Plant Stress Detection Based on Spectral Imaging and Deep Learning

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You need to reword this it is too similar to the original project description i.e. plagiarism

This is good but you need to write this more in terms of a hypothesis so instead of using words like 'will' instead use 'could'

Introduction

Organic growers face a number of challenges they must overcome to deliver high quality food to their customers. The lack of reactive chemical control measures in organic farming requires additional levels of insight in order to optimise plant and hervest schedule. Traditional manual detection can only wait until late crop stress morphological changes, and is generally time-consuming and subjective. However, using spectral imaging technology, the differences in crop physiological structure characteristics will lead to differences in light reflection, absorption and transmission. Studying these differences in spectral imaging can help identify the crop growth status, nutrient and disease.

Previous studies have made extensive fundamental research on crop detection using spectral technology, mainly based on spectral index features and image features. For instance, the olive Verticillium wilt can be diagnosed by images collected from UAV-mounted multi-spectral camera and thermal infrared camera, and it was found that early Verticillium wilt was related to green light band, and chlorophyll fluorescence index decreased with the disease ~~aggravating~~ incedence (Calderón et al., 2013). Moreover, applied hyperspectral imaging techniques to identify the angular leaf spot of cucumber by detecting the contents of chlorophyll and carotenoids showed the feasible feasibility for visualizing the pigment distribution in cucumber leaves in response to angular leaf spot (Zhao et al., 2016). ~~Besides~~, progress has also been made in the research of crop identification (Torres-Sánchez et al., 2013, Laliberte and Rango, 2009), as well as crop growth status monitoring (Vega et al., 2015).

Perhaps a sentence here about the type of spectral imaging hardware used in these studies and the challenges and cost of working with such hardware

Although the identification of different plant stresses has reached a considerable level of accuracy, the pratical plant stress process may be more complicated and the understanding of the spectral images of plant stress could be deeper. In order to explore the feasibility of using spectral imaging to identify complex plant stress and better apply spectroscopy technology to pratical production, we propose the application and research and as follow:

You need an overall aim here i.e. can we use deep learning image analysis of multispectral image data to predict stress levels in plant tissue.

1) How can we build a robust classifier to detect~~e~~ the quality of organically grown broccoli on conveyor belts using spetral imaging?

2) Can we build a robust classifier based on limited data set, using the spectral images ~~collected under~~ to distinguish different combinations of stress (temperature, light, drought)? How can we extend this to the field?

3) Can we use metabolomic analysis to detect changes in secondary metabolism that might influence plant tissue reflectance spectral indicies

3) Deep into a metabolic levels, can we find the evidence to support the classification?

keywords: Organic farming, Deep learning, Plant stress, Spectral imaging, Detection, Metabolomics

Methods

You should mention we have 30 000 + images for training data for the conveyer belt. Talk about the kinds of classifier we will need i.e. incidence detection and potentially segmentation. The initial challenge is segmentation for NDVI analysis of broccoli heads. Classic NDVI does not work well because of the colour of the conveyer belt. We also wish to perform some form of initial cluster/regression analysis to see if there is any variation in this data that could be used to predict shelf life. Failing this we will look at combinations of pixel intensity and texture to seek features predictive of shelf life.
You should also highlight that we will compare different machine learning methods and deep learning architectures to see which provide the best results

First, use multi-spectral imaging technology combined with deep learning algorithms to detecte the quality of organically grown broccoli on conveyor belts.

Once we have a few prediction classes we will use this to group broccoli heads from the conveyer belts and monitor their shelf life after image aquisition

Second, build the same detection model using the data collected by the drone.

Swap second and third

Third, under the environment controlled by the laboratory, collect spectral image data under different combinations of stress (temperature, light, drought) and explore the possibility of establishing a robust classifier in a limited data set.

Expand a bit on this i.e. we will grow plants in controlled environments and expose them to combinations of drought and heat stress. We will sample leaf and flower multispectral reflectance to search for signals that distinguish these treatments.

Fourth, sample and explore molecular differences by GC-MS, to provide classification basis in metabolic levels.

Mention GC-MS will be performed by our collaborator in SK.

Expected Outcomes

Robust spectral images classifiers and matabolomics analysis.

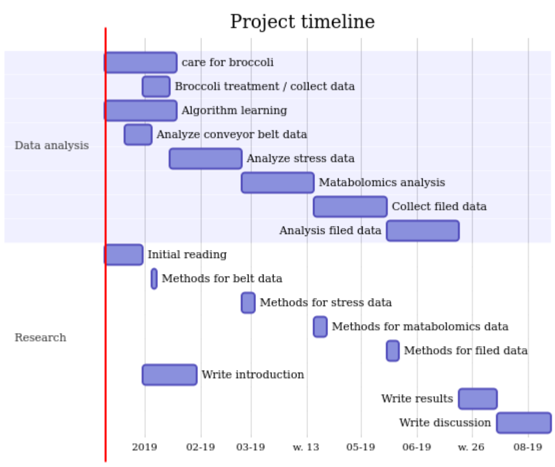
Budget

£500 funded by school for computing hours, printing costs and for travel related to the project.

We will travel to our industrial partner's farm in Yorkshire (Pollybell farms) to collect drone data and additional conveyer belt data

Project Feasibility

Feasible equipment for data collecting and timeline as bellow



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