Single-Stage UAV Detection and Classification with YOLOV5: Mosaic Data Augmentation and PANet

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Agenda

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Introduction

UAVs Applications and Challenges

- Civil and military applications
- Posing Different Challenges
  - Detection, tracking, classification, payload classification, controlling, etc.
- UAV detection for a safe integration
  - Presence of UAVs
  - Different sensor modalities
  - Specifically cameras

A. Mirzaeinia and M. Hassanalian, "Minimum-cost drone–nest matchingthrough the kuhn–munkres algorithm in smart cities: Energy managementand efficiency enhancement,"Aerospace, vol. 6, no. 11, p. 125, 2019.

Introduction

Drone-vs-Bird Detection Challenge in 4th International workshop on small-drone surveillance, detection and counteraction techniques (WOSDETC) of IEEE AVSS 2021

- Drone or bird? Easily confusion
- Challenges:
  - Unfavourable conditions → complex background, occlusion, etc.
  - long range → small objects
  - reduced visibility → weather/illumination

https://science.howstuffworks.com/transport/flight/modern/dutch-police-are-training-eagles-capture-drones-right-out-the-sky.htm

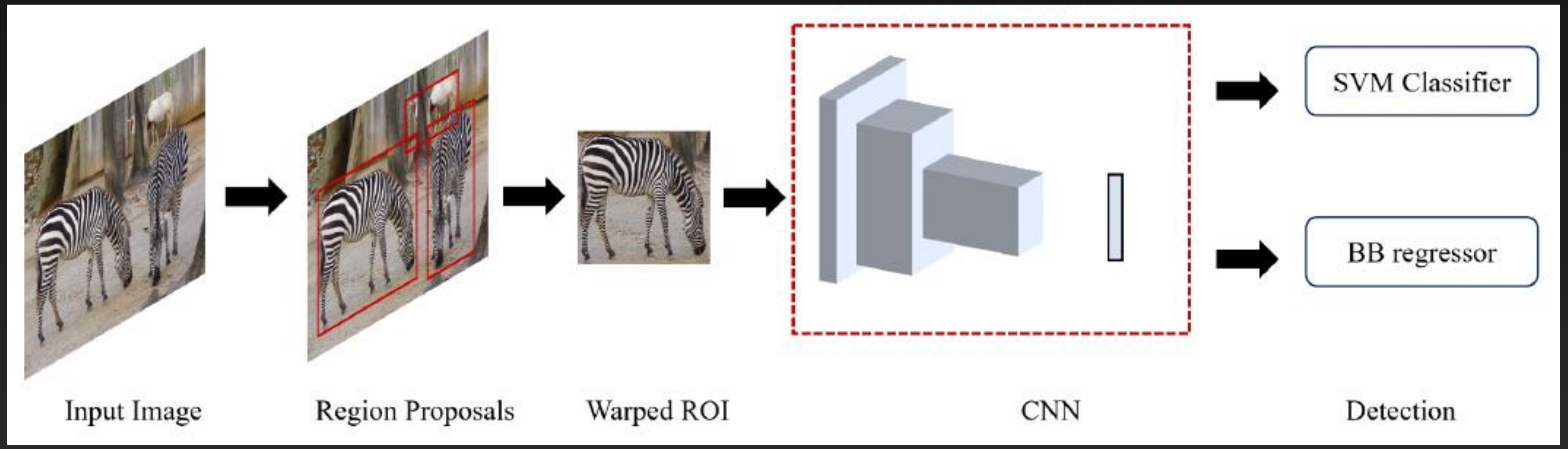
Introduction
Object Detection

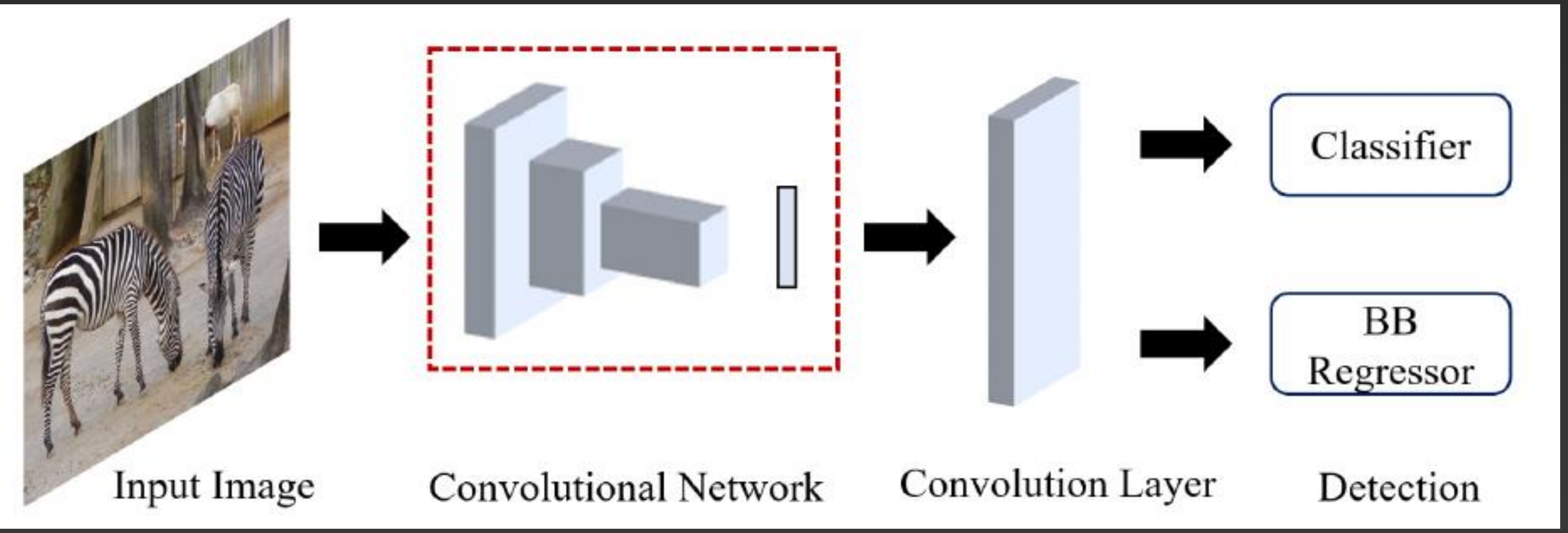
- Potential objects' location and classification
- DL advancements in the field
  - Convolutional Neural Network (CNN)
- Challenges:
  - Complex backgrounds
  - Small Targets
    - feature uncertainty, low-resolution, and imperfect context information
  - Irregular trajectory

Related Work

Object Detection Methods

- Two-stage and single-stage
- CNN: feature maps from raw images
- R-CNN family: R-CNN, Fast R-CNN, Faster R-CNN
  - Slow
  - Accurate
- From YOLO to YOLOV5:
  - Fast
  - Lower accuracy in some scenarios



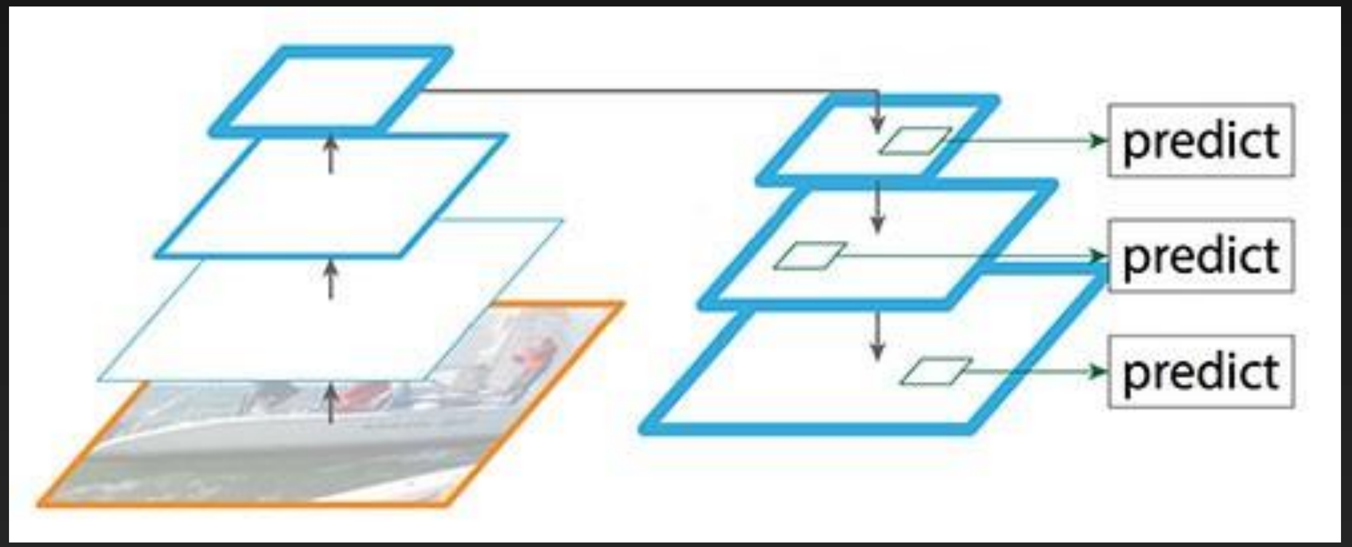


Both images: S. S. A. Zaidi, M. S. Ansari, A. Aslam, N. Kanwal, M. Asghar, and B. Lee,"A survey of modern deep learning based object detection models,"arXivpreprint arXiv:2104.11892, 2021.

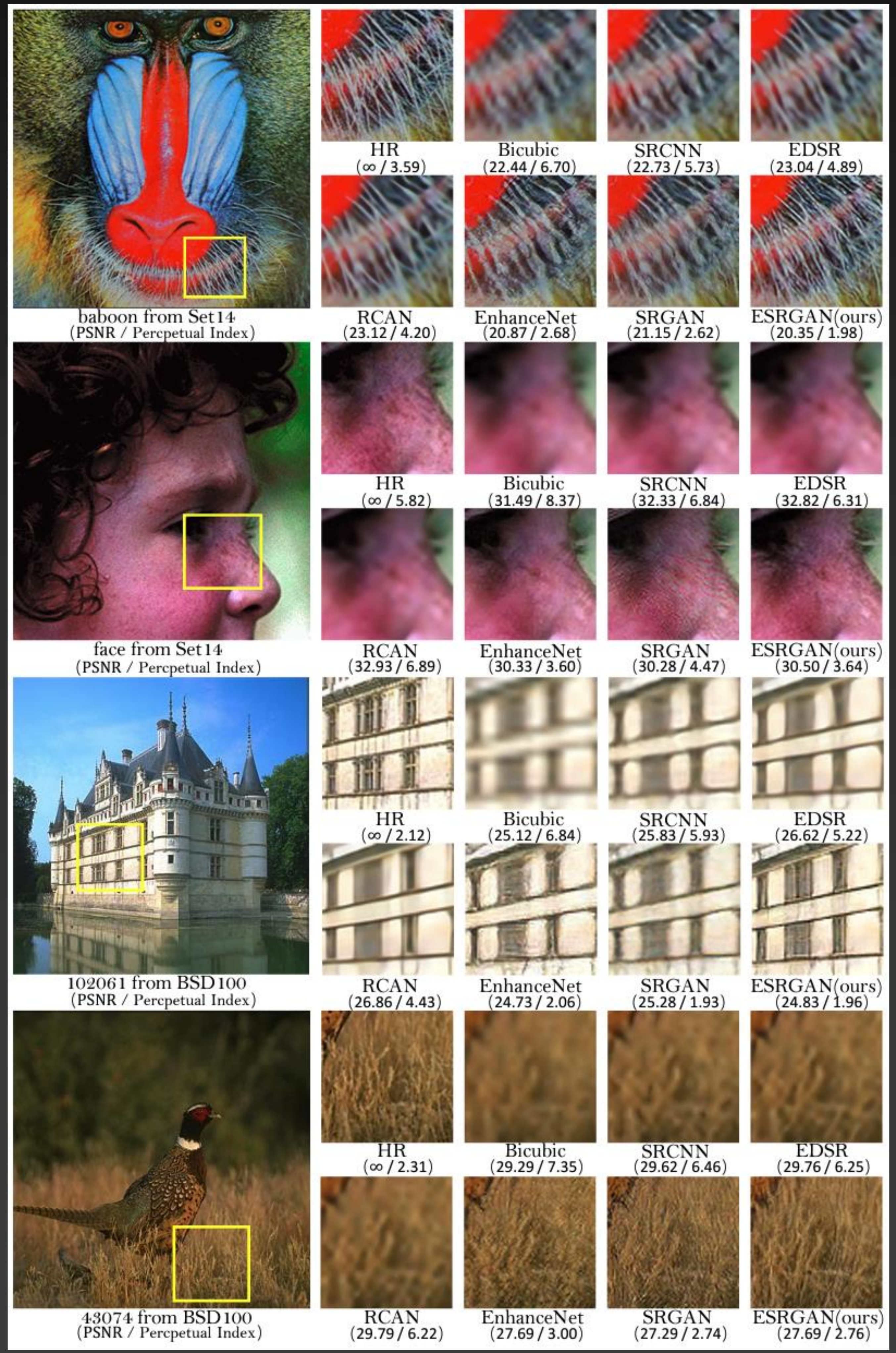
Related Work

Drone Detection Methods

- Previous works:
  - Faster R-CNN + tracker
  - Modified version of YOLOV3
  - YOLOV2
  - Faster R-CNN + background subtraction
  - Faster R-CNN + Feature Pyramid Network (FPN) + Enhanced Super-Resolution GAN (ESRGAN)



T.-Y. Lin, P. Doll´ar, R. Girshick, K. He, B. Hariharan, and S. Belongie,"Feature pyramid networks for object detection," inProceedings of theIEEE conference on computer vision and pattern recognition, 2017, pp. 2117–2125



X. Wang, K. Yu, S. Wu, J. Gu, Y. Liu, C. Dong, C. C. Loy, Y. Qiao, and X.Tang,Esrgan: Enhanced super-resolution generative adversarial networks,2018. arXiv:1809.00219 [cs.CV].

Appropriate Drone Detection Method

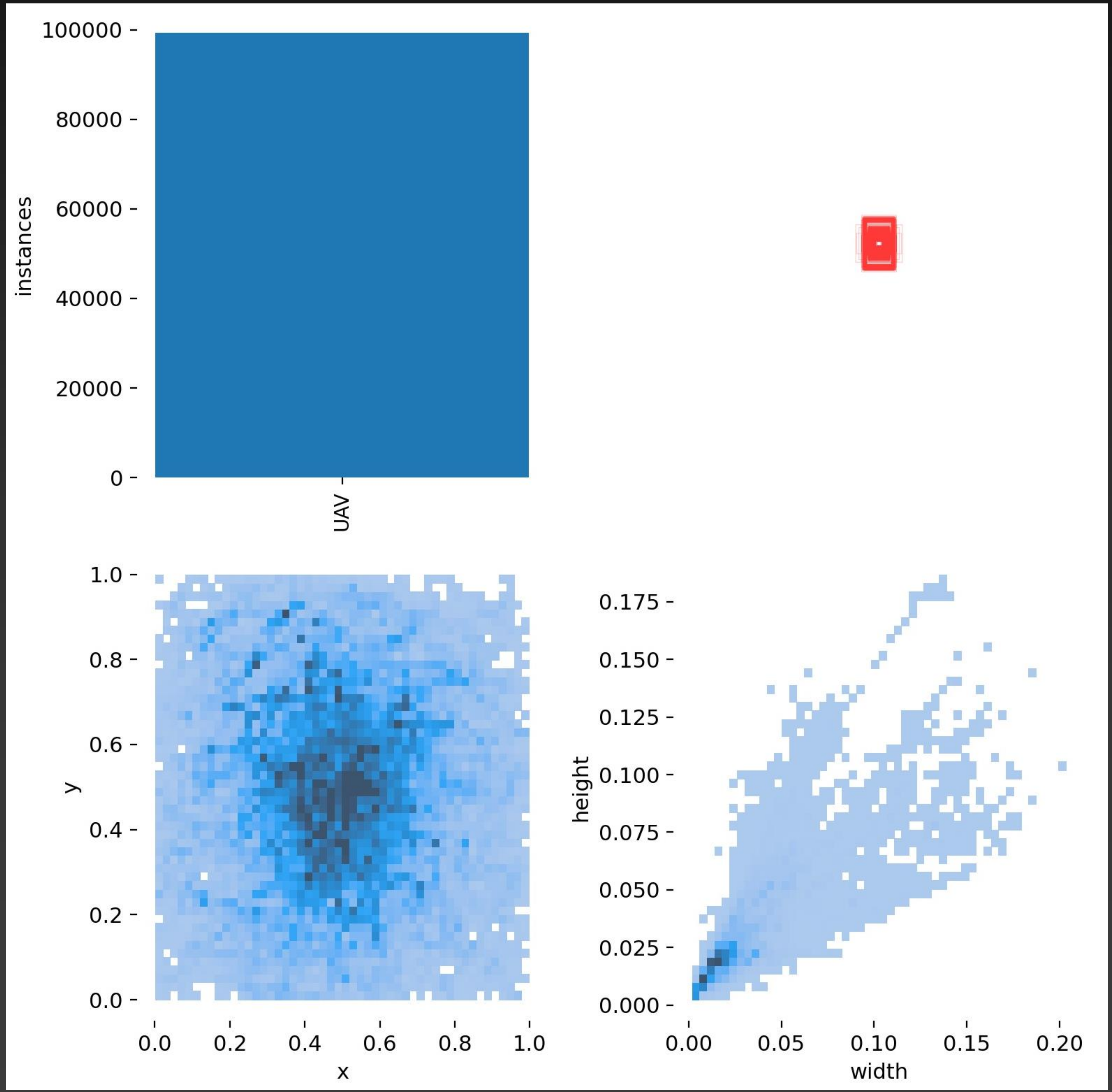
- Fast or accurate?
- Single-stage or two-stage?
- Preprocessing and post-processing?
- Time and resources limitations
- Testing both single-stage and two-stage
- YOLOV5 and Faster R-CNN + FPN
- Dataset combination for increasing the knowledge of network

https://oveisrezvanian.com/time-limit-for-rendering-arbitration-award-under-iran-law/

Dataset

We combined Det-Fly with the competition dataset

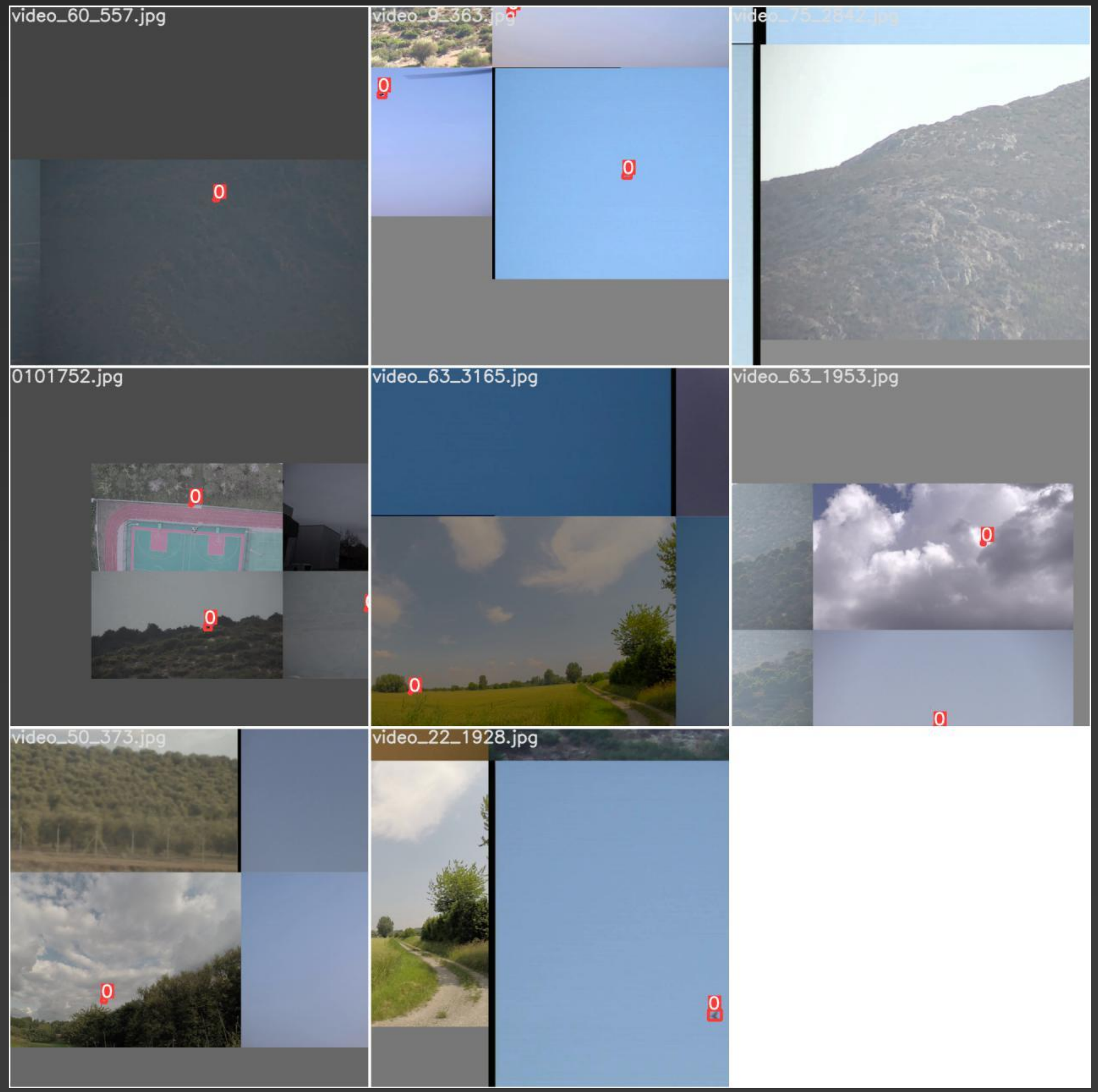
- Number of samples (more than 13K)
- Different lighting situations & backgrounds & Small targets
- After combination:
    - 116,608 (12,367 background frames)
    - training, validation, and testing
    - 80%, 10%, and 10%

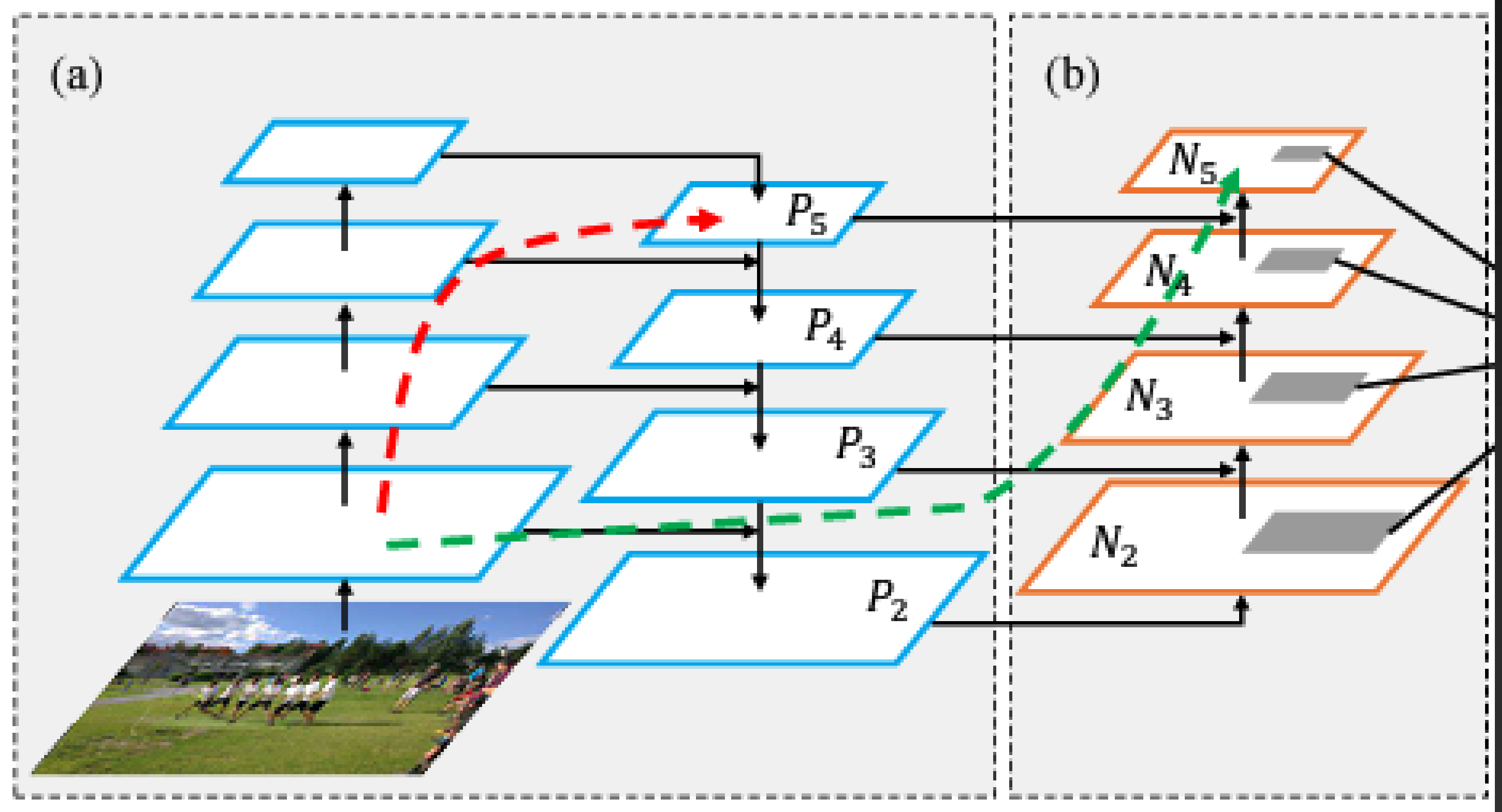


Methodology

YOLOV5

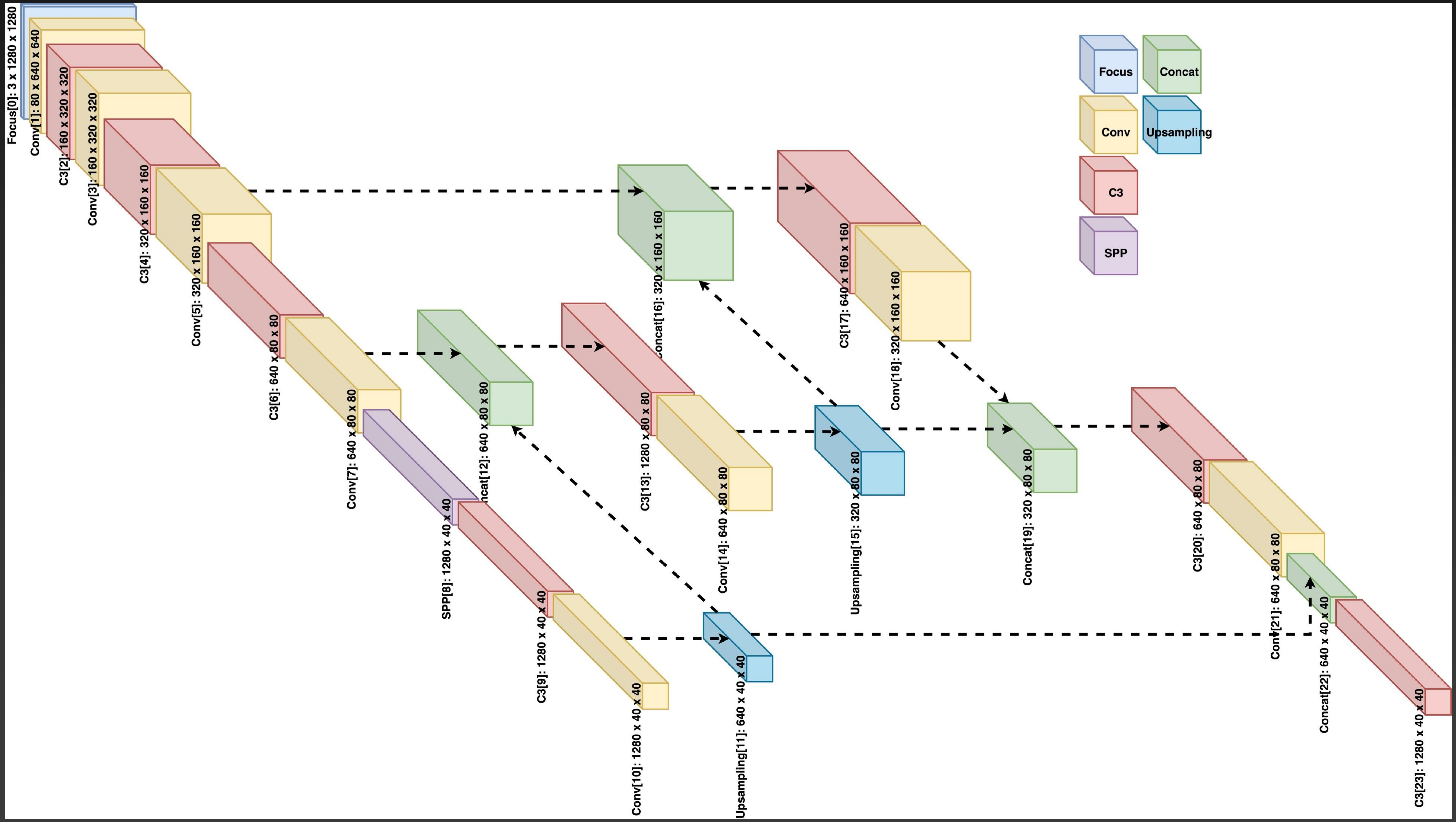
- FPN can help small objects detection
- Path Aggregation Network (PANet) is like FPN
- Augmentation:
  - Scaling
  - Color space adjustments
  - Mosaic augmentation
- Pretrained YOLOV5x





S. Liu, L. Qi, H. Qin, J. Shi, and J. Jia, “Path aggregation network for in-stance segmentation,” inProceedings of the IEEE Conference on ComputerVision and Pattern Recognition (CVPR), Jun. 2018

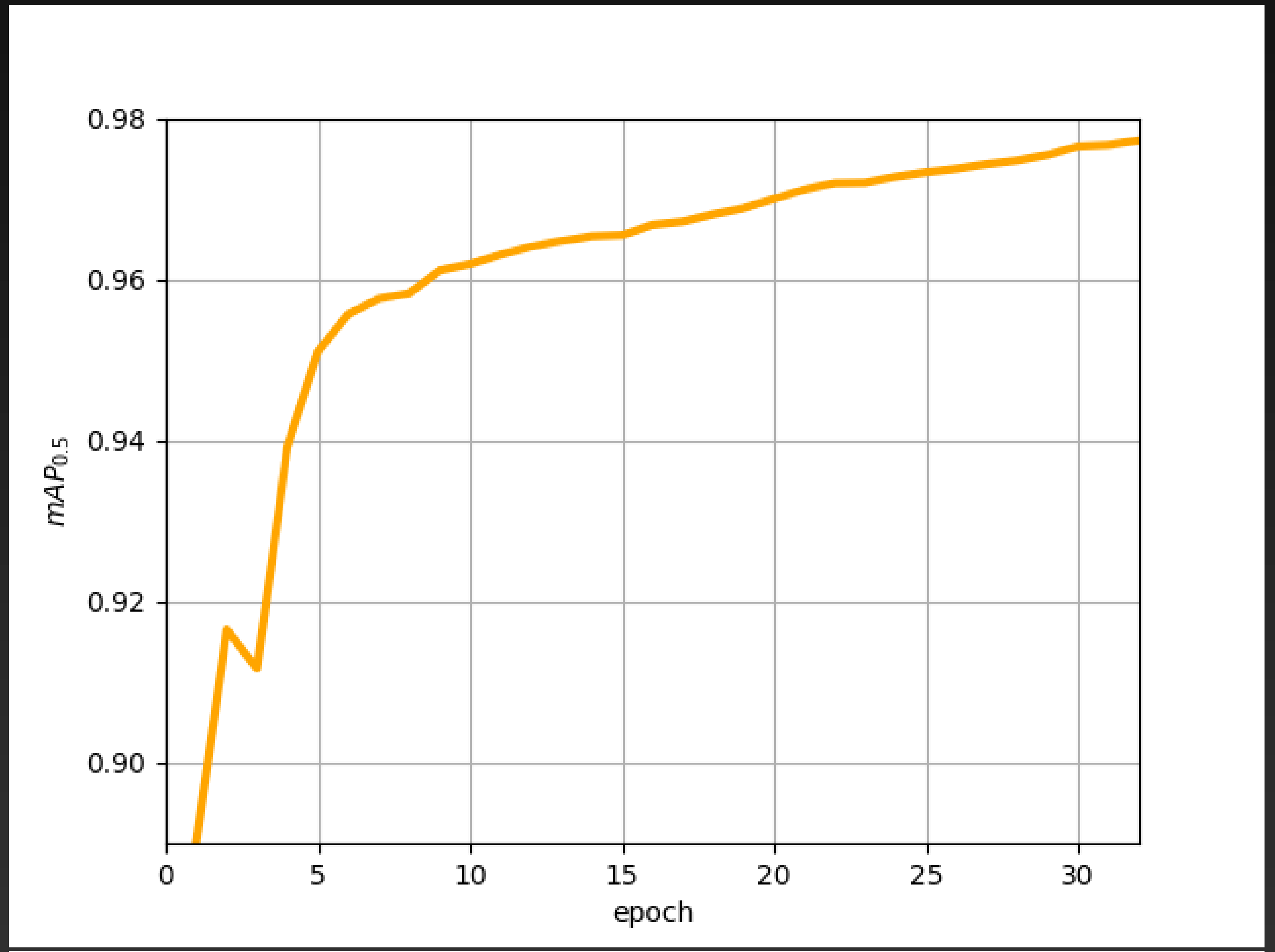
Methodology
YOLOV5x

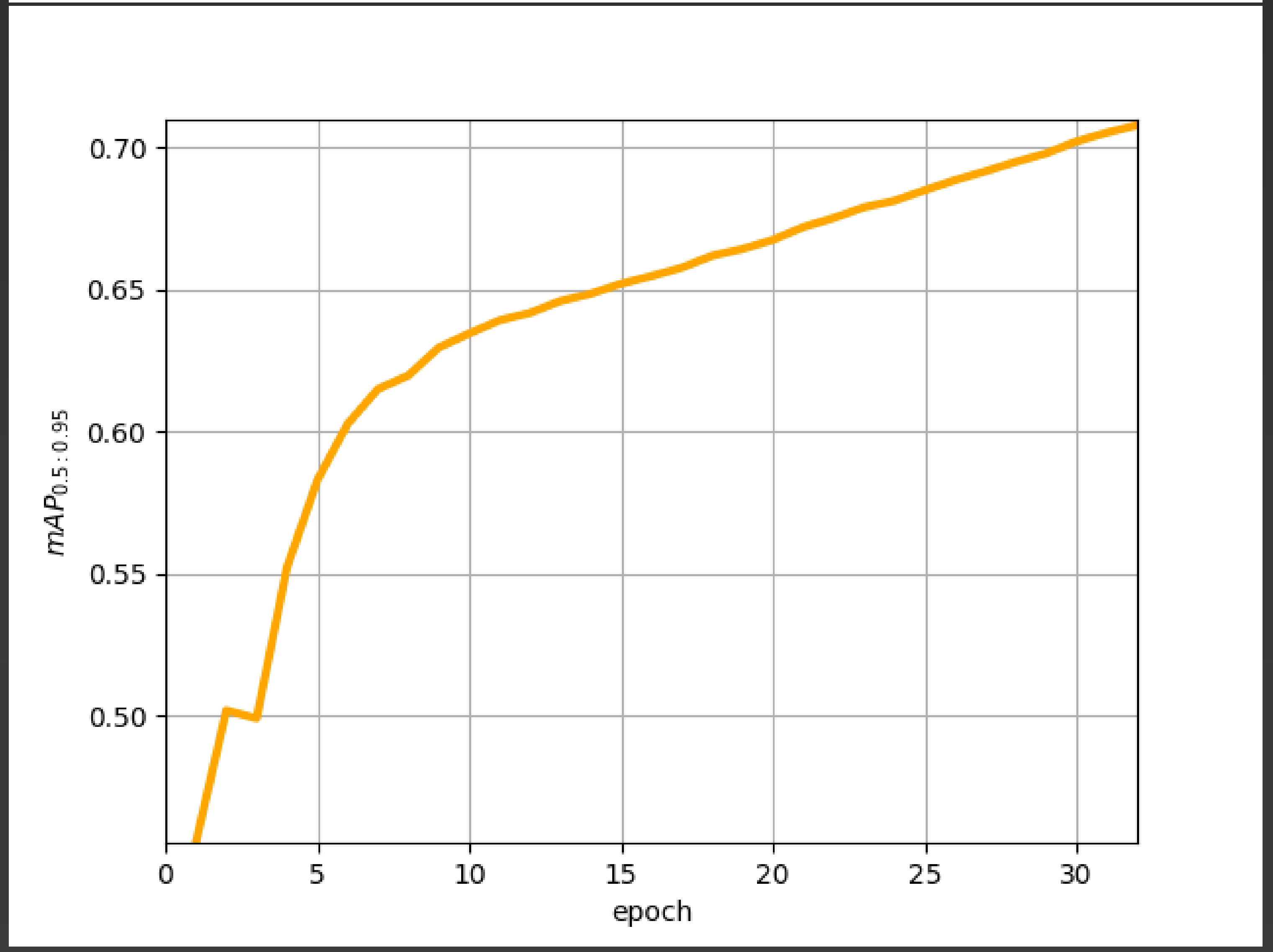


Results

YOLOV5 Training

- 32 epochs in 24 hours
- Mist cluster of ComputeCanada
- 4 Tesla V100-SXM2 32 GB
- Input image: 1280x1280
- Batch size: 32
- $0.98 mAP_{0.5}, 0.71 mAP_{0.5:0.95}$

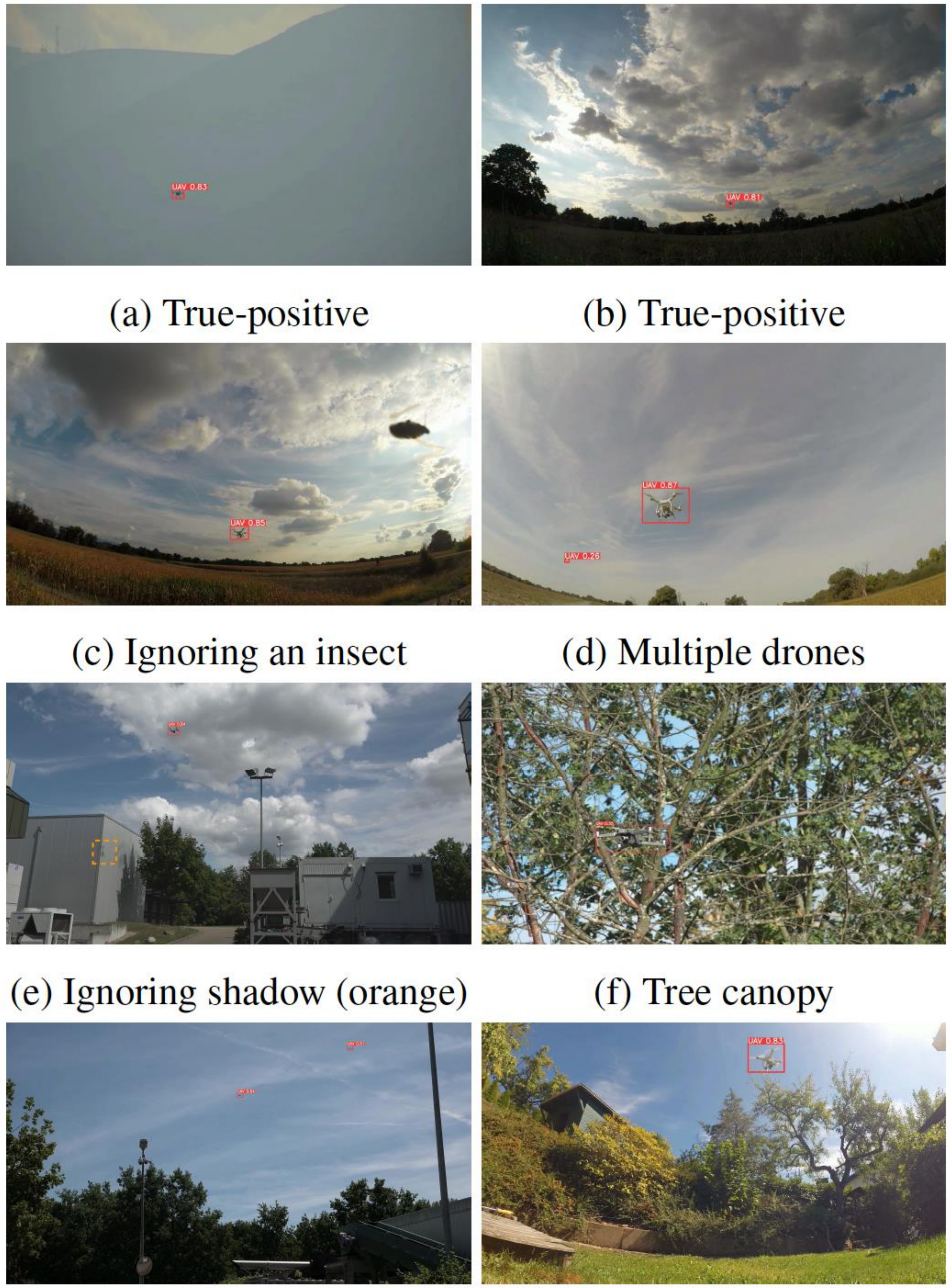




Discussion

YOLOV5 Positive Results

- Small distant objects (sometimes)
- Ignoring some other objects such as insects
- Detecting multiple drones
- Ignoring the drone shadow
- Barely, detecting some objects in complex backgrounds

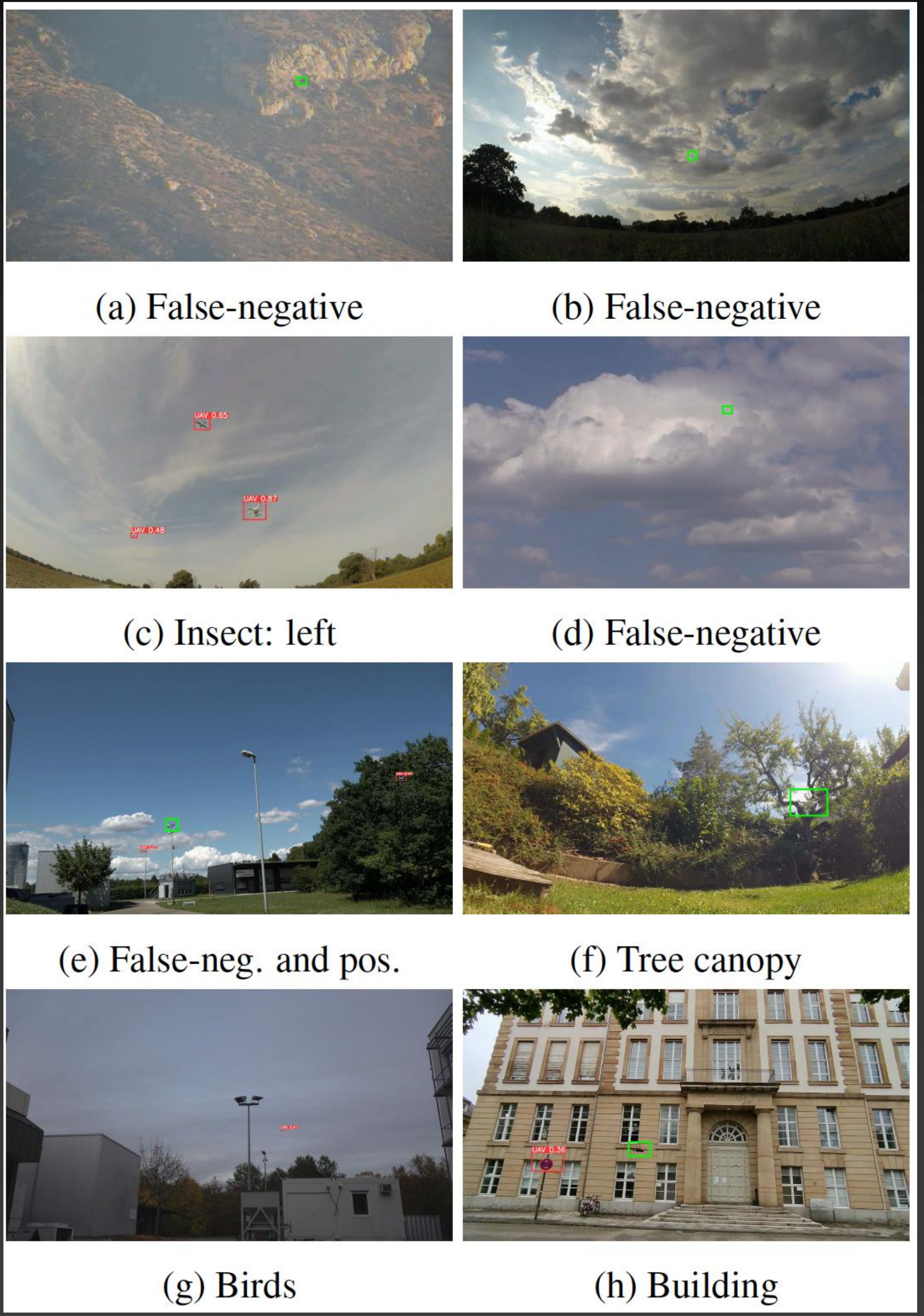


(a) True-positive
(b) True-positive
(c) Ignoring an insect
(d) Multiple drones
(e) Ignoring shadow (orange)
(f) Tree canopy
(g) Multiple drones
(h) Near trees

Discussion

YOLOV5 Negative Results

- Flying in front of some unseen backgrounds
- Occlusion
- Insects, flocks of birds as drones
- Missing the detection of distant drones in complex backgrounds

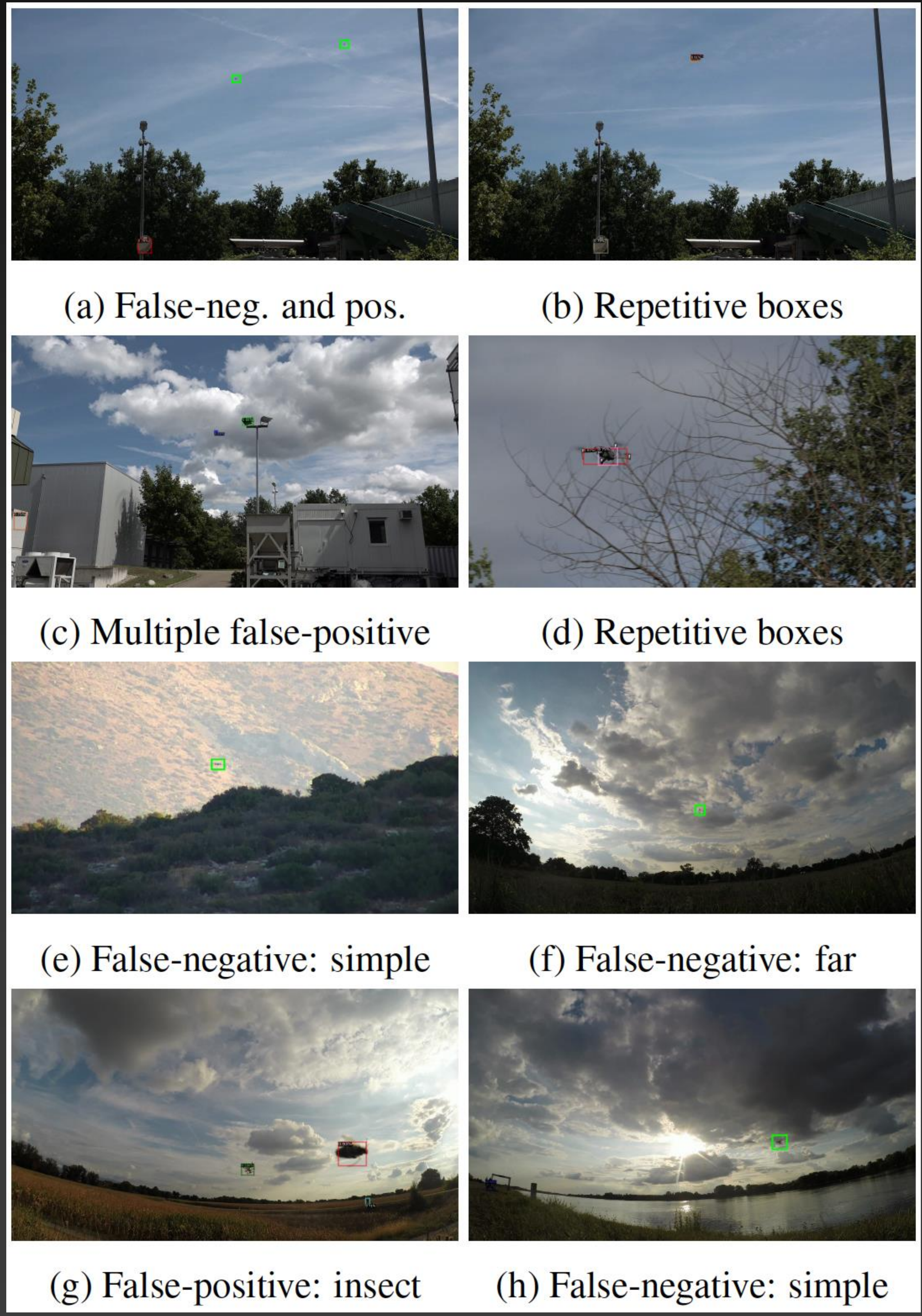


(a) False-negative (b) False-negative
(c) Insect: left (d) False-negative
(e) False-neg. and pos. (f) Tree canopy
(g) Birds (h) Building

Discussion

Faster R-CNN + FPN Drawbacks

- Missing the simple detections
- Too much false negatives
- Repetitive detection for a drone
- False positives: insect



(a) False-neg. and pos.
(b) Repetitive boxes
(c) Multiple false-positive
(d) Repetitive boxes
(e) False-negative: simple
(f) False-negative: far
(g) False-positive: insect
(h) False-negative: simple

Conclusion

- For addressing the drone vs. bird detection: YOLOV5
- Det-Fly: air-to-air publicly available dataset
- Increase the number of small objects and complex backgrounds
- Not only YOLOV5 works better in simple scenarios, but also it beats the Faster R-CNN+FPN model in challenging scenes
- Open problems: small objects detection in complex backgrounds
- Future works: tracking algorithms, test other ideas and methods (we have time and computational resources limitation)

Thanks!

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