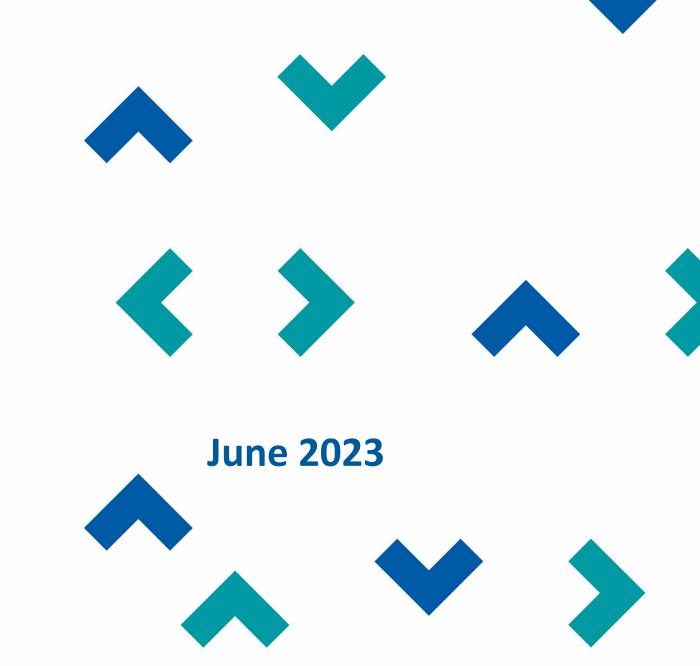
# The detection of aphids in mid-air

A comparison between state of the art object detectors

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## Introduction

- The rapid rise of the potato virus Y heavily threatens the strong Dutch potato export. [1]
- To prevent infection the bearers of this virus, aphids, must be eliminated early with pesticides. This has negative consequences for the environment.
- Letting a computer report aphids as early as possible, minimizes the need for pesticide usage.

## Materials and Methods - Dataset

- To simulate flight, aphids have been dropped in a large wooden box and photographed mid-air
- Other than aphids, the dataset consists of 2 different types of fruit flies as well. These flies look a lot like aphids.
- Previous research has proven that tiling is an effective method [2]. Therefore, it will be applied at this research as well.

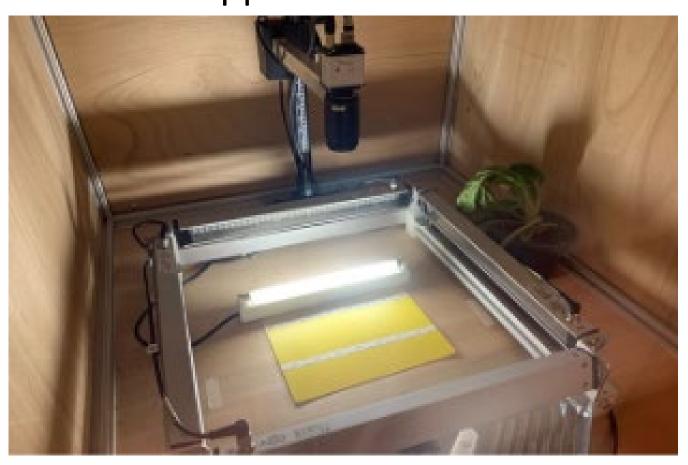


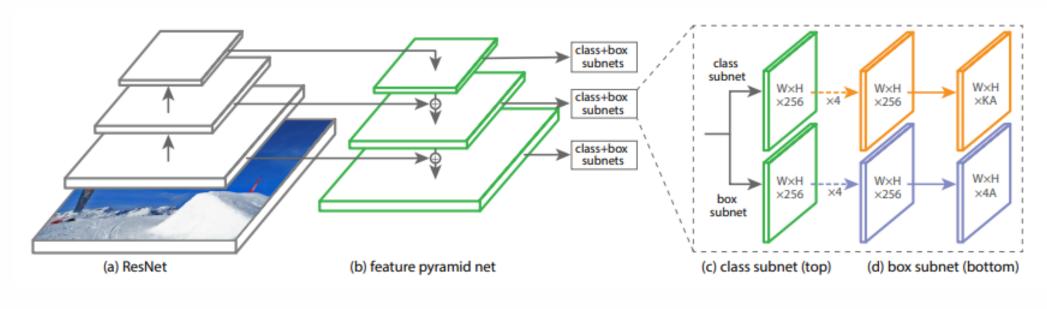
Figure 1. Setup for the acquisition of our dataset.



**Figure 2.** Example of each of the different classes in our dataset. Winged aphid: top left. Wingless aphid: top right. Melanogaster: bottom left. Virilis: bottom right.

### **Materials and Methods - Detectors**

- YOLOv8 is an anchor free object detector developed by Ultralytics.
- RetinaNet is a single, unified network composed of a backbone network and two task-specific subnetworks, that utilizes focal loss. [3]
- YOLOv5 is the predecessor of YOLOv8



**Figure 3.** A visualization of the RetinaNet architecture obtained from [3]. It uses a ResNet backbone, which can have different dpeths. Within this research, backbones of 18, 34, 50, 101 and 152 have been experimented on.

### Abstract

The potato virus Y can infect potatoes and heavily impact the strong Dutch potato export. Because this virus gets carried by aphids, finding them, using computer vision may offer a solution. YOLOv8 and RetinaNet where trained to detect aphids. Not only will these detectors be trained to be able to detect aphids from other insects, but also to determine exactly what the currently viewed insect exactly is. YOLOv8 gives the best F1 score of 0.8425 for determining five different insects. And 0.9082 for just separating aphids from other insects.

# NHL STENDEN

computer vision

& data science

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## **Experiments and Results - Experiments**

- YOLOv8 and RetinaNet have been used on two types of the acquired dataset: on one determining an aphid from any other insect was required, on the other differentiating every different insect was the goal.
- Experiments were performed with YOLOv8 and YOLOv5. To determine what the difference in performance between the two versions is.
- RetinaNet with ResNet backbones of 18, 34, 50, 101 and 152 have been used in the experiments



**Figure 4**. A wingless\_aphid and it's predicted bounding boxes.



**Figure 5.** A winged\_aphid and it's predicted bounding boxes

## **Experiments and Results - Results**

- Results of the experiments can be seen in the figures below. With YOLO in figures 3 and 4. And RetinaNet in figures 5 and 6.
- Figure 3 shows that YOLOv8 outperforms YOLOv5 regarding every metric. When the dataset gets more complex as in figure 4 YOLOv8 and YOLOv5 score equally good.
- Figures 5 and 6 show the results with an IoU threshold of 0.5. Higher thresholds give more precision and less recall, while low thresholds give lower precision and higher recall. The mutation in precision is higher than in recall, so higher IoU thresholds give better F1 scores. However, within the context of this project, recall is more important, so the middle ground of 0.5 has been chosen.

Model	Precision	Recall	MAP-95%	F1-score
two classes				
YOLOv5n	0.90	0.76	0.75	0.81
YOLOv8n	0.98	0.84	0.80	0.90
YOLOv5s	0.93	0.71	0.79	0.81
YOLOv8s	0.98	0.82	0.83	0.89
YOLOv5m	0.96	0.72	0.82	0.83
YOLOv8m	0.98	0.82	0.89	0.89
five classes				
YOLOv5n	0.92	0.76	0.79	0.83
YOLOv8n	0.42	0.73	0.87	0.54
YOLOv5s	0.98	0.75	0.83	0.85
YOLOv8s	0.87	0.73	0.86	0.79
YOLOv5m	0.98	0.69	0.83	0.81
YOLOv8m	0.99	0.73	0.89	0.84

**Figure 6.** Results of different YOLO models.

Model	Precision	Recall	MAP	F1 score
two classes				
ResNet-18	0.91	0.65	0.65	0.76
ResNet-34	0.94	0.59	0.59	0.73
ResNet-50	0.82	0.62	0.61	0.71
ResNet-101	0.85	0.64	0.63	0.73
ResNet-152	0.82	0.63	0.62	0.71
five classes				
ResNet-18	0.78	0.39	0.38	0.52
ResNet-34	0.70	0.43	0.39	0.53
ResNet-50	0.58	0.37	0.34	0.45
ResNet-101	0.74	0.42	0.38	0.53
ResNet-152	0.57	0.35	0.30	0.44

**Figure 7.** Results of different RetinaNet models with an intersection over union threshold of 0.5.

#### **Conclusions and Future Work**

- Models seem to perform better on a dataset with the differentiation between aphid or another insect, than on the dataset that labels every different insect.
- Having the object detector differentiate between aphids in their different stages comes with a cost in the recall.
- YOLO gives more desirable results than RetinaNet with an F1 score increase of 0.15 on the 2-classes dataset and an increase of 0.3 on the 5-classes dataset.
- For future research, testing on insects within their natural habitat is desirable. Complications may arrive with the acquisition of a dataset, because aphids only appear on a specific time of the year.

### References

- [1] Projectplan POP3 profincie fryslân maatregel.
- [2] Klut Sander. Detection of Aphids on Sticky Plates using YOLOv5 with Image Tiling. Research paper.
- [3] Lin Tsung-Yi et al. Focal Loss for Dense Object Detection. URL: https://arxiv.org/pdf/1708.02002v2.pdf