RGB Sensor-Based Drone Imagery for Crop Health Assessment

A BS Final Year Project by

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Certificate of Approval

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In the name of Allah (SWT), the most beneficent and the most merciful

A BS Final Year Project submitted to the

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For the award of the degree of

Bachelor of Science in Electrical Engineering.

Declaration

We hereby declare that this work, neither as a whole nor as a part thereof has been copied out from any source. No portion of the work presented in this report has been submitted in support of any application for any other degree or qualification of this or any other university or instituteof learning. We further declare that the referred text is properly cited in the references.

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- Arduino Ide 2.0
- Google Colab
- Thingspeak
- MIT App Inventer

Abstract

The world population is continuously growing; for that reason, food demand is increasing, and hence more crop production is required. Mainly, there are two options to achieve a desirable food supply: either expansion of agricultural lands, which requires huge resources, or improving the crop yield with the ones we have efficiently. Precision agriculture has the potential to deal with this demand. To this End, the "RGB Sensor-Based Drone Imagery for Crop Health Assessment" aims to develop a system that utilizes drones equipped with RGB sensors to capture high-resolution images of agricultural fields and verified it through ground based sensors. These images are processed and analyzed to assess the health and condition of crops, providing farmers with objective data for decision-making. By leveraging advanced image processing techniques and machine learning algorithms, the system enables the extraction of key crop health parameters such as vegetation vigor and stress levels. The project also includes the development of a user-friendly interface for visualizing and interpreting the assessment results. Overall, this project offers an efficient and accurate approach to crop monitoring, empowering farmers to optimize agricultural practices and enhance crop productivity while promoting sustainable farming methods.

Table of Contents

List of Figures

List of Tables

List of Abbreviations

FYDP	Final Year Design Project
NDVI	Normalize Difference Vegetation Index
UAV	Unmanned Arial Vehicle
RGB	Red Green Blue
WSN	Wire Sensor Network
CHM	Canopy Height Model
OBE	Outcome Base Education
DEM	Digital Elevation Model
ITD	Individual Tree Detection
IOT	Internet of Thing

Chapter 1

Introduction

Agriculture is the lifeblood of Pakistan's economy. It produces about 18.5% of GDP, supports 64% of the rural population and employs 38.5% of the country's total labor force. Expansion of the agricultural sector depends on favorable climatic conditions. There is a close relationship between agriculture and climate, including temperature, precipitation, flooding and other weather factors, which ultimately affect economic performance such as agricultural production, commodity prices and economic growth. Moreover, the world's population continues to grow at a rate of approximately 1.1% each year. As the population grows, the need for food increases, resulting in higher prices for agricultural products. Population growth contributes to increased agricultural production and protection.

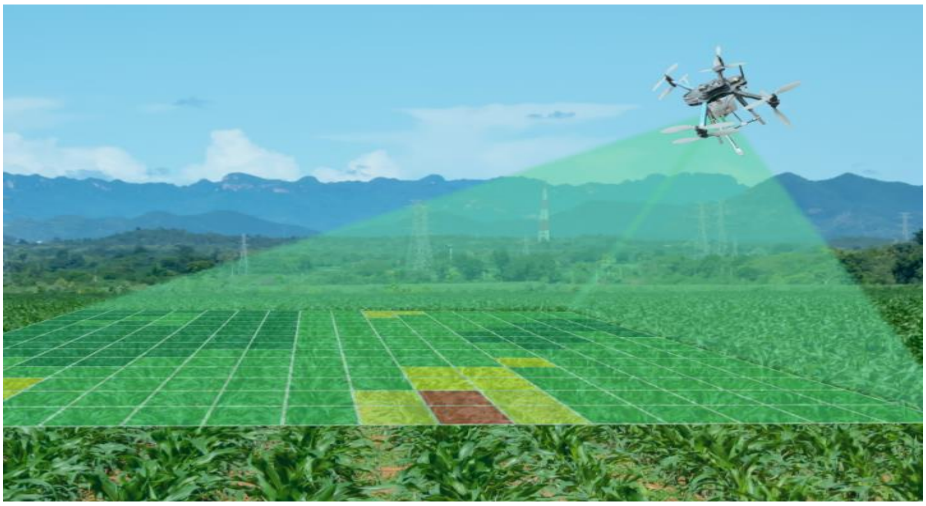

Figure 1 Application of Drone Imager for Crop Health Monitoring

So, broadly speaking, precision agriculture has the potential to deal with this demand. Precision agriculture, with its combination of information systems, smart machinery, sensors, computers, and good management, has enormous promise for addressing modern agriculture's demands. Drones, in particular, have emerged as an important instrument in this field's exploration. Drone technology developments, particularly those outfitted with Remote Sensing (RS) sensors and GIS technologies, have made them the main suppliers of agricultural information. Drones provide useful insights into crop health by utilizing vegetation indices obtained from acquired RGB data, allowing crop health maps to be generated. These maps are a valuable resource for farmers and agronomists, allowing them to make educated judgements on agricultural practices.

When conducting data collection campaigns, it is important to select suitable and accessible research sites. This ensures that the information collected is representative and relevant. Alternative crop health monitoring technologies exist, such as wireless sensor networks (WSNs), ground robots, and satellite imagery, but they often have drawbacks. WSNs have limited coverage and may not provide comprehensive data, ground robots may be limited due to geography and scalability, and satellite imagery may lack the requisite resolution and real-time capabilities.

UAV-based photography, on the other hand, gives a flexible and cost-effective elective for trim observing and administration. Rambles have the good thing about being exceptionally maneuverable, permitting them to effectively cover expansive agrarian districts. They can record exact, high-resolution symbolism, empowering precise edit well-being assessment. Besides, rambles can collect information in real-time, giving agriculturists and agronomists convenient data for speedy decision-making.

Aside from technological advantages, UAV-based images ensures easy access to agricultural information. Farmers can simply analyze and use drone data owing to intuitive crop health maps and vegetation indexes. This enables them to make more informed decisions, better allocate resources, and increase overall productivity.

In Conclusion, the combination of precision agriculture and drone technology offers a promising future for sustainable and efficient farming practices. Farmers and agronomists can take advantage of the flexibility, cost-effectiveness, and accessibility of UAV-based imaging to improve agricultural production, reduce environmental impact, and generate social and economic benefits. increase.

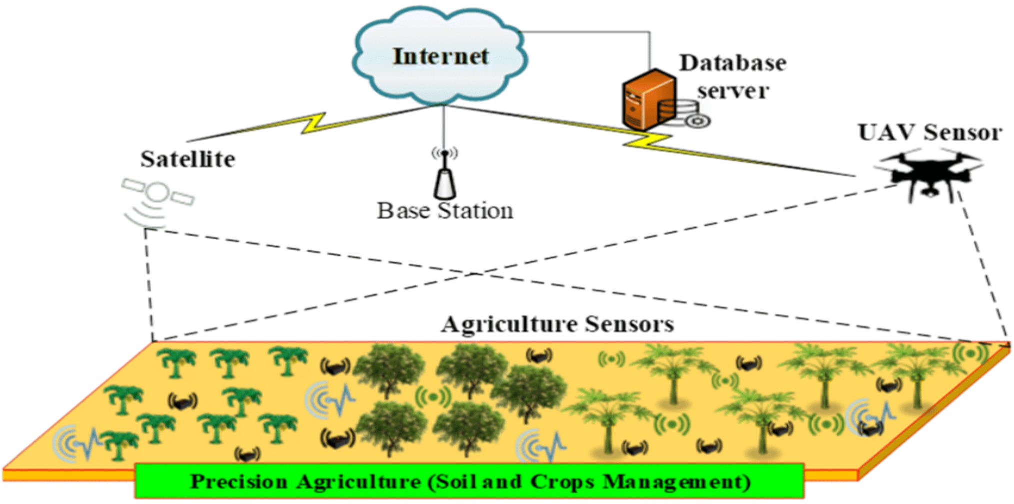

Figure 2 Precision Agriculture

1.1 Problem Statement

The population of the world is currently growing extremely fast. As the population grows, the demand for food also raises as a result the price of agricultural outputs increases. Another critical concern is the influence of climate change on farmers' ability to produce the food we all require. Weather volatility and extreme occurrences like floods and droughts change growing seasons, limit available water, promote weeds, insects, and fungi, and diminish crop output. Farmers cannot also supervise all farming tasks, which may result in areas of the site being left neglected, resulting in unneeded maintenance costs later on. In this scenario, precision agriculture has the potential to deal with this growing demand, which includes a set of tools that incorporate information acquisition, analysis, management, and deployment to help in making site-specific decisions, to maximize production while reducing environmental noise generated by the overuse of fertilizers and chemicals.

1.2 Objectives

The main objectives of this thesis are

- To retrieve real-time information on crop health.
- Monitoring at a large scale with a drone.
- To overcome the food deficiency problem
- To facilitate the farmer and agronomists.
- Real-time assessment for decision making

1.3 Motivation of Study

These research efforts were inspired by the growing demand for efficient and sustainable agricultural practices. As the world's population grows, there is a growing need to maximize crop productivity while reducing resource consumption, environmental impact and production costs. Traditional methods of assessing plant health often rely on time-consuming and labor-intensive manual assessments that are subjective, inefficient and prone to human error. These approaches also fail to provide complete real-time data on plant health.

This project aims to revolutionize crop monitoring and assessment in agriculture by leveraging the capabilities of drones equipped with RGB sensors. Traditional crop analysis methods frequently have disadvantages such as subjectivity, time consumption, and insufficient data. This research proposes a novel approach that use drones to gather high-resolution RGB imagery of agricultural fields, allowing for objective and data-driven crop health evaluation. The project aims to create a comprehensive system that integrates drone technology, RGB sensors, image processing algorithms and user-friendly interface. Drones outfitted with RGB sensors fly over agricultural fields autonomously and record detailed imagery, providing a bird's-eye view of the crops. These photos are analyzed by powerful algorithms to extract important plant health parameters such as vegetation index, color change and stress levels. Nonetheless, drone imaging with RGB sensors has the potential to transform crop monitoring practices and increase agricultural production.

RGB sensors, which capture Red, Green, and Blue color information, have proven to be particularly valuable in crop health assessment. By analyzing the reflectance of light in these spectral bands, RGB sensors provide insights into key crop health indicators such as chlorophyll content, vegetation vigor, and stress levels. The precise color information captured by RGB sensors enables the identification of subtle variations in crop health, allowing farmers to take timely actions and implement targeted interventions.

In summary, the motivation of study RGB sensor-based drone imagery is the demand for efficient and sustainable agricultural practices. Traditional crop health evaluation approaches are time-consuming and lack real-time data. The goal of this project is to provide farmers with tools to accurately and timely assess the health of their crops using drones equipped with RGB sensors. Combining image processing techniques with machine learning algorithms enables meaningful data analysis. Finally, the goal of this research is to improve crop management practices, increase yields and reduce resource consumption in agriculture.

1.4 Significance of Study

The proposed research project is of great importance in the field of precision agriculture. Accurate, real-time assessment of crop health using drone-based RGB sensors and advanced image processing technology to enable farmers to make informed decisions about irrigation, fertilizer application and disease management We aim to be The integration of machine learning algorithms and wireless sensor networks enhances the system's capabilities and ensures the creation of reliable prescription maps for optimizing crop management practices. This research will contribute to advances in precision farming techniques that will ultimately lead to higher crop yields, less wasted resources and greater sustainability.

Chapter 2

Literature Review

This study evaluated the capabilities of UAV LiDAR and surface from motion photogrammetry for monitoring sugar cane growth in northeast Queensland, Australia. The study found that both techniques can accurately measure plant height throughout the growing season. Moreover, both methods found that the structural features of the crop changed as a result of the different nitrogen treatments. Only the Hover map LiDAR system provided sufficient ground signal to compare biophysical samples, confirming its superiority in correlating with optical remote-sensing data on sugarcane properties [1].

This study provides an in-depth investigation of the application of unmanned aerial vehicles (UAVs) and remote sensors in agriculture. It shows how UAV technology and sensor capabilities have grown to more accurately assess crop yield and quality aspects such as water conditions, nutrient stress, weed competition and soil properties. I'm here. Integrating UAV technology into agriculture enables real-time identification of problem areas in the field, enabling rapid corrective action. Additionally, UAVs offer researchers a non-destructive and efficient way to study phenotypic measurements and collect field data to improve agricultural quality. This assessment covers a number of UAV designs, sensor types, imaging capabilities, and practical applications in agriculture [2] .

This study provides an in-depth examination of the application of unmanned aerial vehicles (UAVs) and remote sensors in agriculture. It demonstrates how UAV technologies and sensor capabilities have grown, allowing for more accurate assessment of crop yield and quality aspects such as water status, nutrient stress, weed competition, and soil properties. By incorporating UAV technologies into agriculture, it is possible to identify problem areas in fields in real time, allowing for quick corrective operations. Furthermore, UAVs provide researchers with a non-destructive and efficient method of gathering field data for the study of phenotypic measures and the advancement of agronomic qualities. The evaluation covers numerous UAV designs, sensor kinds, image processing possibilities, and practical applications in agriculture [3] .

The study explores the use of unmanned aerial vehicles (UAVs) and remote sensing systems for hazelnut orchard management is investigated in this study. The goal is to provide a quick technique for calculating canopy area and height using UAV data. The research found a substantial linear relationship between projected canopy area and NDVI values generated from UAV pictures. Individual tree crowns can be identified using high-resolution imagery. Overall, this research demonstrates the utility of UAV-based remote sensing in enhancing hazelnut orchard management and resource efficiency [4] .

This article describes how UAVs can be used to automatically detect and monitor chestnut trees. Individual tree detection and multi-time analysis are achieved using vegetation indices, RGB and NIR bands, and canopy height models. This method provides high segmentation accuracy (over 95%) and can extract features such as number of trees, crown coverage, tree height, and crown diameter. This method replaces time-consuming field campaigns and allows for a quicker and more sustainable approach to managing chestnut orchards [5] .

This study addresses the use of inexpensive cameras mounted on unmanned aerial vehicles (UAVs) to measure the height of mottled canopies. The UAV captures very high resolution images (5 cm pixels 1) and uses automatic 3D reconstruction algorithms to create Orth mosaics and digital surface models (DSMs). Field measurements of tree height were taken for validation and the results showed a high correlation (R2 = 0.83) with a root mean square error (RMSE) of 35 cm. This study also investigated the effect of spatial resolution on the photo reconstruction process and found a strong association between pixel resolutions of 5 cm and 30 cm. Overall, this study shows that using civilian cameras on UAV platforms for accurate tree height estimation is comparable to more expensive LIDAR (light detection and ranging) systems [6] .

This work describes a structure-from-motion method for automatic single tree detection (ITD) that employs a low-cost civilian camera coupled to an unmanned aerial vehicle (UAV) and a canopy height model (CHM) produced from the UAV. Consider using the structure-from-motion (SfM) algorithm. The study was conducted in a private forest in Wyoming, and the system detected trees with an accuracy of over 85%. The researchers investigated the effects of fixed tree window size and smoothing window size on his ITD accuracy and found an inverse relationship between tree density and window size. This result suggests that his UAV-derived CHM can be used to perform his ITD with reasonable accuracy, and that it may improve studies on ground biomass and stem volume estimation using UAV imaging [7] .

In this study, the authors used LiDAR and image sensors mounted on a multi copter UAV to identify microscopic changes in crops. This helps optimize fertilizer management and maximize yield. Ultimately, these innovative technologies will increase the social, economic and environmental benefits of the sugar cane sector. [8]

The purpose of this study is to investigate the use of a UAV-mounted civilian RGB camera for estimating sugar cane yield. The aim of the study is to improve the accuracy of yield estimation by mapping geographical variations in plant height (PH) and stem density using an object-based image processing approach. By subtracting the Digital Elevation Model (DEM), the

UAV imagery is used to build the Plant Surface Model (CSM) and Plant Height Model (PHM). PHM significantly improves classification accuracy, and PH values predicted by UAVs are closely related to ground measurements. Build a regression model using the nutrient index (VI) to estimate millable stem height (MSH), weight, and stem density. Yield is estimated by combining pH, stem density and weight data. The yield is estimated by combining PH, stalk density, and weight data. The results suggest that precisely mapping PH and stalk density has promising potential, with the anticipated output nearly matching the actual harvest yield. This method can aid growers and millers in making decisions [9] .

The purpose of this study is to estimate sugar cane production using a machine learning approach based on UAV LiDAR data. Sugarcane is essential for the production of sugar and renewable bioenergy, and accurate yield assessment is essential for effective agroecosystem management. Using his LiDAR mounted on a UAV, he measured the height and fresh weight of sugarcane plants at 105 sampling points in Fushui County, Chongzuo City, Guangxi Province, China. Field measurements revealed a number of factors. Six regression methods were tested to develop an above-ground fresh weight (AFW) model for sugar cane. Random forest regression (RFR) outperformed the other methods in terms of prediction accuracy (R2 = 0.96, RMSE = 1.27 kg m2 [10] .

This study focuses on creating a self-directed segmentation and classification procedure for mapping crop species in southern Brazil using multi-temporal Landsat-8 data. Manually setting segmentation parameters in object-based image analysis (OBIA) can be a time-consuming and subjective task. To solve this problem, the authors propose a supervised segmentation method that combines segmentation and classification tasks. This approach uses a predefined set of manually interpreted training samples to identify suitable segmentation parameters that are optimized for subsequent classification. His Landsat 8 photographs, site visits and very high resolution photo analysis from August 2013 and January 2014 were used to evaluate the method. The results show that the classification accuracy is high, reaching an overall accuracy of 80% for the following five crop classes. Sugarcane, soybeans, cassava, peanuts, etc. According to the results, sugarcane and soybean were classified best, whereas cassava and peanut were misclassified due to spatial and temporal similarities and within-class variability. Surprisingly, the Random Forest classification margin efficiently uncovered the misclassified pixels. This result demonstrates the potential of the proposed workflow for accurately mapping crop species using remote sensing data [11].

The purpose of this research article is to identify weeds in sugarcane fields using photographs taken by UAVs (unmanned aerial vehicles) and random forest classifiers. Weeds have a significant impact on sugarcane productivity and are usually controlled by herbicide treatments. However, traditional sampling methods used to determine herbicide type and dosage can pose problems as they may not provide a consistent picture of weed presence and species across fields. there is. Analysis of satellite imagery was used instead, but was limited by weed infestation and clear skies. In this study, the authors demonstrate how to use image pattern recognition based on photographs taken by UAVs. By photographing plants up close, With this method, weed species can be detected with low abundance and without being affected by clouds. In preliminary tests, the system achieved an overall accuracy of 82% and a Kappa coefficient of 0.73, demonstrating its potential for effective weed screening in sugarcane fields [12] .

This study examines the use of high-resolution aerial and satellite imagery in precision agriculture to measure variability in crop growth and production. While most yield monitors only provide harvest time data, remote sensing photos captured during the growing season can provide yield maps for in-season and post-season management. This research examines image acquisition, processing, integration, and analysis approaches for image and yield data. Five case studies demonstrate how multispectral and hyperspectral aerial photography, as well as high-resolution satellite images, can be utilized to monitor agricultural output variability. Various image processing techniques, such as vegetation index, unsupervised classification, correlation and regression analysis, principal component analysis, and spectral decomposition, are employed in such instances. This research also investigates the advantages, disadvantages, and issues connected with various types of remote sensing images and yield mapping analytic methodologies..[13]

The purpose of this study is to track wheat growth using satellite and unmanned aerial vehicle (UAV) imagery in combination with soil properties. The study included four satellite images and eight UAV photographs of two wheat fields taken from early June to the end of July 2015. The aim was to track the growth of wheat stocks and study the relationship between satellite-based HIS NDVI and UAV-based Visible Zone Vegetation Index (VDVI) distinctions and soil measurements of grain protein content. They found that NDVI had the strongest correlation with grain protein content at the end of the wheat growing season, just one week before harvest. Furthermore, correlation studies between NDVI and VDVI showed good consistency during the early stages of wheat development. [14]

The purpose of this research is to extract vegetation information from visible photographs taken by unmanned aerial vehicles (UAVs). In this study, we examine the spectral characteristics of vegetation and non-vegetation regions in UAV photography, especially the red, green, and blue bands. It is worth noting that vegetation has a higher reflectance in the green band than in the red and blue bands, while the devoid of vegetation shows a different reflectance pattern. Based on these characteristics and the spectral signature of healthy green vegetation, a new vegetation index called VDVI (Visible Difference Vegetation Index) is being developed. Line charts are used to create and analyze not only the VDVI index, but also other vegetation indices such as EXG, NGRDI, NGBDI, and RGRI. You can see that NGRDI is not suitable for vegetation extraction due to the overlapping values. [15]

This study presents an in-depth survey of the current situation and potential issues associated with deploying wireless sensor networks (WSNs) in agriculture. Explores applications, devices, sensors and communication methods related to his WSN in agriculture. Case studies are provided from both Indian and global contexts. Examine existing solutions and identify opportunities for improvement and future projects using the latest technologies. The purpose of this study is to describe the potential and limitations of WSNs in agriculture and guide future research and development in this field. [16]

Chapter 3

Block Diagram and Hardware Module

In this chapter, we describe the block diagram and hardware module of our thesis titled "RGB Sensor based drone imagery for crop health assessment." This chapter provides an overview of the essential components and system architecture, as well as insights into the integration of RGB sensors and drone technology for accurate crop health evaluation.

3.1 Project Block Diagram

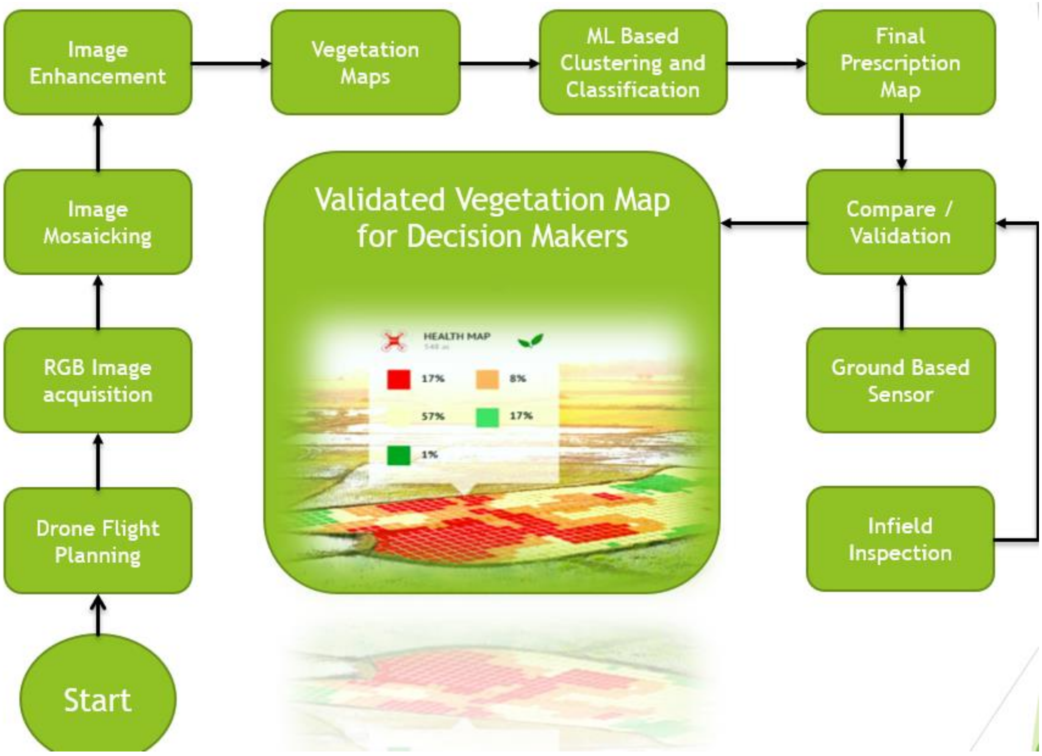

Figure 3 Project Block Diagram

In the start of our project we have made a proper flight plan to fly the drone on a particular area at the agricultural site. After that, we have done the step of RGB Image acquisition in which the multiple images has been captured by the drone. Furthermore, we applied image processing techniques on the multiple images captured by the drone which includes image mosaicking and image enhancement. In the process of image mosaicking we stich multiple images into one large image. The large image has been enhanced in the process of image enhancement which enhances the different attributes of the image. After that, we created Vegetation Map by using RGB Vegetation Indices which can tell us about the crop health parameters. K-means clustering has been applied to classify the data and generate a final prescription map that provides valuable information about crop health. The accuracy and durability of this map has been verified through a WSN and infield inspections conducted via a mobile application developed using an app. The sensor values collected by the drones are transmitted to the ThingSpeak cloud platform using ESP32 Wi-Fi modules and are subsequently utilized by the mobile application for analysis and interpretation.

3.2 Hardware Modules

Hardware modules or systems contain all the necessary devices we used in our project to make it applicable for RGB Sensor-Based Drone Imagery for Crop Health Assessment and complete our respective goals by achieving our project objectives.

3.2.1 DJI Mavic Mini Drone

The DJI Mavic Mini drone is a small, lightweight aerial photography and filmmaking platform. It has a number of qualities that make it appropriate for obtaining high-quality pictures for crop health evaluation. The DJI Mavic Mini's characteristics and essential features are listed below.

Figure 4 DJI Mavic Mini

- **Design and Portability:**

The DJI Mavic Mini is foldable, making it easy to carry and store. Weighing just 249 grams, it is below the weight required for registration in many countries. This makes it extremely portable and convenient for use in the field.

- **Flight Performance:**

Four brushless motors ensure stable flight and maneuverability of the drone. Supports both GPS and GLONASS satellite positioning systems for accurate positioning and navigation. The maximum flight distance is about 4km, which is sufficient for crop evaluation.

- ## Camera:

Mavic Mini has a built-in camera with a 1/2.3-inch CMOS sensor and a 12-megapixel resolution. It can capture still images in JPEG format and record 2.7K resolution video at 30 frames per second. The viewing angle of the camera lens is 83 degrees, allowing you to shoot with a wide field of view.

- **Intelligent Flight Modes:**

Drones can provide various intelligent flight modes to increase the efficiency and effectiveness of data collection. These modes include QuickShot (a pre-programmed flight path for capturing cinematic footage), Dronie, Circle, Helix, and Rocket. It also supports "CineSmooth" mode, which slows down the movement of the drone to achieve smoother and more accurate images.

- **Flight Control and Safety Features:**

The DJI Fly app enables intuitive flight control from your smartphone or tablet. It provides features such as Auto Takeoff, Landing, and Return to Home (RTH) functionality. The drone has built-in obstacle avoidance sensors to ensure a safer flight and minimize the risk of collisions. .

- **Battery Life:**

Mavic Mini is equipped with a 2400mAh Intelligent Flight Battery. A full charge provides up to 30 minutes of flight time, allowing for longer aerial survey missions. The battery can be easily replaced and recharged, providing flexibility for long-term field deployments.

- **Remote Controller:**

The drone comes with a dedicated remote control that provides a reliable and responsive connection. The controller features a compact design with a detachable joystick for easy storage and portability. It features a smartphone holder for attaching mobile devices for live video streaming or flight control.

3.2.2 ESP 32 Microcontroller

The ESP32 microcontroller has gained significant popularity in the field of embedded systems and IoT (Internet of Things) due to its powerful features and versatility. Built on the Xtensa LX6 dual-core processor, the ESP32 offers high computational capabilities and a wide range of built-in connectivity options, including Wi-Fi and Bluetooth. Its ample GPIO pins, memory resources, and energy-efficient design make it suitable for various applications, from sensor integration to data processing and wireless communication. With extensive development support and compatibility with popular programming platforms, the ESP32 provides a robust foundation for developing innovative projects in the realm of IoT and embedded systems.

In our system, we establish a seamless connection between the soil moisture and DHT11 sensors using the ESP32 microcontroller, allowing for reliable communication and real-time readout of their respective readings. This connection delivers critical data inputs for accurate crop health evaluation and enables prompt agricultural decision-making.

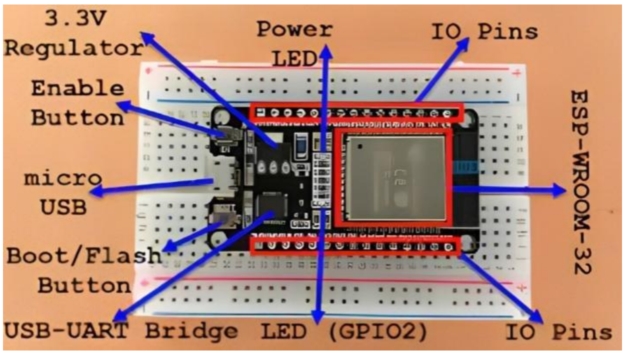

Figure 5 ESP 32 Microcontroller

3.2.3 DHT 11 Sensor

A DHT11 sensor module is used to measure temperature and humidity. It can be used in a wide range of applications, including weather monitoring, home automation, and agricultural applications. In our project, we use a DHT11 sensor module having operating voltages ranging between 3.3V to 5.5V DC. The DHT11 sensor has low power consumption and requires an average current of around 1-2 mA during operation. The DHT11 sensor can measure temperature in the range of 0°C to 50°C with an accuracy of ±2°C. The DHT11 sensor can measure relative humidity in the range of 20% to 90% with an accuracy of ±5%.

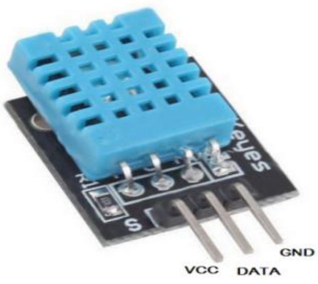

Figure 6 DHT 11 Sensor

3.2.3 Soil Moisture Sensor

Soil moisture sensors are essential components for agricultural and environmental monitoring applications. Specifically designed to measure soil moisture levels, providing valuable insight into irrigation management and plant health assessment. Our project uses a soil moisture sensor to accurately measure the water content in the soil. The sensor operates over a voltage range of 3.3 V to 5.5 V DC, making it compatible with many microcontroller systems. The low power consumption and average current of around 1-2 mA ensure that the sensor works efficiently. The ability to measure soil moisture over a wide range with reliable accuracy enables precise monitoring and control. Data collected by soil moisture sensors help optimize irrigation methods, conserve water resources, and promote healthy plant growth

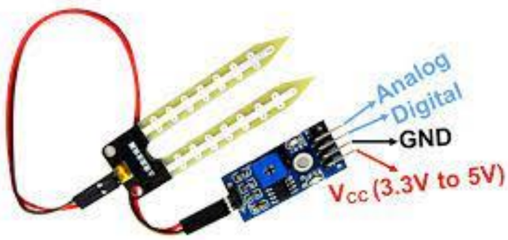

Figure 7 Soil Moisture Sensor

3.2.4 3.7 V 850mah li-ion battery

The 850mAh rechargeable lithium-ion battery serves as a reliable and efficient power source for various portable electronic devices and applications. With its compact size and high energy density, the battery offers extended usage time and increased convenience. In our project, we employ an 850mAh rechargeable lithium-ion battery to power our system, ensuring a stable and long-lasting power supply. This battery's capacity enables prolonged operation, while its rechargeable nature allows for multiple charging cycles, reducing the need for frequent battery replacements. The use of the 850mAh rechargeable lithium-ion battery enhances the portability and sustainability of our project, providing a dependable power solution for our device.

Figure 8 Lithium Ion battery

3.2.5 TP4056

The TP4056 is a popular integrated circuit (IC) used for battery charging and power management applications. Specifically developed to efficiently and safely charge single-cell Lithium-Ion or Lithium-Polymer batteries. The TP4056 IC has various features that make it suitable for portable electronics and low-power applications. It supports charging currents up to 1A and offers adjustable charging parameters, providing flexibility when charging different battery capacities. The TP4056 also features overcharge and over-discharge protection mechanisms that protect the battery from potential damage. Its compact size, ease of use, and cost-effectiveness make the TP4056 ideal for projects requiring battery charging and management capabilities

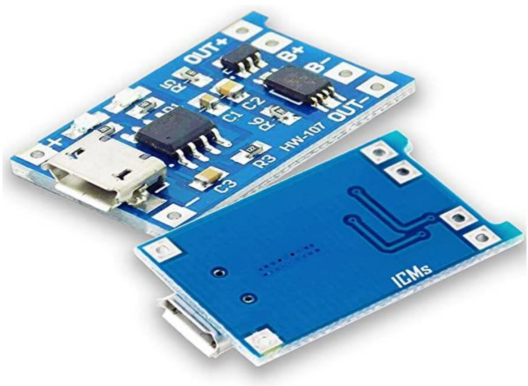

Figure 9 TP4056

3.3 Study Area

The initial testing for our project was done in the field on our university's campus. However, due to unanticipated factors, we ran into some constraints that prohibited us from carrying out the testing in the academic field. Given these obstacles, we took the initiative to seek alternatives that would allow us to continue our research. We asked the Department of Electrical and Computer Engineering for help with the testing phase of our research, and with their help, we produced a letter sent to the Director of the National Agricultural Research Centre (NARC). In this letter, we explained our predicament and asked for permission to do our testing in their agricultural areas. We were glad to reported that NARC accepted our request. We were granted permission to do our testing in their facilities. They specifically designated a spring onion field for our research. This collaboration with NARC not only allowed us to continue our project smoothly, but it also given us a fantastic opportunity to operate in a real-world agricultural situation, increasing the practical significance and applicability of our work. With the field assigned to us at NARC, we immediately began our testing and data collection. We were obliged for this opportunity and appreciative to both our university's Department of Electrical and Computer Engineering and NARC for their assistance and participation in making this endeavor possible. We are convinced that our research in the spring onion area will be beneficial and it will provide vital insights and contribute to agricultural technology advancement.

Figure 10 Spring Onion Field (NARC)

Chapter 4

WSN Design and Implementation

A wireless sensor network (WSN) is a network of standalone sensor nodes that wireless connect to monitor the environment and collect data. Each sensor node is equipped with acquisition, processing, and wireless communication capabilities that enable the detection and monitoring of physical properties such as temperature, humidity, and light. Collected data is sent to a central location or base station for processing and analysis. WSN utilizes a distributed deployment of sensor nodes to enable remote monitoring and data collection from a variety of locations, including hard-to-reach areas and areas where wired infrastructure is impractical.

4.1 Why we use WSN?

To ensure their usefulness in decision-making, the accuracy and reliability of the vegetation map must be evaluated. Wireless sensor networks (WSNs) come into play here. A wireless sensor network (WSN) is a network of small, low-power wireless devices outfitted with sensors that may gather and send data from their surroundings. To check the accuracy of the vegetation map, we deploy a WSN over the same agricultural site that the map covers. Sensor nodes gather real-time data on environmental factors like as temperature, humidity, and soil moisture. We checked the map's correctness by comparing it to vegetation map generated using the Vegetation Indices. We have been confident in the map's correctness, if the vegetation map correlates well with the data collected by WSN. Disparities between maps and WSN data, on the other hand, may indicate flaws or limits in the map generation process. This validation method aids in the refinement of vegetation mapping techniques and the general accuracy of the resultant maps.

4.1 Block Diagram of Sensor Node

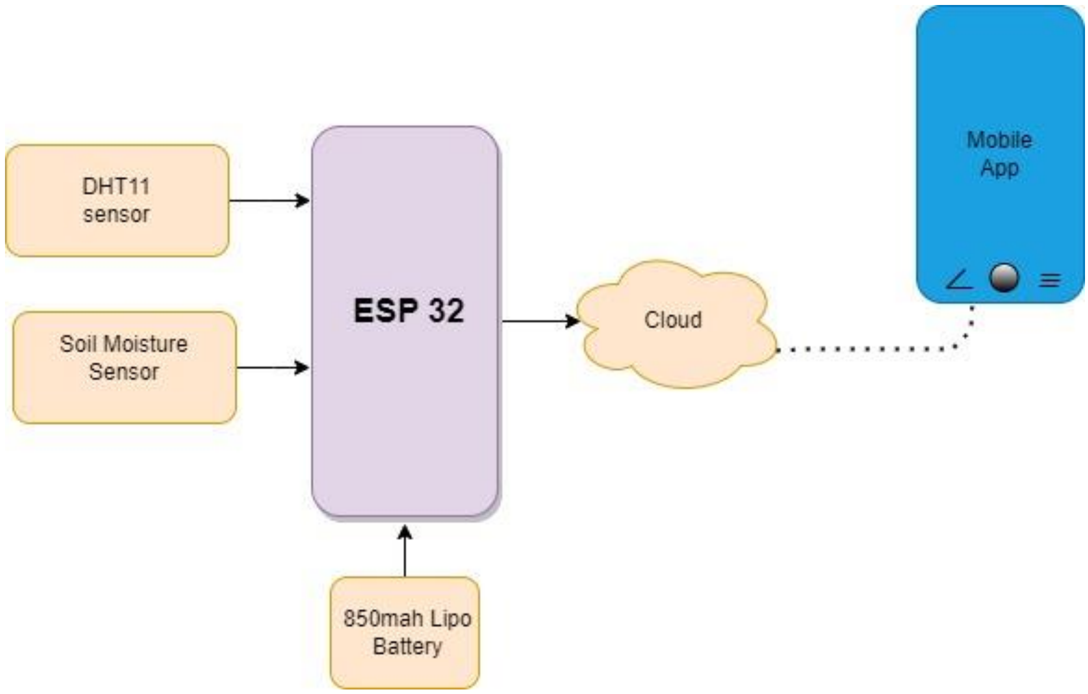

Figure 11 Block diagram of a single Sensor Node

A block diagram of a single sensor node consists of many components sucha as, DHT11 sensor that measures temperature and humidity, and a soil moisture sensor that measures soil moisture content. These sensors are connected to an ESP32 microcontroller and act as a central processing unit to receive and process sensor data. An 850 mAh LiPo battery powers the system. The ESP32 microcontroller then transfers the collected data to a cloud computing platform, the cloud, where the data can be further processed, stored and analyzed. Cloud computing enables centralized data management and centralized data access. Cloud data can also be streamed to mobile apps for real-time monitoring and viewing. Overall, the block diagram shows the flow of data from the sensor to the microcontroller, then to the cloud, and finally to the mobile app, demonstrating the connected nature of wireless sensor network systems.

4.2 Block Diagram of WSN

Wireless sensor network (WSN) block diagram shows the basic components and their interactions. The diagram illustrates the sensor nodes, which are outfitted with various sensors like as temperature, humidity, and soil moisture and serve as the data collection's backbone. These sensor nodes interact wirelessly with a central gateway, generally using Wi-Fi protocols. The gateway connects the sensor nodes to the external network, allowing for easy data transmission and integration with cloud platforms or monitoring systems for further analysis and decision-making. The block diagram depicts the WSN's hierarchical structure and communication flow, allowing for a more complete understanding of its operation.

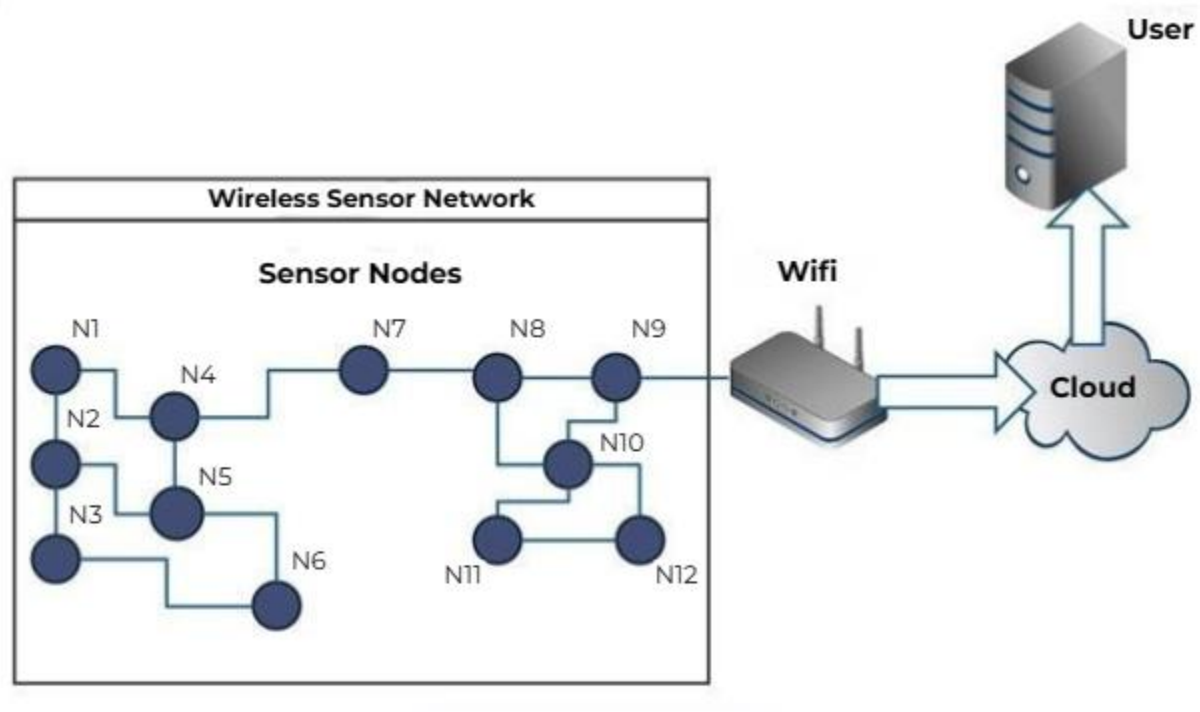

Figure 12 Block Diagram of WSN

In conclusion of this chapter, The block diagrams shown illustrate the architecture of both a single sensor node and the WSN as a whole. We construct a distributed and interconnected network of sensor nodes using WSN, allowing for efficient data collecting from numerous sites in the field. WSN utilization provides benefits such as real-time monitoring, enhanced spatial coverage, and cost-effectiveness, making it an ideal alternative for accurate and complete crop health evaluation.

Chapter 5

Software and App Development

This chapter delves into the Arduino IDE, which acts as the programming environment for integrating and managing our hardware components. We also go over the data transfer procedure to ThingSpeak for real-time data monitoring and analysis. Furthermore, we utilise MIT App Inventor to create a user-friendly smartphone application that allows farmers and agronomists to easily access and comprehend crop health information for optimal decision-making.

5.1 Arduino IDE

The Arduino IDE (Integrated Development Environment) is a software platform that allows users to programme and upload code to Arduino microcontrollers.

In the Arduino IDE, we create a code to connect the ESP32 microcontroller to the DHT11 temperature, humidity, and soil moisture sensors. We improve the functionality of our project and transfer the collected data to the ThingSpeak IoT platform using the WiFi.h, DHT.h, and ThingSpeak.h libraries. First, we use the WiFi.h library, which contains the necessary functions and methods for connecting the ESP32 to a WiFi network. We can connect the ESP32 to our local WiFi network, login with the network credentials, and establish an internet connection using this library. This link is required for data transmission to external platforms. Following that, we include the DHT.h library, which facilitates dealing with the DHT11 sensor. This library contains functions that simplify sensor communication, allowing us to read temperature and humidity data from the DHT11. We abstract the underlying difficulties and focus on utilising the obtained sensor data within our project by using the DHT.h library. In addition, we use the ThingSpeak.h library to transfer the data obtained to the ThingSpeak platform. ThingSpeak is an Internet of Things (IoT) platform that allows users to store, analyse, and visualise sensor data. We may connect the ESP32 to the ThingSpeak platform by incorporating the ThingSpeak.h library into our code. We can communicate temperature, humidity, and soil moisture data over this connection.

5.2 Data transmission to Thingspeak

Securely transmitting sensor data from a WSN to the ThingSpeak IoT cloud platform is part of the process of transmitting data to ThingSpeak. A ESP 32 microcontroller acts as an intermediary device to establish internet connectivity while the WSN's sensors collect environmental data. Collected data is sent to ThingSpeak via protocols such as Wi-Fi and

Ethernet and structured according to its specifications via RESTful APIs or MQTT. ThingSpeak records transmitted data, timestamps it, and allows it to be visualized in charts and graphics. ThingSpeak's API also facilitates data analysis and integration with other applications, providing users with real-time monitoring and data-driven insights for informed decision making. ThingSpeak's data transfer mechanism enables smooth interactions between WSNs and IoT cloud platforms, allowing users to maximize the value of their sensor data.

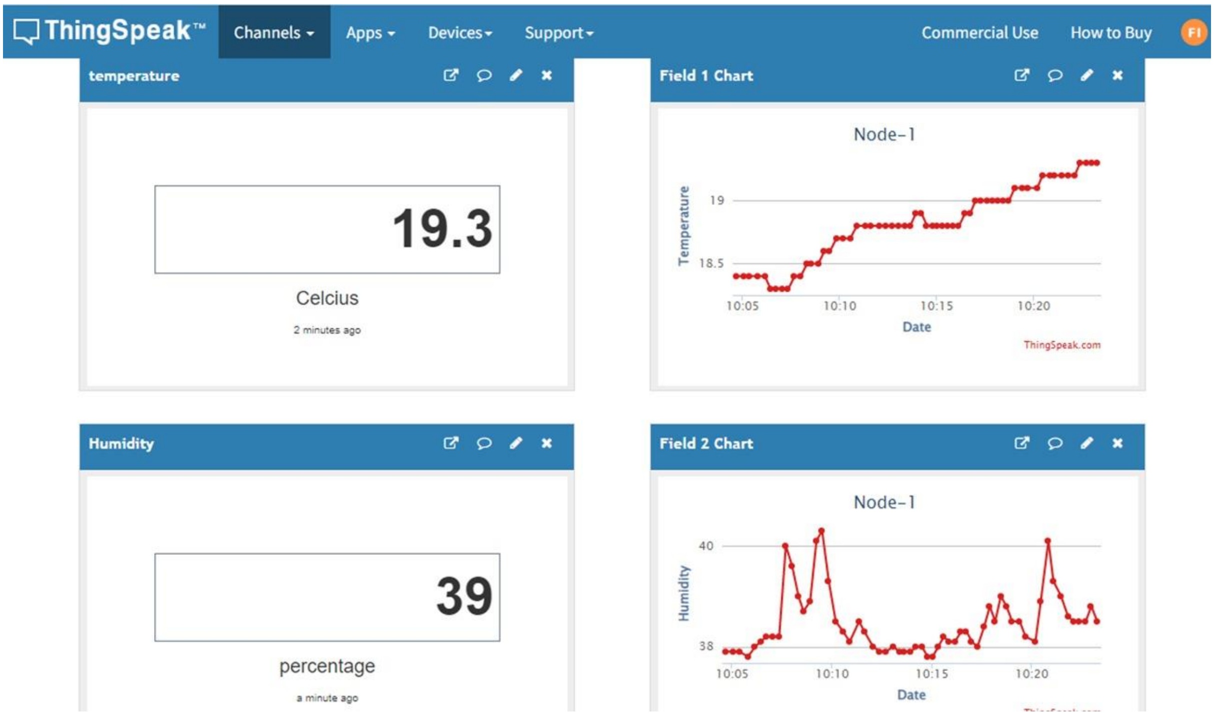

Figure 13 Temp and Humidity data visualization

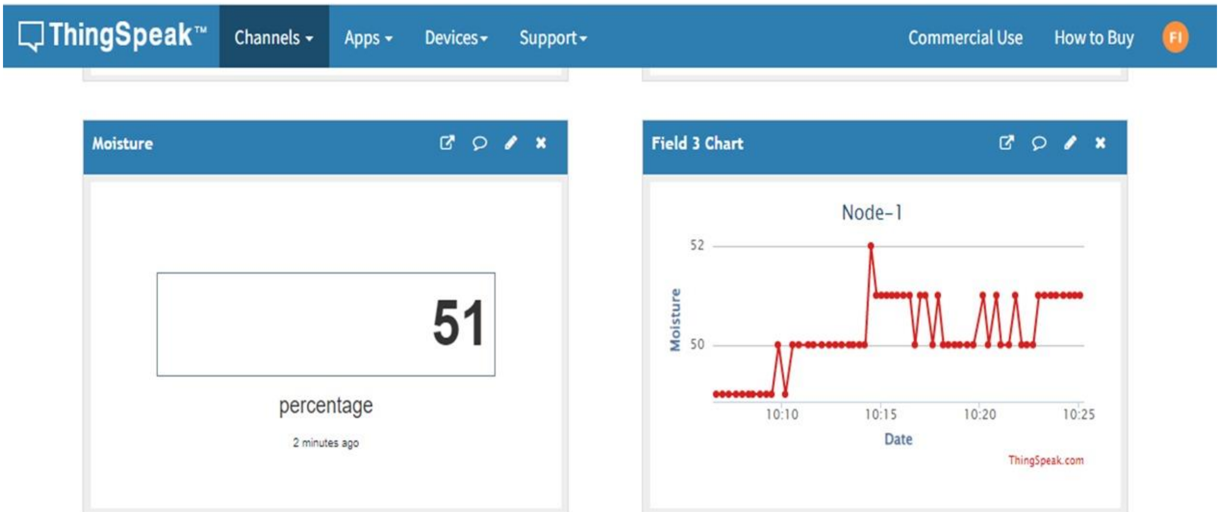

Figure 14 Soil Moisture data visualization

5.3 APP Development

Extend functionality by developing mobile applications with MIT App Inventor. This application serves as a user-friendly interface to access and display data collected by the ThingSpeak platform. Through the app, users can easily check real-time plant health parameters such as temperature, humidity and soil moisture on his mobile device. Data is retrieved from ThingSpeak's API and displayed in the app in a visually appealing and intuitive way. This will allow users to remotely monitor and track plant health.

5.3.1 User interface

Figure 15 App opening logo

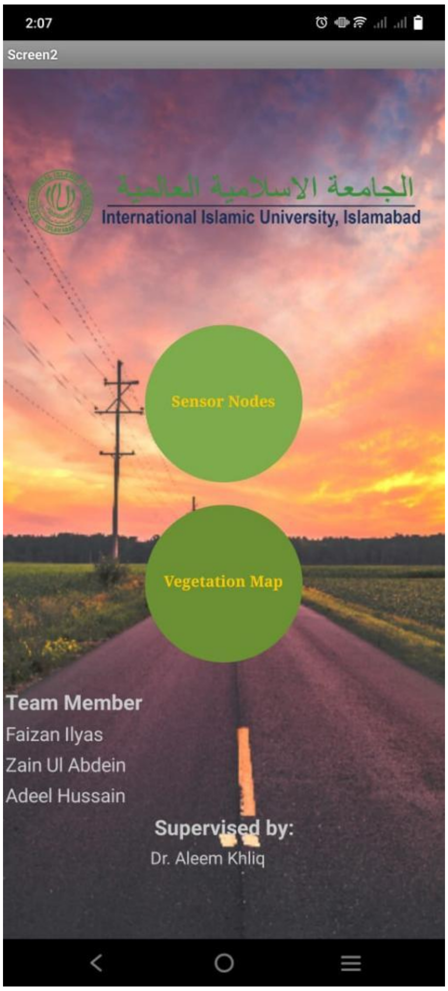

Figure 16 App interface

5.2.3 Mobile App Integration

Mobile app is integrated with an IoT cloud platform such as Thinkspeak. The app provides users with features such as data visualization, data logging, sensor configuration, and wireless sensor network (WSN) remote control. They may also include additional features such as historical data analytics, push notifications and data sharing options. The goal is to provide an overview of the app's functionality and provide a detailed understanding of how the app helps the user manage and operate her WSN.

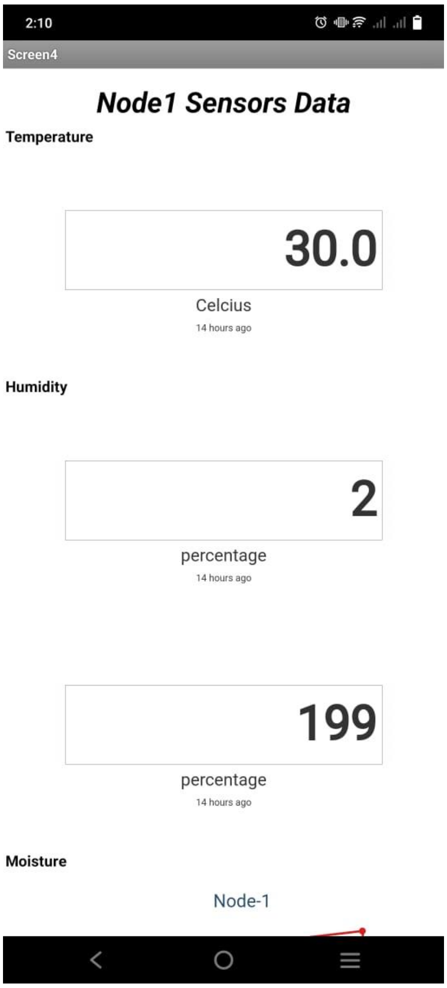

Figure 17 Numerical Visual in App

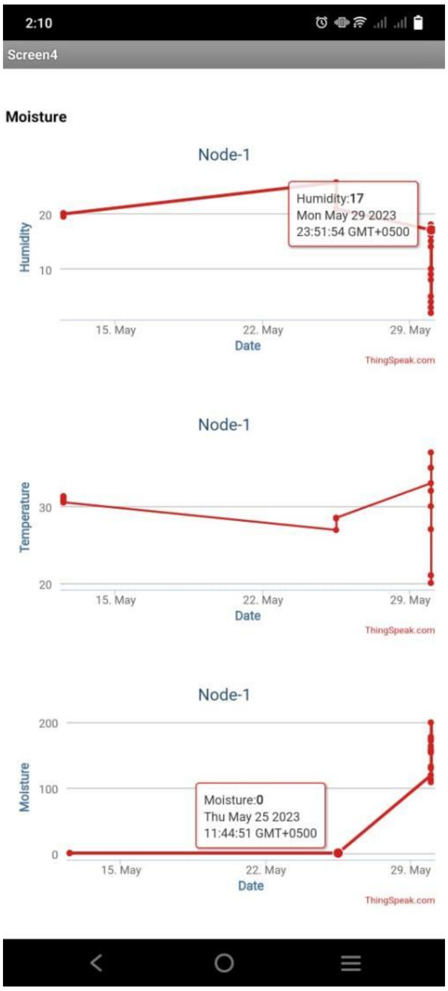

Figure 18 Graphical visual in App

In conclusion, We successfully programmed and managed our hardware modules using the Arduino IDE, ensuring reliable data gathering and integration. The use of data transmission to ThingSpeak enabled real-time monitoring and analysis of crop health indices. Furthermore, the creation of a user-friendly mobile application with MIT App Inventor increased accessibility and provided stakeholders with vital insights for informed agricultural decision-making.

Chapter 6

Vegetation Map Generation from RGB Imagery

Understanding plant health and assessing the general condition of agricultural land relies heavily on vegetation maps. A vegetation map is a graphical representation that provides important details about the location, quantity, and distribution of vegetation. Vegetation maps can be created by examining the spectral characteristics of imagery collected from RGB sensor-based drone data. Using image classification and segmentation techniques, his RGB image data from the drone's RGB sensor is processed to allow the identification and separation of different vegetation types and their associated health conditions. Generated vegetation maps display key data such as vegetation density, growth patterns, and areas of potential stress and disease. Farmers, agronomists and land managers can use it as a useful tool for making decisions about crop management, resource allocation and intervention tactics. Vegetation maps created by RGB sensor drone imagery improve precision agriculture by providing spatially disparate data, maximizing plant health assessments and increasing overall farm productivity.

6.1 Vegetation Indices and Analysis

The RGB Vegetation Index is a powerful tool used to assess and monitor vegetation health and vigor in remote sensing and precision agriculture. These indices are derived from red, green, and blue bands in digital images captured by sensors such as drones and satellites. By quantifying the relationship between reflectance values in these spectral bands, the RGB Vegetation Index provides valuable information on vegetation density, chlorophyll levels, and overall plant health. Our project uses the RGB vegetation index as a non-destructive and efficient method to assess plant health. By combining and analyzing RGB images taken by drones and image processing technology, it is possible to calculate and analyze various RGB vegetation indices and accurately understand the spatial distribution and state of plants. This information enables farmers and agro professionals to make informed decisions about irrigation, fertilization, and disease management, resulting in optimized crop yields and resource utilization.

6.2 Generation and Interpretation Vegetation Map

To create a vegetation map, we first need to segment the processed drone images into different plant classes using an image classification algorithm. The spatial distribution and density of vegetation are then examined to interpret the generated maps. This representation is enhanced by visualization techniques such as color mapping and contour overlays. Precision agriculture is enabled through interpretation that recognizes vegetation patterns, variability and health issues. Vegetation maps help optimize resource allocation, implement targeted interventions, and track overall productivity and farmland health.

Name	Equation	Reference
Modified Green Red Vegetation Index (MGRVI)	$(G)^2 - (R)^2 / (G)^2 + (R)^2$	Bending, et al. (2015)
Green Leaf Index (GLI)	$2G - R - B / 2G + R + B$	Louhaichi, Borman & Johnson (2001)
Modified Photochemical Reflectance Index (MPRI)	$G - R / G + R$	Yang et al. (2008)
Red Green Blue Vegetation Index (RGBV)	$G - (B + R) / G^2 + (R + B)$	Bending, et al. (2015)
Vegetativen (VEG)	$G / R^a + B^{(1-a)}$	Hague et al. (2006)
Excess of Green (ExG)	$2G - R - B$	Woebbecke et al.(1995)

a* = constant with value of 0.667; B=blue, G=green, R= red

Table 1 Vegetation Indices used in study

6.3 Acquired Images

We carefully planned to shoot airborne imagery with a DJI Mavic Mini 1 drone. We flew the drone at a height of 15 metres with meticulous preparation, ensuring optimal coverage of the entire 2.5 kanal field. We used a pace of 2 photos per second to acquire complete data, ensuring high-resolution imagery from multiple perspectives and places.

Following are some images that we acquired during drone flight:

Figure 19 Acquired UAV image 1

Figure 20 Acquired UAV image 2

Figure 21 Acquired UAV image 3

Figure 22 Acquired UAV image 4

6.4 Mosaic Image

To generate a smooth and complete representation of the entire area, we stitched various collected photographs together. We precisely matched and blended the separate photographs using Adobe Photoshop software to generate a single, large-scale image. We were able to overcome the limits of individual photographs by using this image mosaicking technique, which provided a panoramic perspective of the field, allowing for a more complete and comprehensive examination of crop health.

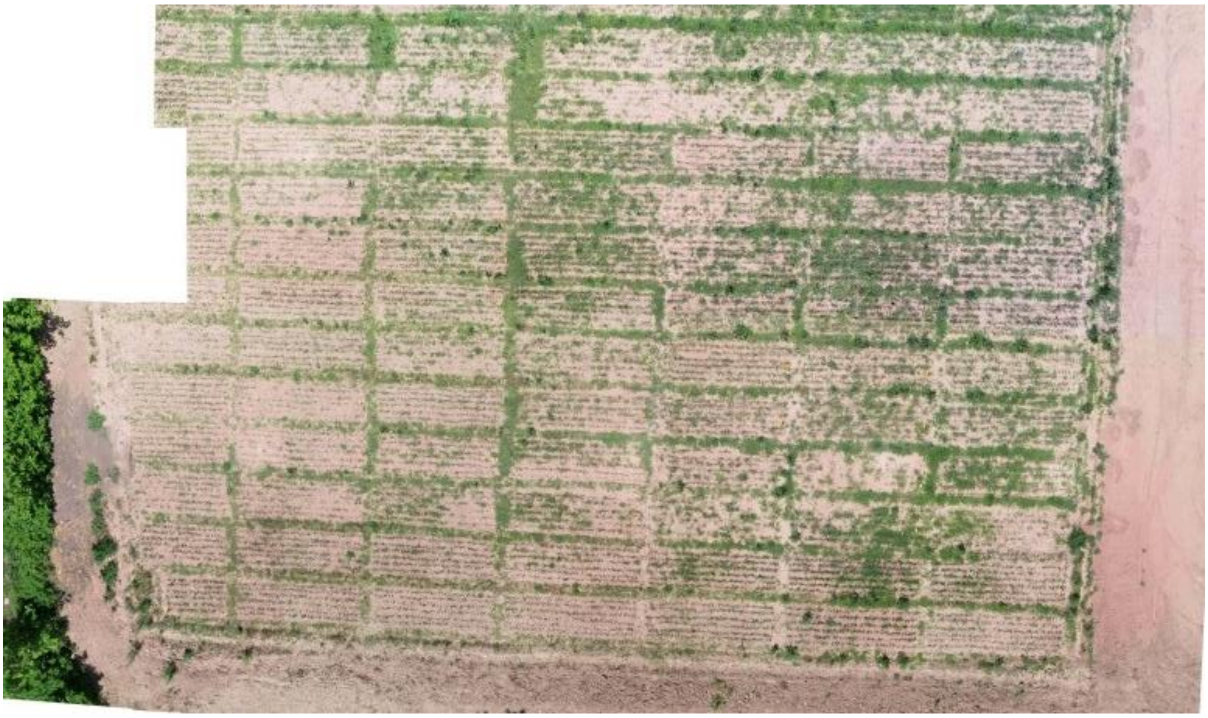

Figure 23 Mosaic Image

6.5 Vegetation Map

We used RGB vegetation indices on the resulting mosaic image and used a color mapping approach to create a map with distinct red, green, and yellow sections. The red color signifies area with unhealthy crop vegetation, whereas the yellow color denotes areas with moderate crop health. Green, on the other hand, shows healthy crop growth areas. This vegetation map depicts crop health distribution over the field, providing useful information for detailed analysis and decision-making.

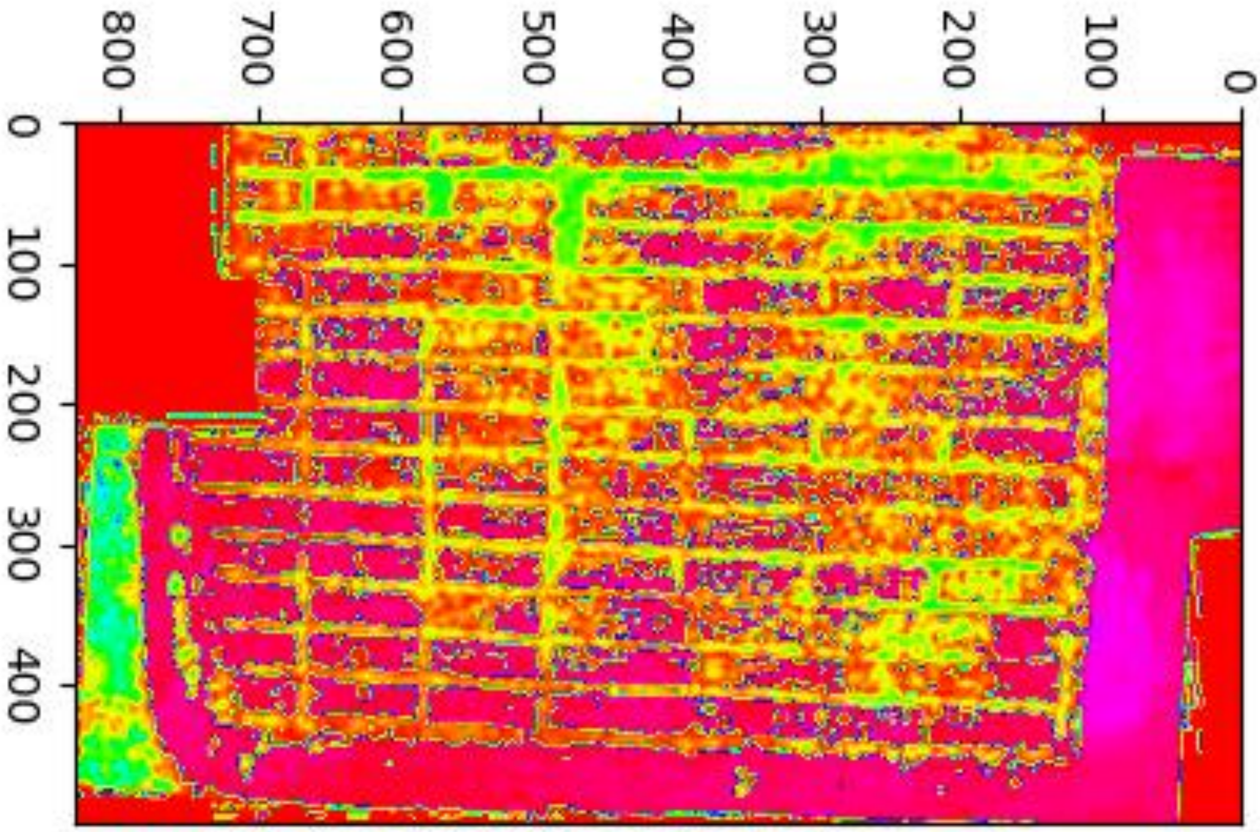

Figure 24 Vegetation Map

Healthy

Moderate

Non-Healthy

Soil

				Node 1		
			Node 2			
	Node 3					
					Node 4	
		Node 5				

Table 2 Grid

In field, we placed 5 nodes at different places for validation. At Node 1 and Node 2 we get 75 to 90% soil moisture, 16 to 29 Celsius temperature and humidity between 30-50% which is good for summer onion crops. And this same information tell us RGB Vegetation map, where we placed node 1 and node 2 in map this place map show green color its mean crop health is good at that place. Similar, at node 3 and node 5 we get soil moisture below 50%, temperature 38 to 45 Celsius and humidity is 18 – 25 % which is not good for summer crop, at this place crop health is not good and this sensor information is validate by RGB Vegetation Map at that specific area of crop map show red color. And same for yellow color in map where crop health is moderate and sensors value is also in between healthy and non-healthy. Hence, we validate the WSN to vegetation map.

Chapter 7

Future Work and Conclusion

7.2 Future Work

While this project has made major advances in crop health assessment through the use of RGB sensor-based drone imaging, there are various opportunities for future research and improvement. Among the potential areas for improvement and expansion are:

- **Integration of additional sensors**: Look into incorporating more advanced sensors, such as multispectral or hyper spectral sensors, to capture extra spectral data for improved crop health analysis.
- **Advanced machine learning algorithms**: Investigate the use of deep learning techniques, such as convolutional neural networks (CNNs), to increase the accuracy and efficiency of crop health assessment and prescription map production.
- **Real-time monitoring and decision support**: Improve the system by harnessing the capabilities of Internet of Things (IoT) and cloud computing technologies to provide real-time monitoring and decision assistance. Farmers will be able to obtain quick crop health updates as well as computerized recommendations for urgent actions.
- **Scaling and validation:**
  Further validation studies and field trials will be conducted to evaluate the scalability and accuracy of the system for different crop species, regions, and environmental conditions. Collaborate with agricultural research institutes and industry stakeholders to collect richer and more diverse data sets.

The RGB Sensor-Based Drone Imagery for Crop Health Assessment system can continue to expand and make major contributions to precision agriculture and crop management practices by addressing these areas for improvement and doing additional research. The project lays the groundwork for a more sustainable and efficient agricultural strategy, allowing farmers to make data-driven decisions, optimize resource utilization, and boost production.

7.3 Conclusion

In Conclusion, the RGB Sensor-Based Drone Footage for Crop Health Assessment project achieved its goal of creating a comprehensive system for analyzing and monitoring crop health using drone footage, image processing techniques, and machine learning algorithms. The project has demonstrated the effectiveness of using RGB vegetation indices derived from drone imagery to evaluate crop health parameters and generate prescription maps for optimized agricultural management. The research has given a strong framework for analyzing and visualizing the collected drone photos by integrating image mosaicking, image processing, and K-mean clustering approaches. The created prescription maps are useful tools for farmers and agricultural experts to make informed decisions about irrigation, fertilization, and disease management, resulting in increased crop output and resource efficiency. Furthermore, the integration of a wireless ground-based sensor network and infield inspection via a mobile app-enabled for prescription map validation and real-time data on crop health metrics. The software, created with MIT software Inventor, provides easy access to crop health information, allowing growers to remotely monitor and manage their crops.

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