Root Monitoring of Valley Heart Lettuce in Hydroponics Systems

Prepared for
Professor C. Madramootoo
BREE 495 Engineering Design 3
Department of Bioresource Engineering
McGill University

By
Abigail Choiniere | Team Leader
Emily Lafond
Jennyfer Liang
Kyle Geddes

April 15th, 2023

Table of Contents

Abstract

Food insecurity is a major global concern, especially in remote areas, such as Indigenous communities in northern Canada. Even though enough food is produced to feed the entire human population, agricultural malpractice causes important food loss in the farming industry. Therefore, our vision is to address the issue of food insecurity in areas with nutrient-deficient waters and soils. To achieve this, our mission is to minimise produce loss from plant health deterioration through root monitoring in hydroponic systems to halt the spread of disease and maximise yields. The social, environmental and economic benefits include producing higher quality and safer food for consumption, generating higher yields, promoting local engagement and stimulating local economies. However, the drawbacks are startup costs, the use of non-sustainable materials, and significant water and energy demands. In our experiment, root health was determined based on colour, with white indicating healthy roots, and the overall weight, with healthy plants having denser roots and foliage. Our hydroponic system consisted of four bins following a deep flow technique (DFT) setup. Bin A was the control system, Bin B had 100% of its true leaves removed, Bin C had a calcium deficiency, and Bin D had an oxygen deficiency by removing the air stone. The root monitoring was done manually with a GoPro to image the roots of each plant. Furthermore, each tray was periodically weighed using two load sensors to measure plant growth (in kg). Data collected was sorted and compiled for analysis. An image analysis model was constructed from healthy and unhealthy images. The model created could successfully identify root health in a binary fashion. Only regenerative stress could be detected, other stresses did not impact the rootzone significantly enough and as such is not suitable for use with the image classification model.

1. Introduction

Food insecurity threatened 50.8% of First Nations households in Canada in 2019, compared to 12% of non-native Canadian households (Deaton et al., 2020). The Food and Agriculture Organization (FAO) of the United Nations states that “a person is food insecure when they lack regular access to enough safe and nutritious food for normal growth and development and an active and healthy life.” From this definition, the four pillars of food security can be recognized: availability, accessibility, utilisation, and stability (Shafiee et al., 2022). Factors affecting the degree of food insecurity include food prices, income, family size, geography and community size (Deaton et al., 2020).

Indigenous communities in northern Canada reported decreasing populations of wildlife, which directly impacts food availability because they rely on hunting and harvesting for traditional food sources (Shafiee et al., 2022). The migration and decrease in abundance of wildlife is likely due to human activities that Indigenous communities have no control over, such as deforestation, overfishing and environmental pollution. As climate change progresses, the availability of traditional foods will further decrease as global temperature, biodiversity loss, resource loss, and extreme weather events increase. Thus, these communities are becoming more dependent on market foods coming from urban centres, however, selection is limited, dairy products and fresh produce are scarce, and access depends on the presence of an all-season road (Shafiee et al., 2022). Furthermore, fresh, nutritious, and healthy foods coming from urban areas are often unaffordable for low income households and might spoil during transportation. This forces them to buy junk food from local convenience stores. Finally, growing crops is increasingly difficult due to unfavourable climatic conditions and restrictions imposed by the government on hunting and harvesting activities.

Therefore, growing food hydroponically in those areas with nutrient-deficient waters and soils could not only save water, but also increase food production locally, thus increasing food availability. However, hydroponic systems are not without drawbacks. Bacteria, fungi, and pests are the culprits of a variety of health issues and diseases in food such as in *Lactuca sativa* L. (lettuce) (Raid, 2004). Lettuce that is grown hydroponically is not at risk for soil-borne pathogens, however, it is not exempt from all diseases either. Depending on the disease, the symptoms can be noticeable on the upper and lower leaf surface and it can affect the lettuce at any point in its development. Furthermore, it may restrict plant growth and development, thus reducing overall yield (Davis et al., 1997). Once the disease has been detected, managing and minimising its spread can be challenging because sometimes the disease can spread through air particles (Raid, 2004). However, other preventative measures including the use of fungicides and limiting the amount of water through proper irrigation practices can be taken as well as controlling the humidity levels and temperature. Some common plant health issues that arise during the production of lettuce in indoor farms are Downy Mildew, Powdery Mildew, Grey Mould, and more (Davis et al., 1997).

Our vision is to address the issue of food insecurity in areas with nutrient-deficient waters and soils. To achieve this, our mission is to minimise produce loss from plant deterioration through root monitoring in hydroponic systems. We proposed a root health monitoring system for hydroponic systems that could successfully catch plant deterioration early to limit the spread of pathogens and maximise yields. Our selected crop for this project was Valley Heart lettuce, but ideally our root monitoring design can be expanded to any crop. Moreover, though our target population is food insecure Indigenous households, we encourage the implementation of our design in both remote and urban regions to avoid unnecessary food loss.

2. Literature Review

2.1 Plant Overview

2.1.1 Plant & Root Physiology

The basic plant physiology is composed of three organs: the stem, the root and the leaves. The stem grows up above soil and supports leaves while the root grows underground to anchor and absorb nutrients and water. The leaves undergo photosynthesis and grow out from the nodes along the stem (Taiz & Zeiger, 2014).

The roots have nodules and hairs that have essential roles in the water and nutrient uptake of the plant. Indeed, not only does root hair help better anchor the plant in the soil, but it increases the surface area of the plant root, which enhances water absorption by passing between soil particles. The xylem is a vascular tissue in the stem and root (not in the root hair) that transports water and nutrients from the root to the rest of the plant. Therefore, by having root hair absorb most of the water and nutrients, the chance of pathogens entering the xylem and spreading the disease throughout the plant is limited. Moreover, root hair increases interaction between the plant and beneficial microorganisms such as mycorrhizal fungi. They form a symbiotic relationship that points to root hair in nutrient rich areas when the plant experiences nutrient deficiency. Thus, root hair will grow longer to reach those rich nutrient areas (Grierson & Schiefelbein, 2002; Petruzzello, 2022; Taiz & Zeiger, 2014).

Furthermore, root hair forms nodules around rhizobia to absorb nitrogen fixed by those bacteria from the atmosphere. This is another symbiotic relationship that enhances root growth and nutrient absorption (Doyle, 1998; Taiz & Zeiger, 2014).

The root physiology of lettuce plants are shown in figures 1 and 2 below. They have a main taproot and secondary roots, meaning that the primary root grows like an anchor, deep in the soil and smaller roots branch out from it. As the taproot grows longer, new roots grow from the sides, therefore, making it difficult to be pulled out (Li et al., 2018; Neumann et al., 2014; Taiz & Zeiger, 2014).

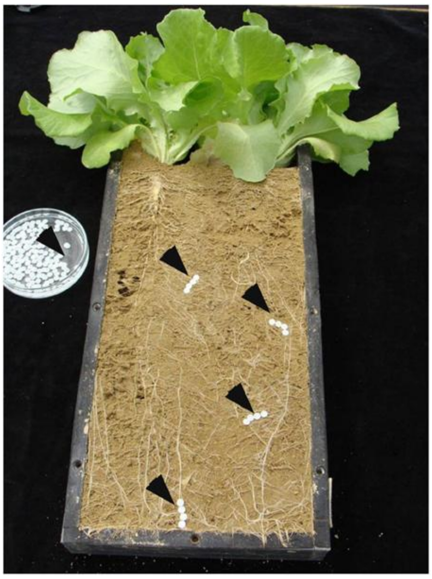


Figure 1. Lettuce plants grown on loess loam in a window of a minirhizotron (rhizobox)(Neumann et al., 2014).

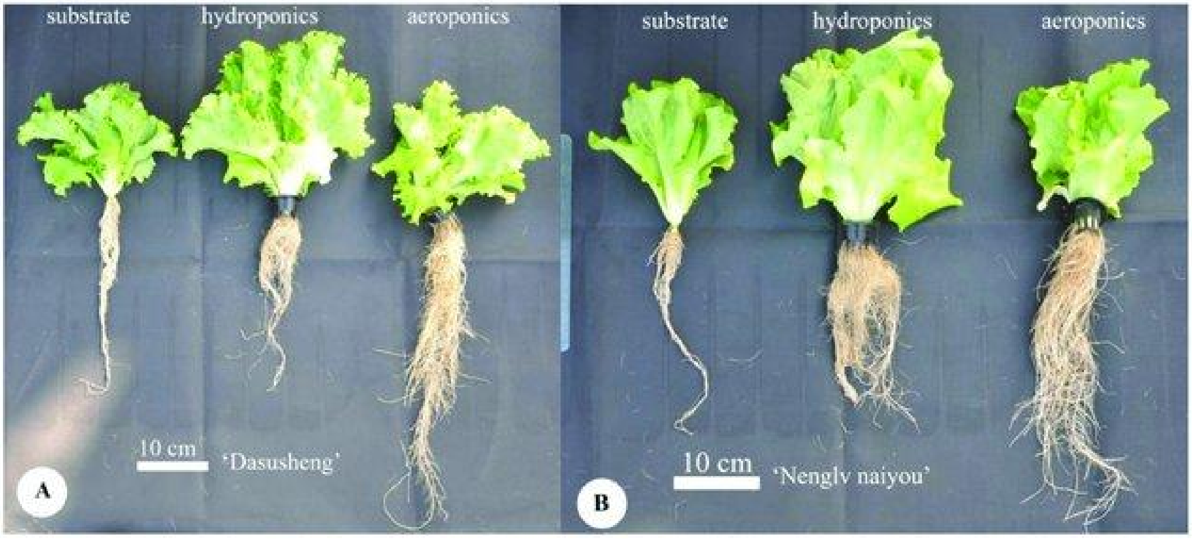


Figure 2. Lettuce plants grown in substrate, hydroponics, and aeroponics (Li et al., 2018).

2.1.2 Plant Requirements & Nutrient Uptake

Plants require several macro and micro nutrients in order to attain healthy and nutrient rich produce. The distinction between macro and micro nutrients refer to the amount they are taken up by the plant. Macronutrients constitute a majority of the plant's structure and are about ten times more present than micronutrients. Nitrogen (N), phosphorus (P), potassium (K), calcium (Ca), sulphur (S), and magnesium (Mg) are inorganic minerals the plant must absorb along with organic elements, such as carbon (C), hydrogen (H), and oxygen (O), which altogether represent the macronutrient demand (Grusak, 2001). The currently identified micronutrients are as follows: iron (Fe), zinc (Zn), manganese (Mn), copper (Cu), boron (B), chlorine (Cl), molybdenum (Mo) and nickel (Ni). Other potential micronutrients, such as cobalt (Co), sodium (Na), silicon (Si), selenium (Se), iodine (I) and vanadium (V), have shown to be beneficial and essential in some plant varieties, but have yet to be widely established. Many other elements are found within plants, but it is theorised that these are absorbed non-selectively and present little to no benefit for the plant. Absence of critical nutrients will result in plants "unable to complete either the vegetative or reproductive stages of its life cycle", e.g. lack of flowering, fruiting, etc. (Grusak, 2001). Many of the required nutrients are absorbed as ions and depend on different mechanisms within the plant to be absorbed.

Nitrogen can be absorbed as ions through ammonium and nitrate, while nitrite is chemically reduced to ammonium within the plant before synthesis of organic molecules.

Alternatively, nitrogen is available as atmospheric nitrogen (N^2) through bacterial processes that fixate the nitrogen. This element is a significant constituent in the synthesis of amino acids and proteins within the plant, and represents a major structural component of chlorophyll.

Potassium is not metabolised by the plant, but is rather absorbed and remains as a K^+ ion. It is abundantly present in the cytoplasm of cells along with other anions. This serves to create electrochemical gradients within the plant and regulate several processes to ultimately determine cell extension and growth (Grusak, 2001). Calcium is absorbed as an ion (Ca^{2+}) and is employed as a signalling chemical. Calcium is responsible for the activation of several enzymes in plant structure, which in turn regulates many cellular processes such as metabolism (Grusak, 2001). Magnesium is available to plants as an ion (Mg^{2+}) and also plays a role in the construction of chlorophyll like nitrogen. Its other purposes involve promoting several enzymes and is essential for ATP synthesis (Grusak, 2001). Phosphorus is crucial for metabolism through synthesis of ATP and attaching phosphate groups to sugars which are essential for cellular respiration and photosynthesis. It is commonly absorbed as orthophosphate anions, $(H_2PO_4)^-$ and $(HPO_4)^{2-}$, and is a structural component of macromolecules and amino acids (Grusak, 2001). Organic macronutrients, such as oxygen, carbon, and hydrogen, are readily available through either the atmosphere, or acquired through hydrogenous compounds and dissolved gases in solutions. Deficiencies in these compounds are rare as they are abundant, with the exception of dissolved oxygen in the solution needed for respiration in the rootzone (Morard & Silvestre, 1996). These components are used extensively structurally and in metabolism. Iron and sulphur micronutrients are employed to regulate redox reactions in the system and construct proteins. Iron is also required in the synthesis of chlorophyll. Sulphur is more crucial in metabolism and can be used to detoxify hazardous components in the plant (Grusak, 2001). Sulphur can be absorbed by the plant either through the atmosphere as SO_2 or through the root system as an ion SO_4^{2-}. Iron is absorbed as an ion, Fe^{2+} and Fe^{3+}, but exists primarily as Fe^{3+}. Different plant species have different mechanisms for absorbing these two ions.

Deficiencies of essential nutrients often characterise themselves in discoloration or lesions in the leaves of the plants. Deficiencies in nitrogen, iron, and magnesium are associated with the yellowing of leaves as these compounds contribute to the production of chlorophyll. Compounds related to metabolism and nutrient transport (phosphorus, potassium and sulphur) cause necrosis in the tip of leaves, also known as tip burn. Calcium deficiencies are also identified by tip burn, however, calcium is not as active or easily transported through plant systems as potassium ions are. As a result, tip burn will occur in newly developed leaves due to calcium deficiencies while potassium deficiencies appear on mature leaves first. Other micronutrient deficiencies from a lack of zinc, copper, and manganese will reduce enzyme activity and result in dressed metabolism, causing similar lesions to calcium, phosphorus, potassium and sulphur deficiencies (Grusak, 2001). Lack of dissolved oxygen in the root zone will cause a decrease of cellular respiration in the roots. Consequently, root rot sets in and appears in the form of root browning (Morard & Silvestre, 1996). This will hinder the uptake of any nutrients in the water because the roots lack the required energy. Excess nutrients also hinder plant quality because too much of one nutrient will promote the formation of toxic compounds. The presence of these nutrients in soil is determined by soil and water properties, while in hydroponic cultures the available nutrients can be controlled through the addition of salts.

Hoagland's solution is the most common mixture used in soilless cultures, at least scientifically, and was first developed in 1933 by Hoagland and Snyder (Meselmani, 2022). This solution is popular because it contains every essential nutrient needed for plant growth and is applicable to a wide variety of plants. The solution has been modified several times since conception, mainly to add iron chelates and other micronutrients (Meselmani, 2022). Other compositions of nutrient solutions exist such as Hewitt, Cooper and Steiner solutions, however, these solutions are not as encompassing as Hoagland's (Meselmani, 2022). A breakdown of each solution and their components can be found in figure 3 below.

Element	Form taken up by plants	Hoagland & Arnon	Hewitt	Cooper	Steiner
	mg L^{-1}				
Nitrogen	NH_4^+, NO_3^-	210	168	200–236	168
Phosphorus	HPO_4^{-2}, $H_2PO_4^-$	31	41	60	31
Potassium	K^+	234	156	300	273
Calcium	Ca^{2+}	160	160	170–185	180
Magnesium	Mg^{2+}	34	36	50	48
sulfur	SO_4^{2-}	64	48	68	336
Iron	Fe^{2+}, Fe^{3+}	2.5	2.8	12	2–4
Copper	Cu^{2+}	0.02	0.064	0.1	0.02
Zinc	Zn^{2+}	0.05	0.065	0.1	0.11
Manganese	Mn^{2+}, Mn^{4+}	0.5	0.54	2	0.62
Boron	H_3BO_3, BO_3^-, $B_4O_7^{2-}$	0.5	0.54	0.3	0.14
Molybdenum	MoO_4^{2-}	0.01	0.04	0.2	Not considered

Figure 3. Nutrient solutions suggested by various scientists (Meselmani, 2022)

As seen in figure 3, Hoagland's solution contains relatively large amounts of nitrogen and potassium, which may be excessive for low nutrient demand species. Although individual plant species have unique nutritional demands and absorption rates, Hoagland's solution can be used as long as the electric conductivity, pH, and nutrient availability remains within the plant's bounds. Often, solution strength is reduced (quartered or halved) for less demanding plants like lettuce, while large plants, including tomatoes and bell peppers, are better suited for full strength (Meselmani, 2022). This is done to avoid excessive salt accumulation and potential toxicity in plants. Nutrient imbalances in the solution can cause precipitation and affect uptake through different antagonism and synergistic structures within the plant (Meselmani, 2022). Different ionic compounds are absorbed by the plant at different rates. Nitrogen, phosphorus, potassium and manganese sources are actively transported and quickly removed from the solution, while calcium and boron sources are passively absorbed (Bugbee, 2004). Other nutrients such as magnesium, sulphur, iron, zinc, copper and molybdenum have intermediate uptake and removal (Bugbee, 2004). Furthermore, the rates at which nutrients are absorbed are subject to change in response to a plant's growth stage. For example fruiting plants often require less calcium and magnesium (Bugbee, 2004). If the solution is refilled without addressing potential nutrient imbalances, the system will encounter a build up of passively absorbed nutrients and shifts in pH. The normal operating range for plants is 5.5 to 6.5 pH, although it can go as low as 4 pH with no major consequences depending on the species (Meselmani, 2022). The pH plays a pivotal role in promoting dissolution and precipitation. Dissolved gases, mainly carbon dioxide, also have an effect on precipitates and will form carbonates out of calcium and magnesium ions (Meselmani, 2022). A solution with a pH above 7 will begin to precipitate iron, zinc, copper, nickel and manganese as hydroxides (Meselmani, 2022). Correction of the solution can be done using acid-containing nutrients, such as carbonic, formic, citric and acetylsalicylic acid (Meselmani, 2022). However, this may cause toxicity from excessive nutrients, and thus a mixture of acids (HNO3, H3PO4, and H2SO4) can be used for better balance instead (Meselmani, 2022). Naturally, hydroponic solutions are poor buffers and pH is subject to rapid changes, thus it is imperative to monitor pH and electrical conductivity to identify issues.

2.1.3 Root Health and Disease

Bacteria, fungi, and pests are the culprits of a variety of health issues and diseases in *Lactuca sativa* L. (lettuce), including Valley Heart romaine (Raid, 2004). Lettuce that is grown hydroponically is not at risk for soil-borne pathogens, however, it is not exempt from all diseases either. Some common plant health issues that arise during the production of lettuce in indoor farms are described below.

2.1.3.1 Downy Mildew

Downy mildew is caused by *Bremia lactucae*, a type of parasitic fungus that develops under cool (about 20℃, but may vary between 5-24℃) and wet conditions (Raid, 2004). It is noticeable on the upper and lower leaf surface with the early signs being light green lesions. As the disease progresses, the lesions become more yellow (chlorosis) and angular, and plant tissues eventually die (necrosis). Lettuce can be affected by downy mildew at any point in its development, though seedlings in particular are susceptible to stem tissue discoloration and fatal infections (Davis et al., 1997).

Managing and minimising the spread of downy mildew can be challenging because *B. lactucae* spreads through air particles (Raid, 2004). Ideally, lettuce cultivars that are resistant to this pathogen should be grown, but genetic variants could still defeat more resistant plants. However, other preventative measures including the use of fungicides and limiting the amount of water through proper irrigation practices can be taken. Furthermore, sporulation can be inhibited by lowering humidity levels and exposing sporangia to bright light conditions (Davis et al., 1997).

2.1.3.2 Powdery Mildew

Powdery Mildew is another fungal disease caused by the parasite *Erysiphe cichoracearum*, and it targets the upper and lower surfaces of the leaves, especially older leaves (Raid, 2004). The most obvious indication of the disease is a white and powdery layer of spores, however, black spotting on the tissues and a "brown, scorched appearance" of the leaves are other possible indicators. Powdery mildew that affects seedlings and young plants may restrict their growth and development, thus reducing overall yield. However, applying sulphur at the first sight of disease can prevent Powdery Mildew from spreading. Furthermore, knowing that *E. cichoracearum* favours a relative humidity between 95% to 98% and a temperature of 18℃, measures to limit humidity can be taken to minimise risks of Powdery Mildew.

2.1.3.3 Grey Mould

Greenhouse farming is more susceptible to grey mould, another fungal-related health issue, than traditional farming, especially post-harvest (Raid, 2004). The fungus *Botrytis cinerea* causes lettuce tissues to look saturated with water before developing grey or brown lesions. If the growing conditions are ideal for sporulation, infected areas may appear fuzzy. The ideal temperature for this pathogen is between 20 and 25℃, but it is possible for the fungi to develop at temperatures between -2 and 25℃.

Measures to prevent the development of grey mould include using fungicides, adequately ventilating the growth space to limit humidity, and avoiding excessive watering. During the post harvest stage, storing the lettuce at cool temperatures of 1.1 to 2.2℃ and under increased carbon dioxide conditions will create an unfavourable environment for grey mould.

2.1.3.4 Pythium Root Rot

Pythiaceae are categorised as aquatic fungi, and therefore, present risks for hydroponic farming (Blancard et al., 2006). Species that cause root rot include *Pythium aphanidermatum*, *Pythium uncinulatum*, *Pythium myriotylum*, *Pythium irregulare*, *Pythium dissotocum*, and *Pythium polymastum*. Pythiaceae develop in cool, wet environments with the optimal temperature being between 15 to 20°C. However, Pythium can develop under a range of temperatures from between 2°C and 42°C, depending on the species. The symptoms of Pythium root rot in hydroponically-grown lettuce are root browning, inhibited growth, wilting, and permanent yellowing of the leaves.

These fungi thrive in aqueous environments and spread very easily in water, and they can sometimes spread through air via splashing. To minimise the risk of Pythium propagation, humidity and temperature must be controlled by adequate ventilation, infected plants should be identified and removed immediately, and fungicides may be added to the nutrient solution in low doses.

2.1.3.5 Aphids

Aphids are a common type of pest that easily transmit diseases and viruses to lettuce through their migration and feeding patterns (Davis et al., 1997). There are two forms of aphids, apterae and alatae, with the latter having wings and being more problematic because of their increased mobility. Although there are more than 250 species, the ones of primary concern are *Acyrthosiphon lactucae*, *Aphis coreopsidis*, cowpea aphid (*A. craccivora)*, melon or cotton aphid (*A. gossypii*), glass-house potato or foxglove aphid (*Aulacorthum solani*), sowthistle aphid (*Hypermyzus lactucae*), potato aphid (*Macrosiphum euphorbiae*), shallot aphid (*Myzus ascalonicus*), violet aphid (*Myzus ornatus*), green peach aphid (*Myzus persicae*), and lettuce aphid (*Nasonovia ribisnigri*).

Aphids have “strawlike mouthparts” which allow them to probe the leaf surfaces and/or penetrate the phloem (Davis et al., 1997). Aphids will become infected with non-persistent viruses if they probe only the leaf surface, however, probing of the phloem may result in persistent viral infections. Infected aphids may transmit viruses, such as cucumber mosaic virus (CMV) and lettuce mosaic virus (LMV), to other lettuce plants during probing via their saliva.

2.1.3.6 Thrips

Thrips are a less common vector of lettuce pathogens than aphids and they are responsible for transmitting tomato spotted wilt virus (TSWV) (Davis et al., 1997). The most common species include tobacco thrips (*F. fusca*) and onion thrips (*Thrip tabaci*). Thrips spread TWSV by inserting eggs into plant tissue layers, which eventually hatch and feed off of the plant, causing eventual damage. Immature thrips that feed off of infected plants may catch the virus and remain infected for the entirety of their lifespan. Infected plants can be treated with insecticides.

2.1.3.7 Whiteflies

Whiteflies are another vector of pathogens that cause lettuce infectious yellows virus (LIYV) and lettuce chlorosis virus (LCV) (Davis et al., 1997). Two species of concern are *Bemisia tabaci* and *B. argentifolii*. Whiteflies lay eggs on plants, which hatch after about 4 to 5 days. Initially, nymphs are able to crawl, then they become sessile, and once they finally reach their full adult form, they can fly for kilometres. Whiteflies are often found feeding or laying their eggs at the bottom of leaves.

2.2 Deep Flow Technique (DFT) in Hydroponics

2.2.1 Open vs Closed Loop Systems

Soilless culture systems may be open cycle in which nutrient solution is drained and discarded, or closed cycle, wherein the solution is collected and recycled (see fig. 4). Evidently, a closed loop system is the more environmentally friendly and water efficient method. Unfortunately, closed loop systems pose many challenges to the hydroponic grower, such as high initial investment, rapid spread of pathogens, and the accumulation of phytotoxic metabolites or organic matter in the recirculating nutrient solution (Maucieri et al., 2019). Despite closed loop systems being mandatory in some European countries, the majority of hydroponic farms remain open cycle. The buildup of salts in irrigation water is a major challenge since it causes an accumulation of ions that the plants cannot fully absorb (Maucieri et al., 2019). Salt accumulation may be addressed by adding a desalination procedure to the closed loop (Goddek & Keesman, 2018).

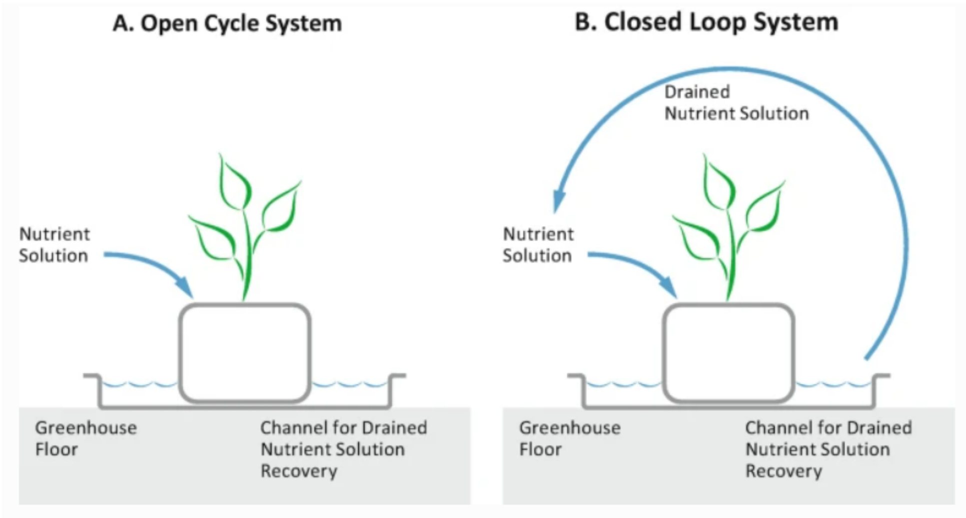


Figure 4. Scheme of open cycle (left) and closed cycle (right) (Maucieri et al., 2019)

2.2.2 Deep Flow Technique (DFT)

In deep flow technique, plants are floating on raft panels or boards in reservoirs containing 10-30 cm of nutrient solution as illustrated in figure 5 (Maucieri et al., 2019). Different installations will have varying depths of nutrient solution, oxygenation and water recirculation. DFT is known for being low-cost and easy to maintain. Minimal nutrient solution corrections are needed, especially in fast growing crops like lettuce, wherein the nutrient solution only needs to be replenished at the end of the cycle and only the oxygen levels need to be maintained around 4-5 mg/L (Maucieri et al., 2019). Moreover, the benefits of using DFT is that the plants can easily float on the water surface without a fixed support. Additionally, DFT is great for water thirsty crops such as lettuce (Soto, 2023). Plus, if a power outage happens or the water pump is down, the plants will have plenty of water to survive. Furthermore, even though DFT are deep to hold a lot of water, the system is small and light enough to be stacked for vertical farming (Soto, 2023).

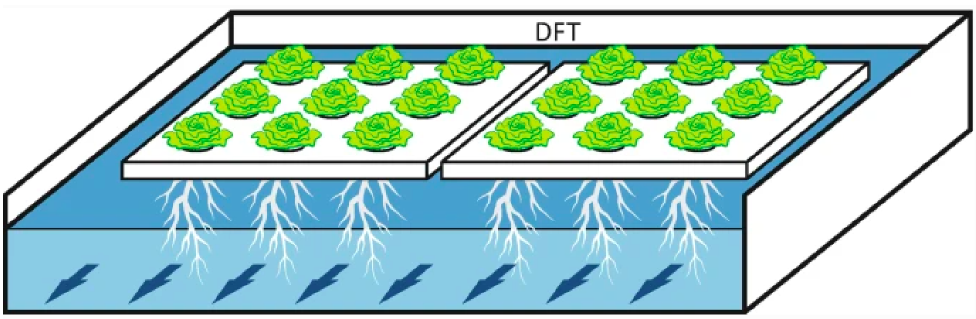


Figure 5. Example of DFT with floating panels (Maucieri et al., 2019)

2.2 Image Analysis & Deep Learning

The purpose of morphological image analysis is to identify an object and derive characteristics based on visual data. In the context of roots, image processing will identify the root from the background and other interferences, and then determine characteristics such as root diameter, discoloration, length, etc. The computer sees images as an array of numbers correlating to each pixel with a distinct value corresponding to their colour. In order to use this information, machine learning and deep learning techniques must be used to process raw data and properly identify objects.

Classical approaches employed machine learning in which an algorithm is created, then the machine learns to identify relationships with this algorithm (Soille, 2004). The basic operation of this technique involves filtering images and feeding them into an algorithm where relationships are formed and validated through testing (Soille, 2004). Many different forms of this approach are used and differ in their targets and structure, but operate similarly (Huisman et al., 2021). Nevertheless, this approach struggles to learn quickly from new tasks, and requires a large source of data and heavy computational power to achieve robust results (Hospedales et al., 2021). However, more comprehensive models have been developed, such as meta-learning, where the program "learns to learn" (Huisman et al., 2021). This method employs prior knowledge to facilitate and accelerate the process of model generation (Hospedales et al., 2021). Meta/deep learning, contrary to machine learning, allows the machine to modify algorithms to alleviate computational stress and improve data usage (Hospedales et al., 2021). This technique is also more aligned with human learning, where results are improved in lifetime and evolutionary timescales (Hospedales et al., 2021). This is accomplished through the employment of inner and outer tasks: inner tasks operate a single task and try to create associations, while outer tasks gather data on inner tasks to modify the inner tasks and operate multiple tasks (Huisman et al., 2021). The inner task can also be referred to as base learning, similar to classic machine learning, and solves the problem at hand, such as image classification (Hospedales et al., 2021). Outer tasks collect metadata on the performance of inner tasks, such as accuracy or speed. The outer tasks then modify inner tasks to improve the performance of outer tasks (Hospedales et al., 2021). The introduction of these parameters can facilitate the process of many similar techniques, such as transfer learning, domain adaptation and domain generalisation, continual learning, multitask learning, etc (Hospedales et al., 2021). For example, in transfer learning where the algorithm attempts to transfer knowledge from a data set, it is trained on to a new distinct data set, the outer task can serve to mitigate variation and act as reference to performance (Huisman et al., 2021). Currently, there are three main categories of meta-learning: metric, model and optimization of which there exist many systems employing each technique, but only principles will be discussed (Huisman et al., 2021).

Contrary to meta-learning principles, metric based meta-learning does not change its algorithm during execution, and is a form of non-parametric learning (Huisman et al., 2021). It is still classified as meta-learning because this method employs prior knowledge from other data sets to "learn" new tasks quicker (Huisman et al., 2021). This method operates by comparing two inputs and determining their similarity to match them to a corresponding output from known inputs and outputs, and aims to improve the outer task (Hospedales et al., 2021). Consequently, this program is typically used for classification purposes with small datasets. Larger datasets may require too much computation to be feasible when creating similarities (Huisman et al., 2021). Advantages of this system include its ability to rapidly create models and the conceptual simplicity of its design, making it convenient and adjustable (Huisman et al., 2021). On the other hand, a drawback is that it has poor adaptability when targets stray too far from the dataset used to train the model, and thus requires supervision (Huisman et al., 2021).

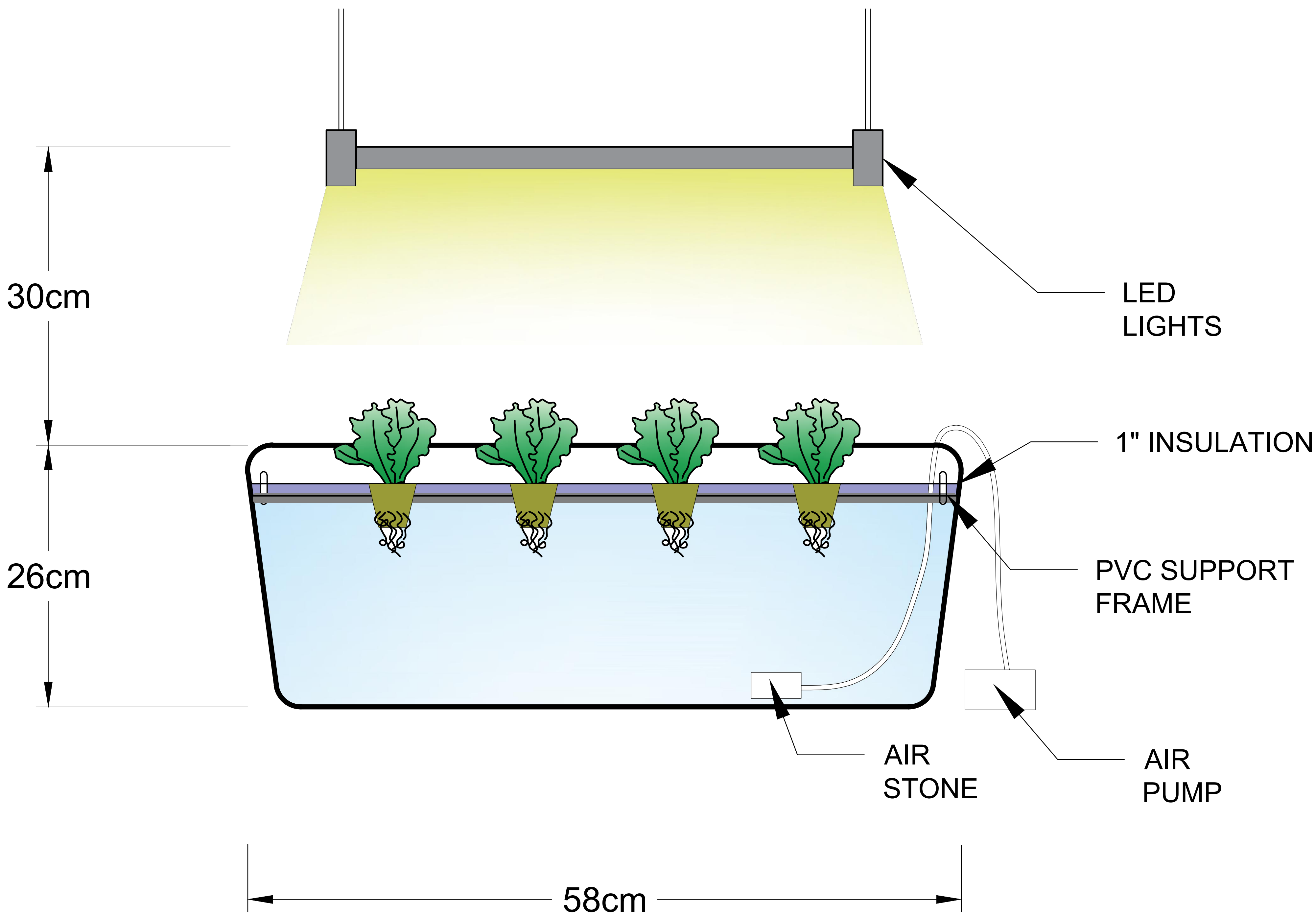
Model based meta-learning, also referred to as black box, focuses on the internal structure of data, which is modified at each step of the process (Huisman et al., 2021). The program attempts to predict a target by creating an asymptomatic model to fit the data (Hospedales et al., 2021). As a result, these systems must feature a memory component as previous data is constantly used to update the algorithm with the inner and outer tasks being closely coupled (Hospedales et al., 2021; Huisman et al., 2021). Similarly to metric, datasets of example train and test data are used to train the program. Unlike metric, the user can determine the internal dynamic of the system rather than simple comparison (Huisman et al., 2021). Furthermore, the internal structure used to predict future samples is modified and improved by the algorithm, providing additional flexibility and adaptability (Huisman et al., 2021). Overall, model-based learning can be applied to a larger range of applications than metric, but still struggles to predict distant data out of its domain (Hospedales et al., 2021).

Optimization-based models are specifically designed for fast learning and often perform bi-level optimization operations on the internal structure of the algorithm (Huisman et al., 2021). As the system optimises the internal functions, the metadata is stored and used to increase the optimization performance (Hospedales et al., 2021). This is done to reduce the amount of steps needed to reach satisfactory validation levels (Hospedales et al., 2021). This process behaves similarly to classical machine learning (gradient learning), but differs in its ability to focus on several tasks, which allow it to learn new tasks faster (Huisman et al., 2021). Similar to the challenges faced in machine learning, this process is computationally heavy as every task assigned is optimised and modified during operation (Huisman et al., 2021).

For the purposes of our design, a combination of model and metric based learning is used where the model attempts to minimise error loss between each training session. This is done to avoid heavy computations and large datasets while still keeping the model effective. Since only inputs and outputs are used for analysis, a black box approach seemed appropriate. An optimization based approach was deemed unnecessary due to limited categories. More specifically, “resnet” structure is used which applies nonlinearity to intermediate functions in order to increase layer capacity as well as skip certain layers during training to avoid vanishing gradient issues (He et al., 2015). Overall, this allows us to have the complexity and accuracy of deeper neural networks without a massive dataset or heavy computation.

3. Design

3.1 Final Design Drawings



AUTHORSHIP:

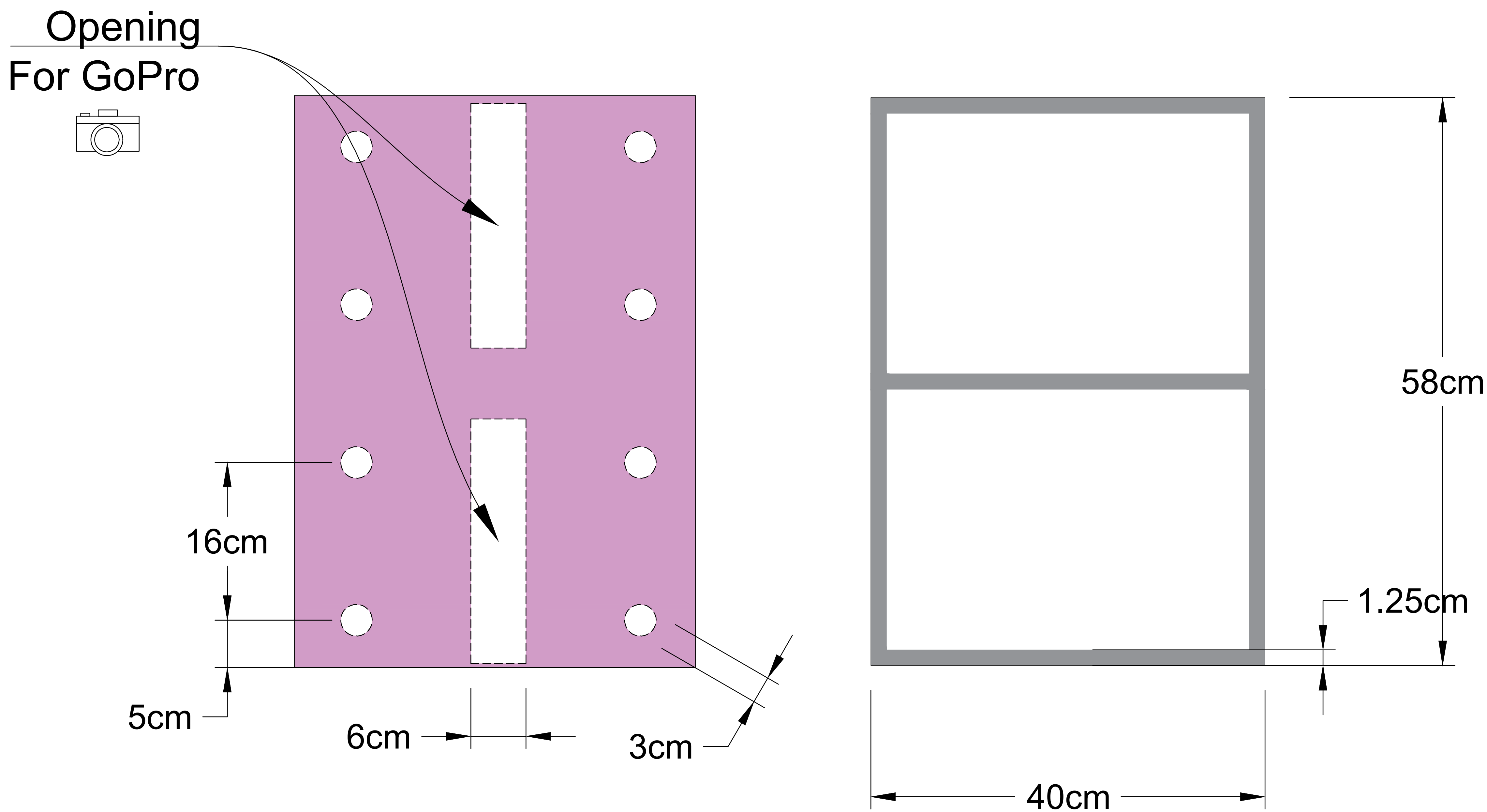
ABIGAIL CHOINIÈRE
KYLE GEDDES
JENNYFER LIANG
EMILY LAFOND

Department of
Bioresource
Engineering
McGill University

project / projet	Root Monitoring of Valley Heart Lettuce in Hydroponics Systems
drawing / dessin	CONTROL SETUP
Scale / Echelle	1:200
	DIMENSIONS IN CM
Date / Date	April 20, 2023
Student No. / No d'étudiant	
Drawn By / Dessiné par	**CHOINIÈRE Abigail**
Drawing no. / No. du dessin	**A-1.0**

11X17 (431x279) W2021

TOP VIEW



AUTHORSHIP:

ABIGAIL CHOINIÈRE
KYLE GEDDES
JENNYFER LIANG
EMILY LAFOND

Department of Bioresource Engineering
McGill University

project / projet	Root Monitoring of Valley Heart Lettuce in Hydroponics Systems
drawing / dessin	FRAME AND STYROFOAM DESIGN TOP VIEW
Scale / Echelle	1:200
	DIMENSIONS IN CM
Date / Date	April 20, 2023
Student No. / No d'étudiant	
Drawn By / Dessiné par	**CHOINIÈRE Abigail**
Drawing no. / No. du dessin	**A-1.1**

3.2 Calculations

3.2.1 Dilutions

Solution	Quantity (ml)
KNO_3	5
$CaNO_3$	5
$MgSO_4$	2
$KHPO_4$	1
Solution B	1
Solution C	1

Table 1. Proportions of solutions added to 1 L (1000 mL) of water

Total Volume= (1000 +5 +5 +2 +1 +1 +1) mL = 1015 mL

% KNO_3= 5/1015 x 100 = 0.5 %

% $CaNO_3$= 5/1015 x 100= 0.5%

% $MgSO_4$= 2/1015 x 100= 0.2%

% $KHPO_4$= 1/1015 x 100= 0.1%

% Solution B= 1/1015 x 100= 0.1%

% Solution C= 1/1015 x 100= 0.1%

% H_2O= 1000/1015 x100 = 98.5%

3.2.2 Energy Requirements

Energy consumption (per week):

Lights: 300W x 17h x 7d = 35700 Wh

GoPro + GoPro light: 3.885 Wh + 11.36 Wh = 15.245 Wh

Airstones: 3W x 24h x 7d= 504 Wh

Raspberry pi: 4.8W x 24h x 7d= 806.4 Wh

Total energy consumption per week: 27.025645 kWh

Price of energy in Quebec: 6.08 cents per kWh

Total price of energy: 6.08c/kWh x 27.025645 kWh = 164.31 cents = $1.64

3.2.3 Data / storage space

Image file size: 2Mb

Sd card storage: 64 Gb

Max images on card: (64Gb x 1000 Mb/Gb)/2 = 32000 images per card

3.3 Materials & Costs

Item	Cost (CAD) before tax	Paid (CAD) before tax	Supplier
4 LED Lights	79.88	0	Lefsrud Lab
2 Load Sensors	37.98	37.98	Amazon
Digital Timer for Lights	25.99	0	Lefsrud Lab
Stainless Steel Wire	12.64	12.64	Home Depot
8 Carabiners	14.56	14.56	Home Depot
PVC	~$0.81/sq.ft	0	Mac Shop
4 Styrofoam Sheets	51.96	0	Mac Shop
2 Airstone Kits (stones, pumps, tubing, accessories)	41.98	41.98	Amazon
GoPro	~ 400	0	Abigail
32 Rockwool Cubes	22.42	0	Lefsrud Lab
64 Valley Heart Lettuce seeds	5.30	0	Lefsrud Lab
5 Bins	49.95	0	Lefsrud Lab
Solution Chemicals	<u>Solution A</u> KNO3: 9.99 CaNO3: 8.99 MgSO4: 5.99 KHPO4: 11.99 <u>Solution B</u> H3BO3: 15.75 MnCl2: 19.00 ZnSO4: 14.99 CuSO4: 56.67 Na2MO4: 36.99	0	Lefsrud Lab

	Solution C Na EDTA: 88.23 FeSO4: 32.01		
Camera Light Attachment	38.99	38.99	Amazon
Battery Packs	65.98	65.98	Amazon
SD Card (64GB)	15.38	15.38	Amazon
Temperature Sensors	18.65	18.65	Amazon

Table 2. Materials Purchased and Costs

4. Methodology

4.1 Plant Growth & Care

The initial stage of the project involved planting the seedlings and nurturing them until they were transplanted to the complete hydroponic system. Thirty-six rockwool cubes were placed in a single growing tray and 2 seeds were inserted into each rockwool cube, for a total of 72 seeds. Our design only required 32 rockwool cubes (8 per bin), therefore, we had 4 extra cubes as backups. Then, water was added to the growing tray and the seedlings were placed in the pilot chamber to germinate for 3 weeks. Every two days, more water was added to the tray for about two weeks. About halfway through the germination period, nutrient solution was introduced to the plants.

4.2 Assembly of Hydroponics Setup

The hydroponic system involved the construction, assembly and preparation of many components: assembling the LED lights, constructing PVC support frames, drilling holes in the styrofoam sheets, conceptualising and testing the weighing system, calibrating the Raspberry Pi and sensors, sanitising the bins and ordering additional materials (air stones, load sensors, etc…).

The LED lights were suspended from the ceiling using thin wires and placed directly above the four bins. A light timer was set to allow for 17 hours of light and 7 hours of darkness per day. The light intensity was adjusted to the maximum setting on the dial.

The PVC frames were constructed in the shop on campus by sawing a large sheet of PVC into smaller rectangular pieces (See Drawing A1.1). The pieces were then assembled together into 4 frames using PVC glue and primer. The styrofoam sheets were also measured, cut, and drilled with holes in the shop. The styrofoam sheets were attached on top of the frames using tape and thin metal wires.

The weighing system is composed of two load sensors, a metal support frame, carabiners, and thin steel wires. Four small holes were drilled into each PVC frame and styrofoam sheets, two on each end. Thin steel wires were passed through the holes and loops were created at the ends. The load sensors were attached to the metal support frame using carabiners. Then, the wire loops were attached to the hanging hooks on the load sensors.

The raspberry pi was assembled in the pilot chamber along with all its sensors. Relative humidity, air temperature, and water temperature sensors were all connected to a sensor box which was connected to the pi. This would reduce the amount of wires connected directly to the pi and reduce accidental plug outs. The raspberry pi is then connected to a power supply and screen monitor along with pins from the sensor box in the proper configuration. First, the date is set on the raspberry pi to ensure measurements are properly identified. Then previous data files are cleared from the system and uploaded to the laptop for further analysis. After this the script can start by typing a command into the raspberry pi. The script would then record measurements from the sensors every 6 minutes. Data from the system would be collected every imaging session and the raspberry would be restarted.

Other miscellaneous tasks included ordering hydroponic accessories, such as air stones and pumps, and sanitising the bins with bleach to eliminate any contaminants present.

4.3 Stressing the Plants

The plants were left in the hydroponic systems for two weeks to adapt to their new environment to avoid causing unwanted stress on the plants, and therefore faulty data. Therefore, each bin possessed all the components to ensure the plants would thrive, including an air stone and nutrients. Following the two weeks of rest, the stresses were applied as planned. Bin A remained the control system. Bin B had 100% of its true leaves cut. Bin C was emptied and filled with a calcium deficiency solution. Bin C had its air stone removed to create an oxygen deficiency. No additional water was added to any of the bins during the following weeks of testing. Moreover, the leaves grew back rapidly in Bin B and the roots were still white (i.e., healthy), so 100% of its true leaves were cut a second time, one week before the experiment ended.

4.3 Imaging

The imaging procedure involved submerging a GoPro with a light attachment underwater to image the roots. Prior to imaging, slits were made in each styrofoam tray to act as an opening for the GoPro to pass. Furthermore, pink duct tape was adhered to the bottom side of the styrofoam to contrast with the white roots. The camera settings were adjusted to capture photo bursts at a speed of 1 second. Once the GoPro was submerged, each plant was imaged for about 30 seconds before rotating the camera clockwise to capture the next plant. This technique was repeated for the other three bins in the following order: Bin A, Bin B, Bin C, Bin D. Imaging was performed twice a week, Monday and Thursday, for about four weeks. After each session, the images were downloaded to a computer, uploaded to a shared drive, and organised by date into their respective folders. It was important to sort the images the same day they were taken to organise them prior to deep-learning analysis.

4.4 Image Analysis

Before image analysis, more organised datasets were needed in which the folder would contain the output label needed for the plants. Training and validation sets were created from the stored images and sorted as either healthy or unhealthy. After this, a portion of the data, around 20%, was used for validation while the rest would be used for the training dataset. These folders were then uploaded to kaggle, a programming platform, as two distinct datasets so that they can be easily managed.

For image analysis, several fast AI libraries were imported into the kaggle platform using python. Many of these libraries provided data management and optimization tools as well as the resnet structure that will be used to create the model. The imported libraries are pictured below.

```
import socket,warnings
try:
    socket.setdefaulttimeout(1)
    socket.socket(socket.AF_INET, socket.SOCK_STREAM).connect(('1.1.1.1', 53))
except socket.error as ex: raise Exception("STOP: No internet. Click '>|' in top right and set 'Internet' switch to on")
```

```
import os
import random

import numpy as np # linear algebra

import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import matplotlib.pyplot as plt # plotting
import matplotlib.image as mpimg
```

```
import os
iskaggle = os.environ.get('KAGGLE_KERNEL_RUN_TYPE', '')
```

Figure 6. Imported Python Libraries

A data block was used to load and parametrize training data into the image analysis model. The data block was set to accept images as inputs and sort these into categories as outputs. The model uses the parent folder names as categories so it is crucial to appropriately name these folders as healthy and unhealthy. Additionally, input images are squished and resized into smaller images, 192 x 192 pixels, in order to reduce computational times and allow for additional fine turning. The data block itself will also set aside some data to be used as validation so that error can be computed in between training sessions. An image of the data block code is included below where these functions can be seen implemented.

```
dls = DataBlock(
    blocks=(ImageBlock, CategoryBlock),
    get_items=get_image_files,
    splitter=RandomSplitter(valid_pct=0.2, seed=42),
    get_y=parent_label,
    item_tfms=[Resize(192, method='squish')]
).dataloaders('/kaggle/input/training-data', bs=32)
```

Figure 7. Data Block Code

The next step in the process was to load the data block into the visual learner, select our desired image analysis structure, determine metric used to train, and optimise the model using fine tuning. The code for this process is included below and will be explained in more detail.

```
learn = vision_learner(dls, resnet18, metrics=error_rate)
learn.fine_tune(3)
```

Figure 8. Model Learner Code

Despite being relatively simple code, this is all that is needed to create the model with imported libraries and the properly configured datablock. Here, resnet18 is being used in which resnet is the convolutional neural network used and the number refers to how many layers are being used. The error rate between modelled outputs and data block created validation sets were used as the metric that the model would reduce. Fine tuning is the process of the model being trained again using layers previously created and adjusting weights and biases for each layer to create a more robust model. Three fine tuning sessions are used as error rate no longer decreases after two sessions but an additional session was still added to reduce training and validation loss. Results from training the model are included below with runtimes, loss values and error rates.

epoch	train_loss	valid_loss	error_rate	time
0	1.047571	0.733850	0.320000	01:13

epoch	train_loss	valid_loss	error_rate	time
0	0.529877	0.482103	0.280000	01:12
1	0.384857	0.408453	0.140000	01:12
2	0.316591	0.259644	0.140000	01:12

Figure 9. Model Accuracy and Train Times

In total, the model took just under five minutes to train and achieved a minimum error rate of 14% which could be attributed to improper sorting of images. This was especially apparent in the unhealthy dataset where many images were ambiguous due to lighting and limited as less unhealthy roots were imaged than expected. Nevertheless, an adequate model was able to be trained.

```
is_healthy,_,probs = learn.predict(('/kaggle/input/validation/OneDrive_2023-03-29 (1)/40 unhealthy trial images/G1064154.JPG'))
print(f"This is: {is_healthy}.")
print(f"Probability it's healthy: {probs[0]:.4f}")
Image.open('/kaggle/input/validation/OneDrive_2023-03-29 (1)/40 unhealthy trial images/G1064154.JPG').to_thumb(256,256)
```

Figure 10. Prediction Input Code

Lastly, the model was asked to predict root health using the validation set by inputting an image into the learn.predict function as seen above. The model would then analyse the image and output a category along with a probability score measuring the confidence of the model. The image being analysed was also displayed using the image.open command so that results could be validated by human observation.

5. Results & Discussion

5.1 Results

5.1.1 Image Analysis Results

Figure 11. Model Prediction Results

Sample results of the model's predictions can be seen above, the top row features unhealthy roots and the bottom row features healthy roots. The model was able to successfully identify roots with reasonable confidence scores for each category. Furthermore, early signs of root rot could be detected such as in the top right image, where only a small portion of the root is actually brown. Some healthy images received lower confidence scores than others despite appearing just as healthy. This is particularly apparent in the third healthy image from the right. This is most likely due to the nature of unhealthy roots to shrink and bunch up, which the model associated with unhealthiness. This bias could be potentially removed with more additions of healthy root images with high root density. Nevertheless, the model was able to detect unhealthy roots in our experiment but will likely need additional images and calibration to be applicable in the industry.

On the other hand, only roots in Bin B were unhealthy enough to be detected by the system. Calcium deficiencies were able to be identified upon inspection of the canopy zone as tip burn was observed, but roots of these plants appeared healthy to the model. The dissolved oxygen deficiency also showed no signs of root rot, this is most likely due to oxygen mixing into the water with every imaging session. This could also introduce bin bias, where the model detects the bin as being unhealthy instead of the roots. However, this was tested against by using earlier images of bin B when the roots appeared healthy. The model was successfully able to distinguish the two and did not detect unhealthiness in the early images. We also suspect there is some sort of lighting bias where poorly lit images will be considered more unhealthy since they appear less white. Poorly lit images are also harder to sort and validate due to lack of observable details. In the images, some roots appear to be blurry since they are too close to the camera but ultimately have no significant effect on the performance of the model contrary to what was expected. Overall, this suggests that this system could prove useful for measuring regenerative stress as seen in bin B, but requires more images and testing to fully eliminate potential biases.

5.1.2 Load Sensor Data

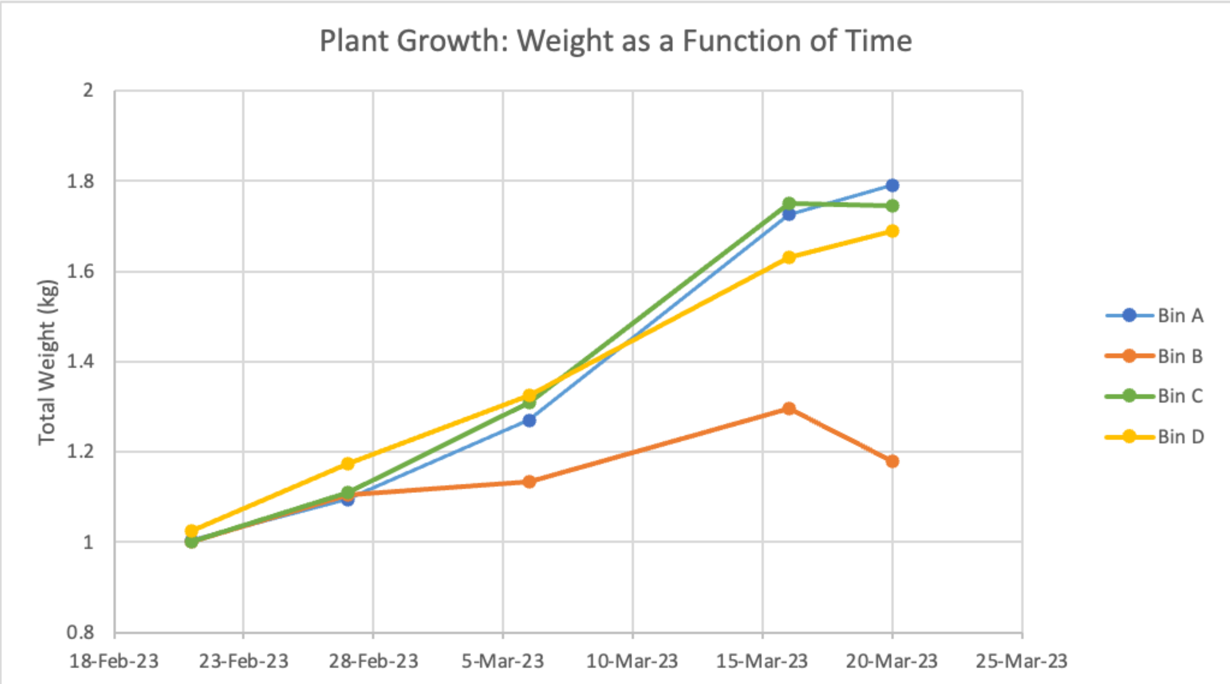


Figure 12. The total weight (in kg) of each lettuce tray as a function of time

The weight of the plants was taken every imaging session simply as a means to verify that growth was occurring. As expected, the Control, Bin A, had the highest average weight, whereas bin D, lacking oxygen, grew the poorest. Bin B, from which the true leaves were removed was still weighed to validate growth once on March 1st and on March 20th, 2023. Due to the removal of the leaves, the weight of lettuce plants in bin B cannot be compared to the other plants weight, since leaves were cut twice.

5.1.3 Raspberry Pi Data

A drop of approximately 6 degrees celsius occurs in the water temperature and air temperature graphs (Figure 13 and Figure 14 respectively). Although we do not know the exact cause of this drop, possibilities are explored in section 5.3.4 (Nearby Construction, the AC Unit Changing). Changing of a ventilation system, as well as the frequent opening and closing of the growth chamber door by other teams and construction workers are possibilities.

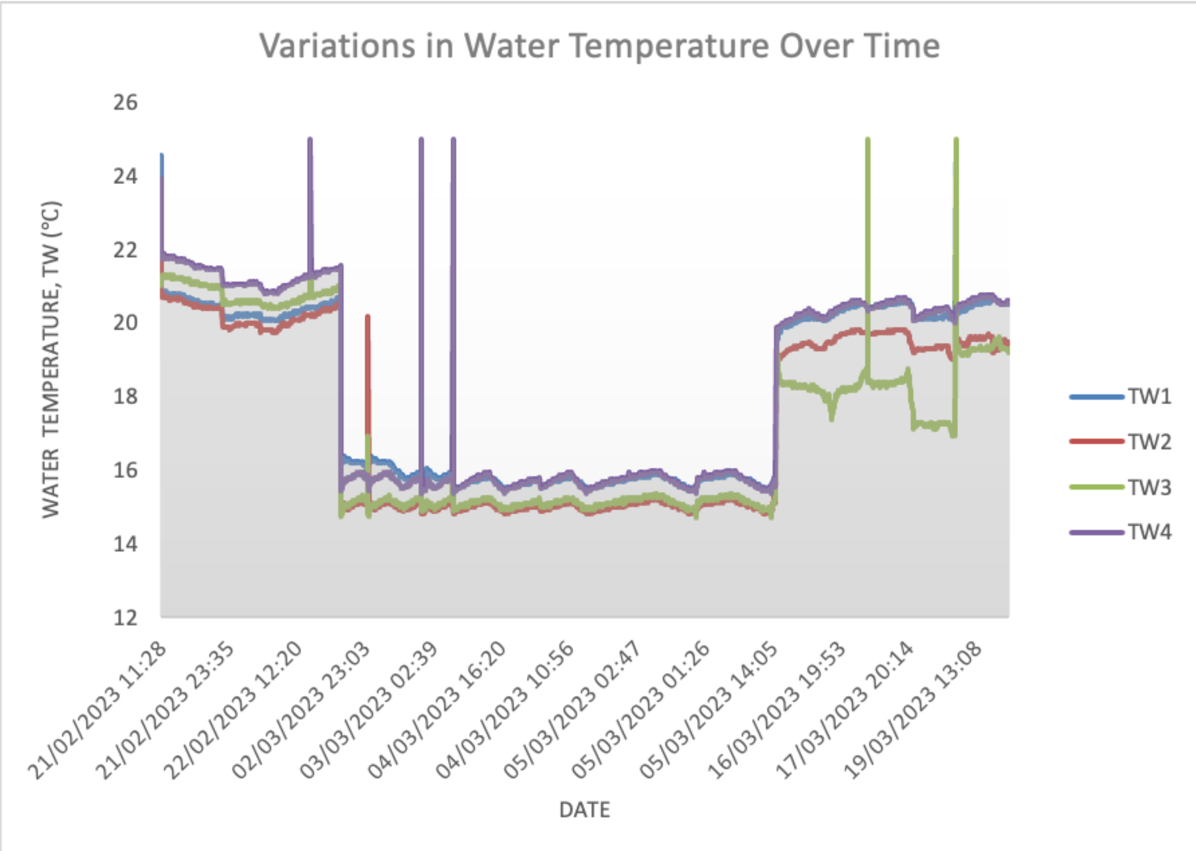


Figure 13. Water Temperature near roots of Lettuce Plants vs. Time

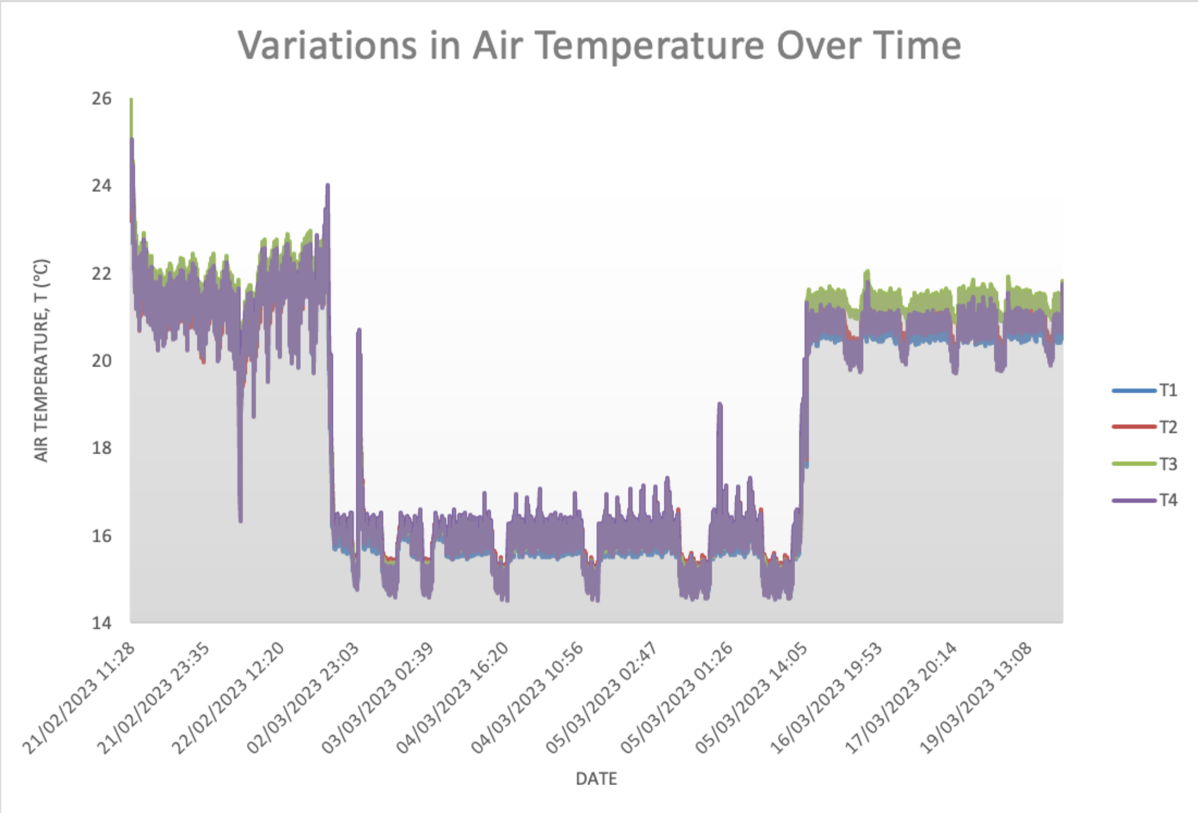


Figure 14. Air Temperature of Growing Room vs. Time

The relative humidity rested at around 30% at the start of the experiment which is too low. A bucket of water was filled and placed in our growth chamber to bring the relative humidity up to 60%, a satisfactory level (See figure 15).

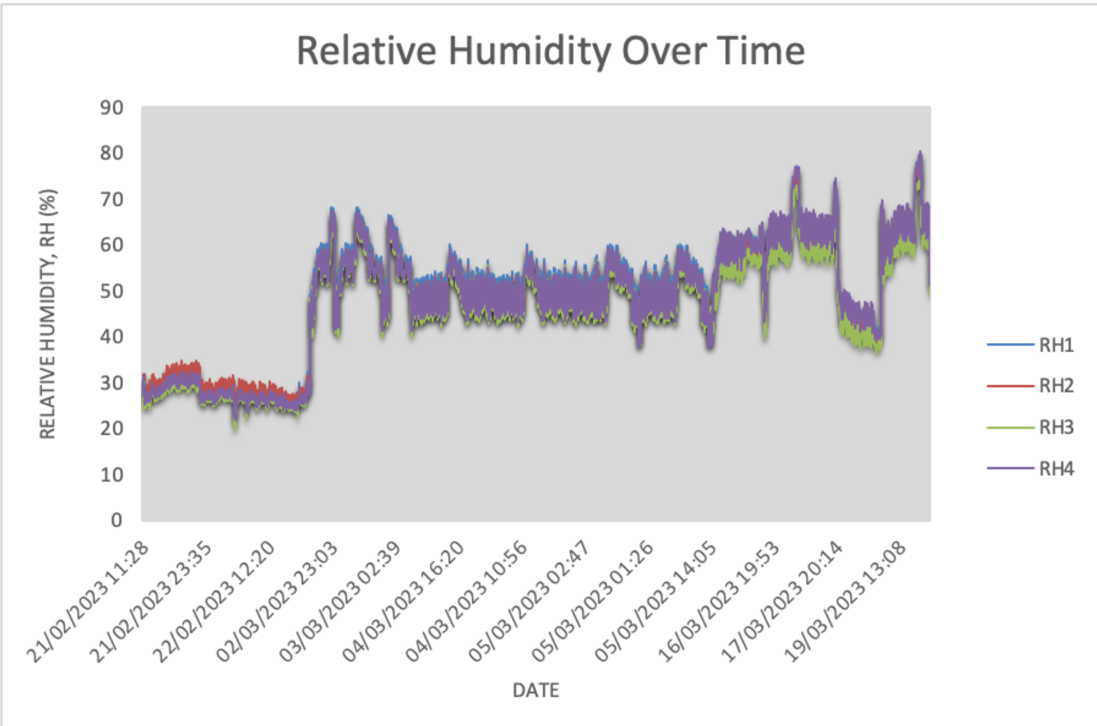


Figure 15. Relative Humidity of Growth Room vs. Time

5.1.4 Harvest Data

At the end of all imaging, all lettuce plants were removed, leaf and root length were measured, as well as fresh weight. Root length is approximate since we recognize roots are easily damaged during the imaging process, but provide an indicator of plant growth nonetheless (See Figure 16). Bin B fresh weight was not recorded seeing as entire leaves had been cut 6 days prior (See Figure 17).

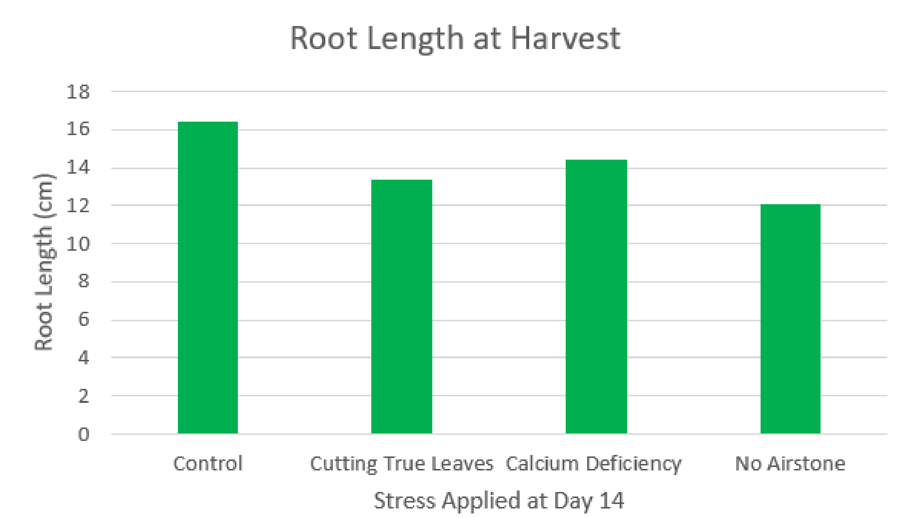


Figure 16. Average Root Length at Harvest

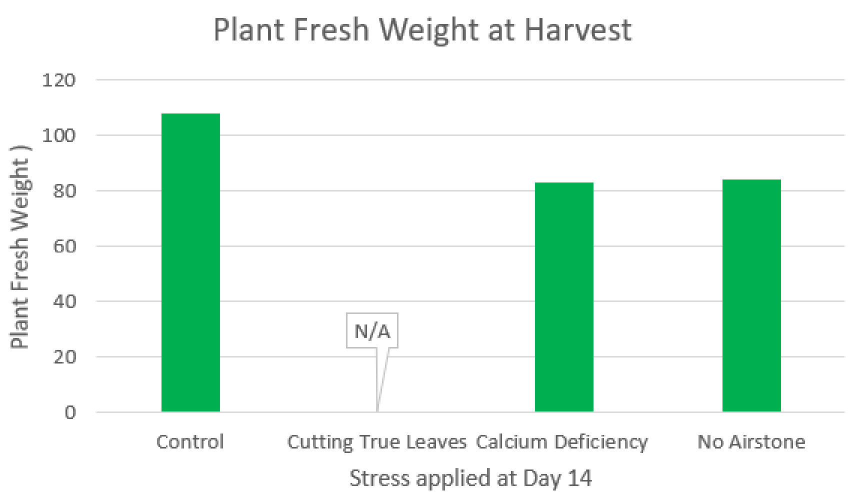


Figure 17. Plant Fresh Weight

5.2 Challenges & Constraints

5.2.1 Asbestos

The closure of the buildings on campus posed a challenge for material acquisition just as our experiment was ready to begin. During the seedling growth period, only a small amount of Hoagland's solution was needed since no more than 2 litres of water was used at a time. The actual experiment required 40 litres of water per bin, thus all the solution quantities in 3.2.1 Dilutions had to be multiplied by a factor of 160 to account for the four bins. When the Raymond building closed due to asbestos, we could not access the solutions or the Raspberry Pi equipment that we needed from the Lefsrud lab. Therefore, the start of our experiment was delayed and dependent on the individuals who could access the building. This delay caused us to fall behind by 2 weeks according to our GANTT chart.

5.2.2 Raspberry Pi

Under normal circumstances, the Raspberry Pi is connected to a wireless internet router and timely data may be monitored remotely. Due to the asbestos situation, the growing space we were allocated was far from the central wireless internet on campus.

The power supply in the pilot chamber suffered from voltage change which would at times turn off the Raspberry Pi, meaning there are time spans of hours without data collection. Had the data been connected wirelessly, team members would be aware of the issue and capable of rapidly reprogramming the python code of the device, but due to there being no remote access, data lags were only discovered hours later.

5.2.3 Camera Focus

Initially, the quality of the GoPro images was satisfactory when the lettuce roots were still short as seen in figure 19. There were no issues with underwater distortions or camera focus. However, as the roots grew longer over the course of the experiment, they eventually reached the camera lens, which resulted in blurry photos. Imaging in storage bins was especially challenging because of the limited depth of the bins. Once the roots reached the camera lens, there was no space left to distance the GoPro from them. Other possible factors that contributed to poorer image quality to a lesser extent were the imaging speed, the movement of the camera, the presence of light and the presence of airstone bubbles. To avoid blurry images, the imaging speed was increased from 0.5 seconds to 1 second. The outcome of this change was not significant, however, because the main issue was root length. Moreover, the water resistance in the bins would sometimes cause the camera to move, which resulted in blurry images. Other controllable factors were the presence of the LED lights and airstone bubbles. If the LED lights were not turned off prior to imaging, a glare would appear in the images. Likewise, if the air stones were not unplugged, bubbles would appear in the images.

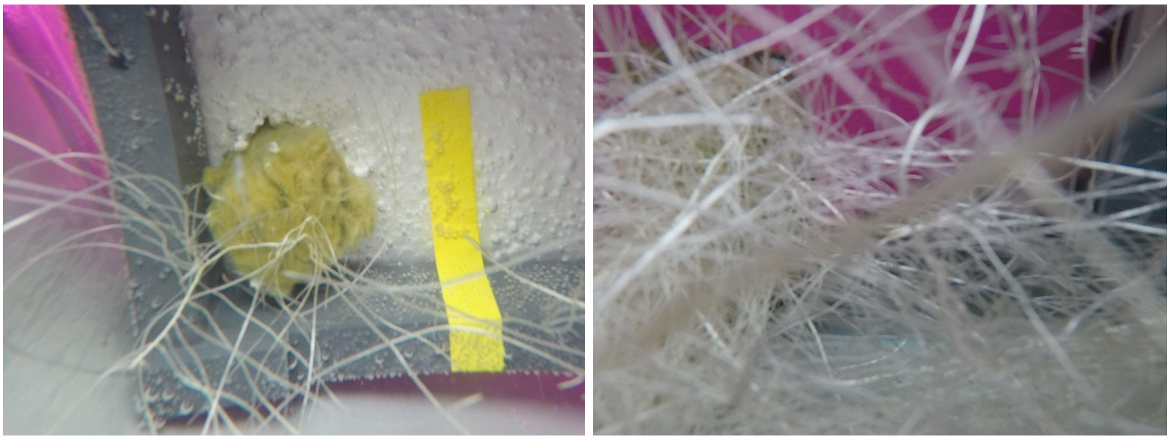


Figure 19. Decreasing camera focus as the roots grow longer

5.2.4 GoPro Live Stream Function

The GoPro live stream function was not available once the camera was submerged underwater. Though the live stream function was more of a luxury than a necessity, it could have helped capture better images by allowing the user to simultaneously see exactly what the camera saw. Instead, imaging was performed blindly, which required practice and coordination by each team member to ensure consistency in the results.

5.2.5 Weighing System

The weighing system was supposed to be used during each imaging session, however, the system that was developed, shown in figure 20, was difficult to use because of the limited space in the pilot chamber. The black metal frame was not practical to place over the four hydroponic bins, and the water-filled bins were too heavy to move to the frame. Thus, in the end, only the metal rod with the two load sensors was used to suspend the growing trays. This adapted method was sufficient to generate an overview of plant growth over time, however, the load sensor measurements were not accurate or precise enough.

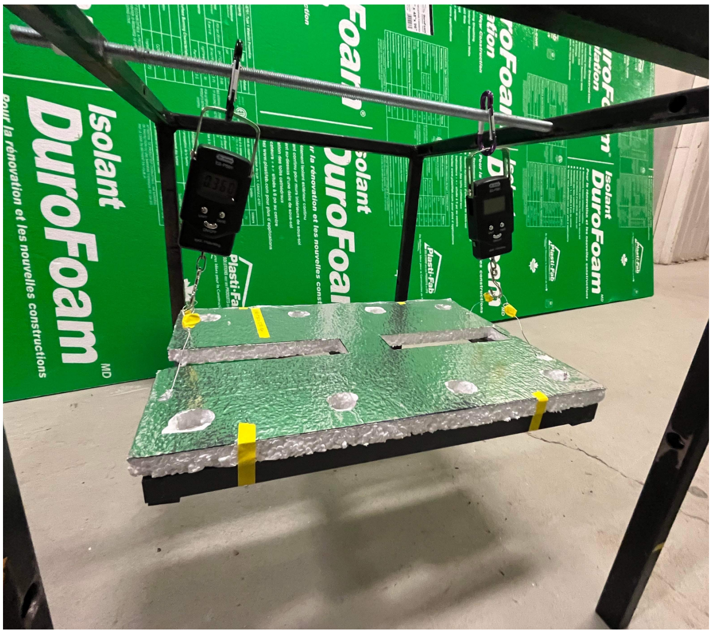


Figure 20. Hydroponic tray weighing system

5.2.6 Frame Fitting

The dimensions of the original PVC frames that were constructed were too large for the bins, thus preventing the trays from resting on the water surface. It was important that the frames fit properly to ensure the plant roots could reach the water level, especially as the water levels dropped from plant absorption throughout the experiment. Therefore, the frames were trimmed to fit the bins and to ensure they could move upwards and downwards with the variations in water level.

5.2.7 Plant Resilience

The plants were more resilient to the stresses than originally expected. By the end of the experiment, the majority of the roots were still healthy (i.e., thin and white), which did not provide enough distinctions for classification during image analysis. In the case of bin B, stressed by cutting the true leaves, the plants continued to regenerate their leaves significantly after the initial cutting, leading to an unplanned second cutting. Thus, either the time required to stress the plants was underestimated or the stress factors were not intense enough.

5.2.8 Underwater Distortions

Most photography devices are designed to be used in dry environments, so underwater photography poses a challenge of encasing the imaging device. There are a number of different shells an imaging device may be enclosed in, and reviewing the applications of diving photography has led us to consider either a flat or dome encasing for our camera.

As is discussed in section 5.2.3 Camera Focus, imaging the roots within their solution made focus and lighting extremely challenging. Despite the GoPro camera being waterproof, lighting accessories were a separate purchase, and it became difficult to fit the camera and light source in our bins; especially as the root systems grew larger and crowded the inside of the bins. All images were taken underwater and therefore the AI had the same bias for every image during its training period. The underwater distortions of the images will not affect the colour values, and therefore is not a concern for measuring the discoloration of lettuce roots.

5.3 Sources of Error

5.3.1 Uneven Light Exposure

Lighting is critical for overall plant health and growth. A light metre was used to map the lighting intensity over the area of our growing space (Figure 21, 22, 23). The lighting intensity was not evenly distributed for all treatments, a major flaw within our experiment. Due to the asbestos in the main building and time constraints of our project, we were not able to access more LED lights or a different space to grow in with even lighting conditions. The light mapping provides a further explanation for many of our results. First off, despite having the highest average light intensity (See Table 3), Bin B had the most discoloured, unhealthy root appearance which then must be attributed to the stress applied: removal of true leaves. Furthermore, the control bin grew best, despite having the lowest average light intensity, confirming the stresses had an effect on the other lettuce. Lighting is not the main focus of our experiment, but there remains potential to test the stresses under uniform lighting conditions to undoubtedly know the effect our stresses had on the lettuce plants.

Treatment	Mean (µmol/s^2)	Variance	Standard Deviation
Bin A : Control	145	1.35e+03	36.7
Bin B: Cut 100% of true leaves	186	624	25.0
Bin C: Eliminate calcium from solution	154	1.05e+03	32.3
Bin D: Remove airstone	177	1.06e+03	32.6

Table 3. Statistical analysis of Lighting Intensity by Bin Area

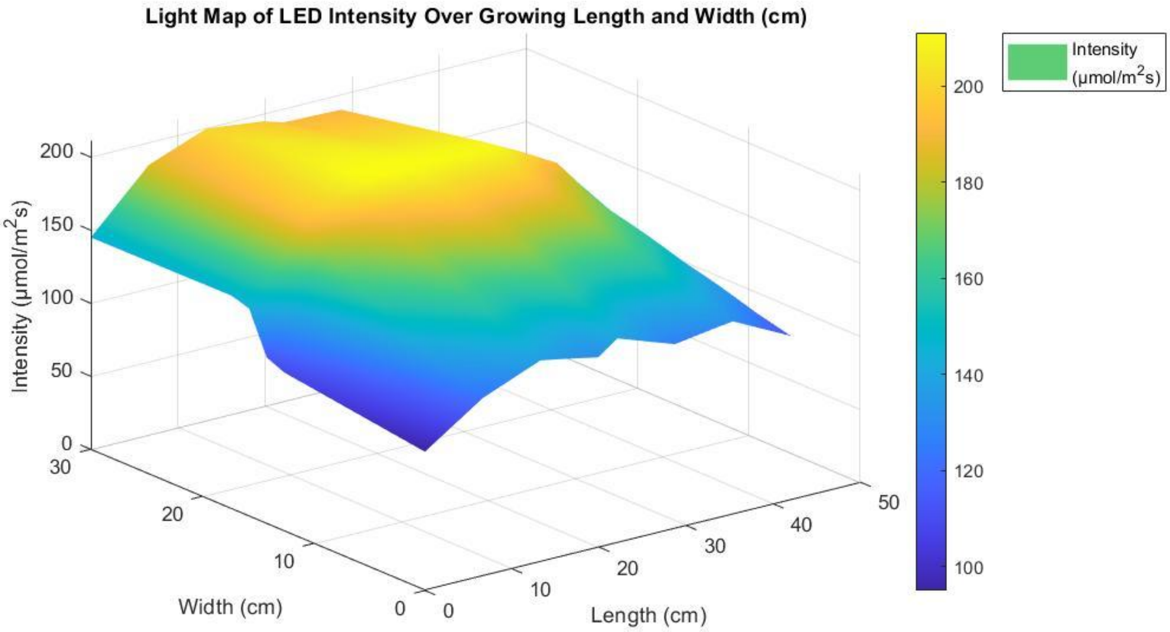


Figure 21. Light Map of LED Intensity Over Growing Space

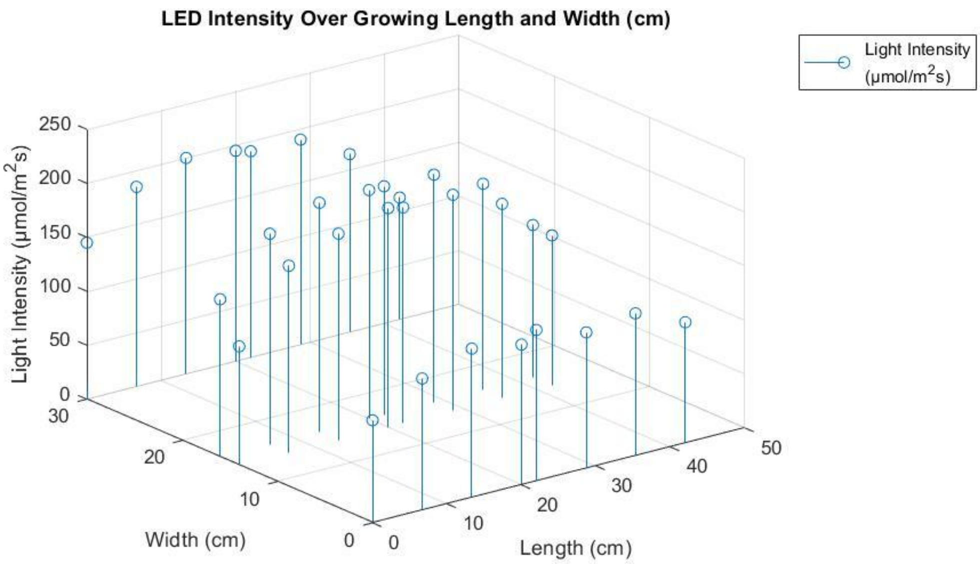


Figure 22. Light Map of LED Intensity Over Growing Space, Data Points (8 per Bin)

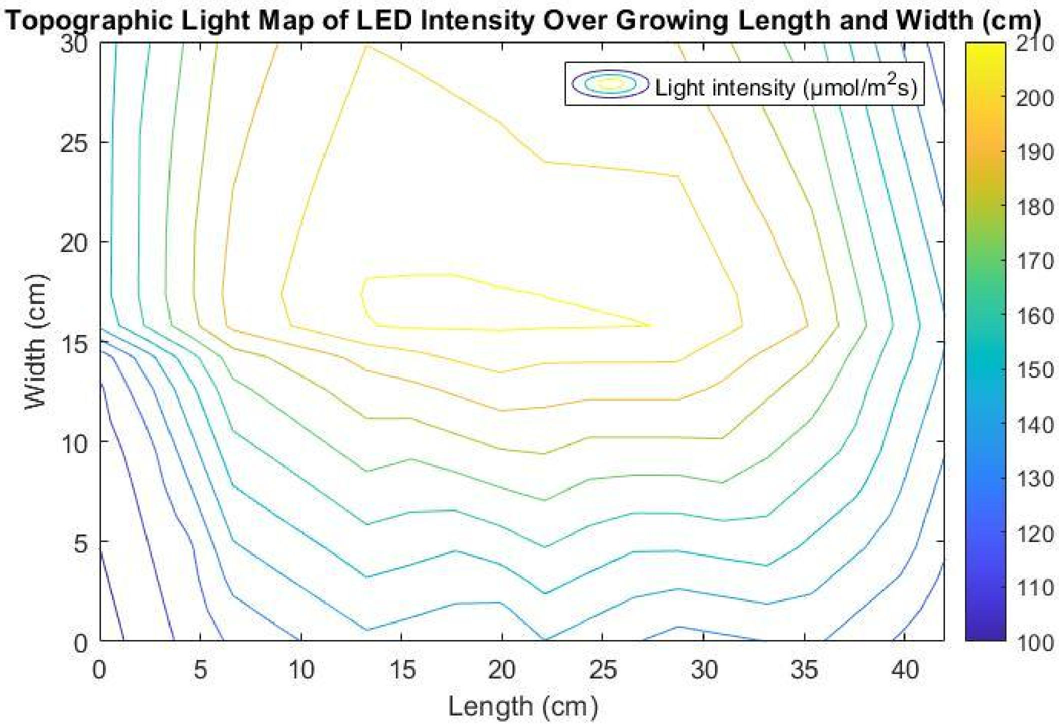


Figure 23. Topographic Light Map of LED Intensity Over Growing Space

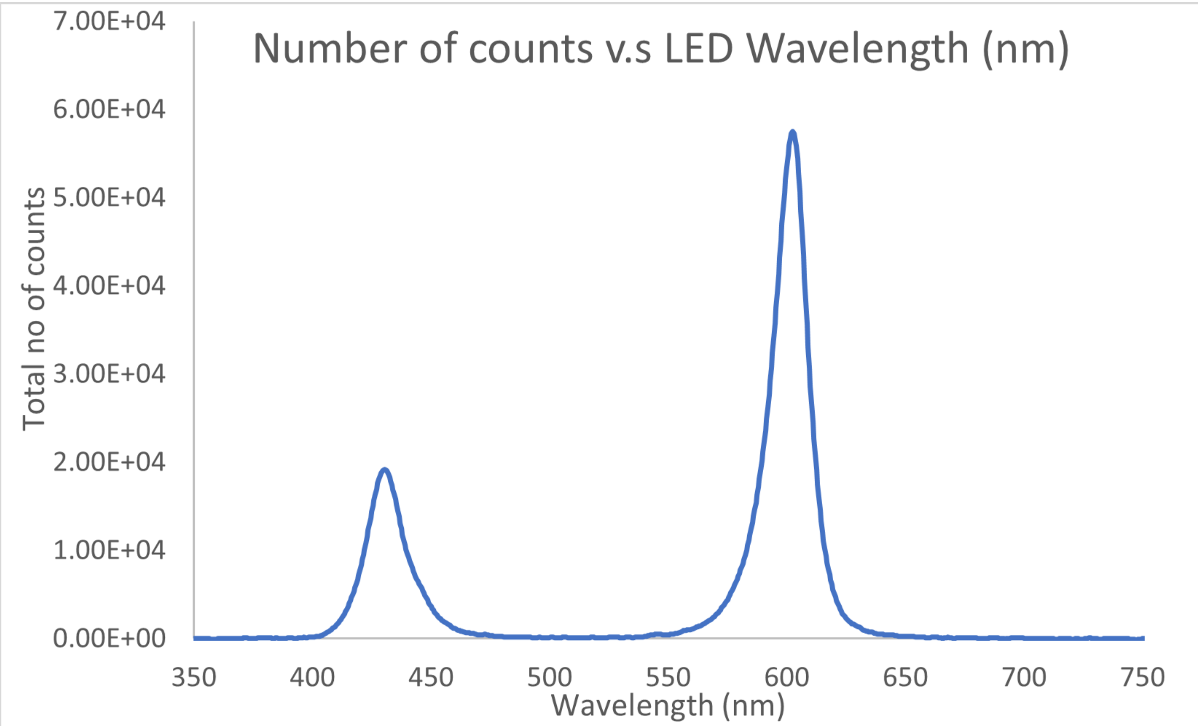


Figure 24. Number of Counts v.s LED wavelength (nm)

A spectroradiometer was used over the growing space to determine the exact wavelength of light the lettuce will receive. The lettuce will receive a combination of indigo and red LED light, as shown in figure 24.

5.3.2 Air Stones Unplugging

During the acclimatisation period, the new air stone tubing loosened and disconnected from the pump. Indeed, the tubes were reattached as soon as the team members noticed the disconnection, but it should be noted that Bin D and Bin B experienced no aeration for approximately two periods of 12 hours during the acclimatisation phase.

5.3.3 Weighing System

Since the plants were only weighed once per imaging session, it is possible roots were removed during the imaging process, changing the true weight of the plants. Bin D (No airstone stress) accidentally had two lettuce plants growing in a single cube of rockwool, which would cause it to make one treatment weigh more than another. The double plant was only discovered halfway through the experiment, and it was decided that it should be kept rather than removed because the latter would cause a sudden weight change.

5.3.4 Nearby Construction, the AC Unit Changing

Due to the asbestos closure, the pilot chamber underwent renovations to allow for more masters and doctoral experiments to continue on campus. The growing room we used had a door removed and replaced, a new ventilation system installed and the original air conditioning unit was removed, causing the growing environment to change considerably during the growing period. When relative humidity was found to be too low, the team placed a bucket of water in the grow space to mitigate air dryness.

5.3.5 Change in Background Colour

Initially, white styrofoam was used as the background for root imaging. However, after meeting with Dr. Shangpeng Sun (Professor in the Department of Bioresource Engineering at the Macdonald Campus of McGill University), it was decided to cover styrofoam sheets with pink duct tape to ensure a better contrast between roots and background. Therefore, the photos from the initial imaging sessions have white backgrounds (and low contrast), and the rest of the photos have pink backgrounds (and high contrast) as can be seen in Figure 19. To minimise sources of error due to background contrast, only images with a pink background were used to train the image recognition AI.

5.3.6 Image Sorting

The same number of images were taken from each treatment bin in equal proportions to train and validate our model. Images of varying quality, focus, and clarity were used in an attempt to make a more robust model. However, we recognize that there may have been human bias when selecting which images were used from each bin.

6. Recommendations

This technology shows great promise in remotely sensing root health in an effective and inexpensive manner with accuracy. However, the data collected was very limited and would benefit from a larger dataset in different growing systems. This method is also unable to detect certain stresses as root rot can manifest after deficiencies or stress can be identified in the canopy zone. However, for regenerative stress, where the leaves are unable to be observed and the only indication of health lies in the roots, this can prove an invaluable asset. Our model also only sorts images into a binary state: healthy or unhealthy. For better categorization and identification, multiple stages of root health could be presented on scale, for example, numbers 1-6 indicating the state of root, 1 for being most healthy and 6 for being dead. In order to measure these different stages, more trial data is needed as the roots showed signs of degradation but dead roots were not able to be imaged before the experiment ended. For more applicability, more stresses that could potentially relate to root health should be identified. In brief, only regenerative stress was able to be detected in the experiment and our data was lacking severely damaged roots which results in the binary and limited nature of the model.

Regenerative stress was successfully predicted by the model and can have further implications when used in practice. Plants will typically regenerate a few times before death and by using image analysis these regenerative cycles can be monitored. With more data pertaining to regenerative stress cycles, empirical relations can be formed examining the roots. Image classification could potentially be used to determine when a plant will no longer be able to regenerate. This could allow for earlier identification of plants that will no longer regenerate and avoid waste of nutrients and time spent into these plants. Image analysis could also potentially reflect the quality of regenerative plants through root health, since poor quality plants will typically not be sold since they are less desirable, this can further avoid wasting resources. Root health is the only indicator of health for these plants since the leaves are cut off, and excessive lights in the root zone or examining the plant out of water will damage the plant itself. This proves to have invaluable potential for growers seeking to maximise usage of a single plant.

Other than regenerative stress, we have found the system is unable to detect other stresses tested in this experiment and as such is not suitable for these uses. Dissolved oxygen stress in our experiment seemed to fail as each imaging session would allow for oxygen and water to mix. For further testing of this deficiency, we recommend that a different setup is adopted, where the camera remains in the water to avoid mixing. On the other hand, other stresses could be identified to allow for more applicability of image analysis on the root zone. Hydroponic diseases could be tested for instead as these are typically waterborne and will initially interact with roots. We recommend that fungal disease such as downy mildew, powdery mildew, and grey mould should be examined to determine if premature signs can be detected. This can be conducted in a similar experimental style with different environmental conditions to favour fungal growth. Additionally other nutrient deficiencies can be tested but judging from our results, are unlikely to be detected in the root zone before the canopy zone. Nitrogen has some promise as nodules can form depending on the form of nitrogen which could be an indicator of health.

A significant limitation of our design was our limited data, only one of bins showed signs of root degradation and we were unable to image the plants until death. This prevented us from employing a scale instead of binary sorting and limited the amount of unhealthy root images. We recommend that plants are imaged until root death to obtain a full spectrum of root health stages. This is important because even though the roots may be unhealthy the quality of the product will be relatively fine with small damage. However, more damaged roots will begin to affect the quality of the plant and can be discarded. Our model is currently unable to distinguish between these two cases and as such will have limited use for this purpose. This may result in premature removal of viable plants. However, with a scale implemented growers can use their own discretion for the degree root degradation deemed unacceptable for growth.

Overall, image classification is a powerful tool that has been demonstrated to function well for binary identification. Further research with more extensive datasets would be able to improve the model and allow it to be used for more practical applications. Ultimately, this system allows for monitoring of root health as a noninvasive or destructive method while being cost and time efficient.

7. Considerations

7.1 Social

7.1.1 Safe for Consumption

Overall, hydroponically-grown lettuce will be safer for consumption because no fertilisers, pesticides or fungicides will be used under controlled environment conditions. This will minimise both consumer and farmer exposure to these carcinogens and irritants. Furthermore, root monitoring will allow early detection of disease and pest outbreaks to prevent the spread and amplification of pathogens. This includes preventing plant-to-human pathogen transmission.

7.1.2 Higher Quality and Yield

Lettuce grown in nutrient-rich solutions have higher nutrient content because they can absorb the nutrients they need without any losses to the environment, for example, losses through runoff. Thus, the lettuce will be of higher quality (i.e., little to no deficiencies) and plant growth will occur at a faster rate since nutrient utilisation by the plants is more efficient. Moreover, monitoring root health will prevent diseases, and therefore food loss. Less food loss and faster plant growth means more produce available to alleviate food insecurity in remote communities.

7.1.3 Promotes Local Engagement

Root monitoring increases local food security by providing nutritious options to community members and minimising waste. This allows consumers to engage in healthy decision-making and learn about sustainability topics, such as food waste and urban agriculture. It also allows community members to obtain hands-on experience through job and volunteer opportunities.

7.2 Environmental

7.2.1 Pathogens & Vectors of Disease

An advantage of growing lettuce hydroponically is the lack of soil-borne pathogens. However, the presence of water-borne pathogens is still possible in the environment of our system, which could lead to the development of grey mould, downy mildew, root rot or other diseases caused by water-craving pathogens. The emergence of unhealthy roots was desired for our project to test the feasibility of the root monitoring and image classification procedure. However, it presents an environmental risk for large-scale hydroponic operations by threatening yields and profits. Thus, our design could help minimise these losses.

Furthermore, any crop, including lettuce, has the potential of attracting vectors of diseases, such as aphids and thrips. Therefore, another environmental risk is pest invasion which may compromise the quality of the lettuce, resulting in financial losses and food waste. Additionally, there will be costs involved in dealing with a pest invasion, if it were to occur.

7.2.2 High Energy Consumption

The air stones and dehumidifier required power for 24 hours a day, and the LED lights ran for 17 hours a day, resulting in relatively high electricity consumption. In regions capable of producing fully renewable energy, such as hydroelectricity or wind power, the environmental impacts of this consumption will be minimal. However, other regions that depend on non-renewable energy sources, such as coal or natural gas, will have higher carbon footprints by allowing the system to run continuously. Thus, the environmental sustainability of this system will vary based on geographic location, and environmental assessments should be conducted to determine whether the system provides more benefits than burdens, or vice-versa.

7.2.3 Non-sustainable Materials

Eight rockwool cubes were required per tray, for a total usage of 32 cubes. An additional four rockwool cubes were used to act as backups if needed. Rockwool is a popular choice of growth medium in the hydroponic industry because of its average porosity, high water retention capacity, and its ability to maintain its structure (Xiong et al., 2017). However, rockwool is inorganic and does not degrade over time, eventually making its way into landfills. Therefore, rockwool is an unsustainable material, especially when experiments are conducted for an extended period of time or when large quantities are used in large-scale operations.

7.2.4 High Water Consumption

The selected design holds 40 litres of water per tray, adding up to a total of 160 litres for the four trays. This represents only the initial amount of water needed for the system and does not account for the tri-weekly water replacement. At the end of the three week experimental period, the water in the trays was dumped and refilled before starting a new trial. Thus, this small-scale system required a decent amount of water and the demand would be further amplified for commercial use.

7.2.5 Fertilisers, Pesticides & Fungicides

Unlike traditional farming, hydroponically-grown crops do not require fertiliser applications, therefore restricting extensive usage. Moreover, no pesticides or fungicides were needed for this experiment. However, the water contained nutrients, including phosphorus and nitrogen, which can enter bodies of water after disposal. Depending on how carefully the water is disposed of, the nutrients in the system could trigger or contribute to eutrophication and algal blooms.

7.2.6 Less Food Waste

A successful root monitoring system can limit the amount of crop losses and food waste by identifying diseases as they emerge and preventing their propagation. By minimising food loss, some of the pressure on the environment to meet the agricultural needs of the growing population can be alleviated. During this experiment, no crops were lost to disease and the lettuce was consumed by the team members post-experiment. Only a percentage of the lettuce was disposed of. However, effective waste management strategies should be developed at a commercial level.

7.3 Economic

7.3.1 Potential for Profits

Through root monitoring, diseases and unhealthy plants can be identified, isolated and/or treated. This will limit the amount of lettuce that is lost from disease outbreaks or insufficient plant requirements. By reducing the amount of produce loss, more lettuce can be sold, hence, more profits can be made. Furthermore, a benefit of growing lettuce hydroponically, compared to traditional methods, is increased yield. The controlled environment allows for year-round production and shorter cycles between harvests (Barbosa et al., 2015). Thus, the combination of reduced produce loss and higher yields increases lettuce supply and availability, as well as the potential to generate revenue.

7.3.2 Startup Costs

Startup costs of hydroponic systems are expensive as there are many equipment requirements (varies based on setup), such as artificial lighting, pumps, air stones, water chamber, temperature controls, growing trays, growth mediums, nutrients, and other specific equipment. Our design requires additional equipment including load sensors, a GoPro, battery packs, camera light attachment, and other miscellaneous materials. For a small-scoped project, the costs were relatively affordable (about $300), however, the extra features in our design will add up for commercial hydroponics. It should also be noted that many of the materials were borrowed, so $300 is an underestimate of the actual costs. Thus, the additional root monitoring features must provide a reasonable return on investment to compensate for startup costs.

7.3.3 Energy Costs

The system requires electricity for many of its components, including lighting, heating and cooling, air pumps, load sensors, and air stones. Thus, the energy demand of these components can be costly and will vary based on region. In areas where relatively cheap and renewable energy sources, such as solar, wind or hydroelectricity, are available, the energy costs would be minimal, making our hydroponic design a suitable choice. However, this design may not be suited for areas that operate on more expensive energy sources, such as nuclear or gas. In Quebec, our system costs $1.64 per week in electricity to operate, which is negligible thanks to hydropower.

7.3.4 Local Economy

The fact that hydroponic systems are grown in soilless mediums and indoors allows it to be done anywhere during any season. Thus, commercial hydroponic operations can be implemented in urban, rural or remote communities to stimulate local economic activity. Furthermore, it provides local communities with job opportunities and fresh produce year-round, which would be especially beneficial for isolated Indigenous communities that are considered food insecure. Our system could hypothetically create jobs because it requires people for maintenance, plant care, harvesting, imaging, and image analysis using AI.

Conclusion

Often deficiencies in plants are identified through the leaves of the plant, however, sooner identification is needed as these plants will no longer be usable or profitable. Furthermore, identification of deficiencies requires sufficient technical knowledge on plant physiology and will result in difficulty for growers. Root monitoring through a digital camera can lower the amount of technical knowledge required and provide early stress detection. Calcium deficiency was selected due to its slow transport through the plant which typically manifests in young leaves. Dissolved oxygen deficiency was selected since it directly interacts with root cellular respiration. Finally, regenerative stress was also chosen due to the roots being the main observable part and indicator of plant health. Several sets of plants were subject to these stresses for five weeks while being imaged twice a week.

Images of the stressed plants were then sorted and fed into a deep learning algorithm where a model learned to sort healthy and unhealthy root pictures. However, only regenerative stress was able to be detected in our experiment but functioned effectively. Calcium deficiency identification was considered undetectable or ineffective in the root zone as tip burn will occur before root rot is observed. The dissolved oxygen deficiency system likely received enough oxygen to remain healthy through mixing when the camera was inserted. Overall, the model was able to identify root rot where root rot was observed and can effectively identify the health of roots. This is also limited by our design due to the limited nature of unhealthy root pictures since only one bin was observed to have degraded roots. This also caused the binary nature of sorting rather than the use of scale. Further implications are possible but require more extensive testing examining regenerative stress under a longer duration.

In conclusion, image analysis of plants in the root zone is a powerful tool that can lower required technical knowledge and assist in hydroponic cultivation. This system was demonstrated to function as intended in our experiment but overall lacked extensive data on failing roots. If this system was implemented in numerous growing setups in collaborative effort, a more robust system can be developed. With extensive and accurate data, several biases would be eliminated or mitigated and create a stronger algorithm overall. Our system could also be built upon to include more categories such as scale or potential identification of individual stresses through root rot. As of now, this system shows the most promise to observe and detect regenerative stress as roots are the main observable indicator of health in these plants. This can also be improved through longer observation of regenerative stress to create empirical categories.

Acknowledgements

We would like to acknowledge and thank Professor Lefsrud for guiding us in our decisions throughout this project and for lending us various supplies. His knowledge and expertise in the field of plant biology and engineering was extremely valuable to our project. His guidance and interest in our work is much appreciated.

We would like to thank Professor Sun for allowing us to tour his lab and for providing us with feedback on our report last semester. We would also like to thank him for providing recommendations this semester to improve our methods, and consequently our results. We appreciate his expertise in root imaging and incorporated his suggestions into our final design.

We would like to thank Eugene Antony Samy from Professor Lefsrud's lab for guiding us in growing Valley Heart Lettuce hydroponically both semesters, lending us his own equipment, helping us troubleshoot the issues with the Raspberry Pi, and being readily available and easily accessible to answer our questions.

A special thanks to all our outside contacts for meeting with us and/or allowing us to tour their facility last semester including Chad Taylor from Jardin Vertical, Tristan Zeman from Interius Farms, Phil Rosenbaum from Vertite, and Justin Dragan from Tulsi Farm.

References

Barbosa, G.L., Gadelha, F.D.A., Kublik, N., Proctor, A., Reichelm, L., Weissinger, E., …, Halden, R.U. (2015). Comparison of Land, Water, and Energy Requirements of Lettuce Grown Using Hydroponic *vs.* Conventional Agricultural Methods. *International Journal of Environmental Research and Public Health*, 12(6), 6879-6891. https://doi.org/10.3390/ijerph120606879

Blancard, D., Lot, H., Maisonneuve, B. (2006). *A Color Atlas of Diseases of Lettuce and Related Salad Crops: Observation, Biology, and Control*. Boston: Elsevier/Academic Press.

Bugbee, Bruce. (2004). *Nutrient management in recirculating hydroponic culture.* Acta Horticulturae. 648. 99-112. 10.17660/ActaHortic.2004.648.12

Davis, M. (1997). *Compendium of Lettuce Diseases*. St. Paul, Minnesota: APS Press.

Deaton, B.J., Scholz, A., Lipka, B. (2020). An empirical assessment of food security on First Nations in Canada. *Canadian Journal of Agricultural Economics*, 68, 5-19. 10.1111/cjag.12208

Doyle, J. J. (1998). Phylogenetic perspectives on nodulation: evolving views of plants and symbiotic bacteria. *Trends in Plant Science*, 3(12), 473-478. https://doi.org/10.1016/S1360-1385(98)01340-5

FAO. Hunger and Food Insecurity. Food and Agriculture Organization of the United Nations. Retrieved from https://www.fao.org/hunger/en/

Goddek, S., & Keesman, K. J. J. D. (2018). The necessity of desalination technology for designing and sizing multi-loop aquaponics systems. *428*, 76-85.

Grierson, C., & Schiefelbein, J. (2002). Root hairs. The arabidopsis book, 1, e0060. https://doi.org/10.1199/tab.0060

Grusak, M. A. (2001). *Plant Macro‐and Micronutrient Minerals*. *e LS*.

He, K., Zhang, X., Ren, S., and Sun, J. (2015). Deep Residual Learning for Image Recognition. arXiv [cs.CV]. *arXiv*. http://arxiv.org/abs/1512.03385

Hospedales, T., Antoniou, A., Micaelli, P., & Storkey, A. (2021). Meta-learning in neural networks: A survey. *IEEE transactions on pattern analysis and machine intelligence*, *44*(9), 5149-5169.

Huisman, M., van Rijn, J.N. & Plaat, A. A survey of deep meta-learning. *Artif Intell Rev* 54, 4483–4541 (2021). https://doi.org/10.1007/s10462-021-10004-4

Li, Q., Li, X., Tang, B., Gu, M. (2018). Growth Responses and Root Characteristics of Lettuce Grown in Aeroponics, Hydroponics, and Substrate Culture. *Horticulturae*, 4(4):35. https://doi.org/10.3390/horticulturae4040035

Maucieri, C., Nicoletto, C., Os, E. v., Anseeuw, D., Havermaet, R. V., & Junge, R. (2019). Hydroponic Technologies. In S. Goddek, A. Joyce, B. Kotzen, & G. M. Burnell (Eds.), Aquaponics Food Production Systems: Combined Aquaculture and Hydroponic Production Technologies for the Future (pp. 77-110). Cham: Springer International Publishing.

Meselmani, M. A. A. (2022). Nutrient Solution for Hydroponics. In M. Turan, A. P. S. Argin, E. Yildirim, & A. Güneş (Eds.), Soilless Culture [Working Title]. IntechOpen. https://doi.org/10.5772/intechopen.101604

Morard, P., Silvestre, J. Plant injury due to oxygen deficiency in the root environment of soilless culture: A review. *Plant Soil* 184, 243–254 (1996). https://doi.org/10.1007/BF00010453

Neumann, G., Bott, S., Ohler, M. A., Mock, H. P., Lippmann, R., Grosch, R., & Smalla, K. (2014). Root exudation and root development of lettuce (Lactuca sativa L. cv. Tizian) as affected by different soils. *Frontiers in microbiology*, 5, 2. https://doi.org/10.3389/fmicb.2014.00002

Petruzzello, M. (2022, October 21). xylem. Encyclopedia Britannica. https://www.britannica.com/science/xylem

Raid, R.N. (2004). Lettuce Diseases and their Management. In Naqvi, S.A.M.H. (eds). *Diseases of Fruits and Vegetables* (Vol.2, pp. 121-147). Dordrecht: Springer.

Shafiee, M., Keshavarz, P., Lane, G., Pahwa, P., Szafron, M., Jennings, D., Vatanparast, H. (2022). Food Security Status of Indigenous Peoples in Canada According to the 4 Pillars of Food Security: A Scoping Review. *Advances in Nutrition*. https://doi.org/10.1093/advances/nmac081

Soille, P. (2004). Introduction. In: Morphological Image Analysis. Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-662-05088-0_1

Soto, L. (2023, March 16). How deep flow technique (DFT) hydroponic systems work. Retrieved April 13, 2023, from https://puregreensaz.com/how-deep-flow-technique-dft-hydroponic-systems-work/

Soto, L. (2023, March 16). The benefits of Deep Flow Technique (DFT) hydroponic systems. Retrieved April 13, 2023, from https://puregreensaz.com/the-benefits-of-deep-flow-technique-dft-hydroponic-system s/

Taiz L. & Zeiger E. (2014). Plant physiology and development: 6th revised edition. SINAUER Associates Inc. U.S.

Xiong, J., Tian, Y., Wang, J., Liu, W., Chen, Q. (2017). Comparison of Coconut Coir, Rockwool, and Peat Cultivations for Tomato Production: Nutrient Balance, Plant Growth and Fruit Quality. F*ront Plant Sci*, 8(1327). 10.3389/fpls.2017.01327

Appendix

Harvest Data

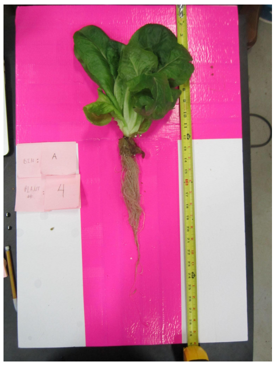
Bin A: Control			
			
			

Table 4. Images of Each individual for Bin A

PLANT #	# of Leaves	Plant height (inches)	Root length (inches)	weight (grams)
1	13	10.25	17.5	74.3
2	15	10.25	17	118.1
3	17	10.25	13.5	107.3
4	17	11	14	127
5	18	10	19	118
6	15	10	18.25	101
7	15	9.75	14	106
8	15	9.75	18	114

AVG	15.6	10.2	16.4	108.2

Table 5. Harvest Data Bin A

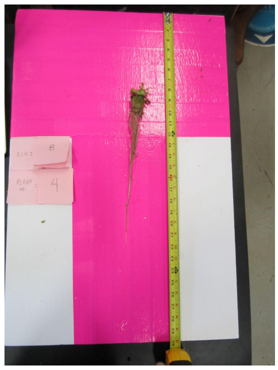
Bin B: Cut 100% of true leaves			
			
			

Table 6. Images of Each individual for Bin B

PLANT #	# of Leaves	Plant height (inches)	Root length (inches)	weight (grams)
1	-	0	18.5	-
2	-	0	15.5	-
3	-	0	12.5	-
4	-	0	13.5	-
5	-	0	5.5	-
6	-	0	13.5	-
7	-	0	11	-
8	-	0	17	-

			13.4	

Table 7. Harvest Data Bin B

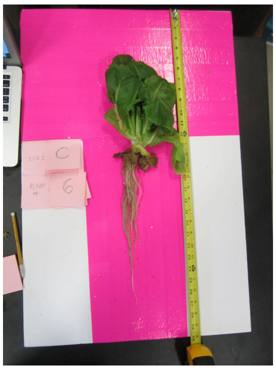
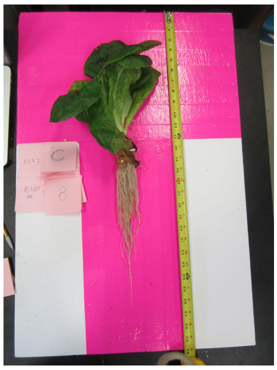
Bin C: Eliminate calcium from solution			
			
			

Table 8. Images of Each individual for Bin C

PLANT #	# of Leaves	Plant height (inches)	Root length (inches)	weight (grams)
1	-		N/A	-
2	11	8	11	45.9
3	13	10.5	18.5	78.4
4	16	10.25	13.5	72.6
5	15	10.25	15	82.3
6	13	9.75	13	81.4
7	16	10.5	15	94.2
8	18	10	15	129.3
	14.6	9.9	14.4	83.4

Table 9. Harvest Data Bin C

Bin D: No Airstone

Table 10. Images of Each individual for Bin D

PLANT #	# of Leaves	Plant height (inches)	Root length (inches)	weight (grams)
1	16	11	10	85
2	14	9.75	15	64.5
3	17	9.5	12	84
4	17	9.25	18	102.5
5	17	9.5	13	86.9
6	18	9.25	10.5	120.8
7	14	10.25	9	81.6
8	13	9	9	48.2
	15.8	9.7	12.1	84.2

Table 11. Harvest Data Bin D