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Ant Detection using YOLOv8: Evaluation of Dataset Transfer Impact

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Abstract. **In order to avoid having to fight with aphids and plant virus diseases caused by them in gardens, it is very important to notice ant colonies. As a result we decided to train artificial intelligence to detect ant colonies, then this artificial intelligence can be integrated into an autonomous orchard monitoring system using unmanned aerial vehicles. However, there is restricted availability of open datasets, which contain natural images and region specific species. In the scope of pilot study we decided to train convolutional neural network using ANTS dataset and to test it on small domain-specific dataset to identify the need to collect new dataset. The experiment was completed using the popular architecture YOLOv8. The YOLOv8n and YOLOv8m models trained on ANTS showed accuracy 98% and 99% mAP@0.5. Meanwhile, their accuracy was only 6% and 5% mAP@0.5 respectively testing on our dataset called "WildAnts". Our pilot study experimentally proves that it is important to collect natural dataset of ant images to train robust artificial intelligence for orchard monitoring using unmanned aerial vehicles. This study will be interesting for all machine learning specialists, because it numerically shows accuracy decrease in the result of dataset transfer.**

Keywords: ant, deep learning, pests, precision farming

I. Introduction

Agricultural yields are affected not only by unstable climatic conditions, but also by various pests. Although Latvia is a relatively small country, the spread of pests can vary in different regions. In general, all pests can be divided into those that multiply and damage specific crops and those that multiply and damage those plants that are available. Agricultural crops in Latvia are affected by pests such as spider mites (Tetranychus urticae), aphids (Aphididae), pear blight beetles (Xyleborus dispar) and many others. If the aforementioned are unequivocally considered as pests, then there are continuous discussions regarding ants (Formicidae) and it is an actual question whether to consider them as pests or, nevertheless, important insects in agriculture [1].

Ants enjoy the sweet juice found in many sweet berries and fruits such as strawberries, cherries, pears, etc., resulting in damage to fruit and berry crops. However, the most significant ant damage is related to aphids. Aphids suck sap and transmit plant viral diseases. Ants, on the other hand, like the liquid secreted by aphids, so they use these pests to their advantage and protect them from natural enemies. Therefore, farmers, in order to free their gardens from aphids, destroy their defenders - ants.

In order to avoid having to fight with aphids and plant virus diseases caused by them in gardens, it is very important to notice ant colonies in time to prevent the spread of aphids.

One of the approaches to ant detection can be autonomous garden monitoring by application of unmanned aerial vehicles (UAVs). A specially designed web-based information system can automatically schedule garden surveillance flights on a regular basis and notify garden personnel as soon as pests have been detected on the imagery of garden plants. To set up such a monitoring the system operator first has to enter their garden details into the system (garden location and boundaries, tree or plant rows, restricted areas, UAV base station location) and the flight mission planner will calculate an optimal surveillance flight plan taking into account UAV flight time, restricted areas and weather conditions.

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Therefore artificial intelligence must be trained to detect ants, which will be integrated into autonomous monitoring systems.

Artificial intelligence usage in the domain of ants, at this point of time, mainly targets ant tracking in the terms of studying ant cluster behavior. In the article "A dataset of ant colonies' motion trajectories in indoor and outdoor scenes were tracked to study clustering behavior" [2], Wu et. al. (2022) developed the ground monitoring tool for ant tracking. Each ant was labeled with an ID to monitor its motion track.

In broader scope, in the article "Tracking Different Ant Species: An Unsupervised Domain Adaptation Framework and a Dataset for Multi-object Tracking" written by Abeysinghe et al. (2023) [3], the framework was created for object tracking tasks, which was tested on ant colonies.

The aim of our study is to train CNN for ant detection. There is an existing image dataset, which can be applied for CNN training. The dataset was collected by Wu et al. (2022) [2] for analysis of ant colonies' motion trajectories in indoor and outdoor scenes (hereinafter ANTS). However, ANTS was collected for specific tasks and can be characterized by laboratory conditions. Therefore, we decided to collect a small dataset with natural images to experimentally test dataset transfer impact on CNN accuracy. We called our dataset "WildAnts".

The experiment was completed using the popular and modern architecture YOLOv8. The YOLOv8n and YOLOv8m models trained on ANTS showed accuracy 98% and 99% mAP@0.5. Meanwhile, their accuracy was only 6% and 5% mAP@0.5 respectively testing on WildAnts. The mirror experiment design showed better results. The YOLOv8n and YOLOv8m models trained on WildAnts showed accuracy 75% and 78% mAP@0.5. Meanwhile, their accuracy was 23% and 29% mAP@0.5 respectively testing on ANTS.

The experiment results shows that it is strongly important to collect domain-specific dataset with natural images for ant detection to train robust CNN for orchard monitoring using UAV.

II. MATERIALS AND METHODS

ANTS dataset:

The dataset "ANTS" was prepared under laboratory and near laboratory conditions for ant path tracking tasks [2]. The dataset consists of 5334 annotated images, which included 712 ants and 114,112 bounding boxes. The image sizes are 1280x720 and 1920x1080. The dataset is available in Mendeley repository under CC-BY4.0 [4]. The ANTS dataset consists of two subdatasets: one contains images collected by imaging ants in a jar (see Fig. 1), another - near anthills (see Fig. 2).

Fig. 1. ANTS dataset: in laboratory conditions [2]

Fig. 2. ANTS dataset: in near laboratory conditions [2]

WildAnts dataset:

The dataset "WildAnts" was created from different videos of ants in natural conditions. Every 12 frames were cut from the collected videos. And then pictures were manually selected. Different sizes and resolutions of images were selected. In result, 253 images were prepared. The images were annotated and saved in YOLO format (see Fig. 3). The image sizes in the dataset vary in a wide range, with the smallest images 640x368 to the largest with dimensions of 3840x2178.

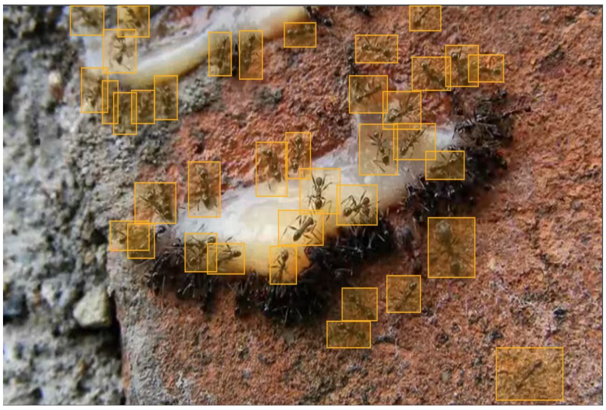

Fig. 3. WildAnts dataset

Fig. 4. WildAnts dataset

YOLOv8 training:

In this experiment, we applied the following YOLOv8 [5] models: YOLOv8n and YOLOv8m. The experiment was conducted on an NVIDIA RTX 2070 GPU.

The obtained datasets, ANTS and WildAnts, were used to train and test the models. Each dataset was randomly divided into training and testing subdatasets using the random shuffle method in Python using proportion 80% and 20%. Each dataset was divided five times and then used for training the models, giving us a total of 10 trained models. The training parameters were the same for both YOLO architectures The training was performed for 200 epochs with a patience of 50 independently on each dataset. The images were of various sizes and were resized to 640x640 pixels using YOLOv8's built-in function. The experiment was designed similarly to Kodors et al. (2023) to get comparable results [6]. When the training was completed the trained models were tested on another dataset to identify the dataset transfer impact on the accuracy (see Fig. 5).

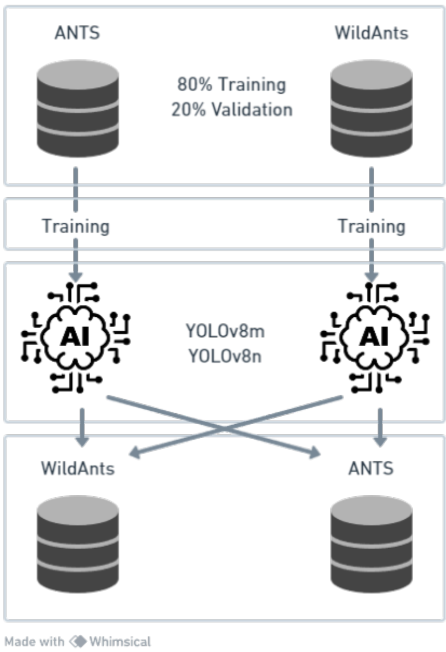

Fig. 5. Experiment design

III. Results and Discussions

Analyzing the results obtained when testing the models on the datasets on which they were trained on, the best result was shown by YOLOv8m equal to 99.0% mAP@0.5 in the case of ANTS dataset (see Tab. 1, median). But for the models trained on the WildAnts dataset, the best result was shown by YOLOv8m equal to 77.4% mAP@0.5 (see Tab. 1, median). Such a difference can be explained by the fact that in the case of ANTS dataset, images were collected under laboratory (see Fig. 1) and near laboratory conditions (see Fig. 2) providing a monotonic background and a good contrast with ants, meanwhile, the dataset WildAnts included images with different scenes and the images are more colorful (see Fig. 3 and 4). The size of objects can not be strongly impactful, because the YOLOv8 architecture was specially enhanced for small object detection [7], meanwhile, the automatic search of optimal bounding box sizes was presented in the YOLOv4 framework [8].

Khalid et al. (2023) compared different YOLO architectures on the natural image dataset of small pests: thistle caterpillars (Vanessa cardui), red beetles (Aulacophora foveicollis), and citrus psylla (Diaphorina citri) [9]. Their experiment showed that YOLOv8n is the most suitable, it depicted the best accuracy equal to 84.7% mAP@0.5 [9]. In our case (see Fig. 6 and 7), the YOLOv8n model trained on ANTS showed better results (max YOLOv8n was 99% mAP@0.5), but the model trained on WildAnts - little smaller accuracy (max YOLOv8n was 81% mAP@0.5).

If we analyze the results obtained by testing the models with swapped datasets (see Fig. 6 and 7), the best result is obtained by the YOLOv8 model trained on the WildAnts dataset with 28.7% mAP@0.5 (see Tab. 2, median). But for a model trained on the ANTS dataset, the best result is shown by YOLOv8n with only 5.5% mAP@0.5 (see Tab. 2, median). Therefore, the models trained on WildAnts are more robust for the dataset transfer.

Analyzing the results in general, it can be seen that the models trained on the dataset ANTS show much worse results when tested on another dataset. But the models trained on dataset WildAnts show much better results compared to ANTS models. That underlines the importance of the natural images collected in the different scenes. The best result was achieved with the YOLOv8m model trained on the WildAnts dataset, it showed relatively good accuracy on own dataset (82% mAP@0.5) and it showed the best accuracy results (32% mAP@0.5) after the dataset change on ANTS.

Our other experiments showed that mosaic and combination of the related datasets can improve accuracy and create more robust models [10]. Therefore, speaking about the best dataset for training, it will be a combination of ANTS and WildAnts. Meantime, the dataset transfer impact shows the importance to continue to collect more natural datasets and tune CNNs for a working environment obtaining user feedback after object detection.

TABLE 1. TRAINING RESULTS (MAP@0.5)

YOLO	Test ANTS model on ANTS dataset		Test WildAnts model on WildAnts dataset	
	v8n	***v8m***	***v8n***	***v8m***
min	0.97307	0.98936	0.68455	0.73213
mean	0.98452	0.99045	0.74711	0.77623
median	0.98848	0.99048	0.76266	0.77475
max	0.98905	0.99109	0.80857	0.82354

TABLE 2. CROSS TESTING (MAP@0.5)

YOLO	Test ANTS model on WildAnts dataset		Test WildAnts model on ANTS dataset	
	v8n	***v8m***	***v8n***	***v8m***
min	0.04252	0.03342	0.18506	0.26863
mean	0.05529	0.04594	0.23334	0.29006
median	0.05540	0.03854	0.23511	0.28765
max	0.07458	0.06638	0.26664	0.31265

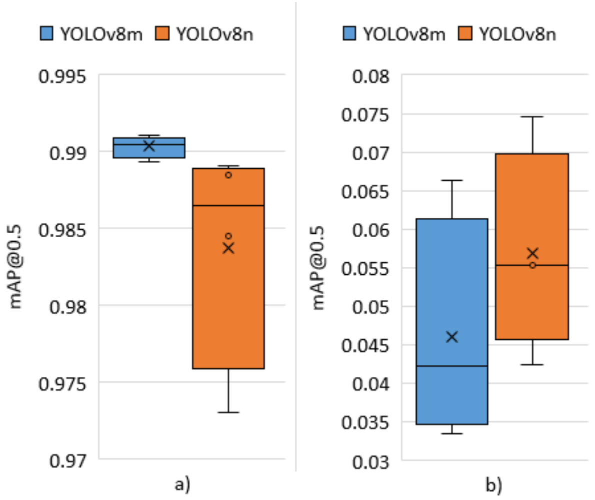

Fig. 6. CNN trained on ANTS dataset [4]: a) tested on ANTS dataset; b) tested on WildAnts dataset

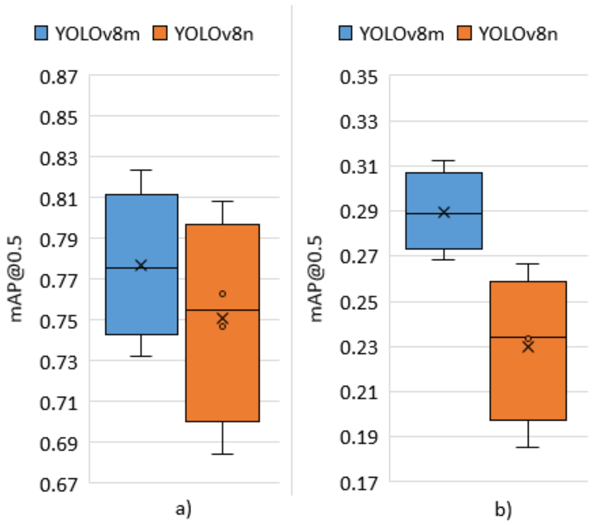

Fig. 7. CNN trained on WildAnts dataset: a) tested on WildAnts dataset; b) tested on ANTS dataset

IV. CONCLUSIONS

We have experimentally shown the importance of natural images for robust CNN training and need to collect the ant dataset with natural images for orchard monitoring.

The best accuracy results showed the YOLOv8m model trained on ANTS dataset, which achieved the maximal accuracy 99% mAP@0.5, but it was possible only to get accuracy 7.5%, when the testing dataset was changed on WildAnts. Meanwhile, the YOLOv8m trained on WildAnts showed 82% mAP@0.5 on itself, but it was more robust for the dataset changing - 31% mAP@0.5 on ANTS dataset.

It is an excellent demonstration of accuracy decrease on the other datasets [51%; 92%], which were unknown for CNN in the training time. Therefore, it is important to continue to collect more natural datasets and tune CNNs for a working environment obtaining user feedback after object detection.

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