Development of an Imaging Tool for Commercial Mushroom Yield and Quality Estimation

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ABSTRACT

Cultivation and production of mushrooms has increased during the previous decade. The production increase is due to the development of farms combined with the rise in consumer’s general understanding of the medicinal and dietary benefits of mushrooms consumption. Improvements in mycology and agricultural technology have allowed farmers to increase their mushroom production. Farmers have been able to create microclimates with specific growing conditions that encourage mushroom growth for large-scale harvesting. Although technological advancements have increased production volume, taking measurements of the size and quality of mushrooms is an arduous process that requires a lot of labor hours to complete. Different methods have been used and proposed to assess the size and quality of mushrooms. Computer based image processing is a promising method to tackle this task by implementing image processing and analysis techniques. Computer aided analytical tool can assist farmers by counting, taking measurements, determining the growth rate of mushrooms and calculating the crop yield. Having this information would allow farmers to adjust microclimate conditions and coordinate harvesting schedules to pick mushrooms when quality is at their peak. This thesis takes a different approach to other projects by collecting image data from a large-scale commercial mushroom farm. The main goal of this paper is to develop a system that can support mushroom farmers decision to become more efficient and to evaluate the feasibility of implementing computer vison assistance in an actual mushroom farm.

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CHAPTER 1: INTRODUCTION

Mushroom production and harvesting have increased throughout the past decade. According to a report released by the National Agriculture Statistics Service (NASS) and the United States Department of Agriculture (USDA) in 2018, the United States produced 917 million pounds of edible mushrooms worth a record high of $1.27 billion [1]. A more recent report released in 2020 shows signs of tougher growing conditions for many growers. Production fell to 846 million pounds and earnings dropped by 8% to a total of $1.13 billion when to compared to the year before [1], [2]. Despite the slight dip in sales and volume, mushroom production has steadily increased and is expected to continue over the next few years. Mushrooms are an excellent source of protein, fibers, unsaturated fatty acids, minerals and essential vitamins making them a nutritious food ingredient [3]. Consumer interest in both the medicinal and dietary benefits of edible mushrooms has made the white button mushrooms into a nutritional staple inside millions of American households. Cultivating and producing high quality edible mushrooms is a meticulous process that requires technological tools and special farming expertise. Large scale producers invest lots of manpower to ensure a good harvest, yet sometimes they are unaware of production yields until the mushrooms have been harvested. This problem often leaves growers guessing and experimenting with the set environmental conditions instead of adjusting as the growing cycle is taking place.

Large-scale facilities capable of harvesting edible mushrooms for commercial purposes, have steadily increased the volume of mushrooms that they are able to produce given the resources, manpower, and space available to them. Evidence of this can be noted in the 2018 NASS and USDA report. Although production of mushroom and total sales continued to rise, the number of individual farmers kept decreasing over time [1]. Meaning, that the farms that are currently operating are becoming bigger exporters of mushrooms, capable of keeping up with current demand while remaining a profitable business. A lot of the success for growing mushrooms is due in part to, the implementation of processes and technologies such as Internet of Things (IoT) devices that have increased the efficiency of crop management and yield production. This technology has allowed farmers to control, monitor, and record data of the microclimates inside of their growing rooms [4]. Through experimentation, growers acquired the knowledge necessary to control the environment in their facilities that results in large yields. However, the current methodology still leaves plenty of room for human error and little chance for redirection and error correction resulting in losses to the mushroom farm.

Mushrooms are fruiting body of fungi that are sensitive to environmental conditions (temperature, light, moisture, and CO_2/O_2 concentration) and require very specific growing conditions to thrive. Growers are vigilant to avoid mushroom overcrowding and constantly battle the spread of contamination on the growing beds. Mushroom crowding builds up pressure which in turn causes malformed mushrooms caps and limited air circulation that leads to browning. On the other hand, contamination can lead to deterioration of the quality of the overall product or the inhibition of mushroom growth [5]. Growers must create and maintain the perfect environment to ensure that they are able to provide quality edible mushrooms. Building a tool that can measure and track mushroom growth during the mushroom growth cycle, can give farmers useful information about how a specific crop is performing and when human intervention is necessary. A tool such as this can assist farm operators by identifying if a crop is underperforming or taking note of what conditions lead to high yields.

Presently, researchers are working on projects that implement computer vision software to support crop management decisions. Recent work in mushrooms agriculture research investigates the implementation of image processing and analysis. Scientists measure mushroom size, identify color changes, and use more complex algorithms to estimate the best harvest times such as the experiment conducted in Taiwan [4]. Other researchers in the Netherlands have conducted experiments using image processing that led to the discovery of mushrooms that are more resistant to harsh environments [6]. All combined, this research serves as the forefront for the development of innovative mushroom tracking methods by using different computer vision algorithms. While this information is useful, few projects try to identify critical information that can be used to make corrections on the spot, while the growing process is taking place inside the growing rooms. Testing has mostly taken place in incubators or laboratory conditions with the goal to address issues with mushrooms quality before or after harvesting. In mushroom farms conditions are not always ideal, there are many moving parts and people that can introduce changes to the environment. The volume of data extracted is also larger than that are collected in a lab. For growers, it is more important to understand what is happening in their growing rooms, instead of focusing on individual mushroom growth, so large volumes of data can be beneficial to establish benchmarks and assess performance for individual growing rooms based on data from the entire facility.

This thesis project was conducted in collaboration with Monterey Mushrooms, a mushroom farm located in Madisonville, Texas. This farm harvests mushrooms for large-scale commercialization and their products can be found on the shelves of popular grocery stores such as HEB, Walmart, and Targets nationwide. According to their website, Monterey Mushrooms employs around 4,000 employees in all of their 8 farm locations. Together, all their farms produce more than 200 million pounds of edible mushrooms every year across the United States. Harvesting mushrooms is a rigorous process that requires a fair amount of physical labor and equipment. Thousands of mushroom pickers have the daily task of collecting mushrooms from the growing beds. After a quick inspection, pickers place the mushrooms into color coded containers. Each color represents a specific size-range and quality. For pickers better quality mushrooms result in higher pay. Facility managers investigate different areas to optimize the use of their resources to harvest mushrooms at their peak quality. Exemplary stock allows Monterey Mushrooms to maximize their revenue and increase profit margins. Technology can help managers adjust staff schedules to get to mushrooms at their optimal harvest times, and they acknowledge the competitive edge technology applications can provide.

The primary aim of this study was to develop a computer vision system that can be utilized in a commercial farm setting, to scan an entire bed of mushroom over weeks for monitoring of mushroom growth. The proposed framework includes a camera system suited to the mushroom growing room setting and an image processing pipeline for mushroom detection and quantification. This study presents a feasibility analysis for development, installation, and implementation of the imaging framework. In addition, an image processing and analysis pipeline is proposed for the detection of mushrooms from time-lapse images taken over a period of about 20 days. Finally, quantitative measurements of mushroom size and growth are performed and analyzed to determine the feasibility of this measuring system to be beneficial in a commercial farm setting. This technology will help farm administrators better manage their staff to harvest top quality mushrooms.

CHAPTER 2: BACKGROUND RESEARCH

This chapter describes the state-of-art mushroom harvesting methods and discusses current processes that are being implemented in the field to address automation of monitoring mushroom growth for harvesting. Finally, gaps in current literature that form the premise for this study are presented.

2.1 Mushroom Farming

The focus of this thesis project is on white button mushrooms, also referred to as common edible mushrooms. The goal is to create a computer vision software that can give growers meaningful data on how their white button mushroom crop is performing. The cultivation process for white button mushrooms can vary depending on location and cultivator needs. However, the methods followed by different farms tend to be similar. One key concern for Monterey Mushrooms and other farms alike is sanitation and hygiene, because a clean environment is essential for mushroom growth. Hand washing stations line the entrance to the farm and a mat powdered with soap lays on the floor to decontaminate the bottom part of shoes. Upon entry employees and guests are given hair nets, gloves, and additional personal protective equipment (PPE) before entering the farming facilities. Contamination of any kind can prevent mushroom development if it infects the substrate or show itself in other forms such a discoloration or a complete change in color of the mushroom cap [5]. To limit the amount of losses associated with contamination, farmers go through great lengths to maintain cleanliness.

The most commonly methods used follows seven processing steps to cultivate and distribute mushrooms include: (i) substrates such as wheat straw, har, or rice straw are wetted in water thoroughly, followed by mixing with cow or horse manure and poultry litter until the carbon nitrogen ration is about 25:1; (ii) the compost pile are mechanically turned and mixed two to three times daily for up to 40 days while purging it with compressed air for better aeration to fasten the composting process; (iii) the composted substrates are transferred to a pasteurization chamber and subjected to steam in two phases, phase I (above 150°F), Phase II (115-140°F). These two-phase pasteurization process takes u[to six days and done to eliminate undesirable insect pests, microbes, and pathogens; (iv) pasteurized composed substrate will be mixed with fungal mycelium (spawn) in the ratio of 15 kg per ton of pasteurized substrate and dispensed on wooden box or long aluminum racks and stored in a growth chamber maintained at a temperature between 14℃ to 18℃ and the carbon dioxide (CO_2) must be kept at a level below 1000 ppm and relative humidity ranging anywhere between 80% to 85% for about two weeks, (v) one inch of pasteurized composted substrate after neutralization with lime and gypsum is spread on the mushroom bed (casing layer) and watered regularly for initiation of primordial pins, (vi) primordial pins turning in to full grown mushroom fruiting body after 25 to 30 days in the growth chamber and (vii) mushrooms are manually picked a different intervals [7], [8]. In each room, during the first harvest break Monterey Mushrooms harvests anywhere between 22,000 to 24,000 lbs.; and about 16,000 to 18,000 lbs. during the second break; and 8,00 to 12,000 lbs. during the third and final break. Figure 1 shows a diagram of the process described. As stated previously, different growers deviate from the method mentioned in this paragraph, but the overall process is still similar.

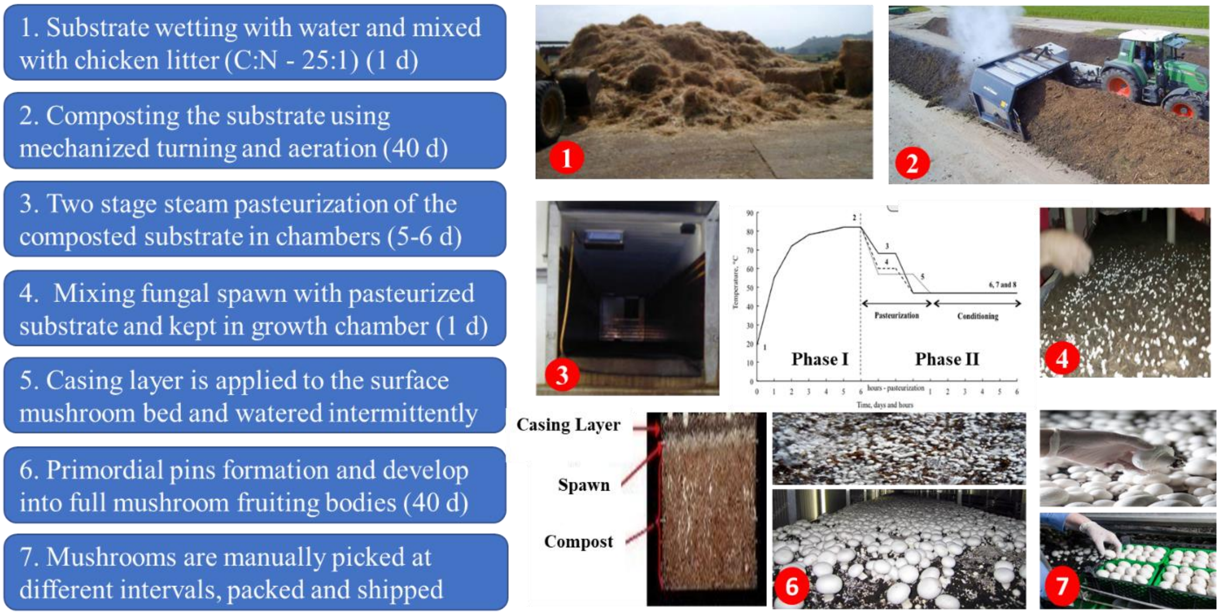

Figure 1: Commercial cultivation steps to produce button mushrooms

2.2 Related Work

It is important to understand how quality is measured and what are the causes of deteriorating health in white button mushrooms. Information about what affects growth and quality can be used to interpret the details that are picked up by photographing mushrooms. Mushrooms are delicate and there are many factors that can affect their appearance, notably, after they have been picked. Mushroom color changes have many causes; such as internal chemical factors, physical damage, abrupt temperature changes, high CO_2 concentration, or relative humidity fluctuations that can all lead to mushroom browning [9]. Mushroom color is the first quality indicator that a customer at a grocery store will notice so it is important for growers to be mindful of appearance. Color can be detected in images to measure and assess overall health.

White button mushroom quality is determined by other features besides color such as texture, cleanliness, and flavor, however, color and appearance are critical. In a study conducted by Wageningen University in The Netherlands, researchers developed a device that can bruise harvested mushrooms to find bruise resistant strains that can be used to reduce discoloration in future strains [6]. Their methods consisted of mushrooms using their special device, photographing them, and then analyzing images by using the Hunter L*a*b color map. Healthy areas of the mushroom were compared to the bruised flesh using the whiteness index (WI) to measure the change in color. This project shows the functionality that can come from simple digital imaging. Useful information can be obtained from using lightness and color scales. Color and lightness make it possible to identify mushrooms, separate them from the background, and asses their health.

Agricultural technology has been expanded due to the need to optimize production to meet high demand. Recent research reviews the benefits of computer vision in agriculture and data analysis to assess harvest quality. Such is the need for assisted quality evaluation that there are studies that explore different data capture methods. Researchers from Ireland set out to determine the best imaging equipment to predict Hunter L-value measurements. Hunter L-value measurements is a common method for quality evaluation in agriculture. This project set out to compare the performance of red-green-blue (RGB) digital images and hyperspectral imaging (HSI). Eight mushrooms were photographed using a Cannon PowerShot A560 for RGB images and a hyperspectral imaging system for HSI images. Images were collected at different times on day two, day four and day eight after harvesting. Their results showed that HSI is better at producing Hunter L-values for prediction maps of the photographed mushrooms [10]. However, the cost of a hyperspectral imaging system is much higher and HSI imaging also takes longer to capture an image when compared to a regular RGB image. At the moment there is also a lot more work needed with HSI to determine which wavelengths are the most informative when photographing mushrooms. Ultimately, it is more affordable and practical to use normal RGB imaging for quality grading. In this study conducted in collaboration with Monterey Mushrooms, the experimental setting is an operational mushroom farm, so care was taken to select equipment that is quick and easy to implement to avoid interruptions as much as possible.

LiDAR in agriculture is another method of data collection that has been proposed by researchers. LiDAR data is spatial information that can be used to take measurements and determine relative location of objects. In mushroom detection, LiDAR use has allowed researchers to scan large section of forests for fungal biodiversity. Edible and poisonous mushroom maps have been developed using this method [11]. Smaller applications of LiDAR do exist in agriculture, because farmers have seen the benefits of spatial data. For example, farmers discovered that crop plants begin to compete for resources when there is high crop density, therefore, crop density must be reduced [12]. To combat this issue, researchers developed a LiDAR based measurement system attached to a cart to make sure that there is enough separation between corn plants. In the case of mushroom farming, equipment size can be an issue because mushrooms grow on aluminum or wooden trays. The trays are stacked on top of one another creating a separation that is only a couple of inches apart making the use of large equipment impractical. The field setting mandated a small and compact framework, since normal farm operations were in place during the execution of this study. LIDAR can provide spatial information; however, the size and lack of color data limit the information that can be obtained. Instead, RGB images can be used because they include color data and spatial information can be derived by using markers of known dimensions to identify location and size.

Image processing and color analysis have been applied in agricultural research, further exposing the potential that RGB imaging has as a more appropriate imaging method in this field. The potential of digital images is being tested to replace older and much slower technology like soil and plant development (SPAD) meters that get chlorophyll estimations of soybean leaves [13]. Although this paper does not relate to mushroom cultivation it helps emphasize the way in which RGB images can be paired with machine learning. In this project, researchers used the dark green color index (DGCI) to estimate total chlorophyll concentration in leaves. The data was then used to test different machine learning models by using the DGCI as inputs and comparing the outputs to the chlorophyll levels measures using the SPAD meter. The models tested were random forest, support vector machine (SVM), multiple linear regression, polynomial regression, and single linear regression. The best performing model was determined using the following metrics: the highest coefficient of determination (R^2), and the lowest root mean squared error (SMSE). Their results concluded that the SVM model was the one that produced the best results. This methodology can also be applied to mushrooms by measuring the different colors detected. More complex image processing can be used to extract structural features and these models can be used to make predictions and estimations regarding mushroom development.

RGB digital images allow for feature extraction that can be used to detect and classify objects. Computer vision applications that use feature extraction can help mushroom farm managers or pickers make important decisions. These applications are important when information is limited or not available at all. This is especially true in the wild where toxic and edible mushrooms can be undistinguishable from one another. A project in the Czech Republic claims that about 1500 species of mushrooms grow in their area, while mushroom pickers are only able to memorize and recognize a maximum of 300 species [14]. By using image segmentation, researchers were able to extract parameters such as stem width and height, cap shape and color, and other details. The data collected serves as an input to a SVM classifier, which can tell the name of the species photographed. This type of application can also be used in other settings. For example, cap measurements can be calculated using feature extraction to help mushroom farmers in large-scale factories make scheduling decisions around harvest times.

More complex algorithms can be used to extract information from RGB images. In Taiwan, a mushroom growth measurement system that uses the You Only Look Once (YOLO) algorithm has been tested in laboratory conditions [4]. YOLOv3 is a convolutional neural network (CNN) used for object recognition in images [15]. This algorithm can be trained to detect objects of interest. The method utilized in the Taiwan study has also been tested against other detection algorithms such as the Circular Hough Transform (CHT) to compare performance [16]. The authors of the Taiwanese study used the YOLOv3 algorithm to detect mushroom caps. Once the mushroom caps were detected the image was processed using color quantization to remove the background, in this case the soil, leaving behind the round mushroom caps. After additional image processing the researchers were able to calculate the centers of the mushrooms detected and take measurements for individual mushrooms. The system that they created could identify mushrooms and predict the hour in which the mushroom can be harvested by sending alerts.

2.3 Current Needs

RGB imaging combined with the right image processing techniques and algorithms, can develop technology that assists commercial mushroom farmers make informed decisions. A system like the one from Taiwan sets the premise for the work in this thesis project. However, ideal laboratory conditions are not found in commercial farms where growing conditions can vary greatly from day to day. The issue with the Taiwanese system is that receiving alerts for individual mushrooms becomes overwhelming when applied to a large-scale operation. There is also the fact that currently, their method predicts harvest times based on the size of mushrooms and there is no mention of how clustering often changes the time when mushrooms must be harvested – mushroom pickers are trained extensively for this. Commercial mushroom farms have such a high yield of mushrooms that space quickly becomes an issue. If the density of mushrooms grown is high, then the pressure of neighboring mushrooms can degrade the quality of those around it. Employees must go and pick mushrooms earlier than others to allow room for more growth. Computer vison projects tend to be very specific to the problem they are addressing, so previous work might not always be as effective in detecting mushrooms in commercial farms. Laboratory settings do not have the capacity to produce such a high volume of mushrooms. Labs also fail to address the challenges of hygiene enough because they do not deal with a constant influx of people walking in and out. Therefore, the system implemented must count mushrooms to locate and treat entire areas where contamination might be present, and space is limited while being versatile enough to withstand the introduction of new obstacles and high levels of humidity.

This project addresses the gaps present in previous work by capturing data in an operational farm to understand the challenges within that environment. A white button mushroom detection algorithm will be designed and implemented on the images captured. The processing and analysis of the images will be used to extract measurements and mushroom count data that can be used to derive further understanding of different stages of mushroom growth in growing chambers. The information will be assessed in collaboration with Monterey Mushroom staff to assess the impact of introducing a large-scale computer vision system into a commercial farming setting in the future.

CHAPTER 3: EXPERIMENTAL SETTING

This chapter discusses the experimental setting implemented at the Monterey Mushrooms farm for data collection. First, the criteria and specifications for the imaging equipment are discussed, followed by a description of equipment placement for image data capture with minimal to no disruption to regular farm operations. Finally, criteria for scheduling imaging equipment set-up and time-period for data acquisition are presented.

3.1 Imaging Equipment

Figure 2: Aluminum trays used at Monterey Mushrooms for mushroom farming.

Figure 3: Wooden trays used at Monterey Mushrooms for mushroom farming

Monterey Mushrooms uses wooden and aluminum trays that are stacked on top of each other to form columns as shown in Figure 2 and Figure 3 to hold the spawn inoculated substrates for producing mushrooms. The wooden trays only have a couple of inches of separation between the bed where the mushrooms grow to the bottom of the tray above, whereas the separation in the aluminum trays is slightly greater. Since the vertical distances between the trays are very small, a compact sized camera was needed so that it could capture images from the tray beds. This project was conducted in a growing room with wooden trays were in use, therefore, the camera size had to be compact to facilitate placement in between the two tray racks. The most practical option was to collect data using a digital camera. Images were captured using the Brinno TLC200 PRO. This compact camera (2.52 in x 2.05 in x 4.21in) comes with a waterproof case that makes it perfect for the high humidity found inside Monterey Mushrooms farms. The camera kit also comes with a clamp that can be used to attach the Brinno to other structures that allow device placement while utilizing minimal space as shown in Figure 4.

Figure 4: Brinno TLC200 Pro with waterproof case and clamp [17]

Monterey Mushrooms usually keeps their growing rooms lights powered off; this created a challenge for the Brinno TLC200 Pro because the camera lacks its own light source. Lights are usually only powered on when staff has pending tasks inside the growing facilities. Staff at Monterey Mushrooms informed the research team that light plays no role in the development of their mushrooms, the only reason lights are powered off is to conserve energy since the rooms are unoccupied throughout the day. Therefore, they had no problem with allowing their fluorescent lights to stay powered on while the experiments were conducted. The camera used for this project uses a band filter. This filter helps with removing the flicker that can sometimes be seen when recording video indoors lit by fluorescent lights. To avoid that flicker in the output video the camera was set to the 60Hz option to match the indoor lighting frequency in the United States. The Brinno TLC200 Pro comes with a high dynamic range (HDR) sensor that allows users to see a wider set color intensity. HDR is important for the mushroom images captured because there are very few variations in color between mushroom caps. HDR allows for more detail and definition when capturing monotonous subjects. This camera has a field of view of 112° and a resolution of 1280 x 720. The Brinno TLC200 Pro also allows for different scene options that capture images in different lighting conditions as well as the selection of different white balance modes [18]. Details about camera set up are discussed more thoroughly later in this thesis paper.

The Brinno TLC200 Pro captures images at user-defined intervals and outputs a video file in AVI format, from which frames can be taken and saved as JPEG images. The camera has multiple capture settings and modes. A scouting trip to Monterey Mushrooms revealed which settings and modes would provide the most detail. According to the Monterey Mushrooms staff, mushroom cap growth rates can peak at 3mm per hour. The Brinno TLC200 Pro manual suggest that for plant life and gardening, users typically set a capture interval anywhere between 1 to 30 minutes. For this project the image capture interval was set to 15 minutes to ensure that enough visual data could be captured while remaining within the memory limitations. Images captured with the "Best" quality option selected can be between 200Kb to 400Kb in size. This camera supports an SD card of 32GB maximum, which translates to an estimated storage capability of about 112,000 images. For a full cycle of 22 days, there will be 2,112 images captured, leaving plenty of memory space for additional rounds of image capture. The actual number of images captured for this project varied due to changes in the schedule and when the camera is set in place and taken down.

A full cycle for a room where the mushrooms are grown lasts about 22 days. During that period, staff needs to water the beds or harvest mushrooms that are fully matured to allow space for more growth. Power for the Brinno TLC200 Pro is provided by four AA batteries. This is another benefit of the camera because it permits data capture without having to install any wiring that may obstruct normal farming operations. According to the manual, when the camera is set to "Day Mode" and the capture interval is set to 10 minutes between images, power is expected to last a total of 43 days. This allowed plenty of time to collect data for a full cycle of growth since the capture interval was set to 15 minutes between images. All the information regarding the camera power capabilities can be found in the user manual [18].

3.2 Project Set-Up

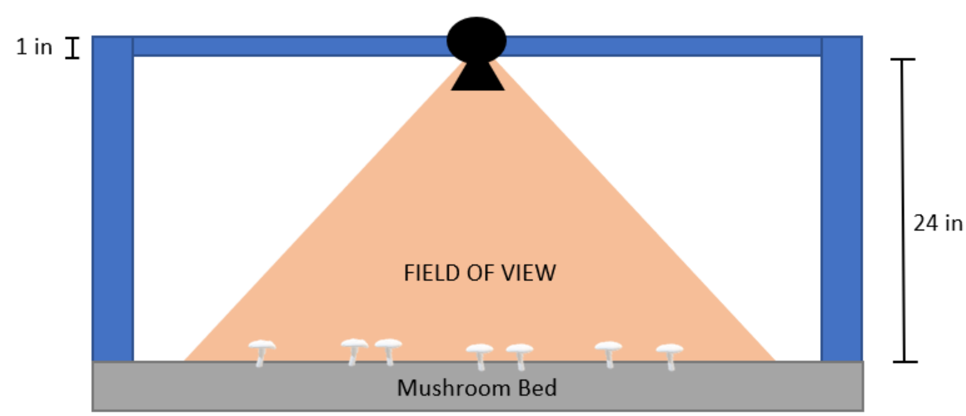

Figure 5: Initial bridge stand design for Brinno TLC200 Pro experimental set-up at Monterey Mushroom

The Brinno TLC200 Pro was placed in one of the rooms with wooden trays. During the first scouting trip to the farm, the camera was placed at an angle looking down onto the bed, however this angular view introduced a lot of distortions in the image. A better approach was to place the camera on the top tray to capture an arial view of the mushroom caps. To do so, a bridge stand structure was built on top of a tray stack. An initial design was sent over to Monterey Mushrooms where the staff helped construct the bridge structure according to specifications The initial design of the bridge stand can be seen in Figure 5. Ideally, the camera had to be parallel to the mushrooms, so that it looked directly down at a height of about 24 inches from the mushroom bed. The bridge stand needed to be long enough to fit the width of the wooden trays allowing the camera to be placed in the center. Actual measurements were taken when the Brinno TLC200 Pro was put in place and the data collection phase of the project commenced.

Figure 6: Photograph of the bridge stand structure used to hold the camera in place

The bridge stand constructed by the Monterey Mushroom staff is comprised of metal beams so that it could remain sturdy throughout the entire process. The structure measured 47.25 inches across and 18.5 inches tall. The stand that was attached to the mushroom trays can be seen in Figure 6. Once the camera was clamped in place, the Brinno TLC200 Pro started collecting data. The camera recorded images for about two weeks. After the first two weeks, the camera was taken down and data was downloaded to be processed and analyzed, then it was placed back in the same location to continue collecting data. To address occasional shifts in the images, metal markers were placed so that images could be registered. This way, any movements that were accidentally introduced could be fixed. The markers had to be made from metal in case that they are lost in the soil, this would allow the Monterey Mushrooms staff to locate them using their metal detectors.

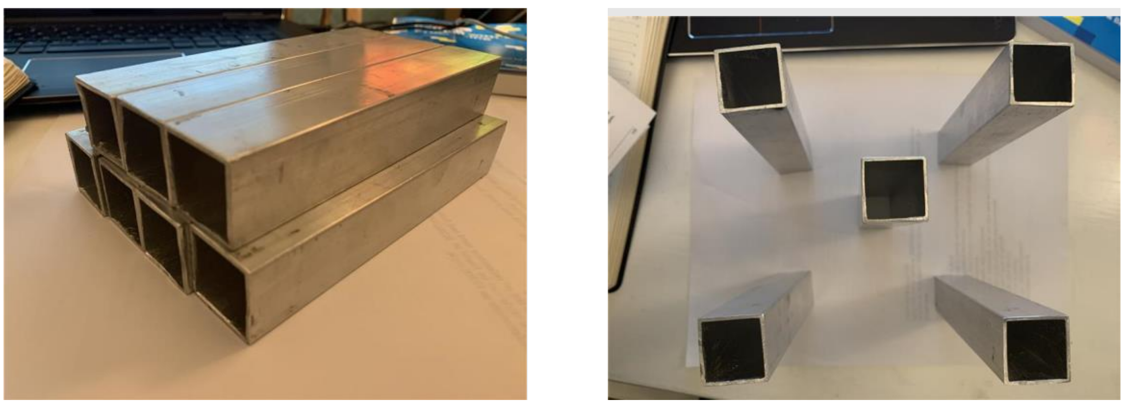

Figure 7: Side and top view of metal tube markers (1in x 6in)

The metal markers were made from aluminum square tubing shown in Figure 7. The metal tubes were one inch wide and were cut to be six inches long. The tubes were inserted into the soil and used to compare the size of the mushrooms. During the first test of the Brinno TLC200 Pro, it was noted that during normal operations a staff member accidentally bumped into the camera and the image was shifted. These square tubes were inserted the sharp corners of the metal squares could be used to align the images if any motion was introduced between frames. In the case that image registration was needed, that work would be done in the image processing stage using MATLAB. Image registration is important because it allows for the tracking of individual mushrooms throughout the entire mushroom growing cycle.

Figure 8: Current project setup at Monterey Mushrooms on the top tray

Figure 8 shows the set up used for the experiment that took place inside Monterey Mushrooms. The camera was placed inside its waterproof casing and clamped at the center of the bridge stand. The Brinno TLC200 Pro’s lens sat 22 inches from the tray bed where the mushrooms begin to grow. Metal markers were placed a couple of inches apart and two inches into the soil. This allowed for four inches of the square metal tubing to be exposed.

3.3 Project Scheduling

The first trip to Monterey Mushrooms was meant to test the Brinno TLC200 Pro in the farm environment. During this trip it was discovered that a full harvest cycle takes about 22 days to complete. This project required planning to stick to the growing schedule that Monterey Mushrooms follows. The goal was to get into a room and set the camera in place ready to take pictures before the fruiting bodies began to develop a mushroom cap. It took about two weeks for the first round of mushrooms to be harvested, this was when the first round of data was collected. Then the camera was placed in the same spot again and it was not to be collected until the entire cycle had been completed. The last two weeks captures the second and third breaks inside of the growing room. The exact dates for when the camera was placed inside the growing room will be discussed later in the next chapter in section 4.1.

CHAPTER 4: METHODOLOGY

Rarely, is one solution the answer to all computer vision problems. Image processing and analysis techniques are unique and specific to the issues that scientists and researchers must address. In this case, enough data had to be collected to detect the mushroom caps as objects and track growth over time. This first step required some image processing techniques that depended on the quality and details captured in the images collected. Once a set of objects is detected; measurements, growth rates, and production yield can be obtained to make predictions in the future. Despite the specificity of each problem, there are similar applications of image processing and analysis techniques that can be used to achieve the goal posed earlier in this thesis. This chapter presents in detail the image processing and analysis pipeline used to detect mushrooms and measure size and growth rate.

4.1 Data Collection

The Brinno TLC200 Pro allows the user to set the intervals between each captured image. For this thesis project the interval between images collected was set 15 minutes, so in one full hour a total of four images were collected. According to the Brinno user manual, 15 frames-per-second (FPS) is the best setting for plant life and gardening, so that was the option selected to record data on mushroom harvesting. Once the time frame for collecting data was over the video file was downloaded from the 32GB memory card, the frames were extracted using MATLAB and saved as a JPEG image so that they could be processed.

The camera was placed on March 4, 2021. The focal length was adjusted to capture objects that are about 24 inches away from the camera lens to ensure that blurriness would be limited if any was present at all. On March 15, 2021, the camera was removed, and the video was downloaded to start extracting the first set of images. Then the camera was placed in the same location to capture images until it was due to be taken down again on March 24, 2021. At this point the second video was downloaded to have image data for a full cycle of mushroom growth. The two videos are read using the *VideoReader()* command on MATLAB, and a total of 1,960 JPEG images were extracted and saved for processing.

4.2 Frame Processing

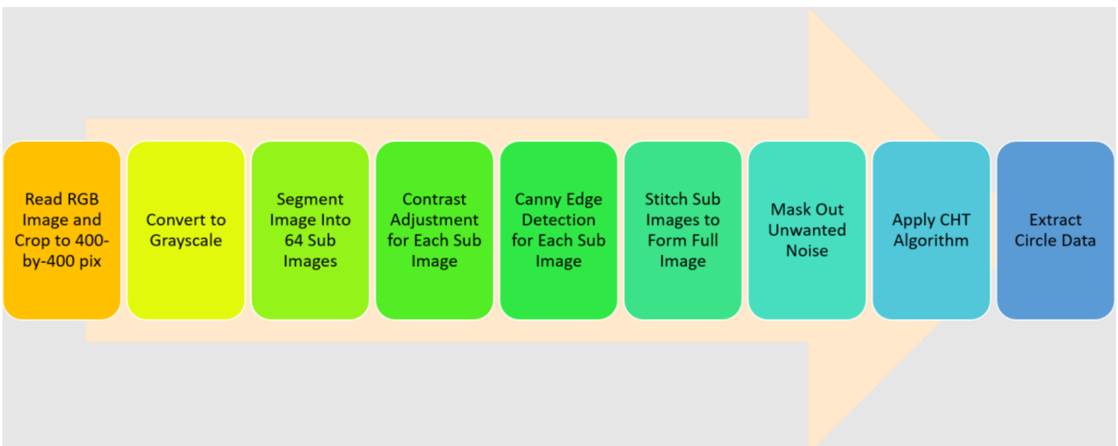

Figure 9: Frame processing steps for the detection of mushrooms

Once the individual frames were collected, the images were processed to extract relevant information about the mushrooms present at that point in time. In this case, the data extracted represents the size of the radius and the center point location for each mushroom located. It is important to note that the process shown is applied to all 1,960 frames that were collected. Figure 9 shows the steps taken to identify mushrooms. First, the image is read and cropped, then a couple of preprocessing steps were applied to make object detection possible, and lastly, a circle detection algorithm was applied. A more detailed explanation of the frame processing sequence used in this project will be discussed in the following sections.

4.2.1 Image Reading and Cropping

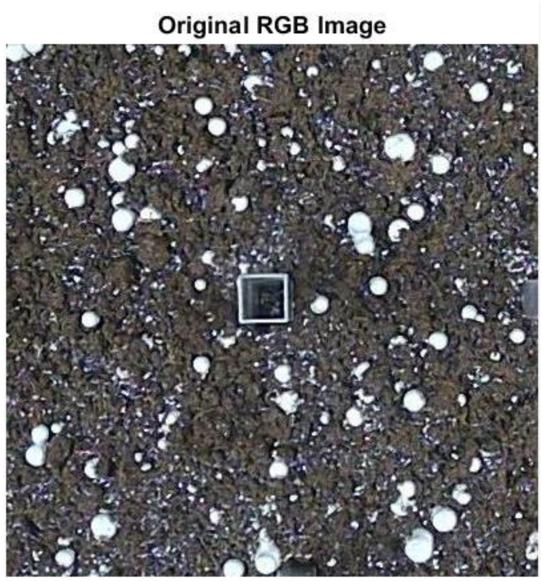

Figure 10: Example of frame 34 cropped to a 400-by-400-pixel RGB image

The first step in the process was to read and crop the images into an area of focus right below the camera lens that is 400-by-400 pixels in size. This allowed the mushroom detection algorithm designed for this thesis to be more accurate than applying it to the entire 1280-by-720-pixel image captured because it made it possible to avoid the distortion on the edges that were present in the images. A combination of the *imread()* and *imcrop()* MATLAB commands were used to produce this output image. Figure 10 shows an example of this process being applied to frame 34. Frame 34 was chosen at random and will continue to be used to demonstrate each step of the process to extract mushroom data. RGB images are represented by an m-by-n-by-3 numeric array. The color of each pixel used to create the entire image is represented by intensities that range between 0 to 255 for each color (R, G, B).

4.2.2 Grayscale Conversion

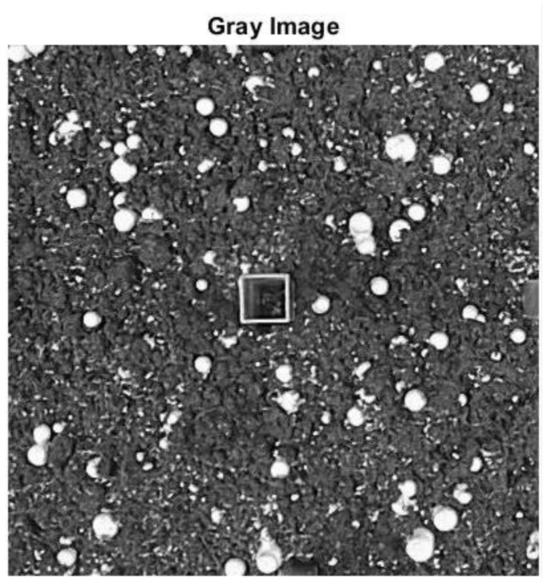

Figure 11: Grayscale output for frame 34 show image's gray level intensities

The second step in the process was to take the RGB image and convert it into a grayscale image. The *rgb2gray()* command takes a m-by-n-3 numeric array and outputs a m-by-n numeric array. Each value inside the output array falls between 0 to 255 and represents shades of black, and white, plus variations of gray hues. Converting to grayscale images allow users to take advantage of other MATLAB commands used later in the process. Figure 11 shows what frame 34 looks like after it has been converted to a grayscale image.

4.2.3 Image Segmentation

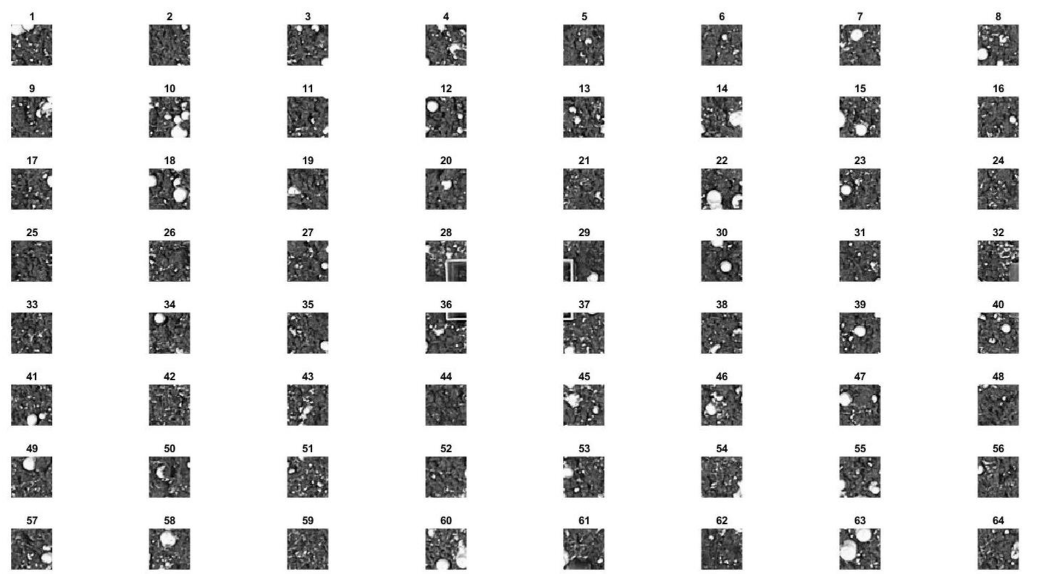

Figure 12: Frame 34 is segmented into sub images with a size of 50-by-50 pixels

The third step in the process was to segment the image into 64 smaller sub images each sized at 50-by-50 pixels. The frames were segmented using the *mat2tiles()* function. This function was obtained from MathWorks File Exchange [19]. The inspiration to apply this method came from a paper on particle size detection where researchers compare measurements taken by hand, to measurements obtained using image segmentation and CHT [20]. Segmenting the mushroom images in this fashion allowed for region specific operations to be applied later in the process. Image segmentation is important when adjusting the contrast in areas where shadows were present, or mushrooms were too crowded because it is possible to focus on more details. Figure 12 shows frame 34 segmented into 64 sub images for further processing.

4.2.4 Contrast Adjustment

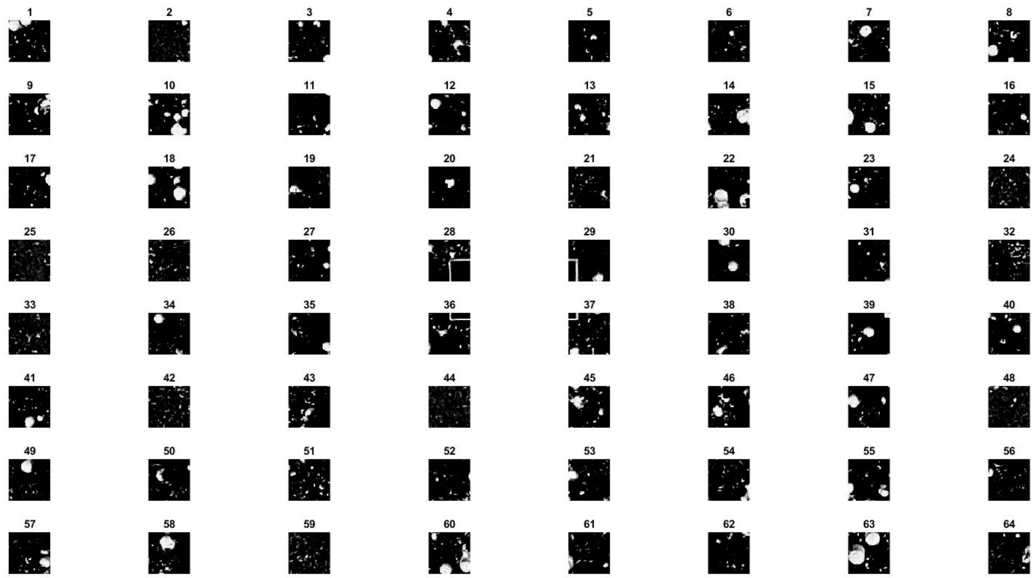

Figure 13: Frame 34 segments have the contrast adjusted individually for each segment

The fourth step was to adjust the contrast for each sub image. First, the global threshold (T) value was calculated for each grayscale sub image using Otsu's method [21]. MATLAB allows users to easily compute this value by using the *graythresh()* command. T is used as lower end for the input range of the *imadjust()* command. This command takes the input range [T 1] and stretches it to represent intensities that cover the full range of grayscale shades [0 1]. If i(m,n) represents a single pixel intensity value, then values where i(m,n) < T will turn into black (0) and the rest of the values are stretched out to cover the full gray level intensity range (0 - 255). The purpose of this step is to enhance the intensities on the edges of the mushrooms so that when the edge detection algorithm is applied, there is a clear definition between objects. Figure 13 is the output result of adjusting the contrast for frame 34 in this manner. As a result, the edges of the brighter mushrooms become more clearly visible.

4.2.5 Canny Edge Detection

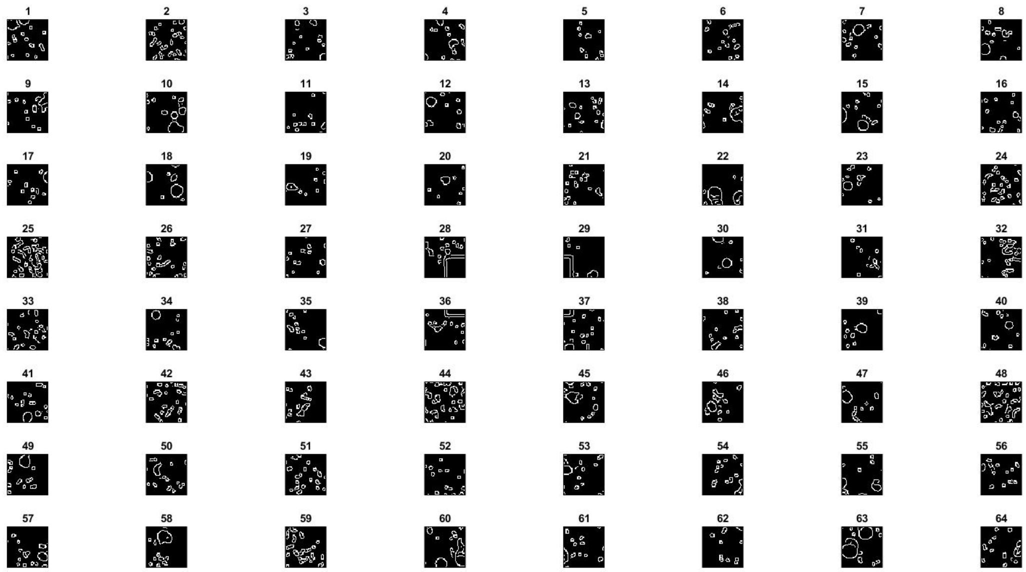

Figure 14: Canny edge detection applied to each sub image for frame 34

The fifth step was to run an edge detection algorithm for each sub image. MATLAB's *edge()* command takes a 2-D grayscale image as an input and outputs a binary image where the edges are represented by white pixels while the rest of the image is blacked out. MATLAB allows users to select from multiple methods; in this case, the Canny edge detection method performed best. Canny edge detection works by calculating the gradient of the image using the derivative of a Gaussian filter then two thresholds are used to detect edges [22]. Figure 14 shows the edges of all the objects that were present in the sub images of frame 34. Now, the sub images are ready to be put together so that the entire frame can be viewed as one single image.

4.2.6 Stitching Sub Images

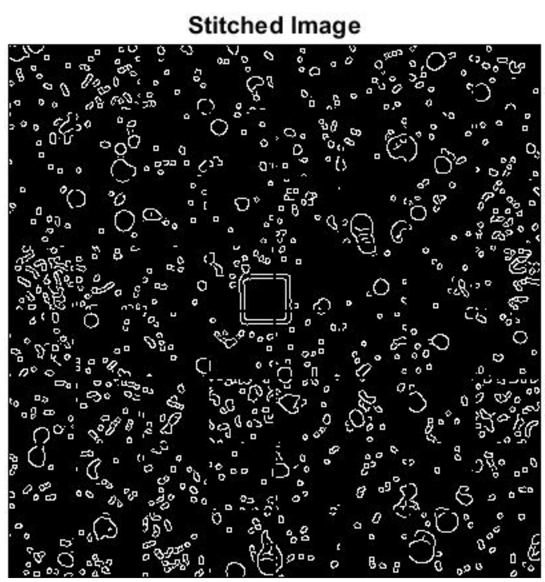

Figure 15: The sub images have been stitched together to show the full image

The sixth step in the process was to take all 64 sub images and stitch them together. Binary sub images were represented by a 50-by-50 numeric array, so these matrixes can be concatenated to reproduce the 400-by-400-pixel image. Figure 15, shows the sub images for frame 34 stitched back together. At this point, Only the edges of the brightest objects that were originally present in the image remain. Since mushrooms are the only objects of interest, other additional objects were considered noise and obstructions, so they had to be removed.

4.2.7 Masking Out Noise

Figure 16: Mycelium growth on the mushroom beds at Monterey Mushrooms

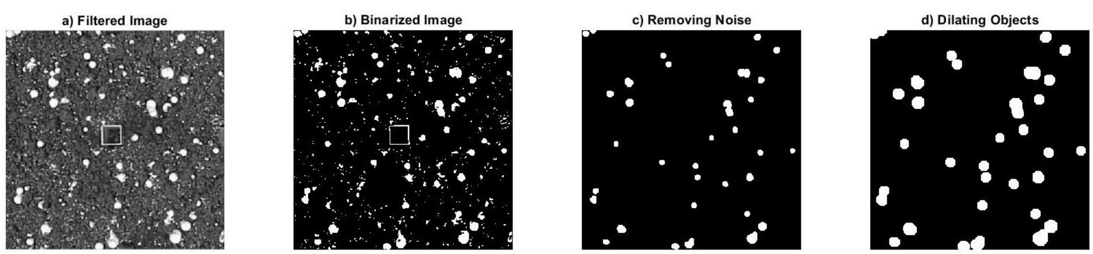

Figure 17: Process for creating a mask for frame 34 to remove excess noise

Mycelium (spawn) growth presented itself as a challenge when detecting the mushrooms in the images. Figure 16 shows a close-up picture taken to show the feathery-like white structures growing on the mushroom beds. When the images are binarized, mycelium presents itself as small specks throughout the image. The specs were troublesome because if enough of them were close together they could be incorrectly labeled as an object. To avoid this problem, a mask was created for each frame. Figure 17 shows the four-step process for creating the mask for each individual frame, the steps are as follows: a) filter the image to create a blurring effect; b) binarize the image so that only the brightest sections are left behind; c) use morphological operations to remove any small noise present and; d) dilate the white objects so that only the area eroded away in the previous step can be replenished. When the mask was multiplied with the stitched image in Figure 15, a result that looks like Figure 18 is the output. All the small objects present in the image were removed and only the edges of the mushrooms were left behind. Now that only the edges of the objects of interest were left behind, measurements could be made.

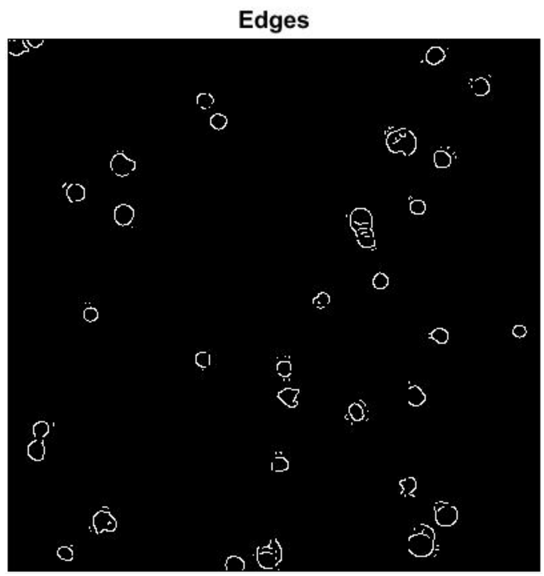

Figure 18: Multiplying the mask and the stitched image gives the mushroom edges

4.2.8 Circular Hough Transform Algorithm

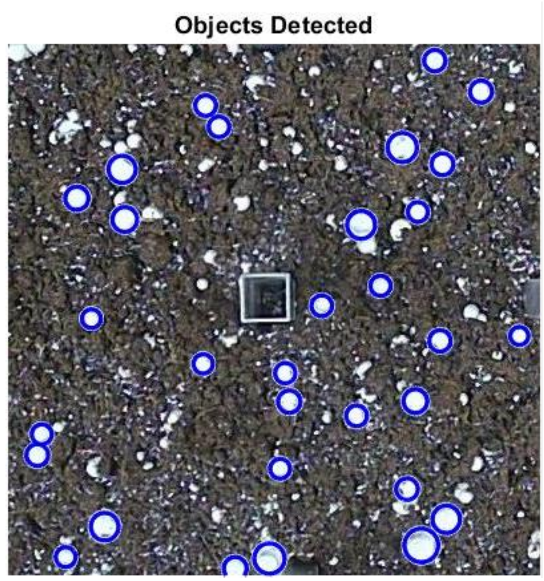

Figure 19: Mushroom identification after using the CHT algorithm for frame 34

Lastly, the CHT algorithm was applied using MATLAB's *imfindcircles()* command. This algorithm takes a binary image and a radius range as inputs. For this application circles that have a radius that falls between six to 100 pixels were detected. The two outputs are the size of the radii in pixels and the coordinates for the center point of the circles that have been detected. Finally, circles can be overlayed on top of the original RGB image to show the location of the mushrooms. Figure 19 shows the circles overlayed on frame 34 to identify the edges of each mushroom. Overlaying the circles on top of frame 34 is only for representation and was not done for every single frame.

4.3 Data Discussion

Table 1: Radii and center point outputs for mushrooms in frame 34

Index	Radii	Centers (x,y)	
1	9.3015613	88.196423	132.58966
2	8.0214471	321.2841	13.059269
3	8.2129771	327.06032	91
4	8.0458823	325.16125	223.99328
5	10.32304	329.91318	358.29568
6	7.6743237	158.97748	62.889914
7	8.1544214	22.443968	309.89581
8	7.5286017	280.50515	182.52778
9	8.6878261	52.152739	116.6718
10	10.977674	296.85164	78.437419
11	10.36818	73.061049	363.87019
12	10.484877	265.87794	136.68887
13	7.4422036	308.55445	126.97625
14	8.9102252	306.69015	269.34497
15	7.4260182	43.741001	386.78365
16	12.683953	311.1599	377.93892
17	11.409288	196.96828	387.87423
18	10.215556	86.201722	94.857059
19	8.2853385	356.02766	36.403315
20	7.5093015	25.779381	294.36585
21	7.8223077	262.447	280.42832
22	7.236801	147.13697	241.32287
23	8.3990184	211.88297	269.75652
24	8.5501882	171.22441	395.26881
25	7.4074313	204.98383	320.26071
26	7.0080093	63.117006	207.25458
27	8.1507831	300.39278	335.61506
28	6.7583643	384.79505	220.29128
29	7.7437977	148.95111	46.912243
30	7.7556722	236.30002	197.55883
31	7.6412967	208.83802	248.30912

Table 1 shows the data extracted from frame 34 after the application of the CHT algorithm. The output of the CHT algorithm is the center of each circle and the radius, so it is possible to visualize and analyze the data for each frame. In this frame, 31 mushrooms were detected, so it is possible to get the size distribution of the harvest at the time when this frame was captured. It is also possible to identify where the circles were located by using the x and y-axis coordinates. Having this data available for each frame in the video allows users to then learn more about the different stages of mushroom growth in the growth chamber.

The radii width was represented in pixels, so it was necessary to convert pixels to convert pixels into inches. When the project was first set up, one-inch-by-one-inch metal markers were inserted into the mushrooms bed. The size of the markers was known, so the width in pixels was determined by measuring the distance between the corners of the metal markers, this means that one inch was equal to 35±1 pixel in the images that were captured. The radii values could then be divided by the 35 pixels per inch, so the data value now represent the mushroom cap size in inches.

CHAPTER 5: RESULTS

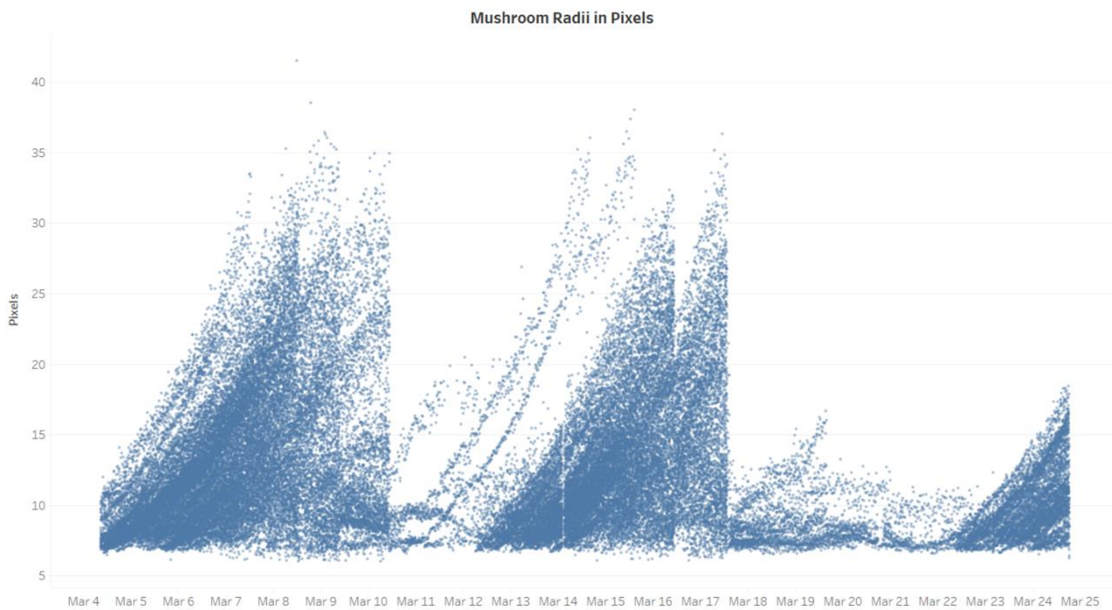

Figure 20: Mushroom radii distribution overtime

When the data for all 1,960 frames was extracted, the distribution of radii measurements that looks like that shown in Figure 20 was synthesized. After some filters were applied to eliminate outliers, a total of 70,781 measurements were collected to produce this visualization. Every 15 minutes a vertical row of circular data marks is plotted; and the number of mushrooms is represented by the number of marks displayed for that row. The data mark location relative to the y-axis represents the size of the radius in pixels for a specific mushroom at that point in time. When the Brinno TLC200 Pro captures an image, a time stamp is added to the bottom of the frame, so date and time could then be quickly paired with the corresponding circle data from each frame. The three waves of mushroom growth seen centered around March 8th, March 16th, and March 24th correspond to the three breaks where pickers go into the room to harvest the mushrooms.

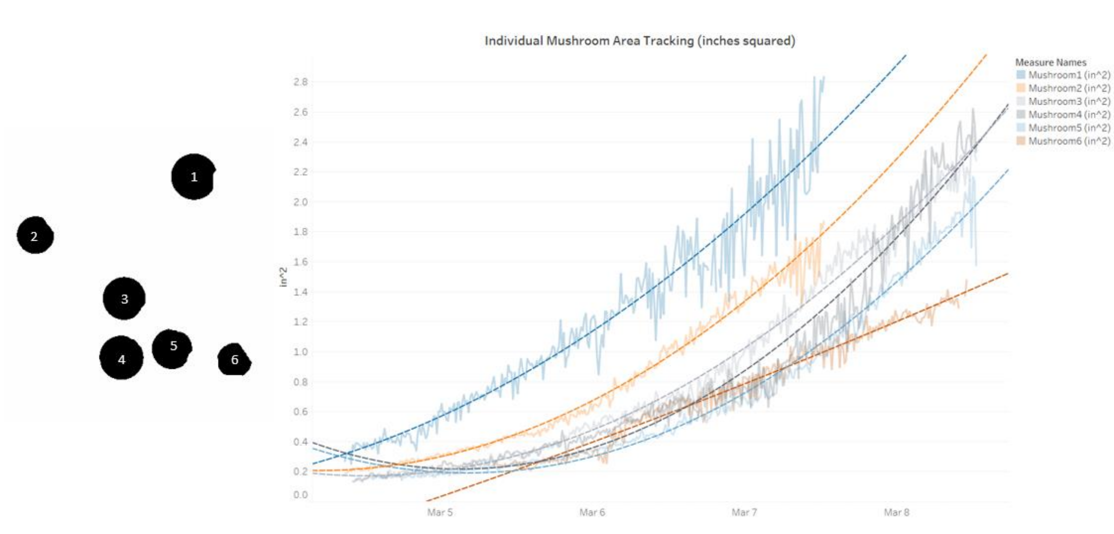

Figure 21: Individual mushroom tracking

Circle data can be used to identify trends and derive further information about what was taking place in the growing rooms during the mushroom growth cycle. Point-to-point tracking makes it possible to take measurements of individual mushrooms from their initial appearance in the detection algorithm, until they had been harvested . This kind of work has already been tested where computer vision systems in incubators calculate harvest times and send alerts to farmers [4]. However, Monterey Mushrooms is looking for more general information of the health and mushroom growth in their growing rooms. In Figure 21, six different mushrooms were identified, and the area is tracked throughout a couple of days. Some mushrooms were detected and harvested earlier than others, nevertheless the trend for growth remains similar for mushrooms one through five. Mushroom six, in Figure 21, has a different shape to its trend line due to being a part of a cluster that has grown too tight. This mushroom species has a very circular shape to its cap, when mushrooms grow in cramped spaces their sides tend to become flat like those shown for mushroom six. When mushrooms grow too dense, air circulation is limited, and pressure causes quality to degrade more quickly than mushrooms with enough space to grow freely. Mushroom six no longer follows the expected trend because it is squeezed on several sides. Noticing those trend changes can be very helpful by identifying areas where mushrooms have been pinned too densely. This type of analysis can also be done in more general terms, by training a computer vision system to look for and localize clusters.

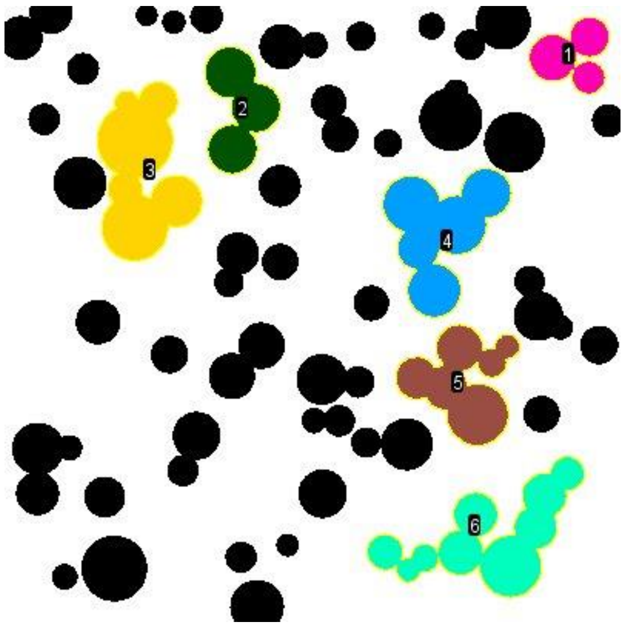

Figure 22: Identifying clustering based on object circularity

Table 2: Object descriptors

Label	Area	X_Coordinate	Y_Coordinate	Perimeter	Circularity	Round	Solidity
1	1622	368.486	31.674	231.037	0.382	0.834	0.828
2	2441	151.982	66.43	263.664	0.441	0.503	0.786
3	4891	89.512	108.73	401.446	0.381	0.494	0.803
4	4356	283.282	146.054	373.889	0.392	0.715	0.783
5	3444	296.812	244.603	363.647	0.327	0.891	0.766
6	4893	315.684	344.017	558.198	0.197	0.476	0.648

To identify clustering and help farmers avoid mushrooms degradation, object circularity can be measured. A circularity measure usually falls between zero and one. A perfect circular object is given a value of one, if the object deviates from a circular form, then the circularity measure nears zero. In the case of Figure 22, six areas with a circularity measure that falls below a set threshold value of 0.50 were highlighted in color. Table 2 shows the following: label number; total area covered by the object; the x and y-coordinates for the center of mass; perimeter; circularity; roundedness; and the solidity of the objects labeled. All the measures listed in the table can be used to send alerts about the size of the areas where clustering is happening so that growers are aware of which sections need to be harvested first to avoid pressure buildup to maintain good airflow and circulation between the mushrooms in the bed. Since the coordinates for the center of mass is also recorded, the location of the cluster can be accurately identified. This opens room for the possibility of automating the identification and localization of densely packed mushroom clusters in the future. This cluster identification will be useful while using robotic arm to pick the mushrooms that are being more prevalent in mushroom industry.

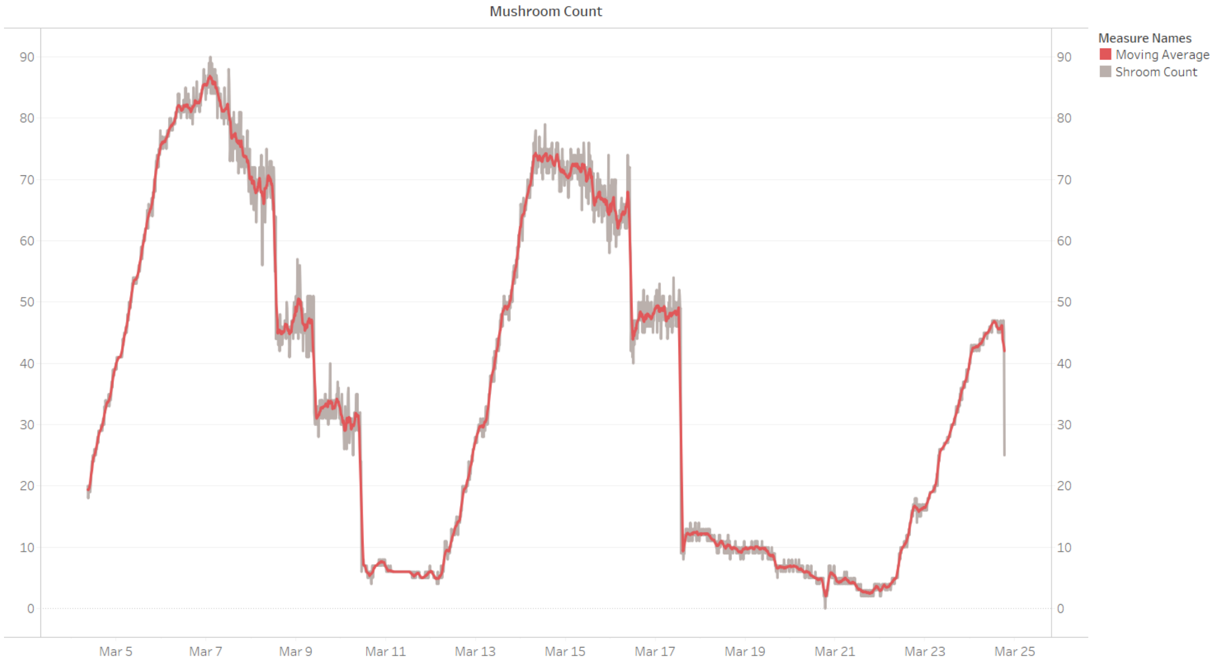

Figure 23: Mushroom count across the mushroom growing cycle

When speaking to the Monterey Mushroom staff, they expressed interested in acquiring generalized information about what is happening on average in their growing rooms. Monterey Mushrooms harvests thousands of pounds per cycle, so it is understandable that they would want to have condensed understanding of each growing room. Mushroom count can be derived from the data collected on circle radii and locations. Due to changes in lighting or new obstructions on the mushroom bed, the mushroom count can have some fluctuations and noise. However, by calculating a moving average using four data measurements prior and four data measurements after the current value (shown in red) to smooth out some of the noise and get an accurate estimate about the number of mushrooms in the area being photographed as shown in Figure 23.

Information like this can be used to assess the current state of the mushroom bed on a given point in time. With more image data from different locations, it is possible to identify patterns that can then tell farmers if a certain crop is underperforming, exceeding expectations, or falling within regular measurements. For example, in Figure 23, three distinct peaks can be seen which correspond to the three harvesting breaks. Note that there is a longer period between breaks two and break three where the number of mushrooms is not increasing. Alerts can also be sent when growth patterns deviate from what is expected. Knowing this information can help mushroom growers assess and identify problems with environmental settings or contamination that could have mistakenly made it onto the growing beds.

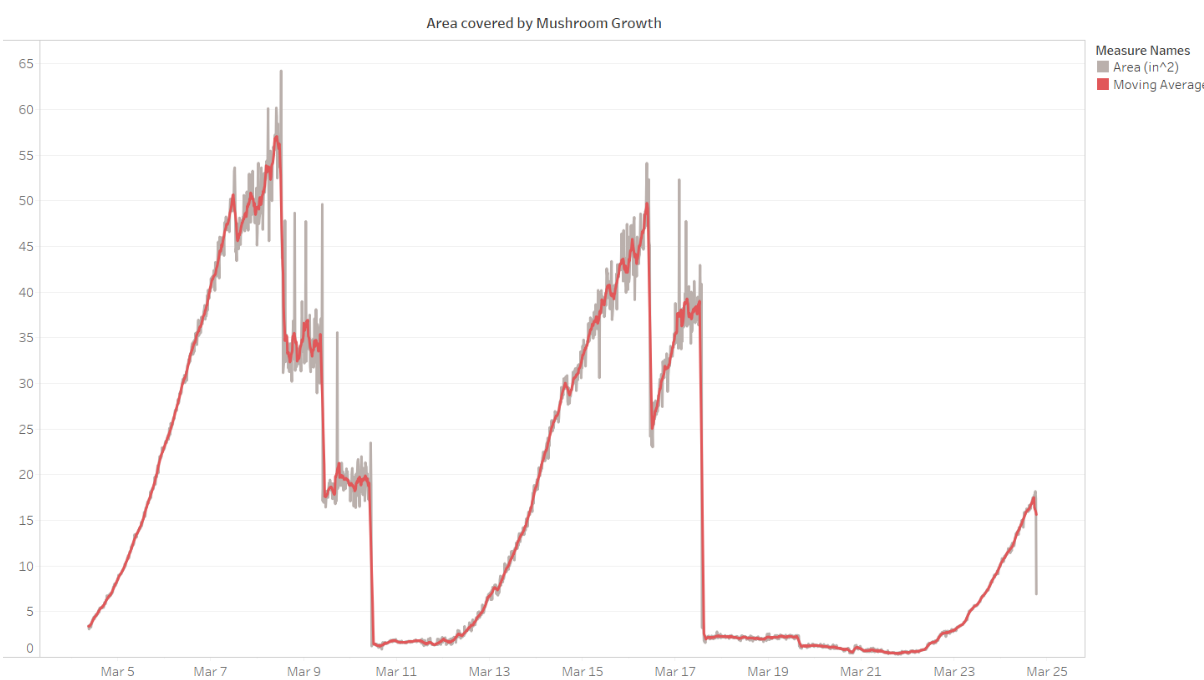

Figure 24: Area in inches squared that are covered in mushrooms in photographed frame

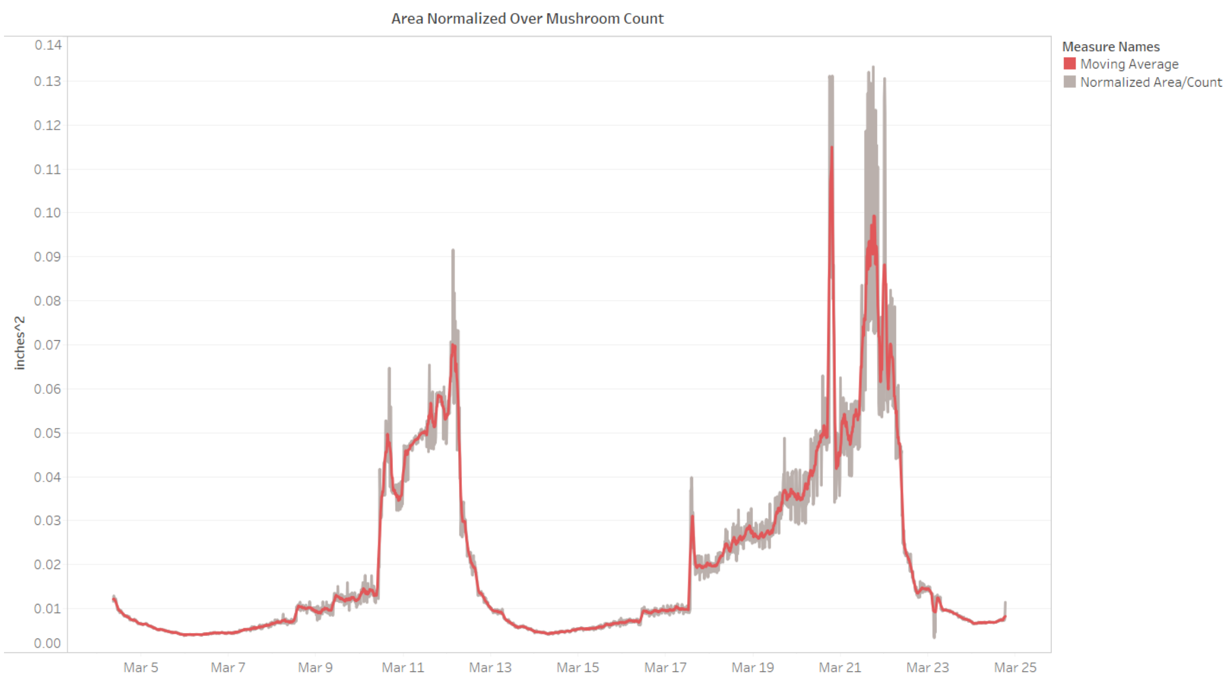

Figure 25: Mushroom area normalized over mushroom count

Data on the radius size of the mushrooms has been obtained, so it is possible to calculate how much area of the bed is covered by mushroom growth. Although the radii data is in pixels, a simple conversion can be made by using the size of the known markers as stated earlier in this paper. Going forward it would be useful to add more known markers around the edges of the growing beds; this could help calibrate the camera to recognize distances as well as make it possible for a larger camera system to locate specific areas within the growing room. Figure 24 shows the area that is covered by mushrooms growth in the section of the bed that was photographed. This data can be useful to growers to detect locations in the growing rooms where mushroom growth fails to meet a predetermined threshold.

Area data can be used for monitoring the general growing trends on the mushroom beds. Figure 25 shows the summation of all the area covered by growth normalized over the total mushroom count to get an average growing rate. This measure trends upwards between harvest times which can be a signal for time periods when mushroom growth is taking place. By collecting data throughout more growing cycles, it is possible to compare these growth rates to assess environmental conditions. Therefore, keeping a close watch over these trends and when they happen can help growers optimize their harvesting schedules.

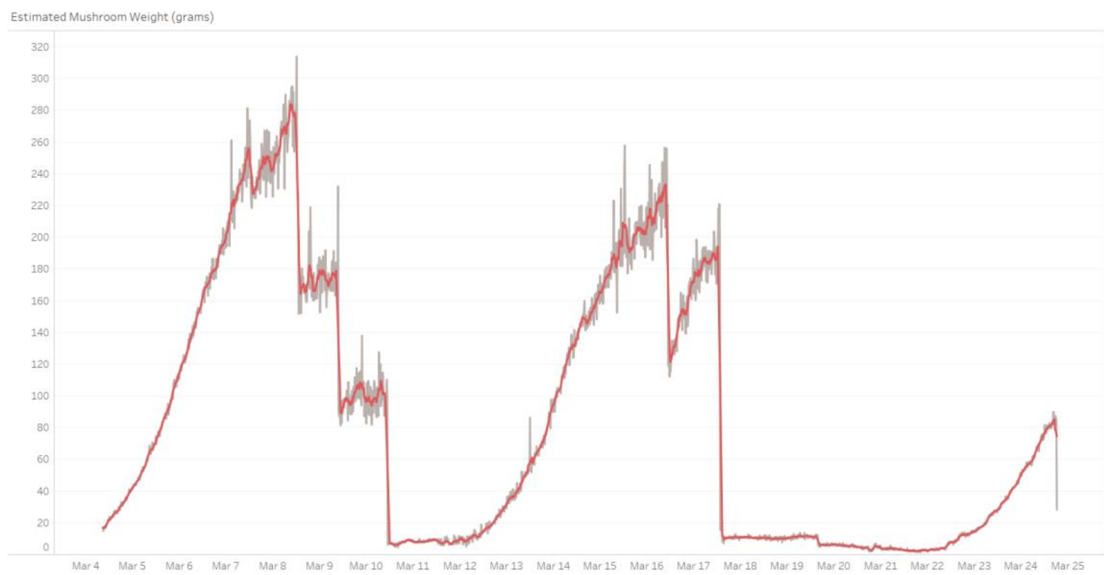

Figure 26: Production yield estimate in grams for mushrooms captured in the images

Since area can be calculated from the data obtained and growers have current knowledge on the size distributions of mushrooms, it is possible to make estimations about the current weight that is present in the growing rooms. At the time this project was conducted, mushroom density data was not available for the specific harvest that was monitored using the Brinno TLC200 Pro, so mushroom density was assumed to be 4.85 g/in^3. Estimating the volume of the mushroom based on the area of the cap can then help make prediction of the total volume and weight found on the growing bed. Figure 26 shows the estimated production yield in grams throughout the harvest cycle, however, more experimentation and accurate data on mushroom density distributions based on size is needed to create better models that can make estimates on product yields.

CHAPTER 6: CONLUSION

6.1 Future Improvements

Monterey Mushrooms is slowly changing their infrastructure to the aluminum growing beds due to the larger separation between each stack. The newer growing racks have rails that would make it much easier to implement camera equipment in different levels and throughout the growing room. At the time of this project space was limited due to the wooden growing beds that are still commonly used in the industry. Perhaps a larger space could allow more flexibility with the placement of camera measuring systems.

Now that the nature of the environment inside a facility such as Monterey Mushrooms is understood, it is possible to extract more information from the images that were captured. Due to the current COVID-19 health crisis, gaining access and traveling to the mushroom farm was challenging, so there was data that could not always be easily accessed. A good start would be to separate the mushrooms grown inside of the frame captured by the Brinno TLC200 Pro and weight them so that a precise count and density value can be obtained. This way the accuracy of the object detection algorithm used to identify the mushrooms can be properly assessed. At the same time, data collected for the mushrooms weight can be used to train a model that can accurately predict mushroom yield based on quantity, area, and color of the mushroom caps.

Having more cameras in different locations would also help to generalize trends and distinguish individual areas that are underperforming in mushrooms growth. This experiment only captured one small section in a growing room that can produce thousands of pounds of mushrooms in a span of 22 days. It would be advisable, that in the next iteration of this project more areas be photographed to get a more comprehensive understanding of what is happening in the growing rooms as a whole. However, to do this, there would need a strict schedule that is followed so that lights can be turned on when the cameras are taking pictures. In our case, Monterey Mushrooms staff allowed the research team to keep the light on throughout the entire process to reduce energy consumption.

Lastly, a small LiDAR application could be designed and paired with the image data that is collected to gain a 3-dimensional representation of the mushrooms. LiDAR would allow users to get precise location data in 3D space, so it is possible calculate volume and make accurate density estimation. However, without digital imaging, color information which is an important characteristic to assess mushroom health and quality would be lost. When the product reaches store fronts, customers refer to color to appraise mushroom quality, so it would be ill-advised to neglect this data altogether

6.2 Conclusion

This thesis experiment began with little knowledge about how to set up a camera monitoring system inside a commercial mushroom farm. After careful planning it was able to design a computer vision algorithm that specializes in the identification of mushrooms in a growing room where mycelium growth and obstructions are common due to the ever-changing conditions inside a busy mushroom farm. The radii measurements obtained, can be used to count, measure area, and identify trends in the growth process.

This thesis aimed to close the gap found in current literature focused on mushroom agriculture. In many cases, these experiments were conducted in very controlled environments with very little room for human error. After visiting Monterey Mushrooms in numerous occasions, it is now easier to comprehend that ideal conditions are rarely found, and this can be detrimental to the accuracy of those systems when placed in a mushroom farm. It is also important to note that the volume of production in a farm can be orders of magnitude grater than those which are produced inside an incubator, so it is unrealistic to alert and track that volume of data. Growers need to get a general understanding of an entire crop to make quick decisions in a fast-paced work environment.

Large-scale mushroom farms require extensive industry knowledge and many laborers to yield high quality products that are ready for human consumption. This experiment shed light on the potential data that can be extracted from digital imaging inside mushroom farms. Although further improvements are needed, farmers can start to use computer vision tools to obtain simple measurements that can improve production yields and profit margins by understanding what is happening in their growing rooms in real time. As more data is collected, these computer vision implementations can evolve to give growers a competitive edge to improve the crop yield and increase the profit margin. In the future, this image capturing technology and data analytics can be made automated so that the managers can track the mushroom growth, quality, and yield for every batch of substrate that are produced.

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