University of Southern Queensland

Computer Vision Applications in Agrifood

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Source: www.trimble.com

Outline

1. Example projects in Australian Agriculture:
    - Pest management in cotton
    - Advanced smartphone sensing
    - And more…

2. Example the types of AI employed in these projects
    - CNNs
    - Classification, regression, clustering
    - Transformer models

My Background

Been working on a range of sensing projects over 10 years in cotton, grains, horticulture and poultry.

Key projects (leading in bold):

- Cotton pest sensing
- **Crop scanning apps with augmented reality**
- **Sprayer based vision work (John Deere)**
- Accelerating adoption of autonomous tractor technologies for Australian grains
- Broiler chicken welfare monitoring with machine vision

Robotics, Machine Vision and Automation Theme

Sensing projects for:

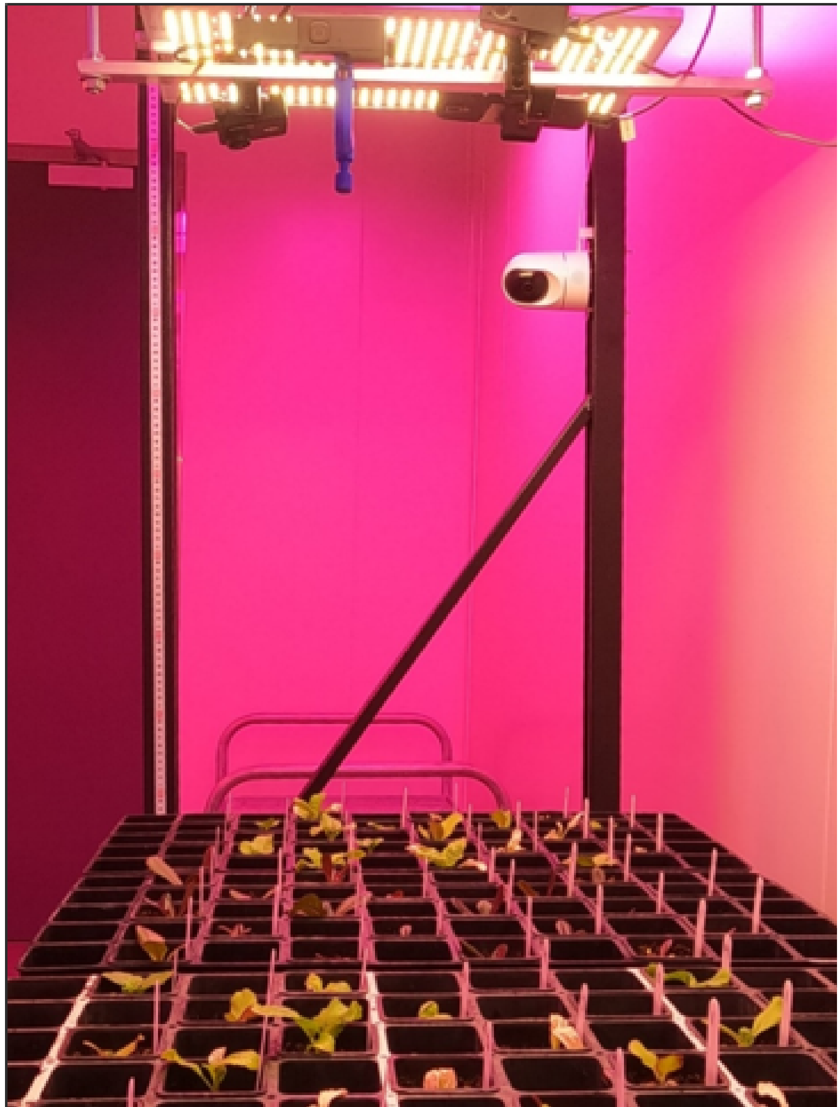
- Fertiliser optimisation
- Weed/disease/pest monitoring
- Irrigation scheduling
- Irrigation/water monitoring
- Agronomic decision making
  - Including in Zero-G
- Agronomic decision support
- Machine automation
- Animal stress monitoring
- Biosecurity

Platforms:

- Smartphones
- Static cameras
- Drones
- Spray boom cameras

Industries:

- Broadacre cropping
  - Cotton/grains/sugar
- Horticulture
- Livestock
- Poultry



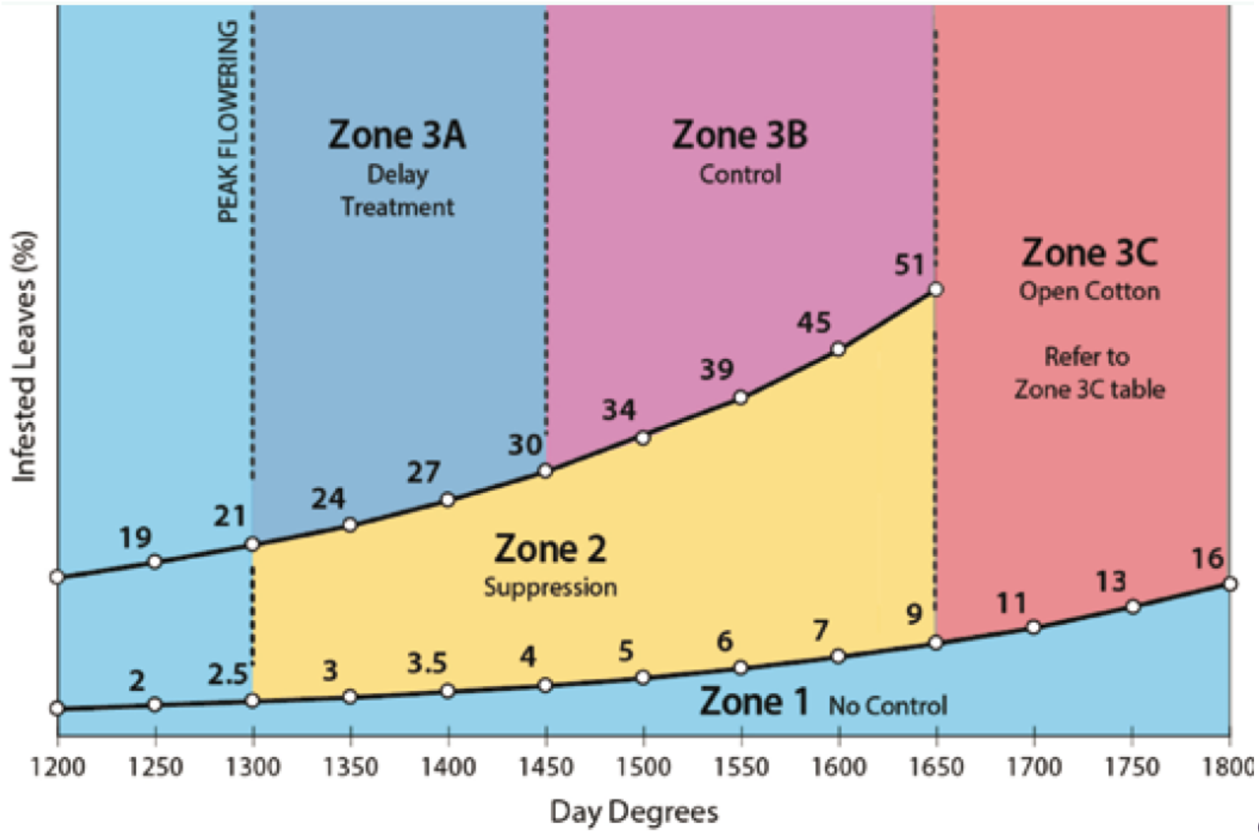
Project #1

Pest management in cotton

Background

SLW sampling and threshold decision making has undergone a number of changes since the first outbreaks in CQ in 2001/02.

- Adults sampled on 5th node leaf.
- 2 or more adults denoted an infested leaf and decisions were made based on level of infestation.
- Approach was a compromise as nymph counts gave better correlation but industry feedback at the time was that nymph counting was unacceptably time consuming.



Background

Research confirmed that adults were highly mobile within the canopy and therefore not a suitable target for sampling.

Nymphs are a more reliable sampling target but not on 5th node leaf.

The redesign of the sampling protocol and control decision matrix was the backdrop for the sensing project.

Sensing opportunities

Nymph classification

Aid bug checkers in quantifying viability rates in late-season.

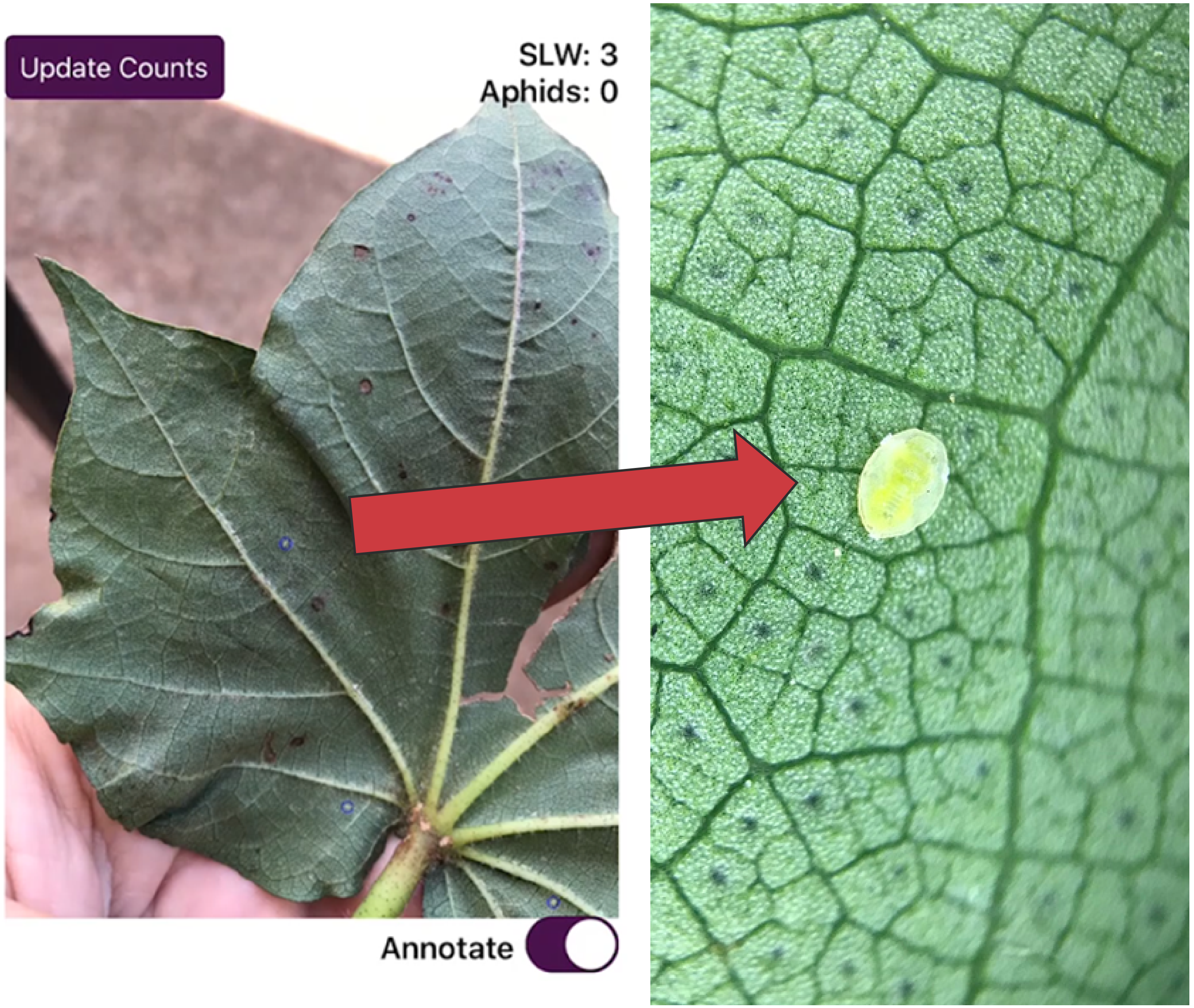
Parasitism hard to see with a hand lens.

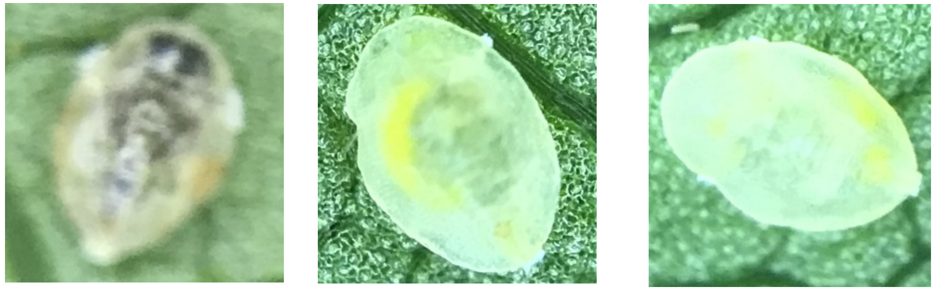
Nymph counting

Make the core of SLW sampling practice digital and link to DST in-app.

Huge time-saving potential.

Development: Lens images





Parasitism

Healthy SLW

Two stage process: one-shot object detection, zoomed-in classification.

1600 annotated images used in development, 94% classification accuracy in internal testing.

Field trial results

Closed beta test carried out in 2023-24 cotton season.

Classification accuracy from field images was 89%.

The object detection step occasionally missed the nymph, requiring a recapture.

Scenario 2: Nymph counts

Also a two-stage process: one-shot object detection and then zoomed-in classification.

Parasitism not detectable at this level, classification more concerned with nymph vs. empty case.

Internal testing yielded an F-score of 75%.

Reflections

The biggest challenge for the project team was building trust in the technology.

There was less room for users to take bad photos with the lens, which made it a more consistent performer in beta testing.

Hardware and software capability only improving with time e.g. increasing MP on phones and new object detection models being released.

Industry outcome

A new pest management protocol for SLW has been recently released to the cotton industry, switching from adults to nymphs.

We were able to integrate offline smartphone sensing into this process, allowing to it aid one of the later-season steps.

The impact is reduced chemical control of pests by equipping the agronomists to justify the decision not to control.

Next step is commercialisation for widespread deployment.

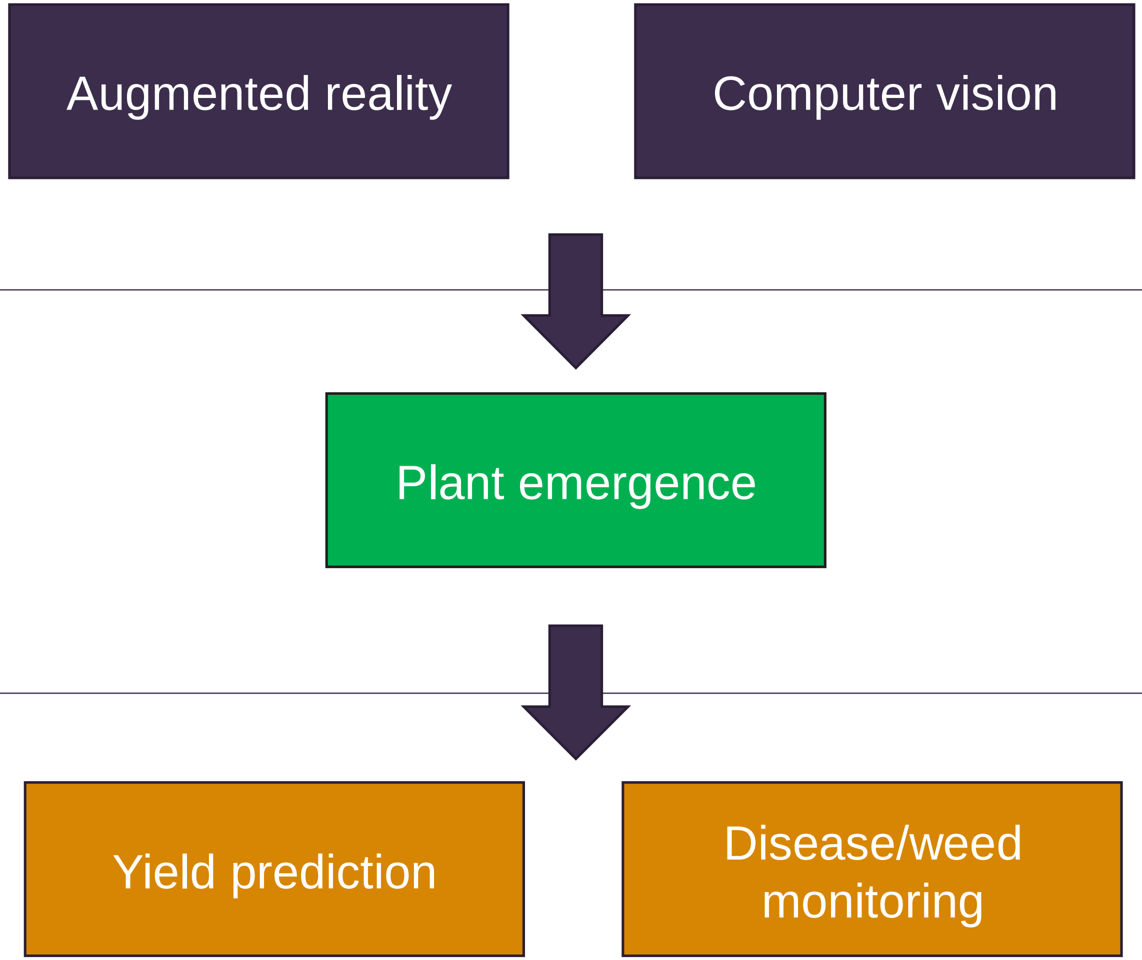
Augmented reality for crop assessment

Background

Smartphones are underutilised in the field for rapid crop assessment.

This project is about exploiting new smartphone capabilities to do advanced crop scanning.

Roadmap



- Fundamental work combining two technologies

- Initial prototyping on a crop agnostic application

- Expansion to advanced crop-specific functions

Plant emergence

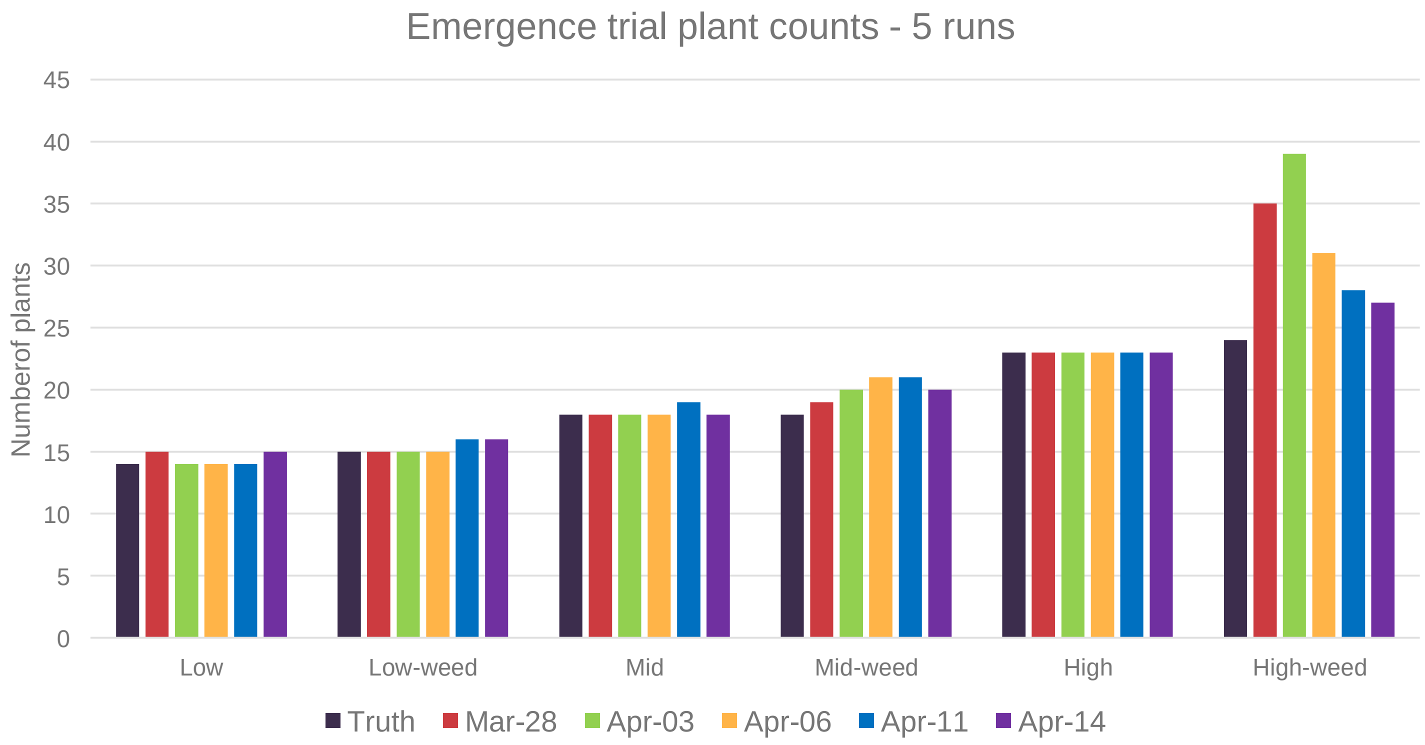
Emergence counting was a logical first step because the computer vision is light.

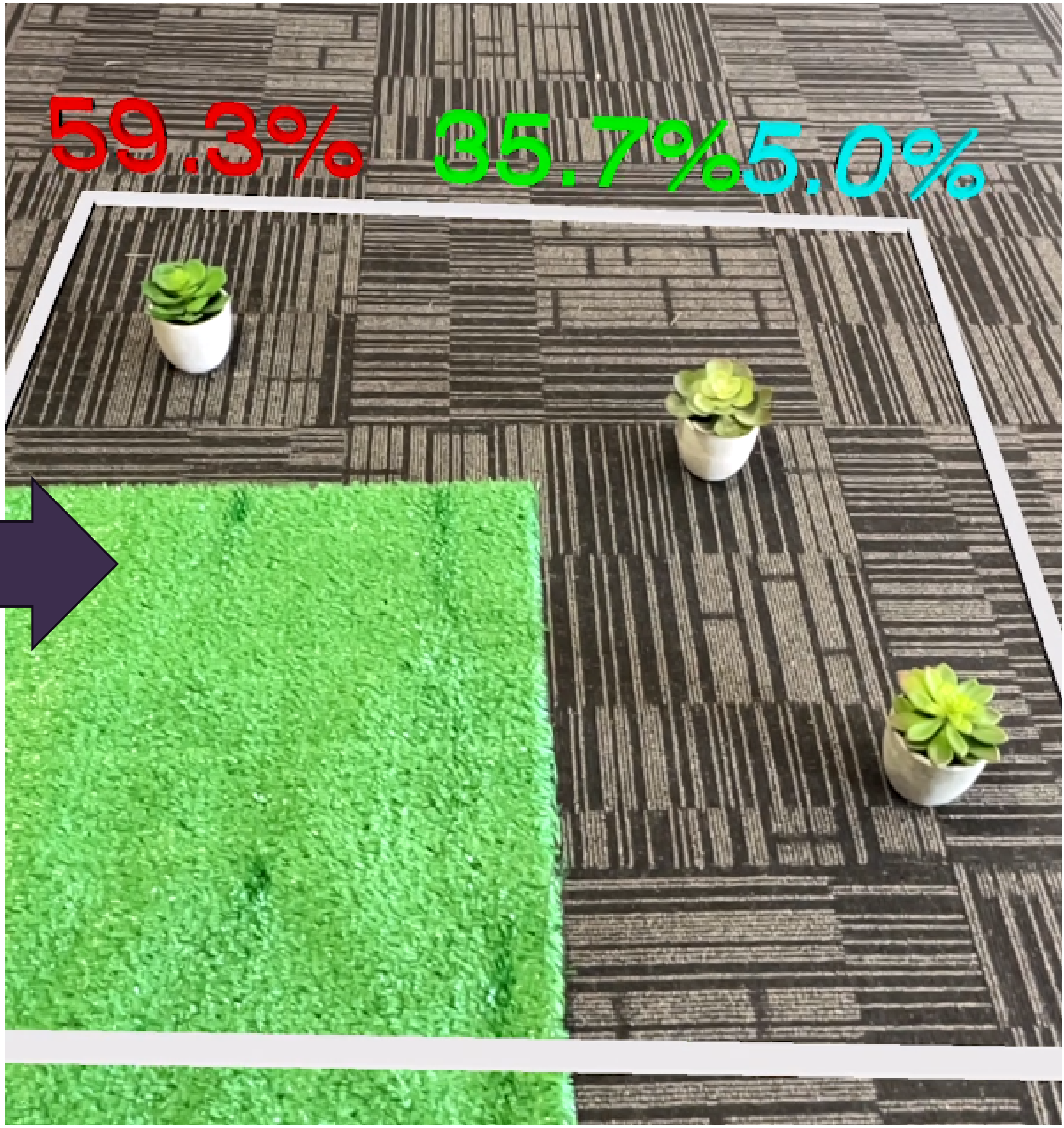
A line scan down the crop row was targeted to return plants/m.

Plant emergence results

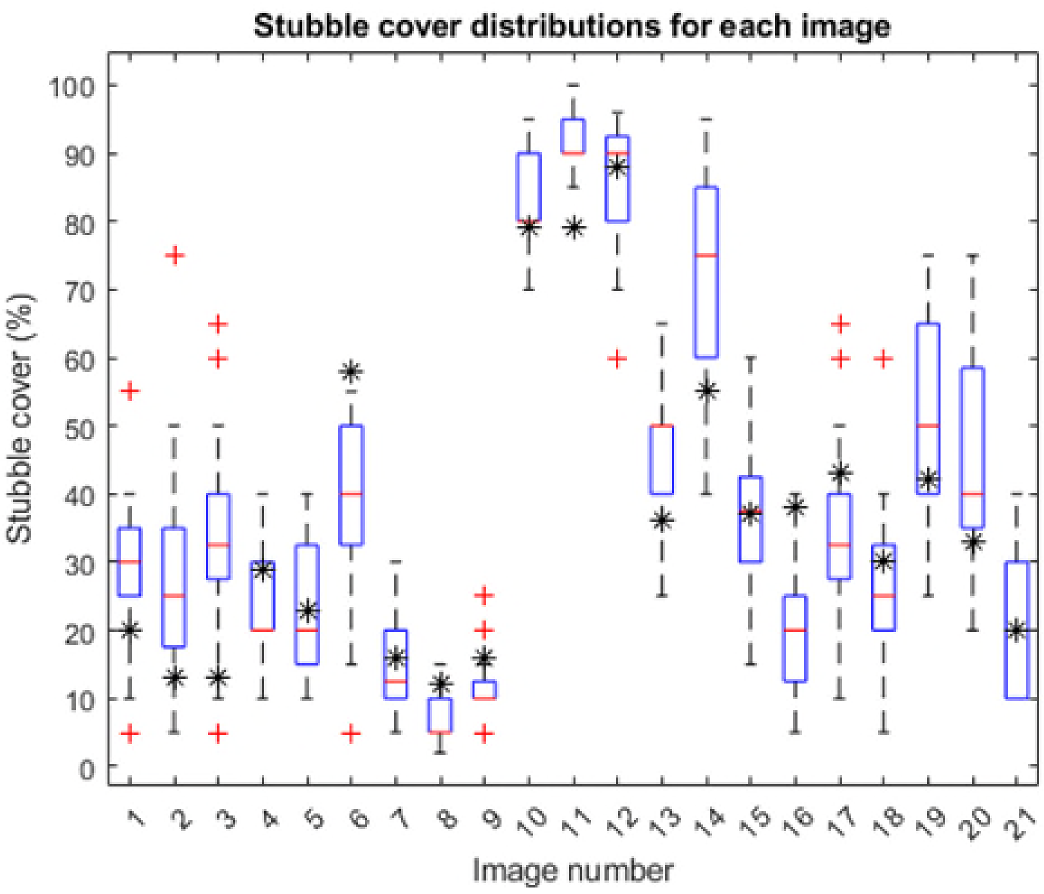
- The smartphone was able to keep accurate distance out to 10 metres ± 30 cm.

- Close matches in plant count apart from medium/high weed pressure.




59.3%
35.7%
5.0%

Virtual quadrat: Stubble cover



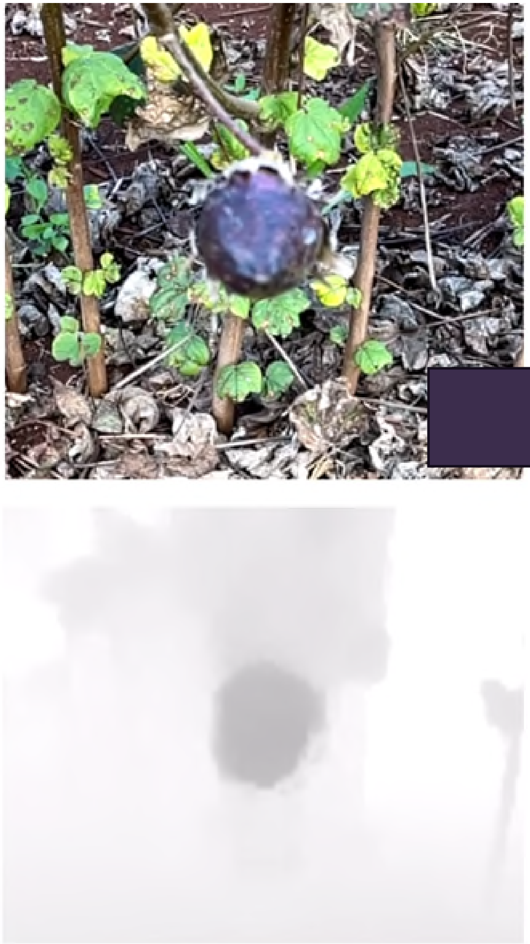
Virtual quadrat applications: wheat

Virtual quadrat could be used for wheat analysis and disease scoring.

Existing wheat head image databases to build from.

Depth camera concepts

The LiDaR packed into every iPhone could also enable plant measurement apps.



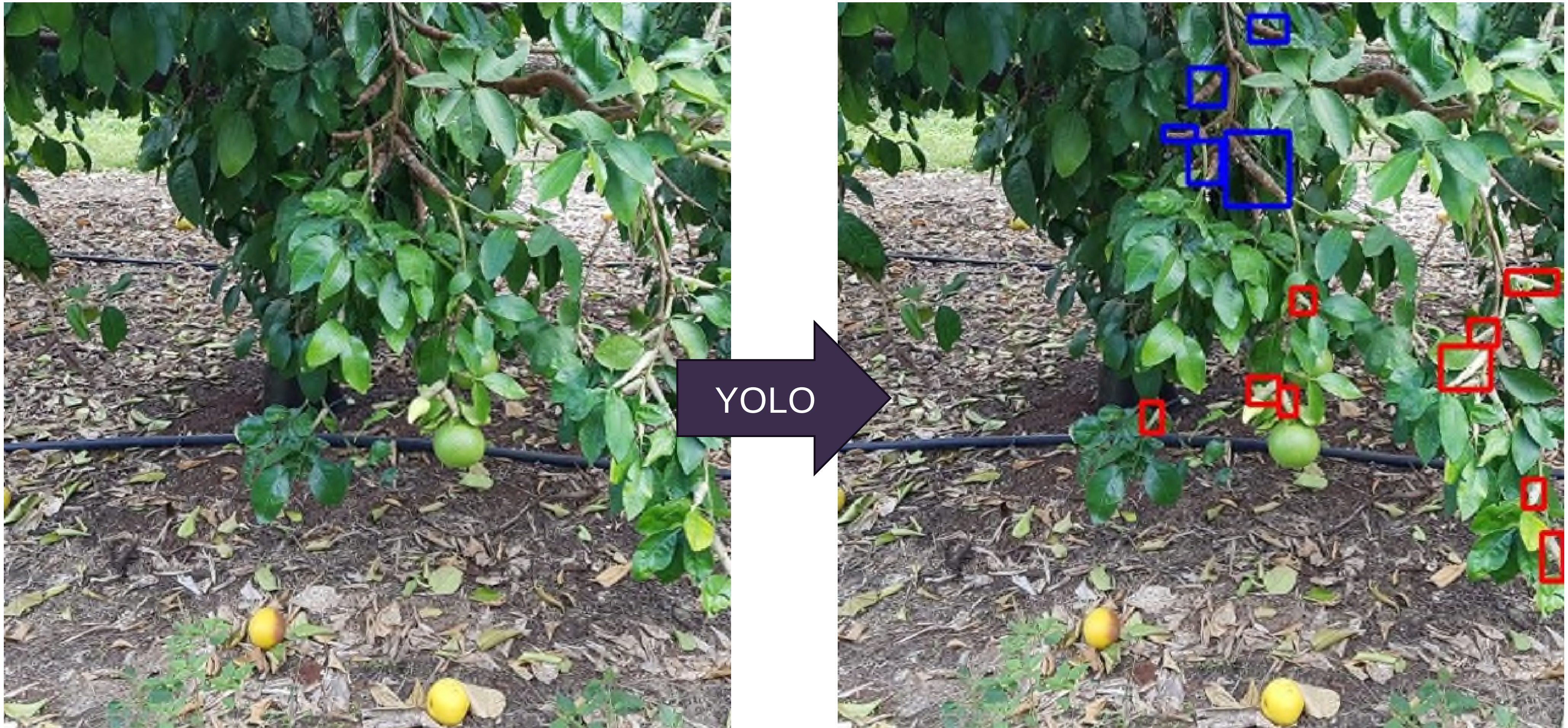
Colour (1920x1440)

Depth (320x240)

More examples

Horticulture examples:

- Pest monitoring
- Gall mapping
- Flower mapping for yield prediction



Horticulture examples:

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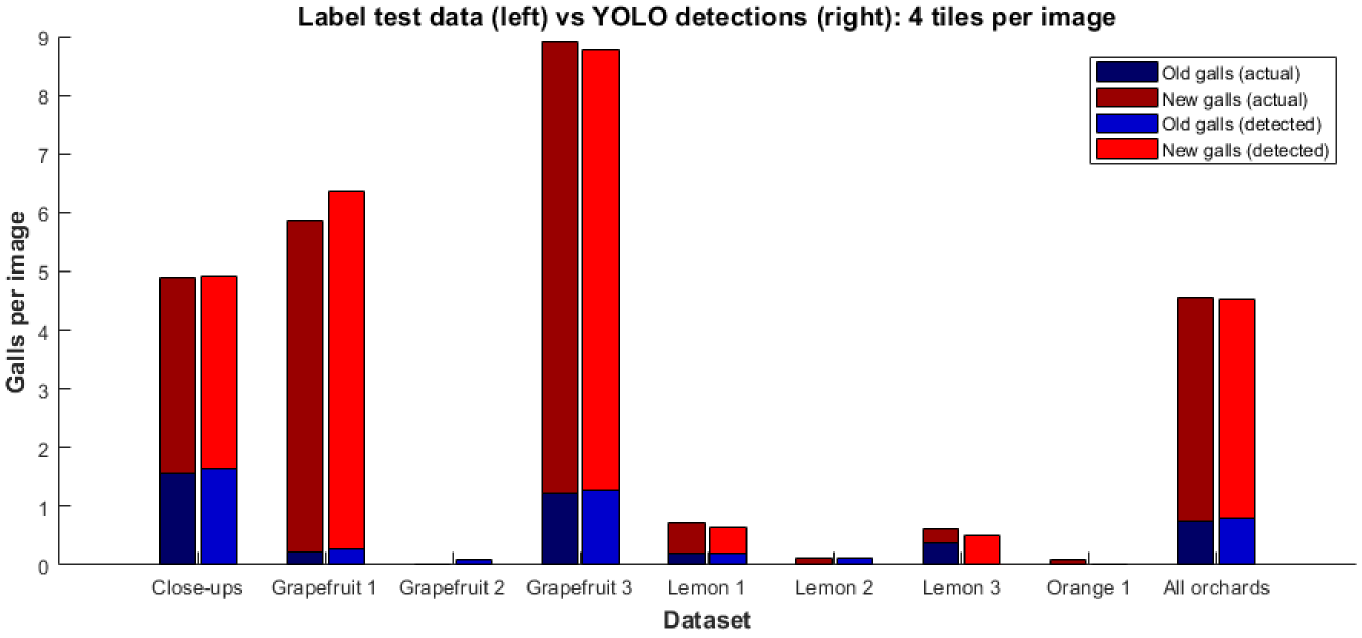


Total of 390 images with approx. 1800 galls: 70/30% train/test split. F-score of 85% on validation dataset.

Irrigation scheduling

Existing irrigation scheduling IoT sensors used a point temperature sensor that took the average over an area.

We were contracted to do a version with an array of those sensors (effectively a low-res thermal camera) to segment out crop temperature.

RGB Image

Multipixel temperature sensor

BOOM SPRAYERS

USQ has contributed to the See & Spray Select system through the licensing of several novel algorithms to John Deere.

Green-on-brown and green-on-green are one of the biggest examples of real-time vision in agriculture.

See & Spray Select. Source: John Deere

CURRENT GREEN-ON-GREEN

Company	Product	Regions	Weeds
Bilberry	Weedetect®	Australia, Europe	Broadleaf in cereals Blue lupins in lupins Blue lupins in canola
John Deere	See & Spray™ Ultimate	U.S.	Weeds in corn, soybean and cotton
Greeneye™ Technology	Selective Spraying System (SSP)	U.S. – midwest only Israel	Broadleaf in corn and soybean
Bosch BASF	ONE SMART SPRAY	Europe – Germany and Hungary	Distinguishing grass from broadleaf
Exxact Robotics	3S spot-spraying system	Europe	Various

OVER THE HORIZON

Three kinds of expansion:

Region expansion – Australia getting access to products in the U.S. market.

Product expansion – All of the listed providers have a roadmap of expanding crop/weed combinations.

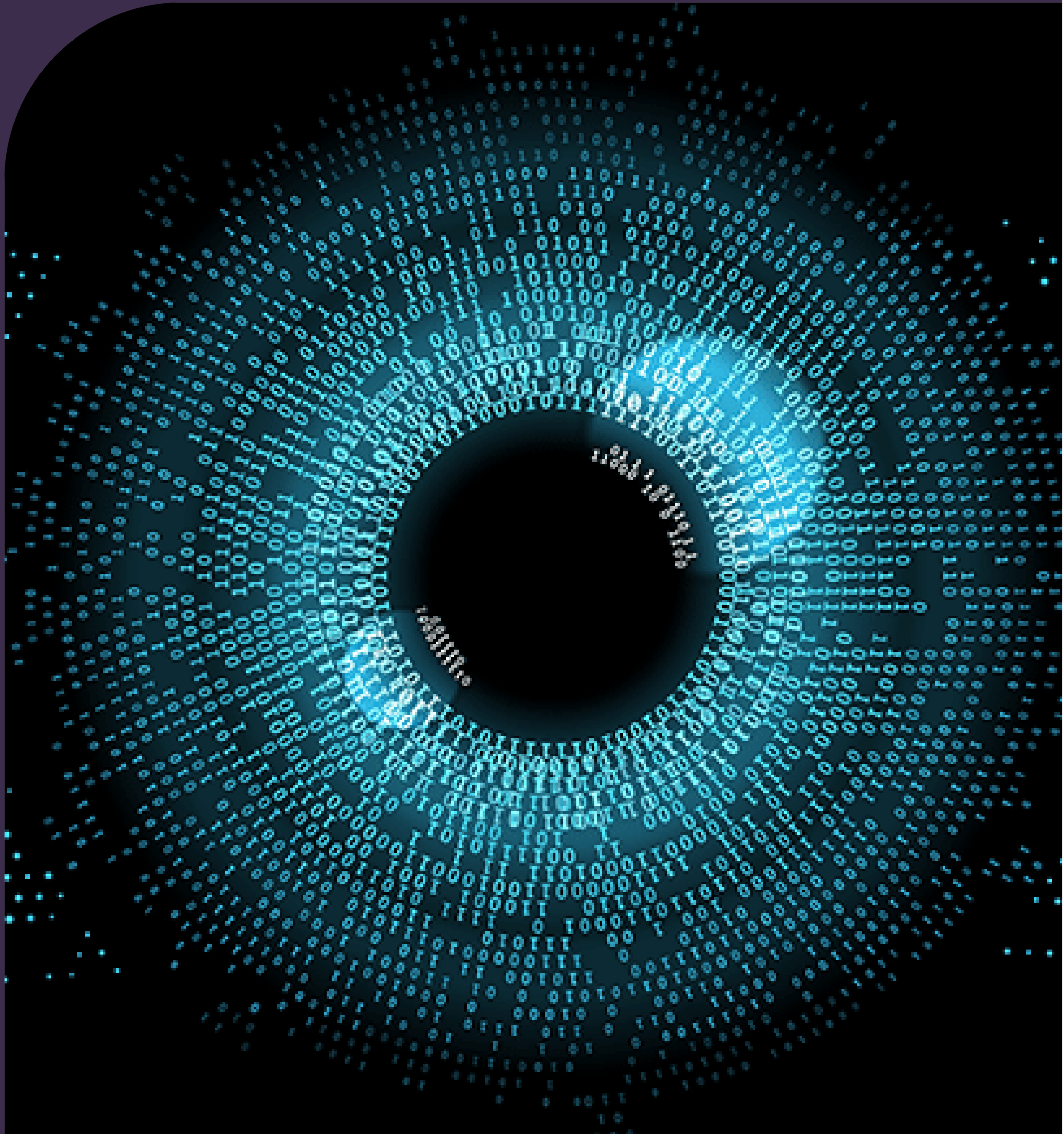
Function expansion – The sensing systems will move beyond weed detection…

OVER THE HORIZON

New functionality:

- Plant stand
- Plant health
- Fungus detection
- Pest detection
- Estimating nutrient requirements

ML Overview



OpenCV

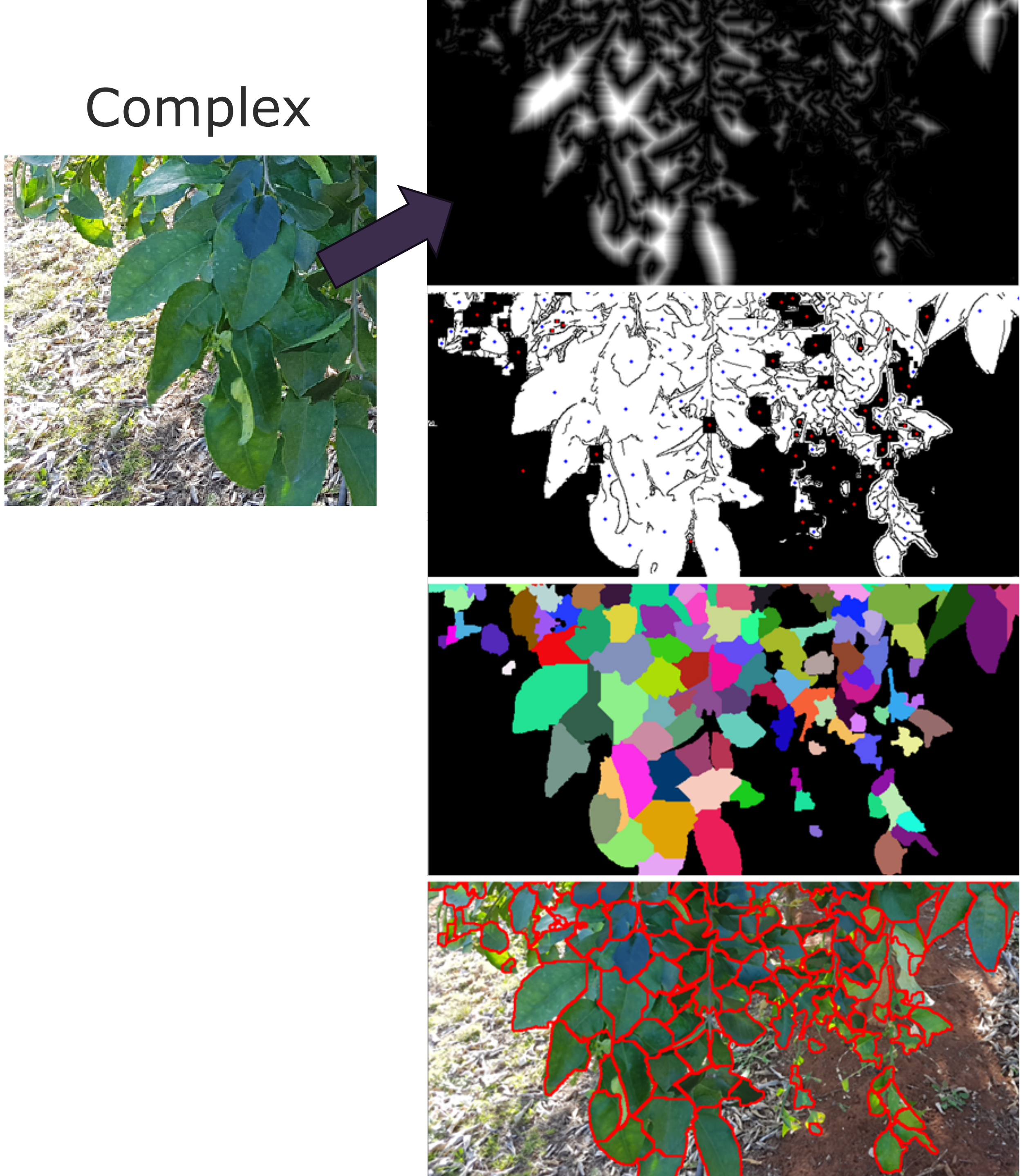
OpenCV is the foundation for a most of our vision-based projects.

At a minimum it is used for preprocessing and organising data, more frequently colour/texture analysis and used as part of the image processing itself.

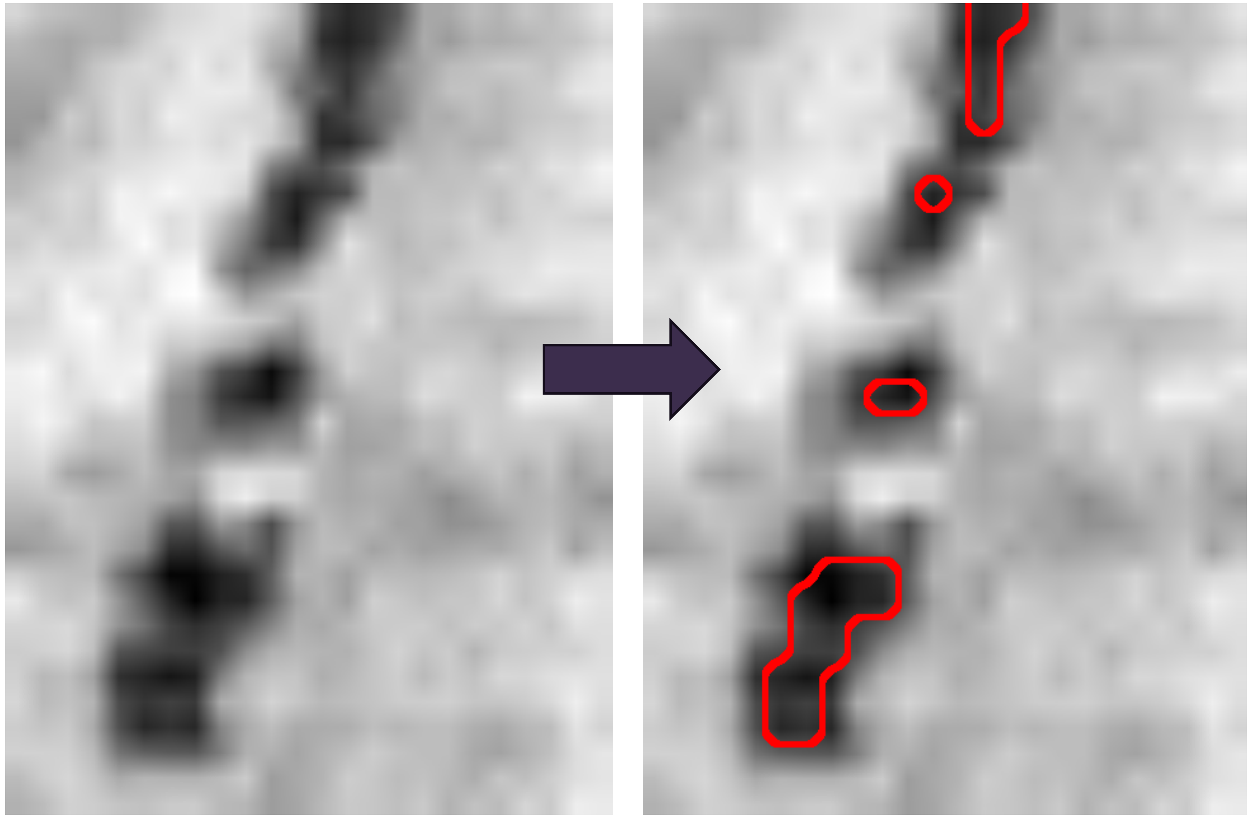
Alternative library – Pillow.

OpenCV examples

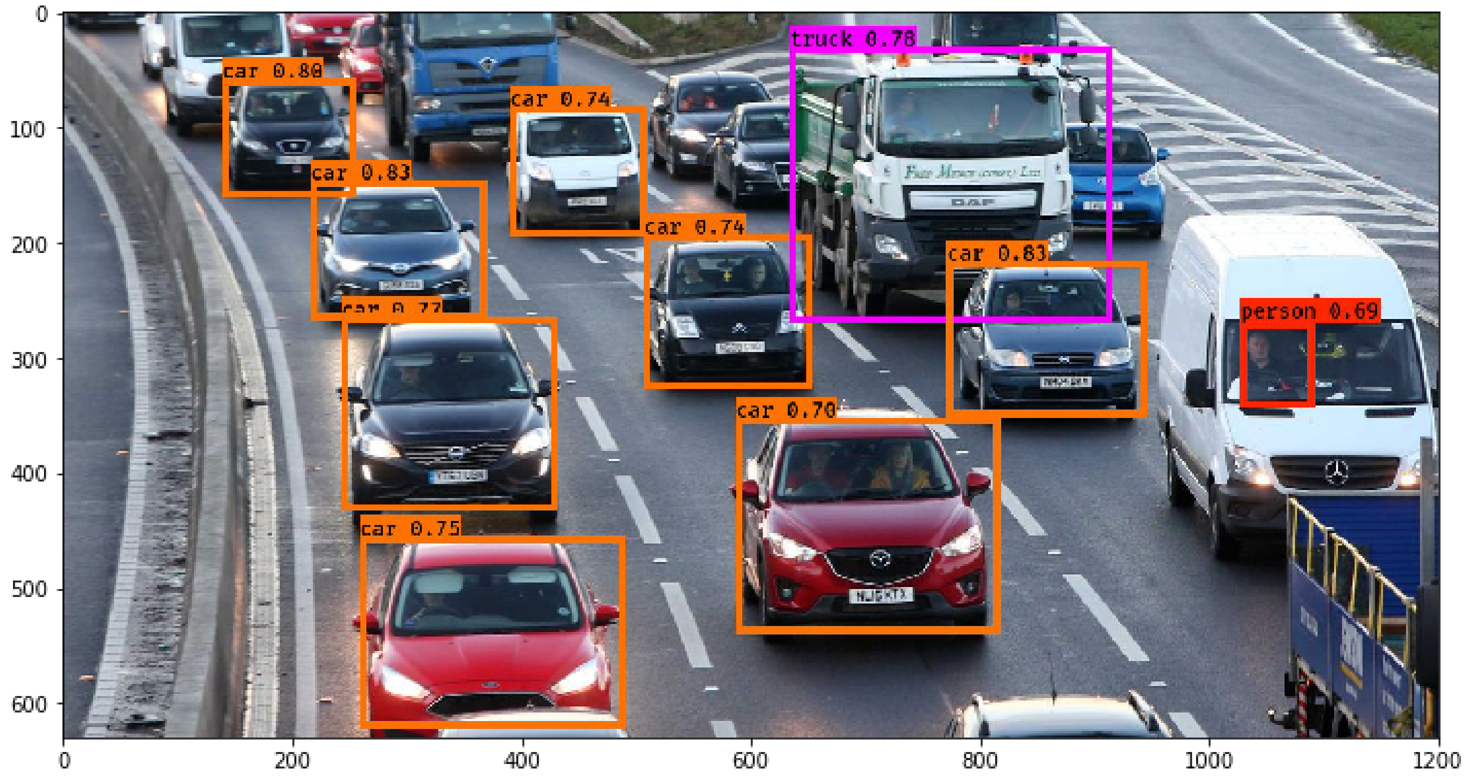
Complex



Simple



CNNs – YOLO



1. Collecting image set
2. Labelling the data
   a. Installing python environments (label-studio, ultralytics)
   b. Installing GPU-compute if desired
   c. Loading image set into label-studio, annotating
   d. Export to YOLO format
3. Pre-processing
   a) Train/test splits
   b) Tiling
4. Training
5. Inference

Considerations in ag applications: imaging constraints

Often, the most critical decisions made are around background and imaging conditions.

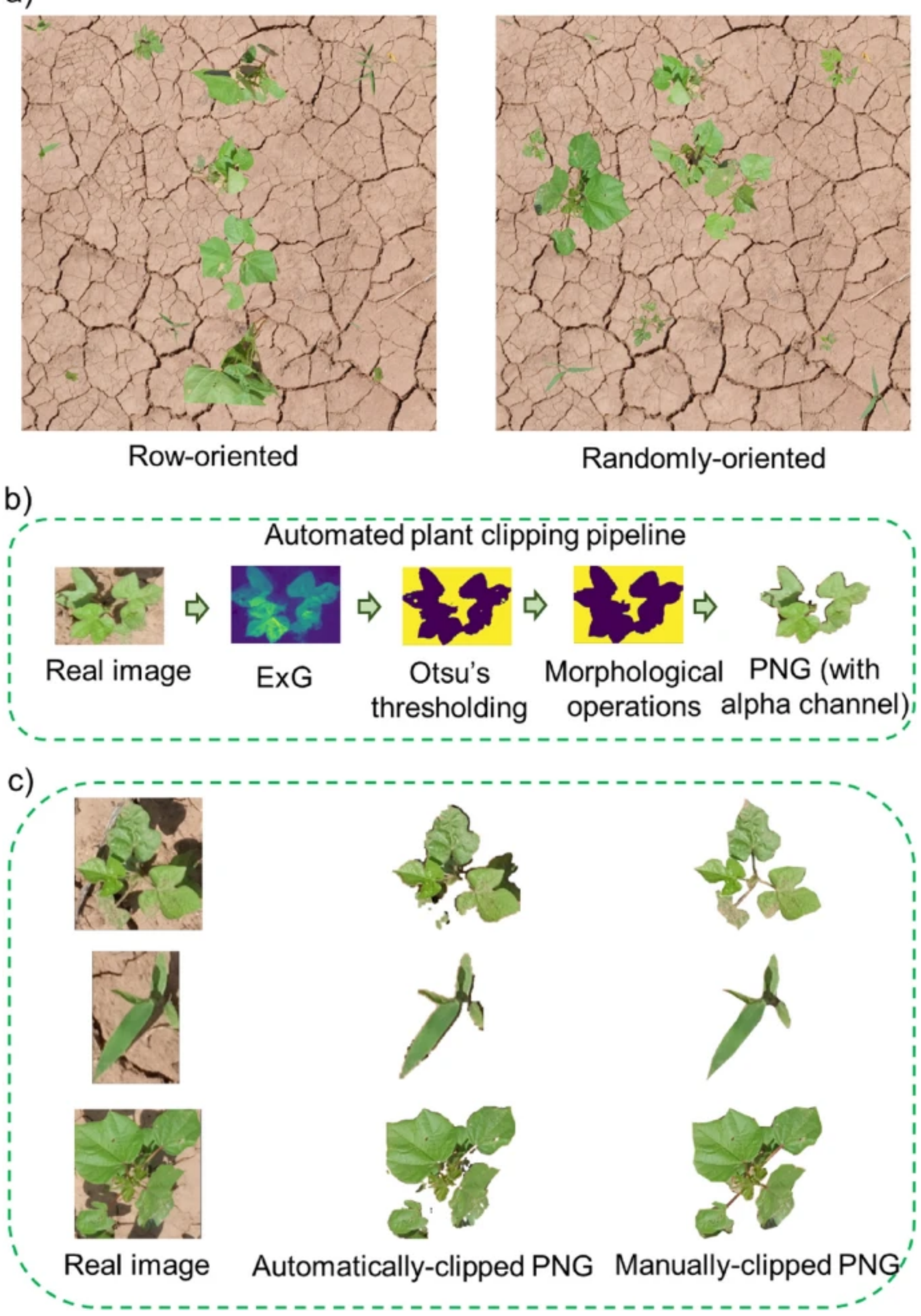
The user experience with the Pest app has vastly different consistencies between the two modes.

Data augmentation

Augmentation is a common process to get better results, which is making slightly different copies of each photo.

Possible augmentations

- Flipping
- Cropping
- Padding
- Normalisation
- Rotation
- Resizing
- Translation
- Contrast
- Gray conversion
- Brightness/hue/saturation /gamma adjustment
- Black patches
- Label dropout
- Blur patches
- Random JPEG quality

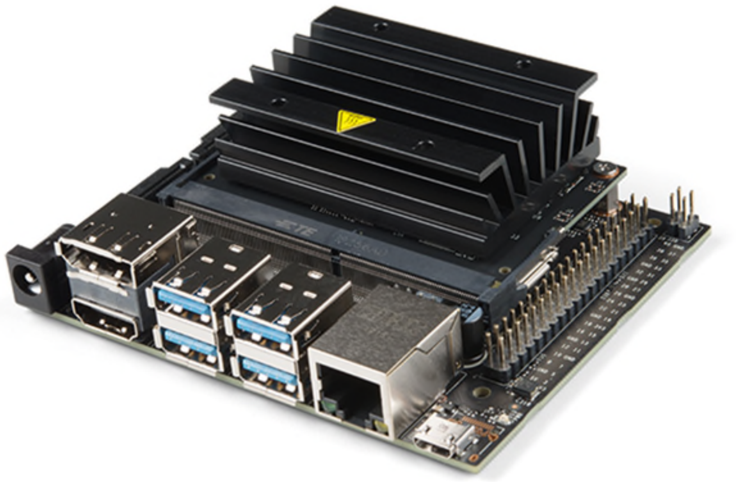


Source: Sapkota et al. (2022)

Deployment – Embedded Systems

A couple of typical options are:

- NVIDIA Jetson Orin Nano
- Raspberry PI with Coral TPU Accelerator



Experience with CNN deployment on Jetson Orin Nano:

- Pytorch
- Tensorflow Lite
- TensorRT
- ONNX runtime

Deployment - Mobile

Native Android (Java/C++ through NDK)

- OpenCV (OpenCV4Android or NDK)
- CNN object detection or classification (Tensorflow Lite)

Native iOS (Swift/Objective-C/C++)

- OpenCV (C++)
- CNN Object detection (Native MLPackage, converted from PyTorch or trained specifically)

Cross-deployable (Xamarin/MAUI)

- OpenCV (EMGU.CV - C#)
- CNN Object detection/classification (EMGU.TF - C#)

Instance segmentation

Moving on from bounding boxes, instance segmentation gives a mask as an output.

Requires pixel-level annotations to match.

Transformer models: Meta's SAM

ViT architecture stands for visual transformer, and operates similar to LLMs do but for images.

Meta's SAM is an example of a ViT model and is open-source.

[Simplification of transformer architecture.]

Other forms of processing - scikit-learn

Scikit-learn is a python library built on Numpy, SciPy and MatPlotlib

Contains models for supervised and unsupervised ML

Widely popular for ML applications in python

Case Study – Nitrogen application in Aus grains

This was a cross-institutional study that compared a range of different techniques for getting an N recommendation, including:

- Big data
- Machine vision sensing
- Reflectance-based sensing (ground and satellite)
- Yield prediction

Precision Agriculture (2024) 25:983–1013
https://doi.org/10.1007/s11119-023-10102-z

Check for updates

Digital strategies for nitrogen management in grain production systems: lessons from multi-method assessment using on-farm experimentation

A. F. Colaço[1] · B. M. Whelan[2] · R. G. V. Bramley[1] · J. Richetti[3] · M. Fajardo[2] · A. C. McCarthy[4] · E. M. Perry[5] · A. Bender[2] · S. Leo[6] · G. J. Fitzgerald[5] · R. A. Lawes[2]

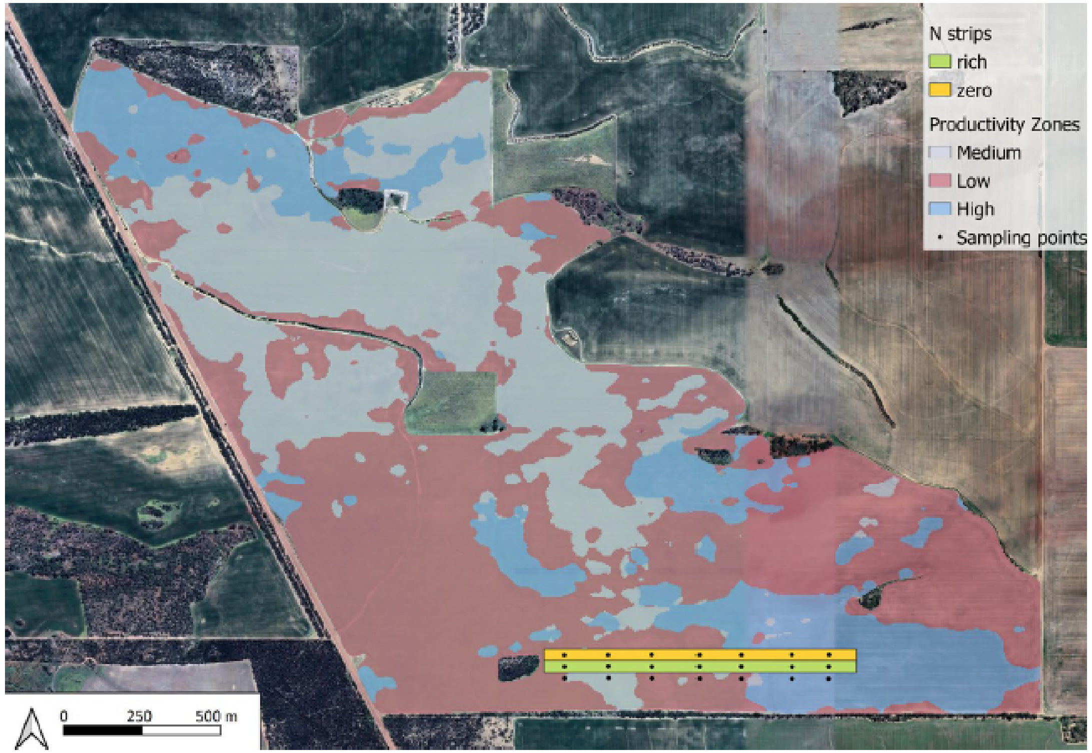


Fig. 1 Example of an N strip experiment and point sample location layout in a 357-ha wheat field near Kalannie-WA, 2019

Case Study – Nitrogen application in Aus grains

Study observations:

- General models are just as good or better than site-specific attempts

- Data driven approaches only excel when given huge amounts of data

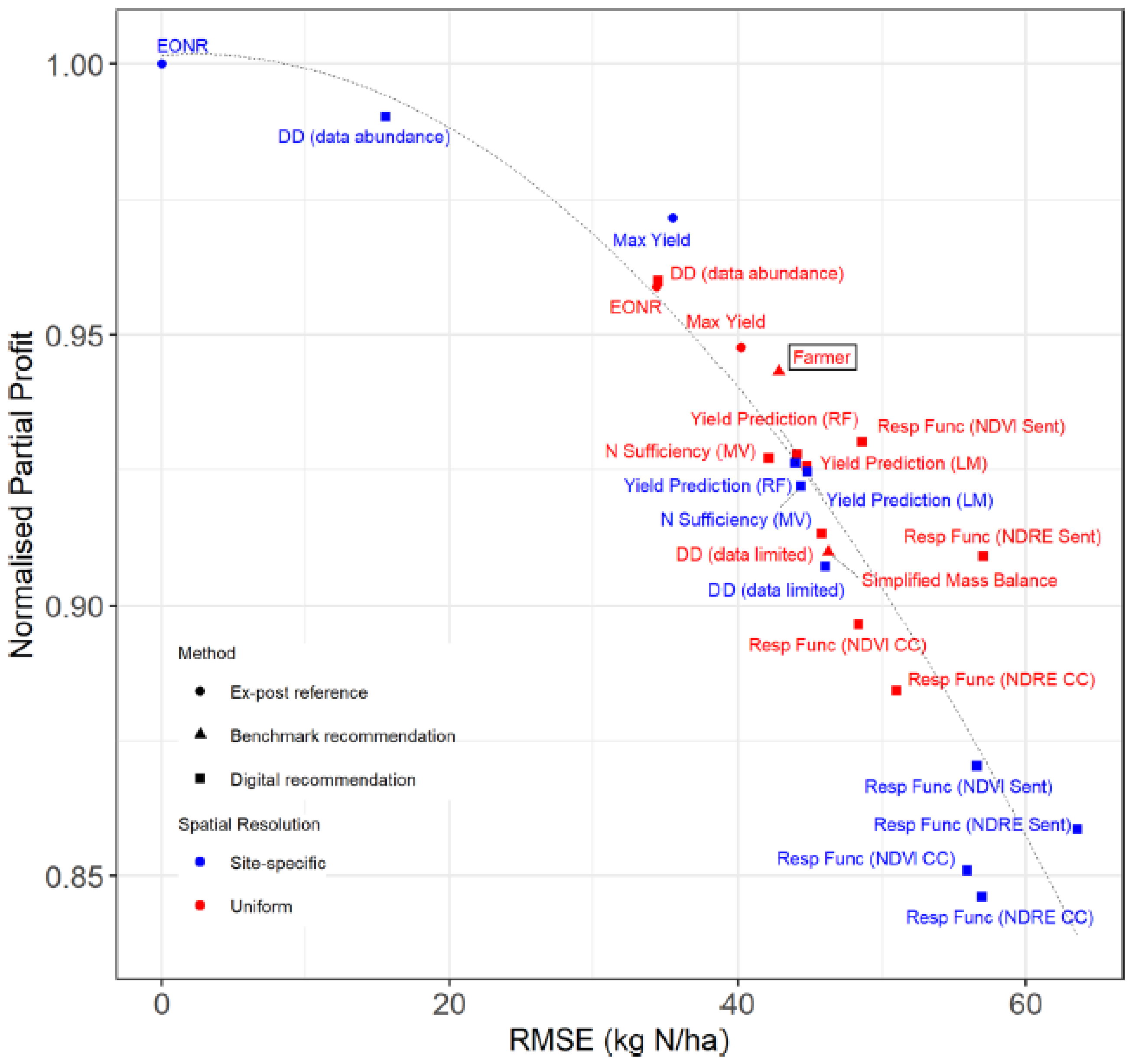


Fig. 5 Error by profit biplot showing the average results of various N recommendation methods across 21 large scale on-farm trials

Gen AI in Ag

ChatGPT

Functionality – Troubleshooting

Online chatbots could be trained on or given access to a wide range of materials e.g. tractor manuals.

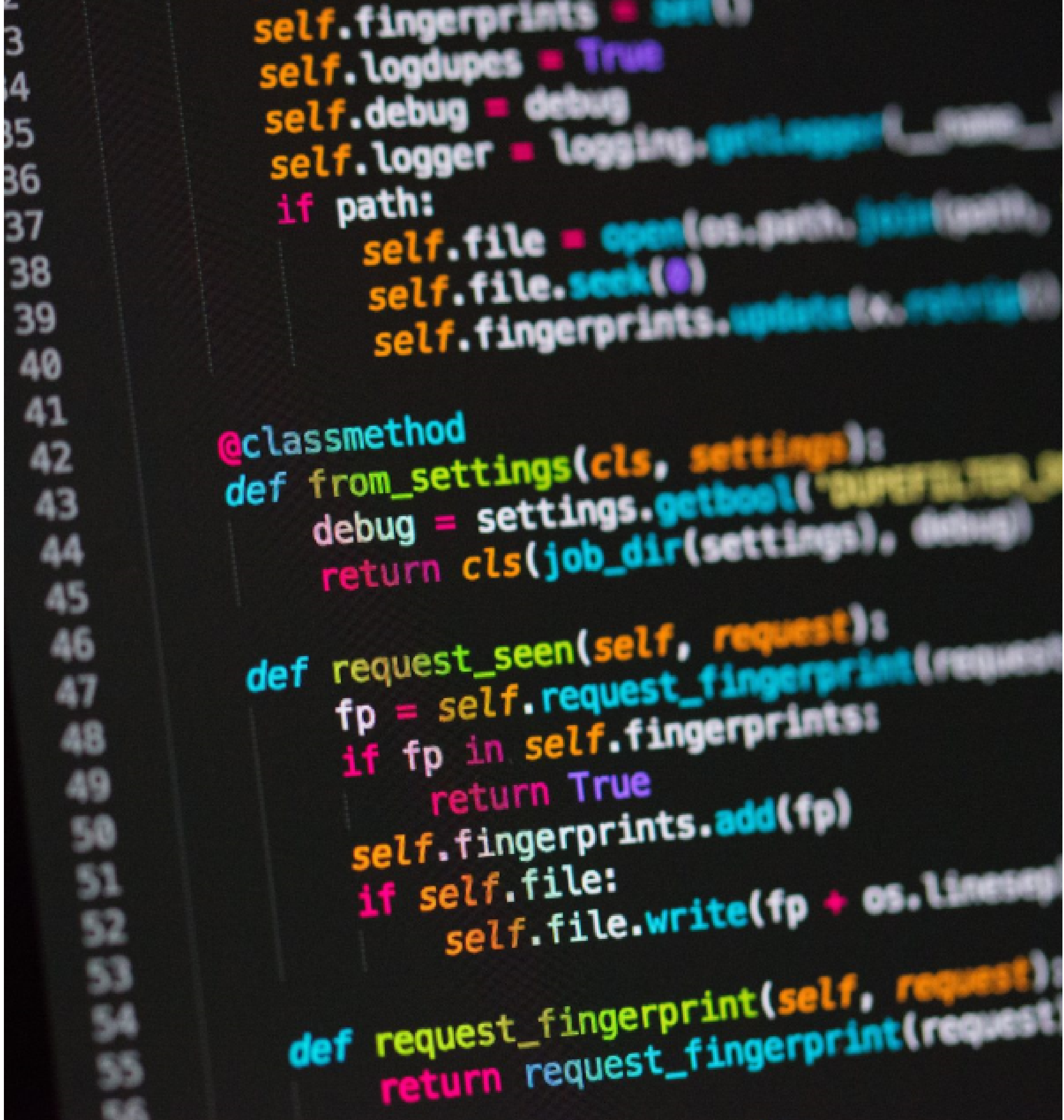
We have had firsthand experience where troubleshooting a tractor issue would have been faster with an AI chatbot.

Functionality – Coding

Very powerful for interacting with code:

- Writing subroutines
- Commenting and querying code functions
- Converting things to different languages

A 2023 Github survey found that 92% of U.S.-based developers use A.I. coding tools.



Example, app development

As part of a project, we were looking at transitioning a pest app to a web tool to lower maintenance costs.

No one on the project team has experience with making a web app, and so normally we would be contracting an external party to develop it.

Case Study – CRDC SLW Web tool

I was able to use ChatGPT to get a proof of concept working very quickly <u>with no web development or backend development experience</u>.

Would not have attempted this without generative AI.

Things ChatGPT did:

- Wrote the HTML/Javascript code for a button that lets you upload photos.
- Showed me how to put it on a web page

- Listed all available services that could be the backend
- Gave an example web app in the language of my choice
- Gave step-by-step instructions to deploy it on the web
- Provided tips on security, scalability and stability considerations.

Outcomes

The project team was able to prevent outsourcing something, significantly reducing the maintenance cost of the web tool.

Once we realised we could function without a contracted developer, we also took over app maintenance as well.

Other examples

1. Writing things in unfamiliar programming languages

2. Website development

3. Make scripts to organise files for me

4. Learn how to setup Linux systems

Examples of students extending…

1. Write a script that scans a folder and check that your data is all within a certain naming convention, fixing up anything that doesn’t comply.

2. Write a script to parse a deep dataset and extract a smaller representative sample for processing

3. Write a script to decode, organise and log raw data from a weather station.

4. Query LLMs to look for alternative angles when trying to justify the value of doing an activity

To Summarise

Sensing (and vision) in ag is playing a role on the journey towards precision agriculture.

The additional information that we can get about our crops and animals allows us to better micromanage them.

Most types of AI packages have a place here – CNNs, classification, regression, clustering, transformer.

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