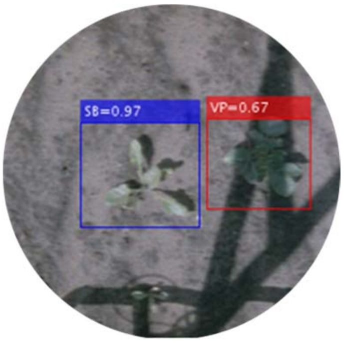
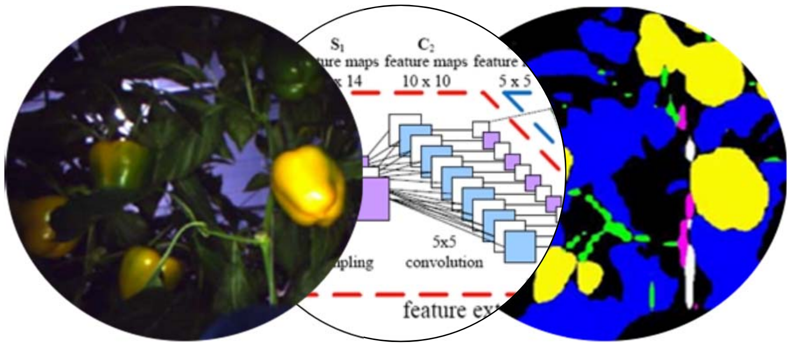
Deep Learning experience WUR

Jochen Hemming
Agro Food Robotics
Wageningen University & Research, The Netherlands





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NVTL study day - March 6, 2018

Intro

- **Jochen Hemming**, PhD in Horticultural Science, Senior Researcher Computer Vision & Robotics in Horticulture.
- Since 2000: at Wageningen University & Research
- Expertise
  - Computer Vision (hard- and software)
  - Robotics
  - Mechatronics & Automation in plant production
  - ICT (Programming, Databases)
- Projects
  - Harvesting robots
  - Bush trimming robots
  - Pest and disease detection
  - Vision based weed control

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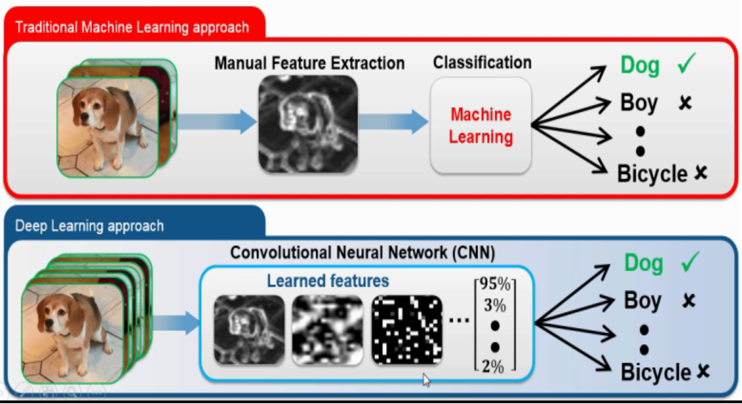
Difference Deep Learning and Machine Learning

- With machine learning, manual extraction of the relevant features of an image is needed.
- With deep learning, the raw images are fed directly into a deep neural network that learns the features automatically.



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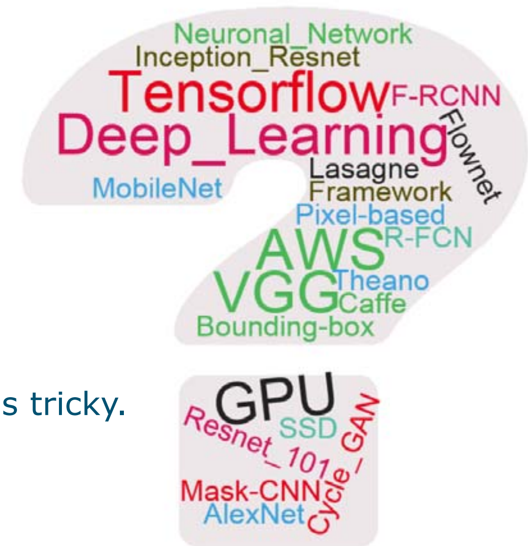
Challenge: Many Deep Learning flavours

- Different frameworks.
- Different network architectures.
- Different platforms/tools
  - Web-based (e.g. AWS)
  - Linux
  - Windows
- The field moves fast and keeping up is tricky.



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Projects @ WUR that are using/have used deep-learning

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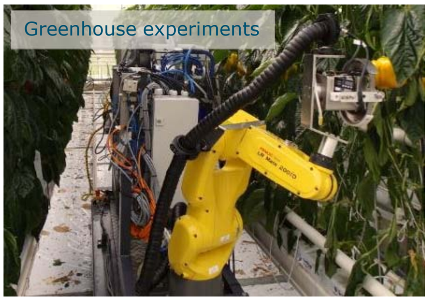
www.agrofoodrobotics.nl

Sweeper

Sweet-pepper robot

- EU Horizon 2020 ICT use case project
- 6 partners from 4 countries (The Netherlands, Belgium, Sweden and Israel).
- The project focusses on technology transfer rather than R&D



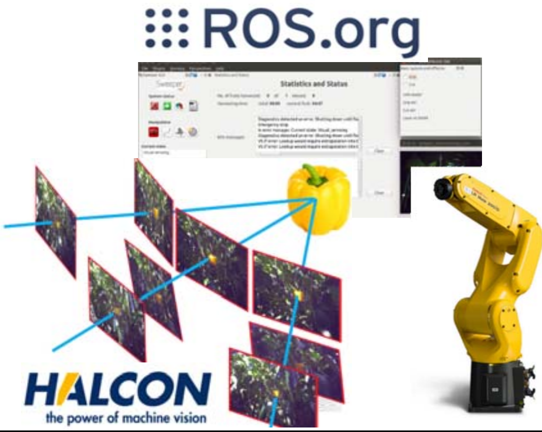
European Commission

HORIZON 2020

The EU Framework Programme for Research and Innovation

Modules

- **End-effector** (grasp, cut)
- **+ Camera** (location, distance and ripeness detection)
- **+ Illumination** (better detection under alternating conditions)
- **Deep-learning** (to avoid obstacles)
- **Robot arm** (to search, move to fruit and convey fruit)
- **Platform** (to move robot in the greenhouse)
- **Logistics** (to convey picked fruits)



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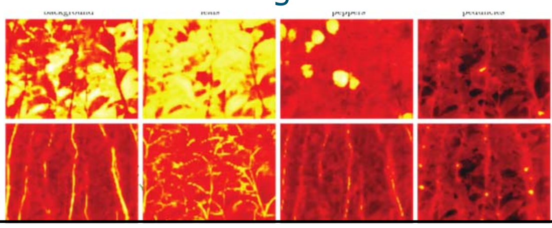
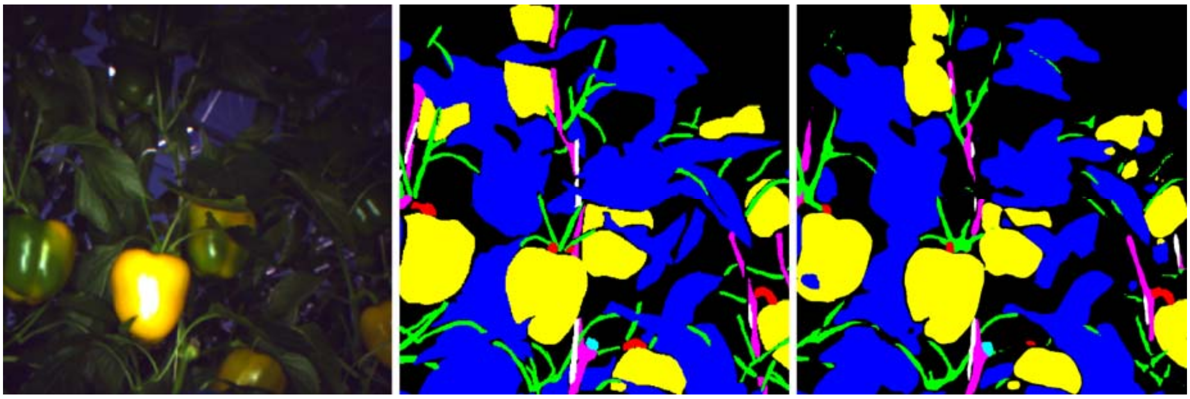
Deep-Learning for plant part localization in images

- DeepLab V2 on top of Caffe for semantic segmentation (per-pixel, no instance detection).
- Synthetic dataset is used to bootstrap the model.
- Trained network deployed for real-time obstacle detection and to determine best end-effector alignment.



Results on empirical images

Empirical images | Ground truth | Segmentation



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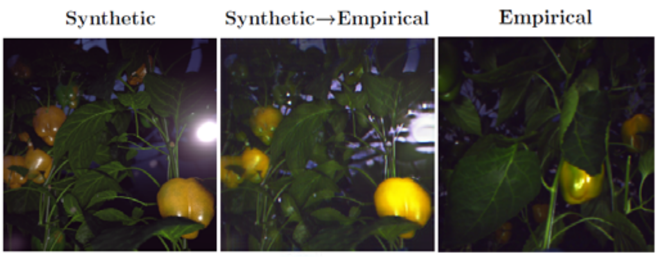
Contact: Ruud Barth

Optimising Realism of Synthetic Images using Cycle Generative Adversarial Networks, Cycle-GAN

- Current bottleneck is the requirement of large annotated datasets.
- Dissimilarity gap remains caused by sub-optimal manual modelling.
- Optimising the realism of synthetic images by unpaired image-to-image translation from the synthetic to empirical domain.



Barth, R. ; IJsselmuiden, J.M.M. ; Hemming, J. ; Henten, E.J. van (2017): Optimising Realism of Synthetic Agricultural Images using Cycle Generative Adversarial Networks. In: Proceedings of the IEEE IROS workshop on Agricultural Robotics 2017.

Hardware used for the training

GPU acceleration is needed to train Deep Learning networks.
4x NVIDIA Titan X 12GB, 128 GB Ram, I7 CPU and a lot of cooling.

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TrimBot2020: A Robot for Hedge, Rose and Topiary Trimming

- Prototyping next generation, intelligent gardening robots.
- Focused on the development of intelligent hedge, rose and bush trimming capabilities.
- Robot navigates over varying garden terrain, to approach bushes, and restore them to their ideal tidy shape.
- Targeting the consumer market, as well as gardening professionals

BOSCH · THE UNIVERSITY of EDINBURGH · ETH zürich · European Commission · UNIVERSITY OF AMSTERDAM · WAGENINGEN UNIVERSITY & RESEARCH · UNI FREIBURG · university of groningen

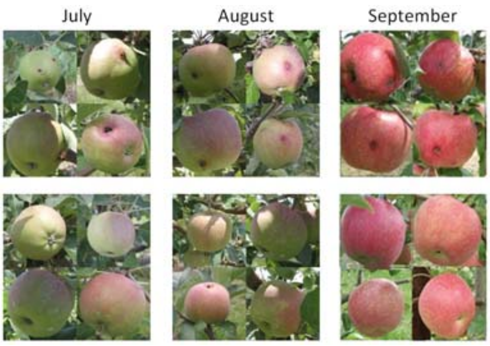
The EU Framework Programme for Research and Innovation

DeepLearning in Trimbot2020

- University of Freiburg
  - FlowNet for Optical Flow Estimation
- University of Amsterdam
  - CNN-based Intrinsic Image Decomposition to decompose images in reflectance (albedo) and shading.
  - Faster-RCNN and SegNet for Semantic Garden Segmentation.

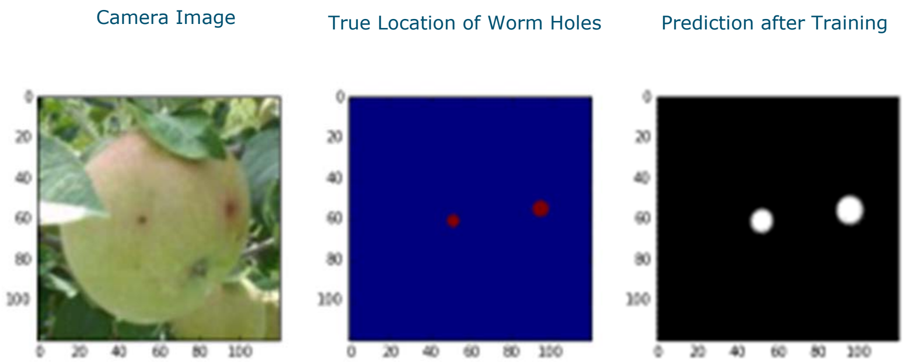
Worm Damage Detection in Apples

- RGB images of apples under uncontrolled conditions in orchard (CASC IFW Apple Dataset from Purdue Univ.)
- Detection of holes left by worms infesting apples.
- Input images from dataset:



Contact: Hennie de Villiers 14

Apples: Disambiguation using context



Context helps distinguish worm damage
from the bottom of the apple.

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15

Apples: Input / Output Pair Examples

Contact:
Hennie de Villiers

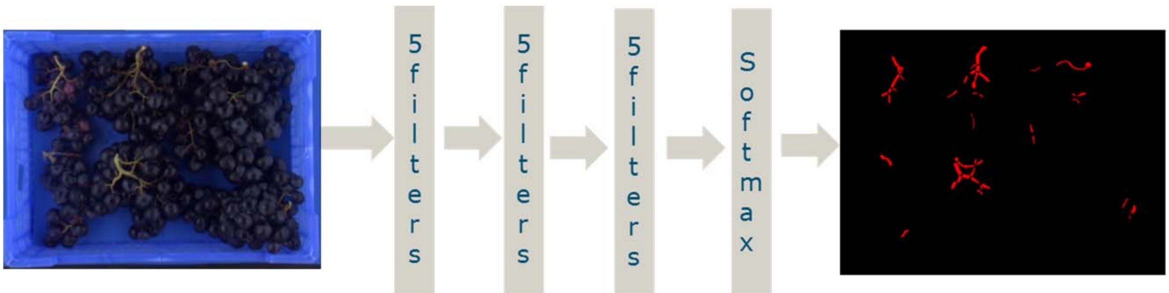
Automated segmentation of grape stem

- RGB images of blue / red and white grapes
- Task is to detect the stalks for subsequent pickup by robot
- Input images from dataset:

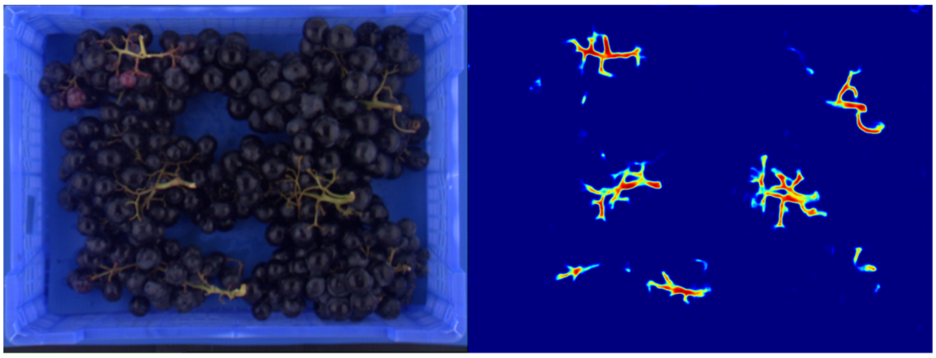
Contact: Hennie de Villiers

Deep Learning for segmentation of grape stem

- Fully Convolutional Neural Networks on Theano/Lasagne



Grapes: Sample Results (Blue Grapes)



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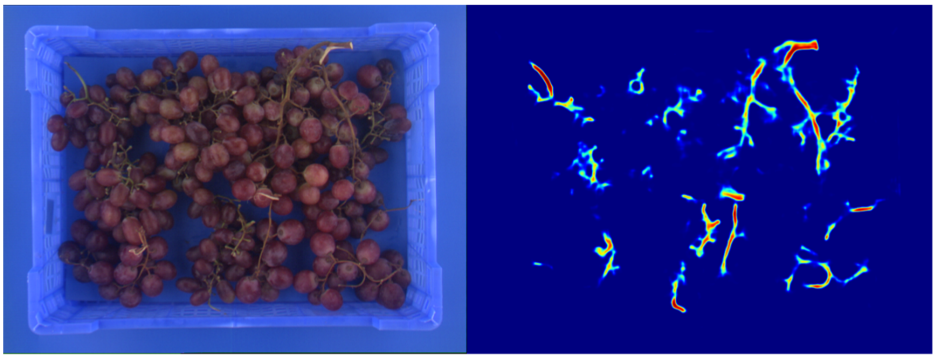
Grapes: Sample Results (Red Grapes)



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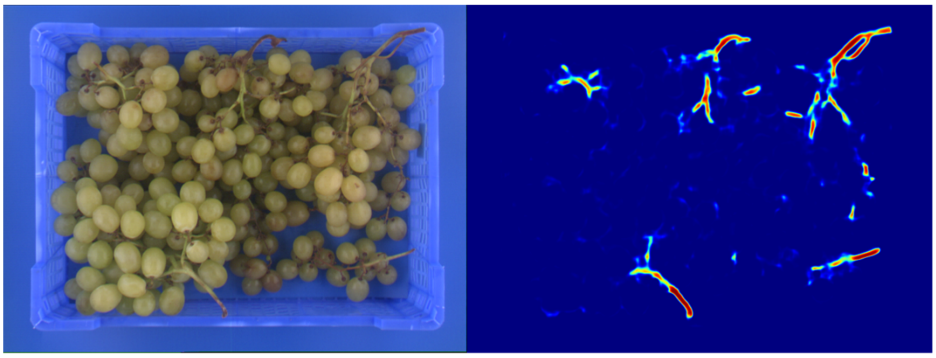
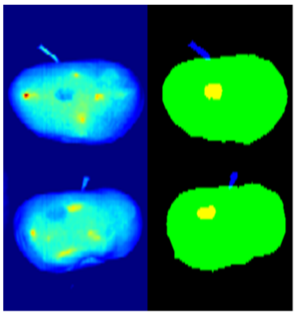
Contact: Hennie de Villiers 20

Grapes: Sample Results (Green Grapes)

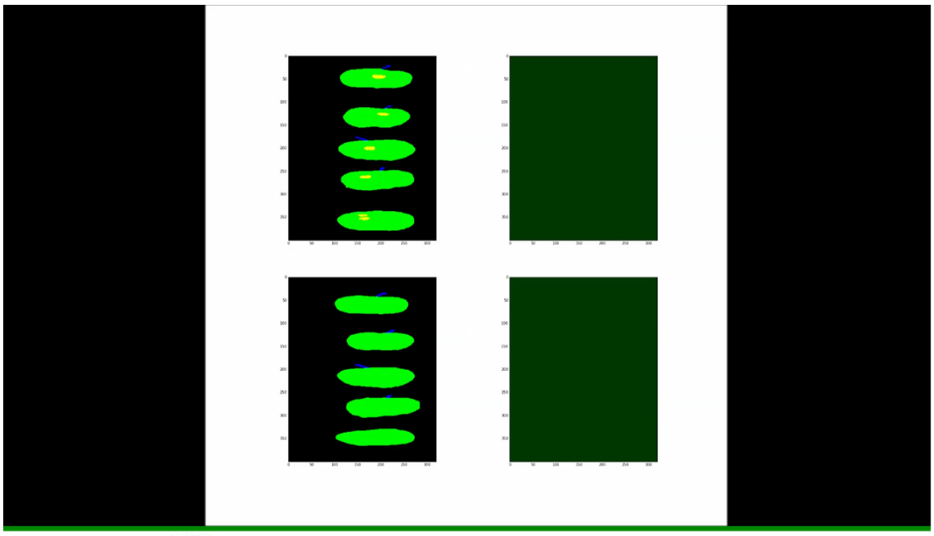


Apple Bruise Detection

- Hyperspectral images of apples (dataset captured by KU Leuven)
- Detection of bruises due to handling
- Fully Convolutional Neural Networks on Theano/Lasagne
- Examples from dataset:



Apples: Training Visualization



Contact: Hennie de Villiers

23

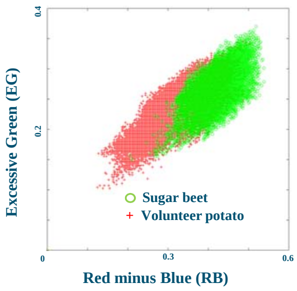
EU SmartBot project: weed classification

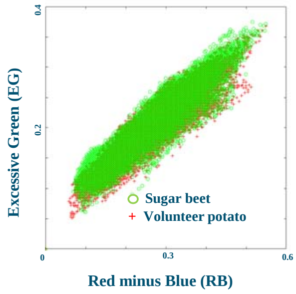
- **Conventional approach (for weed detection):**
  - Color based detection.
  - Use of cover for controlled environment & artificial lighting
- **Problems:** color-based approach not work, requires extra structure

Contact: Hyun Suh

EU SmartBot project: weed classification

Seasonal effects

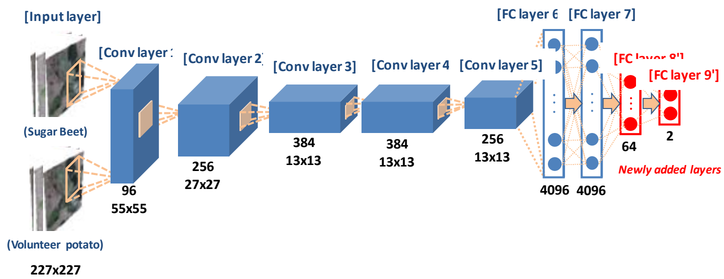




Contact: Hyun Suh

EU SmartBot project: weed classification

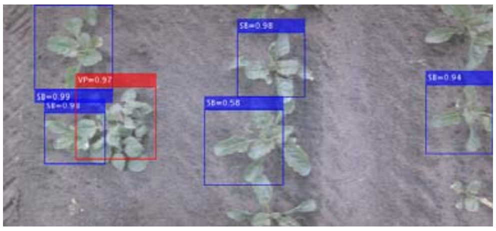
- Deep learning (CNN) for weed/crop classification (2015)
  - Transfer learning based on pre-trained deep network (AlexNet)

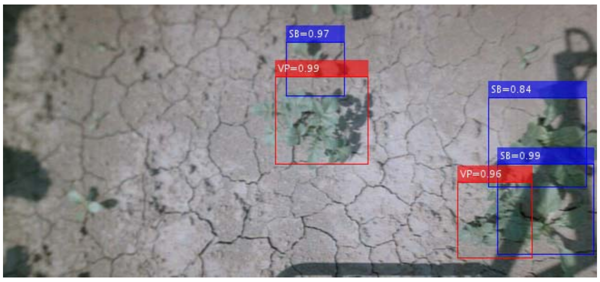


Suh, H.K., J.W. Hofstee, J. IJsselmuiden, & E.J. van Henten (Under review). Transfer learning using AlexNet for the classification of sugar beet and volunteer potato under field conditions (Manuscript submitted for publication in Biosystems Engineering in 2016).

EU SmartBot project: weed detection

- Weed detection: Faster R-CNN
  - VP → Voluteer potaton (weed)
  - SB → Sugar beet (cash crop)





Contact: Hyun Suh

Detecion of bacteria infection in seed potatoes

- Detection of virus infection and Erwinia (bacterium) in seed potato plants.
- Hyperspectral scans of the plants are analysed.
- Deep Learning with PyTorch (Python based scientific computing package).

Contact: Hennie de Villiers/Gerrit Polder/Jan Kamp

PeMaTo-EuroPep (2017–2019) C-IPM Coordinated Integrated Pest Management in Europe

F-RCNN (bounding boxes) for automatic counting of white fly and beneficial insects trapped on yellow sticky traps.

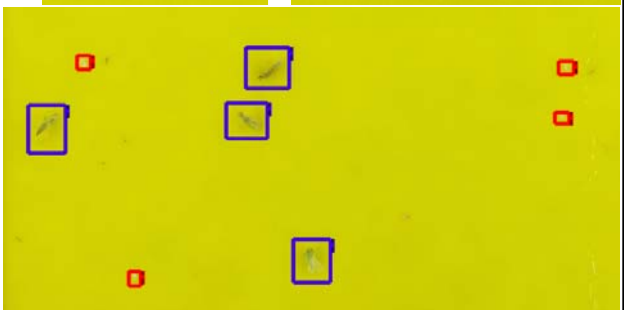


Photo reference:
CC BY-SA 3.0, https://commons.wikimedia.org /w/index.php?curid=39889

Contact: Hyun Suh/Jochen Hemming

Projects @ WUR that plan to use using deep-l.

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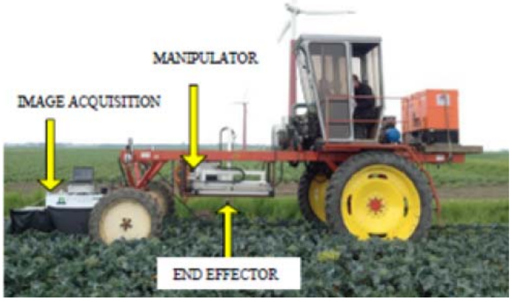
Selective broccoli harvesting robot

- Selective harvesting of broccoli based on minimum diameter of head.
- Deep-learning for better and more robust image classification



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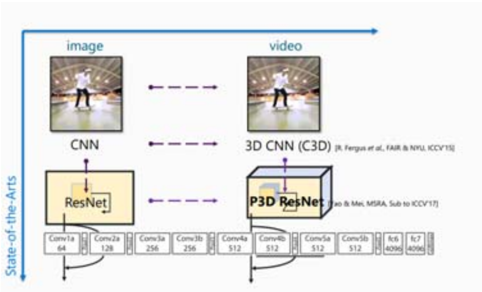
Contact: Pieter Blok

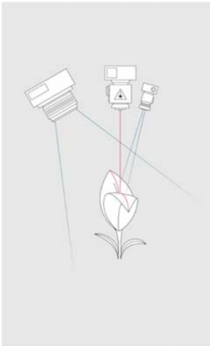
Deep Learning in animal welfare

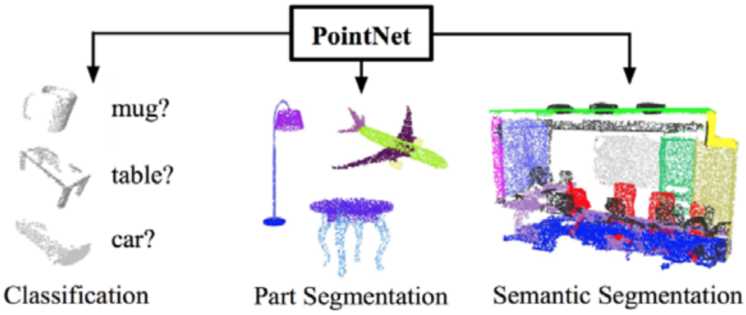
- Detect animal welfare (e.g. maladies) in video images of pigs/cows.
- Observation of the body language.
- Video representation learning.
- Pseudo-3D Residual Networks (P3D) [Yao & Mei, ICCV'17]
- PyTorch Deep Learning (Python based scientific computing package)



3D Tomato plant phenotyping

- Tomato plants scanned whit a 6 DoF robot equipped with two Phenospex cameras for full 3D phenotyping.
- **PointNet**: Deep Learning on Point Sets for 3D Classification and Segmentation

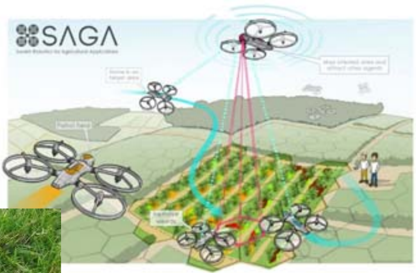




Contact: Rick van de Zedde

Deep learning for weed detection

- SAGA swarm robotics for weed control.
- SMARAGD: smart mechanisation, automation, robotics for arable farming.
- Weed detection on lawn or in grasslands.
- YOLO (You Only Look Once) or Faster RCNN.



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Contact: Gert Kootstra/Frits van Evert/Jan Kamp

Disadvantages Deep Learning

- Training process is based on analysing large amounts of data, labour intensive labelling is needed.
- Expert knowledge is needed to select architecture, to get the (open source) framework installed.
- Expert knowledge is needed to bootstrap and fine tune network.
- Black box: deep-learning is incapable of providing arguments why it has reached a certain conclusion.
- Resource-Demanding Technology. High computational costs.

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Advantages Deep Learning

- No manual feature selection needed.
- Ability to generate new features from limited series of features in the training set.
- Potentially deep learning supports also unsupervised learning techniques.
- Superior classification results.

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Thank you for your attention

Contact:

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www.agrofoodrobotics.nl

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37