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INTELLIGENT SMALL-SCALE STRAWBERRY IRRIGATION SYSTEM FOR DIFFERENT WEATHER CONDITIONS

BY

YE HTET

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YE HTET

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ABSTRACT

People in agriculture are in need of modern agricultural knowledge and technology to make optimal and informed precise decisions. The proposed system focused on efficient water and fertilizers usage for strawberry plants with drip irrigation and fertigation system to produce strawberries all the year-round. The drip pipes for water are applied directly to the root zones of the plants and also a solution of macro-nutrients (Nitrogen, Phosphorus and Potassium) are delivered to the plants along with the irrigation water automatically. Temperature with humidity sensor, soil moisture sensor, and LDR sensor are used for environmental control in different weather conditions within the small-scale farm. Computer Vision with Machine Learning for leaf analysis which is controlled by Raspberry Pi is implemented for monitoring and detection of the various symptoms of plants. As for the communication unit to inform the users the various states and requirements for plants via sensors and image processing, Internet of Things is used. The power unit of this small-scale farm is provided by a solar hybrid power system.

STATEMENT OF ORIGINALITY

I hereby certify that the work embodied in this thesis is the result of original research and has not been submitted for a higher degree to any other University or Institution.

Date

Name

CONTENTS

			PAGE
ACKNOWLEDGMENT			i
ABSTRACT			ii
STATEMENT OF ORGINALITY			iii
CONTENTS			iv
LIST OF FIGURES			x
LIST OF TABLES			xiv
CHAPTER	**1**	**INTRODUCTION**	1
	1.1	Problem statements and solutions	1
		1.1.1 Temperature	3
		1.1.2 Relative Humidity	4
	1.2	Aim and Objectives	4
	1.3	System Overview	4
	1.4	Outlines of thesis	6
CHAPTER	**2**	**THEORETICAL BACKGROUND**	7
	2.1	Strawberry	7
		2.1.1 Plant nutrients and deficiency symptoms	8
		2.1.1.1 Nitrogen	8
		2.1.1.2 Phosphorus	9
		2.1.1.3 Potassium	9
	2.2	Temperature and Humidity Control System	10
		2.2.1 Fan and Pad Evaporative Cooling System	11
		2.2.2 High-Pressure Fog System	12
		2.2.3 Sensors and Controller	12
	2.3	Drip Irrigation System	13
		2.3.1 Water source	13
		2.3.2 Pumps & pumping stations	13
		2.3.3 Power source for the pump	14
		2.3.4 Filtration	14
		2.3.5 Valves	14
		2.3.5.1 Solenoid Valves	14
		(a) Normally Closed or Normally Open	15

(b) Two-way Valve (2/2 Way) 15
(c) Three-way Valve (3/2 Way) 16
(d) Application areas 16
2.3.6 Fertilizer tank 17
2.3.7 Drippers 17
2.3.8 Drip Tapes 17
2.3.9 Controller 17
2.3.10 Pros and Cons for Drip Irrigation System 18
2.4 Nutrient Deficiency Symptoms Detection System 18
2.4.1 OpenCV 18
2.4.2 Image Acquisition 19
2.4.3 Image Pre-processing 19
2.4.3.1 Changing Color-space 19
(a) RGB 19
(b) YUV 19
(c) HSV 20
2.4.3.2 Image Thresholding 20
(a) Simple Thresholding 20
(b) Adaptive Thresholding 20
(c) Otsu’s Binarization 21
2.4.3.3 2D-Convolution (Image Filtering) 21
2.4.3.4 Smoothing Images 21
(a) Image Blurring 22
(i) Averaging 22
(ii) Gaussian Filtering 22
(iii) Median Filtering 22
(iv) Bilateral Blurring 22
2.4.3.5 Edge Detection 23
(a) Canny Edge Detection 23
(i) Noise Reduction 23
(ii) Finding Intensity Gradient 23
(iii) Non-maximum Suppression 24
(iv) Hysteresis Thresholding 24
2.4.3.6 Morphological Transformations 25

(a) Erosion 25
(b) Dilation 26
(c) Opening 26
(d) Closing 26
(e) Morphological Gradient 26
(f) Top Hat 27
(g) Black Hat 27
2.4.3.7 Contours in OpenCV 27
(a) Aspect Ratio 27
(b) Extent 28
(c) Solidity 28
(d) Equivalent Diameter 28
2.4.4 Image Segmentation 28
2.4.4.1 Watershed Algorithm 28
(a) Watershed-by-flooding 29
2.4.5 Feature Extraction 29
2.4.6 Image Classification 30
2.4.6.1 Types of Learning 30
(a) Supervised Learning 30
(b) Unsupervised Learning 31
2.4.6.2 Support Vector Machine (SVM) 33
(a) Non-linear SVM 34
(b) Multiclass SVM 35
(i) One-vs-Rest (OvR) 36
(ii) One-vs-One (OvO) 36
2.4.6.3 SVM parameters 37
(a) C parameter 37
(b) Gamma 37
2.5 Internet of Things (IoT) 38
2.5.1 IoT Application Areas 39
2.5.2 Pros and cons of IoT [18] 39
2.6 Graphical User Interface (GUI) 40
2.7 Controller 40
2.8 Python Language 41

2.8.1 What can Python do? 42
2.8.2 Python libraries 42
2.8.2.1 NumPy 42
2.8.2.2 SciPy 42
2.8.2.3 Matplotlib 43
2.8.2.4 OpenCV 43
2.8.2.5 Mahotas 43
2.8.2.6 Scikit-learn 43
2.8.2.7 Pandas 43
2.9 Summary 44
CHAPTER 3 SYSTEM DESIGN AND METHODOLOGY 45
3.1 Small-scale Farm Structure and Design 45
3.1.1 Frame Design 45
3.1.2 Stands Design 46
3.1.3 Planting Method 47
3.1.4 Soil Mixing 48
3.1.5 Solar Power System 48
3.2 Main Controller 49
3.2.1 Raspberry Pi 3 49
3.3 Requirements for Temperature and Humidity Control Systems 50
3.3.1 Temperature and Humidity Sensor (DHT22) 50
3.3.1.1 DHT22 connection and installation 51
3.3.2 Black-net Shading 52
3.3.3 Exhaust Fans and Cooling Pad 53
3.3.4 Fog-Nozzle Sprinklers 53
3.4 Components for Drip Irrigation System 54
3.4.1 AC Pump 54
3.4.2 DC Diaphragm Pump 54
3.4.3 Drip Kit Components 55
3.4.4 24V DC 1/2" Water Solenoid Valve (Normally Closed) 56
3.4.5 Soil Moisture Data Logging 57
3.5 Requirements for Leaf Size Calculation and NPK Detection 58
3.5.1 Logitech webcam C310 58
3.5.2 Leaf size calculation by mathematical formula 60

3.5.2.1 The “pixels per metric” ratio 60
3.5.3 Image Processing Techniques for Leaf Size Calculation and NPK Detection 61
3.5.3.1 Conversion of RGB to GRAY 61
3.5.3.2 Morphological Operations 62
(a) Erosion 62
(b) Dilation 62
(c) Opening and Closing 62
3.5.3.3 Otsu’s Thresholding 62
3.5.3.4 Pyramid Mean Shift Filtering 63
3.5.3.5 Gaussian Blurring 63
3.5.3.6 Canny Edge Detection 63
3.5.3.7 Watershed Segmentation 64
3.5.3.8 Image Classification Methodology 65
3.5.4 Leaf size calculation by OpenCV 67
3.5.5 NPK Deficiency Detection 68
3.6 Thingspeak IoT Platform 69
3.7 Tkinter (GUI) 70
3.8 HDMI LCD Monitor 71
3.9 Control Panel 72
3.10 Summary 72
CHAPTER 4 TESTS AND RESULTS 73
4.1 Results for Temperature and Humidity Control System 73
4.2 Results for Drip Irrigation System 79
4.2.1 Soil Moisture Data and Leaf Size for Small-scale Farm 79
4.2.2 Soil Moisture Data and Leaf Size for Aung-Chan-Thar Farm 80
4.2.3 Soil Moisture Data and Leaf Size for City Farm-A 81
4.2.4 Soil Moisture Data and Leaf Size for City Farm-B 81
4.2.5 Soil Moisture Data and Leaf Size for City Farm-C 82
4.3 Results for Leaf Size Calculation 84
4.4 Results for Nutrient Deficiency Symptoms Detection System 85
4.4.1 Fertigation (Fertilizers + Drip Irrigation) process 91
4.5 Summary 91

CHAPTER 5 CONCLUSION 92

5.1 Conclusion 92

5.2 Discussion and Further Extensions 92

LIST OF PUBLICATION 94

REFERENCES 95

LIST OF FIGURES

Figure		Page
1.1	Average temperatures in Pyin Oo Lwin	3
1.2	Average humidity in Pyin Oo Lwin	4
1.3	System Overview Design	5
1.4	Image processing methods	6
1.5	Nitrogen, Phosphorus, and Potassium deficiency symptoms on strawberry leaves	6
1.6	Drip Irrigation System	6
2.1	Schematic morphology of a strawberry plant	7
2.2	Signs of Nitrogen Deficiency Symptom	9
2.3	Signs of Phosphorus Deficiency Symptom	9
2.4	Signs of Potassium Deficiency Symptom	10
2.5	Cooling Pads and Their Application	11
2.6	DC Water Solenoid Valve	14
2.7	Circuit Functions of Solenoid Valves	16
2.8	Non-maximum Suppression	24
2.9	Hysteresis Thresholding	24
2.10	Original Image	25
2.11	Erosion	25
2.12	Dilation	26
2.13	Opening	26
2.14	Closing	26
2.15	Morphological Gradient	27
2.16	Top Hat	27
2.17	Black Hat	27
2.18	Topographic Map	29
2.19	Watershed Algorithm Segmentation	29
2.20	Feature Extraction Block Diagram	30
2.21	Binary Classification	30
2.22	Supervised Learning Problems	31
2.23	Unsupervised Learning Problem	31

2.24	Supervised Learning vs Unsupervised Learning	32
2.25	Scikit-learn Algorithm Cheat-sheet	32
2.26	Linear SVM Classification	33
2.27	Non-linear SVM Classification	34
2.28	SVM kernels	35
2.29	One vs Rest Multiclass SVM	36
2.30	One vs One Multiclass SVM	36
2.31	SVM C Parameter	37
2.32	SVM Gamma Parameter	37
2.33	Internet of Things	38
2.34	Example of an IoT System	38
2.35	Main Parts of Raspberry Pi	40
2.36	Guido van Rossum with Python Logo	41
3.1	Frame Design	45
3.2	Covering Processes of the Farm	46
3.3	Plant Stands Design	47
3.4	Installation of PVC pipes, Gutters and Plant stands in the farm	47
3.5	Planting Methods in the Gutter	47
3.6	Soil Mixing Process	48
3.7	Solar Power System	48
3.8	Raspberry Pi 3 and Its GPIO Pinout Diagram	49
3.9	Comparison of Raspberry Pi 3 and other Generations	49
3.10	DHT22 Temperature and Humidity Sensor	50
3.11	Connection Diagram of DHT22 and RPi	51
3.12	Installation of the Sensor in the Farm	52
3.13	Black-net in the Farm	52
3.14	Exhaust Fan	53
3.15	Cooling Pad Design	53
3.16	Fog Nozzle Sprinklers and Its Placement	53
3.17	AC Water Pump	54
3.18	DC Diaphragm Pump	54
3.19	Drip Kit Components	55
3.20	Drip Pipes Position	56
3.21	24V DC Water Solenoid Valve	56

3.22	Testing Soil Moisture Sensor	57
3.23	Data Logging Methods for Soil Moisture of the Plants	57
3.24	Logitech C310 Webcam	59
3.25	Connection Diagram of Webcam with Raspberry Pi	59
3.26	Camera Installation in the Farm	59
3.27	Leaf Image with Reference Object	60
3.28	Reference Object Width	61
3.29	Leaf Size Calculation	61
3.30	Nutrient Deficiency Leaves	65
3.31	Test Images with Correct Labels	65
3.32	Tracing on scikit-learn cheat-sheet	66
3.33	Accuracy comparison of different algorithms	67
3.34	Flowchart for leaf size calculation by OpenCV	68
3.35	Flowchart for NPK Detection System	68
3.36	Thingspeak Homepage	69
3.37	Raspberry Pi connected with Thingspeak	70
3.38	Proposed GUI Design	70
3.39	HDMI 7" LCD Monitor	71
3.40	Connection of LCD with RPi	71
3.41	Control Panel Box Design	72
4.1	Temperature Data inside the Farm	73
4.2	Inside Temperature from February to May	74
4.3	Cooling Pad and Fan at the top	74
4.4	Temperature Data inside the farm (top position)	74
4.5	Cooling Pad and Fan at the middle	74
4.6	Temperature Data inside the Farm (middle position)	75
4.7	Inside Temperature and Humidity Data from August 14 to August 19	75
4.8	Leaf Scorch	76
4.9	Bacterial Blight	76
4.10	Inside Temperature and Humidity from November 4 to November 6	76
4.11	Flowchart for Temperature and Humidity Control	77
4.12	System Flowchart for Temperature Control	77
4.13	System Flowchart for Humidity Control	78
4.14	Updating Data to Thingspeak	79

4.15 Moisture Data and Leaf Size for Small-scale Farm 80
4.16 Moisture Data and Leaf Size for Aung Chan Thar Farm 80
4.17 Moisture Data and Leaf Size for City Farm - A 81
4.18 Moisture Data and Leaf Size for City Farm - B 82
4.19 Moisture Data and Leaf Size for City Farm - C 82
4.20 Soil Moisture Data (duration from 870 to 950) 83
4.21 Soil Moisture Data (duration from 950 to 870) 83
4.22 Leaf Size Calculation Results 85
4.23 NPK Detection Results 87
4.24 Before Parameter Tuning 88
4.25 After Parameter Tuning 88
4.26 Cultivated strawberries during growing seasons 91

LIST OF TABLES

Table		Page
2.1	Nutrient requirements for strawberry plants	8
2.2	Main functions and fertilizers with application rates for NPK	10
3.1	Technical Specifications of DHT22	51
3.2	Electrical Characteristics of DHT22	51
3.3	Specifications for AC Pump	54
3.4	Specifications for DC Diaphragm Pump	55
3.5	Dripline Specifications	55
3.6	Feature, Specifications, and Characteristics for 24V DC Solenoid Valve	56
3.7	Different Strawberry Farms around Pyin Oo Lwin	58
3.8	Specifications for Logitech C310 Webcam	59
4.1	Processes for temperature and humidity control system	73
4.2	Comparison Table	75
4.3	Process and requirements for drip irrigation system	79
4.4	Comparison of Soil Moisture Data and Leaf Size	83
4.5	Duration for Optimal Range by Sensor	84
4.6	Scheduling for Water Supply Duration	84
4.7	Training Set and Testing Set	87
4.8	Parameter Values for Tuning	88
4.9	Parameters for each class	89
4.10	Healthy leaves detection results	89
4.11	Nitrogen Deficiency leaves detection results	90
4.12	Phosphorus Deficiency leaves detection results	90
4.13	Potassium Deficiency leaves detection results	90
4.14	Fertigation process for Nitrogen, Phosphorus and Potassium	91

CHAPTER 1
INTRODUCTION

In Asia, most of the country is mainly depending on agriculture so it becomes the primary occupation of people. Agricultural productivity is something on which the economy highly depends [19]. If proper care is not taken in this area, it can cause serious effects on crops such as quality, quantity or productivity. Myanmar is a fast-developing country and agriculture is the backbone for the country's development in the early stages. In the past several decades, their annual incomes have played an important role for family's expense, now most of the family are facing with financial problems because of crops productivity decline as a result of rapid change or develop in global circumstances. That causes climate change and greatly affects nature. According to the reports, Myanmar is the second place in global climate change. As a consequence, water resources, the most valuable resources for survival, become insufficient especially in the dry season and in the central region of Myanmar.

To overcome this problem, technology is one of the best solutions to apply in the agriculture field, and it will also be the development of transform from traditional agriculture to modern agriculture. Thus, people in agriculture need modern agricultural knowledge to make optimal and precise decisions.

This research will mainly focus on efficient water and fertilizers usage with drip irrigation system in automatic farm control system using the Internet of Things (IoT) technology and also emphasizes to detect, identify, and accurately quantify the first symptoms of plant leaves using image processing techniques. This can be widely adopted in the agriculture filed and the farmer can easily monitor and supervise large crop fields and detect the disease symptoms as soon as appear on the plant. However, due to a high initial set up cost, it prefers the high profitable export crops. Thus, strawberry is chosen for this research by combining agriculture and technology to produce fruits all the year-round within the small-scale farm system.

1.1 Problem statements and solutions

Strawberries are one of the exports of the expensive fruits to either local or abroad from Pyin Oo Lwin (in Mandalay region, Myanmar) because Pyin Oo Lwin has the pleasant weathers all the time and is the suitable place for growing strawberry plants. Thus, most strawberry fields' owners in Pyin Oo Lwin invested in these fruits every year but they have to plant just in the winter season (typically from October to March) because strawberries do not like hot weather and rain.

While winter passed away, people dream about the sweet, juicy strawberries they enjoyed in the last season. To turn that dream into reality, strawberry is chosen for this research. A challenging problem which arises in the domain is the application of optimum watering and mineral nutrition to grow strawberry plants efficiently and effectively. To accomplish this task, the application of automatic control would be very helpful. This research is thus proposed to produce high quality and quantity of strawberry fruits for all seasons (summer through winter) automatically inside the small-scale farm system by using modern technology. Joseph et al. By learning different motivations, many researchers make their own contributions. [13] proposed a method for farm automation, moisture control, and automated fertigation system. The moisture levels in the soil are maintained and mix different nutrients to obtain the required NPK ratio whereas NPK fertilizers are supplied separately and not mix with each other in the proposed small-scale farm.

In real-world, farmers always watch and take care of the various conditions of plants for watering, controlling temperature, feeding fertilizers and preventing plant diseases with the exact time. Traditional direct measurement methods are generally simple and reliable, but they are time consuming and laborious. One approach to solve this problem involves the use of automatic detection of leaf diseases and deficiency symptoms. Pooja et al. [16] proposed an approach for disease detection and classification with the help of machine learning mechanisms and image processing tools. The overall recognition rate was found out to be 92.4% and considered that SVM classifier has enhanced the performance of the system. The proposed system now focuses on the classification of plant deficiency (or excess) symptoms by leaf analysis using SVM classifier and applying the precise amount of fertilizers (separated N, P and K) to the appropriate plants autonomously.

Also, this seems to be a common problem in time-consuming and insufficient water supply due to global climate change. The standard solution to this problem is based on the automatic drip irrigation system to water the plants and feed the fertilizers that can save the amount of water and fertilizers than the traditional system. Mohanraj et al. [14] mainly focused on the automation of the drip irrigation and fertigation process using WSN (Wireless Sensor Network) for precise agriculture. WSN in their research is used to measure parameters like temperature, pressure or any detection of events using sensors, collect it, process it and transmit that data to the base station for the further decisions and actions. In the proposed research, temperature sensors and soil moisture sensors are installed inside the farm to drive the relays which are connected with Raspberry Pi for controlling the motor, drip pipes, fans, and other temperature control equipment. Also, IoT is used to inform the users the different states of plants' requirements to the smartphones or PC with the help of sensors.

As a result of this kind of technology, the plant will produce not only tasty and standardize foods but also a large amount of food as compared to traditional agricultural methods. Not only the berries are tasty and good, but they're also a great way to get started with organic growing. This is why they're ideal for an indoor growing adventure.

The following facts show about the comparisons between the weather of Pyin Oo Lwin and requirements to grow strawberry plants.

1.1.1 Temperature

Strawberries will flower and set berries whenever the temperature is in the range of 20°C to 29°C. The upper limit is considered to be 29°C at which strawberries will produce flowers. When temperatures descend gradually the plant can tolerate even temperatures as low as -6°C, but it will die when temperatures fall to -12°C [21]. Fig. 1.1 shows the average minimum and maximum temperature in Pyin Oo Lwin with degree Celsius. On average, the temperatures are always high, the hottest month is April and the coolest month is January. So, a controllable temperature is needed for the small-scale farm from March to August.

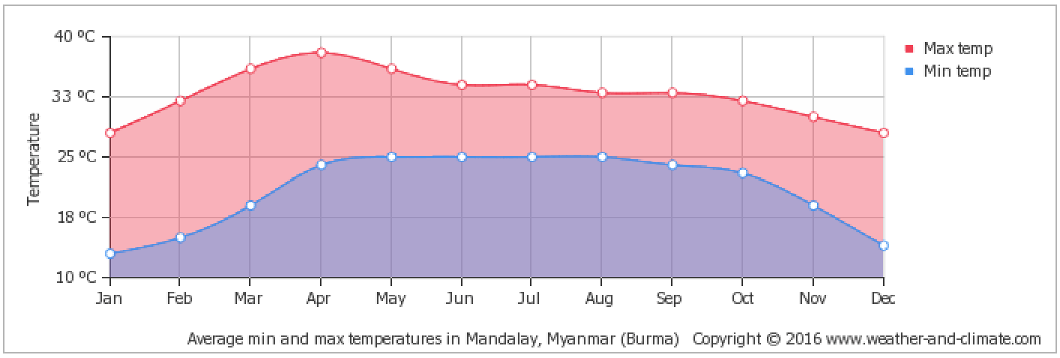


Figure 1.1. Average temperatures in Pyin Oo Lwin [21]

1.1.2 Relative Humidity

Development and spread of powdery mildew and bacterial blight are favored by high relative humidity (RH). High RH also has a deleterious effect on the opening of the pollen sacs of the stamen [21].

In comparison, the graph in Fig. 1.2 shows that the relative humidity is not so very high in Pyin Oo Lwin with the average annual percentage of humidity is 67%. October is the most humid with 80% and March is the least humid month. It is highly important, therefore, to enable good aeration of the plants growing in the small-scale farm during the flowering season if the humidity is higher than acceptable range.

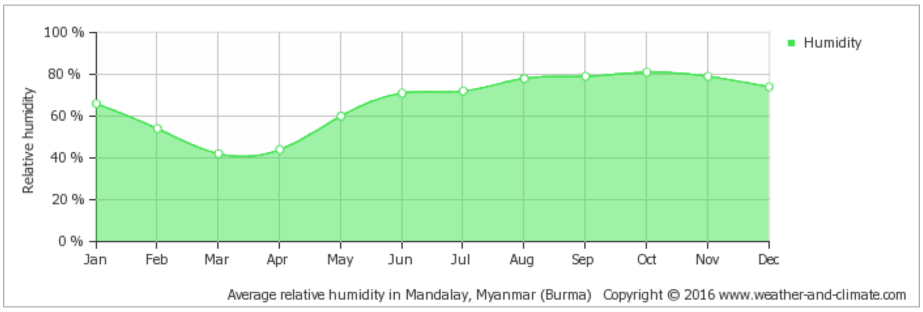


Figure 1.2. Average humidity in Pyin Oo Lwin [21]

1.2 Aim and Objectives

- To cultivate strawberry plants indoor with good efficiency using modern irrigation technology to grow and produce many fruits for different weather conditions.
- To save time and reduce manpower using an automatic drip irrigation system.
- To detect and classify the strawberry plants' leaves so that the feeding fertilizer can be controlled according to nutrient deficiencies via cameras.
- To apply the IoT network to inform and communicate the users about the various saturations of the small-scale farm.

1.3 System Overview

The system design of this thesis is mainly separated into three parts: overview design, nutrient deficiency symptoms detection system and drip irrigation system design.

The overview of the system is shown in Fig. 1.3. Raspberry Pi 3 Model B is used as the main controller. The soil moisture sensor (to detect the various states of soil), temperature and humidity sensor (to determine the inside temperature and humidity of the farm for environmental control) are connected with controller and a medium resolution webcam is used for image processing.

The drip kits, solenoids valves (to supply water and fertilizer to the appropriate plants based on moisture sensors and image processing results), exhaust fan (to circulate the air around the farm), cooling pad and the sprinklers (for cooling the farm) are used as temperature control devices. And LCD monitor is placed inside the farm to check the system functions, settings and logged data. In order to communicate or command the Raspberry Pi from smartphone, laptop or tablet, IoT technology is used. For the power station, solar power energy is used to supply control valves and other technical equipment. As for the programming language, Python language is used and Thingspeak IoT platform is used to monitor the sensor data from anywhere.

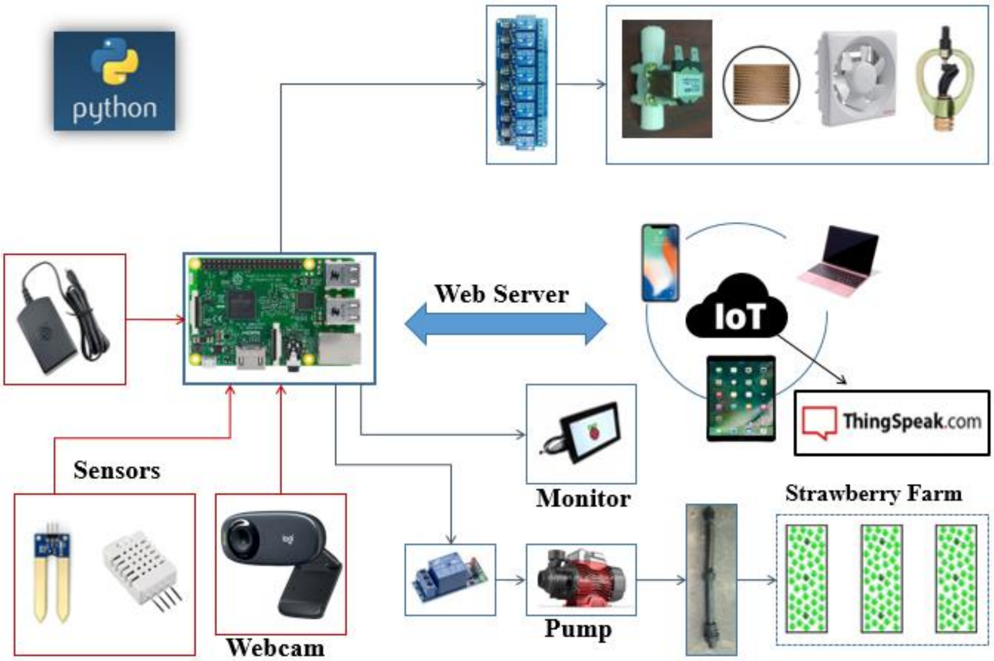


Figure 1.3. System Overview Design

The general proposed method of automatic detection and classification of plant leaf includes five steps; image acquisition, pre-processing, segmentation, feature extraction, and classification. There are about ten nutrient deficiency symptoms (Nitrogen, Phosphorous, Potassium, Calcium, Magnesium, Iron, Manganese, Boron, Zinc, and Copper) for the strawberry leaves to supply but this system only aimed for the three main nutrient deficiencies (Nitrogen, Phosphorous, and Potassium).

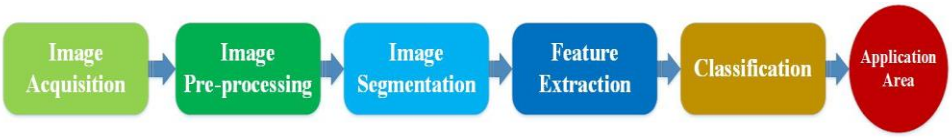


Figure 1.4. Image processing methods

Figure 1.5. Nitrogen, Phosphorus, and Potassium deficiency symptoms on strawberry leaves [12]

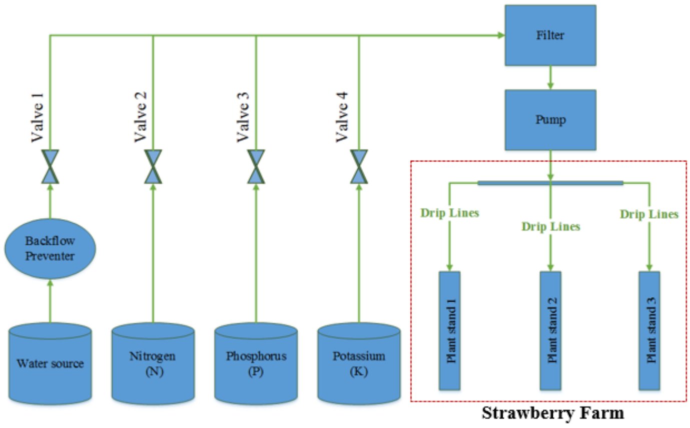


Figure 1.6. Drip Irrigation System

Equipment used in this drip system is a set of drip pipes with a water tank and three fertilizer tanks (N, P, K), filter (to avoid logging of small particles inside drip pipes) and backflow preventer (not to flow chemical fertilizers backward to the water tank). For example, if the system detected that the plants are suffered from Nitrogen deficiency symptom, then the pump absorbs required amount of Nitrogen from the fertilizer tank (N) and apply to the appropriate plant stands.

1.4 Outlines of thesis

The intelligent small-scale strawberry farm is analyzed according to the following plans. Chapter one introduces the agricultural state of Myanmar, problem statement and solutions, aim and objectives, and three parts of system overall design. Chapter two describes the theoretical background of system designs. Chapter three mentions the overall design calculation and methodology of farm control. Chapter four includes the test and result of corresponding parts. Chapter five concludes the discussion, recommendation, and area for further research of this system.

CHAPTER 2
THEORETICAL BACKGROUND

The automatic small-scale farm control system is divided into three main parts: temperature and humidity control system, drip irrigation system and nutrient deficiency symptoms detection system. The overall system is controlled and communicate by IoT technology using IoT platform and the status of the farm and plants can be monitored on the LCD monitor with cool GUI and they all are explained step by step in this chapter. Firstly, the basic concept of strawberry, common nutrient deficiency symptoms and nutrient solutions are described as following.

2.1 Strawberry

Strawberries belong to the crop groups of soft-fruits; they are the best of the berries. They are a highly popular fruit which is often enjoyed during winter. Strawberry plants will require frequent watering, particularly in the summer. Although strawberries do not require too much water, the soil will still need to be kept moist as the plants are shallow-rooted. Strawberries do thrive in dry conditions but still require water regularly during summer. The following figure shows the general structure of a strawberry plant.

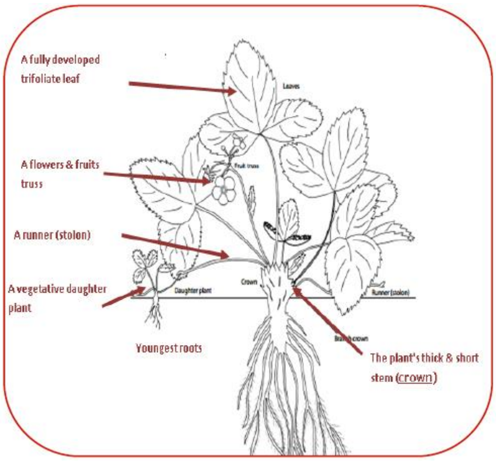


Figure 2.1. Schematic morphology of a strawberry plant [12]

At first, certified strawberry plants should be chosen because strawberries are susceptible to diseases. This will increase the chances of successfully growing strawberries along with the right conditions indoor and plenty of care. There are numerous varieties of strawberries, but there are three main categories; ever-bearing, June-bearing, or day-neutral. Ever-bearing strawberries produce fruit twice a year, in the spring and again late in the summer or early in the fall. June-bearing strawberries produce fruit for about three weeks once a year, usually in June like the name implies. To get the longest fruit-bearing season, the best choice is day-neutral strawberries. These strawberries are capable of producing fruit continuously starting in June all the way through September. Strawberry plants prefer cooler temperatures and won't even bloom or bear fruit when the weather is really hot [12].

Intensively grown strawberries require frequent and precise fertility management. Knowing the exact nutritional needs of the strawberry plant can help better growth and higher yields. Table. 2.1 shows the nutrient requirements for strawberry plants. Nutrients required by strawberry plants in the highest quantity are nitrogen (N), potassium (K) and phosphorus (P) as they are essentially important for optimum yield and quantity. So NPK should be applied carefully to get better yield quality as plant nutrient deficiencies during the growing season can have a major effect on fruit yield and quality.

Table 2.1. Nutrient requirements for strawberry plants

Major elements	Secondary elements	Micronutrients
Nitrogen (N)	Calcium (Ca)	Iron (Fe)
Phosphorus (P)	Magnesium (Mg)	Manganese (Mn)
Potassium (K)	Sulfur (S)	Zinc (Zn)
		Copper (Cu)
		Boron (B)
		Molybdenum (Mo)

2.1.1 Plant nutrients and deficiency symptoms

Among various nutrients required for strawberry plants, only Nitrogen, Phosphorus, Potassium and deficiency symptoms for each nutrient are described as following.

2.1.1.1 Nitrogen

Nitrogen is the central component of all amino acids, which are the building blocks of all proteins and include all functional enzymes. Nitrogen is a highly important plant nutrient, which substantially affects the quality and yield of strawberries. The plant quickly responds to every positive or negative change in its nitrogen status. Application of nitrogen fertilizers stimulates vegetative growth of leaves, petioles, and shoots.

Figure 2.2. Signs of Nitrogen Deficiency Symptom

Nitrogen deficiency is visualized more easily in middle-aged leaves. Fruit size is reduced, and the calyx around the fruit becomes reddish. Lower leaves initially develop a pale green to light yellow coloration. Some older leaves may also develop an orange to reddish coloration [5].

2.1.1.2 Phosphorus

Phosphorus is important in the plant's energy management and it plays a role in fruit development. There is a strong antagonistic relationship between phosphorus and zinc: high phosphorus will invariably reduce zinc uptake, and excess zinc will have the same effect on phosphorus.

The first sign of phosphorus deficiency is a deep green appearance of plants and a reduction in leaf size. Lower leaf color often turns darker green before giving way to a dull green coloration. Under cold growing conditions, the lower can develop a lower leaf orange to reddish coloration. With warmer conditions, lower leaf symptoms may develop a yellow coloration instead [5].

Figure 2.3. Signs of Phosphorus Deficiency Symptom

2.1.1.3 Potassium

Potassium is the third macro-nutrient, (nutritive element required in relatively high amounts) by strawberries. It is an important component of strawberry plants and helps them acquire water by the roots and control water loss by transpiration. Potassium assists in sugar accumulation in the fruit defy fungal and microbial diseases and insect damage and play an important part in tens of enzymatic reactions.

Figure 2.4. Signs of Potassium Deficiency Symptom

The first symptoms of K deficiency appear on the upper leaf margins of the older (lower) leaves. The serration tips redden, the injury gradually progressing inwards between the veins until most of the leaf blade is affected. Fruit quality is also affected by low potassium levels. The fruit can fail to develop full color, be pulpy in texture and lack flavor [5].

The following table shows a summary of the main functions for each nutrient and the fertilizer lists which can be applied for each nutrient which are easily soluble in water and their application rate in liters per 1000 plants. Urea (CH_4N_2O) has the nitrogen content of 46%, Triple Superphosphate ($CaH_4P_2O_8$) has 46% of P and Potassium Chloride (KCl) has potassium percentage of 60.

Table 2.2. Main functions and fertilizers with application rates for NPK

Nutrient	Main functions	Fertilizers	Application Rate (L/1000 Plants)
Nitrogen(N)	Growth and yield	Urea	0.4 – 0.5
Phosphorus(P)	Fruit development	Superphosphate	2.5 – 3
Potassium (K)	Fruit quality and flavor	Potassium Chloride	0.7 – 0.8

2.2 Temperature and Humidity Control System

The small-scale farm inside temperature can quickly become too hot for healthy plant production even in the winter as it is covered by plastics. During summer, extra cooling beyond what fan ventilation can provide may be necessary. Excessive temperatures result in poor plant growth, the need for frequent watering and fans that seem to run all the time. To get adequate cooling on hot, sunny days, evaporative cooling, either a fog system or portable evaporative coolers could give added cooling.

2.2.1 Fan and Pad Evaporative Cooling System

Evaporative cooling will facilitate to take care of a cool summer atmosphere that does not stress the plants [3]. Evaporative cooling, which uses the heat in the air to evaporate water from plants and other wetted surfaces can be used to cool the indoor farm. The fan and pad system are the standard system in use for many years in greenhouses and other segments of agriculture.

The "fan and pad" system uses exhaust fans to drag air through cooling pads. This technique utilizes the cooling effect produced when water evaporates and cools the air as it is forced through the pad. In this system, aspen or cellulose pads are mounted in one end wall or sidewall of the greenhouse. Cellulosic pad materials are the preferred choice as they last longer than aspen pads. They are provided with water from a pipe above the pads and excess water is collected in a gutter at the bottom. Air drawn through the wet pads by fans mounted on the opposite end wall or sidewall is saturated and cools the greenhouse.

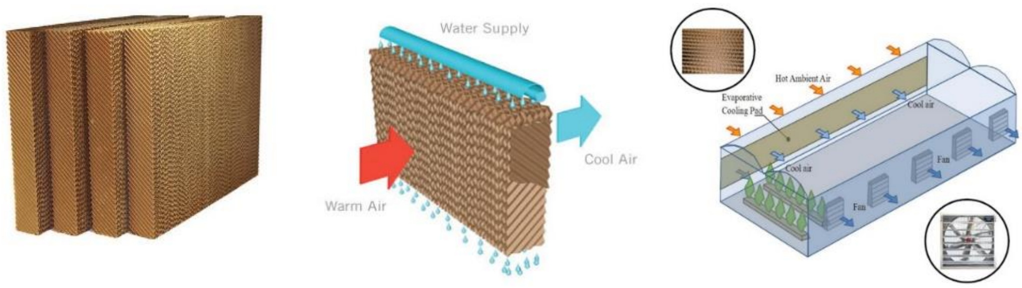


Figure 2.5. Cooling Pads and Their Application

If all vents and doors are closed when the fans operate, the air is pulled through the wetted pads and water evaporates. The air will be at its lowest temperature immediately when passing through the pads. As the air moves across the farm to the fans, the air picks up heat from solar radiation, plants, and soil, and the temperature of the air gradually increases. Evaporative cooling becomes efficient as the relative humidity drops.

Fan and pad systems need to be sized appropriately to achieve maximum cooling efficiency. Cooling pads require regular maintenance to ensure they remain efficient. Algae and mineral build-up can reduce air movement and lower potency. To work effectively, the pads need an adequate supply of water to stay wet.

2.2.2 High-Pressure Fog System

An alternate system uses a fog or fine mist injected into the intake air stream to cool greenhouses. Although several commercial systems are available, growers can assemble and install their own system using a high-pressure piston pump and fog nozzles [4]. These fog systems can be designed and operated to maintain more uniform temperatures and humidities in the indoor farm than are possible with fan and pad systems. When uniform temperatures and high humidity levels are important, fog systems can be the best method of evaporative cooling.

2.2.3 Sensors and Controller

The fan and pad system with fog system are usually activated as the last stage of cooling where the fans can't maintain the desired indoor temperature. It may be controlled by a thermostat, controller or PC. As the controller and computer provide multiple stages of cooling, these are the preferred controls [3]. To prevent excessive humidity in warm weather, the pump on the evaporative cooling system could be controlled by a humidistat. Thermostats and humidistats must be located at the plant level to function properly and should never be located on an outside wall.

A thermostat ought to be used as the main pump management. The thermostat should be set to stop the pump before all the fans go off in order that the pad can dry out. All controls and instruments, including thermostats, humidistats, and thermometers, should be shielded from the direct rays of the sun to avoid being influenced by solar radiation and to provide more accurate readings and control settings [6]. Sensing elements should be mounted so that air can circulate freely around them and they should be located where they represent the average environment conditions at the plant level.

Computers and microcontrollers can use software or hardwired circuits that incorporate logic to make decisions about the exact amount of heat or airflow required to produce desired environmental conditions [6].

Computer-based control systems can be linked to phone systems or to the Internet to allow operators to closely monitor the farm conditions from any location. Computer systems can also keep continuous records of environmental conditions and can be used to send messages or alarms to operators when environmental conditions are out of range or when equipment fails [6]. The increased control provided by these devices results in farm conditions that provide a better environment for crop growth.

2.3 Drip Irrigation System

A drip-irrigation system is used for water and fertilizers to get the required amount for the plants with low wasting. Providing excess or deficient fertilizers will affect the plant photosynthesis process and its growth. As a result, the final yield will get affected. When properly managed and designed, the drip-irrigation system has many advantages over other irrigation systems. The drip pipes for water and fertilizers are applied directly to the root zones of the plants. It can also save time and manpower. If the proper nutrition and water for plants are given in a right amount and time during the growing period, the plants will grow and produce whatever in a normal period of time with a great yield and quality.

A drip irrigation system comprises many components, each one of them playing an important part in the operation of the system.

2.3.1 Water source

There are basically two main types of water sources: groundwater and surface water:

Surface water, however, tends to introduce biological hazards. If wastewater is being considered as a source, quality and clogging potential will vary depending upon the extent of treatment.

Groundwater is mostly of higher quality than surface water. However, iron and manganese levels should be measured, as high levels may lead to dripper clogging, and treatment may be required.

2.3.2 Pumps & pumping stations

Unless the water at the source is supplied at an adequate flow rate and pressure, a pump will be needed to push water from the source through the pipes and drippers. Most irrigation systems embody pumps as an integral part of the drip irrigation system.

Selecting a pump for an irrigation system requires an understanding of the water conditions and local system requirements. Poor pump selection can lead to high operating costs and shortened pump life; this in turn impacts on the performance and reliability of the whole irrigation system. When a pump site is selected it is necessary to consider a range of factors, including availability of power, proximity to the development site and water quality issues.

2.3.3 Power source for the pump

The power source for the pump will depend on the availability and accessibility of the energy resource in the local area. In most instances, electricity is preferred because of reduced labor requirements and higher efficiency, resulting in lower energy cost. If electricity is not available, alternative power sources such as diesel, gasoline, or solar may be used.

2.3.4 Filtration

Filtration is critical in any drip irrigation system. Effective filtration is essential for proper irrigation system operation and long-term performance, as it prevents the irrigation water from clogging the drippers.

2.3.5 Valves

In an irrigation system, water flow rate and pressure throughout the system should be precisely controlled to ensure efficient and timely water application, therefore proper selection and placement of valves are critical. Valves play key roles in controlling pressure, flow, and distribution underneath totally different conditions to optimize performance, facilitate the management, and reduce maintenance requirements.

2.3.5.1 Solenoid Valves

Figure 2.6. DC Water Solenoid Valve

A solenoid valve is an electromechanical actuated valve to control the flow or direction of air or liquid in fluid power systems. It is used to close, dose, distribute or mix the flow of gas or liquid in a pipe. The valve features a solenoid, that is an electrical coil with a movable magnetism core in its center. This core is called the plunger. The coil will exist as any vary of voltage from 12-48 V DC to 110-220 V AC. In the rest position, the plunger closes off a small orifice. An electric current through the coil creates a magnetic field and this magnetic field exerts a force on the plunger. As a result, the plunger is pulled toward the center of the coil so that the orifice opens. This is the fundamental principle that is used to open and close solenoid valves.

A wide range of solenoid valve types is available depending on the specific application requirements. The various functions of a solenoid valve depend on the type of valve and the operation of the valve needed to perform.

(a) Normally Closed or Normally Open

These terms refer to the resting state of the valve, with no power applied. Although they are fairly self-explanatory, they can also be referred to using different terms. A normally closed solenoid valve can be described as ‘energize to open,’ and a normally open solenoid valve can be described as ‘energize to close.’ Normally closed or normally open most commonly refer to diaphragm or poppet type solenoid valves that employ a spring to return the valve to its resting state once the power has been removed from the coil [17].

(b) Two-way Valve (2/2 Way)

The most common solenoid valve is the two-way valve. A two-way valve only has two ports, whereas more advanced designs may have three or more, depending on what it will be used for. Each of the two ports on a two-way valve is alternately used to permit flow as well as close it off. A two-way valve can be specified to be either “normally open" or “normally closed” in its operation which means normally-flowing and normally-blocked, respectively. With a normally open valve, the valve remains open until some type of current is applied to close the valve. Suspension of the electrical power causes the valve to automatically reopen to its normal state. A normally closed solenoid valve is the most common, working in the opposite fashion, remaining closed until a power source causes it to open [17].

(c) Three-way Valve (3/2 Way)

The term three-way is most commonly associated with a spool type solenoid valve, although it is possible to have a poppet type valve in this configuration. These are commonly used when alternate and exhaustive pressure is required for operation, as with a coffee machine or dishwasher. The term 3/2 can be extruded to mean '3 port, 2 positions.' This same formula can be applied to other valve types with a similar abbreviation. In their resting state, the most basic of 3/2-Way valves use port 1 as the valve inlet, port 2 as the outlet and port 3 is the exhaust, but is blocked in its resting state. When power is applied via the solenoid, the spool position changes and port 1 becomes blocked, with port 2 flowing to port 3 and therefore exhausting the system. When power is removed, the spool springs back to its resting position and normal valve function is restored [17].

The specific purpose of a solenoid valve is expressed by its circuit function. The circuit function can be expressed in a symbol. Below are some examples of the most common circuit functions. The circuit function of a valve is symbolized in two rectangular boxes for the de-energized state (right side) and energized state (left side). The arrows in the box show the flow direction between the valve ports. The examples show a 2/2-way Normally Open (NO) valve, a 2/2-way Normally Closed (NC) valve and a 3/2-way Normally Closed valve [20].

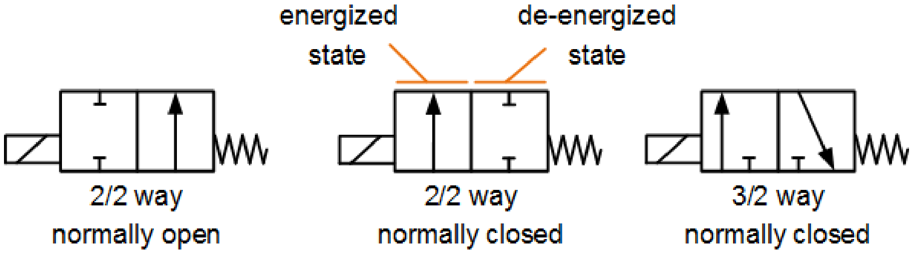


Figure 2.7. Circuit Functions of Solenoid Valves

(d) Application areas

Solenoid valves are amongst the most used components in gas and liquid circuits. The number of applications is almost endless. Some examples of the use of solenoid valves include heating systems, compressed air technology, industrial automation, swimming pools, sprinkler systems, washing machines, dental equipment, car wash systems, and irrigation systems.

Washing machines and gas boilers use these valves, as well as hydraulic pumps and air hammers because they are diverse enough to perform both simple and complex tasks with ease. Solenoid valves can be customized to suit specific needs and can be utilized to control a variety of mediums such as air, electricity, gas, steam, and oil [20].

2.3.6 Fertilizer tank

A fertilizer tank mixes water with fertilizer for quantitative nutrition. It is operated by the hydraulic pressure in the irrigation system and does not need an external energy source (subject to excess pressure available in the system). The desired amount of fertilizer placed in the tank is dissolved and injected into the irrigation system.

2.3.7 Drippers

The drippers are small-sized emitters made of high-quality plastics. The drippers incorporated at uniform spacing along the dripper line deliver water and nutrients directly to the plant root zone. A properly operated and maintained drip irrigation system provides water and nutrients to the crop root zone.

2.3.8 Drip Tapes

These are thin-walled integral drip lines with emission points spaced 10, 20, 30, 45 cm or any other distance apart, delivering lower quantities of water than the standard drippers at very low pressures.

2.3.9 Controller

The best way to make full use of the advantages of a drip irrigation system is by controlling it using an irrigation controller. The controller offers a range of optimal solutions for open-field applications controls such as irrigation valves, irrigation pumps, fertilizer pumps, fertilizer tank selector, cooling system, misting system, an alarm device, water meters, fertilizer meters, EC and pH sensors, temperature & humidity sensors, pressure sensors, and soil moisture sensors.

2.3.10 Pros and Cons for Drip Irrigation System

The advantages of drip irrigation systems are that it can save water and has low labor operating requirements. The disadvantages are its high initial purchase cost and additionally, smart irrigation management is essential for skilled system operation, application of fertigation and maintenance of the head management unit equipment (filters, injectors, etc.)

2.4 Nutrient Deficiency Symptoms Detection System

As shown in the block diagram of nutrient deficiency detection in Fig. 1.4, the main steps are image acquisition, image pre-processing, image segmentation, feature extraction, and image classification and to perform these image processing steps for strawberry plant leaves, a popular computer vision library (OpenCV) is used.

2.4.1 OpenCV

OpenCV is an open-source computer vision library and it is aimed at providing the basic tools needed to solve computer vision problems. Computer vision is the transformation of data from a still or video camera into either a decision or a new representation. A new representation means turning a color image into a grayscale image or removing camera motion from an image sequence.

The library is written in C and C++ and runs under Linux, Windows and Mac OS X. There is active development on interfaces for Python, Ruby, Matlab, and other languages. OpenCV is written in optimized C and can take advantage of multicore processors. OpenCV automatically uses the appropriate IPP library at runtime if that library is installed. The OpenCV library contains over 500 functions. OpenCV also contains a full, general-purpose Machine Learning Library (MLL).

OpenCV was designed to be portable. OpenCV-Python is the Python API of OpenCV. It is an appropriate tool for fast prototyping of computer vision problems and it combines the best qualities of OpenCV C++ API and Python language. OpenCV for Python enables to run computer vision algorithms in real-time [11].

2.4.2 Image Acquisition

For the image acquisition part, the image or video is captured by an individual camera. Then the receive ones are pre-processed for the next steps.

2.4.3 Image Pre-processing

Image pre-processing is a desirable step in every image processing problem to improve its performance and used to reduce variations and produce a more consistent set of data such as color space-changing, resizing, removing noise for smoothing, thresholding, suppressing unwanted distortions and enhancing some image features important for further processing.

2.4.3.1 Changing Color-space

Considering all the color spaces, there are more than 150 color-space conversion methods available in OpenCV. And understanding how color is perceived by humans and represented by computers occupies an entire library of literature itself.

In computer vision and image processing, color space refers to a specific way of organizing colors. A color space is actually a combination of two things, a color model and a mapping function. The mapping function maps the color model to the set of all possible colors that can be represented.

There are many different color spaces that are useful. Some of the more popular color spaces are RGB, YUV, HSV, Lab, and so on. Different color spaces provide different advantages [10].

(a) RGB

RGB is probably the most popular color space. It stands for Red, Green, and Blue. In this color space, each color is represented as a weighted combination of red, green, and blue. So, every pixel value is represented as a tuple of three numbers corresponding to red, green, and blue. Each value ranges between 0 and 255.

(b) YUV

Even though RGB is good for many purposes, it tends to be very limited for many real-life applications. Hence, YUV color space is coming up for different information. Y refers to the luminance or intensity, and U/V channels represent color information. This works well in many applications because the human visual system perceives intensity information very differently from color information.

(c) HSV

As it turned out, even YUV was still not good enough for some applications. The HSV color space is more similar to how humans think and conceive of color. HSV stands for Hue, Saturation, and Value. This is a cylindrical system where we separate three of the most primary properties of colors and represent them using different channels. For HSV in OpenCV, Hue range is [0,179], Saturation range is [0,255] and Value range is [0,255].

2.4.3.2 Image Thresholding

Thresholding is generally the binarization of an image. OpenCV provides different styles of thresholding. Normally, image thresholding is used to focus objects or areas of particular interest in an image [2].

(a) Simple Thresholding

The matter is straight forward for simple thresholding. If the pixel value is greater than a threshold value, it is assigned one value (maybe white), else it is assigned another value (maybe black). Applying simple thresholding methods requires human intervention, it is needed to specify a threshold value by the user.

(b) Adaptive Thresholding

One of the downsides of using simple thresholding methods is that the threshold value is needed to manually supply. But it is not very helpful where the image has different pixel intensities in different areas. In that case, adaptive thresholding is needed to be considered. This method can handle cases where there may be dramatic ranges of pixel intensities and the optimal value may change for different parts of the image. In this, the algorithm calculates the optimal threshold value for a small region of the image but a few experiments are still required.

(c) Otsu's Binarization

Otsu's binarization is usually aiming for bimodal images (images whose histogram have two peaks). In global thresholding, an arbitrary value was chosen for threshold value and this selected value may be good or not randomly. But Otsu's method automatically calculates an optimal threshold value from image histogram. It actually finds a value which lies in between two peaks in the grayscale histogram of an image such that variances to both classes are minimum.

2.4.3.3 2D-Convolution (Image Filtering)

Convolution is a fundamental operation in image processing. Basically, a mathematical operator is applied to each pixel, and change its value in some way. To apply this mathematical operator, a matrix also known as a kernel is used. This kernel is called the image filter and the process of applying this kernel to the image is called image filtering. As for one-dimensional signals, images also can be filtered with various low-pass filters (LPF), high-pass filters (HPF), etc. An LPF helps in removing noise or blurring the image. HPF filters help in finding edges in an image [2].

OpenCV provides a function to convolve a kernel with an image. As an example, a 5x5 averaging filter kernel can be defined as follows:

$$K = \frac{1}{25}\begin{bmatrix} 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \end{bmatrix} \tag{2.1}$$

Filtering with the above kernel results in the following being performed: for each pixel, a 5x5 window is centered on this pixel, all pixels falling within this window are summed up, and the result is then divided by 25. This equates to computing the average of the pixel values inside that window. This operation is performed for all the pixels in the image to produce the output filtered image.

2.4.3.4 Smoothing Images

Image blurring simply happens when the camera takes a picture out of focus, sharper regions in the image lose their details. Practically, this means that each pixel in the image is mixed in with its surrounding pixel intensities. These pixels become the blurred pixels. While this effect is usually unwanted in the photographs, it is actually quite helpful when performing image processing such as thresholding and edge detection, perform better if the image is first smoothed or blurred [2].

(a) Image Blurring

Image blurring is achieved by convolving the image with a low-pass filter kernel. It is useful for removing noise. It actually removes high-frequency content (e.g. noise, edges) from the image resulting in edges being blurred when this is a filter is applied. OpenCV provides mainly four types of blurring techniques.

(i) Averaging

This is done by convolving the image with a normalized box filter. It simply takes the average of all the pixels under the kernel area and replaces the central element with this average. A 3x3 normalized box filter would look like this:

$$K = \frac{1}{9}\begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix} \qquad (2.2)$$

(ii) Gaussian Filtering

Gaussian filtering is similar to average blurring, but instead of using a simple mean, a weighted mean is used where neighborhood pixels that are closer to the central pixel contribute more “weight” to the average. Gaussian filtering is highly effective in removing Gaussian noise from the image.

(iii) Median Filtering

Median filtering computes the median of all the pixels under the kernel window and the central pixel is replaced with this median value. This is highly effective in removing salt-and-pepper noise.

Averaging and Gaussian methods can compute means or weighted means for the neighborhood, this average pixel intensity may or may not be present in the neighborhood. But the median pixel must exist in the neighborhood and by replacing the central pixels with a median rather than an average, noise can be reduced substantially.

(iv) Bilateral Blurring

Bilateral blurring is highly effective at noise removal while preserving edges. Bilateral filtering accomplished this by introducing two Gaussian distributions. Thus, the operation is slower compared to other filters. As a result, this method preserves edges, since for pixels lying near edges, neighboring pixels placed on the other side of the edge, and therefore exhibiting large intensity variations when compared to the central pixel, will not be included for blurring.

2.4.3.5 Edge Detection

Edge detection is an image processing technique for finding the boundaries of objects within images. It works by detecting discontinuities in brightness. Formally, edge detection uses mathematical methods to find points in an image where the brightness of pixel intensities changes distinctly. It is used for image segmentation and data extraction in areas such as image processing, computer vision, and machine vision. Common edge detection algorithms include Sobel, Canny, Prewitt, Roberts, and fuzzy logic methods [2].

(a) Canny Edge Detection

Among them, canny edge detection is a popular edge detection algorithm and it is a multi-stage algorithm. It was developed by John F. Canny in 1986 [2].

(i) Noise Reduction

Since edge detection is susceptible to noise in the image, the first step is to remove the noise in the image with a Gaussian filter.

(ii) Finding Intensity Gradient

Smoothened image is then filtered with a Sobel kernel in both horizontal and vertical direction to get the first derivative in the horizontal direction (Gx) and vertical direction (Gy). From these two images, edge gradient and direction can be calculated for each pixel as follows:

$$\text{Edge Gradient (G)} = \sqrt{G_x^2 + G_y^2} \tag{2.3}$$

$$\text{Angle } (\theta) = \tan^{-1}\left(\frac{G_x}{G_y}\right) \tag{2.4}$$

(iii) Non-maximum Suppression

After getting gradient magnitude and direction, a full scan of an image is done to remove any unwanted pixels which may not constitute the edge. For this, at every pixel, the pixel is checked if it is a local maximum in its neighborhood in the direction of the gradient.

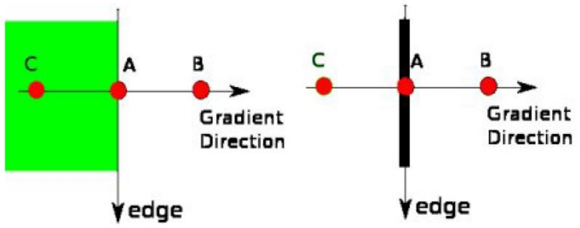


Figure 2.8. Non-maximum Suppression

Point A is on the edge (in the vertical direction). Gradient direction is normal to the edge. Point B and C are in gradient directions. So, point A is checked with point B and C to see if it forms a local maximum. If so, it is considered for the next stage, otherwise, it is suppressed (put to zero).

(iv) Hysteresis Thresholding

This stage decides which are all edges are really edges and which are not.

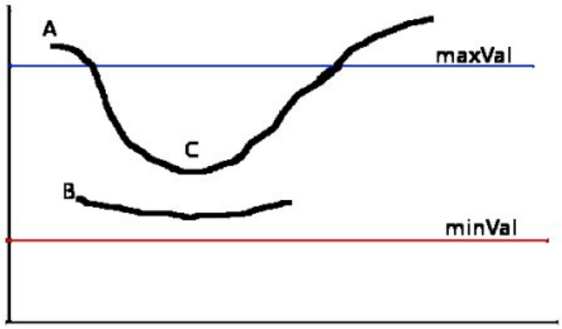


Figure 2.9. Hysteresis Thresholding

For this, two threshold values, minVal, and maxVal are needed. Any edges with intensity gradient more than maxVal are sure to be edges and those below minVal are sure to be non-edges, so discarded. Those who lie between these two thresholds are classified edges or non-edges based on their connectivity. If they are connected to “sure-edge” pixels, they are considered to be part of edges. Otherwise, they are also discarded.

The edge A is above the maxVal, so considered as “sure-edge”. Although edge C is below maxVal, it is connected to edge A, so that also considered as valid edge and we get that full curve. But edge B, although it is above minVal and is in the same region as that of edge C, it is not connected to any “sure-edge”, so that is discarded. So, it is very important to select minVal and maxVal accordingly to get the correct result. This stage also removes small pixels noises on the assumption that edges are long lines. Finally, strong edges appear in the image.

2.4.3.6 Morphological Transformations

Morphological transformations are some simple operations based on the image shape. It is normally performed on binary images. It needs two inputs, one is the original image, the second one is called a structuring element or kernel which decides the nature of the operation. Two basic morphological operators are Erosion and Dilation. Then it's variant forms like Opening, Closing, Gradient, etc. are also coming up [2].

Figure 2.10. Original Image

(a) Erosion

The basic idea of erosion is just like soil erosion only, it erodes away the boundaries of the foreground object. The kernel slides through the image (as in 2D convolution). A pixel in the original image (either 1 or 0) will be considered 1 only if all the pixels under the kernel is 1, otherwise, it is eroded (made to zero). So, all the pixels near the boundary will be discarded depending upon the size of the kernel. Thus, the thickness or size of the foreground object decreases or simply white region decreases in the image. It is useful for removing small white noises detach two connected objects.

Figure 2.11. Erosion

(b) Dilation

It is just opposite of erosion. Here, a pixel element is '1' if at least one pixel under the kernel is '1'. So, it increases the white region in the image or size of foreground object increases. Normally, in cases like noise removal, erosion is followed by dilation. Because, erosion removes white noises, but it also shrinks our object. Since noise is gone, they won't come back, but the object area increases. It is also useful in joining broken parts of an object.

Figure 2.12. Dilation

(c) Opening

The opening is just another name of erosion followed by dilation. It is useful in removing noise.

Figure 2.13. Opening

(d) Closing

Closing is reverse of Opening, Dilation followed by Erosion.

Figure 2.14. Closing

It is useful in closing small holes inside the foreground objects, or small black points on the object.

(e) Morphological Gradient

It is the difference between dilation and erosion of an image.

Figure 2.15. Morphological Gradient

(f) Top Hat

It is the difference between the input image and the Opening of the image.

Figure 2.16. Top Hat

(g) Black Hat

It is the difference between the closing of the input image and the input image.

Figure 2.17. Black Hat

2.4.3.7 Contours in OpenCV

Contours can be explained simply as a curve joining all the continuous points (along the boundary), having the same color or intensity, with no gaps in the curve. The contours are a useful tool for shape analysis and object detection and recognition. There are plenty of features related to contours, like area, perimeter, centroid, bounding box, etc [2].

There are also some frequently used properties of objects like Solidity, Equivalent Diameter, Mask image, Mean Intensity, etc.

(a) Aspect Ratio

It is the ratio of width to height of the bounding rectangle of the object.

$$\text{Aspect Ratio} = \frac{\text{Width}}{\text{Height}} \tag{2.5}$$

(b) Extent

Extent is the ratio of contour area to bounding rectangle area.

$$\text{Extent} = \frac{\text{Object Area}}{\text{Bounding Rectangle Area}} \tag{2.6}$$

(c) Solidity

Solidity is the ratio of contour area to its convex hull area.

$$\text{Solidity} = \frac{\text{Contour Area}}{\text{Convex Hull Area}} \tag{2.7}$$

(d) Equivalent Diameter

Equivalent Diameter is the diameter of the circle whose area is the same as the contour area.

$$\text{Equivalent Diameter} = \sqrt{\frac{4 \times \text{Contour Area}}{\pi}} \tag{2.8}$$

2.4.4 Image Segmentation

Segmentation is the process of grouping together pixels of an image that have similar attributes in an image. It is an important step in many computer vision applications in real-world problems. There are many different ways of segmenting an image such as the GrabCut method, watershed algorithm, etc [2].

Segmentation algorithms generally are based on one of two basic properties of intensity values.

Discontinuity: to partition an image based on abrupt changes in intensity.

Similarity: to partition an image into regions that are similar according to a set of predefined criteria.

2.4.4.1 Watershed Algorithm

Simply defined, the watershed is a transformation on grayscale images. The aim of this technique is to segment the image, typically when two regions-of-interest are close to each other (i.e., their edges touch). This technique of transformation treats the image as a topographic map, with the intensity of each pixel representing the height. For instance, dark areas can be intuitively considered to be ‘lower’ in height and can represent troughs. On the other hand, bright areas can be considered to be ‘higher’, acting as hills or as a mountain ridge [9].

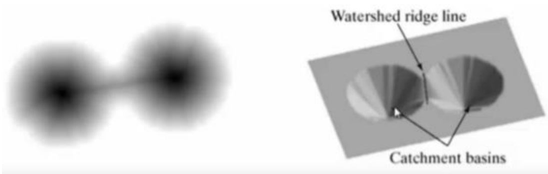


Figure 2.18. Topographic Map [9]

Various algorithms can be used to compute watersheds. One of the most popular algorithms is Watershed-by-flooding.

(a) Watershed-by-flooding

Assume that a source of water is placed in the catchment basins, the areas with low intensity. These basins are flooded and areas, where the floodwater from different basins meet, are identified. Barriers in the form of pixels are built in these areas. Consequently, these barriers act as partitions in the image, and the image is considered to be segmented. The following figure shows the example of segmentation by the watershed algorithm.

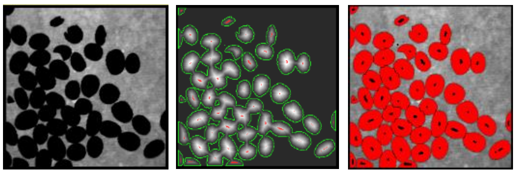


Figure 2.19. Watershed Algorithm Segmentation

2.4.5 Feature Extraction

The image can be described as spatial (locations, spatial information, etc.), color (RGB, HSV, YCrCb, etc.) and texture (rough or smooth, vertical or horizontal, etc.). To encode all this information in a way that a computer can understand it is to apply feature extraction to quantify the contents of an image. In other words, Feature extraction is the process of taking an input image, applying an algorithm, and obtaining a feature vector (i.e. a list of numbers) that quantifies our image. The features are extracted from the data set and applied with the training set and testing set and then the different images are classified with one of the various classifiers.

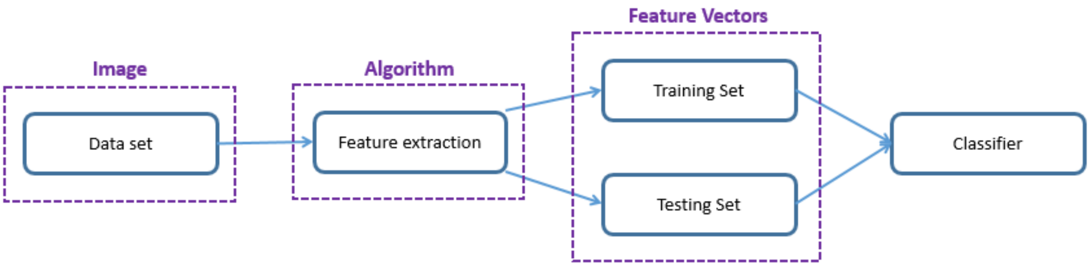


Figure 2.20. Feature Extraction Block Diagram

2.4.6 Image Classification

Image classification is the process of assigning classes to pixels. It is perhaps the most important part of digital image analysis. Depending on the interaction between the analyst and the computer during classification, there are two types of classification learning: supervised and unsupervised. The image classification plays a crucial role in environmental and socioeconomic applications. In order to improve the classification accuracy, scientists have laid path in developing advanced classification techniques.

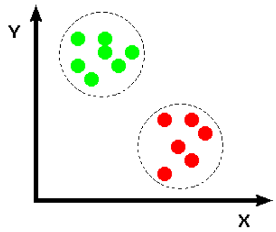


Figure 2.21. Binary Classification

2.4.6.1 Types of Learning

There are two main categories of learning, supervised learning and unsupervised learning.

(a) Supervised Learning

Supervised learning as the name indicates the presence of a supervisor as a tutor. All data is labeled and the algorithms learn to predict the output from the input data, in other words, the dataset is the collection of labeled examples and has the knowledge of output. Learning stops once the algorithm achieves a suitable level of performance.

Supervised learning issues can be further grouped into regression and classification problems.

Classification: A classification problem is when the output variable is a category, such as "red" or "blue" or "disease" and "no disease".

Regression: A regression problem is when the output variable is a real value, such as "dollars" or "weight".

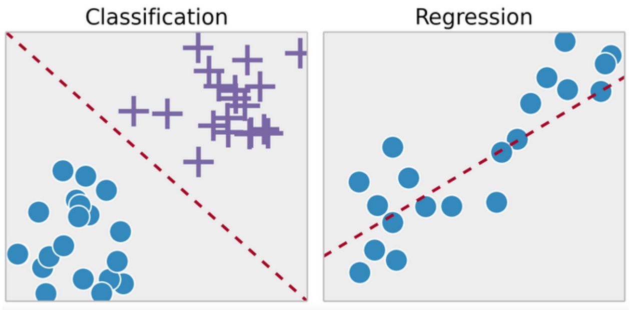


Figure 2.22. Supervised Learning Problems

Some common types of problems built on top of classification and regression include recommendation and time series prediction respectively. Some popular examples of supervised machine learning algorithms are:

1. *Linear regression for regression problems,*
2. *Random forest for classification and regression problems, and*
3. *Support vector machines for classification problems.*

(b) Unsupervised Learning

Unsupervised learning is the training of machine using information that is neither classified nor labeled and allowing the algorithm to act on that information without guidance, in other words, the dataset is the collection of unlabeled examples and has no knowledge of output. Unlike supervised learning, no tutor is provided that means no training will be given to the machine.

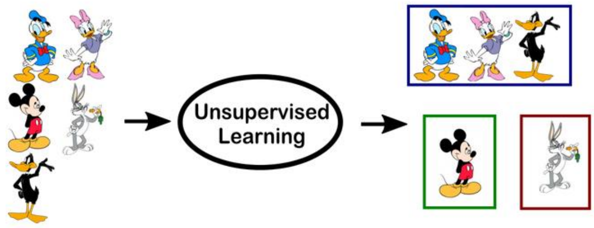


Figure 2.23. Unsupervised Learning Problem

Unsupervised learning classified into two categories of algorithms:

Clustering: A clustering problem is where you want to discover the inherent groupings in the data, such as grouping customers by purchasing behavior.

Association: An association rule learning problem is where you want to discover rules that describe large portions of your data, such as people that buy X also tend to buy Y.

Some popular examples of unsupervised learning algorithms are:

1. *k-means for clustering problems, and*
2. *A priori algorithm for association rule learning problems.*

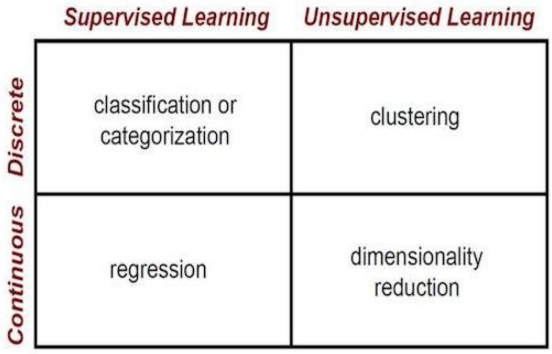


Figure 2.24. Supervised Learning vs Unsupervised Learning

Often the hardest part of solving a problem can be finding the right estimator for the job. Different estimators are better suited for different types of data and different problems. The flowchart below is designed by scikit-learn organization to give users a bit of a rough guide on how to approach problems with regard to which estimators to try on. There are many ways for applying classification, regression, clustering and dimensionality reduction to choose.

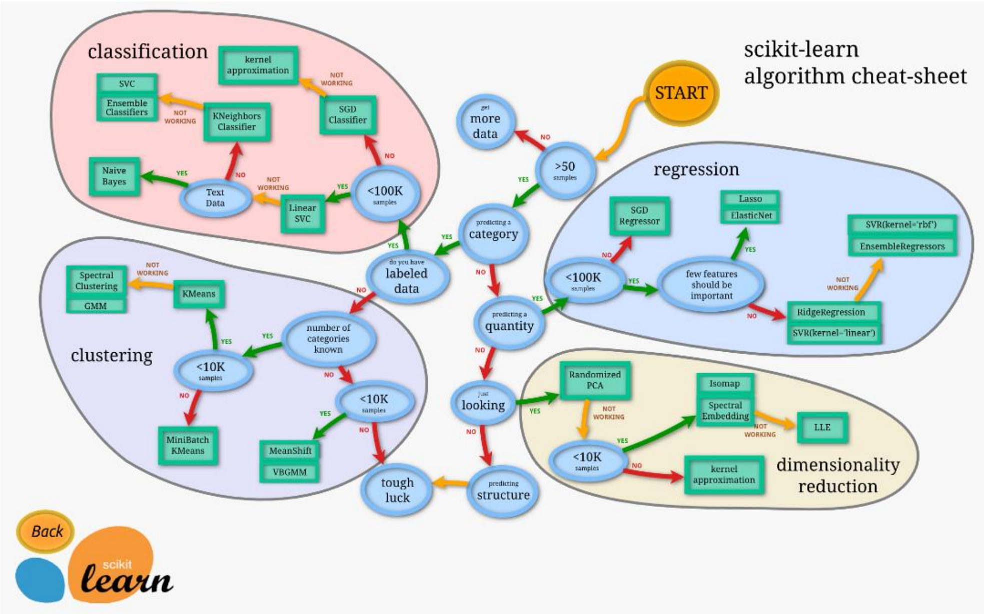


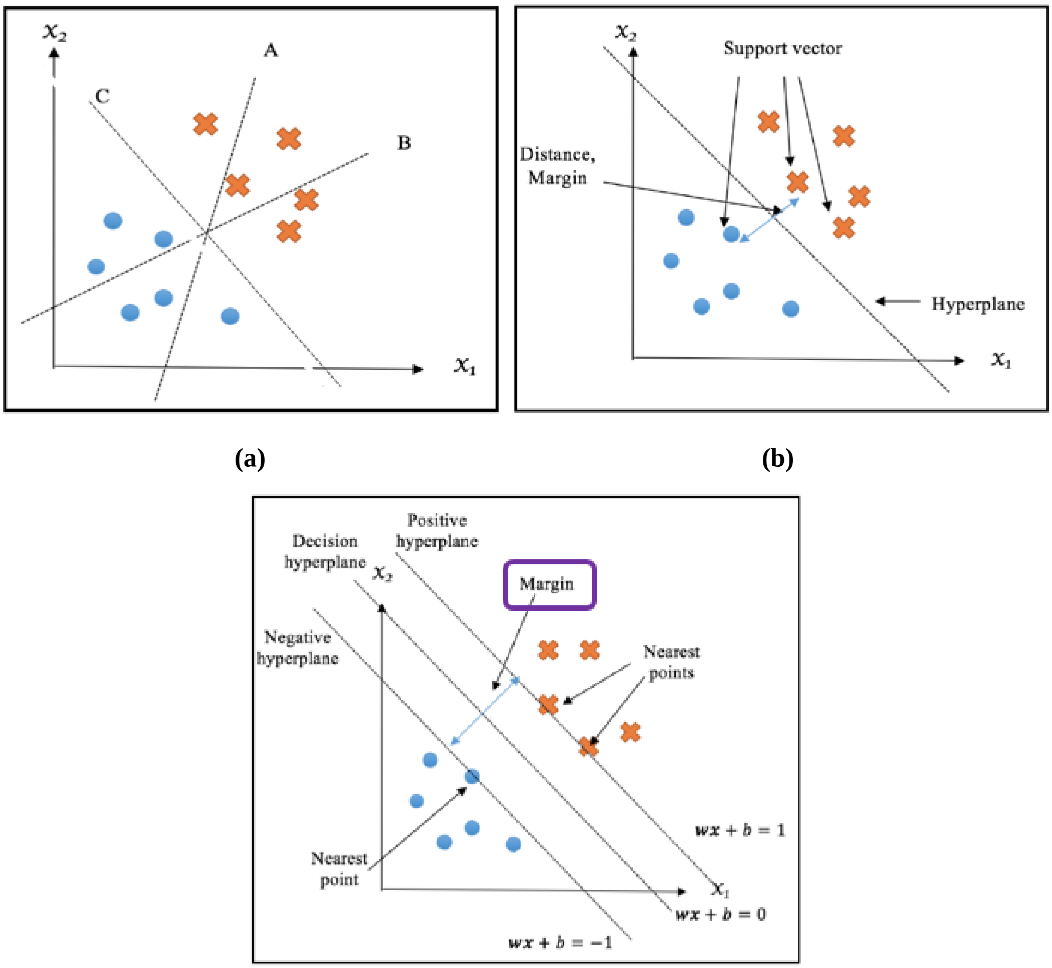
Figure 2.25. Scikit-learn Algorithm Cheat-sheet [15]

Among them, the most popular strategy used for the image classification is the support vector machine (SVM) algorithm.

2.4.6.2 Support Vector Machine (SVM)

Support vector machines (SVMs) are a set of supervised learning methods used for classification, regression and outliers detection. SVM offers very high accuracy compared to other classifiers such as logistic regression, and decision trees. It is known for its kernel trick to handle nonlinear input spaces. It is used in a variety of applications such as face detection, intrusion detection, classification of emails, news articles, and web pages, classification of genes, and handwriting recognition [15].

The ideology behind SVM is that it takes the data as an input and outputs a line that separates the classes. This line is called the decision boundary (or hyperplane).



(c)

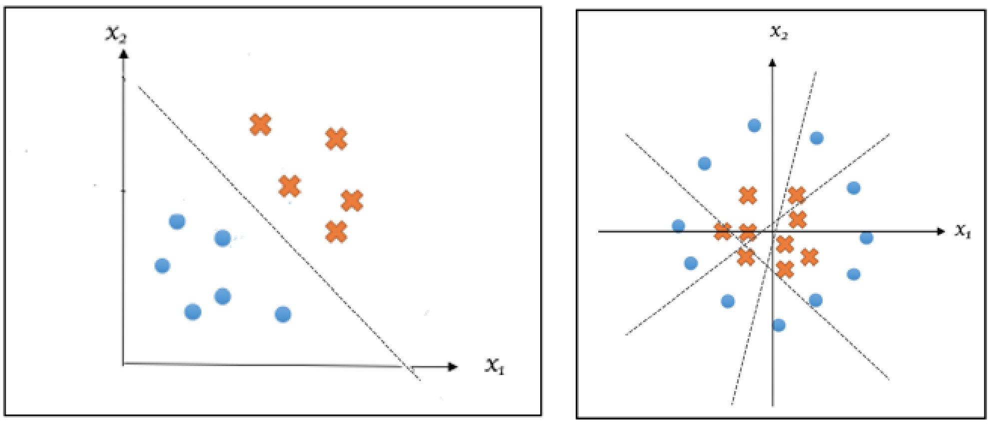
Figure 2.26. Linear SVM Classification

In the above Fig. 2.26(a), there are two classes (blue dots and orange crosses) and these points are features from the appropriate classes. And SVM finds an optimal separating line that best separates the features between data of different classes. A hyperplane is a plane of n-1 dimension that separates the n-dimensional feature space of the observations into two spaces. For example, the hyperplane in a two-dimensional feature space is a line and a surface in a three-dimensional feature space.

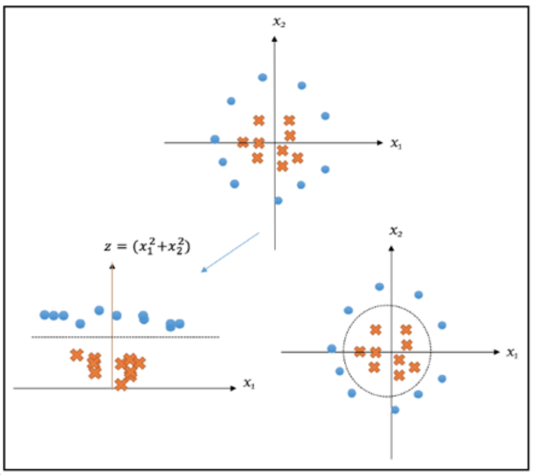
There will be many lines to separate the points in this example, so SVM has to choose which line is the best among them and chose the line C as the optimal hyperplane as in Fig. 2.26(b). SVM picked the optimal hyperplane as line C so that the distance of the margin has maximum distance. The margin is the distance between the line and the nearest points (support vectors) of either of the two classes. And the nearest points are the so-called support vectors.

This example is for an only linear problem. Also, it can solve for linear and non-linear problems.

(a) Non-linear SVM



(a) linear problem **(b) non-linear problem**



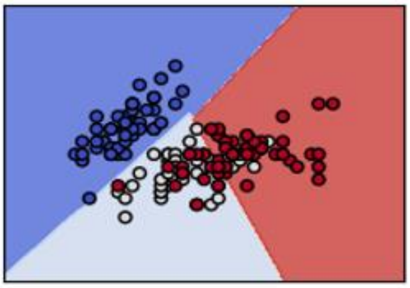
(c)

Figure 2.27. Non-linear SVM Classification

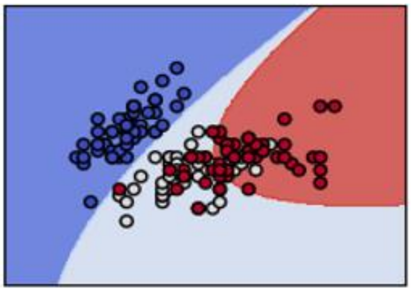
Fig. 2.26 is a linear problem and Fig. 2.27 is a non-linear problem. In the linear problem, it can be classified with a line but cannot be separated with a line in non-linear. In this case, data can be classified by adding an extra dimension to it so that it becomes linearly separable and then projecting the decision boundary back to original dimensions using mathematical transformation. This means that not separable data points are converted to separable data by kernels to get the solution then project back to the original dimension.

So other than X_1 and X_2 dimension, another dimension is taken and do separation with a line then get this equation $Z = (X_1^2 + X_2^2)$, this is the circle equation and get as in Fig. 2.27(c). But finding the correct transformation for any given dataset is not that easy. So, kernels can be applied in sklearn's SVM implementation to do this job.

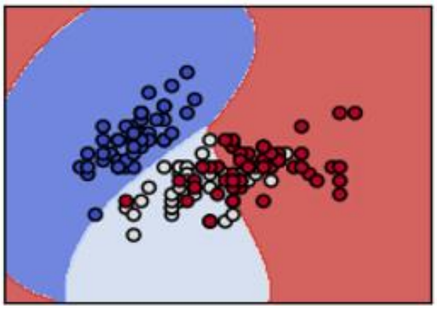
There are three common types of kernels, linear kernel, polynomial kernel, and radial basis function kernel (RBF) or Gaussian Kernel and they are shown in Fig. 2.28.



(a) SVC with Linear kernel



(b) SVC with Polynomial kernel



(c) SVC with RBF kernel

Figure 2.28. SVM kernels [15]

(b) Multiclass SVM

Multiclass classification means a classification task with more than two classes; e.g., classify a set of images of fruits which may be oranges, apples, or pears. Multiclass classification makes the assumption that each sample is assigned to one and only one label: a fruit can be either an apple or a pear but not both at the same time.

Most schemes for multiclass classification work by reducing the problem to that of binary classification. There are multiple ways to decompose the multiclass prediction into multiple binary decisions. Among them, two common strategies are:

(i) One-Vs-Rest (OvR)

The strategy consists in fitting one classifier per class. For each classifier, the class is fitted against all the other classes. It required to fit only *[n_classes]* classifiers. This is the most commonly used strategy and is a fair default choice.

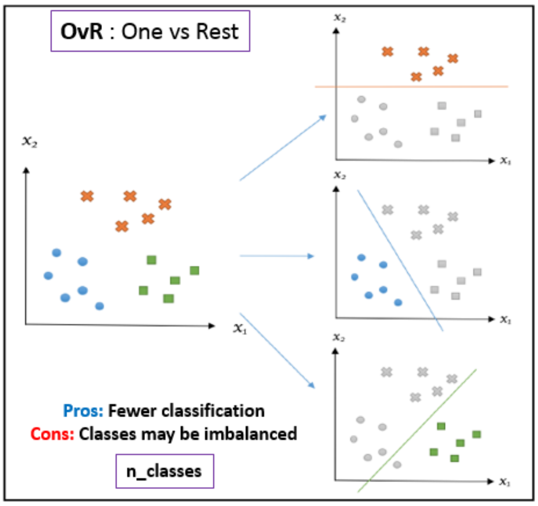


Figure 2.29. One vs Rest Multiclass SVM

(ii) One-Vs-One (OvO)

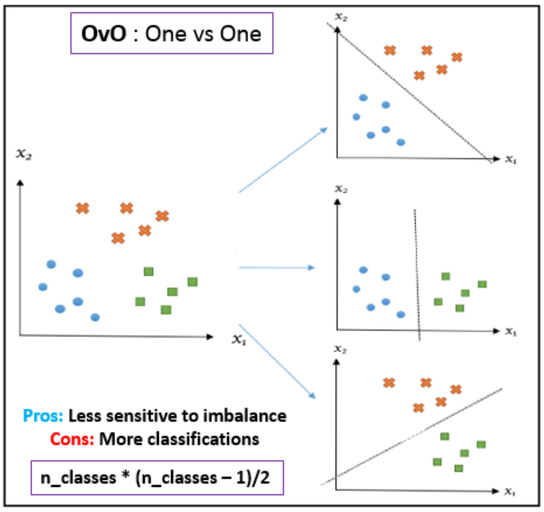


Figure 2.30. One vs One Multiclass SVM

It constructs one classifier per pair of classes. At prediction time, the class which received the most votes is selected.

Since it requires to fit *[n_classes * (n_classes - 1) / 2]* classifiers, this method is usually slower than one-vs-rest. For example, as for 4 classes, OvR requires 4 classifiers and OvO requires 6 classifiers.

2.4.6.3 SVM parameters

Parameters are arguments that are passed when the classifier is created. Following are the important parameters for SVM and the goal for them is to find the balance between "not too strict" and "not too loose".

(a) C parameter

It controls the trade-off between “smooth decision boundary” and “classifying training points correctly”. A small value of C causes misclassification low ("soft margin") and a large value of C causes misclassification high ('hard margin").

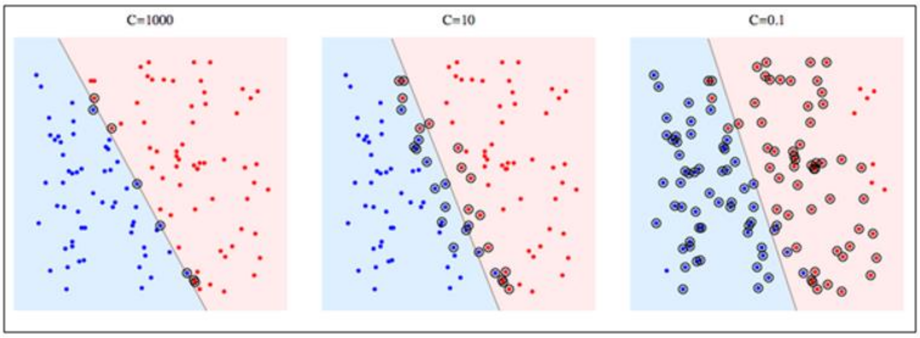


Figure 2.31. SVM C Parameter

(b) Gamma

It defines how far the influence of a single training example reaches. A small value of gamma makes every point has a far reach and large value of gamma makes every point has close reach.

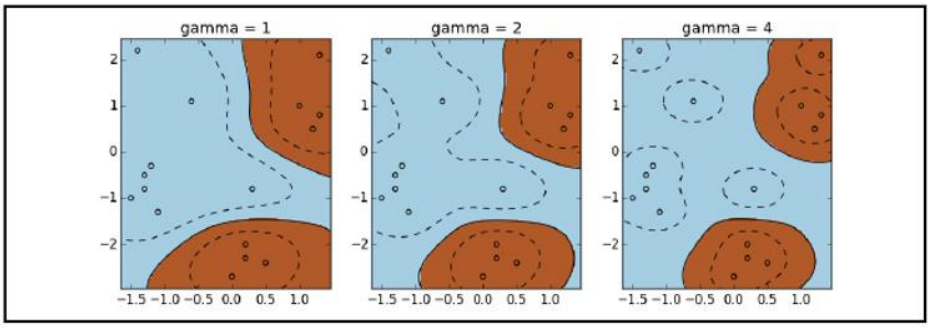


Figure 2.32. SVM Gamma Parameter

2.5 Internet of Things (IoT)

The internet of things, or IoT, is a system of interrelated computing devices, mechanical and digital machines, objects, animals or people and the ability to transfer data over a network without requiring human-to-human or human-to-computer interaction.

A thing in the internet of things can be a person with a heart monitor implant, a farm animal with a biochip transponder, an automobile that has built-in sensors to alert the driver when tire pressure is low or any other natural or man-made object that can be assigned an IP address and is able to transfer data over a network [18].

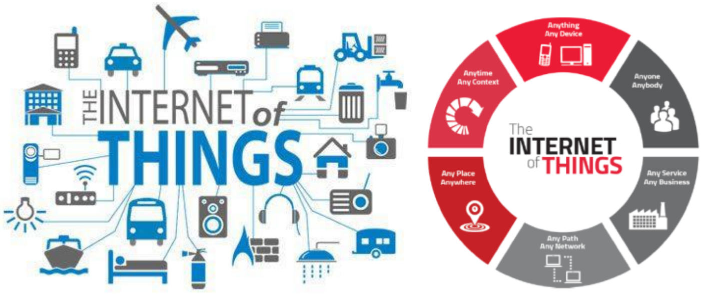


Figure 2.33. Internet of Things

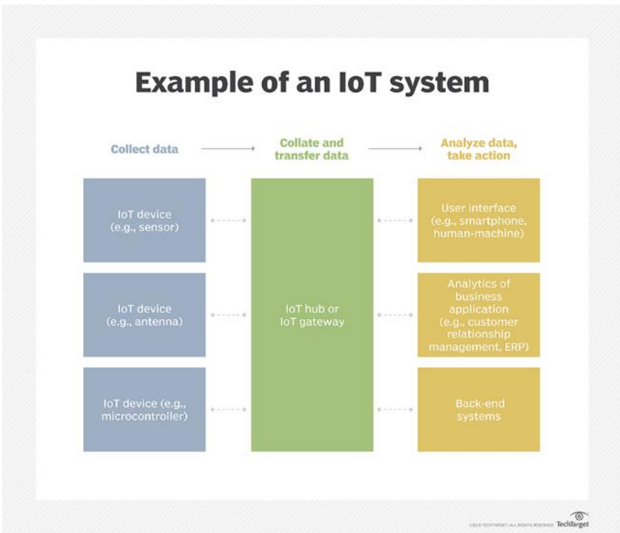


Figure 2.34. Example of an IoT System [18]

An IoT ecosystem consists of web-enabled smart devices that use embedded processors, sensors and communication hardware to collect, send and act on data they acquire from their environments. IoT devices share the sensor data they collect by connecting to an IoT gateway or another edge device where data is either sent to the cloud to be analyzed or analyzed locally. Sometimes, these devices communicate with other related devices and act on the information they get from one another. The devices do most of the work without human intervention, although people can interact with the devices, for instance, to set them up, give them instructions or access the data.

2.5.1 IoT Application Areas

IoT has applications across all industries and markets. It spans user groups from those who want to reduce energy use in their home to large organizations who want to streamline their operations. Some of these are -

1. Media, Marketing, & Advertising
2. Environmental Monitoring
3. Manufacturing Applications
4. Energy Applications
5. Healthcare Applications
6. Building/Housing Applications
7. Transportation Applications
8. Education Applications
9. Government Applications
10. Law Enforcement Applications
11. Consumer Applications

2.5.2 Pros and cons of IoT [18]

Some of the advantages of IoT include:

- Ability to access information from anywhere at any time on any device.
- Improved communication between connected electronic devices.
- Transferring data packets over a connected network save time and money.

Some disadvantages of IoT include:

- An ecosystem of IoT offers little control despite any security measures and thus exposed to various kinds of attackers.
- The sophistication of IoT provides substantial personal data in extreme detail without the user's active participation.
- IoT systems are complicated in terms of design, deployment, and maintenance.

2.6 Graphical User Interface (GUI)

User interfaces are what allows end-users to interact with an application. An application can be excellent, but without a good user interface, it becomes more difficult to use and less enjoyable. It is thus very important to design good user interfaces. Setting up a GUI application is similar to how an artist produces a painting. A good UI can make an application intuitive and simple to use. Excellent applications without good UI will be less popular than inferior ones with good UI.

Several competing GUI toolkits are available to use with the Python language, namely, Tkinter, wxPython, JPython (Jython), PyKDE / PyQt, PyGTK, Win32all.exe, WPY, and X11. With all the competing GUI toolkits available for the Python language, Tkinter stands out of the rest and become most popular toolkit for user interface design because of its layered design, accessibility learning, portability, and availability.

2.7 Controller

The Raspberry Pi is a low cost, credit-card sized computer. It can be considered as a single-board computer that works on the LINUX operating system. The board not only has tons of features it also has terrific processing speed making it suitable for advanced applications. Pi board is specifically designed for hobbyist and engineers who are interested in LINUX systems and IoT (Internet of Things).

It is a capable little device that enables people of all ages to explore computing and to learn how to program in languages like Scratch and Python. It's capable of doing everything like a desktop computer, from browsing the internet and playing high-definition video, to making spreadsheets, word-processing, and playing games.

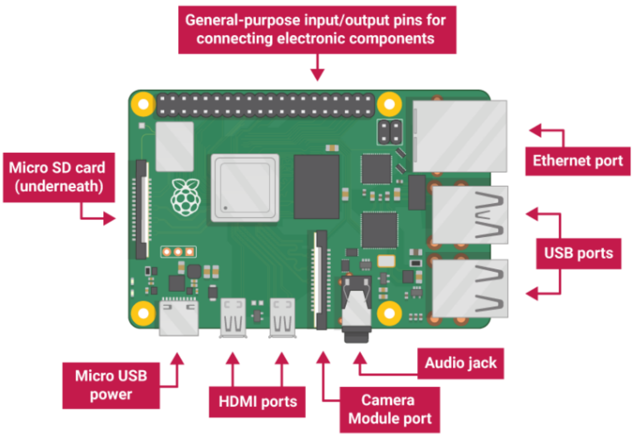


Figure 2.35. Main Parts of Raspberry Pi

Some main parts of the Raspberry Pi from the above figure are USB ports (to connect a mouse and keyboard and also other components, such as a USB drive), SD card slot, ethernet port (to connect Raspberry Pi to a network with a cable), audio jack (to connect headphones or speakers), HDMI port (to connect the monitor or projector), micro USB power connector (to connect a power supply), and finally GPIO (to connect electronic components such as LEDs and buttons).

2.8 Python Language

Python is a popular programming language that works more quickly and integrates systems more effectively. It is a widely-used general-purpose, high-level programming language. It was initially designed by Guido van Rossum in 1991 and developed by Python Software Foundation. In contrast to other popular languages such as C, C++, Java, and C#, Python strives to provide a simple but powerful syntax. It is possible to write Python in an Integrated Development Environment, such as Thonny, Pycharm, Netbeans or Eclipse which are particularly useful when managing larger collections of Python files.

Figure 2.36. Guido van Rossum with Python Logo

Python Syntax compared to other programming languages is that Python was designed for readability, and has some similarities to the English language with influence from mathematics. Its syntax resembles pseudo-code, especially because of the fact that indentation is used to identify blocks. Python is a dynamically typed language and does not require variables to be declared before they are used. Variables “appear” when they are first used and “disappear” when they are no longer needed.

There are two major Python versions- Python 2 and Python 3. Both are quite different. The most recent major version of Python is Python 3. However, Python 2, although not being updated with anything other than security updates, is still quite popular.

Python is also a multi-platform language since the Python interpreter is available for a large number of standard operating systems, including macOS, UNIX, and Microsoft Windows. Python interpreters are usually written in C, and thus can be ported to almost any platform which has a C compiler.

Python is used for software development at companies and organizations such as Google, Yahoo, Facebook, CERN, Industrial Light and Magic, and NASA. Experienced programmers can accomplish great things with Python, but Python's beauty is that it is accessible to beginning programmers and allows them to tackle interesting problems more quickly than many other, more complex languages that have a steeper learning curve.

2.8.1 What can Python do?

(a) Python can be used on a server to create web applications.
(b) Python can be used alongside software to create workflows.
(c) Python can connect to database systems. It can also read and modify files.
(d) Python can be used to handle big data and perform complex mathematics.
(e) Python can be used for rapid prototyping, or for production-ready software development.

2.8.2 Python libraries

2.8.2.1 NumPy

NumPy is a library for the Python programming language that provides support for large, multi-dimensional arrays. Using NumPy, images can be expressed as multi-dimensional arrays. Representing images as NumPy arrays are computational and resource-efficient. Furthermore, by using NumPy's built-in high-level mathematical functions, numerical analysis can be quickly performed on an image.

2.8.2.2 SciPy

SciPy adds further support for scientific and technical computing. When an image is "described", feature extraction has to be performed. Normally after feature extraction, an image is represented by a vector (a list) of numbers. Comparing two images rely on distance functions, such as the Euclidean distance. One of the subpackages of SciPy is the spatial package which includes a vast amount of distance functions.

2.8.2.3 Matplotlib

Matplotlib is a plotting library. When analyzing images, matplotlib is used, whether plotting the overall accuracy of search systems or simply viewing the image itself, matplotlib is a great tool.

2.8.2.4 OpenCV

If NumPy's main goal is large, efficient, multi-dimensional array representations, then, by far, the main goal of OpenCV is real-time image processing. The library itself is written in C/C++, but Python bindings are provided when running the installer.

2.8.2.5 Mahotas

Mahotas, just as OpenCV, rely on NumPy arrays. Much of the functionality implemented in Mahotas can be found in OpenCV, but in some cases, the Mahotas interface is just easier to use, especially when it comes to their features package.

2.8.2.6 Scikit-learn

Scikit-learn is not an image processing or computer vision library, it is a machine learning library. That can't have advanced computer vision techniques without some sort of machine learning, whether it be clustering, vector quantization, classification models, etc. Scikit-learn also includes a handful of image feature extraction functions as well.

2.8.2.7 Pandas

Pandas is a machine learning library in Python that provides data structures of high-level and a wide variety of tools for analysis. Pandas have so many inbuilt methods for grouping, combining data, and filtering, as well as time-series functionality.

2.9 Summary

In this chapter, the theoretical background of the strawberry and automatic farm control system is discussed. Firstly, temperature and humidity control system is described. And then, the drip irrigation system is presented. Moreover, image processing techniques of the nutrient deficiency symptoms detection are discussed in details. Finally, about the IoT, RPi, GUI and Python language are described. In the next chapter, the details design of the proposed system will be presented.

CHAPTER 3
SYSTEM DESIGN AND METHODOLOGY

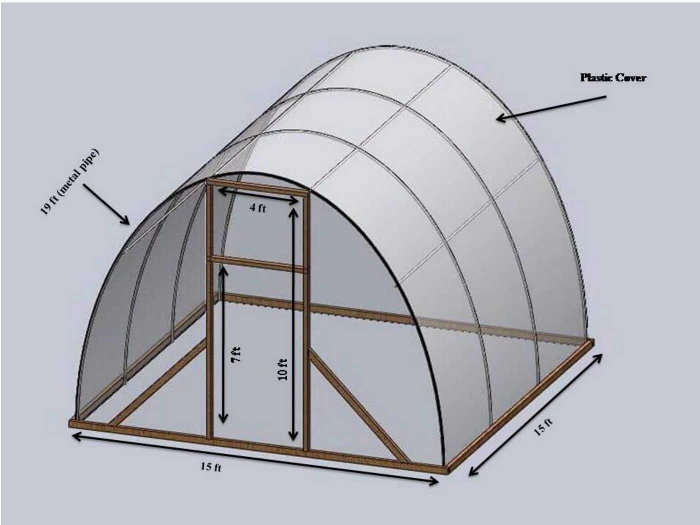
In this chapter, the details of the system design, proposed work and workflow of the methodology are focused.

3.1 Small-scale Farm Structure and Design

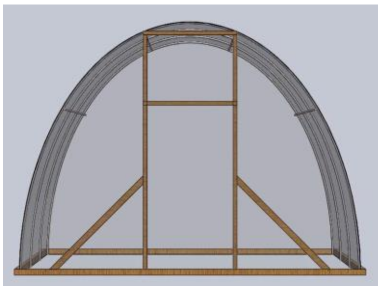
In this section, the design of the frame, plant stands, planting method, soil mixing process, and solar power system will be explained.

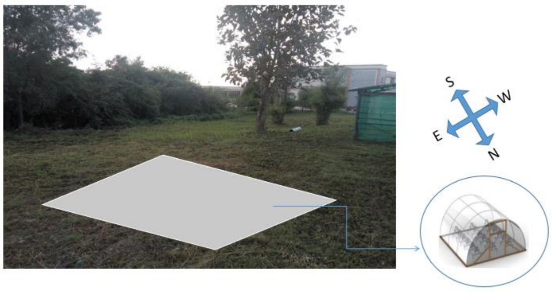
3.1.1 Frame Design

Firstly, the small-scale farm was built within the area of 15 feet around and the height was determined by 10 feet to circulate the air inside the farm effectively.



(a)

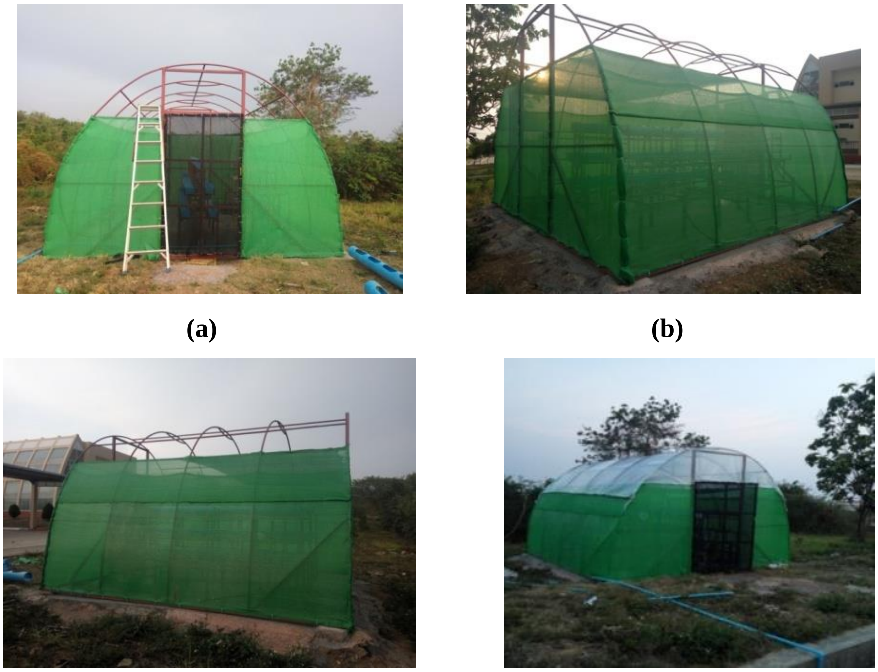




(b) **(c)**

Figure 3.1. Frame Design

The farm was covered by plastic to protect the heavy wind and rain as strawberry plants do not like rain very much. And the front part of the farm was placed towards the north direction as in Fig. 3.1(c). The covering processes of the farm are shown steps by steps in Fig. 3.2.



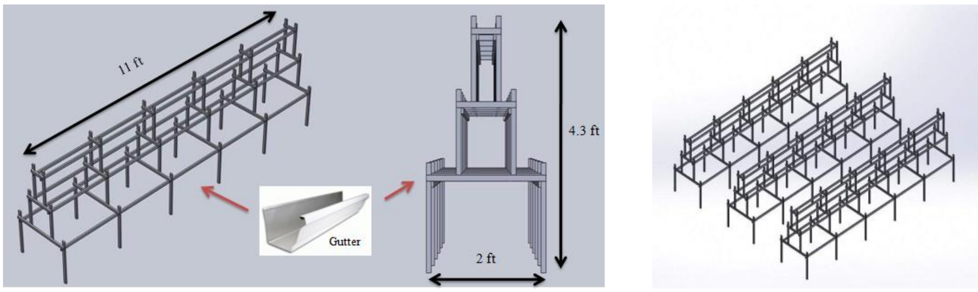
(a) **(b)**

(c) **(d)**

Figure 3.2. Covering Processes of the Farm

3.1.2 Stands Design

Three plant stands were placed inside the farm and each stand was designed as shown in Fig. 3.3(a). As for containers to plant the strawberry, the PVC pipes and gutters were installed on the stands. For PVC pipes, the 6 inches diameter PVC pipes were used to plant strawberries inside. Each hole was separated by one foot to get eleven plants for each pipe. The 5 inches wide PVC gutters were also used to plant inside to get eleven strawberry plants too. Every pipes and gutter were all 11 feet and 4 inches long. Then the three plant stands were placed as in Fig. 3.3(c).

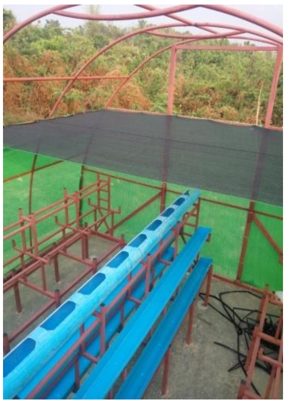


(a) **(b)**

(c)

Figure 3.3. Plant Stands Design

(a)

(b) **(c)** **(d)**

Figure 3.4. Installation of PVC pipes, Gutters and Plant stands in the farm

3.1.3 Planting Method

Figure 3.5. Planting Methods in the Gutter

Inside the gutters and PVC pipes, each plant was separated by one foot to another as shown in Fig. 3.5 for free propagation of roots. The middle plant between plant 1 and 2 is the runner appear from the mother plant (plant 1). If this one is fully rooted and strong enough in the soil, it can be cut and cultivated in another place.

3.1.4 Soil Mixing

The soil compound was mixed with 30% of natural soil, 30% of manure, 20% of the bran and finally 20% of coir as shown in Fig. 3.6.

Figure 3.6. Soil Mixing Process

3.1.5 Solar Power System

The hybrid power system based on solar energy and main electricity provided the required power unit for the AC pump and other electronic devices inside the small-scale farm.

Figure 3.7. Solar Power System

This solar power system was proposed by other research group and the aim of the research is to provide electricity to the electronic lab building in the university campus using renewable solar energy and electricity transmission line by checking the load demand.

3.2 Main Controller

Raspberry Pi board was used as the main controller and it is the heart of the overall system design.

3.2.1 Raspberry Pi 3

Raspberry Pi 3 is a development board in Pi series. Raspberry Pi 3 is chosen over other microcontrollers and development boards where the system processing is huge (RPi3 has 1.2GHz clock speed and 1 GB RAM) and where wireless connectivity is needed (RPi3 has built-in Wi-Fi and Bluetooth).

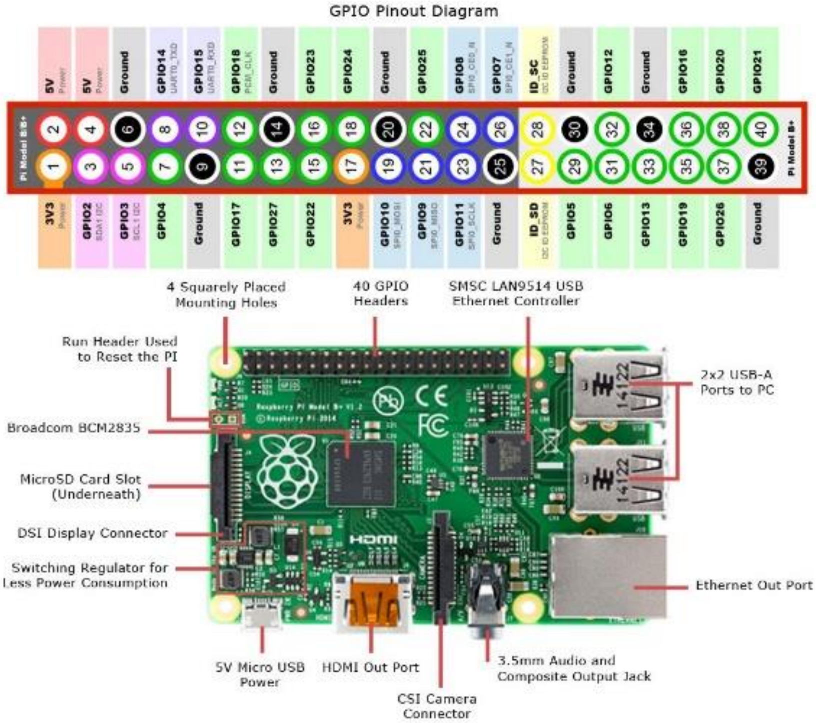


Figure 3.8. Raspberry Pi 3 and Its GPIO Pinout Diagram

	Raspberry Pi 3 Model B	Raspberry Pi Zero	Raspberry Pi 2 Model B	Raspberry Pi Model B+
Introduction Date	2/29/2016	11/25/2015	2/2/2015	7/14/2014
SoC	BCM2837	BCM2835	BCM2836	BCM2835
CPU	Quad Cortex A53 @ 1.2GHz	ARM11 @ 1GHz	Quad Cortex A7 @ 900MHz	ARM11 @ 700MHz
Instruction set	ARMv8-A	ARMv6	ARMv7-A	ARMv6
GPU	400MHz VideoCore IV	250MHz VideoCore IV	250MHz VideoCore IV	250MHz VideoCore IV
RAM	1GB SDRAM	512 MB SDRAM	1GB SDRAM	512MB SDRAM
Storage	micro-SD	micro-SD	micro-SD	micro-SD
Ethernet	10/100	none	10/100	10/100
Wireless	802.11n / Bluetooth 4.0	none	none	none
Video Output	HDMI / Composite	HDMI / Composite	HDMI / Composite	HDMI / Composite
Audio Output	HDMI / Headphone	HDMI	HDMI / Headphone	HDMI / Headphone
GPIO	40	40	40	40
Price	$35	$5	$35	$35

Figure 3.9. Comparison of Raspberry Pi 3 and other Generations

Also, the Pi board has a dedicated port for connecting touch LCD display which is a feature that completely omits the need to monitor and dedicated camera port so one can connect the camera to the Pi board.

3.3 Requirements for Temperature and Humidity Control Systems

To control the indoor environment on the farm automatically, the thermostat or temperature sensor is needed to place inside the farm. From the data of this sensor, the various states of the farm will be controlled by temperature control devices. Thus, as for the sensor, DHT22 and as for the devices, black-net, exhaust fans, cooling pad, and sprinklers were used and how to control by these devices will be explained in this section.

3.3.1 Temperature and Humidity Sensor (DHT22)

DHT22 also named as AM2302 is the digital-output relative humidity & temperature sensor. It utilizes exclusive digital-signal-collecting-technique and humidity sensing technology, assuring its reliability and stability. The sensor comes with a dedicated NTC (Negative Temperature Coefficient) to measure temperature and an 8-bit microcontroller to output the values of temperature and humidity as serial data.

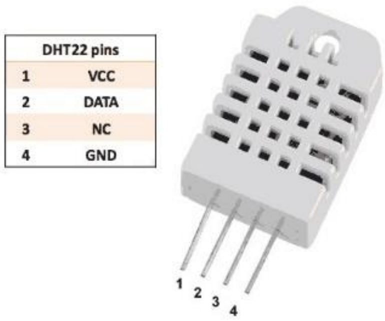


Figure 3.10. DHT22 Temperature and Humidity Sensor

Small size, low consumption, and long transmission distance (20m) enable DHT22 to be suited in all kinds of harsh application occasions. Single-row packaged with four pins, making the connection very convenient. DHT22 is commonly used in the local weather station, automatic climate control, and environment monitoring. Its technical specifications and electrical characteristics are shown in (Table 3.1) and (Table 3.2) respectively.

Table 3.1. Technical Specifications of DHT22

Model	DHT22 (AM2302)	
Output signal	Digital signal via single-bus	
Sensing element	Polymer capacitor	
Operating range	0 to 100% RH	-40 to 80°C
Accuracy	±2% RH	±0.5°C
Resolution or sensitivity	0.1% RH	0.1°C
Repeatability	±1% RH	±0.2°C

Table 3.2. Electrical Characteristics of DHT22

Item	Condition	Min	Typical	Max	Unit
Power supply	DC	3.3	5	6	V
Current supply	Measuring	1	-	1.5	MA
	Stand-by	40	Null	50	uA
Collecting period	Second	-	2	-	Second

3.3.1.1 DHT22 connection and installation

The connection diagram of DHT22 with Raspberry Pi 3 is shown in Fig. 3.11.

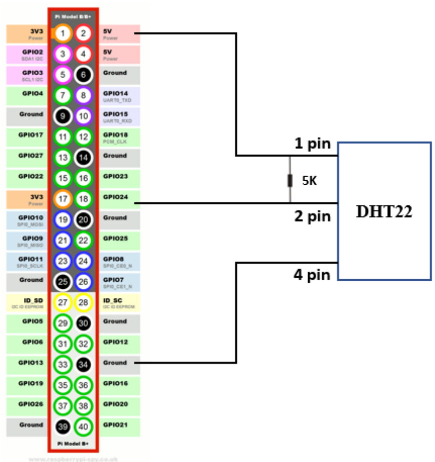


Figure 3.11. Connection Diagram of DHT22 and RPi

The data pin is connected to one of the GPIO pins of RPi and a 5K pull-up resistor is used. This data pin outputs the value of both temperature and humidity as serial data. When RPi sends the start signal, DHT22 change from low-power-consumption-mode to running-mode. When RPi finishes sending the start signal, DHT22 will send response signal of 40-bit data that reflect the relative humidity and temperature information to RPi. Without start signal from RPi, DHT22 will not give a response signal to RPi. One start signals for one time's response data that reflect the relative humidity and temperature information from DHT22. DHT22 will change to low-power-consumption-mode when data collecting finish if it doesn’t receive start signal from RPi again.

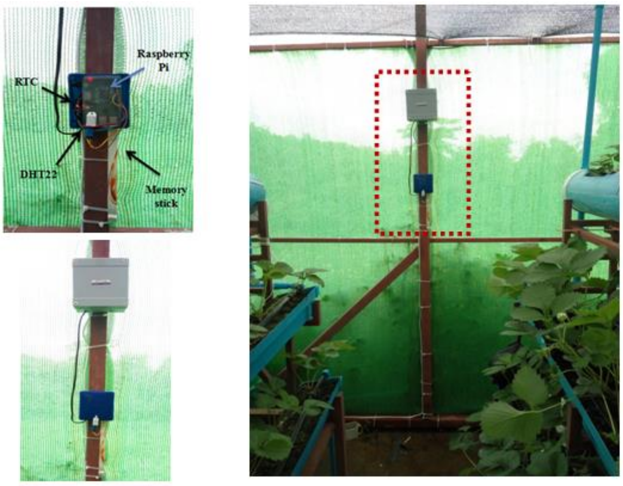


Figure 3.12. Installation of the Sensor in the Farm

The placement of DHT22 is shown in Fig. 3.12. It was placed at about 4ft from the ground. The real-time clock (RTC) was used to get the time correctly even after the RPi is disconnected from Wi-Fi or reboot. Then the temperature and humidity data were logged in the memory stick.

3.3.2 Black-net Shading

The black net between the plastic roof and plant stands in Fig. 3.13 was covered in order to protect the direct sunlight. Only 50 percent of sunlight and heat can pass through this black net to the plants. It will be opened or closed depending upon the various temperature states in the farm.

Figure 3.13. Black-net in the Farm

3.3.3 Exhaust Fans and Cooling Pad

This exhaust fans move and refresh the stagnant air in the greenhouse or building to create a healthier and more productive growing environment. They are great for reducing plant and worker heat stress. They also provide excellent ventilation for high tunnels and cold frames and create a cooler more comfortable growing environment, which can directly contribute to productivity, quality, and profitability. Exhaust fans also work great in workshops and buildings. Also, the cooling pad design is shown in Fig. 3.15.

Figure 3.14. Exhaust Fan

Figure 3.15. Cooling Pad Design

3.3.4 Fog-Nozzle Sprinklers

Also, the three fog nozzle sprinklers were installed between plastic roof and black net and they were used to adjust the inside temperature and cooling the farm.

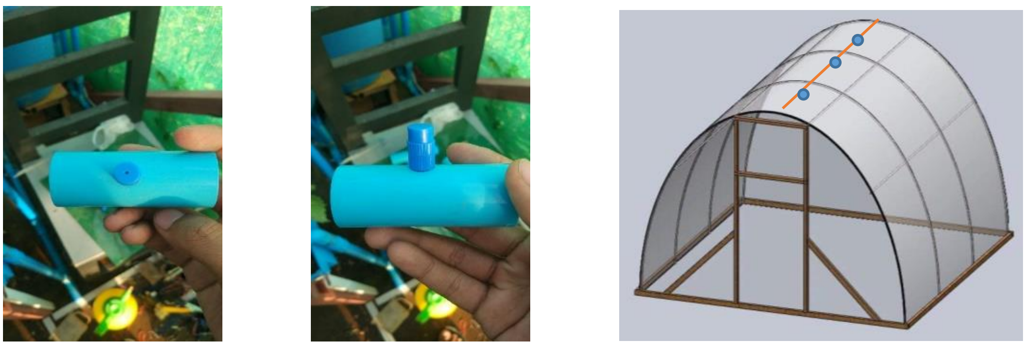


Figure 3.16. Fog Nozzle Sprinklers and Its Placement

They will automatically open and spray like natural rainfall when the inside temperature is very high in the hot season.

3.4 Components for Drip Irrigation System

To supply water to the plants with the drip irrigation system, a pump is needed to push water, drip kits are required to place in the farm and solenoid valves are used between pump and drip kits to open or close according to the controller.

3.4.1 AC Pump

A (1-inch x 1-inch) AC pump was used to push water from the source to the water tank. It also directly supplied water to sprinklers and cooling pads. It has a power rating of 370 Watts (0.5 HP). Table. 3.3 shows the specifications for the pump motor.

Figure 3.17. AC Water Pump

Table 3.3. Specifications for AC Pump

Model	DKm60-1B
Power	370 Watt / 0.5 HP
Voltage	220-230V / 50 Hz
Max flow	30L/min

3.4.2 DC Diaphragm Pump

A 12V DC diaphragm pump was used to push water from the water tank and fertilizers through the pipes and drippers to the plants.

Figure 3.18. DC Diaphragm Pump

Table 3.4. Specifications for DC Diaphragm Pump

Model	DP-528
Voltage	12V DC
Max Amp	2.5A
Max Pressure	0.55MPa
Max Flow	3.5L/min

3.4.3 Drip Kit Components

Fig. 3.19 shows the component lists for the drip kit used in the drip irrigation system of small-scale farm. Each part of the drip kits is shown in Fig. 3.19(d), the label “a” is the offtake with rubber, “b” is LDPE pipe, “c” is male thread adaptor, “d” is 12 mil thickness dripline and “e” is flushing valve and then they were installed on the gutter as in Fig. 3.19(c).

(a) **(b)** **(c)**

(d) **(e)**

Figure 3.19. Drip Kit Components

Table 3.5. Dripline Specifications

Model	FNFL120201P
Inside Diameter	5/8 inch
Wall Thickness	12 mil
Max Pressure	1.3 bar
Flow Rate	1.5 lph @ 1 bar
Spacing	8 inches

There are 15 plant rows in the farm and only 3 solenoid valves were used with drip pipes for each stand.

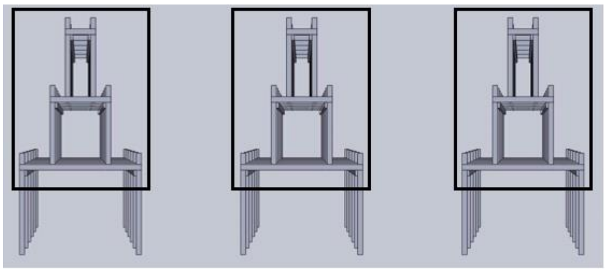


Figure 3.20. Drip Pipes Position

3.4.4 24V DC 1/2" Water Solenoid Valve (Normally Closed)

24V DC 1/2″ Electric Solenoid Water Air Valve Switch (Normally Closed) controls the flow of fluid with air and act as a valve between high-pressure water or any fluid. This type is compact and convenient, easily installed and serviced. Also, it is precise, reliable, and steady flow adjustable. Not only can the constant current steady flow, but also prevent the dry burning and monitoring the flow.

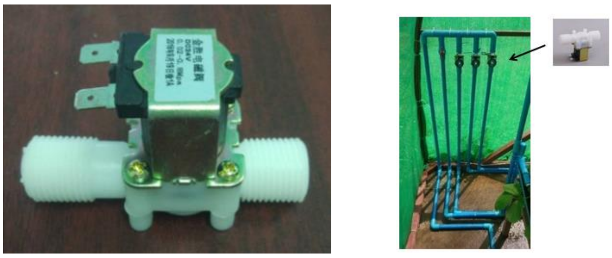


Figure 3.21. 24V DC Water Solenoid Valve

Table 3.6. Feature, Specifications, and Characteristics for 24V DC Solenoid Valve

Features and specifications	
Power	Solenoid
Supply Voltage	24V DC
Rated Power	5W
Operation model	Normally closed (N/C)
Pressure	0.02 - 0.8Mpa
Port size	1/2"
Flow characteristics	
2L/min for 0.02Mpa	10L/min for 0.10Mpa
16L/min for 0.30Mpa	28L/min for 0.80Mpa

The valve works with the solenoid coil which operates electronically with DC 24-volt supply. There are two outlets. Normally, the valve is closed. As it is normally closed assembly, it opens the flow of liquid as soon as 24V DC is applied to the two terminals, and stops/blocks the flow when the supply voltage removed.

3.4.5 Soil Moisture Data Logging

Waveshare soil moisture sensor was used for getting soil moisture data.

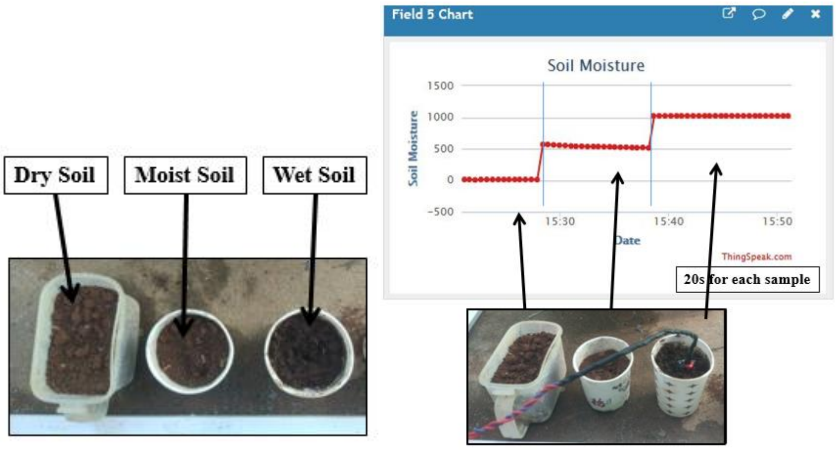


Figure 3.22. Testing Soil Moisture Sensor

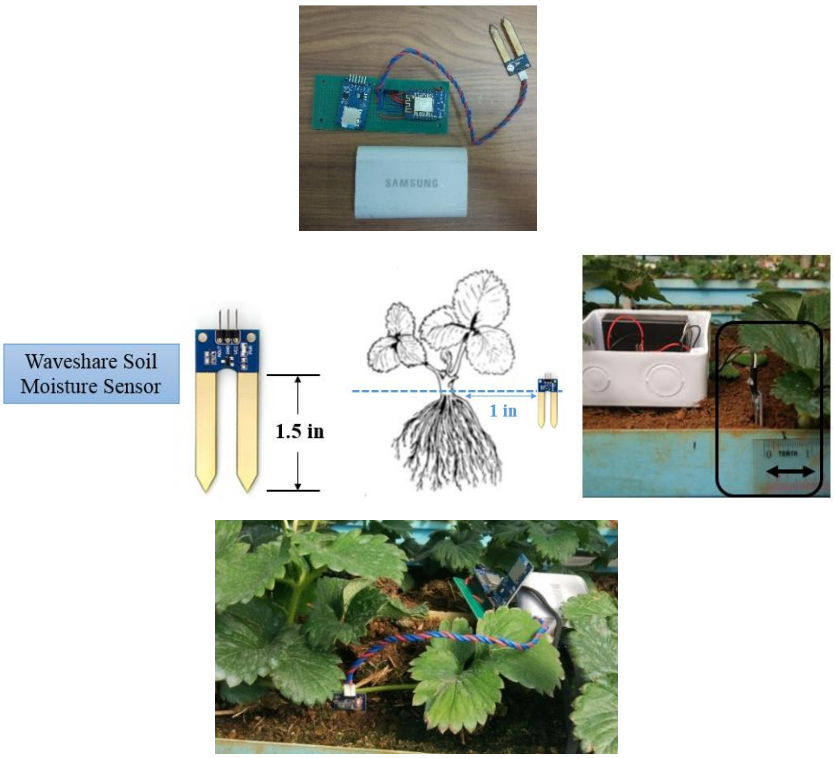


Figure 3.23. Data Logging Methods for Soil Moisture of the Plants

The output is analog output and data reading is from 0 to 1023. The soil moisture sensor was tested with three soil types, dry soil, moist soil, and wet soil firstly.

In the dry soil, the sensor data was around 0. And around 500 in moist soil and finally around 1000 in the wet soil. So, the value should be set between moist state (500) and wet state (1000). But to overcome over-watered or under-watered, moisture values are required to set carefully. Too little moisture can result in plant death and too much can cause root disease and wasted water.

Then to log the moisture data from the farms, Waveshare Soil Moisture Sensor, ESP8266 D1 Mini Board, SD card, SD card Module, and Power bank were used. The sensor was placed in the soil of PVC gutter around the root zone of plant as in Fig. 3.23 which decides whether water is needed to be pumped or not. If needed, water is applied through the drip system.

There are other four strawberry farms around Pyin Oo Lwin used for data logging and to make a comparison for the proposed small-scale farm with these different farms. The growing system and water supply methods used in these farms are shown in Table. 3.7.

Table 3.7. Different Strawberry Farms around Pyin Oo Lwin

Fields	Aung Chan Thar	City Farm-A	City Farm-B	City Farm-C
Growing System	Indoor	Outdoor	Outdoor	Indoor
Farm Structure				
Supply Method	Drip System	Drip System	Drip System	Drip System
Supply Duration	20 minutes (twice a day)	15 minutes (twice a day)	15 minutes (twice a day)	15 minutes (thrice a week)

3.5 Requirements for Leaf Size Calculation and NPK Detection

In the image processing phase, Logitech C310 webcam was used for image capturing device and methodologies of further processing are explained in details.

3.5.1 Logitech webcam C310

Logitech webcam C310 was used as an image acquisition device for image processing. It was connected with the RPi board and captured images for plant deficiency symptom detection. Some of its features are that has an automatic light correction and can capture 5-Megapixel snapshots with software.

The device which has to connect with C310 should have the operation system of Windows 10, 8, 7 or later, Mac OS 10.10 or later and Chrome OS. Also, 512 MB RAM or More, 200 MB Hard Drive Space or More, Internet Connection, and USB 1.1 Port (2.0 Recommended) are the basic requirements to operate with C310. Table. 3.8 shows the technical specifications for C310 model.

Figure 3.24. Logitech C310 Webcam

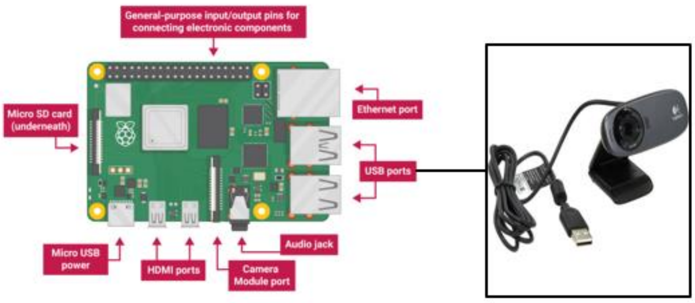


Figure 3.25. Connection Diagram of Webcam with Raspberry Pi

Table 3.8. Specifications for Logitech C310 Webcam

Focus Type	Fixed
Field of View	60°
Still Camera	640 x 480 Up to 5 MP (Software Enhanced)
Connectivity	Hi-Speed USB 2.0 Certified

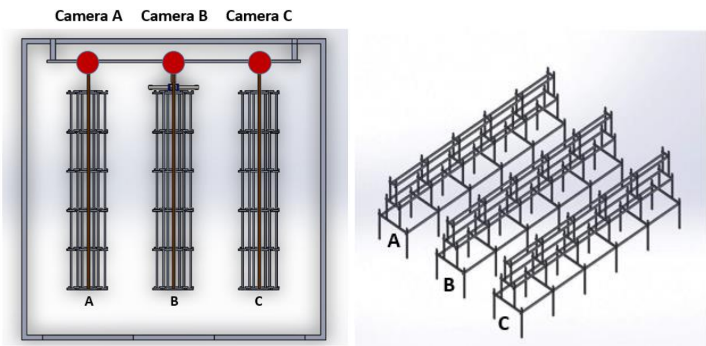


Figure 3.26. Camera Installation in the Farm

3.5.2 Leaf size calculation by mathematical formula

Measuring the size of objects in an image is similar to computing the distance from a camera to an object and in both cases, it is needed to define a ratio that measures the number of pixels per a given metric and this is called the "pixels per metric" ratio.

3.5.2.1 The "pixels per metric" ratio

In order to determine the size of an object in an image, a "calibration" is needed to perform using a reference object. The reference object should have two important properties:

- **Property #1:** the *dimensions of this object* (in terms of width or height) is known in a *measurable unit* (such as millimeters, inches, etc.).
- **Property #2:** this reference object should be easily found in an image, either based on the *placement* of the object or via *appearances*. In either case, the reference should be *uniquely identifiable* in some manner.

As for example in Fig. 3.27, a small black square paper was used as a reference object and ensured it is always the *left-most* object in the image:

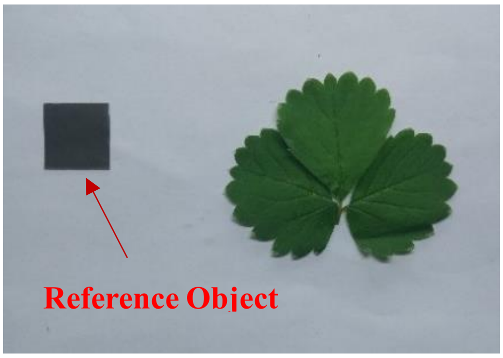


Figure 3.27. Leaf Image with Reference Object

By guaranteeing the black square is the left-most object, object contours can be sorted from left-to-right, grab the black square (which will always be the first contour in the sorted list), and use it to define the *pixels_per_metric* by the following formulae,

$$\text{Pixels per metric} = \frac{\text{Object width (measured in pixels)}}{\text{Known width (measured in metric)}} \tag{3.1}$$

$$\text{Dimension of Leaf} = \text{Leaf width}/\text{Pixels per metric} \tag{3.2}$$

For example, the reference object has a known_width of 2cm and the object_width is computed to be 150 pixels wide (based on its associated bounding box) as in Fig. 3.29.

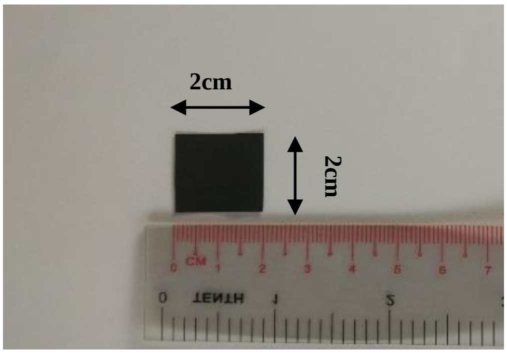


Figure 3.28. Reference Object Width

The Pixels_per_metric is, therefore:

$$\text{Pixels per metric} = \ 150\ \text{px}/2\ \text{cm} = 75\ \text{px}/\text{cm} \qquad (3.3)$$

Thus, implying there are approximately 150 pixels per every 2cm in the image. Using this ratio, the size of leaf in the image can be computed to be:

$$\text{Dimension of leaf} = \ 600\ \text{px}/(75\ \ \text{px}/\text{cm}) = 8\ \text{cm} \qquad (3.4)$$

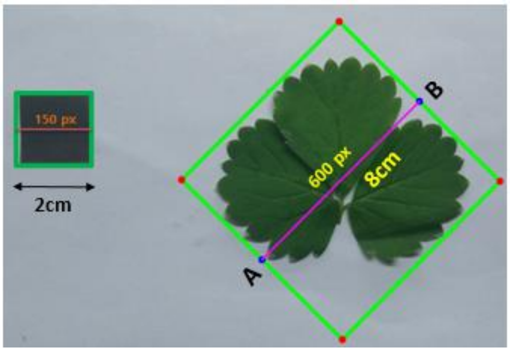


Figure 3.29. Leaf Size Calculation

3.5.3 Image Processing Techniques for Leaf Size Calculation and NPK Detection

In this section, applied methodologies for each stage of the leaf size calculation and NPK detection with OpenCV and Python are discussed.

3.5.3.1 Conversion of RGB to GRAY

For color conversion in OpenCV, the function *cv2.cvtColor(input_image, flag)* can be used, where flag determines the type of conversion. For BGR→Gray conversion, the flag cv2.COLOR_BGR2GRAY is used.

cv2.cvtColor(input_image, cv2.COLOR_BGR2GRAY)

3.5.3.2 Morphological Operations

As for morphological operations, erosion, dilation, opening, and closing were used.

(a) Erosion

The function used for erosion is:

cv2.erode(src, kernel, dst, anchor, iterations, borderType, borderValue)

- *src* – input image
- *dst* – output image
- *kernel* – structuring element
- *anchor* – position of the anchor within the element
- *iterations* – number of times erosion is applied
- *borderType* – pixel extrapolation method
- *borderValue* – border value in case of a constant border

(b) Dilation

The function used for dilation is:

cv2.dilate(src, kernel, dst, anchor, iterations, borderType, borderValue)

The parameters of dilation function have the same definition as in erosion.

(c) Opening and Closing

The function used for opening and closing is:

cv2.morphologyEx(src, op, kernel, dst, anchor, iterations, borderType, borderValue)

Some of the parameters are the same as in erosion and dilation except *"op"*. It is the type of morphological operation. It can be an opening operation (cv2.MORPH_OPEN), an closing operation (cv2.MORPH_CLOSE), a morphological gradient (cv2.MORPH_GRADIENT), top hat (cv2.MORPH_TOPHAT), black hat (cv2.MORPH_BLACKHAT) or "hit or miss" (cv2.MORPH_HITMISS).

3.5.3.3 Otsu's Thresholding

The OpenCV function for Otsu's thresholding is:

cv2.threshold(src, thresh, maxval, type, dst)

The parameters are:

- thresh – threshold value
- maxval – maximum value to use with the THRESH_BINARY and THRESH_BINARY_INV thresholding types
- type – thresholding type (THRESH_BINARY, THRESH_BINARY_INV, THRESH_TRUNC, THRESH_TOZERO, THRESH_TOZERO_INV)

3.5.3.4 Pyramid Mean Shift Filtering

Performs initial step of mean-shift segmentation of an image to help the accuracy of the thresholding step.

cv2.pyrMeanShiftFiltering(src,sp,sr,dst,maxLevel,termcrit)

Its parameters are:

- *sp* – the spatial window radius
- *sr* – the color window radius
- *maxLevel* – Maximum level of the pyramid for the segmentation
- *termcrit* – termination criteria: when to stop meanshift iterations

3.5.3.5 Gaussian Blurring

The OpenCV function is:

cv2.GaussianBlur(src, ksize, sigmaX, dst, sigmaY, borderType)

The parameters are defined as follows;

- *ksize* – Gaussian kernel size
- *sigmaX* – Gaussian kernel standard deviation in X direction
- *sigmaY* – ksize.width and ksize.height
- *borderType* – pixel extrapolation method

3.5.3.6 Canny Edge Detection

The OpenCV function and parameters of the Canny algorithm are:

*cv2.*Canny*(image, threshold1, threshold2, edges, apertureSize, L2gradient)*

- *image* – single-channel 8-bit input image.
- *edges* – output edge map; it has the same size and type as image.
- *threshold1* – first threshold for the hysteresis procedure.
- *threshold2* – second threshold for the hysteresis procedure.

- *apertureSize* – aperture size for the Sobel() operator.
- *L2gradient* – a flag, indicating whether a more accurate L_2_norm should be used to calculate the image gradient magnitude *(L2gradient=true)*, or whether the default L_1_norm is enough *(L2gradient=false)*.

3.5.3.7 Watershed Segmentation

Watershed segmentation was used in the segmentation part of NPK deficiency detection. In this, individual leaf images were segmented from the plant images and watershed can give useful effect on this.

The first step in applying the watershed algorithm for segmentation was to compute the Euclidean Distance Transform (EDT) via the *distance_transform_edt* function. This function computed the Euclidean distance to the closest zero (i.e., background pixel) for each of the foreground pixels.

distance_transform_edt(input, sampling, return_distances, return_indices, distances, indices)

- *input* - Input data to transform.
- *Sampling* - Spacing of elements along each dimension.
- *return_distances* - Whether to return distance matrix.
- *return_indices* - Whether to return indices matrix.
- *distance* - Used for output of distance array, must be of type float64.
- *indices* - Used for output of indices, must be of type int32.

Then find peaks in this distance map with *peak_local_max* function. The output of this function gave markers which will feed into the watershed function.

peak_local_max(*image*, *min_distance*, *threshold_abs*, *threshold_rel*, *exclude_border*, *indices*, *num_peaks*, *footprint*, *labels*, *num_peaks_per_label*)

- *min_distance* - Minimum number of pixels.
- *threshold_abs* - Minimum intensity of peaks.
- *threshold_rel* - Minimum intensity of peaks.
- *num_peaks* - Maximum number of peaks.
- *num_peaks_per_label* - Maximum number of peaks for each label.

And then performed a connected component analysis on the local peaks, then applied the Watershed algorithm.

The function and parameters are:

*cv2.*watershed*(image, markers)*

- *image* – Input 8-bit 3-channel image.
- *markers* – Input/output 32-bit single-channel image (map) of markers. It should have the same size as an image.

3.5.3.8 Image Classification Methodology

Image classification is the task of assigning a label to an image from a predefined set of categories. Practically, this means that the task is to analyze an input image and return a label that categorizes the image.

For example, the images in Fig. 3.30 are categorized as green leaves for healthy, yellow leaves for Nitrogen deficiency, red leaves for Phosphorus deficiency and the others for Potassium deficiency. Then the test images are taken and defined them with correct labels as in Fig. 3.31. These labels are from a predefines set of possible categories and thus this type of classification is included in the supervised learning algorithm.

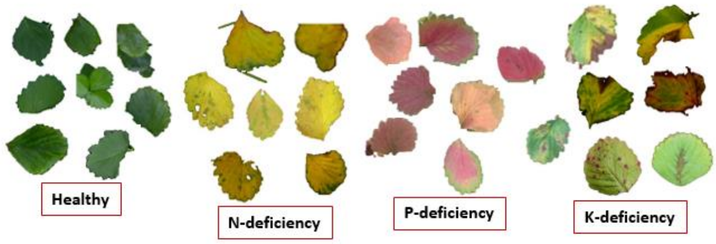


Figure 3.30. Nutrient Deficiency Leaves

Figure 3.31. Test Images with Correct Labels

As for the supervised classifier for the next steps, the SVM classifier was chosen for two reasons, by tracing on the scikit-learn algorithm cheat-sheet and by doing spot-check with other algorithms.

For the first reason why SVM classifier was chosen for classification by tracing on scikit-learn cheat-sheet is shown in Fig. 3.32 and the tracing route is shown with blue boundary outlines. Firstly, start on the cheat-sheet, there is a total of 641 samples in the proposed system and yes, it is more than 50 samples. Then, go to the next step, there are four categories to be predicted which have labels and also less than 100K samples. Thus, it is found that for this NPK classification, the SVM methods (SVC and Linear SVC are under SVM) and KNN can be used.

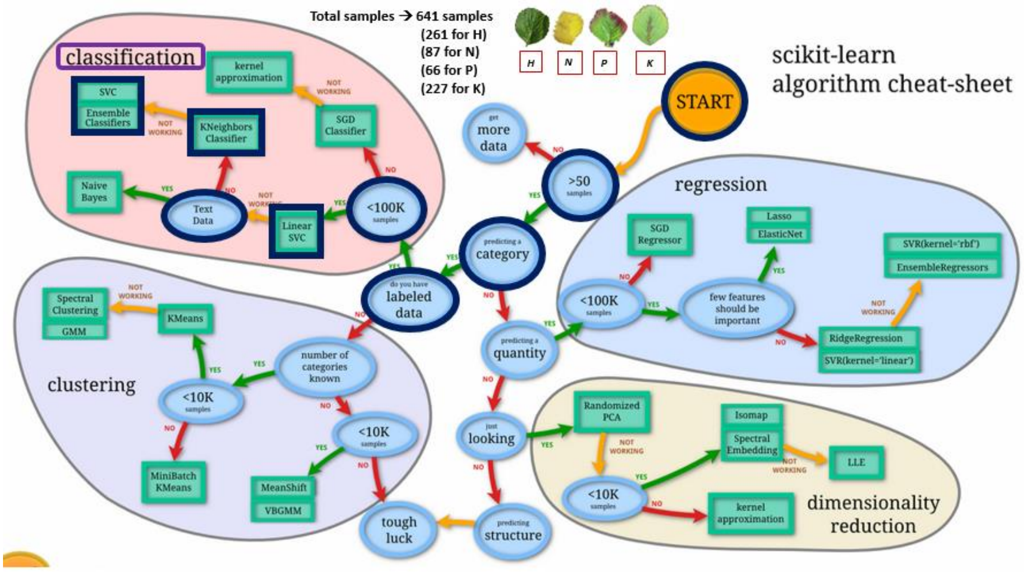
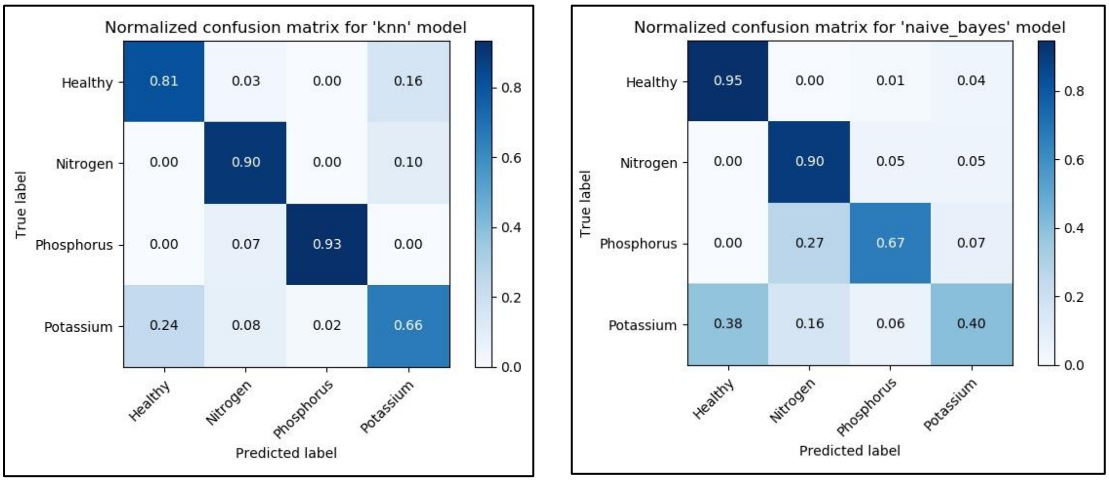
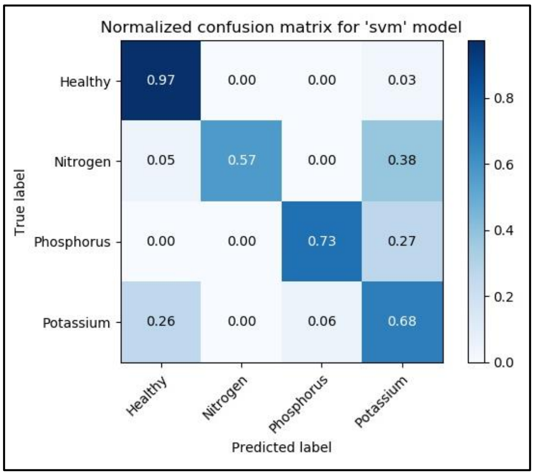


Figure 3.32. Tracing on scikit-learn cheat-sheet

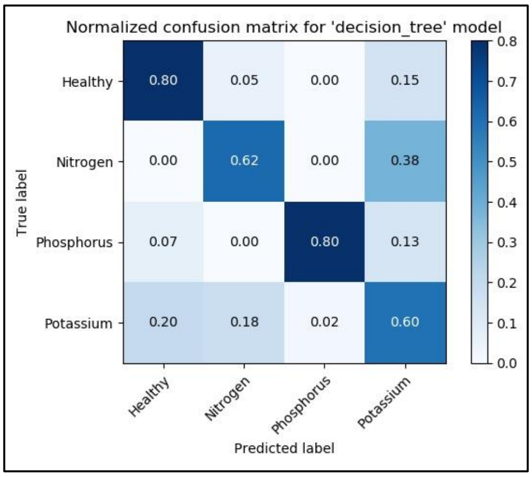
Then, the accuracy of the proposed classification was checked using popular algorithms, K-Nearest Neighbours (kNN), Naïve_Bayes, Support Vector Machine (SVM), Decision Tree and Logistic Regression. And found that, kNN has an accuracy of 78.88%, Naïve_bayes has 74.53%, SVM has 80.75%, decision tree has 73.29% and another 80.75% for logistic regression as in Fig. 3.33.



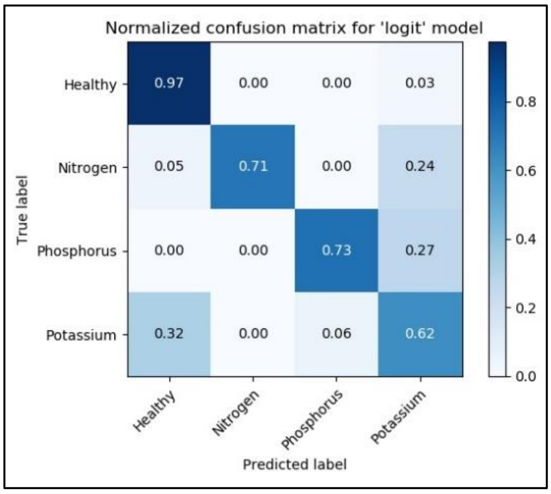
(a) kNN (78.8%) **(b) Naïve_bayes (74.53%)**



(c) SVM (80.75%)



(d) Decision Tree (73.29%)



(e) logistic regression (80.75%)

Figure 3.33. Accuracy comparison of different algorithms

By comparing the results, both SVM and logistic regression have a higher accuracy rate than others but SVM have kernel trick and other parameters that can improve the performance by tuning them. This is another reason why SVM was chosen for the proposed classification.

3.5.4 Leaf size calculation by OpenCV

In the previous section, leaf size calculation with some mathematical methods was described and now it will be implemented in OpenCV and determine the dimensions of the leaf images. The flowchart for the calculation of the dimension of the leaf is shown in Fig. 3.34.

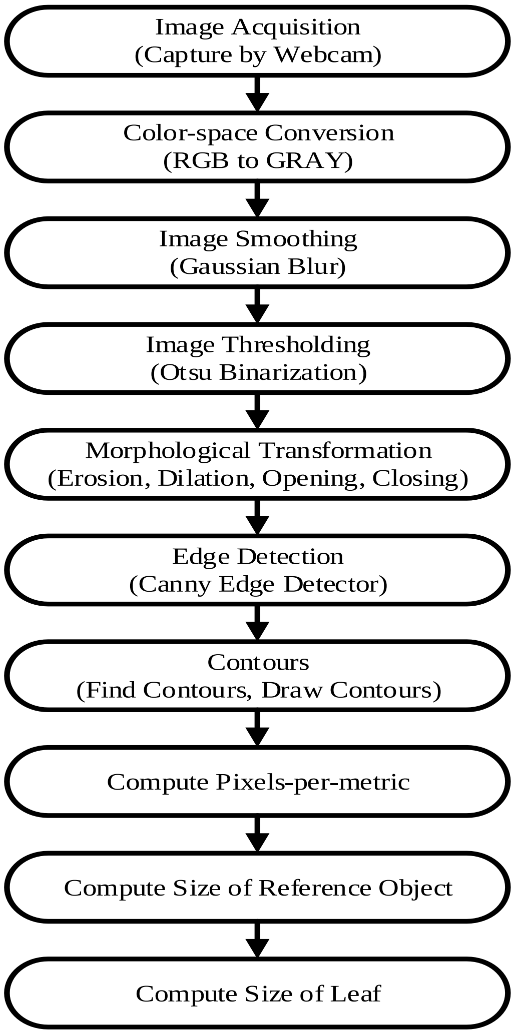


Figure 3.34. Flowchart for leaf size calculation by OpenCV

3.5.5 NPK Deficiency Detection

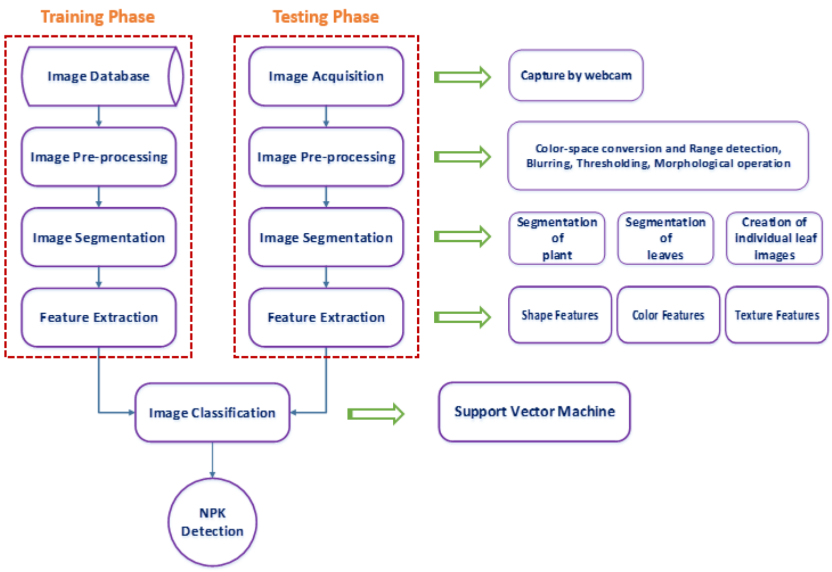


Figure 3.35. Flowchart for NPK Detection System

The block diagram for NPK detection is shown in Fig. 3.35. The left blocks are for the training phase and the right ones are for the testing phase. The image was captured by webcam for image acquisition, then performed some pre-processing methods. For the image segmentation, the plant image was segmented from different background firstly, then the leaves were segmented from the plant image and then created the individual leaf images. For the feature extraction, shape, color and texture features were extracted. Finally, SVM was used for image classification and applied appropriate nutrients to the plants.

3.6 Thingspeak IoT Platform

Thingspeak was used as the IoT platform to send data from the sensor inside the small-scale farm to the cloud. Thingspeak is an Internet of Things (IoT) platform that collects and stores sensor data in the cloud and develops IoT applications. It is an open-source platform for the users and very popular among the internet of things experimenters.

Features of Thing Speak include real-time data collection, data processing, visualizations, apps, and plugins. Sensor data can be sent to ThingSpeak from Arduino, Raspberry Pi, BeagleBone Black, and other hardware [1]. Data can be sent to ThingSpeak from devices, create instant visualizations of live data, and send alerts using web services like Twitter and Twilio. ThingSpeak enables engineers and scientists to prototype and builds IoT systems without setting up servers or developing web software.

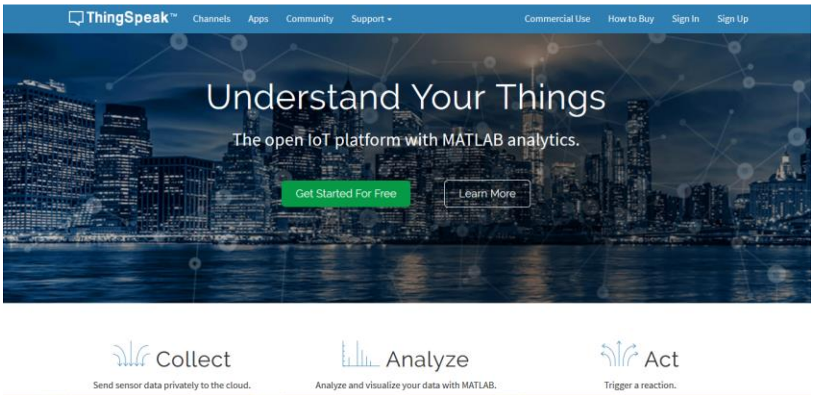


Figure 3.36. Thingspeak Homepage

At the heart of Thing Speak is a Thing Speak Channel. A channel is where the data are stored. Each channel includes 8 fields for any type of data, 3 location fields, and 1 status field.

Figure 3.37. Raspberry Pi connected with Thingspeak

3.7 Tkinter (GUI)

Python is a very powerful programming language. It ships with the built-in Tkinter module [7]. Tkinter is the standard GUI library for Python. Python, when combined with Tkinter, provides a fast and easy way to create GUI applications. Once Tkinter is installed on the system, it will take less than 15 minutes to get the first GUI application running [8].

Tkinter is an open-source, portable graphical user interface (GUI) library designed. It relies on the Tk library, the GUI library used by Tcl/Tk and Perl, which is in turn implemented in C. Tkinter provides a powerful object-oriented interface to the Tk GUI toolkit.

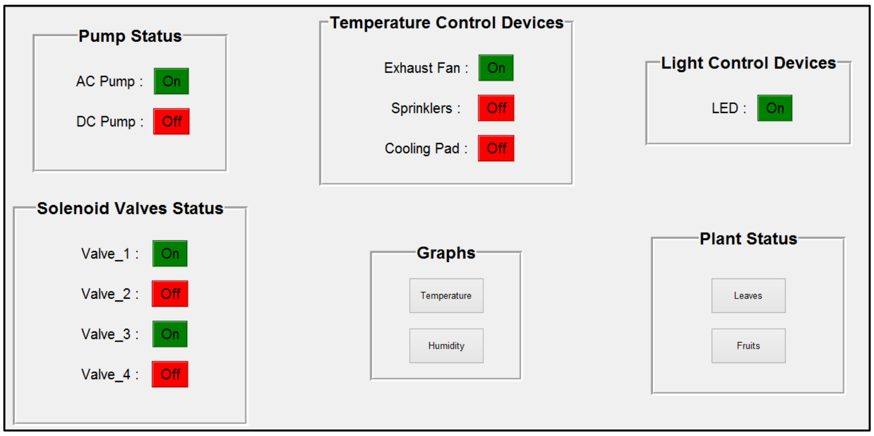


Figure 3.38. Proposed GUI Design

Creating a GUI application using Tkinter is an easy task. Firstly, import the Tkinter module, then create the GUI application main window and add one or more of the widgets to the GUI application and finally enter the main event loop to take action against each event triggered by the user.

Tkinter has many advantages that make it the primary choice for UI design. But it is reasonable to assume that Tkinter is not going to perform well. Tkinter's layered design has two major drawbacks, it slows down the applications and it makes sources more difficult to read.

3.8 HDMI LCD Monitor

The LCD display used for monitoring the states of the plants and farm in this system is 7-inches standard display and has 1024 × 600 resolution. It supports standard HDMI interface input and compatible with and can be directly inserted with Raspberry Pi (3rd, 2nd, and 1st generation). Also has a built-in capacitive touch screen with the maximum support of five-point touch. This type of LCD can be used as general-purpose-use HDMI monitor, for example: connect with a computer HDMI as the sub-display and used as a Raspberry Pi display that supports Raspbian, Ubuntu, Kodi, and win10 IOT with single-touch.

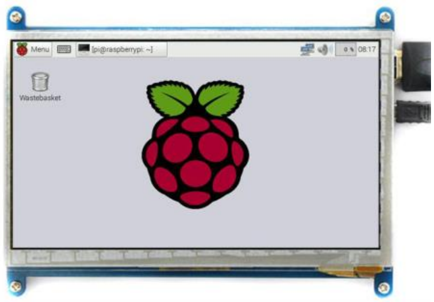


Figure 3.39. HDMI 7" LCD Monitor

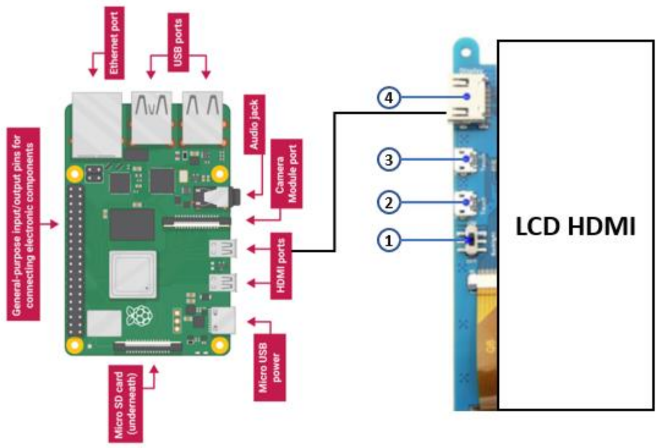


Figure 3.40. Connection of LCD with RPi

① *Backlight Power switch*: Controls the backlight turned on and off to save power.

②③ *USB Touch/power supply connector*: For power supply and touch output, the functions of the both are the same, can just use one of them.

④ HDMI interface: For connecting motherboard and LCD monitor to HDMI transmission.

3.9 Control Panel

The following figure shows the design for control panel box to install inside the small-scale farm. The devices used for this control panel are Raspberry Pi 3 controller board, two 8-channel relay module, temperature and humidity sensor, LDR, 7” HDMI LCD display, two DC fan, and three Logitech webcams.

Figure 3.41. Control Panel Box Design

3.10 Summary

This chapter mainly describes the proposed system designs in details. The frame structure and designs, requirements for temperature control system, drip irrigation system, leaf size calculation, and image processing methodologies were described. Moreover, Thingspeak for IoT platform, Tkinter for GUI and 7” HDMI LCD for the monitor were also explained. In the next chapter, the implementation of the proposed system will be presented.

CHAPTER 4
TESTS AND RESULTS

In this chapter, the experimental results of the proposed system are presented. Moreover, the fertigation process for Nitrogen, Phosphorus and Potassium are also evaluated.

4.1 Results for Temperature and Humidity Control System

Table 4.1. Processes for temperature and humidity control system

Processes	Requirements
Temperature Controlling	Exhaust Fan, Sprinklers, Cooling Pad
Scheduling for Auto Temperature Control System	Logged Temperature Data for Each Season

The following figure shows the inside temp graph from August 2018 to May 2019. The blue line shows the highest temperature, the orange line shows the lowest temperature and the gray line shows the average temperature in each month. Strawberries are started planting in June 2018 and started fruiting in August 2018 (green box in the figure). Then, plenty of fruits from November to January (red box) but just a little amount of fruits is bear because of high temperature from February to May (black box).

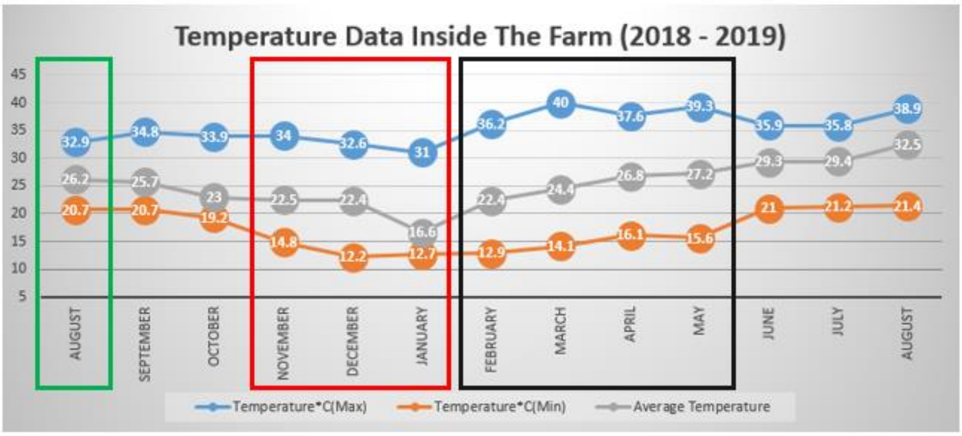


Figure 4.1. Temperature Data inside the Farm

Thus, by determining these four months between February and May (hot season) in Fig. 4.2, the temperature reached up to 40 °C. The strawberries set the berries between the range (20°C to 29°C) and they fail to germinate if the temperature is less than 10°C. So, the inside temperature is needed to reduce at least 11°C to get the optimal state.

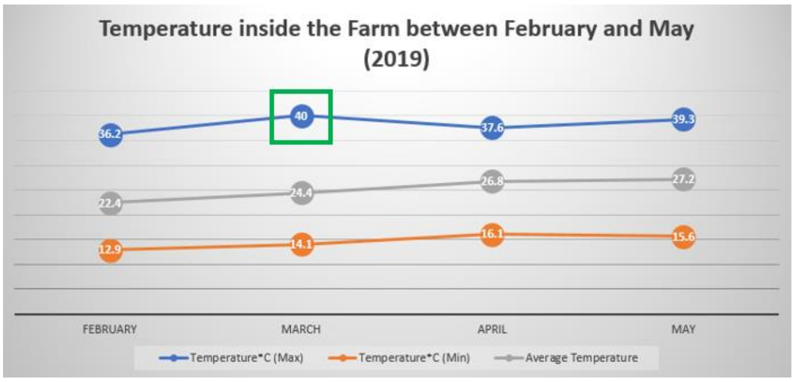


Figure 4.2. Inside Temperature from February to May

In order to reduce the inside temperature, the three temperature control devices are used. The cooling pad and exhaust fan are placed on the top of the farm firstly and then move to the middle of the farm and temperature data are logged for these two situations respectively.

Figure 4.3. Cooling Pad and Fan at the top

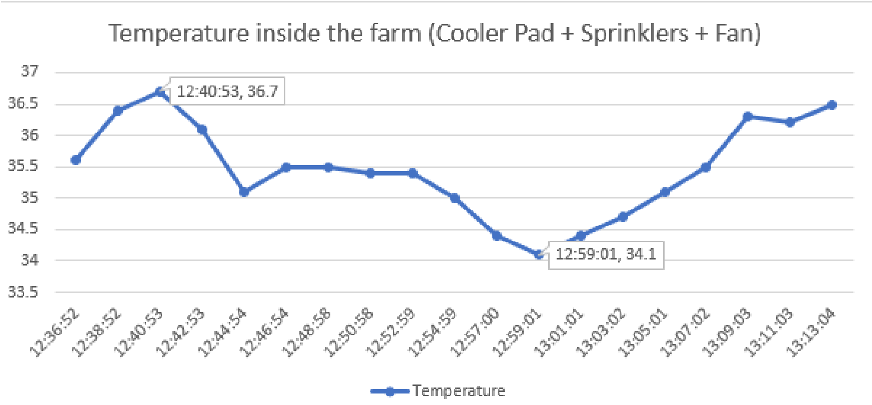


Figure 4.4. Temperature Data inside the farm (top position)

Figure 4.5. Cooling Pad and Fan at the middle

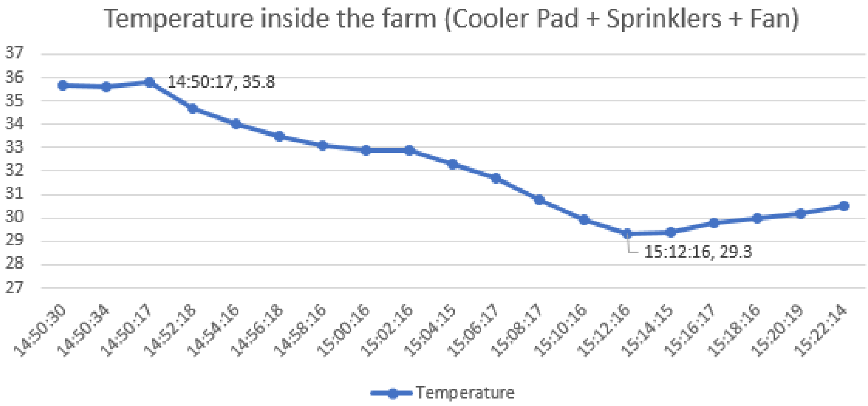


Figure 4.6. Temperature Data inside the Farm (middle position)

Table 4.2. Comparison Table

Devices	Cooler Pad Position	Reduced Temperature
Cooler Pad + Sprinklers + Fan	Upper	2.6°C
Cooler Pad + Sprinklers + Fan	Middle	6.2°C

Fig. 4.4 shows the inside temperature by turning on all three temperature control devices for the top position and Fig. 4.6 shoes the inside temperature for the middle position. So, by comparing all of the logged temperatures, the temperature can only be reduced mostly by 2.6°C (from 36.7°C to 34.1°C) by placing pad and fan in the upper position. But in the middle position, turning on all devices can reduce 6.2°C (from 35.8°C to 29.3°C) and thus it can be decided that this set up is more optimal rather than the upper one.

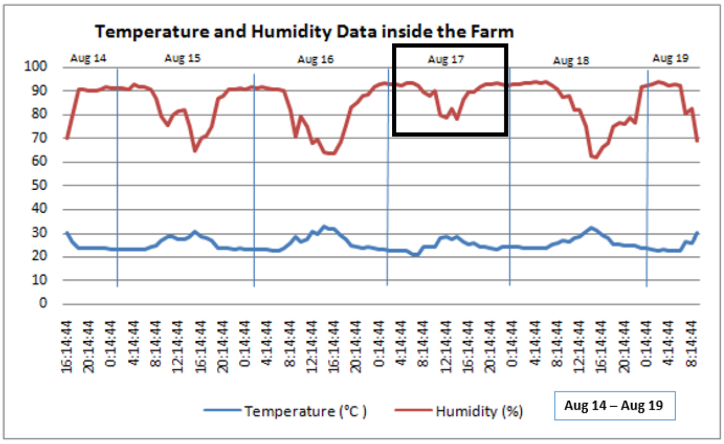


Figure 4.7. Inside Temperature and Humidity Data from August 14 to August 19

The graph in Fig. 4.7 shows the temperature and humidity data inside the farm during the rainy season (August 2018). The humidity is high in raining and misty days (for example on August 17, it was raining and misty a whole day) and started affected by leaf scorch and bacterial blight as in Fig. 4.8 and Fig. 4.9 during these days. So, it is needed to enable good aeration for the plants (by turning on the exhaust fan) if the humidity is higher than the acceptable range.

Figure 4.8. Leaf Scorch

Figure 4.9. Bacterial Blight

The data graph collected at the start of the cold season is shown in Fig. 4.10. Temperature becomes in the range 19°C to 31°C with an average of 23°C and the average humidity is 89%. This is the acceptable range for strawberry plants and bears a few amounts of fruits during these days.

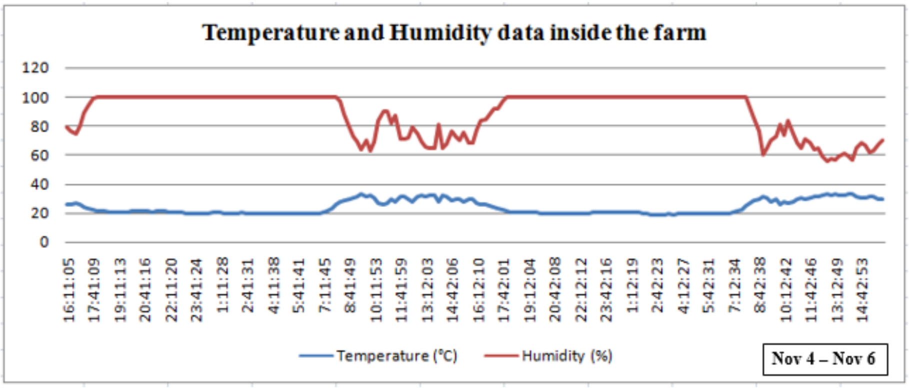


Figure 4.10. Inside Temperature and Humidity from November 4 to November 6

Thus, by determining the logging data from the previous graphs, the environmental control for the next seasons can be predicted. In the hot season, only the temperature is needed to control. During the rainy season, both temperature and humidity need to be controlled and for the cold season, it does not need to be controlled especially. Temperature is controlled by black-net, cooling pad, exhaust fan, and fog nozzle sprinklers. And humidity is controlled by using the only exhaust fan.

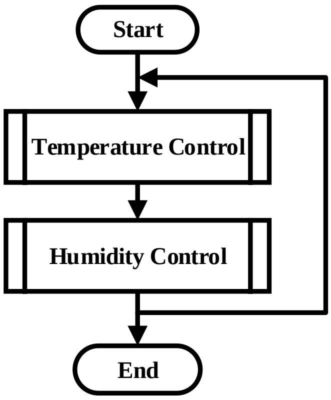


Figure 4.11. Flowchart for Temperature and Humidity Control

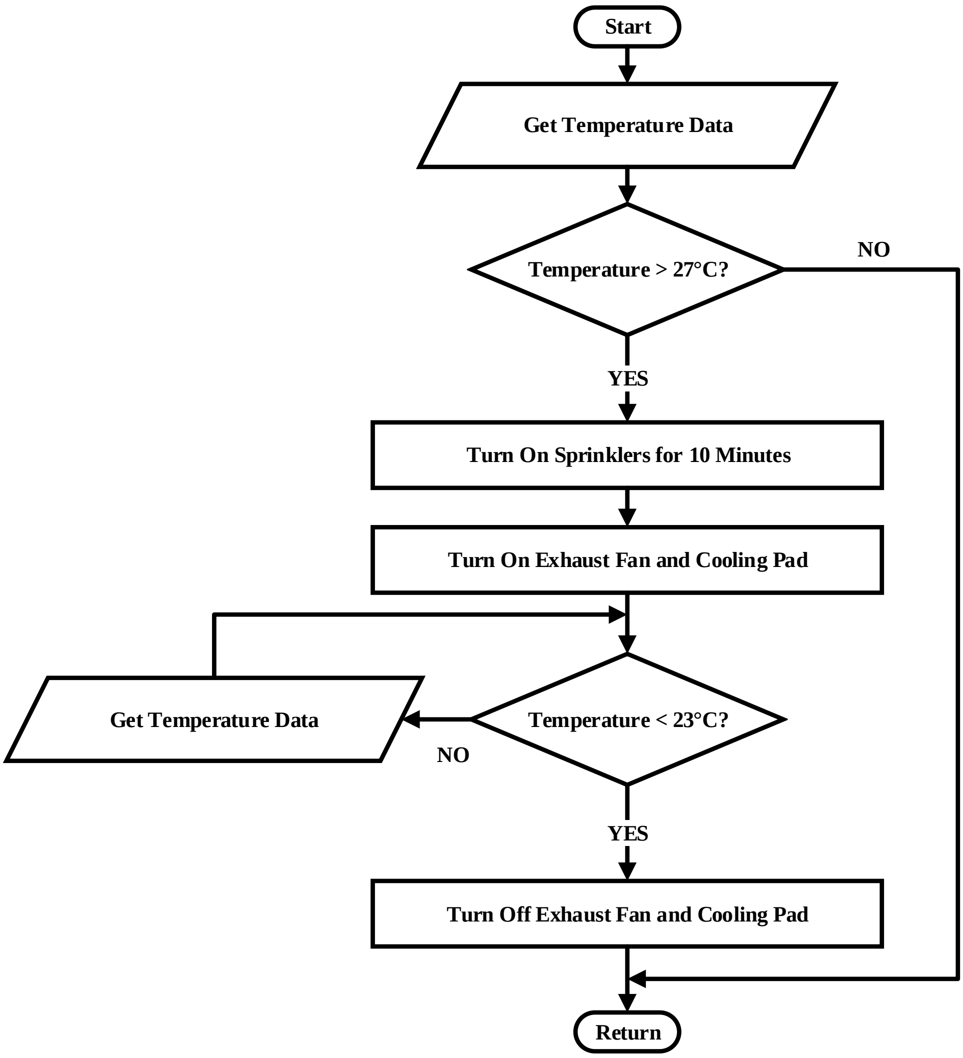


Figure 4.12. System Flowchart for Temperature Control

Fig. 4.11 is the main process for the system flowchart of temperature and humidity control by reading data from the DHT22 sensor and then the processes of temperature control and humidity control are performed separately.

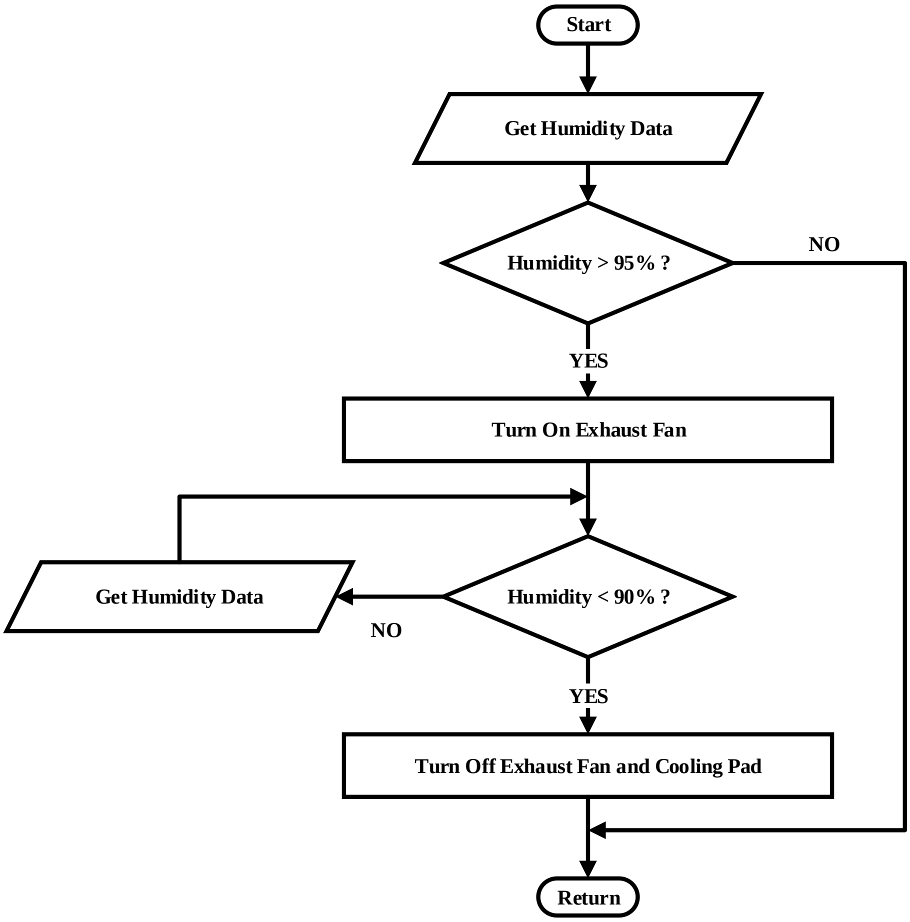


Figure 4.13. System Flowchart for Humidity Control

The optimal temperature range for strawberry plants is between 20°C and 29°C. Thus, for the temperature control, the upper limit is set for 27°C and 23°C for the lower limit as in Fig. 4.12. So that the temperature will stay between 23°C and 27°C within the farm.

Fig. 4.13 is the flowchart for humidity control sub-process. By reminding from the previous results, the plants affected by diseases with the average humidity of 93% and set flowers and fruits with an average of 89%. Too much humidity in the farm can cause the leaves affected by diseases. So, 95% is set for the upper limit and 90% for lower limit so that the humidity inside the farm will be no more than 95%.

Fig. 4.14 is the testing of updating the data on Thingspeak. There are three fields in one channel, soil moisture data, temperature data, and humidity data and the sampling time is set at least 20 seconds for each as Thingspeak takes at least 15 seconds to update data.

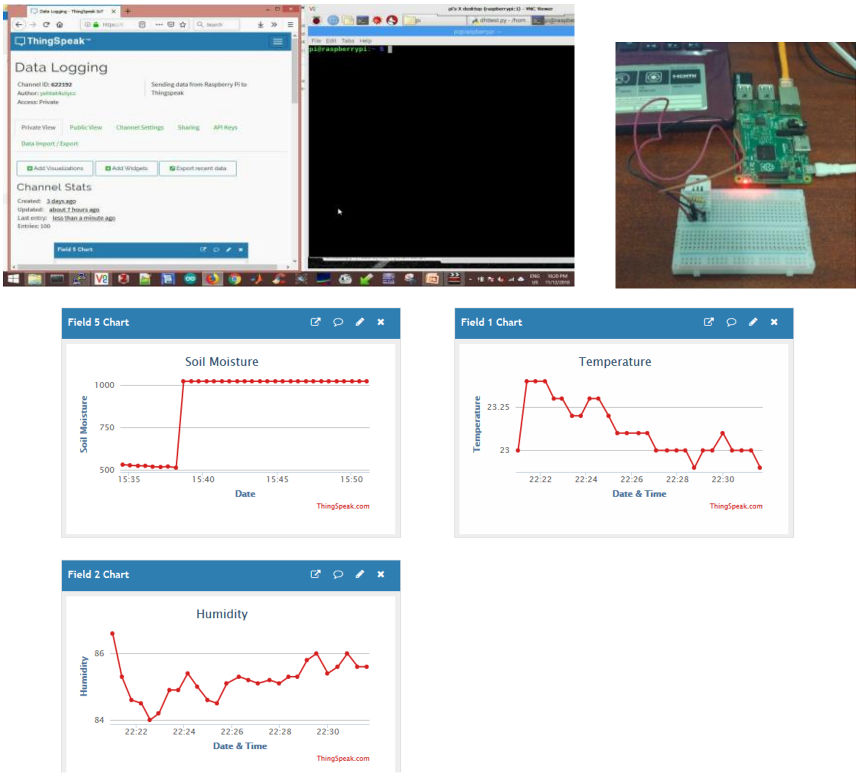


Figure 4.14. Updating Data to Thingspeak

4.2 Results for Drip Irrigation System

In this section, the leaf size and soil moisture value of different farms are compared and prepare the schedule for water supply duration for the proposed small-scale strawberry farm.

Table 4.3. Process and requirements for drip irrigation system

Process	Requirements
Comparison and Scheduling for Water Supply Duration	Soil Moisture Data from Different Farms

4.2.1 Soil Moisture Data and Leaf Size for Small-scale Farm

The moisture range is between 908 and 948 and leaf size is calculated to be 17.0cm x 17.8cm as in Fig. 4.15.

- **Life** - Two months old plants
- **Water supply Duration** - 10 minutes (twice a day)
- **Data logging Time** - Before watering (10 min)
  - After watering (10 min)

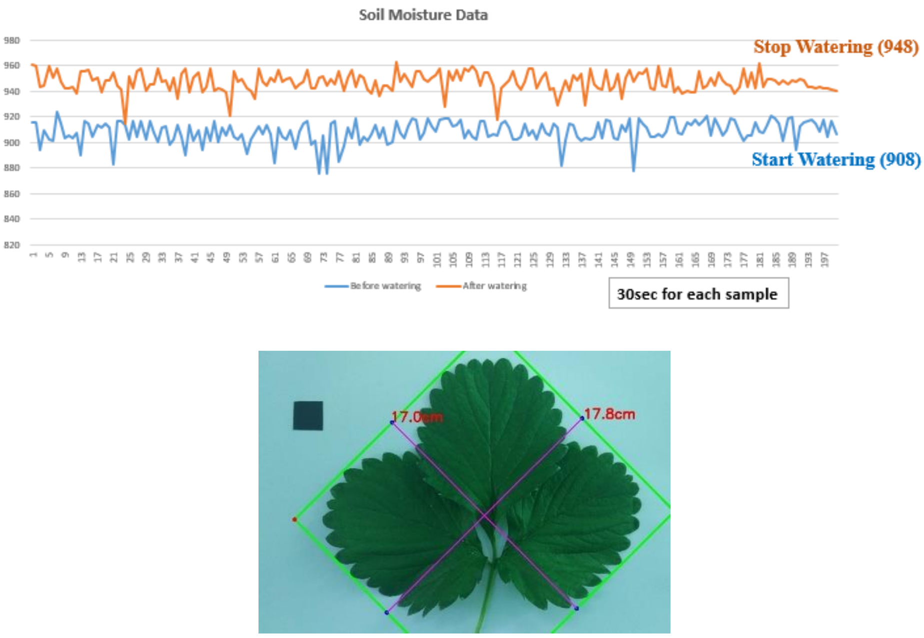


Figure 4.15. Moisture Data and Leaf Size for Small-scale Farm

4.2.2 Soil Moisture Data and Leaf Size for Aung-Chan-Thar Farm

The moisture range is between 876 and 918 and leaf size is calculated to be 13.8cm x 15.7cm as in Fig. 4.16.

- **Life** - Two months old plants
- **Water supply Duration** - 20 minutes (twice a day)
- **Data logging Time** - Before watering (10 min)
  - After watering (10 min)

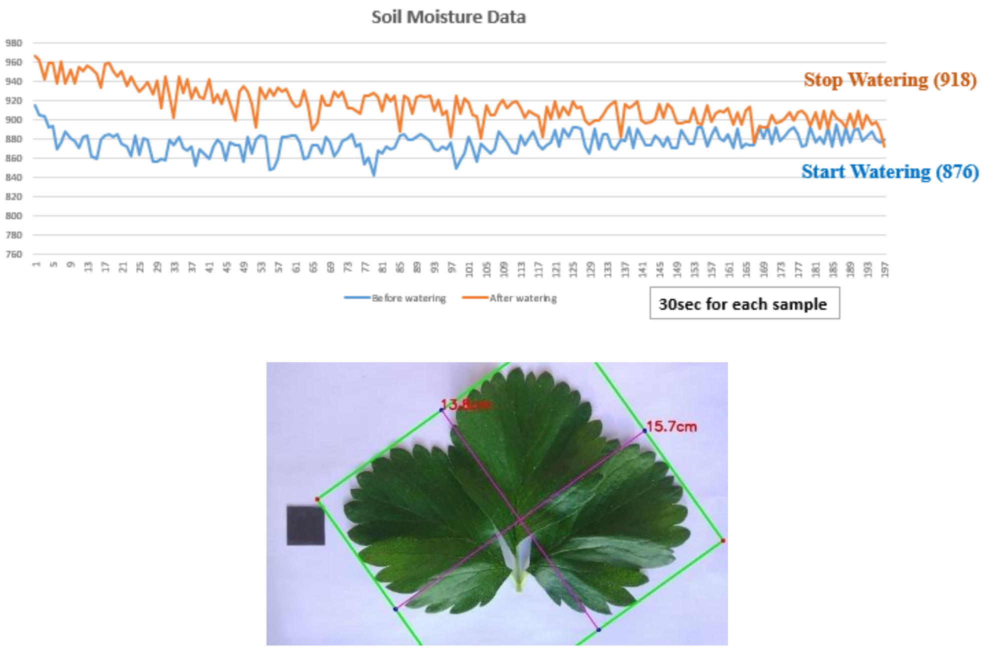


Figure 4.16. Moisture Data and Leaf Size for Aung Chan Thar Farm

4.2.3 Soil Moisture Data and Leaf Size for City Farm-A

The moisture range is between 670 and 907 and leaf size is calculated to be 10.5cm x 9.9cm as in Fig. 4.17.

- **Life** - Two months old plants
- **Water supply Duration** - 15 minutes (twice a day)
- **Data logging time** - Before watering (10 min)
  - After watering (10 min)

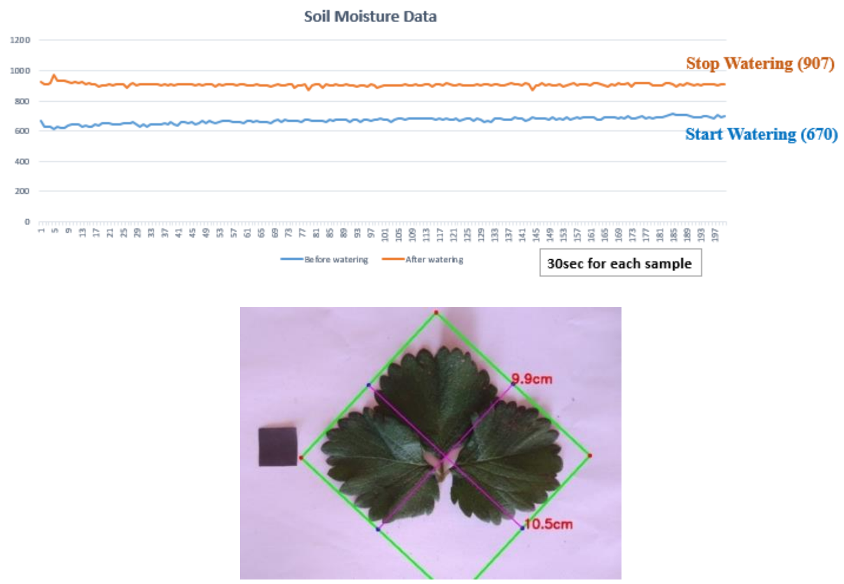
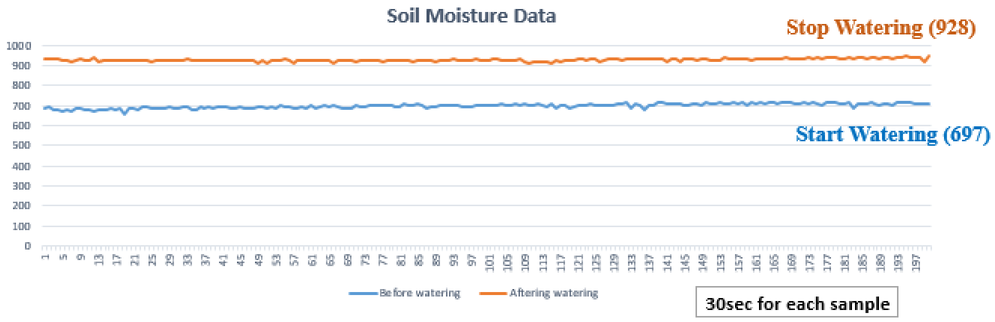


Figure 4.17. Moisture Data and Leaf Size for City Farm - A

4.2.4 Soil Moisture Data and Leaf Size for City Farm-B

The moisture range is between 697 and 928 and leaf size is calculated to be 9.6cm x 9.6cm as in Fig. 4.18.

- **Life** - Two months old plants
- **Water supply Duration** - 15 minutes (twice a day)
- **Data logging time** - Before watering (10 min)
  - After watering (10 min)



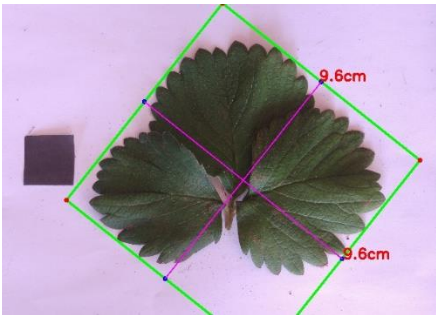


Figure 4.18. Moisture Data and Leaf Size for City Farm - B

4.2.5 Soil Moisture Data and Leaf Size for City Farm-C

The moisture range is between 720 and 927 and leaf size is calculated to be 13.3cm x 13.7cm as in Fig. 4.19.

- **Life** - Two months old plants
- **Water supply duration** - 15 minutes (thrice a week)
- **Data logging time** - Before watering (10 min)
  - After watering (10 min)

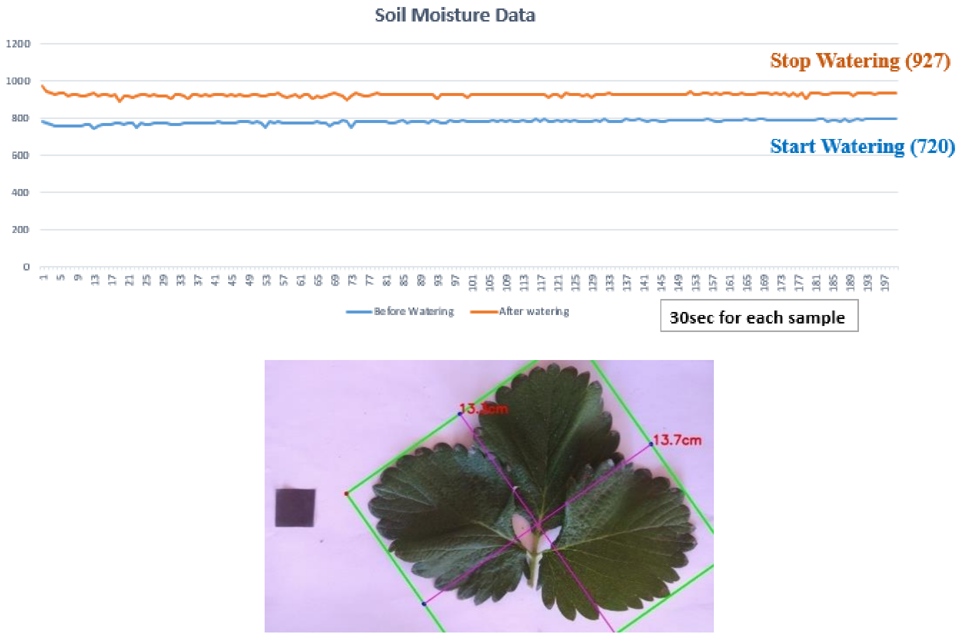


Figure 4.19. Moisture Data and Leaf Size for City Farm – C

By comparing all of the above data from different farms in Table. 4.4, it is found that indoor farms have larger leaf size area than outdoor farms and can be decided that the indoor systems are better than outdoor systems as the larger the leaf area, the more production rate can get.

Table 4.4. Comparison of Soil Moisture Data and Leaf Size

Fields	Growing System	Moisture		Leaf Size
		Min	Max	
Small-scale Farm	Indoor	908	948	17.0cm x 17.8cm
Aung Chan Thar	Indoor	876	918	13.8cm x 15.7cm
City Farm-A	Outdoor	670	907	10.5cm x 9.9cm
City Farm-B	Outdoor	697	928	9.6cm x 9.6cm
City Farm-C	Indoor	720	927	13.3cm x 13.7cm
Optimal State	**Indoor**	**870**	**950**	

So, the moisture values can be set with the data of indoor farms including small-scale farm and found that the minimum value is 720 from City Farm – C and the maximum value is 948 in the small-scale farm. But the water supply method of City Farm – C is thrice a week and thus the moisture value is slightly lower than the daily supply. Thus, this value is neglected and takes the minimum value is 876 from Aung Chan Thar Farm and concluded that the optimal moisture range is from 870 to 950 with the indoor system for drip water supply.

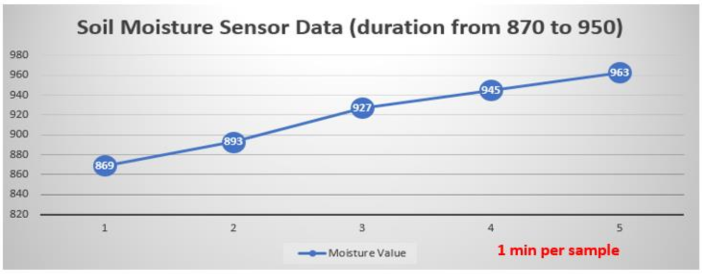


Figure 4.20. Soil Moisture Data (duration from 870 to 950)

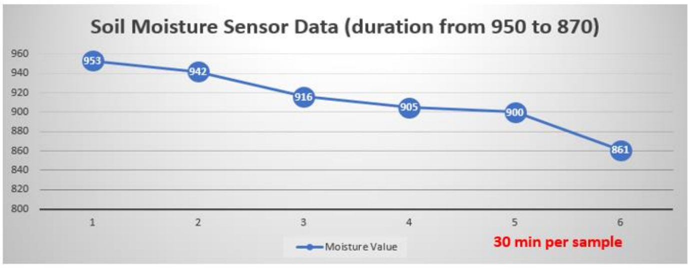


Figure 4.21. Soil Moisture Data (duration from 950 to 870)

According to the previous results, the minimum moisture value is 870 and the maximum moisture value is 950. The graphs in Fig. 4.20 and Fig. 4.21 show that the watering duration with moisture sensor from 870 to 950 last for 5 minutes and return from 950 to 870 last about 3 hours.

Table 4.5. Duration for Optimal Range by Sensor

Moisture Range	Duration
870 to 950 (watering)	5 minutes
950 to 870 (normal)	3 hours

According to this optimal range and duration, how long water should be supplied to the plants can be determined and also make a schedule for water supply duration for the small-scale farm. There will be eight times per day for watering and the duration will be 5 minutes for each. The drip pipe flow rate is 1.95 liters per hour at maximum pressure and water usage can also be calculated as 1.3 liters per plant per day. So, there will be a total of 72 liters (19 gallons) of water usage per day for all 55 plants in the small-scale farm.

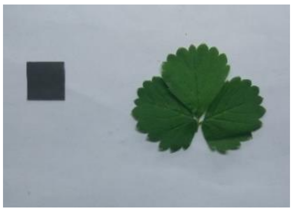
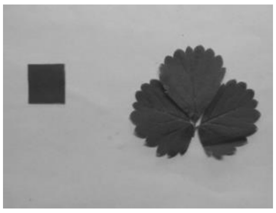
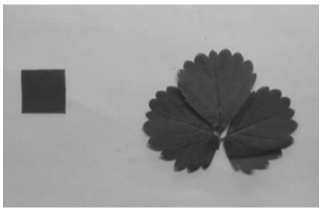
Table 4.6. Scheduling for Water Supply Duration

Schedule		Duration	Drip Pipe Flow Rate	Water Usage
3 AM	3 PM	5 min	1.95 liters per hour	1.3 liter/plant/day
6 AM	6 PM	5 min		
9 AM	9 PM	5 min		
12 AM	12 PM	5 min		

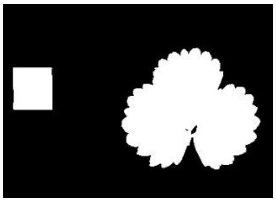
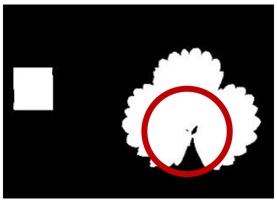
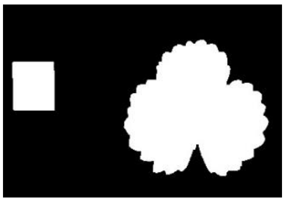
4.3 Results for Leaf Size Calculation

Firstly, the image is captured by webcam then converts from RGB image to GRAY image and perform a little smoothing with Gaussian Blur. Then, the thresholding process is performed with Otsu binarization. To fill the holes in the foreground image as in a red circle, closing is used and edges are detected with Canny edge detector, but the result edges are not very sharp and thus dilation is used again.

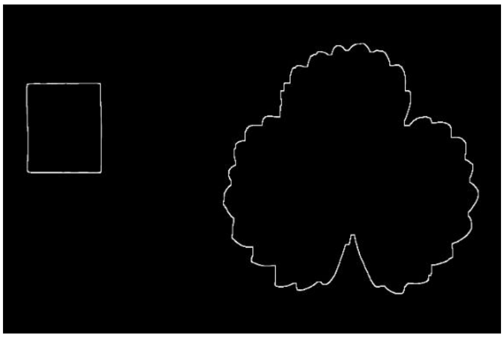
Moreover, find contours from this image, compute pixels-per-metric and size of the reference object. Finally, the leaf size is calculated corresponding to the reference object. The step-by-step results are as shown in Fig. 4.22.

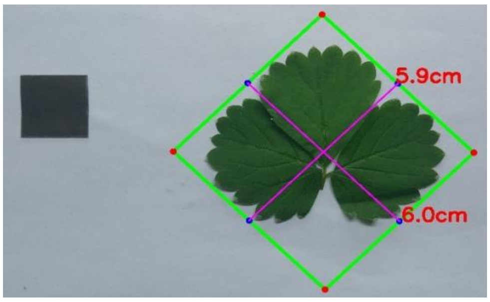
(a) Original Image **(b) Grayscale Image** **(c) Smoothed Image**

(d) Thresholding Image **(e) Holes in Foreground** **(f) Apply Closing**

(g) Edge Detected Image **(h) Dilated Image**



(i) Dimension of Leaf

Figure 4.22. Leaf Size Calculation Results

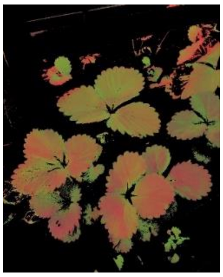
4.4 Results for Nutrient Deficiency Symptoms Detection System

For image acquisition, load the image from the webcam and convert RGB image to HSV image to find the upper and lower boundaries for individual intensities. Then apply pyramid mean shift filtering in order to improve the result and again convert to grayscale. Thresholding is performed by combining the binary method and Otsu binarization, and apply the morphological operation to enhance the image.

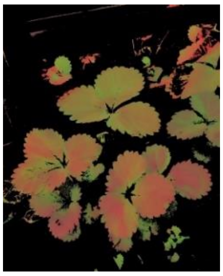
For the segmentation of leaves, draw the contours on the image and apply the watershed algorithm to extract the leaf images, and remove some small unwanted contour areas. Finally, individual leaf image is created by choosing an individual label and do masking. The step-by-step process is shown in Fig. 4.23.

(a) Original Image

(b) RGB to HSV



(c) Find boundaries



(d) Apply PyramidMeanShift Filtering

(e) Grayscale Image

(f) (Binary + Otsu)

(g) Opening

(h) Closing

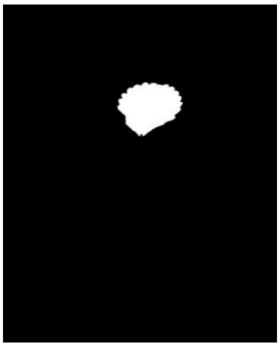
(i)Masking

(j)Draw contours

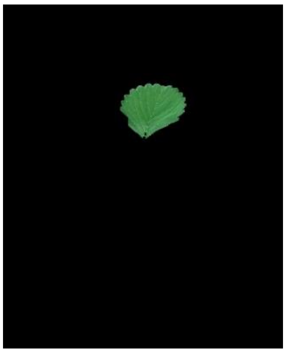
(k) Apply Watershed Algorithm

(l) Remove small contours area

(m) Individual label



(n) Masking



(o) Individual leaf

Figure 4.23. NPK Detection Results

As for feature extraction, shape-based features (area, perimeter, width, height, aspect_ratio, rectangularity, circularity), color-based features (red_mean, green_mean, blue_mean, red_std, green_std, blue_std), and texture-based features (contrast, correlation, inverse_diff_moments, entropy) are extracted. But shape-based features are not used for the proposed system as they have no effect on detecting deficiency symptoms.

For classification, SVM is used with scikit-learn python machine learning algorithm. There is a total of 641 samples and, 80% of total samples are divided as the training data set and the remaining 20% to test on these training sets.

Table 4.7. Training Set and Testing Set

	Total Samples	Training Set (80%)	Test Set (20%)
Healthy	261	209	52
Nitrogen	87	70	17
Phosphorus	66	53	13
Potassium	227	182	45

Table 4.8. Parameter Values for Tuning

Kernel	C	Gamma
RBF	0.001,0.01,0.1,10,25,50,100,1000	1e-2, 1e-3, 1e-4, 1e-5
SIGMOID	0.001,0.01,0.1,10,25,50,100,1000	1e-2, 1e-3, 1e-4, 1e-5
LINEAR	0.001,0.01,0.1,10,25,50,100,1000	-

Then RBF, SIGMOID and linear are set for kernels, C and Gamma are also set with the values in Table. 4.8 and perform parameter tuning. Also, OvR or OvO have to choose for decision function shape. And it is finally found that the highest accuracy rate can get with OvR shape, linear kernel and C value of 1000.

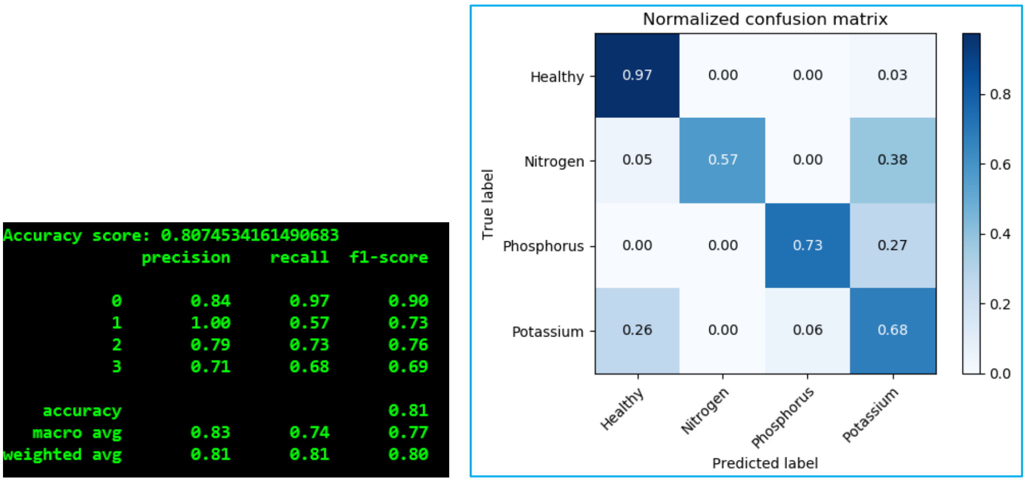


Figure 4.24. Before Parameter Tuning

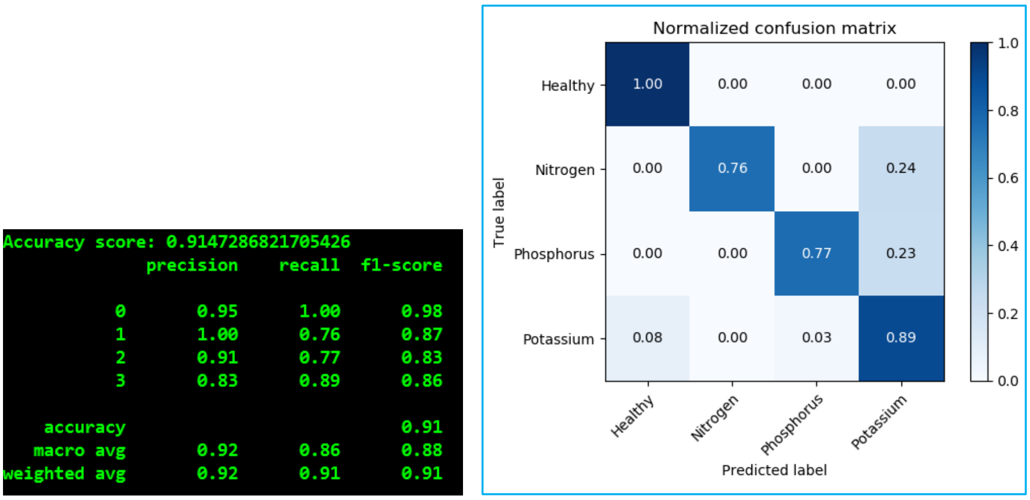


Figure 4.25. After Parameter Tuning

Before parameter tuning, decision function shape and kernels have default values and get the accuracy score of 80.75% with 50% training set mean absolute error and 47% testing set mean absolute error. But after tuning parameters with optimal values, the accuracy improves to 91.47% with lower mean absolute error as shown in Fig. 4.24 and Fig. 4.25.

As for the confusion matrix in these figures, the four diagonal cells show the percentage of correct classifications by SVM. After parameter tuning, healthy leaves are correctly classified from 97% to 100%. Similarly, correctly classified Nitrogen detected leaves from 57% to 76%, Phosphorus from 73% to 77% and Potassium from 68% to 89% based on the training dataset.

The following tables show the test and results for the classification of real-time data. Parameters for each class are chosen as in Table. 4.9. As for the labels in Table. 4.10 through Table. 4.11, "total detected" means the number of leaf images detected from the plant image with different backgrounds, "false detected" means the number of non-leave images detected, "classified correctly" means the number of correctly classified images for appropriate classes and finally, "misclassified" means the number of incorrect classified images as other classes.

Table 4.9. Parameters for each class

Class	Color Space	Lower boundaries	Upper boundaries	Contour Area
Healthy	HSV	[33,39,61]	[74,255,255]	Greater than 500
Nitrogen	HSV	[0,173,119]	[37,255,255]	Greater than 500
Phosphorus	RGB	[0,0,157]	[146,137,255]	Greater than 500
Potassium	HSV	[0,0,53]	[57,255,255]	Greater than 500

Table 4.10. Healthy leaves detection results

Test Images						
Total Detected	19	24	22	14	15	12
False Detected	0(0%)	0(0%)	0(0%)	0(0%)	0(0%)	5(42%)
Classified Correctly	15 (79%)	23 (96%)	20 (91%)	14 (100%)	15 (100%)	3 (25%)
Mis-classified	4(21%)	1(4%)	2(9%)	0(0%)	0(0%)	4(33%)

Table 4.11. Nitrogen Deficiency leaves detection results

Test Images						
Total Detected	1	2	4	6	7	6
False Detected	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)
Classified Correctly	1 (100%)	1 (50%)	4 (100%)	5 (83%)	7 (100%)	3 (50%)
Mis-classified	0 (0%)	1 (50%)	0 (0%)	1 (17%)	0 (0%)	3 (50%)

Table 4.12. Phosphorus Deficiency leaves detection results

Test Images						
Total Detected	3	1	3	0	3	3
False Detected	0 (0%)	0 (0%)	0 (0%)	-	0 (0%)	0 (0%)
Classified Correctly	3 (100%)	1 (100%)	3 (100%)	-	3 (100%)	3 (100%)
Mis-classified	0 (0%)	0 (0%)	0 (0%)	-	0 (0%)	0 (0%)

Table 4.13. Potassium Deficiency leaves detection results

Test Images						
Total Detected	19	18	14	9	10	30
False Detected	0(0%)	0(0%)	0(0%)	0(0%)	0(0%)	4(13%)
Classified Correctly	3 (16%)	3 (17%)	6 (43%)	3 (33%)	5 (50%)	7 (23%)
Misclassified	16 (84%)	15 (83%)	8 (57%)	6 (67%)	5 (50%)	19 (64%)

4.4.1 Fertigation (Fertilizers + Drip Irrigation) process

In this section, the duration for fertilizers supply that will be applied with fertigation are determined. This means that nutrient solutions are applied through the drip pipes along with water based on the classification results. There are three stands in the farm and each stand has 55 plants for five rows and thus the application rate is calculated with liter per 55 plants.

Table 4.14. Fertigation process for Nitrogen, Phosphorus and Potassium

Fertilizers	Application Rate (liter/55 Plants)	Drip Pipe Flow Rate	Supply Duration (minutes/55 plants/week)
Urea	0.022 – 0.0275	1.95 liters per hour	1
Triple Superphosphate	0.1367 – 0.165		5
Potassium Chloride	0.0385 – 0.044		2

Figure 4.26. Cultivated strawberries during growing seasons

Fig. 4.26 shows the cultivated strawberries during growing seasons by applying automatic drip irrigation systems with temperature control inside the small-scale farm system.

4.5 Summary

In this chapter, the experimental results of the three main proposed systems based on applied methods are expressed in details, and also some decisions for water supply and fertigation process from the comparison results of the different strawberry farms around Pyin Oo Lwin are also presented.

CHAPTER 5
CONCLUSION

5.1 Conclusion

In the information age, agriculture in Myanmar is developing towards the direction of information and automation. This proposed research mainly focused on growing strawberry plants for different weather conditions in Pyin Oo Lwin with good efficiency using modern irrigation technology. The experimental results show that the plants can reflect weather and soil conditions although they are growing inside the small-scale farm. The decisions for automatic irrigation can be determined from the logged sensor data using real-time graphs. The usage of drip irrigation greatly saves water and fertilizer than traditional methods ensuring optimal growth in low cost, high reliability, and accuracy. The implementation of leaf analysis using image processing can effectively monitor plant growth trends and detect nutrient deficiency symptoms.

5.2 Discussion and Further Extensions

The small-scale farm is not fully covered by plastic and thus need to protect the plants from insects carefully (especially aphid diseases). Three types of temperature control devices are used but still needed to control with other methods as much amount of temperature (at least 11°C) inside the farm is needed to reduce during the hot season in order to set fruits.

Soil moisture sensor's length that is used for data logging is only 1.5 inches and cannot sense the root zones deeply and it has the problem of electrode corrosion. Only three solenoid valves are used for three plant stands (five rows per one) generally. Fifteen solenoid valves should be used for all 15 plant rows to supply optimal water and fertilizers to only appropriate rows.

There are three stands inside the farm and plants in the middle stand have a better effect than the other two stands. The leaves are large, more flowers are set and the fruits are bigger as they are not directly touched by sunlight (can stay in the shadow) than other two side stands.

In the proposed work, the system was tested and compared on the data that was recorded from just four farms in Pyin Oo Lwin and the plants may have different soil types, soil mixing ingredients, environmental temperatures, water, and fertilizer supply. One of the future works on this research is to take more data in more different farms and perform the experiment on a larger scale.

The potassium deficiency symptom is similar to healthy leaves and nitrogen deficiency symptom, it has the color of both leaves. So, there are some misclassification results as healthy or nitrogen deficiency leaves and thus more features or another algorithm should be added to this system to improve the accuracy for potassium deficiency symptom detection. Therefore, further testing on the feature extraction and classification algorithm could also be future tasks.

Three cameras were used for three plant stands with fixed positions and it limited the viewing angle and area of the scene. Rather than using three cameras, using a high-resolution camera with a motorized camera slider moving around the farm for each plant will reduce the cost for multiple camera usage and also increase the robustness for nutrient detection.

LIST OF PUBLICATION

[1] Ye Htet and Htin Kyaw Oo.: *Intelligent Small-scale Strawberry Irrigation System for Different Weather Conditions,* International Conference on Science, Technology and Innovation (ICSTI), Mandalay, Myanmar, on 4^{th} – 5^{th} October, 2018.

REFERENCES

[1] Akhila, V. et al.: *An IoT based Patient Health Monitoring System using Arduino Uno,* International Journal of Research in Information Technology, (2017) 1-9

[2] Alexandar, M. and Abid, K.: *OpenCV-Python Tutorials Documentation, Release 1*, (2016).

[3] Bartok, J.W, Jr.: *Fan and Pad Evaporative Cooling Systems*, (2005), https://ag.umass.edu/greenhouse-floriculture/fact-sheets/fan-pad-evaporative-cooling-systems

[4] Bartok, J.W, Jr.: *Ventilation for Greenhouses*, (2005), https://ag.umass.edu/greenhouse-floriculture/fact-sheets/ventilation-for-greenhouses

[5] Brian, E. W.: *Strawberry Nitrogen (N) Deficiency*, (2014), https://content.ces.ncsu.edu/strawberry-nitrogen-n-deficiency

[6] Bucklin, R. A. et al.: *Fan and Pad Greenhouse Evaporative Cooling Systems,* (2014).

[7] Burkhard, A. M.: *Python GUI Programming Cookbook,* Packt Publishing Ltd, (2015).

[8] Cuauhtémoc C.: *GUI Programming Using Tkinter*, (2013).

[9] Dhairya, V.: *Intuitive image processing – Watershed segmentation*, Medium, (2018).

[10] Gabriel, G. C.: *OpenCV 3.x with Python By Example: Make the most of OpenCV and Python to build applications for object recognition and augmented reality*, 2nd Edition., Packt Publishing Ltd, (2018).

[11] Gary, B. and Adrian, K.: *Learning OpenCV, Computer Vision with the OpenCV Library,* O'Reilly Media, Inc. (2008).

[12] Haifa Group.: *Nutritional Recommendations for Strawberry*, (2014), http://www.haifa-group.com/files/Guides/strawberry.pdf

[13] Joseph, C. et al.: *Automated fertigation system for efficient utilization of fertilizer and water*, (2017) 1–6.

[14] Mohanraj, I., Gokul, V., Ezhilarasie, R. and Umamakeswari, A.: *Intelligent drip irrigation and fertigation using wireless sensor networks*, (2017) 36–41.

[15] Pedregosa. et al.: *Scikit-learn: Machine Learning in Python*, JMLR12, (2011).

[16] Pooja, V., Das, R. and Kanchana, V.: *Identification of plant leaf diseases using image processing techniques*, (2017) 130–133.

[17] Rachel, W.: *Different types of solenoid valves*, (2016), https://www.mgacontrols.com/different-types-solenoid-valves/

[18] Rouse, M.: *IoT analytics guide: Understanding Internet of Things data,* 2016, https://internetofthingsagenda.techtarget.com/definition/Internet-of-Things-IoT

[19] Singh, V. and Misra, A. K.: *Detection of plant leaf diseases using image segmentation and soft computing techniques,* (2017) 41–49.

[20] Tameson.: *Solenoid valve types,* (2014), https://tameson.com/solenoid-valve-types.html

[21] World weather and climate information.: *Average monthly weather in Pyin-Oo-Lwin, Myanmar (Burma)*, (2018), https://weather-and-climate.com/average-monthly-Rainfall-Temperature-Sunshine,pyin-oo-lwin-mm,Myanmar-Burma