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Deep Learning Empowered Fast and Accurate Multiclass UAV Detection in Challenging Weather Conditions

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***Abstract*—The emergence of Unmanned Aerial Vehicles (UAVs) raised multiple concerns, given their potentially malicious misuse in unlawful acts. Vision-based counter-UAV applications offer a reliable solution compared to acoustic and radio frequency-based solutions because of their high detection accuracy in diverse weather conditions. The existing solutions work well on trained datasets, but their accuracy is relatively low for real-time detection. In this paper, we model deep learning-empowered solutions to improve the multiclass UAV's classification performance using single-shot object detection algorithms (YOLOv5 and YOLOv7). They efficiently and correctly differentiate between multirotor, fixed-wing, and single-rotor UAVs in challenging weather conditions. Experiments show that the suggested technique is reliable with an overall best average-classification precision of 86.7%, 88.5% average recall, 91.8% average mAP, and 58.4% average-IoU.**

***Index Terms*—UAV, Drones, YOLOv7, Multiclass classification, Target detection.**

I. Introduction

Unmanned air vehicles (UAVs) have several applications in mobile communication, academia, and in vertical industries. Besides those applications, the uncontrolled use of UAVs can pose serious security threats to key public and private security sensitive organizations. Federal Aviation Administration (FAA) forecasts that the fleet of small UAVs should quadruple by 2021, increasing from 1.1 million units in 2016 to 3.5 million by 2021 [1]. Nonetheless, the availability of drones has posed a significant privacy and secrecy dilemma. Moreover, to emphasize the significance of the problem, we noticed that there was serious security threats from uncontrolled usage of UAVs, that severely damaged the infrastructure [2] [3] [4]. Drones were initially developed for defense and counterinsurgency, which was controlled by aerospace and defense industries. Usually, the most common types of UAVs adopted in the global military applications are multirotor, fixed-wing, and single-rotor UAVs as shown in Fig. 1. Based on the above facts, we conclude that it is critical to have a drone detection system which should be capable of classification and localization of any type of drone, particularly those posing security threats. UAV detection is an object detection problem that has lately made significant progress. As a result, the object detection task is an essential component of computer vision in which many objects are categorized and their positions are determined. Object localization can be interpreted in a variety of ways, such as by creating a 2D or 3D bounding box around the object of interest or by labeling every pixel in the picture that includes the object. According to Lykou *et al*. 6% UAV detection systems are based on acoustic sensors, 26% are radio frequency (RF), 28% are radar-based, and 40% are visual [5] [27]. YOLO (You Only Look Once), a single shot object detection and deep learning algorithm is popular because of its durability, validity, quick detection, and rapidity which ensures real-time detection [6]. YOLO consumes low computation resources than many deep-CNN detectors, which often demand 4 GB of RAM and computer graphics cards [7]. In this paper, we perform a multiclass and multiscale UAV identification based on the most recent version of the YOLO detector [8]. Below are the main contributions of this paper.

- To boost detection performance, we first created a dataset with multiple types of UAVs in challenging weather conditions that may exist in Pakistan's airspace and then eliminated class imbalance to correctly train the two latest versions of YOLO i.e v5 and v7.
- Detailed performance evaluation of both models in terms of true positive rate (sensitivity), precision, recall, mean average precision (mAP), and intersection over Union (IoU).
- We are the first to provide a multiclass UAV detection and classification, which also include a comparative study of YOLO v5 and V7 compared on a multiclass UAV dataset.

II. Literature Review

Drones have been used for both educational and commercial reasons in a wide range of disciplines. The last decade has seen a surge in studies looking at effective and precise methods for UAV recognition. However, due to the nature of the locations in which drones often operate, identification can be

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Fig. 1. Military UAVs (a) Multi-Rotor [22](b) Fixed-Wing [23] (c) Single-Rotor [24].

a challenge. As a result, sophisticated methods are required for UAV identification, whether they are flying alone or in a swarm. Singha *et al*. developed a YOLOv4-based auto-drone-detection system and tested it on drone footage of drones and birds. This architecture was trained using 479 bird and 1916 drone images gathered from publicly available sources. The achieved F1 score, mAP, recall, and precision values of 79%, 74.36%, 68%, and 95%, respectively, in [9]. YOLOv4 is used to detect and identify UAVs in visual images of helicopters, multirotors, and birds. This network has an mAP of 84% and an accuracy of 83%. This paper excellently addresses the detection problem, but it can only identify multirotor and helicopter drones; it does not perform well for other UAV types [10]. In [11], researchers solved the problem of drones vs. birds by proposing a visual drone detector based on YOLOV5 and an air-to-air UAV dataset containing small objects and complex backgrounds. They additionally trained a model using faster region convolutional neural network (R-CNN) and feature pyramid networks (FPN) techniques. YOLOv5 outperformed the faster R-CNN + FPN in both simple cases and complex settings, with a 0.96 recall and a 0.98 mAP. Coluccia *et al*. classified multirotor and fixed-wing UAVs present in video clips by using YOLOv3 and YOLOv5 architectures. The monitoring system was linked to a warning algorithm that triggers the alarm whenever it detects a drone. In terms of proper detection rate and average accuracy, the results show increased performance, but it still needs additional data in complex weather conditions for further improvements [12]. The neural network was trained, tested, and evaluated by using datasets containing different kinds of UAVs (multirotor, fixed-wing, helicopters, and vertical takeoff landing aircraft) and birds and achieved an 83% mAP [13]. The authors in [14] proposed Yolov5-based multirotor UAV target detection. They replaced the baseline model's backbone with EfficientLite for parameter reduction and computation, introduced adaptive feature fusion to facilitate the fusion of feature maps at various scales, and added angle as a constraint to the baseline loss function. The results showed that EfficientLite struck an optimal balance between the number of parameters and detection accuracy, with enhanced target identification in comparison to the baseline model. [15] proposed one-stage detector-based deep learning with simplified filtering layers. For lower complexity, an SSD-AdderNet was designed to efficiently reduce multiplications performed in the convolutional layer. The video data contained varying sizes of drones. The AdderNet's accuracy was lower than other well-known methods for training on RGB images, but it achieved noteworthy complexity reduction. In contrast, when tested on IR pictures, the SSD performance of AdderNet is much higher than that of competing algorithms. Real-time image classification was performed by training a deep learning model on stereoscopic pictures [16]. This research confirmed that synthetic pictures may be effectively used to speed up the solution of image classification issues for imbalanced, skewered, or no-image dataset problems. A convolutional neural network (CNN) based model presented in [17] detected UAVs present in video footage. This model was trained with computer-generated visuals and then tested using a real-world drone dataset. Drones were categorized as either DJI Mavics, DJI Phantoms, or DJI Inspires with an average accuracy of 92.4%. In [18], researchers used multi-stage feature fusion utilizing multi-cascaded auto-encoders to eliminate rain patterns in input pictures and used ResNet as a feature extractor. This system can successfully block the entry of UAVs into the airspace with an average identification accuracy of 82% and 24 FPS.

After screaming through the literature, we notice that significant improvement in drone detection technology and solutions is required. Multirotor UAVs (quadcopters) have a substantial market share, so these UAVs need to be closely watched those for safe operation as small size drone detection has multiple difficulties. Consumer-grade UAVs often fly at low altitudes, producing complex and changeable backgrounds and frequently being obscured by things like trees and homes. Regular aircraft, such as planes and helicopters, may often fly over a location, such as an airport or a hospital. The detection technique should be capable of distinguishing between them and different types of UAVs. UAVs may emerge from all directions, so monitoring systems should be capable of detecting multiple directions at once. Our problem statement is the multiclass detection and classification of UAVs under complex weather conditions. That's why we used the two latest and fastest object detection algorithms, YOLOv5 and YOLOv7.

III. Single-Stage Object Detection Algorithms

A. *YOLOv5*

YOLOv5 is one of the most recent versions of the YOLO family which is presented in Fig. 2. Likewise, it has been known to exceed every iteration of itself due to advancements in its architecture. YOLOv5 is distinct from earlier releases because it integrated PyTorch instead of Darknet. It uses CSPDarknet53 as its structural support in the backbone block which eliminates the redundant gradient information present in large backbones. It also incorporates gradient change into feature maps, which speeds up the inference rate, improves accuracy, and shrinks the size of the model by reducing the number of parameters. It boosts the information flow by using the path aggregation network (PANet) in the neck block. A novel feature pyramid network (FPN) with numerous bottom-up and top-down layers is adopted by the PANet architecture which enhances the model's transmission of low-level features [19].

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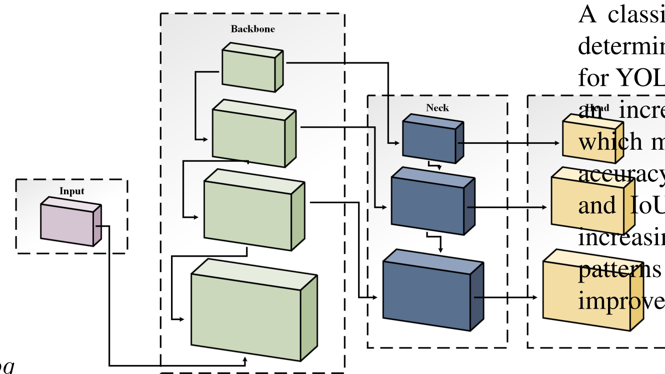
B. YOLOv7

YOLOv7 is a real-time single stage object detection algorithm which is claimed to outperform all YOLO models in precision and speed and achieved the maximum average precision of accuracy of 56.8% [20] on COCO dataset. YOLOv7 has head, a neck, and a backbone in its architecture as shown in Fig2. The projected model outputs are located in the head. YOLOv7 is not constrained to just one head because it was inspired by Deep Supervision, a method used in training deep neural networks. The lead head is in charge of producing the ultimate product, while the auxiliary head is utilized to support middle-layer training. To further improve the model training, a Label Assigner method was developed that assigns soft labels after taking ground truth and network prediction outcomes. The Extended Efficient Layer Aggregation Network (E-ELAN) performs the main computation in the YOLOv7 backbone. By employing ”expand, shuffle, merge cardinality” to accomplish the capacity to constantly increase the learning capability of the network without breaking the original gradient route, the YOLOv7 E-ELAN architecture helps the network improve learning.



detector.jpg

Fig. 2. Block Diagram of Single Stage Object Detector Algorithms.

IV. Dataset and Model Training

In this paper, we evaluate the two most recent models of YOLO, named YOLOv5 and YOLOv7. Both of them require the dataset to be available with the class category, bounding boxes, and annotation files. We used Roboflow [21], an open-sourced dataset platform, to make a dataset that had three different classes of UAV, i.e., multirotor, single-rotor, and fixed-wing. For this, we merged three different datasets depicted in Fig. 3: single-rotor UAVs (1407 images) [22], multirotor UAVs (1263 images) [23], and fixed-wing UAVs (1753 images) [24], and that dataset contained 4423 images. We use 70% of the dataset for training (3096 images), and 30% for testing (1372). Before training, the images underwent preprocessing, including a 416 $\times$ 416 resizing, contrast enhancement, and then model training. To have smooth data training without larger loss and over-fitting, we set the hyper-parameters in the below-discussed manner. The initial learning rate (lr0) for Adam and the SGD optimizer was set at 0.01. For YOLOv7, the one-cycle learning rate (lrf) is 0.1 and for YOLOv5, it is 0.01 at the end. With a weight decay of 0.0005, the momentum for the SGD optimizer was set to 0.937. The first warmup momentum is 0.8 and the initial warmup bias is 0.1 at the warmup epoch of 3.0. The box loss gain is 0, the class loss gain is 0, the object loss gain is 1, and the focal loss gamma is 0. The anchor-multiple threshold is 4.0, the IoU training threshold is 0.20, and there are 0 anchors in each output grid. The dataset was trained on Google Colab with a K80 GPU and 12GB RAM, and then we evaluated the trained models' performance using standard evaluation metrics used in the literature like precision, recall, mAP, and IOU.

The box loss of YOLOv5 during training went from 0.090.04, while for YOLOv7 it was 0.005-0.035, shown in Fig. 4. YOLOv7 has low box loss, which means that it has excellent capability to locate an object's center point and with a predicted bounding box that covers the specific object quite well. The objectness loss for YOLOv5 is 0.019-0.014 during training and YOLOv7 has 0.008-0.006. Each box has an associated prediction called ”objectivity”. YOLOv7 performs quite well in scoring objects with high precision values. That's why its object loss is quite low as compared to YOLOv5. A classification loss is applied to train the classifier head to determine the type of target object. Its values are 0.035-0.010 for YOLOv5 and 0.0150-0.0025 for YOLOv7. YOLOv5 shows an increased classification loss as compared to YOLOv7, which means that YOLOv7 will have high threshold detection accuracy in unknown scenarios. The precision, recall, mAP, and IoU graphs over 10 epochs for both models show an increasing trend, which implies that both models' learning patterns are going well. These results still have room for improvement, which will be addressed in future work.

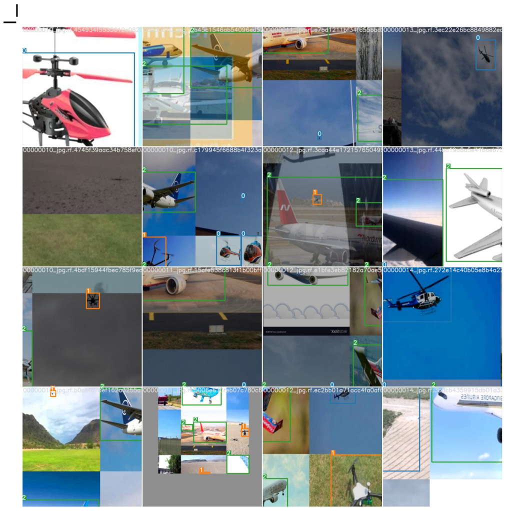


Fig. 3. Annotated Dataset: Bounding boxes on Ground truth images [22]-[24].

V. Evaluation of Trained Models

The models' evaluation is performed using multiple evaluation metrics like confusion matrix, precision, recall, mAP, and

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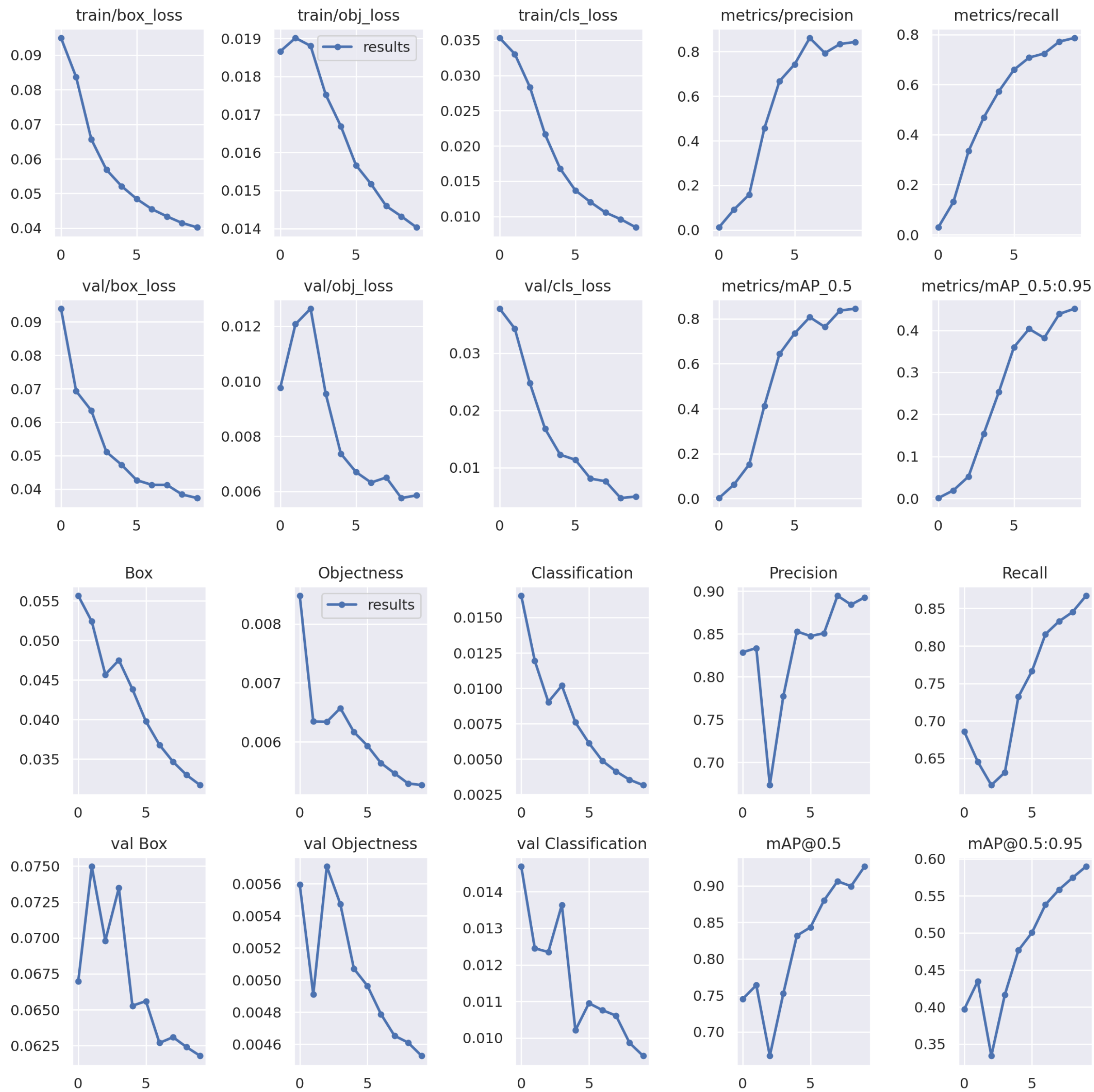

Fig. 4. Training Performance w.r.t epochs (a) YOLOv5 (b) YOLOv7.

IoU values. Table I and II give us the detailed performance evaluation of each target class. YOLOv5 achieved the highest precision of 92.7% while detecting single-rotor UAVs, the highest recall of 92.1%, the highest mAP of 93.8%, and the highest IoU of 50% for multirotor UAVs. This means that YOLOv5 has the best capability for immediate multirotor UAV detection for real-time scenarios as shown in Table I. YOLOv7 achieved the highest precision of 94.4% and the highest IoU of 60.5% when faced with single-rotor UAVs. It achieved the highest recall of 92.5% and the highest mAP of 94.9% for multirotor UAVs. This means that YOLOv7 has improved detection competence for both single and multirotor UAVs in challenging and complex conditions. For fixed-wing UAVs, YOLOv5 achieved the highest precision of 80% and YOLOv7 achieved the highest recall value of 84.3%, the highest mAP of 86.6%, and the highest IoU of 59%.

TABLE I
EVALUATION METRICS FOR YOLOV5

Class	Precision(%)	Recall(%)	mAP(%)	IOU(%)
Fixed wing	80	69.8	75.6	40
Multirotor	81.4	**92.1**	**93.8**	**50**
Single-rotor	**92.7**	74.4	84.8	45.5
Average	84.7	78.8	87.4	42.5

If we compare the overall/average metrics evaluation as presented in Fig. 5, then YOLOv7 achieved the best average

TABLE II
EVALUATION METRICS FOR YOLOv7

Class	Precision(%)	Recall	mAP(%)	IOU(%)
Fixed wing	78.1	84.3	86.6	59
Multirotor	90.3	**92.5**	**94.9**	55.7
Single-rotor	**94.4**	88.7	94.0	**60.5**
Average	**87.6**	**88.5**	**91.8**	**58.4**

precision of 87.%, best average recall of 88.5%, best average mAP of 91.8%, and best average IoU of 58.4% for multiclass detection and classification of UAVs. This makes YOLOv7 the best model when anyone wants to perform multi-sized and multiclass UAV target detection in the sky, urban, and complex weather conditions. In real-time whenever we want a model to recognize all UAVs operating inside the specified territory, the by seeing the precision performance [25] we suggest that YOLOv7 be used. The recall score indicates the learning model's ability to properly identify positives from real positives. Unlike the precision metric, this value assesses the effectiveness of the algorithm based on the correctness of all positive predictions [26]. YOLOv7 has greater recall score which indicates that it has the increased and efficient ability to perform classification between multiple types of UAVs relevant to our application.

Fig. 6 depicts the confusion matrix of the trained models over 10 epochs. Multirotor has the highest true positive rate (TPR) of 97% for the YOLOv5 model, single-rotor has the highest TPR of 82% for the YOLOv7 model, while fixed-wing UAV showed the highest TPR of 91% during YOLOv5 model training. TRP is also called "Sensitivity". That means that the YOLOv7 model is most sensitive to single-rotor and fixed-wing UAVs. Fig. 7 shows the results of the models when they were tested with very small-sized targets for detection and classification. YOLOv7 achieved the best test accuracy of 98% for single-rotor UAV, YOLOv5 achieved the best test accuracy of 87% for multirotor UAV, and YOLOv7 achieved the best test accuracy of 90% for fixed-wing UAV. Both YOLO v7 and v5 were trained using 10 epochs each. The epochs were completed in 1.341 hours by YOLOv7, compared to 0.314 hours by YOLOv5. YOLOv5 utilized 283 total layers and extracts 6465087 training parameters and 6465087 training gradients with 20.8 GFLOPs, while YOLOv7 utilized 314 layers total and extracts 36492560 training parameters and 6194944 training gradients with 103.2 GFLOPs for 10 epochs.

A. Comparison with State-of-the art

The state-of-the-art comparison of the proposed YOLOv5 and v7 with the schemes mentioned in the literature is shown in Table III. It is evident that mAP of YOLOv5 and v7 has outperformed the work given in [9], [10], [11] and [13]. The proposed YOLOv5 scheme has also performed well in terms of F1 score and yielded the highest value compared to both the YOLOv4 and YOLOv5 existing schemes. Moreover, we identified that no prior work has considered YOLOv7 for drone detection and classification. Therefore, in this paper, we implemented YOLOv7 on the same data set and achieved a 91.8% mAP. Present study[1] shows the results achieved by training dataset on YOLOv7 and Present study[2] represents results on YOLOv5.

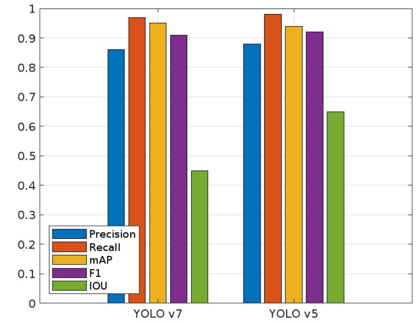

Fig. 5. Average Evaluation Metrics of YOLOv5 and YOLOv7.

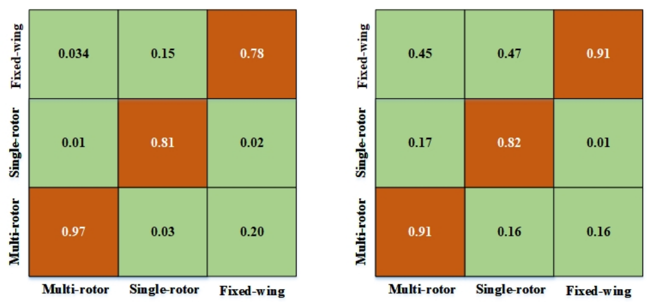

Fig. 6. Confusion Matrix(a) YOLOv5 (b) YOLOv7.

VI. CONCLUSION

In this paper, we show how a single-stage object detector (YOLOv5/v7) based on a deep neural network can detect and identify multirotor, fixed-wing, and single-rotor UAVs. That's why we grounded a multiclass UAV dataset with automatic annotation, and then we made sure that all classes had the same number of images for model training. This step removed the problems of data imbalance and model over-fitting. This dataset contained images with varied, complex, and challenging backgrounds, which increased the trained model's credibility for real-time detection. The results showed that the trained models can perform multiclass classification and detection with high precision and mAP. In our future study, we intend to prove the feasibility of detecting small flying objects through camera images using our improved drone detector in real-time with implementation on leading-edge devices.

VII. ACKNOWLEDGMENT

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TABLE III
COMPARISON WITH START-OF-THE-ART.

Reference	Dataset	YOLO version	mAP (%)	Recall(%)	F1 (%)
Present study[1]	Roboflow	YOLOv7	91.8	88.5	91
Present study[2]	Roboflow	YOLOv5	87	78	92
[9]	Self Collected	YOLOv4	74.36 (↓ 17.44)[1] (↓ 12.64)[2]	68(↓ 20.5)[1](↓ 10)[2]	79 (↓ 12)[1](↓ 13)[2]
[10]	Drone-Data-Set	YOLOv4	84 (↓ 7.8)[1](↓ 3)[2]	84 (↓ 4.5)[1](↓ 6)[2]	83 (↓ 8)[1](↓ 9)[2]
[13]	Self Collected	YOLOv4	83 (↓ 8.8)[1] (↓ 4)[2]	83 (↓ 5.5)[1](↓ 5)[2]	83 (↓ 8)[1](↓ 9)[2]
[11]	Det-fly & Competition	YOLOv5	71 (↓ 20.8)[1](↓ 16)[2]	96 (↑ 7.5)[1](↑ 18)[2]	Not mentioned
[12]	Little Birds in Aerial Images, Competition & Windmills dataset	YOLOv5	93.55 (↑ 1.75)[1](↑ 6.55)[2]	87.4 (↓ 1.1)[1](↑ 9.4)[2]	78 (↓ 13)[1] (↓ 14)[2]

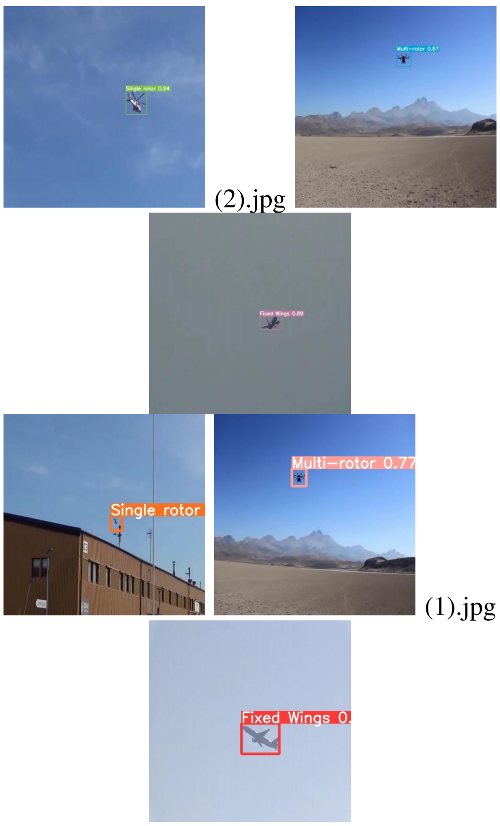

Fig. 7. Detection Results of Single-rotor, Multirotor and Fixed-wing UAVs by (a) YOLOv5 (b) YOLOv7

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