

Weed detection for targeted weed management and control

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Computer vision could offer the potential to **discriminate weed plants from crops** in-field. A growing body of work is attempting to **develop this technology** and **apply it to precision weed management**.

Precision weed management might deliver both **economic** and **ecological** benefits via reduced herbicide use – **provided weeds can still be controlled simply and effectively**

- Weed detection using Drones
- Weed detection using on-farm machinery

Example: the Crop and Weed dataset - https://paperswithcode.com/dataset/cropandweed-dataset



Blackgrass: Alopecurus myosuroides



- An outcrossing, predominantly autumn germinating annual species.
- \circ $\,$ Increasing distribution and abundance in the UK and NW Europe.
- \circ Can it be detected and mapped autonomously via images?





Case study 1: Using UAVs



<u>AiScope</u>

Using **UAVs** (drones) to capture imagery in-field, and train algorithms to recognise weeds

In this case, Blackgrass at the flowering stage











Mapping Blackgrass using UAV imagery





Attempt to map Blackgrass (*Alopecurus myosuroides*) at flowering using drones

- Created high quality dataset of 34 imaged wheat fields in 2021
- Images at 1cm resolution using a DJI M210 UAV, with X7 sensors

Lesson 1: *Resolution and timing of imagery collection is supremely important*



Imagery types:





Captured images with two different camera types:

- Standard RGB images using the visible light spectrum.
- Multispectral images
 collecting data at wavelengths
 475, 560, 668, 717, and
 840nm

Normalized Difference Vegetation Index (NDVI)



$$VI = \frac{(NIR - Red)}{(NIR + Red)}$$

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- Provides a measure of "greenness"
- Standard measure in assessment of crop health and development



Lesson 2: NDVI was no help for detecting Blackgrass at flowering





- Images annotated and two models trained: RGB only, and RGB + Multispectral data
- Accuracy and recall was generally high: the model found most of the weed labelled pixels correctly
- Precision was low: The model overpredicted around patches, and identified un-annotated weeds

Lesson 3: Including multispectral data did not improve model performance

Dataset	Metric	Value (SD)
Test data	Accuracy	0.92 (0.01)
	Recall	0.89 (0.02)
	Precision	0.41 (0.03)
Unseen fields (out-of-bag)	Accuracy	0.91 (0.05)
	Recall	0.72 (0.23)
	Precision	0.35 (0.06)

RGB only

RGB+Multispectral

Dataset	Metric	Value (SD)
Test data	Accuracy	0.92 (0.01)
	Recall	0.88 (0.04)
	Precision	0.42 (0.02)
Unseen fields	Accuracy	0.91 (0.03)
(out-of-bag)	Recall	0.72 (0.27)
	Precision	0.35 (0.11)

Comparison: Spatial distribution of Blackgrass



AI model prediction

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The model predictions were converted to a format equivalent to our in-field weed survey data:

- **Spatial arrangement of Blackgrass patches** Ο conforms well with in-field mapping
- Strong positive correlation between model Ο predictions and actual measured abundance



Predictions vs. in-field surveys

3.5

Blackgrass 'severity': Estimated by model

A Deep Learning Application to Map Weed Spatial Extent from Unmanned Aerial Vehicles Imagery. (2022). Remote sensing. https://doi.org/10.3390/rs14174197

Taking weed detection and mapping further





Case study 2: In-field machinery







D - BASF We create chemistry

BOSCH



<u>SmartSprayer</u>

Upgrading **farm machinery** to incorporate cameras / sensors to detect weeds

Again, focussed on Blackgrass detection

"Smart-sprayer" system



Bosch and BASF have jointly created a camera equipped **"smart" spraying system.** Current UK Innovate project is to build one of these (Chafer machinery), and trial it for detection of Blackgrass.



Before starting in the field, built a testrig at Rothamsted mimicking the sprayer boom.

- Initial work has been to grow many Blackgrass and wheat seedlings in separate soil trays.
- Imaged over a range of growth stages from seedling to large vegetative plants

Controlled imaging









Controlled imaging



Building up a large library of Blackgrass and Wheat imagery. Captured using the same camera and lighting equipment deployed in the field. Creating an imagery database to aid algorithm development

Gray Scale Image after Processing the Raw Images



Blackgrass object detection



Testing in-field





Sprayer deployed in field over spring 2023 to collect imagery

Complemented by in-field surveys of the weed population

More imaging over the 2023-2024 season



Imaged a variety of crops and weeds



Early and late-stage Blackgrass





Volunteers and other weed species







Broad-leaved crop







Raw (left) and processed (right) imagery collected in-field

Object-detection allows segmentation of plants from the background, soil, straw etc.



Lesson 4: Weeds can be successfully detected at earlier stages, but the bottleneck is annotation of imagery

An initial model has been trained, but only on a very limited training data-set

Algorithm classifies detected plants as weeds or crop. Detected weeds are currently grouped as Blackgrass (purple) or broad-leafed weeds (red).

Provides a proof-of-concept for image collection, processing, and algorithm development – but needs a lot more work!







- For UAV mapping, resolution was the most important aspect, followed by speed (slow!), lighting, and timing.
- Increased infrared data from the multispectral sensor did not aid model performance.
- NDVI was not helpful in detecting flowering blackgrass, but is useful in separating vegetative plants from background: soil, crop residues etc.
- The smart-sprayer system is allowing us to collect large amounts of cropweed imagery.
- The real bottleneck now is finding ways to accurately and quickly annotate images for model training.



Thanks for listening