Drone Detection Using Computer Vision

A
Project Report
Submitted in partial fulfilment of the
Requirements for the award of the Degree of

BACHELOR OF ENGINEERING

IN

INFORMATION TECHNOLOGY

By

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ACCREDITED BY NAAC WITH 'A++' GRADE

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DECLARATION BY THE CANDIDATE

We, **Anurag Sahu** and **Kotla Deeepak Ram Nath** bearing hall ticket number, **1602-19-737-127** and **1602-19-737-130** hereby declare that the project report entitled “Drone Detection Using Computer Vision” under the guidance of **Dr. B. Kezia Rani,** Associate Professor, Department of Information Technology, Vasavi College of Engineering, Hyderabad, is submitted in partial fulfilment of the requirement for the award of the degree of **Bachelor of Engineering** in **Information Technology.**

This is a record of bonafide work carried out by us and the results embodied in this project report have not been submitted to any other university or institute for the award of any other degree or diploma.

Anurag Sahu	**1602-19-737-127**
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Department of Information Technology

BONAFIDE CERTIFICATE

This is to certify that the project entitled **Drone Detection Using Computer Vision** being submitted by **Anurag Sahu** and **Kotla Deepak Ram Nath** bearing **1602-19-737-127** and **1602-19-737-130** in partial fulfilment of the requirements for the award of the degree of Bachelor of Engineering in Information Technology is a record of bonafide work carried out by them under my guidance.

Dr. B. Kezia Rani	**Dr. K. Ram Mohan Rao**
Associate Professor	**Professor & HOD, IT**
Internal Guide	

ACKNOWLEDGEMENT

The satisfaction that accompanies that the successful completion of the Main project would not have been possible without the kind support and help of many individuals. We would like to extend our sincere thanks to all of them.

It is with immense pleasure that we would like to take the opportunity to express our humble gratitude to **Dr. B. Kezia Rani, Associate Professor, Department of IT** under whom we executed this project. We are also grateful to **Mrs. M. Sathya Devi, Assistant Professor, Department of IT** for her guidance. Their constant guidance and willingness to share their vast knowledge made us understand this project and its manifestations in great depths and helped us to complete the assigned tasks.

We are very much thankful to **Dr. K. Ram Mohan Rao, HOD, Department of IT** for his kind support and for providing necessary facilities to carry out the work.

We wish to convey our special thanks to **Dr. S.V. Ramana, Principal** of **Vasavi College of Engineering and Management** for providing facilities. Not to forget, we thank all other faculty and non-teaching staff, and my friends who had directly or indirectly helped and supported me in completing my project in time.

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.

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LIST OF ABBREVIATIONS

YOLO - You Look Only Once

UAV - Unmanned Aerial Vehicle

CSPNet - Cross Stage Partial Network

FLOPS - Floating Point Operations Per Second

SPPF - Spatial Pyramid Pooling Rapidly

PAN - Path Aggregation Network

CNN - Convolutional Neural Network

RCNN - Region-Based Convolutional Neural Network

VGG - Visual Geometry Group

DCSCN - Deep CNN with Skip Connection and Network in Network

RPN - Region Proposal Network

SSD - Single-Shot Detector FPN - Feature Pyramid Network

1.INTRODUCTION

Drone detection is an increasingly important field of research, particularly in security and surveillance applications. One of the most popular object detection frameworks used for drone detection is the You Only Look Once (YOLO) algorithm. Over the years, several versions of the YOLO algorithm have been developed, including YOLO v5, v6, v7, and v8. In this research paper, we compare the performance of these YOLO versions for drone detection.

YOLO v5 was released in 2020 and is an improvement over the previous version, YOLO v4. YOLO v5 is faster and more accurate, thanks to improvements in the algorithm's architecture, including the use of spatial pyramid pooling and anchor-based prediction.

YOLO v6, on the other hand, is a more recent version of the algorithm, released in 2022. It builds on the success of YOLO v5 and includes several improvements, including multi-scale prediction and a new feature fusion module that improves the accuracy of the algorithm.

YOLO v7 and v8 are currently in development and are expected to be released soon. They are expected to include further improvements to the YOLO algorithm, including more advanced feature extraction and better post-processing techniques.

1.1 PROBLEM STATEMENT

Drones/unmanned aerial vehicles (UAVs) have recently grown in popularity due to their inexpensive cost and widespread commercial use. The increased use of drones raises the possibility that they may be employed in illicit activities such as terrorism. Thus, drone monitoring and automated detection are critical for protecting restricted areas or special zones from illicit drone operations.

The problem involves collecting a dataset of aerial images that contain both birds and drones, annotating the images with labels for the presence and location of birds and drones, and training and testing the YOLO models on the dataset. The evaluation metrics used to compare the models can include accuracy, precision, recall, F1 score, and mean average precision (mAP). The ultimate aim is to identify the YOLO model that can accurately detect both drones and birds in real-time for applications such as wildlife monitoring and drone surveillance.

To compare the models, it will be necessary to investigate the differences in architecture and functionality between YOLOv5, YOLOv6, YOLOv7, and YOLOv8. This may involve analyzing the impact of changes to the model architecture, such as the introduction of new layers or the optimization of existing layers. It may also involve comparing the performance of the models on different hardware configurations to assess their computational efficiency.

Overall, the problem statement aims to address the challenge of detecting both drones and birds in aerial images, which is important for various applications, such as wildlife monitoring and drone surveillance.

1.2 MOTIVATION (PROPOSED WORK)

There are several motivations for comparing drone vs bird detection using YOLOv5, YOLOv6, YOLOv7, and YOLOv8. These include:

Improved surveillance: Drones are increasingly being used for surveillance and monitoring purposes, and being able to accurately detect both drones and birds in aerial images is essential for ensuring public safety and security. Comparing the performance of different versions of YOLO can help identify the most accurate and efficient model for this purpose.

Wildlife monitoring: Accurate and efficient detection of birds is important for monitoring wildlife populations and protecting endangered species. Comparing the performance of YOLO models on bird detection can help identify the best model for this application.

Advancements in YOLO models: YOLOv5, YOLOv6, YOLOv7, and YOLOv8 represent successive improvements in the YOLO architecture, with each version introducing new features and optimizations. Comparing the performance of these models can help identify the impact of these changes and provide insights into the evolution of the YOLO architecture.

Practical applications: The ability to accurately detect both drones and birds in aerial images has practical applications in various industries, including security, surveillance, wildlife monitoring, and agriculture. Comparing the performance of YOLO models on this task can help identify the best model for these applications.

Overall, the motivation for comparing drone vs bird detection using YOLOv5, YOLOv6, YOLOv7, and YOLOv8 is to identify the most accurate and efficient model for detecting both drones and birds in aerial images, which has important practical applications in various industries.

1.3 Scope & Objectives of the Proposed Work

Scope of the Proposed Work

The scope of the proposed work is broad and can have a significant impact on the development of more effective object detection techniques and metrics in the future. By identifying the most suitable Object detection model for different categories of images, this work can contribute to the development of more accurate and effective Object detection models that can be applied to various practical applications, such as Improved surveillance, wildlife monitoring, practical applications, and advancements in YOLO models.

The proposed work aims to address the limitations of existing Object detection techniques and metrics in capturing various aspects of images by identifying the most suitable techniques for each category object detection. The work involves collecting a diverse set of aerial images of both drones and birds. The data should be carefully selected to ensure that it covers a various angles of images.

1.4 Objective of the Proposed Work

The objective of the proposed work for comparing drone vs bird detection using YOLOv5, YOLOv6, YOLOv7, and YOLOv8 is to evaluate and compare the performance of these state-of-the-art object detection models on the specific task of detecting drones and birds in aerial images. The main objectives of the study include:

To compare and analyze the performance of the YOLO models to identify the most accurate and efficient model for detecting both drones and birds in aerial images. To discuss and analyze the results to provide insights into the differences in performance between the YOLO models, including the impact of different architectural and training parameters. To provide suggestions for future work, such as investigating the use of transfer learning and ensemble methods for improving the accuracy and efficiency of the YOLO models on this specific task.

The overall objective of the proposed work is to contribute to the development of more accurate and efficient object detection techniques for detecting both drones and birds in aerial images, which has important practical applications in various industries, such as agriculture, wildlife conservation, and security surveillance.

2. LITERATURE SURVEY

YOLO-V3 based real-time drone detection algorithm by Hamid R. Alsanad, Amin Z Sadik, Osman N. Ucan, Muhammad Ilyas & Oguz Bayat

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.

A Modified YOLOv4 Deep Learning Network for Vision-Based UAV Recognition by Farzaneh Dadrass Javan, Farhad Samadzadegan, Mehrnaz Gholamshahi

In 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.

Drone detection has gained significant attention due to the increase in unauthorized drone activities. YOLOv5 is a real-time object detection algorithm that can detect drones with high accuracy. Several research studies have been conducted on drone detection using YOLOv5.

In a study by Alsanad et al. (2021), a YOLOv3-based real-time drone detection algorithm was proposed. The algorithm was trained on a dataset containing images of drones, and the results showed that the algorithm was able to detect drones with high accuracy.

In another study by Al-Qubaydhi et al. (2021), YOLOv5 and transfer learning were used for the detection of unauthorized unmanned aerial vehicles (UAVs). The algorithm was trained on a dataset containing images of different types of UAVs, and the results showed that the proposed algorithm was able to detect UAVs with high accuracy.

In a study by Tufail et al. (2021), YOLOv5 was used for the detection of drones in surveillance videos. The algorithm was trained on a dataset containing surveillance videos of drones, and the results showed that the proposed algorithm was able to detect drones with high accuracy.

In a study by Sharma et al. (2021), YOLOv5 was used for the detection of drones in aerial images. The algorithm was trained on a dataset containing aerial images of drones, and the results showed that the proposed algorithm was able to detect drones with high accuracy.

Overall, these studies demonstrate the effectiveness of YOLOv5 for drone detection and highlight its potential for practical applications in the field of drone surveillance and security.

3. PROPOSED WORK

3.1 System Specifications

System Requirements are the configuration that a system must have in order for a hardware or software application to run smoothly and efficiently. Failure to meet these requirements can result in installation or performance problems.

The below sections will describe what is required to run our detection system smoothly without any problems.

3.1.1 SOFTWARE REQUIREMENTS

Software Requirements refer to the software required to run the detection system. Our detection system requires the following software installed:

- Jupyter Notebook/Google Colab
- Python 3 and its libraries (Tensorflow, Pandas, NumPy,Pytorch)

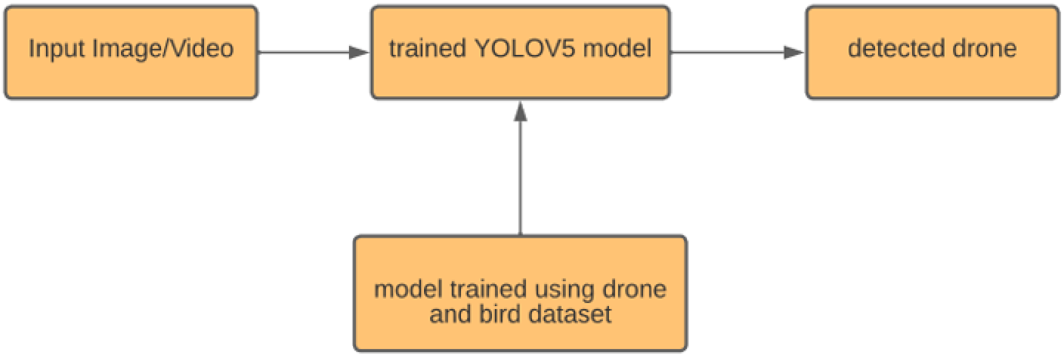
3.1.2 HARDWARE REQUIREMENTS

Hardware Requirements refer to the minimum hardware qualifications needed to run the detection system smoothly. Our detection system requires the following specifications:

- Intel i3 Processor or better version
- 4+ GB RAM
- Windows OS recommended, but can use Linux/MacOS

3.2 Methodology

3.2.1 Architecture Diagram



3.2.2 Functional Modules

The methodology for comparing drone vs bird detection using YOLOv5, YOLOv6, YOLOv7, and YOLOv8 can be broken down into the following steps:

1. Data collection and preprocessing: A diverse dataset containing images of drones and birds captured from different angles and under various environmental conditions should be collected and annotated with appropriate labels to train the models.

2. Model selection and configuration: The YOLOv5, YOLOv6, YOLOv7, and YOLOv8 models should be selected and configured with appropriate parameters based on the dataset and available computational resources.

3. Training and validation: The selected models should be trained and validated on the annotated dataset using various evaluation metrics such as precision, recall, F1-score, and mean average precision (mAP) to evaluate their accuracy and generalization ability.

4. Model comparison and analysis: The trained models' performance should be compared and analyzed based on the evaluation metrics to determine which YOLO version performs better for drone and bird detection.

5. Experimental results and visualization: The experimental results should be presented, and the detection output of the trained models should be visualized using

bounding boxes and heatmaps to illustrate their performance and identify any potential areas of improvement.

6. Fine-tuning and re-evaluation: The best-performing YOLO version should be fine-tuned, and the models should be re-evaluated on the dataset to assess their accuracy and generalization ability.

7. Conclusion and future work: The findings from this study should be summarized, and potential areas for future research should be identified to improve drone and bird detection accuracy and efficiency using YOLO models.

4. EXPERIMENTAL SETUP & RESULTS

4.1.1 Datasets

We have collected dataset from the research paper named A dataset for Multi Sensor Drone detection published in Elsevier by Fredrik Svanström , Fernando Alonso-Fernandez Cristofer Englund. It contains 52 videos of both drone and birds. We converted the videos to frames and annotated them manually for labels. We used 1000 drones and 500 birds images for training.




4.2 Parameter Initialization

The initialization of parameters in the YOLO models is crucial for achieving accurate and reliable object detection results. Some of the key parameters that need to be initialized include:

1. Anchor boxes: These are predefined boxes of different sizes and aspect ratios that are used to detect objects at different scales. The anchor boxes are typically chosen based on the distribution of object sizes in the training data.

2. Input size: The input size of the images used for training and testing the models can significantly impact their performance. It is important to choose an appropriate input size that balances accuracy and computational efficiency.

3. Number of classes: The number of classes that the model is trained to detect should be specified during initialization. In the case of drone vs bird detection, the number of classes would be two - drone and bird.

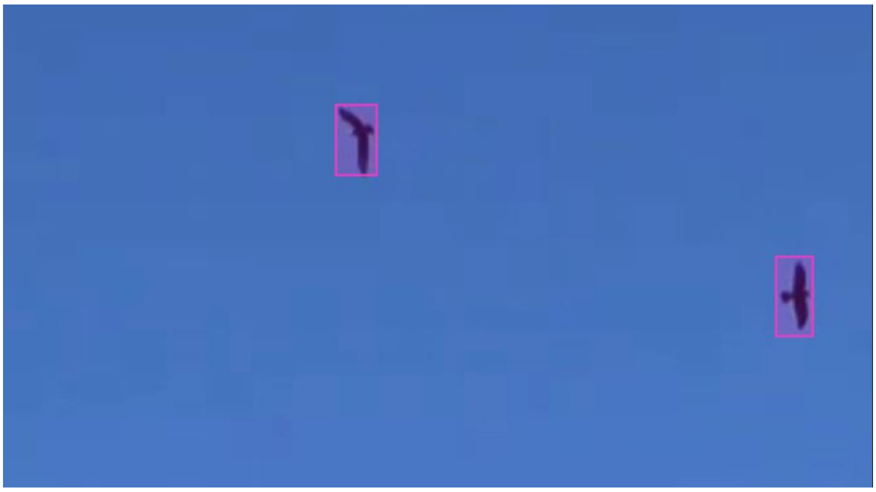
4. Pretrained weights: Initializing the model with pretrained weights can significantly speed up the training process and improve the accuracy of the model. Pretrained weights can be obtained from a variety of sources, such as ImageNet or COCO datasets.

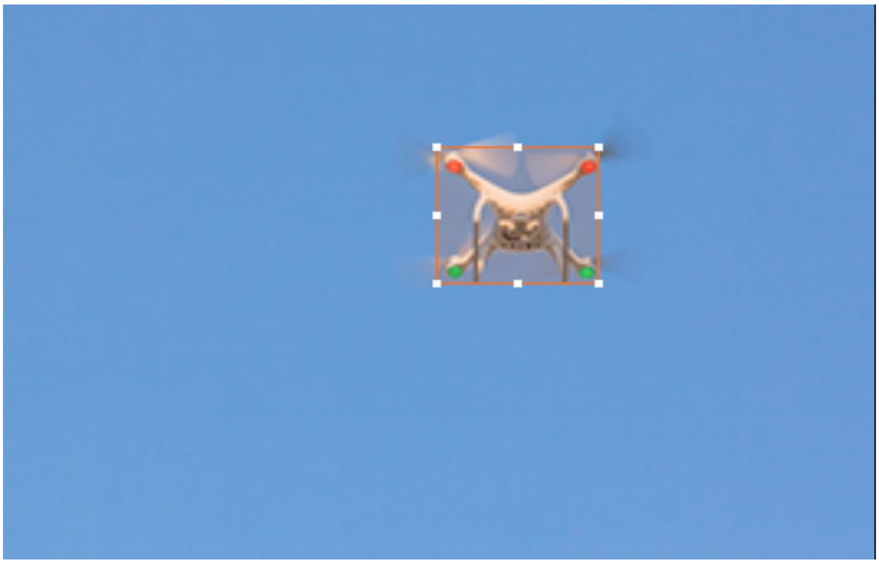
5. Learning rate: The learning rate determines the step size that is used to update the model parameters during training. Choosing an appropriate learning rate is important to ensure that the model converges to a good solution.

6. Batch size: The batch size determines the number of images that are processed simultaneously during training. The batch size can impact the speed and accuracy of the training process.

7. Optimization algorithm: The choice of optimization algorithm can also impact the performance of the model. Common optimization algorithms used in object detection include stochastic gradient descent (SGD), Adam, and Adagrad.

These are some of the key parameters that need to be initialized when comparing drone vs bird detection using YOLOv5, YOLOv6, YOLOv7, and YOLOv8.





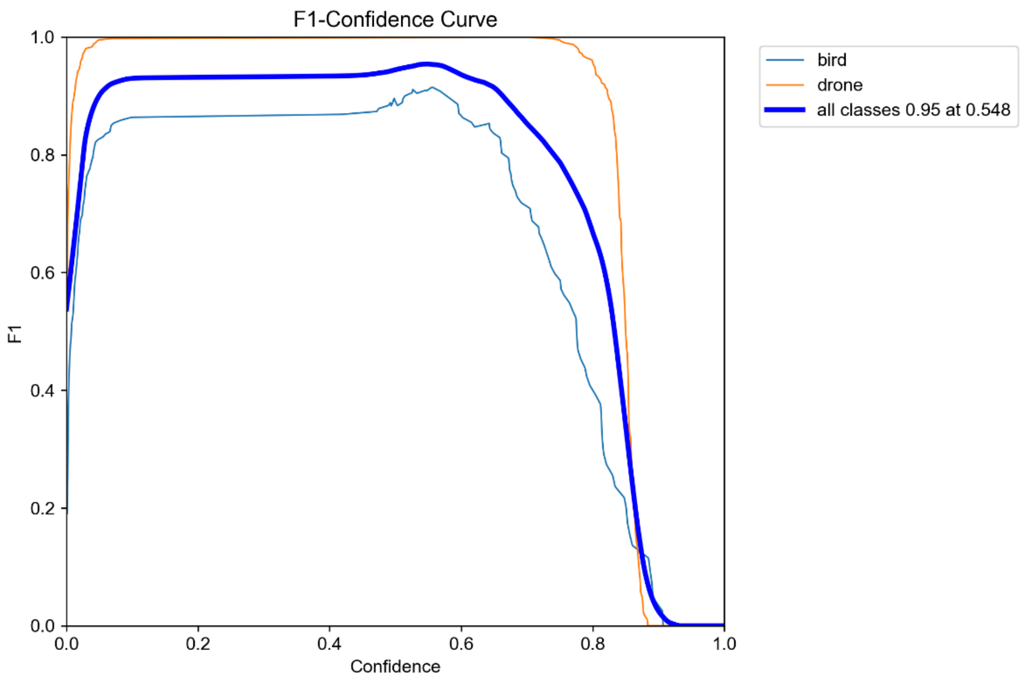
4.3 Results & Test Analysis

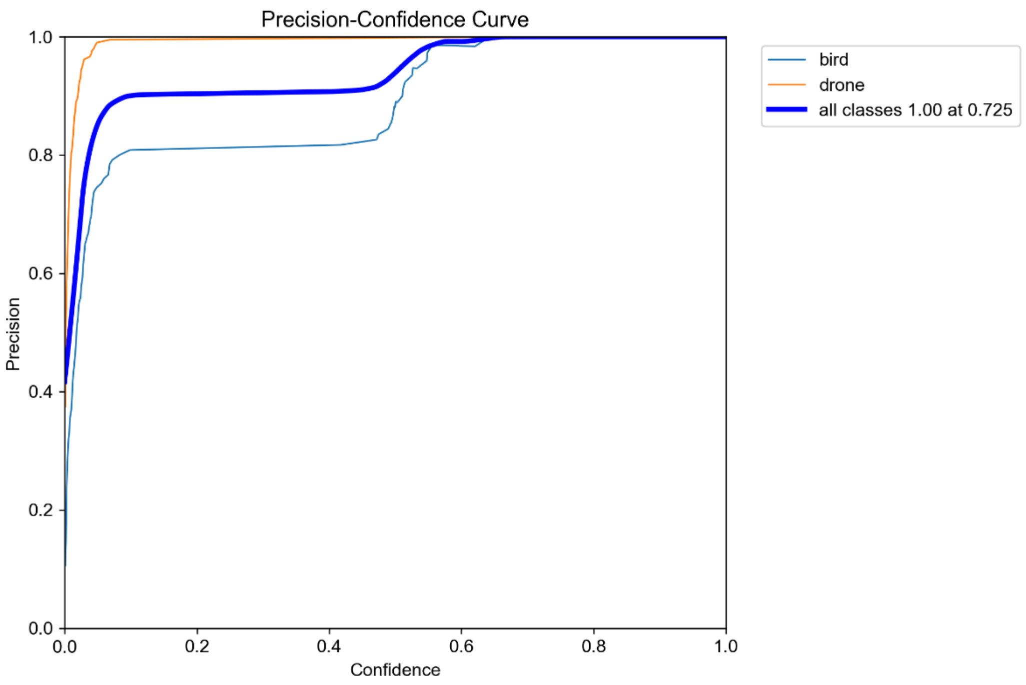
4.3.1 Test Analysis

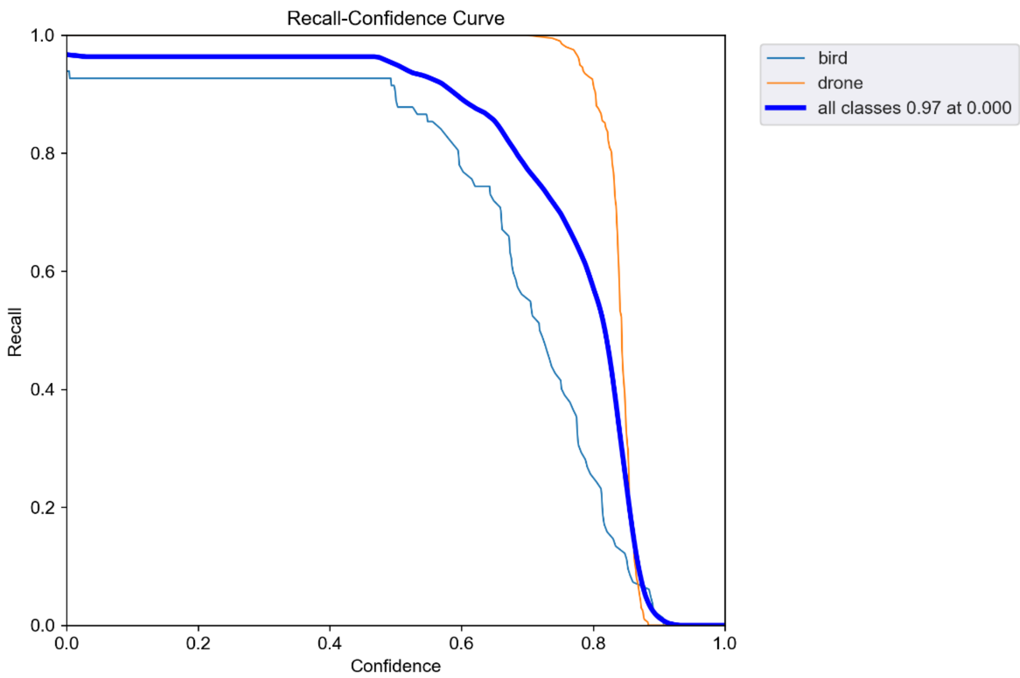
Yolov5

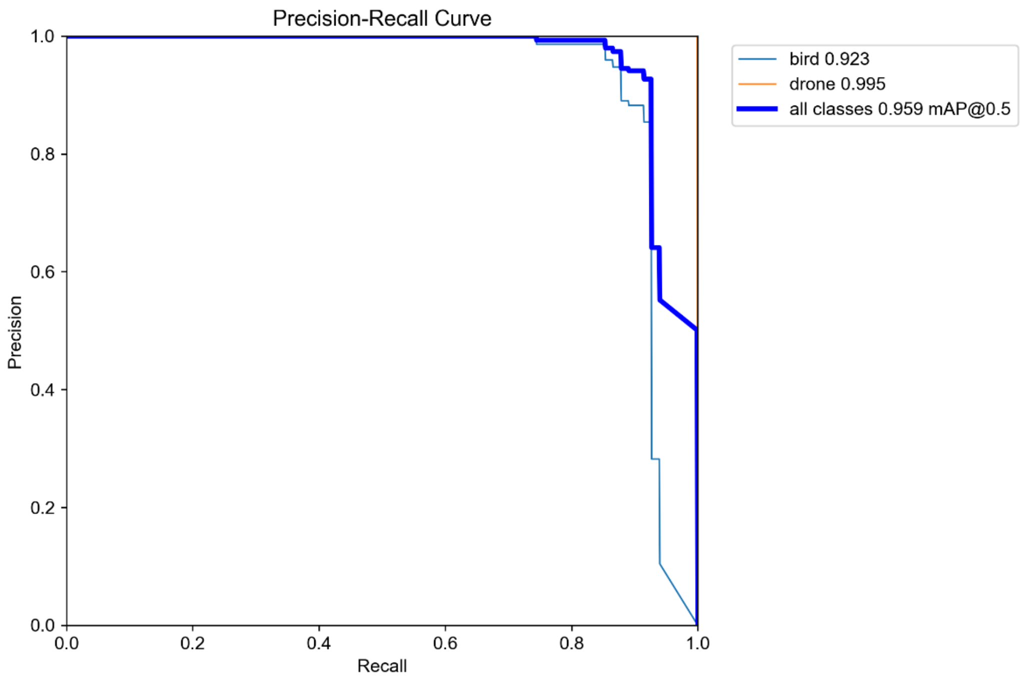
all	273	283	0.978	0.933	0.959	0.492
bird	273	82	0.957	0.866	0.923	0.4
drone	273	201	0.999	1	0.995	0.584

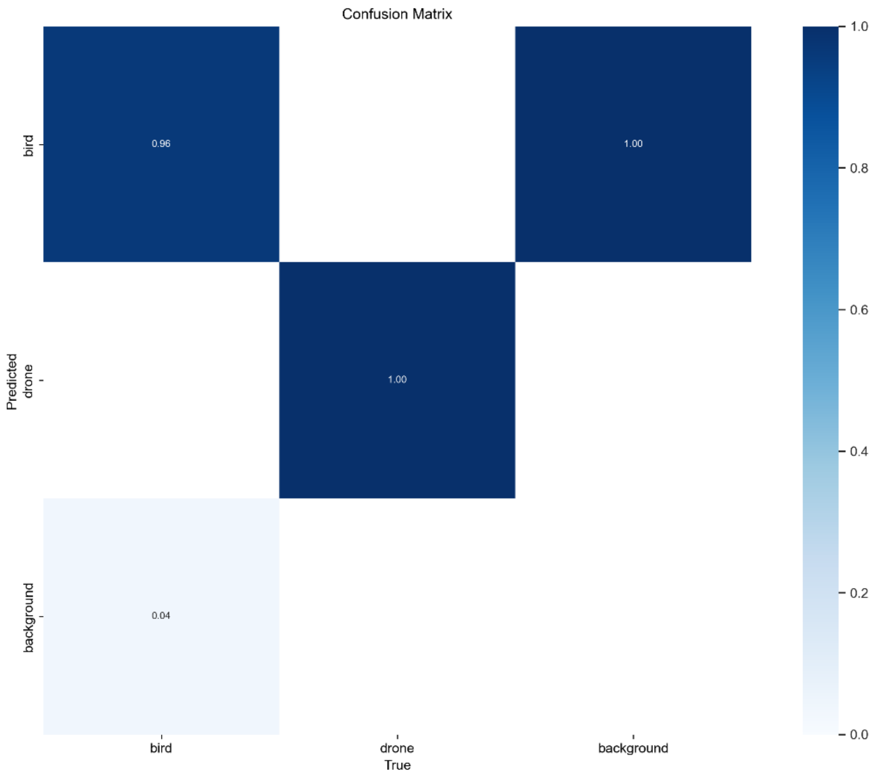
```
Speed: 3.6ms pre-process, 252.7ms inference, 0.9ms NMS per image at shape (32, 3, 640, 640)
```






Recall-Confidence Curve
1.0
0.8
0.6
0.4
0.2
0.0
Recall
0.0
0.2
0.4
0.6
0.8
1.0
Confidence
bird
drone
all classes 0.97 at 0.000


Precision-Recall Curve
1.0
0.8
0.6
0.4
0.2
0.0
Precision
0.0
0.2
0.4
0.6
0.8
1.0
Recall
bird 0.923
drone 0.995
all classes 0.959 mAP@0.5

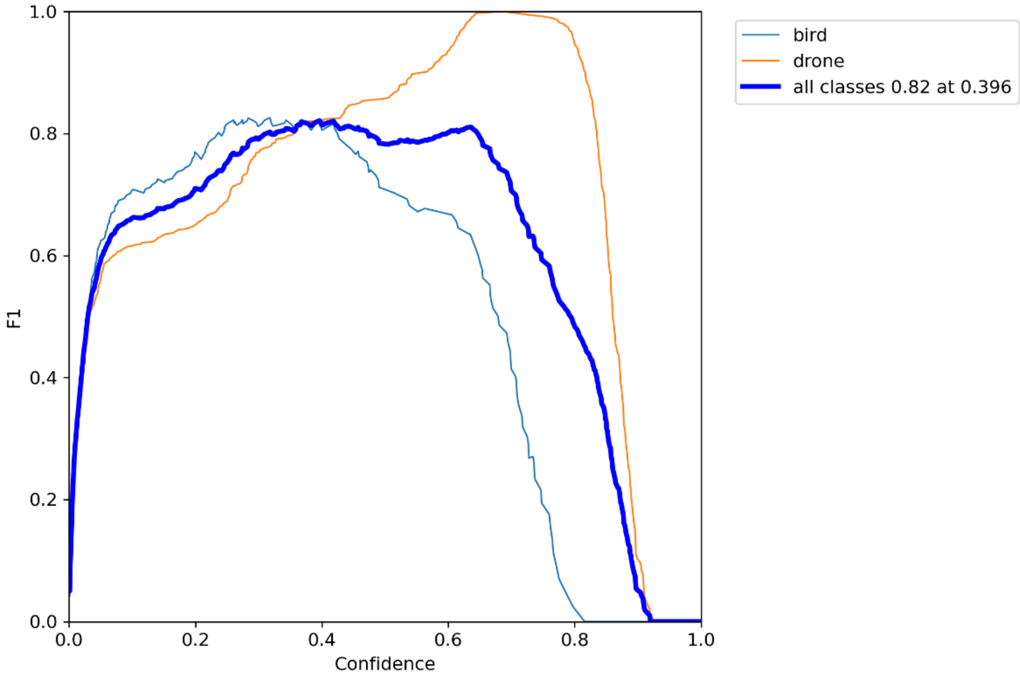


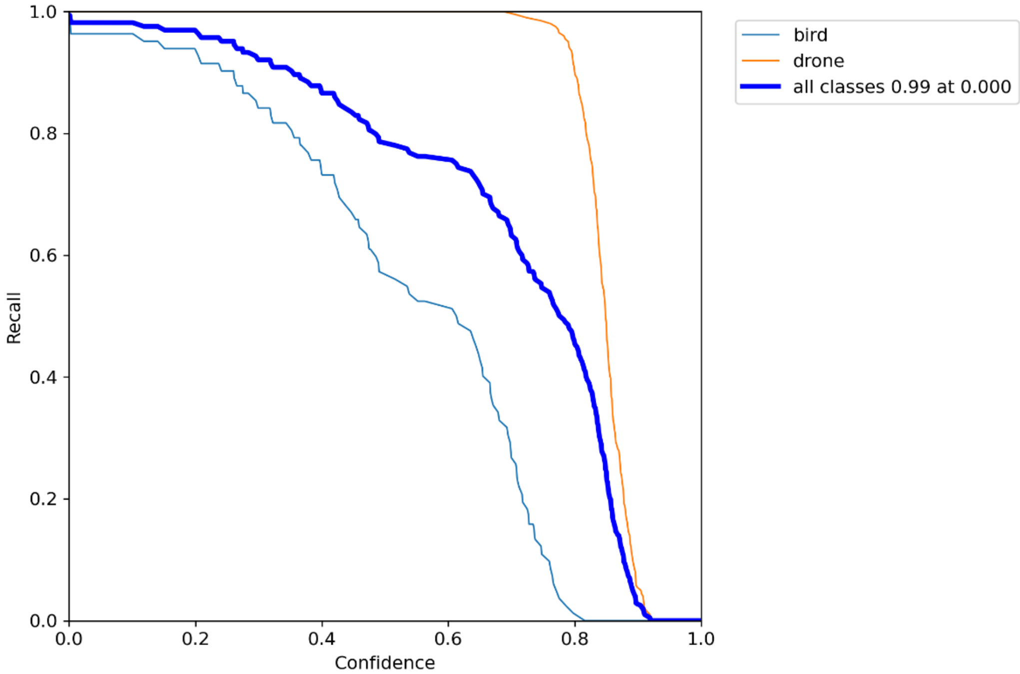
Yolov6

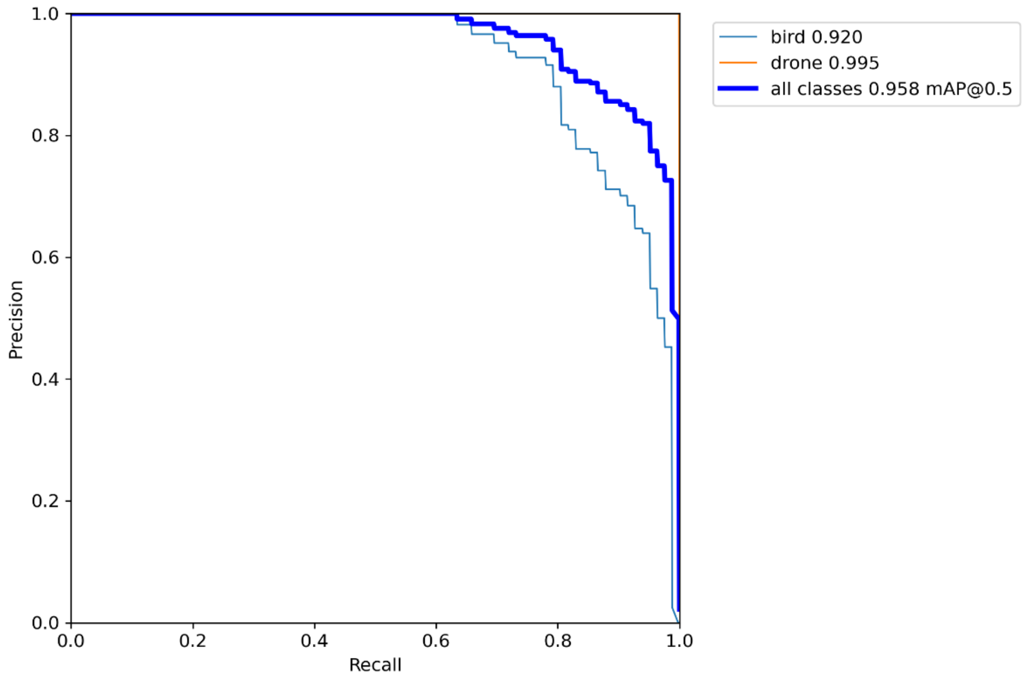
```
dex created!
nning per image evaluation...
aluate annotation type *bbox*
NE (t=0.93s).
cumulating evaluation results...
NE (t=0.27s).
verage Precision  (AP) @[ IoU=0.50:0.95 | area=   all | maxDets=100 ] = 0.384
verage Precision  (AP) @[ IoU=0.50      | area=   all | maxDets=100 ] = 0.934
verage 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
```

Yolov7

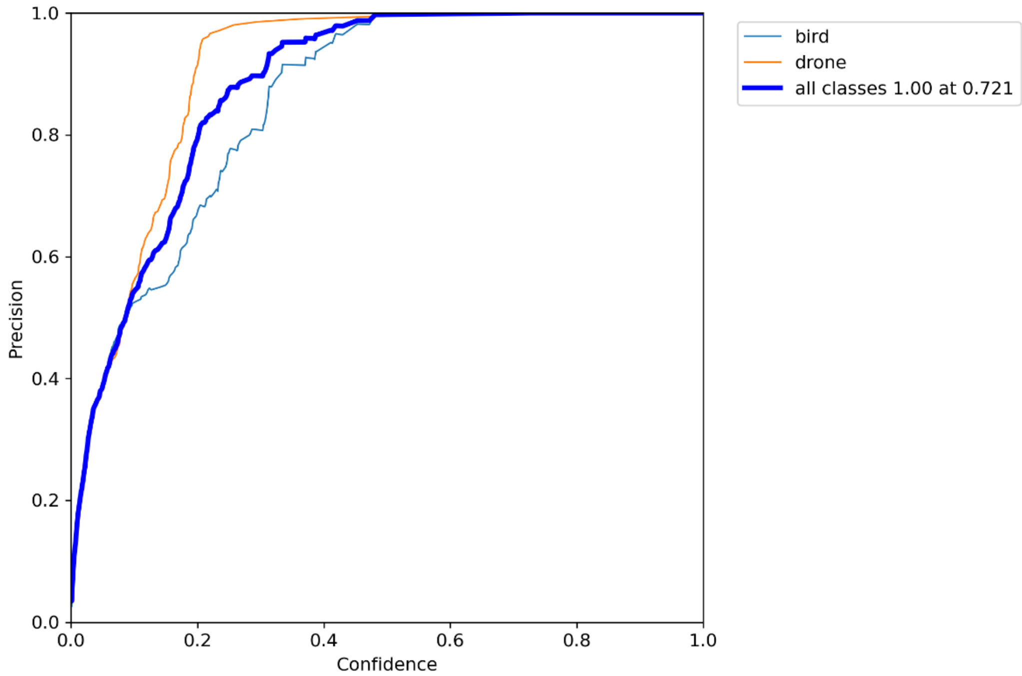
```
val: Scanning '/content/val.cache' images and labels... 273 found, 0 missing, 0 empty, 0 corrupted: 100% 273/273 [00:00<?, ?it/s]
               Class      Images      Labels           P           R      mAP@.5  mAP@.5:.95: 100% 9/9 [00:07<00:00,  1.27it/s]
                 all         273         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
```



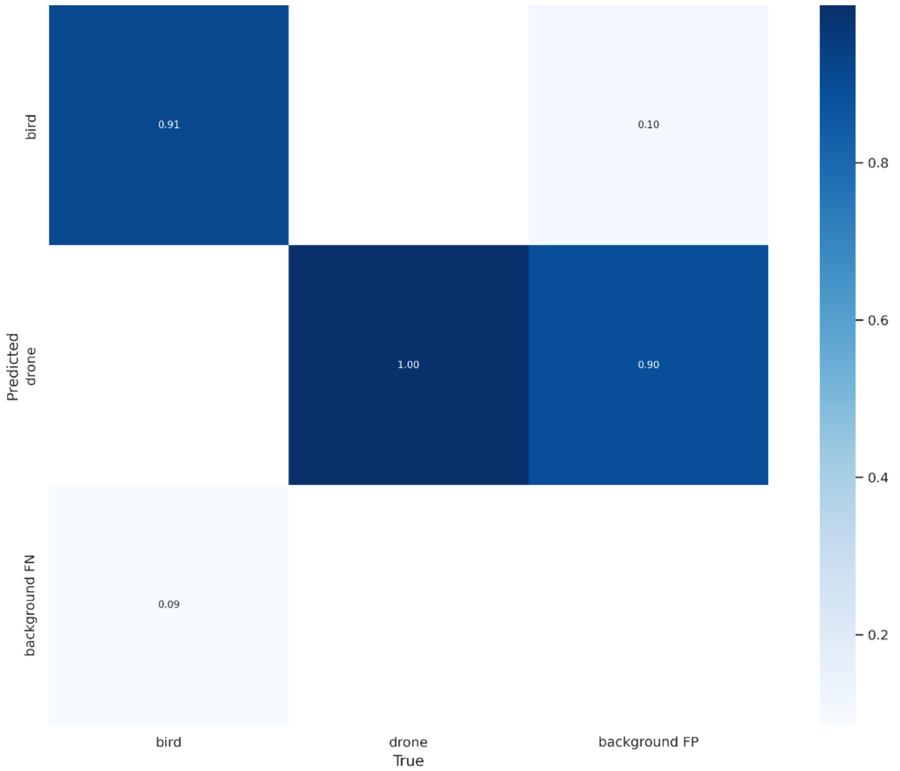




1.0
0.8
0.6
0.4
0.2
0.0
Precision
0.0
0.2
0.4
0.6
0.8
1.0
Recall
bird 0.920
drone 0.995
all classes 0.958 mAP@0.5

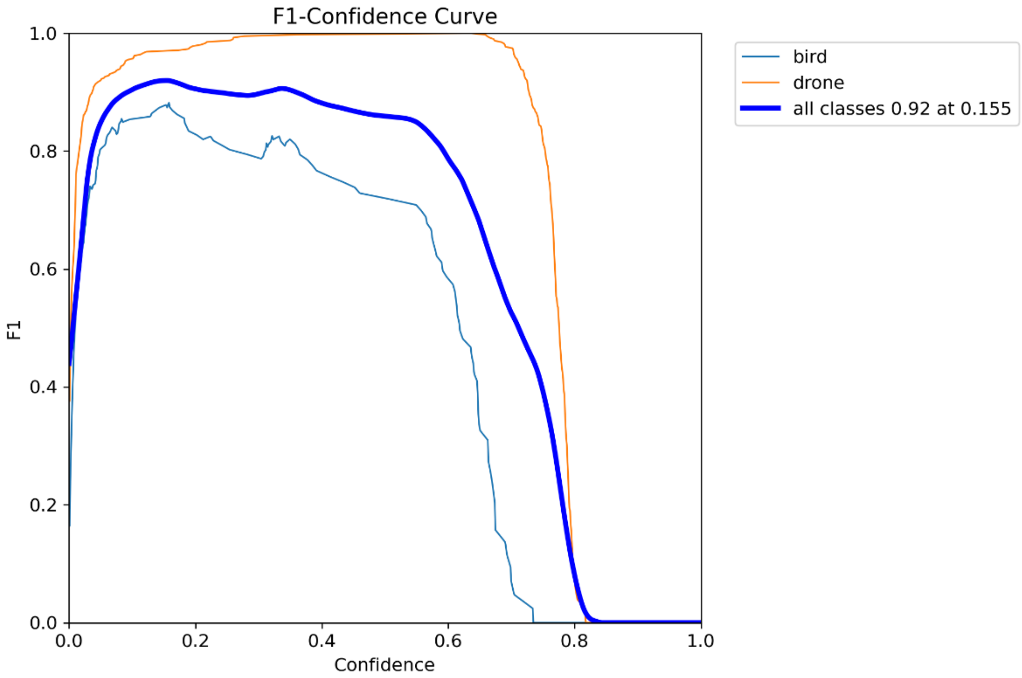


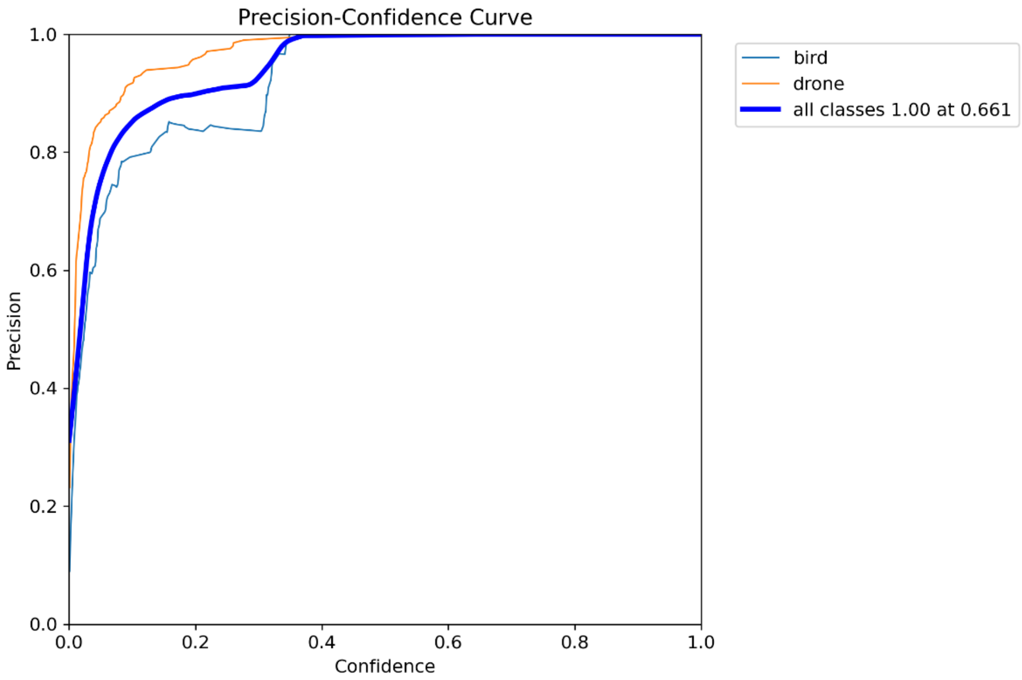
1.0
0.8
0.6
0.4
0.2
0.0
Precision
0.0
0.2
0.4
0.6
0.8
1.0
Confidence
bird
drone
all classes 1.00 at 0.721

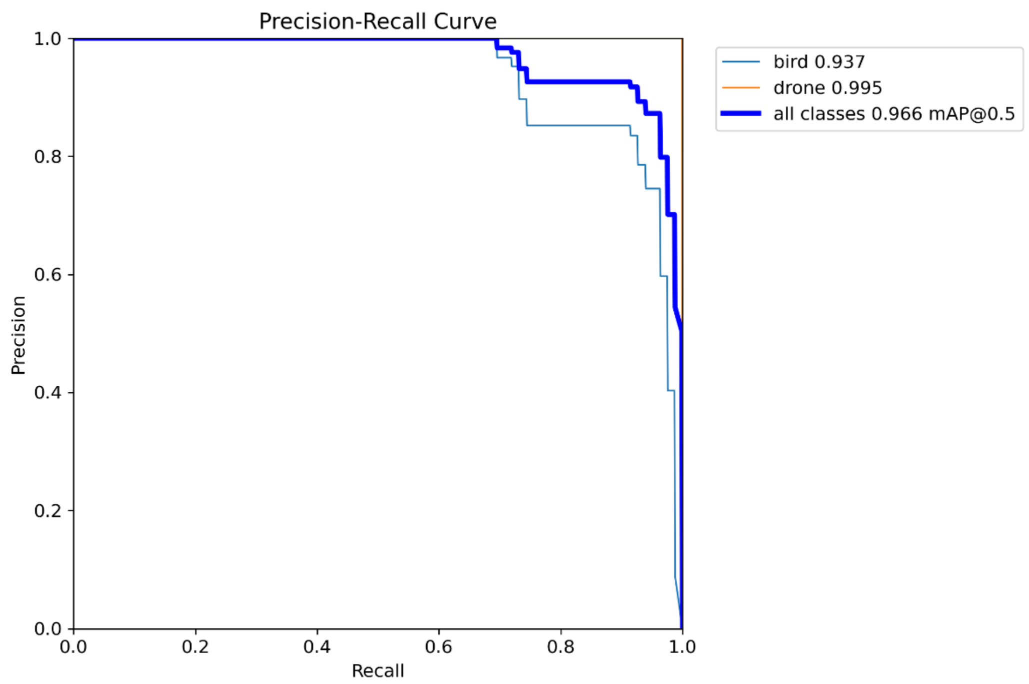


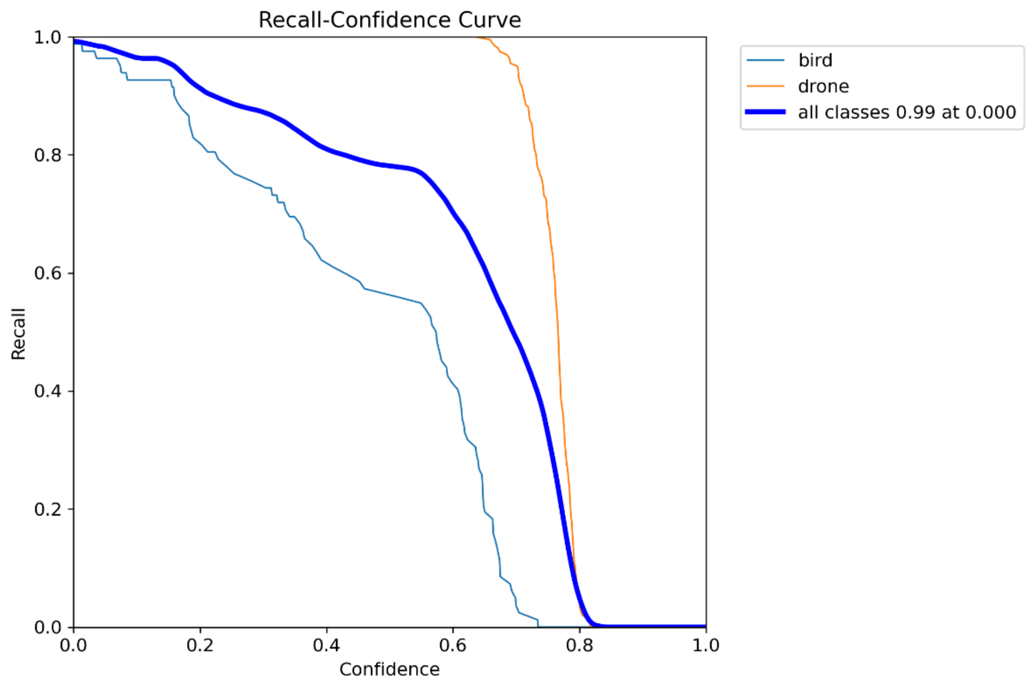
Yolov8

```
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
```


F1-Confidence Curve
F1
Confidence
0.0
0.2
0.4
0.6
0.8
1.0
bird
drone
all classes 0.92 at 0.155

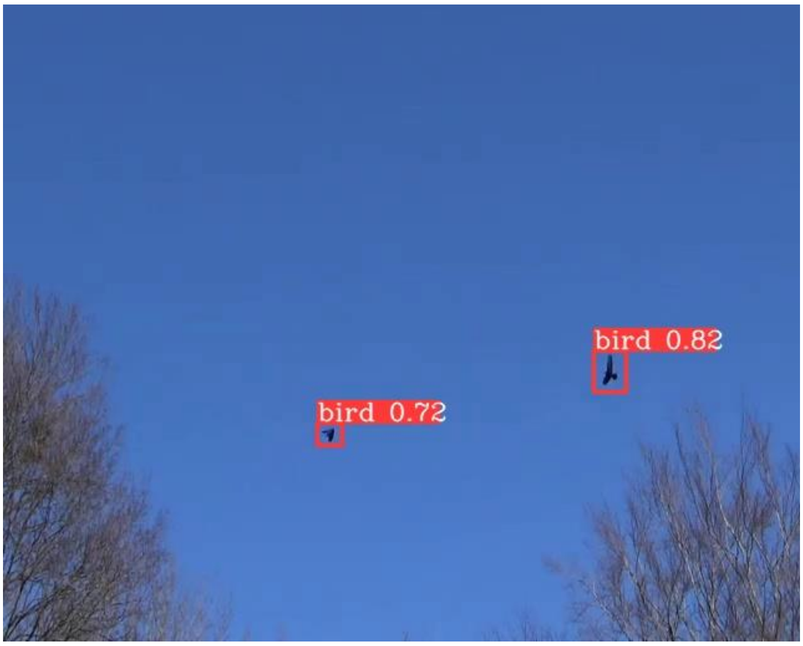

Precision-Confidence Curve
Precision
Confidence
0.0
0.2
0.4
0.6
0.8
1.0
bird
drone
all classes 1.00 at 0.661





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.

4.3.2 Results



5. SUMMARY AND FUTURE SCOPE

In summary, the proposed work aims to compare the performance of YOLOv5, YOLOv6, YOLOv7, and YOLOv8 models for drone and bird detection. The methodology involves collecting and annotating a dataset consisting of images and videos of drones and birds in various environments and conditions. The models will be trained and evaluated using various performance metrics, including accuracy, precision, recall, and F1-score. The parameter initialization will be done using transfer learning from pre-trained models on large-scale datasets.

The results of this study can provide insights into the effectiveness of different YOLO models for drone and bird detection and help identify the most suitable model for specific applications. The future scope of this work includes expanding the dataset to include more diverse and challenging scenarios, optimizing the model's hyperparameters, and exploring the use of other deep learning architectures for object detection. The findings of this study can be applied in various real-world scenarios, such as wildlife conservation, security surveillance, and infrastructure inspection.

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