DLP Object Detection

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Task and Dataset

DLP Object Detection | Kaggle

Identifying potentially dangerous mosquito types (classes) can help collecting valuable information about their migrations and even saving people’s lives.

Raw dataset statistics:

	min	median	max
image (w, h)	(152, 106)	(2592, 1456)	(9000, 12000)
bbox (relative area)	0.000004	0.073	0.957

Initially, the dataset has been split into training and testing sets, with 93.5% of the images allocated for training (7500 images) and 6.5% for testing (525 images).

Our train/validation split is 80/20%.

Class	albopictus	culex	culiseta	japonicus/koreicus	anopheles	aegypti
Count (base)	3334	3312	460	300	59	35
Count (yolo-final-augmented)	2620	2627	1810	1422	987	588

	min	median	max
bbox (relative area)	0.0007	0.11	0.999

Faster R-CNN

Existing solutions, rationale

Yang Liu, Peng Sun, Nickolas Wergeles, Yi Shang, **“A survey and performance evaluation of deep learning methods for small object detection”** - the article provides an overview of small object detection methods and confirms the effectiveness of using Faster R-CNN for such tasks.

H. Xiao, N. Zhao, X. Cui and Z. Gao, **"Research and application of improved Faster R-CNN model for pest identification”** - Faster R-CNN is used as the basis along with the Region Proposal Network.

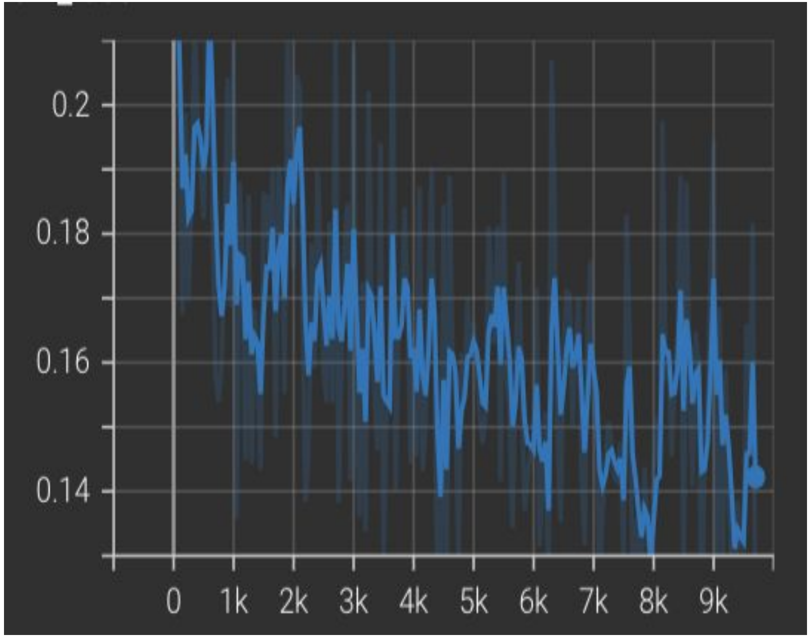
Architecture

- Backbone - ResNet-50:
  ResNet-50 is used as the backbone for extracting high-level spatial features from input images. The residual connections enable training even with a large network depth.

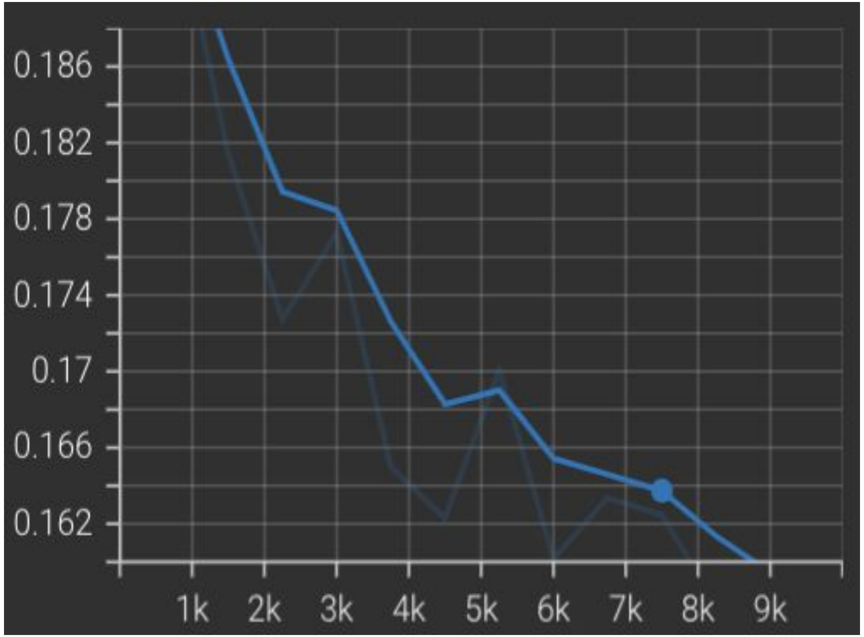
- Feature Pyramid Network (FPN):
  FPN is built on top of the ResNet-50 backbone and enhances the model's ability to detect objects of different sizes and levels of detail by utilizing multi-level features.

Intermediate results – Kaggle 17th Place

0.47342



Train loss



Validation loss

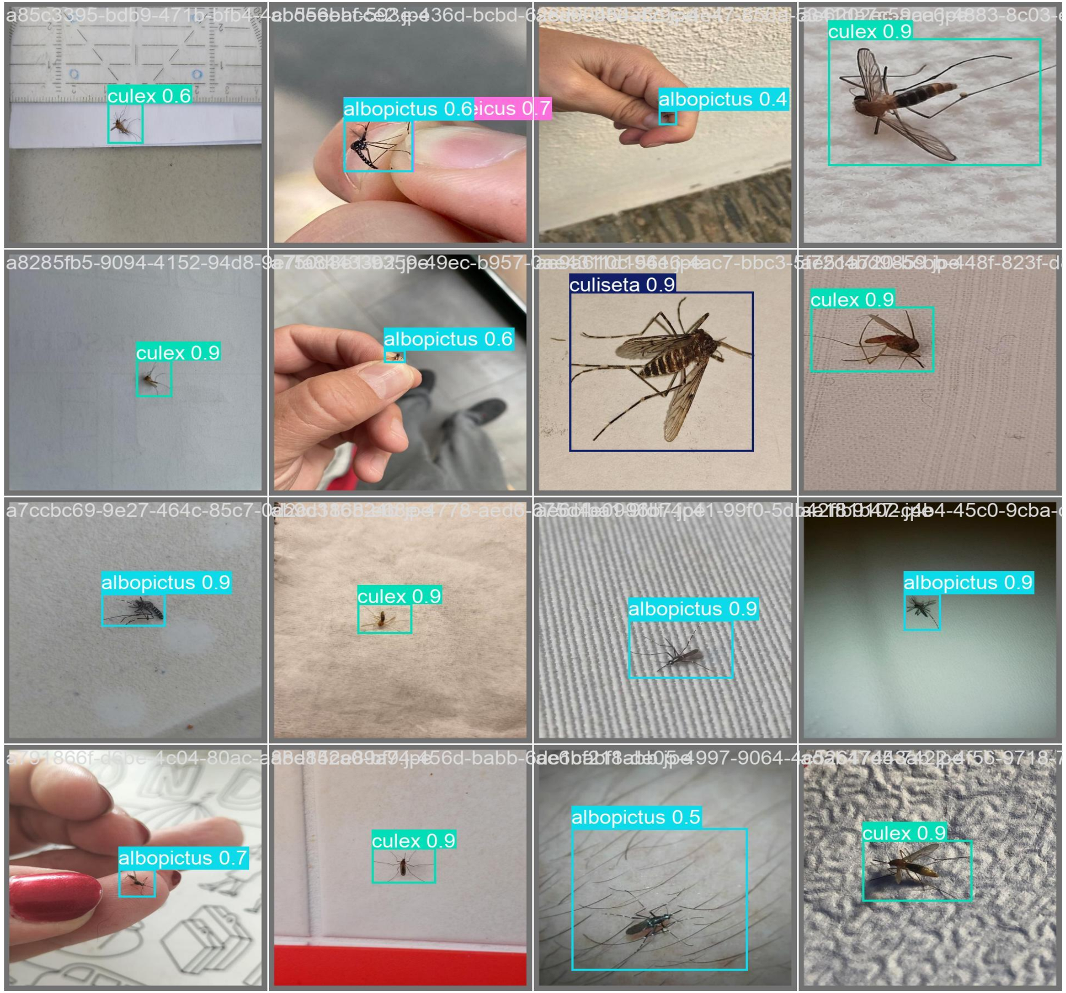
Loss for 10k steps. LR=0.005. Batch size=8.

YOLO v11

Existing solutions, rationale

A. M. Hubalde, D. A. Padilla and D. A. C. Santos, **"A YOLO-Based Approach for Aedes Aegypti Larvae Classification and Detection"** - study implemented the YOLO algorithm to detect and classify mosquito larvae, specifically identifying the Aedes aegypti species.

Camila Laranjeira, Daniel Andrade, Jefersson A. dos Santos, **“YOLOv7 for Mosquito Breeding Grounds Detection and Tracking”** - work utilized YOLOv7 to localize and track mosquito breeding sites in videos captured by unmanned aerial vehicles, highlighting YOLO's capability in detecting environments conducive to mosquito proliferation



Model: YOLO11m

20.1M parameters

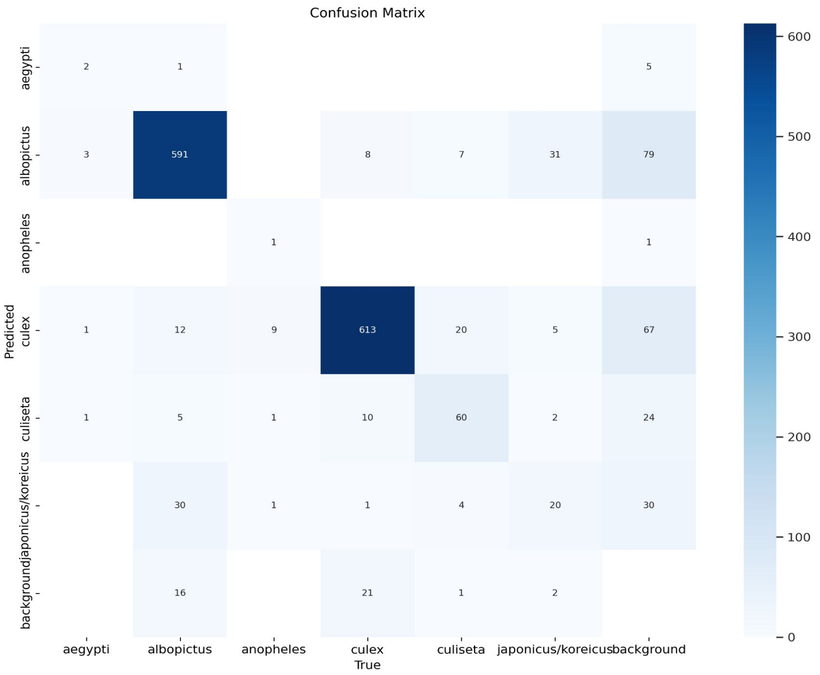
Focal Loss

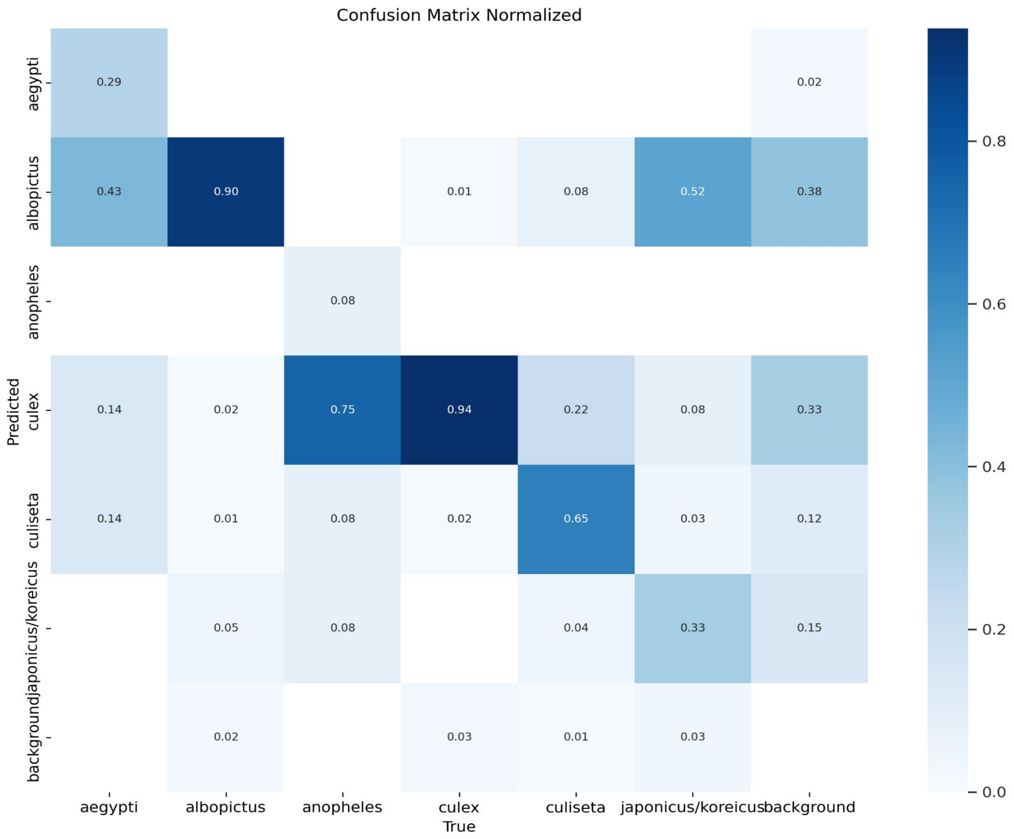
#	Team	Members	Score	Entries	Last	Solution
1	21F1005524		0.66123	5	3mo	
2	21F1000460		0.65875	2	3mo	
3	21F1000722		0.65664	7	3mo	
4	test		0.61441	1	3mo	
5	mosqui		0.58929	2	3mo	

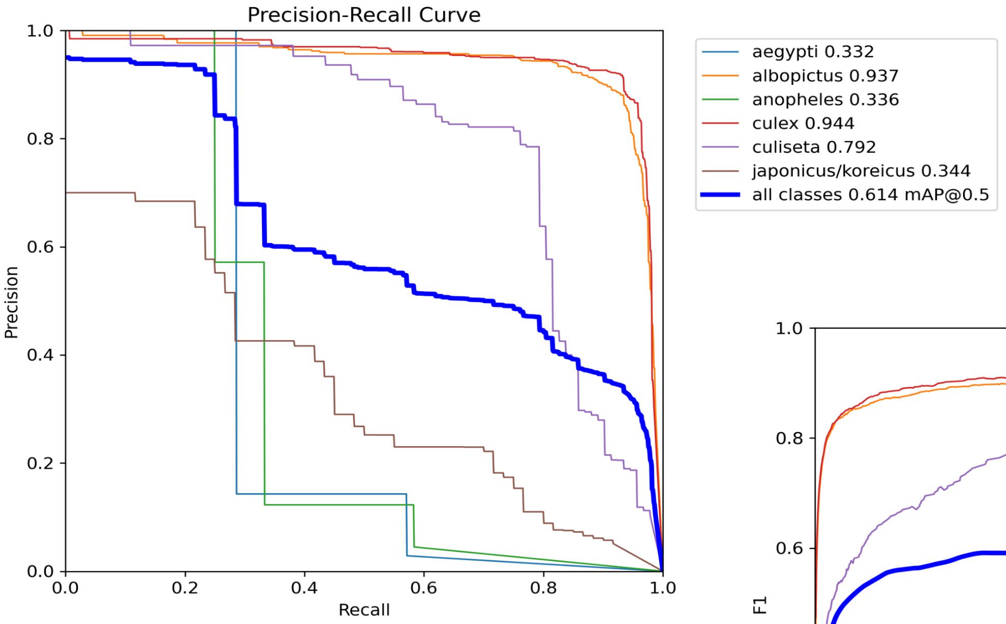
mAP:

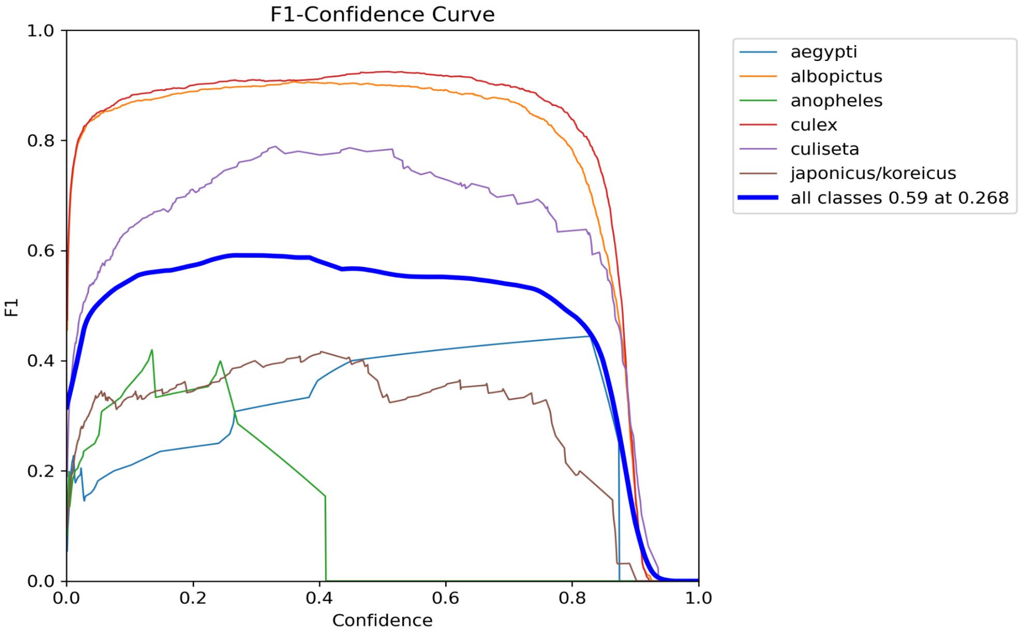
- Base (Raw DS): 0.648
- Size filters: 0.649
- Augmentations: 0.665

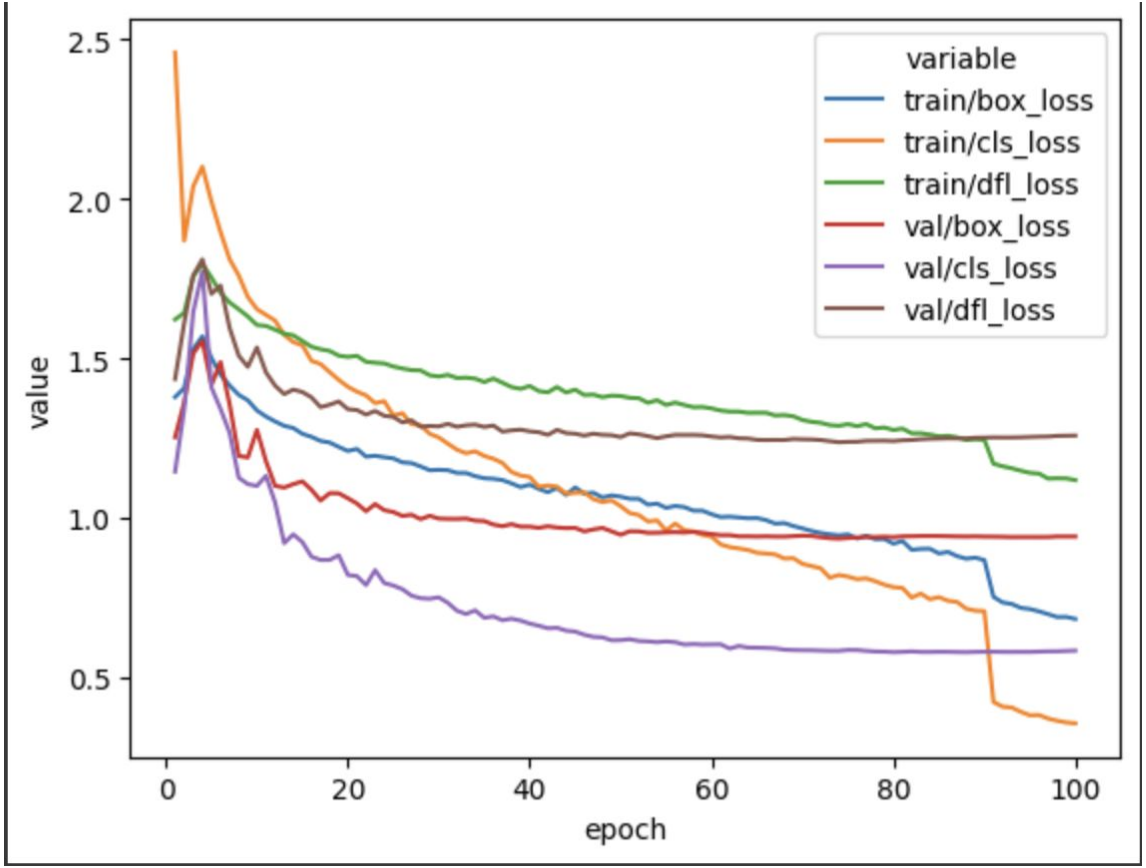
Final result is higher than the first place.


Confusion Matrix
aegypti
albopictus
anopheles
culex
culiseta
japonicus/koreicus
background
Predicted
True
2 1 5
3 591 8 7 31 79
1 1
1 12 9 613 20 5 67
1 5 1 10 60 2 24
30 1 1 4 20 30
16 21 1 2
0
100
200
300
400
500
600


Confusion Matrix Normalized
aegypti
albopictus
anopheles
culex
culiseta
japonicus/koreicus
background
Predicted
True
0.29 0.02
0.43 0.90 0.01 0.08 0.52 0.38
0.08
0.14 0.02 0.75 0.94 0.22 0.08 0.33
0.14 0.01 0.08 0.02 0.65 0.03 0.12
0.05 0.08 0.04 0.33 0.15
0.02 0.03 0.01 0.03
0.0
0.2
0.4
0.6
0.8


Precision-Recall Curve
Precision
Recall
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0
aegypti 0.332
albopictus 0.937
anopheles 0.336
culex 0.944
culiseta 0.792
japonicus/koreicus 0.344
all classes 0.614 mAP@0.5


F1-Confidence Curve
F1
Confidence
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0
aegypti
albopictus
anopheles
culex
culiseta
japonicus/koreicus
all classes 0.59 at 0.268



100 epochs
Batch size 8
LR 0.01

```
Speed: 0.4ms preprocess, 22.5ms inference, 0.0ms loss, 0.9ms postprocess per image
```

Key Takeaways

- Faster R-CNN demonstrates acceptable accuracy in mosquito classification but may be less suitable for real-time applications due to its computational complexity and slower inference speed.
- High-performing classes: Culex and Albopictus have strong precision-recall tradeoffs and high F1-scores.
- Poorly detected classes: Aegypti, Anopheles, and Japonicus/Koreicus need improvement, possibly due to data imbalance or feature overlap.
- Further improvements: We may consider data augmentation, class rebalancing, and improved feature extraction for underperforming classes.