Machine vision and learning to rapidly assess crown-rot in wheat

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Background

Wheat crown rot, occurring in many arid and semi-arid cropping regions around the globe can be responsible for up to a 40% yield reduction under conducive conditions. In severe cases this disease can lead to necrosis of the stem, limiting grain production. The lack of readily discernible visible symptoms until late in the season with the appearance of white heads causes delays in production decision making, potentially tying up resources in areas where productivity will be low. Improvements in disease identification, rapid phenotyping, and decision making, will help growers remain profitable and operations sustainable.

Currently, crown rot assessment involves physical removal of the plant from the soil followed by removal of the leaf sheaths around the lower internodes and colour assessment by a trained rater. This process is time consuming, difficult to use on a large scale and prone to variation due to human bias and significant environment/pathogen interactions. A machine vision-based system can be used to rapidly assess disease incidence and severity with high repeatability with the exclusion of this bias.

A series of experiments were undertaken in glasshouse and field trials in Southern Queensland from 2017 to 2019. These experiments evaluated the ability of non-invasive near infrared crop sensors and machine learning methods to detect and quantify *Fusarium pseudograminearum* in bread wheat.

This project aims to determine the potential of a machine sensing system to identify and quantify crown rot in wheat utilising unique signatures obtained from the near infrared spectrum and analysed using machine learning techniques. The goal is a robust system for use across cropping environments for rapid assessment and phenotyping of crown rot reducing labour and time costs for plant breeders allowing for resistant material to become available to growers more quickly. Direct grower benefits include increasing operation profits by freeing up resources from diseased crops for use in increasing yield in other areas of operations.

Key words

crop disease, crown rot, machine-learning, proximal sensing, remote sensing

Call to action/take home messages

- Non-destructive sensing enables automated detection of crown rot that previously could only be detected manually.
- Machine learning models enhance classification results over traditional analysis techniques.
- Machine learning based, near infrared sensing has potential to be deployed as a handheld or drone-based tool for both paddock level disease detection and phenotyping.
- Embracing new sensing technologies enables rapid management decisions to maximise profit by applying inputs where most profitable.

Methods

Glasshouse trials were conducted at QDAF and USQ facilities in Toowoomba, QLD. In 2018 and 2019, five bread wheat genotypes were observed under positive or null, inoculation with *F. pseudograminear*um colonised wheat grain (Percy et al, 2012). Each treatment was replicated 6 times. Pots in the glasshouse trials were configured in randomised block designs and watered to field capacity as required. The temperature was maintained at 20-25 degrees Celsius. Inoculum was applied individually to coleoptiles of each plant at the two-leaf stage.

Two field trials were conducted at the Tosari research station (-27.859964, 151.452766), planted in June of 2018 and 2019. Paired, inoculated and non-inoculated 6m x 2m plots were arranged in a strip plot design in a randomised block with three replications. *F. pseudograminear*um colonised millet inoculum was applied into the furrow above the seed at planting. Six randomly selected plants from each plot were chosen, corresponding to each of the five genotypes in the glasshouse trials.

Measurements were taken using the near infrared point sensor with a sensitivity of 900–1700 nm once a week throughout the growing season for nine weeks, from three weeks post inoculation. Technical issues caused week 8 in the glasshouse 2 trial to be lost. The maximum separation between all other measurement dates is 8 days. Readings were collected from the center of the newest emerged tiller, the leaf determined to be center-most and the youngest flag leaf. Calibration reflectance measurements were gathered from a 10% grey, a 60% grey and a 99% white reference Spectralon® panel.

Observed plants in both sets of trials were pulled at maturity and scored manually at the Centre for Crop Health for the presence and severity of *F. pseudogramearum* induced crown rot.

Machine learning techniques including linear regression, clustering techniques and neural nets were evaluated for effectiveness in discriminating and quantifying *F. pseudograminearum* induced crown rot in bread wheat. All analysis and model creation was performed in the Python computing environment (Python version 3.6.8; Python Software Foundation, 2019), using the SciPy ecosystem (Jones & Peterson, 2016) and the Scikit-learn library (Pedregosa et al., 2011).

Results and discussion

Machine learning models where compared for the ability to accurately discriminate crown rot at different timepoints from inoculation. The results show crown rot detection ability with accuracies ranging from 55–100%. The top performing model, of the machine learning algorithms tested, was an artificial neural network classifier (ANN), which performed with an accuracy of up to 100.00% under optimal glasshouse conditions (Figure 1). The lower classification accuracies observed in the field trials may be due to low levels of disease, particularly in genotypes with some resistance. Further analysis is being completed to determine the impact of false positives. Differences between the waveform signatures of inoculated and uninoculated treatments indicate that this sensing approach has potential to be scaled to a camera-based system for use on remote sensing platforms (i.e. UAVs). Further work has been conducted and analysis is currently underway to better understand the viability of such an approach, which is an important step towards large-scale, automated disease discrimination.

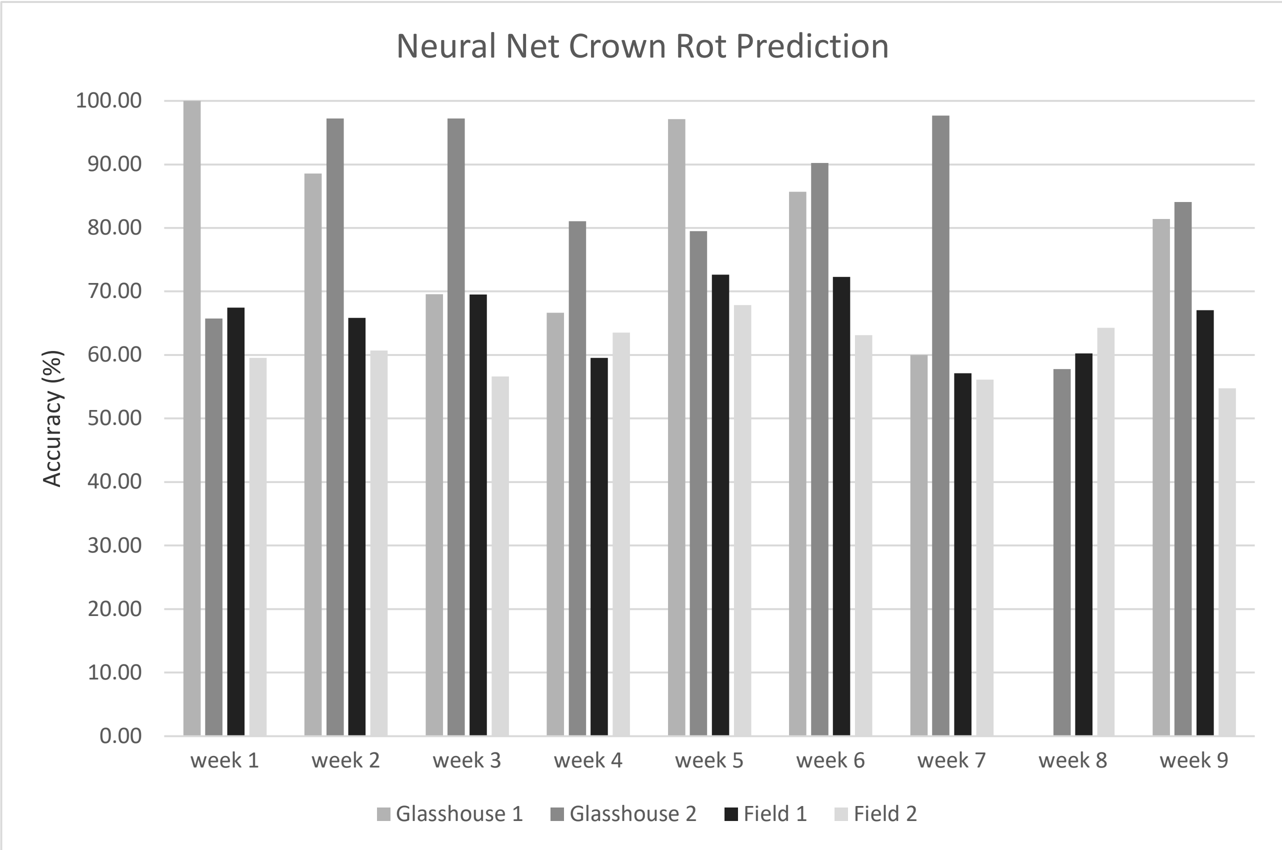

Figure 1: Average classification accuracies of crown rot detection (+ or -) of an optimised artificial neural network for nine weeks, from three weeks post inoculation.

Early detection of crown rot is crucial to optimise operation profits by enabling growers to reduce inputs on affected properties (i.e. foliar N) and plan future rotations and management strategies. Estimated potential annual yield loss from *F. pseudogramearum* is 22.2% (Murray & Brennan, 2009). With an estimated cost of nitrogen at $66.25–$71.11 /Ha, dependent upon utilised product, potential savings of excess inputs can be estimated at between $2.92 (0.044*$66.25) and $15.79 /Ha (0.222*$71.11) if *F. pseudogramearum* presence is detected early (Doyle, 2013). The results of the near infrared-based, machine learning models show detection capability at three weeks post inoculation, allowing time to make these production decisions.

Additional benefits exist to plant breeders and researchers which provide further, indirect, benefits to growers. Rapid phenotypic assessment of crown rot may allow for reduced sunk costs for plant breeders allowing for resistant lines to be released to growers in less time.

Summary

Near infrared technology provides non-destructive disease sensing enabling rapid, automated detection of crown rot that previously could only be detected manually, through destructive methods. Embracing these new non-invasive sensing technologies may enable rapid management decisions to maximise profit by optimising input timing and restricting input application to the areas where the highest return on investment can be expected. The adoption of near infrared sensing by plant breeders may provide tools to more rapidly release resistant lines, further indirectly benefiting growers. This technology has the potential to be deployed as a handheld or drone-based sensor for rapid characterisation of paddock disease levels.

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