Friendly Smart Crop Observation System

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Abbreviations

CPS	Cyber-physical Systems
GIS	Geographic Information System
GPS	Global Positioning System
IoT	Internet Of Things
ML	Machine Learning
PA	Precision Agriculture
RS	Remote Sensing

Chapter 1

INTRODUCTION

1.1 Project Overview

The past decade has seen the rapid development and usage of Internet of Things (IoT) in the field of agriculture [1], specifically in the rapid developing precision agriculture (PA) or its equivalent, smart agriculture [2]. Yield loss is undoubtedly one of the most worrying aspects in crop management. As growing demands of food in proportion to worldwide population implies the need for more efficient management, the topic of automation becomes a hot spot of interest among farmers and agricultural companies.

In proceeding decades, the shifting focus of labour from agrarian-based activities to digital-based industries also demands additional attention towards practical automation to sustain the former without the need for more manpower, which in turn reduces overall cost in maintenance, heightened productivity, and increased farmers' income [3]. To automate and enhance the collection as well as analysis of relevant agricultural data from crops, Machine Learning (ML) techniques are widely used in tandem with IoT applications in various fields or agricultural practices. Such technology is often used to predict the health of the crop with the current data sets gathered from sensors that detect the condition around the crop's vicinity.

Hence, this project seeks to propose a monitoring/sensing device as a preliminary prototype to alert farmers or cultivators of crucial information and warnings against critical levels of soil moisture, air temperature and humidity surrounding the crop's vicinity. In it, application of IoT, data analysis and ML techniques are implemented into the design of the said prototype which will be further utilised to evolve the continuously gathered data to construct meaningful forecast of what constitutes a healthy crop and other actionable information. As a result, more meaningful measures can be taken to ensure the safety of the crop based on gradually enhanced and improved data sets in a long run which may help increasing the standards of practice in the evolving agricultural industry.

1.2 Proposal Structure

The remaining of this proposal document is organized as follows. In Chapter 2 literature review regarding the addressed issue as well as previous attempts of creating an effective and efficient crop management system using IoT and ML technologies will be discussed. Design methodology of the proposed prototype which is aimed to satisfy the proposed solution of ensuring crop health will be analysed in Chapter 3. And finally in Chapter 4, the results given by the simulated test environment will be revealed with in-depth analysis.

Chapter 2

LITERATURE REVIEW

2.1 Yield Loss in Agricultural Domain

Crop or yield loss, per definition given by the research of Nutter and others, is a reduction in value and financial return due to the effects of one or more pathogens or pests [4]. What leads to the pathogenic infestation on crops are largely caused by the soil condition, according to the study conducted by Irmak and Rathje [5]. With this, there are several contributing factors that can result in yield loss of crops varying in plant types, soil nutrient composition or characteristics, duration of excess flooding and so on. In addition, no Southeast Asian country has been spared in recent years from climate-induced plant calamities. Throughout the agricultural-dependent Indochina peninsula, drastic variations in traditional weather patterns and monsoon systems continue to impose great hardship on peasants [6].

While drought and salt-water intrusion events dominated headlines in Thailand, Vietnam, Indonesia, and the Philippines through the Modern Solar Minima maximum in 2015, we have been logging a growing number of crop failure reports associated with severe precipitation, tropical storms, cyclones, and hailstorms. Even the rice crop has been washed away en masse, which is one of the most flood-friendly of all staple crops. Although the most consumed grain in the world can survive waterlogged conditions for longer than most other crops in the field, it can succumb to mould, fungi, and rot if left over for more than a few days. Another climate pattern on our radar with cloudier skies in the forecast is warmer weather, which can be catastrophic when combined with dry conditions [6].

There are many areas where climate change has influenced yields. Not all the changes are negative: in some places, some crop yields have increased. However, overall, climate change is reducing global staple production such as rice and wheat. And when we translate crop yields into consumable calories–the real food on the plates of people. It is found that climate change is already shrinking food supplies, especially in developing countries with food insecurity [7].

During the reproductive stage of development, the major impact of warmer temperatures was and grain yield in maize was significantly reduced from a normal temperature regime by as much as 80% to 90% in all cases. It is estimated that the possible temperature changes over the next 30–50 years will be 2–3 °C [8]. It is also taken to account, If the relative humidity level is 75% at 80 °F, this means that each kilogram of air in the respective space contains 75% of the maximum water it can hold for the given temperature [9].

For semi-arid regions, soil moisture limits forage the most potential for growth. Estimated efficiency of water use for irrigated and dry land crop production systems is 50%, and available soil water has a significant impact on year-round management decisions taken by producers. Required soil moisture for plant growth makes up about 0.01 percent of the available water in the world [10]. On the flip side, factors found to be influencing the rate of crop loss have been explored in several studies. Based on Chuang Zhao and Bing Liu studies, production of agriculture is vulnerable to climate change. Understanding climate change, especially the impacts of temperature. It is seen that agriculture is very climate

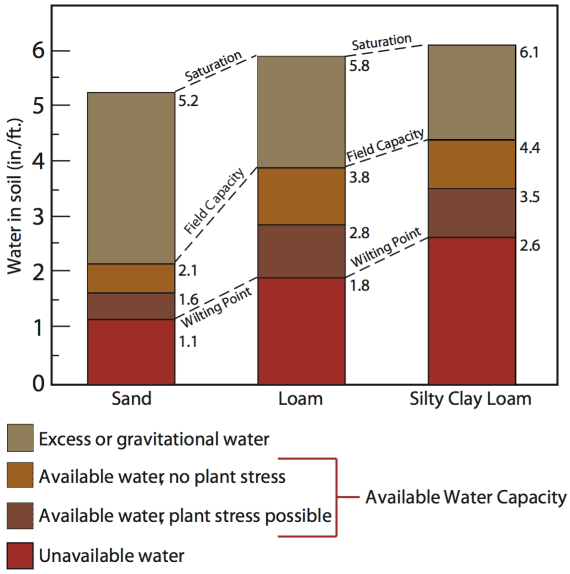


Figure 2.1: Water capacity by soil texture.

sensitive and Chuang Zhao and Bin Liu suggest that farmers adapt with technologies to challenge the problem [11]. According to Fischer and Hagan in 1965, crop plants are also susceptible to water stress caused by over-irrigation of soil as well [12]. In the past decade a number of researchers have sought to determine soil over-irrigation as prime candidate factor of soil degradation which results in crop loss. According to Irmak and Rathje [5], flooding and over-irrigation can render the soil devoid of essential nutrients crucial for the health of the crop. Therefore, a more sophisticated approach is required for proper timing and effective amount of irrigation, in which the use of PA technology is paramount in the continuing success of increased crop yield.

2.2 Factors That Lead to Crop Loss

Agriculture is an integral part of every countries economy and it was a global invention that further evolve with the technology of the world [7]. There are many countries in this world that is situated in different climates which produces different crops. Each climate differs by altitude, pressure, wind patterns, latitude and geographical characteristics which in fact determines the temperature and humidity of the air of an area [13]. There are 3 major climate zones, which can be broken down to tropical, temperate and polar climates. The difference of these climate zones that interest this finding are the temperature and precipitation [14]. Countries that are Tropical climates are in South East Asia and much of Central and South America and are wet and warm throughout the year [14]. Countries and continents that are both above below the equatorial region that experience a 4-season such as winter, spring, summer and autumn are called Temperate climates. Antarctica, which is usually dry as well as cold throughout the year is it a polar climate zone [14]. Thus, after much research, despite the different climate condition, there are 3 factors that are constant, which determines the health of the plant.

The first factor would be the temperature around the crops. Depending on the crop, temperature plays an important role on the entire process. There are crops which are temperature dependent and if its not in the right temperature, the production of the crop will be greatly affected and, in some cases, it will not be able to grow [15]. For instance, the production of the Maize pollen decreases when it is exposed to temperatures higher than 35°C which is one of the most likely phenological stages [8]. Temperature responses by the crop differs by the type of species and stages of the plant development [15]. It is imperative to know the exact temperature for each crop species and the stages of its development to achieve a high production rate.

Humidity is one of the environmental factor that affects a plants growth and relative humidity is the quantity of water vapor that is hold by the air at a specific temperature [9]. The stomata, which is located under the leaf of the crops or plants is used to transpire and is affected by the relative humidity levels. A scenario whereby the relative humidity levels or the warm ambient condition are very high, causes the stomata to close which gradually results in the suffocation of the plant as the plant conserve water and the process of absorbing carbon dioxide gas is momentarily paused [9]. Based on Rachel Holder and K. E. Cockshull search, it is stated that the high humidity has also reduced the quality of the fruit. It was concluded that the cost of reducing humidity to vapour pressure deficits greater than 0.3 kPa was likely to exceed any economic gain due to very small yield response to lower humidity [16].

Lastly, another import component in the plant growth process is the soil moisture [17]. Before soil is used by plants, it acts as a storage medium for farm waters as water is in the spaces between soil particles [18]. There are different types of soil and each type of soil has different water storage contains. The composition of soil of different particle size in a specific soil mass is referred to as the soil texture. The spaces between the soil particles is known as soil porosity and it is determined by the texture and structure of the soil. There are fine soil and course soil, thus, fine soils is able to store more water compared to course soil due to the fact it has smaller but more numerous pores which makes it more firm and tighter [10]. Based on H. G. Zandstra findings, too much or too little moisture contain in the soil is not good for the growth of the plant [19]. That is why it is imperative to know the suitable moisture contain to have the best results.

Plant diseases are also one of the major reasons of crop loss and it is caused by environmental factors such as temperature, relative humidity and soil moisture. Storage temperatures of crops are controlled and maintained to prevent the growth of fungi and bacteria and disease development can be regulated by greenhouse temperatures [20]. It is also imperative to make sure that the relative humidity is maintained between 85 to 90 percent to prevent the growth of diseases caused by fungi, water molds and bacteria [20]. Examples of disease are Rhizopus fungus, Cladosporium fulvum and many more. The development of root rot diseases is dependent on the moisture of the soil and high soil moisture is a common problem and it introduces water mold fungi such as species of Aphanomyces, Pythium and Phytophthora due to excessive watering [20].

Available Water Capacity by Soil Texture	
Textural Class	Available Water Capacity (Inches/Foot of Depth)
Coarse sand	0.25–0.75
Fine sand	0.75–1.00
Loamy sand	1.10–1.20
Sandy loam	1.25–1.40
Fine sandy loam	1.50–2.00
Silt loam	2.00–2.50
Silty clay loam	1.80–2.00
Silty clay	1.50–1.70
Clay	1.20–1.50

Figure 2.2: Water capacity by soil texture.

2.3 Role of IoT in Agricultural Domain

Previous studies have reported that, according to UN and Agricultural Organisation, an additional 50% food is needed to feed the increasing population in 2050 than in 2012 [21]. Since the Green Revolution takes hold of every modern agricultural practice since the 1960s, there are reduced land clearing rates compared to those of temperate latitudes between 1850 and 1950. However, these lands still provide the exponentially rising human population despite the case [22]. Hence, maintaining a steady supply of food through new agricultural means presents numerous great challenges because there are many factors that may lead to potential yield failure. For instance, high demand of food supply implies that water for irrigation must satisfy crop's nutrient intake from irrigated soils. To put into wider perspective, human agricultural activities account for approximately 92% of water footprint [22].

In recent decades, farming has witnessed a number of technological changes, becoming more industrialised and technology-driven. Farmers have gained better control over the process of raising livestock and growing crops through the use of various smart agricultural gadgets, making it more predictable and improving its efficiency. On the other hand, smart agriculture is mostly used to denote the use of IoT solutions in agriculture. The same applies to the definition of smart agriculture. There are 5 way IoT can significantly improve the farming experience and there are collecting data from smart sensors, lowering production risks by controlling the internal processes, better control in cos management and waste reduction and accurate climate condition monitoring [23].

However, as mentioned in *2.1: Yield Loss in Agricultural Domain*, excessive implementation of water to the crops have negative impacts to the overall yield, like soils more susceptible to algal blooms, anoxic dead zones and potential water stress [5] [12]. Thus, the use of IoT compensates the need for manual monitoring and instead focuses on low-input, high efficiency and sustainable system with a variety of PA technologies which include different types of smart sensors (infrared, microwave etc.) [24] [25], Global Positioning System (GPS) and Geographic Information System (GIS) [26]; in which they are collectively interlinked to form an extensive cloud computing system with the aid of internet connection [27]. Moreover, IoT enables the use of multimedia among farmers to enquire more about their decisions during the agricultural process [28]. For instance, by putting sensors on the soil, farmers will have access to data regarding the status and condition to the soil and plant, thus, being able to make a more accurate decision to the problem.

Based on G. Naveen Balaji and others' extensive research, many farmers still use traditional methods of farming but in order to help with the economy and enhance crop yield, farmers have to integrate technology into their farming method [29]. Furthermore, Carlos Cambra Baseca and others mentioned in her studies that new technologies have the potential to transform agriculture and reduce the impact of the transition on the environment. IoT-based application development platforms have the potential to run farm management tools that can monitor events in real time when integrated into interactive irrigation innovation models [30].

An extreme transition is taking place over the past two decades from advanced mechatronic systems to cyber-physical systems (CPS). In the field of PA, CPS should play an important role and productivity is expected to improve in order to feed the planet and avoid famine. In order to speed up and accelerate the realisation of CPS in the field of precision farming, it is necessary to develop methods, tools, hardware and software components based on trans-disciplinary approaches, together with the validation of the principles through prototypes and test beds. In this context, this paper presents an integrated system architecture based on CPS for precision agricultural management [31].

2.4 Crop Health Analysis with ML

2.4.1 Background

Machine learning today is not like the machine learning of the past because of modern computing technologies. It was born out of pattern recognition and the theory that computers could learn to perform specific tasks without being programmed; researchers interested in artificial intelligence wanted to see if computers could learn from data. While there have been many machine learning algorithms around for a long time, a recent development is the ability to automatically apply complex mathematical equations to big data. The iterative aspect of machine learning is important because they can adapt independently as models are exposed to new data. They learn to produce reliable, repeatable decisions and results from previous calculations [32].

The resurgent interest in machine learning stems from the same causes that have made data mining and Bayesian analysis more common than ever before. All of these things mean that models that can process larger, more complex data and generate quicker, more reliable results can be generated rapidly and auto-

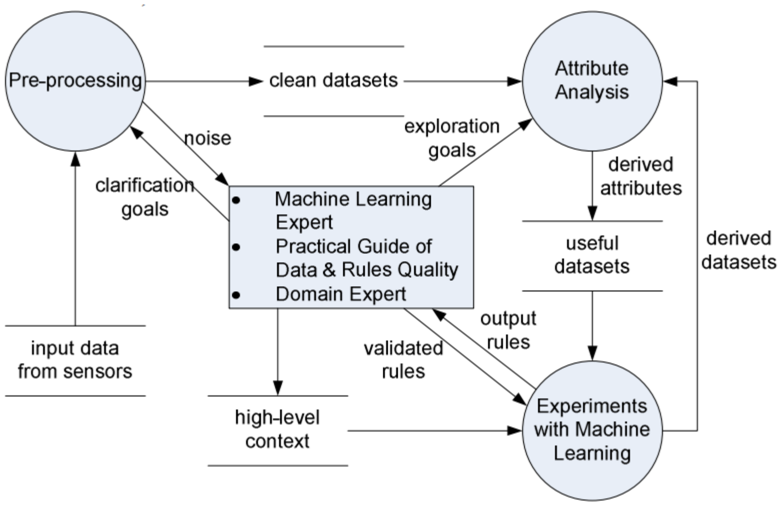


Figure 2.3: Machine learning process model [34].

matically–even on a very large scale. And an organisation has a better chance of identifying profitable opportunities by building precise models–or avoiding unknown risks [32]. The type of machine learning that has been termed as deep learning is neural network. Neural network is a form of machine learning that models after the brain of humans. This creates an artificial neural network that, by incorporating new data, enables the machine to learn through an algorithm [33].

2.4.2 Application in Agriculture

PA is a farming management concept based on observing, measuring and responding to any variability in crops for the purpose of identifying the best form of farm management with improved returns on inputs. In other words, it is the application of technologies and principles to manage spatial and temporal variability associated with all aspects of agricultural production for improving production and environmental quality [35]. In an effort to enforce the practice of PA, a primary concern to the automation of agricultural monitoring is that it requires in-depth contextual knowledge of how crop reacts in different environments, which in the scope of the proposal, the soil condition and its surroundings [36]. Suffice to say, by utilising ML in monitoring soil condition and crop health, the training model needs to evolve alongside continuously changing data sets to maximise the accuracy of the analytical results.

The concept of ML in utilising agricultural data had been curiously discussed since 1995, with the pioneering study conducted by McQueen and others concerning the [37]. During the times of ML infancy, McQueen and others dictate the importance of domain experts in specialising data sets in order to maximise accuracy of training an interpretative machine learning model. In addition, it is essential to carefully complement data transformation in tandem with specific domain expertise and required ML processing skills to further process the given data sets.

A considerable amount of literature has been published on the application of ML and other relevant techniques in designing efficient and effective crop management solutions, such as using deep learning, neural networks and so on. One of the studies includes the use of sophisticated Remote Sensing (RS) systems in approximating yield rate and optimising nitrogen management to the soil with additional ML integration in processing a huge amount of data constantly being streamed from the sensors to the training model to produce an effective system viable for such tasks [38].

Another notable research aims at making new decision rules on the administration of water to crop plants with data mining and ML. As shown in Figure 2.3, plant science domain expert is included inside the learning model in which new rules can be systematically created in each iteration of input data gathered from the sensors. With the use of ML, farmers are able to obtain predictive data from previous results and data to assist in better judgement of the situation [28] [32] [38]. Data are collected over time to track the condition of the equipment in predictive maintenance scenarios. The goal is to find trends that can help predict failures and ultimately avoid them [34]. According to the study conducted by

Kejela and others, it is due to malfunctioning sensors or broken communication channel, accurate predictive analytic of large sensor data can be used to estimate missing values or delete inaccurate readings. It can also be used to predict circumstances that aid in different decision taking, including maintenance and project preparation [39].

Chapter 3

DESIGN METHODOLOGY

The design for the proposed Smart Crop Observation (SCO) module is based on a soil moist sensor (SMS) module by hackster but with a temperature/humidity sensor and a wifi section of each module added. The modules act in a data input from the sensors where the readings are added to the neural network. There are three kinds of actions that are developed in parallel, which are, Circuit Design and Neural Network.

3.1 Circuit Design

As mentioned before, the SCO module is modeled by the SMS module parts like Arduiuno, DHT11 Temperature/Humidity Sensor and ESP8266 Wifi Module, which transmit data to ThingSpeak, an application and API that stores and retrieve data through wifi, with the existing components Soil Moisture Hygrometer Sensor connected with the main component which is the Arduino Uno. Additionally, for a small display, a i2c 8x8 matrix LED is used, which are matrices that is also called 'Matrixpled'.

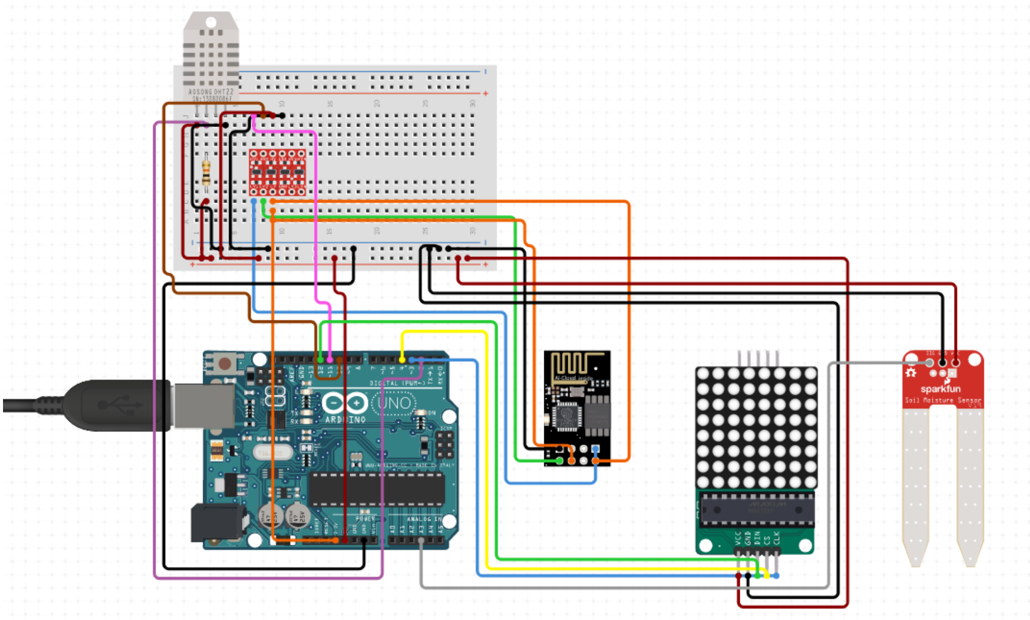
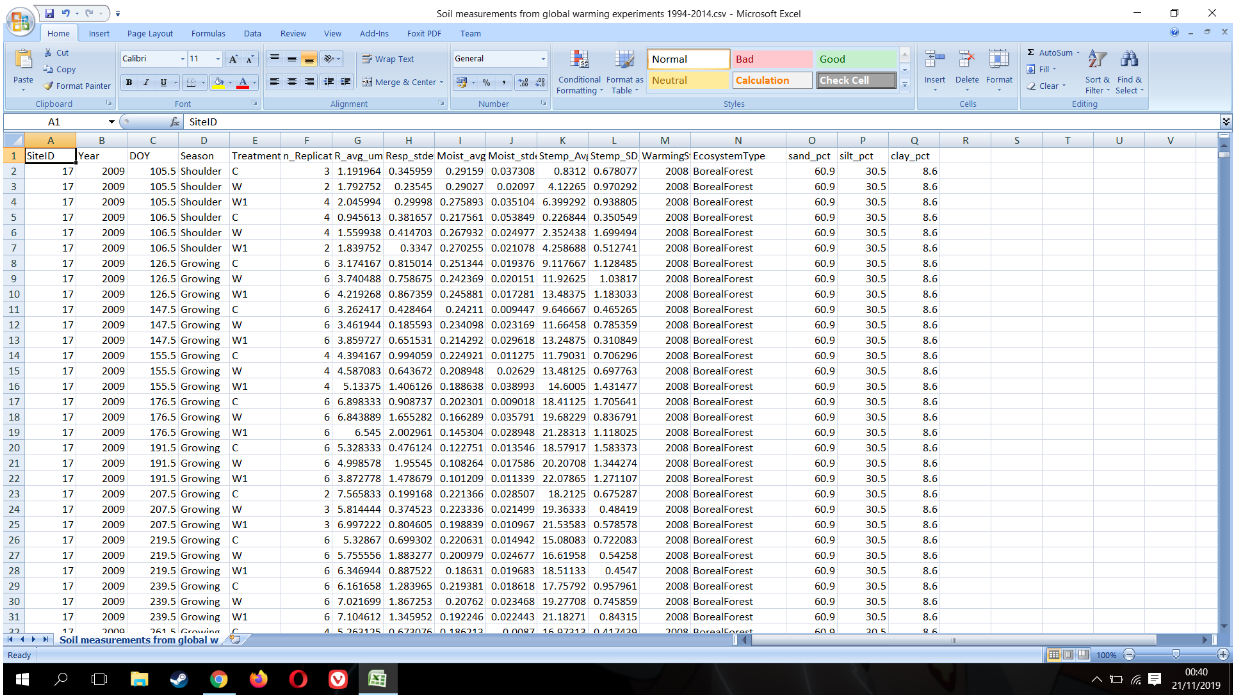


Figure 3.1: Circuit Design.

3.2 Neural Network Design

The neural network design is smart as it takes a set of data which is used for training and it develops a system based on the data acquired and learn and recognize a pattern for better accuracy and prediction. This learning process is also called 'deep learning'. These are dataset obtained by Joanna C. Carey. This dataset is the largest global dataset to date of soil respiration, moisture, and temperature measurements, totaling at 3800 observations representing 27 temperature manipulation studies, spanning nine biomes and nearly two decades of warming experiments. Data for this study were obtained from a combination of unpublished data and published literature values.

By using deep learning neural network, the training by the system was able to develop two hidden layer with 5 hidden neurons and 4 hidden neurons respectively. The model is implemented using Neural Designer, a software tool for data analytics based on neural networks. Furthermore, the algorithm is able to use Hyberbolic Tangent and Linear as an activation function. In the end, the system/algorithm is able to produce an Error Rate of 0.000156 (see Figure 3.9),



SiteID	Year	DOY	Season	Treatment	n_Replicat	R_avg_um	Resp_stde	Moist_avg	Moist_std	Stemp_Av	Stemp_SD	WarmingS	EcosystemType	sand_pct	silt_pct	clay_pct
17	2009	105.5	Shoulder	C	3	1.191964	0.345959	0.29159	0.037308	0.8312	0.678077	2008	BorealForest	60.9	30.5	8.6
17	2009	105.5	Shoulder	W	2	1.792752	0.23545	0.29027	0.02097	4.12265	0.970292	2008	BorealForest	60.9	30.5	8.6
17	2009	105.5	Shoulder	W1	4	2.045994	0.29998	0.275893	0.035104	6.399292	0.938805	2008	BorealForest	60.9	30.5	8.6
17	2009	106.5	Shoulder	C	4	0.945613	0.381657	0.217561	0.053849	0.226844	0.350549	2008	BorealForest	60.9	30.5	8.6
17	2009	106.5	Shoulder	W	4	1.559938	0.414703	0.267932	0.024977	2.352438	1.699494	2008	BorealForest	60.9	30.5	8.6
17	2009	106.5	Shoulder	W1	2	1.839752	0.3347	0.270255	0.021078	4.258688	0.512741	2008	BorealForest	60.9	30.5	8.6
17	2009	126.5	Growing	C	6	3.174167	0.815014	0.251344	0.019376	9.117667	1.128485	2008	BorealForest	60.9	30.5	8.6
17	2009	126.5	Growing	W	6	3.740488	0.758675	0.242369	0.020151	11.92625	1.03817	2008	BorealForest	60.9	30.5	8.6
17	2009	126.5	Growing	W1	6	4.219268	0.867359	0.245881	0.017281	13.48375	1.183033	2008	BorealForest	60.9	30.5	8.6
17	2009	147.5	Growing	C	6	3.262417	0.428464	0.24211	0.009447	9.646667	0.465265	2008	BorealForest	60.9	30.5	8.6
17	2009	147.5	Growing	W	6	3.461944	0.185593	0.234098	0.023169	11.66458	0.785359	2008	BorealForest	60.9	30.5	8.6
17	2009	147.5	Growing	W1	6	3.859727	0.651531	0.214292	0.029618	13.24875	0.310849	2008	BorealForest	60.9	30.5	8.6
17	2009	155.5	Growing	C	4	4.394167	0.994059	0.224921	0.011275	11.79031	0.706296	2008	BorealForest	60.9	30.5	8.6
17	2009	155.5	Growing	W	4	4.587083	0.643672	0.208948	0.02629	13.48125	0.697763	2008	BorealForest	60.9	30.5	8.6
17	2009	155.5	Growing	W1	4	5.13375	1.406126	0.188638	0.038993	14.6005	1.431477	2008	BorealForest	60.9	30.5	8.6
17	2009	176.5	Growing	C	6	6.898333	0.908737	0.202301	0.009018	18.41125	1.705641	2008	BorealForest	60.9	30.5	8.6
17	2009	176.5	Growing	W	6	6.843889	1.655282	0.166289	0.035791	19.68229	0.836791	2008	BorealForest	60.9	30.5	8.6
17	2009	176.5	Growing	W1	6	6.545	2.002961	0.145304	0.028948	21.28313	1.118025	2008	BorealForest	60.9	30.5	8.6
17	2009	191.5	Growing	C	6	5.328333	0.476124	0.122751	0.013546	18.57917	1.583373	2008	BorealForest	60.9	30.5	8.6
17	2009	191.5	Growing	W	6	4.998578	1.95545	0.108264	0.017586	20.20708	1.344274	2008	BorealForest	60.9	30.5	8.6
17	2009	191.5	Growing	W1	6	3.872778	1.478679	0.101209	0.011339	22.07865	1.271107	2008	BorealForest	60.9	30.5	8.6
17	2009	207.5	Growing	C	2	7.565833	0.199168	0.221366	0.028507	18.2125	0.675287	2008	BorealForest	60.9	30.5	8.6
17	2009	207.5	Growing	W	3	5.814444	0.374523	0.223336	0.021499	19.36333	0.48419	2008	BorealForest	60.9	30.5	8.6
17	2009	207.5	Growing	W1	3	6.997222	0.804605	0.198839	0.010967	21.53583	0.578578	2008	BorealForest	60.9	30.5	8.6
17	2009	219.5	Growing	C	6	5.32867	0.699302	0.220631	0.014942	15.08083	0.722083	2008	BorealForest	60.9	30.5	8.6
17	2009	219.5	Growing	W	6	5.755556	1.883277	0.200979	0.024677	16.61958	0.54258	2008	BorealForest	60.9	30.5	8.6
17	2009	219.5	Growing	W1	6	6.346944	0.887522	0.18631	0.019683	18.51133	0.4547	2008	BorealForest	60.9	30.5	8.6
17	2009	239.5	Growing	C	6	6.161658	1.283965	0.219381	0.018618	17.75792	0.957961	2008	BorealForest	60.9	30.5	8.6
17	2009	239.5	Growing	W	6	7.021699	1.867253	0.20762	0.023468	19.27708	0.745859	2008	BorealForest	60.9	30.5	8.6
17	2009	239.5	Growing	W1	6	7.104612	1.345952	0.192246	0.022443	21.18271	0.84315	2008	BorealForest	60.9	30.5	8.6

Figure 3.2: Dataset used for training.

Data statistics results

The table below shows the minimums, maximums, means and standard deviations of all the variables in the data set.

	Minimum	Maximum	Mean	Deviation
DOY	11.50	356.50	179.45	74.30
Season	0.00	1.00	0.78	0.41
R_avg_umol.m2.s	0.01	3.86	1.34	0.80
Resp_stdev	0.02	1.12	0.26	0.19
Moist_avg_cm3.cm.3	0.09	0.38	0.20	0.07
Moist_stdev	0.00	0.11	0.03	0.02
Stemp_Avg_C	-0.07	29.61	15.95	6.72
Stemp_SD_C	0.02	2.15	0.49	0.46

Figure 3.3: Statistic of the dataset.

which is a very good lowered error rate during the training phase. From this, it can be concluded that the error Rate of 0.000156 is a very good error rate as the benchmark for average error rate in Neural Network is around 0.1.

Neural network graph

A graphical representation of the network architecture is depicted next. It contains a scaling layer, a neural network and an unscaling layer. The yellow circles represent scaling neurons, the blue circles perce
unscaling neurons. The number of inputs is 7, and the number of outputs is 1. The complexity, represented by the numbers of hidden neurons, is 5:4.

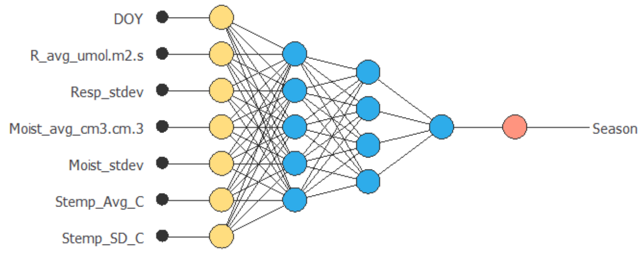


Figure 3.4: Neural Network Model used for training.

Scaling layer

The size of the scaling layer is 7, the number of inputs. The scaling method for this layer is the Automatic. The following table shows the values which are used for scaling the inputs, which include the minim
standard deviation.

	Minimum	Maximum	Mean	Deviation
DOY	11.5	357	0	1
R_avg_umol.m2.s	0.01	3.86	0	1
Resp_stdev	0.02	1.12	0	1
Moist_avg_cm3.cm.3	0.085	0.379	0	1
Moist_stdev	0	0.109	0	1
Stemp_Avg_C	-0.07	29.6	0	1
Stemp_SD_C	0.022	2.15	0	1

Figure 3.5: Scaling layer of network.

Perceptron layers

The number of perceptron layers in the neural network is 3. The following table depicts the size of each layer and its corresponding activation function.

	Inputs number	Perceptrons number	Activation function
1	7	5	HyperbolicTangent
2	5	4	HyperbolicTangent
3	4	1	Linear

Figure 3.6: Preceptron layer of the network.

Optimization algorithm

The quasi-Newton method is used here as optimization algorithm. It is based on Newton's method, but does not require calculation of second derivatives. Instead, the quasi-Newton method computes an appr
Hessian at each iteration of the algorithm, by only using gradient information.

	Description	Value
Inverse Hessian approximation method	Method used to obtain a suitable training rate.	BFGS
Training rate method	Method used to calculate the step for the quasi-Newton training direction.	BrentMethod
Loss tolerance	Maximum interval length for the training rate.	0.001
Minimum parameters increment norm	Norm of the parameters increment vector at which training stops.	1e-09
Minimum loss decrease	Minimum loss improvement between two successive epochs.	1e-12
Loss goal	Goal value for the loss.	1e-12
Gradient norm goal	Goal value for the norm of the objective function gradient.	0.001
Maximum selection error increases	Maximum number of epochs at which the selection error increases.	100
Maximum iterations number	Maximum number of epochs to perform the training.	1000
Maximum time	Maximum training time.	3600
Reserve parameters norm history	Plot a graph with the parameters norm of each iteration.	false
Reserve error history	Plot a graph with the loss of each iteration.	true
Reserve selection error history	Plot a graph with the selection error of each iteration.	true
Reserve gradient norm history	Plot a graph with the gradient norm of each iteration.	false

Figure 3.7: Optimization Algorithm used.

Quasi-Newton method errors history

The following plot shows the training and selection errors in each iteration. The blue line represents the training error and the orange line represents the selection error . The initial value of the training error is
287 epochs is 0.0001559. The initial value of the selection error is 3.87469, and the final value after 287 epochs is 0.139135.

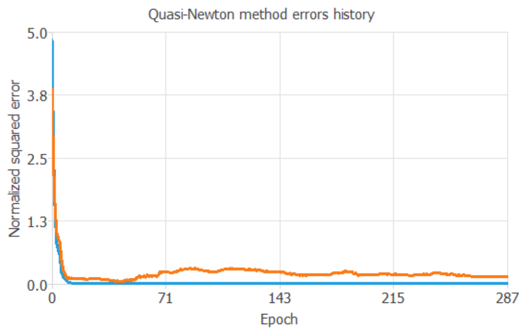


Figure 3.8: Error rate returned after training finished.

Quasi-Newton method results

The next table shows the training results by the quasi-Newton method. They include some final states from the neural network, the loss functional and the optimization algorithm.

	Value
Final parameters norm	4.37
Final training error	0.000156
Final selection error	0.139
Final gradient norm	0.000973
Epochs number	287
Elapsed time	00:00
Stopping criterion	Gradient norm goal

Figure 3.9: Results of the finished neural network.

Chapter 4

RESULTS

4.1 Friendly Monitoring System

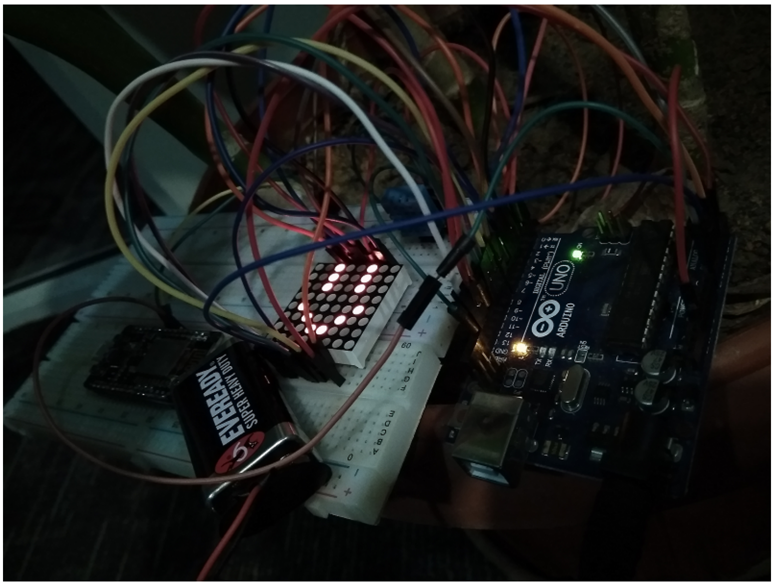


Figure 4.1: Result of smiley face when plant is healthy.

After the training process has been completed, the resultant system is now able to detect, monitor and analyse the temperature and humidity of the soil. As shown in Figure 4.1, during the test of 2 different soil samples, the LED display gives out a ”smiley face”, indicating the soil that is being tested on is, according to the knowledge base trained from the aforementioned data sets, healthy and is suitable for plant life. Conversely, a ”sad face” is displayed when the sensor has

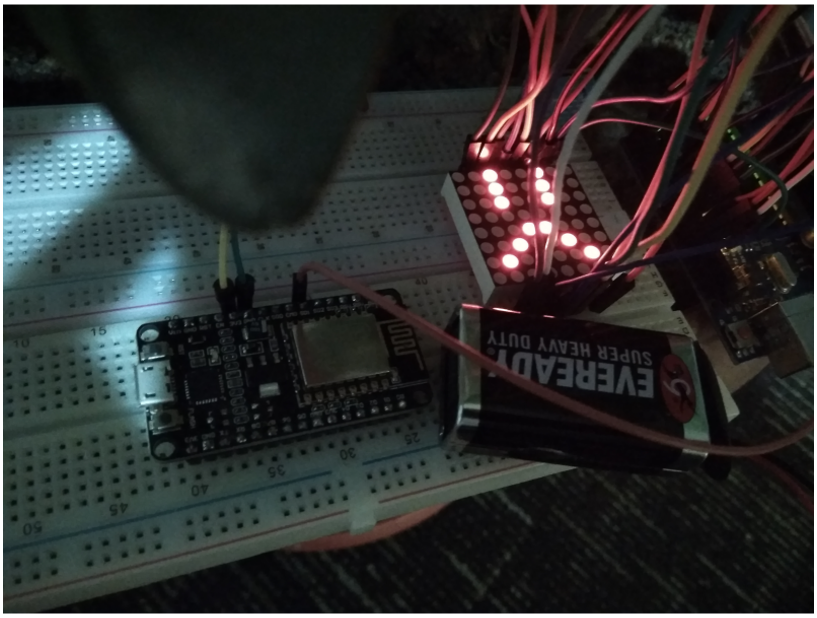


Figure 4.2: Result of sad face when plant is unhealthy.

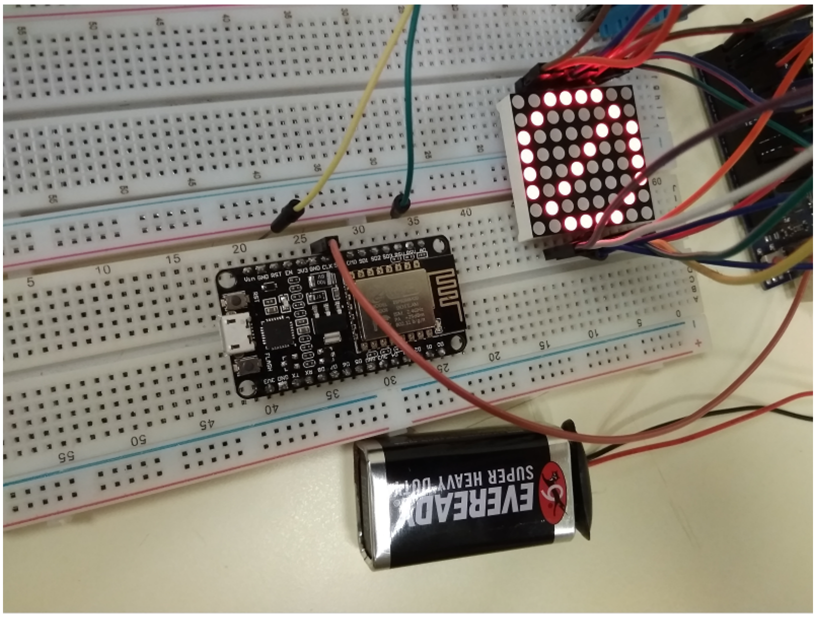


Figure 4.3: Result of error sign when not detecting any plant.

detected the soil sample with poor temperature and humidity levels, which imply unhealthy plant (see Figure 4.2). When the sensor does not detect any plant or soil, a "stop" sign will be displayed indicating their absence (see Figure 4.3).

4.2 Data Sent to ThingSpeak

During the sensing process, temperature and humidity data are continuously collected to the soil sensing app via Wi-Fi connection as shown in Figure 4.4. The data gathered is then restructured into readable graphs that illustrate the temperature and humidity levels with passing time (alongside average values for each attribute, as displayed at each graph's center).

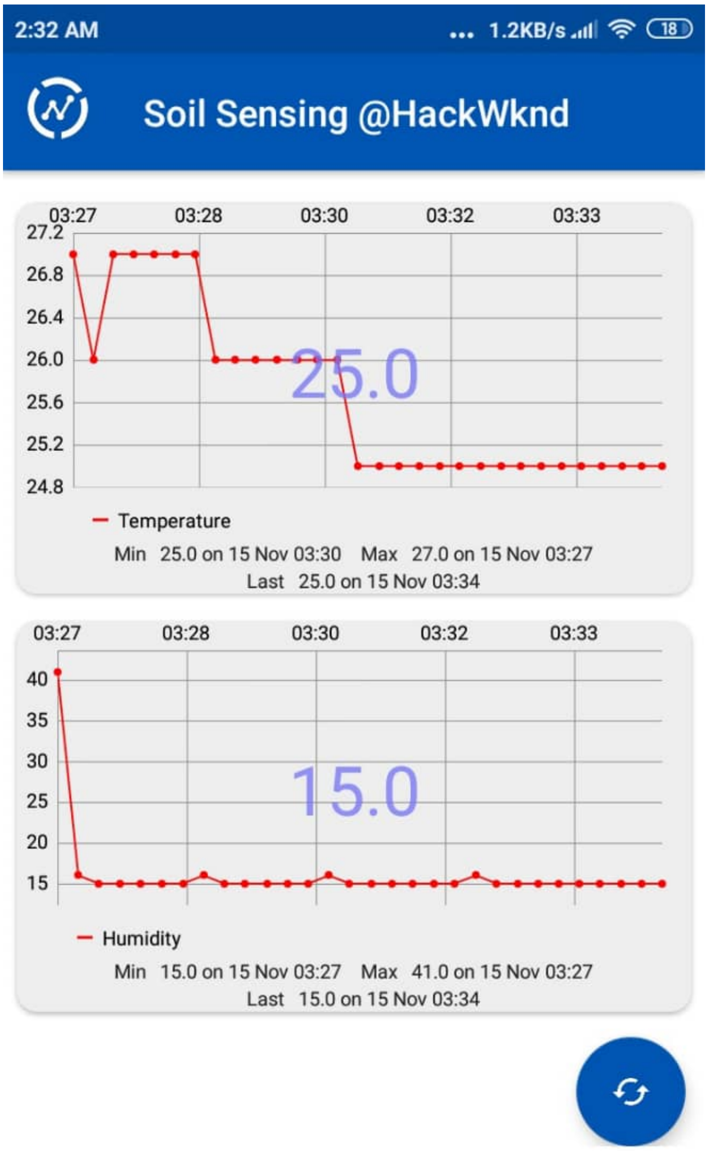


Figure 4.4: Returning the results to ThingSpeak.

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