Weed and Water Stress Detection Using Drone Video

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Abstract. Precision agriculture has greatly improved the quality and quantity of crop yield over the last four decades. However, this approach depends on the availability of sufficient quality data. Determining the amount of weed coverage and crop damage is crucial in crop management. In addition, water stress, which has been exacerbated because of Climate Change, has significantly affected crop yield. All this while population growth is increasing the need for improved food security. We report on the results of a project funded by the National Geographic Society on the application of Artificial Intelligence (AI) to Precision Agriculture. We use AI to investigate weed detection and water-stress estimation on a tropical island. These algorithms are built on data collected with an Unmanned Aerial Vehicle (UAV). We used several Machine Learning models including XG-Boost, Support Vector Machine (SVM), Naive Bayes, Convolutional Neural Networks (CNN), Mobile-Net and Random Forest. Data collected for use with these models is being made available to the public.

Keywords: AI · Agriculture · CNN · Water stress · Drone · UAV

1 Introduction

The maintaining of crop yield, when faced with climate change and its impacts, has been mitigated using precision agriculture techniques [1, 4]. Precision agriculture techniques can achieve this through the continuous surveying of an area for key indicators and applying localized solutions [5]. In tropical areas the application of pesticides, herbicides and fertilizers must be done with precision to prevent an excess of chemical run off since rainfall occurs for 6 months in a year. A proposed solution is robotic systems that can replace manual procedures that are precise enough to minimize harsh chemical run off.

AI is being applied to various areas of agriculture for both large and small-scale farming [7, 9, 14]. This project is aimed at small-scale farming since most farms in tropical islands are limited in size [6].

We focused on building machine learning models which can be used by farmers for weed detection in their local environments. The resulting Farming Adaptation and Artificial Intelligence for Resilience (FAAIR) project seeks to build tropical crop data

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sets and AI-powered applications which can assist local small-holder farmers in these areas [16].

The FAAIR project has initially chosen crops grown by small-holder farmers, namely, Capsicum Chinensis which is harvested throughout the year [2, 3]. The team is collaborating with several small-holder farmers across the country for the experimental use of their farms. FAAIR uses Computer Vision to process images and videos. The machine learning models used will perform Image Segmentation on the image data collected to label the pixels as weeds or crops and to detect water stress [15].

In addition, we are developing an AI-powered mobile application that can assess water-stress levels of Brassica Chinensis L., determine the commercial viability of the crops, and determine the weed-crop ratio in a specified area via image segmentation. These functions can be summarized into three main solutions referred to as Water-Stress Detection, Commercial Viability Predictions and Weed Detection. The application is being built with local farmers in mind. Farmers will be able to upload images of Brassica Chinensis L. and view the parts of the crop which are water stressed. Farmers will also be able to upload images of their Capsicum Chinensis plants and receive data and suggestions relating to weed coverage around the crops.

Site specific weed control is a weed management approach where weed control treatments are applied only to targeted weeds, thus reducing the overall volume of treatment used [8]. The success of this method is highly dependent on the accurate detection and localisation of weeds. Weed detection can prove to be quite challenging in scenarios where there are closely related species of weeds and crops in one area. The open-sourced Weed-AI repository allows users to upload or browse and select weed image data from their online repository and access the relevant metadata such as camera specifications, crop stage and background conditions [10, 17]. We recognised the lack of available tropical weed and crop image data and so, as part of this project, have developed our own dataset.

Hassanein *et al.* [18] proposed a new weed detection methodology. They used a low-cost UAV system for detecting the high-density vegetation spots as indication for weed patches in various cropped agricultural fields at flight heights of 20, 40, 80, and 120 m. In contrast, the FAAIR project used flight heights of 5 m and below, accommodating for both mobile and drone imagery. Hassanein et al. also discussed several traditional strategies such as Expósito et al. [20] and Göktoğan et al. [19] where factors such as geometry, elevation and vegetation density were used. However, these approaches were either inapplicable to regular agricultural fields or required time-consuming processes.

Barragán et al. [21] later began using a combination of crop row detection and vegetation indices such as Normalized Difference Vegetation Index (NDVI) to detect weeds with improved accuracy. Hassanein et al.'s [18] approach involved the detection of weed patches as opposed to individual weed plants since the spatial resolution required for weed patches is lower. For this reason, the UAV must be flown higher [13].

The FAAIR project's approach on weed detection differs from Hassanein et al. in this regard. Using a pixel classification approach [11, 12], our goal is to produce highly accurate weed detection results for every individual weed plant.

With increased global food production needs compounded with limited water resources, irrigation scheduling has also grown in importance [22].

Soil moisture measurements and meteorological variables are conventionally used for monitoring crop water stress by estimating the amount of water lost from a plant-soil system [23].

Other methods of water stress detection in crops involve soil water balance calculations and direct or indirect measurement of plant water status. Although these approaches are considered reliable, they are also labour intensive, destructive, and unsuitable for automation [22].

Ramos-Giraldo et al. [24] developed a smart camera system to detect water stress in corn and soybean crops using a low-cost smart camera system. The authors created a computer vision and Machine Learning system with a WiFi-enabled embedded platform. Cameras were mounted at different angles depending on the crop and photos were automatically taken at regular intervals throughout the day. The camera system comprised of different Raspberry Pi devices and sensors which were used for data collection. The authors were able to achieve 74 percent accuracy with a TensorFlow lite model.

Instead of using a camera system, FAAIR's applications are created for use by farmers who already own a smart phone with no further requirements.

Freeman et al. [25] also did some work around water stress detection by assessing the use of cloud-based AI to detect early indicators of such. Using a small, unmanned aircraft system, images were taken at a height of 30 m. The plants were separated into three categories, no, low, and high-water stress conditions. With a total of 150 images of 36 plants, the IBM Watson Visual Recognition tool generated models [25] that were able to detect early indicators of water stress after only 48 h of water deprivation, and some after 24 h of water deprivation. FAAIR uses a similar approach to data collection where three categories of water stressed Bok Choy plants were used in the experimental set up. However, in contrast to Freeman et al., we programmed our own artificial intelligence models using several well-known classical machine learning algorithms rather than using an analytics tool with computer vision capabilities. Note that we tried all the major algorithms that are used for this type of analysis to see which works best. In general, we found XG-Boost performed optimally.

2 Methodology

Small scale vegetable farmers were approached for data collection. The video data of the Capsicum annum mono-cropped field was collected using a DJI Phantom V4 Pro drone. For this proof of concept, we used Brassica Chinensis L and Capsicum annum as shown in Figs. 1 and 2 respectively. It takes images at approximately 3 m off the ground at a speed of 2 m/s. A video is collected, and frames are extracted at intervals of 30 frames. The extracted images are then filtered for duplicates and redundant data. The images are scanned and filtered for any inappropriate objects or reflective surfaces. Image augmentation techniques such as filtering, rotating, flipping, cropping and more are then applied to the images to generate additional data which makes the models more robust. The images are then uploaded into MATLAB where they are labelled by trained individuals.

Since DJI drones are highly dependent on GPS, small farms near residential areas and farms with soil that had a high metal content posed a challenge since the drone

Fig. 1. Crops for Experiments (Bok Choy)

Fig. 2. Crops for Experiments (Peppers).

must be a considerable distance away from all metal, buildings, and tall trees for proper satellite signal strength. We waited until the sun was at an appropriate position to prevent the formation of major shadowing around the crops or on the crops from the shadow of the drone itself. In areas where the land was not level, we carefully adjusted the height of the drone to maintain a 3-m distance from the ground. We were unable to effectively use the NDVI sensor for the small-holder farms visited since the sensor can only be activated when the camera is used at a height of 50 m above ground.

We trained some students to perform labelling of weeds and crops and showed them how to identify and label water-stressed plants.

Collected images were automatically synced to an iPad where they could easily be uploaded to a Shared Drive so all members of the labelling team had access. Images were uploaded as 2D image files to MATLAB's Image Label Application in the Computer Vision Toolbox.

Labels were set up as ROI pixel labels and a unique colour and name was assigned to each label. When the relevant labels were completed, the images were then exported as ground truth labelled PNG files along with their corresponding image labelling session files. These files were then saved in the same order as the order in the folder containing the original images.

One completion of the project the data sets generated will be uploaded to the UCI Machine Learning repository to produce open-source data sets of Brassica Chinensis L and Capsicum annum.

3 Experimental Results

The dataset was split with 70% used for training and 30% used for testing the model. The K-fold cross-validation setup was repeated 3 times per model and the average accuracy of these computed.

We ran several algorithms including Random Forest, Naive Bayes, Support Vector Machine (SVM), UNet, SegNet, DeepLab and XG-Boost. In the Random Forest algorithm, multiple decision trees are built using different sample subsets and the majority vote classification is then used. Naive Bayes is a statistical technique based on Bayes' Theorem in which the most probable class is chosen for a given sample. Support Vector Machine finds the hyperplane that maximizes the separation of the training samples and then uses it to classify unknown samples. UNet, SegNet and DeepLab are all based on fully convolutional neural networks which are decision networks that attempt to emulate the human brain. Finally,

XG-Boost is a popular implementation of the gradient boosted trees algorithm in which many simple, weak models are combined using a gradient boosting framework for improved predictions.

For each of these algorithms we computed the mean IoU metric. IoU (Intersection over Union) is the area of overlap between the predicted and ground truth areas divided by the union of these areas. The mean IoU is calculated by taking the IoU of each class and averaging them. Therefore, perfect prediction results in a score of 100%. The values for the various algorithms are provided in Table 1. Note that these algorithms are most used for this type of analysis which is why we applied each of them.

We can also demonstrate results by using a distinct colour for the detected weeds. The best results were obtained for XG-Boost with an accuracy of 92%. For this algorithm we provide, a sample of an image of crops and weeds in Fig. 3 and the results of weed detection for this image in brown areas in Fig. 4. We believe that we can significantly improve performance by using a larger dataset.

Table 1. Accuracy of Machine Learning Models for Weed detection.

Model	Accuracy
Support Vector Machine	0.48
Random Forest	0.88
Naïve Bayes	0.32
XGBoost	0.92
UNet	0.79
SegNet	0.76
DeepLab	0.71

Fig. 3. Original Image.

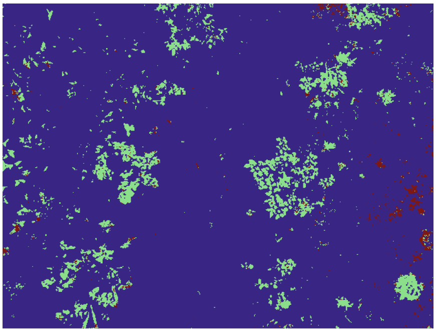

Fig. 4. Brown = Weed, Green = Plant

In addition to detecting weeds, we also compute weed density values and categorized as High, Medium and Low values. These metrics can be used to trigger certain actions to be taken (e.g., apply weedicide when density exceeds some value). Figure 5 contains an example of images and the classified categories. The classifications (high, moderate, and minimal) were determined by using Machine Learning algorithms to estimate the fraction of plant contained in the image and using a threshold to determine the class.

We also did some multi-class classification with each class being a growing stage of the crop. One can estimate crop maturity to compare growth rate on different parts of the farm. For this problem we obtained an accuracy of 90%. This was achieved with a Convolutional Neural Network (CNN) with a dataset of over 600 images. The CNN was trained using tagged images with different crop stages. Figure 6 contains an example of sampled crops at different stages of growth.

Next, we describe our water-stress experiments. For this objective we got access to an experimental Government farm to generate the data required to train the machine learning models. Hence, we needed samples at different levels of water stress. The clay like soil retained water extremely well and was a suitable medium for this experiment. A 50 by 40-m area was separated into nine beds. The beds were at a 15-degree slope to get a variation of samples. The first three rows were over-watered, rows four to six were moderately watered and rows seven to nine were not watered. Drip feed watering was

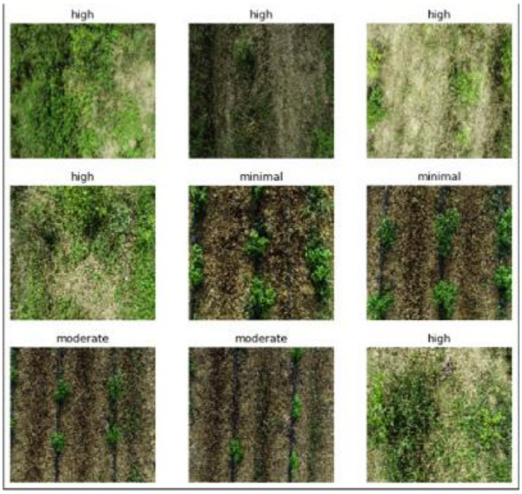

Fig. 5. Weed Density Examples

Fig. 6. Crop Stage Determination

used whereby, using a measuring cylinder, the water at the end of the feed was collected through a feed hole until the desired threshold was met. The plants were planted 30 cm apart. The over-watered plants were provided with at least 76 ml of water, the moderately watered plants were given 50–60 ml of water and the rest were not watered [3].

With this approach we observed the physical changes the plant went through based on watering. The models directly learn the features of over-watering through the labelling of images.

The soil type was ideal since it allowed for the retention of water but the time of year the experiment was conducted introduced limitations in collecting under-watered crop data. The data is labelled in a binary format to facilitate the use of binary classifiers. The images were labelled using MATLAB with semantic segmentation techniques. The resulting accuracy results for the various algorithms are provided in Table 2. XG-Boost again performed the best but this time with an accuracy of 76%. Figure 8 provides a visual example of the result for the XG-Boost case for the original image shown in Fig. 8.

Table 2. Accuracy of models for Water Stress Classification

Model	Accuracy
Support Vector Machine	0.37
Random Forest	0.70
Naive Bayes	0.40
XG-Boost	0.76
U-Net	0.48

Fig. 7. Test image used for water-stress detection.

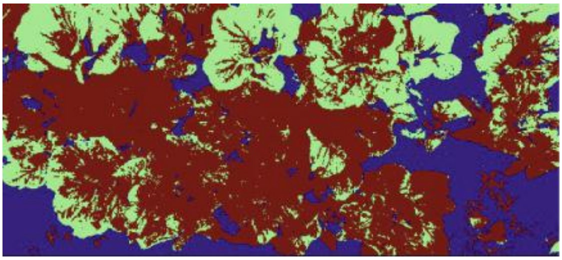

Fig. 8. Detected Water Stress (green).

4 Conclusion

The objective of this project was to illustrate that, even in Small Island Developing States, Data Science techniques can be applied to improve crop yield by early detection of problems such as weed growth and water stress. Our environment is unique since farms are small, we must deal with climate change and our crops are not typical. This requires an understanding of what advanced technologies are suitable and cost effective for our environment. We plan to extend our work to other crops and to include objectives such as pest infestations. We are also developing web and mobile applications for use by farmers. Since farmers cannot afford drones, we are working with the Government to help them provide this service to farmers at a minimal fee. Our results illustrate that, in general, the XG-Boost algorithm works best because of its robust performance and its avoidance to over-fitting.

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