

# AUTOMATED IMAGE DATASET COLLECTION SYSTEM FOR COTTON CROP LEAVES



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## CERTIFICATE

This is to certify that **Project/Thesis Report on, “Automated Image Dataset Collection System For Cotton Crop Leaves”** is submitted in partial fulfillment of the requirement for the degree of Bachelor of Electronic Engineering by the following students:

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## **ABSTRACT**

Today, automation is navigating and processing the evolution of the industry, and is a forerunner in most areas. However, subsidies for agricultural automation appear to be very low in Pakistan. We all know that manual labor in the fields is very tiring, difficult and time consuming for a person and also, manually collecting photos of cotton. If regarding the aspect of collection of images of cotton crop leaves, then the person will have to carry the camera and other required equipment with him to collect the images. That is why, our goal is to develop a semi-automatic robotic system that collects images of cotton leaves in the field. Therefore, integrating automation into agriculture can improve efficiency and productivity in many ways. This project brings a specific approach to automate farming that improves irrigation, land conservation, and health management. This process is carried out by semi-autonomous agricultural vehicle. The vehicle moves around the field, displays live streaming of data collected through on-board cameras, and finally detects the presence of cotton crop leaves. This semi-autonomous vehicle also records the humidity, soil moisture, GPS location and stores the images and sends those images to cloud and finally the vehicle is moved one step. This whole process is the continuous process and we have used machine learning algorithms for its functioning on raspberry pi, in order to make it more efficient and to process huge number of captured images. This semi-autonomous vehicle would be very cost effective and efficient. In the future, our goal is to further enhance this system by adding more vitals measurement capabilities and make it commercially available in all those areas where we are aiming it to be.

# Table of Contents

<b>ABSTRACT</b> .....	<b>iv</b>
<b>Table of Contents</b> .....	<b>v</b>
<b>List of Tables</b> .....	<b>ix</b>
<b>List of Figures</b> .....	<b>x</b>
<b>List of Abbreviations</b> .....	<b>1</b>
<b>1. INTRODUCTION</b> .....	<b>2</b>
1.1 INTRODUCTION OF SEMI-AUTONOMOUS <b>Error! Bookmark not defined.</b>	
1.2 HISTORY..... <b>Error! Bookmark not defined.</b>	
1.3 PROBLEM STATEMENT .....	3
1.4 RESEARCH QUESTIONS.....	3
1.5 MOTIVATION .....	4
1.6 PROJECT IDEA .....	4
1.7 FLOW CHART .....	5
1.8 AIM AND OBJECTIVES.....	5
1.8.1 AIM.....	5
1.8.2 OBJECTIVES.....	5
1.9 THESIS LAYOUT.....	6
<b>2. LITERATURE REVIEW</b> .....	<b>7</b>
2.1 RESEARCH GAP .....	11
<b>3. DESIGN AND METHODOLOGY</b> .....	<b>12</b>
3.1 HARDWARE COMPONENT.....	12
3.1.1 SOIL MOISTURE SENSOR.....	12
3.1.1.1 SOIL MOISTURE SENSOR FEATURES.....	13
3.1.2 PAN-TILT STRUCTURE.....	14
3.1.2.1 PAN-TILT STRUCTURE FEATURES.....	14
3.1.2.2 PAN-TILT STRUCTURE SPECIFICATION.....	15

3.1.3 BATTERY.....	15
3.1.3.1 SPECIFICATION.....	16
3.1.3.2 FEATURES.....	16
3.1.4 RASPBERRY PI 4 MODEL B.....	17
3.1.4.1 RASPBERRY PI 4 MODEL B FEATURES.....	17
3.1.5 5MP RASPBERRY PI CAMERA MODULE.....	18
3.1.5.1 PORTS CONNECTION.....	18
3.1.5.2 SPECIFICATION.....	19
3.1.6 VEHICLE PARTS.....	20
3.1.6.1 CHASSIS.....	20
3.1.6.2 WHEELS.....	20
3.1.6.3 DC GEAR MOTOR METAL.....	21
3.1.6.3.1 SPECIFICATION.....	22
3.1.6.3.2 FEATURE.....	22
3.1.6.4 MICRO SD CARD 32GB.....	22
3.1.6.4.1 SPECIFICATION.....	23
3.1.6.5 MICRO HDMI TO VGA CONVERTER WIRE.....	24
3.1.6.5.1 FEATURES.....	24
3.1.6.6 POWER SUPPLY FOR RASPBERRY PI.....	24
3.1.6.6.1 FEATURES.....	25
3.1.6.6.2 SPECIFICATION.....	25
3.1.6.7 DHT-11 TEMPERATURE AND HUMIDITY SENSOR.....	25
3.1.6.7.1 FEATURES.....	26
3.1.6.7.2 SPECIFICATION.....	26
3.1.6.8 NEO 6M GPS MODULE.....	27
3.1.6.8.1 FEATURES.....	27

3.1.6.8.2 SPECIFIATION.....	28
3.2 SOFTWARE DISCRPTION .....	37
3.2.1 PYTHON PROGRAMMING LANGUAGE.....	37
3.2.2 TENSOR FLOW.....	37
3.2.3 KERAS .....	38
3.2.4 PYCHARM IDE.....	38
3.2.5 LABELIMG .....	39
3.2.6 PYTHON LIBRARIES.....	39
3.2.6.1 OS .....	39
3.2.6.2 SYS.....	39
3.2.6.3 NUMPY.....	40
3.2.6.4 CV2.....	40
3.2.6.5 CVzone .....	40
3.3 METHODOLOGY.....	40
3.3.1 FLOWCHART OF MODEL TRAINING .....	41
3.3.2 DATA COLLECTION .....	41
3.3.3 DATA LABELLING .....	42
3.3.4 TRAINING DATASET .....	43
3.3.5 TESTING DATASETS.....	44
3.3.6 SYSTEM BLOCK DIAGRAM.....	44
3.3.7 SYSTEM FLOW CHART.....	45
3.3.8 FINAL VEHICLE MODEL.....	45
<b>4. RESULTS AND DISCUSSION .....</b>	<b>46</b>
4.1 COTTON LEAVES DETECTION RESULTS AND DISCUSSION.....	46
4.2 TEMPERATURE AND HUMIDITY READING RESULT AND DISCUSSION..	47
4.3 GPS LOCATION (LONGITUDE AND LATITUDE) RESULT AND DISCUSSION.....	47
4.4 SOIL MOISTURE RESULT AND DISCUSSION.....	48

<b>5. CONCLUSION AND FUTURE RECOMMENDATIONS .....</b>	<b>49</b>
5.1 CONCLUSION .....	49
5.2 ADVANTAGES.....	49
5.3 APPLICATION.....	50
5.4 FUTURE WORK.....	50
<b>REFERENCES.....</b>	<b>51</b>



## List of Tables

Table 3-1: Soil Moisture Sensor Pin Configuration .....	13
Table 3-2: Battery Specification .....	16
Table 3-3 Raspberry-pi 4 Model b specification .....	18
Table 3-4: Micro SD Card Specification.....	23
Table 3-5: DHT-11 Digital Temperature And Humidity Sensor.....	26

## List of Figures

Figure 3.1: soil-moisture-sensor-device

Figure 3.2: soil-moisture-sensor

Figure 3.3: Pan-Tilt Structure

Figure 3.4 : 12v 7.2AH Valve Regulated Lead Acid AGM Battery

Figure 3.5: Raspberry Pi 4 Model B

Figure 3.6: 5mp Raspberry Pi Camera Module

Figure 3.7: Chassis

Figure 3.8 Vehicle Wheel

Figure 3.9: DC 6-12V Gear Motor Metal

Figure 3.10: SanDisk 32GB microSDHC Memory Card

Figure 3.11: Micro HDMI To VGA Converter Wire

Figure 3-12 Power Supply for Raspberry Pi

Figure 3-13 DHT-11 Digital Temperature and Humidity Sensor

Figure 3-14 UBLOX NEO-6M V2 GPS MODULE

Figure 3-15: PyCharm IDE Environment

Figure 3-16: labellmg Environment

Figure 3-17: Flow Chart of Model Training

Figure 3-18: Labelling Of Cotton Crop Leaves And Flate Surface Using Labelimg

Figure 3-19: shows all the datasets are labelled and the required .xml files have been Generated

Figure 3-20: shows training of mode

Figure3-21: shows required keras model has been achieved

Figure3-22: System Block diagram

Figure 3-23: System Flow Chart

Figure 3-24: Final Vehicle

Figure 4-1: shows detection of cotton crop leaves

Figure4-2: Shows TEMPERATURE AND HUMIDITY READING

Figure 4-3 Shows Longitude And Latitude Reading of Current GPS Recorded Location

Figure 4-4: shows soil moisture is detected

## List of Abbreviations

S-A	Semi-Autonomous
ML	Machine Learning
GPS	Global Positioning System
SV	Servo Motor
PH	Potential Hydrogen
RGB	Red Green Blue
LED	Light Emitting Diode
PWM	Pulse Width Modulation
RPM	Revolution Per Minute
SVR	Support Vector Regression
SVM	Support Vector Machine
MLR	Multi Linear Regression
VGA	Video Graphic Array
HDMI	High Definition Multimedia Interface
DHT	Digital Humidity Temperature
IC	Integrated Circuit
CSI	Camera Serial Interface
AGM	Absorbed Glass Mat
mm	Milli Meter

# CHAPTER-1

## INTRODUCTION

### 1.1 INTRODUCTION OF SEMI-AUTONOMOUS

The name “Semi-autonomous image dataset acquisition system for cotton leaves” has two broad terms: “autonomous” and “dataset acquisition”. Both terms belong to regions that were brilliant and popular during the agricultural age. Cotton is one of the biggest crop-growing challenges in agriculture because it randomly spawns everywhere and competes with crops for resources. Crop yields decline as a result of this competition for resources. Yield reduction depends on factors such as cotton species, population density, relative timing of emergence and dispersal, soil type, soil moisture, pH and fertility.

Many researchers have found strong links between cotton competition and reduced yields for different plant types.

“Semi-Autonomous”, Detection of plant leaves by automated techniques is advantageous as it reduces a large amount of surveillance work on large farms and detects disease symptoms even at the very early stages, when they appear on the leaves of plants. Here, the detection of leaves of this plant is all based on image processing technology. Image processing technique provides more efficient ways to detect the plant leaves in the form of disease that is caused by fungus, bacteria or virus on plants because mere observations by eyes to detect are not accurate.

Here, the usage of the dataset is to collect multiple samples of leaves because the whole information of plant leaves lie in dataset and this dataset contains information for creating the automated model.

Here, a requirement for multiple records is that the records are collections of instances that all share common attributes. After feeding these training and validation sets into the system, subsequent datasets can be used to shape future machine learning models. The more data you provide to your machine learning system, the faster this model will learn and improve.

The different modules will be used in the designing of this semi- autonomous vehicle and these are: GPS module, humidity sensor and camera for collecting images

### 1.2 HISTORY

A small autonomous transport vehicle with a trolley self-correcting system developed in 1991 at Ehime University for greenhouses. Greenhouses cover up to 47,000 hectares in Japan. Height adjustment system for this vehicle. The front wheels move along b-a lines c-d perpendicular to the steering shaft. As the left front axle advances to crest height H, the wheel center shifts from 0 to percent, creating steering angle b. As a result, the car turns right and automatically corrects the angle of inclination. With a fully charged battery, this vehicle can run for 9.5 hours for him with a weight of 52 kg.

In 2014-2015, global cotton production surpassed 400 lakh bales. Cotton disease is a key contributor to lower cotton yields. The disease is seen on the leaves of cotton in

about 70% to 80% of cases. Cotton leaf diseases may be thoroughly researched using image processing and diagnosis using Android applications. In today's environment, having such an android application that provides a result in a short amount of time and at a reasonable cost is crucial thanks to the integration of digital tools, sensors and control technologies with great promise and benefits in modern agriculture. These advances include everything from scanning crops and fields by capturing timely, accurate and detailed temporal and spatial data, to performing complex nonlinear control tasks for robotic navigation. Semi-autonomous guided tractors and agricultural machinery with local and global sensors for use in row crops and orchards have already proven.

### **1.3 PROBLEM STATEMENT**

Dataset Collection is very important for detecting the symptoms of diseases i.e. when they appear on plant leaves. The reason to collect this huge amount of dataset is that the more data you provide to the machine learning system, the faster that model can learn and improve. If this dataset collection is done by using automatic technique, then less efforts are utilized. Because manual collection is very difficult and time consuming.

### **1.2 RESEARCH QUESTIONS**

How can an accurate, commercial and effective system of semi-Autonomous be developed?

How it can be used?

How it will be commercially used?

Will it be the best possible solution for the semi-Autonomous field?

### **1.5 MOTIVATION**

Manual dataset collection is very difficult and time consuming and also, it does not provide such accurate results. Now, our motivation behind this project is to design an semi-autonomous vehicle that will:

- 1) Collect dataset of cotton crop leaves.
- 2) Record the GPS information.
- 3) Record the soil moisture and temperature.
- 4) Store the collected images and save these to the cloud.

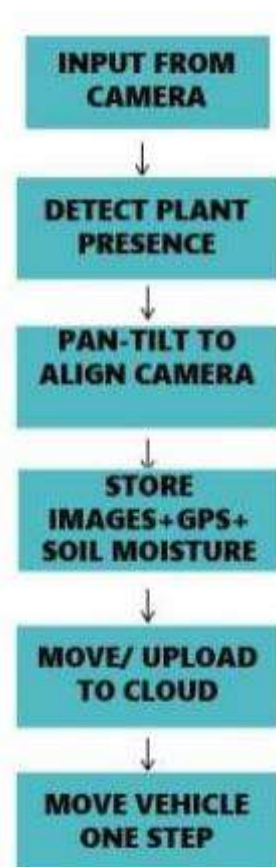
These datasets will then be used in other parts of the project as it is funded project and our project is small task of that project.

Also, another reason behind the designing of a such semi-autonomous vehicle is that it will solve real life problems quite efficiently and quickly regarding to disease and pests.

## 1.6 PROJECT IDEA

This project is about the development of an semi-automated robotic system that will collect the images of cotton crop leaves in the field., record the GPS information., record the soil moisture and store the images and sends those images to cloud and finally the vehicle is moved one step. This whole process is the continuous process and we have used machine learning algorithms for its functioning on raspberry pi, in order to make it more efficient and to process huge amount of captured images. Our this semi autonomous vehicle would be very cost effective and efficient.

## 1.7 FLOW CHART



## **1.8 AIM AND OBJECTIVES**

### **1.8.1 AIM**

The aim of this project is to develop an semi-automated robotic system to collect the images of cotton crop leaves in the field.

### **1.8.2 OBJECTIVES**

Objective No#1: - Plant leaf detection by using Image processing technique

Objective No#2: - Development of semi- autonomous vehicle and assembly of vehicle, different modules and camera

Objective No#3: - Communication of the whole system and testing

## **1.9 THESIS LAYOUT**

The thesis is consisting of 6 chapters and it is organized in the following way:

- Chapter 1: This chapter is about project overview, providing a through introduction about the project and it includes Problem Statement, Research Questions, Motivation, Project Idea, Aim and Objectives of the project that has been successfully achieved.
- Chapter 2: This chapter contains a Literature review of the entire project where we have listed and discussed all those Researchers papers through which we have done our survey.
- Chapter 3: This is about components and tools, in this chapter we have discussed the methods, equipment, hardware tools, components, tools used in this project.
- Chapter 4: This chapter on project design and methodology, this chapter contains the whole methods and procedures discussion that are used to develop the entire system.
- Chapter 5: Results and discussion chapters in which we have listed all the test results and discussions accordingly.
- Chapter 6: Conclusion and future work: This chapter is consisting of overall achievement and future enhancements that can be achieved in the future.



## Chapter-2

### LITERATURE REVIEW

Since 1978, an automatic guidance system for agricultural purposes has been available with the Class autopilot. Originally manufactured for choppers, the modified version for tractors. The Class autopilot is a highly refined and dependable autonomous guidance system for a wide range of agricultural equipment. Its popularity has grown steadily since its launch. Class sells roughly 90% of their choppers and 15% of their combine harvesters fitted with the automatic steering system, as well as about as many of their autopilots licensed in other manufacturers' vehicles, according to Diekhans (1999). That implies it is the most popular, if not the only guidance system for agricultural vehicles available in Europe, with around 2500 sold systems per year. The problem with the Class system is that its mechanical sensors, like those of the Wulf systems, are confined to crops that provide reliable tracing guidelines. This need is addressed in maize, grain, and sugar beet harvesting, but jobs like weeding and spraying require non-contact object detection.

National and public research institutes have recently pooled their experience in the new autonomous navigation technology, in 1995 the Agricultural Machine Development Project and the Practical Promotion Project were launched [2] under these principles, with the goal of developing agricultural robots and systems for autonomous field navigation because of some requirements and enhancement needed to further processed and improvements their project.

In 2000, It was a first time that vehicle has been driven by an autonomous vehicle in agriculture [3]. It will Use a laser system that set a exact position determination, even in three dimensions, but the need of precise placed reflectors for each field boundary that makes it too inflexible and expensive. GPS systems have the problem that positioning the antenna on the rooftop of an agricultural vehicle with implements working on ground level means, on slope ground and with changing soil conditions, deviations occur between the virtual guideline and the path described by the implement. Solving this needs attitude measurement, which can be achieved by attitude measurement. Guidance systems utilizing machine vision in addition have to deal with changing light conditions, shadows, direct sunlight and other difficulties with extracting guidelines from images captured in the working environment Sensors, including mechanical ones, global navigation satellite systems (GNSS), machine vision, laser triangulation, ultrasonic and geomagnetic, generate position, attitude and direction-of-movement information. Actuators, like hydraulic valves, are used to transform guidance information into changes of position and direction.

Navigation in a car Color information was employed in (2004) to detect crop rows.[4] that employed color information for real-time image processing in maize fields to distinguish between crops and weeds. In the meantime, texture classification is part of the image processing research. In the year (2009) suggested a multilayer CCR (Coordinated Clusters Representation) to classify texture images, that proposed is Radom transform and multiscale analysis that is combined a CCR, LBP (Local Binary Pattern), and Gabor features to classify texture images. In a ridged field with no crops, we describe an image processing method for distinguishing between traversable (furrow) and non-traversable (ridge) regions. Instead of using crop color and information about the presence of shade and the texture of the soil were used.

In 2010, Precision farming technology [5] involved in various ways: low-cost sensor and servomotors, low-cost microprocessors, Cloud-based systems, crucial data analysis, expanded automation capabilities, and an onboard computer. This transition began in tandem with a comparable trend in the industrial world, dubbed Industry 4.0, and as a result, the name Agriculture 4.0 has been coined to describe agriculture's future production vision. Agriculture 4.0 refers to a network of agricultural operations that is both internal and external, implying that digital formats exist in all sectors. Other frequent themes linked with Agriculture 4.0 are intelligent agriculture and digital farming, which are predicated on the growth of intelligent technology and gadgets in agriculture, which open the ground for subsequent transformations through remote controlled decision-making systems. Adaptability of agricultural systems, crop enhancement and efficiency, water use optimization, and phytosanitary products are the major goals, all of which have their roots in precision farming.

In the year 2011, an image processing techniques to discriminate between crops and weeds in maize fields, as well as texture and shade images[6]. Here, is present an image processing method for discriminating between traversable and non-traversable regions of a field that has no crops in it. In this method, it will be detected 100% of upper ridge edges in an image that has not only shade by ridges but also shade by a pole or something; nevertheless, this method detected edges successfully because Hough transform was used. Note that this method for images with shade was not influenced by shade of artificial structures such as poles or other structures. This method detected 87% of furrow center lines successfully. The difference of looking between ridge and furrow was focused on. Because of that, for images that have rough looking furrow or collapsed ridge, which is similar to ridge looking, this method did not provide proper center lines. And this Method combining grey level histogram and DFT sorted images with shade from images with no shade 100% correctly. Test images were 53, consisted of 30 images with shades and 23 images with none.

In 2014-2015, using Android Application technique [7] that performs the basic operations like color transformation, Thresholding and edge detection. It identifies the

actual type of disease and its symptoms. Using SVM-GA classifier to Diagnosis the cotton leaf disease symptoms, remedy measures and recovery suggestions are given at a very less time. SVM with genetic algorithm-based method given higher accuracy rate and error rates than existing models for cotton leaf disease classification. Existing Algorithms BPN, Fuzzy logic and SVM Classifiers with Edge, CMYK Color splitting model features have been combined and tested with our own collected cotton leaf data sets. For classification made with genetic for separating cotton leaf diseases. Results for SVM-GA classifier. The disease is detected early on before diseases affect the Entire plant.

In the year 2016, a Deep Fruit Detection in Orchards [8] was developed it tries to create an accurate and reliable image-based fruit detection system for agriculture tasks, such as yield mapping and robotic harvesting. The architecture of the network is based upon Faster RCNN, which has become quite a popular method due to its high accuracy and reliability. In this research paper, are presented the Deep Fruit Detection. In this is a ability to detect the image data captured from orchards it is using the state art detection framework R-CNN. Studies were conducted over 3 orchard fruit types: Apple, Mangos and Almond. A fruit detection was considered to be a true positive if the predicted and the Ground truth bounding box had an Intersection over Union (IoU) greater than 0.2. This equates to a 58% overlap along each axis of the object, which was considered sufficient. Faster R-CNN .This is not the first blog that discusses the implementation of Faster R-CNN, which has become quite a popular method due to its high accuracies it can achieve on object detection. Anchor boxes that lie outside of the image are not used for training and are removed.

In 2017, a method for disease identification and classification using machine learning mechanisms and image processing[9] tools was designed. For the task of disease categorization, they used Support Vector Machines Classifiers. The results of a survey on several disease classification and identification approaches can be found in 2016. A rover with a camera mounted on it that goes around the field and collects data can be used to capture the current state of the crops. Algorithms can be used to process the images acquired by the camera, and classifiers can be used to identify the disease, allowing appropriate measures to be done. Because agricultural farms feature uneven terrain, a rover must be built to be capable of driving on such a rough surface.

In 2016, 2017, and 2018, was developed in a field of RobHortic is a proximate sensing based remote-controlled[10] for the designed to evaluate the presence of pests and diseases in horticultural crops field tests were conducted. The first two years were spent primarily on developing the robot, improving the software, and setting up the sensors in a real-world setting, while the 2018 assays focused on collecting and analyzing crop data. Since they were commercial crops of carrots cv 'Soprano F10, and the fields alter the crop every year, a different test field was chosen each year depending on

availability. The fields, which range in size from 0.5 to 2 ha, were chosen by specialists. The crop was planted in rows with a width of roughly 1 m and three ridges in each row in all cases. Photographs of the testing grounds. Autonomous robot navigation in orchards and open fields is difficult because it relies on guidance systems that must be extremely precise in constantly changing, unstructured environments with a wide range of crops and production systems. The navigation of agricultural robots on rugged and uneven terrain or in various weather situations is much more difficult, which means that navigation algorithms must adapt to identify specific aspects of the target crop. The first two years were spent developing and fine-tuning the robot and sensors, as well as testing data capture and geolocation. Tests were carried out in the third year to detect asymptomatic infected plants. As a reference, plants were analyzed by molecular analysis using a specific real-time Polymerase Chain Reaction (PCR), to determine the presence of the target bacterium \sand compare the results with the data obtained by the robot.

In the year 2019, an Smart Irrigation with Field Protection Crop and Health Monitoring system[11] was developed to automate agriculture which enhances irrigation, protection of farmlands and health management. the system's outcomes will take agriculture to the next level of development. The design will reduce manual effort and errors, resulting in increased agricultural output. Crops receive the optimal level of water and water waste can be avoided by following the irrigation method outlined in the paper. The early detection of nutritional deficiencies and illnesses aids the farmer in lowering output losses and protecting the farmland from physical damage. When connected to the Internet of Things, the system allows farmers to monitor their crops from afar. When all of the information on all of the crops is gathered, this model may be applied to all plants, allowing farming to be automatized.

In the year 2020, Precision agriculture (PA) [12] has become a trending research topic due to the increasing demands for environmental protection, cost reduction and yield enhancement for the propose of a new set of solutions to precisely manage the farm fields. A team of researchers have developed a way to detect the rover's position inside a furrow using advanced computer vision algorithms. They are able to adaptively adjust the threshold to segment crops in the picture according to the ambient Light intensity and crop size at the time when the picture is taken.

## **2.1 RESEARCH GAP**

In the research survey, we read so many research papers where we found that from the beginning of semi-autonomous till now, the use of technology is continuously changing. As mentioned in the literature review, in the year 1978, the 1 st technology used for the manufactured for choppers, they are a modified version for tractors is a

highly refined and dependable autonomous guidance system for a wide range of agricultural equipment. All the work done previously is for the monitoring and collecting dataset, in the case of any cotton crop leaves detection and dataset collection, Here have to many techniques and methods are used in literature papers to identify the cotton crops leaves detection and classification such as image processing and Android Application techniques are used, which is highly effective for providing a dataset collection and identification. Our goal is to develop a semi-automatic robotic system that collects images of cotton leaves in a field. Therefore, integrating automation into agriculture can improve efficiency and productivity in many ways. This project brings a specific approach to automated farming that improves irrigation, land conservation, and health management. This process is carried out by semi-autonomous agricultural vehicles. The vehicle moves around the field, displays live streaming of data collected through on-board cameras, and finally detects the presence of plants in the field. This semi-autonomous vehicle also records the humidity ,soil moisture, GPS location and stores the images and sends those images to cloud and finally the vehicle is moved one step. This whole process is the continuous process and we have used machine learning algorithms for its functioning on raspberry pi, in order to make it more efficient and to process huge amount of captured images. Our this semi-autonomous vehicle would be very cost effective and efficient.

## Chapter-3

### COMPONENTS AND TOOLS

In this chapter, all the hardware and software tools, technologies and specifications that we have utilized in our project to achieve our tasks are described.

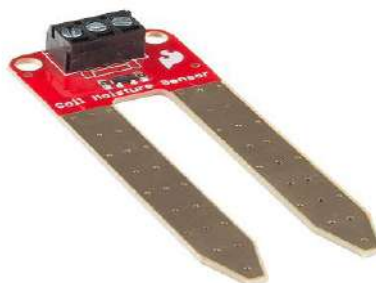
#### 3.1 HARDWARE COMPONENTS

The project's hardware description includes the components and materials needed to build the system prototype.

##### 3.1.1 SOIL MOISTURE SENSOR

Both the irrigation industry and botanical gardens rely on soil moisture. Water must be provided to regulate the temperature of the plant so that the soil nutrients provide the food it needs to grow. Soil moisture sensors are used to estimate the volumetric water content of soil. The direct gravimetric dimension of soil moisture should be removed, dried, and the sample weighted. These sensors indirectly sense volumetric water content by replacing water content with electrical resistance, neutron interaction, dielectric constant, and some other principles.

Figure 3.1: soil-moisture-sensor-device



Changes to the connection between the calculated property and soil moisture are required, and these changes may be influenced by factors such as temperature, soil type, or electric conductivity. Mainly used in hydrology and agriculture, reflected microwave radiation can be affected by soil moisture content. Capacitance is primarily used in this sensor to measure soil moisture content (permittivity). This sensor works by inserting it into the soil and can provide the moisture content status of the soil as a percentage.

Table 3-1: Soil Moisture Sensor Pin Configuration

Pin No.	Pin Name	Description
1	VCC	It provides a power to the module
2	A0	This pin provide analog output
3	D0	This pin provide digital output
4	GND	This pin is used to ground

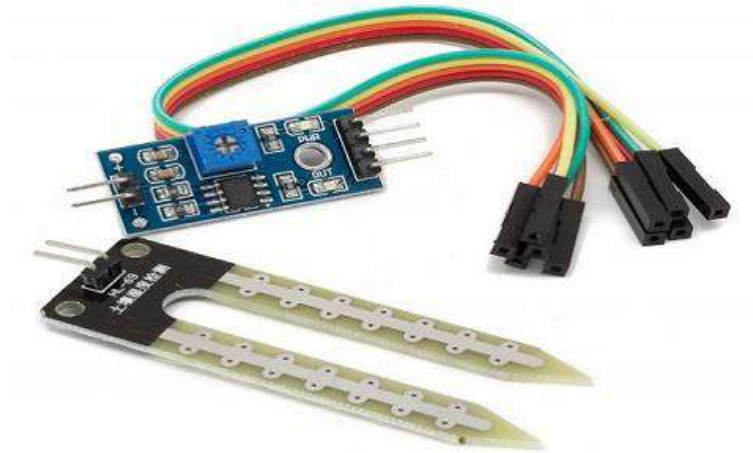


Figure 3.2: soil-moisture-sensor

### 3.1.1.1 SOIL MOISTURE SENSOR FEATURES

- Operating voltage: 3.3V to 5V DC.
- Operating Current: 15mA.
- Digital Output – 0V to 5V, trigger level adjustable from preset.
- Analog Output - 0V to 5V based on the infrared radiation from the flame striking the sensor.
- Output and power indicated by LED's

### 3.1.2 PAN-TILT STRUCTURE

A camera-based Pan-Tilt device controller. This technique uses the target picture feature to rapidly move the Pan-Tilt device toward the target. Due to the fact that these systems are commonly installed on portable equipment, energy efficiency is another crucial issue to take into account. To improve the attached camera's associated Pan-Tilt system's control energy efficiency



Figure 3.3: Pan-Tilt Structure

You may attach and operate the pan-tilt modules directly on the top of your Raspberry Pi using the Pan-Tilt HAT. You may separately control the two servos (pan and tilt) as well as up to 24 conventional LEDs (with PWM control) or NeoPixel RGB (or RGBW) LEDs using the HAT and its on-board microprocessor. The servo, LED, and camera wires may easily be run through a convenient slot. The module pans and tilts in both axes by 180 degrees. Face tracking with a Pi camera and Pan-Tilt HAT. Or attach it as eyes on top of your mobile robot. The pan/tilt module's servos are connected by female jumper wires and connected by soldering a series of right-angle header pins to the underside of the HAT, so no soldering is required (optional NeoPixel strips or ring).

#### 3.1.2.1 PAN-TILT STRUCTURE FEATURES

- Pan-tilt module with 2 servos (180-degree movement about each axis)
- HAT with 2 servo channels, 1 PWM or NeoPixel RGB (or RGBW) LED channel
- Bottom of HAT for servos Right angle headers and LED channels pre-soldered to
- Slots for feeding servos, LEDs, and camera cables through
- Acrylic brackets for mounting Pi cameras and Neo Pixel strips (with diffuser)
- Pan /Tilt HAT Pinout
- Compatible with all 40-pin headers on the Raspberry Pi Models
- Python Library



- Fully assembled

### **3.1.2.2 PAN-TILT STRUCTURE SPECIFICATION**

- Operating Voltage: 3.3V/5V
- Control Chip: PCA9685
- PWM Resolution: 12-bit
- Ambient Light Sensor: TSL25911FN
- Ambient Light Resolution: 12-bit
- Logic Voltage : 3.3V
- Communication: I2C
- Dimension: 56.6\*65mm/2.23\*2.56"

### **3.1.3 BATTERY**

Currently, lead-acid batteries are the most common type of battery Used for solar and wind energy storage. Lead acid batteries are a poor choice in terms of cost and environmental efficiency due to their low cycle number and short lifespan.

In the development of 12V tubular flooded lead acid batteries, Volta is a pioneer. These Deep Cycle batteries were designed specifically for Solar & UPS applications. This battery's manufacturing architecture is distinct from existing SLI (Starting, Lighting & Ignition) and traditional UPS batteries. It contains thick plates for the negative for deep discharges and tubular plates for the positive to increase battery life. All applications now have portable batteries that can easily replace current lead-acid batteries. It weighs 47.6 kg and measures just 151mm x 65mm x 98mm (5.9" x 2.5" x 3.8"), less than 1/4 the weight of traditional lead-acid batteries.



Figure 3.4 :12v 7.2AH Valve Regulated Lead Acid AGM Battery

### 3.1.3.1 SPECIFICATION

Table 3-2: Battery Specification

Battery Type	Sealed (Dry) Battery: No Tubular Battery: Yes Deep Cycle Battery: Yes
Capacity & Plates	Capacity: 135 Ah Number of Plates: 7
Dimensions	Length (mm): 506 Width (mm): 220 Height (mm): 296
Battery Weight (Kg)	47.6 Kg

### 3.1.3.2 FEATURES

- Tubular Positive Plate & Thick Negative Plate for increased battery life.
- Low internal resistance with good electrical performance
- Float indicators are provided to help determine electrolyte level easily.
- These batteries have life of over 1500 cycles at 60% Dept of Discharge (DoD).  
(For details refer to DoD graph in 'stats for geeks' section)
- Easy Carrying Handles
- Low self-discharge

### 3.1.4 RASPBERRY PI 4 MODEL B

The Raspberry Pi 4 Model B is the latest in the popular Raspberry Pi computer series. It offers a leap in processor speed, multimedia performance, storage, and connectivity compared to his Raspberry Pi 3 Model B+ of the previous generation, while maintaining backwards compatibility and comparable power consumption. For end users, the Raspberry Pi 4 Model B offers desktop performance that rivals entry-level x86 PC systems.

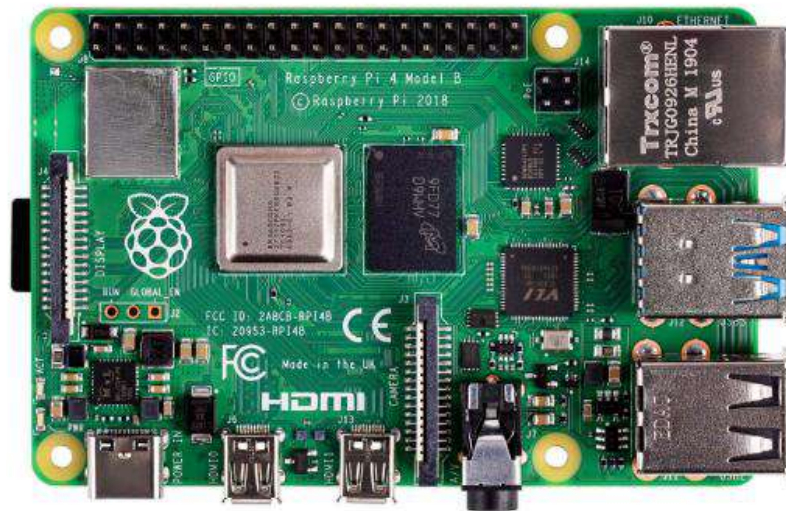


Figure 3.5: Raspberry Pi 4 Model B

#### 3.1.4.1 RASPBERRY PI 4 MODEL B FEATURES

- Powerful 64-bit quad-core processor
- Dual display support at resolutions up to 4K via a pair of micro-HDMI connectors
- Hardware video decoding up to 4Kp60, up to 4GB RAM
- Dual band 2.4/5.0 GHz WiFi, Bluetooth 5.0
- Gigabit Ethernet, USB 3.0, and PoE capability (via separate PoE HAT add-on).

Table 3-3 Raspberry-pi 4 Model b specification

<b>Parameters</b>	<b>Specification</b>
Processor	Cortex-A72 (ARM v8) 64-bit SoC @ 1.5GHz
Memory	1GB, 2GB or 4GB LPDDR4
Connectivity	2.4 GHz and 5.0 GHz IEEE 802.11b/g/n/ac wireless LAN, Bluetooth 5.0, BLE
GPIO	Standard 40-pin GPIO header
Video & sound	2 × micro-HDMI ports (up to 4Kp60 supported)
Multimedia	H.265 (4Kp60 decode); H.264 (1080p60 decode, 1080p30 encode)
Micro-SD card support	Micro SD card slot for operating system and the data storage
Input voltage	5V DC via USB-C connector (minimum 3A)
Environment	Operating temperature 0–50°C

### **3.1.5 5MP RASPBERRY PI CAMERA MODULE**

This 5MP Raspberry Pi Camera Module Rev 1.3 attaches straight to your Raspberry Pi and supports 1080p video and picture images. Connect the aforementioned ribbon wire to the Raspberry Pi's CSI (Camera Serial Interface) connector.

With dimensions of around 25 x 20 x 9 mm and a weight of little over 3 g, the board itself is incredibly small, making it ideal for mobile devices or other applications where size and weight are crucial considerations. The product's sensor features a fixed-focus camera lens with a native resolution of 5 megapixels. The camera is capable of 2592 x 1944 pixel still photos and also supports video in 1080p30, 720p60, and 640x480p60/90.

#### **3.1.5.1 PORTS CONNECTION**

1. Soft cable, 90-degree vertical shape connector, HDMI port next to it. When linking the contact side is facing the HDMI interface.
2. Tear protective film with the camera lens.

3. Bare boards, pay attention to ESD damages, beware of static electricity.

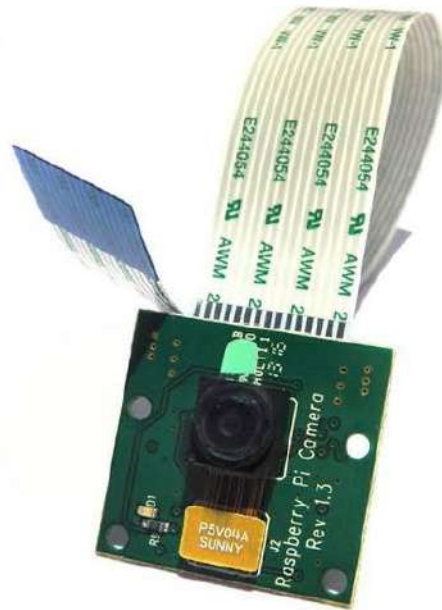


Figure 3.6: 5mp Raspberry Pi Camera Module

### 3.1.5.2 SPECIFICATION

- Fully compatible with Model A and Model B Raspberry Pi
- 5MP Omnivision 5647 Camera Module
- Still image resolution: 2592 x 1944
- Video: - pin serial MIPI camera interface - plugs directly into Raspberry Pi board
- Size: 20 x 25 x 9mm
- Weight 3g
- Fully compatible with many Raspberry Pi

## 3.1.6 VEHICLE PARTS

### 3.1.6.1 CHASSIS

In automobile chassis is the external structure of the vehicle which houses the all the components of the vehicle and mounted on the wheels of vehicle with help of frame.

Frame is an integral part of chassis on which the whole body of vehicle is mounted.

The following plastic sheets have been used for the chassis of vehicle designing:

- 12 inch x 12 inches (3 black pieces of plastic sheets )
- 13x 16 inches ( 1 white piece of plastic sheet)
- 8x6 inches (2 black plastic sheets)
- 9x7inches (1 white plastic sheet)



Figure 3.7: Chassis

### 3.1.6.2 WHEELS

Wheels are the foundation of vehicle designs since they are easy to utilise. The two front wheels are normal wheels that are powered by motors, and when we talk about a wheel's size, we often mean its diameter rather than its radius (which is half the diameter). The circumference of the wheel is calculated by multiplying the diameter by pi (approximately 3.1415926), and it affects the design of many elements such as the chassis design, the motor speed ratings and vehicle, and the motor controller programming. The size of the wheels also affects how much surface area they come into contact with, which is different from what is typically the case with wheels. and as a result exert a much lower force per unit area on the ground being traversed.



Figure 3.8 Vehicle Wheel

### **3.1.6.3 DC GEAR MOTOR METAL**

The 6V-12V DC Gear Motor packs a lot of power into a reasonably small space using a metal gearbox and a brushed DC motor with extra-strong magnets. These devices have a D-shaped output shaft that is 0.315" long and 4 mm in diameter. The recommended voltage for these motors is 6 V. Although they can start rotating at voltages as low as 1 V, these types of motors can often work at voltages above and below this nominal voltage, thus they should perform easily in the 3 - 9 V range. Higher voltages may begin to shorten the motor's lifespan.

This gearmotor has a strong 24V brushed DC motor, a 6.25:1 metal gearbox, and an incorporated quadrature encoder that offers a resolution of 64 counts per motor shaft rotation, which equates to 400 counts each gearbox output shaft revolution. These devices feature a D-shaped output shaft that is 16 mm long and 6 mm in diameter. The motor accelerates to 10,000 rpm at 24V before slowing down.



Figure 3.9: DC 6-12V Gear Motor Metal

### 3.1.6.3.1 SPECIFICATION

- Gear Ratio: 98.78:1
- Nominal Voltage: 6V
- No Load RPM: 97
- No Load Current: 0.55A
- Rated RPM: 65
- Rated Torque: 47 oz-in
- Stall Current: 6.5A
- Stall Torque: 210 oz-in
- Shaft Type: D-Shaped

### 3.1.6.3.2 FEATURE

- Full metal construction for impact resistance and long durability.
- Output 220 complete pulses everytime the motor output shaft revolve one circle.
- up to 64 RPM
- Stable performance, high reliability, low running noise.
- Small volume, light weight, easy to install.

### 3.1.6.4 MICRO SD CARD 32GB

A Secure Digital High Capacity memory card in the micro size is the SanDisk 32GB micro SDHC Memory Card Ultra Class 10 UHS-I. The card's 32GB of data storage capacity offers plenty of room for pictures and movies taken with your camera or smartphone. With read and write speeds up to 30MB/s and lower write rates that should at least be able to reach the Class 10 minimum of 10MB/s, it offers an SD Class 10 rating in addition to an Ultra High Speed Class 1 rating. The card is perfect for HD1080p video capture and transmission thanks to these speeds. The SD adapter has a built-in write-protect switch that avoids unintentional data loss.



### 3.1.6.4.1 SPECIFICATION

Table 3-4: Micro SD Card Specification

Parameters	Specification
Brand	Sandisk
Warranty	Check at Delivery
Internal Memory	32GB
Memory Type	MicroSD
Class	10



Figure 3.10: SanDisk 32GB MicroSDHC Memory Card

### 3.1.6.5 MICRO HDMI TO VGA CONVERTER WIRE

A foldable HDMI to VGA converter that connects your smart device to a monitor with a VGA port. This portable micro HDMI to VGA converter can be used to connect your tablet, smartphone or other device to a monitor or projector with a VGA port. The connection between the adapter and a monitor or projector also needs a VGA cable, which is not provided with this adapter.



Figure 3.11: Micro HDMI To VGA Converter Wire

#### **3.1.6.5.1 FEATURES**

- Connect your tablet, smartphone, or other device with micro-HDMI to a monitor or projector with a VGA port.
- USB POWERED ACTIVE MICRO HDMI to VGA converter. Equipped with an integrated IC chip for better compatibility between devices and displays. LEGACY
- COMPANION for existing monitors or projects using VGA.

#### **3.1.6.6 POWER SUPPLY FOR RASPBERRY PI**

Raspberry pi 4 generation power supply interface, type-B can be inserted both front and back side, it will not appear the issue of plugging reverse. It included different of function, such as over power protection, over current protection, short circuit protection, over voltage protection, under voltage protection, electrostatic protection.

Note: Raspberry PI 4 special power supply, could not support 3B+/3B!



Figure 3-12 Power Supply For Raspberry Pi

### **3.1.6.6.1 FEATURES**

- AC 100-240V 50/60Hz input with US plugs
- DC 5.1V 3A output
- 15.3W maximum output power
- 1.5m 18 AWG cable
- USB-C output connector

### **3.1.6.6.2 SPECIFICATION**

- 2.5A output
- 1.5m lead
- Interchangeable heads for different countries
- Short circuit, over current and over voltage protection
- 50,000 hours MTBF
- 1 year warranty

### **3.1.6.7 DHT-11 TEMPERATURE AND HUMIDITY SENSOR**

DHT-11 is simple, incredibly affordable Digital Temperature and Humidity Sensor / Humidity is monitored using a capacitive humidity sensor and thermistor to generate a digital signal on the data pin (no analog input pin required). It's fairly easy to use, but collecting data requires precise timing. This sensor's sole significant flaw is that it can only provide you with fresh information once every two seconds. The sensor reading interval in your code should be set to at least two seconds as a result



Figure 3-13 DHT-11 Digital Temperature And Humidity Sensor

### 3.1.6.7.1 FEATURES

- Energy efficiency.
- Relative Humidity and Temperature Measurement
- Fully Calibrated Digital Output
- Excellent Long-Term Stability
- No Additional Components
- Long Range Signal Transmission
- Ultra Low Power
- Complete changeable

### 3.1.6.7.2 SPECIFICATION

Table 3-5: DHT-11 Digital Temperature And Humidity Sensor

Humidity Measurement in (%)	20 to 90
Temperature Measurement ( $\hat{A}^{\circ}\text{C}$ )	0 to +50
Humidity Accuracy in (%)	$\hat{A}\pm 5.0$
Temperature Accuracy	$\hat{A}\pm 2.0$
Response Time(s)	<5
Length (mm)	23

Width (mm)	12
Height (mm)	5.5
Shipment Weight	0.02 kg
Shipment Dimensions	3.5 × 2 × 6.5 cm

### 3.1.6.8 NEO 6M GPS MODULE

A whole GPS module is the U-blox NEO-6M. The powerful U-blox 6 positioning engine is utilized by a variety of standalone GPS receivers referred to as the NEO-6 module series. This gadget uses the latest U-blox technology and features a larger built-in 25 x 25mm active GPS antenna with UART-TTL connectivity to provide the most accurate location information. The ardupilot mega v2 may make use of this improved GPS module. This GPS module provides optimal position data for improving multirotor performance on the Ardupilot or any multirotor control platform.



Figure 3-14 UBLOX NEO-6M V2 GPS-MODUL

### 3.1.6.8.1 FEATURES

- 5Hz position update rate
- Operating temperature range: -40 to 85 °C CUART TTL socket
- EEPROM for saving configuration settings
- Rechargeable battery for backup
- 38 seconds cold start time and 1 second
- Supply voltage: 3.3V
- Configurable rate from 4800 baud to 115200 baud. (default 9600)
- SuperSense<sup>®</sup> Indoor GPS: -162 dBm Tracking sensitivity
- Supports SBAS (WAAS, EGNOS, MSAS, GAGAN)
- 18 x 18 mm independent GPS antenna

### 3.1.6.8.2 SPECIFICTION

- Power Supply Range: 3 V to 5 V
- Model: GY-GPS6MV2
- Ceramic antenna
- EEPROM for saving the configuration data when powered off
- Backup battery
- LED signal indicator
- Antenna Size: 25 x 25 mm
- Module Size: 25 x 35 mm
- Mounting Hole Diameter: 3 mm
- Default Baud Rate: 9600 bps

## 3.2 SOFTWARE DISCRPTION

### 3.2.1 PYTHON PROGRAMMING LANGUAGE

Python was designed by Guido van Rossum and published in 1991. Python is a high-level, object-oriented programming language that is user-friendly for beginners. It is also known as a general-purpose programming language. Python is cross-platform compatible (Windows, Mac, Linux, Raspberry Pi, etc). Its straightforward syntax is identical to that of English. Additionally, compared to certain other programming languages, it offers a syntax that enables developers to build programs with less lines. Python operates on an interpreter system, allowing for the immediate execution of written code. As a result, prototyping may proceed quickly.

### 3.2.2 TENSOR FLOW

Tensor Flow is an end-to-end platform that makes it simple to design and execute machine learning models. We get features like keras and API for complicated topologies, you can train and deploy your model on servers, edge devices, or the web with ease thanks to TensorFlow, which has always provided a straightforward way to get your code into production. Only a handful of the advanced add-on libraries and models offered by TensorFlow include Ragged Tensors, TensorFlow Probability, Tensor2Tensor, and BERT. Abstraction is a key advantage that TensorFlow offers for machine learning development. Developers can focus on the overall logic of the program instead of worrying about algorithmic implementation details or figuring out how to connect the results of one function to the inputs of another.

The details are processed in the background via Tensor Flow. Developers that need to debug and gain insight into TensorFlow can take advantage of extra conveniences provided by TensorFlow, as well as flexibility and control. Whatever the case language or platform you choose TensorFlow apps. Each graph operation can be evaluated and modified separately and transparently, instead of constructing the entire graph as a single opaque object and evaluating it all at once. This so-called "eager execution mode," provided as an option in older versions of TensorFlow, is now standard.

### 3.2.3 KERAS

A Python interface for artificial neural networks is provided by the open-source software package known as Keras. The TensorFlow library interface is provided by Keras. TensorFlow, Microsoft Cognitive Toolkit, Theano, and PlaidML were just a few of the backends that Keras supported up until version 2.3. The three main goals of Keras are modularity, usability, and extensibility. Low-level computations are sent off to the Backend, a different library, rather than being handled by it.

In the middle of 2017, Keras was adopted and incorporated into TensorFlow. It is accessible to users through the `tf.keras` module. The Keras library may still function independently and individually, though. Developers that seek a plug-and-play framework that enables them to design, train, and assess their models rapidly are better suited for Keras. Additionally, Keras provides simpler model export and additional deployment choices. When it comes to tiny datasets, quick prototyping, and numerous back-end support, Keras excels. Due of its relative simplicity, it is the most widely used framework. It functions on Windows, Mac OS, and Linux.

### 3.2.3 PYCHARM IDE

PyCharm has been regarded as the greatest IDE for Python developers and is used by the majority of professional developers in industries. This cross-platform IDE was created by the Czech firm JetBrains. It provides daily advice on how to utilize it more effectively, which is a very great feature. It is available in two versions: a community version and a professional version, the former of which is free and the latter of which is not. These IDE's additional features are shown below.

- It is regarded as a smart code, quick and secure refactoring, and intelligent code editor.

- Tools for the database, debugging, profiling, remote development, code testing, auto code completion, rapid fixes, and error detection.
- Assistance with well-liked web technologies, web
- Support for Popular web technologies, web frameworks, scientific libraries, and version control.

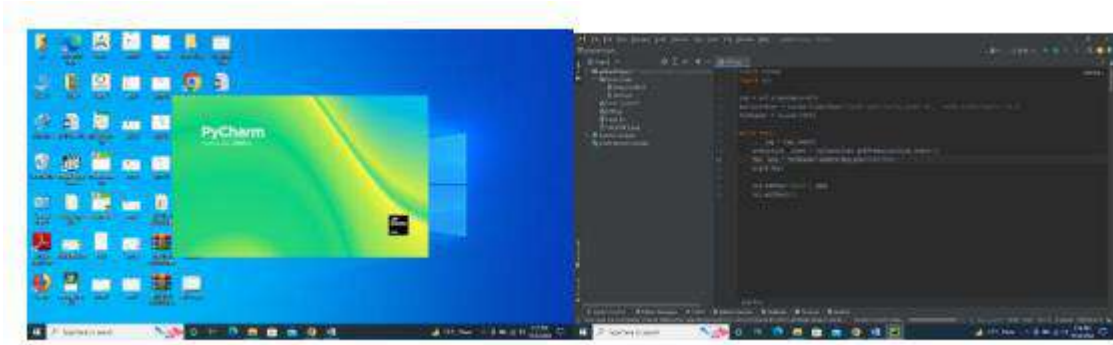
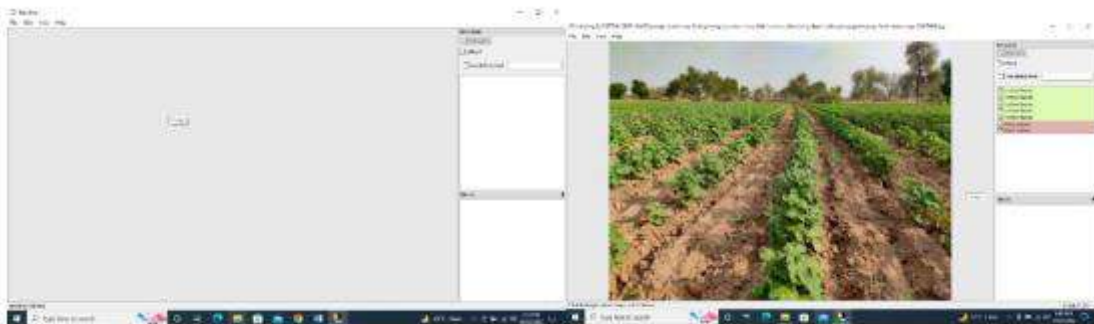


Figure 3-15: PyCharm IDE Environment

### 3.2.4 LABELIMG

An open source, free program for visually tagging pictures is called LabelImg. It uses QT for its graphical user interface and is developed in Python. To test out your upcoming object identification project, label a few hundred photographs using this simple and cost-free method. It also automatically stores the XML files of your labelled photos. LabelImg is a graphical image annotation tool that lets you visually box in your items in each image. It is a simple and cost-free approach to tag your photograph.

Figure 3-16: labelImg Environment



### 3.2.6 PYTHON LIBRARIES

A program's libraries are pre-expressed techniques that it can utilize. The schemes are sometimes referred to as modules, and they are saved in an object.

#### 3.2.4.1 OS

The library os is referred to the operating system. It is used to create or to remove the directory or a folder. It is used for the interfacing with the operating system.



### 3.2.4.2 SYS

The sys module in Python contains several methods and variables for manipulating various aspects of the Python runtime environment. It helps you to work with the interpreter since it gives you access to variables and functions that work closely with it.

### 3.2.4.3 CV2

It is a module which comes in the packages of OpenCV. It is an open-source machine learning and computer vision library. It can recognize objects, people, and even a person's handwriting in pictures and videos. As, it is an open-source library that can be used to perform tasks like face detection, objection tracking, landmark detection, and much more. It supports multiple languages including python, java C++.

### 3.2.4.4 CVZone

This is a Computer vision package that makes its easy to run Image processing and AI functions. At the core it uses OpenCV and Mediapipe libraries.

### 3.2.4.5 NUMPY

A library called NumPy is used to work with arrays, the Fourier transform, linear algebra, and matrices. It is a modification of Numerical Python. Compared to ordinary Python lists, NumPy provides an object array that is fifty times faster. Arrays are used when processing is sufficient and resources and speed are important. Arrays should be maintained in a continuous region where processes and actions may easily access and alter them, according to the locality of reference concept, on which NumPy is built.

## 3.3 METHODOLOGY

### 3.3.1 FLOW CHART OF MODEL TRAINING

The flowchart of model training is given below:

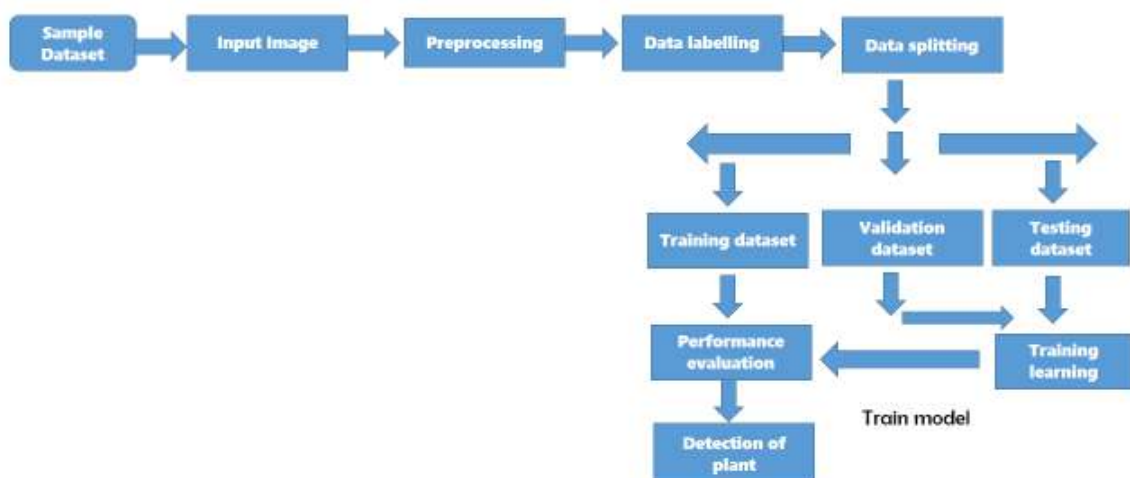


Figure 3-17:Flow Chart of Model Training

The model training requires four phases which are described below:

- 1) Data collection
- 2) Data labelling
- 3) Training datasets
- 4) Testing datasets

### 3.3.2 DATA COLLECTION

The entire collection of datasets is done manually by visiting field or by taken some of the datasets from kaggle.

### 3.3.3 DATA LABELLING

All those collected datasets are labelled by using software named as labelImg. During the labelling, two classes are defined: one is of cotton leaves and another one is of flate surface.

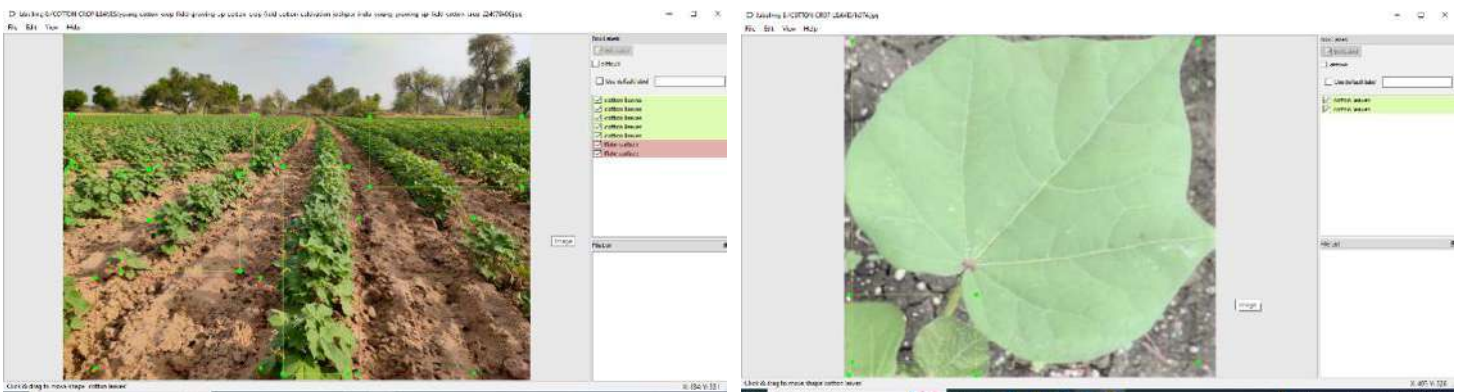


Figure 3-18: Labelling Of Cotton Crop Leaves And Flate Surface Using Labeling

Afterwards, during labelling, the .xml file is generated and it is saved with the same datasets and process of labelling is continued for the remaining datasets. This process of labelling is continued until all the datasets are labelled and the required .xml files are generated.

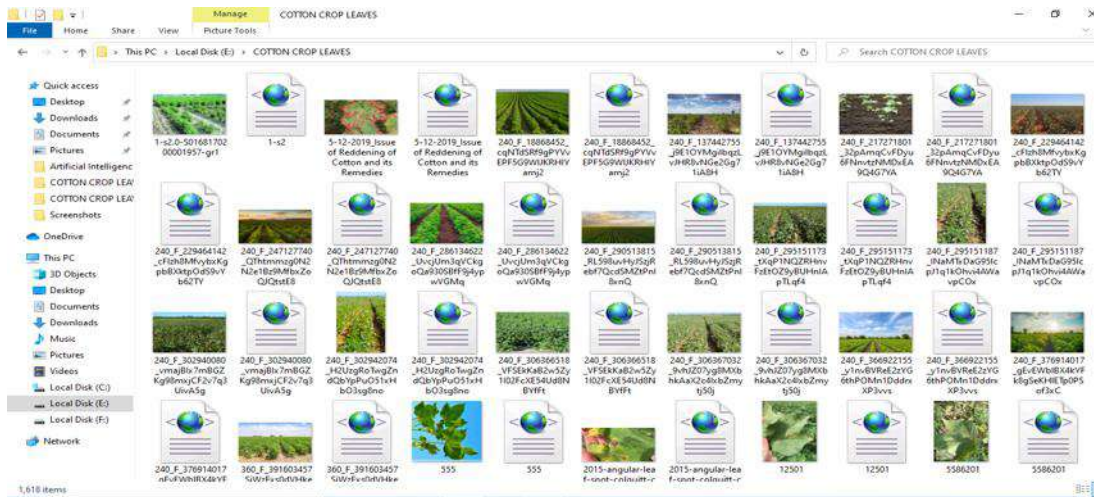


Figure 3-19: shows all the datasets are labelled and the required .xml files have been generated

### 3.3.4 TRAINING DATASETS

For training the model, 80% percent of the datasets are kept in the category of training. For this purpose, the required .xml file is converted into csv file, and the test and train labels are marked separately. Finally, the tf record is generated and the required training is started in order to have the trained model.

```

C:\Windows\System32\cmd.exe - python ssd_train.py --logtostderr --train_dir=training/ --pipeline_config_path=training/ssd_mobilenet_v2_coco.config
INFO:tensorflow:Saving checkpoint to path training/model.ckpt
2025 20:53:50.996833 7068 learning.py:507] global step 74: loss = 7.8949 (474.599 sec/step)
INFO:tensorflow:Saving checkpoint to path training/model.ckpt
2025 20:53:57.040204 8528 supervisor.py:1117] Saving checkpoint to path training/model.ckpt
INFO:tensorflow:Recording summary at step 74.
2025 20:54:38.462022 11236 supervisor.py:1050] Recording summary at step 74.
INFO:tensorflow:global step 75: loss = 7.5244 (583.472 sec/step)
INFO:tensorflow:Saving checkpoint to path training/model.ckpt
2025 21:07:54.757197 7068 learning.py:507] global step 75: loss = 7.5244 (583.472 sec/step)
INFO:tensorflow:Saving checkpoint to path training/model.ckpt
2025 21:07:55.003805 8528 supervisor.py:1117] Saving checkpoint to path training/model.ckpt
INFO:tensorflow:Recording summary at step 75.
2025 21:09:43.463923 11236 supervisor.py:1050] Recording summary at step 75.
INFO:tensorflow:global step 76: loss = 7.3923 (459.718 sec/step)
INFO:tensorflow:Recording summary at step 76.
2025 21:12:09.913860 11236 supervisor.py:1050] Recording summary at step 76.
INFO:tensorflow:Saving checkpoint to path training/model.ckpt
2025 21:24:12.946132 8528 supervisor.py:1117] Saving checkpoint to path training/model.ckpt
INFO:tensorflow:global step 77: loss = 8.2509 (564.980 sec/step)
INFO:tensorflow:Recording summary at step 77.
2025 21:31:13.041459 11236 supervisor.py:1050] Recording summary at step 77.
INFO:tensorflow:Saving checkpoint to path training/model.ckpt
2025 21:34:51.207692 8528 supervisor.py:1117] Saving checkpoint to path training/model.ckpt
INFO:tensorflow:global step 78: loss = 7.7830 (376.675 sec/step)
INFO:tensorflow:Recording summary at step 78.
2025 21:39:17.354472 7068 learning.py:507] global step 78: loss = 7.7830 (376.675 sec/step)
INFO:tensorflow:Saving checkpoint to path training/model.ckpt
2025 21:42:42.591387 8528 supervisor.py:1117] Saving checkpoint to path training/model.ckpt
INFO:tensorflow:Recording summary at step 78.
2025 21:52:42.591387 7068 learning.py:507] global step 79: loss = 8.8987 (705.921 sec/step)
INFO:tensorflow:Recording summary at step 79.
2025 21:53:35.161933 11236 supervisor.py:1050] Recording summary at step 79.
INFO:tensorflow:global step 80: loss = 7.5534 (592.984 sec/step)
INFO:tensorflow:Saving checkpoint to path training/model.ckpt
2025 22:05:14.954526 7068 learning.py:507] global step 80: loss = 7.5534 (592.984 sec/step)
INFO:tensorflow:Saving checkpoint to path training/model.ckpt
2025 22:09:52.582507 8528 supervisor.py:1117] Saving checkpoint to path training/model.ckpt
INFO:tensorflow:Recording summary at step 80.
2025 22:16:44.090370 11236 supervisor.py:1050] Recording summary at step 80.
INFO:tensorflow:Saving checkpoint to path training/model.ckpt
2025 22:19:06.090370 8528 supervisor.py:1117] Saving checkpoint to path training/model.ckpt
INFO:tensorflow:global step 81: loss = 7.6403 (701.131 sec/step)
2025 22:30:16.090370 7068 learning.py:507] global step 81: loss = 7.6403 (701.131 sec/step)

```

Figure 3-20: shows training of model

After that, the trained model is converted into keras for easily accessing it into pycharm IDE for opencv library package for the purpose of detection of cotton crop leaves and Flate surface.

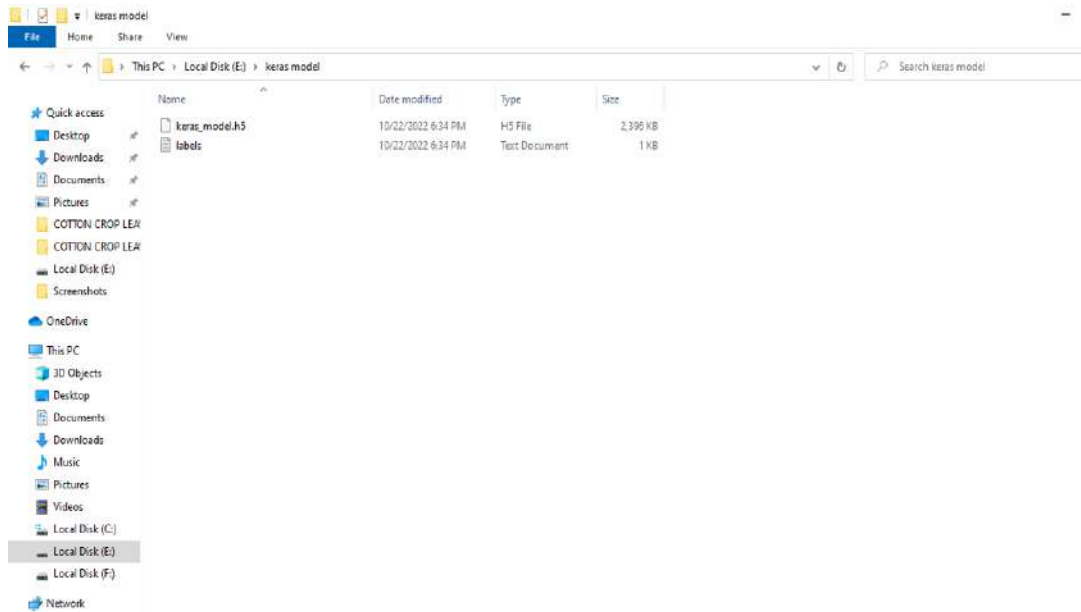


Figure3-21: shows required keras model has been achieved

### 3.3.5 TESTING DATASETS

For testing purpose, we have kept 20% datasets into the testing folder, in order to check the model for the purpose of detection of cotton leaves and flate surface.

### 3.3.6 SYSTEM BLOCK DIAGRAM

The system block diagram is given below:

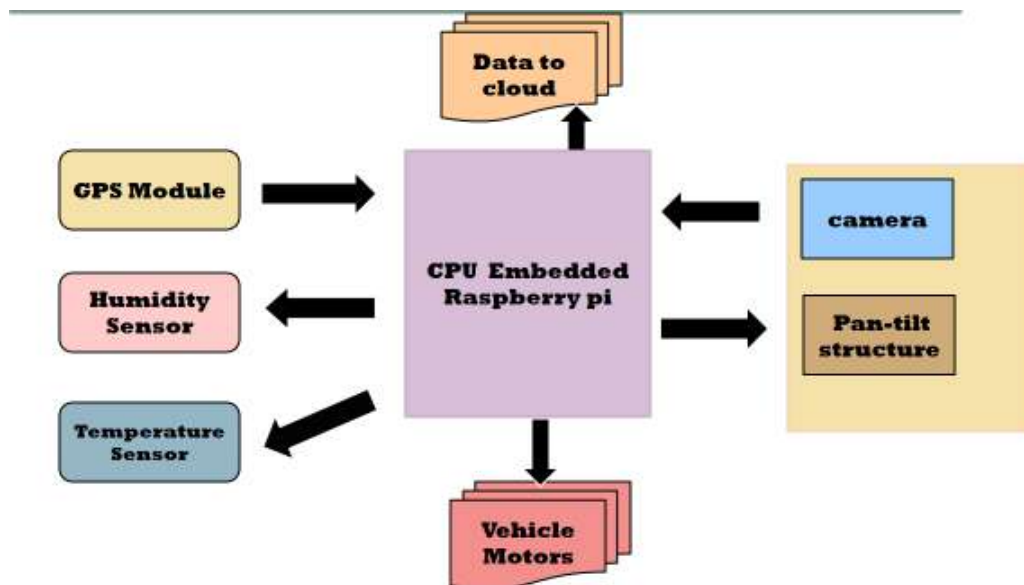


Figure3-22: System Block diagram

### 3.3.7 SYSTEM FLOW CHART

The system flowchart is given below:

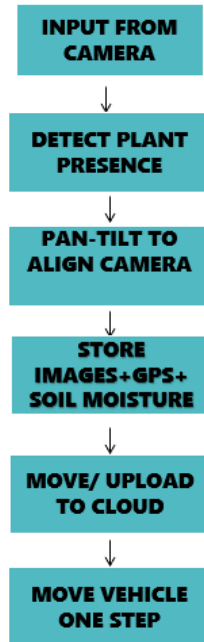


Figure 3-23: System Flow Chart

### 3.3.8 FINAL VEHICLE MODEL

The final designed and implemented vehicle model is given below:

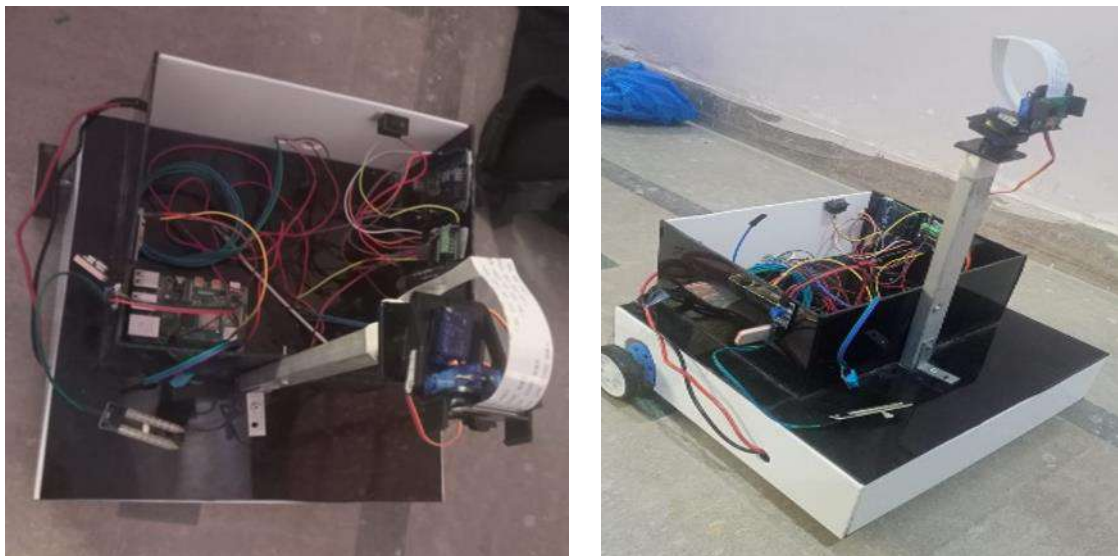


Figure 3-24: Final Vehicle



## Chapter-4

### RESULTS AND DISCUSSION

#### 4.1 COTTON LEAVES DETECTION RESULT AND DISCUSSION

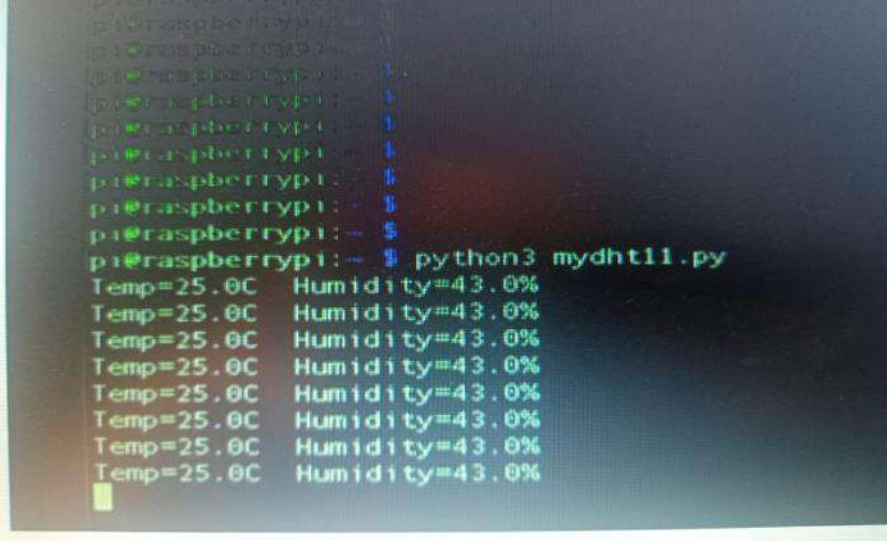
The following cotton leaves' detection results have been achieved by keras model. At the first, the tensor flow model is trained and designed. Afterwards, this tensor flow model is converted into keras model in order to make it easily accessible in opencv and cvzone python package. As, there are only two classes which have already been defined during labelling: one is of cotton leaves and another is of flate surface. So, by exporting keras model into PyCharm-IDE, the following results are achieved which are correctly detecting the cotton crop leaves.



Figure 4-1: shows detection of cotton crop leaves

## 4.2 TEMPERATURE AND HUMIDITY READING RESULT AND DISCUSSION

As, the DHT11 temperature and humidity sensor is interfaced with raspberry pi in this vehicle, in order to get the proper reading of temperature and humidity according to the available condition of environment. The following result has been achieved by importing Adafruit library, designing the python based code and by implementing the code into the Raspberry pi IDE environment. The readings of temperature and humidity completely depends on the environment, so these readings can vary every time.



```
pi@raspberrypi:~$ python3 mydht11.py
Temp=25.0C Humidity=43.0%
Temp=25.0C Humidity=43.0%
Temp=25.0C Humidity=43.0%
Temp=25.0C Humidity=43.0%
Temp=25.0C Humidity=43.0%
Temp=25.0C Humidity=43.0%
Temp=25.0C Humidity=43.0%
Temp=25.0C Humidity=43.0%
```

Figure4-2: Shows TEMPERATURE AND HUMIDITY READING

## 4.3 GPS LOCATION (LONGITUDE AND LATITUDE) RESULT AND DISCUSSION

The UBLOX NEO-6M V2 GPS MODULE is interfaced with raspberry pi in this vehicle, in order to get the proper reading of longitude and latitude of the available location. The following results have been achieved by importing some libraries, designing the python based code and by implementing the code into the Raspberry pi IDE environment. The readings of longitude and latitude of the GPS module completely depends on the current situation, so these readings are variable.





## **Chapter-5**

### **CONCLUSION AND FUTURE RECOMMENDATIONS**

#### **5.1 CONCLUSION**

The project's design is centered on the agricultural industry. Our goal is to create a robotic system that is semi-automated and will take pictures of cotton crop leaves in the field. Therefore, efficiency and production in the sector of agriculture may be improved in a variety of different ways by incorporating automation. This project highlights specific agricultural automation techniques that improve irrigation, farmland preservation, and health management. An agricultural vehicle that is semi-autonomous completes this procedure by moving about the field, transmitting data collection live from a camera mounted on it, and then seeing the existence of plants. Additionally, this semi-autonomous vehicle logs the temperature, soil moisture, GPS location, and saves and transmits photos. These images to save a cloud and finally the vehicle is moved one step. This whole process is the continuous process and we have used machine learning algorithms for its functioning on raspberry pi, in order to make it more efficient and to process huge number of captured images.

#### **5.2 ADVANTAGES**

Automated Image Dataset collection system for cotton crop leaves has the following Benefits:

1. The system has automatic measurement facilities
2. Fewer chances of error as compared to manual entries
3. Cost-effective system
4. Time-saving process
5. Hardware and software can be used independently
6. Easy to used
7. Less number of labors Required
8. Reduces large-scale surveillance work on large farms

### **5.3 APPLICATIONS**

1. Our system can be used in cotton crops field to reduce the number of labors required.
2. Our system can be used where manually dataset collection are not available.
3. Our system also used to record real time live streaming.
4. This system is also used to monitor big farms of crops leaves.

### **5.4 FUTURE WORK**

The system is somewhat autonomous now, but we can make it totally automatic in the future. The system only records four vitals, including humidity, soil moisture, GPS position, and picture storage. More vitals might be recorded, such as the detection, categorization, and treatment of illnesses. In this project, the Raspberry Pi and PyCharm IDE are used to process and operate the hardware component.

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