Classification of Flying Objects Using Data from UAV Mounted Radar

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Abstract— **Unmanned aerial vehicles (UAVs)/Drones have been broadly used in modern civilization over the past few years due to their low cost and ease of accessibility, which has raised concerns about privacy and security. It needs to classify flying objects, such as helicopters, birds, UAV/drone, etc., in order to maintain a watchful eye on the invader UAV/drone in the restricted area. In this paper classification of the flying object is done using Hybrid Convolutional Neural Network-Memetic (CNN-Memetic) Algorithm based on Micro-Doppler Signature (MDS) for various arrangement of radar array in order to verify the significance of direction of signal received. The evaluation is done based on data acquired from the radar borne on the drone by varying different specifications.**

Keywords—***Classification, Convolutional Neural Network-Memetic (CNN-Memetic) Algorithm, Micro-Doppler Signature (MDS), Radar***.

I. INTRODUCTION

Unmanned aerial vehicles (UAVs) are stimulating industries all over the world. By outfitting drones with cutting-edge devices like GPS, radar, cameras, and lidar, drone technology is constantly developing. Their wide use in photography, mapping, agriculture, transportation, military surveillance, and leisure activities are only some of their many applications. Despite the useful uses of drones, there is an increasing amount of misuse of drones that is being reported on a global scale [1].

Drone usage presents serious security, privacy, and safety risks. Globally, the usage and management of drones has faced regulatory problems in recent years. Although there are some worldwide guidelines regarding the use of drones, these regulations still need to be developed using various technologies that could be used to improve their application. assisting in the detection and enforcement of any violations. Drone study and development are entering a new age thanks to the harmful use of drones. The process of determining the use or occurrence of drones through the strengthening of technology is known as drone detection and is frequently referred to as an anti-drone method. The majority of the methods for detecting drones that have been recognized in recent years use algorithms grounded on modes like sound, micro-Doppler Signature (MDS), vision, and Radio Frequency (RF) signal. Radar sensors continue to be a vital part of drone scrutiny systems [2]. As is well known, this method is fundamentally based on the electromagnetic principle of backscattering, which ensues when a radar beam illuminates an object. The key challenge for tiny drones is that its radar cross section is low because of which probability of detection decreases. As a result, novel radar setups have been designed to analyse MDS by utilising backscatter from moving objects such as propellers and rotors. The detection problem has been discussed in a few works as a component of a larger classification problem [3]. A micro-Doppler-based approach is suggested in [3] to identify and categorise drones without the use of CFAR statistic synthesis. The utilisation of a sensor network made up of inexpensive radar sensors allows for the detection and differentiation of drones from other target types that are prevalent in metropolitan settings. Data is gathered using a multistatic radar system (NetRAD) in [4], a follow-up study to [5]. In [6] static array of HB100 radar is used for categorizing flying object based on MDS with hybrid Convolutional Neural Network-Memetic (CNN-Memetic) Algorithm. This work is an extension of the previous work in a dynamic situation, where the array of radar is placed on the UAV. Different configurations of the radar array mounted on a UAV, such as the Uniform Linear Array (ULA) and the Uniform Rectangular Array (URA), are used to categorise flying objects. As the object is being classified on a moving platform, the effects of different orientations or placements of the radar antenna array are examined. For the experimentally obtained data from three different flying objects (Drone, Helicopter, Artificial Bird), the accuracy of CNN-Memetic algorithm is assessed using HB100 radar placed on UAV utilising different array configurations, i.e., ULA and URA.

The rest of the paper is organized as follows. Section II contains the description of the dataset Section III, contains the explanation of the hybrid CNN-Memetic algorithm. Section IV contains the results and discussion and finally, section V concludes the work.

II. DATASET DESCRIPTION

Fig. 1 shows the block diagram of the experimental setup for locating the flying object. The micro-Doppler effect of flying objects (such a bird, a helicopter, or a drone) is recorded by HB100 radar placed on a UAV. After capturing the micro-Doppler effect from the designated objects, the transmitted signal returns to the radar and is available at the IF terminal of the device. The radar is linked to the amplifier circuit to strengthen the signal because its output is in microvolts. The amplifier circuit's output is connected to the Zigbee module in order to transmit the data to the Personal Computer (PC) for further processing in MATLAB. $\lambda/2$ is considered as the spacing because it has the ideal mutual coupling between the antenna elements since $< 0.3\lambda$ inter-

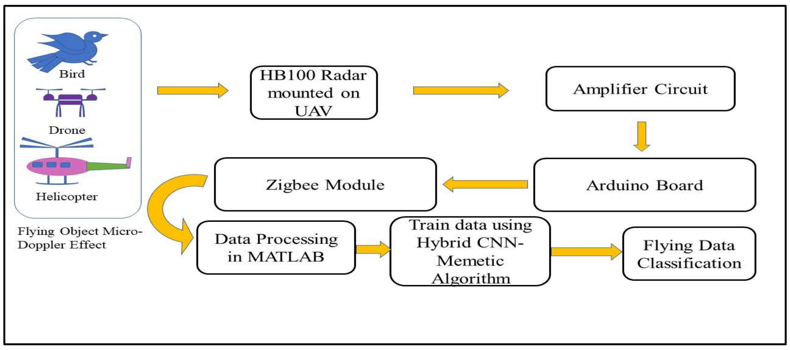

Fig.1. Block Diagram

element spacing affects the directivity of antenna array and degrades the performance of the system [7]. 20000 samples were collected, where 7500, 7500, and 5000 are collected from drones, helicopter and artificial bird, respectively for ULA and URA arrangement mounted on UAV and at three different angles 0°, 30° and 45° individually. So, the total collected samples were 120000. Finally, attributed to the experimental setup, in order to detect the object, UAV mounted radar was at a distance of 15 m with a speed of 25 m/s. Fig 2 - 7 shows the representation of the experimental setup. The artificial bird dataset collection utilising the ULA and URA HB100 radar configuration is shown in Fig 2 and and 3. The dataset for the drone employing the ULA and URA configuration is shown in Fig 4 and 5. The collection of helicopter datasets employing ULA and URA setups is shown in Fig 6 and 7.

Fig. 2: Experimental set up for Artificial Bird with ULA arrangement

Fig. 3: Experimental set up for Artificial Bird with URA arrangement

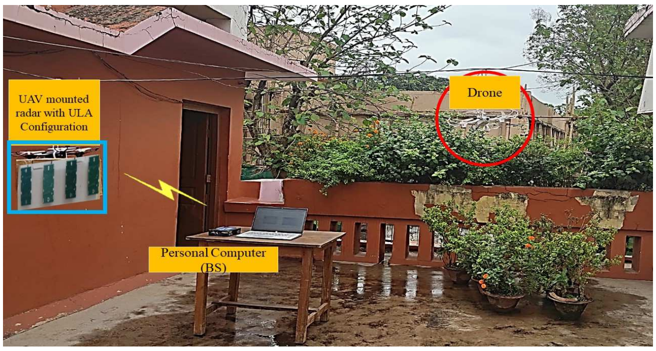

Fig. 4: Experimental set up for Drone with ULA arrangement

III. HYBRID CNN-MEMETIC ALGORITHM

In this section CNN-Memetic Algorithm [6] is used to extract flying object categorization features from real-time data collected by the experimental setup through the radar-based data obtained from the moving platform (i.e., UAV mounted radar). The algorithm is depicted in Algorithm 1.

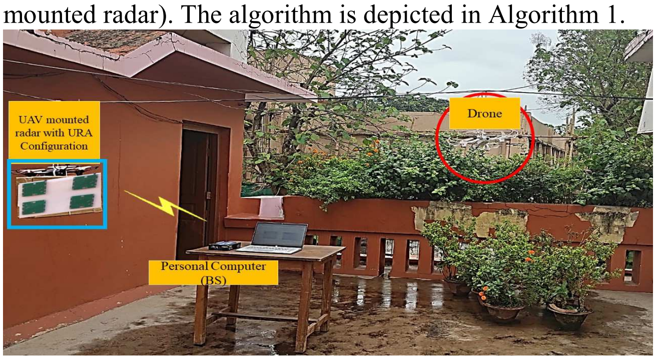

Fig. 5: Experimental set up for Drone with URA arrangement

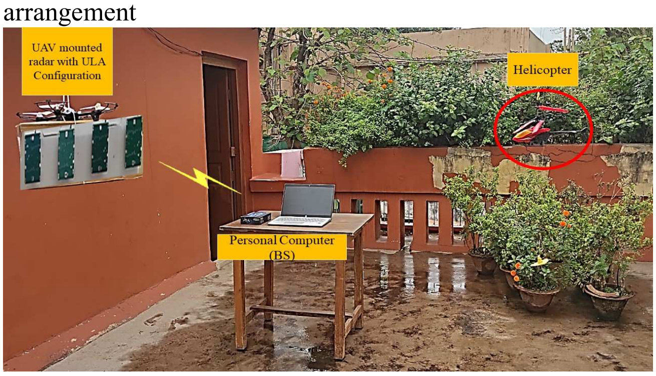

Fig. 6: Experimental set up for Helicopter with ULA arrangement

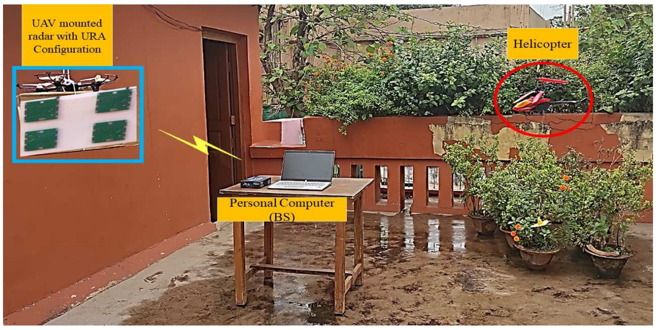

Fig. 7: Experimental set up for Helicopter with URA arrangement

Algorithm 1 Hybrid CNN-Memetic Algorithm

1: Initialize the number of filters and its size, for m and s number of iterations and generations respectively.

2: Randomly initialization of population of weight W

$$W = W_1, W_2, \dots, W_M$$

3: for $h = 1\ to\ gen_{max}$

4: for $m = 1\ to\ M$

5: Evaluation:

(a) CNN:

for n = 1 to 6

Convolution: $\boldsymbol{Z} = W_m.\boldsymbol{Y} + \boldsymbol{B}$

ReLU: $\boldsymbol{Z}' = \begin{cases} 0\ if \boldsymbol{Z} \leq 0 \\ \boldsymbol{Z}\ if \boldsymbol{Z} > 0 \end{cases}$

Pooling: $X = max(Z')$

end for

(b) Output Prediction: TP, TN, FP, FN

(c) Fitness Function: Calculate the accuracy using (13) in [6].

$$Q(s) = [FF_1(s), FF_2(s), \dots, FF_m(s)]$$

6: end for

7: Selection: $\boldsymbol{Q}_{\ sorted} = [\boldsymbol{Q}_1(s), \dots, \boldsymbol{Q}_h(s)]$

8:Crossover:

$$\boldsymbol{Q}_{\ c} = [\boldsymbol{Q}_1(fn(\boldsymbol{W_2})), \boldsymbol{Q}_2(fn(\boldsymbol{W_1})), \dots, \boldsymbol{Q}_h(fn(\boldsymbol{W_{h-1}}))]$$

9: Local Search:

(a) w_n = reshape(W_m) (Convert matrix to vector)

(b) w_{mshuf} = W_m (randperm(length(W_m)))(shuffle randomly the weight vector)

10: Mutation: $w_{new} = \psi[w_{mshuf}]$

W_m = reshape(w_{new}) (Convert vector to matrix)

11: end for

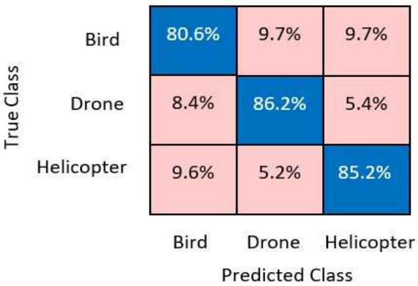

Fig. 8: Confusion Matrix for ULA arrangement at 0°

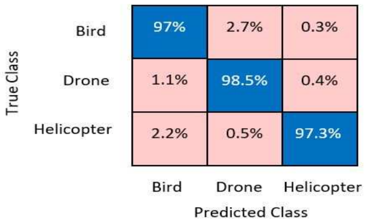

Fig. 9: Confusion Matrix for ULA arrangement at 30°

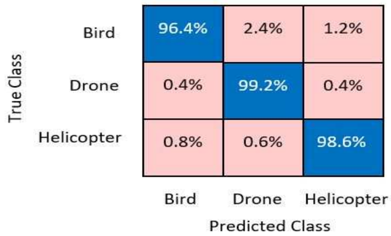

Fig. 10: Confusion Matrix for ULA arrangement at 45°

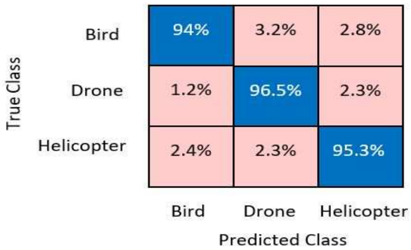

Fig. 11: Confusion Matrix for URA arrangement at 0°

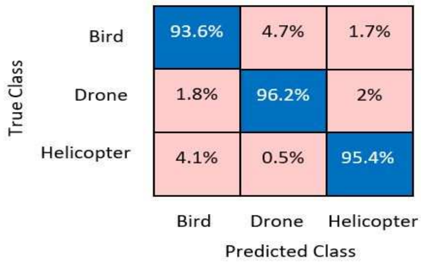

Fig. 12: Confusion Matrix for URA arrangement at 30°

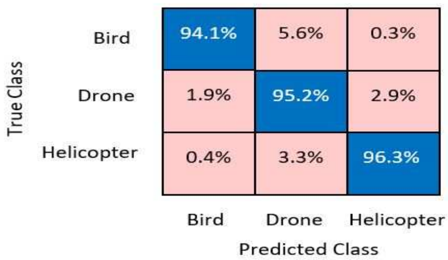

Fig. 13: Confusion Matrix for URA arrangement at 45°

Firstly, the filter weights are generated randomly with known weights and considered as initial population. The MDS data of flying object is passed through the convolutional layer same as in [6]. Followed by the max pooling and ReLU is considered as the activation layer.

Based on the fitness function (FF) sorting is done until the required number of parents are required. Crossover is performed in the weight matrix to search locally. Then with the new configuration of the population called mutation, accuracy is analysed until the maximum number of iterations.

Table. 1. Classification accuracy based on Batch size with various iterations for experimental dataset

Batch	Iterations	0°		30°		45°	
		ULA	URA	ULA	URA	ULA	URA
32	100	63.4%	85.4%	88.1%	85.8%	89.61%	86.8%
32	250	70.59%	86.04%	88.5%	86.2%	90.03%	87.2%
32	500	72.76%	90.83%	93.4%	91.04%	93.43%	91.7%
32	1000	76%	91.6%	94.2%	91.8%	95.2%	92.4%
64	100	77.6%	91.9%	94.5%	92.1%	95.7%	93.01%
64	250	78.72%	92.09%	95.3%	92.8%	96.01%	93.1%
64	500	81.3%	94.04%	96.6%	93.08%	97.11%	93.36%
64	1000	83.24%	94.22%	96.72%	93.7%	97.2%	94.03%
128	100	83.5%	94.4%	96.81%	94%	97.41%	95.04%
128	250	83.8%	94.72%	97%	94.1%	97.53%	95.09%
128	500	84%	95.26%	97.6%	95.06%	98.06%	95.2%
128	1000	84.04%	95.14%	97.23%	95.01%	96.74%	95.06%

Table. 2. Classification Accuracy based on Mutation Rate (MR) for experimental dataset

Batch	Iteration	ULA						URA					
		MR=0.01			MR=0.1			MR=0.01			MR=0.1		
		0°	30°	45°	0°	30°	45°	0°	30°	45°	0°	30°	45°
32	100	60.2%	87.7%	88.95%	63.7%	88.1%	89.61%	84.32%	85.78%	86.43%	85.4%	85.8%	86.8%
32	500	63.76%	92.77%	93.35%	72.76%	93.4%	94.43%	85.35%	86.9%	87.45%	90.83%	91.04%	91.7%
64	100	69.59%	94.46%	95.67%	77.6%	94.5%	95.71%	86.09%	87.58%	88.4%	91.9%	92.1%	93.01%
64	500	75.09%	96.4%	96.03%	81.3%	96.6%	97.11%	87.49%	88.09%	89.4%	94.04%	93.08%	93.36%
128	100	80.07%	96.73%	97.14%	83.5%	96.81%	97.41%	88.03%	89.53%	90.11%	94.4%	94%	95.04%
128	500	82.6%	96.07%	97.06%	84%	97.6%	98.06%	89.68%	90.47%	91.27%	95.26%	95.06%	95.2%

Table. 3. Classification Accuracy based on Initial population size for experimental dataset

BATCH	ITERATION	ULA									URA								
		PS=25			PS=50			PS=60			PS=25			PS=50			PS=60		
		0°	30°	45°	0°	30°	45°	0°	30°	45°	0°	30°	45°	0°	30°	45°	0°	30°	45°
32	250	69.1%	85.16%	86.11%	70.59%	88.5%	90.03%	70.2%	87.4%	88.69%	77.7%	82.03%	83.1%	86.04%	86.2%	87.2%	84.3%	85.07%	85.8%
32	500	70%	87.77%	89.3%	72.75%	93.4%	93.43%	72.69%	92.5%	93.09%	78.6%	83.18%	85.49%	90.83%	91.04%	91.7%	85.1%	89.7%	89.77%
64	250	76.6%	88.32%	90.01%	78.72%	95.3%	96.01%	76.74%	93.6%	94.83%	82.2%	84.04%	86.11%	92.09%	92.8%	83.1%	91.72%	90.16%	91.13%
64	500	80.21%	91.09%	93.76%	81.3%	96.6%	97.11%	78.02%	94.36%	96.01%	83.02%	87.3%	90.62%	94.04%	93.08%	93.36%	92.68%	91.37%	92.35%
128	250	82.6%	93.63%	95.15%	83.8%	97%	97.53%	80.43%	95.8%	96.15%	88.1%	89.6%	91.39%	94.72%	94.1%	95.09%	93.55%	92.13%	93.19%
128	500	83.07%	95.28%	96.66%	84%	97.6%	98.06%	82.32%	96.27%	98.27%	94.53%	91.04%	93.2%	95.26%	95.06%	95.2%	94.03%	93.18%	93.4%

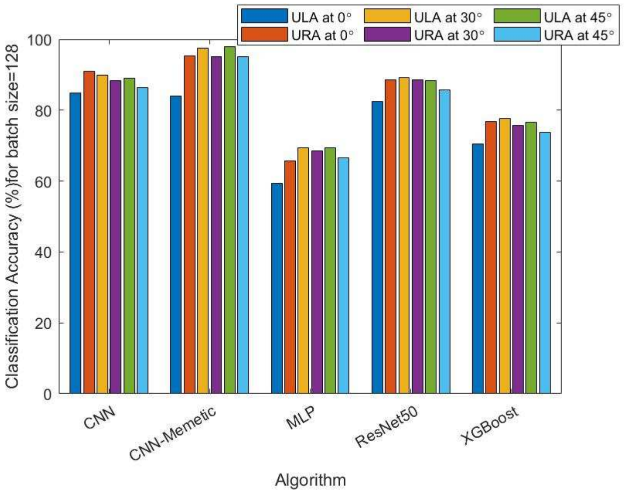

Fig. 14: Classification Accuracy for Batch Size=128 at various angles

IV. Result And Discussion

MATLAB 2022b software is used to analyse the MDS data. The suggested approach is used to train the MDS datasets in order to determine classification accuracy. The dataset is divided into 70:30 with 50 epochs for training and testing. Initially, the weights are considered at random. The confusion matrix depicted from Fig 8-13, as well as the impact of the original population and MR, are evaluated for assessing classification accuracy. The MR is the number of times the response must be modified in order to produce the new progeny, i.e., a more correct result. The mutation is preferred in order to minimise trapping at a local minimum. Mutation following crossover and local search increases variety and prevents premature convergence. The mutation rates of 0.01 and 0.1 were used in the analysis.

Table 1 represents the classification accuracy based on the batch size. For evaluation three batch sizes are considered i.e., 32, 64, and 128 with various iterations, targets located at 0°, 30°, and 45°. It became apparent that towards the end-fire direction, i.e., 0°, ULA configuration accuracy is more acute than in other directions, i.e., 30° and 45°. Whereas URA excels in the end-fire direction. This is due to the fact that in ULA, all of the elements of the antenna do not operate evenly. It makes better use of edge components. As a result, is not treated equitably. This restricts the ULA's field of view. It is unable to identify or detect adequately from all angles. URA, on the other hand, has a symmetry array construction, therefore the field of view is nearly 360 degrees with no variation in beamwidth or sidelobe level. An additional finding is that as the assortment of batch sizes increases, so does the accuracy up to 128 batch sizes and 500 iterations, after which the accuracy declines in all circumstances. At 128 batch size (500 iterations), this experimental analysis achieves greater accuracy. This is due to the proposed algorithm's weight being updated both locally and globally.

Then, different values of the MR are used to analyse the accuracy, such as MR=0.01 and 0.1. From Table 2, it can be shown that classification accuracy is higher at MR=0.1 than it is at MR=0.01. After crossover, mutation is crucial in creating variety in the search space and allowing for further exploration. Accuracy is poor at MR=0.01, possibly as a result of the early convergence. Premature convergence may be avoided by high MR in order to obtain good accuracy. Similar to Table 1, Table 3 analyses the effect of initial population size from several perspectives. There are three various population sizes taken into account, including PS=25, 50, and 60. According to Table 3, the initial population size of 50 offers the best accuracy in every situation. Accuracy for PS=25 is lower than PS=50 or PS=60. The lack of diversity in the search space is to blame for this. The difficulty of classification rises with population size, resulting in lower accuracy at PS=60 than PS=50.

Comparison is done for the CNN-Memetic Algorithm with the existing algorithms as depicted in Fig. 14. It is observed that CNN-Memetic Algorithm outperforms in all the scenarios mentioned above. The best accuracy obtained is 95.26 % (URA 0°), 97.6% and 98.06% (ULA 30° and 45° respectively) at PS =50, and batch size =128 at 500 iterations. From the analysis it could be said that CNN-Memetic Algorithm is robust in both static [7] and dynamic condition for classification of flying object.

V. Conclusion

The intruder surveillance system in the restricted region depends on the classification of the flying object. With respect to this application, the CNN-Memetic Algorithm, which performs better than the existing algorithms, is used to classify the flying object. The experimental evaluation is conducted for both ULA and URA towards the various directions, with URA performing better in the 30° and 45° and ULA performing better in the end-fire direction 0°. The CNN-Memetic Algorithm is reliable for classifying flying objects in both static as well as dynamic data acquisition conditions.

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