# RF-based UAV Identification and Classification


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***Abstract*—RF Based UAV Detection and Defense Systems have become increasingly important as the use of unmanned aerial vehicles (UAVs) continues to grow in popularity. Deep learning, a subset of machine learning, has shown great potential for improving the accuracy and reliability of these systems. In this paper a machine learning based approach for detection and classification of radio frequency signals from drones is proposed. As data source the DroneDetectV2 data set is used. Specifically, we focus on the application of deep learning techniques for UAV detection and classification using RF signals. We also discuss the challenges involved in training deep learning models for UAV detection and propose possible solutions to overcome these challenges. In this study, we have compared the classification results for two cases, while taking/ not taking flight modes of the drones into consideration. The results of this study demonstrate that deep learning can significantly enhance the accuracy and reliability of RF-based UAV detection and defense systems, making them an effective tool for protecting critical infrastructure and public safety.**



***Index Terms*—Radio Frequency Signals, Unmmaned Aerial Vehicle, Deep Learning**


## I. Introduction

The use of unmanned aerial vehicles (UAVs) has seen a significant increase in recent years due to their many benefits, including their ability to reach remote or inaccessible locations, operate in hazardous environments, and gather critical data. However, the rise of UAVs also brings new security challenges, as these devices can be used for illegal or malicious purposes, such as conducting surveillance or delivering explosives. Detecting and identifying UAVs is essential for maintaining security, privacy, and safety. One promising approach for UAV detection is the use of radio frequency (RF) signals. UAVs use RF signals for communication and navigation, and these signals can be detected and analyzed by specialized RF sensors. RF signals are electromagnetic waves that travel through the air and can be used to transmit information. They are commonly used in various wireless communication systems, including cell phones, Wi-Fi, and Bluetooth devices. UAVs also use RF signals to communicate with their operators or GPS systems, which makes them susceptible to RF detection. UAV detection using RF signals involves the analysis of RF signals to identify the unique characteristics of UAVs. These characteristics include the frequency range used by UAVs, the modulation scheme used for communication, and the GPS signals used for navigation. The analysis of these features allows for the identification and classification of UAVs from other RF sources. Deep learning algorithms can learn to recognize patterns and features in large datasets and can be trained to perform specific tasks, such as image classification or speech recognition.

Combining RF signals and deep learning has the potential to improve UAV detection and tracking. Deep learning algorithms can be trained to analyze RF signals and identify the unique features of UAVs, such as their modulation schemes and GPS signals. This allows for more accurate and reliable detection of UAVs, even in complex environments with high levels of background noise. One of the main challenges in using deep learning for UAV detection is the lack of large and diverse datasets. To address this issue, researchers have developed simulation environments to generate realistic RF signals from UAVs and other sources. These simulations can be used to train deep learning algorithms and test their performance in different scenarios. Another challenge is the need for real-time processing of RF signals. The large amount of data generated by RF sensors requires efficient and scalable algorithms to analyze and classify the signals in real time. Researchers have developed various techniques to address this issue, such as parallel processing and hardware acceleration. UAV detection using RF signals and deep learning has many potential applications in various fields, including defense, law enforcement, and public safety. RF detection systems can be used to monitor airspace and detect unauthorized UAVs in real time, allowing for timely and effective responses. In addition, deep learning algorithms can be used to track the movement of UAVs and predict their future trajectories, which can be useful for identifying potential threats and planning countermeasures.

In this paper, the approach for the detection and classification of RF signals from drones is proposed. In the next section of this paper, a short look at some related work in this field of research is given, followed by a description of the used data set and the approach used is discussed before initial results and a look ahead at the future work is presented in later sections, respectively.

## II. Related Work

Unmanned aerial vehicles (UAVs) have become increasingly popular for various applications, from surveillance and monitoring to delivery and transportation. Researchers have developed various methods for UAV detection and classification to address these concerns. In this literature review, we have examined the existing research work on UAV detection and classification based on RF signals and deep learning, focusing on the methods used, their accuracy, and the challenges researchers face in developing reliable and effective systems. One research work designed an intelligent algorithms using three layers of deep neural network to detect and identify intruding drones using the developed RF database [1]. Allahham et al. created their own data set of UAV RF signals [2]. Enzuma et al. present a system for detection and classification of 14 different UAV controllers [6]. Raw RF signals are transformed into the wavelet domain for detection, and then a naïve Bayes classifier based on Markov models is used to categorise the data. On energy transient signals, features are chosen for categorization using an NCA. These are then classified using a variety of machine learning methods. Medaiyese et al. [12] propose a semi-supervised Framework for UAV detection, using wavelet analysis. A accuracy between 86 percent and 97 percent was achieved, depending on the signal-to-noise ratio.

In [13], authors designed three deep neural networks (DNN) for UAV presence, type, and flying modes detection and classification which were validated by 10-fold cross-validation and evaluated using various metrics. A method for classification of drone signals using a pretrained neural network and transfer learning is proposed by Swinney and Woods [16] RF samples from the drone are used to calculate a spectrogram or PSD with FFT size of 1024. This neural network has 13 convolutional and five pooling layers. The data is then classified either by a SVM, LR or random forest. LR has shown a slightly better performance than the others. Taha and Shoufan [18] consider machine learning based classification for radar, visual data, acoustic data and radio frequency based systems. The principal component analysis (PCA) approach was used to minimise the dimensionality of a UAV detection and identification system based on WiFi signal and radio frequency (RF) fingerprint [15]. In order to weigh the dimensions of the two characteristics, axially integrated bispectra (AIB) and square integrated bispectra (SIB), they also used the neighbourhood component analysis (NCA) algorithm. Authors compare the effectiveness of well-known deep learning algorithms including Deep Neural Networks (DNN), Convolutional Neural Networks (CNN), and Long Short Term Memory (LSTM) [9] for the detection and identification of UAVs using audio data. A kernel entropy based approach [10] is used to partition the RF signal into bins and detect the presence of UAV. Authors of [4] proposed a WiFi-based approach aimed at detecting nearby aerial devices by performing statistical fingerprint analysis on wireless traffic. One study [8] radar detecting drones in rocky areas. Ground-based radar sends signals to analyze drone movements. To combat the multipath effect and low signal-to-noise ratio (SNR), researchers created [5] a time difference of arrival (TDOA) estimate algorithm based on Gauss prior probability density function. A detection algorithm [21] for UAV signals with an adaptive threshold based on Gaussian mixture model(GMM) is proposed. The proposed method [11] consists of two stages: extracting suspected targets and obtaining their trajectories. The first stage involves using a Double-GMM-Iteration method to remove the background and obtain suspected UAV targets. The second stage uses multi-frame information and an improved track-before-detect method to obtain suspected target trajectories. A passive radar array system is discussed [20] to receive and process the Orthogonal Frequency Division Multiplexing (OFDM) echoes of UAV, which are originally transmitted by the nearby base stations. Authors consider a WiFi based approach [3]aimed at detecting nearby unmanned aerial vehicles, by performing statistical fingerprint analysis on wireless traffic. The feasibility of inexpensive RF-based detection of the presence of drones [14], authors examined whether physical characteristics of the drone, such as body vibration and body shifting, can be detected in the wireless signal transmitted by drones during communication. The performance of the NCA and five different ML classifiers are studied [7] for 15 different types of UAV controllers. Also there are works like [19] where feature engineering is carried out to describe the signature of different micro-UAV signals.

## III. Dataset

The DroneDetectV2 data set, which is created by Swiney and Woods [17] is also available for free download at the IEEEDataPort. This data set contains raw IQ data captured with a BladeRF SDR. The samples are recorded with a sample rate of 60 Mbit/s at a center frequency of 2.4375 GHz. The data set contains recordings from seven drone models (six different DJI models and a Parrot Disco). Recordings are made in three different flight modes (switched on, hovering and flying). In ON mode, the drones are switched on but are not airborne. The distance between antenna and drone is 4 m. Additionally, the measurements are repeated with various types of radio interference. The interference modes are CLEAN (no interference), BLUETOOTH (interference created by a Bluetooth speaker), WIFI (created by personal WiFi hotspot from an Apple MacBook, used for video streaming) and BOTH (with simultaneous Bluetooth and WiFi interference). Unfortunately, some files (such as DJI Phantom in flying mode without interference) seem to be missing from the downloadable data set. In this study, we have worked on CLEAN subset of the dataset which consists of RF signals without any interference

## IV. Methodology

The work presented in this paper uses various machine-learning and deep-learning algorithms to classify different UAVs using raw RF signals as input to the model after feature extraction using PCA.

### A. Principal Component Analysis

Principal component analysis, or PCA, is a dimensionality reduction method that is used to reduce the dimensionality of large data sets, by transforming a large set of higher dimensions into a smaller one that still contains most of the information in the large set.PCA chooses the eigenvectors of the covariance matrix corresponding to the largest eigenvalues. The eigenvalues correspond to the variance of the data along the eigenvector directions. Therefore, PCA projects the data along the directions where the data varies most. PCA preserves as much information in the data by preserving as much variance in the data.

Suppose a vector X can be represented by N components:

$$X \in R^N$$

$$X = x_1 + x_2 ... + x_N$$

Assuming the standard base¡v1, v2, ..., vN¿ (i.e., unit vectors in each dimension), xi can be obtained by projecting x along the direction of vi:

$$x_i = X^T v_i / v^T v_i = X^T v_i$$

x can be "reconstructed" from its projections as follows:

$$X = \sum_{i=1}^{N} x_i v_i = x_1 v_1 + x_2 v_2 ... + x_N v_N$$

PCA seeks to approximate x in a subspace of RN using a new set of K less than N basis vectors ¡u1, u2, ...,uK¿ in RN:

$$X^{`} = \sum_{i=1}^{K} y_i u_i = y_1 u_1 + y_2 u_2 ... + y_N u_N$$

where :

$$x_{`} = y_1 + y_2 ... + y_K$$

$$y_i = X^T u_i / u^T u_i = X^T u_i$$

such that loss ( x - x') is minimized:

The "optimal" set of basis vectors ¡u1, u2, ...,uK¿ can be found as follows:

- Find the eigenvectors ui of the covariance matrix of the (training) data
$$\sum_x u_i = z_i u_i$$
- Choose the K "largest" eigenvectors ui (i.e., corresponding to the K "largest" eigenvalues zi) ¡u1, u2, ...,uK¿ correspond to the "optimal" basis!

We refer to the "largest" eigenvectors ui as principal components.

K is typically chosen based on how much information (variance) we want to preserve:

$$\sum_{i=1}^{K} z_i / \sum_{i=1}^{N} z_i \; > T$$

where T is the threshold value. In our data, a threshold value of 0.9 has been used, which indicated that PCA preserves 90 percent of the information in our data.

### *B. Logistic regression*

Logistic regression is one of the most popular Machine Learning algorithms, which comes under the Supervised Learning technique. It is used for predicting the categorical dependent variable using a given set of independent variables. Therefore it is used to classify the two UAVs using their respective RF signals.

### *C. Support Vector Machine*

Support Vector Machine or SVM is one of the most popular Supervised Learning algorithms, which is used for Classification as well as Regression problems. However, primarily, it is used for Classification problems in Machine Learning. The goal of the SVM algorithm is to create the best line or decision boundary that can segregate n-dimensional space into classes so that we can easily put the new data point in the correct category in the future. This best decision boundary is called a hyperplane.

### *D. Decision Tress*

A decision Tree is a supervised learning method used in data mining for classification and regression methods. It is a tree that helps us with decision-making purposes. The decision tree creates classification or regression models as a tree structure. It separates a data set into smaller subsets, and at the same time, the decision tree is steadily developed. The final tree is a tree with decision nodes and leaf nodes. A decision node has at least two branches. The leaf nodes show a classification or decision. We can't accomplish more split on leaf nodes-The uppermost decision node in a tree that relates to the best predictor is called the root node. Decision trees can deal with both categorical and numerical data.

### *E. Random Forest*

Random Forest is a popular machine learning algorithm that belongs to the supervised learning technique. It can be used for both Classification and Regression problems in ML.As the name suggests, "Random Forest is a classifier that contains a number of decision trees on various subsets of the given dataset and takes the average to improve the predictive accuracy of that dataset." Instead of relying on one decision tree, the random forest takes the prediction from each tree and based on the majority votes of predictions, and it predicts the final output. The greater number of trees in the forest leads to higher accuracy and prevents the problem of overfitting.

### *F. Naive Byes*

The Naïve Bayes algorithm is a supervised learning algorithm, which is based on the Bayes theorem and used for solving classification problems. It is mainly used in text classification that includes a high-dimensional training dataset. Naïve Bayes Classifier is one of the simple and most effective Classification algorithms which helps in building the fast machine learning models that can make quick predictions. It is a probabilistic classifier, which means it predicts on the basis of the probability of an object.

### *G. K-nearest neighbour*

K-Nearest Neighbour is one of the simplest Machine Learning algorithms based on Supervised Learning technique. K-NN algorithm assumes the similarity between the new case/data and available cases and put the new case into the category that is most similar to the available categories. K-NN algorithm stores all the available data and classifies a new data point based on the similarity. This means when new data appears then it can be easily classified into a well suite category by using K- NN algorithm. K-NN algorithm can be used for Regression as well as for Classification but mostly it is used for the Classification problems.

### *H. Deep Neural Network*

A deep neural network (DNN) is an ANN with multiple hidden layers between the input and output layers. Similar to shallow ANNs, DNNs can model complex non-linear relationships. The main purpose of a neural network is to receive a set of inputs, perform progressively complex calculations on them, and give output to solve real-world problems like classification.

In this paper, a Deep Neural Network consisting of an input layer, five dense layers, and an output layer is used to classify the two UAVs.

### *I. Convolutional Neural Networks*

Convolutional Neural Networks are a typical type of neural network used for analyzing images and videos. CNNs are made up of numerous layers of linked processing nodes and are intended to spot patterns in input data.

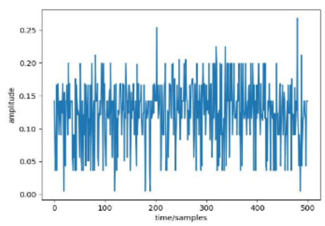
The ability of CNNs to automatically learn hierarchical representations of input data is its distinguishing characteristic. Early layers of a CNN often pick up on basic elements like edges and corners, whereas later layers pick up on more intricate aspects like forms and textures. By identifying these properties at various levels of abstraction, the network is able to recognize objects in a picture or video thanks to its hierarchical structure. Since our data is one-dimensional, we have used 1D CNN. A one-dimensional CNN is a type of Convolutional Neural Network that is specifically designed to process one-dimensional data, such as time series or signals. The one-dimensional CNN contains filters that scan through one-dimensional signals, as opposed to the standard two-dimensional CNN used for image processing, which has filters that scan across two-dimensional images. Numerous applications, such as speech recognition, music classification, and sensor data processing, have made use of one-dimensional CNNs.

### *J. Long Short-Term Memory*

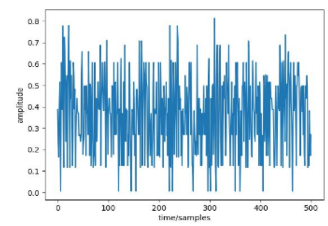
LSTM stands for Long Short-Term Memory, which is a type of recurrent neural network (RNN) architecture that is commonly used for processing sequential data, such as text, speech, or time-series data.LSTMs are designed to address the vanishing gradient problem that can occur in traditional RNNs, which can make it difficult for the network to learn long-term dependencies in the input data. LSTMs use a gating mechanism to selectively remember or forget information at each time step, which allows them to preserve important information over longer periods of time. The core component of an LSTM is the memory cell, which is a state vector that stores information over time. The memory cell is updated at each time step based on the current input and the previous state, and the output of the LSTM is a function of the current input and the current state of the memory cell.

## V. Working

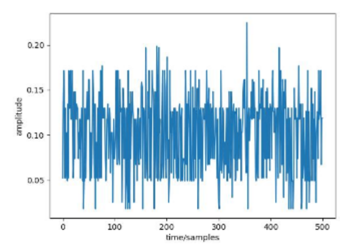
After taking into account all the drones and their states, along with missing data for three classes, we have a total of 18 classes for the “CLEAN” data set. The data set consists of signals captured in raw I/Q data format which consists of complex numbers in the form ($a+bj$). Hence, to convert the data set in a format suitable to be fed for training, the two real and imaginary parts of the complex signal values were taken separately($a$,$b$), and then PCA was performed. The following figures (1) are the visual representations of signals of three flying modes of *DJI Mavic pro 1 drone*.




(a) MP1_FY




(b) MP1_HO




(c) MP1_ON

Fig. 1. Signal amplitude visualization of DJI Mavic pro 1 drone: (a): FLY-mode, (b): HOVER-mode, (c): ON-mode

In figure 2, we can see the model architecture of Deep Neural Network used for classification consisting of a total of 6 layers. The model consists of one input, four hidden and one output layer with inner activation function ’relu’ and outer activation function ’softmax’ for classification. Similarly, the CNN model used in this study is shown in figure 3. This model consists of nine different layers including one input, two Conv1d, two Dropout, one Flatten, one MaxPooling1D and one output layer.

Figure 4 represents the architecture of the LSTM+CNN based model used for classification consisting of a total of 15 layers. This model consists of one Input, four Conv1D, four BatchNormalization, four MaxPooling1D, one LSTM, and one Output layer.

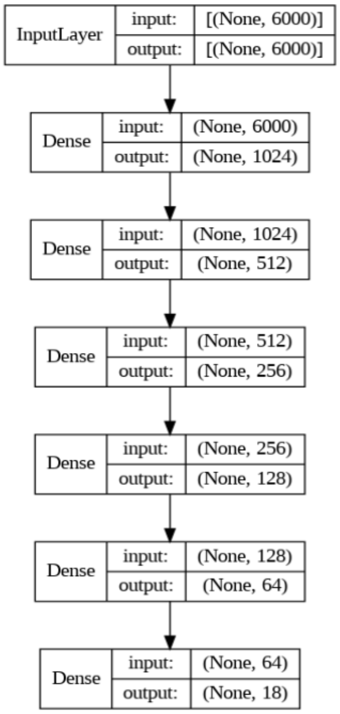



Fig. 2. Architecture of DNN model

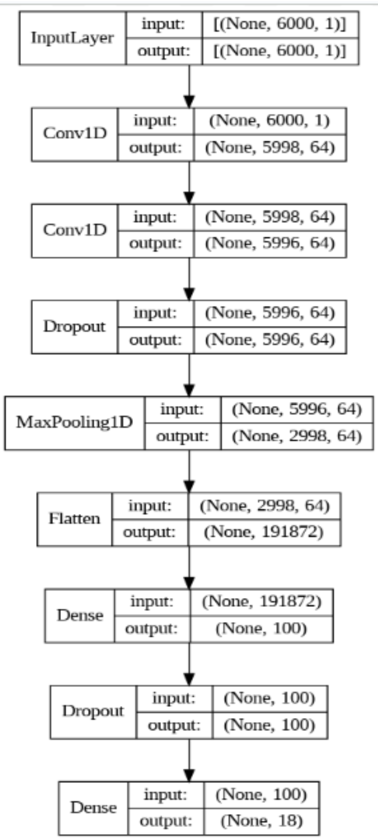



Fig. 3. Architecture of CNN model

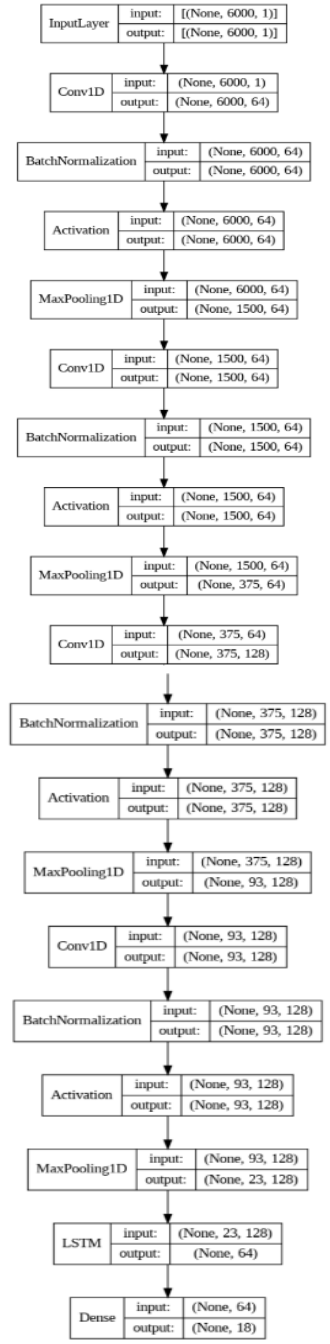



Fig. 4. Architecture of LSTM + CNN model

## VI. Results and Explanation

In this study, we have performed classification for two different cases. In the first case, we have classified different drones while taking into consideration their flight modes. In the second case, we have only classified different types of drones. Then we compared the difference between the results we obtained for the two cases. First, PCA was performed on the dataset for feature extraction and then classification was performed using different Machine learning and Deep learning approaches after a test-train split of 80:20 on the dataset. Each row of the input matrix consists of 600000 samples (5ms of signal) on which principle component analysis was applied to reduce the dimensionality with a variance threshold of 0.9; thus reducing the dimension of each row of data from 600000 samples to 6000 samples.

The different parameters which we have used for training the Deep learning based models are:

- Number of epochs: 25
- Batch size: 16
- Learning rate: 1e-3
- Optimizer: Adam

### *A. Classification of different types of drones along with their flying modes*

Table I shows the results obtained from different machine learning and deep learning algorithms for the classification of different drones on the complete data-set consisting of 18 classes including their flight modes.

TABLE I
CLASSIFICATION RESULTS WITH DIFFERENT FLIGHT MODES

| Models | Accuracy % |
|---|---|
| **KNN** | 3.96 |
| **SVM** | 6.7 |
| **Logistic Regression** | 8.4 |
| **ANN** | 31.7 |
| **Naive Bayes** | 57.1 |
| **Random Forest** | 68.8 |
| **Decision Trees** | 82.9 |
| **CNN** | 85 |
| **LSTM** | **87.56** |

Figure 5 shows classification accuracies for the classification of different drones along with their flight modes. The highest accuracy was obtained by the LSTM+CNN-based model as **87.56%**.

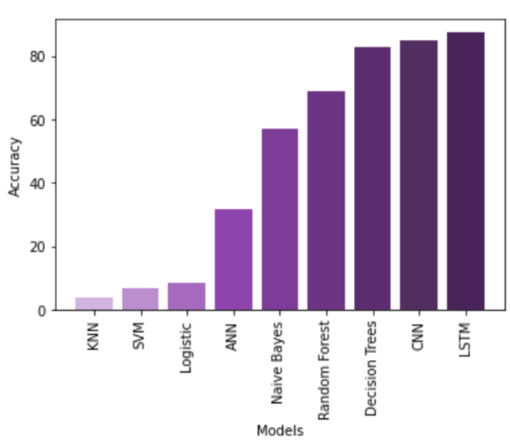



Fig. 5. Accuracies of classification of different drones with their flight modes

Figures 6, 7 and 7 represent the confusion matrices obtained after the classification of the test-dataset on the trained models- DNN, CNN, and LSTM respectively. The matrix shows how many true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN) the model generated using the test data.

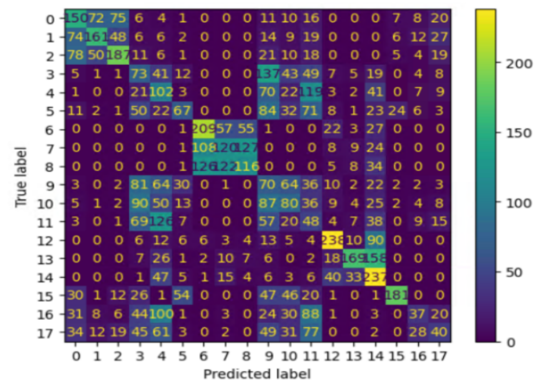



Fig. 6. Confusion matrix of DNN model

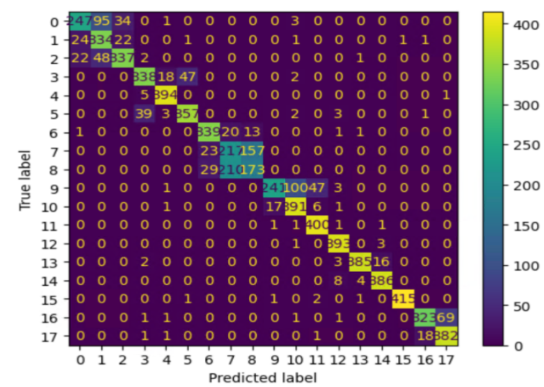



Fig. 7. Confusion matrix of CNN model

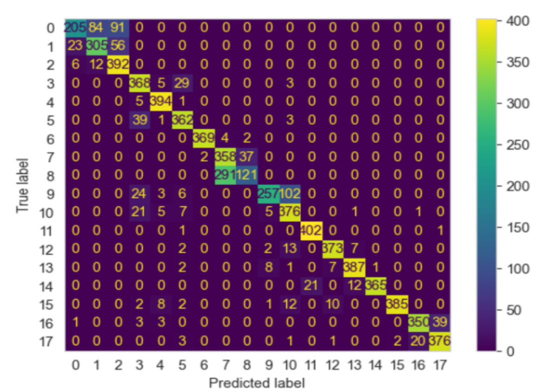



Fig. 8. Confusion matrix of LSTM + CNN model

### B. Classification of different types of drones

Table II shows the results obtained from different machine learning and deep learning algorithms for the classification of different drones on the complete dataset. For this classification, the datasets of different flight modes of the same drone were merged to give the new classes consisting of only different types of drones.

TABLE II
CLASSIFICATION RESULTS OF ONLY DIFFERENT TYPES OF DRONES

| Models | Accuracy % |
|---|---|
| **KNN** | 9.12 |
| **SVM** | 26.3 |
| **Logistic Regression** | 31.4 |
| **ANN** | 37.7 |
| **Naive Bayes** | 59.24 |
| **Random Forest** | 72.9 |
| **Decision Trees** | 92.8 |
| **CNN** | 95.25 |
| **LSTM** | **97.04** |

Figure 9 shows classification accuracies for the classification of different drones. The highest accuracy was obtained by the CNN-based model as **97.04%**.

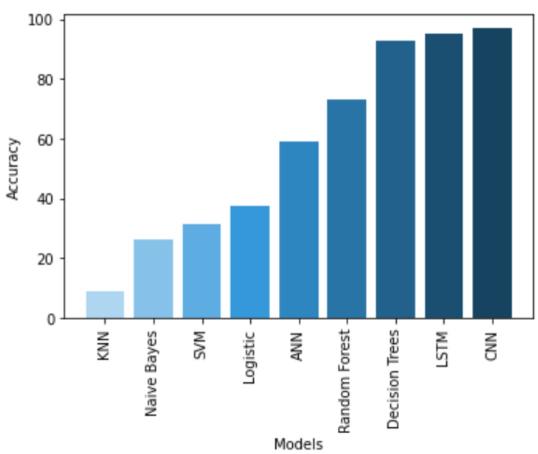



Fig. 9. Accuracies of classification of different drones

Figures 10, 11 and 12 represent the confusion matrices obtained after the classification performed on the test-dataset by the trained models- DNN, CNN, and LSTM respectively.

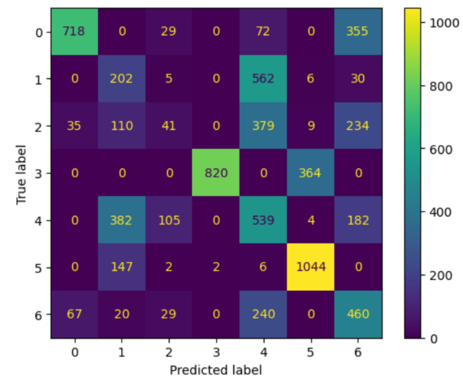



Fig. 10. Confusion matrix of DNN model for only drones classification

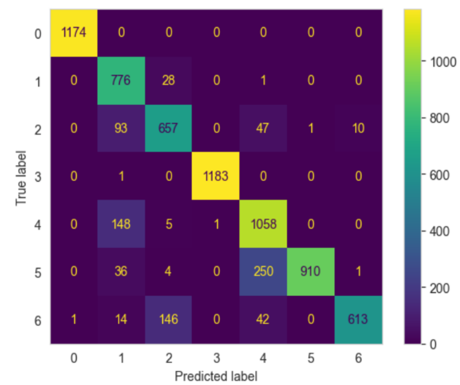



Fig. 11. Confusion matrix of LSTM model for only drones classification

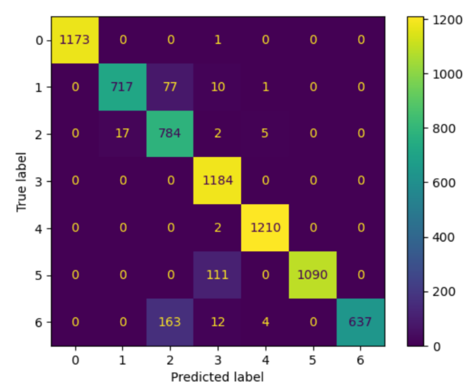



Fig. 12. Confusion matrix of CNN model for only drones classification

## VII. CONCLUSION

The best results for the classification of different types of drones along with their flying modes were given by: CNN+LSTM model with a validation accuracy of 87.56%. Also, for the classification of only different types of drones, the best results were by CNN model as 97.04%. From the tables I and II we can infer that the classification of only drones while ignoring their different flight modes gives considerably better results with a difference in the accuracy of 10% than the classification of drones along with their flight modes.

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