YOLOv5 Based Drone Detection and Identification

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Abstract

Drones are one of the popular devices now a days not only for entertainment purposes but also in various of applications such as engineering, security in airport disaster management, delivery of goods and others. In addition to their useful applications, frightening concern regarding physical infrastructure safety and airports surveillance has arisen due to the frequency of their use in nasty activities. These days, there have been numerous incidents of drones being used improperly at airports and interfering with airline operations. This work suggested a deep learning-based solution for the effective detection and identification of two types of drones, birds and helicopter to solve this problem. Evaluation of the proposed approach with the prepared image dataset demonstrates better efficiency compared to existing detection systems in the literature. Furthermore, due to their physical characteristics and behaviours, drones are frequently mistaken with birds and helicopter . The suggested YOLOv5 method is not only capable of determining if drones are present or absent in the given area, but it can also recognize two types ie, multirotor and single rotor drones, birds and helicopters as helicopter has very much resemblance of single rotor drones . The dataset used in this work to train the network consists of 4000 visible images containing two types of drones as multirotors, Single rotor, helicopters, and also birds. The suggested deep learning method can directly detect and recognize two types of drones and distinguish them from birds and helicopter with a precision score of 0.9757, recall score of 0.98, as well as mAP(Mean Average Precision) scores of 0.98 and 0.62 for @0.5 IOU (Intersection Over Union)and @0.95 IOU respectively.

Keywords- *Deep learning, YOLOv5, precision, reall, mAP, IOU.*

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1.0 Introduction

The number of drones being utilised for military, commercial and security purposes is growing as a result of development of drone technology and production. Due to their effectiveness in applications including airport security, facility protection and integration with security and surveillance systems, several drone. In recent years, the use of different types of drones has received much attention due types have recently drawn a lot of attention. On the other hand, drones can also be seenas a significant threat in these security areas, so it is important to develop a reliable method to identify different types of drones in these applications [7–9]. To avoid drone incursion or to ensure their security, such technologies can be deployed in military systems and airport security . Consequently, the detection, recognition, and identification of UAVs are important while discussing public safety and the threats posed by their existence.

Identification is the process of diagnosing the type of target category. Detection is the process of watching the target, and this target may be suspicious and pose a threat to the security of the target environment. In this paper two types of drones are identified and distinguished from birds and helicopter based on the physical and behavioural similarities. Different sensors like radar,LIDAR,and RF based sensors ,can be used for this purpose. Acoustic sensors and thermal sensors have also been used for drone detection and identification. However, using these sensors is expensive and energy -consuming.

Due to the weight and size requirements, drone integration with these sensors is also constrained, especially in the case of thermal imagery, sensors often have a low resolution. The integration of sensors and drones does not, however, present any issues with the use of visible imagery, and unlike thermal sensors, it has a greater resolution. Visible imaging, however , also has issues including occluded

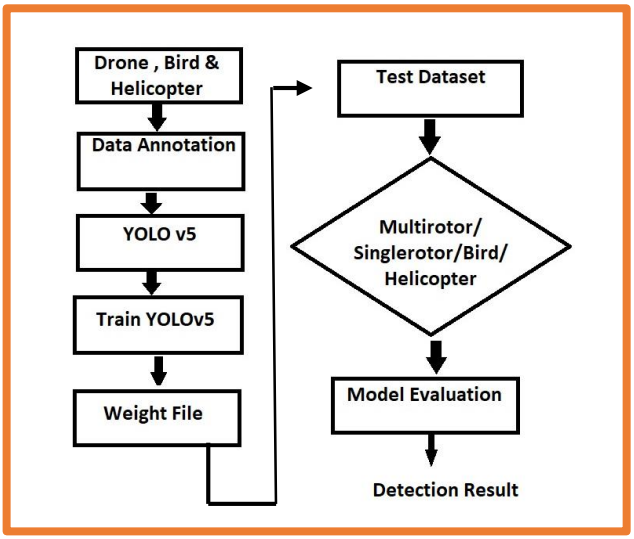
portions,crowded background, and poor lighting inside the image. The technique utilised to find and identify the drone will therefore determine how to solve this issue. Deep learning networks have emerged as the top model for visual processing in the last ten years, including object tracking and identification.

Due to its increased processing power and accuracy, object detection using deeplearning network has drawn a lot of interest Convolutional neural network (CNN) are the most effective deep neural networks are the most effective deep neural network for object detection.Since these networks are effective at extracting features, they have been given additional thought and research for object recognition. As they extract more features than traditional object detection methods, they are more desired for object detection.

Due to the difficulties presented by dense background and the small size of the drones in these images,it is required to employ an appropriate strategy to address these challenges. Due to its photographs, it is required to employ an appropriate strategy to address these difficulties. Due to its greater, precision , speed and precise analysis of the input images, YOLO Deeplearning network is the best solution to these problems. The most recent version among all the networks of YOLO , YOLOv5 offers higher speed and accuracy to detect any object. This study examines drone detection and identification using YOLOv5 Deep convolutional neural network.

2.0 Method

In this paper, a deep learning-based method is proposed due to the difficulties in drone identification and recognition such as crowded background, a near resemblance to birds and helicopters, smaller size of drones, longer distance, and lighting problems in the image. The basic steps of the proposed drone detection and identification method are shown in Figure 1.1 The first step is to correctly prepare the data of Drones (Multi rotor and Single Rotor), Birds and Helicopter for the suggested architecture's input. The network training phase, which is used to detect and identify two different types of drones as well as birds and helicopter, is the next step. The trained model is then put to the test utilising a wide range of drone, bird and helicopter datasets in the another stage. Finally, the model's performance is evaluated, and the detection and recognition process is performed on the input test data.



2.1 Input Preparation

Data collection-A collection of visible images from birds,helicopter and drones is produced to be put into the suggested network during training. The remaining images are utilised for validation, with the remaining images being used for training in total. Total 80% images are used for training and 20% for validation.

2.2 Data Annotation

Preparation of input data involves labelling various images of Multirotor, Single rotor and Birds and Helicopter using Make sense AI. Make Sense AI is a software available online which helps in data labelling.

2.3 Training the Deep Learning Network

The YOLOv5 deep learning network is used in this paper to detect flying drones birds and helicopters in cluttered situations, taking into account the advantages discussed above. The proposed network has an input, backbone, neck, and head that are each divided into four sections.

Backbone- Backbone is used to extract key features from an input image. CSP(Cross Stage Partial Networks) are used as a backbone in YOLO v5 to extract rich in useful characteristics from an input image.

Neck -The Model Neck is mostly used to create feature pyramids. Feature pyramids aid models in generalizing successfully when it comes to object scaling. It aids in the identification of the

same object in various sizes and scales. PANet is used as a neck in YOLO v5 to get feature pyramids.

Head: The model Head is mostly responsible for the final detection step. It uses anchor boxes to construct final output vectors with class probabilities, objectness scores, and bounding boxes.



Fig. 3 Training Data

2.4 Testing the Deep Learning Network

To evaluate the capacity of proposed deep learning network to detect and identify drone (multirotor,single rotor) and to differentiate drones from bird and helicopter. The created weight file, which is the outcome of the training stage, is then applied to the images The proposed method additionally employs the non-maximum suppression (NMS) methodology to choose the drone, bird or helicopter from best control bounding boxes among several predicted bounding boxes. Using this technique, one can eliminate predicted bounding boxes and choose the ideal one that contain the drone, bird or helicopter. The target objects contained by bounding boxes and the bounding box's output parameter are presented.



Fig. 4 Test Results

3.0 Evaluation and results

We made use of YOLOv5s implementation with the annotations in YOLO format and trained across 300 epochs. After the training process, we evaluated the performance of the model using several metrics including Precision, Recall, and mAP (mean Average Precision) when IOU are at 0.5 (50%) and 0.95 (95%). Figure 2 shows the graphs of the metrics curves as training progresses.

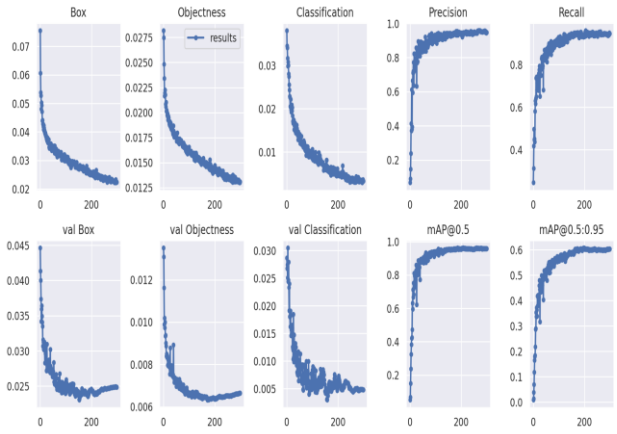


Fig. 5 After Training Results

After evaluation, the YOLOv5 model had a validation precision score of 0.9757, recall score of 0.98, as well as mAP scores of 0.98 and 0.62 for @0.5IOU and @0.95IOU respectively. This result confirms the effectiveness of our approach in predicting drones performed in diverse environments correctly.

4.0 Conclusion

Due to the emerging and development of the application of drones and the security threats associated with their presence in sensitive locations such as airports, drone detection and recognition has attracted much attention. Due to similar behaviour and appearance of drones and birds in the sky, as well as their high speed and problems such as crowded backgrounds, the presence of hidden areas, lighting problems in the images, and the small size of drones at long distances, this paper proposes a new deep learning-based method for detecting and recognizing drones and birds to solve the problems caused by their unauthorized existence. In this study, two types of drones,

helicopter and birds were extracted from videos and images. A collection of 4,000 visible images were collected. The training, testing, and evaluation of the model were performed on the collected dataset. The performance of the model using several metrics was improved. Future work will use other deep learning networks to compare their performance in drone-vs-bird, helicopter detection, and identification will be performed in addition to detection and recognition. The dataset can be enhanced for more similar object to drones.

5.0 References

[1] Pathak, A. R., Pandey, M., & Rautaray, S. (2018). Application of deep learning for object detection. *Procedia computer science*, *132*, 1706-1717.

[2] Ren Shaoqing, Kaiming He, Ross Girshick, Jia n Sun Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks. IEEE transactions on pattern analysis and machine intelligence, 39 (6) (2017), pp. 1137-1149

[3] Samadzadegan, F., Dadrass Javan, F., Ashtari Mahini, F., & Gholamshahi, M. (2022). Detection and Recognition of Drones Based on a Deep Convolutional Neural Network Using Visible Imagery. *Aerospace*, *9*(1), 31.

[5] Seidaliyeva, U., Akhmetov, D., Ilipbayeva, L., & Matson, E. T. (2020). Real-time and accurate drone detection in a video with a static background. *Sensors*, *20*(14), 3856.Chen, B., Medioni, G., (2016, March). Persistent 3D Stabilization for Aerial Imagery. In Applications of Computer Vision (WACV), 2016 IEEE Winter Conference on IEEE.

[6] Unlu, E.; Zenou, E.; Riviere, N.; Dupouy, P. Deep learning-based strategies for the detection and tracking of drones using several cameras. IPSJ T Comput. Vis. Appl. 2019, 11.Available online: doi:10.1186/s41074- 019-0059-x.

[7] Craye, C.; Ardjoune, S. Spatio-temporal Semantic Segmentation for Drone Detection. In Proceedings of the AVSS, Taipei, Taiwan, 18–21 September 2019.

[8] Taha, B.; Shoufan, A. Machine Learning-Based Drone Detection and Classification: State-of-the-Art in Research. IEEE Access 2019, 7, 138669–138682.

[9] S. Ren, K. He, R. Girshick, and J. Sun, "Faster r-cnn: Towards real-time object detection with region proposal networks," in Advances in neural information processing systems, 2015, pp. 91–99.

[10] IEEE. IEEE code of ethics. http://www.ieee.org/about/corporate/governance/p7-8.html, 2017. Online; accessed 15 Mars 2019.

[11] Caselitz T. Tipaldi G.D. Dewan, A. and W. Burgard. Motion-based detection and tracking in 3d lidar scans. In 2016 IEEE International Conference on Robotics and Automation (ICRA), pages 4508–4513, 2016.

[12] N. Srivastava, G. Hinton, A. Krizhevsky, I. Sutskever, and R. Salakhutdinov, "Dropout: a simple way to prevent neural networks from overfitting," The Journal of Machine Learning Research, vol. 15, no. 1, pp. 1929–1958, 2014.

[13] X. Glorot, A. Bordes, and Y. Bengio, "Deep sparse rectifier neural networks," in Proceedings of the fourteenth international conference on artificial intelligence and statistics, 2011, pp. 315–323.

[14] W. Shi, J. Caballero, F. Huszar, J. Totz, A. P. Aitken, R. Bishop, ´ D. Rueckert, and Z. Wang, "Real-time single image and video superresolution using an efficient sub-pixel convolutional neural network," in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2016, pp. 1874–1883.

[15] C. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. Reed, D. Anguelov, D. Erhan, V. Vanhoucke, and A. Rabinovich, "Going deeper with convolutions," in Proceedings of the IEEE conference on computer vision and pattern recognition, 2015, pp. 1–9.

[16] Stanford University. Cs231n: Convolutional neural networks for visual recognition. http://cs231n.stanford.edu/, 2019. Online; accessed 11 February 2019

[17] Moafa, A. (2020). Drones Detection Using Smart Sensors.

[18] S. Yoo, J. Jung, A. Y. Chung, K. Kim, J. Lee, S. Park, S. K. Lee, H. K. Lee, and H. Kim,

"Empowering drones teamwork with airborne network," in Advanced Information Networking and Applications (AINA), 2017 IEEE 31st International Conference on. IEEE, 2017, pp. 678–685

[19] SHIKHA TIWARI USAGE OF DRONES AS A MEDICAL APPLICATIONS,INTERNATIONAL JOURNAL OF HEALTH CARE,2022, HTTPS://DOI.ORG/10.53730/IJHS.V6NS1.7854

[20] Vedant Shrivastava, Tejas Nahargadkar, Shikha Tiwari A Survey on Applications of Drones, International Journal of Mechanical Engineering. ISSN: 0974-5823, Vol. 7 (Special Issue 5, April-May 2022)

[21] Ms Shikha Tiwari, Dr.Guddi Singh/Analysis of Various Drone Detection Techniques, Neuro Quantology | September 2022 | Volume 20 | Issue 9 | Page 2177-2183 | doi: 10.14704/nq.2022.20.9.NQ44255