Aphid Recognition using Multi-Scale Feature Representations with Vision Transformers

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### Introduction

- Aphids are mainly responsible for infecting seed potatoes with viruses during their growth [1].
- To find out if pest control is more effective when applied at the right time, aphids must be accurately detected on crops.
- Currently, the detection of aphids is done by placing yellow sticky plates next to the agricultural crops and letting personnel check them.

### **Experiments and Results**

- A grid search is used to find the best configuration for each of the three architectures.
- Each model was evaluated with 108 configurations.
- Each configuration was performed four times to collect average scores.
- Table 1 depicts the best-performing configurations sorted by the F1-score.
- This research specifically investigates the classification performance of separating aphids from other insects.
- Vision Transformers have proven to be a well-performing alternative to CNNs [2].
- Single-scale architectures, based on CNN and ViT are used as baselines.
- The Cross-Attention Multi-Scale Vision Transformer (Cross-ViT) is used to classify the wide range of image resolutions and assess the impact of multi-scale feature representations [3].

# **Materials and Methods**

- We gathered 6508 images. There are 682 images of aphids and 5826 that are not. Due to this class imbalance, the aphid images are oversampled.
- The labels for the images are determined in cooperation with a domain expert in which aphids are separated from non-aphids. Figures 1 and 2 depict examples of aphids and non-aphids.
- Multiple data cleaning iterations are performed to improve the quality of the annotations.

### Abstract

We evaluated Multi-Scale and Single-Scale architectures to improve aphid classification on images. As a result, we used three different deeplearning models (ResNet, ViT, and Cross-ViT) to classify aphids using our own dataset. The model with the highest F1-score (84.88%) was Cross-ViT. Images are tokenized into various sizes because Cross-ViT is based on ViT but has been expanded to a Multi-Scale architecture. The Multi-Scale approach shows promising performance.



Model	Start LR	Patience	Batch size	Augmentations	F1-Score
ResNet-50	0,05	5	16	Enabled	84.95% ±2.09%
ViT16	0,0001	20	8	Disabled	86.51% ±2.15%
ViT32	0,0001	10	8	Disabled	85.33% ±0.77%
Cross-ViT 12/16	0,0005	10	8	Enabled	85.33% ±1.37%

#### Table 1. Results of the grid search performed on the validation set.

- ViT16 is selected as a baseline since it outperformed ViT32.
   The numbers following the abbreviation, 16 and 32, are patch sizes.
- Augmentations improve ResNet-50 and Cross-ViT performance but not plain ViT's.
- The final experiments were done with the parameters found in the grid search (see Table 1).
- The final classification performance is depicted in Table 2, and more metrics are included to make our model selection clear.
- The ResNet-50 baseline model is 95.11 % accurate in classifying aphids.
- ResNet-50 was outperformed by ViT16 in terms of a higher F1-score of 1.94 % and a lower standard deviation of 3.66 %.
- Cross-ViT outperforms ViT16 by 3.51 % on the F1-score. Besides this, the standard deviation is lower.

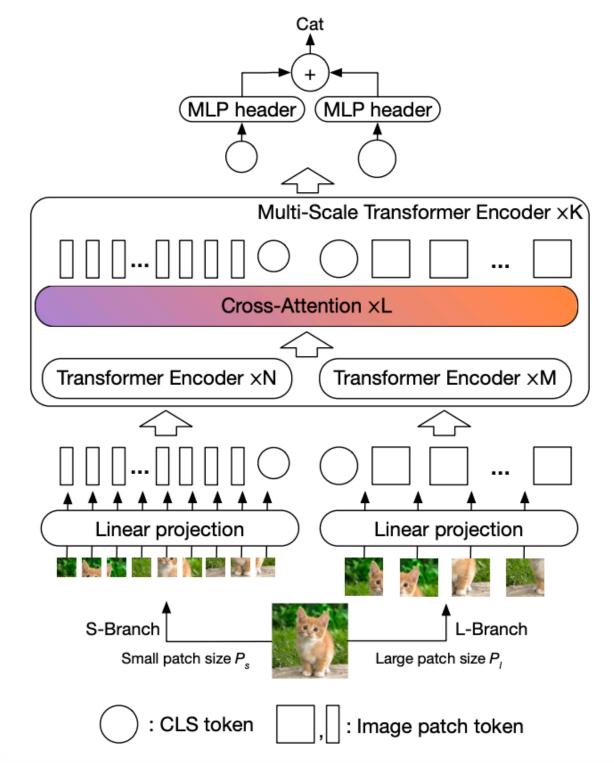


Figure 1. Examples of non-aphids stuck on the yellow sticky plate.

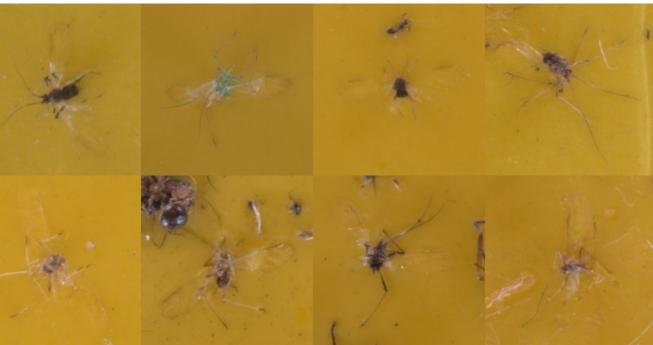


Figure 2. Example of aphids stuck on the yellow sticky plate.

- Three architectures were evaluated:
- ResNet

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- Vision Transformers (ViT)
- Cross-Attention Multi-Scale ViT (Cross-ViT) [3], as illustrated in Figure 3
- ResNet and ViT, being single-scale approaches, while Cross-ViT is a multiscale approach.
- Model selection is based on pre-training and the number of parameters.

• To understand the shortcomings of the classifier and dataset, some misclassified images are depicted in Figure 4.

Model	Accuracy	Precision	Recall	F1-score
ResNet-50	95.11% ±1.69%	90.41% ±2.56%	71.12% ±8.26%	79.43% ±5.70%
ViT16	95.81% ±0.61%	88.72% ±1.84%	75.29% ±4.45%	81.37% ±2.04%
Cross-ViT 12/16	96.54% ±0.28%	94.36% ±2.34%	77.18% ±2.20%	84.88% ±1.06%

#### Table 2. Final results from experiments on the test set.

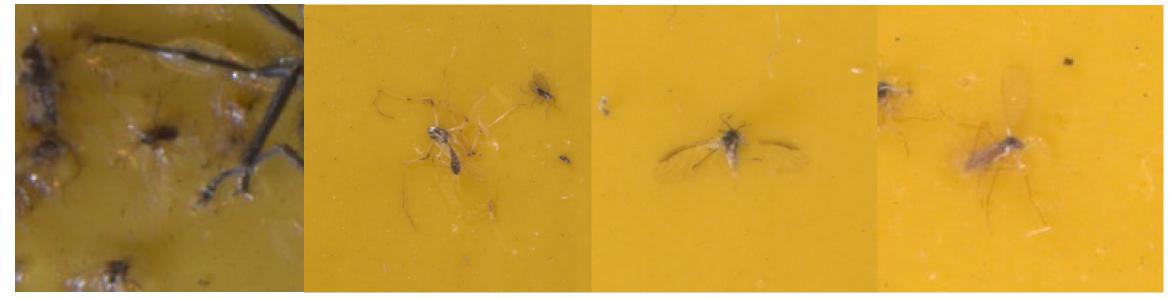


Figure 4a. Example of<br/>multiple insectsFigure 4b. Example of<br/>misclassified insectFigure 4c. Example of<br/>misclassified insectFigure 4d. Example of<br/>misclassified insect

### Conclusions

• We can conclude that Multi-Scale representations of features with Vision

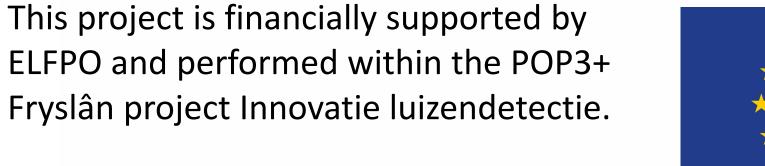
**Figure 3.** Cross-Attention transformer architecture illustration

- Augementations are applied to vary the orientation, colour and noise during training.
- The F1-score is used to compare the performance of the model.
- Transformers improve classification for this problem.
- Model selection based on precision and recall was not needed since the Cross-ViT model outperformed ResNet-50 and ViT16 on all calculated metrics.
- The current classification performance provides a stable foundation for supplying the necessary data for the pesticide feasibility study.

## Acknowledgements



GeJo





Europees Landbouwfonds voor Plattelandsontwikkeling: Europa investeert in zijn platteland

okkem

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