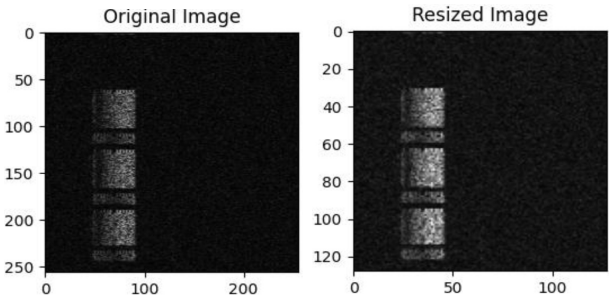
(a) Pixel intensity (b) Average spectrogram

Fig. 2. Spectrogram analysis of the dataset

captured for machine learning algorithms [25]. Fig. 2(b) shows the average spectrogram across the entire dataset. This representation highlights the dominant frequency and time patterns that recur across different signals, offering insights into the common features of drone and Wi-Fi transmission. This visible vertical lines in the spectrogram indicates persistent frequency components that may be characteristics of specific types of signals, such as those used by drones for control and communication.

C. Data pre-processing

In this paper, the spectrograms images are resized to images of 128×128 pixels using a high-order spline interpolation method to balance computational efficiency with preservation of essential data features. This particular method has shown superiority compared to simpler methods bases on nearest neighbours or bilinear interpolation. Spline interpolation allows for smoother transitions between pixels, preserving more detail and reducing artefacts, making it especially affective for maintaining the quality of resized images in tasks that require precise feature extraction [27]. The proposed resolution is chosen to maintain sufficient detail for feature extraction while keeping low computational resources. Fig. 3 shows an example of the spectrogram resizing using the higher-order spline interpolation method.



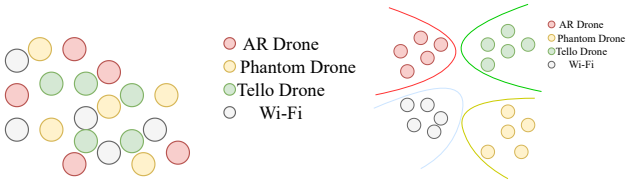
(a) Original image (b) Resized image

Fig. 3. Spectrograms resizing using High-order spline interpolation

The results show that the interpolation method effectively maintains the quality of the image such that its properties, e.g., its eigenvalues remain almost unaffected.

D. Feature Extraction: PCA and Modulation index

Feature extraction [28] is implemented using principal component analysis (PCA) on the resized spectrogram images, alongside the modulation index feature. PCA is applied to reduce the 128×128 pixel spectrograms into single-dimensional arrays, capturing the most significant data variance. The number of PCA components used varied which is explained further in the next section. Simultaneously, the modulation index [29], representing signal modulation characteristics, is extracted as a single-dimensional array, providing critical insights into signal differentiation. Here, the incorporation of the modulation index helps to transform the non-linear separable classification problem into a linear separable problem as shown in Fig. 4.



(a) Non-linear separable using PCA features (b) Linear separable model using PCA features and modulation index

Fig. 4. Transformation of a non-linear separable model into a linear separable model

Standardisation is applied to the modulation index to normalize the scale. This process ensures that all features contributed equally to the machine learning model by recalling the have a mean of zero and standard deviation of one. The standardised modulation index and PCA features are then concatenated, forming a comprehensive feature set.

E. Machine Learning Models

The five machine learning models used in this work are

1) **Support vector Classifier (SVC)**: A Gaussian kernel is used in this model.
2) **Decision Tree**: The tree is built by selecting features that provide the maximum information gain, creating branches until the model can classify the input data into respective categories
3) **1D Convolutional Neural Network (CNN 1D)**: The architecture consisted of four convolutional layers, each followed by batch normalisation and max pooling to reduce dimensionality while retaining important features. The model concluded with fully connected layers, leading to the final classification output.
4) **Long Short-term Memory (LSTM)**: The architecture consisted of two LSTM layers, each followed by batch normalisation, which helps stabilise the training process. The output from the last LSTM unit is passed through fully connected layers to produce the final classification.
5) **1D Convolutional neural Network combined with LSTM (CNN 1D-LSTM)**: The architecture first applied several convolutional layers to extract local features from the input sequence. The output from the convolutional layers is then reshaped and passed through LSTM layers to capture the temporal dependencies [30].

TABLE I

COMPARISON RESULTS. BEST RESULTS ARE IN BOLD

Model	Multi-Class					Binary (Drone vs. Wi-Fi)				
	Train Accuracy	Train Loss	Test Accuracy	Test Loss	Inference Time	Train Accuracy	Train Loss	Test Accuracy	Test Loss	Inference Time
SVC	60	1.6702	58.00	1.8557	-	75.00	1.5400	64.00	1.9800	-
Decision Tree	68	1.8887	54.00	2.6000	-	78.00	1.7200	72.00	1.8400	-
CNN1D	97.25	0.0010	99.20	0.0002	**0.0641**	98.10	0.0004	**99.78**	**0.0001**	**0.0652**
LSTM	98	0.0009	**99.50**	**0.0002**	0.0906	99.14	0.0006	99.51	0.0002	0.1024
CNN1D-LSTM	**98.07**	**0.0008**	98.82	0.0045	0.1424	**99.15**	**0.0003**	99.47	0.0002	0.1308

All hidden layers use ReLU as activation function. The activation function for the output layer is either a sigmoid or softmax function depending of the problem, i.e., binary or multi-class classification. The models are trained using the Adam optimiser.

1) Hyperparameters: The proposed methodology has key hyperparameters to tune, mainly: the learning rate, the number of PCA components, and the batch size. We test the following values for the learning rate: 0.01, 0.001, and 0.0001. Different batch sizes are used in the training phase. The proposed values are 16, 32, 64, and 128 which allows to determine the sensitivity of the model. For the PCA, we test 50, 60, and 70 principal components.

2) Performance metrics: The performance of the system is evaluated using a variety of metrics, including accuracy, precision, recall, F1 score to provide a comprehensive assessment of the system's performance.

III. RESULTS

The models are trained using Azure Lab Services by Microsoft, utilising a Tesla A100 GPU with 56 GB RAM.

A. Comparison Results

Table I summarizes the results of the best trained models under the following hyperparameters: 70 principal components, learning rate of 0.01, and batch size of 64. We provide results for both training, testing and inference time.

The obtained results show that the LSTM model has the best performance in testing for the multi-class classification task with 99.50% of accuracy, whilst the CNN1D performs better for the binary classification task with 99.78% of accuracy. Notice that the classical machine learning models such as SVC and decision trees, do not perform properly since they do not exploit the high dimensional features of the PCA and modulation index. The hybrid model CNN1D-LSTM outperforms in the training accuracy of both classification tasks since the model has some overfitting, which is directly observed in the testing accuracy that has a lower value. In terms of inference time, convolutional models have a faster inference time than recurrent models (e.g., LSTMs). All neural models have good results which demonstrate the effectiveness of the approach in identifying drones accurately from the fingerprint of their spectrograms.

B. Hyperparameters testing

We test different configurations of hyperparameters to identify the values that give better prediction results. Table II summarizes the accuracy results of the deep learning-based models under different hyperparameters configurations for the multi-class classification problem.

TABLE II

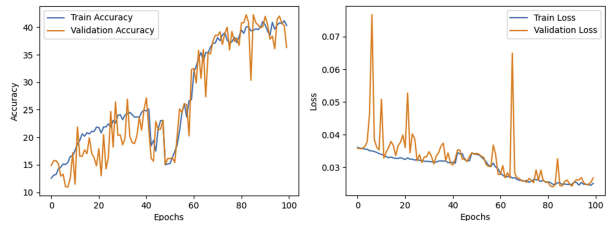
HYPERPARAMETER TESTING. BEST RESULTS ARE IN BOLD

Model	PCA Component	Learning Rate	Batch Size	Test Accuracy	Test Loss
CNN1D	50	0.1	32	10.51	0.7219
		0.01	64	97.31	0.0011
		0.001	128	97.68	0.0006
	60	0.1	32	15.15	0.0686
		0.01	64	96.86	0.0011
		0.001	128	98.86	0.0003
	70	0.1	32	10.51	0.0722
		0.01	64	97.97	0.0011
		0.001	128	**99.20**	**0.0002**
LSTM	50	0.1	32	97.85	0.0056
		0.01	64	99.35	0.0002
		0.001	128	98.77	0.0003
	60	0.1	32	98.01	0.0007
		0.01	64	98.57	0.0005
		0.001	128	98.86	0.0003
	70	0.1	32	98.94	0.0008
		0.01	64	**99.55**	**0.0002**
		0.001	128	99.17	0.0003
CNN1D-LSTM	50	0.1	32	97.89	0.0095
		0.01	64	98.42	0.0006
		0.001	128	98.62	0.0002
	60	0.1	32	96.85	0.0008
		0.01	64	97.60	0.0009
		0.001	128	97.97	0.0003
	70	0.1	32	98.54	0.0004
		0.01	64	98.46	0.0007
		0.001	128	**98.77**	**0.0002**

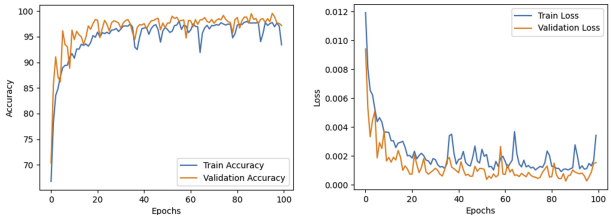
From the results obtained in Table II, we can observe the following key points: (1) For the CNN 1D algorithm, the best result is achieved with the following hyperparameters configuration: 70 PCA components, a learning rate of 0.001, and a batch size of 128. (2) The CNN1D-LSTM model has the best test accuracy of 98.77% under the following hyperparameters configuration: 70 PCA components, a learning rate of 0.001, and a batch size of 128. (3) For the LSTM model, the best performance is achieved with the following hyperparameters configuration: 70 PCA components, learning rate of 0.01, and a batch size of 64. This combination achieves the highest test accuracy of 99.55% with a test loss of 0.0002. This configuration demonstrates that a moderate learning rate combined with a medium batch size can yield excellent performance, likely due to a balanced gradient descent process that avoids both underfitting and overfitting.

C. Ablation studies

In this experiment, we aim to show how the performance of the machine learning models are notably degraded without the modulation index as feature. This defines the proposed ablation study as well as comparison with the previous approach [18] which aim to classify drones through the input features of the spectrogram images.



(a) Accuracy without modulation index (b) Loss without modulation index



(c) Accuracy with modulation index (d) Loss with modulation index

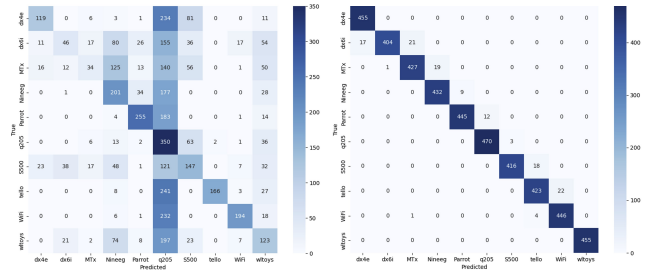
Fig. 5. Ablation studies for the LSTM model for the multi-class classification problem

TABLE III

ABLATION STUDIES RESULTS ACROSS ALL MODELS AND METRICS FOR THE MULTI-CLASS CLASSIFICATION PROBLEM

Model	Without Modulation				With Modulation			
	Accuracy	Precision	Recall	F1-score	Accuracy	Precision	Recall	F1-score
SVC	0.41	0.40	0.38	0.39	0.60	0.55	0.49	0.52
Decision-tree	0.45	0.44	0.42	0.43	0.68	0.65	0.55	0.60
CNN1D	0.60	0.75	0.59	0.66	0.97	0.98	0.97	0.975
CNN1D-LSTM	0.62	0.76	0.61	0.68	0.98	0.95	0.95	0.95
LSTM	0.41	0.55	0.37	0.44	0.98	0.98	0.97	0.975

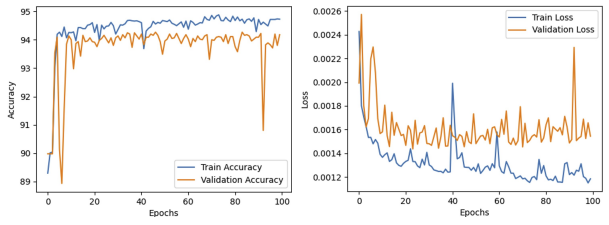
1) Multi-class classification: The ablation studies for the multi-class classification task using the proposed machine learning algorithms across diverse metrics are observed in Table III. All the models use 70 principal components, a learning rate of 0.01, and a batch size of 64.



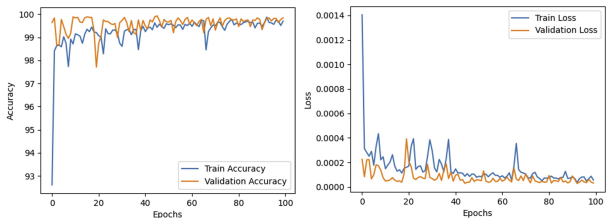
(a) Without modulation index (b) With modulation index

Fig. 6. Confusion matrix of the LSTM model for the multi-class classification problem

The results clearly shows how the performance of the machine learning models is degraded when the modulation index is not used as feature. Here, the LSTM model that shows the best performance in Table I is drastically affected with an accuracy of 41%. This model without the modulation index has a underfitting problem due to the complex non-linear nature of the principal components. Conversely, the use of the modulation index helps the models to increase their performance notably, almost twice, with consistent accuracy and without overfitting problems. Fig. 5 shows the accuracy and loss plots for the LSTM model with and without modulation index.



(a) Accuracy without modulation index (b) Loss without modulation index



(c) Accuracy with modulation index (d) Loss with modulation index

Fig. 7. Ablation studies of the CNN1D model for the binary classification problem

The results demonstrate the underfitting problem of the LSTM when the modulation index is not used. In addition, it also shows how the same LSTM model notably improve its performance with the modulation index without overfitting problems. Fig. 6 shows the confusion matrices obtained for the multi-class case.

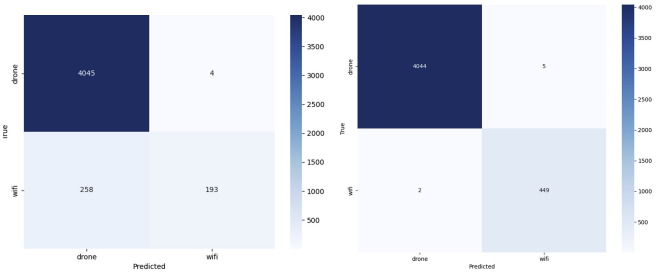
2) Binary classification problem: We conduct the same ablation study for the binary classification task. The results are observed in Table IV.

TABLE IV

ABLATION STUDIES RESULTS ACROSS ALL MODELS AND METRICS FOR THE BINARY CLASSIFICATION PROBLEM

Model	Without Modulation				With Modulation			
	Accuracy	Precision	Recall	F1-score	Accuracy	Precision	Recall	F1-score
SVC	0.65	0.59	0.63	0.61	0.75	0.73	0.77	0.75
Decision-tree	0.70	0.7	0.72	0.71	0.78	0.76	0.77	0.77
CNN1D	0.94	0.94	0.99	0.96	0.99	0.99	0.99	0.99
LSTM	0.93	0.92	0.99	0.95	0.99	0.99	0.99	0.99
CNN1D-LSTM	0.94	0.91	0.99	0.94	0.99	0.99	0.99	0.99

The results without modulation index are slightly better in comparison with the multi-class task. However, these models have large overfitting as observed in the Recall and F1-scores. For this case, the CNN1D performs better for this task as shown in Table I, however we observe a relative good accuracy, but poor recall which suggests the model is overfitting the data. On the other hand, the incorporation of the modulation index highly improve the models to almost a perfect score. Fig. 7 shows the accuracy and loss curves of this ablation study which show overfitting in the loss curve without modulation index. The results using the modulation index exhibit high prediction accuracy with a stable and convergent loss curve. The confusion matrices of the ablation studies are given in Fig. 8.



(a) Without modulation index (b) With modulation index

Fig. 8. Confusion matrix of the CNN1D model for the binary classification problem

IV. Conclusions

In this paper we propose to identify drones by uncovering its unique fingerprint from spectrogram images. A framework is developed to capture the unique features associated to a specific drone that can facilitate the fingerprint discovery. PCA feature extraction and the modulation index are used to obtain the sufficient features to classify diverse drone models. Exhaustive experiments are conducted to demonstrate the benefits of the framework across different metrics and hyperparameter configurations. Further work will consider the use of sensor fusion to combine the benefits of spectrograms, detection cameras, radars and radio-frequency sensors to obtain a robust detection system that can enhance the protection of key assets and people from malicious drone usage. Other future work will explore developing internal open radio access network (ORAN) apps to self-analyse the spectrum for safe low altitude economy monitoring.

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