Development of the Internet of Things based smart multi-sensor system for early prediction of plant growth

by

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ABSTRACT

The application of the Internet of Things (IoT) has become an important part of our daily lives in diverse areas. IoT provides the ability to integrate and communicate between different objects using smart sensors, cameras, and actuators through an Internet connection. In recent years, a combination of IoT technologies has begun to play an important role in monitoring plant health and growth condition in agricultural systems. Monitoring plant conditions and the effect of abiotic stresses in the early stages is very crucial since it can maximize crop productivity and enable producers to provide products of superior quality. The objective of this research study was to design, develop, and deploy a Raspberry Pi-based smart multi-sensor system for real-time monitoring of plant health conditions at various soil moisture levels. The developed prototype was successfully tested by conducting a series of calibration tests at known soil moisture and temperature conditions. The results obtained from five calibration tests demonstrated that the temperature and soil moisture sensors were accurate and robust over the selected period. The Raspberry Pi-based smart imaging enabled capturing images of plants in real-time for predicting their health and growth condition. To predict the critical time for irrigation, mathematical models were developed that established a relationship between the number of green (i.e. healthy) areas of the plant and soil moisture condition for each soil moisture content (i.e., 0, 20, 40, 60, and 80%). It was observed that the value of the green area of plants decreased with a decrease in soil moisture content. These models could be applied for integrating IoT-based systems in various environmental conditions.

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TABLE OF CONTENTS

		Page
ABSTRACT		2
ACKNOWLEDGEMENT		3
TABLE OF CONTENTS		4
LIST OF TABLES		6
LIST OF FIGURES		7
CHAPTER I	INTRODUCTION	
1.1	Problem statement	8
1.2	Research objectives	9
CHAPTER II	LITERATURE REVIEW	
2.1	Abiotic stress	10
2.2	Plant (Peperomia)	12
2.3	Remote control	13
2.4	Internet of Things (IoT)	14
	2.4.1 Introduction	14
	2.4.2 Benefits and challenges of IoT	15
	2.4.3 Internet of Things in agriculture	16
	2.4.4 Precision agriculture	22
	2.4.5 Image processing	23
CHAPTER III	METHODOLOGY	
3.1	Experimental setup	26
3.2	Soil sample preparations	29
3.3	Data acquisition	30
3.4	Image processing	32
3.5	Smart sensor calibration and validation procedure	34
3.6	Calibration criterion	36
	3.6.1 Accuracy	36
	3.6.2 Stability	36
	3.6.3 Repeatability	36
	3.6.4 Linearity	37
	3.6.5 Homogeneity	37
3.7	Statistical analyses	37
3.8	Plant health prediction and modeling	38
CHAPTER IV	RESULTS AND DISCUSSION	
4.1	Calibration results for temperature sensors	40
4.2	Calibration results for moisture sensors	40
	4.2.1 Accuracy	40
	4.2.2 Stability	42
	4.2.3 Repeatability	43
	4.2.4 Linearity	45
	4.2.5 Homogeneity	46
4.3	Temperature sensors	47

4.4	Moisture sensors	48
4.5	Raspberry Pi images	49
4.6	Plant health prediction	52
4.7	Correlation between soil moisture content and plant green area.	53
4.8	Linear regression and modeling	54
CHAPTER V	CONCLUSIONS AND RECOMMENDATIONS	
5.1	Summary of the study	56
5.2	Most important achievements	56
5.3	Suggestions for future work	57
REFERENCES		58
APPENDICES		
Appendix A		61
Appendix B		65

LIST OF TABLES

Table No.		Page
Table 4.1	Results of average daily temperature for trial one over 14 days.	48
Table 4.2	Results of average daily moisture content for the first experimental trial over 14 days.	49

LIST OF FIGURES

Figure No.		Page
Figure 3.1	Schematic design of the experimental setup.	26
Figure 3.2	Analog waterproof capacitive soil moisture sensor.	28
Figure 3.3	Soil temperature and moisture sensor.	28
Figure 3.4	Raspberry Pi camera board V2 (8 MP).	30
Figure 3.5	Smart multi-sensor system based on imaging and soil moisture sensors.	31
Figure 3.6	Soil moisture sensors calibration setup: Raspberry Pi, mainboard, analog-digital convertor, wire connection, and power supply.	32
Figure 3.7	Steps of image processing: (a) separation of the image into the area defined by the pot, (b) masking of the image, and (c) detection of the green area of a plant.	34
Figure 3.8	Calibration of soil temperature and moisture sensors for five moisture levels of soil.	36
Figure 4.1	Accuracy calibration plots for five moisture sensors, where the signal is measured in arbitrary units (AU).	41
Figure 4.2	Stability calibration plots for the five moisture sensors, where the signal is given in arbitrary unit (AU).	43
Figure 4.3	Repeatability calibration plots for five moisture sensors, where the signal is given in arbitrary unit (AU) for day 1.	44
Figure 4.4	Repeatability calibration plots for five moisture sensors, where the signal is given in arbitrary unit (AU), for day 5.	44
Figure 4.5	Repeatability calibration plots for five moisture sensors, where the signal is given in arbitrary unit (AU) for day 7.	45
Figure 4.6	Linearity calibration plots for five moisture sensors, where the signal is given in arbitrary unit (AU) for day 7.	46
Figure 4.7	Measured homogeneity of the soil sample.	47
Figure 4.8	Typical images from topside camera over one trial (day 14).	50
Figure 4.9	Selected pictures of five days from the first trial experiment	51
Figure 4.10	Typical images from the side-view camera.	51
Figure 4.11	Results from image processing for all trials including absolute value of the green area of plants and normalized value.	53
Figure 4.12	A plot of moisture content and green area of the plant.	53
Figure 4.13	Linear regression models based on the correlation between moisture content and green area values of plants for the first trial of the experiment.	55

CHAPTER I

INTRODUCTION

1.1 PROBLEM STATEMENT

The Internet of Things (IoT) is the application of a worldwide network as a medium to interconnect physical objects within the virtual world, which has revolutionized several disciplines (i.e., industry, healthcare, management, and agriculture). The IoT technologies have been applied in agro-industrial and environmental fields for various purposes (diagnostics, monitoring of plants, soil, greenhouses, food supply chains, animals, etc.) as well as controlling agricultural systems. In recent years, IoT technologies have begun to play a major role in agriculture. These technologies could be widely employed in agriculture and would help to improve agricultural productivity. Increased connectivity allows us to maximize crop production while minimizing the burden on farmers through the development of IoT-based smart farming and sustainable agricultural systems.

To date, most studies on crop health monitoring have been based on remote sensing data, which have a low-quality resolution. Thus, the lower spectral resolution in captured data greatly reduces the accuracy of monitoring and controlling. However, abiotic stresses such as temperature and moisture of soil can significantly affect plant health and growth. Therefore, novel, low-cost and real-time imaging systems coupled with various smart sensors (i.e., temperature, humidity, weather condition, etc.) are required for accurate predictions of plant health and growth conditions. This will provide an effective and comprehensive data management for plant health monitoring.

1.2 RESEARCH OBJECTIVES

The overall objective of this research was to investigate the potential of a smart, multi-sensor, IoT-based system for plant health monitoring under abiotic stress conditions. The specific objectives of this research were as follows:

1. Develop a prototype of a smart multi-sensor system for real-time and remote sensing of selected soil-plant parameters. Calibrating each smart soil sensor separately to be fused into current research and real condition.

2. Monitor changes in green areas of plant images under pre-determined five soil moisture contents conditions in the short and long-term periods.

3. Develop regression mathematical models to determine and predict the critical time of irrigation to prevent plants from wilting.

CHAPTER II

LITERATURE REVIEW

2.1 ABIOTIC STRESS

Requisites for plant growing, expansion, productivity, and reproduction are optimal light intensity, levels of water, carbon, and mineral nutrients. Due to their stationary nature, plants experience a wide spectrum of stresses including non-living environmental stresses and stresses prompted by living beings. Any level of stress below or above optimal is considered an extreme condition that can induce adverse effects on a plant's development and growth (Lata et al. 2018).

While *biotic stress* refers to harmful effects due to living organisms (like viruses, fungi, bacteria, harmful pests, parasites, weeds, and cultivated or local plants), *abiotic stress* is known as the deteriorative impact of external and non-living environmental factors such as temperature and relative humidity on the living organism. The growth, development, and reproduction of living organisms like crops can be affected by both abiotic and biotic stresses (Ferrante and Mariani 2018).

Abiotic stresses are recognized as serious threats and the main causes of crop production reduction and environmental deterioration. Drought, extreme temperatures, excessive salinity, acidic conditions, heavy metal, chemical toxicity, nutrient deficiency, and starvation are all considered major sources of abiotic stresses that cause various amounts of damage in plants (Chaves and Oliveira 2004). Research on the global yield losses of crops connected with abiotic stresses has been conducted by Boyer (1982) and Farooq et al. (2009). They estimated the losses amount to 70%, while Farooq et al. (2009) presented results of 13-94%.

Agricultural crop yields are affected by the interaction of various factors including the above-mentioned abiotic and biotic factors and genotype of crops and agronomic management. Influencing factors like adaptability to various conditions, and types of genotypes, along with evolving agricultural cropping systems can result in different yield productions. However, due to the development of new devices and improvements to the biotechnological genetics of high-performance cultivars, agricultural systems have been rapidly evolving (Ferrante and Mariani 2018).

The growth and development of a plant are adversely affected by abiotic stress-related changes, like physiological, morphological, biochemical, and molecular changes (Wang et al. 2003).. Stress factors such as drought and salinization can cause osmotic stress, resulting in ion disruption as well as disruption of homeostasis in water potential. These kinds of harmful changes can occur at two levels: cellular or systemic (Zhu 2001).

To maintain growth and productivity, plants activate their defense mechanisms in order to respond to abiotic and biotic stresses. In the early stages of stress exposure, no visible symptoms are obvious, despite deep changes to physiology, such as increased production of bioactive compounds (Ferrante and Mariani 2018).

Different abiotic stress factors can have different effects on plants. For example, early exposure to varying levels of acidic conditions results in an abnormal physiological pattern of growth of plants (Munns and Tester 2008).

Soil moisture content, particularly drought, is recognized as the main factor leading to substantial decreases in agricultural production. Plant growth is affected by the soil moisture conditions so plants respond to soil moisture conditions in every stage. It is important for farmers and producers to know the critical point of soil water condition. Based on this information, the best time and proper amount of water required can be predicted and applied. This kind of information cannot be reached just by theoretical consideration. *In-situ* studies, such as the current one, are necessary to obtain data under experimental or real conditions to accurately calibrate the program. Enduring water stress for extended periods has adverse consequences on aspects of plant health, such as decreasing leaf water potential, reducing the size of the leaf, halting root growth, reducing quantity and quality of agricultural yield, delaying blossoming and fruiting, and restricting plant development and productivity (Xu et al. 2016). Drought also results in a reduction of photosynthesis, and the turgor in cells drops substantially (Sevanto 2014).

One essential step that can be taken to mitigate the destructive effects of abiotic stresses on plant growth and health is to monitor plant conditions from the early stages to help farmers and producers to predict and prevent damage.

2.2 PLANT (*PEPEROMIA*)

Peperomia plants (radiator plants) are pan-tropical plants that belong to the family Piperaceae, a large family of basal angiosperms comprising approximately 3,700 known species (Christenhusz 2016). There are five genera of *Piperaceae* family such as *Verhuellia*, *Piper*, *Manekia*, *Peperomia,* and *Zippelia*. With nearly 1500-1700 different species, *Peperomia* is one of the richest genres in its family (Pino et al. 2012). *Peperomia pellucida* is mainly distributed in countries of Southeast Asia, Central and South America, Africa, and Australia (Loc et al. 2010). Based on a former study conducted by Nelson and Platnick (1981), the leading cause of the vast geographical distribution of *Peperomia* worldwide was vicariate dispersion. However, recent studies have recognized other factors related to this broad distribution, including carrying sticky seeds by birds and cultivation all around the world because of the ornamental popularity of some species (Smith et al. 2008). In folk culture, *Peperomia* plants have been traditionally used for medicinal applications for millennia, and the most common *Peperomia, Peperomia pellucida* Kunth, is reported as a medicinal species (Lowe et al. 2001and Telban 1988). *Peperomia* plants are mostly considered low-maintenance indoor plants since they require little watering. With the help of a moisture meter, the timing and duration of plant watering can be determined. The *Peperomia* plants with thinner leaves require more frequent watering than those with thick waxy leaves.

Peperomia pellucida was selected for this study for certain reasons. First, this tropical plant is well-suited for an indoor environment and laboratory experiment. Secondly, by having round-shaped leaves, this plant can indicate minor changes in abiotic stresses by grossly changing the size and color of its leaves.

2.3 REMOTE CONTROL

Remote control and supervision are employed for various reasons, including: 1) time constraints, 2) easy access for humans to the work zone, 3) safety reasons, and 4) economic reasons (Wong et al. 2017).

Remote access to data and supervision has been implemented for several non-agricultural fields, including health, industry, military, and smart cities. Results from these experiences can be adapted to agricultural systems. Remote control and accessing of information have been practiced both in-field and outside the field. Remotely supervised equipment with controllers, smart sensors, and cameras that can navigate fields have been applied for monitoring crops and soil conditions. Moreover, this remote monitoring system can be applied for weeds detection, crop growth, soil deficiencies, livestock management, and irrigation mapping applications (Vasconez et al. 2019).

2.4 INTERNET OF THINGS (IOT)

2.4.1 Introduction

The IoT is described as a system of physical interrelated objects, or “Things”, with unique identities that are embedded within other objects, devices, and technologies with the ability to exchange data over the network, without any human interference (Elijah et al. 2018). According to the Cisco Internet Business Solutions Group, the IoT can be simply defined as the time when the number of “things or objects” connected to the Internet surpass the number of people (Cisco IBSG 2011).

Due to the connection of multiple technologies, machine learning, commodity sensors, and embedded systems, ‘things’ have been evolving. The term “internet of things” was initially coined by Kevin Ashton in 1999, and later by the Massachusetts Institute of Technology, from work at the Auto-ID Center and on radio frequency identification (Ashton 2009).

At the time of Ashton’s definition, the IoT was completely dependent on humans, since almost all the data available on the Internet was captured or created by human beings. The problem is that people have restrictions in terms of time, accuracy, attention, and comprehension of subjects. Therefore, it was suggested that it would be beneficial if gathered data could be used without human interference. The IoT has the potential to change the world, but it needs fundamental infrastructure (e.g. computer power, sensors, and software).

It was estimated that in 2020, 50 billion objects were connected via the internet. Plenty of opportunities for novel applications have already been demonstrated in the IoT, including monitoring systems for home and the workplace, precision agriculture, data and supply chain management, and much more (Poornima et al. 2018). IoT is a massive source of information and data provided through the IoT has been used to improve many aspects of our quality of life in different parts of the globe. In daily life, IoT technology is mostly concerned with the concept of 'smart homes', which manifests in various realms, including the monitoring and controlling of household devices and appliances as well as security systems. The IoT improves data managing systems, enhances smart city infrastructures, and helps to accelerate economic growth in various areas. (Ramirez 2015). The IoT can be used in building a healthcare system; e.g., implementing smart beds in hospitals and automated-medicine dispensers in homes that can upload patients' data to alert the care team (Elanthiraiyan and Babu 2015). Already, many IoT-related projects have been undertaken to improve the distribution of the resources and help to understand our planet, so that people can be more proactive instead of reactive (Evans 2011).

2.4.2 Benefits and challenges of IoT

The IoT has the ability to improve communication between connected devices. Various technologies like radio frequency identification, middleware, sensor networking, cloud computing, and other user-related applications have been integrated into the IoT (Manrique et al. 2016).

In social services and businesses, IoT could assist to increase the quality of services and reduce the demand for human intervention. Therefore, IoT creates beneficial endless streams of data with possibilities for harnessing the gathered data, utilizing more integrated automated systems that could lead to more savings in time, energy and money. Due to the wide-ranging implementation of the IoT, challenges are inevitable (Elijah et al. 2018).

The IoT has some privacy and security complications. It is said that there are three major challenges related to the IoT: (1) pervasive data collection, (2) fraud in consumer data, and (3) heightened security risks. All these problems can be overcome once they are taken into consideration in the design of the fundamentals of the system infrastructure. During the process of building hardware for IoT, hardware developers should take three key steps to enhance security and privacy and build trust in consumers of IoT by: (1) initiating of more secure design; (2) reducing data dimensions, and finally (3) providing more transparent and appropriate datasets for consumers avoiding of any unexpected data (Ramirez 2015).

In IoT-based systems interconnection is made based on existing and real-time updated information before communication technologies supply advanced services. By way of the IoT, data can be transferred over the network from every object as it relates to others, without human interference, however, the IoT has proven to be a highly distributed network of connections between humans and devices (Fan et al. 2014).

2.4.3 Internet of Things in agriculture

In recent years, IoT has helped to make smart connections and interconnections between different objects via devices in various aspects of our daily life. Precision agriculture has capitalized on the recent trend of using IoT-related technologies within its domain.

In the agricultural sector, IoT technologies have been mostly applied for the purpose of diagnostics, control, and monitoring, by providing information gathered by ground-based and aerial-based smart sensors (i.e., weather stations, soil sensors, remote imaging, etc.). Smart and precision agriculture has derived benefits from IoT in some agricultural sectors, like diagnosis purpose, disease, and pest detection, weed control, analyzing field and soil variables, precise cultivation, irrigation, and water quality monitoring, smart crop spraying, evaluating field variables like soil monitoring, climate change monitoring, and monitoring growth and health condition of plants (Ayaz et al.). The number of articles with the keyword "IoT in agriculture" in Elsevier publisher showed a drastic increase in 2020 and 2021, resulting in 1004 and 1491, respectively. This indicates an increasing trend in research studies and interest in the application of IoT in the agri-food domain.

IoT in agricultural systems is formed by four main components: 1) IoT-related smart devices, 2) technology used for communication, 3) collected data and analyzing process, and 4) the Internet connection (Elijah et al 2018). A monitoring system for a greenhouse based on wireless sensors and the Internet was promising, according to a study by Ji-Chun Zhao et al. (2010) about the application of IoT in agriculture. An information management system was designed, and special software for monitoring data and readings was developed. Recently, smart-based systems for monitoring water quality and pollution have been utilized, due to innovation in IoT-related technology and sensors.

In an IoT-based smart water quality monitoring (SWQM) research, Mukta et al. (2019) developed a system monitoring water quality to have incessant measurements of four physical parameters of water condition; i.e., temperature, pH, properties of turbidity, and electric conductivity. All sensors were linked with Arduino Uno (a programmble microcontroller board, which is low-cost and flexible) to measure water parameters. Data from the sensors were transferred to a desktop application in the .NET platform and then comparisons were made between collected data from sensors and standard values from the World Health Organization (WHO). Results from this study demonstrated that water quality parameters could be investigated through the use of the SWQM monitoring system and fast forest binary classifier. On the basis of the developed model, sample water could be classified as polluted or unpolluted.

In another related study of water quality monitoring, a cost-effective system which made use of different sensors such as pH, temperature, and turbidity has been proposed. Sensors relate to Raspberry Pi (RPi) throughout an analog to digital converter. Based on extracted data from sensors and RPi, the water flow provided from an overhead tank to houses can be stopped with a valve. The designed system saved time and energy as the process can be carried out without human interference (Sengupta et al. 2019).

Bhatnagar and Chandra (2020) proposed an IoT-based soil health monitoring system, with the objective of helping producers to monitor soil parameters like moisture, pH, and temperature with their android smartphones. The system was designed to provide recommendations on soil additives like sulfur and lime based on measured pH. The developed monitoring system was calibrated and validated with values recorded in laboratories. Results showed no significant differences between the field and the lab data. The IoT-based system was installed on android smart-phone and now can be practically applied to assist agricultural experts and producers as well as IoT researchers.

IoT-based systems have been used for water management and improving irrigation systems. Kamaruddin et al. (2019), proposed an IoT irrigation management and monitoring model which applied Arduino technology as a smart processor. The results showed that an implemented system can manage an irrigation process successfully with data derived from soil moisture content. The irrigation system prevents the release of water for irrigation (water and wastewater) whenever soil moisture is above an acceptable level or during rainfall. Moreover, the proposed system has other applications; i.e., wireless communication between sensors, android applications, and Wi-Fi processors.

In another study, Seethalakshmi et al. (2020), investigated the implementation of an automated and smart irrigation system for an optimized greenhouse based on IoT-designed technology. The proposed model works based on data collected from digital soil moisture and temperature sensors and on information regarding upcoming precipitations received from an Open Weather Map. The system results in energy and water conservation as well as increases in productivity and crop yields.

Vani and Rao (2016) proposed that for agricultural development purposes, monitoring and measurement of the related agricultural parameters are crucial especially in real-time. To monitor and measure soil moisture by using Cloud for IoT and Android system, a system was designed and then tested under closed laboratory conditions. The person can check the real-time data that had been recorded using Cloud technology and the Blynk application. Therefore, a quick reaction to these recorded soil moistures anywhere at in anytime would be possible.

In a recent study, carried out by the same research group (Vani and Rao 2019), they suggested a solution to a common problem in the agricultural system which is analyzing the variation of soil moisture on yield every day. Sensors are placed and the reading moisture of the soil is collected every day using an implementation of smart technologies: IoT, GSM (Global Service Message) communication, and Cloud Computing technology. Their designed system is applied Wi-Fi and GSM-based communications for transferring sensor data to Cloud storage and/or mobile devices. Also, special hardware, as well as, the software is developed. To save the sensor readings, Thing Speak Cloud Computing technology is applied. It has been stated that the final system implementation is done easily, and moisture information is received remotely.

In a survey of recent advances and future challenges of IoT technology in agriculture, Tzounis et al. (2017) pointed out that IoT structure is rooted in three layers: i) the sensing layer, ii) the data transfer layer, and iii) the application and data storage layer and manipulation). It has been concluded that IoT in agriculture is a mean to optimize production, but the security section is vital in this regard. Moreover, for having a safe market and control over the access to information, related data cannot be accessible and retrieved by non-authorized entities.

There are some similar studies to the current research which employed precision agriculture applications as well as IoT technologies to improve plant health conditions. Several factors can be monitored by employing IoT in agriculture. There are several examples showing that IoT has been applied in various parts of agricultural studies like the proposed thesis.

The health and growth quality of plants have been monitored via IoT-related devices like sensors as well as image processing. Data from image processing and environmental changes help to detect and classify plant disease, particularly in the early stages. In related research, an IoT-designed RPi-based model was developed which was able to capture images of plants, extracted and sent environmental sensings such as air humidity, soil moisture content, ambient temperature, and soil pH in a database in real-time. Captured images were preprocessed and converted into CIELAB color, (L*A*B: L* for perceptual lightness, A* and B* for: red, green, blue, and yellow) with a cluster algorithm to divide infected parts of plants from non-infected ones. To detect and classify plant disease, multi-class support vector machine is utilized. Results from the research showed that the proposed system can categorize crop diseases accurately with 97.33% of accuracy (Pavel et al. 2019).

Siddagangaiah (2016) proposed a system based on IoT technologies to monitor a plant's health condition. The implemented system monitored and measured environmental parameters such as air humidity, soil moisture, temperature, and intensity of light employing sensors. Then all collected data was sent to the IoT application. By using a smartphone, any deviation in environmental measured values from sensors can be detected by sending alert message. It is concluded that the experimental system is a great option for monitoring factors affecting plant health and can provide remote access to the information as well as alert about any probable deviation.

In an IoT-based disease identification for rice in India performed by Ramesh and Rajaram (2018), a user-friendly IoT reference architecture is developed to provide on-field disease detection. Also, a prediction system is designed that will be able to detect diseases in the earlier stages of crop growth. The collected information is classified in order to help farmers protect their crops.

The challenges associated with the IoT technology and various applications have been discussed in a research carried out by Agrawal and Lal Das (2011). This research revealed some key challenges: standardization, data security, and privacy, procedures for identification and integration, as well as overall regulation and ownership. It has been concluded that the gap between theoretical and practical implementations of IoT applications can be bridged using advanced communication technologies such as Radio Frequency Identification (RFID), WiFi sensor networks, and cellular communications. Although several studies have been conducted on the application of IoT for plant monitoring, there is still a gap in adapting results to real applications. Challenges like wireless coverage issues, the high price of devices, lack of required devices in some areas, battery life or other electrical supply issues, so to solve these issues privacy measurements and security need to be taken into consideration.

Although the overall precision and accuracy of individual sensors is checked by the manufacturers prior to commercialization, sensors from different vendors require calibration and validation prior to use in any real-time experiment or real farming system. Calibration and validation of sensors are highly required to ensure the best possible performance of sensors. Moreover, the most important reason for calibration is to ensure that both precision and accuracy maintain at an acceptable level based on standard values.

In the current research, sensors were calibrated to be applied in a smart setup. To address some IoT-related challenges and provide mathematical models for different soil conditions that can be used for real farming condition, a smart monitoring system was implemented in a lab. The main goal of conducting this research was to develop a system to enable the monitoring of plant health and prevent wilting at critical times, which could later be used in a larger system and real conditions.

2.4.4 PRECISION AGRICULTURE

Precision agriculture (PA) is a management philosophy in agriculture which makes use of smart technology and advanced devices like sensors and cameras in agricultural systems (Ratnaparkhi et al. 2020). PA can also be defined as an integrated agricultural management system which can help to maximize production efficiency and minimize environmental damages and losses by applying site-specific crop management practices to collect site-specific data (Gozdowski 2007). Precision agriculture has enhanced farm machine efficiencies and reduced drudgery and harm to operators. PA can also help to increase the yield of crops and reduce production costs and environmental effects.

Precision agriculture has incorporated various science disciplines like plant science and agricultural engineering. As a result of this advanced technology in agriculture, numerous tools like geographic information systems, Global Positioning System, automatic systems, variable rate applications, data management systems, and remote sensing yield monitors have been introduced and widely applied in agricultural systems. PA makes use of information technologies (IT) by focusing on creating immediate benefits from the available environment. By using IT in precision agriculture, collecting diverse data of the farms and plants is possible. These results can help farmers and producers to recognize various production resources and apply precise treatments as necessary (Aubert et al. 2012). It is predictable that in the near future, agricultural processes that involve this equipment may no longer require physical presence of an operator. Currently, studies and research are focusing on approaches that take advantage of the complete automation systems of agricultural field equipment and machines, combines, and irrigation systems to achieve this ultimate objective.

2.4.5 IMAGE PROCESSING

Image processing has been effectively applied in various domains since it is a beneficial tool/technique for analyzing data and parameters. In agricultural-related system and studies (sustainable and precision agriculture), image processing has been utilized as an important new emerging technology.

Most remote sensing systems function on the basis of collected images from a plant or field; therefore, image processing and the development of accurate image processing algorithms have played an important role in smart systems for agriculture.

Digital images are made of pixels from a 2-dimensional grid of elements. Due to the human vision that is restricted to the visible portion of the electromagnetic spectrum (wavelengths from 380 to 700 nanometers), digital images which provide a vast range of spectrum of observation can be a sufficient replacement for human vision. In research conducted by Gonzalez and Woods (2002), image processing was explained as a digital process where images are used as input to obtain some image or non-image quantitative outputs, like graphs or values.

Images undergo a transformation before they can be analyzed. Obtaining segmented binary images containing black and white features that need to be measured would be a typical first step. Required procedures such as image registration, georectification, miscellaneous image enhancements, and edge or target detection can be performed in software like MATLAB (Simoes 2018).

Analysis and processing of images in the agri-food industry has been established in the early 80's. Objects or work-pieces in agri-food have natural properties which require flexible processing techniques with the ability to cope with natural variability (Tilet 1991). The installation and usage of image processing systems have been expanded in the food processing area. Examples of applications are sorting raw material and production and packaging inspection. Because of the rapid development of enhanced image processing techniques in the agri-food industry, inefficient processes of manual product inspection have been reduced. Algorithms are typically applied for the processing of images so that most image processing applications are implemented using sophisticated software toolboxes (Nair and Manikanda 1997).

The application of image processing in agriculture broadly expanded into various fields, including monitoring plant health conditions, fruit grading, disease or weed detection, yield forecasting, and irrigation scheduling. This machine vision system can effectively help to save costs, and improve the environment, for instance: weeds can be classified with the accuracy of 85-96% which is a high accurate classification. However, the accuracy is affected by the algorithm and restriction due to captured images. Also, the classification accuracy for fruit grading can be up to 96% depending on the applied algorithm and image processing technique (Vibute and Bodhe 2012).

In a study carried out by Ozdogan et al. (2010), the benefits and challenges of remote sensing to monitor irrigated lands in agricultural system were discussed. Remote sensing was applied to provide mapping for irrigation area for three different scales: local, regional and global. It was indicated that larger scales required more study to get the best method of digital image classification and best irrigation timing.

To investigate the objective of developing an image processing algorithm with the ability to detect green areas of plants automatically in real-time, the system was designed and modified. Smart system on small scales can produce more than thousands of images over time remotely and automatically like the system that was applied for the current study. The proposed system took and saved images at interval of every 30 minutes, but it can capture images and data every minute depending on application, aims of research and devices capacities (like RPis). Because of the system limitation, the analysis process has been done offline, after capturing and sorting out all required data.

CHAPTER III

METHODOLOGY

3.1 EXPERIMENTAL SETUP

The first stage of the experimental work was to design and build a smart system based on connected sensors. The next step was to calibrate and validate all selected sensors for real-time monitoring of plant health conditions and investigate the effect of soil moisture content and temperature.

The schematic design of the experimental setup is shown in Figure 3.1. The original setup was made of a preliminary wooden box.

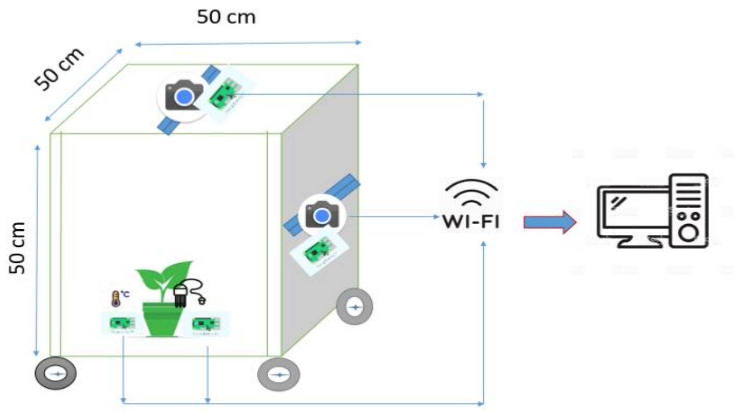


Figure 3.1. Schematic design of the experimental setup.

The final system was composed of four connected components: (1) two monitors, (2) Raspberry Pi (RPi) cameras, (3) temperature sensors, (4) humidity sensors.

Among a wide range of camera selections, low-cost Raspberry Pi (RPi) cameras were selected for their convenience in prototyping applications. Although cost is not the only criterion for its popularity, RPi can be integrated with other mechanical devices and it can be employed successfully with a vast range of ribbon cables (Salem et al. 2020). This camera is well suited for Lab photography and motion detection applications. The latest version of two RPi 4 Model B/ 4GB was used in this study. The fast-networking RPi 4 came with dual displays, Gigabit Ethernet, and USB ports along with Bluetooth. Furthermore, their specification and excellent quality made all the system highly reliable.

The RPi cameras were connected to a RPi baseboard that is further connected to acquisition monitor devices. Both RPi run Python-based software with custom codes and integration to the network (Appendix A and B). Since the setup employed the 'multi-camera' function, image acquisition was synchronized across multiple cameras by executing similar codes on both RPis. The two RPis were connected using a cable and triggered by the main RPi. The coding section for the main RPi with the side camera included sensors parts as well.

Moisture sensors (analog waterproof capacitive soil moisture sensor), and analog waterproof capacitive soil moisture sensor (DFRobot SKU: SEN0308) were used for this study. The moisture sensor, as shown in Figure 3.2 contains one metal probe with the dimension of (L x W) 175 x 30 mm that can detect the capacitance caused by the changes in the dielectric property due to changes in soil moisture content with the built-in voltage regulator chip which supports a wide range of voltage (support 3.3~5.5 V).

Figure 3.2. Analog waterproof capacitive soil moisture sensor.

Five units of waterproof soil temperature/moisture sensors (SLHT5) were implemented in the setup design. The temperature was obtained with a soil temperature/moisture sensor with an accuracy of ±4.5% RH. The SLHT5 soil temperature and humidity sensor included capacitive moisture-sensitive components and a temperature measuring element. This sensor has a range of -40 to + 123.8℃ and accuracy of ± 0.5 to 1℃ depending on environment temperature. These purchased sensors came with core wire package, sensor, and the lead between the connector form (Figure 3.3).

Figure 3.3. Soil temperature and moisture sensor.

Sensors were connected to the main RPi, and a 30-minute interval was set for all readings and captured image frames stored in the RPis. In addition, two blackboards were used as a background for each camera to control environment-lighting conditions and reduce background noises, resulting in accurate image acquisition of the plants. To provide a neutral background, one black board was placed beneath imaging subjects, which made an ideal background for the top camera, and another black board was fixed across from the side camera.

3.2 SOIL SAMPLE PREPARATIONS

Triple blend gardening soil (peat moss, composted manure, and humus) was prepared. The soil was kept in the oven overnight (24 hours) at 130°C to completely dry. The soil was then kept in sealed double-wrapped plastic bags one night at room temperature.

Five pots with five different soil moisture conditions were prepared: 0, 20, 40, 60, and 80% (dry basis) for each trial of experiment. To prepare these soil samples with desired moisture content, about 150 g of oven-dried soil was mixed with the desired amount of water. For instance, to prepare 20% moisture content (MC) soil, 30 ml distilled water was mixed with 150 g dry soil. The prepared soil samples with desired moisture contents were poured into pots. *Peperomia pellucida* plants were cultivated in the pots, and the pots were covered with double-wrapped plastic bags to prevent moisture exchange between the soil and the atmosphere during the test. However, it did not prevent some water loss through absorption by the roots and release via transpiration. All experiments were performed at room temperature (25°C). The prepared pots were placed on the blackboard on the stand, and moisture and temperature sensors were inserted in the pots to get high-quality pictures of plants (1080x1080 pixels) compared to low-quality frames which only contain 200x200 pixels.

Finally, a preliminary experiment was run for 24 hours to check and optimize selected settings. During this time, measurements were captured at 15-minute intervals. Reading of these testing trials and graphs have been compared with those of calibration, and it was concluded that sensors and cameras provided accurate and reliable measurements and frames, so the same could be applied for the real trials.

3.3 DATA ACQUISITION

Two elements were required to acquire images from plants: (1) a suitable camera that could be fitted in assembled setup as well as providing high-quality output, and (2) a digital converter to convert the cameras' output into images. Based on finalized design to capture an image of samples, all pots for each trial were placed on one stand. For this study, two set of RPi camera boards (V2, 8 MP) were employed. This camera module can be connected to all RPi models, capturing 1,080 × 1,080 pixels images or videos. The module has small dimensions of 25 mm × 20 mm × 9 mm, and a resolution of 8 megapixels with a focusing lens, and a weight of 3 grams that makes them a perfect option for this system because weight was an important factor in this study.

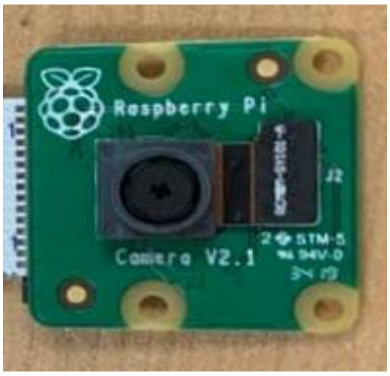


Figure 3.4. Raspberry Pi camera board V2 (8 MP).

The top camera in the developed setup (Figure 3.5) was mounted with a lens facing downward on the top part of the stand. The top camera was positioned approximately 50 cm above the samples. The side camera was affixed to the lab table at a sufficient distance (about 50 cm) that can provide images with full coverage of samples. Top and side cameras were connected by a wire to provide synchronized acquisition of images. Cameras and RPis were connected to two monitors separately. All five humidity and temperature sensors were inserted in samples to measure data from soil (Figure 3.5).

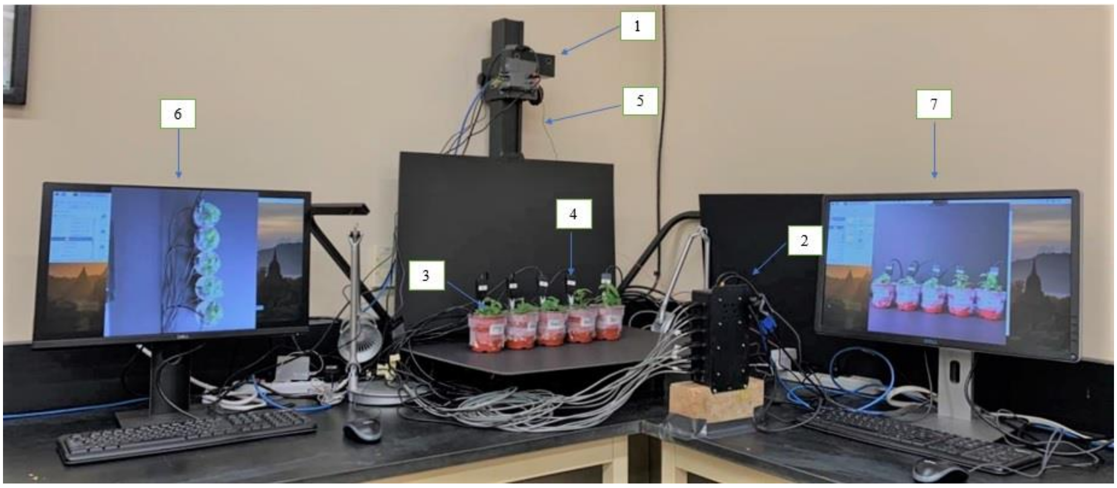


Figure 3.5. Smart multi-sensor system based on imaging and soil moisture sensors. 1- top camera, 2- side camera, 3- temperature sensors, 4- moisture sensors, 5- camera connection, 6 and 7- monitors.

Figure 3.5 shows the data acquisition system, which consisted of RPi, monitor, mainboard, soil moisture sensors, soil samples, and wired connection. The monitor and sensors were connected via the mainboard and controlled by a written Python code to capture moisture readings at the interval of 15 minutes.

Using FileZilla and VNC viewer, the extracted data on RPi were remotely transferred to a computer system where they could be saved and analyzed. Soil samples for calibration were prepared with the same method applied for the real experiment.

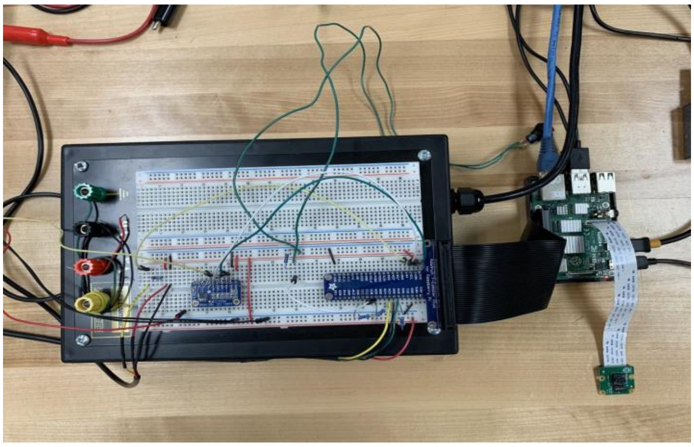


Figure 3.6. Soil moisture sensors calibration setup: Raspberry Pi, mainboard, analog-digital convertor, wire connection, and power supply.

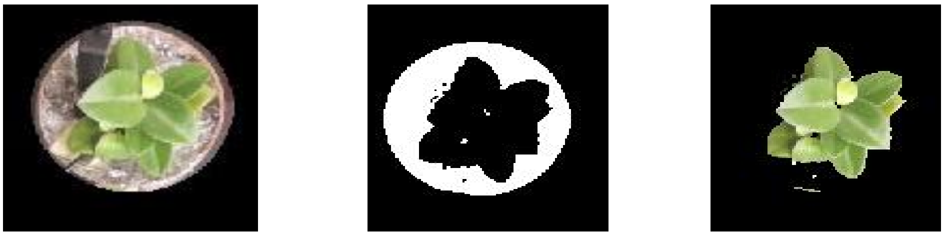
3.4 IMAGE PROCESSING

Image processing was applied to identify green areas of plants in this study. A band of wavelength (550-650 nm) was studied instead of merely one wavelength. The number of green area of plants and calculated information was used to predict plant health condition. To obtain information from green spectra, other wavelengths should be masked. For this purpose, MATLAB software was used along with IoT-related software. A proposed algorithm written in MATLAB software read .jpg files taken from plants and processed each individual image from the top camera. All deemed irrelevant pixels (like pixels from outside of the pots or light reflection) were eliminated by applying the developed MATLAB algorithm and custom codes. This algorithm provided two image processing operations: thresholding and masking. The first step of image processing was to separate pixels within the plant from those in the background. All the images were converted into bi-level images with only two-pixels values: black (intensity level of 255) and white (intensity level of 0). This part of image processing is called thresholding (Luo 1997).

For the current research, the image processing program involved 11 steps that have been used for top view and side view captured images. For top view images, saved data were navigated and for each day representative image was picked by the user with the help of the Guided User Interface. Two ultimate points across from each other on the circumference of the pot were marked and this distance in pixels was applied as the calculated pot diameter. The center of each pot was marked manually, and the center markings were propagated to all the pictures in the time series. For the masking step, a circle containing the pots' top side view with the calculated diameter was drawn around the marked center point, the pixels within the circle were kept as marked in pixels. While the pixels outside the circle were discarded. In the next step of coding, there was an option to review masked images and check if the area of the pot/plant was captured accurately. All the previous steps can be repeated as needed. If the masking section has been done accurately, other steps can be continued. The number of the green pixels in the green area of plants (pixels where the G (green) value exceeds that of the R (red) and B (blue) value, given the RGB of the colored pixel) is counted for the masked area. The counts of the desired pixels of plants were plotted or for the sake of normalization, the number of green pixels can be divided by the first value recorded for the time series that can be plotted as a percentage.

Image processing for the side view images has some similar steps. Points above and below and to the left and right side of the pot/plant' images are defined by the user. These four designated points were used to make a rectangular area and then applies as a masking image including the plants to be studied. Other steps were run just like the top side image processing steps explained above.

Figure 3.7 is a sample of masking and extracting green areas of plants for this study. The same process was conducted for all other captured images.



(a) (b) (c)

Figure 3.7. Steps of image processing: (a) separation of the image into area defined by the pot, (b) masking of the image, and (c) detection of the green area of a plant.

3.5 SMART SENSOR CALIBRATION AND VALIDATION PROCEDURE

In this study, two types of commercially available, and low-cost soil sensors were tested. These capacitive sensors were (1) the DFRobot Gravity: Analog Waterproof Capacitive Soil Moisture Sensor and (2) the 1298 soil temperature/ moisture sensor. The DFRobot SKU: SEN0308 analog waterproof capacitive soil moisture and the 1528-2209-ND soil temperature/moisture sensor was used to obtain measurements of the soil for this calibration study.

A calibration was performed to study the accuracy and reliability of the soil moisture and temperature sensors under laboratory conditions and to prepare these sensors for a real test and data acquisition. The calibration was conducted in a controlled laboratory environment with temperature 23-25 °C and relative humidity 55-60% at the University of Manitoba. In this research project, the sensors capturing temperature, moisture, and visible images were calibrated and validated for different soil conditions without plants present.

Five soil moisture sensors and five soil temperature/moisture sensors have been calibrated and validated to measure moisture content and temperature of various soil samples, including moisture levels of soil (MC = 0, 20, 40, 60, and 85%).

The procedure for soil temperature sensor calibration entailed two ultimate conditions of water, five packages of smart soil temperature/moisture sensor as well as two mercury temperature scales. For temperature calibration two different conditions were set, stirred ice bath with 0 °C and boiling water at 99.8 °C, reaching an exact temperature was influenced by factors like elevation and ambient pressure. Once both extreme water conditions were prepared, each temperature sensor was kept in a water condition for 15 minutes until their readings stabilized. These measurements were compared with the readings recorded from a mercury thermometer which was kept in similar water conditions. The same procedure has been repeated for all five sensors.

The next step involved soil moisture sensor calibration. Five different criteria have been applied for this part of validation. For online acquisition, remotely accessing and recording data of soil moisture sensors, FileZilla software and Virtual Network Computing (VNC) have been applied. Necessary codes were written in a Python-based environment.

Figure 3.8, shows one step of the sensors' calibration test where all soil moisture sensors were inserted into one pot. For each part of the calibration, sensors were placed in prepared samples, and measurements from samples were logged and saved in .csv file format once a day. Two IoT-related programs were used: FileZilla and VNC viewer, and Internet connection to all the data on RPi's could be remotely transferred to a PC where they were saved and analyzed.

Figure 3.8 Calibration of soil temperature and moisture sensors for five moisture levels of soil.

3.6 CALIBRATION CRITERIA

The following five criteria were considered during the calibration:

3.6.1 Accuracy

The accuracy of the temperature and moisture sensors was tested to ensure that under the same soil condition and as each sensor measures values that are close to the average value. The values obtained from the coefficient of determination/correlation and results from mean square error, respectively are indications of the accuracy of the sensors which are varied between movements and sensors.

3.6.2 Stability

In order to investigate whether the sensors are stable over a short and long-period of time, the stability test was conducted. Every single sensor was kept in one soil condition overnight, while sensor readings were measured every 15 minutes for 12h and were saved on the RPi system.

3.6.3 Repeatability

Repeatability is defined as how close a specific reading from the same device is relative to other results under the same conditions. Sensor readings were measured and saved for three different days: Day 1, Day 5, and Day 7. Every single day, five moisture sensors were inserted in one soil sample pot with moisture content that have been already provided. For instance, all five Analog Waterproof Capacitive Soil Moisture Sensors inserted into a pot of MC = 0%, sensors were let to achieve equilibrium in soil condition for 15 min. Then, three readings for each sensor with an interval of 15 minutes were measured and saved. While all these sensors and pots have been covered with a double wrapped plastic wrap to minimize humidity transfer.

3.6.4 Linearity

The linearity performance for each sensor was investigated and determined by analyzing each sensors' graph and by calculating the R^2. Even though the calibration curves could show a negative or positive correlation between factors, linearity can be indicated by using same procedure.

3.6.5 Homogeneity

For this part of calibration, each sensor was inserted in one pot, for instance, sensor one in pot one with dry soil condition and so on. After the first reading, the same sensor was taken out and inserted in the new spot of the same pot, so three readings for each soil condition at 15 min intervals were collected. The calibration testing occurred over a period of 48 h. Sensors had to be operated continuously for 2 to 3 h. If the sensors did not provide stable results within 2-3 h, the calibration was stopped and restarted.

3.7 STATISTICAL ANALYSES

Extracted data were statistically analyzed to examine the objectives and effect of one variable on another one. Several statistical parameters have been calculated for the current study: Coefficient of correlation R, average determination coefficient (R^2), root mean square error (RMSE), standard deviation, and mean. Since the number of collected data and images per trial was huge, it is necessary to calculate the average values. For instance, for each single day, images were extracted every 30 min, and the mean value was calculated per day. Standard deviation and the RMSE were also calculated at the same time. The correlation coefficient between two variables was developed using MS Excel.

3.8 PLANT HEALTH PREDICTION AND MODELING

To monitor the changes in leaf surface area and pigmentation through the number of the green area of plants over time, the experiment was repeated four times and for two weeks. To evaluate the relationship between these changes and potting in soil with various moisture contents, five different soil samples were prepared. To predict health conditions as well as provide a mathematical model, we provided a condition where the green area of plants would change over time. The correlation between moisture content and the number of the green area of plants, and time has been evaluated. Finally, mathematical models were developed to predict plant health conditions that can be applied for future studies. MATLAB algorithm was applied to demonstrate the correlation between the green area of plants and time for all trials. Also, similar plots with a normalized green area of plants versus time were produced. Normalized data have been used to attempt to account for different initial plant conditions and the starting number of the green area of plants.

The correlation between soil moisture content and the green area of plants was evaluated to find out the best soil condition for plant healthy growing. Furthermore, to investigate changes in two desired factors, moisture content and the number of the green area of plants, during a period of the experiment two-way lots have been produced.

For each soil moisture condition, a mathematical equation was applied as a model. Developing mathematical models to determine and predict the critical time for the plant's health and growing condition in this experiment. Moreover, the coefficient of determination (R^2) of the linear regression was calculated and applied to make a prediction of soil moisture content value at any desired and provided number of the green area of plants.

CHAPTER IV

RESULTS AND DISCUSSION

4.1 CALIBRATION RESULTS FOR TEMPERATURE SENSORS

Reading from smart temperature sensors and mercury thermometer were saved and compared with each other. Readings from the temperature sensor for a stirred ice bath and boiling condition were 0.05 and 98.7°C. The mercury thermometer readings for an ice bath and high-level temperature showed 0°C and 99.8°C. The temperature sensor has an error of ±0.5°C in -10 to +85°C and ±1°C in -30 to +100°C. Therefore, these temperature sensors were reliable for this study.

4.2 CALIBRATION RESULTS FOR MOISTURE SENSORS

4.2.1 Accuracy

Minor variations in signal strength were observed for all conditions (Figure 4.1). This variation in reading for this type of sensor, is theoretically, defined as an acceptable variation by the factor of 80 for air or dry condition when it compared with wet conditions, however, in the real condition, it does not happen due to factors like longitudinal geometry of sensors and material of the probe (Okasha et al. 2021). Therefore, this minor variation is considered acceptable based on standard accuracy variation for these sensors. It was also observed that the prepared sample of soil with 20% MC was associated with the highest measurement values in comparison to other samples.

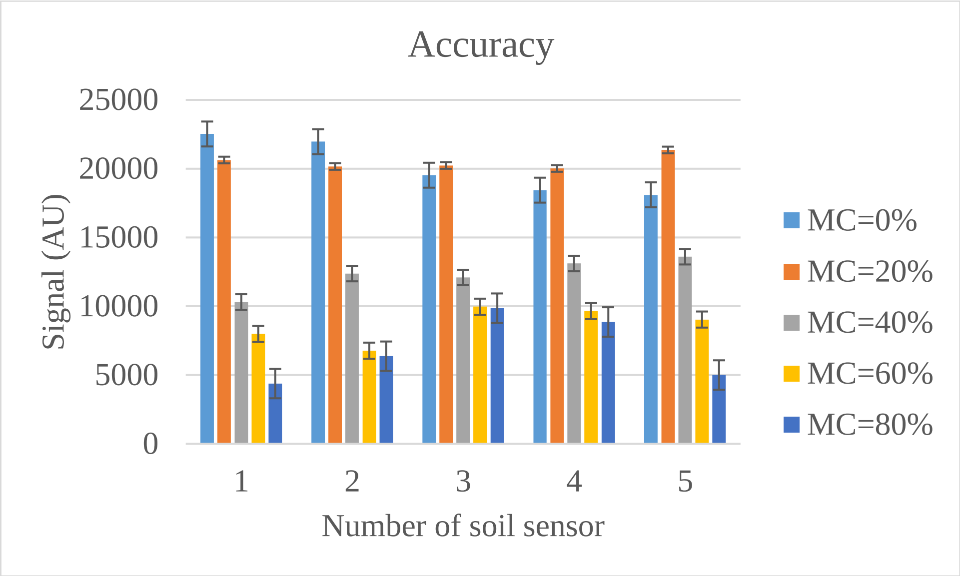


Figure 4.1. Accuracy calibration plots for five moisture sensors, where the signal is measured in arbitrary units (AU).

Calibration plots indicated that with increasing moisture content from dry condition to really wet condition, the sensor reading decreased. This is in line with the negative correlation between moisture content and sensors readings. For the dry soil condition (MC = 0%), sensors must show value around 22,000 AU. However, sensor # 5 showed the lowest signal value around 20,000 AU.

The soil sample with MC equal to 20% had a sensor reading average of 20,481.8 AU. For samples that contained soil moisture content equal to 40%, all the sensor measurement values were more than 10,000 AU with one exception for sensor #1. The standard deviations for all sensors (1 to 5) in the soil sample with MC = 60% ranged between 7,000 to 10,000 AU. The samples with MC of 80% had the sensor readings higher values for sensors 3 and 4 in comparison with other samples under the same condition.

Although there were variations in sensor readings considering soil moisture conditions, these variations can be considered negligible based on the sensor datasheet and acceptable accuracy. Since these sensors are detecting soil moisture based on the capacitive principle of sensing, they could show different signal values when inserted in different soil moisture contents, depending on tightness and insertion depth. Even in the same place and the same depth, after the first extraction following insertion may show lower signal values because of the loosening of soil caused by the previous insertions.

This demonstrated that a calibration process for accuracy was essential, even between sensors from the same manufacturer, and of the same model and maker.

4.2.2 Stability

The results of stability testing are shown in Figure 4.2. All the sensors exhibited a stable trend considering soil sample moisture conditions although sensor #1, #2 and #3 demonstrated an increasing trend, while reading from sensor #3 contained some fluctuation over the first 100 minutes. Preparation time for reading adjustment and stabilization was required. An interval of 100 min was needed for all sensors #2 and #3 for stabilization. Therefore, all readings were taken after considering preparation time in the later experiments.

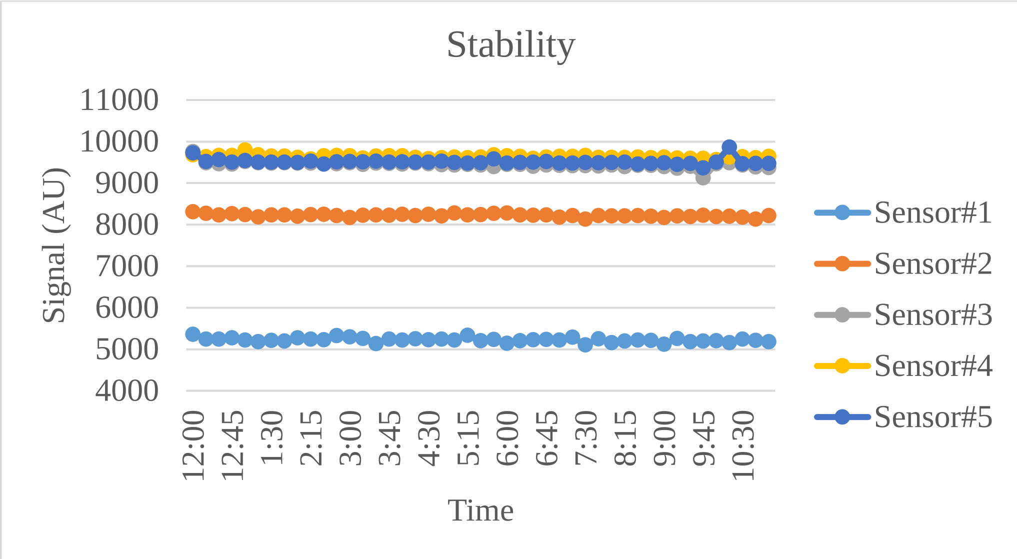


Figure 4.2. Stability calibration plots for the five moisture sensors, where the signal is given in arbitrary unit (AU).

4.2.3 Repeatability

Repeatability tests (Fig. 4.3) showed more consistent measurements for samples with lower moisture contents. For sensors inserted in samples with higher moisture content, keeping the soil moisture condition under control is more complex. Despite plastic bags wrapped in the pots which form a barrier to prevent moisture loss, some evaporation and soil moisture loss occurred. For example, for 80% MC soil, readings for one week demonstrated higher value, especially for sensor #2 on day 5 and sensor #4 on day 4. Another factor that should be taken into consideration was the structure of the sensors. As mentioned in Section 4.1.1, these sensors apply a capacitive principle of sensing moisture which means it is possible to record different measurements values, depending on the spots of insertion, soil compaction around the sensors, and the depth of the sensor in the soil. Based on these influencing factors, sensors are more probable to produce lower values, especially for higher humidity.

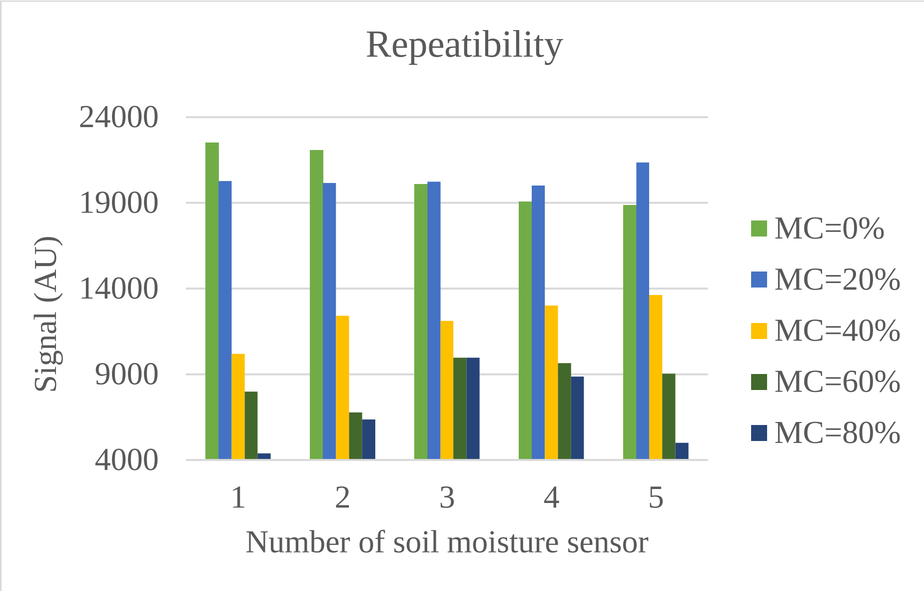


Figure 4.3. Repeatability calibration plots for five moisture sensors, where the signal is given in arbitrary unit (AU) for day 1.

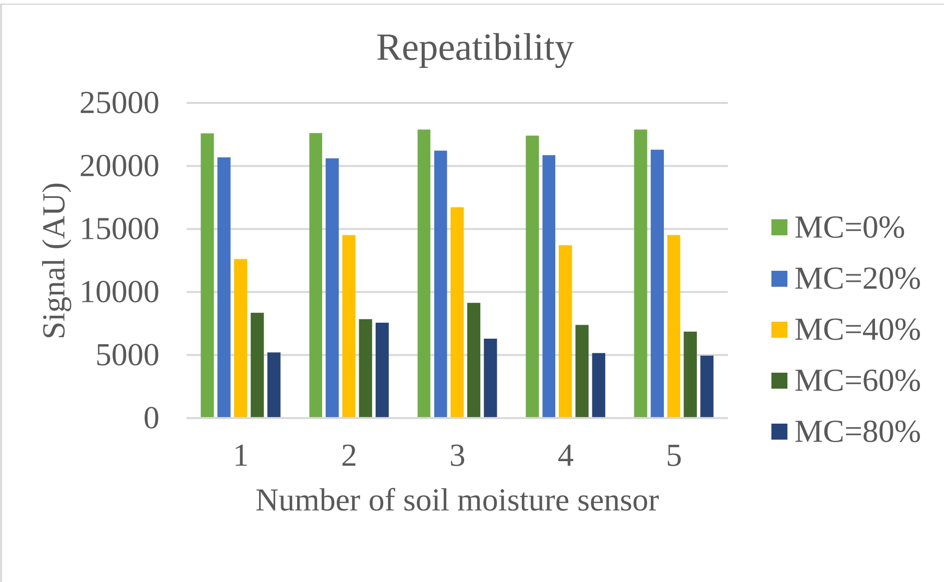


Figure 4.4. Repeatability calibration plots for five moisture sensors, where the signal is given in arbitrary unit (AU), for day 5.

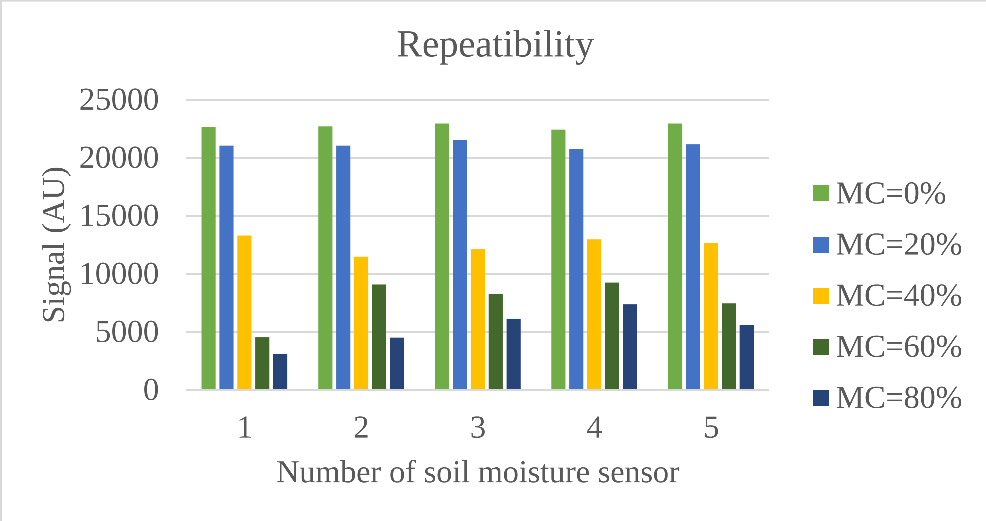


Figure 4.5. Repeatability calibration plots for five moisture sensors, where the signal is given in arbitrary unit (AU) for day 7.

4.2.4 Linearity

For each sensor, a linear calibration curve was developed. These equations could be interpolated to predict moisture content given a signal for a validated analytical range. Dry soil had the highest signal value with an average of 22,670 AU, while the lowest signal value was associated with the soil sample with 80% moisture content with an average of 5,834 AU. The R^2 value for all sensors was close to 1, which indicates that these soil moisture sensors had a great linear performance. Although sensors number one and two produced the best linear trend, the results of the other sensors were moderate (Figure 4.6).

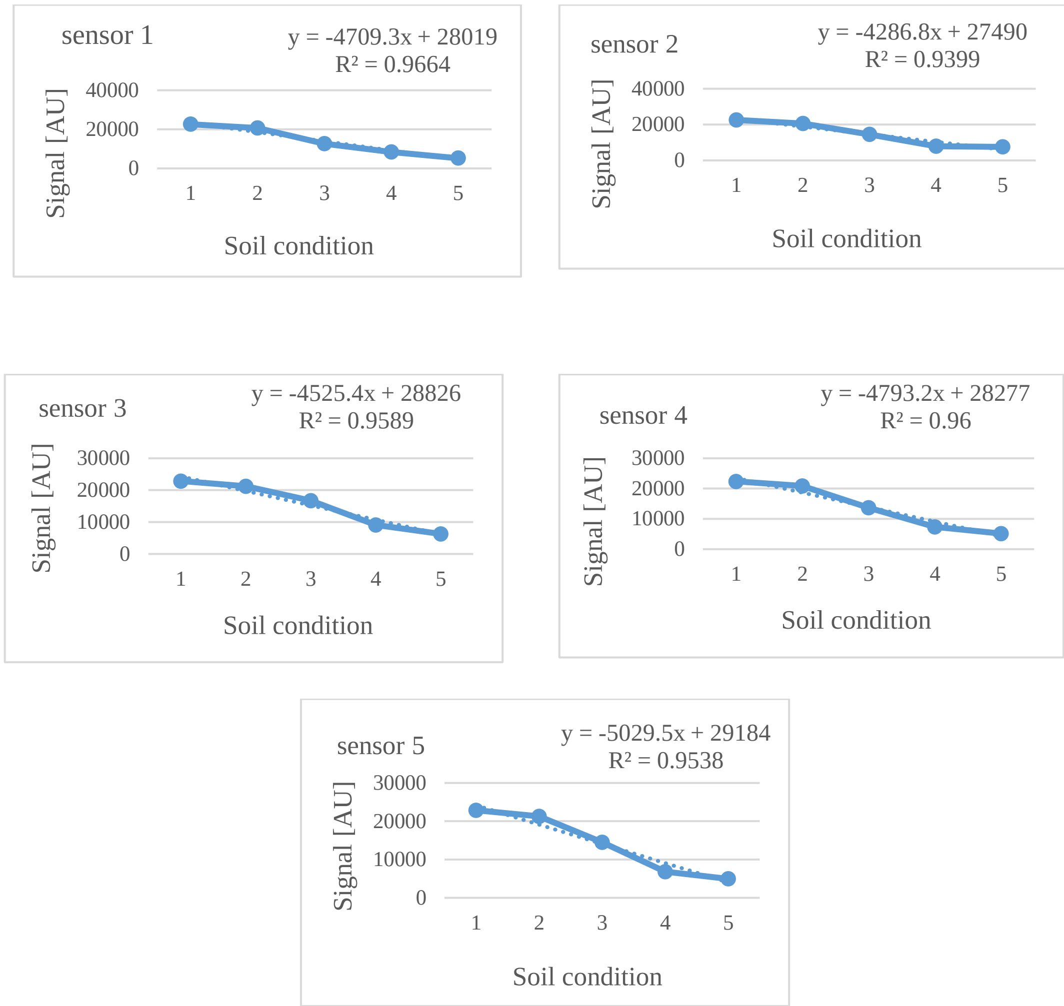


Figure 4.6. Linearity calibration plots for five moisture sensors, where the signal is given in arbitrary unit (AU) for day 7.

4.2.5 Homogeneity

Figure 4.7 illustrates a linear trend for sensor readings with minor fluctuation due to the type of the soil and dryness for the sample with lower moisture content. Thus, the soil samples were homogenous for the type of soil that was applied for this study.

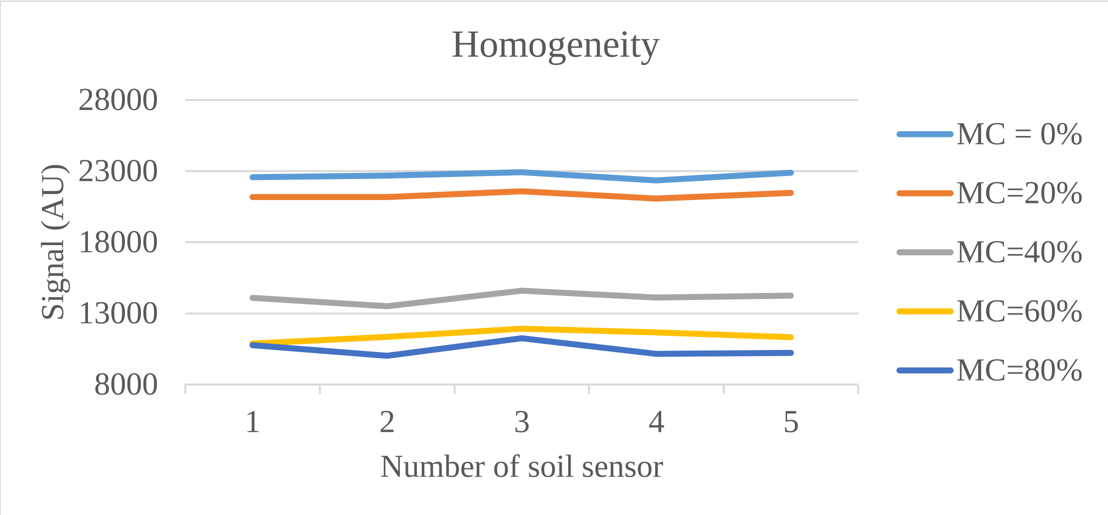


Figure 4.7. Measured homogeneity of the soil sample.

4.3 TEMPERATURE SENSORS

Temperatures recorded over the course of the trial were stable and reliable with a standard deviation below 0.8°C for all sensors. The reading temperature for all days could show changes around ± 0.8, which means the temperature reading of sensors was highly stable and reliable.

Table 4.1. Results of average daily temperature for trial one over 14 days.

Trial one	**Average daily temperature (°C) Sensor**				
day	1	2	3	4	5
1	25.25	25.07	24.85	24.62	25.18
2	26.81	26.73	26.85	26.72	26.11
3	25.20	24.96	25.03	24.85	25.28
4	25.26	24.96	24.95	24.75	25.18
5	24.92	24.70	24.55	24.35	24.81
6	24.90	24.70	24.55	24.35	24.81
7	24.71	24.53	24.34	24.13	24.59
8	26.55	26.26	26.03	25.81	26.21
9	26.94	26.73	26.48	26.28	26.70
10	25.84	25.71	25.44	25.25	25.70
11	25.48	25.33	25.03	24.80	25.23
12	24.77	24.69	24.36	24.10	24.54
13	24.89	24.77	24.44	24.17	24.59
14	25.03	24.99	24.70	24.46	24.91
Standard deviation	**0.81**	**0.78**	**0.84**	**0.86**	**0.83**

4.4 MOISTURE SENSORS

Table 4.2 demonstrated results from five similar soil moisture sensors inserted in five different samples. Extracted data for each day was calculated based on reading from sensors with the interval of 30 min. For the first sensor at 0% MC, the standard deviation was the lowest compared with other soil moisture conditions. This means that changes in moisture level in this sample were lower in comparison with other studied samples. Other sensors witnessed more fluctuation. The standard deviation for sensor # 3 at 40% MC was 2,583.9, which means that this soil condition experienced the highest moisture fluctuation. Sensors at 60 and 80% MC performed fewer changes.

Table 4.2. Results of average daily moisture content for trial one over 14 days.

Trial one	Average daily moisture content Sensor				
Day	1	2	3	4	5
1	22799.7	20774.5	15145.2	13841.5	12525.2
2	22849.4	21039.9	14550.8	12545.6	11061.9
3	22686.5	21190.0	13674.1	10793.9	9932.7
4	22713.3	21439.7	13863.0	10606.8	10065.4
5	22684.9	21642.5	14509.0	11019.8	10574.9
6	22677.6	21826.3	15275.5	11540.9	10873.3
7	22665.1	21989.6	16041.9	11903.9	11049.6
8	22834.8	22290.5	16961.4	12276.9	11382.5
9	22868.4	22454.8	17760.6	12574.0	11684.6
10	22776.3	22476.8	18442.8	12898.2	11914.4
11	22761.0	22536.4	19105.3	13380.7	12182.5
12	22687.5	22520.7	19884.0	14850.7	13136.3
13	22696.4	22572.2	20692.8	16690.3	14387.1
14	22703.5	22627.5	21167.6	17567.0	17968.7
Standard deviation	**70.6**	**639.9**	**2583.9**	**2103.2**	**2084.2**

4.5 RASPBERRY RI PI IMAGES

Acquired images for the first trial of the experiment were presented in figure 4.8. Overall the designed setup captured more than 3,000 images throughout the whole experiment. Also, the sensors have the same number of readings. For each day of the trial, one specific image from one specific time in the afternoon was picked as a sample, all captured images from 1:00 pm.

Images were selected for day 1, 3, 7, and 14 (Figure 4.9). All sample plants on day 1 were healthy. After 2 days, the plant at 0% MC was completely wilted. Images from day 7 showed that the dry sample died while plants in pots with 20 to 60% MC were not in healthy condition anymore. After 2 weeks, all samples were wilted or died even at 80% MC. The same process was conducted for all trials.

Figure 4.8. Typical images from topside camera over one trial (day 14).

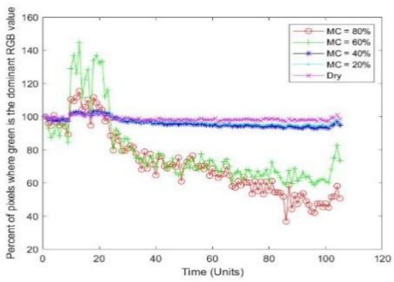
Day 1 Day 3 Day 7 Day 14

Figure 4.9. Selected pictures from trial one.

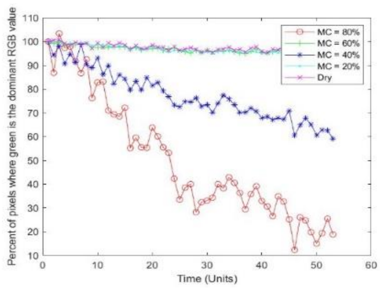
Figure 4.10. Typical images from the side-view camera.

4.6 PLANT HEALTH PREDICTION

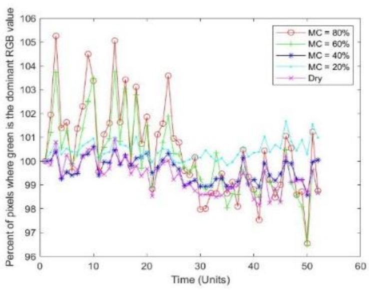
Mathematical models were developed to predict plant health conditions. Figure 4.11 shows correlations between the green area of plants and time for all four trials. Acquired results for correlation between the normalized green area of plants and time (Figure 4.11 a and b) for the first and second trials demonstrated that there was a dropping trend for a number of the green area of plants over time. For the sample, with the lowest moisture content condition, this decrease in value of the green area of plants had the sharpest trend. Results from third trial image processing showed a decreasing trend for all soil samples' moisture content conditions with fluctuation during the period of the experiment (Figure 4.11 d). Also, the very last trial experienced the same dropping trend while for higher moisture content from 40 to 80% green area of plants had not decreased dramatically.



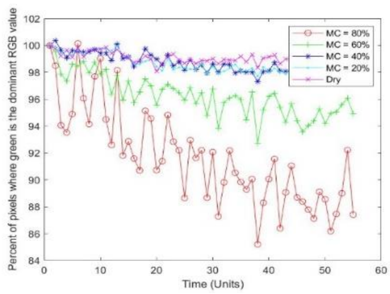
(a)



(b)



(c)



(d)

Figure 4.11. Results from image processing for all trials including absolute value of the green area of plants and normalized values.

4.7 CORRELATION BETWEEN MC AND GREEN AREA OF PLANTS

To evaluate the correlation between moisture content and the green area of plants, related plots have been produced for all trials. Figure 4.12 contains the results of the first trial of the experiment. For the soil samples with moisture, contents equal 0 and 20%, there were parallel lines for MC and green area of plants. Due to the severe condition of these two soil samples, these two factors did not have any significant correlation. These soil conditions do not provide a good environment in which to grow healthy plants. Plants begin to wilt and eventually die completely without considerable alterations to the soil moisture condition.

Results from other soil which have moderately better-growing conditions for plants in terms of soil moisture revealed that MC and the value of the green area of plants had a linear relationship. In general, decreasing soil MC led to lower amounts of the green area of plants in images of plants.

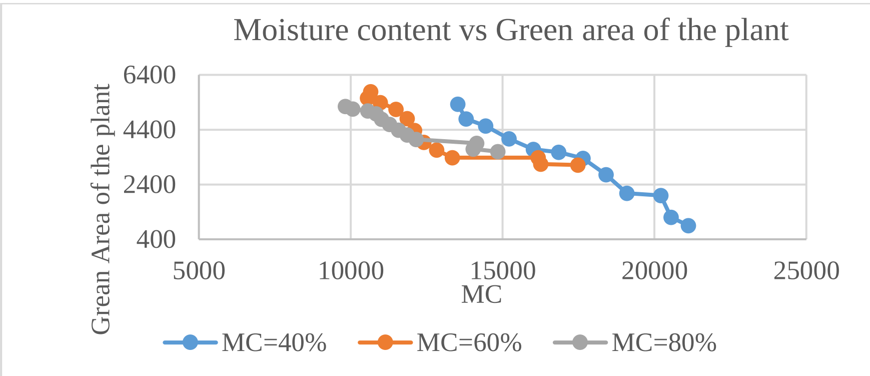
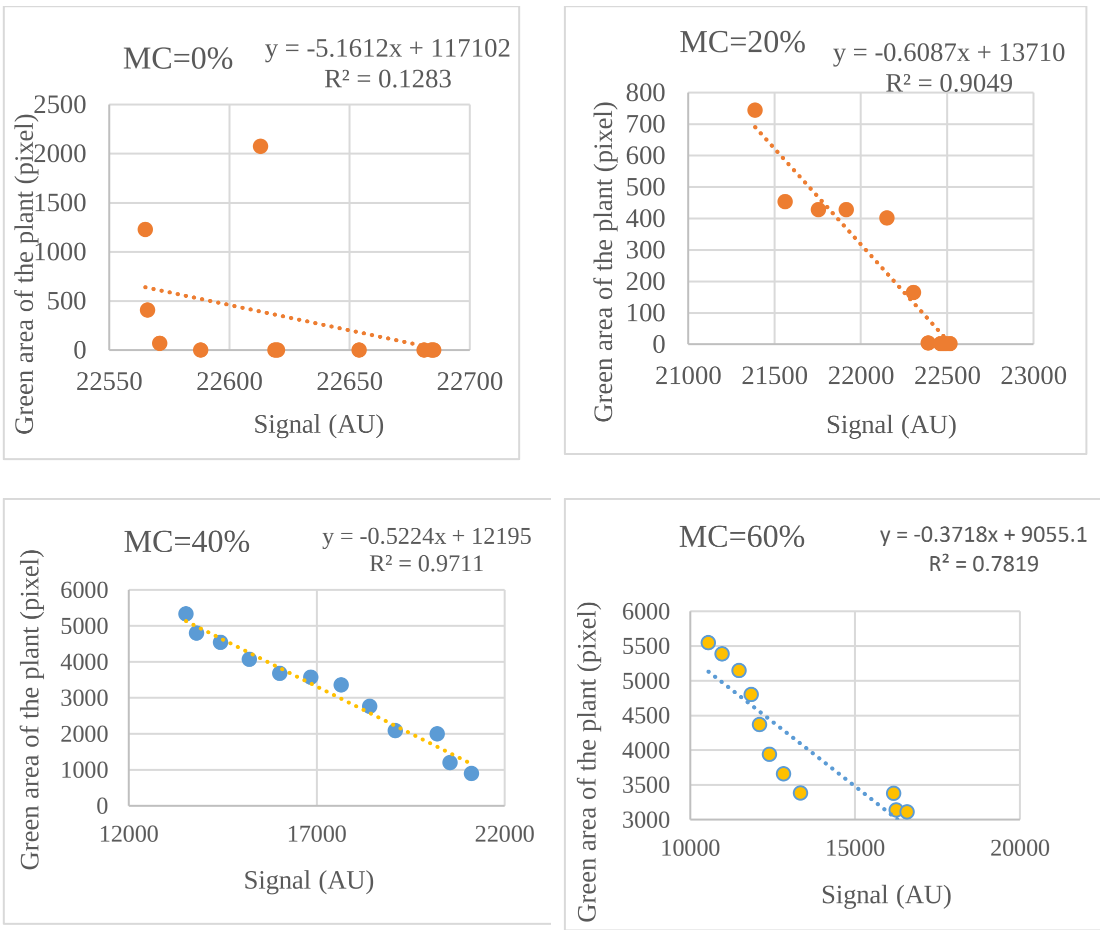


Figure 4.12. A plot of moisture content and green area of the plant.

4.8 LINEAR REGRESSION AND MODELING

Linear regression for the first trial of the experiment at all soil sample conditions was provided in figure 4.14. The coefficient of determination (R^2) of the linear regression increased considerably with increasing soil moisture contents. Samples which 20 to 80% MC demonstrated the best linear relationship with $R^2 \cong 0.9$.

For each condition, a linear equation was produced which can be applied for the prediction of soil moisture content at any desired number of the green area of plants. For instance, at 80% MC, if we want to obtain the green area of plants around 4,000 AU, the suitable moisture content should be about 13,500 AU.



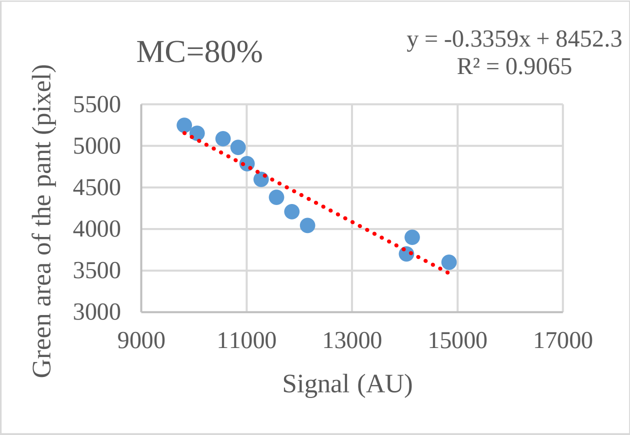


Figure 4.13. Linear regression models based on the correlation between moisture content and the green area values of plants for the first trial of the experiment.

CHAPTER V

CONCLUSION AND RECOMMENDATIONS

5.1 SUMMARY OF THE STUDY

The current study was conducted to evaluate three suggested objectives: 1) developing and proposing a multi-sensor smart system for a soil-plant system; 2) remote sensing and monitoring any changes in the green area of plants in the short and long period of time; and 3) developing mathematical models for predicting the critical point of irrigation and ultimately preventing plants wilting. To achieve these objectives, a smart multi-sensor system was designed and assembled. Two different types of sensors were applied for this research. All the smart sensors were calibrated and validated successfully. Accuracy and stability showed some minor variations. Also, image processing systems including camera, RPis, and connected monitors were calibrated and tested primarily.

All data from smart sensors and cameras were collected. Having remote access and applying IoT-related technologies and devices resulted in collecting data for a long period of time during daytime and nighttime. Under tested conditions, there were inevitable changes in soil and growing conditions. Even at the driest soil sample condition changes were observed over 24 h of monitoring. Eventually, the green area of plants dropped due to changes in MC condition.

5.2 MOST IMPORTANT ACHIEVEMENTS

1- The negative relation between soil moisture content and plant green area of plants. The correlation between these two factors was strong.
2- Development of a remote access and control system. This remote monitoring system provided access to the collected data anytime and anywhere.

Mathematical models were developed based on a number of the green area of plants under different soil moisture contents. These models and equations can be applied for predicting soil water conditions by using the value of the green area of plants.

5.3 SUGGESTION FOR FUTURE WORK

It is suggested to use more sensors for future work, for the sake of accuracy and stability. Although, making comparisons between results from different types of plants can lead to more models for different types of plants. These models can help to make a precise prediction for different plants. Applying more cameras, capturing images from three different angles, and finally obtaining 3D images are highly suggested for future research. The recent experiment had some restrictions and was conducted in a controlled environment; thus, the meteorological data were not included in this study. Upcoming research can use weather data to provide more realistic models.

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APPENDICES

APPENDIX A

RASPBERRY PI CODES: Sensors

```
# Temp sensor: ds18b20
# Moiasture sensor: SEN0308(DF Robot)
# Signal to Rpi2: GPIO25
# module import
import os
from time import sleep
import time
from datetime import datetime
import RPi.GPIO as GPIO
import busio
import board
from picamera import PiCamera
import adafruit_ads1x15.ads1115 as ADS
from adafruit_ads1x15.analog_in import AnalogIn
from w1thermsensor import W1ThermSensor

#ds18b20 temp sensor
sen1  = W1ThermSensor(W1ThermSensor.THERM_SENSOR_DS18B20,
"01145b910345") #sensor ID
sen2  = W1ThermSensor(W1ThermSensor.THERM_SENSOR_DS18B20,
"01145b913b25") #sensor ID
sen3  = W1ThermSensor(W1ThermSensor.THERM_SENSOR_DS18B20,
"01145b89063b") #sensor ID
sen4  = W1ThermSensor(W1ThermSensor.THERM_SENSOR_DS18B20,
"01145bb240e7") #sensor ID
sen5  = W1ThermSensor(W1ThermSensor.THERM_SENSOR_DS18B20,
"01145b912eeb") #sensor ID
sen6  = W1ThermSensor(W1ThermSensor.THERM_SENSOR_DS18B20,
"01145b82e879") #sensor ID

#camera object
mycamera = PiCamera()

#folder directory-----------------------------------------
day = datetime.now().date()
now = datetime.now().strftime("%Y-%m-%d %X")
#temp file dir
dir_temp = "/home/pi/Desktop/TempLog/"
#filename_temp = ("TempLog%s" %now)
filename_temp = ("TempLog%s" %day)
path_temp = dir_temp + filename_temp+".csv"
```

```
datalog_title =
"Time,Temp1,ADC1,Temp2,ADC2,Temp3,ADC3,Temp4,ADC4,Temp5,ADC5,Temp6,
ADC6,\n"
#image
path_image ="/home/pi/Desktop/Maryam_image1"
dir_image = path_image + "/image%s" %day
#---------------------------------------------------------

#GPIO setting
sigout = 24
GPIO.setmode(GPIO.BCM)
GPIO.setup(sigout,GPIO.OUT)
GPIO.output(sigout,GPIO.HIGH) #active low

#------DFrobot moist sensor with ADS1115 (adafruit)----
i2c = busio.I2C(board.SCL, board.SDA)
ads1 = ADS.ADS1115(i2c,address=0x48) # add - gnd
ads1.gain=1 # range = +/-4.096V
ads2 = ADS.ADS1115(i2c,address=0x49) # add - vcc
ads2.gain=1

rdg1=AnalogIn(ads1,ADS.P0)
rdg2=AnalogIn(ads1,ADS.P1)
rdg3=AnalogIn(ads1,ADS.P2)
rdg4=AnalogIn(ads1,ADS.P3)
rdg5=AnalogIn(ads2,ADS.P0)
rdg6=AnalogIn(ads2,ADS.P1)

#----- camera setting ---------
mycamera.resolution = (800,800)
mycamera.framerate = 15
mycamera.rotation = 270


#------- create a folder for temp logs and images -----
try:
   os.mkdir(dir_temp)
except OSError as error:
   print(error)

try:
   os.mkdir(dir_image)
except OSError as error:
   print(error)

#------- create a file for temp log ----------
file = open(path_temp ,"a")
if os.stat(path_temp ).st_size == 0:
       file.write(datalog_title)
```

```
#-----------------------------
print("program start in 5 sec")
sleep(5)

#-------------------------------
#------ main loop --------------
while True:
   time1 = time.perf_counter() #start timer 1
   newday = datetime.now().date()

    #create a new folder/file for different day --------
   if day != newday:
      file.close()
      day = newday

      #temp
      filename_temp = ("TempLog%s" %day)
      path_temp = dir_temp + filename_temp+".csv"
      file = open(path_temp,"a")
      if os.stat(path_temp).st_size == 0:
         file.write(datalog_title)

      #image
      dir_image = path_image + "/image%s" %day
      try:
         os.mkdir(dir_image)
      except OSError as error:
         print(error)
      print("created new file and folder for " + str(day))
   #--------------------------------------------------

   now = datetime.now().strftime("%Y-%m-%d %X")
   print(now)

   #send trigger to slave camera
   GPIO.output(sigout,GPIO.LOW)
   sleep(0.2)
   GPIO.output(sigout,GPIO.HIGH)

   #capture image and save in [dir_image]
   file_image = dir_image + "/image%s.jpg" %now
   mycamera.capture(file_image)
   print("image saved in" + file_image)

   #read temp sensor
   temp1 = sen1.get_temperature()
   print("Temp1 =  " + str(temp1) + " C")

   temp2 = sen2.get_temperature()
```

```
    print("Temp2 =  " + str(temp2) + " C")
        temp3 = sen3.get_temperature()
    print("Temp3 =  " + str(temp3) + " C")
        temp4 = sen4.get_temperature()
    print("Temp4 =  " + str(temp4) + " C")
        temp5 = sen5.get_temperature()
    print("Temp5 =  " + str(temp5) + " C")
        temp6 = sen6.get_temperature()
    print("Temp6 =  " + str(temp6) + " C")

    #read moisture sensor
    adc1 = rdg1.value
    vol1 = rdg1.voltage
    print('ch1: ADC = ',str(adc1) + '   vol = {:2.4f}'.format(vol1) + 'Vdc')

    adc2 = rdg2.value
    vol2 = rdg2.voltage
    print('ch2: ADC = ',str(adc2) + '   vol = {:2.4f}'.format(vol2) + 'Vdc')

    adc3 = rdg3.value
    vol3 = rdg3.voltage
    print('ch3: ADC = ',str(adc3) + '   vol = {:2.4f}'.format(vol3) + 'Vdc')

    adc4 = rdg4.value
    vol4 = rdg4.voltage
    print('ch4: ADC = ',str(adc4) + '   vol = {:2.4f}'.format(vol4) + 'Vdc')

    adc5 = rdg5.value
    vol5 = rdg5.voltage
    print('ch5: ADC = ',str(adc5) + '   vol = {:2.4f}'.format(vol5) + 'Vdc')

    adc6 = rdg6.value
    vol6 = rdg6.voltage
    print('ch6: ADC = ',str(adc6) + '   vol = {:2.4f}'.format(vol6) + 'Vdc')

    #save the data

file.write(str(now)+","+str(temp1)+","+str(adc1)+","+str(temp2)+","+str(adc2)+","+str
(temp3)+","+str(adc3)+","+str(temp4)+","+str(adc4)+","+str(temp5)+","+str(adc5)+",
"+str(temp6)+","+str(adc6)+"\n")
    file.flush()
    print()

    while True:
        time2 = time.perf_counter()
        timediff = time2 - time1
        if timediff > 1800:   #change number here to change interval (sec)
            time1 = time.perf_counter()
            break
```

APPENDIX B

RASPBERRY PI CODES: Cameras

```
#camera only

# module import
import os
from picamera import PiCamera
from time import sleep
import time
from datetime import datetime
import RPi.GPIO as GPIO

#create object
mycamera = PiCamera()

#folder directory---------
day = datetime.now().date()

#image
path_image ="/home/pi/Desktop/Maryam_image2"
dir_image = path_image + "/image%s" %day

#set GPIO
sigin = 22
GPIO.setmode(GPIO.BCM)
GPIO.setup(sigin,GPIO.IN)

#----- camera setting ---------
mycamera.resolution = (800,800)
mycamera.framerate = 15
mycamera.rotation = 0

#------- create a folder for images  -----
try:
   os.mkdir(dir_image)
except OSError as error:
   print(error)

def take_image():
   now = datetime.now().strftime("%Y-%m-%d %X")
   file_image = dir_image + "/image%s.jpg" %now
   mycamera.capture(file_image)
   print("image saved in " + file_image)
   print()

#------------------------------
#------ main loop -------------
print("start")
```

```
while True:
    time1 = time.perf_counter() #start timer 1
    newday = datetime.now().date()

    #create a new folder/file for different day --------
    if day != newday:
        #file.close()
        day = newday
        #image
        dir_image = path_image + "/image%s" %day
        try:
            os.mkdir(dir_image)
        except OSError as error:
            print(error)
        print("created new file and folder for " + str(day))
    #----------------------------------------------------

    while GPIO.input(sigin): # while waiting for the signal from Rpi 1
        time2 = time.perf_counter()
        timediff = time2 - time1
        if timediff > 1803:
            print("time out %s" %timediff)
            break

    take_image()
```