Real-Time Root Monitoring of Hydroponic Crop Plants: Proof of Concept for a New Image Analysis System

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Abstract. This paper presents a new autonomous system that allows for the capturing and analysis of root systems of hydroponic crop plants without removing them from the growing environment. Disturbing the delicate roots of these plants can cause stress and increase the chance of mechanically spreading diseases. The first task carried out was the taking of simple measurements of root thickness and assess the feasibility of this concept. The second task involved inflicting two of four plants with an arbitrarily chosen plant sickness, in this case aluminum toxicity, and autonomously capture pictures of each plant over the course of approximately three weeks. Then, image analysis and machine learning techniques were applied to identify sick plants from healthy plants.

1 Introduction

The need for food across the globe is in more demand than ever before, and traditional agriculture methods are straining to sustain this need. In 2012, United States Department of Agriculture (USDA) found that general agriculture development accounted for over 40% of land use in America [1]. Of this, approximately 42% was used for food crops, with the remaining land used for pasture, grazing, and other needs. A 2011 Report from the United Nations Food and Agriculture Organization explains that worldwide agriculture land use for food crops range by geographic location, from under 5% in places like Northern Africa, to 50% in South Asia [2]. Many areas, in both developed and under-developed countries, are putting stress on their water resources due to an increase in agriculture activities. Over the last 40 years, irrigated farmland has increased substantially, and the amount of water consumption has nearly doubled as well. General agriculture activities account for approximately 70% of water use worldwide [3]. On top of that, approximately 1.8 to 2.9 billion people live in areas with severe water scarcity 4 to 6 months out of the year, and half a billion people live in areas

V.H. Duy et al. (eds.), *AETA 2017 - Recent Advances in Electrical Engineering and Related Sciences: Theory and Application*, Lecture Notes in Electrical Engineering 465,
https://doi.org/10.1007/978-3-319-69814-4_31

with severe water scarcity year round [4]. Numerous statistics can be found that correlate with these figures above. What do these figures say? Worldwide population is always growing, increasing the demand for food, which increases the land required for agriculture activities, and this increase in agriculture activities increases the overall water usage.

Hydroponic farming offers a unique solution to the complicated problem of efficiently providing a food source on a large scale with reduced usage of our natural resources. A study conducted by Arizona State University concluded that lettuce grown in a hydroponic farm offers 11 times higher yield per m^2 and uses 13 times less water than conventional methods [5]. Another benefit of hydroponic farming is the capability to grow produce throughout the entire year [6,8]. Another study conducted by the University of Nevada with strawberries, found that the strawberries grown in soil used 30% more water than their hydroponically grown counterparts [7]. Had they been grown in a field rather than buckets water usage would have been even more. The hydroponic strawberry plants in this study had a 17% higher yield than those plants grown in soil, by individual strawberry count. The survival rate for hydroponic strawberry plants was also almost twice that of those grown in soil. These are just two of many studies that provide clear evidence of the benefits of hydroponic farming and how it relates to reduced water consumption, greater yeilds, and less space required. The hydroponic farming industry is growing rapidly, and estimated to be worth over $550M, and growing [8]. This method can solve major world problems but it does not come without problems of its own.

One of those problems lies in root inspections. The current method for viewing hydroponic plant roots require an individual to remove the plants one at a time for visual inspection and assessment. This exposes the roots to the outside environment and creates an opening for undesired contaminants to enter the system. The plant is easily stressed, which can cause stunted growth and increased susceptibility to further complications. Maintaining a hydroponic system requires an immense amount of time and the precise control of several factors, and outside of nutrient delivery systems there is currently there is no autonomous system capable of such task. There are many cases where the roots of a plant would need to be viewed in both commercial and research applications. Some diseases spread so rapidly they can affect an entire crop, such as the common Pythium pathogen [9]. Early detection of a contagion can prevent an entire crop from harm and alleviate some of the additions and attention a farmer would need to place on their system. Also, researchers will have a new tool to study hydroponic plant roots in a completely new way. Our primary goal is to develop an autonomous system capable of root growth monitoring and problem identification. To these ends we ultimately aim to increase the productivity of hydroponic crop farms, and provide a new platform for advanced agriculture research.

2 System Design

The only notable work discovered during a literature review measured the growth of leaf crops with a system designed to take overhead pictures of the crops at predefined intervals, and then use various image analysis techniques to attain accurate measurements [10]. That system is designed more for research than commercial applications, and does not measure or analyze root health. Using some of the ideas from the above research, the new system detailed below solely focuses on the roots.

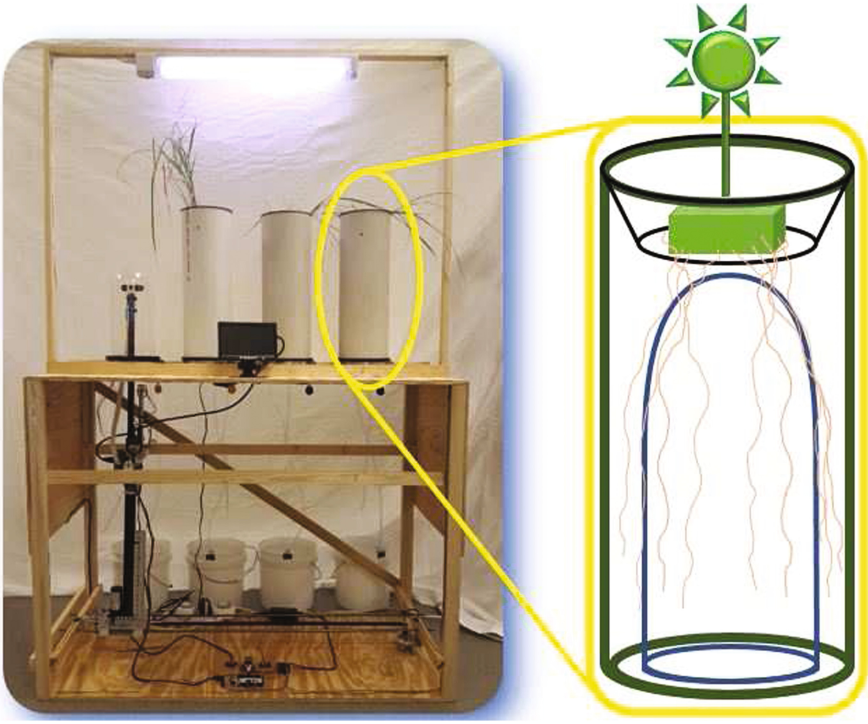

Fig. 1. System overview

Initially, a simple setup consisting of only one grow chamber was constructed to test the quality of images captured of roots submerged in water. This was the root measurement phase of the project and proved fruitful, as will be detailed below. Figure 1 shows the second prototype built capable of growing four plants, and is ready for immediate use, complete with a wireless keyboard and mouse as well as a 7” HDMI monitor. An intuitive manual control program allows any user to harness the power of the complete setup with only a few keypresses. A linear actuator traverses left and right, while a pan and tilt camera unit moves up and down inside the sealed glass dome, and takes pictures of the roots growing between the glass dome and outer PVC tubing.

2.1 Setup and Operation

Figures 2 and 3 provide detailed views of the system and components. Figure 2 is a view from the backside, where the air pump and solution tubing can be seen, as well as a close up of the OV 5647 5MP infrared camera, the sealed glass dome, and the Raspberry Pi 3, a quad-core single board computer (SBC).

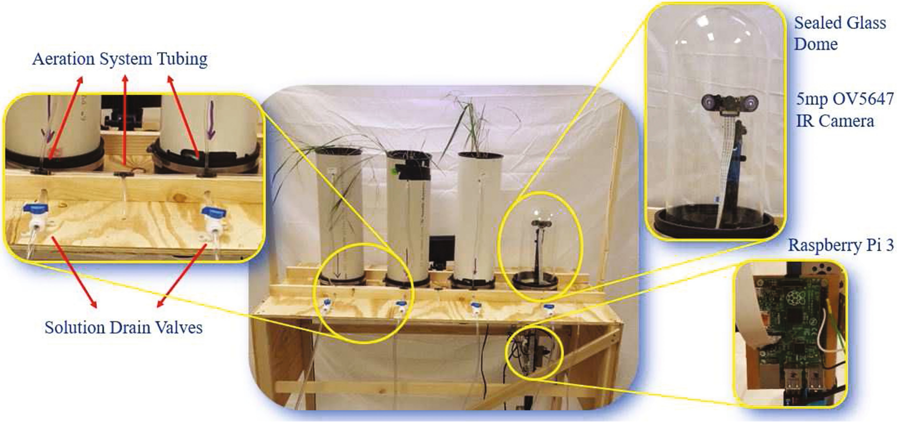

Fig. 2. System detailed view (A)

Figure 3 is a more detailed diagram of the setup. At the top left is the RFID reader, which rests on an extended support connected to the top of the linear actuator housing and isn't visible in the main picture. A geared 12v dc motor drives a 5 mm geared-tooth pully system that connects to the horizontal movement sled where the linear actuator rests upon. On either side of the sled is an extension that contacts a limit switch on either side of the movement bed to bound the left and right traversal limits. The timers control the light for a 13 h on, 11 h off light cycle, as well as the airpump to run on and off every 30 min. Central to controlling all electromechanical components is an Atmel ATmega 2560 based microcontroller (MCU) development board, enlarged at the bottom right. The linear actuator and pully motor connect to a 2 amp dual H-bridge L298 motor driver, which passes signals from the MCU to the motors. The power distribution board passes 12v to the L298 motor driver, the air pump, and the MCU, and 5v to the SBC and RFID reader.

This system operated for one month and captured pictures either automatically or manually. For manual operation, the user would first move the linear actuator into position horizontally, then extend the actuator vertically into position where he or she can then pan the camera left or right as well as move the sled in increments as small as 5 mm forward or reverse to adjust the focus. An RFID tag is directly below each plant which is used to properly identify and label the pictures as they are captured. Automatic mode is just like manual mode, only

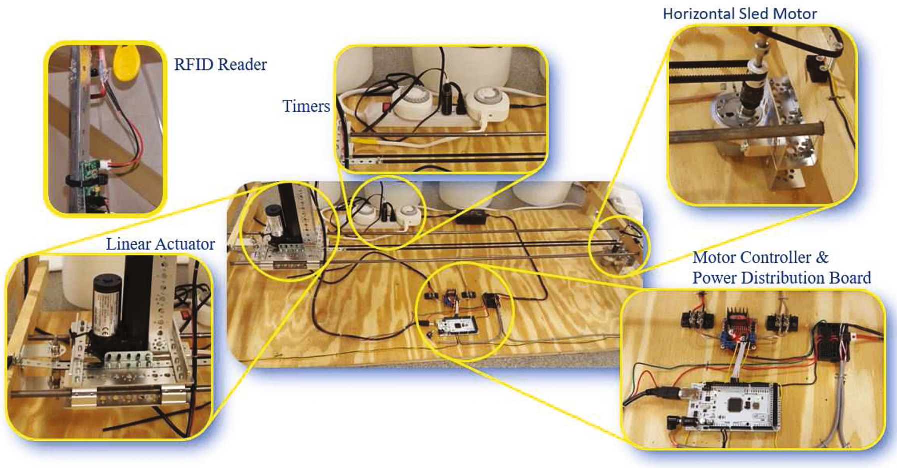

Fig. 3. System detailed view (B)

it works off a timer stops at the plants by an RFID tag read-interrupt, where it navigates to pre-determined locations and takes a predetermined number of pictures.

2.2 Root Measurement

In this phase, the primary goal was to attain quality pictures and accurate measurements of roots. A root system was closely monitored for almost one month and pictures were captured every 4 h. After collecting the pictures, the root system was removed for a scale picture next to a quarter and tape measure. Root thickness measurements of two arbitrarily chosen points were manually made, to provide a comparison for the measurements made by simple image analysis. The image processing was carried out using Python and OpenCV. The same section of roots that were manually measured were first highlighted a solid red or green (Fig. 4), then color-matching, bounding boxes, and dimensional measurements were used to determine the thickness of the root section.

2.3 Problem Identification

In this phase, the primary goal was to distinguish between a healthy plant and a sick plant. Aluminum Toxicity was artificially induced in two of the four plants by the Agriculture Department. After collecting 1000 images from 16 individual roots from four different plants, they were divided into two groups, a training set and a validation set. The training set consisted of 1000 images, and was used to build a support vector machine with a linear kernel. The model is able to classify an image into one of two groups, either a healthy root, or a sick root. The linear kernel was chosen over other kernels such as the radial based function

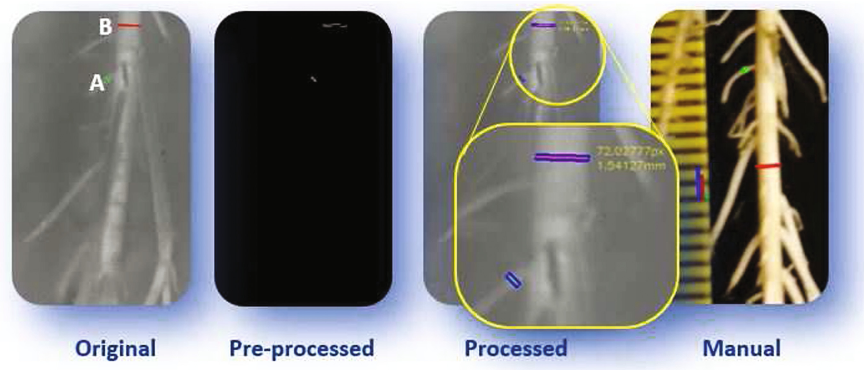

Fig. 4. Root measurement

because it is less complex and depending on the data size or number of features the mapping to non-linear space may be unnecessary [11]. The polynomial kernel was not implemented because of two reasons, first, the linear kernel worked, and second, there are more parameters to fine tune and over fitting could results. Also, the goal was to use the simplest model that worked, and in this case, that was with the linear kernel.

Figure 5 depicts a process diagram for binary classification. First, a local binary pattern is calculated for each gray-scale image. The arbitrarily chosen sickness, aluminum toxicity, affects the root morphology and the root system of a sick plant has a different contour, or texture, when compared to that of a healthy plant. Using the rotation-invariant principle outlined in [12], the orientation of the roots can vary like they would in a real-world setting and the accuracy will not be affected. A uniform density distribution histogram is then calculated and passed along with its corresponding label to the fit function of the linear support vector classifier. After the entire training set is processed the model is complete

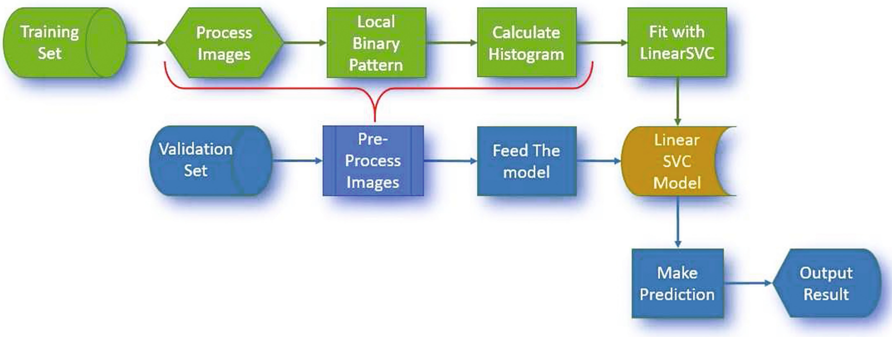

Fig. 5. Binary classification

and ready for validation. The validation set images are processed in the same way and fed to the predict function of the model without the corresponding label. The model makes a prediction on 200 images, and the final accuracy is calculated based on the resulting number of matches.

3 Results

The results for both phases exceeded expectations. The camera is able to resolve sub-millimeter root features and the supervised learning approach achieved 100% identification accuracy. Below are the details.

3.1 Root Measurements

Figure 6(A) shows the root system at the beginning of the study. (B) is a high-resolution close up where each red circle points out root features of approximately 1/8 to 1/2 mm in size. (C) is the root system after 22 days of growth, and in

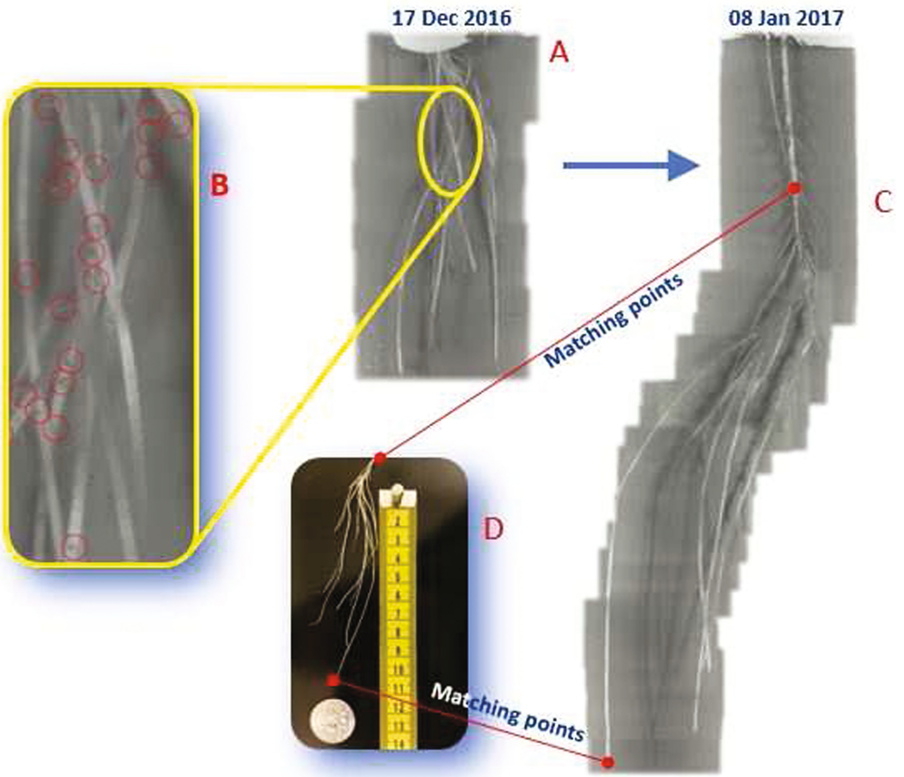

Fig. 6. Root measurement results

(D) a visual scale shows how small the root system actually is. Figure 7 is the output from the program written to process and measure root thickness. An arbitrarily chosen point on the main root stem was measured by hand to be 1.48 mm in diameter. The image analysis measured it at 1.54, providing a marginal difference of approximately 4%. Accounting for errors in hand measurements and the accuracy rating of the program, this is well within acceptance.

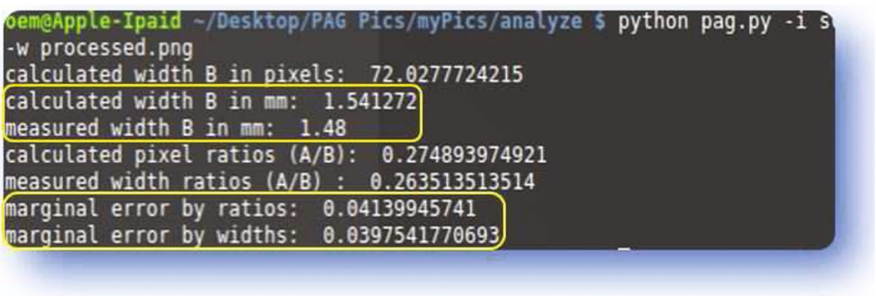

Fig. 7. Root measurement results

3.2 Problem Identification

On the left side of Fig. 8 is the output of three trial runs of the root identification program, and on the right is a sample output of a properly predicted group A (top) and group B (bottom) root. The r and p values that change from the various trial runs refer to the *radius* and *number of points* property of the rotation

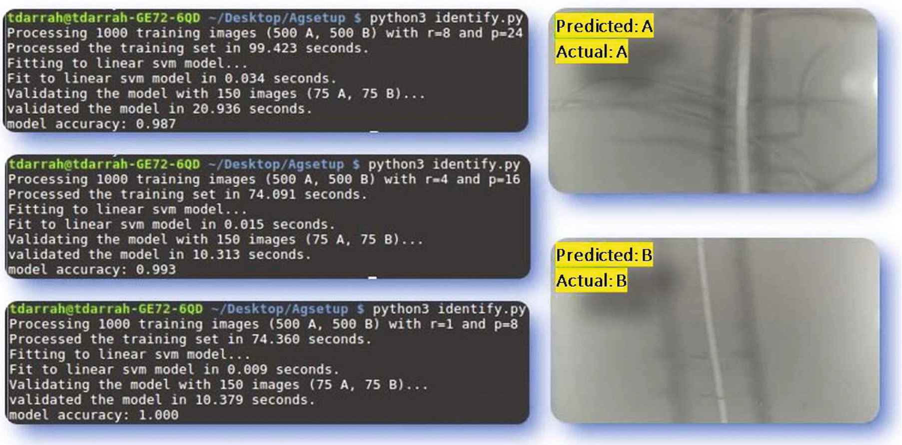

Fig. 8. Problem identification results

invariant local binary pattern algorithm. As these change the patterns of uniformity also change. Modifying the histogram properties also affected accuracy. In the last trial, 100% prediction accuracy was obtained. The human eye can rather quickly distinguish the difference between these two roots, however here it was done at the rate of 15 images a second, and becomes a very appealing platform for the commercial industry to incorporate into their systems.

A random selection of histograms is shown in Fig. 9. The top comparison, Fig. 9(a), is of a group A training histogram and group A validation histogram. The middle comparison, Fig. 9(b), depicts a group A histogram and a group

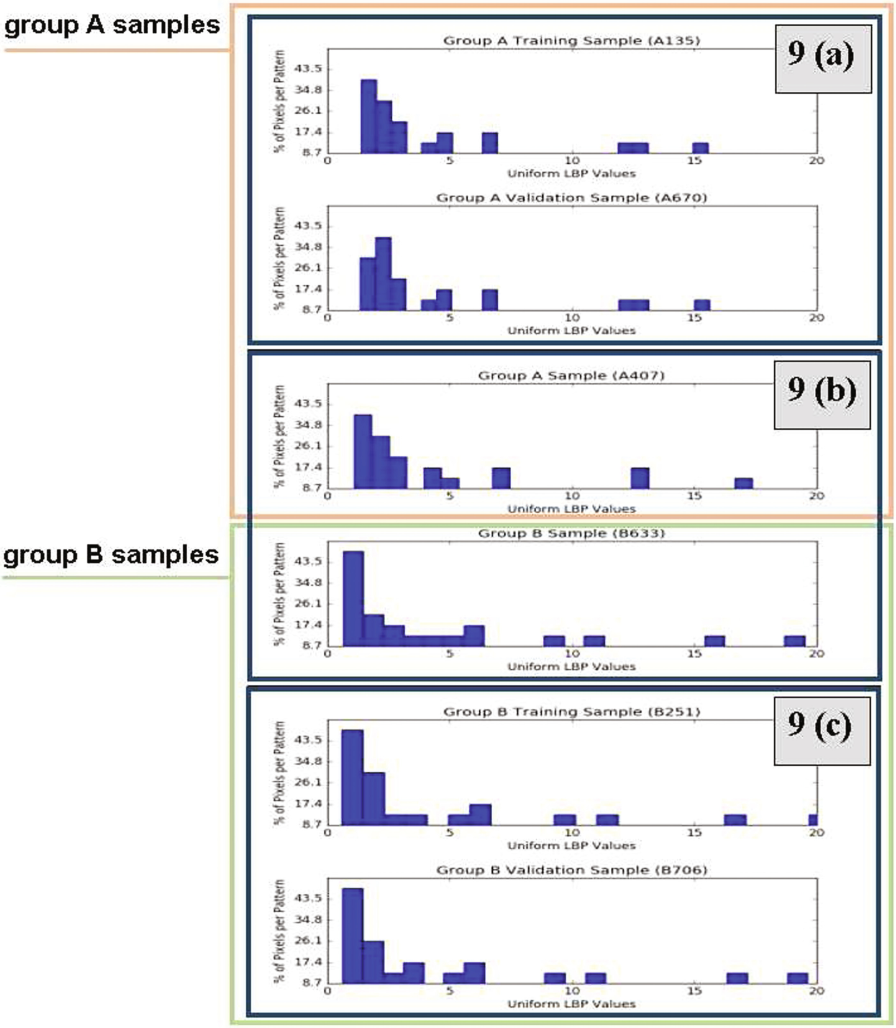

Fig. 9. Problem identification histograms

B histogram together. The bottom comparison, Fig. 9(c), compares a group B training histogram with a group B validation histogram. Also in Fig. 9, the three group A samples are outlined in orange, and the three group B histogram samples are outlined in green. This is to bring attention to the similarities within each group, and makes the differences between the groups easier to see. The x-axis of the histograms represents the scaled distrobution of local binary patterns, and the y-axis represents the percentage of pixels per pattern.

4 Further Work

The technique presented here only carries out simple classification of an image into one of two pre-exesting groups. A more robust machine learning approach should be implemented to classify more than one plant ailment. The system should be implemented on a larger scale to allow for training sets to be developed for multiple root problems, which can be used on mobile or other autonomous systems. Another area to explore is the effectiveness of unsupervised learning on an unknown set of images, which would have many practical applications. Also, an improved horizontal carriage system should be used as well, since during travel the vertical height of the linear actuator fluctuates by approximately 5 mm. Another improvement to the system would include a high precision linear actuator with a motor encoder, which would increase the image processing information by providing reliable position data of the camera.

5 Conclusion

The system presented has numerous commercial and research applications that should be explored. The feasibility to capture viable root images *in situ* is readily apparent. This type of setup has the potential to substantially increase the quality of research in the areas of agriculture, agriculture engineering, bioengineering, genomics, and more. The system was buiilt with cheap, readily available materials and components, with a total cost less than $300usd. No proprietary software was used either. This will allow for easy replication in any lab so that more researchers can begin to set up new experiments themselves. As detailed above many improvements can be made, however a milestone has been achieved in the advancement of engineering techniques used in cross-disciplinary research areas.

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