

Profiling the *Arion rufus* snails with computer vision

CINTI 2022

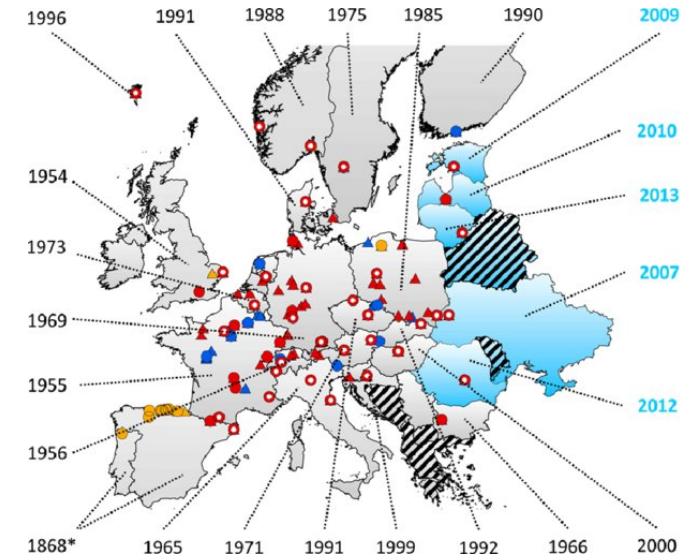
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Outline

- Introduction
- Snails dataset
- Object detection
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Introduction

- Agriculture is one of essential domains for dealing with the challenge of feeding people
- Challenge of providing such a large amount of food encourages higher production of food
- Emerging smart farming
 - Searching for natural solutions against different pests that prevent the expected growth of crops
- Slugs (*Arion vulgaris*, *Arion rufus*, *Arion ater*) are one of the most destructive pests in Europe
 - Invasive species with practically no natural enemies
 - Can also host lungworms
 - If accidentally eaten, there is a significant disease risk
- Farmers usually use different baits
 - Harmful effects on fertile soil
 - Not following ecological food production
- Environmentally friendly is physically removing the snails



Source: Zemanova, Miriam A., Eva Knop, and Gerald Heckel.
"Phylogeographic past and invasive presence of Arion pest slugs in Europe." Molecular Ecology 25.22 (2016): 5747-5764.

Motivation

- AI is used in every aspect of our lives
- Snails can be hard to detect:
 - Slugs's trail of movement may be slightly visible
 - Their color can very similar to the their surroundings
- **Idea:** Try to identify the slugs using machine learning
 - Collect and prepare slugs dataset
 - Utilize object detection computer vision algorithm based on the You-Only-Look-Once (YOLO) framework

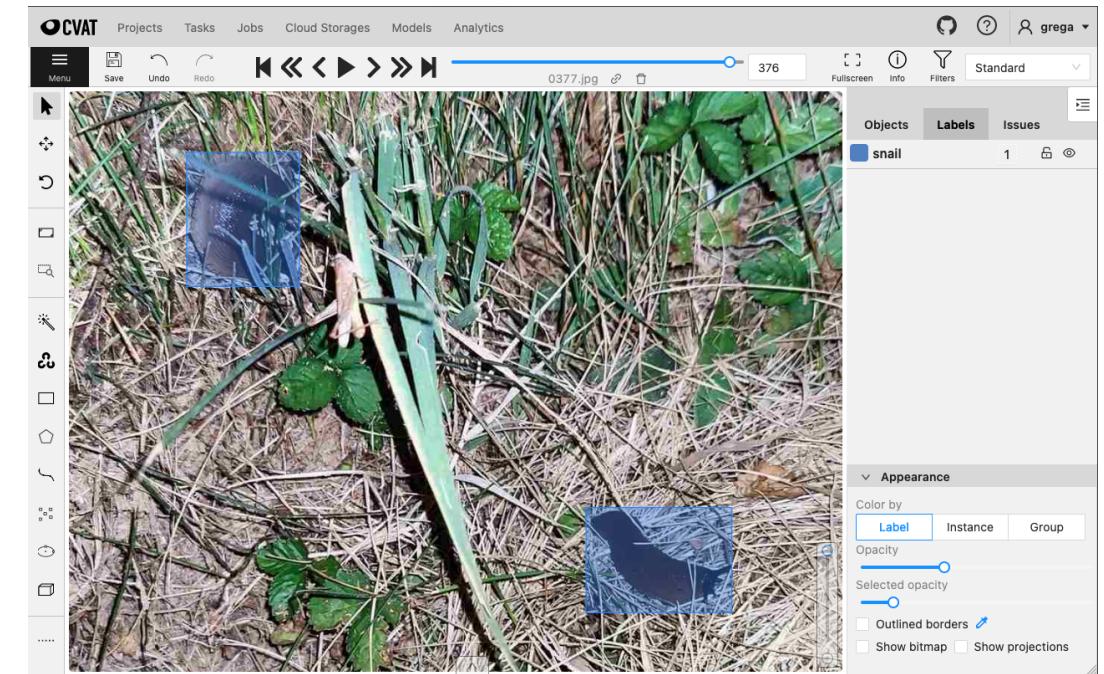
Snails dataset

- Lack of *Arion rufus* snails datasets
- Collection of our own *Arion rufus* snails dataset
- Obtaining images in a real environment:
 - Northeastern region of Slovenia
 - Between June and August of 2022
 - The micro-locations of captured images:
 - Ordinary house backyards,
 - Meadow next to the forest,
 - Forest footpaths, etc.
 - Capturing the images:
 - From around 10cm - 50cm above the ground
 - At different angles
 - The collected images were in different sizes



Pre-processing and labeling the images

- Image pre-processing:
 - Elimination of duplicates, blurry images and images without Arion rufus snail(s) present
 - From around 500 images, 396 were selected as suitable for dataset
- Labeling snails
 - Using graphical image annotation tool (CVAT)
 - Marking each Arion rufus snail in each image
 - Conducted independently by the two researchers

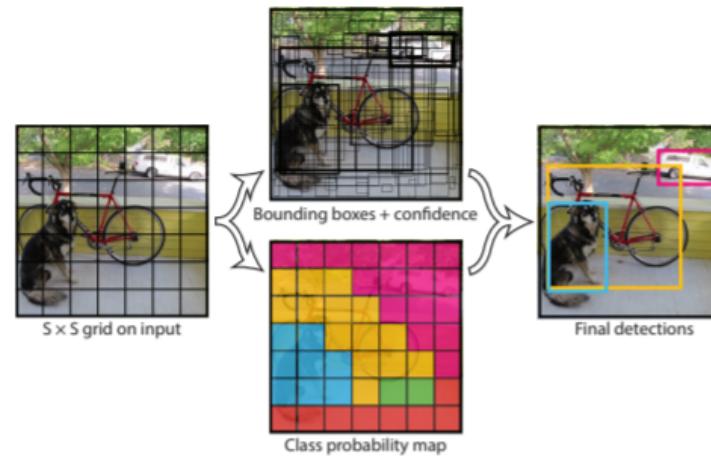


Object detection

- Classify and precisely estimate the concepts and location of objects contained in each image
- One of the fundamental computer vision problems
- Through the years, many successful attempts proposed to address the problem of object detection
- Most typical representatives:
 - R-CNN based methods,
 - AttentionNet,
 - YOLO methods,
 - SSD and derivates, etc.

You-Only-Look-Once

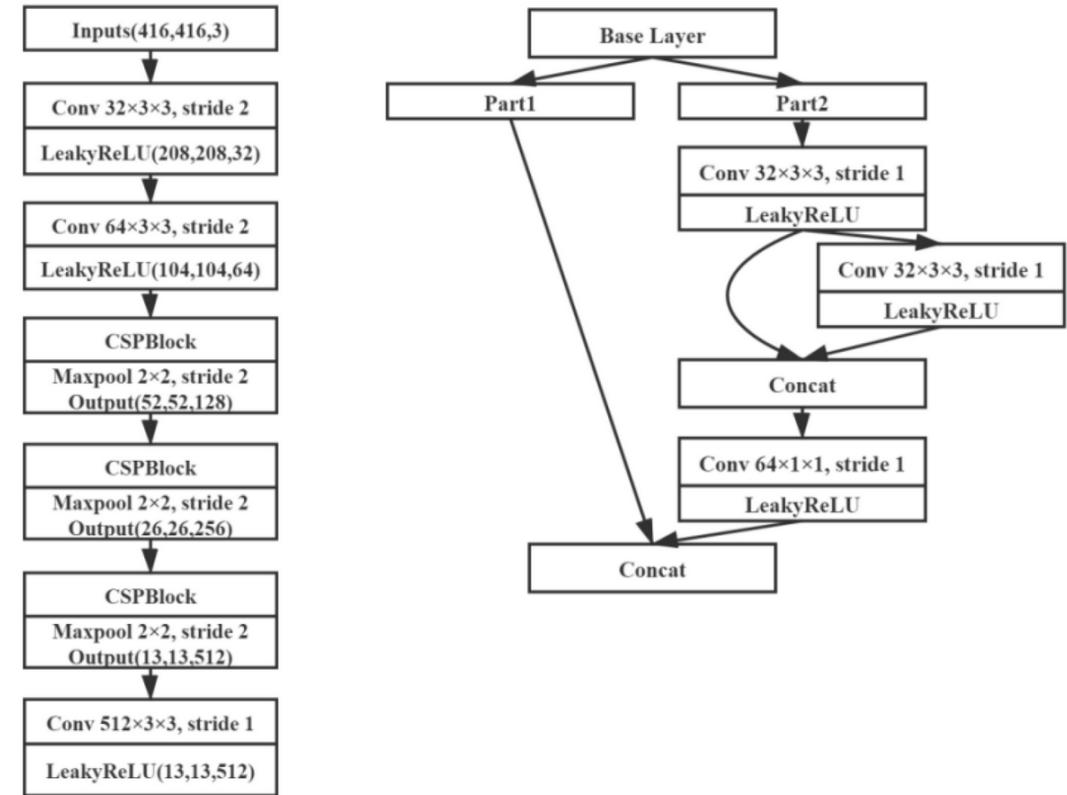
- Exploits CNN capabilities to detect objects with only one forward propagation through neural network
- Image passed in on input is divided into $S \times S$ uniform grid of non overlapping cells
- For each cell boundary box is predicted
 - x, y - position coordinates of boundary box
 - w, h - width and height of the boundary box
 - $C(\text{Object})$ - prediction of C categories, reflecting the probability of the model to include the target object



Source: Redmon, J., Divvala, S., Girshick, R., & Farhadi, A. (2016). You only look once: Unified, real-time object detection. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 779-788).

YOLOv4-tiny

- Great trade-off between training time and accuracy
- Building image detection model:
 - Network architecture with 30 layers in total
 - Utilize transfer learning
 - Use the model weights from trained YOLOv4-tiny against the Common Objects in Context (COCO) dataset.



Source: Xu, P., Li, Q., Zhang, B., Wu, F., Zhao, K., Du, X., ... & Zhong, R. (2021). On-board real-time ship detection in HISEA-1 SAR images based on CFAR and lightweight deep learning. *Remote Sensing*, 13(10), 1995.

Experimental settings

- Experiments were conducted on a dataset of 396 snail images
 - 318 images for training,
 - 36 images for validation,
 - 40 images for test
- Images were resized to 416×416
- Training process was run for 6,000 batch iterations
 - On every 100 iterations calculating validation mean average precision (mAP) metric
 - Batch size was set to 64
- The model with the highest achieved mAP was stored and used for the evaluation phase
- Evaluation:
 - Calculate mAP on test images
 - Use different threshold values of intersection over union (IoU) metric

Results

- Even at a small IoU threshold values the model performs best with the highest mAP value
 - Is not falsely detecting more objects as snails, as we would expect
- After IoU is starting to increase above 0.5, the mAP starts rapidly dropping
- At default IoU value of 0.5, model achieves mAP of 0.936
 - Most similar studies we could find report mAP of 0.691

IoU	mAP	Precision	Recall
0.10	0.957	0.92	0.92
0.20	0.957	0.92	0.92
0.30	0.957	0.92	0.92
0.40	0.957	0.92	0.92
0.50	0.936	0.91	0.91
0.60	0.875	0.88	0.88
0.70	0.842	0.86	0.86
0.80	0.585	0.66	0.66
0.90	0.090	0.22	0.22

Results

Multiple snails detected in complex visual environment



Multiple snails detected with false detection of wild strawberry



Conclusion

- Machine learning methods can also be applied in the agriculture domain
- Presented the approach of detecting *Arion rufus* snails with YOLOv4-tiny
- Prepared and labeled the snail dataset
- Achieved encouraging results of the identification performance of trained model

Future work

- Try to address the problem of partially visible snails
- Increase the number of images in dataset
- Prepare a dedicated test dataset for evaluating real-life performance of models
- Expand the approach to detect different types of slugs

Thank you for you attention!