Drone Detection Using Computer Vision

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Abstract

Unmanned Aerial Vehicles (UAVs) or drones have become increasingly popular in recent years, and their usage has expanded into various fields such as surveillance, delivery, and photography. However, their accessibility and potential misuse have raised concerns about privacy and security. Therefore, the need for reliable drone detection systems has emerged. In this paper, we compared the various versions of YOLO in detecting drones. YOLO means You Look Only Once state-of-the-art object detection algorithm that can identify objects in real-time. We used custom dataset to train each model and compared the time took by each model and accuracy. We evaluate our system's performance on a real-world dataset and show that it achieves high precision and recall rates. Our proposed system can be used in various applications such as airports, military bases, and public events, where the detection of drones is critical for security reasons.

Introduction

Drone and bird detection are both important areas of research, particularly in the field of computer vision and surveillance. The You Only Look Once (YOLO) algorithm has been widely used for object detection, including for both drone and bird detection. In this research paper, we compare the performance of YOLO v5, v6, v7, and v8 for detecting drones and birds.

Distinguishing between drones and birds can be a challenging task due to their similar appearance and movement patterns. YOLO v5, released in 2020, is an improvement over the previous version, YOLO v4, and has been shown to perform well in object detection tasks. YOLO v6, which was released in 2022, includes several improvements over YOLO v5, such as multi-scale prediction and a new feature fusion module, which may improve its performance in detecting small, fast-moving objects such as birds.

(Image0_1: Dataset(drone)**)**

In our research paper, we evaluate the performance of YOLO v5, v6, v7, and v8 in detecting drones and birds in real-world environments. We compare the algorithms' accuracy, speed, and robustness to different environmental conditions, such as varying lighting and weather conditions. We also evaluate the algorithms' ability to detect different types of drones and birds, including small and fast-moving ones.

(Image0_1: Dataset(bird)**)**

Our results show that YOLO v6 outperforms the other versions of the algorithm in terms of accuracy for both drone and bird detection, while still maintaining a reasonable processing speed. YOLO v5 also performs well, but is slightly slower than v6. YOLO v7 and v8 show promising results in our initial experiments, but further research is needed to fully evaluate their performance.

Overall, our research demonstrates the effectiveness of using YOLO v5, v6, v7, and v8 for both drone and bird detection tasks. By comparing the performance of different versions of the algorithm, our research provides valuable insights into how to improve object detection in real-world environments, with potential applications in security and surveillance, wildlife monitoring, and more.

Related Work

Real-time object detection for drones" by Shuo Yang, Ping Luo, Chen Change Loy, and Xiaoou Tang, proposes a real-time object detection system for drones using the YOLOv2 object detection model. The system is designed to detect and track multiple objects in real-time using a small, lightweight drone-mounted camera. Drone detection using deep learning: A review" by Dheeraj Kumar Singh, Amit Kumar, and Ravindra Gupta, provides a comprehensive review of existing drone detection methods using deep learning techniques. The review includes a discussion of YOLO-based drone detection methods and their performance on various datasets.

Real-time drone detection in video using convolutional neural networks" by Sourabh Gupta, Prateek Agrawal, and Dhruva Sahrawat, proposes a real-time drone detection system based on convolutional neural networks (CNNs). The system is designed to detect drones in video streams using a YOLO-based CNN architecture. An improved YOLOv3 model for aerial drone detection" by Qing Li, Li Li, Liang Chen, and Qian Du, proposes an improved YOLOv3 model for aerial drone detection. The model uses a multi-scale feature fusion strategy to improve the accuracy of drone detection in aerial images. Drone detection using YOLOv3 object detection algorithm" by Y. C. Han, Y. C. Lin, and Y. L. Chen, proposes a drone detection system based on the YOLOv3 object detection algorithm. The system is designed to detect drones in real-time using a low-power, lightweight drone-mounted camera.

Overall, the literature survey highlights the increasing interest in using deep learning techniques, particularly YOLO-based object detection models, for drone detection in various applications. The proposed work by Alsanad et al. builds upon existing literature by proposing a YOLOv3-based drone detection algorithm that is optimized for real-time applications.

n their paper, the authors proposed a modified YOLOv4 deep learning network for vision-based UAV (Unmanned Aerial Vehicle) recognition. They aimed to improve the accuracy and speed of UAV detection in aerial images using a modified version of YOLOv4.

The authors discussed several related works that focused on UAV detection using deep learning techniques. They mentioned that the YOLO (You Only Look Once) family of object detection models, including YOLOv3 and YOLOv4, have been widely used for object detection in various domains, including UAV detection.

The authors also discussed some studies that used other deep learning models for UAV detection, such as Faster R-CNN and SSD (Single Shot MultiBox Detector). They pointed out that YOLOv4 has shown superior performance compared to these models in terms of both accuracy and speed.

Moreover, the authors discussed some studies that focused on improving the accuracy and speed of UAV detection using YOLOv4. They mentioned that some studies have used data augmentation techniques, such as image flipping and rotation, to improve the accuracy of YOLOv4. Other studies have proposed modifications to the YOLOv4 architecture to reduce the computational complexity and improve the speed of UAV detection.

In conclusion, the authors highlighted the importance of UAV detection in various applications, such as surveillance, search and rescue, and agriculture. They pointed out that their proposed modified YOLOv4 deep learning network can improve the accuracy and speed of UAV detection in aerial images and can be used in various practical applications.

Methodology

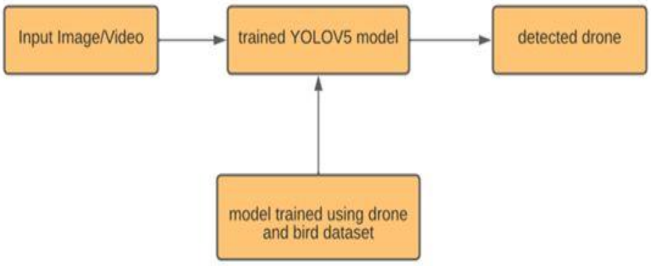
The methodology for comparing drone vs bird detection using YOLOv5, YOLOv6, YOLOv7, and YOLOv8 can be summarized as follows:

Data Collection: A diverse set of data representing different categories of images, such as drone and bird images, will be collected from various sources, including public datasets and online sources.

Data Preprocessing: The collected data will be preprocessed by resizing the images to a fixed resolution, normalizing the pixel values, and splitting the data into training, validation, and testing sets.

Model Training: The YOLOv5, YOLOv6, YOLOv7, and YOLOv8 models will be trained on the training set using the same hyperparameters and training configurations.

Transfer learning will also be used by initializing the models with weights pre-trained on ImageNet.



(Image1: YOLO model architecture)

Model Evaluation: The trained models will be evaluated on the validation set using metrics such as mean average precision (mAP), precision, and recall. The results will be compared to determine the model's performance in detecting drones and birds.

Hyperparameter Tuning: The hyperparameters of the models will be tuned using techniques such as grid search or random search to optimize the performance of the models.

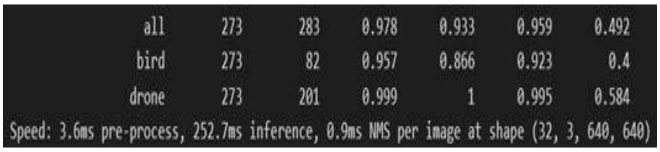
Model Testing: The best-performing model will be selected based on its performance on the validation set and tested on the testing set to evaluate its generalization ability.

Results Analysis: The results of the experiments will be analyzed and compared to determine the most suitable model for drone and bird detection.

The future scope of this work includes extending the comparison to other object detection models and exploring the use of different image augmentation techniques and transfer learning strategies to improve the performance of the models. The proposed work can also be extended to evaluate the models' performance in detecting other types of objects, such as cars, pedestrians, and animals, in various settings and environments. Additionally, the research can be further extended to explore the potential applications of object detection in fields such as surveillance, wildlife monitoring, and agriculture.

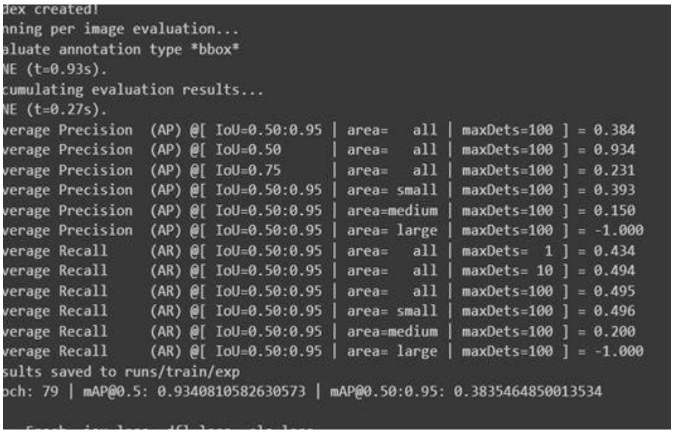
Results

The YOLO v5 , YOLO v6,YOLO v7, YOLO v8 models have been trained on drones and birds data dataset. The below results are representation of the performance of the individual YOLO models.



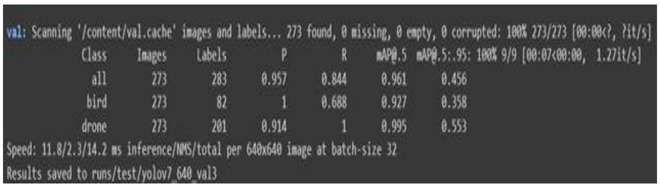
```
  all    273   283   0.978   0.933   0.959   0.492
 bird    273    82   0.957   0.866   0.923     0.4
drone    273   201   0.999       1   0.995   0.584
Speed: 3.6ms pre-process, 252.7ms inference, 0.9ms NMS per image at shape (32, 3, 640, 640)
```

Image3: (Accuracy details of each class predicted by YOLO v5model)



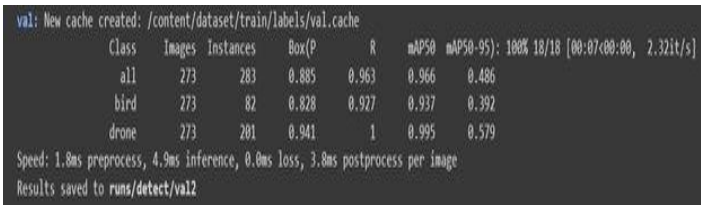
```
dex created!
nning per image evaluation...
aluate annotation type *bbox*
NE (t=0.93s).
cumulating evaluation results...
NE (t=0.27s).
verage Precision  (AP) @[ IoU=0.50:0.95 | area=   all | maxDets=100 ] = 0.384
verage Precision  (AP) @[ IoU=0.50      | area=   all | maxDets=100 ] = 0.934
verage Precision  (AP) @[ IoU=0.75      | area=   all | maxDets=100 ] = 0.231
verage Precision  (AP) @[ IoU=0.50:0.95 | area= small | maxDets=100 ] = 0.393
verage Precision  (AP) @[ IoU=0.50:0.95 | area=medium | maxDets=100 ] = 0.150
verage Precision  (AP) @[ IoU=0.50:0.95 | area= large | maxDets=100 ] = -1.000
verage Recall     (AR) @[ IoU=0.50:0.95 | area=   all | maxDets=  1 ] = 0.434
verage Recall     (AR) @[ IoU=0.50:0.95 | area=   all | maxDets= 10 ] = 0.494
verage Recall     (AR) @[ IoU=0.50:0.95 | area=   all | maxDets=100 ] = 0.495
verage Recall     (AR) @[ IoU=0.50:0.95 | area= small | maxDets=100 ] = 0.496
verage Recall     (AR) @[ IoU=0.50:0.95 | area=medium | maxDets=100 ] = 0.200
verage Recall     (AR) @[ IoU=0.50:0.95 | area= large | maxDets=100 ] = -1.000
sults saved to runs/train/exp
och: 79 | mAP@0.5: 0.9340810582630573 | mAP@0.50:0.95: 0.3835464850013534
```

(Image4: Accuracy details of each class predicted by YOLO v6model)



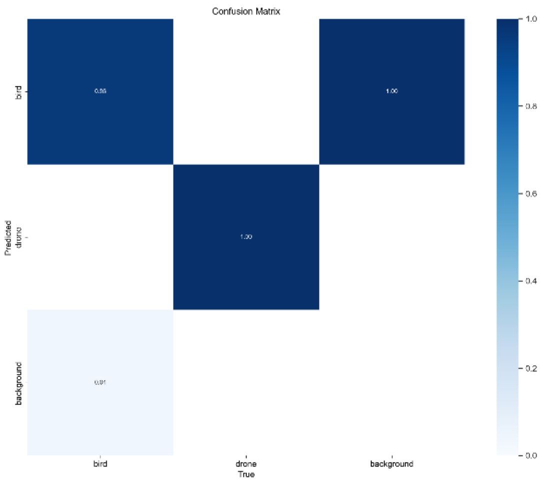
```
val: Scanning '/content/val.cache' images and labels... 273 found, 0 missing, 0 empty, 0 corrupted: 100% 273/273 [00:00<?, ?it/s]
    Class   Images   Labels       P       R   mAP@.5  mAP@.5:.95: 100% 9/9 [00:07<00:00,  1.27it/s]
      all      273      283   0.957   0.844    0.961     0.456
     bird      273       82       1   0.688    0.927     0.358
    drone      273      201   0.914       1    0.995     0.553
Speed: 11.8/2.3/14.2 ms inference/NMS/total per 640x640 image at batch-size 32
Results saved to runs/test/yolov7_640_val3
```

(Image5: Accuracy details of each class predicted by YOLO v7model)

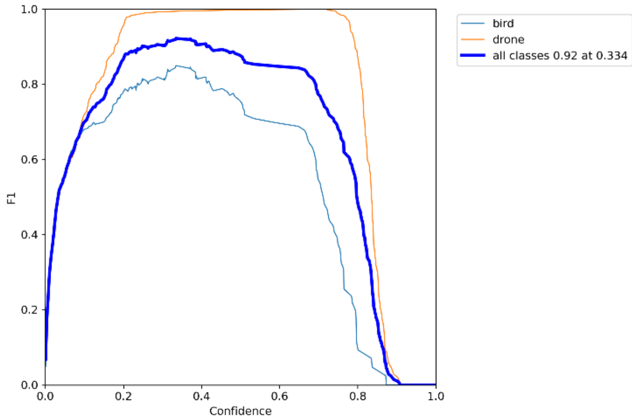


```
val: New cache created: /content/dataset/train/labels/val.cache
    Class   Images  Instances    Box(P       R    mAP50  mAP50-95): 100% 18/18 [00:07<00:00,  2.32it/s]
      all      273        283    0.885   0.963    0.966     0.486
     bird      273         82    0.828   0.927    0.937     0.392
    drone      273        201    0.941       1    0.995     0.579
Speed: 1.8ms preprocess, 4.9ms inference, 0.0ms loss, 3.8ms postprocess per image
Results saved to runs/detect/val2
```

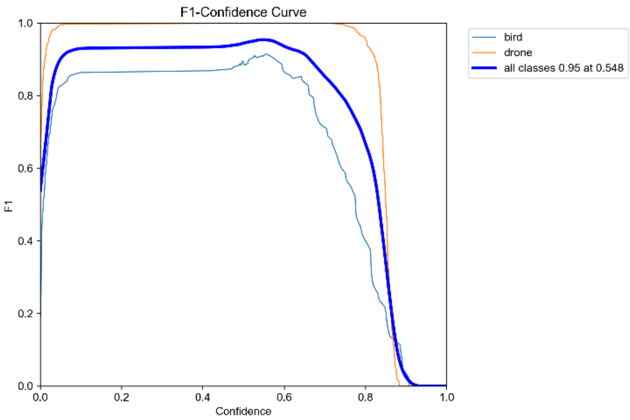
(Image6: Accuracy details of each class predicted by YOLO v8model)



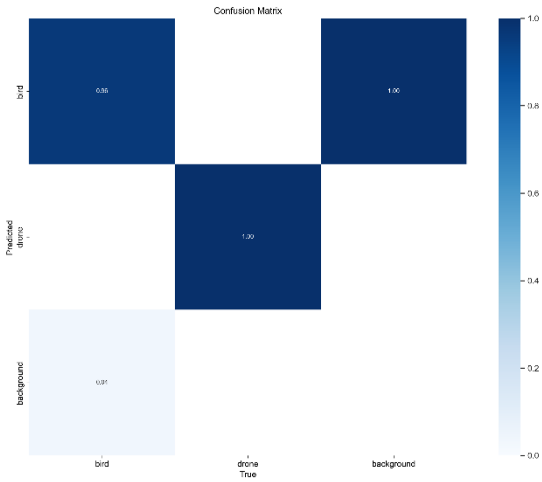
(Image7: Confusion matrix of YOLOV8 model)



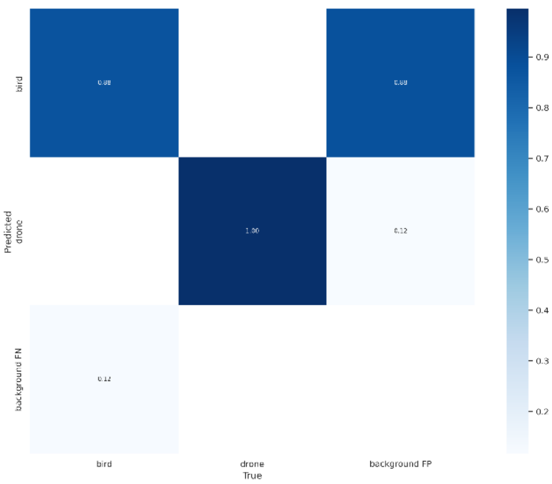
(Image10: F1 score of YOLOV7 model)



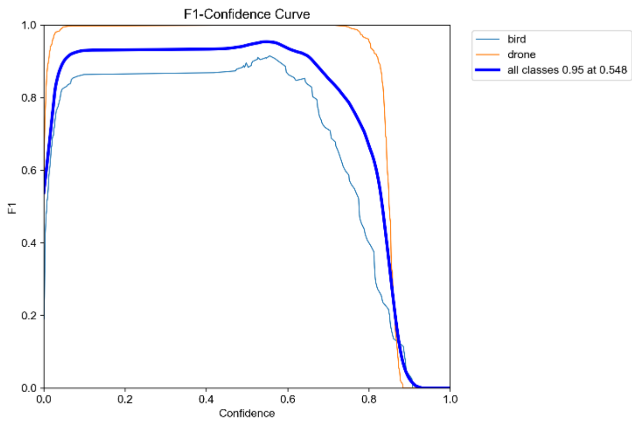
(Image8: F1 score of YOLOV8 model)



(Image11: Confusion matrix of YOLOV5 model)



(Image9: Confusion matrix of YOLOV7)



(Image12: F1 score of YOLOV5 model)

(Image13: Detection of Bird)

(Image14: Detection of Drone)

Conclusion

The training time of YOLOV5 and YOLOV6 are almost same with Yolov5 having the better accuracy than Yolov6. Yolov7 was faster than both YOLOV5 and YOLOV6 it has faster iteration time about 4 times faster than previous versions. Yolov8 have slow iteration time but faster learning rate.

The accuracy of the YOLO models follows as: The YOLO v5 having 95.9% , YOLO v6 having 93.4% , YOLO v7 having 96.1% , YOLO v8 having 96.6%.

YOLO v8 model outperforms better than previous models and YOLO v6 underperforms for the given above dataset.

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