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Object Detection for Unmanned Aerial Vehicles : A Comprehensive Review

Varun Ved1, Prathamesh Prabhu2, Pranav Waghmare3, Suyash Desai4, Mayuresh Gulame5

1Dept. of Computer Science & Engineering, MIT School Of Computing, MAEER's MIT ADT University, Pune, India

2Dept. of Computer Science & Engineering, MIT School Of Computing, MAEER's MIT ADT University, Pune, India

3Dept. of Computer Science & Engineering, MIT School Of Computing, MAEER's MIT ADT University, Pune, India

4Dept. of Computer Science & Engineering, MIT School Of Computing, MAEER's MIT ADT University, Pune, India

5Dept. of Computer Science & Engineering, MIT School Of Computing, MAEER's MIT ADT University, Pune, India

ABSTRACT

Goal: Researchers studying artificial intelligence have focused a lot of emphasis on computer vision in drones. Drones with intelligence can tackle a lot of issues in real time. For the purpose of monitoring particular surroundings, computer vision tasks like object identification, object tracking, and object counting are important. It becomes increasingly difficult to do, though, due to elements like motion blur, occlusion, camera angle, and altitude.

Methodology: A thorough assessment of the literature on object identification and tracking with unmanned aerial vehicles (UAVs) in relation to various applications has been done for this research. This study highlights the research gaps and provides a summary of the results of previous

studies.

Contribution: Detailed and categorized object identification techniques are used in UAV photos. A selection of UAV datasets tailored to object identification tasks is provided. Summaries of current research projects in various applications are provided. In order to alleviate highlighted research limitations, [1] a secure onboard processing system on a strong object detection framework in precision agriculture is finally presented.

1. INTRODUCTION

[5] Recent improvements in deep learning algorithms, hardware specifications, and dataset accessibility, computer vision has already made significant progress. Because object detection has so many uses, it [8] is the most common inquiry activity carried out by researchers. The aim of object detection is to identify things belonging to a specific category (for example, people, dogs, cars, motorbikes, or cats, for instance) in a photo and, if applicable, output the size and scope of each instance of an object. That forms [4] the foundation for resolving intricate and advanced computer activities using vision, including crowd monitoring, activity monitoring, object tracking, segmentation, event detection, and picture captioning acknowledgement. In order to create broad object detection systems that can identify several kinds of items, researchers began to tackle this difficulty that correspond to those of humans.

Compared to other applications, precision agriculture is anticipated to expand significantly since [17] the use of UAVs is becoming an essential component of managing agricultural chores. Precision agriculture encompasses several techniques for monitoring crops, gathering information, and performing well-informed crop management duties, such choosing the best water source and herbicides. UAVs may help farmers [4] with a wide range of tasks, including farm monitoring to evaluate crop growth and health and planning and assessing agricultural plantations. In 1940, the benefits of airborne services for agriculture led to the extension of fertilizer use from the air to other applications, including top dressing. Although a single-rotor UAV is capable of carrying large payloads, its mechanical complexity drives up costs. Multirotor [11] unmanned aerial vehicles (UAVs) are widely used by both experts and laypersons. It can follow the specified target or hover over it.

Fixed-wing UAVs require a runway for takeoff and landing even if they have a high flying speed and can carry large payloads. A better fixed-wing drone is the hybrid drone, which is currently in development.

In drone footage, there is more contextual information in the area and the camera is positioned higher. However, the problem of object recognition in drones is more difficult than standard object detection because to changes in viewpoint and size. Drones are used in traffic surveillance to capture traffic from the air. This has the benefit of recording vehicle traffic up to a height of 100 meters.

Research on item recognition in aerial view is confronted with additional obstacles related to biased datasets. To avoid this problem, real-world applications must be labeled into the dataset. As such, it frequently happens that aerial photographs do not align with object recognition algorithms that are trained on reference pictures.

1.1 Research Motivation

Compared to fixed cameras, drone surveillance offers more mobility and a wider observation area. Its limited resolution, shifting lighting, and erratic backdrop are only a few of its flaws. In practical applications, intelligent drones are much sought after. Nevertheless, drone image or video object detection differs from conventional object discernment. Aerial photographs of object instances differ in size. Not at all due to the size of the sensor as well as the spatial sensor resolutions variations within the same kind of thing. Aerial pictures are packed with little instances of items, such as automobiles and vehicles in the ships and a parking area at a port. Therefore, the purpose of this study is to examine real-time applications of object recognition in drone photos and to describe the state-of-the-art methodologies in this field.

2. Detailed Literature Review

A detailed literature review of existing research papers and existing technologies for object detection has been summarized in the table below (Table 1). The table displays the existing paper title, it's authors, publication year, source title, methodology used in the particular paper, the approach for detecting objects, performance metric and datasets used.

1 Table 1. Summary of existing works on object detection in drone images and videos.

S No.

Title

Authors

Year

Source title

Methodology

Approach

Metric

Dataset Used

1

A survey and performance evaluation of deep learning methods for small object detection[1]

Liu Y., Sun P., Wergeles N., Shang Y.

2021

Expert Systems with Applications

Fast R-CNN,Faster R-CNN,,Mask R-CNN,Feature pyramid network

Deep learning

IoU, mAP

DOTA,WIDER FACE,COCO and SUN

2

Cascade R-CNN: High quality object detection and instance segmentation[2]

Cai Z., Vasconcelos N.

2021

2 IEEE Transactions on Pattern Analysis and Machine Intelligence

Faster R-CNN

Deep learning

IoU, mAP

COCO, PASCAL VOC, KITTI, CityPersons, and

3

Sensor and sensor fusion technology in autonomous vehicles: A review[3]

Yeong D.J., Velasco-hernandez G., Barry J., Walsh J.

2021

Sensors

YOLO

Deep learning

IoU, mAP

KITTI

4

Deep Multi-Modal Object Detection and Semantic Segmentation for Autonomous Driving: Datasets, Methods, and Challenges[4]

Feng D., Haase-Schutz C., Rosenbaum L., Hertlein H., 23 Glaser C., Timm F., Wiesbeck W., Dietmayer K.

2021

2 IEEE Transactions on Intelligent Transportation Systems

LiDAR

Deep learning

precision, recall, Average precision (AP),

KITTI

5

PBNet: Part-based convolutional neural network for complex composite object detection in remote sensing imagery[5]

Sun X., Wang P., Wang C., Liu Y., Fu K.

2021

ISPRS Journal of Photogrammetry and Remote Sensing

VGG-16

Deep learning

precision, recall, Average precision (AP),

DIOR-composite,STP

6

A Survey of Deep Learning Applications to Autonomous Vehicle Control[6]

Kuutti S., Bowden R., Jin Y., Barber P., Fallah S.

2021

IEEE Transactions on Intelligent Transportation Systems

VGG-16

Deep learning

precision-recall (PR) curve, and frames per second (FPS)

Sewage treatment plant dataset, DIOR dataset

7

YOLOv4-5D: An Effective and Efficient Object Detector for Autonomous Driving[7]

6 Cai Y., Luan T., Gao H., Wang H., Chen L., Li Y., Sotelo M.A., Li Z.

2021

26 IEEE Transactions on Instrumentation and Measurement

YOLOv4,CSPDarknet53_dcn

Deep learning

FPS,accuracy

BDD

8

Deep Affinity Network for Multiple Object Tracking[8]

Sun S., Akhtar N., Song H., Mian A., Shah M.

2021

2 IEEE Transactions on Pattern Analysis and Machine Intelligence

CNN-based Deep Affinity Network (DAN)

Deep learning

CLEAR MOT,MT/ML

MOT15

9

DC-SPP-YOLO: Dense connection and spatial pyramid pooling based YOLO for object detection[9]

Huang Z., Wang J., Fu X., Yu T., Guo Y., Wang R.

2020

Information Sciences

DC-SPP-YOLO

Deep learning

(mean Average Precision,fps

PASCAL VOC 2007,UA-DETRAC

10

Fusion of 3D LIDAR and Camera 4 Data for Object Detection in Autonomous Vehicle

Applications[10]

Zhao X., Sun P., Xu Z., Min H., Yu H.

2020

IEEE Sensors Journal

3D LIDAR

deep learning

accuracy

KITTI

11

Recent advances in small object detection based on deep learning: A review[11]

Tong K., Wu Y., Zhou F.

2020

Image and Vision Computing

29 context-based detection and GAN-based detection

deep learning

Average Pre- cision

MS-COCO and PASCAL-VOC

12

Drone-surveillance for search and rescue in natural disaster[12]

Mishra B., Garg D., Narang P., Mishra V.

2020

Computer Communications

SAR

deep learning

mAP and IOU

Okutama action

13

UA-DETRAC: A new benchmark and protocol for multi-object detection and tracking[13]

Wen L., Du D., Cai Z., Lei Z., Chang M.-C., Qi H., Lim J., Yang M.-H., Lyu S.

2020

19 Computer Vision and Image Understanding

Creation of dataset

deep learning

precision–recall

UA-DETRAC

14

Object detection algorithm based on improved YOLOv3[14]

Zhao L., Li S.

2020

Electronics (Switzerland)

YOLOv3, K-Means Clustering

Deep Learning

Avg 4 IOU (Intersection over Union) & Running time

PASCAL VOC & MS COCO

15

Multi-object Detection and Tracking (MODT) Machine Learning Model for Real-Time Video

Surveillance Systems[15]

Elhoseny M.

2020

Circuits, Systems, and Signal Processing

MODT (Multi-object Detection & Training), Kalman Filtering, Grasshoper Algorithm, Region

Growing

Machine Learning

Accuracy

Own Dataset

16

Thermal Object Detection in Difficult Weather Conditions Using YOLO[16]

Kristo M., Ivasic-Kos M., Pobar M.

2020

IEEE Access

Faster R-CNN, SSD, Cascade R-CNN, YOLOv3, FCOS

Deep Learning

Accuracy, Inference Time, FPS processing, Precission, Recall

UNIRITID, Own Dataset

17

Tinier-YOLO: A Real-Time Object Detection Method for Constrained Environments[17]

Fang W., Wang L., Ren P.

2020

IEEE Access

Tinnier-YOLO

Deep Neural Networks (Deep Learning)

mAP, Runtime Speed, Model size, FPS, BFLOP/s

PASCAL VOC & MS COCO

18

Convolutional neural networks for object detection in aerial imagery for disaster response and recovery[18]

Pi Y., Nath N.D., Behzadan A.H.

2020

Advanced Engineering Informatics

CNN, YOLOv2

Deep Learning

mAP, IoU, Precision, Recall & F1 Score

COCO, YouTube, VOLAN2018 (Own Dataset), VOC

19

Vision-based vehicle detection and counting system using deep learning in highway scenes[19]

Song 18 H., Liang H., Li H., Dai Z., Yun X.

2019

European Transport Research Review

YOLOv2/3, ORB Algorithm, SIFT, SURF, CNNs, R-CNN, R-FCN, Mask R-CNN, FPN, BN

Deep Learning

Avg IOU, Accuracy, Precision, Recall

Own Dataset, KITTI, Tsinghua-Tencent Traffic- Sign Dataset, Stanford Car Dataset,

20

7 Object Detection with Deep Learning: A Review[20]

Zhao Z.-Q., Zheng P., Xu S.-T., Wu X.

20 2019

IEEE Transactions on Neural Networks and Learning Systems

CNN, R-CNN, YOLO, Generic Object Detection, SPP, R-FCN, SSD, FPN

Deep Learning

Precision, Recall, mAP, FPS, Test Time

PASCAL VOC, MS COCO

21

A Survey on 3D Object Detection Methods for Autonomous Driving Applications[21]

Arnold 13 E., Al-Jarrah O.Y., Dianati M., Fallah S., Oxtoby D., Mouzakitis A.

2019

7 IEEE Transactions on Intelligent Transportation Systems

3D Object Detection, Mono3D, SubCNN, 3DOP, 3DVP, NMS, Fast R-CNN,

Deep Learning

Recall, Precision, Average Precision (AP), Average Orientation Similarity (AOS), IoU,

ImageNet, KITTI,

22

10 ORSIm Detector: A Novel Object Detection Framework in Optical Remote Sensing Imagery Using

Spatial-Frequency Channel Features[22]

Wu X., Hong D., Tian J., Chanussot J., Li W., Tao R.

2019

25 IEEE Transactions on Geoscience and Remote Sensing

SFCF, ORSIm detector, feature learning, fast image pyramid estimation, , Adaboost

Machine Learning

Precision, Recall, AP, Average Recall (AR), Average F1-score (AF)

TAS aerial car detection data, NWPU VHR-10

23

Salient object detection: A survey[23]

Borji A., Cheng M.-M., Hou Q., Jiang H., Li J.

2019

14 Computational Visual Media

Salient Object Detection, Object Detection, Fixation Prediction, CNNs,

Deep Learning

Precision-recall, F-measure, ROC, AUC, MAE

MSRA, SED, SOD, ASD, Infrared, ImgSal, etc

24

SINet: A Scale-Insensitive Convolutional 9 Neural Network for Fast Vehicle Detection[24]

Hu X., Xu X., Xiao Y., Chen H., He S., Qin J., Heng P.-A.

2019

2 IEEE Transactions on Intelligent Transportation Systems

CNN, SINet (Scale-insensitive CNN)

Deep Learning

AP, IoU

KITTI, Own Dataset

25

A survey of deep learning-based object detection

Jiao L., Zhang F., Liu F., Yang S., Li L., Feng Z., Qu R.

15 2019

IEEE Access

HoG-SVM, R-CNN, ResNet, Faster R-CNN

Deep Learning

AP, IoU, Precision-Recall, Accuracy, Processing Time

PASCAL VOC, MS COCO, ImageNet & other datasets

26

An Improved Faster R-CNN for Small Object Detection[25]

Cao C., Wang B., Zhang W., Zeng X., Yan X., Feng Z., Liu Y., Wu Z.

2019

IEEE Access

R-CNN, NMS

Deep Learning

IoU, RoI, Loss Function, Preciosion-recall, Accuracy

TT100K

3. Identified Research Gaps

Although 2 there have been many advances, there are still many problems with deep learning techniques, drone technologies, and their combination.

1. There are many unanswered 21 questions in the deep learning field, such as why some network architectures perform better than others and how to solve the objective function when there is no understanding of geometry. Given the high cost of labeling large amounts of data, it is important to develop an effective unsupervised deep learning algorithm.

2. 22 According to the review of the literature, deep learning or conventional image processing techniques are used by the researchers to identify drones in images. Because 5 deep learning algorithms excel at both feature extraction and classification, they are a better choice. Onboard processing is a challenge due to the drone's restrictions on weight, size, and power consumption. When

there is 8 a lack of bandwidth and there is a need to transmit large amounts of image data, it becomes more difficult. Researcher efforts to create more effective deep learning architectures are encouraged by these difficulties.

3. Internet use by UAVs in real-time applications introduces 6 security and privacy risks. UAV applications need their own specific security measures.

4. Proposed Framework

16 A secure onboard processing method for an effective object detection framework is suggested (Fig. 1) to fill in the identified research gaps. . The images are pre-processed onboard a platform with an embedded GPU when data is first acquired by UAV. Crop detection is accomplished using a compact 4 deep learning model. A blockchain-based encryption technique is used to safely transmit the resulting images to the ground control station. Our future work entails implementing the suggested framework.

Figure 1. Proposed Framework

5. Conclusion & Future Scope

With so many real-time applications, drone 1 object detection is a promising research area. Existing research works are examined in this review paper. The works are arranged based on their methods and applications. In order to detect drone objects, this paper investigates deep learning and conventional image processing techniques. Additionally covered are the 14 dataset and evaluation metrics. 5 Deep learning algorithms outperform conventional image processing techniques, according to the literature. It's crucial to create an effective deep learning algorithm for drone object detection even though the drones have limited power and size. 4 The object detection algorithms must also handle the important challenge of variations viewpoint. We planned to look into object detection with UAVs in agricultural applications in future research. By gathering and evaluating data, precision agriculture aims to keep an exact eye on the fields. Using UAVs to obtain aerial photos is less expensive than using satellites. One crucial area of research to look into is 1 object detection in UAV aerial images for precision farming. In this paper, we proposed a secure onboard object detection framework in precision agriculture, which we will work on implementing in the future.

KEYWORDS

YOLO

CNN

RCNN

UAV

4 Object Detection

Deep Learning

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